A Climate Change Impact Assessment Study on Mountain Soil Moisture with Emphasis on Epistemic Uncertainties

Dissertation

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A Climate Change Impact Assessment Study on Mountain Soil Moisture with Emphasis on Epistemic Uncertainties

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Inhaltsverzeichnis

Zusammenfassung

Generell wird davon ausgegangen, dass sich der Klimawandel besonders gravierend in den Gebirge auswirken wird. Untersuchungen zu den Auswirkungen des Klimawandels (Climate Change Impact Assessment Studies – CCIAS) in Gebirgen und die daraus zu entwickelten Anpassungsstrategien sind daher von herausragender Bedeutung. Heutzutage sind CCIAS ein häufig benutzter Ansatz, und viele Studien zu den hydrologischen Auswirkungen des Klimawandels wurden bislang publiziert; allerdings beschränken sich die Allermeisten auf die Änderung des Abflusses. Es fehlen jedoch CCIAS, die einen Fokus auf die räumlich explizite Beschreibung der Bodenfeuchteänderung legen und hier insbesondere auf der Einzugsgebietsskala. Die bisherige Nichtberücksichtigung der Bodenfeuchte in der Forschungsgemeinschaft steht in großem Widerspruch zu ihrer Bedeutung in den Ökosystemen und hebt den großen Bedarf für CCIAS mit Fokus auf die Bodenfeuchte nochmals deutlich hervor. In der vorliegenden Studie wurde ein weitverbreiteter CCIAS Ansatz angewandt, der sich zusammensetzt aus: (1) einem physikalisch basierten Modell, welches unter den derzeitigen klimatischen Bedingungen kalibriert und validiert wurde und (2) aus zwei regionalen Klimamodellen (RCM), die durch drei unterschiedliche Ansätze auf die Modell- bzw Stationsskala überführt wurden (Downscaling). Die sich daraus ergebenden sechs Modelansätze wurden auf einen Referenz- (1960-1990) und einen Szenariozeitraum (2079-2100) angewendet. Eine wesentliche Herausforderung stellt dabei die Fortpflanzung von Unsicherheiten der einzelnen Teilabschnitte dar, die die Modellergebnisse in Frage stellen könnten. Für eine belastbare CCIAS sind diese Unsicherheiten notwendigerweise zu bestimmen. In dieser Studie wurde der Fokus auf die strukturellen Unsicherheiten gesetzt, die unter anderem aus der Koppelung von hydrologischem Modell, Downscaling-Ansätzen und Klimamodellen entstehen. Dafür wurde ein analytischer Ansatz entwickelt, der auf dem Konzept zur Unsicherheitsfortpflanzung und der sogenannten Unsicherheitskaskade basiert. Die CCIAS wurde in einem Gebirgseinzugsgebiet (160km²) in den Schweizer Alpen mit einer hohen räumlichen Auflösung von 50m durchgeführt. Zunächst wurde das häufig eingesetzte physikalisch basierte, distributive hydrologische Modell WaSiM-ETH auf einen aktuellen Zeitraum angewandt (2001-2007), um eine solide Kalibrierung und Validierung gegen Abfluss und Bodenfeuchtedaten zu ermöglichen und die Unsicherheiten zu bestimmen. Möglichkeiten und Grenzen von WaSiM-ETH bei der Simulation der Bodenfeuchtedynamik und des räumlichen Musters wurden aufgrund von umfangreichen Bodenfeuchtemessungen auf Stundenbasis ermittelt. Während WaSiM-ETH den Abfluss mit einer sehr hohen Genauigkeit (R^2=0,95; ME=0,8; IoA=0,95) wiedergeben kann, ist die Simulation der Bodenfeuchte in verschiedenen Höhenlagen und Landnutzungstypen begrenzt, da das Modell nicht die gesamte Variabilität der Bodenfeuchtedynamik abbilden kann und stattdessen zu Mittelwerten tendiert. Ein angepasster RMSE, der die standortinterne Variabilität mit berücksichtigt, wurde für die

Bodenfeuchte von 8,0 Vol-% berechnet. Neben der Evaluierung des hydrologischen Modells ist die zweite Quelle von Unsicherheiten in den heruntergerechneten RCMs zu sehen. Eine vergleichende Studie, die auf zwei Downscaling-Ansätzen (statistisches Downscaling (SD) - und direkte Verwendung - direct use (DU) sowie auf zwei RCMs (CHRM, REMO-UBA) basiert, wurde für den Referenzzeitraum 1960-1990 auf Tagesbasis durchgeführt. Es wurde festgestellt, dass in den verschiedenen Ansätzen die auftretenden Unsicherheiten ungleichmäßig in Bezug auf die untersuchten hydrologischen Variablen und ungleichmäßig stark über die Zeit auftreten. Eine Downscaling-Model-Kombination, die die geringsten Unsicherheiten für alle verschiedenen hydrologischen Variablen wie Abfluss, reale Evapotranspiration und Bodenfeuchte im gleichen Maße aufzeigt, konnte nicht identifiziert werden. Darüber hinaus wurden die Unsicherheiten in Bezug auf Bodenfeuchte und Verdunstung räumlich explizit untersucht. Dabei zeigte sich, dass die Wahl des Downscaling-Ansatzes nur eine untergeordnete Bedeutung bei der Modellierung des Abflusses und der Wasserbilanz hat, allerdings ist die Wahl des Downscaling-Ansatzes für alle räumlichen Variablen wie Bodenfeuchte und Evapotranspiration maßgeblich. In einem nächsten Schritt wurden die Auswirkungen des Klimawandels auf die Bodenfeuchte unter Anwendung von drei verschiedenen Downscaling-Ansätzen und den zwei RCMs für den Szenariozeitraum 2070-2100 simuliert. In Ergänzung zu den SD- und DU-Ansätzen, wurde der sehr oft verwendete *Delta-Change*-Ansatz verwendet, der die Klimadaten des Referenzzeitraumes mit Hilfe des Klimawandel-Signals des Szenariozeitraums skaliert. Daher war eine Analyse der Unsicherheiten für den *Delta-Change*-Ansatz nicht notwendig. Der gleichzeitige Einsatz von verschiedenen Downscaling-Ansätzen bei Untersuchungen zu den Auswirkungen des Klimawandels auf die Bodenfeuchte im Gebirge wurde so erstmalig durchgeführt. Es zeigte sich, dass die Wahl des Downscaling-Ansatzes sehr viel größere Auswirkungen auf die Modellergebnisse hat, als das verwendete RCM. Dieses Ergebnis stellt die Modellergebisse anderer Studien in Frage, die ausschließlich auf einem Downscaling-Ansatz beruhen, oder die die große Bedeutung der RCMs heraus stellten. Grund hierfür mag die häufige Beschränkung auf eine Zielvariable, zumeist den Abfluss sein. Inhaltlich zeigte sich bei der Analyse der Auswirkungen des Klimawandels auf die Hydrologie eine große Übereinstimmung mit vorangegangenen Studien. Hinsichtlich der Bodenfeuchte ergänzt die vorliegende Studie durch ihre hohe räumliche und zeitliche Auflösung der prognostizierten Bodenfeuchtedaten vorangegangene Untersuchungen von Jasper et al. (2004, 2006), indem sie ortsgenaue Daten zur Abnahme der Bodenfeuchte und Trockenstress auf der Einzugsgebietsskala liefert. Das gemeinsame Ergebnis der sechs Modell-Ansätze (kombiniert aus zwei RCMs und drei Downscaling-Ansätzen) zeigt, dass die waldbestandenen Gebiete unter 1800m ü.d.M. am stärksten vom Klimawandel in den Jahren 2070-2100 (+/-10Vol-%) betroffen sein werden. Die Streuung der Ergebnisse der sechs Modellrechnungen ist allerdings sehr hoch. So decken die Ergebnisse eine Bandbreite ab, die von zukünftig nahezu unveränderten Bedingungen der Bodenfeuchte bis zu einer starken Ausdehnung des Trockenstresses reichen. Zusätzlich wurden die Unsicherheiten des angewandten hydrologischen Modells und den Downscaling-Ansätzen verwendet, um die Ergebnisse einordnen zu können. Die aufsummierten

Unsicherheiten (+/-10Vol-%) entsprechen den durchschnittlich zu erwartenden Abnahmen der Bodenfeuchte (-10Vol-%). Die Ergebnisse müssen daher vorsichtig interpretiert werden. Probabilistische Vorhersagesysteme mit mehreren hundert Modellläufen könnten gegebenenfalls in weiteren Studien die beobachtete Tendenz einer abnehmenden Bodenfeuchte weiter bestätigen.

Summary

Mountains are expected to respond sensitive to climate change. Thus, sound climate change impact assessment studies focusing on mountain areas are strongly needed to estimate changes and to develop adaptation strategies. Nowadays, climate change impact assessment studies (CCIAS) are a common approach and many publications on hydrological responses to climate change have been published. Nonetheless, CCIAS focusing on soil moisture are widely missing especially at the catchment scale; even more, as to our knowledge there are only two studies on mountain soil moisture at a coarse scale. The wide neglect of soil moisture in climate change impact assessment studies contrasts the key role of soil moisture in ecosystems. This clearly shows the strong demand for CCIAS on mountain soil moisture. In this study, a commonly used CCIAS approach was used, comprising (1) of a physically based model that was calibrated and validated under recent climate conditions, (2) that was driven by downscaled regional climate models (RCMs) for a reference and a future scenario climate conditions. A major challenge in CCIAS is the propagation of uncertainties that questions the model results. In this study a special focus is set on the structural uncertainties originating from the use of downscaling approaches and climate models. Therefore, an analytic framework was developed based on the both concepts of uncertainty propagation and the uncertainty cascade. The concept comprehensively summarizes all uncertainties occurring in climate change impact assessment studies and illustrates how the uncertainties propagate. We conducted the CCIAS in a mountain catchment (160 km²) in the Swiss Alps at a high spatial resolution (50m). At first, the frequently used, physically based, distributed hydrological model was successfully applied to the catchment for recent years (2001-2007) to provide a sound calibration and validation. The potentials and the limitations of WaSiM-ETH to simulate soil moisture dynamics and patterns were shown by comparing model results with extensive soil moisture measurements at an hourly time step. While WaSiM-ETH was able to reproduce discharge with a high accuracy (R^2 = 0.95, ME = 0.8, IoA = 0.95), the simulation of soil moisture for different altitudes and land use types is partly limited, since the model was unable to model the total variability of the soil moisture dynamic, but tended to mean values. An adjusted RMSE of 8.0 Vol-% that takes the intra-plot variability into account was calculated for soil moisture. A necessary prerequisite is the validation of the ability of the downscaled RCM data to drive the hydrological model in such that the hydrological processes are reproduced. A comparative study was

conducted based on two common downscaling approaches (statistical downscaling (SD) and direct use (DU)) and two RCMs (CHRM, REMO). Uncertainties were found to be unsteadily distributed, both in terms of variables and time. The “one” model approach that shows least uncertainty for all kinds of hydrological variables like discharge, actual evapotranspiration, and soil moisture was not found. This finding adds considerable value to the scientific discussion, since most previous studies focus on one variable or one downscaling approach alone. In addition, we evaluated the spatial uncertainties of soil moisture and evapotranspiration. We showed that the choice of downscaling approaches is of circumstantial relevance for discharge and water balance, while for all spatial variables, we found SD approaches to perform better than DU approaches. Next, we simulated the impact of climate change on mountain soil moisture by applying three different downscaling approaches and two RCMs. In addition to the SD and DU-models, the very popular delta change approach (Δ) was applied that scales the climate observation by adding the climate signal. Therefore, uncertainty assessment for the Δ-approach was not necessary. The use of multiple downscaling techniques in an ensemble forecast is new for soil moisture impact studies. The study proved the partly superior role of downscaling approaches when focusing on the impact *per se* under future climate and thereby contrasting findings of recent publications. Moreover, it questions results from studies that are based on one downscaling approach alone. The study provided detailed data on climate change impact on the hydrology of the catchment that are completely in line with previous findings. The high spatio-temporal resolution of the study add value to previous mountain soil moisture studies of Jasper et al. (2004, 2006) by providing site specific data on soil moisture decrease and drought stress potential at the catchment scale. The consensus of six models driven by two threefold downscaled RCM reveals the forested areas below 1800 m a.s.l. to be most affected by climate change in 2070-2100 (-10 vol-%). The variability of the results from the six ensembles were remarkably high, offering a bandwidth of possibilities from nearly unchanged soil moisture conditions to strong expansion of drought stress in the future. In addition we found uncertainties from the applied hydrological model and downscaling approaches in the magnitude of the predicted changes (+/- 10 vol-%). Therefore, the results have to be interpreted carefully. Probabilistic forecasting with several hundred model runs might confirm the found tendency of soil moisture decrease in future studies.

1. Introduction

1.1 Recent research needs

Climate change is expected to cause profound environmental changes with respect to sea level rise (Gornitz et al. 1995; Radic and Hock 2011), permafrost melting (Lawrence and Slater, 2005), animal ranges (Walther et al. 2002), vegetation productivity (Nemani et al. 2003, Cramer et al. 2001), plant species distribution (Walther et al. 2005; Theurillat and Guisan 2001), and terrestic hydrological processes (Bates et al. 2008).

In current climate change research ecosystems that are expected to respond most sensitively to climate change like coastlines, polar regions, and mountains are of major interest. For the European Alps, IPCC (2007) and the PRUDENCE ensemble project (Christensen et al. 2002) estimated an increase of up to 5°C annual temperature with up to 9°C in the summer months by 2070-2100 under the IPCC A2-scenario (Räisänen et al. 2004). Simultaneously, precipitation is expected to decrease slightly over the year (-20%) showing an enhanced decrease during summer (-50%, Räisänen et al. 2004). IN this context, mountains are a highly important part of the earth cover 27% of the world surface (Ives et al. 1997; Viviroli et al. 2003), they provide 10% of the world`s ecosystem services (Price 1995), and 50% of the world`s population depend on the essential surplus of water from mountains (Viviroli et al. 2007). Hence, mountains were called the water towers of the world (e.g. Mountain Agenda, 1998).

Mountains are assumed to respond sensitively to climate change since wide ranges of climate zones occur at a very small horizontal extend. Moreover, the zero-degree-temperature-line being a major threshold in biological and physical processes is present in all mountain ranges of the world (Viviroli et al. 2011). A shift of this line under climate change will likely cause major biological and physical responses in wide areas. Hence, mountains are expected to face multiple challenges: changes in vegetation range and species composition, as well as extinction of species are likely effects of rising temperatures and shifts in variability of precipitation (Price 2008; Schöb et al. 2009; Kreyling et al. 2010). Global warming may further affect the glacial and periglacial areas of the mountains. Most likely consequences are the retreat of glaciers and permafrost, eventually promoting rock instability and increased debris flows (Kääb 2008; Harris et al. 2009).

In terms of hydrospheric responses, a potential effect of climate change is the acceleration of the hydrological cycle (Beniston et al. 1997; Beniston 2003) with a higher proportion of liquid to solid precipitation and enhanced evapotranspiration, as well as snow and glacier melting that is equivalent to a cutback of water storages and storage times. This enhancement in turn will likely cause changes in the discharge regime towards higher winter discharge, earlier snow melt floods, decreasing mean annual discharge (Etchevers et al. 2001; Middelkoop et al. 2001; Horton et al. 2006), as well as glaciers shrinkages (Zemp et al. 2006, Paul et al. 2007). As a result, drastic effects on socio-economic systems are expected (Koenig and Abegg 1997; Breiling and Charmanza 1999).

In 1998, Wigley showed that even under the consideration of an unlikely post-Kyoto emisson reduction, climate change is still likely to occur (Wigley 1998). Thus, the development of mitigation and adaptation strategies is regarded as reasonable response to ecosystem changes (IPCC 2001, Smit and Wandel 2006). Feenstra et al. (1998) pointed out that it is essential to assess the severity of climate change impact to develop strategies that modify or prevent these impacts. Hence, robust climate change impact assessment studies (CCIAS) are needed, to assess the vulnerability of given system and to develop reliable adaptation strategies.

According to Feenstra et al. (1998), climate change impact assessment studies can be conducted using five different approaches:

(1) analyzing historic climate changes and their impacts on socio- and ecosystems;

(2) analyzing climatic events (like the year 2003) that might be analogous to future climate conditions;

(3) analyzing present day impacts of climate and climate variability;

(4) analyzing climate change impacts by applying physically-based models

(5) using expert judgment

In terms of climate change impact assessment studies focusing on hydrological issues, physically-based models are most frequently used. Mountain areas are however rarely the target. Analyzing the publication numbers of climate change impact assessment studies in mountain areas in specific, the results clearly show four groups of similar proportion: biosphere, cryosphere, anthroposphere, and hydrosphere (Figure 1). In terms of mountain hydrology, discharge is by far the best investigated variable, while evapotranspiration and soil moisture studies are very few. In addition to this coarse analysis, a much more detailed analysis of recent literature was conducted to elucidate research needs and demands from the state-of-the-art research.

Several climate change impact studies have been conducted to assess the effects of climate change on mountain catchments. They found a strong impact of climate change on glacier and snow melt and thereby on discharge dynamics: Zierl and Bugmann (2005) analyzed five different mountain catchments in different parts of the European Alps and found overall discharge regime shifts with increased winter runoff, decreasing summer discharge and earlier snow melt, especially in snow dominated catchments. These findings are in line with earlier studies of Etchevers et al. (2002) in the Rhône catchment, Middelkopp et al. (2001) in the Rhine catchment, Horton et al. (2006) for 12 minor catchments in Switzerland, and Shinohara et al. (2009) for the Japanese Hida mountain chain. Due to the very similar results from different studies at multiple scales, the impact of climate change on discharge in snow and glacier dominated catchments can be considered as largely understood.

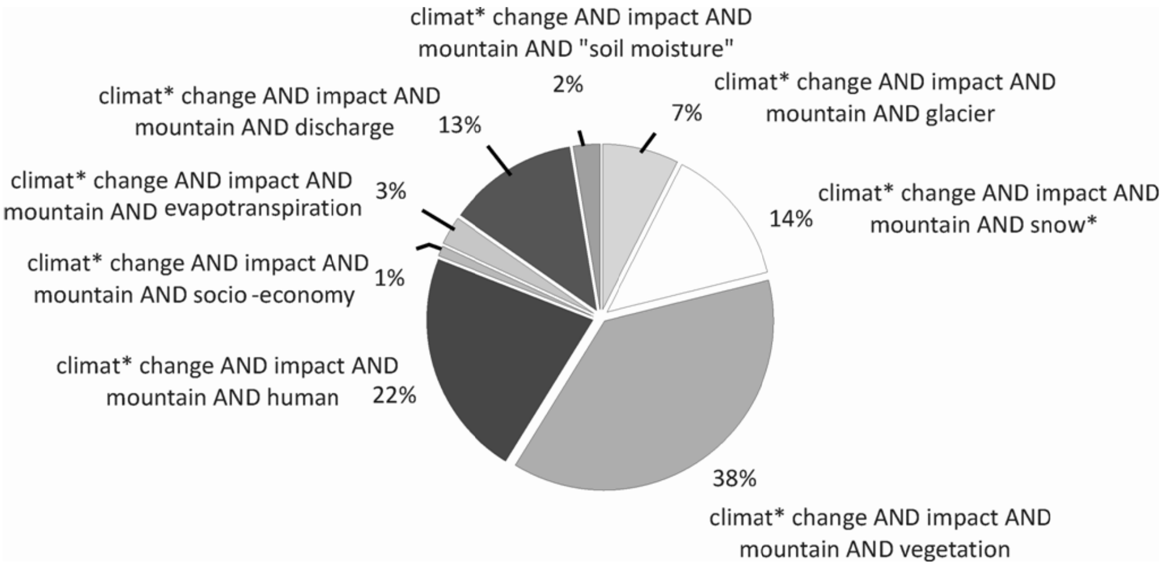


Figure 1: Proportion of publication focusing on climate change impact assessment studies in mountains (data source: ISI Web of Knowledge).

Research on climate change impact assessment on the non-cryospheric water like evapotranspiration and soil moisture in mountains are far less conducted or at least published (Figure 1). Calanca et al. (2006) conducted a study on summer evapotranspiration in the Swiss Alps and found decreasing actual evapotranspiration at lower elevation and in the inner-alpine region and increasing actual evapotranspiration at higher elevation and at the southern rim of the Alps.

Studies addressing soil moisture response under climate change impact are also few. Some studies examined climate change impact on soil moisture in the frame of a water balance analysis: Etchevers et al. (2001) analyzed the overall effect on soil moisture in the Rhône catchment. Especially in the American scientific community, soil moisture changes have been studied in climate change impact assessment studies at coarse scales (e.g. Wood et al. 2004, Hamlet et al. 2006). Calanca (2004) used a stochastic model to analyze the major determinants of soil moisture in order to interpret the results in terms of climate change. They found a strong dependency of soil moisture towards the variability of storm arrivals and stated that a future change in the climate variability as illustrated by Schär et al. (2004) will have a major impact. At the same time, Jasper et al. (2004) published a comprehensive climate change impact assessment study on soil moisture for two catchments in Switzerland and found a reduction of soil water availability.

Later Jasper et al. (2006) conducted a spatially explicit analysis of climate change impact on soil moisture They used a 1km x 1km spatial resolution in a pre-alpine valley and stressed the importance of slope and land use besides the already known determinates temperature and precipitation. To the author’s knowledge, this was the first spatial explicit climate change impact assessment analysis in a predominantly mountainous area. The reciprocal influence of these two climate variables was estimated by Yang et al. (2009) for soils in the Taihang Mountains in China. They conducted a sensitivity analysis of possible future climate conditions and showed that an increase of precipitation by 20% can partly balance the loss of soil water caused by increased evapotranspiration.

In the author’s view, only Jasper et al. (2004) and Jasper et al. (2006) provided mountain soil moisture scenarios that go beyond the very general result of soil water depletion in former studies. These studies may enable adaptation strategies at regional scales. It should be noted that spatially-explicit climate change impact assessment studies on soil moisture exist (Naden and Watts 2001; Bronstert et al. 2007). They are however restricted to coarse scales in lowland areas. Nevertheless, a high research deficit is obvious in terms of mountain hydrology that goes beyond analysis of discharge. This conclusion was also reached by a very recent review (Viviroli et al. 2011) on mountain hydrology and climate change. In this review the relevance of detailed regional studies was emphasized.

➔ **Research need I: Application of climate change impact assessment studies on hydrology at a regional level , especially in terms of soil moisture**

The wide neglect of soil moisture in climate change impact assessment studies contrasts the key role of soil moisture in ecosystems for it determines primary production of plants, controls matter flows and affects insect as well as soil organism reproduction (Rodriguez-Iturbe, 2000). It further influences the micro-climate, erosion, and soil development (Legates et al. 2011). Moreover, soil moisture is an indicator for the amount of water supply to an ecosystem since it integrates the spatially dynamic processes precipitation, evapotranspiration, and runoff. The nonlinear response of soil moisture to variables like soil properties (especially the extreme variability in skeleton fraction), topography and climate, causes highly variable soil moisture, temporally and spatially. Very extreme and complex variability occurs in high mountains, where variability of topography occurs at fine spatial scales (Gurtz et al. 1999) leading to fine-scale variability in snow distribution (Singh and Singh, 2001; Anderton et al. 2002), temperature (Pape and Löffler 2004; Löffler et al. 2006), evapotranspiration (Barry 2008; Emanuel et al. 2010), and vegetation composition (Gjærevoll 1956; Löffler 2005). In order to characterize alpine ecosystems in terms of water balance, all these spatio-temporal patterns need to be taken into account.

Comprehensive research has been conducted in high mountains to investigate soil moisture dynamics, especially in combination with plant-water interactions (for a review see Körner 2003). By contrast, investigations that focus on the emergence of spatio-temporal patterns in soil moisture and underlying drivers in mountains are very few (but see Löffler 2005; Löffler et al. 2006). A major obstacle in analyzing the spatial distribution and temporal dynamics of soil moisture is the limited possibility for spatial monitoring of soil moisture. Robinson et al. (2008) and Tobb et al. (2003) gave a very comprehensive review about possibilities of soil moisture measurements. Direct measurement methods are restricted to the point scale (e.g. TDR); spatial monitoring designs based on point measurements as applied by Western and Grayson (2000) are costly and time consuming. A great advantage of TDR/FDR measurements is their robustness towards suboptimal measurement conditions like high proportion of skeleton fraction as shown by Schmid and Löffler (2008). Small scale 2D-measurement techniques using geo-electric methods (Rings et al. 2006) are promising but limited to a small area. Indirect spatial measurements of soil moisture using radar remote sensing (SAR images, ERS-2, < 1 km) are available but improved process understanding and algorithms are needed to enable the use of these data in the future (Wagner et al. 2007). Moreover, radar images are only able to assess the first few centimeters of soil moisture (Robinson et al. 2008), which is uninteresting for most hydrological studies. Strong limitations of those techniques occur in mountain areas due to scatter effects due to complex topography (Lillesand and Kiefer 2003).

Due to these restrictions and the complexity of high mountain ecosystems, process-based hydrological modeling provides a possibility to characterize soil moisture patterns at the catchment scale (Gurtz et al. 2003; Jasper et al. 2004). Still, the sound application of hydrological models to simulate soil moisture with adequate accuracy in highly variable and complex areas like mountains remains challenging. Uncertainties arise from the simplifying character of all hydrological models, model choice, parameter settings (Beven 2005) and from uncertainties of measured values due to the spatial variability of parameters (Lenhart et al. 2002). A further drawback is related to insufficient process understanding leading to inadequate algorithms (Beven 2005). These uncertainties and shortcomings have to be taken into account when applying process-based hydrological models.

Hydrological models are mainly calibrated and validated using measured runoff. However, since runoff processes do not reveal much insight into internal processes (Grayson et al. 1992a; Grayson et al. 1992b), soil moisture simulations need to be additionally validated. Therefore, extensive soil moisture data need to be recorded. However, very few data sets exist, especially for mountain areas. Viviroli et al. (2011) put emphasis on this fact in terms of climate station data. This problem is even more pressing for soil moisture data or even longer time series of soil moisture. Moreover, extensive spatial data and careful consideration of all input variables such as meteorological data, topography, soil property and land cover are needed to enable a correct simulation (Gurtz et al. 1999).

➔ **Research need II: Provision of extensive data to enable a sound calibration and validation of hydrological models**

WaSiM-ETH (Schulla and Jasper, 2007) is a frequently used physically-based, distributed hydrological model that was originally developed to simulate the water balance in the low mountain range of Germany. Later it was adapted to Swiss pre-alpine catchments and successfully transferred to several high mountain catchments (Middelkoop et al. 2001; Gurtz et al. 2003; Verbunt et al. 2003; Jasper et al. 2004, 2006). The model was further applied to a pre-alpine catchment to simulate the effects of climate change on soil moisture at the catchment scale by Jasper et al. (2004, 2006). They validated the model with data from a single lysimeter site, but proved the ability of the model to represent soil moisture dynamics like Gurtz et al. (2003). Nevertheless, a sound validation of the model to represent soil moisture dynamics at several plots need to be conducted to evaluate the uncertainties or biases introduced by the hydrological model. Moreover, a sensitivity analysis of WaSiM-ETH for high mountain catchments remains to be implemented.

➔ **Research need III: Evaluation of the potential and limitation of WaSiM-ETH to model mountain soil moisture dynamics and patterns**

To quantify the magnitude of climate change impacts, physically-based models driven by global climate models (GCMs) are regarded as one standard approach (cp. Feenstra et al. 1998; Leavesley 1999). Nevertheless, the major challenge of this approach is to bridge the gap between the spatial resolution of GCM outputs and the input data required by the hydrological models. For hydrological modeling, point data from meteorological stations are generally required (Xu 1999; Fowler et al. 2007). The bridging is basically performed by one of three different approaches: dynamical downscaling, statistical downscaling or delta change approach. Moreover, combinations of dynamic and statistical methods have just recently been proven to add great value (Segui et al. 2010). In the last two decades, several review papers on downscaling approaches have been published (cp. Hewitson and Crane 1996; Wilby and Wigley 1997; Xu 1999; Fowler et al. 2007; Maraun et al. 2010). The overall statement of the review is that the choice of downscaling approach and climate model remains a crucial step in all climate change impact assessment studies; the ability of the downscaling techniques to represent observed processes have to be evaluated (Wood et al. 2004). Although it is a necessary pre-requisite, this evaluation is sometimes missing. Thus, studies comparing different models and downscaling approaches that evaluate the model performance to represent hydrological processes are of great importance.

Today, most climate change impact assessment studies apply different climate models (mostly GCMs) and/or different emission scenarios that are downscaled to the model scale using one downscaling approach that appears to be the most suitable. Although comparative downscaling studies are common today (Fowler et al. 2007), only a few articles have addressed the impact of different downscaling approaches *per se*, and even fewer studies focus on hydrological issues (Fowler and Wilby 2007), but see Graham et al. (2007) and Lenderink et al. (2007) who focus on discharge. Especially the latter nicely showed the considerable impact of the chosen downscaling approach on the model results. Thus, instead of validating the quality of the target variable (e.g., water discharge, evapotranspiration, soil moisture), most downscaling studies assess the quality of downscaled climate values by comparing averaged model outputs. In this way, the spatial and/or temporal averages of climate model outputs are compared to observed values (Bronstert et al. 2007). Due to the non-linear processes in a hydrological system, the analysis of climatic factors alone is insufficient to fully describe hydrological systems.

➔ **Research need IV: Application of different downscaling approaches in climate change impact assessment studies focusing on reproducing hydrological target variables.**

To evaluate future behavior of hydrological systems using climate scenarios, the uncertainties of model results should not be ignored (Pappenberger and Beven 2006). In climate change impact assessment studies, possible uncertainties originate from a variety of sources: the underlying GCM, the structure and the parameters of the climate model, the downscaling method, the structure and the parameters of the hydrological model, as well as from all underlying structural data (e.g., topography and soil maps). A theoretical concept that incorporates all these sources of uncertainties for the use in climate change impact assessment studies is missing. Moreover, a major task remains the evaluation of these uncertainties to enable modelers to choose the best methodology and to advise decision makers on the basis of profound scenario quantifications under the consideration of uncertainties.

The assessment of parameter uncertainties of a single model is fairly common (e.g., Beven, 1993). In climate change impact assessment studies focusing on hydrology, very little research has been done to evaluate the uncertainties related to the use of different downscaling approaches and different climate models (see also Buytaert et al. 2010). Recently, Segui et al. (2010) presented a comprehensive work on discharge uncertainties related to downscaling approaches in southern France. They found distinct geographical and seasonal patterns of uncertainty with respect to the applied downscaling method. We agree with the authors that further studies are needed to evaluate these spatio-temporal uncertainties. Otherwise the outcomes of future impact assessment studies will be interpreted without appropriate context.

➔ **Research need V: Assessment of spatio-temporal uncertainties with respect to different downscaling approaches**

➔ **Research need VI: Development of a theoretical concept that incorporates the manifold sources of uncertainties in climate change impact assessment studies**

Earlier, a conclusion from the literature review revealed climate change impact assessment studies at a high spatial and temporal resolution to be urgently needed to develop mitigation and adaption strategies, especially for inhabited areas. In particular at the watershed scale, adaptation strategies are readily viable (Viviroli et al. 2011). Downscaled global circulation models (GCMs) are unable to reproduce this small-scale variability adequately (e.g. Calanca et al. 2006). Hence, several studies (Jasper et al. 2004; Segui et al. 2010) started to combine different regional climate models (RCMs) with downscaling approaches to meet the apparent scale mismatch between the driving climate model and the catchment scale.

Great uncertainties in climate change impact assessment studies arise from the choice of climate model, emission scenario, and downscaling approach (e.g., Wood et al. 2004; Jasper et al. 2004, Graham et al. 2007). Bates and Granger (1969) introduced ensemble forecasting to meet these challenges. Under the assumption that each model is unbiased, the ensemble forecasting method produces lower mean errors than single models. Subsequently, forecast ensembles are commonly used in climate change studies in climatology (Stott and Forest 2007), land use change (Viney et al. 2009), and hydrology (e.g., Christensen and Lettenmaier 2007). Ajauro and New (2007) published a comprehensive review on the different ensemble forecast methods and the overall combining approaches. Up to date, many studies simulate ensembles based on different climate models or emission scenarios (Horton et al. 2006, Jasper et al. 2004). More recently, especially in hydrological studies, the combination of different hydrological models and different climate model data resulted in very comprehensive studies (Christensen and Lettenmaier 2007). Less focus has been laid on the combination of different downscaling approaches with different climate models to drive the hydrological model in an ensemble forecast approach.

➔ **Research need VII: Ensemble forecasting with downscaling and climate models focusing on mountain soil moisture**

In a study on future mountain soil moisture in Switzerland, Jasper et al. (2006) found a drastic reduction of soil water in areas already affected by periodic drought stress. In the European Alps, leeward side effects lead to continental dry areas in humid temperate mountains, for example the inner-alpine region of the Alps (cp. Frei and Schär 1998). Already today sporadic drought is common, resulting in drought stress among coniferous trees in the inner-alpine region (Rebetez and Dobbertin 2004). Drought stress may create considerable challenges for forest management as it may for example weaken avalanche protection forests (Schneebeli and Bebi 2004, Teich and Bebi 2009). A further expansion of drought stress may thus lead to far-reaching and costly consequences, demanding sound climate change impact assessment studies, especially in the transition zone between dry and moist areas. Catchments within this transition zone therefore seem of great scientific interest. In addition, the European Alps are regarded as best monitored mountain range (Viviroli et al. 2011), enabling the most favorable data set for such studies. Therefore, catchments located between the dry inner-alpine and the rainy northern rim of the Alps are regarded as most favorable for this study area.

1.2 Objectives and outline

Table 1: Research needs, approaches, and aims.

	Research needs	Approaches	Aims
I	climate change impact assessment studies on hydrology at the catchement scale, especially in terms of soil moisture	application of a hydrological model driven by climate data for reference and scenario conditions	to simulate future mountain soil moisture at the catchment scale
II	extensive data to enable a sound calibration and validation of hydrological models	measurement of soil moisture along altitudinal and land cover gradients	to enable the calibration and validation of the applied hydrological model
III	evaluation of the potentials and limitation of WaSiM-ETH to model mountain soil moisture dynamics and patters	validation of simulated soil moisture and sensitivity analysis	to test the models ability to simulate mountain soil moisture and to assess teh uncertainties
IV	application of different downscaling approaches in climate change impact assessment studies focusing on reproducing hydrological target	two common downscaling approches were applied and evaluated as to the reproducation performance	evaluation of uncertainties origin from downscaling approaches
V	spatio-temporal uncertainty assessment with respect to different downscaling approaches	comparison of spatial and temporal data of models driven by downscaled data with a reference	the spatio-temporal evaluation of uncertainties
VI	a theoretical concept that incorporates the manifold sources of uncertainties in climate change impact assessment stud	development of a theoretical concept	to develop an analytic framework
VII	ensemble forecast with downscaling and climate models focusing on mountain soil moisture	two RCM were downscaled using three most common downscaling approaches and model consensus were analyed	to simulate future soil moisture

The derived research needs were targeted within this thesis by addressing research approaches and aims (Table 1). As a basic precondition, extensive soil moisture measurements were conducted to derive basic spatial soil moisture patterns and to provide validation data for the hydrological model. Second, a state-of-the-art hydrological model was applied and validated with the extensive soil moisture measurements. This hydrological model was used to simulate the hydrological processes in general and the soil moisture pattern in specific. Moreover, a sensitivity analysis was conducted to understand the major dependencies of simulated soil moisture, as well as to assess the origin of possible model uncertainties. Thus, an extensively evaluated hydrological model was obtained and used in the following studies.

Next, we aimed to assess the impact of different downscaling approaches and different climate models on the model performance to reproduce hydrological processes. Uncertainties were comprehensively derived, both spatially and temporally. Therefore, we compared the results of the calibrated hydrological model WaSiM-ETH based on observations alone (reference model) with the results of the unchanged hydrological model that was driven by two regional climate models (RCMs) and two downscaling approaches (statistical downscaling and direct use). Furthermore, a methodological concept was developed to allocate the observed uncertainties in the modeling process and to provide an analytic framework for further studies. At last, an ensemble forecast based on the hydrological model, three different downscaling approaches (statistical downscaling, direct use, and delta change) and two RCMs was conducted. The impact of the different approaches was analyzed and consensus as well as variability of future soil moisture conditions calculated. These results were finally discussed against the background of the comprehensive uncertainty analysis.

2. Theory on uncertainty propagation

In addition to the major challenge of how to “bridge the gap” between the spatial resolution of a GCM output and the input data required by the hydrological model, a second difficulty emerges from coupling the climate and the hydrological model: the propagation of uncertainty. Many authors have described the effect of uncertain GCM data being downscaled with uncertainties, and these data are further incorporated into uncertain hydrological models (e.g., Pappenberger and Beven 2006; Buyaert et al. 2010; Segui et al. 2010). Brown and Heuvelink (2005) developed a theoretical sketch to illustrate the uncertainty propagation in hydrological models, which also comprises the linkage with uncertainties in the observed data. They emphasized the fact that uncertain model parameters are fitted against uncertain observations by inverse modeling and, thereby, are seemingly improved. However, because observations are themselves uncertain, Heuvelink and Pebesma (1999) stated that deviation of model outputs from observations cannot simply be ascribed to model uncertainties alone. The uncertainty of the model parameters, themselves, can be assessed by statistical methods (Beven, 2001; Beven 2009). Hölzel (2010) extended the sketch in terms of inherent model specifications of uncertainties, such as spatial and temporal discretization, the numerical solution of the model, the choice of model configuration (Addiscott et al. 1995), and external sources of model uncertainties, like initial boundary conditions or data preparation (Beven, 2001). We combined this comprehensive sketch (Figure 2) with the idea of the uncertainty cascade (e.g., Pappenberger and Beven 2006). In most hydrological impact assessment studies, hydrological models are calibrated with observed data and produce uncertain model outputs, as described above. Subsequently, uncertain climate model outputs are generally downscaled to the resolution of the hydrological model and serve as uncertain input data for hydrological model. Depending on the climate model and the downscaling approach applied, different uncertainties for hydrological model inputs will occur. The uncertain hydrological model outputs of each model run are then compared with observations and with uncertain output results based on observations. Thus, deviations between model outputs resulting either from climate model data or model outputs from models driven by observations can be regarded as the uncertainties that originate from the climate model and downscaling approaches, respectively. These uncertainties can be regarded as epistemic uncertainties in the sense of Beven (2009:24) because they are non-random factors but are also structural settings. The presented approach is a rather coarse estimation of the total uncertainties, as it is not able to determine to uncertainties of single models, parameters, or settings.

Nevertheless, it is still promising to evaluate parts of the uncertainty cascade, as described above. In this study, the focus is set on the uncertainties originating from the downscaling approach and therefore on the epistemic uncertainties. Figure 2 presents a comprehensive description of the approach of our study, the challenges that are faced, and to provide an analytic framework for existing and future studies.

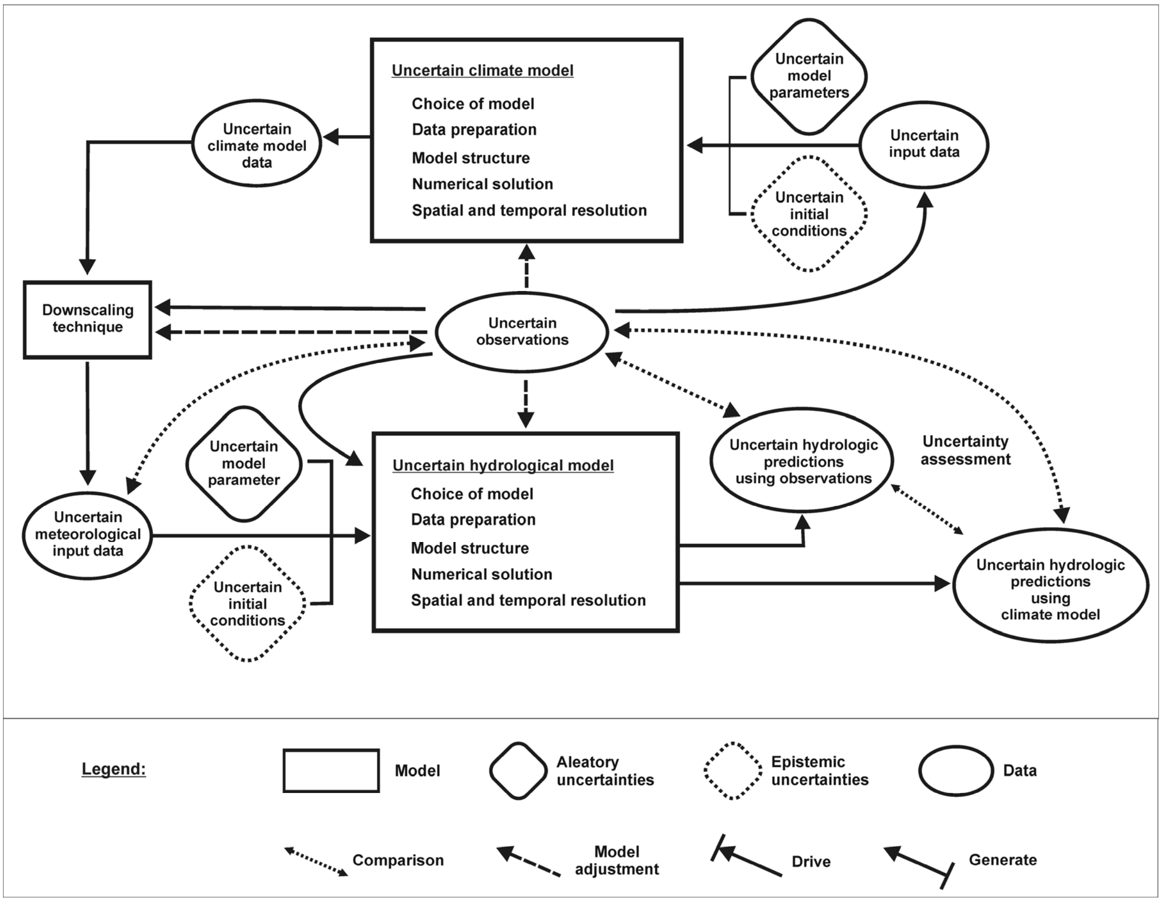


Figure 2: Uncertainty propagation by coupling hydrological and climate models with downscaling techniques. Hydrological models are driven by uncertain observations and further affected by several model internal uncertainties like model structure, numerical solution, etc., as well as external uncertainties like initial conditions (e.g., soil moisture) and model parameters (e.g., LAI). Hence, hydrological predictions are uncertain but compared with uncertain observations to seemingly improve the hydrological model (cp. Brown and Heuvelink, 2005; Hölzel 2010). By coupling climate models with hydrological models uncertainties increase: Uncertain climate models affected by the same uncertainties as hydrological models generate climate data that are used in downscaling techniques to produce meteorological input data for the hydrological model. Because uncertain climate model data are validated and calibrated against uncertain observations, resulting meteorological data are uncertain as well. Hydrological predictions of the coupled models are consequently uncertain and the magnitude of these predictions as well as the origin can be approximately assessed by comparing the different hydrological predictions with observation.

3. Study Area


Picture 1. Impressions from the study area, illustrating the main valley and the official discharge gauge at Blatten during low flow in late autumn (October 30th, 2007).

This study was conducted in the partly glaciated (18.3%) Lötschen valley in the Bernese Alps, central Switzerland (46°25' N, 7°50' E, Figure 3). The valley (160 km²) is drained by the river Lonza, which runs into the Rhône, and is characterized by a glacio-nival discharge regime (Aschwanden and Weingärtner 1985). The valley can be subdivided into the wider, mainly cultivated valley where all settlements are situated (hereafter called main valley), and a steeper gorge-like part in the south (hereafter called south gorge). The elevation of the valley floor ranges from 600 m a.s.l. at the outflow to 1400 m a.s.l. The highest peaks reach nearly 4000 m (Bietschhorn 3934 m a.s.l.). The climate is characterized by an annual mean temperature of 4.9 °C and 1120 mm precipitation at 1480 m a.s.l. (meteorological station 1974-1998 *Ried,* Börst 2005). On average, 42% of precipitation is in the form of snowfall (Schmidt et al. 2009). The valley is situated in the transition zone between the very warm and dry inner alpine Rhône valley and the coldest and most rainy area at the Jungfrau massif. The only discharge gauge in situated in the centre of the valley at Blatten (white triangle right). Mean annual discharge (Ø 4.6 m³/d) is measured at the center of the valley, where 36.5% of the corresponding catchment is glaciated (FOEN 2010). Picture 1 (right) shows the v-shaped profile of the gauge at low flow during late autumn. The vegetation of the valley stretches across several altitudinal vegetation belts, ranging from deciduous forests to sub-alpine coniferous forests to alpine meadows, nival debris, rocks and areas of little vegetation (Figure 3, right). The forests in the region have been partially replaced by meadows, pastures and settlements.

Table 2 summarizes the main proportion of major land cover and topographical features. The soil consists predominantly of thin, skeleton-rich soil layers of loamy-silt texture originating from glacial till. Many meadows in the valley have been irrigated for centuries by glacial melt water (glacier milk). This has generated a silt-dominated, skeleton-free topsoil layer (silt in Figure 7, left). The parent rock material is mainly gneiss and granite, while calcareous rock material is scarce (Hügi et al. 1988).

Table 2: The main characteristics of the investigated catchment Lötschen valley.

	[km²]	[%]
total size	166.6	100
glacier	29.5	17.7
rock	39.8	23.9
debris	22.3	13.3
coniferous forest	26	15.7
mixed forest	1.5	<0.1
alpine heath	12.5	7.5
shrub	3.3	1.9
settlement	0.6	0.4
arable	0.1	<0.1
mire	2	0.1
grassland	29	17.4
deciduous	1.5	1.4
water	0.15	<0.1
elevational range	600 - 3958 m a.s.l.	
mean altitude	2345 m a.s.l.	
mean slope angle		
south-facing	35 °	
north-facing	28 °	

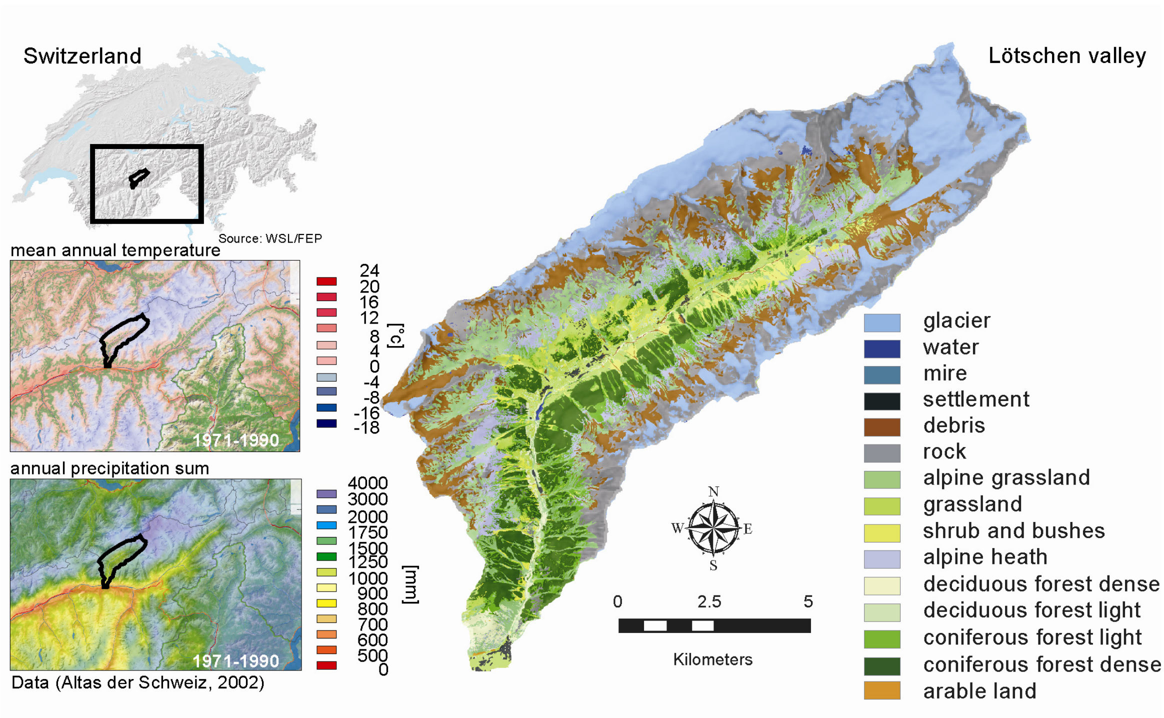


Figure 3: Location of the investigated catchment Lötschen valley, Bernese Alps, Switzerland (top left), and land cover map (right) of the 160 km² Lonza catchment (derived from Hörsch 2001 and GEOSTAT 2002), and its location in the transition zone between dry inner alpine and the very rainy northern rim.

4. Methods

4.1 Research design

To meet the research need and to address the aims, a research design was set up that incorporates all analytics. Figure 4, comprehensively illustrates the research design that is based on five different steps as indicated by the differently colored puzzles. At first, the performance of the hydrological model was calibrated and validated using extensive soil moisture and discharge data from 2001-2007 at hourly resolution (blue puzzle). Deviations are regarded as uncertainties origin from the hydrological model (here WaSiM-ETH). At second (green puzzle), the calibrated hydrological model was transferred to the reference time period 1960-1990 with daily resolution and driven by observations as well as by data from two RCMs that are downscaling using two different approaches (SD: statistical downscaling, DU: directly used). The results of the last four models are compared (curved arrows) with the model driven by observation and uncertainties originating from the downscaling approach are derived (grey thick arrow). At third (red puzzle), the hydrological model is driven by two RCM under future scenario conditions (2070-2100) that was downscale using three different downscaling approaches. The configuration of the SD model concord with the Sd model under reference conditions. Besides SD and DU methods we applied the delta change approach (Δ) that is most prominent in literature. Since Δ simply scales the observations of the reference period in terms of climate change signal, the results of the Δ-model are compared with the reference model. In turn, no downscaling uncertainties arise. SD and DU models are compared with the according SD and DU model results. At this stage, the changes caused by climate change on the model results are obtained (orange puzzle). Finally, future changes according to the model results are synthesized (purple puzzle) by (a) analyzed in terms of a model consensus, and (b) they are compared with the results of the uncertainty analysis, both of downscaling approach and hydrological model. Furthermore, the latter can be summed up in a model consensus of changes at regards uncertainties.

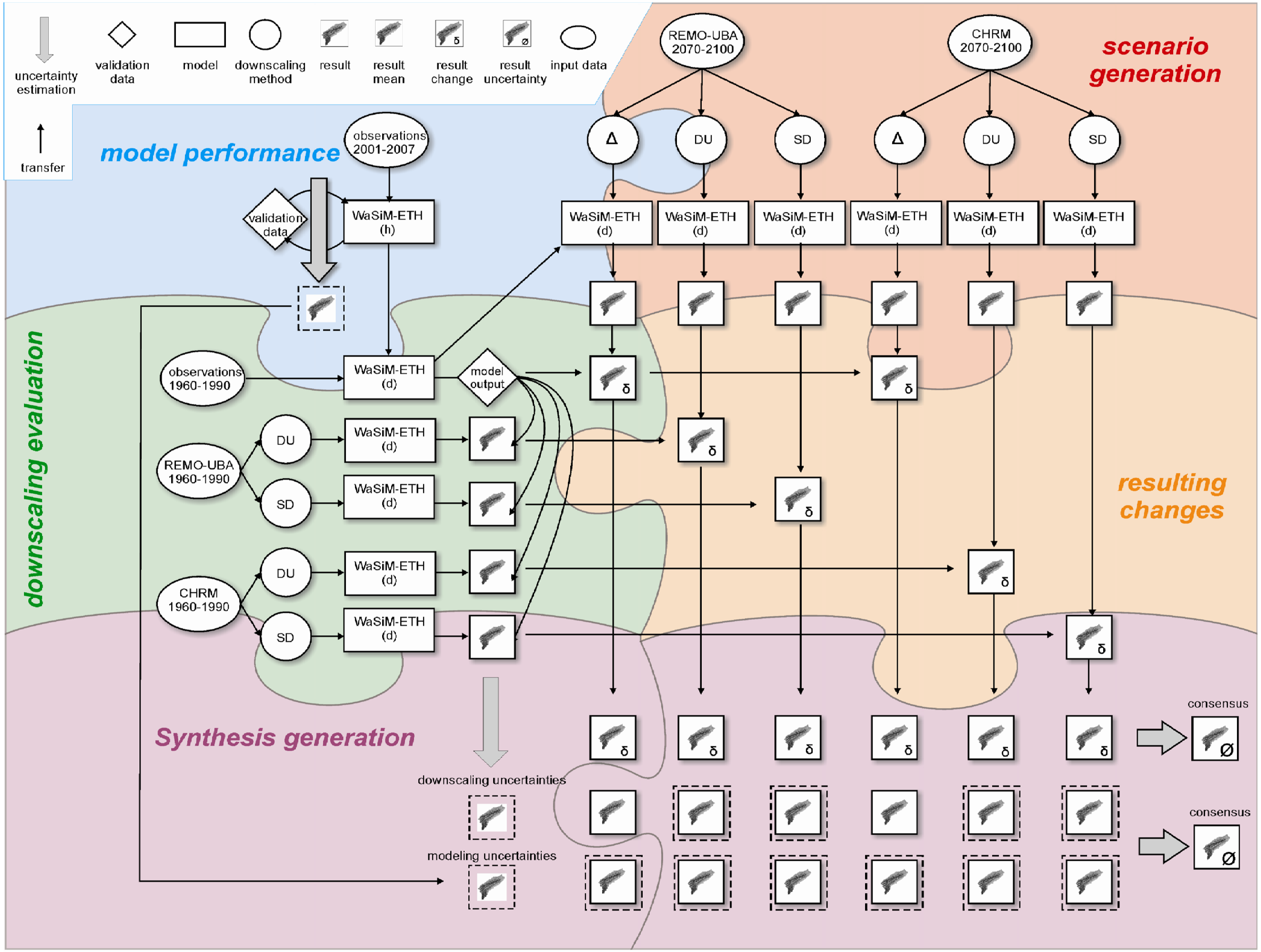


Figure 4: Structure of the entire study and the interaction between the five parts of the study. Abbrev: WaSiM-ETH: hydrological model applied in this study; REMO-UBA and CHRM: two RCMs applied; SD: statistical downscaling; Δ: delta change approach; DU: direct use. Puzzle parts refer to the parts of the study.

4.2 Measuring design

In the course of a former DFG-project (Börst 2005), five major meteorological stations were mounted in the year 2000 representing two crossing transects: one transect stretches along the valley floor, the second covers the north- and the south-facing slopes. These major stations recorded all main meteorological data (e.g. temperature (+200cm), wind speed, relative humidity, global and net radiation, and precipitation). The altitudinal gradient covered by the major stations has been refined in 2006 by setting up four minor stations measuring basic meteorological data and continuous soil moisture. The station were mounted on north and south facing slope at 1900m asl within a forest and on an avalanche track to record effects of different land uses. Unfortunately, the stations in the forests had major technical problems, thus the analysis is based on only two of four minor stations situated in an avalanche slope (Figure 5). To derive basic soil moisture patterns and to validate the hydrological model in terms of soil moisture level and dynamic, these two continuous soil moisture measurement plots for analyzing the soil moisture dynamic (minor stations, Figure 5) are accompanied by 13 discontinuous TDR measurement sites for absolute soil moisture of different elevations and land covers (basic stations, Figure 5). All stations were mounted along an altitudinal gradient (1400m - 2700m a.s.l.), on both north-facing (six sites) and south-facing (seven sites) slopes to cover topographical differences. In addition to obtain a comparable data set, both minor and basic stations record major meteorological data continuously and discontinuously (Figure 5). The two automatic stations were set up in sub-alpine avalanche tracks to record soil moisture in the top layer using FD-sensors (Delta-T SM200, +/-3% accuracy, 0-50% range). The FD-sensors were buried in horizontal position at 10 cm depth. In addition, soil moisture was measured at each of the 13 plots with three samples and three replications in 0-15cm depth using an uncalibrated handheld TDR-probe (Imko Trime-FM with P3 probe, at least +/-3% accuracy, 0-70% range) to meet the plot-intern spatial variability. Since lateral flows are only simulated conceptionally in the model, measure-plots were located on convex structures (2x2m) merely independent from lateral flows. In total, we conducted 10 - 28 handheld measurements at each in the period 2006 – 2007. Since handheld soil moisture measurements were only recorded in summer, the validation of soil moisture at all sites is only valid for the simulated summer soil moisture. The performance of the model to simulate soil moisture during other seasons is done by using continuous measurements.

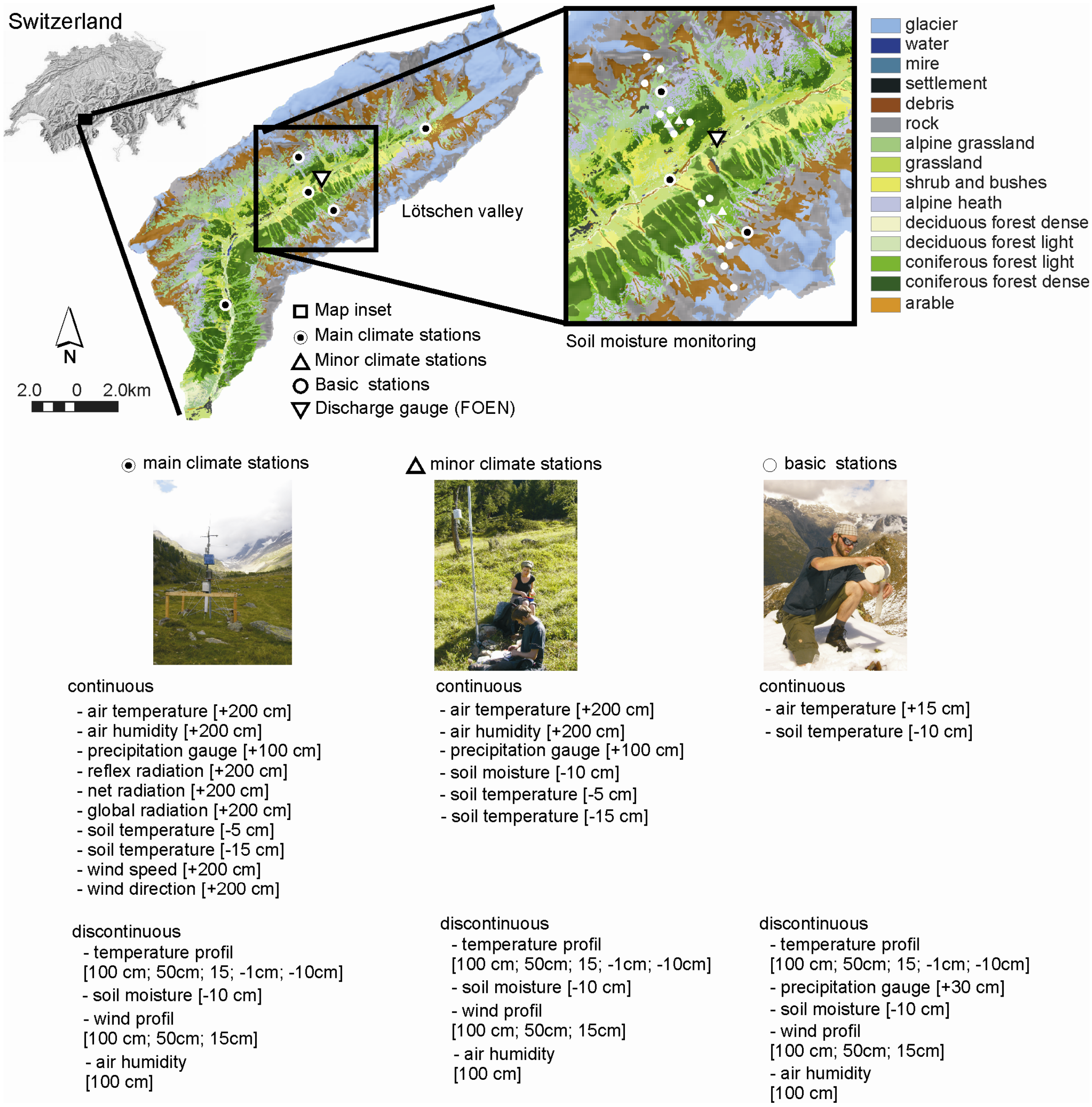


Figure 5: Location of the alpine Lötschen valley in the Bernese Alps, its land cover and the measurement design. The major meteorological stations are distributed along the valley floor and on the two opposite slopes covering the total area. The focus of the measurements is laid on the transect in the middle of the valley stretching across all elevational belts from valley at 1400 m to the nival zone at 2700 m.

4.3 Hydrological Model WaSiM-ETH

4.3.1 Model description

WaSiM-ETH (Schulla and Jasper 2007) is a frequently used, physically based, and spatially distributed hydrological model that was originally developed to simulate climate change effects on low-mountain-range-catchments (Schulla 1997). Since the incorporation of a glacier simulation modul, the model has successfully been transferred to several high mountain catchments (Middelkoop et al. 2001; Gurtz et al. 2003; Verbunt et al. 2003; Jasper et al. 2004). In this study, we used WaSiM-ETH version 7.9.11 and 8.0.11 in its Richard-equation configuration. WaSiM-ETH requires meteorological data, such as temperature, precipitation, relative humidity, wind speed, and solar radiation, as well as spatial data, including elevation, vegetation, soil properties, and glacier coverage. Vertical and horizontal water fluxes are calculated for each raster cell for user defined temporal and spatial time steps. Infiltration rates are simulated based on the approach by Green and Ampt (1911); vertical processes in the unsaturated zone are modeled using the Richards-equation (1931). WaSiM-ETH is able to simulate the interflow of each modeled raster cell. It is, however, not able to model the lateral routing of the water fluxes like the convergence of soil water, since interflow is not routed to the adjacent cell, but directly added to the natural drainage channel (Japser et al. 2004). Although Gurtz et al. (2003) and Jasper et al. (2006) showed the ability of the model to reproduce soil moisture and interflow in a pre-alpine area, this is a disadvantage especially in mountain areas of high relief complexity. Despite these drawbacks the model was considered appropriate for our study, for it proved to perform well in earlier applications for Swiss high mountain catchments (Verbunt et al. 2003; Jasper et al. 2006). However, the drawbacks have to be considered in the interpretation of results.

The applied versions of WaSiM-ETH included a dynamic time step control that considers the Courant criterion and thereby enables the calculation of water fluxes in the unsaturated zone in small time steps independent from the general time step. In turn, this enables the application of several thin numerical layers and is thus able to simulate the vertical dynamic of shallow soil depths that are typical of high mountain areas. In this study, soil profiles of the first 60cm are split into six numerical layers of 10cm each and four numerical layers of 30cm (60cm to 180cm) which may consists of different soil properties (soil layers). At the borders of these different soil layers, interflow may be generated. Due to the unavailability of groundwater data, the groundwater table is simulated within the model of the unsaturated zone. Thereby, the height of the ground water level is assumed to agree with the highest saturated numerical layer. Within a numerical layer, the ground water level is interpolated according to the actual soil water content. Groundwater recharge is calculated as the balance of vertical inflows and outflows to the layer containing the groundwater level (Schulla and Jasper 2007). Baseflow generation is done in a conceptual approach, since no lateral flows are simulated. For each raster cell baseflow is derived from groundwater table (Equation 1):

$$Q_B = Q_0 \times K_S \times e^{\frac{(h_{GW}-h_{alt})}{k_B}} \qquad (1)$$

with	Q_B	base flow [m/s]
	Q_0	scaling factor for base flow (or maximum baseflow if the soil is saturated) [-]
	K_S	saturated hydraulic conductivity [m/s]
	h_{GW}	height of groundwater table [m a.s.l.]
	h_{alt}	altitude of raster cell [m a.s.l.]
	k_B	recession constant for base flow [m]

The parameters Q_0 and k_B have to be calibrated.

In WaSiM-ETH a topographically dependent correction of temperature and radiation according to Oke (1987) is calculated to integrate shading effects, which are very prominent in steep valleys like the Lötschen valley, where there is an average slope angle of 40° for the north-facing slopes and 35° for the south-facing slopes. The temperature and radiation correction are very essential, since all major processes like glacier and snow melt and evapotranspiration highly depend on temperature and radiation. The correction of precipitation amounts using wind speed was not used since unrealistic bias frequently occurred.The simulation of snow and glacier accumulation and melting is of crucial importance. For both processes, WaSiM-ETH uses a simple temperature-index approach that is modified in terms of glacier melt by shadow-corrected radiation following the method of Hock (1999). Both are modeled in WaSiM-ETH using a degree-day factor algorithm after Martinec (1975) that is corrected in terms of glacier melt by radiation intensity after an approach by Hock (1999; Schulla and Jasper 2007). Moreover, different melt factors for snow and ice are used since snow cover on glaciers is melted before glacier melt begins (Equation 2):

$$Q_{glac} = \begin{cases} \left(\frac{1}{n} \times MF + \alpha_{snow\backslash ice} \times I_0 \times \frac{Gs}{Is}\right) \times (T - T_0) & T > T_0 \\ 0 & T \leq T_0 \end{cases} \qquad (2)$$

with	Q_{glac}	glacier melt [mm/time step]
	n	number of time steps per day [-]
	α	empirical coefficient for snow, and ice
	I_0	potential direct incoming shortwave radiation for each grid cell [Wh*m^{-2}]
	G_S	observed radiation at the same time [Wh*m^{-2}]
	T	air temperature in 2 m height [°C]
	T_0	threshold temperature for melt [°C]

Hence, glacier melt is a direct function of temperature and glacier extent. The applied versions of WaSiM-ETH are not able to simulate changes in the glacier extent. Hence, glacier melt and in turn discharge under future scenario condition with most likely completely different glacier extends is highly biased and therefore not used or interpreted. In 2010 a model update (Version 8.8.0) was published that considers glacier changes and thus enables the analysis of glacier and discharge changes in future studies. Snow cover in non-glaciated areas is calculated for each raster cell as an SLS for which the magnitude is determined by snow fall and melting processes (Equation 3):

$$M = c_0 \times (T - T_0) \times \frac{\Delta T}{24} \qquad (3)$$

with	M	melt [mm/time step]
	c_0	degree-day-factor [mm/(°C*timestep)]
	T	air temperature [°C]
	T_0	threshold temperature for melt [°C]
	ΔT	time step [h]

The actual evapotranspiration is modeled in a two step approach: first, the potential evapotranspiration is simulated using the Penman-Monteith equation (Monteith 1975; Burtsaert 1982 in Schulla and Japer 2007, Equation 4:).

$$\lambda E = \frac{3.6 \times \frac{\Delta}{\gamma p} \times (R_N - G) + \frac{\rho \times c_p}{\gamma \times r_a} \times (e_s - e) \times t_i}{\frac{\Delta}{\gamma p} + 1 + \frac{r_s}{r_a}} \qquad (4)$$

with	λ	latent vaporization heat λ=(2500.8 – 2.372xT) [kJ/kg]
	E	latent heat flux [mm/m²]
	Δ	tangent of the saturated vapor pressure curve [hPa/K]
	R_N	net radiation
	G	soil heat flux, here 0.1*R_N
	P	density of dry air [kg/m³]
	c_p	specific heat capacity of dry air at constant pressure, cp = 1.005 kJ/(kg*K)]
	e_s	saturation vapor pressure at temperature T [hPa]
	e	observed actual vapor pressure [hPa]
	t_i	number of seconds within a time step
	γ_p	psychrometric constant [hPa/K]
	r_s	bulk-surface resistance [s/m]
	r_a	bulk-aerodynamic resistance [s/m]

Some of these parameters like bulk resistances are difficult to determine and therefore derived from parameters more easily available. Vapor pressure is derived from temperature, the psychrometric constant (γ_p) is a function of pressure and temperature, net radiation of global radiation and albedo. Parameters r_s, r_a are estimated from wind speed and leaf area index and aerodynamic resistance, after the following equations (Equation 5):

$$r_a = \frac{4.72 \times \left(\ln \frac{z}{z_0}\right)^2}{1 + 0.54 \times u} \qquad (5)$$

and for vegetation heights above 2 m,

$$r_a = \frac{25}{(1 + 0.54 * u)} \qquad (6)$$

with	r_a	aerodynamic resistance [s/m]
	z	height of vegetation [m]
	z_0	aerodynamic roughness length
	u	wind speed [m/s]

Bulk-surface resistance r_s is derived from leaf area index for day and night time separately.

Day time:

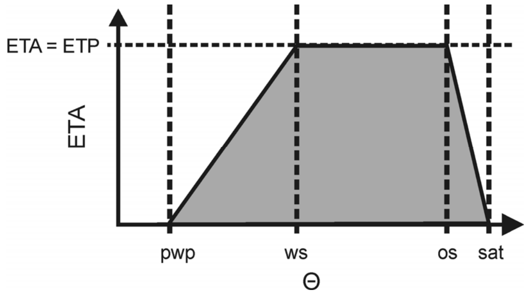
$$\frac{1}{r_s} = \frac{(1-A)}{r_{sc}} + \frac{A}{r_{ss}} \qquad (7)$$

Night time

$$\frac{1}{r_s} = \frac{LAI}{2500} + \frac{1}{r_{ss}} \qquad (8)$$

with	rs	minimum surface resistance [s/m]
	r_{sc}	minimum surface resistance of the plant [s/m]
	r_{ss}	surface resistance of bare soil (~150 s/m) [s/m]
	1-A	evaporative effective coverage, with A being a function of LAI

Second, the actual evapotranspiration is derived from the potential evapotranspiration by applying the Feddes approach (Feddes et al. 1976; Brutsaert 1982), which is a linear reduction depending on the matrix potential within the root zone. Soil hydrological properties are parameterized according to the van Genuchten approach. For more detailed information and equations see Jasper et al. (2006) (Equation 9):



$$ETA = \begin{cases} \theta_{act} < \theta_{pwp} & = 0 \\ \theta_{pwp} \leq \theta_{act} \leq \theta_{ws} & = ETP \times (\theta_{act} - \theta_{pwp})/(\theta_{ws} - \theta_{pwp}) \\ \theta_{pwp} \leq \theta_{os} & = ETP \\ \theta_{os} \leq \theta_{act} \leq \theta_{sat} & = ETP \times (\theta_{sat} - \theta_{act})/(\theta_{sat} - \theta_{os}) \end{cases} \qquad (9)$$

In case daily time steps are used, the calculation of evapotranspiration for each time step is split into day and nighttime in order to modify the temperature applied in the Penman-Monteith equation (Schulla and Jasper, 2007). For temperature, mean daily temperatures are modified by adding a term (for daytime values) and deducting a term (for nighttime values) that depends on the relative sunshine duration and an empirical factor (Schulla and Jasper, 2007):

$$\Delta T = \Delta T_{sea} \times SSD \times e^{-\frac{h}{k_t}} \qquad (10)$$

with ΔT_{sea} temperature range valid for sea level and for Julian day

K_T recession constant [m]

h altitude [m a.s.l.]

SSD relative sunshine duration [1/1]

Monthly values of temperature have been derived from Ried station data in the Lötschen valley for 2002-2007 (Table 3).

Table 3: ΔT_{sea} values applied for calculating day and night time temperatures in the Penman-Monteith Equation (Equation 10)

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
ΔT_{sea}	8.3	13.4	11.1	11	10.1	10.6	11.1	9.6	8.5	8.5	8.6	9.0

To conclude, although it was tried to derive most equation from observations, several empirical parameters are still to be parameterized to calculate evapotranspiration: that is albedo, aerodynamic resistance, height of vegetation, leaf area index (LAI). To calculate snow and glacier melt, day-degree-factors and radiation modifying coefficients need to be evaluated. At last, the simulation of baseflow requires the parameterization of 7he parameters Q_0 (scaling factor for baseflow) and k_B (recession constant for baseflow).

4.3.2 Model setup

For the evaluation of the ability of models to reproduce hydrological processes and soil moisture in specific in the Lötschen valley, we applied the model to the years 2001-2007. 2001 served as pre-run to balance all initial storages. Calibration was done for 2002, while 2003-2007 served as validation period. A simulation of at least 5 years was conducted to ensure a leveling of all processes and to avoid an overestimation of single extreme events. In accordance with Verbunt et al. (2003), a temporal resolution of one hour was chosen in this glaciated catchment to meet the diurnal discharge rhythm of glacier melt.

The application of the hydrological model in the climate change assessment study required a change in temporal resolution. Due to the long time period of 30 years, the application of the model using an hourly resolution was unrealistic in terms of computation time. Moreover, CHRM model data were only available at daily time steps. Therefore, the hydrological model needed to be adapted to daily time steps.

In terms of spatial resolution, Verbunt et al. (2003) concluded that 100m spatial resolution is sufficient in mountain catchments. To meet the complex interactions and fine scale variations present in high mountain areas whilst staying within a reasonable computation time, a spatial resolution of 50 m was used in all simulations.

4.4 Observed meteorological and climate data used in the model

Hourly meteorological data of 2001-2007 from five meteorological stations were provided by MeteoSwiss, Switzerland. These stations were located around the valley covering an altitudinal gradient from 640 m up to 3580 m (Figure 6, triangles). We used only meteorological stations situated nearest to the Lötschen valley. Precipitation data were not available for the highest station at *Jungfraujoch*. The five additional stations (major stations, Figure 5) run by our department within the Lötschen valley (1370m - 2347m) served for a refinement of the gradients (major stations, Figure 5). Due to great uncertainties regarding the snowfall measurements, precipitation data from these stations within the valley were not used.

Observed meteorological data for the time period 1960 to 1990 were obtained at daily resolution from official meteorological stations located around the investigated catchment (Figure 6). Air temperature (200 cm), dew-point temperature (200cm), sunshine duration, and wind speed were acquired from nine stations (red dots) covering an altitudinal gradient from 577 m a.s.l. to 3580 m a.s.l. Relative humidity was derived from dew-point temperature, and global radiation was derived from sunshine duration using the classical approach of Ångström (1924). Precipitation data was used from 20 stations (Figure 6, asterisks) covering an altitudinal gradient from 482 m a.s.l. to 1980 m a.s.l. Unfortunately, no precipitation stations were available above 2000 m a.s.l., resulting in uncertain precipitation gradients above this altitude.

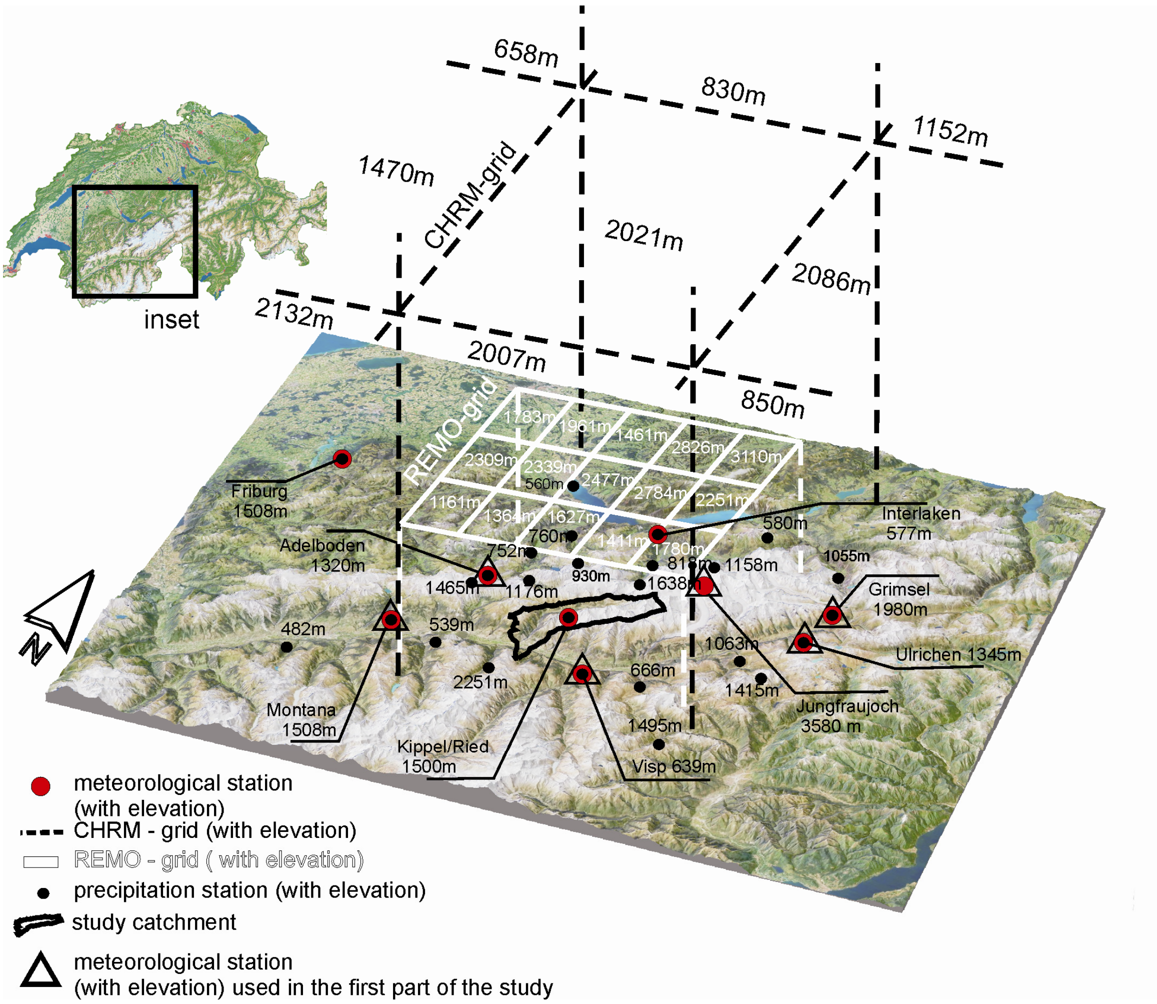


Figure 2: Location of the study catchment in Switzerland, meteorological stations used, and grid cells of RCMs, CHRM and REMO.

4.5 Regional Climate Models: REMO-UBA and CHRM

Regional Climate Models are used to drive the hydrological model under reference (1960-1990) and future scenario conditions (2070-2100). First, we evaluated the uncertainties introduced by the usage of climate model data during the reference period. Second, we applied the RCM to assess the climate impact on hydrology and soil moisture in special. We chose two RCMs of similar structure but different spatial resolution and with different underlying GCMs. The two applied RCMs are both based on the Europa Model (EM, Majewski and Schrodin 1994; Lüthi et al. 1996). The Climate High Resolution Model (CHRM, Lüthi et al. 1996; Vidale et al. 2003) driven by HadCM3 (Pope et al. 2000) is a specification of the EM from the Institute for Atmospheric and Climate Science of the ETH Zurich. It was explicitly developed for use in climate studies and offers a spatial resolution of 0.5° and daily time steps. The second climate model applied was REMO (Jacob 2001) developed at the MPI in Hamburg. The version REMO-UBA 5.8 provides a spatial resolution of 10 km (0.088° degree) and is driven by ECHAM5 (Roeckner et al. 2003). Both models were used in the Europe-wide climate model evaluation PRUDENCE (Christensen et al. 2007). Table 4 summarizes the main characteristics in terms of similarities and dissimilarities, while Figure 6 illustrates the location of the meteorological stations, as well as the grid cells of CHRM and REMO-UBA. Differences in the length of the model year (360 d for CHRM vs. 365.25 d for REMO) were adapted to 365.25 d using spline interpolation. Two main differences in the models must be considered: (a) the driving GCM and (b) the spatial resolution, indicating that CHRM is not able to simulate the special inner-alpine climate (personal communication Schär 2008), while REMO-UBA was found to substantially add value to the inner alpine representation of temperature (Prömmel 2008).

Table 4: Main characteristics of the applied RCMs.

	CHRM	REMO
Driving GCM	HadCM3	ECHAM5
Basic model	Europa Model	Europa Model
Temporal resolution	daily	hourly, aggregated to daily
Spatial resolution	0.5° ≈ 55km	0.088° ≈ 10km
Model year length	360d, transferred to 365.25d	365.25d

4.6 Regionalization of meteorological data

As part of the modeling process, WaSiM-ETH requires spatial data for all meteorological variables. Furthermore, the regionalization from point to spatial data is a crucial task in the modeling process. For the interpolation of meteorological data to the catchment scale, WaSiM-ETH offers a variety of techniques. Among others these are Thiessen-polygons, linear altitudinal regression, and a more elaborate technique like bilinear regression for downscaling of gridded climate data (Schulla and Jasper 2007). For two reasons, we opted for an elevation-depended linear regression for all meteorological variables.

First, the advantage of this approach lies in the consideration of the strong altitudinal range occurring in the valley and the consideration of temporary variable lapse rates. This range is crucial, at least for elevation-depended variables, such as temperature, precipitation, and relatively humidity. Second, the approach determines regional climate patterns, in contrast to local climate patterns, as are produced by other interpolation approaches, such as inverse distance weighting (IDW) or Thiessen polygons. Because we partly aimed at the comparison of hydrological model results based on a meteorological station dataset and RCM datasets, a focus on regional climate pattern was chosen to better match the characteristics of the RCMs. A focus on local climate patterns might have been more appropriate to simulate the actual hydrological conditions in the valley, but the resolution of the meteorological stations nor the patterns represented by the RCMs were sufficient for this.

The elevation-depended linear regression was calculated for each time-step (hourly and daily, respectively) and for each variable in a preprocessing procedure. This procedure allows the definition of two inversion layers, enabling the estimation of three gradients at maximum that differs with altitude. Using these inversion layers, some unrealistic sequences of gradients occurred during a test run. In addition, the definition of these inversing layers was found to be rather arbitrary. Therefore, we decided to use only one linear regression for the entire altitude. Based on these linear regressions, spatial data for each variable were generated directly in the hydrological model run. To avoid unrealistic values at the margins of the regression lines, upper and lower limits for each variable were defined. Theses threshold values were -40° and 40°C for temperature, 15mm/h and 150 mm/d for precipitation, resp., 40 m/s for wind, 1000 W/m² for radiation, and 100 percent relatively humidity.

4.7 Preparation of spatial data

A digital elevation point data set (Swisstopo 2004) with a spatial resolution of 25 m was used to model the topography of the catchment using the TOPOGRID algorithm in ArcInfo under consideration of rivers. The consideration of rivers, sometimes referred to as “river burning into the DEM” provides a method which ensures depth contours to correspond to the actual rivers in the catchment (cp. Davies et al. 2007).

Land cover information consisting of 13 classes was derived from a detailed vegetation map (5 m resolution) developed by Hörsch (2001) and from an official survey (GEOSTAT, 2002). See Table 2 for the coverage percentages of the all classes. Spatial data sets were re-sampled to a resolution of 50 m. Figure 7 shows the derived land cover classes in the Lötschen valley

In contrast to these comprehensive and high resolution data sets, spatial information on soil properties was missing or of insufficient resolution. Consequently, a conceptual soil property map (Figure 7, Table 5) was developed. This map was based on data of 231 soil profiles compiled within this study, as well as geological (Hügi et al. 1988) and geomorphological maps (Welpmann 1997, Eilers 2000), and an official survey on a soil suitability map (1:200,000; GEOSTAT, 2000). The latter map depicts soil types, as well as the suitability of soils for agricultural use. However, information on soil texture and skeleton is missing. Based on the mentioned maps, five different classes were delineated:

(1) soils origin from periglacial shaped glacial till covering most of the catchment consists of loamy material (loam, USPA/FAO-classification, Scheffer and Schachtschabel 2002),

(2) huge fluvial fans extending into the valley inhere a higher proportion of sandy material (sandy loam, USPA/FAO-classification),

(3) accumulated silt (silty loam, USPA/FAO-classification) originating from the widespread historic use of irrigation channels fed by glacier melt water that carries a high proportion of fine material (cp. Crook and Jones, 1999).

(4) rocks, and

(5) debris areas.

To specify the derived classes in terms of soil properties, the 231 soil profiles that have been randomly distributed across the catchment and assigned to the classes. This approach was also suggested by Voltz and Webster (1990) for regions where data are still too few to consider the heterogeneity of soil distributions. For each profile soil textures, soil depth, root depth, as well as skeleton fraction were estimated on site (AdHoc Boden 1994) and assigned to the classes. Soil textures of each profile were estimated in the field after AdHoc Boden (1994) and soil textures of 125 soil samples were verified in the lab using Köhn analysis (Köhn 1928). Table 5 summarizes the lab results that are used to specify the soil map units presented in Figure 7, left. Soil hydraulic parameters were derived based on the pedo-transfer-function of Brakensiek and Rawls (1994) that considers skeleton fractions and has proved to perform well for a wide range of soil textures (Tietje and Tapkenhinrichs 1993).

Table 5: Summary of the mean values for soil texture and skeleton fraction in the four different soil classes. Soil classes were delineated and the corresponding hydrological properties calculated using the pedo-transfer-function (PTF) after Brakensiek and Rawls (1994).

	measured				calculated with PTF after Brakensiek and Rawls (1994)				
	sand [%]	silt [%]	clay [%]	skeleton [%]	saturated conductivuty [m/s]	residual water content [vol-%]	saturated water content [vol-%]	N [-]	alpha [1/m]
loam / glacial till	42.3	41.8	15.9	41.0	$1.82 * 10^{-5}$	3.6	39.5	1.31	11.26
silt loam / irrigated pastures	36.2	46.4	16.9	32.0	$1.73 * 10^{-5}$	4.3	45.6	1.33	9.80
sandy loam /alluvial fen	47.8	42.7	9.5	55.6	$1.65 * 10^{-5}$	1.7	32.5	1.33	10.80
loam / debris	40.7	41.9	17.3	41.2	$2.10 * 10^{-5}$	3.6	43.0	1.30	11.32

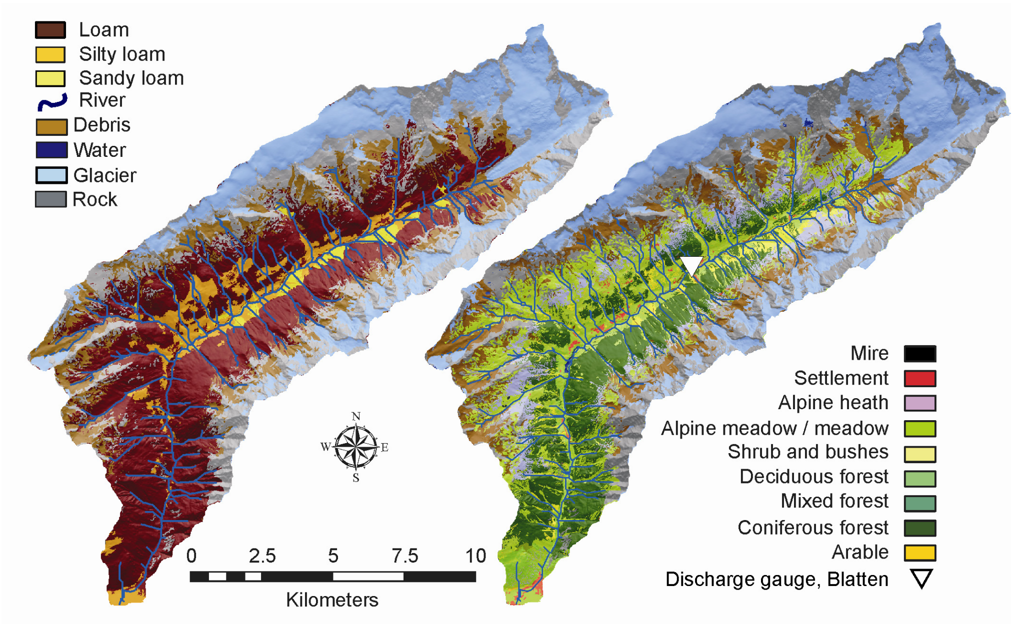


Figure 3: Soil map (left), and land cover map (right) of the 160 km² Lonza catchment. The only discharge gauge in situated in the centre of the valley at Blatten (right).

4.8 Model parameterization

First, the hydrological model based on hourly time steps was calibrated by means of actual discharge of the river *Lonza*. Unfortunately, the only existing official gauging station (FOEN, Switzerland) in the valley is situated in the center (Figure 7). Data from the reservoir unfortunately were unavailable. Hence, calibration of the model was only possible for the upper part (78km², 49%) of the catchment. It was assumed that the calibrated model was still valid for the entire valley. The model was calibrated using a pre-run period (2001) and a calibration period (2002) of twelve months each. For parameterization purposes of land cover, measured values like vegetation height and root depth were used as far as available. Further parameters like leaf area index or aerodynamic resistance could not be assessed within this study. They were thus derived from Schulla (1997), Schulla and Jasper (2007). Table 6 summarizes the parameters of all vegetated land covers. Soils were parameterized in terms of van Genuchten parameters (Table 5) or retained standard model values. We did not calibrate the model in terms of soil and vegetation parameters since both vary significantly in space (Herbst et al. 2006). Moreover, a calibration to point scale soil moisture data would have altered the soil properties derived from soil texture, or measured parameter like root depth. Due to the extensive soil profile mapping, reliable data on soil properties and vegetation data are available in the *Lötschen valley*. Recalibrating the parameters for modeling purpose seemed not appropriate here. A two step calibration to fit the model to the discharge was applied: at first a manual parameterization was conducted to broadly define the parameters, followed by an automatic parameter optimization using the program PEST (Parameter EStimation Tool, Doherty 2005). The model was validated for the time period 2003-2007.

Table 6: Model parameters of land cover types.

Land cover	LAI [-]		Albedo	Root depth	Aerodynamic resistence	Roughness length
	winter	summer	[1/1]	[m]	$[sm^{-1}]$	[m]
Coniferous forest	8	12	0.12	0.8	80 – 55	10
Deciduous forest	0.5	5	0.2	1	90 – 60	10
Mixed forest	0.5	5	0.15	1	90 – 60	10
Shrubs and bushes	3	5	0.2	0.3	90 – 45	1.5 – 2.5
Alpine meadows /meadows	2	4	0.25	0.4	90 – 40	0.15 – 0.4
Alpine heath	2	4	0.25	0.4	90 – 40	0.15 – 0.4
Mire	2	4	0.25	0.2	90 – 40	0.15
Arable land	0	5	0.5- 0.25	0 – 0.4	90 – 40	0 – 1

Second, a hydrological model using daily time steps was manually parameterized against discharge based on the model parameterization of the hourly model. Therefore, only the most influencing parameters on discharge are changed, while soil and land use parameter remained the same. Table 7 summarizes the results of the hourly parameter optimization and the partly changed parameters for the daily model. Changes are only visible in terms of snow and glacier melt factors. For a sound model calibration and validation Krause et al. (2005) in line with Legates and McCabe (1999) recommend the use of multiple statistic values in combination with total mass balance. In accordance, the quality of the results was calculated in terms of linear correlation with Pearsons-R;

the model efficiency (ME, Nash and Sutcliffe 1970), as well as the index of agreement (IoA, Wilmott, 1981) for the period 2003 – 2007 in hourly time steps. Besides these pure statistical tests, simulation results were validated regarding deviations in water balance. Since catchment runoff does not provide much insight into the internal processes (Grayson *et al.* 1992a; Grayson *et al.* 1992b), simulated soil moisture of the first soil layer was additionally validated using empirical data. Again, Pearsons-R, ME as well as IoA were used to statistically describe the agreements with soil moisture.

Table 7: Model parameters of soil, snow and glacier models with their estimated values of hourly and daily time steps.

parameter	value (hourly model)	value (daily model)
snow model		
snow melt temperature [°C]	0.0	0.0
lower temperatur limit for rain [°C]	0.65	0.65
degree-day-factor for snow [mm d^{-1} C^{-1}]	5	5
ice model		
degree-day-factor for ice [mm d^{-1} C^{-1}]	5	5
Minimal factor for radiation correction for ice [m^2 W^{-1} mm h^{-1} C^{-1}]	$3.3 * 10^{-4}$	$5.0 * 10^{-4}$
Maximal factor for radiation correction for ice [m^2 W^{-1} mm h^{-1} C^{-1}]	$1.1 * 10^{-4}$	$4.0 * 10^{-4}$
Minimal factor for radiation correction for snow [m^2 W^{-1} mm h^{-1} C^{-1}]	$1.0 * 10^{-3}$	$4.0 * 10^{-4}$
Maximal factor for radiation correction for snow [m^2 W^{-1} mm h^{-1} C^{-1}]	$3.45 * 10^{-5}$	$5.0 * 10^{-5}$
glacier configuration		
single linear storage constant ice [h]	40	10
single linear storage constant firn [h]	100	100
single linear storage constant snow [h]	5	1
initial reservoir for ice discharge [m^3]	0	0
initial reservoir for firn discharge [m^3]	10	10
initial reservoir for snow discharge [m^3]	0	0
soil model		
base flow recession parameter [-]	0.25	0.25
scaling factor for base flow [-]	0.1	0.1
drainage density [-]	10	10
interception model		
interception layer on leafs [mm]	0.2	0.2

4.9 Sensitivity analysis based on the hourly model run

A local sensitivity analysis was conducted to assess the relative importance of the parameters as well as model uncertainties that may originate from simulation parameters. The relative importance of the parameters to model discharge and soil moisture was defined based on an approach by de Roo and Jetten (1999); 10 percent changes for each parameter were calculated to estimate a sensitivity index (Equation 11)

$$Si = \frac{|R_{p10} - R_{m10}|}{R_{norm}} \qquad (11)$$

with:	si	sensitivity index
	R_{p10}	parameter increased by 10 percent
	R_{m10}	parameter decreased by 10 percent
	R_{norm}	parameter

4.10 Evaluation of spatio-temporal patterns of hourly hydrological model

Spatio-temporal patterns of soil moisture were analyzed from a seasonal perspective. Mean values of the validation period 2003 – 2007 were calculated for winter (January, February, March), spring (April, May, June), summer (July, August, September), and autumn (October, November, December) to exclude inter-annual differences. Finally, soil moisture dynamics were analyzed in relation to altitude and land cover, which were assumed to be of superior impact. To evaluate the model performance in terms of soil moisture content and dynamic, the simulation results of the first 20cm (two soil layers within the model) of the corresponding grid cell (50 x 50m) were compared with the mean soil moisture and variance of measure plots in 2006 and 2007.

4.11 Downscaling of RCM data

The downscaling of the RCM climate data remains a crucial step in hydrological impact assessment studies (Fowler et al. 2007) and it has been shown that different downscaling approaches are differently able to represent the hydrological processes of the investigated catchment (Wood et al. 2004). We applied three different downscaling approaches: delta change, statistical downscaling, and direct usage.

4.11.1 Delta change approach (Δ)

The simplest and most popular downscaling approach is the delta change approach (Arnell and Reynard 1996, Prudhomme et al. 2002, Graham et al. 2007) that modifies observed data with respect to the related scenario data signal. In this study, we applied the method of Köplin et al. (2010) who modified the meteorological observations with the average of a moving window of 30 days of the climate change signal. This signal is determined as the difference between future and reference climate data. In terms of temperature, delta change signals were added, whereas precipitation values were multiplied with their percentage of change. All three other meteorological data, wind speed, relative humidity, and global radiation remained unchanged.

4.11.2 Direct use of the RCMs (DU)

Another very simple approach is the direct forcing of the hydrological model wit an RCM or GCM. This direct use approach ensures the full conservation of the data variability (Lenderink et al. 2007). To implement the DU approach, we applied the grid values of the two RCMs as “virtual stations” that were interpolated using elevation-dependent regression. To verify whether this approach was appropriate for the studied catchment, we compared the elevation-dependent regression lines based on the observed data with the regression lines based on the grid cells of both models. We found the mean regression gradient and the standard deviation of temperature and precipitation to be quite similar to the gradients of both RCMs (Table 8), thus justifying the direct use of the grid cells without bias correction.

Table 8: Mean and standard deviation (brackets) of observed and climate model gradients of precipitation and temperature against elevation justifying the direct use of the grid cells without bias correction.

	Observed mean (standard deviation)	CHRM mean (standard deviation)	REMO mean (standard deviation)
Precipitation [mm/100m]	0.165 (0.37)	0.128 (0.44)	0.149 (0.39)
Temperature [K/100m]	-0.55 (0.11)	-0.58 (0.14)	-0.61 (0.14)

4.11.3 Statistical downscaling (SD) using SDSM

To statistically downscale the grid cell values of the RCMs to the point scale of the meteorological stations, we applied the program SDSM 4.2 (Wilby and Dawson 2007). SDSM can be characterized as a hybrid of a stochastic weather generator and regression-based methods (Wilby et al. 2001) and has been successfully applied in several studies (Benestad 2004; Khan et al. 2006; Khan and Coulibaly 2010). SDSM is basically a multiple linear regression that is extended by an autoregression term and a stochastic element. The latter is used to: a) stochastically inflate the variance of the downscaled data, resulting in a better agreement with daily observed data and b) “generate ensembles of climate time series that differ in their individual time evolution, inter-annual means and variance” (Diaz-Nieto and Wilby 2005). SDSM was originally developed for downscaling GCMs. The model is usually calibrated by a linear regression based on NCEP reanalysis data and meteorological station data that is subsequently applied to GCM data. In this study, we used SDSM to downscale RCM data and meteorological measurements, without using observed grid cell data (e.g., NCEP reanalysis data) because these data are of a much coarser resolution than the RCMs.

Unfortunately, RCM outputs driven by observed grid cell data were not available. Therefore, we calibrated the statistical model using GCM-driven RCM data and validated the regression model using cross-validation. The time period of 1960 to 1975 served as the calibration period, while the output was validated from 1975 to 1990. SDSM offers the possibility of finding annual, seasonal, and monthly regression functions to downscale the meteorological variables. Although we aimed at using monthly regression functions, the correlation between the data produced by the meteorological stations and the grid cell prediction was found to be too weak for this purpose. Hence, we opted for downscaling with an annual regression function. The precipitation, temperature, wind, radiation, and relative humidity data of each meteorological station served as predictands, while the surrounding grid cells for the same variable of each climate model served as predictor variables. We thus took into consideration that the best predictive skill is not necessarily provided by the nearest grid cells, as described by Brinkmann (2002). Each variable was tested for normal distribution before the application of an ordinary least square regression (OLS) with autoregression. In the case of precipitation, we transferred the predictand and predictor by applying an x' = log(x+1) transformation to account for the zero values in the data. Moreover, no autoregression term was introduced for precipitation. One great advantage of using statistical downscaling is the possibility of generating statistical ensembles. In this study, we generated 20 ensembles and used them for hydrological modeling. Table 4 summarizes the quality of the statistical downscaling by providing the regression coefficients of the validation time period (1975-1990) and shows that regression coefficients vary considerably as to the temporal basis. Temperature and partly radiation reveal best agreement with observations, while the linear correlation of all other variable is very low. This is not surprising since the statistical model is unable to reproduce the dynamic, but predicts the total sum or mean and the distribution of values. Therefore, Figure 8 presents the probability density function of all climate variables and each station, illustrating a very high accordance between observed and simulated value. Moreover, the agreement of total sums and means are presented in Figure 9 by comparing boxplots of simulated and observed values as to each station used. Again a high agreement is found, proving the ability of the SDSM model to correctly downscale the climate variables in the reference period.

Table 9:: Persons-R correlation coefficients for meteorological variables of observed and statistical downscaling results based on CHRM and REMO data with respect to daily, monthly, and annul time steps.

		Temperature		Relative humidity		Global radiation		Wind speed		Precipitation	
		CHRM	REMO	CHRM	REMO	CHRM	REMO	CHRM	REMO	CHRM	REMO
Regression coefficients (Pearsons - R)	daily	0.68	0.63	0.14	0.06	0.43	0.38	0.11	0.04	0.04	0.03
	monthly	0.89	0.85	0.24	0.22	0.88	0.83	0.19	0.15	0.23	0.21
	annually	0.54	0.48	0.52	0.52	0.49	0.36	0.52	0.43	0.49	0.46

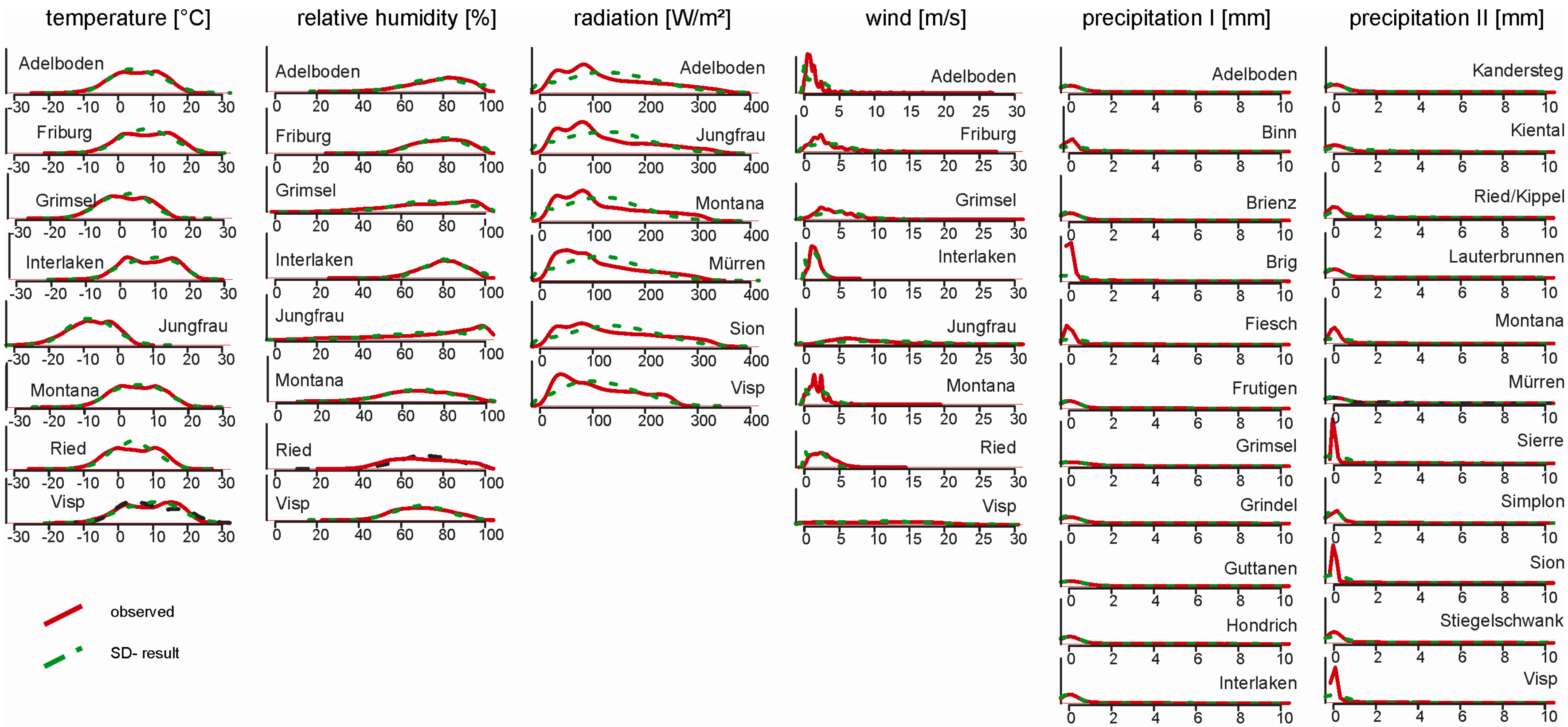


Figure 8: Agreement of probability density functions (PDFs) of observed and downscaled variables with respect to meteorological parameter and meteorological station used.

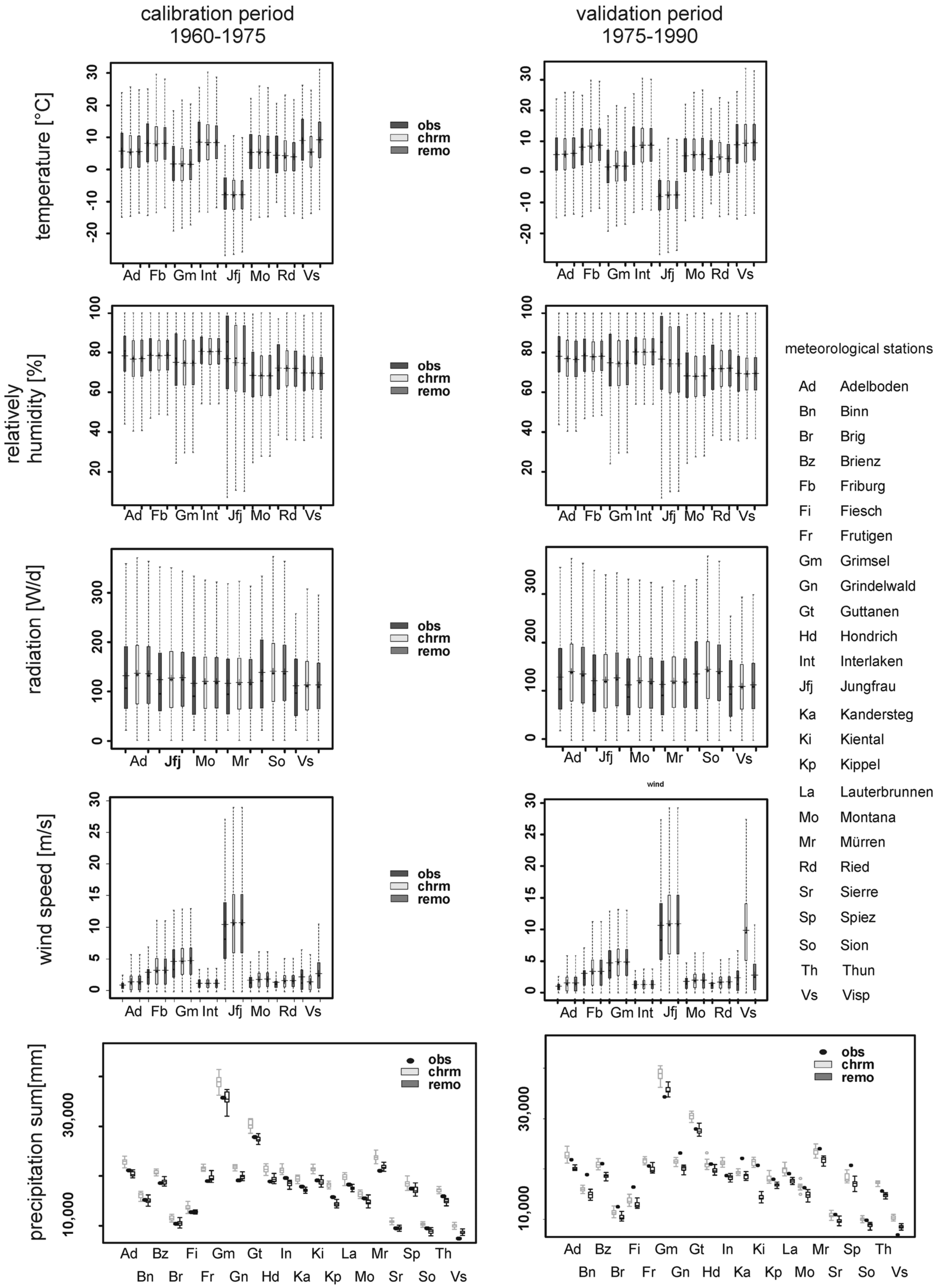


Figure 9: Boxplots of absolute sum of variables after downscaling for calibration (left) and validation (right) period indicating a good performance of the statistical downscaling.

4.12 Analysis of uncertainties

To analyze the uncertainties of four different climate-downscaling combinations (DU-CHRM, DU REMO, SD-CHRM, SD-REMO), a reference model was set up driven only by observations from meteorological station data for 1960 to 1990 at a daily time step. The Δ-change approach was not considered as it is based on the reference model based on observations. Subsequently, the hydrological model was driven by the four climate model data approaches and evaluated with respect to water balance and discharge, as well as major spatially distributed data, such as soil moisture, evapotranspiration, and snow storage. Disagreements were considered as uncertainties that originated from the climate model and the downscaling approach, respectively. In case of the water balance, the mean annual values between 1960 and 1990 were simply compared. Deviations in discharge were evaluated based on: (i) model quality measures, such as Pearsons-R, model efficiency (ME, Nash and Sutcliffe 1970), and Index of agreement (IoA, Wilmott 1981), (ii) visual comparison, and (iii) exceedance probability. The last factor calculates the probability of the dataset to exceed a certain value (Maidment 1993) and evaluates the uncertainties for future flood simulation.

In addition to the highly integrative point data for discharge, the spatio-temporal agreements of the models in terms of actual evapotranspiration and soil moisture were analyzed. While the former refers to uncertainties in temperature, wind and relative humidity, the latter is a highly integrative variable determined by evapotranspiration, precipitation, and snow melt. Spatial uncertainties for soil moisture and actual evapotranspiration are calculated as Root-Mean Square Errors (RMSE) of each raster cell on a monthly basis. Thus, glaciers and rocks were eliminated from the analysis. Spatio-temporal uncertainties were estimated in two different ways: (i) the residuals between the reference model and test models of each month were visualized by boxplots and compared with deviations of the assumed predictors mean monthly temperature and monthly precipitation sums, as well as mean snow melt rates; (ii) instead of boxplots of the monthly residuals, we calculated a map agreement index (MAI, Eq. 1 below) that was based on the fuzzy-kappa index for numerical maps (Hagen-Zanker et al. 2006) but only regards a cell-by-cell comparison:

$$MAI(a,b) = mean\left(1 - \left(\frac{|a-b|}{max(|a|,|b|)}\right)\right) \qquad (11)$$

with: a: raster cell value map a

b: raster cell value map b

4.13 Analyzing the effects of climate change

The analysis of climate change impacts on hydrology in general and on soil moisture in specific was carried out in two parts. First, the general hydrological impact of climate change based on probability density functions (hereafter PDF) was analyzed for selected parameters and changes to the water balance. Second, changes were compared with respect to the spatial and temporal distribution of soil moisture and actual evapotranspiration and related those differences to changes in temperature, precipitation, and discharge. In terms of discharge, the proportion of discharge without glacier melt was calculated, since changes in glacier extent is not considered and unknown for 2070-2100.

A special focus is set on changes in soil moisture and drought risk. Soil moisture changes were evaluated with respect to seasons, as changes during the vegetation period are much more relevant. To evaluate the occurrence of droughts or drought stress within the valley, three different approaches were applied. First, the evapotranspiration reduction resulting from increased suction pressure (after Feddes et al. 1976, see above) was used. The evapotranspiration deficit expressed by the ratio of actual (ETA) to potential (ETP) evapotranspiration (Jasper et al. 2004, 2006) or by an index (ETP-ETA/ETP, Narasimhan and Srinivasan 2005) has been frequently used as an indicator for drought stress. Second, Jasper et al. (2006) in accordance with Allen et al. (1998) defined a threshold at 30% (sever) and 50% (moderate) of plant-available-water as critical level. For comparative reasons, the 30%-threshold was adopted and counted the number of days for which simulated water availability was below. Since plants can cope with sporadic but suffer from prolonged drought stress (Larcher 2003), the maximum length of successive days below this threshold was estimated to evaluate the length of drought stress periods. Due to the computational effort, spatial explicit analyses in terms of SD-models were conducted for one ensemble (the closest to mean of all ensembles) only. Third, an index was calculated which considers the ratio in evapotranspiration deficit as well as their absolute values (Equation 11). The difference between potential and actual evapotranspiration for each time step was calculated, summed up, and weighted by the magnitude of the evapotranspiration deficit (ETA/ETP):

$$WDS = \sum_{i=1}^{n=11322} \left(\frac{ETA_i}{ETP_i}\right) \times (ETP_i - ETA_i) \qquad (12)$$

with: WDS: weighted deficit sum

ETA: actual evapotranspiration [mm/d]

ETP: potential evapotranspiration [mm/d]

n. number of days [d]

4.14 Ensemble forecasting

Ensemble forecasts are widely used to achieve more robust simulations. Depending on the total number of simulations conducted, ensemble forecast analyses stretch from simply averaging the forecasts and evaluating their variability using bounding boxes, to much more sophisticated approaches analyzing the probabilities of forecasts (Araujo and New 2007). For the latter a high number of ensembles are necessary exceeding the computational effort in most physically based, distributed models. In this study, 20 ensembles based on the SD approach were simulated to evaluate the general impact on hydrology (water balance, discharge, evapotranspiration deficit) and one model run of Δ and DU, respectively. In terms of spatial differences of climate change impact assessment, computational and storage shortage forced a restriction of only one SD model as well. Therefore, the model with the least deviation from ensemble mean in terms of precipitation and temperature were chosen. Spatial consensus of six model runs (three downscaling approaches and two regional climate models) with respect to soil drought was estimated by arithmetic means and the variability was analyzed using quantiles.

5. Results

5.1 Uncertainty estimation of the hydrological model

5.1.1. Model sensitivity

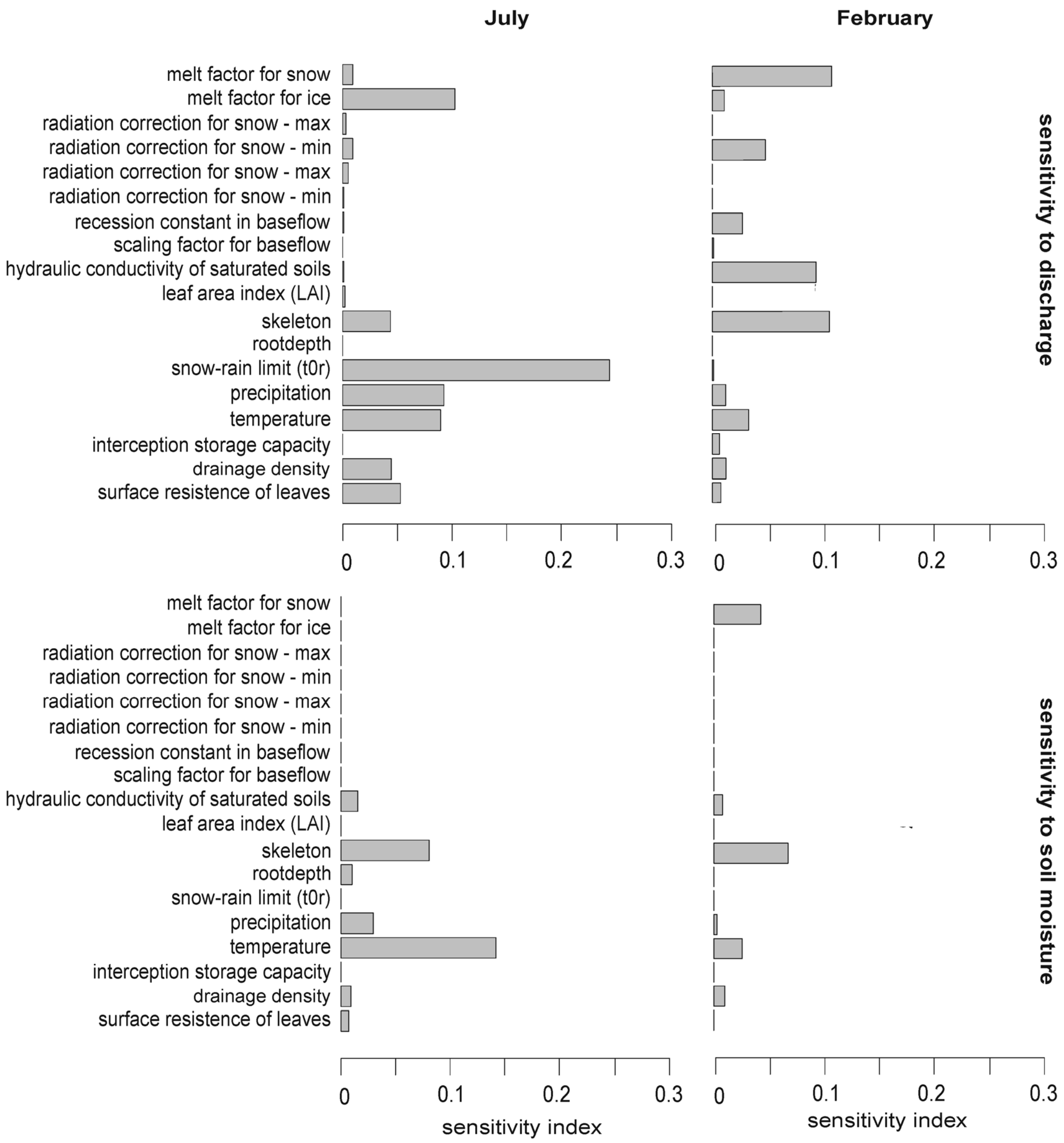


Figure 10: Seasonal sensitivity analysis for several effective parameters and two input variables (temperature and precipitation) for soil moisture and discharge in July and February.

The results for the sensitivity analysis are given in Figure 10. Differences in the relevance of the parameters occurred for soil moisture and discharge, as well as for different seasons. Overall, discharge was much more sensitive to the tested parameters than soil moisture. In summer, both discharge and soil moisture reacted sensitively to the meteorological input parameters temperature and precipitation. Discharge was furthermore influenced by the melt rate of ice. Radiation correction modifying the melt rate was found to be of much lower sensitivity. In contrast, the snow-melt factor was postponed since most of the snow had already melted in July. This relation was reversed in winter where little changes in temperature led to snow-melt and hence increased discharge and soil moisture, whereas glacier melt remained unaffected. In summer, snow-melt had no effect on soil moisture (excluding highest altitudes). Changes in skeleton fraction were relatively sensitive for both discharge and soil moisture in both time periods as it affects the hydraulic properties of the soils. Problematically, the skeleton fraction was also one of the most difficult parameters to measure spatially. Changes of land cover parameters like root depth and LAI or parameters know to be sensitive like leave surface resistance and drainage density were of subsidiary relevance. In conclusion, the most sensitive parameters were the meteorological input parameters, effective parameters like snow-melt factor that need calibration, and skeleton.

5.1.2. Model validation

The model was validated using hourly discharge data from the period 2003 to 2007. In Figure 11 simulated discharge (continuous line) is plotted against observed discharge (dashed line) as daily values. The graph illustrates the ability of the model to describe the discharge dynamic. It depicts pronounced seasonal dynamic with low winter discharge, an abrupt rise in late spring (May, June), and high discharge with strong daily fluctuations in summer typical of a nival-glacial discharge regime. Limitations of the model occurred for the winter period where the low flow was underestimated and for the autumn season where higher deviations indicated an omission of occurring processes. The validation was carried out by means of calculated quality parameters (Table 10) and water balance (Table 11). Qualitative parameters indicated that the temporal dynamic, expressed by Pearson's-R and IoA, was more precisely simulated than the absolute agreement (ME). This may be due to the sensitivity of ME towards outlier peaks and the deviations of the model in autumn.

Table 10: Model efficiency (ME), index of agreement (IoA), and Pearson-R prove the quality of the model in terms of linear correlation (R), absolute (ME), and temporal agreement (IoA)

	Pre-run 2001	Calibration period 2002	Validation period 2003-2007	2003	2004	2005	2006	2007
Index of agreement (Willmott 1980)	0.93	0.96	0.95	0.97	0.95	0.93	0.96	0.95
Model efficiency (Nash & Sutcliff 1970)	0.72	0.84	0.80	0.84	0.78	0.69	0.83	0.83
Pearsons - R	0.87	0.94	0.95	0.95	0.92	0.89	0.92	0.92

The validation of model results concerning the water balance is summarized in Table Table 11. The water balance was calculated for a hydrological year from October 1st to September 30th when temporal water storage such as snow and glacier ice is at its lowest. The data were mean values for the entire catchment and for the gauged subcatchment. Both balances show a similar distribution of processes, confirming the assumption that the subcatchment is representative for the entire catchment. The proportion of input processes as well as output processes shifted slightly from the entire to the gauged subcatchment in accordance with the average elevation of the catchments: the proportion of runoff and snowfall increased with elevation and were higher in the subcatchment, while proportions of rainfall and evapotranspiration decreased. Simulated runoff (mean 1836mm, 2003-2007) slightly underestimated (3.3%) the measured runoff (1917mm, 2003-2007) in the gauged subcatchment (48.6% of the entire catchment). In contrast, the water balance showed overestimations in total (+3.7% for the entire catchment and 1.8% for the gauged catchment). Snow storage data indicated that this surplus was accumulated in some years at unglaciated highest elevations where snow storages are not completely melted in spring. The reason for this accumulation may be the omission of snow relocation processes through, e.g., avalanches in the model. In the simulated five years the glaciers were shrinking, as indicated by the negative water balance for the glacier. Considering both criteria – the water balance and the quality parameter – a very good accordance in terms of discharge both for the calibration and for the validation period was achieved.

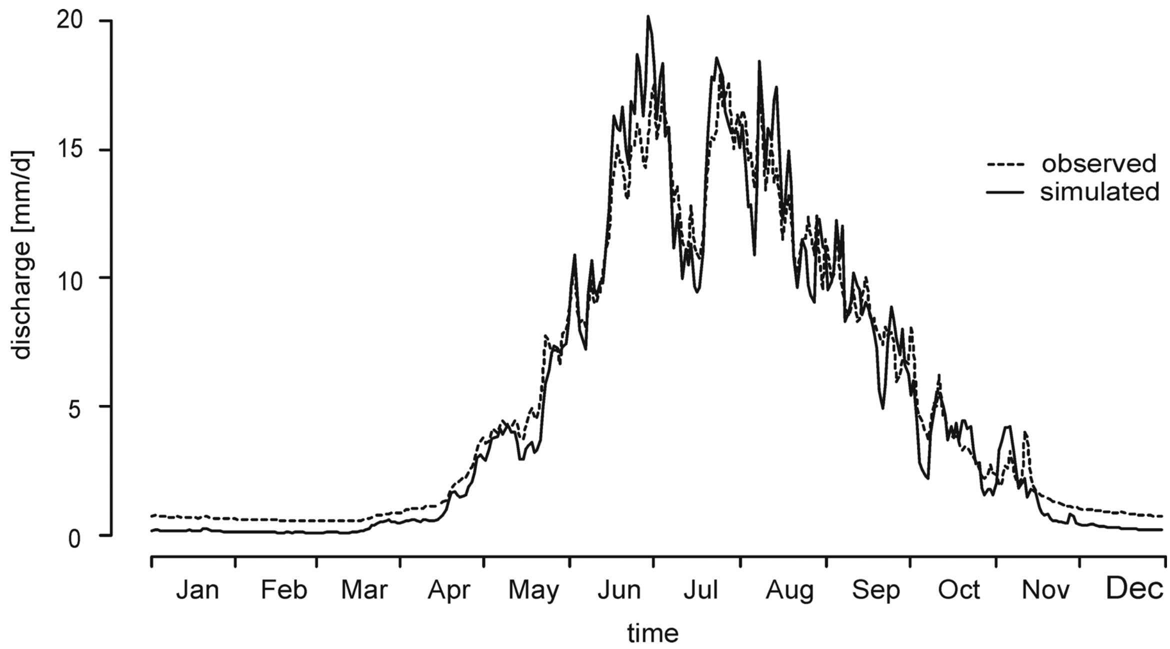


Figure 11: Mean hourly observed (dashed line) and simulated (continuous line) discharge values summed up to daily values for the Lonza catchment of 2003 - 2007. The year 2001 was used as a pre-run to the calibration year 2002 in order to ensure all temporal water

Table 11: Water balance for selected water balance parameters, processes and water storage (mean data of 2003-2007) for the entire studied catchment Lötschen valley (160 km²) and the gauged subcatchment (78km²).

	entire catchment m³	gauged subcatchment m³	entire catchment mm	gauged subcatchment mm	entire catchment percent	gauged subcatchment percent
input						
snow	41536	20738	1126	1414	63	69
rain	24641	9298	668	634	37	31
Total	66215	30052	1795	2049	100	100
output						
runoff	55813	26928	1513	1836	76	83
runoff (measured)				1917		
evapotranspiration	17485	5412	474	369	24	17
total	73298	32340	1987	2205	100	100
storage						
snow (unglaciated areas)	2951	3006	80	205		
soil storage	-7.4	14	-0.2	1		
sum	-9960	-704	-991.8	50		
glacier balance	-7291	-1295	-965	-201		
bias	-2669 (3.7%)	591 (1.8%)				

Besides discharge, the results of the model were validated in terms of soil moisture of the top 20 cm for both absolute soil moisture and soil moisture dynamic. The absolute soil moisture was evaluated for different elevations and land covers, while soil moisture dynamic was evaluated using continuous measurements of two sites. The results of the absolute soil moisture validation for different elevations and land covers are summarized in Figure 12. The linear correlation of the simulated vs. the discontinuous observed measures of soil moisture revealed a high significance ($p < 0.05$) with a moderate correlation ($R = 0.37$, Figure 12a). Taking the spatial variability within each measurement site into account this value increased to 0.47 (adjusted linear regression, Figure 12a). Plotting the residuals of the normal linear model against altitude (Figure 12b) showed the model to overestimate soil moisture at lower elevations and to underestimate soil moisture at the higher elevations. Moreover, forested areas were measured to be drier and open areas moister than simulated values indicated (Figure 12c). Consequently, we were able to simulate the spatial variability of absolute soil moisture using the WaSiM-ETH model with only limited success.

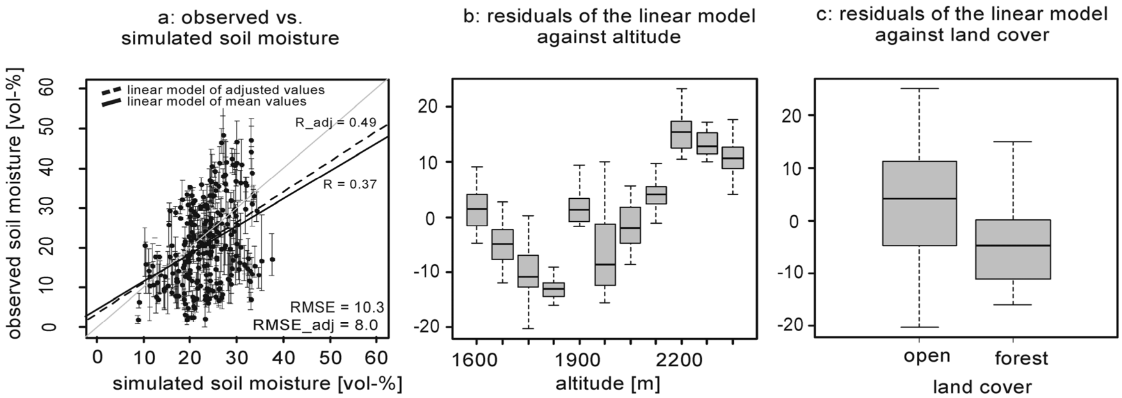


Figure 12: Validation of absolute soil moisture using 13 discontinuously measured plots. (a) shows the scatter plot of observed versus simulated values with error bars referring to the spatial variation within the measured plot. Continuous line indicates linear model of mean observed vs. simulated data, dashed line on linear model of adjusted observed values. The residuals of the linear model were plotted against altitude (b) indicating an overestimation ofsoil moisture at lower elevations and an overestimation at higher elevations; plotting the residuals of the linear model against land cover (c) revealed an overestimation of soil moisture in forested areas.

The measured soil moisture dynamic of two sites from opposite slopes are compared with simulated soil moisture for one year (Figure 13). In addition, two insets illustrate the soil moisture dynamic of spring and early summer and a scatter plot indicates the quality of the simulation. The comparison showed a good reproduction of soil moisture dynamics by the model for the south-facing slope as indicated by the statistical quality of parameters (R = 0.70, IoA = 0.81), while on the north-facing slope statistical values indicate the temporal quality to be moderate (north-facing slope: R = 0.69, IoA = 0.66). The quantity of the simulated soil moisture content was weak for both slopes (south-facing, ME = 0.03; north-facing, ME = 0.13). Especially, the soil moisture dynamic on the north-facing slope shows strong underestimations, indicating that soil porosity of the soil class loam is not valid for this site. In contrast, soil moisture dynamics that refer to the van Genuchten parameters of the PTF are successfully simulated, especially on the south-facing slope. The soil moisture dynamic was characterized by two different processes: a period of diurnal oscillations of soil moisture during April and May in the first 20 centimeters which was superseded by irregular fluctuations during summer and autumn. Detailed previous investigations (Rößler and Löffler 2010) showed that the first processes can be clearly ascribed to snow-melt infiltration, while the latter represents a typical response to rainfall. In winter the soil is frozen and therefore soil water fluctuations were hardly observed. Deviations between simulated and observed soil moisture at the beginning of the validation period were visible for both slopes (see Figure 13, detailed graph). The simulated diurnal fluctuations started earlier than measured that have to be interpreted as the result of too early snow-melt estimation. Moreover, the snow-melt period was simulated too long with lower diurnal soil water increases. This deviation can be interpreted as an overestimation of snow-fall and a result of missing snow redistribution. In contrast, transition from snow-melt to precipitation dependent fluctuation was reproduced correctly for both slopes. The very high soil water content measured in spring 2006 on the north-facing slope (Figure 13, right) exceeded the calculated maximum water content for this soil texture (39 %). This may be interpreted as a period of oversaturated conditions (> saturated water content) during snow-melt that cannot be simulated with WaSiM-ETH. The reason for the high oversaturation may be due to an avalanche that caused high amounts of snow to accumulate at the investigated site. Since these high values are rarely measured (Figure13, left), a measurement error cannot be excluded. To conclude, WaSiM-ETH is not able to simulate the quantity of soil water content for these two plots, but soil moisture dynamics are reproduced.

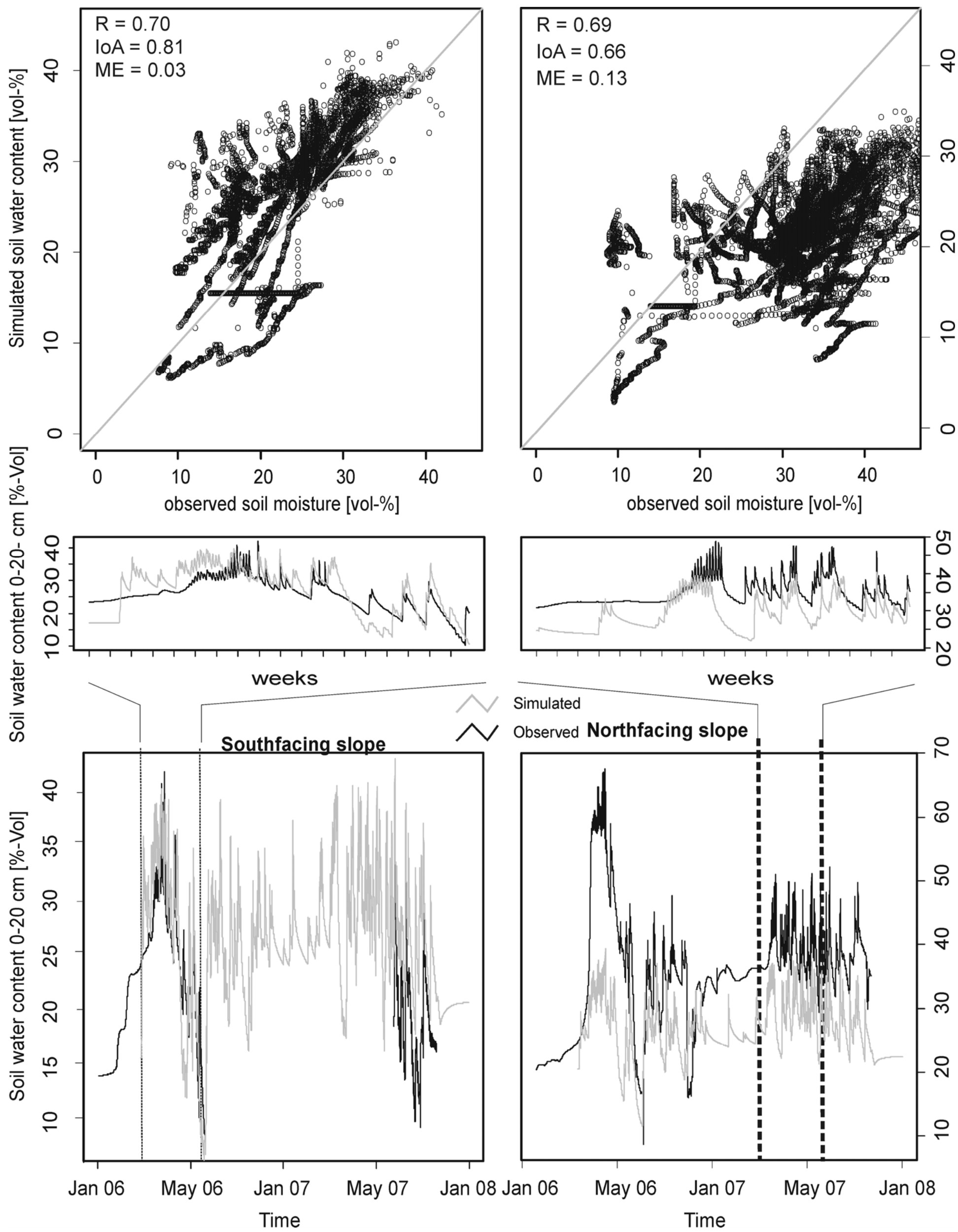


Figure 13: Validation of soil moisture dynamics of the top 20 cm; simulated soil moisture dynamics (black line) and observed soil moisture dynamics (grey) on opposite slopes (north facing slope (right), south facing (left)) for the entire observation period (below) and for two periods during snow melt (middle). In addition, a scatter plot for the entire period indicates the quality of simulations.

5.1.3 Simulated spatio-temporal patterns of soil moisture

The simulated spatio-temporal soil moisture patterns illustrated in Figure 14 were subdivided into four seasons: January, February and March for winter (JFM); April, May, and June for spring (AMJ); July, August and September for summer (JAS) and October, November and December for autumn (OND). The maps show mean values for each season during the validation period 2003–2007. In winter, soil moisture in the catchment was relatively homogenously distributed at a medium level (22.8 Vol-% for all vegetated land cover types excluding grasslands) as a result of minimized vertical water fluxes. Only, formerly irrigated pastures and grasslands at the valley floor had a higher water content due to higher proportion of silt and clay (cp.Table 5), as well as their location on comparatively plane surfaces. During snow-melt in spring, intensified spatial differentiation of soil moisture is visible in the catchment. Besides a pronounced trend to moister conditions at higher elevations, pastures as well as depressions showed moister soils while alluvial fens were characterized by drier soils. Elevation trend as well as soil classes were traced in this spatial distribution. Spring was the wettest season regarding soil moisture. In summer the higher spatial variability of the spring soil moisture pattern was superposed by a distinct altitudinal trend from dry to moist conditions throughout the valley. This trend varied strongly according to soil texture and land-cover dependent differences resulting in a heterogeneous pattern. At the highest altitudes, soil moisture remained constantly near the saturation level throughout summer (35-40 Vol-%) due to the continuous surplus of snow-melt water, while water stress occasionally occurred at lower elevations like alluvial fens and the forest areas near the valley floor (< 10 Vol-%). The high spatial difference of soil moisture in summer is leveled again in autumn due to enhanced desiccation at higher altitudes and refilling of the soil water storage at the valley floor.

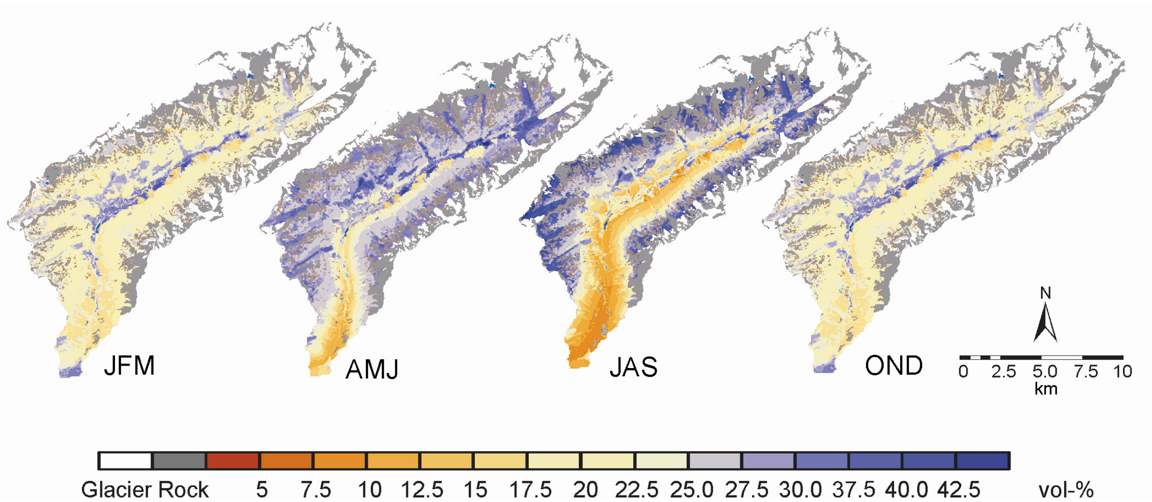


Figure 14: Mean seasonal soil moisture patterns (mean of 2003 – 2007) in the Lötschen valley for winter (JFM), spring (AMJ), summer (JAS), and autumn (OND).

The temporal dynamic of simulated soil moisture was analyzed in more detail for altitude and land cover (Figure 15). While simulated soil moisture values were very homogenous in winter regardless the land covers or elevation, great differences occurred in summer. Lower altitudes (600–1400 m a.s.l., Figure 15 below) showed an early decrease of simulated soil moisture in spring from moderate winterly contents to dry conditions in summer and autumn. With increasing altitude, simulated soil moisture showed later but steeper rises in water content and highest soil moistures occurred during summer. While below 2200 m a.s.l. soil water decreased throughout the summer, soil moisture content rose above 2200 m a.s.l. elevation, indicated that drought stress never occurred at higher altitudes. On loamy soils, drought stress (indicated by the permanent wilting point (pf > 4.2 ≙ 15000hPa)) was never simulated in the *Lötschen valley*. The driest land cover types were the subalpine coniferous forests followed by shrub vegetation growing on the alluvial fens (cp. Figure 3). Grassland, alpine grassland and alpine heath vegetation types were characterized by balanced simulated soil moisture content in summer (Figure 15 top). Debris soils at highest altitudes attained their highest soil moisture values in summer when snow-melt at this altitude was strongest. Hence, with increasing altitude simulated soil moisture was more and more influenced by later snow-melt and soils remained moist due to increased liquid precipitation amounts in summer. In total, the simulated soil moisture dynamic was determined by snow-melt and precipitation as well as evapotranspiration demand. These parameters affected the simulated soil moisture change over time and space and were strongly altered by elevation and land cover: on the one hand the influence of elevation on simulated soil moisture in summer and autumn were owed to all meteorological factors being a function of elevation. On the other hand the influence of land cover increased with increasing influence of meteorological data, and higher values for the leaf area index (LAI) during summer. In summer when vertical processes like evapotranspiration are greatest, the influence of soil texture accordingly is highest as well.

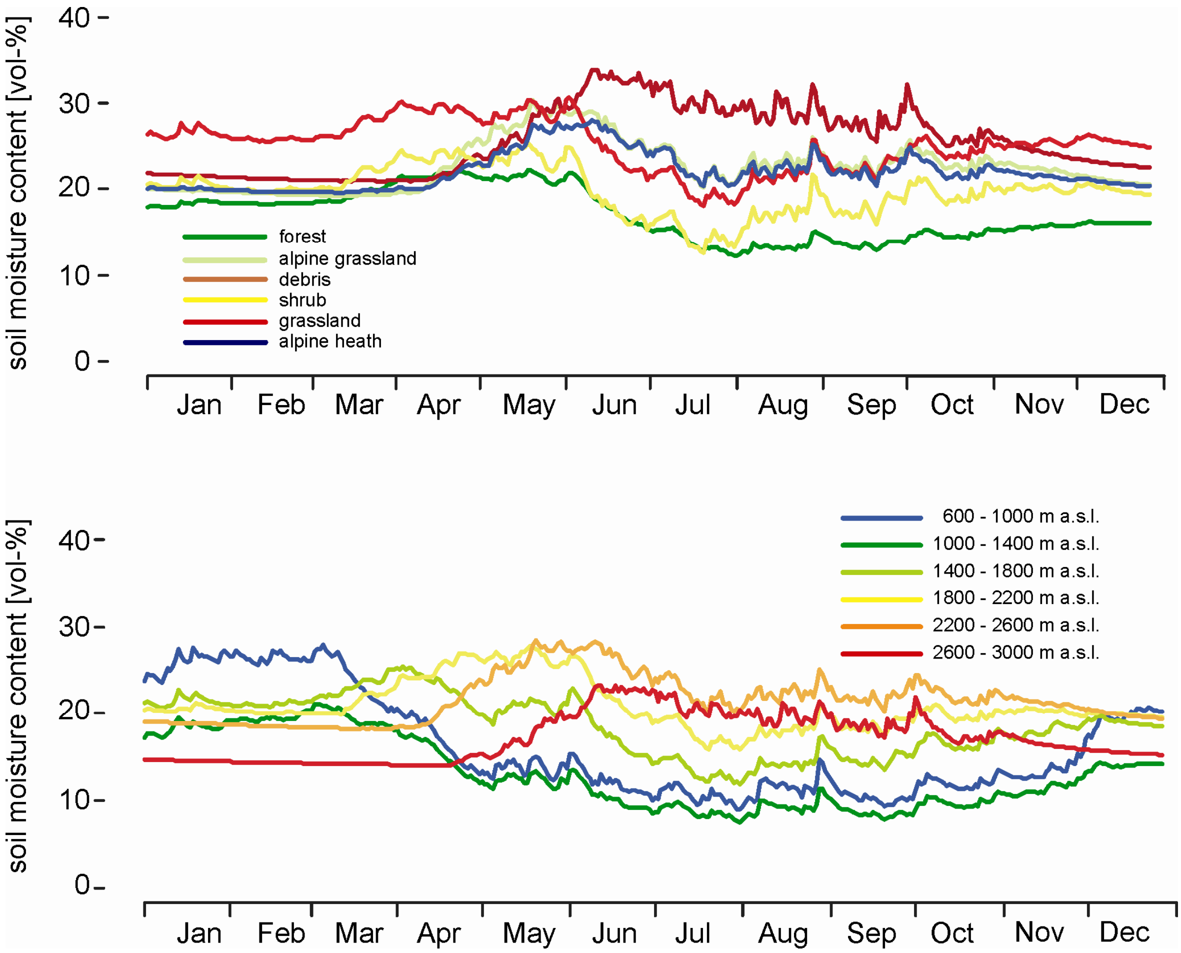


Figure 15: Annual soil moisture dynamic (mean of 2003–2007) with respect to land cover (top) and altitude (below) for loamy soils.

5.2 Evaluating uncertainties of different downscaling approaches

To estimate the uncertainties of different downscaling approaches four different approaches were compared with the reference model for 1960-1990 at a daily basis. The water balance provides the basic and most comprehensive overview of all hydrological processes and storages, enabling an easy comparison of the quality of the different models and downscaling approaches (Table 12). The table summarizes the high variability of the different model results, indicating the much better performance of SD-models (absolute bias). In terms of discharge, all models except for the DU-REMO model underestimated the observed discharge. This trend was predefined in the reference model, which also slightly underestimated the discharge amount (-6%). The SD-CHRM model agreed very well with the reference model (+0.24% deviation), while DU-CHRM and SD-REMO largely underestimated the discharge amount (-15% and 16%, resp.). Although the overestimation of discharge was not very large at the gauge (+6.6%), DU-REMO showed a rather coarse approximation to the reference model, with only single variables agreeing more or less randomly with the reference model, e.g., summer temperature and glacier balance, while precipitation, evapotranspiration, and annual mean temperature strongly deviated. The DU-CHRM approach showed similar deviations in terms of temperature, but precipitation was more similar to the reference model. In contrast to the direct use of the RCMs, the statistical downscaling models agreed much better with the reference model. However, SD-REMO presented drastically low discharge values, in combination with lower summertime temperatures and lower glacier melt water (Table 12). Interestingly, no model was consistently able to perform best for all output variables, although SD-CHRM was closest to the reference model.

Table 12: Water balance results of hydrological models driven by REMO and CHRM climate model applying both downscaling approaches and comparing them against the reference model run and the observed discharge.

	Reference model	DU-CHRM	Deviation from reference model	DU-REMO	Deviation from reference model	SD-CHRM Ø	Deviations from reference model	SD-REMO Ø	Deviation from reference model	Observed
Discharge (gauge) [mm]	1471*	1251*	-15.0%	1567*	6.5%	1476*	0.24%	1251*	-16.1%	1565*
Temperature [°C]	-0.3	-1.38	-1.08	-1.1	-0.7	-0.15	+0.15	-0.16	+0.14	
Summer temperature (Jun. - Sept.) [°C]	5.38	5.04	+0.34	5.43	+0.05	5.48	+0.1	4.58	-0.8	
Precipitation [mm]	1418	1482	+64 mm, +4.5%	1939	+512mm, +36.7%	1534	+116 mm, +8.15%	1408	-10 mm, -0.7%	
Discharge (total) [mm]	1239	1401	+162 mm, +13.0%	1607	+368mm, +29.7%	1248	+9mm, +0.65%	1076	-163mm, -13.2%	
Snow fall [mm]	907	876	-31 mm, -3.4%	1202	+295mm, +32.5%	917	+10mm, +1.1%	822	-85mm, -9.3%	
Rain fall [mm]	510	606	+96mm, +18.8%	736	+226 mm, +44.2%	617	+107 mm, +20.8%	585	+75mm, 12.8%	
Evapotranspi -ration [mm]	326	267	-59mm, -18.1%	368	+42 mm, +12.9%	388	+62 mm, +19.1%	375	+49 mm, +13.0%	
Snow storage [mm]	42	65	+ 23mm, +54.7 %	54	+12 mm, 26.5%	62	+20 mm, 45.1%	69	+27 mm, 64.3%	
Glacier balance [mm]	-440	-325	+115 mm, +26%	-214	+226 mm, +51%	-512	-72 mm, -16%	-457	-17 mm, +4%	
Absolute bias [mm]			+305		+1106		+135		-114	

*** relates to an area of 77.8 km² (48.6 %)**

The long-term mean discharge is given in Figure 16 (a-d) while in Figure 17 (a-d) the related exceedance probabilities are presented. Figure 16 shows the annual mean discharge curves from 1960 to 1990 for the reference model (top left) and models driven by DU-models (top right), SD-REMO (bottom left), and SD-CHRM (bottom right), plotted against observed discharge (black dotted line) and reference model (dark gray line). The observed discharge, with a characteristic glacio-nival discharge regime, was very accurately reproduced by the reference model, as shown by the high statistical values obtained (R^2 = 0.99, ME = 0.97, IoA = 0.99, Figure 16a). All other approaches were able to simulate the general patterns (Figure 16 a-d), but revealed strong deviations for some variables. For SD approaches, we illustrated the total range of 20 ensembles (shaded gray area). The discharge simulated by SD-CHRM data showed the smallest deviation, although an overestimation occurred in early summer, indicating an overestimation of snow melt processes. The two DU-models overestimated discharge in summer (Figure16b), especially the DU-REMO approach, while both models underestimated discharge during all other seasons. The strong underestimation of discharge using SD-REMO, as also presented in the water balance table, was restricted to the summer months, when lower temperatures lead to lower glacier melt and result in a too low level of discharge. In general, all discharge curves revealed an inflated amplitude, which was most likely caused by the temperature amplitude of the RCMs being too high. Thus, CHRMs performed much better than REMO models, independent of the applied downscaling approach. This indicates a weaker correlation with temperatures for REMO models that is only slightly weakened by statistical downscaling.

A second analysis concerning discharge was performed that focused on the reproduction of daily discharge amounts. The exceedance probability illustrates the probability of occurrence of a certain daily discharge amount. In contrast to the mean annual discharge curve, the reference model showed considerably higher extreme values and an underestimation of discharge values between 10 and 20 m^3/d. Because the calibration of the model was performed in a superior manner based on the annual mean curves of 1960 to 1965, this deviation is unsupported. Disregarding the overestimation of extreme discharges that is predefined in the reference model, DU-REMO and DU-CHRM, as well as SD-CHRM showed very good agreement in terms of the exceedance probability. These model approaches showed even better agreements with the observed discharge exceedance probability than the reference model. Only SD-REMO revealed strong deviations, mainly for medium values. In addition to the classical analyses of discharge, which depend mainly on snow and glacier melt, we analyzed spatial variables, such as evapotranspiration and soil moisture, by calculating the RMSE for each raster cell on a monthly basis, excluding rock and glaciated areas (Figure 18). Regardless of the model approach, the deviations for actual evapotranspiration were large and represented spatial patterns mostly in terms of land use type.

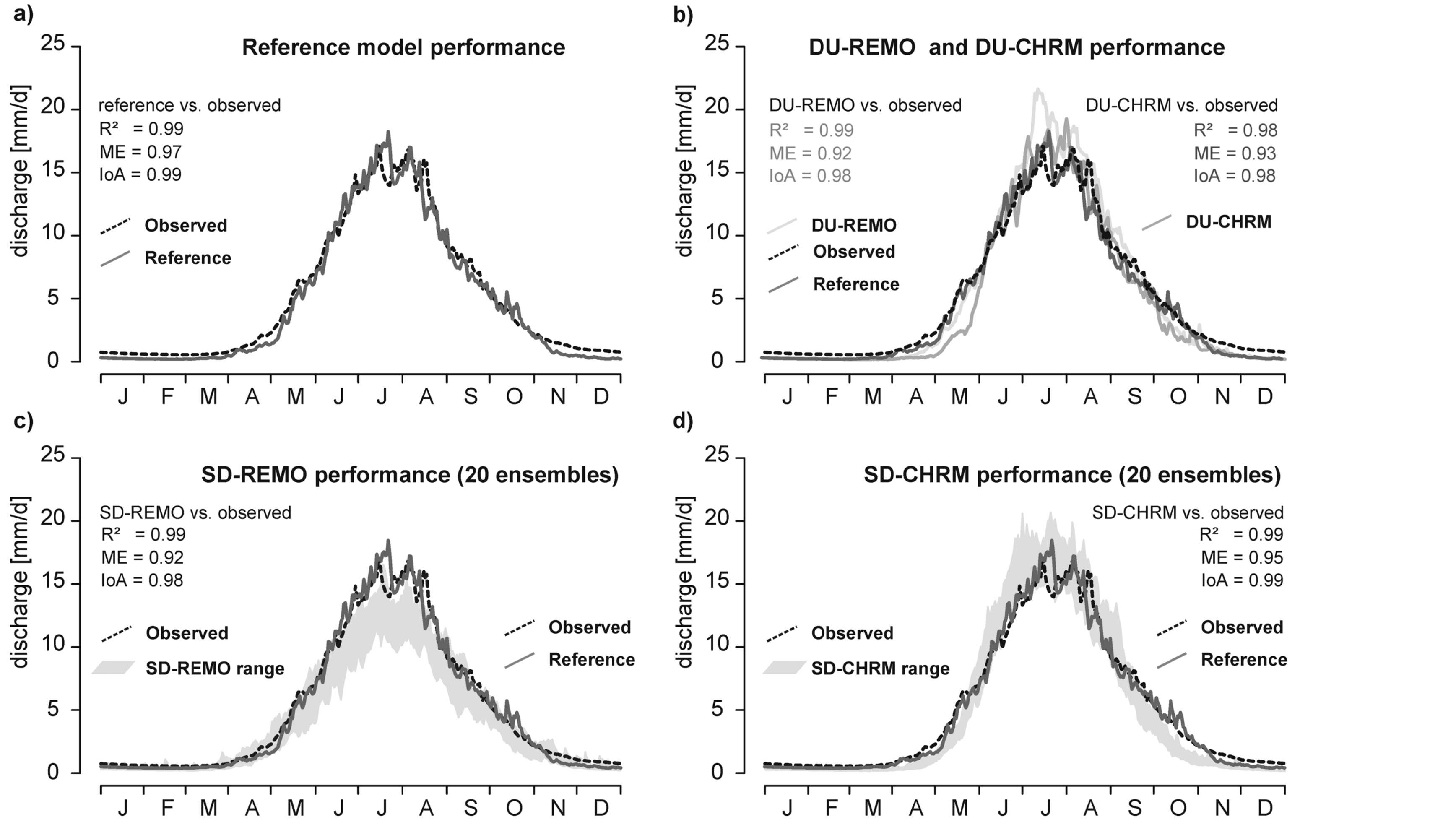


Figure 16: Discharge performances of the reference model and the four different climate driven models. Illustrated are mean discharge curves of 1960-1990. Shaded areas indicate the range of ensemble runs.

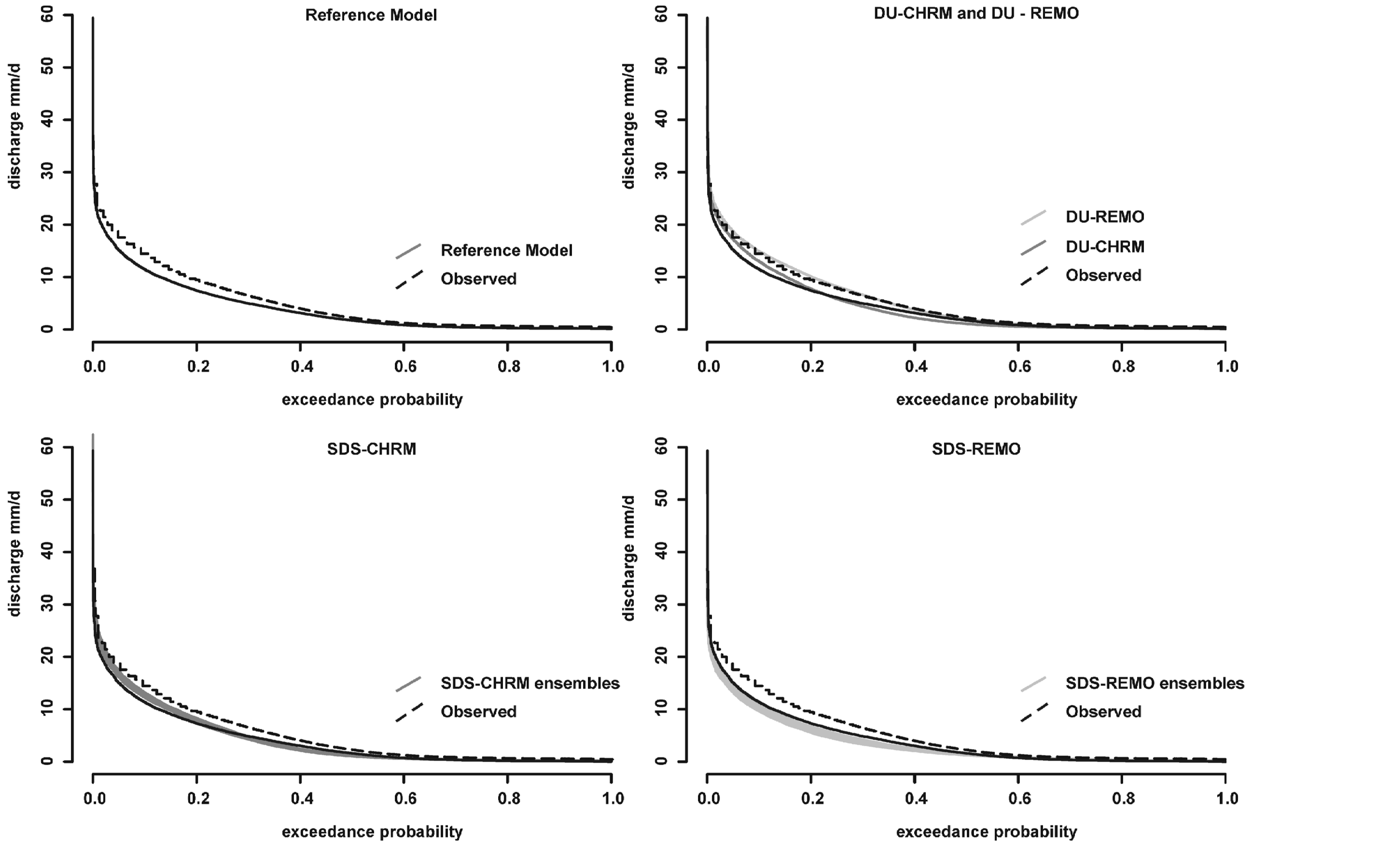


Figure 17: Exceedance probability (1960-1990) of observed discharge in comparison with simulated discharge of the reference model, and both climate model data with both downscaling techniques.

Considering the annual mean evapotranspiration sum of 270 to 380 mm (depending on model approach, Table 12), mean RMSEs of 14-17 mm per month amounted to 60% of the annual sum. Because the annual mean sums deviated from the reference model by only 20% at most, the high RMSE value indicates a strong temporal disagreement with the reference model. Although all model approaches suffer from these very high RMSEs, SD models, especially the SD-REMO approach, performed best by showing the lowest deviations. In contrast, monthly soil moisture showed few deviations from the reference model. Both SD models, as well as the DU-CHRM approach were able to reproduce the monthly soil moisture with an error-range of +/- 3 Vol-% to a large degree. Again, the DU-REMO model showed the lowest agreement with the reference model. At the southern gorge and at lower elevations, deviations became more disctinct, ranging up to 10 vol-%.

Finally, we analyzed the spatial dataset in terms of seasonal aspects of the observed uncertainties by calculating the median and quantiles of the spatial residuals and determining the map agreement index (Figure 19). We assumed that these deviations mainly resulted from deviations of temperature and precipitation, as well as snow melt, and we therefore presented the deviations of these variables in combination with the spatial residual of evapotranspiration and soil moisture. The deviations of soil moisture, illustrated as medians and upper and lower quantiles (Figure 19) showed a slight overestimation, independent of the approach used. For the spring, a distinct decrease of statistical values indicated an underestimation of soil moisture with respect to the reference model. In contrast, during the summer months, soil moisture was overestimated. This general pattern, which was also illustrated by the MAI, was more pronounced in DU models. A partially delayed, but subsequently enhanced snow melt was the reason for this soil moisture uncertainty pattern.

Precipitation or temperature deviations were found to have less direct influence on a monthly basis, but precipitation overestimation causes positive deviations for the DU-REMO approach. The lowest deviations among all approaches were found in winter (cp. MAI-values in Figure 19), when the hydrological cycle is least pronounced. The uncertainties of evapotranspiration for SD models showed constantly moderate deviations from the reference model, while we found a strong, but inconsistent uncertainty pattern for DU models: the DU-CHRM approach largely underestimates evapotranspiration during early spring, while parts of the evapotranspiration map show a pronounced overestimation, as indicated by the upper quantiles. In conclusion, spatial uncertainties were found to be variable to some degree over time and are much more distinct for DU models than for SD models.

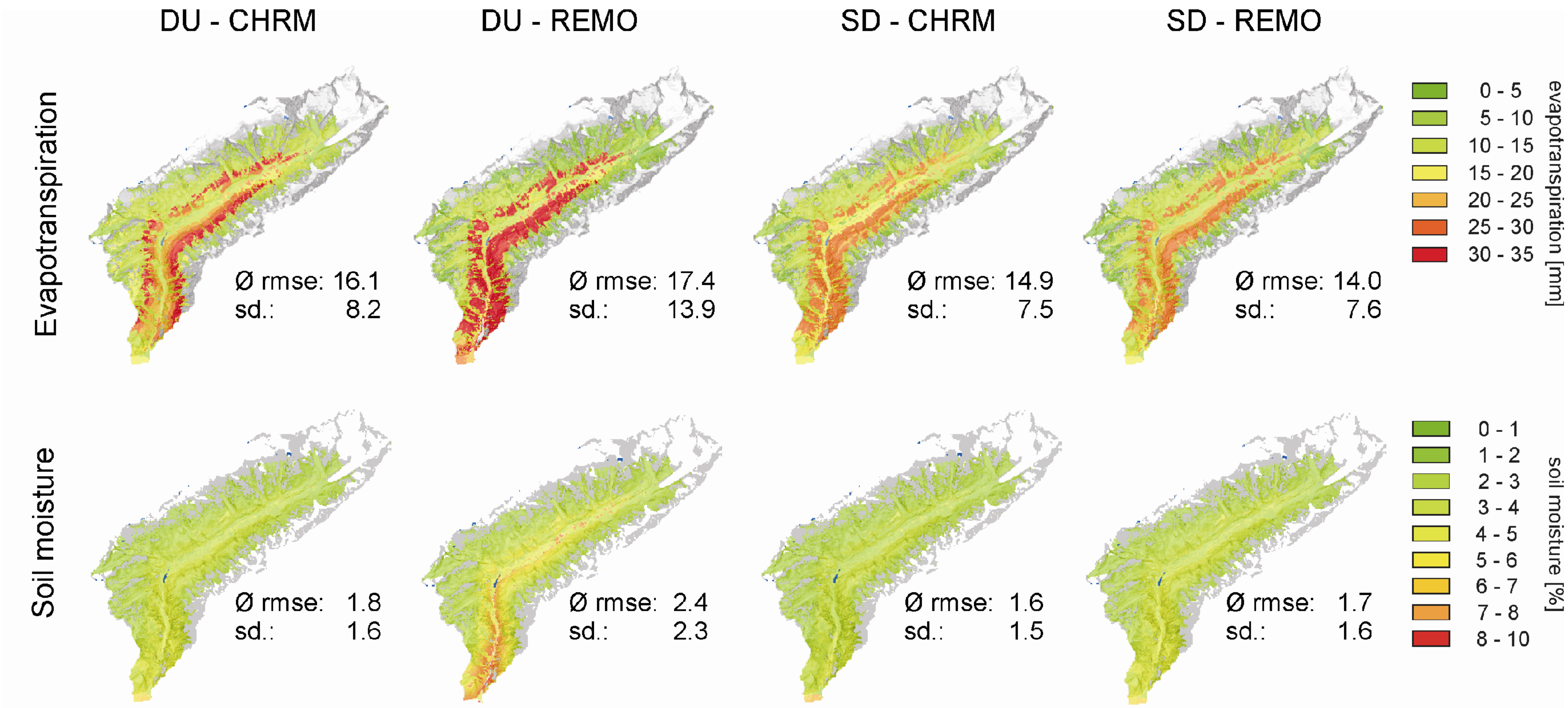


Figure 18: Spatial uncertainty of soil moisture and actual evapotranspiration expressed by RMSE on a monthly basis between 1960-1990 of the two models and the two approaches against the reference model.

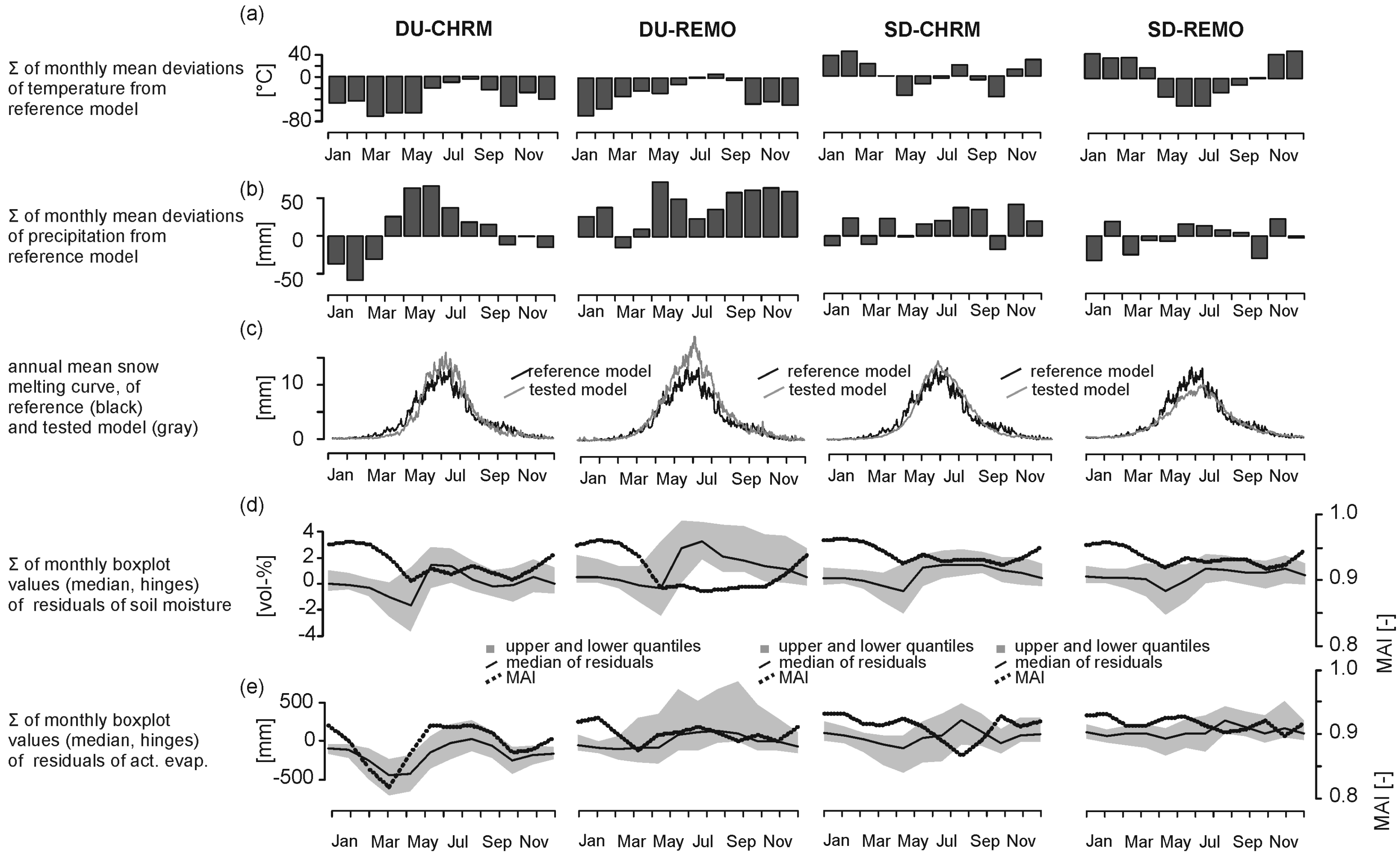


Figure 19: Spatio-temporal agreement between reference model and SD- and DU-driven models in terms of soil moisture (d) and evapotranspiration (e), and according meteorological parameter (temperature (a), precipitation (b), as well as snow melting (c). Map agreement index (MAI), as well as median and quantiles of residuals indicate spatio-temporal unsteadiness of uncertainties. Greatest uncertainties are found during the snow-melt season

5.3 Assessing climate change impact on hydrology and soil moisture

5.3.1 Climate change impact on the hydrologic cycle

The impact of climate change on the hydrologic cycle is most concisely summarized as changes to the probability density function of the hydrological variables (Figure 20). Depending on climate model and downscaling approach, slightly different temperatures and precipitation distributions were simulated that again led to varying magnitudes of change in terms of actual evapotranspiration and monthly soil moisture values. Temperature distributions for all six model-approaches shifted by some degrees under all scenarios applied. High temperature values revealed thereby a stronger shift than low temperatures - a fact that is even more pronounced applying REMO climate models. In addition, an expected flattening of the curves under scenario conditions indicating an increased variability was hardly detectable. Differences in precipitation amounts were just restricted to the medium values. By contrast, DU-models and Δ-CHRM were characterized by an increase of low precipitation amounts under future scenario. In terms of Δ-CHRM this is attributed to an increase of values slightly higher than zero. Changes in the variability of precipitation amounts were negligible. Only Δ-REMO showed a decrease of low precipitation amounts under future scenario conditions, but higher total amounts of precipitation. The impacts of changed meteorological conditions on water of non-glaciated areas were illustrated by changes in actual evapotranspiration and soil moisture. The PDFs of actual evapotranspiration showed similar changes under future scenario conditions for all six approaches. We found a shift of low actual evapotranspiration sums (<<1 mm/day) to values around 1 mm/day. This shift was slightly not achieved by the DU-CHRM model. In addition, highest evapotranspiration values remained unchanged except for the Δ-models that showed higher extreme values. In terms of soil moisture, all model approaches showed a similar unimodal distribution characterized by a mean probability density of ±20 vol-%. Under future scenario conditions a distinct flattening of the density-curve occurred, indicating an increased variability which was accompanied by a shift of the mean density from 20 Vol-% to 25 vol-%. The main difference between the model approaches were changes at the lower and upper values of the density function: both SD-models and the Δ-REMO model showed a distinct rise in density for values of 25 and 30 vol.% and no change for lower soil moisture values. In contrast, both DU-models and the Δ-CHRM approach revealed an increase of densities of values from 20 – 7% indicating a shift to much drier conditions under future scenario conditions. Applying the Δ-REMO approach, this soil moisture depletion trend could not be traced. In summary, concerning the PDF function, we found mostly very similar functions and changes that result in a two-parted response in terms of monthly soil moisture: a strong depletion (DU-models and the Δ-CHRM approach) or a shift to even moister conditions (all other).

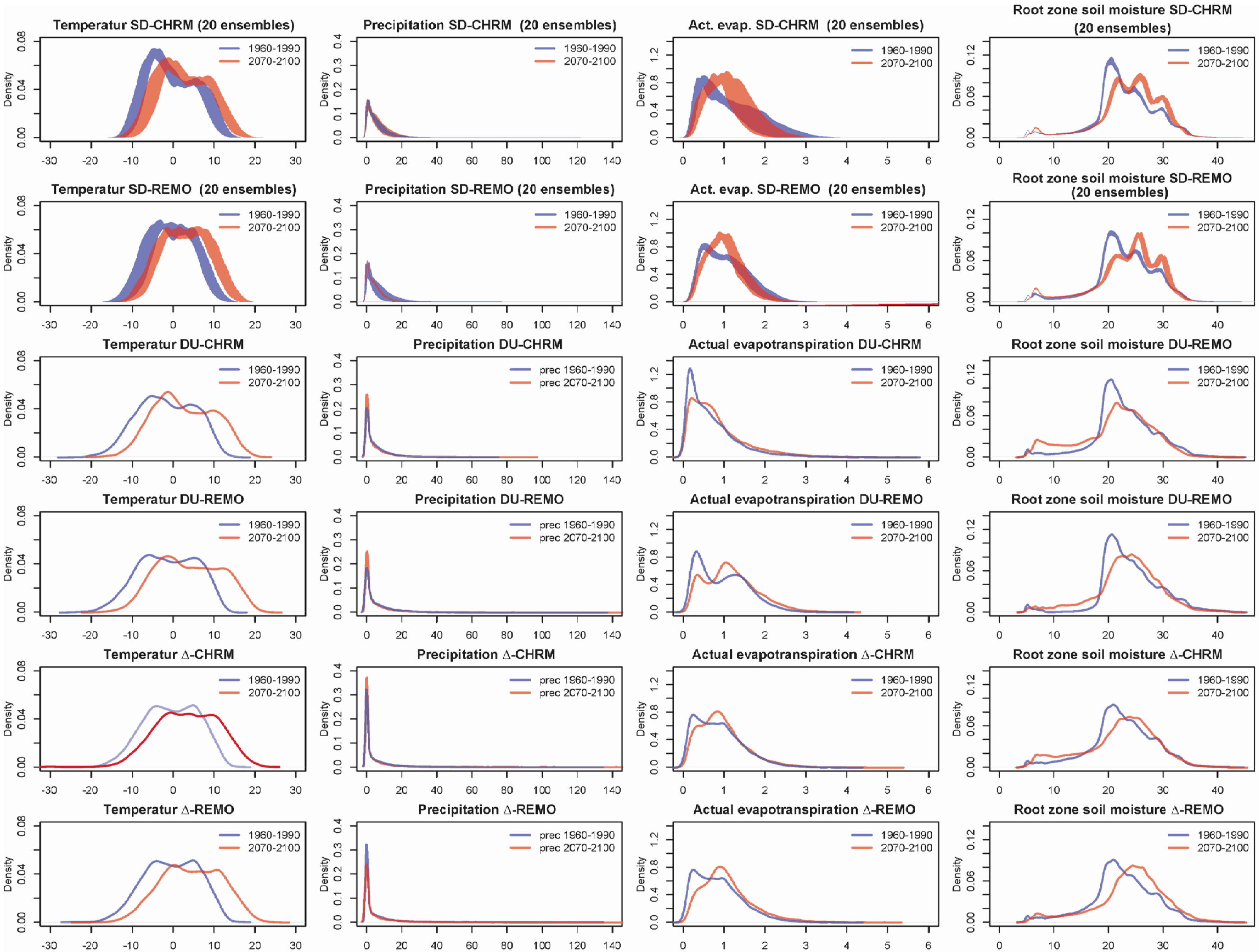


Figure 20: Comparison of reference (1960-1990, blue) versus scenario (2070-2100, red) temperature, precipitation, actual evapotranspiration, and soil moisture of two RCMs (CHRM, REMO) and three downscaling techniques (SD: statistical downscaling, DU: direct usage, Δ: Delta-change-approach).

At next, the impact of climate change on the water balance was calculated (Table 13). For SD and DU-models, we found a strong increase of temperatures and unchanged precipitation amounts which causes a shift from snow to rainfall, enhanced ablation of snow and glacier, and consequently increased discharge. For Δ-models with both increasing temperatures and increasing precipitation amounts, snow and rainfall amount rose, and partly filled the losses of snow and glacier storages caused by higher temperatures and lead to increased discharge. The response of evapotranspiration to climate change can be directly linked to the temperature increase, except for the smaller increase of Δ-CHRM indicating a reduction of actual evapotranspiration due to drought stress. The overall pattern of the water balance emphasizes the higher importance of downscaling technique than the climate models applied. In addition, major differences are caused by the different precipitation amounts, while deviations in temperature increase are negligible.

Table13: Effects of climate change on the water balance with respect to the two RCMs and three downscaling techniques, expressed by annual mean and sum values, respectively, as well as the percentage change. Colored arrows mark on the magnitude of change.

		Temp [°C]	Summer-temp [°C]	Precipitation [mm]	Total runoff [mm]	Runoff at gauge [mm]	Snowfall [mm]	Rain [mm]	Evapotrans-piration [mm]	Snow storage [mm]	Galcier balance [mm]
1960-1990	SD-CHRM	-0.15	5.5	1534	1248	1476	917	617	388	62	-1732
2070-2100	SD-CHRM	2.4	8.1	1491	1644	2196	622	868	385	7.8	-8002
	[% - Δ]	↑	↗	-2.8 →	31.7 ↗	48.8 ↗	-32.2 ↘	40.7 ↗	-0.8 →	-87.4 ↓	-362 ↓
1960-1990	SD-REMO	-0.17	4.56	1410	1073	1247	824	585	377	69	-1141
2070-2100	SD-REMO	2.38	7.18	1348	1381	1826	543	805	376	5.8	-5722
	[% - Δ]	↑	↑	-4.4 →	28.7 ↗	46.4 ↗	-34.1 ↘	37.6 ↗	-0.3 →	-91.6 ↓	-401.5 ↓
1960-1990	DU-CHRM	-1.38	5.04	1482	1401	1251	876	606	267	65	-2768
2070-2100	DU-CHRM	2.26	9.2	1344	2482	1789	665	678	325	1	-12009
	[% - Δ]	↑	↑	-9.3 →	77.2 ↑	43 ↗	-24.1 ↘	11.9 ↗	21.7 ↗	-98.5 ↓	-333.9 ↓
1960-1990	DU-REMO	-1.11	5.43	1939	1606	1567	1202	736	368	53	-2434
2070-2100	DU-REMO	3.24	10.6	1774	2812	2139	777	996	447	3.7	-13352
	[% - Δ]	↑	↑	-8.5 →	75.1 ↑	36.5 ↗	-35.4 ↘	35.3 ↗	21.5 ↗	-93.0 ↓	-448.6 ↓
1960-1990	Reference	-0.3	5.38	1418	1239	1471	907	510	326	42	-2345
2070-2100	Δ-CHRM	2.95	9.34	1747	3729	2641	973	773	360	-9	-20050
	[% - Δ]	↑	↑	23.2 ↗	201 ↑	79.5 ↑	7.3 →	51.6 ↑	10.4 →	-121.4 ↓	-755 ↓
1960-1990	Reference	-0.3	5.38	1418	1239	1471	907	510	326	42	-2345
2070-2100	Δ-REMO	3.73	10.2	2410	4697	3432	1129	1281	404	-3	-21586
	[% - Δ]	↑	↑	70.0 ↑	279.1 ↑	133.3 ↑	24.5 ↗	151.2 ↑	23.6 ↗	-107.1 ↓	-821 ↓

↓ < -50% ↘ -10 - -50% → -10 - 10% ↗ 10 - 50% ↑ > 50%

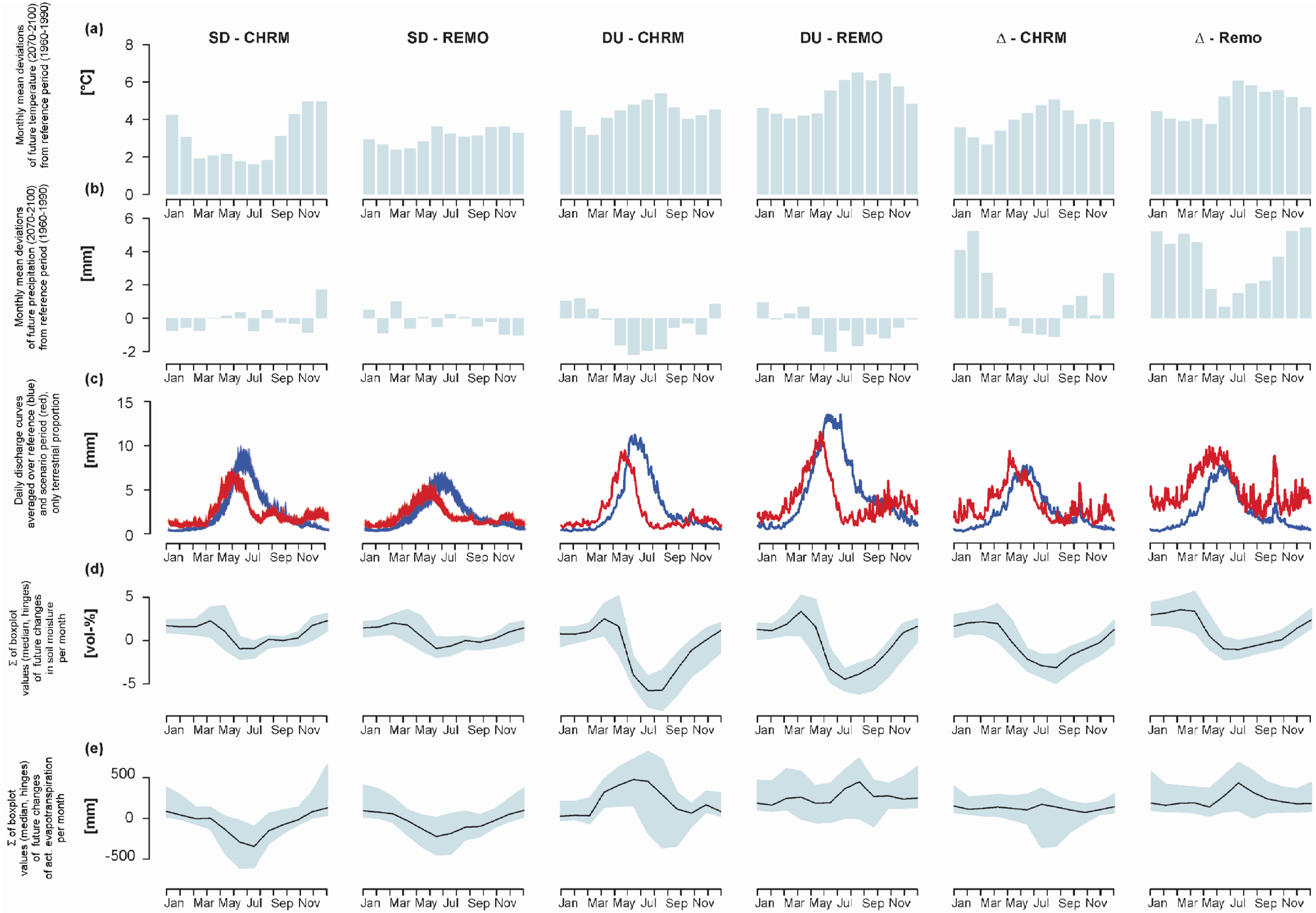


Figure 21: Model approach depended, intra-annual changes to (a) temperature, (c) precipitation, and (d) discharge from non-glaciated areas, as well as spatial differences of soil moisture and actual evapotranspiration under reference (1960-1990) and climate change conditions (2070-2100).

Figure 21 comprehensively illustrates the spatio-temporal impacts of climate change on major variables with respect to the six model-approaches: The difference of variables between reference and future scenario conditions are graphed as barplots for the meteorological variables (Figure 21a,b), as two separate mean annual curves of discharge from non-glaciated discharge (blue and red, Figure 21c), and as differences in the spatial distribution of soil moisture (Figure 21d) and actual evapotranspiration (Figure 21e) expressed as median and hinges.

The plots indicate that the increase in temperature is equally distributed throughout the year for all model approaches (Figure 21a, b). In contrast, higher precipitation sums were only found for Δ-models and were dominantly apportioned to winter months. This explains the trend to higher snow fall sums found for Δ-models (Table 13). The meteorological changes led to a shift in the terrestrial discharge dynamic: under reference conditions all model approaches produced a single-peak curve resulting from snow melt on glacier-free areas. Under future scenario conditions, this discharge characteristic was preponed by approx. one month and showed smaller maximum discharge values as a result of decrease snow storages.

Since the Δ-REMO approach provided the highest snow fall increase, a smaller temporal shift and a lower reduction of maximum discharge was found. In addition, noticeable discharge peaks during winter for Δ- and DU-models indicate a shift from glacio-nival to pluvial discharge regimes. Differences between reference and future scenario conditions in terms of the monthly mean soil moisture showed a strong dependency on the preponed snow melt processes: future soil moisture surplus concords with earlier snow melt, as well as a loss of soil moisture during the snow melt period of the reference model. This characteristic holds true for all model approaches at different magnitudes.

For SD-models showing the least change in precipitation and temperature, we consequently found only small changes in the soil moisture dynamic, although these small changes had a drastic impact on actual evapotranspiration. Evapotranspiration was significantly reduces during summer for some areas under SD-CHRM. DU-models imply the strongest temperature increase and decreasing summer precipitation, resulting in strongest differences both for soil moisture and actual evapotranspiration. Thereby, soil moisture distinctly decreased in summertime and at the same time actual evapotranspiration values increased. The great variability of values that is expressed by the wide range of hinges indicates enhanced evapotranspiration driven by temperature and at the same time the evapotranspiration deficit caused by dry soils. The Δ-models showed intermediate differences, particularly in terms of soil moisture which is increasing during wintertime and that is partly decreasing in summer.

For the Δ-CHRM approach we found soil drought dependent evapotranspiration drop in parts of the valley as indicated by the lower hinge. In conclusion, we found a preponed discharge from non-glaciated areas under climate change conditions, indicating an earlier snow melt causing preponed soil moisture dynamics too. Moreover, we found some evidence that evapotranspiration is reduced due to soil drought in some parts of the area.

To verify this soil drought dependent evapotranspiration decrease and to analyze the impact of climate change on soil droughts in general, we calculated the evapotranspiration deficit for reference and future scenario conditions (Figure 22) based on daily means for the entire catchment. We found a strong increase of the evapotranspiration deficit during summer for DU and DT-models under future scenario conditions; DU-CHRM was characterized by the highest soil moisture depletion (Figure 22). Furthermore, the magnitude of enhanced evapotranspiration deficit found for the different models concords with the magnitude of decreased soil moisture. In contrast, the expected enhanced evapotranspiration deficit in summer for the SD-CHRM cannot be confirmed.

5.3.2 Climate change impact on soil moisture patterns

The impact of climatic change on soil moisture patterns is illustrated by the differences of seasonal means of soil moisture, based on daily records. Figure 23 assembles the results of all six model approaches and the consensus of the models expressed by mean and 0.25 and 0.75 quantiles, respectively. For each seasons we found differences between downscaling approaches to be much higher than between climate models applied. Strongest depletion of future soil moisture conditions was found for DU-models across all seasons. Especially in summer (JAS), declines of up to -25 vol % were simulated at the south facing slope and for the grasslands of the valley floor that exhibit high soil moister contents in the reference simulation. This depletion lasted until autumn (OND). In contrast, SD-models gave a rather retentive simulation of climate change impact on soil moisture. Excluding the steep gorge, we found no noteworthy depletion of soil moisture (<-2%) and nearly no increase at non-forested areas during winter (<+5%). Δ-models reveal an increase of soil moisture (+5%) in all parts of the catchment during winter (JFM), while again we found no great change to soil moisture in all other seasons.

Accordingly, the consensus of the model approaches revealed a rather slight change in soil moisture but great variability with respect to the model applied. We found an increase of soil moisture during winter (JFM) with a maximum for grassland at the south facing slope. During spring (AJM) wide areas were slightly drier under future scenario conditions while highest elevations showed a rise in soil moisture. In summer, the soil moisture decline was highest (up to -5 vol-%), affecting mainly the forested areas at the south facing slope. In addition, 0.25 and 0.75 quantiles indicate large variability of the ensemble modeling ranging from nearly no change in summer and a considerable increase of soil moisture in winter, to depletion in summer (-5% to -10%) and even a slight decrease of soil moisture during winter. This wide corridor of changes in soil moisture challenges the interpretability and the relevance of soil moisture in climate impact assessment studies. Therefore, a more detailed, day-to-day analysis was conducted to evaluate climatic change impact on soil moisture and drought stress at a higher temporal resolution.

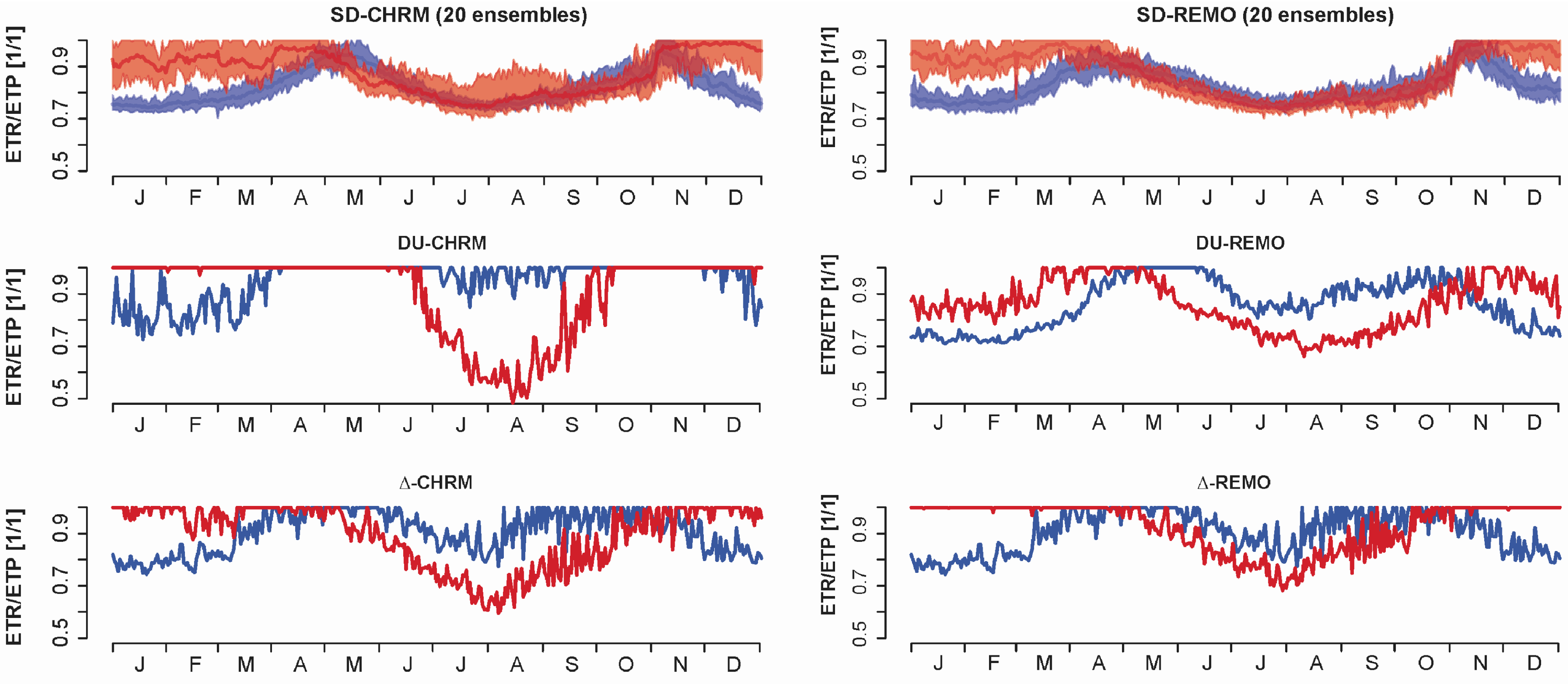


Figure 22: Comparison of the averaged evapotranspiration deficit in the studied catchment based on three downscaling methods and two RCMs, illustrating strong difference. Blue colours indicate the reference run (1960-1990), red colours to the future scenario run (2070-2100). Shaded areas point to the range of ensembles conducted within the SD approach and thick line indicate the ensemble mean.

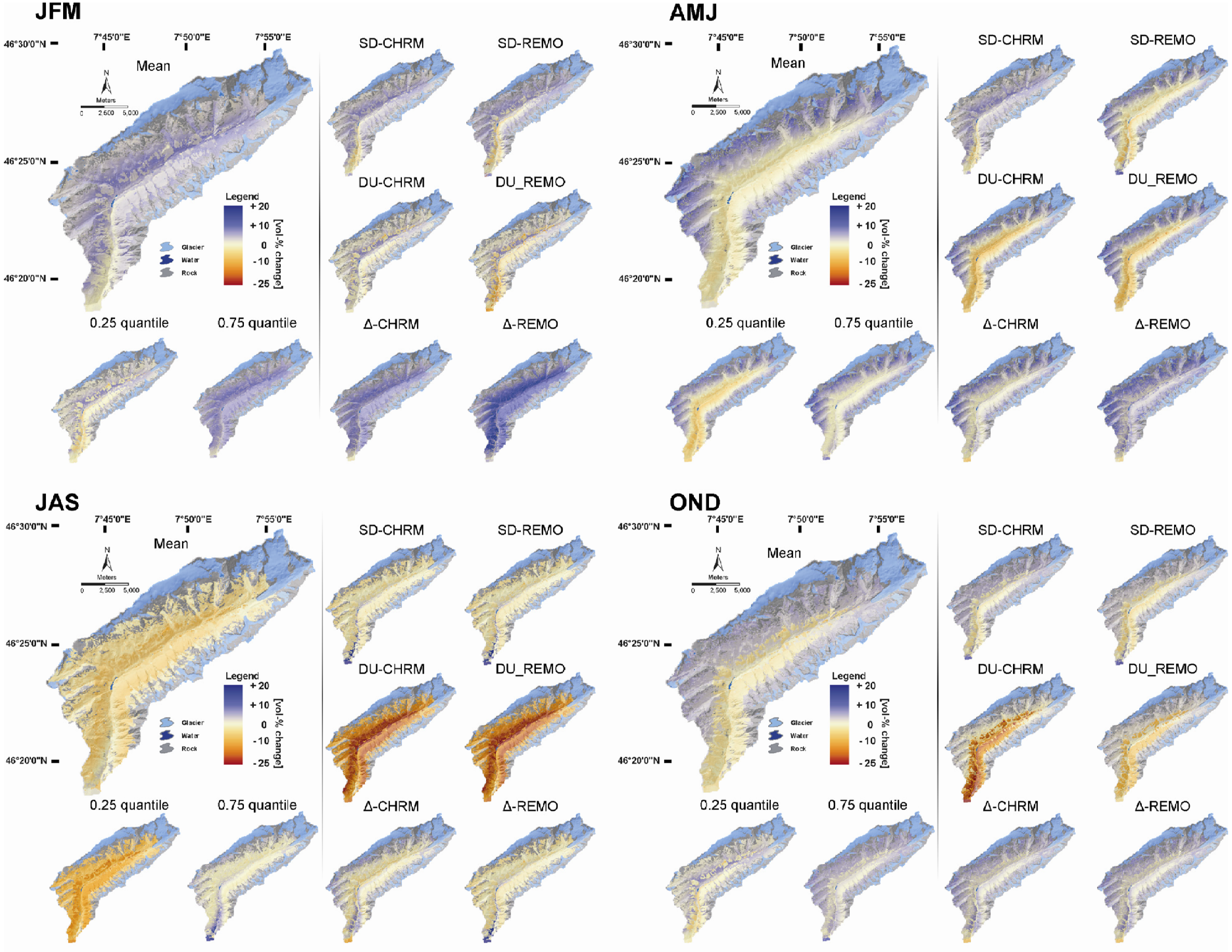


Figure 23: Average seasonal (JFM, AMJ, JAS, OND) soil moisture decrease between reference (1960-1990) and future scenario conditions (2070-2100) for different model approaches and the consensus of the models expressed by

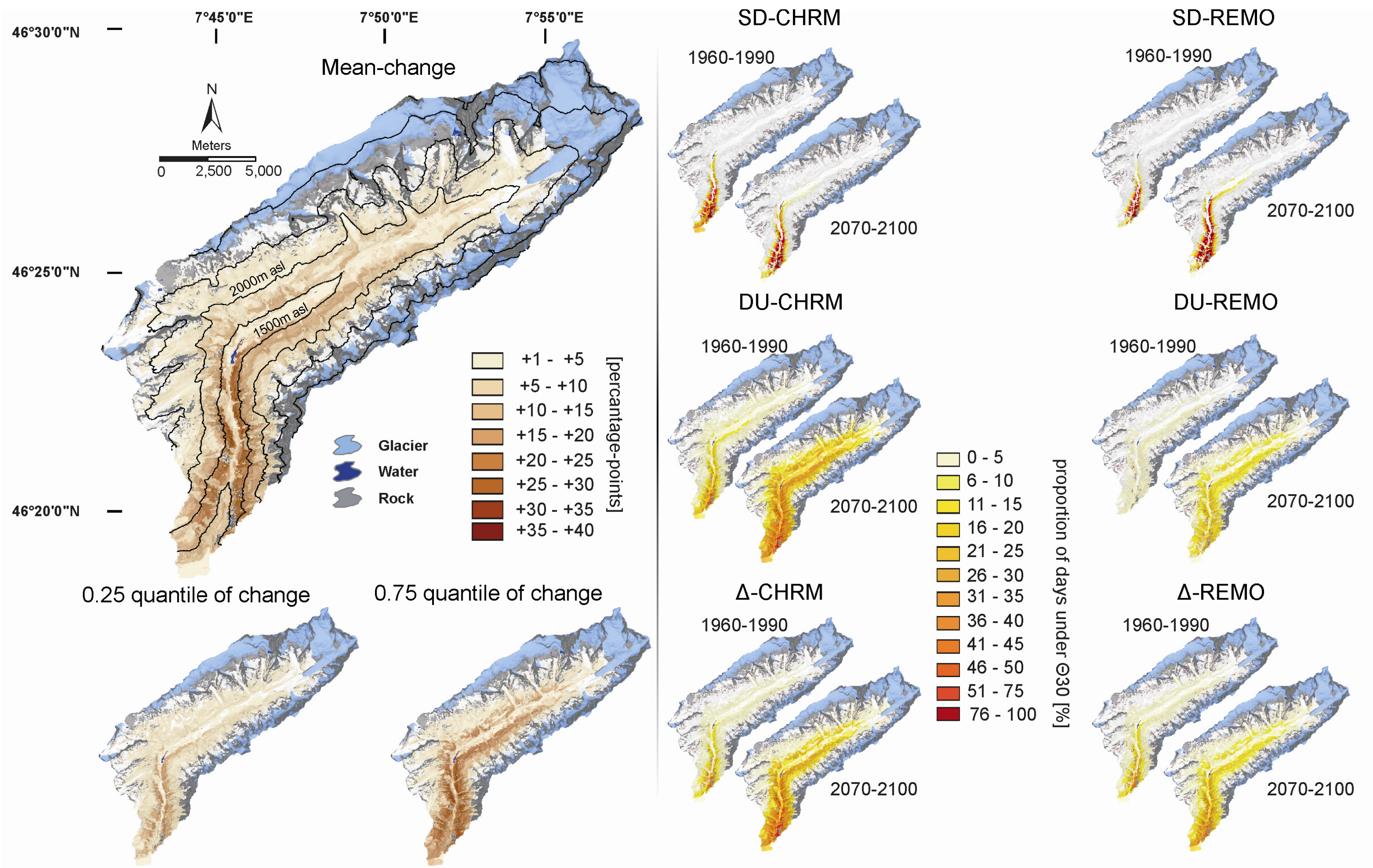


Figure 24: Proportion of days the soil moisture drops below a critical level (defined as 30% of field capacity, cp. Allen et al. 1998). Reference and scenario results for each model approach (right), as well as model consensus (left).

The percentage of days on which soil moisture dropped below a critical level is given in Figure 24. Under reference conditions soil moisture in the main valley rarely fell below the critical level (0-5% of the regarded time period). In contrast, the steep gorge to the south was regularly affected by drought stress as indicated by all applied model approaches. In DU- and Δ-models with future scenario conditions, drought stress became much more frequent and occurred in wide areas of the valley. Thereby, a decreasing trend with altitude and an enhancing effect of forested areas were visible. Most retentive assessment of climate change was again simulated applying SD-models. DU- and Δ-model approaches and especially those driven by CHRM climate data showed a strong signal towards 30% of drought stress days with even higher proportion in forested areas. In accordance, the consensus showed an increase of 15-30 percentage points of drought stress days in forested areas in altitudes up to 1750m asl, whereas grasslands and alpine areas showed no major increases (+1 to +5 percentage points). In contrast to the seasonal soil moisture analysis we found a distinct increase of critical soil moisture levels (<30% of field capacity). Because this increase was not reproduced by the SD-models, the variability of the ensembles remain rather high and range from drastic increase of drought stress days in a limited area (steep gorge, 0.25 quantile) to the serious expansion of drought stress into all forested areas below 1750m asl.

In addition to the absolute sum of days with drought stress, we analyzed the length of drought stress and its change under climate change conditions (Figure 25). Again, drought stress was defined as 30% of field capacity. In agreement with the proportion of drought stress days (Figure 24), DU and Δ-models showed a much stronger depletion of soil moisture than the retentive SD-model approaches with least changes. While most parts of the valley (DU-CHRM, or at least the forested areas (DU-REMO, Figure 25) experience short term drought stress during the reference period, a distinct length of the drought stress duration is simulated for DU and Δ-models. CHRM-driven simulations revealed an even enhanced signal. Although a slight increase in length was also visible for the SD-models, the desiccation affected only a limited area in lower altitudes. The consensus of the differences of the six models revealed in general a strong lengthening of the drought stress duration (~+70 days) that was again amplified for non-forested areas (~+85 days). The latter is ascribed to the higher potential for non-forested areas to lengthening drought stress time, because of the higher reference soil moisture. The strong lengthening trend found in the consensus is accompanied with a high variability of simulation as indicated by the quantiles: while at least an endurance of 30 days is likely (0.25 quantile) a drastic lengthening of 90 days and more can also be expected (0.75 quantile).

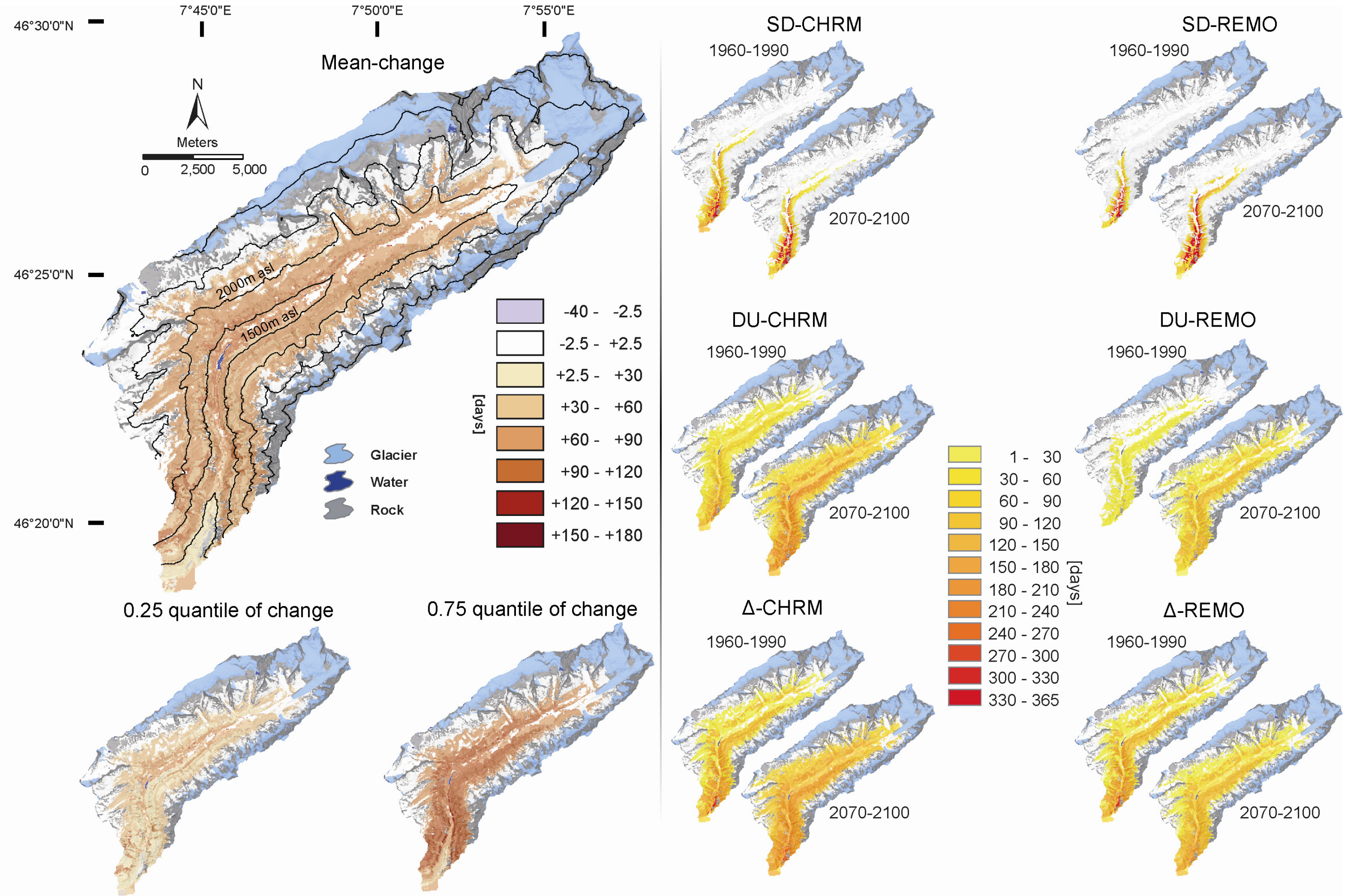


Figure 25: Sum of days the soil moisture drops below the critical level of 30% field capacity in a row for each model under reference and future scenario conditions (right), as well as model consensus of changes.

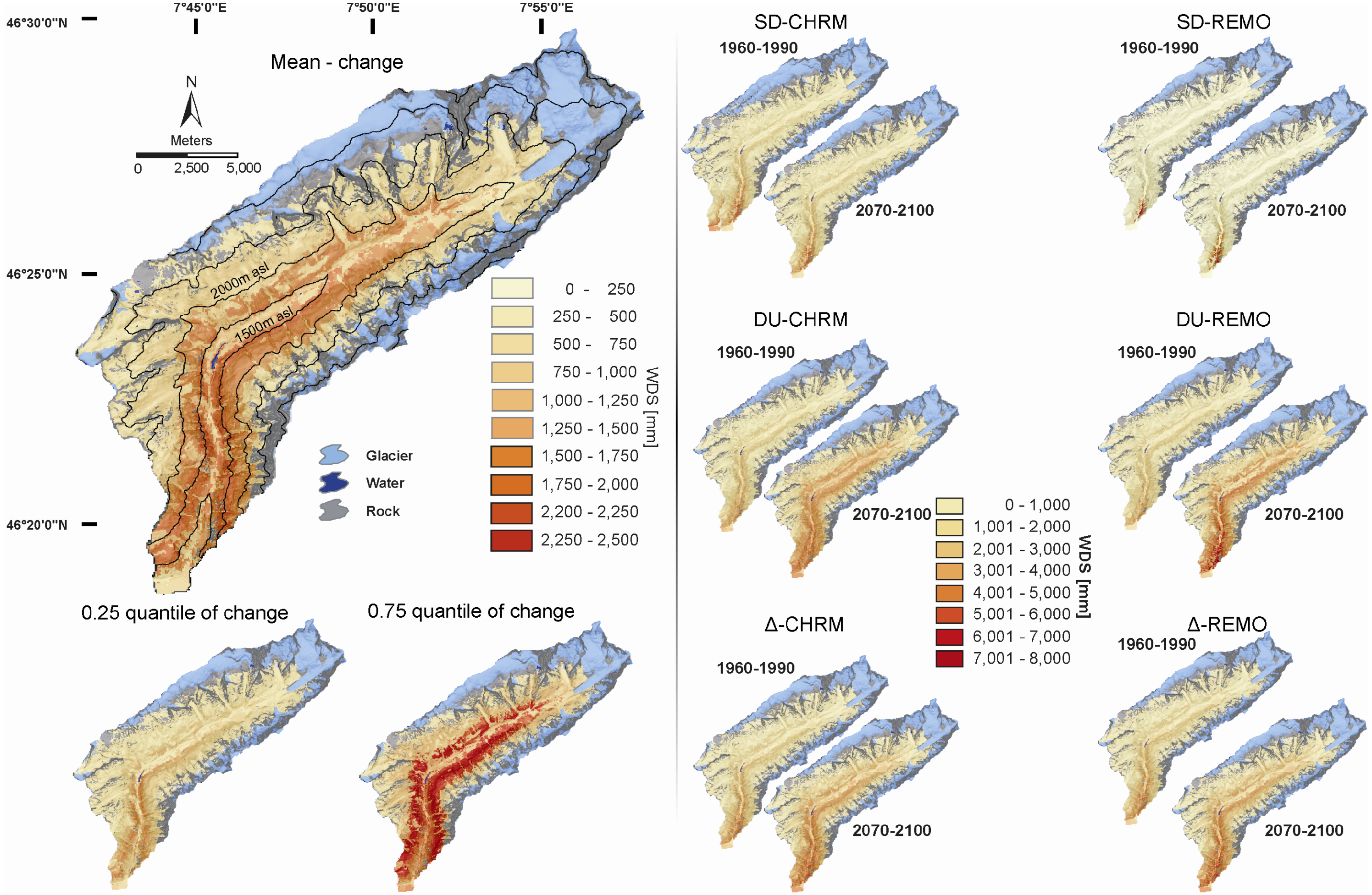


Figure 26: The weighted deficit sum (WDS) for the different model approaches as well as the model consensus of changes as expressed by mean and quartile values.

In general, the WDS confirms the pattern of the previous analysis, but even more elucidates the impact of climate change on soil moisture and the differences between the model approaches. Strongest increase +150% (+2300mm) of WDS under future scenario conditions was found for DU-models. This increase was simulated extensively within the valley, especially for forested areas up to an elevation of 1800m a.s.l. (Figure 26). Grasslands and all higher elevations (>2000m a.s.l.) showed hardly any change. WDS of Δ-models were in line with the pattern found for DU-models, but at a minor level with lower increases (+100%, +1500mm). Only SD-models revealed much lower WDS values and only small changes, excluding some changes in the south gorge. The according consensus of models followed the pattern of DU- and Δ-models by depicting strong increases of evapotranspiration deficits in all forested areas of the valley at lower and medium elevations (<1800m a.s.l.). Due to the deviant simulation of the SD-models, the variability of the models was very high, ranging from nearly no changing up to +2500mm WDS.

In summary, we found partly very deviating results depending on downscaling technique and the climate model applied. It was shown that the choice of downscaling techniques is much more relevant than the choice of climate model. Statistical downscaling showed a very retentive estimation of future hydrology and soil moisture in specific while especially the direct use of climate models revealed very drastic changes. In addition, we found a drastic decrease of snow and ice storages, a preponed terrestrial discharge, and nearly unchanged evapotranspiration sums. Soil moisture depletion at a seasonal resolution showed hardly any change. However, strong effects on evapotranspiration deficit and drought stress at a daily basis were achieved; forested-areas at elevations below 1800m were affected at most. But, the ensembles revealed such high variability that the confidence of the results needs to be questioned. The cause for this variability was traced to differences in temperature and precipitation (a,b). In addition, we assumed that differences in soil drought stress and evapotranspiration deficit depend either on the length of a dry spell or on the re-occurrence frequency of dry spells. In Figure 27, we tested both explanatory approaches in dependence of a threshold defined as dry spell. Since the definition of a dry spells is not fixed, we calculated the average length of a dry spell, using increasing definitions of a dry spell threshold. This approach was also applied to the length of rainy days that is the opposite of a dry spell and accounts for the re-occurrence frequency of dry spells. Figure 27 presents the results of the analysis: On the left side, the average length of a rainy period is plotted against the definition of a rainy day with increase values from 1 to 10 mm rainfall per day. On the right side, the average length of a dry spell is graphed against the definition of a dry spell. For example, if a dry spell is defined as days with precipitation amounts below 8 mm/d, the average length of a dry spell under Δ-change approach for 1960-1990 is ~6 days. Hence, differences of the approaches in terms of re-occurrence frequency were found to be restricted to the definition of a rainy day below 2 mm/d. This indicates that differences between the model approaches that could explain the found soil moisture patterns are likely found in the length of dry spells. Actually, the length of dry spells is very differently simulated using different model approaches. The dry spell length using SD models are much lower than DU and Δ-models and show no difference for reference and future scenario conditions. DU-models show differences in the length of dry spells at higher dry spell definitions. Due to the scaling character of the method, under reference and future scenario conditions the same frequency of dry spells with complete dry days need to occur. Strikingly, the order of the model approaches in terms of average length of dry spells for precipitations below 6mm/d agrees with the order of spatial soil moisture decrease (cp. Figure 23 – Figure 26).

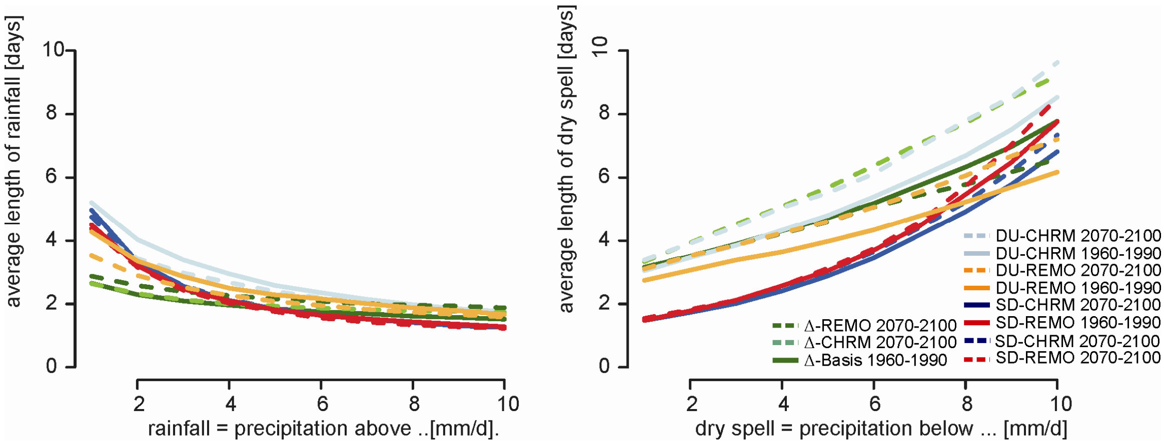


Figure 27: Analysis weather drought stress is predominantly affected by length of dry spell (right) or the re-occurrence frequency of dry spells (=the length of rainfall days, left), depending on the definition of a dry spell.

6. Discussion

6.1 Evaluation of WaSiM-ETH to model mountain soil moisture

In this study, the hydrological model WaSiM-ETH was applied to the *Lötschen valley*. It revealed results concerning the water balance comparable with those of Verbunt *et al*. (2003) for three alpine valleys. Due to the similarity of the valleys this successful application is not surprising, but it does prove the transferability of the model.

The sensitivity analysis revealed a completely different response of parameters to discharge and soil moisture. These findings underline the statement by Grayson et al. (1992a, 1992b) that discharge does not give much inside to internal hydrological processes. Meteorological input parameters and related factors like the degree-day-factor for snow and ice were found to be of superior relevance for discharge, a finding that is in line with literature (Schulla 1997). Soil moisture was found to react especially sensitive to changes of skeleton fraction. This sensitivity was a result of the used PTF of Brakensiek and Rawls (1994). The PTF considers skeleton fraction and alters the soil porosity and thereby all soil hydraulic properties. This effect is confirmed by empirical studies (Mehuys et al. 1975, Poesen and Lavee 1994, Sauer and Logsdan 2002) on skeleton fraction and soil properties.

Temporal dynamics and spatial patterns of simulated soil moisture showed a clear seasonal variability: homogenous relatively dry soils in winter, wettest soils during the snow-melt season, and dry soils in summer at low altitudes and relatively moist conditions at high altitudes as a consequence of precipitation and evapotranspirative demand, followed by an alignment of soil moisture values in autumn. This spatio-temporal pattern was found to be similar to patterns found by Löffler (2005) on a much finer scale in a Norwegian mountain catchment. Other studies dealing with these annual patterns in humid high mountains are rare.

Based on extensive soil moisture measurements in a New Zealand lowland catchment Wilson et al. (2004) emphasize the equal relevance of topography, vegetation and soil properties and depicted a strong seasonality of soil moisture. Our study is completely in line with this finding of seasonality as primary factor. Temporal shifting of different processes has already been described for lowland catchments of different climates by Grayson et al. (1997). They stated four preferred states for soil moisture: (1) always dry, (2) always wet, (3) wet and dry with rapid transition and (4) wet and dry with slow transition that can be used for index based modeling approaches. In high mountain areas preferred states of soil moisture were found in the Pyrenees by Gallart et al. (2002) who delineated evaporative demand as the driving variable for such a shift. Our findings support the observation of strong seasonality in soil moisture patterns and the shift of underlying processes. Moreover, general patterns simulated in this study corresponded to those in literature, meaning WaSiM-ETH is able to reproduce these general patterns.

In our study, snow-melt, summer precipitation and evapotranspiration were found to be of superior importance for simulated seasonal soil moisture patterns. While the rain distribution and snow-melt processes strongly depended on altitude (cp. Verbunt et al. 2003), evaporative demand depended on land-cover types in the different altitudinal zones. Thus, the relation between liquid water input and evaporative demand and their spatio-temporal distribution was of importance. The dependency of high mountain soil moisture on snow-melt and evapotranspiration during summertime is described in the literature from point scale measurements (Billings and Bliss, 1959; Isard, 1986; Litaor *et al.* 2008) indicating the ability of the model to reproduce these processes.

The wilting point (pf 4.2) was only simulated for the lowest altitudes and never occurred in the alpine belt. This finding is in line with a well known fact that drought stress never occurs in the alpine belt that is constantly encountered (May, 1976; Löffler, 2003), and that is comprehensively reviewed by Körner (2003). Drought stress may occur at lower elevations, especially in warmer years or coarser soil textures. Since simulated soil moisture tends to mean values, periodically drier soil moistures are, in reality, more likely to occur.

We found that altitude and land cover influenced most of the mean annual values of simulated soil moisture. On the one hand, mainly the linear regression of meteorological parameters against altitude appears in these results. On the other hand, land cover parameterization led to the differences found. The modeling results were hence mainly the effect of model parameterization. Nevertheless, we found these results to be in line with literature concerning empirical and modelling studies (Swanson et al. 1988; Quinn, 1998, Grayson and Western, 2001; Jasper et al. 2006).

The validation of the simulated soil moisture using fifteen different plots in total (Figure 12 and Figure 13) showed the ability to simulate the soil moisture dynamic for different altitudes and land cover types. However the accuracy of the modeled soil water content was partly limited. The weakness of the model to simulate soil moisture was especially owed to its inability to simulate the total variability as discussed along Figure 12. The reasons for this limitation are numerous: first of all, major uncertainties occur due to the incommensurateness of point scale measurements with the model scale grid cell results (Beven 2001). This scale discrepancy cannot be solved by using a higher model resolution (<10 m²) since neither soil properties nor micro-climate are available at this scale with reasonable accuracy. Measured values are aggregated at the model level and thereby averaged (Blöschl and Sivapalan 1995). An effect that was observed in this study was a tendency to mean soil moisture values. Moreover, the selected measuring plot may have been inappropriate to validate the model grid cell values. Second, the sensitivity analyses showed the relevance of skeleton and temperature for soil moisture. Meteorological parameters are highly variable, especially in mountain areas (Gurtz et al. 2003, Barry 2008). The linear, elevation dependent interpolation of the meteorological input parameter used in this model hence remains only an approximation and results are subject to high uncertainty. The underestimation of desiccation in lower elevations and the underestimation of soil water at higher elevations may also be a result of a too shallow gradient of temperature and precipitation. This effect is very likely since linear regression describes medium values instead of extreme values as they would be necessary in hydrological studies. More sophisticated interpolation techniques are possible (Schulla and Jasper 2007), but the data basis for applying a more differentiated method at least in the *Lötschen valley* is missing. For example, snow-fall data of the meteorological stations within the *Lötschen valley* were not available. Moreover, the use of macro-scale meteorological data in general leads to erroneous results at fine-scales (Pape et al. 2009). Although, the used interpolation method proved to perform well for discharge and the water balance (cp. Figure 11, Table 10, Table 11), the usability for simulating spatio-temporal patterns of soil moisture is limited.

Beside the interpolation techniques, the second major source of uncertainty is skeleton fraction. The sensitivity of skeleton for the spatio-temporal modeling was proved by Figure 10. This is in line with literature since skeleton fraction alters the hydrological response of soils significantly (Poesen and Lavee 1994). This effect is very often ignored in hydrological modeling, most likely because skeleton fraction cannot be determined spatially and thus remains a great source for uncertainty. In summary, these limitations in simulating soil moisture of the model must be considered when interpreting the modeled results from high mountain areas, where the extremely high variability of the skeleton fraction is one of the main features (Broll et al. 2005). Two further limitations have not been considered within this study: the effect the lateral flow in high mountains, and the validating of the snow model. The conceptual approach to reproduce lateral flows in WaSiM-ETH may have a great influence on the ability to simulate spatio-temporal distributions. In this model we handled this limitation by adjusting the sampling design. The influence of interflow on soil moisture should be investigated by comparing WaSiM-ETH with models simulating this process. Moreover, the validation of the snow model with observed snow covers and snow equivalent is of greatest interest.

To conclude, the simulation of the highly variable soil moisture dynamics and corresponding spatial patterns with WaSiM-ETH in the Lötschen Valley was partly successful. The validation with extensive soil moisture data revealed potentials and limitations concerning the simulation of soil moisture: WaSiM-ETH was able to simulate mean values and general spatio-temporal patterns, but showed at the same time limitations in its ability to cover the total spatial-variability of soil moisture. These limitations may be attributable to skeleton variability and coarse meteorological input data, since these parameters were found to be very sensitive to soil moisture. Greatest efforts should be laid on the exact determination of fine scale meteorological data and spatial skeleton estimation to improve soil moisture modeling in high mountain areas in the future. Nevertheless, the simulation of soil moisture was feasible and revealed pronounced seasonal patterns of soil moisture depending on snow-melt and/or rain as well as evapotranspiration.

6.2 Downscaling approach related uncertainties

For sound climate change impact assessment studies an uncertainty analysis of used climate models and downscaling methods is a necessary pre-requisite. Uncertainties of different magnitudes for all investigated hydrological output variables were found, depending on the climate models and downscaling approaches used. Table 14 summarizes the quality of reproducing the reference model by simply ranking the model approaches according to their performance in terms of the investigated variables. For all spatial variables, SD approaches performed better than DU approaches. In contrast, linear variables and the water balance were better represented by CHRM model data, and in this case, the chosen downscaling approach was of circumstantial relevance. The exceedance probability was an exception to this regularity. This finding reveals that the spatial resolution of the climate models is of minor importance for the quality of hydrological prediction. In this study, discharge was found to be highly related to glacier and snow melt and, thus, to temperature. Prömmel et al. (2009) evaluated the performance of REMO temperature data in alpine regions at a high resolution and stated, in accordance with Moberg and Jones (2004) that the validation of the model against observed data showed large differences. In a comprehensive study, Prömmel (2008) found winter temperatures to be underestimated and summer temperatures to be slightly higher than the observed data (HISTALP dataset). This is in accordance with our findings on discharge (Figure 11, and Table 12). In terms of CHRM data quality, Lüthi et al. (1996) found only small biases for temperature and uncertain summer precipitation, and Vidale et al. (2003) comprehensively analyzed the predictability and sensitivity of the CHRM model: biases of 2 K (+0.6 K model uncertainty) for temperature and up to 2 mm/day (+0.6 mm/day model uncertainty) for precipitation were found for mountain areas. For REMO, we calculated a bias of 1 K for temperature and found precipitation to agree well with the observations. The most likely cause for the better performance of CHRM in this study is higher annual amplitude of temperature.

The strong deviations from the reference model found in this study may also result from the choice of the evaluated climate models and the downscaling approaches used. The application of additional models and downscaling approaches that generate less uncertainty will be worthwhile. However, many studies, especially those using the DU approach, have found some models to be deficient to some degree (Wood et al. 2004). The magnitude and the steadiness under other downscaling approaches than those chosen may be analyzed in future studies. In our study, we used two simple but common approaches for comparative reasons and to ensure the relevance of our results.

Table 14: Simple ranking of the performance of the different approaches in terms of tested variables based on statistical values and percentage differences (diff-%).

	DU-CHRM		DU-REMO		SD-CHRM		SD-REMO	
Water balance absolute bias [mm]	+305	III	+1106	IV	+135	II	-114	I
Annual discharge [Σ (R^2, IoA, ME)]	2.893	III	2.894	II	2.922	I	2.885	IV
Exceedance probability of discharge [Σ(|diff|)]	30411	II	30145	I	31156	III	33709	IV
RMSE soil moisture [Ø-RMSE]	1.800	III	2.400	IV	1.600	I	1.700	II
RMSE actual evapotranspiration [Ø-RMSE]	16.100	III	17.400	IV	14.90 0	II	14.000	I
Spatio-temporal soil moisture [Ø-MAI]	0.934	III	0.915	IV	0.941	I	0.937	II
Spatio-temporal evapotranspiration [Ø-MAI]	0.890	IV	0.910	III	0.930	II	0.930	I

Although hydrological impact assessment studies are very common at present, a critical discussion of uncertainties within the obtained results is mostly missing. In fact, many papers have been published on climate model performance in combination with a hydrological model, but these papers have mainly focused on the reproducibility of climate variables and discharge (e.g., Haylock et al. 2006; Chiew et al. 2009). The most comprehensive analysis in this respect was conducted by Wood et al. (2004), who tested the seasonal and spatial anomalies produced by different models and downscaling approaches. A focus on hydrological target variables is mostly missing in the literature. Bronstert et al. (2007) tested the reliability and ability of climate model data from three RCMs to represent current hydrological processes and concluded that none of the tested models was "good", although processes governed by temperature were better represented than those governed by precipitation. However, the question that remains to be answered is that of quantity. How good are the best models, and how well do they reproduce hydrological processes? Additionally, what kind of uncertainty do they incorporate?

Recently, Segui et al. (2010) reported geographical and seasonal anomalies mainly related to discharge introduced by different downscaling approaches and concluded that these anomalies have to be regarded as uncertainties that must be incorporated in the interpretation of hydrological impact assessment studies. We completely agree with Segui et al. (2010), and our results strongly confirm their findings of the spatial and temporal patterns of uncertainties at a much finer scale and for difference hydrological parameters. Additionally, our analysis of the different hydrological variables and, especially, the spatio-temporal determination of uncertainties add considerable value to the discussion: we found uncertainties to be unsteadily distributed across different hydrological variables and to be unsteady over time. Thus, we have not found one model that performs best for all variables and any analysis, nor did any model show steady uncertainties over time. The unsteadiness of variables is demonstrated best for the finding that the annual mean discharge curve is reproduced most accurately by the SD-CHRM model approach, while DU-REMO performed best in terms of exceedance probability. Therefore, the choice of the model and downscaling approach used in climate impact assessment studies must be based on the evaluation of the specific target variable. An evaluation of water balance and discharge alone is not sufficient. Moreover, hydrological impact assessment studies often apply the rather simple but easy-to-handle delta approach (e.g., Buytaert et al. 2010; Köplin et al. 2010). In addition to the advantages that have been discussed here, the uncertainties of an RCM are directly incorporated into its results of the future and uncertainties cannot be considered adequately. We showed that the uncertainties of DU approaches are rather negligible for some variables (e.g., soil moisture or exceedance probability of discharge), while it is careless to use this approach for other variables, such as actual evapotranspiration.

To conclude, regardless of the model and downscaling approach chosen, an uncertainty analysis of specific target variables must be carried out in hydrological impact assessment studies. The RMSE analysis has to be considered to be a rather simple but effective method to implement for this purpose. Carrying out future simulations and relate these to the found uncertainty ranges (e.g., RMSE) will enable colleagues and decision makers to better judge the quality and the reliability of these simulations. In this report,it was only focused on the uncertainty of different climate models and downscaling approaches. As illustrated in the theory section, there are many more sources of uncertainty that must be considered in future impact assessment studies. In consideration of the great challenge that this claim implies, we agree with Pappenberger and Beven (2006) that “ignorance is bliss,” but to truly assess future impact and to advise decision makers in better ways, we are forced to carry on with these efforts.

6.3 Minor differences reveal a bandwidth of possibilities

The application of an ensemble forecast of two RCMs and three downscaling approaches revealed summer soil moisture to decrease strongly (-10 vol %) under future climate conditions, most of all at lower and forested areas. This desiccation was accompanied by a wide range of possible scenarios ranging from dramatic decrease to nearly unchanged conditions depending on model approach. We showed that the choice of downscaling technique is much more relevant to the magnitude of depletion than the applied RCM. This adds considerable value to the discussion on uncertainties and variability of climate change impact assessment studies. The use of multiple downscaling techniques in an ensemble forecast is new for soil moisture impact studies. Nevertheless, commonly, ensemble forecasts are conducted with several climate models and emission scenarios, applying only one downscaling technique. These simulations revealed contrasting results: Zierl and Bugmann (2005) found as large effects on uncertainties for climate models and emission scenario. Jasper et al. (2004) emphasized the superior role of scenarios, while Horton et al. (2006) found the different underlying GCMs to cause greater variability of the results. Jasper et al. (2004) emphasized the superior role of scenarios, while Horton et al. (2006) and Wilby and Harris (2006) found the different climate models to cause greater variability of the results. This study prove the superior role of downscaling approaches to the model results and at the same time question the validity of forecasts based on single downscaling approach.

Furthermore, in this study statistical downscaling showed a very retentive estimation of future hydrology and soil moisture in specific with least changes, while especially the direct use (DU) of climate models revealed strong changes. Major deviations occurred in terms of temperature and especially in the average length of dry spells, indicating the inability of the SD to reproduce the change of variability in climate models under future conditions (Schär et al. 2004). First, the loss of variability during the downscaling procedure is one of the major disadvantages of statistical downscaling (Wilby et al. 2001, Fowler et al. 2007, Maraun 2011). Second, the statistical model calibration was performed based on one regression disregarding seasonal or monthly changes in the predictor’s weight. Nevertheless, the SD method proved to reproduce the hydrological processes under reference conditions; especially spatial variables like soil moisture (see section above). Nevertheless, more sophisticated statistical downscaling approaches like quantile-mapping (e.g. Segui et al. 2010) may generate better results in future studies.

In contrast to the SD-model results, DU-models generated the strongest change as a result of decreasing summer precipitation (Figure 19) and longest average dry spells (Figure 27). The DU of RCMs is prone to biases in the climate model (e.g. Bosshard et al. 2011). In this study this disadvantage is partly absorbed by the applied regionalization regression, which tends to mean values. But, the great surplus of this approach lies in the application of unchanged model outputs with no loss of variability, resulting in the most distinct difference of dry spells length under reference and future scenario conditions. We are in line with Calanca (2007) and Jasper et al. (2004) who put emphasis on the finding of Schär et al. (2004) that shifts in variability of temperature will occur and need to be regarded in climate change studies. In terms of soil moisture studies, shifts in the variability of precipitation need to be regarded too. We found very small differences in PDF of temperature and precipitation for reference and future scenario conditions of DU (Figure 8) that lead to drastic changes in soil moisture. Over and above, the length of dry spells needs to be considered. In summary, although the DU of RCMs has been reported to be peppered with errors, it provides the best transformation of the highly important variability.

Graham et al. (2007) found the Δ-approach to be a method that produces coherent results that even preserve changes in the variability of climate models. We state that this preservation can only be partly achieved, due since to the simply scaling character of the Δ-approach. Changes in the presents or absence of precipitation are not considered as well as future extreme values are diminished. The variability of the climate model is best preserved applying the DU-approach. This is in line with findings of Lenderink et al. (2007) who compared DU and Δ-approach. Moreover, the Δ-approach showed strong deviations in terms of precipitation that was caused by the usage of the moving average to derive the Δ-signal and the resulting high Δ-change factors. Hence, the reliability of the Δ-change method - at least in terms of soil moisture studies - has to be questioned.

Concerning the results of the ensemble forecast, we found a strong decrease of snow and ice storages, a preponed discharge, and only slight increased evapotranspiration sums. These results are completely in line with studies from the Swiss Alps by Horten et al. (2006) in terms of discharge, Etchevers et al. (2002) and Calanca (2007) as to evapotranspiration, and Milner et al. (2009) in terms of snow and glacier. We follow the argumentation of Jasper et al. (2004) that this accordance confirms our model outputs in general and urge to transfer the results to similar catchments.

In terms of soil moisture and drought stress, comparative studies are few, but Jasper et al. (2004) showed similar evapotranspiration deficit dynamics under different climate scenarios to our dynamic of Δ-change (Figure 22). In addition, Jasper et al. (2006) found similar soil moisture depletion at a much coarser scale and pointed out the effect of altitude, slope, texture, and land use. In our study we found a major dependency on altitude and land use, most likely LAI and root-depth dependent. Due to the linear regression with altitude, the effect of elevation on soil moisture is not surprising. Further studies with multiple hydrological models and different regionalization methods should be applied to derive catchment specific patterns of strongest response towards climate change. The combination of several models in a multi-model can further increase the confidence in the model result (Breuer et al. 2009).

Despite the good agreement of our results with other studies, there are some uncertainties originating from the hydrological model and the regionalization method applied. At first, uncertainty results from the simulation of soil moisture in this catchment at a high resolution. As shown above, this is mainly a consequence of the model sensitivity towards skeleton fraction and the high spatial heterogeneity of soil properties in high mountain ecosystems (Löffler 2005, Löffler and Rössler 2005). Further uncertainties originate from the hydrological model, since WaSiM-ETH uses a simple conceptual interflow approach (Schulla and Jasper 2007). Especially in mountain areas of high relief complexity this disadvantage should be kept in mind. The lack of interflow algorithms is not WaSiM-ETH specific but a general problem that arises from the model algorithms and the lack of detailed data. A second source of uncertainty originates from model parameterization. As far as possible, all parameters were derived from field observations (e.g., vegetation height and root depth). Parameters that could not be derived were taken from models with similar catchment characteristics (Schulla 1997, Verbunt et al. 2003) or suggested standard values (Schulla and Jasper 2007). Nevertheless, extended uncertainty analyses would increase the confidence in the results of the hydrological model (Saltelli et al. 2008). In total, these uncertainties are summed up in the RMSE value of 8 Vol-% found earlier in this study for soil moisture at a hourly basis (Figure 12). The main second source of uncertainty originating from the downscaling approach was discussed before. We found the different downscaling approaches to deviate from the basis run and estimated spatial explicit RMSE values (Figure 18).

Being aware of these uncertainties, are the impacts of climate change on soil moisture and drought stress still relevant? Assuming that the uncertainties remain constant for reference and future scenario condition, the change of soil moisture and drought stress indexes like WDS has still to be fully considered. Nevertheless, if changes are at the same magnitude of model uncertainty, scenario results should be treated with caution. As presented in Figure 20, the decrease of future soil moisture in most parts of the study area lies within -10 Vol-% and therefore has to be interpreted carefully.

Assuming that the uncertainties remain constant for reference and future scenario condition, what are the consequences of the partly strong increased drought stress? Predicted summer drought stress is likely to have severe effects on the ecosystem, especially on vegetation. In a review, Theurillat and Guisan (2001) discussed the possible effects of summer drought stress on vegetation and confirm this interpretation but also point out that vegetation might adapt to changed climatic conditions. This adaptation of course cannot be simulated within the model. Nevertheless, Allen et al. (2010) also reviewed actual impacts of recent climate change on forests world-wide and concluded that an amplified tree mortality due to climate change already occurs. Even today first responses to recent heat waves like in 2003 are visible in a decline of the pine forest in the adjacent Rhône valley as a result of drought stress and subsequent insect calamities (Dobbertin et al. 2007). Pine forests are present in the studied catchment up to 1500m asl (Hörsch 2001) and are therefore affected the most under future scenario conditions. Drought-affected forests are a major threat for valley dwellers, since these forests are used for avalanche projection forest (Brang et al. 2006).

To conclude, an ensemble forecast of future soil moisture was successfully conducted with two threefold downscaled RCMs to a meso-scale mountain catchment at high temporal and high spatial resolution. Small differences in the variability of the downscaled data caused major variability in daily drought stress. In consensus of all models soil moisture was found to decrease partly drastically especially in areas already affected and found a strong expansion of drought stress into the main valley. This will likely affect the growth of forests in the transition zones of dry and moist mountain ranges, while areas above 1800m remain nearly unaffected. Due to the high spatial resolution, climatic change impact assessment on soil moisture patterns can be easily appointed to forested and lower elevation areas. This adds considerable value to the findings of Jasper et al. (2006) at a coarser scale. Due to the uncertainty of the hydrological model and the downscaling approaches, the decrease of soil moisture of up -10 Vol-% must be interpreted carefully. In addition, these ensemble forecast results are not at all alike but rather offer a corridor of possibilities as indicated by the ensemble variability.

It was elucidated that the choice of downscaling technique is much more relevant to the magnitude of depletion than the applied RCM. Over and above, it was found that uncertainties are unsteadily distributed across different hydrological variables and unsteady over time. Thus, the “one” model performing best for all variables and any analysis was not found, nor did any model show steady uncertainties over time. This adds considerable value to the discussion on uncertainties and variability of climate change impact assessment studies. Up to now, uncertainties were ascribed to either GCM or emission scenario only.

In conclusion, this study in conjunction with the many published studies point to the fact that uncertainties result from each step of the climate change assessment study. Thereby, magnitudes change in the studies conducted. A general pattern is hence unlikely to be derived. Therefore, all sources of uncertainty postulated in the opening theoretical conception of uncertainty propagation should be incorporated in an ensemble modelling. This should include the use of multi hydrological models since it has been proven that the use of different models increase the uncertainty of the results by far Schaefli (2005). The idea of a multi-model ensemble forecasting was recently applied for discharge in Ireland by Bastola et al. (2011) and showed remarkable results wih hydrological model being the greatest source of uncertainty. The application of such a model to mountain soil moisture would be a great advantage. In addition, to meet the multiple sources of uncertainties the application of probabilistic forecasting as suggested by Araujo and New (2007) might be an appropriate approach, but demand enormous computational effort. Nevertheless, probabilistic forecasting might also be an interesting approach to communicate the uncertain results of such complex model approaches to the local managers and decision makers, for it is much easier to deal with probabilities than with ranges of possible values.

7. Main findings

In this study, the impact of climate change on mountain soil moisture dynamics and patterns on a catchment in the Swiss Alps was addressed. Therefore, a commonly used approach was used, comprising (1) of a physically based model that was calibrated and validated under recent climate conditions, (2) that was driven by downscaled RCMs for a reference and a future scenario climate conditions. In contrast to this standard approach, the focus on soil moisture dynamics and patterns in a meso-scalic mountain catchment (160 km²) is new and challenging since major uncertainties in every parts of the approach can be expected. In the opening chapters, seven research needs were derived from recent literature on this topic that should be addressed in this study. We concisely summarized what we have learned from this study by answering the research needs, as follows:

Research need II: Provision of extensive data to enable a sound calibration and validation of hydrological models

An extensive measurement design consisting of continuous and discontinuous measurements was mounted (Figure 5) and accomplished in 2006 and 2007 during summer months. The data cover a strong altitudinal gradient (1400-2700m a.s.l.), two expositions, and four land cover types. This data set enables the calibration and validation of the applied hydrological model in terms of soil moisture dynamic and pattern. Hence, the research need was fulfilled, but further data are always needed and would improve the modeling research for sure. In this study, data on discharge at the mouth of the valley, additional soil moisture data, snow depletion data, and soil property map of higher resolution would have improved the hydrological model.

Research need III: Evaluation of the potential and limitation of WaSiM-ETH to model mountain soil moisture dynamics and patterns

The potentials and the limitations of WaSiM-ETH to simulate soil moisture dynamics and patterns were shown by comparing model results with extensive soil moisture measurements at an hourly time step. While WaSiM-ETH was able to reproduce discharge with a high accuracy (R^2 = 0.95, ME = 0.8, IoA = 0.95), the simulation of soil moisture for different altitudes and land use types is partly limited, since the model was unable to model the total variability of the soil moisture dynamic, but tended to mean values. An adjusted RMSE of 8.0 Vol-% that takes the intra-plot variability into account was calculated. The reasons for the uncertainty originate from (a) the rather simple model algorithms used and (b) from the very high variability of soil properties on short spatial scales.

In this study, for the first time a local sensitivity analysis was conducted for WaSiM-ETH that focuses on soil moisture and discharge, both in summer and winter. While discharge is mainly sensitive toward changes in temperature or melt factors, soil moisture depends on changes in skeleton fraction and in temperature. Unfortunately, skeleton fraction remains a very problematic factor due to the impossibility to determine it spatially. Since skeleton fraction strongly influences the soil hydraulic properties, we assume that the high uncertainty of the hydrological model to simulate soil moisture is mainly due to the high variability of skeleton fraction. Both, model validation and the analysis of local sensitivity with respect to soil moisture shows the potential and limitations of modelling mountain soil moisture dynamics and patterns: Mountain soil moisture modeling with WaSiM-ETH is possible and provides realistic overall dynamics and patterns, while the accuracy is partly limited. A comparative study of different hydrological models to simulated mountain soil moisture might evaluate the pro and cons of WaSiM-ETH at best.

Research need VI: Development of a theoretical concept that incorporates the manifold sources of uncertainties in climate change impact assessment studies

In this study a theoretical concept is presented that combines for the first time the idea of the uncertainty cascade (e.g. Pappenberger and Beven 2007) with the approach of uncertainty propagation in physically based models by Brown and Heuvelink (2005) and therefore add value to the discussion on uncertainties. The concept comprehensively summarizes all uncertainties occurring in climate change impact assessment studies and illustrates how the uncertainties propagate. It provides an analytic framework for existing and future studies.

Research need V: Assessment of spatio-temporal uncertainties with respect to different downscaling approaches

A comprehensive uncertainty assessment study was conducted that focuses on the spatio-temporal uncertainties originating from two downscaling approaches of two RCMs. Uncertainties were found to be unsteadily distributed, both in terms of variables and time. First, a model approach that shows the least uncertainty for all kinds of hydrological target variables like discharge, actual evapotranspiration, and soil moisture was not found. This finding adds considerable value to the scientific discussion, since most previous studies focus on one variable or one model approach alone. Second, we evaluated the spatial uncertainties of soil moisture and evapotranspiration. The spatial analysis of uncertainties is borrowed from climatologically studies of much coarser scales. Here, the idea is transferred to soil moisture and evapotranspiration of much finer scale. The unsteady distribution of uncertainties over variables and time and the spatial mapping of uncertainties to our knowledge is the most comprehensive analysis of epistemic uncertainties. This analysis enables the spatial explicit evaluation of climate change impact assessments.

Research need IV: Application of different downscaling approaches in climate change impact assessment studies focusing on reproducing hydrological target variables.

Three different, commonly used downscaling approaches were applied to downscale two RCMs in the climate change impact assessment study. The use of multiple downscaling techniques in an ensemble forecast is new for soil moisture impact studies. The study proved the partly superior role of downscaling approaches when focusing on the impact *per se* under future climate and thereby contrasting the findings of recent publications reporting climate models and emission scenarios to determine the variability of the results. Moreover, our findings question results from studies that are based on one downscaling approach alone. We showed that the choice of downscaling approaches is of circumstantial relevance for discharge and water balance, while for all spatial variables, we found SD approaches to perform better than DU approaches. Because most previous studies focused on discharge mainly, the disregard in research night by explainable. Moreover, we showed that very small differences in downscaled data can cause major effects on the target variables. Therefore, more studies and different downscaling approach like neural networks or quantile mapping should be conducted to better assess the influence of downscaling approaches on target variables.

Research need I: Application of climate change impact assessment studies on hydrology at a regional level, especially in terms of soil moisture

Research need VII: Ensemble forecasting with downscaling and climate models focusing on mountain soil moisture

A comprehensive climate change impact assessment study on the hydrological processes and on soil moisture in specific was successfully conducted at the catchment scale (160 km²) with a high spatial and temporal resolution. The study provided detailed data on climate change impact on the hydrology of the catchment that are completely in line with previous findings. The high spatio-temporal resolution of the study add value to previous mountain soil moisture studies of Jasper et al. (2004, 2006) by providing site specific data on soil moisture decrease and drought stress potential at the catchment scale. The consensus of six models driven by two threefold downscaled RCM reveals the forested areas below 1800 m a.s.l. to be most affected by climate change in 2070-2100. The variability of the results from the six ensembles were remarkably high, offering a bandwidth of possibilities from nearly unchanged soil moisture conditions to strong expansion of drought stress in the future. In addition we found uncertainties from the applied hydrological model and downscaling approaches in the magnitude of the predicted changes. Therefore, the results have to be interpreted carefully. Probabilistic forecasting with several hundred model runs might confirm the found tendency of soil moisture decrease in future studies.

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