



Doctoral School in
Agrifood and Environmental Sciences

Michele Bozzoli

Snow dynamics in the Alps: long-term trends and remote
sensing-driven hydrological modeling

Supervisor(s)
Dr. Giacomo BERTOLDI

Co-supervisor(s)
Prof. Giuseppe FORMETTA, Dr. John Mohd WANI

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“Today’s snow is tomorrow’s water”.

Francesco Avanzi

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Abstract

Snow represents a key component of the Alpine hydrological cycle, strongly influencing water availability, ecosystems, and natural resource management. In the context of rapid climate change, understanding the evolution of snow conditions and developing reliable tools for snow monitoring have become increasingly important, particularly in mountain regions. This PhD thesis addresses these issues by focusing on the Central Alps region, considering long-term observational analyses and innovative monitoring approaches integrating satellite remote sensing, hydrological modeling and machine learning.

In the first part of the work, long term changes in snow conditions are investigated using in-situ snow and meteorological observations. The results reveal a pronounced decrease in seasonal snow accumulation, with statistically significant negative trends at the regional (Trentino – South Tyrol) and Alpine scales. These changes are particularly evident at mid-to low elevations and are consistent with increasing winter air temperatures, leading to changes in snow/rain partitioning.

These findings highlight the need for effective tools to monitor the spatial and temporal variability of snow and snowmelt dynamics. In this context, Sentinel satellite missions provide valuable information due to their high spatial and temporal resolution. However, satellite observations alone are insufficient to fully characterize key snow variables such as SWE, which is essential for quantifying the amount of water stored in the snowpack.

The final part of this thesis presents an innovative framework for integrating remote sensing products into a semi-distributed hydrological model with the aim of improving spatial estimates of SWE. The proposed method enables the downscaling of the semi-distributed hydrological model GEOframe with high-spatially distributed satellite-derived snow cover duration information, using a machine learning approach. In this way, the catchment-scale mass balance of the hydrological model is preserved, addressing one of

the main limitations of traditional data assimilation techniques. Results demonstrate that this integration leads to a more realistic and spatially consistent representation of SWE and snowmelt processes, enhancing the model's ability to capture snow dynamics in complex Alpine environments, using limited observations for model training and minimal additional computational load.

Overall, this thesis advances the understanding of climate change impacts on Alpine snow and proposes a novel methodological strategy for snowmelt modeling, emphasizing the value of collecting long-term ground observations and integrating satellite remote sensing with hydrological models for hydrological applications and water resource management in mountain regions.

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List of Abbreviations

AMO Atlantic Multidecadal Oscillation

AO Arctic Oscillation

DEM digital elevation model

HN snowfall

HS snow depth

NAO North Arctic Oscillation

P precipitation

RF random forest

SAR synthetic aperture radar

SCA snow cover area

SCD snow cover duration

SWE snow water equivalent

TMEAN mean air temperature

Chapter 1

Introduction

In recent decades, the Alpine region has experienced strong and persistent warming. Air temperature has increased faster than the global average, with particularly pronounced changes since the 1980s (Dumont et al., 2025; Zimmermann et al., 2013). This warming is having clear effects on the cryosphere and, in particular, on seasonal snow. Decreases in snow cover area (SCA), snow cover duration (SCD), snow depth (HS), and snow water equivalent (SWE) have been reported in several regions, especially at low and mid elevations (Colombo et al., 2022; Marke et al., 2018; Marty et al., 2023; Matiu et al., 2021; Olefs et al., 2020; Valt & Cianfarra, 2010). These changes are generally attributed to increasing temperatures, which affect both snow accumulation and melt. The decline in seasonal snow has been identified by the Intergovernmental Panel on Climate Change (IPCC) as a key indicator of climate change, reflecting the strong dependence of snowpack dynamics on air temperature. These changes have widespread implications. Snow plays a crucial role in regulating the hydrological cycle by acting as a natural water reservoir, storing precipitation during winter and releasing it during spring and summer. A reduction in snow accumulation and earlier melt alter runoff seasonality and may significantly affect water availability downstream (Bavay et al., 2009; Milner et al., 2017). Beyond hydrology, snow is a fundamental component of the Alpine socio-ecological system, influencing ecosystem functioning, hydroelectric production, agricultural water supply, and economic activities such as winter tourism (Aragon & Hill, 2024; Beniston, 2012; Rixen et al., 2011). Understanding how snow conditions are changing in the Alps is therefore essential.

The research activity of the PhD was structured into two complementary parts. The first part focused on the climatological analysis of long-term snowfall (HN) variability and

trends in the Alpine region, with the aim of quantifying recent changes and identifying their main meteorological and large-scale atmospheric circulation drivers. The second part addressed the hydrological implications of these changes by developing snow modeling approaches that integrate remote sensing observations with hydrological models to improve the spatial representation and estimation of SWE and snow-melt processes.

1.1 Snowfall long-term trends analysis in the Alps

As previously mentioned, numerous studies have documented declines in snow-related variables across the Alps, especially at low and mid elevations. However, most of the existing literature has focused on variables that describe the state of the snowpack, rather than on HN itself, which represents the main input to the seasonal snow reservoir. HN is a key variable for understanding snowpack evolution. It directly reflects the interaction between precipitation (P) and mean air temperature (TMEAN), as it depends on both the amount of P and its phase. Changes in HN therefore provide direct information on how climate change is altering P regimes in mountain regions (Serquet et al., 2011). Despite its importance, HN has received relatively limited attention in Alpine-scale studies. This is partly due to data limitations and to the complexity of HN measurements in mountainous terrain (Levizzani et al., 2011). As a result, there is still an incomplete picture of how HN has changed across different elevations, seasons, and regions of the Alps, and how these changes relate to other meteorological drivers.

The Alps are characterized by a dense but heterogeneous network of meteorological stations. These include official stations operated by national and regional agencies, as well as long-term observations collected by local institutions and amateur observers. While official networks provide high-quality data, they often are scarce, both at high elevations, where observations are more complex, and at low elevations, where HN is less frequent, but more affected by climatic variability. Amateur observation networks are increasingly contributing to complement official meteorological by filling these gaps (Endfield & Morris,

2012; Wolters & Brandsma, 2012). However, combining data from different sources requires careful data collection, quality control, and homogenization (Buchmann et al., 2022, 2023; Marcolini et al., 2019). A part of the research activity during this PhD was dedicated to building consistent HN datasets by integrating official and non-official station data.

The first HN database was composed of 122 time series from snow monitoring stations in the Trentino–South Tyrol region, covering the period 1980–2020. Specifically, the dataset collected by Matiu et al. (2021) was further extended and validated by considering 115 series of daily HN observations provided by the Meteorological Services of the Provinces of Bolzano and Trento. These were integrated with 7 HN time series at monthly resolution provided by the amateur association Meteo Trentino–Alto Adige (MTTA), which allowed to increase the data coverage below 1000 m a.s.l. The second HN database included 70 stations in the Alpine region with at least 100 years of data. However, only 46 were suitable for trend analysis due to fragmented and incomplete records in the remaining stations, which were used only for homogenization. Since data availability was highest in the early 1900s and decreased in recent years because several records had not yet been fully updated at the time of data collection, the analysis focused on the 1920–2020 period. Data were kindly provided by several organizations, including GeoSphere Austria (GSA), the Swiss Federal Office of Meteorology and Climatology (METEOSWISS), the Slovenian Environment Agency (ARSO), Società Meteorologica Italiana (SMI), Meteotrentino (MTN), Meteo Trentino–Alto Adige (MTAA), Società Meteorologica Alpino-Adriatica (SMA-A), Fondazione Osservatorio Meteorologico Milano Duomo (OMD), and Osservatorio Meteorologico di Parma (OMP). This effort made it possible to improve spatial coverage and to perform robust climatological analyses over long time periods.

Using these datasets, statistical analyses were conducted to assess HN variability and long-term trends in the Trentino–South Tyrol region and across the Alpine area, following widely adopted non-parametric approaches commonly applied to hydro-climatic time series. Trends were quantified using the Sen’s slope estimator and their significance evaluated

with the Mann–Kendall test (Kendall, 1975; Mann, 1945; Sen, 1968). Relationships between HN and key meteorological variables (TMEAN, P) were examined through Pearson correlation (Freedman et al., 2007), while the influence of large-scale atmospheric circulation was explored using teleconnection indices (Arctic Oscillation (AO), North Arctic Oscillation (NAO), Atlantic Multidecadal Oscillation (AMO)). The relative contribution of multiple drivers was further assessed through ANOVA based on multiple linear regression models (R. Miller, 1997). Overall, the results indicate a widespread decline in HN, particularly over the 1980–2020 period and at low to mid elevations, whereas higher elevations show weaker trends, which are often not significant or even slightly positive. The methods and results of these analyses are presented and discussed in detail in Chapter 2 and 3 forming the basis of this thesis.

1.2 Snow modeling in mountain catchments

Changes in HN regimes directly affect the hydrological response of Alpine catchments. Snow acts as a temporary storage of water, releasing it during the melt season. A reduction in HN and a shift toward warmer conditions lead to changes in both the amount and timing of snowmelt. In many mountain basins, these changes translate into increased and earlier snowmelt, altered seasonal runoff patterns, and reduced water availability during summer (Majone et al., 2016). To quantify these impacts, it is necessary to accurately estimate the amount of water stored in the snowpack and its spatial distribution.

Within this context, this PhD activity also contributed to the "SnowTinel" project, which comes from a collaboration between the WSL Institute for Snow and Avalanche Research SLF (WSL/SLF) in Davos and EURAC Research in Bolzano, supported by the Swiss National Science Foundation and the Province of South Tyrol in Italy. The project focuses on improving the monitoring and modeling of snowmelt processes in mountain environments through the integration of radar remote sensing, in situ observations, and snow and hydrological modeling (Fig. 1).

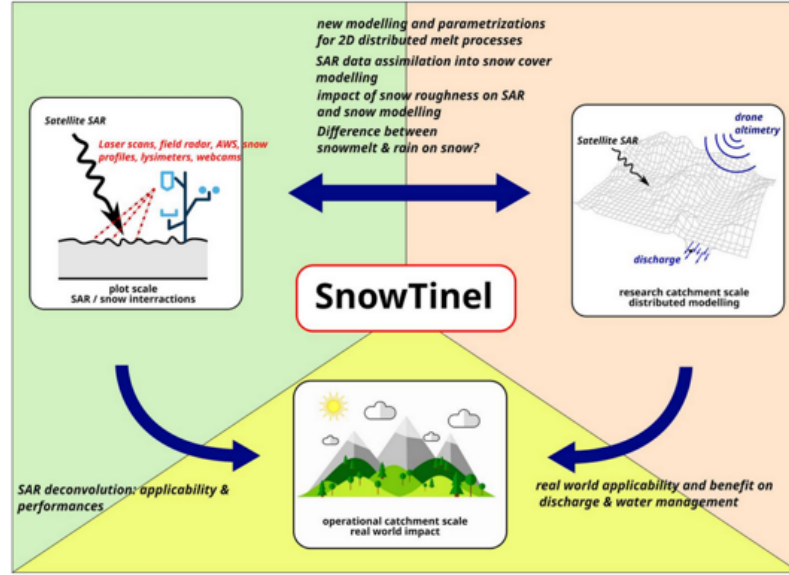


Figure 1 – Conceptual scheme of the “SnowTinel” research project.

The project exploits the high spatial and temporal resolution of synthetic aperture radar (SAR) data acquired by the radar sensors onboard Sentinel-1 to improve the detection of wet snow conditions and melting phases (Marin et al., 2020). In addition, optical data from Sentinel-2 are used to monitor snow cover evolution (Premier et al., 2023). These complementary sources of information allow the transfer of snow-related information across spatial scales, from local experiments to headwater and larger Alpine catchments. The analyses are conducted at three representative scales, ranging from the radar footprint at the Davos Laret site ($\sim 1 \text{ ha}$), to a small headwater basin in the Dischma Valley ($\sim 40 \text{ km}^2$) in Switzerland, and up to the larger Venosta catchment in South Tyrol ($\sim 1500 \text{ km}^2$). This PhD thesis focused on the Working Package (WP) 3 of the “SnowTinel” project, addressing catchment-scale applications. The research activities were developed and implemented for the Dischma Valley, which was selected as a representative Alpine case study to investigate snow-related processes and their hydrological implications at the basin scale. Ongoing work is currently extending the application to larger catchments, such as the Venosta basin (see Sec. 5.2). This multi-scale approach supports the development of methods for estimating SWE and snowmelt runoff more accurately, providing additional tools to link changes

in HN and snowpack dynamics with their hydrological consequences.

SWE is the key variable used to quantify snow storage and snowmelt potential. SWE represents the amount of water contained in the snowpack and is therefore essential for hydrological modeling. However, direct SWE measurements in the Alps are sparse and mostly limited to point-scale observations, which do not capture the strong spatial variability of mountain snowpacks (Guidicelli et al., 2021; Huss et al., 2015). Remote sensing provides valuable information on snow cover and snow dynamics with high spatial and temporal detail. Satellite observations are particularly effective in capturing the spatial variability and persistence of snow across complex mountain terrain (Z. S. Miller et al., 2022; Shaw et al., 2020). Nevertheless, remote sensing-based SWE estimates do not explicitly account for snow mass balance and often lack temporal consistency.

To bridge this gap, the second part of the PhD activity was dedicated to find how to best integrate remote sensing information with hydrological modeling. A first approach was carried out by directly incorporating the SWE product of Premier et al. (2023) into the semi-distributed hydrological model GEOframe (Formetta, 2013; Formetta, Antonello, et al., 2014; Formetta et al., 2011). In this configuration, the internal snow module of the model was bypassed, and the estimated SWE was prescribed as input, assuming it as a reliable representation of snow storage. However, this straightforward substitution led to a deterioration of the simulated streamflow performance. Thus, a second approach was tried in order to exploit the spatial detail provided by satellite observations and the mass balance closure ensured by physical hydrological models. In this second approach the catchment-averaged SWE simulated by GEOframe is redistributed pixel by pixel over the basin. Spatial redistribution is performed through redistribution factors estimated with a random forest (RF) regression function trained on terrain features (Breiman, 2001), derived from the swissALTI3D digital elevation model (DEM), and SCD information, derived from the multi-source remote sensing method of Premier et al. (2021). The validation dataset for the SWE maps is derived from high-resolution HS maps of Bührle et al. (2022) and then

converted to SWE by using the snow density parameters described by Jonas et al. (2009). This procedure produces SWE maps that reproduce realistic spatial patterns while remaining consistent with the simulated mass balance, thereby improving the representation of snow accumulation and melt dynamics at the catchment scale. The methodology, results and its application are described in detail in Chapter 4. The thesis ends with Chapter 5 that summarizes the main findings and discusses their broader climatic and hydrological implications, as well as future research perspectives.

1.3 Goals and aims

The main scope of the first part of this thesis is to provide a quantitative and spatially consistent assessment of how climate change is modifying HN in the Alps and how these changes influence snow storage and the hydrological response of mountain catchments. This objective is addressed through a set of guiding research questions: how is HN changing over time? Are trends uniform across the Alps, or do they exhibit regional and elevational differences? What are the main climatic drivers behind the observed changes? To answer these questions, the first objective is the construction of robust and homogeneous HN datasets by integrating official measurements with amateur and citizen science observations. This allows the development of long, quality-controlled, and comparable time series across different elevations and regions, while also exploring how official and non-official observations can be effectively combined. Using these data, the second objective is to describe variability and trends, and to identify the main drivers of HN changes in space and time. This provides a spatially consistent and multi-decadal view of HN changes and represents a key novelty of the work.

The second part of the thesis aims to investigate the hydrological impacts of changing HN by improving the estimation of SWE in mountain catchments. It is guided by the following research questions: does the integration of remote sensing products improve performances of a semi-distributed hydrological model? How this information can be inte-

grated without altering the overall water budget? As direct SWE measurements are sparse and limited to point locations, while both remote sensing products and hydrological models present structural limitations, a key objective is to develop approaches that combine these complementary sources of information in a physically consistent way. First, a simplified regression framework based on RF is developed to predict the spatial distribution of SWE using topographic features and SCD, avoiding the need for a full energy-balance formulation. Then, spatially distributed SWE maps are generated that reproduce realistic snow patterns while remaining constrained by the mass balance simulated by a hydrological model. This integrated strategy allows spatial detail from remote sensing to be incorporated into hydrological simulations without modifying the catchment-scale water balance, ensuring more realistic and consistent simulations of snow-melt processes.

Chapter 2

Diverging snowfall trends across months and elevation in the northeastern Italian Alps

This Chapter is published on the International Journal of Climatology on behalf of Royal Meteorological Society, with the title "Diverging snowfall trends across months and elevation in the northeastern Italian Alps". The paper has been coauthored by Giacomo Bertoldi, Alice Crespi, Michael Matiu, Lorenzo Giovannini, Dino Zardi, and Bruno Majone.

2.1 Abstract

Snowfall and snow accumulation play a crucial role in shaping ecosystems and human activities in the Alpine region. This resource is under threat as a consequence of the visible effects of global warming, and, therefore, it appears urgent to understand how snowfall trends have changed in time and space. In this context, we recovered data from over a hundred snowfall (HN) time series covering the period 1980-2020 over the mountain region of Trentino-South Tyrol in the northeastern Italian Alps and analysed them to understand snowfall climatology in the region, recent trends and their dependence on elevation and timing of the season.

Negative, although not always statistically significant, trends were found in the lowest elevation range (0-1000 m a.s.l.) over the whole winter season, while some positive and even significant trends were found from January to March above 2000 m a.s.l. The intermediate elevation range (1000-2000 m a.s.l.) exhibits a strong variability with no clear trend. Negative and statistically significant trends were found in April for all elevations.

An attribution analysis was performed using precipitation (P), mean air temperature (TMEAN), and large-scale synoptic descriptors, such as the North Atlantic Oscillation (NAO) and the Arctic Oscillation (AO) indices. The analysis shows that, overall, P is the driver that best explains the snowfall trends, but, for low elevations, especially during mid-winter, TMEAN is more relevant. Low elevations are facing a clear decrease in HN due to a significant increase in mean temperatures, while high elevations during mid-winter display a slight increase in HN, associated with a general increase in precipitation. NAO and AO indices exhibit no significant correlations with HN, except at the lowest elevations and at the beginning of the season.

2.2 Introduction

Snow is a key component of the water cycle in mountain watersheds, controlling timing and magnitude of runoff generation processes (Di Marco et al., 2021; Majone et al., 2016; Marke et al., 2018). Snow contributes to the seasonal storage of water that becomes available later through snowmelt, for agricultural, civil and industrial uses. Moreover, snow plays an important role in shaping the natural environment of mountain regions, affecting the vegetation cycle, mountain flora and fauna, biodiversity and related ecosystem services (Keller et al., 2005). Snow cover is also one of the key elements of the Earth's energy budget, since it strongly affects the surface heat and radiation balance, significantly influencing near-surface air temperature (Jin & Miller, 2007). Finally, the presence and availability of snow are the fundamental prerequisites for many economic and recreational activities, as, for instance, hydropower production (Majone et al., 2016) and winter mountain tourism (Olefs et al., 2020).

Considering current threats posed by climate change on the cryosphere (P. Frei et al., 2017; Huss et al., 2017; Kotlarski et al., 2022; Mote et al., 2018), it is urgent to recover historical snow observations to understand how snowfall trends have been changing over time. During the past decades, a decreasing trend has been detected from reanalyses for

snowfall amounts and snowfall days over most regions of Eurasia (Lin & Chen, 2022). Over northern Eurasia, H. Ye and Cohen (2013) found a mean decrease in the duration of the snowfall season of 6.2 days per 1°C of temperature increase, split between the start (-2.8 days) and end of the season (-3.4 days). The frequency of daily snowfall events is projected to further decrease across much of the Northern Hemisphere, except at the highest latitudes such as in northern Canada, northern Siberia, and Greenland (Danco et al., 2016).

Snow and snow cover can be quantified using different parameters. The most commonly used are snow depth (HS), depth of fresh snow precipitation (HN, also denoted as snowfall), snow water equivalent (SWE), snow cover area (SCA) and snow cover duration (SCD) (see e.g., Haberkorn (2019) and Pirazzini et al. (2018)). Almost all the studies available in the literature are focused on HS, SWE or SCD, while limited attention has been given to snowfall (HN). However, it is important to recover HN observations, understand its change over time and compare HN with liquid precipitation trends, as HN and the solid-liquid precipitation ratio are very sensitive to climate change (Guo & Li, 2015). Moreover, since snowfall is a solid precipitation, it is more easily compared with the liquid precipitation than with the snow depth. Therefore, the comparison of snowfall trends with those of liquid precipitation and mean air temperature is essential to better understand which of these two drivers plays a more important role depending on elevation and local climate, especially in mountain regions.

The detected general snow decrease over the Alps in the last decades is projected to continue during the 21st century on the basis of the available climate change scenarios (Kotlarski et al., 2022). Superimposed on the long-term trend, however, there is a low-frequency variability of snowfall associated with multi-decadal changes in the large-scale circulation. In fact, the leading mode of wintertime atmospheric variability over the North Atlantic-North Eurasia sector is dominated by the the Arctic Oscillation (AO) and the North Atlantic Oscillation (NAO), with this latter found to contribute significantly to recent trends in surface air temperature, snowfall, snow water equivalent and snow cover over Eurasia K.

Ye et al. (2022). For those reasons, in order to understand the major climatic drivers driving snowfall trends in the Alpine region, besides considering surface variables as precipitation and temperature, it is important to take in account large-scale indices as NAO and AO.

In recent years, several efforts have been undertaken to build reliable snow climatologies worldwide, including mountain regions, where orography strongly influences temperature and precipitation gradients and therefore snowfall climatology exhibits complex spatial patterns (Beniston et al., 2018; Pepin et al., 2022). In this respect, remote sensing (Hammond et al., 2018) and climate model reanalyses (Li et al., 2021; Olefs et al., 2020) can provide reliable spatially-distributed data, but with some limitations. In fact, on one hand, remote sensing can provide high-resolution information on snow covered area only after 2000 with the introduction of the MODIS constellation (Fugazza et al., 2021; Notarnicola, 2020). On the other hand, reanalyses may suffer from accuracy limitations (Vernay et al., 2022), mainly due to the low spatial resolution and to the poor representation of sub-grid processes (e.g., convection and associated precipitation, thermal inversion in mountain valleys controlling snowfall line). Both issues are particularly relevant in regions characterized by complex terrain (Kotlarski et al., 2014). In this context, it is evident that reliable identification of long-term snow trends should still mostly rely on long and accurate time series of ground observations. On the other hand, high-quality ground observations could serve for validating remote sensing and modelled snow products. Furthermore, detailed analyses of snowfall data are required to better constrain and quantify climate change impacts in mountain regions and their relation to elevation (Beaumet et al., 2021), whereby understanding how warming rates are stratified by elevation, which is still a current open research question (Pepin et al., 2022).

Focusing on the European Alps, a large number of snow-recording stations, operated by different authorities, some of them dating back to the late 18th century (Leporati & Mercalli, 1994), allow to draw a general picture of current snow trends. At the European scale, it has been observed that snow cover during the period 1972-2006 was related to

large scale atmospheric patterns, in particular it was strongly connected to AO observed during wintertime (Bartolini et al., 2010). Concerning SWE, a significant decrease has been noticed during the last six decades, more pronounced during spring than during winter, and quite independent of latitude and longitude (Marty et al., 2017). Also for snow depth, decreasing trends have been observed for the entire Alpine region by Matiu et al. (2021), who evaluated linear trends of mean monthly HS between 1971 and 2019 and concluded that 87% of the stations analysed are characterized by a decrease in snow depth, with stronger negative trends from March to May than from December to February.

At a regional scale, different studies were also performed taking advantage of databases from national monitoring networks. In particular, Marke et al. (2018) performed a comparison of SCD in different sub-regions of Austria during the periods 1950-1979 and 1980-2009, highlighting a general decreasing trend with mean changes between -11 and -15 days. Olefs et al. (2017) and Olefs et al. (2020) confirmed a negative trend for SCD, though not strongly related to elevation. In the Swiss Alps, Scherrer et al. (2013) calculated snow climate indicators such as new snow sums (NSS), maximum new snow (MAXNS) and days with snowfall (DWSF) and analysed their variability and trends. Looking at NSS, MAXNS and DWSF, they found a large decadal variability with phases of low and high values and the lowest values and unprecedented negative trends in the late 1980s and 1990s. This was confirmed also by Marty (2008). Analysing the number of days with snow cover from 34 long-term stations between 200 and 1800 m a.s.l., he found an unprecedented series of low snow winters in the last 20 years. In a more recent study, Marty and Blanchet (2012), using snowfall data from 25 stations (between 200 and 2500 m a.s.l.) collected during the last 80 winters (1930/31 to 2009/2010), discovered that all the stations, even the highest one, showed a decrease in extreme snow depth, which was mainly significant at low altitudes (below 800 m a.s.l.). A negative trend was also observed for extreme snowfalls at low and high altitudes, but the pattern at mid-altitudes (between 800 and 1500 m a.s.l.) was less clear.

In France, Durand et al. (2009) analysed snow data from the Crocus snow model driven by reanalyses in the period 1958-2005, highlighting that snow patterns are characterized by a marked declining trend from the northwestern foothills to the southeastern interior regions. This situation applies mainly to both HS and SCD, which exhibits a maximum variation at 1500 m a.s.l. of about 60 days, decreasing strongly with elevation. Moreover, they noticed that SCD shows a significant general signal of decrease at low and mid elevations, but this signal is weaker in the southern than in the northern France, and less visible at high elevation.

Finally, studies on snow trends are also available for northern Italy, although covering a limited spatial extent. Valt and Cianfarra (2010) highlighted the presence of breakpoints between 1984 and 1994. These breakpoints mark a drastic change of trend in the time series: a positive trend characterises the time series before the breakpoint and a decreasing trend characterises the historical record after the breakpoint. In particular, stronger negative trends below 1500 m a.s.l. were found during springtime, associated with a precipitation decrease. In Piedmont, the analysis of six long-term snow depth stations located between 960 and 2177 m a.s.l. highlighted a significant decrease of snow depth in the period 1951–2010, with the main contribution from spring months (Terzago et al., 2013). In the Adige catchment (Trentino-South Tyrol, northeastern Italy) Marcolini et al. (2017) analysed data of mean seasonal snow depth and SCD collected in the period 1980-2009, showing that different dynamics can be observed above and below 1650 m a.s.l., with a large reduction of average snow depth and SCD for stations below that elevation.

For the Italian Alps, numerous (300+) HN daily observations have been recently collected by Matiu et al. (2020), covering several decades, mainly collected by local institutions in mountain ski resorts for avalanche prevention purposes. However, observations are scarce, both at high elevations, where observations are more complex, and at low elevations, where snowfall is less frequent, but more affected by climatic variability. In the last years, amateur observation networks, managed by individuals with great competence and

passion, are increasingly contributing to complement official meteorological observation networks (Endfield & Morris, 2012; Mateus, 2021; Wolters & Brandsma, 2012). However, to our knowledge, such HN observations have never been exploited so far, at least for scientific climatological purposes.

The first objective of this study is to collect and analyse snowfall data of the northeastern Italian Alps during wintertime, coming from both official and amateur observations. The second objective is to analyse snowfall trends and compare them with those of snow depth, retrieved from Matiu et al. (2021). Another important purpose of this study is to understand what are the main factors influencing snowfall and its trend, depending on the elevation. We select four different drivers: precipitation (P), mean air temperature (TMEAN), North Atlantic Oscillation (NAO) and Arctic Oscillation (AO) indices. The first two are self-explanatory, as HN is directly influenced by both P and TMEAN. The other two are taken into consideration to evaluate if HN can be related to some indices of large-scale circulation patterns, as suggested for example by Quadrelli et al. (2001). Therefore, we conduct a so-called "driver attribution" analysis, in order to better understand which driver among P, TMEAN, NAO and AO plays a more relevant role to explain HN variability.

The paper is structured as follows: Sect. 2.3 and 2.4 describe all the preliminary operations done to prepare the database and the techniques used to evaluate statistics and trends. Sect. 2.5 provides results and Sect. 2.6 discusses them. Finally, Sect. 2.7 summarizes the results and draws some conclusions.

2.3 Study area and available data

The Trentino-South Tyrol region is located in the northeastern part of the Italian Alps. Its territory is mainly mountainous, with a mean elevation of 1600 m a.s.l. (Fig. 2). Elevations range from 65 m a.s.l. to 3900 m a.s.l., determining a strong local climatic variability. Valley floors typically experience warmer temperatures than mountainous areas, but with a much more pronounced annual temperature amplitude, with hot summers, but also low

temperatures in winter, especially for the frequent occurrence of ground based thermal inversions, associated with reduced incoming solar radiation. High elevation areas, on the other hand, experience colder temperatures and a smaller seasonal temperature range. Precipitation is influenced by orography, with higher values in the mountainous areas than in the valleys, especially over the mountain chains well exposed to southern moist airflows (see e.g., Laiti et al. (2018)). Precipitation is mainly concentrated in autumn and spring in the southern part of the region, while the regime is more continental in the northern part, close to the main Alpine divide, where maximum precipitations are experienced in summer (Brunetti et al., 2006). A comprehensive overview of the regional climate can be found in Chiogna et al. (2016) and Adler et al. (2015).

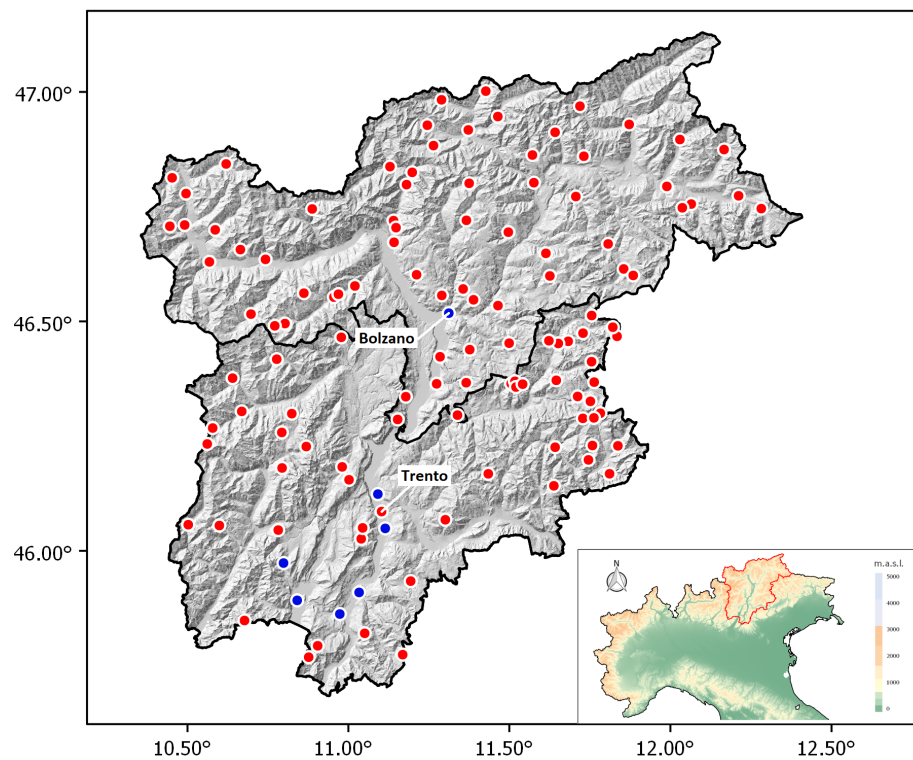


Figure 2 – The study region of Trentino – South Tyrol with institutional (red) and amateur (blue) snow stations (dots). The lower right inset shows the location of the study region in the Italian territory.

2.3.1 Data

The HN database exploited in this study is composed of 122 time series from long-term snow monitoring stations in the Trentino-South Tyrol region (Fig. 2). Most of the information was retrieved from the Alpine-wide observation database set up by Matiu et al. (2021). Specifically, we considered 115 series of daily HN observations provided by the Meteorological Services of the Provinces of Bolzano and Trento (red dots in Fig. 2). These data had already been preliminary quality-checked for detecting possible macroscopic wrong recordings (e.g., negative values of HN), but no detailed quality check had been performed before this work. For the present study, the database was integrated with 7 HN time series at monthly resolution, provided by the amateur association “Meteo Trentino-Alto Adige” (MTTA), which allowed to increase the data coverage below 1000 m a.s.l., especially in the Province of Trento (blue dots in Fig. 2). The official observations were collected by following the MOD1 AINEVA protocol (<https://content.meteotrentino.it/neve-ghiacci/Husky/mod1/legenda-mod1.pdf>), which requires a daily measurement of the snowfall over a wooden table in the early morning hours, generally between 7:00 and 9:00. Instead, the amateur stations measured the total snow accumulated at the end of the event on an empty and clean surface, a wooden table or short grass. If the event lasted several days, a measurement was taken once a day to mark the daily accumulation, with the exception of Riva del Garda and Rovereto stations (see Fig. 5a for the exact location), where measurements were taken three times a day, approximately every seven hours. At these two stations the daily total was calculated as the sum of the three measurements taken during the day. Following Helfricht et al. (2018), Anderson’s equation (Anderson, 1976) was used to estimate the measurement error due to snow settlement, which resulted in a maximum daily error of about 10% for standard snowfall rates (precipitation intensity less than 5 mm/h) and air temperature below 0 °C. This error is acceptable and in line with the one mentioned for the official networks. For more detailed information on the measuring procedures, we refer to the European Snow Booklet (Haberkorn, 2019). Values of HN were rounded to full

centimetres.

The spatial distribution of HN stations is quite uniform over the entire region, as shown in Fig. 2. In terms of elevation distribution, most of the sites (82) are located between 1000 and 2000 m a.s.l., 26 are below 1000 m a.s.l., and 14 are above 2000 m a.s.l. (Fig. 3a). Thanks to the technological development and the transition of the nivological monitoring competences to the autonomous provinces of Trentino-South Tyrol, the number of available stations strongly increased after 1980 (Fig. 3b).

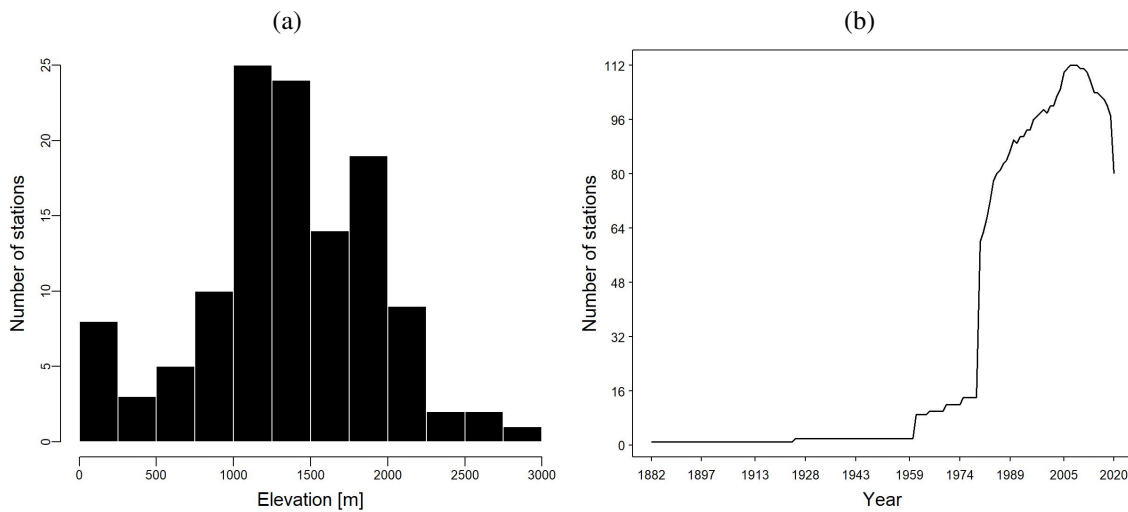


Figure 3 – Number of available stations per elevation (a) and year (b).

In order to better discuss and interpret HN trends, the monthly records of total snow depth (HS) for the same sites and time period, except for the MTTA ones, were also considered. HS data were extracted from the quality-checked and gap-filled HS database released by Matiu et al. (2020). All the applied quality controls and data validation criteria for HS are described in detail by Matiu et al. (2021).

Furthermore, monthly time series of total precipitation (P) and mean temperature (TMEAN) at each site were also retrieved, in order to perform a formal attribution analysis. Most of the snow stations are located near temperature stations, but many of them do not include liquid precipitation observations. To overcome this problem, the TMEAN and P series

were extracted from the grid cell closest to the snow station location, as provided by the high-resolution 250-m gridded observational database for Trentino-South Tyrol produced by Crespi et al. (2021) and covering the period 1980-2018. The database was created starting from an archive of daily observation time series from more than 200 meteorological stations by means of an anomaly-based interpolation scheme. Crespi et al. (2021) reports an accuracy for the daily records, evaluated in terms of mean absolute error (MAE), of about 1.5 °C for TMEAN and 1.1 mm for P fields. The spatial resolution of this database is accurate enough to consider as negligible the errors attributable to the difference between station locations and grid points. The database provided by Crespi et al. (2021) was also updated to 2020 in order to extend the comparison over the entire period spanned by HN data. As further potential drivers of HN variability, the 1980-2020 monthly series of NAO and AO were retrieved from the National Oceanic and Atmospheric Administration (NOAA) website (<https://psl.noaa.gov/data/climateindices/list>). These indices are called "teleconnection indices" and are used as descriptive parameters of the synoptic conditions that can occur over Europe, especially from autumn to spring (Bartolini et al., 2010; Capozzi et al., 2021). We selected NAO and AO since those indices explain most of the Alpine precipitation variance (Quadrelli et al., 2001).

2.4 Methods

2.4.1 Data processing

Since the aim of the present study is to analyse long-term snowfall (HN) trends over Trentino-South Tyrol on a monthly and seasonal scale, all daily data retrieved from Matiu et al. (2021) were converted into monthly series by computing the total HN accumulated over each month. In order to avoid underestimations of monthly totals due to missing daily records, monthly aggregations were computed only if less than 30% of daily values in the month were missing. This threshold was defined in order to minimize the fraction of missing monthly values and, at the same time, to ensure the reliability of the aggregation

procedure. The analysis covers the period 1980-2020, which corresponds to the years with the highest data availability (Fig. 3b). In fact, most of the collected series start after 1980 and only 15 sites include records covering earlier decades. After aggregating at the monthly time scale data were subjected to a quality check to assess spatial and temporal consistency. Furthermore, a gap-filling procedure was implemented for maximizing the data availability.

2.4.2 *Data quality check and gap filling*

The spatial and temporal consistency of the database were evaluated following a scheme similar to the one proposed by Matiu et al. (2021) for the snow depth (HS). This procedure is able to reconstruct monthly values of a station (test station) through an average of the records available from up to 10 neighbouring stations (reference stations). The reference stations are selected using a proximity criteria in which horizontal and vertical distances from the test station are weighted differently. Weights are evaluated using an exponential decay (“half-time” transformation of decay constant). In the case of Matiu et al. (2021), this implies that the weights are halved every 200 km and 500 m for the horizontal and vertical distances, respectively. Only stations including available data for the considered month, and covering at least 10 years of data in common with the site under reconstruction are considered as reference. Each reference value is re-scaled by the ratio of test and reference mean HN for the considered month and the final prediction value is defined as the average of all the values reconstructed by using the reference stations. Different tests were performed changing the previous parameters in order to assess the sensitivity. However, since our study area is smaller than that of Matiu et al. (2021) and HN time series are much more discontinuous, the best solution was found setting 20 km and 200 m for the horizontal and vertical distance halving coefficients, respectively, and 10 years as the minimum number of common years between test and reference stations.

The quality check of the data was thus performed by applying this procedure to the monthly HN time series of each observation site. Each simulated series was then compared

with the observed one and the agreement was evaluated in terms of mean error (BIAS), mean absolute error (MAE), in both absolute and relative terms, and squared correlation (R2). Relative errors were calculated with respect to the monthly average HN of each time series. To identify possible erroneous series, we looked at the error distributions (see Appendix A.1). We then derived the following thresholds, which separate the main from marginal errors: 4% for the relative BIAS, 45 % for the relative MAE, or below 0.5 for R2. The aim here is not to find an automatic procedure to remove stations, but to identify the cases with the lowest agreement between observed and simulated values. The stations outside these thresholds were further checked manually. From these, only one obvious outlier in February 2014 for Cortaccia (South Tyrol) station was detected and removed. The average reconstruction BIAS, MAE and R2 over all sites were 0.6 cm (1.5%), 12.1 cm (32.4%) and 0.74 respectively.

After the quality check, the same procedure was used for gap filling to reconstruct missing monthly entries of all HN series. Considering only the months analysed, i.e. from October to April, 53% of the total monthly data were missing. After the gap filling, this percentage was reduced to 27%. However, a portion of missing values at the beginning and at the end of the snow season was not reconstructed, especially for the Province of Trento, since many stations are not active in these months, as no important snow events are expected. Moreover, a sensitivity analysis has been performed to better understand how much the resulting trends were affected by the gap filling procedure. It was decided to discard the time series where the gap filling data gain was above a certain threshold. The thresholds imposed on the % of data gained thanks to the gap filling procedure were 10, 20, and 30%. In Appendix A.2, all the three different test cases and a comparative table of trends are reported. It can be seen that, besides the reduction in the stations number, the trends pattern is the same as the one obtained using no thresholds (see Fig. 6). Also, looking at the trend values, not much differences can be seen, except for the stations on the highest elevation band, which are too few (only 5) to make a robust trend estimation.

Therefore, it was decided to keep the full set to get a better spatial overview.

2.4.3 *Temporal homogeneity check*

The assessment of homogeneity of climate series represents a crucial aspect when long-term trends are analysed. While several homogeneity tests have been developed and are a common practice for temperature and precipitation series, only a few studies discussed and addressed the homogenization of snow series (Buchmann et al., 2021, 2022; Marcolini et al., 2017, 2019; Schöner et al., 2019). However, due to the relative short temporal extent of the HN series analysed here, and the lack of homogeneous series to be used as reference, no systematic test for homogeneity assessment and series homogenization was applied to the HN database. Nevertheless, the procedure for analysing the spatial and temporal consistency previously described did not highlight suspicious deviations and drifts with respect to nearby observations for any site. In addition, a change-point detection analysis based on the Pettitt's test (Pettitt, 1979) was performed for all time series. The test was implemented considering the period from December to February, due to the more limited data availability in autumn and spring. Fig. 4 shows that the Pettitt's test detected only two significant changing points: December 1986 for "Diga_di_Valdaora_Osservatore" in the northeastern part of the Bolzano province and February 2000 for "Predazzo_gardone" in the northeastern part of the Trento province. Changing points for all sites above 1000 m a.s.l. mostly occurred in two periods: in the late 1980s and from 2000 to 2008 (Fig. 4). The breakpoints at the end of the 1980s are all negative and represent a climate anomaly, as supported by the conclusions reported in several studies performed in the region (Durand et al., 2009; Mallucci et al., 2019; Valt & Cianfarra, 2010) and also at global level (Reid et al., 2016). Instead, the changing points in the 2000s are mostly positive, indicating a possible phase of increasing snowfall, especially for mid-high altitudes (see Section 2.6 for further considerations). Therefore, there is no evidence of relevant inhomogeneities in the HN time series, which have been then used in this work to detect long-term trends.

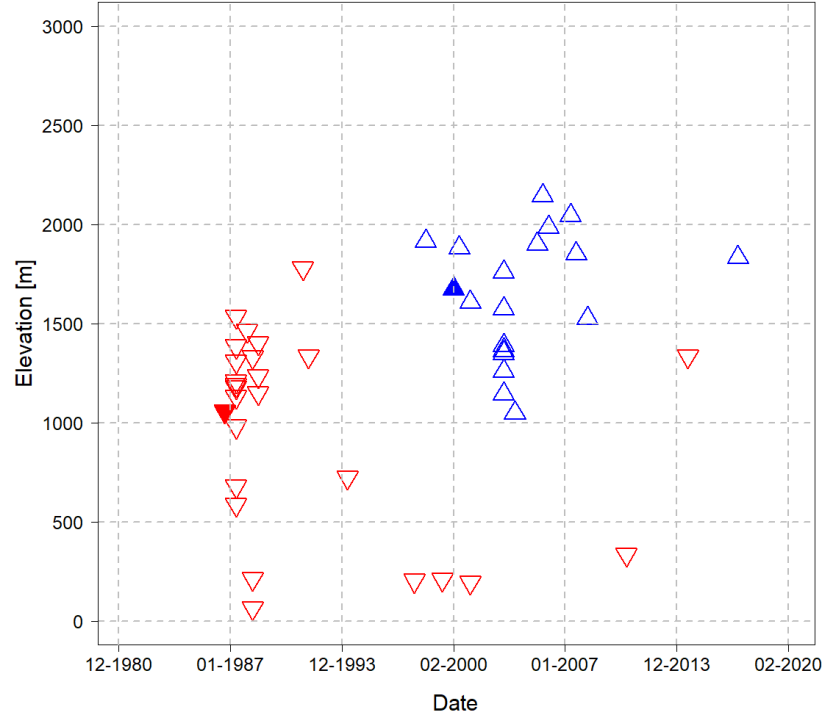


Figure 4 – Time series changing points as function of elevation. Each point represents one station. Blue (red) triangles indicate positive (negative) changing points. Full triangles indicate significant changing points.

2.4.4 Statistical analyses

Different statistical tests were performed to detect, assess and attribute snowfall long-term trends. To evaluate trends significance over time, the Mann-Kendall (MK) trend test (Kendall, 1975; Mann, 1945) was used. MK tests for a monotonic upward (or downward) trend, which indicates that the variable consistently increases (or decreases) over time, no matter if the trend is linear or nonlinear. In this work, statistical significance implies a p-value less than 0.05, unless otherwise stated. For assessing the trend magnitudes the non-parametric procedure developed by Sen (1968) was used, which estimates the trend slope in the sample of all N data pairs. The value of the median of all the slopes evaluated for each data pair reflects the overall steepness of the trend. Sen's slope is a non-parametric alternative to trend evaluation by means of ordinary least squares, and it is considered as a robust estimator, particularly in the case of nonlinear trends. Mean values of the absolute

and relative trends were computed for three different elevation ranges: (0, 1000], (1000, 2000] and (2000, 3000] m, that will be hereafter termed as "low", "medium" and "high" altitudes, respectively.

To measure the bi-variate relationship between time series of variables (HN vs. P, TMEAN, NAO, and AO), the Pearson correlation coefficient was used, which is based on the evaluation of covariance between two variables (Freedman et al., 2007). It provides information about the magnitude of the linear association, as well as the sign of the relationship. The stronger the association of the two variables, the closer the Pearson correlation coefficient r will be to either +1 or -1, depending on whether the relationship is positive or negative, respectively. A value of 0 indicates that there is no association between the two variables.

In the end, as a quantitative measure of the influence and relative importance of multiple drivers controlling HN, an analysis of variance (ANOVA) was conducted based on multiple linear regression models (R. Miller, 1997). In the linear model, the outcome was HN and the predictors were P, TMEAN, NAO, and AO, considered as acting simultaneously. The analysis of the regression sum of squares (RSS) of each explanatory variable enabled calculating the explained variance of the concurrent drivers and therefore determining which of them explains better HN. Moreover, ANOVA provides the residuals, which is the variance not explained by individual predictors. The used sum-of-squares are of type I, which corresponds to a sequential analysis of variance.

2.4.5 Code and data availability

All computations were performed with the statistical software R (version 4.0.2), using the RStudio interface version 1.1.463 (R Core Team, 2020). Some maps were produced using QGIS (version 2.18.13), a free Geographic Information System (GIS) software (QGIS Development Team, 2016). R scripts and the final revised database are openly available in Bozzoli (2022) and under github (<https://github.com/MBozzoli94/SnowTrendsAnalysis>).

2.5 Results

This section presents first the HN climatology based on the collected observations, then the analysis of the monthly and seasonal trends of HN, HS, P and TMEAN. It follows the drivers correlation and attribution of HN to P, TMEAN, NAO and AO.

2.5.1 *Snowfall climatology*

The average total seasonal (October - April) HN climatology for the region is illustrated in Fig. 5a. The October - April period was chosen to maximise the availability of fresh snow data on the study region. The region exhibits a high variability, with a minimum of 19 cm in Riva del Garda at 65 m a.s.l. and a maximum of 588 cm in Passo Tonale at 1880 m a.s.l., on the western border of the Trento province. Also, the year-to-year variability is very relevant for some stations, especially for low elevation stations, where snowfall events are more sporadic (see Appendix A.3).

It is interesting to notice that in the Adige Valley bottom, which is the main valley crossing the whole region from north to south, the average total seasonal HN is about 30 cm, with the maximum in the Trento area (40-44 cm) and the minimum in Rovereto (25 cm). Bolzano, on the other hand, with a slightly higher elevation with respect to Trento, presents an average seasonal value of 27 cm, because a drier winter climate. Higher accumulations are recorded in the valleys in the upper part of the study area. Looking at the overall elevational distribution of HN (Fig. 5b), it can be seen how the increase of seasonal HN with elevation is not linear, with a low increase up to about 750 m a.s.l. and a higher increase above. The more or less constant values up to 750 m a.s.l. are probably due to the development of cold pools in valleys, leading to a more uniform distribution of snowfall with elevation. Above 1800 m a.s.l. the distribution becomes more dispersed, due to the larger variability of measured HN at high elevations (Fig. 3a), as proved also by Blanchet et al. (2009).

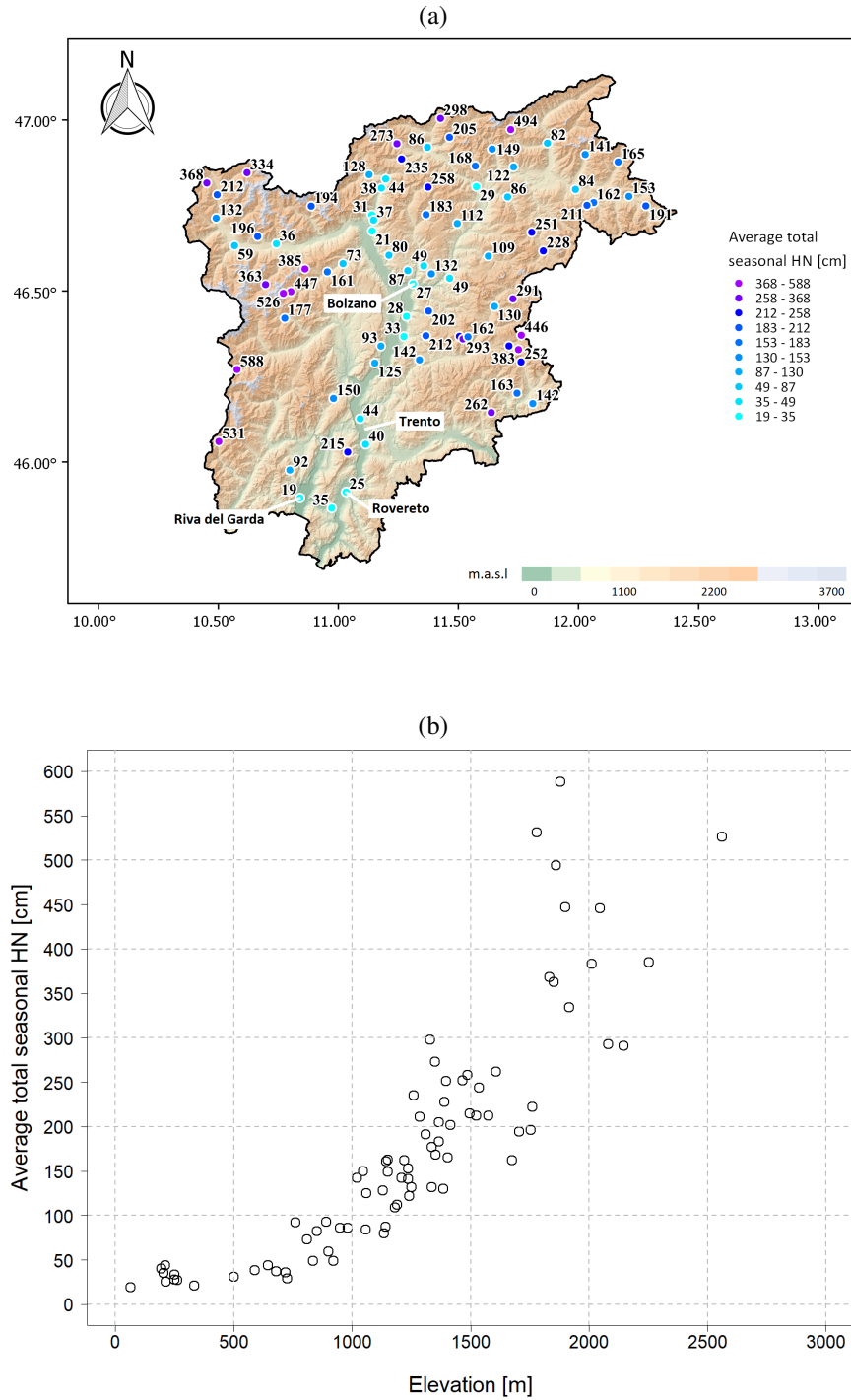


Figure 5 – Spatial (a) and elevational (b) distribution of the average total seasonal HN over Trentino - South Tyrol in the period 1980 - 2020. Each point represents one station and the corresponding climatological value.

2.5.2 Snowfall trend analysis

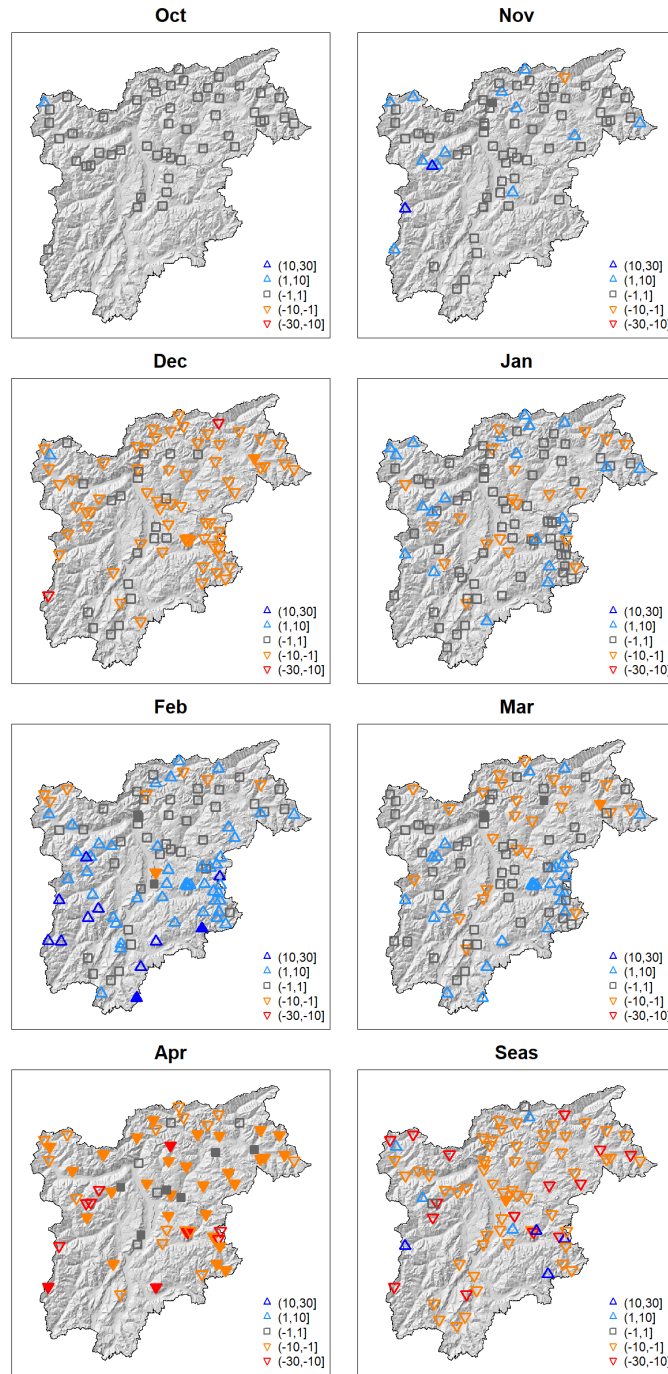


Figure 6 – Spatial distribution of monthly (October - April) and seasonal snowfall (HN) trends expressed in [cm/decade]. Each point represents one station and the corresponding trend value: blue (red) triangles indicate positive (negative) trends; gray squares indicate negligible trends (i.e., between -1 and 1). Full symbols indicate significant trends. Trentino-South Tyrol hill-shade is plotted in the background.

The spatial distribution of the HN trends is highlighted in Fig. 6, in connection with the individual months from October to April and for the entire snow season (Seas). HN trends in October are almost zero, except one in the northwestern part of the study area equals to +1.67 cm/decade, but not significant. However, during this month most of the stations usually have not yet recorded any significant snowfall, hence, for this month, results are not easy to be interpreted. Also in November, most of the trends are close to zero (51/66), but nevertheless 14 positive trends are identified, most of them at altitudes higher than 1500 m a.s.l. as shown in Fig. 7, where the monthly trends are reported as a function of elevation. Only one trend in the northern part of the study region results to be negative and equals to -6.67 cm/decade. December and April are the months with the largest fraction of negative trends. In December, 76 % of the trends are negative (67/88), while in April the number of negative trends is 83 % (54/65). The lowest absolute trends are observed at mid and high elevations, especially in April, when there is the strongest HN decrease and 62 % of the trends are also statistically significant ($p < 0.05$) (Fig. 7). In April the mean trends for (1000, 2000] and (2000, 3000] m are -5.1 and -12.9 cm/decade, respectively, corresponding to relative losses of 19.2 % and 14.6 %/decade, respectively (Tab. 1).

During the core of the winter season (January-March), both positive and negative trends are found. Most of them are not significant, though. In any case, they exhibit consistent spatial patterns (Fig. 6). Most of the negative trends are found at low elevations, while positive trends occur mainly at high elevations (see also Fig. 7). In particular, the southern part of the region at mid and high elevations exhibits increasing HN in February, with a maximum trend of +17.06 cm/decade registered in the south-eastern part of the region. However, these trends are statistically significant at two sites only (Fig. 6). In February mean trends for the mid and high elevations are +3.9 and +7.5 cm/decade, respectively, corresponding to a percentage increase of 7.1 % and 10.9 %/decade (Tab. 1). For what concerns the low elevations, all trends are mostly negative (Fig. 7) and the greatest loss is registered in December, with a mean trend of -1.0 cm/decade (Tab. 1).

At the seasonal scale, trends are mainly negative, especially at low elevations, although at altitudes above 1500 m a.s.l. 8 positive trends are detected. However, at these elevations trends are affected by large uncertainty, as highlighted by the increase in the 95% confidence interval of the estimation (see *Seas* subplot in Fig. 7). The increased uncertainty of the trends with elevation characterises also the monthly time scale, as shown in all subplots of Fig. 7. In addition, HN at these altitudes is very variable: years with high values alternate to others with much lower values, in contrast to low altitudes, where the average values are lower and more constant.

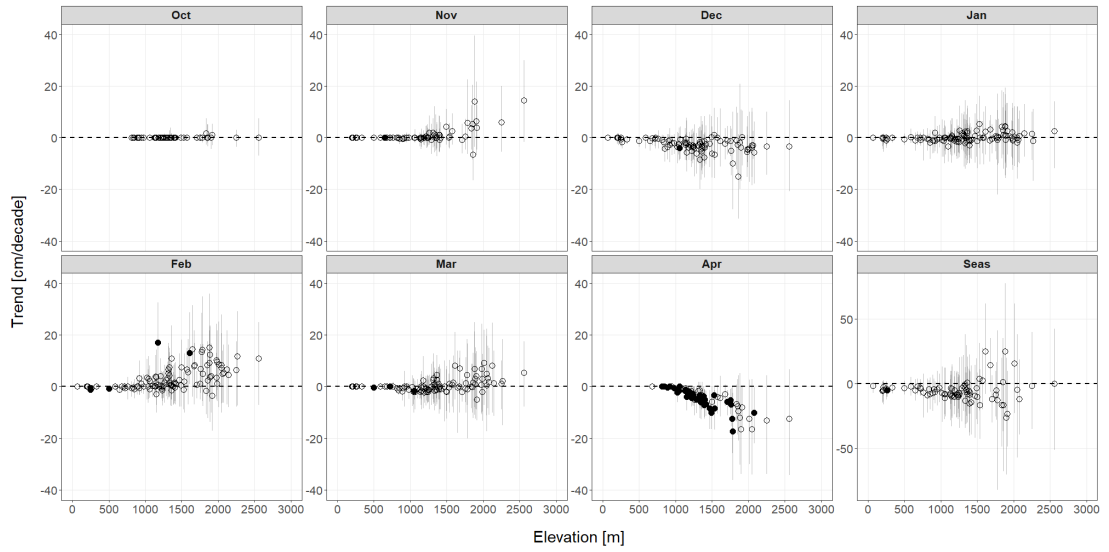


Figure 7 – Monthly (October - April) and seasonal snowfall (HN) trends as function of elevation. Each point represents one station. Points with lines indicate the trend with the associated 95% confidence interval. Full dots indicate significant trends.

Overall, averaged seasonal trends are negative for all elevation ranges, as shown in the last row of Tab. 1. It is interesting to notice that in absolute terms the maximum negative trend of -6.4 cm/decade is at intermediate elevations (1000, 2000] m, while in relative terms it is at the lowest elevations (0, 1000] m with -10.3 %/decade, due to the lower total seasonal accumulation. Instead, the highest elevations (2000, 3000] m exhibit much less negative trends, with a mean value of -0.5 cm/decade (-0.3 %).

	(0, 1000] m			(1000, 2000] m			(2000, 3000] m		
	#	AT	RT	#	AT	RT	#	AT	RT
Oct	8	0.0	0.0 %	39	0.1	0.3 %	2	0.0	0.0 %
Nov	23	-0.1	-0.6 %	41	1.1	2.0 %	2	10.2	14.1 %
Dec	25	-1.0	-6.2 %	56	-3.5	-9.4 %	7	-3.8	-6.7 %
Jan	25	-0.4	-2.6 %	67	0.4	0.2 %	9	0.3	0.7 %
Feb	25	-0.1	-3.6 %	69	3.9	7.1 %	10	7.5	10.9 %
Mar	24	-0.3	-3.1 %	68	0.4	0.5 %	10	3.9	5.1 %
Apr	8	-0.1	-2.1 %	52	-5.1	-19.2 %	5	-12.9	-14.6 %
Seas	24	-4.5	-10.3 %	51	-6.4	-3.7 %	5	-0.5	-0.3 %

Table 1 – Summary of monthly (October - April) and seasonal snowfall (HN) trends. For each elevation range the number of stations used for the the calculation of the trend (#) and the mean value of the absolute (AT) and relative (RT) trends are indicated. AT are expressed in [cm/decade], RT are expressed in [%/decade].

2.5.3 Snow depth trend analysis

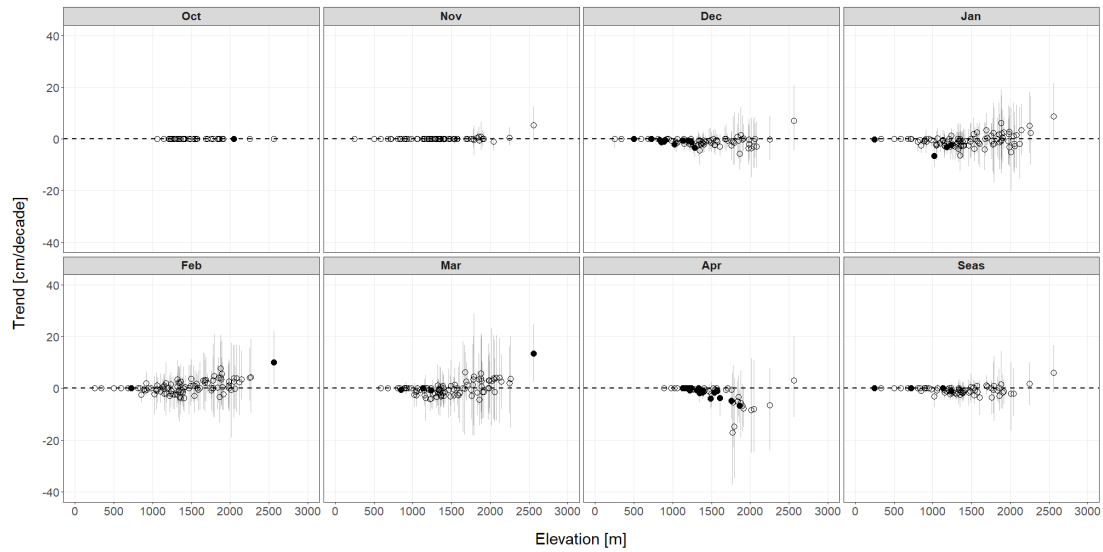


Figure 8 – Monthly (October - April) and seasonal snow depth (HS) trends as function of elevation. Each point represents one station. Points with lines indicate the trend with the associated 95% confidence interval. Full dots indicate significant trends.

The monthly and seasonal HN trends were compared with those of HS for the same gauging stations to evaluate their consistency. Trends for HS at monthly and seasonal time scales are reported in Fig. 8 as a function of the elevation. In general, HS exhibits trends

similar to those detected for HN, as it can be seen by visual comparison of Fig. 7 with Fig. 8. Also in this case, mid-low altitudes show negative trends, while at high altitudes from January to March some positive trends are present. However, there are some small differences, in particular during December and January. In December HS trends are less negative than the HN counterparts and in January at high elevations (above 2000 m a.s.l.) HS trends are on average more positive. This behaviour is consistent with findings shown in Matiu et al. (2021), where mean positive HS trends are reported from November to January for the highest elevations (2000, 3000] m in the southern Alpine region. At seasonal level and below 2000 m a.s.l., trends are negligible or slightly negative, while positive trends were found only in the two highest stations. This is confirmed also at monthly level, where the highest station always records positive trends and sometimes even statistically significant. As noticed for HN trends, also for HS mid-high elevation trends are characterized by large uncertainty. However, HS trends are less uncertain than those of HN, being HS a much more continuous variable through the winter with respect to HN.

2.5.4 *Precipitation and mean air temperature trend analysis*

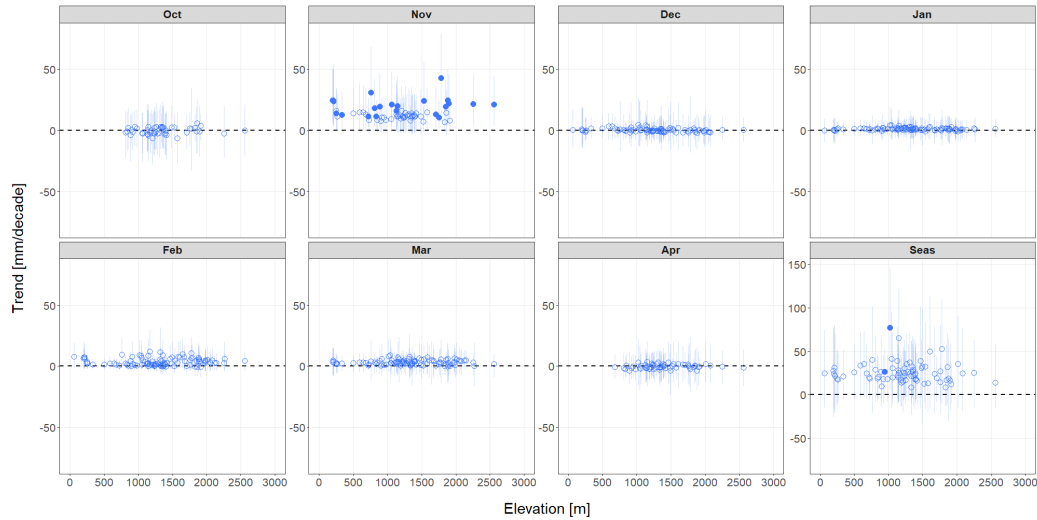


Figure 9 – Monthly (October - April) and seasonal precipitation (P) trends as function of elevation. Each point represents one station. Points with lines indicate the trend with the associated 95% confidence interval. Full dots indicate significant trends.

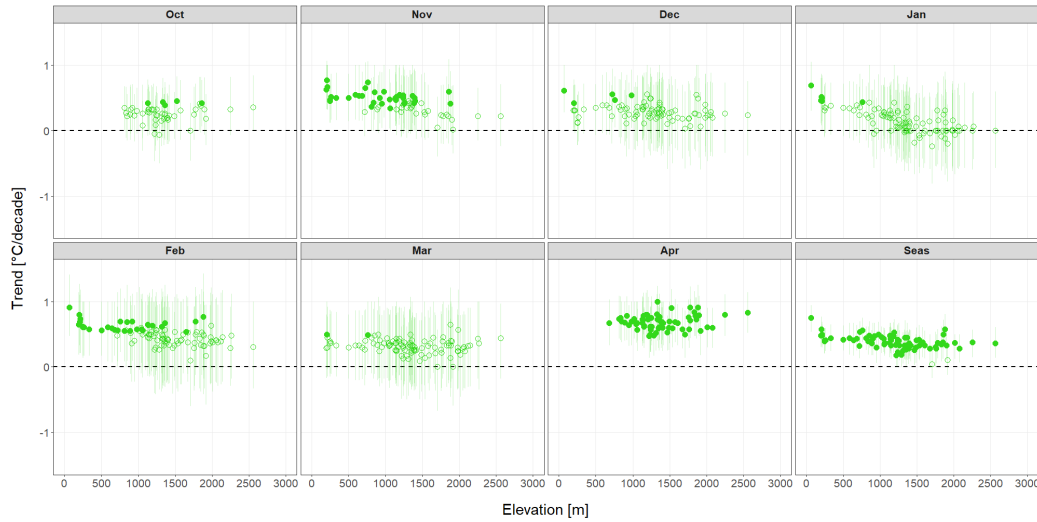


Figure 10 – Monthly (October - April) and seasonal mean air temperature (TMEAN) trends as function of elevation. Each point represents one station. Points with lines indicate the trend with the associated 95% confidence interval. Full dots indicate significant trends.

The precipitation (P) trends analysis indicates that the strongest signals are detected in November, when all trends are positive and many of them are also statistically significant (Fig. 9). Most of the trends are in the range between 10 and 40 mm/decade, with the maximum of 43.0 mm/decade at "Malga Bissina" station (1780 m a.s.l.), on the western border of Trentino. Some positive trends also occur in January, February and March, but they are not statistically significant. In the other months (October, December and April), trends are almost zero or slightly negative. However, on the aggregated seasonal scale, all trends are positive or strongly positive, but remain limited in relative terms. In fact, only in two stations statistically significant trends are detected. Remarkably, there is no evidence of elevation dependence in precipitation trends.

Trends analysis for TMEAN clearly shows that, except for January, trends are positive for each investigated elevation, with the largest trends detected at low elevations (Fig. 10). The largest positive trends are recorded in April, all of them being statistically significant and in the range 0.5-1.0 °C/decade. On the contrary, the smallest trends are in January, with values above 1500 m a.s.l. that are close to zero or slightly negative. However, none of the negative trends is statistically significant. From November to March, trends are dependent

on elevation: strongly positive trends are found at low elevations, and less positive trends at high elevations. At seasonal scale, patterns of trends are similar to those computed in the individual months. Trends are all positive, especially at low elevations, and the majority of them are statistically significant, with values between 0.2 and 0.6 °C/decade.

2.5.5 Correlation of HN with P, TMEAN, NAO and AO

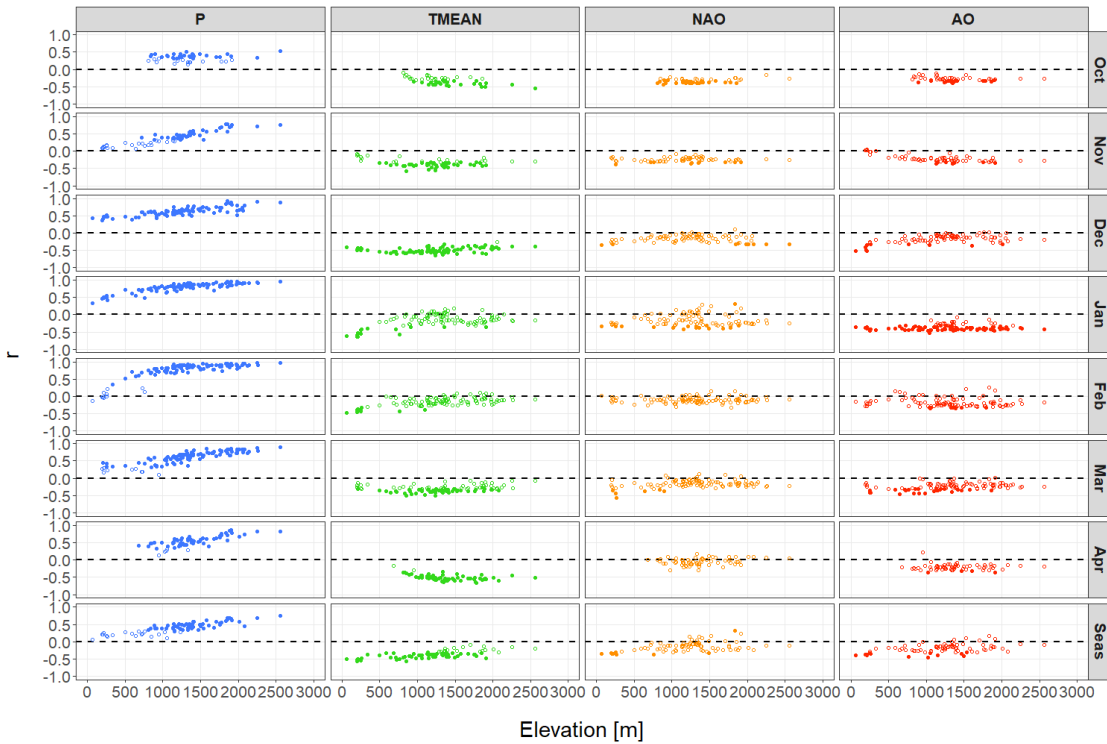


Figure 11 – Correlation (r) between HN and P, TMEAN, NAO and AO, respectively, as a function of elevation evaluated at monthly and seasonal scale. Each point represents one station. Full dots indicate significant correlations.

Fig.11 shows the results of the correlation analysis between the HN time series and those of P, TMEAN, NAO and AO. The highest degree of correlation is between HN and P, especially above 1000 m a.s.l. and during the period December - March. The occurrence of statistically significant values close to +1 indicates a strong positive correlation between HN and P, suggesting that, as precipitation increases, also snowfall increases. Indeed, this is consistent, considering that for those elevations and periods temperatures are low

enough to guarantee solid precipitation (i.e., snowfall) in most of the cases. Concerning low elevation sites, the highest degree of correlation is found between HN and TMEAN, especially in January and February. In this case the correlation is negative, and, as can be expected, the lower the mean temperatures, the higher the possibility of snowfall is. Again, the result is consistent, as temperatures are a limiting factor for snowfall at low altitudes. On the other hand, for the mid and high elevations, negative correlation between HN and TMEAN is found in November, December, March and April. The correlation between HN and the teleconnection indices is rather weak. The only variable exhibiting relevant correlations is the AO index during December and January at low elevations. In these cases, favorable large-scale circulation patterns appear to be associated with snowfall. At seasonal level, it can be noted that for low elevations (below 1000 m a.s.l.) the highest degree of correlation is between HN and TMEAN. Between 1000 and 1500 m a.s.l. the correlation with P and TMEAN is comparable, while above 1500 m a.s.l. the strongest correlation is with P. The correlation with the teleconnection indices is less strong and often not significant, except for a few specific cases at low elevations.

2.5.6 Attribution of HN to P, TMEAN, NAO and AO

In this section the attribution of HN variability to the predictors P, TMEAN, NAO and AO is discussed in terms of explained variance (EV). The results of the analysis of variance (ANOVA) are illustrated in Fig.12. At high elevations, P represents the driver that best explains HN, especially in January and February, when the fraction of HN variance explained by P is between 75 and 95 %: this suggests that during these two months at these altitudes most of the precipitation occurs as snow. Instead, at low elevations during January and February, TMEAN is the most important driver, since here temperatures are not always sufficiently low to allow for snowfall. This confirms the results presented above in terms of linear correlation analysis. On the other hand, TMEAN becomes more relevant for mid elevations during November and April, where the EV by TMEAN is 15-40 % and 10-25

%, respectively. In December and March at low elevations, P and TMEAN exhibit more or less the same fraction of EV, while at higher altitudes the variance is mostly explained by P, exceeding 75 % in March. In October, the fraction of variance explained by each driver is very low ($< 25\%$), since in this month most of the stations have not yet recorded any significant snowfall, making the analysis not particularly meaningful, and quite difficult to interpret.

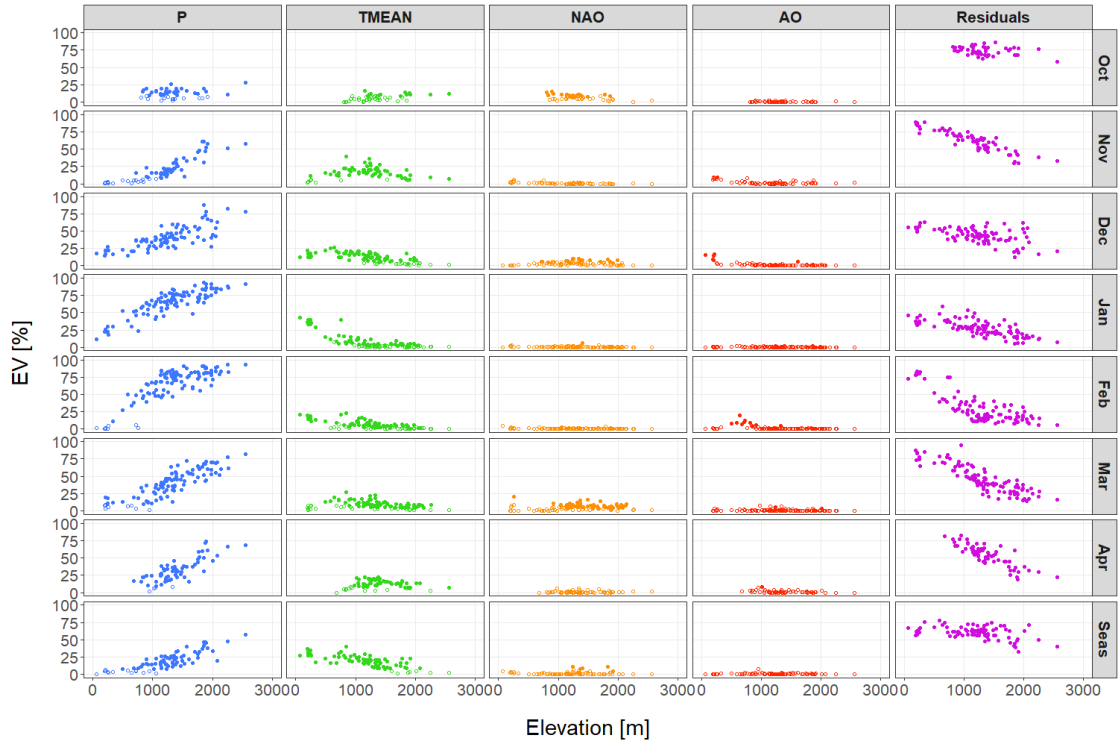


Figure 12 – Fraction of explained variance (EV) in linear models of HN as a function of P, TMEAN, NAO, AO at monthly and seasonal scale. Each point represents one model, that is one series. Full dots indicate significant values.

The contribution of NAO and AO is not relevant, except for specific months and at low elevations. More in detail, NAO presents non-negligible values of EV in October and March, while AO in November, December and February. The latter result is in agreement with that highlighted in the linear correlation analysis. Looking at the monthly unexplained variance (last column in Fig. 12), it can be noticed that at low elevations HN can be explained only considering the simultaneous combination of all the drivers (residuals), while

at mid-high elevations the variance explained by P is predominant. Also, at seasonal level, HN is mostly explained by the combination of all the drivers (see bottom-right subplot in Fig. 12), with values between 50 and 75 %. However, the EV of the single drivers is similar to that obtained at monthly scale: TMEAN is the best predictor below 1000 m a.s.l., while P above 1500 m a.s.l., confirming again the outcomes of the linear correlation analysis.

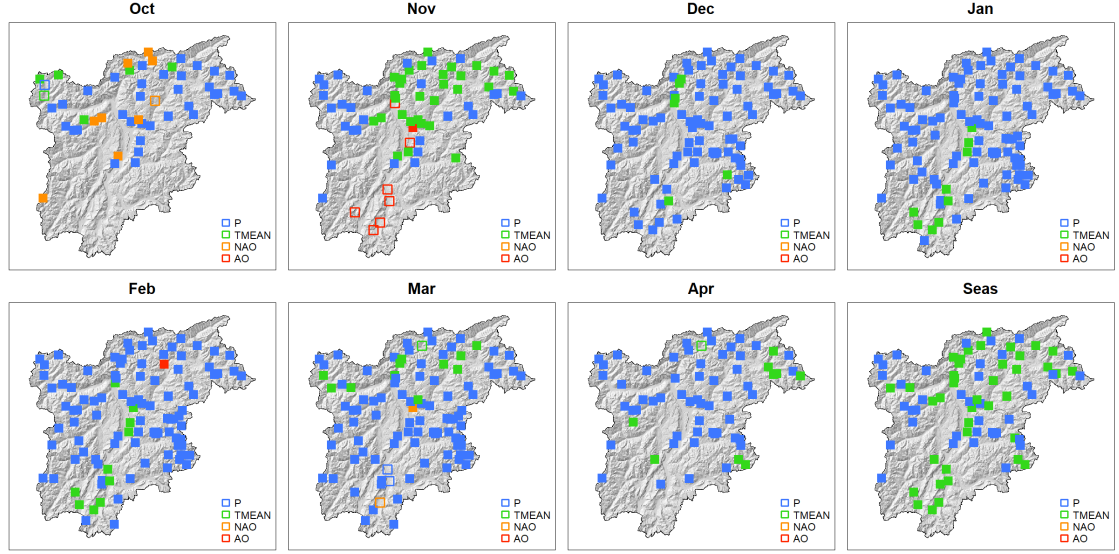


Figure 13 – Spatial distribution of the driver with the highest explained variance for HN at monthly and seasonal scale. Full squares indicate significant values.

The above results can also be appreciated by analysing the spatial distribution of the driver presenting the highest EV for each considered time series (Fig.13). P is the predominant driver in explaining HN for the majority of the time series, especially at high elevations and from December to April. An exception is represented by the sites in the Adige Valley, which are the ones at the lowest elevations (< 500 m a.s.l.), where in January and February TMEAN plays the most important role. In October and November the analysis shows uncertain results and the teleconnection indices also come into play. Finally, the analysis at seasonal level confirms that P prevails at high elevations while TMEAN at low elevations. The majority of the points is also statistically significant, suggesting the overall robustness of the attribution analysis.

2.6 Discussion

Altogether, our results show how seasonal trends are negative, especially at the lowest elevations, while some positive trends have been found at the highest elevations. This result confirms the findings presented for extreme snowfall events simulated for the French Alps by Roux et al. (2021), who showed that the majority of trends are decreasing below 2000 m a.s.l. and increasing above that altitude. The dependence of snowfall trends on elevation highlighted in this work has been confirmed in other mountain chains, as found by Li et al. (2021) over the Tianshan Mountains, by X. Zhu et al. (2017) over the Qinghai-Tibet Plateau, and by Serquet et al. (2011), who reported a strong elevation dependence of the trends for snowfall / precipitation day ratio in Switzerland.

The results the attribution analysis agree with Hammond et al. (2018), who presented global trends of snow persistence in the period 2001–2016. They showed how Europe at the latitude of the Alpine chain is one of the world's regions where the relative importance of temperature versus precipitation in controlling snow presence is strongly determined by the elevation. The general picture is therefore that at low elevations and mid-latitudes there are decreasing trends in snowfall and particularly in the snowfall / precipitation ratio (Safeeq et al., 2016), while at high elevations or in cold/polar regions the decreasing trends are less evident. On the contrary, even some increasing trends are detected during the core of the winter season, when an increase in precipitation is found (Bjorkman et al., 2015; Colucci et al., 2021; H. Wang & He, 2013). The attribution analysis in our study highlights that decreasing HN trends at low altitudes are mainly explained by positive temperature trends, while increasing HN trends at higher elevations, found especially in the core winter months, are connected to positive trends in precipitation. Moreover, the combination of temperature and precipitation plays a relevant role in the warmer snow-season months, with a consequent earlier snow melt, confirming the findings by Knowles (2015) and Feng and Hu (2007) in the United States.

The attribution analysis also shows that the contribution of NAO and AO is not so relevant, except for specific months and at low elevations. This is in contrast with Beniston (1997) and Kim et al. (2013) where highlighted that periods with relative low snow amounts and duration are closely linked to the anomalies of the NAO index. However, Kim et al. (2013) proved that the regional scale changes of winter snow cover vary significantly from one region to another. On the other hand, there is a good agreement of NAO and AO time series with the analysis of HN time series changing points presented in Fig. 4. In fact it shows a considerable number of negative changing points in the late 1980s/early 1990s, exactly when both NAO and AO registered a positive phase (See figure in Appendix A.4). In this condition Hurrell (1995) proves that the polar cell becomes strongly compact relegating all the cold air masses to high European latitudes, causing mild, dry winters in southern Europe. Those breakpoints were first described here by Marty (2008) and later also demonstrated on the global level (Reid et al., 2016).

The analysis of changing points is coherent with the NAO and AO evolution also in the 2000s, when a consistent number of positive changing points are present, especially at high altitudes, and both NAO and AO show a neutral or slightly negative phase (Appendix A.4). This negative phase might be associated to an unstable and cold atmospheric pattern over the southern sectors of Europe, which caused frequent precipitation, often in form of snowfall during the winter seasons, leading to an increase in the average HN over the southern Europe (Hurrell & Van Loon, 1997; Hurrell et al., 2003; Trigo et al., 2002).

This negative phase ended in 2010, when the strongest negative value of the AO index was recorded (-4.27 in February 2010). Notice that during that year a temporary decrease in average European temperatures was registered (Cattiaux et al., 2010; Seager et al., 2010; C. Wang et al., 2010). In the most recent years it has been observed a tendency toward the positive phase of both NAO and AO (Capozzi et al., 2021).

Looking at the overall elevation distribution of HN (Fig. 5b), the cumulative HN vertical gradient appears to increase with elevation. Moreover, in the present case, Fig. 5b

shows that the average HN seasonal total is roughly constant up to 750 m a.s.l. A possible explanation is that in winter in the main valleys snowfall events at low elevations are often controlled by the occurrence of cold pools and associated ground-based thermal inversions, implying low vertical temperature gradients and therefore a more uniform distribution of snowfall with elevation. Moreover, the development of an isothermal layer with near-freezing temperatures is favoured in valleys by the cooling of the air due to melting precipitation (Unterstrasser & Zängl, 2006).

At the lowest elevations on the valley floor (Adige Valley) snowfall occurrence is becoming more occasional in connection with the ongoing climate change. The current climatology shows an average total seasonal HN of about 30 cm, and trends are of about -4.5 cm/decade. If these trends will also be confirmed in the future, there could be a strong reduction in the seasonal snowfall, with a nearly null accumulation by 2090, This will have several impacts on natural systems and human society (Rydén, 2015).

At the highest elevations, where snow exerts a key hydrological, ecological and economic relevance, negative snowfall trends are weaker at the seasonal scale and even slightly positive in the core winter months, but strongly negative in spring. The consequence of this strongly negative trends in spring are already visible in the spring water availability and river regimes (Diamantini et al., 2018; Lutz et al., 2016; Mallucci et al., 2019). Instead, stable or positive trends in the core winter months could support winter tourism and ski industry.

2.7 Conclusions

This study analysed 122 snowfall (HN) time series during the period 1980-2020 over a mountain region in the northeastern Italian Alps (Trentino-South Tyrol). To complement official monitoring networks and increase the data availability at lower elevations, amateur observations were included. After a preliminary quality check and a gap-filling procedure, HN trends were identified using the Sen's slope estimator and the Mann-Kendall trend test,

and compared with precipitation (P) and mean air temperature (TMEAN) trends. Moreover, also large-scale predictors as the North Atlantic Oscillation (NAO) index and the Arctic Oscillation (AO) index were considered. A variance decomposition analysis was used to identify the drivers that better explain HN trends with respect to the month and the elevation.

HN trends were found to be strongly dependent on elevation, even if only in some cases they were statistically significant. Overall, the driver that best explains HN is the precipitation. However, for low elevations temperature assumes a more relevant role.

At seasonal scale, HN trends are mostly negative, especially at mid-low elevations, while at high elevations trends become more uncertain. In particular, in the core of the winter season (from January to March), positive HN trends were detected, especially for the mid-high elevations. HN trends in April were strongly negative and statistically significant. Considering three main elevation ranges, the following conclusions can be derived:

- (0 – 1000] m: the reduction of snowfall at this elevation range can be explained by the strong increase of TMEAN. P does not play a relevant role to explain HN. In October and March, a certain contribution from NAO is detected, while AO becomes more relevant in November, December and February.
- (1000 – 2000] m: this elevation range exhibits a strong variability. At the start and at the end of the winter season almost all the series recorded a reduction in snowfall, while during the core of the winter some of them recorded an increase of snowfall. Both P and TMEAN play a relevant role in explaining HN.
- (2000 – 3000] m: the slight increase of snowfall during the core of the winter season can be explained by a slight increase in P, given also that mean air temperatures at this elevation range are still sufficiently low to allow for snowfall in most cases. Therefore, P is the most important driver to explain HN.

At low elevations there is a clear decrease in HN due to a significant increase in the

mean temperature. However, a relevant part of the variance was not explained by the considered predictors, suggesting a strong inter-annual variability. Suitable conditions for snowfall at low elevations are increasingly occasional and dependent on favourable large-scale atmospheric patterns. At high elevations, on the other hand, the slight increase in precipitation and the lower increase in the mean temperature, and, therefore, the presence of average temperatures still low enough to allow snowfall, favour the possibility to have an increase of HN in the core winter months. However, in spring, when temperatures are a limiting factor also at high elevations, HN trends are overall strongly negative.

Only few studies in the literature analysed HN time series. One reason might be the challenging task of quality checking the series. Our study is among the first ones performing a spatial consistency check of HN. While it was only applied at monthly scale, the method proved to be extremely useful in assessing the quality of the series and, for the future, it could enable more robust studies of HN in other study areas.

In the future, the analysis can be extended to higher temporal resolutions, such as weekly or daily values. The assessment of HN series and their trends adds valuable information to that derived from other snow-related parameters, such as HS, SCD, or SWE. Altogether, an integrated analysis based on multiple snow-related variables can give a more comprehensive picture of snow cover changes. Additionally, high-quality and dense observation databases allow a better validation of physical model outputs or remote sensing products.

The presented snowfall climatology integrates and expands existing databases (Adler et al., 2015; Matiu et al., 2021) of a variable, HN, for which high quality and continuous records are difficult to find, especially at the lowest and highest elevations. However, in this work, thanks to the remarkable amount of 122 gauging stations distributed fairly uniformly over the study area, it was possible to attain a good spatial coverage across a large elevation gradient. In this study, official observations from institutional stations have been integrated with long-term time series from citizen observations. The availability of citizen weather stations has increased dramatically in recent years (Nipen et al., 2019),

representing an important resource which can integrate observational records coming from official networks. In particular, the inclusion of amateur (citizen science) time series of HN opens up new pathways for conducting snow cover research. The series passed all quality checks and can be considered of the same quality as series from meteorological offices. The procedure for measuring HN is rather straightforward, and the most stringent requirement for climatological analyses remains the completeness and length of available records. Passionate amateurs might perform rigorous measurements as fixed employees. Citizen science can thus represent a great potential to improve data coverage in space and time by providing observations for those locations not monitored by the official station networks, which is especially useful for variables, such as snowfall, that vary strongly over time and space. Citizen science could also involve different components of the society, for example school children, similarly to what has been proposed by Menzel et al. (2020) for analysing phenological observations. A benefit is that many find snowfall a fascinating topic, and fascination creates motivation, a key component of any scientific endeavor.

Chapter 3

Long-term snowfall trends and variability in the Alps

This Chapter is published on the International Journal of Climatology on behalf of Royal Meteorological Society, with the title "Long-term snowfall trends and variability in the Alps". The paper has been coauthored by Alice Crespi, Michael Matiu, Bruno Majone, Lorenzo Giovannini, Dino Zardi, Yuri Brugnara, Alessio Bozzo, Daniele Cat Berro, Luca Mercalli, Giacomo Bertoldi.

3.1 Abstract

Snow is particularly impacted by climate change and therefore there is an urgent need to understand the temporal and spatial variability of snowfall (HN) trends. However, the analysis of historical HN observations on large-scale areas is often impeded by lack of continuous long-term time series availability.

This study investigates HN trends using observed time series spanning the period 1920-2020 from 46 sites in the Alps at different elevations. To discern patterns and variations in HN over the years, our analysis focuses also on key parameters such as precipitation (P), mean air temperature (TMEAN), and large-scale synoptic descriptors, i.e. the North Atlantic Oscillation (NAO), Arctic Oscillation (AO) and Atlantic Multidecadal Oscillation (AMO) indices.

Our findings reveal that in the last 100 years and below 2000 m a.s.l., despite a slight increase in winter precipitation, there was a decrease in HN over the Alps, especially for southern and low-elevation sites. The South-West and South-East regions experienced an average loss of 4.9 and 3.8 %/decade, respectively. A smaller relative loss was found in the

Northern region (2.3 %/decade). The negative HN trends can be mainly explained by an increase of TMEAN by 0.15 °C/decade.

Most of the decrease in HN occurred mainly between 1980 and 2020, as a result of a more pronounced increase in TMEAN. This is also confirmed by the change of the running correlation between HN and TMEAN, NAO, AO over time, which until 1980 were not correlated at all, while the correlation increased in later years. This suggests that in more recent years favourable combinations of temperature, precipitation, and atmospheric pattern have become more crucial for snowfall to occur. On the other hand, no correlation was found with the AMO index.

3.2 Introduction

Snow plays a critical role in our planet and its ecosystems, influencing many environmental processes. Snow acts as a freshwater reservoir, storing a substantial portion of the annual precipitation on the Earth (Aragon & Hill, 2024; Isotta et al., 2014). This stored water gradually melts during warmer months, supporting river flows and groundwater recharge in mountain and downstream areas (Qi et al., 2020). Furthermore, the reflective properties of snow affect the planet's energy balance, influencing radiative forcing and regional climate patterns (Perovich, 2007; Zhuravleva & Kokhanovsky, 2011). Surface-layer turbulence, land-atmosphere exchanges and transport processes in the atmospheric boundary layer are strongly modified over snow-covered terrain (Tomasi et al., 2017). Finally, the presence and availability of snow are the fundamental prerequisites for many recreational activities, and therefore a key factor for winter mountain tourism (Beniston, 2012; Olefs et al., 2020; Rixen et al., 2011).

It is well known that climate change also affects snow dynamics. The consequences of warming temperatures on snow cover and associated environmental systems are underscored by a wealth of scientific literature. Carrer et al. (2023), Mote et al. (2018), Olefs et al. (2017), and Valt and Cianfarra (2010) show the observed decrease in snow cover and

duration in various regions due to increasing temperatures. This phenomenon, highlighted as a key indicator of climate change by the Intergovernmental Panel on Climate Change (IPCC), is modifying the hydrological cycle and will affect the availability of water resources (Bavay et al., 2009; Milner et al., 2017).

The necessity of establishing and maintaining long-term snow observations is strongly recommended, as these records play a crucial role in understanding the interplay between snow dynamics, climate change, and associated environmental impacts. In addition, it helps to provide indications for adaptation to changing snow regimes, water resources management, and the improvement of climate models. Leporati and Mercalli (1994) highlight the importance of continuous snow observations to assess trends in the extent, duration and properties of snow cover over long periods. Brown and Mote (2009) believe that long snow cover datasets are essential for improving our understanding of the response of the northern hemisphere snow cover to climate change, and for projecting potential shifts in water availability (Barnett et al., 2008). However, maintaining comprehensive and consistent long-term snow observations faces several challenges, including instrument reliability, funding stability, and data harmonization (Marcolini et al., 2017, 2019). Moreover, the analysis of long time series requires dealing with artificial inhomogeneities introduced by station relocations and changes in the measurement procedure (Buchmann et al., 2022; Resch et al., 2023).

Numerous studies on long-term trends of snow in the Alps have yielded valuable information about the impacts of climate change in this region. Durand et al. (2009) and Marty (2008) documented a consistent trend of declining snow cover duration (SCD) and snow depth (HS) over decades. According to Marty et al. (2017, 2023) the snow water equivalent (SWE) showed a significant decrease during the last six decades in the European Alps, more pronounced during spring than during winter, with the snow becoming wetter and more variable. Those results were also confirmed for the Italian Alps by Colombo et al. (2022). Decreasing trends of HS were observed for the entire Alpine region by Matiu et al.

(2021). They evaluated linear trends of mean monthly HS between 1971 and 2019. The study concluded that 87% of the stations analyzed were characterized by a decrease, with stronger negative trends from March to May than from December to February. An overall declining trend showing a reduction ranging from 11 to 15 days was found by Marke et al. (2018), where SCD was compared among various sub-regions of Austria for the time intervals 1950-1979 and 1980-2009. Laternser and Schneebeli (2003) conducted a study in the Swiss Alps, noting that the average HS and SCD showed similar patterns from 1931 to 1999: an initial general increase until the 1980s was followed by a statistically significant decrease towards the end of the century. These findings were also confirmed by Serquet et al. (2011), who examined seasonal trends and the temperature-dependent relationship between snowfall and precipitation days in Switzerland from 1961 to 2008.

The interplay between snow and various climatic factors, including precipitation, temperatures, and teleconnection indices, represents a complex interaction, and significantly influences snow dynamics with implications for regional climates. In the Trentino-South Tyrol region (south-eastern Alps), Bertoldi et al. (2023) found that precipitation patterns directly influence snowfall accumulation and subsequently shape snow cover extent and depth. Temperature changes, as discussed by Beniston et al. (2018) and Serquet et al. (2011), can alter the phase of precipitation from snow to rain, impacting snowpack persistence and seasonal patterns. Teleconnection indices, such as the North Atlantic Oscillation (NAO) and the Arctic Oscillation (AO), play a role in modulating large-scale atmospheric circulation patterns that influence regional climate and precipitation, as shown by Hurrell et al. (2003). For example, on a European level, Bartolini et al. (2010) noted a connection between snow cover and large-scale atmospheric patterns over the period 1972-2006, specifically highlighting a robust correlation with AO during the winter months. Another important index is the Atlantic Multidecadal Oscillation (AMO), which varies on multi-decadal timescales, alternating warm and cool phases that can last for several decades each (Abiy et al., 2019). AMO can influence various aspects of climate, including patterns

of temperature and precipitation, which can, in turn, impact snowfall in different regions (Hunter et al., 2006).

It was decided to choose depth of snowfall (HN) because it is the variable that best represents the total winter solid precipitation. It is important to recover HN observations, understand their change over time, and compare them with liquid precipitation trends, as HN and the solid-liquid precipitation ratio are very sensitive to climate change (Bertoldi et al., 2023; Guo & Li, 2015). HN, being a solid precipitation, is easier to compare with liquid precipitation than HS. This comparison is essential for understanding the relative influence of snowfall and liquid precipitation on climate trends. Additionally, the seasonal HN is crucial for assessing the suitability of winter sports activities (Morin et al., 2021). While SWE is more meaningful hydrologically, long-term data for it are scarce. Historical records, particularly at low elevations, often focus on HN rather than HS or SWE, making this study an opportunity to highlight and utilise these historical time series.

Efforts to analyse historical HN observations on large-scale areas are often impeded by the challenges of retrieving and harmonizing long, continuous observed time series across extensive geographical areas. Thus, the main novelty of this study is the investigation and analysis of long-term series of HN observations that cover at least 100 years from 1920 to 2020. In addition to the length of the series, another relevant novelty compared to previous studies is the coverage of the whole Alpine domain using 46 sites located at different elevations (from 57 m up to 1878 m a.s.l.), whereas previous studies on HN often focused on the northern or southern part of the Alps. Therefore, the objectives of this study are to evaluate how HN has changed in the past century and to analyze the spatial variability of trends. Furthermore, in order to identify the drivers behind these changes, we test correlations between HN and precipitation (P), mean air temperature (TMEAN) and large-scale synoptic descriptors, i.e., NAO, AO and AMO indices, and assess if and how these correlations have changed over time. From here on we will refer to depth of snowfall as simply snowfall.

The paper is structured as follows: sections 3.3 and 3.4 describe the observation database and the techniques used to derive statistics and trends. Section 3.5 provides results on trends, and section 3.6 discusses them. Finally, section 3.7 summarizes the results and draws some conclusions.

3.3 Data

3.3.1 Study area

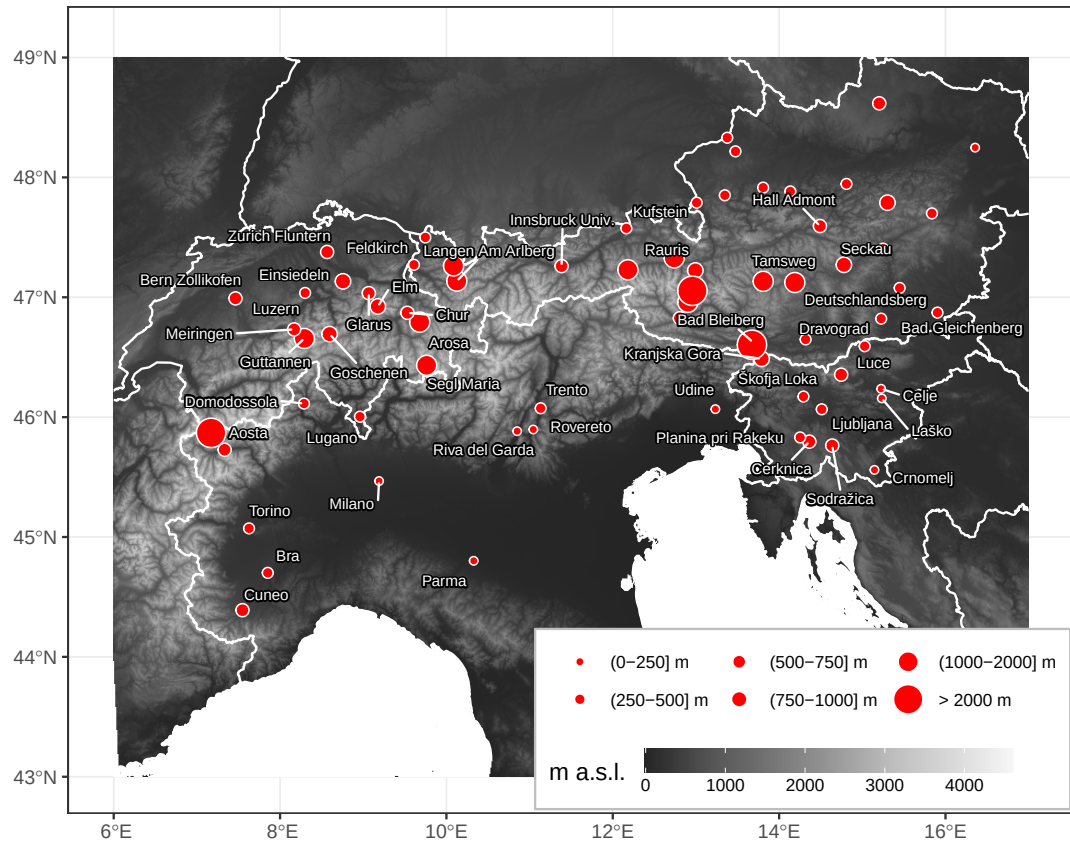


Figure 14 – Location of the snowfall (HN) stations in the Alps. Labeled dots indicate stations used for trend analysis. The size of the dots is proportional to the site elevation.

The study area of this work is an extended region of the Alpine domain, similar to the “Greater Alpine Region” defined by Auer et al. (2007). Stretching over a distance of more than 1000 km, the Alps form an arc-shaped structure that spans from the Mediterranean

coasts of France and Italy to the Lowlands east of Vienna. They cover southeastern France, Switzerland, northern Italy, southern Germany, Austria, and Slovenia (Fig. 14). The Alpine region displays intricate topography, marked by substantial elevation shifts and deep valleys oriented in various directions, intersecting the main ridge and forming numerous mountain massifs.

In terms of climate, the Alps occupy a transition zone where three major climatic influences converge. The Atlantic Ocean region, characterized by a moderately humid climate, the Mediterranean Sea region, marked by dry summers and mild, wet winters, and the European continental area with cold, dry winters and warm summers (Auer et al., 2005; Monteiro & Morin, 2023). In addition to these three climatic zones, local effects related to elevation and the complex Alpine terrain must also be considered. As a consequence, the interplay of these three climatic zones, combined with the Alps topography, gives rise to climatic gradients along both the north-south and west-east axes.

3.3.2 *Snowfall data*

The HN database used in this study is composed of 70 stations located in the Alpine region (Fig. 14). The list of all the stations used and their relative metadata can be found in Tab. 3. However, only 46 of them are used for trend analysis, as the remaining time series are very fragmented with many missing data, allowing them to be used only for the homogenization procedure (see section 3.4 for details on data homogenization). The highest number of stations and data starts from the early 1900s (Fig. 15). Moreover, the number of available stations has decreased in the most recent years, since not all of the series were kept regularly up to date. For this reason, the period 1920-2020 was chosen for the analysis.

Data were kindly provided by several organizations, such as GeoSphere Austria (GSA), Swiss Federal Office of Meteorology and Climatology (METEOSWISS), Slovenian Environment Agency (ARSO), Società Meteorologica Italiana (SMI), Meteotrentino (MTN),

Meteo Trentino Alto Adige (MTAA), Società Meteorologica Alpino-Adriatica (SMA-A), Fondazione Osservatorio Meteorologico Milano Duomo (OMD) and Osservatorio Meteorologico di Parma (OMP).

HN data are taken daily. The largest part of the data comes from manual measurements. As suggested by Matiu et al. (2021), while the observers follow slightly different guidelines in each country or network, the observation modalities are remarkably similar, thus allowing a combination of the different sources. A daily measurement of HN is taken using a ruler and measuring the height of fresh snow that had fallen in the previous 24 hours over a wooden table in the early morning hours, generally between 07.00 and 09.00 LST (UTC+1). For more detailed information on the measuring modalities, we refer to the European Snow Booklet (Haberkorn, 2019). Data were provided as monthly sums, except for data from Slovenia, which were provided with daily frequency. We then aggregated the monthly values into seasonal sums considering the months from November to May. This definition of the snow season was chosen in order to maximize the availability of HN data in the study region and cover both winter and spring.

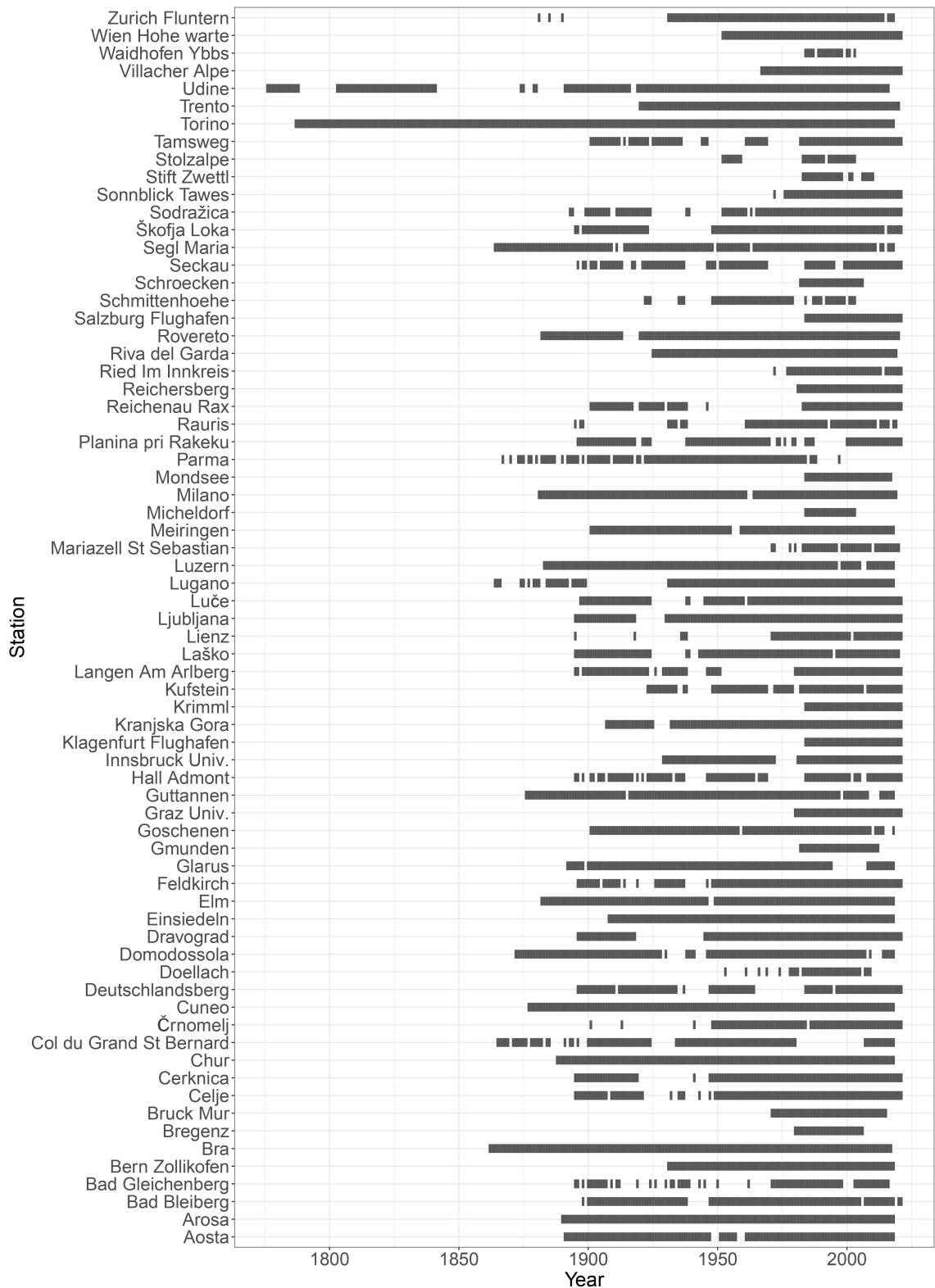


Figure 15 – Seasonal snowfall (HN) data availability for each station per year. Gray bars indicate that data are present; white spaces indicate no data available.

3.3.3 *Meteorological data and teleconnection indices*

We analyze long-term homogenized weather data in the Alps in order to compare HN to meteorological data. For TMEAN, we use the Historical Instrumental climatological Surface Time series of the greater ALPine region (HISTALP, Auer et al., 2007) (version Grid-mode-2). The Grid-mode-2 dataset includes values of monthly mean air temperature distributed on a regular grid with a resolution of 5', ranging from 4° to 19°E and from 43° to 46°N, covering the period 1780-2014. For P, we use the Long-term Alpine Precipitation reconstruction dataset (LAPrec, Isotta et al., 2024) (version LAPrec1901.v1.1), which combines the high-resolution spatial information from the Alpine Precipitation Grid Dataset (APGD) with homogenized temporal information from HISTALP precipitation series. The LAPrec1901.v1.1 version is a gridded dataset that includes monthly precipitation sums from 1901-01-01 to 2019-12-31 with a grid spacing of 5 km covering the Alpine region (approx. from 43–49°N to 4–17°E, land area only). TMEAN and P time series at each station location were extracted from the gridded datasets by considering the nearest neighboring grid cell. For the TMEAN data, as suggested by Rolland (2003), we applied a correction for the elevation mismatch between the HISTALP grid and the stations, considering a lapse rate correction of 0.5 °C/100 m. Both TMEAN and P dataset end a few years earlier compared to the considered HN time series. However, adding more recent observations from other sources could introduce inhomogeneities that can affect the analyses, so we limit the comparison of HN to weather data to 2014. For teleconnection indices, series of NAO, AO and AMO are obtained from the National Oceanic and Atmospheric Administration (NOAA) website (<https://psl.noaa.gov/data/climateindices/list>), with data starting in 1950. In the end, all those data are aggregated to seasonal scale, i.e. from November to May.

3.4 Methods

3.4.1 *Quality check, homogenization and gap filling*

Quality control procedures are crucial for identifying anomalies or deviations in HN data series (Baronetti et al., 2019). As suggested by Diodato et al. (2020), in order to study long-term HN regime changes and assess climate anomalies, the homogeneity of HN time series has to be investigated to identify breakpoints and the impact of the possible corrections.

In this work we use the Climatol procedure, as implemented in the R package "climatol" version 3.1.1 (Guijarro, 2018) to check the homogeneity of the HN time series. Climatol evaluates the homogeneity using the Standard Normal Homogenization Test (SNHT, Alexandersson & Moberg, 1997) (see below for details in Appendix B.2). Since Climatol revealed that all the time series were sufficiently homogeneous, we did not apply any specific corrections. However, considering the monthly HN distribution of each station, 24 stations resulted not suitable for the trend analysis due to the presence of frequent missing data and a total of 46 stations are those selected for the trend analysis (see "Use" = HT in Tab. 3).

To fill in the gaps of the monthly HN series, we follow the procedure proposed by Bertoldi et al. (2023) and Matiu et al. (2021). This procedure is able to reconstruct monthly values of a station (test station) through a weighted average of the records available from up to 10 neighbouring stations (reference stations). The reference stations are selected using a proximity criterion considering weights depending on horizontal and vertical distances. The weights are evaluated using an exponential decay ("half-time" transformation of the decay constant). In our case, we found the best reconstruction accuracy setting 50 km and 250 m for the horizontal and vertical distance halving coefficients for station weights, respectively, and 10 as the minimum number of years with common data between test and reference series. Considering only the months analysed, 12.1% of the total monthly data

were missing. After the gap filling reconstruction, all the data are aggregated into seasonal sums.

3.4.2 *Statistical analyses*

Long-term trends in HN data are detected with a series of statistical tests. With the Mann-Kendall (MK) trend test (Kendall, 1975; Mann, 1945) we assess the significance of trends over time. The MK test detects monotonic upward or downward trends, indicating consistent increases or decreases in the variable over time, regardless of whether or not the trend is linear. In this study, statistical significance is indicated by a p-value less than 0.05 unless otherwise specified. The trend magnitudes are assessed with the non-parametric method developed by Sen (1968). This approach estimates the linear trend slope in the sample of all N data pairs. The median value of all the slopes calculated for each data pair reflects the overall steepness of the trend.

Finally, to assess the bivariate relationship between time series of variables (HN vs. P, TMEAN, NAO, AO, and AMO), we use the Spearman correlation coefficient ρ . The parameter ρ tends toward either +1 or -1 when the monotonic association between the two variables is stronger, with negative numbers describing anti-correlation. A value close to 0 denotes the absence of any association between the two variables.

3.4.3 *Regionalization*

We identify groups of similar stations with an automated clustering procedure based on k-means of monthly HN series without including any location information. Based on the elbow method and silhouette metrics, three clusters are identified as optimal (see Appendix B.3). The resulting clusters are named South-East (SE), South-West (SW), and North (N). The SE cluster counts 16 stations that range from 113 m to 909 m a.s.l. with a mean elevation of 442 m a.s.l. It includes all Slovenian stations, some Austrian stations (Bad Bleiberg, Deutschlandsberg, Bad Gleichenberg, Seckau) and Udine in north-eastern Italy.

Here, HN is favoured by the advection of cold air from northern or northeastern Europe, which then interacts with the wetter and warmer air of the Mediterranean Sea. The SW cluster has 11 stations ranging from 57 to 565 m a.s.l., with a mean elevation of 272 m a.s.l. It covers almost the entire southern side of the Italian Alpine region, including some stations in the Po Valley (e.g. Torino, Milano, Parma) and others in the Alpine valleys (e.g. Aosta, Domodossola, Trento). In this region, snow is mainly caused by the advection of warm and humid air from the south flowing over pre-existing cold air. The N cluster counts 19 stations going from 438 m to 1878 m a.s.l., with a mean elevation of 850 m a.s.l. and includes all Swiss stations and the Austrian stations that are not included in the SE cluster. HN is mainly caused by the descent of cold air masses from northern Europe, which, colliding with the Alpine chain, can lead to cold temperatures and heavy precipitation.

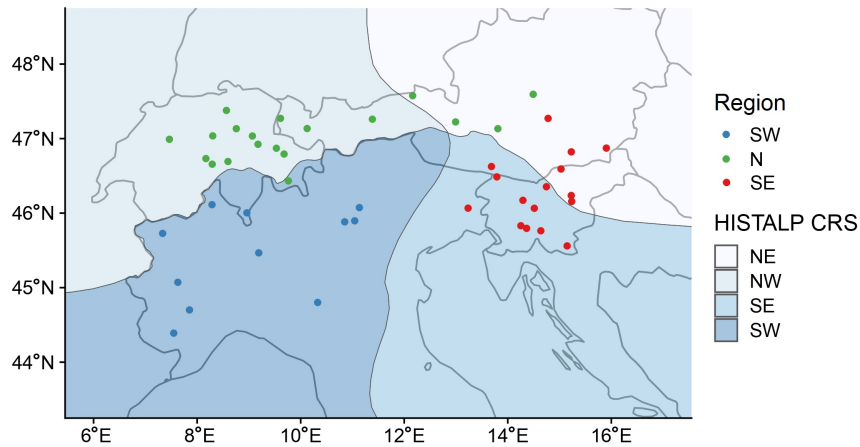


Figure 16 – Clustering of stations based on seasonal snowfall (HN) data. Three regions are detected: South-West (SW) (blue dots), North (N) (green dots) and South-East (SE) (red dots). Underlaid are the HISTALP coarse-resolution subregions (Auer et al., 2007).

These three clusters are compared with the regionalization obtained from the HISTALP project (Auer et al., 2007) in Fig. 16. There is an overall agreement between the clusters identified from HN series and the climate regions of HISTALP, which are based on a combination of air temperature, precipitation, air pressure, sunshine, and cloudiness. The mismatch in the northern and eastern parts of the Alpine region is likely due to the fact

that the largest contribution to the HISTALP region definition comes from air temperature, while the division based on HN is more driven by the precipitation regime. Finally, it is worth noting that the HN regions are qualitatively similar to the clusters based on snow depth (HS) identified by Matiu et al. (2021).

All computations are performed with the statistical software R (version 4.2.2), using the RStudio interface version 1.1.494 (R Core Team, 2020).

3.5 Results

3.5.1 Climatology

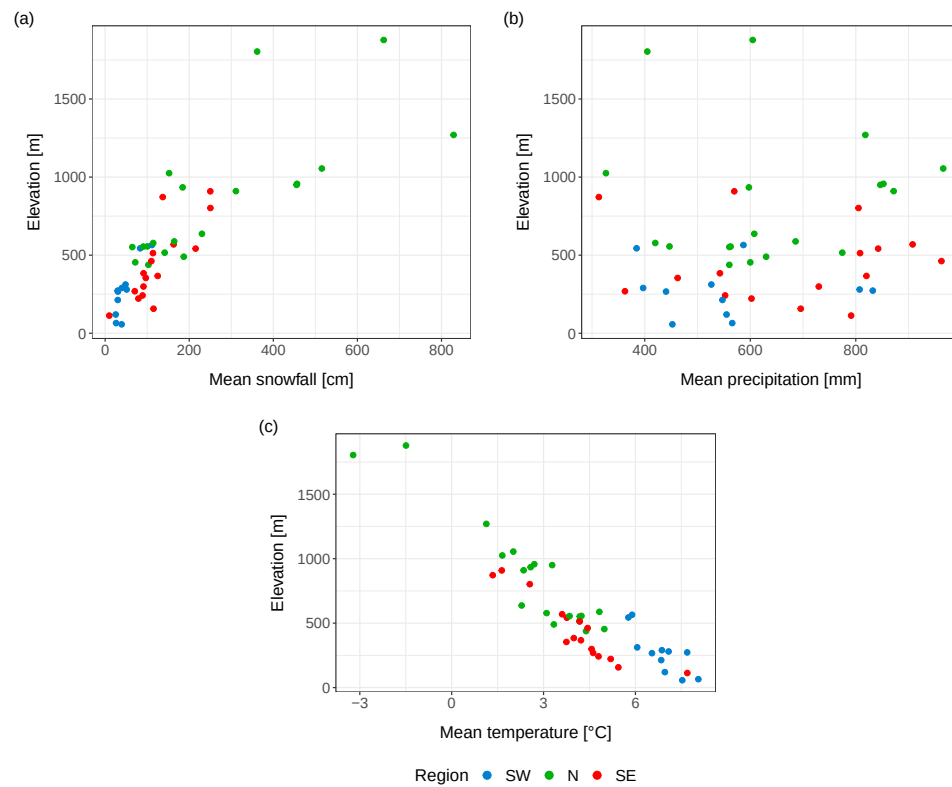


Figure 17 – Elevation distribution of seasonal snowfall (HN) (a), precipitation (P)(b) and mean air temperature (TMEAN) (c) climatology grouped by region.

HN, P and TMEAN climatology for all the stations analysed is shown in Fig. 17. Data are divided following the three reference areas discussed in the previous section and refer

to all the months included in the snow season, i.e. November to May, from the 1920-21 to the 2019-20 season.

As can be seen in Fig. 17a, HN values increase with elevation, with the highest stations recording the highest seasonal accumulations. However, this increase is not entirely linear. It remains so up to around 700 m a.s.l. and then the signal starts becoming more noisy, also due to the low number of stations at high elevations. The maximum value of the average seasonal HN accumulation is at Langen Am Arlberg (1270 m a.s.l.) with 829 cm, followed by Arosa (1878 m a.s.l.) and Guttannen (1055 m a.s.l.) with 663 cm and 516 cm, respectively. Note that all these stations are located in the N region, where stations are on average at higher elevations than in the others. In the SE and SW regions the average seasonal HN accumulation is much lower, with a maximum of 250 cm at Kranjska Gora (802 m a.s.l.) and 111 cm at Cuneo (565 m a.s.l.). However, the comparison of HN totals at locations at the same elevation in the SW and SE regions shows that the latter records more snow than the former, indicating that the SE region is more snowy than the SW region.

The distribution of seasonal P climatology is very irregular (Fig. 17b), without a clear correlation with elevation. No differences in P climatology among the regions are evident and the distribution with elevation exhibits a strong variability among the sites, since orography affects P at a much smaller spatial scale in such a complex area as the Alpine chain. However, this can be reasonable if we think that here we are considering averages made with 100 years of cumulative seasonal P data, i.e. from November to May. Therefore, it is plausible that the orographic pattern of P with elevation tends to be smoother. On average, in the SW region the seasonal P accumulation is 554 mm, slightly less than the 673 mm of the SE region and the 639 mm of the N region. However, from Fig. 17b it is clear that P is very variable in all the three regions, so these average values are not representative of the P climatology of the single stations. Guttannen (1055 m a.s.l.) in the N region and Planina pri Rakeku (462 m a.s.l.) in the SE region are the two stations with the highest values of seasonal P accumulation: 966 mm and 962 mm, respectively.

The seasonal TMEAN climatology, as expected, is highly correlated with elevation: the warmest value is $+8.1^{\circ}\text{C}$ at Riva del Garda (65 m a.s.l.) and the coldest one is -3.2°C at Segl Maria (1804 m a.s.l.). It is interesting to notice that, while at the same elevation the stations in the N and SE regions have comparable values, the locations in the SW region are warmer. On average, the seasonal TMEANs for N, SE and SW stations are $+2.7^{\circ}\text{C}$, $+4.1^{\circ}\text{C}$ and $+6.9^{\circ}\text{C}$, respectively.

3.5.2 Trend analysis

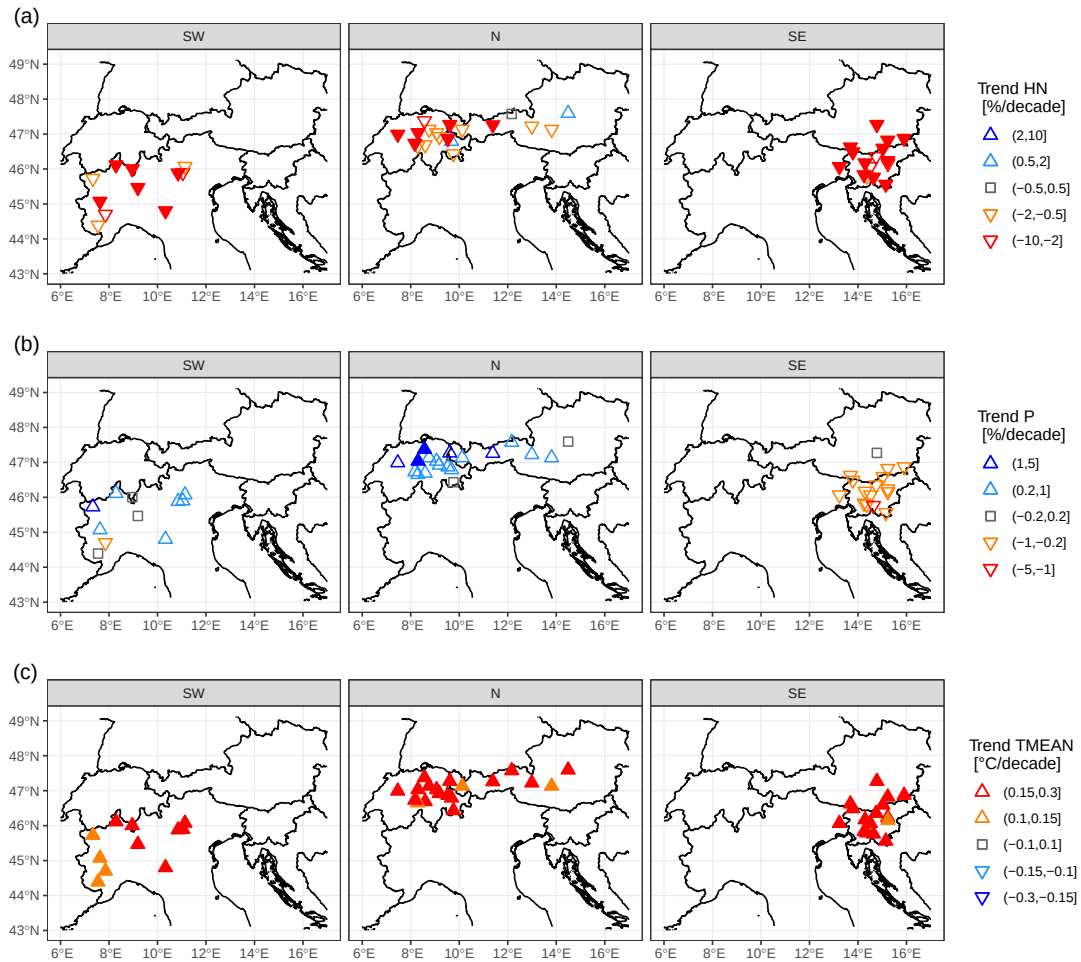


Figure 18 – Spatial distribution of seasonal snowfall (HN) (a), precipitation (P)(b) and mean air temperature (TMEAN) (c) trends expressed in [%/decade], [%/decade] and [$^{\circ}\text{C}/\text{decade}$], respectively. Each point represents one station and the corresponding trend value: blue (red) triangles indicate positive (negative) trends; gray squares indicate negligible trends. Full symbols indicate significant trends.

This section presents the results of the trend analysis and how trends change with elevation. As shown in Fig. 18, over the last 100 years, most stations record a negative HN trend. On average, the trend is of -3.4 %/decade. The only three stations that show a positive trend are Hall Admont (637 m a.s.l.), Arosa (1878 m a.s.l.), and Kufstein (490 m a.s.l.), all in the N region, with +0.9, +0.5 and +0.4 %/decade, respectively. However, none of them turn out to be statistically significant. HN trends are highly elevation-dependent (Fig. 19). The stations in the SW region and thus those at lower elevations, are experiencing the greatest losses in terms of HN, with all stations showing negative trends and 54.5% of them also statistically significant. Instead, the dependence on altitude is less pronounced for the SE region. However, also in this case the majority (87.5%) of the trends are negative and statistically significant. Note that, at the same elevation, stations in the SE region have less negative trends than those in the SW region. For the N region, again the dependence on elevation is very strong. Stations at lower elevations show negative and significant trends, while trends are less negative for higher stations.

P trends show a different behaviour depending on the region. There is a clear prevalence of increasing trends in the SW and N regions, with average values of +0.3 and +0.8 %/decade, respectively. However, only two cases in the N region are statistically significant: Luzern (454 m a.s.l.) with +1.3 %/decade and Zurich Fluntern (555 m a.s.l.) with +1.6 %/decade, which represents the highest P trend of the dataset. Instead, in the SE region, trends are all negative, with an average of -0.7 %/decade and a minimum of -1.1 %/decade at Sodrazica (542 m a.s.l.). However, none of them is statistically significant. In contrast to HN trends, there is no dependency on elevation (Fig. 19).

In all the three regions, TMEAN trends are all positive and statistically significant. On average, the SW, N and SE regions present very similar trends: +0.15, +0.16 and +0.16 °C/decade, respectively. Also the variability between the single stations is rather low, with no dependence on elevation. The maximum positive trend is at Zurich Fluntern (555 m a.s.l.) in the N region with +0.18 °C/decade, while Bra (290 m a.s.l.) in the SW region

shows the lowest warming, with $+0.13$ $^{\circ}\text{C}/\text{decade}$.

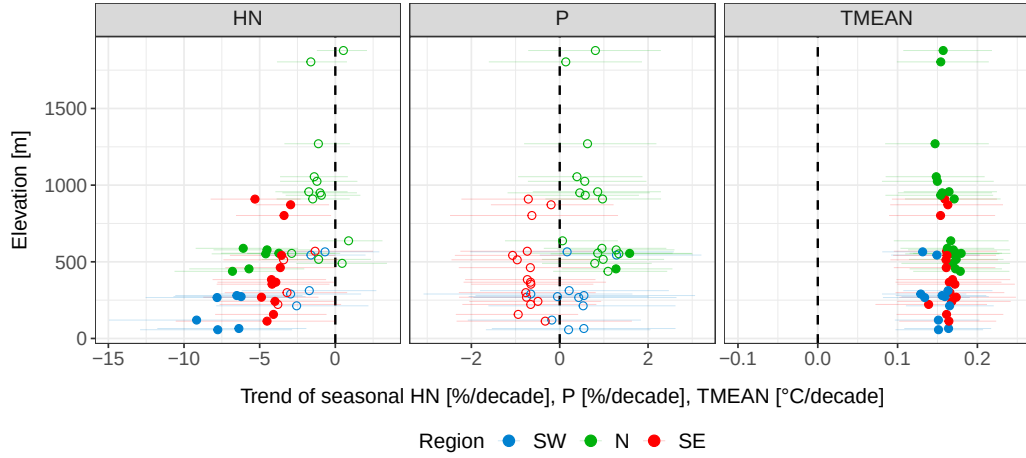


Figure 19 – Seasonal snowfall (HN), precipitation (P) and mean air temperature (TMEAN) trends as a function of elevation expressed in [%/decade], [%/decade] and [$^{\circ}\text{C}/\text{decade}$], respectively. Each point represents one station. Points with lines indicate the trend with the associated 95% confidence interval. Full dots indicate significant trends.

3.5.3 Trend temporal variability

Besides considering the overall trend, it is interesting to analyse how HN, P and TMEAN change over time. To this purpose, we consider here 21-year moving average anomalies of seasonal HN, P and TMEAN. HN and P anomalies are calculated by dividing every time series by its mean and then multiplying them by 100 to get % values, while TMEAN anomalies are calculated by subtracting the long-term mean from every time series. Thus, for each year, a centered 21-year moving average is calculated considering the 10 years before and after. We did test other time windows (e.g. 11-year, 31-year), but we find the 21-year window to be the best compromise between a strong noisy signal (11-year) and a too smoothed one (31-year). Fig. 20 shows the 21-year moving average anomalies of seasonal HN, P and TMEAN for the three regions with respect to the 1920-2020 long-term averages. For HN, until the 1980s, anomalies are positive in all three regions. In all cases, HN anomalies reach a peak of around $+25\%$ during the 1970s. Afterward, the anomalies decrease until they become negative. This shift is very evident in the SW and SE regions, where average anomalies change from $+25\%$ and $+23\%$ to -30% and -23% , respectively.

HN decreases at a smaller rate in the N region, where anomalies vary from +24% to -20%. Note that, in the SE region, Udine (113 m a.s.l.) has a more extreme behavior compared to the other stations. It shows strongly positive anomalies up to the 1960s, with a peak of +86% in the season 1947-48, and then, starting from the season 1979-80, negative anomalies are registered.

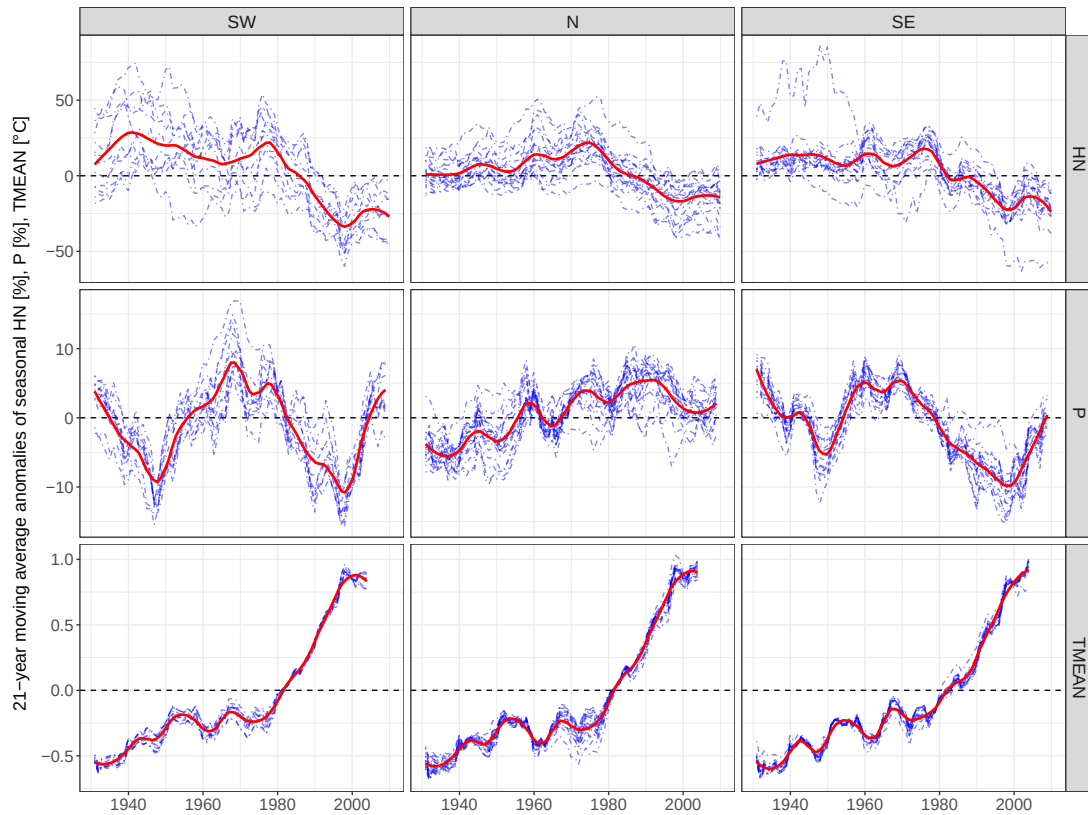


Figure 20 – 21-year moving average anomalies of seasonal snowfall (HN), precipitation (P) and mean air temperature (TMEAN) (blue) for the 1920-2020 period. The red bold thick line indicates the local polynomial regression fitting.

Considering P, the SW and SE regions show a reduction of up to 10% between the 1980s and 2000s. Another period with negative P anomalies is between the 1940s and 1960s for the SW region and at the end of the 1940s for the SE region. However, for the N region, P has slightly increased over the decades, registering positive anomalies over the last 20 years, with a slight reduction towards values closer to the long-term average in the 2000s. In all cases, a period with more P is between the 1960s and 1980s. The time series

of TMEAN trends are similar in the three regions, with a moderate increase since 1970s and a stronger increase in the last 40 years, when TMEAN anomalies have moved from slightly negative values to $\sim +1$ °C.

3.5.4 Correlation

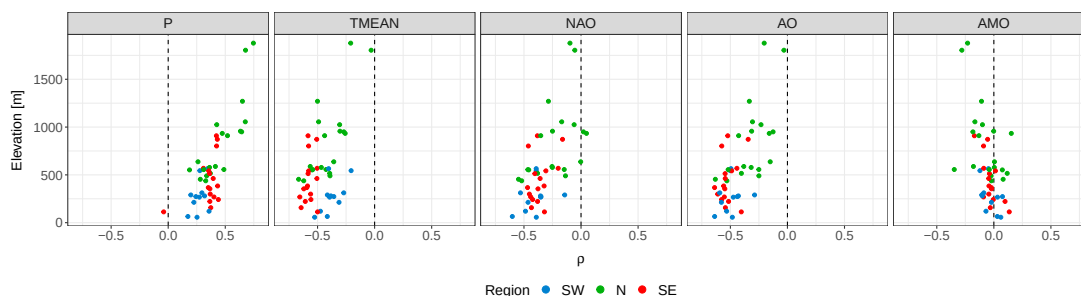


Figure 21 – Rank correlation between snowfall (HN) and precipitation (P), mean air temperature (TMEAN), North Atlantic Oscillation index (NAO), Arctic Oscillation index (AO) and Atlantic Multidecadal Oscillation index (AMO) grouped by region.

To better understand which factor plays a major role in controlling HN trends, we calculate the rank correlations between HN and P, TMEAN, NAO, AO and AMO grouped by the three regions (Fig. 21). As expected, the correlation between HN and P increases with elevation, while the correlation between HN and TMEAN tends to zero at the highest stations, suggesting that TMEAN is a limiting factor at low levels, while HN at high elevations is mainly controlled by P. The mean correlation values between HN and P (TMEAN) are: +0.27 (-0.38), +0.36 (-0.57) and +0.46 (-0.41) for the SW, SE and N regions, respectively. The correlation between HN and NAO, and AO shows the strongest negative correlations for the low-elevation stations in the SW and SE regions, with mean values of -0.37 and -0.41 for NAO, and -0.53 and -0.50 for AO, respectively. This result suggests that for low-elevation regions the presence of specific circulations associated with negative NAO and AO phase is crucial for the occurrence of abundant HN. On the other hand, little or no correlation is found between HN and the AMO index for all regions.

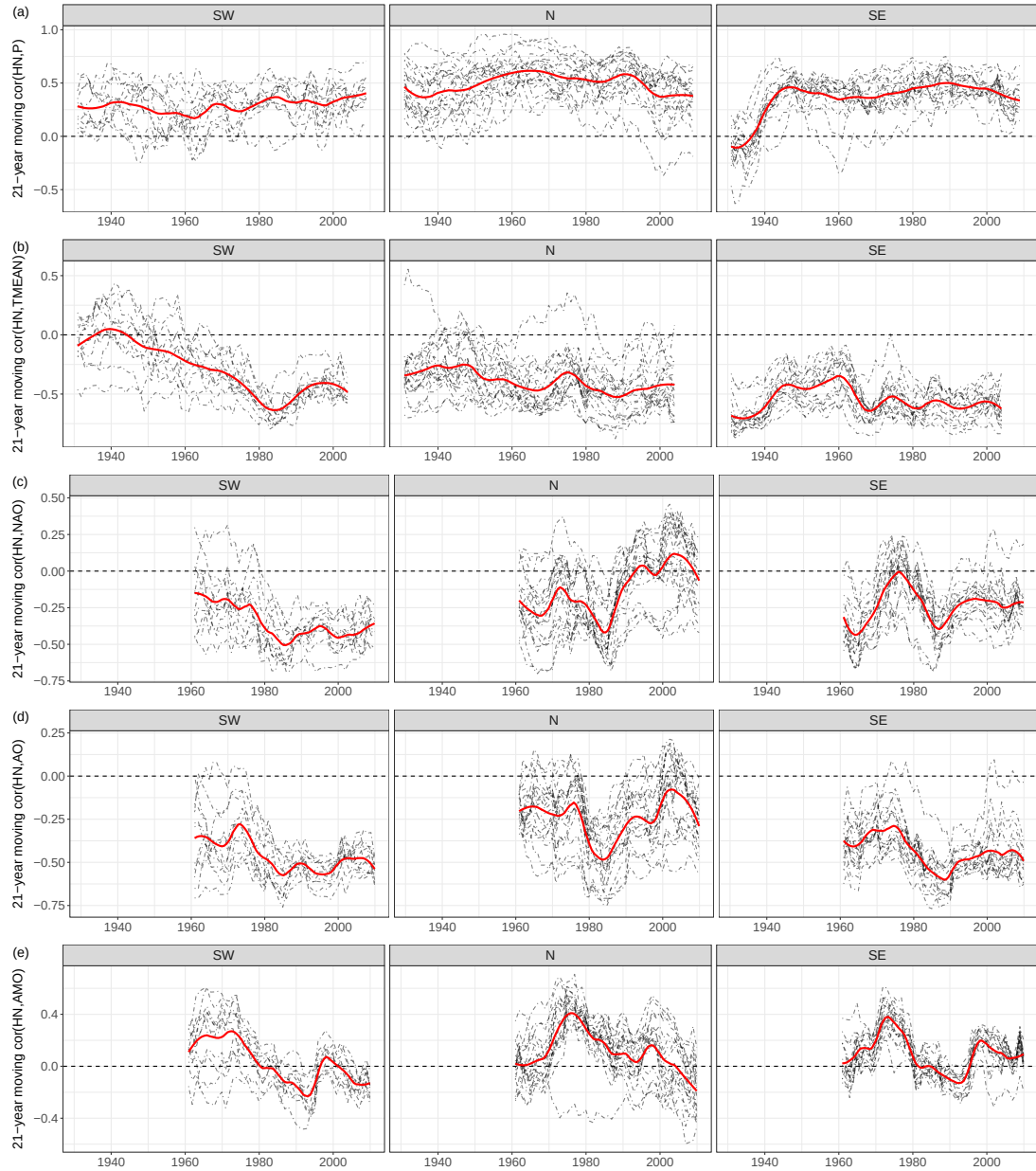


Figure 22 – 21-year moving average of the rank correlation between snowfall (HN) and precipitation (P), mean air temperature (TMEAN), North Atlantic Oscillation index (NAO), Arctic Oscillation index (AO) and Atlantic Multidecadal Oscillation index (AMO) (black). The red bold thick line indicates the local polynomial regression fitting.

The temporal evolution of the correlations is analysed from the 21-year moving average of the rank correlations between HN and P, TMEAN, NAO, AO, AMO. For the SW region, the correlation between HN and TMEAN has become more negative over the years. Around the 1940s, for almost all stations, the correlation was 0, while afterwards the value gradually

decreased until it reached a minimum of -0.62 in the 1980s and remained more or less in the same range for the following years (Fig. 22). The correlation of HN with the NAO and AO indices has also become more marked, settling on average at -0.5. A similar behavior can also be observed for the SE region, except that TMEAN correlations were already moderate from the early period. Instead, in the N region the correlation with the circulation indices is lower, due to a different type of circulation that brings snow over this region (see section 3.4, Regionalization). On the other hand, the correlation between HN and P is more stable and has remained between 0.3 and 0.5 for all regions, except for a short period with lower values in the SE region in the 1930s. Finally, regarding the correlation with the AMO index, it can be seen that in recent years this has been near zero, but with a period of higher correlation in the 1970s, when the N region recorded a peak of 0.4.

3.6 Discussion

This study has shown that in the last one hundred years, seasonal HN has experienced a considerable reduction in most of the analysed locations covering the whole Alpine region. This result has been highlighted in many recent studies at the regional level, but in this work observed HN records have been analysed for a long period (100 years) and for the entire Alpine region. However, a limitation of this study is that most of the analysed stations are located below 1000 m a.s.l., as at higher elevations it is much more difficult to have long and continuous HN observations. To overcome this problem, other studies have analysed HS or SWE. For example, Colombo et al. (2022) modelled SWE using daily HS data obtained from 19 historical stations located in the southern European Alps (Italy) covering an elevation range from 750 to 2600 m a.s.l. They analysed extended-term (1930–2020) fluctuations in the monthly Standardised SWE Index (SSWEI) and investigated its associations with climate change and large-scale atmospheric forcings through teleconnection indices. Their results confirm highly negative trend values of SSWEI in the last few decades (1991–2020) and indicated the increase in TMEAN as the main driver.

Other studies have investigated HN trends, albeit for shorter periods, considering the complex interactions between climate change and the unique geography of the Alpine region. Considering more than 100 observed HN time series located over the northeastern part of Italy, Bertoldi et al. (2023) have shown how seasonal HN trends are negative in the period 1980-2020, especially at the lowest elevations, while some positive trends have been found above 2000 m a.s.l. This result confirmed the findings referring to extreme HN events simulated for the French Alps presented by Roux et al. (2021), who showed that the majority of trends are negative below 2000 m a.s.l. and positive above that altitude. In our analysis we also found a slightly positive trend for the thigh altitude station of Arosa (1878 m a.s.l.) in the N region. A possible explanation for this result could be linked to the combination of a slight increase in P in the N region together with generally low winter temperatures at high altitudes, despite the significant warming trend.

In this regard, our analysis highlighted that the most negative trends are found for the stations located at the lowest elevations, where TMEAN is increasingly becoming a limiting factor for HN, due to its strong increasing trend (Fig. 21). This is particularly true for the low-elevation stations in the SW region, which, as can be seen from the climatology (Fig. 17), presents a higher TMEAN than the stations at the same elevation in the SE region (Chimani et al., 2013). Furthermore, it has to be noted that the weather patterns at the origin of HN in the two regions are significantly different. In the SW region, these almost exclusively occur with frontal systems associated with Mediterranean southerly winds, leading to milder conditions which (in a context of long-term atmospheric warming) more and more often cause rain rather than snow to fall at lower altitudes. Instead, in the SE region, HN - although decreasing everywhere - remains relatively easier to observe because it is often associated with longer persistence of cold inversional air layers and cold air flows coming from the northeast or east, weather patterns that are marginal for the development of snow events south of the Alps.

Thanks to the availability of centennial series, it was possible to analyse how, until

the 1980s, positive HN anomalies were recorded in all the three regions, with a peak in the 1970s. Afterwards, the anomalies started to change sign, passing from positive to negative, indicating the presence of less snow during winter, especially in the SW and SE regions. The reason for this is to be found in the TMEAN anomalies, as suggested also by Farinotti et al. (2015), Laternser and Schneebeli (2003), Marty (2008), and Mote et al. (2018). As highlighted in the results section, starting from the 1980s, TMEAN anomalies in all the three regions began to rise considerably, reaching values of almost $+1^{\circ}\text{C}$ compared to the centennial average of the stations themselves. Another factor that can explain the reduction in HN since the 1980s is the reduction in winter P in recent decades, especially for SW and SE regions. This corresponds to a probable global atmospheric circulation regime shift (Reid et al., 2016). Moreover, while P returns to the long-term average after 2000 in the SW and SE regions, HN does not increase and remains below the long-term average, highlighting the crucial contribution of climate warming. In fact, after the 1980s, the limiting factor for HN is mainly TMEAN, especially at low elevations, as shown in Bertoldi et al. (2023).

The correlation analysis shows that the contribution of NAO and AO is different from the contribution of AMO. For the lowest stations of the SW and SE regions, NAO and AO have a moderate correlation (-0.5) with HN, while AMO does not show any correlation. The connection between HN and NAO, and AO has been proved also by Beniston (1997) and Kim et al. (2013). They highlighted that periods with relatively low snow amounts and duration are closely linked to the anomalies of the NAO index. An interesting result we found is that, starting from the 1980s, especially for the SW region, the NAO and AO indices began to have a higher correlation with HN. A possible explanation is that, due to the rise in TMEANs starting from the 1980s, the favourable combination of more drivers (TMEAN, P and atmospheric circulation) is needed for HN occurrence. This regional strong correlation between HN events and the NAO and AO indices might be exploited to improve long-term HN forecasts in the Alps. Finally, the absence of correla-

tion between HN and AMO can be explained considering that this index influences P and TMEAN mainly in spring and less during wintertime (Zampieri et al., 2017).

3.7 Conclusions

This study analysed 46 long-term series of snowfall (HN) observations during the period 1920-2020 over the whole Alpine domain. After a check on quality, homogeneity and gaps, HN trends were identified using the Sen's slope estimator and the Mann-Kendall trend test, and compared with trends of precipitation (P) and mean air temperature (TMEAN). Moreover, also large-scale predictors, i.e. the North Atlantic Oscillation (NAO), Arctic Oscillation (AO) and Atlantic Multidecadal Oscillation (AMO) indices were considered. Data have been grouped in three sub-regions: South-West (SW), South-East (SE) and North (N).

Negative seasonal HN trends are found in all the three regions, especially for the SW and SE regions, with overall values of -4.9 and -3.8 %/decade, respectively. Only three positive trends are found and all are in the N region, which recorded on average a trend of -2.3 %/decade. Since the average elevation of the stations analysed in this region is the highest of the three, this suggests that the decrease in HN is particularly affecting the lower elevations, while the higher ones suffer less. This is also confirmed by the analysis of trends as a function of elevation, which shows that stations at lower altitudes have larger negative trends than those at higher elevations. The main factor responsible for the reduction in HN is TMEAN, which for all stations shows a positive or strongly positive and statistically significant trend with an overall value of +0.16°C/decade. A slight increase in winter precipitation is detected, especially for the N region, which can partially explain the few positive HN trends found in this area. In fact, despite the temperature increase, at certain elevations the average winter temperatures are still sufficiently low to allow HN to occur. For both P and TMEAN, no elevation dependency has been found.

By looking at how trends have changed over the past 100 years, this study has revealed that the sharp decline in HN has mainly occurred over the last 40 years. Until the 1980s,

HN anomalies remained at consistently positive values, and only afterwards they started to decrease. This occurred for all the three regions. Clearly, the key role in this steep decline was played by TMEAN, which has increased significantly since the 1980s. On the other hand, the role of P is more difficult to interpret. For the SW and SE region, for example, a cyclical pattern can be seen and it seems to have influenced HN only from the 1980s, when both negative HN and P anomalies were recorded. Instead, for the N region, it can be seen that HN and P anomalies have a similar behaviour until the 1980s, but then start to diverge, suggesting that also in this region TMEAN starts to become the main limiting factor for HN.

This study also showed that there is a positive correlation (greater than 0.5) between HN and P for stations in the N region above 1000 m a.s.l., suggesting that in winter P is in the form of snow in most cases. As elevation decreases, the correlation decreases too. Instead, an opposite behaviour has been found for the correlation between HN and TMEAN, NAO, AO: stations at lower elevations are better correlated than stations at higher elevations. This suggests that, at low elevation, the combination of TMEAN and atmospheric circulation is more crucial for HN occurrence than at higher elevation. However, this correlation has increased since the 1980s, suggesting that TMEAN has become an increasingly limiting factor for HN in the last 40 years, especially in the SW and SE regions. No correlation between HN and AMO has been found, neither looking at the entire period nor over time.

Our study is among a few that consider one hundred years of HN data from over 40 stations over all the Alps. The method used to check the spatial consistency and homogeneity of HN data proved to be extremely useful in assessing the quality of the series and, in the future, it could enable more robust studies of HN in other areas. In the future, the quality-check analysis can be extended to higher temporal resolutions, such as monthly or daily values. The assessment of HN series and their trends adds valuable information to that derived from other snow-related parameters, such as snow depth (HS), snow cover area (SCA) or snow water equivalent (SWE). The integrated analysis based on multiple snow-related

variables and high-quality and dense observation databases can provide a more comprehensive picture of snow cover changes and can be used for a wide range of applications, such as the validation of climatic reanalyses, snow hydrological models or remote sensing products.

Chapter 4

Integrating multi-source high-resolution satellite data to redistribute SWE in semi-distributed hydrological modeling using a random forest approach

This Chapter has been submitted and is currently under review on the Water Resources Research journal, with the title "Integrating multi-source high-resolution satellite data to redistribute SWE in semi-distributed hydrological modeling using a random forest approach". The paper has been coauthored by Valentina Premier, Cristian Tonelli, Giuseppe Formetta, Carlo Marin, Mathias Bavay, Giacomo Bertoldi.

4.1 Abstract

Alpine regions are highly sensitive to climate change, and snow melt dynamics are crucial in their hydrological processes. A key variable is the SWE, but direct measurements are rare and limited, making spatial estimates difficult. Remote sensing (RS) provides well-established, high-spatial resolution SCA observations, yet lacks accurate water mass balance information essential for hydrological modeling.

To overcome these limitations and improve high-resolution SWE estimates, we developed a redistribution approach combining semi-distributed hydrological modeling and remote sensing information. SWE simulated by a semi-distributed model (GEOframe) was redistributed at high spatial resolution using a RF regression trained on topographic features and a dynamic SCD derived from optical remote sensing. The methodology was tested in an alpine catchment (Dischma, Switzerland) using available hydrological and high-resolution snow datasets for validation.

The semi-distributed hydrological model reproduces discharge dynamics, achieving Kling – Gupta efficiency (KGE) values of 0.90 and 0.73 during calibration and validation, but provides coarse SWE spatial patterns. The proposed redistribution approach effectively improves the spatial representation of SWE, achieving a mean bias error (MBE) of -27.48 mm and a Pearson correlation coefficient (CORR) of 0.74 at SWE peaks. In addition, re-distributed SWE maps show high agreement with the operational snow-hydrological model system (OSHD), with a CORR of 0.89. Overall, the catchment-average SWE is bound to the water mass balance estimated by the hydrological model, ensuring consistency with hydrological processes and improving the spatial and temporal representation of snow-melt dynamics.

4.2 Introduction

Snow is a fundamental component of mountain hydrology and climate systems, influencing water availability, vegetation dynamics, and human activities such as ski tourism and hydropower generation (Aragon & Hill, 2024; Beniston, 2012; Rixen et al., 2011). In recent years, climate change has led to a reduction in the SCD, particularly in alpine regions (Notarnicola, 2020). Many studies have demonstrated significant negative trends in SCA and HS in the Alps as a consequence of warming temperatures that result in changes in snowmelt, highlighting the need for improved monitoring and modeling approaches for water resources estimation (Bozzoli et al., 2024; Carrer et al., 2023; Matiu et al., 2021).

Because snow distribution in mountain regions is highly heterogeneous in space and time, there is a growing need for snow information with both high spatial and temporal resolution. Snow redistribution processes are strongly controlled by topography, radiation, wind exposure, and precipitation patterns, leading to large spatial variability even at short distances (Helbig et al., 2024; Mott, Winstral, et al., 2023; Mott et al., 2010). In this context, SWE is a key variable since it quantifies the amount of water stored in the snowpack and directly controls snowmelt contribution to runoff. However, direct SWE observations

are generally sparse and limited to point-scale measurements (Archer & Stewart, 1995; Meløysund et al., 2007), making spatial estimation particularly challenging in complex terrain.

Remote sensing (RS) products provide spatialized observations over large and often inaccessible mountain areas (Balk & Elder, 2000; Nolin, 2010; Rees, 2005). Optical RS products are widely used to retrieve SCA and SCD (Tedesco, 2015), while microwave observations can provide SWE estimates, although their application in mountainous regions is limited by coarse spatial resolution and reduced retrieval accuracy (Tsang et al., 2022). Recent optical missions such as Sentinel-2 allow snow mapping at high spatial resolution, but temporal continuity is often affected by revisit frequency and cloud cover (Gargiulo et al., 2019). Consequently, RS products can effectively describe the spatial evolution of snow cover, but they do not directly constrain snow water mass balance.

To estimate SWE and snowmelt dynamics and the connected hydrological processes, hydrological models coupled with a snow melt module have been traditionally an effective solution. The latter range from physically based energy-balance snow models to more computationally efficient temperature-index approaches (Dong, 2018; Hock, 2003). Physically based models such as CROCUS (Brun et al., 1992), Alpine3D (Lehning et al., 2006), FSM2 (Essery et al., 2025), GEOTop (Rigon et al., 2006), and openAMUNDSEN (Strasser et al., 2024) can reproduce detailed snowpack processes and spatial snow redistribution. However, as highlighted by Bavay and Egger (2014), their application requires very detailed spatial meteorological data, and is computationally intensive when applied to large basins at high spatial resolution (on the order of 10 m), which are the most relevant scales for modeling such processes. For operational hydrological applications, simplified semi-distributed approaches are often preferred. One example is GEOframe (Formetta, 2013; Formetta et al., 2013; Formetta et al., 2011), a physically based semi-distributed hydrological model that reconstructs SWE through a temperature-index approach and has been applied for runoff simulations (Formetta, Antonello, et al., 2014; Formetta, Kampf, et al.,

2014). However, because SWE is simulated at the sub-catchment scale, semi-distributed hydrological models are limited in reproducing fine-scale spatial variability of snow distribution.

To overcome these limitations, several studies have investigated statistical and machine-learning approaches for the spatial refinement and downscaling of snow-related variables such as HS, SWE, SCA, and SCD (Matiu & Hanzer, 2022; Pflug et al., 2024; Revuelto, Alonso-González, Gascoin, et al., 2021; L. Zhu et al., 2021). These methods commonly exploit meteorological forcings together with topographic predictors including elevation, slope, aspect, and terrain roughness, which are known to strongly influence snow accumulation and melt patterns (Helbig et al., 2024; Molotch & Margulis, 2008). In recent years, machine-learning approaches such as RFs have shown promising capabilities in capturing nonlinear relationships between snow distribution and terrain characteristics (López-Moreno et al., 2017; McCreight et al., 2014). Moreover, snow persistence indicators derived from optical RS products, such as SCD, provide valuable information on the seasonal evolution of snow cover and can support SWE spatial reconstruction.

In this work, we exploit a recent high spatio-temporal resolution SCD product derived from optical RS to spatially redistribute SWE simulated by the GEOframe model (Premier et al., 2021). More specifically, we develop a RF regression approach that combines a dynamic SCD, representing, for each pixel and date, the remaining number of days before the next snow-free day, and topographic features to predict the spatial variability of SWE within a mountainous catchment. The proposed methodology wants to exploit the constrain of two complementary sources of information. First, it preserves the basin-scale snow water mass balance estimated by the semi-distributed hydrological model. Second, the spatial redistribution of SWE is performed consistently with the satellite-derived snow cover maps, such that snow is redistributed only within pixels identified as snow-covered by the RS product. In this way, the approach aims to improve the representation of local snow distribution patterns across space and time while maintaining consistency with both

hydrological processes and observed snow cover dynamics.

The paper is structured into six sections. Section 2 presents the study area and all the datasets used in our analysis. Sect. 3 illustrates the methodology, while Sect. 4 shows the main results. In Sect. 5, we discuss the main insights of this work. Finally, Sect. 6 draws the conclusions of the work.

4.3 Study area and datasets

This section introduces the different datasets used in the analysis. First, the study area of the Dischma Valley is described, outlining its main geomorphological and climatic characteristics. Starting from the DEM of this area, a set of topographic parameters was derived and used to support the SWE redistribution within the GEOframe modeling framework. In addition, daily dynamic SCD maps, obtained from a multi-source combination of optical satellite data, has been used to increase the spatial and temporal resolution, and to take into account the snow persistency. Finally, two independent datasets used as benchmarks for SWE data are presented. The first consists of high-resolution (20 m) HS maps, subsequently converted into SWE, which are available only once per year during the period of maximum snow accumulation. The second is the Swiss operational snow-hydrological model system, which provides daily snow-related variables at a spatial resolution of 250 m, offering a complementary reference for evaluating the temporal evolution of SWE.

4.3.1 Study area

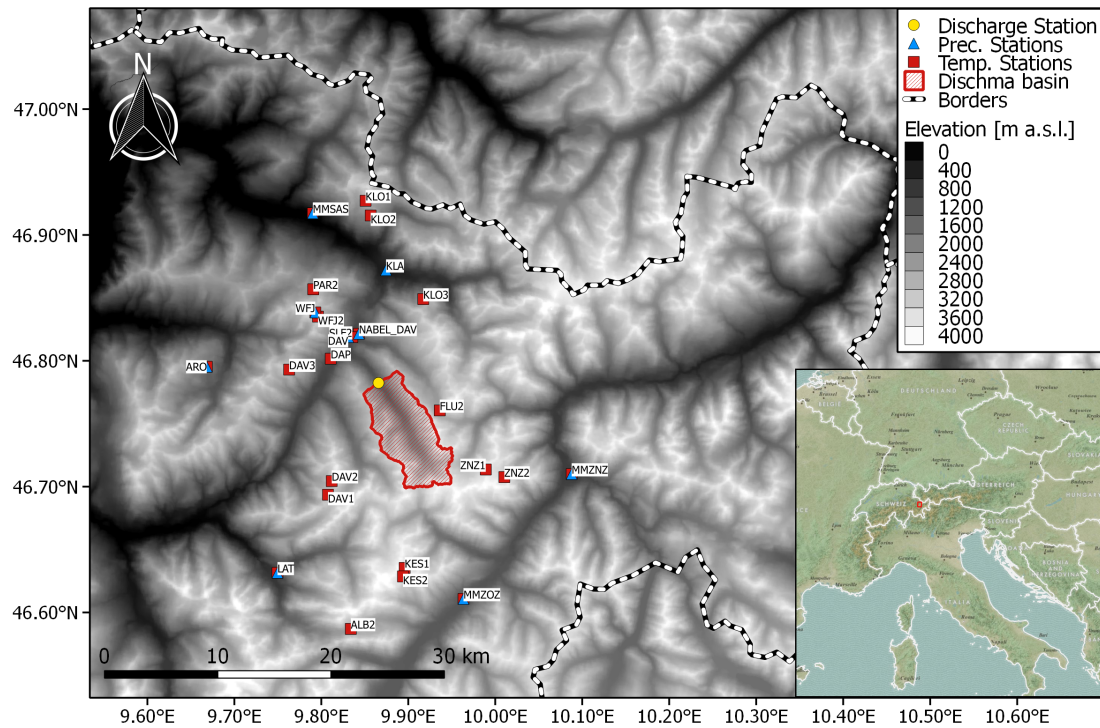


Figure 23 – Location of the Dischma catchment in Switzerland and in Europe (bottom right panel). Markers indicate the available automatic weather stations. Blue (red) triangles (squares) indicate precipitation (temperature) stations. The yellow dot indicates the discharge station at the outlet point of Davos-Kriegsmatte.

The Dischma Valley, a small mountain catchment located in the central Swiss Alps, serves as the study area (Figure 23). This region is an ideal test site for assessing snow hydrology models, due to its topographical and climatic characteristics, and its extensive monitoring. It is a steep, high-altitude Alpine catchment situated in the eastern Swiss Alps. Elevation ranges from 1666 to 3139 m a.s.l., with an average altitude of 2369 m a.s.l. It originates from two equal source streams, which have their headwaters at Scaletta Pass and Fuorcla da Grialetsch. These streams merge at Dürrboden, after which the Dischmabach flows northwest for 15 km before joining the Landwasser in Davos Dorf. The catchment lies in a climatological transition zone between the wet northern Alps and the drier central Alps, with a south/southeast to north/northwest orientation. The eastern part of the basin is

characterized by an alternating pattern of ridges and concave landforms such as depressions or hollows. It covers an area of 43.3 km², including a small glaciated portion accounting for 2.1% of the catchment. Snow accumulation occurs between November and February in the lower regions, while in the highest areas, the accumulation season extends until April (Zappa et al., 2003).

4.3.2 *Analyzed topographic features*

Geomorphological variables and terrain characteristics significantly influence the snow distribution. To quantitatively characterize the basin morphology, several topographic parameters were used, including elevation, slope, aspect, the topographic curvature, the sky view factor, the topographic position index, the topographic ruggedness index, and the diurnal anisotropic heat index. They were derived from the swissALTI3D DEM, freely available at <https://www.swisstopo.admin.ch/en/height-model-swissalti3d>. The DEM was downloaded at 2 m resolution and then aggregated at 20 m resolution. Elevation (elev) represents the absolute terrain height expressed in meters, while slope (slp) and aspect (asp) describe the inclination and orientation of hillslopes, respectively. The topographic curvature (curv), computed following Zevenbergen and Thorne (1987) using a second-order polynomial approximation, was used to identify concave and convex landforms. The sky view factor (SVF) measures the proportion of the sky visible from a given point (Zakšek et al., 2011). It is commonly used as a proxy to identify flat areas and ridges, which receive greater illumination, and depressions, which appear darker due to reduced illumination. The SVF values range from 0 to 1. Among the derived indices, the topographic position index (TPI) classifies landforms by comparing the elevation of each pixel to the mean elevation of its surroundings, thereby distinguishing ridges, slopes, and valleys (Wilson et al., 2007). The terrain ruggedness index (TRI) quantifies local topographic heterogeneity by expressing surface roughness as the elevation difference between a central pixel and its neighboring cells (Wilson et al., 2007). Finally, the diurnal anisotropic heat (DAH) index

accounts for the combined effects of slope and aspect on the spatial distribution of incoming solar radiation and temperature (Cristea et al., 2017). It is highest on steep south/southwest facing slopes, which experience greater afternoon heating, and lowest on steep north facing slopes, while it equals zero on flat terrain. It ranges between -1 and 1.

4.3.3 *Multi-source high-resolution dynamic SCD data*

Optical RS sensors have been widely used for retrieving SCA (Dietz et al., 2012). However, current operational products derived from well-established sensors such as MODIS (Riggs et al., 2015) and Sentinel-2 (Gascoin et al., 2019) face a trade-off between spatial and temporal resolution: MODIS provides daily observations but at a coarse spatial resolution (500 m), whereas Sentinel-2 offers finer spatial resolution (20 m) but with a lower revisit frequency (approximately every five days, depending on latitude). Moreover, data availability is further limited by cloud cover, which frequently obstructs optical observations (Parajka & Blöschl, 2006).

To accurately capture rapid changes in SCA and generate a gap-free product suitable for ingestion into hydrological models, we employed the gap-filled SCA dataset developed by Premier et al. (2021). This approach integrates multi-source optical satellite data from MODIS and Sentinel-2 to produce daily gap-filled high-resolution binary snow cover maps, i.e. pixels are classified as snow (1) or snow-free (0). The method is based on the premise that snow cover patterns are influenced by local topographic and climatic conditions—regions with similar elevation, slope, and aspect often exhibit comparable snow dynamics, such as accumulation and melt. By leveraging a long-term archive of high-resolution imagery, the approach learns these spatial-temporal patterns and applies them through an iterative gap-filling and downscaling process, further refined using machine learning techniques. For a detailed description of the methodology, refer to Premier et al. (2021).

Starting from daily SCA maps, daily dynamic SCD maps are computed by determining,

for each pixel and each date, how many days remain until the next snow-free day. This results in daily SCD maps in which each pixel represents the number of remaining snow-covered days before the next snow-free day after the given time step.

4.3.4 SWE peak validation data

The SWE peak validation dataset (SWE_R) was derived from high-resolution HS maps of Bührle et al. (2022) and then converted to SWE by using the snow density parameters described by Jonas et al. (2009). Bührle et al. (2022) HS maps have a spatial resolution of 0.5 m, generated from imagery captured by the Vexcel Ultracam survey camera mounted on a piloted aircraft. These images were acquired around the peak of winter accumulation, typically end of March/beginning of April. HS maps were computed by subtracting a summer digital terrain model (DTM) from a processed winter digital surface model (DSM) corresponding to the same area. The summer DTM was derived from an airborne laser scanning (ALS) point cloud collected in 2020. Several masks were applied to improve the reliability of the HS maps: settled areas, high-frequented streets, technical structures, pixels with tall vegetation (height > 0.5 m), outliers, and unrealistic HS values were excluded. HS maps were then aggregated at a resolution of 20 m by considering the average of all the pixels that fall inside this area to be comparable with dynamic SCD maps. Five maps were available, one for each season from 2017 to 2022: 11 April 2018, 16 March 2019, 6 April 2020, 16 April 2021, and 23 March 2022. However, the first map was discarded as it only covered part of the study area.

The HS maps were subsequently converted to SWE maps using Equations (5) and (6) in Jonas et al. (2009), along with the parameter values provided in Tables (1) and (2) of the same study. For each pixel, the parameters a and b were chosen based on the month of data acquisition (either March or April) and their elevation. The value for $offset_{reg}$ was selected from Region 5, as the study area falls within this region, as shown in Figure 1 of Jonas et al. (2009).

4.3.5 *Swiss operational snow-hydrological model SWE data*

Since only four high-resolution SWE maps were available, the Swiss operational snow-hydrological (OSHD) model system was included in the analysis as an additional benchmark for comparison. OSHD is a high-resolution modeling framework developed to provide daily analyses and forecasts of snow cover dynamics across Switzerland, addressing the critical role of snow in the hydrological cycle, microclimate regulation, and natural hazard processes (Mott, Winstral, et al., 2023). The system is specifically designed for complex alpine terrain and integrates dense in situ station observations with high-resolution meteorological forcing data and multiple reanalysis products. A key strength of OSHD lies in its combination of physically based snow modeling with advanced data assimilation and meteorological downscaling techniques, allowing for an accurate representation of spatial variability in snow accumulation and melt processes. The system further incorporates advanced process representations and subgrid parameterizations at the snow–canopy–atmosphere interface, which are particularly important in heterogeneous mountainous environments.

OSHD provides two main datasets. The first dataset provides a climatology of SWE, snowmelt runoff, and snow cover fraction over the period 1998–2022, with daily temporal resolution and a spatial resolution of 1 km. The second dataset used in this study consists of daily estimates of HS, SWE, snowmelt runoff, and snow cover fraction for the hydrological years 2016–2022 at 250 m spatial resolution, and is freely available at <https://www.doi.org/10.16904/envidat.404>. Once downloaded, FSM2oshd daily SWE maps were extracted for the Dischma Valley. SWE maps were available from 1 October to 30 June of the following year.

4.4 **Methods**

In this section, first, the GEOframe modeling system is described. Then, we describe the RF algorithm as the method to redistribute SWE. Lastly, we show the SWE redistribu-

tion scheme used to redistribute the daily basin-averaged SWE estimated by the GEOframe model.

4.4.1 *GEOframe model*

The GEOframe modeling system (Bancheri et al., 2019; Formetta, Antonello, et al., 2014) is a semi-distributed hydrological modeling framework based on a hillslope-link partitioning of the catchment. The fundamental spatial unit of the model is the Hydrological Response Unit (HRU), with an area typically ranging from 0.1 to 10 km², depending on user requirements. For each HRU, the model solves the energy and water balance using systems of ordinary differential equations in a non-linear, reservoir-based approach. For each link (i.e. river reach), it performs runoff routing.

The GEOframe system comprises a suite of components that include meteorological variable interpolation (e.g., Bancheri et al. (2018)); shortwave and longwave radiation balance (Formetta et al., 2013; Formetta et al., 2016); evapotranspiration estimation; snow dynamics simulation (Formetta, Kampf, et al., 2014); water infiltration into the root zone; groundwater storage modeling; and runoff generation with river routing (Figure 24). The model has been successfully applied across a wide range of case studies, from small catchments (e.g., Abera, Formetta, Borga, and Rigon (2017)) to large river catchments such as the Blue Nile (e.g., Abera, Formetta, Brocca, and Rigon (2017)), and in both natural and anthropized catchments (e.g., Morlot et al. (2024)). The snow model implemented in each HRU includes a rainfall–snow partitioning algorithm that applies a smoothed threshold filter (Kavetski et al., 2006). It solves two ordinary differential equations: one for the solid water equivalent and one for the liquid water content of the snowpack (Formetta, Kampf, et al., 2014). Both snowmelt and refreezing processes are simulated using a classical degree-day or temperature-index approach (e.g., Hock (2003)).

For this study, the model was initialized using the swissALTI3D DEM (see Sect. 4.3.2). After the geomorphological analysis, the catchment has been divided into 52 subcatch-

ments, each ranging in area from 0.5 to 1.5 km^2 , allowing for a detailed hydrological assessment of its drainage patterns and water distribution. Hourly temperature and precipitation data provided by several institutions were obtained from the data portal of the Federal Office of Meteorology and Climatology (MeteoSwiss). This data was subsequently aggregated to a daily scale. Their location is shown in Figure 23, while the complete list of stations and the institution they belong to is available in Appendix C.1. The model was then calibrated over the first two years, i.e. from 1 October 2017 to 30 September 2019, using daily discharge data measured at the Davos-Kriegsmatte outlet point provided by the Swiss Federal Office for the Environment (FOEN). The calibration was performed based on maximising the Kling-Gupta efficiency (KGE) between observed and modeled daily discharge data. The remaining three years, i.e. from 1 October 2019 to 30 September 2022, were used for validation. Since the model provides an output for each subcatchment, we calculated the average SWE for the whole catchment and for each day: $SWE_G(t)$. This was introduced because the model is calibrated only at the catchment outlet, not across individual subcatchments, potentially introducing discrepancies at the subcatchment scale while still yielding accurate estimates for the full catchment.

4.4.2 *Random forest regression analysis*

RF (Breiman, 2001) is a machine learning algorithm based on an ensemble of decision trees. It builds many different trees, each trained on a random subset of the training data. Both the observations and the variables (predictors) are sampled with replacement when constructing each tree, so that every tree sees a slightly different version of the dataset. The predictions of the individual trees are combined to obtain a more robust and accurate result. This process reduces model variance and makes it possible to effectively use correlated features in the dataset. Every tree in the forest produces a prediction, and the final output of the model is obtained by averaging these predictions. Thus, the RF algorithm can handle correlated variables without degrading performance, scales well to large datasets,

and provides estimates of predictor importance during training (Liaw & Wiener, 2002). However, this structure also makes the algorithm sensitive to the specific characteristics of the training data. For example, if the model relies heavily on a predictor deemed highly important, it may perform poorly in scenarios where that predictor is no longer relevant (Revuelto et al., 2020).

In this study, we employed the RF algorithm to estimate snow redistribution factors (r) for redistributing the SWE simulated by the GEOframe model. Following Revuelto et al. (2020) and Strasser et al. (2024), we considered as predictors elev, slp, asp, curv, SVF, TPI, TRI, DAH (see Sect. 4.3.2), and dynamic SCD (see Sect. 4.3.3). The response variable was represented by the r values derived from SWE_R (see Sect. 4.3.4). They were calculated as the ratio of the SWE_R in each pixel to the total SWE_R across all pixels. The RF regression model was trained using only r values coming from the first available SWE peak map, i.e. 16 March 2019, and 25% of the pixels. Pixels were chosen randomly. The trained model was then applied to the entire basin across all days from 1 October 2017 to 30 September 2022, based on the dynamic SCD maps. The decision to use only one year for training was taken looking at SWE_R . While the total snow amounts vary from year to year, the spatial distribution of snow remains broadly consistent across the analyzed years. In contrast, the choice to use only 25% of the pixels was based on a preliminary sensitivity analysis comparing three subsets (25%, 50%, and 75%). Results showed that although the model performance improved slightly when using 75% of the pixels, the computational cost in terms of time and resources was higher. Therefore, the 25% subset was chosen as an optimal trade-off between efficiency and accuracy.

4.4.3 SWE redistribution scheme

From the GEOframe model, we know the basin-averaged SWE at each time t , hereafter denoted as $SWE_G(t)$. Moreover, the basin can be represented as a high-resolution grid composed of N pixels (20 m in this case), identified by $i = 1, \dots, N$. Hence, $SWE_G(t)$ can

be expressed as:

$$SWE_G(t) = \frac{\sum_{i=1}^N SWE_P(x, y, t)}{N} \quad (1)$$

where $SWE_P(x, y, t)$ is the pixel-scale SWE at location (x, y) and time t . We can assume that exists a matrix of snow redistribution factors $R(x, y, t)$ that relates the basin-averaged $SWE_G(t)$ to the point-scale $SWE_P(x, y, t)$, such that:

$$SWE_P(x, y, t) = R(x, y, t) \cdot SWE_G(t) \quad (2)$$

$R(x, y, t)$ describes how the SWE is distributed spatially across the basin. By replacing Eq. 2 in Eq. 1, we can derive:

$$\frac{\sum_{i=1}^N R(x, y, t)}{N} = 1 \quad (3)$$

This indicates that in order to preserve the basin-averaged $SWE_G(t)$, the sum of $R(x, y, t)$ divided by the total number of pixels has to be exactly 1.

$R(x, y, t)$ can be expressed as an approximate regression function $f(\cdot)$ of topographic features ($T(x, y)$) and a dynamic snow cover duration ($SCD(x, y, t)$):

$$R(x, y, t) \cong f(T(x, y), SCD(x, y, t)) \quad (4)$$

As described in Sect. 4.4.2, to estimate this function, we use a RF regression model. The model was trained using r values from the first available SWE peak map (16 March 2019), and 25% of the pixels. The training dataset includes r as the response variable and elev, slp, asp, curv, SVF, TPI, TRI, DAH, and dynamic SCD as predictors:

$$f(\cdot) = fit(r \sim elev + slp + asp + curv + SVF + TPI + TRI + DAH + SCD) \quad (5)$$

To satisfy the mass balance constraint of Eq. 3, the predicted redistribution matrix $R(x, y, t)$ is rescaled with respect to its sum. This post-processing step ensures that the final redistributed SWE map is unbiased at the basin scale. Moreover, since $R(x, y, t)$ depends on $SCD(x, y, t)$, which is in turn derived from the SCA maps of Premier et al. (2021), SWE is always redistributed consistently with this product. In practice, snow is assigned only to pixels identified as snow-covered by SCA, while snow-free pixels are set to zero. Once trained, the function $f(\cdot)$ can be used to reconstruct $SWE_P(x, y, t)$, by combining $R(x, y, t)$ with $SWE_G(t)$, known from the GEOframe model, using Eq. 2. A conceptual scheme of this process is described in Figure 24.

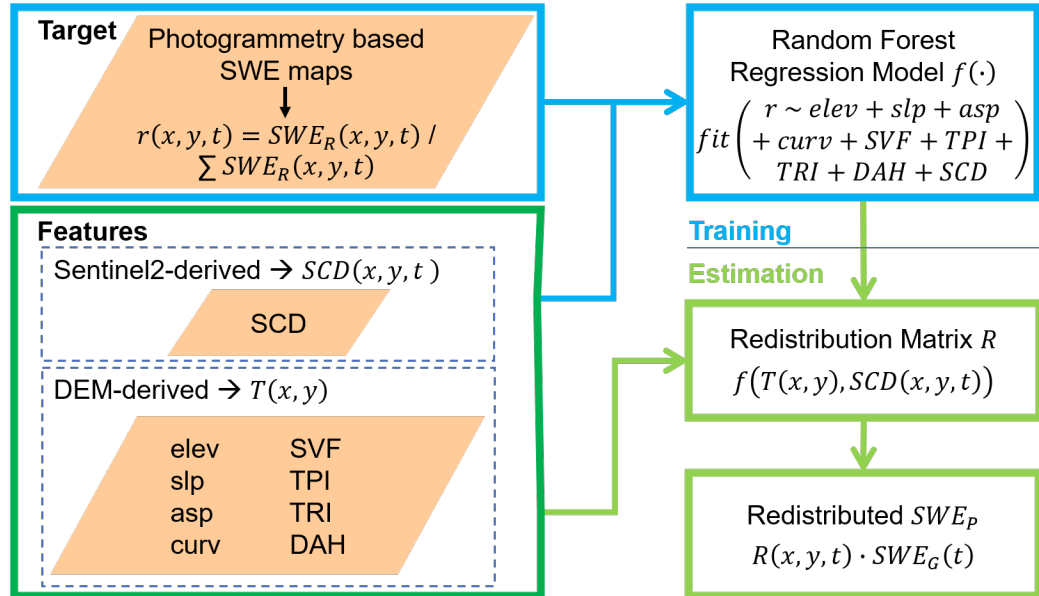


Figure 24 – Schematic representation of the SWE redistribution framework. Photogrammetry based SWE maps (SWE_R) are used to derive the snow redistribution factors r . This serves as the target variable for training a RF model using terrain and snow-related predictors, i.e. elevation (elev), slope (slp), aspect (asp), curvature (curv), sky view factor (SVF), topographic position index (TPI), topographic ruggedness index (TRI), diurnal anisotropic heat (DAH), and dynamic snow cover duration (SCD). The trained model is then applied to estimate pixel based SWE from the redistribution matrix R and the GEOframe basin-averaged SWE.

4.5 Results

This section presents the main results of the study. First, the performance of the GEOframe model is evaluated against observed discharge and FSM2oshd modeled SWE.

Next, the overall contribution of the explanatory variables in describing the redistribution of SWE is analyzed. Then results focus on the comparison between validation (hereafter denoted as observed), FSM2oshd and GEOframe redistributed SWE maps, highlighting how the latter is highly effective at capturing spatial patterns. Finally, the daily evolution of GEOframe redistributed SWE, aggregated by elevation range, is compared with FSM2oshd to assess model performance at a daily scale, beyond peak SWE conditions.

4.5.1 *GEOframe model performance*

The time series comparison of observed and simulated discharge suggests that the model overall performs well in capturing the hydrological dynamics of the catchment (Figure 25a). The simulated discharge closely follows the observed values, both during calibration and validation. However, the baseflow is slightly overestimated during the validation period. The model is particularly effective during periods of increased flow, such as peak discharge events. These peaks likely correspond to seasonal hydrological processes, such as snowmelt or heavy rainfall (Figure 25b).

This is also confirmed by looking at the error metrics. For a full description of error metrics used in this work, refer to Appendix C.2. Using the first two years for calibration and the remaining three years for validation, KGE values of 0.90 during calibration and 0.73 during validation indicate reasonable agreement between simulated and observed streamflow, and a reasonable generalization capability of the model. A similar pattern is observed for the Nash–Sutcliffe efficiency (NSE), which decreases from 0.87 in calibration to 0.74 in validation, confirming a slight reduction in performance while still maintaining good predictive skill. The root mean square error (RMSE) remains low in both periods ($0.75 \text{ m}^3/\text{s}$ in calibration and $0.68 \text{ m}^3/\text{s}$ in validation), indicating limited deviations between simulated and observed streamflow. The percent bias (PBIAS) shifts from a slight underestimation during calibration (-7.6 %) to a modest overestimation during validation (6.7 %), particularly during baseflow conditions, indicating a small change in water balance

representation while overall the model behavior remains consistent. This overestimation of the baseflow during validation is due to differences between the two periods, as the calibration years were wetter and more snow-rich, while the validation years were drier. As a consequence, the model tends to release more water.

Overall, the basin-averaged SWE from GEOframe and FSM2oshd show a similar temporal evolution, with a Pearson correlation coefficient (CORR) of 0.95 (Figure 25b). The FSM2oshd model was introduced to provide a daily benchmark, since the photogrammetry based SWE maps are available only at four snow peak accumulation time acquisitions (see Sect. 4.3.4). This model was selected because it is the reference operational snow-hydrological model for Switzerland and provides open-source daily SWE maps at 250 m resolution for the Dischma catchment (see Sect. 4.3.5). A more pronounced difference is observed during the first two years, when FSM2oshd generally estimates lower SWE values compared to GEOframe with a mean bias error (MBE) of -53.63 mm. In addition, GEOframe more accurately reproduces the observed SWE peak values (black stars in Figure 25b), with a MBE of -42.59 mm compared to -86.62 mm for FSM2oshd, except in 2021, when a slight underestimation is observed. A slight earlier beginning of the melt is observed in GEOframe compared to FSM2oshd. However, since no validation data are available during the melt period, we cannot quantify the accuracy of the method in this period.

These results highlight the capability of the GEOframe model to simulate the water budget within the Dischma catchment and provide a realistic catchment-averaged estimate of both discharge and SWE. For this reason, we aim to integrate these model outputs with RS observations and several topographic features to improve the estimation of SWE spatial patterns.

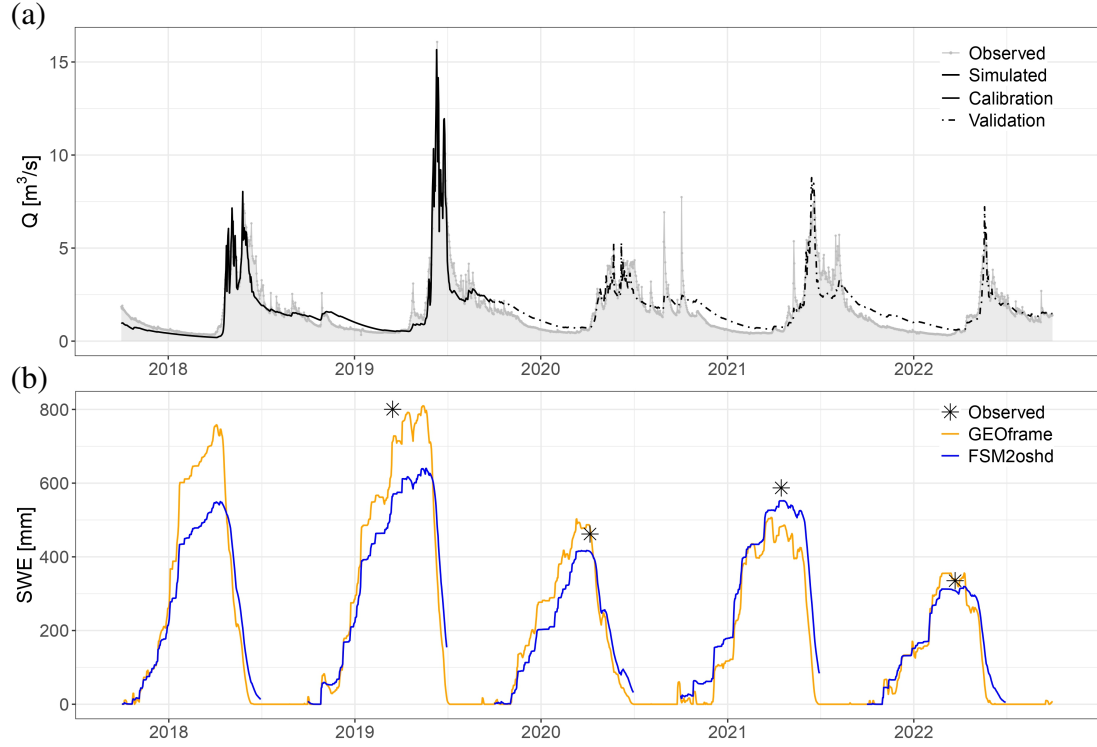


Figure 25 – Q , SWE GEOframe model performance validated against observed data and FSM2oshd model. (a) The dotted-solid (solid) grey (black) line indicates the observed (simulated) discharge at the Davos-Kriegsmatte outlet point. Calibration (validation) period is marked in black solid (dotted-dash) line. (b) The solid orange (blue) line represents the basin-averaged SWE simulated by GEOframe (FSM2oshd), while black dotted stars denote the observations.

4.5.2 Overall features contribution for explaining SWE redistribution

The RF model was trained to identify the relative importance of the selected predictors in explaining the SWE redistribution in our study area. The training dataset consisted of 24208 samples and 9 predictors, derived from r values of the first available SWE map (16 March 2019), using a random subset of 25% of the pixels (see Sect. 4.4.2). Model performance was evaluated using a 5-fold cross-validation approach. The tuning of the $mtry$ parameter, defined as the number of variables randomly sampled as candidates at each split, showed a slight improvement in performance with increasing values. The optimal configuration was obtained for $mtry = 9$, corresponding to the highest coefficient of determination (R^2) of 0.70.

The analysis of variable importance expressed by the percentage of increase in mean squared error (%IncMSE) highlights a clear hierarchy among predictors (Figure 26). This metric represents the increase in model error when a given predictor is randomly permuted, thus quantifying how much the model relies on that variable. Higher values indicate a stronger contribution to the predictive skill of the model. Dynamic SCD emerges as the dominant variable, with a percentage of increase in mean squared error (%IncMSE) of 116.1, indicating that model performance strongly degrades when this information is removed. Among the topographic predictors, SVF (55.2), asp (50.6), and DAH (41.1) show the highest importance, suggesting a key role of radiative processes and terrain-driven snow redistribution. Elev, slp, and TPI exhibit intermediate importance, while curv and TRI have a relatively lower contribution.

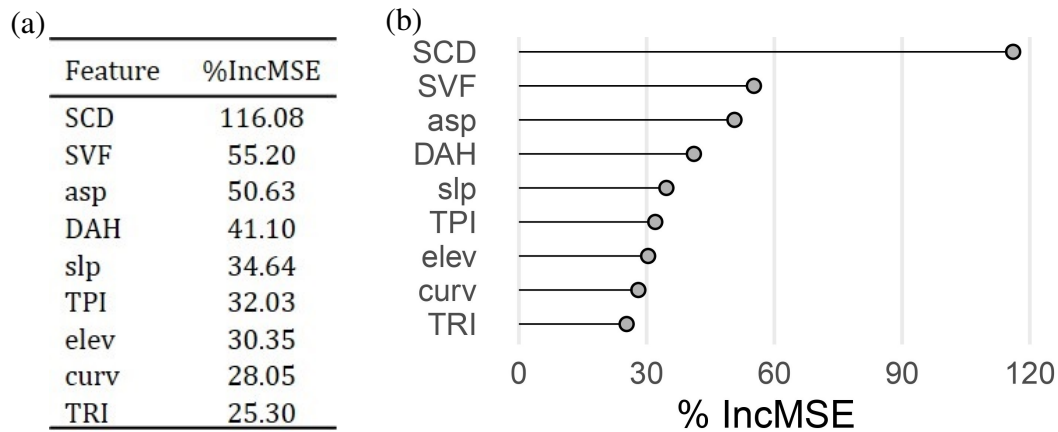


Figure 26 – (a) Table and (b) graphical representation of the percentage of increase in mean squared error (%IncMSE) for each feature used to train the RF regression model.

4.5.3 Redistributed SWE

Figure 27a illustrates the SWE spatial distribution in the Dischma catchment across four available observation dates: 16 March 2019, 6 April 2020, 16 April 2021, and 23 March 2022. Rows represent the different products, ordered from top to bottom as follows: observed, GEOframe redistributed, and FSM2oshd. At the bottom, the corresponding difference maps (GEOframe redistributed - observed) for the same dates are also shown (Figure 27b). "No Data" are marked in black.

Overall, the GEOframe redistributed model shows a more accurate spatial detail, as its higher spatial resolution allows for a more accurate representation of SWE spatial patterns. However, it tends to overestimate SWE on southwest-facing slopes on 6 April 2020 and to underestimate accumulation areas on 16 April 2021 (see Figure 27b). This behavior likely reflects the model training performed on 16 March 2019, a year characterized by abundant snow cover. FSM2oshd operates at a coarser spatial resolution, as it is applied over the entire Switzerland. Consequently, it cannot incorporate highly detailed snow redistribution schemes and is therefore less capable of reproducing fine-scale spatial patterns of SWE, which are primarily driven by elevation and aspect.

After the qualitative assessment based on spatial maps, a more quantitative evaluation is carried out using aggregated scatter plots, where all datasets are resampled to a common spatial resolution of 250 m to ensure comparability (Figure 28). Also at this resolution, GEOframe redistributed shows high agreement with observed SWE values, as indicated by the performance metrics. In contrast, FSM2oshd shows reduced variability, suggesting a tendency to smooth the spatial signal and attenuate local differences, which may limit its ability to capture the full range of SWE variability observed in the data. In fact, the performance metrics for FSM2oshd are considerably lower. All the metrics shown in Figure 28 are explained in Appendix C.2.

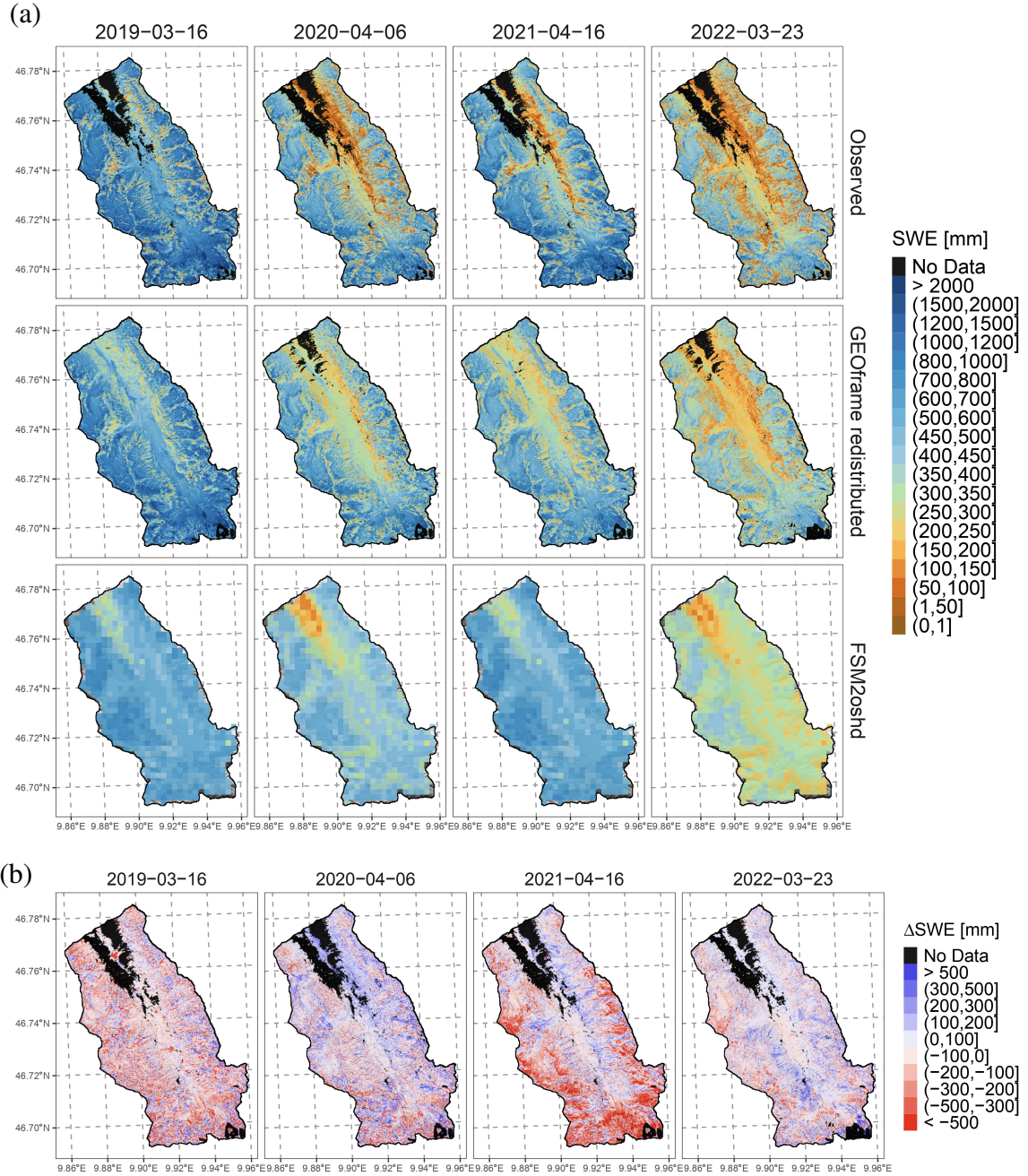


Figure 27 – (a) Spatial distribution of observed and modeled SWE for the four available dates: 2019-03-16, 2020-04-06, 2021-04-16 and 2022-03-23. Rows represent the different products, ordered from top to bottom as follows: observed, GEOframe redistributed, and FSM2oshd. (b) Corresponding difference maps (GEOframe redistributed - observed) for the same dates.

More in detail, on 16 March 2019, the simulation of the GEOframe redistributed closely matches the observed spatial patterns: lower SWE on exposed ridges and steep slopes due to wind erosion and gravity, and higher SWE in sheltered valleys. The high performance

of the model is also evident in the difference map, where differences are fairly random without showing any clear spatial pattern. This is expected given that the first year is the trained year. Quantitative evaluation for the first date analyzed shows a slight overall SWE underestimation (MBE = -67.61 mm), with more noticeable local discrepancies (RMSE = 92.33 mm). $R^2 = 0.94$ indicates that the model not only captures the spatial distribution of SWE effectively but also aligns well in terms of magnitude and variability.

On 6 April 2020, with reduced snow amount, both observed and GEOframe redistributed SWE still show similar spatial distribution patterns. However, discrepancies increase, particularly due to aspect-related differences (lower SWE on sun-exposed southwestern slopes compared to shaded northeastern ones). The model continues to reflect general spatial trends, but slightly overestimates SWE (MBE = 13 mm), with an RMSE of 70.15 mm. This is also evident looking at the difference map where blue colors are predominant. R^2 of 0.84 suggests still a good spatial alignment.

In terms of MBE and RMSE, the worst agreement between GEOframe redistributed and observation occurs on 16 April 2021. Here, the model significantly underestimates the accumulation areas and slightly overestimates the erosion areas. The result is an MBE of -91.49 mm and a RMSE of 162.66 mm. This is also clearly reflected in the difference map, where red areas are prevalent. Despite this, the model maintains a reasonable representation of spatial patterns with R^2 of 0.76. On 23 March 2022, SWE levels are significantly lower. Accordingly, MBE and RMSE decrease in absolute terms (8.36 mm and 62.04 mm, respectively). However, this reduction does not indicate improved performance, but rather reflects the lower magnitude of SWE values. In fact, the R^2 value (0.69) is the lowest among the four dates, indicating weaker agreement in spatial patterns and overall reduced model performance.

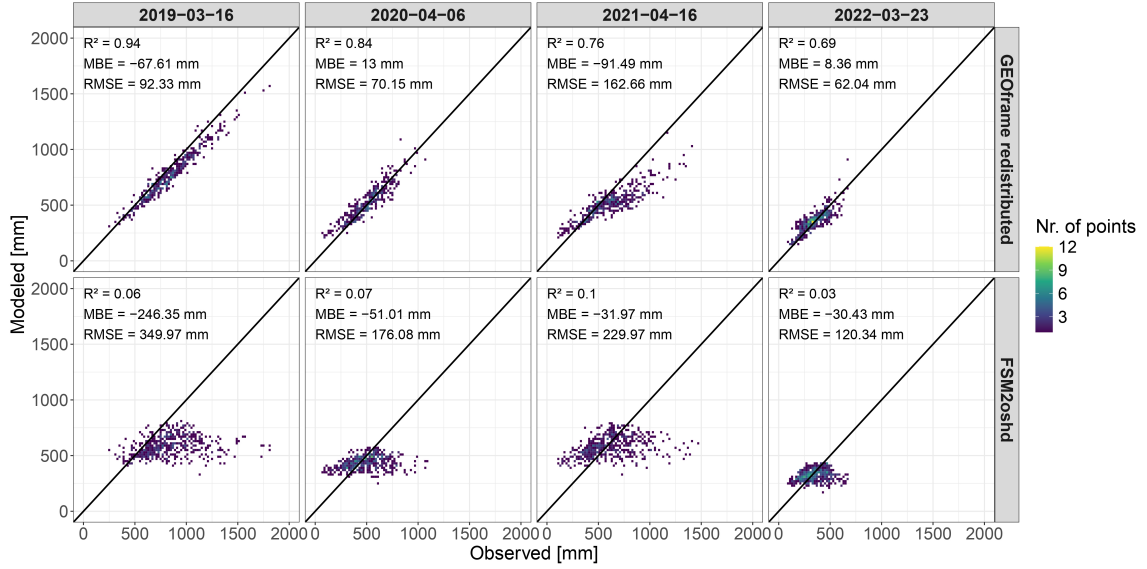


Figure 28 – Distribution of observed against modeled SWE values aggregated at 250 m for the four available dates: 2019-03-16, 2020-04-06, 2021-04-16 and 2022-03-23. The first (second) row corresponds the GEOframe redistributed (FSM2oshd) model.

4.5.4 Daily SWE evolution

The daily evolution of SWE across elevation bands further highlights the performance of the GEOframe redistributed product. Figure 29 shows the daily evolution of SWE for four elevation bands (1600–2000 m, 2000–2400 m, 2400–2800 m, and 2800–3200 m). The solid orange and blue lines represent the basin-averaged SWE simulated by the GEOframe redistributed and FSM2oshd model, respectively, while the black dotted stars indicate the observations. For all elevation ranges, the SWE temporal evolution closely follows that of the reference FSM2oshd model, with CORR values that remain high but gradually decrease with elevation, ranging from 0.93 at lower elevation band to 0.85 at higher elevation band. A systematic earlier beginning of the melt phase is observed in the GEOframe redistributed compared to FSM2oshd, consistent with the behavior already identified at the basin scale (Figure 25a). As discussed in Sect. 4.5.1, it is difficult to assess whether this earlier melt is more realistic, due to the lack of validation data during the ablation period.

In terms of SWE peak, the GEOframe redistributed generally shows a better agreement with observations compared to FSM2oshd, with an average MBE values of -28.36 mm and

-76.89 mm, respectively. An exception is found for the hydrological year 2021 at the higher elevation bands (2400–2800 m and 2800–3200 m), where both models underestimate the observed peaks. Overall, the comparison with FSM2oshd makes it possible to extend the validation of the GEOframe redistributed product from SWE peak to the full daily SWE evolution. This highlights that the product performs well not only in reproducing peak conditions but also at the daily scale. Despite being trained using only SWE peak from the first available year and considering just 25% of the pixels, the GEOframe redistributed is able to effectively reconstruct daily SWE maps. This is achieved through the combination of dynamic SCD information and topographic features, which guide the spatial distribution of SWE from the GEOframe model on a day-by-day basis. An example of daily SWE maps from 15 May 2019 to 13 June 2019 is provided in Appendix C.3.

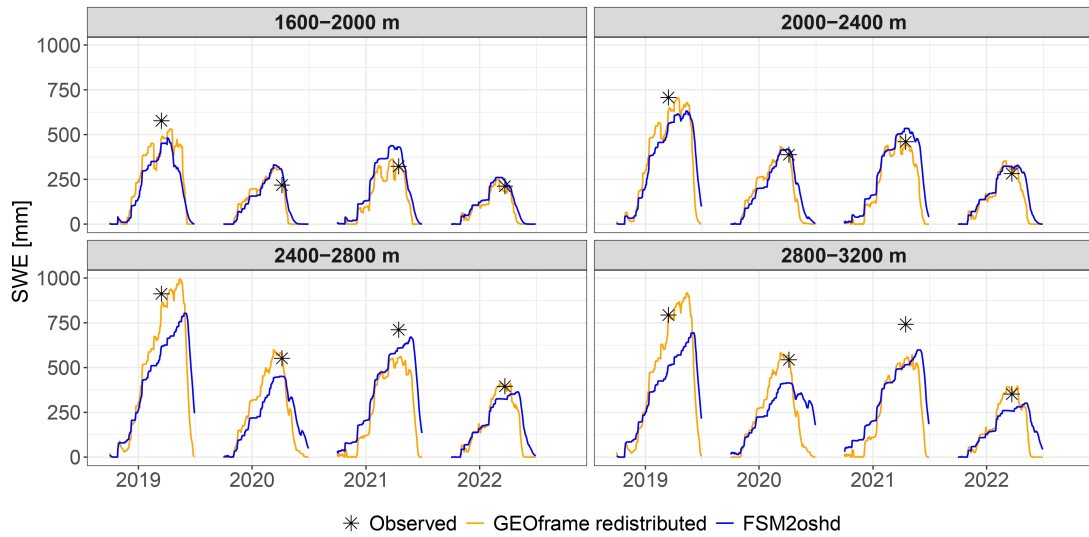


Figure 29 – Daily evolution of SWE grouped into four elevation bands: 1600–2000 m, 2000–2400 m, 2400–2800 m, and 2800–3200 m. The solid orange (blue) line represents the basin-averaged SWE simulated by GEOframe redistributed (FSM2oshd), while black dotted stars denote the observations.

4.6 Discussion

The semi-distributed GEOframe model, once calibrated, exhibited a generally good ability to reproduce the Dischma catchment’s hydrological dynamics. Peak discharges

were very well captured, while baseflow was slightly overestimated, especially during the validation period. Of particular interest is the high discharge peak in late spring 2019, which stands out as the largest across the analyzed period. This peak can be attributed to unusually high snow accumulation during the preceding winter, consistent with recent findings documenting increasing variability in snow accumulation and melt across the European Alps (Marty et al., 2023). Such events confirm the model’s ability to reflect the strong influence of snow processes on the basin’s hydrological regime, which has also been shown to be a dominant driver of both extremes and drought dynamics in Alpine systems (Brunner et al., 2023). Importantly, although the calibration was performed on discharge, the resulting simulations remain consistent with the catchment averaged estimates of SWE, reinforcing confidence in the model’s capacity to represent snow-driven dynamics. This coherence between discharge calibration and snow-related processes highlights the robustness of the model, supporting its application in snow-dominated catchments, particularly in light of long-term SWE observations that provide essential benchmarks for model validation (Ranzi et al., 2024). Moreover, it highlights how a semi-distributed hydrological model, with a relatively simple snowmelt component, when well calibrated for discharge, can realistically represent the catchment-averaged mass balance.

A slightly earlier beginning of the snowmelt is observed in GEOframe compared to FSM2oshd. It is difficult to assess which model is more accurate, as no validation data were available during the melt period. However, FSM2oshd without the optimal interpolation correction on precipitation tends to overestimate the maximum snow peak, which in turn can lead to a delayed snowmelt, and may partly explain the difference (Mott, Winstral, et al., 2023). In this context, the earlier melt simulated by GEOframe could suggest a better representation of the timing of the snowmelt, although this cannot be confirmed with the available data. Since the timing of the snowmelt plays an important role in runoff generation in snow-dominated catchments, this aspect may represent a potential added value of the GEOframe model.

Good results were obtained with our method for spatializing SWE, which relies on a RF approach to train a model on the main factors driving SWE redistribution. The method combines topographic parameters derived from a high-resolution DEM with pixel-based dynamic SCD derived from daily high-resolution SCA maps as explanatory variables, consistent with findings that topography and snow persistence metrics are key predictors for SWE distribution in Alpine catchments (Carturan et al., 2020; Revuelto, Alonso-González, Morán-Tejeda, et al., 2021). At the same time, our approach remains constrained by a mass balance imposed by the hydrological model, ensuring physical consistency and preventing purely data-driven predictions from diverging from hydrological plausibility, in line with the need for process-informed data assimilation highlighted also by A. Frei et al. (2022). The combination of machine learning with a process-based constraint represents a key novelty of our work, as it bridges the gap between statistical flexibility and hydrological realism in the spatial representation of snow processes, consistently with ongoing efforts in the European Alps to develop hybrid models for SWE mapping and runoff forecasting (Berezowski et al., 2023; Mazzotti et al., 2023).

By constructing the redistribution method as previously described, the resulting SWE patterns reflect the combined effects of several processes acting during the snow season in this catchment. In particular, the method captures spatial patterns that are consistent with the influence of precipitation events, wind redistribution, gravitational transport, and intermittent melting, which are known to control snow accumulation in mountainous environments (Blöschl & Kirnbauer, 1991; Blöschl et al., 1991; Liston, 1999; Liston & Sturm, 1998). This is further supported by the analysis of feature importance from the trained RF model. The results show that dynamic SCD is the most important predictor, suggesting that it effectively integrates the combined impact of the previously mentioned processes. Indeed, high dynamic SCD values are typically associated with areas of persistent snow cover, which are likely characterized by enhanced accumulation, reduced solar radiation, limited wind exposure, and contributions from gravitational transport. On the other hand,

low dynamic SCD values indicate areas with low snow persistence, such as steep and sun-exposed slopes, often subject to stronger wind erosion. This finding is particularly relevant, as it highlights the ability of dynamic SCD to act as a proxy for multiple controlling processes, and may represent a promising direction for future developments in snow downscaling approaches. Among the topographic predictors, the SVF also emerged as one of the most important variables controlling SWE redistribution. Low SVF values are generally associated with sheltered and topographically confined areas, where reduced radiative forcing and enhanced snow persistence favor higher SWE accumulation. While SVF has been commonly used in fields such as urban meteorology and forest canopy studies (López-Moreno & Latron, 2008; Morais et al., 2018; Svensson, 2004), its application in SWE redistribution and snow downscaling remains limited. In this context, our results suggest that the inclusion of SVF provides valuable additional information for capturing fine-scale snow spatial variability, representing a further element of novelty of the proposed approach.

A clear limitation of this study is that our validation dataset was composed of only four SWE maps available for different days within the study period, and all of them were carried out at peak SWE conditions. As a result, the method may be less accurate in representing early-season snowfall events, when accumulation and redistribution dynamics can differ substantially from peak conditions, as previously highlighted in studies on Alpine snowpack variability and redistribution (Blöschl & Kirnbauer, 1991; Mott, Paterna, et al., 2023). This limitation has been partially addressed by introducing the FSM2oshd model as an additional benchmark, which allowed for a daily comparison of the simulated SWE data. This extended evaluation indicates that, despite the RF model being trained only on SWE peak conditions from the available first year, it is able to perform reasonably well also at the daily scale. A key factor supporting this result is the use of a dynamic SCD, which provides day-by-day information on snow persistence and thus guides the spatial redistribution of SWE, while maintaining consistency with the high-resolution SCA data. In this framework, the total SWE is constrained by the hydrological model, ensuring con-

sistency with the catchment-scale mass balance, whereas its spatial distribution is informed by high-resolution satellite-derived SCA. This combined approach helps to improve the temporal consistency of the results and partly compensates for the limited availability of spatial validation data beyond peak conditions.

A notable strength emerging from our results is the efficiency of the training process: the model was able to achieve robust performance even when trained with only 25% of the available pixels, and even a single acquisition was sufficient to provide a reliable reference. Similar findings have been reported in recent studies, in which sparse but representative datasets were shown to be sufficient to constrain snow distribution models (Berezowski et al., 2023; Revuelto, Alonso-González, Morán-Tejeda, et al., 2021). This feature could be highly advantageous in remote mountain areas, where acquiring snow distribution data is logistically challenging and expensive. In such contexts, a single snapshot of peak-season snow distribution combined with accurate observed discharge data may already enable the model to reproduce snow patterns with reasonable accuracy across multiple years. In addition, the methodology itself is very straightforward: the final SWE can be directly computed as the matrix of redistribution factors multiplied by the average SWE simulated by the hydrological model (see Eq. 2). This simplicity makes the approach not only computationally efficient but also easily transferable to larger Alpine catchments, where discharge observations are available and therefore well calibrated hydrological models can be set.

4.7 Conclusions

Our study highlights the importance of using high-resolution snow cover products satellite products, as well as the use of hydrological models for estimating SWE in mountainous catchments. For our work, we selected the product developed by Premier et al. (2021), which integrates MODIS and Sentinel-2 data to provide daily high-resolution (20 m) SCA maps, from which dynamic SCD data were derived. Using dynamic SCD data and topographic features we develop an approximate regression function, based on a RF approach,

to redistribute the SWE output of the GEOframe model in the Dischma catchment (Switzerland).

The GEOframe model effectively reproduced discharge dynamics in the Dischma catchment, particularly peak flows related to snowmelt and rainfall. During the validation period, model performance was $KGE = 0.73$, $NSE = 0.74$, $RMSE = 0.7 \text{ m}^3/s$, and $PBIAS = 6.7\%$. At the catchment scale, GEOframe SWE also showed strong agreement with the Swiss operational model FSM2oshd ($CORR = 0.95$), supporting its consistency in representing basin-scale snow processes. The spatial validation of redistributed SWE reproduced the main snow distribution patterns of the catchment, with higher SWE in sheltered valleys and lower values on exposed ridges and steep slopes, consistent with known effects of wind redistribution, slope, and aspect. The RF analysis identified dynamic SCD as the most important predictor, suggesting that it effectively captures several processes controlling snow redistribution. Model performance varied with snow conditions. Under well-developed snowpacks, the agreement with observations was stronger (e.g., 16 March 2019, $R^2 = 0.94$), while larger underestimations occurred under fragmented and shallow snow cover (e.g., 16 April 2021, $MBE = -91.49 \text{ mm}$, $R^2 = 0.75$). Temporal validation against FSM2oshd further showed that the redistributed SWE product reproduced the seasonal SWE evolution across elevation bands, with an average $CORR$ of 0.89, although correlations decreased at higher elevations.

The key novelty of our method for spatializing SWE lies in the use of a RF approach trained on topographic predictors and dynamic SCD, while enforcing two main consistency constraints. On one hand, the method preserves the mass balance provided by the hydrological model. On the other hand, SWE is redistributed in a way that is consistent with daily high-resolution snow covered area maps derived from optical satellite data. This integration bridges statistical flexibility with physical plausibility, ensuring realistic spatial patterns of snow distribution. Despite some limitations, most notably the restricted spatial validation dataset, which consists of only four SWE maps acquired at peak conditions, the

method has shown encouraging robustness. In particular, it performed reliably even when trained on a reduced dataset (25% of the pixels or a single acquisition), a property that could be highly advantageous in remote mountain regions where snow distribution data are sparse.

In the end, the presented approach could be seen from a two-fold perspective. Either a redistributing procedure to improve the capability of a semi-distributed hydrological model to estimate high-resolution SWE pattern in mountain regions, or a method to estimate SWE from multi-source satellite observations using the constraint on catchment-scale water budget coming from a hydrological model. This can lead to an important improvement for the snow hydrology modeling, particularly in the context of climate change adaptation and water resource management.

Chapter 5

Conclusions

5.1 Concluding remarks

This doctoral research investigated changes in HN and SWE in the Alpine region, combining climatological analyses of HN with innovative SWE spatial modeling approaches based on satellite data and hydrological modeling. The three studies together provide a multi-scale perspective on snow dynamics in the Alps: from century-long HN trends across the entire Alpine region, to detailed monthly and elevational analyses in the northeastern Italian Alps, and finally to high-resolution spatial redistribution of SWE in a representative mountain catchment. Overall, the results consistently show that HN in the Alps is declining, especially at low and mid elevations, and that TMEAN has become the dominant limiting factor. At the same time, P remains an important driver at high elevations and during the core winter months. Moreover, results show that it is possible to address the hydrological implications of these changes by developing an integrate system based on remote sensing observations and hydrological modeling to improve the spatial representation and estimation of SWE and snow-melt processes.

Chapter 2 presented a detailed view of recent HN changes, with monthly resolution and a wide elevation gradient (0–3000) m a.s.l., based on a dense network of 122 HN time series in Trentino–South Tyrol during 1980–2020. A major finding is that HN trends vary strongly with both elevation and month. The low elevation range (0–1000 m a.s.l.) HN show a clear and significant decrease. The main driver is the strong increase in TMEAN. P does not explain much of the variance in HN trends. Suitable thermal conditions for HN are becoming increasingly rare. In this elevation band, HN is now highly dependent

on favorable large-scale atmospheric patterns (NAO-, AO-), which can temporarily create cold conditions. This indicates that HN at low elevations is shifting from being a regular winter feature to an occasional event. The mid elevation range (1000-2000 m a.s.l.) show strong variability. At the beginning and end of the winter season, HN decreases almost everywhere. However, during the core winter months (January–March), some stations show stable or even increasing HN. In this band, both TMEAN and P are important drivers. This elevation range can be considered a transition zone, where warming is progressively shifting the snow–rain boundary upward. The high elevation range (2000-3000 m a.s.l.) has more uncertain HN trends. During the core winter months, a slight increase in HN is detected, mainly due to a small increase in P. Since temperatures remain sufficiently low, P still falls as snow. However, in spring (especially April), HN trends are strongly negative, even at high elevations. In spring, TMEAN becomes a limiting factor everywhere. Looking at the overall seasonal pattern, HN trends are mostly negative, especially at mid–low elevations. Another key finding is the presence of positive trends during January–March at mid–high elevations. This diverging monthly behavior shows that annual or seasonal averages may hide important sub-seasonal differences. This study also demonstrated the importance of quality control and spatial consistency checks. It integrated official station data with long-term citizen science observations. The inclusion of amateur data significantly improved spatial coverage, especially at low elevations, where HN data are often scarce. After quality checks, these data proved to be reliable and comparable to official records. The integration of citizen science represents an important methodological contribution. It shows that high-quality HN climatologies can be built by combining institutional and non-institutional observations. This is particularly valuable for variables like HN, which exhibit strong spatial variability.

Chapter 3 shows the trend analysis of 46 long-term HN series covering the period 1920–2020 across the entire Alpine domain. The results clearly show a widespread decline in seasonal HN over the last century. Negative trends were detected in all three

macro-regions (South-West, South-East, and North), with the strongest decreases in the southern sectors (-4.9 %/decade in SW and -3.8 %/decade in SE). The northern region showed a smaller average decline (-2.3 %/decade) and included the only three stations with null or slightly positive trends. One of the most important results is that the decline in HN is elevation-dependent. Stations at lower elevations exhibit stronger negative trends than those at higher elevations. This confirms that warming has a stronger impact where mean winter temperatures are closer to the freezing point. In contrast, high-elevation stations are still cold enough in winter to allow HN, even in a warmer climate. The analysis also shows that the most pronounced decline occurred after the 1980s. Until that decade, HN anomalies were generally positive. The sharp decrease observed over the last 40 years coincides with a strong increase in TMEAN, which, on average over the entire period, have increased by 0.16°C per decade. This indicates that TMEAN is the primary driver of long-term HN decline. P trends are more complex. A slight winter increase in P was detected, particularly in the northern Alps. In some high-elevation areas, this increase in P partly compensated for warming, allowing HN to remain stable or even increase slightly. However, at lower elevations, TMEAN has become the main limiting factor, and HN declines even when P does not decrease. The correlation analysis further confirms this interpretation. At high elevations in the northern Alps (above 1000 m), HN is strongly correlated with P, indicating that most winter P still falls as snow. At lower elevations, HN is more strongly correlated with TMEAN and large-scale circulation indices such as NAO and AO. This shows that HN occurrence at low elevations increasingly depends on specific atmospheric patterns that temporarily allow cold conditions. In summary, the century-scale analysis demonstrates that: (i) HN is declining across the Alps; (ii) the decline is stronger at low elevations; (iii) the steepest decrease occurred after the 1980s, (iv) TMEAN is the dominant driver of this decline; (v) P still plays a role at high elevations.

Results of Chapter 2 and 3 have had a tangible impact at both the local and international levels. An intensive dissemination effort was undertaken, including a series of talks,

workshops, courses, and radio-TV interviews. In the small scale of this PhD activity, these presentations helped strengthen the connection between research and society, ensuring that the findings are accessible, understandable, and practically useful for a wide range of audiences.

Chapter 4 addressed a complementary aspect of snow research: the spatial distribution of SWE in mountain catchments. While the first two studies focused on HN trends at points scale, this study moved toward spatially distributed modeling. Using the Dischma catchment in Switzerland as a test case, high-resolution (20 m) SCA data derived from MODIS and Sentinel-2 were combined with a semi-distributed hydrological model (GEOframe). A RF approach was developed to redistribute modeled SWE based on a dynamic SCD and topographic predictors. During the validation period, GEOframe showed good performance in simulating discharge ($KGE = 0.73$), while its SWE estimates exhibited high agreement with the Swiss operational model FSM2oshd ($CORR = 0.95$), supporting the consistency of its representation of basin-scale snow processes. This provided a robust reference for SWE redistribution. The RF-based method successfully reproduced realistic spatial patterns of snow accumulation: higher SWE in sheltered valleys, lower SWE on exposed ridges and steep slopes, and the clear influence of wind redistribution and aspect. Model performance was particularly strong during well-developed snowpack conditions. Under shallow or fragmented snow cover, performance decreased. Temporal validation against the FSM2oshd model further showed that the redistributed SWE product can be applied at a daily timescale and accurately reproduces the seasonal evolution of SWE across elevation bands, with an average $CORR$ of 0.89, although performance declined at higher elevations. The main innovation of this work is the use of a RF model trained on topographic predictors and dynamic SCD while preserving hydrological-model mass balance and consistency with daily high-resolution satellite-derived snow cover maps. This combination ensures physically consistent and realistic snow distribution patterns. Despite the limited validation dataset, the method showed robust performance and remained reliable

even when trained on substantially reduced data. This property could be highly advantageous in remote mountain regions where snow data are sparse. This approach can be interpreted either as a method to improve semi-distributed hydrological models or as a method to estimate high-resolution SWE using satellite data constrained by catchment-scale water balance. This development is highly relevant in the context of climate change, where accurate snow distribution modeling is essential for predicting water availability and extreme events.

In conclusion, this doctoral work demonstrates that HN in the Alps is undergoing significant changes driven primarily by warming. The strongest impacts occur at low elevations and during the transition seasons. High elevations remain partly resilient in mid-winter but are not immune to spring warming. At the same time, by linking these findings with a spatially explicit SWE redistribution approach based on satellite data, machine learning, and hydrological mass-balance constraints, this thesis moves beyond a simply trend detection and improves the representation of how snow is distributed and stored in mountain catchments. Together, these contributions provide a comprehensive framework for analysing, monitoring, and modeling snow in mountain regions. In the context of ongoing climate change, such integrated approaches are essential to support adaptation strategies and sustainable water resource management in Alpine environments.

5.2 Future perspectives

Looking ahead, several directions emerge for extending and applying the results of this PhD research. On the climate trends analyses, the HN dataset could be updated to include the most recent years, allowing trends to be monitored continuously and ensuring that analyses reflect ongoing climate changes. Expanding the study area to cover additional mountain regions and integrating HN trends with other snow-related variables, such as SCA or SWE, would provide a more comprehensive understanding of snow dynamics. Another potential direction for this part of the work would be to build a systematic collection of

SWE observations, which would complement existing HN and HS datasets and provide a stronger basis for hydrological modeling and climate impact studies.

For the GEOframe-based SWE downscaling part, an important methodological development would be the integration of the SWE redistribution procedure directly within the GEOframe modeling system. Instead of applying the redistribution as an external post-processing step, a dedicated module could be developed to automatically downscale and spatialize SWE during model simulations. Such integration would ensure consistency between snow accumulation, melt processes, and water balance constraints, while increasing computational efficiency and reproducibility. Embedding this functionality into GEOframe would transform the framework into a fully integrated, multi-scale snow–hydrology modeling system.

Another important improvement would be working at the sub-catchment scale making it easier to redistribute SWE with high spatial resolution and maintain scalability for larger catchments. However, this approach also introduces boundary-related challenges, particularly when applying redistribution across connected sub-catchments with heterogeneous snow and hydrological regimes.

In this context, the application and upscaling of the SWE redistribution framework to more complex and human-influenced basins is already underway. The methodology is currently being implemented in the Venosta basin (Val Venosta, South Tyrol), which is significantly larger and more heterogeneous than the Dischma catchment. Preliminary results are encouraging, indicating that the redistribution framework is able to reproduce realistic spatial patterns of SWE even under more complex physiographic conditions. A comparison between the redistributed GEOframe SWE product and simulations from the physically based GEOTop model (Endrizzi et al., 2014) further supports the potential of the approach, showing good agreement in the spatial distribution of snow (Fig. 30).

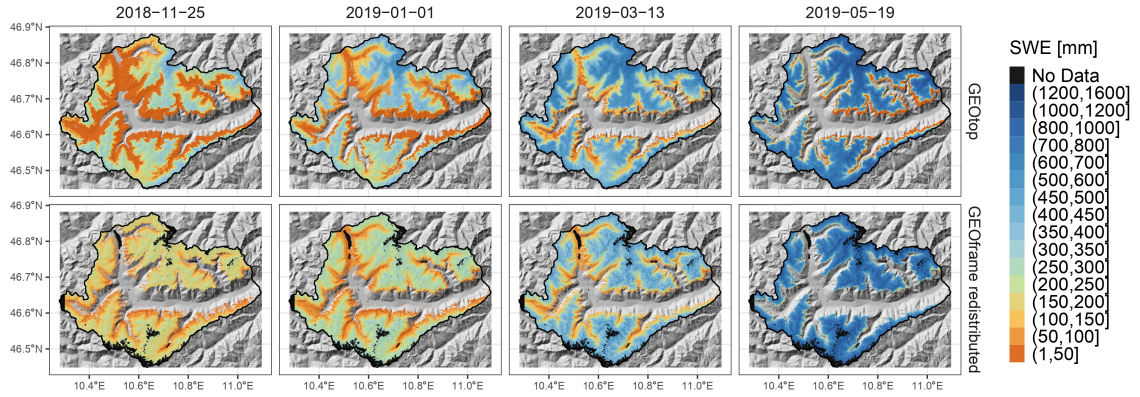


Figure 30 – Spatial distribution of modeled SWE for four dates: 2018-11-25, 2019-01-01, 2019-03-13 and 2019-05-19. Rows represent two different models, GEOtop and GEOframe redistributed, respectively.

The Venosta basin is characterized by strong human activities, including intensive agriculture and extensive hydropower regulation, which alter the natural flow regime and water storage dynamics. Applying the SWE redistribution approach in such a context represents a more challenging test, both in terms of spatial scale and process complexity, allowing the evaluation of its performance where natural snow processes interact with managed reservoirs, river networks, and irrigation demands. This is particularly relevant for water resource planning in regions where snowmelt dynamics are tightly coupled with economic activities. For the Venosta application, the framework exploits the high-resolution HS product developed by Dunmire et al. (2024), which provides HS data at 100 m resolution across the entire Alpine region. The availability of such a consistent and spatially extensive dataset greatly enhances the transferability and scalability of the method, enabling its application beyond a single catchment and paving the way for a standardized, Alps-wide implementation of high-resolution SWE spatialization.

A further step would be then extend also to very large river basins, such as the Po River basin. In this case, the objective would not only be to improve the spatial detail of SWE at mountain scale, but also to assess whether a more realistic spatialization of snow storage leads to better estimates of the total water volume circulating within the basin. Given

that the Po basin integrates multiple Alpine sub-catchments and represents a critical water resource system for northern Italy, improving the representation of snow accumulation and melt could enhance seasonal water availability forecasts and large-scale hydrological simulations.

The ultimate goal would be to move from a research-oriented framework to an operational product that concretely supports agriculture, hydropower management, and civil protection. A more accurate and high-resolution estimate of SWE is essential to better quantify the real amount of water stored in the snowpack and therefore available in spring and summer. In basins with intense anthropogenic activity, such as the Venosta, this information is crucial for irrigation planning, reservoir operation, drought and flood risk assessment. Providing reliable, spatially detailed SWE maps and seasonal water storage indicators could significantly improve decision-making processes and strengthen climate adaptation strategies in Alpine regions.

Appendix A

Snowfall trends in the northeastern Italian Alps

A.1 Errors distribution

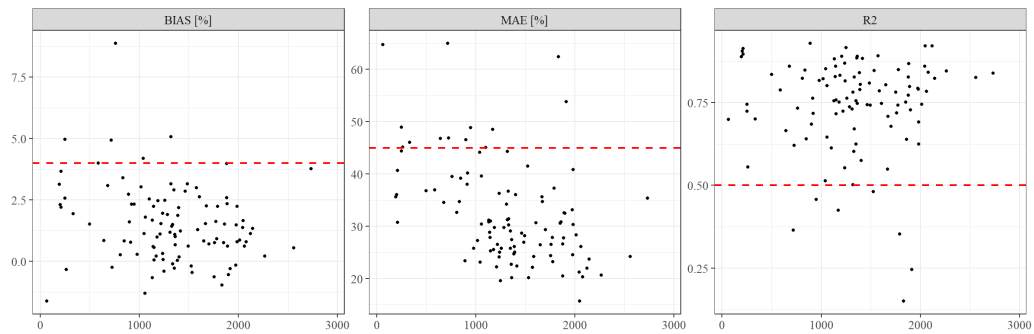


Figure 31 – Errors distribution for observed and reconstructed time series: relative BIAS, relative MAE and R2. Red dashed lines indicate thresholds of 4%, 45% and 0.5, respectively.

A.2 Gap filling and trends comparison

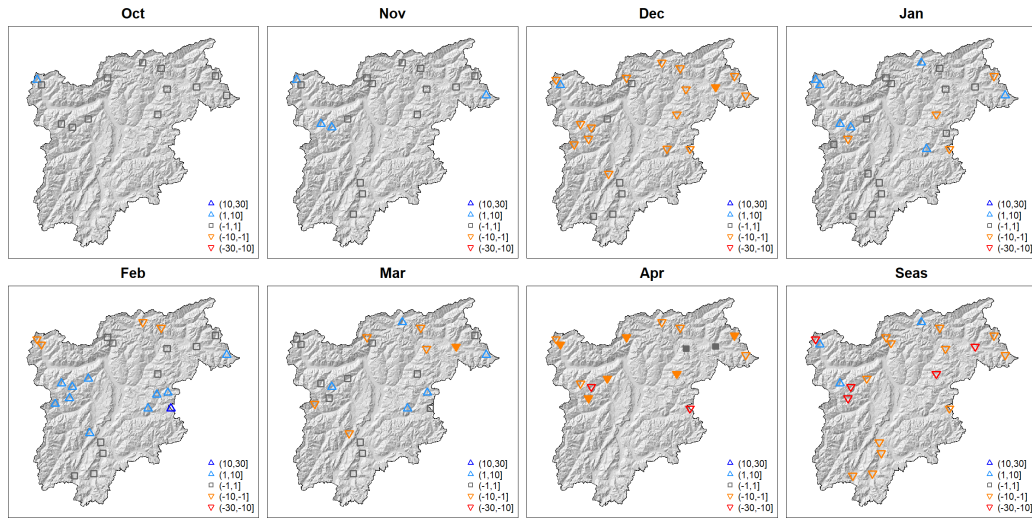


Figure 32 – Spatial distribution of monthly (October - April) and seasonal snowfall (HN) trends expressed in [cm/decade]. Each point represents one station and the corresponding trend value: blue (red) triangles indicate positive (negative) trends; gray squares indicate negligible trends (i.e., between -1 and 1). Full symbols indicate significant trends. Trentino-South Tyrol hill-shade is plotted in the background. Threshold imposed on the % of data gained after gap filling: 10 (trend case 1).

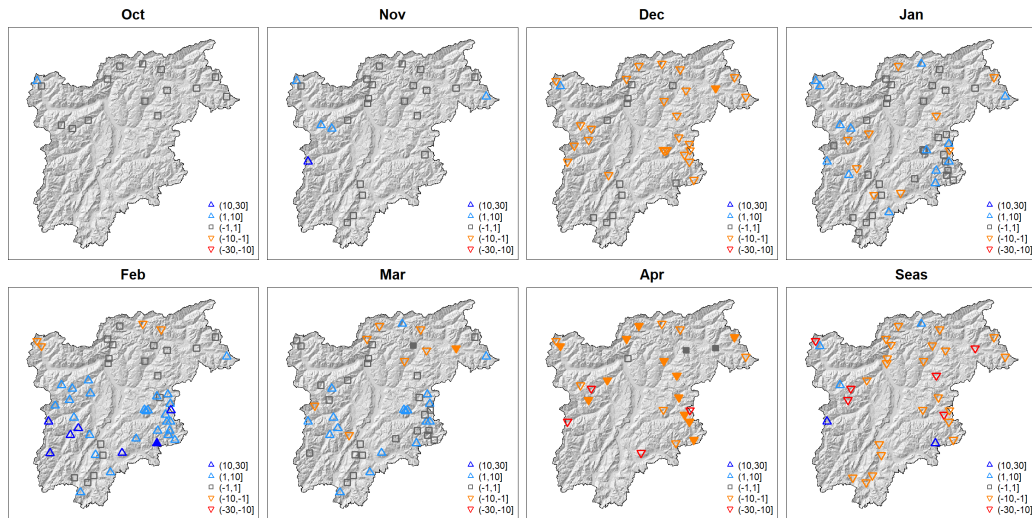


Figure 33 – Same as Fig. 32. Threshold imposed on the % of data gained after gap filling: 20 (trend case 2).

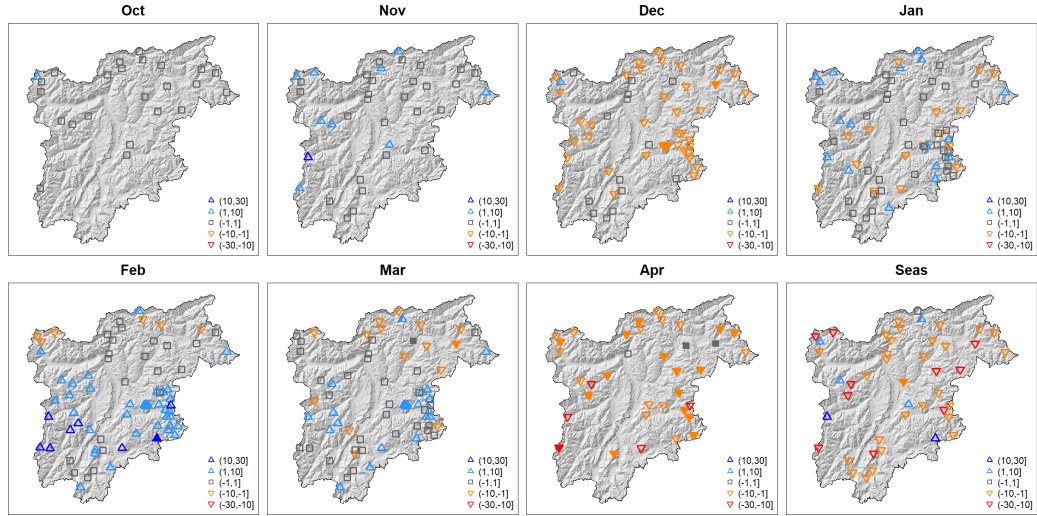


Figure 34 – Same as Fig. 32. Threshold imposed on the % of data gained after gap filling: 30 (trend case 3).

	(0, 1000] m			(1000, 2000] m			(2000, 3000] m		
	#	AT	RT	#	AT	RT	#	AT	RT
Trend reference case	24	-4.5	-10.25 %	51	-6.36	-3.71 %	5	-0.51	-0.3 %
Trend case 1	6	-3.27	-8.83 %	12	-7.3	-4.25 %	1	-4.76	-1 %
Trend case 2	10	-3.35	-9.9 %	24	-4.04	-2.88 %	1	-4.76	-1 %
Trend case 3	12	-3.77	-10.42 %	34	-5.25	-3.24 %	3	-0.32	-0.33 %

Table 2 – Comparison between trends calculated in the reference case and in the three test cases. Trend case 1, 2, 3 represents the trends evaluated with the data set obtained considering only the time series with less than the 10, 20, 30 % of data gained thanks to the gap filling procedure, respectively. For each case and elevation range the number of stations used for the the calculation of the trend (#) and the mean value of the absolute (AT) and relative (RT) trends are indicated. AT are expressed in [cm/decade], RT are expressed in [%/decade].

A.3 Seasonal snowfall data

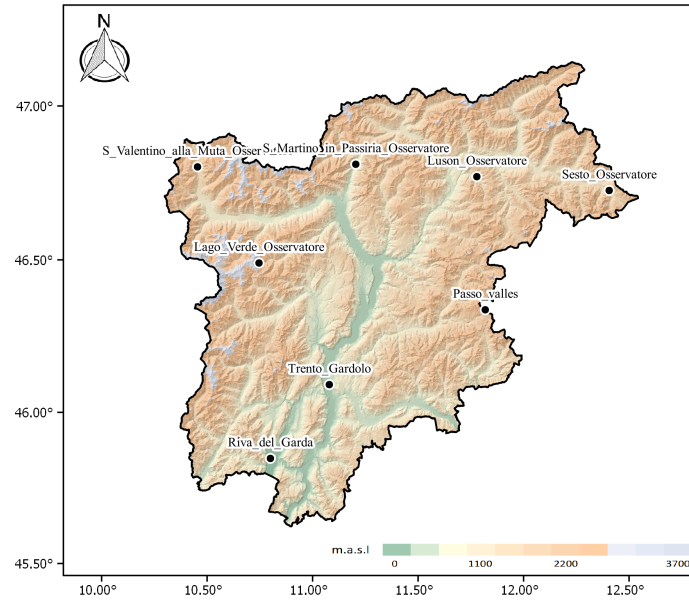


Figure 35 – Location of the eight stations selected to show the seasonal snowfall variability.

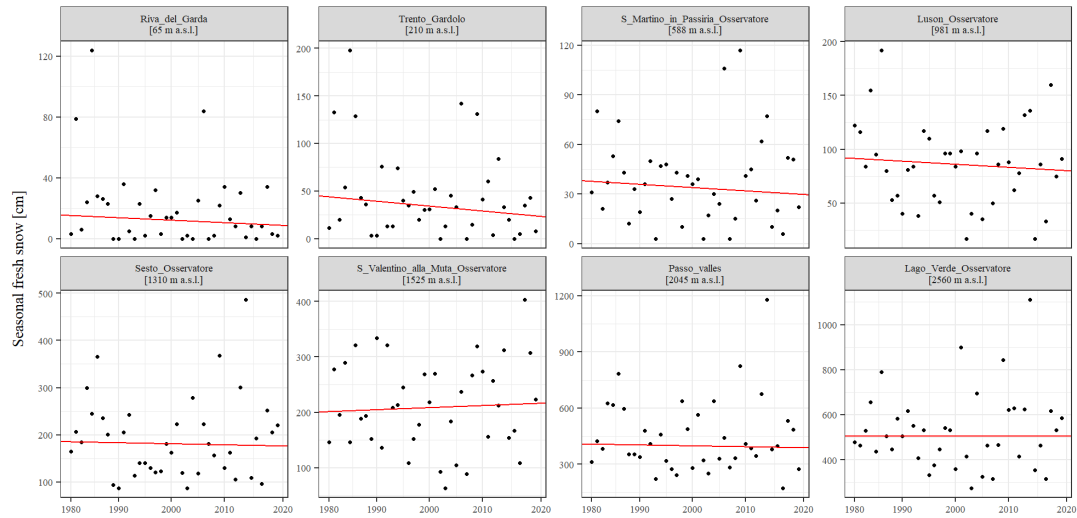


Figure 36 – Seasonal snowfall time series of the eight stations selected to show the seasonal snowfall variability. Red lines indicate the trend.

A.4 NAO and AO index

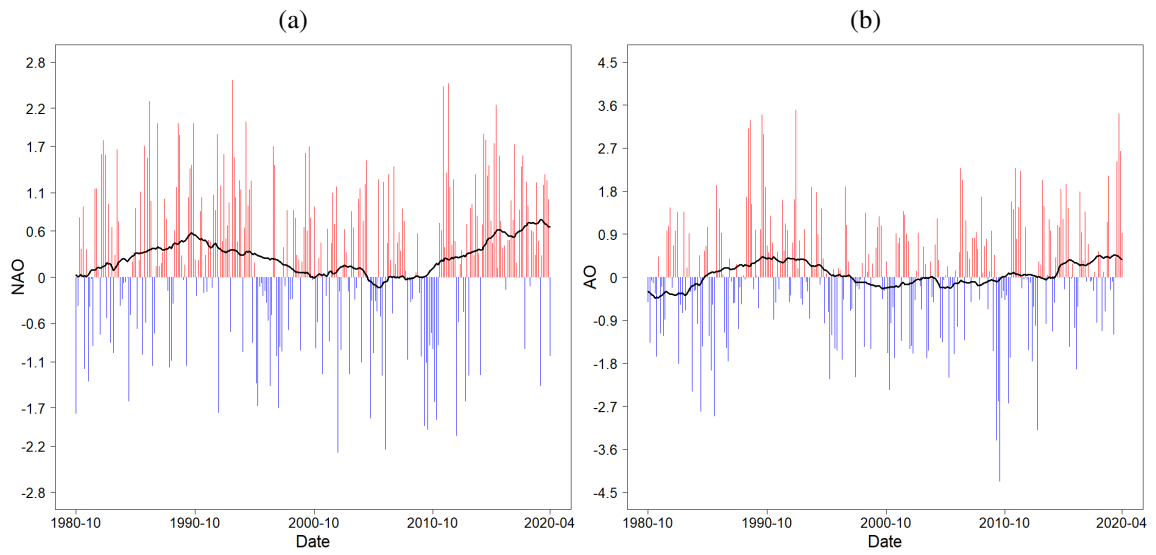


Figure 37 – Monthly (October - April) NAO (a) and AO (b) time series during the period 1980-2020. The black line indicates the 10-year moving average.

Appendix B

Long-term snowfall trends in the Alps

B.1 Snowfall stations meta data

ID	Prov	Name	Long (°)	Lat (°)	Elev (m)	SY	EY	Use
1	IT SMI	Aosta	7.3334	45.728	544	1891	2019	HT
2	CH METEOSWISS	Arosa	9.679	46.7926	1878	1890	2020	HT
3	AT GSA	Bad Bleiberg	13.6844	46.6253	909	1896	2022	HT
4	AT GSA	Bad Gleichenberg	15.9036	46.8722	269	1861	2022	HT
5	CH METEOSWISS	Bern Zollikofen	7.464	46.9907	552	1897	2020	HT
6	IT SMI	Bra	7.8519	44.701	290	1862	2018	HT
7	AT GSA	Bregenz	9.7461	47.4992	424	1869	2022	H
8	AT GSA	Bruck Mur	15.2497	47.4056	482	1895	2022	H
9	SI ARSO	Celje	15.2259	46.2366	242	1893	2022	HT
10	SI ARSO	Cerknica	14.3634	45.7956	569	1894	2022	HT
11	CH METEOSWISS	Chur	9.5305	46.8704	556	1888	2020	HT
12	CH METEOSWISS	Col du Grand St Bernard	7.1707	45.8691	2472	1865	2020	H
13	SI ARSO	Črnomelj	15.1462	45.56	157	1882	2022	HT
14	IT SMI	Cuneo	7.5478	44.3897	565	1877	2019	HT
15	AT GSA	Deutschlandsberg	15.2269	46.8217	354	1895	2022	HT
16	AT GSA	Doellach	12.9025	46.9581	1071	1871	2022	H
17	IT SMI	Domodossola	8.2877	46.1133	280	1872	2019	HT
18	SI ARSO	Dravograd	15.0283	46.5919	384	1885	2022	HT
19	CH METEOSWISS	Einsiedeln	8.7565	47.133	910	1907	2020	HT
20	CH METEOSWISS	Elm	9.1753	46.9238	957	1881	2020	HT
21	AT GSA	Feldkirch	9.6097	47.2711	438	1875	2022	HT
22	CH METEOSWISS	Glarus	9.0669	47.0346	516	1891	2020	HT
23	AT GSA	Gmunden	13.8075	47.9147	424	1892	2016	H
24	CH METEOSWISS	Goschenen	8.5954	46.6927	950	1901	2020	HT
25	AT GSA	Graz Univ.	15.4489	47.0778	367	1851	2022	H
26	CH METEOSWISS	Guttannen	8.2917	46.6565	1055	1876	2020	HT

ID	Prov	Name	Long (°)	Lat (°)	Elev (m)	SY	EY	Use
27	AT GSA	Hall Admont	14.4908	47.5944	637	1895	2022	HT
28	AT GSA	Innsbruck Univ.	11.3842	47.26	578	1866	2022	HT
29	AT GSA	Klagenfurt Flughafen	14.3183	46.6483	450	1813	2022	H
30	SI ARSO	Kranjska Gora	13.7891	46.4865	802	1895	2022	HT
31	AT GSA	Krimml	12.1819	47.2292	1009	1891	2022	H
32	AT GSA	Kufstein	12.1628	47.5753	490	1905	2022	HT
33	AT GSA	Langen Am Arlberg	10.1247	47.135	1270	1881	2022	HT
34	SI ARSO	Laško	15.2341	46.1565	222	1895	2022	HT
35	AT GSA	Lienz	12.8064	46.8256	661	1895	2022	H
36	SI ARSO	Ljubljana	14.5124	46.0655	299	1895	2022	HT
37	SI ARSO	Luče	14.7457	46.3543	513	1893	2022	HT
38	CH METEOSWISS	Lugano	8.9603	46.0042	273	1864	2020	HT
39	CH METEOSWISS	Luzern	8.301	47.0364	454	1883	2020	HT
40	AT GSA	Mariazell St Sebastian	15.3022	47.7892	864	1889	2022	H
41	CH METEOSWISS	Meiringen	8.1692	46.7322	588	1901	2020	HT
42	AT GSA	Micheldorf	14.1344	47.8831	459	1901	2022	H
43	IT OMD	Milano	9.19	45.4669	120	1881	2020	HT
44	AT GSA	Mondsee	13.3472	47.8508	481	1892	2022	H
45	IT OMP	Parma	10.328	44.8015	57	1867	2021	HT
46	SI ARSO	Planina pri Rakeku	14.2525	45.8308	462	1894	1988	HT
47	AT GSA	Rauris	12.9925	47.2236	934	1875	2022	HT
48	AT GSA	Reichenau Rax	15.837	47.6997	488	1865	2022	H
49	AT GSA	Reichersberg	13.3761	48.3311	351	1881	2022	H
50	AT GSA	Ried Im Innkreis	13.475	48.2172	427	1872	2022	H
51	IT MTAA	Riva del Garda	10.85	45.883	65	1921	2020	HT
52	IT MTAA	Rovereto	11.044	45.897	213	1882	2021	HT
53	AT GSA	Salzburg Flughafen	13.0083	47.7894	430	1874	2022	H
54	AT GSA	Schmittenhoehe	12.7381	47.3286	1956	1880	2022	H
55	AT GSA	Schroecken	10.0861	47.2617	1244	1895	2022	H
56	AT GSA	Seckau	14.7786	47.2708	872	1895	2022	HT
57	CH METEOSWISS	Segl Maria	9.7623	46.4323	1804	1864	2020	HT
58	SI ARSO	Škofja Loka	14.2924	46.172	367	1895	2022	HT
59	SI ARSO	Sodražica	14.6382	45.7629	542	1892	2022	HT
60	AT GSA	Sonnblick Tawes	12.9575	47.0542	3109	1886	2022	H
61	AT GSA	Stift Zwettl	15.2036	48.6178	502	1883	2022	H
62	AT GSA	Stolzalpe	14.1883	47.1231	1291	1921	2022	H

ID	Prov	Name	Long (°)	Lat (°)	Elev (m)	SY	EY	Use
63	AT GSA	Tamsweg	13.8083	47.1331	1025	1895	2022	HT
64	IT SMI	Torino	7.6272	45.0721	267	1787	2020	HT
65	IT MTN	Trento	11.1331	46.0742	312	1920	2020	HT
66	IT SMAA	Udine	13.233333	46.066667	113	1776	2000	HT
67	AT GSA	Villacher Alpe	13.6733	46.6036	2140	1876	2022	H
68	AT GSA	Waidhofen Ybbs	14.8097	47.9456	384	1896	2022	H
69	AT GSA	Wien Hohe warte	16.3564	48.2486	198	1775	2022	H
70	CH METEOSWISS	Zurich Fluntern	8.5657	47.3779	555	1864	2020	HT

Table 3 – List of the snowfall (HN) stations used. For each station are indicated ID number (ID), provider (Prov), station name (Name), longitude (Long), latitude (Lat), elevation (Elev), start year (SY), end year (EY), use (Use). H indicates HN stations used only for homogenization, while HT for both homogenization and trend analysis.

B.2 Homogeneity check

In this work, the Climatol procedure, as implemented in the R package "climatol" version 3.1.1 (Guijarro, 2018), was used to check the homogeneity of the HN time series. Other procedures could be applied, such as the HOMogenization softwarE in R (HOMER; Caussinus and Mestre (2004)) or the Adapted Caussinus-Mestre Algorithm for Networks of Temperature series (ACMANT; Domonkos (2011)). However, as suggested by Buchmann et al. (2022), HOMER is very time-consuming for the user and also requires extensive expert knowledge. On the other hand, ACMANT is easier to apply, but implies a lot of postprocessing, due to the large number of break points detected, and also requires in-depth knowledge about the station network. Moreover, Coll et al. (2020) recommended Climatol as the method to be used for precipitation, because the identified break points appeared likely to be more realistic than the ones found with either ACMANT or HOMER. Therefore, for these reasons, Climatol was chosen in this study.

Climatol uses composite reference series and detects breaks one-by-one with the Standard Normal Homogenization Test (SNHT; Alexandersson and Moberg (1997)) applied to anomaly series between observed and reference data. Data are normalized based on ratio

or difference, depending on the climate variable, with respect to the mean climatological value of the series. The normalization based on the ratio is applied to HN series, since it is more suitable for skewed data. Reference series are estimated from the nearest observed series based on geographical proximity using Euclidean distances (Luna et al., 2012). Series of anomalies are obtained by subtracting the estimated values from the observed ones (always in normalized form).

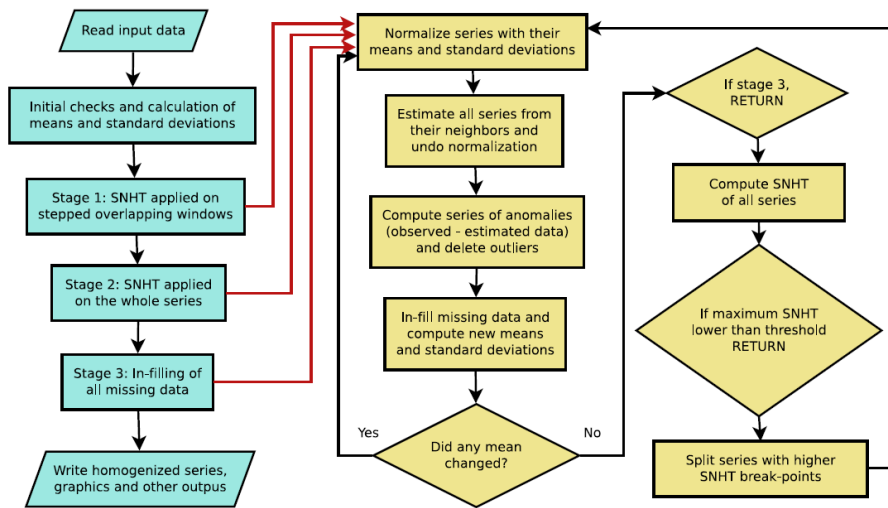


Figure 38 – Climatol operational flowchart (Guijarro, 2018).

When the SNHT statistics of the series are greater than a prescribed threshold, the series is split at the point of maximum SNHT, moving all data before the break to a new series. This procedure is done iteratively, splitting only the series with the higher SNHT values at every cycle, until no series is found inhomogeneous. Since SNHT was originally designed for identifying a single break-point, the existence of two or more shifts in the mean with similar values could mask its results. To minimize this problem, SNHT is applied in a first stage to stepped overlapping temporal windows (stage 1), followed by a second stage applying SNHT to the entire series (stage 2), which is where the test exhibits more power of detection. Finally, a third stage is dedicated to in-fill all missing data in all homogeneous series and sub-series with the same data estimation procedure (stage 3). All these processes are described in the flow-chart shown in Fig. 38. Thresholds for outlier rejection and

break-point detection can be very different depending on the data periodicity and cross-correlation of the series. Therefore, it is highly recommended to make a first run in the so-called "exploratory" mode in order to detect these thresholds.

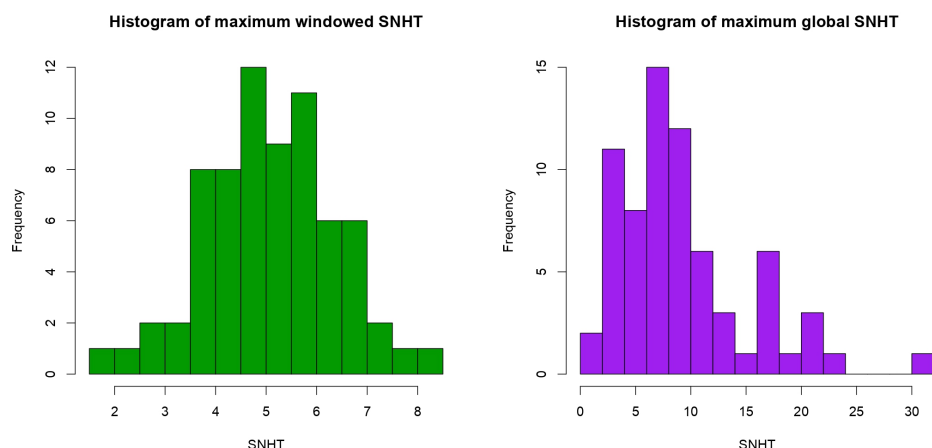


Figure 39 – Histograms of the maximum SNHT values found on overlapping stepped windows (a) and on the whole series (b) using Climatol exploratory mode.

Following the procedure described above, Climatol was applied to our HN dataset. From the exploratory analysis, histograms of maximum windowed and global SNHT were used to choose the thresholds to detect changes in the mean of the series (Fig. 39). These histograms display a prominent occurrence of low values, leading to the conclusion that all the series should be fairly homogeneous. However, considering the histogram of maximum global SNHT, there is one higher and more isolated cluster representing a possible inhomogeneous case. As suggested by Guijarro (2018), when there is a distinct separation (or a well-defined minimum), the threshold for detection stages can be set to a certain value between them. Therefore, in our case, the threshold value for the stepped SNHT window test applied in stage 1 (snht1) was set to 10, while the threshold value for the SNHT test applied to the complete series in stage 2 (snht2) was set to 30. Moreover, by default, vertical coordinates in meters and horizontal coordinates in kilometers are equally weighted. As done by Buchmann et al. (2022), to consider the impact of elevation, which is a crucial factor for snow, the scale parameter was adjusted to 0.1, so that elevation was given 100

times more weight.

Once the parameters were set, Climatol was run. Fig. 40 shows the distribution of station ID numbers (see Tab. 3) according to their final Root Mean Squared Error (RMSE) and SNHT values. RMSEs are calculated by comparing the estimated and the observed data in every series. High values may indicate poor quality of the series, whereas homogeneous series tend to be clustered in the left bottom part of the plot (Guijarro, 2018). In our case, almost all stations were found to be in the left bottom part of the plot and all stations present SNHT values below the threshold imposed in stage 2 ($snht2 = 30$), leading to the conclusion that all our series were sufficiently homogeneous. However, there were three of them with a higher RMSE (#54, #12, #60). From Tab. 3, it can be seen that these stations are those at the highest elevation and consequently those most subjected to errors in HN estimates. For this reason, we decided to not consider these stations for the trend analysis. After a manual quality check, other 21 stations were found to be not suitable for the trend analysis due to the presence of frequent missing data.

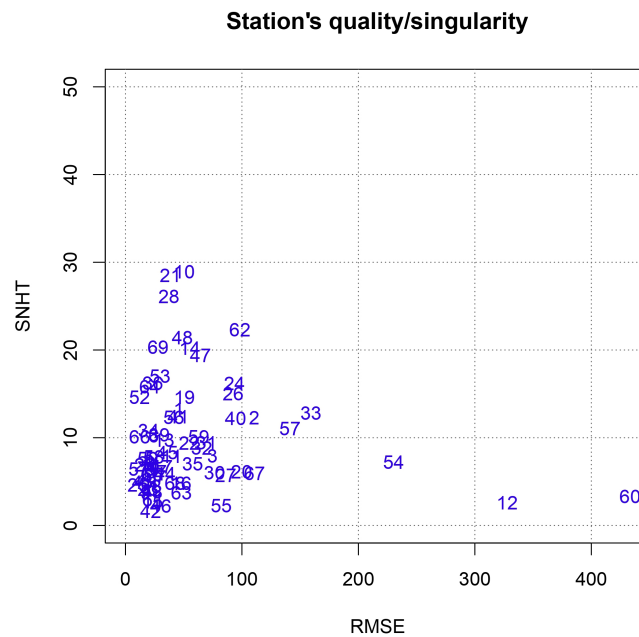


Figure 40 – Distribution of station ID numbers according to their final Root Mean Squared Error (RMSE) and Standard Normal Homogenization Test (SNHT) values evaluated by Climatol.

B.3 Regionalization overview

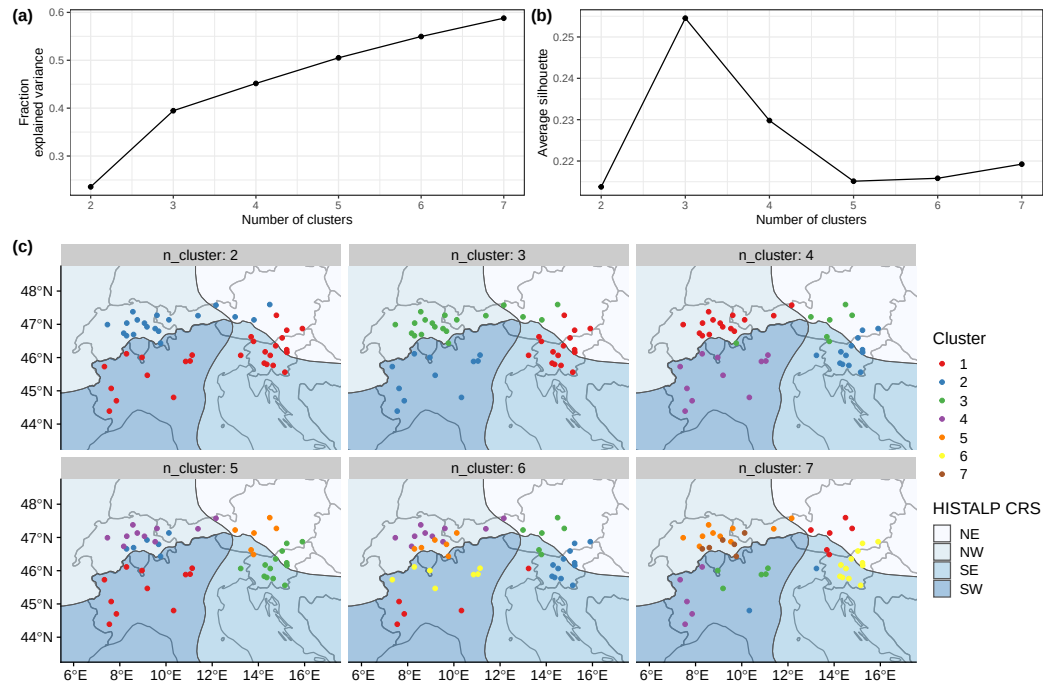


Figure 41 – Evaluation of k-means clustering results of monthly snowfall (HN) for different numbers of clusters: ratio of explained variance (a), silhouette (b), and maps (c).

Appendix C

SWE redistribution using satellite data and semi-distributed hydrological modeling

C.1 Meteorological inputs

Code	Name	Prov.	X	Y	Elev. [m]	Var.
ALB2	Albulapass	SLF	2783748	1161660	2322	TA
ARO	Arosa	MeteoSwiss	2771030	1184830	1878	TA-PSUM
DAP	Davos Platz/Promenade	ANU	2781970	1185540	1558	TA
DAV1	Davos/Chrachenhorn	SLF - Davos municipality	2781730	1173520	2891	TA
DAV2	Davos/Barentalli	SLF - Davos municipality	2782062	1174726	2558	TA
DAV3	Davos/Hanengretji	SLF - Davos municipality	2778300	1184580	2450	TA
DAV	Davos	MeteoSwiss	2783518	1187458	1594	TA-PSUM
FLU2	Fluela/Hospiz	SLF	2791600	1180975	2390	TA
KES1	Kesch/Piz Val Mura	SLF	2788500	1167050	3160	TA
KES2	Kesch/Porta d'Es-cha	SLF	2788350	1166300	2725	TA
KLA	Klosters	MeteoSwiss	2786857	1193366	1186	PSUM
KLO1	Klosters/Sant Jaggem	SLF - Klosters municipality	2785050	1199500	2542	TA
KLO2	Klosters/Madrisa	SLF - Klosters municipality	2785500	1198200	2140	TA
KLO3	Klosters/Gatschiefer	SLF - Klosters municipality	2790141	1190813	2299	TA
LAT	Bergun/Latsch	MeteoSwiss	2777273	1166618	1407	TA-PSUM
MMSAS	Saas im Prättigau	DTN	2780393	1198400	1000	TA-PSUM
MMZNS	Zernez	DTN	2803244	1175347	1474	TA-PSUM
MMZOZ	Zuoz	DTN	2793693	1164310	1662	TA-PSUM
NABEL.DAV	Davos/Seehornwald	FOEN - EMPA - ETHZ - WSL	2784460	1187745	1637	TA-PSUM
PAR2	Davos/Parsenn	SLF	2780430	1191680	2290	TA
SLF2	Davos/Stilli	SLF	2783879	1187447	1563	TA
WFJ2	Davos/Weissfluhjoch	SLF	2780850	1189260	2540	TA
WFJ	Weissfluhjoch	MeteoSwiss	2780614	1189634	2691	TA-PSUM
ZNZ1	Zernez/Sarsura Pitschen	SLF	2795660	1175750	3134	TA
ZNZ2	Zernez/Pulscheggia	SLF	2797300	1175080	2680	TA

Table 4 – List of the weather stations used as input for the GEOframe model. For each station, code number (Code), station name (Name), provider (Prov.), x-coordinate (X), y-coordinate (Y), elevation (Elev. [m]), variables (Var.) are indicated. TA (PSUM) indicates air temperature (total precipitation). The following abbreviations are used for the providers: ANU (Amt für Natur und Umwelt Graubünden, Graubünden administration for nature and the environment), DTN (DTN Schweiz AG), EMPA (Swiss Federal Laboratories for Materials Science and Technology), ETHZ (Swiss Federal Institute of Technology Zurich), FOEN (Federal Office for the Environment), MeteoSwiss (Federal Office of Meteorology and Climatology), SLF (WSL Institute for Snow and Avalanche Research SLF), WSL (Swiss Federal Institute for Forest Snow and Landscape Research WSL).

C.2 Validation metrics

Statistical metrics are used to assess the models predictive performance. Four metrics are used to assess the predictive performance of the GEOframe model with respect to discharge: the percent bias (PBIAS, Eq. 6), the root mean square error (RMSE, Eq. 7), the Nash–Sutcliffe efficiency (NSE, Nash and Sutcliffe (1970), Eq. 8), and the Kling–Gupta efficiency (KGE, Gupta et al. (2009), Eq. 9).

$$PBIAS = 100 * \frac{\sum_{t=1}^N (M_t - O_t)}{\sum_{t=1}^N O_t} \quad (6)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^N (M_t - O_t)^2}{N}} \quad (7)$$

$$NSE = 1 - \frac{\sum_{t=1}^N (M_t - O_t)^2}{\sum_{t=1}^N (O_t - \bar{O})^2} \quad (8)$$

$$KGE = 1 - \sqrt{(CORR - 1)^2 + (\alpha - 1)^2 + (\beta - 1)^2} \quad (9)$$

M_t and O_t represent the modeled and observed values, respectively, for each time step t , and N is the total number of time steps. With respect to KGE (Eq. 9), there are three main components involved: $CORR$ - the Pearson correlation coefficient, α - the variability ratio, which can be computed using the standard deviation ($\frac{\sigma_M}{\sigma_O}$), and β - the mean ratio, which can be computed using the mean ($\frac{\mu_M}{\mu_O}$).

For assessing the GEOframe SWE redistribution, four metrics are used: the mean bias error (MBE, Eq. 10), the root mean square error (RMSE, Eq. 11), the Pearson correlation coefficient (CORR, Eq. 12), and the coefficient of determination (R^2 , Eq. 13).

$$MBE = \frac{\sum_{i=1}^N (M_i - O_i)}{N} \quad (10)$$

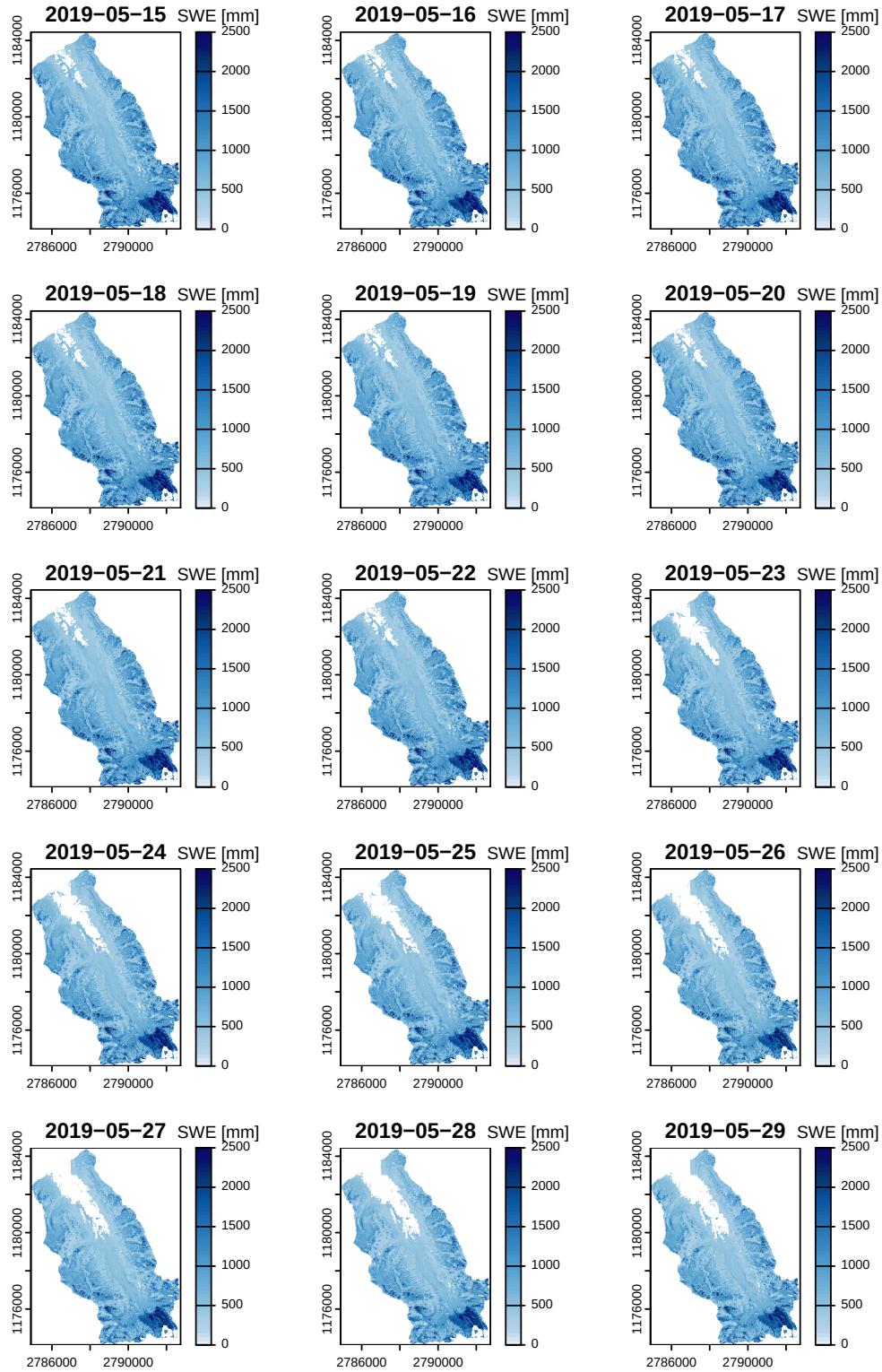
$$RMSE = \sqrt{\frac{\sum_{i=1}^N (M_i - O_i)^2}{N}} \quad (11)$$

$$CORR = \frac{\sum_{i=1}^N (M_i - \bar{M}) * (O_i - \bar{O})}{\sqrt{\sum_{i=1}^N (M_i - \bar{M})^2 * \sum_{i=1}^N (O_i - \bar{O})^2}} \quad (12)$$

$$R^2 = CORR^2 \quad (13)$$

M_i and O_i represent the modeled and observed values, respectively, for each pixels i , and N is the total number of pixels.

C.3 Daily SWE maps



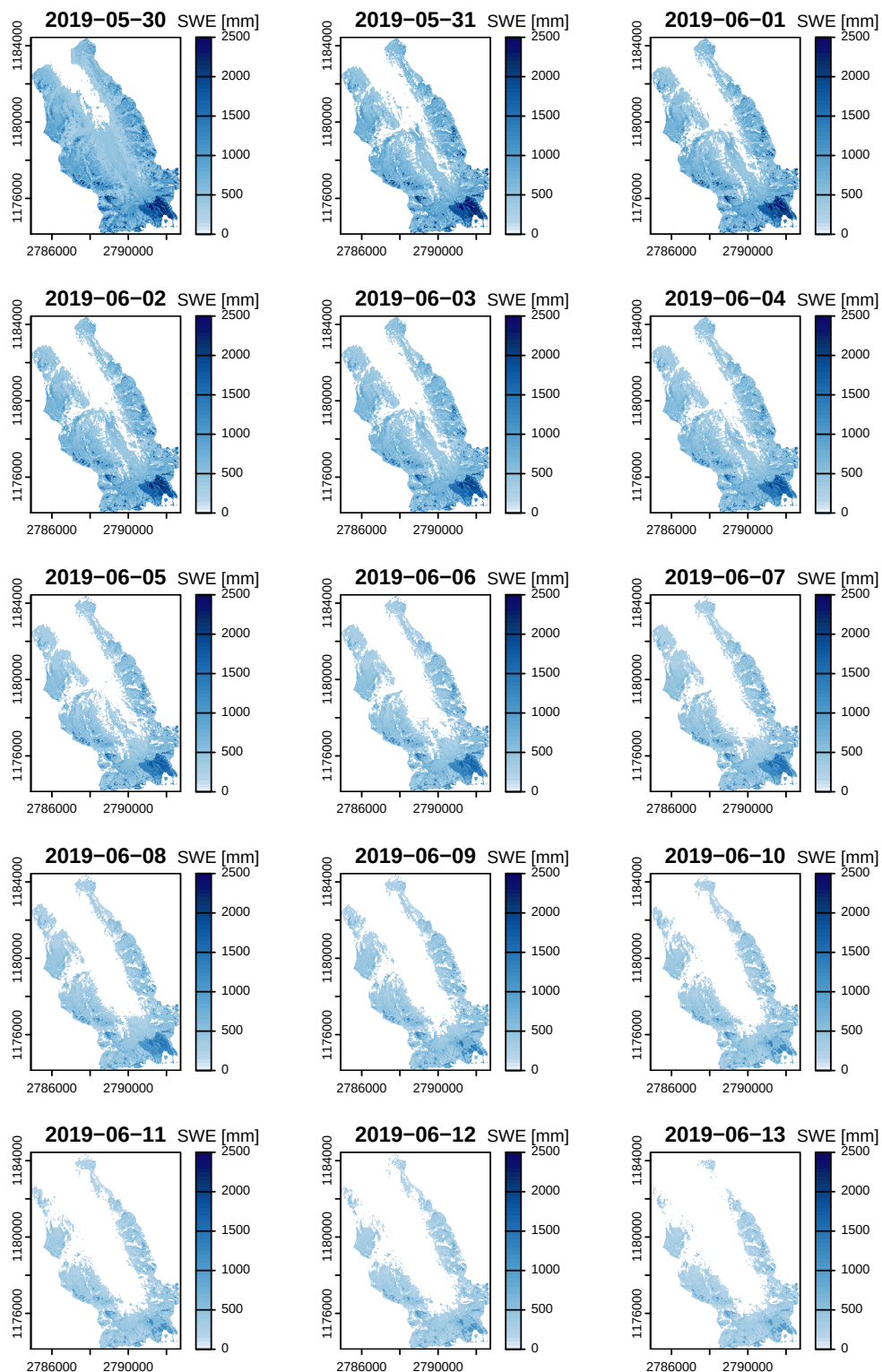


Figure 42 – Daily distribution of the GEOframe redistributed SWE from 15 May 2019 to 13 June 2019.

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