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Assessing the performance of adaptation measures in the water sector under changing climatic and socio-economic conditions

GEO 511 Master's Thesis

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Abstract

Located in the northwest Peruvian Andes, the catchment of the Quillcay River catchment is subject to severe implications of shrinking glaciers. With climate models projecting an ongoing rise in temperature and an enhanced precipitation seasonality, the availability of water for the local population for irrigation and domestic uses during the precipitation-scarce austral summer months is threatened. Due to large uncertainties arising from scarce availability of data and little knowledge about the interactions of hydro-climatic and socio-economic variables, traditional probabilistic models have strong limitations to perform under this context. Using Exploratory Modeling and Analysis (EMA), this thesis attempts to couple socio-economic and hydro-climatic variables to simulate thousands of plausible scenario combinations until the year 2050, and to present potential adaptation measures against water scarcity which incorporate a high robustness against uncertain future states. The simulations confirm that, while without the adaptation of current water management policies, in future dry seasons, water scarcity is common, this risk can be strongly mitigated with the introduction of improved adaptation measures. The combination of measures that resulted to be most robust in the scenarios is the construction of a reservoir with a volume of at least 2.2 million cubic meters and at least a 3% increase of the water use efficiency for irrigation water demand. The results of this thesis can serve as a valuable basis for an integrated water use management with the direct involvement of local stakeholders and decision makers to promote water security in the catchment.

Table of Contents

Table of Figures

Table of Tables

1 Introduction

In the surroundings of high mountain ranges, many people strongly rely on the discharge of rivers flowing down from high altitudes for irrigation and domestic use (Messerli et al., 2004). Many of such rivers are fed by glacial melt water, discharging directly into the rivers, or water that is temporarily stored in glacier lakes. With ongoing climate change, changing ablation from the glaciers could significantly affect discharge volume and characteristics, potentially having a possibly strong impact on the local population living downstream (Drenkhan et al., 2019; Immerzeel et al., 2019). Especially in tropical high mountain areas with a strong seasonality of precipitation, the dependence on this freshwater source is high (Schauwecker et al., 2017). During the dry season of the year, a large factor in runoff consists of glacial melt water (Buytaert et al., 2017). Due to rising temperatures, this source is endangered. Glaciers in tropical areas such as in the northern Andes were found to be highly sensitive to temperature changes, as historical seasonality is not predominantly determined by temperature changes, but rather by changes in precipitation. With a rising annual mean temperature, the shrinkage of tropical glaciers is expected to strongly increase towards the end of the century. As glaciers act as a buffer for seasonal runoff and thus as the main contributor to the composition of freshwater sources in the dry season, the decrease in glacier area in a catchment could lead to scarcity of water availability in the dry season (Buytaert et al., 2017; Rabatel et al., 2013).

In combination with an increased irrigation demand due to smaller amounts of precipitation during the dry season of the year, a decrease in the availability of glacial melt water would lead to a deficit in water supply and thus strongly affect the populations livelihoods (Motschmann et al., 2020; Gurgiser et al., 2016). In addition to glacial meltwater, another uncertain factor is precipitation, whose annual amount is likely to decrease toward the end of this century in the tropical high mountain ranges. In addition, the seasonal water availability could shift to a more severe dry season and a wet season with an over availability of water. Therefore, these changes could enhance the water scarcity in these regions (Juen et al., 2007; Neukom et al., 2015). Motschmann et al. (2020) framed water scarcity as a 'slow-onset process that is generated through climate change impacts due to receding glaciers and changes in precipitation patterns, as well as through the unsustainable use of water'.

Motivation

The impacts of climate change on the population in the Peruvian high mountain ranges have been widely studied (e.g., Gurgiser et al. 2016; Buytaert, 2017; Juen et al., 2007). Especially detailed is the availability of research assessing natural hazards in the Huaraz region, which has been strongly affected by GLOFs (glacier lake outburst floods) (Frey et al., 2018, Vilimek et al., 2005; Mergili et al., 2020).

Although it has been found in past research (Schauwecker et al., 2017; Drenkhan et al., 2019) that the water resource from tropical glaciers in the Andes is threatened to disappear towards the end of this century, specific adaptation measures which could cope with the shrinking water supply and altered demand in the future are highly difficult to confine.

Traditional frameworks aiming to assess options for decision makers are performing their assessments probability based. In order to assess future water availability, considering large varieties in future climatic conditions and socioeconomic trends in a specific region, one must cope with large uncertainties and many factors – some of which are only partially understood, and some might not be known at all today (Kundzewicz et al., 2018). These circumstances call for assessment methods that are not focusing on probability and the best possible solution, but rather on a method that can consider several possible scenarios of various uncertain input parameters and identify strategies that show a high robustness to these uncertainties (Marchau et al., 2019, Muñoz et al., 2024).

With Exploratory Modeling and Analysis (EMA), a concept recently became more popular to simulate future states of a system with many parameters bound to large uncertainty boundaries (Kwakkel, 2017).

While past research focused more on the evaluation of the performance of EMA in this research field (Muñoz et al., 2024), this thesis will lay its focus on a catchment with a larger population and thus a slightly increased availability of data. The input parameters can be assessed in more detail and therefore provide a more concise view of future challenges and opportunities considering the implementation of adaptation measures against possible water scarcities.

The aim of this thesis is to apply the concept of exploratory modeling and analysis on to a case study in the data-scarce region of the Peruvian Andes to systematically explore the uncertainty range of various plausible climatic and socio-economic scenarios in the time until 2050. The outcomes of this analysis are presenting adaptation strategies against possible water scarcities with a high robustness towards the uncertain climatic and socioeconomic scenarios to stakeholders in straightforward and comprehensible results. These can then serve as a basis for concrete projects in the catchment area and support water availability for future generations.

Research questions

The aim of this thesis is to apply the concept of EMA onto a hydrological model to simulate the uncertain future development of climatic and socioeconomic variables in the Quillcay catchment in the Peruvian Andes. The outcomes of this analysis will be the performance of possible adaptation measures against water scarcity.

In order to put the purpose of this research in perspective, the following research questions were defined:

- Under which conditions do the designed adaptation measures show a successful effect in the scenarios?
- Which combinations of adaptation measures are the most robust?
- What are the limitations and opportunities to implement the most robust adaptation measures?

2 Study site

This research was carried out in the form of a case study to directly apply the principles of robust decision-making on a local scale where data availability is limited, with the aim of supporting local decision-makers to find robust adaptation measures against possible future scarcities.

Located in the northwestern Peruvian Andes, the catchment of the river Quillcay was chosen as the study site for this research. The Rio Quillcay is a tributary to the larger Rio Santa, with the confluence in the city of Huaraz at 3050 m above sea level. For the city and its neighborhoods, the river serves as the main source of freshwater (Heikkinen, 2017). The catchment is strongly dominated by the surrounding high mountain ranges of the Cordillera Blanca (CB), with several peaks which have altitudes over 6000 m above sea level and the highest being the Chinchey mountain, which reaches up to 6309 m above sea level. The catchment area is over 250 km^2, with about 29.93 km^2 covered by glaciers in 2021.

Figure 1. Lake Palcacocha in the North-Eastern part of the catchment, with its artificial dam stabilizing the lake outflow area (Picture retrieved from Zdenek Patzelt, 2004 in Vilimek et al., 2005).

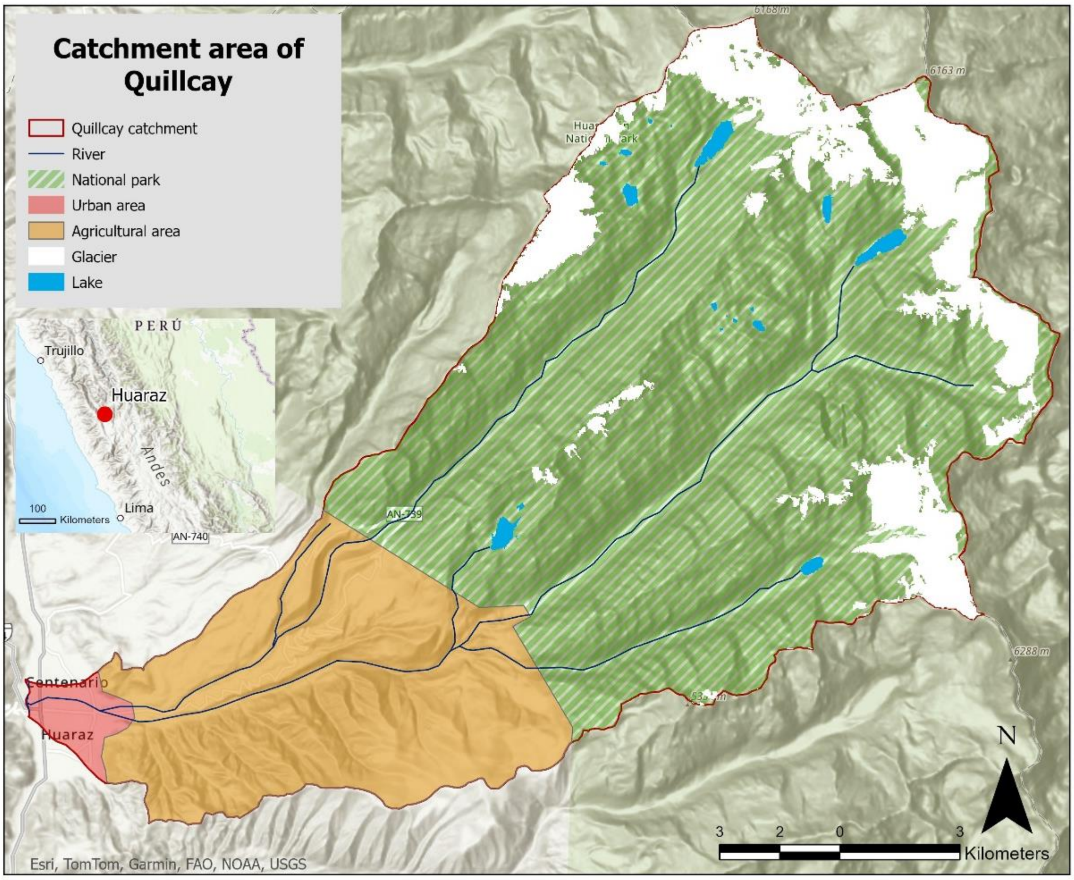


Figure 2. Map of the catchment area of the River Quillcay.

In the mountains of the northern Peruvian Andes, the precipitation seasonality strongly determines the runoff regime. The months of the austral winter between May and September mark the dry season, with very little to no precipitation, and the period between October and April corresponds to the wet season with higher amounts of precipitation (Motschmann et al., 2020). In the dry season, river runoff and thus the water supply for inhabitants of the catchment consists predominantly of glacial meltwater (Buytaert et al., 2017). In contrast to alpine glaciers, tropical glaciers in Peru, specifically in the Quillcay catchment, show opposite characteristics in their mass balance seasons. The main accumulation of mass occurs in the precipitation-rich summer months, while in the dry season, the ablation dominates (Rabatel et al., 2013).

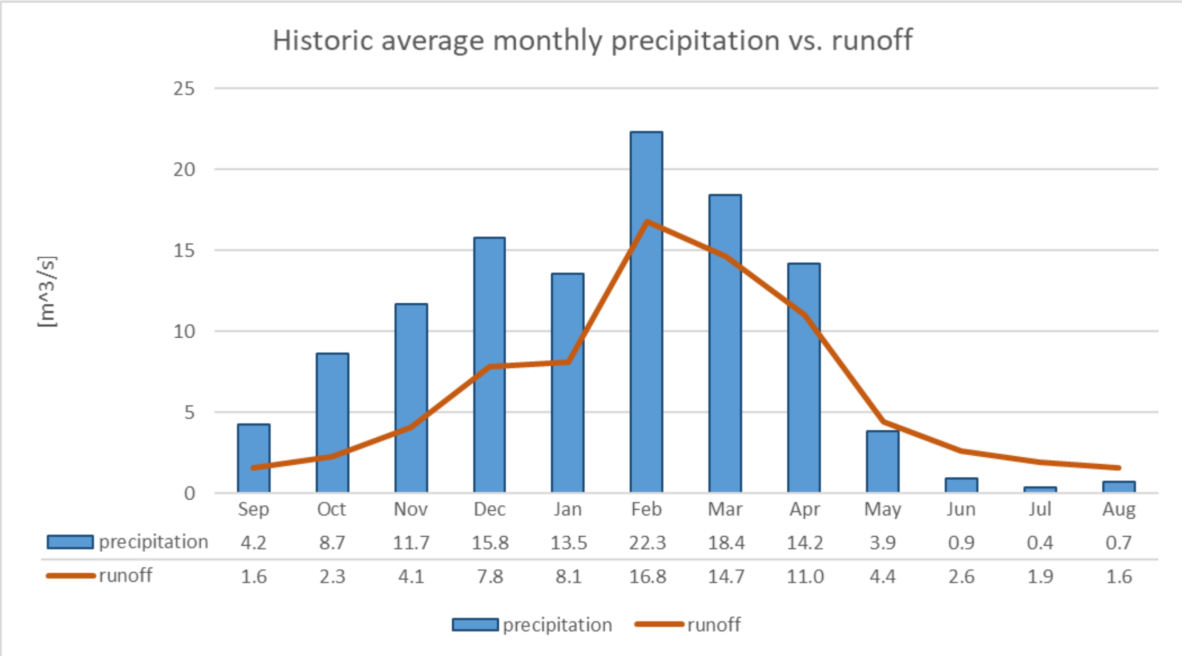


Figure 3. Graph of monthly averages of precipitation and river runoff for the Quillcay catchment in the historic period from 1981 to 2016. In the first months of the dry season, runoff predominates precipitation amounts, being fed in the majority of glacier melt water.

The catchment is a frequent location for studies focusing on water availability (Kroneberg et al. 2016), glacier shrinkage (Schauwecker et al., 2016, Jara et al., 2023), and most importantly, the natural hazards occurring in high mountain areas, such as floods originating from GLOFs (glacier lake outburst floods) (Motschmann et al., 2020; Vilimek et al., 2005).

Quillcay is part of the two districts Huaraz and Independencia, which again belong to the Ancash region. Its capital is the city of Huaraz, which is an important regional center with about 120’000 inhabitants in 2017 (Frey et al., 2018). According to the Peruvian government, approximately 145000 people live in the catchment area (INEI, 2017). In the last 30 years, strong population growth was recorded with an increase of inhabitants of about 58% (retrieved from INEI, 1993 and INEI, 2017).

Apart from employment in the Regions administrative, the mining sector and other businesses, many livelihoods in the city of Huaraz depend on touristic activities (Motschmann et al., 2020), as Huaraz is a starting point for climbing and hiking in the Cordillera Blanca. The Huarascan National Park, with a total area of 3400 km^2 over the CB mountain range, also covers a large fraction of the Quilllcay catchment, starting around the altitude of 4000 m a.s.l. and reaching up to the glacierized mountain tops (Barker, 1980). Together with the idea of conserving the unique nature of the region, the hope to boost tourism, and thus creating new sources of income for the often small-scale farmers as well as the hope to help combat the rural poverty were driving factors behind the creation of this natural reserve in the 1960s (Barker, 1980).

Unlike large industrialized large farms closer to the coast of Peru, in highland areas such as the Huaraz region, agriculture is characterized by small-scale farms that disperse in the surroundings of the city on the ascending hills until the border of the National Park (Heikkinen, 2017, Mark et al., 2010). Local reports concluded that in 2010, about 40 km^2 were considered agricultural land for crops cultivation during the wet season, which is 16% of the catchment area. The most abundant crop types in this area are alfalfa, which can be grown throughout the year and is used as fodder for livestock, barley, potatoes and wheat. The latter three and most other crop types with smaller cultivation areas have their growing period only during the rainy season (Quesquén, 2008).

Currently, most agricultural fields are rain-fed, and although some of the farms rely on irrigation in addition to natural precipitation, the current irrigation systems are most often quite simple. In most cases, naturally occurring springs are conducted to the desired farmland by pipes, canals, or artificially created creek beds (MINAM, 2014, Heikkinen, 2017).

Figure 4. Irrigation water canal collecting water from natural streams and conducting it to the agricultural fields (Image retrieved from MINAM, 2014).

3 State-of-the-art

3.1 Impacts of Glacier Retreat on the hydrological system

The Cordillera Blanca (CB), the second large mountain range from the pacific coast of Peru, is home to about 70% of all tropical glaciers in the world (Jara et al., 2023). Over the last few decades, the glaciers in the CB have shown an accelerated retreat, and in 2023, the loss in glacier area in the CB was measured to be about 30% in comparison to 1986 (Jara et al., 2023). The annual mass balance of tropical glaciers is predominantly controlled by changes in precipitation, in contrast to the mass balance of alpine glaciers, which are predominantly affected by temperature changes. The rise in temperature in the tropical Andes with a rate of 0.1 ° C per decade in the last 70 years played a significant role in the shrinkage of glaciers at lower altitudes (Rabatel et al., 2013).

The dependence of the catchments in the proximity of glaciers on glacial meltwater to river runoff is very strong and decreases steadily further down the stream and at lower altitudes (Buytaert et al., 2017). While the annual average contribution of glacial meltwater already shows high dependencies in regions with large glacier coverages such as parts of the Santa River (see Figure 5), this dependance has its peak during the dry season with very little to no precipitation (Juen et al., 2007, Motschmann et al., 2022).

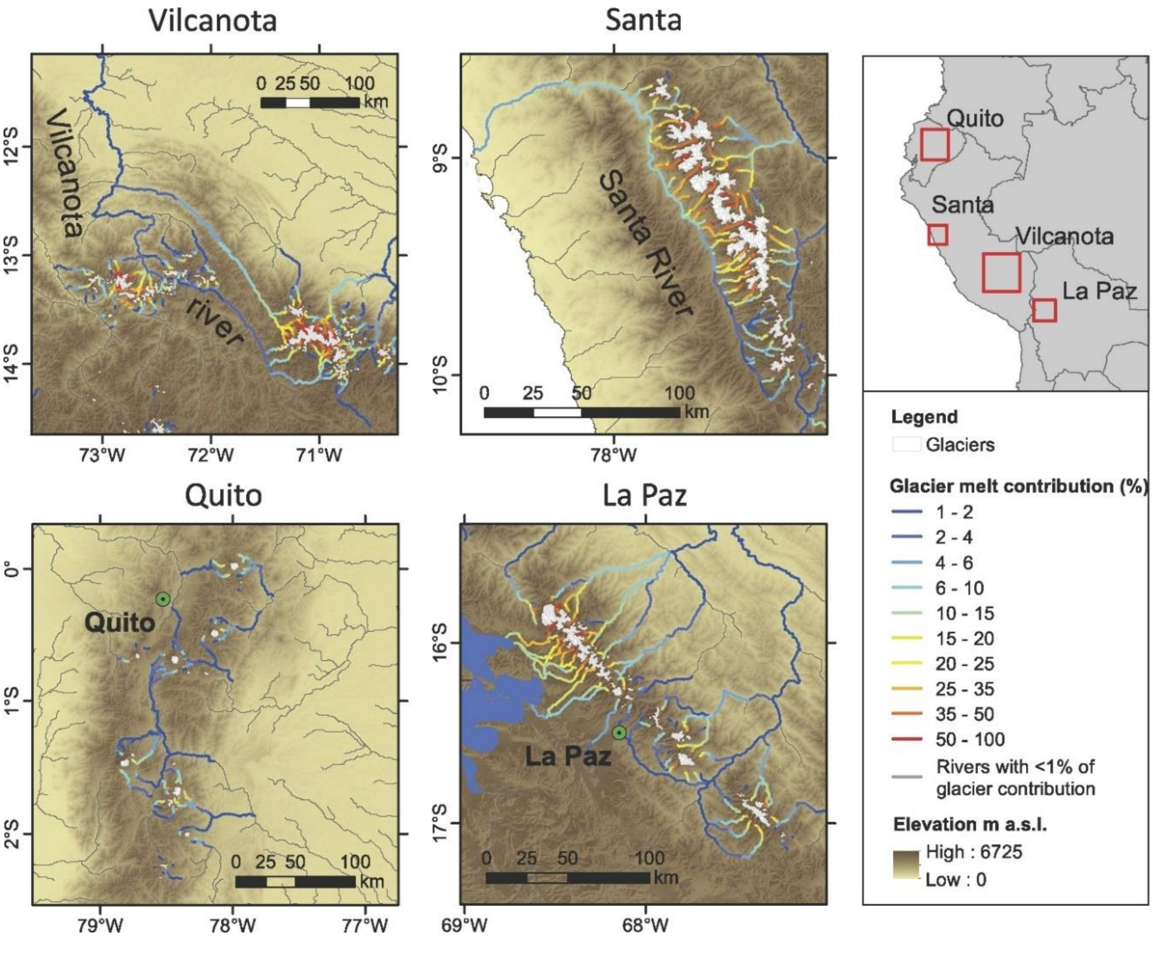


Figure 5. The annual average contribution of glacial melt water to river runoff in four regions of the tropical Andes (Figure retrieved from Buytaert et al., 2017).

Simulations of the retreat of glacier areas with rising temperatures predict a continuous and significant decrease of the tropical glaciers in Peru, even when considering optimistic climatic scenarios. In the pessimistic climatic scenario in their study, Schauwecker et al. (2017) expect glacial coverage in the tropical Andes only to exist above altitudes of 5800 m a.s.l. at the end of the century. This implies that the hydrological systems in Peruvian high mountain catchments would lose most of their dry season runoff contribution from glaciers, thus even stronger decreasing the dry season water availability (Jara et al., 2023; Buytaert et al., 2017). Annual precipitation amounts are expected to increase in the CB according to climatic scenarios. However, seasonal variability of precipitation is also expected to increase, with higher amounts during the rainy season and even scarcer precipitation during the dry season (Neukom et al., 2015; Motschmann et al., 2022). In combination with a diminished runoff buffering effect resulting from retreating glaciers, runoff during the dry season is expected to decrease even more (Juen et al., 2007).

3.2 Water security

The goal of achieving water security can be seen as one of the most important policy areas of the Anthropocene (Allan et al., 2013). Although no general definition of the concept of water security is available, the term has found itself subjected to a growing interest in recent years (Cook & Bakker, 2012). Depending on the abundant causes of stress on water resources in a specific region, different aspects of water security can be integrated into the concept. Grey and Sadoff (2007) attempted a definition of the term water security, which is 'the availability of an acceptable quantity and quality of water for health, livelihoods, ecosystems and production, coupled with an acceptable level of water-related risks to people, environments and economies.' Common among the various aspects of water security is that water management practices always need to be adaptive to suit changing demands or react to possible hazards threatening water security (Allan et al., 2013).

Assessments of water security with an emphasis on water availability can be referred to as an indication of water stress. With this indicator, the water demand in a research area is compared to available freshwater (van Beek et al., 2011). Water security can hence be achieved in times when water availability is greater than water demand. In practice, a threshold describing water security could not be established at 100%, describing that water availability is always greater than water demand, but rather at a high proportion of that value due to constraints in water allocation systems (Kalra et al., 2015; Muñoz et al., 2024).

3.3 Adaptation measures against water scarcity

In the mountain region of the CB, current water management practices can be considered quite primitive. The most important adaptation measures against water scarcity were identified as measures that increase water availability during the dry season and the reduction of the growing population (Drenkhan et al., 2019; Ale Pezo, 2019; Motschmann et al., 2020).

Agricultural fields are mainly dependent on precipitation water, and where irrigation was implemented, water is directed from natural storages such as lakes and groundwater storage in aquifers to fields via canals and pipes (MINAM, 2014). Therefore, the water allocation system incorporates a small efficiency with large amounts of water lost due to leakages in the order of 30 – 45 % (Drenkhan et al., 2019).

The shrinkage of glaciers poses a large threat to dry season water supply, in an order which these natural storages cannot counterbalance. Construction of new reservoirs for freshwater supply is often bound to large opposition from the local population due to little trust in the government and foreign companies to implement measures which could support the water availability for locals (Drenkhan et al., 2015; Moulton et al., 2021). To successfully implement large-scale adaptation measures, it is therefore crucial to employ an integrated water resources management concept that includes local socio-economic in addition to hydroclimatic parameters (Drenkhan et al., 2015; Motschmann et al., 2022).

3.4 Decision making under Deep Uncertainty

The process of trying to assess complex systems and address possible implications in such an uncertain space is called Decision Making under Deep Uncertainty (DMDU) (Marchau et al., 2019). Modeling future developments is important to help integrative assessments for stakeholders make robust decisions which favor water security for many possible futures. Instead of aiming to obtain the single best solution and thus incorporating a high risk that this solution will not perform under conditions which are not deemed realistic today, but could still occur in the future, recent research has been increasingly adopting an exploratory approach to modeling future states (Kwakkel, 2017; Quinn et al., 2020; Muñoz et al., 2024).

With exploratory Modeling and Analysis (EMA), a concept was developed to systematically explore such uncertain future scenarios in various research fields. EMA has been used in studies investigating financial crises (Pruyt, 2010) or the spread of diseases (Adeniyi et al., 2020). In the water sector, it has been used to investigate physical and chemical components of water (Ayoko, 2007), water supply (Gold et al., 2019), and flood simulations (Morante-Carballo et al., 2022).

When assessing the hydrological system of a catchment, issues can arise from large uncertainties in input parameters, originating from the interpolation of sparsely distributed data points, and inconsistencies in measurements from different sources or data points which are only conditionally comparable due to large topographic influences in mountainous regions (Kundzewicz et al., 2018).

Decision-making of large-scale infrastructure projects or long-range and complex interventions in existing structures is often bound to deep uncertainty emerging from unknown societal and climatic developments (Kundzewicz et al., 2018). Exploratory Modeling and Analysis (EMA) provides a methodology which not only can perform under such deep uncertainties, but even incorporates these to systematically explore a wide range of plausible future developments of a system. Using a conceptual model as its core module, EMA runs different sets of combinations of input uncertainty parameters in multiple model runs in order to simulate various possible future conditions of the researched system. Following the modeling part, the analysis part of the EMA can help to identify parameters or measures that can perform under the in advance initialized range of scenarios and thus show a high robustness against various uncertainties in the future (Moallemi et al., 2020, Bankes et al., 2013).

Recently, the focus has grown on the application of EMA in fields that assess future water availability on a catchment basis and the exploration of potential adaptation measures against water scarcity. Because of the deep uncertainty involved in simulating future developments of climatic, hydrological, and socioeconomic variables, EMA represents a promising concept to apply under such conditions (Moallemi et al., 2020).

3.5 A hydrological model that works under large uncertainty

The Shaman hydrological model is characterized by the ability to simulate hydrological conditions despite requiring only few input parameters and has been successfully applied in studies of mountainous catchments in data-scarce regions such as the tropical Andes (Muñoz et al., 2021). The calibrated runoff from the historical runoff time series then serves as an input for future runoff estimations.

The Shaman model is a lumped glacio-hydrological model which requires only a single time series of input data. The catchment discharge gets simulated in the two modules glacierized and non-glacierized areas. The non-glacierized areas module again consists of the two sub-modules fast and slow runoff. The former accounts for surface runoff and quickly released water in the upper part of the soil after precipitation events. The latter represents the runoff from precipitation which can be accumulated in the lower parts of the soil for a longer time after a precipitation event (Muñoz et al., 2021).

For this module, only the input parameters precipitation, minimum and maximum temperature, and potential evapotranspiration (PET) are required, while ETP is calculated through the first two parameters. In the module simulating the discharge from glacial meltwater, calculations consist of the parameters glacier area, seasonal melting factors, and the ratio from accumulation and ablation area (AAR) (Muñoz et al., 2021).

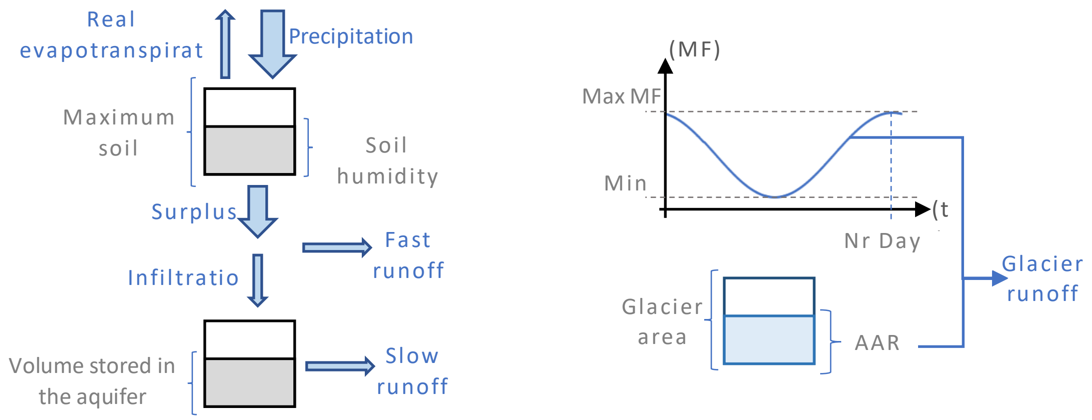


Figure 6. Schematic description of the two modules contained in the Shaman hydrological model, with the non-glacier areas module on the left and the glacier areas module on the right side. The three runoff components fast, slow and glacier runoff summed result in the total runoff (Figure retrieved from Muñoz et al., 2021).

3.6 The operationalization of the EMA concept

In order to help organizing and structuring all the parameters involved in exploratory modeling, the XLRM framework is applied as a subconcept of EMA. It structures the parameters into the categories uncertainties (X), policy levers (L), relationships (R), and performance metrics (M). Uncertainties are parameters which are outside the control of decision makers, but nevertheless have an impact on the policies, such as future climatic conditions or economic growth. Policy levers can be defined as potential actions whose influence and performance decision makers want to explore. In economic studies, the price level of a product could be identified as policy. The relationship category combines uncertainty and policy parameters and describes their relationship. In hydrology, for instance, a hydrological model can be applied as a relationship combining climatic uncertainties with policies which would decrease hazards from floods. The performance metric is a pre-defined indicator of the performance of policy options for the information towards decision makers. In economic studies, possible metrics could be the return on investment on different price policies (Lempert et al., 2003; Moallemi et al., 2018).

The XLRM framework is composed like a function, where different combinations of X and L are simulated in the model (R), which finally creates the output metric (M). This allows researchers to compress complex parameters and uncertain developments into a function whose output metric can serve as a basis for straightforward information to decision-makers (Lempert et al., 2003; Kwakkel, 2017).

The prepared data are then simulated in the EMA workbench. The workbench is an open-source library implemented in Python, allowing to simulate the hydrological system with various combinations of its established uncertainty boundaries in thousands of model runs. The resulting range of future states can then be further analyzed in the vulnerability analysis and the evaluation of the robustness of the designed adaptation measures through the implemented model metric (Kwakkel, 2017).

In each of the conducted simulations, a value within the previously defined parameter range of each variable is randomly chosen. This combination acts as a plausible future development of the catchment characteristics. The sampling of the variables is randomly chosen by the Latin hypercube sampling strategy. After the sampling has been repeated for the predefined number of simulations, the results depict the future states of the desired system, with each simulation representing one possible pathway. With the larger number of simulations chosen to be performed for the experiment, the bandwidth of each parameter value can be simulated in narrower intervals, leading to a better understanding of the influence of each parameter on the model metric and thus providing a more accurate knowledge of the vulnerability towards water scarcity.

The thousands of simulations are first analyzed with the feature scoring algorithm to obtain the relative influence of each uncertainty and each policy lever on the model metric. Following this, the exploration of the results can be performed through scenario discovery with the Patient Rule Induction Method (PRIM) algorithm (Friedman & Fisher, 1999) or Classification and Regression Trees (CART) (Breiman et al., 1984). These algorithms allow the exploration of combinations of parameters to obtain information about which parameter or combination of parameters lead to a successful model metric or which result in unsuccessful metric values. This allows researchers to explore specific cases of interest and to examine under which conditions objectives are being fulfilled or not (Kwakkel, 2017, Muñoz et al., 2024).

In a previous study, Muñoz et al. (2024) have successfully applied the concept of exploratory modeling and analysis in the water sector on a catchment basis to simulate the performance of adaptation measures under uncertain scenarios. This research concluded that EMA could provide valuable information on water availability and demand even in regions with a large data scarcity.

3.7 Coupling hydrological simulations with socio-economic developments

When modeling possible future climate scenarios, not only the natural development of the climate, but also the interaction with human implications on the environment, through carbon emissions and land cover changes, for instance, is crucial (Carey et al., 2014). The development of society is often coupled with an increase in resource demand. Apart from the altered emission of carbon to the atmosphere, societies could possibly change their demand for water, concerning water for domestic uses, irrigation of farmland, or industrial usages as well (Magnússon et al., 2020).

In the past, research often focused on changes of water availability and neglected social changes in water demand which were not driven by a change in availability. Carey et al. (2014) therefore call for the development of hydrological models in future research which can also incorporate societal developments and thus the implications of an altered water demand onto a catchment system.

The Shared Socio-Economic Pathways (SSPs) represent an effort to present countless different developments of societal and economic variables into specific narratives for plausible pathways in the future up to the year 2100.

Developed by a collaboration of the international scientific community, the SSPs have become a widely used framework to explore the potential implications of climate change coupled with different socioeconomic developments (Riahi et al., 2017). Five different baseline SSPs have been developed, each describing a narrative about a possible development on a global scale. This includes trends in demography, technology, society, economy, and politics (O'Neill et al., 2017).

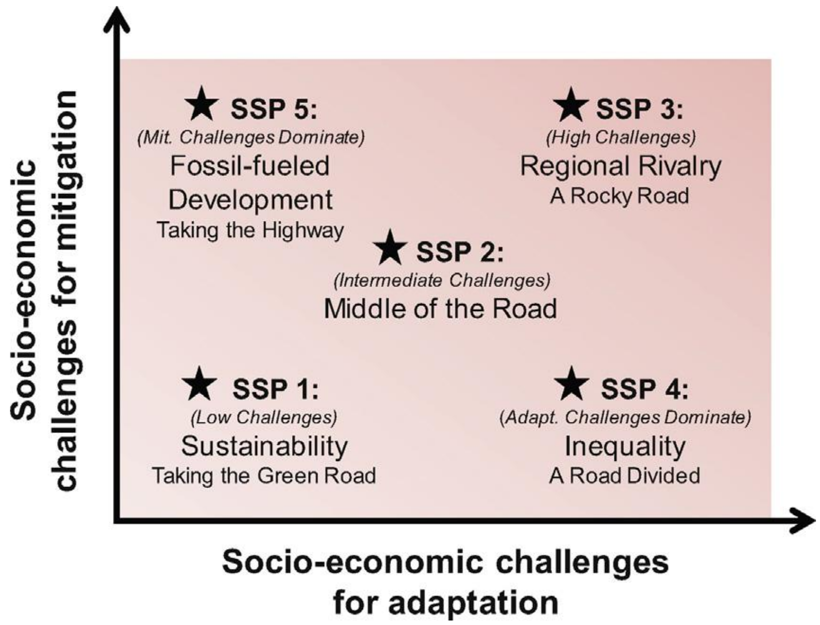


Figure 7. The five baseline Shared Socioeconomic Pathways (SSPs) put into the context of mitigation and adaptation challenges (retrieved from O'Neill et al., 2017).

The five baseline scenarios can be described to represent the following pathways of future socioeconomic development.

SSP1: Sustainability (Taking the Green Road): This pathway emphasizes global cooperation, resource efficiency, and clean energy technologies, resulting in a future of low emissions.

SSP2: Middle of the Road: This represents a continuation of current trends with moderate challenges for mitigation and adaptation.

SSP3: Regional Rivalry (A Rocky Road): This pathway depicts a fragmented world with regionalized economies and energy systems, which poses great challenges for both mitigation and adaptation.

SSP4: Inequality (A Road Divided): This scenario highlights a world with high levels of inequality, where technological advancements benefit only a portion of the global population, creating significant adaptation challenges.

SSP5: Fossil-fueled Development (Taking the Highway): This pathway represents a future with continued reliance on fossil fuels and limited international cooperation, resulting in high greenhouse gas emissions and severe climate impacts.

The SSPs can be combined with climate models, using the Representative Concentration Pathways (RCPs) with its different climate forcing scenarios to explore possible impacts from different climate change and socioeconomic scenarios on regions and people. This allows researchers to assess possible vulnerabilities and opportunities in a more systematic approach and thus to identify strategies for climate change adaptation and mitigation, which are robust against various uncertain future developments (Riahi et al., 2017, van Vuuren et al., 2014).

4 Methods

To assess the historic and current state of the hydrological system of the Quillcay catchment, simulations from a hydrological model were used in this study. The glacier area is investigated through satellite imagery with the Normalized Difference Snow Index (NDSI). Calculations of current water demands for domestic and agricultural purposes are based on findings of reports from the local agriculture office. These input data represent the historical time series, covering the years 1981 to 2016.

Future climatic conditions are simulated with climate scenarios obtained from the World Climate Research Programme 6 (CMIP6). Through population and agricultural development scenarios estimated with the Shared Socioeconomic Pathways (SSPs), various scenarios for future water demand are modeled. Possible adaptation measures or policies are introduced. They will be based on findings from the literature or sensitivity analyses but presented as a possibility without introducing a particular adaptation project.

The main assessment of this thesis is carried out within the EMA framework, a concept which allows to connect the above-mentioned input variables to simulate various scenarios of future conditions of the Quillcay catchment and its inhabitants. In order not to stress the boundaries of uncertainty arising from long-term scenarios, the simulation timeframe will cover the period from 2024 up to 2050.

4.1 The Shaman hydrological model

Simulations of the hydrological system of the catchment were performed with the Shaman hydrological model (Figure 6). In a first step, the historical simulations were calibrated to depict the hydrological processes in the Quillcay catchment. Embedded in the EMA concept, it later acted as the connecting module between the climatic and socioeconomic scenarios and the resulting model performance indicator.

The simulation time series of the hydrological model was divided into the calibration period between 1981 and 2000 and the validation period between 2001 and 2016. Calibration was performed using multidata calibration parameters, being the Nash-Sutcliffe efficiency, logarithmic Nash-Sutcliffe efficiency, the Kling-Gupta efficiency and BIAS score (Muñoz et al., 2021).

4.2 Climatic data

Historical climatic data

The precipitation and temperature input climatic data were obtained from the Peruvian Interpolated data of SENAMHI's Climatological and Hydrological Observations (PISCO), a dataset hosted by the National Service of Meteorology and Hydrology of Peru (SENAMHI) (Aybar et al., 2020). It offers daily or monthly timesteps of gridded temperature and rainfall data with a spatial resolution of 0.1°, a cell size accounting for approximately 100 km^2 (Aybar et al., 2020). For this research, the minimum and maximum temperature and precipitation data from the updated PISCOp v1p1 was obtained on a monthly time step for the whole available period 1981 – 2016. As there is no specific cell in the PISCO data set that exactly covers the whole area of the catchment, a grid cell that contains the majority of the area was selected to represent the climatic data.

Potential evapotranspiration (ETO) was calculated from minimum and maximum temperatures on a monthly scale, using the ETo calculator program of the United Nations Food and Agriculture Organization (FAO). Additional information describing the area with the location, approximate wind speeds and general climatic conditions, was added to support the calculation (FAO, 2012).

4.3 Glacier area estimation

Historical glacier area

Glacial meltwater is an important contributor to the water balance in the dry season in the tropical Andes and thus to agricultural, domestic, and hydropower water demand (Buytaert et al., 2017). To obtain a trend in the decline of glacial areas, three multispectral satellite images covering the region were used. They were selected to cover the historic time period in equally distributed time steps. To avoid areal distortions from snow cover during winter, only imagery from the end of the dry season (August and September) was considered. Due to cloud influences on the images and general data availability, the finally selected data was from the month of August in the years 1988, 1995 and 2010 (Veettil, 2018).

The calculation of the NDSI (Normalized Difference Snow Index) was applied to Landsat 5 Thematic Mapper imagery to separate glacier area from other forms of land cover such as lakes or rock. Due to strong influences of cast shadows, water body reflection, and bright rocks, the computational classification was additionally assessed by comparing the data to Google Earth imagery and manually adjusting the NDSI threshold (Veettil, 2018).

Estimation of future glacier area

The estimated glacier area from 2010 was then again used as input data for the estimation of the implications of rising temperatures on the future glacier coverage. The 2010 glacier area was applied to a Digital Terrain Model (DTM) to link the shrinkage of glacier area with the mountainous surface. Following the research by Schauwecker et al. (2017), which applied a temperature lapse rate to the Freezing Level Height (FLH) of glaciers in the Cordillera Blanca to estimate the loss in glacier area if challenged with an increasing 0 ° altitude, the same principle was applied to glaciers in the Quillcay catchment. Assuming that at tropical glaciers, 15% of glacier area would be below FLH, and that this fraction would remain constant under withdrawing glaciers, the temperature-controlled FLH could serve as a proxy to estimate future glacier areas (Schauwecker et al., 2017). The lapse rate of -0.0065°/m was connected to the mean temperatures of the calibrated climate scenarios, and thus the glacier areas were calculated under all climate scenarios in 2050.

4.4 Water demand estimations

The estimation of water demand in the catchment area is classified into domestic and agricultural water demand. Although there are other sectors that claim demand in water, such as hydropower generation and the mining industry, these were not considered in this study due to their location of water withdrawal which does not affect the discharge of the Quillcay River (Motschmann et al., 2020).

Historical irrigation water demand

Water demand for irrigation purposes was calculated based on a report from the local administration (Quesquén, 2008), which assessed the irrigated areas in the catchment on a monthly basis. The irrigated areas were assumed to have remained constant during the historical period (1981 – 2016), as no other local scale could be found. Due to the lack of in situ measurements of the specific water demand for each crop, the approximate amount for water allocation at 1 l/s/ha was applied to the irrigated areas to obtain the monthly water demand (MINAM, 2014). The allocation from natural streams to agricultural fields in rural areas of Peru is associated with high losses through spillage and backflows, and thus a water use efficiency factor of 35% was applied to the irrigation demand (MINAM, 2014; Quesquén, 2008).

Historical domestic water demand

Water demand for domestic purposes during the historic period, for instance for, drinking water, was estimated from a constant allocation amount per inhabitant and the population living in the catchment area using national census data (INEI). Relevant census years were available in 1993, 2005, 2007 and 2017 for the area of the districts of Huaraz and Independencia. The specific water demand per capita was estimated in the local report from MINAM (2014), which allocated 210 liters per capita per day, with an already incorporated allocation efficiency of 76%. A linear interpolation of the population census data multiplied by the water demand per capita led to the estimation of the domestic water demand during the historic period. It was assumed that the amount of water allocation would remain constant as no time series depicting a trend in specific water demand in the study area could be obtained. Due to the high fraction of population living under urban conditions in Huaraz, both the specific water demand and allocation efficiency are higher compared to areas with a larger rural population.

Estimation of future water demand

For the estimation of future developments of water demand, the trends of the two main water use sectors (domestic and irrigation water demand) in the Quillcay catchment were approximated based on the SSP baseline projections 1 to 5 up to 2050. The projections of population development and agricultural areas were only available on the continental scale of South America and therefore had to be calibrated to study site size by applying the annual growth rates of the two SSP categories to local data from the report and the government census. The initial population number was obtained from the 2017 national census data for the catchment area (INEI, 2017) and the irrigation water demand was estimated based on findings in the local report (MINAM, 2014), which calculated the irrigated areas in the catchment area. In the rainy season months, the largest irrigated area was 4000 hectares, which was taken as the starting point of the scenarios. Due to the absence of a specific category that examined the irrigated agricultural areas with SSPs, the growth rate of all agricultural areas was considered a suitable input to estimate the trend in the irrigated areas in the catchment area.

Climatic and socio-economic scenarios

To estimate possible future trends of the climatic variables precipitation and temperature, global climatic simulations from the World Climate Research Programme and its latest set of simulations in the Coupled Model Intercomparison Project (Phase 6) (CMIP6) were used as input data (Riahi et al., 2017). Three different climate models, CanESM5, MPI-ESM1, and IPSL, were considered, each covering the historical period and five different climate scenarios (SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5) until 2050.

Each of the climate series had to be bias corrected to better fit the local conditions from the study site. Using the multivariate bias correction method (MBC), the Global Climate Models (GCM) were calibrated to the historical time series of the climate models and PISCO to obtain a calibrated Regional Climate Model (RCM) for the Quillcay catchment for the years 1950 – 2014 (historical) and 2015 – 2050 (projections) (Kim et al., 2023). Three different methods of MBC were applied to the GCM data, being the Pearson correlation coefficient, the Spearman Rank correlation coefficient, and the N-dimensional probability density function transform. For all the historic and future climate projections, the Spearman Rank correlation was found to provide the best fitting results and was thus chosen for the MBC.

In this study, the shared socioeconomic pathways (SSPs) were considered to represent plausible developments in population numbers and the area of irrigated agricultural fields in the time until 2050. To obtain a broad bandwidth of scenarios, from each of the five pathways, the baseline scenario was obtained from the SSP database (Riahi et al., 2017).

4.5 Policy levers

One way to cope with an uncertain future development of water availability is to decrease the population's demand for water. As for both irrigation and domestic water demand the consumption rate per capita or per irrigated area, respectively, had to be assumed to remain constant during the simulation period until 2050, the largest factor steering the amount of water need was found to be the water use efficiency. For irrigation water, the water use efficiency (WUE) was reported to be at 35% in the region (MINAM, 2014). With technological improvements and more efficient infrastructure, for instance, sprinkler or drip irrigation techniques, the WUE could be strongly improved to up to 85% (Meredith & Blais, 2019). For this study, doubling of the WUE up to 70% was considered feasible. For domestic water use, an efficiency bandwidth was applied to depict the boundaries of domestic WUE in rural areas up to strongly improved urban levels (90%). Historical domestic efficiency was reported to be 76% in the area (MINAM, 2014).

The other possibility to decrease the possibility of water scarcity is the extension of water supply. To substitute the seasonal runoff buffer, which glaciers were representing in past times, and are endangered to disappear even in the near future, the construction of a water reservoir arises. This fictionally implemented water body would serve the sole purpose of a water storage facility for domestic or irrigation purposes, not accounting for electricity production or recharging other reservoirs in the region. It was implemented within the hydrological circle in the Shaman model, with a sub catchment simulating the possible water input and storage during the rainy season and a release of a part of the stored amount when the natural runoff is small during the dry season. The volume limit of this potential reservoir was estimated to be about 30 million m^3, so it could cover the annual historical annual water demand in a pessimistic scenario. The annual total of domestic and irrigation water demand was calculated to be approximately 23.5 million m^3.

4.6 The XLRM framework

The uncertainties (X) in the XLRM framework are factors that are not directly controllable by decision makers. In this research, climate scenarios, the scenarios of population and irrigated area scenarios, irrigation water backflow and the parameters of the hydrological model controlling groundwater storage and release are considered as uncertainties. As policy levers (L) are the adaptation measures changes in efficiency of domestic and irrigation water demand and the size of a potentially constructed reservoir. Land cover changes, such as those affecting forests and irrigated areas, are considered policy levers, although they are less directly controllable. The relationship (R) is represented by the Shaman hydrological model after its calibration. The model serves as a simulation of the whole catchment system and the water demand of its population. The metric (M) is the actual output of all simulations and can be defined to assess if there is a negative or positive water balance when policy levers are implemented. In this research, the metric was designed to depict situations in which water security can be achieved in the study area. In particular, the calculation of the metric was designed as follows.

The fraction of the number of months in which the water supply is greater than 90% of the water demand, selecting only the months of the dry season (from May to September).

This metric would hereby provide an answer to which adaptation measure or combination of measures would succeed in providing water in most of the months it would be required, the dry season of the year.

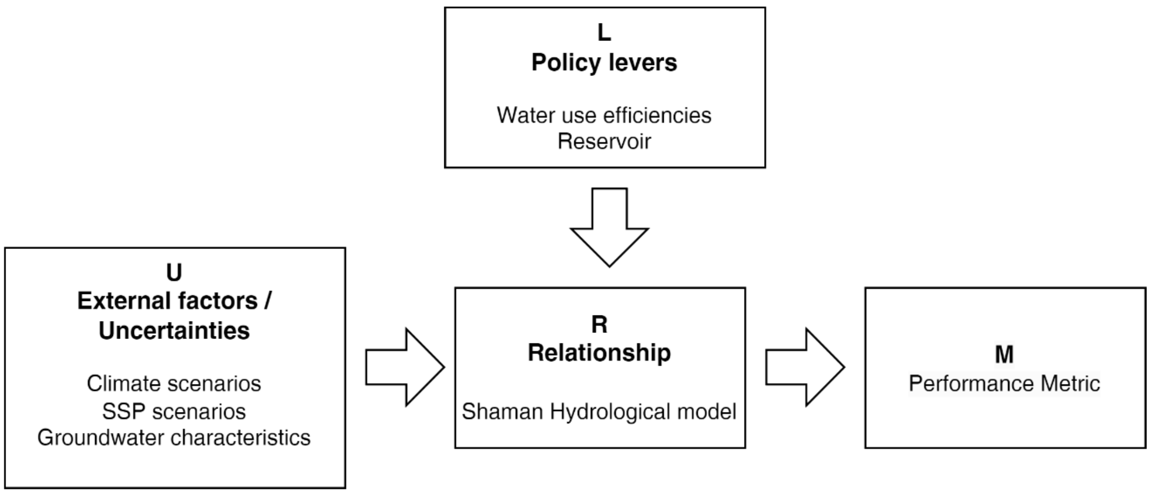


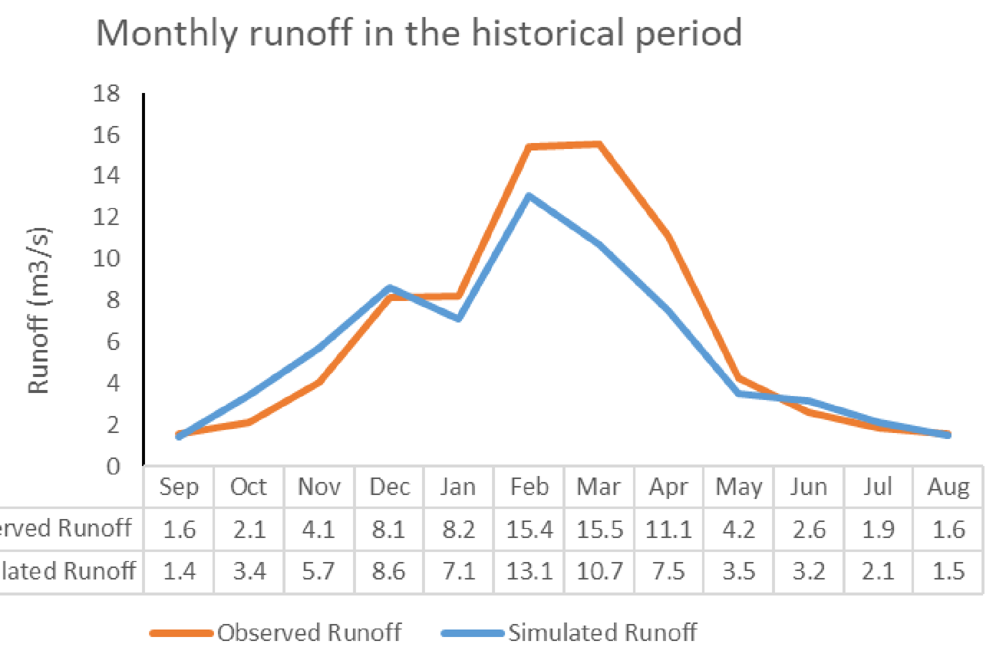
Figure 8.Schema of the XLRM framework describing the organization of variables in Exploratory Modeling and Analysis (EMA).

Table 1. List of Uncertainties, Policy levers, and Metric, with their respective parameter ranges.

Variable	Description	Value ranges
Uncertainties (U)		
u_climate_sce	Uncertainty in climatic scenarios up to 2050	3 climate models with 5 climate scenarios
		each: SSP119, SSP126, SSP245, SSP370 and
	Uncertainty in population and irrigated	SSP585
u_ssp	areas	Baseline scenarios SSP1, SSP2, SSP3, SSP4,
		and SSP5
	Uncertainties in the hydrological model	
c_var	regarding the sub-surface water storage	-10% to +10% of the value in the calibrated
hmax_var	and release	hydrological model
imax_var		
alfa_var	Uncertainty in the backflow from irrigation	
Irr_back		50% to 70% of the net irrigation water
		demand
Policy levers (L)		
frac_forest	Change in % of the land cover class forest	0% to 40% (none to twice of current levels)
frac_irr	Change in % of land cover class irrigated	0% to 30% (none to irrigation of all
	areas	agricultural area)
domeff		45% to 90% (rural to urban efficiency levels)
irreff	Changes in % in the domestic water	30% to 70% (existing levels to high
	efficiency	technological improvements)
	Changes in % in the irrigation water	0 to 30 million m^3
k_vol	demand efficiency	
	Volume of a potential water reservoir	
Metric (M)	Number of months in the dry season in which the water supply is greater than 90% of the water demand, in a fraction	0 to 1

5 Results

5.1 Hydrological Simulations



	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
Observed Runoff	1.6	2.1	4.1	8.1	8.2	15.4	15.5	11.1	4.2	2.6	1.9	1.6
Simulated Runoff	1.4	3.4	5.7	8.6	7.1	13.1	10.7	7.5	3.5	3.2	2.1	1.5

Figure 9. Multiannual averages of runoff of the River Quillcay during the historical period (1981 – 2016) on a monthly basis. The simulated runoff is the calibrated result of the hydrological simulations from the Shaman model, and the observed runoff is retrieved from PISCO data.

The calibration of the Shaman hydrological model to depict the characteristics of the Quillcay catchment resulted in acceptable model performance indicators (Table 2). The performance was almost identical between the calibration and validation period, with the indicators showing differences of only 1%. The indicators showed coherences to the observed runoff of about 80% for the Kling-Gupta efficiency (KGE), Nash-Sutcliffe and logarithmic Nash-Sutcliffe efficiency. The BIAS-Score indicator resulted in a remarkably high coherence of 98%. The slightly higher logarithmic Nash-Sutcliffe efficiency compared to the regular Nash-Sutcliffe efficiency indicates that low flows are slightly better represented in the simulations than high flows. This is also supported in the visual analysis of the multi-annual runoff in Figure 9. During the rainy season, runoff is simulated at lower values of up to 4.8 m^3/s compared to observed runoff. During the dry season, the two curves show minor differences, and thus a better coherence. In Figure 10, the coherences of the two runoff timeseries for low flows are also visible, while the runoff peaks resulted in larger discrepancies.

Table 2. Statistical indicators of the calibration performance of the hydrological simulations in the Shaman hydrological model.

Indicators of model performance		
Indicator	Calibration period (1981 – 2000)	Validation period (2001 – 2016)
Nash	0.84	0.83
Nash-Logarithmic	0.87	0.88
KGE	0.79	0.80
BIAS-Score	0.98	0.98

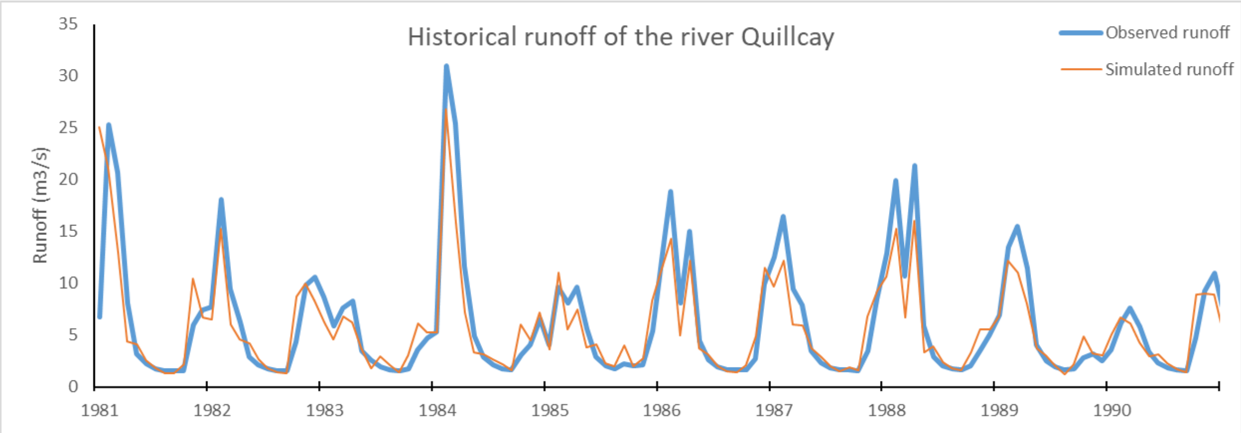


Figure 10.Subsection of the Quillcay river runoff during the calibration period (1981 – 1999). The simulated runoff is the calibrated result of the hydrological simulations of the Shaman model.

5.2 Glacier area

According to the classification of the NDSI-calculated glacier images, the dry-season glacier area within the catchment corresponded to 34.7 km^2 in 1986, 31.7 km^2 in 1995 and 23.6 km^2 in 2010 (Figure 11). Historical glacier areas using the Landsat-5 imagery show a strong recline during the historical period. On average, the area decreased by approximately 0.5 km^2 per year.

Between 1986 and 1995, mostly the lowest altitudes of the glaciers were affected by shrinkage, whereas between 1995 and 2010 also areas in higher altitudes were becoming ice-free. After a visual comparison with Google Earth imagery, these sites were found to correspond to steep mountain slopes.

The Freezing Level Hight FLH was calculated to be at 4948 m a.s.l. in 2010, an altitude which is aligning with estimations of Schauwecker et al. (2017), where the FLH for the Cordillera Blanca was found to be in altitudes between 4900 and 5010 m a.s.l.

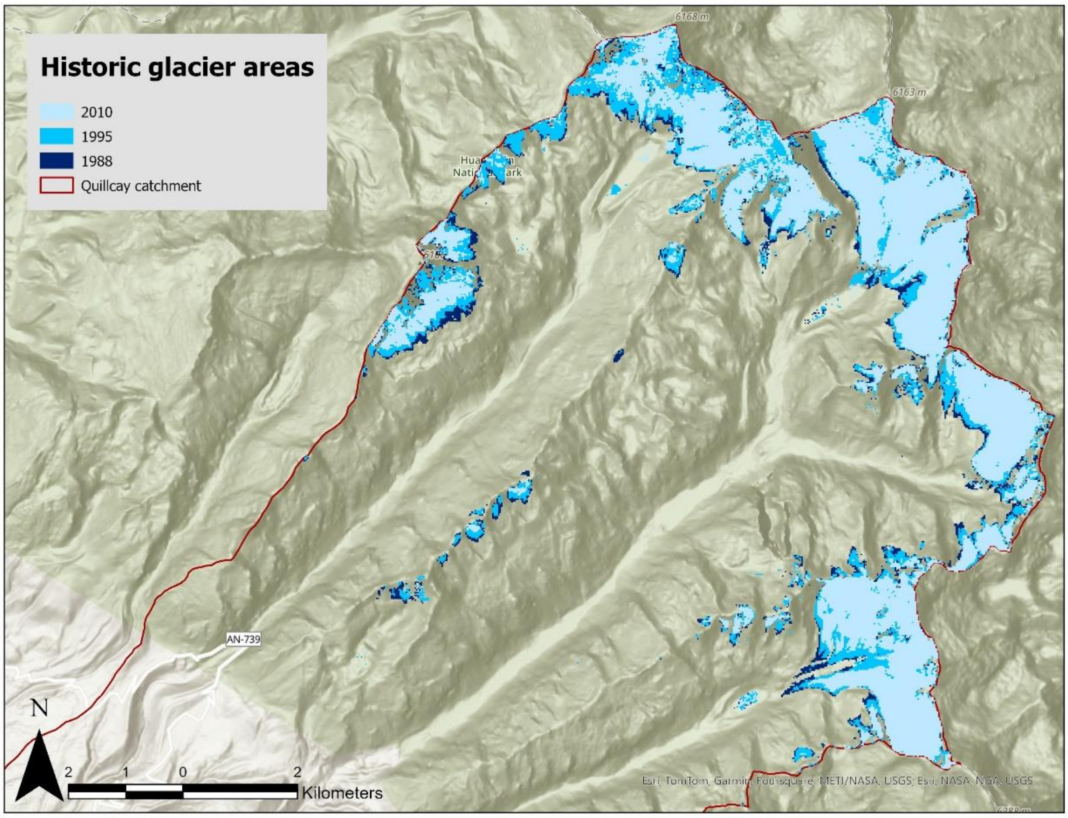


Figure 11. Map of historic glacier areas in 1986 (34.7 km2), 1995 (31.7 km2) and 2010 (23.6 km2), calculated with the NDSI-threshold and Landsat 5 satellite imagery.

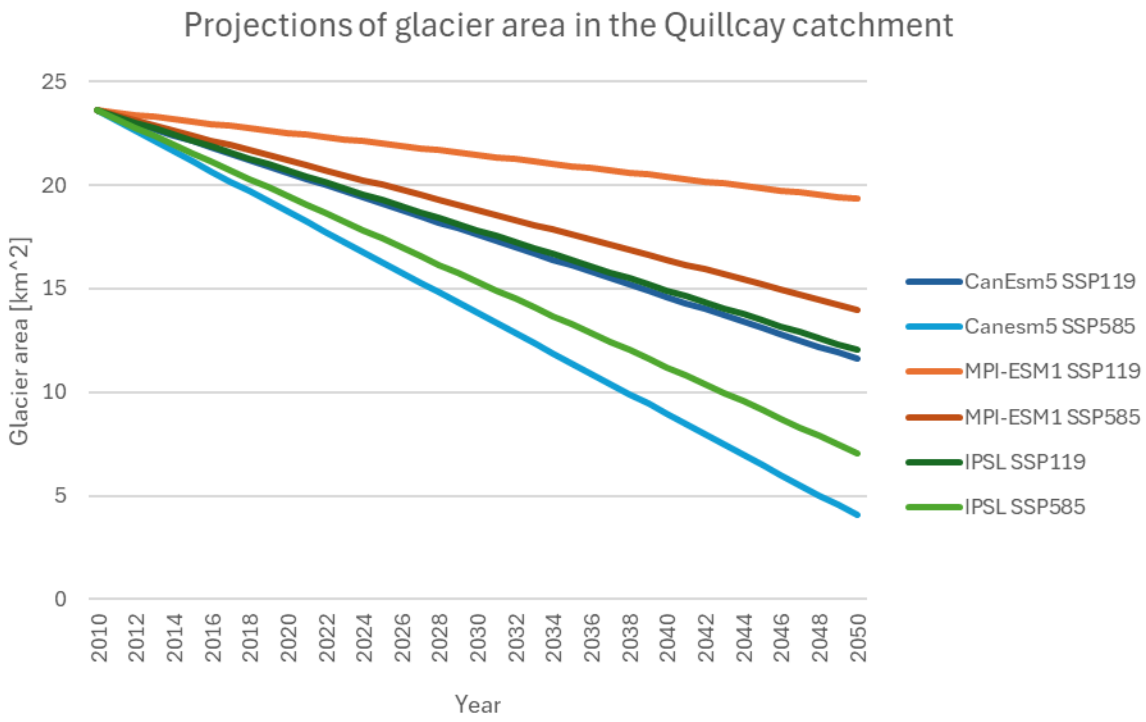


Figure 12. Estimations of future glacier areas under different climatic models and scenarios. For illustrative reasons, only the least and most severe scenario of each climate model was depicted in this figure.

Future scenarios of glacier area up to 2050 are based on 15 climate scenarios. In all cases, a clear decline in glacier area compared to 2010 resulted. The increase in freezing level height (FLH) between the latest obtained Landsat 5 imagery in 2010 and 2050 was linearly interpolated to obtain an annual increase in FLH and therefore an approximated annual glacier area. For demonstrative reasons, only the SSP119 and SSP585 of the three climate models were included in Figure 12. The other scenarios show results ranging between their climate model's optimistic and pessimistic scenarios considering the rise in temperature. Under the SSP585 scenarios, glacier areas show a stronger decline compared to the SSP119 scenarios. While the scenarios based on the climate models Can-Esm5 and IPSL resulted in similar trends of glacier decline due to their trends of temperature, the scenarios based on the MPI-ESM1 climate model show a far more optimistic trend, compared to the optimistic SSP119 climate scenarios of the other two climate models. In numbers the glacier area is decreasing from 23.6 km^2 in 2010 to 19.3 km^2 in 2050 under the scenario with the least glacier shrinkage (-18%) down to 4.1 km^2 in the worst-case scenario (-83%).

5.3 Climatic scenarios

For better visibility, the graphs showing the annual mean temperatures and the annual total precipitation depict the trends of the two variables, each SSP time series as the average of its three climate models.

The annual mean temperature increases under all climate scenarios in the simulation period, compared to the historic period (PISCO time series). The largest difference from the of 12 ° C of the historical period average was observed in the SSP585 scenarios with an increase of 2 °C, the least difference under the SSP119 scenarios with an increase of 1.4 °C on average (Figure 13).

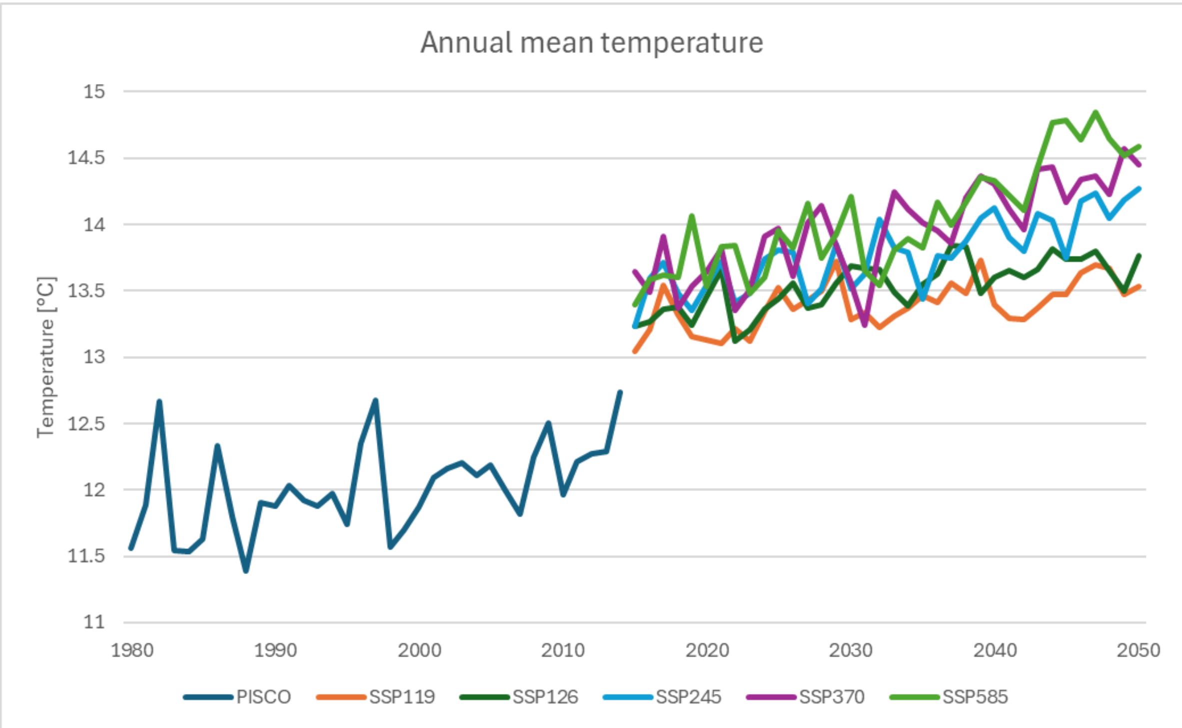


Figure 13. The annual mean temperature in the catchment under the different climate scenarios. For illustrative reasons, each SSP scenario represents the average of the three climate models.

In Figure 14, the variability of increase of temperature is shown. The Can-ESM5 climate model incorporates the scenarios with the largest increase in temperature (SSP370 and SSP585) and also the largest variability in its scenarios. The IPSL represents the climate model with an overall medium temperature increase of 2 °C on average. The MPI-ESM1 climate model simulates its five scenarios with a smaller variability and also the smallest average temperature increase of 1 °C compared to the average temperature during the historical period.

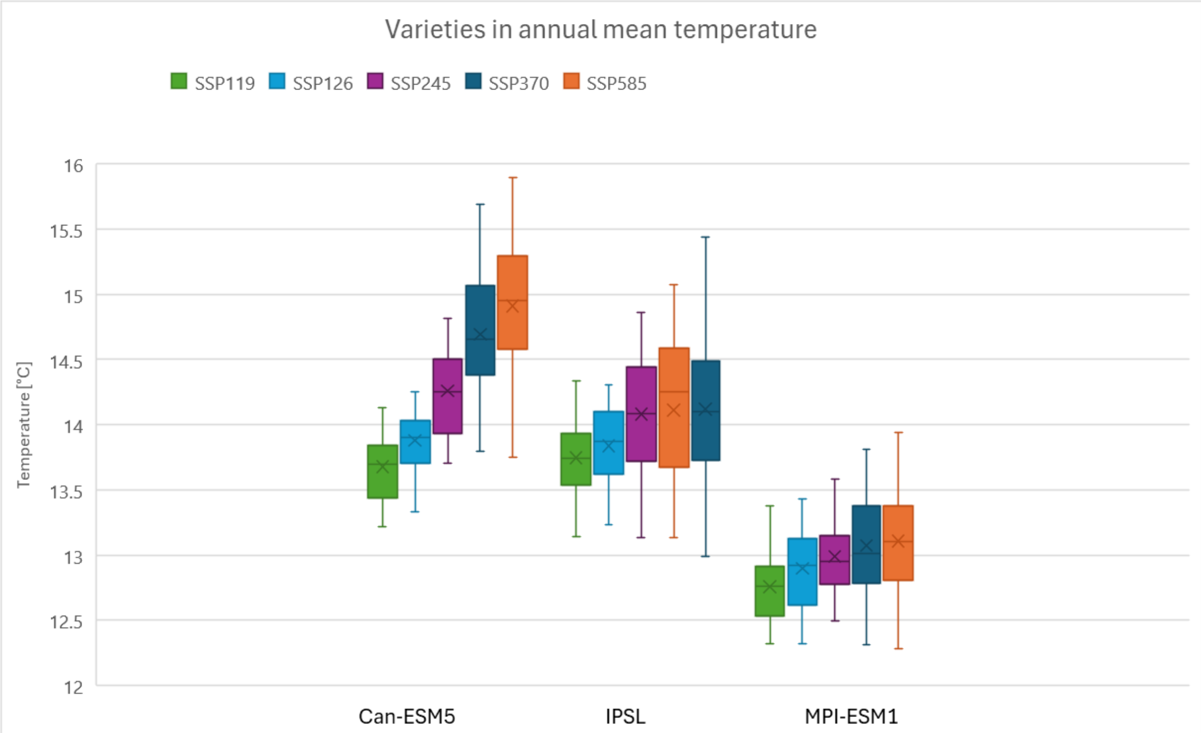


Figure 14. The annual mean temperature in the catchment for each climate scenario between 2024 and 2050.

Climate scenarios for precipitation in the area also show an increase in the total annual precipitation (Figure 15). The increase in annual precipitation ranges from 169 mm/a (SSP119) to 264 mm/a (SSP245) compared to the historical mean of 984 mm/a. Trends in the scenarios are positive for SSP245, SSP370 and SSP585, neutral in the case of SSP126 and even negative in the SSP119 scenario with the least climate forcing scenario. On average, over all scenarios and models, there is a small increase in annual precipitation amounts (red curve) compared to current amounts.

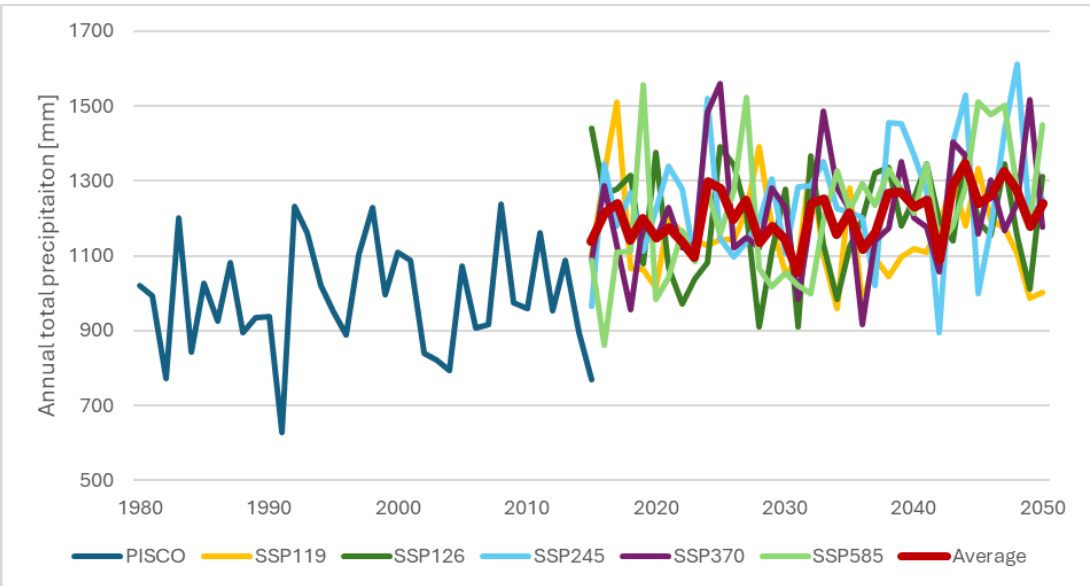


Figure 15. The annual total precipitation in the catchment under the climate scenarios. Each scenario represents the average value of the three climate models. The red curve represents the average of all scenarios until 2050.

5.4 Socioeconomic scenarios

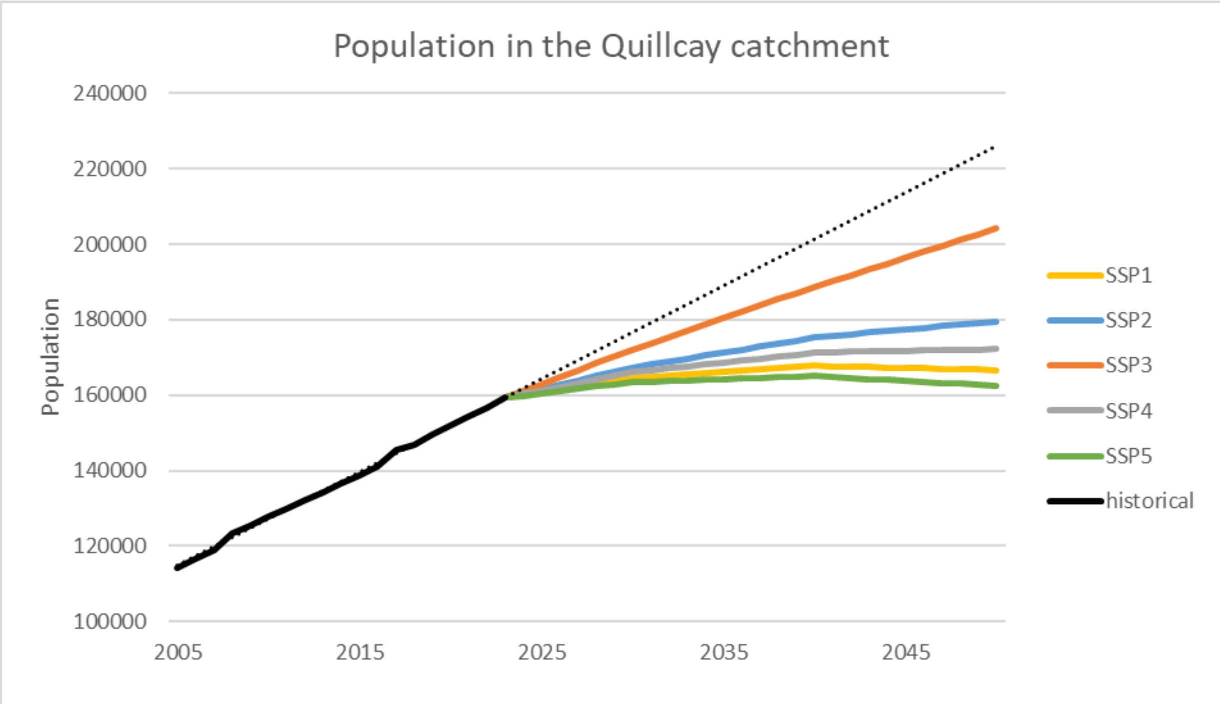


Figure 16. Scenarios of population development in the catchment area until 2050. The five scenarios are represented by estimations based on the Shared Socioeconomic Pahtways (SSPs).

Population growth trends were estimated through the SSP baseline scenarios for South America and applied to local historical data. Under all all scenarios, the population is expected to increase in the years up to 2050 in comparison to todays levels. Under the SSP3 scenario the largest population increase of 28% is expected. The other four scenarios expect only moderate growths of 2 - 13% compared to 2024. The SSP1 and SSP5 even estimate a small population shrinkage toward 2050, which would lead to the numbers of inhabitants in the catchment in the middle of the century converging to today's numbers (Figure 16).

Trends in irrigated areas were approximated using the 4000 hectares reported in 2008 and the SSP baseline scenarios. In all scenarios, a total increase compared to historical data (Figure 17). Compared to scenarios in population development, the scenarios for irrigated areas show more diverse trends. While SSP2 and SSP3 assume a constant increase in area, SSP4 and SSP5 assume a stop in area increase after 2040. Under the SSP1 scenario, there is even a temporary decline in irrigated areas until 2030, which then counterbalances with a strong increase in area until 2050.

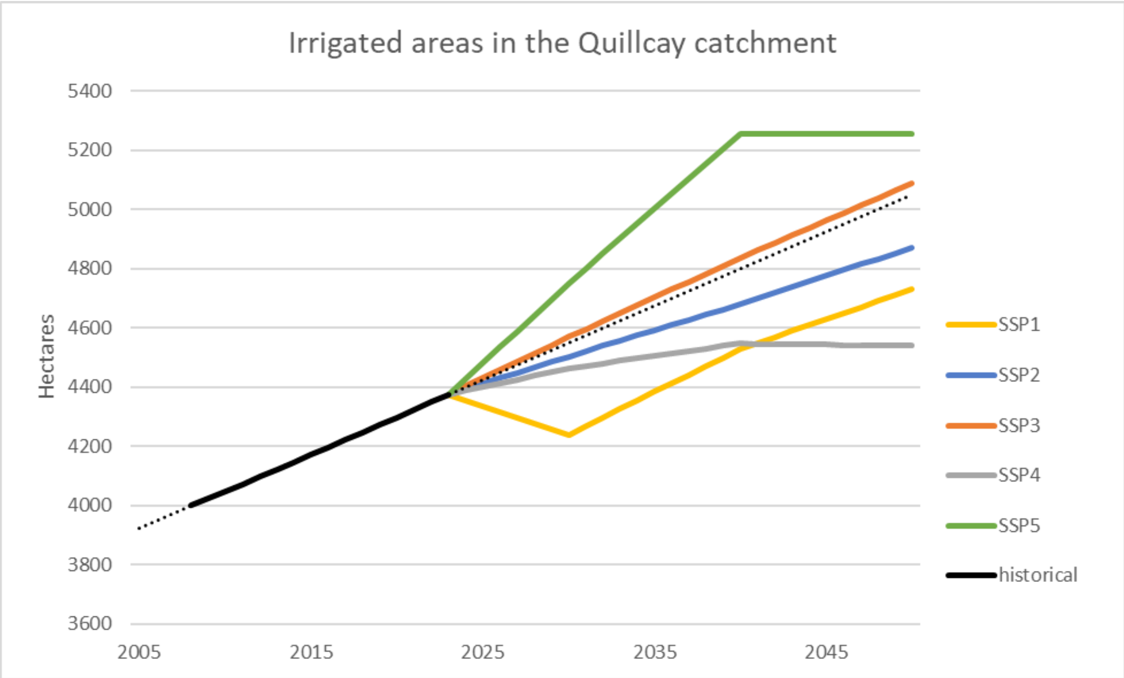


Figure 17. Scenarios of the development of the irrigated areas in the catchment area until 2050. The five scenarios are represented by estimations based on the Shared Socioeconomic Pahtways (SSPs).

5.5 EMA model results

Simulations without adaptation measures

In a comparison model run with 900 simulations, the future development of water availability was simulated without any adaptation measures. Therefore, the current parameter values for the policies were applied, without any boundaries. However, uncertainties from the climate and SSP scenarios were implemented in the simulations. The simulation metric showed that very few model runs being successful with the task to provide water security in the dry season, with only 30% of runs showing a metric value higher than 0.9.

With the feature scoring method, the simulations can be further analyzed to show the parameters that influence the performance the most. In Figure 18 depicting the feature scoring of the no-policies model, the climate scenarios emerge as the most important variable affecting the results of the metric at 33%. SSP scenarios that combine irrigation and domestic water demand scenarios, on the other hand seem to have little influence on the overall results. Due to their larger parameter boundaries, the variables from the hydrological model and the irrigation backflow have medium influences of about 10% each on the overall model result (Figure 18).

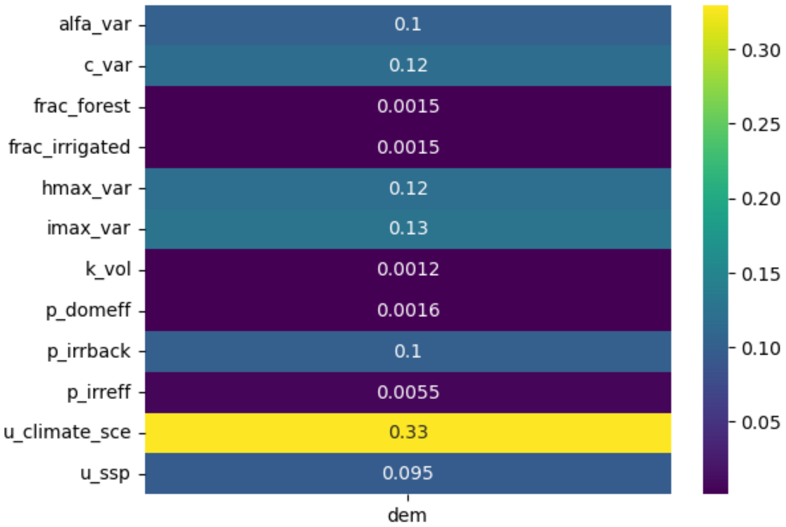


Figure 18. Feature scoring results of the first simulations considering only the uncertainty parameters of the metric to explore future states of the catchment system without adaptation measures.

Simulations including adaptation measures

The main simulations were carried out in 4900 model runs with combinations of parameters with their respective value boundaries listed in Table 19. The overall performance of the simulations was again measured with the previously defined model metric. With the consideration of adaptation measures against water scarcity, the metric now showed a very high rate of cases where water scarcity could be avoided. More than 84% of the 4900 model simulations incorporated a metric larger than 0.9, and therefore were considered successful in providing water security to the catchment and its inhabitants. Only 16% of all simulations resulted in a metric below 0.9, indicating water scarcity to the region.

The influence of each parameter on the metric was again assessed using the feature scoring method (Figure 19). With the abundance of adaptation measures, the influence of uncertainty parameters is strongly diminished. Apart from the uncertainties emerging from the hydrological model, the climatic and socioeconomic scenarios now play a minor role in influencing the metric as well. Due to the large fraction of irrigation water demand on the total water demand and the wide parameter range of the irrigation efficiency, p_ireff now acts as the key influencer on the metric with 41%. The parameter of the construction of a reservoir for water allocation was found to be the second largest influencing parameter, with 16% influence. The third largest influencer was the domestic efficiency p_domeff, which was responsible for 14% influence on the metric.

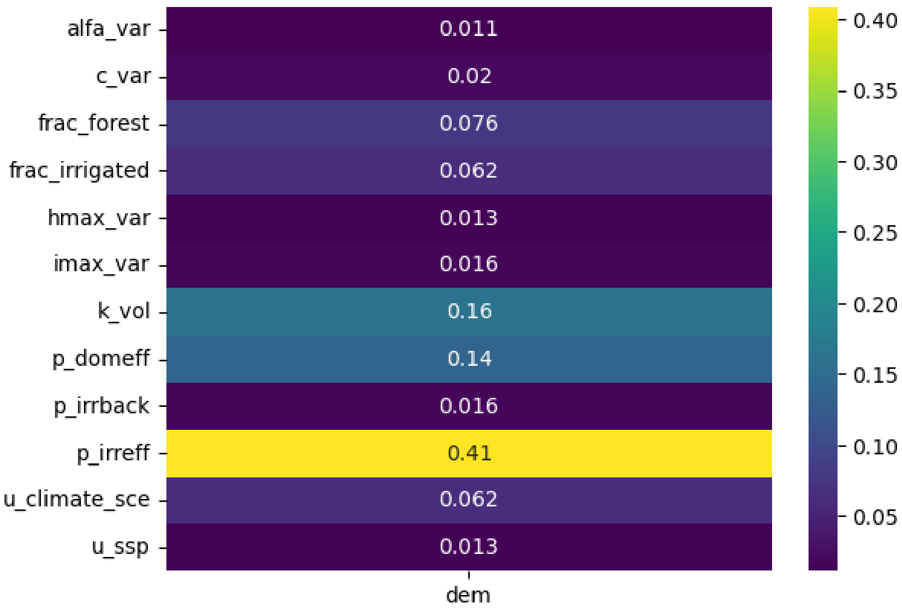


Figure 19. Feature scoring results of all simulation parameters with their respective influence on the metric.

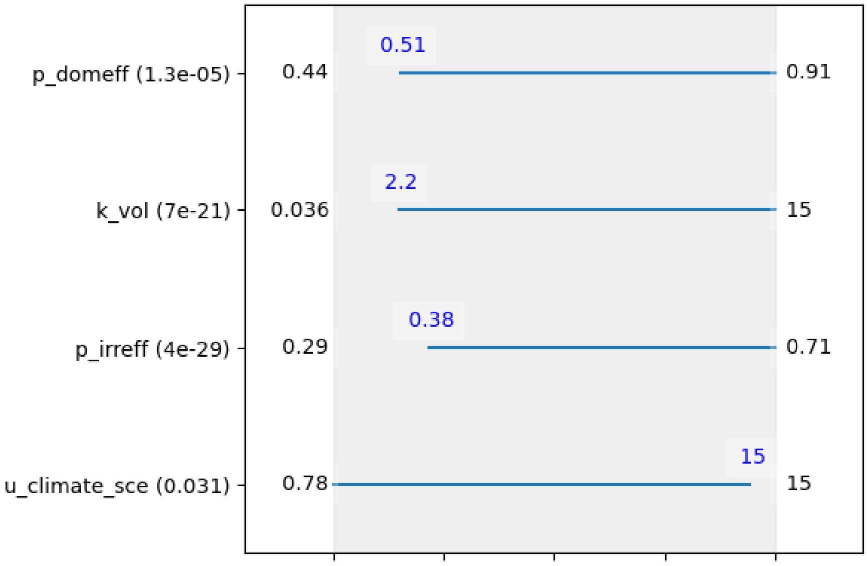


Figure 20. Parameter ranges across simulations with the metric m >= 0.9, where they were influential (blue line across the total parameter bandwidth) and their statistical significance in influencing the model metric (p-value in brackets).

Figure 20 shows the value limits of the parameters where they significantly led to a successful model metric and therefore could achieve water security. From the combination with the largest significance on the metric, the climate scenarios showed the lowest significance in the model. The operational range reaches over the whole parameter value boundary and thus implies that the metric shows successful cases over all the climate scenario ranges. The policy measures the changes in efficiency of domestic and irrigation water demand on the other hand, imply a specific minimum threshold for a successful model metric. For p_domeff, this threshold lies are 51% (current levels at 76%), implying that even a reduced WUE could lead to success in achieving water security. For p_ireff, the threshold lies at a WUE of 38%, slightly above the current levels of 35%. With this result, at least a small increase in irrigation WUE would be needed to gain a robust adaptation measure. For the potential reservoir, the results show significant cases of a successful model metric if the reservoir contains a minimum volume of 2.2 million m^3.

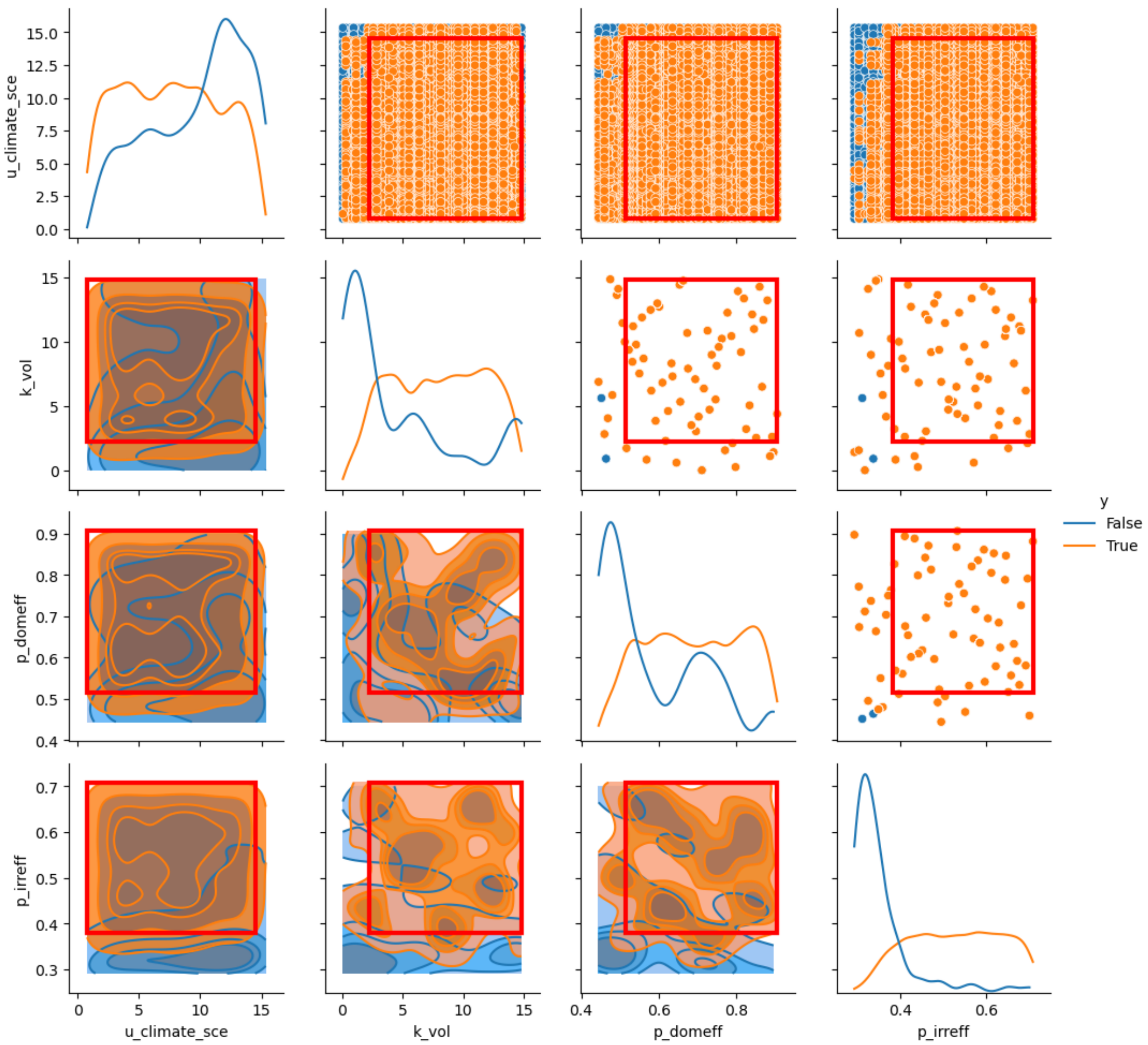


Figure 21. Scatter plots of the parameters that influence the metric to depict successful simulations (with metric >= 0.9) in orange and unsuccessful simulations (metric < 0.9) in blue. The red rectangle represents the boundary of significant parameter combinations. Line plots depict the operational values of a single parameter.

To reduce the complexity of the multidimensionality arising from the comparisons of the seven uncertainties and the five policy levers and for a better readability of the results, the combinations of simulation parameters were analyzed using the PRIM algorithm and depicted in scatterplots (Figure 21). The line graphs represent the depiction of successful versus unsuccessful values of each parameter. As there is no single best result in exploratory modeling, but rather simulations with significant combinations of parameters, the results have to be explored through scenario discovery. For this, amongst all simulations, those simulations which obtained parameters with statistically significant influences on the model metric were further analyzed.

For the climatic scenarios (top-left plot in Figure 21), the number of cases where the metric cannot be achieved increases along with the number of the scenario and the successful metric values decrease along with the increase of the climate scenarios. Thus, climate scenarios with stronger climate forcing from u_climate_sce 10 and upward (SSP370 and SSP585) would lead to a lowered chance of success in achieving water security.

The investigation of the single parameter reservoir (k_vol in second row, second plot) shows again the minimum threshold of about 2 million cubic meters, above which the successful cases of the metric dominate. The tipping point in achieving water security when only looking at the domestic WUE (third row, last plot) lies at around 50%. Above this threshold, the successful cases prevail, while below, the number of unsuccessful cases is much higher. When only looking at the irrigation WUE (bottom right plot), the successful cases predominate the unsuccessful ones above the 40% mark. Below this threshold, it is significant that the system metric cannot succeed, also illustrated through the large difference between the two lines (compare Figure 20, statistical significance).

When looking at variable combinations with the scatterplots to achieve water security in the catchment, it becomes evident that while both WUE parameters have an operational range along the whole climate scenario spectrum, they require a minimum threshold in order to avoid water scarcity. In the scatterplot comparing the two efficiencies against each other (third row, right plot), this appears clearer, as the operational range in the red rectangle is depicted within the lower boundaries of 38% for irrigation WUE and 51% for domestic WUE. The reservoir in combination with the other three parameters always shows its minimum volume of 2.2 million cubic meters as the lower boundary of the operational range.

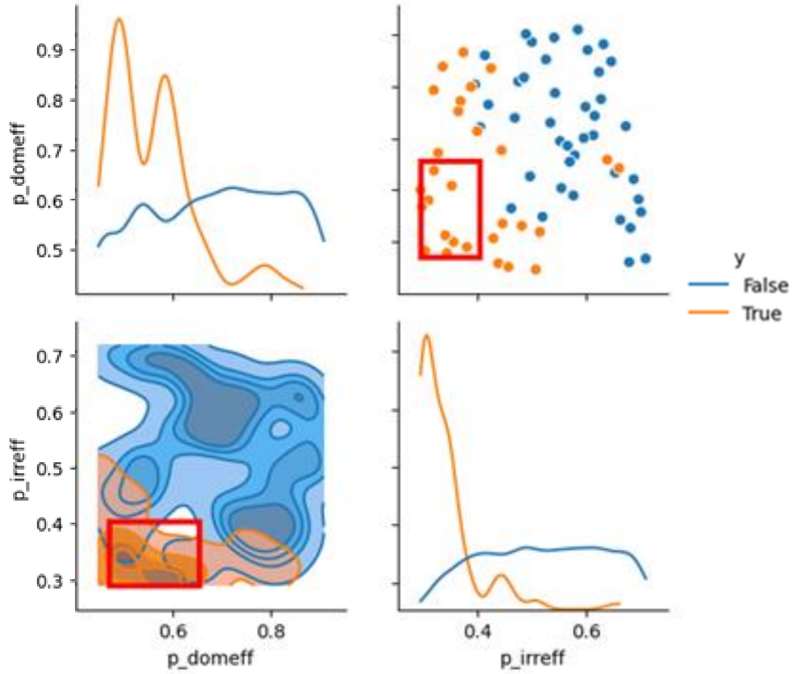


Figure 22. Scatterplots of parameters that influence the metric to depict unsuccessful cases (with metric < 0.9) in orange and successful cases (metric >= 0.9) in blue. The red rectangle represents the boundary of significant parameter combinations.

Instead of showing simulations in which the metric is greater than 0.9, an alternative exploration method is to analyze under which conditions the system is not successful, translating to where the metric is less than 0.9.

In this case, the adaptation parameter reservoir did not cause significant impacts on the model metric. Rather, the parameters change in domestic and irrigation WUE resulted to be the parameters with the largest influence on the model metric.

For the exploration of the two WUE, the scatterplot shows a more compact operational range (top-right plot in Figure 22). Comparing this with the statistical analysis of the parameter ranges, the results suggest that a domestic WUE below 65% in combination with an irrigation WUE below 41% would result in a failure of the aspired metric of 0.9. These results indicate a higher minimum WUE instead of those under which the system is successful, but also state that beyond this threshold, water security can be achieved under most scenarios.

6 Discussion

Coping with uncertainties

In situations where the future states of a system exhibit profound uncertainty due to a multitude of uncontrollable factors, traditional probabilistically oriented predictive methods reach their limitations. Consequently, decision-making frameworks specifically designed to address deep uncertainty, such as Decision Making Under Deep Uncertainty (DMDU), become essential for robust decision-making (Marchau et al., 2019). With EMA, a method that can cope with such requirements was developed and already successfully applied in research (Kwakkel, 2017, Muñoz et al., 2024). Nevertheless, an appropriate handling of the abundant data is crucial in order not to increase the uncertainty in that dimension. Without the restriction of uncertainty into feasible boundaries, the detail of the simulations could be affected, and thus the results could also lead to maladaptation of measures (Kundzewicz et al., 2018).

6.1 Evaluation of simulations

Glacier area

Estimates of future trends in glacier cover in the catchment have shown a moderate (-18%) to rapid (-83%) decline in glacier area with climate scenarios up to 2050. The estimations of the current freezing level height (FLH) were coinciding with the findings of Schauwecker et al. (2017). However, the calculation of the NDSI values of Landsat 5 imagery have resulted in a more rapid recline in glacier areas during the historic period compared to the findings of previous research for this region (Stitelmann, 2023; Veettil, 2018). The largest discrepancy in area was in 2016, where this research estimated the glacier area to be 23.6 km2, while 30.4 km^2 was calculated based on GLIMS data (Stitelmann, 2023). The root cause for this discrepancy might be in the computational analysis of the satellite images. Compared to Sentinel-2, Landsat 5 imagery has been found to incorporate a reduced performance of NDSI-based glacier classification caused by a poorer accuracy in identifying debris-covered parts of the glacier and misinterpretations of areas in steep terrain and cast shadows (Veettil, 2018). However, in order to have consistent data sources over the historical period, Landsat 5 data was deemed suitable for this purpose. Combined with the different severities of temperature rises in the climate scenarios, the moderate to severe recline in glacier areas could still be estimated.

Hydrological simulations

Due to the limitations of available data, the Shaman hydrological model was employed in this research, as it has shown a good performance in depicting hydrological conditions when data is scarce. However, due to model's simplicity, implications on the hydrological circle, such as altitude bands or sub catchments with in-situ measurements implemented in the HBV-light model, are not considered (Muñoz et al., 2021). The high-flow peaks in river runoff (NSE) could be represented with a high accuracy of 84%. The logarithmic NSE that accounts for the low flows in runoff was slightly higher at 87%. For this study, the representation of low flows was deemed the most important characteristic and therefore considered acceptable.

Additionally, the model parameters influencing groundwater flow and storage were obtained by calibrating the model and could not be compared to in situ data because of no availability and a very limited understanding of these processes, especially in data-scarce regions (Baraer et al., 2014). Despite these limitations associated with the employment of this model, seasonal runoff patterns and the order of magnitude in runoff resulting from hydrological simulations were in line with previous research using different hydrological models (Motschmann et al., 2020) and local reports (MINAM, 2014) in the Quillcay catchment. The seasonality of the glacial melt water content in the river runoff from the catchment with a contribution of up to 67% of dry season runoff showed very well comparable patterns to the findings of Buytart et al. (2017), who estimated the content of glacial meltwater at 53.4% in the dry season and an annual average contribution of 19%.

Climatic and socio-economic scenarios

The variability between the three climate models and their respective five scenarios was found to be large (compare Figure 14), although the underlying conditions were chosen to be constant between the models. However, they were relevant for this study to portray the large uncertainty concerning the climatic conditions even in the near future, as the seasonality of precipitation was well comparable to the historical period. General trends in a higher annual precipitation amount and rising temperatures up to 2050 remain in ranges found in past research for the Huaraz region and the Cordillera Blanca (Juen et al., 2007, Mark et al., 2010).

The trends in future developments of the population size in the catchment and the area of irrigated agricultural land with the SSP scenarios represent only the larger region-scale socio-economic trends and have limited knowledge and understanding of processes on a local scale. Thus, due to the lack of local estimations on these trends, a fundamental estimation considering detailed local developments and limitations was hindered.

6.2 Evaluation of adaptation measures

Conditions for successful adaptation measures

As the exploration of the EMA results have shown, all three potential adaptation measures incorporate successful effects on the water balance in all climate scenarios. Constraints from the different SSP scenarios could not be significantly indicated, as well as the uncertainty parameters from the hydrological model itself, which showed little influence on the performance of the measures. These results are supported by the findings of Buytaert et al. (2017) and Motschmann et al. (2020), which concluded that regardless of changes in water availability, the management of water demand will be crucial in order to avoid water scarcities in the Peruvian Andes. To increase dry season water availability, Motschmann et al. (2022) also propose investing in water infrastructure with carefully planned reservoirs.

These findings would suggest that the conditions for the adaptation measures to show a successful effect would not depend on the climatic or socio-economic scenarios but rather be influenced by the other adaptation measures.

Most robust adaptation measures

The results obtained through the scenario simulations in this research would therefore incorporate the recommendation for stakeholders to take measures in order to avoid a potential water scarcity in the Quillcay catchment area until 2050. Most importantly, the implementation of measures to increase the irrigation WUE would be recommended, as this parameter has shown the largest impact on a successful model metric (41% of the total influence of the metric). By increasing the efficiency of irrigation water use by at least 3%, one could reach the desired threshold of 38%, above which water scarcity could be avoided in most future scenarios. In combination with maintaining a similar or even up to 25% lower domestic WUE at a minimum of 51% and the construction of a reservoir for irrigation and domestic water use with a size of at least 2.2 million cubic meters, this would represent the most robust combination of adaptation measures to avoid water scarcity up to the year 2050.

Without considering the reservoir parameter, the WUE parameters would need to obtain higher efficiencies to be considered robust, with at least 65% for domestic and at least 41% for irrigation water use efficiency in order to avoid water scarcities.

While the combinations of adaptation measures definitely would need to be locally assessed for a successful implementation, the explorations of results in this research showed the importance of adaptation measures to be considered in the Quillcay catchment. Without any measures, water scarcities during the dry season would be imminent.

Presentation for policy makers

The multiple simulations of future states of the system with a large set of input variables can lead to complex results, a decreased readability, and difficulties in assessing adequate adaptation measures. With exploratory modeling and analysis (EMA) employed in this study, a concept was used that can reduce the complexity of such multidimensional problems and facilitating the communication of results to decision makers (Kwakkel, 2017).

Due to the large uncertainties originating from scarcely available model input data, many assumptions had to be made. Regarding, for instance, that per capita water consumption, or evaporation from the reservoir and the land cover classes had to be assumed to remain constant. Therefore, it must be communicated to stakeholders under which assumptions the simulations were performed and which limitations they incorporate. Furthermore, the recommendations concluded in this investigation are only valid for this specific study area and period (Kundzewicz et al., 2018).

Inherent in the name exploratory modeling is also the process of obtaining the results, which is not by aiming at a single best solution but rather by presenting robust solutions that can cope with most of the uncertain future system states (Bankes et al., 2013). It must be therefore communicated to decision makers how the implemented policy parameters would affect the simulations and pre-define policy parameter boundaries, which already incorporate a realistic feasibility. The resulting operational ranges of the parameters by applying the PRIM algorithm and the importance of each parameter with the feature scoring approach can be used as a straightforward communication of results to decision makers and used as guidelines for the real-world implementation of adaptation measures (Kwakkel, 2017).

Limitations (challenges for real-life implementations)

This study focused on exploring the potential range of parameter values for adaptation measures and policies. If local authorities or even the national government of Peru decided to employ this type of research to identify particular adaptation measures against water scarcity, prioritization of policies or distinct policy ranges with higher feasibilities needed to be implemented within the EMA process.

The reason for this is that, in this research, limitations of the applied policy parameters became obvious. The policy of constructing a reservoir was implemented in the hydrological model, so the reservoir was acting as a runoff buffer. Its water intake was the total runoff from the sub catchment in which it was located, an area of 80 km^2. During the wet season, the reservoir was filled and during the dry season, its purpose was to increase the water balance by an increase in spill water. In the first sets of simulations, the maximum capacity of the reservoir was set at 30 million cubic meters. In the exploration of results, it became obvious that although the reservoir supported the water balance during the dry season, it never had a significant influence on the model metric. The reason behind this was found in the total volume of water stored in the reservoir, which never exceeded values of 15 million cubic meters. The water intake area was too small to feed the reservoir with precipitation and glacier meltwater. Thus, the maximum capacity in the next sets of simulations was set at this threshold, and this parameter now showed a higher influence on the metric.

The dam of the reservoir in this case was fictionally built in the Cojup valley in the northern part of the catchment, right on the border of the Huarascan National Park, because of the steep mountain flanks in this valley which could condemn the lake surface area to a minimum to reduce the evaporation water loss due to evaporation. For a concrete project within this park area, legal and political assessments would be needed if it would outweigh the interests of natural conservation, which is currently the most important purpose of such parks (Barker, 1980).

In addition to the arguable location of such a reservoir, the question of financing quickly arises and thus also the number of different stakeholder groups. Past research on the implications of technological innovations in the region has shown that along with the construction of water management facilities, the number of stakeholders with different interests and thus also the conflicts on the commonly used resource grow (Carey et al., 2012).

Apart from the resource-intensive reservoir policy, the increase of the domestic or irrigation water use would imply large-scale financial investments. To reach an irrigation efficiency of up to 70%, the implementation of a drip irrigation system would be required throughout the irrigated agricultural area (Meredith & Blais, 2019).

Opportunities accompanying adaptation measures

While existing adaptation measures in the Peruvian Andes predominantly focused on increasing water availability to avoid water scarcities, the results obtained here also propose the implementation of measures decreasing water demand through increased water use efficiencies. While this case study has implemented possible trajectories of societal development in the future up to 2050 in the simulations, the societal response to potentially implemented measures such as a reservoir or decreased water demand could not be implemented. For an integrative assessment of the reaction of social behavior towards implemented adaptation measures, an adaptive parameter steering the water demand in the hydrological model is currently lacking (Carey et al., 2014).

For the potential reservoir, opportunities can be identified through a comparison with the case of Lake Parón in the vicinity of the Quillcay catchment. In this case, local stakeholders were not included in the planning and operation of the hydroelectric management of a previously undisturbed lake and therefore formed severe opposition against the operating company (Carey et al., 2012). With the participation of the local population and stakeholders in planning a reservoir in the Quillcay catchment, decision makers could better evaluate the needs and expectations of the affected people and thus prevent potential opposition against infrastructure projects (Motschmann et al., 2020).

Furthermore, the participation of many stakeholder groups would increase the sustainability and thus robustness of potential adaptation measures, because they would also incorporate also a social robustness (Motschmann et al., 2020). Resulting from the participation of the local population, a "water citizenship" could be established, which would favor trust and thus also the willingness to financially and conceptionally contribute to adaptation projects (Paerregaard et al., 2016, Ale Pezo, 2019).

Evaluations of this research

Due to the many assumptions and parameter approximations which needed to be considered for the completion of this study, the here presented results and recommendations certainly need to be considered with caution for decision makers. For a more integrative approach, in-situ measurements of irrigation water demand in the catchment area for instance, or the implementation of a parameter describing the vulnerability of different socio-economic groups in the population, could strongly improve the estimations of water demand and therefore decrease the risk of maladaptation. While the performance metric and the implemented threshold in this study only considered the comparison of dry season water availability and demand, a more sophisticated metric could be established with the collaboration with local stakeholders. An additionally assessed metric could be the implementation of a feasibility metric, which would incorporate the financial consequences of the potential adaptation measure (Kalra, 2015).

7 Conclusion

In this research, hydrologic simulations in the Quillcay catchment could confirm existing literature that found river runoff to be heavily dependent on glacial meltwater during the dry season (May – September). To examine future impacts of glacier retreat on water availability in the catchment, this study calibrated climate models to depict local trends of precipitation and temperature. Under all 15 implemented climate scenarios, precipitation and temperatures are expected to rise in the simulation time until 2050. Simulations of future states of glaciers feeding the river resulted in moderate glacier area decrease under more optimistic climatic and socio-economic scenarios. Under less optimistic scenarios, a severe recession of glacier area was simulated.

With the application of the concept Exploratory Modeling and Analysis in this thesis, the various uncertainties from climatic and socioeconomic parameters could be combined to simulate plausible developments of future water availability. Together with a rising water demand, resulting from growing population and irrigated areas in the study area, an increased stress on the water resources is expected in the future. Without any adaptation measures in the catchment area, in 70% of simulations until 2050 there is the risk of having a water scarcity during the dry season.

The results obtained in this study have shown that with the implementation of adaptation measures that increase dry season water availability (reservoir) and change the water use efficiency for domestic and irrigation water demand, the cases describing water scarcities could be drastically reduced. Specifically, this research estimates that the combination of adaptation measures which is most robust is the construction of a reservoir with at least 2.2 million m^3 water capacity combined with measures which increase the WUE of irrigation water demand from currently 35% to at least 38%. With its weaker influence on the model metric, the domestic WUE would not be considered as an urgent adaptation measure in these simulations. The exploration of the EMA results has also shown that these adaptation measures would have a positive impact on the water balance during the dry season regardless of the severity of the climatic or socio-economic scenarios and thus can be considered robust against uncertain future states of these scenarios. As a communication toward stakeholders, this study would conclude that in the Quillcay catchment, increasing water supply with the construction of a reservoir only makes sense in combination with implementing an improved WUE in order to decrease the risks of water scarcity, but consequently, actions that combat the threat of water scarcities are crucial.

These recommendations are common with such from previous research that proposed the construction of reservoirs (Motschmann et al., 2022) and the reduction of water demand (Drenkhan et al. 2015). However, this approach contributes to the research assessing water scarcity by incorporating the various uncertainties due to scarce data availability within the simulations with the emerging approach of Exploratory Modeling and Analysis. With this research, it could be confirmed that EMA is a valuable instrument in assessing data-scarce systems in the water sector and to present robust adaptation measures against water scarcity under deep uncertainty.

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9 Appendix

Hydrological simulations

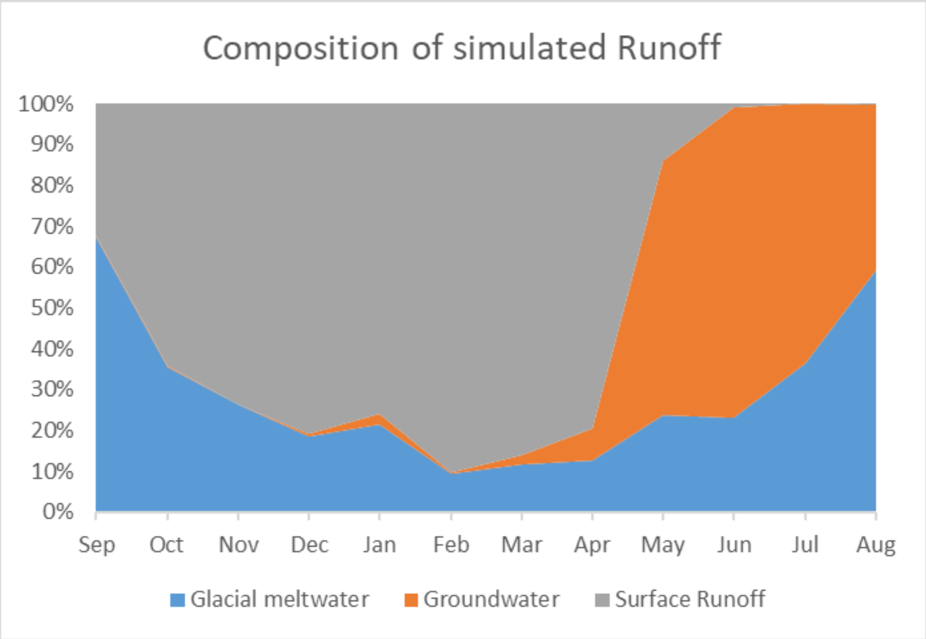

Figure 23. Multi-annual averages of the composition of river runoff during the historical period (1981 – 2016) on a monthly basis.

In Figure 23, the composition of the Quillcay river runoff gets depicted. It shows the high fraction of glacial meltwater onto the total runoff in the dry season, peaking at 67% in September. During the rainy season, the fraction of surface runoff from precipitation events dominates. Towards the end of the rainy season with decreasing precipitation, the release of groundwater from soils and aquifers begins to partially compensate for the precipitation fraction. During the first months of the dry season, this factor is almost negligible as the groundwater storage first needs to be refilled.

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.

P. Minsch

Zurich, 30.06.2024 Peter Rudolf Minsch