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Scenicness Model Based on the British Scenic-or-Not Data Set for Switzerland, Landscape Beauty Through the Eyes of a Computer

GEO 511 Master's Thesis

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Abstract

The importance of landscape preservation has been widely accepted. Experiencing landscape beauty has health benefits and enables the touristic economy sector in Switzerland to create a wide range of job opportunities. In order to better understand how people perceive landscape, this thesis aims at analyzing the Scenic-or-Not data set to build a machine learning model that predicts landscape beauty. The resulting model was tested on its accuracy through manual image evaluation on their scenic beauty and comparing the scores to the value the model predicted. Validation sites were visited around Switzerland to view how the scenic scores from the model represented the real world. Further the useability of the resulting scenic map in decision making processes was analyzed with the ultimate goal to use the model as a landscape preservation tool. Having a national scenic map could bring benefits when planning infrastructure projects like wind turbines or highway routes. Such a scenic map might capture public opinion on specific landscape scenes and enable precise landscape preservation and through this win public approval for large infrastructure projects.

Zusammenfassung

Die Bedeutung des Landschaftsschutz ist allgemein anerkannt. Das Erleben von Landschaftsschönheit wirkt sich positiv auf die Gesundheit aus und schafft eine Vielzahl von Arbeitsplätzen im Tourismussektor in der Schweiz. Um besser zu verstehen, wie Menschen Landschaft wahrnehmen, zielt diese Arbeit darauf ab, den Scenic-or-Not Datensatzes zu analysieren und ein maschinelles Lernmodell zu erstellen, dass Landschaftsschönheit vorhersagen kann. Das daraus resultierende Modell wurde auf seine Genauigkeit getestet, indem manuelle Bildauswertungen auf ihre landschaftliche Schönheit untersucht und die Ergebnisse mit dem vom Modell vorhergesagten Wert verglichen wurden. Es wurden Validierungsstandorte in der Schweiz besucht, um zu sehen, wie die landschaftlichen Bewertungen des Modells die reale Welt repräsentieren. Des Weiteren wurden die Möglichkeiten der resultierenden Landschaftsschönheitskarten in Entscheidungsprozessen analysiert, mit dem Ziel das Modell als Instrument zum Landschaftsschutz einzusetzen. Eine nationale Karte für Landschaftsschönheit könnte bei der Planung von Infrastrukturprojekten wie Windkraftanlagen oder Autobahntrassen von Vorteil sein. Eine solche Landschaftskarte könnte die öffentliche Meinung zu bestimmten Landschaften einfangen und einen präzisen Landschaftsschutz ermöglichen. Dadurch könnte mehr öffentliche Befürwortung für große Infrastrukturprojekte gewonnen werden.

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1 Introduction

The word landscape has multiple meanings in society. As Bell (1999) describes in his book “Landscape, Pattern, Perception and Process”, landscape has many connotations which range from it being a piece of land, to being a painting of an area. The way an observer perceives landscape depicts their individual interests. As an example Bell (1999) describes a remote sensing scientist who looks through a lens of a satellite, and a botanist who looks down upon a flower bed; Both of them might use the word landscape to describe their view, but the real world extent of space and the features in it, could not differ more (Bell, 2012).

A fitting illustration how landscape can influence the human well-being and be perceived is Jürg Müller’s image series called “Alle Jahre wieder saust der Presslufthammer nieder”. The series of images show multiple perspectives of a lovely little family home and how the surroundings slowly but surely are changed into an urban modern city landscape. The small village grows, shopping malls and office buildings are built and in the last image of the series the idyllic village is barely recognizable except for the small centrally placed family home which stayed the same over the years (Nüesch, 2015). When asked about the image series, Jürg Müller talks about the feeling he had when whole neighbourhoods of family homes were torn down in his home town in order to make space for a large industrial building. When applying Bell’s (1999) approach, to the image series of Jürg Müller they show his knowledge and feelings which he associates with the village he depicts in his image series. The change of the environment he had known moves him. Jürg Müller’s image series is a great example of how landscape is valued and how large changes to it are perceived. The image series depicts the importance of preserving beautiful landscapes in Switzerland. The following thesis explores the perception of landscape based on different landscape characteristics and the possibility of predicting the perception of landscape beauty using machine learning. It is therefore important to understand the meaning of the word landscape and how it relates to our history and culture. In the following chapters I will explore the changing definition of landscape over time and the factors that lead us to describe landscape as beautiful.

1.1 Defining Landscape

The word landscape exists in the German language as well as in the English language. This master thesis aims to compare the perception of landscape beauty in Switzerland and Great Britain. Because a majority of people who live in Switzerland speak German, it is important to define both the English word and the German word. In both languages landscape can be split into the word “land” and the word “scape” or in German “schaft”. The suffix “scape” is equivalent to the suffix “ship” and originates from the old English word “scyppan” which means “to shape”. Additionally, the suffix “schaft” also originates from the German word “schaffen” and is therefore linked. The words "landscape" and "Landschaft" have a similar history and origin and can be linked to each other, although they don't mean the exact same thing (Kenneth R Olwig, 2005) (Makhzoumi and Pungetti, 2003). When one looks closer at the word landscape one can find multiple connotations. The oldest definition of the word landscape was mentioned in the English dictionary in 1755 by Samuel Johnson: "a region; the prospect of a country". The word landscape focuses on the idea of an enclosed region and belonging to someone or something (Kenneth R. Olwig and Rose, 2022). In those days ownership was of great importance with imperialism on its peak. Most European countries were obsessed with owning as much land as possible.

A more recent definition includes: "a picture, representing an extent of space, with the various objects in it" (Kenneth R. Olwig and Rose, 2022). In this definition the focus suddenly changes from ownership to what the actual landscape includes in terms of objects, colors or texture.

With the invention of virtual reality, the definition of landscape includes a whole new area which changes its importance once again. In today's Europe the word landscape has been defined as follows: "an area, as perceived by people, whose character is the result of the action and interaction of natural and/or human factors" (EU, 2023). In this definition, just like Bell (1999) described, the perception is a key part when talking about landscape. The transformation of the word landscape, first defined as ownership, later including the real physical objects and colors, and to finally including the individual perception and relationship with a specific landscape shows the complexity of the word and its value.

Stevens (1974) identified four basic patterns that every landscape consists of and which we as humans perceive: (1) spirals, (2) meanders, (3) branches and (4) explosions (Stevens, 1974). The patterns fill the available space and form the starting point to explore the signification of "Landscape" (Bell, 2012). The analysis of Stevens (1974) breaks down the landscape into its most basic components and helps to deeper understand its meaning. The classification into four different patterns was not always satisfactory and leads Bell to include the concept of mosaic landscapes. Here landscape is not seen as one unit but as a multilayered construct where different patterns interact with each other and are hard to separate from each other. According to Bell (1999) humans are the only species capable of consciously designing objects in a creative way. Early on humans used landscape features and its objects to influence styling of artifacts or tools. Landscape was, is and always will be important for human cognitive development and well-being (Bell, 2012).

1.2 Landscape Beauty

1.2.1 Aesthetics of Landscape

Bell (1999) defines five areas which influence perceived landscape beauty. (Bell, 2012)

1. Diversity / Complexity
2. Coherence
3. Spirit of Place
4. Mystery
5. Multiple Scales
6. Strength

1. **Diversity / Complexity** The diversity or the complexity of the landscape shows how healthy the ecosystems in it are. When a landscape is untouched and unaltered it usually has a certain complexity which is shown in a multi-layered and multi-scaled landscape with various healthy ecosystems in it. If this multi-layered theme is not present, the landscape probably is simplified by human intervention (Bell, 2012). Hunziker and Kienast (1999) come to the same conclusion. They used spatial metrics to determine the correlation between diversity and scenic value of a landscape and could show that the relationship between the two variables was statistically significant (Hunziker and Kienast, 1999).

2. **Coherence** Coherence in this context is defined as an ordered structure which humans can understand. The comprehensions of the whole scene is more significant than understanding singular parts of a landscape.

3. **Spirit of Place** Spirit of place or the Genius loci, is the aspect of uniqueness to a place. The ancient Romans used this expression to describe religious sites or special architectural buildings (Bell, 2012).

4. **Mystery** The factor mystery describes the situation in which a landscape can be perceived at once or if there are areas which could be explored further (Bell, 2012).

5. **Multiple Scales** The scales of the landscape patterns compared to the human size generate a comparative feature to the landscape and makes it more attractive (Bell, 2012). Also Havinga et al (2021) conclude in their research how visual scale has an impact on perceived landscape beauty. In the research of Having et al (2021) it was addressed that this could be caused by our prey

and predator history and the elevation differences could provide refuge for us as hunted species (Havinga et al., 2021b).

6. **Strength** The overall mixture of the factors one to five is defined as "strength" (Bell, 2012).

1.2.2 Tranquility

Landscape is described in various ways and is deemed beautiful or dull very subjectively. But the decision to call a landscape aesthetic, is not only influenced by visual components but also smell, sound or touch. Tudor (2014) describes a framework to characterize landscapes which is named the Landscape Character Assessment. In figure 1 the different framework components also include audio and tactile aspects which influence how people experience landscape (Tudor, 2014).

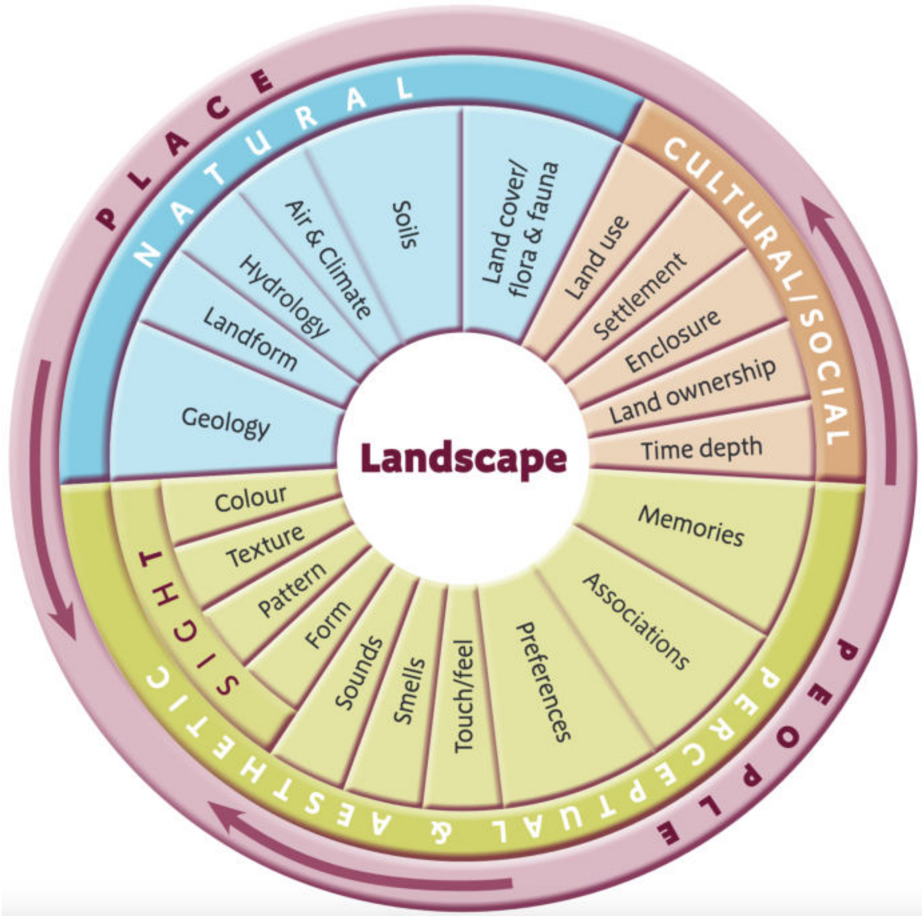


Figure 1: Division of Landscape into different subtopics as proposed by Tudor (2014) (Tudor, 2014).

Chesnokova et al (2018) focus on the concept of sound and how this influences the perception of landscape. Because sound might affect us more constantly than any other sense it is therefore crucial to capture the perception of landscape. In the article Chesnokova et al (2018) used two different word corpuses where the contents were analyzed based on references to acoustic features or sounds. They concentrated on their analysis on perception of sound and landscape (Chesnokova, Taylor, et al., 2018). In order to analyze sound and noise as a physical feature a different approach might give additional insights into how the actual landscape scene is influenced. Wiener et al (1965) approached this issue by studying how sound propagates in urban areas and used a data set which is corrected for inverse square law. Thus they were able to model sound levels in urban area (Wiener et al., 1965). The inverse square law describes how sound travels through the medium of air, where disturbances or hindrances of the sound wave are neglected. It is assumed that the sound waves move through an ideal space filled with air (see figure 2).

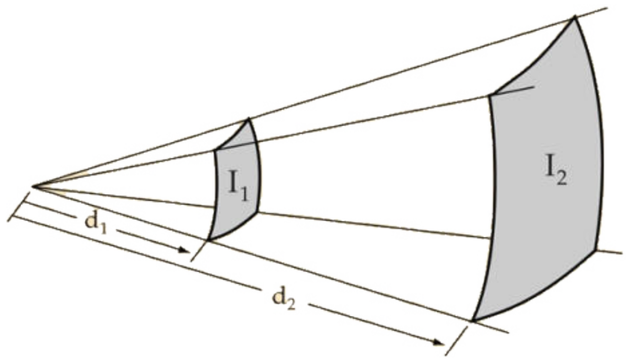


Figure 2: Moving sound waves inside of an ideal medium as described by the inverse square law (Hyperphysics, 2023).

The sound levels experienced by the human ear can be calculated and generally decreases by six decibel per doubling of distance to the source. This number is based on the formula of the inverse square law for sound level calculations and is not exactly true for every scenario in nature. It is more of an approximation, suited for the role noise plays in this master thesis.

$$L_2 = L_1 - |20 \times log(\frac{r_1}{r_2})| \tag{1}$$

Equation 1 shows the mathematical basis for the approximation which is used for this thesis and represents the basis for the basic noise data which is generated (Hyperphysics, 2023).

1.2.3 Importance of Landscape Beauty for the Community

According to Krebs (2014) human well-being starts with landscape (Krebs, 2014). Experiencing a beautiful landscape makes us feel at home. Early in the existence of humankind, people identified different features of landscape with feelings and most importantly, their health. The ancient Persians experimented with gardens and searched for the optimal scene for a garden, where feelings of humans climaxed and made them feel comfortable and at ease. Architects would design and shape gardens in order to recreate an Eden-like environment, where fruit and plants would prosper and symbolize the a garden of life. These gardens usually were only accessible to a selected group of people (Thompson, 2011). In the 18th century the importance of green spaces for the overall health of the population was rediscovered. Especially in industrialized cities such as London a process was started where the English government built parks which then became known as "the lungs of London". For the first time green spaces were created and designed specifically to increase public health. At first these parks were not publicly accessible but after some years and a devastating cholera epidemic, the city decided to start opening the parks and other green areas with the goal to improve public health (Thompson, 2011). This development spread quickly and other European cities followed suit. Today it is widely acknowledged that the effects of experiencing landscape beauty have a positive impact on one's physical or psychological well-being. Among other issues it may help with short-term recovery from stress or mental fatigue (Velarde, Fry, and Tveit, 2007). Today most European cities and federal institutions have carefully planned guidelines on how green spaces and recreational areas are to be created and maintained. The federal bureau for environment in Switzerland (BAFU), discusses in its guidelines how creative solutions are crucial to generate enough green spaces for the increasing population in urban areas. This is especially important to prevent urban sprawl. Urban communities are becoming denser and with it the pressure on the population increases. The authors name issues like the low life expectancy for urban trees because of missing root space or salt overdoses. Overall the issue of urban green spaces has become more complicated. Human needs have changed and minimal life standards have increased. Additionally, the urban heat island effect as well as climate change in general have become increasingly important issues. Green areas are therefore included in cities development guidelines in Europe and around the world (BAFU, 2023).

Switzerland has a unique mountainous landscape and a large economic sector is dependent on the effect the landscape has on people who visit Switzerland for touristic or health reasons. Another aspect where landscape perception has a large influence are political decisions. Because Switzerland has a direct democracy, it enables the people to have a strong voice and they can influence decisions. The perception of landscape may influence how and if large infrastructure projects are implemented. One example where the state repeatedly has difficulty to communicate its importance, is the construction of wind parks. These would be much needed for the energy diversification goal which Switzerland is trying to implement. Reto Rigassi, CEO of Suisse-Eole, which is the trade association of Swiss wind energy, explained in an interview that most of the wind park projects are being blocked by objections which are coming from the general public. He suspects that people might not like the sight of large wind turbines in front of their homes and that they would be afraid that the turbines would not only be hideous, but devaluing their properties as well as being the cause of noise pollution (Winzenried, 2018). Due to this issue the state ordered a research project for the evaluation of general approval ratings of the public towards different energy sources and their effects on landscape. Hunziker and Salak (2022) have done two online questionnaires with more than a thousand participants. The first questionnaire was done in 2018 and the second in 2022. The research team then compared how the approval had changed over time and classified for which landscape type the approval had gone up or down. Hunziker and Salak (2022) have found that in general the public wants to see these renewable energy sources like windparks developed and implemented in Switzerland but not in areas like the Jura, Voralpen or in untouched mountainous regions (Salak and Hunziker, 2022). This shows how difficult it is for decision makers to find a suitable location for infrastructure projects that change the Swiss landscape immensely.

Another field where landscape preservation is important, is the urban sprawl which has massively increased in Switzerland (Jaeger, Bertiller, and Schwick, 2007). Jaeger et al (2007) have found that over the whole of Switzerland the urban sprawl has increased by 20% per inhabitant. The urban sprawl needs to be given more attention and the research team surrounding Jaeger have proposed various different strategies to contain the issue at hand. One of the proposed strategies is a better understanding of landscape to enable better spatial planning (Jaeger, Bertiller, and Schwick, 2007). This means landscape studies have to be conducted to develop a research based understanding of how the Swiss people view landscape and which aspects are more valued than others. To tackle the issue a quantification of landscape value has to be done. Scotland for example has created a national data set which shows national landscape features "of outstanding scenic value in a national context" (UK, 2023). Such a data set is missing for Switzerland and could be a useful basis for future decision makers and spatial planners. Not only would there be general basis for scenic landscapes but further studies and improvements could be promoted. The lengthy and resource intensive process of planning new infrastructures could be rethought and bring about change in areas like energy diversification, nature preservation or green area planning without losing important scenic landscapes.

1.3 Machine Learning

When looking at a phenomena on a large scale with multiple variables and complex relationships, machine learning is an appropiate and interesting approach to consider. In this chapter the idea behind machine learning is explained and different algorithms are presented.

1.3.1 What is Machine Learning

Humans learn from experience. Based on experience a human mind can make decisions and usually our decision making skills improve with increasing experience. This principle also applies to machine learning. In the year 1950 Alan Turing, who is portrayed in the Hollywood movie "The Imitation Game", suggested that computers could be able to think with the right programming and data input. In his paper "Computing Machinery and Intelligence" he describes a framework for building such a machine and how to test its intelligence (Turing, 1950). The issue until 1957 was that computers could not store enough data and had long computation times. Then suddenly from 1957 to 1974 artificial intelligence (AI) development picked up speed. Today AI is everywhere and, with the most recent and prominent example of ChatGPT, has reached a wide range of applications. ChatGPT is an AI which can answer questions and remembers topics from earlier conversations (Anyoha, 2017). AI systems are built on a variety of different algorithm approaches such as linear regression, decision tree, random forest algorithm or convolutional neural network. The developer starts with a large data base which represents the phenomena that is to be modelled. To build a model a machine learning algorithm approach is chosen and in a first phase the model is trained with a subset of the available data. In the training phase the algorithm learns by searching for patterns inside the data. The other unused data entries are later used to test the accuracy of the model. In this step the model actively predicts certain outcomes based on the test data set as input and the patterns that the algorithm has learned in the training phase (Mahesh, 2018)(Goodfellow, Bengio, and Courville, 2016).

1.3.2 Importance of Machine Learning

Since the years between 2010 and 2013 machine learning as a scientific concept has developed immensely. This can be explained by the following two developments: The first is the progress of easy to use machine learning frameworks that were released (Hey et al., 2020). Two famous frameworks were Keras (Chollet, 2023) and Scikit-learn (Pedregosa et al., 2011) which opened up machine learning models as a concept to a wider audience. A second important factor was the rapid growth of large data availability. An example for this availability is the Swiss geodata platform geo.admin.ch that was created in the year of 2010, and through which geodata on diverse topics for the whole of Switzerland was made accessible. Such open data platforms supported the development towards machine learning applications and research projects in this field (Swisstopo, 2023c).
In short, machine learning is a type of artificial intelligence that allows computers to learn from large data sets and improve their performance on specific tasks over time. Machine learning is used in different fields to improve our everyday life. It can automate many tasks that would otherwise require human intervention, and thus

can save time and money for businesses as well as individuals. Among other things, machine learning can be used to automate customer service inquiries, detect fraud, or optimize supply chain operations. Further machine learning algorithms can analyze vast amounts of data to identify patterns, predict an individuals' preferences or behavior. This kind of analysis would take humans months or even years to conduct and therefore the huge effort would be disproportionate compared to the yield. Such models can further be used for various tasks such as personalized recommendations, ads, or other content generation to improve online user experience. Furthermore, machine learning is increasingly being put to use in medicine to identify patterns that might not be obvious to human doctors at first. This can lead to earlier and more accurate diagnoses and better treatment outcomes. On the whole, machine learning is important because it has the potential to revolutionize whole industries and improve our lives in countless ways. Its ability to learn from extensive data sets and make predictions based on that data means that it can help us make better decisions, automate tedious tasks, and gain insights that might not be discernible with human analysis alone (Hey et al., 2020)(Goodfellow, Bengio, and Courville, 2016).

Random Forest Algorithm

As mentioned before, machine learning is not a specific algorithm but much more a set of different algorithm approaches, each with its advantages and disadvantages. An algorithm type which is relevant for this thesis is the Random Forest family. Random Forest is used for classification and regression and is essentially the construction of multiple decision trees. The model is usually fed with an input vector filled with different dependent X variables and an independent variable Y which is an one dimensional array of the same length as the X variables. The algorithm then builds multiple decision trees based on the input vectors and each decision tree delivers a result. All these decision trees form the random forest model and depending on the input variables for the prediction, the model chooses the best suited decision tree. One advantage of random forests is bagging. Bagging is a technique used in machine learning to reduce variance. Further overfitting can be prevented with bagging which is a big issue when training a machine learning model. Random forest uses bagging to build multiple decision trees and combine their predictions. In bagging, multiple subsets of the original dataset are created by randomly sampling data points. These subsets are used to train individual models, and their predictions are combined to make a final prediction. In the context of random forests, bagging is used to create multiple decision trees, each of which is trained on a different subset of the original data. In addition to random sampling, random forests also use feature bagging, where a random subset of features is selected for each decision tree. This further increases the diversity of the trees and helps prevent overfitting. Once all the decision trees have been trained, their predictions are combined by taking the

average (for regression) or majority vote (for classification). This ensemble approach helps to improve the accuracy and robustness of the model.
Another important advantage is that random forest uses Classification and Regression Trees (CART), which are its base estimator. Using the CART approach enables the random forest algorithm to gain additional advantages. One of these is the non-parametric aspect, which means that CART do not make any assumptions about the distribution of the data. Also, CART can handle both categorical and continuous input variables and can be used for both classification and regression tasks. Further CART ensures better interpretability because the resulting decision tree from the CART algorithm can be easily interpreted and visualized. The reasoning behind the model's predictions can thus be easily explained. Additionally, CART is not sensitive to outliers or missing data, which makes it a robust algorithm for handling noisy data. And lastly CART can handle large datasets with a high number of features, making it suitable for big data applications.
A large issue with random forest approaches in general and where users should be careful, is the fact that random forest algorithms have a tendency to over fit. This is something one should bear in mind when interpreting results and predictions from a random forest model (Yingchun and Liu, 2014)(Goodfellow, Bengio, and Courville, 2016).

1.3.3 Overfitting and Underfitting

One danger which often occurs when training a machine learning model are so called fitting issues. Fitting describes the process when a function is applied to the underlying data or specifically on top of the X variables of the model. This is the step where the model learns and tries to understand underlying patterns within the data. If the relationship is clearly recognisable for the algorithm and the data has very few outliers, this process usually works very well. However, these circumstances rarely occur, which is when the issue of overfitting or underfitting arises.
Overfitting describes a problem where the algorithm fits its function too well onto the training data set and tries to include data points like outliers or noise. This procedure leads to a drop in accuracy when evaluating the test data set with the model, because it is not able to generalize on patterns that occur within the whole data set but only inside the training data set (Khan, 2015). On the right side in figure 3 overfitting is visualized in a simplified example. The error function increases again after the optimal learning capacity has been reached.
Underfitting is the opposite problem. Here the machine learning model does not learn enough to draw a relationship between the data points which results in a poor performance. The underlying issue is that the model is too simple to capture the complexity of the data. This scenario is visualized on the left side in figure 3. Here the error function further decreases because the model has not reached the optimal learning capacity yet and the underlying data is much more complicated than the

model can predict yet (Khan, 2015)(Goodfellow, Bengio, and Courville, 2016).

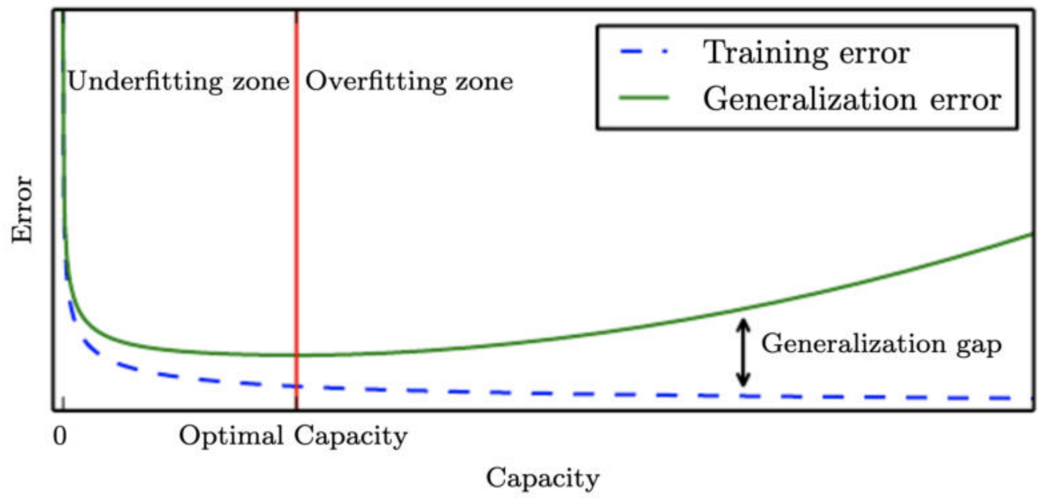


Figure 3: This figure shows how a loss function could look like when a model underfits or overfits. On the left side of the graph the model underfits because the learning potential is not completely exploited. On the right side of the graph the model tries to learn more from the underlying data, even though the error increases again at red line. The red line represents the full learning potential of the model (Goodfellow, Bengio, and Courville, 2016).

1.3.4 One-hot Encoder

To ensure that a machine learning model can read and learn from the data which it is provided with, string type data needs to be encoded into numeric values. For this, various different methods can be used, where the label encoder and the one-hot encoder are the two methods which are discussed in the scope of this master thesis.

The one-hot encoder is an encoding mechanism which takes all the possible values the data provides and creates a presence matrix.

ID	Category
1	Bird
2	Dog,Cat
3	Cat
4	Fish,Dog
5	Dog

ID	Bird	Dog	Cat	Fish
1	1	0	0	0
2	0	1	1	0
3	0	0	1	0
4	0	1	0	1
5	0	1	0	0

Figure 4: Example of a one-hot encoded data set. All possible category values get a column and each column is filled with either a one if the category is present for the data entry or a zero if the category is not present.

Figure 4 shows a simplified example of how string format data is encoded using a one-hot encoder. The resulting presence matrix on the right represents the data which can be fed into a machine learning model. The advantage of such an encoder is that when decisions are traced back, it is easy to see which subcategories were effective in correct predictions of the model.

1.3.5 Label Encoder

The label encoder is another method to encode data in order to make it readable for machine learning algorithms. Here the data is taken and for each unique value a numeric value is given. The user ends up with a numeric key book which corresponds to a string value list. This numeric key book is then inserted into the machine learning algorithm.

1.3.6 Performance Analysis

When implementing a machine learning model, it is crucial to test different hyper-parameters. The performance of the model could significantly improve when the right hyper-parameter values are chosen. Such an analysis can also give insights to whether the model being under- or overfitted. When using Python and the Scikit-Learn framework, a selection of the following hyper-parameters is usually tuned to achieve the best accuracy.

Maximum depth describes how deep the tree is allowed to go. Consider Figure 5 which on the right-hand side shows the maximum depth variable for the example tree. That variable defines that this tree is not allowed to go past two splits and is basically defining the maximal depth the tree is supposed to grow. Depending on the data the random forest regressor could be worse when the algorithm keeps splitting nodes excessively and at the same time the underlying pattern in the data is better modelled when staying in a shallower depth pattern.

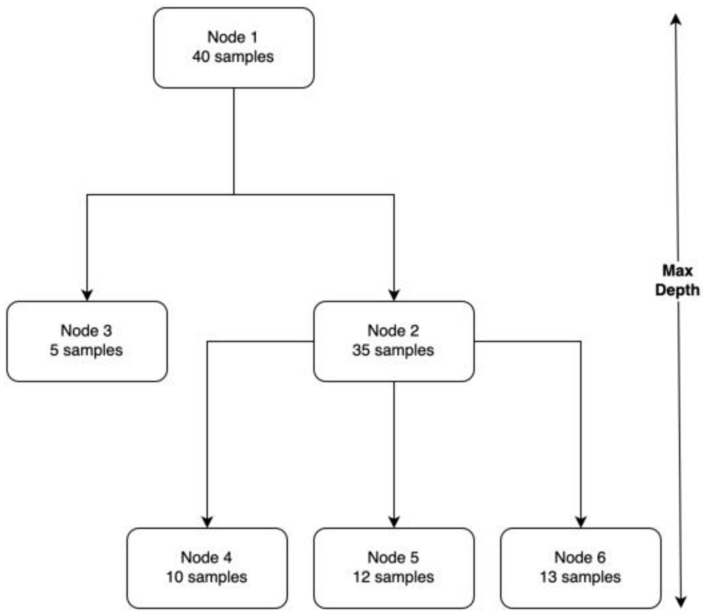


Figure 5: Example of a decision tree where the rectangular boxes represent nodes. The depth to where the tree is built until a node is considered a leaf is called the max depth.

When considering the same example from Figure 5, the minimum sample split represents the minimal required number of samples inside of a node to allow a split. If

the number of samples inside of the particular node is smaller than the minimum sample split value, the node will not be split again.
The maximum leaf node variable defines how many final nodes at the end of the tree are allowed. Usually, the regressor starts with one node and continues down until different hyper-parameters limit the further growing of the tree or the leaf cannot split into further leaves. With maximum leaf nodes set to a value, the tree stops growing when the lowest layer of the tree contains the number of leaves which corresponds to the previously set value of the maximum leaf node variable.
In the above mentioned example from Figure 5 the variable minimum sample leaf describes the minimum number of samples a leaf needs to have, so it is allowed to be defined as a leaf. If a node is prepared to be split and one of the resulting leaves from this node split will have less than the minimum sample leaf hyper-parameter, the split will not occur.
The maximum sample hyper-parameter defines the number of samples that are used for each tree building process. This is only done if bootstrap is activated. Bootstrap is a training process where each tree is not trained with the complete data set for the X variables, but only gets a subset of the data set. The maximum sample refers to the size of the subset which gets put into the tree building process.
The maximum feature attribute defines how many features of the X variable data set are to be considered. This is an interesting parameter, because not all features might have an effect on the training progress of the model. Some variables describe the underlying phenomenon well and others might not be as descriptive.

There are several different accuracy scores to evaluate how well the model predicted the test samples. For a regression model the R^2 value is commonly used. The R^2 value is a mathematical term to describe how much of the variance in the data can be explained (Chesnokova, Nowak, and Purves, 2017).
Another accuracy score which is relevant for classification models is the F1 score. This describes the number of correctly classified samples. Predictions can be categorized into the following four groups:

- False positive: these are samples which were categorized in a certain category even though they do not belong there.
- False negative: these are samples which were not categorized in a certain category even though they belong there.
- True positive: these are samples which were categorized correctly.
- True negative: these are samples which were correctly not categorized in a certain category.

The F1 score is then calculated based on following equation 2:

$$F_1 = \frac{2 \times (TruePositives)}{2 \times (TruePositives) + FalsePositives + FalseNegatives} \quad (2)$$

Source: (Scikit, 2023)

1.3.7 Interpolation Methods

Interpolation is a spatial prediction technique which includes a wide range of different methods, each with its own advantages and disadvantages. In this chapter two interpolation methods that are relevant to this thesis will be presented.

1.3.7.1 Inverse Distance Weighted Interpolation

A first relevant interpolation method for this master thesis is the inverse distance weighted interpolation. This is a popular method of interpolating point data. Here the sample point's weight decreases with increasing distance to the target point. The user has to be careful to take into consideration that the quality of the prediction of data decreases with this method when the distribution of sample points is uneven (QGIS, 2023).

1.3.7.2 Multilevel B-Spline

A second possible interpolation method that is relevant to discuss is the multilevel B-spline interpolation method. Here a smooth surface is put through a set of points on different detail levels. The process which the algorithm goes through, includes choosing a basis function and control points. Then this basis function is fitted to the control points. In the multilevel B-spline interpolation method this process is done on different levels. The method has different advantages such as noise reduction with its changing level of detail. Through this the method is also great to use on large and irregular distributed data sets (Lee, Wolberg, and Shin, 1997).

1.4 Previous Work

There are multiple projects that aim to quantify landscape beauty, as such a quantification method can be an important variable for decision makers to consider in construction or zoning projects. The issue which usually arises is that landscape beauty as a concept is hard to quantify. Different approaches have been tried ranging from small-scale participatory studies to large scale volunteered geographic systems (VGI). In this chapter some of the existing projects will be presented.
Müller, Backhaus and Buchecker (2020) did a small-scale participatory study with the goal of identifying suitable locations for wind energy turbines. They chose three study sites where wind energy projects were already planned. By doing qualitative

interviews with people of the affected municipalities the research team tried to evaluate meaningful places and with this give a prediction where wind energy project might have a high approval rate among the inhabitants. The possible wind sites which were looked at were in the municipalities Surselva, Schwyberg and Vechigen, all of which financially live predominantly from tourism and agriculture. Müller, Backhaus and Buchecker (2020) realized that the meaningful places did not differ substantially between the supporters and opponents of the wind projects. It was more the value a wind turbine and the perceived meaning which differed between the two groups. Where the supporters saw potential for a well placed wind turbine on a piece of land which had multiple advantages like clear ownership or sufficient wind speeds, the opponents usually argued that the planned areas were meaningful because they were unspoiled, natural or peaceful and should be left that way. Contrary to the supporters the opponents did not see a benefit of contributing to the energy transition of Switzerland and that this contribution could be worth altering the planned wind site area. Müller, Backhaus and Buchecker (2020) realized that their approach did not have the desired effect, for which they give three possible explanations. A first explanation for the unexpected outcome could be unfortunate timing of the interviews, which was when the the specific sites were already chosen and the population already polarized on the topic (Müller, Backhaus, and Buchecker, 2020). Müller, Backhaus and Buchecker (2020) and Moore and Hacket (2016) have both found that the time of including the public is crucial to achieve the best results in finding a suitable site (Müller, Backhaus, and Buchecker, 2020) (Moore and Hackett, 2016). According to Moore and Hacket (2016) the project should be specific enough to include the public, but not yet specific enough to ensure no political polarization occurs (Moore and Hackett, 2016). Also Müller, Backhaus and Buchecker (2020) have identified a specific moment to include the public. Ideal would be just after the identification of suitable planning areas in the cantonal zoning plan and before the designation of specific sites in the municipal zoning plan. Otherwise the population will have made up their minds towards refusal and decision makers will have problems convincing the people (Müller, Backhaus, and Buchecker, 2020). Another reason they have identified as a possible reason for their unexpected outcome to their study is the lack of embeddedness of the wind park project into local developments. This includes ensuring that the local residents realise that the project is not just of national and global importance and therefore completely detached from the local community, but rather that the project could fit into the region and have subsequent benefits for the local community (Müller, Backhaus, and Buchecker, 2020). This has been confirmed by Devine-Wright (2011) who shows how planners should invest a considerable amount of time embedding such a project, otherwise the local population will take over which will result in very contrasting meanings of place and landscape (Devine-Wright, 2011). As a last aspect Müller, Backhaus and Buchecker (2020) found the struggle over hegemony where supporter and opponents of wind

energy projects see very differing landscapes and that these spatial perceptions are a manifestation of a political disagreement within the local community (Müller, Backhaus, and Buchecker, 2020). It is important to note that in the study Müller, Backhaus and Buchecker (2020) the people who were questioned were local people. One could argue that evaluating the opinions of local people differs substantially from the meaning national or global people would ascribe to the same landscape scenes.
The issue with local approval rates of wind parks was recognized by McKenna et al (2021) as well and was analyzed by them in their research which focuses on cost efficiency and public approval ratings (McKenna et al., 2021). McKenna et al (2021) focus on an approach where they try to evaluate a larger area using the Scenic-or-Not data set which is also used in this thesis. Just like Fast et al (2016) have concluded that even though approval for wind parks has increased over the last years, many wind projects still encounter local resistance which only seems to intensify if the local population is not included in the decision making process (Fast et al., 2016). This issue is central in the research which McKenna et al (2021) have done and they propose a quantitative framework to explore the relationship between cost efficiency and landscape beauty using the Scenic-or-Not data set, that is also used in this thesis. The Scenic-or-Not project consists of a web interface where users can view an image and give it a score between one and ten. The application has been gathering scores by different users until 2015 and the data covers nearly 95% of the 1 km squares of land mass in Great Britain and contains 1,536,054 ratings for 212,212 images (McKenna et al., 2021). By questioning the British public on how they would evaluate the image of a landscape in an image and saving the scores over some time, their project has given the science community a data set to investigate what people value most as landscape features. Using this data set McKenna et al (2021) build different regression models with various predictors, like distance to national parks or distance to airports. The results showed that an increase of 1% higher scenic value has 6% lower probability of being evaluated positively. These results show how vital scenic beauty and its preservation is. They also show how the Scenic-or-Not data set can be used to analyze large areas based on the scenic value. The difference between the machine learning approach by McKenna et al (2021) and the participatory study drawn up by Müller, Backhaus and Buchecker (2020) in terms of spatial dimensions and included data, leads to different areas of application for the two approaches. Olafsson et al (2022) have emphasized that both approaches have their advantages but should be used for different tasks concerning landscape evaluation. Olafsson et al (2022) conclude that when using Flickr images, the majority of images correlate to places which can be accessed easily. At the same time the images originated from local people as well as from visitors and tourists. On the other hand, the information gathered from the public participatory geographic information system (PPGIS) which they have built, more likely includes less accessible locations and

therefore differs from the Flickr data. The research of Olafsson et al (2022) hinted that PPGIS is better suited for the analysis of a larger range of different intrinsic and social affective landscape values. Olafsson et al (2022) conclude that decision makers can draw from Flickr data when looking at aesthetic value of landscapes but when the goal is to assess more detailed information on landscape, PPGIS should be used to arrive at appropriate decisions concerning landscape conservation (Olafsson et al., 2022).

It is without a doubt that the spatial researchers benefit from such large scale image and text data like Flickr or the Scenic-or-Not data set which allow great insights into the perception of landscape. This potential of the Scenic-or-Not data set was also picked up by Seresinhe, Preis and Moat. Seresinhe, Preis and Moat did several research projects using the Scenic-or-Not data and were able to show how they could not only link scenery with different distinct features but also use the data and a deep learning model to predict scenic values for areas which did not have any data points. As a deep learning scene recognition model, they used the Places365 CNN (Seresinhe, Preis, and Moat, 2017)(Zhou et al., 2016). This is a pre-built convolutional neural network which was trained with 1.8 million images from 365 scene categories. This model is able to detect landscape features with a calculated accuracy. They found that on one hand, natural areas usually correlate to higher scenic values but on the other hand also man-made objects may have a higher scenic value. Examples could be: viaducts, windmills or a light house. They also believe, like Ulrich (1993), that certain preferences could be developed through evolution. Because people feel more at ease when they have some form of shelter or a place which we think might be interesting to explore (Ulrich, 1993). This would support also their findings which show that not only natural landscape have high scenic values. Man-made structures can act as safe spots and because of evolution could correlate to more comforting landscapes (Seresinhe, Preis, and Moat, 2017).

A different approach when working with the Scenic-or-Not data is not looking at the images themselves but analyzing the tags and description which are associated in the data with the Geograph images. Chesnokova, Nowak, and Purves (2017) show in their research how also a language based random forest model is able to predict scenic values based on the votes of the Scenic-or-Not images. One issue they were faced with were certain words that were written in Gaelic which causes a misclassification of the word. Further issues were user bias, caused due to a single user posting multiple images onto the platform Geograph and then being voted on for the Scenic-or-Not project. This led to using 850 voted Scenic-or-Not images which were described and tagged by a single user. A last interesting aspect in the paper was the fact that the performance of the model increased when the resolution decreased. Chesnokova, Nowak, and Purves (2017) changed their grid resolution from 2.5 kilometers to 10 kilometers and with this could explain 67% of variance instead of 41% (Chesnokova, Nowak, and Purves, 2017). Similarly like Chesnokova, Nowak, and Purves (2017), Havinga et al (2021) used a random forest algorithm to evaluate Flickr images and environmental indicators to predict scenic beauty using the Scenic-or-Not data set as a scenic referference value. For the environmental variables Havinga et al (2021) chose three different factors which consisted of naturalness, visual scale, complexity and uniqueness. The environmental indicator "Naturalness" referred to the percentage of ecosystem types which aimed at integrating the humans innate biological need to affiliate with nature. "Visual Scale" targets at representing our interpretation of higher elevations and the possibility of seeking refuge within elevation differences. For this the elevation difference was calculated and implemented in the model. With the variable "Complexity" our need to explore was integrated. The variable complexity consisted of Patch Density Index (PDI) which represents the spatial distribution of continuous ecosystem patches within a certain area. Additionally, the Shannon Diversity Index (SDI) was calculated which is a measure of biodiversity that looks at the number of different species in a specified ecosystem and their corresponding abundance. Lastly, uniqueness was chosen as an environmental indicator which integrated the fact that unique elements generate a greater aesthetic value. When looking at a city environment, a green patch with trees and a small pond with ducks swimming it, will uplift the general scenic value of the particular area. On the other hand also man-made structures like historical points of interest can have a similar effect on a more natural area (Havinga et al., 2021b).

As a modelling approach a random forest regression model was chosen and implemented. First a model for the environmental indicators was built and resulted in a R^2 of 0.82. A second model which was built based on the labels and words of Flickr image metadata, also performed well and achieved a R^2 of 0.679. The combinated model out of the Flickr and the environmental indicator model performed the best with a R^2 of 0.829. Just like Chesnokova, Nowak, and Purves (2017), Havinga et al (2021) were able to show that it is possible to build a scenic model based only on aesthetically connotated words and additionally were capable of building a model based on a selection of environmental variables. Havinga et al (2021) do emphasize however, that a more accurate model could be achieved by altering certain environmental variables (Havinga et al., 2021a).

1.5 Research Gap

The research area of landscape beauty and scenic perception has been growing in the last years and has become a major component when talking about human health. The reason why this area of research is so interesting, is that a data layer with the scenic value for a specific area has a large range of different possible application fields. These range from planning large infrastructure projects to landscape preservation. To tackle this Scotland among other European countries has developed a data set which is called National Scenic Areas. The government defines the data set as "[...] a national landscape designation of areas that have been identified as having outstanding scenic value in a national context. The designation's purpose is both to identify our finest scenery and to ensure its protection from inappropriate development through the planning system [...]" (UK, 2023). Such a data set is not present on a national level for Switzerland and could have an impact on infrastructure planning.

Switzerland as a direct democracy allows their people to have a voice when it comes to projects surrounding their homes or which change local recreational areas. This makes project planning and execution a hard task for decision makers. When looking at the example of wind energy, Salak and Hunziker (2022) concluded in their research, which involved a large scale questionnaire on the views of the population on possible wind park locations, that although the Swiss people are in favour of wind energy they cannot agree on a location. Landscape preservation and site planning are important issues in which the Swiss population expressed its opinion and showed some hesitation. Untouched mountainous regions for example had a low approval rating whereas suburbs or urban areas had a higher one (Salak and Hunziker, 2022). To further explore the correlation between different landscape features and scenic beauty, more research needs to be done. This could be based on the Scenic-or-Not data set, similarly to the studies of Chesnokova, Nowak, and Purves (2017) or McKenna et al (2021) have done. Both these studies focused on the British mainland and concluded that their model could hold up when evaluating scencic beauty and could possibly be used to develop a deeper insight into landscape beauty. McKenna et al (2021) as well as Chesnokova, Nowak, and Purves (2017) mention in their discussion the possibility of further evaluating a machine learning model based on the Scenic-or-Not data set for a geographically different region and see if such a model is transferrable (McKenna et al., 2021). This could give insights on how different cultures that are used to experience different landscape features, evaluate their landscape. The Swiss and the British landscape have some similarities but differ in many aspects such as the coastal area in Great Britain or the Alps in Switzerland. A transferred model, where machine learning insights of one country are used to develop a data set in a different country could further give insights as to whether or not a data set like Scenic-or-Not can be used to determine larger areas than those included in the data set. This might shorten data gathering processes for other projects and show how people perceive landscape interculturally.

Olafsson et al (2022) have discussed that when decision makers want to make well founded decisions and want to include landscape beauty, a mixture of data of both large scale scenic models and PPGIS should be used. Such a large scale data set for landscape beauty in Switzerland could give more context and might help develop frameworks like Müller, Backhaus and Buchecker (2020) try to use, to assess landscape beauty. As a result the process of planning infrastructure like wind parks, industrial complexes or highways could be sped up without risking large political debates within community members.

1.6 Research Goals and Questions

This master thesis aims to develop and evaluate a machine learning model which predicts landscape beauty in Switzerland. The evaluation of landscape images based on scenic beauty is subjective and can result in large variations between votes. Here, a machine learning model might have difficulties finding patterns because they possibly do not exist or not sufficient data is given to the model to learn relationships. Still, with the help of additional variables like elevation, land use or noise, the goal is to see where and how well computers can learn scenic beauty as humans see it. If successful, such an approach could have a significant impact on new planning processes where landscape beauty is suddenly a constant value which can be integrated into the suitability analysis and enhance PPGIS in the affected communities. For this thesis, the following goals are defined:

- Explore different aspects of landscape beauty and the possibility of transferring an interpretation of scenic beauty to a different region.
- Analyze the performance of machine learning approaches using spatial data and a British data set as training data to predict scenic beauty in Switzerland.
- View how a resulting scenic layer impacts planning processes in Switzerland and be a useful aspect when trying to achieve high public approval ratings for infrastructure projects.

Out of these goals, four research questions were formulated which will be tackled and answered in this master thesis.

1. How can scenicness of landscape be measured and transferred to different geographic regions using a machine learning model?
2. What are the limitations of using a machine learning model when looking at a topographically complex country like Switzerland?
3. How accurately can scenic areas be mapped and used as a planning tool for decision makers who plan infrastructure projects like wind parks or roads?

   If the model does not hold up as predicted, research question four will be looked at more closely than research question three, in order to get deeper insights as to where the model shows weaknesses.
4. In which areas and how could the model be improved so that a suitable scenic map can be developed for Switzerland?

2 Methods

In this chapter the process of developing the scenic landscape model based on the British Scenic-or-Not data set is described. The model development was the first step in the process towards predicting landscape beauty for Switzerland. Furthermore this chapter also describes the data preparation for the British data layers on the one hand and the Swiss data layers on the other. Finally, this chapter addresses how the scenic map for Switzerland was calculated.

2.1 British Random Forest Model

The following chapters describe the development process of the different random forest machine learning models. Different approaches were tried and assessed and only the best models were used in a second phase to predict the scenic scores.

2.1.1 Data Selection

Random Forest is the machine learning model which was chosen for this task. It uses a vector of independent X variables and a single value for the dependent Y variable. The X variables are then used within the machine learning model to search for patterns. The algorithm learns and later uses these patterns to predict Y values. Random forest is one of many algorithm and was in this thesis chosen because of its good interpretability. The user can trace back the models decisions and display the prediction path in the form of a decision tree. For the British model the Y variable was represented first by the mean value of the Scenic-or-Not images votes and later simplified by using different categories. Four different data input layers were selected as a first basis for the X variable vector:

- Scene categories
- Land use classes
- Elevation
- Noise levels

Scene Categories: The choice of using the Places365 model is based on the research done by Seresinhe, Preis, and Moat (2018) where they used the Places365 model to gain more information on what is visible inside of the images that are fed into the model (Seresinhe, Moat, and Preis, 2018).

Land Use: The spatial variable land use was included as an estimation for landscape diversity and as a tool to detect how natural a place is. Landscape diversity was identified by Bell (1999) as being an important factor (Bell, 2012). Hunziker and Kienast (1999) also found a statistically significant relationship between diversity and scenic value of landscape (Hunziker and Kienast, 1999).

Elevation: Elevation was introduced as an estimation for item *Multiple Scales* defined by Bell 1999 as a factor that influences perceived landscape beauty (Bell, 2012). This preference could be caused by our prey and predator history (Havinga et al., 2021b).
Noise levels: As a tranquility variable a basic noise estimation was introduced as a spatial variable. Sound influences the perception of landscape and could be seen as one of the most important variables when it comes to perceived landscape beauty. Because sound affects us more constantly than any other sense it is therefore crucial to include some form of noise analysis when evaluating landscape beauty (Chesnokova, Taylor, et al., 2018).

In a second phase two additional feature classes were added to try and improve the models performance:

- Dominant image color
- Object detection

Dominant image color: The feature of extracting color from the images was based on the Landscape Character Assessment by Tudor (2014) where they identified color as being an important aspect of what the visual sensory system records and through this influences landscape perception (Tudor, 2014).
Object detection: The object detection model which is trained on COCO17 data, was introduced in a later stage to act as a complementary variable to the Places365 model to extract more information from the provided images (Tensorflow, 2023).

For the data of the scene categories a pre-built machine learning model was used to generate the data by predicting different scene categories for the Scenic-or-Not image data set. The land use data set was taken from the CORINE land cover data set which splits the data set into 45 different land use categories. The elevation data was taken from the OS Terrain 50 data set which is distributed in grid cells. Noise levels were calculated from street and rail networks using the inverse square law and where buffers were laid around the rail and road network.

2.1.2 Data Pre-Processing

Scenic-or-Not data set

The Scenic-or-Not project is a web platform where people can vote on images showing British landscape. The score scale ranges from one to ten. The web platform saves these votes in a database which was downloaded and used for the training of the British random forest models. As mentioned before the application has been gathering data until 2015. The data set covers nearly 95% of the 1 km squares of land mass in Great Britain and contains 1,536,054 ratings for 212,212 images.

Figure 6: Example of an Scenic-or-Not image with the votes symbolized as hearts above the corresponding score (Geograph, 2023)(Seresinhe, Moat, and Preis, 2023).

Figure 6 shows the graphical user interface and an example image from the Scenic-or-Not data set with the votes symbolized as the hearts above the corresponding score. Because of the great spatial resolution, this data set has a lot of potential to cover different landscape scenes. The data set built the basis for the machine learning models.

Places365

Places365 is a pre-trained Convolutional Neural Network (CNN) which is able to recognize 365 different scene categories in an image. Convolutional neural network (CNN) is a machine learning approach and concentrates on processing grid data. In general, CNN are mostly used for image and video processing. CNN's are very successful in tasks such as image recognition, object detection, and image segmentation, and have been used in a wide range of applications, including self-driving cars, medical imaging, and facial recognition.

The Scenic-or-Not images were run through the Places365 model and this built the first layer of the data input vector that is later fed into the random forest model. Here, in a first phase each Scenic-or-Not image was loaded and the Places365 CNN predicted different scene categories for the image. The model outputs a prediction accuracy for each possible scene category but as the accuracy dramatically decreased after the fifth category, only the top five predictions with the highest accuracy scores were used. All possible features are listed in the Appendix A. In figure 7 the predictions for a sample image out of the Scenic-or-Not data set are shown. The Places365 CNN takes the image and predicts different scene categories with an corresponding accuracy score. From top to bottom the accuracy decreases, which means that the scene category *driveway* is most likely and the scene category *tree farm* is least likely. This pretrained model was used to predict all Scenic-or-Not images and the corresponding scene categories were added to a shapefile which included all value for the performed votes, variance, average, image link and the corresponding location of the image. A small number of images were dislocated on the Geograph server infrastructure and therefore could not be found anymore, which meant that the number of samples which could be drawn from the Scenic-or-Not data set decreased slightly. Because the model predicts with a certain accuracy score and the model was designed in a way where it outputs a prediction score for all classes, the list of scene categories which was added to the shapefile, was limited to the first five predictions. In previous tests with the model the first five predictions still had some statistical relevance. Figure 7 shows an example of a Scenic-or-Not image with the

Figure 7: Example of a Scenic-or-Not image with the calculated scene predictions, generated by the Places365 model (Geograph, 2023).

predicted Places365 scenes and the corresponding accuracy scores. The predicted scene category tree farm has only a score of just over 2%. This means in other words that the Places365 model predicts with just over 2% confidence that the image scene is a tree farm. All predictions for other scene categories were lower than 2% for this image, except the five categories which are listed in figure 7.

The categories had to be encoded in order to make it readable for the random forest model. For this a one-hot encoder was chosen to ensure good traceability to important subfeatures (see chapter 1.3.4).

Elevation

The OS terrain 50 data is distributed as a split multi-tile grid which means that the data for the UK is divided into individual layers (Survey, 2023b). A first step was to create a single file by computing a so-called virtual layer (VRT) out of all the grid cells. Because the resolution is 10 km x 10 km, normally the resulting file size would become immense. With VRT files the user has the option to compute and merge multiple tiles faster to save storage space when writing the file to the computer memory. For this step the library GDAL was used. This library contains the function *gdalbuildvrt* which takes a list of file names and an output file name as an input parameter. The output file in the format *.vrt* can easily be imported into QGIS without an exceedingly long loading time.

In a next step the virtual layer was rasterized and exported as a TIFF file. For each image a kernel was then placed over the x- and y-coordinate of the image to compute the average meter above sea level for this specific location. The kernel size was set to a three by three matrix where each cell was 100 by 100 meters. The search kernel had a search dimension of 10'000 square meters around the point of interest. The average meters above sea level formed the next independent X-variable and was in a floating point format.

Land Use

For the land use data the CORINE land use data set was integrated (Cover, 2023). The reason for the choice of this data set is that the same data set is also available for Switzerland. This minimizes inaccuracies when discussing the way the data was collected and evaluated and allows the machine learning model to learn from similar data structures. The received data consisted of a vector layer with a polygon for every location which had been assigned the land use class as an attribute. To make it an interpretable data structure for the machine learning model, in a first step the data set was rasterized and exported as a TIFF file. As a fixed grid cell size 100 by 100 meters was chosen.

Again for each image of the Scenic-or-Not data set a kernel was placed around the x- and y-coordinates. For the land use layer an array was gathered of all land use classes which were detected inside of the kernel and the resulting array represented an additional X-variable for the random forest regression model. The string type data for the land use classes were then encoded once again using a one-hot encoder (see chapter 1.3.4).

Noise

As a further element a noise layer was incorporated into the input data. The goal was to differentiate between very loud or busy places and more quiet and natural places. To achieve such a data layer, the rail network for Great Britain was downloaded from the data share platform (Addy, 2023). The railway layer was merged with the road network of Great Britain which was downloaded from the OS Open Road project (Survey, 2023a). The resulting layer showed where possible noise pollution could emerge. Noise emissions from air traffic were left out, as airports usually are surrounded by an intricate network of roads and railways causing high noise levels anyway.
To evaluate how noisy a place really is, the inverse square law was used. This law describes how different sound attributes change over time and distance to the source. Due to limited time and the fact that noise is only a small part of the model, the simple approximation of the inverse square law is deemed sufficient for the scope of this master thesis. Overall, with the inverse square law noise is overestimated because the method does not take topography or man-made structures into consideration, which would block sound more than an even surface of the earth. The search kernel for the noise layer was a three by three grid cell and here the median noise class was inserted as the noise variable.

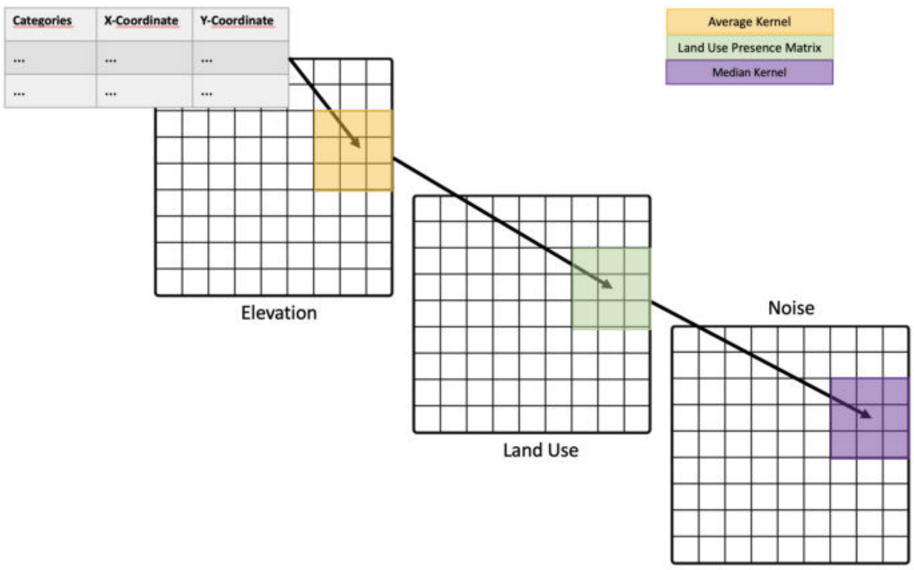


Figure 8: The graph shows the processing steps of how the spatial features elevation, land use and noise were extracted out of the raster files for the individual images.

Figure 8 summarizes the data gathering process and lists how the elevation data was gathered using an average kernel. For the land use data, the land use classes were gathered within an array and added to the input data for the machine learning model. For the noise data a median kernel was used where the most dominant noise class was gathered and added to the input vector. Similar to the land use classes, the scene categories were represented as a presence matrix.

2.1.3 Hyper-Parameters and Model Fitting

When the data was prepared and the model was first trained with the prepared features and most hyper-parameters were set to the default value, the performance was not optimal. Machine learning models, depending on the underlying concept used, have various parameters which influence performance. These parameters are relevant to improve the model's performance and need to be adjusted. For the random forest regressor model different parameter options were looped over and evaluated with the R^2 value. For this step it was important to keep all parameters constant except the parameter that was fitted so that the effects of the tested hyper-parameter can be evaluated.

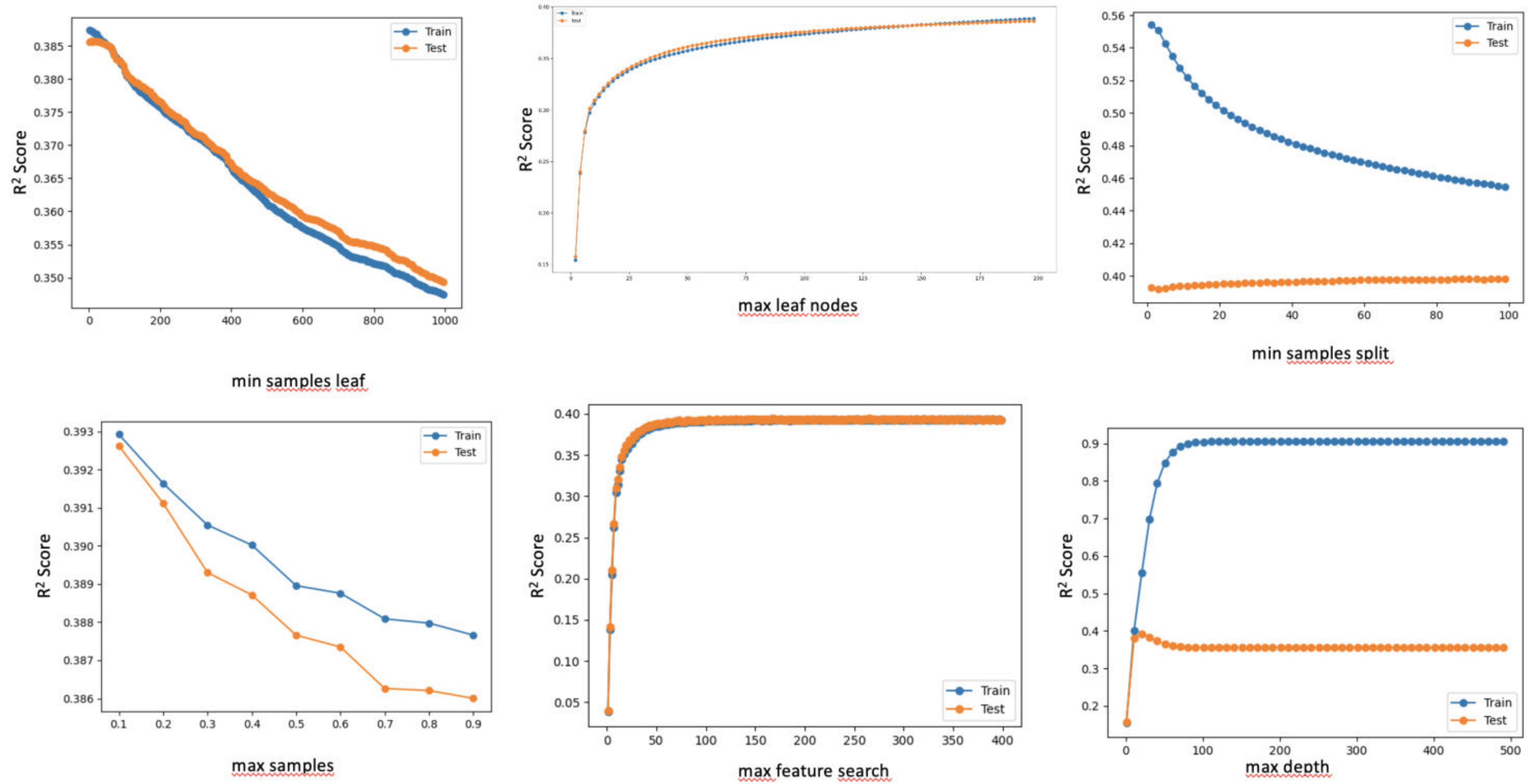


Figure 9: Different R^2 score values for the looped hyper-parameter searches to optimize the random forest regressor. The blue line represents the training process and the orange line represents the test phase.

For the regressor the R^2 accuracy metric was chosen to assess how well the X-variables explain the variation of the predicted Y-variable which could further give insights into how well the features were chosen. When trained, the regressor is supposed to predict continuous values based on the average vote which acted as the dependent y-variable. When looking at the variance of the predicted value and the actual average voting values, the performance of the model does not hold up and has a R^2 of around 0.4.
Figure 9 shows how the different parameters affect the R^2. It seems as if the model did not have enough data points to learn enough relationships to predict the test data set correctly. This is clearly visible in the graph on the bottom right of figure 9. It was the last test iteration to search for the optimal parameter value for the maximum depth. This value controls how deep a tree is allowed to be built. This particular graph indicates that the model learned sufficient relationships from the training data but could not use the insights to sufficiently predict test data points. The test data accuracy never exceeded 0.4. Such a graph suggests that the model overfits (see chapter 1.3.3). To solve the issue of insufficient prediction accuracy, different solution approaches could be considered.

1. Increase training data
2. Simplify learning task
3. Change feature number

A first possible improvement could be to increase the training data so that the algorithm has more samples to learn relationships between the different features. Since data gathering has stopped a few years ago, increasing the training data size was not an option in this case.
Simplifying the learning task is a different approach, in which one switches the machine learning strategy in order to try improve the accuracy. In this case the regressor approach proved to be too complex when considering the complexity of the underlying problem. Some insight into why predicting scenic beauty based on the Scenic-or-Not data set is too complex, is visible in the distribution of the variance between the individual votes inside of the Scenic-or-Not data set.

Figure 10 shows that the variance is rather high within the different votes for each image. This highlights how difficult it is to fit a model to evaluate landscape beauty when even real people do not agree with one another. The clear discrepancies in the perceived scenicness of the landscape make it hard to detect a clear relationship between certain features and the resulting Scenic-or-Not average voting value.

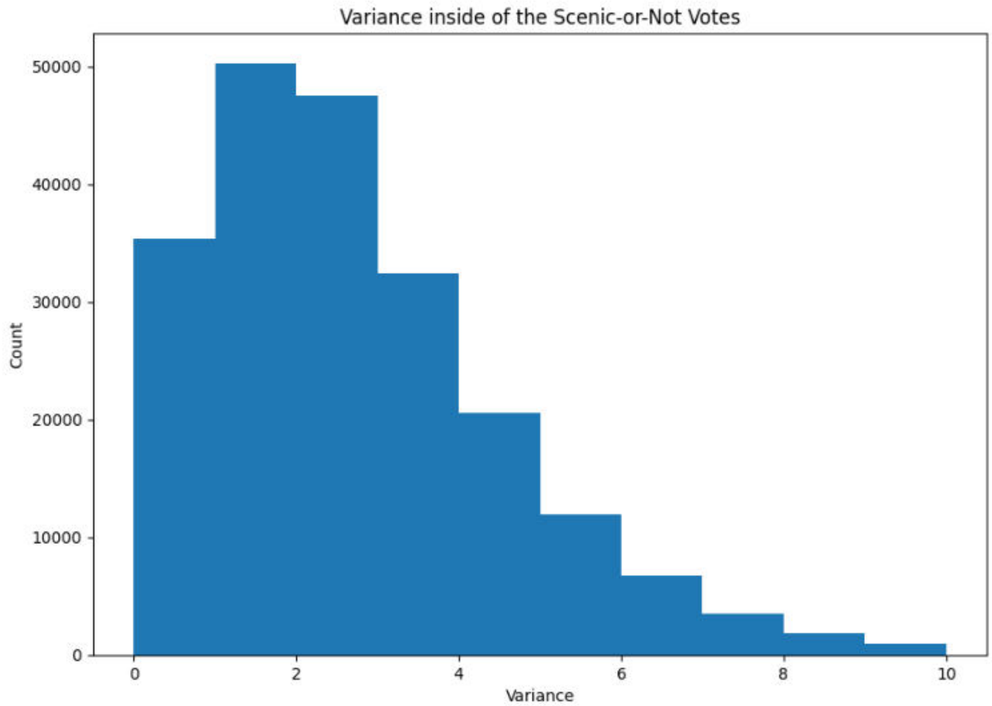


Figure 10: The distribution of the variance within the votes for the individual Scenic-or-Not images.

2.1.4 Random Forest Classifier

In a second approach a random forest classifier was implemented in order to test the limits of machine learning in its ability to recognize landscape aesthetics. The goal of this approach was a simplification of the prediction task (see chapter 2.1.3. With the classifier model the Y-variable of the model had to be refactored in order to fit the constraints of the random forest classifier concept. The random forest classifier model does not predict continuous values, like the random forest regressor does, but rather predicts categories.
As an experiment to further understand if machine learning can differentiate between the two options scenic or not scenic landscapes, once again using the Scenic-or-Not data set as a scenic reference value, a dual classifier random forest model was built. This gave some insights on the possibility of training a machine learning model on the most basic decision.

As a accuracy metric the F1 score was chosen because the metric assesses the performance of a model well even though the data is imbalanced. Additionally, using a confusion matrix the F1 score gives a great overview over how good the accuracy scores are for the different classes. The F1 scores for the dual category random forest are summarized in table 1. Table 1 and figure 11 show that the model can detect the difference between scenic and not scenic places.

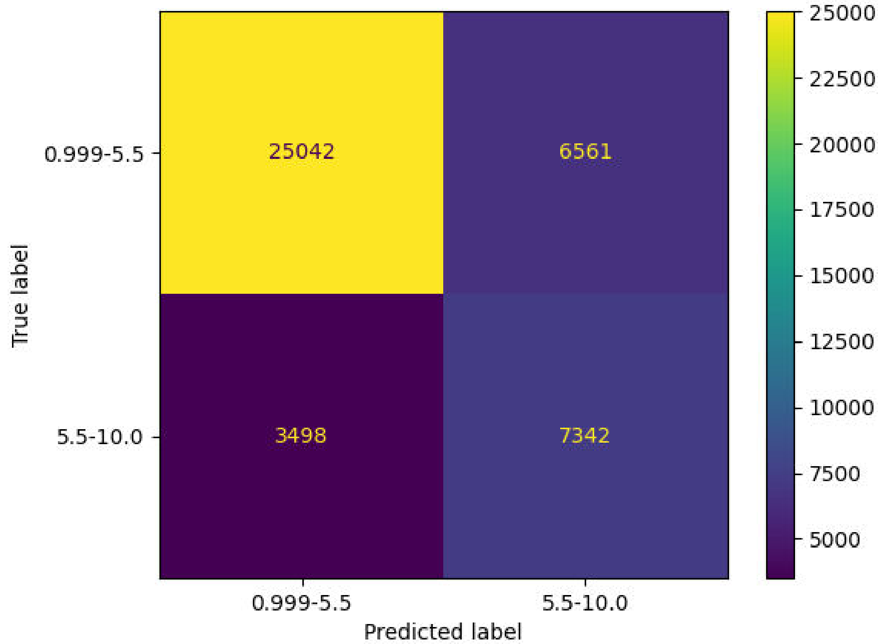


Figure 11: Confusion matrix for the dual classifier random forest model.

	Label 1	Label 2
F1 Score	0.83	0.59

Table 1: F1 scores of the dual category random forest classifier.

Because the scenic score are so unevenly distributed as seen in figure 12, a function of the well known python module *numpy* was used, called *qcut()*. This function allows to categorize data into groups where each group fulfills a certain condition. In the scope of this task, the categorization satisfied the condition that each group had an equal number of samples. In this attempt the data was categorized into five groups as follows:

- Values between 1.0 and 3.0 received label 1
- Values between 3.0 and 4.0 received label 2
- Values between 4.0 and 4.778 received label 3
- Values between 4.778 and 5.8 received label 4
- Values between 5.8 and 10.0 received label 5

Because of the increased sample size for the extreme classes, the expected result was that the model would perform better and had less difficulties to predict accurately. A disadvantage of this interval size is that the higher scenic rated areas are more generalized and the model has less capabilities to differentiate between the high scenic beauty areas and the very high scenic beauty areas. With this classification

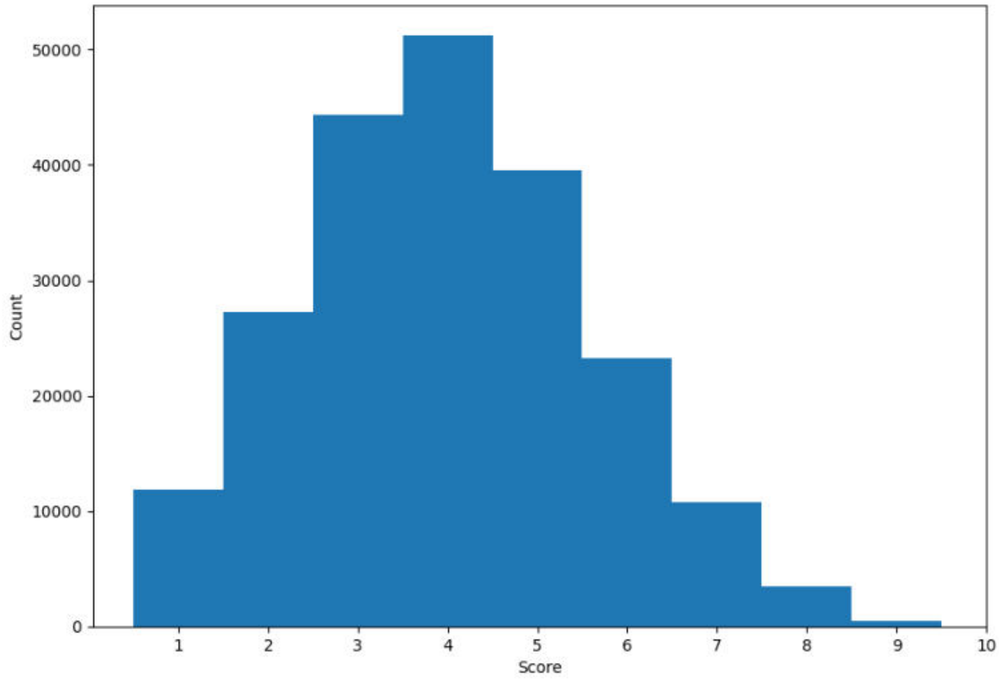


Figure 12: This figure shows the score distribution for the Scenic-or-Not data set. This histogram is based on the average vote values of the images.

approach the performance did not improve significantly. An optimal confusion matrix has a diagonal orientation where the fields from the top left corner to the right bottom corner are filled with prediction records. On the y-axis (bottom to top) are true labels and on the x-axis (bottom left to bottom right) the predicted labels can be read. There is a top left to bottom right diagonal tendency visible but the F1 scores show that the model still does not explain enough of the variance and still predicts a lot of test samples incorrectly (see figure 13).

	Label 1	Label 2	Label 3	Label 4	Label 5
F1 Score	0.52	0.31	0.24	0.18	0.56

Table 2: F1 scores of the five quantile class random forest classifier.

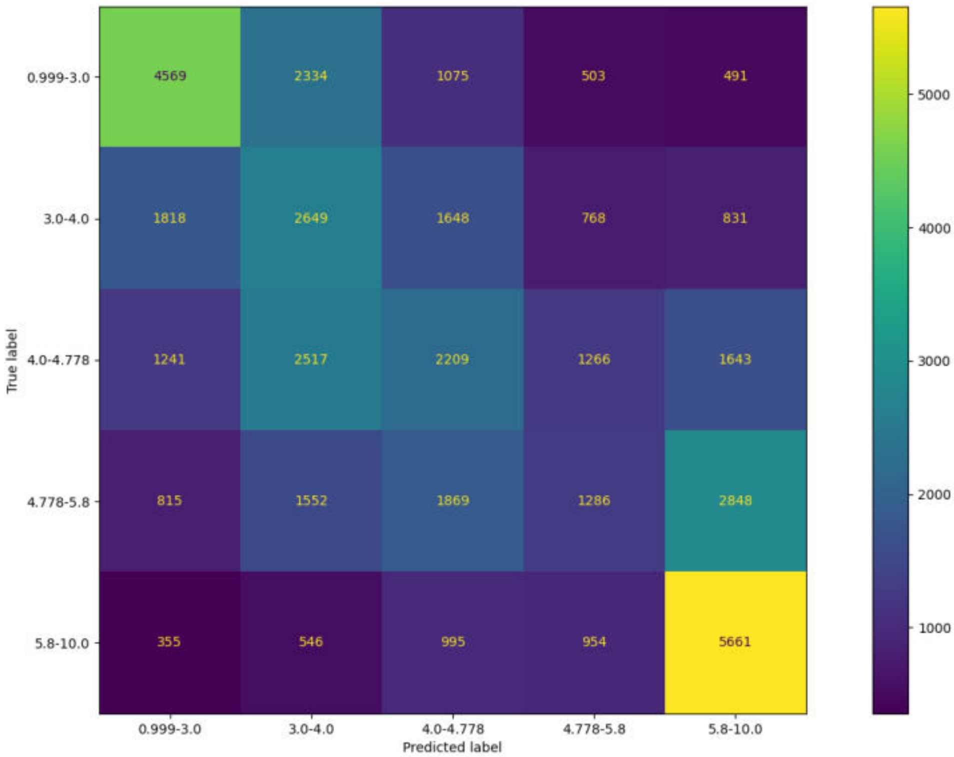


Figure 13: Confusion matrix of a five quantile class categorization model where the model predicts five classes and each class had an equal amount of training samples.

To improve the classification model further, the number of classifying labels were reduced from five to four. This helps on one side to increase the number of samples per label but also simplifies the classification task for the random forest model as explained in chapter 2.1.3.
In this next step the model was reduced to a four label classification model with an equal interval label groupings. The intervals were chosen as follows:

- Values between 1.0 and 3.25 received label 1
- Values between 3.25 and 5.5 received label 2
- Values between 5.5 and 7.75 received label 3
- Values between 7.75 and 10.0 received label 4

In this approach it was once again important to balance the training samples per category. For this model the quantile categorization method using categories with an equal sized interval was chosen over the method in which each category has an equal number of samples. For the building of the training data set a function was used in which a provisional training data set was created first. This provisional data set was then searched for the lowest common denominator for the number of samples each class had. The value of the common denominator was then used to choose a random equally sized selection of samples from the other categories which then represented the training data set which was used to build the model. This was done multiple times to ensure that the model was fed with as many different samples as possible.

Additional Features

Additional to the model, the last possible improvements implemented were mentioned under point 2.1.3. Two more features were introduced to the model which could have beneficial effects on the models performance. A first feature was another CNN which detects basic objects inside an image. This model was pre-trained and accessed through the *Tensorflow* library (Tensorflow, 2023). The range of objects the model detects is listed in the appendix C and corresponds to the label list of the COCO 2017 data set (COCO, 2023). The found object categories were then encoded using a one-hot encoder approach which is discussed in chapter 1.3.4. In a next step this data is fed into the random forest model alongside the original X-variable data.

A second feature was the analysis of the dominant color within the image. Based on the LCA by Tudor (2014) which is visualized in figure 1, color plays a role in the human perception of landscape and since color is easily extracted out of an image, it is a well suited feature to possibly enhance the random forest models performance. For this the image was read and the three most dominant colors were extracted from each image. These colors were hex encoded and had to be encoded once again with a label encoder to make it readable for the random forest model. For the colors a label encoder approach was used where all three columns were encoded with the same encoder. The label encoder approach is explained in chapter 1.3.5.

The F1 scores show better trained low scenic classes where more training data was available and low scores for the higher scenic classes. The confusion matrix in figure 14 shows better accuracy for the low scenic classes and lower accuracy for the higher scenic score classes.

	Label 1	Label 2	Label 3	Label 4
F1 Score	0.55	0.51	0.21	0.19

Table 3: F1 scores of the four category random forest classifier.

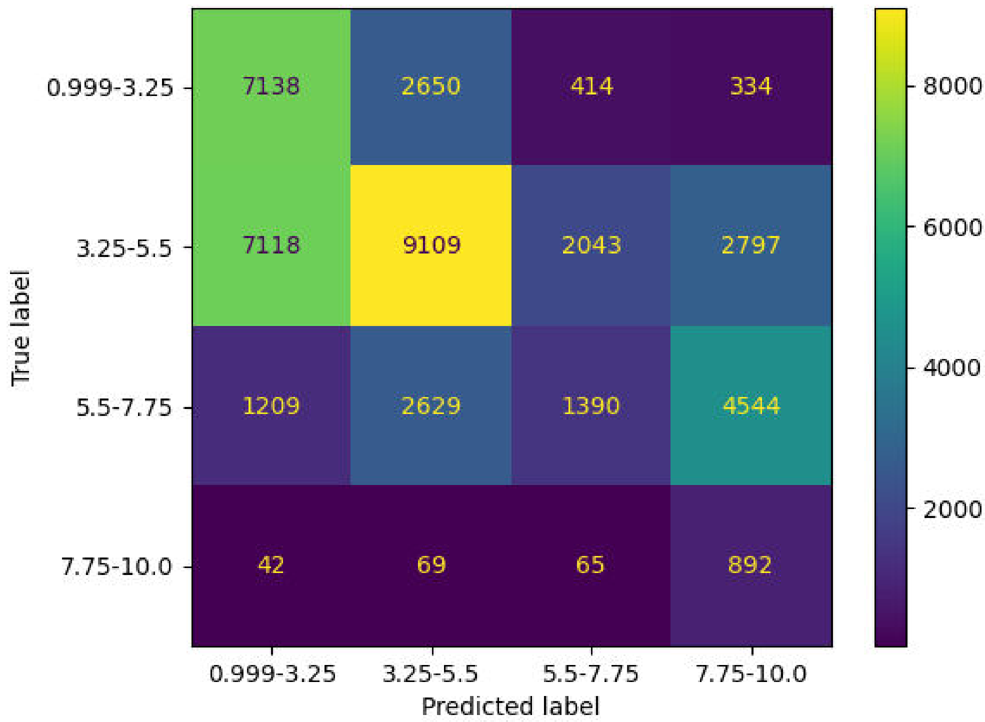


Figure 14: Confusion matrix with a four equal interval class categorization model.

Due to time constraints and the complexity of the research questions as well as the variance within the different Scenic-or-Not votes (see Figure 10), the further development of the British model was abandoned. When further analyzing it becomes clear that the model can not become more accurate than the underlying data already is. Figure 15 shows how accurate the British model is when looking at border cases. The absolute majority of test samples were classified within a range of 1.0 points difference to a class border value. This final model was then used to predict Swiss data samples.

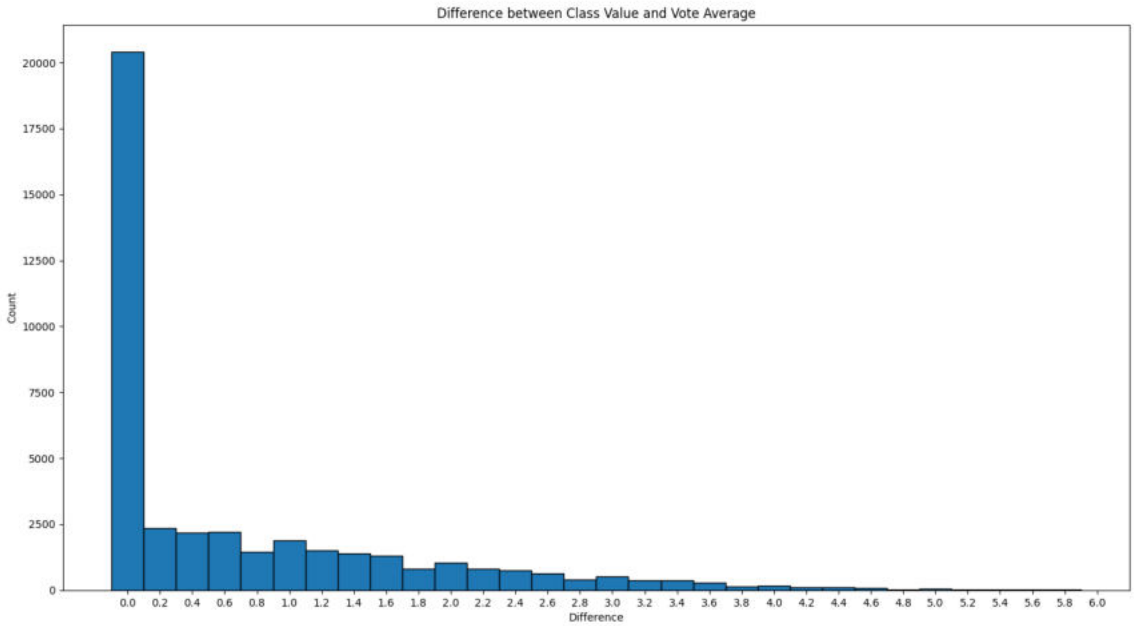


Figure 15: Shows the difference between the class border values and the real mean voting value of the test data set. If the vote average of the Scenic-or-Not image was within the class limits of the prediction, the difference was counted as zero.

2.2 Swiss Scenic Predictions

The Swiss scenic predictions are based on the random forest model which was generated with the British Scenic-or-Not data, elevation data, noise levels, land use classes, object detection model and dominant image colors.

Flickr data set

Flickr is the image data set that is used to predict scenic scores. Using the British random forest classifier, the Flickr images are then fed into the model and act as sample points to be later interpolated. Flickr is an online platform for people who would like to share or store their images. The images get a geotag and a date and are stored. Through Alexander Dunkel from the Dresden University of Technology I was able to obtain a subsample of Flickr images for Switzerland. In figure 16 the spatial distribution of the Flickr images is visible. The map shows where Flickr images are present as a density estimate. Large cities like Zürich, Bern or Genève show a high density of Flickr images. Other areas that stand out are places with a high touristic visitor number like Luzern or the area around the Jungfraujoch.

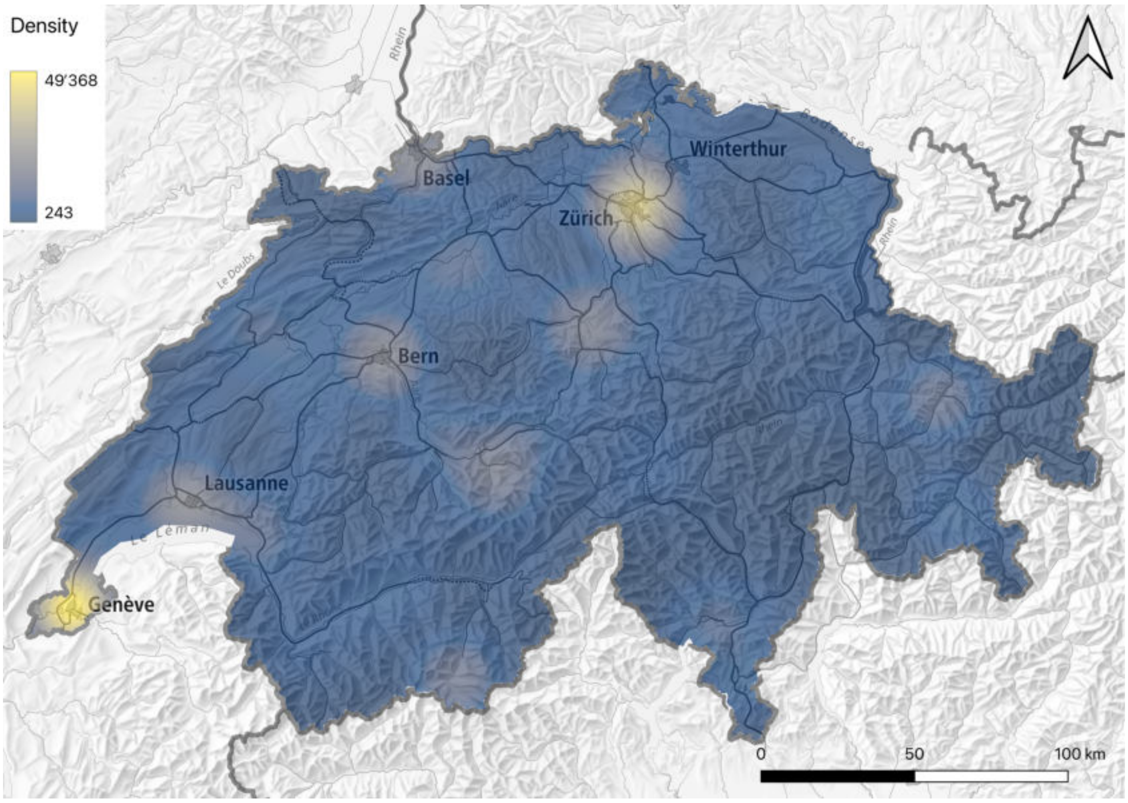


Figure 16: This heatmap depicts all Flickr images that were used in this thesis as a density estimate. This heatmap was calculated using the QGIS heatmap interpolation method (QGIS, 2023)(Swisstopo, 2022).

2.2.1 Data Pre-Processing

In a first phase to build the Swiss model, the Swiss data had to be prepared. Here, the extensive list of Flickr images was filtered and only images of 2016 and later were selected. It is highly plausible that radical changes like infrastructure projects might have occurred between for instance 2007 and 2016, which could falsify the predictions of the Places365 model or the object detection model as scenes or objects which have disappeared might be detected.

As image input, a Flickr image data set is used or the time frame between 2016 to the present. It was taken from the Flickr platform (Flickr, 2023). Every image previous to the ones of 2016, at the risk of looking different and therefore at risk to falsify the outcome of the scene recognition model or the object detection model, was taken out. Each image was loaded into the Places365 model and the scene categories were saved as strings to the informational dataframe of the images. According to the workflow with the British images, the first five scene predictions from the Places365 model were chosen.

In a similar way the object detection model predicted the different objects present in the image which were then also added as string values. For the elevation data, the newest Swisstopo elevation model was used with a grid size of 200m (Swisstopo, 2023a). This was resampled to achieve a 100m grid size.

The land use data was taken from the same provider as the British data provider.

This way uncertainties in how data is handled and what kind of classes are included, can be remedied. For such a case the CORINE data set is an optimal choice (WSL, 2023).
The noise layer was constructed identical to the British data and based on the road and rail network of Switzerland. The network maps were downloaded from the Swisstopo SwissTLM3D program (Swisstopo, 2023b). For the street layer only specific streets were chosen. Only streets on which there is regular motorised traffic were relevant to evaluate noise. Therefore, the following street feature classes were chosen:

- 10 meter streets
- 8 meter streets
- 6 meter streets
- 4 meter streets
- 3 meter streets
- Main roads
- Highways

Equivalent to the process of the British data preparation, the inverse square law of sound was used to calculate the noise levels. Based on the inverse square law the sound level experienced by the human ear decreases by six decibel per doubling of distance to the source. With this simple data preparation, multiple buffers were laid over the road and railway infrastructure and merged in a raster calculation. The result was a categorized noise map, where a higher class number represented a higher noise pollution.

The resulting Swiss data structure consisting of elevation data, scene categories, detected object classes, dominant image colors, noise levels and land use classes was fed into the final classifier and final regressor model. The performance for the classifier model can be viewed in figure 14 and the performance for the regressor model can be viewed in chapter 2.1.3. The result was a list of predicted scores for every Flickr image.

2.2.2 Interpolation

In a final step the predicted data points were loaded into QGIS and with the help of spatial interpolation a scenic map was created. Here a 100m x 100m resolution was chosen. First, the time consuming computation resulted in a 1000m x 1000m resolution scenic map. The result showed that a 1000m x 1000m resolution would be too coarse to explore research goal number three. This research goal aims at

the possibilities of using a scenic map as an additional planning tool. To assess suitability for smaller infrastructure objects a 100m x 100m gives more insight on specific locations. In order to get more insight into how well the different models performed overall and in comparison to each other, the predictions for the regressor model were also interpolated. For the predicted data of the regressor model the IDW interpolation method was chosen. Just like the regressor the IDW algorithm outputs continuous data and takes into account the distance between the sampled point and the surrounding data points to predict the actual value of the sampled point (see chaopter 1.3.7).
For the classifier prediction data set, the IDW algorithm has an important downside which is the output data type. The classifier outputs classes and the IDW interpolation outputs continuous data. When using the IDW method on the classifier's predictions one gets float numbers which do not say much when considering the classifier models output type. For this reason here the SAGA multilevel B-spline for categories interpolation tool was used. This interpolation method outputs discrete values and because of the nature of the output adheres more to the classifier's predictions (Lee, Wolberg, and Shin, 1997).

2.2.3 Change Analysis

Because the Flickr images are date encoded, it is an interesting additional information by doing a temporal analysis. Here for each year between 2016 and 2018, which are the years with a sufficient number of samples in the selected subset of the Flickr data set, an additional scenic map was created. For the year 2016 210'685 data samples were used. For the year 2017 177'255 data samples were used. And for the year 2018 123'195 data samples were used. Using the timestamp, the predictions were filtered by year and then interpolated identically as the main classifier map in figure 21. The resulting raster files enabled different calculations and the results of these calculations can be used to show local changes in the years 2016, 2017 and 2018. For this thesis the raster layers were subtracted from each other. Year 2017 was subtracted from year 2016, year 2018 was subtracted from year 2017 and in an additional output subtracted from year 2016. With this step more aspects of the accuracy of the scenic map can be explored for example if such a timeline can be used to assess the models ability to detect landscape beauty changes where large infrastructure projects were built or changes in the use of landscape occurred.

3 Results

After developing the British model and predicting the scenic scores for the Swiss Flickr image samples the resulting scenic map was created through interpolation. In this chapter the various results based on the different model alterations are visualized.

3.1 Random Forest Regressor

In a first phase the random forest regressor model was developed and with the latest and most accurate model a scenic map was built. This map is shown in figure 17 and is displayed as a heatmap. The scale of values in the legend correspond to the scores originally taken from the Scenic-or-Not data set.
Since a random forest regressor model predicts continuous data and a classifier predicts label data, the regressor map was classified with identical intervals in order to compare the results, as can be seen in the classifier map in figure 21. The map showed some features with higher scenic values, but on the whole had large uniform areas where most predictions lied within the interval classes *3.25 - 5.5* and *5.5 - 7.75*. Furthermore, the model did not predict values higher than 6.75 and lower than 3.75, although the scenic scale of the Scenic-or-Not data set ranged from 1 to 10.
Figure 18 shows the same predicted data set from the random forest regressor as figure 17 but is not classified into four equal intervals. Here more distinct features can be observed. The northern midland of Switzerland is generally classified lower than the alps and higher regions. Exceptions to these observations are main roads in the valleys, for instance in the canton of Wallis where the scenic score drops in the major valley of the river Rhône. Local hotspots which were generated through the prediction algorithm correspond to places where more pictures were taken such as the *Jungfraujoch* in the alp region of Bern or the *Säntis* in the north east of Switzerland.

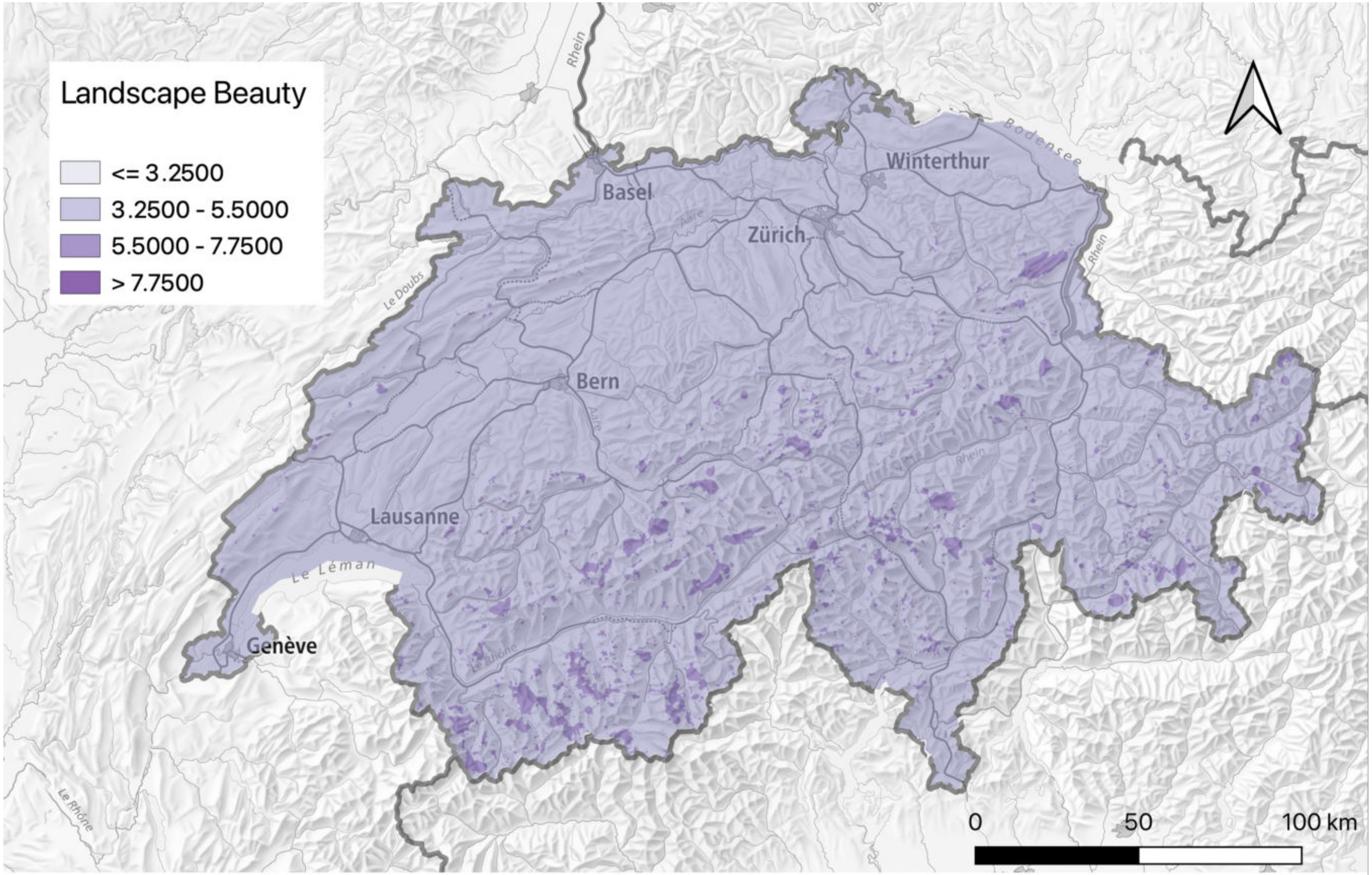


Figure 17: The regressor map which resulted from the Swiss Flickr image predictions with the random forest regressor model where the data was classified identically as the classes were chosen for the random forest classifer model in chapter 2.1.4. In a second step the pixels between the predicted Flickr images were interpolated using the IDW interpolation method from QGIS (QGIS, 2023)(Swisstopo, 2022).

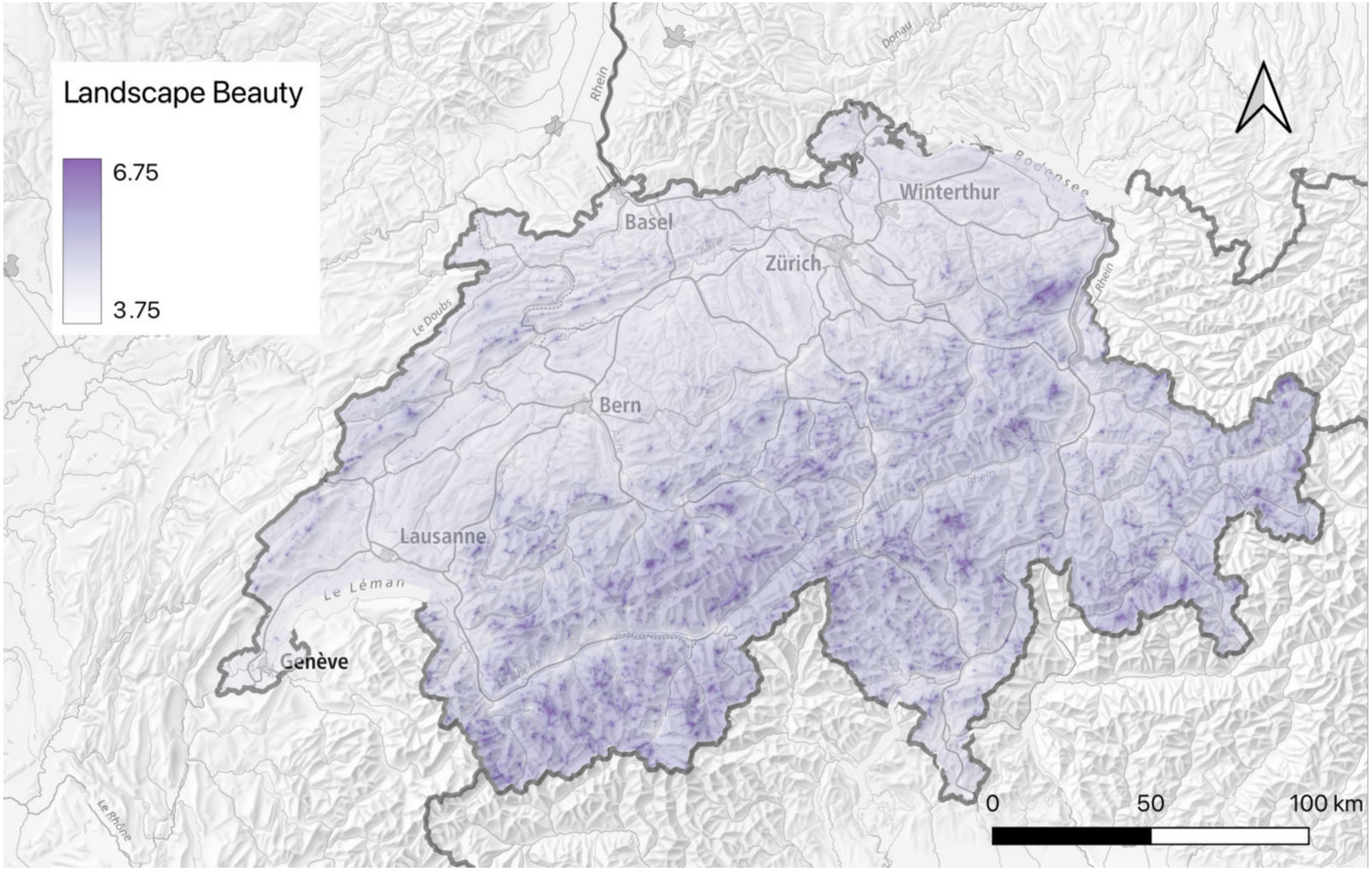


Figure 18: The regressor map which resulted from the Swiss Flickr image predictions with the random forest regressor model. In a second step the pixels between the predicted Flickr images were interpolated using the IDW interpolation method from QGIS (QGIS, 2023)(Swisstopo, 2022).

3.2 Random Forest Classifier

To improve prediction accuracy a random forest classifier model was developed. In figure 21 the resultant scenic map can be viewed. The scale of values in the legend correspond to the originally taken scores from the Scenic-or-Not data set.
A clear pattern of the northern midlands of Switzerland being less scenic as opposed to the better scores for the alps can be observed in figure 21 as well as in figure 17. The classifier model distinguishes more between high and very high scenic scores as well as between low and very low scenic scores. Low scenic scores can be observed along major transport axes, for instance along the highway A1 between Zürich and Bern or along the highway A2 between Lugano and Bellinzona. These are mostly accompanied by major railway routes.

The semivariogram in figure 19 shows the spatial autocorrelation for the predicted scenic scores for the Flickr images inside the polygon displayed in figure 20. Due to the large number of data points, it was not possible to calculate the semivariogramm for the whole of Switzerland. The semivariogram algorithm grouped the distances between the Flickr data points into 200 distance groups (number of lags) and considered distances up to two kilometers (maximum lag distance). It is clearly visible that the similarity between Flickr image predictions between distances of 0 and 250 metres slightly decrease and that the semivariance remains on a similar level after 250 meters. This means that there is spatial autocorrelation between the Flickr image predictions up to 250 meters.

In table 4 the importance scores for the X-variables are showed. Features that stand out in terms of importance are noise, scene categories and land use.

	Color	Noise	Elevation	Scene Categories	Land Use	Object Detection
Importance Score	0.0006	0.0054	0.0020	0.0049	0.0319	-0.0003

Table 4: Here the feature importance scores are listed for the different X-variables that were used to build the random forest classifier model.

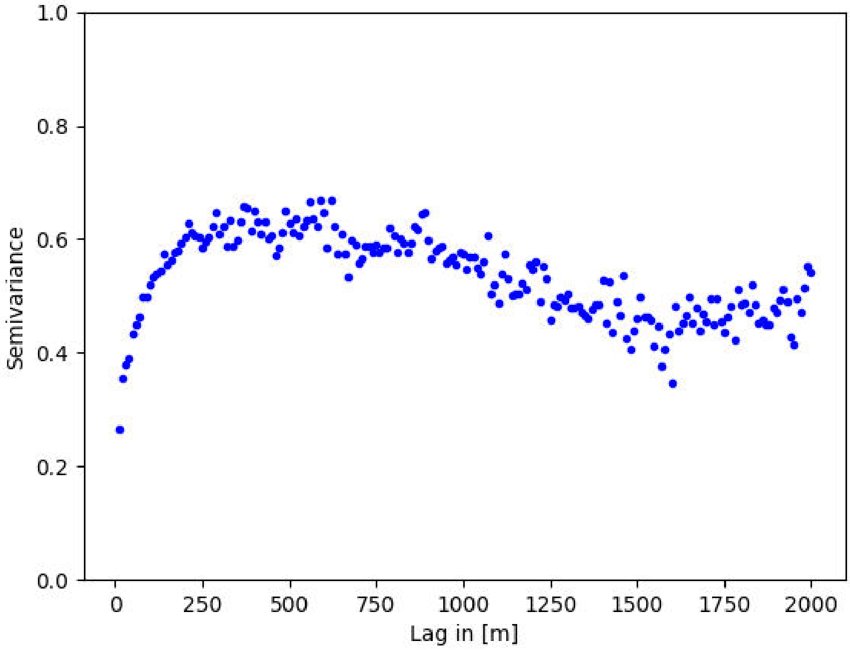


Figure 19: The semivariogram shows possible spatial relationship for a subset of data sample from all predicted Flickr images. The subset is spatially visualized in figure 20.

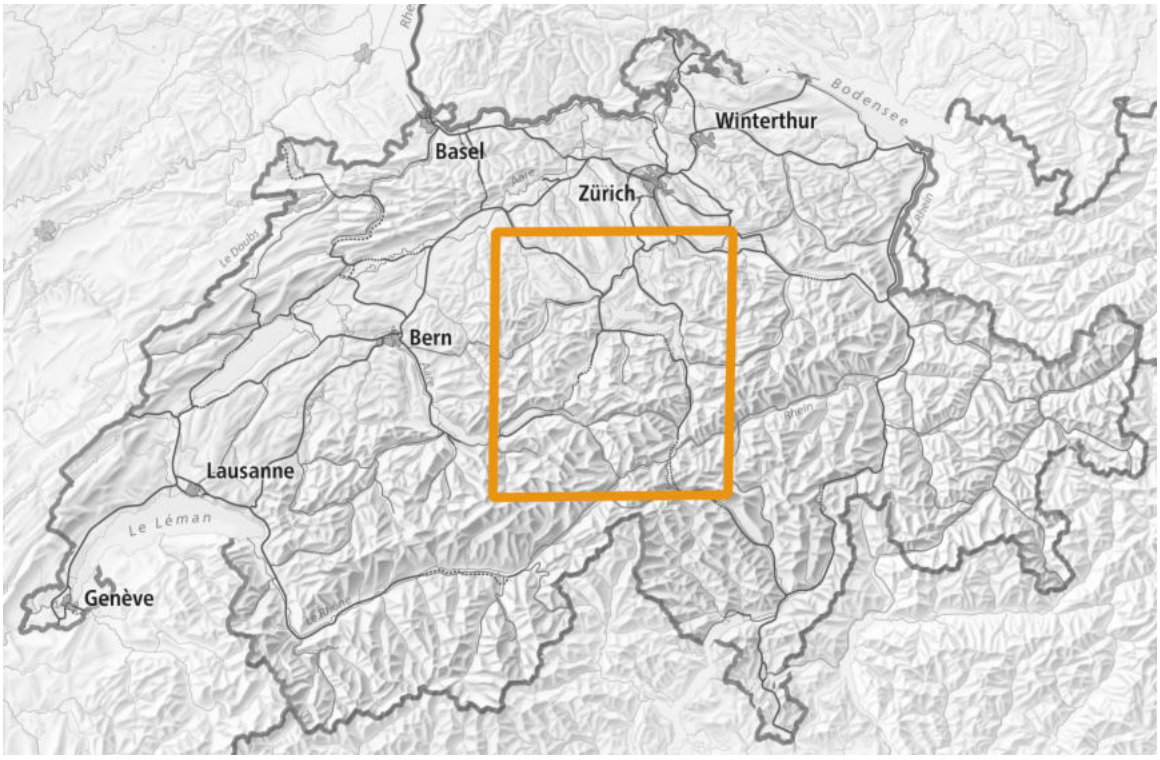


Figure 20: This subset of Flickr images was used to calculate the semivariogram in figure 19 (Swisstopo, 2022).

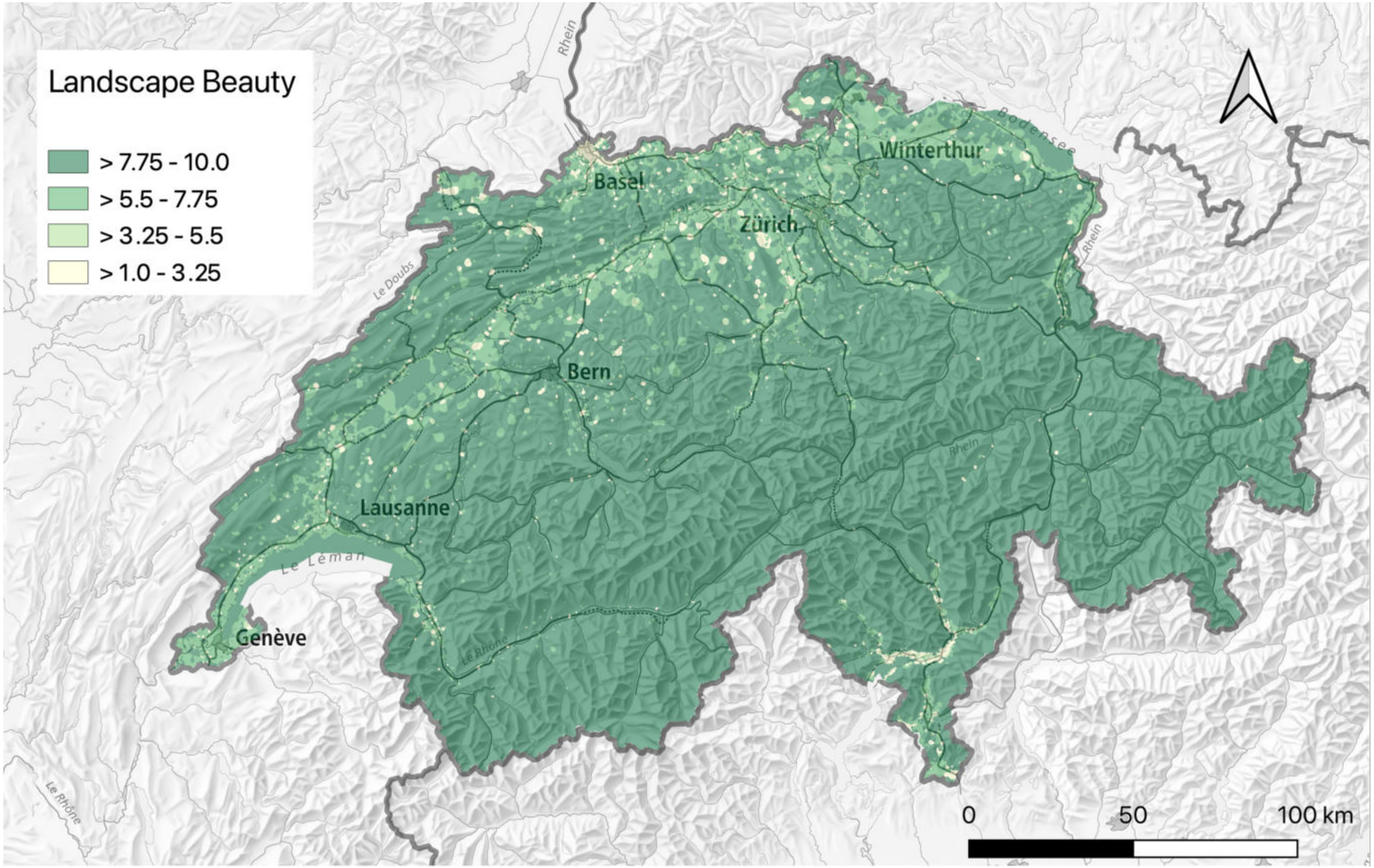


Figure 21: The classifier map which resulted out of the Swiss Flickr image predictions with the random forest classifier model. In a second step the pixels between the predicted Flickr images were interpolated using the SAGA multilevel b-spline interpolation method for categorical data (Lee, Wolberg, and Shin, 1997)(Swisstopo, 2022).

3.2.1 Timeline

Because the Flickr data assigns a time stamp for each image, the predicted scenic scores are ideal to use to create a timeline along the years. This has been done by filtering for specific years. Each year shows a similar pattern in which areas have a low and which have a high scenic score. Urban areas have lower scenic score and more natural areas like the alps have higher scenic scores. It is visible that even though similar regions have similar scores in each region, the patterns are not always identical. In year 2016 an area that stands out is along the highway near Bassecourt in the canton Jura which cannot be found again in the years after. A different abnormality is the the low scores which occur in the Magadino plane in the canton of Ticino. Further south of the Magadino plane towards Lugano and Mendrisio the scenic scores rise again.

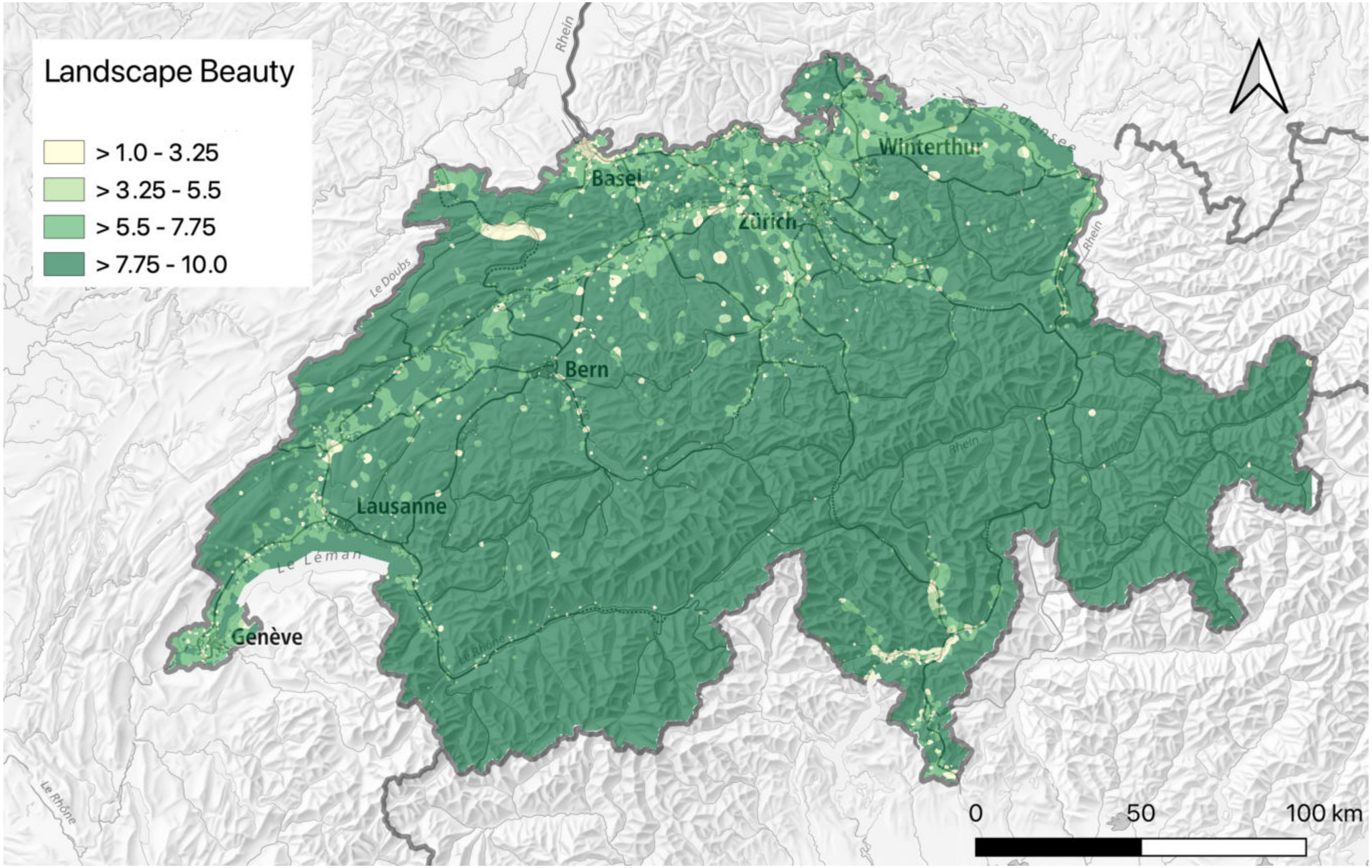


Figure 22: Map which resulted from the Swiss predictions with the random forest classifier model with predicted data points from the year 2016 (Swisstopo, 2022).

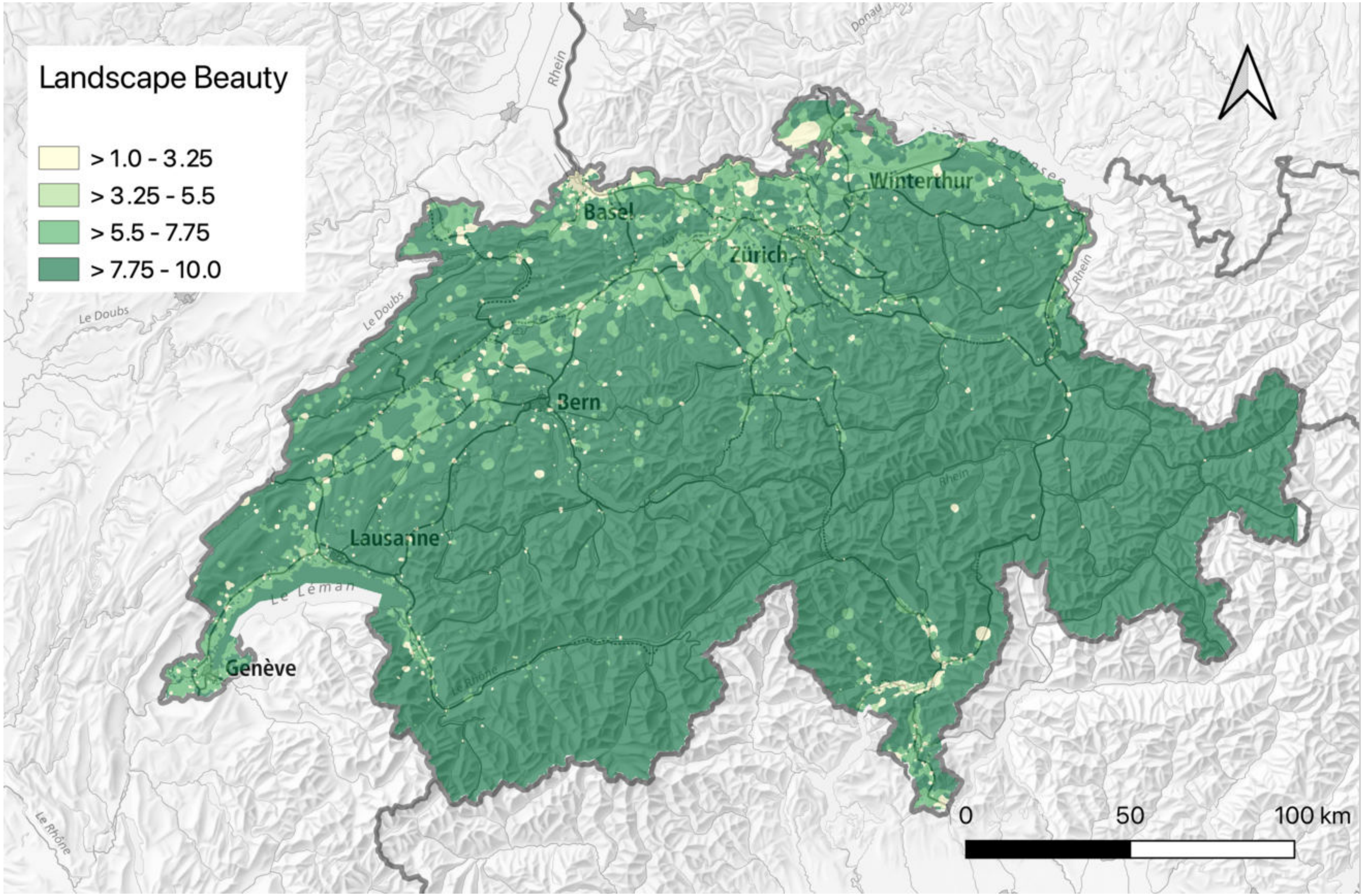


Figure 23: Map which resulted from the Swiss predictions with the random forest classifier model with predicted data points from the year 2017 (Swisstopo, 2022).

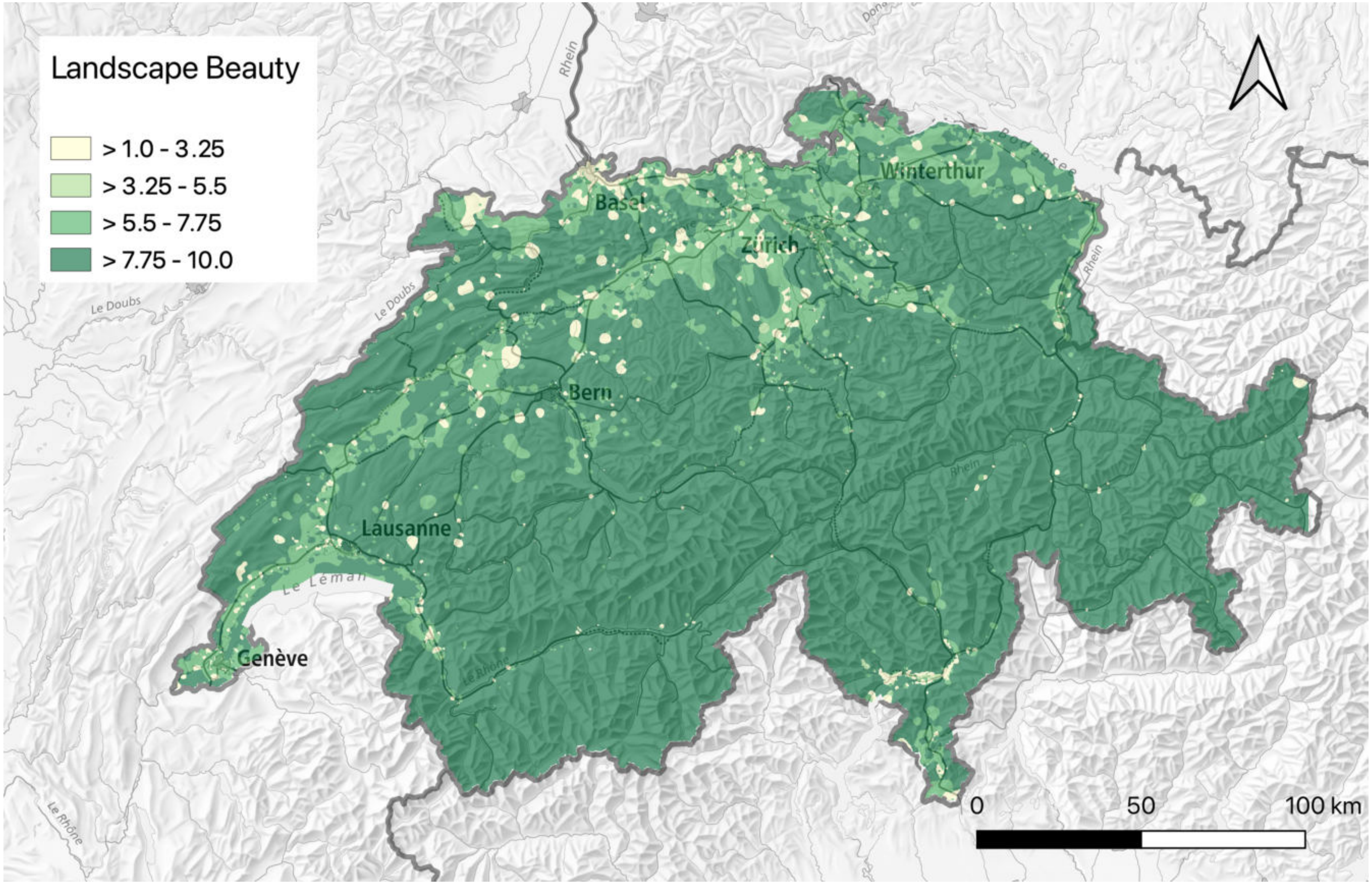


Figure 24: Map which resulted from the Swiss predictions with the random forest classifier model with predicted data points from the year 2018 (Swisstopo, 2022).

Change Detection

Within the change detection maps in figure 25, figure 26 and figure 27 similar areas stand out as in the yearly scenic maps in figure 22, figure 23 and figure 24. The area of Bassecourt shows a massive increase in scenicness whereas the same area shows a very low scenic score in 2016. The alps appear stable in their scenic score. Most scenic changes can be seen in the more urban areas of the northern midlands of Switzerland as well as along the highways with heavy traffic, for instance the highway leading up to the Gotthard tunnel around Biasca and Bellinzona.

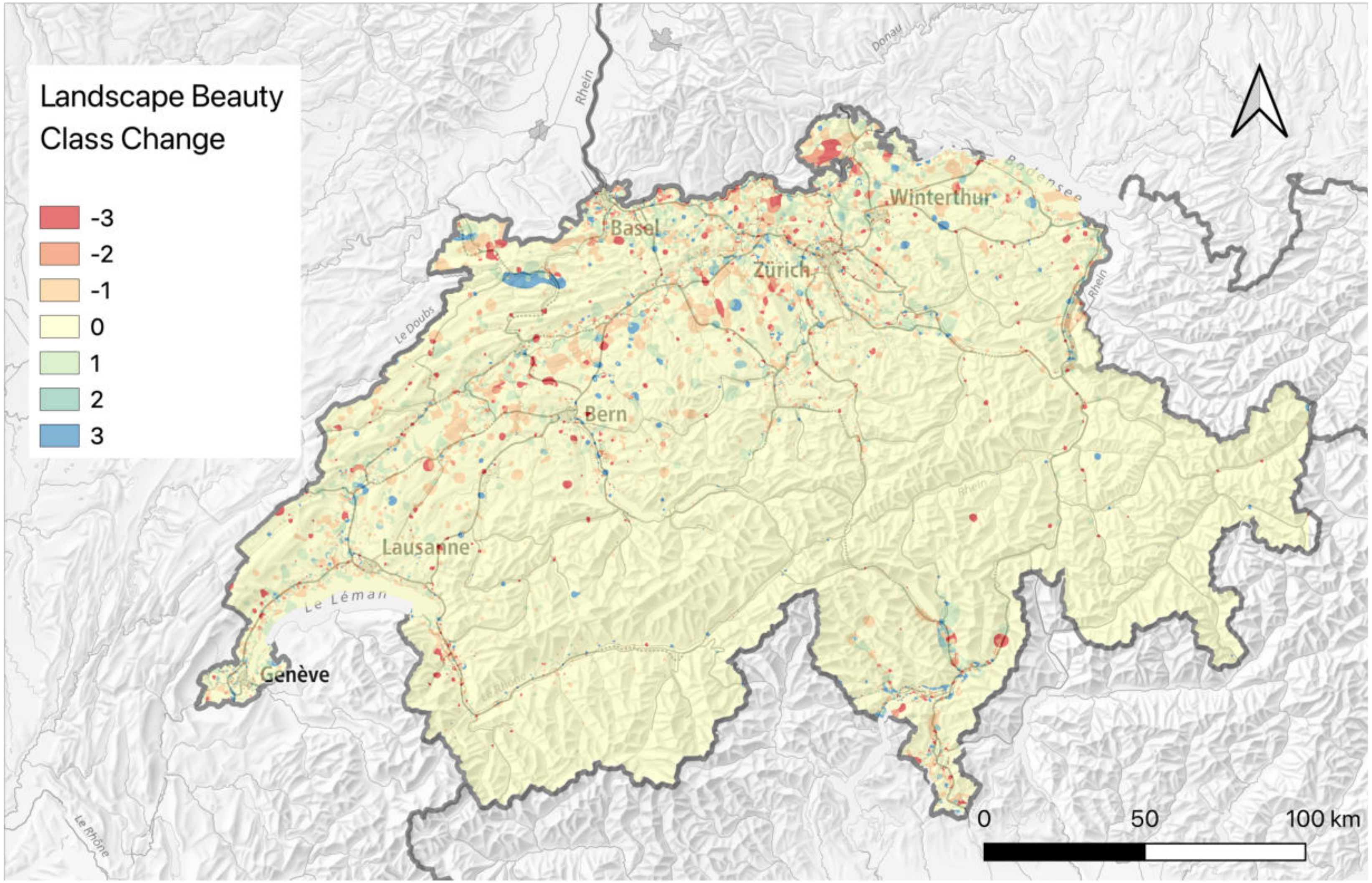


Figure 25: Change map which resulted from subtraction of the classifier map layer from the year 2017 in figure 23 and the classifier map layer from the year 2016 in figure 22 (Swisstopo, 2022).

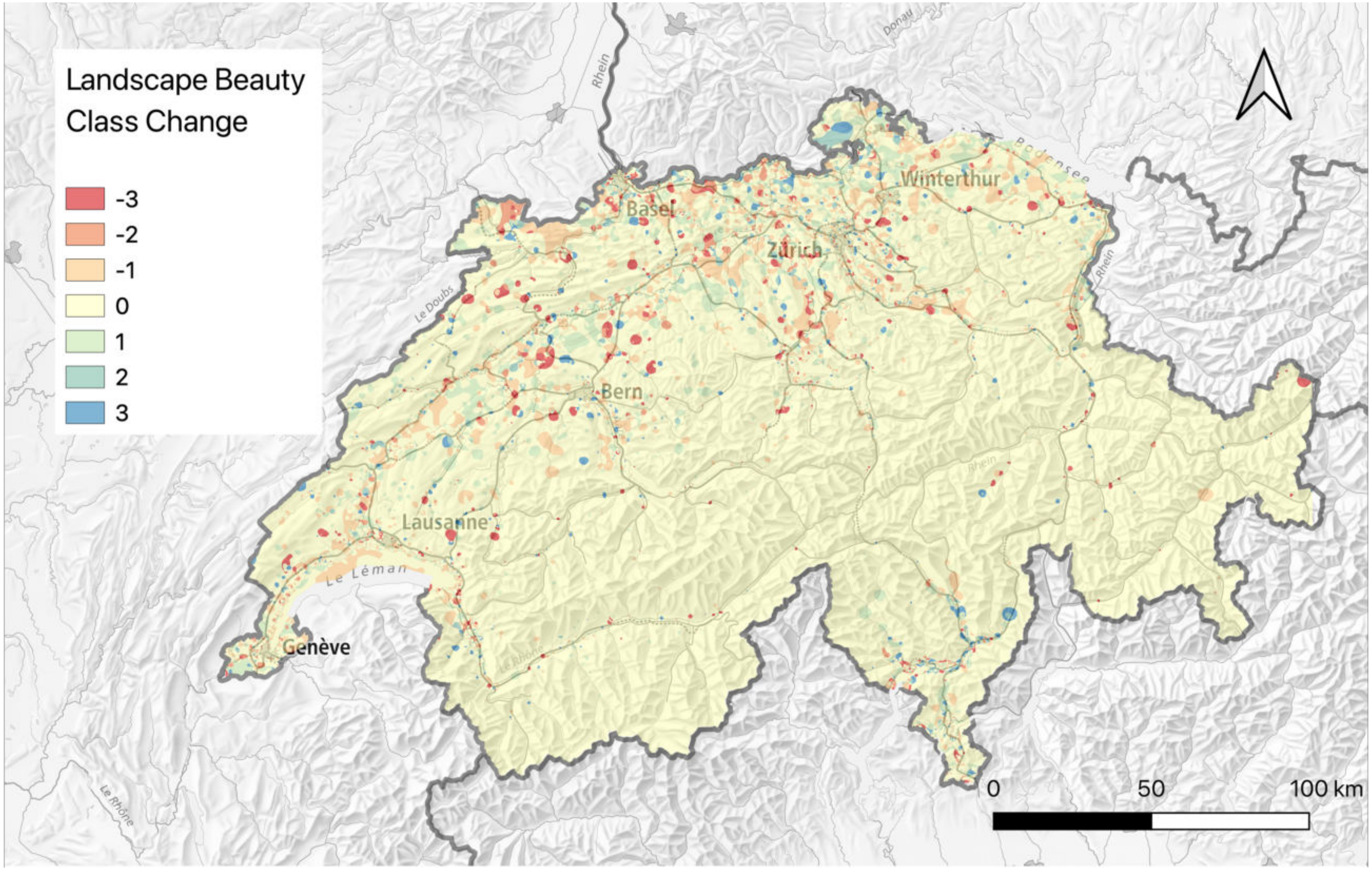


Figure 26: Change map which resulted from subtraction of the classifier map layer from the year 2018 in figure 24 and the classifier map layer from the year 2017 in figure 23 (Swisstopo, 2022).

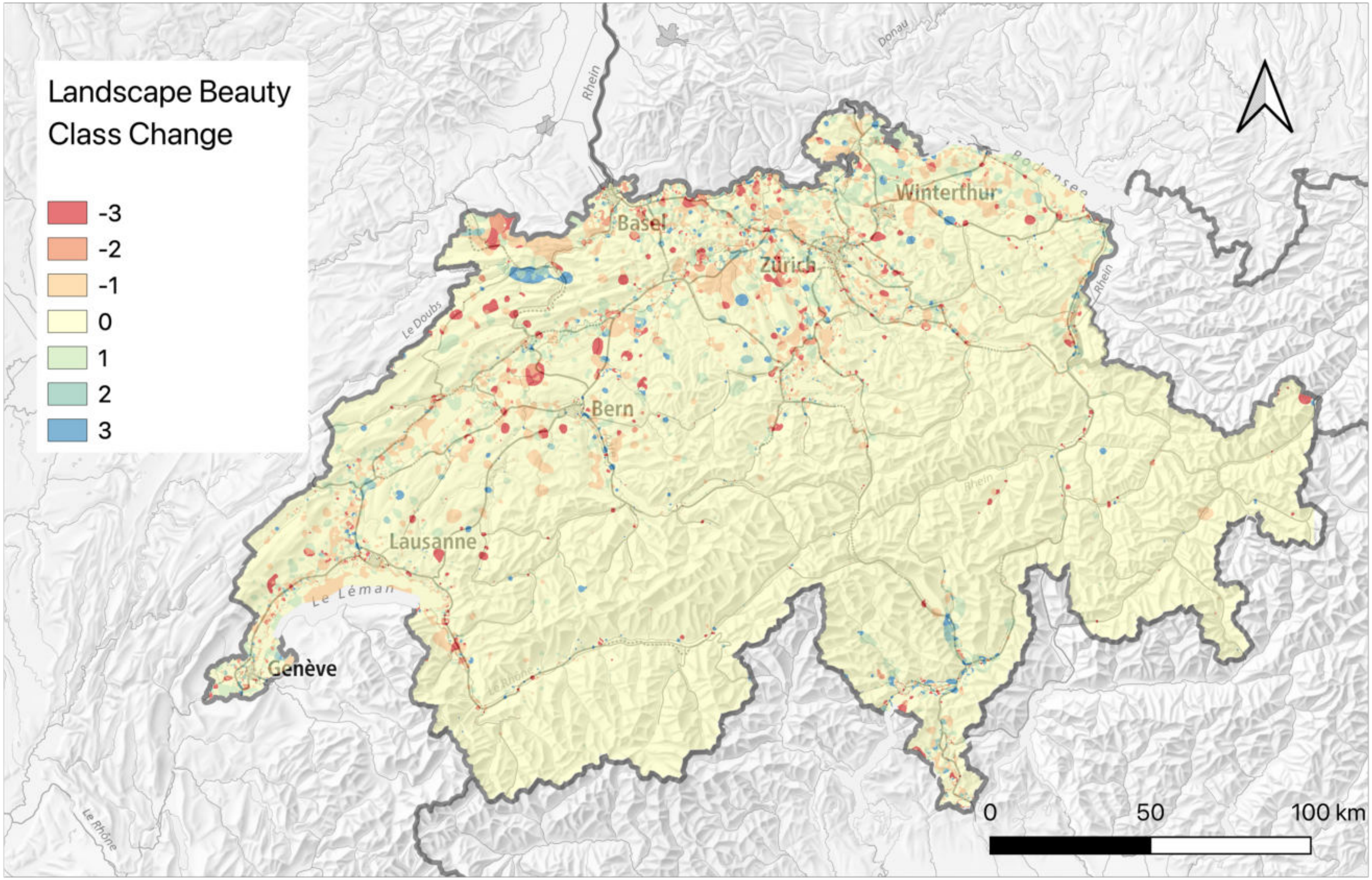


Figure 27: Change map which resulted from subtraction of the classifier map layer from the year 2018 in figure 24 and the classifier map layer from the year 2016 in figure 22 (Swisstopo, 2022).

3.2.2 Manual Flickr Validation

The manual Flickr validation was a process where 225 Flickr images were looked at and evaluated based on my personal landscape beauty preference. In doing so some reference data was generated to see how well the model performed and what kind of images were included in the predictions. Figure 28 shows that out of 225 images 40 of the images showed an indoor scene and 185 images showed an outdoor scene. In a second step these 185 images were scored in a similar way as the Scenic-or-Not images were scored (from 1 to 10). Figure 29 shows the confusion matrix for the manually scored Flickr images. A large number of Flickr images were located in the Alps and because of this the very high scenic class with scores between 7.75 and 10.0 had more samples than the other classes. This class was also the one that scored the best concerning F1 score (see table 5). Classes that scored worse were class one with scenic score between 1.0 and 3.25 or class 3 with scenic scores between 5.5 and 7.75.

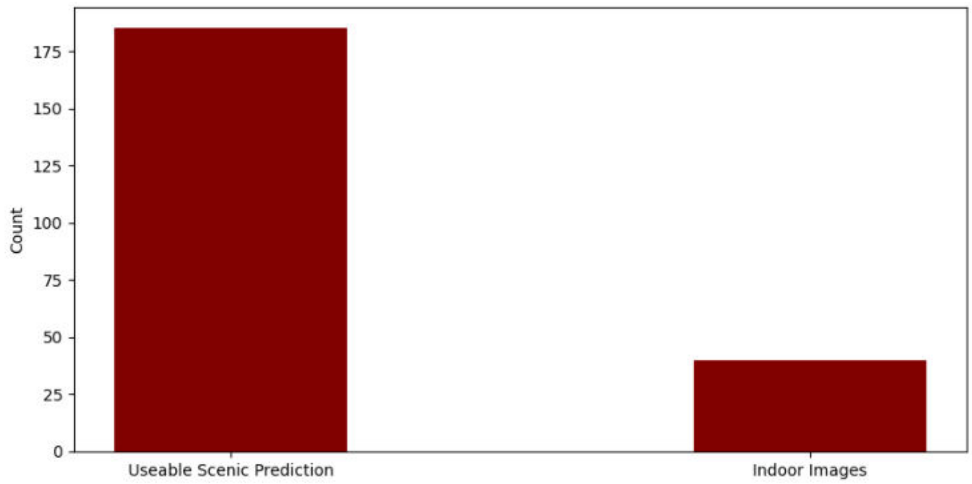


Figure 28: The bar chart shows the number of images that were useable for the scenic landscape analysis and the number of images that showed an indoor scene and were therefore not ideal to assess landscape beauty.

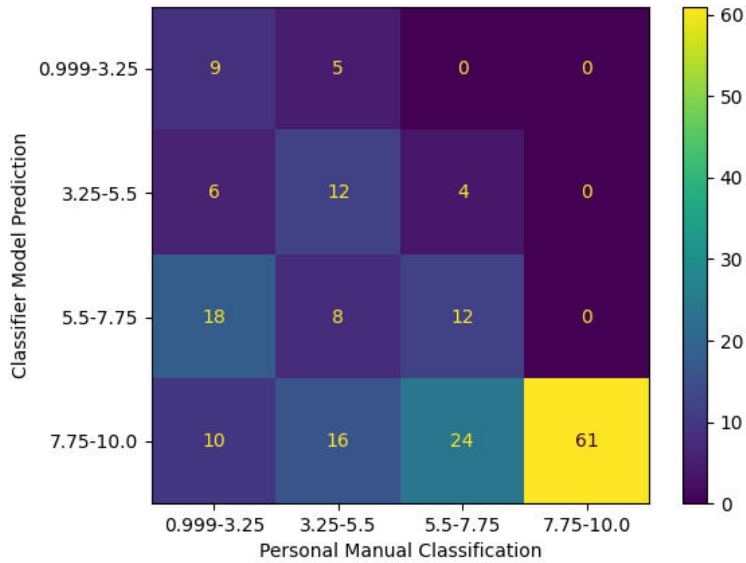


Figure 29: This figure shows a confusion matrix for the validation Flickr images that were scored by the model and by myself .

	Label 1	Label 2	Label 3	Label 4
F1 Score	0.32	0.38	0.31	0.71

Table 5: F1 scores for the four categories when comparing the classifier model's prediction and my scenic scoring for the validation images.

3.2.3 Validation Sites

As a final analysis step, a local validation procedure was done. Here three different locations were chosen and visited. During my visit, pictures of and notes on the surrounding landscape were taken. In figure 30 the validation sites are visualized which included Biasca (TI), Bassecourt (JU), and Oetwil am See (ZH). Here the urban areas within the villages were less important than the surrounding non-urban landscape features.

Figure 30: This map shows the three validation sites which were chosen to compare the scenic maps with the landscape scene score using images that were taken during the validation visit.

The first validation site was Bassecourt (JU) in the canton of Jura. By train from Basel one enters the valley from the east. At first it is a narrow valley with the river Birs running through it. Then, after passing the town of Delémont, the valley widens to include an agricultural landscape. I walked from the village of Bassecourt to the neighbouring town of Courfaivre. Between the villages agricultural areas dominated the landscape. Between the different plots the streets were narrow and rarely used for car traffic. The local population however was able to enjoy the relative quietness of the streets and used them for walking their dogs or for an occasional bike ride. Some areas were recreational, idyllically positioned along the small river Sorne which runs through the valley. The areas, sometimes equipped with grill spots hinted at regular usage by families. Visually the landscape seemed populated with few full natural places or special habitats. When leaving Bassecourt the large electricity power plant stands out.

On an audible scale one realizes quite soon that with the *A16* the valley also accommodates an important traffic axis running from other parts of Switzerland, through Delémont and Porrentrury in Switzerland to France. The noise from the continuous traffic of cars from the highway carried to every spot I visited during the short walk from Bassecourt to Courfaivre. Because of the elevated location and direct line between highway and the walking route, the noise carried far and thus had a large impact on the audible experience at Bassecourt. Figure 31 and 32 show the resulting scenic beauty and scenic beauty class change calculated from the random forest model surrounding the validation location. Scenic value according to the random forest classifier based on the Flickr images and in combination with the multilevel b-spline interpolation predicts a decreasing scenicness when walking from Bassecourt to Courfaivre. The Flickr images have a low spatial and temporal resolution for this particular area. When looking at the validation images this pattern is the opposite way. When moving spatially from image 1 to image 8 in figure 31 and 32 and running the validation images at figure 33 through the random forest classifier, the scenic value decreases overall compared to the scenic classifier map in figure 21 but locally increases when moving to Courfaivre.

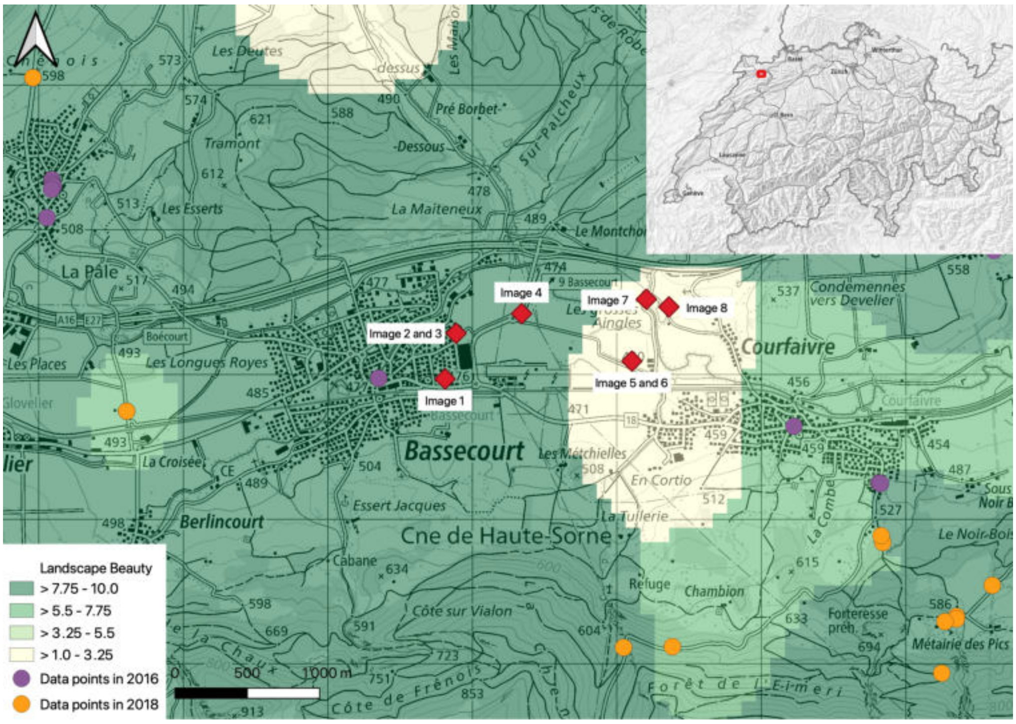


Figure 31: This map shows the validation images at Bassecourt which were taken at the red diamond markers and the results from the classifier map as a base map.

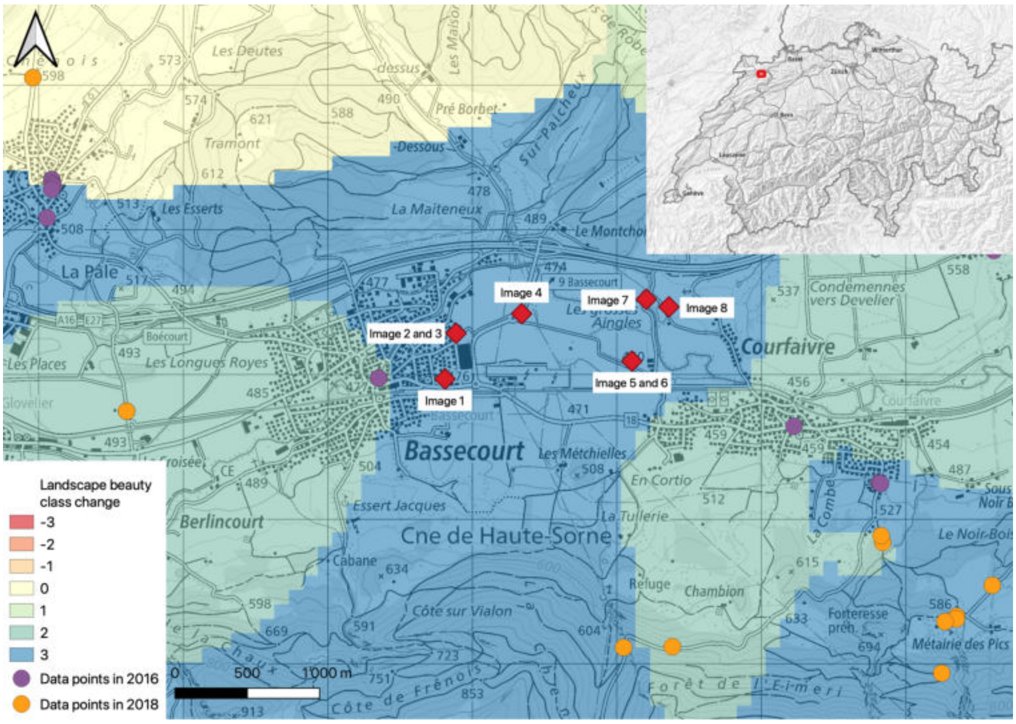


Figure 32: This map shows the validation images at Bassecourt which were taken at the red diamond markers and the change detection map between the year 2018 and 2016 as a base map.

(a) Image 1 with a predicted scenic score between 1.0 and 3.25.

(b) Image 2 with a predicted scenic score between 1.0 and 3.25.

(c) Image 3 with a predicted scenic score between 1.0 and 3.25.

(d) Image 4 with a predicted scenic score between 3.25 and 5.5.

(e) Image 5 with a predicted scenic score between 3.25 and 5.5.

(f) Image 6 with a predicted scenic score between 3.25 and 5.5.

(g) Image 7 with a predicted scenic score between 3.25 and 5.5.

(h) Image 8 with a predicted scenic score between 3.25 and 5.5.

Figure 33: Validation images which were taken around the area of Bassecourt and run through the random forest classifier model. The scores are noted in the caption of the individual image.

As a second validation spot, Biasca (TI) in the canton of Tessin was chosen. As one of the bigger towns after the Gotthard tunnel and an important meeting point of on the one hand the highway axis between Bellinzona and the German speaking part of Switzerland and on the other hand the axis of the mountain pass of Lucomagno connecting Disentis with the Italian speaking part of Switzerland, Biasca is an urban village with the river Brenno flowing into the larger river Ticino. The massive mountains which surround Biasca make it an impressive sight. In figure 21 the surrounding area around Biasca is classified as very scenic except for a part of the highway and an industrial area which lie in the west of Biasca. Going around the village, one undoubtedly notices the two rivers meeting, green spaces and beautiful scenery. At the same time the noise of highway was once again omnipresent and stretched across various natural landscape features such as a river or grassland.

Similar to the validation images from Bassecourt the images from Biasca in figure 36 when run through the random forest classifier show a lower scenic score than the scenic map in figure 21 would suggest. Only image 5 which shows slightly less man-made structures than image 4 at the same location shows a medium scenic score.

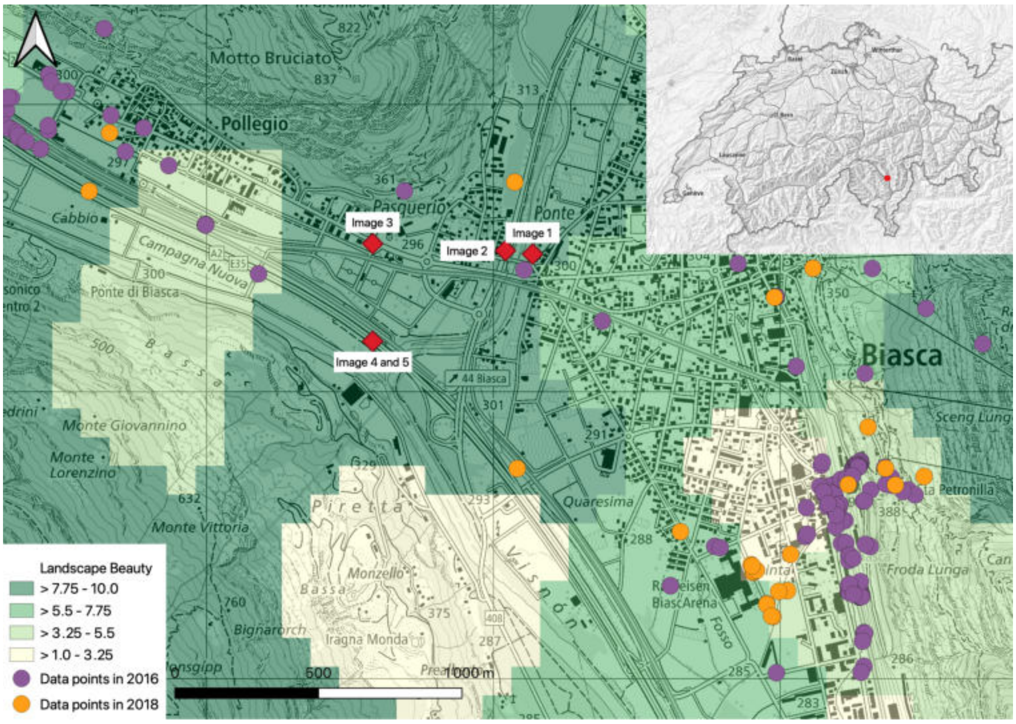


Figure 34: This map shows the validation images at Biasca which were taken at the red diamond markers and the results from the classifier map as a base map .

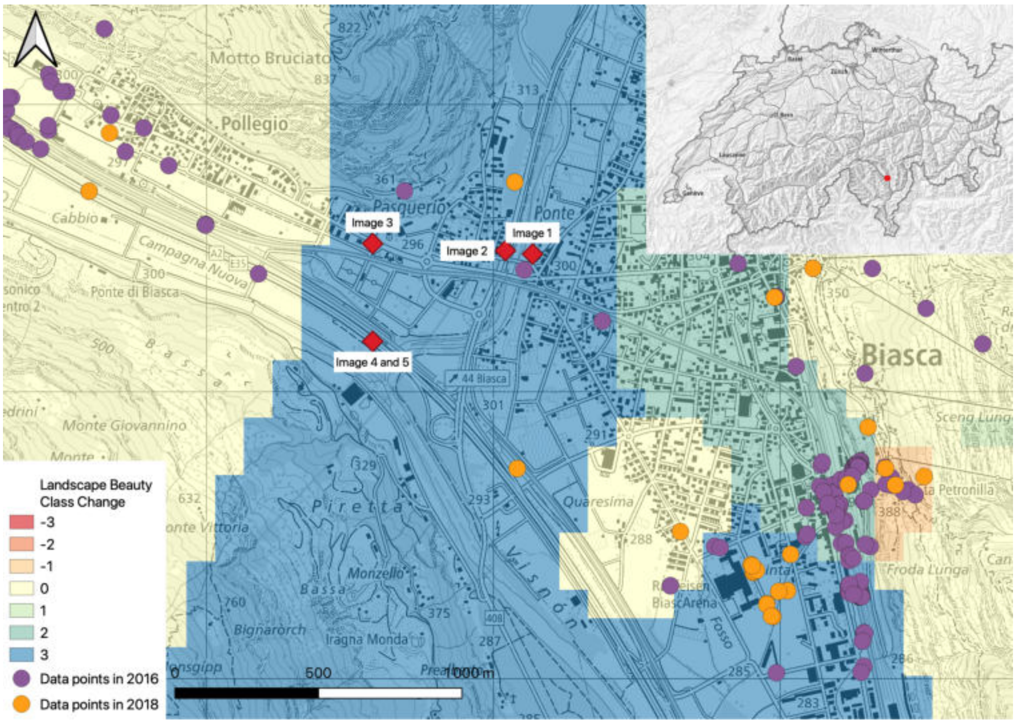


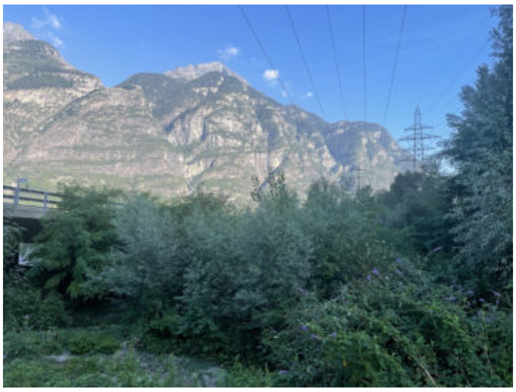
Figure 35: This map shows the validation images at Biasca which were taken at the red diamond markers and the change detection map between the year 2018 and 2016 as a base map .

(a) Image 1 with a predicted scenic score between 1.0 and 3.25.

(b) Image 2 with a predicted scenic score between 1.0 and 3.25.

(c) Image 3 with a predicted scenic score between 1.0 and 3.25.

(d) Image 4 with a predicted scenic score between 1.0 and 3.25.



(e) Image 5 with a predicted scenic score between 3.25 and 5.5.

Figure 36: Validation images which were taken around the area of Biasca and run through the random forest classifier model. The scores are noted in the caption of the individual image.

As a last validation location Oetwil am See was chosen. The surrounding area of Oetwil am See consists of agricultural areas where corn is grown or cows are grazing. The small village is not connected to the railway network and can only be reached by car or by bus. It was the quietest town of the three validation locations visited. Most of the agricultural area around Oetwil am See in figure 21 is classified as very scenic. Only the village itself has a very low scenic value and in figure 38 shows a possible scenic class change.
The validation images show an equal scenic score between 3.25 and 5.5 when run through the random forest classifier. However, the scores still are clearly below the scores the scenic map in figure 37 suggested for the area.

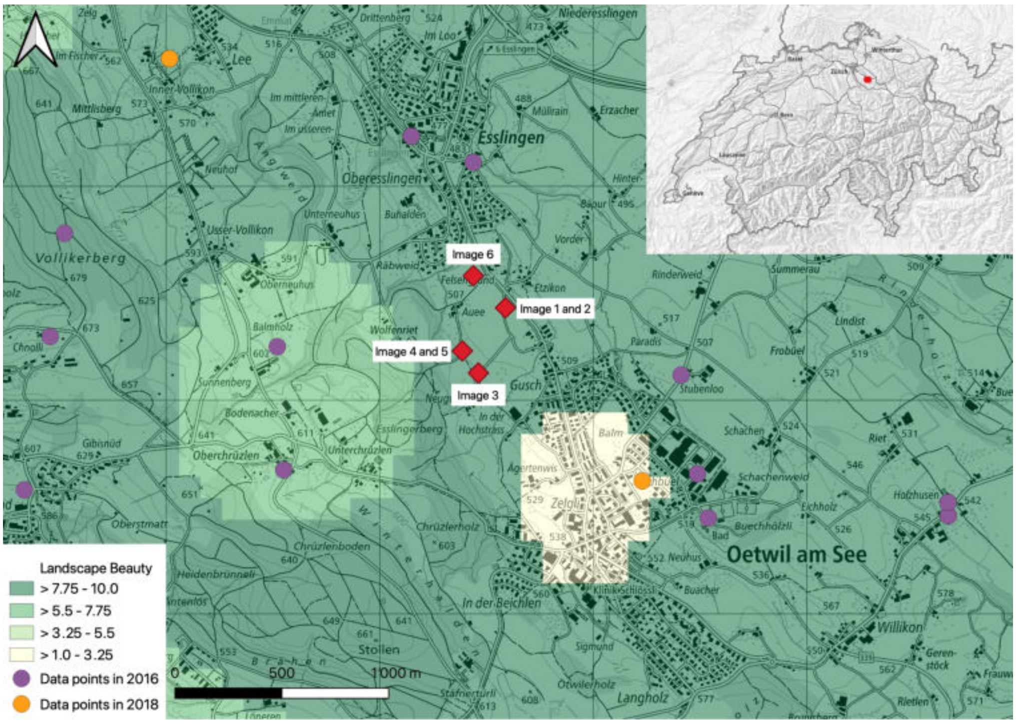


Figure 37: This map shows the validation images at Oetwil am See which were taken at the red diamond markers and the results from the classifier map as a base map .

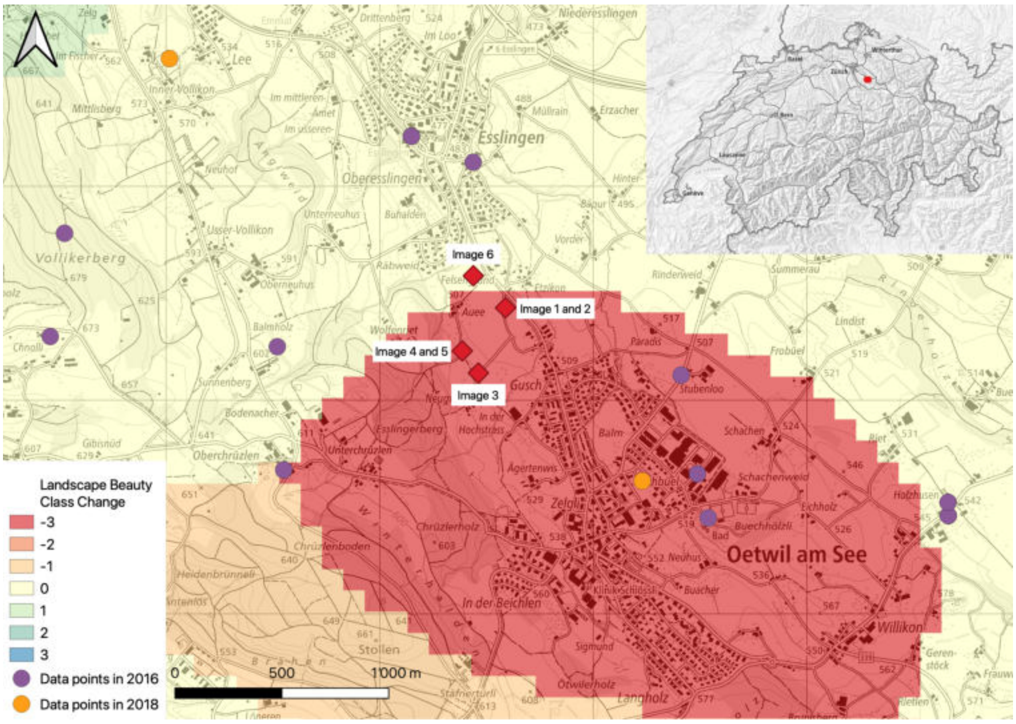


Figure 38: This map shows the validation images at Oetwil am See which were taken at the red diamond markers and the change detection map between the year 2018 and 2016 as a base map .

(a) Image 1 with a predicted scenic score between 3.25 and 5.5.

(b) Image 2 with a predicted scenic score between 3.25 and 5.5.

(c) Image 3 with a predicted scenic score between 3.25 and 5.5.

(d) Image 4 with a predicted scenic score between 3.25 and 5.5.

(e) Image 5 with a predicted scenic score between 3.25 and 5.5.

(f) Image 5 with a predicted scenic score between 3.25 and 5.5.

Figure 39: Validation images which were taken around the area of Oetwil am See and run through the random forest classifier model. The scores are noted in the caption of the individual image.

4 Discussion

Overall this master thesis shows that a machine learning model can be used to assess landscape beauty on a large scale based on a selection of spatial variables. It is important to remember that the definition of landscape is vital when it comes to selecting a scenic reference value for the model. When analyzing the Swiss-wide scenic map in figure 21, it becomes clear that on one hand the goal of transferring landscape beauty from one region to a geographically different region succeeded on a basic level. However, the model had some difficulties differentiating scenic scores in areas where Switzerland differs fundamentally in a geographical sense from Great Britain. The basic pattern of the northern and more urban areas having a lower scenic score and the more natural alps have higher scenic scores. This is visible in the resulting scenic map in figure 21. Furthermore, the model was able to differentiate between scenic and not scenic places as is shown in the confusion matrix in figure 11. When looking at the opportunities the resulting scenic maps open up for decision makers and planners, it is clear that the precision and spatial resolution do not suffice yet to use them as a basis to locate suitable sites for infrastructure projects like highways or wind turbines in terms of community acceptance.

4.1 Measuring and Transferring Scenic Beauty

Research question number one aims at exploring the term landscape beauty. This is not a term that means the same to everyone. Questionnaires where people can rate landscape beauty will get various results for the same landscape images, as the Scenic-or-Not data set has shown. The variance within the votes for a specific image (see figure 10) leads to the question whether a definition of landscape beauty as the Scenic-or-Not project tries to find it, is even attainable. Due to this discrepancy in the human perception, a machine learning model will always have its inaccuracies because it can not learn patterns that are not clearly discernible in the underlying data. This aspect was also discovered by Olafsson et al (2022) where they pointed out that a machine learning model can be used to assess landscape beauty but its application will not cover all fields where landscape beauty analysis is needed (Olafsson et al., 2022). In this thesis the issue with differing landscape beauty perception was also tackled. First the regressor model was not able to learn sufficiently from the Scenic-or-Not data set to predict landscape beauty with a sufficient accuracy (chapter 2.1.3). With the regressor model continuous data was predicted with a two decimal point accuracy which when looking at the variance of the Scenic-or-Not data set in figure 10 is methodically hard to justify. Because of the issue with different perceptions within the voters of the Scenic-or-Not project, a classifier model was developed that had better accuracy scores (see figure 14). With this generalization in terms of score prediction, the task of the model was made easier and smoothed out possible variance within the training data. As Chesnokova, Nowak, and Purves

(2017) have done by changing spatial resolution from a 1 km to a 10 km resolution, smoothing out variances within the Scenic-or-Not votes will improve the accuracy score of the underlying model.

Although the development of a classifier model increased the performance, other issues with transferability of landscape beauty based on spatial variables arose. This question of transferability was identified as research goal number one at the start of this thesis because Great Britain and Switzerland have some differences concerning topography and landscape. Great Britain is not known for its high mountains and this led to some inaccuracies in the higher altitude regions of Switzerland. The classifier model predicted high scores for the alps and did not often differentiate between high scenic value (scores between 5.5 - 7.75) and very high scenic value (scores between 7.75 - 10.0). Even though this correlates to the real distribution of natural areas in Switzerland and to expected patterns of a Swiss scenic map, there are still various industrial areas above 1000 meters above sea level which therefore should not be classified as very scenic. Figure 21 shows that also larger cities like Davos, St. Moritz or Visp which are located in the alps have a very high scenic value. This is caused by the fact that the maximum height above sea level in Great Britain is not as high as in Switzerland and higher places in Great Britain often are scenic places that offer a nice view with natural landscapes. In Switzerland the high altitudes led to higher regions being classified as scenic or very scenic due to the importance elevation as a variable was given inside of the classifier model (see table 4). This means that when transferring a scenic model to Switzerland and the model has not been trained on high altitude locations, the variable elevation might have to be left out to ensure a more nuanced map in high altitude regions.

4.2 Limitations of Machine Learning

An aspect that is relevant for every machine learning model is the data basis on which it is built on and the data set it uses to predict new values. As McKenna et al (2021) explain in their research, the Scenic-or-Not data set is advantageous to use as a base input because it covers the area of Great Britain very evenly and through this includes many different landscapes (McKenna et al., 2021). The issue with using the data set as a scenic reference value as in this thesis, is the immense variance within the scores for the same picture. This variance distribution is visualized in figure 10 and shows the disparity of landscape perception of the voters. When people's opinion differ, the machine learning model will have troubles predicting a scenic score accurately, especially, when using a random forest regressor which predicts continuous data. The random forest classifier performed a bit better in these cases than the regressor. The performance increased even further when changing the model from a five class to a four class classifier model. This is not unexpected because by switching to a classifier model and reducing the number of predicting classes the task is made easier for the machine learning model. These improvements contributed towards assessing research question number two and showed that different steps can be taken to improve the machine learning models performance.

In general, one can conclude that both the classifier and regressor scenic map in figure 21 and figure 18 respectively, show a plausible pattern where the northern more urban areas have a lower scenic scores and the alps with an overall more natural landscape have higher scenic scores. The manual validation of Flickr images showed that the classifier model was able to identify almost all areas that were identified as high scenic areas during the manual validation phase (see figure 29). The F1 scores in table5 suggest that the classifier model had great success finding the scenic places among the Flickr images. Here it should be mentioned that for this scenic class the highest number of images were inside the subsample. Most very scenic images showed peoples impressions from glacier hikes or ski trips and often depicted landscape scenery that Switzerland is known and visited for. With the ultimate goal being that a map depicting landscape beauty could act as an additional decision making tool and to show which landscapes are to be protected, the referenced maps do not suffice in terms of spatial resolution and accuracy. More data points would need to be introduced in order to generate an accurate estimate of the most important areas. It is hard to pin point suited areas to build, for example a wind turbine based solely on this map and even though the classifier model identified most of the favoured Flickr images from the manual validation phase as scenic (see figure 29), the places falsely identified as scenic make the classifier map as presented in this thesis prone to error (see figure 21). Additionally, the validation sites have shown, the predicted scores from the random forest classifier model differ from the scenic scores that were found through interpolating the scores of the Flickr images. More images could improve the interpolation result and with it its application potential for decision makers. If more training data and prediction data points are available, the number of classes could be increased without a relevant loss in accuracy. Ideally, rough project locations could be selected using the scenic classifier map. In a second step at a more specific planning stage, using a PPGIS like Müller, Backhaus and Buchecker (2020) and Moore and Hacket (2016) suggest, a precise project locations could be selected (Müller, Backhaus, and Buchecker, 2020)(Moore and Hackett, 2016).

4.3 Accuracy and Useability

The Flickr images usually correlate with places which are easy accessible. This makes it harder to assess landscape beauty in more remote areas (Olafsson et al., 2022). One could argue that research question number three and the goal of the scenic map itself, does not include mapping remote areas. Research question number three of this thesis aims at trying to generate a layer for planners and decision makers that is accurate enough to identify suitable location for infrastructure projects like highways or wind farms. Very remote and rarely visited areas are usually not interesting locations for building new power plants, wind farms or highways. These remote places of which only a few Flickr images exist, often are high up in the mountains and it would be expensive to develop the place and connect it to existing infrastructure. It is crucial to maintain infrastructure objects such as a wind turbine so they need to be accessible by car. Depending on the goal of the map, Flickr images could thus be an valid option if the goal is not to map all of Switzerland.

Further, it is important to add that when using such open source image data, the user never really knows what type of theme they get in an image. For this thesis only images of outdoor scenes are of interest. For the validation site Bassecourt in figure 31, specifically the data point in the middle of the village of Bassecourt, the classifier model predicted a high scenic value. This is questionable for such an urban environment. When looking up the specific image in the Flickr data set, it became clear that the image showed a close-up of two people standing together in a closed room. Such an image is not suitable to assess landscape beauty. This issue when using Flickr images for landscape beauty analysis was also made a subject of discussion by Seresinhe, Preis and Moat (2018). Using Flickr images in the landscape beauty analysis could add to the uncertainty of the model (Seresinhe, Moat, and Preis, 2018). When using an open source image data set this effect is hard to avoid. During the manual validation of a subsample of Flickr images, the ratio of images adding to uncertainty became clear. Figure 28 visualizes that out of 225 manually validated and scored images only 185 images were actually useable. The other images showed indoor scenes. All these indoor images added uncertainty to the interpolation and influenced the accuracy of the scenic map. To solve this issue one could add some kind of word analysis algorithms which analyzes so called tags and tries to find out what theme the image has (A tag is a word which is linked to the image which the user can choose freely but usually pertains some connection to the image and what is in it). This could improve the selection of Flickr images that are included in the analysis. Another issue with open source data sets could be relocated images. Here the big advantage with using additional spatial variables like elevation and land use together with the image analysis variables with the scene recognition and object detection, the model stays more stable because it has still data to predict scenic scores even though the scene recognition and object detection did not generate useable information.

The machine learning model predicted Flickr image data points and to create a surface covering Switzerland a multilevel b-spline interpolation for categorical data was done. Due to this dual nature of the results, not only the Flickr image data points need to be discussed but also how good the interpolation results were. The heatmap in figure 16 shows the density of the Flickr images. Places that stand out with a high density of Flickr images are large cities like Zürich, Bern or Genève. Additionally, touristic places like the Jungfraujoch or Luzern have a high density of Flickr images. As a consequence of this density distribution, the accuracy of the classifier map in figure 21 is higher in the areas with a high Flickr image density because more data has been included in the interpolation. Values in areas where only few Flickr images occur the interpolated value is influenced only by a few images which might be kilometers away. Once again depending on the goal of the map, this issue with data availability should be kept in mind.

As a further test to assess the application of the scenic maps, timeline maps were developed. The goal was to see if the algorithm could detect new structures or land use changes which would potentially affect landscape beauty. Different maps from the years 2016 to 2018 were compared to the validation sites and aerial images for the different years were observed. The resulting changes in figures 25, 27 and 26 did not correspond to real visible changes around the validation sites. One of the reasons for this outcome was the number of samples which was available for each year. When analyzing the number of data points, it becomes clear that they were not sufficient in numbers to assess temporal change. Furthermore, the spatial distribution of the data points needs to be even to ensure a good interpolation result. For the subset of the years 2018, 2017 and 2016 the data basis did not suffice, and had some unsuited patterns which are visualized in figure 32, figure 35 and figure 38. It is visible that there is a very coarse spatial distribution and this coarsely distributed data set is even coarser when looking at each data point year by year. This means that in one year an area could have had no data point and for the year that was subtracted, suddenly one or more data points would have been included. The issue which occurs here is that in one year a data point could influence the surrounding area during the interpolation process and in the next year the same area is influenced by a data point of a different location or a different Flickr picture of the same location. This often results in a landscape beauty class change even though there is no change in the landscape itself. Here a larger temporal interval should have been applied. By doing this more Flickr images are included in the different subsets which can in a seperate step be used to do a change analysis. This would mean that a change analysis would be done over a five year period instead of a one year period. Such a adjustment could be able to show landscape beauty changes more definitive and accurately.

As a last issue concerning the useability of the landscape beauty maps as a basis for decision makers to identify beautiful landscape scenes, is the perception of landscape scenes by the local population. At the validation sites different pictures were taken to see what the local landscape looked like. In a second step the self-made pictures were then run through the machine learning model to see if the predicted scenic score came close to the scenic score which was given in the scenic map in figure 21. Bassecourt in the canton of Jura was the first validation site. During the short walk from Bassecourt to Courfaivre what stood out immediately was the number of people who were enjoying the area by horse riding, walking their dogs or jogging even though the area was not extraordinary or had a very natural scenery. The noise of the highway was omnipresent, almost all fields were used for agricultural purposes and there were industrial complexes surrounding the edges of the village of Bassecourt. The question arose, how this area could be classified as high as it had been by the classifier model? The resulting map in the surrounding area of Bassecourt is visualized in figure 31 and shows scenic values of 7.75 to 10.0 for images 1 to 4 in figure 33. When running the images of the local validation through the model the scenic score is considerably lower. The validation image scenic scores were 1.0 to 3.25 or 3.25 to 5.5. The score which resulted from the classifier models seems more plausible than the scores for the same location calculated through interpolation of the Flickr data points. A similar pattern could be seen in Biasca. Here the highway was even closer but the area was still used as a local recreation area where families walked with strollers or people walked their dogs. In Biasca the validation images in figure 36 resulted in scenic scores of about 1.0 to 3.25 or 3.25 to 5.5 and are therefore much lower than the interpolated results in the classifier map in figure 21 first suggested. Within these validation locations a deeper issue is evident which was also discovered by Olafsson et al (2022) or Müller, Backhaus and Buchecker (2020), when analyzing landscape beauty with a PPGIS approach: Asking the local population will change the outcome of evaluating landscape beauty. To an outsider the surrounding landscape is not necessarily uniquely beautiful but the importance of the area for the local population, is evident. The question that is relevant in these cases is what the map is used for and what goals are pursued with it. Depending on the person that looks at the images or at the scenic maps, a different meaning will be associated to specific landscape scenes. As Bell (1999) described with their example comparing the remote scientist to the botanist, the individual interest will influence the meaning associated to their observations. As a Swiss geoinformation scientist who is evaluating landscape beauty on a national level, areas surrounding Bassecourt or Biasca are not necessarily very beautiful compared to an area like the Jungfraujoch and could be potantially be included as a possible site for a wind turbine. In this thesis the goal is to create a data layer which serves a similar purpose as the data layer published by the British government to avoid scenic pollution in these outstanding scenic areas (UK, 2023). As a consequence this means that even though the landscape surrounding Biasca and Bassecourt is used as a leisure area and is therefore valued by the local population, this does not mean that the scenic value which resulted for the validation images in figure 33 and in figure 36 were not justified for the task at hand. To ensure that recreational areas are valued appropriately in planning stages a PPGIS might be more appropriate (Olafsson et al., 2022).

4.4 Possible Improvements

In future the results from this master thesis can be included to follow up on identifying feature variables which describe landscape beauty. Just like Havinga et al (2021) have pointed out, research into more spatial variables which describe landscape beauty even better could further enhance machine learning models (Havinga et al., 2021a). Additionally, an alternative scenic reference data set could be developed and included. The Scenic-or-Not data set has various advantages but the issue with the large variance within the different votes for an image, shows that more votes are needed to assess a common denominator for scenic and not scenic landscapes. Optimally, a Scenic-or-Not data set should be created for Switzerland to make sure that inaccuracies which occur when transferring landscape beauty perceptions are minimized. Furthermore, more Flickr images should be included to improve the spatial coverage. As Olafsson et al (2022) pointed out, the spatial coverage for Switzerland will probably never be as well distributed as the Scenic-or-Not data set guarantees because most Flickr image posts follow easy accessible locations. Hopefully, a larger Flickr image subset will bring a more nuanced result around urban areas.

4.5 Further Works

As a final input, a next project could research how PPGIS might compliment such a large scale landscape beauty map such as the one visualized in figure 21 to see if a compromise with the local communities could be found or not. This could also give some new perspectives on PPGIS approaches like Müller, Backhaus and Buchecker (2020) have done. This proposed research could follow up on research goal number three and show the potential of a scenic map when used in tandem with an PPGIS approach.

5 Conclusion

How can scenicness of landscape be measured and transferred to different geographic regions using a machine learning model?

In this thesis different machine learning approaches were explored to assess whether the scenicness of a landscape can be measured by a machine learning model. The regressor model and different classifier models were able to assess landscape beauty. With a dual class random forest classifier approach the resulting model was able to differentiate between beautiful and less beautiful places. The higher number class models then showed the possibility of creating a nuanced scenicness model using noise, elevation and land use as input variables with additional variables being generated by scene recognition, color extraction and object detection. The Scenic-or-Not data set with its spatially well distributed images built a good base searching for landscape beauty patterns, even though the data set had some disadvantages like the high variance within the votes (see figure 10) or the distribution of different average scenic scores along the whole possible spectrum (see figure 12).

The goal of transferring possible results to different geographic regions was explored using a British data set to train the model and then testing it on Swiss landscapes. Landscape beauty in Switzerland was predicted using Flickr images. This was complicated due to the geographically unique environment of Switzerland that led to a partly inaccurate scenic evaluation, especially in areas that are uncommon in Great Britain like high altitude regions.

What are the limitations of using a machine learning model when looking at a topographically complex country like Switzerland?

A machine learning model can only predict values based on information it has seen before in the training phase. This leads to inaccuracies when using x-variables that differ significantly between the training landscape and the target landscape. In this thesis the model was trained on the British landscape, which has lower elevation values and is an overall less mountainous country. Therefore, the different models had difficulty generating nuanced landscape values for the Swiss alps which appear to have uniformly high scenic values.

How accurately can scenic areas be mapped and used as a planning tool for decision makers who plan infrastructure projects like wind parks or roads?

The classifier scenic map (see figure 21) depicts a plausible landscape beauty layer for Switzerland. The validation sites have shown that using the classifier scenic map as a singular planning step concerning public approval, will not suffice to capture the landscapes importance in locals everyday lives. Nevertheless, the scenic map can be a helpful addition for planners and decision makers to identify unique and important landscape scenes that need to be protected and in doing so can pin point possible suitable locations for large infrastructure projects.

How could the model be improved, that a suitable scenic map can be compiled for Switzerland?
Most inaccuracies in the classifier scenic map (see figure 21) could be remedied by using more data in the model's training phase. This would enable the model to build more decision trees and thus gain more insight into data patterns. During the predicting phase when building the classifier map, more values for the scenic map would have to be added to balance out results from unwanted pictures that do not show landscape scenes. Lastly, spatial variables could be chosen more carefully to make sure that the range of the variables is similar between the training region and the target region that are described with the spatial variables. This would help to build a model that recognizes the topography and spatial features of the area that is supposed to be mapped. To create a scenic map for an area as large and diverse as Switzerland an immense amount of training data of various regions would have to be gathered. An important next step to building such a model would thus be to generate sufficient training data for the model to learn the crucial relationships that make a beautiful landscape.

6 Personal Declaration

I hereby declare that the submitted Thesis is the result of my own, independent work. All external sources are explicitly acknowledged in the Thesis.

Quinten Groenveld
Zürich, September 30, 2023

7 Acknowledgement

I want to express my gratitude for the immense support I have received during this master thesis. It was a challenging topic which I have studied for the first time in my studies and this meant that there was a lot of new theories to study. Here Maximilian Hartmann was a great support who took time to explain and discuss various aspects around coding and improving the machine learning models.

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8 Code Repository

The used code with the final random forest classifier model and the final random forest regressor model can be found on Github under following link:
https://github.com/qjgit1996/masterthesis_quintengroenveld

1. **Masterthesis:** Here the British models were developed.
2. **Masterthesis2:** In this project the Swiss Flickr images were run through the models and a score was predicted for them.
3. **flickrHandler:** These scripts entail how the Flickr images were handled and filtered.
4. **discussion:** In this project the graphs and the semivariogram for the validation phase were run.
5. **cls_model_final_v2:** This is the final version of the random forest classifier model.
6. **model_n600:** This is the final version of the random forest regressor model.

The **Places365** project was cloned from following Github project: https://github.com/GKalliatakis/Keras-VGG16-places365

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A Places365 Scene Categories

- airfield
- airplane cabin
- airport terminal
- alcove
- alley
- amphitheater
- amusement arcade
- amusement park
- apartment building/outdoor
- aquarium
- aqueduct
- arcade
- arch
- archaelogical excavation
- archive
- arena/hockey
- arena/performance
- arena/rodeo
- army base
- art gallery
- art school
- art studio
- artists loft
- assembly line
- athletic field/outdoor
- atrium/public
- attic
- auditorium
- auto factory
- auto showroom
- badlands
- bakery/shop
- balcony/exterior
- balcony/interior
- ball pit
- ballroom
- bamboo forest
- bank vault
- banquet hall
- bar
- barn
- barndoor
- baseball field
- basement
- basketball court/indoor
- bathroom
- bazaar/indoor
- bazaar/outdoor
- beach
- beach house
- beauty salon
- bedchamber
- bedroom
- beer garden
- beer hall
- berth
- biology laboratory
- boardwalk
- boat deck
- boathouse
- bookstore
- booth/indoor
- botanical garden
- bow window/indoor
- bowling alley
- boxing ring
- bridge
- building facade
- bullring
- burial chamber
- bus interior
- bus station/indoor
- butchers shop
- butte

- cabin/outdoor
- cafeteria
- campsite
- campus
- canal/natural
- canal/urban
- candy store
- canyon
- car interior
- carrousel
- castle
- catacomb
- cemetery
- chalet
- chemistry lab
- childs room
- church/indoor
- church/outdoor
- classroom
- clean room
- cliff
- closet
- clothing store
- coast
- cockpit
- coffee shop
- computer room
- conference center
- conference room
- construction site
- corn field
- corral
- corridor
- cottage
- courthouse
- courtyard
- creek
- crevasse
- crosswalk
- dam
- delicatessen
- department store
- desert/sand
- desert/vegetation
- desert road
- diner/outdoor
- dining hall
- dining room
- discotheque
- doorway/outdoor
- dorm room
- downtown
- dressing room
- driveway
- drugstore
- elevator/door
- elevator lobby
- elevator shaft
- embassy
- engine room
- entrance hall
- escalator/indoor
- excavation
- fabric store
- farm
- fastfood restaurant
- field/cultivated
- field/wild
- field road
- fire escape
- fire station
- fishpond
- flea market/indoor
- florist shop/indoor
- food court
- football field
- forest/broadleaf
- forest path
- forest road
- formal garden
- fountain
- galley
- garage/indoor

- garage/outdoor
- gas station
- gazebo/exterior
- general store/indoor
- general store/outdoor
- gift shop
- glacier
- golf course
- greenhouse/indoor
- greenhouse/outdoor
- grotto
- gymnasium/indoor
- hangar/indoor
- hangar/outdoor
- harbor
- hardware store
- hayfield
- heliport
- highway
- home office
- home theater
- hospital
- hospital room
- hot spring
- hotel/outdoor
- hotel room
- house
- hunting lodge/outdoor
- ice cream parlor
- ice floe
- ice shelf
- ice skating rink/indoor
- ice skating rink/outdoor
- iceberg
- igloo
- industrial area
- inn/outdoor
- islet
- jacuzzi/indoor
- jail cell
- japanese garden
- jewelry shop
- junkyard
- kasbah
- kennel/outdoor
- kindergarden classroom
- kitchen
- lagoon
- lake/natural
- landfill
- landing deck
- laundromat
- lawn
- lecture room
- legislative chamber
- library/indoor
- library/outdoor
- lighthouse
- living room
- loading dock
- lobby
- lock chamber
- locker room
- mansion
- manufactured home
- market/indoor
- market/outdoor
- marsh
- martial arts gym
- mausoleum
- medina
- mezzanine
- moat/water
- mosque/outdoor
- motel
- mountain
- mountain path
- mountain snowy
- movie theater/indoor

- museum/indoor
- museum/outdoor
- music studio
- natural history museum
- nursery
- nursing home
- oast house
- ocean
- office
- office building
- office cubicles
- oilrig
- operating room
- orchard
- orchestra pit
- pagoda
- palace
- pantry
- park
- parking garage/indoor
- parking garage/outdoor
- parking lot
- pasture
- patio
- pavilion
- pet shop
- pharmacy
- phone booth
- physics laboratory
- picnic area
- pier
- pizzeria
- playground
- playroom
- plaza
- pond
- porch
- promenade
- pub/indoor
- racecourse
- raceway
- raft
- railroad track
- rainforest
- reception
- recreation room
- repair shop
- residential neighborhood
- restaurant
- restaurant kitchen
- restaurant patio
- rice paddy
- river
- rock arch
- roof garden
- rope bridge
- ruin
- runway
- sandbox
- sauna
- schoolhouse
- science museum
- server room
- shed
- shoe shop
- shopfront
- shopping mall/indoor
- shower
- ski resort
- ski slope
- sky
- skyscraper
- slum
- snowfield
- soccer field
- stable
- stadium/baseball
- stadium/football
- stadium/soccer

- stage/indoor
- stage/outdoor
- staircase
- storage room
- street
- subway station/platform
- supermarket
- sushi bar
- swamp
- swimming hole
- swimming pool/indoor
- swimming pool/outdoor
- synagogue/outdoor
- television room
- television studio
- temple/asia
- throne room
- ticket booth
- topiary garden
- tower
- toyshop
- train interior
- train station/platform
- tree farm
- tree house
- trench
- tundra
- underwater/ocean deep
- utility room
- valley
- vegetable garden
- veterinarians office
- viaduct
- village
- vineyard
- volcano
- volleyball court/outdoor
- waiting room
- water park
- water tower
- waterfall
- watering hole
- wave
- wet bar
- wheat field
- wind farm
- windmill
- yard
- youth hostel
- zen garden

B Land Use Categories

- Artificial surfaces;Urban fabric;Continuous urban fabric
- Artificial surfaces;Urban fabric;Discontinuous urban fabric
- Artificial surfaces;Industrial, commercial and transport units;Industrial or commercial units
- Artificial surfaces;Industrial, commercial and transport units;Road and rail networks and associated land
- Artificial surfaces;Industrial, commercial and transport units;Port areas
- Artificial surfaces;Industrial, commercial and transport units;Airports

- Artificial surfaces;Mine, dump and construction sites;Mineral extraction sites
- Artificial surfaces;Mine, dump and construction sites;Dump sites
- Artificial surfaces;Mine, dump and construction sites;Construction sites
- Artificial surfaces;Artificial, non-agricultural vegetated areas;Green urban areas
- Artificial surfaces;Artificial, non-agricultural vegetated areas;Sport and leisure facilities
- Agricultural areas;Arable land;Non-irrigated arable land
- Agricultural areas;Arable land;Permanently irrigated land
- Agricultural areas;Arable land;Rice fields
- Agricultural areas;Permanent crops;Vineyards
- Agricultural areas;Permanent crops;Fruit trees and berry plantations
- Agricultural areas;Permanent crops;Olive groves
- Agricultural areas;Pastures;Pastures
- Agricultural areas;Heterogeneous agricultural areas;Annual crops associated with permanent crops
- Agricultural areas;Heterogeneous agricultural areas;Complex cultivation patterns
- Agricultural areas;Heterogeneous agricultural areas;Land principally occupied by agriculture, with significant areas of natural vegetation
- Agricultural areas;Heterogeneous agricultural areas;Agro-forestry areas
- Forest and semi natural areas;Forests;Broad-leaved forest
- Forest and semi natural areas;Forests;Coniferous forest
- Forest and semi natural areas;Forests;Mixed forest
- Forest and semi natural areas;Scrub and/or herbaceous vegetation associations;Natural grasslands
- Forest and semi natural areas;Scrub and/or herbaceous vegetation associations;Moors and heathland
- Forest and semi natural areas;Scrub and/or herbaceous vegetation associations;Sclerophyllous vegetation
- Forest and semi natural areas;Scrub and/or herbaceous vegetation associations;Transitional woodland-shrub
- Forest and semi natural areas;Open spaces with little or no vegetation;Beaches, dunes, sands
- Forest and semi natural areas;Open spaces with little or no vegetation;Bare rocks

- Forest and semi natural areas;Open spaces with little or no vegetation;Sparsely vegetated areas
- Forest and semi natural areas;Open spaces with little or no vegetation;Burnt areas
- Forest and semi natural areas;Open spaces with little or no vegetation;Glaciers and perpetual snow
- Wetlands;Inland wetlands;Inland marshes
- Wetlands;Inland wetlands;Peat bogs
- Wetlands;Maritime wetlands;Salt marshes
- Wetlands;Maritime wetlands;Salines
- Wetlands;Maritime wetlands;Intertidal flats
- Water bodies;Inland waters;Water courses
- Water bodies;Inland waters;Water bodies
- Water bodies;Marine waters;Coastal lagoons
- Water bodies;Marine waters;Estuaries
- Water bodies;Marine waters;Sea and ocean

C Object Detection Categories

- 1: 'person'
- 2: 'bicycle',
- 3: 'car',
- 4: 'motorcycle',
- 5: 'airplane',
- 6: 'bus',
- 7: 'train',
- 8: 'truck',
- 9: 'boat',
- 10: 'traffic light',
- 11: 'fire hydrant',
- 12: 'stop sign',
- 13: 'parking meter',
- 14: 'bench',
- 15: 'bird',
- 16: 'cat',
- 17: 'dog',
- 18: 'horse',
- 19: 'sheep',
- 20: 'cow',
- 21: 'elephant',
- 22: 'bear',
- 23: 'zebra',
- 24: 'giraffe',
- 25: 'backpack',
- 26: 'umbrella',

- 27: 'handbag',
- 28: 'tie',
- 29: 'suitcase',
- 30: 'frisbee',
- 31: 'skis',
- 32: 'snowboard',
- 33: 'sports ball',
- 34: 'kite',
- 35: 'baseball bat',
- 36: 'baseball glove',
- 37: 'skateboard',
- 38: 'surfboard',
- 39: 'tennis racket',
- 40: 'bottle',
- 41: 'wine glass',
- 42: 'cup',
- 43: 'fork',
- 44: 'knife',
- 45: 'spoon',
- 46: 'bowl',
- 47: 'banana',
- 48: 'apple',
- 49: 'sandwich',
- 50: 'orange',
- 51: 'broccoli',
- 52: 'carrot',
- 53: 'hot dog',
- 54: 'pizza',
- 55: 'donut',
- 56: 'cake',
- 57: 'chair',
- 58: 'couch',
- 59: 'potted plant',
- 60: 'bed',
- 61: 'dining table',
- 62: 'toilet',
- 63: 'tv',
- 64: 'laptop',
- 65: 'mouse',
- 66: 'remote',
- 67: 'keyboard',
- 68: 'cell phone',
- 69: 'microwave',
- 70: 'oven',
- 71: 'toaster',
- 72: 'sink',
- 73: 'refrigerator',
- 74: 'book',
- 75: 'clock',
- 76: 'vase',
- 77: 'scissors',
- 78: 'teddy bear',
- 79: 'hair drier',
- 80: 'toothbrush'