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Visualization of uncertainty on climate change forecasts: The effects of emotional narratives and personal attitudes towards climate change on map understanding and map-based decision-making

GEO 511 Master's Thesis

Author
Sergio Bazzurri
15-915-333

Supervised by
Prof. Dr. Sara Irina Fabrikant

Faculty representative
Prof. Dr. Sara Irina Fabrikant

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Department of Geography, University of Zurich

Abstract

Climate change and its consequences are an impending challenge for our society and thus policymakers must take important decisions rapidly in order to mitigate the repercussions. Climate change data is confronted with uncertainties, as all kind of data is. This need to be effectively communicated, to both guarantee transparency of science, and allow the most informed as possible decision-making. Uncertainty is however a difficult variable to display on maps, with the effects of its visualization being still currently discussed by the scientific community. Further, in the divisive context of climate change, with segments of the population showing a sceptic attitude, the effect of such information is questionable. Finally, the effect of emotionally charged communication of uncertain information in this context is still investigated. In order to research how uncertainty visualization, emotions, and climate change attitudes interplay in the context of climate change forecasting maps, an empirical map-based online study with mixed factorial design has been developed. Using the rich pool of candidate participants offered by the recruiting platform of Prolific, 109 participants could take part to this study. Participants were either presented with an emotional stimulus together with a map, or without any emotional element and just the map. Drawing from the climate change forecasts in the Swiss Scenarios CH2018 for the year 2060, 18 map stimuli have been designed, using three climatic variables as basemap: summer mean temperature, summer mean precipitation, and number of hot days. Each type of map was presented either without certainty depiction, or with certainty represented in the form of a pattern of dots or lines. Participants were then exposed to all 18 maps in random order and performed a decision-making task, assessed the levels of certainty and severity of the depicted change, and provided their level of trust on the presented map. The results of the empirical study indicate that no significant effect of emotional narratives on participant performances subsists. This may be due to the ineffectiveness of the devised emotional stimulus to elicit strong emotional responses in participants. In contrast, a significant difference in the assessments of severity and trust given by participants depending on their climate change attitude is found. The trust for maps without certainty information is significantly lower than when this information is given for both climate change attitudes, with a stronger increase in trust by believing participants. Further, pattern-based depictions of certainty significantly increase the time required to complete the tasks. Future research should deepen the understanding of which emotional stimuli influence the understanding of climate change visualization and the influence of the different types of climate scepticism.

Keywords: Uncertainty, Uncertainty Visualization, Uncertainty Communication, Climate Change, Attitudes, Scepticism, Decision-making, Emotions

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Abbreviations

ANOVA	Analysis of Variances
ART	Aligned Rank Transformation
AS method	Average Score method
AT	Area Type
CCA	Climate Change Attitude
CET	Central European Time
GEW	Geneva Emotion Wheel
GIS	Geographic Information System
GIVA	Geographic Information Visualization and Analysis
IPCC	Intergovernmental Panel for Climate Change
IQR	Interquartile Range
M	Mean
MAD	Median Absolute Deviation
NE	No Emotion
NS method	Normalized Score method
RCP	Representative Concentration Pathway
RGB	Red Green Blue (a colour model)
SAM	Self-Assessment Manikin
SD	Standard Deviation
SE	Standard Error
SEW	Small Emotion Wheel
TEQ	Toronto Empathy Questionnaire
UVis^3	Uncertainty Visualization Cube
WE	With Emotion

1 Introduction

1.1 Motivation

Various researchers described the ongoing climate change as an urgent threat and a very tough challenge for our society (Battocletti et al., 2023; Herrando-Pérez et al., 2019; Poortinga et al., 2011; von Gal et al., 2024). A large amount of evidence is linking these climatic mutations to human related activities, such as greenhouse gases emissions from the burning of fossil fuels for heating, transport, and industry, as well as emissions due to land-use and land use change (IPCC, 2023). The consequences for the natural environments and ecosystems, the health and wellbeing of society, the human infrastructures, and the economic system in case of high magnitude climate change due to continued emissions at the current rate are expected to be dramatic and burdensome (IPCC, 2023). However, with proactive protective actions and the reduction of the emissions, it is possible to mitigate the effects of climate change and to adapt our society and infrastructures to the new climatic conditions and related issues (IPCC, 2023). Thus, faced with this impelling challenge, it is vital to communicate scientific findings on the matter efficiently and effectively, as well as suggestions and possible solutions, to both policymakers and non-experts, in order to act rapidly and resolutely on this regard (Battocletti et al., 2023). Several studies stressed the great importance of the transparent communication of scientific findings, which does include the proper communication of the uncertainties tied to those findings, being these in scientific reports addressed to policymakers, or in material to inform non-experts (Bhatt et al., 2021; EFSA et al., 2019; Kamal et al., 2021; Maier et al., 2016; Smith & Stern, 2011; Wardekker et al., 2008).

As Kamal et al. (2021) argued, uncertainty is a challenging and complex concept to fully comprehend that, nonetheless, cannot be simply ignored, otherwise the repercussions of this exclusion lead to erroneous or ambiguous decisions. Scientific research agrees that uncertainty is a difficult variable to display on maps with other variables for numerous reasons, such as increased complexity when reading and understanding the information displayed (Kinkeldey, MacEachren, et al., 2014; MacEachren et al., 2005). Hence, the challenge of how to effectively visualize uncertainty is a largely discussed topic in the scientific community (Kamal et al., 2021; MacEachren et al., 2005; Maier et al., 2016; Wardekker et al., 2008). The first researches and implementations on the subject took place in the field of Geographic Information Systems, and then extended to other areas, such as medicine, geography, or physics (Kamal et al., 2021). Despite the issues that are bound to uncertainty visualization, it is central for the credibility of science to put effort in the communication of this aspect, since uncertainty is a crucial element that policymakers feel the need to be informed about in order to be able to take sensible decision (EFSA et al., 2019).

According to McMahon et al. (2016), the perception of uncertainty is heavily influenced by the way it is displayed. Evidence for differences in the effects of a visualization on the performed tasks were identified in numerous studies in the review by Kinkeldey et al. (2017), where for instance, they noted that different uncertainty depictions had different effects for aspects such as the decision performance or risk assessment. Thus, those differences call for attention when the goal of the representation is to increase the understanding of the depicted information or the decision-making process, in order to avoid introducing biases due to the chosen representation (Kinkeldey et al., 2017). Other instances of dissimilarities in the outcomes of decisions due to different visualization are reported by Retchless & Brewer (2016), that have highlighted how the user’s performance in ranking the temperature change and uncertainty of various regions on a climate change map does change due to different uncertainty depictions. Similarly, Schneider et al. (2022) remarked that the accuracy in reading the uncertainty differed depending on the visualization the participants saw. Likewise, in the study of Ruginski et al. (2016), the various uncertainty visualisation types led the participants to assess differently the damage done by the passage of hurricanes, with participants reporting diverse heuristics and reasonings for their evaluation depending on which types of visualization was proposed.

Uncertainty is found in almost all kinds of data and fields of research (Kamal et al., 2021), and therefore climate change is not an exception (Moser, 2010). In the climate change forecast maps by the Intergovernmental Panel for Climate Change (IPCC), the depiction of uncertainty and the problematics related to its depiction have been a discussed issue by various studies; on the one hand with efforts to understand the cognitive processes related to the understanding of visualizations and on the other hand with the aim to develop suggestions and guidelines for scientists to enable an efficient communication (Budescu et al., 2012; H. Fischer et al., 2020; Harold et al., 2016, 2020; McMahon et al., 2016; Molina & Abadal, 2021). In the Swiss context, a scientific taskforce in 2018 released the Swiss Climate Change Scenarios (CH2018, 2018; NCCS, 2018b), which forecasted possible future developments of climate change for Switzerland. However, in those forecasts the uncertainty is not directly represented in the maps themselves, but instead different scenarios with varying levels of confidence are presented, e.g. lower estimate and upper estimates. Besides, the informative material of the Swiss Scenarios also contains the depiction of some characters, with the intention to give a human face to the data and the changes depicted (NCCS, 2018b).

The depiction of characters or narratives may then provoke emotive responses in the end-users of those maps. The influence of emotions in the process of decision-making and on approaching concepts as uncertainty or risk has been often highlighted (Bloodhart et al., 2018; Zinn, 2016). Zinn (2016) argued that to some degree there are almost always emotions involved in decisions, either as the main drivers or as an accompaniment or complement to the decision strategies of an individual. Moreover, as illustrated by Marx et al. (2007), the presentation and description of facts and events in a more personalized and emotive way, compared to an abstract or statistical description (Grupe & Nitschke, 2011), induces an increased attention and engagement, and may amplify risk perceptions. N. Smith & Leiserowitz (2014) equally highlighted that emotions can lead to increased attention and thus to process and analyse more carefully the data presented. Additionally, Hengen & Alpers (2021) stated that there is convincing evidence that stress and anxiety occupy cognitive resources during information processing, while Grupe & Nitschke (2011) noted that uncertainty amplifies the negative impact of aversive events in the perception of people.

Another aspect to consider concerns the effects that uncertainty visualization has on the trust of users on the model outputs, and consequent decisions based on those outputs, which is still a discussed topic, with results indicating both increase as well as decrease in trust, acceptance, and willingness to follow the model (Gustafson & Rice, 2020; Joslyn & Leclerc, 2016; Leffrang & Muller, 2021). While Leffrang & Muller (2021) found that more salient visualization of uncertainty lead to decreased willingness of participants to follow the forecasts, Joslyn & Leclerc (2016) detected a slight increase of trust when uncertainty is visualized, even for people with a more conservative attitude. Gustafson & Rice (2020) argued that uncertainty due to disagreement in the scientific consensus causes detrimental effects, while uncertainty deriving from technical reasons does tendentially cause neutral or positive effects on the public. Karduni et al. (2021) found instead, that participants exposed to uncertainty visualization showed less change of belief, thus maintaining their prior belief. Further, Cliburn et al. (2002) reported that some participants of their study argued that uncertainty could be used to dismiss or downplay the predicted outcomes of a model. Furthermore, many studies indicated that the attitudes that an individual holds towards climate change have an effect in their actions and what they decide to support (Howell et al., 2016; van Valkengoed et al., 2021; van Valkengoed & Steg, 2019). Given that the topic of climate change is a highly divisive and polarized one, with a fraction of the population having a sceptic stance towards it, the way in which climate change and its uncertainties are communicated plays a significant role in the population acceptance of climate change mitigation and adaptation measures (Capstick & Pidgeon, 2014; Corner et al., 2012; Howell et al., 2016; Jylhä & Hellmer, 2020; Marlon et al., 2019; Poortinga et al., 2011).

1.2 Research Gap and Goal of the Thesis

As outlined in the previous chapter, uncertainty is a central but at the same time complex concept in scientific research, both to understand and to effectively communicate or visually display. Moreover, it has been remarked how there are numerous factors that play important roles in the process of decision-making and in dealing with uncertainty, such as the emotions and the attitude of each individual. Further, as Kinkeldey et al. (2017) called for, there is the need to deepen the understanding on the cognitive processes and the factors that influence the decision-making process when uncertainty is visualized. Moreover, Kause et al. (2021) stressed the need of more research on understanding how users respond to the communication of climate change uncertainty and which factors play a role in this process. There seems to be a lack of research in the field of uncertainty visualization for what concerns effects of emotional narratives on the interpretation of uncertainty in climate change maps, as well as their interaction with individual attitudes towards climate change. There is thus a research gap in the understanding of how those factors interplay in the reading and understanding of maps with uncertainty display. Hence, inspired by the depiction of the characters in the Swiss Scenarios CH2018 (NCCS, 2018b), my thesis aims to investigate how an emotional narrative and the climate change attitudes of participants influence their reading and understanding of climate change maps with different uncertainty visualizations. To achieve the goal to deepen the current knowledge on the role and effects of emotions and attitudes in the context of climate change uncertainty display, an empirical study has been developed, with both map and emotional stimuli, where participants had to complete tasks on map understanding and interpretation.

1.3 Research Questions

On the ground of the stated goal and motivation of the thesis, as well as the aforementioned research gaps, the following three research questions were formulated. These research questions will be answered in the course of this work. The first research question aims to investigate the effect of emotions, evoked in the form of images and narratives, in the sensitive context of climate change communication and the understanding of its uncertainty, to see how they affect the interpretation of the presented information.

Research Question 1

How does the presence of an emotional narrative in the presentation of climate change maps with (or without) uncertainty depiction affect a user's interpretation of the map, with respect to the severity of the climatic variable change and its uncertainty?

With the second research question it is intended to investigate the influence of the personal attitude towards climate change in the interpretation and level of trust of climate change related information and how it does interact with the display of uncertainty.

> **Research Question 2**
>
> *How does the individual attitude towards the ongoing anthropogenic climate change (sceptic/oppositive vs believing/supportive) affects the user's trust and interpretation of a climatic variable and its uncertainty visualized on a climate change map with (and without) uncertainty depiction?*

The third research question aims to give more insights into the effects of different uncertainty visualization methods on the ability of users to understand in the map both the uncertainty and the underlying variable and thus identify which visualization does allow a better comprehension.

> **Research Question 3**
>
> *How do different ways of representing uncertainty on climate change forecast maps affect user's trust and perception of the climatic variable change and its uncertainty?*

1.4 Hypotheses and Expectations

Based on the posed research questions the following hypotheses were formulated.

> **Hypothesis 1**
>
> *The emotional narrative in the presentation of climate change maps with uncertainty visualization will lead the participants to invest more time in the evaluation of the maps and cause them to overestimate the change and the uncertainty of change.*

> **Hypothesis 2**
>
> *Participants already having a sceptic attitude towards climate change will tend to underestimate and trust less, in contrast to participants with a believing attitude, the climate changes depicted in the maps, however when uncertainty is visualized, this effect is decreased.*

Hypothesis 3

The different uncertainty visual representations lead to different level of trust and different interpretations of the users in the severity degree of the depicted change, as well as of the uncertainty of the change.

Based on the hypotheses outlined above, the expected outcomes of the thesis are the following: Firstly, it is expected that the outcomes of this work will increase the knowledge on the influence of emotions in reading and understanding uncertainty information and thus provide indications for better considering and, when necessary, incorporating this aspect into science communication. Secondly, it is expected to deepen the understanding of how the individuals with different climate change attitudes interact with the presentation of climate change information associated with its uncertainty and thus allow a more effective communication of those scientific findings to the different population groups. Finally, it is expected that this work will contribute to extend the body of knowledge on how to visualize uncertainty in maps in ways that support a correct and easy reading of the information.

1.5 Structure of the work

This work is composed of six sections and is structured as it follows: After having introduced the topic, goal, and the research questions of the thesis in this first section, the next section will delve into the literature and illustrate in detail the state-of-the-art of the research about the relevant topics for this thesis. These ranges from the communication of uncertainty and its visualization, to climate change forecasting and its communication, as well as the human emotions and their role in people’s understanding and relationship with the challenging concepts of uncertainty and climate change. Afterwards, in section three, the methods applied to create the empirical study used in this work are explained. Hence, the reasoning and the details of the creation process of the stimuli and of the various components of the whole experiment are illustrated. The fourth section will present the results of the experiment and provide a detailed statistical analysis of those outcomes, as well as their graphical illustrations. In section five, the answers to the stated research questions are given, through a comprehensive discussion of the results, which will relate the findings of this work with the existing literature, indicating possible explanations of the findings, and produce a critical reflection on the limitations of this study. Finally, in the sixth and last section of this thesis, the conclusions are drawn and an outlook and advice for future research on these topics are given.

2 Literature Review

This section of the thesis presents the current state of the art of the research in the fields of interest for this work, which touches aspects from various disciplines, from geography to psychology. The literature cited thus is mostly from the fields of geovisualization, climate change science, communication science, as well as psychology and cognitive science. In the first part is presented the concept of uncertainty and how it is communicated and visually represented, which is the central concept of this thesis. In the next chapter the effect of uncertainty on decision making is elucidated. Subsequently, an overview on the topic of climate change, its communication with the broader population and policymakers, and the different attitudes that individuals possess towards this issue, as well as their influence on decision-making, is illustrated. In the final chapter, an overview on the concept of emotions and how they can be measured, is provided, followed by an examination of how emotions play a role in communication and decision-making.

2.1 Definition and sources of uncertainty

2.1.1 Uncertainty definition

Uncertainty cannot be avoided and everybody encounters it in every situation happening in the real world (Li et al., 2013). Uncertainty arises in any data, such as the uncertainties in weather forecasts due to the lack of prediction accuracy, sensors uncertainties, incomplete measurements, or inaccuracies (Kamal et al., 2021). Since uncertainty is so ubiquitous in everyday life and can be found in most fields of scientific research, it is a topic that has been widely discussed in the scientific community for decades (Kamal et al., 2021; Li et al., 2013; MacEachren et al., 2012). However, finding a common, simple, and precise definition of what is uncertainty, has revealed to be a difficult task, with different researchers from different fields providing numerous distinct definitions (Kamal et al., 2021). On a superficial level, uncertainty, as the name suggests, is the counterpart of certainty; if certainty can be described as the perception or belief of a certain system or phenomenon to exist or not, uncertainty is instead the lack of such belief or trust (Li et al., 2013). Li et al. (2013) recall that for instance the US National Research council defines uncertainty as the lack of sureness about something or someone, which can range from just being almost certain to the complete lack of conviction about it. As remarked in Walker et al. (2003), uncertainty can be described as inadequate information, either because it is inexact, or unreliable or bordering with ignorance, while also indicating that sometimes even an increase in available information could lead to uncertainty.

As aforementioned, depending on the field or type of research, the definitions vary by including other factors or by associating it with similar concepts (Li et al., 2013; MacEachren et al., 2005), to the point that often for each new decision problem a new specific definition is created (Samson et al., 2009). As MacEachren et al. (2005) recalled, the boundaries between uncertainty and related concepts, such as data quality, accuracy, error, or reliability, are often ambiguous, hence the base for different interpretations. For instance, in their work, Joslyn & Savelli (2021) defined uncertainty as the likelihood estimates of future events (i.e. outputs from weather forecasting modelling), although the true likelihood remains unknown. Additionally, uncertainty could often be paired with the concept of risk, to the point of merging the two and considering both synonyms of the same underlying concept, as Samson et al. (2009) noted. Or conversely, in other studies the two concepts are regarded as strictly separated ones (Samson et al., 2009). In their review, Walker et al. (2003) proposed as a general definition for uncertainty, in order to encompass all its dimensions, the following: "*uncertainty is any departure from the unachievable ideal of complete determinism*" (p. 8). Hence, as Kamal et al. (2021) summarize, uncertainty is a multi-faceted concept, encompassing various related aspect such as incompleteness, inconsistency, unreliability, ignorance, or error.

2.1.2 Uncertainty sources and typologies

Uncertainty can enter into the data at any of the various stages of the information processing and communication pipelines, such as data acquisition, transformation, interpolation, and visualization, through various possible sources (Bonneau et al., 2014; Kamal et al., 2021). The sources of uncertainty along this pipeline have been traditionally categorized into three main groups: the sampling uncertainties, the modelling uncertainties, and the visualization uncertainties (Bonneau et al., 2014). A set of data can be affected by uncertainties coming from one or more of those groups, since uncertainty tends to accumulate as a phenomenon is measured, modelled, and visualized (Bonneau et al., 2014; Kamal et al., 2021). With regard to the uncertainties coming from the sampled data, the sources range from missing, incomplete, or contradicting data, to interpolations and other manipulations of the data, or noisy instruments and human errors (Bonneau et al., 2014) In the modelling phase, models or simulations can introduce uncertainty by a number of sources, such as residual variability from simplifications, variability in the mechanism, potential errors in the inputs given to the model or incorrect model parameters as well as imprecisions in the knowledge used to create the model (Bonneau et al., 2014). Finally, during the data visualization, the sources of uncertainty are due to effects of magnification or modifications of the uncertainties present in the inputs, as well as the perceptual and cognitive influences on the understanding of uncertainty from different audiences (Bonneau et al., 2014). A fourth kind of uncertainty sources has been more recently proposed by Kamal et al. (2021), which is the group of decision uncertainties. They argued that uncertainty is not only a property of the relationship between data describing the world and the real world, but it is also a property of the relationship between the data and the decision-maker. This last group encompasses uncertainties arising from the interaction between the data and its usage, meaning the subjective aspects of the data processing, such the definition of criteria and strategies for the assessments of data integrity, completeness, or interrelatedness (Kamal et al., 2021). A visualization of the different sources of uncertainties and at which stage in the information processing and communication pipeline they could happen is illustrated in Figure 1. As displayed, the sampling and modelling uncertainties influence each other, while both contribute to the uncertainties in visualization, which in turn influence the decision uncertainties.

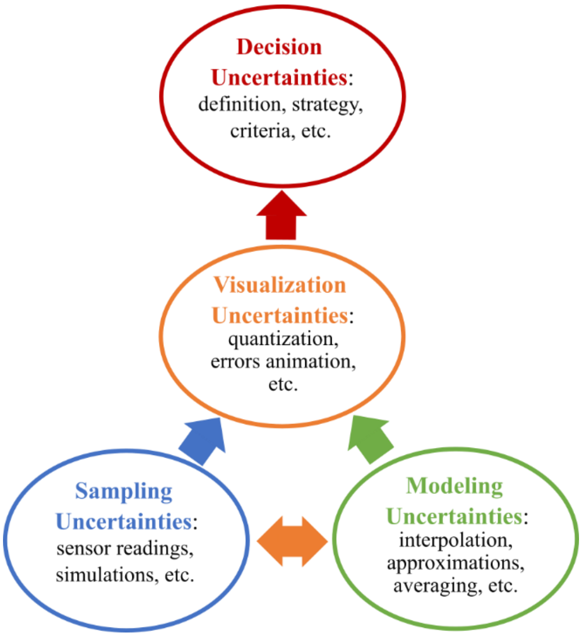

Figure 1*: Schematic overview of the various sources of uncertainty along the stages of the process of information gathering and communication (Kamal et al., 2021).*

Over the course of the decades, various categories and typologies of uncertainty have been described and proposed, due to the variegated and multifaceted nature of this concept. According to Li et al. (2013), when using the origin of uncertainty as a classification criterion, two main broad categories can be distinguished: the aleatory uncertainty and the epistemic uncertainty. With aleatory uncertainty it is meant the uncertainty arising from the natural variability of the physical world, thus being an inherent feature of nature itself, independent from human knowledge, which cannot be reduced or eliminated with more knowledge or information (Li et al., 2013). Conversely, the epistemic uncertainty found its origin in the human lack of knowledge of the physical world and of limits in measuring and modelling, thus it can be reduced or even eliminated through the gaining of more knowledge or by using better instruments and methods (Li et al., 2013). Subsequentially, Spiegelhalter (2017) proposed a tripartite categorization of uncertainty, where another category is added to the first two, namely the ontological uncertainty. With ontological uncertainty is meant the uncertainty due to the limit of human knowledge, hence the subjective and qualitative assessment of the limitation of the entire modelling process to being able to fully describe reality (Spiegelhalter, 2017). Walker et al. (2003) presented a model of uncertainty classification that considered it as composed by three dimensions of location, level, and nature. The first dimension indicates the location where the uncertainty manifests itself in the model, the second informs about its intensity on a spectrum between deterministic knowledge and complete ignorance, while the last one informs whether the uncertainty is epistemic or aleatory (Walker et al., 2003). An approach to understand and analyse uncertainty in the context of geospatial information is the typology illustrated in MacEachren et al. (2005), which proposes nine types of uncertainties describing various aspects of information and their possible uncertainty sources. Those types are shortly described in Table 1. Further, these types of uncertainty can be matched with the three components of geospatial data, hence space, time, and attribute (MacEachren et al., 2005).

***Table 1**: Nine types of uncertainty according to the typology presented by MacEachren et al. (2005, 2012). For each type is given a brief definition and then it is presented an example for each one of the three components of the information in the geographical interpretation (MacEachren et al., 2005, 2012).*

Category	Definition	Space	Time	Attributes
Accuracy/error	Difference between observation and reality (based on estimates)	Coordinates, buildings	± 1 day	Counts, magnitude
Precision	Exactness of measurement/estimate	1 degree	Once a day	Nearest 1000
Completeness	Extent to which information is comprehensive	20% cloud cover	5 samples for 100	75% reporting
Consistency	Extent to which the information components agree	From/for a place	5 say Monday, 2 say Tuesday	Multiple classifiers
Lineage	Process through which information has passed	# of input sources	# of steps	transformations
Currency/timing	Time span from the occurrence of the information collection to its use	Age of maps	$C = t_{present} - t_{info}$	Census data
Credibility	Combination of factors such as experience, reliability, or motivation of the information source	Knowledge of place	Reliability of model	U.S. analyst vs informant
Subjectivity	Extent to which the human interpretation or judgement is involved in information construction	Local ↔ outsider	Expert ↔ trainee	Fact ↔ guess
Interrelatedness	Source independence from other information	Source proximity	Time proximity	Same author

2.2 Uncertainty Communication

Established that uncertainty is a variegated and difficult concept to define as well as to categorize in sensible and workable components, how to properly communicate the inevitable uncertainties associated with scientific findings is the subsequent challenge that the scientific community has to tackle. As Spiegelhalter (2017) expressed, the aim of a successful communication is being able to provoke in the audience the intended outcomes, hence in the case of scientific communication to fulfil the duty to inform policymakers and non-experts. For what concerns the case of uncertainty, there are arguments both in favour as well as against its integration in the communication (EFSA et al., 2019; Hullman, 2020; Karduni et al., 2021; Maier et al., 2016; Spiegelhalter, 2017; van der Bles et al., 2019), however, the positive effects are deemed to outweigh the negatives (Bhatt et al., 2021; van der Bles et al., 2019). One of the main issues of the communication of uncertainty is that it might come with increased complicatedness of already complex problems and possibly lead to misunderstandings or manifestations of distrust (Hullman, 2020; Maier et al., 2016; van der Bles et al., 2019; Wardekker et al., 2008); nonetheless there are benefits under various aspects, from decision making to fairness of the models (Bhatt et al., 2021; van der Bles et al., 2019). In support of the latter point, numerous studies stressed the need to transparently communicate all the uncertainties tied to scientific findings, both to contribute to the credibility and transparency of science and to allow a more accurate and informed decision-making process (Bhatt et al., 2021; EFSA et al., 2019; Wardekker et al., 2008). Moreover, L. A. Smith & Stern (2011) asserted that in case science fails in its responsibility to successfully communicate the relevance of uncertainties in findings to policymakers, it risks its future credibility and thus they firmly support an open and constructive communication of uncertainty.

Concerning the negative aspects of communicating uncertainty, an issue that has been risen is that it may have a negative effect on trust. For instance, the study of Leffrang & Muller (2021) found that participants exposed to the presence of uncertainty in the model trusted less the outcomes of the model and were more prone to retain their prior assessments. Similarly, van der Bles et al. (2019) reviewed that in some studies it was retrieved a decrease in trust and increase in the perception of incompetence when communicating uncertainty, and that it may be affected by the level of numeracy of the audience. However, the aspect of trust is still a debated one, since indications of increased trust are also present (as will be discussed in the next paragraph). Another issue cited is that the integration of uncertainty may constitute a cognitive overload in the non-experts, and hence, it causes a decrease of motivation and attention on the matter (Maier et al., 2016). Further, Maier et al. (2016) reported that the expectations of the broad public in regard to uncertainty were mixed, with segments of the audience asking for this information and other segments avoiding it and being unsettled when this aspect is disclosed. Hullman (2020) listed some reasons why communicators resist the idea to present uncertainty; they range from the belief that audience will not understand or not tolerate uncertainty, to the belief that it complicates the decision-making process. Another concern regards the potential use of uncertainty in the findings to stimulate political and social debate in the general public about an untrue lack of consensus in the scientific community (Molina & Abadal, 2021). A final aspect that is evoked as a reason that plays against the communication of uncertainty, is the one that for visualization designers there is still a difficulty to find a suitable and robust format to visualize and communicate uncertainty (Hullman, 2020; Kamal et al., 2021).

Looking at the positive aspects of promoting the communication of uncertainty in scientific reports, there are various indications of benefits for both the scientific community and the non-expert audience. In that regard, the contribute of Bhatt et al. (2021) highlights in particular three aspects of uncertainty communication that are deemed as beneficial for the effectiveness of scientific communications: fairness of the models, support to better decision-making and help in building trust. These reasons thus, prompted the researchers to call for a more transparent and widespread integration of uncertainty in science communication (Bhatt et al., 2021). A factor stressed by the researchers in supporting the integration of uncertainty in communication of science regards the fairness of this practice; they argue that transparency on the uncertainties allows to better assess the models and the potential biases that they have, thus providing a tool to prevent and mitigate those biases (Bhatt et al., 2021). Various studies indicated that the communication of uncertainty provides an important and positive effect on decision-making (Bhatt et al., 2021; EFSA et al., 2019; Wardekker et al., 2008). Suppling information on uncertainty allows decision-makers to make more sound decisions and to assess with more nuances the available options (van der Bles et al., 2019). It is also noted that without knowing the inherent uncertainties of models, decision-makers may be led to erroneously over-rely on their outcomes, or on the contrary to under-rely, while a transparent communication allows decision-makers to have a more aware integration of the model outputs on their decisions (Bhatt et al., 2021). Wardekker et al. (2008) further claimed that presentation of uncertainty is useful to support decision-making and allows policymakers to better evaluate the possible outcomes of a decision and the implications of uncertainty in those outcomes. A final aspect to be considered when communicating uncertainty is its effects on trust. Is argued that a well communicated uncertainty can be seen by the audience as a sign of trustworthiness, while a defective communication can make uncertainty incomprehensible and thus create negative perceptions, confusion, or rejection (Bhatt et al., 2021). Joslyn & Leclerc (2016) retrieved that future climate prediction were acknowledged with more trust by the participants of their study when information about the uncertainty of the forecast was provided. Likewise, van der Bles et al. (2019)

recalled that the transparent communication of uncertainty helps to retain both the trust of the audience and the credibility of findings. Furthermore, as Gustafson & Rice (2019, 2020) argued, when the presented uncertainty was due to technical reasons (such as errors in measurement or modelling approximation) the trust was positively affected, while on the contrary if the source of uncertainty was the presence of debate in the scientific community it was detrimental to the trust.

As L. A. Smith & Stern (2011) warned, in order to be effective, scientists need to understand both the audience with which they are communicating and the level of details as well as the framing of uncertainty that this audience needs, and consequently adapt the approach with which the uncertainty is communicated. A framework which can help producing an effective communication of uncertainty, hence that considers the issues of the audience and the form of communication listed by L. A. Smith & Stern (2011), is for instance the one developed by van der Bles et al. (2019). They argue that their framework combines both statistical approaches to quantify uncertainty, as well as psychological perspectives on the effect of uncertainty communication on the audience, which should provide guidance in communicating uncertainty transparently (van der Bles et al., 2019). The focus is on who communicates what, in what form, to whom and to what effect while keeping the context in consideration as part of the characteristics of the audience (van der Bles et al., 2019). When communicating uncertainty, they advise researchers to pay attention to what is the uncertainty about (i.e., hypothesis, specific numbers) and the reasons why there is present (i.e., limited knowledge, natural variation), while choosing a communication format that considers the audience, the desired effect on the audience and their relationship with the researchers (van der Bles et al., 2019). In Figure 2 it is offered an overview on the communication framework they developed, with its five components and the associated relevant factors (van der Bles et al., 2019). Some further indications on how to communicate uncertainty more effectively are provided by Spiegelhalter (2017). He argued that positive framings are better received by the audience (i.e., 98% success rate instead of 2% mortality rate for a medical procedure), and that it is essential to make absolutely clear to which outcomes or events are referred the expressed probabilities and uncertainties (Spiegelhalter, 2017). On that point, van der Bles et al. (2019) stressed the importance to keep the expressions of the magnitude of uncertainty clearly separated from the magnitude of the phenomenon (its effect). Another aspect highlighted by Spiegelhalter (2017) is the difference in graphical, verbal, and numerical communication method. The graphs are deemed as effective in transmitting the gist of the message, whereas numerical formats are more appropriate for detailed information (Spiegelhalter, 2017). In contrast, using words alone to communicate uncertainty is not advised, since they are less trusted than numbers and they may lead to less accurate evaluations and increased loss aversion, hence the suggestion is to use them together with numerical expressions, as labels to give context to the numbers (Spiegelhalter, 2017). The difference in the effect of verbal and numerical expression have been likewise found in the study by Jenkins & Harris (2017), where the numerical format was associated with more credibility even after erroneous predictions.

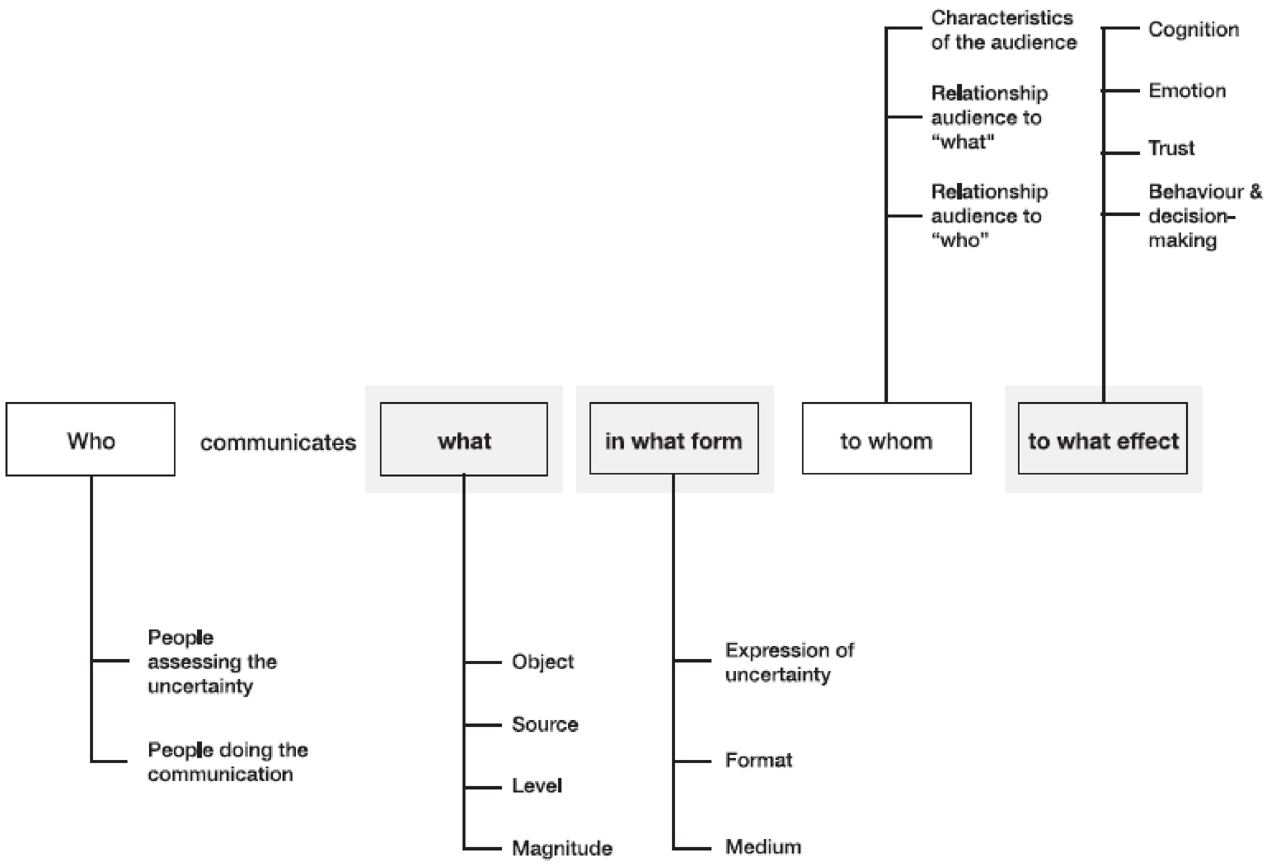

Figure 2: *Framework for the communication of epistemic uncertainty developed by van der Bles et al. (2019).*

2.3 Uncertainty Visualization

Visualization of uncertainty is a topic that has sparkled active research during the last three decades (Kinkeldey, MacEachren, et al., 2014). Pang et al. (1997) stated that the aim of uncertainty visualization is to present the data together with auxiliary uncertainty information, since this kind of visualization present a completer and more accurate rendition of data for further analysis. Moreover, it has to be remembered that the main goal of visualization is to effectively display a potentially large amount of data in an understandable manner (Bonneau et al., 2014). However, as argued by Kamal et al. (2021), despite uncertainty being inherently associated with any kind of information, there is an issue that repeatedly arises once the data has been visualized, namely the fact that the visualized information is often assumed to be accurate. They further argue that in the visualization field uncertainty is considered a difficult variable to display, both due to practical visualization issues and to the modelling of uncertainty relative to the decision-making process (Kamal et al., 2021). Nonetheless, the visualization of uncertainty is regarded as an important and central aspect of effective communication and an important tool to improve the understanding of data (Kamal et al., 2021; Kinkeldey et al., 2017; Potter et al., 2012; Schumann & Griethe, 2005).

Over the years numerous have been the techniques developed and proposed to visualize uncertainty, with new ideas and applications coming from various fields of science, e.g. hurricane path forecast (Millet et al., 2022; Ruginski et al., 2016), weather forecast (Clive et al., 2023; Nadav-Greenberg et al., 2008; Scholz & Lu, 2014), climate change mapping (Reusser et al., 2011), natural hazard risk assessments (Cheong et al., 2016; Kunz et al., 2011; Miran et al., 2019; Schneider et al., 2022), demography (Slingsby et al., 2011), water availability (Deitrick, 2007, 2012), land and urban planning (Aerts et al., 2003; Evans, 1997; Hope & Hunter, 2007b) or uncertainty in sets (Tominski et al., 2023). Hence in recent years numerous researchers undertook the endeavour to provide an overview on the variegated and rich solutions and approaches in the world of uncertainty visualization (Bonneau et al., 2014; Brodlie et al., 2012; Kamal et al., 2021; Kinkeldey et al., 2017; Kinkeldey, MacEachren, et al., 2014; Padilla et al., 2022; Potter et al., 2012). Padilla et al. (2022) described two main categories of uncertainty visualization techniques: on the one hand the graphical annotations of distributional properties such as mean, confidence intervals, or distributions; on the other hand, the visual encoding of uncertainty through controlling aspects such as colours, position, transparency, or fuzziness. They further argue that a combination of the two techniques into hybrid approaches is possible, for instance in visualization of uncertainty in so-called contour box plots or probability density and interval plots (Padilla et al., 2022). As reviewed by Kinkeldey, MacEachren, et al. (2014), uncertainty visualizations can be often categorized with the help of a series of dichotomic categories. These dichotomies are briefly thematised in Table 2. A model proposed by Kinkeldey, MacEachren, et al. (2014) to categorize the different methods of visualizing uncertainty according to these concepts of dichotomic categories is displayed in Figure 3. This framework is based on three dichotomies: intrinsic – extrinsic, coincident – adjacent, and static – dynamic, which according to Kinkeldey, MacEachren, et al. (2014) better allow a systemic approach to categorize and explore visualization techniques. The dichotomy explicit – implicit was deemed as not equally relevant, since most of the visualizations are of explicit nature, while the differentiation between visually integral and visually separable is more about human visual processing than signification and is generally congruent with the intrinsic – extrinsic dichotomy (Kinkeldey, MacEachren, et al., 2014). In Chapters 2.3.2, 2.3.3 and 2.3.4 these three dichotomies are elucidated with more detail and examples of how they appear in practice are provided.

***Table 2**: The five dichotomies used for the categorization of uncertainty visualization signification (Kinkeldey, MacEachren, et al., 2014).*

Dichotomy	Description
Explicit – Implicit	*Explicit*: direct representation of uncertainty in the same visualization of the related variable, e.g. through glyphs or other graphical signs. *Implicit*: indirect representation of uncertainty, e.g. by providing multiple visualizations of the variable, showing in each one a possible outcome or a level of uncertainty.
Intrinsic – Extrinsic	*Intrinsic*: visualizing uncertainty by altering the existing symbology, through manipulation of the visual variables, e.g. by altering the colour value or saturation. *Extrinsic*: Visualizing uncertainty by adding a new object/layer to the display, e.g. glyphs, grids.
Visually integral – separable	*Integral*: the visualized uncertainty cannot be perceptually separated by the data. *Separable*: data and uncertainty can be read independently.
Coincident – Adjacent	*Coincident*: variable and uncertainty are represented in the same visualization (integrated view). *Adjacent*: variable and uncertainty are represented in separated visualizations (separated view).
Static – Dynamic	*Static*: classical, static, stand-alone map with no manipulation or interaction from the user possible. *Dynamic*: interactive or animated display, where user can interact with it, e.g. by toggling between different views.

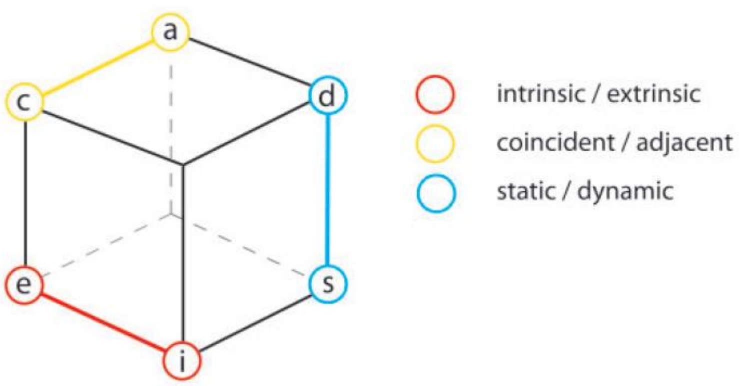

***Figure 3**: The framework of the Uncertainty Visualization cube (UVis³) for categorizing uncertainty signification in visualizations proposed by Kinkeldey, MacEachren, et al. (2014).*

2.3.1 *Characteristics of uncertainty visualization studies*

A review of how uncertainty visualization evaluation studies are constructed and what are their main features is provided by Hullman et al. (2019). Most studies that investigated the effectiveness and suitability of the various uncertainty visualization types concentrated on the performance of the users (how effective are users at extracting information, making inferences or decisions based on the map), followed by studies that analysed the interpretation of the visualization (associating uncertainty with the encoding), while a few also recorded the quality of the user experience (feedback given by the users) (Hullman et al., 2019). Concerning the investigation of the audience background in those studies, usually the focus was on the expertise in map reading, uncertainty understanding or domain-specific expertise (Kinkeldey, MacEachren, et al., 2014). Some studies used this information on the expertise background to compare results of experts versus non-experts (Kinkeldey, MacEachren, et al., 2014). Investigations with online setting usually have the highest number of participants, as well as studies aiming at providing quantitative results, while qualitative studies usually work with smaller samples (Kinkeldey, MacEachren, et al., 2014). As described by Hullman et al. (2019) there are different main aims that an empirical study on uncertainty visualization can set itself to reach. Most of them aim to compare the impacts of two or more visualization types, or to determine the impact of presenting the uncertainty to users (hence having both visualization with and without uncertainty) (Hullman et al., 2019). Further possible aims are to investigate the interactions between the visualization and the characteristics of the users (expertise, attitudes) or to understand the how and why a type of visualization works (investigate judgements and heuristics), while a minor part of studies also aims to validate the effectiveness of a specific visualization type (verify improvements in performance) (Hullman et al., 2019). With regard to the type of task proposed in these investigations, Kinkeldey, MacEachren, et al. (2014) identified two main groups: tasks with objective assessments and tasks with subjective assessments. The former encompasses tasks such as value retrieval (of the uncertainty, of the displayed variable, or both) from the reading of the map, rating of uncertainty, aggregating the value of uncertainty over an area, ranking data or uncertainty, or to search for entities with specific characteristics; the latter are usually assessments from the respondents about their confidence on the performance, their preference for one type of visualization with respect to other, or assessment about ease-to-use, difficulty, attractiveness, or intuitiveness of the map (Kinkeldey, MacEachren, et al., 2014). A final observation to be made is that many studies are domain specific and thus, it can be difficult at time to generalize the findings of one study or relate the findings of multiple studies (Kinkeldey, MacEachren, et al., 2014).

2.3.2 *Intrinsic versus extrinsic visualization*

The first dichotomic axis in the UVis[3] is the one opposing the intrinsic visualizations to the extrinsic ones. As reviewed by Kinkeldey, MacEachren, et al. (2014), the representation with intrinsic methods is the most common approach, where uncertainty is displayed through variation of the visual variable in the map, as colour value or transparency. Conversely the application of extrinsic methods is less popular (Kinkeldey, MacEachren, et al., 2014). There are however examples of those kind of approach, for instance in the works by Sanyal et al. (2009) and Kinkeldey, Mason, et al. (2014). For the extrinsic visualization of uncertainty, which have a long history in the field of scientific visualization, the most commonly used technique involves the use of glyphs, thus of signs that can be mapped above the visualized data (Kinkeldey, MacEachren, et al., 2014). Glyphs are geometrical signifiers, that encode information in their colour, shape, size, or orientation (Kamal et al., 2021; Pang et al., 1997). The visual variables mostly used for depicting uncertainty in this approach are colour (hue, value, saturation), whitening (fading to white), transparency, blur, or resolution (Kinkeldey, MacEachren, et al., 2014). The relevance of the manipulation of colour in its various form in this context is consistent with the findings of Wolfe & Horowitz (2004), where colour is identified as one of the strongest elements that guide human visual attention. Texture is also a viable option to map uncertainty in an intrinsic way, with possibility to be modified with opacity, hue, or texture irregularities (Bonneau et al., 2014; Kinkeldey, MacEachren, et al., 2014). The modification of orientation and size of patterns is also consistent with the findings of Wolfe & Horowitz (2004), since also those two attributes are strong guides of visual attention. In regard to the application of intrinsic representation of uncertainty in the visual variables it is noteworthy the work by MacEachren et al. (2012). The results of their study, which investigated the suitability of different visual variables to represent uncertainty, indicated that the audience associate uncertainty mostly with the variables of fuzziness, location, colour value, arrangement, size, and transparency (MacEachren et al., 2012). On the contrary, the colour saturation did not perform equally well (MacEachren et al., 2012). In Figure 4 are illustrated the application of uncertainty to the visual variables explored by MacEachren et al. (2012).

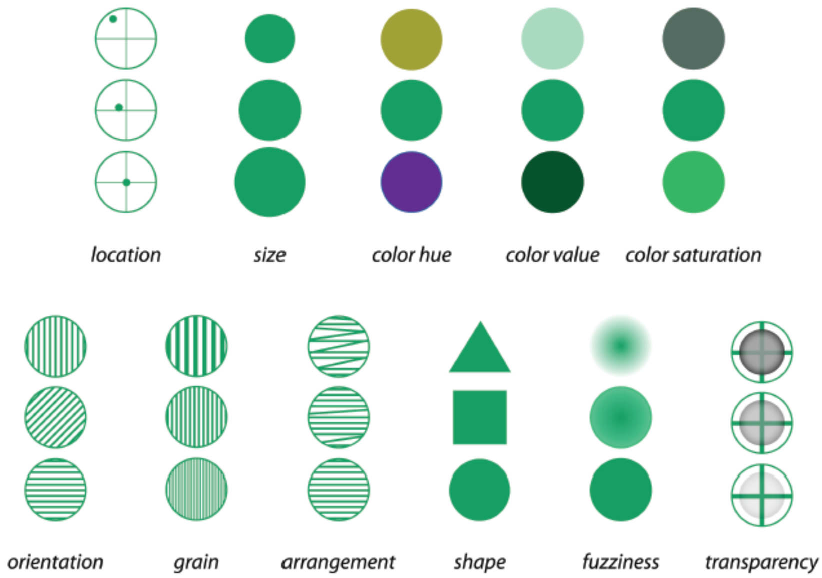

***Figure 4**: Intrinsic uncertainty representation obtained by manipulation of the visual variables on point symbols as has been investigated by MacEachren et al. (2012).*

Examples of studies that used variation of colour as an approach for intrinsic visualization from the most various applications are Aerts et al. (2003) and Leitner & Buttenfield (2000) in urban planning, Miran et al. (2019) for risk assessment or Nadav-Greenberg et al. (2008) in weather forecast. Regarding the effectiveness of colour, the study of Leitner & Buttenfield (2000), which tested colour value, saturation, and texture, retrieved that colour value (with uncertainty coded as low value) performed better in terms of user accuracy compared to the two other options. If colour value cannot be used since already applied to visualize another feature, they suggest the use of texture (Leitner & Buttenfield, 2000). Another investigation that focused not only the manipulation of the colour value, but also blur and pattern, is provided by Kübler et al. (2020). In their study the visual variables were used to depict fuzzy borders between different risk zones, as depicted in Figure 5. As was the case in Leitner & Buttenfield (2000), also in this study each representation of uncertainty lead to different performances of the respondents, although there was no strictly correct or wrong answer (Kübler et al., 2020). It was also reported that the visualization with colour value led participants to choose locations inside the uncertain high-risk zone more often, thus suggesting that perhaps this kind of visualization may have misled the participants to interpret low colour value as less occurrence of risk instead of less certainty in the categorization of the location (Kübler et al., 2020). Another example of intrinsic visualization of uncertainty used for depicting areas with uncertain borders with multiple kinds of visual variables manipulation is the study by Cheong et al. (2016). Here six different ways of communicating uncertainty were compared, where five of them were intrinsic representations and one was a verbal description of uncertainty (Cheong et al., 2016). In Figure 6 two examples of those visualization types are displayed. The outcomes of the study suggested that the preference of participants for one method, i.e. the colour hue, did not lead to difference in the performance (Cheong et al., 2016), as equally retrieved in other studies (Kinkeldey, MacEachren, et al., 2014). Further it was assessed that while text-based uncertainty information led to better understanding and performance in simple tasks, once the complexity increased the map-based approaches outperformed the text (Cheong et al., 2016).

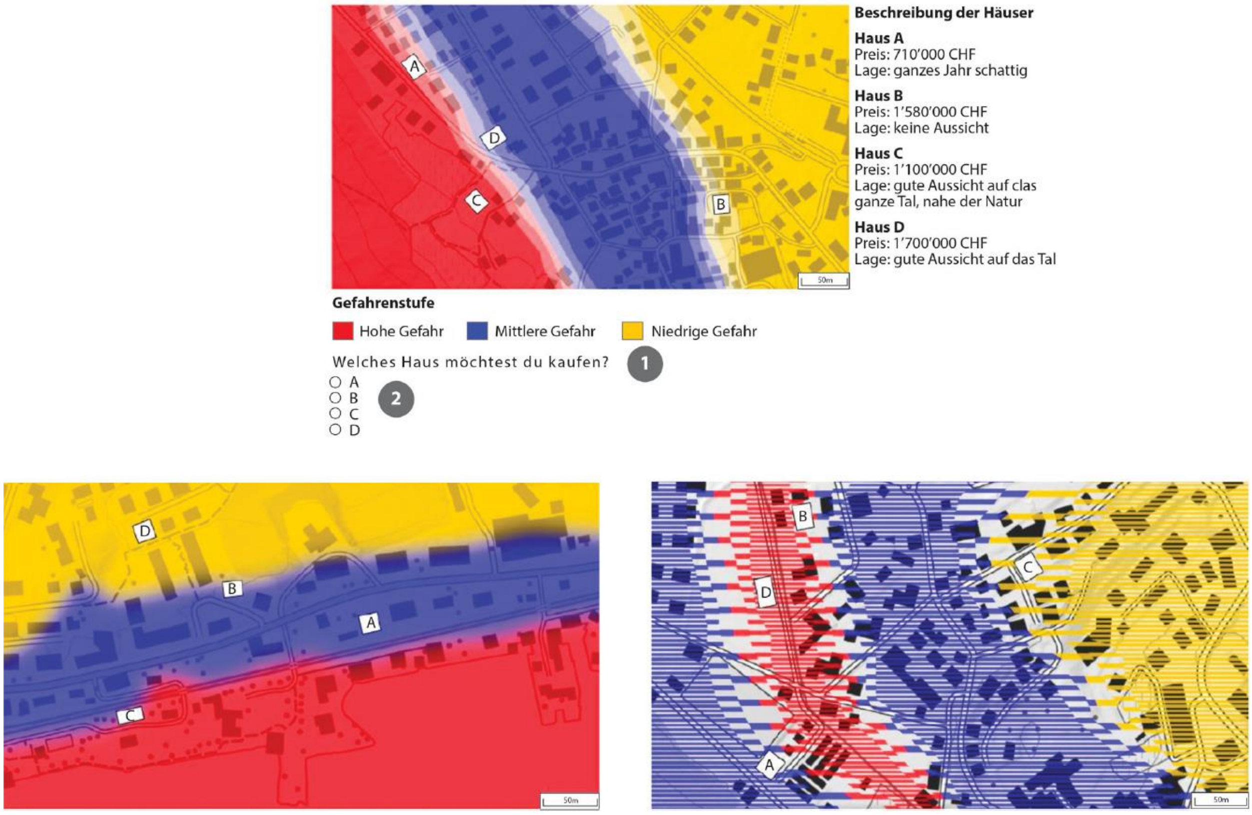

Figure 5: Intrinsic representation of uncertainty for borders between different risk area tested by Kübler et al. (2020), using colour value on the upper map, blur on the lower left map, and pattern density on the lower right map.

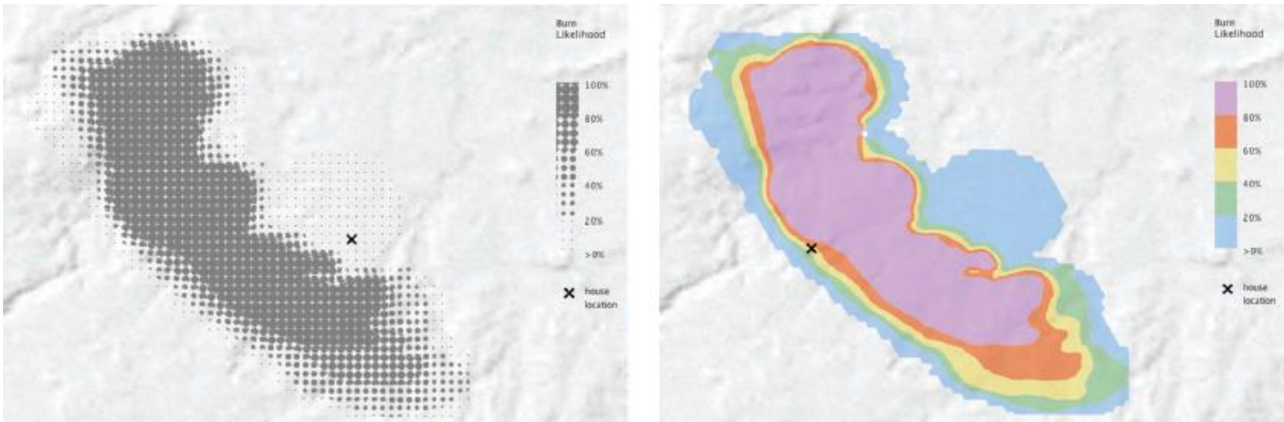

Figure 6: Examples of wildfire range uncertainty depicted with different intrinsic methods, pattern on the left and colour hue on the right (Cheong et al., 2016).

Intrinsic methods have not only been applied to classical 2D map features, but also to other kinds of data visualization. The work by Boukhelifa et al. (2012) analysed the representation of uncertainty on linear features with various methods (blur, dashing, greyscale, sketchiness) and attempted to propose the use of sketchiness as an additional visual variable to depict uncertainty. They retrieved that sketchiness may need a legend to be appropriately associated to uncertainty by participants and it was generally not perceived as an elegant variable to represent uncertainty, nonetheless they found that it did perform similarly to the other tested options in terms of accuracy (Boukhelifa et al., 2012). Further, it is stressed that those visual variables may be more adapted to represent ordinal data than for quantitative data (Boukhelifa et al., 2012). In Figure 7 an overview on the four visual variables applied to linear features is provided.

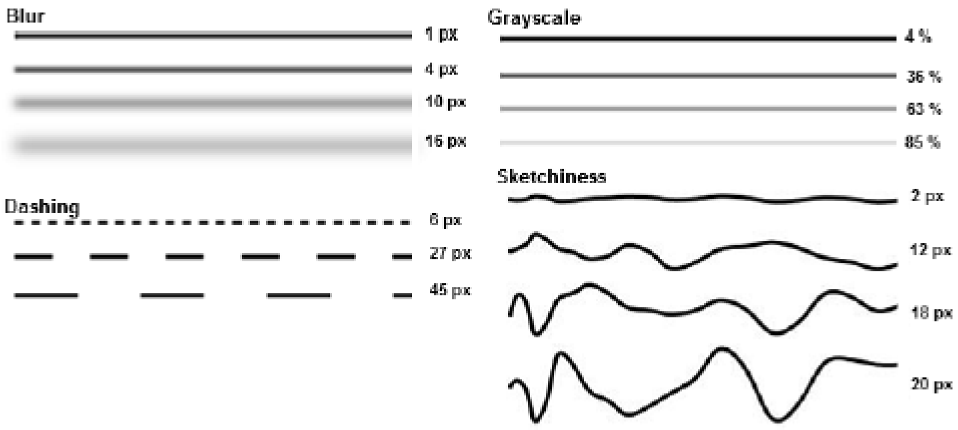

Figure 7*: Sketchiness and other uncertainty visualization types for data expressed as linear features (Boukhelifa et al., 2012).*

With regard to the extrinsic kind of visualisations, uncertainty can be represented as glyphs which characteristics varies with the level of uncertainty. For instance, Sanyal et al. (2009) investigated the effectiveness of various glyphs and of error bars for representing uncertainty in 1D and 2D dataset displays. In Figure 8 are portrayed two types of glyphs variations that were used in the study, one by varying the size of the glyph and the other by varying the colour value (Sanyal et al., 2009). Interestingly, they found that the glyphs performed better than the error bars for what concerns the efficiency of users to retrieve information, while the efficacy of the single different types of glyphs varied with the type of task that was asked (Sanyal et al., 2009). Another study which used the approach of glyphs added to the base information, but this time applied to a map situation, is the one proposed in Hope & Hunter (2007b), where each area was marked with a simple glyph indicating either high or low certainty, as illustrated in Figure 9. They reported that the visualization of uncertainty had an effect on the choices that the participants made when comparing different zones in the maps, with participants preferring high certainty zones even when the conditions in the low certainty zone were better (Hope & Hunter, 2007b).

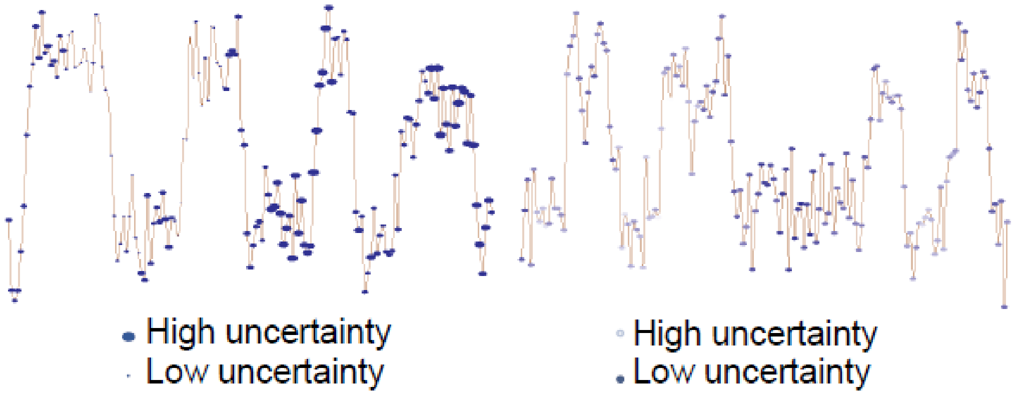

***Figure 8**: Variation of the glyphs representation to show different uncertainty levels as inquired in the study of Sanyal et al. (2009).*

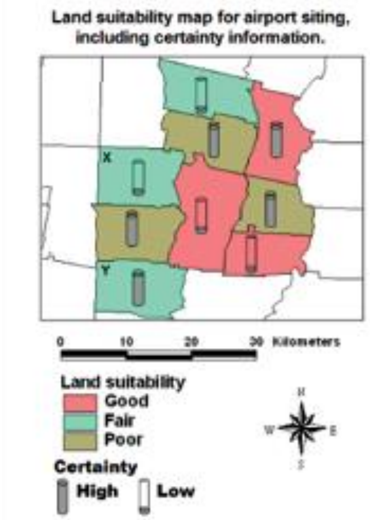

***Figure 9:** Uncertainty represented as a glyph overlayed on the mapped variable indicating either low or high uncertainty in the task designed by Hope & Hunter (2007b).*

A distinct approach for extrinsic visualizations is the one which uses a grid-based representation, where uncertainty is for instance depicted through noise added to the lines of the grid, as depicted in Figure 10 (Kinkeldey, Mason, et al., 2014). As the authors argue, in maps with various features with diverse geometry and areas, hence not homogenous as for instance choropleth maps, extrinsic methods based on grids appear as promising approaches since they are independent from the geometry of the underlying data (Kinkeldey, Mason, et al., 2014). While various manipulations can be applied, such as width, sharpness, or amplitude of the grid, the use of noise is deemed as particularly suitable for encoding a concept as uncertainty (Kinkeldey, Mason, et al., 2014). They noted that this method is understood by users and thus constitute a viable alternative to intrinsic methods when the map is composed by many heterogeneous features (Kinkeldey, Mason, et al., 2014). Further it was noted a decrease in the efficiency and accuracy of participants with increasing number of uncertainty classes (Kinkeldey, Mason, et al., 2014).

Figure 10*: Uncertainty of the underlying mapped variable represented as increasing noise on the map grid from the study of Kinkeldey, Mason, et al. (2014).*

A comparison between the intrinsic and extrinsic method done by Šašinka et al. (2019) on the example of avalanche risk assessment maps (see Figure 11), reveals that intrinsic visualizations lead to more eye movement between the legend and the map, longer fixation on the map and more time spent on the legend compared to extrinsic approach, thus indicating a higher cognitive load to decipher the map. Further, it appears that for users with map reading expertise, the intrinsic visualization helps more analytically oriented individuals, while the extrinsic visualization performs better for globally oriented individual (Šašinka et al., 2019). Hence the two approaches of visualizing uncertainty require different cognitive strategies (Šašinka et al., 2019). According to Kinkeldey, MacEachren, et al. (2014), many researchers agree that while extrinsic methods are more suited for qualitative information communication, the use of intrinsic representation is more useful when the aim is communicating quantitative information about the uncertainty. However, it may be the case that sometimes is the type of task that determines which visualization approach is more appropriate (Kinkeldey, MacEachren, et al., 2014).

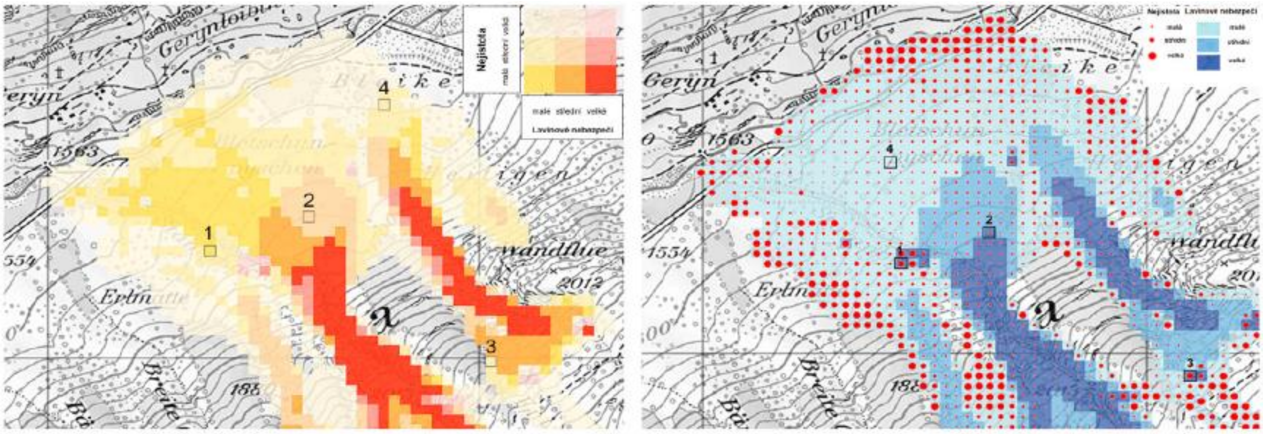

Figure 11*: Comparison between an intrinsic and an extrinsic visualization method for avalanche risk assessment developed by Kunz et al. (2011), as done in the study by Šašinka et al. (2019).*

2.3.3 Coincident versus adjacent visualization

The contrast between coincident and adjacent representation constitutes the second element of the UVis[3]. This dichotomy has been investigated since the beginning of the research on uncertainty visualization, although most studies have concentrated on analysing coincident approaches there are nonetheless also investigations that made direct comparisons between these two methods (Kinkeldey, MacEachren, et al., 2014). Studies that delve into this topic are for instance Viard et al. (2011) in the context of geology (see Figure 12), Kubíček & Šašinka (2011) with an application in soil science, and Schneider et al. (2022) with maps about aftershock forecasts. As found in the study by Viard et al. (2011), the coincident visualization performed better than the adjacent one with increasing difficulty of the task requested to the participants, prompting the authors to hypothesise that in complex tasks the adjacent maps introduce a perceptual and cognitive overload. Kinkeldey, MacEachren, et al. (2014) remarked that the main difference between the two approaches resides in the fact that adjacent maps require more eye movements to analyse both maps and retrieve information. Kubíček & Šašinka (2011) further found that coincident representation led to quicker answer by participants. Thus, as suggested by Viard et al. (2011), visualizations of real-world application should tendentially be constructed in compact ways, so to reduce the cognitive burdens of users. The coincident approach can lead to potential problems due to its higher complexity and cluttering of information, as noted by Kinkeldey, MacEachren, et al. (2014), however no occurrence of such complications appeared in the study of Viard et al. (2011). In contrast with the points raised by Viard et al. (2011), in the study of Schneider et al. (2022) the adjacent visualization was the approach that led to the most accurate answers by the participants, while the coincident methods were more prone to errors, such as misclassification of the underlying data values. In their review, Kinkeldey, MacEachren, et al. (2014) argue that adjacent approaches may be better for retrieval of single values, but coincident maps are preferable since they simplify the retrieval of both the uncertainty and the data in complex tasks. However, Kubíček & Šašinka (2011) found that in the adjacent view participant were slightly better at retrieving values, while Schneider et al. (2022) detected that the retrieval of uncertainty in coincident maps was worse compared to adjacent. Hence, since each method led to a better understanding of different features of the maps, the choice of one method over the other may be depending on the aim of the communication, as suggested by Schneider et al. (2022).

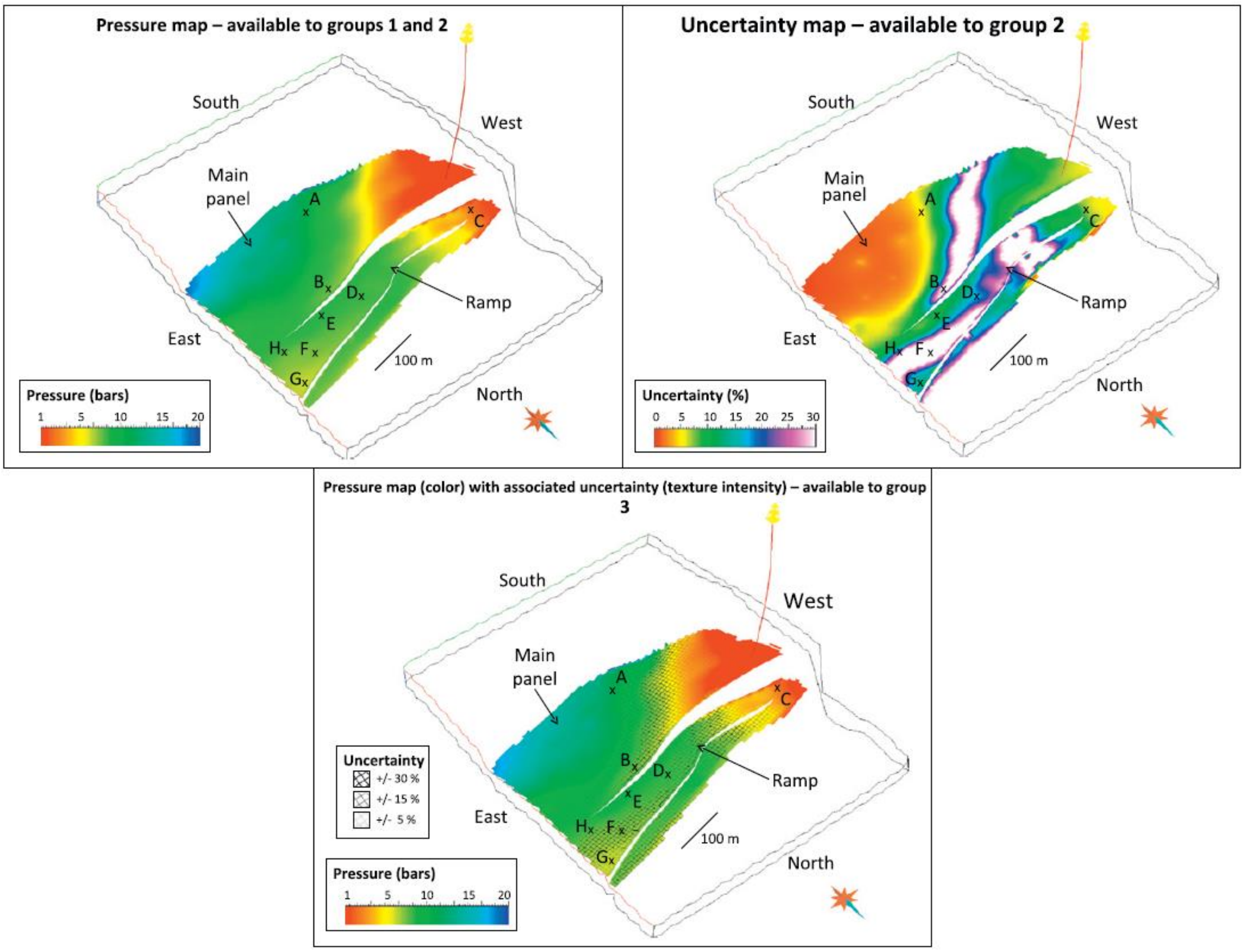

Figure 12: *Adjacent (above) and coincident (below) presentation of uncertainty in geological maps. In the adjacent maps both the uncertainty and the pressure data are represented as colour hue variation, while in the coincident map the uncertainty is mapped as pattern (Viard et al., 2011).*

Bivariate (coincident) maps in climate change forecasts

The bivariate maps used in the context of climate change forecast represent a particular kind of coincident visualization relevant for this thesis. In this type of coincident visualization bivariate map, the adopted technique is to visualize the variation of climatic variable over a field and its uncertainty in the same map, where one visual variable, usually colour, encodes the phenomenon and another visual variable is used for the uncertainty (Johannsen et al., 2018; Kaye et al., 2012; MacEachren, 1992; Retchless & Brewer, 2016). While these kinds of bivariate maps have been also applied in the field of natural hazard, for instance in the works of Kunz et al. (2011) or Schneider et al. (2022), it is a type of visualization that is deemed as particularly suitable for climate change forecast, as argued by Kaye et al. (2012). The reasons reside in the fact that it creates a single map with variable and uncertainty while preserving standard cartographic principles, such as appropriate colour symbolism, visually intuitive design, and a classification scheme that do not misrepresent data (Kaye et al., 2012). In recent years some studies inquired the effectiveness and characteristics of this approach, e.g. Johannsen et al. (2018) and Retchless & Brewer (2016). While the approach proposed in Kaye et al. (2012) was based on using the variation of colour for both the climatic variable and the uncertainty (hue and respectively value) as shown in Figure 13, Retchless & Brewer (2016) also tested other combinations, such as the use of patterns for uncertainty (see Figure 14). The results of their research indicate that map users where able to read better both the climatic variable value and the uncertainty level when the map was created with any of the proposed colour-pattern approaches, while the colour-colour approaches consistently performed significantly worse (Retchless & Brewer, 2016). Moreover, it was suggested to adopt the pattern with dots, since it was the best performer in terms of accuracy in climatic variable reading, second best in uncertainty reading, and the overall preferred visualization technique; if the use of colour-colour approaches cannot be avoided, then the coding the climatic variable with hue or lightness and of uncertainty with methods that manipulate lightness or saturation is suggest (Retchless & Brewer, 2016). With regard to the use of patterns as visual variable to represent uncertainty in climate bivariate maps, noteworthy is the work by Johannsen et al. (2018), where it has been retrieved that the respondents generally interpreted the increase of density of the dot pattern as an increase of the level of certainty. Hence, in accordance with the cartographic principle of "darker-is-more", it is suggested to use patterns with increasing density to map the increase of certainty (Johannsen et al., 2018). As Retchless & Brewer (2016) remarked, there is still the need to investigate into the effects of such representations for more complex tasks than simple value retrieval, where uncertainty information has to be taken into account for decision-making.

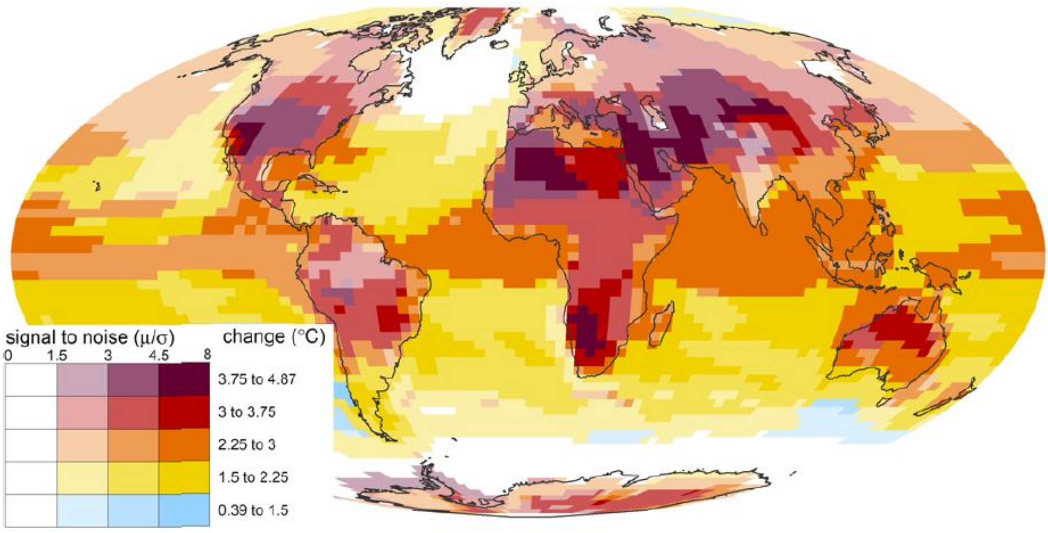

***Figure 13**: The bivariate map for temperature change forecast under climate change originally proposed by Kaye et al. (2012), with a colour-colour approach, hence where the manipulation of colour characteristics is used both to represent the climatic variable and the uncertainty level.*

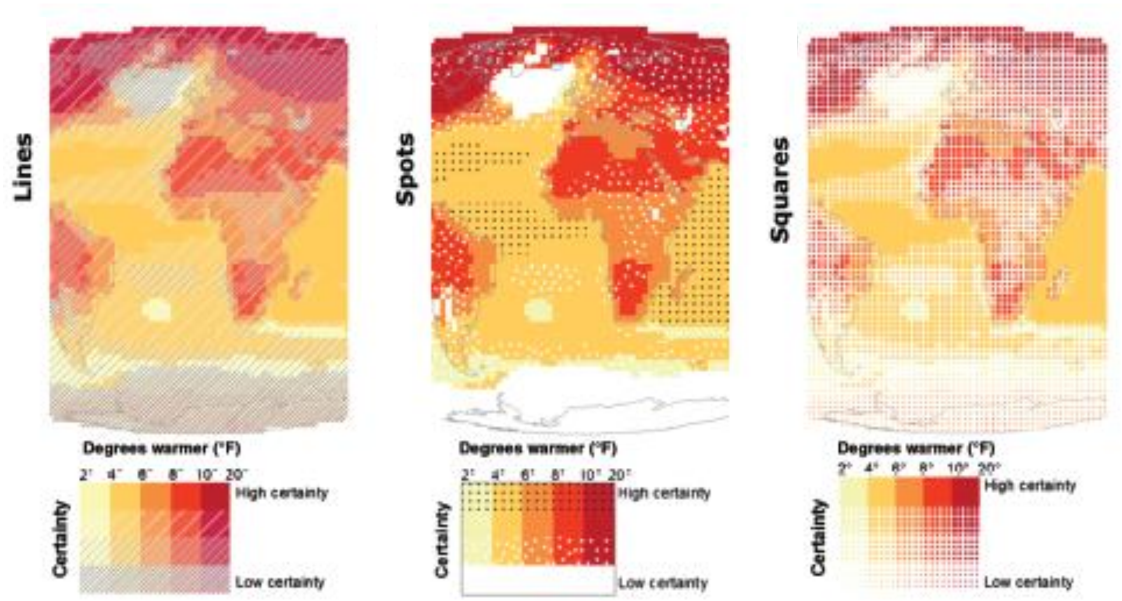

Figure 14*: Bivariate maps with colour-pattern scheme as proposed in the work by Retchless & Brewer (2016), where the variation in temperature is represented by manipulation of colour hue, while the variation of certainty is represented by manipulation of the density of patterns.*

2.3.4 Static versus dynamic visualization

As third dichotomy relevant to the categorization of uncertainty visualization according to Kinkeldey, MacEachren, et al. (2014), the opposition between static and dynamic displays is investigated. While the majority of the works dealt with classical static map displays, there are nonetheless some studies that inquired the effect of animated presentation of uncertainty, although non-interactive modes are more common than interactive interfaces (Kinkeldey, MacEachren, et al., 2014). To add dynamic components to the visualization, the parameters that can be manipulated range from speed, to blinking, motion blur, oscillation, movement order or range of movement (Schumann & Griethe, 2005). Examples of interactive displays include the possibility to toggle or click locations in map to discover uncertainty (Schumann & Griethe, 2005). Brodlie et al. (2012) recalled that when using animation there is the need to be careful in how it is implemented, since animation can bring to additional complications and pitfalls. Kinkeldey, MacEachren, et al. (2014) observed that since there are numerous ways to combine elements of animation and interaction, it is difficult to draw conclusions on its effectiveness as method to represent uncertainty, also due to the smaller number of studies compared to static designs. However, Kamal et al. (2021) argued that since there are such a rich range of parameters that can be used to visualize uncertainty, animation is a powerful and unambiguous method to show uncertainty without cluttering the display. While the effectiveness of animated displays in providing a first overview and exploration of the data and its uncertainty is recognized by Kinkeldey, MacEachren, et al. (2014), it is equally stressed that various studies indicated that classical static approaches generally perform better than dynamic ones, in terms of user accuracy or speed. For instance, the study of Aerts et al. (2003) indicated that toggling led to lower accuracy. Further they retrieved that the interactive display changed the preferred uncertainty visualization type between single-colour scheme and bi-colour-scheme, with participants in the toggle group equally preferring the two types, while for the static group a clear preference for single-colour was present (Aerts et al., 2003). Moreover, Evans (1997) found that while the performance between static and dynamic were similar in his study, the participants remarked a preference for the static view, with some being annoyed by the animation. In contrast, Kunz et al. (2011) found that their users were satisfied with the interactive display and felt that it has the potential to help them in the analysis, interpretation, and assessments of the data, however, it has to be noted that the audience was composed of domain-experts.

2.4 Decision-making under uncertainty

Since uncertainty is ubiquitous in the real world, the decisions that people take every day are often bound to some degree of uncertainty, hence, as argued by Bland & Schaefer (2012), being able to detect, process and resolve such uncertainty is fundamental for adaptive behaviour. Preuschoff et al. (2013) stated that while on the one hand the different forms of uncertainty cause different behaviours and learning experiences, on the other hand it has also to be considered that the cognitive processing of uncertainty is strongly dependent on both situation and context in which are presented. Further it is highlighted that the uncertainties generated from the social context in which decisions are taken, are influenced by affective processes (Preuschoff et al., 2013). As stated by Raue & Scholl (2018), taking decisions under uncertainty or risk is potentially a very complex issue. This is due to numerous constraints, as the fact that the human mind can only evaluate a limited amount of information at time, possible time pressure and level of complexity of the decision, hence the need to simplify the complexity of the decision through so called heuristics. Heuristics are short-cuts and “rule of thumbs” that the human mind takes in order to reduce the amount of time and effort needed to analyse the situations, and so being able to take quick decisions and judgments that most of the time are sufficiently good for the need of the individual (Raue & Scholl, 2018). An important contribute to that context is represented by the seminal paper by Tversky & Kahneman (1974), where they presented the concepts of three heuristics and biases to take a decision under conditions of uncertainty. In Table 3 are briefly described the heuristics introduced by Tversky & Kahneman (1974) in their work. A further aspect that plays a role in decisions under uncertainty is the so-called loss aversion, which states that in the decision process losses are weighted more than gains; Thus, in decisions with uncertainty this effect leads to avoid risky conditions (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). Over the course of the years successive the work of Tversky & Kahneman (1974), other types of heuristics for dealing with uncertainty have been proposed and described, such as the affect heuristic, the take-the best heuristic, the recognition heuristic, or the framing, to name a few (Ehrlinger et al., 2016; Raue & Scholl, 2018). As Raue & Scholl (2018) remarked, some heuristics are useful and help to take effective decisions in complex situations, while other are more prone to lead to biases and erroneous interpretations.

***Table 3**: The three types of heuristic for decision-making under uncertainty as have been defined by Tversky & Kahneman (1974).*

Heuristic	**Description**
Representativeness	It indicates the tendency of individuals to judge the likelihood that a certain object belongs to a certain category by the extent to which this object appears to be a good representant of that category, meaning how much the object resembles the other object in that category.
Availability	It describes the tendency of individuals to assess the likelihood of an event to occur or to consider them common by referring to the easiness with which instances or past occurrences of such events come to their mind.
Adjustment and Anchoring	It describes the tendency of individuals to assess situations or make estimates by using a starting point, often suggested by the way the question is framed, that then is adjusted to reach the final answer.

As reported by Bonneau et al. (2014), the more complex is a task of decision-making under uncertainty, the more complex are also the strategies that it requires, coupled with increase of the relevance of past experiences, with also neurological evidence that the brain parts involved in strategy formation and adjustment are more activated. For instance, Hansen et al. (2012) illustrated that the prior knowledge plays a relevant role in biasing their decisions under uncertainty, with different neuronal areas activating to respect to situations with absence of prior knowledge. Further, it is also remarked that different kinds of uncertainty, likewise, activate different areas of the brain during decision processes (Hansen et al., 2012). Another important aspect to consider with regard to decisions to be taken under conditions of uncertainty, is the relevance of the context in which the uncertain information is communicated, as it has been illustrated by Fox & Irwin (1998). They argue that the social, informational, and discourse context in which belief and statements are created add multiple cues to the message, which influence the understanding of the listeners and hence bias their decisions (Fox & Irwin, 1998).

2.4.1 *Effect of uncertainty visualization on decision-making*

The depiction of uncertainty in maps have an effect on the decisions that users have to take using those maps as support for the analysis and decision process, as the research conducted in recent years in the uncertainty visualization field indicate (Bisantz et al., 2011; Cheong et al., 2016; Deitrick, 2007; Hope & Hunter, 2007b; Kinkeldey et al., 2017; Korporaal et al., 2020; Kübler et al., 2020; McKenzie et al., 2016; Padilla et al., 2018; Roth, 2009a). As Roth (2009a) illustrated in his study, the uncertainty in geographic information is a central element along all the process that leads to the visualization and the decision-making phase. The typologies of uncertainty, as described in MacEachren et al. (2005), that are deemed as the most important during decision-making are the ones of accuracy, precision, and currency (Roth, 2009a). In Figure 15 is portrayed a scheme on the steps of the process of decision-making under uncertainty with visualized uncertainty and how this uncertainty flows across the decision making-process (Roth, 2009a). The effects of visualized uncertainty on the decisions of users can range from the accuracy of the decisions of the users, the time they need to take the decision, the perception of difficulty of the task and their confidence on the taken decision (Roth, 2009a).

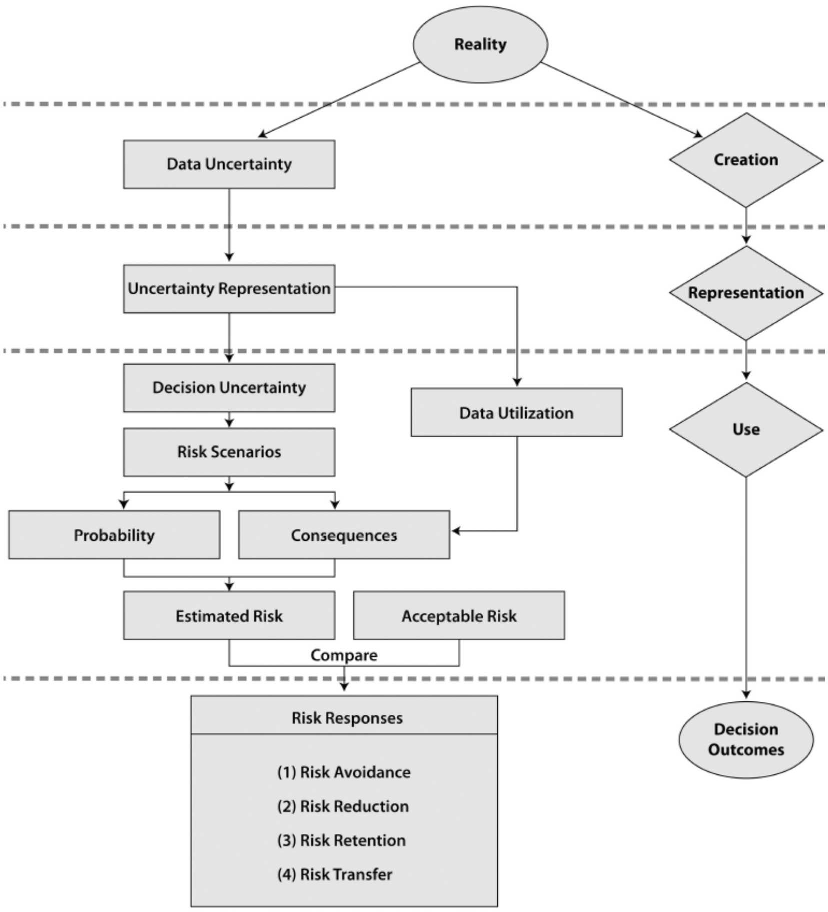

Figure 15*: Schematic overview of the decision-making process under uncertainty with the integration of how the visualized uncertainty intervenes flows along the process, as proposed in Roth (2009a).*

Effects that have been often investigated and detected are the ones concerning the differences in the accuracy of the decision outcomes and the differences in the performance of users in terms of speed and choices made (Deitrick, 2012; Deitrick & Edsall, 2006; Hope & Hunter, 2007b, 2007a; Leitner & Buttenfield, 2000; Riveiro et al., 2014). In their study, Hope & Hunter (2007b), noticed that depiction of uncertainty can lead to irrational choices by participants. In contrast, Leitner & Buttenfield (2000) argued that in their study the presence of uncertainty lead to more accurate and informed decisions. It appears that findings concerning the effect of uncertainty are sometimes contrasting. Namely, as reviewed by Kinkeldey et al. (2017) in some studies the visualization of uncertainty lead to the identification of an increase in the time required for taking the decisions compared to the visualization without uncertainty, while in other studies no significant difference in the decision speed was found. Further, similar contrasting results have been found for the accuracy of the responses, with both studies detecting a positive, or negative, effect of uncertainty visualization on accuracy and other not detecting significant deviations between the groups with and without uncertainty depiction (Kinkeldey et al., 2017). Nonetheless, even in studies where the overall accuracy or time performance was similar in the two conditions, differences were detected in the specific choices made by participants (Kinkeldey et al., 2017). For instance, Riveiro et al. (2014) reported that participants with uncertainty visualization set different priorities in the task, basing their choices on a "worst-case-scenario".

It is also important to underscore that the chosen method to represent uncertainty has a substantial effect, leading sometimes to noticeably different outcomes, as retrieved in numerous studies that compared the performances across multiple kinds of visualization (Cheong et al., 2016; Kübler et al., 2020; McKenzie et al., 2016; Padilla et al., 2015; Ruginski et al., 2016). McKenzie et al. (2016) noted that the way positional uncertainty was depicted (either as gaussian fade or as an opaque circle indicating the 95% confidence interval) significatively impacted both the time required to take decisions as well as the accuracy of their judgments. Further it was noted that different visualization prompted the use of different heuristic by the participants to make their assessments, namely the use of distance heuristic for gaussian fade but containment heuristic for the opaque circle (McKenzie et al., 2016). Noteworthy, also in the work of Ruginski et al. (2016), which investigated hurricane forecast visualizations, it has been recorded that the different types of visualization led to different assessments of risk, different heuristics for making the assessments and also different understanding of how hurricanes evolve over the course of time. As Kübler et al. (2020) further highlighted, while all uncertainty visualizations led to more risky choices than when uncertainty was not visualized, the visualization with colour value was more prone to lead this kind of behaviour. An additional aspect that appears to have influence on the outcomes of decision-making with uncertainty visualization is the expertise and previous knowledge of the users (Kinkeldey et al., 2017; Riveiro, 2016; Roth, 2009b). Kinkeldey et al. (2017) argued that two types of expertise may play a role: on the one hand the spatial and map reading expertise may help in tasks as value retrieval, on the other hand expertise in the domain or in statistics may lead to better performance in decision-making and assessments based on map information. For instance, Riveiro (2016) found that domain-experts were reporting higher confidence in their choices, required slightly more time, and consulted more often the additional information, which lead to higher situation awareness and but also higher workload, compared to non-experts. Similarly, Roth (2009b) reported significant differences between experts and novices in the risk assessment (experts assigned higher risks), the perceived risk difficulty (lower difficulty for the experts), and assessment confidence (experts are more confident). He further stressed that different expertise (different domain) also have an influence (Roth, 2009b). Conversely Hope & Hunter (2007b) assessed that both novices and experts of spatial analysis do not have intuitive understanding of how to work and make decisions with uncertainty and performed similarly. If in addition to uncertainty is also present a time constraint, then outcomes of the decision-making process can be influenced in different ways, which ranges from accuracy of responses to applied strategies and heuristics (Cheong et al., 2016; Korporaal et al., 2020; Riveiro et al., 2014). While Cheong et al. (2016) retrieved that under time pressure the participants performed better with different visualizations techniques compared to the situation without time pressure, Korporaal et al. (2020) did not found differences in the accuracy of the answers given by participants under time pressure with respect to the ones without time constraints. Nonetheless, the analysis of eye-tracking data revealed that with time pressure different amount of time were spent on the uncertainty legend and the map compared to the condition without time pressure (Korporaal et al., 2020).

The use of qualitative and mixed methods, such as open-text questions or verbal feedback ("think-aloud"), to measure and gather more insights on the effects of uncertainty on the decision-making process was highly supported in the review of Kinkeldey et al. (2017). As they argued, there is the need in the field of uncertainty visualization to investigate more into the effects of visualized uncertainty on decision-making, as well as to understand the cognitive processes and the heuristics used by map readers to take their decisions when uncertainty is depicted (Kinkeldey et al., 2017). On that matter, Padilla, Castro, et al. (2021) suggested a new explanatory theory, based on the framework for analysing decision-making supported by visualizations developed by Padilla et al. (2018), which identifies in the limits of the working memory as a reason for explaining the errors made in decisions under uncertainty. In this framework, Padilla et al. (2018) define two types of decision process that the user can make: so-called Type 1 decisions, which are defined as fast, easy, and light effort decisions, and the so-called Type 2 decisions, which instead are defined as slower, contemplative, and effortful decisions. Under conditions of uncertainty, it is argued that the increased demand of working memory contributes to the biases that are often found in decisions with visualized uncertainty (Padilla, Castro, et al., 2021). Are further identified three stages of the analysis of a visual depiction of uncertainty and the associated problems that may lead to those increased demand of working memory (Padilla, Castro, et al., 2021).

2.5 Climate change and its communication

2.5.1 Climate change: causes, consequences, and mitigation

Considering the increasing number of issues arising in various and diverse fields due to the ongoing climate change, numerous studies argued that this phenomenon is the major and toughest challenge that the human society has ever faced (Abbass et al., 2022; Battocletti et al., 2023; Dietz et al., 2020; Herrando-Pérez et al., 2019; von Gal et al., 2024). Over the decades, an increasing amount of evidence from various sources have been gathered, which points towards the decisive and ascertained anthropic contributions to the changes that the climate of our planet is currently experiencing (Dietz et al., 2020; IPCC, 2023; Vijayavenkataraman et al., 2012). As the collected evidence indicates, the main causes of climate change are to be found in the human activities that after the industrial revolution brought constantly increasing amounts of greenhouse gases into the atmosphere (Abbass et al., 2022; IPCC, 2023; Vijayavenkataraman et al., 2012). These activities range from the burning of fossil fuels for heating, transport, and industry, to deforestation, land use changes, agricultural practices, and waste management (Abbass et al., 2022; IPCC, 2023; Tian et al., 2016; Vijayavenkataraman et al., 2012).

The consequences of climate change are expected to be far reaching and to affect various aspects of both the natural environment and the human society (IPCC, 2023). To name a few, as summarized by Abbass et al. (2022) and Vijayavenkataraman et al. (2012), the impacts of climate change will affect the agricultural production due to increased droughts, extreme events, and diffusion of pests; increase economical burdens and instability due to natural catastrophes, food security challenges; exacerbate the melting of glaciers and polar caps, with the consequent sea-level rise will endanger coastal communities and impact freshwater availability; reduce mental and physical health of the more vulnerable segments of population and put them under further pressure. For instance, related to the latter point, the increase of temperature associated with the climate change will lead to an intensification of the urban heat island phenomena and heat-related health issues (Åström et al., 2011), as well as an expansion of the areas affected by vector-borne diseases that until now are limited to the tropics (Abbass et al., 2022; Anderko et al., 2020). Further, major losses for the biodiversity of our planet are expected, with a large number of species facing extinction or having their distribution areal greatly reduced withing the next decades (Bellard et al., 2012; Warren et al., 2013).

Despite the magnitude and pervasiveness of those impacts, there are actions and adaptations that can be undertaken in order to attempt to mitigate and minimize the harmful effects (IPCC, 2023). The mitigation measures encompass efforts to both reduce the current rate of greenhouse gases emissions, for instance by reducing fossil fuels use, incentivise more efficient energy use, or increase of sustainable energy sources, as well as by increasing carbon sinks, for instance with reforestation (IPCC, 2023; Vijayavenkataraman et al., 2012). As stated by Vijayavenkataraman et al. (2012), in order to be successful, mitigation measures require a collaboration of both the governments as well as of the broad population. Other possible actions are represented by adaptations, which allow to minimize the harmful and adverse effects of the changes that are already affecting the society, such as more efficient water and resource management, enhancement of the health system or improvement and hardening of the coastal defences (IPCC, 2023). Figure 16 provides an overview of the challenges that policymakers and society must handle to mitigate the magnitude of climate change and to adapt to the novel conditions.

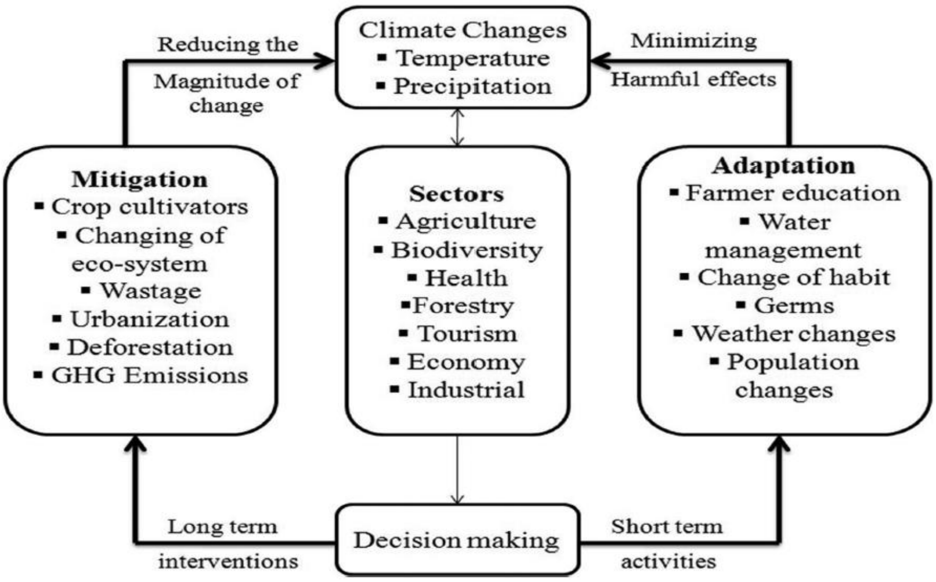

Figure 16*: Schematic overview on the impacted sectors and challenges to tackle in order to mitigate and adapt to the impacts of climate change (Abbass et al., 2022).*

2.5.2 Climate change uncertainties and communication

Climate change is a particularly difficult topic to be communicated efficiently to the broader public and policymakers, due to numerous reasons, such as the invisibility of its causes (the greenhouse gases are invisible and do not have direct immediate implications), the temporal distance of the impact of the more severe changes, and because of its complexity and uncertainties (Moser, 2010). As stated by Moser (2010) climate change is an immensely complex phenomenon, and despite the great progress of scientific research in the last decades, uncertainties about the magnitude of its effect are still present, since not all the underlying processes and interactions are fully understood. The sources of uncertainties in climate change research can arise from lack of data or errors in the measurements, still incomplete understanding of the interactions of the various components of the earth system, inherent limits of models to fully represent the real world, different datasets used in the models, limitations of the computational resources available or the unavoidable aleatory uncertainty (Moser, 2010; van der Bles et al., 2019).

Verbal communication

Kause et al. (2021) argued that several aspects have an influence on the response of users to the communication of climate-related uncertainty, for instance the type of uncertainty, the portrayed variable as well as the user characteristics, such as their attitudes, numeracy, or political affiliation. In the context of climate change research and communication, the IPCC is the organ tasked with providing comprehensive reports, aimed mainly to policymakers, on the state of knowledge on the causes, consequences and possible mitigation and adaptation to climate change (Janzwood, 2020). In order to have a common structure to express the uncertainty tied to climate change between the various research groups and reports, the IPCC has developed a reference uncertainty language framework (Janzwood, 2020). This framework is based on the use of three different but related scales: The first one is providing information on the assessed amount and quality of the evidence (robustness based on the degree of consistent and independent lines of high-quality inquiry) and scientific agreement of the working group on the discussed finding (Janzwood, 2020; van der Bles et al., 2019). The second scale is closely tied with the first, since the combination of the assessed evidence and agreement defines the confidence in the finding, which is a qualitative judgment of its validity (Janzwood, 2020; van der Bles et al., 2019). Finally, the third scale defines the likelihood of such finding, thus quantifying its uncertainty in a probabilistic manner (Janzwood, 2020; van der Bles et al., 2019). In Figure 17 are schematically summarized the different scales and concepts of this framework.

The approach of IPCC to communicate climate change uncertainties has been investigated and scrutinized by numerous studies (Aven, 2020; Budescu et al., 2012; Janzwood, 2020; Molina & Abadal, 2021; Wüthrich, 2017). Molina & Abadal (2021) recognized that over the years the uncertainty language of the IPCC has improved, by becoming more direct and by integrating the uncertainty terms in a clearer and easily identifiable manner, without rendering the text more complex. However, as Janzwood (2020) highlighted, there is still an inconsistent use of such terms in the reports, due to sources of confusions in the authors of the reports about the choices of when to use the different scales. Further, Wüthrich (2017) argued that the framework has several underlying problems, due to the ambiguity in how to assess aspects such as agreement and confidence, as well as the absence of clear rules for when to provide the likelihood information and where to only give qualitative assessments. Concerning the understandability for the general audience, a major issue that Budescu et al. (2012) have raised in their paper concerns the fact that the uncertainty expressions used in the IPCC were consistently misunderstood in an underestimating manner by the audience, meaning that the statements were considered as less extreme than what the IPCC authors intended. This prompted Budescu et al. (2012) to suggest the use of both verbal and numerical expression, which showed to produce better understanding of the terms.

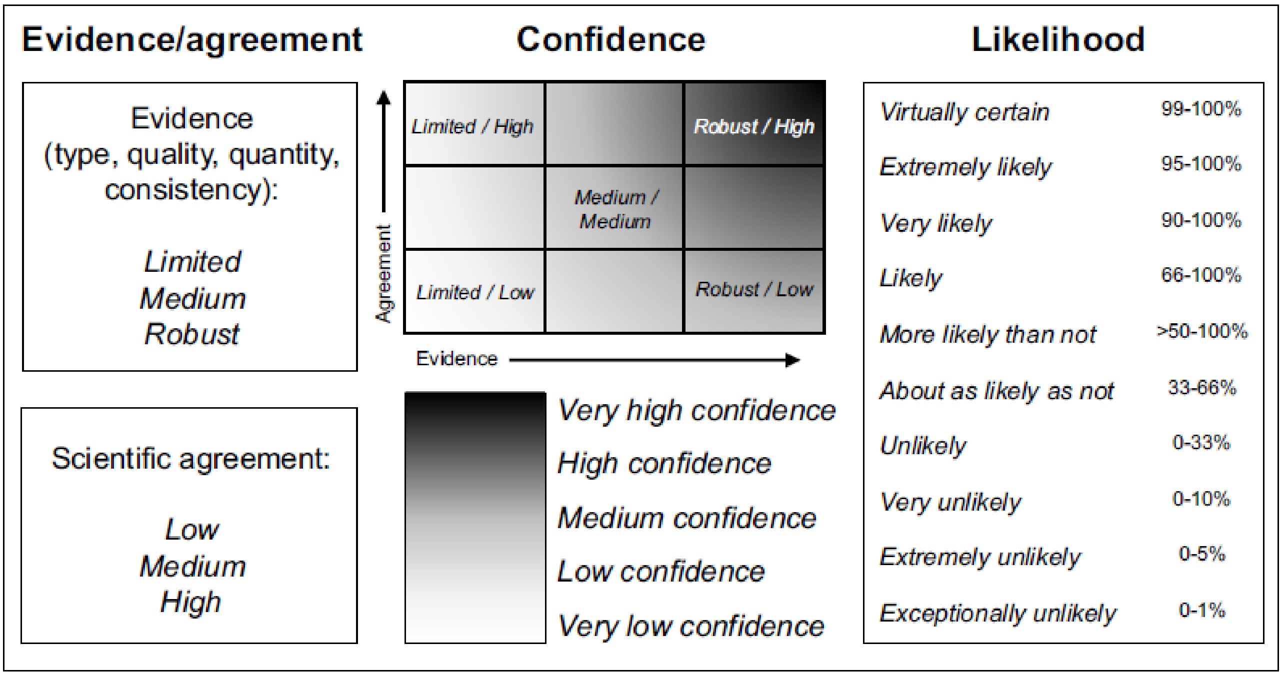

***Figure 17**: The uncertainty framework for the IPCC reports. The scientists writing the reports issued by the IPCC follow these guidelines to present the degree of certainty of the causes, forecasted consequences and possible adaptation and mitigation solutions, expressed with the two metrics of confidence in science and likelihood levels (Janzwood, 2020).*

Visual communication

Even though climate change and its uncertainty remain a complex topic to communicate, appropriate and clear visualizations can nonetheless help in making the results of climate change research, such as the IPCC reports, reach the general public (Harold et al., 2016). As Kaye et al. (2012) remarked, the use of maps to represent climatic and weather phenomena has a long tradition and is now a crucial asset for the successful communication of climate change to a wider audience, for instance through bivariate maps. This kind of maps are one of the adopted methods for the visualization of uncertainty in the IPCC reports, with use of both patterns of dots and lines in the fifth assessment report (IPCC, 2013), while for the sixth assessment only a pattern of lines is utilized (Gutiérrez et al., 2021; IPCC, 2021). In Figure 18 is displayed an example of how the uncertainty was depicted on the fifth report, while in Figure 19 the current implementation is shown, as seen in the IPCC Atlas. The visualization of climatic variable and uncertainty with bivariate maps in the context of climate change mapping has been assessed as a suitable method; though there is the need to consider that not all the kind of patterns convey uncertainty with the same efficacy and that depending on the scale of the maps other methods may be more suitable (e.g., bivariate maps work well for “big picture”, but less so for detailed information) (Kaye et al., 2012; Retchless & Brewer, 2016).

As stated by Harold et al. (2020), graphical visualizations are an important component of IPCC reports and it is therefore central that these are both a robust and accessible representation of the science behind them. Hence, over the last decade the visuals of IPCC reports have been subject of intense scrutiny by numerous studies, aimed to understand how they were interpreted by the audience and how to improve them (Battocletti et al., 2023; H. Fischer et al., 2020; Harold et al., 2016, 2020; McMahon et al., 2015, 2016). In that sense, H. Fischer et al. (2020) argued that IPCC visuals should strive to follow intuitive designs, since as their study showed, counterintuitive representations led respondents to not only misunderstand the information displayed, but to be highly confident of their incorrect interpretation. Further, Harold et al. (2016) argued that the mental representation that map readers make of the visualization is influenced by prior knowledge and goals. Hence, they stressed the need for IPCC visuals to take advantage of the insights from the cognitive and psychological research about how to make visualization accessible and draw the attention of readers to the most relevant information portrayed (Harold et al., 2016). Another point that has been stressed was to pay attention to the visual complexity of the visualization, which, when to high, may be detrimental to the correct understanding (Harold et al., 2020). Concerning the visualized uncertainty, McMahon et al. (2015) noted for instance in their study that the respondents were not always able to distinguish between which uncertainty was caused by imperfect knowledge and limitations of the models and which was due to the different possible socio-economical scenarios, systematically interpreting both of them as uncertainty of models. Further McMahon et al. (2016) retrieved that, while for some visualizations the removal of uncertainty information made them more understandable, this is practice is not easily appliable in the context of the IPCC reports, since the uncertainty communication is deemed as fundamental for the honest and transparent communication of the IPCC.

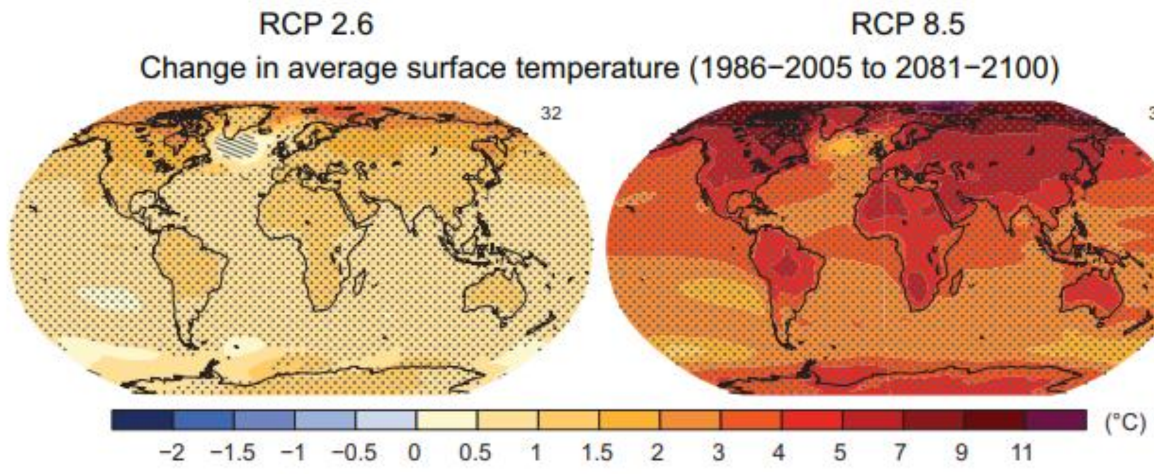

***Figure 18**: Display of a climatic variable change and its uncertainty, here the average temperature, as made at the time of the fifth report assessment of the IPCC, where in areas with the pattern of lines there is high uncertainty in the prediction, while in the areas with pattern of dots there is low uncertainty (IPCC, 2013).*

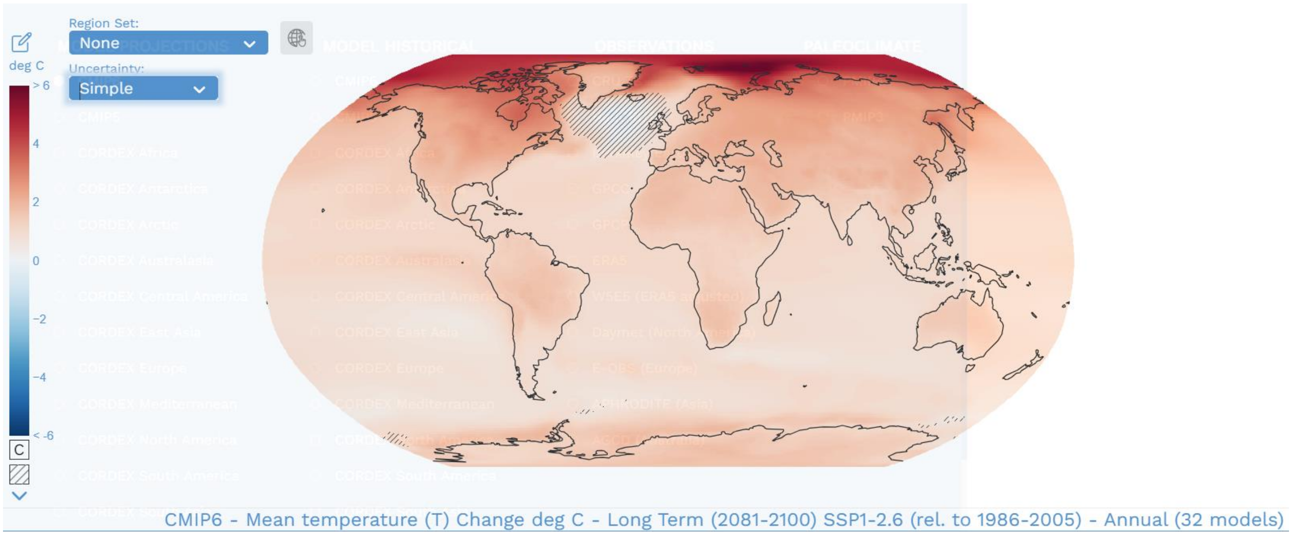

***Figure 19**: Current display in the IPCC Atlas of a climatic variable change, in this case average temperature change, and its uncertainty, represented as the areas with pattern of lines (Gutiérrez et al., 2021).*

2.5.3 Climate change attitudes

Definition of attitude

Attitudes are a core concept in psychology and can be defined as an evaluation of an object of thought, which can be anything, from things to people or ideas (Bohner & Dickel, 2011). A slightly different definition is given by Scherer (2005), who defines attitudes as rather enduring beliefs and predispositions towards specific objects or persons. Attitudes can be understood as being composed of a cognitive component, which is the belief towards the object, an affective dimension, which is the pleasure or displeasure caused by the object, and a behavioural component, in the form of a tendency to avoidance or approach to the object (Scherer, 2005). There are essentially two approaches to measure attitudes, either through explicit measurements with self-report scales, or with implicit measurements, mostly by time-based methods, where attitudes are inferred by the reaction times to stimuli, or with association tests (Bohner & Dickel, 2011). While explicit measurements can be subject to errors and biases due to respondents not willing to share their attitude or unbale to introspect themselves, implicit methods avoid these types of biases and also allow to infer aspects of the attitudes that are not retrievable by introspection (Bohner & Dickel, 2011).

Climate change attitudes and scepticism

In the context of the ongoing climate change, attitudes of the broad population and policymakers have an important role. Climate change revealed to be a divisive topic, with part of the society accepting and believing at the reality of the phenomenon and its impacts, as well as the responsibility of human activities, while other segments of the population showing a more sceptic or dubious stance, arriving in some cases to completely reject the idea of climate change (Capstick & Pidgeon, 2014; Jylhä & Hellmer, 2020; Poortinga et al., 2011, 2019). Intensive research has been made on the reasons that causes scepticism in these segments of population, on how they relate with climate change information, as well as on how to successfully communicate and present them the issues bound climate change (Capstick & Pidgeon, 2014; Corner et al., 2012; Howell et al., 2016; Lee et al., 2015; Poortinga et al., 2011; van Valkengoed & Steg, 2019; Weber, 2010; Whitmarsh, 2011). The practical consequences of the presence of segments of population with sceptic stance, particularly if is diffused, can result in difficulties to implement mitigation measures and/or promote virtuous responses, since either these segments are resistant to change or the policymakers may be hesitant to take actions that discontent a large amount of population (Capstick & Pidgeon, 2014; Poortinga et al., 2019; N. Smith & Leiserowitz, 2012, 2014). In addition, it has to be considered the aspect that numerous actions to reduce the impact of society on climate require active engagement and partaking of the population on an individual basis (Capstick & Pidgeon, 2014; O'Neill & Nicholson-Cole, 2009; N. Smith & Leiserowitz, 2012, 2014).

The factors that can lead to the development of scepticism in the population are variegated. Several studies found a link between climate change scepticism or denial and aspects such as older age, right-wing political affiliation, as well as some more conservative personal values and cultural worldviews (Corner et al., 2012; Lee et al., 2015; Poortinga et al., 2011, 2019; N. Smith & Leiserowitz, 2012, 2014; Whitmarsh, 2011). Further, some external factors such as issue fatigue, phases of economic crisis or stagnation and fluctuation in the media coverage on the topic may contribute to increase the share of population with sceptic stance (N. Smith & Leiserowitz, 2014). Noteworthy, is also the issue that for some segments of population climate change may seem as something distant in time and space, which does not concern them personally (Harth, 2021; Moser, 2010; Spence et al., 2011).Another aspect that contributes to the scepticism are the uncertainties tied to the findings in climate change science (Corner et al., 2012; Moser, 2010; Poortinga et al., 2011). Concerning the Jylhä & Hellmer (2020) climate change denial, Jylhä & Hellmer (2020) found that it does often correlate with factors such as anti-egalitarian preferences, acceptance of group-base hierarchies, traditional values, as well as more likelihood to have other pseudoscientific beliefs. As reviewed by Capstick & Pidgeon (2014) climate change scepticism has been defined in different ways, depending on the study, ranging from doubts about the scientific debate to doubts about the reliability of climate science and the anthropogenic causes, or complete denial and association with conspiracy theories. However, Capstick & Pidgeon (2014) noted that two main categories of scepticism arise, which they call epistemic scepticism and response scepticism. While the former is due to doubts about the climate science and the physical dimensions of climate change, the latter is characterized by the doubts on the efficacy of the proposed mitigation actions and the relevance of climate change for society (Capstick & Pidgeon, 2014). In Figure 20 are summarized key elements cited by the participants in the study by Capstick & Pidgeon (2014) that allowed to define the two types of scepticism. In Poortinga et al. (2011), it is also recalled a distinction between different types of sceptics, such as trend sceptics (scepticism about the increase of global temperatures), attribution sceptics (scepticism about the anthropogenic causes) and impact sceptics (who while agreeing on the reality of climate change and the human accountability, are sceptic about the magnitude of the impacts). It has also been stressed that it is important to distinguish between these different levels of scepticism, as for instance the response scepticism is more permeable to good communication of climate change and thus can be more easily tackled (Capstick & Pidgeon, 2014).

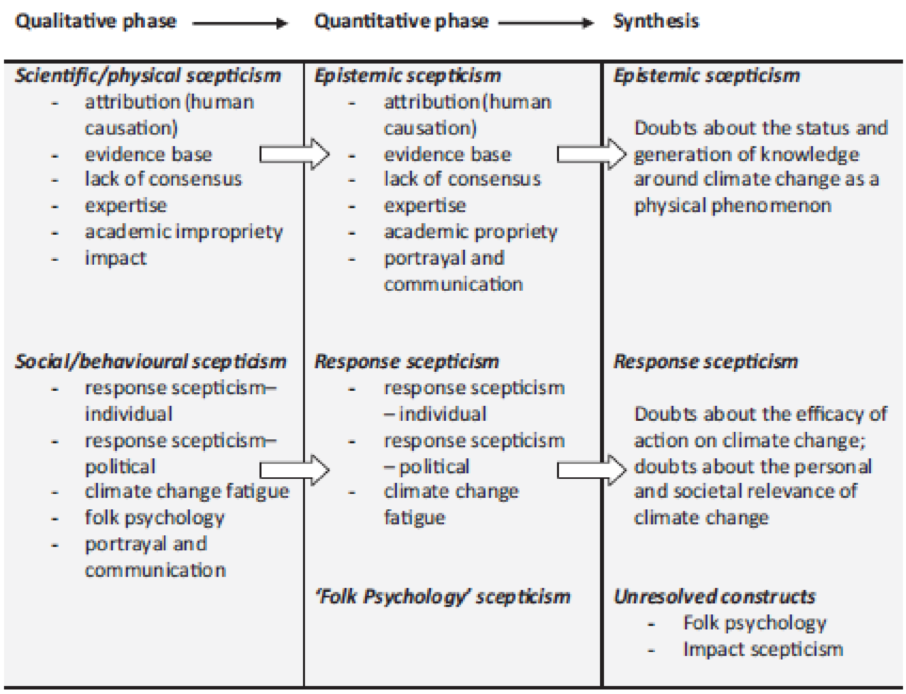

***Figure 20**: The two types of climate change scepticism proposed by Capstick & Pidgeon (2014) and the characteristic elements of each type that have been retrieved from the feedback and the questionnaire compiled by the respondents in their study.*

2.5.4 Influence of attitudes on information processing and decision-making

As stated by Bohner & Dickel (2011), the attitudes are particularly relevant in social psychology since they have a large influence on both the behaviour and the information processing of an individual. Namely, the stronger is the attitude of a person towards an issue, the more that person will tend to selectively search and choose information congruent with their belief (selective exposure, confirmation bias); further, also the level of motivation of a person to defend their attitude plays an important role in the processing of information (Bohner & Dickel, 2011). In the case of decision-making when presented with climate change information and related uncertainties, attitudes have a relevant influence. Namely, climate change attitude can act as a filter to the presented information and lead users to selectively search for information confirming their view (Kause et al., 2021). Weber (2010) recalled that worldviews and beliefs determine which climate information people care and attend to and which they chose to ignore or undermine. For instance, Budescu et al. (2012) noted that respondents with sceptical stance were more prone to read the uncertainty statements in the IPCC reports in an underestimating manner compared to respondents with believing stance, which supports the point that people tend to interpret uncertainty expression in ways that are consistent with their beliefs. Further evidence of the effect of attitudes towards climate change leading to biased assimilation has been determined by Corner et al. (2012). In their study, both sceptical and believing respondents were confronted with contrasting information about the uncertainty of climate change, which showed that the sceptics were rating as more convincing the information against climate change rather than to the one supporting it, whereas the contrary was true for believing respondents (Corner et al., 2012). It was also detected a slight tendency to attitude polarisation in the stance that the respondents gave after performing the task (Corner et al., 2012). A study by Howell et al. (2016) retrieved information about mitigation and adaptation measures affected differently the participants depending on their attitudes. Participants that stated a higher level of concern were more engaged with mitigation measures, whereas participants that were less concerned by climate change were more engaged by the adaptation measures (Howell et al., 2016). Further, there are some indications that people sceptical towards climate change tend to maintain their attitude even after experiencing extreme events, since they interpret the event as natural and not linked to climate change (Carlton et al., 2016). Hence, while these experiences may lead them to increased risk perception and to be more favourable to localised risk prevention adaptation, their acceptance of mitigation and adaptation measure remain unlikely (Carlton et al., 2016).

2.6 Emotions

2.6.1 Definition of emotion

While the concept of emotion is commonly evoked in everyday life and appears as a straightforward term, defining precisely what is an emotion and how to categorize different emotions is a difficult endeavour, as noted by Scherer (2005), with numerous different attempts to come with a definition along the past century. Often, these definitions are specific for the purpose of the field or research presented; for instance, in the framework of his development of a method to measure emotions, Scherer (2005) defined an emotion as an "*episode of interrelated synchronized changes in the states of all or most of the five organismic subsystems in response to the evaluation of an external or internal stimulus event as relevant to major concerns of the organism*" (p. 697). In Harley (2015) instead, the definition used for emotions is that they are the responses of an individual to situations that are perceived as relevant to reach their current goals and are composed of three components: feelings, behaviours, and physiological responses. According to the appraisal theory, as recounted by Soleymani et al. (2014), the appraisal of, or cognitive judgment of, a situation is the core element in the formation of emotional response. An emotion, or multiple emotions, are experienced as consequence of a perception, followed by an evaluation on the base of personal wishes, ideals, or norms, of an object, event, or action (Soleymani et al., 2014). What can be deduced from these definitions is that human emotions are a multifaceted phenomenon, that can be understood as encompassing many components, from cognitive to physiological ones. While the discussion of how many emotions exists and how they can be classified in relation to each other is still field of debate among the emotion researchers (Harley, 2015), the broad classification of emotions along the three main dimensional axes of pleasure, arousal, and dominance is a solid and accepted framework (Bakker et al., 2014; Bradley & Lang, 1994; Harley, 2015). These three dimensions have been used since long time by psychologists to describe human perception of the environment and are considered as the three basic dimensions of emotional responses to describe the state of feeling of an individual (Bakker et al., 2014).

An important aspect to consider, is to avoid confusion with terms that, although related to emotions, do indicate different facet of the human affective experience. On that regard, Soleymani et al. (2014) recall that, while often used interchangeably, the concepts of mood and emotion are different. While moods are general, slow moving affective state not strictly bound to a specific object or event, emotions have instead to be understood as short and intense moment of affective reaction to an object or event (Soleymani et al., 2014). Scherer (2005) further illustrated other affective phenomena that are related but distinguished from emotions: preferences, attitudes, affect dispositions and interpersonal stances. An overview of the related affective phenomena terms is given in Table 4.

***Table 4**: Related affective phenomena, distinct from emotions, as have been described in Scherer (2005).*

Affective phenomenon	**Description**
Preferences	Relatively stable judgments (liking or disliking a stimulus), which generate appraisal independently from current needs or goals. They cause tendencies to approach or avoidance towards the stimulus.
Attitudes	Relatively enduring beliefs and predispositions towards specific objects or persons. They do not need to be triggered by the object, although the presence of the object may make them more evident. They cause affective states such as hating, valuing, or desiring towards the object.
Affect dispositions	Tendency of experiencing certain moods more often or reacting with a certain range of emotions to stimuli. E.g. personality traits and behaviours as depressive, jealous, reckless, irritable.
Interpersonal stances	Affective style that either naturally develops or is strategically used in social contexts, in interactions with another person. E.g. being polite, cold, warm, supportive.

2.6.2 Measuring the emotions

Measuring the emotions is an inherently difficult task, due to the multifaceted nature of the concepts and its various components, thus, as argued by Scherer (2005), only a group of measurements assessing each single component could reach a comprehensive analysis of an emotion, which however is not practical or feasible. As expressed by Soleymani et al. (2014), being able to understand which emotions were truly felt by a participant in an experiment has always been a challenge for researchers. Nonetheless, various methods have been developed, each one of them approaching the emotion measurement from different perspectives and based on different components, as illustrated in the review by Harley (2015). It is possible to broadly divide these methods in three categories: the approaches that rely on measuring the behaviour of people, the ones based on the measurements of physiological changes, and the ones based on the collection of affective self-reports of people (Bradley & Lang, 1994; Harley, 2015; Scherer, 2005).

Concerning the behavioural-based methods, examples of such are the recognition of facial expressions, vocal expression, or body posture analysis (Harley, 2015; Scherer, 2005). In regard to the use of those methods for computer-based experiments, Harley (2015) expressed that while some measurements, as the facial expression recognition, are empirically grounded and well supported by a growing body of new technological developments, other kinds of behavioural measurements, such as the body posture analysis are more disputed. For the physiological approaches, are intended the methods that measure changes or fluctuation on the electrical activity of the brain, heart, muscles, and skin, which past researches have associated with emotions (Harley, 2015). While in recent years there has been an increase of availability and non-invasiveness of the employed tools, still remain limitations due to costs and the required training and expertise to correctly use and interpret the collected data (Harley, 2015) Noteworthy, a novel and promising method that lingers between behavioural and physiological measurement is the use of eye-tracking, which has been increasingly used to detect and study emotions in computer-based studies (Harley, 2015). The category of affective self-report measures presents a vast and rich range of possible approaches, from the free-response formats to a numerous pool of questionnaires that have been developed over the years (Bradley & Lang, 1994; Soleymani et al., 2014). As Harley (2015) stated, the self-report measures are among the most empirically grounded approaches and are often seen as the "gold standard" for measuring psychological phenomena. However, a drawback of self-report methods is indeed the large amount of different available scales and measures (Bradley & Lang, 1994). Other issues are on the one hand that the free-response formats may be underperforming in the case of respondents not able to label their emotions or with different way of labelling them, and on the other hand the fact that, although emotions and emotional states are subjective experience, no objective methods for measuring such subjective experiences exist (Scherer, 2005). Nonetheless, Soleymani et al. (2014) argued that both the dimensional representation of emotions, such as the Self-Assessment Manikin by Bradley & Lang (1994) or the Geneva Emotion Wheel by Scherer (2005), and discrete representation (the way people describe their emotions on their own words), are important contributions to the understanding of the emotional experience of respondents and can work well together.

2.6.3 Influence of emotions in communication and decision-making

Emotions in communication

The emotions play a compelling role in human interactions and thus in communication (Dennison, 2024). It is known that communication that activate emotions can be particularly efficient in overriding identity-based concerns and lead people to engage deeper with the provided information, as well as promoting persona rather than ideological reasoning (Dennison, 2024). This is because emotions can impact on the effective dimension of attitudes (Chapman et al., 2017; Dennison, 2024). Further, it has been suggested that information that stimulate affective responses can influence the individual assessments of risk and consequent behaviours more than the crude facts, leading to different judgments about likelihood and severity of an event (Shanahan et al., 2019). It has also been argued that the implementation of emotion in communication strategies should be tailored to the intended audience characteristics rather than using a one-size-fits-all formula (Chapman et al., 2017). Central in this emotion-based communication is the fact that emotions should be only used as support and to make more resonant an already solid argument and not as the base of the argument, since otherwise that would be a logical fallacy known as "appeal to emotion" (Dennison, 2024). As noted in Moser (2010), messages are more than the words they are composed with, hence the framing and the evoked imagery should be carefully considered. In order to create an emotional response and reduce the psychological distance between the audience and the presented topic, various are approaches the that could be used, ranging from narratives and personal-based messages, to facial expressions and body language or aesthetics; moreover, also the framing, intensity, and ordering can be effectively used to shape the emotional response (Dennison, 2024).

According to Dennison (2024), climate change communication is the most tested form of emotion-based public communication. The effects of emotions in this context, both as emotion embedded in the way of communicating the findings as well as the emotions felt by the audience about climate change and its impacts, have been inquired by numerous investigations conducted in the recent years (Chapman et al., 2017; Marlon et al., 2019; Shanahan et al., 2019; N. Smith & Leiserowitz, 2014; Weber, 2010). Chapman et al. (2017) claimed that while the role of emotion in climate-related communication should neither be underestimated nor used only as levers to direct the public to the desired outcome, it is nonetheless necessary to view emotion as part of a broad communication strategy, due to the intertwinement between emotion, communication, and engagement. Still, as N. Smith & Leiserowitz (2014) found, emotions alone are able to explain up to 50% of the variance in support of population of climate change policies, thus being the strongest predictor of policy support even when controlling for political affiliation, ideology, demographics, or values.

Discrete emotions as worry, interest, and hope are mostly associated with increased support to climate policies, thus suggesting that communications that create motivation through carefully calibrated worry and at the same increase public interest, inspiring both hope and positive feelings, may be particularly effective and successful (N. Smith & Leiserowitz, 2012). The research conducted by Marlon et al. (2019) investigated the effect of hope and doubt, two commonly felt emotions with respect to climate change and its communication, on the willingness to support mitigation actions and policies. They found that for communicators. there might be benefits in conveying in their message constructive hope, meaning hope in human scientific and technological progress, and constructive doubt, meaning that while the threat is real and there is need to action, humanity can address the problem (Marlon et al., 2019). Further, Moser (2010) recalled that messages that cause increases of emotions such as worry, concern or fear need to be coupled with positive and solution-oriented information, otherwise the audience will direct their feelings towards the internal emotional experience instead of directing it towards the external issue that the communicators evoked. The counterproductive effect of promoting negative and fear-inducing communication has been stressed by O'Neill & Nicholson-Cole (2009). Meijnders et al. (2001) found that moderate fear can induce virtuous action with regards to energy, however they remarked that to avoid boomerang effects and feeling of lack of control there is the need to provide clear explanation on the solutions and the relation between risk and individual behaviour. In contrast (Bloodhart et al., 2018) did not find particular adverse effects due to negative emotions in communications, but instead retrieved that the presence of emotions, both positive and negative, contributed to the perception by the audience that both the communicated message was felt as important by the communicators. Moreover, in one hand the presence of emotion created the impression of higher level of strength, competence, and rationality of the communicators, while on the other hand presence of emotions resonated better for audiences composed by women or progressive political views (Bloodhart et al., 2018).

Emotions in decision making

The cognitive process of decision-making is complex and various factors interact with each other in order to provide the final outcome of the decision, and emotions are one of those factors (Bloodhart et al., 2018; Zinn, 2016). As argued by Zinn (2016) emotions are always present to some degree in the process of taking decisions, either as major drivers or as a support to other decisional strategies of the individual. As recalled by Dennison (2024) often the logic reasoning intervenes only after an internal, subconscious emotional decision has been taken. Moreover, even so-called incidental emotions, hence emotions that are not related to or evoked by the object of the decision, can have a significant effect on the final reached resolution (Achar et al., 2016; Bartholomeyczik et al., 2022). In addition, also from the neurological point of view, there are evidence that processes related to the emotional states influence and potentially bias judgement and decisions (Dolan, 2002; Quartz, 2009). For instance, the state of arousal of a person affects their decisions, where individuals with higher level of awareness of their state of arousal perform better judgement compared to less aware individuals (Dolan, 2002). It has also been proposed that the evocation of past feelings during similar decision situations can biases the current or future decisions (Dolan, 2002).

The influence of emotions as relevant factor in decision-making strategies when confronted with uncertain situations has been widely investigated, revealing that humans do not approach those decisions rationally, but are instead impacted both by choice-related emotions (called integral emotions), as well as by emotions not related to the choice (incidental emotions) but caused by precedent events or unrelated circumstances (Achar et al., 2016; Bartholomeyczik et al., 2022; Zinn, 2016). Choice-related emotions have the potential to be positive for the decision (e.g., fear due to uncertainty causing precaution), while of incidental emotions can be both beneficial or negative, whereas however only anger appears to lead to significantly more risky and uncertain choices (Bartholomeyczik et al., 2022). Zinn (2016) further argued that the use of "irrational" strategies based for instance on hope or other emotions in contexts involving uncertainty should be seen as a resource and an efficient way to deal with the issue when knowledge or resources of the individual are limited.

Regarding climate change, the deep uncertainties that are present in the discourse lead to the fact that the decision-making process of people about their future is often made more on narratives than on accurate risk assessments (Constantino & Weber, 2021). As Marx et al. (2007) warned, while most climate change communications assume that people will assess them based on analytical reasoning, the reality is that often people rely on past experiences and feelings. Further, Harth (2021) reiterated that emotions are a major driver of actions towards climate change, both at an individual level as well as group level, where positive affect and emotions can stimulate broader thinking and likely activate positive and creative transformative processes. A significant finding by Wang et al. (2018) indicates the emotions felt by people in regard to climate change can give insights to their likelihood to support climate defence policies. They argued that people who care about climate change and its consequences are actually moved by their feeling that the objects they value, which the authors call "objects of care", are threatened by the climate change (Wang et al., 2018). These objects of care reduce the psychological distance between them and the climate change, making it more personally relevant and emotionally stronger, which leads to increased likelihood to action against climate change e policy support (Wang et al., 2018). N. Smith & Leiserowitz (2012) further claimed that worry can be an efficient motivator to action, since it stimulates more intense cognitive and analytical processing of information, hence leading to problem identification and analysis, option seeking and iterative evaluation and adjustment of the implemented solutions. Nonetheless, it has also to be accounted that worry is a finite resource, meaning that people can worry only for a limited number of issues, usually the more pressing ones for them at the moment, so climate change worry have to challenge the other ones (N. Smith & Leiserowitz, 2014; Weber, 2010).

3 Methods

In order to answer the research questions posed in Chapter 1.3, an empirical online study has been developed. In this section, the methods and processes adopted for the development of the map stimuli used in the experiment, as well as the other various components of the experiment, will be illustrated. Firstly, an overview on the structure and on the design of the study will be given; secondly, the process of the recruiting of participants, as well as the platforms used for creating and then running the experiment, will be presented. This will be followed by a thorough explanation of all the single components of the study, from the pre-test to the post-test. Finally, a short introduction on how the collected data will be analysed is provided.

3.1 Study structure

This empirical study encompassed three main components. There was a first part where the participants had to answer some general demographics and background knowledge questions and then compiled three personality questionnaires, intended to assess the traits relevant to the study and their emotional state before the start of the experiment. The three questionnaires to be filled were: the Self-Assessment Manikin (Bradley & Lang, 1994), the Toronto Empathy Questionnaire (Spreng et al., 2009), and the Climate Change Attitude questionnaire (adapted from Whitmarsh, 2011). The second part consisted of the main map-based experiment, where participants have been divided in two experimental groups and took decisions on climate change maps, both with and without the certainty visualization. Participants had to select an area in the map, according to the question posed, and to assess the severity and certainty of the change of the climatic variable displayed in that location. In one experimental group the maps have been accompanied by an emotional stimulus, represented by a character and the consequences of climate change for their life; while in the other group no emotional stimulus was presented. Lastly, in the third part of the study, they had to complete another Self-Assessment Manikin on their emotional state after the experiment, an emotion wheel (adapted from Scherer et al., 2013), and finally to answer some follow-up questions about the completed experiment. An overview of the study structure is illustrated in Figure 21.

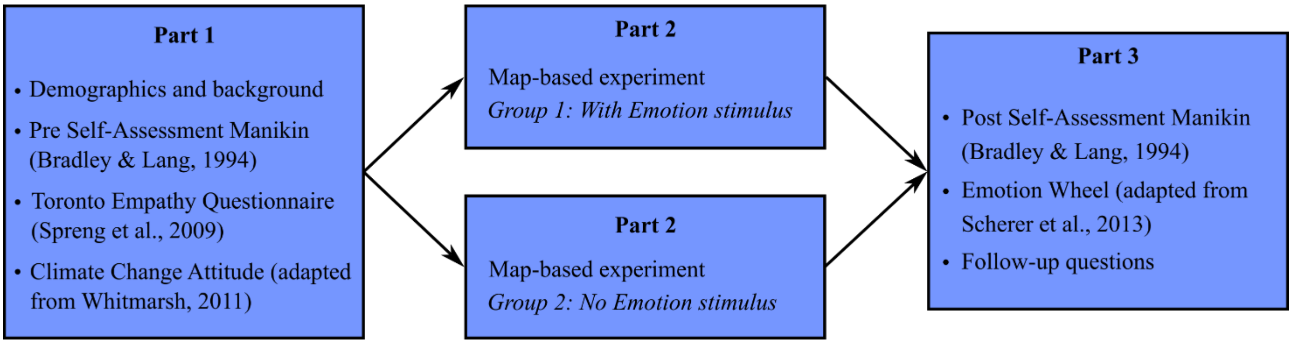

***Figure 21**: Schematic overview of the study structure.*

1) A test run of the study made with volunteers indicated that the average completion time lied between 30 and 40 minutes. The study run for a couple of days, from 12:10 (CET) on the 20th of December 2023 to 12:45 (CET) on the 22nd of December 2023. The study was accessible to registered users on Prolific (www.prolific.com), an online research platform offering a large pool of candidate participants for surveys and studies (further details on the platform will be given in Chapter 3.3). Participants meeting the inclusion criteria were allowed to view and access from their Prolific dashboard the main screen of the study in Prolific (see Appendix A) and from there reach the Informed Consent page (see Appendix B). Once consent was given, they could start the study.

3.2 Study Design

For this thesis, an empirical study has been designed, which results would provide the answers to the research questions stated in Chapter 1.3. In an empirical study the aim of the research is to investigate the change of one or more variables, called dependent variables, due to the variation of one or more other factors, termed independent variables (Martin, 2008). The variables of interest for this study will now be listed and explained.

3.2.1 Independent Variables

The independent variables are the ones who are not influenced by the participants, but instead are the ones that the researcher will manipulate in the study to investigate their effect on the dependent variables (Martin, 2008). For this study those variables were three, each one arising from the respective research question and hypothesis. Namely from the first research question arose the independent variable of the emotional narrative. The attitude towards climate change was the second independent variable, from the second research question. Finally, to investigate the third research question, the independent variable of the uncertainty visualization was needed. The influence of those three variables on the performance of participants when interpreting the presented climate change maps have been investigated.

3.2.2 Dependent Variables

In contrast to the independent variables, the dependent variables are influenced by participants, being namely the behaviour, the response, of participants to the manipulation of the independent variable (Martin, 2008). Therefore, those variables were the ones measured by the researcher in order to detect whether the manipulation had an effect (Martin, 2008). In the context of this study, those variables were the following. It has been measured the task completion time, the area the participant selected in the map-based task, their severity assessment of the area, their certainty assessment of the area, their trust rating of the map, and their emotional response to the task.

3.2.3 Control Variables

As Martin (2008) remarked, other circumstances could potentially influence the outcomes of the experiment. Ideally, all other external factors and circumstances that may affect the results should stay constant during the execution of an experiment; hence the need for the researcher to minimize, as far as possible, the influence of those factors (Martin, 2008). Those factors are the so-called control variables (Martin, 2008). In this study the variables that were controlled to assure that the outcomes of the experiment result from the variation of the independent variables were the demographics of participants, their personal background, and their experience with the treated topics, as well as their level of empathy. Since the study was conducted online and thus participants were accessing it from their devices at a location of their discretion, factors such as time of the day, lighting and noise conditions or technical hardware could not be controlled. Nonetheless, as Martin (2008) argued, due to the need of external validity of the experiment, it is reasonable not having control of all of the variables. Furthermore, given that in real-life people are confronted with maps in all kinds of conditions, this setup could be more representative of the general conditions of the public dealing with maps.

3.2.4 Mixed factorial design

An experiment can be conducted with one of two main approaches, either as a within-subject experiment or as a between-subject one, as illustrated by Martin (2008). In the first case the participants are exposed to all levels of the independent variable, while in the latter the participants are divided in groups, where only one level of the independent variable is exposed to each group (Martin, 2008). Both approaches offer their own specific advantages and disadvantages, where the within-subject method require less participants but exposes participants to all levels of the independent variable, in contrast, in the between-subject method there is no risk of contamination due to exposure to all levels, but it requires more participants and attention in building similar groups (Martin, 2008). Given that for some independent variables, e.g. the emotional narrative, is not possible to reverse the effect of a previous exposure to one of the levels (Martin, 2008), in the framework of this work, a 2x2x3 mixed factorial design has been chosen, hence a design with both within- and between-subject factors.

Going into detail about the mixed design of this study, the within-subject factor was the different types of certainty visualizations. This factor had three levels, namely there were either no certainty visualization, certainty visualized as a pattern of dots, or certainty visualized as a pattern of lines. The choice of those two types of certainty visualization was based on the work from Retchless & Brewer (2016), further details on the visualization types are given in Chapter 3.6.1. Conversely, there were two between-subjects factors, the emotional narrative and the participants attitude towards climate change. The emotional narrative factor had two levels, specifically the presence or absence of the emotional stimulus. The emotional stimulus, represented by a character and the consequence of climate change for their life will be thoroughly explained in Chapter 3.6.1. The participants attitude towards climate change also had two levels, namely a sceptic/oppositive attitude and a believing/supporting attitude. For simplicity of language, from now on participants with the former attitude will be referred to as sceptics and the participants with the latter will be referred to as believers. An overview of the study design is displayed in Figure 22.

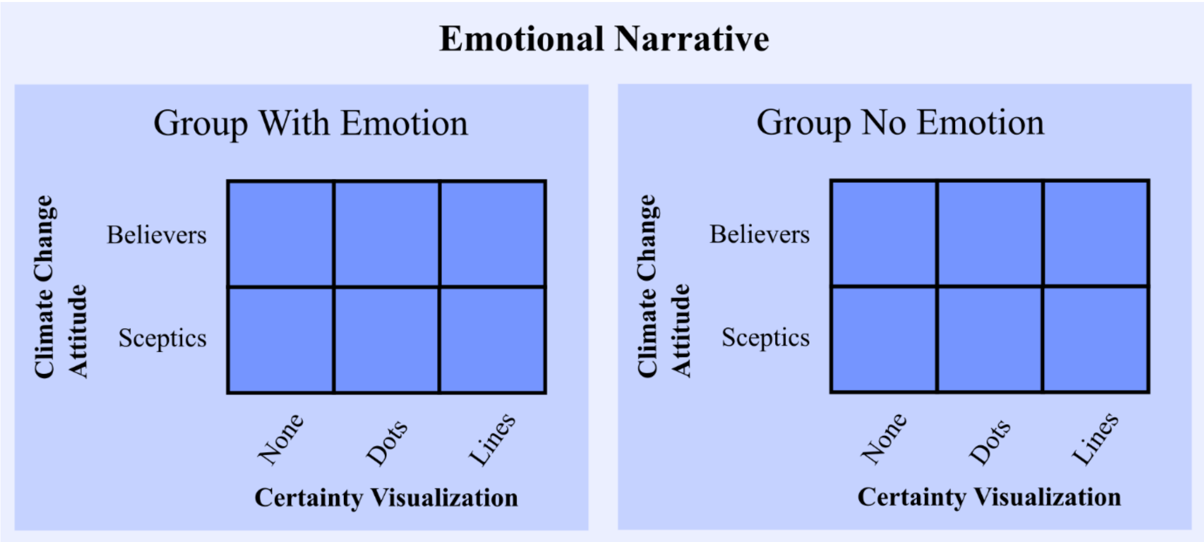

Figure 22: *Schematic overview of the study design.*

Summarizing, all participants went through all the types of certainty visualization during the experiment tasks. However, while one group had to complete the experiment where together with the maps was also present an emotional narrative, the other group completed the task with just the maps and no emotional narrative. In both experimental groups were present both believing and sceptical participants. Martin (2008) warned against the risk of learning effects during an experiment, meaning that in the course of the experiment participants could become more able to read information from the map, thus making results obtained at the beginning of the experiment different from the results of the final part. To minimize the influence of such effects on the results, the order with which participants viewed the maps was completely randomized, hence each participant viewed the maps in a different order.

3.3 Participants and the platform Prolific

The study has been conducted entirely online, with participants recruited through the platform Prolific (www.prolific.com), which is an online crowdsourcing platform, designed with the purpose of providing a pool of participants for online questionnaires and experiments (Eerola et al., 2021; Palan & Schitter, 2018; Peer et al., 2017). The main reasons that led to the decision of implementing a fully online study were two: the required sample size and the needed composition of the sample for investigating the second research question, which are now further elucidated.

According to the power calculations performed with the statistical software for power analysis *GPower 3.1* (release 3.1.9) (Erdfelder et al., 2009; Faul et al., 2007), the mixed factorial design of the experiment conceived for this thesis required a minimal sample size of at least 100 people in order to detect a medium effect size of $r = 0.25$, with a power of 80%. Being able to recruit such a large number of participants to take part to in-person experiment sessions in the laboratory of the Geographic Information Visualization and Analysis (GIVA) unit at the University of Zurich's Irchel Campus was likely not to be feasible. Furthermore, it has to be considered that there were also noticeable limitations due to time constraints, since in the laboratory would have been possible to work with only one participant at time. For instance, previous similar studies conducted in the GIVA laboratories usually reached between 34 and 43 participants (Bracher, 2022; Korporaal, 2017; Kübler, 2016).

The second reason for opting for a full online study resided in the desired target pool of participants, namely a group people that were mostly non-expert in topics of cartography, geovisualization, and climate change, but that rather represented the variegate levels of knowledge of the general population. As many researchers noted, while it is a common practice for simplicity and economic convenience to draw samples from students at the university campus, this practice could be problematic (Cappelen et al., 2015; Chandler et al., 2019; Hanel & Vione, 2016). This is firstly because students are a more homogeneous group and can differ in numerous aspects from the general population (from demographic composition to personal attitudes) and thus potentially cause important biases when trying to generalize the results (Cappelen et al., 2015; Hanel & Vione, 2016). Secondly, a specific characteristic of the participants was required for this study, namely, to have both people that were supportive of the idea of an ongoing anthropic climate change as well as people that had a sceptical stance towards it. However, recruiting a balanced samples of participants with a specific characteristic with conventional methods could be quite challenging (Chandler et al., 2019).

Due to those reasons, Prolific became a reasonable and practical alternative. On one hand it offered the opportunity to recruit study participants from a wide pool of potential participants; on the other hand, it possessed a rich range of built-in screeners to adapt the study sample pool to the specific needs of the research, as for instance a screener for climate change belief, that was central for this study (Palan & Schitter, 2018). Participants in Prolific are people residing in the countries of the OECD, which need to pass through a verification process before being allowed to participate in surveys (Palan & Schitter, 2018). Prolific invests great effort in assuring a great transparency in the whole process, from having a reliable and varied pool of participants, as well as to provide researchers with rules for paying participants and how to correctly treat them, thus providing a good ethical framework for research (Palan & Schitter, 2018). When a study is published, users of Prolific can participate on it on a "first come, first serve" principle as long as there are spaces available in the study.

The suitability of Prolific as a platform for recruiting participants in academic works has been investigated and proved to be valid and reliable in numerous studies, performing considerably better than other competitors (Armitage & Eerola, 2020; Palan & Schitter, 2018; Peer et al., 2017, 2022; Uittenhove et al., 2023). Possible problematic issues that can arise with online recruitment platform, compared to lab-based experiments, are the impossibility to control the surrounding environment or avoid participants distractions, as well as the non-naivety and potential cheating behaviour of some participants (Palan & Schitter, 2018; Peer et al., 2017, 2022). Nonetheless, studies have shown that more importantly than the way (online vs lab-based) with which is conducted an experiment, is the aspect of who is in the pool that plays a relevant role (Peer et al., 2017, 2022; Uittenhove et al., 2023). Nevertheless, there are advantages in using crowdsourcing platforms, such as efficiency in the recruiting process, testing more participants simultaneously, no need for rooms or in-person presence of participants and researchers, less economical costs, and better similarity with the general population (Grootswagers, 2020). Finally, in the specific case of Prolific, it is worth to highlight that the platform has been designed by former graduates of Oxford and Sheffield Universities for the specific purpose to serve as a pool for academic studies, thus with a particular commitment to guarantee a higher standard (Palan & Schitter, 2018; Peer et al., 2017).

For this study, three Prolific built-in screeners were employed to define the target sample pool, namely the *Languages proficiency* screener, the *Sex* screener, and the *Climate Change Belie*f screener. In order to have a balanced sample, it was necessary to create four distinct sub-studies in Prolific, so that the correct screeners could be applied. Hence, to balance both sex and climate change belief of participants, one sub-study had the screeners allowing the participation of only sceptic males, one of only sceptic females, one for believing males, and lastly one for believing females. The assignment in the experimental groups with and without an emotional stimulus happened afterwards inside the study, on a random principle (for more detail see Chapter 3.4). The *Languages proficiency* screener was needed to allow only participants proficient in the English language to participate, since the entire study was written in English, and was set in all four sub-study. The exact wording of the questions that participants answered on the built-in screeners are reported in Table 5. For the purpose of this thesis, the *Climate Change Belief* screener has been used as a proxy for balancing the climate change attitude of the participants. The group of sceptics has been defined as the participants that answered "No" to the *Climate Change Belief* screener, while for the believing group were considered the participants that answer "Yes".

Table 5*: Listing of the exact wording of the questions and answers of the three used screeners in Prolific.*

Screener	Question	Possible Answers
Sex	What is your sex, as recorded on legal/official documents?	Male
		Female
Languages proficiency	Which of the following languages are you fluent in?	*List of languages to select from*
Climate Change Belief	Do you believe in climate change?	Yes
		No
		Don't know
		Not applicable / rather not say

In the front page of the study in Prolific (see Appendix A), a brief summary of the most important information of the study was displayed. Thus, the participants were advised that the study required a desktop or laptop to be completed. Also, a short description of the study was provided. Participants were informed that for completing this study an estimated time of 40 minutes was expected, and that they would have received a monetary compensation of £8. Prolific does require a minimum hourly rate of £6.00 as compensation for the participants, however they suggest to consider to give at least £9.00 per hour (Prolific, 2023). Considering that the compensation of £8 for this study was thought for a completion time of 40 minutes, the actual hourly rate was of £12.00.

3.4 Implementation in PsyToolkit

For the creation of the experiment, the online psychological platform of *PsyToolkit* version 3.4.4 (Stoet, 2010, 2017) was used. *PsyToolkit* is a free web-based service that has been created by the psychologist and professor Stoet, to allow the creation of questionnaires and experiments with an easy and intuitive scripting language that leaves ample space for personalized development of surveys and experiments, with students in mind as target users (Stoet, 2017).

While there is a wide range of other tools and platforms for the development of online questionnaires and experiments, so-called experiment builders, such as *PsychoPy*, *Gorilla*, or *Qualtrics*, *PsyToolkit* comes with a number of particularly useful features (Eerola et al., 2021; Stoet, 2010, 2017). Stoet (2017) identified two main limitations when creating psychological and cognitive experiments, especially when students are concerned, namely the costs and the technical skills. Thus, *PsyToolkit* has been developed to tackle those issues and is indeed free for non-commercial uses, allowing students and other researchers or academic institutions with limited budget to create their experiments (Stoet, 2010, 2017). Moreover, due to this focus on students, the programming language of *PsyToolkit* results intuitive and fast to learn, where few hours of practice allow to reach already a good level and implement quite complex experiments (Stoet, 2017). Worth to mention is that it has been specifically designed for cognitive psychological experiment (Stoet, 2017), such as the one implemented in this thesis. Another highlight is that the website comes with a large library of examples and tutorials, that support the learning of this tool (Stoet, 2010, 2017). Very importantly, *PsyToolkit* can create experiments with various trials, each one with a different stimulus, and handle reaction time measurements with high precision (up to ms) (Stoet, 2010, 2017). Lastly, *PsyToolkit* allows to embed such reaction time experiments within a survey or an online questionnaire (Stoet, 2017). All those features came quite helpful in the framework of this study, due to financial constraints and the need not to invest excessive time in learning a new tool. Moreover, it was also necessary to implement both an experimental part with recording of choices and reaction times, as well as a part with a number of questionnaires. The validity of the use of *PsyToolkit* to conduct experiments has been tested in various studies, by comparing it with other tools, both online and lab-based, which confirmed the accuracy and reliability of the results obtained with this instrument (Armitage & Eerola, 2020; Eerola et al., 2021; J. Kim et al., 2019). For instance, in their study, J. Kim et al. (2019) compared the response choice and response time between the web-based *PsyToolkit* and a lab-based measurements, noticing that for both parameters the performance with *PsyToolkit* was comparable to the lab-based ones. Thus, they argued that *PsyToolkit* constitutes a viable method for conducting experiments with choices and reaction time recordings.

On the technical side, the survey scripting language of *PsyToolkit* allows to create a wide range of question types, such as open free-text questions, multiple choices and radio questions, and Likert scales, all of which were needed for this work; moreover, it supports the upload of images, which was also needed (Stoet, 2010, 2017). Furthermore, it is possible to randomly assign a participant to one condition or another (Stoet, 2010). The experiment scripting language allows the positioning of stimuli and other objects, like text or images, on the experiment screen, to record the mouse interactions with the screen and measuring the response time of participants (hence the time from the showing of the stimulus to the selection of an answer) (Stoet, 2010, 2017). Thus, with the scripting language for the survey, the demographic and background questions, the Toronto Empathy Questionnaire and Climate Change Attitude questionnaire, and the follow up questions have been created. Thanks to the possibility to randomly assign a participant to a condition, it was possible to write the questionnaire code so that a participant was either in the experimental condition with an emotional stimulus or in the experimental condition without emotional stimulus. Instead, the experiment scripting language has been used for the construction of the main map-based experiment and the presentation of the experiment’s instructions. Likewise, the Self-Assessment Manikin and the emotion wheel tools, due to the need to allow participants to select either images or circles on a wheel scale, required the use of the experiment scripting language to obtain a good implementation. All the parts created with the experiment scripting language had a resolution of 1200x1800 pixels. The *PsyToolkit* codes for both the survey part and the experiment part can be found in Appendix M.

3.5 Pre-test

In the pre-test part of the study, the participants had to complete a series of questionnaires, intended to assess how the pool was composed and to ensure that in both experimental groups there was a similar composition of participants (Martin, 2008). The first questionnaire comprised a group of demographics and background questions. Afterwards they had to complete a Self-Assessment Manikin, a Toronto Empathy Questionnaire, and a Climate Change Attitude questionnaire, which will be described in further detail in the following subchapters.

3.5.1 Demographic and background questions

In the very first part of the study, participants had to fill in a short list of demographic questions. The asked demographics were about their gender, age, and the country from which they were completing the survey. Afterwards there was a question inquiring whether they had been diagnosed with any vision impairment: In case they stated the need of glasses or contact lenses, they were further asked if they were wearing them as they were participating. These questions were important since this experiment was based on map-reading tasks, therefore was necessary that participants were in the conditions to actually see well the maps (Bracher, 2022; Korporaal, 2017; Kübler, 2016). For participants that stated to have colour blindness the maps were still readable, since this aspect has been considered and verified (more details in Chapter 3.6.1). The next group of questions were about their background, to verify the previous knowledge and competence of the participants with regard to the topics covered in the study, since as other studies showed, previous knowledge does influence the information retrieval and how information is evaluated (Barzilai et al., 2020; Muresan et al., 2006). This point was equally stressed by Kinkeldey et al. (2017) in their review of uncertainty visualization. They identified two criteria to investigate this aspect, one by assessing expertise in topics such as map reading, statistics, or domain expertise, while the second through self-reporting of metrics as for instance frequency of map use, years in a profession or number of courses taken (Kinkeldey et al., 2017). Thus, the following aspects were asked: the achieved level of education, how frequently they used maps in everyday life and their familiarity with a range of task-related topics. The topics asked for familiarity were uncertainty, statistics, cartography, Geographical Information Science (GIS), climate change mapping, and the IPCC. The familiarity was asked as five-point Likert-item, from 1 = *Not familiar at all* to 5 = *Completely familiar*. The choice of a five-point Likert-item has been made due to the ease of read and its reliability (Wakita et al., 2012; Willits et al., 2016). Thanks to those questions it was possible to assess whether the composition of the two experimental groups was similar enough (Martin, 2008). The exact wording of the questionnaire items and the answer options can be found in Appendix C.

3.5.2 The Pre-Test Self-Assessment Manikin

In order to assess the emotional effect of a stimulus on a participant, different methods could be used, from physiological measurements (e.g. electrodermal activity, EDA) to eye tracking or self-reported questionnaires (Harley, 2015). Since this study was conducted online, the application of tools as the EDA or eye-tracking was not possible, thus the measurement of emotion relied on standardized self-report questionnaires. In her thesis, Lendenmann (2023) retrieved that the results from physiological emotion measurements (EDA) and subjective self-assessment (Self-Assessment Manikin) of participants were consistent. Hence, the choice to use the latter as tool to measure the emotions in this study was taken. The Self-Assessment Manikin (SAM) questionnaire is a simple, non-verbal, pictogram-based tool for the assessment of self-perceived emotional state, which was first proposed by Bradley & Lang (1994). This tool offers the advantages to be a quick and easy method to assess emotive reaction to an event, as well as to assess which dimensions of the human emotional experience are affected (Bradley & Lang, 1994). The SAM is based on three subscales, each one representing one of the three major affective dimensions of human emotionality, which are the pleasure (also called valence), the arousal and the dominance (Bradley & Lang, 1994). The pleasure is described as a continuum from extreme unhappiness to extreme happiness, while arousal is conceived as a mental activity ranging from deep sleep to frantic excitement and finally the dominance describes the feelings of control on a range from dominance to submissiveness (Bakker et al., 2014).

The SAM as developed by Bradley & Lang (1994) presents itself as three series of five pictograms of a man-like figure, as displayed in Figure 23. The pleasure ranges from a smiling and happy figure on the left (maximal pleasure) to an unhappy, sad one on the right (minimal pleasure), while the arousal ranges from a highly excited, wide-eyed pictogram on the left (maximal arousal) to a sleepy one on the right (minimal arousal); lastly, the dominance goes from a small figure on the left (minimal dominance) to a very large one on the right (maximal dominance) (Bradley & Lang, 1994). The person filling in the SAM has the possibility to describe their emotional state by selecting one of the five pictograms of each dimension, or the space between two pictograms, for a total of nine options for each dimension (Bradley & Lang, 1994).

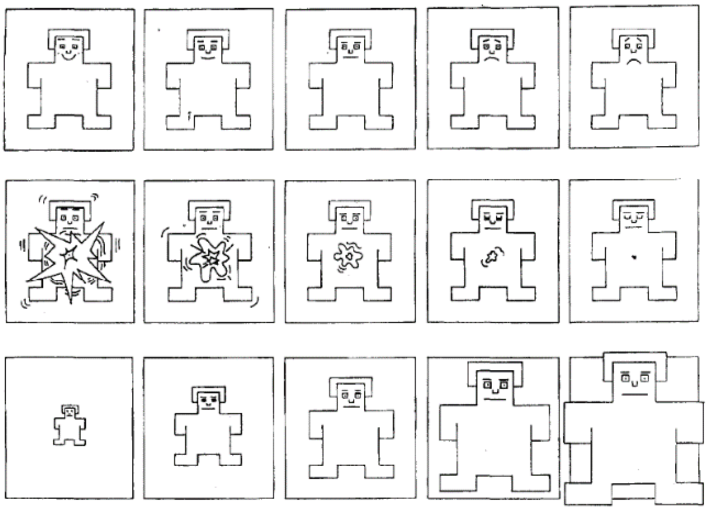

Figure 23*: The Self-Assessment Manikin pictograms in the version presented by Bradley & Lang (1994). In the first row there are the pictograms of pleasure, in the second row the pictograms for arousal, while in the third one are shown the pictograms of dominance. Participants could cross a pictogram for each line or the space between two pictograms.*

Since for this work the SAM was presented on a computer screen, the five original pictograms were extended to a scale of nine pictograms, as Figure 24 illustrates, in order to allow an easier implementation (since allowing to select the space between two figures is not possible in *PsyToolkit*). The 9-items SAM scale was retrieved and adapted from the version presented by Soleymani et al. (2014). Also, even though the pictogram should be self-explicatory in the declared intentions of Bradley & Lang (1994), to avoid possible misunderstanding on the meaning of the scales, labels on both sides of the series of pictograms were applied, as already done in the works of Lombard et al. (2000) and Ziat et al. (2020). The couples of labels were *happy-unhappy* for the pleasure, *excited-calm* for the arousal dimension, *controlled-in control* for what concerns the dominance. The participants were asked to select for each scale the image that better described their current emotional state (see Appendix C). In order to assess whether during the experiment happened a change in the emotional state of participants with help of the SAM, another SAM had to be completed in the post-test part of the study, so that the results of the two SAMs could be compared (see Chapter 3.7.1).

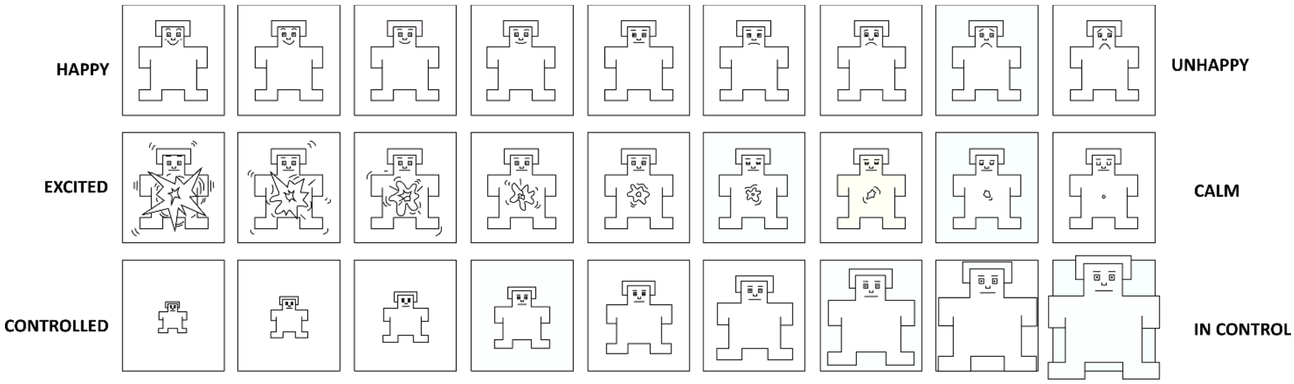

Figure 24*: The version of SAM used in the experiment, with the nine pictograms for each dimension and their respective labels on the sides of the rows (adapted from Soleymani et al., 2014).*

3.5.3 The Toronto Empathy Questionnaire

Empathy is a central element for the human communication and social interaction, which is however difficult to conceptualize and test, with numerous different self-report measures developed in the course of the past decades (Janelt et al., 2023; Spreng et al., 2009). The Toronto Empathy Questionnaire (TEQ) is a short questionnaire intended to investigate affective empathy, developed by Spreng et al. (2009) with the main goal to be both concise and homogeneous, by avoiding a long tedious list of items, and at the same time being psychometrically sound, robust, and internally consistent. The questionnaire is composed of 16 items, drawn from a wide range of other empathy questionnaires, with the aim of extracting a group of highly related items, while at the same time covering the various theoretical facets of empathy (Spreng et al., 2009). Each item is rated with a five-point Likert scale corresponding to different levels of frequency, ranging from 0 = *Never* to 4 = *Always*, where eight items are negatively scored; the scores of the single items are then summed to obtain the TEQ total score, where higher total score means higher empathy (Spreng et al., 2009). The validity of the questionnaire has been tested and compared with other scales in numerous other studies, which assessed its consistency and validity (Janelt et al., 2023). This questionnaire was integrated in the study in order to verify that in both experimental groups similar conditions of empathy were present, to avoid biases arising due to a group being particularly less or more empathically responsive and thus affecting the results of the first research question (Martin, 2008). The wording of the items of the TEQ can be read in the Appendix C.

3.5.4 The Climate Change Attitude Questionnaire

Since participants had already answered to the Prolific’s *Climate Change Belief* screener, their stance with regard to climate change should already be clear. However, no information was given about when they answered to the screener and thus if this stance was still valid at the time of the experiment. Thus, to better understand whether the groups of believers and sceptics from Prolific did really differ in terms of their attitude in regard to climate change, a small questionnaire was created, which will be referred to as Climate Change Attitude questionnaire (CCA). Drawing from the empirical research described in the work of Whitmarsh (2011), a selection of nine items has been chosen. The items mostly came from the first dimension (six items), called the Scepticism Scale, plus three items selected from the second dimension in order to also account for the feelings towards climate change (Whitmarsh, 2011). The decision to take just a selection of items and form a shorter scale was taken so as to not overwhelm participants with an excessively long pre-test part (Willits et al., 2016). Each item could be rated with a 5-point Likert scale ranging from 1 = *Agree strongly* to 5 = *Disagree strongly* (Whitmarsh, 2011), where three items were negatively scored; scores were summed to obtain the total CCA score, where higher score means a more positive (believing) attitude on climate change. This test allowed on one hand to verify whether the believers and the sceptics participants did actually differ in their attitude towards climate change, and on the other hand to assess that in both experimental conditions (with/without emotional stimulus) the believers and sceptics participants were similar. The full CCA questionnaire can be seen in Appendix C.

3.6 Main Experiment

3.6.1 Stimuli Design

For the main part of the experiment, the participants had to take decisions on several climate change forecast maps. More precisely, they had to select on the map the area that best suited the given question, out of the six areas marked on it, and then assess the intensity of the severity of change and the certainty of change in this chosen location. Depending on which experimental group they were assigned to, the map was either accompanied by an emotional stimulus or just by a short emotionless description of the map. The different components of the stimuli and the process of creation of those maps is described in the following subchapters.

Map stimulus basemap

Central element of the stimulus in each trial of the experiment was the climate change forecast map. It has been chosen to work with maps depicting real climate change forecasts in order to have a basemap that appeared close to reality and not just fictional data made for the experiment. The depicted maps were snippets taken from the forecast scenarios of the Swiss Climate Scenarios CH2018 (CH2018, 2018; NCCS, 2018b). The CH2018 scenarios are the results of a joint effort of various research institutions, such as MeteoSwiss, the ETH Zürich, and the University of Bern, among others, and they provide the more up-to-date and accurate information on climate and future developments due to climate change for Switzerland (CH2018, 2018). The outcomes of this research serve as a base for the assessment of climate change impacts and the development of adaptation and mitigation measures (CH2018, 2018). The developed scenarios encompass a wide range of projections for different variables, which both depict mean climate and extreme events for different regions, future time frames, and different projections of CO_2 emissions (CH2018, 2018). The maps of the different forecasted scenarios can be downloaded from the CH2018 Web Atlas (NCCS, 2018a), in Figure 25 is illustrated an example of one of the forecast maps for the CH2018 scenarios.

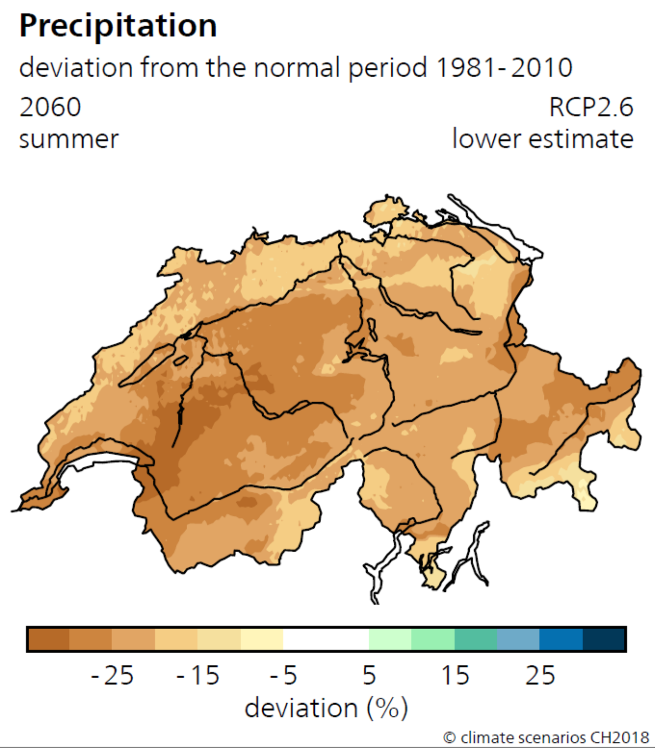

Figure 25*: Example of a forecast map from the Swiss Scenarios CH2018 (NCCS, 2018a). Here it is displayed a map of the expected change of summer precipitations, with respect to the reference period 1981-2010, for 2060 according to the lower estimate based on the RCP2.6.*

For the execution of this thesis, the climatic variables chosen for the maps used in the experiment were the change of temperature, the number of hot days and the change of precipitations. Reasons for this choice were on one hand the need to use understandable and commonly experienced variables to reduce an effect of distancing from the presented phenomenon, since participants were expected to be non-experts (Jones et al., 2017). On the other hand, also because those were the variables presented in the Swiss Scenarios which have been associated with a character and its problems due to climate change in the informative brochure of the Swiss Scenarios, which has been the inspiration for this work (NCCS, 2018b). Furthermore, it has been chosen to select the forecasts for the year 2060, so that while is a timeframe in the future, is still near enough so that most of participants could imagine reaching that future. A final criterium for the selection of the maps was that the map presented at least four categories of the climatic variables and that the distribution of those classes on the map created areas with them occurring near to each other.

Once downloaded, the forecast maps were further elaborated to prepare them for the experiment. For manipulating the maps and adding all the other necessary elements, the free graphical software *Inkscape 1.3*, (version 0e150ed6c4, 2023-07-21) (Inkscape Team, 2023), was used. To not make the regions in the maps easily recognizable to the participants, to avoid possible biases due to participants trying to interpret the data on the base of their previous knowledge of the regions (Deitrick, 2007), several steps were taken. To begin with, each time only a small box of the whole forecast map of Switzerland was shown, as in the forecast maps of Schneider et al. (2022). The file of the whole map had the dimensions of 321.3x359 pixels, while the boxes had the dimensions of 45x31.5 pixels for the hot days forecast and 69.3x48.5 pixels for the precipitation and temperature forecasts. This different size of the boxes was due to the different scale of the phenomena depicted on the maps, namely the spatial variation of the number of hot days was narrower than the one of the two other climatic variables. Afterwards all the boxes were zoomed to the size of 900x630 pixels for the final layout. To create all the necessary map stimuli, 19 boxes from a total of eight different forecast maps of the CH2018 scenarios were taken. The chosen maps and the relative boxes taken to create the map stimuli of the experiment can be seen in Appendix J. Given that the forecast maps with suitable areas, meaning areas where the four classes of the climatic variable appeared inside the box, were limited, both a vertical and a horizontal box were taken, so that a total of 19 maps for the experiment could be reached. The vertical boxes were then rotated by 90 degrees anti-clockwise and mirrored (horizontal mirroring), to reduce the risk of a possible recognition of the region between the map originating from the vertical box and the one from the horizontal box. Finally, for all the obtained maps, in order to make the region of the map not recognizable by the participants, the depicted borders and the rivers were removed, similarly to Schneider et al. (2022). Afterwards a layer of fictional borders was added, depicted with a grey line (RGB: 125, 125, 125).

With regard to the colour scales of the climatic variables on the maps, the same scales used in the original maps were kept. The RGB values for the four classes of change of the three climatic variables are reported in Table 6.

Table 6*: Colour scheme for the three climate variables, the colours are described in RGB values.*

Climatic variable	**Low**	**Medium-low**	**Medium-high**	**High**
Hot days	254, 241, 121	251, 186, 91	249,156, 79	231, 102, 54
Precipitation	245, 205, 132	225, 165, 100	205, 133, 63	182, 106, 40
Temperature	251, 106, 74	240, 60, 43	204, 24, 30	166, 15, 20

Forecast uncertainty

On a second step, a layer depicting the certainty of the prediction was added to the basemap. As Johannsen et al. (2018) found in their empirical study, participants interpreted the increasing density of a dot pattern as increasing certainty, hence this representation of uncertainty (the denser the more certain) was adopted for the visualizations in this thesis. In the remainder of this thesis, the term certainty will be used when referring to the visualized variable of uncertainty. Three types of certainty visualizations were selected and implemented. These were: the certainty represented as a pattern of dots, as a pattern lines, and as nothing in the case of no certainty representation. Both the representation as lines and as dots was inspired by the work from Retchless & Brewer (2016). The use of pattern densities as method to represent certainty in maps has been widely used for different kind of maps and tasks (Cheong et al., 2016; Johannsen et al., 2018; MacEachren, 1992; Retchless & Brewer, 2016; Šašinka et al., 2019). Particularly, the pattern of dots has been adopted in numerous applications (Johannsen et al., 2018; Retchless & Brewer, 2016; Šašinka et al., 2019) and found to be quite effective in being understood by users (Retchless & Brewer, 2016). Finally, it is worth noticing that the IPCC represents uncertainty as a pattern of lines (Gutiérrez et al., 2021). In Retchless & Brewer (2016), both the pattern with dots and the one with lines presented white and black elements, with white indicating less certain and black more certain information. For this thesis the change of certainty was only represented by the change of density of the patterns of dots and lines, with the colour of dots and lines being consistently kept to black (RGB 255, 255, 255), similarly to Johannsen et al. (2018). A visualization of the four levels of certainty for the two different visualization is shown in Figure 26. To create the certainty layers in Inkscape, the shape of the areas to be depicted with a certain level of certainty were built, and then as filling for the shape the required pattern was chosen. The parameters to create the different density patterns of dots and lines for the four different levels of certainty are summarized in Table 7.

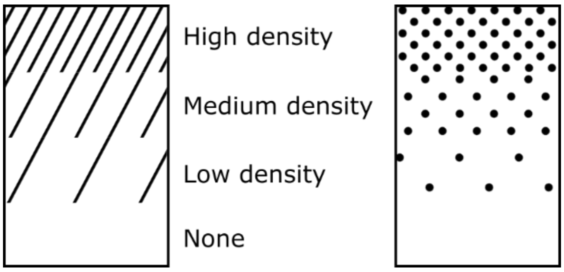

***Figure 26**: Overview on the certainty scale for the pattern of lines and the pattern of dots. With increasing density, it increases the certainty.*

***Table 7**: Description of the parameters set in the shape filling tab of Inkscape to create the patterns of the different levels of certainty for the visualizations with lines and with dots.*

Type	Low	Medium	High
Dots	Pattern: Packed circles Scale X and Y: 0.107 Orientation: 45 Offset X and Y: 420%	Pattern: Packed circles Scale X and Y: 0.107 Orientation: 45 Offset X and Y: 200%	Pattern: Packed circles Scale X and Y: 0.107 Orientation: 45 Offset X and Y: 100%
Lines	Pattern: Stripes 04 (1:3) Scale X and Y: 0.400 Orientation: 28 Offset X and Y: 380%	Pattern: Stripes 01 (1:1) Scale X and Y: 0.400 Orientation: 28 Offset X and Y: 380%	Pattern: Stripes 01 (1:1) Scale X and Y: 0.400 Orientation: 28 Offset X and Y: 140%

Similarly to the process used by Johannsen (2017), the certainty on the map was depicted using a grid scheme, which resembled the raster outcomes of satellite images and climate models. The dimensions of the grid used for the maps were of 30x21 "pixels", which granted a good granularity of the certainty distribution while each "pixel" was large enough to allow the depiction of the lower level of certainty. For each map a new grid scheme was created, so that participant would not recognize a recurring distribution pattern. In the creation of the certainty layer, attention was posed in making sure that the transition from a certain to a not certain area was smooth, when possible, hence avoiding posing "pixels" with two opposite certainty levels next to each other.

For the presentation of the climatic variable and the certainty in the legend, the design style implemented by Retchless & Brewer (2016) was adopted. An example of how the legend appeared to participants is provided in Figure 27, on the example of the maps for the number of hot days.

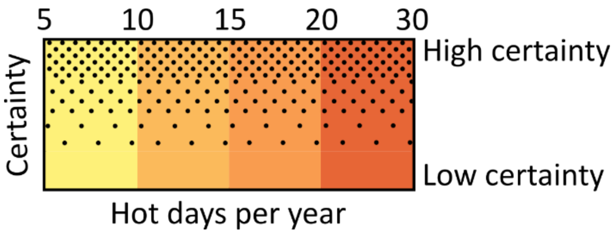

Figure 27: *Example of the map legend for the maps depicting the number of hot days.*

Selectable areas

In each map six areas were marked with a blue box and an associated letter (from A to F), representing the areas from which the participants could select their answer for the area choice task, as shown in Figure 28 (more details on the task are in Chapter 3.6.2).

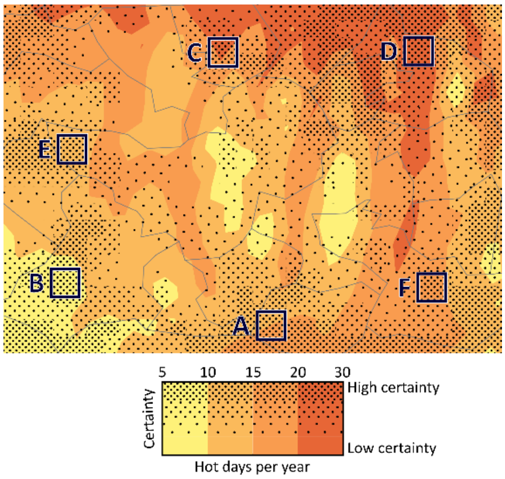

Figure 28: *Example of the final map layout with the six lettered blue boxes indicating the selectable areas.*

In order to have in all maps the occurrence of marked areas covering both high and low certainty and high and low climatic variable change, the disposition of the boxes was made according to three distribution variants that have been developed by the author of this thesis. In Table 8 are presented the created variants. There was always at least one box in each of the five main combinations of climatic variable change and certainty, where in each variant the sixth box was posed either in the combination of low change and high certainty, or high change and high certainty or in the combination of medium change and certainty. Figure 29 schematically illustrates on the example of the legend for hot days the guidelines used to define the five main combinations of variable and certainty. Hence, the upper right area is the *Low* change with *High* certainty, the upper left area the *High* change with *High* certainty, and so forth for the other three categories. All maps assigned to a variant thus shared the same distribution of areas in those five main categories. For instance, for variant 1 the area in the *Mid-Mid* category was always located where there was the second lowest level of change and the second lowest level of certainty. See Appendix G for the whole overview on the locations of the areas.

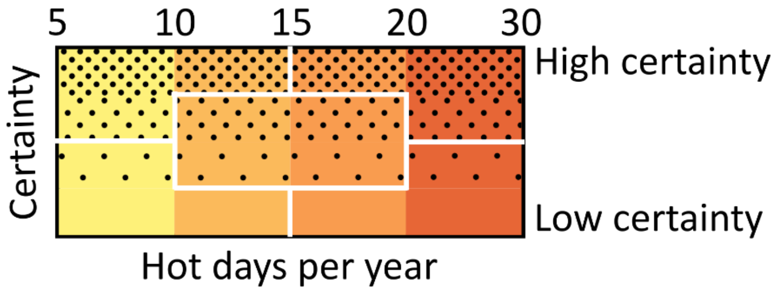

Figure 29: *Using the legend as basis, the white lines delimitate the combinations of climatic variable and certainty used to define the five categories of areas for the variants. The upper left zone corresponds to combinations with low climatic variable change and high certainty (Low-High); the upper right zone are combinations of both high climatic variable change and certainty (High-High); the central zone the combinations with both mid climatic change and certainty (Mid-Mid); the lower left represents combinations with both low climatic change and certainty (Low-Low); the lower right zone has high climatic variable change but low certainty (High-Low).*

Table 8: *Listing of the three developed variants for distributing the selectable areas in the maps, with the number of selectable areas occurring for each category. For each variant, a category is represented by two selectable areas, otherwise in the other categories there is only one selectable area.*

Variant	Low-High	Low-Low	Mid-Mid	High-High	High-Low
Variant 1	1	1	1	2	1
Variant 2	2	1	1	1	1
Variant 3	1	1	2	1	1

Each variant was then assigned to the maps of a climatic variable on a random principle[1]. In order to avoid that participants during the course of the experiment could associate a letter to a specific condition, the letters associated to a box were changed from map to map. The rotations of the letters between the different box conditions were made according to a Latin square design[2]. Each one of the six maps of the respective climatic variable was assigned to a rotation of letters, based on a random principle[3]. In Appendix G are summarized both the assignment of the maps to a variant and to the rotations of letter, as well as the Latin square distribution of the letters for the different rotations.

Colour blindness

Colour blindness is an important issue that must be considered when creating maps and other visual outputs, since the prevalence in the general population of a form of colour blindness is estimated to be of about the 8% for males and 0.4 for females (Jenny & Kelso, 2007). Hence, possible issues for people with colour blind vision were checked with the *Color Oracle* tool (version 1.3) by Jenny & Kelso (2007) This tool was developed by the authors in order to provide cartographers and designers with a practical way to test cartographic outputs and other graphical works for the three major types of colour vision deficiencies (Jenny & Kelso, 2007). *Color Oracle*

[1] With https://www.random.org
[2] With https://cs.uwaterloo.ca/~dmasson/tools/latin_square/
[3] With https://www.random.org

applies a layer on the screen that allows to visualize it as it would appear to a person with one of the three forms of colour blindness: deuteranopia (red-green, common), protanopia (red-green, rare) and tritanopia (blue-yellow, very rare) (Jenny & Kelso, 2007). The inspection of the maps created for the experiment with this tool indicated that the four severity classes for all the three climatic variables would be sufficiently distinguishable for people with colour blindness too, for all the three types of colour deficiency. In Figure 30 is displayed an example of the three outputs of *Color Oracle* for one of the maps, more precisely a map of precipitation changes. Thus, colour blind people were allowed to complete the experiment and their responses could be analysed.

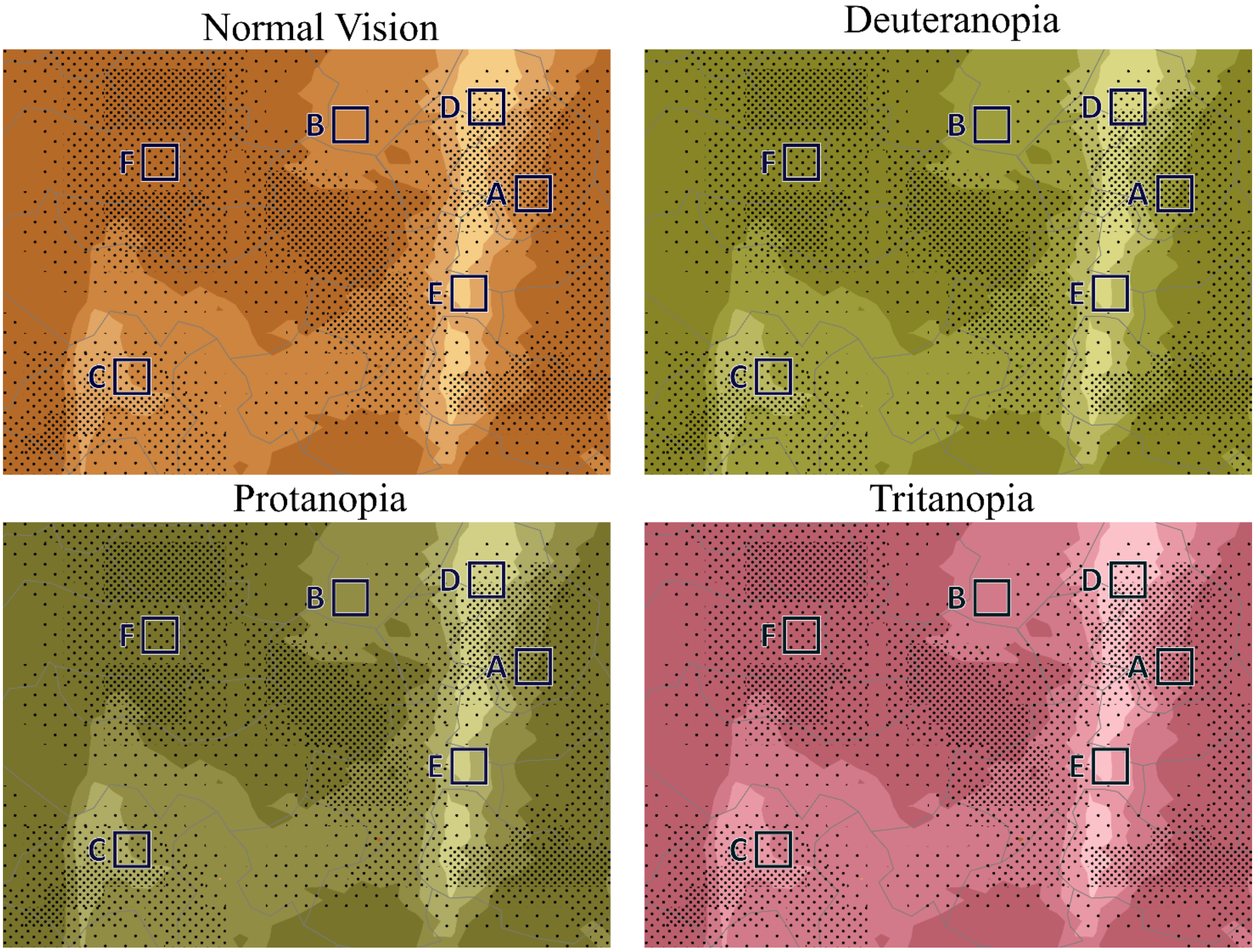

***Figure 30**: Example of how would be the appearance of the precipitations map for the three types of colour vision impairment, according to Color Oracle. The four colours of the climatic variable are still distinguishable in all the vision conditions.*

Characters and emotional stimulus

Depending on the experimental group, on the left of the map there was a different emotional stimulus. For the group with emotional narrative (WE group), the maps in this experimental condition were accompanied by the representation of one character and its story. For the group with no emotional narrative (NE group) instead only a short, non-emotional description of what the map was depicting was provided.

The three characters, one for each climatic variable, are here further explained. All of them were female characters, to avoid possible influences due to gender preferences of participants if both male and female characters were present (Johns & Shephard, 2007). These characters were inspired by three of the characters presented in the Swiss Scenarios informative material (see Figure 31), namely: an elderly lady dealing with the increase of hot days during the year, a farmer confronted with the consequences of less precipitations in summer and a child dealing with increased winter temperature and the consequent scarcity of snow (NCCS, 2018b). While in the CH2018 the child character was a boy and the related climatic variable was the mean temperature in winter (NCCS, 2018b), for the purpose of this work the child was a girl (to avoid the aforementioned gender preference biases) and the climatic variable was changed to the mean temperature in summer. The reason for changing the variable from mean winter temperature to mean summer temperature was twofold. On one hand, in this way there was a common theme of the presented variables, as all of them were related with concepts as heat or summer. On the other hand, maps of the mean summer temperature satisfied the requirement to have four classes of climatic variable change, which was not met by the mean winter temperature maps.

***Figure 31**: The original characters depicted in the informative material from the Swiss Scenarios (Ryser, 2018).*

For the design of the characters, free SVG files from the user *brgfx* on Freepik[4] were utilized (see Figure 32). The face of the character of the farmer was slightly modified and pumpkins were added in order to make the image more consistent with the style of the other two characters. The SVG files were also edited with *Inkscape*.

[4] https://www.freepik.com

***Figure 32**: The character design of the three characters presented in the experiment. The elderly lady is on the left, the farmer is in the middle, and the little girl is on the right (images adapted from www.freepik.com).*

For describing the consequences of climate change for the three characters, known issues related to climate with expected severity increase, were presented to the participants. Hence, for the elderly lady the heat-related health problems, such as circulatory and respiratory issues, were evoked (Åström et al., 2011; Dardir et al., 2023; Lin et al., 2011). Similarly, for the little girl the risk associated to the expansion of vector-borne diseases and wildfires were pointed out (Ahdoot et al., 2024; Anderko et al., 2020; Hanna & Oliva, 2016). Whereas for the farmer were presented the concerns for water scarcity and droughts (Bohnert & Martin, 2023; Grillakis, 2019; Javadinejad et al., 2021). The overview on the characters and their descriptions, as well the emotionless counterpart for the NE group, is reported in Appendices D and H.

3.6.2 Task design

As illustrated on Figure 33, the full stimulus with which participants were confronted was composed by three different parts. On the left was depicted the map stimulus with the legend, on the right the emotional stimulus with the character image and the consequences of climate change for their life (only for WE group) or just a simple emotionless description of the map (only for NE group) and below the question with the possible answer options.

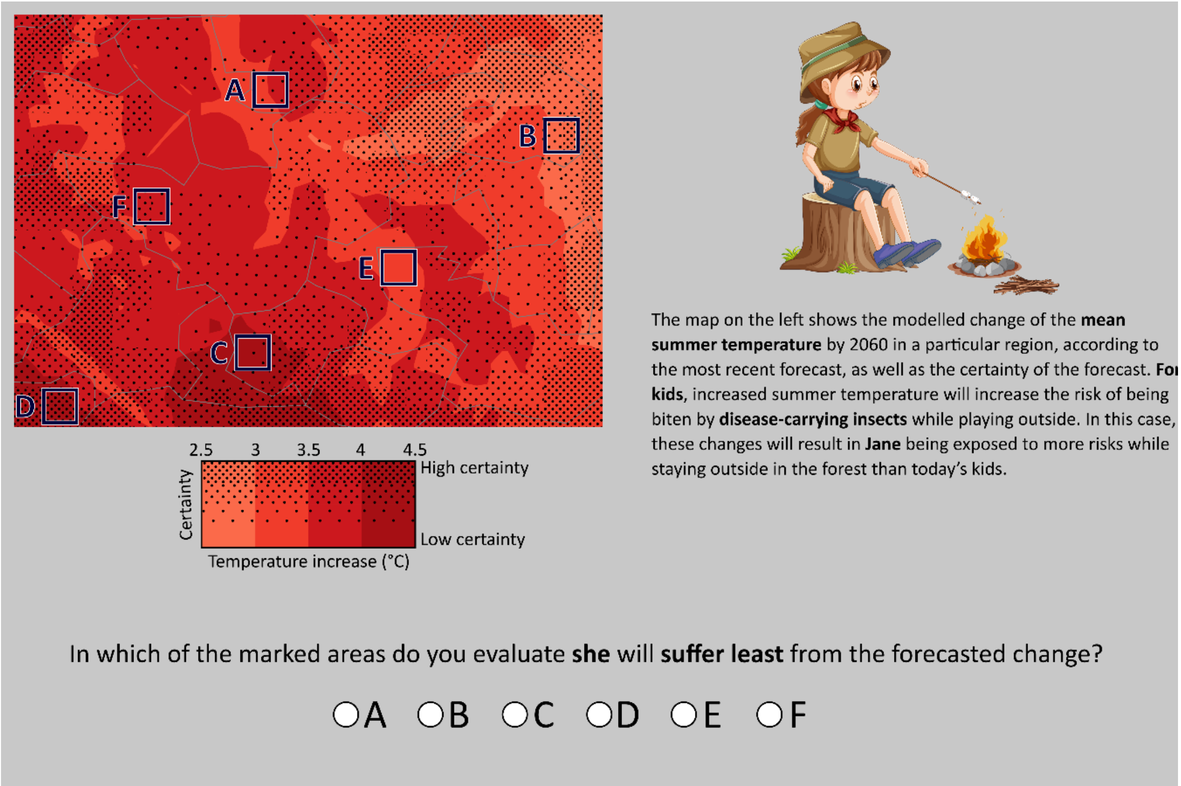

Figure 33*: Full layout of the task stimulus (emotional stimulus plus map stimulus) and task question on the example of the mean summer temperature map.*

Each map was one trial, for a total of 19 trials in the whole experiment, where one was a warm-up trial while the other 18 trials were part of the real experiment. In each trial, the participants were asked to answer four questions about what was depicted in the map. The first question concerned the choice of the area that best suited the inquired condition, i.e. to assess which area would be the least, or respectively the most, affected by the depicted change of the climatic variable. Half of the maps asked for the most affected region, while the other half asked for the least affected one, with both questions appearing for each combination of certainty visualization and climatic variable displayed (see Appendix G for the assignment of the maps to the question condition). Tasks in which participants had to infer information from the map by considering multiple variables and then took decisions between two or more options, either by choosing between different areas or choosing to perform an action (e.g. stay/leave), are very common in studies on certainty visualization (Cheong et al., 2016; Johannsen et al., 2018; Kübler et al., 2020; Miran et al., 2019; Schneider et al., 2022). Subsequently, the second and third questions were related to the choice made in the first one. Namely, participants had then to evaluate the level of severity and the level of certainty of the change in the area they selected on a scale from 1 to 7. For the severity, this scale corresponded to 1 = *Not severe at all* to 7 = *Very severe* and respectively for certainty to 1 = *Not certain at all* to 7 = *Very certain*. The choice to use a seven-point Likert-type item for those questions was due to the actual number of severity and certainty levels in which an area might be, namely they might either be completely inside one of four classes or split between two classes. Asking the participants to give an assessment of the depicted variable or of the certainty is a type of task often used in other studies to investigate how the participants interpret the combination of those two factors when assessing features of the map (Bracher, 2022; Retchless & Brewer, 2016; Šašinka et al., 2019; Schneider et al., 2022). Finally, the last question the participants had to answer was an assessment of the trust they put on the map, again on a 1 to 7 Likert-like item, from 1 = *Not trustworthy at all* to 7 = *Very trustworthy*. The seven-point Likert-like item was chosen to keep consistency with the previous questions. In Appendices D and E the wording of the questions and the layout of the task can be seen.

3.6.3 Procedure

The procedure of the main experiment which the participants went through is now described. Once the experiment started, the participants received an introduction the topic of uncertainty and to the task. If they were assigned to the experimental group with the emotional stimulus, also the three characters were introduced. Afterwards, participants had the opportunity to practice with the task, as well as familiarize with the map and its components thanks to a warm-up trial. Finished with this warm-up, the real experiment began. In total, after the warm-up trial, there were 18 other trials, presented in a different, random order to each participant, with the 18 maps created for the experiment.

Going through the procedure steps in more detail, the first information that the participants saw was the introduction to the concept of prediction certainty and its representation on the map. The description of forecast certainty and sources of uncertainty was adapted from the one used by Johannsen (2017), while the description of effects of certainty depiction in the map followed the one provided by Retchless & Brewer (2016) in their study. In Appendix D the introductive slide on certainty representation can be viewed. If participants were in the group with emotional stimuli, they also had the introduction to the characters. Each character was introduced with their own slide, where it was displayed their image, a description of how their life was at the time, and which changes due to climate change could happen to them and how this could worsen their current life conditions. For the description of the characters, the feedback and suggestions of testers from the author entourage were used to made them relatable figures. The three slides of the description of the characters can be found in Appendix D. Finally, an introduction of what the participants were asked to do in the main experiment was provided. That slide informed them of what they would see on the trials, and that it was expected that they would select one of the marked areas, the one that they considered to be the more appropriate to answer the question, and provide an assessment of the severity and certainty of the chosen area. They were also advised that after that slide they would have a warm-up trial. Participants had the opportunity to move back and forth between those slides as long as they desired, to reread information if they felt the necessity, and the experiment began only after they chose to click on the "Start" button (see Appendix D).

In the warm-up trial participants went through a complete task. Hence, they had first to select the most appropriate area, then to give a severity assessment of the chosen area, followed by the assessment of the certainty, and finally they were asked to give the trust rating of the whole map. Participants could not go back and change their answers once submitted. Once finished with the warm-up trial, they could start with the real main experiment. All of the 18 trials of the main experiment followed the same structure of the warm-up trial, with just the map stimulus and corresponding emotional stimulus changing from one trial to the other.

3.7 Post-test

In the post-test part of the study the participants were tested again for their emotional state and were inquired about different aspects of their experience with the experiment, asking them to share their feelings and comments. Aim of this part was to gather information about the emotions and cognitive processes related to the execution of the map-based tasks performed. This step was deemed as important since, as argued by Kinkeldey et al. (2017) past research on uncertainty visualization has often only focused on the quantitative effects of uncertainty on participants performance, ignoring the related impact on reasoning and decision-making. More precisely, the participants in that part went through another SAM, filled in an Emotion Wheel, and answered to follow-up questions. Finished with those questions, an end of the study screen thanked them and prompted them to click on the provided link to return on the Prolific completion page and, by doing so, correctly finishing the study (see Appendix F).

3.7.1 The Post-Test Self-Assessment Manikin

As mentioned in Chapter 3.5.2, the participants had to complete again a full SAM, to assess how they felt just after completing the experiment. The wording of the question explicitly asked them to rate their emotional state at that time after having finished with the experiment (see Appendix F). Otherwise, the post-test SAM was completely equal to what participants encountered in the first part of the study. This second SAM allowed to analyse what changes brought the experiment to their emotional state, with the analysis of the SAM scores in the pre- and post-test, which followed the procedure used in the work of Murdoch et al. (2019). The absolute change in scores between the two SAMs as well as the relative change, hence how many participants had an increase, decrease, or stayed the same, were analysed (Murdoch et al., 2019). This was made both between the two experimental groups (with/without emotional stimulus) and between the two climate change attitudes (believers vs sceptics).

3.7.2 Geneva Emotion Wheel

In order to gather a more detailed overview on the emotions felt by participants while completing the tasks and understand whether the presence (respectively absence) of an emotional stimulus led to different emotions, an adapted version of the Geneva Emotion Wheel (GEW) was implemented (Scherer, 2005; Scherer et al., 2013). The GEW is an instrument developed with the aim of addressing the issue of measuring self -reported emotions, which is a quite complex endeavour due to their fuzzy nature (Scherer, 2005). Further, the GEW is an instrument that both covers the semantical space distribution of emotions (along two axes, representing the dimensions of valence and dominance) and the intensity of the subjective feeling of such emotions (Scherer, 2005). The current version of the GEW, as illustrated in Figure 34, displays 20 emotion families, which disposition and structure have been reviewed and validated (Scherer et al., 2013). The felt emotions can be rated on a five-point scale from 1 = “low intensity” to 5 = “high intensity”, represented by the circles of increasing size the more intense the emotion had been felt (Scherer et al., 2013). Further, the GEW gives the option to select that no emotion at all had been felt or the option to define another emotion when none of the provided is able to describe what the participants felt (Scherer et al., 2013).

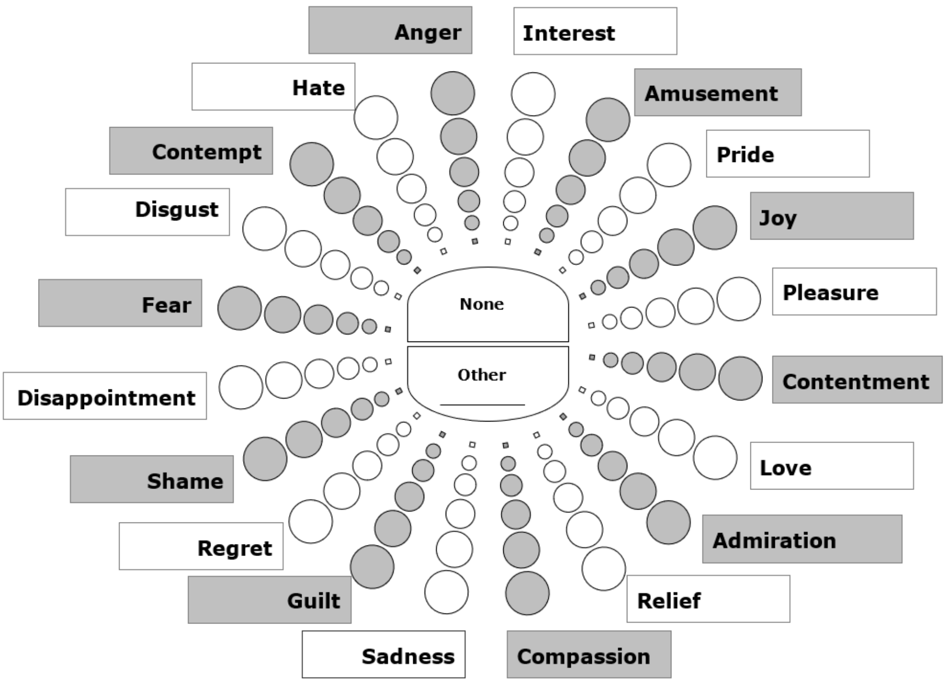

Figure 34*: Current rendition of the Geneva Emotion Wheel, version 3.0 (Scherer et al., 2013). The GEW presents 20 emotions disposed in circle, with in the centre the options of “None” and “Other” emotion felt. From the centre, the five intensity levels irradiate towards the labels of the emotions.*

The adapted implementation of the GEW for this thesis, from now on referred to as Small Emotion Wheel (SEW), was a reduced version with just eight emotions and without the items at the centre of the wheel (option to choose for "None" and "Other" emotions), as can be seen in Figure 35. This choice was made in order to avoid the dispersion of the answers between too many options, given that the number of participants of the study was limited to around a hundred. The eight chosen emotions were retrieved by selecting emotions often used in questionnaires about climate change or self-reported by participants of other studies, trying to encompass both positive and negative emotions (A. Fischer et al., 2012; Leviston et al., 2014; Wang et al., 2018). Those emotions were excitement, joy, hope, compassion, indifference, shame/guilt, concern/fear, and anger. The SEW was constructed respecting the two main axes of the GEW, thus the vertical axis of dominance and the horizontal axis of valence (Scherer, 2005; Scherer et al., 2013). The emotions were placed trying to respect their position relative to those axes and if already present in the GEW by respecting their placing. Participants were asked to select the emotion that they felt more during the experiment and its respective intensity. In Appendix F is reported the explanation of how to use the SEW given to participants, the posed question and how the SEW appeared to them.

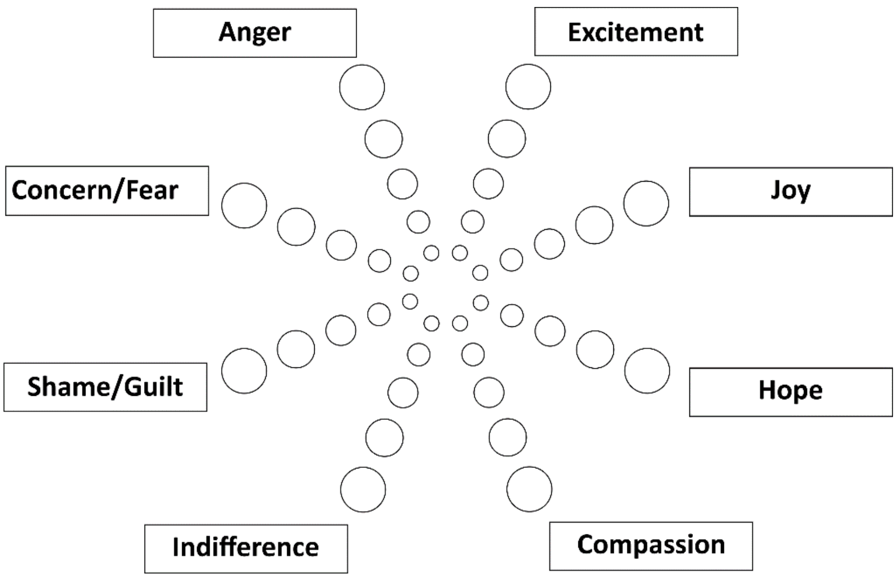

Figure 35*: The reduced version of the GEW developed for this study. The central items where dropped, while it retained the intensity scale and followed the same principles of the GEW for the disposition of the emotions along the wheel.*

3.7.3 Follow-up questions

The final section of the post-test, and therefore of the whole study, was composed by a series of questions, both as Likert-type items, radio question and open free-text questions. Those follow-up questions and written feedback were important in order to gather more information about the cognitive processes of decision-making of participants, as remarked by Kinkeldey et al. (2017). The participants were asked to describe in their own words what they felt about the forecasted climatic changes during the experiment, and thus to deepen what they expressed in the SEW. Next, the interest was in whether they thought about their own situation, or the situation of their relatives/acquittances when analysing the maps. This question was posed as a five-point Likert-type question, from 1= *Not considered at all* to 5 = *Very much considered*. The following question concerned the given trust ratings. Namely it was asked, as an open free-text question, which elements, which strategy, they used to assess how much trust to put into the maps. Afterwards the perceived difficulty of the task was investigated, first with a Likert-type question (from 1 = *Very Easy*, to 5 = *Very difficult*), then with an open free-text question where they could elaborate more in detail which elements or issues caused them to experience difficulty, if any. Another question was asked to assess their confidence with the decisions they took in the experiment, again posed as a Likert-item from 1 = *Not confident at all* to 5 = *Very confident*. Finally, it was asked which visualization of certainty was preferred between the dots, lines, or none representation. Firstly, they had to choose with a radio question one of the visualization types, then an open free-text question was provided as well, prompting them to further illustrate the reasons why one visualization was deemed better than the others. Assessing the user visualization preferences and their confidence in the performed task were metrics also considered in other studies (Kinkeldey, MacEachren, et al., 2014). See Appendix F for an overview of the follow-up questions and their wording.

3.8 Data Analysis

The data collected in this study had both quantitative as well as qualitative elements. Namely, the answers to the open free-text questions in the post-test part of the study had a qualitative nature, while conversely all other data was of quantitative nature. Thus, the data analysis was performed with two different approaches depending on the type of the data.

For the analysis of the quantitative data, the statistical software *RStudio*, version 2023.12.1 build 402 (Posit Team, 2024), was adopted, with the *R* programming language installed, version 4.3.2 (Eye Holes) (R Core Team, 2023). Different packages were employed in order to clean, analyse, and visualize the collected data. Where possible, the use of packages belonging to the *tidyverse* framework (Wickham et al., 2019), or that have been developed to work in harmony with *tidyverse*, was preferred. Those packages provided an environment featuring various tools for data analysis that work well together, where the output of one tool could be easily used as input of the next (Wickham, 2014; Wickham et al., 2019). The main advantage of the *tidyverse* and *tidyverse*-oriented packages is that they operate with tidy data, as the name suggests, which is a principle that provides a clear and efficient standard to organize data within a dataset and thus enabling an easier exploration, analysis and then visualization of the data (Wickham, 2014). Specifically, the *tidyverse* packages *tidyr*, *dplyr*, *forcats* and *stringr*, as well as the tidyverse-oriented *janitor* (Firke, 2023) were used both for data cleaning and for data wrangling, in order to tidy and prepare the data into the right format for the analysis. For the statistical analysis and testing of the results, functions from base *R* as well as from the *tidyverse*-oriented package *rstatix* (Kassambara, 2023b) and the packages *plotrix* (Lemon, 2006) and *ARTool* (Kay et al., 2021) were employed. Base *R* and *plotrix* were applied for determining the descriptive statistics, while *rstatix* and *ARTool* provided the tools for the statistical testing. For the graphical illustration of the results, the *tidyverse* plotting package *ggplot2* and the *tidyverse*-oriented packages *ggpubr* (Kassambara, 2023a), *ggsci* (Xiao, 2023), *patchwork* (Pedersen, 2024), and *ggstatsplot* (Patil, 2021) were used (for some graphs, the significance brackets have been added later with *Inkscape*).

Concerning the qualitative data of the study, the feedback and comments of participants from the open free-text questions were manually analysed by the author of the thesis and categorized according to the named feelings, difficulties, or issues raised, depending on the question that was analysed. The aim of the qualitative analysis was in fact to explore and understand social phenomena; thus categorizing, or coding, the comments of participants was an important task that revolved around identifying the main themes evoked by those comments and assign each snippet of text to the belonging category, for then look at patterns and relationships (Jamieson, 2016).

4 Results

In this section of the thesis the results of the online study are illustrated and statistically analysed. The data is presented in the order in which it has been recorded in the study. Therefore, the results of the pre-test will be displayed first (Chapter 4.1), followed by the outcomes of the main map part of the study (Chapter 4.2), while in the final chapter of this section (Chapter 4.3) the results of the post-test part are illustrated. A result with a *p*-value lower than 0.05 is considered significant. For all the significant result, the associated effect size has been calculated, with the size being interpreted in accordance with the guidelines outlined in Cohen (1988). A summary of the different indices used to describe the effect size and their interpretation is summarized in Table 9. The values of the test statistics, *p*-values, and effect sizes (when result is significant) are reported in the main text. All the full outcomes of the performed statistical tests in *R*, as well as the results of the checks for the normality of the distribution (Shapiro-Wilk test) and homogeneity of variances (Levene test) are reported in Appendix L.

Table 9*: Listing of the three effect size indices used in this thesis and their interpretation.*

Indices	Small	Medium	Large
Pearson’s *r*	0.1	0.3	0.5
Partial η^2	0.01	0.06	0.14
Cohen’s *d*	0.2	0.5	0.8

4.1 Results of the pre-tests

4.1.1 Participation

From the data overview page of the study in PsyToolkit web platform it is possible to retrieve how many people accessed the starting page of the study, how many did start it, and finally the number of people that completed the study. This data reveals that the starting page of this study has been reached by 159 visitors, while the people that decided to continue the rest of the experiment after reading the informed consent page were 117, the 73.58%. Of those, 113 completed all the tasks and questions and reached the end of the study. Thus, this results in a participation rate of 71.10% and a completion rate of 96.58% with a dropout rate of 3.42%. However, 3 participants among the 113 who concluded the study had to be excluded from further analysis since they did not meet the inclusion criteria (they declared the need to wear glasses/lenses but also declared that they were not wearing them during the compiling). A further participant has been excluded for completing the study in an extremely short time (< 7 minutes).

4.1.2 Background of the participants

Gender and age

The 109 participants that completed the study were equally distributed in the two experimental groups: 54 participants in the With Emotion (WE) group, 55 participants in the No Emotion (NE) group. The gender distribution of the participants is even, with 53 people identifying themselves as female, 54 as male and 2 as non-binary. This condition of even gender distribution has been maintained also in the two groups, where in the WE group there were 27 males and 27 females, while in the NE group there were 27 males, 26 females and two non-binaries.

The overall age distribution of the participants shows a range from 20 to 79 years old, where the mean age is of 34 years old (SD = 12.1). Most participants have an age that ranges between 20 and 40 years old, as reported in Figure 36. The age distribution in the two experimental groups is similar; in the NE group the age ranges between 20 and 56, with an average age of 33 years old (SD = 10.6), while for the WE group the range is between 20 and 79, with the average age being 34.9 (SD = 13.4). Hence, the WE group has slightly higher average age and higher upper range. Nonetheless, the Kolmogorov-Smirnov test indicates that both groups have the same distribution (D = 0.0852, p = 0.924 > 0.05). The Kolmogorov-Smirnov test is a non-parametric goodness-of-fit test useful to determine if two sample distributions differ from each other or they originate from the same distribution (Dodge, 2008). Compared to the Wilcoxon test or the Mann-Whitney U test, it has the advantage to consider the whole distribution function and not just the mean or median (Dodge, 2008).

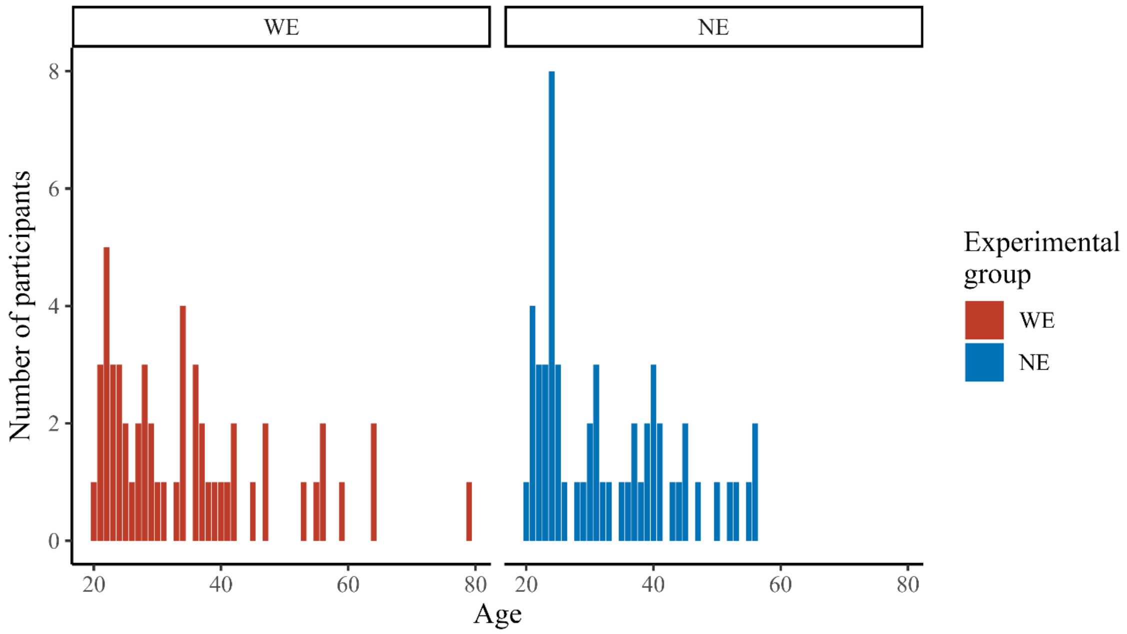

Figure 36*: Distribution of the age of the participants in the two experimental groups. Can be noted the tendentially young audience, with nonetheless a few of older participants.*

Geographical distribution

The participants indicated from which country they were completing the study. The consequent geographical distribution that can be retrieved is illustrated in Figure 37. As it is shown, 37 participants, corresponding to the 33.94% of the pool, comes from South Africa. This may be due to the timing in which the study was published (at noon, CET) and the fact that Prolific is an English-speaking platform, and English is a language largely spoken in South Africa. The other countries majorly represented are the UK (15), Poland (12) and Portugal (9). South Africa is the only African country represented, Chile with 1 participant is the only country from South America, while the Asian continent has 1 participant from Israel. Overall, 21 countries from 6 continents are represented, of these the majority of countries (14) are European, with the number of participants from Europe as a whole being 61, corresponding to the 55.96% of the pool.

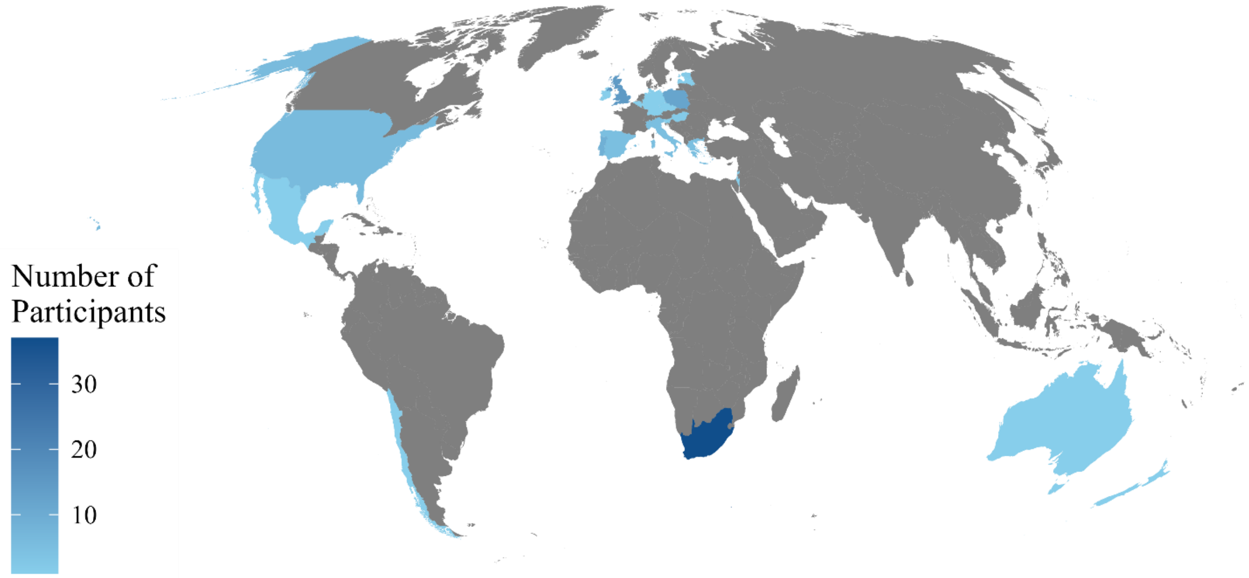

Figure 37*: Geographical distribution of the participants. The darker is the colour of the country, the higher is the number of participants from that country.*

Visual impairment

Concerning the visual impairment, 58 participants (53.21%, thus the majority) have never been diagnosed with any visual impairment. A total of 48 participants (44.04%) declared they need the help of glasses or lenses. A participant however noted that they need to use the glasses just for driving. The impairment due to colour blindness is present in only 3 participants (2.75%). None have the co-occurrence of both colour blindness and the need of glasses/lenses. A Fisher's exact test have been performed to check whether the occurrence of visual impairment is related to the group assignment. The result indicates that there is no association between the group assignment and the visual impairment (p = 0.162 > 0.05). The Fisher's exact test has been chosen since the sample is both small and at least one expected value is less than 5, thus this test offers a more accurate *p*-value than the Chi-square test (H.-Y. Kim, 2017).

Educational background and previous knowledge

With the regard to the educational background of the participants, the majority, namely 71 people, have completed a university degree (65.14%). The second most achieved level of education is high school or equivalent, with 32 participants (29.36%). The other backgrounds have been indicated by fewer people, namely 3 respondents (2.75%) have completed the secondary school, 2 (1.83%) have obtained a doctoral degree and one person (0.92%) declared to have attended the university but not having completed the degree. As can be seen in Figure 38, the distribution between the two groups of participants is roughly similar, whereas the WE group has a bit more participants with a university degree (WE: 38, NE: 33) while the NE group has more participants with the high school degree (WE: 13, NE: 19). To statistically check whether the educational background in the two groups is similar, a Fisher's exact test has been performed (since there are many expected values smaller than 5), which indicates that there is no statistically significant association between the assigned group and the educational background of the participants ($p = 0.303 > 0.05$).

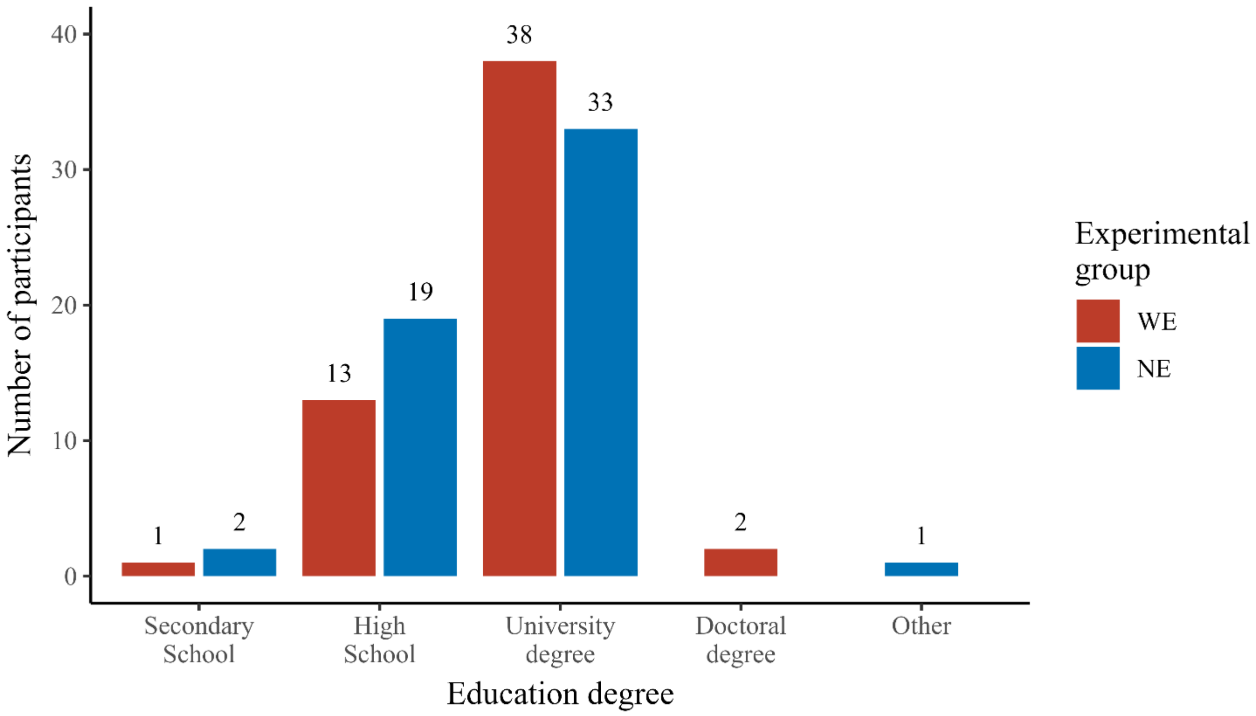

***Figure 38**: Distribution of the achieved education degree of participants in the two experimental groups.*

The frequency with which the participants engage with maps in their everyday life (e.g., through navigation, Google Maps, atlas, maps in newspapers) is illustrated in Figure 39. In both groups the distribution is rather similar, with very few people (namely 6, the 5.5%) engaging with maps only on an annual rate or that never have engaged with them. Overall, the use of maps in quotidian life is rather frequent, with the majority (74 respondents, the 67.89%) using them weekly or daily. The most selected frequency is the weekly rate, indicated by as many as 50 participants (45.87%). In the NE group there are slightly more people engaging daily and weekly with maps compared with the WE group. In contrast the WE group has more participants with a monthly use of maps and the occurrence of the only participant that never engaged with maps. Nonetheless, the Fisher's exact test (since there are expected values smaller than 5) indicates that there is no significant difference in the distribution of map use frequency between the two groups ($p = 0.402 > 0.05$).

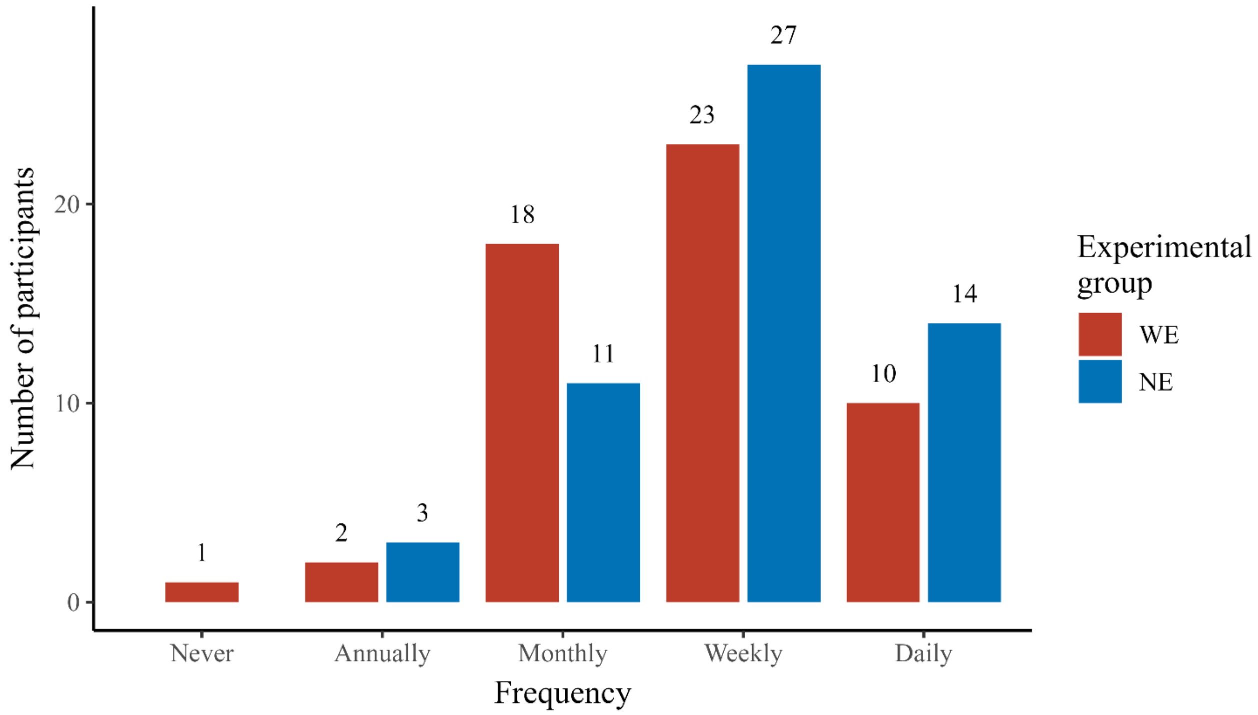

Figure 39*: Distribution of the frequency of map use in everyday life by the participants in the two experimental groups.*

The previous knowledge of the participants on the topics of cartography, GIS, climate change mapping, IPCC, statistics, and uncertainty are illustrated in Figure 40. It is visible that most of the concepts seem to be not completely familiar to participants. More than half of the participants stated that they have none or slight familiarity with the concepts. The ones that appear to be most known by the respondents are uncertainty and statistics, both having about the 40% of participants indicating either a complete or fair familiarity with them. Further, a moderate familiarity is still possessed by the 20.18% for uncertainty and respectively by the 28.44% for statistics. In contrast, the concept of IPCC is mostly completely unfamiliar to the participants, with as many as the 72.48% stating that are not familiar at all with it, and just a 13.76% being fairly to moderately familiar and none asserting to have a complete familiarity with this concept. While not being as strongly unfamiliar as the IPPC, also the topics of GIS, cartography, and climate change mapping show a high percentage of respondents indicating no familiarity (between 29.36% to 44.04%) or just slight familiarity (26.61% to 34.86%) to them.

Overall, the concepts most associated with climate change and maps result the lesser known, while the concepts bound to uncertainty are more familiar to the participants. Thus, the majority of the audience of this study is not deeply familiar with the thematic topics treated in it, whereas a small group of more expert participants on those topics is also present. Considering the diverse backgrounds of the pool of candidate participants on Prolific, those results appear to reflect this diversity. Since topics as GIS, cartography or IPCC are likely better known to people from specific fields such as geography or climate sciences, which are possibly a minority, fewer participants are familiar with them; topics as uncertainty and statistics, which can come across in multiple fields as well in everyday life, are thus known and familiar to a wider audience. In regard to the similarity of the knowledge level in the two groups, the performed Fisher's exact tests on the six concepts reveal that it subsists no statistically significant difference between the two groups with respect to their familiarity of the concepts (uncertainty: p = 0.294 > 0.05; statistics: p = 0.481 > 0.05; IPCC: p = 0.93 > 0.05; GIS: p = 0.338 > 0.05; climate change mapping: p = 0.317 > 0.05; cartography: p = 0.771 > 0.05).

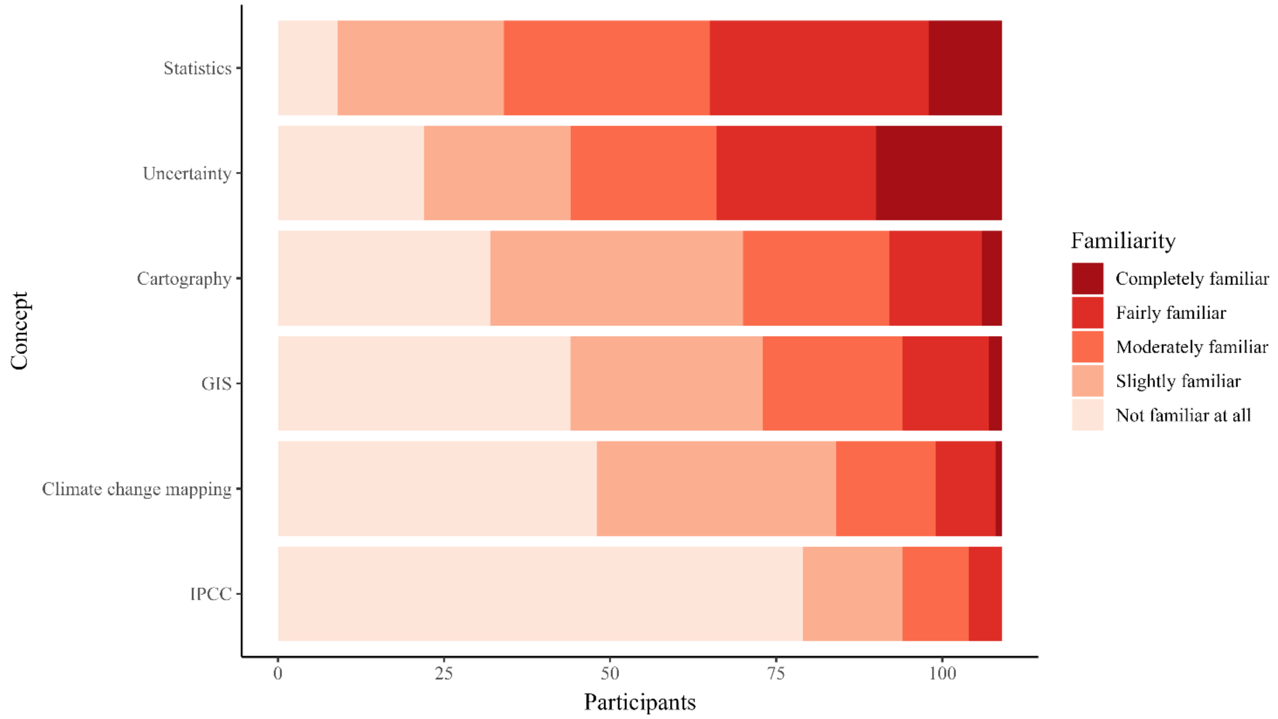

Figure 40*: Distribution of the familiarity of participants to the concepts related to the study. Concepts are ordered from more familiar on the top to less familiar on the bottom.*

Therefore, the background of participants among the two experiment groups appears to be consistently similar through the range of demographics and background aspects here analysed, hence, in this regard the groups could be considered as equivalent and the results in the main experiment should not be affected by underlying differences in the groups due to those aspects (Martin, 2008).

4.1.3 Pre-experiment Self-Assessment Manikin

The results of the SAM questionnaire completed before starting the experiment indicate that participants of both groups had a generally similar emotional state in the phase before the beginning of the experiment. By looking at the boxplots of each dimension, as illustrated in Figure 41, in both groups the dimension of dominance has a similar median and range of values. Conversely, the dimension of pleasure shows that while the medians are similar, the spread in the WE group is noticeably wider. Concerning the arousal dimension, again the medians occur in the same region, however the interquartile range of the NE group is larger. A few outliers can be noticed in both groups for the dominance dimension, for the pleasure dimension in NE and for the arousal dimension in WE.

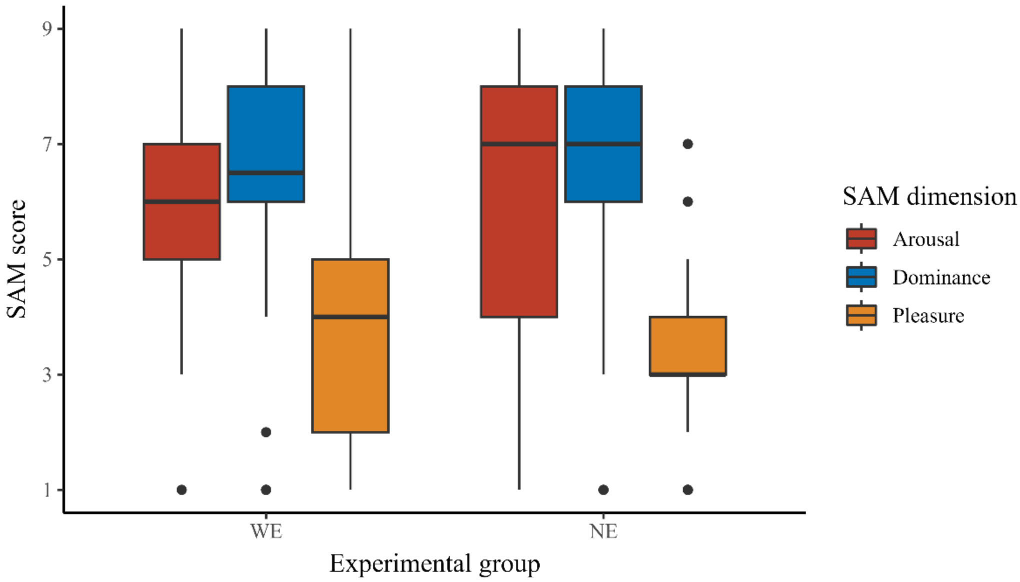

Figure 41*: Boxplots of the scores in the three SAM dimensions for the two experimental groups. In the boxplot the black central line indicates the median, the coloured box represents the Interquartile Range (IQR), the thin lines departing from the box depict the rest of the data within 1.5 time the IQR, while the dots are the outliers.*

The statistical descriptive terms of the pre-experiment SAM illustrate with further details the distribution between NE and WE groups, as summarised in Table 10. The median of the pleasure dimension is slightly higher in WE compared to NE (4 vs 3). Conversely, for the dimension of arousal and dominance the WE median slightly lower (6 vs 7, respectively 6.5 vs 7). By looking at the means however, the three dimensions in the two groups seems very similar. Nonetheless, in order to statistically verify this apparent similarity, the Mann-Whitney U test has been performed on each of the three dimensions between the NE and WE group, since the distribution of the SAM values is significantly not normally distributed (Shapiro-Wilk test, $p < 0.05$). The Mann-Whitney U test is the non-parametric version of the t-test for independent samples (McKinght & Najab, 2010). The results of the Mann-Whitney U test indicate that no significant difference in the central tendency of the SAM dimensions occurs between the groups (pleasure: $U = 1402$, $p = 0.61 > 0.05$; arousal: $U = 1480$, $p = 0.978 > 0.05$; dominance: $U = 1460$, $p = 0.878 > 0.05$).

Table 10*: Descriptive statistics of the scores of the pre-experiment SAM.*

Group	Dimension	Mean	Median	Standard deviation	IQR	Range
NE	**Pleasure**	3.33	3	1.40	1	1 – 7
	Arousal	6.13	7	2.28	4	1 – 9
	Dominance	6.53	7	1.87	2	1 – 9
WE	**Pleasure**	3.56	4	1.82	3	1 – 9
	Arousal	6.26	6	1.82	2	1 – 9
	Dominance	6.54	6.5	2.12	2	1 – 9

These results suggest that the emotional state of participants at the start of the experiment was similar. Thus, according the SAM questionnaire, the participants felt generally happy, calm, and mostly in control of the situation. In Chapter 4.3.1 the results of the post-experiment SAM will be presented and the change of the emotional state between before and after the experiment will be analysed.

4.1.4 Toronto Empathy Questionnaire

The levels of empathy of the participants, as retrieved by the scores measured with the TEQ, appears to be similar in both the experimental groups (WE and NE), since their TEQ scores follow a comparable distribution. The boxplots in Figure 42 display clearly that in the two experimental conditions the median TEQ score is the same for both groups, while they also possess a similar range of values, with the NE groups being slightly less spread. Namely, both groups have a median score of 56, with a range from 42 to 66 for the NE group and from 38 to 64 for the WE group. The mean TEQ score in the WE group is of 56 ($SD = 4.55$), while for the NE group is of 55.4 ($SD = 4.26$). To decide the appropriate statistical test to assess whether the two groups differentiate themselves in the TEQ score, a Shapiro-Wilk test has been carried out to assess for the normality of the samples. The results indicate that the scores in WE are significantly not normally distributed ($p < 0.05$), while in NE no significant deviation from normality is found ($p > 0.05$). Therefore, the Mann-Whitney U test has been chosen and applied, which outcome indicates that no statistically significant difference occurs between the TEQ scores of the two groups ($U = 1331$, $p = 0.35 > 0.05$). Hence, both groups had analogous levels of empathy, therefore, this should not bias the performance of one group compared to the other.

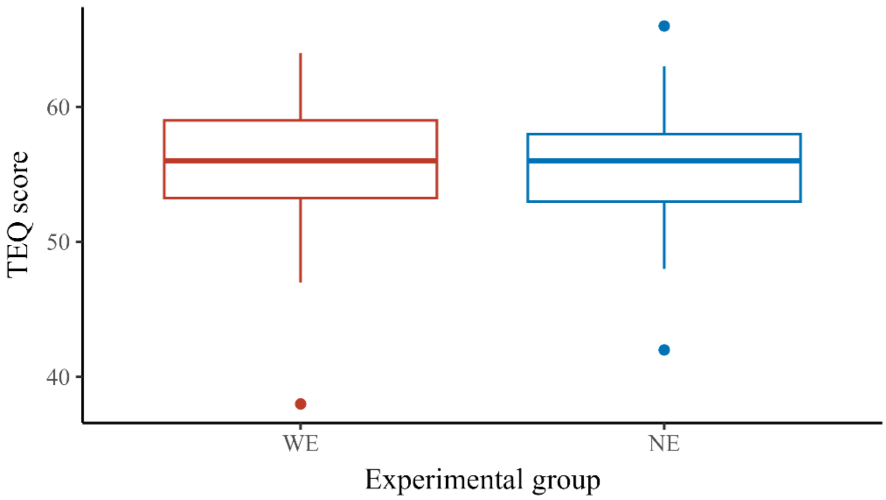

***Figure 42**: Boxplots of the distribution of the TEQ scores for the two experimental groups.*

4.1.5 Climate Change Attitude Questionnaire

The results of the CCA questionnaire are displayed in Figure 43. While the range in both groups is similar (NE from 9 to 43, WE from 9 to 45), the NE group has a slightly higher median (31) compared to the WE group (26). The mean score is however more similar, 29 (*SD* = 9.37) for NE and 28.3 (*SD* = 9.91) for WE.

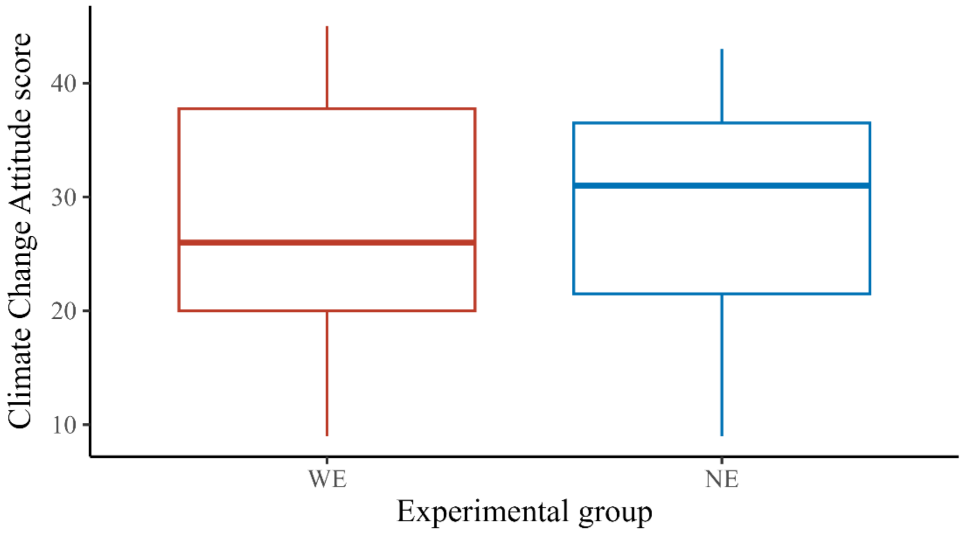

***Figure 43**: Boxplots of the distribution of the scores from the CCA questionnaire for the two experimental groups.*

However, by analysing the results of the CCA questionnaire with respect to the stated belief in climate change given in Prolific, it can be noticed that in both groups the sceptical participants scored similarly low, while the believing participants in both groups scored similarly higher, as visible in Figure 44. The sceptical participants in WE had a mean score of 21 (*SD* = 6.72) while in NE the average is 22.0 (*SD* = 7.55) For the supportive participants, in WE there is a mean of 35.7 (*SD* = 6.49) while in NE is of 36.2 (*SD* = 4.16). Noticeably, there are some outliers, where some participants, that in Prolific defined themselves as not believing the climate change, in the CCA questioned scored as high or er than most of the declared pro climate. Conversely, none of the participants that stated in Prolific to believe in the climate change had a CCA score as low as the median score of the sceptical participants. To statistically verify whether the sceptical participants in both groups, and respectively the believing participants, scored similarly in the CCA questionnaire, a Mann-Whitney U test has been performed, since the scores in the WE group are non-normally distributed (Shapiro-Wilk test, $p < 0.05$) The results of the Mann-Whitney U test indicate that no significant difference subsists in the two groups of sceptics and in the two groups of believers (sceptics: $U = 412$, $p = 0.572 > 0.05$; believers: $U = 344$, $p = 0.735 > 0.05$). Further, the difference between the sceptics and the believers in the WE group, and respectively in the NE group, is tested. The outcomes of the Mann-Whitney U test indicate that there is indeed a significant difference between believers and sceptics in both experimental conditions, with also a large effect size (NE: $U = 53.5$, $p < 0.001$, $r = 0.738$; WE: $U = 57$, $p < 0.001$, $r = 0.725$). Hence, as expected, the believers and the sceptics differ in their scores in the CCA questionnaire, while sceptics, and respectively the believers, in both groups have similar scores. For the rest of this thesis the belief expressed in Prolific in regard to climate change will be used to divide between participants with sceptical and believing attitude towards climate change and hence also addressed as such.

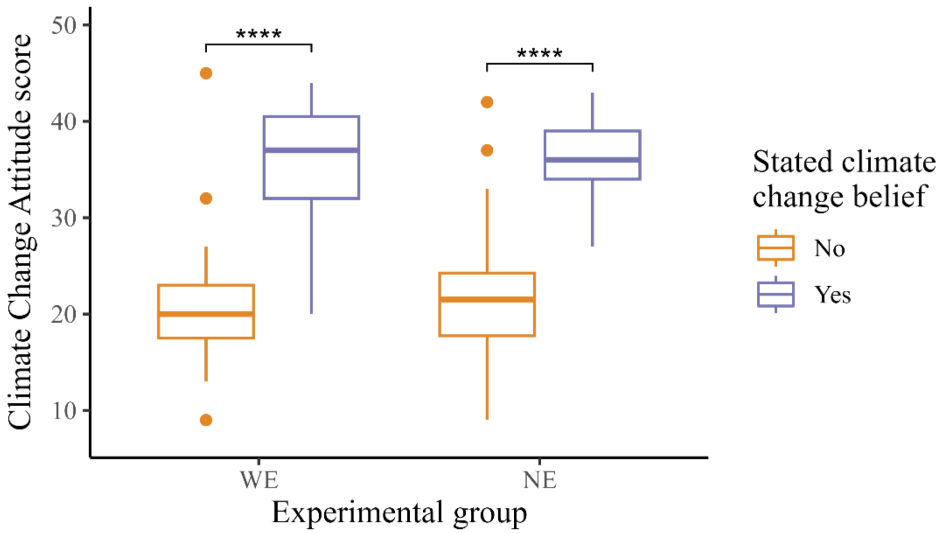

***Figure 44**: Boxplots of the CCA scores between participants that stated to believe and the ones that stated not to believe in the climate change belief screener in Prolific for the two experimental groups.*

4.2 Results of the main experiment

4.2.1 Classification of the area choice data

Before proceeding with the analysis and presentation of the results of the main experiment, the data regarding the areas chosen by participants have to be classified. As thoroughly outlined by

Korporaal (2017), there are different ways in which the outcomes of a study with choices made on maps could present themselves. In some studies, as for instance in Retchless & Brewer (2016) and Schneider et al. (2022), the choices of the participants in the map experiment were clearly identifiable as correct or incorrect answers, thus they could be directly evaluated and compared between different groups of participants. Conversely, in other studies the choices of the participants were completely free, in the sense that no strictly wrong or correct answer existed, but instead the focus was more on letting participants express their preferences based on a series of factors, as in Kübler (2016) or Ruginski et al. (2016). In the latter case, since all answers are equally valid, the evaluation of the answers needed to be based not on their correctness but instead on assessing which type of selectable item, which set of specific attributes was more prevalently chosen on different contexts or by different groups of participants (Korporaal, 2017).

In the framework of this study, a situation somewhat in between the two previously proposed arise, similarly to the work of Korporaal (2017). As detailed out in Chapter 3.6.2, the participants had to choose which area out of six possible provided areas (labelled from A to F) would be the most affected, respectively less affected (depending on the question posed for each map), by future climate change. However, while in the maps without the representation of the forecast certainty there are areas clearly identifiable as *correct*, *incorrect*, or *very incorrect*, in the maps with the depiction of forecast certainty the borders between a *correct* and an *incorrect* answer become more blurred. For instance, when choosing for the least affected area, an area with low change but high uncertainty could still be correct, but also, due to the uncertainty, could become a very affected one in the future. Thus, while for some of the maps there is a situation with clear correctness of the answer, for the others sometimes a wider range of optimal and less optimal solution are present for the participants to choose. Hence, as it was the case for Korporaal (2017), in order to evaluate the answers given for the area choice there is the need to classify the areas in categories reflecting their main attributes. From that classification is then possible to analyse the participants answers.

Since the boxes with the selectable areas could be entirely inside an uncertainty class and climatic variable class, or split between maximum two of them, there are 40 possible type of areas that may happen (16 combinations of climatic variable and certainty plus 24 mixed conditions). 17 of those possible types appears as selectable areas in at least one of the maps. Those 17 possibilities have been grouped in nine main categories, which reflect a specific range of certainty and variable that have been deemed to represent a sensible grouping. The classification in the designed Area Types (ATs) is illustrated in Figure 45 and Table 11. For instance, AT1 represents a low change with an elevated certainty, while AT2 is still low change but with lower certainty, and AT3 represent a medium low change with high certainty. In the case of maps without certainty representation, there are only five AT, which are called as the categories with highest certainty for the maps with certainty depiction. In this way, in the further steps of the analysis, the choices in the certainty maps and without certainty maps can be compared.

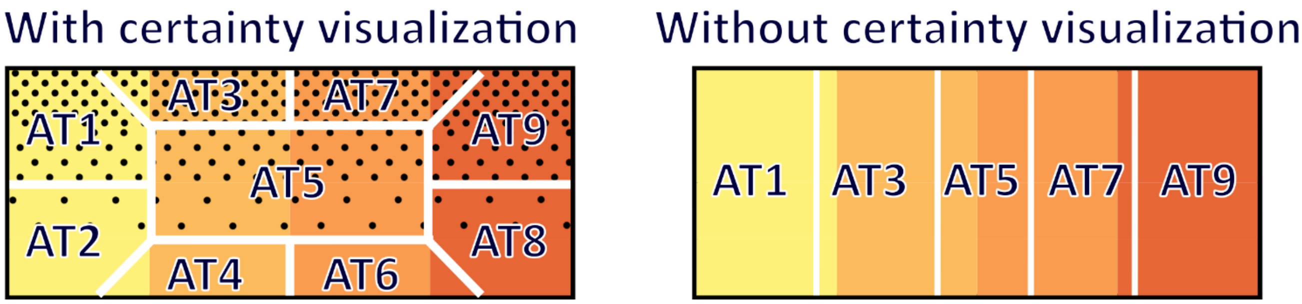

Figure 45: *Categorization of the combinations of climatic variable change and certainty level in the different ATs. In the left is depicted the categorization for maps with certainty visualization, on the right the one for the maps without certainty visualization.*

Table 11 provides an overview of the types of areas and in how many maps they are present (frequency), as well as their correctness depending on which kind of area was asked. As it can be seen, due to lower certainty some ATs are not strictly *correct* or *incorrect*, but may be both. This since, due to lower certainty, the severity of the change might be as forecasted or not.

Table 11: *Characteristics and frequency of the area types and their correctness classification depending on the inquired kind of area (most or least affected). Rows coloured in light blue indicate area types occurring both in the maps with and without certainty visualization (in parenthesis the frequency of this area type in the maps without certainty visualization).*

Climatic variable change	Certainty	Area Type	Frequency	Correctness for the most affected area	Correctness for the least affected area
Low	High	1	14 (6)	Very incorrect	Correct
Low	Low	2	8	Very incorrect	Correct/incorrect
Medium low	High	3	14 (6)	Very incorrect	Incorrect/correct
Medium low	Low	4	4	Very incorrect	Incorrect/correct
Medium	Medium	5	14 (2)	Incorrect/correct	Incorrect/correct
Medium high	Low	6	4	Incorrect/correct	Very incorrect
Medium high	High	7	14 (6)	Incorrect/correct	Very incorrect
High	Low	8	8	Correct/incorrect	Very incorrect
High	High	9	14 (6)	Correct	Very incorrect

Scoring method

Once defined the types of areas, the answers of participants can then be assigned to the belonging class and then the performance of a participant can be compared to ones of the others. As highlighted by Kübler (2016) and Korporaal (2017), the evaluation of the choices can be effectuated by applying two main different methods. A first approach consists in calculating the mean value of the choices of the participants, while the second way accounts for the different frequencies of each selectable area and thus it gives a weighted score to those choices (Korporaal, 2017; Kübler, 2016). Both ways will now be explained with more detail.

The first method, which from now on will be referred as the *average score method (AS method)*, consists of giving to each AT a score, then multiply this score by how many times a participant selected each AT, sum the results, and divide by the number of questions asked (i.e. calculate the mean). Concretely, AT1 will have score 1, AT2 will have score 2 and so forth for all ATs. This process will thus roughly indicate which AT has been in average chosen most often by the participant. However, as Korporaal (2017) noted, a couple of issues arise with this method. On one hand this score only gives an indication of the general direction of the choices of participants, e.g. if they chose more areas with lower change or areas with more change, but do not give information on the specific choices that were made (Korporaal, 2017). On the other hand, the obtained mean score could indicate an AT that the participant never actually selected, but instead the distribution of their choices resulted in such a mean AT; hence, those mean scores should not be interpreted as an indication of actual preference for a specific AT (Korporaal, 2017). As an example, to illustrate the calculation made with this method and how the obtained mean score may indicate a different AT from the actual selected ATs, if a participant selected 2 times AT1, 3 times AT4 and once the AT6, then their score would be calculated as showed in equation (1):

$$Score_{AS} = \frac{2*1+3*4+1*6}{6} = 3.33 \tag{1}$$

The second method, which from now on will be referred as the *normalized score method (NS method)*, builds up from the first method and considers that not all choices (ATs) are available for all the maps, therefore their frequency in the experiment differs (Korporaal, 2017). Consequently, with this method it is calculated the normalized frequency with which each AT is selected. Namely the scores of the single ATs are retrieved by dividing the number of times the participant selected an AT by the frequency of occurrence of such AT in the maps (Korporaal, 2017). Therefore, in this way can both be retrieved the specific choices of a participant and the relative distribution of those choices between the different ATs, while also considering the different frequencies with which the ATs appeared as options in the maps. As an example, to illustrate the calculation made with this method, if a participant selected 2 times AT1, 3 times AT4 and once the AT6, where the frequency of AT1 is 4, for AT4 the frequency is 3 and for AT6 is 3, then their score would be calculated as in equations (2):

$$score\ AT1 = \frac{2}{4} = 0.5 \qquad score\ AT4 = \frac{3}{3} = 1 \qquad score\ AT6 = \frac{1}{3} = 0.33 \tag{2}$$

4.2.2 Analysis of the Area Choices

Comparing the mean score calculated with the AS method between the experimental groups

A visual inspection of the resulting mean scores calculated with the *AS method* for the groups WE and NE, as visible in graph A of Figure 46, suggests that the average score given by participants in group NE (M = 5.14, SE = 0.09) is slightly higher than the group WE (M = 4.88, SE = 0.11). This indicates that participants in group NE choose more often areas in higher categories, thus areas with higher climatic variable change. An analysis of graph B shows that, as expected, the areas selected for answering the least affected area question have a low score (WE: M = 2.53, SE = 0.17; NE: M = 2.61, SE = 0.20) thus indicating the selection of locations with lower climatic change. Conversely, the locations selected for the most affected area question have higher score, thus meaning locations with higher change of the variable (WE: M = 7.24, SE = 0.20; NE: M = 7.67, SE = 0.13). An interesting feature that can be noted is that while the for the least affected area both groups have similar score, for the most affected area participants in WE group have lower score than NE. This suggests that they tended to select more often AT7 or lower, hence towards categories representing medium high change and high to low certainty.

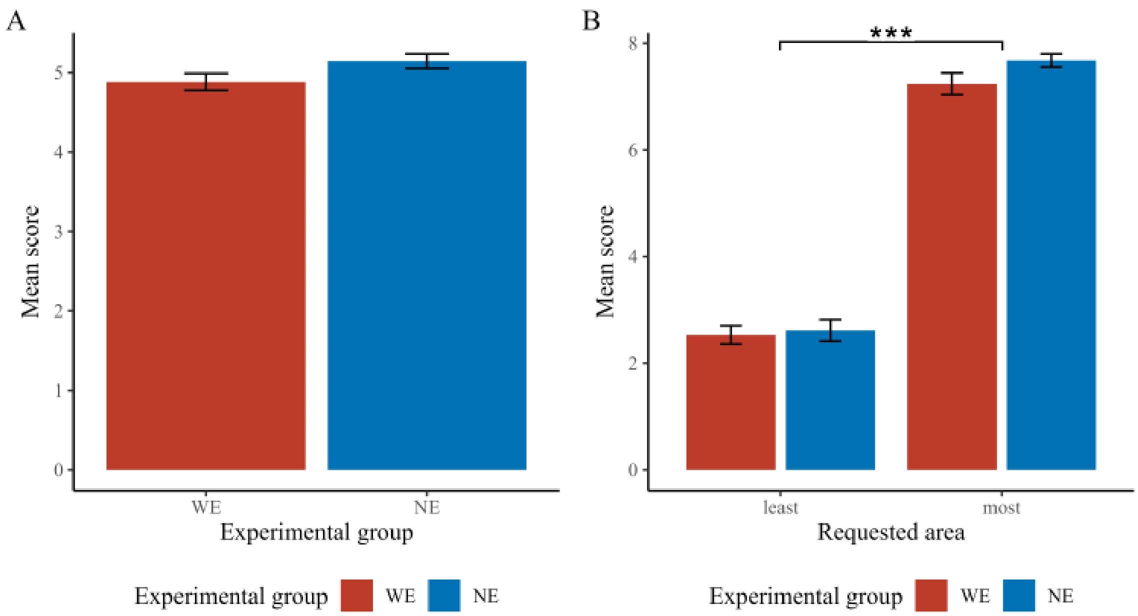

Figure 46*: Mean scores calculated with the AS method for the two experimental groups, both (A) by considering all the areas selected and (B) by comparing the scores divided between the kind of requested area (mean ± 1 SE).*

From the results of the performed Shapiro-Wilk normality tests, it can be retrieved that the mean scores are significantly not normally distributed (p < 0.001). Thus, to statistically assess whether the two groups performed differently, a non-parametric test has been chosen. The results of the Mann-Whitney U test fail to reject the null hypothesis, thus there is no significant difference in the mean scores of participants in group WE compared to group NE (least: U = 1248, p = 0.151 >

0.05). Since the distribution of the scores is not normal, the assumptions for a mixed ANOVA are violated. In order to still be able to statistically compare and verify the difference between the experimental groups and the different kind of area requested, with also the opportunity to consider interactions between the factors, a possible approach is to use the Aligned Rank Transformation (ART) as explained by Wobbrock et al. (2011). This method performs two operations, first the alignment of data and then the averaged ranking is made, after which it is possible to apply to the obtained transformed data the common ANOVA procedures (Wobbrock et al., 2011). Since those kinds of non-parametric data is often present in experiments with human-computer interactions (Wobbrock et al., 2011), as it is the case for this thesis, a useful tool to handle this issue with the ART procedure is the *R* package *ARTool*, developed by Kay et al. (2021). The ANOVA performed on the ART data indicates that, as expected, a significant difference in the scores between most and least affected area is present ($F(1, 107) = 455.788$, $p < 0.001$, partial $\eta^2 = 0.809$), while no significance of experimental group ($F(1, 107) = 1.026$, $p = 0.313 > 0.05$) and no interaction between experimental group and kind of requested area are found ($F(1, 107) = 0.844$, $p = 0.360 > 0.05$). Hence, the score is significantly different between the most and least affected area, but no significant effect of the experimental group on the score has been found.

Comparison of the mean score calculated with AS method between the experimental groups depending on the climate change attitude

As Figure 47 illustrates, the climate change attitude does not seem to have had an influence on the choices of participants, with the mean scores very similar to almost identical for both believers (WE: $M = 4.84$, $SE = 0.15$; NE: $M = 5.14$, $SE = 0.16$) and sceptics (WE: $M = 4.93$, $SE = 0.15$; NE: $M = 5.14$, $SE = 0.10$). The Shapiro-Wilk test of normality outcomes indicate a significative deviation from normality for the area choice data ($p < 0.001$), thus not meeting the assumption for a mixed ANOVA. The ART procedure was then applied and the results applied ANOVA indicate that there is no significant influence of the experimental group ($F(1, 105) = 1.846$, $p = 0.177 > 0.05$) and of the climate change attitude ($F(1, 105) = 0.023$, $p = 0.880 > 0.05$) on the mean score of the participants: It further shows that no significant interaction between the climate change attitude and the assigned experimental group subsists ($F(1, 105) = 0.422$, $p = 0.517 > 0.05$). Hence, participants' attitude towards climate change had no significant effect on their mean score performance in both experimental conditions.

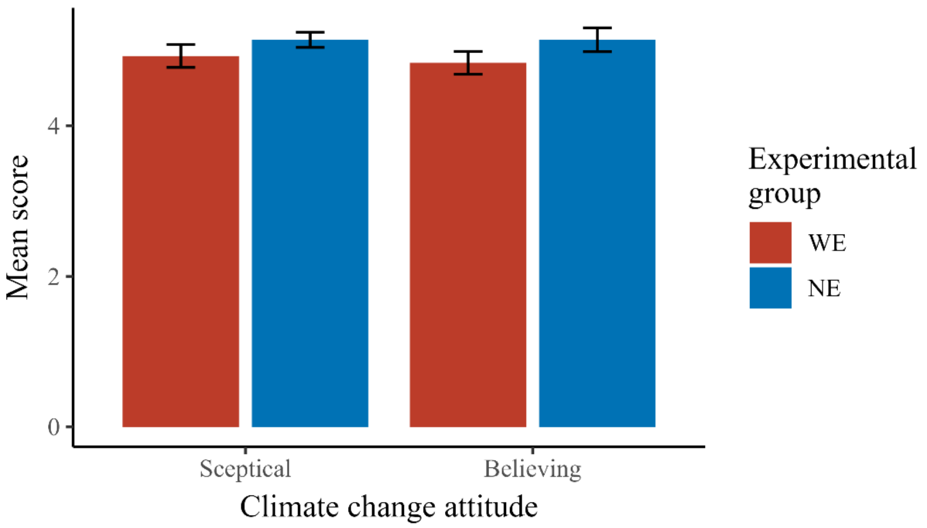

***Figure 47**: Mean scores calculated with the AS method depending on the climate change attitudes of participants for the two experimental groups (mean ± 1 SE).*

Comparison of the mean score calculated with AS method between the experimental groups depending on the certainty visualization type

By taking a closer look at the different certainty visualizations in Figure 48, it does not appear that large differences subsist between the three types of visualization. Only for the representation with lines there seems to be a somewhat larger difference between the WE and NE group. This appears to be the only occasion where the certainty representation led to a more prominent difference in the two experimental groups. Otherwise, the mean score is similar for all the certainty visualization types and experimental groups. Due to the outcomes of the normality tests, which indicates statistically significant deviation from the normal distribution (Shapiro-Wilk test, $p < 0.001$), in order to test whether there is a difference in between the two groups depending on the certainty visualization type, another ANOVA on ART corrected data has been performed. The results indicate that there is no significant difference in the mean score between the experimental groups ($F(1, 107) = 1.098$, $p = 0.297 > 0.05$) and between the different certainty visualization types ($F(2, 214) = 1.617$, $p = 0.201 > 0.05$).The obtained outcome further indicates that the interaction between the experimental groups and the visualization types is non-significant ($F(2, 214) = 0.609$, $p = 0.545 > 0.05$). Thus, the three different types of certainty visualization did not have a significant influence on the choices of participants in both groups.

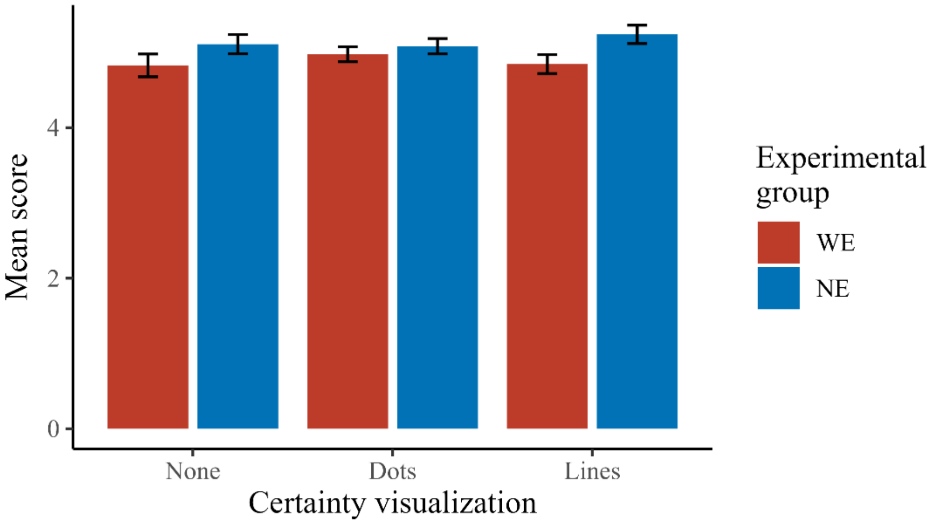

***Figure 48**: Mean scores calculated with the AS method depending on the certainty visualization type for the two experimental groups (mean ± 1 SE).*

Comparison of the mean score calculated with NS method between the experimental groups

As introduced in Chapter 4.2.1, a second method to analyse the area choice of participants is the *NS method*. This method should provide more details in understanding which AT the participants selected in the two experimental conditions. **Errore. L'origine riferimento non è stata trovata.** p rovides an overview of the choices of participants in both groups according to the *NS method*, from which can be seen that all the area types have been chosen at least once, since no normalized mean is equal to zero.

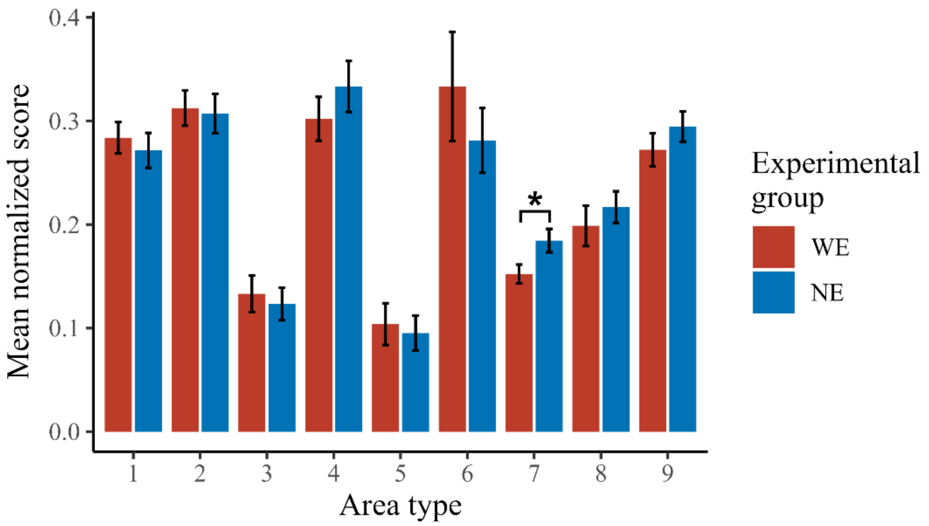

***Figure 49**: Mean scores of the nine area types calculated with NS method for the two experimental groups (mean ± 1 SE).*

Noticeably, for both groups there is a slight preference for AT2, which indicates an area with low change but also low certainty compared to AT1, which in contrast is a low change with high certainty. This two ATs have been probably selected for answering the question about the least affected area. It is interesting noting that while AT1 is more present than AT2 as an answer option, AT2 is more selected in percentage. This may suggest that the lower certainty has been interpreted as a possibility that the depicted change was not happening and thus being preferred to AT1. Also, AT4 and AT6 are rather often selected, thus two ATs characterized by the lowest certainty level and a medium change (medium low for AT4, medium high for AT6). It seems that categories with low certainty have been preferred by participants. Further, the AT9 option is selected more often than AT8 and AT7, hence, in contrast to what happened for the ATs indicating low change, here the AT with most certainty has been chosen more often than the option with less certainty. Finally, it can also be noticed that AT3 and AT5, representing a medium change with high certainty are the least chosen. When considering the difference between the two experimental groups, for most of the cases the mean normalized score appears to be almost the same, with just the AT7 showing a more pronounced difference with small error bars, whereas AT4 and AT6, while also having different scores between the groups, have in addition larger error bars.

Since the mean normalized score are not normally distributed (Shapiro-Wilk test, $p < 0.001$), the Mann-Whitney U test has been used to verify if the scores of each ATs differ between the experimental groups. The outcome of the tests indicate that only for the AT7 there is a significant difference in the mean normalized score between the two experimental groups (AT7: $U = 1623$, $p = 0.04 < 0.05$, $r = 0.056$), which is however a very small effect, while for the other ATs no significant result has been found (AT1: $U = 2720$, $p = 0.504 > 0.05$; AT2: $U = 1294$, $p = 0.744 > 0.05$; AT3: $U = 252$, $p = 0.812 > 0.05$; AT4: $U = 252$, $p = 0.342 > 0.05$; AT5: $U = 52$, $p = 0.841 > 0.05$; AT6: $U = 29$, $p = 0.415 > 0.05$; AT8: $U = 329$, $p = 0.414 > 0.05$, AT9: $U = 2496$, $p = 0.502 > 0.05$). Hence, the participants in NE group selected significantly more frequently AT7, which indicates a medium high change with high certainty. This represent a suboptimal response in case they selected it for the most affected area and AT9 was also present, or completely wrong in the case of the least affected area.

Comparison of the mean score calculated with NS method depending on the climate change attitude

The *NS method* applied with respect to the climate change attitude shows similar general pattern of selection frequency for what concerns the most selected categories, as Figure 50 depicts. With regard to the comparison between sceptics and believers of climate change, there are slight differences between believers and sceptics for the frequency of selection of various ATs. For instance, the AT1 is selected more often by believers, while on the contrary AT2 is more preferred by sceptics. Further, the AT5 has been selected more frequently by believers. Concerning the selection AT associated with high change, differences are noticeable in the higher frequency of AT8 by sceptics and the higher selection of AT7 and AT9 by believers. Interestingly, in both the case of

AT2 and AT8, sceptics have preferentially selected an area with lower level of certainty, while instead the believers by selecting AT1, AT7 and AT9 have preferred areas with more certainty.

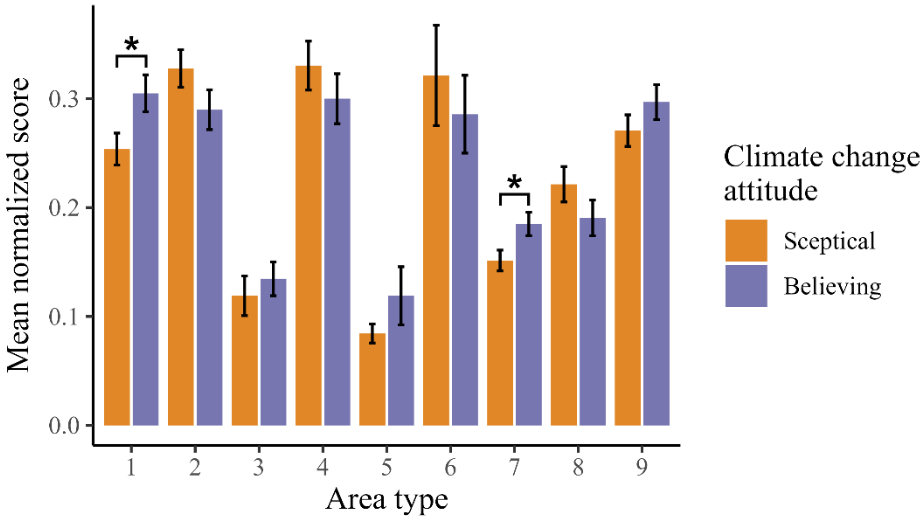

Figure 50*: Mean scores of the nine area types calculated with the NS method, depending on the climate change attitude of participants (mean ± 1 SE).*

Since the Shapiro-Wilk test indicates a significant deviation from normality ($p < 0.001$), the Mann-Whitney U test is used to verify whether the differences in area type frequencies between the two stances towards climate change are statistically significant. The performed tests indicate that a significant difference exists for the frequency of AT1 and AT7, even though the effect sizes are rather small (AT1: U = 2002, p = 0.026 < 0.05, r = 0.187; AT7: U = 1576, p = 0.0211 < 0.05, r = 0.204). For the other ATs no significant difference has been found (AT2: U = 1456, p = 0.132 > 0.05; AT3: U = 206, p = 0.459 > 0.05; AT4: U = 314, p = 0.363 > 0.05; AT5: U = 40, p = 0.368 > 0.05; AT6: U = 28, p = 591 > 0.05; AT8: U = 428, p = 0.271 > 0.05; AT9: U = 2306, p = 0.158 > 0.05). Hence, the believers selected significantly more often than sceptics areas with higher certainty level. Sceptics selected more often than the believers the areas with lower certainty, however the difference is not large enough to be significant.

4.2.3 Analysis of the severity rating

Comparison of the severity rating between the two experimental groups

The rating of the severity given from participants to the areas they selected for both groups and kind of requested area (most or least affected) is summarized in Figure 51. From graph A it can be seen that the NE group (M = 4.53, SE = 0.07) gave a slightly higher rating of severity than group WE (M = 4.43, SE = 0.06). In graph B (Figure 51) it is visible that the locations selected for the least affected region have lower severity ratings, while the ones selected for the most affected area have higher severity ratings. Interestingly, the severity ratings for the least affected area are particularly high, almost reaching the middle of the scale. A further aspect that is visible in graph B, is that there is a difference between the two groups depending if they were rating a location to answer the least affected area question or the most affected area question. The NE group (M = 3.08, SE = 0.08) gave lower severity rating for the least affected areas compared to WE group (M = 3.32, SE = 0.07), while for the most affected area the contrary is true, so the NE group (M = 5.98, SE = 0.05) gave higher rating than WE (M = 5.54, SE = 0.07). Thus, it may be that WE participants were giving slightly more neutral severity ratings compared to the NE participants, which appears to have gravitated more towards the two extremes.

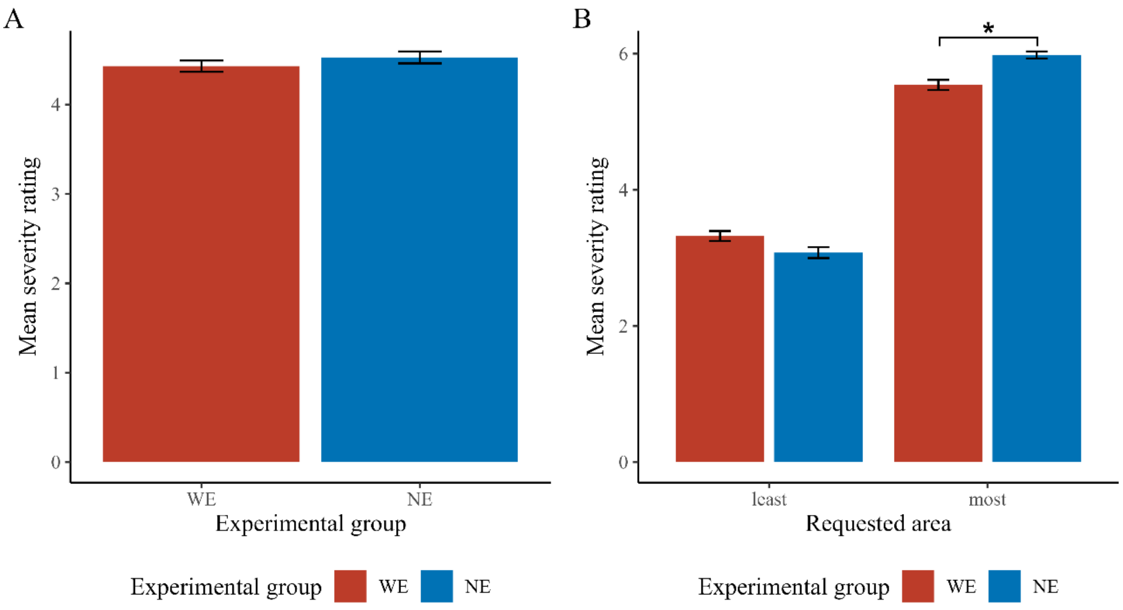

Figure 51: *Mean severity ratings given by participants for the two experimental groups, both (A) by considering all the areas selected and (B) by comparing the mean severity ratings between the kind of requested area (mean ± 1 SE).*

The severity rating shows a significant deviation from normality according to the Shapiro-Wilk test ($p < 0.001$). Thus, to statistically assess the difference in rating between the two groups, the ART method has been implemented. The obtained results from the ANOVA on the ART data indicate that no significant difference occurs in the mean severity rating between the two groups ($F(1, 107) = 0.609$, $p = 0.437 > 0.05$). However, if the type of requested area is considered, then the ANOVA shows that there is a significant interaction between experimental group and type of requested area, with medium effect size ($F(1, 1851) = 16.225$, $p < 0.001$, partial $\eta^2 = 0.009$). The post-hoc comparisons (with Bonferroni correction) reveal that a significant difference in the severity rating between WE and NE group for the most affected area ($t(159)$ = , $p = 0.043 < 0.05$, d = 0.43). Thus, the presence of an emotional narrative, has had an influence on the perception of the severity by participants, when assessing the most affected area, with however a small to medium effect size.

Comparison of the severity rating depending on the climate change attitude

When considering the effect of climate change attitude on the severity ratings (see Figure 52), the participants stating a more sceptical stance in regard to climate change appear to give lower ratings to their choices (WE: M = 4.30, SE = 0.09; NE: M = 4.33, SE = 0.10), compared to participants that have a believing stance (WE: M = 4.56, SE = 0.09; NE: M = 4.73, SE = 0.09). This is visible in both experimental conditions, whereas the NE group has a tendence to give higher severity ratings. Given that the samples present a significant non-normal distribution (Shapiro-Wilk test, p < 0.001), and the homogeneity of variance is not present for the ratings of sceptical participants (Levene test, p < 0.001), the ART procedure was applied and the differences of rating between groups and climate stance is tested with the ANOVA on the ART corrected data. The outcome indicates that it exists a significant effect of climate change attitude on the severity rating, where the effect size is nonetheless to be considered small ($F(1, 1{,}105) = 5.446$, $p = 0.022 < 0.05$, partial $\eta^2 = 0.05$). Further, the results of the ANOVA found no significant interaction between the climate change attitude and the experimental group assignment (least: $F(1, 105) = 0.005$, $p = 0.945 > 0.05$). Hence, the climate change attitude had an influence, even though small, in the perceptions of the participants of the severity of change, where believers in the climate change where more prone to give higher severity assessments.

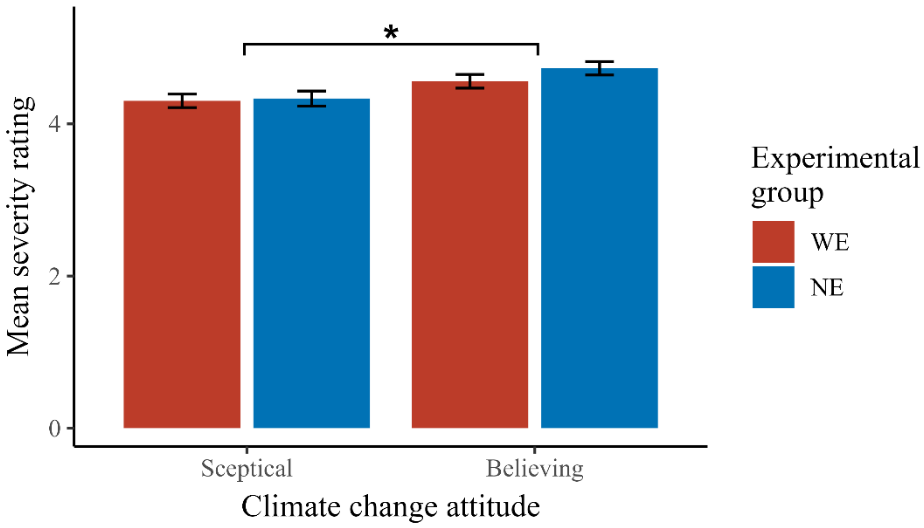

***Figure 52**: Mean severity ratings given by participants depending on the climate change attitudes for the two experimental groups (mean ± 1 SE).*

Comparison of the severity rating depending on the type of certainty visualization

By comparing the severity rating across the different certainty visualisations, no evident difference appears, where just for the visualisation with lines it can be noticed a very slight tendency to higher severity rating (see Figure 53). Otherwise, the only other noticeable pattern is the already noted tendency of the NE group (none: M = 4.49, SE = 0.12; dots: M = 4.49, SE = 0.11;

lines: *M* = 4.60, *SE* = 0.11) to give higher severity ratings compared to the WE group (none: *M* = 4.43, *SE* = 0.11; dots: *M* = 4.40, *SE* = 0.11; lines: *M* = 4.47, *SE* = 0.11), which appears again in this case for all the certainty visualization types. To statistically substantiate this visual impression, since the data is not normally distributed (Shapiro-Wilk test, $p < 0.001$), the ART procedure was applied. The outcomes of the ANOVA on the ART corrected values indicate that no significant difference due to the visualization type has been found ($F(2, 1849) = 0.251$, $p = 0.778 > 0.05$), while however the experimental group is found to have a significant effect ($F(1, 107) = 4.331$, $p = 0.04 < 0.05$, partial $\eta^2 = 0.04$). Furthermore, no significant interaction between the certainty visualization type and the experimental group is to be found ($F(2, 1849) = 0.026$, $p = 0.974 > 0.05$). Therefore, those results indicate that the depiction of certainty did not influence the perception of participants, and thus the ratings of the severity, when assessing the areas they selected.

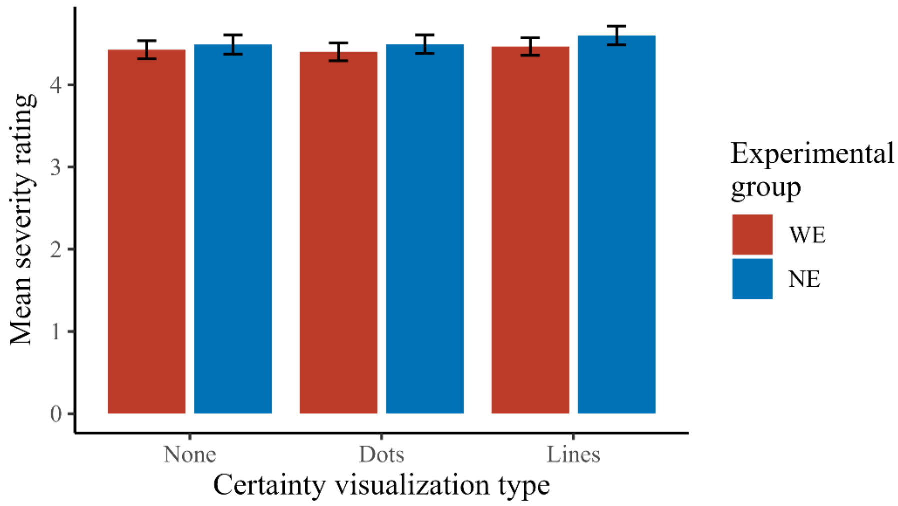

Figure 53*: Mean severity ratings given by participants depending on the certainty visualization type for the two experimental groups (mean ± 1 SE).*

Comparison of the difference between severity ratings given by participants and the reference

Given that the selectable areas could either be entirely inside one of the four climatic variable change classes or split between two adjacent classes, there are in total seven possible levels of severity in which an area might be located. Hence, to each selectable area could be assigned a specific value on the 1-7 scale that was given to the participants for the rating task. Taking this value as a reference for the severity of each area, it can be then compared with the severity rating given by the participants. Therefore, on a second analysis step, the difference between the rating given by the participants and the reference value of severity for their selected area has been computed. The rating difference has been calculated as indicated in the formula (*3*):

$$severity_{diff} = severity_{participant} - severity_{reference} \tag{3}$$

The obtained rating differences are then compared between the experimental groups, the climate change attitude, and the different certainty visualization types, to investigate whether any significant difference arises between those factors. This was made both as comparison of the percentage of areas that have been rated as the reference, or over- and underestimated, as well as the average difference from the reference of the given ratings.

An overview on the distribution of the participants ratings is given in Table 12, from which it can be seen that in all the groups of participants and for all the certainty visualization types it was very common to overestimate the severity of the selected area. In almost half of the ratings the WE group gave an overestimation of the severity. Similarly, also for the believers the half of the severity ratings given are an overestimation, compared to the reference value for their selected area. In addition, the WE group had more tendency to overestimate severity in comparison to the NE group. The same holds true between the believing and the sceptical participants. Further, the sceptics seems to have the higher percentage of underestimation. Finally, while it is a small-scale difference, it appears that the maps with no certainty representation led to slightly less overestimation and slightly more underestimation than the other two certainty representations.

***Table 12**: Percentages of maps where the severity of the selected area was overestimated, underestimated, or estimated equal to the reference. Comparisons between the two experimental groups, the climate change attitudes, and the types of certainty visualization.*

Category	Overestimation (%)	Equal (%)	Underestimation (%)
Experimental group			
WE	48.56	25.93	25.51
NE	40.51	32.82	26.67
Climate change attitude			
Believers	49.90	26.95	23.15
Sceptics	39.19	31.82	28.99
Certainty visualization type			
None	42.20	29.20	28.60
Dots	44.65	30.43	24.92
Lines	46.64	28.59	24.77

From Figure 54 it is clearly visible that both groups in average overestimated by about half a point the severity of the areas they selected, compared to the reference value. Interestingly, the NE group (M = 0.431, SE = 0.06) has been more accurate than WE group (M = 0.556, SE = 0.07) in giving the severity rating to the selected areas. Meaning that the higher severity rating given by NE participants noted in previous subchapters is both due to their selection of regions with intrinsic higher severity, plus some overestimation. Conversely, for WE participants as already noted in previous chapters their severity ratings were lower, thus this indicates that the WE participants generally selected areas with lower severity but overestimated more the severity. Given the non-normality of the distribution of the differences (Shapiro-Wilk test, $p < 0.01$) and their non-homogeneity of variances (Levene test, $p < 0.001$), the ART method has been selected to verify whether a significant difference arises between the experimental groups. The resulting ANOVA found no significant difference in the severity ratings between NE and WE group ($F(1, 107) = 3.257$, $p = 0.074 > 0.05$).Thus, the emotional stimulus did not have a significant effect in leading participants to overestimate the severity of change in an area compared to the absence of the emotional stimulus.

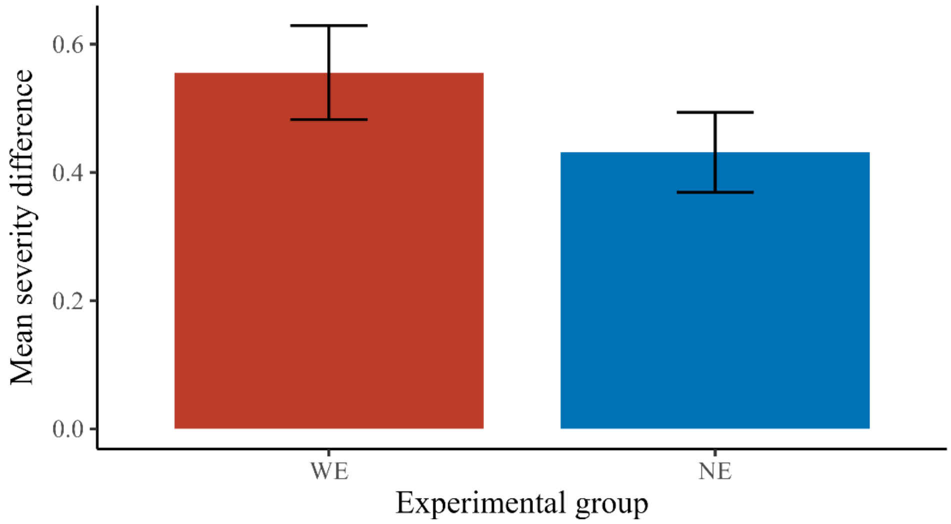

Figure 54*: Mean difference of severity ratings from the reference for the two experimental groups (mean ± 1 SE).*

With regard to the attitude towards climate change, a pronounced difference is noticeable between believing participants and sceptical participants, as displayed in Figure 55. In both experimental conditions the sceptics (WE: $M = 0.39$, $SE = 0.11$; NE: $M = 0.26$, $SE = 0.09$) tended to be more accurate that the believers (WE: $M = 0.72$, $SE = 0.10$; NE: $M = 0.60$, $SE = 0.09$), which in contrast did overrate the severity of the selected region. The average overestimation of the believers is almost the double of the average overestimation made by the sceptics; hence it appears a large difference. To confirm this visual impression, since the severity ratings are not normally distributed (Shapiro-Wilk test, $p < 0.001$) and for the sceptics the homogeneity of variance is not met (Levene test, $p < 0.01$), non-parametric tests were used. The ART procedure was applied and the results of the ANOVA show that there is indeed a significant effect of climate change attitude on the overrating of the severity of the change ($F(1, 105) = 5.571$, $p = 0.020 < 0.05$, partial $\eta^2 = 0.050$), nonetheless, with a small effect size. The ANOVA outcomes further indicate that no significant interaction exists between the climate change attitude and the experimental group (least: $F(1, 105) = 0.327$, $p = 0.569 > 0.05$). Hence, the climate change attitude had an effect on the perception of severity of participants, leading believers to overestimate more than the sceptics the severity of change depicted on the map at the location they selected.

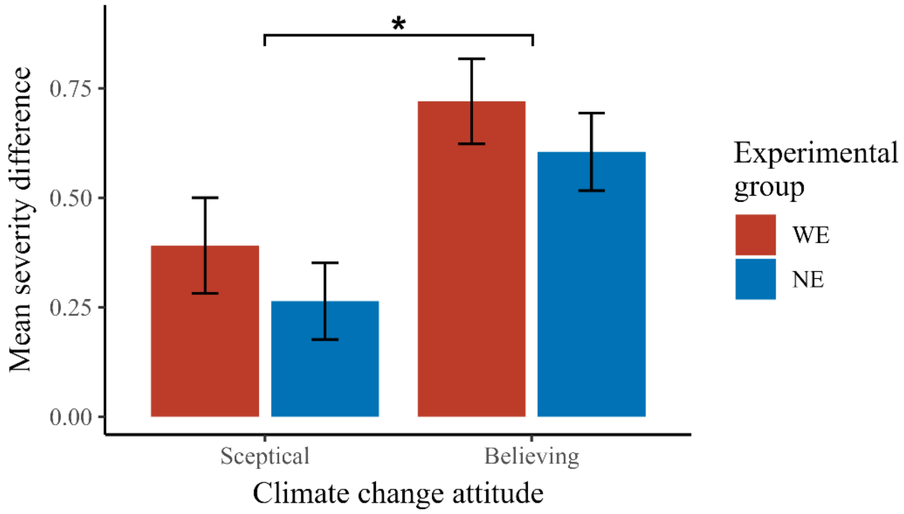

Figure 55*: Mean difference of severity ratings from the reference depending on the climate change attitude for the two experimental groups (mean ± 1 SE).*

Finally, a look is taken at the difference of severity rating given by participants compared to the reference value for the three different visualizations of certainty. As portrayed in Figure 56, the magnitude of the difference is generally similar for all three types of representation. There are some small-scale differences, e.g., for the depiction with dots in both groups the level of overestimation is similar. However, due to the large error bars, the differences are do not appear noteworthy.

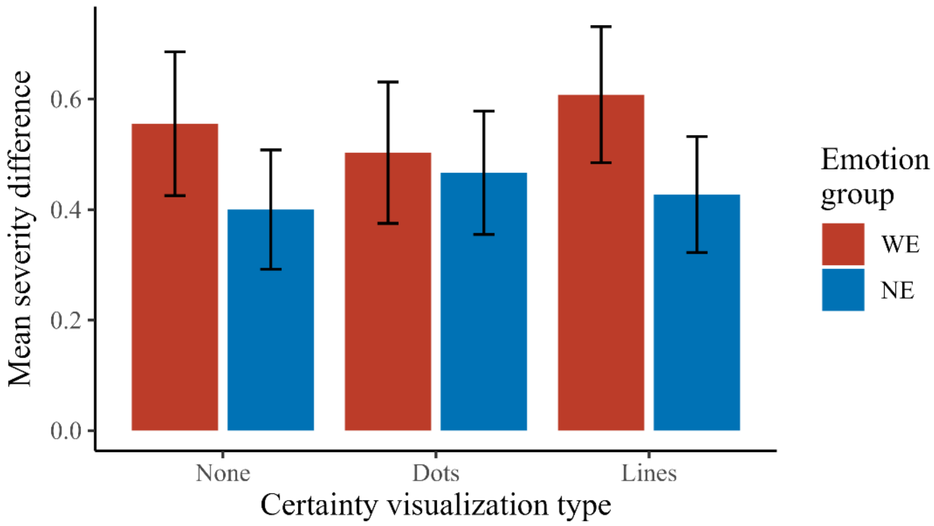

Figure 56*: Mean difference of severity ratings from the reference depending on the type of certainty visualization for the two experimental groups (mean ± 1 SE).*

The data is not normally distributed (Shapiro-Wilk test, $p < 0.001$), thus non-parametric approaches were used. The performed ANOVA on the ART corrected data indicates that the certainty visualization type did not influence the overestimation of the severity ($F(2, 1849) = 1.038$,

p = 0.354). Moreover, no significant interaction between the experimental group and the certainty visualization type occurs ($F(2, 1849) = 0.209$, $p = 0.811 > 0.05$). Hence, the severity assessment has not been influenced the way certainty was represented.

4.2.4 Analysis of the certainty rating

Comparison of the certainty ratings between the two experimental groups

Participants had also to assess the certainty of the area they selected. Looking at the results of the certainty rating given by the respondents (see Figure 57 graph A), it appears that only a small difference between the two experimental groups occurred, with the NE group (M = 4.61, SE = 0.06) having a slightly higher average certainty rating than WE (M = 4.54, SE = 0.06). The certainty rating is at about 4.5, thus, a slight tendency to assess the selected region as certain, however the rating is not much distant from the neutral standpoint of 4. By looking at the certainty ratings with also the distinction of which kind of area was requested, as illustrated in graph B in Figure 57, it is noticeable that for both experimental groups the certainty given to the selected most affected areas (WE: M = 4.89, SE = 0.09; NE: M = 5.05, SE = 0.08) is larger than the certainty given for the chosen least affected areas (WE: M = 4.18, SE = 0.08; NE: M = 4.18, SE = 0.08). Given that the certainty rating given to the least affected area is just slightly above the neutral point, it seems to indicate that participants never felt that the change in this case was completely certain. Further, for the most affected area it appears to exist a small difference in the rating given by the two groups, with the NE group slightly more prone to give higher certainty rating.

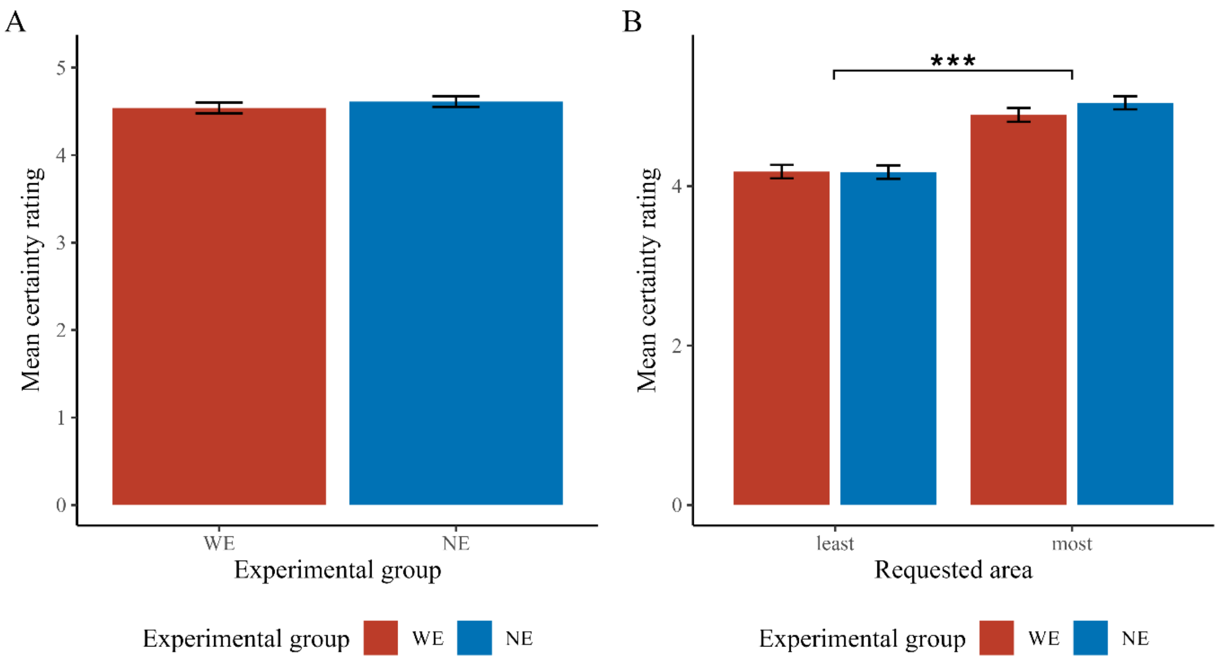

***Figure 57**: Mean certainty ratings given by participants in the two experimental groups, both (A) by considering all the areas selected and (B) by comparing the mean certainty ratings between the kind of requested area (mean ± 1 SE).*

According to the results of the Shapiro-Wilk test, the certainty ratings are significantly non-normally distributed ($p < 0.001$), thus the ART procedure was used to test the difference between the groups. The outcome of the applied ANOVA shows that, as the visual inspection suggested, no significant difference in the certainty ratings between the two experimental groups is found ($F(1, 107) = 0.062$, $p = 0.805 > 0.05$). However, the effect of the requested area (most or least affected) on the certainty rating is significant ($F(1, 1851) = 126.481$, $p < 0.001$, partial $\eta^2 = 0.064$) with a moderate effect size. Between the experimental group and the kind of area requested, no significant interaction is found ($F(1, 1851) = 0.316$, $p = 0.574$).

Comparison of the certainty ratings depending on the climate change attitude

With regard to the attitude towards climate change, the visual investigation of Figure 58 only suggests a small difference, with sceptical participants (WE: $M = 4.50$, $SE = 0.08$; NE: $M = 4.46$, $SE = 0.09$) giving slightly lower certainty rating to their areas compared to believing respondents (WE: $M = 4.58$, $SE = 0.09$; NE: $M = 4.77$, $SE = 0.08$). Given that the data is not normally distributed (Shapiro-Wilk test, $p < 0.001$) and the certainty ratings of the believers have no homogeneous variance (Levene test, $p < 0.05$), the ART procedure was applied to investigate the interaction between climate change attitude and certainty ratings. The outcomes of the ANOVA performed on the ART corrected data indicate that climate change attitude had no significant effect on the certainty ratings of the participants ($F(1, 105) = 1.701$, $p = 0.195 > 0.05$). Moreover, it also indicates that there is no significant interaction between climate change attitude and experimental group (least: $F(1, 105) = 0.130$, $p = 0.719 > 0.05$). Hence, the climate change attitude had no effect on the participants' assessment of the certainty level of their selected areas.

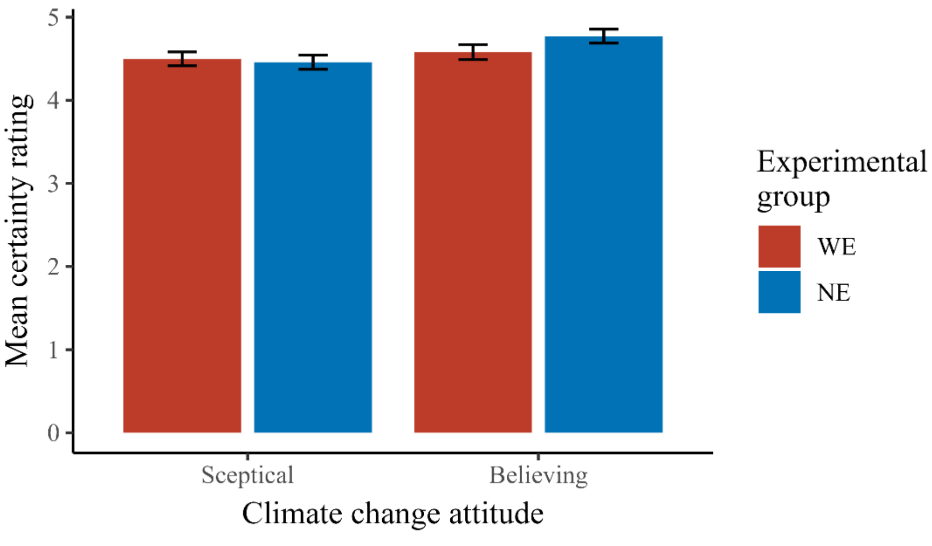

Figure 58*: Mean certainty ratings given by participants depending on the climate change attitude for the two experimental groups (mean ± 1 SE).*

Comparison of the certainty rating depending on the certainty visualization type

By looking at Figure 59, it appears evident that the participants in both groups consistently rated the certainty of the selected area way lower in the maps without certainty representation compared to the maps with certainty represented as dots or lines. The certainty ratings in maps without certainty representation are in average below 4, hence with a tendency towards the negative pole of the certainty scale. Conversely, for the maps with one of the two certainty representations, the certainty is rated on average at about 5. This seems to suggest that in absence of a layer depicting the certainty, participants either took a neutral stance on the certainty of the data or even considered the data as not certain. Between the two other representation of certainty no particular difference arises at the visual inspection. To confirm those impressions, since the data is not normally distributed (Shapiro-Wilk test, $p < 0.001$) an ART procedure was applied. The results indicate that a significant effect due to the certainty visualization type exists, which also has a very large effect size ($F(2, 1849) = 122.37$, $p < 0.001$, partial $\eta^2 = 0.117$), while there is no significant interaction between experimental group and certainty visualization type (least: $F(2, 1849) = 2.827$, $p = 0.059 > 0.05$). The post-hoc contrasts on the certainty visualization types show that the difference in certainty rating between the representation with dots and no representation, as well as between the representation with lines and no representation, is significant (none-dots: $t(1849) = -13.237$, $p < 0.001$, $d = 0.62$; none-lines: $t(1849) = -13.839$, $p < 0.001$, $d = 0.64$). Thus, these results indicate that the absence of certainty visualization led to an important and significant decrease in the certainty rating that the participants were willing to give to the changes in their selected areas compared to the maps where certainty depictions were available.

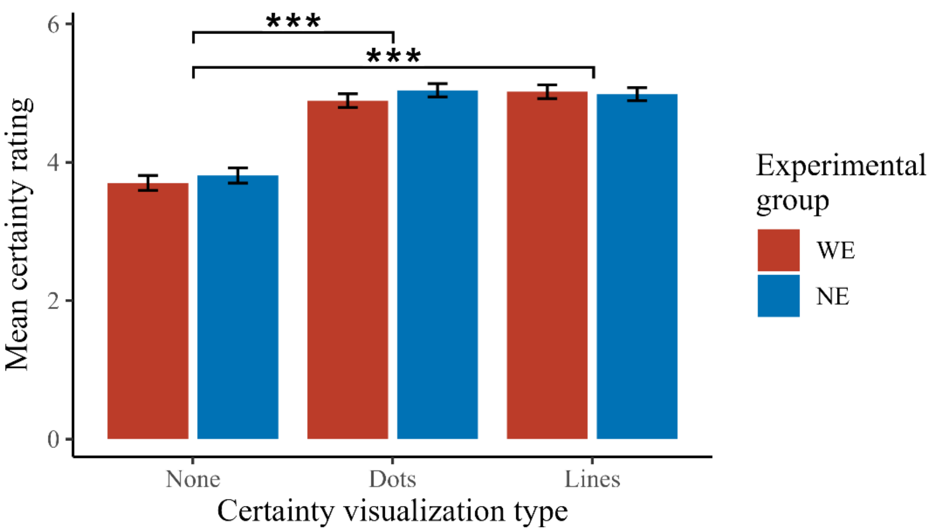

***Figure 59**: Mean certainty ratings given by participants depending on the type of certainty visualisation for the two experimental groups (mean ± 1 SE).*

Comparison of the difference from reference of the certainty ratings

Similarly to what has been done for the severity rating analysis, also for the certainty rating analysis a second step was performed, where the difference between the rating given by the participants and the reference value of certainty for their selected area has been computed. The selectable areas could either be entirely inside one of the four certainty classes or split between two adjacent classes, giving a total of seven possible levels of certainty in which an area might be located. Hence, as was the case for the severity, to each selectable area could be assigned a specific value on the 1-7 scale that was given to the participants for the rating task. This value has been then taken as reference for the certainty of each area. Since in the maps without certainty layer it is not possible to assign a pre-determined reference value, only for the maps with certainty representation this analysis step was done. The rating difference has been calculated as shown in the formula (4):

$$certainty_{diff} = certainty_{participant} - certainty_{reference} \tag{4}$$

The obtained rating differences are then compared between the experimental groups, the climate change attitude, and the different certainty visualization types. This was made both as comparison of the percentage of areas that have been rated as the reference, or over- and underestimated, as well as the average difference from the reference of the given ratings.

From Table 13 it is noticeable that, in general, it has been more common to underestimate the certainty of the selected area, with this patter present across all the levels of the three factors. Particularly pronounced is the percentage of underestimations made in the maps with certainty represented as lines. Further, between the WE and NE group there is no particular difference in the occurrence of over- or underestimation. Moreover, believers appear to be more prone to overestimate the certainty compared to the sceptics.

***Table 13**: Percentages of maps where the certainty of the selected area was overestimated, underestimated, or estimated equal to the reference. Comparisons between the two experimental groups, the climate change attitudes, and the types of certainty visualization.*

Category	Overestimation (%)	Equal (%)	Underestimation (%)
Experimental group			
WE	32.25	30.09	37.66
NE	32.73	29.24	38.03
Climate change attitude			
Believers	35.76	26.67	37.57
Sceptics	29.17	32.71	38.12
Certainty visualization			
Dots	35.47	29.51	35.02
Lines	29.51	29.82	40.67

When taking a look at the mean difference from the reference, as Figure 60 illustrates, on average participants tended to give a rating of certainty higher than the reference in both experimental groups, with the participants in WE group (M = 0.21, SE = 0.09) being slightly more prone to overestimate than NE group (M = 0.34, SE = 0.08). Nonetheless, the difference between the groups appears to not be significant, as the error bars are large. Further, the overestimation of the certainty is less pronounced than the overestimation of severity seen in the previous chapter.

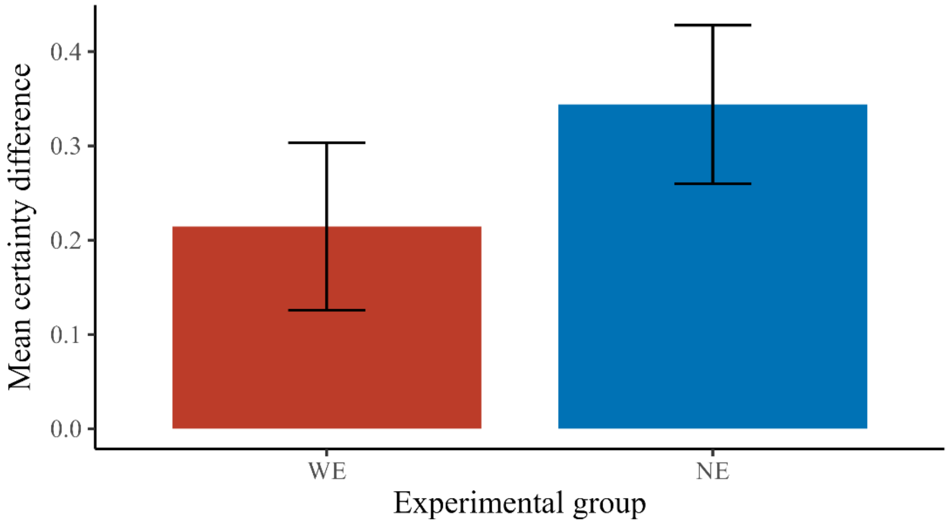

Figure 60*: Mean difference of certainty ratings from the reference for the two experimental groups (mean ± 1 SE).*

Since the differences from reference are not normally distributed (Shapiro-Wilk test, $p < 0.001$), the ART procedure was again used. The results of the ANOVA indicate that no significant dissimilarity occurs in the difference from reference between the two groups ($F(1, 107) = 0.108$, $p = 0.744 > 0.05$). Thus, the emotional stimulus did not lead to a difference in the overestimation from the reference value.

Interestingly, the influence of attitudes towards climate change to the certainty ratings given by participants seems to have led believing participants in group WE to lower overestimation of the certainty value of their chosen areas, by almost answering in average the reference value (see Figure 61). On the contrary believers in NE group and the sceptics in both groups overestimated more. Certainty ratings data is non-normally distributed (Shapiro-Wilk test, $p < 0.001$), hence to test the difference between climate change attitudes, the ART procedure was applied, with the ANOVA results indicating that no significant influence of climate change attitude has been found ($F(1, 105) = 0.068$, $p = 0.795 > 0.05$). Further, no significant interaction between climate change attitude and experimental groups subsists ($F(1, 105) = 0.031$, $p = 0.862 > 0.05$). Hence, while in the graph a difference in the overestimation made by believers in the WE group is visible, it is not large enough to be a significant one, and so the climate change attitude did not lead to differences in the overestimation of certainty.

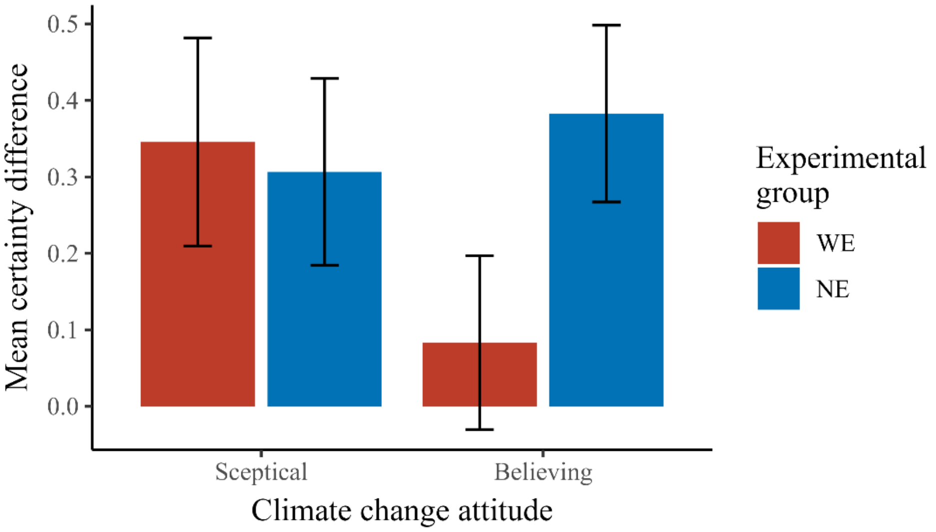

Figure 61*: Mean difference of certainty ratings from the reference depending on the climate change attitude for the two experimental groups (mean ± 1 SE).*

Concerning the influence that certainty visualization had on the certainty rating, illustrated in Figure 62, it appears that the representation with dots led the participants in the NE group to overestimate slightly more the certainty level of the areas (dots WE: $M = 0.25$, $SE = 0.12$; dots NE: $M = 0.55$, $SE = 0.12$; lines WE: $M = 0.18$, $SE = 0.13$; lines NE: $M = 0.14$, $SE = 0.12$).

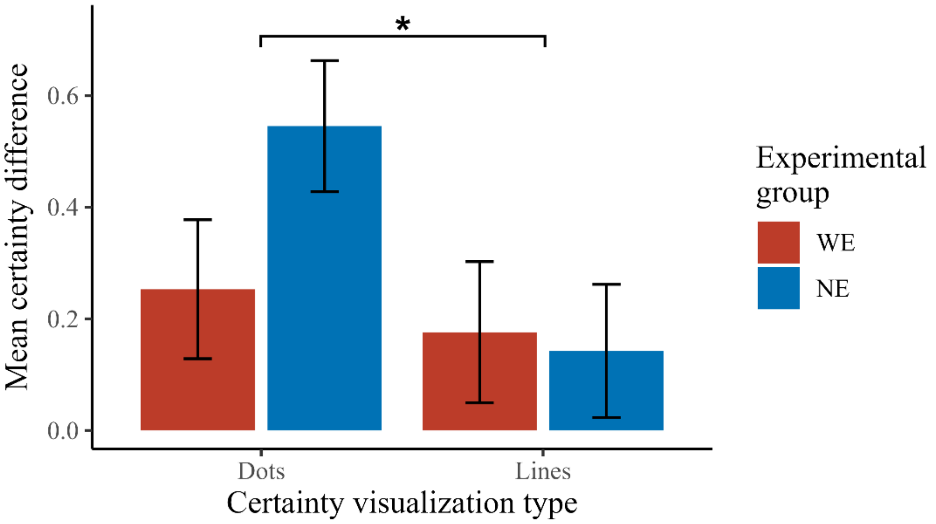

Figure 62*: Mean difference of certainty ratings from the reference depending on the type of certainty visualization for the two experimental groups (mean ± 1 SE).*

Since data is not normally distributed (Shapiro-Wilk test, $p < 0.001$), the ART procedure was used to verify the differences between the groups and certainty visualization types. The ANOVA on the ART corrected data shows that a significant influence of the certainty visualization type exists, even though with a very small effect size ($F(2, 1197) = 6.299$, $p = 0.012 < 0.05$, partial $\eta^2 = 0.005$), while conversely no significant interaction exists between the experimental groups and the certainty visualization type ($F(2, 1197) = 2.332$, $p = 0.127 > 0.05$). Hence, only a significant but small effect of certainty visualization has been found, with the representation of dots leading to slightly higher overestimation.

4.2.5 Analysis of the trust rating

Comparison of the trust rating between the two experimental groups

From Figure 63 the trust rating given in the two experimental groups appears to be the same, with only a slightly higher trust rating given in the WE group (WE: M = 4.71, SE = 0.05; NE: M = 4.68, SE = 0.05). Given that a trust rating of 4 would be the neutral position on the trust scale, in both groups the tendency is towards considering the presented maps as trustworthy. Since trust ratings are not normally distributed (Shapiro-Wilk test, $p < 0.001$), the data was prepared with the ART procedure. The result of the ANOVA on the ART corrected data indicate that, as the visual inspection suggested, no significant difference exists in trust rating between the experimental groups ($F(1, 107) =$, $p = 0.855 > 0.05$). Hence, the presence of an emotional stimulus did not influence the trust that participants were willing to give to the maps.

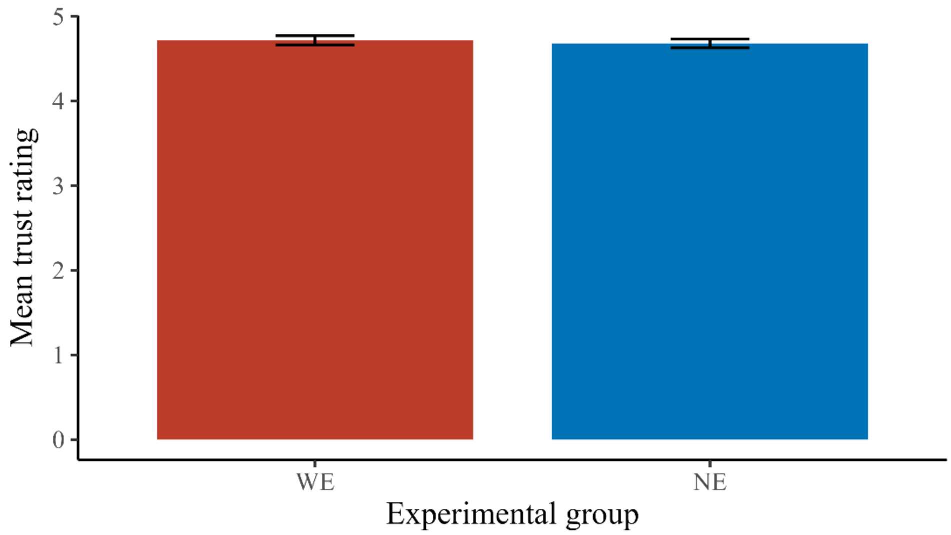

Figure 63*: Mean trust ratings given to the maps by participants for the two experimental groups (mean ± 1 SE).*

Comparison of the trust rating depending on the climate change attitude

An evident difference in the trust rating between sceptical and believing participants can be noted in Figure 64, where the believers ($M = 4.98$, $SE = 0.05$) consistently rated with higher trust the maps than the sceptics ($M = 4.42$, $SE = 0.05$). While in both cases the tendency is towards considering the maps trustworthy, the sceptics are closer to the neutral position. Since trust ratings are not normally distributed (Shapiro-Wilk test, $p < 0.001$), the ART procedure was applied to test the difference in rating between the two stances towards climate change. The results proves that the climate change attitude had a significant effect on the trust ratings with a medium effect size (F(1, 105) = 8.338, p = 0.005 < 0.05, partial η^2 = 0.074), while no significant interaction has been found between experimental group and climate change attitude (F(1, 105) = 0.418, p = 0.519 > 0.05). Thus, climate change attitude had a medium significant effect in the participants' trust ratings, leading to lower ratings given by sceptics compared to the believers.

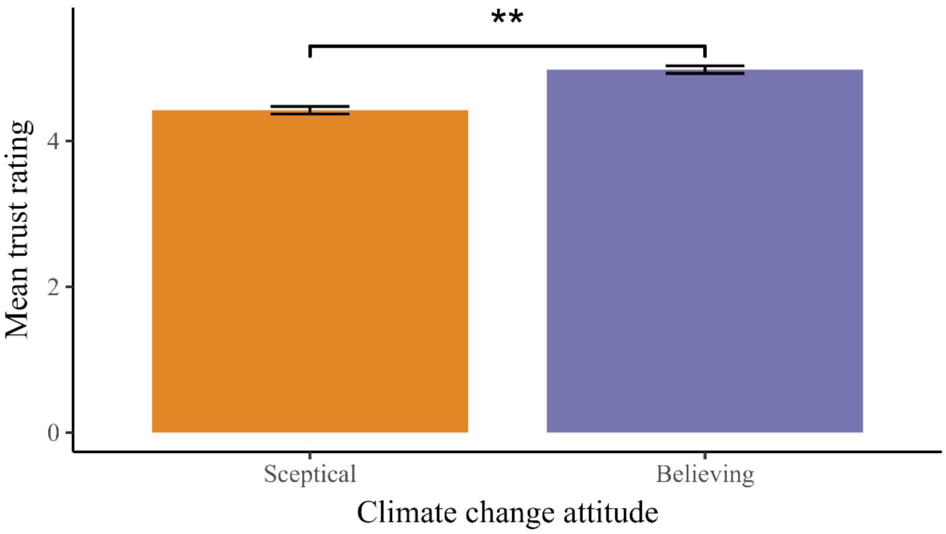

***Figure 64**: Mean trust ratings given to the maps by participants for the two climate change attitudes (mean ± 1 SE).*

Comparison of the trust rating depending on the certainty visualization type

Interestingly, the maps without certainty depiction (M = 3.98, SE = 0.07) led to a noticeably lower trust rating than the two other types of certainty depiction (dots: M = 5.09, SE = 0.06; lines: M = 5.03, SE = 0.06), as Figure 65 illustrates. It appears that in absence of certainty representation the trustworthiness of the maps has been rated as neutral, while with presence of one of the two certainty representations the maps are often rated as trustworthy.

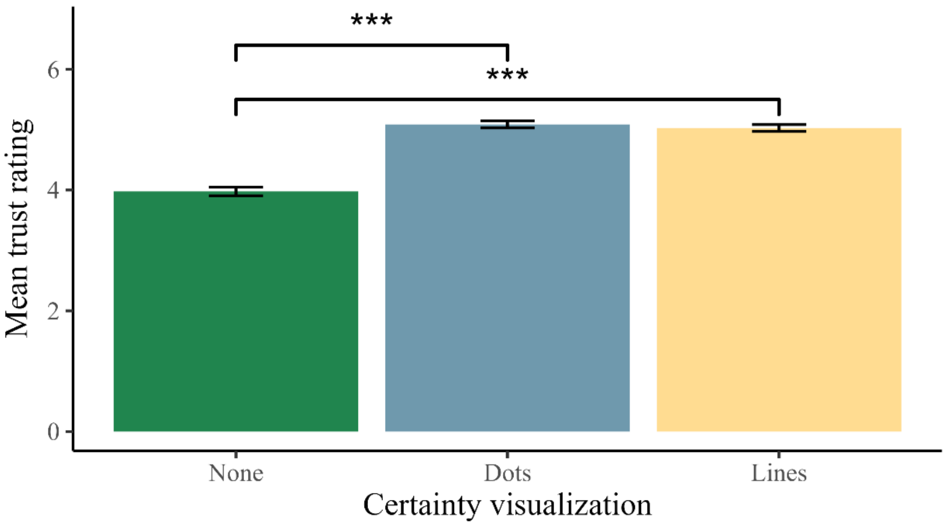

***Figure 65**: Mean trust ratings given to the maps by participants for the three types of certainty visualization (mean ± 1 SE).*

To test the differences, due to the trust rating being not normally distributed (Shapiro-Wilk test, $p < 0.001$), the ART procedure was applied, which ANOVA returned as outcome that the certainty visualization type do have a significant effect on the participants' trust ratings, with also a large effect size ($F(2, 1849) = 167.872$, $p < 0.001$, partial $\eta^2 = 0.154$). Conversely no significant interaction exists between experimental group and certainty visualization type ($F(2, 1849) = 2.501$, $p = 0.082 > 0.05$). The post-hoc comparisons between the certainty visualizations indicate that the trust ratings between the representation with dots and no representation, as well as between representation with lines and no representation, are significant (none-dots: $t(1849) = -16.396$, $p < 0.001$, d = 0-76; none-lines: $t(1849) = -15.282$, $p < 0.001$, $d = 0.71$). Hence, the presence of a certainty representation increased the trust of the maps compared to no representation. Further, as illustrated in the Figure 66, there is a difference in the trust ratings given to the visualization type depending on the climate change attitudes of the participants. It seems that the presence of certainty increased the trust of believers more than what it did for the sceptics. The ANOVA performed on the ART corrected data indicates that there is a significant interaction between climate change attitude and certainty visualization type ($F(2, 1849) = 12.232$, $p < 0.001$, partial $\eta^2 = 0.013$). The post-hoc tests (with Bonferroni correction) show that the difference in trust ratings between believers and sceptics is significant for the maps with dots ($t(136) = -3.788$, $p = 0.003 < 0.05$, $d = 0.65$) and with lines ($t(136) = -3.741$, $p = 0.004 < 0.05$, $d = 0.64$), while no significant difference is found for the trust ratings given to the maps without certainty depiction ($t(136) = -0.914$, $p = 1 > 0.05$). Hence, the presence of certainty visualization (both as dots and as lines) increased the trust of believing participants significantly more than for the sceptical participants, compared to the maps without certainty representation.

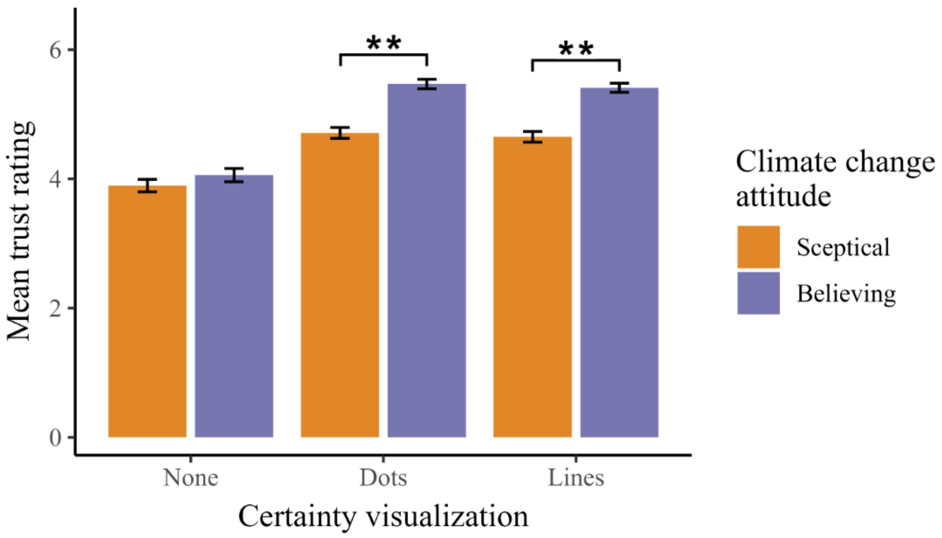

***Figure 66**: Mean trust ratings given to the maps by participants for the three types of certainty visualization depending on their climate change attitude (mean ± 1 SE).*

Correlation between the trust, the severity, and the certainty ratings

In order to further investigate which factors might have a relationship with the trust given by participants to the maps, a correlation matrix has been made. As illustrated in Figure 67, there are significative correlations between all of the three ratings given by participants in the task. Nonetheless, the correlation between severity rating and trust rating, as well as between severity rating and certainty rating, is low to medium. In contrast, there is a strong positive correlation between the certainty rating and the trust rating, with a Spearman's ρ of 0.63, which may suggest that participants may have associated one concept with the other.

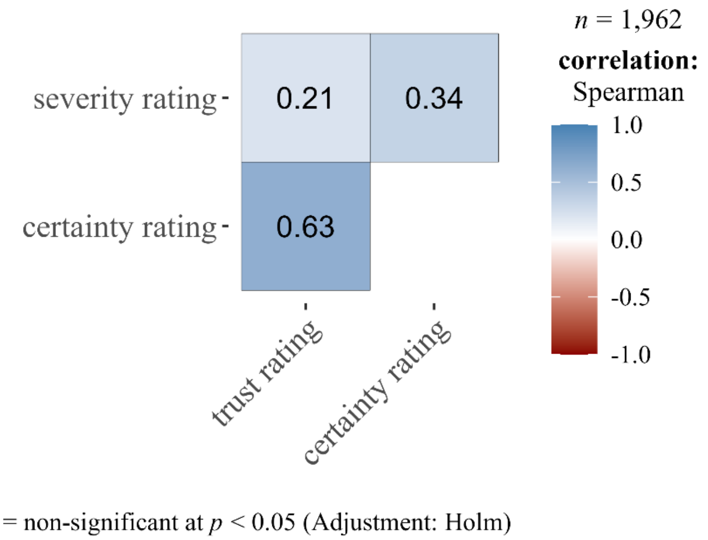

***Figure 67**: Correlation matrix between trust, certainty, and severity ratings given by participants. The more intense is the blue colour, the more positive is the correlation; the more intense is the red colour, the more negative is the correlation. If a correlation coefficient is crossed, it means that the correlation is not significant.*

4.2.6 Analysis of the required time to complete the experiment

Mean required time for each trial along the whole experiment

Figure 68 illustrates that during the execution of the experiment the participants went through a learning process, that led the average completion time per map to sink from the initial 75s to about 30-40s. After trial nine the mean completion time just oscillates between 30 and 40 seconds, while in the first eight trials there is a trend of diminish required time to complete the trials. Another prominent feature visible on the plot, is the exceptionally higher completion time during trial seven compared to the previous and subsequent trials, which also shows a particularly large standard error with respect to the other trials. This abnormal behaviour could be reconducted to the presence of large outliers, possibly due to participants distracting from the tasks.

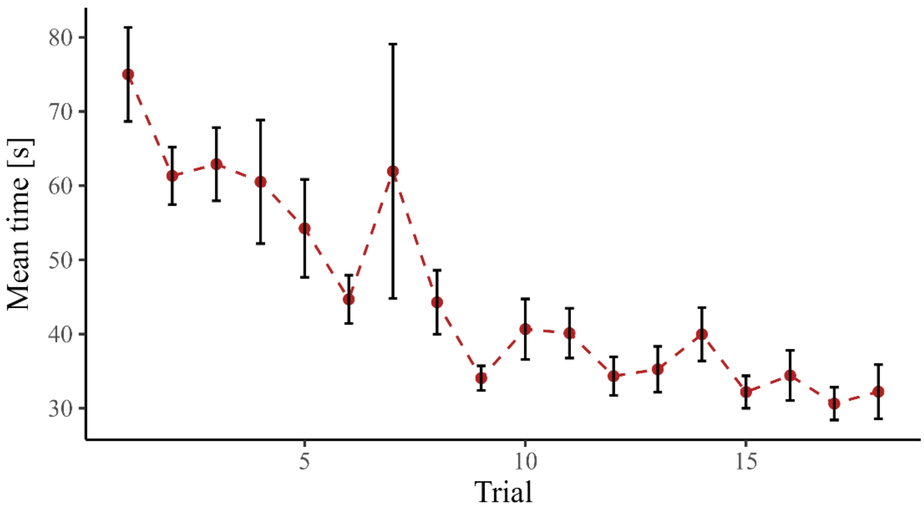

Figure 68: Progression in the course of the experiment of the mean required time for completing each trial (mean ± 1 SE).

In order to remove the outliers from the time data, the suggested procedure from Leys et al. (2013) has been applied. Leys et al. (2013) advise to use the Median Absolute Deviation (MAD) as a more robust way to identify outliers instead of the classical method of three times the SD from the mean, since both means and SDs are strongly affected by the outliers and thus may lead to not correctly detect the outliers. By applying the MAD method on the time data, with a data point considered an outlier with a distance greater than ±2.5MAD from the median, a total of 51 entries (out of 1962) have been detected as outliers, hence removed from further analysis. The times of the outliers ranged from to 120s to 1885s, where the times around 120-180s are often from the last trials, while times higher than 400s from the earlier ones. The resulting completion time progression once the outliers have been removed is displayed in Figure 69. The graph shows that without the outliers the progression is smoother, without the abnormal change in trial seven and smaller SE for the early trials, and the learning process of participants through the experiment is clearer.

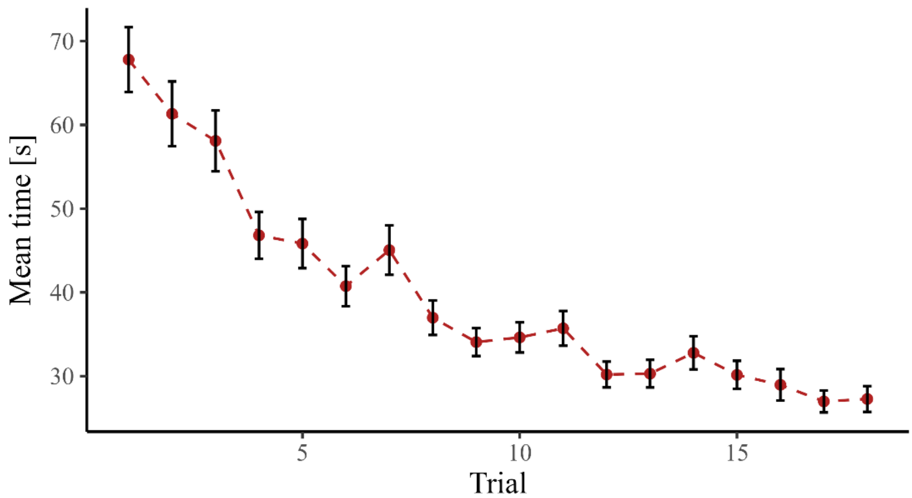

Figure 69: Progression in the course of the experiment of the mean required time to complete each trial once removed the outliers (mean ± 1 SE).

A comparison of the time series for both experimental groups (see Figure 70) shows a very similar progression for both of them, without any major difference arising. In no trial a significant difference in time has been found, according to the Mann-Whitney U tests performed (see Appendix L). Hence, it appears that the emotional stimulus did not lead to investing a different amount of time in analysing the maps and that in both groups a similar learning process happened.

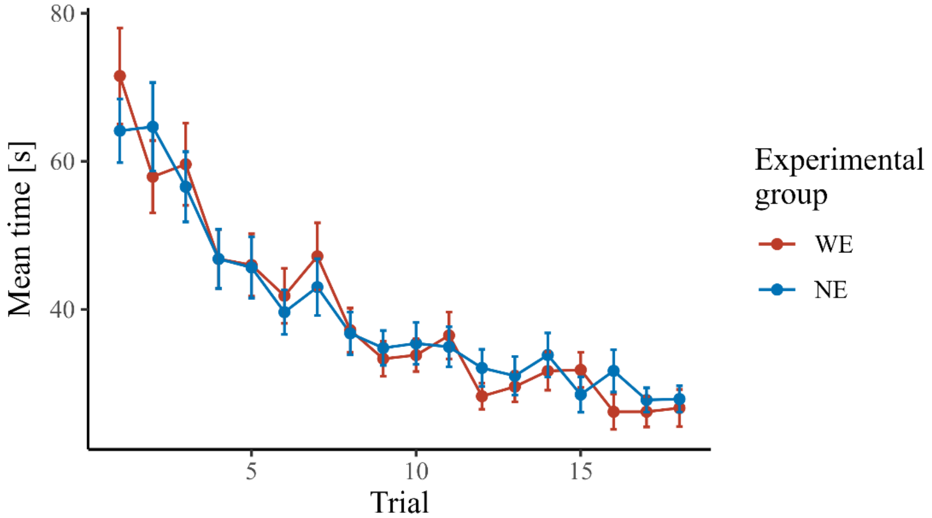

Figure 70*: Progression in the course of the experiment of the mean required time to complete each trial for the two experimental groups (mean ± 1 SE).*

With regard to the different attitudes towards climate change, as Figure 71 illustrates, it can be noted in the progression along the trials that the believers took slightly less time to complete the task on the mid-section of the experiment. This may indicate a somewhat faster learning effect than the climate change sceptics, however the difference appears small in all the trials, with a significant difference only in trial ten, as the outcomes of the Mann-Whitney U tests indicate (see Appendix L).

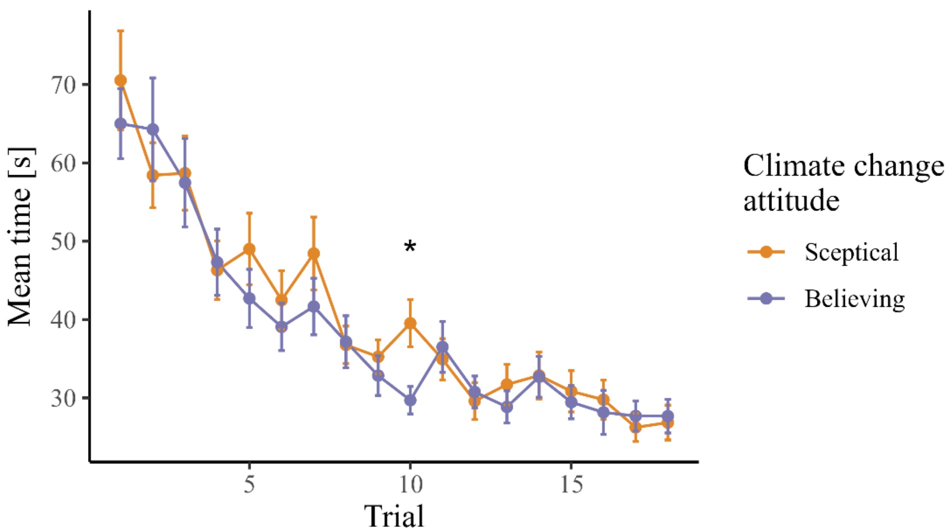

Figure 71*: Progression in the course of the experiment of the mean required time to complete each trial depending on the climate change attitude (mean ± 1 SE).*

Comparison of the mean required time to complete a trial between the two experimental groups

By looking at the mean required time to complete a trial, as visible in Figure 72, no noteworthy difference in the mean completion time between the two experimental groups arises (WE: M = 39.65s, SE = 0.94s; NE: M = 39.81s, SE = 0.87s). The ANOVA applied to the ART corrected data (since also in this case time is not normally distributed, Shapiro Wilk test, $p < 0.001$) further supports this visual impression, given that no significant difference is found ($F(1, 107) = 0.069$, $p = 0.793 > 0.05$). Therefore, the depiction of emotional narratives had no effect on the time participants spent on the maps for completing the tasks.

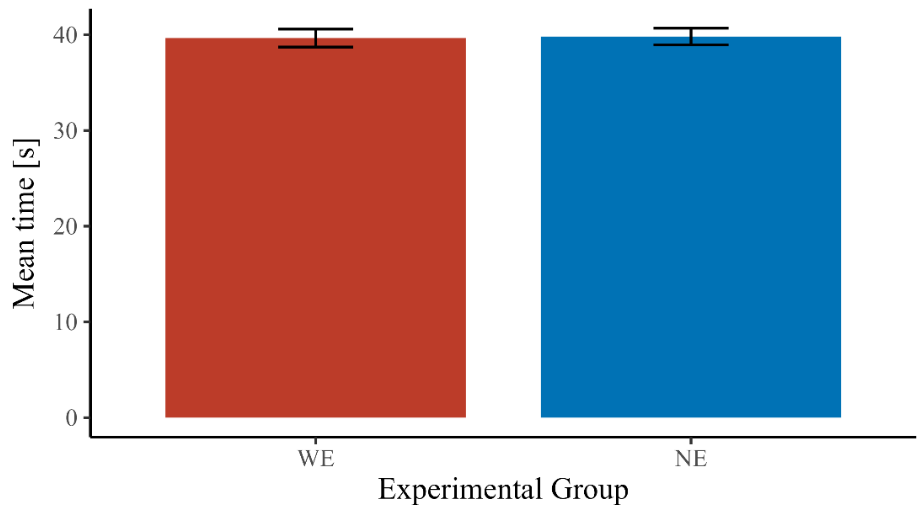

Figure 72*: Mean required time per trial for the two experimental groups (mean ± 1 SE).*

Comparison of the mean required time to complete a trial depending on climate change attitude

A visual inspection of the completion time depending on the climate change attitude, represented in Figure 73, depicts a difference between required time for believers (M = 41.70s, SE = 1.18s) and sceptics (M = 47.34s, SE = 1.69s). Nonetheless, the outcome of the ANOVA on the ART corrected data which has been performed (since also in this case the data is not normally distributed, Shapiro-Wilk test, $p < 0.001$), indicates that there is no significant effect of climate change attitude on the time required by participants ($F(1, 105) = 0.575$, $p = 0.45 > 0.05$), as well as no significant interaction between climate change attitude and experimental group ($F(1, 105) = 0.004$, $p = 0.951 > 0.05$). Hence, even if a small difference is visible, the climate change attitude did not lead to significant effect on the time required to solve the tasks.

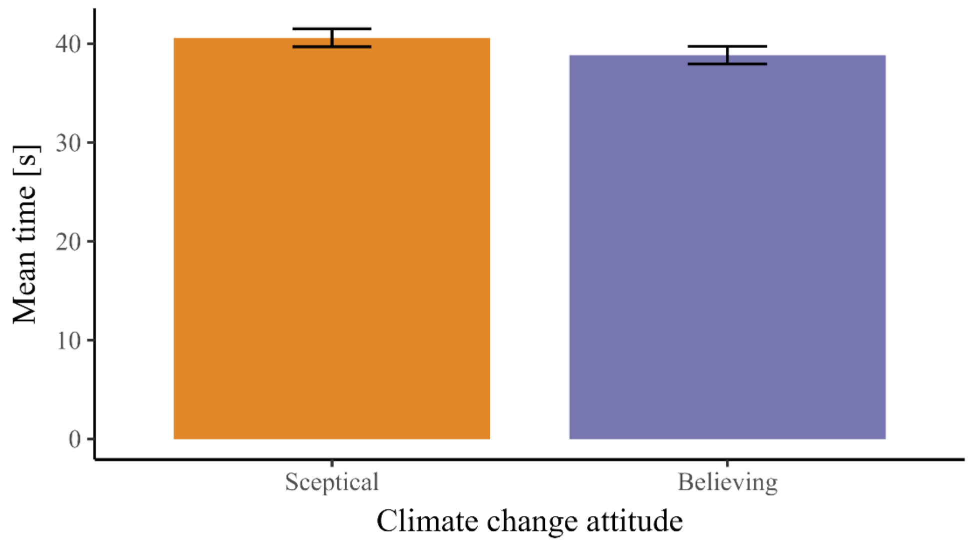

Figure 73*: Mean required time per trial depending on the climate change attitude (mean ± 1 SE).*

Comparison of the mean required time to complete a trial depending on the certainty visualization type

Examining the time required to complete the tasks for the different visualisations of certainty displayed in Figure 74, highlights the shorter amount of time needed to complete the tasks with the maps without representation (none: M = 37.00s, SE =1.06s; dots: M = 40.64s, SE = 1.10s; lines: M = 41.57s, SE = 1.16s). This could indicate that the absence of the additional information, lead to faster reading and decisions. Additionally, it is detectable a small difference in time also between the representations with lines and the one with dots, with the lines requiring slightly more time. Due to the non-normality of distribution of the time data (Shapiro-Wilk test, $p < 0.001$) the ANOVA on the ART corrected data has been applied. The outcome indicates that a significant effect of certainty visualization is present, with also a medium effect size ($F(1, 1798.4) = 11.340$, $p < 0.001$, partial $\eta^2 = 0.012$), while no significant interaction between experimental group and certainty visualization has been found ($F(2,1798.4) = 1.176$, $p = 0.309 > 0.05$). The post-hoc contrasts (with Bonferroni correction), shows a significant difference between the representation with dots and no certainty representation ($t(1798) = -3.528$, $p = 0.001 < 0.05$, $d = 0.17$), as well as between the representation with lines and no certainty representation ($t(1798) = -4.53$, $p < 0.001$, $d = 0.21$).

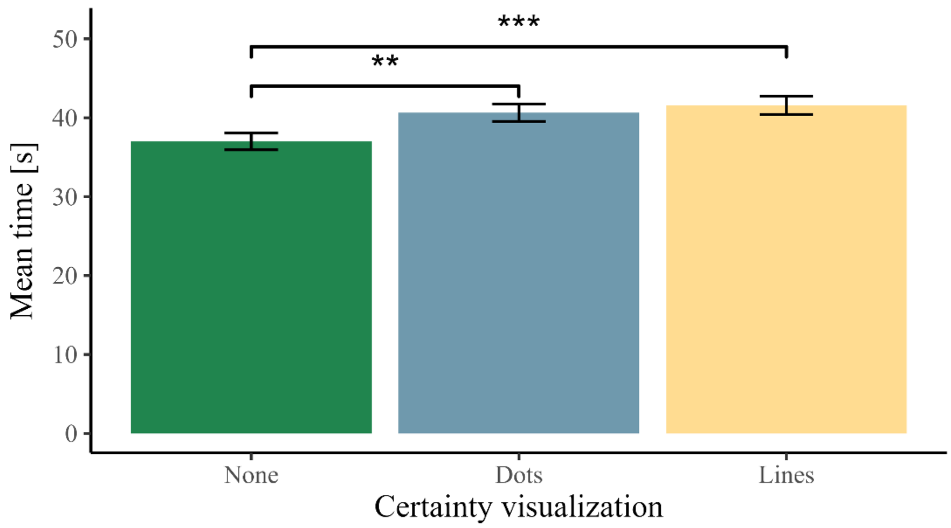

Figure 74: *Mean required time per trial depending on the type of certainty visualization (mean ± 1 SE).*

4.3 Results of the post-tests

4.3.1 Post experiment SAM

After completing the part with the main experiment, participants filled another SAM questionnaire, which results are displayed in Figure 75. From the inspection of the boxplots, it appears that in both groups the emotional state after the completion of the main experiment is similar. In both groups the dimensions of dominance and pleasure have a similar median and range of scores. In contrast, the dimension of arousal shows slightly different medians, with also a narrower spread of the scores in the WE group. Further, only an outlier can be noticed in the arousal dimension for the WE group.

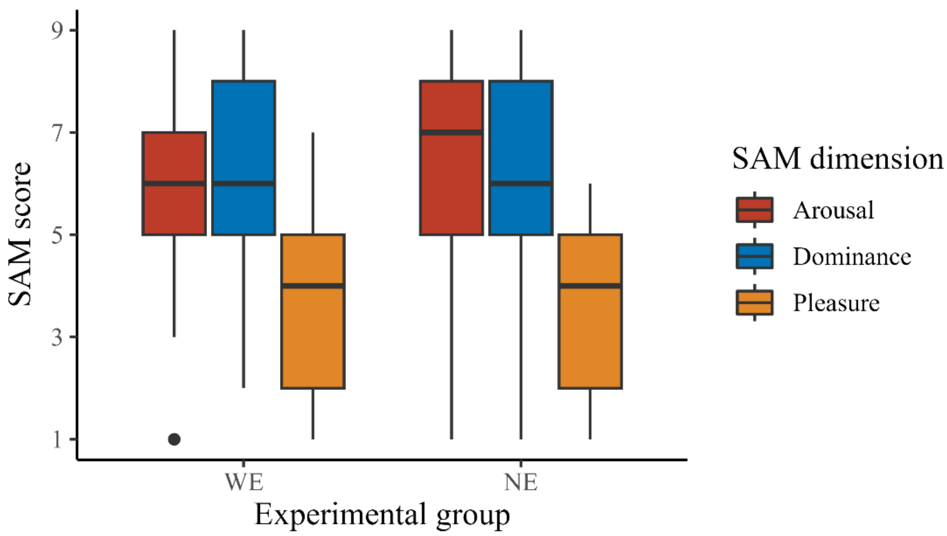

Figure 75: *Boxplots of the distribution of scores in the three dimensions of the post-experiment SAM for the two experimental groups.*

The statistical descriptive terms of the post-experiment SAM are summarised in Table 14. Apart from the arousal, all dimensions have same medians across the NE and WE group. By looking at the means, again all dimensions seem to be very similar between the two groups. To statistically verify if any significant difference is present, the Mann-Whitney U test has been performed on each of the three dimensions between the NE and WE group, since the distribution of the SAM scores is significantly not normally distributed (Shapiro-Wilk test, $p < 0.05$). The results of the Mann-Whitney U tests indicate that no significant difference in the central tendency of the SAM dimensions occurs between the groups (pleasure: $U = 1505$, $p = 0.904 > 0.05$; arousal: $U = 1442$, $p = 0.794 > 0.05$; dominance: $U = 1525$, $p = 0.809 > 0.05$).

***Table 14**: Descriptive statistics of the scores of the post-experiment SAM.*

Group	Dimension	Mean	Median	Standard deviation	IQR	Range
NE	**Pleasure**	3.55	4	1.40	3	1 – 6
	Arousal	6.15	7	2.26	3	1 – 9
	Dominance	6.16	6	1.96	3	1 – 9
WE	**Pleasure**	3.57	4	1.66	3	1 – 7
	Arousal	6.11	6	2.10	2	1 – 9
	Dominance	6.30	6	1.99	3	2 – 9

Following the procedure described in Murdoch et al. (2019), the difference in the pre- and post-experiment SAM scores are calculated per each experimental group and category of climate change attitude, to get an overview of how the emotional state of the different subgroups of participants changed after performing the experiment. The change in means and their standard deviation, as well as the respective effect size are reported in Table 15. All effect sizes are generally small, with a couple of moderate effects. None of the changes are significant, as the results of the Wilcoxon signed rank test indicate. Nonetheless, some general remarks can be drawn: The sceptics tendentially had more negative changes than the believers, i.e., while the pleasure of sceptics diminished or stayed the same, the pleasure of believers increased. The same holds true for the arousal. While in contrast, the dominance in both cases diminished, but the sceptics had a larger decrease. Another point to be noted is that in the WE group the increase of pleasure is less marked for both sceptics and believers, and similarly is more marked the decrease in arousal for sceptics. Finally, the dimension of dominance is the one that shows greater overall change for both experimental conditions.

***Table 15**: Comparison of the difference of scores between pre- and post-experiment SAM in the three SAM dimensions for the two experimental groups. On the left side are listed the overall change and the changes depending on the climate change attitudes, on the left are listed their respective effect sizes.*

Group	**Mean change (*SD*)**			**Effect size *r***		
	Overall	**Sceptics**	**Believers**	**Overall**	**Sceptics**	**Believers**
Pleasure						
WE	0.019 (1.77)	-0.370 (2.15)	0.407 (1.22)	0.14	0.05	0.34
NE	0.218 (1.41)	0 (1.33)	0.444 (1.48)	0.16	0.03	0.31
Arousal						
WE	-0.148 (2.23)	-0.407 (2.27)	0.111 (2.19)	0.12	0.16	0.07
NE	0.018 (1.87)	-0.143 (1.92)	0.185 (1.84)	0	0.16	0.18
Dominance						
WE	-0.241 (2.00)	-0.296 (2.45)	-0.185 (1.47)	0.15	0.16	0.15
NE	-0.364 (1.53)	-0.429 (1.62)	-0.296 (1.46)	0.12	0.12	0.11

As proposed by Murdoch et al. (2019), a further way to describe the changes happening more accurately inside a group of participants, is to see the actual number of participants that had an increase, a decrease or remained stable in their SAM scores, as Table 16 illustrates. From there it can be seen that more participants that believed in climate change had an increase in pleasure compared to the sceptics.

***Table 16**: Type of change (increase, decrease, no change) in the three dimensions of SAM for the two experimental groups depending on the climate change attitude, expressed both as percentage of participants that changed in that direction and as mean (SD) change of the score.*

	Sceptics					**Believers**				
Group	**No change**	**Increase**		**Decrease**		**No change**	**Increase**		**Decrease**	
	%	**%**	***M* (*SD*)**	**%**	***M* (*SD*)**	**%**	**%**	***M* (*SD*)**	**%**	***M* (*SD*)**
Pleasure										
WE	48.2	25.9	1.57 (1.13)	25.9	-3 (2.45)	44.4	40.8	1.55 (0.82)	14.8	-1.5 (0.58)
NE	46.4	25	1.57 (1.13)	28.6	-1.38 (1.06)	37	44.5	1.75 (0.75)	18.5	-1.8 (0.84)
Arousal										
WE	40.8	22.2	2.17 (0.98)	37	-2.4 (2.32)	33.3	25.9	3.14 (1.21)	40.8	-1.73 (1.19)
NE	28.6	28.6	2.12 (1.73)	42.9	-1.75 (0.75)	29.6	44.4	1.67 (0.99)	25.9	-2.14 (1.46)
Dominance										
WE	51.9	18.5	3 (2.12)	29.6	-2.88 (2.03)	37	26	1.5 (1.07)	37	-1.57 (1.13)
NE	46.4	25	1.14 (0.38)	28.6	-2.5 (1.51)	44.4	26	1.29 (0.49)	29.6	-2.12 (1.13)

4.3.2 *Small Emotion Wheel*

The outcome of the SEW from which the participants had to select their most felt emotion and its intensity during the experiment is presented in the heatmap in Figure 76. The two most selected emotions where two opposite emotions: *Indifference* (26) and *Concern/Fear* (26). In contrast, the emotions of *Shame/Guilt* (3) and *Anger* (2) where the less commonly felt. Further, the group of positive emotions of *Excitement*, *Joy* and *Hope* where often chosen (15 each). Concerning the intensity of the emotions, as visible in Figure 76, the intensities 4 and 5 were the most prevalent (32 and 39 selections respectively), while the lowest intensity of 1 only appears twice, always for *Shame/Guilt*. Thus, most participants felt strongly one of the proposed emotions.

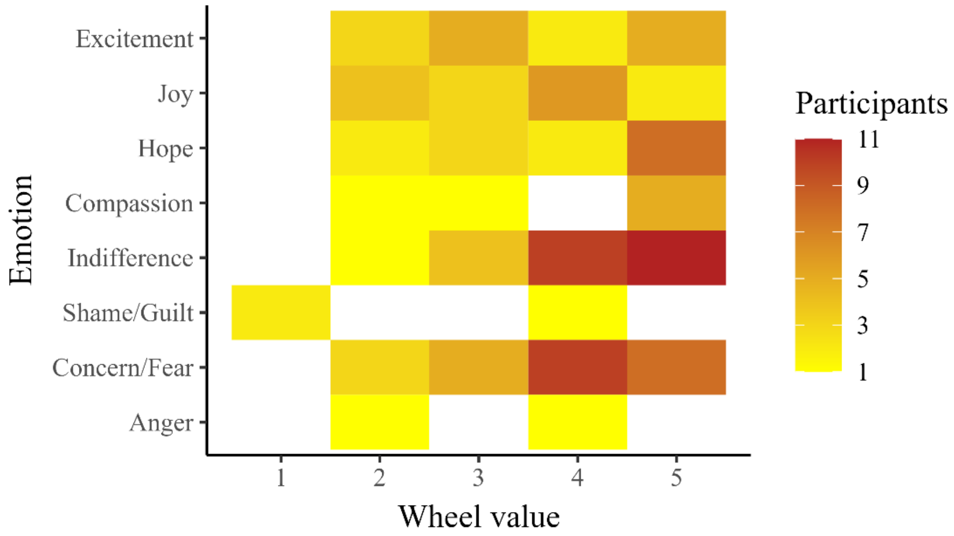

Figure 76*: Heatmap of results of the SEW, displaying the distribution of the type and intensity of emotions felt by the participants. The redder is the colour, the more participants felt that combination of emotion and intensity.*

By looking at the difference in most felt emotions between the two experimental groups (see Figure 77), it can be noted that although *Indifference* is the most selected one in NE (17), in WE it is only the third most selected emotion (9), with *Concern/Fear* (13) and *Hope* (11) being the two most selected. *Hope* is, on the other hand, not felt by the NE group (4). Further, the emotion *Joy* is prevalently felt in the NE group (11 versus 4), while *Compassion* is more selected in WE. However, from a statistical point of view, the differences between the WE and NE group are not significant, as the Fisher' exact test indicates ($p = 0.101 > 0.05$). Thus, while some interesting indications can be retrieved from the different emotions felt in the two groups, those differences are still not large enough to be statistically relevant.

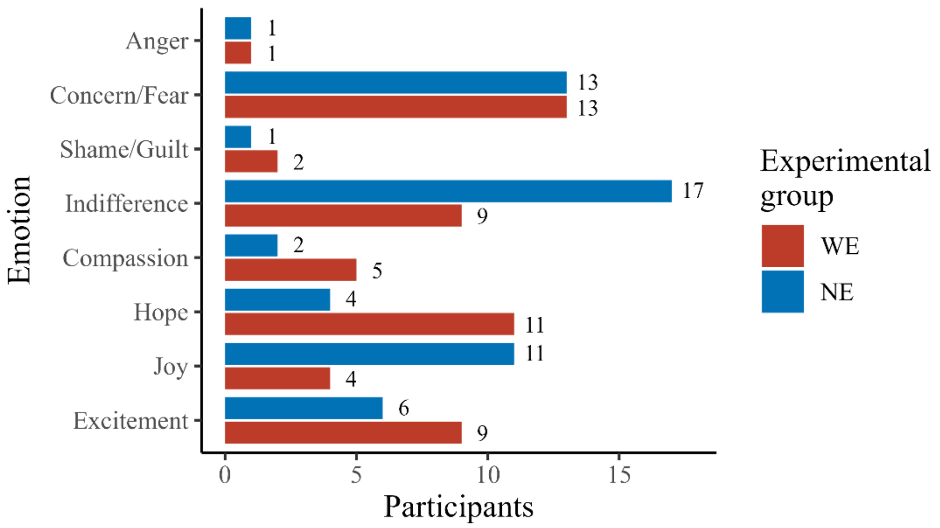

***Figure 77**: Distribution of the emotions felt by participants for the two experimental groups.*

When the focus is on the climate change attitude of the participants (see Figure 78), the outcoming picture is the following. The emotion of *Concern/Fear* is almost only felt by believers (21 vs 5), while conversely *Indifference* is more common for sceptics (16 vs 10), though it is still cited by some believers, as well as for the *Excitement* (10 vs 5). Interestingly, *Compassion* is more felt in the sceptics’ participants (5 vs 2), however this difference may also be due to the small number of participants. The performed Fisher’s exact test shows that when considering the climate change attitude there is a significative difference in the emotions felt by participants (p = 0.021 < 0.05).

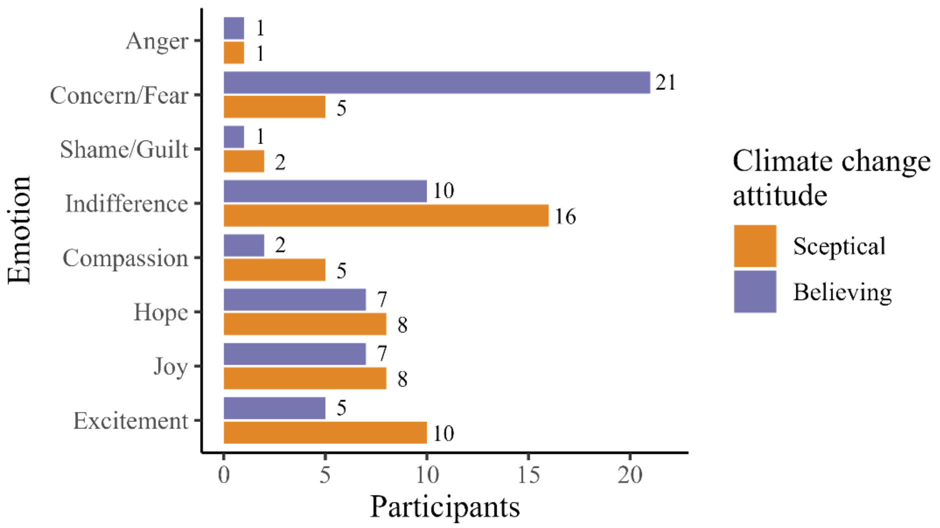

***Figure 78**: Distribution of the emotions felt by participants depending on the climate change attitude.*

4.3.3 Feelings during the experiment

The feelings described by the participants in the open free-text question have been categorized and listed in Table 17. As many as 107 participants out of 109 provided a written commentary about what and how they felt in the experiment. The feeling of worry and concern (27), expressed in regard of themselves or for next generations, is the most prevalent together with the cluster of joy, pleasure, and interest (26), evoked for describing a sense of accomplishment in doing well the task. Compellingly, the former is more cited by believers (19 versus 8), while in contrast the latter is more evoked by sceptics (19 versus 7). Interestingly, some participants stated that because of them being particularly focused on the task they did not feel anything particular, they remained calm and collected, or simply felt as usual (7). Although hope has often been selected in the SEW, only the comments of four believing participants evoked it. A feeling of scepticism and distrust has been frequently evoked in the comments of sceptic participants (12), while conversely for the believing participants there is a major presence of feelings of powerlessness and hopefulness (12). A sizeable number of participants (11) expressed that during the task they felt unsure and confused about the task and the correct interpretation of the maps.

***Table 17**: Broad categories of what participants felt while performing the tasks according to their comments and number of times that are cited. If in their comment a participant cited several categories of feelings, the comment is counted for both categories. (B = believers, S = sceptics).*

Feeling description	Total	NE	WE	B	S
Worried and concerned for possible future effect on self and others	27	15	12	19	8
Pleasure, joy, and interest in doing/understanding the task	26	11	15	7	19
Powerlessness, hopefulness, scared, feel of impending doom	13	4	9	12	1
Feeling sceptic, not trusting the maps, forecast are just forecast	13	7	6	1	12
Indifference to what is depicted, feeling no connection	12	8	4	4	8
Unsure, confusion and /or difficulty in understanding task	11	6	5	3	8
Feeling as usual, calm, focused on task	7	4	3	3	4
Hope that the changes can be mitigated, avoided	4	1	3	4	0
Anger towards people/institutions not believing or acting	3	1	2	3	0

4.3.4 Consideration of the own situation

In Figure 79 it is visualized the level to which participants considered their own situation or the situation of a relative when solving the experiment, both depending on the two experimental group (A) and depending on the climate change attitude (B). From graph A it can be noticed that while the WE group had more participants strongly considering their own situation (9 versus 5), the NE group had in contrast more participants not considering it at all (16 versus 10). Nonetheless, it is also visible that in the mid categories there are more WE participant that only slightly considered their situation (17 versus 7), while NE group more often had a moderate to fair consideration (27 versus 18). Hence, there is a peculiar inversion of tendency between the extremes of the scale and the central options. From graph B (Figure 79), the difference between sceptics and believers is evident, where almost only believers selected *Very much considered*, whereas the opposite is true for the selection of *Not considered at all*. The visual inspection of graph B additionally suggests that the distribution of answers by the believers is skewed towards considering their own situation and the one of their relatives during the experiment, while the answers of sceptics are skewed towards not considering this aspect. The results of the performed Fisher's exact tests do support the fact that sceptics and believers of climate change answered differently in this regard (p = 0.001 < 00.5), while no significant difference is found between the NE and WE group (p = 0.075 > 0.05).

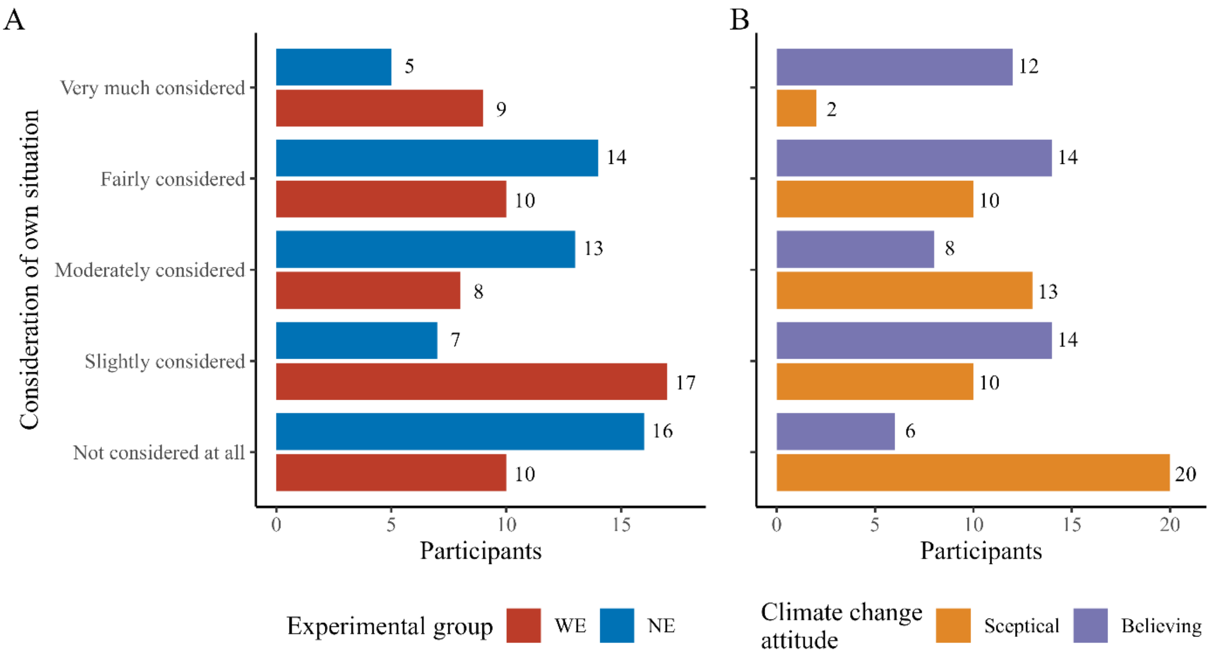

Figure 79*: Distribution of the consideration that participants had of their own situation (or the one of relatives), both for (A) the two experimental groups and (B) the two climate change attitudes.*

4.3.5 Trust evaluation factors

103 of the 109 participants shared their reasons for trusting, respectively not trusting, the data illustrated in the map-based tasks they performed, which are reported in the Table 18. While most issues are neutral in nature, meaning that they could either be used as a positive element to give trust or respectively as negative element that increased distrust, several distinctly positive and negative elements can be identified. For instance, the presence of the certainty scale in the map was a positive factor for trust, while its absence was seen as negative. Noticeably, for some participants, especially the sceptics, no factor could positively influence trust. They stated that they were already starting with low to no trust, and commented either that forecasts are only assumptions or that by default they are not trusting such kind of maps. Furthermore, seven participants stated that they needed to have more information about the regions and the source of the data to be able to trust

them. Conversely, a few participants stated that they were confident the data was coming from researchers and thus were willing to trust it.

Table 18: *Factors that contributed to the trust (respectively distrust) of the participants towards the maps, as retrieved from the given feedback. If in their comment a participant cited several factors, the comment is counted for both factors. Factors are categorized as positive (increased, favourited trust), negative (decreased trust), or neutral (could both cause an increase or a decrease, the comment do not specify it further). (B = believers, S = sceptics).*

Factor	Total	WE	NE	B	S
Positive					
Presence of the certainty scale increase trust	8	5	3	5	3
Trusting the researchers and the data given	4	1	3	4	0
Neutral					
Using the certainty scale as a measure of trust	40	21	19	22	18
Looking at the colours/looking at the severity of change	15	11	4	4	11
Looking at the whole map, considering its complexity and variety	8	3	5	3	5
Looking at the general situation of map and compare it to where is located the chosen area	6	1	5	2	4
Negative					
Absence of certainty scale decrease trust	9	2	7	3	6
By default, not trusting the maps	9	4	5	2	7
Need more data/maps and/or knowledge of the region	7	4	3	3	4
Forecasts are only assumptions and uncertain, not fully trustworthy	6	2	4	2	4

4.3.6 Difficulty of tasks and confidence in the performance

For most of the respondents the difficulty of the experiment has been rated as fair (see Figure 80). This particularly for the NE group, while in the WE group this opinion is less pronounced, with more participants also indicating both an easy and a difficult rating. Nonetheless, the experiment was generally felt as fair or easy by most participants, independently from their assigned experimental group. The Fisher's exact test indicates that no significant difference subsists (p = 0.560 > 0.05).

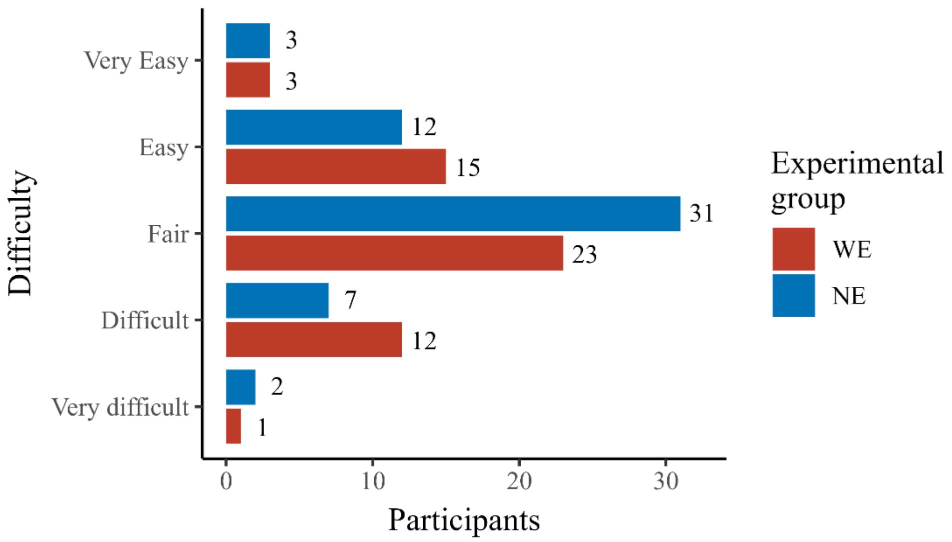

Figure 80*: Distribution of the difficulty rating of the tasks given by participants for the two experimental groups.*

107 participants out of 109 gave their opinion on the level of difficulty, with 38 of them stating that no issues have been encountered. Some mentioned that the experiment required them to focus and read well the instructions and the maps, but it was otherwise fair. In regard to the answers describing the aspects that the participants found to be difficult during the experiment, Table 19 provides an overview of those issues.

Table 19*: Difficulties and issues listed by the participants in their feedback. If in their comment a participant cited several issues, the comment is counted for both issues.*

Difficulty	Total	NE	WE
Understanding the maps and its features in general	17	8	9
Evaluating areas in maps without certainty representation	14	8	6
Choose between areas with similar characteristics or that seem both viable	9	4	5
Deciding how much they trust the map, how to evaluate the trust	8	6	2
Understanding how to read the legend	6	3	3
Distinguish some of the colours	5	3	2
Understand the certainty scale and use it to evaluate the area	4	3	1
Understanding the instructions of the task	4	3	1
Understanding the precipitations maps	4	2	2
Need of more information (number of effects, region history, more data, …)	3	2	1
Understanding the climate data itself	2	0	2
Other (statistics, being objective, confused by dots, too much info)	4	1	3

The majority of the issues are related to the understanding of either the map as a whole or specific parts of the map, such as the legend or the certainty scale. Interestingly, the map of precipitation constituted a difficulty for four persons. Five participants also stated the difficulty to distinguish some colours, however this is not coming from the participants who declared to have colour vision impairments. Another issue cited by several participants relate to how to evaluate the maps without certainty representation. One aspect often mentioned concerns the difficulty in deciding on which factors to base their trust assessment of the maps. Likewise, frequently cited issue are the decisions where more areas with similar characteristics are present, hence in the same severity category or similar severity but with different certainty level.

The confidence of participants in their performance is visualized in Figure 81, where graph A shows the confidence depending on the experimental group and graph B illustrates the answers depending on the climate change attitude. From graph A it is identifiable that the most participants felt fairly to moderately confident (46 and 36 respectively), with only five who felt very confident and three who felt not confident at all. Participants in the WE group did feel slightly less confident compared to the NE group, with less participants selecting moderately confident (14 versus 22) and more indicating to be slightly confident (12 versus 7). What can be retrieved from graph B is that no major difference appears between the two stances towards climate change. Although there are slightly more sceptics indicating to be very to fairly confident, the only participants indicating to have no confidence at all in their performance are the sceptics. The performed Fisher's exact tests do support the fact that in both cases no significative differences are present (experimental group: $p = 0.448 > 0.05$, climate change attitude: $p = 0.371 > 0.05$).

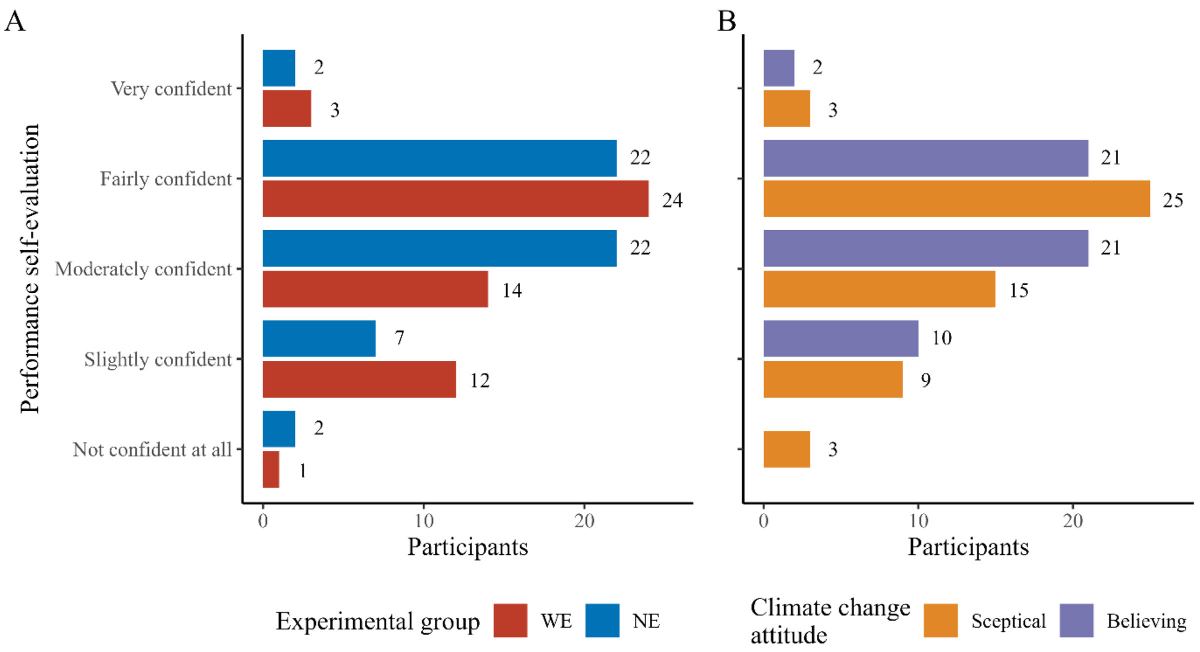

Figure 81: *Distribution of the confidence of participants in their performance, both (A) for the two experimental groups and (B) for the two climate change attitudes.*

4.3.7 *Certainty visualisation preference*

As visualized in Figure 82, the certainty visualization method of the dots has been largely preferred by the participants, with 77 preferences. No major difference arises between the two experimental groups. While there is a slightly higher preference for the dots in the WE group (40 versus 37) and for lines in NE group (8 versus 13), these differences do not change the general picture. As the Fisher's exact test indicates, no significant difference between the visualization preferences is found (p = 0.507 > 0.05).

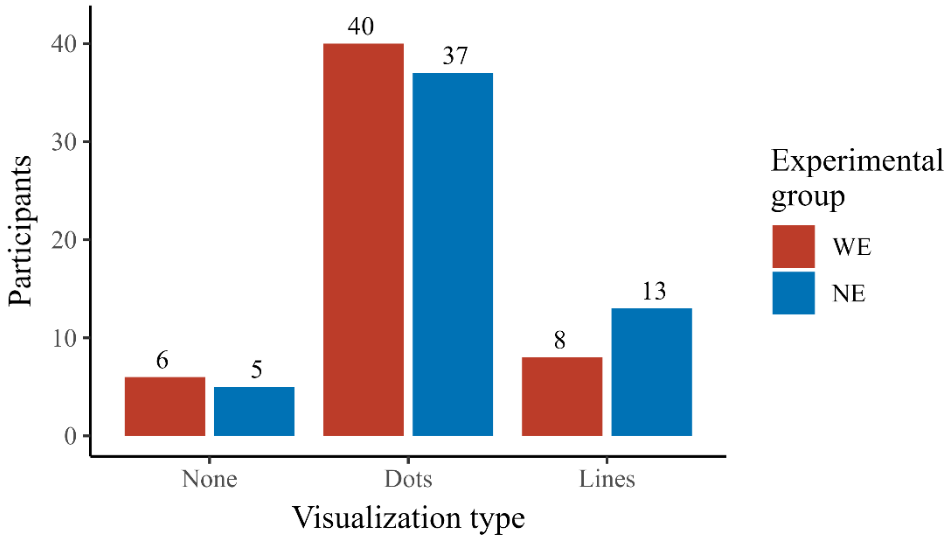

Figure 82: *Distribution of preferences for a certainty visualization type for the two experimental groups.*

107 out of 109 participants elaborated on the reasons why they preferred one type of certainty visualization compared to the others (see Table 20). A couple of them commented that both lines and dots where equally fine, hence they answered the previous question by just randomly picking one. Interestingly, for the visualization with lines the reason of aesthetical pleasure is more often cited than in the dots. For the visualization with dots, the main reasons for preferring it are in the first place the ease to interpret the different certainty levels, while as second reason the fact that this visualization makes the map clearer and less confusing to interpret. Noticeably, the aspect of major clarity of the map is also the most indicated reason by the participants who preferred the visualization without any certainty represented. Finally, an aspect cited by 21 participants for explaining their preference states that the selected visualization eased to read through the layer and better understand the severity of the depicted variable.

***Table 20**: Number of mentions of the reasons for the certainty visualization preference cited by participants. If in their comment a participant cited several reasons, the comment is counted for both reasons.*

Reason	Total	None	Lines	Dots
Aesthetically more pleasing	11	0	6	5
Easier to interpret the different certainty levels	49	2	5	42
Easier to look at the severity value behind, the relationship between severity and certainty	21	3	3	15
Map looking clearer, less confusing. Easier to understand area with/without certainty	44	6	9	29

5 Discussion

In this section of the thesis, the results obtained by the empirical study at the core of this work are critically discussed and interpreted, by relating them with the existing literature on the topics of uncertainty visualization, decision-making under uncertainty, and effects of emotions and climate change attitudes when dealing with climate change and uncertainty. At first, there is a general discussion on the aspects and findings that are overall valid for this study, while the subsequent chapters delve deeper into the specific outcomes related to the individual research questions, dedicating a whole chapter for each one of them. Lastly, the potential limitations and issues encountered in this study are critically discussed.

5.1 General Discussion

Main goal of the study was to deepen the current knowledge on the roles and effects that emotional narratives and individual attitudes have in the context of climate change uncertainty display, hence in the reading and interpretation of climate change forecast maps with the representation of the inherent uncertainty of these forecasts. Guided by the three research questions posed in Chapter 1.3, the effects of these factors have been investigated through means of an online study, which main component was a map-based experiment. As previously mentioned, in this chapter the focus is on the results that apply generally to the whole thesis.

5.1.1 Composition and expertise of the study sample

Similarly to other past studies on uncertainty visualization, the sample pool of this thesis was composed of a heterogeneous group of people (Kinkeldey, Mason, et al., 2014; Miran et al., 2019; Retchless & Brewer, 2016), recruited trough Prolific, that should mostly be composed of individuals non-expert of the domain and with diverse backgrounds. According to Kinkeldey et al. (2017), one of the types of expertise that can have an effect on map-based decisions is the domain and statistical expertise. The low level of domain expertise in the pool was visible in the self-assessments that the participants gave in the pre-test part. Most participants reported a low familiarity for topics such as IPCC, climate change mapping or GIS. Partially different is the case of statistical expertise, with about a third of the participants that reported to feel from fairly to completely familiar with the concepts of statistics and uncertainty. Hence there is a pool of respondents with a certain degree of statistical expertise. Similar distribution of expertise in groups of non-experts of the investigated domain have been found in other studies, for instance in Kinkeldey, Mason, et al. (2014). Nonetheless, the influence of expertise on the performance of the participants was beyond the scope of this thesis, and since the different levels of expertise are equally distributed in both experimental groups, it can be assumed that the results between the group have not been skewed by the level of expertise. Further, most of the participants have an educational background at university or high school level, with also the majority of respondents reporting to use maps on weekly and daily base, again equally distributed between the two experimental groups. Likewise, in other investigations on non-experts, similar levels of education (Retchless & Brewer, 2016) and map use have been found (McKenzie et al., 2016). The sample of participants of this thesis appears thus to be relatable with the ones of similar studies on uncertainty visualization. A further aspect to be considered regarding the composition of the sample that may have had some influence, is that many participants were from South Africa. The discourse of climate change in South Africa is characterized by a large number of people unaware or sceptic of climate change, seen as luxury problem or a threat to economic development, even though among the population of coal regions and in the well-educated urban public a degree of awareness is present (Levi, 2021). Nonetheless, since both believing and sceptical participants from South Africa are equally present in both experimental groups, it can be assumed that this subset of participants did not skew the results of one group compared to the other, although their written comments may show issues and feedback more specific to their circumstances.

5.1.2 Decision-making strategies and heuristics

As described in Raue & Scholl (2018), in front of complex and cognitively demanding decisions, the human mind applies heuristics as a way to simplify the process and obtain solution that most of the time are adequately good. From the written comments left by the participants of this experiment, some inferences on the possibly applied strategies and heuristics can be made. The main type of strategies that can be noticed are:

- Counting the dots and lines inside the boxes. E.g. "*It is easier to see which area has more dots*" (sceptic, NE group), *"[…] checking how many dots would fit in the selected area […]*" (believer, NE group).
- Basing the choice on the degree of severity of the underlying variable. E.g. "*I looked at the colour and the intensity*" (believer, WE group), "*I was looking at the value of the precipitation and temperature to assess the map*" (sceptic, NE group).
- Size of the region, or how far inside (how much contained) was the selectable area. E.g. *"[…] I was making choice based on the size of the area*" (believer, WE group) or *"[…] how far inside a range was my selected area*" (sceptic, NE group).

- Considering the neighbouring regions and make an average based assessment. E.g. "*I was considering their location in wider surroundings to check how the entire region was going to change*" (sceptic, NE group).
- Using their previous belief on the matter. E.g. "*I based my decisions on what I believe to be true about climate change and how it will affect people*" (sceptic, WE group).
- Taking the "best" option. E.g. "*I always chose the best colour for each person*" (believer, WE group).
- Using other derived variables, as perceived accuracy. E.g. "*I cared a lot about how accurate each section was*" (believer, NE group).

The use of some of those strategies for dealing with uncertain information have equally been reported in other studies on decision-making with the support of maps with uncertainty depictions, such as the counting, severity intensity, and the size approaches in Ruginski et al. (2016), or the containment approach or derived variables (choosing the "best", accuracy) in McKenzie et al. (2016). Further some comments let assume the presence of an anchoring heuristic for some participants (Tversky & Kahneman, 1974), where the previously seen maps influence the assessment of the current map, e.g. "*[I] tried to determine whether the changes presented were similar between different maps*" (believer, NE group). An aspect that however shows the difficulty of non-expert to deal with uncertainty and their tendency to conflate it with other variables, as argued by Joslyn & Savelli (2021), is highlighted by comments equate the concentration of dots with the severity of the change. For instance, "*For me the concentration of dots represented the severity of the climate conditions*" (sceptic, WE group) and "*The dots could be a representation or emphasis on the severity of the climate*" (sceptic, WE group).

5.2 Research Question 1: Role of emotions in reading climate change maps with(out) uncertainty

The first research question intended to investigate the effect of emotions in the communication and understanding of climate change maps and the related uncertainty, to infer how they influence the interpretation of the displayed information. In the context of the main experiment of this study, the emotional response of participants was evoked by means of a visual emotional stimulus (in the form of depicted characters) for one of the two experimental groups, while the other group remained unexposed to such kind of emotional stimulation. The hypothesis that has been made for this research question is that the emotional narrative in the presentation of climate change maps with uncertainty visualization leads to longer response time and to an overestimation of both the severity of change and its uncertainty compared to the situation with no emotional narrative.

5.2.1 *Did the emotional stimulus work?*

In order to assess whether emotions had an effect on the decision outcomes and the assessments of participants, it is necessary to first verify whether the presented emotional stimulus had an effect on the emotional state of the participants. For both groups the empathy level of participants was measured (with the TEQ), to control for the similarity of the composition of the groups, to avoid biases due to different capacity to emotionally engage with the experimental setting and respond to emotional stimuli (Martin, 2008). The outcomes of the TEQ indicates that both groups are similar in terms of empathy levels distribution. Further, to investigate the change of the emotional state of participants between the beginning and the end of the experiment, the completion of two SAMs have been integrated in the study. The obtained results indicate that while there are some differences in the emotional state before and after the completion of the task, and thus after being exposed to the emotional stimulus, those differences are not large enough to be statistically significant. Hence, the possible explanations for this result could be that either the emotional stimulus was not emotionally challenging enough to drive a detectable significant change, or that the emotional stimulus did have an influence on the emotional state of participants, but the SAM was not the most appropriate method to assess it. For instance, Lanini-Maggi et al. (2024) reported that while the SAM measure indicated an emotional response from the participants, the facial recognition software detected no emotion, which lead the researchers to speculate that the evoked emotions were not sufficiently intense to be detected by the software. Moreover, Korporaal et al. (2020) used a self-report questionnaire to assess whether the participants in the time pressure condition felt stressed, which indicated no significant stress increase between the pre- and post-test, however the participants indicated to have felt stress in the direct question. Hence also in the experiment of this thesis it may have happened that either the emotional stimulus or the adopted measurement technique was not effective. A possible explanation that could support the point that the emotional stimulus was not sufficiently emotionally engaging is that climate change is a polarized and discussed topic, that participants are already "pre-treated" by factors such as the media coverage or political influences, hence they may be less receptive to such stimuli, as argued Battocletti et al. (2023) when discussing the results of their climate change map reading experiment. There, Battocletti et al. (2023) found that colour, which is an element often associated with emotional responses, appeared to not have influenced the choices of participants. In contrast, the findings of Shanahan et al. (2019) for what concerns the effect of narratives in the emotional response of communication of risk and natural hazards showed that participants have emotional responses. As illustrated by Shanahan et al. (2019), while the simple introduction of the characters and the framing of the problem was not eliciting particular emotions, once the potential consequences that the characters may have to endure in the forecasted situation were presented, the affective response of participants significantly increased. In the experiment of this thesis, although after the introduction of the characters also their consequences have been presented, such increase of the affective response is not as clearly detectable.

5.2.2 Effect of emotions on the area choice

The outcomes of the main experiment for what concerns the choices of participants for the least (respectively most) affected area in the map, calculated with the *AS method*, indicate that no significant difference in the choices is present. When the choices are looked with respect to the kind of requested area (least versus most affected), it appears that only for the selection of the most affected area a small difference is present. Nonetheless, the difference between the groups is not large enough to be significant. The outcomes of the area choice according to the *NS method* indicate that the participants in the WE group had the tendency to select more often the ATs with lower severity, even though only for AT7 this difference is significant. The tentative indication that can be drawn from these results is that when selecting the most affected area, participants in the WE group were considering areas with lower certainty as potentially more severely affected, since the effect of low certainty can be both a decrease as well as an increase of the actual severity. Nonetheless, as discussed in Chapter 5.2.1, the absence of significant differences may be due to the ineffectiveness of the emotional stimulus.

5.2.3 Effect of emotions on the severity and certainty assessment

With regard to the effect of the emotional narrative on the assessments of severity, the results show that the severity was assessed higher for the NE group, which is consistent with their important selection of areas with higher severity detected previously in Chapter 5.2.2. A further noteworthy aspect is that there is an interaction between the severity rating and the kind of requested area. While in the area choice for the least affected area both groups were similar, here the WE group assessed as slightly more severe the changes of the area they selected. On the contrary, the NE group assessed as more severe the changes in the most affected area. Concerning the certainty, both groups gave higher certainty assessments to the areas they selected for the most affected area. This result is interesting since it appears that participants were more inclined to accept less certain areas for least affected but for the most affected, they were less willing to select uncertain areas. This may be due to a non-linear perception of the relation between the uncertainty and the visual variable (Sanyal et al., 2009). Another possibility may be that for the choice of the most affected area, the certainty level caused a loss aversion effect (Kahneman & Tversky, 1979) in the sense that when choosing an area of high change, the effect of low certainty may lead to greater sense of loss compared to high certainty.

5.2.4 Effect of emotions on the trust rating

The mean trust rating of the maps given by participants in both groups is equal, hence tit appears to be no effect of emotions on the level of trust. The written feedback given by participants also does not differ strongly between the two groups. It can be noticed that without the emotional stimulus the participants more often cited the aspect of looking at the general picture and the specific location of their chosen region compared to the distribution of the climatic variable and certainty to assess the trust, while in the situation with emotional stimulus there are more participants stating to have looked at the severity to give trust to the map. This may suggest that in the presence of emotional distress the level of severity acquired a higher relevance in the trust evaluation. The finding concerning effect of emotion on the trust rating is unexpected, since emotions, especially negative ones, have an effect on trust (Dunn & Schweitzer, 2005; Myers & Tingley, 2016). Since it was expected that the emotional stimulus could evoke potentially negative emotions as concern, anger and guilt, an effect on the trust rating was anticipated. The absence of such effect could be due to the fact that the emotional stimulus was not sufficiently evoking, as discussed in Chapter 5.2.1. Another possibility is that since climate change already evokes various emotions (Marlon et al., 2019; N. Smith & Leiserowitz, 2014; Wang et al., 2018), this aspect caused both groups to be affected by emotions due to climate change as general topic, and not from the emotional stimulus, in their process of assessing trust.

5.2.5 Effect of emotions on the required time

Looking at the required time for completing the task, it does not appear that the emotional stimulus had an effect on the time invested in the task. This result is unexpected, since the hypothesis was that in order to find the most suitable area for the characters, the participants would have invested more time to be sure of their decision. It was thought that additional stress from having to think on the consequences of the characters while answering would have led to longer response time, since stress do increase the cognitive burden of decisions under uncertainty (Hengen & Alpers, 2021). This could be reconducted again to the fact that the emotional stimulus was not sufficiently stimulating to create a strong emotional response.

5.2.6 *Effect on the post-test measures: SEW, feelings, consideration of own situation, difficulty, and confidence*

The answers given on the SEW reveal that the emotions felt by participants in the two experimental groups differ (even though not significantly) in the extent that in the group without emotional narrative the feeling on indifference was more marked, with also an unexpected peak of joy, while the group with emotion saw a larger presence of hope and compassion. This indicates that even though the results of the SAM were not significant in detecting a difference in the two groups, the expression in discrete emotions shed more lights on the effect of the emotional stimulus on the elicited emotions. Nevertheless, it does not seem that the emotional stimulus was enough to gather a stronger emotional response. In the feedback given by participants, however, is to be noted that for some of them the presented characters did have an effect and they were concerned about their situation while answering the questions. Whereas, other participants, in both groups, said that the experiment simply felt like a task or that they were not moved by the experiment. This suggest that the experimental setting may have been not suitable to evoke emotional feelings as well as identification with the characters and the depicted forecasts. An additional aspect that supports the weak emotional effect, is given by the fact that both groups had similar consideration of their own situation and the ones of the relatives, with just small, non-significant, differences. The presence of the emotional stimulus may have made the experiment slightly more difficult by introducing the element of the character and increasing the cognitive load, according to the self-assessed difficulty rating, although the difference of the rating between emotional and control group is not significant. Moreover, the confidence on the performance is not affected by the experimental group. Overall, the measures of the post-test phase seem to support the aspect discussed in Chapter 5.2.1 that the emotional stimulus did not have a relevant impact on the participants.

5.3 Research Question 2: Role of the climate change attitude in reading climate change maps with(out) uncertainty

The aim of the second research question was to increase the understanding on the influence that the personal attitude of an individual in regard to climate change have on how climate change related information and their uncertainty is understood, and how the trust they have on the showed information is affected. The working hypothesis for this research question was that the sceptical participants tend to underestimate and trust less the climate changes depicted in the maps, in contrast to believing participants, but then when uncertainty is visualized, this effect is mitigated. In order to have a balanced sample of both attitudes towards climate change, participants were recruited on Prolific with the help of the *Climate Change Belief* screener. Their stance was further verified in the study by means of a short questionnaire, so to be sure about the presence of both participants having a sceptical and a believing stance towards climate change. The outcome of this questionnaire strongly supported the fact that two groups with distinct attitudes towards climate change were present, hence the effect of this attitude on the participants choices and assessments can be investigated.

5.3.1 Effect of climate change attitude on the area choice

What could be gathered from the outcomes of the main experiment in regard to the area choices between the two stances towards climate change is that, according to the *AS method*, no difference arises between them. By taking a look at the answer with the *NS method* however some significant differences in the selection of individual ATs are present. Namely, believing participants selected more often areas with higher certainty, while the sceptics show a tendency for preferring lower certainty. These results suggest that believers where less willing to take risky zones for their assessment. A reason could be that, since for believers climate change is happening, they are less prone to hope that uncertainty might turn a low change area in a better zone, thus that areas with low change and high uncertainty can result in lesser change, hence their preference for zones with higher certainty for that selection. A mirrored reasoning could explain the choice for the most affected area. This effect may be related to the loss aversion theory from Kahneman & Tversky (1979), which states that losses are weighted more that gain and thus individuals try to avoid taking risk of more losses. It can be hypothesized that for climate change believers, this weighting of the losses of choosing a “wrong” area (e.g. that will have more severe change that expected) is increased by their attitude towards the topic of climate change.

5.3.2 Effect of climate change attitude on the severity and certainty assessment

Although both sceptics and believers selected areas with similar severity but different certainty, the severity assessment they gave is significantly different. Sceptics rated as less severe the changes in their areas compared to believers. This may be linked to the fact that they selected more uncertain areas and undervalued the degree of severity because of uncertainty. The comparison between reference value and participant assessment further highlights that while participants of both attitudes overestimated severity, the believers made it by two folds in contrast to the sceptics. This different approach to assess the severity of the change, can be reconducted to influences of the availability heuristics, which states that events that more easily come to mind lead to assess those events as more likely or frequent (Ehrlinger et al., 2016; Tversky & Kahneman, 1974). In that sense, for believing participants the consequences of severe change may be easier to think and imagine, which may lead to increase the perception of severity of the depicted change. Differently from the severity case, for the certainty rating no significant difference arise, even though believers gave slightly higher certainty rating. Only in the WE group the believers were closer to the reference value while the other groups overrated certainty. From this outcome it can be deduced that the reading of certainty was not influenced by the attitude of participants, even though according to the availability heuristic (Tversky & Kahneman, 1974) the believing participants should have felt more certain and likely those changes. Hence, the availability heuristic may not be the best explanation for this occurrence.

5.3.3 Effect of climate change attitude on the trust rating

The climate change attitude had a significant medium effect on the trust ratings of participants, with maps where certainty is represented obtaining higher trust. This result is in line with the working hypothesis of this thesis and with the findings of other studies, for instance Joslyn & Leclerc (2016). By looking at the comments left by participants on their reasons for trusting or less the maps, is evident that certainty played a major role, with mostly sceptics citing the absence of the scale as reason to distrust, while believers put the emphasis on its presence for trusting more the map. Further, it has to be noticed that sceptical participants have the tendency to assess trust based on considering the map as a whole, hence looking how much certainty is present overall and how much change is depicted. A further aspect, that is however in contrast with the working hypothesis, is that the displayed certainty did not influence the average trust rating by decreasing the difference between the two climate change attitudes, but instead increased the difference in trust. Namely, while the participants of both attitudes rated similarly the visualizations without certainty and there is an increase in trust for both once the certainty of the forecast is visualized, the increase showed by the sceptics is significantly lower compared to believers. Although the increase of trust with the depiction of certainty is in line with Joslyn & Leclerc (2016), the fact that the divergence in trust between sceptics and believers increased is a contrasting finding. Joslyn & Leclerc (2016) retrieved that the both the presentation and the absence of information about uncertainty lead to a high and stable trust rating for the believers, while in contrast the sceptics showed higher trust once the uncertainty was revealed, thus diminish the distance between the two groups.

5.3.4 Effect of climate change attitude on the required time

Even though in some trials the sceptical participants took in average more time to finish the tasks, the average completion time per trial over the whole experiment is not significantly different between the two stances, although slightly smaller for the believers. Hence the attitude had no effect on the time required. No specific working hypothesis has been made for the effect of climate attitude on time, but this result suggests that climate change attitude is not a factor influencing the decision-making under this aspect, as on the contrary does for the selection of suitable areas.

5.3.5 Effect on the post-test measures: SEW, feelings, consideration of own situation, and confidence

The emotions retrieved through the SEW clearly show that sceptics and believers felt different discrete emotions during the task. A prevalence of indifference and, unexpectedly, excitement for sceptics, and a large majority of concern/fear by believers. The important presence of feelings of concern and fear has been often found in climate defence supporting segments of the population (N. Smith & Leiserowitz, 2014). The indifference and unconcern towards climate related topics were also widely associated with individuals with sceptical attitude (A. Fischer et al., 2012). An analysis of the comments reveals that especially the sceptics felt pleasure, interest, and joy in completing the task. For instance, a participant reported that he "*[…] felt excited and aroused because was the first time I had solved such an experiment*", while another expressed that "*it felt great to read the map and give my take on how I see it*". In contrast, images of doom, fear and concern for the future were more often cited by believers. E.g. "*I feel concerned about the future, especially for very young and old people*" or "*The future feels bleak and I feel helpless*". As further evidence of the different stances of the two segments of the population, the believers thought of their own situation and family more than sceptics. No indication of significant difference in the evaluation of the performance confidence has been detected. Nonetheless, as mentioned in Kinkeldey et al. (2017), the confidence of participants on their performance is usually not impacted by the representation of uncertainty.

5.4 Research Question 3: Role of the type of certainty visualization in reading climate change maps

With the intention of gaining more insights into which kind of visualization of uncertainty provides a more accurate understanding of both the depicted variable and the associated uncertainty the third question was posed. The related hypothesis was that the different types of representations would lead the users to have different levels of trust and different interpretations of both the severity and the uncertainty degree of the depicted change. As explained in Chapter 3.6.1, in the context of this thesis the concept that has been visualized in the map was the certainty, hence indicating more certain and less certain area instead of more and less uncertain. In this study certainty was represented to the participants as a pattern of dots, as a pattern of lines or not represented.

5.4.1 Effect of certainty visualization on the area choice

The outcomes of the study do indicate that for all the three types of visualization, the choices of participants were not significantly different, meaning that no difference was detected between maps with and without certainty and between the two patterns for depicting certainty. Hence, in this work, in contrast to other studies (Korporaal et al., 2020; Kübler et al., 2020), the visualization of certainty does not appear to have significantly influenced the choices of participants about which option to select to answer the posed question.

5.4.2 Effect of certainty visualization on the severity and certainty assessment

No significant difference in the given severity rating has been found, hence the retrieval of the severity value was not influenced by the type of visualization adopted. Similarly, Retchless & Brewer (2016) did not find a significant difference in the retrieval of severity between different visualization methods. In contrast, for the certainty assessments there is a significant result. The visualization without certainty representation led to lower certainty assessment than the two visualization types where uncertainty is depicted. Namely, without the presence of a certainty scale, the participants rated the certainty as just slightly below the medium value of 4, hence even judging the certainty in those maps less than the neutral stance. This appears to indicate that without certainty rating they were not willing to assess the forecast as certain. A possible explanation could reside in the fact that, since they were exposed to both maps with and without certainty, this may have increased a negative reaction to the ones without. Thus, a between-subject study design between maps with and without depiction of certainty may provide further indications on the matter. For instance, Retchless & Brewer (2016) noted different performances in terms of certainty value retrieval between the investigated methods, where the version without visualization of certainty lead to large and consistently different rating in contrast to maps where certainty was provided.

An unexpected finding is that in the map with dots there has been a larger tendency to overestimate the certainty of the selected area. This may be due to the feeling that the pattern of dots was denser, as some comments hinted at, while the lines were perceived as sparser, possibly causing this contrasting rating. Therefore, the same level of certainty represented with dots, perceived as denser, lead to interpret the area as having higher certainty, compared to an area with the same level of certainty but depicted with the pattern of lines.

5.4.3 Effect of certainty visualization on the trust rating

As hypothesized, the trust rating for the maps without certainty was significantly lower than for the others. As various researchers stated, even if there is a belief in the scientific community that communicating uncertainties may decrease the value of findings, the general public does instead appreciate this information, and when compared with both versions, the one with certainty appears as more trustworthy (Bhatt et al., 2021; Gustafson & Rice, 2019; Joslyn & Leclerc, 2016; van der Bles et al., 2019). This stance is clearly delineated in a comment of a participant (believer, WE group) that stated *"[…] being honest about how certain you are makes me believe the results*". Other participants shared a similar view, indicating that "*If there was no certainty rating available, it meant the forecast was not accurate enough to be trusted*" (sceptic, WE group) or that "*if they can show how certain the changes are I'm more likely to think is trustworthy […]*" (believer, WE group). Further, it is noteworthy that apparently the participants associate the concept of trust with the certainty, with the average trust rating of a map being highly correlated with the average certainty rating of the region they selected. This is similar to what found by Padilla, Powell, et al. (2021), where low trust ratings were associated with low levels of forecast confidence and vice versa for the high trust ratings. Furthermore, they found that the given statements of certainty were more impactful on the trust of participants than the actual range of variability (Padilla, Powell, et al., 2021). On this matter, a participant shared that "*It was a bit difficult to differentiate between the certainty of the predictions and the trustworthiness of the predictions*" (believer, NE group).

5.4.4 Effect of uncertainty visualization on the required time

The visualization without certainty depiction required in average less time for completing the task, which indicates that the maps with visualization of certainty required more cognitive load to inspect them, to understand them, and proceed with the next task. In the literature the findings on the effect of uncertainty visualization on decision speed are mixed, with studies reporting either no effects or indicating changes in the time required (Kinkeldey et al., 2017; Korporaal et al., 2020). The result of this thesis further supports the findings of the investigation of Korporaal et al. (2020), where the visualization of uncertainty led to an increase of the required time for performing the task compared to the case without this information. The authors argued that the reason for this longer time may reside in the texture-based approach to visualize uncertainty, however the literature to support this hypothesis was still scarce at the time (Korporaal et al., 2020). The main reason is that, since most studies focused on comparing the effects of different visualization methods and not on investigating the difference of effects between no uncertainty visualization and uncertainty visualized with a single visual variable (Korporaal et al., 2020). Hence the study at hand in this thesis provides further insights into this research gap, by supporting the influence of texture-based representation of certainty in the time required for decision-making.

5.4.5 *Effect on the post-test measures: preference*

The certainty visualization type clearly preferred by participants was the representation with dots, which was described as the clearest, which allowed for better legibility of the underlying variable. A point that was often cited, concerns the density of the pattern, that was seen as denser and easier to count in the boxes indicating the areas. As one participant (sceptic, NE group) expressed, "*It was easier to see how populated a square was with dots than it was with diagonal lines*". This result further supports the preference for this kind of representation already reported by Retchless & Brewer (2016) and Korporaal et al. (2020). Nonetheless, as remarked by Kinkeldey, MacEachren, et al. (2014) and Cheong et al. (2016), the preference for one visualization did not lead to significantly different or better performance, as also seen in this study. Both lines and dots performed generally the same across all the factors and measured variables, except for the difference of certainty rating given by participant with respect to the reference value. A possible reason for the strong preference showed for the representation with dots could be that dots are already familiar to many audiences, since a similar approach has been widely used in climate assessment reports, as recalled by Retchless & Brewer (2016).

5.5 Limitations of the study

As it is often the case for controlled experiments and online studies, also this work comes with a number of limitations, that are further discussed in this chapter. A first limitation of this study concerns the fact that in order to have a pool composed of both participants with believing attitude towards climate change and sceptical ones, it has been necessary to opt for an online study with participants sampled from a recruiting platform. As Eerola et al. (2021) and Grootswagers (2020) remarked, while offering a good alternative to in-person setting with regard to costs and potential to obtain a heterogeneous sample, there are also some drawbacks to consider. Some issues that may arise due to the online setting are for instance that participants can be dishonest or distract themselves during the experiment and the fact that the researcher has no control of the experimental environment (e.g. lighting, used device) (Grootswagers, 2020; Palan & Schitter, 2018; Peer et al., 2022). The occurrence of such problems could not be excluded in the context of this thesis. For instance, it has been noted that in few occasions some participants took over 300 seconds to answer a single trial. While this may be due to honest attempts to understand the map in a moment of confusion, it may also be indicative of participants distracting themselves from the task. Another important aspect is the impossibility to clarify doubts of participants about the given instructions. From the comments left by the respondents, is noticeable that some participants cited understanding the instructions as major difficulty, however, offering support was not possible. A further aspect with online studies, regards the loading time of the visual stimuli or of the experiment as a whole. For instance, Kinkeldey, Mason, et al. (2014) reported that even though they compressed the map images, there were still varying loading times of the maps depending on the Internet connection. It cannot be excluded that also for the study presented in this thesis issues bound to loading time of the different maps were present, since this problem is not possible to be verified. Nonetheless, no participant has reported to have encountered such kind of problems, while the test run of the study made with members of the author entourage likewise showed that no particular instance of loading issues was encountered.

A further methodological limitation, due to the online nature of the study, was that the measurement of the emotional response of the participants was restricted to self-report methods. Even though the application of software for the recognition of facial expressions is possible also in online studies, as was the case for Lanini-Maggi et al. (2024), in this study it was not employed. As Harley (2015) declared, each of the different methods developed to measure emotions have its advantages that may be more useful in a condition compared to the other. Had this experiment been conducted in the context of a controlled laboratory environment, then other tools for the measurement of the emotional response of participants could have been implemented together with self-reports, e.g. the eye-tracking or the EDA, and their results compared, as for instance Lendenmann (2023) did.

On the methodological side of the analysis of the answers given in the experiment, an aspect that can constitute a limitation consists in the scoring method, similarly to what already acknowledged in the works of Korporaal (2017) and Kübler (2016). As for these two other studies, the collected data for the area choices are of categorical nature and not easy to statistically analyse, since they needed to be transformed in numerical values with the two methods presented in Chapter 4.2.1. As reported by Kübler (2016) however, these methods must be used together in order to have a correct picture of the whole situation, because, for instance, the *AS method* only gives an overview on the average choices, that can lead to misrepresentation of the real choices of participants, while the NS method can give insights on the frequency with which the single options were selected.

A problem often cited as a limitation in similar studies on uncertainty visualization and decision made on the base of those depictions, regards the aspect of the similarity to real world situations and decision-making processes of the proposed experimental setting and decision situation (Padilla, Powell, et al., 2021; Ruginski et al., 2016; Schneider et al., 2022). Concretely on the case of this work, it could be questioned if it was realistic to ask to a general audience to think about climate change consequences expected for the year 2060. Nevertheless, the nature of the climate change requires to analyse its impact with these large timeframes, as the policymakers must do with the IPCC reports. Other aspects about the similarity with real world setting are related with the presented data and uncertainty. While the climatic data was not artificially created, the maps were nonetheless presented without the context of what region they depicted, while the uncertainty layer has been artificially created. However, working with partially artificial data in order to obtain a pool of suitable maps for the experiment is common also in other studies on uncertainty visualization (Kübler et al., 2020; Schneider et al., 2022).

Another limitation of this study concerns the factors that were beyond the scope of the thesis, but that may still have had an impact on the performance of the participants. For instance, the expertise has not been investigated. Moreover, the influence of the depicted climatic variables has also not been inquired. However, as some comments left by the participants let assume, not all the climatic variables have been perceived as having the same easiness of interpretation. For instance, the precipitation maps have been pointed out by some participants as being more difficult to read and understand than the two other climatic variables.

Finally, an additional aspect that might constitute a limitation, is that the study design did not allow to analyse possible variations of some elements for the within conditions, as was the case for Bracher (2022); for instance, the aspects of the performance confidence and the felt difficulty of the task. Those two elements were only evaluated in the post-test phase, allowing a comparison only for the between-subject conditions. So, it is not possible to retrieve whether a specific visualization was felt as more difficult than the other, if not for the comments. Similarly, it was not possible to assess which type of certainty visualization led to more (or less) confidence in the own performance. Nonetheless, since the experiment already required the participants to answer to four questions for each of the 18 maps, it has been deemed that adding additional questions would have resulted in an excessively long experiment.

6 Conclusions and Outlook

6.1 Conclusions

Uncertainty is a complex and multi-faceted concept, that while it poses challenges in its definition and communication, does nonetheless appear almost in any kind of data (Kamal et al., 2021; Li et al., 2013). In the field of uncertainty visualization there have been calls for further research in the understanding of how decision-making is influenced when uncertainty is visualized and which factors play a role in those situations (Kause et al., 2021; Kinkeldey et al., 2017). Despite progresses in climate research, due to the complexity of the phenomenon, climate change still possesses uncertainties about the magnitude of its effects and of possible mitigation measures (IPCC, 2023; Moser, 2010). Given the urgency of the threat posed by the consequences of climate change for the environment and the human society, the communication of findings and possible solution to this issue is vital (IPCC, 2023; Moser, 2010; N. Smith & Leiserowitz, 2014). However, the communication of the uncertainties tied to climate change poses challenges, due to both the difficulty of the concept of uncertainty to be understood, communicated, and visualized, as well as the different attitudes of the general population towards this polarizing topic (Capstick & Pidgeon, 2014; Kinkeldey et al., 2017; Poortinga et al., 2011; van der Bles et al., 2019). Furthermore, emotions were proven to have an influence on decision-making, especially in contexts of uncertainty and risk such as climate change and its impact on society (Harth, 2021; Marx et al., 2007; N. Smith & Leiserowitz, 2014; Weber, 2010).

The goal of this thesis was to extend the understanding around the visualization of uncertainty in the framework of climate change communication and to further examine how aspects such as emotions and individual attitudes influence the reading and understanding of relevant topic specific maps and information. Based on this goal, the three main research questions presented in Chapter 1.3 have been posed, which served as guidelines for this study. The research questions aimed to steer this work towards investigating the effects of emotional narratives, climate change attitudes and uncertainty visualization in the perception and interpretation by non-expert participants of climate change maps, as well as the level of trust that they were willing to put into the presented information. More precisely, the first research question intended to examine the effect of emotions, evoked by displaying of images and narratives, in the interpretation of climate change maps with and without uncertainty depiction. For the second research question, the focus was instead on the influence that the personal attitudes towards climate change (sceptic vs believing) have in the interpretation and in the level of trust of climate change related information, as well as how they interact with the display of uncertainty. Lastly the third research question inquired the effects of different uncertainty visualization methods on the ability of users to understand in the map both the uncertainty and the underlying variable.

In order answer the research questions, an empirical online study, with as main component a map-based experiment, with mixed factorial design has been developed. Participants were either in the group with the presence of the emotional stimulus together with the map or were in the group without any emotional element. Drawing from the climate change forecasts depicted in the Swiss Scenarios CH2018 for the year 2060 (CH2018, 2018), eighteen map stimuli have been designed, using three climatic variables as basemap: summer mean temperature, summer mean precipitation, and the number of hot days. Each map had one of the three developed representations of certainty, which could either be represented as a pattern of dots, as pattern of lines, or not being represented. Participants were then exposed to all eighteen maps in random order and performed a series of tasks, from the selection of a suitable region according to the posed question, to assessing the levels of certainty and severity of the change, as well as to provide their level of trust of the depicted map. Using the curated and rich pool of candidate participants offered by the research platform of Prolific, 109 participants took part to this online map-based study. The analysis of the answers provided by the participants of the study in the main experiment, as well as in the pre and post experiment questionnaire, has revealed the following main outcomes.

Regarding to the first research question, it has been found that in general there is no significant effect of the emotional narrative on the performance of the participants, in terms of choices made, assessments of certainty, severity, and trust, as well as the time required to complete the tasks. This absence of effects is unexpected, but the performed measurement of the emotional response to the experiment likewise indicates the absence of significant reactions. This may be explained by two possible reasons. On the one hand it is possible that the devised emotional stimulus (the presentation of a character and the consequences of climate change for their life) was not an effective depiction to elicit strong emotional responses in the participants. On the other hand, it may be that the applied methods to measure the emotional response, the SAM and the SEW, were not the most suited instruments to detect an emotional change.

Considering the second research question, the main findings regard the fact that the depiction of certainty had a significant effect on both the evaluation of the severity of change and the level of trust. Sceptics participants were found to assess their selected region as less severely affected. Moreover, the presence of certainty information increased the level of trust that both sceptics and believers of climate change were willing to give to the visualizations. In contrast for both stances the absence of certainty information led to similarly lower trust levels. Interestingly, the increase of trust by believers is more intense than for the sceptics, in contrast to what detected in previous studies.

The outcomes of this study, for what concerns the research question number three, indicate that no significant difference occurs in the choices of participants between the visualization of climate change without certainty information and the ones with certainty information. However, significant differences arise between the maps with and the ones without certainty depiction, in terms of retrieval of the certainty value. This difference, in contrast to previous studies, is also detectable in the time required to complete the task, which may indicate more cognitive load for the interpretation of these kind of map when certainty is present. Further, the pattern of dots is the preferred visualization type to illustrate certainty. Finally, the trust level of participants is significantly higher when confronted with maps where the certainty information is provided.

This study could not find significative differences regarding the presence of emotional narratives. Moreover, the outcomes of the experiment provided further evidence that the presentation of certainty information influences the trust that people give to the visualization, by increasing their willingness to trust it. This effect is valid both for believers and sceptics, though more intensely for the former. Finally, it provided additional support that the depiction of certainty with pattern-based methods influences the time required to perform decisions on visualizations with certainty information.

6.2 Outlook

With this thesis, an investigation on the challenging topic of uncertainty visualization in the context of climate change has been performed. It allowed to shed more lights onto how the factors of emotions and climate change attitudes influence the interpretation and trust of climate change visualizations with forecast certainty information. Nonetheless, research gaps in the field remains to be filled with future works.

To further extend the knowledge on the topic of uncertainty visualization and what factors influence its understanding it is suggested to carry additional investigations on the effect of emotion, to confirm or improve the results of this study. In this context, it is advised to deepen the knowledge of what kind of emotional stimuli (character depictions, stories, framings) are more suited to elicit an emotional response in participants, possibly by conducting preliminary studies for determining this aspect before running the main experiment. Furthermore, due to time and resource limits, aspects such as the influence of the displayed climatic variable, the expertise of participants, the kind of requested area, or geographical differences could not be properly investigated, because they were deemed as beyond the scope of this endeavour. However, from the results obtained there are indications that the aspects such as the depicted variable (as the amount of precipitation) may also have an influence on the understanding of the map and consequent decision-making process of non-experts. Since the research on climate change scepticism highlighted the presence of different types of climate scepticism, it would be interesting in future studies to deeply investigate how those different nuances of scepticism interplay with the presentation of visualized certainty on climate change maps. Given the limitations regarding to the methodological approach to the categorical data collected in this study, another point to take care in future research would be to investigate what other alternative evaluation methods could offer a different and potentially better interpretation tool.

In conclusion, although communicating and visualizing uncertainty on the divisive and emotionally charged topic of climate change remains a difficult task, which may increase the cognitive load of map readers, the transparency in the communication of these uncertainties increases the trust of the public on the presented forecasts.

7 Literature

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8 Appendix

A Study front page in Prolific

The front page of the study in Prolific, from which the participants could read some basic information about the study and its requirements, in order to decide whether they want to access it or not, is reported here.

Certainty Visualization on climate change forecast maps

This is a study conducted by Sergio Bazzurri (sergio.bazzurri@uzh.ch) as part of his Master's thesis research on **the depiction of certainty in climate change forecast maps**, carried out at the Geography Department of the University of Zurich (UZH), in Zurich, Switzerland.

Aim of the study is to gain new insights into how visualization of data certainty influences map reading, analysis, and understanding.

The study consists in a first part with demographic questions, a second part where you will perform map-based decision tasks and a third part where you will be asked to answer some questions about the tasks you performed.

The study requires about **40 minutes**. Please complete the study on a **laptop or desktop computer screen (minimal display size 11.6 inches). Smartphones or tablets** are **not** considered.

Your submission will be reviewed, and the reward approved, within a couple of days after your completion.

B Informed consent

University of Zurich[UZH]

Department of Geography

Welcome and thank you for your interest in participating in this web-based online study! Before proceeding further, please read carefully all the following information.

You are invited to participate in a study conducted by Sergio Bazzurri (sergio.bazzurri@uzh.ch) as part of his Master's thesis research on **the depiction of certainty in climate change forecast maps**, carried out at the Geography Department of the University of Zurich (UZH), in Zurich, Switzerland. The project is supervised by Prof. Dr. Sara Irina Fabrikant (sara.fabrikant@geo.uzh.ch).

Purpose of the study

With this study, we wish to gain new insights into how visualization of data certainty influences map reading, analysis, and understanding.

General information

The study will be conducted entirely online, and it will require about **40 minutes** of your **uninterrupted time**. Because the study focuses on graphics and the display of geographic information, it requires a minimal **diagonal display size of 11.6 inches (29.5 cm)** to work. We ask that you please complete the study on a **laptop or desktop computer screen. Smartphones or tablets** are **not** considered.

Procedure of the study

If you decide to hopefully take part in this study, you will be first filling in demographic information including your background and training and study related preferences. In the main part of the study, the actual experiment, you will work on a series of tasks with climate change forecast maps. More detailed information about the tasks will be given during this portion of the study. After completing the map-based part, you will be asked to answer some questions about the tasks you performed and your preferences regarding the seen visualizations. The following data is recorded anonymously: your responses to all the questionnaires and map-based tasks and your response times.

Voluntary Participation:

Your participation in the study is **entirely voluntary**. You may withdraw your consent to participate in the study at any time without providing notice or reasoning.

Inclusion and exclusion criteria

Any healthy adult may participate in the experiment.

Obligations of the participant

It is expected that you will carefully follow the given instructions, and fully and faithfully complete all questionnaires and experiment tasks.

Risk to the participants

The study entails no foreseeable risks to you. The study is carried out in an online environment and there are no physical or other effects to affect participants' health.

Benefits to the participant

The study provides you with a **monetary compensation** for the time you invested, which will amount to **£8**.

Data confidentiality

Any information that can be linked to you during the study will be treated confidentially and will only be passed on to third parties with your expressed permission. With your consent, you allow us to publish the (anonymised) study results several times. No information will be published that makes it possible to identify you. All data collected will be kept encrypted and archived on a secure server located at the University of Zurich, only accessible by the study conductors.

Costs

The entire study will not bear any costs to the participants.

Termination of participation

The participation will be cancelled in the case you decide to withdraw from the study. All obtained data will be permanently deleted.

Study Results

If you would like to be informed about the results of this study, you can contact the researcher with the Prolific internal messaging system or at the email address below. A copy of the study results or the full Master's thesis manuscript can then be sent to you at a later date.

Contact persons

If you have any questions or worries about the study, please contact the persons listed below.

Sergio Bazzurri (sergio.bazzurri@uzh.ch)

Prof. Dr. Sara Irina Fabrikant (sara.fabrikant@geo.uzh.ch)

Geography Department, University of Zurich, Winterthurerstrasse 190, CH-8057 Zurich

INFORMED CONSENT

By participating in this study, I agree and affirm that:

1) I was given enough time to read this information sheet.
2) I understand the requirements of the experiment and I agree to participate in this study.
3) My participation is entirely voluntary, and I have not been forced to participate in this study in any way.
4) I acknowledge that I may withdraw my consent to participate in this study at any time without any further notice or reasoning.
5) I agree that my data may be used in anonymized form for research purposes only and may be published in academic research publications.
6) I understand that my personal information will be kept confidential under all circumstances.
7) I understand that the study directors, in the interest of the study, may terminate my participation at any time.
8) I understand that I must follow the instructions of the instructor and comply with the requirements of this and other instruction sheets.

☐ I understand the conditions of this study and I consent to participate

C Pre-test

Certainty Visualization

Welcome!

Thank you again for participating in my study! Your participation is very important for my Master's thesis research and contributes to deepen the understanding of certainty visualization on maps.
In this first part of the study, you will be asked to provide general demographic information and to complete a couple of background questionnaires. Following that, you will proceed to the map experiment part of the study.
Please, do not use your browser's back navigation button to change your answers. To start, click on the button below.

Click this button to continue

Certainty Visualization

How would you best describe your gender?

- Male
- Female
- Non-binary
- Prefer to self-describe

How old are you?

In which country do you currently live?

Have you ever been diagnosed with a visual impairment by a specialist (optician, ophthalmologist)?

- [ ] Yes, colour blindness
- [ ] Yes, glasses or contact lenses
- [ ] No
- [ ] Other visual impairment (please specify)

In case you answered "Yes, glasses or contact lenses" in the previous question, are you wearing them as you are participating in this study?
If this question does not apply to you, please answer "No, I do not need them".

- ◯ Yes, I am wearing them now
- ◯ No, I am not wearing them now
- ◯ No, I do not need them

What is the highest level of education you have completed?

- ◯ No qualification
- ◯ Primary school
- ◯ Secondary school or equivalent
- ◯ High school or equivalent
- ◯ University degree
- ◯ Doctoral degree
- ◯ Other educational qualification (please specify)

How often do you deal with maps in your everyday life (navigation, Google Maps, atlas, maps in newspapers, ...)?

- ◯ Never
- ◯ Annually
- ◯ Monthly
- ◯ Weekly
- ◯ Daily

How familiar are you with...

Cartography

Not familiar at all | Slightly familiar | Moderately familiar | Fairly familiar | Completely familiar

Geographic Information Systems (GIS)

Not familiar at all | Slightly familiar | Moderately familiar | Fairly familiar | Completely familiar

Climate Change mapping

Not familiar at all | Slightly familiar | Moderately familiar | Fairly familiar | Completely familiar

Intergovernmental Panel on Climate Change (IPCC)

Not familiar at all | Slightly familiar | Moderately familiar | Fairly familiar | Completely familiar

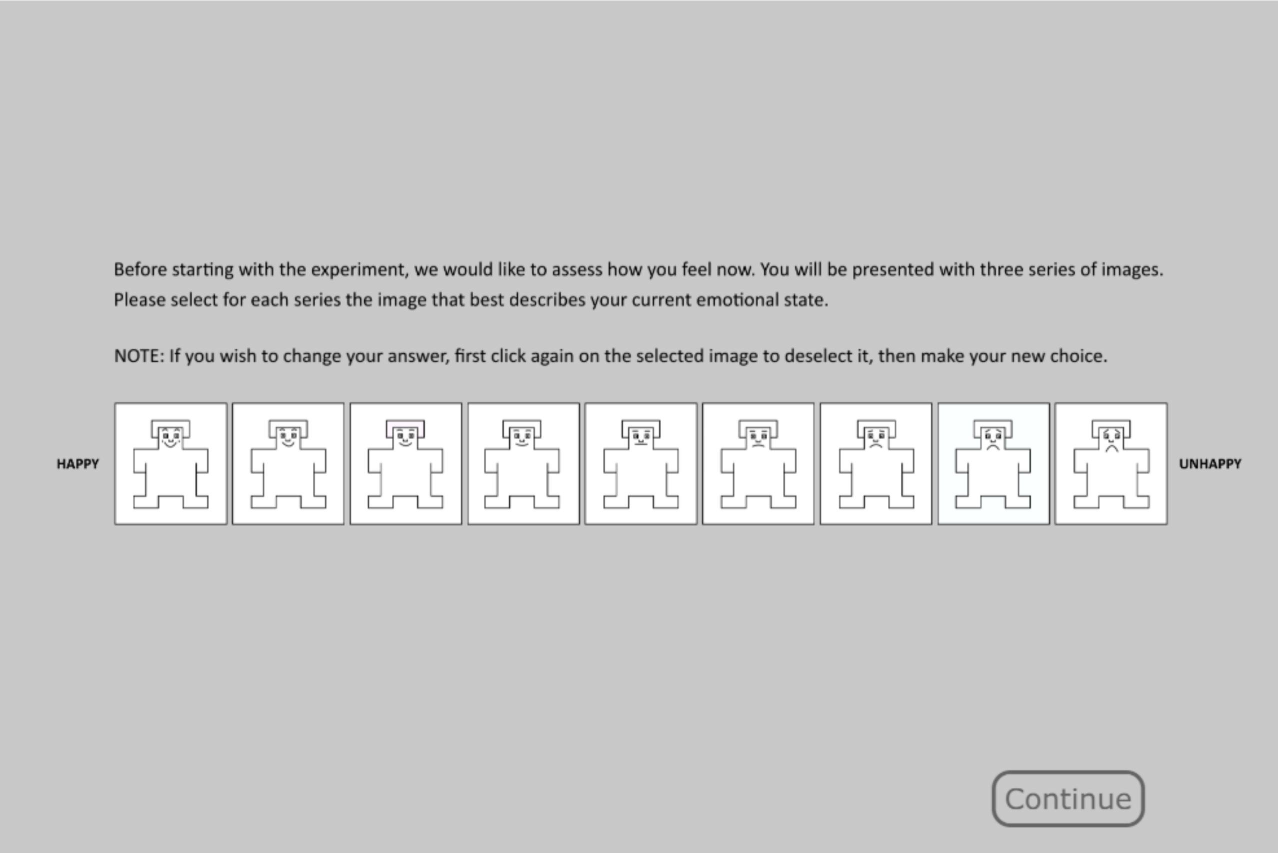
Statistics

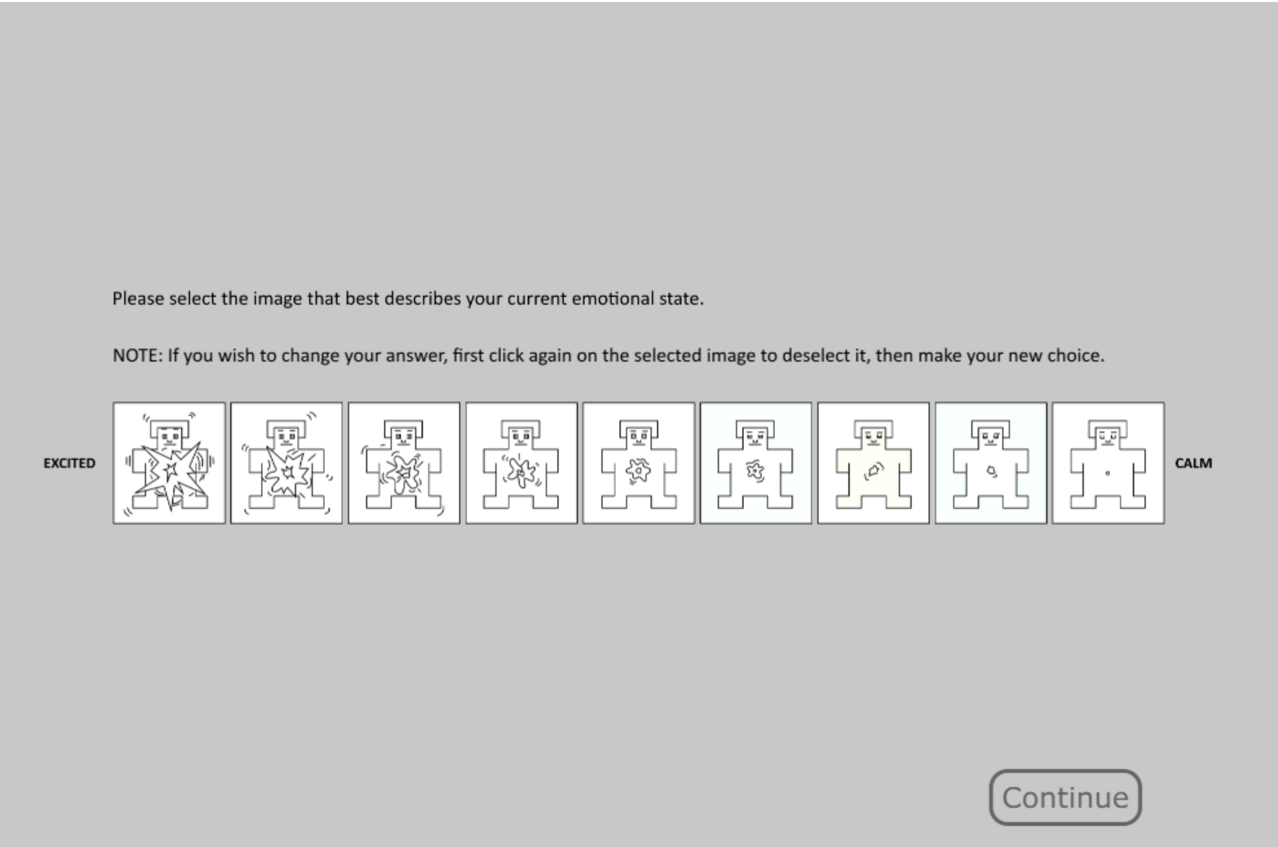
Not familiar at all | Slightly familiar | Moderately familiar | Fairly familiar | Completely familiar

Uncertainty

Not familiar at all | Slightly familiar | Moderately familiar | Fairly familiar | Completely familiar

Click this button to continue

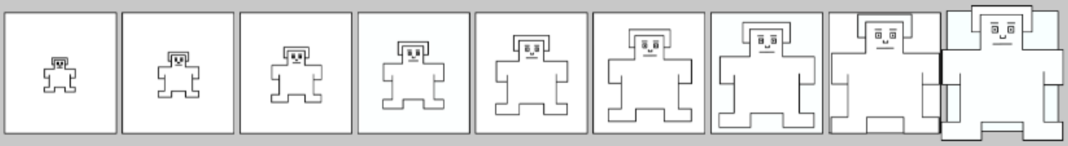

Before starting with the experiment, we would like to assess how you feel now. You will be presented with three series of images.
Please select for each series the image that best describes your current emotional state.
NOTE: If you wish to change your answer, first click again on the selected image to deselect it, then make your new choice.
HAPPY
UNHAPPY
Continue


Please select the image that best describes your current emotional state.
NOTE: If you wish to change your answer, first click again on the selected image to deselect it, then make your new choice.
EXCITED
CALM
Continue

Please select the image that best describes your current emotional state.

NOTE: If you wish to change your answer, first click again on the selected image to deselect it, then make your new choice.

CONTROLLED



IN CONTROL

Continue

Certainty Visualization

Next you will be presented with 16 statements. Please read each statement carefully and rate how frequently you feel or act in the manner described. There are no right or wrong answers or trick questions. Please answer each question as honestly as you can.

1. When someone else is feeling excited, I tend to get excited too

Never | Rarely | Sometimes | Often | Always

2. Other people’s misfortunes do not disturb me a great deal

Never | Rarely | Sometimes | Often | Always

3. It upsets me to see someone being treated disrespectfully

Never | Rarely | Sometimes | Often | Always

4. I remain unaffected when someone close to me is happy

Never | Rarely | Sometimes | Often | Always

5. I enjoy making other people feel better

Never	Rarely	Sometimes	Often	Always

6. I have tender, concerned feelings for people less fortunate than me

Never	Rarely	Sometimes	Often	Always

7. When a friend starts to talk about his\her problems, I try to steer the conversation towards something else

Never	Rarely	Sometimes	Often	Always

8. I can tell when others are sad even when they do not say anything

Never	Rarely	Sometimes	Often	Always

9. I find that I am "in tune" with other people's moods

Never	Rarely	Sometimes	Often	Always

10. I do not feel sympathy for people who cause their own serious illnesses

Never	Rarely	Sometimes	Often	Always

11. I become irritated when someone cries

Never	Rarely	Sometimes	Often	Always

12. I am not really interested in how other people feel

Never	Rarely	Sometimes	Often	Always

13. I get a strong urge to help when I see someone who is upset

Never	Rarely	Sometimes	Often	Always

14. When I see someone being treated unfairly, I do not feel very much pity for them

Never	Rarely	Sometimes	Often	Always

15. I find it silly for people to cry out of happiness

Never	Rarely	Sometimes	Often	Always

16. When I see someone being taken advantage of, I feel kind of protective towards him\her

Never	Rarely	Sometimes	Often	Always

Click this button to continue

Certainty Visualization

Next you will be presented with 9 statements. Please read each statement carefully and rate how much do you agree with it. There are no right or wrong answers or trick questions. Please answer each question as honestly as you can.

1. Claims that human activities are changing the climate are exaggerated

Agree strongly	Agree	Neither agree nor disagree	Disagree	Disagree strongly

2. Climate change is something that frightens me

Agree strongly	Agree	Neither agree nor disagree	Disagree	Disagree strongly

3. Climate change is just a natural fluctuation in earth's temperatures

Agree strongly	Agree	Neither agree nor disagree	Disagree	Disagree strongly

4. I feel a moral duty to do something about climate change

Agree strongly	Agree	Neither agree nor disagree	Disagree	Disagree strongly

5. I do not believe climate change is a real problem

Agree strongly	Agree	Neither agree nor disagree	Disagree	Disagree strongly

6. I am uncertain about whether climate change is really happening

Agree strongly	Agree	Neither agree nor disagree	Disagree	Disagree strongly

7. There is too much conflicting evidence about climate change to know whether it is actually happening

Agree strongly	Agree	Neither agree nor disagree	Disagree	Disagree strongly

8. The effects of climate change are likely to be catastrophic

Agree strongly	Agree	Neither agree nor disagree	Disagree	Disagree strongly

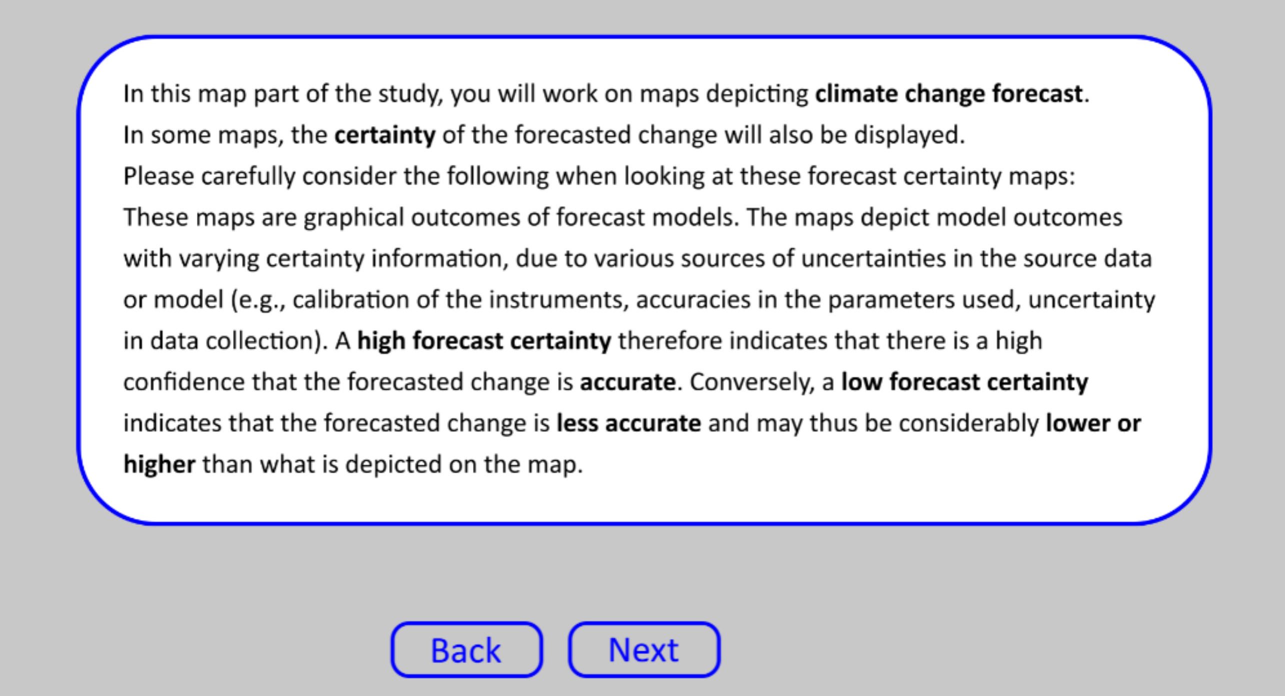
9. Climate change is too complex and uncertain for scientists to make useful forecasts

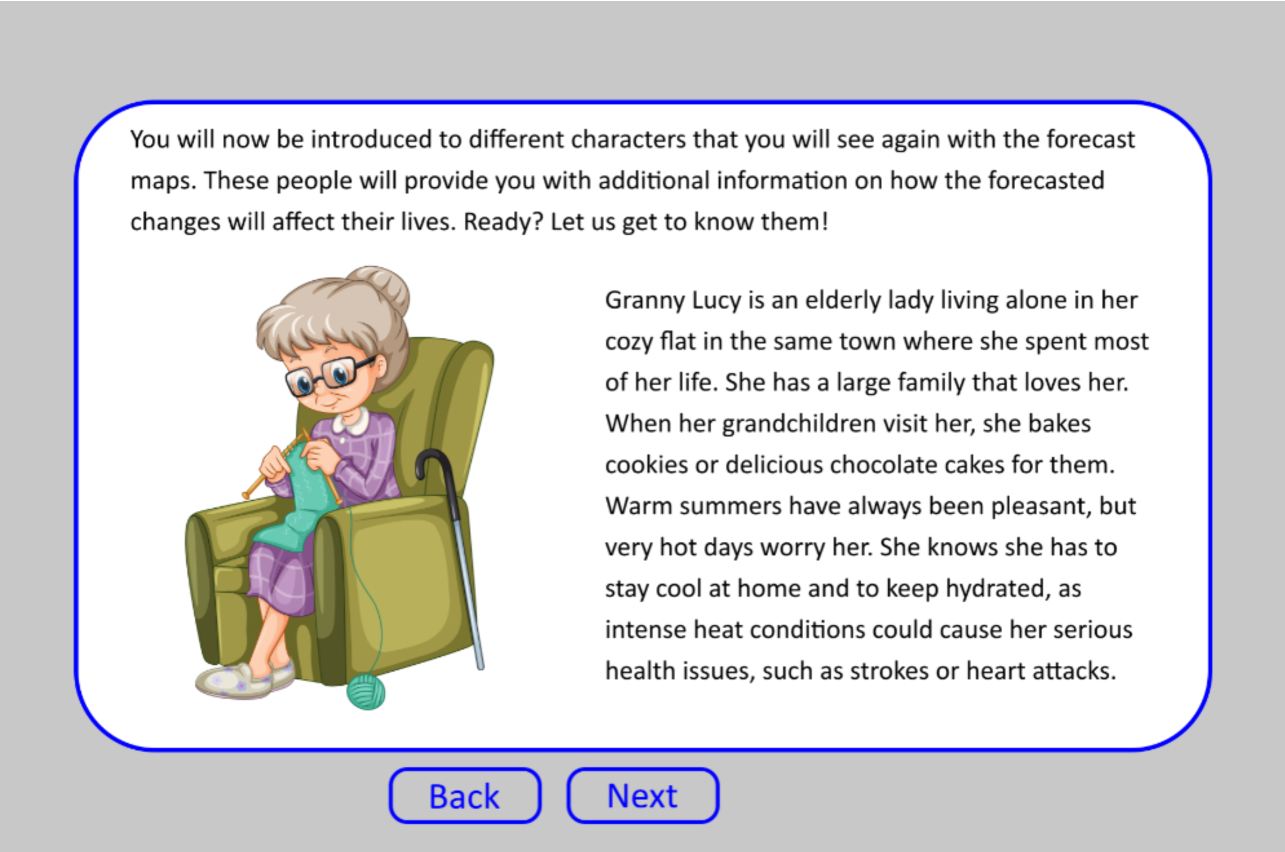
Agree strongly	Agree	Neither agree nor disagree	Disagree	Disagree strongly

Click this button to continue

D Main Experiment version With Emotion (WE)

Since the 18 trials in the main experiment follow the same structure of the warm-up trial, only the warm-up trial is shown in its entirety. The map stimuli of the 18 trials of the main experiment can be seen in Appendix I.





Valery is a keen and entrepreneurial farmer. She regularly supplies the neighbouring town with her fresh vegetables and other organic agricultural products. She loves the orange colour of pumpkins and always ends up growing more of them for the sake of their beauty. Farming is hard work and provides only a small income, but Valery appreciates working surrounded by nature. However, long, dry seasons seriously worry her. This especially, when they occur several years in a row, as this could ruin her entire harvest. The increased cost for irrigation is a big burden to bear.

Back Next

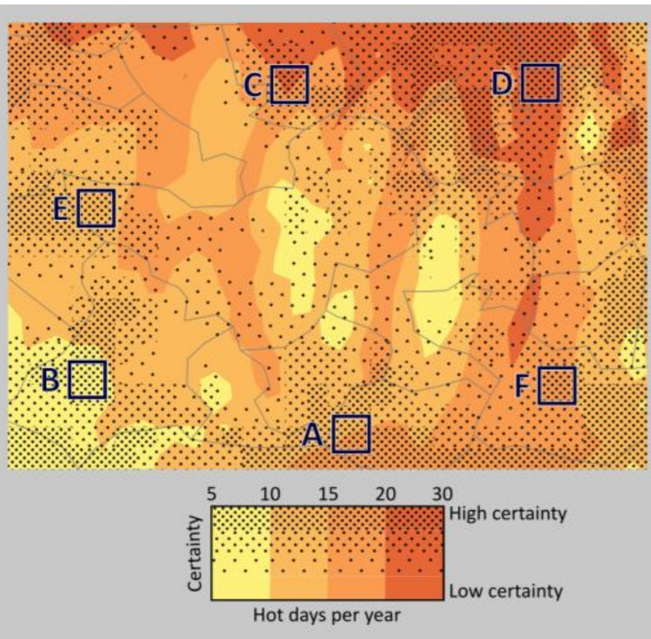
Jane is a young girl living in a town on a hillside. She loves the forest animals living nearby. When she grows up she wants to live in a tree house. Summer is a season she enjoys very much, as she can spend many hours playing outside, exploring the forest, and picnicking with the girl scout group. However, her parents are concerned that with increasingly hot summers, the chances will also increase that their little girl will be bitten by disease-carrying insects, such as ticks and mosquitoes. They also worry that she will be increasingly facing the chance of forest fires breaking out while she roams the forest with her girl scout group.

Back Next

Ok, now on to the forecast maps that will be presented next. In the map-based portion of this study you will see a map on the left hand side, displaying the forecasted **change of a given climatic variable** due to climate change in a given region by **2060**. The legend below the map depicts the classes of the **climatic variable** (left to right) and the **certainty of the forecast** (bottom to top). Note that for some maps certainty information on the forecast will not be available. On the right you will be presented with one of the **characters to whom you were already introduced** beforehand, who happen to be living in the mapped region and **how this change might affect their lives**. Given this information, your task is to assess in which of the areas highlighted on the forecast map the character will be **least/most affected** by the forecasted change and to assess the severity and the certainty of the forecasted change in this area. On the next slide, you will be able to practice the task with a **warm-up trial**.

When you are ready to begin the warm-up trial, click on "Start".

Back Next Start

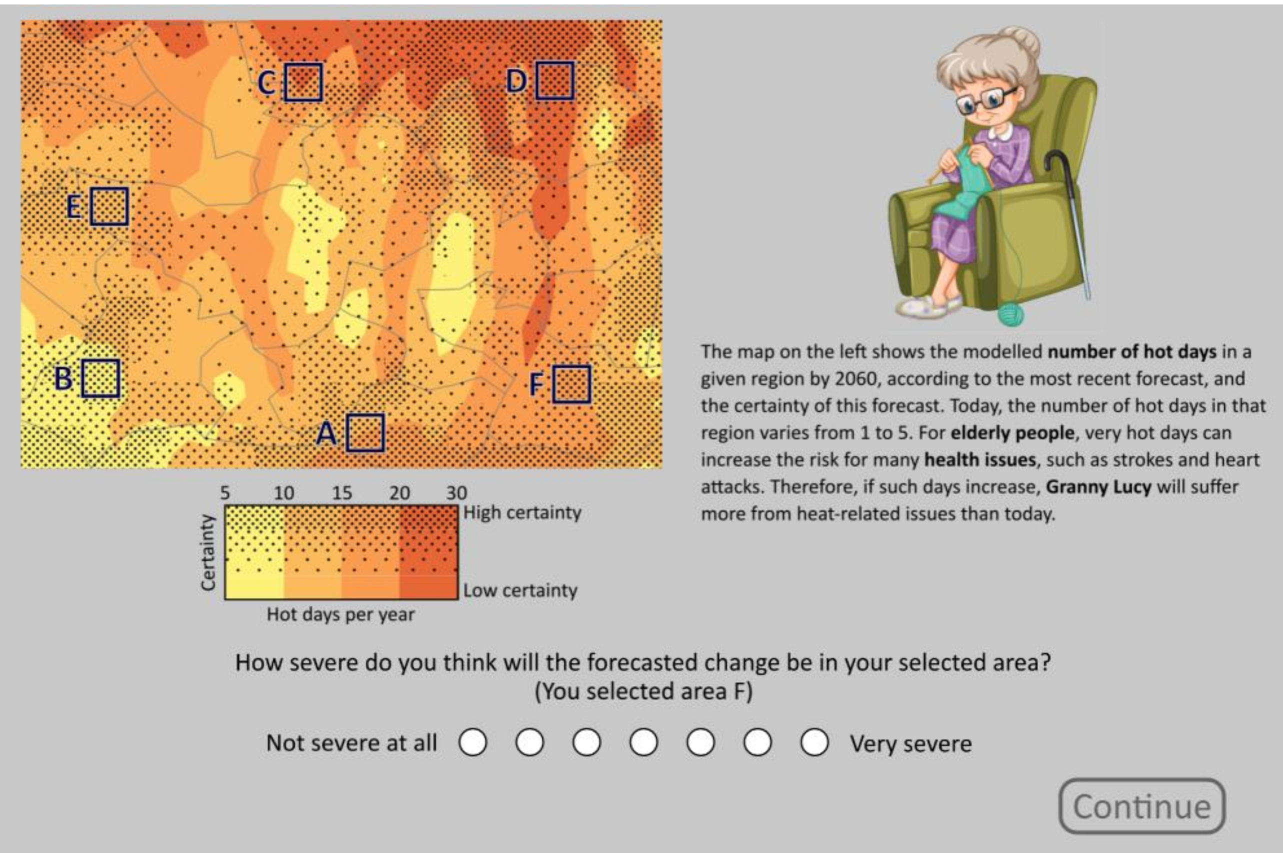


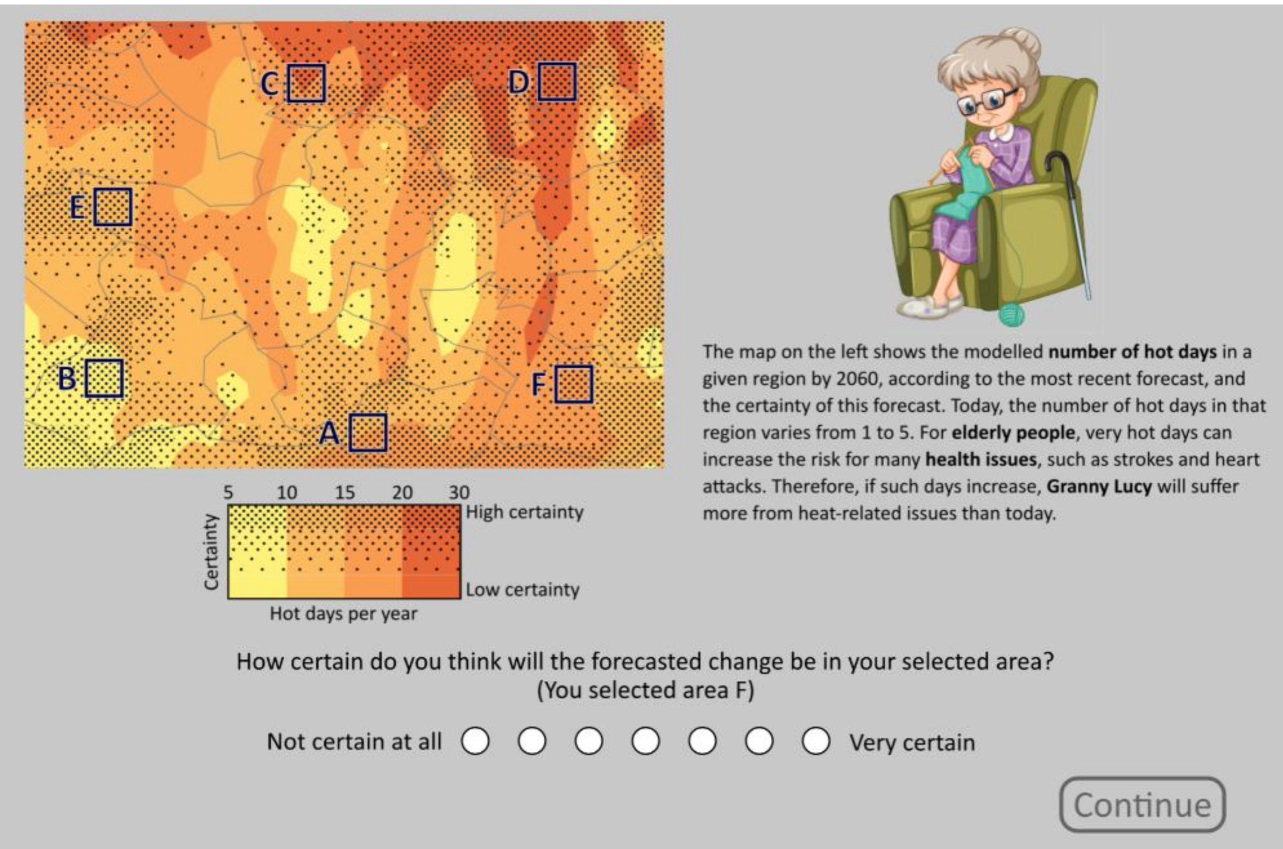
The map on the left shows the modelled **number of hot days** in a given region by 2060, according to the most recent forecast, and the certainty of this forecast. Today, the number of hot days in that region varies from 1 to 5. For **elderly people**, very hot days can increase the risk for many **health issues**, such as strokes and heart attacks. Therefore, if such days increase, **Granny Lucy** will suffer more from heat-related issues than today.

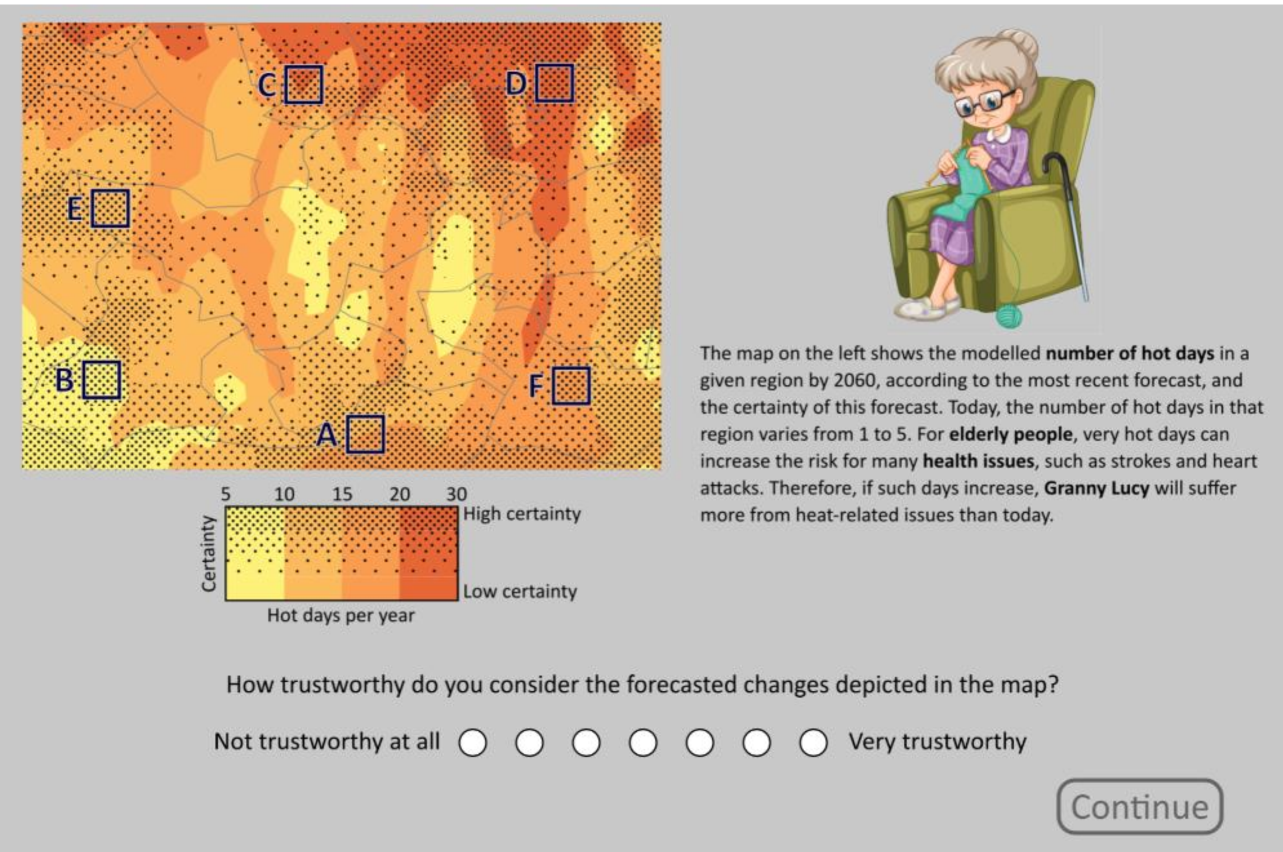
In which of the marked areas do you think **she** will **suffer least** from the forecasted change?

○ A ○ B ○ C ○ D ○ E ○ F

Continue

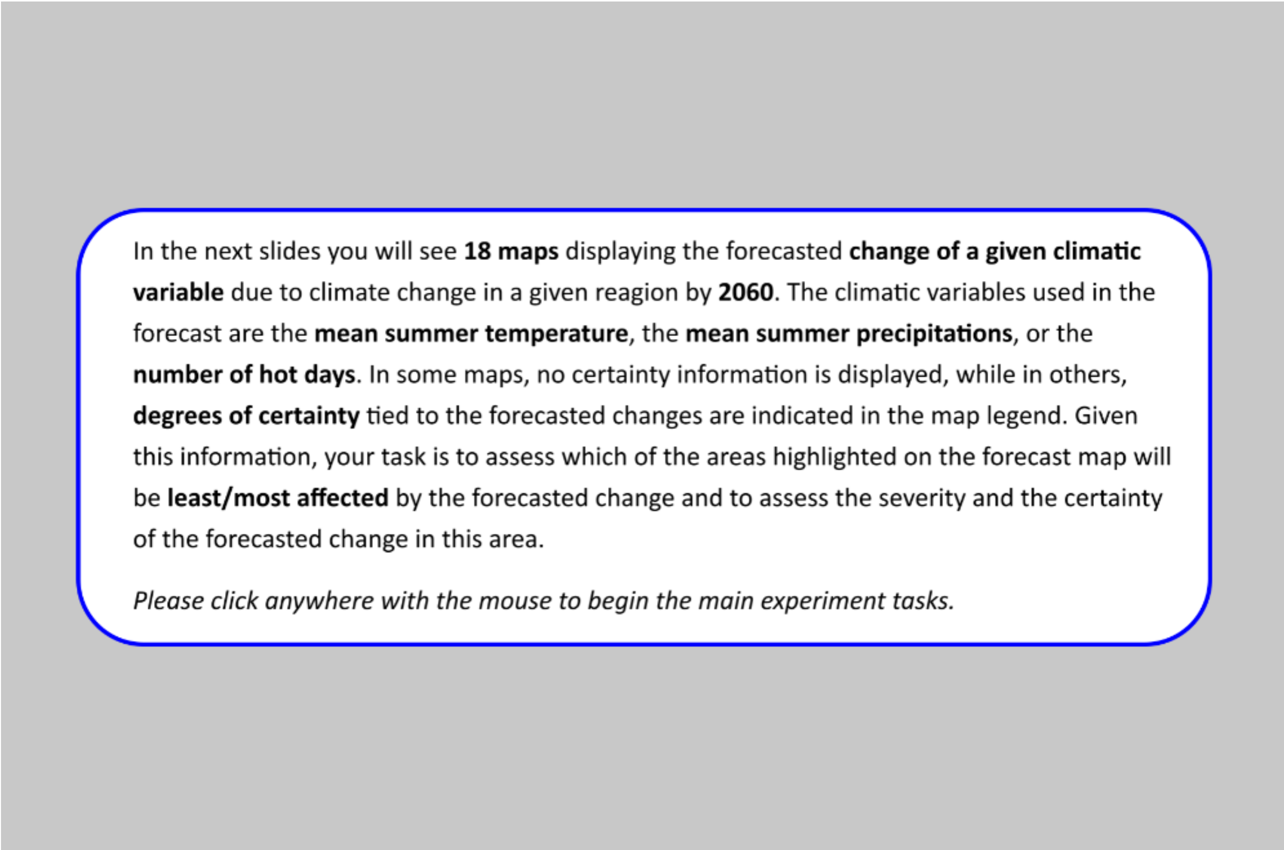

C
D
E
B
F
A
5 10 15 20 30
High certainty
Certainty
Low certainty
Hot days per year
The map on the left shows the modelled **number of hot days** in a given region by 2060, according to the most recent forecast, and the certainty of this forecast. Today, the number of hot days in that region varies from 1 to 5. For **elderly people**, very hot days can increase the risk for many **health issues**, such as strokes and heart attacks. Therefore, if such days increase, **Granny Lucy** will suffer more from heat-related issues than today.
How severe do you think will the forecasted change be in your selected area?
(You selected area F)
Not severe at all
Very severe
Continue


C
D
E
B
F
A
5 10 15 20 30
High certainty
Certainty
Low certainty
Hot days per year
The map on the left shows the modelled **number of hot days** in a given region by 2060, according to the most recent forecast, and the certainty of this forecast. Today, the number of hot days in that region varies from 1 to 5. For **elderly people**, very hot days can increase the risk for many **health issues**, such as strokes and heart attacks. Therefore, if such days increase, **Granny Lucy** will suffer more from heat-related issues than today.
How certain do you think will the forecasted change be in your selected area?
(You selected area F)
Not certain at all
Very certain
Continue



The warm-up trial is finished, you will now proceed to the main experiment.

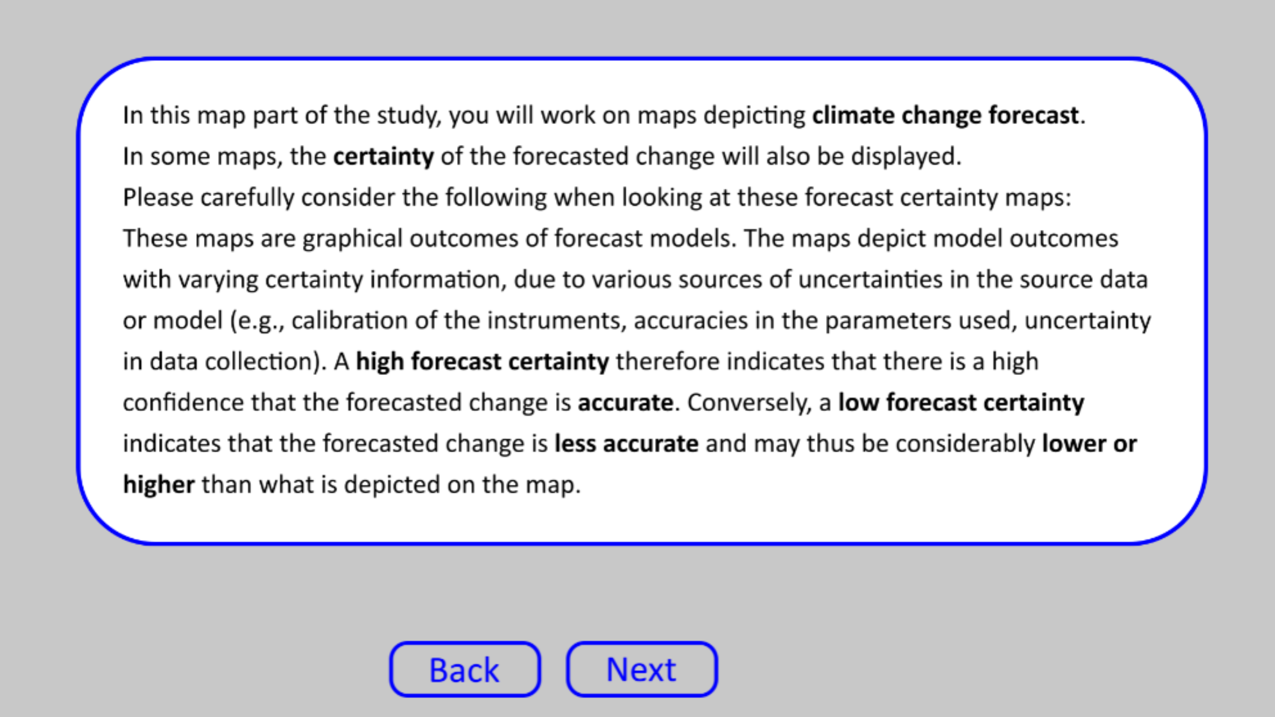
Please click anywhere with the mouse to start the map experiment part of this study.

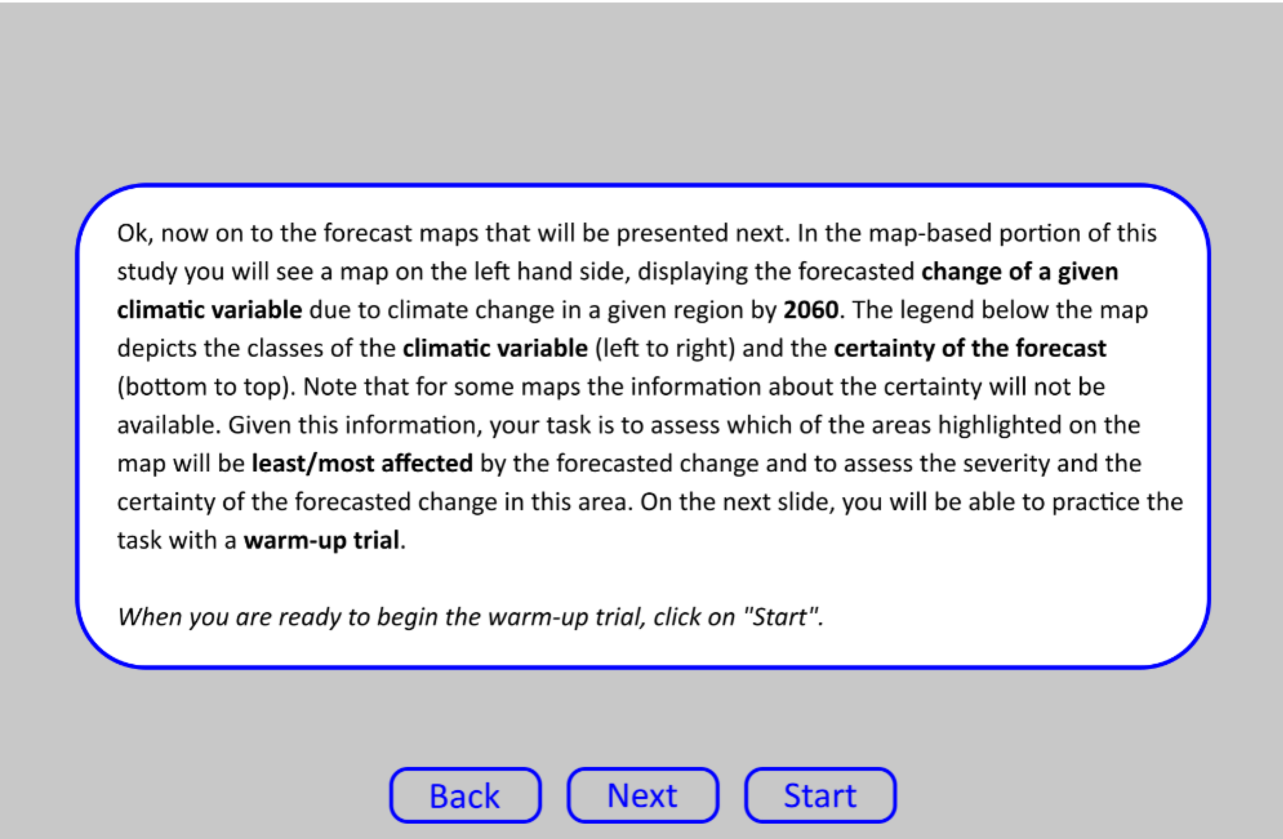


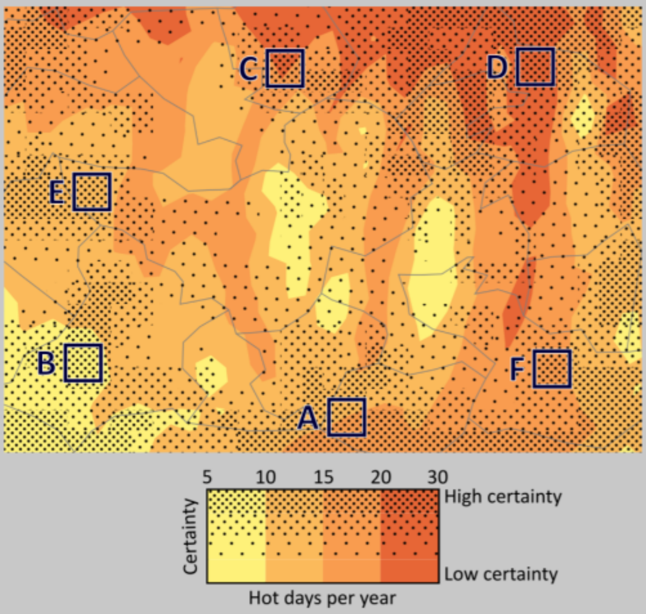
After this slide the 18 trials of the main experiment begin.

E Main Experiment version No Emotion (NE)

Since the 18 trials in the main experiment follow the same structure of the warm-up trial, only the warm-up trial is shown in its entirety. The map stimuli of the 18 trials of the main experiment can be seen in Appendix I.





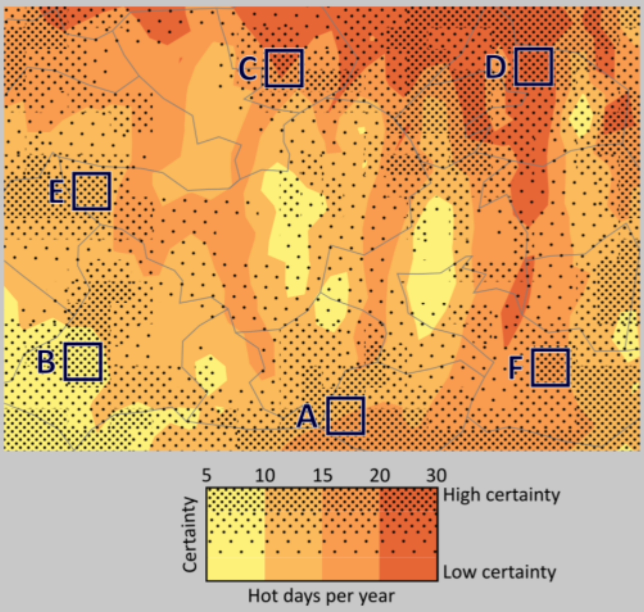


The map on the left shows the modelled **number of hot days** in a given region by 2060, according to the most recent forecast, and the certainty of this forecast. Today, the number of hot days in that region varies from 1 to 5.

Which of the marked areas do you think will **suffer least** from the forecasted change?

○ A ○ B ○ C ○ D ○ E ○ F

Continue

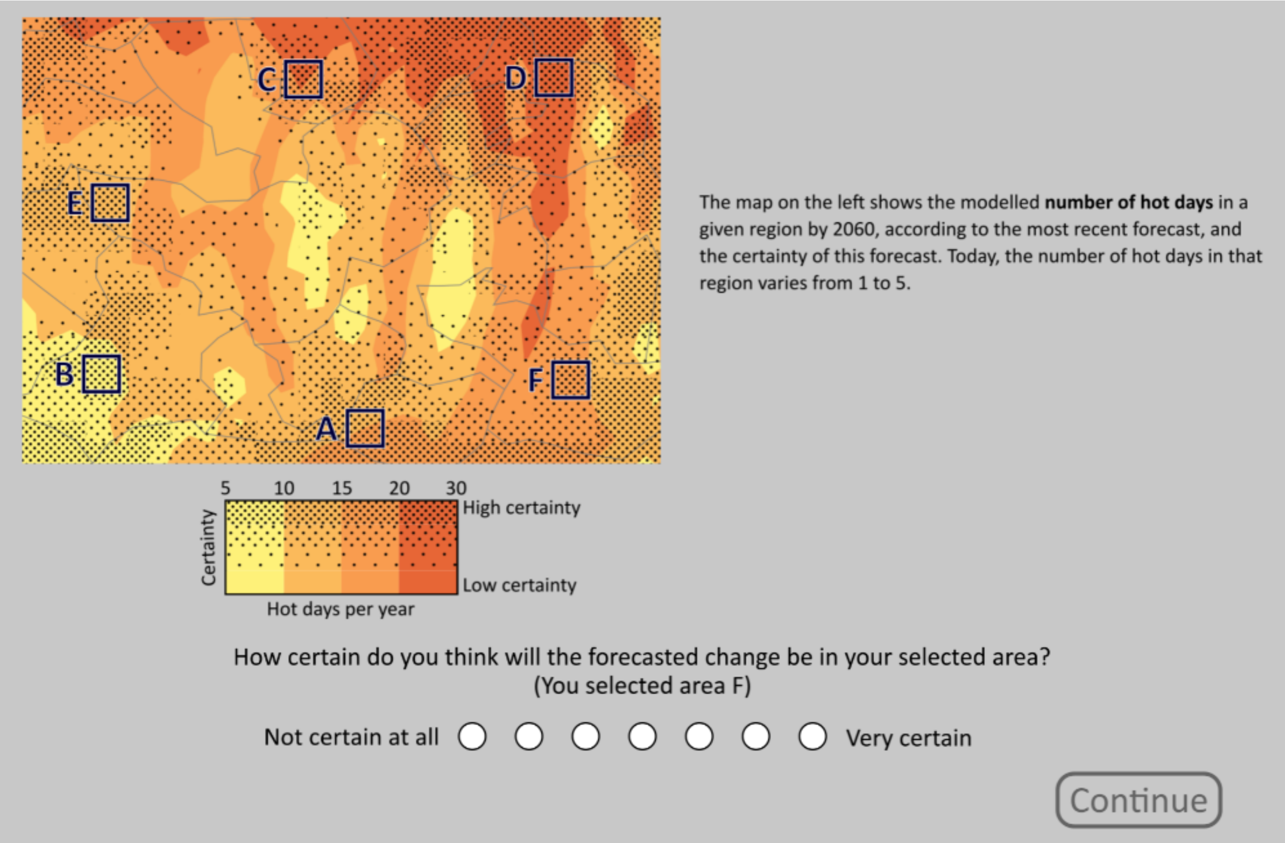


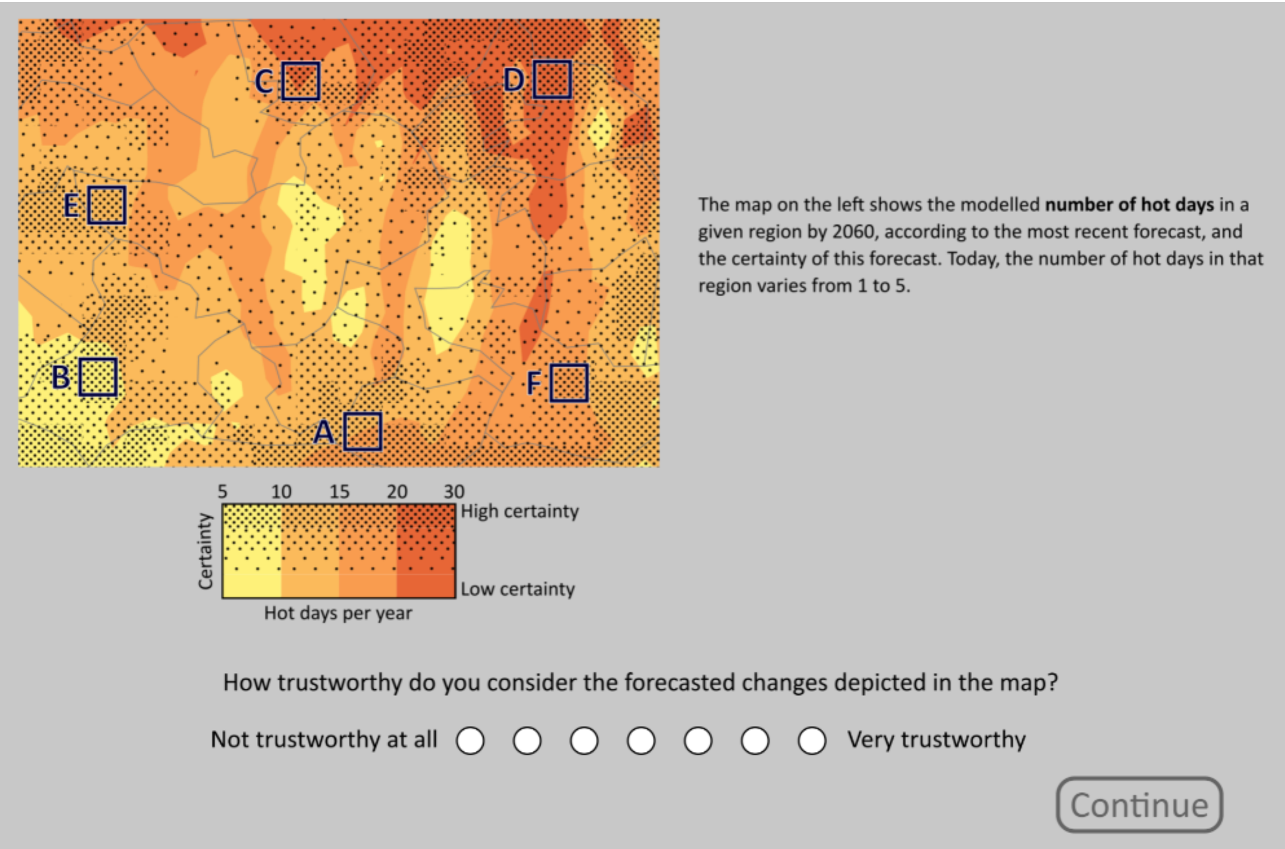
The map on the left shows the modelled **number of hot days** in a given region by 2060, according to the most recent forecast, and the certainty of this forecast. Today, the number of hot days in that region varies from 1 to 5.

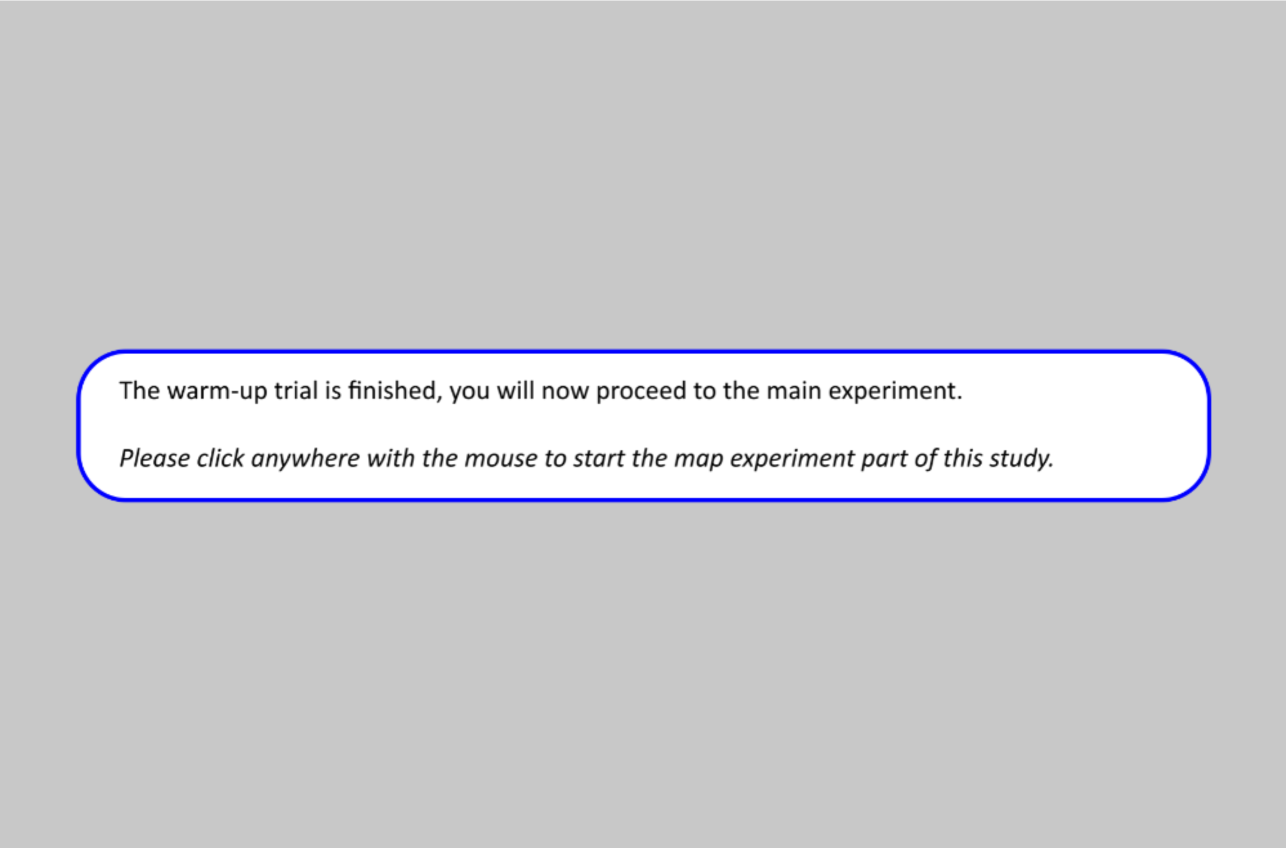
How severe do you think will the forecasted change be in your selected area?
(You selected area F)

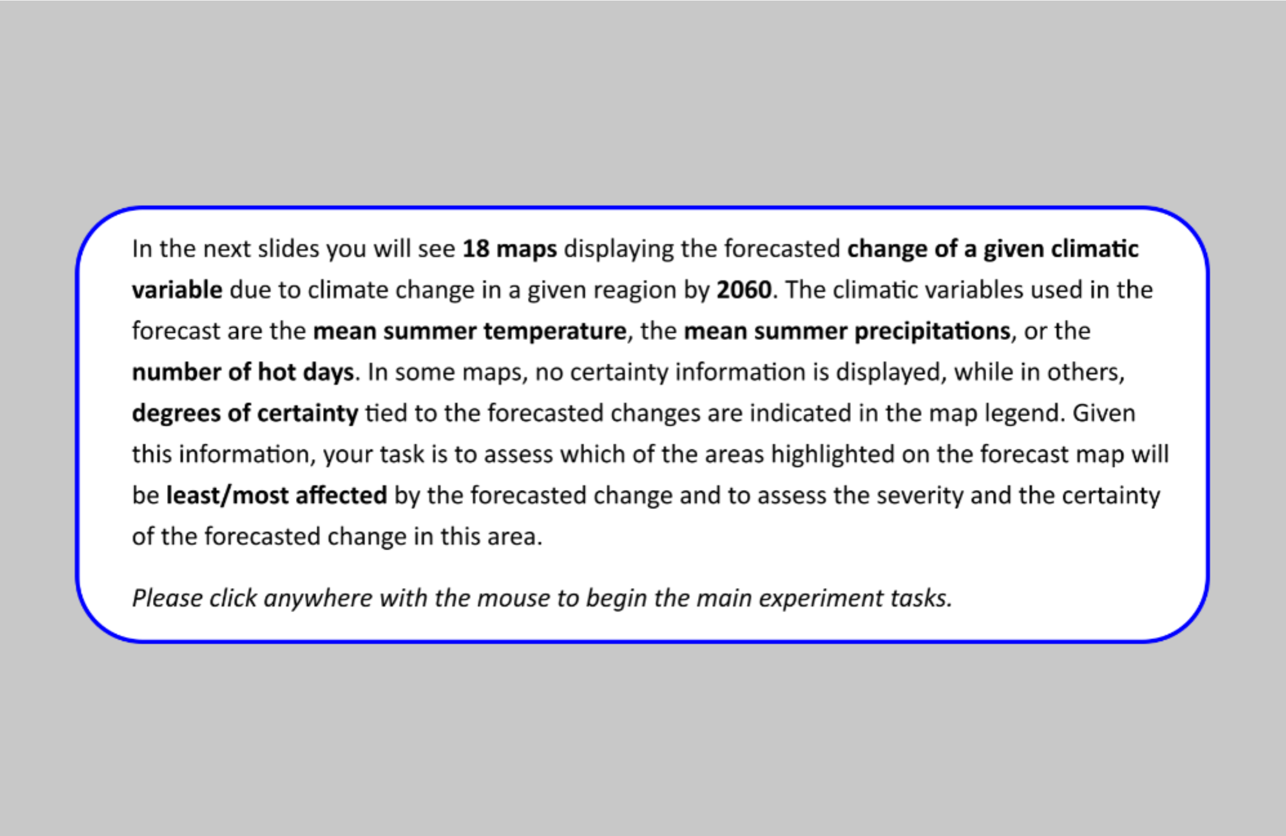
Not severe at all ○ ○ ○ ○ ○ ○ ○ Very severe

Continue


C
D
E
B
F
A
5 10 15 20 30
High certainty
Low certainty
Certainty
Hot days per year
The map on the left shows the modelled **number of hot days** in a given region by 2060, according to the most recent forecast, and the certainty of this forecast. Today, the number of hot days in that region varies from 1 to 5.
How certain do you think will the forecasted change be in your selected area?
(You selected area F)
Not certain at all
Very certain
Continue

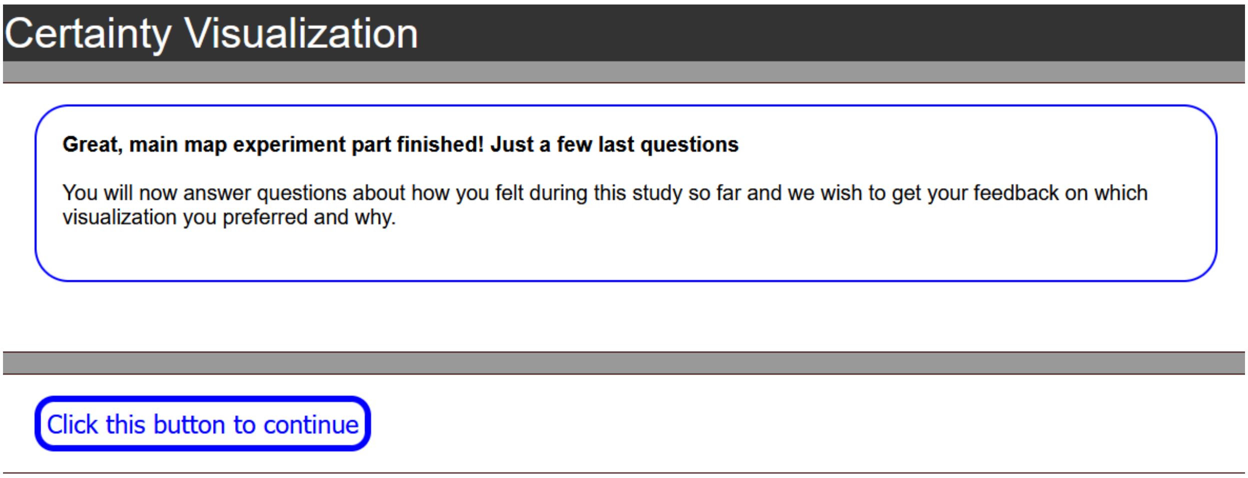

C
D
E
B
F
A
5 10 15 20 30
High certainty
Low certainty
Certainty
Hot days per year
The map on the left shows the modelled **number of hot days** in a given region by 2060, according to the most recent forecast, and the certainty of this forecast. Today, the number of hot days in that region varies from 1 to 5.
How trustworthy do you consider the forecasted changes depicted in the map?
Not trustworthy at all
Very trustworthy
Continue

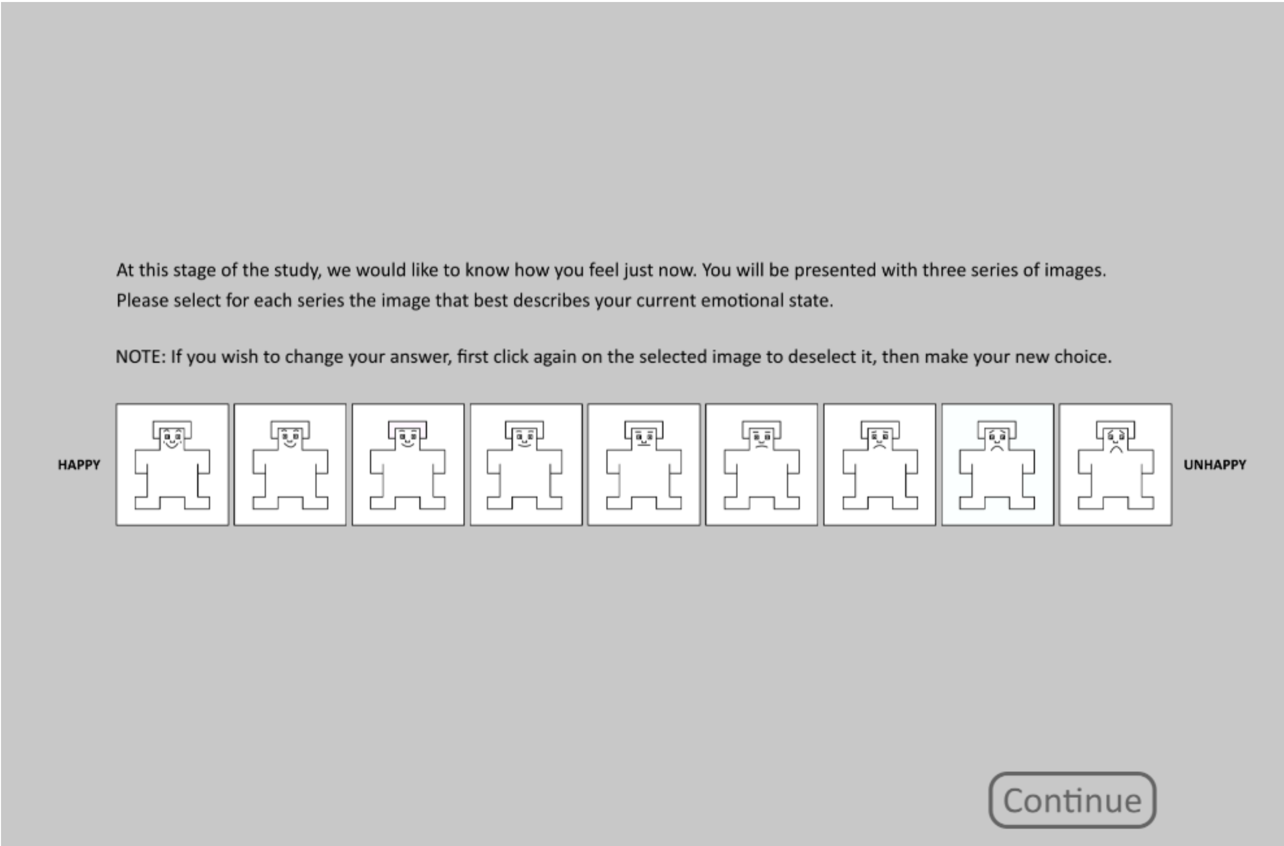


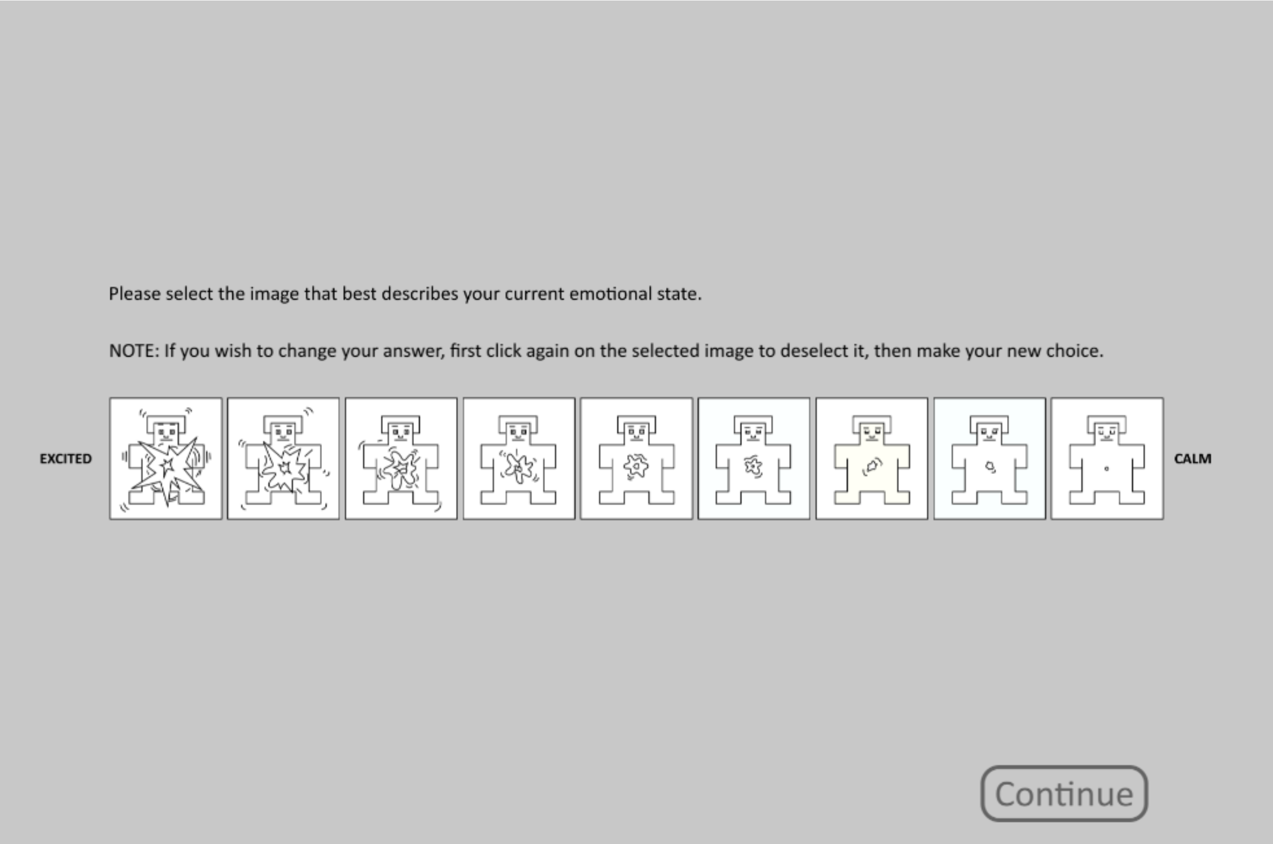


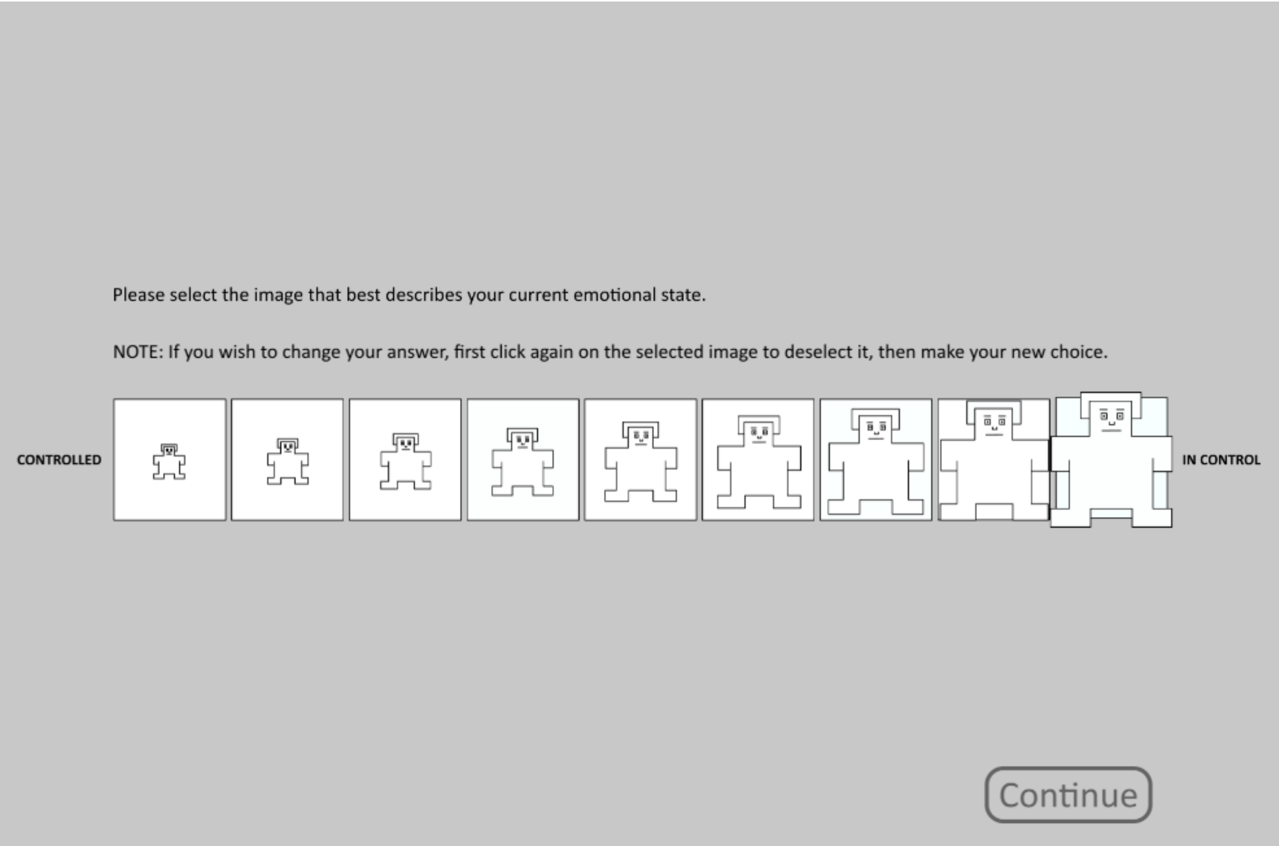
After this slide the 18 trials of the main experiment begin.

F Post-test


Certainty Visualization
Great, main map experiment part finished! Just a few last questions
You will now answer questions about how you felt during this study so far and we wish to get your feedback on which visualization you preferred and why.
Click this button to continue

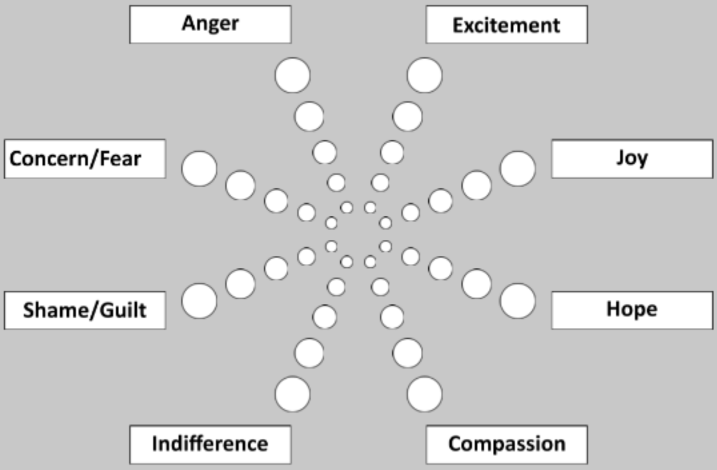

At this stage of the study, we would like to know how you feel just now. You will be presented with three series of images.
Please select for each series the image that best describes your current emotional state.
NOTE: If you wish to change your answer, first click again on the selected image to deselect it, then make your new choice.
HAPPY
UNHAPPY
Continue


Please select the image that best describes your current emotional state.
NOTE: If you wish to change your answer, first click again on the selected image to deselect it, then make your new choice.
EXCITED
CALM
Continue


Please select the image that best describes your current emotional state.
NOTE: If you wish to change your answer, first click again on the selected image to deselect it, then make your new choice.
CONTROLLED
IN CONTROL
Continue

Felt emotions contain different components and dimensions, including the type or quality of felt emotion (i.e., positive or negative) and its intensity (or strength). Please note that emotion labels on the emotion wheel below are representative emotion labels that cover a range of similar emotions, e.g., the anger emotion label can also include rage, irritation, annoyance, indignation, fury, exasperation for you. Given all presented information in the forecast maps, please **rate** the intensity of **your felt emotion**. Click the white response circle that best represents the type of felt emotion (label) and its intensity; the larger the circle, the more intense you felt this particular type of emotion.

NOTE: You can select **only one emotion and respective intensity that best reflects your current state**. If you wish to change your answer, first click again on the selected circle to deselect it, then make your new choice.



Continue

Certainty Visualization

Please explain in your own words how you felt about the forecasted climatic changes while solving the forecast map tasks.

Click this button to continue

Certainty Visualization

How much have you considered your own (future) situation, or that of your family members, when assessing the forecast maps?

Not considered at all	Slightly considered	Moderately considered	Fairly considered	Very much considered

Click this button to continue

Certainty Visualization

What of the presented information, if anything, did you take into consideration in assessing how much trust to put into the forecast map?

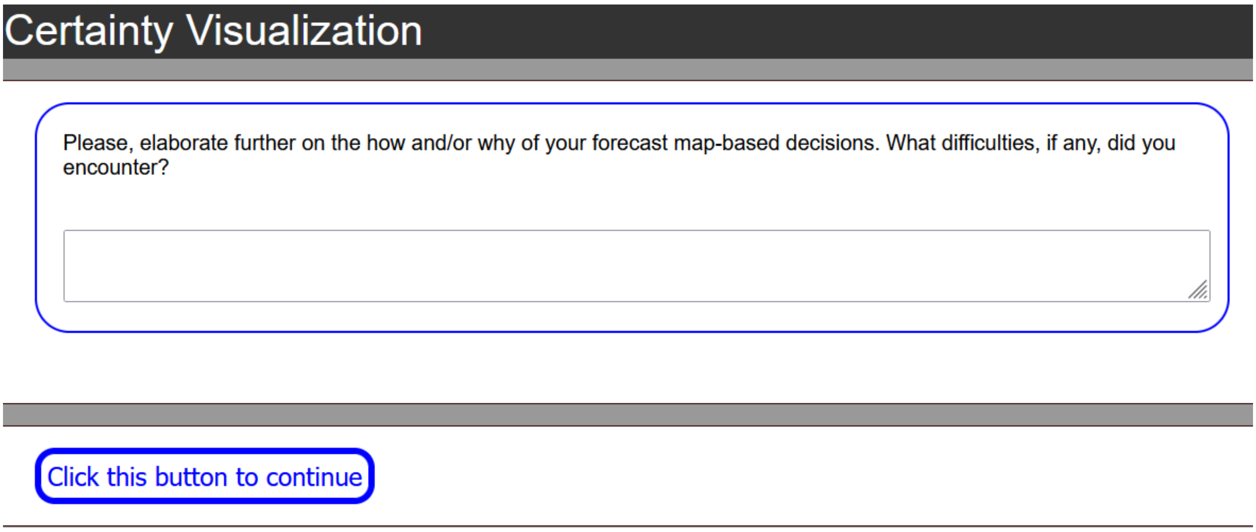
Click this button to continue

Certainty Visualization

How difficult was it for you to make your map-based decisions?

Very difficult	Difficult	Fair	Easy	Very easy

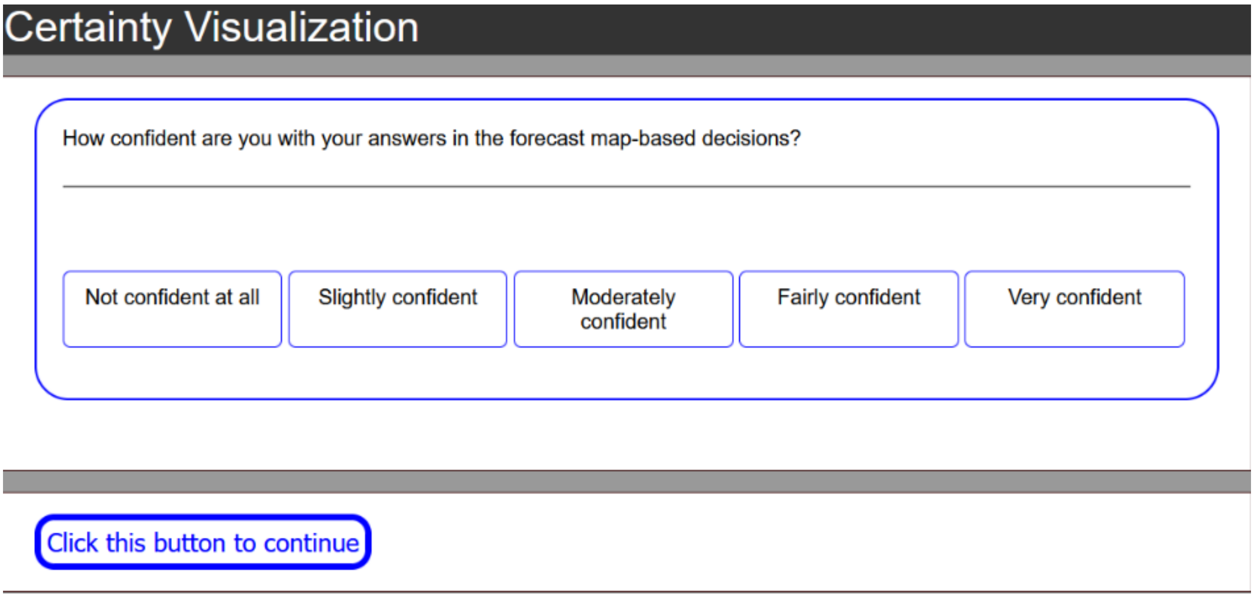
Click this button to continue



Certainty Visualization

Please, elaborate further on the how and/or why of your forecast map-based decisions. What difficulties, if any, did you encounter?

Click this button to continue



Certainty Visualization

How confident are you with your answers in the forecast map-based decisions?

Not confident at all

Slightly confident

Moderately confident

Fairly confident

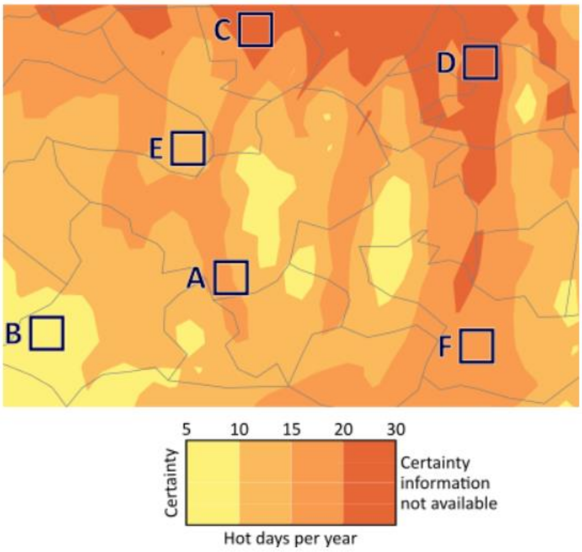
Very confident

Click this button to continue

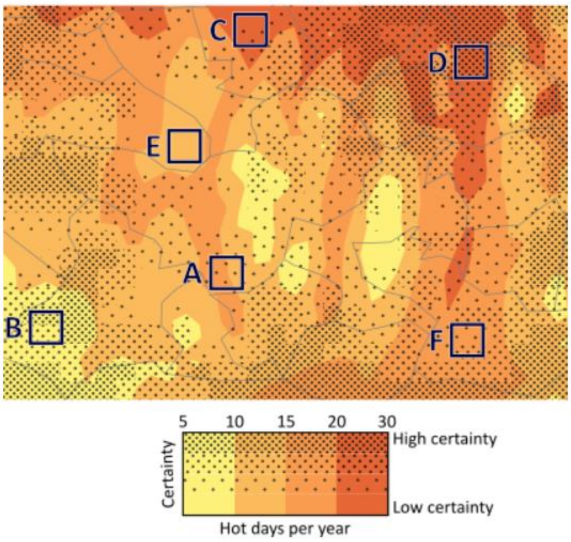
Certainty Visualization

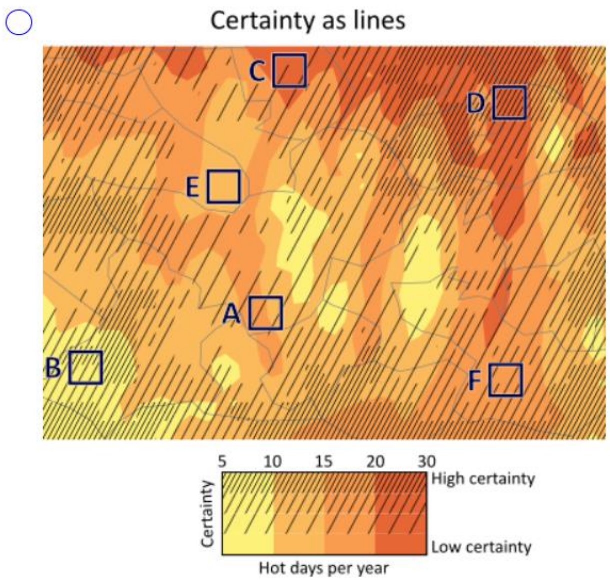
Which type of forecast certainty visualization did you find most helpful for solving the forecast map tasks?

○ No information about certainty



○ Certainty as dots





Click this button to continue

Certainty Visualization

Please, elaborate further on the why you found a type of forecast certainty visualization more helpful than the others.

Click this button to continue

Certainty Visualization

Thank you for your participation on this study! If you would like to be informed on the results of the study, please contact the researcher through the Prolific internal messaging system or via email (sergio.bazzurri@uzh.ch).

Please, click on the link below to return to Prolific, so that your completion status is registered correctly!

You are now done with this survey: Now click here to leave this website.

G Tables for distributing the areas on the maps

***Table 21**: Listing of the rotations of the letters trough the six possible locations of an area in the maps, obtained with a Latin square design.*

Rotations	Low-High (A1)	Low-Low (A2)	Mid-Mid (A3)	High-High (A4)	High-Low (A5)	Changing (A6)
Rotation 1	A	B	F	C	E	D
Rotation 2	B	C	A	D	F	E
Rotation 3	C	D	B	E	A	F
Rotation 4	D	E	C	F	B	A
Rotation 5	E	F	D	A	C	B
Rotation 6	F	A	E	B	D	C
Rotation 7 (Example)	B	E	A	D	C	F

***Table 22**: Listing of the assignments of the maps to a variant, to a rotation, and to the kind of requested area in the first question of the task. Each map possesses a different combination of those three elements.*

Map	Variant	Rotation	Requested area
Hot days dots 1	2	6	Least
Hot days dots 2	2	1	Most
Hot days lines 1	2	5	Least
Hot days lines 2	2	3	Most
Hot days none 1	2	4	Least
Hot days none 2	2	2	Most
Precipitation dots 1	1	4	Least
Precipitation dots 2	1	5	Most
Precipitation lines 1	1	3	Least
Precipitation lines 2	1	1	Most
Precipitation none 1	1	6	Least
Precipitation none 2	1	2	Most
Temperature dots 1	3	2	Least
Temperature dots 2	3	3	Most
Temperature lines 1	3	1	Least
Temperature lines 2	3	4	Most
Temperature none 1	3	6	Least
Temperature none 2	3	5	Most

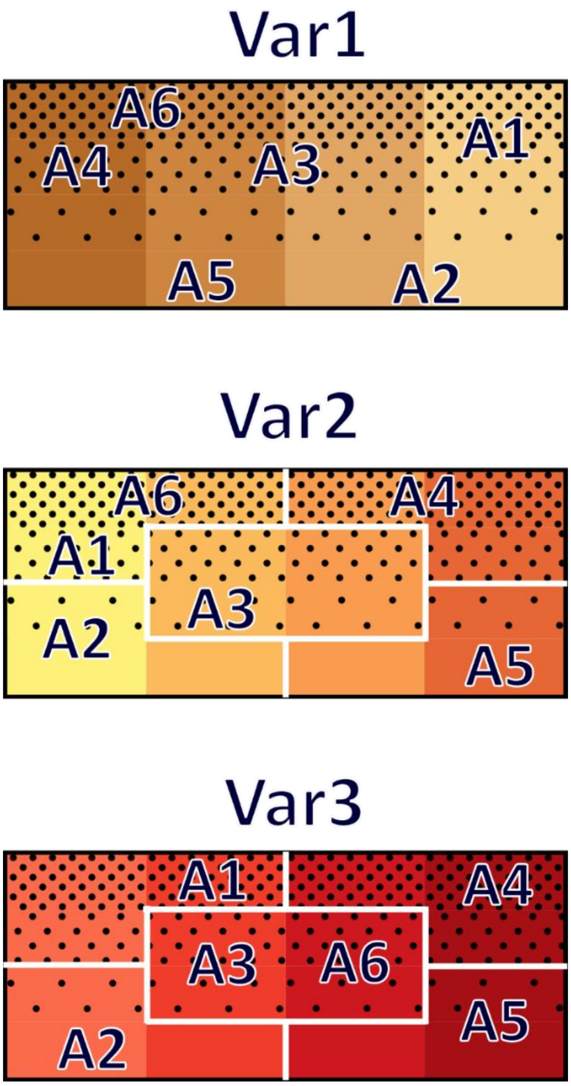
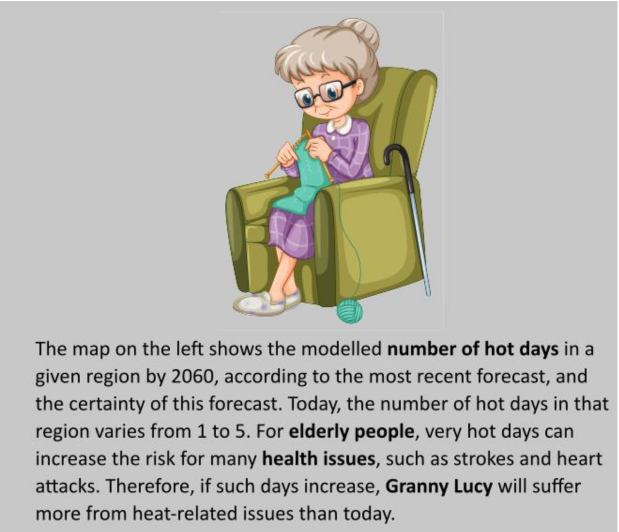
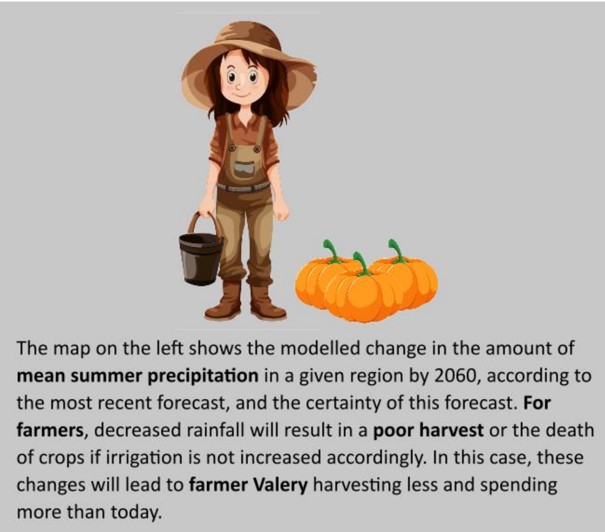


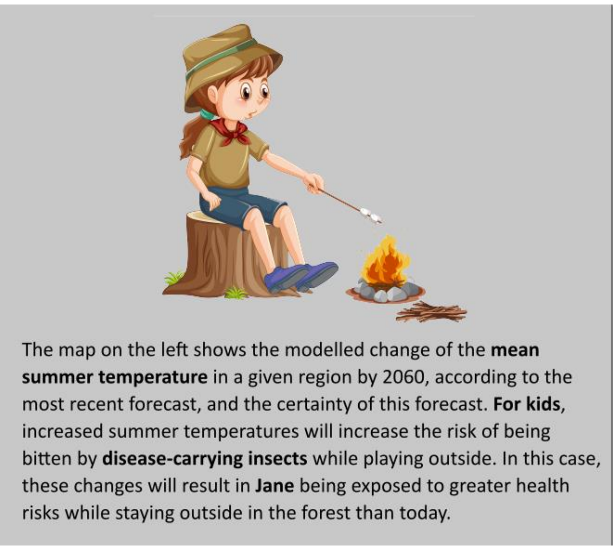
***Figure 83**: Combination of certainty level and climatic variable level for all the six area locations in the three variants.*

H Emotional stimuli

H.1 Emotional stimuli for the WE group







H.2 Texts for the NE group

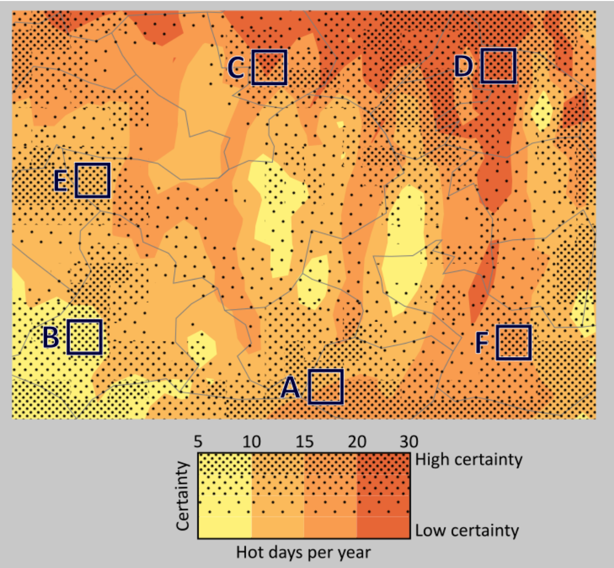
The map on the left shows the modelled **number of hot days** in a given region by 2060, according to the most recent forecast, and the certainty of this forecast. Today, the number of hot days in that region varies from 1 to 5.

The map on the left shows the modelled change in the amount of **mean summer precipitation** in a given region by 2060, according to the most recent forecast, and the certainty of this forecast.

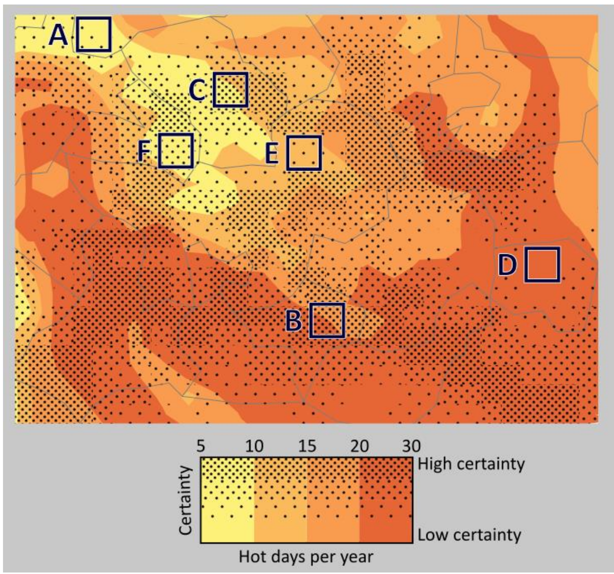
The map on the left shows the modelled change of the **mean summer temperature** in a given region by 2060, according to the most recent forecast, and the certainty of this forecast.

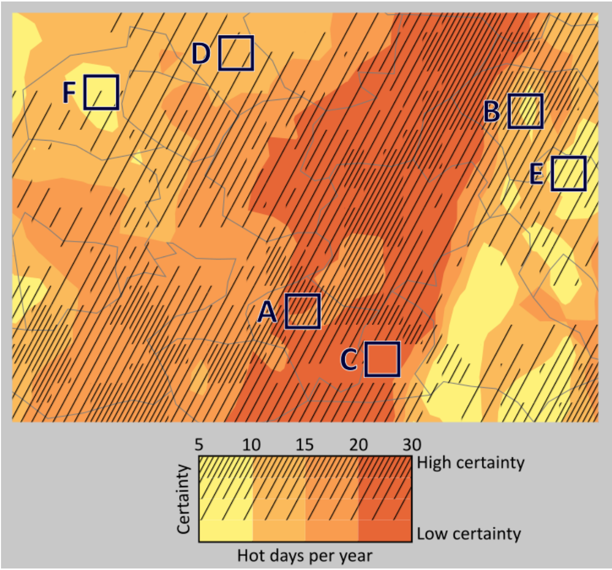
I Map stimuli

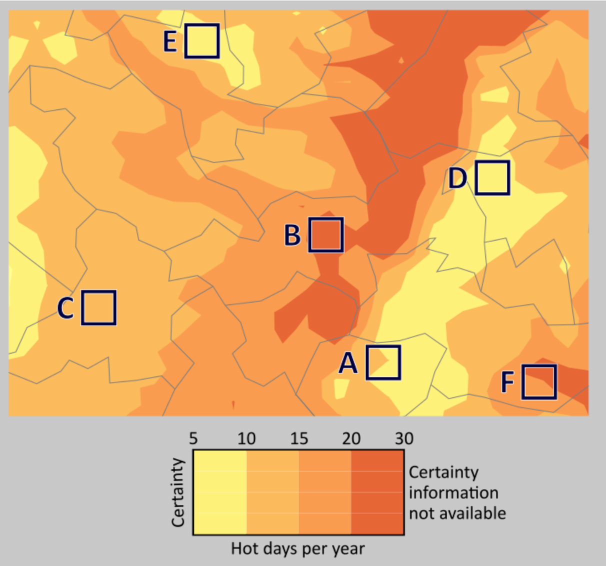
I.1 Example map stimulus

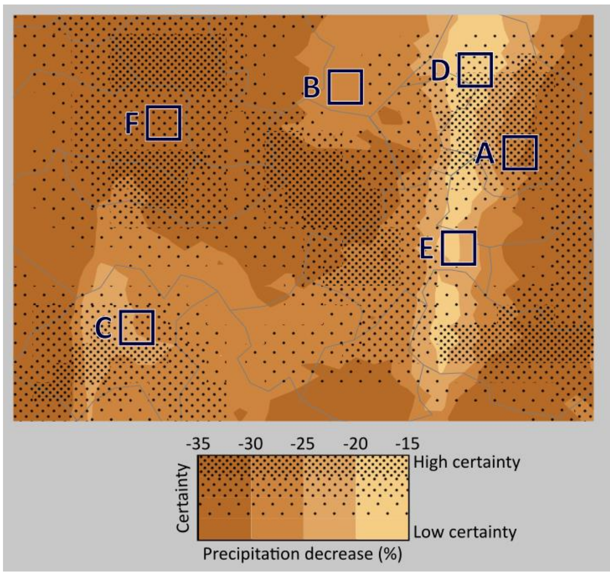


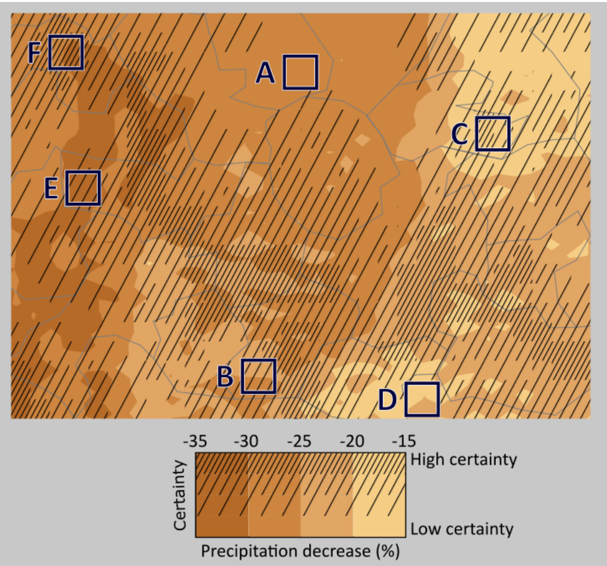
I.2 Map stimuli for the question about the least affected area

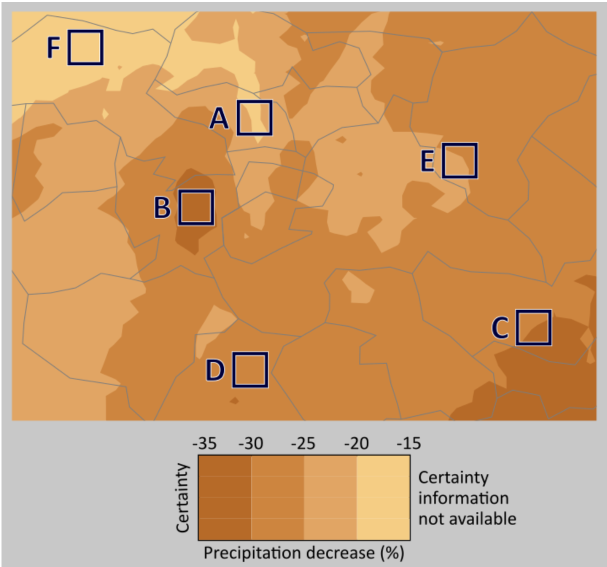


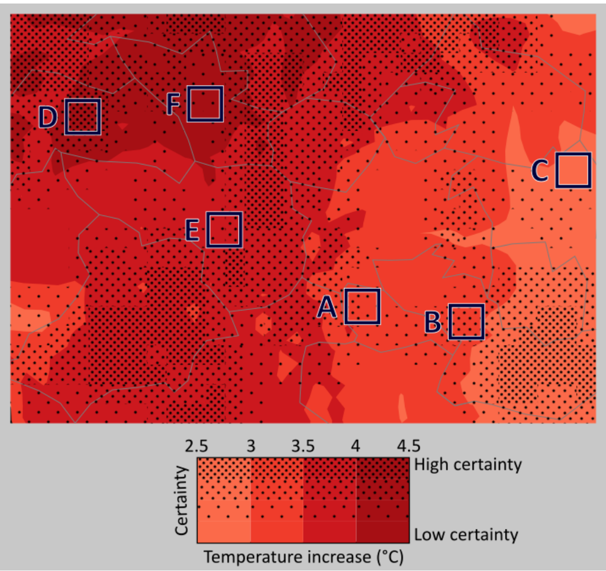


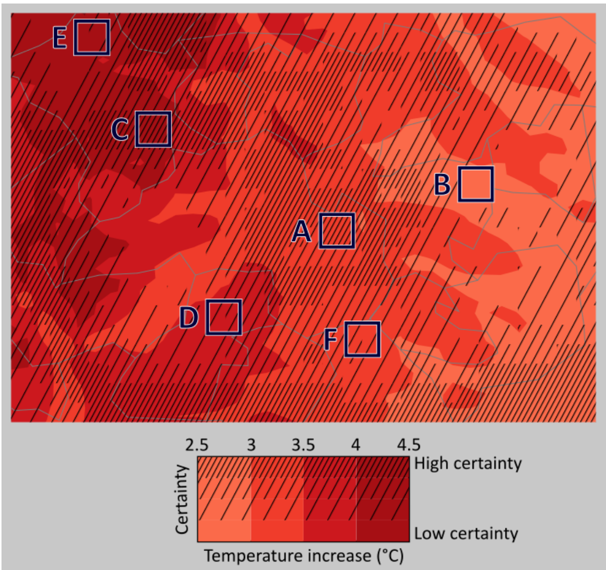

E
D
B
C
A
F
5 10 15 20 30
Certainty
Certainty information not available
Hot days per year

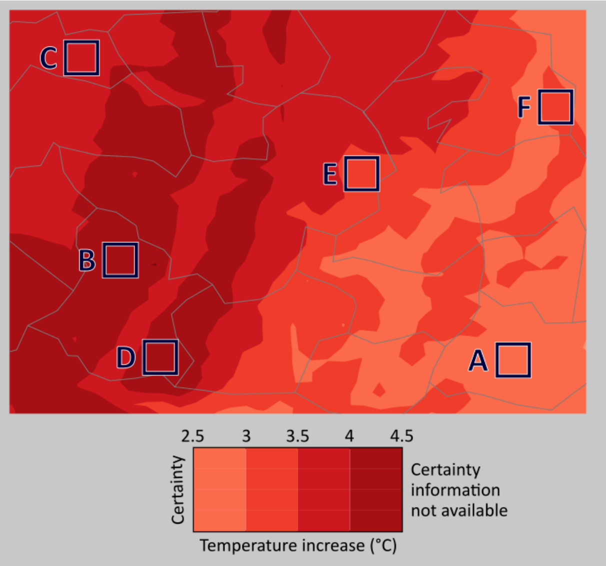

B
D
F
A
E
C
-35 -30 -25 -20 -15
Certainty
High certainty
Low certainty
Precipitation decrease (%)


F
A
C
E
B
D
-35 -30 -25 -20 -15
Certainty
High certainty
Low certainty
Precipitation decrease (%)

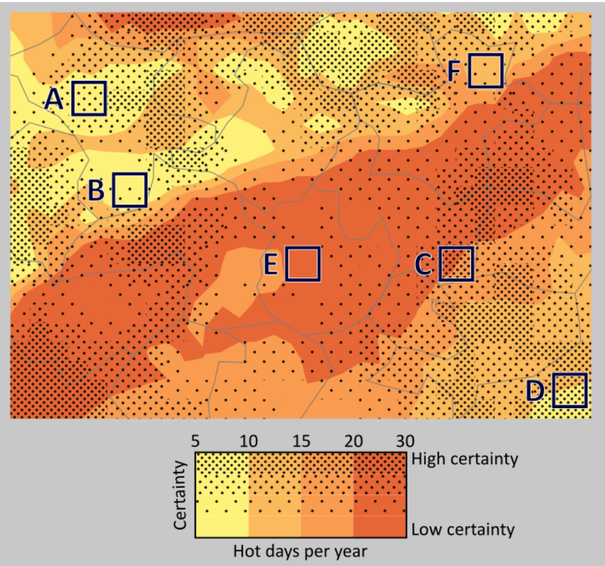

F
A
E
B
C
D
-35 -30 -25 -20 -15
Certainty
Certainty information not available
Precipitation decrease (%)

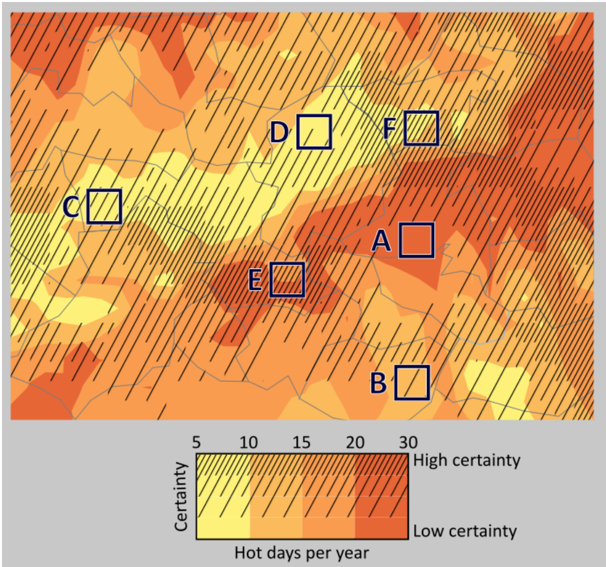

D
F
C
E
A
B
2.5 3 3.5 4 4.5
Certainty
High certainty
Low certainty
Temperature increase (°C)

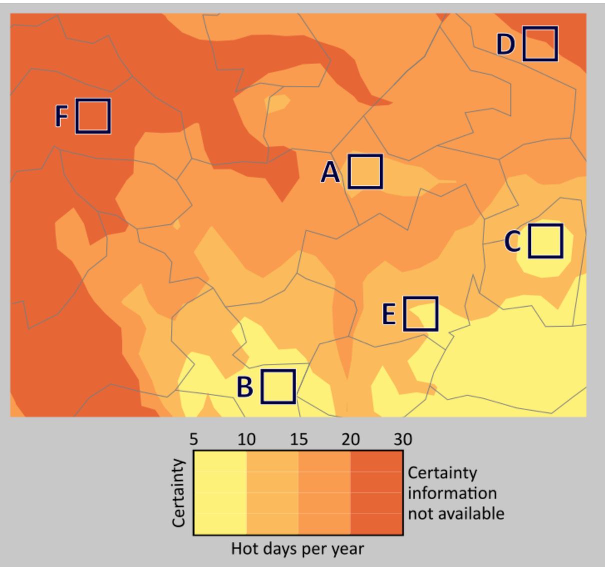

E
C
B
A
D
F
2.5 3 3.5 4 4.5
Certainty
High certainty
Low certainty
Temperature increase (°C)

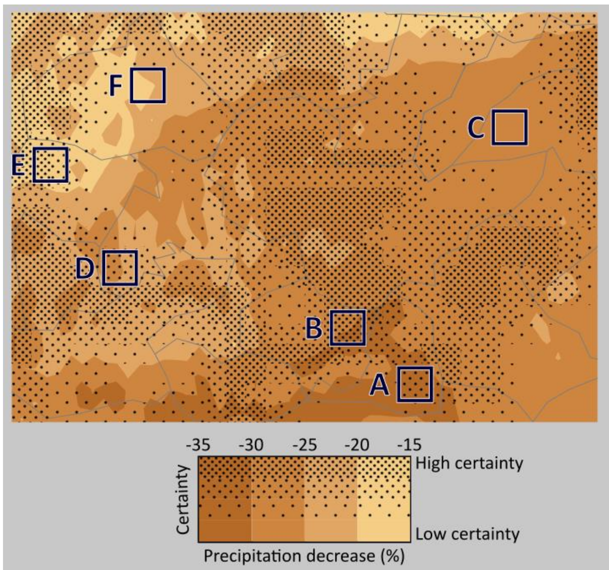


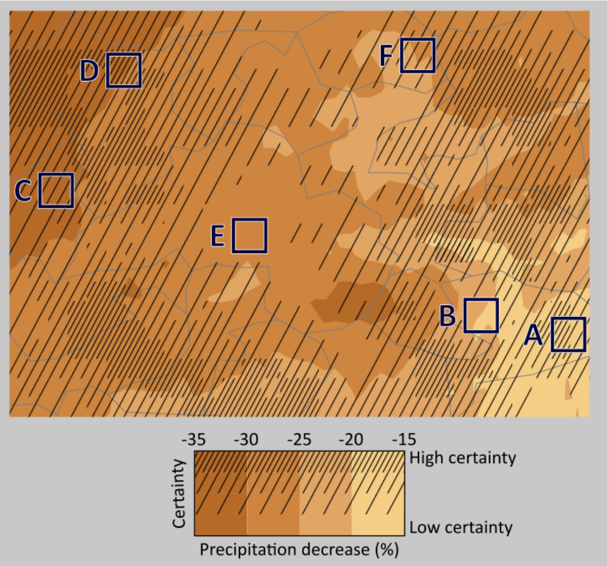
I.3 Map stimuli for the question about the most affected area

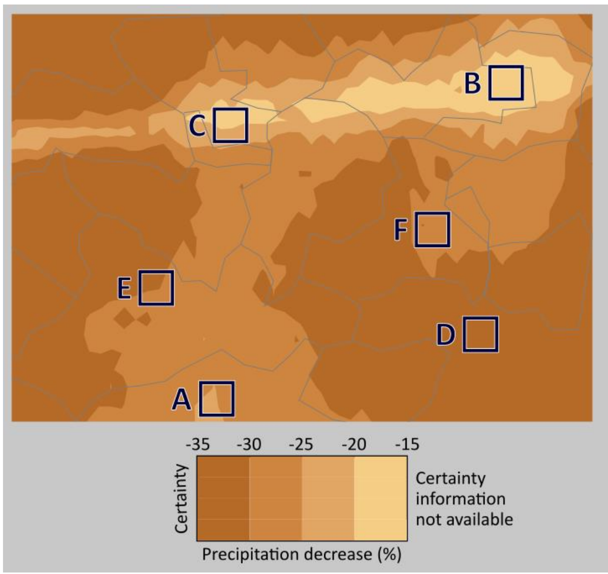


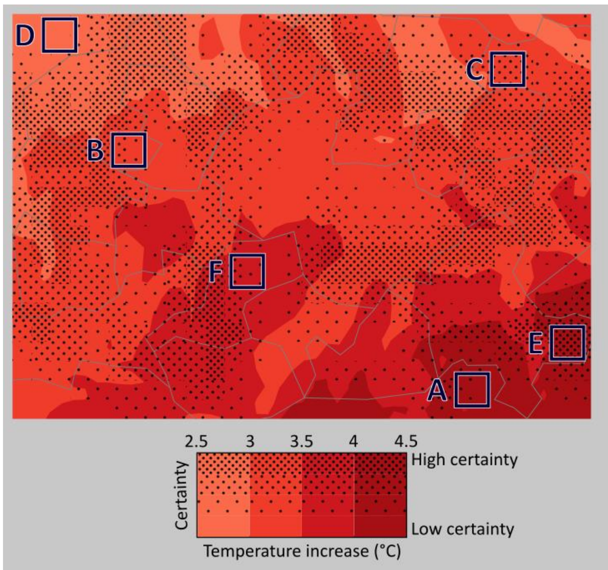


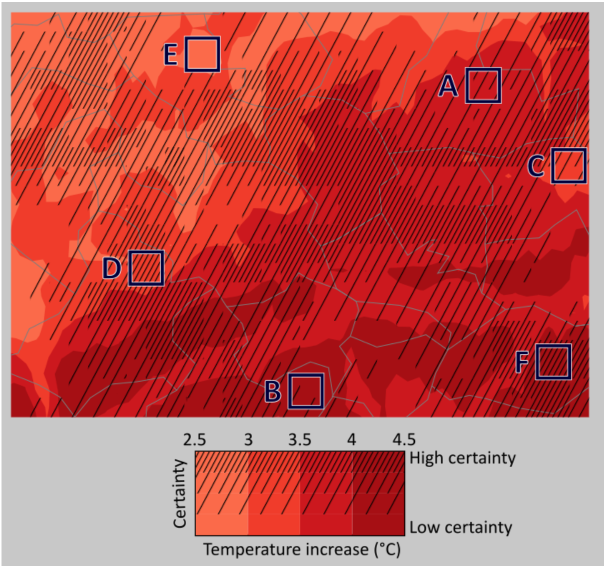


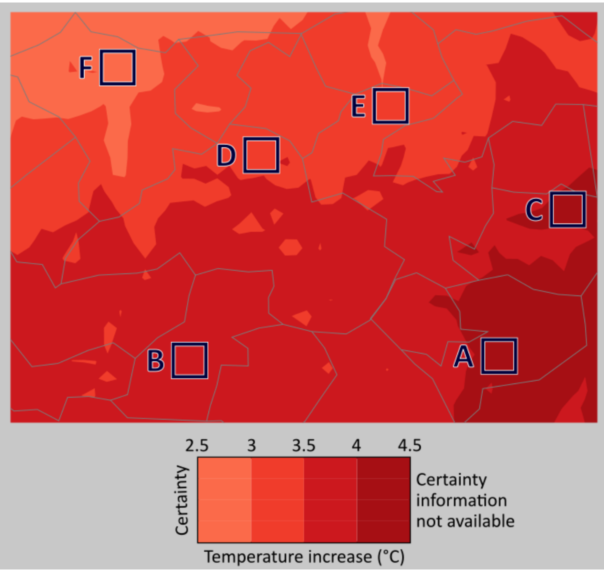



D
F
C
E
B
A
-35 -30 -25 -20 -15
Certainty
High certainty
Low certainty
Precipitation decrease (%)

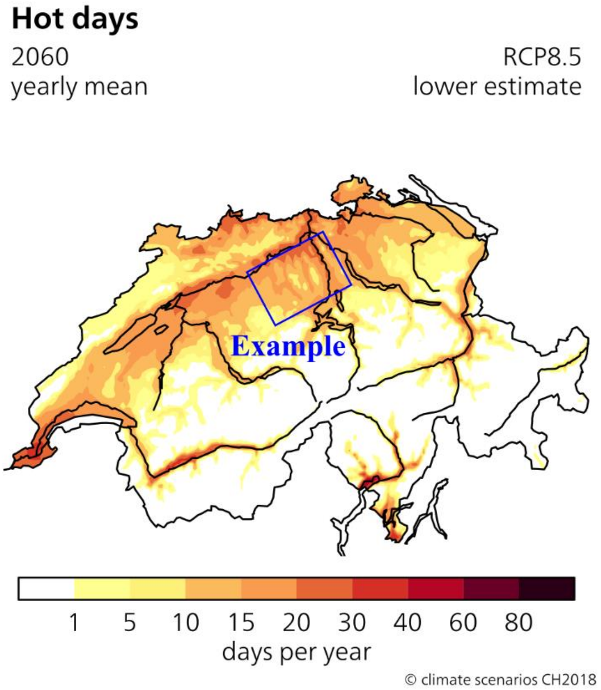

B
C
F
E
D
A
-35 -30 -25 -20 -15
Certainty
Certainty information not available
Precipitation decrease (%)

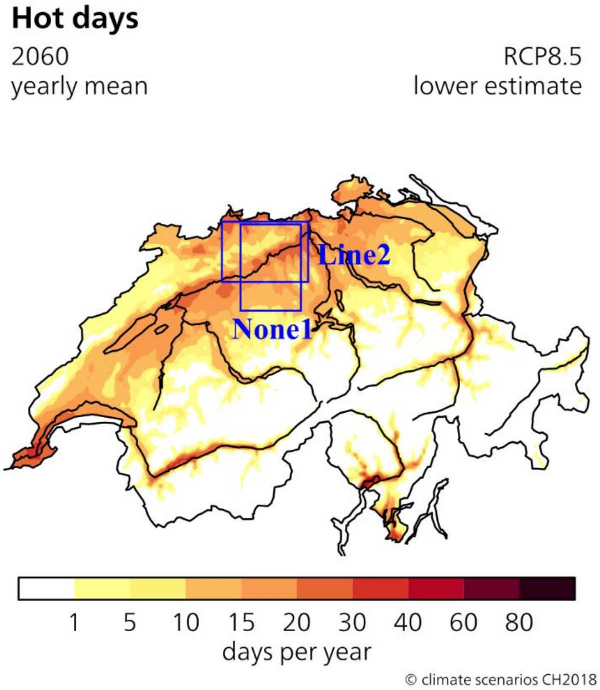

D
C
B
F
E
A
2.5 3 3.5 4 4.5
Certainty
High certainty
Low certainty
Temperature increase (°C)

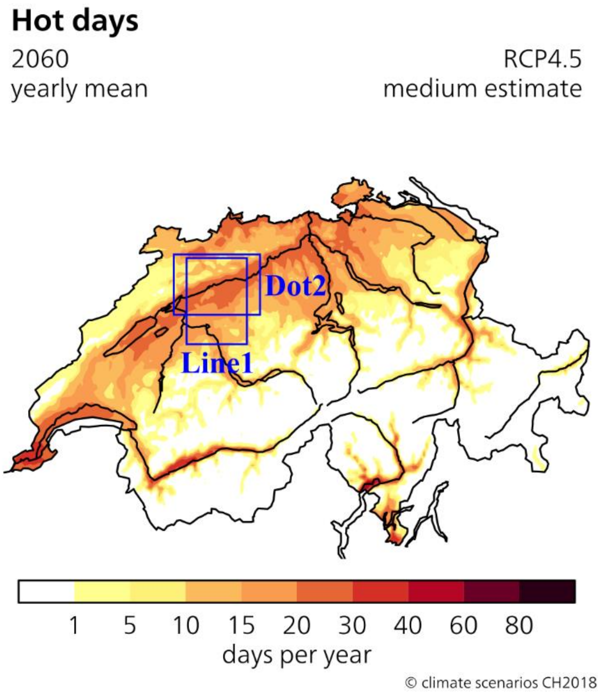

E
A
C
D
F
B
2.5 3 3.5 4 4.5
Certainty
High certainty
Low certainty
Temperature increase (°C)

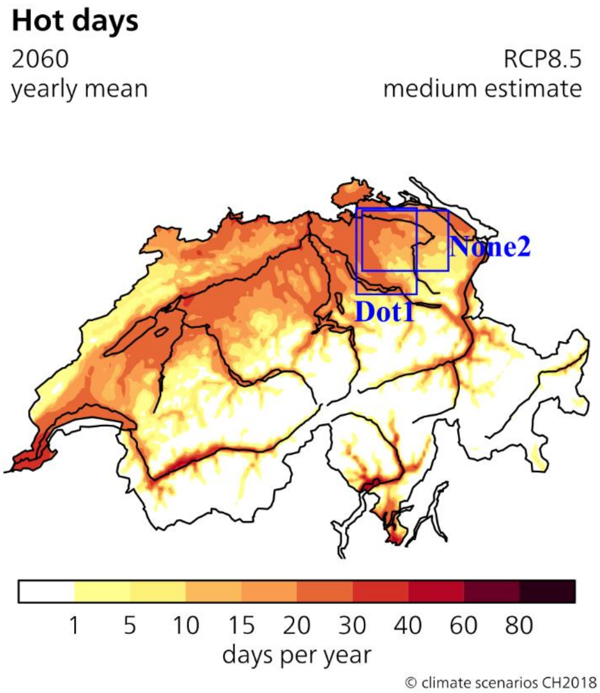

F
E
D
C
B
A
2.5 3 3.5 4 4.5
Certainty
Certainty information not available
Temperature increase (°C)

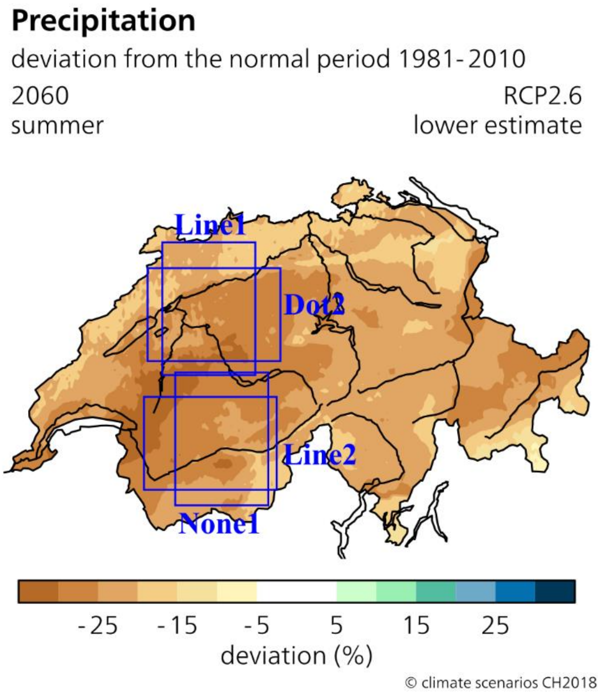
J Swiss Scenarios CH2018 maps

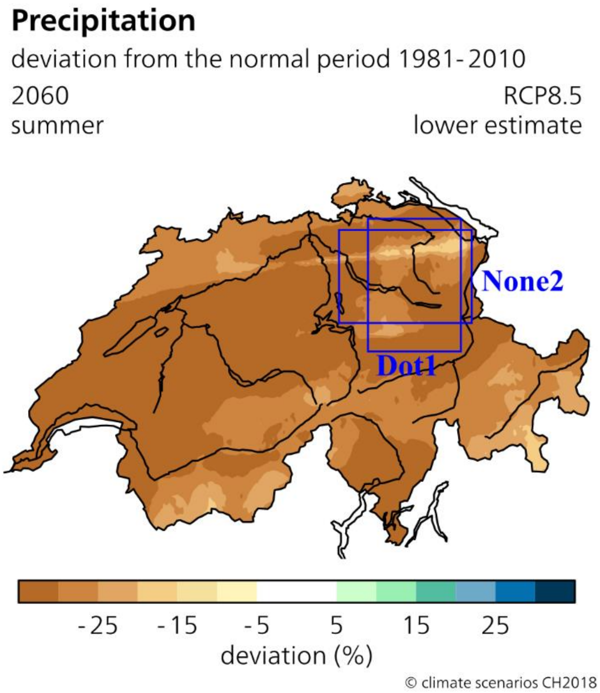


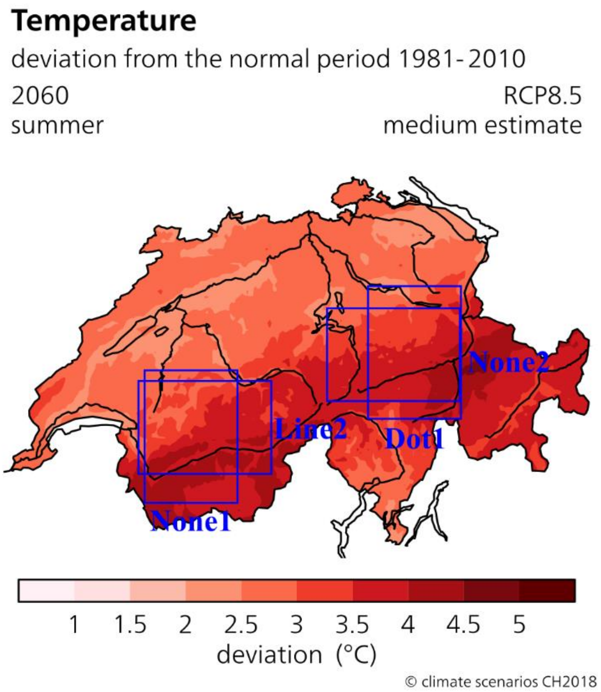


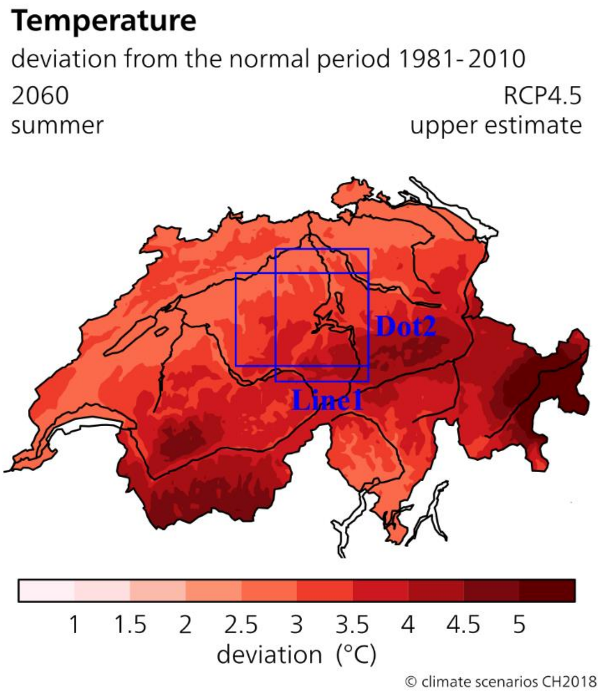





Precipitation
deviation from the normal period 1981-2010
2060
RCP2.6
summer
lower estimate
Line1
Dot2
Line2
None1
-25 -15 -5 5 15 25
deviation (%)
© climate scenarios CH2018


Precipitation
deviation from the normal period 1981-2010
2060
RCP8.5
summer
lower estimate
None2
Dot1
-25 -15 -5 5 15 25
deviation (%)
© climate scenarios CH2018


Temperature
deviation from the normal period 1981-2010
2060
RCP8.5
summer
medium estimate
None2
Line2
Dot1
None1
1 1.5 2 2.5 3 3.5 4 4.5 5
deviation (°C)
© climate scenarios CH2018


Temperature
deviation from the normal period 1981-2010
2060
RCP4.5
summer
upper estimate
Dot2
Line1
1 1.5 2 2.5 3 3.5 4 4.5 5
deviation (°C)
© climate scenarios CH2018

K Selectable areas characteristics

***Table 23**: Listing of the area types for all the selectable areas in each map.*

Map	Requested area	A	B	C	D	E	F
Hot days dots 1	Least	2	7	3	8	5	1
Hot days dots 2	Most	1	2	7	3	8	5
Hot days lines 1	Least	7	3	8	5	1	2
Hot days lines 2	Most	8	5	1	2	7	3
Hot days none 1	Least	3	9	3	1	1	7
Hot days none 2	Most	3	1	1	7	3	9
Precipitation dots 1	Least	7	6	5	1	4	9
Precipitation dots 2	Most	9	7	6	5	1	4
Precipitation lines 1	Least	6	5	1	4	9	7
Precipitation lines 2	Most	1	4	9	7	6	5
Precipitation none 1	Least	3	9	7	7	5	1
Precipitation none 2	Most	5	1	3	9	7	7
Temperature dots 1	Least	5	3	2	9	5	8
Temperature dots 2	Most	8	5	3	2	9	5
Temperature lines 1	Least	3	2	9	5	8	5
Temperature lines 2	Most	5	8	5	3	2	9
Temperature none 1	Least	1	9	7	9	3	3
Temperature none 2	Most	9	7	9	3	3	1
Example map	Least	5	1	7	9	3	7

***Table 24**: Listing of the reference value of severity for all selectable areas in each map.*

Map	Requested area	A	B	C	D	E	F
Hot days dots 1	Least	1	6	2	7	3	1
Hot days dots 2	Most	1	1	6	2	7	3
Hot days lines 1	Least	6	2	7	3	1	1
Hot days lines 2	Most	7	3	1	1	6	2
Hot days none 1	Least	2	7	3	1	1	6
Hot days none 2	Most	3	1	1	6	2	7
Precipitation dots 1	Least	6	5	4	1	2	7
Precipitation dots 2	Most	7	6	5	4	1	2
Precipitation lines 1	Least	5	4	1	2	6	7
Precipitation lines 2	Most	1	2	7	6	5	4
Precipitation none 1	Least	2	7	6	5	4	1
Precipitation none 2	Most	4	1	2	7	6	5
Temperature dots 1	Least	3	3	1	7	5	7
Temperature dots 2	Most	7	3	3	1	7	5
Temperature lines 1	Least	3	1	7	5	7	3
Temperature lines 2	Most	5	7	3	3	1	7
Temperature none 1	Least	1	7	5	7	3	3
Temperature none 2	Most	7	5	7	3	3	1
Example map	Least	4	1	6	7	3	5

***Table 25**: Listing of the reference value of certainty for all selectable areas in each map. In maps without certainty representation no reference value is available.*

Map	Requested area	A	B	C	D	E	F
Hot days dots 1	Least	2	7	7	1	3	5
Hot days dots 2	Most	5	2	7	7	1	3
Hot days lines 1	Least	7	7	1	3	5	2
Hot days lines 2	Most	1	3	5	2	7	7
Hot days none 1	Least	-	-	-	-	-	-
Hot days none 2	Most	-	-	-	-	-	-
Precipitation dots 1	Least	7	1	5	6	1	5
Precipitation dots 2	Most	5	7	1	5	6	1
Precipitation lines 1	Least	1	5	6	1	5	7
Precipitation lines 2	Most	6	1	5	7	1	5
Precipitation none 1	Least	-	-	-	-	-	-
Precipitation none 2	Most	-	-	-	-	-	-
Temperature dots 1	Least	4	5	1	7	4	2
Temperature dots 2	Most	2	4	5	1	7	4
Temperature lines 1	Least	7	1	7	4	2	4
Temperature lines 2	Most	4	2	4	7	1	7
Temperature none 1	Least	-	-	-	-	-	-
Temperature none 2	Most	-	-	-	-	-	-
Example map	Least	7	7	7	7	7	7

L Statistical results

For the interpretation of the shown significance codes please use the following guidelines.

ANOVA: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 0.

All other tests: 0 '****' 0.0001 '***' 0.001 '**' 0.01 '*' 0.05 'ns' 0.

L.1 Pre-test part

Kolmogorov-Smirnov test for the age distribution

```
        Exact two-sample Kolmogorov-Smirnov test

data:  age_WE and age_NE
D = 0.085185, p-value = 0.9241
alternative hypothesis: two-sided
```

Fisher test for visual impairment

```
        Fisher's Exact Test for Count Data

data:  .
p-value = 0.162
alternative hypothesis: two.sided
```

Fisher test for the educational background

```
        Fisher's Exact Test for Count Data

data:  .
p-value = 0.3031
alternative hypothesis: two.sided
```

Fisher test for the map use frequency

```
        Fisher's Exact Test for Count Data

data:  .
p-value = 0.4018
alternative hypothesis: two.sided
```

Fisher tests for the familiarity to concepts

The tests are presented in this order: cartography, GIS, climate change mapping, IPCC, statistics, uncertainty.

```
        Fisher's Exact Test for Count Data

data:  .
p-value = 0.7708
alternative hypothesis: two.sided


        Fisher's Exact Test for Count Data

data:  .
p-value = 0.3377
alternative hypothesis: two.sided
```

```
        Fisher's Exact Test for Count Data

data:  .
p-value = 0.3171
alternative hypothesis: two.sided


        Fisher's Exact Test for Count Data

data:  .
p-value = 0.9301
alternative hypothesis: two.sided


        Fisher's Exact Test for Count Data

data:  .
p-value = 0.481
alternative hypothesis: two.sided


        Fisher's Exact Test for Count Data

data:  .
p-value = 0.2943
alternative hypothesis: two.sided
```

Normality tests for pre-SAM scores distribution (Shapiro-Wilk)

```
  emotion_group variable           statistic        p
  <fct>         <chr>                  <dbl>    <dbl>
1 NE            pre_pleasure_value     0.924 0.00189
2 WE            pre_pleasure_value     0.911 0.000699


  emotion_group variable          statistic       p
  <fct>         <chr>                 <dbl>   <dbl>
1 NE            pre_arousal_value     0.921 0.00149
2 WE            pre_arousal_value     0.944 0.0143


  emotion_group variable            statistic         p
  <fct>         <chr>                   <dbl>     <dbl>
1 NE            pre_dominance_value     0.912 0.000658
2 WE            pre_dominance_value     0.883 0.0000758
```

Mann-Whitney U test for comparison between experimental groups of pre-SAM scores

```
  .y.                group1 group2    n1    n2 statistic     p p.signif
  <chr>              <chr>  <chr>  <int> <int>     <dbl> <dbl> <chr>
1 pre_pleasure_value NE     WE        55    54      1402  0.61 ns


  .y.               group1 group2    n1    n2 statistic     p p.signif
  <chr>             <chr>  <chr>  <int> <int>     <dbl> <dbl> <chr>
1 pre_arousal_value NE     WE        55    54      1480 0.978 ns


  .y.                 group1 group2    n1    n2 statistic     p p.signif
  <chr>               <chr>  <chr>  <int> <int>     <dbl> <dbl> <chr>
1 pre_dominance_value NE     WE        55    54     1460. 0.878 ns
```

Normality test for the TEQ scores (Shapiro-Wilk)

```
  emotion_group variable  statistic       p
  <fct>         <chr>         <dbl>   <dbl>
1 NE            TEQ_score     0.980 0.498
2 WE            TEQ_score     0.930 0.00352
```

Mann-Whitney U test for comparison between experimental groups of TEQ scores

```
  .y.       group1 group2    n1    n2 statistic     p p.signif
  <chr>     <chr>  <chr>  <int> <int>     <dbl> <dbl> <chr>
1 TEQ_score NE     WE        55    54      1331  0.35 ns
```

Normality test for the CCA scores (Shapiro-Wilk)

```
  emotion_group variable      statistic       p
  <fct>         <chr>             <dbl>   <dbl>
1 NE            climate_score     0.946 0.0152
2 WE            climate_score     0.938 0.00767

  emotion_group prolific_climate variable      statistic       p
  <fct>         <fct>            <chr>             <dbl>   <dbl>
1 NE            No               climate_score     0.949 0.191
2 NE            Yes              climate_score     0.967 0.522
3 WE            No               climate_score     0.861 0.00194
4 WE            Yes              climate_score     0.913 0.0263
```

Mann-Whitney U test for comparison between experimental groups and climate change attitude of CCA scores

```
  prolific_climate .y.           group1 group2    n1    n2 statistic     p
  <fct>            <chr>         <chr>  <chr>  <int> <int>     <dbl> <dbl>
<chr>
1 No               climate_score NE     WE        28    27       412  0.572
2 Yes              climate_score NE     WE        27    27       344. 0.735


  emotion_group .y.           group1 group2    n1    n2 statistic            p
  <fct>         <chr>         <chr>  <chr>  <int> <int>     <dbl>        <dbl>
<chr>
1 NE            climate_score No     Yes       28    27      53.5 0.0000000469
2 WE            climate_score No     Yes       27    27      57   0.000000105
```

L.2 Main experiment part

Normality test for the mean scores depending on the experimental group (Shapiro-Wilk)

```
  emotion_group variable       statistic           p
  <fct>         <chr>              <dbl>       <dbl>
1 WE            mean_score_tot     0.810 0.000000713
2 NE            mean_score_tot     0.836 0.00000270


  most_least emotion_group variable       statistic           p
  <fct>      <fct>         <chr>              <dbl>       <dbl>
1 least      WE            mean_score_tot     0.842 0.00000491
2 most       WE            mean_score_tot     0.790 0.000000241
3 least      NE            mean_score_tot     0.810 0.000000591
4 most       NE            mean_score_tot     0.885 0.0000773
```

Homoscedasticity test for mean scores depending on the experimental group (Levene)

```
    df1   df2 statistic     p
  <int> <int>     <dbl> <dbl>
1     1   107    0.0868 0.769


  most_least   df1   df2 statistic      p
  <fct>      <int> <int>     <dbl>  <dbl>
1 least          1   107     0.300 0.585
2 most           1   107     3.46  0.0657
```

Mann-Whitney U test for the mean scores depending on the experimental group

```
  .y.            group1 group2    n1    n2 statistic     p p.signif
  <chr>          <chr>  <chr>  <int> <int>     <dbl> <dbl> <chr>
1 mean_score_tot WE     NE        54    55      1248 0.151 ns
```

ANOVA on ART data for mean scores depending on the experimental group and kind of requested area

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(mean_score_tot)

                                   F Df Df.res  Pr(>F) eta.sq.part
1 emotion_group              1.02603  1    107 0.31338   0.0094980
2 most_least               455.78811  1    107 < 2e-16   0.8098752 ***
3 emotion_group:most_least   0.84443  1    107 0.36020   0.0078301
```

Normality test for mean scores depending on the climate change attitude (Shapiro-Wilk)

```
  emotion_group prolific_climate variable       statistic           p p.signif
  <fct>         <fct>            <chr>              <dbl>       <dbl> <chr>
1 WE            No               mean_score_tot     0.939 0.116       ns
2 WE            Yes              mean_score_tot     0.609 0.000000263 ****
3 NE            No               mean_score_tot     0.917 0.0285      *
4 NE            Yes              mean_score_tot     0.788 0.0000851   ****
```

Homoscedasticity test for mean scores depending on the climate change attitude (Levene)

```
  prolific_climate   df1   df2 statistic     p p.signif
  <fct>            <int> <int>     <dbl> <dbl> <chr>
1 No                   1    53     1.95  0.169 ns
2 Yes                  1    52     0.331 0.568 ns
```

ANOVA on ART data for mean scores depending on experimental group and the climate change attitude

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Anova Table (Type III tests)
Model: No Repeated Measures (lm)
Response: art(mean_score_tot)

                                 Df Df.res  F value  Pr(>F)
1 emotion_group                   1    105 1.845532 0.17722
2 prolific_climate                1    105 0.022795 0.88028
3 emotion_group:prolific_climate  1    105 0.422142 0.51729
```

Normality test for mean scores depending on the certainty visualization (Shapiro-Wilk)

```
  certainty_type emotion_group variable           statistic           p p.signi
  <fct>          <fct>         <chr>                  <dbl>       <dbl> <chr>
1 none           WE            mean_score_vis_type     0.736 0.0000000160 ****
2 dots           WE            mean_score_vis_type     0.841 0.00000443   ****
3 lines          WE            mean_score_vis_type     0.916 0.00107      **
4 none           NE            mean_score_vis_type     0.813 0.000000705  ****
5 dots           NE            mean_score_vis_type     0.909 0.000516     ***
6 lines          NE            mean_score_vis_type     0.820 0.00000107   ****
```

Homoscedasticity test for mean scores depending on the certainty visualization (Levene)

```
  certainty_type   df1   df2 statistic     p
  <fct>          <int> <int>     <dbl> <dbl>
1 none               1   107    0.0164 0.898
2 dots               1   107    0.114  0.736
3 lines              1   107    0.220  0.640
```

ANOVA on ART data for mean scores depending on experimental group and the certainty visualization type

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(mean_score_vis_type)

                                     F Df Df.res  Pr(>F)
1 emotion_group                1.09837  1    107 0.29699
2 certainty_type               1.61723  2    214 0.20086
3 emotion_group:certainty_type 0.60947  2    214 0.54458
```

Normality test for normalized scores depending on the experimental group (Shapiro-Wilk)

```
   emotion_group region_type variable   statistic            p p.signif
   <fct>         <fct>       <chr>          <dbl>        <dbl> <chr>
 1 WE            1           normalized     0.917 0.000164     ***
 2 WE            2           normalized     0.875 0.0000579    ****
 3 WE            3           normalized     0.721 0.0000363    ****
 4 WE            4           normalized     0.503 0.00000000598 ****
 5 WE            5           normalized     0.574 0.0000120    ****
 6 WE            6           normalized     0.640 0.00135      **
 7 WE            7           normalized     0.841 0.000000486  ****
 8 WE            8           normalized     0.742 0.0000696    ****
 9 WE            9           normalized     0.863 0.000000984  ****
10 NE            1           normalized     0.904 0.0000478    ****
11 NE            2           normalized     0.857 0.0000336    ****
12 NE            3           normalized     0.725 0.0000409    ****
13 NE            4           normalized     0.598 0.000000586  ****
14 NE            5           normalized     0.564 0.0000359    ****
15 NE            6           normalized     0.418 0.00000105   ****
16 NE            7           normalized     0.898 0.000109     ***
17 NE            8           normalized     0.787 0.0000145    ****
18 NE            9           normalized     0.908 0.0000666    ****
```

Homoscedasticity test for normalized scores depending on the experimental group (Levene)

```
  region_type   df1   df2 statistic      p p.signif
  <fct>       <int> <int>     <dbl>  <dbl> <chr>
1 1               1   141    2.60   0.109  ns
2 2               1    98    0.0283 0.867  ns
3 3               1    42    0.169  0.683  ns
4 4               1    46    0.928  0.340  ns
5 5               1    18    0.103  0.752  ns
6 6               1    12    0.809  0.386  ns
7 7               1   126    2.86   0.0932 ns
8 8               1    54    0.0377 0.847  ns
9 9               1   144    1.53   0.217  ns
```

Mann-Whitney U test for normalized scores depending on the experimental group (with effect sizes)

```
  region_type .y.        group1 group2    n1    n2 statistic      p p.signif
  <fct>       <chr>      <chr>  <chr>  <int> <int>     <dbl>  <dbl> <chr>
1 1           normalized WE     NE        72    71     2720   0.504  ns
2 2           normalized WE     NE        52    48     1294   0.744  ns
3 3           normalized WE     NE        22    22      252.  0.812  ns
4 4           normalized WE     NE        24    24      252   0.342  ns
5 5           normalized WE     NE        11     9       52   0.841  ns
6 6           normalized WE     NE         6     8       29   0.415  ns
7 7           normalized WE     NE        68    60     1623   0.0396 *
8 8           normalized WE     NE        22    34      329   0.414  ns
9 9           normalized WE     NE        74    72     2496.  0.502  ns


  .y.        group1 group2 effsize region_type    n1    n2 magnitude
* <chr>      <chr>  <chr>    <dbl> <fct>       <int> <int> <ord>
1 normalized WE     NE      0.0561 1              72    71 small
2 normalized WE     NE      0.0330 2              52    48 small
3 normalized WE     NE      0.0379 3              22    22 small
4 normalized WE     NE      0.139  4              24    24 small
5 normalized WE     NE      0.0560 5              11     9 small
6 normalized WE     NE      0.242  6               6     8 small
7 normalized WE     NE      0.182  7              68    60 small
8 normalized WE     NE      0.110  8              22    34 small
9 normalized WE     NE      0.0557 9              74    72 small
```

Normality test for normalized scores depending on the climate change attitude (Shapiro-Wilk)

```
   prolific_climate region_type variable   statistic           p p.signif
   <fct>            <fct>       <chr>          <dbl>       <dbl> <chr>
 1 No               1           normalized     0.925 0.000246    ***
 2 No               2           normalized     0.877 0.0000575   ****
 3 No               3           normalized     0.661 0.0000291   ****
 4 No               4           normalized     0.591 0.000000112 ****
 5 No               5           normalized     0.486 0.00000102  ****
 6 No               6           normalized     0.600 0.000275    ***
 7 No               7           normalized     0.850 0.00000104  ****
 8 No               8           normalized     0.786 0.0000112   ****
 9 No               9           normalized     0.910 0.0000532   ****
10 Yes              1           normalized     0.897 0.0000426   ****
11 Yes              2           normalized     0.873 0.000112    ***
12 Yes              3           normalized     0.759 0.0000385   ****
13 Yes              4           normalized     0.495 0.000000289 ****
14 Yes              5           normalized     0.683 0.000889    ***
15 Yes              6           normalized     0.453 0.00000414  ****
16 Yes              7           normalized     0.890 0.0000509   ****
17 Yes              8           normalized     0.729 0.0000647   ****
18 Yes              9           normalized     0.865 0.00000204  ****
```

Homoscedasticity test for normalized scores depending on climate change attitude (Levene)

```
  region_type   df1   df2 statistic     p p.signif
  <fct>       <int> <int>     <dbl> <dbl> <chr>
1 1               1   141  1.59     0.210 ns
2 2               1    98  0.0993   0.753 ns
3 3               1    42  0.419    0.521 ns
4 4               1    46  0.850    0.361 ns
5 5               1    18  1.80     0.196 ns
6 6               1    12  0.375    0.552 ns
7 7               1   126  0.631    0.428 ns
8 8               1    54  0.505    0.480 ns
9 9               1   144  0.000468 0.983 ns
```

Mann-Whitney U test for normalized scores depending on the climate change attitude (with effect sizes)

```
  region_type .y.        group1 group2    n1    n2 statistic      p p.signif
  <fct>       <chr>      <chr>  <chr>  <int> <int>     <dbl>  <dbl> <chr>
1 1           normalized No     Yes       76    67     2002. 0.0258 *
2 2           normalized No     Yes       53    47     1456  0.132  ns
3 3           normalized No     Yes       18    26      206  0.459  ns
4 4           normalized No     Yes       28    20      314  0.363  ns
5 5           normalized No     Yes       11     9       40  0.368  ns
6 6           normalized No     Yes        7     7       28  0.591  ns
7 7           normalized No     Yes       67    61     1576  0.0211 *
8 8           normalized No     Yes       35    21      428. 0.271  ns
9 9           normalized No     Yes       76    70     2306. 0.158  ns


  .y.        group1 group2 effsize region_type    n1    n2 magnitude
* <chr>      <chr>  <chr>    <dbl> <fct>       <int> <int> <ord>
1 normalized No     Yes      0.187 1              76    67 small
2 normalized No     Yes      0.151 2              53    47 small
3 normalized No     Yes      0.114 3              18    26 small
4 normalized No     Yes      0.133 4              28    20 small
5 normalized No     Yes      0.213 5              11     9 small
6 normalized No     Yes      0.168 6               7     7 small
7 normalized No     Yes      0.204 7              67    61 small
8 normalized No     Yes      0.148 8              35    21 small
9 normalized No     Yes      0.117 9              76    70 small
```

Normality test for severity rating depending on the experimental group (Shapiro-Wilk)

```
  emotion_group most_least variable       statistic        p p.signif
  <fct>         <fct>      <chr>              <dbl>    <dbl> <chr>
1 WE            least      severity_value     0.926 1.07e-14 ****
2 WE            most       severity_value     0.822 7.87e-23 ****
3 NE            least      severity_value     0.875 1.53e-19 ****
4 NE            most       severity_value     0.801 3.30e-24 ****


  emotion_group variable       statistic        p p.signif
  <fct>         <chr>              <dbl>    <dbl> <chr>
1 WE            severity_value     0.907 7.17e-24 ****
2 NE            severity_value     0.876 2.37e-27 ****
```

ANOVA on ART data for severity rating depending on experimental group

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(severity_value)

                      F Df Df.res  Pr(>F)
1 emotion_group 0.60892  1    107 0.43692
```

ANOVA on ART data for severity rating depending on experimental group and kind of requested area

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(severity_value)

                                   F Df Df.res     Pr(>F) eta.sq.part
1 emotion_group           4.3375e-02  1    107    0.83542  0.00040521
2 most_least              1.5198e+03  1   1851 < 2.22e-16  0.45086682 ***
3 emotion_group:most_least 1.6225e+01  1   1851 5.8514e-05  0.00868947 ***
```

ART data contrasts between most and least affected area for the severity rating

```
             contrast  estimate       SE        df    t.ratio       p.value sig
1  NE,least - NE,most -784.5687 25.24466 1851.0000 -31.078605 3.179690e-170 ***
2 NE,least - WE,least  -55.3072 42.05700  159.3841  -1.315053  1.000000e+00
3  NE,least - WE,most -669.8905 42.05700  159.3841 -15.928156  5.269106e-34 ***
4  NE,most - WE,least  729.2615 42.05700  159.3841  17.339835  9.589461e-38 ***
5   NE,most - WE,most  114.6782 42.05700  159.3841   2.726731  4.267864e-02   *
6  WE,least - WE,most -614.5833 25.47733 1851.0000 -24.122752 3.031626e-111 ***
```

Normality test for severity rating depending on the experimental group and climate change attitude (Shapiro-Wilk)

```
  emotion_group prolific_climate variable       statistic        p p.signif
  <fct>         <fct>            <chr>              <dbl>    <dbl> <chr>
1 WE            No               severity_value     0.921 2.73e-15 ****
2 WE            Yes              severity_value     0.880 6.23e-19 ****
3 NE            No               severity_value     0.866 2.32e-20 ****
4 NE            Yes              severity_value     0.879 5.31e-19 ****
```

Homoscedasticity test for severity rating depending on climate change attitude (Levene)

```
  prolific_climate   df1   df2 statistic          p p.signif
  <fct>            <int> <int>     <dbl>      <dbl> <chr>
1 No                   1   988      21.5  0.0000411 ****
2 Yes                  1   970      3.37 0.0668     ns
```

ANOVA on ART data for severity rating depending on experimental group and climate change attitude

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(severity_value)

                                        F Df Df.res   Pr(>F) eta.sq.part
1 emotion_group                 0.5643079  1    105 0.454210  5.3456e-03
2 prolific_climate              5.4457725  1    105 0.021521  4.9307e-02 *
3 emotion_group:prolific_climate 0.0048235  1    105 0.944762  4.5936e-05
```

Normality test for severity rating depending on experimental group and the certainty visualization type (Shapiro-Wilk)

```
  emotion_group certainty_type variable       statistic        p p.signif
  <fct>         <fct>          <chr>              <dbl>    <dbl> <chr>
1 WE            none           severity_value     0.903 1.40e-13 ****
2 WE            dots           severity_value     0.909 4.47e-13 ****
3 WE            lines          severity_value     0.908 4.07e-13 ****
4 NE            none           severity_value     0.872 6.36e-16 ****
5 NE            dots           severity_value     0.881 2.74e-15 ****
6 NE            lines          severity_value     0.873 7.71e-16 ****
```

Homoscedasticity test for severity rating depending on the certainty visualization type (Levene)

```
  certainty_type   df1   df2 statistic     p p.signif
  <fct>          <int> <int>     <dbl> <dbl> <chr>
1 none               1   652     2.14  0.144 ns
2 dots               1   652     1.01  0.315 ns
3 lines              1   652     0.375 0.540 ns
```

ANOVA on ART data for severity rating depending on experimental group and the certainty visualization

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(severity_value)

                                      F Df Df.res   Pr(>F) eta.sq.part
1 emotion_group                4.331094  1    107 0.039809  3.8903e-02 *
2 certainty_type               0.251208  2   1849 0.777887  2.7165e-04
3 emotion_group:certainty_type 0.026462  2   1849 0.973886  2.8622e-05
```

Normality test for the difference from reference of severity rating depending on the experimental group (Shapiro-Wilk)

```
  emotion_group variable      statistic        p p.signif
  <fct>         <chr>             <dbl>    <dbl> <chr>
1 WE            severity_diff     0.967 5.56e-14 ****
2 NE            severity_diff     0.931 5.31e-21 ****
```

Homoscedasticity test for the difference from reference of severity rating depending on the experimental group (Levene)

```
    df1   df2 statistic           p p.signif
  <int> <int>     <dbl>       <dbl> <chr>
1     1  1960      28.1 0.000000128 ****
```

ANOVA on ART data for the difference from reference of severity rating depending on the experimental group

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(severity_diff)

                    F Df Df.res   Pr(>F) eta.sq.part
1 emotion_group 3.2574  1    107 0.073915    0.029544 .
```

Normality test for the difference from reference of severity rating depending on the experimental group and climate change attitude (Shapiro-Wilk)

```
  emotion_group prolific_climate variable      statistic        p p.signif
  <fct>         <fct>            <chr>             <dbl>    <dbl> <chr>
1 WE            No               severity_diff     0.976 3.08e- 7 ****
2 WE            Yes              severity_diff     0.946 2.28e-12 ****
3 NE            No               severity_diff     0.910 9.34e-17 ****
4 NE            Yes              severity_diff     0.943 9.06e-13 ****
```

Homoscedasticity test for the difference from reference of severity rating depending on the climate change attitude (Levene)

```
  prolific_climate   df1   df2 statistic            p p.signif
  <fct>            <int> <int>     <dbl>        <dbl> <chr>
1 No                   1   988     30.9  0.0000000343 ****
2 Yes                  1   970      1.38 0.241        ns
```

ANOVA on ART data for the difference from reference of severity rating depending on the experimental group and the climate change attitude

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(severity_diff)

                                       F Df Df.res  Pr(>F) eta.sq.part
1 emotion_group                  2.72278  1    105 0.10191   0.0252758
2 prolific_climate               5.57070  1    105 0.02011   0.0503813 *
3 emotion_group:prolific_climate 0.32724  1    105 0.56851   0.0031069
```

Normality test for the difference from reference of severity rating depending on experimental group and the certainty visualization type (Shapiro-Wilk)

```
  emotion_group certainty_type variable      statistic        p p.signif
  <fct>         <fct>          <chr>             <dbl>    <dbl> <chr>
1 WE            none           severity_diff     0.971 4.40e- 6 ****
2 WE            dots           severity_diff     0.957 3.31e- 8 ****
3 WE            lines          severity_diff     0.966 7.30e- 7 ****
4 NE            none           severity_diff     0.932 4.24e-11 ****
5 NE            dots           severity_diff     0.927 1.40e-11 ****
6 NE            lines          severity_diff     0.924 6.08e-12 ****
```

Homoscedasticity test for the difference from reference of severity rating depending on the certainty visualization type (Levene)

```
  certainty_type   df1   df2 statistic       p p.signif
  <fct>          <int> <int>     <dbl>   <dbl> <chr>
1 none               1   652     10.7  0.00113 **
2 dots               1   652      6.83 0.00919 **
3 lines              1   652     10.7  0.00112 **
```

ANOVA on ART data for the difference from reference of severity rating depending on experimental group and the certainty visualization type

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(severity_diff)

                                     F Df Df.res  Pr(>F) eta.sq.part
1 emotion_group                1.89032  1    107 0.17204  0.01735984
2 certainty_type               1.03830  2   1849 0.35426  0.00112183
3 emotion_group:certainty_type 0.20901  2   1849 0.81141  0.00022603
```

Normality test for certainty rating depending on the experimental group (Shapiro-Wilk)

```
  emotion_group variable        statistic        p p.signif
  <fct>         <chr>               <dbl>    <dbl> <chr>
1 WE            certainty_value     0.906 5.85e-24 ****
2 NE            certainty_value     0.899 4.78e-25 ****


  emotion_group most_least variable        statistic        p p.signif
  <fct>         <fct>      <chr>               <dbl>    <dbl> <chr>
1 WE            least      certainty_value     0.925 6.71e-15 ****
2 WE            most       certainty_value     0.876 2.74e-19 ****
3 NE            least      certainty_value     0.922 2.62e-15 ****
4 NE            most       certainty_value     0.859 1.19e-20 ****
```

Homoscedasticity test for certainty rating depending on the experimental group (Levene)

```
    df1   df2 statistic     p p.signif
  <int> <int>     <dbl> <dbl> <chr>
1     1  1960      1.02 0.312 ns


  most_least   df1   df2 statistic     p p.signif
  <fct>      <int> <int>     <dbl> <dbl> <chr>
1 least          1   979     0.264 0.608 ns
2 most           1   979     2.29  0.131 ns
```

ANOVA on ART data for certainty rating depending on the experimental group

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(certainty_value)

                      F Df Df.res Pr(>F)
1 emotion_group 0.16735  1    107 0.6833
```

ANOVA on ART data for certainty rating depending on the experimental group and kind of requested area

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(certainty_value)

                                     F Df Df.res  Pr(>F) eta.sq.part
1 emotion_group               0.061576  1    107 0.80450  0.00057515
2 most_least                126.481048  1   1851 < 2e-16  0.06396069 ***
3 emotion_group:most_least    0.316221  1   1851 0.57396  0.00017081
```

Normality test for certainty rating depending on experimental group and climate change attitude (Shapiro-Wilk)

```
  emotion_group prolific_climate variable        statistic        p p.signif
  <fct>         <fct>            <chr>               <dbl>    <dbl> <chr>
1 WE            No               certainty_value     0.919 1.56e-15 ****
2 WE            Yes              certainty_value     0.885 1.57e-18 ****
3 NE            No               certainty_value     0.907 4.90e-17 ****
4 NE            Yes              certainty_value     0.886 1.90e-18 ****
```

Homoscedasticity test for certainty rating depending on experimental group and the climate change attitude (Levene)

```
  prolific_climate   df1   df2 statistic       p p.signif
  <fct>            <int> <int>     <dbl>   <dbl> <chr>
1 No                   1   988      1.28 0.258   ns
2 Yes                  1   970      6.94 0.00856 **
```

ANOVA on ART data for certainty rating depending on experimental group and climate change attitude

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(certainty_value)

                                        F Df Df.res  Pr(>F)
1 emotion_group                   0.14651  1    105 0.70267
2 prolific_climate                1.70051  1    105 0.19507
3 emotion_group:prolific_climate  0.12968  1    105 0.71948
```

Normality test for certainty rating depending on experimental group and certainty visualization type (Shapiro-Wilk)

```
  emotion_group certainty_type variable        statistic        p p.signif
  <fct>         <fct>          <chr>               <dbl>    <dbl> <chr>
1 WE            none           certainty_value     0.913 1.04e-12 ****
2 WE            dots           certainty_value     0.902 1.19e-13 ****
3 WE            lines          certainty_value     0.879 2.62e-15 ****
4 NE            none           certainty_value     0.911 5.17e-13 ****
5 NE            dots           certainty_value     0.878 1.52e-15 ****
6 NE            lines          certainty_value     0.888 8.61e-15 ****
```

Homoscedasticity test for certainty rating depending on the certainty visualization type (Levene)

```
  certainty_type   df1   df2 statistic     p p.signif
  <fct>          <int> <int>     <dbl> <dbl> <chr>
1 none               1   652     0.661 0.417 ns
2 dots               1   652     0.119 0.730 ns
3 lines              1   652     1.68  0.195 ns
```

ANOVA on ART data for certainty depending on experimental group and certainty visualization type

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(certainty_value)

                                        F Df Df.res    Pr(>F) eta.sq.part
1 emotion_group                8.9559e-03  1    107 0.924781  8.3693e-05
2 certainty_type               1.2237e+02  2   1849  < 2e-16  1.1689e-01 ***
3 emotion_group:certainty_type 2.8278e+00  2   1849 0.059397  3.0494e-03
```

ART contrasts for certainty rating depending on certainty visualization type

```
      contrast   estimate       SE   df     t.ratio      p.value sig
1  none - dots -347.55396 26.25544 1849 -13.2374090 8.328271e-38 ***
2 none - lines -363.33726 26.25544 1849 -13.8385533 4.871591e-41 ***
3 dots - lines  -15.78331 26.25544 1849  -0.6011443 1.000000e+00
```

Normality test for the difference from reference of certainty rating depending on the experimental group (Shapiro-Wilk)

```
  emotion_group variable        statistic        p p.signif
  <fct>         <chr>               <dbl>    <dbl> <chr>
1 WE            certainty_diff      0.941 2.04e-15 ****
2 NE            certainty_diff      0.920 3.54e-18 ****
```

Homoscedasticity test for the difference from reference of certainty rating depending on the experimental group (Levene)

```
    df1   df2 statistic     p p.signif
  <int> <int>     <dbl> <dbl> <chr>
1     1  1306     0.253 0.615 ns
```

ANOVA on ART data for the difference from reference of certainty rating depending on the experimental group

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(certainty_diff)

                    F Df Df.res  Pr(>F)
1 emotion_group 0.10756  1    107 0.74358
```

Normality test for the difference from reference of certainty rating difference depending on experimental group and climate change attitude (Shapiro-Wilk)

```
  emotion_group prolific_climate variable       statistic        p p.signif
  <fct>         <fct>            <chr>              <dbl>    <dbl> <chr>
1 WE            No               certainty_diff     0.961 1.53e- 7 ****
2 WE            Yes              certainty_diff     0.893 2.53e-14 ****
3 NE            No               certainty_diff     0.944 5.76e-10 ****
4 NE            Yes              certainty_diff     0.879 2.82e-15 ****
```

Homoscedasticity test for the difference from reference of certainty rating depending on the climate change attitude (Levene)

```
  prolific_climate   df1   df2 statistic      p p.signif
  <fct>            <int> <int>     <dbl>  <dbl> <chr>
1 No                   1   658      3.77 0.0526 ns
2 Yes                  1   646      1.56 0.213  ns
```

ANOVA on ART data for the difference from reference of certainty rating depending on experimental group and climate change attitude

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(certainty_diff)

                                        F Df Df.res  Pr(>F)
1 emotion_group                  0.014368  1    105 0.90482
2 prolific_climate               0.067688  1    105 0.79524
3 emotion_group:prolific_climate 0.030508  1    105 0.86168
```

Normality test for the difference from reference of certainty rating depending on experimental group and certainty visualization type (Shapiro-Wilk)

```
  emotion_group certainty_type variable       statistic        p p.signif
  <fct>         <fct>          <chr>              <dbl>    <dbl> <chr>
1 WE            dots           certainty_diff     0.949 3.47e- 9 ****
2 WE            lines          certainty_diff     0.931 4.49e-11 ****
3 NE            dots           certainty_diff     0.918 1.99e-12 ****
4 NE            lines          certainty_diff     0.917 1.57e-12 ****
```

Homoscedasticity test for the difference from reference of certainty rating depending on the certainty visualization type (Levene)

```
  certainty_type   df1   df2 statistic     p p.signif
  <fct>          <int> <int>     <dbl> <dbl> <chr>
1 dots               1   652    0.228  0.633 ns
2 lines              1   652    0.0542 0.816 ns
```

ANOVA on ART data for the difference from reference of certainty rating depending on experimental group and certainty visualization type

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(certainty_diff)

                                       F Df Df.res   Pr(>F) eta.sq.part
1 emotion_group                 0.093644  1    107 0.760189  0.00087442
2 certainty_type                6.299346  1   1197 0.012209  0.00523506 *
3 emotion_group:certainty_type 2.331970  1   1197 0.127006  0.00194439
```

Normality test for trust rating depending on experimental group (Shapiro-Wilk)

```
  emotion_group variable    statistic        p p.signif
  <fct>         <chr>           <dbl>    <dbl> <chr>
1 WE            trust_value     0.921 3.59e-22 ****
2 NE            trust_value     0.919 1.20e-22 ****
```

ANOVA on ART data for trust rating depending on experimental group

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(trust_value)

                       F Df Df.res  Pr(>F)
1 emotion_group 0.033391  1    107 0.85535
```

Normality test for trust rating depending on climate change attitude (Shapiro-Wilk)

```
  prolific_climate variable    statistic        p p.signif
  <fct>            <chr>           <dbl>    <dbl> <chr>
1 No               trust_value     0.930 4.27e-21 ****
2 Yes              trust_value     0.896 4.05e-25 ****
```

Homoscedasticity test for trust rating depending on climate change attitude (Levene)

```
    df1   df2 statistic      p p.signif
  <int> <int>     <dbl>  <dbl> <chr>
1     1  1960      2.96 0.0855 ns
```

ANOVA on ART data for trust rating depending on experimental group and climate change attitude

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(trust_value)

                                         F Df Df.res    Pr(>F) eta.sq.part
1 emotion_group                   0.025776  1    105 0.8727575  0.00024542
2 prolific_climate                8.338343  1    105 0.0047142  0.07357036 **
3 emotion_group:prolific_climate 0.418185  1    105 0.5192553  0.00396691
```

Normality test for trust rating depending on the certainty visualization type (Shapiro-Wilk)

```
  certainty_type variable    statistic        p p.signif
  <fct>          <chr>           <dbl>    <dbl> <chr>
1 none           trust_value     0.934 2.26e-16 ****
2 dots           trust_value     0.908 1.76e-19 ****
3 lines          trust_value     0.910 3.12e-19 ****
```

Homoscedasticity test for trust rating depending on the certainty visualization type (Levene)

```
    df1   df2 statistic           p p.signif
  <int> <int>     <dbl>       <dbl> <chr>
1     2  1959      15.2 0.000000280 ****
```

ANOVA on ART data for trust rating depending on experimental group and certainty visualization type

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(trust_value)

                                        F Df Df.res   Pr(>F) eta.sq.part
1 emotion_group                   0.10461  1    107 0.746997  0.00097671
2 certainty_type                167.87270  2   1849  < 2e-16  0.15367713 ***
3 emotion_group:certainty_type    2.50073  2   1849 0.082303  0.00269766   .
```

ART contrasts for trust rating between certainty visualization types

```
      contrast   estimate       SE   df    t.ratio      p.value sig
1  none - dots -358.74818 21.88034 1849 -16.395918 4.894832e-56 ***
2 none - lines -334.38429 21.88034 1849 -15.282411 2.884633e-49 ***
3 dots - lines   24.36389 21.88034 1849   1.113506 7.969075e-01
```

ANOVA on ART data for trust rating depending on experimental group and certainty visualization type

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(trust_value)

                                          F Df Df.res     Pr(>F) eta.sq.part
1 prolific_climate                   6.0825  1    107   0.015241    0.053788   *
2 certainty_type                   174.1581  2   1849 < 2.22e-16    0.158519 ***
3 prolific_climate:certainty_type   12.2320  2   1849 5.2792e-06    0.013058 ***
```

ART contrasts for trust rating between certainty visualization types

```
              contrast   estimate       SE        df    t.ratio      p.value sig
1    No,Dots - No,Lines   21.17273 30.28598 1849.0000  0.6990933 1.000000e+00
2     No,Dots - No,None  251.42121 30.28598 1849.0000  8.3015704 2.936887e-15 ***
3    No,Dots - Yes,Dots -277.51178 73.26698  136.4716 -3.7876786 3.407350e-03  **
4   No,Dots - Yes,Lines -252.92228 73.26698  136.4716 -3.4520635 1.111550e-02   *
5    No,Dots - Yes,None  184.48359 73.26698  136.4716  2.5179635 1.943852e-01
6    No,Lines - No,None  230.24848 30.28598 1849.0000  7.6024771 6.887429e-13 ***
7   No,Lines - Yes,Dots -298.68451 73.26698  136.4716 -4.0766591 1.157947e-03  **
8  No,Lines - Yes,Lines -274.09501 73.26698  136.4716 -3.7410440 4.034469e-03  **
9   No,Lines - Yes,None  163.31086 73.26698  136.4716  2.2289830 4.117530e-01
10   No,None - Yes,Dots -528.93300 73.26698  136.4716 -7.2192545 4.962738e-10 ***
11  No,None - Yes,Lines -504.34349 73.26698  136.4716 -6.8836394 2.906516e-09 ***
12   No,None - Yes,None  -66.93763 73.26698  136.4716 -0.9136124 1.000000e+00
13 Yes,Dots - Yes,Lines   24.58951 30.56512 1849.0000  0.8044956 1.000000e+00
14  Yes,Dots - Yes,None  461.99537 30.56512 1849.0000 15.1151166 1.396038e-47 ***
15 Yes,Lines - Yes,None  437.40586 30.56512 1849.0000 14.3106209 5.853210e-43 ***
```

Mann-Whitney U tests of the required time per trial depending on experimental group

```
   trial .y.                group1 group2    n1    n2 statistic     p p.signif
   <dbl> <chr>              <chr>  <chr>  <int> <int>     <dbl> <dbl> <chr>
 1     1 tot_task_time_sec WE     NE        53    54      1432  0.998 ns
 2     2 tot_task_time_sec WE     NE        54    55      1375  0.507 ns
 3     3 tot_task_time_sec WE     NE        54    53      1459  0.864 ns
 4     4 tot_task_time_sec WE     NE        52    53      1399  0.895 ns
 5     5 tot_task_time_sec WE     NE        53    54      1407  0.884 ns
 6     6 tot_task_time_sec WE     NE        54    52      1401  0.987 ns
 7     7 tot_task_time_sec WE     NE        53    55      1569  0.495 ns
 8     8 tot_task_time_sec WE     NE        53    52      1364  0.931 ns
 9     9 tot_task_time_sec WE     NE        54    55      1368  0.48  ns
10    10 tot_task_time_sec WE     NE        52    54      1409  0.977 ns
11    11 tot_task_time_sec WE     NE        53    53      1460  0.728 ns
12    12 tot_task_time_sec WE     NE        52    53      1318  0.703 ns
13    13 tot_task_time_sec WE     NE        52    53      1400  0.89  ns
14    14 tot_task_time_sec WE     NE        50    53      1233  0.546 ns
15    15 tot_task_time_sec WE     NE        53    54      1615  0.253 ns
16    16 tot_task_time_sec WE     NE        52    53      1150. 0.144 ns
17    17 tot_task_time_sec WE     NE        52    53      1203  0.263 ns
18    18 tot_task_time_sec WE     NE        54    52      1161  0.125 ns
```

Mann-Whitney U tests of the required time per trial depending on the climate change attitude

```
   trial .y.                group1 group2    n1    n2 statistic      p p.signif
   <dbl> <chr>              <chr>  <chr>  <int> <int>     <dbl>  <dbl> <chr>
 1     1 tot_task_time_sec No     Yes       54    53      1424  0.968  ns
 2     2 tot_task_time_sec No     Yes       55    54      1511  0.877  ns
 3     3 tot_task_time_sec No     Yes       55    52      1560  0.42   ns
 4     4 tot_task_time_sec No     Yes       53    52      1396  0.911  ns
 5     5 tot_task_time_sec No     Yes       53    54      1587  0.333  ns
 6     6 tot_task_time_sec No     Yes       52    54      1550  0.358  ns
 7     7 tot_task_time_sec No     Yes       54    54      1584  0.441  ns
 8     8 tot_task_time_sec No     Yes       51    54      1495  0.451  ns
 9     9 tot_task_time_sec No     Yes       55    54      1700  0.194  ns
10    10 tot_task_time_sec No     Yes       53    53      1795  0.0137 *
11    11 tot_task_time_sec No     Yes       54    52      1406  0.992  ns
12    12 tot_task_time_sec No     Yes       52    53      1258  0.444  ns
13    13 tot_task_time_sec No     Yes       53    52      1503  0.425  ns
14    14 tot_task_time_sec No     Yes       52    51      1241  0.577  ns
15    15 tot_task_time_sec No     Yes       53    54      1403  0.864  ns
16    16 tot_task_time_sec No     Yes       52    53      1572. 0.214  ns
17    17 tot_task_time_sec No     Yes       52    53      1271  0.495  ns
18    18 tot_task_time_sec No     Yes       53    53      1318  0.587  ns
```

Normality test for mean task time depending on experimental group (Shapiro-Wilk)

```
  emotion_group variable          statistic        p p.signif
  <fct>         <chr>                 <dbl>    <dbl> <chr>
1 WE            tot_task_time_sec     0.788 2.33e-33 ****
2 NE            tot_task_time_sec     0.786 1.19e-33 ****
```

Homoscedasticity test for mean task time depending on experimental group (Levene)

```
    df1   df2 statistic     p p.signif
  <int> <int>     <dbl> <dbl> <chr>
1     1  1960     0.523 0.470 ns
```

ANOVA of ART data for mean task time depending on experimental group

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(tot_task_time_sec)

                       F Df Df.res  Pr(>F)
1 emotion_group 0.069095  1 106.99 0.79316
```

Normality test for mean task time depending on experimental group and climate change attitude (Shapiro-Wilk)

```
  emotion_group prolific_climate variable          statistic        p p.signif
  <fct>         <fct>            <chr>                 <dbl>    <dbl> <chr>
1 WE            No               tot_task_time_sec     0.242 2.52e-40 ****
2 WE            Yes              tot_task_time_sec     0.669 1.14e-29 ****
3 NE            No               tot_task_time_sec     0.557 9.43e-34 ****
4 NE            Yes              tot_task_time_sec     0.635 7.48e-31 ****
```

Homoscedasticity test for mean task time depending on experimental group and climate change attitude (Levene)

```
  prolific_climate   df1   df2 statistic     p p.signif
  <fct>            <int> <int>     <dbl> <dbl> <chr>
1 No                   1   988     0.324 0.569 ns
2 Yes                  1   970     0.319 0.572 ns
```

ANOVA on ART data for mean task time depending on experimental group and climate change attitude

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(tot_task_time_sec)

                                        F Df Df.res  Pr(>F)
1 emotion_group                 0.0688206  1 104.99 0.79358
2 prolific_climate              0.5746941  1 104.99 0.45010
3 emotion_group:prolific_climate 0.0037816  1 104.99 0.95108
```

Normality test for mean task time depending on experimental group and certainty visualization type (Shapiro-Wilk)

```
  emotion_group certainty_type variable          statistic        p p.signif
  <fct>         <fct>          <chr>                 <dbl>    <dbl> <chr>
1 WE            none           tot_task_time_sec     0.768 6.38e-21 ****
2 WE            dots           tot_task_time_sec     0.796 1.57e-19 ****
3 WE            lines          tot_task_time_sec     0.798 1.32e-19 ****
4 NE            none           tot_task_time_sec     0.721 7.94e-23 ****
5 NE            dots           tot_task_time_sec     0.830 3.95e-18 ****
6 NE            lines          tot_task_time_sec     0.796 1.15e-19 ****
```

Homoscedasticity test for mean task time depending on certainty visualization type (Levene)

```
  certainty_type   df1   df2 statistic     p p.signif
  <fct>          <int> <int>     <dbl> <dbl> <chr>
1 none               1   639    0.164  0.686 ns
2 dots               1   633    0.0186 0.892 ns
3 lines              1   633    1.06   0.303 ns
```

ANOVA of ART data for mean task time depending on the experimental group and certainty visualization type

```
Analysis of Variance of Aligned Rank Transformed Data

Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-
Roger df)
Model: Mixed Effects (lmer)
Response: art(tot_task_time_sec)

                                       F Df Df.res     Pr(>F) eta.sq.part
1 emotion_group                 0.062272  1  107.0    0.80342  0.00058167
2 certainty_type               11.339503  2 1798.4 1.2768e-05  0.01245327 ***
3 emotion_group:certainty_type  1.175809  2 1798.4    0.30881  0.00130587
```

ART contrasts for mean task time between the certainty visualization types

```
      contrast   estimate       SE       df    t.ratio      p.value sig
1  none - dots  -85.96899 24.36849 1798.354 -3.5278752 1.288286e-03  **
2 none - lines -110.36841 24.36635 1798.327 -4.5295430 1.889884e-05 ***
3 dots - lines  -24.39942 24.43579 1798.668 -0.9985118 9.544967e-01


              contrast    estimate       SE        df     t.ratio     p.value
sig
1  NE,dots - NE,lines   11.570752 34.44215 1798.5993  0.33594747 0.999436019
2   NE,dots - NE,none  102.709981 34.29406 1798.3326  2.99497914 0.033125820
*
3   NE,dots - WE,dots   52.887070 74.16533  146.0598  0.71309694 0.980108077
4   NE,dots - WE,lines   -5.836332 74.10469  145.5829 -0.07875793 0.999999566
5    NE,dots - WE,none  121.415579 74.08618  145.4459  1.63884240 0.574321260
6   NE,lines - NE,none   91.139229 34.42995 1798.3468  2.64709147 0.086780970
.
7   NE,lines - WE,dots   41.316319 74.23165  146.5731  0.55658630 0.993565150
8  NE,lines - WE,lines  -17.407084 74.17106  146.0954 -0.23468834 0.999900919
9   NE,lines - WE,none  109.844827 74.15257  145.9582  1.48133536 0.676690731
10   NE,none - WE,dots  -49.822911 74.16216  146.0385 -0.67181040 0.984763257
11  NE,none - WE,lines -108.546313 74.10152  145.5616 -1.46483249 0.687095091
12   NE,none - WE,none   18.705598 74.08301  145.4246  0.25249511 0.999857868
13  WE,dots - WE,lines  -58.723403 34.66452 1798.7369 -1.69404898 0.535878738
14   WE,dots - WE,none   68.528508 34.62188 1798.3749  1.97934128 0.354594178
15  WE,lines - WE,none  127.251911 34.48068 1798.3068  3.69052822 0.003147842
**
```

L.3 Post-test part

Normality tests for post-SAM scores depending on the experimental group (Shapiro-Wilk)

```
  emotion_group variable            statistic       p
  <fct>         <chr>                   <dbl>   <dbl>
1 WE            post_pleasure_value     0.923 0.00192
2 NE            post_pleasure_value     0.925 0.00205


  emotion_group variable           statistic        p
  <fct>         <chr>                  <dbl>    <dbl>
1 WE            post_arousal_value     0.927 0.00269
2 NE            post_arousal_value     0.916 0.000944


  emotion_group variable             statistic       p
  <fct>         <chr>                    <dbl>   <dbl>
1 WE            post_dominance_value     0.930 0.00381
2 NE            post_dominance_value     0.949 0.0208
```

Mann-Whitney U test for the post-SAM scores between experimental groups

```
  .y.                 group1 group2    n1    n2 statistic     p p.signif
  <chr>               <chr>  <chr>  <int> <int>     <dbl> <dbl> <chr>   
1 post_pleasure_value WE     NE        54    55      1505 0.904 ns      


  .y.               group1 group2    n1    n2 statistic     p p.signif
  <chr>             <chr>  <chr>  <int> <int>     <dbl> <dbl> <chr>   
1 post_arousal_value WE     NE        54    55      1442 0.794 ns      


  .y.                 group1 group2    n1    n2 statistic     p p.signif
  <chr>               <chr>  <chr>  <int> <int>     <dbl> <dbl> <chr>   
1 post_dominance_value WE     NE        54    55      1525 0.809 ns      
```

Wilcoxon signed test between pre and post SAM scores

```
  emotion_group .y.      group1             group2    n1    n2 statistic     p p.signif
  <fct>         <chr>    <chr>              <chr>  <int> <int>     <dbl> <dbl> <chr>   
1 WE            pl_value post_pleasure pre_pleasure    54    54      240. 0.635 ns      
2 NE            pl_value post_pleasure pre_pleasure    55    55      330. 0.205 ns      

  emotion_group prolific_climate .y.      group1  group2    n1    n2 statistic     p
p.signif
  <fct>         <fct>            <chr>    <chr>   <chr>  <int> <int>     <dbl> <dbl>
<chr>   
1 WE            No               pl_value post_p… pre_p…    27    27      41.5 0.503 ns      
2 WE            Yes              pl_value post_p… pre_p…    27    27      87   0.122 ns      
3 NE            No               pl_value post_p… pre_p…    28    28      60   1     ns      
4 NE            Yes              pl_value post_p… pre_p…    27    27     107   0.149 ns      


  emotion_group .y.      group1            group2              n1    n2 statistic
p p.signif
  <fct>         <chr>    <chr>             <chr>            <int> <int>     <dbl>
<dbl> <chr>   
1 WE            ar_value post_arousal pre_arousal    54    54      282. 0.802 ns      
2 NE            ar_value post_arousal pre_arousal    55    55      382. 0.91  ns      


  emotion_group prolific_climate .y.      group1 group2     n1    n2 statistic     p
p.signif
  <fct>         <fct>            <chr>    <chr>   <chr>   <int> <int>     <dbl> <dbl>
<chr>   
1 WE            No               ar_value post_a… pre_a…    27    27      57.5 0.599 ns      
2 WE            Yes              ar_value post_a… pre_a…    27    27      89   0.895 ns      
3 NE            No               ar_value post_a… pre_a…    28    28      84   0.437 ns      
4 NE            Yes              ar_value post_a… pre_a…    27    27     112   0.498 ns      


  emotion_group .y.      group1       group2          n1    n2 statistic     p p.signif
  <fct>         <chr>    <chr>        <chr>        <int> <int>     <dbl> <dbl> <chr>   
1 WE            do_value post_domina… pre_domina…    54    54      180  0.277 ns      
2 NE            do_value post_domina… pre_domina…    55    55      160. 0.132 ns      


  emotion_group prolific_climate .y.      group1  group2    n1    n2 statistic     p
p.signif
  <fct>         <fct>            <chr>    <chr>   <chr>  <int> <int>     <dbl> <dbl>
<chr>   
1 WE            No               do_value post_d… pre_d…    27    27      35.5 0.504 ns      
2 WE            Yes              do_value post_d… pre_d…    27    27      60   0.434 ns      
3 NE            No               do_value post_d… pre_d…    28    28      40.5 0.268 ns      
4 NE            Yes              do_value post_d… pre_d…    27    27      43.5 0.354 ns      
```

Fisher' exact test for the emotions from SEW

The first test is between the experimental groups, the second is between the climate change attitudes.

```
        Fisher's Exact Test for Count Data

data:  .
p-value = 0.1014
alternative hypothesis: two.sided


        Fisher's Exact Test for Count Data

data:  .
p-value = 0.02136
alternative hypothesis: two.sided
```

Fisher's exact test for the follow up questions between the experimental groups

The tests follow this order: consideration own situation, difficulty of the tasks, self-evaluation of the performance, map preference.

```
        Fisher's Exact Test for Count Data

data:  .
p-value = 0.07549
alternative hypothesis: two.sided


        Fisher's Exact Test for Count Data

data:  .
p-value = 0.5603
alternative hypothesis: two.sided


        Fisher's Exact Test for Count Data

data:  .
p-value = 0.4478
alternative hypothesis: two.sided


        Fisher's Exact Test for Count Data

data:  .
p-value = 0.5069
alternative hypothesis: two.sided
```

Fisher's exact test for the follow up questions between the climate change attitudes

The tests follow this order: consideration own situation, self-evaluation of the performance.

```
        Fisher's Exact Test for Count Data

data:  .
p-value = 0.001404
alternative hypothesis: two.sided


        Fisher's Exact Test for Count Data

data:  .
p-value = 0.3714
alternative hypothesis: two.sided
```

M PsyToolkit codes

M.1 Questionnaire code

```
# Definition of the scales for the Likert scales

scale: agree
- Agree strongly
- Agree
- Neither agree nor disagree
- Disagree
- Disagree strongly

scale: frequency
- Never
- Rarely
- Sometimes
- Often
- Always

scale: familiarity
- Not familiar at all
- Slightly familiar
- Moderately familiar
- Fairly familiar
- Completely familiar

scale: confident
- Not confident at all
- Slightly confident
- Moderately confident
- Fairly confident
- Very confident

scale: difficult
- Very difficult
- Difficult
- Fair
- Easy
- Very easy

scale: consideration
- Not considered at all
- Slightly considered
- Moderately considered
- Fairly considered
- Very much considered

#########################################################################

# Pre-test

page: begin

l: pre_test_intro
t: info
q: <b>Welcome!</b><br>
Thank you again for participating in my study! Your participation is very
important for my Master's thesis research and contributes to deepen the
understanding of certainty visualization on maps.
```

```
In this first part of the study, you will be asked to provide general emographic
information and to complete a couple of background questionnaires. Following
that, you will proceed to the map experiment part of the study.
<b>Please, do not use your browser's back navigation button to change your
answers</b>. To start, click on the button below.

page: end

page: begin

l: gender
t: radio
q: How would you best describe your gender?
- Male
- Female
- Non-binary
- Prefer to self-describe

l: age
t: textline
q: How old are you?
- {min=18,max=100,p=Please enter your age}

l: country
t: textline
q: In which country do you currently live?
- {other, size=40}

l: visual_impairment
t: check
q: Have you ever been diagnosed with a visual impairment by a specialist
(optician, ophthalmologist)?
- Yes, colour blindness
- Yes, glasses or contact lenses
- No
- {other, size=40} Other visual impairment (please specify)

l: wearing_glasses
t: radio
q: In case you answered "Yes, glasses or contact lenses" in the previous
question, are you wearing them as you are participating in this study?
If this question does not apply to you, please answer "No, I do not need them".
- Yes, I am wearing them now
- No, I am not wearing them now
- No, I do not need them

l: education_degree
t: radio
q: What is the highest level of education you have completed?
- No qualification
- Primary school
- Secondary school or equivalent
- High school or equivalent
- University degree
- Doctoral degree
- {other, size=40} Other educational qualification (please specify)

l: map_use_freq
t: radio
q: How often do you deal with maps in your everyday life (navigation, Google
Maps, atlas, maps in newspapers, ...)?
- Never
- Annually
```

```
- Monthly
- Weekly
- Daily

l: concept_familiarity
q: How familiar are you with...
o: buildup
t: scale familiarity
- Cartography
- Geographic Information Systems (GIS)
- Climate Change mapping
- Intergovernmental Panel on Climate Change (IPCC)
- Statistics
- Uncertainty

page: end

l: SAM_pre
t: experiment
- SAM_pre

page: begin

l: TEQ
q: Next you will be presented with 16 statements. Please read each statement
carefully and rate how frequently you feel or act in the manner described. There
are no right or wrong answers or trick questions. Please answer each question as
honestly as you can.
o: buildup
t: scale frequency
- 1. When someone else is feeling excited, I tend to get excited too
- {reverse} 2. Other people’s misfortunes do not disturb me a great deal
- 3. It upsets me to see someone being treated disrespectfully
- {reverse} 4. I remain unaffected when someone close to me is happy
- 5. I enjoy making other people feel better
- 6. I have tender, concerned feelings for people less fortunate than me
- {reverse} 7. When a friend starts to talk about his\her problems, I try to
steer the conversation towards something else
- 8. I can tell when others are sad even when they do not say anything
- 9. I find that I am “in tune” with other people’s moods
- 10. I do not feel sympathy for people who cause their own serious illnesses
- {reverse} 11. I become irritated when someone cries
- {reverse} 12. I am not really interested in how other people feel
- {reverse} 13. I get a strong urge to help when I see someone who is upset
- 14. When I see someone being treated unfairly, I do not feel very much pity
for them
- {reverse} 15. I find it silly for people to cry out of happiness
- {reverse} 16. When I see someone being taken advantage of, I feel kind of
protective towards him\her

page: end

l: TEQscore
t: set
- sum $TEQ

page: begin

l: climate_attitude
q: Next you will be presented with 9 statements. Please read each statement
carefully and rate how much do you agree with it. There are no right or wrong
answers or trick questions. Please answer each question as honestly as you can.
o: buildup
```

```
t: scale agree
- 1. Claims that human activities are changing the climate are exaggerated
- {reverse} 2. Climate change is something that frightens me
- 3. Climate change is just a natural fluctuation in earth's temperatures
- {reverse} 4. I feel a moral duty to do something about climate change
- 5. I do not believe climate change is a real problem
- 6. I am uncertain about whether climate change is really happening
- 7. There is too much conflicting evidence about climate change to know whether
it is actually happening
- {reverse} 8. The effects of climate change are likely to be catastrophic
- 9. Climate change is too complex and uncertain for scientists to make useful
forecasts

page: end

l: climate_attitudescore
t: set
- sum $climate_attitude

page: begin

l: pre_test_end_begin_experiment
t: info
q: <b>Great, you have already concluded the first part of this study!</b><br>
You will now proceed to the map experiment part. We will ask you to solve tasks
with various maps displaying climate change forecasts, that contain data
certainty information. First, we ask you to carefully study the test
instructions. Depending on your internet connection, <b><i>this part of the
experiment may require a bit of patience to load, please bear with us</b></i>,
the experiment will start soon. When you are ready, please click on the button
below.

page: end

#########################################################################

# Experiment

#l: grouping
#t: set
#- random 1 2

#l: WEgroup_or_NEgroup_exp
#t: jump
#- if $grouping == 1 then goto experiment_WE
#- if $grouping == 2 then goto experiment_NE

#l: experiment_WE
#t: experiment
#- Uncertainty_exp_WE

#j: post_test_intro

l: experiment_NE
t: experiment
- Uncertainty_exp_NE

#########################################################################

# Post-test

page: begin
```

```
l: post_test_intro
t: info
q: <b>Great, main map experiment part finished! Just a few last
questions</b><br>
You will now answer questions about how you felt during this study so far and we
wish to get your feedback on which visualization you preferred and why.

page: end

l: SAMpost_and_EmoWheel
t: experiment
- SAMpost_EmoWheel

page: begin

l: evaluation_emotion_text
t: textbox
q: Please explain in your own words how you felt about the forecasted climatic
changes while solving the forecast map tasks.

page: end

page: begin

l: consideration_own_situation
t: scale consideration
q: How much have you considered your own (future) situation, or that of your
family members, when assessing the forecast maps?
o: buildup
-

page: end

page: begin

l: assessing_trust
t: textbox
q: What of the presented information, if anything, did you take into
consideration in assessing how much trust to put into the forecast map?

page: end

page: begin

l: decisions_difficulties_scale
t: scale difficult
q: How difficult was it for you to make your map-based decisions?
o: buildup
-

page: end

page: begin

l: decisions_difficulties_text
t: textbox
q: Please, elaborate further on the how and/or why of your forecast map-based
decisions. What difficulties, if any, did you encounter?

page: end

page: begin
```

```
l: performance_self_evaluation
t: scale confident
q: How confident are you with your answers in the forecast map-based decisions?
o: buildup
-

page: end

page: begin

l: map_preference
t: radio
q: Which type of forecast certainty visualization did you find most helpful for
solving the forecast map tasks?
- {image=preference_nothing.png}
- {image=preference_dots.png}
- {image=preference_lines.png}

page: end

page: begin

l: map_preference_text
t: textbox
q: Please, elaborate further on the why you found a type of forecast certainty
visualization more helpful than the others.

page: end
```

M.2 Main Experiment WE group code

```
options
  fullscreen
  scale
  resolution 1830 1200
  background color 200 200 200
  loading text Experiment loading, wait few seconds

# Define the bitmaps used for stimuli and other objects in the tasks

bitmaps
  instruction          # bitmap showing instructions for main experiment
  intro_certainty
  intro_character1
  intro_character2
  intro_character3
  intro_trial          # instructions for test trial
  trial_finish         # information at the end of the trial
  selection_item       # for selecting options
  left_trust           # left label of trust Likert scale
  left_severity        # left label of severity Likert scale
  left_certainty       # left label of certainty Likert scale
  right_trust          # right label of trust Likert scale
  right_severity       # right label of severity Likert scale
  right_certainty # right label of certainty Likert scale
  A_region             # bitmaps of the labels of the 6 regions
  B_region
  C_region
  D_region
  E_region
  F_region
  selected_A
```

```
  selected_B
  selected_C
  selected_D
  selected_E
  selected_F
  continue_allowed      # button to continue
  continue_restricted
  selected_symbol # to highlight the selection
  back                  # buttons for the introduction
  next
  start
  stimulus_example      # the example stimulus
  stimulus_WE1          # bitmaps of the 18 map stimuli
  stimulus_WE2
  stimulus_WE3
  stimulus_WE4
  stimulus_WE5
  stimulus_WE6
  stimulus_WE7
  stimulus_WE8
  stimulus_WE9
  stimulus_WE10
  stimulus_WE11
  stimulus_WE12
  stimulus_WE13
  stimulus_WE14
  stimulus_WE15
  stimulus_WE16
  stimulus_WE17
  stimulus_WE18
  quest_certainty       # bitmap certainty question
  quest_severity              # bitmap severity question
  quest_region_least          # bitmaps region choice question
  quest_region_most
  quest_trust                 # bitmap trust question

# Define table with all the stimulus used in the task, that all
# participants will go trough

table stimulus_table
  "hotday dots 1" stimulus_WE1      1     "region_quest"    "severity_quest"
      "uncert_quest"    "trust_quest"     "least"
  "hotday dots 2" stimulus_WE2      2     "region_quest     "severity_quest"
      "uncert_quest"    "trust_quest"     "most"
  "hotday nothing 1"    stimulus_WE3      1     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "least"
  "hotday nothing 2"    stimulus_WE4      2     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "most"
  "hotday lines 1"      stimulus_WE5      1     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "least"
  "hotday lines 2"      stimulus_WE6      2     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "most"
  "prec dots 1"         stimulus_WE7      1     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "least"
  "prec dots 2"         stimulus_WE8      2     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "most"
  "prec nothing 1"      stimulus_WE9      1     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "least"
  "prec nothing 2"      stimulus_WE10     2     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "most"
  "prec lines 1"        stimulus_WE11     1     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "least"
```

```
  "prec lines 2"       stimulus_WE12     2     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "most"
  "temp dots 1"        stimulus_WE13     1     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "least"
  "temp dots 2"        stimulus_WE14     2     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "most"
  "temp nothing 1"     stimulus_WE15     1     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "least"
  "temp nothing 2"     stimulus_WE16     2     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "most"
  "temp lines 1"       stimulus_WE17     1     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "least"
  "temp lines 2"       stimulus_WE18     2     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "most"

table example_table
  "example dots hotday" stimulus_example        1     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "least"

# Define the task. Each complete task is composed of 4 subtasks, namely
# the one in which the participants choose the region, the task where
# they evaluate the severity, the one where they evaluate the
# uncertainty, finally the one on the trust.

task example
  table example_table
  show bitmap @2 0 -150
  if @3 == 1
    show bitmap quest_region_least 0 360
  fi
  draw off
    show bitmap selection_item   -540 450
    show bitmap selection_item   -340 450
    show bitmap selection_item   -140 450
    show bitmap selection_item     60 450
    show bitmap selection_item    260 450
    show bitmap selection_item    460 450
    show bitmap A_region         -480 450
    show bitmap B_region         -280 450
    show bitmap C_region          -80 450
    show bitmap D_region          120 450
    show bitmap E_region          320 450
    show bitmap F_region          520 450
  draw on
  choose option exit continue_allowed continue_restricted 700 530
  choose option minselect 1
  choose option maxselect 1
  choose option select selected_symbol
  choose 3600000 3 8
  set $selection CHOSEN_1
  save @1 @4 @8 CHOSEN_1 RT BLOCKNAME
  clear screen
  show bitmap @2 0 -150
  show bitmap quest_severity 0 330
  if $selection == 3
    show bitmap selected_A  0 370
  fi
  if $selection == 4
    show bitmap selected_B  0 370
  fi
  if $selection == 5
    show bitmap selected_C  0 370
  fi
```

```
if $selection == 6
  show bitmap selected_D  0 370
fi
if $selection == 7
  show bitmap selected_E  0 370
fi
if $selection == 8
  show bitmap selected_F  0 370
fi
draw off
  show bitmap left_severity      -410 440
  show bitmap selection_item     -240 440
  show bitmap selection_item     -160 440
  show bitmap selection_item      -80 440
  show bitmap selection_item        0 440
  show bitmap selection_item       80 440
  show bitmap selection_item      160 440
  show bitmap selection_item      240 440
  show bitmap right_severity      375 445
draw on
choose option exit continue_allowed continue_restricted 700 530
choose option minselect 1
choose option maxselect 1
choose option select selected_symbol
choose 3600000 5 11
save @1 @5 @8 CHOSEN_1 RT BLOCKNAME
clear screen
show bitmap @2 0 -150
show bitmap quest_certainty 0 330
if $selection == 3
  show bitmap selected_A  0 370
fi
if $selection == 4
  show bitmap selected_B  0 370
fi
if $selection == 5
  show bitmap selected_C  0 370
fi
if $selection == 6
  show bitmap selected_D  0 370
fi
if $selection == 7
  show bitmap selected_E  0 370
fi
if $selection == 8
  show bitmap selected_F  0 370
fi
draw off
  show bitmap left_certainty     -410 440
  show bitmap selection_item     -240 440
  show bitmap selection_item     -160 440
  show bitmap selection_item      -80 440
  show bitmap selection_item        0 440
  show bitmap selection_item       80 440
  show bitmap selection_item      160 440
  show bitmap selection_item      240 440
  show bitmap right_certainty     375 445
draw on
choose option exit continue_allowed continue_restricted 700 530
choose option minselect 1
choose option maxselect 1
choose option select selected_symbol
choose 3600000 5 11
```

```
  save @1 @6 @8 CHOSEN_1 RT BLOCKNAME
  clear screen
  show bitmap @2 0 -150
  show bitmap quest_trust 0 360
  draw off
    show bitmap left_trust         -445 440
    show bitmap selection_item     -240 440
    show bitmap selection_item     -160 440
    show bitmap selection_item      -80 440
    show bitmap selection_item        0 440
    show bitmap selection_item       80 440
    show bitmap selection_item      160 440
    show bitmap selection_item      240 440
    show bitmap right_trust         415 440
  draw on
  choose option exit continue_allowed continue_restricted 700 530
  choose option minselect 1
  choose option maxselect 1
  choose option select selected_symbol
  choose 3600000 4 10
  save @1 @7 @8 CHOSEN_1 RT BLOCKNAME

task uncertexp
  table stimulus_table
  show bitmap @2 0 -150
  if @3 == 1
    show bitmap quest_region_least 0 360
  else
    show bitmap quest_region_most 0 360
  fi
  draw off
    show bitmap selection_item   -540 450
    show bitmap selection_item   -340 450
    show bitmap selection_item   -140 450
    show bitmap selection_item     60 450
    show bitmap selection_item    260 450
    show bitmap selection_item    460 450
    show bitmap A_region         -480 450
    show bitmap B_region         -280 450
    show bitmap C_region          -80 450
    show bitmap D_region          120 450
    show bitmap E_region          320 450
    show bitmap F_region          520 450
  draw on
  choose option exit continue_allowed continue_restricted 700 530
  choose option minselect 1
  choose option maxselect 1
  choose option select selected_symbol
  choose 3600000 3 8
  set $selection CHOSEN_1
  save @1 @4 @8 CHOSEN_1 RT BLOCKNAME
  clear screen
  show bitmap @2 0 -150
  show bitmap quest_severity 0 330
  if $selection == 3
    show bitmap selected_A  0 370
  fi
  if $selection == 4
    show bitmap selected_B  0 370
  fi
  if $selection == 5
    show bitmap selected_C  0 370
  fi
```

```
if $selection == 6
  show bitmap selected_D  0 370
fi
if $selection == 7
  show bitmap selected_E  0 370
fi
if $selection == 8
  show bitmap selected_F  0 370
fi
draw off
  show bitmap left_severity      -410 440
  show bitmap selection_item     -240 440
  show bitmap selection_item     -160 440
  show bitmap selection_item      -80 440
  show bitmap selection_item        0 440
  show bitmap selection_item       80 440
  show bitmap selection_item      160 440
  show bitmap selection_item      240 440
  show bitmap right_severity      375 440
draw on
choose option exit continue_allowed continue_restricted 700 530
choose option minselect 1
choose option maxselect 1
choose option select selected_symbol
choose 3600000 5 11
save @1 @5 @8 CHOSEN_1 RT BLOCKNAME
clear screen
show bitmap @2 0 -150
show bitmap quest_certainty 0 330
if $selection == 3
  show bitmap selected_A  0 370
fi
if $selection == 4
  show bitmap selected_B  0 370
fi
if $selection == 5
  show bitmap selected_C  0 370
fi
if $selection == 6
  show bitmap selected_D  0 370
fi
if $selection == 7
  show bitmap selected_E  0 370
fi
if $selection == 8
  show bitmap selected_F  0 370
fi
draw off
  show bitmap left_certainty     -410 440
  show bitmap selection_item     -240 440
  show bitmap selection_item     -160 440
  show bitmap selection_item      -80 440
  show bitmap selection_item        0 440
  show bitmap selection_item       80 440
  show bitmap selection_item      160 440
  show bitmap selection_item      240 440
  show bitmap right_certainty     375 440
draw on
choose option exit continue_allowed continue_restricted 700 530
choose option minselect 1
choose option maxselect 1
choose option select selected_symbol
choose 3600000 5 11
```

```
  save @1 @6 @8 CHOSEN_1 RT BLOCKNAME
  clear screen
  show bitmap @2 0 -150
  show bitmap quest_trust 0 360
  draw off
    show bitmap left_trust         -445 440
    show bitmap selection_item     -240 440
    show bitmap selection_item     -160 440
    show bitmap selection_item      -80 440
    show bitmap selection_item        0 440
    show bitmap selection_item       80 440
    show bitmap selection_item      160 440
    show bitmap selection_item      240 440
    show bitmap right_trust         415 440
  draw on
  choose option exit continue_allowed continue_restricted 700 530
  choose option minselect 1
  choose option maxselect 1
  choose option select selected_symbol
  choose 3600000 4 10
  save @1 @7 @8 CHOSEN_1 RT BLOCKNAME

# Define blocks, the one with the example trial and the real experiment,
# where all 18 stimuli appear, without repetition or excusions

block exampleblock
  pager option mouse back -250 520 next 0 520 start 250 520
  pager intro_certainty intro_character1 intro_character2 intro_character3
intro_trial
  clear screen
  tasklist
    example 1
  end
  message trial_finish mouse

block mainexp
  message instruction mouse
  tasklist
    uncertexp 18 all_before_repeat
  end
```

M.3 Main Experiment NE group code

```
options
  fullscreen
  scale
  resolution 1830 1200
  background color 200 200 200
  loading text Experiment loading, wait few seconds

# Define the bitmaps used for stimuli and other objects in the tasks

bitmaps
  instruction          # bitmap showing instructions for main experiment
  intro_certainty
  intro_trial_NE       # instructions for test trial
  trial_finish         # information at the end of the trial
  selection_item       # for selecting options
  left_trust           # left label of trust Likert scale
  left_severity        # left label of severity Likert scale
  left_certainty       # left label of certainty Likert scale
  right_trust          # right label of trust Likert scale
```

```
  right_severity        # right label of severity Likert scale
  right_certainty # right label of certainty Likert scale
  A_region              # bitmaps of the labels of the 6 regions
  B_region
  C_region
  D_region
  E_region
  F_region
  selected_A
  selected_B
  selected_C
  selected_D
  selected_E
  selected_F
  continue_allowed      # button to continue
  continue_restricted
  selected_symbol # to highlight the selection
  back                  # buttons for the introduction
  next
  start
  stimulus_example_NE   # the example stimulus
  stimulus_NE1          # bitmaps of the 18 map stimuli
  stimulus_NE2
  stimulus_NE3
  stimulus_NE4
  stimulus_NE5
  stimulus_NE6
  stimulus_NE7
  stimulus_NE8
  stimulus_NE9
  stimulus_NE10
  stimulus_NE11
  stimulus_NE12
  stimulus_NE13
  stimulus_NE14
  stimulus_NE15
  stimulus_NE16
  stimulus_NE17
  stimulus_NE18
  quest_certainty       # bitmap certainty question
  quest_severity              # bitmap severity question
  quest_region_most_NE  # bitmap region choice question
  quest_region_least_NE # bitmap region choice question
  quest_trust                 # bitmap trust question

# Define table with all the stimulus used in the task, that all
# participants will go trough

table stimulus_table
  "hotday dots 1" stimulus_NE1      1     "region_quest"    "severity_quest"
      "uncert_quest"    "trust_quest"     "least"
  "hotday dots 2" stimulus_NE2      2     "region_quest"    "severity_quest"
      "uncert_quest"    "trust_quest"     "most"
  "hotday nothing 1"    stimulus_NE3      1     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "least"
  "hotday nothing 2"    stimulus_NE4      2     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "most"
  "hotday lines 1"      stimulus_NE5      1     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "least"
  "hotday lines 2"      stimulus_NE6      2     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "most"
  "prec dots 1"         stimulus_NE7      1     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "least"
```

```
  "prec dots 2"         stimulus_NE8      2     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "most"
  "prec nothing 1"      stimulus_NE9      1     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "least"
  "prec nothing 2"      stimulus_NE10     2     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "most"
  "prec lines 1"        stimulus_NE11     1     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "least"
  "prec lines 2"        stimulus_NE12     2     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest”     "most"
  "temp dots 1"         stimulus_NE13     1     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "least"
  "temp dots 2"         stimulus_NE14     2     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "most"
  "temp nothing 1"      stimulus_NE15     1     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "least"
  "temp nothing 2”      stimulus_NE16     2     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "most"
  "temp lines 1"        stimulus_NE17     1     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "least"
  "temp lines 2"        stimulus_NE18     2     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "most"

table example_table
  "example dots hotday" stimulus_example_NE     1     "region_quest"
      "severity_quest"        "uncert_quest"    "trust_quest"     "least"

# Define the task. Each complete task is composed of 4 subtasks, namely
# the one in which the participants choose the region, the task where
# they evaluate the severity, the one where they evaluate the
# uncertainty, finally the one on the trust.

task example
  table example_table
  show bitmap @2 0 -150
  if @3 == 1
    show bitmap quest_region_least_NE 0 360
  else
    show bitmap quest_region_most_NE 0 360
  fi
  draw off
    show bitmap selection_item   -540 450
    show bitmap selection_item   -340 450
    show bitmap selection_item   -140 450
    show bitmap selection_item     60 450
    show bitmap selection_item    260 450
    show bitmap selection_item    460 450
    show bitmap A_region         -480 450
    show bitmap B_region         -280 450
    show bitmap C_region          -80 450
    show bitmap D_region          120 450
    show bitmap E_region          320 450
    show bitmap F_region          520 450
  draw on
  choose option exit continue_allowed continue_restricted 700 530
  choose option minselect 1
  choose option maxselect 1
  choose option select selected_symbol
  choose 3600000 3 8
  set $selection CHOSEN_1
  save @1 @4 @8 CHOSEN_1 RT BLOCKNAME
  clear screen
  show bitmap @2 0 -150
```

```
show bitmap quest_severity 0 330
if $selection == 3
  show bitmap selected_A  0 370
fi
if $selection == 4
  show bitmap selected_B  0 370
fi
if $selection == 5
  show bitmap selected_C  0 370
fi
if $selection == 6
  show bitmap selected_D  0 370
fi
if $selection == 7
  show bitmap selected_E  0 370
fi
if $selection == 8
  show bitmap selected_F  0 370
fi
draw off
  show bitmap left_severity      -410 440
  show bitmap selection_item     -240 440
  show bitmap selection_item     -160 440
  show bitmap selection_item      -80 440
  show bitmap selection_item        0 440
  show bitmap selection_item       80 440
  show bitmap selection_item      160 440
  show bitmap selection_item      240 440
  show bitmap right_severity      375 445
draw on
choose option exit continue_allowed continue_restricted 700 530
choose option minselect 1
choose option maxselect 1
choose option select selected_symbol
choose 3600000 5 11
save @1 @5 @8 CHOSEN_1 RT BLOCKNAME
clear screen
show bitmap @2 0 -150
show bitmap quest_certainty 0 330
if $selection == 3
  show bitmap selected_A  0 370
fi
if $selection == 4
  show bitmap selected_B  0 370
fi
if $selection == 5
  show bitmap selected_C  0 370
fi
if $selection == 6
  show bitmap selected_D  0 370
fi
if $selection == 7
  show bitmap selected_E  0 370
fi
if $selection == 8
  show bitmap selected_F  0 370
fi
draw off
  show bitmap left_certainty     -410 440
  show bitmap selection_item     -240 440
  show bitmap selection_item     -160 440
  show bitmap selection_item      -80 440
  show bitmap selection_item        0 440
```

```
    show bitmap selection_item       80 440
    show bitmap selection_item      160 440
    show bitmap selection_item      240 440
    show bitmap right_certainty     375 445
  draw on
  choose option exit continue_allowed continue_restricted 700 530
  choose option minselect 1
  choose option maxselect 1
  choose option select selected_symbol
  choose 3600000 5 11
  save @1 @6 @8 CHOSEN_1 RT BLOCKNAME
  clear screen
  show bitmap @2 0 -150
  show bitmap quest_trust 0 360
  draw off
    show bitmap left_trust         -445 440
    show bitmap selection_item     -240 440
    show bitmap selection_item     -160 440
    show bitmap selection_item      -80 440
    show bitmap selection_item        0 440
    show bitmap selection_item       80 440
    show bitmap selection_item      160 440
    show bitmap selection_item      240 440
    show bitmap right_trust         415 440
  draw on
  choose option exit continue_allowed continue_restricted 700 530
  choose option minselect 1
  choose option maxselect 1
  choose option select selected_symbol
  choose 3600000 4 10
  save @1 @7 @8 CHOSEN_1 RT BLOCKNAME

task uncertexp
  table stimulus_table
  show bitmap @2 0 -150
  if @3 == 1
    show bitmap quest_region_least_NE 0 360
  else
    show bitmap quest_region_most_NE 0 360
  fi
  draw off
    show bitmap selection_item   -540 450
    show bitmap selection_item   -340 450
    show bitmap selection_item   -140 450
    show bitmap selection_item     60 450
    show bitmap selection_item    260 450
    show bitmap selection_item    460 450
    show bitmap A_region         -480 450
    show bitmap B_region         -280 450
    show bitmap C_region          -80 450
    show bitmap D_region          120 450
    show bitmap E_region          320 450
    show bitmap F_region          520 450
  draw on
  choose option exit continue_allowed continue_restricted 700 530
  choose option minselect 1
  choose option maxselect 1
  choose option select selected_symbol
  choose 3600000 3 8
  set $selection CHOSEN_1
  save @1 @4 @8 CHOSEN_1 RT BLOCKNAME
  clear screen
  show bitmap @2 0 -150
```

```
show bitmap quest_severity 0 330
if $selection == 3
  show bitmap selected_A  0 370
fi
if $selection == 4
  show bitmap selected_B  0 370
fi
if $selection == 5
  show bitmap selected_C  0 370
fi
if $selection == 6
  show bitmap selected_D  0 370
fi
if $selection == 7
  show bitmap selected_E  0 370
fi
if $selection == 8
  show bitmap selected_F  0 370
fi
draw off
  show bitmap left_severity      -410 440
  show bitmap selection_item     -240 440
  show bitmap selection_item     -160 440
  show bitmap selection_item      -80 440
  show bitmap selection_item        0 440
  show bitmap selection_item       80 440
  show bitmap selection_item      160 440
  show bitmap selection_item      240 440
  show bitmap right_severity      375 440
draw on
choose option exit continue_allowed continue_restricted 700 530
choose option minselect 1
choose option maxselect 1
choose option select selected_symbol
choose 3600000 5 11
save @1 @5 @8 CHOSEN_1 RT BLOCKNAME
clear screen
show bitmap @2 0 -150
show bitmap quest_certainty 0 330
if $selection == 3
  show bitmap selected_A  0 370
fi
if $selection == 4
  show bitmap selected_B  0 370
fi
if $selection == 5
  show bitmap selected_C  0 370
fi
if $selection == 6
  show bitmap selected_D  0 370
fi
if $selection == 7
  show bitmap selected_E  0 370
fi
if $selection == 8
  show bitmap selected_F  0 370
fi
draw off
  show bitmap left_certainty     -410 440
  show bitmap selection_item     -240 440
  show bitmap selection_item     -160 440
  show bitmap selection_item      -80 440
  show bitmap selection_item        0 440
```

```
    show bitmap selection_item       80 440
    show bitmap selection_item      160 440
    show bitmap selection_item      240 440
    show bitmap right_certainty     375 440
  draw on
  choose option exit continue_allowed continue_restricted 700 530
  choose option minselect 1
  choose option maxselect 1
  choose option select selected_symbol
  choose 3600000 5 11
  save @1 @6 @8 CHOSEN_1 RT BLOCKNAME
  clear screen
  show bitmap @2 0 -150
  show bitmap quest_trust 0 360
  draw off
    show bitmap left_trust         -445 440
    show bitmap selection_item     -240 440
    show bitmap selection_item     -160 440
    show bitmap selection_item      -80 440
    show bitmap selection_item        0 440
    show bitmap selection_item       80 440
    show bitmap selection_item      160 440
    show bitmap selection_item      240 440
    show bitmap right_trust         415 440
  draw on
  choose option exit continue_allowed continue_restricted 700 530
  choose option minselect 1
  choose option maxselect 1
  choose option select selected_symbol
  choose 3600000 4 10
  save @1 @7 @8 CHOSEN_1 RT BLOCKNAME

# Define blocks, the one with the example trial and the real experiment,
# where all 18 stimuli appear, without repetition or exclusions

block exampleblock
  pager option mouse back -250 520 next 0 520 start 250 520
  pager intro_certainty intro_trial_NE
  clear screen
  tasklist
    example 1
  end
  message trial_finish mouse

block mainexp
  message instruction mouse
  tasklist
    uncertexp 18 all_before_repeat
  end
```

M.4 Pre-test SAM code

```
options
  fullscreen
  scale
  resolution 1800 1200
  background color 200 200 200

# Define the bitmaps used for stimuli and other objects in the tasks

bitmaps
  arousal_1
```

```
  arousal_2
  arousal_3
  arousal_4
  arousal_5
  arousal_6
  arousal_7
  arousal_8
  arousal_9
  dominance_1
  dominance_2
  dominance_3
  dominance_4
  dominance_5
  dominance_6
  dominance_7
  dominance_8
  dominance_9
  pleasure_1
  pleasure_2
  pleasure_3
  pleasure_4
  pleasure_5
  pleasure_6
  pleasure_7
  pleasure_8
  pleasure_9
  instruction_sam_pre
  short_sam
  note_sam
  continue_allowed
  continue_restricted
  selectedsam_symbol
  happy
  unhappy
  excited
  calm
  controlled
  incontrol

table sam_table
"pleasure"  "arousal"   "dominance"

#   Define task

task sam
  table sam_table
  show bitmap instruction_sam_pre   -3 -200
  show bitmap note_sam             -42 -100
  draw off
    show bitmap happy          -790 50
    show bitmap pleasure_1     -660 50
    show bitmap pleasure_2     -495 50
    show bitmap pleasure_3     -330 50
    show bitmap pleasure_4     -165 50
    show bitmap pleasure_5        0 50
    show bitmap pleasure_6      165 50
    show bitmap pleasure_7      330 50
    show bitmap pleasure_8      495 50
    show bitmap pleasure_9      660 50
    show bitmap unhappy         800 50
  draw on
  choose option exit continue_allowed continue_restricted 600 520
  choose option minselect 1
```

```
  choose option maxselect 1
  choose option select selectedsam_symbol
  choose 3600000 4 12
  save @1 CHOSEN_1 RT
  clear screen
  show bitmap short_sam        -324 -180
  show bitmap note_sam         -42 -100
  draw off
    show bitmap excited        -800 50
    show bitmap arousal_1      -660 50
    show bitmap arousal_2      -495 50
    show bitmap arousal_3      -330 50
    show bitmap arousal_4      -165 50
    show bitmap arousal_5         0 50
    show bitmap arousal_6       165 50
    show bitmap arousal_7       330 50
    show bitmap arousal_8       495 50
    show bitmap arousal_9       660 50
    show bitmap calm            780 50
  draw on
  choose option minselect 1
  choose option maxselect 1
  choose 3600000 4 12
  save @2 CHOSEN_1 RT
  clear screen
  show bitmap short_sam        -324 -180
  show bitmap note_sam         -42 -100
  draw off
    show bitmap controlled     -815 50
    show bitmap dominance_1    -660 50
    show bitmap dominance_2    -495 50
    show bitmap dominance_3    -330 50
    show bitmap dominance_4    -165 50
    show bitmap dominance_5       0 50
    show bitmap dominance_6     165 50
    show bitmap dominance_7     330 50
    show bitmap dominance_8     495 50
    show bitmap dominance_9     660 50
    show bitmap incontrol       815 50
  draw on
  choose option minselect 1
  choose option maxselect 1
  choose 3600000 4 12
  save @3 CHOSEN_1 RT

#    Define block

block samtask
  tasklist
    sam 1
  end
```

M.5 Post-test SAM and SEW code

```
options
  fullscreen
  scale
  resolution 1800 1200
  background color 200 200 200

#   Define the bitmaps used for stimuli and other objects in the tasks
```

```
bitmaps
  arousal_1            # all the single SAM items
  arousal_2
  arousal_3
  arousal_4
  arousal_5
  arousal_6
  arousal_7
  arousal_8
  arousal_9
  dominance_1
  dominance_2
  dominance_3
  dominance_4
  dominance_5
  dominance_6
  dominance_7
  dominance_8
  dominance_9
  pleasure_1
  pleasure_2
  pleasure_3
  pleasure_4
  pleasure_5
  pleasure_6
  pleasure_7
  pleasure_8
  pleasure_9
  instruction_sam_post  # instructions for the SAM task
  short_sam
  note_sam
  continue_allowed            # buttons
  continue_restricted
  selectedsam_symbol          # square indicating the selected SAM item
  happy                       # SAM labels
  unhappy
  incontrol
  controlled
  calm
  excited
  cross                       # cross for selection for the Emotion Wheel
  instruction_emowheel  # instructions for the Emotion Wheel
  note_emowheel
  circle1                     # response circles Emotion Wheel
  circle2
  circle3
  circle4
  circle5
  shame_guilt                 # Emotion labels
  indifference
  joy
  anger
  excitement
  hope
  compassion
  concern_fear

#   Define Tables

table sam_table
"pleasure"  "arousal"   "dominance"

table emowheel_table
```

```
"EmoWheel"

#   Define tasks

task sam
  table sam_table
  show bitmap instruction_sam_post  -46 -200
  show bitmap note_sam              -42 -100
  draw off
    show bitmap happy          -790 50
    show bitmap pleasure_1     -660 50
    show bitmap pleasure_2     -495 50
    show bitmap pleasure_3     -330 50
    show bitmap pleasure_4     -165 50
    show bitmap pleasure_5        0 50
    show bitmap pleasure_6      165 50
    show bitmap pleasure_7      330 50
    show bitmap pleasure_8      495 50
    show bitmap pleasure_9      660 50
    show bitmap unhappy         800 50
  draw on
  choose option exit continue_allowed continue_restricted 600 520
  choose option minselect 1
  choose option maxselect 1
  choose option select selectedsam_symbol
  choose 3600000 4 12
  save @1 CHOSEN_1 RT
  clear screen
  show bitmap short_sam        -324 -180
  show bitmap note_sam         -42 -100
  draw off
    show bitmap excited        -800 50
    show bitmap arousal_1      -660 50
    show bitmap arousal_2      -495 50
    show bitmap arousal_3      -330 50
    show bitmap arousal_4      -165 50
    show bitmap arousal_5         0 50
    show bitmap arousal_6       165 50
    show bitmap arousal_7       330 50
    show bitmap arousal_8       495 50
    show bitmap arousal_9       660 50
    show bitmap calm            780 50
  draw on
  choose option minselect 1
  choose option maxselect 1
  choose 3600000 4 12
  save @2 CHOSEN_1 RT
  clear screen
  show bitmap short_sam        -324 -180
  show bitmap note_sam         -42 -100
  draw off
    show bitmap controlled     -815 50
    show bitmap dominance_1    -660 50
    show bitmap dominance_2    -495 50
    show bitmap dominance_3    -330 50
    show bitmap dominance_4    -165 50
    show bitmap dominance_5       0 50
    show bitmap dominance_6     165 50
    show bitmap dominance_7     330 50
    show bitmap dominance_8     495 50
    show bitmap dominance_9     660 50
    show bitmap incontrol       815 50
  draw on
```

```
  choose option minselect 1
  choose option maxselect 1
  choose 3600000 4 12
  save @3 CHOSEN_1 RT

task emotionwheel
  table emowheel_table
  show bitmap instruction_emowheel   -12 -480
  show bitmap note_emowheel          -13 -315
  draw off
    show bitmap excitement          202 -186
    show bitmap joy                 373 -3
    show bitmap hope                373 203
    show bitmap compassion          202 386
    show bitmap indifference       -202 386
    show bitmap shame_guilt        -373 203
    show bitmap concern_fear       -373 -3
    show bitmap anger              -202 -186
    show bitmap circle1        90 -117
    show bitmap circle2        67 -61
    show bitmap circle3        46 -12
    show bitmap circle4        30 29
    show bitmap circle5        16 63
    show bitmap circle1              217 10
    show bitmap circle2              161 33
    show bitmap circle3              112 54
    show bitmap circle4              71 70
    show bitmap circle5              37 84
    show bitmap circle1         217 190
    show bitmap circle2         161 167
    show bitmap circle3         112 146
    show bitmap circle4         71 130
    show bitmap circle5         37 116
    show bitmap circle1               90 317
    show bitmap circle2               67 261
    show bitmap circle3               46 212
    show bitmap circle4               30 171
    show bitmap circle5               16 137
    show bitmap circle1          -90 317
    show bitmap circle2          -67 261
    show bitmap circle3          -46 212
    show bitmap circle4          -30 171
    show bitmap circle5          -16 137
    show bitmap circle1                -217 190
    show bitmap circle2                -161 167
    show bitmap circle3                -112 146
    show bitmap circle4                 -71 130
    show bitmap circle5                 -37 116
    show bitmap circle1           -217 10
    show bitmap circle2           -161 33
    show bitmap circle3           -112 54
    show bitmap circle4            -71 70
    show bitmap circle5            -37 84
    show bitmap circle1                  -90 -117
    show bitmap circle2                  -67 -61
    show bitmap circle3                  -46 -12
    show bitmap circle4                  -30 29
    show bitmap circle5                  -16 63
  draw on
  choose option exit continue_allowed continue_restricted 650 530
  choose option minselect 1
  choose option maxselect 1
  choose option select cross
```

```
  choose 3600000 11 50
  save @1 CHOSEN_1 RT

#    Define blocks

block samtask
  tasklist
    sam 1
  end

block emowheel
  tasklist
    emotionwheel 1
  end
```

Personal Declaration

I hereby declare that the submitted Thesis is the result of my own, independent work. All external sources have been explicitly acknowledged in the Thesis. I have not submitted this Thesis, or any part of it, previously to any institution for assessment purposes.

In this Thesis, I used Microsoft Word's built-in spell checker and DeepL. These tools helped me fix spelling mistakes and get suggestions to improve the writing of the paper. If not noted otherwise in a specific section, these tools were not used in other forms.

Date, Place:

30.04.2024, Zürich

Signature:

Sergio Bazzurri

Sergio Bazzurri