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Towards decadal hydro-glaciological forecasts for the hydropower sector

GEO 511 Master's Thesis

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

Davide [illegible]

Abstract

Hydropower and water resources management are an important issue in most countries of the world, included Switzerland. The scientific community is currently engaged to produce numerical models and simulations which aim at understanding the most important concurring factors of climate with the support of different tools and methods, at both regional and global scales. In this case, the purpose is to simplify reality while reducing errors and uncertainties related to streamflow prediction. The latter uncertainties can be due to different sources, such as the initial hydrologic conditions of a catchment, the hydrological model's input data and structure, or a too high amount of subjectivity which is applied while implementing such modelling procedures.

The aim of this work is to investigate the propagation of uncertainties from the input meteorological forecasts to the resulting streamflow predictions. A weather generator has been used to create synthetic weather decadal forecasts. These forecasts have then been fed into the hydrological model *Hydrologiska Byråns Vattenbalansavdelning* (HBV), and simulations have been run in order to obtain corresponding runoff forecasts. The accuracy of the meteorological and runoff forecasts has been calculated with similar statistical metrics with the aim to assess the propagation of uncertainty. Three statistical metrics, defined as "skill scores", have been applied for this purpose. The experiment was performed for two glacierized catchments both located in the Swiss Alps, Findelen and Gries. The simulations were performed by assuming different scenarios of glacier extent in order to observe the influence of the amount of ice present in the catchment on the results. The effect of a varying input glacier extent on simulated runoff has then been studied, together with an assessment of the modifications on the hydrological regime. The simulations have been run by applying the recently-implemented glacier routine in the hydrological model with different settings, with the aim to analyze how skill transfer can be affected. In addition, a sensitivity analysis has been performed on the parameters and routines of the hydrological model in order to study their contribution to model efficiency.

It has been observed that the influence of precipitation on runoff forecasts is lower than the one of temperature for highly-glacierized catchments. This influence increases with diminishing glacierization. In a hypothetical ice-free catchment, the effect of precipitation on skill transfer tends to become more relevant, for both Findelen and Gries catchments. Another important factor of skill transfer is the lead time from which a forecast is produced, and also the morphological and topographical features of the catchment. Moreover, the application of different settings of the glacier routine can also have an influence on skill transfer and on the influence of temperatures and precipitation.

Keywords: Decadal forecast, streamflow forecast, synthetic forecast, forecast skill, forecast lead time, uncertainty propagation, skill score, scenario, "perfect" model, glacierized catchment, *Hydrologiska Byråns Vattenbalansavdelning* (HBV) model.

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Equations

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Equation 5, determination of *m* and *n* slope parameters → $Qskill = m * Tskill + n * Pskill$

Equations to determine skill difference between weather and runoff → $(\frac{Tskill+Pskill}{2}) - Qskill$

Equations to determine skill scores:

a) RMSE (Root Mean Square Error) → $\sqrt{\frac{1}{N}\sum i(f_i - o_i)^2}$

b) RV (Reduction of Variance) → $1 - \frac{\frac{1}{N}\sum(f_i - o_i)^2}{var_r^2}$

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1. Introduction

1.1. General introduction

Hydropower and water management are an issue in most countries of the world, included Switzerland. The scientific community is currently engaged to produce numerical models and simulations which aim at understanding the most important concurring factors of climate with different tools and methods, at both regional and global scales, with the purpose to simplify reality and reducing errors and uncertainties at the same time. Uncertainties can arise from the initial hydrologic conditions of a catchment, the hydrological model input data and structure, and an excessive user's empiric evaluation characterized by a too high amount of subjectivity. Determining and assessing the sources of uncertainties of forecasts' accuracy, and how this uncertainty is transmitted during time, has long been a research topic among the scientific community. However, progresses need still to be done for research at a decadal temporal range (Meehl *et al.*, 2014 ; Murphy *et al.*, 2010 ; Solomon *et al.*, 2010).

The hydropower sector has faced a lot of challenges recently, due to the variability of energy prices and to the availability of energy sources. Consequently, there is the need to find more efficient and alternative energy production procedures for the coming years, and this is particularly due to climate change and its environmental consequences (Appenzeller *et al.*, 2011). In Switzerland, an important element towards the shift to renewable energy sources is the "Energy Strategy 2050" (Section 2.1), which aims at preparing the transition towards a more sustainable energy production mechanism. A milestone of this "strategy" is the phasing out of nuclear energy, which has been voted by the Swiss population in May 2017 (Hediger, 2016 ; Schillinger *et al.*, 2016). The energy production shift will favour the utilization of renewable sources such as hydropower. Most hydropower plants can be found in the mountainous regions of the Swiss Alps, because in this case the advantage is that the runoff from snowmelt and glaciers can also be exploited to produce energy.

Glaciers are important as water reserves and storage reservoirs (Chapters 2 and 3), but also to determine the amount of energy which is produced periodically by hydropower infrastructures. Moreover, they have a prominent role to do more studies and assess more considerations related to climate change (Barry and Chorley, 2009 ; Huss *et al*., 2008 ; Jansson *et al*., 2003). Runoff in glacierized catchments has an influence on the amount of hydropower energy which is produced by an infrastructure in a defined periodical range: this amount of energy, according to the nivo-glaciological regime, is higher between May and September than in the rest of the year. However, the provision of decadal weather and runoff forecasts aims at studying this variability at an intermediate time scale between short- and mean-term forecasts (spanning from days to seasons) and climate scenarios (spanning from decades to centuries). Moreover, this typology of forecasts can be applied and produced at either a local or regional scale in different regions of the world.

The provision of forecasts is intimately related to technological progresses of software and programming techniques, particularly during the last decades. Currently, the scientific community is engaged to follow an integrated approach to couple weather and hydrological numerical streamflow modelling in order to understand the influence of climate change on glaciers' dynamics and on the most relevant hydrological properties of catchments at a variable spatial and temporal scale. Numerical models are relevant for glaciology and hydrology because they aim at simulating natural processes by representing them with a model that works with mathematical formula and equations (Bergström, 1992 ; Seibert, 1997 ; Seibert and Beven, 2009; Seibert *et al*., 2010). The aim of these models is to include a glaciological module in the hydrological analysis by applying a modelling procedure which can represent glacier processes in a detailed way (Freudiger *et al*., 2017 ; Seibert *et al*., 2017). Moreover, these models can be of variable complexity regarding the main parameters and settings that are used.

Hydrological models are useful to simulate the main properties of hydrological catchments in a numerical framework. By applying some parameters which represent the catchment in an idealized way, the aim is to obtain the highest degree of correspondency between observed and simulated runoff. Hydrological models have been applied recently in order to perform analyses of forecasts accuracy at some specific time scales (Farinotti, 2013 ; Shukla *et al.*, 2013 ; Yossef *et al*., 2013), and also integrated procedures by coupling hydrological models with glaciological models and climate models (Douglas *et al*., 2016 ; Seibert *et al*., 2017 ; Shresta *et al*., 2013). The integration of models to analyze glacier dynamics and mass balance evolution in hydrological models and their relations with climate change is currently an issue, which can be particularly relevant to determine the consequences of glaciers shrinking (i.e. for hydropower production, and to study the hydrological, topographical and morphological properties of catchments). This integration between hydrological and glaciological models is therefore important also to assess the most important elements and characteristics of climate and climate change.

After integrating weather models and numerical streamflow modelling procedures, another relevant issue among the scientific community is to determine the accuracy (i.e. efficiency or "skill", see Chapter 2 for more technical information about this topic) of the produced forecasts. To achieve this objective, there is the need to implement statistical metrics and measures which could assess forecasts' accuracy and how this evolves during time. This statistical analysis can be performed at every timescale. However, it is more challenging to study forecasts' accuracy at a longer timescale (i.e. decades or centuries) in order to relate this with climate change and with the shrinking tendency of glaciers in case of glacierized catchments of the mountainous regions. Some progresses have been made recently in this regard, but the study of accuracy (or "skill") transfer is still in its infancy, and more experiments and analyses need still to be done, especially at the decadal temporal range (Section 2.2). Decadal forecasts are characterized by an intermediate temporal range between short-term forecasts (i.e. weather and seasonal forecasts) and long-term forecasts (i.e. climate projections and scenarios). As it will be described in the next section (Section 1.2), this thesis is regarded by an experiment of decadal weather forecasting.

1.2. Objectives and purposes of the thesis

This thesis is embedded in a larger project of forecasts accuracy assessment, at a decadal time scale, for the Swiss hydropower energy sector. Numerical streamflow modelling has been applied for an actuality topic such as the "Energy Strategy 2050" through the study of accuracy transfer from forecasts to hydrological runoff for two highly-glacierized mountainous catchments. The experiment has been performed in an idealized modelling framework.

This thesis aims at answering three research questions around which the whole analysis has been developed. First, the research is centred on studying how a given skill (or accuracy) in meteorological input variables translates itself into the skill of the corresponding hydrological forecast. To determine this accuracy transfer, weather forecasts at a decadal time-scale have first been produced as synthetically-generated time-series of precipitation and temperatures. These time-series have then been used to force the hydrological model HBV with the aim to produce runoff forecasts. The temporal range of all forecasts was 19 years, and their skill scores have been determined with three statistical methods (Section 3.4). Finally, weather and hydrological forecasts have been integrated in order to determine how accuracy is transferred from the first to the latter. The second aim of this thesis is to determine the influence of shrinking glaciers on skill transfer. Therefore, the relation between catchments' morphological features and skill transfer has been studied by assuming a variable ice extent and volume. In this case, the aim is to identify trends and tendencies that a shrinking glacier can have on the skill transfer and on the accuracy of decadal forecasts in general. Moreover, also an ice-free catchment is assumed as a hypothesis. The analysis has been performed for two different catchments in order to observe eventual differences in skill transfer. The third purpose of this thesis is to understand which hydrological compartments do affect skill transfer the most. To achieve this objective, different parameters of the hydrological model have been analyzed to understand how skill transfer from climate forecasts to hydrological runoff is affected by assuming a higher (or lower) variability of a specific routine or model parameter. This research has been performed also by determining the degree of correlation between the parameters of the hydrological model with a sensitivity analysis. The outcomes of the sensitivity analysis have then been integrated with an assessment of the main outputs of the model in order to derive some considerations about model settings and functions.

The thesis begins with an introduction of the main topic by defining objectives and research questions (Chapter 1). The following chapter (Chapter 2) defines the most important concepts related to the topic, and the most relevant scientific studies and experiments which have recently been performed in this regard. The methodology chapter (Chapter 3) allows to establish the most important procedural steps that have been followed during the research framework (e.g. implementation and forcing of the hydrological model, accuracy transfer from weather to hydrological forecasts, and simulations with variable glacier extent and ice dynamics). The two study sites are presented in chapter 4 by including a morphological and physical description of both. Results (Chapter 5) are divided into four sections, one for each problematic that has been developed. Then, interpretations and conclusions are given in Chapters 6 and 7 respectively by following the same structure as for the results. Some appendixes are included to represent more plots and tables which are linked with the rest of the content, and to explain some complements about the skill transfer analysis and the hydrological analysis.

2. Scientific background and context

2.1. Hydropower in Switzerland

Hydropower is an important energy source for Switzerland, and it currently counts for more than 50% of domestic electricity production (Barry *et al*., 2016 ; Gaudard *et al*., 2017 ; Hediger, 2016; Notter, 2015). Its production is favoured by the topographic peculiarities of Switzerland, and the high levels of annual rainfall that can be detected in its territory. Hydropower has experienced a period of expansion particularly between 1945 and 1970, while since 1970s there has been the need to find more sustainable techniques for energy production. According to the Swiss Federal Office of Energy (SFOE), there are currently 643 hydropower plants in Switzerland with a total production of 36264 GW/h per year, 48.2% of which is produced in run-off-the-river power plants, 47.5% in storage power plants, and about 4.3% in pumped storage power plants.

Since the events of Fukushima of the 11th of March 2011, Switzerland and the other European countries became aware of the need to enhance the exploration of alternative and renewable energy sources by phasing out fossil energy sources and nuclear power. Switzerland has planned a set of interventions since 2007 (Betz *et al*., 2016 ; Hediger and Voegeli, 2017 ; Weinhold and Lorenz, 2014), the “Swiss Energy Strategy 2050”. This “strategy” is a set of decisions and plans which aims at increasing the efficiency of energy production in Switzerland. According to some authors (Barry *et al*., 2016; Schumann, 2016 ; Voegeli, 2016 ; Voegeli *et al*., 2016), the “Energy Strategy 2050” should enable Switzerland to make advantageous utilization of renewable sources and to maintain its high supply standard. Moreover, it should also contribute to reduce Switzerland’s energy-related environmental impact, and it is based on three main milestones:

1. Optimization of energy exploitation and of production efficiency;
2. Enhancement of the utilization of renewable energy sources;
3. Build large power plants for electricity production with better standards.

After some years of discussions and debates, the set of plans and decisions related to the “Energy Strategy 2050” has been confirmed in May 2017, especially after the popular vote of the 29th of May 2017 to phase out nuclear energy by 2035. For the implementation of this action plan, eight specialized competence centres and two National Research Programmes have been developed in collaboration with Swiss National Science Foundation: “Energy Turnaround” and “Managing Energy Consumption” (Barry *et al*., 2016 ; Braunreiter *et al*., 2016). Moreover, the Swiss Energy Center for Energy Research (SCCER-SOE) constantly does research related to this Strategy.

According to Barry *et al*. (2016), a 10% increase for the Swiss hydropower sector is foreseen by 2050, and this is relevant given that today it represents already 50% of the total Swiss energy production. However, there is the need to consider also uncertainties and issues related to hydropower energy production (Baur and Hediger, 2016 ; Hediger, 2016 ; Hediger, 2017). The involved factors can be natural (i.e. boundary conditions of the hydrologic system), technical (i.e. engineering aspects), political and legal (i.e. regulations and acceptance), related to management (i.e. costs and decision-making), or commercial (i.e. system stability and energy markets). This thesis is embedded in the study of the natural factors that can have an influence on the hydrological properties of catchments and, consequently, also on the hydropower production.

Some authors (Gaudard *et al*., 2015 ; Schillinger *et al*., 2016 ; Schlecht and Weigt, 2016) have tried to understand the impact of climate change on hydropower production by mixed qualitative and quantitative methods. The purpose in this case is to try to reduce uncertainties related to hydropower production, to balance hydropower with other renewable energy sources (e.g. wind and solar energy), to involve decision-makers and stakeholders particularly in the mountainous cantons, and to couple climate models to hydrological and glaciological models in order to have a better understanding of the process of hydropower production related to physical factors (Schwanitz and Wierling, 2016). To count for consequences of climate change for hydropower production in Switzerland, a multidisciplinary and integrated approach is needed with the aim to consider all factors that can contribute to a modification of hydropower energy production in the coming years: climate models, emission scenarios, hydrological and glaciological numerical models, and reservoir management models (Gaudard *et al.*, 2016). Figure 1 illustrates all these aspects, and how they are mutually linked together.

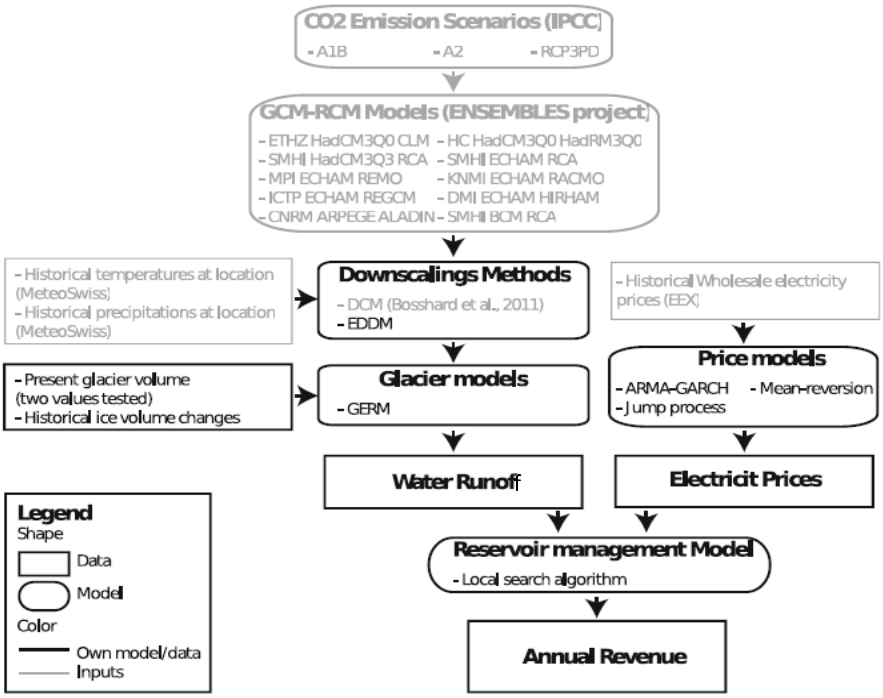


Figure 1: Components and elements of the integrated approach for hydropower production in the specific case of annual income determination. This approach can be applied to quantify the evolution of the produced hydropower energy in the future (Gaudard *et al*., 2016).

According to Figure 1, different aspects should be considered while doing predictions of hydropower energy production. Therefore, it is relevant to define objectives and to implement a methodological framework that allows to give reliable predictions in the mean- and long-term in the future. Climate change will have a strong impact on hydropower energy production because of a shift of hydrological regime and, in the alpine glacierized catchments, also because of changes in glaciers' contribution to runoff due to their shrinking tendency (Appenzeller *et al*., 2011 ; Pachauri *et al*., 2014). For glacierized catchments, the consequences of this process will be a lower energy production in summer and a more distributed energy production in the rest of the year. The hydrological regime will progressively shift from glacial to nival (Farinotti, 2013 ; Uhlmann-Schneiter, 2011), and this aspect should be considered for hydropower production in Switzerland in the next years, given that most of hydropower energy production derives from glacierized catchments located in the Alps (Schwanitz and Wierling, 2016).

2.2. Numerical streamflow in glaciology

Hydrological modelling in high-mountain glacierized catchments

Glaciers are a matter of concern for analyses related to numerical streamflow modelling, and numerical models have generally progressed a lot recently (Seibert *et al*., 2017). Glacier meltwater contributes to runoff in high-mountain catchments, particularly in summer, according to the nivo-glacial hydrological regime. Glacierized catchments should always be considered in relation to climate change and to the dynamicity of climate parameters such as precipitation and solar radiation. The simplest approach to do this, is to regularly update the hydrological model with an externally-simulated glacier extent, by using a hydro-glaciological model (Farinotti *et al*., 2012 ; Seibert *et al*., 2017). According to Seibert *et al.* (2017), it is more difficult to simulate natural physical conditions in glacierized catchments (Section 3.3). In this case, the similarity to real-world conditions is not relevant, but an additional hydrological analysis has been done in order to simulate such conditions in a reliable way (Section 3.3), with the aim to establish the effects of glacier retreat on the catchment's hydrological properties (Section 5.4).
Glacier shrinking has both negative and positive consequences for the Swiss hydropower sector. The melting of glaciers can increase the quantity of water available for energy production of hydropower plants. But, because of the hydrological regime shift that is foreseen for the coming years, there will probably be less water availability during Summer months (Chapter 5). Moreover, there will probably be an augmented influence of precipitation (snow or rain) on streamflow, particularly after the glaciers will have melted completely (Bavay *et al*., 2013).

Hydrologically, the two catchments of Findelen and Gries belong both to the Rhone hydrological basin, and their discharge rate is quite high given that they are both situated in the Alpine region. Figure 2 represents discharge rates of the most important hydrological basins in Switzerland.

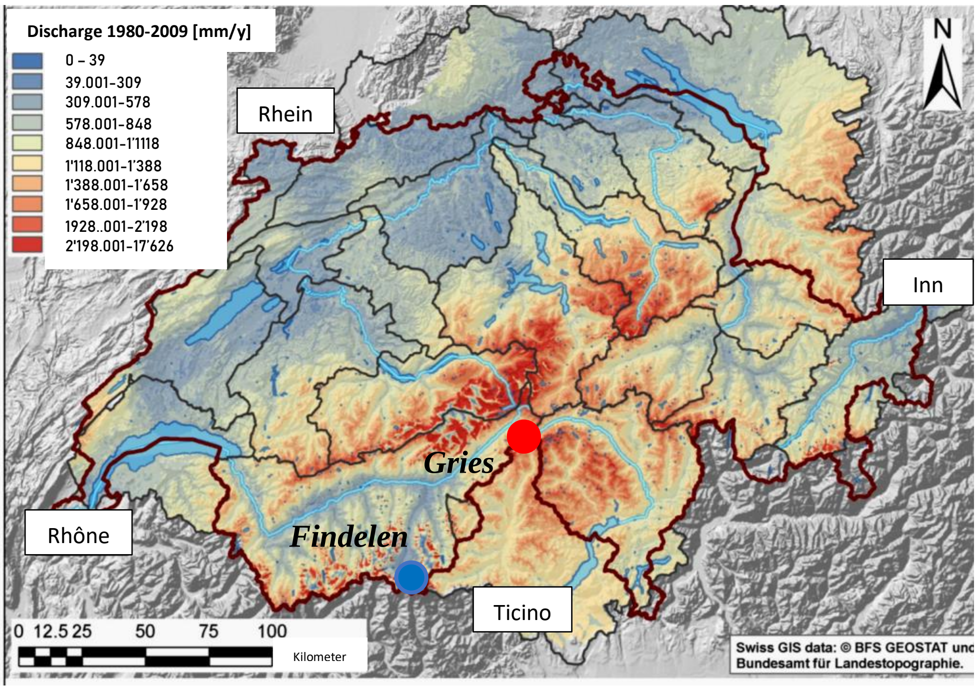


Figure 2: Components and elements of the integrated approach for hydropower production in the specific case of annual income determination. This approach can be applied to quantify the evolution of the produced hydropower energy in the future (Gaudard *et al*., 2016).

According to Bosshard *et al*. (2011), while doing such kind of research, it is important to perform hydrological impact studies by considering more extended contexts, such as the economic and social consequences of a hydrological regime modification. Climate change impacts on water resources in the Alps should also be assessed whenever possible: for example, the initiative "CCHydro" aims at understanding climate change impacts in Switzerland.
The climate change impacts on water resources in the Alps have been analyzed and assessed according to global and regional climate scenarios to study impacts and considerations related to glacier retreat tendency. An interdisciplinary approach is therefore needed to couple physical features of a catchment (e.g. presence of glaciers, rocks or vegetation) with increasingly high-resolution models (Bosshard *et al*., 2011 ; Zappa, 2016). In order to simulate hydrological processes, the HBV model has been used in this case (Section 3.3), but also other models can be implemented, such as the semi-distributed PREVAH model (Jörg-Hess *et al*., 2015). Hydrological models can also be applied at a hourly time-step, for example to study flooding events or for risk analysis assessment (Barry *et al*., 2016; Beven, 2012). Ensemble techniques are another approach for hydrological modelling: they are applied by including many climate variables rather than only precipitation and temperature, and by coupling hydrological and climate models (Farinotti *et al*., 2012 ; Zappa, 2016). These techniques are diffusing rapidly because they allow to demonstrate the feasibility of studies about weather forecasts (Bosshard *et al*., 2011).

Technical considerations about hydrological modelling

Models are useful tools to study hydrological catchments, to do predictions into the future and to measure the impact of hydrological changes (Beven, 2012). Catchments are often treated as black boxes with inputs and outputs but without a detailed physical description of involved processes. The modelling steps have been described by Beven (2012), and they are summarized in Table 1.

Table 1: Description of the most important modelling steps in hydrology and their main features. The steps are ordered from the first basic to the final one, applied at the end of the modelling procedure (Beven, 2012).

Modelling step	Modelling step name	Technical description of the modelling step
1	Perceptual model	It is composed by the ensemble of perceptions related to a catchment, so it has a high subjectivity from the user (empirical assessment of the process to study)
2	Conceptual model	It is based on hypotheses which aim at conceptually describing catchments and their main properties
3	Mathematical model	It involves the setting up of the model with the support of equations and mathematical formula
4	Procedural model	It is formed by codes which are run on the computer with different programming software and processes
5	Model calibration	Calibration can be done manually or automatically (manual trial-and-error, Monte-Carlo runs)
6	Model evaluation and validation	The user decides if the parameters and calibration settings can be applied to a catchment and how

According to Beven (2012), hydrological models should be composed by the following elements:

a. *Inputs*: climate variables that allow the model to produce numerical computations and simulations of hydrological processes (e.g. precipitation, temperatures, solar radiation);

b. *Outputs*: time-series of runoff simulations, analysis of runoff and discharge projections, assessment of how simulated and observed discharge do relate (i.e. the "outcomes");
c. *Model parameters*: parameters that define the physical features of a catchment, they are normally grouped into different routines related to the catchment's physical features.

The purpose of hydrological models is to achieve the best match between simulations and observations, by trying to reduce uncertainties. An example of hydrological model is the Hortonian model (Beven, 2012 ; Solomatine and Wagener, 2011), in which runoff is generated by an infiltration excess all over the hillslopes, by involving a lot of processes. Runoff generation controls how much water gets into the stream and flows towards the catchment outlet within the considered timeframe (Beven, 2012). Another example is the TOPMODEL which deals with a topographic representation of catchments and how this relates to hydrological elements.
To ameliorate calibration of hydrological models, a sensitivity analysis is normally done in order to assess the variability of parameters and their uncertainty. For example, the concept of "equifinality" (Beven, 2012 ; Rosbjerg and Madsen, 2005) is determinant in hydrological modelling, because more parameter sets allow to obtain an equally relevant model efficiency. However, there are often parameter sets that are unrealistic or do not reproduce natural and processes in a reliable way. In this thesis, a comparative approach between different parameter sets has also been adopted in order to describe the concept of "sensitivity analysis" (Section 5.4).

Glacier storage and numerical streamflow modelling

Glacier storage is a widely used term in hydrological technical terminology, applied to different processes and time scales by different scientific disciplines. According to Jansson *et al*., (2003), storage can essentially occur at three time scales: long-term storage (i.e. ice and firn as glacier up to many years), intermediate-term storage (i.e. storage and release of snow and water on a seasonal scale), and short-term storage (i.e. diurnal effects of drainage through the glacier including routing through snow, firn and englacial pathways). Glaciers are valuable natural reservoirs of water exerting a strong control on drainage characteristics of alpine catchments, storing water as ice and releasing it when melted, depending on climate factors (Jansson *et al.*, 2003). An example of study related to glacier storage and ice dynamics has been conducted by Huss *et al.* (2008), who have studied runoff from three glacierized alpine catchments for the period 2007-2100 by using a model including the change in glacier coverage, scenarios for seasonal changes of precipitation and temperatures, glacier surface mass balance and runoff on a daily time step. Moreover, other studies include the investigation of Shresta *et al.* (2013) about Numerical Weather Prediction Models (NWPM) of forecasts for short-term streamflow. In this case, the main outcomes are concerned with the fact that forecasts accuracy tends to decrease by increasing lead time, and that precipitation forecasts are generally less accurate than temperature ones. This experiment is partly linked to that of Beran (1999) about accuracy displayed by modelled hydrographs, or to the one of Funk *et al.* (2011) about ice thickness supported by numerical streamflow modelling in order to assess the variability of glacier extent for Findelen and Gries for the next century. According to Funk *et al*. (2011), glacier mass balance of Gries glacierized catchment has always been negative since the end of the 19th century, more than the one of Findelen. Therefore, Gries glacier is more prone to disappear within 2100. For Findelen glacier, the interpretative conceptualization is somewhat different: in 2045-2070, the volume of ice will have been halved and some ice will remain until 2100, but the glacier's Equilibrium Line Altitude (ELA) will be displaced in the catchment's uppermost limit (Funk *et al.*, 2011).

Weather forecasts and climate projections

"Weather" and "climate" are two concepts that should be distinguished because they are concerned by different spatial and temporal scales. On the one hand, "weather" is more related to the regional variability of parameters and variables at a shorter time range. On the other hand, "climate" projections are done more ahead in the future: they can span over years, decades, or even centuries (Appenzeller *et al.*, 2011). Forecasts accuracy has improved sharply since the development of more sophisticated computer models (Belousov and Berkovich, 2008). For this thesis, synthetically generated weather forecasts are used (Section 3.2) to produce outcomes of a possible climate evolution at a decadal time scale for two alpine catchments (Chapter 4). Forecasting can be applied at a short-range or long-range timeframe. Different forecast types have been distinguished and assessed by Murphy (1973, 1988) and mentioned in Table 2.

Table 2: Forecasts' types and their temporal range, according to Murphy (1988). The column on the right shows the category of forecast types, which is related to their assignation to "weather forecasts" or "climate scenarios".

Forecast type	Temporal range	Categorical conceptualization
Nowcasting	0-2 hours	Weather forecasts: their most important application is related to flood forecasting
Very short-range forecasting	2-12 hours	Weather forecasts: they are mainly applied to storms and extreme events
Short-range forecasting	12-72 hours	Weather forecasts: this is the "normal" range with a generally high accuracy
Medium-range forecasting	72-240 hours	Weather forecasts, often applied by meteorological services
Extended-range forecasting	10-30 days	Weather forecasts for many days ahead, accuracy is usually lower
Long-range forecasting	30 days-2 years	Seasonal or monthly outlook related to climate evolution during time
Climate forecasting	Beyond two years (2-5 years)	Climate forecasts for some years ahead
Decadal forecasting	Decadal time range	Climate forecasts at a decadal time range, it is a still developing research field, but many progresses have been made recently
Climate scenario	Century time range	Climate predictions and scenarios at a very extended time range, such as the scenarios of CH2011 (Appenzeller *et al.,* 2011)

Assessing the impact of climate change on runoff is of great interest because Switzerland is mentioned as the "water tower of Europe" (Appenzeller *et al*., 2011). Moreover, relevant shifts and modifications of hydrological regime are expected for the coming years, especially on highly-glacierized catchments (Chapter 4): in this case, this is due to a hydrological regime shift from a glacial or nivo-glacial to a nivo-pluvial hydrological regime (Section 2.1). Therefore, providing reliable hydrological predictions in the Alps is a challenge because it is a complex system.
The Alps are hydrologically relevant because their runoff has been quantified as being 3.3 times larger than in the rest of Europe due to the higher amounts of precipitation that can be detected at higher altitudes (Keenlyside and Ba, 2010 ; Palmer *et al*., 1993 ; Viviroli and Weingartner, 2004). Consequently, hydrological analyses can provide further insights on the variability and evolution of the hydrological regime in mountainous catchments, as it has already been done by some authors (Funk *et al.*, 2011 ; Houtekamer and Derome, 1995 ; Molteni *et al.*, 1995).

In order to properly implement a hydrological analysis, the relative contribution of initial conditions and meteorological forcing should be determined, and also the uncertainty sources: these include incomplete observations, modelling errors, and user's subjectivity during model verification and evaluation (Rossa *et al*., 2011). Forecast uncertainty related to glacier's response to climate change has also been studied by Farinotti (2013), by detrending climate variables at yearly, monthly and daily timescale with the provision of ENSEMBLES forecasts.

An example of procedure that counts for many factors in hydrological analysis is the Ensemble Streamflow Prediction (ESP), which aims at using historical data as input for hydrological models, providing information on future river stage, flow and volume. Ensemble predictions are concerned with integrations from different initial states or multi-model ensembles (Fowler *et al*., 2012). Moreover, an integration between a "normal" (*ESP*) and a "reverse" (*revESP*) Ensemble Streamflow Prediction approach can be applied: a hydrological model with assumed perfect initial conditions is forced by a forecast ensemble resampled from observed meteorological sequences, whereas the *revESP* approach combines an ensemble of resampled initial conditions with a perfect meteorological forecast (Farinotti *et al*., 2012 ; Shukla *et al.*, 2013 ; Yossef *et al.*, 2013).
An experiment has been done by Addor *et al.* (2011) for the city of Zurich and its protection against floods of the Sihl river, by assessing Hydrological Ensemble Predictions for Sihl river's discharge while considering deterministic and probabilistic climate models, a hydraulic model, and the hydrological model PREVAH. Another study conducted by Olsson and Lindstrom (2007) has analyzed the daily operational hydrological ensemble forecast during 18 months with a probabilistic evaluation to distinguish perfect forecasts from actual discharge observations. Wood and Lettenmaier (2008) have done a similar experiment for the Rio Grande basin in California, whereas Rossa *et al.* (2011) have performed such an experiment for the rivers Thur and Landquart.

Skill scores and Skill quantification for forecasts

Nowadays, it is common practice to summarize and define the skill (or accuracy) of weather forecasts by calculating it with different statistical methods (often termed as "skill scores"), which aim at determining the differences between forecasted values for a climate variable (e.g. precipitation or air temperatures), and a reference forecast which usually corresponds to observed values (Gandin and Murphy, 1992 ; Hamill and Juras, 2006 ; Lawrence and Hisdal, 2011).
Various definitions of skill scores have been proposed recently by many authors (Demargne *et al.*, 2009 ; Murphy, 1988) due to their utility for a variety of reasons (e.g. administrative, scientific and economic purposes). The majority of skill scores have values which show a specific range between forecasts that are less or more skillful than the reference (Fowler *et al*., 2012 ; Hamill and Juras, 2006). Skill scores are statistical measures that allow to determine the relevance and entity of forecasts' accuracy: they are determined with different statistical metrics which determine the variability of accuracy compared to a reference (generally climatology or persistence). A score is assigned by assuming that forecasts can be "perfect", "good" or "bad". This is a qualitative judgment; however, it is determined with statistical quantitative methods that do often vary between -∞ and 1, 1 indicating a "perfect" forecast (Murphy, 1988). Frei (2008) has defined a general formula for "skill scores" (Equation 1).

$$\mathrm{SS} = \frac{\mathrm{A} - \mathrm{A_{ref}}}{\mathrm{A_{perf}} - \mathrm{A_{ref}}} \tag{1}$$

This generic formula (Equation 1) allows to have a quantitative and statistical difference between forecasts and reference values of climate variables (i.e. precipitation and temperatures). Climatological forecasts can also be based on observations from one historical period or on the sample of observations from the experimental period. Therefore, skill scores can be decomposed between historical climatology, forecasts' bias, and the differences between mean historical and sample climatologies (Mason, 2004). Determination of skill scores of weather forecasts generally shows also a not negligible amount of uncertainty, which can be related to forecasting instruments or to calculation errors. Therefore, there is the need to deal with intrinsic uncertainty of skill scores and with their seasonal and geographical variability (Hamill and Juras, 2006 ; Murphy and Epstein, 1989). Skill scores can be either deterministic or probabilistic, categorical or continuous. Continuous skill scores measure real values like daily air temperatures at a specific location, categorical skill scores determine values in discrete classes (e.g. cold, normal or warm) or events (e.g. prediction of a tornado), deterministic measurements are performed for a single number (e.g. expected temperature), while probabilistic measurements consider the probability of reproduction of a phenomenon (e.g. probability of rain for a specific day). Generally, probabilistic statistical metrics seem to allow better results to be obtained (Frei, 2008).

Uncertainty in forecasts and hydrological models is mainly due to Numerical Weather Prediction Models, errors in model structure and parameterization techniques. Therefore, the concept of "lead time" should also be properly defined and assessed: lead time can be defined as "the length of time between the issuance of a forecast and the occurrence of the predicted phenomena" (Demargne *et al.,* 2009). According to some authors (Mason, 2004 ; Pingel *et al.,* 2005), not only uncertainty should be considered related to numerical streamflow modelling, but also "reliability" and "resolution". The first is defined as the assessment of the affordability of forecasts, while the latter can be conceptualized as the spatial and temporal range of a forecast's framework.
Algorithms can also be used to determine the skill of a forecast. Roulin and Vannitsem (2006) tried to quantify uncertainties for short-range forecasts using an ensemble integrated approach, while algorithms have also been applied to perform a rainfall-runoff modelling and flood forecasting (Dawson and Wilby, 2001 ; Jeong and Kim, 2005). Luo *et al.* (2007) have done a similar study by using a Bayesian approach to merge previously generated climate forecasts by multiple climate models. Another similar study has been performed by Krzysztofowicz (1992).

Decadal forecasts and their properties

A recently-implemented research field related to weather forecasts is done at a decadal time scale. The fact that extreme events are detected with increasing frequency today (Appenzeller *et al*., 2011) has pushed some researchers towards the provision of decadal forecasts. Those forecasts are spread over a time range of 10-30 years, referred to as decadal time scale. Forecast analyses at a decadal time-scale are a current necessity due to the need to deepen the study of natural occurring variability, both intrinsic and extrinsic (Clivar *et al.,* 2011 ; Corti *et al.,* 2012). Natural variability includes volcanic eruptions or solar cycles, while extrinsic variability includes anthropogenic climate change. Moreover, benefits and limits of decadal forecasts should be evaluated in appropriate decision-making environments and be compared with forecasts at a shorter or longer time-scale (Meehl *et al*., 2009, Murphy *et al*., 2010).
Decadal weather forecasts can be produced by stochastic weather generators. A stochastic weather generator produces synthetic time series of weather data of unlimited length for a location based on the statistical features of observed weather (Ailliot *et al*., 2015). Models of this type can be implemented by generating daily (or hourly) time series of climate variables, such as:

precipitation, air temperature, solar radiation and humidity. Some experiments have been done recently in climatological and meteorological sciences with the support of data produced by weather generators (Ailliot *et al.*, 2015 ; Dubrovsky *et al.*, 2004 ; Semenov, 2008).

Decadal predictions generally show less uncertainties than climate scenarios (Meehl *et al.*, 2009), but the potential for skilful decadal predictions depends largely on whether models do simulate sufficient decadal climate variability both in terms of magnitude and structure. Some examples of processes related to decadal variability include the periodic ENSO processes (El Niño Southern Oscillation), the Pacific Decadal Oscillation (PDO) and the North Pacific Index (NPI), as well as the Atlantic Multidecadal Oscillation (AMO) and Rossby waves movement (Meehl *et al.*, 2014 ; Solomon *et al*., 2010). To evaluate decadal predictions, both deterministic and probabilistic measures can be used. Moreover, decadal forecasts are useful to understand the changing composition of the atmosphere and the changing radiative external forcing during the last years, mainly related to human activities. Decadal forecasting procedures are generally expensive and quite difficult to implement (Lee *et al.*, 2006 ; Meehl *et al*., 2014), so some technical ameliorations and evolutions can contribute to improve their performance. Ambitious efforts to produce decadal forecasts have been initialized at a global scale, motivated by the possibility that the climate models used for climate change projections can capture not only the impact of changing atmospheric composition, but also the evolution of slow natural variations of the climate system when it is initialized with observations (Solomon *et al.*, 2010). Therefore, physical parameters are determinant to identify and analyze trends at a decadal time-scale: good initializations allow to obtain reliable input data in order to increase the possibilities to do a reliable skill analysis.

Decadal weather forecasts will also become useful for society in the future, because of their utility to understand the evolution of climate in an "intermediate" time scale between yearly forecasts and climate scenarios up to centuries. Another important point is to solve biases and uncertainties by enhancing the existing observational systems and by increasing the modelling resolution (Mehta *et al.*, 2009). Moreover, improvements in satellite systems and technologies can also be a valuable solution (Haines *et al.*, 2006 ; Van Oldenborgh *et al.*, 2012), and new ways to assimilate observations from atmosphere and oceans into climate models should be integrated, such as 4D-climate models and projects at a regional and continental spatial scale. In this case, the Global Climate and Energy Project (GCEP) can represent a relevant example (Haines *et al*., 2006 ; Van Oldenborgh *et al.*, 2012): it is an experiment which aims at improving oceans' coupled models by studying land surface and sea ice distributions and their influence on past time series or "hindcasts". Other projects (e.g. Hurrell *et al.,* 2006) aim at relating decadal forecasts with forecasts that have been produced at a shorter time scale (mainly 1-year or seasonal forecasts) and with climate scenarios at a longer time scale (more decades, or even centuries). However, only a few experiments have been done until now, and consequently this research field is still at its early stage of development.

3. Methodology

3.1. General framework of the project

The general methodology of this study about decadal forecasts is presented in this section and in Figure 3. The details about each individual step which represents the methodological framework of this thesis are explained in the next sections (from Section 3.2 to Section 3.4). The main aspects which are explained are the synthetic weather generator to produce forecasts files, the main settings and functions of the hydrological model HBV, and the calculation of skill scores.

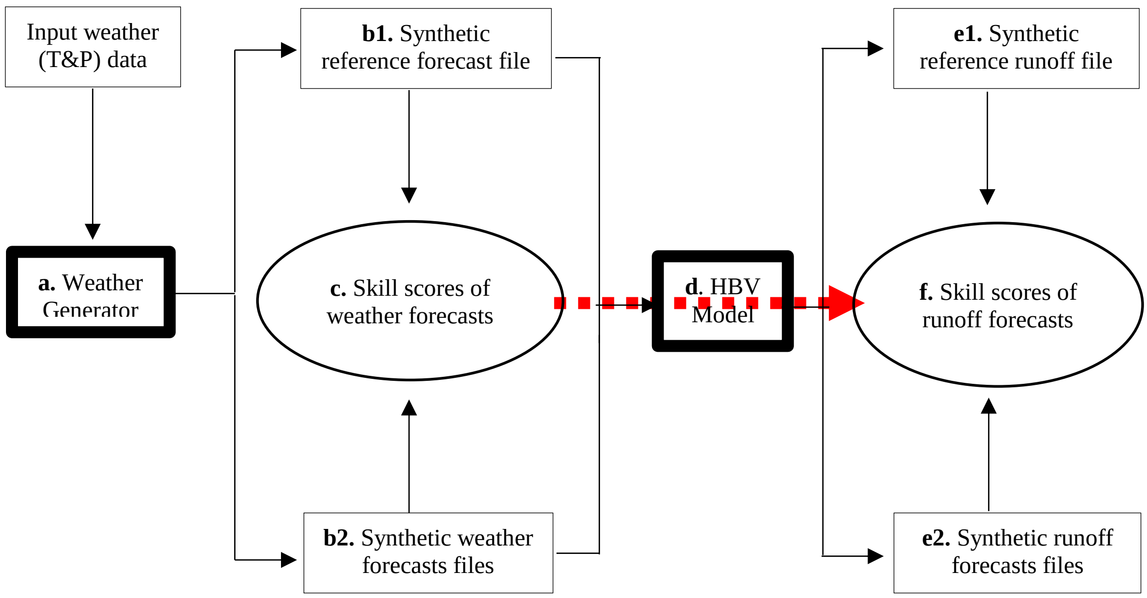


Figure 3: Methodology of the project, the general purpose is to understand how the skill is transferred between weather forecasts and hydrological forecasts with the help of a hydrological model (i.e. red marked arrow in the figure).

The aim of this study is to assess the skill transfer from weather to runoff forecasts. To achieve this objective, input weather daily values of temperatures and precipitation are used to run the synthetic weather generator by Farinotti (2013) (Figure 3a). Synthetic weather forecasts are produced with the weather generator (Figures 3b1 and 3b2). A file which contains reference values of temperatures and precipitation is first produced, and it has been considered as a “perfect forecast”. Then, forecasts files are produced by varying the internal parameters of the weather generator in order to differentiate them (see Section 3.2 for more information about the synthetic weather generator). Skill scores of decadal forecasts are calculated based on the reference file (Figure 3c). The synthetic weather forecasts are successively fed in the hydrological model HBV with the utilization of its main input files (Figure 3d) and calibrated in order to produce synthetic runoff forecasts and a synthetic reference runoff evolution (Figures 3e1, 3e2). Then, skill scores are calculated also for the runoff forecasts based on the relation between reference and forecast files (Figure 3f), and the accuracy transfer is finally determined. This procedure has been applied by considering different model settings and modes related to the glacier routine. The transfer of forecasts’ skill between weather variables and simulated runoff is assessed in Chapters 5 and 6.

3.2. Weather generators and synthetic forecasts

The weather generator by Farinotti (2013) has been used in this case to determine daily precipitation and temperatures for the two analyzed catchments (described in Chapter 4). It has been implemented by generating daily precipitation and temperature values by including different statistical parameters which allow to obtain a variability on forecasts. A time-series which is statistically equivalent to the observed one has been generated, and it has been used as a synthetic reference forecast. The length of the forecasts can be chosen by the user, in this case a length of 19 years has been applied at a daily resolution to the reference time-series. Then, this reference time-series has been modified to create a weather forecast every 15 days for 9 years. This process is illustrated below for both precipitation (Figure 4) and temperature (Figure 5) forecasts.

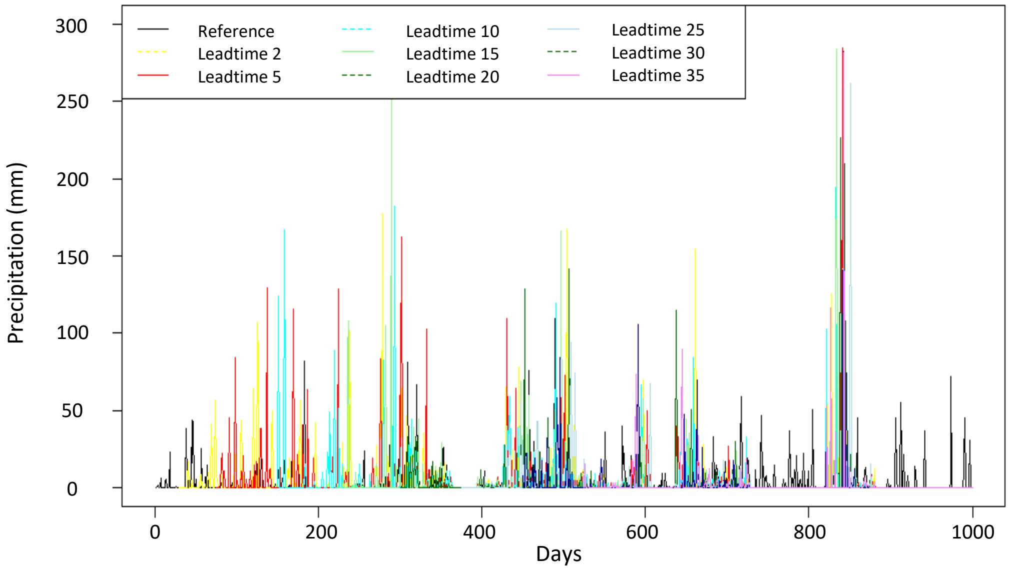


Figure 4: Illustration of a precipitation synthetic time-series of three years. Each colored line corresponds to a specific precipitation forecast which is generated every 15 days for a total length of 9 years.

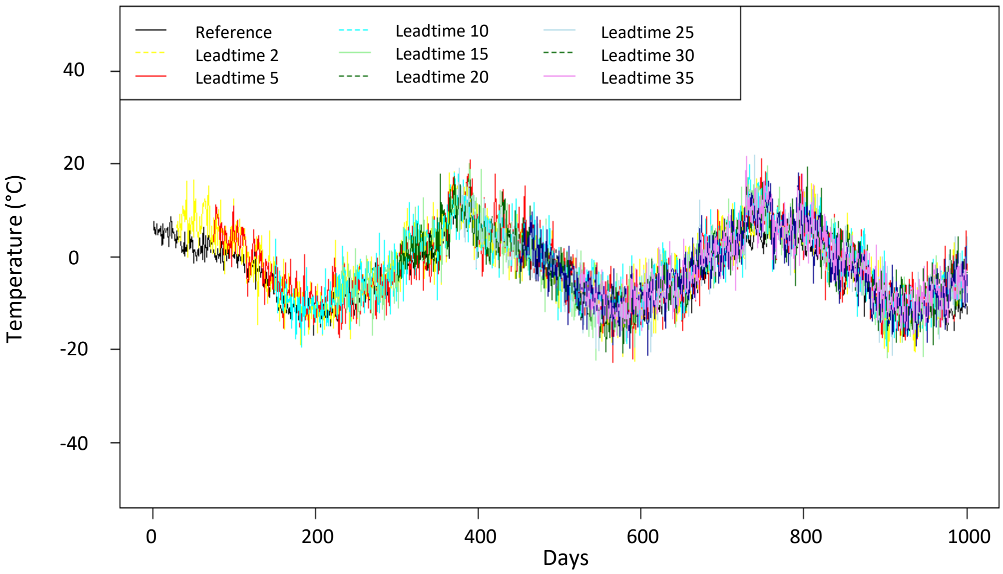


Figure 5: Illustration of a temperature synthetic time-series of three years. Each colored line corresponds to a specific temperature forecast which is generated every 15 days for a total length of 9 years.

Including different statistical parameters has then allowed to modify the reference time-series in order to produce decadal forecasts (Figure 4). Those parameters include the addition of daily trend, daily bias, daily and yearly variance and daily noise, which have been applied to the weather generator for a variable range of values. One value of each of these parameters has been applied on the reference forecast in order to create a forecast block with a total of 216 forecasts over 9 years. 150 different values were tested, resulting to 150 forecast blocks, and the forecasts generated in this way allowed to obtain forecasts of different accuracies.

Given that varying the input parameters of the synthetic weather generator has a not negligible consequence on the process of skill scores calculation, an assessment of the representations of accuracy metrics according to the choice of these parameters has been done in Chapter 5 and discussed in Chapter 6 for all the three skill scores which have been used for the analysis. In the next section (Section 3.3), the methodological processes related to the hydrological model HBV (i.e. settings, parameters, routines, calibration, etc.) are described in detail.

3.3. Hydrological modelling

3.3.1. The HBV Model

One widely-used hydrological model is the HBV model (Bergström, 1976), named after the *Hydrologiska Byråns Vattenavdelning* unit at the Swedish Meteorological and Hydrological Institute (SMHI), where its development has already been started in the 1970s by S. Bergström (Seibert and Vis, 2012). In this case, the version "HBV-Light 2.0", extended by Prof. Dr. Jan Seibert from the University of Zurich starting from the first version produced at the University of Uppsala in 1993, has been used and integrated in this project's framework. This model version is user-friendly and good for education purposes, and the most important element which has been introduced compared to the previous versions is the possibility to run simulations with variable time steps and for several sub-catchments (Seibert and Vis, 2012). The HBV model is a conceptual rainfall-runoff model which simulates daily discharge using daily rainfall and air temperature, and daily or monthly estimates of potential evapotranspiration as input. Conceptual models are characterized by procedures which aim at simulating the most important hydrological processes of catchments by using a small number of routines and parameters (Abebe *et al*., 2010; Driessen *et al*., 2010 ; Seibert, 1996). The HBV model consists of routines representing snow accumulation and melt by a degree-day method, groundwater recharge and actual evaporation as functions of water storage in a soil box, groundwater by three linear reservoir equations, and channel routing by a triangular weighting function (Seibert, 1997 ; Seibert and Beven, 2009).

Soil and snow routines are distributed representations of catchments, while response function and routing routine are lumped representations. For each routine, different parameters are involved, which represent each a specific property of a hydrological catchment. The model can be applied by considering different user-defined variants and settings. For example, it can be chosen to insert a variable number of parameters, or to divide the catchment into different sub-units, but also to decide about whether to include a glacier in the simulations with the recently-implemented glaciological routine (Seibert and Vis, 2012). Moreover, the model allows also to distinguish between different elevation and vegetation zones with variable orientations, i.e. cardinal points (Seibert and McDonnell, 2010 ; Zhang and Lindström, 1997). For this experiment, the model has been forced by considering the presence of a glacier with five different scenarios of glacier extent, which are explained in Figure 6 (see Chapter 4). Consequently, the glacier area has been varied in the catchment settings of the HBV model, while the other glacier properties have been modified by changing the glacier profile file. Variable elevation and vegetation zones have not been considered in this case, as well as variable orientations of the glacier's slopes.

3.3.2. Model inputs and files

For the analysis related to this thesis, several input files are needed to run the HBV model. Additional input files have also been inserted in it because the glacier mode has been included in the model settings. Figure 5 shows all the input files for the Gries catchment.

a

DATE	P	T	Q
20000101	9.38	-9.26	0.15
20000102	2.4	-8.87	0.15
20000103	0.08	-11	0.15
20000104	0	-11.1	0.15
20000105	0	-8.64	0.14
20000106	0	-11.34	0.14
20000107	5.97	-11.14	0.14
20000108	0	-9.09	0.14
20000109	0	-11.14	0.14
20000110	0	-10.01	0.14
20000111	0	-8.21	0.14
20000112	0	-7.94	0.13
20000113	0.41	-10.76	0.13
20000114	0	-7.18	0.13
20000115	0.82	-10.19	0.13
20000116	0	-9.12	0.13

b

9.735	1		
Elevation	Area	WE	EleZone
2300	0	0	2350
2400	0	0	2450
2410	0	0	2450
2420	0.0001	4400	2450
2430	0.0008	49100	2450
2440	0.0019	339200	2450
2450	0.0077	6244300	2450
2460	0.02	18986900	2450
2470	0.0163	13139100	2450
2480	0.0137	9198700	2450
2490	0.0084	6018600	2450
2500	0.0061	4182900	2550
2510	0.0065	4191000	2550
2520	0.0053	3259900	2550
2530	0.005	2681800	2550

c

Lowerbound	upperbound	remains
2500	3100	500

d

Gries
-9.5
-9.9
-9.9
-11
-10.4
-10.4
-10.3
-10.6
-9.8
-9.4

e

gries_EVAP
0.021
0
0.036
0
0.072
0.235
0.457
0.089
0.154
0.224

f

Date	Glacier
20011001	-23
20021001	-94.8
20031001	-246.4
20041001	-451.7
20051001	-799.5
20061001	-918.9
20071001	-1256
20081001	-1417.8
20091001	-1531.5
20101001	-1916.2
20111001	-2036.1
20121001	-2213.7
20131001	-2351.6
20141001	-2652.5

g

Date	SnowCover
20001001	0.15
20001002	0.15
20001003	0.15
20001004	0.15
20001005	0.15
20001006	0.49
20001007	0.58
20001008	0.51
20001009	0.9
20001010	0.81
20001011	0.75
20001012	0.74
20001013	0.71
20001014	0.66

Figure 6: Description of the HBV model inputs. The most important is the "PTQ" input (Figure 6a), which defines daily time series of precipitation ("P"), temperatures ("T") and discharge ("Q"). Other important inputs are: the glacier profile (Figure 6b), snow redistribution (Figure 6c), mean temperatures (Figure 6d), and mean potential evaporation rate (Figure 6e). The last two inputs are related to "goodness-of-fit" functions for the model efficiency: the glacier mass balance (Figure 6f), and the fraction of the catchment which is covered by snow at a daily timescale (Figure 6g).

The most relevant input data to run the HBV model are concerned by daily time-series of precipitation, temperature and observed discharge (Figure 6a). On the one hand, time-series of precipitation (“P”) and temperature (“T”) come from synthetic forecasts that have been produced with the weather generator by Farinotti (2013) (Section 3.1). On the other hand, daily time-series of observed discharge (“Q”) have been obtained from the glaciological model “GERM” (Glacier Evolution and Runoff Model). GERM is a deterministic and fully-distributed glaciological model, which simulates catchment runoff at daily time-scales. The model is constituted of different modules, namely accumulation, ablation, glacier evolution, evapotranspiration and runoff routing (Douglas *et al*., 2016 ; Funk *et al*., 2011 ; Gabbi *et al*., 2012 ; Huss *et al*., 2008 ; Jansson *et al*., 2003). Several input data have been generated with the GERM hydrological model, and data about mass balance and the glacier’s main properties (i.e. mass balance, equilibrium line altitude, etc.) have been used as inputs of the HBV model.

Other input files rather than the “PTQ” have been inserted in the HBV model. First, daily mean values (independent of years) have been produced to determine mean temperatures (Figure 6d) and the mean actual evapotranspiration (Figure 6e). Then, a glacier profile has been added to the input files (Figure 6b) in order to allow simulations to be performed with the dynamic glacier routine. This profile is composed by columns representing respectively 10m elevation zones of the glacier, the area of the glacierized sector, the water equivalent (in mm), and the 100m elevation zones which have been inserted in the catchment settings of the hydrological model. The glacier profile is utilized by the model during simulations in the dynamic glacier setting of the model. According to Huss *et al.* (2010), the *Δh parameterization* method assumes a variable glacier area and volume, which is updated at the beginning of every hydrological year (Figure 7).

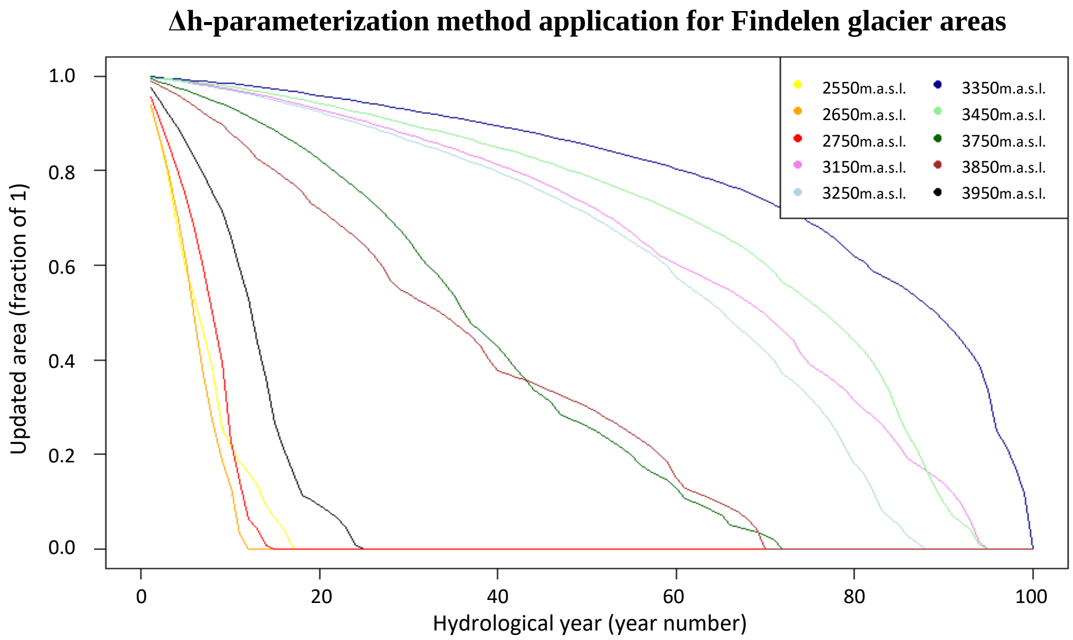


Figure 7: Application of the *Δh-parameterization* method by Huss *et al.* (2010) for the dynamic glacier routine of the HBV model. The x-axis indicates years, while the y-axis is related to the areal fraction of 1.

A snow redistribution file has been inserted into the model together with the glacier profile to determine the area where snow redistribution should be applied: the lowerbound corresponds to the elevation of the glacier tongue, while the upperbound corresponds to the equilibrium line elevation derived from existing scientific studies. Finally, two more files have been inserted into the HBV model: one containing data about the glacier mass balance (Figure 6f), and one containing daily values of the catchment fraction which is covered by snow (Figure 6g).

3.3.3. Calibration procedure

The HBV model has been calibrated with synthetic daily time-series of precipitation and temperatures from the synthetic weather generator by Farinotti (2013), and with daily synthetic time-series of discharge from the GERM model for each specific scenario. These time-series are 20 years-long, and therefore they have a temporal range which allows to obtain a meaningful and reliable calibration, because the model requires at least 5 to 10 years to calibrate properly (Seibert, 1997; Seibert and Vis, 2012). The calibration procedure can be either manual or automated (Lindström, 1997), and in this case an automated Monte-Carlo calibration has been chosen with the aim to find the combination of parameters which produces the highest efficiency in a user-defined number of runs. Two calibrations have been done with this method, both with 200’000 runs. The first calibration has been applied to hydrological simulations because it allows to obtain a slightly higher model efficiency according to the Nash-Sutcliffe criterion (Section 5.4): it has been done once for each catchment and then applied to all simulations, with both approaches, first by assuming fully-glacierized elevation zones, and then by distinguishing between glacierized and not glacierized areas. Obtaining a high model efficiency is challenging, because more parameters and routines should be considered simultaneously, particularly during the calibration and validation procedures. The Nash-Sutcliffe Efficiency is defined from 1 (perfect fit between simulated and observed runoff) to -∞ (very poor fit) (Equation 2).

$$1-\frac{\sum(\mathrm{Q_{sim}}-\mathrm{Q_{obs}})^2}{\sum(\mathrm{Q_{obs}}-\overline{\mathrm{Q_{obs}}})^2} \tag{2}$$

The second calibration has been performed by reducing the parameter range of the Monte-Carlo simulation in order to allow a lower parameter variability while considering user-defined values that can be related with more natural and realistic conditions (the values for both calibrations can be found in Table 3). For the Monte-Carlo analysis, lowerbounds and upperbounds are defined for each parameter according to feasibility ranges that have been partly determined according to the existing scientific literature, and partly according to the features of the catchment and to the results of a previous manual trial-and-error calibration procedure. Generally, a Monte-Carlo calibration approach is efficient and practical, but some uncertainties can characterize individual parameters or parameter sets (Seibert, 1997 ; Seibert, 2000). Consequently, a sensitivity analysis has been performed by studying for which values each parameter can give an acceptable model efficiency. This analysis has been applied to the most realistic situation of hydrological modelling on glacierized catchment, i.e. by distinguishing between glacierized and not glacierized areas in each elevation zone. Moreover, a comparison between different efficiency critieria has been performed by establishing their correlation for both catchments and for all scenarios (Section 5.4).

The elevation zones are used to lapse precipitation and temperature variability with elevation: precipitation is assumed to increase by 10% every 100m elevation, while temperature is assumed to decrease by 0.6°C per 100m elevation. Lake fraction is set to 0.056 for Gries catchment due to the presence of Gries Lake, while no lake is included for Findelen catchment. Elevation of precipitation and temperatures are not fixed in this case, but variable according to the elevation point where the highest model efficiency is obtained during calibration. 200’000 runs have been done with Monte-Carlo method in order to find out the best parameter set combination. Table 3 illustrates the model parameters and their feasibility ranges used in the Monte-Carlo calibration, by considering the ranges used for both calibrations, the one which has been used for simulations and the one used to perform the hydrological analysis (Chapter 5). 200’000 runs represent the maximum number which has been applied to the calibration procedure because of the high computational requirements which would have been required by assuming more runs.

Table 3: Parameters and feasibility ranges used in the Monte-Carlo calibration for both catchments. For minimum and maximum values, the left column (marked in blue) shows the parameter ranges of the calibration used for simulations, while the right column (marked in orange) is related to the calibration used for the hydrological analysis.

Parameter/routine	Explanation	Minimum		Maximum		Unit
TT, Snow Routine	Threshold temperature	-1.5	-0.5	2.5	0.5	°C
CFMAX, Snow Routine	Degree-day factor	2	3	5	5	mm °C^{-1}d^{-1}
SP, Snow Routine	Seasonal degree-day factor	0.01	0.5	1	1	-
SFCF, Snow Routine	Snowfall correction factor	0.5	0.6	1.2	1.2	-
CWH, Snow Routine	Water Holding capacity	0	0.1	0.2	0.1	-
CFR, Snow Routine	Refreezing coefficient	0	0.04	0.1	0.06	-
CFglacier, Glacier Routine	Correction factor, glacier albedo	1	1	2	2	-
CFSlope, Glacier Routine	Correction factor, topography and slope of the catchment	1	1	2	2	-
KSI, Glacier routine	Snow to ice conversion factor	0.001	0.001	0.1	0.004	Δt^{-1}
KGmin, Glacier Routine	Minimum outflow coefficient	0.001	0.001	0.2	0.1	t^{-1}
DKG, Glacier Routine	Maximum minus minimum outflow coefficient	0.001	0.001	0.5	0.2	t^{-1}
AG, Glacier Routine	Calibration parameter of the glacier routine	0.001	0.001	0.1	0.1	mm^{-1}
FC, Soil Moisture Routine	Maximum of storage in soil box	50	50	500	500	mm
LP, Soil Moisture Routine	Threshold for the reduction of evapotranspiration	0.3	0.3	1	1	-
BETA, Soil Moisture Routine	Shape coefficient	1	1	6	6	-
CET, Soil Moisture Routine	Correction factor for the potential evapotranspiration	0	0	0.3	0.3	°C^{-1}
K0, Response Routine	Recession coefficient (upper box)	0.01	0.01	0.5	0.5	d^{-1}
K1, Response Routine	Recession coefficient (upper box)	0.01	0.01	0.5	0.2	d^{-1}
K2, Response Routine	Recession coefficient (lower box)	0.001	0.001	0.5	0.1	d^{-1}
PERC, Response Routine	Maximal flow from the upper to the lower box	0	0	4	4	mm d^{-1}
MAXBAS, Routing Routine	Routing parameter, length of a triangular weighting function	1	1	7	7	d
PCALT & TCALT	Gradients of P and T every 100m	10, 0.6	10, 0.6	10, 0.6	10, 0.6	mm °C/ 100m
Pelev and *Telev* (for the Gries and Findelen catchments resp.)	Elevation of precipitation and temperature measurements	2500/ 2800	2500/ 2800	2900/ 3500	2900/ 3500	mm °C (m.a.s.l)

According to Table 3, a total number of 21 parameters has been considered for the Monte-Carlo calibration. In this case, more parameters are detectable because of the inclusion of the glacier mode in the HBV model. The parameters are described and defined below.

Snow accumulation and melt are computed using a threshold temperature *TT* [°C] and a degree-day coefficient *CFMAX* [mm/Δt °C], which normally varies between 1.5 and 4 [mm/Δt °C], with lower values for forested areas. Whenever precipitation is simulated as snow (temperature below *TT*), then the amount of precipitation is multiplied by a snowfall correction factor *SCF* [-]: usually *SCF* tends to be smaller for forested areas than for open areas (Seibert, 1999). The snowpack retains meltwater until the amount exceeds a certain portion (*CWH* [-], usually around 0.1) of the water equivalent of the snowpack. The parameter *SP* [-] indicates the seasonal variability of the degree-day temperature factor, and more variability is defined if this parameter is smaller than 1. The glacier routine is composed by a glacier correction factor (*CFGlacier* [-]) and a slope correction factor (*CFSlope* [-]). The glacier correction factor represents the different albedo of ice compared to snow, and it is useful to simulate ice melt in the recently implemented model glacier routine (Seibert and Vis, 2012). Ice melt is added to the glacier's liquid component, from which the outflow is computed individually for each elevation zone to account for the enlargement of glacial conduits over the melt season. Equation 3 defines the glacier routine (Seibert *et al.*, 2017):

$$Q(t) = S(t) * (K_{min} + K_{range} * e^{-AG * SWE(t)}) \tag{3}$$

Q is the outflow, S the liquid water content of the glacier, SWE the water equivalent of the snowpack, K_{min} [t^{-1}] and K_{range} [t^{-1}] are the minimum outflow coefficient and maximum range of outflow coefficient values, and *AG* [mm^{-1}] a calibration parameter. Snow redistribution can be applied at the end of each time step to avoid unrealistic multiyear snow accumulation known as "snow towers" (Seibert *et al.,* 2017). During snow redistribution, the snow layer of all non-glacier areas above a user-specified upper elevation and threshold, is redistributed evenly between the lower and the upper elevation (Freudiger *et al*., 2017 ; Seibert *et al*., 2017).
For the soil moisture routine, three parameters can be identified: the maximum soil moisture storage *FC* [mm], the soil moisture value *LP* [-] above which actual evaporation reaches potential evaporation, and the parameter *BETA* [-] which indicates the relative contribution to runoff from rain or snowmelt. For the runoff routine, five parameters are considered: the threshold parameter *PERC* for percolation [mm/Δt], the threshold parameter *UZL* [-], and the three storage or recession coefficients *k0* [1/Δt] (for the upper box), *k1* [1/Δt] (for the upper box) and *k2* [1/Δt] (for the lower box). Moreover, the routing routine is represented by the parameter *MAXBAS* [Δt], which represents the length of the triangular weighting function: the generated runoff of one-time step is distributed on the following time steps using an equilateral triangular weighting function.
After calibration, the values of each parameter corresponding to each combination have been inserted in the model again, and a new simulation has been done with this combination of parameters for the reference file of both catchments. Then, this "optimal combination" has been applied to all forecasts to determine skill transfer (Chapter 5). An additional calibration with 1'000'000 runs has also been done, but the calibration with 200'000 parameter sets has been preferred because it requires less memory and time with a similar model efficiency. The application of the same parameter combination and input files (daily time-series of temperatures, precipitation and observed runoff) to all simulations allows to assess how a variable glacier extent influences skill transfer and runoff simulated by the hydrological model (Sections 5.3 and 5.4).

3.4. Skill scores in meteorological and runoff forecasts

Forecast evaluation and verification involves the investigation of pairs of data between forecasts and a reference observation. Metrics called "skill scores" are used to assess the accuracy of forecasts, based on a reference time-series (Fowler *et al*., 2012 ; Frei, 2008 ; Meehl *et al*., 2014 ; Murphy, 1988). Different skill scores which are suitable for both weather and runoff forecasts have been computed. The first selected skill score is the Root Mean Square Error (RMSE) which is the square root of the average of the squared differences between forecasts and observations. This skill score puts more focus on large errors rather than smaller ones, and its perfect score is 0 (Corti *et al*., 2012 ; Crochemore *et al*., 2016 ; Demargne *et al*., 2009 ; Farinotti *et al*., 2012). The second skill score is the Reduction of Variance (RV) which measures the percent improvement of the forecast compared to the observed values of the reference (Cloke and Pappenberger, 2009; Frei, 2008). The third skill score is the Correlation Coefficient (CC) which measures the degree of linear association: in this case, plots of forecasts against observed values have also been produced in order to determine the linear regression and the correlation degree between forecasts and the referemce data (Cloke and Pappenberger, 2009 ; Frei, 2008). Other two skill scores have partly been used for the general analysis but not integrated to the assessment of results (Chapter 5) and to their interpretations (Chapter 6): Mean Absolute Error (MAE) and Linear Regression (R2). Table 4 defines the three skill scores which have been chosen for the analysis by giving their mathematical formula and their variability range between the best and the worst score value.

Table 4: Skill scores used for the quantification of decadal forecasts. Skill scores are calculated between the forecast (*f*) and the observed values of the reference (*o*) time-series at a daily temporal range for each lead time. "*Var*" indicates the variance and "*sd*" the standard deviation. "*N*" relates to the total number of lead times.

Skill Score name	Mathematical formula	Variability range
Root Mean Square Error (RMSE)	$\sqrt{\frac{1}{N}\sum_{i(f_i-o_i)^2}}$	0 (best score) < RMSE < ∞ (worst score)
Reduction of Variance (RV)	$1 - \frac{\frac{1}{N}\sum(f_i-o_i)^2}{var_r^2}$	-∞ (worst score) < RV < 1 (best score)
Correlation Coefficient (CC)	$\frac{\frac{1}{N}\sum_i^N (f_i - \bar{f}) * (o_i - \bar{o})}{sd_f * sd_o}$	-1 (worst score) < CC < 1 (best score)

The three skill scores which have been used for the analysis have been defined in Table 4. Skill scores have been determined on a daily time-scale for a lead time of 9 years, for both weather (temperatures and precipitation) and hydrological forecasts (as described in Section 3.2).

For every forecast block from the total of 150 (Section 3.2), daily skill scores have been calculated and plots have been produced. These visual representations have allowed to analyze the evolution of accuracy for the two weather variables and for the simulated runoff. Figure 8 shows an example of daily skill scores calculation for synthetic the two weather input variables (precipitation and temperatures) and for the simulated runoff.

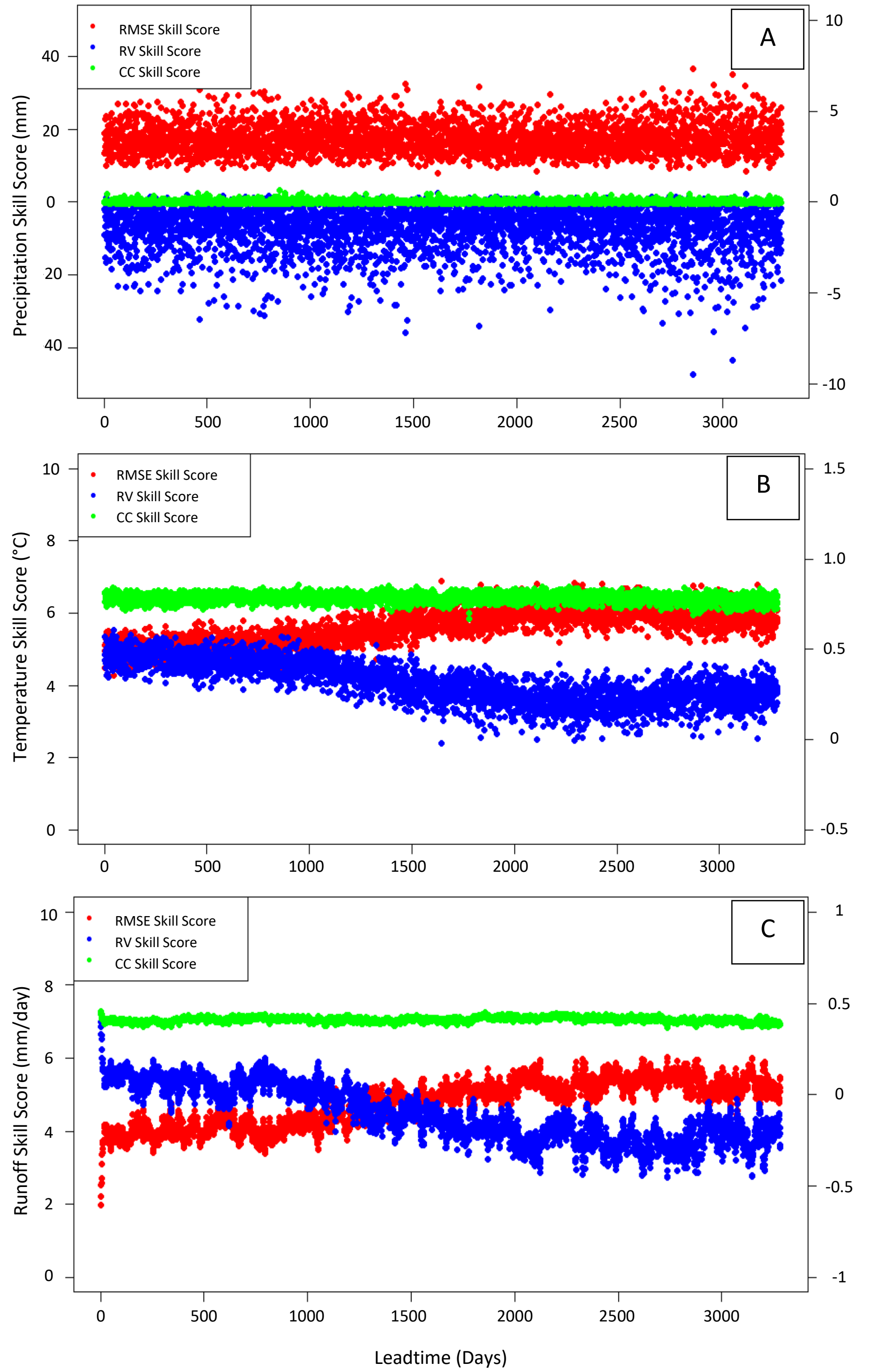


Figure 8: Daily runoff skill scores for precipitation (Figure 8A), temperature (Figure 8B), and simulated runoff (Figure 8C). Temperature skill score values are given in °C, precipitation ones in mm, while values of simulated runoff are given in mm/day. The x-axis represents the leadtime (in days), while the y-axes represent the RMSE skill score values for the axis on the left, and the RV and CC skill score values for the axis on the right.

The plots illustrated above (Figure 8) have been produced for all forecast blocks and for both Findelen and Gries catchments. Together with the data from the skill score calculation and the visual representations of forecasts variability, they have been integrated to the analytical framework in order to quantify skill transfer according to lead time (Sections 5.2 and 5.3).

4. Study sites

This study focuses on two glacierized catchments in the high-mountain regions of Switzerland, both situated in the Wallis canton, in the central-western part of the Swiss Alps (Figure 9): the Findelen and Gries catchments. “Glacierized catchment” means that a glacier is comprised in the area of the catchment and its runoff contributes to the total hydrological regime. Figure 9 shows a representation of the geographical location of both catchments, by including an illustration of their most relevant surface types: ice, lakes, vegetation, rocks.

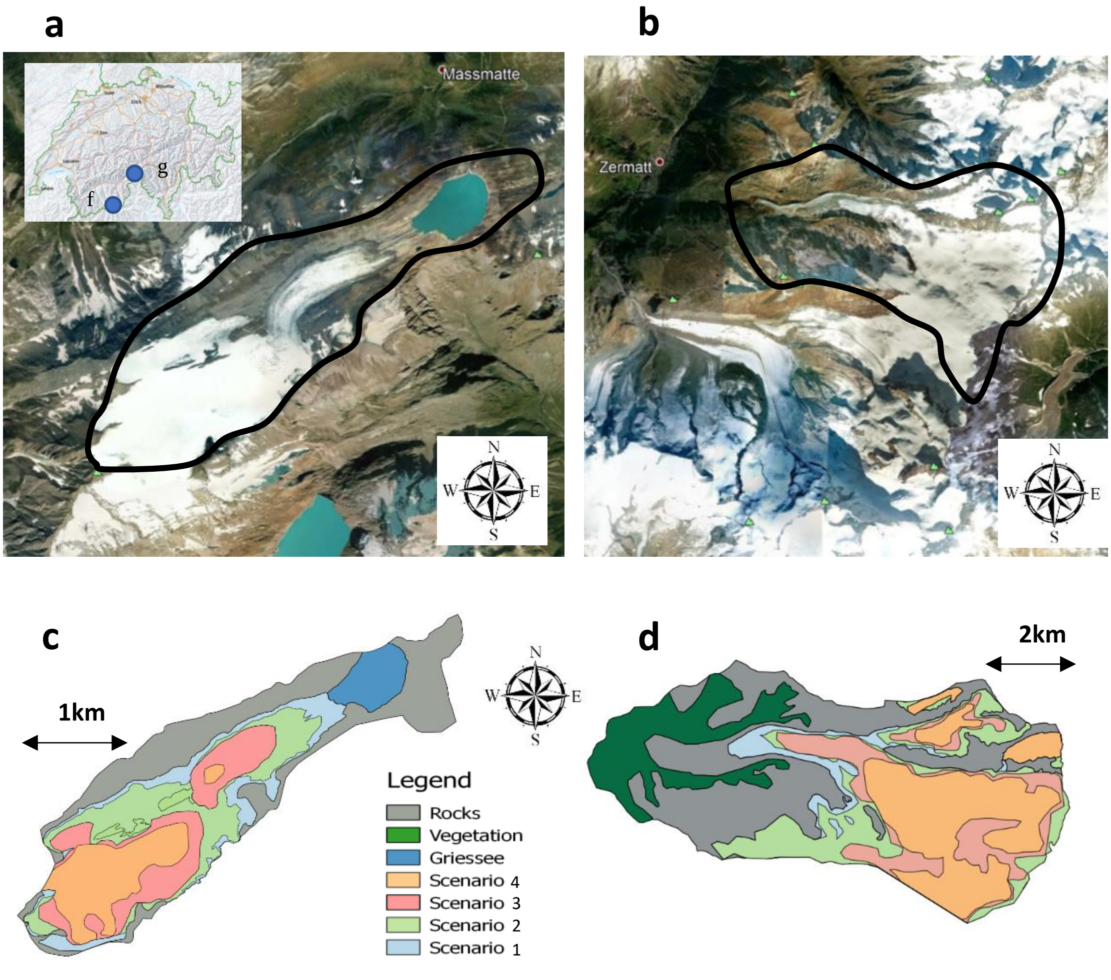


Figure 9: Geographic situation of Gries and Findelen glacierized catchments: satellite representations including outlines, surface type and glacier extent for different scenarios. In the localization map of the two catchments, „f“ indicates the Findelen catchment, while „g“ represents the Gries catchment (source: QGIS software).

The Gries catchment is located in Wallis canton (Figures 9a and 9b), near the Nufenenpass. Its elevation is comprised between about 2350m.a.s.l. at the basis of the artificial lake’s dam and 3374m.a.s.l. of the Blinnenhorn. The catchment has a surface of 10km^2, of which currently about 50% are covered by the glacier, while the lake has a surface of about 0.6km^2 (Funk *et al.*, 2011). Gries glacier is a temperate valley glacier that flows in a north-east direction from 3305m.a.s.l. down to 2425m.a.s.l. According to the classification of glaciers by their thermal state, “temperate” glacier means that it is at melting points from the surface to the bed throughout the year (Bauder *et al.*, 2017). The glacier had a length of 5.7km and a surface of 6.3km^2 in 1973 (data from the Swiss Glacier Monitoring Network, 2016), while its surface was of 6.1km^2 in 1986 and 4.8km^2 in 2014 (Bauder *et al.*, 2017). Gries glacier has experienced a pronounced retreat tendency during the last century: this has been confirmed by measurements which have been done by the Laboratory of Hydraulics, Hydrology and Glaciology of the ETH Zürich. Given its position and orientation, it is one of the glaciers that suffers the most the effects of climate change, and it is expected to melt completely at around 2080-2110 (Appenzeller *et al.*,2011 ; Pachauri *et al.*, 2014).

The Findelen glacierized catchment is the second study site, and it is also located in Wallis canton, in the region of Zermatt, with a NW orientation pattern (Bauder *et al.*, 2017 ; Uhlmann-Schneiter *et al*., 2013). The catchment extends from 4120m.a.s.l. down to about 2200m.a.s.l., while the glacierized area currently covers an elevation range from 2580m.a.s.l. to 4120m.a.s.l. (Bauder *et al.*, 2017). The catchment has an area of 37.4km^2 of which 48% are covered by the glacier and 12% by vegetation (Funk *et al.*, 2011). In 1973, the glacier had a length of 7.8km and a surface of 17.36km^2, while its surface was of about 17km^2 in 1982, and 12.9km^2 in 2014. Findelen catchment is located in an area which is characterized by gently sloping high-elevation accumulation basins and a narrow glacier tongue. The region is one of the driest in Switzerland, and its equilibrium line is at around 3200m.a.s.l. (Bauder *et al.*, 2017). The runoff of Findelen glacier is not exploited directly by basins located in the catchment, but the meltwater is deviated to other retention lakes in the surroundings, such as the Grande Dixence. This catchment is divided into three glacierized sectors: the Findel glacier, its tributary Adler glacier (2km^2 surface in 2014, according to Bauder *et al*. (2017)), and a small glacierized sector that is not directly linked to Findelen glacier, but whose mass balance is counted together with it.
A visual representation of the two glaciers provides insight on their morphololological and topographical features, particularly concerning the glacier tongue (Figures 10 and 11).

Figure 10: Findelen hydrological catchment in the year 2009 (https://content.meteoblue.com/fr/meteoscool/).

Figure 11: The Gries catchment (glacier and lake) in 2005 (http://www.unifr.ch/geoscience/geographie/ssgmfiches/glacier/).

According to researchers from ETH Zürich, who have studied the length variability of the two glaciers, both glaciers have been characterized by a shrinking tendency during the last two centuries. Gries glacier has lost 2892m of ice (~3km) from 1847 to 2015, while Findelen glacier has lost 2496m of ice (~2.5km) from 1885 to 2015 (Swiss Glacier Monitoring Network, 2016). Gries glacier has regularly lost ice, while this tendency seems to have been consolidated also for Findelen during the last two decades (Bauder *et al*., 2017 ; Funk *et al*., 2011).

5. Results

In the following sections, the results generated by forcing the hydrological model HBV with the 150 synthetic forecast blocks are shown. First, a preliminary analysis of results is presented (Section 1). Then, results are presented for the scenario related to the highest degree of glacierization (Scenario 1, Section 5.2). Afterwards, results are shown for all the other scenarios comprising a variable degree of glacierization (Scenarios 2-5, Section 5.3). The last section of the results chapter (Section 5.4) shows the most relevant results of a sensitivity analysis which has been performed on the parameters and routines of the HBV model.

5.1. First analysis about skill scores and skill transfer

Normalization of skill scores and aggregation of all forecasts blocks

After having calculated skill scores for the weather variables (i.e. precipitation and temperatures) and for the simulated runoff, a normalization procedure has been necessary in order to allow a quantification of skill transfer. The normalization assessment aims at uniforming all units of all the three considered variables, and it is based on a mathematical calculation (Equation 4).

$$zi = \frac{xi - \min(x)}{\max(x) - \min(x)} \quad 4)$$

Figures 12, 13, and 14 give an example of the RMSE normalized skill scores for precipitation, temperature and runoff respectively. In the representations, only a few forecast blocks are displayed for a better visualization.

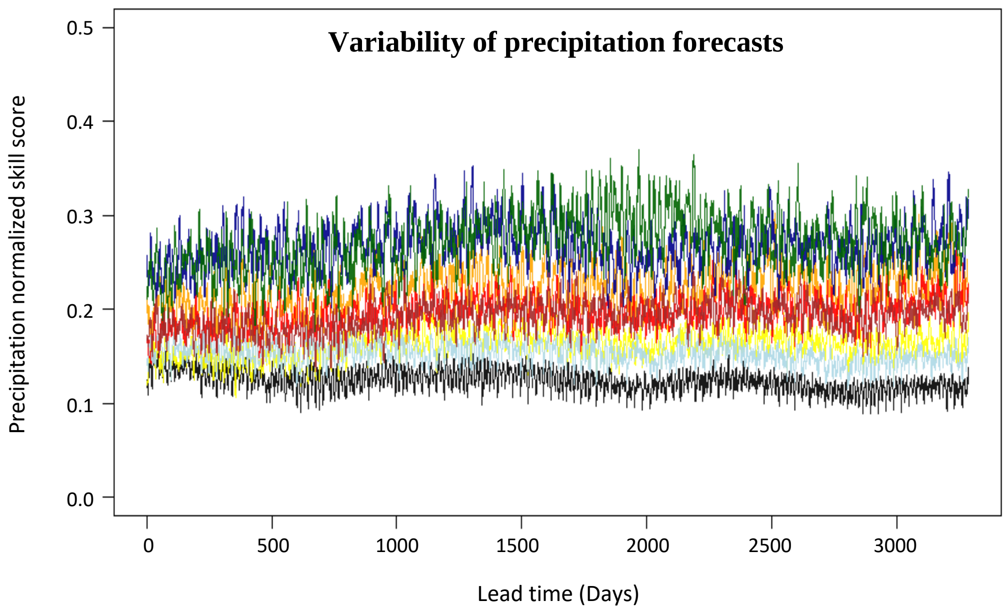


Figure 12: Normalized precipitation skill scores according to the forecast block. Each colored line corresponds to a different forecast block, an example is shown in this case for the Findelen catchment.

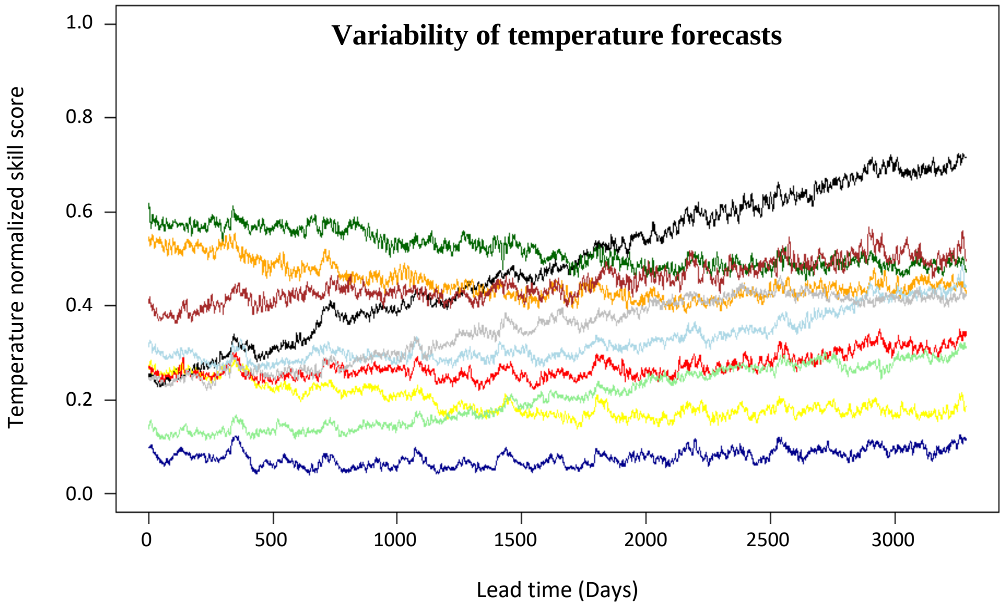


Figure 13: Normalized temperature skill scores according to the forecast block. Each colored line corresponds to a different forecast block, an example is shown in this case for the Findelen catchment.

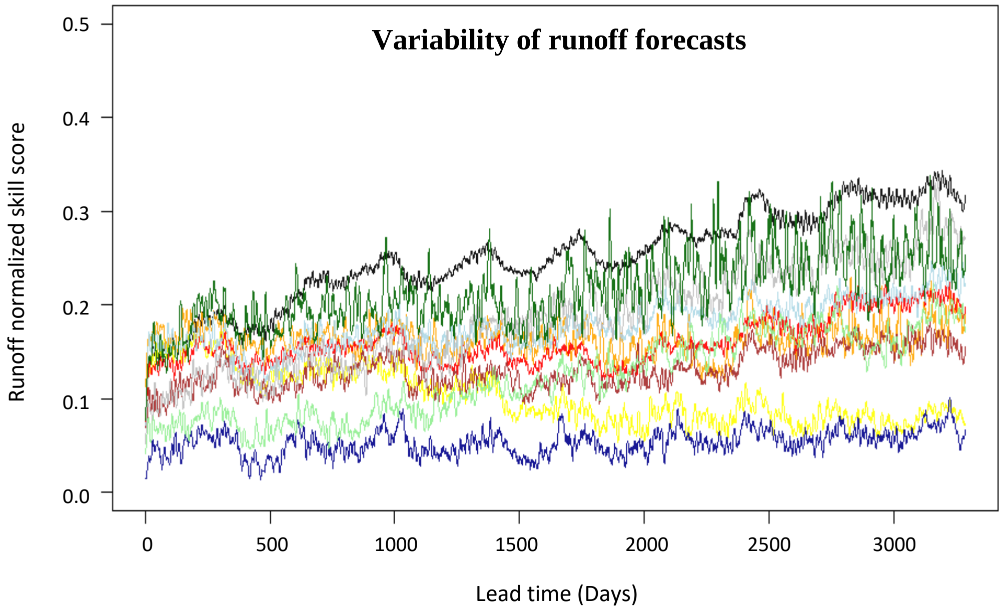


Figure 14: Normalized runoff skill scores according to the forecast block. Each colored line corresponds to a different forecast block, an example is shown in this case for the Findelen catchment.

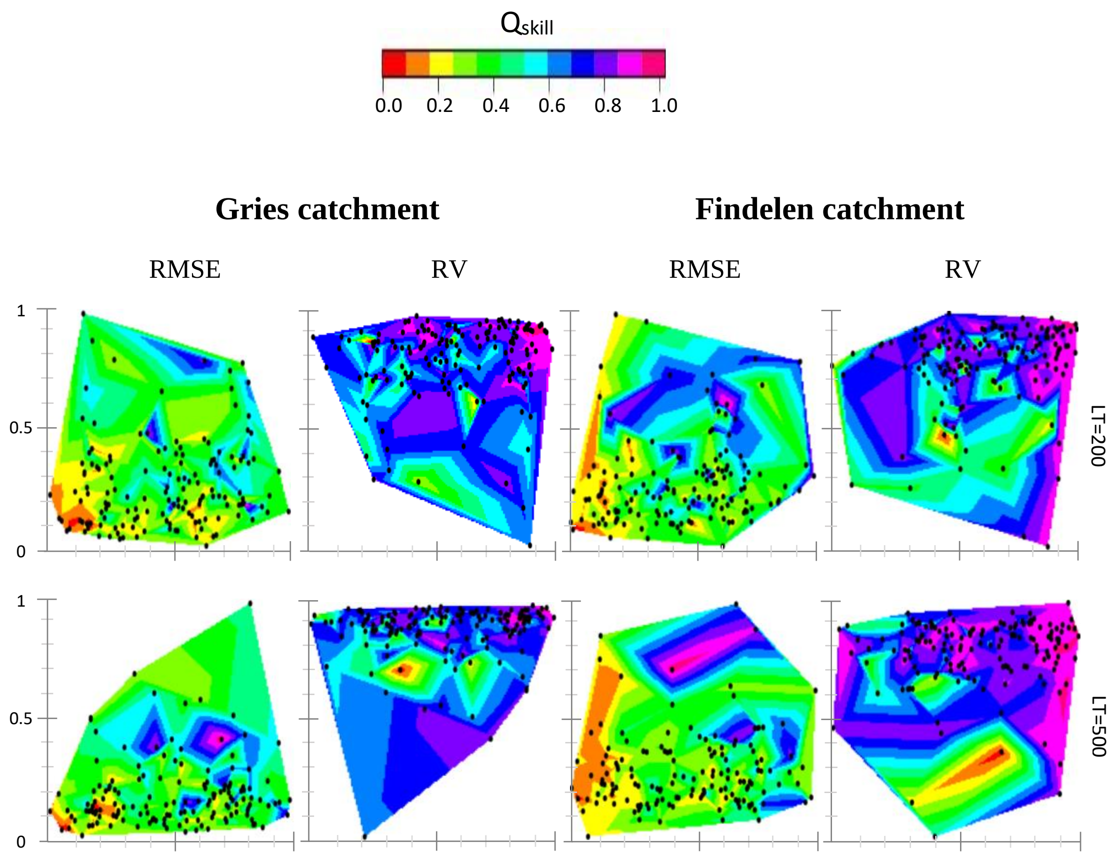
After determining daily skill scores for both catchments, for all scenarios and for all the three implemented statistical metrics, and after having normalized them (with values ranging from 0 to 1), the aim was to analyse how skill of meteorological forecasts is transferred into runoff forecasts. A multiple linear equation has been applied for this purpose, by relating the runoff (*Qskill*) forecasts as a linear function of the skill scores of temperatures (*Tskill*) and precipitation (*Pskill*):

$$\mathrm{Qskill} = \mathrm{m} * \mathrm{Tskill} + \mathrm{n} * \mathrm{Pskill} \qquad 5)$$

In Equation 5, parameters *m* and *n* are related to the quantification of the influence of temperatures and precipitation on runoff forecasts, respectively. Before quantifying skill transfer with the above equation, skill scores have been normalized for all lead times in order to perform also a comparison between the different lead times. This analysis has been applied to both catchments and to all scenarios assuming a variability of glacierization from the highest amount (i.e. Scenario 1) to a completely ice-free catchment (i.e. Scenario 5). For all scenarios, the analysis has been performed by assuming a dynamic glacier evolution during time, meaning that the glacier extent and volume are updated at the end of every hydrological year, based on the *Δh-parameterization* approach described by Huss *et al.* (2010). However, also the static glacier routine of the hydrological model (Seibert *et al.*, 2017), which considers only a constant areal extent of the glacier without taking into account mass balance and water equivalent, has been compared with the dynamic one (Section 6.1). The same parameter values from the Monte-Carlo calibration (Section 3.3) have been applied to both modes of the glacier routine by varying the glacier extent.

First assessment of skill transfer

The analysis related to skill transfer has first been performed for the scenario which considers the highest amount of glacierization (Scenario 1), and then for all the other scenarios (Scenarios 2 to 5). In this case, the first step was to assess skill transfer by selecting some individual lead times in order to implement some considerations about accuracy transmission from weather to runoff forecasts. Figure 15 illustrates an example of the relation between *Tskill*, *Pskill*, and *Qskill* for seven different lead times and for the first scenario. RMSE and RV skill scores are represented for both catchments, while the results of CC skill score are shown on Appendix A.2.1 and A.2.2.



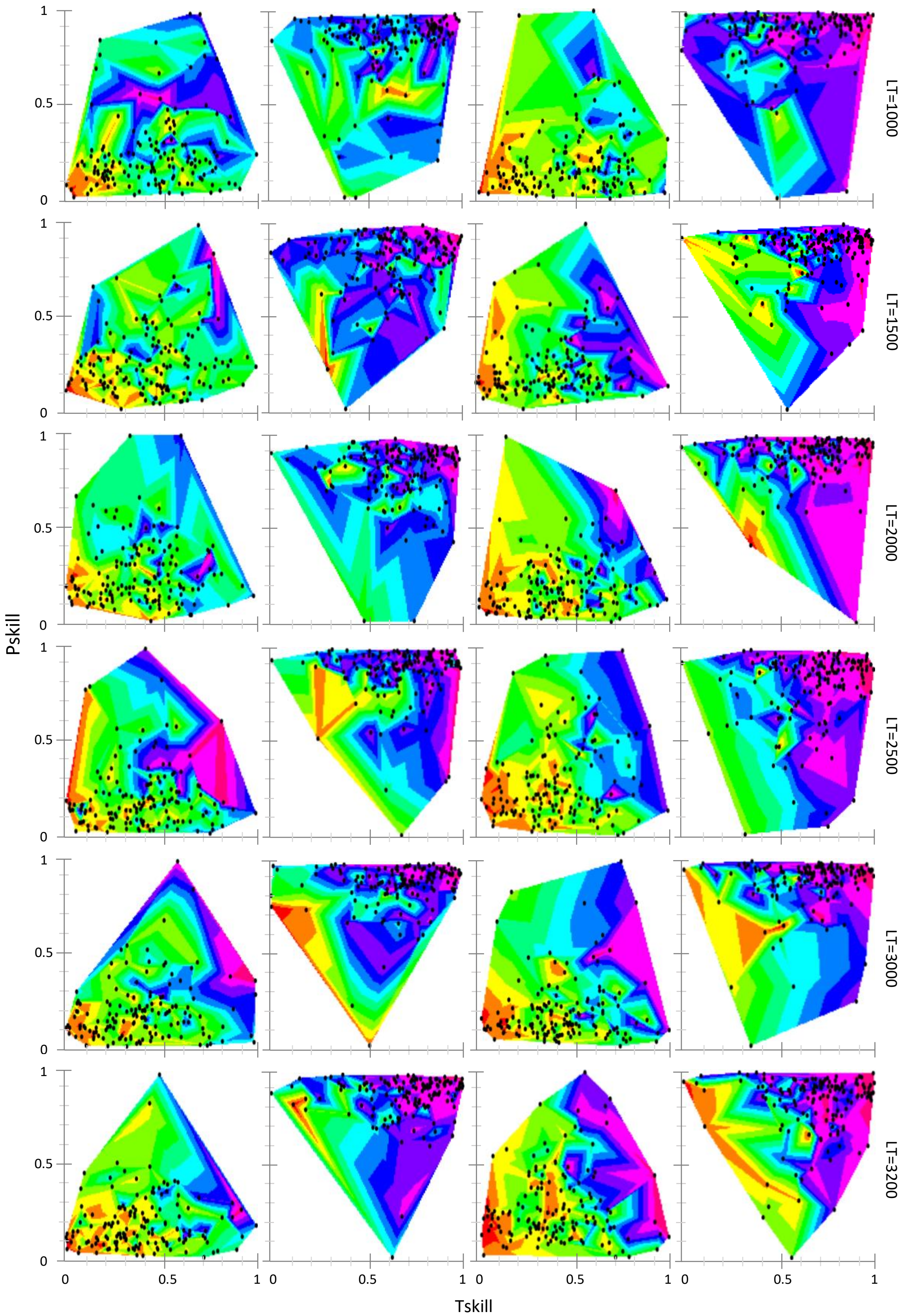
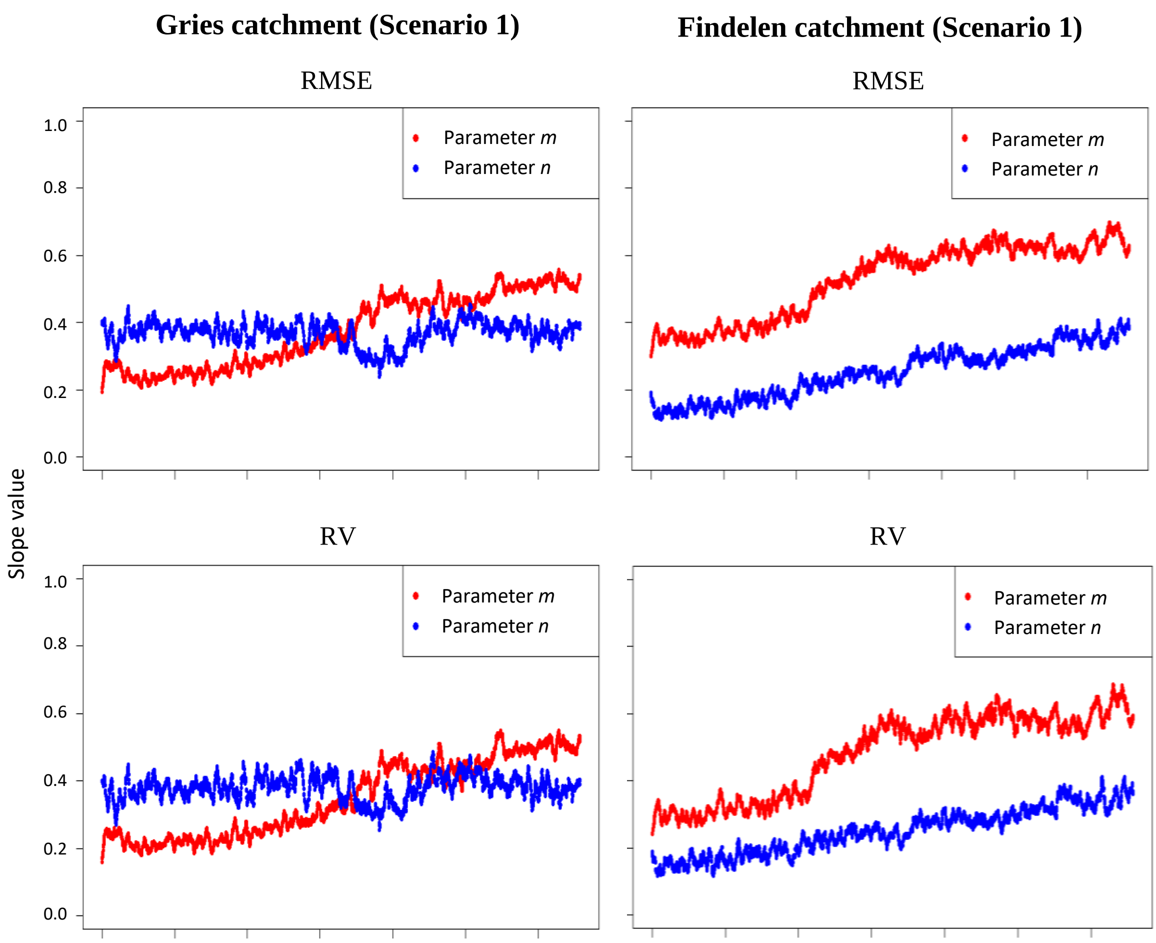


Figure 15: Relation between temperature, precipitation and runoff skill scores (RMSE and RV) for the two catchments and Scenario 1. The runoff skill scores have been interpolated by applying a linear interpolation with colors, while areas with no values are shown in white. The black dots represent the 150 different forecasts. Results are represented for individual lead times (LT) between 200 and 3200 days, and they have been produced with the HBV model.

For the scenario assuming the highest glacierization (Scenario 1), skill transfers quite similarly for both catchments (Figure 15), assigning a similar trend according to lead time. However, some differences can be detected: precipitation influence on accuracy transmission is generally higher for the Gries catchment compared to Findelen, where temperature is the predominant factor for the majority of the selected lead times. Another point to mention is that the assessment of daily lead times has been necessary because of the higher variability of daily skill scores, particularly for precipitation. Consequently, assessing trends related to skill transfer is easier to perform with the support of the equation exposed above (Equation 5). The first analysis and interpretation of skill transfer which has been performed for selected lead times (Figure 15) for Scenario 1 has been repeated for all scenarios assuming a variable glacierization (Scenarios 2 to 5), as shown on Appendix A.1.1 to A.1.4.

5.2. Skill transfer for the first glacier extent scenario

For the Scenario comprising the highest glacierization (Scenario 1), the influence of temperature and precipitation forecasts skills on runoff predictions has been analysed. It has been observed that the influence of temperatures is higher than the one of precipitation for the Findelen catchment, while for the Gries catchment, temperature effect is also relevant, but precipitation shows a slightly higher influence. Figure 16 shows the evolution of temperature and precipitation influence on skill transfer for all the three skill scores (RMSE, RV and CC) for both catchments.



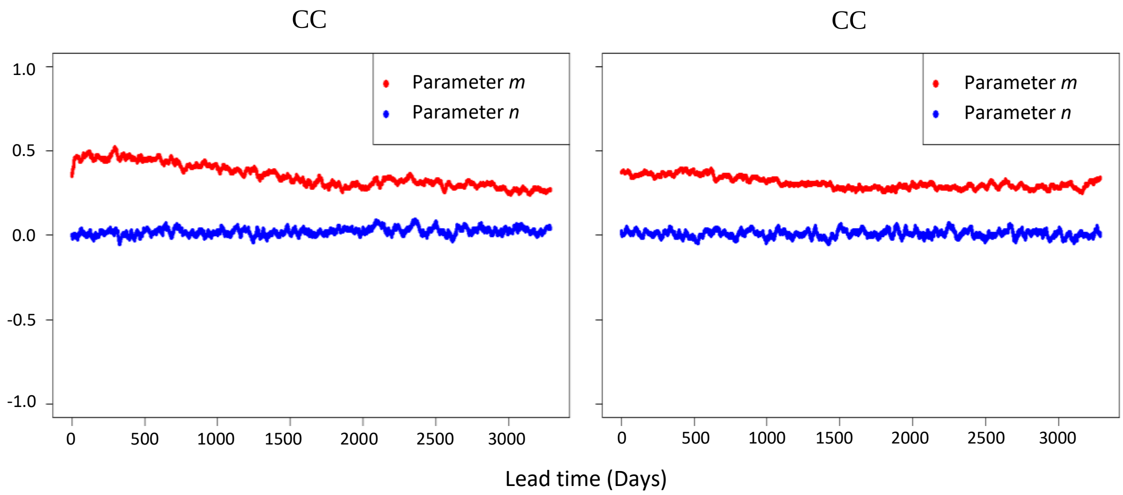


Figure 16: Parameters *m* and *n* for Scenario 1 and for both Gries and Findelen catchments. Gries catchment is shown on the left column, while the Findelen catchment is represented on the right column.

According to Figure 16, the relationship between *Tskill* and *Qskill* is stronger in the Findelen catchment compared to the Gries catchment, and this tendency is confirmed for all the three implemented skill scores. CC skill score shows a different representation compared to the other two metrics, mainly because of this different variability range (Section 3.4). The coefficients of determination r^2 and the variability of the parameters *m* and *n* have been detected for all lead times in order to obtain a statistically robust assessment of the relations between *Tskill*, *Pskill* and *Qskill*. Given that RMSE and RV show similar results, their most important parameters and statistical assessments are described together in this section, while CC is described separately.

For RMSE (RV), the coefficient of determination r^2 obtained from the application of Equation 5 ranged between 0.118 (0.086) and 0.567 (0.583) for the Gries catchment, and between 0.149 (0.081) and 0.625 (0.621) for the Findelen catchment. By considering all lead times for Scenario 1, the mean values which have been calculated for the *m* and *n* parameters related to the RMSE metric are *m* = 0.375 and *n* = 0.369 for the Gries catchment, and *m* = 0.526 and *n* = 0.253 for the Findelen catchment. For the RV skill score, values of *m* and *n* were of *m* = 0.348 and *n* = 0.379 for the Gries catchment, and of *m* = 0.481 and *n* = 0.250 for the Findelen catchment (all values of *m* and *n* for all Scenarios 1 to 5 are illustrated in Table 6, see Section 5.3).
Daily variability of skill scores has also been considered while assessing *Tskill* and *Pskill* influence on *Qskill* for Scenario 1. For RMSE (RV), parameter *m* ranged between *m* = 0.102 (0.074) and *m* = 0.694 (0.733) for the Gries catchment, and between *m* = 0.146 (0.095) and *m* = 0.915 (0.998) for the Findelen catchment. The parameter *n* ranged between *n* = 0.026 (0.002) and *n* = 0.859 (0.985) for the Gries catchment, and between *n* = -0.069 (-0.095) and *n* = 0.697 (0.824) for the Findelen catchment. Over individual lead times, *m* parameter varies between *m* = 0.129 (0.100) at lead time 1 (LT = 1) and *m* = 0.524 (0.522) at lead time 3284 (LT = 3284) for the Gries catchment and between *m* = 0.146 (0.095) at lead time 1 (LT = 1) and *m* = 0.663 (0.632) at lead time 3284 (LT = 3284) for the Findelen catchment. Parameter *n* varies between *n* = 0.261 (0.245) at lead time 1 (LT = 1) and *n* = 0.367 (0.350) at lead time 3284 (LT = 3284) for the Gries catchment, and between *n* = 0.271 (0.236) at lead time 1 (LT = 1) and *n* = 0.463 (0.417) at lead time 3284 (LT = 3284) for the Findelen catchment. It should also be noted that, for a given lead time, both skill scores RV and RMSE show similar results, and that temperatures follow a quite well-defined increasing trend, while precipitation does not show a clear tendency.

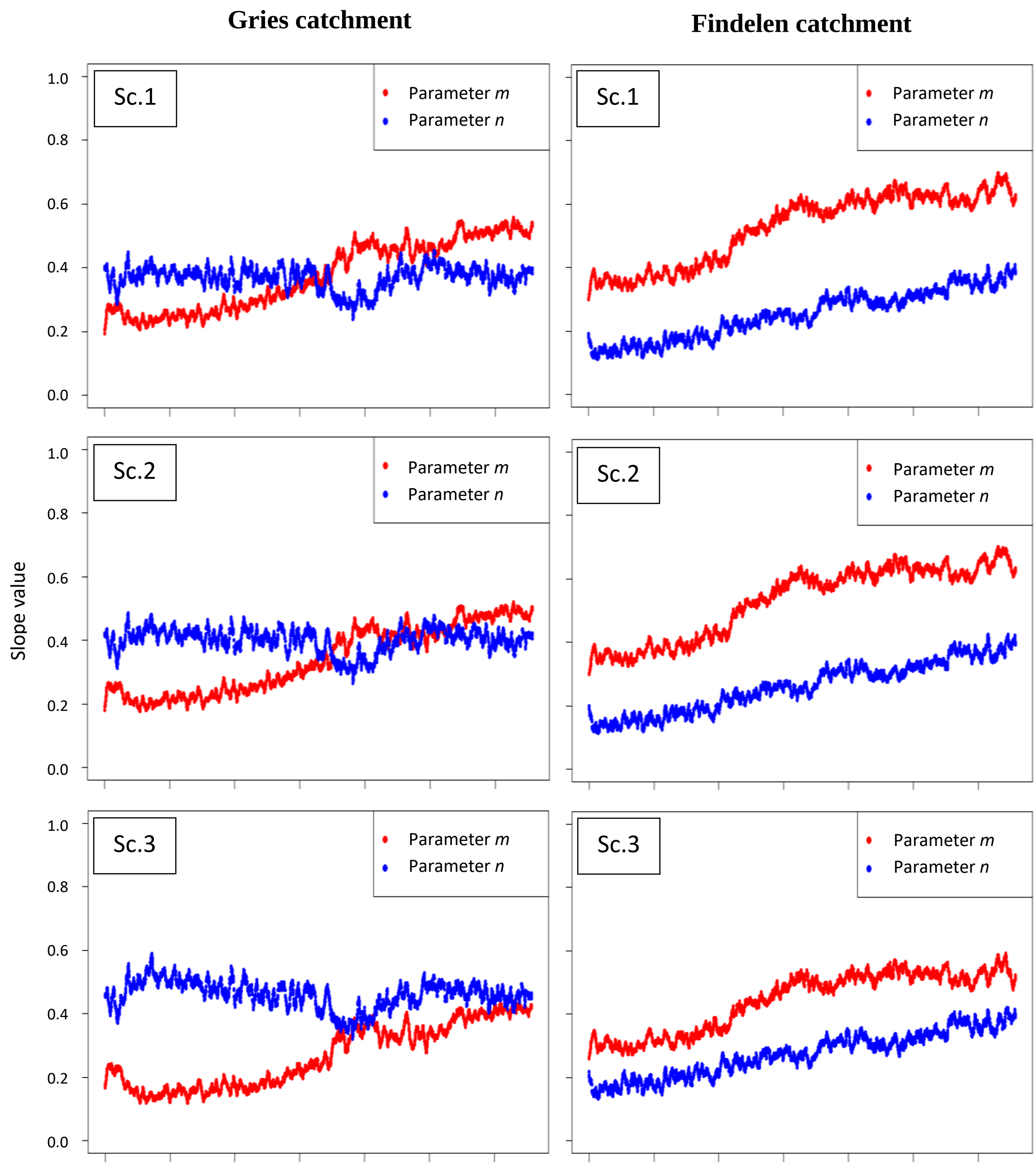
For the CC skill score, the coefficient of determination r^2 obtained with the application of Equation 5 has also been determined. It ranged between 0.046 and 0.433 for the Gries catchment, and between 0.046 and 0.321 for the Findelen catchment. By considering all lead times for Scenario 1, the mean values which have been calculated for the *m* and *n* slope parameters related to the CC statistical metrics are m = 0.354 and n = 0.023 for the Gries catchment, and m = 0.311 and n = 0.009 for the Findelen catchment. It should be mentioned that CC skill score mainly relates to correlation of variables: as it will be explained next (Chapter 6), precipitation tendency according to lead time does generally not follow a specific tendency such as temperatures.
Daily variability of skill scores has also been considered while assessing *Tskill* and *Pskill* influence on *Qskill* for Scenario 1. For CC, m ranged between m = 0.158 and m = 0.644 for the Gries catchment, and between m = 0.165 and m = 0.518 for the Findelen catchment. The parameter n ranged between n = -0.313 and n = 0.370 for the Gries catchment, and between n = -0.367 and n = 0.380 for the Findelen catchment. Over individual lead times, m parameter varies between m = 0.175 at lead time 1 (LT = 1) and m = 0.310 at lead time 3284 (LT = 3284) for the Gries catchment and between m = 0.199 at lead time 1 (LT = 1) and m = 0.358 at lead time 3284 (LT = 3284) for the Findelen catchment. Parameter n varies between n = -0.033 at lead time 1 (LT = 1) and n = 0.106 at lead time 3284 (LT = 3284) for the Gries catchment, and between n = -0.001 at lead time 1 (LT = 1) and n = 0.049 at lead time 3284 (LT = 3284) for the Findelen catchment. Table 5 assesses the variability of m and n parameters by every 200 lead times, for all skill scores.

Table 5: Variability of *m* and *n* parameters (related to *Tskill* and *Pskill*, respectively) for both catchments and for all the three implemented statistical metrics. The predominant parameter related to the effect on *Qskill* is marked in orange for each lead time, while the parameter which shows the lowest influence on runoff skill is marked in light blue.

Leadtime	Gries catchment						Findelen catchment					
	RMSE		RV		CC		RMSE		RV		CC	
	m	*n*	*m*	*n*	*m*	*n*	*m*	*n*	*m*	*n*	*m*	*n*
1	0.129	0.261	0.100	0.245	0.175	-0.03	0.317	0.237	0.264	0.237	0.199	0.000
200	0.252	0.282	0.226	0.255	0.456	0.10	0.342	0.258	0.297	0.274	0.323	0.023
400	0.194	0.309	0.148	0.270	0.413	0.01	0.417	0.147	0.375	0.172	0.421	0.016
600	0.289	0.362	0.256	0.382	0.513	-0.01	0.360	0.199	0.307	0.214	0.380	0.097
800	0.287	0.469	0.251	0.526	0.484	0.044	0.411	0.166	0.352	0.192	0.382	-0.05
1000	0.325	0.288	0.310	0.309	0.381	0.048	0.386	0.204	0.325	0.194	0.300	0.107
1200	0.310	0.265	0.271	0.251	0.353	0.064	0.533	0.278	0.480	0.331	0.332	-0.06
1400	0.396	0.229	0.357	0.231	0.440	0.199	0.489	0.253	0.455	0.244	0.265	0.000
1600	0.330	0.455	0.315	0.509	0.272	0.115	0.552	0.249	0.507	0.301	0.279	0.027
1800	0.485	0.365	0.470	0.393	0.259	0.033	0.451	0.288	0.378	0.246	0.247	0.000
2000	0.444	0.379	0.434	0.375	0.218	0.241	0.560	0.402	0.525	0.433	0.279	-0.10
2200	0.431	0.156	0.406	0.167	0.342	0.037	0.633	0.298	0.615	0.326	0.300	0.010
2400	0.468	0.349	0.437	0.352	0.278	-0.02	0.761	0.257	0.735	0.249	0.332	0.079
2600	0.415	0.345	0.389	0.338	0.297	-0.17	0.484	0.439	0.394	0.409	0.269	0.005
2800	0.455	0.323	0.422	0.313	0.332	0.038	0.617	0.282	0.551	0.298	0.320	-0.19
3000	0.516	0.434	0.500	0.515	0.252	-0.05	0.616	0.499	0.584	0.501	0.258	0.017
3200	0.573	0.285	0.572	0.265	0.269	-0.15	0.722	0.396	0.712	0.449	0.345	-0.05
3284	0.524	0.367	0.522	0.350	0.310	0.106	0.663	0.463	0.632	0.417	0.358	0.049

5.3. Skill transfer with variable glacierization

Glaciers in alpine catchments are currently retreating since the end of the 19th century, and they are expected to melt completely in the coming decades, particularly until the end of the 21st century (Appenzeller *et al*., 2011 ; Bauder *et al*., 2017 ; Pachauri *et al*., 2014). With decreasing ice area and properties (i.e. volume and mass balance), the relation between *Tskill*, *Pskill* and *Qskill* (Equation 5) is expected to change. Figure 17 shows the slope parameters *m* and *n* over all lead times for both Gries and Findelen catchments and for all Scenarios 1 to 5 (from the most glacierized one to the one which considers a completely ice-free catchment), while Figure 18 illustrates the same aspect but with all scenarios grouped together. Results are shown for RMSE, while RV and CC can be found in the Appendix A.3.1 and A.3.2.



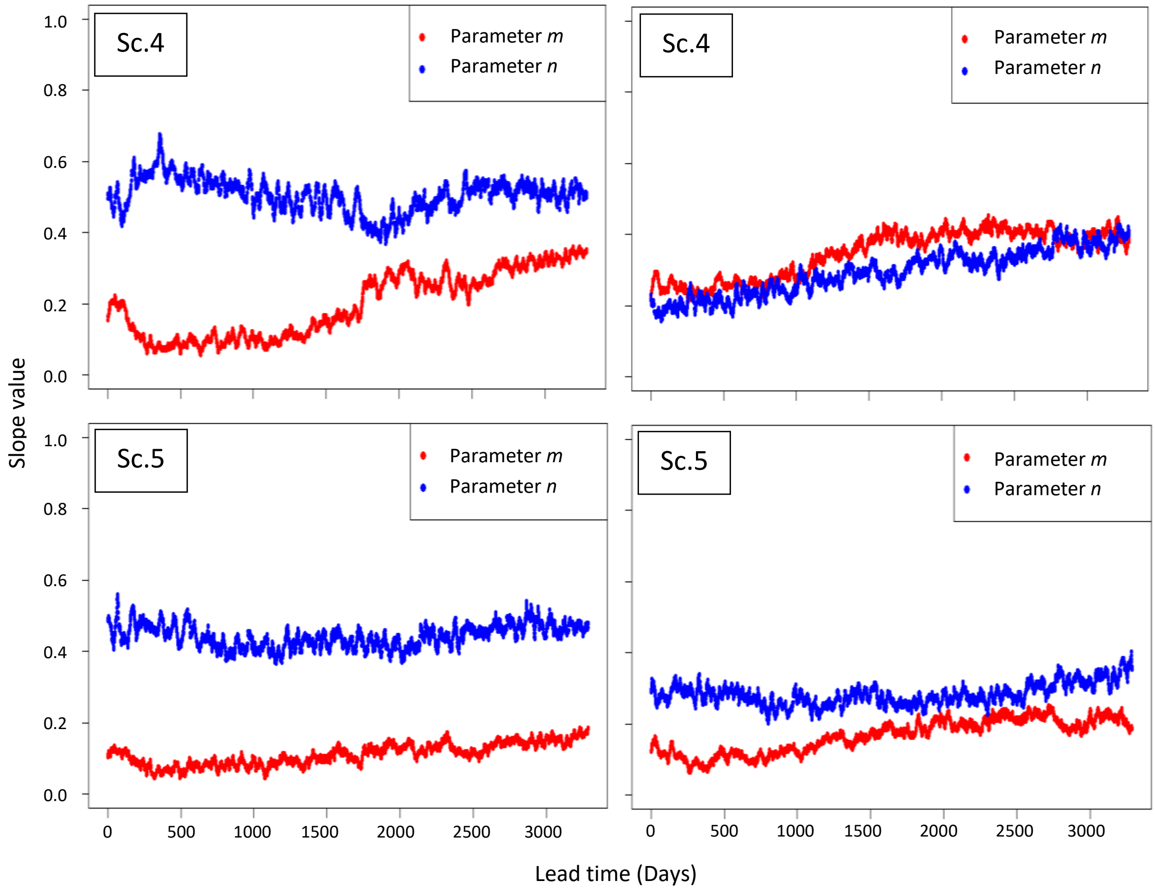
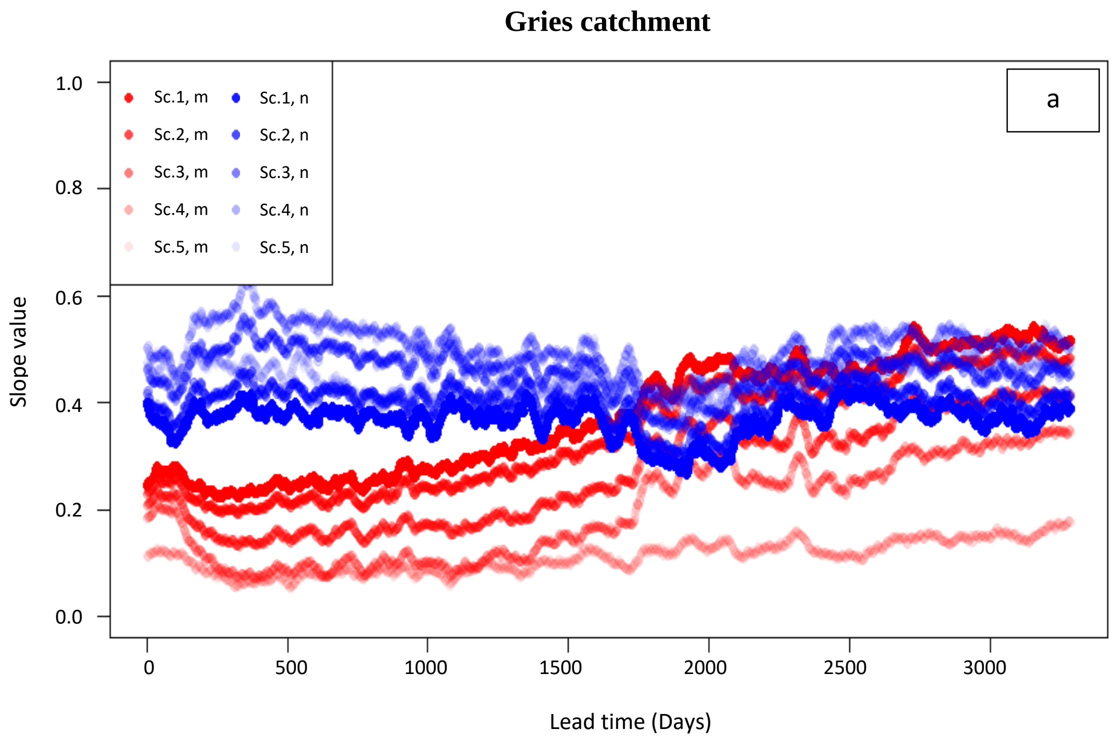


Figure 17: Parameters *m* and *n* for Scenarios 1 to 5 for both catchments (RMSE skill score). The Gries catchment is shown on the left column, while the Findelen catchment is represented on the right column.



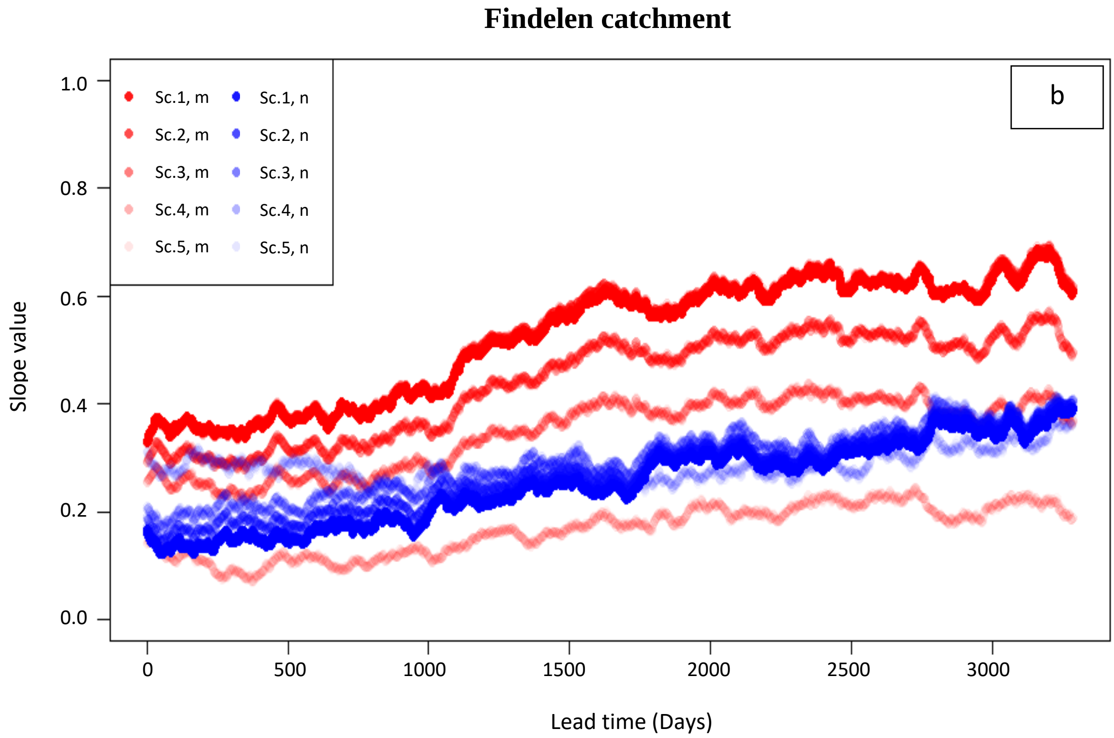


Figure 18: Parameters *m* and *n* (cf. Equation 5) for (a) Gries catchment and (b) Findelen catchment. The color saturation is related to the degree of glacierization which corresponds to each Scenario.

For both catchments, the value of parameter *m* tends to decrease for a decreasing glacierization, while the value of parameter *n* tends to slightly increase in case of a shrinking glacier, and this relation is valid for both catchments. This means that the impact of *Tskill* on *Qskill* decreases in case of a more reduced glacier extent, while *Pskill* increases its influence. On the one hand, for a completely ice-free catchment, *Pskill* shows the highest influence and *Tskill* the lowest. On the other hand, for the scenario assuming the highest glacierization (Scenario 1), *Pskill* is related to the lowest influence on *Qskill*, while the contrary is true for *Pskill*. Table 6 quantifies skill transfer by representing mean values of the parameters *m* and *n* for both catchments and for all skill scores. Table 7 defines the variability of *m* and *n* slope parameters every 200 lead times.

Table 6: Parameters *m* and *n* (cf. Equation 5) for both Gries and Findelen catchments. The mean values of the slope parameters are represented for all skill scores.

	Gries catchment						**Findelen catchment**					
Scenario	**RMSE**	**RMSE**	**RV**	**RV**	**CC**	**CC**	**RMSE**	**RMSE**	**RV**	**RV**	**CC**	**CC**
	m	*n*	*m*	*n*	*m*	*n*	*m*	*n*	*m*	*n*	*m*	*n*
1	0.38	0.37	0.35	0.38	0.35	0.02	0.53	0.25	0.48	0.25	0.31	0.01
2	0.34	0.40	0.31	0.41	0.34	0.02	0.53	0.26	0.49	0.26	0.30	0.01
3	0.27	0.46	0.24	0.48	0.32	0.03	0.44	0.27	0.38	0.26	0.30	0.01
4	0.20	0.51	0.17	0.52	0.28	0.03	0.35	0.30	0.28	0.28	0.31	0.01
5	0.12	0.45	0.09	0.41	0.33	0.02	0.17	0.28	0.12	0.24	0.33	0.00

Table 7: Variability of *m* and *n* parameters (related to *Tskill* and *Pskill*, respectively) for (a) Gries catchment and (b) Findelen catchment, for the RMSE skill score. The predominant slope parameter on *Qskill* is marked in orange for each lead time, while the slope parameter which shows the lowest influence on runoff skill is marked in light blue.

a)

Leadtime	Gries catchment									
	Scenario 1		Scenario 2		Scenario 3		Scenario 4		Scenario 5	
	m	*n*	*m*	*n*	*m*	*n*	*m*	*n*	*m*	*n*
1	0.129	0.261	0.119	0.268	0.113	0.289	0.111	0.309	0.094	0.381
200	0.252	0.282	0.232	0.328	0.190	0.430	0.138	0.493	0.115	0.573
400	0.194	0.309	0.159	0.346	0.089	0.446	0.033	0.566	0.088	0.442
600	0.289	0.362	0.253	0.414	0.173	0.547	0.081	0.541	0.011	0.619
800	0.287	0.469	0.254	0.511	0.193	0.603	0.114	0.616	0.039	0.440
1000	0.325	0.288	0.291	0.336	0.206	0.409	0.120	0.436	0.229	0.511
1200	0.310	0.265	0.278	0.290	0.222	0.358	0.169	0.443	0.199	0.369
1400	0.396	0.229	0.347	0.261	0.253	0.324	0.175	0.385	0.026	0.424
1600	0.330	0.455	0.282	0.470	0.202	0.500	0.138	0.514	0.063	0.475
1800	0.485	0.365	0.456	0.397	0.401	0.463	0.329	0.518	0.080	0.507
2000	0.444	0.379	0.419	0.407	0.373	0.480	0.292	0.527	0.106	0.534
2200	0.431	0.156	0.384	0.171	0.289	0.195	0.213	0.226	0.082	0.409
2400	0.468	0.349	0.422	0.372	0.340	0.430	0.255	0.491	0.112	0.407
2600	0.415	0.345	0.391	0.376	0.337	0.439	0.253	0.464	0.079	0.264
2800	0.455	0.323	0.434	0.360	0.394	0.444	0.282	0.445	0.105	0.398
3000	0.516	0.434	0.485	0.475	0.406	0.549	0.316	0.633	0.052	0.552
3200	0.573	0.285	0.543	0.300	0.470	0.331	0.405	0.370	0.201	0.324
3284	0.524	0.367	0.498	0.395	0.441	0.444	0.384	0.521	0.250	0.651

b)

Leadtime	Findelen catchment									
	Scenario 1		Scenario 2		Scenario 3		Scenario 4		Scenario 5	
	m	*n*	*m*	*n*	*m*	*n*	*m*	*n*	*m*	*n*
1	0.317	0.237	0.145	0.270	0.108	0.291	0.093	0.306	0.027	0.277
200	0.342	0.258	0.334	0.251	0.280	0.301	0.208	0.348	0.135	0.280
400	0.417	0.147	0.407	0.151	0.377	0.177	0.311	0.194	0.097	0.267
600	0.360	0.199	0.375	0.194	0.293	0.226	0.232	0.254	0.085	0.270
800	0.411	0.166	0.423	0.179	0.358	0.223	0.311	0.312	0.220	0.111
1000	0.386	0.204	0.390	0.218	0.311	0.200	0.243	0.198	0.081	0.176
1200	0.533	0.278	0.539	0.294	0.463	0.293	0.356	0.281	0.123	0.265
1400	0.489	0.253	0.489	0.261	0.404	0.264	0.305	0.276	0.100	0.301
1600	0.552	0.249	0.564	0.252	0.468	0.269	0.354	0.271	0.137	0.286
1800	0.451	0.288	0.472	0.293	0.350	0.305	0.243	0.324	0.139	0.189
2000	0.560	0.402	0.579	0.413	0.476	0.405	0.373	0.513	0.147	0.378
2200	0.633	0.298	0.635	0.319	0.539	0.282	0.457	0.265	0.136	0.274
2400	0.761	0.257	0.759	0.264	0.668	0.280	0.583	0.328	0.427	0.186
2600	0.484	0.439	0.508	0.469	0.366	0.436	0.254	0.439	0.279	0.538
2800	0.617	0.282	0.623	0.300	0.522	0.304	0.413	0.338	0.168	0.268
3000	0.616	0.499	0.625	0.509	0.514	0.529	0.370	0.557	0.181	0.376
3200	0.722	0.396	0.695	0.403	0.636	0.413	0.545	0.437	0.102	0.230
3284	0.663	0.463	0.660	0.472	0.572	0.493	0.472	0.556	0.241	0.527

Table 6 shows that *m* slope parameter decreases with decreasing glacierization while the contrary is true for the *n* parameter. A detailed analysis of this process has been assessed also for selected lead times, by computing the values of *m* and *n* parameter every 200 lead times (Table 7), for both catchments (the calculations for RV and CC skill scores are represented in Appendix A.4.1 and A.4.2). A decreasing glacierization has detectable consequences also on the hydrological regime and on the mean yearly runoff of both catchments. Generally, a progressively decreased contribution of glacier melt runoff can be identified by forcing the hydrological model HBV, as illustrated by Figure 19 (results are shown for the reference files and for the second Monte-Carlo calibration, cf. Sections 3.1 and 3.3).

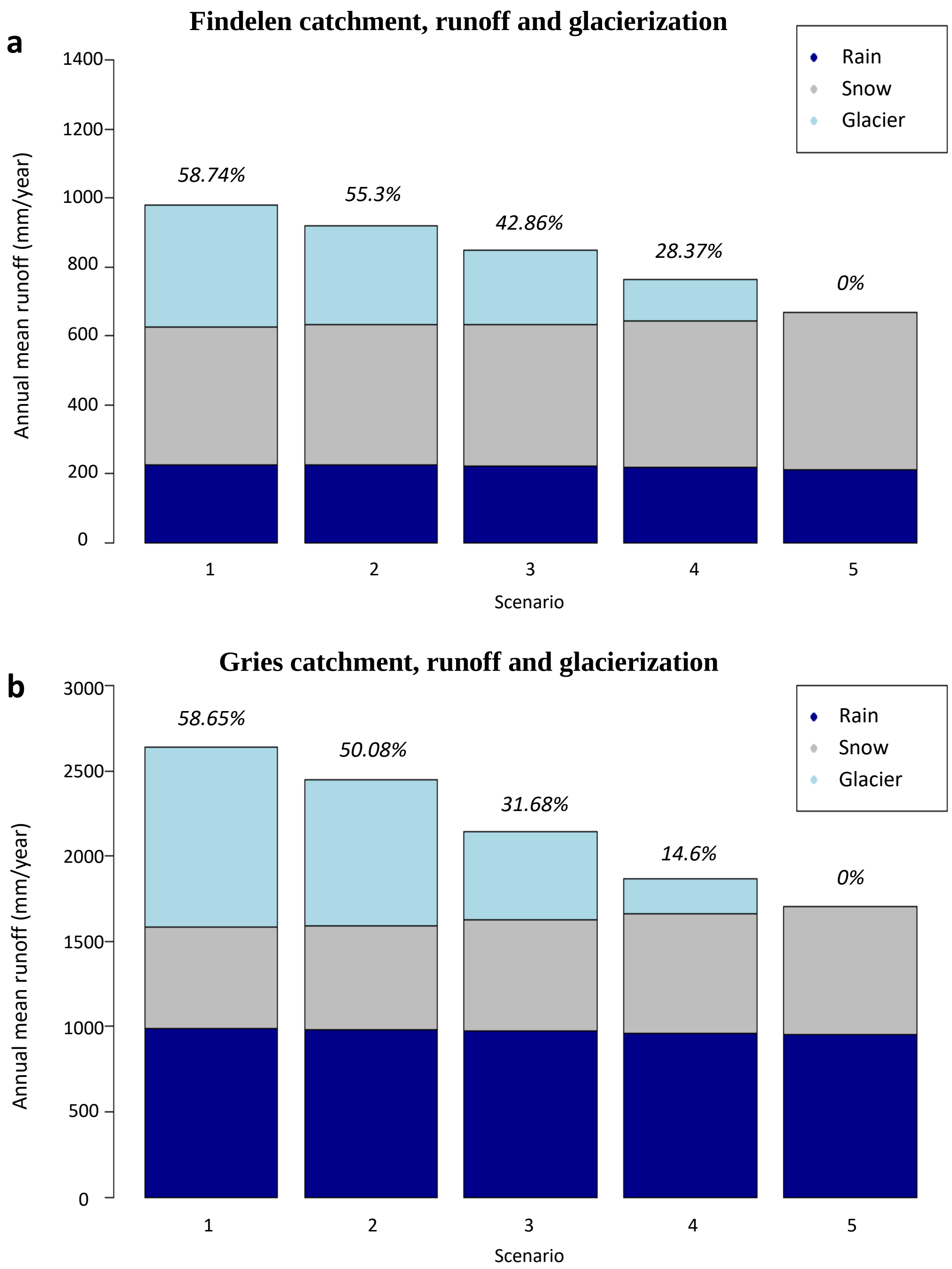


Figure 19: Representation of the three main components of simulated runoff: rain, snow and glacier melt. Mean daily runoff is indicated for both Findelen (a) and Gries (b) catchments. The percentage of glacierization is shown on the top of each barplot in both cases.

Figure 20 presents the difference between the skill in the meteorological forecasts (average values calculated for temperature and precipitation skill, *Tskill* and *Pskill* respectively) and the skill of the resulting runoff predictions *Qskill* for all the considered daily lead times. This difference doesn't show relevant modifications over the lead times, but the skill of both temperature and precipitation forecasts has been detected as being decreasing with increasing lead time. Figure 20 indicates that the interrelations between the three analysed variables are independent from the lead time. This means that the combination of a temperature and a precipitation forecast both characterized by a high level of accuracy results in a good runoff forecast, whilst the combination of a poor temperature and a poor precipitation forecast results in a low accuracy runoff forecast.

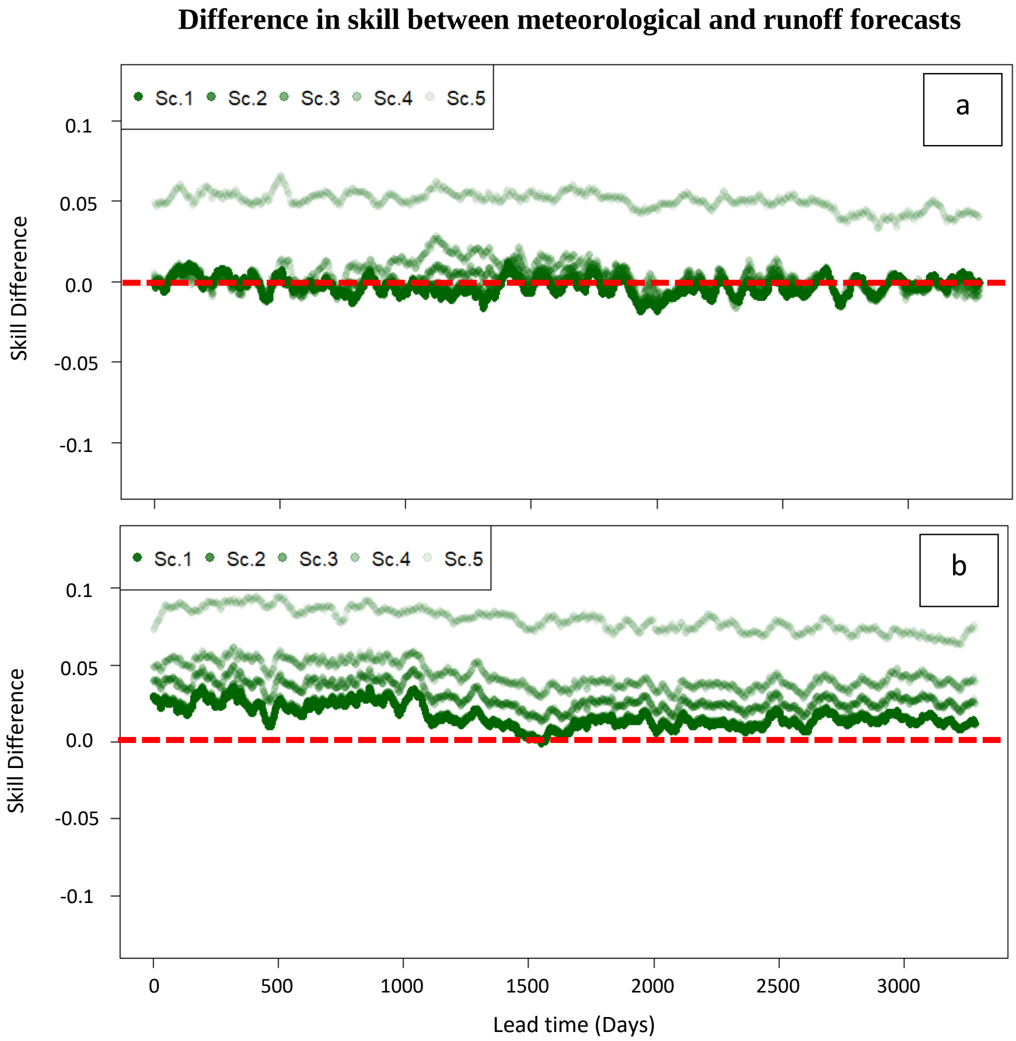


Figure 20: Difference in RMSE skill between meteorological and runoff forecasts over all lead times. Each line refers to a Scenario (each scenario is defined by a different degree of color saturation) for both Gries (a) and Findelen (b) catchments. The formula $\frac{(Tskill+Pskill)}{2} - Qskill$ has been applied to determine skill difference.

The next section (5.4) exposes the most important results related to a hydrological analysis which has been performed by testing different parameters and routines of the hydrological model HBV, and by applying a sensitivity assessment on its parameters and efficiency criteria. The main focus of most of this chapter (Sections 5.1-5.3) is related to skill analysis and accuracy transmission from weather to runoff forecasts, but the mentioned hydrological analysis has proved to be a valid complement in order to assess the performance of the model and its core functionalities.

5.4. Sensitivity analysis on the hydrological model HBV

Figure 21 illustrates the sensitivity analysis for the Gries catchment (see Appendix A.8 for results about the sensitivity analysis of the Findelen catchment). This analysis has been performed on both calibrations (Section 3.3), but here only the results of the realistic calibrations are shown.

Sensitivity analysis on the parameters and routines of the HBV hydrological model

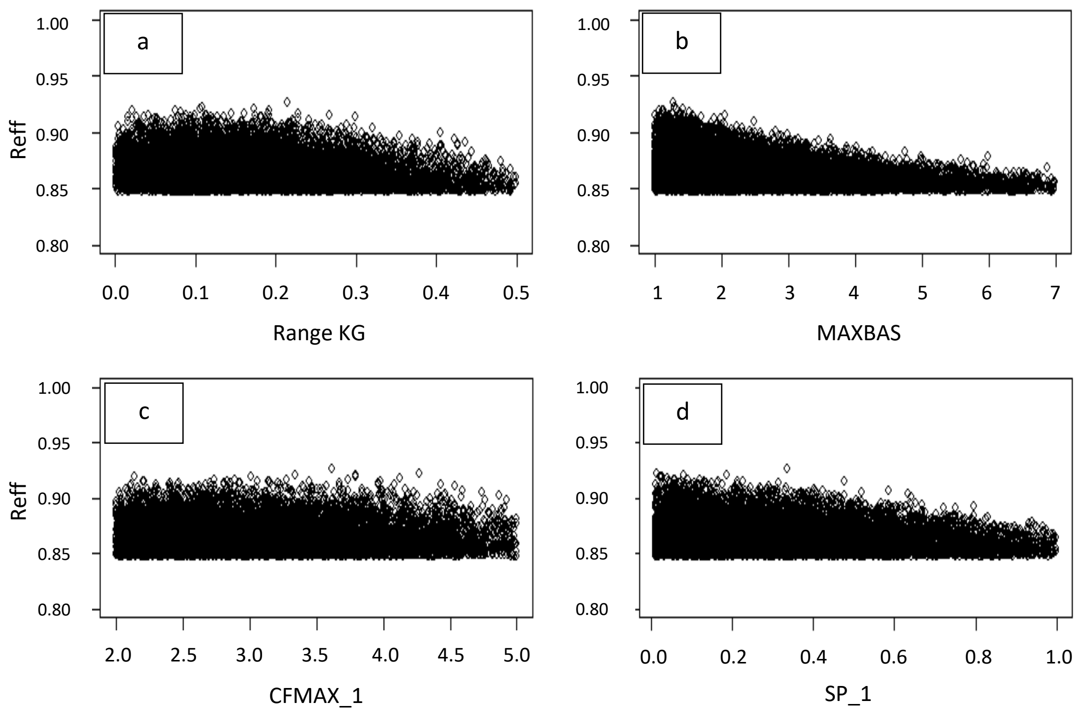


Figure 21: Parameters of the HBV model which show the highest contribution to model efficiency according to the outcomes of the sensitivity analysis which has been performed on the Monte-Carlo automated calibration procedure. On the y-axes, the value of the Nash-Sutcliffe coefficient („*Reff*“) is represented.

According to Figure 21, different parameter ranges which allow to obtain a high model efficiency have been identified in each single case, and some most sensitive parameters have been identified. First, the *dKG* parameter (Figure 21a) of the glacier routine (Section 3.3) has proven to influence model efficiency once it reaches values higher than 0.2-0.3 (the variability range of this parameter is between 0 and 0.5). Second, the *MAXBAS* parameter (Figure 21b) of the routing routine (i.e. the last routine preceding the generation of the simulated runoff). Third, the degree-day factor parameter of the snow routine *CFMAX* (Figure 21c) has been assessed to influence model efficiency for values higher than 3.8-4.2. Another parameter which has proven to be particularly sensitive according to the Nash-Sutcliffe efficiency is the *SP* parameter (Figure 21d) of the glacier routine (i.e. the seasonal degree-day factor). Generally, the parameters of the soil moisture routine do not influence a lot the simulated runoff because groundwater is not relevant in mountainous highly-glacierized catchments. In the case of the two analysed catchments, the routines which seem to be hydrologically more sensitive are the snow and glacier routines, because a modification of the value of the parameters of these two routines tends to have a relevant influence on model efficiency. Table 8 shows how model efficiency evolves according to the different scenarios for both catchments, by considering both types of glacier routine of the HBV model.

Table 8: Variability of the model efficiency and simulated runoff for all scenarios and for both Findelen and Gries catchments. Results are shown by both assuming a static or a dynamic glacier area, for the second Monte-Carlo calibration, which is the one based on more „realistic“ parameter ranges used for this hydrological analysis. „*Reff*“ indicates the value of the Nash-Sutcliffe criterion, while „*Qsim*“ is related to the mean yearly runoff (in mm/year).

Scenario	Findelen, static glacier routine		Findelen, dynamic glacier routine		Gries, static glacier routine		Gries, dynamic glacier routine	
	Reff	*Qsim*	*Reff*	*Qsim*	*Reff*	*Qsim*	*Reff*	*Qsim*
1	0.7632	915.71	0.8053	978.79	0.8429	2648.21	0.8417	2640.06
2	0.7543	854.36	0.7986	920.35	0.8320	2456.02	0.8313	2448.86
3	0.7099	754.84	0.7956	849.18	0.8199	2145.42	0.8223	2142.22
4	0.6404	636.72	0.7780	765.02	0.7941	1867.15	0.8003	1867.32
5	0.4007	472.67	0.5879	666.13	-0.3438	1691.88	-0.4761	1706.86

For both catchments, the model efficiency seems to be quite stationary for the first four scenarios, while it decreases rapidly for the last scenario (particularly for the Gries catchment). This could be due to the absence of a glacier in the last scenario, which increases model uncertainties while performing simulations. Another aspect which has been considered for this hydrological analysis is the correlation between the efficiency criteria of the model. Figure 22 illustrates this aspect with "dotty plots", in this case an example is shown for Gries catchment (more examples on A.9).

Comparison between different efficiency criteria of the HBV model

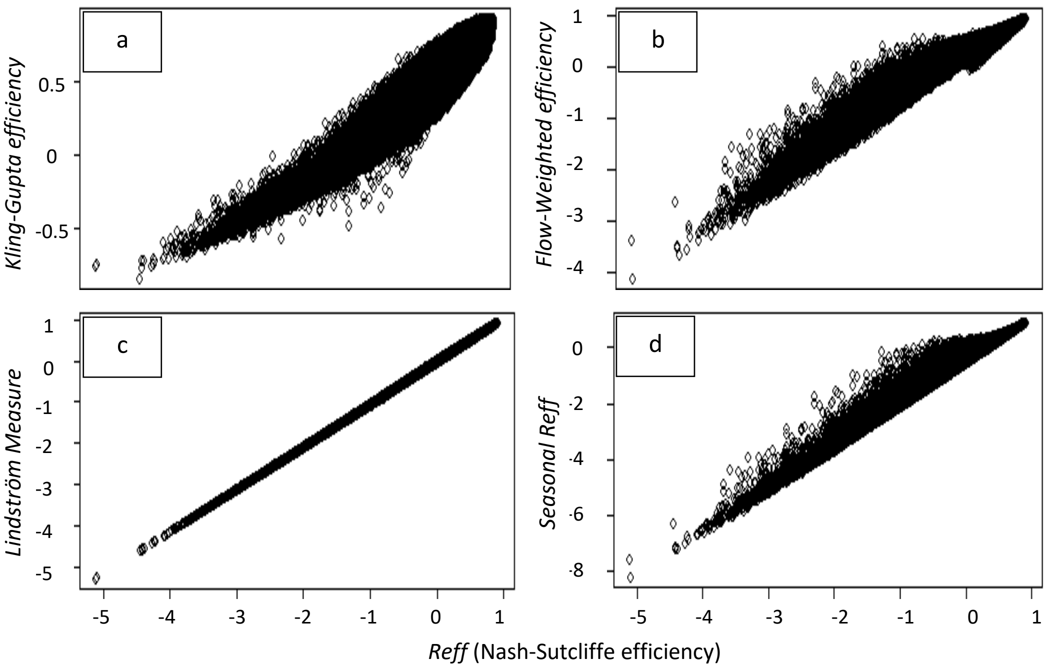


Figure 22: Correlation between some efficiency criteria of the HBV model. The correlation is done between a certain criteria and the one which has been used for the hydrological analysis of this chapter, the Nash-Sutcliffe metric. The x-axis always indicates the Nash-Sutcliffe efficiency criteria. In the first case (Figure 22a), the y-axis indicates the Kling-Gupta efficiency metric, then the Flow Weighted Efficiency is shown (Figure 22b). Next, the Lindström measure is illustrated (Figure 22c), and last the seasonal Nash-Sutcliffe metric is represented (Figure 22d). All parameters illustrated in the x- and y-axes are coefficients without units.

Figure 22 shows the most correlated efficiency criteria to the Nash-Sutcliffe one, which are the *Kling-Gupta*, the *Flow Weighted Efficiency*, the *Lindström Measure* and the *Seasonal Nash-Sutcliffe* criterion of model performance. Consequently, a comparable hydrological analysis could potentially have been obtained also by implementing the analysis for the other well-correlated efficiency criteria. Figure 23 and Table 9 quantify another aspect of the hydrological analysis which has been considered, i.e., the difference on performing the same simulations by varying the HBV model settings. On Figure 23, the example of Scenario 3 for Findelen catchment is shown. Table 9 represents a comparison of the mean yearly runoff for all model settings.

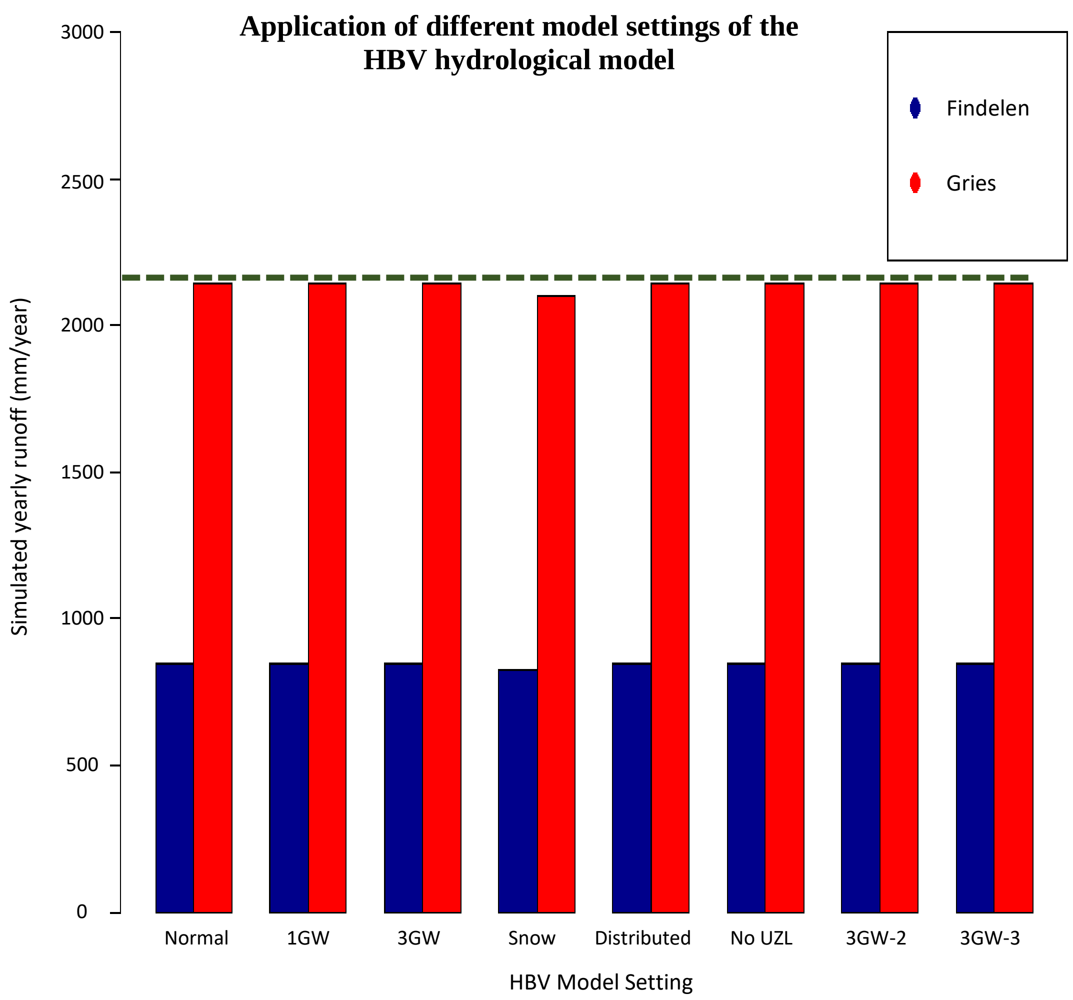


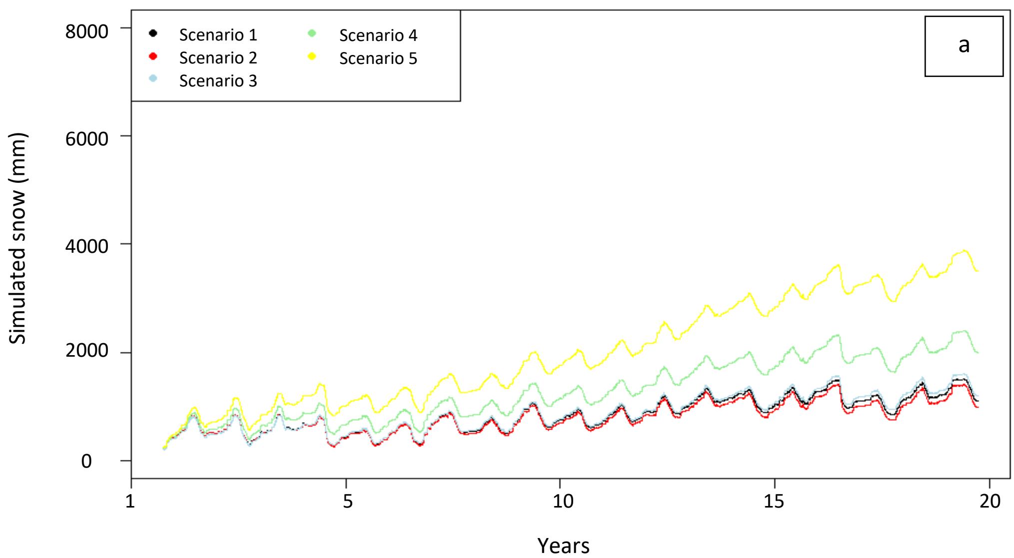
Figure 23: Variability of simulated daily runoff (for the dynamic glacier routine) by varying model settings. "Normal" is related to the simulations which have been regularly performed to determine skill transfer, "*1GW*" and "*3GW*" are the model setting which consider only one or three groundwater boxes respectively. The "*Snow*" setting is related to a modified snow routine, "Distributed" indicates a modification in the distributed core modality of the model, "*No UZL*" assumes the absence of the parameters "*UZL*", "*K0*" and "*K1*" (see Section 3.3), while "*3GW-2*" and "*3GW-3*" are related to two more variants of a model setting with three groundwater boxes. On the one hand, the "*3GW-2*" setting is related to the introduction of three groundwater boxes in the model by using another groundwater box called „*STZ*" (storage in top soil zone). On the other hand, the "*3GW-3*" setting is regarded by a similar procedure of the distributed part of the model, but in this case an upper soil zone groundwater box is also applied. The green dashed lines above the bars of the plots allows for a more efficient visual comparison.

Table 9: Variability of simulated runoff of the HBV model by assuming different model settings. Results are represented for Scenario 3 and for both Gries and Findelen catchments.

Model Setting	*Gries*	*Findelen*
Basic Model Setting	2143.4520	849.6725
One Groundwater Box	2143.6840	850.3170
Three Groundwater Boxes	2143.4510	849.6740
Only-Snow Routine	2099.5970	825.3707
Distributed Model Application	2143.4600	850.2713
Basic Modality but without UZL	2143.4490	849.6739
Three Groundwater Boxes, 2nd setting	2143.4500	849.6868
Three Groundwater Boxes, 3rd setting	2143.4550	850.2665

Generally, there is not a high variability of model efficiency and simulated runoff if the model settings are changed. The only statistically more significative difference can be detected by introducing an *only-snow-routine* setting and by forcing the model with this modality. In this case, a slightly lower runoff has been simulated for both catchments: 825 mm/year mean yearly runoff instead of 850 mm/year mean yearly runoff which has been simulated with the dynamic glacier routine for the Findelen catchment, and 2100 mm/year mean yearly runoff instead of 2143 mm/year mean yearly runoff for the Gries catchment. Other two simulations have been performed by assuming no lake presence on the Gries catchment, and by varying the water equivalent of the two glaciers. As it will be explained in the next chapter (Chapter 6), no quantifiable change has been found for a variable glacier water equivalent, whilst a lake absence has as a consequence a slightly lower runoff amount, because lakes are an important storage reservoir in hydrological catchments, so it could have an influence on the total runoff of a catchment if it is neglected.
Snow redistribution has also been considered by comparing simulations performed by applying or not this input file (Section 3.3). In general, there have not been relevant differences neither in model efficiency nor in skill transfer, but unrealistic situations called „snow towers“ are a consequence of not introducing snow redistribution to the performed simulations, as it is demonstrated by Figure 24. However, it may be worthy to remind that snow redistribution has always been applied while performing simulations with the dynamic HBV glacier routine.

Simulation performed with the application of snow redistribution



Simulation performed without the application of snow redistribution

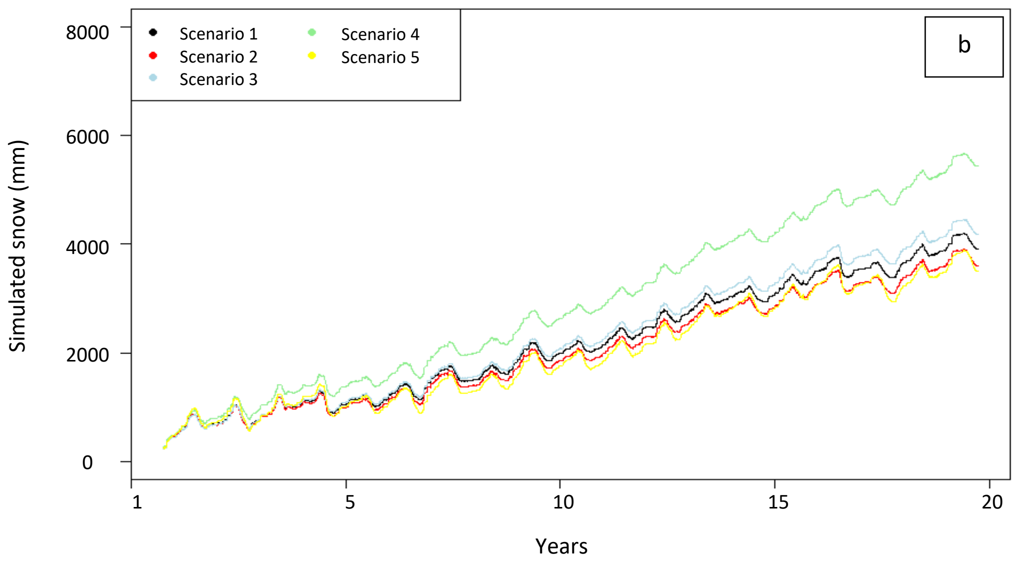


Figure 24: Difference between a simulation of the snow amount which has been performed by applying snow redistribution (Figure 24a), and one which has been performed without applying it (Figure 24b). The x-axis shows years related to the time-series of 19 years which has been applied for this experiment (Section 3.1), while the y-axis illustrates the simulated amount of snow (in mm).

Figure 24 allows to assess the important role of snow redistribution for the HBV model. The difference between applying or not this input file is clearly visible for all scenarios, and particularly for Scenario 5. In this case, as the glacier will have melted completely, precipitation (either in liquid and solid form) will be the main driver of runoff, and so their "hydrological role" will be more relevant compared to the first scenarios where the glacier is still present.

The next chapter is related to the discussion of the main outcomes which have been found in this experiment. The focus will be put particularly on skill transfer, but also the results of the hydrological and sensitivity analyses will be discussed and commented.

6. Discussions and interpretations

6.1. Discussion about skill analysis and skill transfer

This chapter aims at interpreting and discussing the main findings from the analysis presented in Chapter 5 which has been generated from the simulations with the HBV model. It is structured similarly as the previous chapter in order to allow a better readability and to easily interpreting the main thesis results. First, a general discussion about skill analysis and skill transfer is given (Section 6.1) for all scenarios (from Scenario 1 which considers the highest amount of glacierization to Scenario 5 which considers a completely ice-free catchment). After that, the results of the hydrological analysis are discussed in Section 6.2, particularly by focusing on the sensitivity analysis which has been performed on the parameters and routines of the model, and also on the effects of introducing variable model settings to force the hydrological model. Then, the whole project will be summarized in the conclusions chapter (Chapter 7), by proposing some open questions and ameliorations for future experiments.

Skill transfer and glacierization amount

Skill score analysis and determination of skill transfer have been performed for three skill scores (RMSE, RV and CC) and for both Gries and Findelen glacierized catchments. Generally, temperature influence on skill transfer has been found to be higher for the first two scenarios (Scenario 1 and 2) compared to the others (Scenarios 3 to 5), for both catchments. This suggests that temperature has a larger influence on runoff compared to precipitation for glacierized catchments because temperature has a direct impact on snow and ice melt, and consequently also on runoff generation. Moreover, given the percentages of glacierization according to the different scenarios (Figure 19), it can be assessed that temperature tends to be the dominant factor on skill transfer for a glacierization higher than 50%, and for a snow- and glacier melt contribution higher than 60% (Figure 19); then, an intermediary or "transitional" situation can be identified for the third scenario (which considers glacierization rates between 30% and 40%), whilst for the last two scenarios (Scenarios 4 and 5), precipitation becomes predominant over temperatures, particularly for the fifth scenario which assumes a completely ice-free catchment.

Given that skill transfer has been found to be variable according to the amount of glacierization, for both Findelen and Gries catchments, specific trends related to the variability of *m* and *n* slope parameters have been identified. Generally, temperature effect on runoff skill tends to decrease with a decreased glacierization, whilst precipitation influence tends to slightly increase (Table 6). However, some differences have been identified between the two catchments: while on Findelen temperature tends to maintain a quite a high control on skill transfer even in case of a completely ice-free catchment (for Scenario 5), a quite different tendency has been detected for Gries. In this case, precipitation has been shown to have a more relevant influence on accuracy transmission, also for the scenarios assuming a higher glacierization such as Scenarios 1 and 2 (Table 6), and this tendency can be identified also by analysing specific lead times separately (Table 7, A.4.1 and A.4.2). This difference between the two catchments could be due to the different amount of yearly precipitation related to their different geographical situation (Chapter 4). The Findelen catchment is located in an "internal" valley in Wallis canton; consequently, mean annual precipitation tend to be lower in this case because most of the humidity is held back by the highest peaks of the Penninic Alps (Appenzeller *et al*., 2011 ; Pachauri *et al*., 2014). On the contrary, the Gries catchment is located in a region where peaks are not characterized by a too high elevation (the highest peak is the Blinnenhorn with a 3374 m.a.s.l. elevation, as affirmed by Bauder *et al.* (2017)), which means that more humidity is present which could cause higher amounts of precipitation in this case (1283.99mm/year precipitation have been simulated for the Findelen catchment for this experiment, whilst 2068.57mm/year precipitation have been simulated for Gries). Moreover, mean yearly temperatures tend to be slightly higher on Gries than on Findelen (Bauder *et al*., 2017) and this can also have an influence on the variability of the slope parameters *m* and *n* between the two catchments: according to the data of the reference forecast file (Sections 3.1 and 3.2), a mean yearly temperature of -1.32°C has been simulated over the whole time-series on Gries, whilst a mean yearly temperature of -3.53°C has been simulated on Findelen over the same period. Consequently, this could be a reason of the higher influence of *Tskill* on *Qskill* which has been detected on Findelen compared to Gries (as mentioned in Sections 3.1 and 3.2, the values of the input temperature and precipitation forecast files are always the same for all scenarios in order to study the contribution of the variability of glacier extent to skill transfer).

Another explanation of the variability of *m* and *n* slope parameters between the two catchments can be related to the values of the parameters which have been determined according to the Monte-Carlo automated calibration of the hydrological model HBV (Section 3.3). If values of parameters have been identified as being different between the two catchments as a result of the calibration procedure, these values could also have an influence on the simulated runoff and on the simulated amount of snow. For example, for the Findelen catchment, a value of the *CFMAX* parameter of around 3 has been identified (the *CFMAX* parameter is the one related to the application of the degree-day method to the snow routine, as mentioned in Section 3.3), while for Gries a higher value (around 3.8) has been determined. This means that, given the high variability of *CFMAX*, differences in its value could also be a factor of influence of model performance and skill transfer. The same considerations can be applied also for other parameters of the HBV model which generally show a higher variability compared to the others, such as *SP* and *MAXBAS* (Figure 22).

Another point is that the three skill scores (RMSE, RV and CC) showed quite different results, particularly the CC metric. Results on skill transfer for RMSE and RV were generally quite similar, whilst correlation skill score simulated a higher value of *m* parameter for all scenarios and very low values of *n* (i.e. near 0 or slightly negative), which could be interpreted as a higher temperature effect on runoff skill. But the ranges and values of each skill score should also be interpreted in order to assess an answer to this aspect: CC skill score shows a different variability compared to RMSE and RV (cf. Section 3.4, where CC is defined as having a variability between -1 and 1), focusing on the correlation between variables. Therefore, a higher value of temperatures could mean that its tendency during time is more well-defined and characterized by a specific trend compared to the one of precipitation, which generally showed values near 0 (Table 6), thus indicating a lower correlation. Consequently, CC metric can be useful to interpret the evolution of skill of weather and runoff forecasts over time, but less to interpret skill transfer and the influence of temperatures and precipitation on runoff skill. This is because RMSE and RV have been considered for the majority of the results exposed above (Sections 5.2 and 5.3), while the results of CC are mainly exposed in the Appendix (A.2, A.3.2).

Correlation between skill transfer and lead time

The variability of the slope parameters *m* and *n* has been considered as a factor to interpret skill transfer and its evolution according to a variable glacier extent. Table 6 (Section 5.3) illustrates the variability of the slope parameters *m* and *n* for all glacier extent scenarios and for both catchments (see Equation 5). A tendency to have an increased temperature influence on skill transfer with increased lead time has been detected in Section 5.3 for all scenarios (particularly for Scenarios 1 to 4). This can be due to either the simulated glacier melt for the last considered lead times if the dynamic glacier routine of the model is implemented or to uncertainties during the forecasting procedure: if uncertainties characterize weather or runoff forecasts, then they could propagate thus generating some slight differences (or "deviations") from the real values of skill transfer. Another result which has been detected is that the variability of skill transfer is quite independent from the forecasts skill (Figure 20, A.7.1, A.7.2). The difference between the skill in the meteorological forecasts (*Tskill*, *Pskill*) and the skill in the resulting runoff predictions (*Qskill*) tends to remain quite constant for all scenarios (Scenarios 1 to 5), despite the fact that the skill of both precipitation and temperature forecasts tends to decrease with increasing lead time (Section 3.2). Generally, a higher difference between skill of weather variables and runoff can be identified for the Scenarios 4 and 5, being of around 0.06-0.09 for both catchments. This can be due to a reduction in efficiency of the HBV simulations, or to the variability of the produced simulated runoff due to the variable glacier extent. This means that the hydrological model, after detecting a variable glacier extent and area (i.e. a shrinking glacier which has been considered in the catchment settings in order to run simulations), probably simulates runoff differently compared to the most glacierized scenarios (Scenarios 1-3), thus producing slightly more runoff as it should be simulated. Consequently, some uncertainties could also characterize the core functionalities of the HBV model and its recently-implemented glacier routine (Seibert *et al*., 2017): hydrological models always show a certain amount of uncertainty when they reproduce reality (Section 2.2).

Comparison with the glaciological model GERM

By comparing the results obtained in this thesis with the ones obtained from a similar experiment performed with the GERM model (see Section 3.2 for a short description of this hydrological model), similar tendencies have been found, and results are similar for both hydrological models (A.5.1, A.5.2). However, the GERM model tends to simulate a slightly higher influence of temperatures on *Qskill* for the first two scenarios compared to HBV. For the Findelen catchment, the tendencies detected for the two models are similar, simulating a higher influence of temperatures on *Qskill* in both cases. Moreover, the GERM model tends to produce a more variable influence of both temperature and precipitation according to daily lead times, particularly for the scenarios with a glacierization amount higher than 50% (i.e. Scenarios 1 and 2).

Consequence of assuming a different implementation of the HBV glacier routine

A particular element which has been identified while performing the simulations with the HBV model and while producing results is the distinction between the two applicable glacier routines related to the hydrological model (Seibert *et a*l., 2017), the one which considers a static glacier by only changing its area, and the one which considers a dynamic glacier with varying mass balance and water equivalent. The distinction between these two settings has not been performed in many experiments beforehand (the most important in this sense is the one of Seibert *et al*. (2017)), so this thesis has been a good occasion to understand how the HBV model simulates runoff first by varying only glacier extent, and then by changing also water equivalent and mass balance. Generally, once the area of the glacier is defined, there are not many differences in the simulated runoff between the two settings, but some discrepancies can be detected with reduced glacier dimensions, such as in the glacierization-scenarios 3 and 4. This is because a more rapid glacier melt is probably simulated by the model for the dynamic glacier routine, producing slightly more runoff compared to the static glacier routine.

6.2. Sensitivity analysis on the hydrological model HBV

Generally, glacier and snow routines are the most important for model efficiency and skill transfer because the whole analysis has been performed on alpine highly-glacierized catchments. The hydrological regime shift is detectable for both catchments, as exposed in the previous chapter (Section 5.4, Figure 19), but it is slightly more evident for Gries compared to Findelen, particularly for the last scenario (Scenario 5). This is essentially due to their different hydrological and morphological properties, and to the fact that Gries glacier is currently shrinking more rapidly compared to Findelen (Bauder *et al*., 2017), and it will probably be disappeared before the end of the 21st century (Appenzeller *et al.*, 2011 ; Bauder *et al*., 2017 ; Pachauri *et al*., 2014).

Some more experiments have been performed by varying the lake extent on the Gries catchment (by considering Scenario 2 as a representative example), by varying the water equivalent of the glacier profile (Section 3.3) considering Scenarios 1 and 4 as representative examples, by varying the runoff input data (the "Q" variable of the PTQ input file) for Scenario 2, and by modifying model settings. In this last case, the following variants have been applied for both catchments by taking Scenario 3 as an example: *only snow-routine* simulations (i.e. it only considers parameters of the snow routine computing simulated runoff quite differently), variable groundwater boxes (one or three) or distributed simulations without considering the *UZL* parameter (see Section 3.3). First, it has been found that an increase of the lake's area has only a small influence on the simulated runoff, and a negligible impact on skill transfer. This is due to the topographical situation of the lake, which is situated in the lowest elevation ranges of the catchment, thus contributing only slightly to its total runoff. Moreover, a hypothetical bigger (or smaller) lake allows to produce a higher (or lower) amount of hydropower energy, which could be of relevance given the challenges of the energy production shift related to the "Energy Strategy 2050" (Section 2.1). Second, variable observed runoff input data does not cause a high modification on the simulated runoff, but it tends to worsen model efficiency if parameters are kept to the same value as previously determined in the calibration (Chapter 3). Third, changing model settings by assuming an "only snow-routine" mode does not cause relevant variability of the simulated total runoff, but a small modification of the contribution of snow and glacier melt (it generally tends to be slightly lower, as exposed in Table 9). This could be due to the major contribution of the snow routine to the generation of the total runoff, thus reducing the amount of runoff from glacier melt. Other outcomes have been obtained by varying the number of groundwater boxes: assuming that groundwater has a negligible effect on runoff and that it is a not relevant contributor to the hydrological equilibrium of glacierized catchments because of the lower mean annual temperatures at the higher elevations, soil properties probably play a minor role in these situations.

7. Conclusions

In this experiment, synthetic weather forecasts of temperatures and precipitation have been created with the support of a weather generator. These forecasts have been fed into the hydrological model HBV in order to obtain corresponding simulated runoff predictions. An accuracy assessment of the meteorological and runoff forecasts was calculated with three different skill scores, namely RMSE, RV and CC. The aim of this procedure was to assess the skill transfer from meteorological to runoff forecasts. The glacier extent of both catchments has been artificially modified to represent different degrees of glacierization from highly glacierized (Scenario 1) to ice-free catchment (Scenario 5), in order to observe the influence of glaciers on the skill transfer both in the Gries and Findelen glacierized catchments.

It has been found that temperature forecasts have a larger influence on runoff predictions than precipitation in the Findelen catchment when the degree of glacierization is very high (Scenario 1). The opposite is found for the Gries catchment, where precipitation has the highest impact on runoff. The resulting difference between both catchments might come from the different amount of yearly precipitation which has been fed into the hydrological model HBV (the yearly sum of precipitation on Gries is two times higher compared to Findelen), and also to the higher temperatures which have been fed into the model for simulations performed on the Gries catchment. Given that temperatures are an important control factor of snowmelt and runoff generation for highly-glacierized catchments, higher yearly mean temperatures could thus lead to a higher precipitation influence on skill transfer. Another possible explanation of this difference of accuracy transmission between the two catchments could be related to the uncertainties related to the parameter values obtained from the Monte-Carlo calibration. The same calibration has been performed for the two catchments with the same parameter range but different input files, thus leading to different “optimum parameter sets”, which could on their turn have influences on skill transfer and runoff generation.

A similar procedure than above was conducted for the four other scenarios (i.e. with variable glacier extents). It has been found that the transfer of accuracy between the meteorological and the runoff forecasts varies over the different glacierization scenarios, showing some specific tendencies for each catchment. First, the influence of precipitation on skill transfer tends to increase for both catchments in case of a reduced (or absent) glacierization (i.e. Scenarios 4 and 5) compared to the other scenarios. However, the influence of precipitation for Scenario 5 is not so pronounced for the Findelen catchment compared to Gries. This is because, probably, the Gries glacier is expected to completely melt before the end of the 21st century, while the Findelen glacier will take some more decades before melting completely. Consequently, the influence of temperatures on runoff will remain higher for Findelen catchment compared to Gries until Scenario 4. For Scenario 5, temperature effect on skill transfer is lower compared to the other Scenarios for both catchments, but precipitation effect is lower for Findelen than for Gries. This result can be due to either the lower yearly amount of precipitation or to the lower temperatures which have been fed into the HBV model for Findelen. By comparing the HBV results about skill transfer with those obtained from another hydrological model (GERM), it has been found that the tendencies are quite similar, except from a quite higher contribution of temperature to skill transfer which has been simulated in this latter case on the Gries catchment for a higher glacierization (i.e. for Scenarios 1 and 2).

Generally, a slight difference on skill transfer has been found between the two different implemenations of the glacier routine. Precipitation influence on skill transfer tends to be slightly lower for the static glacier routine compared to the dynamic one, particularly for lead times starting from four to six years (i.e. about 1500-2000 days). This is due to the decreased glacier area and to a volume reduction which are simulated by the hydrological model HBV by applying the dynamic glacier routine compared to the static one.

The hydrological analysis which has been performed for the reference files of both catchments has been useful to assess the evolution of glaciers during time, and how this tendency can be linked to a shift in the hydrological regime which is expected for the next decades. Particularly, the progressive reduction of the glacier contribution to the total runoff shows a hydrological shift from a glacier melt-dominated to a precipitation-dominated regime (either liquid or solid). Moreover, other three tendencies have been detected thanks to the hydrological analysis. First, it has been established that the actual evapotranspiration will progressively increase for both catchments due to the higher temperatures and to the glacier melting process. Second, snowcover and the amount of simulated snow tend to decrease for each scenario due to the simulated higher temperatures which have as an effect that a higher amount of yearly precipitation is simulated to be rain rather than snow. Third, the introduction of snow redistribution has not caused relevant differences on the simulated runoff, but the simulated amount of snow in the catchment has become more “realistic” by avoiding the phenomenon of “snow towers”.
Other aspects related to accuracy transfer have been the study of the role of lakes and the variability of glaciers’ water equivalent. In both cases, no relevant differences related to skill transfer have been found, but lakes will serve as storage sources for a catchment, thus increasing the amount of energy produced by hydropower companies. A last complementary analysis has been the implementation of additional simulations with the “only snow-routine” mode in the HBV model, and by varying the number of groundwater boxes from the model settings. In this case, a quantifiable difference of the total simulated runoff has generally not been found, except from a slight decrease of the simulated runoff for the “only-snow routine” mode.

The results obtained in this Master thesis are of relevance for the application of decadal predictions, as those have been shown to be more skillful in predicting temperature than precipitation. Some additional challenges and open questions however remain open. First, an interesting complement for the future can be to perform similar experiments in other alpine highly-glacierized catchments in Switzerland or in other regions of the world. Second, other integrated experiments by coupling hydrological and glaciological models could be applied in order to increase the available scientific background about this topic. Another challenge for the future could be to assess the variability of skill transfer and of the generation of simulated runoff by studying catchments with variable structure and geometry. In the coming years, more focus could be put on doing comparable experiments by using other hydrological and glaciological models. Performing reliable decadal forecasts is of particular relevance in today’s context of highly variable climatic conditions and highly ductile energy market. Therefore, there is the need to find a compromise between science and economics in order to avoid either experiments which cause the introduction of norms and rules that are respectful of climate but too expensive, but also to implement experiments which cause harmful measures for the environment to be introduced.

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9. Appendix

9.1. R-Studio scripts and programming steps

A0. Programming methodological application related to HBV and skill transfer

Extract #1) Create folders directly on the computer

```
for (i in 1 : length (Weather)) {
  newdir <- paste0 (forecasts, i)
  dir.create (newdir)
  for (i in 1 : 240) {
    newdir1 <- paste0 (newdir, "/", blocks, i)
    dir.create (newdir1)
    newdir2 <- paste0 (newdir1, "/", "data")
    dir.create (newdir2)
    newdir3 <- paste0 (newdir1, "/", "Results")
    dir.create (newdir3)
  }
}
```

Extract #2) Definition of potential evapotranspiration from the Penman-Monteith equation

```
# "Lambda" is the latent heat flux in MJ/kg^-1
# "rho" is the water density in kg*m^-3
# "PE" is the potential evaporation in mm/day
# The extraterrestrial radiation is computed as a function for PET
# "lat_rad" is the latitude in radiants
# "Gsc" is the solar constant in MJ*m^-2*min^-1
# "dr" is the inverse relative distance Earth-Sun
# "delta" is the solar declination
# "omegas" the sunset hour angle
# "Ra" is the extraterrestrial radiation

# Compute potential evaporation and the extraterrestrial radiation
Ta <- Tmeanevap_day
j <- c (15, 45, 74, 105, 135, 166, 196, 227, 258, 288, 319, 349)
lat <- latitude
pet <- function (Ta, j, lat){
  lambda <- 2.26
  rho <- 1000
  PE <- re (j, lat) / (lambda * rho) * (Ta + 5) / 81 * 1000
  PE [Ta < (-5)] = 0
  return (PE)
}
re <- function (j, lat) {
  lat_rad <- lat * pi / 180;
  Gsc <- 0.0820
  dr <- 1 + 0.033 * cos (2 * pi / 365 * j)
  delta <- 0.409 * sin (2 * pi / 365 * j - 1.39)
  omegas <- acos (-tan (lat_rad) * tan (delta))
  Ra <- 24 * 60 / pi * Gsc * dr * (omegas * sin (lat_rad) * sin (delta) + cos (lat_rad) * cos (delta) * sin (omegas))
  return (Ra)
}
```

Extract #3) Looping procedure to run the HBV model with a CLI interface

```
for (eachblocks in BlockFolders) {
  catchmentFolder1 = eachblocks
  hbvPath = "C: / Program Files (x86) / HBV-light / HBV-light-CLI.exe";
  outFolder = "Results"
  catchments1 = list.dirs (path = catchmentFolder1,  full.names = TRUE)
  catchments1 <- mixedsort (catchments1)
  for (i in 1 : length (catchments1)) {
    print (catchments1 [i])
    system (paste0 ("\"", hbvPath, "\" Run ", catchments1 [i], " SingleRun ", outFolder), TRUE);
  }
}
```

Extract #4) Production of the final skill transfer plots (example of RMSE skill score, the same procedure has been applied also for RV and CC)

```
# Normalization process of all the skill scores
# Normalization of precipitation skill scores
Skillplotsprecrmse [1 : lengthblock, ] <- (skillplotsprecrmse [1 : lengthblock, ] – min (skillplotsprecrmse [1 : lengthblock, ])) / (max (skillplotsprecrmse [1 : lengthblock, ]) – min (skillplotsprecrmse [1 : lengthblock, ]))
colnames (skillplotsprecrmse) <- paste ("lt", 1 : (leadtime - 2))
# Normalization of temperature skill scores
Skillplotstemprmse [1 : lengthblock, ] <- (skillplotstemprmse [1 : lengthblock, ] – min (skillplotstemprmse [1 : lengthblock, ])) / (max (skillplotstemprmse [1 : lengthblock, ]) – min (skillplotstemprmse [1 : lengthblock, ]))
colnames (skillplotstemprmse) <- paste ("lt", 1 : (leadtime - 2))
# Runoff
Skillplotsdischrmse [1 : lengthblock, ] <- (skillplotsdischrmse [1 : lengthblock, ] – min (skillplotsdischrmse [1 : lengthblock, ])) / (max (skillplotsdischrmse [1 : lengthblock, ]) – min (skillplotsdischrmse [1 : lengthblock, ]))
colnames (skillplotsdischrmse) <- paste ("lt", 1 : (leadtime - 2))

# Skill transfer
resultslt <- list ()
for (i in 1 : length (skillplotsprecrmse)) {
  skillplotsrunoffrmse <- cbind (skillplotsdischrmse [, i], skillplotsprecrmse [, i], skillplotstemprmse [, i])
  skillplotsrunoffrmse <- as.data.frame (skillplotsrunoffrmse)
  lreg <- lm (skillplotsrunoffrmse $ V1 ~ skillplotsrunoffrmse $ V3 + skillplotsrunoffrmse $ V2, data = skillplotsrunoffrmse)
  summary (lreg)
  coeff <- summary (lreg) $ coefficients [, 1]
  coeff <- as.data.frame (coeff)
  resultslt [[i]] <- coeff
}
```

Extract #5) Skill scores calculation (only the example of temperatures is shown)

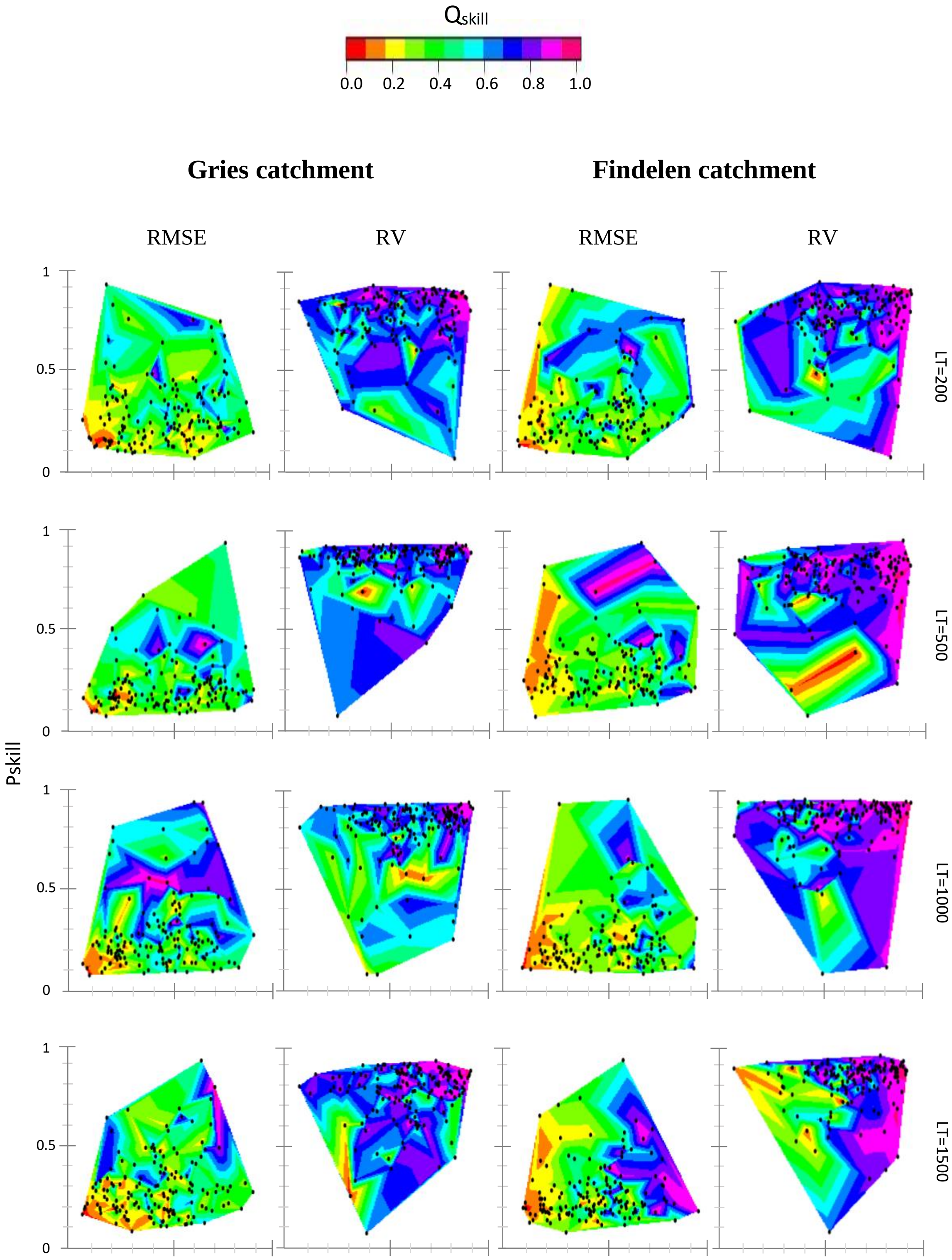
```
## Loop to determine values for precipitation and temperatures
# Initialize the loop to determine skill scores
for (each_block in 1 : length (All_fcst_blocks)) {
  All_fcst_in_block <- list.files (All_fcst_blocks [each_block], full.names = TRUE)
  All_fcst_in_block <- All_fcst_in_block [1 : 216]
  dataframe_fcst_t <- as.data.frame (array (NA, dim = c (length (ref.t.day), length (All_fcst_in_block))))
  count = 1
  for (each_fcst in 1 : length (All_fcst_in_block)) {
    fcst_list <- All_fcst_in_block [each_fcst]
    fcst <- read.table (fcst_list,header = TRUE, skip = 1)
     ii <- which(fcst $ year >= yr.start & fcst $ year <= yr.end)
     fcst <- fcst [ii, ]
     t.day <-ts (fcst $ temp,start = fcst $ year [1], freq = 365)
     t.day <- t.day [274 : (length (t.day) - 92)]
     dataframe_fcst_t [, count] <- t.day
```

```
    count = count + 1
  }
  arraytemp <- array (NA, dim = length (dataframe_fcst_t [1, ]))
  arraydifftemp <- array (NA, dim = c (length (dataframe_fcst_t [, 1]), leadtime))

# Initializing the arrays
# Initialize the arrays for the skill scores related to daily length and for lead time for T and P
RMSE_fcstt <- arraytemp ; RV_fcstt <- arraytemp ; CCSS_fcstt <- arraytemp
RMSE_leadtime_t<-arrayleadtime ; RV_leadtime_t <- arrayleadtime ; CCSS_leadtime_t <- arrayleadtime
# Determine arrays for variance and for the differential values
css_var_simt <- arraytemp ; css_var_reft <- arraytemp ; Difftemp <- arraytemp ; Difftemp_all <- as.data.frame
(arraydifftemp)

# Loop to calculate skill scores
for (j in 1 : (leadtime - 1)) {
   a = 1
   count = 2
   for (i in 1 : (length (dataframe_fcst_t [1, ]) - 1)) {
     # Skill scores for temperatures according to leadtime
     meanfcstt <- as.numeric (lapply (dataframe_fcst_t [i], mean, na.rm = TRUE))
     meanreft <- as.numeric (lapply (ref.t.day [i], mean, na.rm = TRUE))
     RMSE_fcstt [i] <- ((dataframe_fcst_t [j + a, i] - ref.t.day [j + a]) ^ 2)
     RV_fcstt [i] <- ((dataframe_fcst_t [j + a, i] - ref.t.day [j + a]) ^ 2)
     CCSS_fcstt [i] <- (dataframe_fcst_t [j + a, i] - meanfcstt) * (ref.t.day [j + a] - meanreft)
     css_var_simt [i] <- cbind ((dataframe_fcst_t [j + a, i]))
     css_var_reft [i] <- (ref.t.day [j + a])
     Difftemp [i] <- (dataframe_fcst_t [j + i, i] - ref.t.day [j + i])
     a = a + day_steps [countt]
     count = count + 1
   } # i
   # css_var_simt2 <- subset (css_var_simt, (! is.na (css_var_simt)))
   # conditional.quantile (css_var_simt, css_var_reft, bins = 10)
   DFT <- data.frame (VART1 = css_var_simt, VART2 = css_var_reft)
   data.lmt <- lm (VART2 ~ VART1, data = DFT)
   RMSE_leadtime_t [j] <- sqrt (sum (RMSE_fcstt, na.rm = TRUE) / (length (RMSE_fcstt) - 1))
   RV_leadtime_t [j] <- 1 - ((sum (RV_fcstt,na.rm = TRUE) / (length (RV_fcstt) - 1)) / var (ref.t.day, na.rm = TRUE))
   #CCSS_leadtime_t [j] <-  (sum (CCSS_fcstt, na.rm = TRUE) / (length (CCSS_fcstt) - 1)) / (sd (css_var_simt, na.rm=
TRUE) * sd (css_var_reft, na.rm = TRUE))
   CCSS_leadtime_t [j] <-  cor.test (DFT $ VART1, DFT $ VART2, method = "pearson", conf.level = 0.95, na.rm = TRUE) $ estimate
   } # leadtime j

  # Group all scores together
  All_scores_days_t <- cbind (RMSE_leadtime_t, RV_leadtime_t, CCSS_leadtime_t)
  colnames (All_scores_days_t) <- c ("RMSE", "RV", "CCSS")
  All_scores_days_t <- as.data.frame (All_scores_days_t)

  # Save skill scores
  # Temperatures, forecasts values --> group all skill scores and write the final table
  fcsttemp <- paste (out.path, "/", skilltfcst, "/", "t_ss_day_block", format (each_block, width = 6, flag = "0"), ".dat", sep = "")
  filefcstt <- file (fcsttemp)
  fcstt.line1 <- paste ("Skill Scores for temperature decadal weather forecasts, Block", each_block, sep = "")
  fcstt.line2 <- paste ("RMSE RV CCSS")
  writeLines ( c (fcstt.line1, fcstt.line2), filefcstt)
  write.table (All_scores_days_t, file = fcsttemp, append = TRUE, sep = "\t", row.names = FALSE, col.names = FALSE)
  close (filefcstt, overwrite = TRUE)

# Close device
  dev.off ()
```

9.2. Images and technical / visual representations

A.1. Skill transfer for selected lead times

A.1.1. Skill transfer for selected lead times, Scenario 2 (see Figure 15 for Scenario 1)



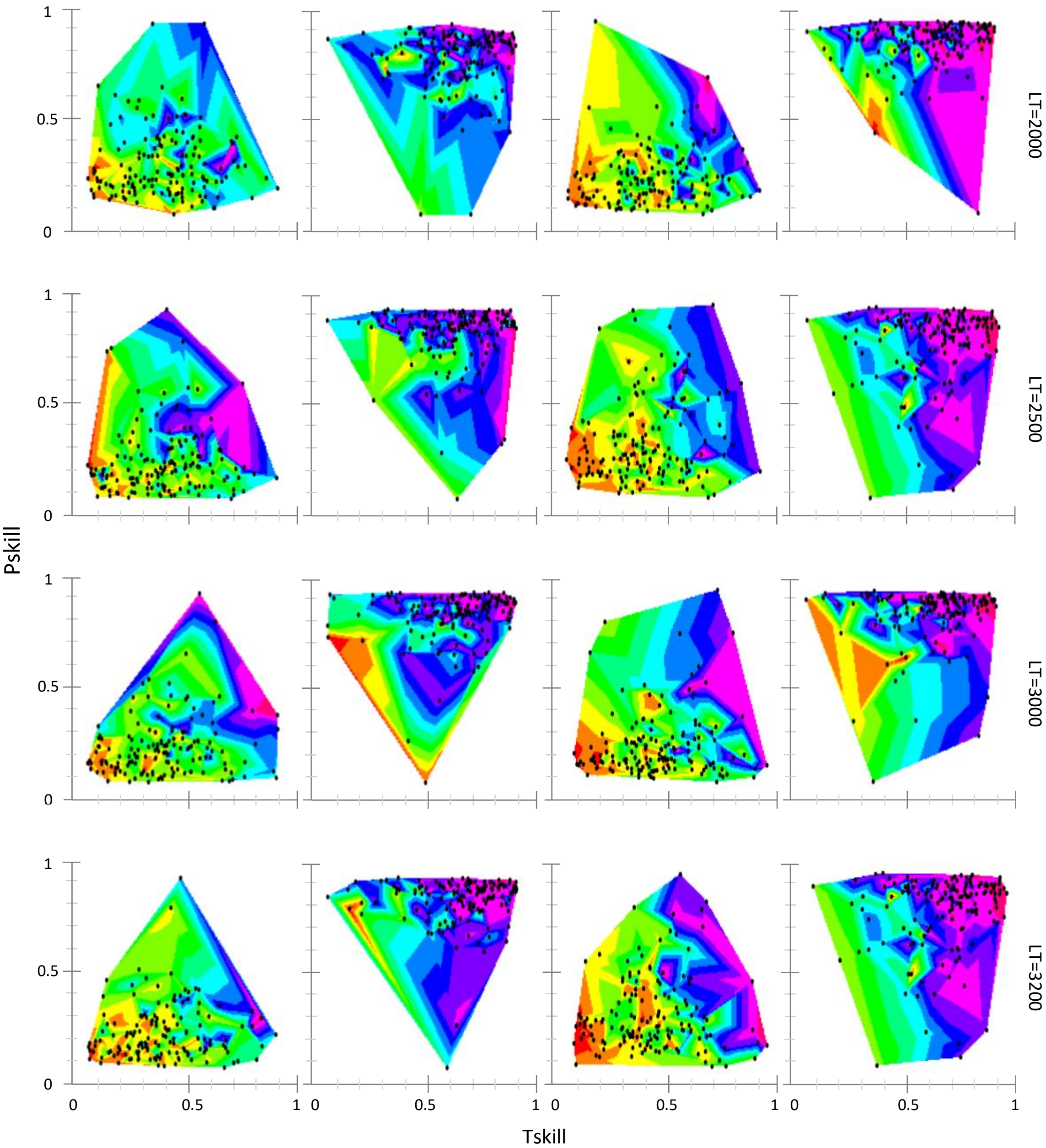
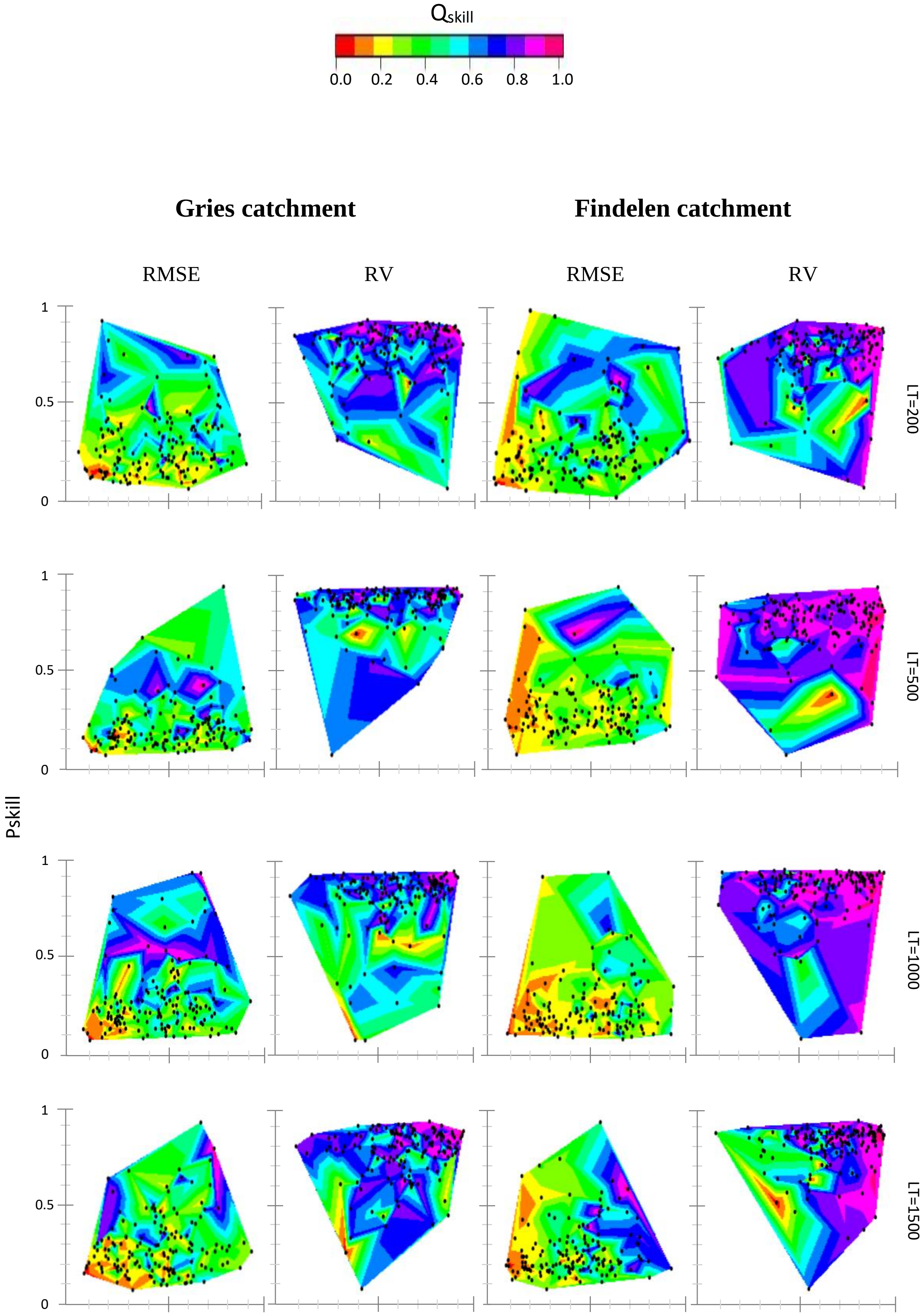


Figure 1, A.1.1: Relation between temperature, precipitation and runoff skill scores (RMSE and RV) for the two catchments and Scenario 2. The runoff skill scores have been interpolated by applying a linear interpolation with colors, while areas without values are shown in white. The black dots represent the 150 different forecasts. Results are represented for individual lead times between 200 and 3200 days, and they have been produced with the HBV model.

A.1.2. Skill transfer for selected lead times, Scenario 3 (see Figure 15 for Scenario 1)



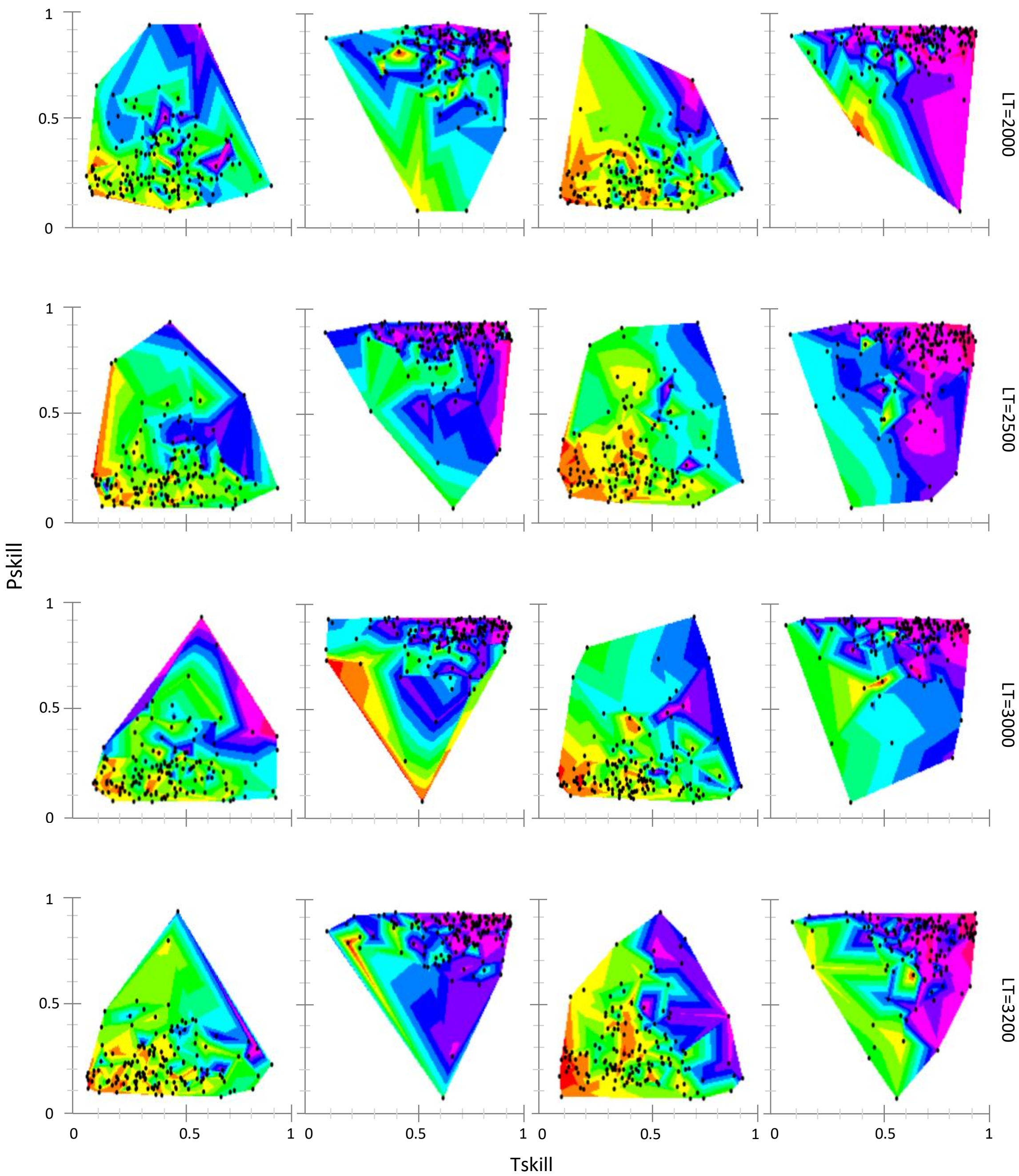
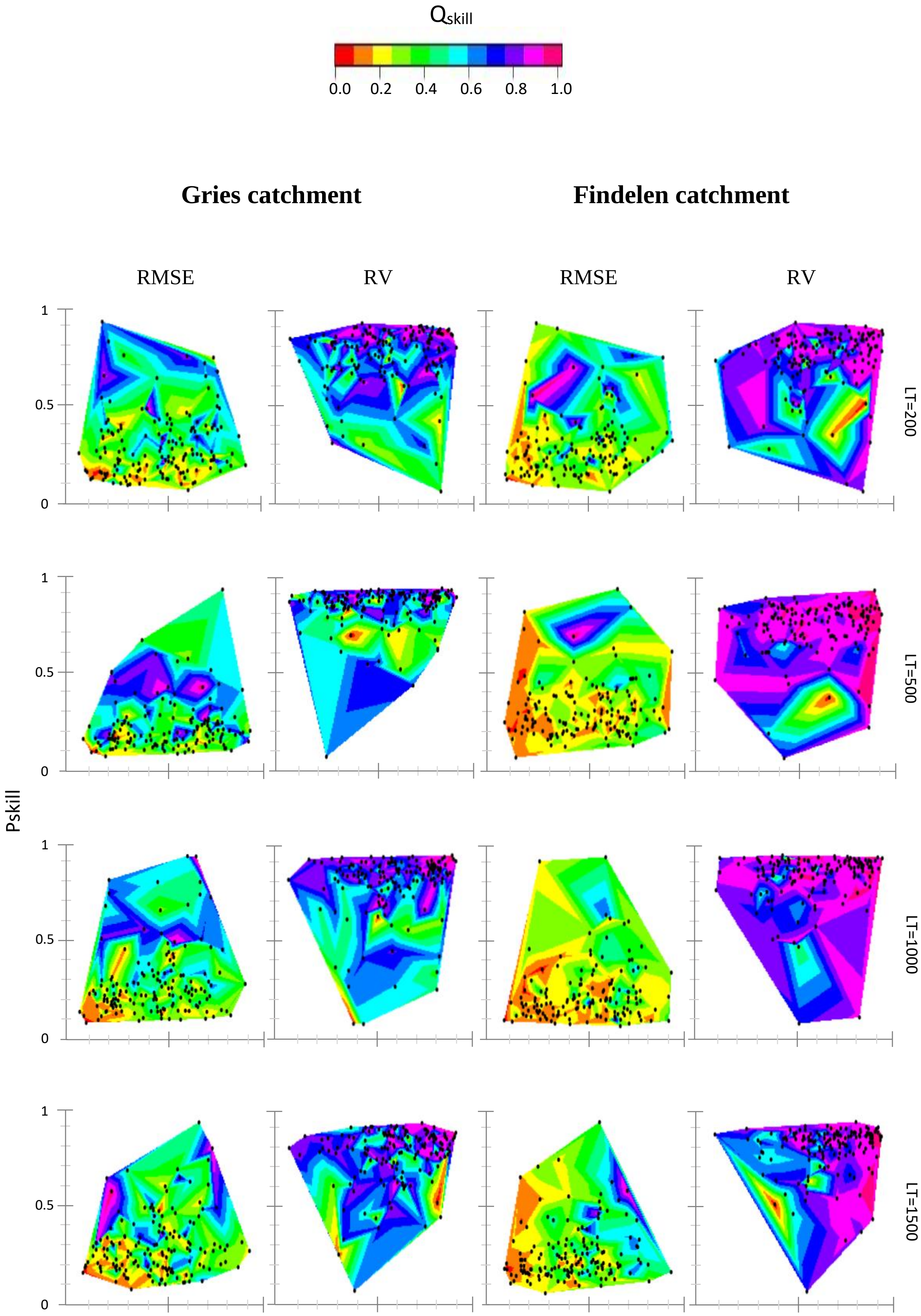


Figure 1, A.1.2: Relation between temperature, precipitation and runoff skill scores (RMSE and RV) for the two catchments and Scenario 3. The runoff skill scores have been interpolated by applying a linear interpolation with colors, while areas with no values are shown in white. The black dots represent the 150 different forecasts. Results are represented for individual lead times between 200 and 3200 days, and they have been produced with the HBV model.

A.1.3. Skill transfer for selected lead times, Scenario 4 (see Figure 15 for Scenario 1)



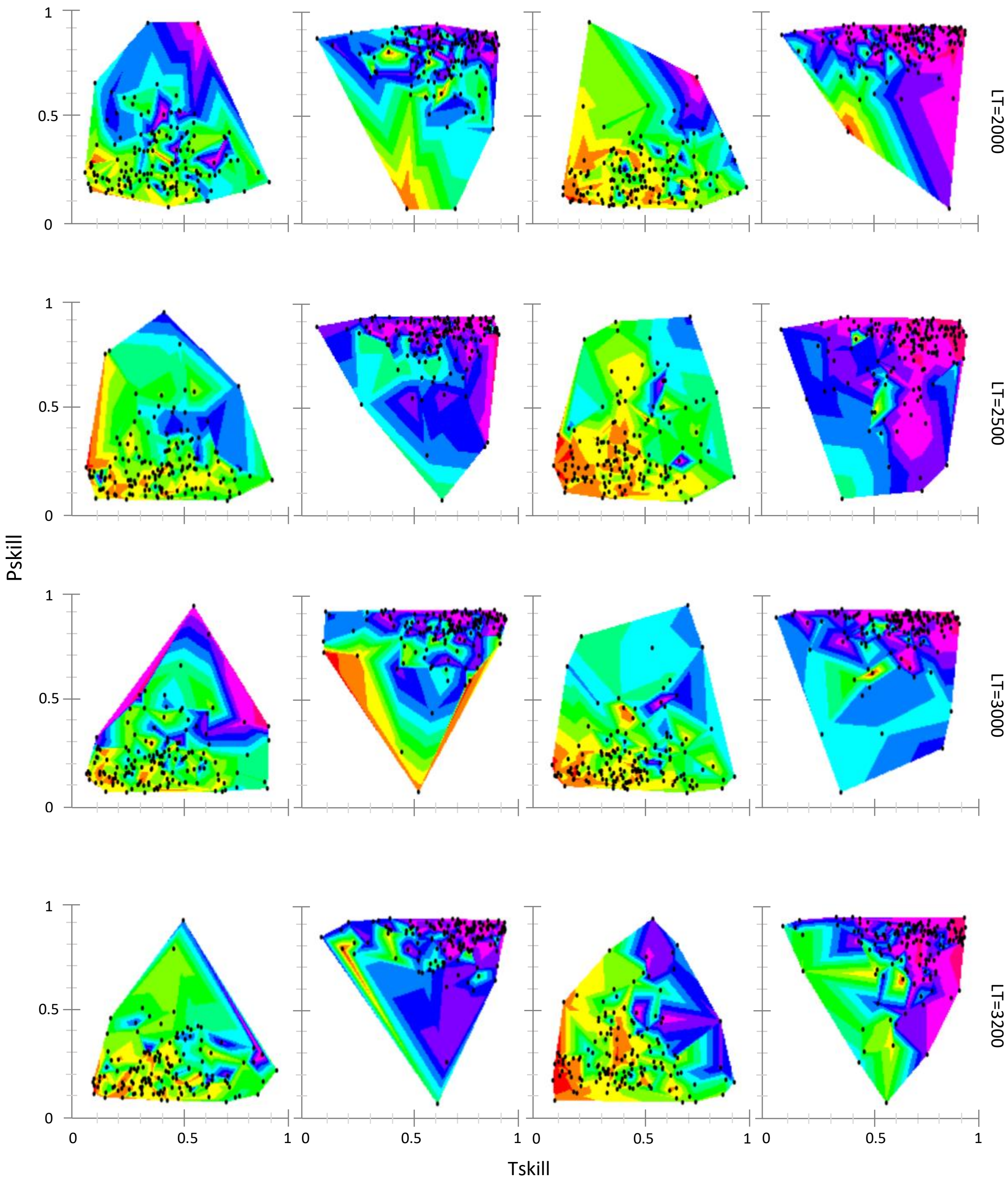
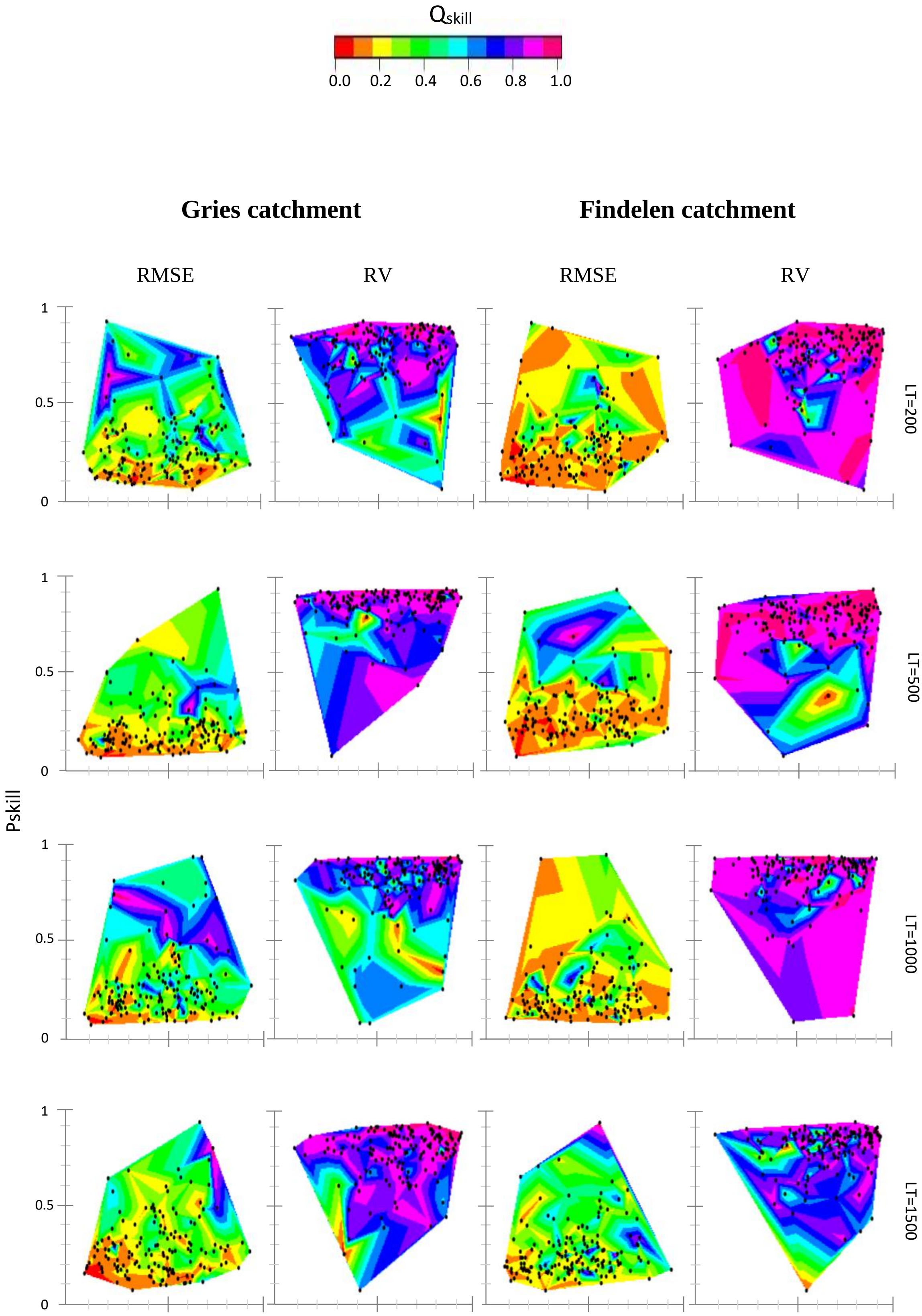


Figure 1, A.1.3: Relation between temperature, precipitation and runoff skill scores (RMSE and RV) for the two catchments and Scenario 4. The runoff skill scores have been interpolated by applying a linear interpolation with colors, while areas with no values are shown in white. The black dots represent the 150 different forecasts. Results are represented for individual lead times between 200 and 3200 days, and they have been produced with the HBV model.

A.1.4. Skill transfer for selected lead times, Scenario 5 (see Figure 15 for Scenario 1)



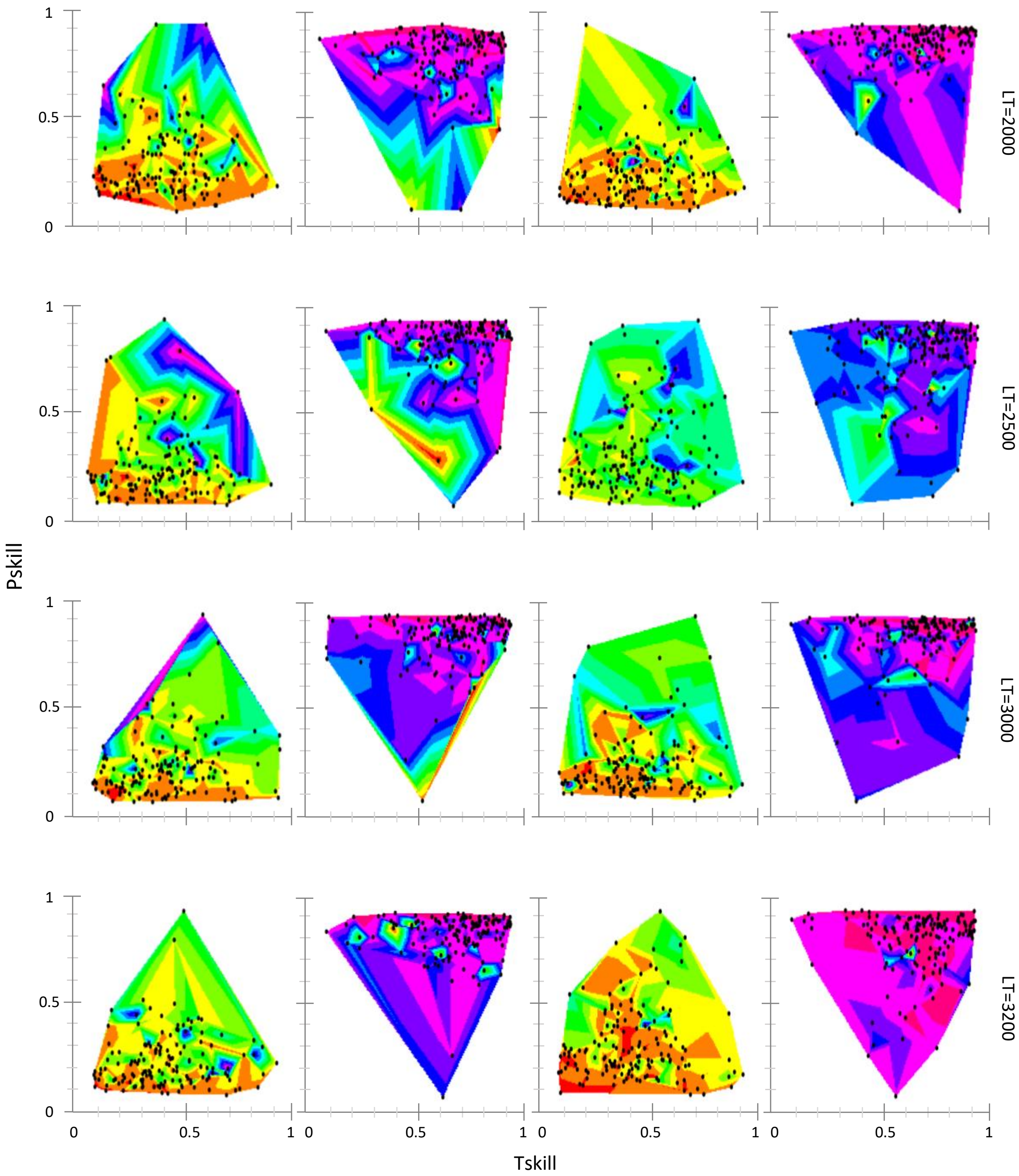
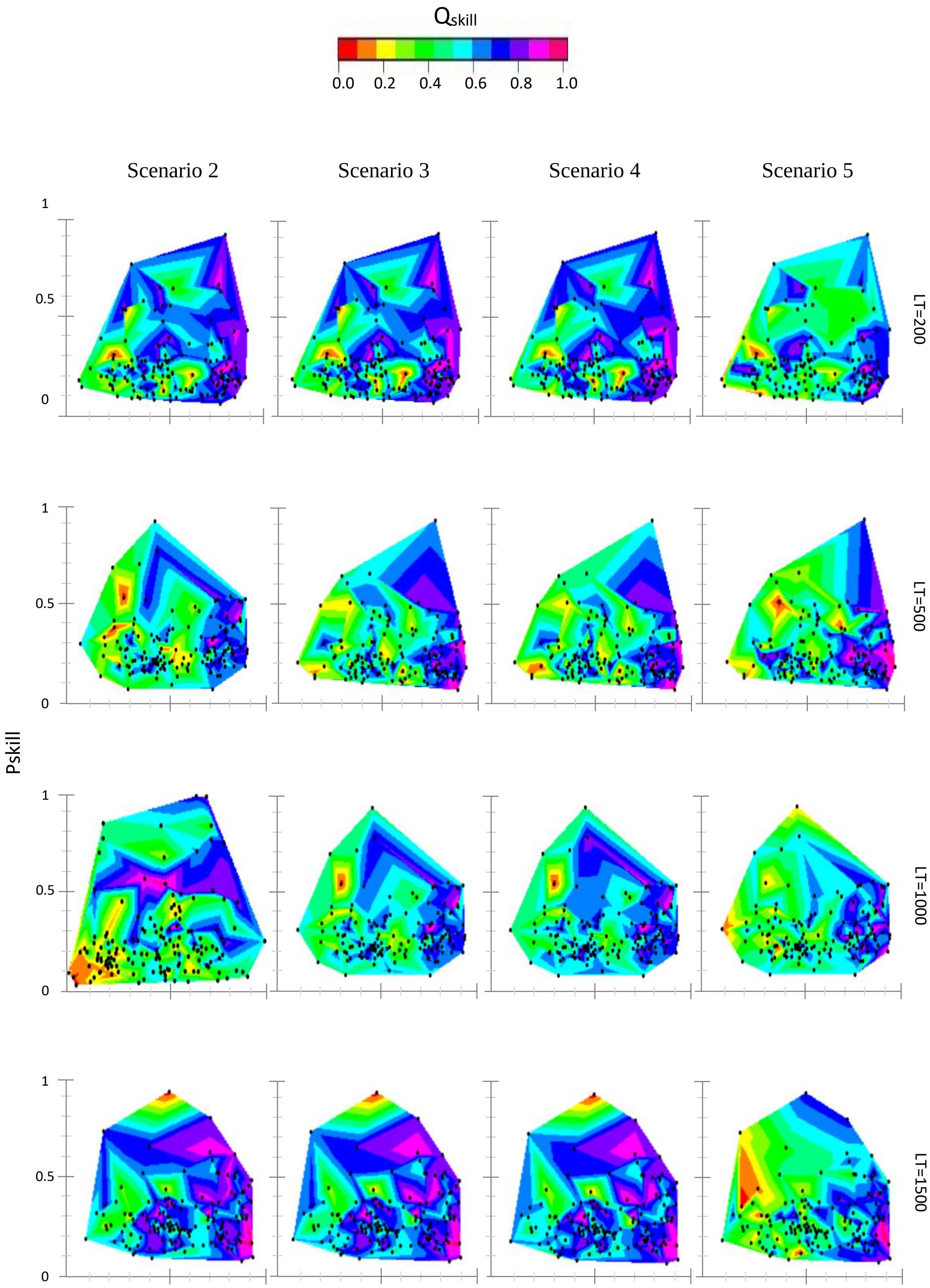


Figure 1, A.1.4: Relation between temperature, precipitation and runoff skill scores (RMSE and RV) for the two catchments and Scenario 5. The runoff skill scores have been interpolated by applying a linear interpolation with colors, while areas with no values are shown in white. The black dots represent the 150 different forecasts. Results are represented for individual lead times between 200 and 3200 days, and they have been produced with the HBV model.

A.2. Skill transfer for CC skill score

A.2.1. Skill transfer for CC skill score for Scenarios 2-5 for the Gries catchment (Scenario 1 has not been included because it showed similar outcomes as Scenario 2)



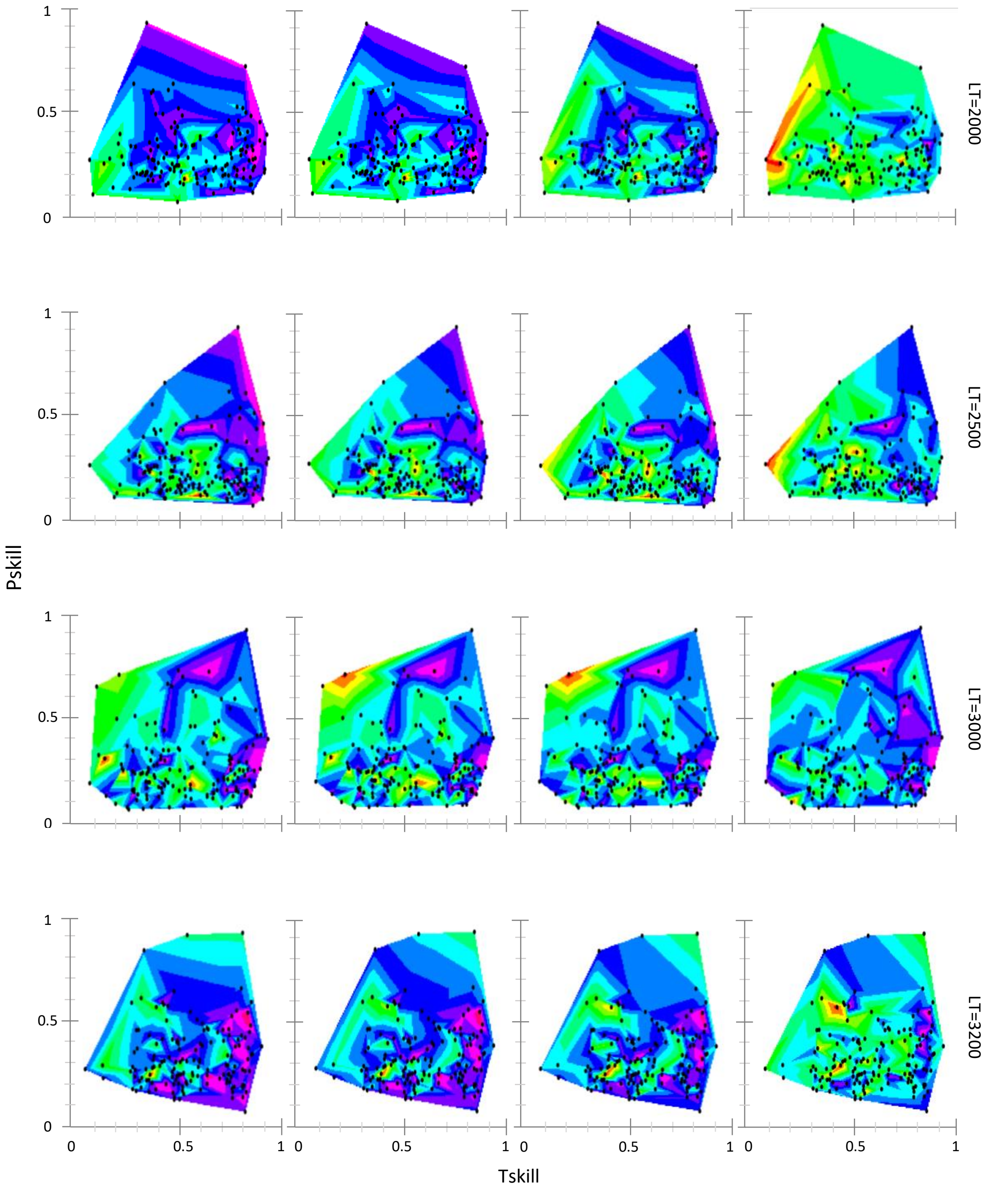
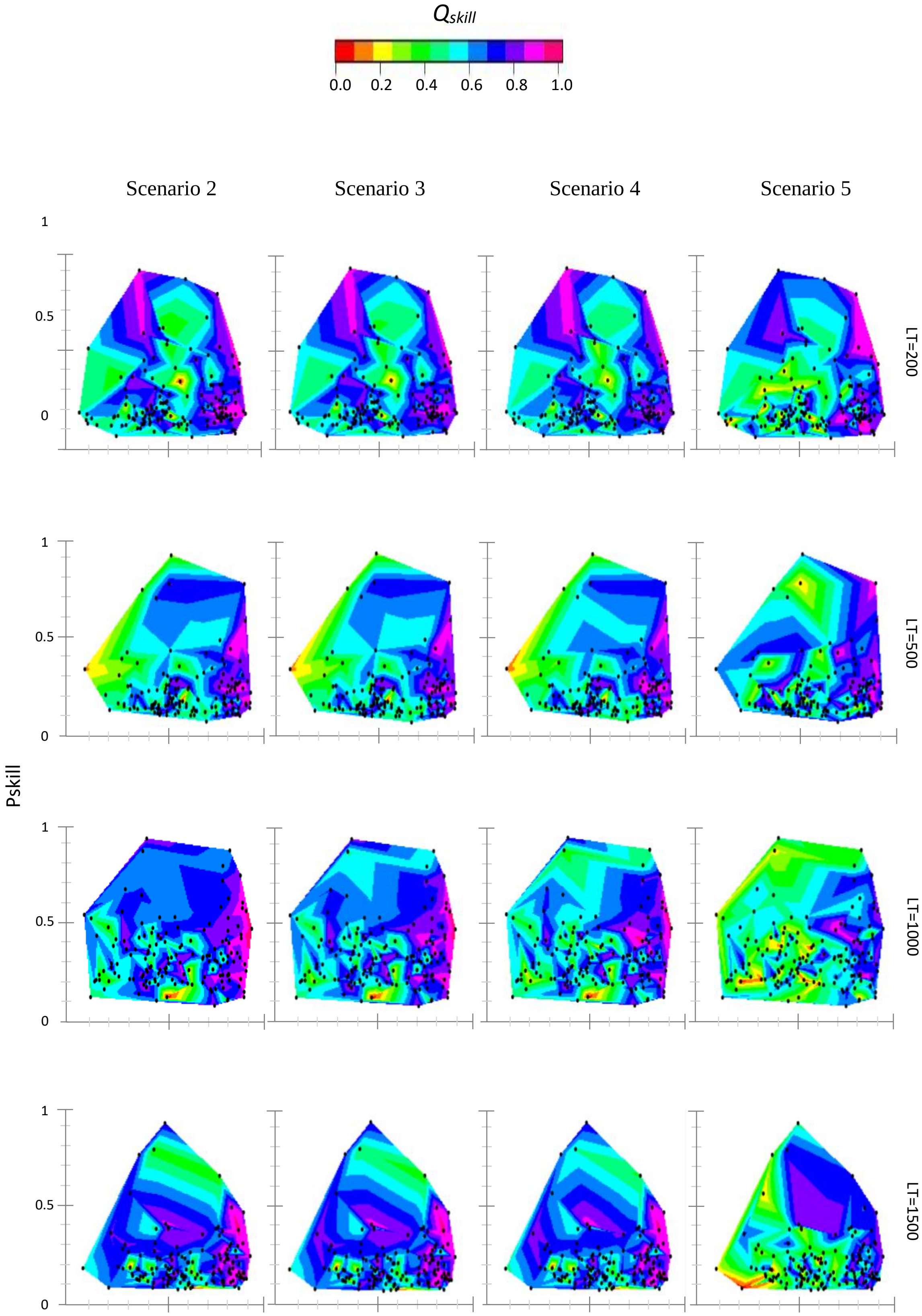


Figure 1, A.2.1: Relation between temperature, precipitation and runoff skill scores (CC) for Scenarios 2-5 in the specific case of Gries catchment. Runoff skill scores have been interpolated by applying a linear interpolation with colors, while areas with no values are shown in white. The black dots represent the 150 different forecasts. Results are represented for individual lead times between 200 and 3200 days, and they have been produced with the HBV model.

A.2.2. Skill transfer for CC skill score, Scenarios 2-5 for the Findelen catchment (Scenario 1 has not been included because it showed similar outcomes as Scenario 2)



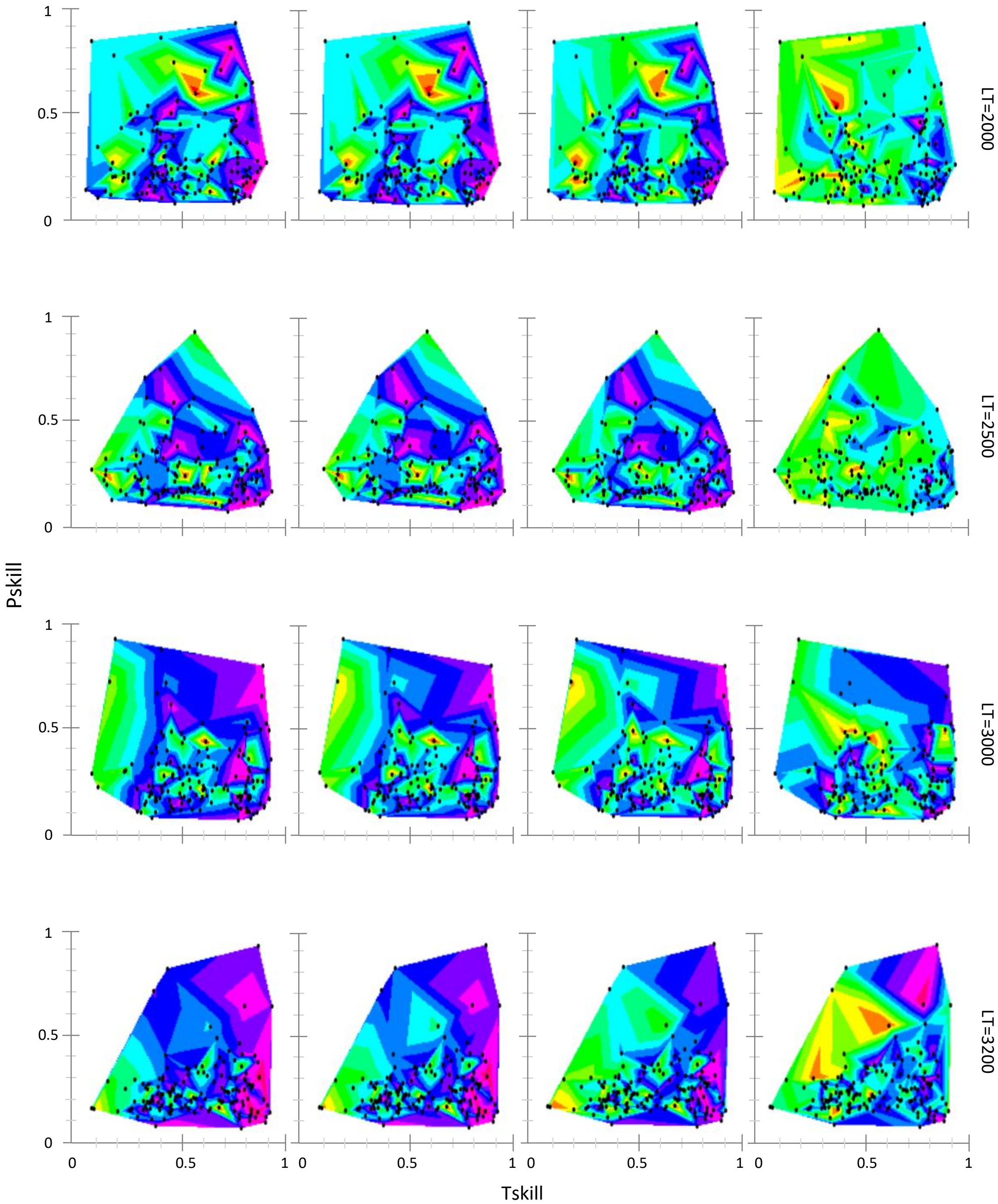
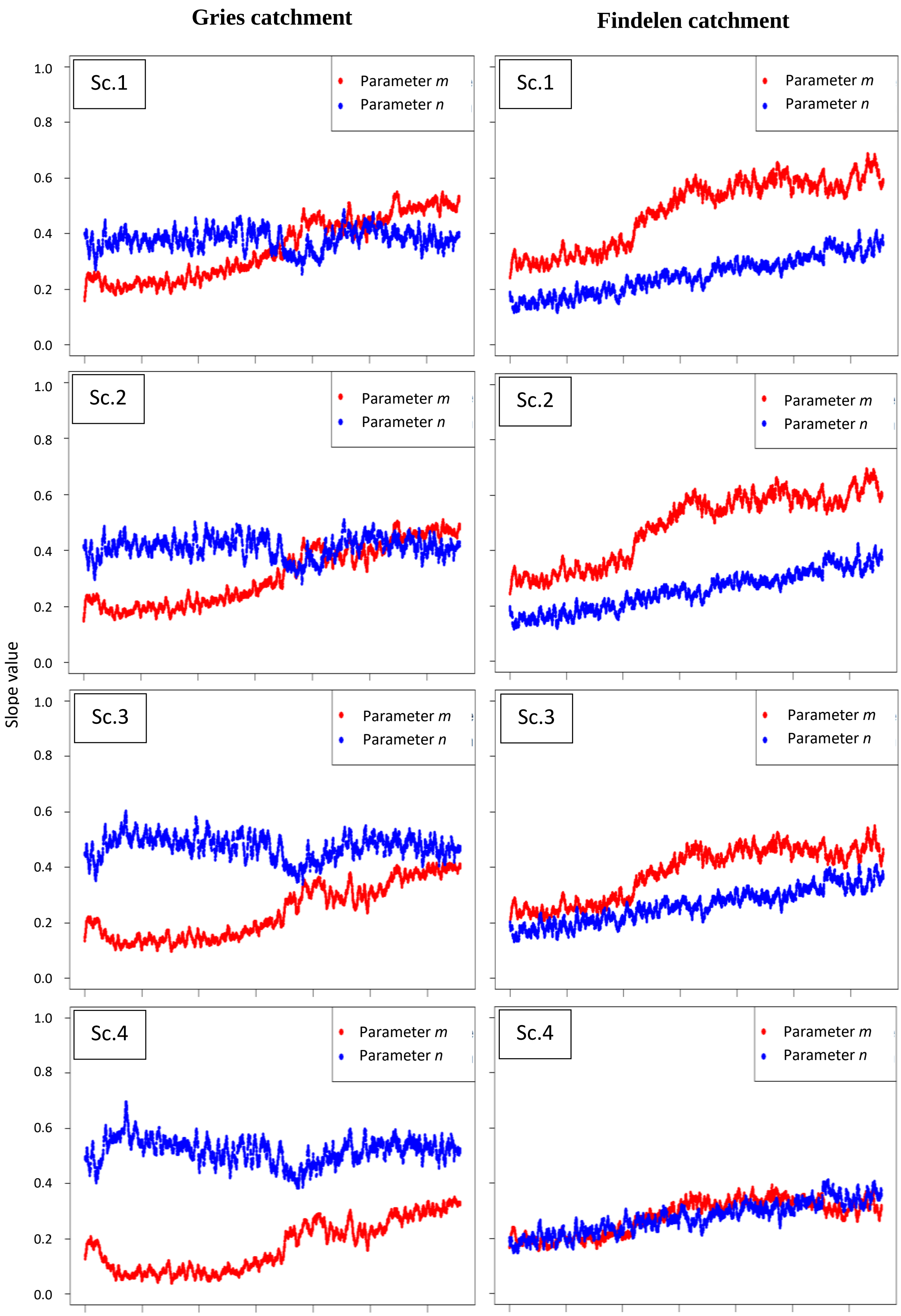


Figure 1, A.2.2: Relation between temperature, precipitation and runoff skill scores (CC) for Scenarios 2-5 in the specific case of Findelen catchment. Runoff skill scores have been interpolated by applying a linear interpolation with colors, while areas with no values are shown in white. The black dots represent the 150 different forecasts. Results are represented for individual lead times between 200 and 3200 days, and they have been produced with the HBV model.

A.3. Skill transfer for daily lead times

A.3.1. Skill transfer for daily lead times, RV skill score (see Figure 17 for RMSE)



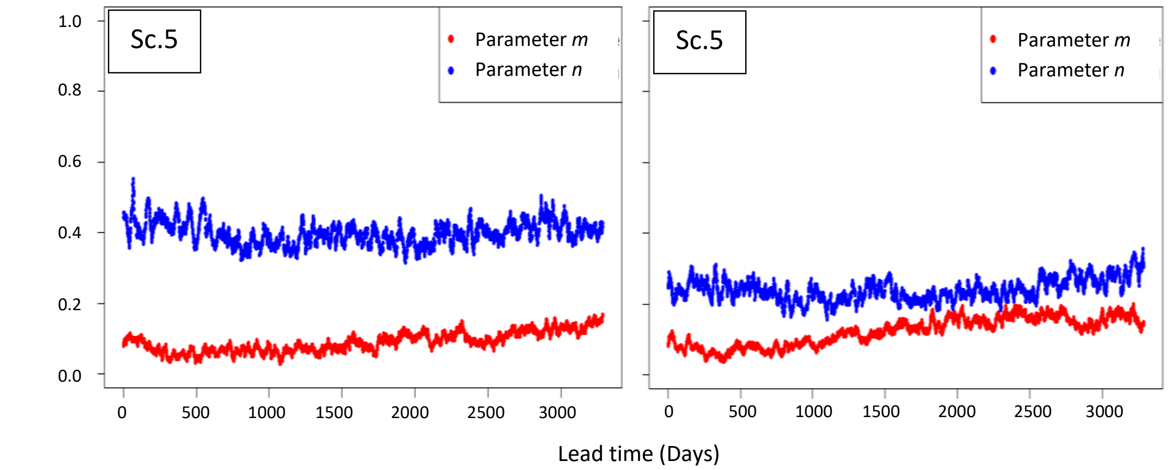
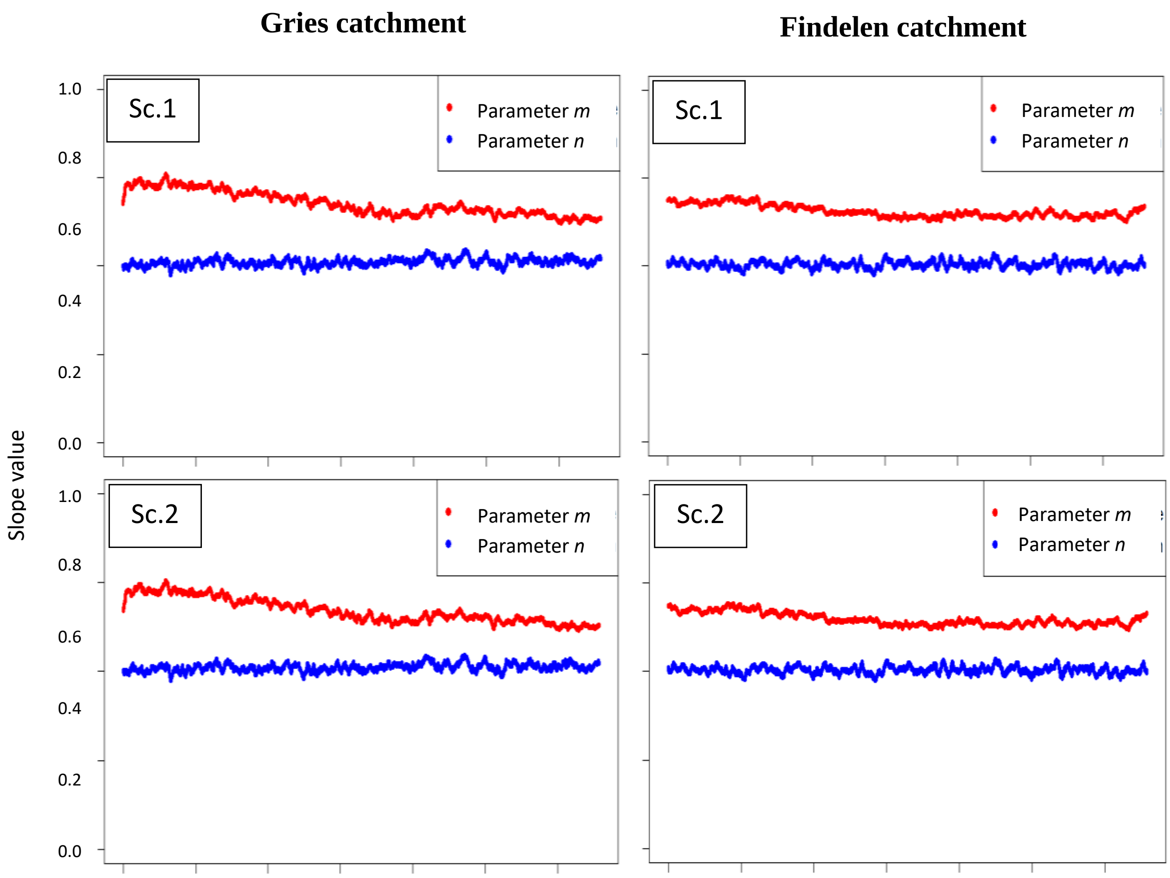


Figure 1, A.3.1: Parameters *m* and *n* for Scenarios 1 to 5 for both catchments (RV skill score). The Gries catchment is shown on the left column, while the Findelen catchment is represented on the right column.

A.3.2. Skill transfer for daily lead times, CC skill score (see Figure 17 for RMSE)



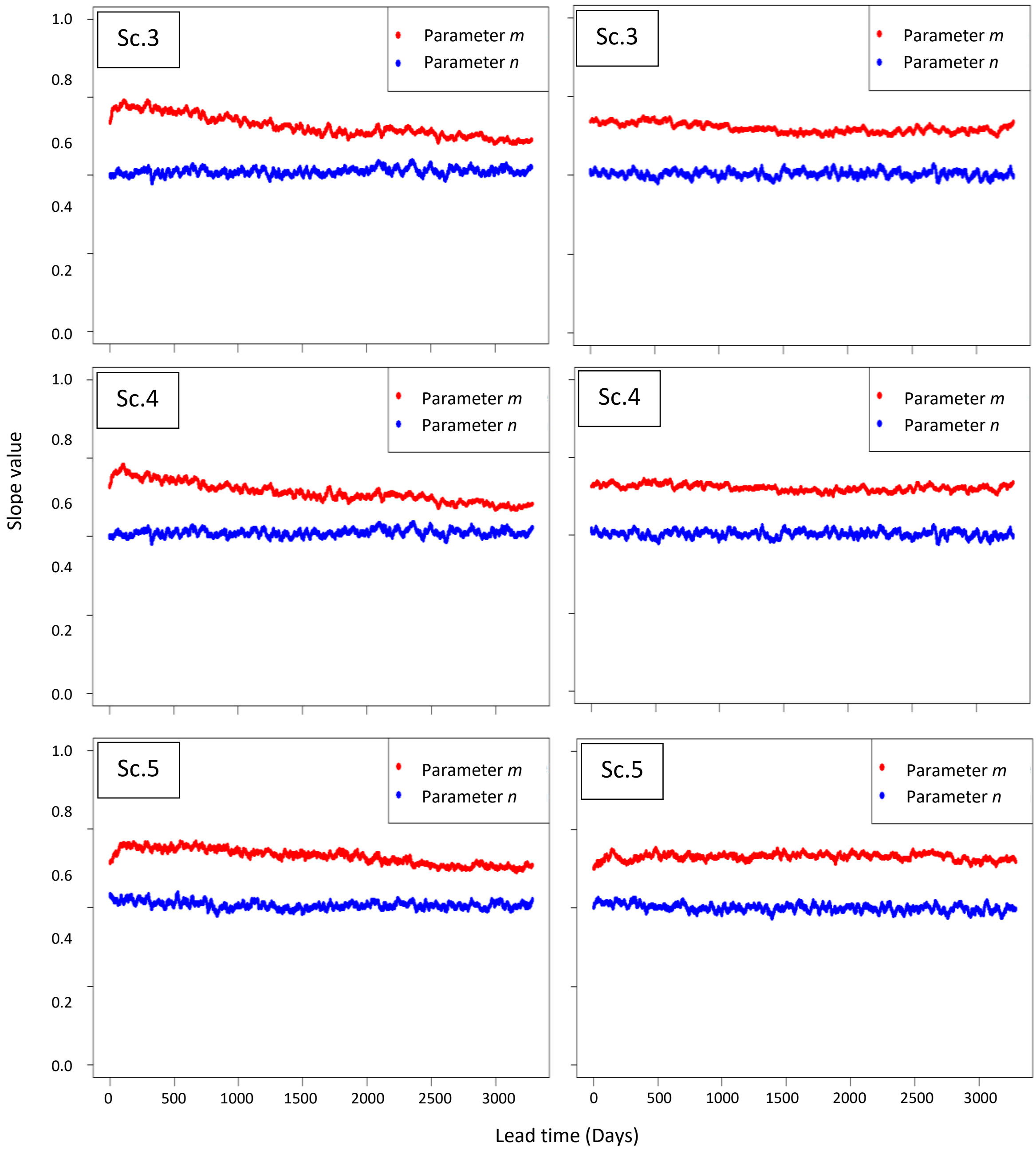


Figure 1, A.3.2: Parameters *m* and *n* for Scenario 1 to 5 for both catchments (CC skill score). The Gries catchment is shown on the left column, while the Findelen catchment is represented on the right column.

A.4. Analysis of *m* and *n* parameters for selected lead times

A.4.1. Analysis of selected lead times and for all Scenarios (1 to 5), RV skill score

Table 1, A.4.1: Variability of RV *m* and *n* slope parameters according to the glacier extent Scenario for Gries. The lowest value is marked in blue, while the highest value is marked in orange.

Leadtime	Gries catchment									
	Scenario 1		Scenario 2		Scenario 3		Scenario 4		Scenario 5	
	m	*n*	*m*	*n*	*m*	*n*	*m*	*n*	*m*	*n*
1	0.100	0.245	0.091	0.249	0.088	0.266	0.090	0.282	0.059	0.288
200	0.226	0.255	0.209	0.302	0.174	0.410	0.124	0.478	0.101	0.532
400	0.148	0.270	0.122	0.306	0.069	0.415	0.025	0.562	0.079	0.369
600	0.256	0.382	0.225	0.436	0.155	0.591	0.065	0.552	0.019	0.619
800	0.251	0.526	0.217	0.570	0.156	0.668	0.081	0.654	0.014	0.401
1000	0.310	0.309	0.277	0.364	0.185	0.445	0.095	0.454	0.209	0.499
1200	0.271	0.251	0.241	0.274	0.190	0.346	0.140	0.435	0.182	0.320
1400	0.357	0.231	0.309	0.265	0.218	0.334	0.145	0.403	-0.001	0.399
1600	0.315	0.509	0.260	0.518	0.172	0.547	0.107	0.558	0.034	0.460
1800	0.478	0.393	0.449	0.432	0.399	0.520	0.327	0.586	0.065	0.432
2000	0.434	0.375	0.412	0.411	0.371	0.512	0.287	0.577	0.082	0.520
2200	0.406	0.167	0.355	0.182	0.252	0.201	0.179	0.226	0.072	0.330
2400	0.437	0.352	0.388	0.373	0.310	0.445	0.231	0.521	0.089	0.361
2600	0.389	0.338	0.364	0.368	0.309	0.430	0.220	0.440	0.063	0.158
2800	0.422	0.313	0.400	0.352	0.367	0.447	0.243	0.420	0.099	0.299
3000	0.500	0.515	0.468	0.565	0.390	0.646	0.304	0.731	0.023	0.569
3200	0.572	0.265	0.540	0.282	0.467	0.316	0.401	0.355	0.195	0.245
3284	0.522	0.350	0.497	0.379	0.437	0.434	0.379	0.515	0.248	0.582

Table 2, A.4.1: Variability of RV *m* and *n* slope parameters according to the glacier extent Scenario for Findelen. The lowest value is marked in blue, while the highest value is marked in orange.

Leadtime	Findelen catchment									
	Scenario 1		Scenario 2		Scenario 3		Scenario 4		Scenario 5	
	m	*n*	*m*	*n*	*m*	*n*	*m*	*n*	*m*	*n*
1	0.095	0.236	0.097	0.239	0.068	0.240	0.059	0.255	0.019	0.246
200	0.297	0.274	0.290	0.264	0.231	0.318	0.155	0.356	0.094	0.217
400	0.375	0.172	0.367	0.175	0.337	0.201	0.265	0.208	0.059	0.194
600	0.307	0.214	0.328	0.211	0.233	0.233	0.173	0.256	0.079	0.261
800	0.352	0.192	0.367	0.204	0.297	0.242	0.252	0.333	0.157	0.054
1000	0.325	0.194	0.332	0.210	0.244	0.169	0.181	0.146	0.049	0.110
1200	0.480	0.301	0.491	0.348	0.401	0.343	0.276	0.313	0.096	0.261
1400	0.455	0.244	0.457	0.250	0.348	0.249	0.235	0.253	0.045	0.218
1600	0.507	0.301	0.519	0.307	0.411	0.304	0.284	0.276	0.098	0.241
1800	0.378	0.246	0.403	0.250	0.270	0.243	0.172	0.241	0.088	0.113
2000	0.525	0.433	0.557	0.444	0.422	0.471	0.311	0.523	0.106	0.331
2200	0.615	0.326	0.623	0.343	0.495	0.303	0.409	0.284	0.076	0.245
2400	0.735	0.249	0.731	0.247	0.615	0.276	0.521	0.334	0.388	0.147
2600	0.394	0.409	0.428	0.439	0.263	0.388	0.161	0.381	0.221	0.481
2800	0.551	0.298	0.560	0.310	0.438	0.311	0.334	0.338	0.152	0.230
3000	0.584	0.501	0.597	0.512	0.450	0.506	0.287	0.504	0.120	0.266
3200	0.712	0.449	0.679	0.443	0.584	0.459	0.471	0.480	0.050	0.144
3284	0.632	0.417	0.633	0.417	0.517	0.437	0.409	0.485	0.207	0.509

A.4.2. Analysis of selected lead times for all Scenarios (1 to 5), CC skill score

Table 1, A.4.2: Variability of CC *m* and *n* slope parameters according to the glacier extent Scenario for Gries. The lowest value is marked in blue, while the highest value is marked in orange.

Leadtime	Gries catchment									
	Scenario 1		Scenario 2		Scenario 3		Scenario 4		Scenario 5	
	m	*n*	*m*	*n*	*m*	*n*	*m*	*n*	*m*	*n*
1	0.175	-0.033	0.166	-0.036	0.164	-0.044	0.167	-0.060	0.269	0.118
200	0.456	0.099	0.451	0.090	0.444	0.070	0.393	0.064	0.358	0.016
400	0.413	0.008	0.391	-0.011	0.358	-0.055	0.321	-0.102	0.364	-0.127
600	0.513	-0.092	0.506	-0.095	0.450	-0.087	0.361	-0.066	0.316	0.035
800	0.484	0.044	0.458	0.031	0.404	0.006	0.315	-0.023	0.390	-0.121
1000	0.381	0.048	0.354	0.030	0.307	0.001	0.278	-0.030	0.432	-0.063
1200	0.353	0.064	0.338	0.063	0.317	0.058	0.317	0.054	0.295	0.054
1400	0.440	0.199	0.436	0.185	0.406	0.137	0.395	0.072	0.394	-0.007
1600	0.272	0.115	0.276	0.125	0.288	0.149	0.270	0.161	0.330	0.128
1800	0.259	0.033	0.247	0.029	0.220	0.030	0.207	0.020	0.255	-0.010
2000	0.218	0.241	0.212	0.238	0.203	0.229	0.187	0.219	0.284	0.068
2200	0.342	0.037	0.329	0.031	0.311	0.009	0.298	0.006	0.350	-0.092
2400	0.278	-0.024	0.266	-0.032	0.246	-0.069	0.220	-0.119	0.247	-0.132
2600	0.297	-0.175	0.289	-0.155	0.279	-0.121	0.238	-0.062	0.237	-0.085
2800	0.331	0.038	0.326	0.039	0.304	0.040	0.252	0.053	0.221	0.061
3000	0.252	-0.048	0.246	-0.053	0.213	-0.049	0.165	-0.027	0.264	0.010
3200	0.269	-0.153	0.249	-0.143	0.211	-0.120	0.193	-0.092	0.213	-0.023
3284	0.310	0.106	0.302	0.123	0.259	0.146	0.231	0.156	0.305	0.210

Table 2, A.4.1: Variability of CC *m* and *n* slope parameters according to the glacier extent Scenario for Findelen. The lowest value is marked in blue, while the highest value is marked in orange.

Leadtime	Findelen catchment									
	Scenario 1		Scenario 2		Scenario 3		Scenario 4		Scenario 5	
	m	*n*	*m*	*n*	*m*	*n*	*m*	*n*	*m*	*n*
1	0.199	0.027	0.199	0.025	0.195	0.040	0.218	0.042	0.091	0.002
200	0.323	0.023	0.321	0.018	0.279	0.031	0.256	0.052	0.374	0.076
400	0.421	0.016	0.404	0.007	0.410	0.014	0.425	0.019	0.451	-0.025
600	0.380	0.097	0.366	0.096	0.347	0.087	0.335	0.077	0.280	-0.048
800	0.382	-0.054	0.362	-0.046	0.368	-0.046	0.360	-0.030	0.513	-0.088
1000	0.300	0.107	0.289	0.120	0.292	0.096	0.295	0.087	0.283	0.052
1200	0.332	-0.056	0.310	-0.061	0.319	-0.051	0.326	-0.055	0.255	-0.036
1400	0.265	-0.071	0.252	-0.067	0.252	-0.080	0.262	-0.079	0.355	-0.172
1600	0.279	0.027	0.261	0.024	0.274	0.015	0.298	-0.005	0.260	0.023
1800	0.247	0.025	0.229	0.052	0.209	0.035	0.210	0.008	0.477	-0.296
2000	0.279	-0.096	0.253	-0.103	0.287	-0.096	0.306	-0.075	0.356	-0.025
2200	0.300	0.009	0.273	0.103	0.279	0.005	0.291	-0.010	0.362	0.076
2400	0.332	0.079	0.328	0.080	0.321	0.092	0.371	0.095	0.383	-0.060
2600	0.269	0.005	0.248	-0.006	0.258	0.037	0.268	0.078	0.402	0.207
2800	0.320	-0.191	0.301	-0.198	0.356	-0.210	0.376	-0.157	0.207	0.070
3000	0.258	0.017	0.232	0.022	0.264	-0.001	0.263	-0.008	0.235	-0.095
3200	0.345	-0.051	0.334	-0.045	0.375	-0.068	0.422	-0.085	0.261	-0.049
3284	0.358	0.049	0.347	0.043	0.380	0.075	0.403	0.114	0.312	0.089

A.5. Results of skill transfer for GERM simulations

A.5.1. GERM simulations, RMSE skill score, example of the Findelen catchment (see Figure 18 for the results related to the simulations performed by the HBV model)

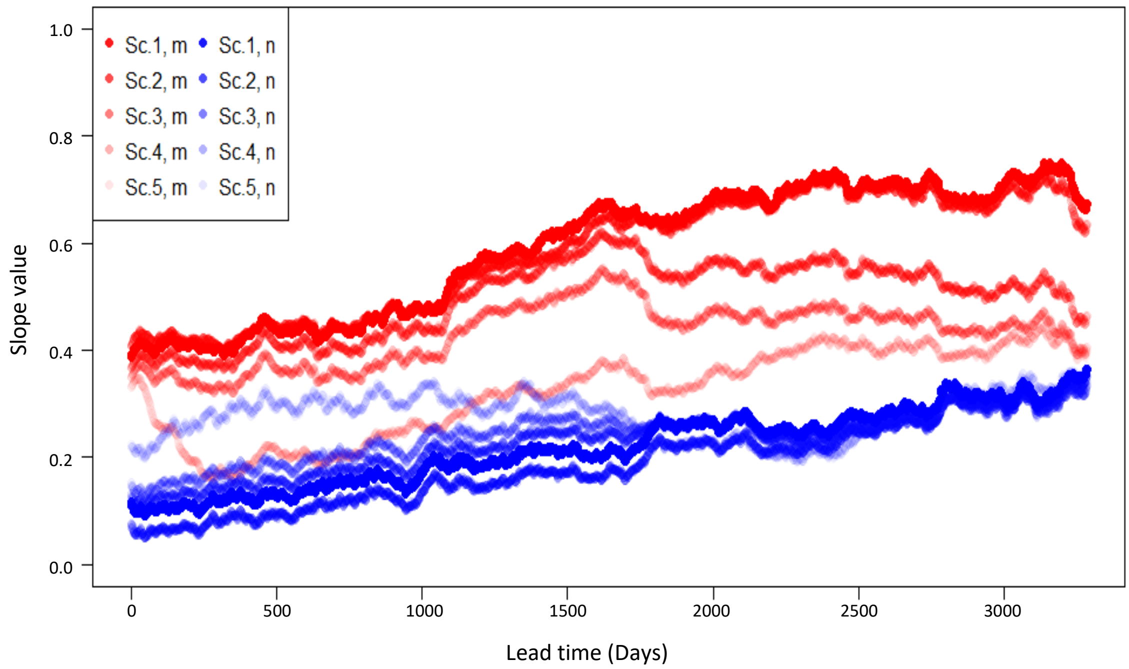


Figure 1, A.5.1: Parameters *m* and *n* for Scenarios 1 to 5 referred to the GERM simulations (RMSE skill score).

A.5.2. GERM simulations, CC skill score, example of the Findelen catchment (see Figure 18 for the results related to the simulations performed by the HBV model)

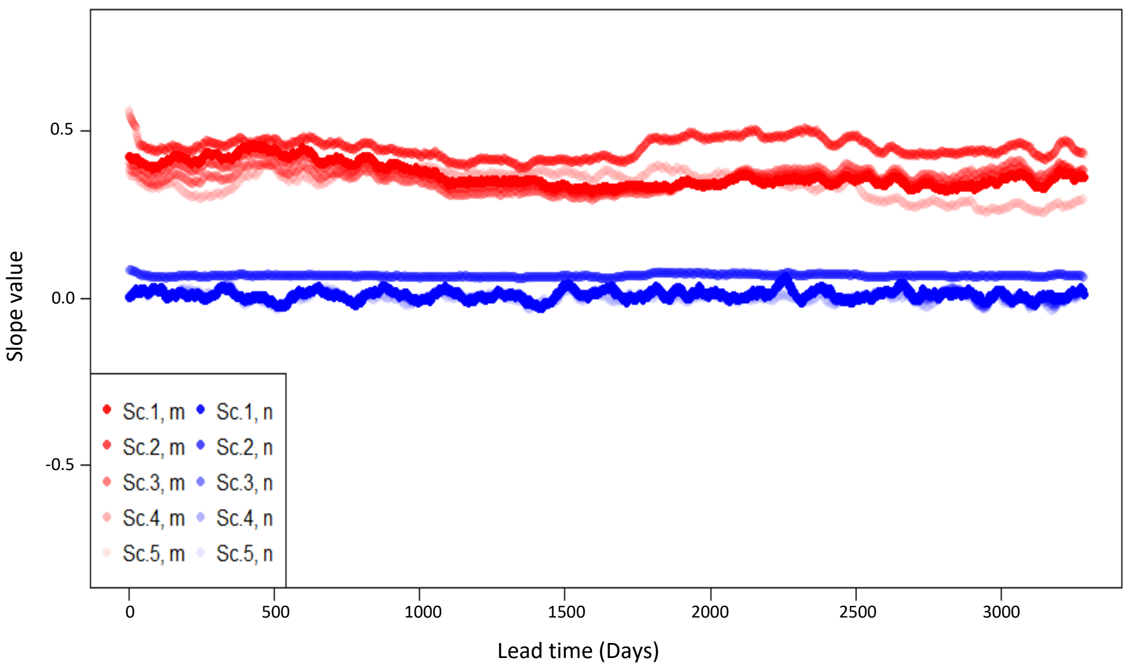


Figure 1, A.5.2: Parameters *m* and *n* for Scenarios 1 to 5 referred to the GERM simulations (CC skill score).

A.6. Comparison of skill transfer: static vs dynamic HBV glacier routine

A.6.1. Comparison between static and dynamic glacier routines for RMSE (only RMSE is shown, for RV and CC slight differences between the two routines have been detected)

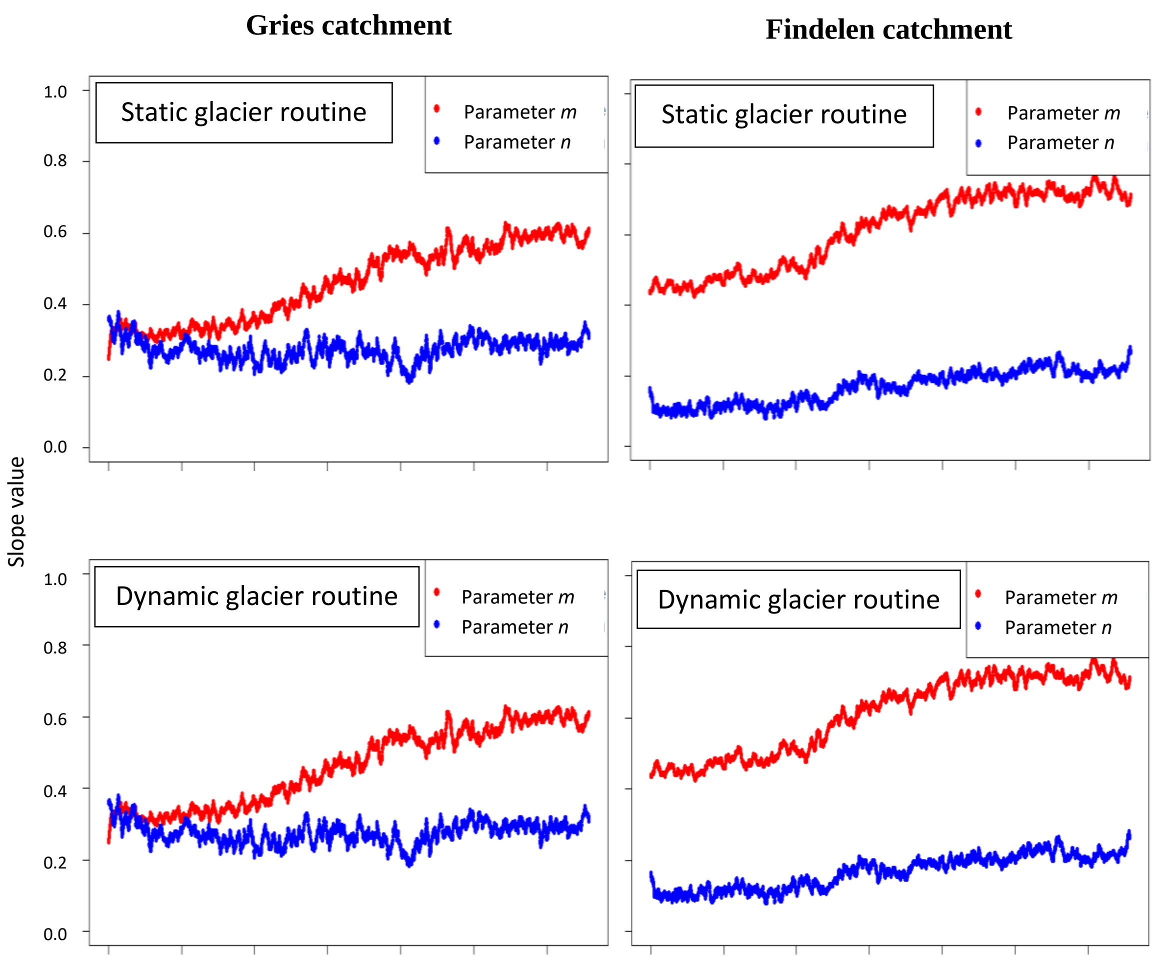


Figure 1, A.6.1: Comparison of the slope parameters *m* and *n* between the static and dynamic glacier routines for Scenario 1. Gries catchment is shown on the left column, while Findelen catchment is shown on the right column.

A.7. Skill difference between *Tskill*, *Pskill* and *Qskill*

A.7.1. Skill difference between *Tskill*, *Pskill* and *Qskill*, RV skill score

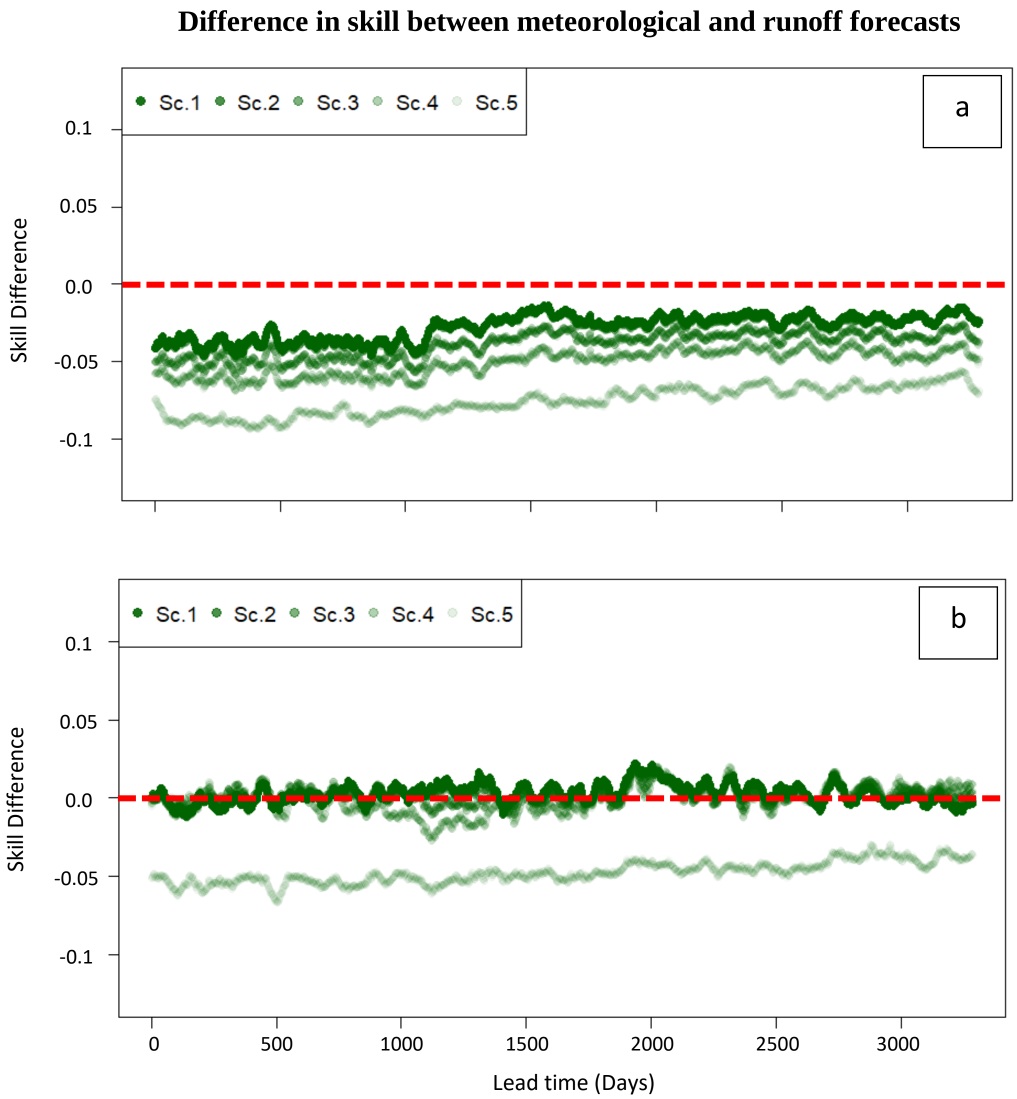


Figure 1, A.7.1: Difference in RV skill between meteorological and runoff forecasts over all lead times. Each line refers to a Scenario (each scenario is defined by a different degree of color saturation) for both Gries (a) and Findelen (b) catchments. The formula $\frac{(Tskill+Pskill)}{2} - Qskill$ has been applied to determine skill difference.

A.7.2. Skill difference between *Tskill*, *Pskill* and *Qskill*, CC skill score

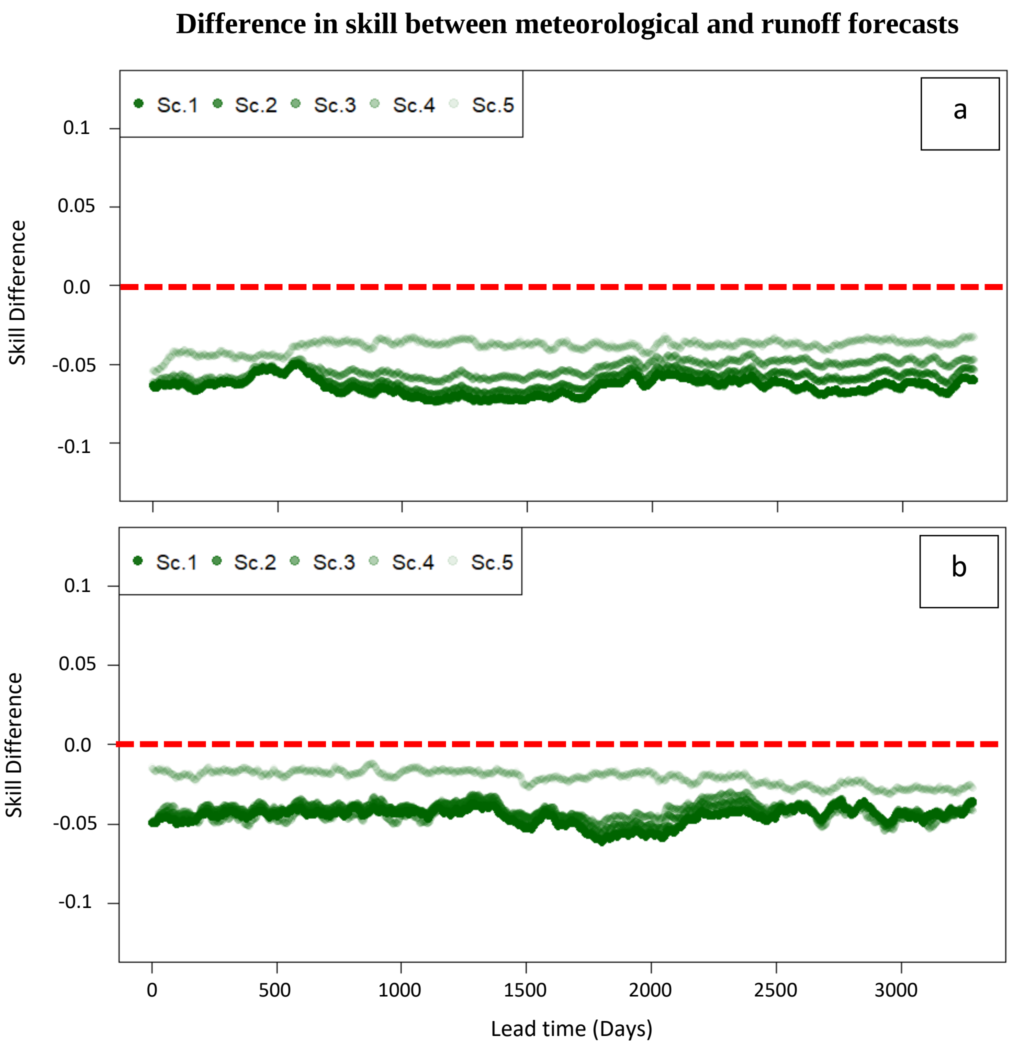


Figure 1, A.7.2: Difference in CC skill between meteorological and runoff forecasts over all lead times. Each line refers to a Scenario (each scenario is defined by a different degree of color saturation) for both Gries (a) and Findelen (b) catchments. The formula $\frac{(Tskill+Pskill)}{2} - Qskill$ has been applied to determine skill difference.

A.8. HBV simulations of hydrological properties

A.8.1. Runoff hydrological regime

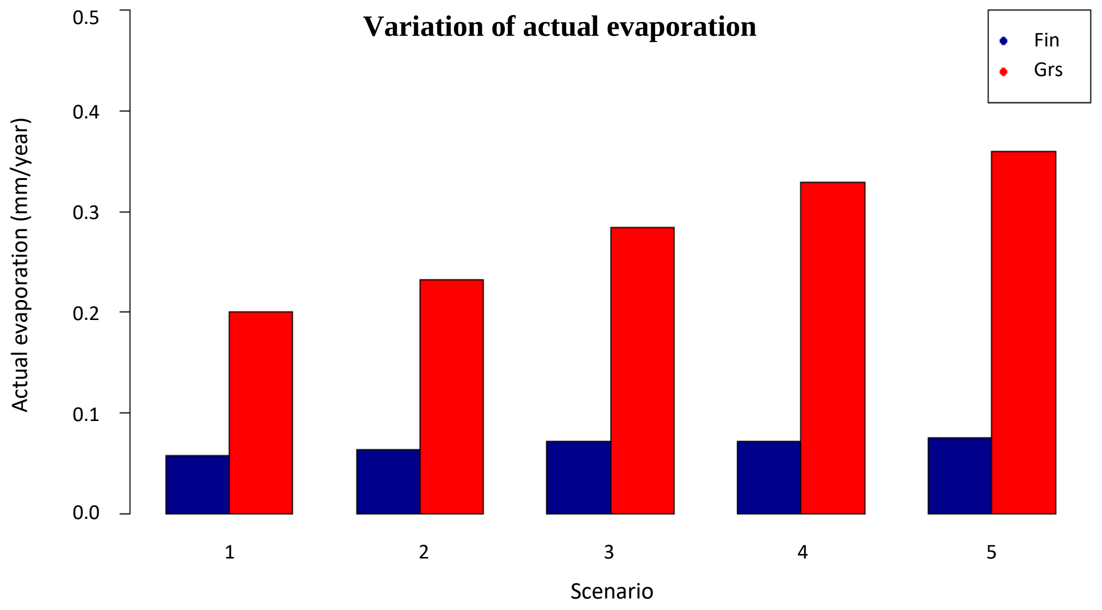


Figure 1, A.8.1: Variability of actual evaporation according to each glacier extent scenario. Findelen („Fin“) catchment is represented in blue, while Gries („Grs“) catchment is indicated in red.

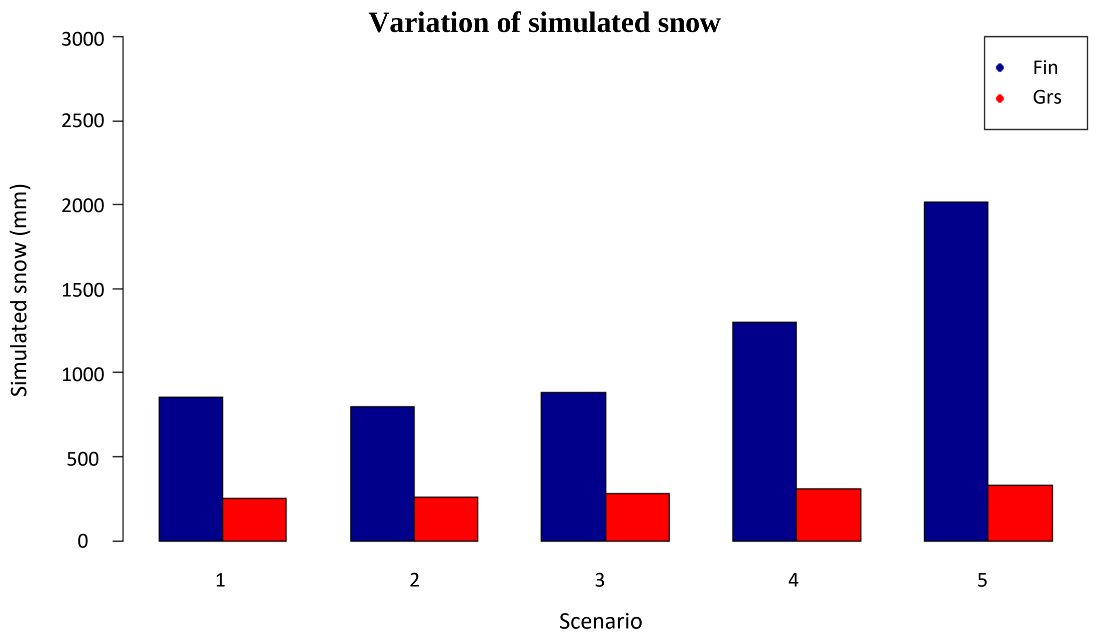
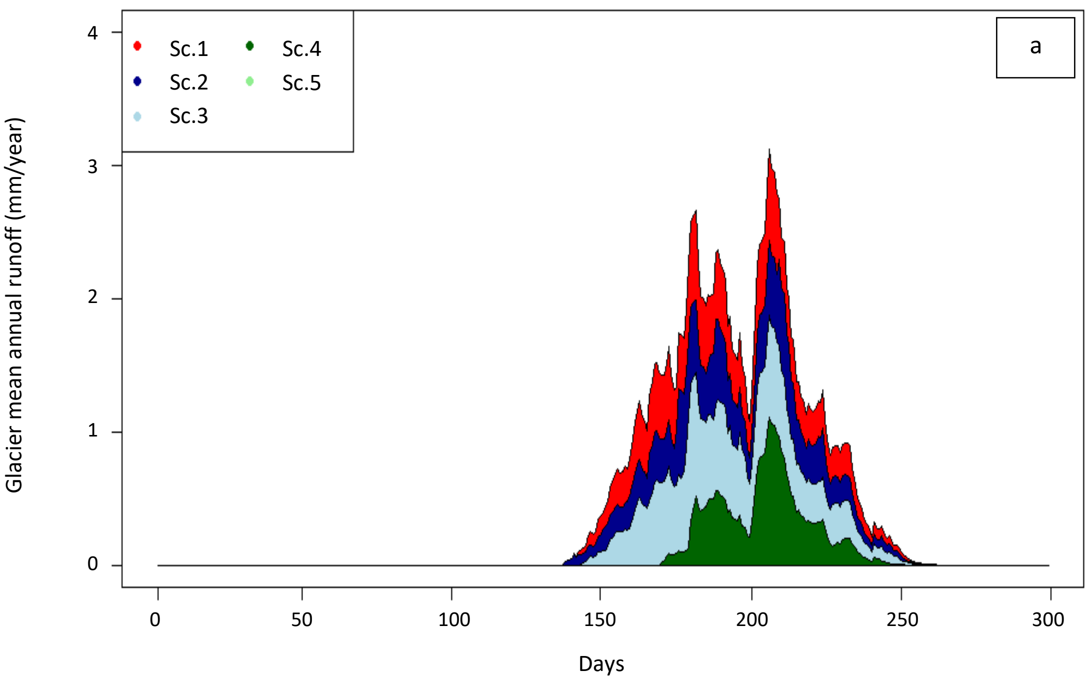


Figure 2, A.8.1: Variability of simulated snow according to each glacier extent scenario. Findelen catchment („Fin“) is represented in blue, while Gries („Grs“) catchment is indicated in red.

Findelen glacier melt runoff (Scenarios 1-5)



Gries glacier melt runoff (Scenarios 1-5)

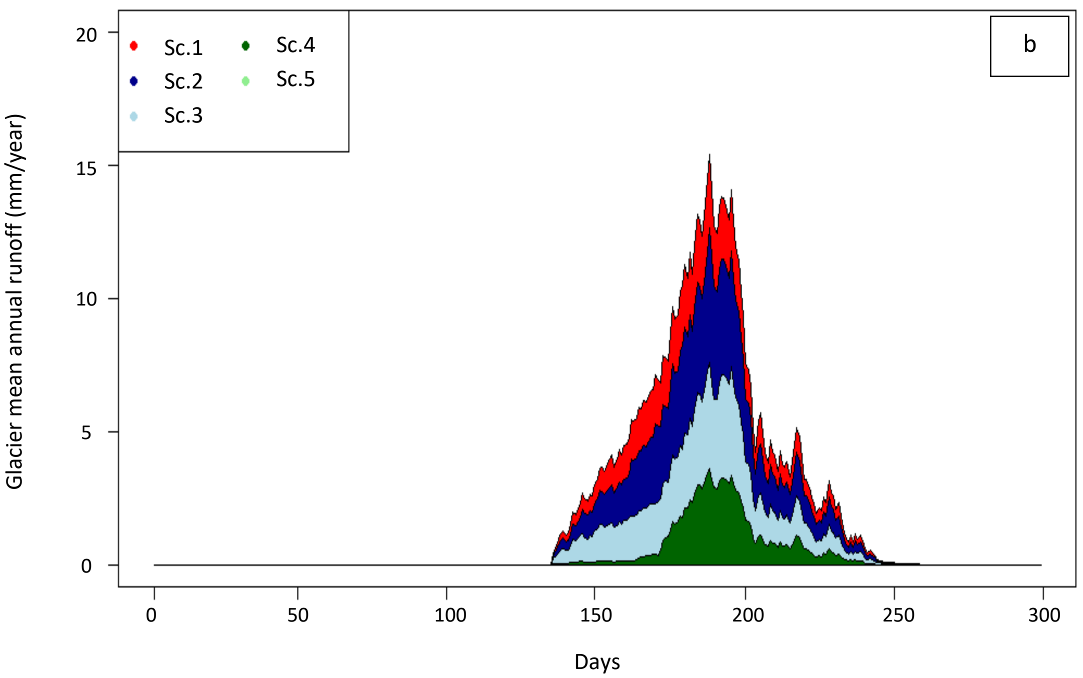
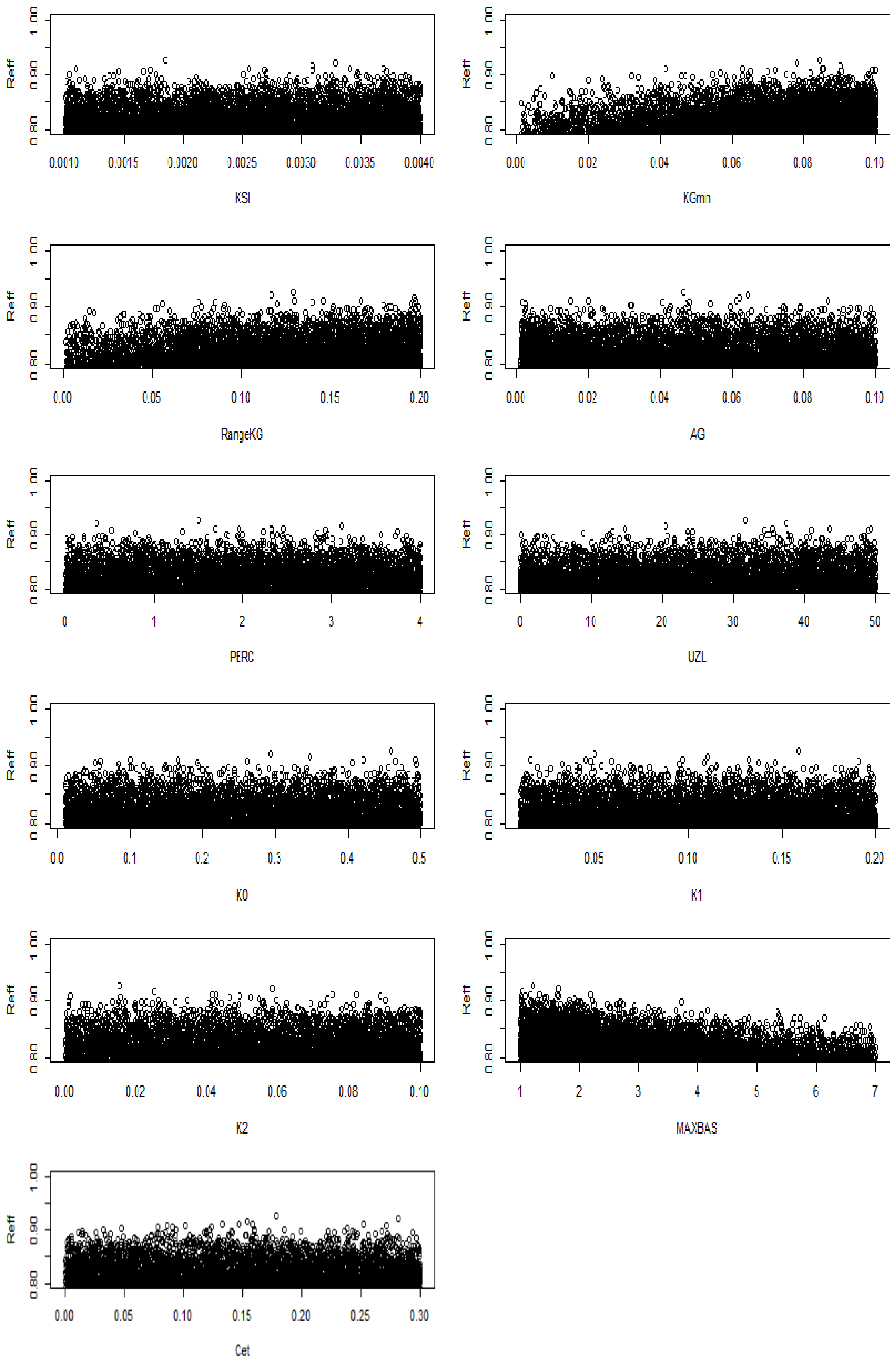


Figure 3, A.8.1: Variability of simulated glacier melt runoff for Findelen (a) and Gries (b) catchments. Each colored polygon corresponds to a different Scenario related to a variable glacierization.

A.9. Sensitivity analysis on the hydrological model HBV

A.9.1. Variability of model efficiency for each parameter and routine



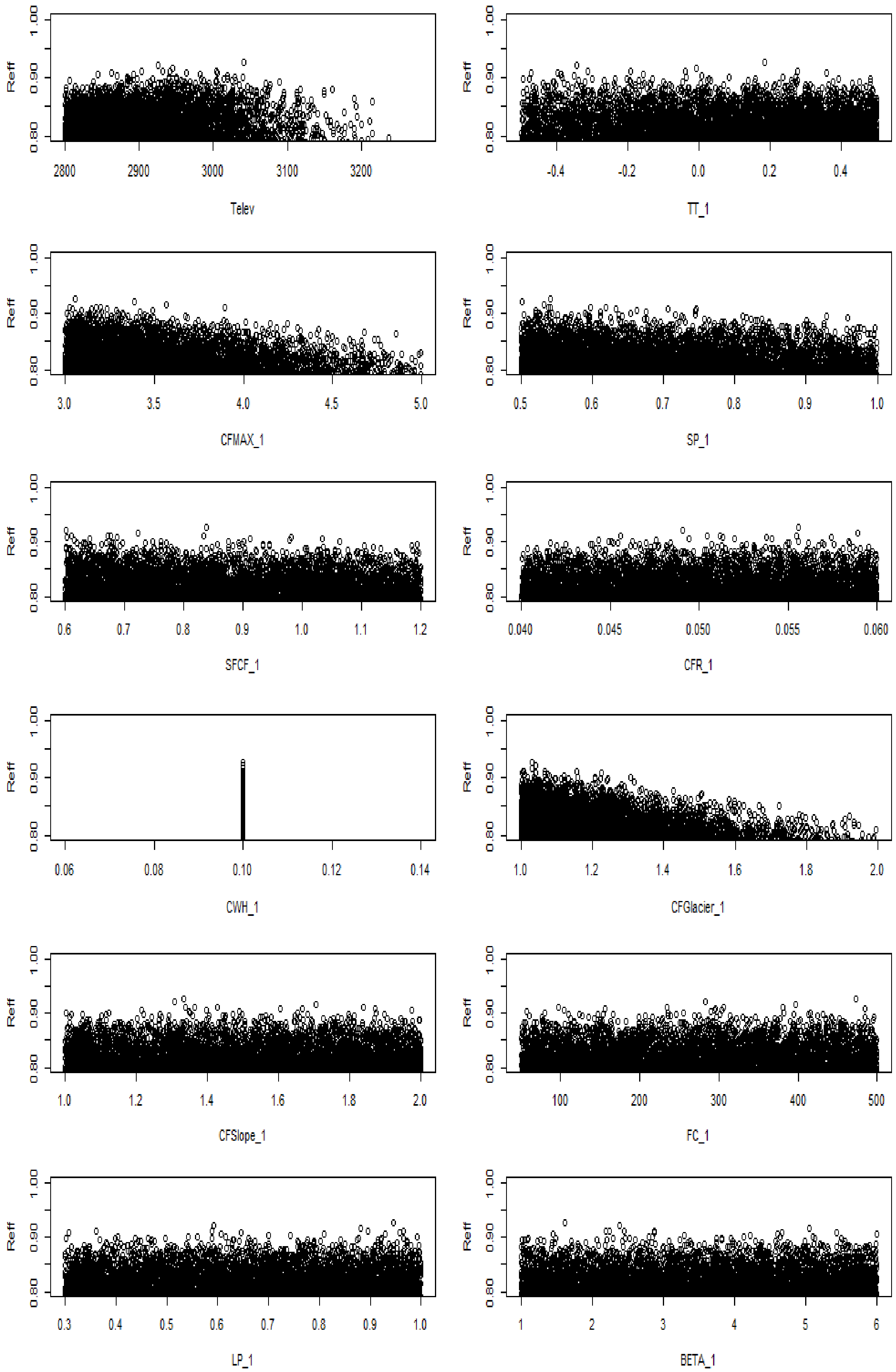
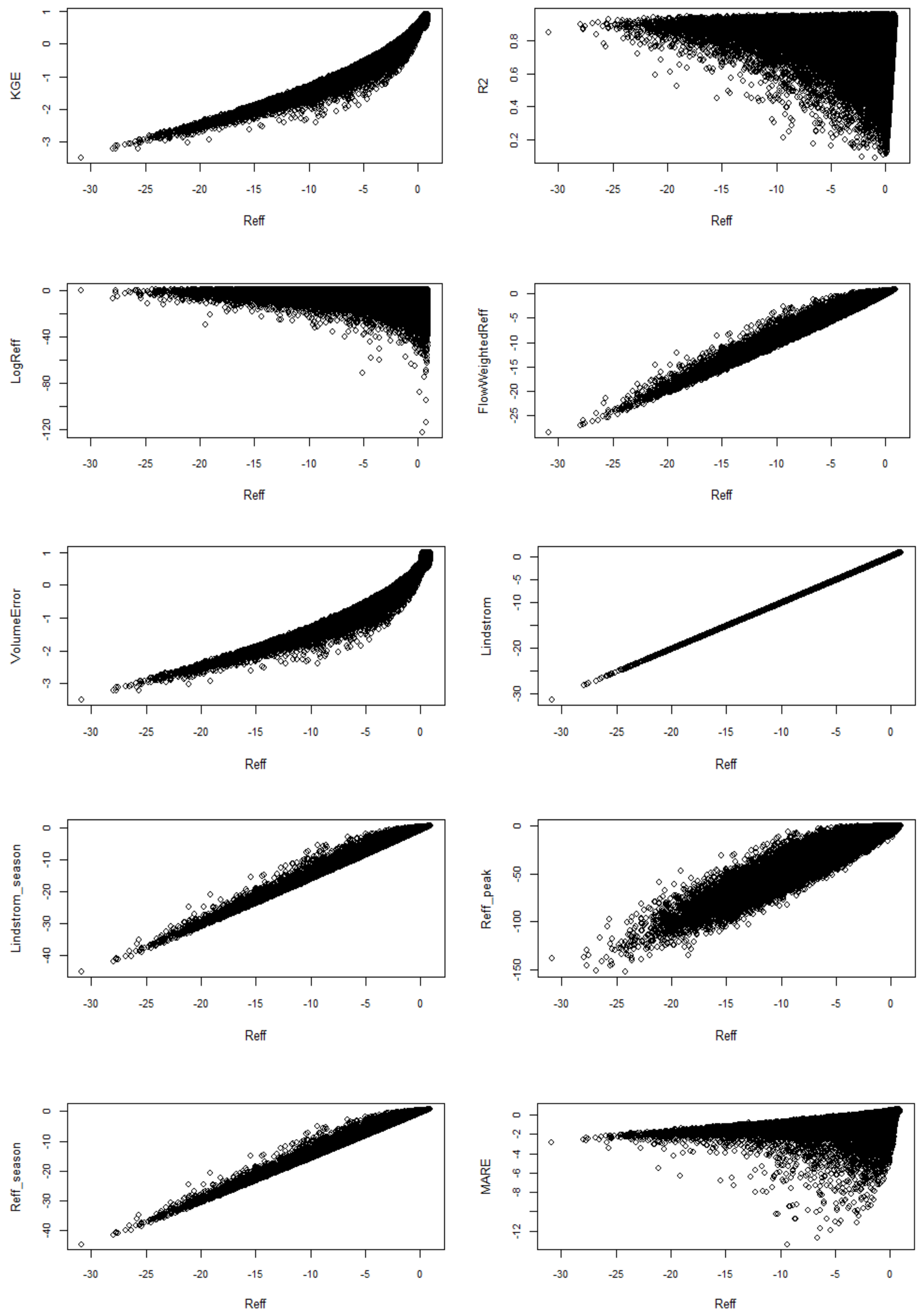


Figure 1, A.9.1: Example of sensitivity analysis performed on all parameters and routines of the HBV model. The procedure has been repeated for both catchments with the „realistic“ Monte-Carlo calibration (Section 3.3).

A.9.2. Comparison between different model efficiency criteria



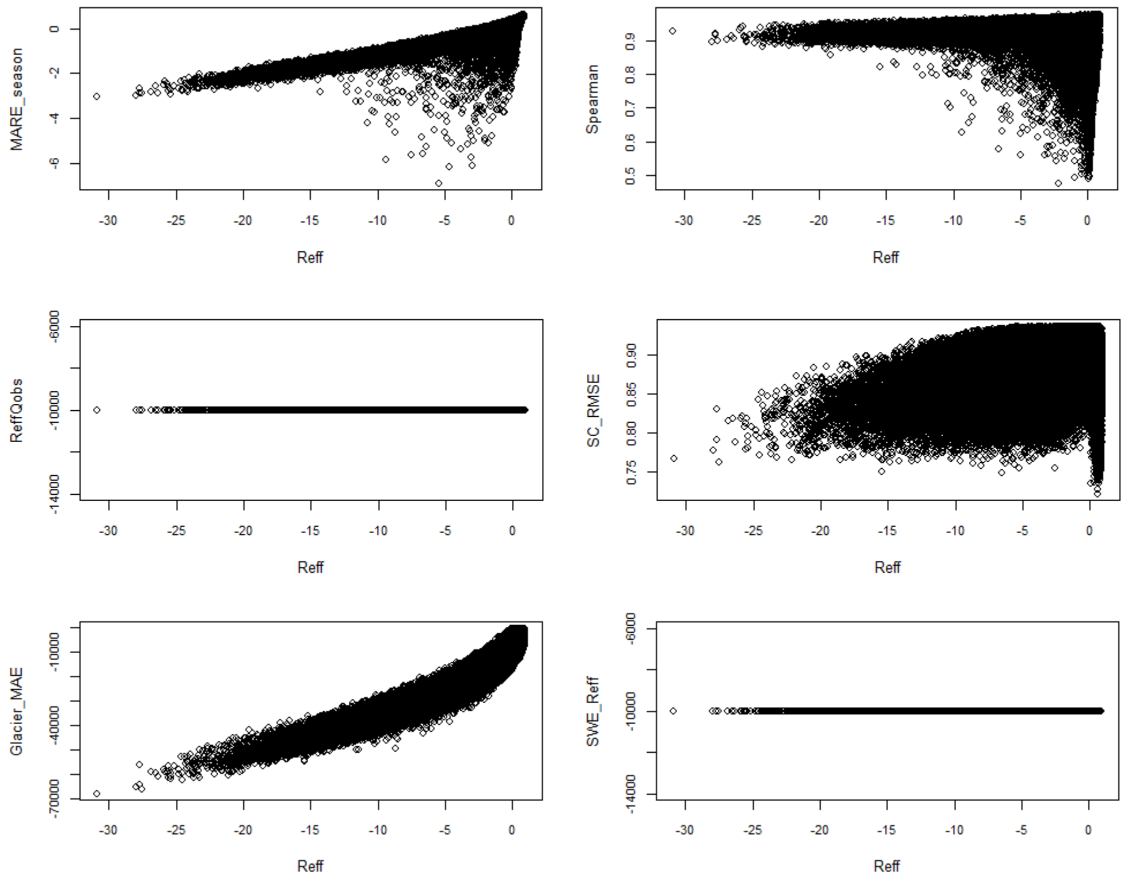


Figure 1, A.9.2: Example of comparative analysis on the efficiency criteria of the HBV model.