



# SNOW ACCUMULATION AND MELT RESPONSES TO WARMING ACROSS THE NORTHERN HEMISPHERE

By

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## ABSTRACT

Snow is an essential component of many Earth systems and its response to global warming is critical to understand. This thesis aims to advance our understanding of snow accumulation and melt responses to global warming. However, research into snow accumulation and melt is hindered by a lack of observations of snowpacks in space and time. This thesis provides a novel, open access dataset of continuous snow water equivalent (SWE) time series across the Northern Hemisphere (the NH-SWE dataset) based on observations of snow depth. This uses an established model to convert snow depth to SWE as well as a regionalisation of model parameters for application at the global scale. The model shows an excellent performance for key snow indicators such as peak SWE and the onset of snowmelt. The new hemispheric dataset is used for investigating long-term trends in snow accumulation and melt. Widespread declines in snow accumulation are shown across the Northern Hemisphere except the coldest climates. The response of snowmelt rates to warming is more complex, and this work demonstrates a range of both faster and slower melt responses to warming that depends on the combined effects of changes in snow accumulation, amount of warming, and timing of the snow season. As a result, a diversity of snowmelt rate trends is observed across the Northern Hemisphere, highlighting snowmelt changes are complex to predict regionally, and requires understanding the nuances of the key drivers. Additionally, this thesis provides insights into temperature-index snowmelt modelling for applications at the global scale. We show the robustness of using simple snowfall and snowmelt temperature thresholds and estimated degree-day factors validated using the NH-SWE dataset. A simple temperature-index model using temperature and precipitation time series from climate networks shows a good performance in simulating snow water equivalent time series for most stations across the Northern Hemisphere.

## DEDICATION

This thesis is dedicated to all snow enthusiasts. Only by taking good care of our planet and making the right decisions today can we ensure the preservation of our snow resources and continue to enjoy them in the future.

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# Chapter One

## Introduction

### 1.1 Why snow?

#### 1.1.1 Global importance of snow

Water is an essential resource that sustains both ecosystems and human societies, and its movement on the Earth's systems occupies a focal point in water resource assessments (Oki & Kanae, 2006). As an essential component of the Earth's water cycle, snow plays a crucial role in multiple Earth systems, encompassing hydrology, ecology, climate dynamics, and society.

Snow functions as a natural water reservoir, accumulating during winter months as snow and releasing this as water during the melt season (Kuppel et al., 2017). Mountains are globally acknowledged as the world's "water towers" due to their ability to store water as snow and ice and subsequently release this water downstream, sustaining ecological and human water demands (Viviroli et al., 2007; Immerzeel et al., 2020; Drenkhan et al., 2023). However, the presence and importance of snow extend beyond mountain regions, encompassing high latitudes characterised by substantial seasonal snow cover extent and duration. Pulliainen et al. (2020) estimate on average 37 million square kilometres above 40°North are covered by seasonal snow in midwinter, with alpine areas only contributing

15% of that area, but at least 25% of the mass. Nearly one-sixth of the world's population resides within areas where snowmelt contributes to a minimum of 50% of the annual water runoff (Barnett et al., 2005). When human water demand is considered, runoff derived from snowmelt plays an important role in water supply in several world river basins representing more than 2 billion people (Mankin et al., 2015). Beyond its quantitative contribution, the timing of water release from snow is also essential for hydropower production (Kopytkovskiy et al., 2015) and for agriculture (Qin et al., 2020). Insufficient snow accumulation has the potential to exacerbate hydrological droughts (Livneh & Badger, 2020), and the occurrence of rain-on-snow events can exacerbate floods (Vormoor et al., 2016; Berghuijs et al., 2019), highlighting the importance of snow for hydrological extremes. Beyond hydrological implications, snow is also key for ecosystem services such as a water source for the onset of forest greening (Trujillo et al., 2012) and vegetation productivity (Rumpf et al., 2022), tree recruitment (Perry et al., 2020), and even microbial communities and biogeochemical cycling (Broadbent et al., 2021). Furthermore, snow also plays a role in modulating the Earth's climate system through albedo feedbacks (Déry & Brown, 2007; Thackeray & Fletcher, 2016), a dynamic process mediated by snow reflecting large fractions of the incoming solar radiation that would otherwise participate in the land energy balance as a heat flux. Regarding the societal impact of snow, a study by Sturm et al. (2017) valued the economic contribution of snow in trillions of dollars. Additionally, winter tourism and local economies may heavily depend on snow resources (Abegg et al., 2007; Beniston, 2012; François et al., 2023).

### **1.1.2 Snow and global warming**

Snow and ice are very sensitive to warming temperatures because of the transition from solid to liquid water that can be initiated at 0°C Celsius. As such, the modification of the global cryosphere due to global warming and climate change has had a long and detailed history (Barry, 1985; Kuhn, 1989; Walsh, 1995; Weller, 1998; Barry, 2005; Slaymaker & Kelly, 2009; Liston & Hiemstra, 2011; McDowell et al., 2014; Pörtner et al., 2019; Beniston et al., 2018; Barry & Gan, 2022; Huai et al., 2023).

Warming temperature trends that result in more time spent above the freezing point can impact snow in many ways, such as reducing snowfall amounts due to a decreased solid-to-liquid precipitation ratio, decreasing snow accumulation on the ground, increasing accumulation season snowmelt, reducing the snow cover extent and duration, shifting the timing of snow accumulation and snowmelt, and changing melt rates. An overview of the literature that has investigated historical and future trends in key snow variables is provided below.

### **Historical trends**

Many snow cover changes have already been observed over the last decades and are attributed to global warming. Increasing temperatures may, for instance, change the precipitation phase from snow to rain. Knowles et al. (2006) documented a trend towards less winter snowfall over the period 1949-2004 in the Western United States as a response to warming across the region. Serquet et al. (2011) found decreasing trends in snowfall days relative to precipitation days over Switzerland from 1908 to 2008, with the strongest trends at the lowest elevations due to their closer proximity to the freezing point during winter. Trends in extreme snowfall in the French Alps have been reported to be elevation-dependent and increasing above 2000 metres above sea level but decreasing below 2000 metres from 1959 to 2019 (Le Roux et al., 2021). A decrease in snowfall to rainfall ratio has also been observed in the Tibetan Plateau from 1961 to 2013 (Wang et al., 2016), and over the contiguous United States from 1949 to 2005 (Feng & Hu, 2007).

In terms of snow accumulation, many studies have also observed declines over the 20th century and the beginning of the 21st century. Decreasing mean winter snow depth trends have been reported, among others, over Europe (Fontrodona Bach et al., 2018), the European Alps (Matiu et al., 2021a), the Pyrenees (López-Moreno et al., 2020b), Norway (Dyrørdal et al., 2013), Finland (Luomaranta et al., 2019), Poland (Falarz, 2004), North America (Dyer & Mote, 2006), the Great Lakes basin (Suriano et al., 2019), China (Zhang et al., 2021) and the Tibetan Plateau (You et al., 2011). However, some of the coldest climates in those studies have also reported relatively stable or unchanging mean snow depth, or even increasing mean

snow depth. These may also be attributed to warming trends leading to increased global precipitation (Lambert et al., 2008), which may lead to increased snowfall if temperatures are still below freezing. Trends in various snow water equivalent (SWE) indicators are less common because measured data is comparatively rare; however, reported SWE trends are usually very similar to snow depth trends (Mote, 2003; Skaugen et al., 2012; Brown et al., 2019; Colombo et al., 2022), with widespread declines except for some colder climates and higher elevations.

In terms of snow cover extent and duration, reductions have been observed over Eurasia (Brown & Derksen, 2013), over High Mountain Asia (Ackroyd et al., 2021), over global mountain regions (Notarnicola, 2020, 2022), and over the whole Northern Hemisphere (Bormann et al., 2018). These reductions in snow cover extent are stronger than previously predicted by models (Derksen & Brown, 2012; Mudryk et al., 2017) and commonly attributed to anthropogenic influences on warming temperatures (Najafi et al., 2016). Snow cover duration reductions have mostly been reported as being due to an earlier end of the snow cover period rather than a later start (Klein et al., 2016; Essery et al., 2020).

Warming temperatures have been shown to advance the onset of spring snowmelt and to enhance winter snowmelt over Arctic Eurasian rivers (Tan et al., 2011) and over North America (Clow, 2010; Fritze et al., 2011; Uzun et al., 2021). Interestingly, earlier snowmelt in spring has been shown to lead to lower melt rates due to melt occurring at reduced levels of solar radiation earlier in spring (Harpold & Brooks, 2018; Wu et al., 2018).

### **Future trends**

In the future, snowfall is projected to decrease by as much as 30% per degree warming over Europe, except over highest elevations and parts of higher latitudes (Vries et al., 2014). Snowfall may be reduced up to 80% in lower elevations of alpine regions, but slight increases in snowfall may also occur at higher elevations because slight warming of very cold climates may enhance vapour transport and lead to more favourable conditions for high snowfall intensities and extremes (Frei et al., 2018). Over the Northern Hemisphere, it has

been suggested that snowfall trends will diverge between increasing and decreasing trends at the  $-11^{\circ}\text{C}$  winter isotherm (Räsänen, 2016). However, accumulated snow on the ground integrates the effect of temperatures not only at the time of precipitation but through the entire winter, as snow can melt more frequently than before during the accumulation season because of warming, reducing the total snow accumulation. Although long time series from some colder climates and higher elevations display no trend or even increasing snow depth and SWE, future climate projections for as soon as 2030-2050 anticipate snow depth reductions for all elevations and emission scenarios in the Swiss Alps (Bavay et al., 2009; Marty et al., 2017a), and snow water equivalent reductions in Northern Europe (Räsänen, 2021). More ephemeral snow (intermittent, short periods of snow cover) and even complete snow disappearance is projected across some parts of the western United States (Siirila-Woodburn et al., 2021), and western Canada, albeit with higher elevations likely less affected (Mortezapour et al., 2022). Snow cover extent over the Northern Hemisphere is also projected to decrease even after accounting for the uncertainty spread of the simulations (Thackeray et al., 2016). Interestingly, rain-on-snow events will likely decrease at low elevations due to a reduction in snow persistence and increase at higher elevations due to a higher rain-to-snow ratio (Musselman et al., 2018).

### **1.1.3 Implications of changing snow**

The widespread acknowledgement of changing snow cover due to climate change and global warming detailed above has the potential for substantial implications across the many processes and dependencies in which snow is involved (Elias et al., 2021). Hydrologically, a shift from snow to rain may lead to annual reductions in streamflow (Berghuijs et al., 2014), and increased accumulation season snowmelt may lead to strong declines in snow water resources available in spring (Musselman et al., 2021). A shift to earlier and less snowmelt will decrease the snow influence on spring runoff (Grogan et al., 2020) and exacerbate summer low flows (Jenicek et al., 2016; Jenicek & Ledvinka, 2020). Changing snow may impact hydrological extremes, such as snow droughts (Huning & AghaKouchak, 2020), which may more than

double in the future (Cowherd et al., 2023). These potential reductions in snow resources will challenge existing water management strategies (Siirila-Woodburn et al., 2021), affect the energy sector through changing hydropower production (Golombek et al., 2012), and pose a considerable risk to the ski tourism industry (François et al., 2023). Decreasing snow cover also reduces land albedo, increasing the energy available for the land surface energy balance (Euskirchen et al., 2016), although there are large uncertainties in future projections trying to capture these climate feedbacks (Thackeray et al., 2019). The impacts of declining snow resources are very diverse on vegetation and ecosystems. Earlier snowmelt can be detrimental for grassland greening (Revuelto et al., 2022) but may be beneficial for late blooming species (Pardee et al., 2019). For Arctic tundra plant species, the interaction between changing snowmelt timing and warming temperatures controls reproductive effort and growth (Frei & Henry, 2022).

In light of these multifaceted and interdisciplinary impacts of changing snow on hydrology, ecology, climate, and society, better understanding the nature of changing snow resources is vital to managing and mitigating the wide-ranging consequences of shifting snow patterns driven by climate change and global warming. The details of how this PhD thesis fits into this global challenge and aims to increase our understanding of changing snow resources are outlined below.

## 1.2 Research gap and objectives

Despite the importance of global snow and the numerous studies exploring the various impacts of changing snow and global warming, important knowledge gaps and research needs remain. This thesis identifies and addresses some of these interlinking gaps and research needs, specifically: a lack of available and reliable observations of snowpacks at the global scale (gap 1), the need for a hemispheric perspective on long-term trends in snow accumulation and melt and their drivers (gap 2), and the need to robustly simulate snowpacks at the global scale using a simple approach (gap 3). A more detailed preview of each of these gaps

is provided below:

**Gap 1:** The limitations of our knowledge on changing snow are partly due to a scarcity of continuous observations of the snowpack in space and in time. Although snowpack observations may be available and abundant for small scale studies, observations at the global scale are scarce or not openly available. Snow is challenging to continuously measure over uninhabited areas, and even more difficult to measure over complex terrain such as high elevations, where snow accumulation is typically of a higher magnitude. Furthermore, measuring snow water equivalent (SWE), a key parameter for water resources assessments and hydrological modelling, is challenging due to its reliance on the measurement or estimation of snow density (Jonas et al., 2009). In contrast, measuring snow depth is considerably simpler, and thus is more readily available as continuous time series. Remote sensing techniques for measuring snow offer the possibility to measure at larger spatial scales. Remote sensing methods include measurements from satellite observations (Dietz et al., 2012), uncrewed aerial vehicles (Harder et al., 2020), airborne sensors such as lidar (Webster et al., 2020), and ground-based webcams (Portenier et al., 2022), among others. These methods are developing and progressing very quick and might overcome some of the challenges. However, remote sensing observations provide much more accurate estimates of snow cover extent than snow water equivalent (Dawson et al., 2018), challenging the reliability of accurate snow accumulation and snowmelt estimations. At the global scale, remote sensing estimates of snow water equivalent are typically limited to shallower snowpacks (Luo et al., 2021). Furthermore, remote sensing relies on ground observations for evaluating their performance (Mortimer et al., 2020), and thus larger validation datasets are clearly required. To address this gap, a novel and open access dataset of snow water equivalent time series based on ground measurements of snow depth covering the Northern Hemisphere is developed. This dataset also contributes to covering gap 2 and gap 3.

**Gap 2:** Among the extensive research on the impacts of global warming on snow, the study of changing snowmelt rates is relatively recent and there is uncertainty surrounding the impact of global warming on snowmelt rates. Existing studies have produced diverse findings,

even if there is some consensus towards the counterintuitive response of melt rates becoming slower along with warming temperatures. Musselman et al. (2017) suggested snowmelt will be slower in a warmer world as snowpacks will melt earlier in the year at a time of lower solar radiation. Harpold and Brooks (2018) and Wu et al. (2018) observed slower snowmelt rates in spring based on snow measurement time series. However, these studies also found a range of responses and a high spatial variability across climates that was not explained. Faster snowmelt has also been projected in some studies due to higher temperatures (López-Moreno et al., 2013b) or due to higher snow accumulation melting later (Krogh & Pomeroy, 2019). Investigating historical trends in snowmelt rates requires continuous observations of the snowpack, from which snowmelt can be inferred. However, these are rarely available, let alone at the global or Northern Hemisphere-scale. The novel dataset that is produced for research gap 1 enables investigating snowmelt rates across the Northern Hemisphere for the historical period. Therefore, the objective to contribute to covering research gap 2 is to shed light into the diverse responses of snow and its rate of melt across a wide range of climates covering the Northern Hemisphere.

**Gap 3:** Investigating changing snow dynamics by analysing historical observations and inferring trends enhances our understanding and provides evidence of environmental shifts (gap 2). Nevertheless, simulating the response of snowpacks to future perturbations in environmental variables is needed to inform present-day decision making and policies to adapt to or mitigate future challenges. Model simulations are challenged by uncertainty (Oreskes et al., 1994), which may arise from natural variability, parameter uncertainty (Günther et al., 2020), forcing data uncertainty (Günther et al., 2019), the ability or inability of models to represent certain processes and the choice of model configurations - e.g., model structures (Essery et al., 2013), or even subjective modelling decisions (Melsen et al., 2019). However, two crucial aspects to model development and model applications are the lack of model evaluation data and the challenge of reliably estimating model parameters. Physics-based snow modelling at the global scale is complex because of computational demands and the extensive data requirements, while simpler temperature-index based modelling at the global scale is challenged by uncertainty in model parameters across climates and scales and

because key physical processes are not represented. The novel dataset produced to address research gap 1 provides a valuable opportunity to gain insights into the applicability of a simple snow model at the global scale. Therefore, research gap 3 is addressed by providing a hemispheric evaluation of critical snowfall and snowmelt temperature thresholds, as well as degree-day factors, that can be used to understand the utility, robustness, and limits of snowpack simulation from temperature-index models.

### 1.3 Thesis structure overview

To address the aforementioned research gaps and objectives, this thesis is divided into three independent but interlinked paper-type chapters, one for each research gap. Each of these paper-type chapters contains its own introduction, data, methods, results, discussion, limitations and conclusions. The introduction of each chapter reemphasizes and expands on the contextualisation and research gaps presented in this overall thesis introduction. After the last paper-type chapter there is an overall conclusion and outlook chapter highlighting key research findings across all chapters, as well as potential directions for future research. A concise overview of each chapter is presented here:

#### **Chapter 2: Generating the NH-SWE Dataset**

This chapter addresses a significant challenge in understanding snow accumulation and melt responses to a warming climate: the scarcity of reliable snow water equivalent (SWE) data, which hampers accurate assessments of snowpack changes. This chapter addresses this limitation by introducing the NH-SWE dataset, a valuable compilation of pan-Northern Hemisphere in situ snow depth time series converted into SWE using a robust model ( $\Delta$ SNOW; Winkler et al. (2021)). The dataset has already been published in the journal *Earth System Science Data* (Fontrodona-Bach et al., 2023a; Fontrodona-Bach et al., 2023b). By bringing together diverse in situ snow depth datasets from across the Northern Hemisphere and using a regionalised conversion model, the NH-SWE dataset offers a valu-

able resource for various applications, including climate research (explored in Chapter 3), hydrological modelling (explored in Chapter 4), and validation of remote sensing products (a potential future research direction).

### **Chapter 3: Historical trends in snowmelt**

As the climate warms, understanding historical trends in snowmelt becomes paramount to enhance our understanding of the natural environment. This chapter explores the impact of global warming on snowmelt rates by utilizing the NH-SWE dataset alongside temperature, precipitation, and radiation data. This chapter discerns key drivers of snowmelt rate changes and their spatial variability across diverse climates in the Northern Hemisphere. Through a comprehensive analysis of causes and effects, it uncovers the complex interplay between changing temperature, changing precipitation, and shifts in radiation due to moving snow seasons, all conspiring to shape the different responses of snowmelt rates to global warming.

### **Chapter 4: Exploring temperature-index snow modelling**

Simulating the future response of snowpacks to further warming and its impacts is crucial to inform current decision-making and policies. This chapter explores the potential use of temperature-index models at the global scale. This modelling approach offers a computationally efficient means of assessing snowpack sensitivity to warming, but is challenged by the simplicity of model parameterisations and difficulty to reliably apply these across different climates. By combining the NH-SWE dataset and corresponding climate observations of temperature and precipitation, this chapter investigates the variability of temperature-index model parameters across diverse climates and evaluates the performance of this approach over the Northern Hemisphere. Through this exploration, it seeks to uncover the regions and conditions where temperature-index modelling can serve as a robust tool for understanding changing snow resources.

## Chapter 5: Conclusion

A final conclusion and outlook chapter highlights the key research findings as well as potential directions for future research.

In summary, this thesis provides insights into the complexities of snow accumulation and melt responses to a warming climate and offers valuable contributions to the field of snow dynamics and hydrology. By introducing the NH-SWE dataset, exploring historical trends, and evaluating modelling approaches, it enhances our understanding of the consequences of climate change on snow.

**Note on writing style:** While this overall introduction section has been presented in an impersonal writing style, the subsequent paper-type chapters employ the first-person plural "we", a convention often observed in scientific publications due to the collaborative nature of research and the guidance provided throughout this PhD thesis by dedicated supervisors.



# Chapter Two

## The NH-SWE dataset

*This chapter has been peer-reviewed and published in the scientific journal "Earth System Science Data" from Copernicus Publications:*

Fontrodona-Bach, A., Schaeffli, B., Woods, R., Teuling, A. J., and Larsen, J. R.: NH-SWE: Northern Hemisphere Snow Water Equivalent dataset based on in situ snow depth time series, Earth Syst. Sci. Data, 15, 2577–2599, <https://doi.org/10.5194/essd-15-2577-2023>, 2023.

Published: 23 June 2023

*The dataset is published and available at:*

Fontrodona-Bach, Adrià, Schaeffli, Bettina, Woods, Ross, Teuling, Adriaan J, & Larsen, Joshua R. (2023). NH-SWE: Northern Hemisphere Snow Water Equivalent dataset based on in situ snow depth time series and the regionalisation of the  $\Delta$ SNOW model [Data set]. Zenodo. <https://doi.org/10.5281/zenodo.7565252>

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## Abstract

Ground-based datasets of observed Snow Water Equivalent (SWE) are scarce, while gridded SWE estimates from remote-sensing and climate reanalysis are unable to resolve the high spatial variability of snow on the ground. Long-term ground observations of snow depth, in combination with models that can accurately convert snow depth to SWE, can fill this observational gap. Here, we provide a new SWE dataset (NH-SWE) that encompasses 11,071 stations in the Northern Hemisphere, and is available at [doi.org/10.5281/zenodo.7515603](https://doi.org/10.5281/zenodo.7515603) (Fontrodona-Bach et al., 2023b). This new dataset provides daily time series of SWE, varying in length between one and seventy-three years, spanning the period 1950-2022 and covering a wide range of snow climates including many mountainous regions. At each station, observed snow depth was converted to SWE using an established snow-depth-to-SWE conversion model, with excellent model performance using regionalised parameters based on climate variables. The accuracy of the model after parameter regionalisation is comparable to that of the calibrated model. The key advantages and strengths of the regionalised model presented here are its transferability across climates and the high performance in modelling daily SWE dynamics in terms of peak SWE, total snowmelt and duration of the melt season, as assessed here against a comparison model. This dataset is particularly useful for studies that require accurate time series of SWE dynamics, timing of snowmelt onset, and snowmelt totals and duration. It can e.g. be used for climate change impact analyses, water resources assessment and management, validation of remote sensing of snow, hydrological modelling and snow data assimilation into climate models.

## 2.1 Introduction

The modification of the cryosphere is one of the most visible effects of ongoing climate warming (Beniston et al., 2018). In this context, snow cover is particularly important, as it provides an important seasonal hydrologic buffer over high latitudes and high elevations, through storage over the accumulation season and a delayed release of water in the subsequent melt season (Kuppel et al., 2017). Snow cover also plays an important role in the Earth’s climate through snow-albedo feedbacks (Déry & Brown, 2007). Studies showing the impact of global warming on snow are numerous: declining trends in snow depth have been observed over the European Alps (Matiu et al., 2021a), the Pyrenees (López-Moreno et al., 2020b), and all of Europe except the coldest climates (Fontrodona Bach et al., 2018); decreasing snow cover duration and extent have been reported over the Northern Hemisphere (Bormann et al., 2018; Mudryk et al., 2020) and over 78% of global mountain regions (Notarnicola, 2020); and increasing snowmelt in winter has been observed in western North America (Musselman et al., 2021). Regions whose water resources strongly depend on snow water storage are at risk of large declines in spring and summer streamflow, posing a potential future threat to human water used for  $\sim 2$  billion people (Mankin et al., 2015). There is therefore an ongoing need for access to wide coverage and reliable snow data and research.

There are various ways to measure snow, which serve different scientific purposes. Snow depth is the thickness of snow accumulated above ground level and can easily be measured manually with a ruler or automatically with an acoustic sensor that measures snow height. The depth of water that is actually stored in a snowpack is referred to as snow water equivalent (SWE) and corresponds to the depth of liquid water that would result from melting the entire snowpack.

Reliable estimates of SWE, rather than snow depth, are thus needed for water resources assessments across scales. However, limitations arise when estimating SWE at regional, continental or global scales. Remote sensing estimates of SWE provided by satellite measurements are in constant development but currently have low accuracy and are limited

to shallow ( $< 150$  mm) snowpacks (Luo et al., 2021). Estimates of SWE resulting from reanalysis and land surface modelling rely on snow models forced with meteorological data and are also subject to biases and errors (Brun et al., 2013; Broxton et al., 2016; Muñoz-Sabater et al., 2021). A common limitation of these gridded SWE estimates is that they cannot reproduce the high spatial variability of snow on the ground, especially for mountain regions and complex terrain (Clark et al., 2011; López-Moreno et al., 2013a), although reliability and resolution can be improved by assimilating measurements of snow depth and SWE (Zeng et al., 2018). A review of global gridded datasets of SWE shows up to a 50% variability in peak snow accumulation between different datasets (Mudryk et al., 2015).

Adding to the complexity of obtaining reliable SWE data, large-scale estimates of SWE often have limited validation against observed ground data, which is scarce in time and in space. In fact, both manual and remotely sensed measurement techniques exist for SWE, but they are either complex, time consuming, or require specialised equipment (Jonas et al., 2009; Winkler et al., 2021). In contrast to complex SWE measurements, manual and automatic snow depth measurements are more straightforward and therefore more widespread. Many regional snow depth datasets exist or are emerging, with an increasing number of national hydrological and meteorological services making snow depth data publicly available and easily downloadable through site portals and application programming interfaces (API). However, an estimate of snow density is needed together with a snow depth measurement to obtain the snow water equivalent.

There is an increasing number of models that can accurately convert snow depth to SWE using simple empirical regressions (Mizukami & Perica, 2008; Jonas et al., 2009; Sturm et al., 2010; Bormann et al., 2013; McCreight & Small, 2014; Pistocchi, 2016; Hill et al., 2019; Ntokas et al., 2021). These regression-based methods require paired snow depth-SWE ground measurements to calibrate parameters that later on are used to estimate SWE when only snow depth measurements are available. Some of the approaches generalise parameters regionally, based on elevation and on the day of the year (Jonas et al., 2009), or globally based on climatological variables (Sturm et al., 2010; Hill et al., 2019; Szeitz & Moore,

2023). Physics-based snow models can also regionalise and cluster snow parameters based on climate variables (Dawson et al., 2017; Sun et al., 2019, 2022), but the parameterisation is more data intensive than for simple regression-based approaches. The common limitation of using regression-based approaches is that a SWE value on a given time step is estimated independently for each snow depth value, irrespective of snow depth values on preceding time steps. Therefore, conversion of time series of snow depth to SWE leads to an incorrect temporal evolution of SWE because the regression cannot account for the settling of new snow nor for the compaction of the snowpack (Jonas et al., 2009). This problem has been addressed by considering the temporal evolution of snow depth in the conversion model (McCreight & Small, 2014; Winkler et al., 2021), but, to date, no approach has generalised this method for regional or global use.

Here we bring together the increasing number of available in situ snow depth datasets and the increasing number of snow depth to SWE conversion models to produce a new, freely available SWE dataset: the NH-SWE dataset. This compilation and analysis provides i) the first pan-Northern Hemisphere in situ snow depth time series compilation and ii) a conversion from depth to SWE using an established model ( $\Delta$ SNOW, Winkler et al., 2021). This SWE dataset can be extremely useful across a wide variety of applications such as validation of remote sensing products, hydrological and environmental modelling, assimilating snow data into models, and general climate research.

This paper is organised as follows: (1) we show data sources used to calibrate, regionalise and evaluate the model for snow depth to SWE conversion (Section 2.2); (2) model development and implementation (Section 2.3); (3) performance of the model across a variety of variables (Section 2.4); and (4) demonstration of some key features of the NH-SWE dataset (Section 2.5), including its usage and limitations (Section 2.6).

## 2.2 Data sources

The data used to compile NH-SWE from in situ snow depth observations can be divided into two main groups: group HS-SWE includes all stations that have both snow depth (height of snow, HS) and SWE data available; group HS includes all stations that have only HS observations available.

Group HS-SWE data can be further split for the purposes of model implementation into a) data used for model regionalisation and b) data used for independent evaluation. The HS data group then provides the input data to generate the new SWE estimates within the NH-SWE dataset (Section 2.5) but is not used in model implementation. We evaluate the model using independent HS-SWE datasets, different from the one used to regionalise the  $\Delta$ SNOW model from Winkler et al. (2021). This approach enables us to evaluate SWE estimates for as wide a range of snow climate conditions as possible combined with an independent evaluation process to test the transferability of the model regionalisation to other independent datasets, such as our collection of Northern Hemisphere snow depth time series. A summary chart of the workflow to produce the final SWE dataset is shown in Figure 2.1. An overview of all the data used to derive the NH-SWE dataset is shown in Table 2.1, and the spatial distribution of the data and sources is shown in Figure 2.2.

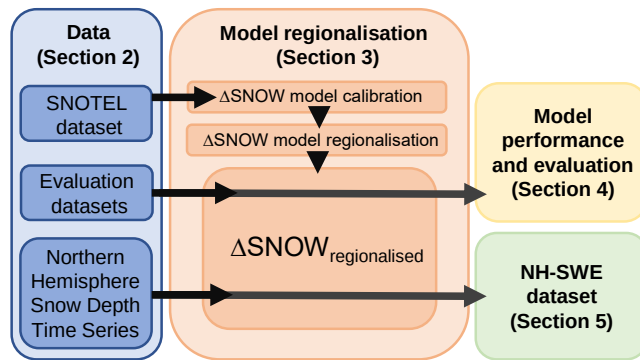


**Figure 2.1:** Workflow chart to obtain the NH-SWE dataset. The  $\Delta$ SNOW model is from Winkler et al. (2021).

### 2.2.1 HS-SWE data for model regionalisation

The SNOwpack TELemetry Network (SNOTEL) dataset contains a large network of automated sub-daily observations of HS and SWE data over the western United States and is freely available (USDA NRCS, 2022). The dataset covers a wide range of snow climates and characteristics such as the the wet and mild Pacific Northwest (including the maritime Cascades mountain range), the continental cold and snowy Rockies, the Mediterranean climate from California, the arid climate from the southwest, and even high-latitude tundra/taiga in Alaska (Serreze et al., 1999; Sun et al., 2019). The SNOTEL dataset only contains measurement stations where a minimum of 40 days of continuous snow cover is observed on average (since it has been designed to monitor seasonal snowpacks). We use this dataset to calibrate and regionalise the  $\Delta$ SNOW model (Winkler et al., 2021) over a wide range of hydroclimates, and we assess the transferability of the regionalisation by evaluating the model over fully independent datasets from other climates. We retain only measurements stations with joint HS and SWE records. We apply the same data preprocessing and outlier removal as Hill et al. (2019), based on the Mahalanobis distance (De Maesschalck et al., 2000), which quantifies how far a point lies from the mean of a bivariate distribution. In this case a threshold quantile of 0.999 was chosen, to be consistent with the method of Hill et al., 2019. The resulting dataset for model regionalisation contains 812 sites with daily HS-SWE time series data ranging from 1 to 25 years in length (see Table 2.1 and Figure 2.2a).

### 2.2.2 HS-SWE data for model evaluation

We independently evaluate the  $\Delta$ SNOW model using a SWE dataset from Canada (Vionnet et al., 2021), which contains 2,607 stations with historical HS and SWE measurements. Selecting only those stations with daily observations of HS and SWE, and applying gap-filling and quality control (see Appendix A.1), 68 stations distributed over eastern and western Canada are retained for model evaluation (see Figure 2.2a and Table 2.1).

To assess the transferability of the model to outside North America, we compiled 20

**Table 2.1:** Overview of datasets and sources used for model regionalisation, model evaluation and input for the final NH-SWE dataset. *Model regionalisation* and *model evaluation data* refer to Sections 2.2.1 and 2.2.2, and *input data* refers to Section 2.2.3. SWE<sub>d</sub> for daily measurements, SWE<sub>b</sub> for biweekly measurements. The number of sites is after quality control and selection. The minimum length is 1 year for all datasets.

| Data Source      | Data Type           | Data Use              | Number of sites | Length (years) |     | Reference                                |
|------------------|---------------------|-----------------------|-----------------|----------------|-----|------------------------------------------|
|                  |                     |                       |                 | mean           | max |                                          |
| SNOTEL           | HS-SWE <sub>d</sub> | Model regionalisation | 812             | 14             | 25  | USDA NRCS, 2022                          |
| CanSWE           | HS-SWE <sub>d</sub> | Model evaluation      | 68              | 8              | 28  | Vionnet et al., 2021, 2022               |
| GCOS-CH          | HS-SWE <sub>b</sub> | Model evaluation      | 8               | 57             | 70  | Marty, 2020                              |
| RIHMI-WDC        | HS-SWE <sub>b</sub> | Model evaluation      | 2               | 30             | 34  | RIHMI-WDC, 2022                          |
| NVE              | HS-SWE <sub>d</sub> | Model evaluation      | 6               | 3              | 9   | NVE, 2022                                |
| Kuhtai-AT*       | HS-SWE <sub>d</sub> | Model evaluation      | 1               | 23             | 23  | Krajčič et al., 2017                     |
| Sodankylä-FI*    | HS-SWE <sub>d</sub> | Model evaluation      | 1               | 6              | 6   | Essery et al., 2016                      |
| Col-de-Porte-FR* | HS-SWE <sub>b</sub> | Model evaluation      | 1               | 18             | 18  | Morin et al., 2012                       |
| Alptal-CH*       | HS-SWE <sub>b</sub> | Model evaluation      | 1               | 1              | 1   | Stähli, 2018                             |
| ECA&D            | HS                  | Input data for NH-SWE | 3,050           | 40             | 70  | Klein Tank et al., 2002                  |
| FMI              | HS                  | Input data for NH-SWE | 204             | 36             | 63  | FMI, 2022                                |
| Matiu20          | HS                  | Input data for NH-SWE | 535             | 34             | 60  | Matiu et al., 2021b; Matiu et al., 2021a |
| RIHMI-WDC        | HS                  | Input data for NH-SWE | 543             | 61             | 69  | RIHMI-WDC, 2022                          |
| GHCNd            | HS                  | Input data for NH-SWE | 6,478           | 23             | 71  | Menne et al., 2012                       |
| MeteoSwiss/SLF   | HS                  | Input data for NH-SWE | 261             | 33             | 70  | MeteoSwiss, 2022                         |

\*Referred as "single sites" in Figure 2.2a

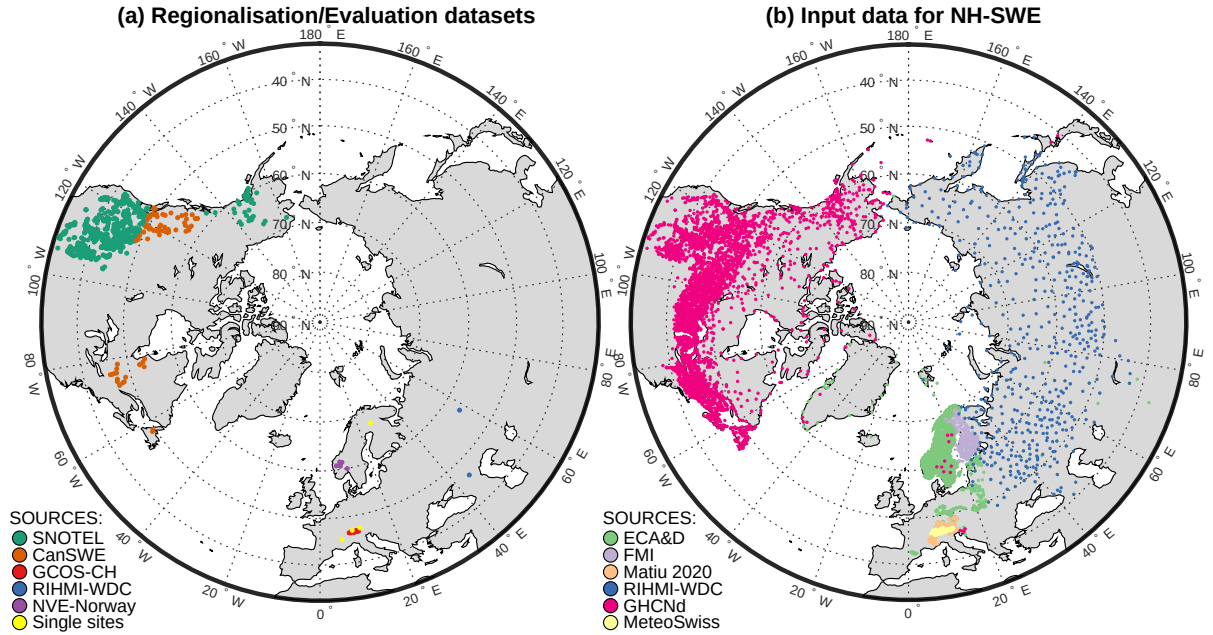


**Figure 2.2:** Spatial distribution of stations in the datasets used. (a) Paired HS-SWE datasets for model regionalisation and evaluation and (b) HS data used as model input for the final modelled SWE dataset (NH-SWE). In (a), SNOTEL is used for model regionalisation, and the rest are evaluation datasets. See Table 2.1 for more information on the sources.

additional HS and SWE datasets from seven different sources: 8 stations from the Global Climate Observing System (GCOS) in Switzerland (Marty, 2020); 2 stations from the All-Russia Research Institute of Hydrometeorological Information - World Data Center (RIHMI-WDC, 2022); 6 stations from the Norwegian Water Resources and Energy Directorate (NVE, 2022); and 4 single-station observations from different sources over the European Alps and Finland (Stähli, 2018; Krajčič et al., 2017; Essery et al., 2016; Morin et al., 2012). The number of additional stations available for independent validation outside North America is low because 1) continuous observation of both HS and SWE is much rarer and 2) if collected is also rarely provided within open-data repositories. Most of this additional validation data contain daily observations of SWE, but some contain only weekly or biweekly measurements (see Table 2.1). This change in temporal resolution in turn reduces the metrics that can be evaluated. For example, the timing of snowmelt onset cannot be accurately determined without daily SWE measurements (see Section 2.3.6). Furthermore, the daily observations of SWE were obtained automatically and are typically co-located with the snow depth measurements. However, the biweekly SWE measurements are usually acquired through manual profiles, a destructive method that may introduce spatial variability in the measurements due to differences in the location of sampling relative to the HS data, which are typically obtained from fixed installed stakes, snow courses, or automatic snow depth measurements.

### 2.2.3 HS data as model input for the NH-SWE dataset

We have gathered and compiled pan-Northern Hemisphere datasets of in situ daily HS observations from different sources. This relies on the European Climate Assessment and Dataset (ECA&D), which has already been described (Klein Tank et al., 2002) and analysed in previous studies (Fontrodona Bach et al., 2018), but with some important additions and updates. Gaps in time series from Finland in the ECA&D have been filled where possible by downloading HS time series directly from the Finnish Meteorological Institute (FMI). The underrepresentation of alpine sites in the ECA&D has been reduced through data obtained from the MeteoSwiss data portal IDAWEB, which includes data from MeteoSwiss, the SLF

(WSL Institute for Snow and Avalanche Research), and the Autonomous Province of Bolzano - Südtirol. We have also included alpine data published by Matiu et al. (2021b) and Matiu et al. (2021a). The ECA&D coverage over Russia has been completely replaced by data from the All-Russia Research Institute of Hydrometeorological Information - World Data Center (RIHMI-WDC), which contains longer and updated coverage of many sites. The western half of the Northern Hemisphere is well covered by data available from the Global Historical Climatology Network daily (GHCNd) dataset. In the case of multiple time series from the same location being available across the compiled datasets, we selected the time series with the most updated record or the one with fewer gaps. Because of the sharp increase in data availability and quality after 1950 (Fontrodona Bach et al., 2018; Matiu et al., 2021a) our data compilation begins from 1 September 1949 to 31 August 2022. Most snow depth measurements are manual with a precision of  $\pm 1$  cm, but automatic measurements with higher precision are also present. Due to the large amount of data gathered, we do not provide information on the type of measurements for each snow depth dataset.

Following this initial compilation, we obtain 21,502 individual time series of snow depth, upon which we apply further selection criteria before further use. The  $\Delta$ SNOW model (Winkler et al., 2021) requires a gap-free record of daily snow depth. Therefore we use a robust gap-filling procedure to the HS time series (see Appendix A.1). We quality control the gap-filling based on confidence criteria and we select stations with at least one entire gap-free snow year between 1950 and 2022. We define a snow year from 1st of September to 31st of August, since this was the first day of the month with most snow-free records over the entire dataset. Furthermore, the  $\Delta$ SNOW model can only be reliably applied over seasonal snowpacks (Winkler et al., 2021), and the SNOTEL dataset (used here for model regionalisation) contains only sites with a minimum of 40 days of continuous snow cover. Because of the uncertainty in model performance for shorter snow cover durations, we retain only stations where the mean continuous snow cover duration is at least 40 days. The number of stations in the dataset after quality control and selection criteria is 11,071. An overview of the datasets and sources is available in Table 2.1 and the spatial coverage is shown in Figure 2.2b.

We are not allowed to republish the original HS data used as source to derive the SWE dataset because it is already freely available (See references in Table 2.1). More information on the data sources and how to download the HS data can be found in the "code and data availability" section.

## 2.3 Method: snow depth to water equivalent conversion

### 2.3.1 Definitions

We show in Figure 2.3 the terms to describe the snow season. The day count of a snow year starts on 1 of September, which is day 1. The annual snow season is the longest period of continuous snow cover ( $\text{SWE} > 0 \text{ mm}$ ) in a snow year. The maximum snow water equivalent value in the annual snow season is the peak SWE. For biweekly SWE measurements, peak SWE is the highest observed SWE and is compared with the modelled SWE on the same date for the purpose of model evaluation. The value of peak SWE can last for days while there is no more snow accumulation, until the snowpack starts to melt. Snowmelt is defined as a decrease in SWE. The timing of snowmelt onset corresponds to the last day of peak SWE and divides the annual snow season into the accumulation season and the snowmelt season. Snow seasons can have more complicated accumulation and melt patterns than the one in Figure 2.3, for instance if peak SWE occurs very early in the season, followed by a long cold period without a decrease in SWE. However, for computing snowmelt volume and duration, we only use days with a decrease in SWE and thus the results should not be heavily affected by our definitions.

### 2.3.2 Model choice and brief description

We use the  $\Delta\text{SNOW}$  model of Winkler et al. (2021) to convert snow depth (HS) to snow water equivalent (SWE) time series. We use the  $\Delta\text{SNOW}$  model because of its low complex-

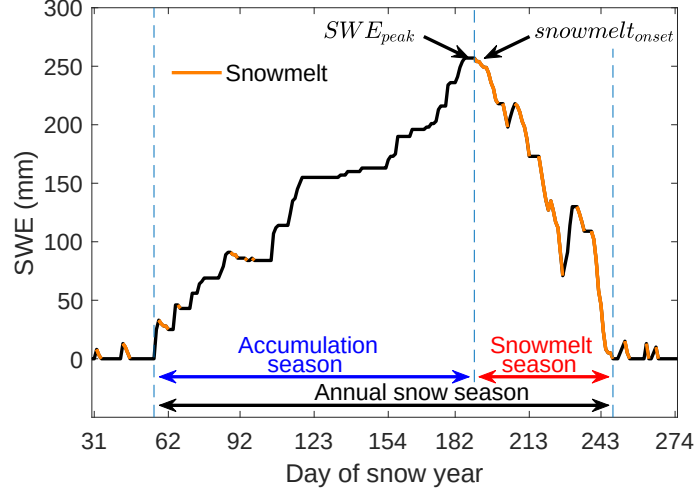


**Figure 2.3:** Snow season terms and definitions.  $SWE_{peak}$  is the highest snow water equivalent value. Snowmelt onset is the last day of peak SWE and divides the snow season into accumulation season and snowmelt season.

ity and little input data required, given that most snow depth time series do not contain other meteorological data (see Section 2.2). Furthermore, the  $\Delta$ SNOW model shows a high accuracy compared to other conversion models (Winkler et al., 2021), especially because of its ability to integrate the temporal evolution of snow depth into the model. Here, we further test its ability to accurately model the temporal dynamics of SWE by evaluating the model performance on other variables (see Section 2.3.6) than simulated daily SWE and simulated peak SWE, which were the main evaluated variables in previous studies (Hill et al., 2019; Winkler et al., 2021). In addition, the low number of required parameters makes it possible to regionalise the model and to transfer it to different types of snowpacks and climates, as shown in Section 2.3.4.

The model estimates total snowpack SWE by accumulating, compacting and drenching a series of snow layers, based on the temporal evolution of snow depth and 7 parameters that need to be calibrated. The model has four modules for HS computation, which are activated according to the value of  $\Delta HS(t)$  (the change in depth of the entire snow pack between  $t - 1$  and  $t$ ), the density of the snow layers ( $\rho_l$ , which can reach a maximum density of  $\rho_{max}$ ), and a *threshold deviation* parameter ( $\tau$ ). The four modules are:

- (i) new snow and overburden module, activated if  $\Delta\text{HS}(t) > \tau$ ;
- (ii) dry compaction module, activated at every time step if  $\rho_{lj} < \rho_{\max}$  for at least one snow layer  $j$ ;
- (iii) drenching module if  $\Delta\text{HS}(t) < -\tau$  and runoff submodule when  $\rho_l = \rho_{\max}$  for all snow layers;
- (iv) scaling module when  $|\Delta\text{HS}(t)| < |\tau|$ .

Each increase in snow depth activates the new snow module and creates a new layer in the snowpack. The parameter *new snow density* ( $\rho_0$ ) determines the density of the new layer. In case the snowpack already contains one or more layers, the overburden submodule is activated, which increases the density in underlying snow layers due to the weight of the new snow. The *overburden parameters* ( $k_{ov}, c_{ov}$ ) control this submodule. There is no maximum number of snow layers, and their thicknesses are determined by the temporal evolution of snow depth.

A snow accumulation event is generally followed by a decrease in snow depth due to snow metamorphism. This process densifies the snowpack but does not imply a decrease of SWE. This densification of snow layers is computed by the dry compaction module and occurs at every time step until all layers in the snowpack reach the *maximum snow density* ( $\rho_{\max}$ ). The densification is controlled by the *viscosity parameters* ( $\eta_0, k$ ).

A decrease in snow depth also activates the drenching module, which simulates wet metamorphism and snowpack water percolation from the top to the bottom layers, further densifying the snowpack layers until all layers have reached  $\rho_{\max}$ . During dry compaction and drenching, SWE does not decrease even though snow depth does. When all layers have reached the *maximum snow density*, the runoff submodule is activated and a decrease in snow depth leads to a decrease in SWE (i.e. snowmelt).

The scaling module intervenes when  $|\Delta\text{HS}(t)| < |\tau|$  and avoids excessive mass loss or mass gain from uncertainties in manual and automatic snow depth measurements. When

$|\Delta HS(t)| < |\tau|$ , the model re-evaluates dry compaction and makes small adjustments to HS within *threshold deviation*  $\tau$ . Figure 2.4 shows a schematic of the  $\Delta$ SNOW model and its modules and submodules as described above. The evolution of the densification of each snow layer is clearly seen, and no decrease in SWE occurs until the density of all snow layers reaches  $\rho_{\max}$ . For further details on the model and its equations, we refer the reader to Winkler et al. (2021).

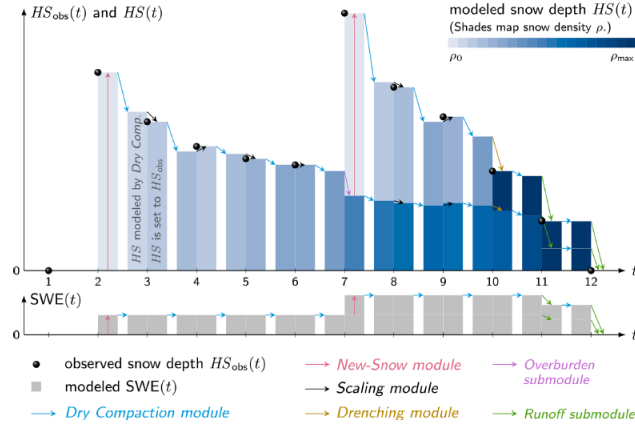


**Figure 2.4:** Conceptual schematic of the modules and submodules of the  $\Delta$ SNOW model. Figure extracted from Winkler et al. (2021).

### 2.3.3 $\Delta$ SNOW model calibration

The  $\Delta$ SNOW model (Winkler et al., 2021) contains seven parameters that might be site-specific or depend on local conditions. The model was originally developed and calibrated over 15 alpine sites in the Swiss and Austrian Alps with continuous measurements of snow depth (HS) and biweekly measurements of SWE. One unique set of optimised parameters was obtained by Winkler et al. (2021) for the European Alps only (Table 2.2). Here we use continuous time series of daily HS and SWE from 812 sites from the SNOTEL dataset (see Section 2.2.1) to calibrate the model, and we obtain one set of optimised parameters per site.

The *new snow density* ( $\rho_0$ ) is the most sensitive model parameter, largely controlling the bias in daily SWE and peak SWE (Winkler et al., 2021). Our initial tests showed that

the *maximum snow density* ( $\rho_{\max}$ ) has a stronger impact on the timing of modelled peak SWE than on the modelled daily SWE, a sensitivity which was not explicitly tested in the work of Winkler et al. (2021). This sensitivity is not surprising, because the *maximum snow density* determines the maximum densification of the snowpack, after which any decrease in snow depth will lead to a decrease in SWE. However, the magnitude of modelled peak SWE is still mostly controlled by the *new snow density* parameter. Even though Winkler et al. (2021) suggest calibration of all seven parameters of the model, our tests showed that  $\rho_0$  and  $\rho_{\max}$  are the only two parameters that exhibit some relationship with the climate variables that we used (see Section 2.3.4). Therefore, we focus here on the calibration of these two key parameters,  $\rho_0$  and  $\rho_{\max}$ , and retain the values determined in the analysis of Winkler et al. (2021) (see Table 2.2) for the remaining five ( $\eta_0$ ,  $k$ ,  $c_{ov}$ ,  $k_{ov}$ ,  $\tau$ ).

To identify the optimum values for  $\rho_0$  and  $\rho_{\max}$ , we search within the original calibration ranges provided by Winkler et al. (2021), which are  $\rho_0 \in [50, 200] \text{ kg m}^{-3}$  and  $\rho_{\max} \in [300, 600] \text{ kg m}^{-3}$ . We use Latin hypercube sampling (McKay et al., 1979) to obtain 1000 parameter sets with  $\rho_0$  and  $\rho_{\max}$ .

The performance of each model run is evaluated using the root-mean-square error of: daily SWE ( $R_{\text{daily}}$ ), peak SWE ( $R_{\text{peak}}$ ) and day of the year of peak SWE ( $R_{\text{peakdoy}}$ ). See Section 2.3.1 for the definition of peak SWE and day of peak SWE. We normalise each metric by the mean of the 1000 simulations to sum the three metrics into one single value to be minimised ( $R_{\text{min}}$ ). We also test different weighted sums of  $R_{\text{daily}}$ ,  $R_{\text{peak}}$  and  $R_{\text{peakdoy}}$  to minimise also the bias for the same three quantities. These tests lead to the following final objective function to minimise:

$$R_{\text{min}} = 0.13 \cdot R_{\text{daily}} + 0.45 \cdot R_{\text{peak}} + 0.43 \cdot R_{\text{peakdoy}} \quad (2.1)$$

which ensures peak SWE and day of peak SWE have the largest weight on the overall model performance. This is because the model is unlikely to reach an optimal fit for peak SWE and day of peak SWE without a correspondingly good fit for daily SWE during the snow accumulation season.

For each of the 812 SNOTEL sites, the parameter set with the minimum  $R_{\min}$  according to Equation 2.1 is retained.

### 2.3.4 Regionalisation of $\Delta$ SNOW model parameters

In order to make the modelled SWE estimates as transferable as possible to different types of snowpacks and climates where calibration is not possible, we used regional climate variables to estimate key model parameters. For each of the 812 SNOTEL sites, we compared the optimised parameter sets for  $\rho_0$  and  $\rho_{\max}$  against selected monthly climate variables from the WorldClim2 global dataset (Fick & Hijmans, 2017) which was used because of its high spatial resolution ( $\sim 1$  km) and global extent. Appendix A.2 provides details on all the variables tested.

We further complement this analysis with the dimensionless climate index parameters proposed by Woods (2009) to analytically describe snow cover dynamics. These index parameters namely include  $\overline{T}^*$ , which is defined by Woods (2009) as the ratio between mean annual temperature and the amplitude of the annual temperature cycle.

We then use a stepwise linear regression to determine which variables best account for the variation in the  $\Delta$ SNOW optimised model parameters  $\rho_0$  and  $\rho_{\max}$ . This is similar to the approach used by Hill et al. (2019) to find explanatory climate variables for the snow density parameters in their SWE estimation model. The stepwise linear regression finds the best explanatory variable and includes additional variables if the adjusted  $R^2$  improves by 0.02 or greater compared to its exclusion.

The final regression model for  $\rho_0$  reads as follows (see also Figure 2.5a):

$$\rho_0 = 206.71 \cdot P_V + 51.547, \quad (2.2)$$

The final regression model for  $\rho_{\max}$  reads as (see also Figure 2.5b):

$$\rho_{\max} = 42.82 \cdot \overline{H}_{\max} + 85.82 \cdot \overline{T}^* + 324.76, \quad (2.3)$$

**Table 2.2:** The  $\Delta$ SNOW model parameters as originally calibrated by Winkler et al. (2021) and with our regionalised approach (Section 2.3.4).

| Model version                         | $\rho_0$ ( $kg\ m^{-3}$ ) | $\rho_{max}$ ( $kg\ m^{-3}$ ) | $\eta_0$ ( $Pa\ s$ ) | $k$ ( $m^3 kg^{-1}$ ) | $k_{ov}$ (-) | $c_{ov}$ ( $Pa^{-1}$ ) | $\tau$ (cm) |
|---------------------------------------|---------------------------|-------------------------------|----------------------|-----------------------|--------------|------------------------|-------------|
| $\Delta$ SNOW <sub>Original</sub>     | 81                        | 401                           | $8.5 \cdot 10^6$     | 0.030                 | 5.1          | $0.38 \cdot 10^{-4}$   | 2.4         |
| $\Delta$ SNOW <sub>Regionalised</sub> | Equation 2.2              | Equation 2.3                  |                      |                       |              |                        |             |

where  $P_V$  is the mean December-January-February water vapour pressure in the atmosphere, which was taken from the WorldClim2 dataset (Fick & Hijmans, 2017);  $\bar{H}_{max}$  is the average maximum snow depth in metres; and  $\bar{T}^*$  is a dimensionless climate index defined by Woods (2009) and calculated based on WorldClim2 (Fick & Hijmans, 2017). See Appendix A.2 for further description of the climate variables. We set a minimum of 54 and a maximum of  $197\ kg\ m^{-3}$  for  $\rho_0$  and a minimum of 309 and maximum of  $580\ kg\ m^{-3}$  for  $\rho_{max}$ , as these were the minimum and maximum calibrated values (See Section 2.3.3).

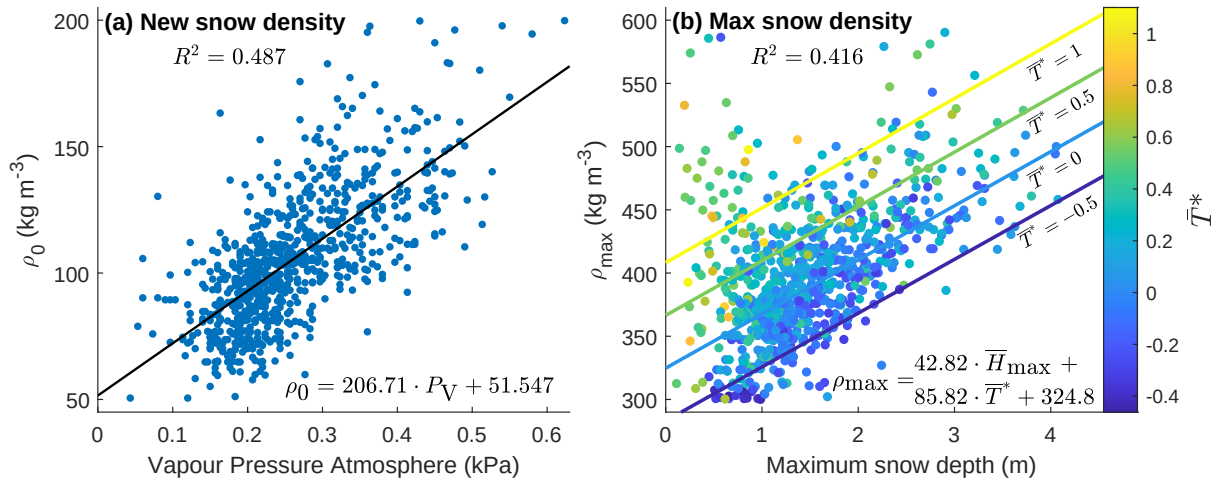


**Figure 2.5:** Regionalisation of  $\Delta$ SNOW model parameters. (a) Fresh snow density ( $\rho_0$ ) against mean December-January-February atmospheric vapour pressure ( $P_V$ ) from WorldClim2 dataset. (b) Maximum snow density ( $\rho_{max}$ ) against maximum snow depth ( $\bar{H}_{max}$ ) and dimensionless temperature index ( $\bar{T}^*$ ). Equation 2.2 is shown in panel (a) together with the simple linear regression line. Equation 2.3 is shown in panel (b) together with regression lines for four values of  $\bar{T}^* = [-0.5, 0, 0.5, 1]$ . Adjusted r-squared is displayed in each panel.

The new snow density parameter  $\rho_0$  is best explained ( $R^2 = 0.49$ ) by the mean December-January-February (DJF) atmospheric vapour pressure. This influence is consistent with observed climatic controls for snow density, where more humid climates and mar-

itime climates will typically have higher snow densities than drier climates, such as tundra and taiga (Bormann et al., 2013). The maximum snow density parameter  $\rho_{\max}$  is best explained ( $R^2 = 0.42$ ) by a combination of the average annual maximum snow depth and  $\overline{T}^*$ . This conforms to broad expectations from snowpack dynamics, whereby the greater mass of a deeper snowpack contributes to higher densification. An estimated value for average annual maximum snow depth should always be available since the model needs continuous time series of snow depth. The dependence on  $\overline{T}^*$  (ratio between mean and amplitude of annual temperature) reveals an additional link between  $\rho_{\max}$  and the regional climate, whereby close to zero  $\overline{T}^*$  arises for high temperature amplitudes (typically continental climates) or for marginal snow areas with mean annual temperatures close to zero. In contrast, high positive or negative  $\overline{T}^*$  values correspond to low temperature amplitudes (typically maritime climates) or highly negative or positive mean annual temperatures. This relationship can be observed in Figure 2.5 if we consider the hypothetical scenario of two sites with equal maximum snow depth. In this case, the site located in a warmer climate is likely to have a higher maximum snow density, which is consistent with previous literature (Bormann et al., 2013).

Based on the two linear regression models, we estimate the *new snow density* and *maximum snow density* parameters for all the sites in the regionalisation, evaluation and model input datasets (see Section 2.2) and run the  $\Delta$ SNOW model for all of the snow depth time series. The performance of the model using these regionalised parameters ( $\Delta$ SNOW<sub>Regionalised</sub>) is analysed in Section 2.4.

The final modelled NH-SWE dataset presented in Section 2.5 is based on the parameters estimated using this approach. Furthermore, we provide code for the user to extract the  $\Delta$ SNOW<sub>Regionalised</sub> model parameters for any point in the Northern Hemisphere. Latitude-longitude coordinates and a value for maximum snow depth need to be provided by the user (see the "Code and data availability" section).

### 2.3.5 Comparison with an alternative SWE estimation approach

In order to provide broader context for our Northern Hemisphere SWE estimates, we compare these results with a previously published statistical SWE estimation model (Hill et al., 2019) (from now on the "Hill model"). The Hill model also estimates SWE using snow depth data and climatological variables but does not need a complete time series of snow depth and can instead estimate single values based on an estimate of snow density. There is some similarity in the climatological variables found by Hill et al. (2019) that best estimate snow density variation and those used in the present paper (see Section 2.3.4). The Hill model estimates higher snow density for locations with a higher mean winter precipitation (humid climates) and a lower snow density for locations with a high temperature difference between warmest and coldest month (continental climates). In addition, in the Hill model, the day of the hydrological year contributes to estimating snow density, with higher densities towards the end of the snow season, when the snowpack is deeper and more compact.

We use the WorldClim2 global dataset of monthly climate variables (Fick & Hijmans, 2017) to obtain the Hill model parameters, namely mean winter precipitation (PPTWT) and the temperature difference between the warmest and coldest month (TD). The reader is referred to the work of Hill et al. (2019) for more details on the model. We run the Hill model for all the sites in the regionalisation and evaluation datasets (see Section 2.2). The performance of the Hill model is analysed in Section 2.4 as a comparison along with the regionalised  $\Delta$ SNOW model ( $\Delta$ SNOW<sub>Regionalised</sub>).

### 2.3.6 Extended model performance assessment

Previous snow depth to SWE conversion models have evaluated model performance based on root-mean-square error and bias of daily SWE and of peak SWE, which we also employ to enable comparisons. This is mostly due to a lack of data to evaluate more metrics. For example, continuous measurements of SWE are required to assess the model performance on timing of snowmelt onset, but these are rarely available. In order to assist with potential

applications in water resources management and modelling, here we use our extensive HS-SWE data compilation (see Section 2.2) to assess additional aspects of the SWE model performance, namely: the relative bias of peak SWE, the daily SWE time series variability, the timing of snowmelt onset, the total snowmelt and the snowmelt duration.

**Table 2.3:** Summary of model performance assessment variables and metrics. All performance variables are computed for each annual snow season. Snow seasons with non-daily SWE observations or with gaps do not allow for the computation of snowmelt onset and snowmelt total. All the biases are computed as modelled minus observed.

| Performance variable | Performance metric                   | Description                                                                                                                                                              |
|----------------------|--------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| SWE daily            | RMSE (mm),<br>Bias (mm)              | The root-mean-square error of all modelled daily SWE values. The mean difference (bias) between all modelled and observed daily SWE values.                              |
| SWE peak             | RMSE (mm),<br>Bias (mm),<br>Bias (%) | The root-mean-square error of modelled peak SWE values. The difference (bias) between modelled and observed peak SWE (see Figure 2.3), also in percentage.               |
| SWE time series      | NSE (-)                              | The Nash-Sutcliffe efficiency (Nash & Sutcliffe, 1970) of daily SWE time series (see Eq. 2.4 as $R_{\text{NASH}}$ ). One NSE value for each modelled annual snow season. |
| Snowmelt onset       | Bias (days)                          | The difference (bias) between modelled and observed timing of onset of the snowmelt season (see Figure 2.3).                                                             |
| Snowmelt total       | Bias (mm)                            | The difference (bias) between modelled and observed cumulative total snowmelt for the annual snow season and for the melt season (see Figure 2.3).                       |
| Snowmelt duration    | Bias (days)                          | The difference (bias) between modelled and observed number of snowmelt days during the annual snow season and during the melt season (see Figure 2.3).                   |

The performance variables and metrics together with their description are shown in Table 2.3. The reproduction of the daily SWE time series dynamics is assessed based on the well-known Nash-Sutcliffe criterion (Nash & Sutcliffe, 1970), widely used in streamflow

model assessment:

$$R_{\text{NASH}} = 1 - \frac{\sum_{t=1}^N (x_{\text{obs}}(t) - x_{\text{mod}}(t))^2}{\sum_{t=1}^N (x_{\text{obs}}(t) - \overline{x_{\text{obs}}})^2}, \quad (2.4)$$

where  $x_{\text{obs}}$  is the observed quantity (here daily SWE) at time step  $t$ ,  $x_{\text{mod}}$  is the corresponding modelled quantity and  $\overline{x_{\text{obs}}}$  is the mean of all  $N$  observed values.

## 2.4 Model performance and evaluation

Here we give a summary of the  $\Delta$ SNOW regionalised (see Section 2.3.4) model performance using both the regionalisation and evaluation datasets.

### 2.4.1 Daily SWE, peak SWE and snowmelt onset

The daily SWE values (Figure 2.6a,b) and the peak SWE values (Figure 2.6c,d) reproduce the observed values well and show a comparable performance to previous efforts to convert snow depth to snow water equivalent (Jonas et al., 2009; Sturm et al., 2010; Hill et al., 2019; Winkler et al., 2021). The regionalisation dataset is generally unbiased for daily SWE and peak SWE, while the evaluation datasets show a slight but spatially consistent negative bias (FigureA.5). This negative bias is largely driven by the Canadian SWE dataset because it contains a large amount of data and very deep snowpacks. But the median relative bias across the entire dataset is only  $-11.3\%$  (Table 2.4), and the spatially consistent negative bias is smaller for European sites and for relative bias of peak SWE (FigureA.5). The mean relative bias across all datasets given equal weight is  $-1.7\%$ , and the largest relative bias is  $17\%$  (Table 2.4). For the GCOS-CH and Kuhtai-AT datasets, the regionalisation of parameters yields a lower model performance for daily SWE and peak SWE than using the original  $\Delta$ SNOW model parameters (see Table A.1) obtained for the European Alps. This is because these two datasets were among others used by Winkler et al. (2021) to calibrate the model. It should also be noted that the model from Hill et al. (2019) had a better performance than the  $\Delta$ SNOW regionalised model for five of the nine datasets used,

showing that the Hill model is also an excellent option for estimating daily SWE. The timing of snowmelt onset is well reproduced by the  $\Delta\text{SNOW}_{\text{Regio}}$  model, with a 1.45 day bias for the regionalisation dataset and a 1.34 day bias for the evaluation datasets (Figure 2.6e,f). The spatial distribution of the bias in timing of snowmelt onset shows the dominance of small positive biases except for some sites with a larger positive bias in eastern Canada (Figure A.5). The positive bias in the timing snowmelt onset may indicate a very small model delay in the densification of all the snowpack layers to  $\rho_{\text{max}}$ . Nonetheless, the model performance is excellent considering no information on daily temperature or any other variable is used to model the start of the snowmelt season. For comparison, the regression model from Hill et al. (2019) has a negative bias of 15 days for the SNOTEL dataset and 17 days for the CanSWE dataset (see Table A.1). This very premature onset of the snowmelt season occurs in the regression model because the day of peak SWE corresponds to the day of maximum snow depth, which is not realistic as snowpack compaction and ripening can still occur prior to melt loss. A period of snow depth decline but no change in SWE can last for many days. This can be observed in Figure 2.7a. Thus, the improved capacity to capture accurate timing is a key advantage of using the  $\Delta\text{SNOW}$  model.

### 2.4.2 Daily SWE time series

In terms of daily SWE dynamics, Figure 2.7b shows that the  $\Delta\text{SNOW}_{\text{Regio}}$  model can reach very high Nash-Sutcliffe efficiencies as the bias in daily SWE approaches zero, all data considered. This is shown by the high density of points close to a NSE of 1 in Figure 2.7b. In contrast, the regression model from Hill et al. (2019) shows lower NSE values in general for an unbiased daily SWE performance (Figure 2.7d), shown by a lower density of points close to a NSE of 1. Only the regionalisation dataset is analysed here, because many time series in the evaluation datasets are not continuous daily measurements and thus do not allow for NSE estimates for the entire snow season. The better performance of the  $\Delta\text{SNOW}_{\text{Regio}}$  model is explained by the inclusion of snowpack metamorphism processes which are not included in regression models (e.g. compaction and ripening, see Section 2.3.2). An example can be seen

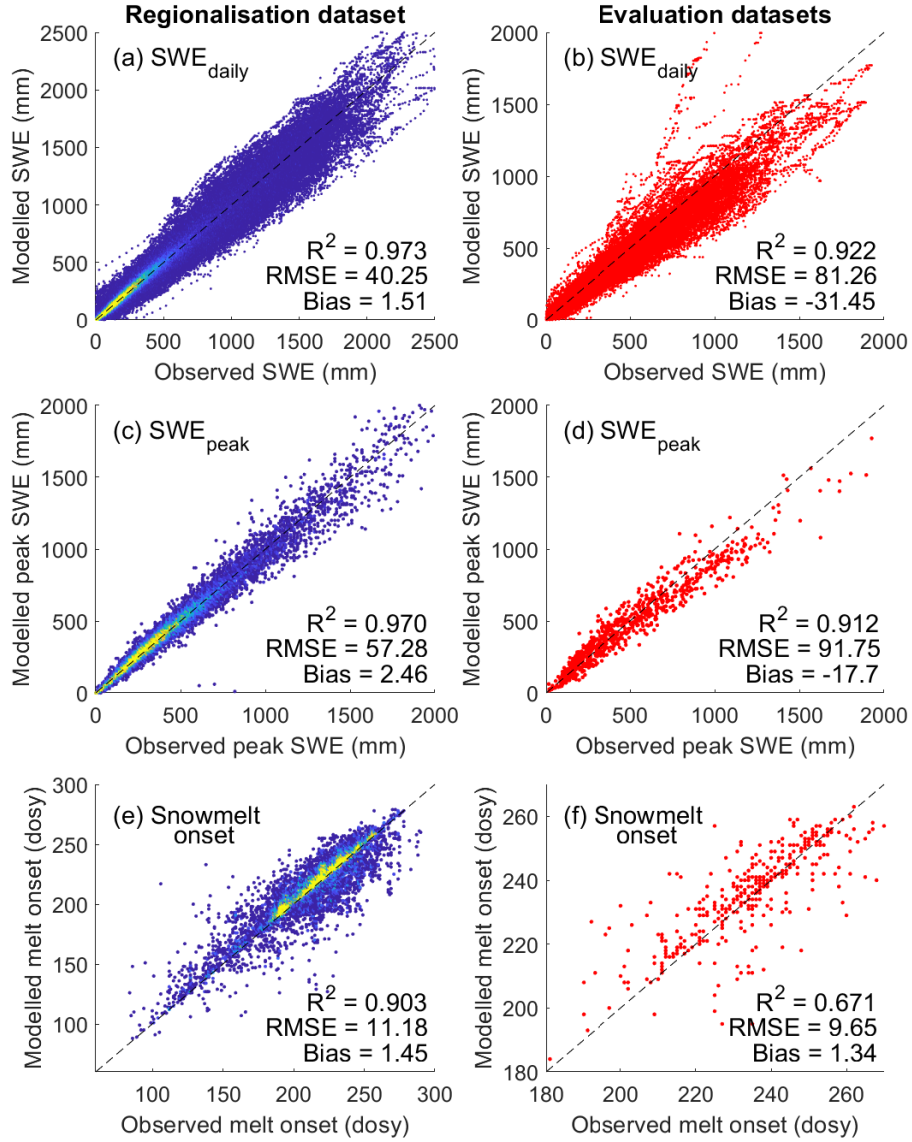


**Figure 2.6:** Model performance of  $\Delta\text{SNOW}_{\text{Regio}}$ . For the regionalisation (a,c,e) and evaluation (b,d,f) datasets, performance of all modelled daily SWE (a,b), modelled peak SWE (c,d) and day of snowmelt onset (e,f) are given. Colours in the left column show scatter density. "dosy": day of snow year starting on 1st of September.

in Figure 2.7a and 2.7c, where similar unbiased performances for both models show a higher NSE (0.94) for the  $\Delta\text{SNOW}_{\text{Regio}}$  compared to the regression model (0.89). The NSE values of modelled daily SWE in Figure 2.7a are closer to 1, while the NSE values of the regression model in Figure 2.7c are lower and clearly show that the model has difficulty accurately capturing snowpack changes due to daily snow accumulation and settling processes.

**Table 2.4:** Performance across datasets for daily SWE, peak SWE and timing of snowmelt onset. For each dataset, the mean performance of all stations is shown. SNOTEL is the regionalisation dataset, and the others are evaluation datasets (see Section 2.2).

|                 | <b>SWE daily</b><br>bias (mm) | <b>SWE peak</b><br>bias (mm), bias (%) | <b>Snowmelt onset</b><br>bias (days) |
|-----------------|-------------------------------|----------------------------------------|--------------------------------------|
| SNOTEL          | 1.0                           | 3.4 (−1.0%)                            | 1.6                                  |
| CanSWE          | −34.0                         | −56.4 (−11.3%)                         | 3.0                                  |
| GCOS-CH         | −0.6                          | 50.9 (17.2%)                           | -                                    |
| RIHMI-WDC       | −16.9                         | −16.2 (−14.6%)                         | -                                    |
| NVE             | −15.3                         | −32.5 (−5.9%)                          | −1.3                                 |
| Kuhtai-AT       | 7.5                           | 47.7 (12.7%)                           | −7.3                                 |
| Sodankylä-FI    | −15.4                         | −29.8 (−15.0%)                         | -                                    |
| Col-de-Porte-FR | −28.8                         | 9.7 (2.5%)                             | -                                    |
| Mean            | −12.8                         | −2.9 (−1.7%)                           | −1.0                                 |

### 2.4.3 Snowmelt duration and total snowmelt

The general daily SWE dynamics are well reproduced by the  $\Delta\text{SNOW}_{\text{Regio}}$  model. However, a negative bias in total snowmelt and snowmelt duration is observed when the full annual snow season is considered (Figure 2.8a). This negative bias occurs because small snowmelt events ( $< 5$  mm) during the accumulation season are not well captured by the  $\Delta\text{SNOW}_{\text{Regio}}$  model. The model snow layers do not reach the maximum snow densification for a short period of snowmelt, and the 1 centimeter precision of snow depth measurements that drive the  $\Delta\text{SNOW}$  model make the minimum modelled melt 3–5 mm (depending on the snow density). During the snowmelt season, the total snowmelt exhibits little to no bias, and the snowmelt duration has a slight negative bias. The negative bias in the duration of the snowmelt season is largely due to the positive bias in the timing of snowmelt onset (2.5 days on average), resulting in a shorter modelled total snowmelt season. Despite the slight negative biases shown for snowmelt duration and total snowmelt, the overall performance is very good and enables confidence in the application of modelled SWE using the  $\Delta\text{SNOW}_{\text{Regio}}$

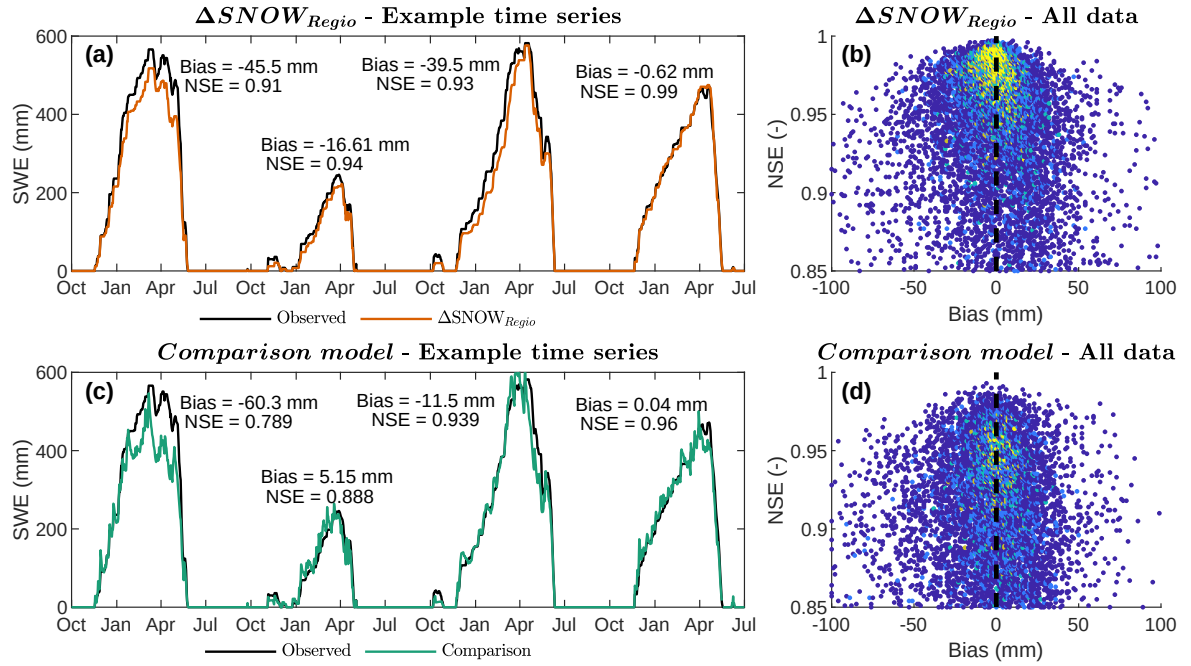


**Figure 2.7:** Model performance for daily time series. Nash-Sutcliffe efficiency (NSE) vs bias of daily SWE for (b) the  $\Delta\text{SNOW}_{\text{Regio}}$  and (d) the comparison (Hill) model. Colours show scatter point density. One example time series of observed daily SWE and modelled daily SWE for (a) the  $\Delta\text{SNOW}_{\text{Regio}}$  and (c) the regression model (Hill model) for comparison. Time series from the 2017-2020 water years of SNOTEL is shown, station ID 371; Buck Flat, Utah, United States; latitude: 39.1300; longitude: -111.44; elevation: 2,868 m.a.s.l.

model. This confidence is not possible for regression model estimates of SWE, especially for cumulative variables such as snowmelt duration and total snowmelt, which can be greatly overestimated (although peak SWE magnitudes can be equally well estimated).

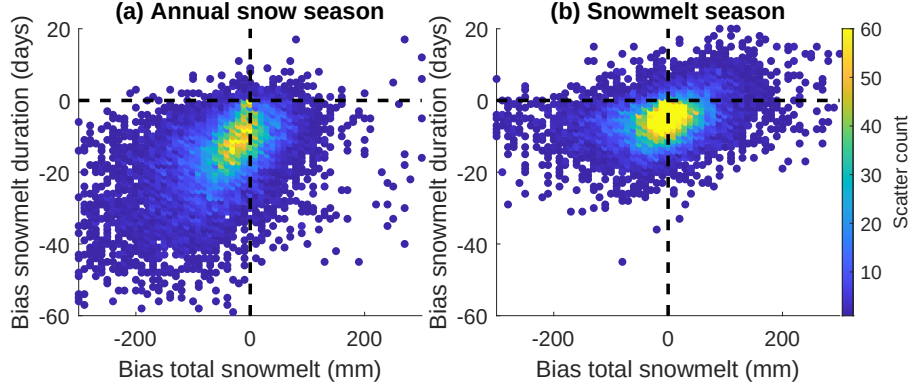


**Figure 2.8:** Bias in snowmelt duration vs bias in snowmelt depth for  $\Delta\text{SNOW}_{\text{Regio}}$ . (a) Annual snow season bias and (b) snowmelt season bias only. See Section 2.3.6 for definitions of snowmelt season and biases.

#### 2.4.4 Performance summary

The previous evaluation sections show model performance inclusive of all daily data from the regionalisation and evaluation datasets. In order to provide a more general overview, in Figure 2.9 we display a summary comparing three model scenarios, regionalisation and evaluation datasets, and the six different performance metrics (see Table 2.3). The three model scenarios are the  $\Delta\text{SNOW}$  model with its original parameters from Winkler et al. (2021), the  $\Delta\text{SNOW}_{\text{Regio}}$  with our regionalised approach, and the Hill model (Hill et al., 2019). Mean performance values for each station are used for forming a boxplot in Figure 2.9. This avoids over-weighting performance interpretations due to, for example, stations with very long time series or outliers in model performance. An important highlight from this comparison is the clear benefit in estimating  $\rho_0$  and  $\rho_{max}$  from regional climate data ( $\Delta\text{SNOW}_{\text{Regio}}$ ), which is apparent in the better performance across all six metrics compared to using the original values ( $\Delta\text{SNOW}_{\text{Original}}$ ) obtained by Winkler et al. (2021) for the European Alps only. The full results for all these comparisons are also available in Table A.1. The regionalised  $\Delta\text{SNOW}$  model performs better than the original  $\Delta\text{SNOW}$  model for 77% of all performance metrics and datasets, and better than the Hill model for 60% (see Table A.1).

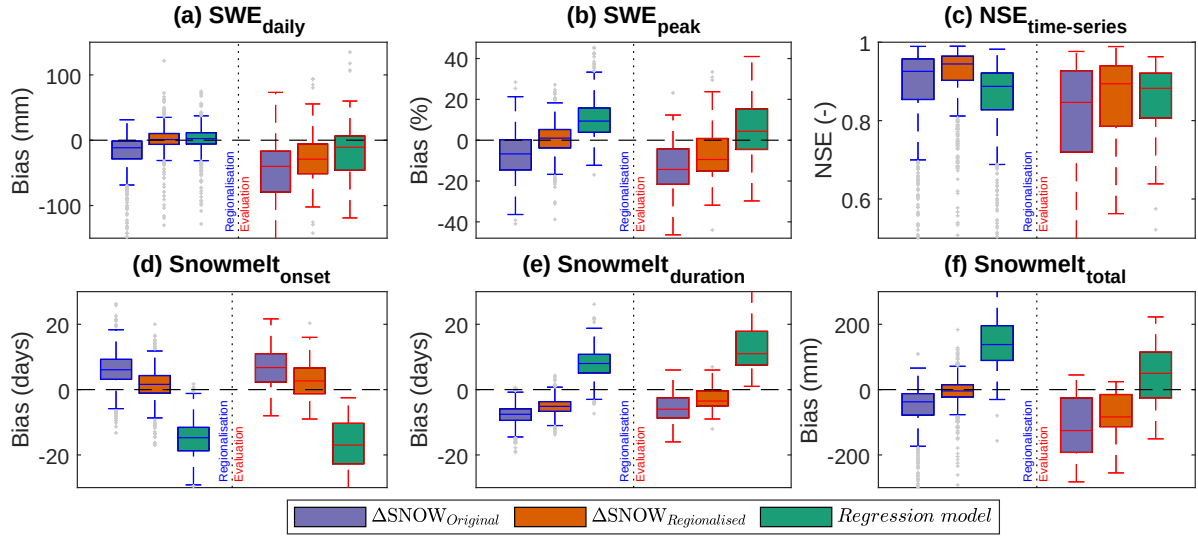


**Figure 2.9:** Model performance summary. Each subplot is split in two sides: the performance for the regionalisation dataset (left, blue lines) and the performance for the evaluation datasets (right, red lines). Boxes are built from mean values for all stations in each dataset, instead of considering all data points (i.e. a box for the regionalisation dataset is built from the mean performance for that model at each of the 812 SNOTEL sites).

## 2.5 Final product: the NH-SWE dataset

### 2.5.1 Snow climatologies and data characteristics

We present an overview of some of the key features of the final NH-SWE dataset in Figure 2.10. The dataset contains 11,071 time series of daily SWE and estimated snow density at the point scale. The climatic range is broad, which can be seen in the large variability of peak SWE and of snow cover duration across the sites (Figure 2.10a,b). The deepest snowpacks (largest peak SWE) are generally located in high latitudes and mountainous areas, such as western North America, the European Alps and Scandinavia, but deep snowpacks can also occur at high elevation stations surrounded by lower elevation stations with shallow snowpacks, such as the isolated high peak SWE stations that stand out in Poland in Figure 2.10a. Snowpacks are generally shallower in relatively warmer locations where higher temperatures limit snowfall (e.g. southern parts of Canada, Germany and Sweden). Shallow snowpacks are also found in very cold climates, where precipitation is limiting due to low water vapour

in the atmosphere (e.g. Siberia and northern Canada). Regarding snow cover duration, the spatial patterns are well linked to mean energy availability, with the higher latitudes and higher elevations having the longest snow cover duration.

In Figure 2.10c, we compare the links between peak SWE, snow cover duration and  $\overline{T}^*$ . This demonstrates the large variation in the interplay between precipitation and temperature in determining snowpack dynamics. All temperature regimes can produce a low peak-SWE if snow input (i.e. snowfall) is limited. For regimes with low peak-SWE, all snow cover durations are possible, depending on the temperature regime. In very cold climates (e.g. Siberia, Alaska), peak-SWE conditions can last for several months; in warmer climates (e.g. south Scandinavia), the snow will melt quickly.

On the contrary, there is a very clear link between snow cover duration and peak-SWE for temperature regimes that lead to high peak-SWE. In fact, if peak SWE increases, snow cover duration also increase. Peak-SWE convergences to highest values towards intermediate  $\overline{T}^*$ , i.e. neither too cold nor too warm for large amounts of snow to occur and stay for long on the ground.

The median time series length in the dataset is 15 years; however, the distribution is slightly bimodal with the overall average being 35 years, and a second peak in the availability of very long time series (up to 73 years) (Figure 2.10d). The distribution of site elevations reflects the large number of time series at low lying parts of coastal Norway, of Canada, and of Siberia. However, more than 1,000 sites are located above 1,000 meters a.s.l., providing good representation of snow dynamics from higher elevations (Figure 2.10e).

## 2.5.2 Quality control and uncertainty

We provide quality control and uncertainty flags for the SWE time series to signal the values that should be handled with care. We flag the effect of the  $\tau$  parameter (see Section 2.3.2) on the  $\Delta$ SNOW model when an increase in snow depth is smaller than  $\tau$  (2.4 cm). This

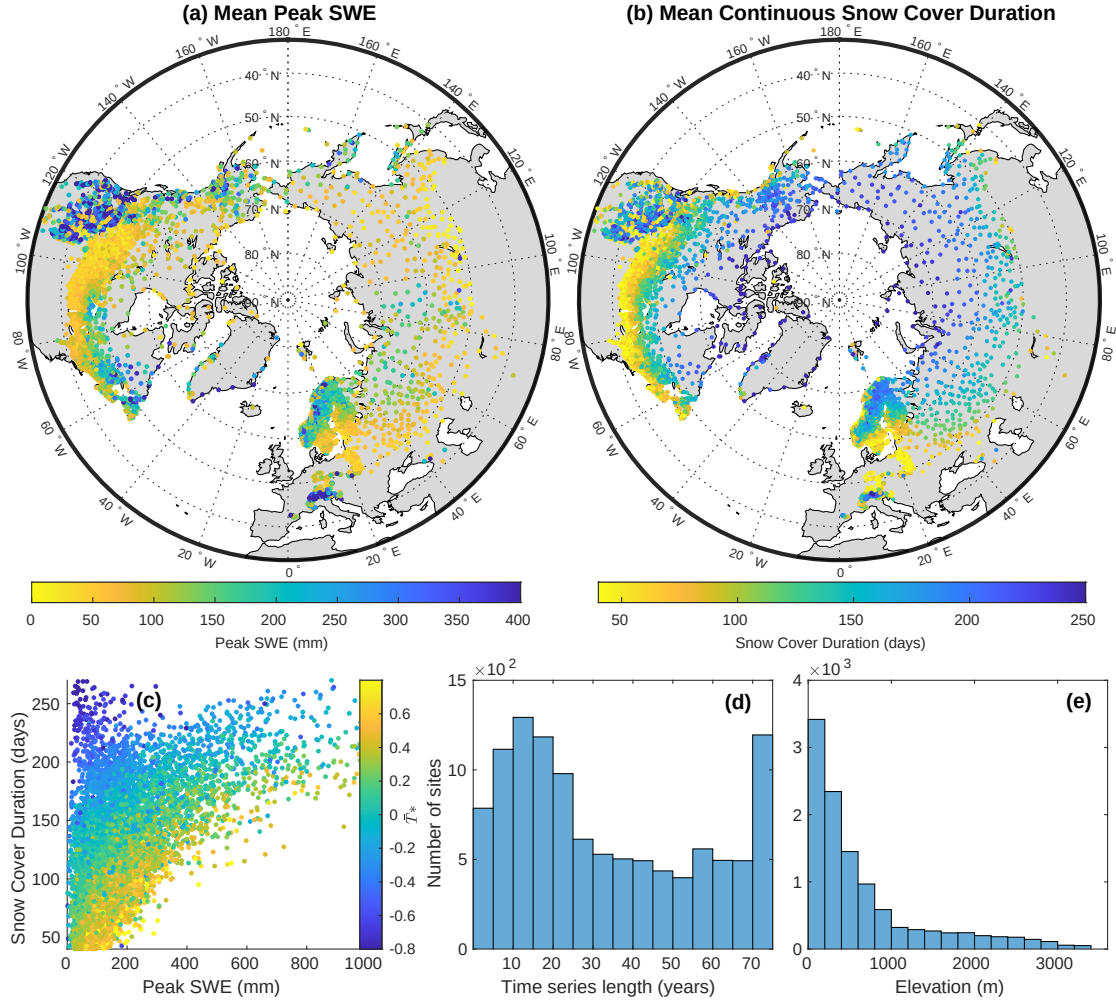


**Figure 2.10:** Features of the NH-SWE dataset. (a) Mean yearly peak SWE at each station; (b) mean continuous snow cover duration at each station; (c) correlation between peak SWE, snow cover duration and  $\bar{T}^*$ ; (d) distribution of time series lengths in years; and (e) distribution of station elevations.

means that sometimes there is a small increase in snow depth without an increase in SWE, leading to an artificial decrease in snow density. We correct this decrease in snow density and flag the value. Even though this is good for uncertain measurements, care should be taken for snow climates where small snow depth increments are normal. We also flag days when the computed snow density would fall below the fresh snow density parameter value. These are flagged as 1 in the quality control flag in the dataset.

We also flag all the values that result from gap-filling of snow depth. The gap-filling

algorithm performs well overall (see Appendix A.1); however, we cannot guarantee that all gap-filled records are realistic. Special care is required if the data are filled across gaps longer than 15 days because of the reduction in gap-filling performance (see Appendix A.1). We flag days that are gap-filled with the neural network algorithm with an "N", and we flag linearly interpolated gaps with an "L".

## 2.6 Usage and limitations

### 2.6.1 Potential applications

The SWE dataset presented here can be used freely and has a variety of potential applications. This data may be especially useful for applications where an accurate reproduction of the SWE dynamics in terms of timing of snow accumulation and melt is required. Additional uses include data assimilation into hydrological and climate models or validation of remote sensing products. A key strength of the dataset is accuracy in the timing of peak SWE and of snowmelt onset, as well as snowmelt duration, which makes it valuable for water resources assessment and management. In particular, many remote sensing techniques for alpine snow rely on the detection of wet snow (Awasthi & Varade, 2021), indicating snow is at melting point, and this dataset could provide valuable comparisons for these developing methods. The spatial extent of the dataset offers opportunities for snow climate research and in particular to assess Northern Hemisphere-scale climate change impacts on snow water resources. We note, however, that some key snow regions are not yet included due to lack of long-term data or a lack of data access (e.g. Himalaya, Central Asia and Tibetan Plateau).

The presented NH-SWE dataset is based on a model but also based on actual measurements of snow depth, making this the only point-scale Northern Hemisphere SWE dataset based on in situ snow data. Main advantages compared to other recently published Northern Hemisphere gridded SWE datasets (Luo et al., 2021; Shao et al., 2022) are the following: (i) NH-SWE includes mountains across the Northern Hemisphere; (ii) it includes deep

snowpacks exceeding 200 mm; (iii) it has along temporal coverage, dating back to 1950s for some locations; (iv) it uses actual point-scale observations of snow depth.

It is noteworthy that we not only publish the NH-SWE dataset but also the underlying  $\Delta$ SNOW model parameterisation, which can be used to estimate the model parameters for any point in the Northern Hemisphere. In addition, we provide code for this purpose along with the publication of the dataset on Zenodo (see "Code and data availability" section), which enables any user to obtain the model parameters to run the  $\Delta$ SNOW model of Winkler et al. (2021) for any given daily time series of snow depth.

## 2.6.2 Limitations

A few limitations should be considered before using the data or our regionalised parameterisation of the  $\Delta$ SNOW model of Winkler et al. (2021).

Although our analysis applied quality control measures to the daily SNOTEL data used for calibration, potential errors or biases in the data may still exist. As described in the literature, SNOTEL measurements can suffer from overestimation/underestimation of measurement, and these errors are often challenging to detect (Avanzi et al., 2014; Hill et al., 2019). The  $\Delta$ SNOW model considers the uncertainty associated with snow depth measurements through the threshold deviation parameter ( $\tau = 2.4 \text{ cm}$ ), but larger measurement errors may still be present. Nevertheless, it should be noted that our calibration is based on a sufficiently large sample of data, which likely reduces the impact of potential errors on both the calibration and regionalisation of the model.

Uncertainty in the evaluation datasets should be noted too. Although the evaluation of the SWE estimates for datasets with biweekly measurements (see Table 2.1) may be somewhat biased due to spatial variability between SWE and HS measurements, the error range for all datasets is similar, indicating that this did not significantly affect the overall model evaluation. The evaluation of the estimated peak SWE provides valid bias measures in terms

of SWE magnitude estimates, but not in terms of timing, which we do not consider for these biweekly estimates. The peak SWE biases for the datasets with biweekly SWE measurements are also similar to the ones found in the datasets with daily SWE measurements (see Table 2.1).

The  $\Delta$ SNOW model requires good quality time series of snow depth (e.g. gap-free, low measurement uncertainty). Measurement errors can accumulate and bias the SWE simulations for an entire season, especially if snow depth data are erroneous for a significant number of days. If the quality of the snow depth observations is poor or not continuous, we recommend using the regression model of Hill et al. (2019) to convert snow depth to SWE.

Our quality control flags capture gap-filled records and unrealistic snow densities, but the amount of data limits our capacity of exhaustive quality checks; unrealistic time series could exist in the dataset. We show that our regional parameterisation performs well especially in terms of snow cover dynamics and timings, but some SWE time series might nevertheless be slightly biased, resulting, for example, from an over or underestimation of model parameters. It is worth noting that while two parameters were calibrated in the regional parameterisation of the  $\Delta$ SNOW model of Winkler et al. (2021), five other parameters were not calibrated due to data limitations and their lack of clear link with climate variables. However, adding five additional calibration parameters would significantly increase parameter uncertainty, and a thorough sensitivity analysis of the model parameters is provided by Winkler et al. (2021), who highlight the importance of the snow density parameters. Our approach is a prudent one in terms of being able to track assumptions and uncertainty. Despite the lack of calibration of the other parameters, our model evaluation demonstrates that the regionalisation of the density parameters still results in acceptable model performance.

The user should also be cautious with any snow cover duration period of less than 40 days, or with snowpacks shallower than 50 mm of SWE. Even though we selected stations with an average of 40 days of snow cover, interannual variability could mean some years are shorter, making the model performance uncertain (see Section 2.2.3). Snow sublimation and snow drift are also processes that are not captured by the  $\Delta$ SNOW model.

Furthermore, the user should be aware of the spatial and temporal inhomogeneity of NH-SWE; the dataset covers most of the Northern Hemisphere, but some areas have a high station density (e.g. Scandinavia), while others show a rather low density (e.g. Siberia and Alaska). The time series lengths also vary from 1 to 73 years. Finally, NH-SWE does not include the original snow depth data, which has to be directly downloaded from the data source, but we provide modelled snow density along with the SWE time series.

## 2.7 Conclusions

This paper presents NH-SWE, a dataset of snow water equivalent (SWE) time series based on in situ observations of snow depth that are freely available across the Northern Hemisphere. The dataset is based on an established model for continuous snow-depth-to-SWE conversion (Winkler et al., 2021), for which we regionalised the model parameters for application at the Northern Hemisphere scale. The dataset contains 11,071 time series covering most areas of the Northern Hemisphere with a seasonal snow cover and spans the period 1950-2022.

The modelled daily SWE values and seasonal dynamics of SWE are generally well reproduced over the wide range of climates in the regionalisation and evaluation datasets (SNOTEL, CanSWE, GCOS-Switzerland, RIHMI-WDC, NVE, and other). The model has a slight delay towards a later start of snowmelt after the peak of snow accumulation, leading to a small negative bias in the duration of the melt season, but peak SWE and total snowmelt are generally unbiased.

Compared to SWE datasets based on remote sensing or climate reanalysis data, with a typical resolution of  $\sim 10$  km, NH-SWE is based on in situ observations of snow depth on the ground and therefore provides a higher confidence in the magnitude and dynamics of snow accumulation and melt at the point scale.

This dataset can be used for a variety of applications that require reliable SWE estimates rather than snow depth, in particular in the fields of water resources and snow

climate research, environmental and hydrological modelling, validation of remote sensing products or climate change impact research.

## 2.8 Code and data availability

The NH-SWE dataset is free to access and available at <https://zenodo.org/record/7515603> (Fontrodona-Bach et al., 2023b). The dataset is provided in two different formats (matrices and vectors) and contains modelled daily SWE, estimated snow density, and the quality control and gap-filling flags. An extensive metadata file includes information on station coordinates, elevation, length of time series, model parameters and the climate variables used to estimate them, as well as average snow climatology such as average maximum snow depth, average peak SWE and average maximum snow cover duration. The code used to estimate  $\Delta$ SNOW regionalised model parameters can be found together with the NH-SWE dataset at <https://zenodo.org/record/7515603> (Fontrodona-Bach et al., 2023b).

## Chapter Three

# Spatial trends and drivers of snowmelt variability

*A synthesized version of this chapter is being prepared for submission to a peer-reviewed scientific journal*

Josh Larsen, Bettina Schaepli, Ross Woods and Ryan Teuling have all contributed to the supervision of this PhD chapter.

## Abstract

Snow is a key component of the cryosphere and the water cycle. Changing snowmelt patterns due to global warming has implications for climate, hydrology, and ecosystems. Previous studies focusing on changing snowmelt patterns, particularly snowmelt rates, have shown high spatial variability in trends, but none has addressed it. We investigate changing snowmelt rates and their main drivers over the Northern Hemisphere. We use a novel dataset of snow water equivalent at the point scale from 1980 to 2022 based on actual in situ snow observations. We show a wide diversity of trends: 93% of stations show a warming trend; 79% of stations show a declining trend in the duration of the snow season; 65% of stations show a decreasing trend in peak snow water equivalent, mainly located over warmer and wetter climates; and 35% show an increase in peak snow water equivalent, mainly located over colder and drier climates. Declining snow accumulation is linked to warming temperatures through a later start and earlier end of the snow season, and increasing ephemerality of snow is observed. Decreasing seasonal precipitation can enhance snow losses, but increasing precipitation can compensate for warming temperatures. We emphasize that peak snow water equivalent is the central control for changing snowmelt rates in the melt season. Slower snowmelt rates are more likely at stations with strong negative trends in snow accumulation, which melt earlier at a time with lower solar radiation. However, faster melt rates can occur if warming temperatures compensate for earlier melt or if increasing snow accumulation trends lead to later melt. The high spatial variability of snowmelt rate trends across climates responds to the high diversity of trends in drivers, which are more spatially consistent than the snowmelt rate trends. This study shows the response of snowmelt to global warming is complex to generalise. More detailed analyses need to be performed at the global, regional and catchment scales if the implications for climate, hydrology, and ecosystems are to be assessed.

### 3.1 Introduction

Snowmelt plays a crucial role in a wide range of ecological and hydrological processes, making it a vital component of the Earth's water cycle. The volume of snowmelt in a season is linked to forest greenness (Trujillo et al., 2012) and to net carbon uptake by forests (Winchell et al., 2016). Hydrologically, snowmelt influences droughts (Livneh & Badger, 2020) and floods (Vormoor et al., 2016; Berghuijs et al., 2019), as well as streamflow timing and magnitude (Clow, 2010; Dudley et al., 2017; Gordon et al., 2022). Consequently, volume of snowmelt and its timing play a vital role for basins where snowmelt provides water for agriculture (Qin et al., 2020), for hydropower generation (Kopytkovskiy et al., 2015), and even for tree recruitment in riparian forests (Perry et al., 2020).

The snowmelt rate is a key hydrological process that is the primary determinant of how meltwater from the snowpack will be partitioned into infiltration, runoff and evaporation. Fast snowmelt rates have been linked to increased subsurface flow and positive streamflow anomalies (Barnhart et al., 2016). However, this can be counteracted in areas with deep soils and a high plant available water storage, reducing runoff (Barnhart et al., 2020). The timing of snowmelt onset and the rate of melt also determine the time of snow disappearance, which influences various environmental factors, including the annual peak of soil moisture (Harpold et al., 2015), the duration of soil water stress (Bales et al., 2011), albedo and energy balance partitioning (Skiles & Painter, 2017), the occurrence of wildfires (Westerling, 2016), and plant population growth (Campbell, 2019). Understanding the significance of snowmelt is essential for comprehending the implications of global warming on these processes.

Snowmelt rates have a high spatial and temporal variability, as they are controlled by the complex interactions between spatial and temporal variations in the surface energy balance during the snow season and at the time of melt (Pomeroy et al., 2003). Mazzotti et al. (2023) found higher melt rates in canopy gaps on south-facing slopes, which initiate early-season melting due to radiation exposure. Also, higher melt rates were observed on north-facing high-elevation areas, attributed to the delayed arrival of radiation on north-

facing slopes coinciding with higher temperatures later in the season. Pomeroy et al. (2015) found differences in melt rates between alpine, forest, and clearing environments. Barnhart et al. (2020) found melt rates that differed from 4-20 mm day<sup>-1</sup> at the same site over two consecutive years.

The impact of global warming on snow adds to the complexity of snowmelt rates. In a future warmer world with thinner snowpacks, snowmelt has been hypothesised to begin earlier in the season when less net energy (i.e. solar radiation) is available for melt, causing snow to melt at lower rates (Musselman et al., 2017). Consequently, the typically late-season high melt rates will be critically reduced because the snowpack will be fully melted earlier. This counterintuitive finding of slower snowmelt in a warmer world had already been simulated by López-Moreno et al. (2013b), who predicted earlier and slower melt for a warmer future in the Pyrenees, and by Pomeroy et al. (2015), who predicted melt rate reductions under forest canopies and clearings in the Canadian Rockies, but smaller reductions at alpine sites. In simulations for headwater basins, Rasouli et al. (2022) found the reduction in melt season length was less strong than the overall snow cover duration reduction due to slower snowmelt compensating for the earlier start of the melt season. The varying global sensitivity to warming temperatures between peak SWE and snow cover duration trends also indicates a complex response of snowmelt rate to warming (López-Moreno et al., 2020a). Furthermore, changes in the frequency of rain-on-snow events can enhance snow ablation, especially for warmer basins (López-Moreno et al., 2021). Besides simulations, slower snowmelt is also supported by a few historical observations. Over the United States, station data showed increasing trends in midwinter snow ablation events and decreasing trends in spring melt rate, which denotes earlier melt (on average 5 days per decade) at a slower rate (Harpold & Brooks, 2018). Remote sensing data over the Northern Hemisphere also showed decreasing trends in high melt rates and increasing trends in low melt rates since the 1980s, although mountainous regions were excluded (Wu et al., 2018). In contrast, López-Moreno et al. (2013b) suggested faster snowmelt would be expected if the melting timing remains constant and temperatures rise or if an increase in precipitation moves the melt season towards later in the season at a time with higher energy inputs. Future simulations for an Arctic headwater

basin show a doubling of the ablation rate by the end of the century due to increasing snowfall predicted by Global Climate Models for high latitudes together with an exceptionally high temperature warming in spring of 7°C by then (Krogh & Pomeroy, 2019).

Despite efforts to disentangle the counteracting effects of increasing temperatures, earlier snowmelt and changing precipitation, high uncertainties still exist on the impact of global warming on snowmelt and particularly on snowmelt rates. Climate simulations for the end of the century show a widespread and spatially consistent reduction in high melt rates, which are typical of deep, late-lying snowpacks, as snowpacks will be fully melted earlier in the season (Musselman et al., 2017). Consequently, there will be an increase in low melt rates, typical of early season and midwinter melt events. However, this is built upon the emission scenario RCP8.5, where most areas show a steep decline in snowpack depth and an apparent contraction of the snow season length (Musselman et al., 2017). Krogh and Pomeroy (2019) found differing trends in melt rate even at the catchment scale between a gully and a drift. Other future simulations show slower snowmelt when perturbing the current climate by uniformly increasing the mean yearly temperature (Pomeroy et al., 2015). Still, warming can have differing magnitudes at different times of the season (Essery et al., 2020) and at different elevations (Pepin et al., 2015). Even though a few studies show trends towards slower snowmelt rates based on actual snow observations and not simulations, these trends are generally weak and highly spatially inhomogeneous (Harpold & Brooks, 2018; Wu et al., 2018). The spatial variability in melt rate change was not addressed. A large-scale analysis of the drivers and causes of melt rate change, besides the shifting of the timing of the melt season, has not been performed to date.

In this study, we investigate the effect of global warming on snowmelt dynamics, particularly on snowmelt rates and its main drivers, across the Northern Hemisphere, for the historical period 1981-2022. We provide an analysis based on snow water equivalent (SWE) time series based on actual snow observations. The NH-SWE dataset (Fontrodona-Bach et al., 2023a; Fontrodona-Bach et al., 2023b) provides high performance on key snowmelt variables such as peak snow water equivalent (SWE) and the timing of snowmelt, providing

an adequate framework for this novel analysis. Other variables, such as the snow season onset and the date of snow disappearance, are based on point-scale snow depth observations and are therefore not model-dependent. Our analysis is complemented by temperature, precipitation and radiation from observation-based gridded datasets.

Here, we provide a comprehensive analysis of changing snowmelt patterns that can already be observed in historical data, and we analyse its main causes. We try to answer the following questions: i) What are the main drivers of snowmelt rate change, and how are these changing? ii) how are snowmelt rates changing, and how can differing trends be explained? iii) what are the spatial variability and consistency of snowmelt rate changes across climates?

This paper is structured as follows: firstly, we present the data we use; secondly, we define the melt rate and the driving variables that we explore in our study, explain the quality control and evaluation procedures, and describe the trend analysis; thirdly, we present the results of our analysis, divided into a section for presenting trends in the drivers of melt rate, and a section presenting trends in melt rates, their spatial variability, and their causes; finally, we discuss the results of the study, its limitations and implications, and present our conclusions.

## 3.2 Data

### 3.2.1 Snow Water Equivalent data

The NH-SWE dataset (Fontrodona-Bach et al., 2023a; Fontrodona-Bach et al., 2023b) (Chapter 2) provides daily time series of modelled Snow Water Equivalent (SWE) at the point scale and covers large areas of the Northern Hemisphere, including mountain regions, for the period 1950-2022. This dataset is useful for investigating the impact of global warming on snowmelt dynamics because SWE data allows for the computation of snowmelt variables.

Furthermore, the NH-SWE dataset is based on a modelling approach that incorporates actual snow measurements. Specifically, the  $\Delta$ SNOW (Winkler et al., 2021) model used to generate the time series of SWE is forced with snow depth observations, and the start and end of the snow cover season are observed rather than modelled. Using model output based on actual snow depth observations provides an advantage over SWE datasets that are solely based on physics-based models forced with other meteorological variables. An example of daily SWE time series can be observed in Figure 3.1a.

In addition to the NH-SWE dataset, we use the SNOwpack TELemetry Network (SNOTEL) dataset (USDA NRCS, 2022) to provide additional validation and quality control for our analysis. This extends the thorough performance analysis conducted by Fontrodona-Bach et al. (2023a) and enables us to evaluate the effectiveness of the  $\Delta$ SNOW model (Winkler et al., 2021) for studying snowmelt rates. The SNOTEL dataset consists of an extensive network of automated sub-daily observations of snow water equivalent (SWE) and snow depth over the western United States, and it is freely available. Similar to Fontrodona-Bach et al. (2023a), we use quality-controlled time series of SWE and snow depth and apply the regionalised version of the  $\Delta$ SNOW model to all time series to evaluate the model’s effectiveness in analysing changing snowmelt rates.

### 3.2.2 Temperature, Precipitation, and Radiation data

We obtain historical daily temperature and precipitation time series for each station in the NH-SWE dataset. We source daily temperature and precipitation data for European stations from the gridded E-OBS (v25.0e) dataset (Haylock et al., 2008; Cornes et al., 2018), a daily observational dataset that covers Europe and is based on blended time series from the European Climate Assessment & Dataset project’s station network. The E-OBS dataset has a resolution of 0.1 degree regular grid and a longitudinal limit of 45°E. For stations located further east, only found in Russia, we directly obtain temperature and precipitation station observations from Meteo Russia (RIHMI-WDC, 2022) for the same locations as the

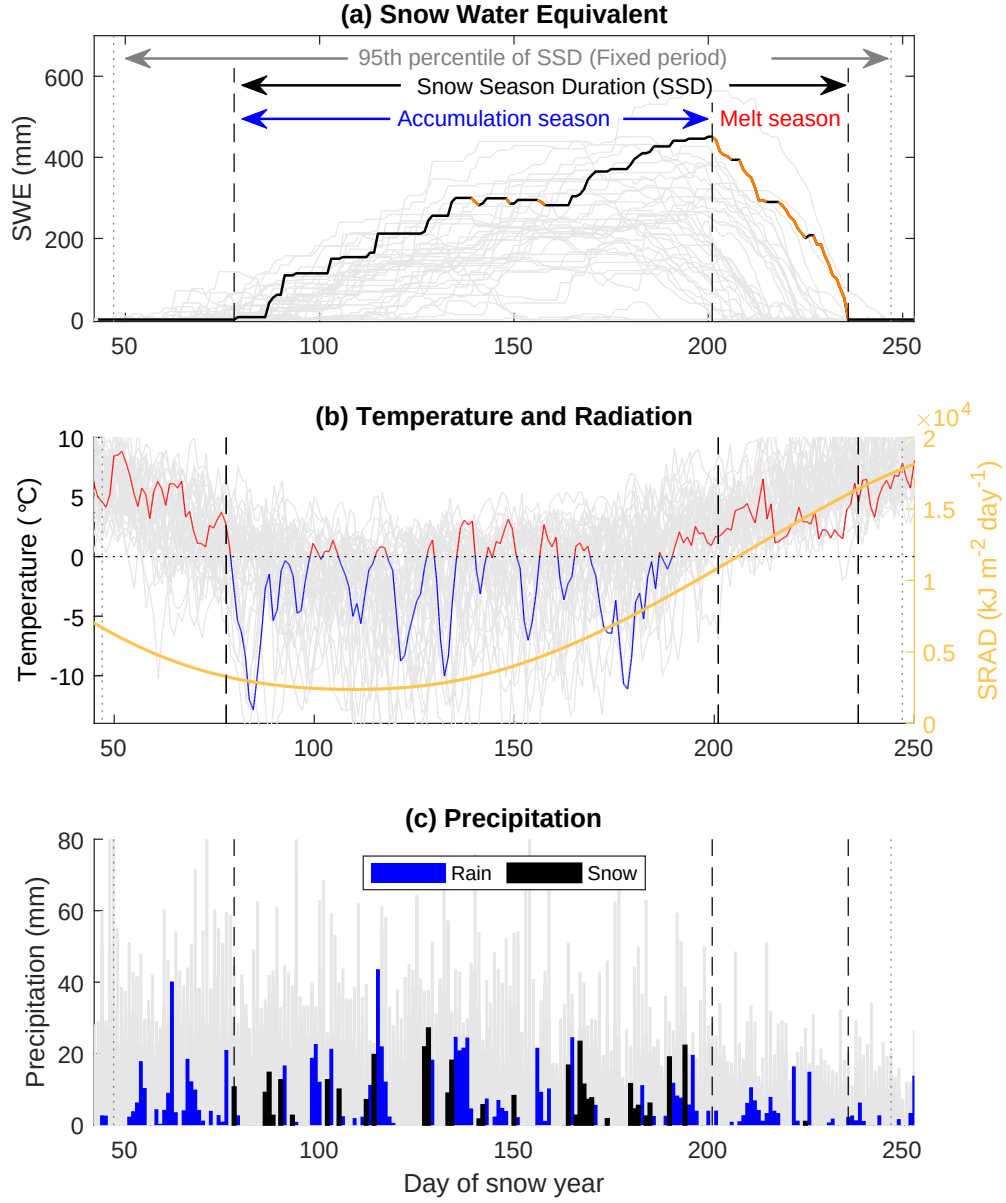


**Figure 3.1:** Example time series of SWE, Temperature, Radiation (SRAD) and Precipitation. Data from Whistler, Canada, Latitude = 50.133, Longitude = -122.950, Elevation = 658 m, Station ID (NH-SWE dataset) = 400017. Highlighted lines for SWE, Temperature and Precipitation correspond to the water year 2011, and grey background lines correspond to the rest of the years. In (c), precipitation is defined as snow only if it is matched by a concurrent increase in SWE in (a).

SWE data. For NH-SWE stations located in North America, we use daily temperature and precipitation data from DAYMET (Thornton et al., 2022), a gridded dataset based on daily meteorological observations that provide estimates of weather parameters, such as temperature and precipitation, on a 1 km x 1 km surface over North America. This approach provides comprehensive coverage of the necessary climate variables for our study. An example of temperature and precipitation time series can be observed in Figure 3.1b,c.

We obtain radiation data for each station in the NH-SWE dataset from the WorldClim 2 global dataset of monthly climate variables (Fick & Hijmans, 2017). We use the monthly average incoming shortwave radiation to extrapolate an average daily time series of incoming daily shortwave radiation, which we assume does not change in time. The rationale for using radiation data is that a shift towards an earlier or later snow cover season implies a different shift in incoming radiation depending on latitude, elevation, and aspect. We chose the WorldClim 2 dataset because of its high spatial resolution (1 km) and global coverage and to have a consistent radiation estimation procedure for all stations. In contrast, the datasets used for temperature and precipitation contain varying radiation estimation methods, which complicate comparison. Figure 3.1b shows an example of daily radiation time series. Unlike temperature and precipitation, radiation does not vary from year to year, as we only want to account for differences between radiation at different latitudes or elevations. Adding variable radiation would increase the complexity of the analysis, and we assume potential radiation does not significantly change at a fixed point in time.

## 3.3 Methods

### 3.3.1 Variables and definitions

For each time series of daily snow water equivalent (SWE), we compute several aggregated snow variables related to the snow cover season, snow accumulation, and melt dynamics. We define the snow cover season as the longest continuous snow cover period each year and

the peak SWE as the highest water equivalent of snow accumulation. The first day with a decrease in SWE after the peak SWE is defined as the snowmelt onset, and the snow cover season is divided into an accumulation season and a melt season, separated by the snowmelt onset, as shown in Figure 3.1a.

The interannual variability of the length of the snow cover season complicates the temporal trend analysis of certain variables, such as cumulative precipitation during the snow season and the number of positive-degree days during the snow season. To account for the effect of shifting snow season coverage, we also define a fixed period for each time series based on the 95th percentile of all observed annual snow cover durations at that location.

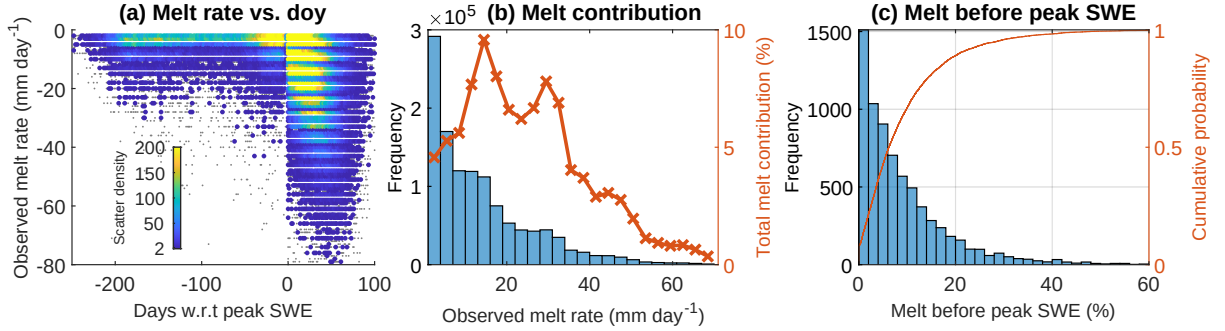


**Figure 3.2:** Snowmelt features based on observations from the SNOTEL dataset. (a) Melt rate magnitude with respect to date of peak SWE; (b) Observed daily melt rates and their contribution to total snowmelt; (c) Observed percentage of snowmelt before and after peak SWE.

In this study, we focus on the melt season only for snowmelt variables. Snowmelt events during the accumulation season before peak SWE are usually small ( $< 5 \text{ mm day}^{-1}$ , Figure 3.2a) and not well captured by the  $\Delta$ SNOW model in the NH-SWE dataset (Fontrodona-Bach et al., 2023a). Even more sophisticated models may fail to predict melt events during the accumulation season (Essery et al., 2013). Moreover, low melt rates account for less than 10% of the total snowmelt water (Figure 3.2b), and around 90% of all snow seasons experience more than 80% of the total snowmelt after peak SWE (Figure 3.2c). Therefore, we define the snowmelt rate as the net water loss during the melt season. Specifically, snowmelt rate ( $R_{melt}$ ) is defined as the total snow water equivalent, SWE, that melts during the melt season ( $M_{snow}$ ) divided by the number of snowmelt days in the melt season ( $D_{melt}$ ). The

equation reads as follows:

$$R_{melt} = \frac{M_{snow}}{D_{melt}} \quad (3.1)$$

where  $D_{melt}$  is defined as the sum of days when there is a decrease in SWE:

$$D_{melt} = \sum_{t_i \in \Upsilon} 1 \quad (3.2)$$

where  $t_i$  is a time step in the set  $\Upsilon$  of melt days, defined as days after the onset of the melt season and before the end of the melt season with  $H_{SWE}(t_i) - H_{SWE}(t_{i-1}) < 0$ .  $M_{snow}$  is the sum of snowmelt on snowmelt days:

$$M_{snow} = \sum_{t_i \in \Omega} \frac{H_{SWE}(t_i) - H_{SWE}(t_{i-1})}{t_i - t_{i-1}} \quad (3.3)$$

where  $\Omega$  is the set of days with snowmelt in the melt season. Note that with this formulation, any accumulation during the melt season will be accounted for, as the day when accumulation (an increase in SWE) occurs does not compute as a melt day.

In addition to the three variables that define the melt rate, we define and aggregate a few more variables based on the SWE, temperature, precipitation, and shortwave radiation time series, which we use for our analysis. A summary of the most important variables explored in our study can be found in Table 3.1. For spatial contextualisation of the study, Figure 3.3 shows the average snow climatologies for each of the NH-SWE stations. A wide range of snow climatologies can be observed, from shallow to deep snowpacks, from short to long snow cover and snowmelt seasons, as well as high and low snowmelt rates.

**Table 3.1:** Summary of variables used in this study.

| Variable name               | Abbr.      | Units                  | Description                                                                                                                |
|-----------------------------|------------|------------------------|----------------------------------------------------------------------------------------------------------------------------|
| Snow season duration        | $SSD$      | $days$                 | The longest period with continuous snow cover ( $SWE > 0$ ) in a year                                                      |
| Fixed period                | -          | $days$                 | Period covering the 95th percentile of snow season durations at a specific station (Fig. 3.1a)                             |
| Peak SWE                    | -          | $mm$                   | The highest Snow Water Equivalent value in the snow season                                                                 |
| Day of snow year            | $d.o.s.y$  | $days$                 | Day of the snow year, which starts on 1st of September                                                                     |
| Snow season onset           | $SSO$      | $d.o.s.y$              | The first day with snow cover ( $SWE > 0$ ) in the snow season                                                             |
| Snowmelt onset              | $MOT$      | $d.o.s.y$              | First day with a decrease in SWE after peak SWE, defining the start of the melt season                                     |
| Accumulation season length  | $ASL$      | $days$                 | Length of the accumulation season from snow season onset to snowmelt onset                                                 |
| Snowfall days               | $D_{snow}$ | $days$                 | The number of days with an increase in SWE                                                                                 |
| Snowmelt days               | $D_{melt}$ | $days$                 | The number of days with a decrease in SWE (melt) in the melt season (Eq. 3.2)                                              |
| Peak $SWE_m$                | $M_{snow}$ | $mm$                   | Cumulative snowmelt in the melt season, also equal to peak SWE plus any snow that accumulates in the melt season (Eq. 3.3) |
| Snowfall rate               | $R_{snow}$ | $mm\ day^{-1}$         | The rate at which snow falls, defined as the mean SWE increase per snowfall day in the accumulation season                 |
| Snowmelt rate               | $R_{melt}$ | $mm\ day^{-1}$         | The rate at which snow melts in the melt season, defined as Peak $SWE_m$ divided by the number of snowmelt days (Eq. 3.1)  |
| Temperature fixed period    | $T_{fp}$   | $^{\circ}C$            | The mean temperature in the fixed period                                                                                   |
| Temperature snow season     | $T_{ss}$   | $^{\circ}C$            | The mean temperature in the snow season                                                                                    |
| Temperature melt season     | $T_{melt}$ | $^{\circ}C$            | The mean temperature in the melt season                                                                                    |
| Negative degree days onset  | $NDD_o$    | $d.o.s.y$              | Onset of a sustained period of temperatures below $0^{\circ}C$ near the snow season onset                                  |
| Positive degree days onset  | $PDD_o$    | $d.o.s.y$              | Onset of a sustained period of temperatures above $0^{\circ}C$ near the melt season onset                                  |
| Solar radiation melt season | $SRAD$     | $kJ\ m^{-2}\ day^{-1}$ | The average daily incoming shortwave radiation in the melt season                                                          |

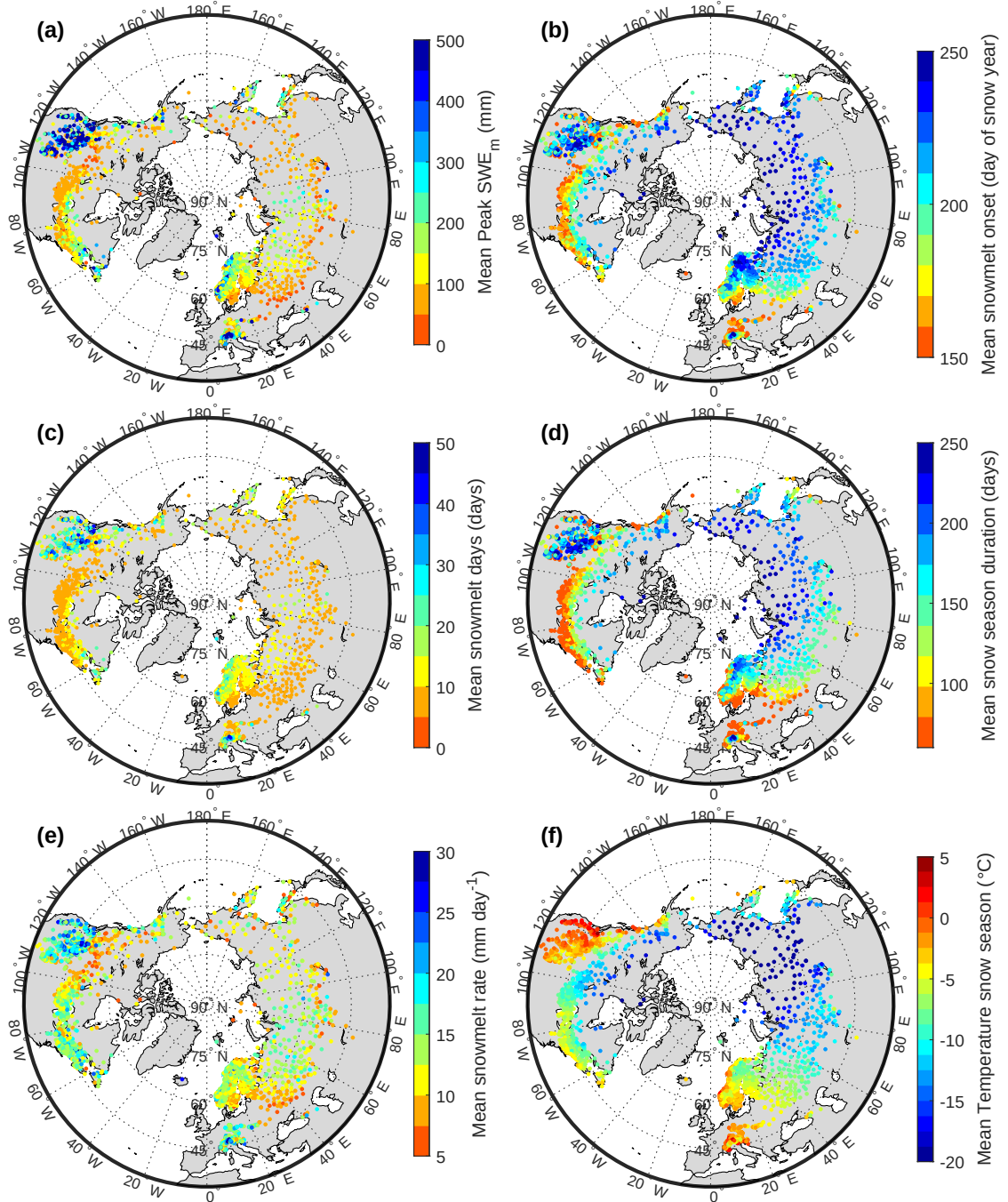


Figure 3.3: Spatial distribution of key snow variables at the NH-SWE dataset stations.

### 3.3.2 Snowmelt rate Quality Control and Evaluation

The NH-SWE dataset was evaluated by Fontrodona-Bach et al. (2023a) and showed a satisfactory quality, with peak SWE errors generally not exceeding 15% across datasets, and a small delay of one day on average in the onset of the melt season. In addition, the duration of the snow cover season is observed, since it is based on ground observations of snow depth. Here we further evaluate the potential limitations and uncertainty associated with investigating snowmelt rates with the NH-SWE dataset. We focus on the snowmelt season as this was shown to provide high confidence in estimates of snowmelt amount and duration (Fontrodona-Bach et al., 2023a).

To assess the confidence in snowmelt rate estimates computed using the  $\Delta$ SNOW model used to produce the NH-SWE dataset, we compare the distribution of melt rates in the NH-SWE dataset with the distribution of observed snowmelt rates from the SNOTEL dataset, which covers a wide range of snow climates. We use the SNOTEL data for comparison because its continuous observations of snow water equivalent allow us to estimate actual melt rates. The range of modelled total snowmelt, snowmelt days and snowmelt rate in the NH-SWE dataset is very similar to the observed ranges in the SNOTEL dataset (Figure 3.4). This shows confidence that the NH-SWE dataset provides realistic estimates on these snow variables. However, very high melt rates are estimated in the NH-SWE dataset for snowpacks shallower than 400 mm that melt in less than 10 days. These very high melt rates in the lower left part of the figures are not observed in the SNOTEL dataset and might be due to a variety of reasons: i) The NH-SWE dataset contains a much larger number of stations in the transition between seasonal and ephemeral snow, which tend to be shallower and have lower melt duration (Figure 3.5); ii) Some of these shorter lasting snowpacks have warmer average snowmelt seasons, as seen in Figure 3.4 where the closer to the high snowmelt rate line of 62 mm/day, the warmer the snowmelt season is; iii) There is a slight model delay in the timing of snowmelt season onset, as reported by Fontrodona-Bach et al. (2023a). This can make the modelled snowmelt season a couple of days shorter than in reality, making the snowmelt rate faster. Overall, Figure 3.6 shows a satisfactory performance of snowmelt rates

modelled by the  $\Delta$ SNOW model, but there is consistent positive bias in modelled snowmelt rates compared to observed snowmelt rates, which is linked to the slight model delay reported by Fontrodona-Bach et al. (2023a).

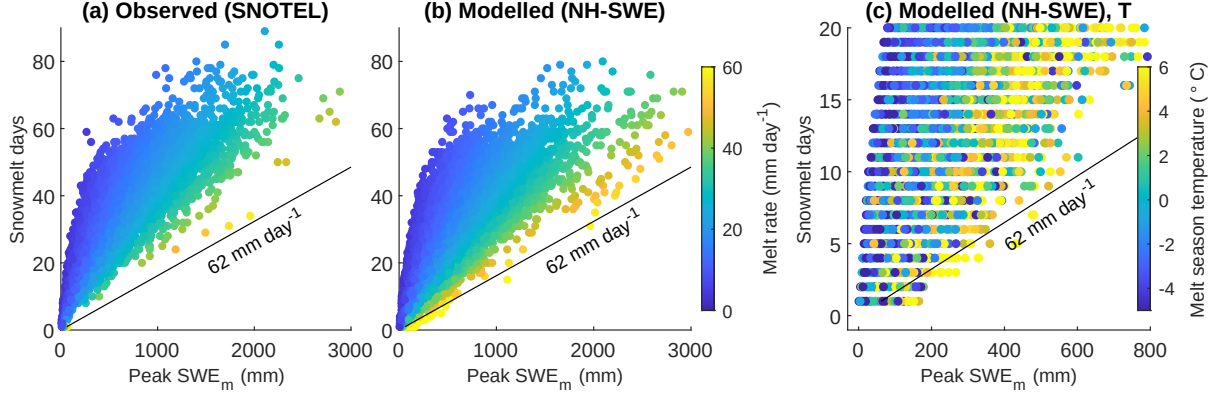


**Figure 3.4:** Observed snowmelt rates in the SNOTEL data (a) and modelled snowmelt rates in the NH-SWE dataset (b). Melt rate is computed by dividing Peak  $SWE_m$  (x-axis) by the snowmelt days (y-axis). Black line indicates the  $62 \text{ mm day}^{-1}$  melt rate, which is the 99.99 percentile of all observed melt rates in the SNOTEL dataset and therefore our estimate of the highest likely melt rate. (c) Modelled melt rates coloured by temperature of the melt season.

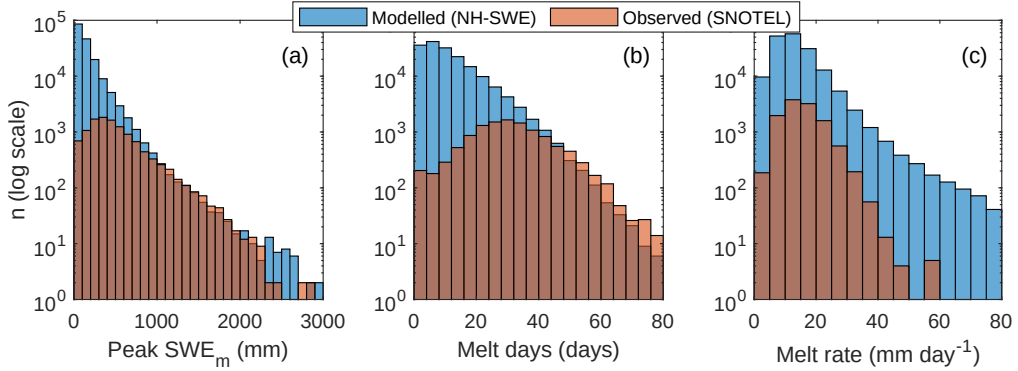


**Figure 3.5:** Distribution of Peak  $SWE_m$  (a), snowmelt days (b), and snowmelt rates (c) in the modelled NH-SWE dataset and the observed SNOTEL dataset. Note that the y-axis scale is logarithmic to be able to compare the distributions, but there is up to 100 times more data in the NH-SWE than in SNOTEL in some histogram bins.

Given the snowmelt rate evaluation analysis above, we remove from the dataset any snowmelt rate higher than  $62 \text{ mm/day}$ , which is the 99.99 percentile of all observed net melt rates in the SNOTEL dataset (Figure 3.4). We interpret this to be an estimate of the highest likely melt rate. Values higher than that may be unrealistic, erratic, or due

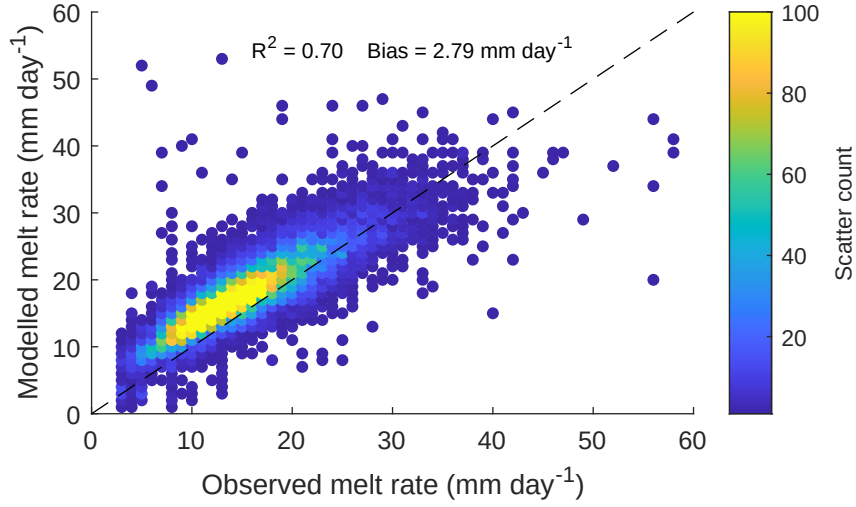


**Figure 3.6:** Observed snowmelt rates in the SNOTEL dataset vs Modelled snowmelt rates using the  $\Delta$ SNOW regionalised model approach as in Fontrodona-Bach et al. (2023a)

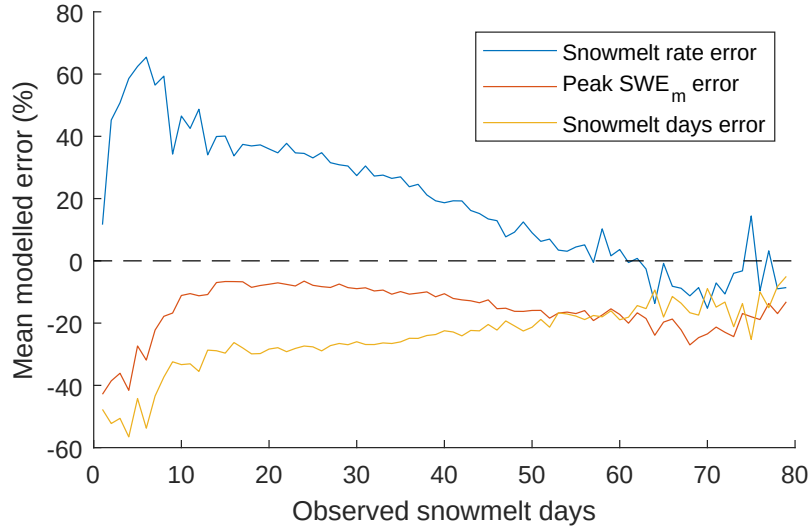


**Figure 3.7:** Mean relative modelled error vs snowmelt season duration in days for the three key snow variables.

to extreme events or processes that are not captured by the model used to generate the NH-SWE dataset based on snow depth observations. Most of the high snowmelt rates that we remove occur for snowmelt seasons that last one week or shorter (Figure 3.4). We further investigate whether a quality control threshold should also be applied for these short snowmelt seasons. The relative modelled error in a snow season for total snowmelt,

snowmelt days, and snowmelt rate is considerably higher for snowmelt seasons shorter than 5 days (Figure 3.7). There is a sharp reduction in modelled error for snowmelt seasons longer than 5 days and a steady reduction in error with melt season lengths longer than 10 days. The snowmelt rate error becomes negligible for snowmelt seasons of 60 days, even if that is a combination of a negative and equal relative error in total snowmelt and snowmelt days (Figure 3.7). We initially remove stations from the NH-SWE stations with less than 20 years of available data from 1980, which reduces the number of available stations from 11,071 to 5,185. We decide to remove from our analysis those stations in the NH-SWE dataset with snowmelt seasons (snowmelt days) shorter than 5 days on average, which reduces the number of available stations from 5,185 to 3,539. We also remove from the analysis specific years with less than 3 snowmelt days only, as these have high model errors and are on average only 20 mm snowpacks for which investigating snowmelt rates is out of the scope of our analysis.

### 3.3.3 Trend analysis

We calculate trends in the described variables in Table 3.1, for the period 1981-2022. We use the period from 1981 to 2022 because of the acceleration of global warming since the 1980s (Haustein et al., 2017; Richardson, 2022; NOAA, 2023). The effect of accelerated warming on snowpacks is reported in the literature by regime shifts of snow days (Marty, 2008) and accelerated declining trends in snow-related variables (Fontrodona Bach et al., 2018; Luomaranta et al., 2019), and is a common period of study for changing snow conditions (Mudryk et al., 2020; Pulliainen et al., 2020). For a trend to be calculated for the period 1981-2022, we require at least 20 years of available data in the period. The years do not need to be continuous, but we allow a maximum gap of 4 years within the time series to calculate a trend.

We estimate trend magnitudes using the Theil-Sen method, a robust nonparametric slope estimator for linear regression introduced by Sen (1968). Some variables with a low interannual variability and that are defined by integer numbers might yield a trend equal to

zero with this method. For clarity in figures and to avoid clustering of data on the zero line, if a Sen Slope estimator method yields a trend that is equal to zero, we calculate a linear trend by the least squares method, which gives then a trend that is very close to zero but not exactly zero and improves clarity in figures without changing the overall results.

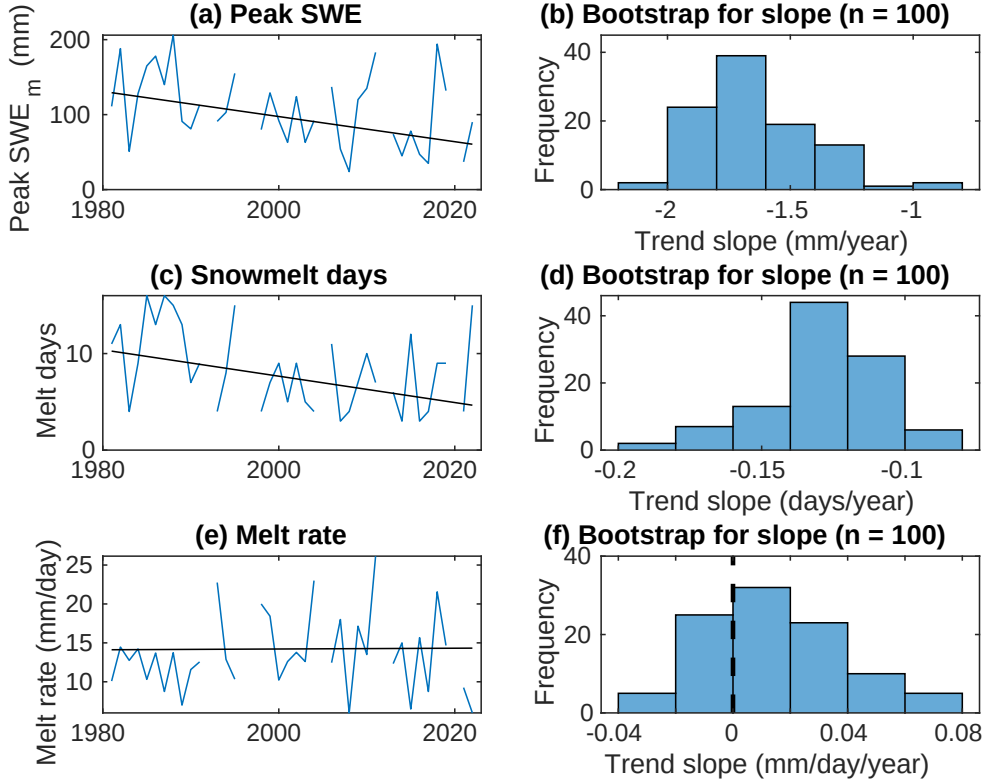


**Figure 3.8:** Example time series with fitted trends using the Theil-Sen method (left column), and the one hundred bootstrapping slopes for each of the trends by removing 10% of the time series for each slope estimation (right column).

It is common to assess trend significance using the Mann-Kendall test (Mann, 1945). However, the low number of years can make significance detection challenging. Instead, we assess our confidence in the sign of the estimated trend by using bootstrapping. For each time series we remove 10% of the available years and calculate a new trend slope with the remaining years in the time series. The distribution of removed years in the time series is random. We repeat this process 100 times, and we take the 95% percentile of the slope

estimates as our highest confidence interval for the trend slope. If the highest slope confidence value has the same sign (positive or negative) as the trend slope calculated with all available years, we consider the trend slope reliable and different from zero. The method is illustrated in Figure 3.8 with a reliable decreasing trend in the time series of cumulative snowmelt, a reliable decreasing trend in snowmelt days (i.e. all one hundred trends are negative for both variables), and a trend in snowmelt rate that is not different from zero (i.e. a mix of positive and negative slopes among the one hundred trends). This is because melt rate is defined as the cumulative snowmelt divided by several snowmelt days (Equation 3.1); thus, an equal change in these two variables yields a zero trend in melt rate. The bootstrapping method is, therefore, useful to establish sites without trends either because of no change in the drivers, or alternatively a change of equal magnitude in the melt rate drivers. For simplicity, we simply refer to reliable trends as trends, and to zero (i.e. non reliable) trends as no trends.

### 3.3.4 Data selection: seasonal snow

In addition to the quality control, we select data based on average snow cover duration at the NH-SWE stations. The NH-SWE dataset contains stations with a minimum of 40 days of continuous snow cover duration on average. In order to focus on locations where snow plays a larger role in the climate, water and ecological cycles, we focus our analysis on seasonal snow, which we define as a minimum of 60 days of continuous snow cover on average. Stations between 40 and 60 days of continuous snow cover are in the transition zone between ephemeral and seasonal snow (442 stations out of the remaining 3,539 stations). Transition snowpacks are located around seasonal snowpacks in coastal areas, lower elevations or lower latitudes. A map showing the distribution of seasonal and transition snow stations can be found in Figure 3.9. Stations with shorter snow cover seasons have shallower snowpacks, shorter melt seasons, and earlier melt onsets (Figure 3.10). However, their interannual variability is similar to or even larger than for seasonal snowpacks. A larger ratio of interannual variability concerning the mean makes it more complicated to estimate temporal trends. These snowpacks' duration, timing and depth are more linked to the interannual variability

of meteorological conditions than to long-term climatological trends. Therefore, we exclude transition snowpacks from all our analysis except a small part of section 3.4.1 where we specifically explore snowpacks that cross from seasonal to transition zone.

After quality control and selection of stations with a minimum of 20 years of valid and available data and a minimum of 60 days of continuous snow cover on average, there are 3,097 stations available out of 11,071 stations from the NH-SWE dataset.

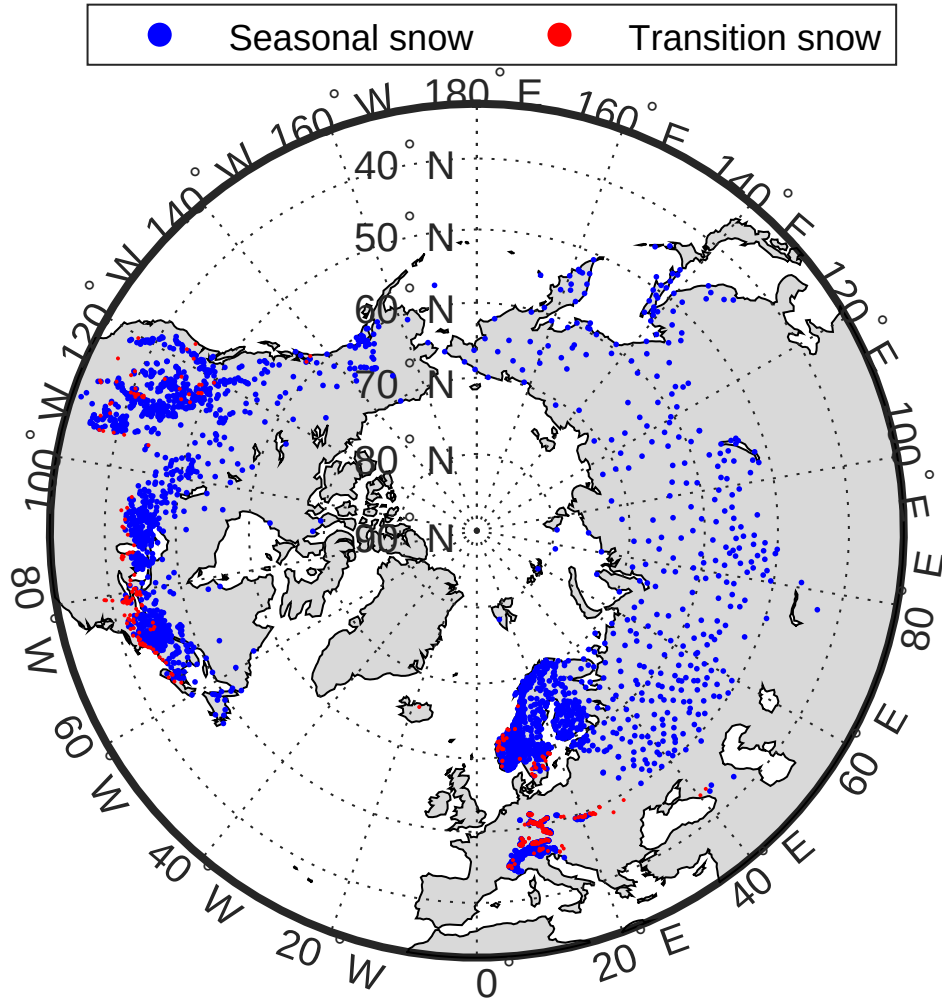


**Figure 3.9:** Distribution of seasonal and transition snow stations in the NH-SWE dataset.

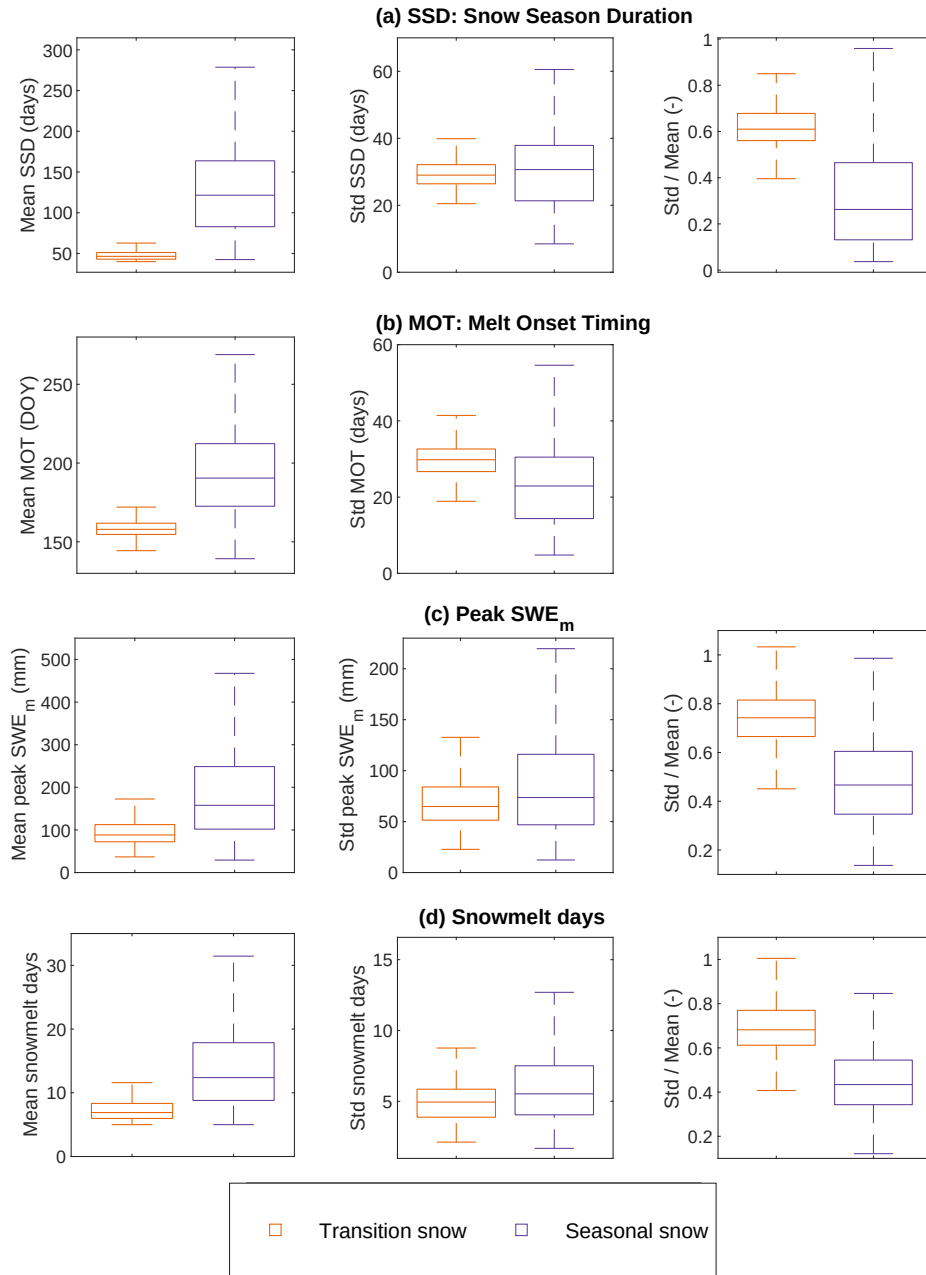


**Figure 3.10:** Statistical differences between seasonal and transition snowpacks for (a) snow season duration, (b) melt onset timing, (c) peak SWE<sub>m</sub> and snowmelt days. Left shows the mean, middle the standard deviation, and right the ratio of mean standard deviation to mean, for all stations available. Note melt onset timing does not contain the ratio of mean to standard deviation as the variable is measured in an arbitrary datum.

## 3.4 Results

Here we show the results of our analysis divided into the trends in drivers of snowmelt rate and the trends in snowmelt rates. We try to answer why and where snowmelt rates are becoming faster or slower.

### 3.4.1 Trends in drivers of snowmelt rate

To examine the drivers influencing changing snowmelt rates across different climates, our analysis begins by exploring key variables associated with snow accumulation leading to the peak snow water equivalent. This involves an in-depth exploration of snow season duration, variations in snowfall intensity and frequency, and differences between climatic conditions. Subsequently, our investigation explores the temporal aspects of changing snowmelt rate drivers, such as the timing and duration of snowmelt, while also considering the overarching influence of warming trends and the shifts in radiation.

#### **Snow season duration**

The duration of the snow season is shortening by an average of 5.0 days per decade. The contraction of the snow season is spatially consistent, except for some of the coldest climates, such as parts of Eurasia and parts of the Canadian prairies, which mostly show no trends (Figure 3.11). For 23.3% of the stations in the NH-SWE dataset, the snow season contraction means crossing the threshold from seasonal to transition snow or becoming even closer to ephemeral snow (Figure 3.12a). Note that in Figure 3.12, we use all available stations before selecting seasonal snow (3,539 stations). Decreasing trend magnitudes for stations that fall in the transition zone are similar to those of seasonal snow (Figure 3.12b), suggesting that warmer climates where transition snow occurs are proportionally more affected than colder climates with seasonal snow. Overall, 79.0% of stations show a declining trend in snow season duration (Figure 3.12b).

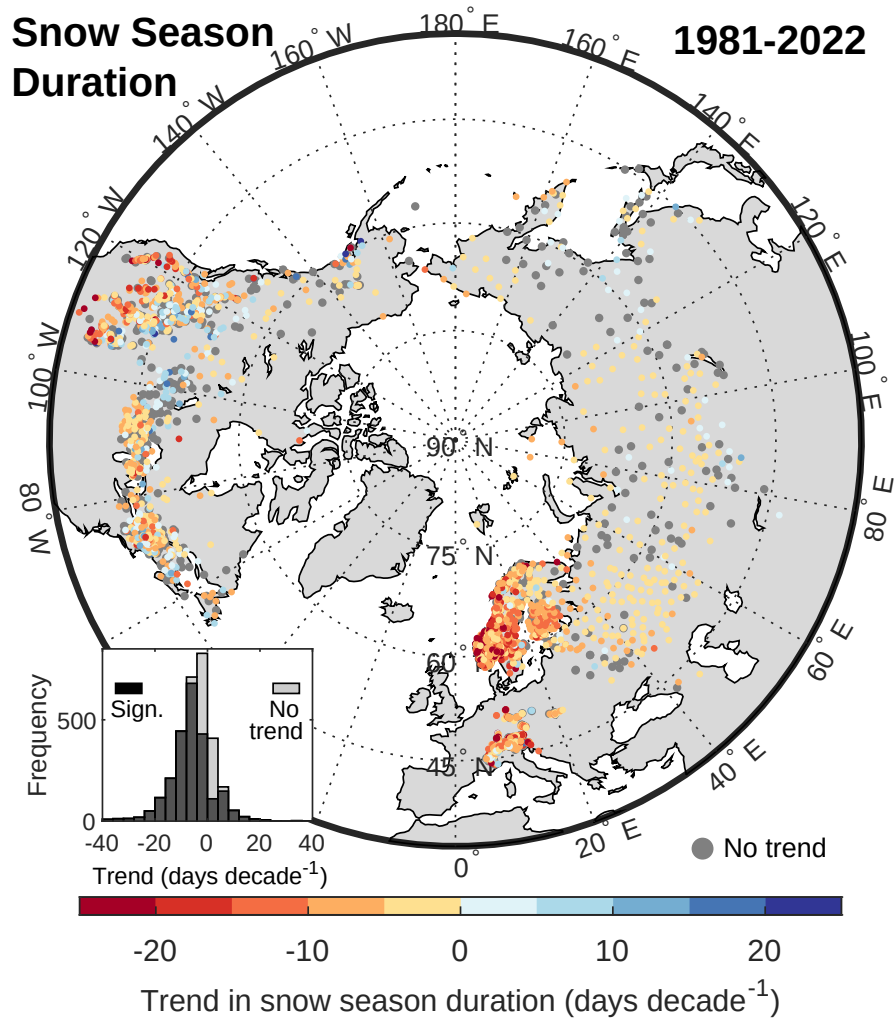


**Figure 3.11:** Spatial distribution of trends in snow season duration.

### Accumulation season length

The snow season duration depends mainly on the duration of the accumulation season, and the accumulation season duration explains 31% of the variance in peak SWE trend (Figure 3.13a), suggesting other temperature and precipitation factors affect the trend in peak SWE too. A decrease in the duration of the accumulation season generally leads to a decrease in peak SWE. While 73.5% of stations show a decreasing trend in accumulation season length, only 64.6% of stations show a decreasing trend in peak SWE, suggesting that an increase in precipitation can compensate for a shorter accumulation season. In turn, Figure 3.13b shows a change in the accumulation season length is best explained by

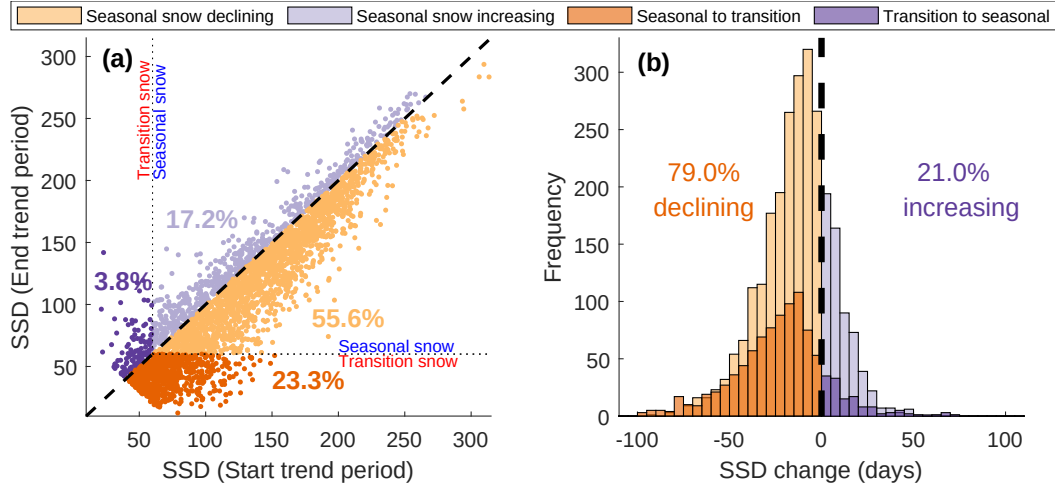


**Figure 3.12:** Snow season duration change. (a) Comparison between SSD at the beginning of the trend period and the end of the trend period. (b) SSD changes between the beginning and the end of the trend period, stratified by seasonal or transition snowpacks.

temperature trends, with 93% of stations showing a warming trend in the fixed snow season period, and 61% of those showing a decreasing trend in accumulation season length.

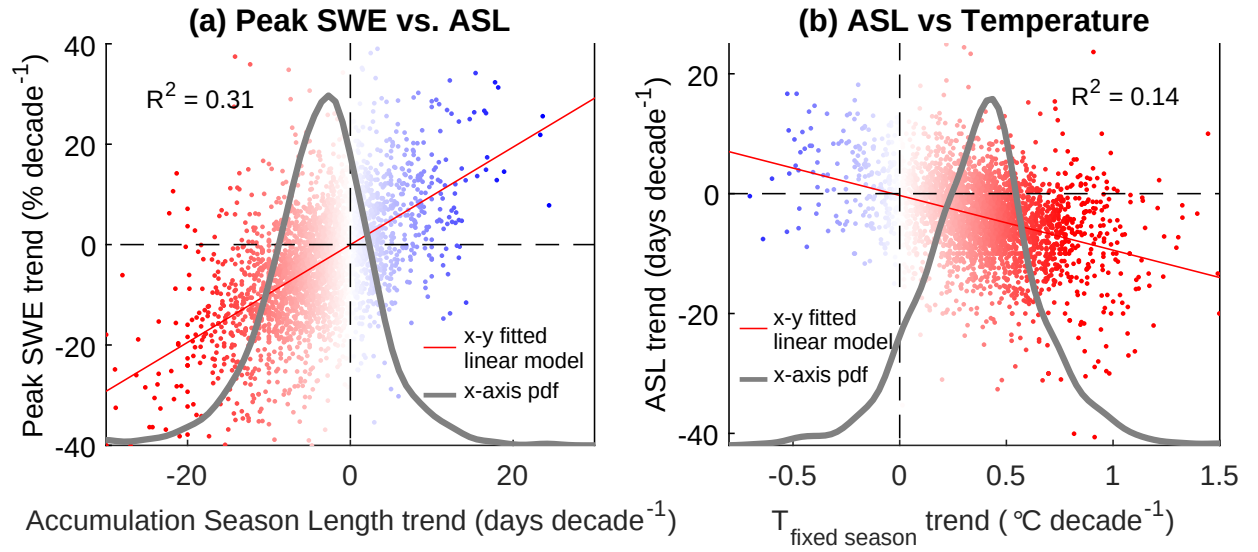


**Figure 3.13:** Link between snow accumulation and temperature. (a) Trends in peak SWE and accumulation season length (ASL); (b) Trends in accumulation season length and temperature in the fixed period.

The duration of the accumulation season depends partly on the onset of the snow season and the onset of the melt season:

### Onset of the snow season

The onset of the snow season is generally linked to the onset of a period with temperatures that consistently fall below zero degrees, the Negative Degree Days (NDD) onset (Figure 3.14a). Most stations show a trend towards a later NDD onset (83.9%) and a later snow onset (79.4%). A later onset of the NDD leads to a later onset of the snow season, a shorter accumulation season length, and a lower peak SWE.

Furthermore, Figure 3.15 shows that a later snow onset is associated with an increasing ephemerality of snow, with 55% of stations showing an increasing amount of snow that accumulates and melts before a period of sustained snow cover starts. This is because ephemeral snow cover periods can occur early in the year due to short periods with negative degree days, before the actual onset of the sustained period with negative degree days. An increasing number of positive degree days (PDD) between the first yearly snow and the start of the main snow season contributes to melting the snow before the actual onset of sustained negative degree days (Figure 3.15).

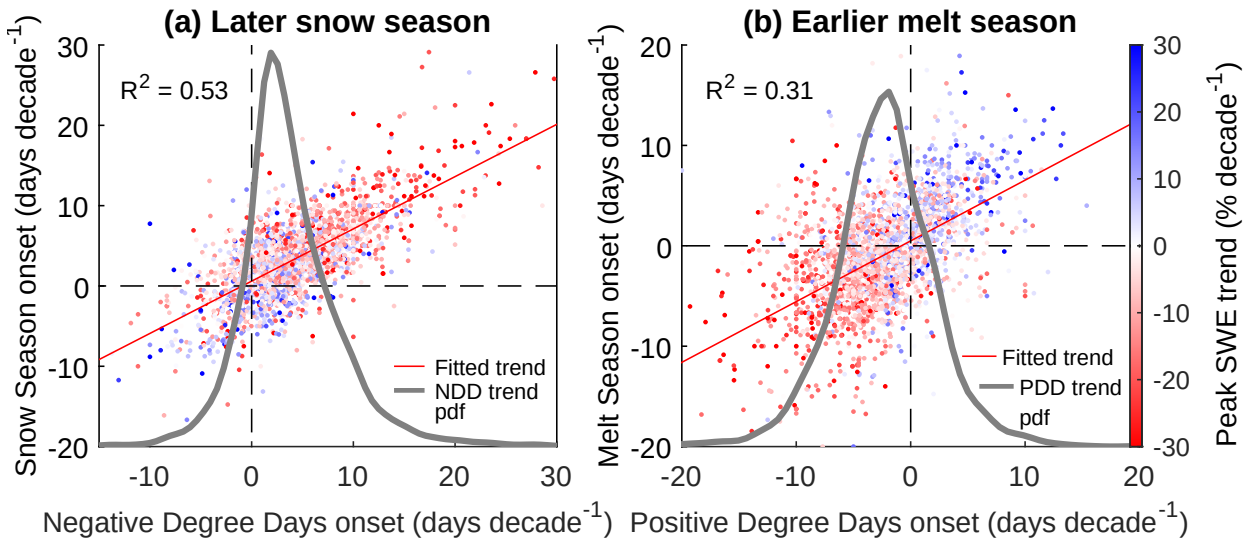


**Figure 3.14:** Snow season onset, melt onset, temperature, and peak SWE. (a) Link between trends in snow season onset and trends in the onset of sustained negative degree days (NDD) and peak SWE; (b) Link between trends in melt season onset and trends in the onset of sustained positive degree days (PDD) and peak SWE.

### Onset of the melt season

The duration of the accumulation season depends on the onset of the melt season, too. The onset of the melt season is linked to the onset of a period with temperatures that consistently rise above zero degrees, the Positive Degree Days onset (Figure 3.14b). The majority of stations show a trend towards an earlier PDD onset (73.12%), and an earlier melt season onset (59.9%).

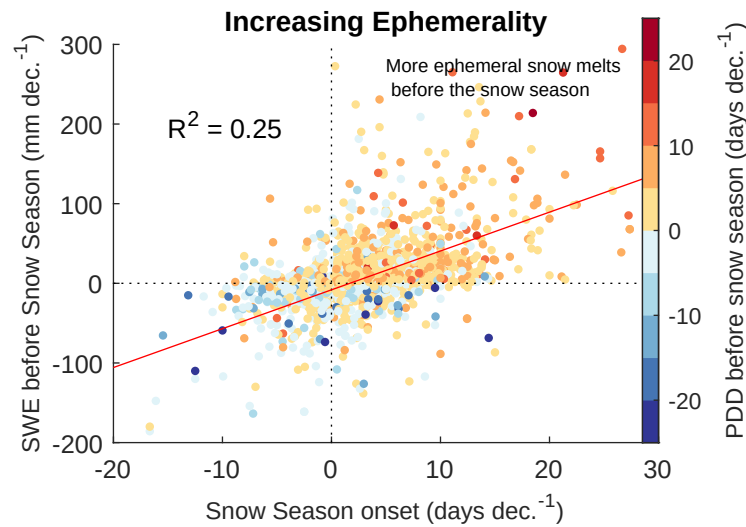


**Figure 3.15:** Increasing snowmelt before the snow season. Link between trends in amount of snow that melts before the main snow season, the snow season onset, and warming before the snow season. Red line shows the fitted x-y linear trend.

Together, the trends in timing of negative and positive degree days onset determine the duration of the accumulation season length and the amount of snow that can accumulate. These temperature-related drivers affect the edges of the snow season and only explain 31% of the variance of the trend in peak SWE. This indicates that other temperature and precipitation-related drivers also affect the trend in peak SWE.

### Snowfall intensity and frequency

Precipitation and temperature interact to determine the snowfall frequency (number of days with snowfall) and the snowfall intensity (mean snowfall per day). Together, they determine the total snow accumulation during the snow season. Decreasing snowfall days lead to decreasing total snow accumulation unless an increasing snowfall intensity compensates for the decreasing snowfall days. In this case, accumulation might not change or even slightly increase, but this only occurs for 7.0% of the decreasing trends in snowfall days (Figure 3.16a). Conversely, an increasing number of snowfall days leads to increasing snow accumulation unless decreasing snowfall intensity compensates, but this only occurs for 5.5% of the increasing trends in snowfall days (Figure 3.16a).

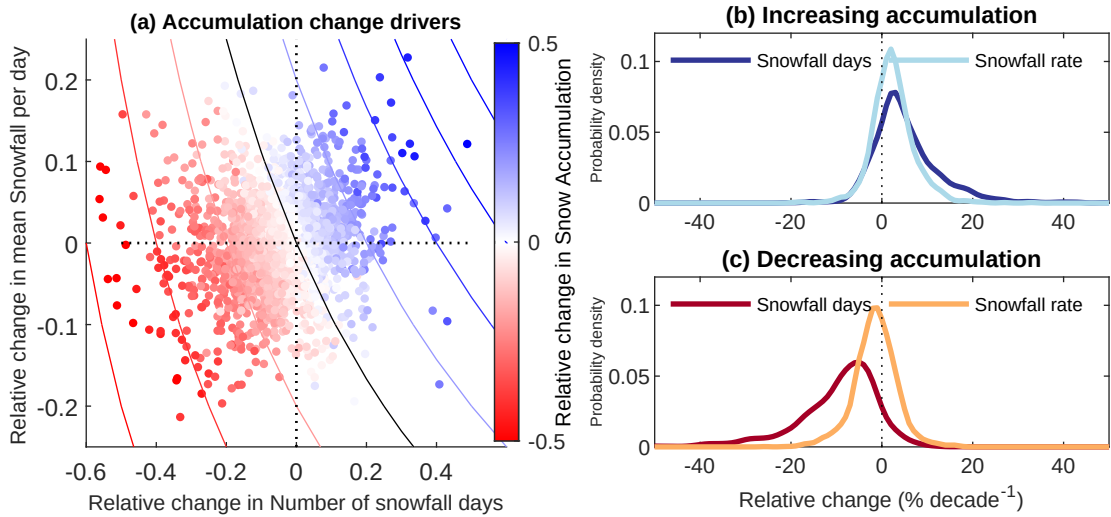


**Figure 3.16:** Snow accumulation change drivers. (a) Link between changing mean snowfall per day, number of snowfall days, and the overall change in snow accumulation. Trends in snowfall days and snowfall rate stratified by increasing accumulation (b) and decreasing accumulation (c).

For increasing accumulation trends, both the increasing snowfall frequency (mean +5.3% per decade) and the increasing mean snowfall rate (+2.5% per decade) contribute to the increasing accumulation (Figure 3.16b). For decreasing accumulation trends, a decline in snowfall frequency (mean -9.7% per decade) is larger than the decline in mean snowfall rate (-1.5% per decade) (Figure 3.16c).

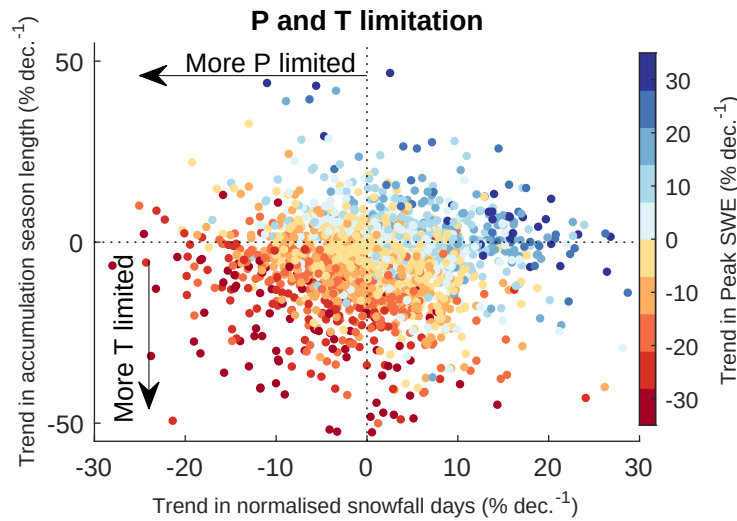


**Figure 3.17:** Interaction between temperature (T) and precipitation (P) limitation affecting trends in accumulation season length, trends in normalised snowfall days, trends in and peak SWE.

To better constrain the effect of precipitation, we normalise the number of snowfall days by the length of the snow season. A decrease in number of snowfall days per unit day of snow cover would suggest either a decreasing trend in precipitation frequency or a higher rainfall-to-snowfall days ratio. Assuming temperatures are warming and precipitation days are evenly distributed across the accumulation season, an increase in normalised snowfall days would suggest an increase in precipitation days frequency. Figure 3.17 shows the strongest declines in peak SWE are for stations with both a decrease in accumulation season length and a decrease in normalised snowfall days, a combination of precipitation and temperature limitation. The strongest positive trends in peak SWE are observed for stations with a strong increase in normalised snowfall days, despite small trends in accumulation season length, showing no precipitation or temperature limitation (Figure 3.17).

Based on a stepwise multilinear regression model, the relative trend in accumulation season length (34%), the relative trend in normalised snowfall days (30%), and the relative trend in snowfall rate (18%), explain 82% of the variance in the relative trend in peak SWE. These partial regression coefficients differ from the single correlation coefficients in Figure 3.13. This shows that both temperature and precipitation effects have an influence on peak

SWE trends, but suggests temperature is the dominant driver.

### **Peak SWE**

The combination of changing drivers of peak SWE lead to a decline in peak snow accumulation dominating over large parts of the Northern Hemisphere (Figure 3.18), representing 49.9% of trends with an average trend in Peak SWE<sub>m</sub> of -3.9 % per decade. Note Peak SWE<sub>m</sub> also includes accumulation during the melt season (Table 3.1). Largely decreasing trends are observed in the European Alps, Scandinavia, and western and eastern North America. The mean for declining trends is -12.4 % per decade. There are also large geographical areas with increasing Peak SWE<sub>m</sub> trends or with no trends, mainly located in the coldest winter temperature climates (Figure 3.3f), such as Eurasia, the most northern and continental parts of Scandinavia, and continental Canada. Increasing peak snow accumulation trends represent 24.6% of trends with an average of +9.82% per decade. Stations with no trends occur at 25.5% of stations and are distributed over the entire Northern Hemisphere but are proportionally more frequent in areas with increasing accumulation trends. Even though there is generally a spatial consistency in trend signs, there is a high spatial variability in trend magnitudes.

### **Differences between climates**

The spatial variability of trends in peak SWE observed in Figure 3.18 indicate that climate has an influence on trend signs and magnitudes. This is supported by Figure 3.19, showing trends in peak SWE and seasonal precipitation against mean temperature, and Figure 3.20, showing trends in peak SWE and seasonal precipitation against mean seasonal precipitation. Put simply, agreement between trends in peak SWE and trends in seasonal precipitation would suggest a dominant precipitation effect on peak SWE trends, or a combination of precipitation and temperature. Disagreement between trends in peak SWE and trends in seasonal precipitation would suggest a dominant temperature effect on peak SWE trends.

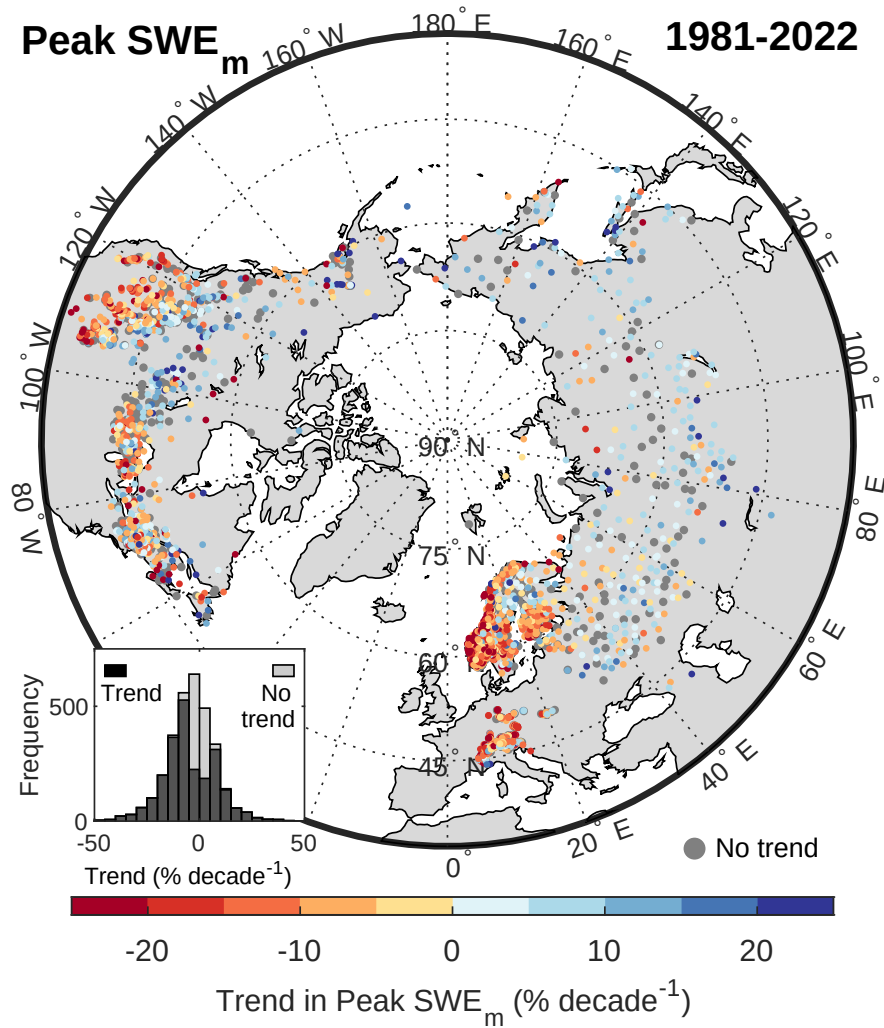


**Figure 3.18:** Spatial distribution of trends in Peak SWE<sub>m</sub>.

### Temperature climate

For the coldest climates (mean temperature below  $-9^{\circ}\text{C}$ ) in Figure 3.19c, both the mean Peak SWE<sub>m</sub> trend and mean precipitation trend are around  $+3\%$  to  $+5\%$  per decade, and around 70% of stations show increasing peak SWE and matching increasing precipitation trends. An increase in precipitation leads to an increase in peak SWE, as temperatures are well below freezing despite warming trends. In these climates there is a dominance of the precipitation effect over the temperature effect. At mean temperatures between  $-9^{\circ}\text{C}$  and  $-6^{\circ}\text{C}$ , the mean precipitation trend remains positive at around  $+2.5\%$  per decade, but the increasing mean peak SWE trend starts to drop. Here, warming temperatures start to play

a part in reducing the peak SWE trends despite the increasing seasonal precipitation. At climates between  $-6^{\circ}\text{C}$  and  $0^{\circ}\text{C}$ , the mean trend in seasonal precipitation remains positive but starts to drop, and the mean peak SWE trend becomes increasingly negative, reaching  $-6\%$  per decade, and 70% of trends showing declines in peak SWE. At this mean temperatures, the warming trend effect has taken over the precipitation trend effect, leading the decline in peak SWE. For the warmest climates above  $0^{\circ}\text{C}$ , there is no apparent trend in seasonal precipitation, and over 75% of peak SWE trends are negative, indicating a strong effect of the temperature trend and no apparent effect of precipitation trends.

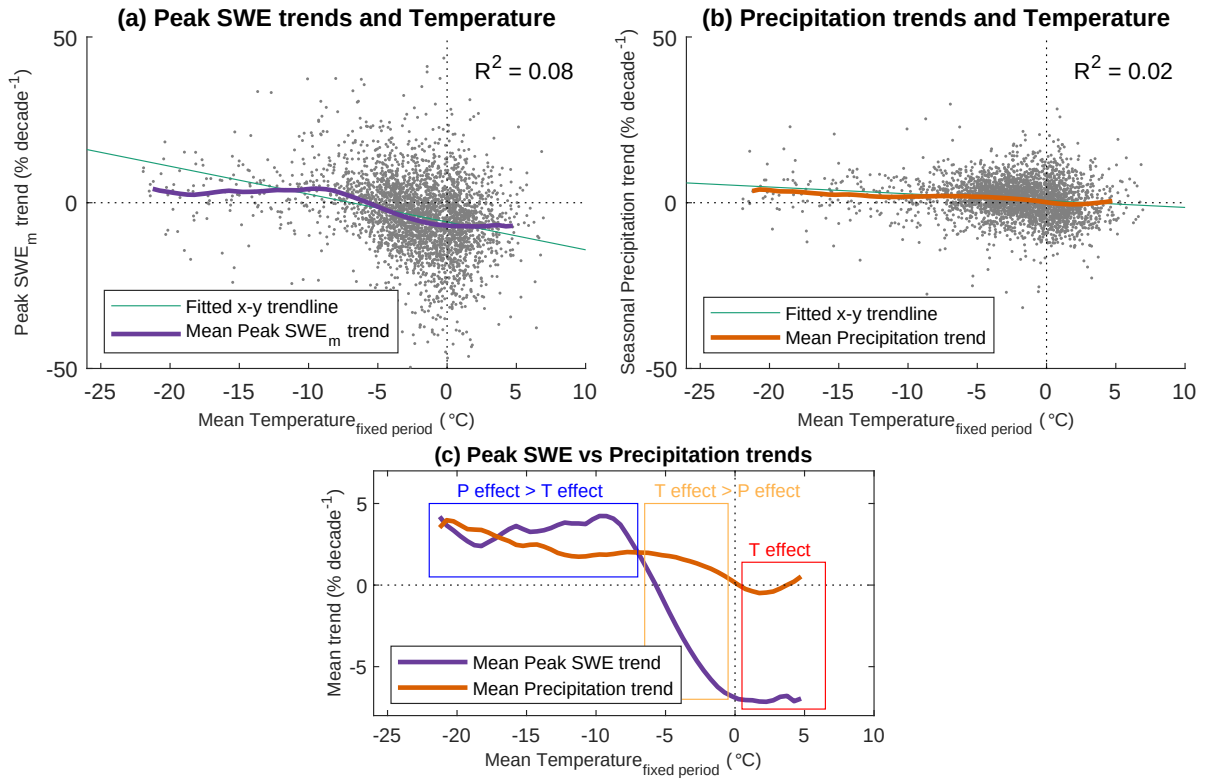


**Figure 3.19:** Trends and temperature climate. Link between peak SWE trends and mean Temperature (a), and between Precipitation trends and mean Temperature (b). (c) Zoomed-in combination of panels a-b. Solid lines show the mean of the point cloud for each  $1^{\circ}\text{C}$  temperature bin on the x-axis. Coloured rectangles indicate the dominance of a precipitation trend effect or temperature trend effect on peak SWE trends.

### Precipitation climate

For the drier climates, receiving less than 200 mm of seasonal precipitation on average, the mean peak SWE trend is around  $+2.3\%$  per decade, and the mean seasonal precipitation

trend is around +2.5% per decade (Figure 3.20). Over 70% of trends in peak SWE are positive and match with over 70% of increasing seasonal precipitation trends. Here, the increasing precipitation trend effect clearly dominates over the temperature trend effect, leading to increasing snow accumulation. Increasing precipitation trends remain for climates receiving less than 600 mm of seasonal precipitation, but the mean trend in peak SWE rapidly drops for climates receiving more than 200 mm of seasonal precipitation. Here, the effect of warming trends dominates over the effect of increasing precipitation. For the wetter climates, no trend in precipitation is apparent, but peak SWE trends become increasingly negative, indicating a strong effect of the temperature trend and no apparent precipitation trend effect.

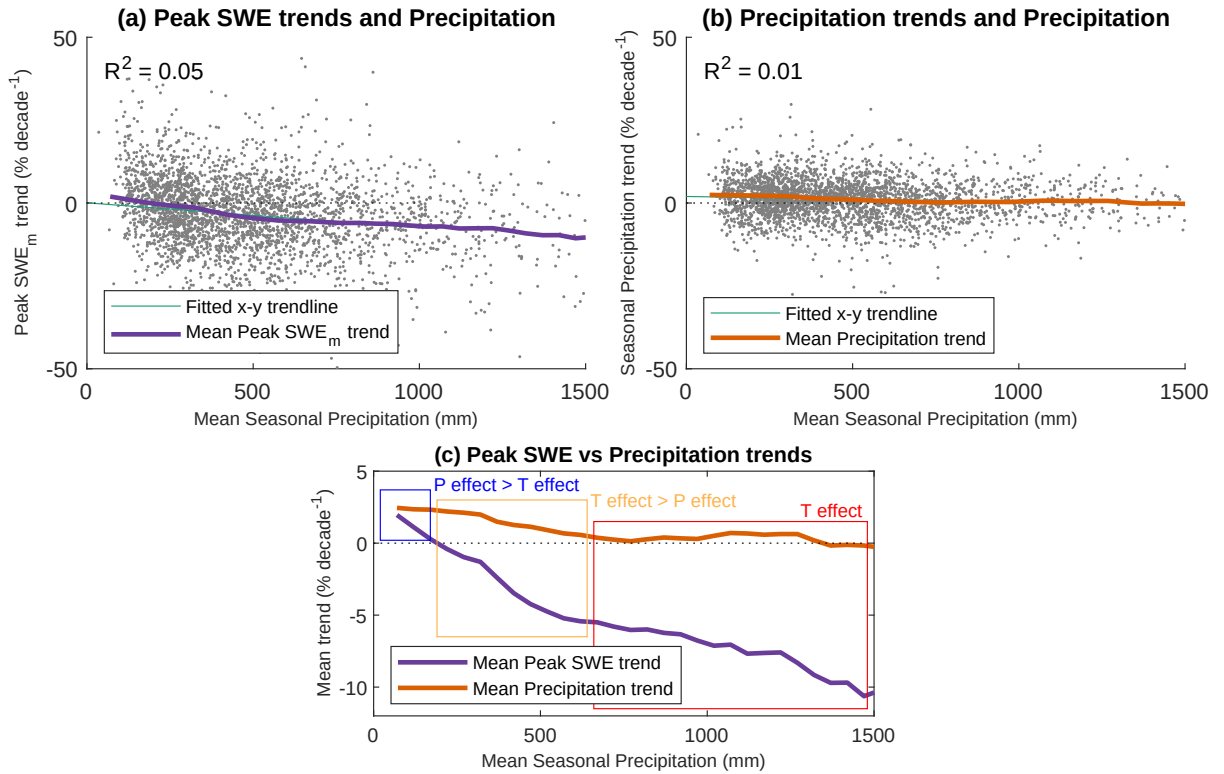


**Figure 3.20:** Trends and precipitation climate. Link between peak SWE trends and mean precipitation (a), and between Precipitation trends and mean Precipitation (b). (c) Zoomed-in combination of panels a-b. Solid lines show the mean of the point cloud for each 50 mm bin in the x-axis. Coloured rectangles indicate the dominance of a precipitation trend effect or temperature trend effect on peak SWE trends.

Our analysis indicates that the colder and drier climates are seeing an increase in

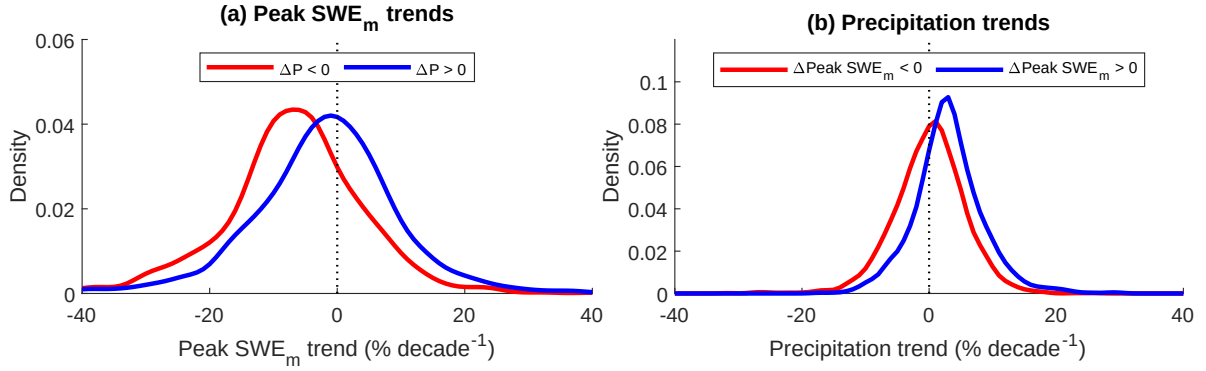


**Figure 3.21:** Distribution of peak SWE trends stratified by precipitation trends (a). Distribution of precipitation trends stratified by peak SWE trends (b).

snow accumulation which is driven by increasing precipitation, despite warming trends, as temperatures are still well below freezing. Warmer and wetter climates are seeing large declines in snow accumulation, regardless of the direction of seasonal precipitation trends, due to the effect of warming temperatures dominating over any change in precipitation.

The general effect of temperature and precipitation on trends can also be inferred from Figure 3.21. The distribution of trends in peak SWE is centered around zero when precipitation is increasing Figure (3.21a), but shifted to negative peak SWE trends if precipitation is decreasing. This suggests that when precipitation is increasing, peak SWE trends can be positive if warming does not have a strong effect, or negative if warming temperatures compensate for increasing precipitation. When precipitation is decreasing, peak SWE trends are likely negative due to the combined effect of less precipitation and warmer temperatures. Conversely, the distribution of precipitation trends is shifted to positive values when increasing peak SWE trends are considered (Figure 3.21b), while the distribution of precipitation trends is centered around zero when peak SWE is decreasing. This suggests that if peak SWE is increasing it is likely due to the increasing precipitation rather than a cooling of temperatures. However, if peak SWE is decreasing, it might be due to decreasing precipitation trends and warming, or increasing precipitation trends and warming.

## Snowmelt duration

Trends are far less clear than for the snow season duration when looking at the duration of snowmelt (snowmelt days), i.e. how many days it takes to melt the snowpack. Spatially, trends in number of snowmelt days resemble the trends in peak SWE (Figure 3.22). Indeed, the trend in peak SWE alone explains 52% of the variance in trends in snowmelt days (Figure 3.23a). This is not surprising, since less snow should take less time to melt, and more snow should take more time to melt. However, there is a much larger number of stations that show no trend (i.e. non reliable trends) for snowmelt days (51%) (Figure 3.22) compared to peak SWE (26%) (Figure 3.18). This is particularly the case for areas where the snowmelt season is quite short, between 5 and 10 days only (Figure 3.3c), indicating either that snowmelt days are not changing or that trends are difficult to detect for such short snowmelt seasons.

In addition to the influence of peak SWE, we explore the influence of other factors on the trend in snowmelt days. Figure 3.23a-b demonstrates that a change in average daily shortwave radiation during the melt season accounts for 5% of the residual variance in the trend of snowmelt days, after accounting for the impact of the peak SWE trend. Although this is a small value, it could be that part of the effect of shifting radiation is removed with the trend in peak SWE, as a reduction in peak SWE is intrinsically associated with a reduction in radiation due to earlier melt, and an increase in peak SWE associated with an increase in radiation due to later melt (Figure 3.24). Note that all seasonal snow stations in the NH-SWE dataset experience snowmelt before the summer solstice, and therefore, earlier melt means lower average daily shortwave radiation, and later melt means more average daily shortwave radiation, as illustrated in Figure 3.1b. The decrease in average daily shortwave radiation during the melt season can offset the magnitude of the trend in snowmelt days by 5%, making it appear longer than expected based solely on the relative reduction in peak SWE.

We also assess the influence of warming trends during the melt season on the trend in snowmelt days. Similar to the previous analysis, Figure 3.23c-d reveals that a trend towards

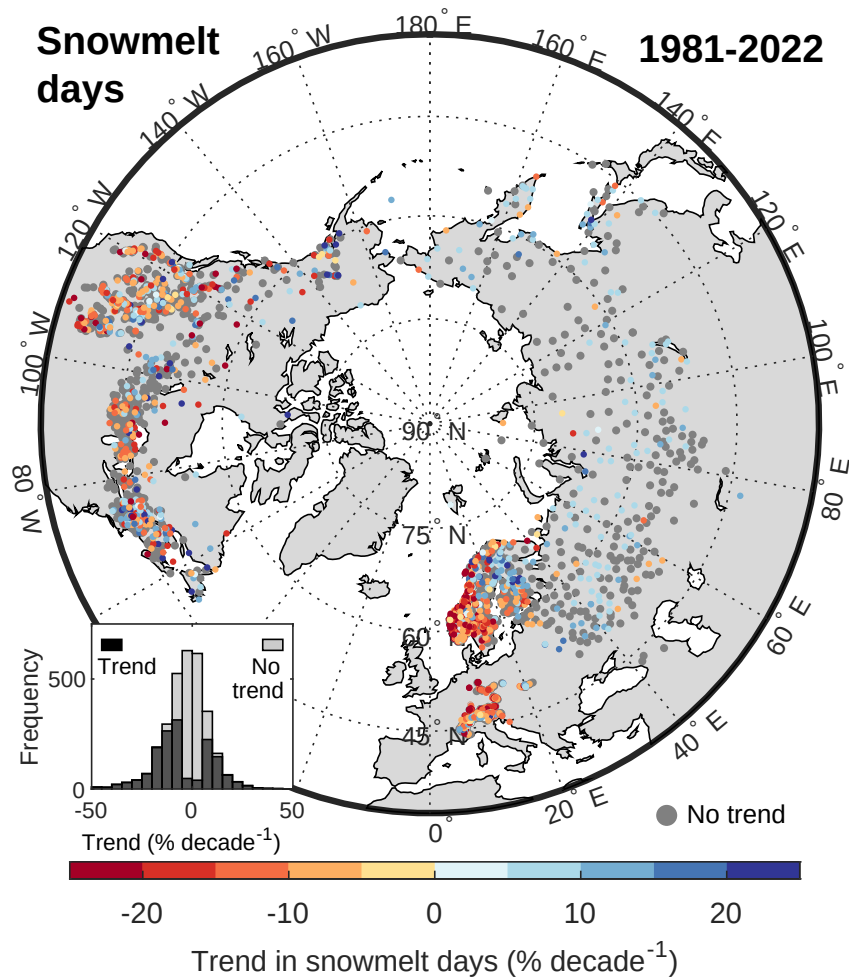


**Figure 3.22:** Spatial distribution of trends in snowmelt days.

warmer temperatures during the melt season explains an additional 6% of the residual variance in the trend of snowmelt days after accounting for the peak SWE trend. In contrast to the earlier explanation involving a shift towards earlier melt and lower radiation, a rise in temperatures during the melt season contributes to a shorter duration of melt days, making it appear shorter than anticipated solely based on the relative reduction in peak SWE.

This analysis shows that while peak SWE explains most of the variance of melt duration, shifts in radiation and temperature contribute to determining which side of the slope 1 line a trend will fall. Earlier melt implies lower average daily radiation, which might positively offset the reduction in melt duration, while warming temperatures might compensate and negatively offset the reduction in melt duration, making it even shorter.

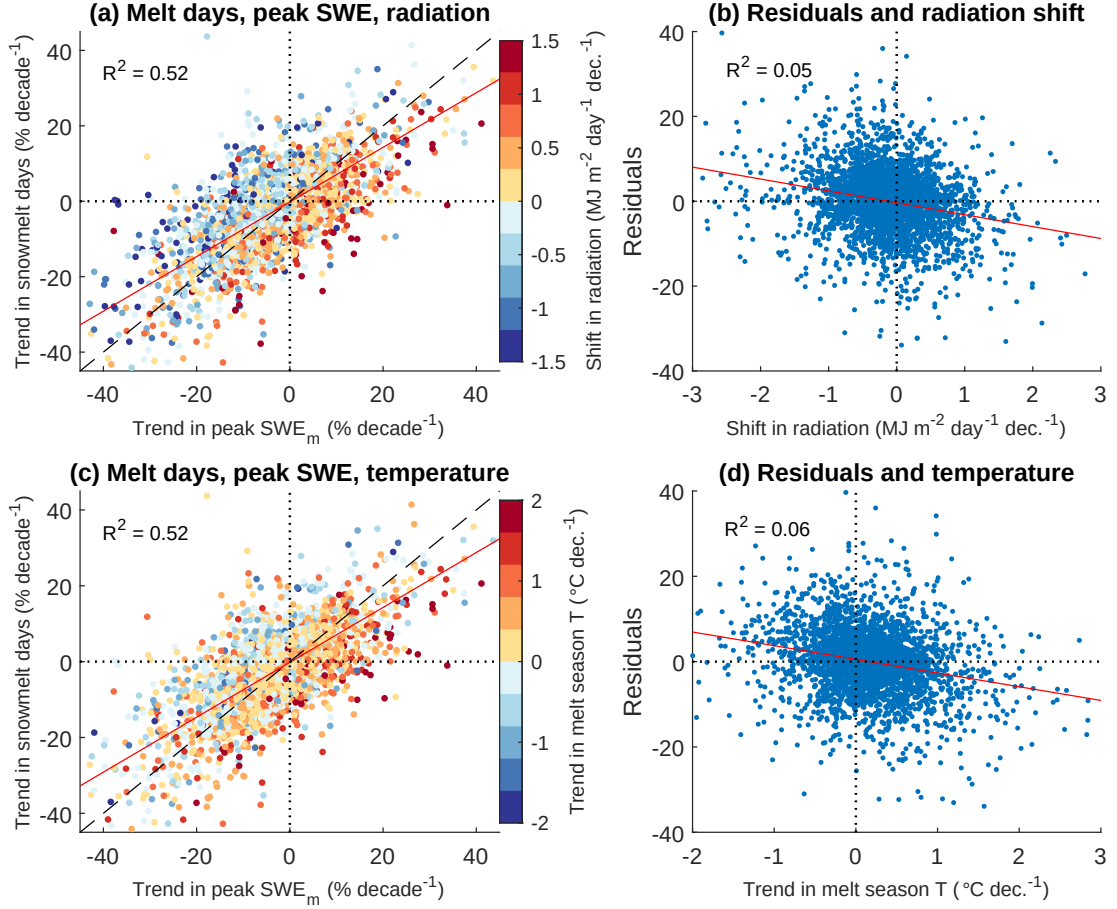


**Figure 3.23:** Drivers of snowmelt days. (a) Melt days, peak SWE and average daily shortwave radiation ; (b) Residuals of melt days and peak SWE, linked to average daily radiation shift; (c) Melt days, peak SWE and melt season temperature; (d) Residuals of melt days and peak SWE, linked to trends in melt season temperature.

However, temperature and radiation are also linked. This is further described in the next section.

### Temperature and radiation

It is important to note that temperature and shortwave radiation are linked via the energy balance, and we would expect a shift towards earlier melt and lower average daily shortwave radiation to go together with a temperature cooling earlier in the season. Conversely, later snowmelt associated with a shift towards higher average daily shortwave radiation in the

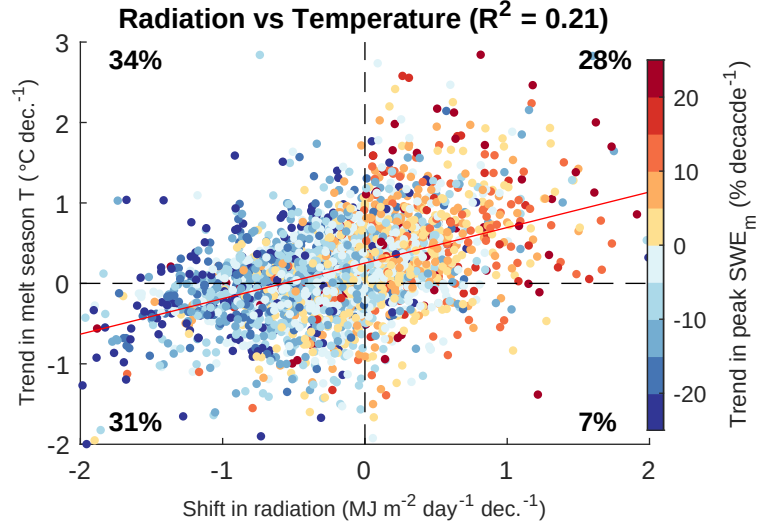


**Figure 3.24:** The link between temperature trends and radiation shifts. Percentages indicate the share of points in each quadrant.

melt season, should be associated with an increase in temperature. This is in fact what Figure 3.24 shows, with some nuances. An increase in peak SWE leads to later melt, as it takes longer to overcome the energy deficit of the snowpack (top right quadrant in Figure 3.24). A decrease in peak SWE leads to earlier melt, as it takes shorter to overcome the energy deficit of the snowpack (left half of Figure 3.24). However, the shift in radiation explains only 21% of the temperature trend in the melt season.

Quantitatively, Figure 3.25a shows that later snowmelt is associated with a mean temperature increase in the snow season of  $+0.45^{\circ}\text{C}$  per decade, and 80% of stations with a trend towards later snowmelt show a warming trend. However, for stations with trends towards earlier melt, there is no clear cooling or warming trend in the melt season. The mean trend is  $+0.0^{\circ}\text{C}$  per decade, 52% of trends show a warming trend and 48% show a cooling trend. For earlier melt, the interplay between lower average daily shortwave radiation and temperature is more complex, as warming trends and lower radiation counteract each other. Figure 3.25b shows that when the entire snow season is considered, the mean temperature trend rises to  $+0.27^{\circ}\text{C}$  per decade, and 81% of stations show a warming trend. Warming trends are strongest when the fixed season period (see Table 3.1) is considered, with 92% of trends showing increasing temperatures, and a mean of  $+0.38^{\circ}\text{C}$  per decade.

This analysis shows that warming has different magnitudes and signs depending on what periods are considered in a year with respect to the snow cover season. Warming is stronger and more unequivocal the longer the period considered, and the more fixed the period is in time.

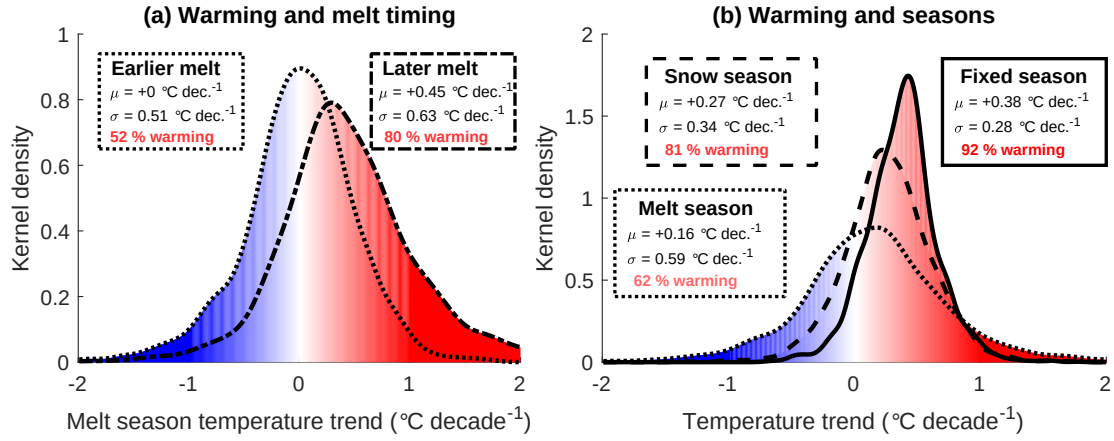


**Figure 3.25:** Distribution of warming trends for different intraannual periods. (a) Comparison of temperature trends at stations showing earlier melt timing and later melt timing; (b) Comparison of temperature trends for different periods in a year.

### 3.4.2 Trends in snowmelt rate

The last key driver to analyse for investigating changing snowmelt dynamics is the rate of snowmelt, and whether this is happening faster, slower, or not changing.

#### Melt rate trends decomposition

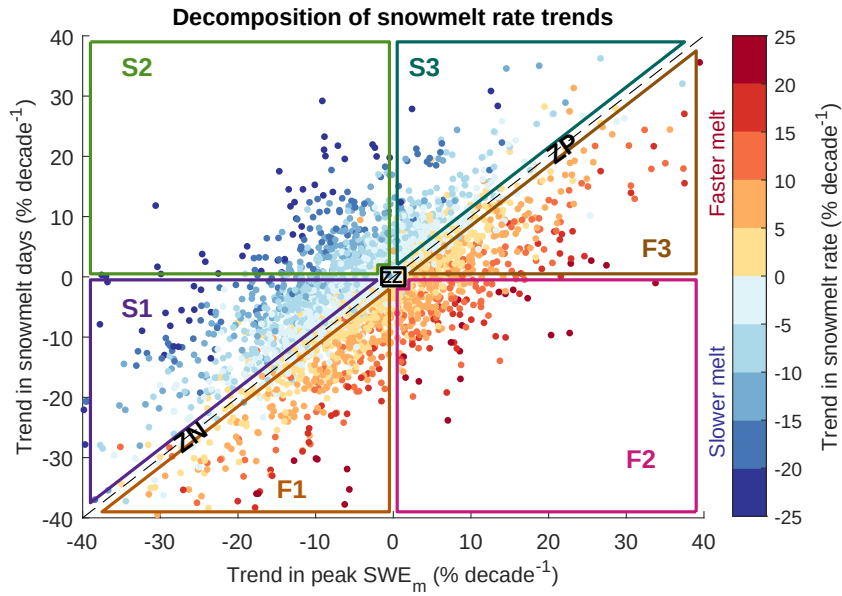


**Figure 3.26:** Snowmelt rate trend decomposed by its drivers: peak SWE and snowmelt days. Slower snowmelt (blue points) are divided into three subgroups, S1, S2, and S3, based on the different drivers of melt rate trend. Faster snowmelt (red points) are divided into three subgroups, F1, F2, and F3, based on the different drivers of melt rate trend. There are three additional zero groups for no trend in melt rate: ZN, ZZ, and ZP.

The snowmelt rate depends on the amount of snow to melt and how many days it takes to melt, as seen in Equation 3.1. Therefore, the interplay between the change in peak SWE and the change in snowmelt days determines the changing rate of melt. Figure 3.26 shows that a relative equal change in Peak SWE<sub>m</sub> and snowmelt days leads to no change in melt rate (i.e. a 10% declining trend in Peak SWE<sub>m</sub> and a 10% declining trend in snowmelt days yields a 0% trend in melt rate). A deviation from the slope 1 line in Figure 3.26 determines whether melt rates become faster or slower. However, equal trends in snowmelt

rate can be due to different drivers, and similar drivers can have different trends. Therefore, we have divided the trends in Figure 3.26 into 9 groups based on their driving factors.

**Table 3.2:** Differences between the defined groups in Figure 3.26.  $\Delta$  denotes increasing trends and  $\nabla$  denotes decreasing trends. Two  $\Delta$  denote a stronger increase, and two  $\nabla$  a stronger decrease. No change (no trend) is denoted with  $=$ .

|                 | Slower         |          |                | Faster         |          |                | No change |          |          |
|-----------------|----------------|----------|----------------|----------------|----------|----------------|-----------|----------|----------|
|                 | S1             | S2       | S3             | F1             | F2       | F3             | ZZ        | ZN       | ZP       |
| Peak SWE trend  | $\nabla\nabla$ | $\nabla$ | $\Delta$       | $\nabla$       | $\Delta$ | $\Delta\Delta$ | $=$       | $\nabla$ | $\Delta$ |
| Melt days trend | $\nabla$       | $\Delta$ | $\Delta\Delta$ | $\nabla\nabla$ | $\nabla$ | $\Delta$       | $=$       | $\nabla$ | $\Delta$ |
| Melt rate trend | $\nabla\nabla$ | $\nabla$ | $\nabla$       | $\Delta$       | $\Delta$ | $\Delta\Delta$ | $=$       | $=$      | $=$      |

Table 3.2 qualitatively summarises the differences between each of the groups, and Table 3.3 shows a quantitative summary with the mean trends of all drivers, as well as the mean trends in melt season temperature and mean daily shortwave radiation shift described in the previous section. Groups S1 (21%) and F1 (15%) are the ones with the most number of stations. Together with group ZN they add up to 48% of all trends. Stations with no trend in either driver is the smallest group with only 6% of trends, suggesting most snowpacks are changing in some way.

The melt rate trend decomposition in Figure 3.26 shows that stations with similar drivers can show opposite trends in melt rate (e.g. group S1 and group F1), and stations with very similar melt rate trends can have very different drivers (e.g. group F1 and F3), highlighting the complex path to determining the impact of climate changes on snowmelt rates.

Figure 3.27 helps explaining the differences between groups. The arrows indicate the mean change for each group and variable, with the tail of the arrow showing the mean value in 1980 and the head of the arrow showing the mean value in 2022. The slope and length of the arrow depend on the magnitude of the mean trend for each group and for each variable. A few striking differences between groups arise from Figure 3.27.

In line with Figures 3.19 and 3.20, the three groups with increasing trends in peak

**Table 3.3:** Summary of mean trends for each of the groups formed for snowmelt rate trend decomposition in Figure 3.26. For each trend (rows), the largest negative value is shown in **bold**, and the largest positive value is underlined.

|                                                                             | ZN<br>(12%) | S1<br>(21%)  | S2<br>(13%)  | S3<br>(8%)  | ZP<br>(7%) | F3<br>(9%)  | F2<br>(8%)  | F1<br>(15%)  | ZZ<br>(6%) |
|-----------------------------------------------------------------------------|-------------|--------------|--------------|-------------|------------|-------------|-------------|--------------|------------|
| Peak SWE <sub>m</sub> (%<br>decade <sup>-1</sup> )                          | -11.5       | <b>-13.9</b> | -6.1         | 5.5         | 8.1        | <u>12.6</u> | 5.0         | -9.1         | -0.4       |
| Snowmelt days<br>(% decade <sup>-1</sup> )                                  | -11.3       | -7.6         | 5.2          | <u>11.5</u> | 7.8        | 6.3         | -5.0        | <b>-15.9</b> | -0.6       |
| Snowmelt rate<br>(% decade <sup>-1</sup> )                                  | 0.0         | -6.8         | <b>-10.4</b> | -6.0        | 0.3        | 7.2         | <u>9.4</u>  | 6.4          | 0.1        |
| SRAD shift<br>(MJ m <sup>-2</sup><br>day <sup>-1</sup> dec. <sup>-1</sup> ) | -435        | <b>-491</b>  | -273         | 4           | 84         | <u>273</u>  | 135         | -384         | -57        |
| T <sub>meltseason</sub><br>(°C decade <sup>-1</sup> )                       | 0.13        | <b>-0.04</b> | 0.00         | 0.09        | 0.22       | <u>0.54</u> | 0.41        | 0.24         | 0.22       |
| T <sub>fixedperiod</sub><br>(°C decade <sup>-1</sup> )                      | <u>0.44</u> | 0.43         | 0.43         | 0.35        | 0.30       | <b>0.27</b> | <b>0.27</b> | 0.40         | 0.32       |

SWE correspond to the colder climates with shallower snowpacks, while the three groups with decreasing peak SWE trends correspond to warmer climates with deeper snowpacks (Figure 3.27a). All groups are shifting to a warmer climate, with temperature increases up to 1.9°C over the whole study period. Paradoxically, at the beginning of the period, the three slower snowmelt groups used to have the highest melt rates, and the three faster snowmelt groups used to have the lowest melt rates. At the end of the period, the slower snowmelt groups have the lowest melt rates, and the faster snowmelt groups have the highest melt rates (Figure 3.27b). This is likely because the faster snowmelt groups used to have lower melt season temperatures, but are now warming, making melt rates faster. Conversely, the slower snowmelt groups used to have higher melt season temperatures, but are not warming or warming less than the other groups in the melt season (Figure 3.27b). Less melt season warming in these groups is probably due to earlier melt onset timings (Figure 3.27c). Furthermore, the three faster snowmelt groups used to have a higher number of negative degree days in the melt season. Because of warming, there are fewer days below freezing during the melt season period (i.e. less interruptions of melt, which can bring back the energy

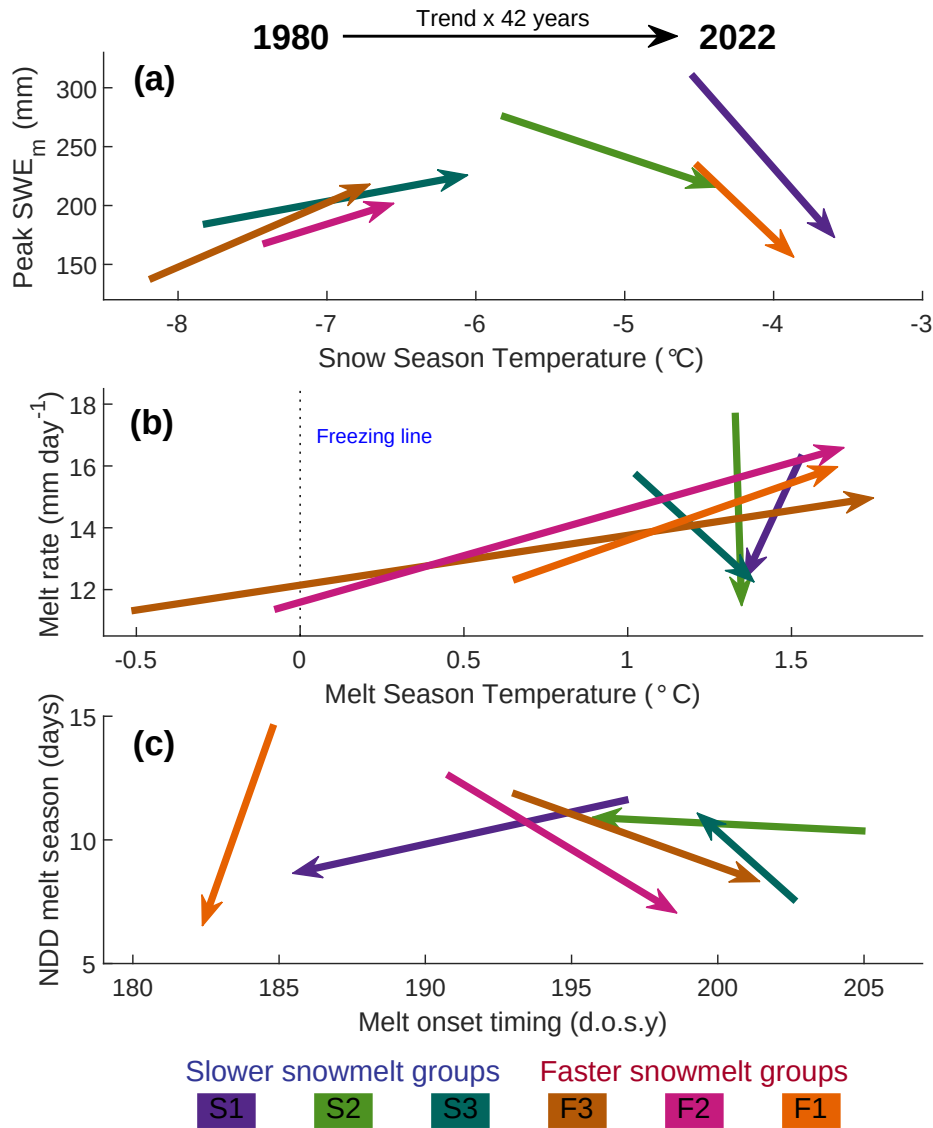


**Figure 3.27:** Slower vs faster snowmelt groups. Change from 1980 to 2022 for each of the melt rate groups in Figure 3.26. (a) Change in Peak SWE<sub>m</sub> and snow season temperature; (b) Change in melt season temperature and melt rate. (c) Change in negative degree days in the melt season and change in melt onset timing. Arrows are built based on mean trend values for all trends within a group, with the tail of the arrow showing the mean value in 1980 and the head of the arrow showing the mean value in 2022.

deficit of the snowpack), and therefore faster melt rates. The three slower snowmelt groups show smaller changes in negative degree days, and even an increase for group S3 (Figure 3.27c), suggesting there is a lower influence of negative degree days change on snowmelt rates for these groups.

Overall, slower snowmelt groups seem to be radiation driven, and faster snowmelt groups seem to be more temperature driven. Differences between groups that have similar drivers but opposite trends, and groups that have similar trends but different drivers, are described below.

### **Similar drivers, opposite trends:**

Groups S1 and F1 exhibit similar drivers in peak SWE and melt days, and a similar behaviour in Figure 3.27a, but display contrasting trends in melt rate. Group S1 used to melt later, at higher temperatures and higher melt rates than group F1 (Figure 3.27b-c). The stronger reduction in peak SWE experienced by group S1 compared to F1 causes a much earlier onset of snowmelt, which is not compensated by warming temperatures, resulting in a slower melt rate. Group F1 used to melt earlier, at lower temperatures and lower melt rates (Figure 3.27b-c), likely due to shallow snowpacks melting earlier in the season. Melt season temperatures used to be closer to zero degrees (Figure 3.27b) and used to have many more negative degree days (Figure 3.27b-c), resulting in slower melt rates. However, warming trends have raised melt season temperatures well above zero degrees for group F1 (Figure 3.27b) and have halved the number of negative degree days in the melt season (Figure 3.27c), leading to faster melt rates. Despite a substantial reduction in peak SWE, the snowpacks in group F1 melt only slightly earlier than before (Figure 3.27c), indicating that earlier melt might not be feasible due to the lower temperatures and lower daily shortwave radiation earlier in the season. Despite the differences observed between the groups, it is worth noting that group ZN, which exhibits an equal decrease in peak SWE and melt days without a change in melt rate, accounts for 12% of all trends, suggesting a delicate equilibrium between belonging to group S1 and F1.

Groups S3 and F3 exhibit similar drivers in peak SWE and melt days, and a similar behaviour in Figure 3.27a, but display contrasting trends in melt rate. Group S3 used to melt later, at higher temperatures and higher melt rates than group F3 (Figure 3.27b-c). However, towards the end of the period, group F3 melts later and at higher temperatures than S3, probably due to a larger increasing trend in peak SWE for group F3 than group

S3. Increased peak SWE prolongs the time required for the snowpack to reach isothermal conditions, delaying the onset of snowmelt. Mean melt season temperatures for group F3 used to be below freezing but have experienced a substantial increase of more than 2°C, resulting in accelerated melt rates. In contrast, group S3 is melting earlier despite an increase in peak SWE. A smaller increase in peak SWE, compared to group F3, together with a strong snow season warming suggests that snowpacks are reaching isothermal conditions earlier, and at lower radiation but with more snow to melt than before, making melt rates slower. Despite the differences observed between the groups, it is worth noting that group ZP, which exhibits an equal increase in peak SWE and melt days without a change in melt rate, accounts for 7% of all trends, suggesting a delicate equilibrium between belonging to group S3 and F3.

### **Similar trends, opposite drivers:**

Groups F1 and F3 display similar trends towards faster snowmelt, but different factors drive them. Group F1 exhibits decreasing trends in both drivers, whereas group F3 shows increasing trends in both drivers. The main similarity between the groups is a pronounced warming temperature during the melt season and a reduction of negative-degree days. This compensates for slightly earlier melt in F1 and adds to increased radiation due to later melt in F3. In contrast, groups S1 and S3 display similar trends towards slower snowmelt, but different factors drive them. Group S1 exhibits decreasing trends in both drivers, whereas group F3 shows increasing trends in both drivers. The main similarity between the groups is that they melt earlier. Group S1 melts much earlier due to a strong decreasing trend in peak SWE, while group S3 melts slightly earlier only. However, the increased peak SWE, together with more negative-degree days in the melt season, contribute to slower melt rates in F3.

Other groups with similar trends exhibit more nuanced differences. Groups S1 and S2 demonstrate substantial similarities, but S2 is found in colder climates, and the reduction in peak SWE is less strong than in S1. As a result, the number of melt days is less affected, or even increased due to earlier melt, compared to group S1, which is located in a warmer climate and experiences a reduction in melt days more closely aligned with the decrease in

peak SWE (Figures 3.26 and 3.27). Similarly, group F2 is found in a slightly warmer climate and shows a less strong increase in peak SWE than group F3. Consequently, the number of melt days is more affected by warming despite increasing SWE in group F2. At the same time, group F3 exhibits an increasing number of melt days that align more closely with the increasing peak SWE.

### **Probability of changing melt rates**

The trends in snowmelt rate can be seen as a probability function based on the trend in peak SWE, the trend in snowmelt days, the trends in melt season temperature, and the trend toward earlier or later snowmelt and the associated average daily shortwave radiation shift (Figure 3.28). The probability of slower or faster melt in Figure 3.28a is based on the percentage of slower or faster melt trends in Figure 3.26 along the magnitude of peak SWE trend.

For declines in peak SWE stronger than -15% per decade (indicated by the blue rectangle in Figure 3.28a), the probability of slower snowmelt trends is above 70%, and 30% for faster snowmelt trends. In this blue rectangle, Figure 3.28b shows the strong decline in peak SWE leads to much earlier snowmelt, a strong negative shift in average daily incoming radiation in the melt season, and no apparent warming or cooling trend. This is mainly observed in group S1 and means the probability of slower snowmelt is high and dominated by the reduction in peak SWE and radiation.

The probability of slower snowmelt drops from 70% to 30% for trends in peak SWE as the probability of faster snowmelt increases from 30% to 70% (indicated by the orange rectangle in Figure 3.28a). For negative trends in peak SWE smaller than -15% per decade, a warming trend starts to be apparent and may compensate for the reduction in average daily radiation associated with earlier snowmelt, increasing the probability of faster snowmelt (Figure 3.28b). This is an expected behaviour of trends in group F1. The likelihood of faster or slower snowmelt becomes equal when trends in peak SWE equal -2% per decade. For

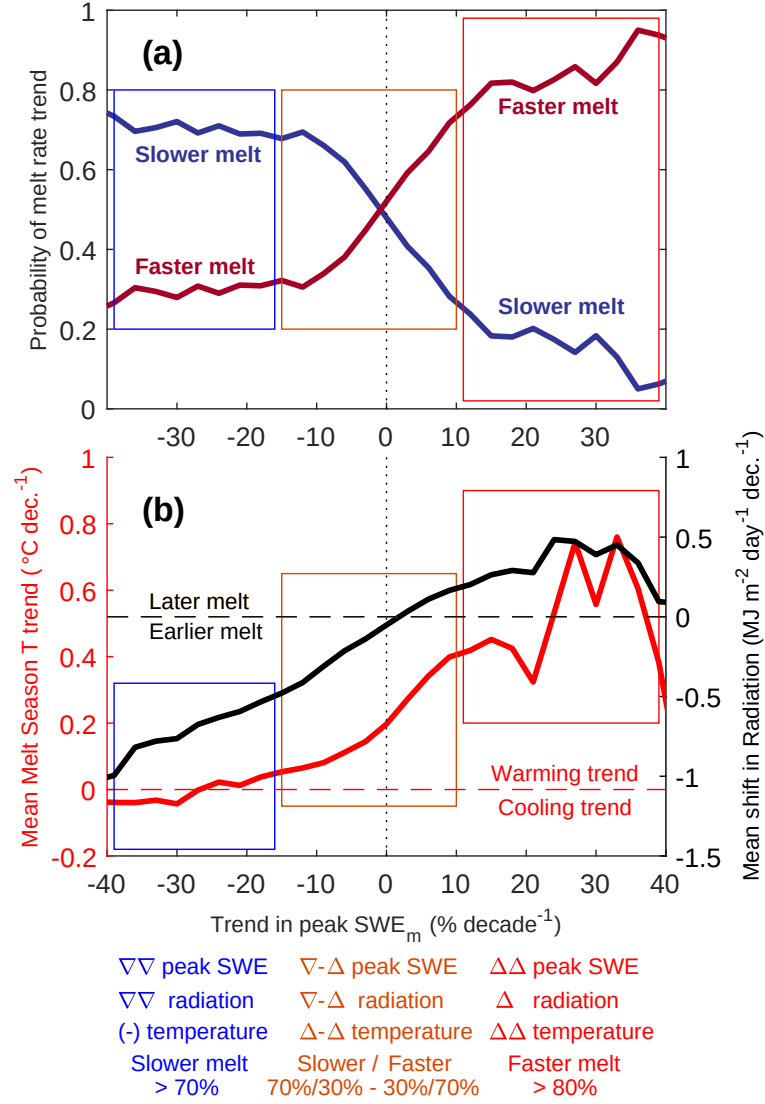


**Figure 3.28:** Probability of faster or slower melt. (a) Average daily shortwave radiation shift and melt season temperature trend against the trend in Peak SWE<sub>m</sub>; (b) Probability of faster or slower melt based on the trend in Peak SWE<sub>m</sub>.

increasing trends in peak SWE up to +10% per decade, the warming trend becomes stronger and adds to an associated increase in average daily radiation due to later melt, further increasing the probability of faster snowmelt trends (Figure 3.28b). This is an expected behaviour of trends in group F2, where the increase in peak SWE is not substantial enough to extend the duration of the melt season, while the intensifying warming trend leads to a reduction in the number of melt days.

For increasing trends in peak SWE higher than +10% per decade (indicated by the red rectangle in Figure 3.28a), the probability of faster snowmelt trends increases up to 90% as the probability of slower snowmelt trends decreases down to 10%. Within this red rectangle, there is an increased average daily radiation and a strong warming trend associated with delayed snowmelt due to increased snow accumulation (Figure 3.28b). This is an expected behaviour of trends in group F3.

### Spatial variability of melt rate trends

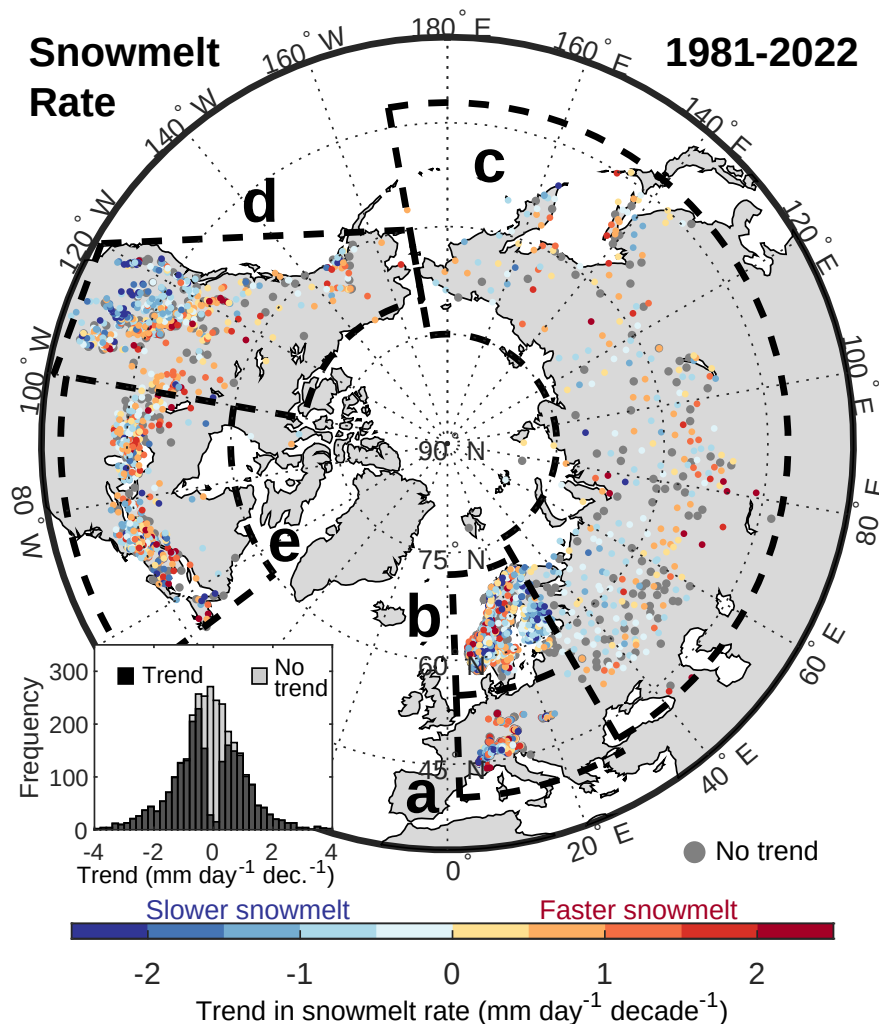


**Figure 3.29:** Spatial distribution of snowmelt rate trends. Five geographical areas defined as *a* to *e*.

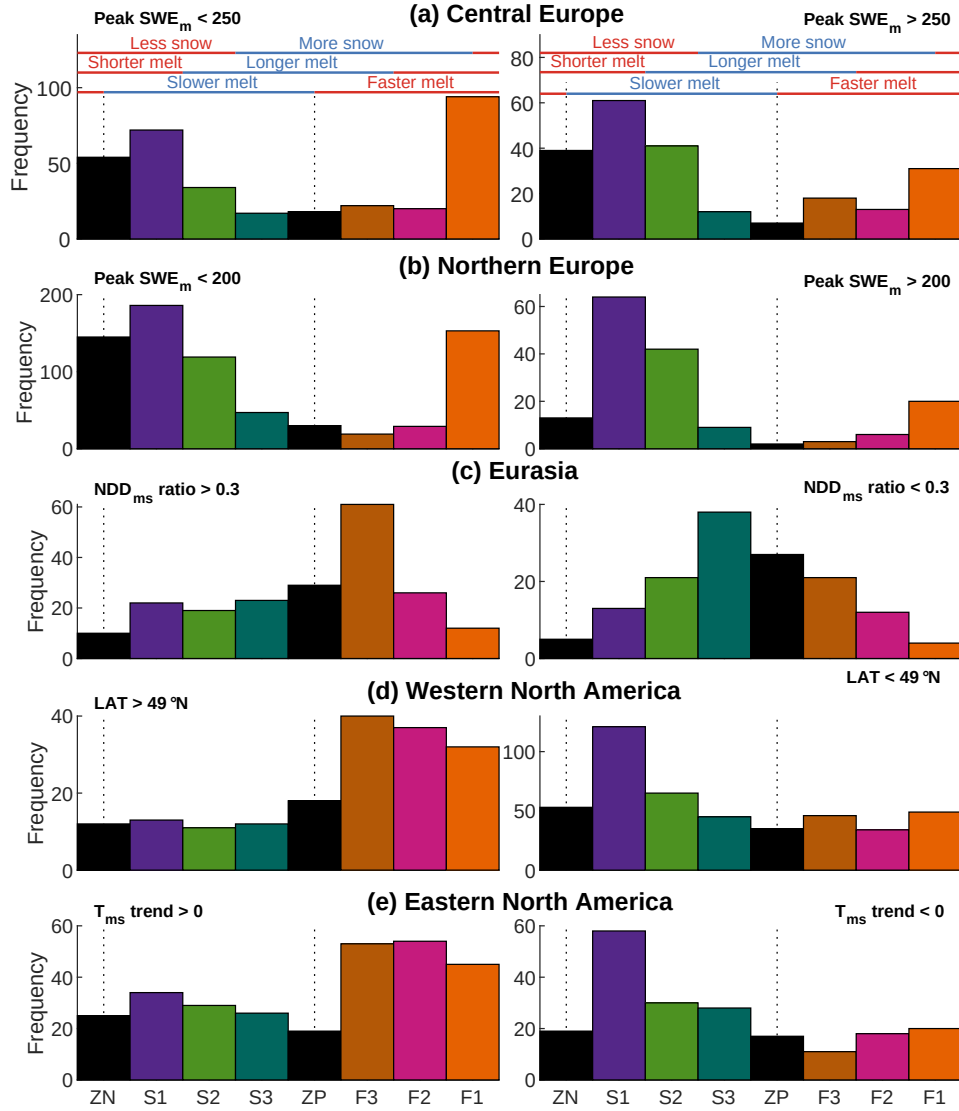


**Figure 3.30:** Distribution of melt rate trend groups defined in Figure 3.26, for each of the five geographical areas defined in Figure 3.29, and stratified by diverse variables in each area.

The complexity of the interactions between drivers, and the sensitivity of snowmelt rate change to trends in drivers, leads to high spatial variability of snowmelt rate trends over the Northern Hemisphere (Figure 3.29). The mean snowmelt rate trend is  $-0.15 \text{ mm day}^{-1} \text{ decade}^{-1}$  ( $-0.9\% \text{ decade}^{-1}$ ), with 55% of stations showing a trend towards slower snowmelt, and 45% showing a trend towards faster snowmelt. However, 25% of all trends are classified as not reliable trends. Despite the high spatial variability, some broad spatial consistency patterns are visible. Slower snowmelt is observed in the southwest areas of North America,

Finland, the European Alps and northern parts of Eurasia. Faster snowmelt is consistently observed in the northern parts of North America, southern parts of Eurasia and some areas in central Europe. Zoomed-in maps for each of the five zones marked in Figure 3.29 can be found in the Appendix B: Central Europe (Zone a, Figure B.2), Northern Europe (Zone b, Figure B.3), Eurasia (Zone c, Figure B.4), western North America (Zone d, Figure B.5), and eastern North America (Zone e, Figure B.6).

Although there is a high spatial variability in melt rate trends, its drivers have a high spatial consistency. Figure 3.30 shows the distribution of melt rate trend groups (defined in Figure 3.26) for each of the five geographical areas defined in Figure 3.29. Central Europe shows dominance of less snow and shorter melt seasons (groups F1, ZN, S1). In line with our analysis, faster snowmelt trends (group F1) dominate for snowpacks shallower than 250 mm, but slower snowmelt trends dominate for snowpacks deeper than 250 mm, primarily located in Alpine areas. A similar picture occurs in Northern Europe, with slower snowmelt (groups S1 and S2) dominating for the deepest snowpacks. However, slower snowmelt is also the dominant trend in Finland, where snowpacks typically do not exceed 200 mm. In Eurasia, a clear distinction is observed between climates where the mean negative degree day ratio (NDD ratio) in the melt season is below 0.3, which shows faster melt (group F3), and climates where the mean NDD ratio in the melt season is above 0.3, which shows slower melt (group S3). This is also in line with our results, showing that snowpacks that used to melt at temperatures closer to zero degrees are now melting faster due to the increase in temperatures, bringing the melt season well above the freezing line and reducing the number of negative-degree days. In western North America, the high Alpine sites from latitudes below 49°N show a dominance of slower melt due to decreasing trends in peak SWE (group S1). In comparison, the mostly non-Alpine sites north of 49°N show a dominance of faster melt, but both increasing and decreasing trends in peak SWE are observed (groups F1, F2 and F3). Lastly, trends in eastern North America are the most spatially heterogeneous, with no clear geographical pattern. However, the trends in drivers are still consistent and in line with our results, with sites showing a warming trend in the melt season melting faster and sites without a warming trend in the melt season melting slower.

## 3.5 Discussion

### 3.5.1 Conceptual summary of drivers and trends

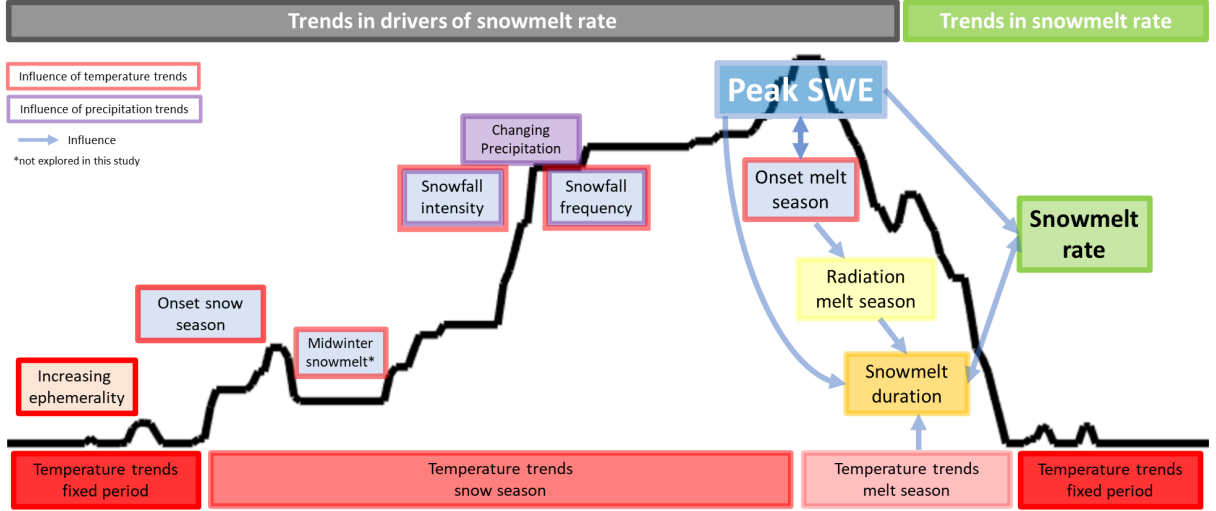


**Figure 3.31:** Conceptual summary of the results on drivers of snowmelt rate. The black solid line is a hypothetical snow water equivalent curve for one winter. As per our results, red outlines indicate that temperature trends have an influence on that driver, and purple outlines indicate that precipitation trends influence that driver. Arrows show the influence of one driver on another driver. The intricacies of the interactions between direct drivers of snowmelt rate are conceptualised in Figure 3.32.

Our results shed light on a series of interactions between snowmelt rates and its main drivers, which are summarised in Figure 3.31. Our findings demonstrate the importance of peak snow water equivalent (peak SWE) as the key from which snowmelt related changes follow, as it determines the duration and timing of the snowmelt period. In turn, Peak SWE is driven by a series of temperature and precipitation related drivers during the accumulation season. In general, increasing ephemerality and later snow onsets due to strong warming trends are contributing to shorter snow seasons and less snow accumulation. Warming trends in the snow season are the main contributors to decreasing frequency of snowfall days and snowfall rates, further reducing peak SWE. Increasing snowfall frequency and intensity are contributing to higher snow accumulation in the coldest climates where temperatures remain well below freezing even with warming trends. Warmer temperatures facilitate an earlier onset of the melt season and therefore shorten the accumulation season, lowering

peak SWE, while lower peak SWE facilitates overcoming the energy deficit of the snowpack and initiating snowmelt, creating a positive feedback between melt onset and peak SWE. The timing of snowmelt onset determines the average daily shortwave radiation available to melt, and together with the temperature trend in the melt season, determine the change in energy available for melting snow at the time of melt. Peak SWE (i.e. the amount of snow to melt), together with the energy available for melt, determine how long it takes to melt the snowpack and therefore the snowmelt rate.

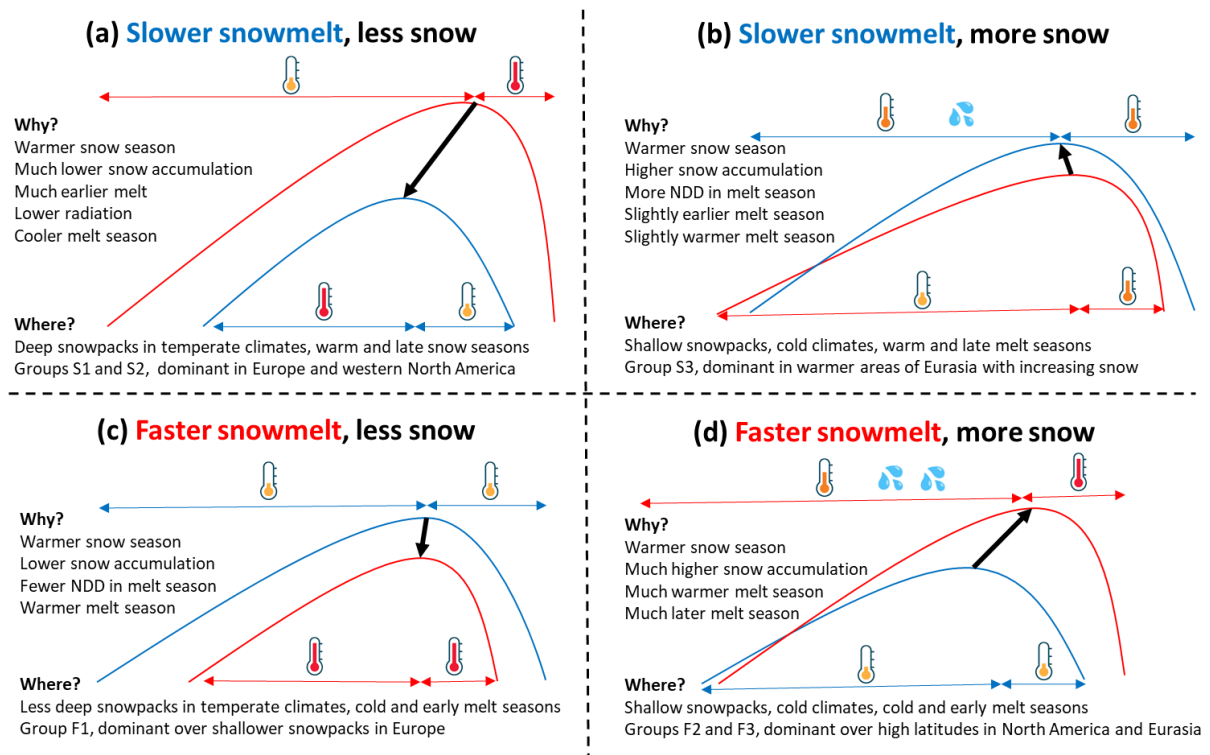


**Figure 3.32:** Conceptual summary of the results on snowmelt rate trends. Red (faster snowmelt) and blue (slower snowmelt) lines represent hypothetical SWE curves. Black arrows show the increase or decrease in peak SWE and the shift to earlier or later melt onset. Small thermometers show qualitative warming or cooling trends between the red and blue curves. Small water droplets show an increase in precipitation.

The balance between changing peak SWE, changing energy, and changing melt duration is complex and depends on climatic and geographic factors as conceptualised in Figure 3.32. Slower snowmelt occurs where a strong reduction in snow accumulation due to a warmer snow season leads to much earlier melt, with an associated shift towards significantly less average daily radiation in the melt season and cooler temperatures (Figure 3.32a). Slower

snowmelt may also occur where a warmer snow season leads to earlier melt despite increased snowfall, which is common for cold climates with warming trends and slight increases in precipitation (Figure 3.32b). In contrast, faster snowmelt occurs where snowmelt seasons used to be early and cold with low melt rates. Strong warming trends in the melt season compensate for a slight reduction in radiation associated with only slightly earlier melt, making melt rates faster (Figure 3.32c). Faster snowmelt is also more likely in areas where increased snowfall, driven by increased precipitation and a delayed onset of snowmelt, results in greater energy availability during the melt season (Figure 3.32d).

### 3.5.2 Diversity of trends in drivers

Our study is, to date, the largest analysis of changing snowmelt rates and its drivers due to global warming. Our findings reveal a diverse range of trends in key snow accumulation and melt indicators and their drivers. The range of trends and drivers is much wider than previous studies addressing changing snowmelt rates, which have mainly focused on slower melt rates due to warming and highlights a more complex response of snowmelt rates to warming.

The results show a decrease in total snowmelt amounts due to reduced snow accumulation at 50% of all stations analysed. These are mainly located in areas where snow water resources are crucial as peak SWE represents a large fraction of the annual precipitation, such as the mountains of western North America, Scandinavia, and the European Alps (Figure B.1). These trends align with previous literature showing declines in snow resources over these regions (Musselman et al., 2017, 2021; Fontrodona Bach et al., 2018; Luomaranta et al., 2019; Matiu et al., 2021a; Marty et al., 2017b; Colombo et al., 2022). Our analysis shows that warming trends are responsible for the decreasing snow accumulation, due to changing precipitation phase from snow to rain, through the combined effect of increasing ephemerality of snow, later snow onsets, earlier melt onsets, reduced snowfall frequency, and reduced snowfall intensity. Warming trends are stronger around the edges of the snow season

than during the snow season, making the length of the accumulation season a main control on peak SWE. Decreased seasonal precipitation can exacerbate the decreasing snow accumulation trends, but was not found to be a significant driver in our analysis. Decreasing snow accumulation is typical for climates with mean snow season temperatures warmer than  $-6^{\circ}\text{C}$ , as warming temperatures lead to more positive degree days and dominate a reduction in snow accumulation over any change in precipitation.

Our findings also reveal a large fraction (25%) of trends towards increased snow accumulation and melt over Eurasia and North America, and the same fraction (25%) with no detectable trends. These findings are in line with previous regional findings (Bulygina et al., 2011; Zhong et al., 2018; Pulliainen et al., 2020), but demonstrate a more robust causal link between the increasing snow accumulation being due to increasing seasonal precipitation (Bintanja, 2018). These trends are occurring over the coldest climates, where mean snow season temperatures are below  $-6^{\circ}\text{C}$ , meaning warming has limited impact on precipitation phase. These sites are also located at higher latitudes. Our observation based result is similar to model determined  $-11^{\circ}\text{C}$  threshold by Räisänen (2016) determining increasing or decreasing snowfall for the twenty first century, and similar to the simulated  $-8^{\circ}\text{C}$  threshold for increased peak SWE sensitivity to warming for global mountain snowpacks (López-Moreno et al., 2020a). For climates below these threshold temperatures, warming in mid winter does not impact snow accumulation as temperature are still well below freezing (Essery et al., 2020), but changes in snow cover duration can still occur due to warming impacts at the beginning and the end of the season, when temperature are close to  $0^{\circ}\text{C}$  (Pomeroy et al., 2015; López-Moreno et al., 2020a).

Despite the robustness of increasing snow accumulation and decreasing snow accumulation patterns, not all trends may be attributed to temperature trends. In the Canadian prairies, we observe spatially consistent increasing trends in snow accumulation and snow cover duration, but Mudryk et al. (2018) linked this trend to spring temperature cooling due to the influence of the Pacific Decadal Oscillation cooling sea surface temperatures for the last 35 years. The substantial spatial variability in snow accumulation trends across

North America aligns with the findings of Pulliainen et al. (2020), who observed an initial increase in snow mass from 1980 to 1990, followed by a subsequent decline. This underscores the challenge of assuming a uniform trend, given the variations in data availability and time periods across nearby monitoring stations in this study. In fact, Mudryk et al. (2020) showed that the probability of detecting a significant negative trend in snow cover over the Northern Hemisphere is 80% for 20 years of data, and 95% for over 30 years of data. Given our analysed trend period is from 1981 to 2022 and we require a minimum of 20 years of available data for a trend, it is likely that many stations (25%) show no trends due to the period of study being too short. On the other hand, there is a trade-off between the length of a period and the robustness of its trend. Trends may be more reliably detected for longer periods, but may diminish in magnitude, as (Fontrodona Bach et al., 2018) showed with their stronger trend magnitudes from 1980 compared to trend magnitudes from 1950. The results in this study may be even more robust if at least 30 years of data were available for all stations across the Northern Hemisphere.

When examining the duration of the snow season, trends are less diverse, with the majority of stations showing shorter snow seasons, in line with previous global studies on snow cover duration (Bormann et al., 2018; Connolly et al., 2019; Notarnicola, 2020; Mudryk et al., 2020). Our results show a widespread later snow season onset due to increased ephemeral snow periods. This suggests that the first day with snowfall is less sensitive to warming than the overall snow cover period, which is becoming more discontinuous.

The trends in duration of the melt season are far less conclusive, and more diverse, than the trends in the total snow cover duration. This is because the change in snowmelt season duration depends mainly on the change in peak SWE (52% of variance explained), and because the drivers in peak SWE are diverse, so too are the melt season duration trends. A shift in radiation and temperature trends explain only an additional 5% and 6% of the residual variance. This makes the duration of the melt season the least changing snow indicator in this study, with 52% of stations showing no detectable trends. This, however, highlights that no change in the duration of the melt season does not mean no change

in snow cover patterns. The total snow accumulation and the snowmelt rate may both be changing despite no change in the duration of the melt season, as seen in Figure 3.26. Consequently, this highlights the importance of investigating the drivers of changing trends, as a non-detectable trend may hide the confluence of two significant trends.

Warming at a fixed period around the snow season is the most unequivocal and less diverse of all trends in our study, with 92% of trends showing an increase in temperatures. However, warming trends are diverse at different times of the season, and have varying effects across different climates. In the melt season, temperature trends are very diverse. Increased snow accumulation leads to delayed snowmelt, which is associated with a time of year of increasing average daily radiation and therefore increased temperature. This can be amplified by warming trends, making temperatures in the melt season warmer at 80% of stations that also have increasing snow accumulation. In theory, the reverse should also be true, i.e. reduced snow accumulation leads to earlier melt, a time of year with reduced average daily radiation and therefore cooler temperatures. However, overall warming trends may counteract this impact of early melt timing, which is why only 52% of stations analysed show warming and 48% of trends show cooling in the melt season despite earlier melt. This aligns with Essery et al. (2020), who found months with no warming trends at some sites for the period 1980-2010 but found the strongest trends in snow disappearance date if the snowmelt season occurred in months with warming trends.

The robustness of decreasing and increasing snow accumulation, snow cover duration, and snowmelt duration trends across Northern Hemisphere climates had not previously been shown at spatial scale presented here. The scale of the study highlights the diverse response of snow to warming trends, which are responsible for reducing snow accumulation in the warmer climates, and may increase snow accumulation through increased precipitation in the colder climates. Warming or cooling in the melt season have an influence on the number of snowmelt days, and together with the associated shift in radiation due to earlier or delayed snowmelt, determine the change in snowmelt rate.

### 3.5.3 Diversity of snowmelt rate trends

We show trends in snowmelt rates have the highest spatial variability of all components in this study and a high number of stations with no trends (25%), indicating that no change in melt rate in response to warming temperatures is actually more common than previously appreciated. This does not mean no changes to snow resources are occurring, but rather that an equal relative decrease in snow accumulation and snowmelt days combine to ensure the melt rate remains unchanged. Thus, no change in melt rate may hide strong changes in snow accumulation and duration of melt, highlighting the importance of analysing the drivers of a changing melt rate trend.

Our results support slower snowmelt in a warmer world (López-Moreno et al., 2013b; Pomeroy et al., 2015; Musselman et al., 2017; Harpold & Brooks, 2018; Rasouli et al., 2022), but only when specific trends in drivers are met, i.e. a strong decline in snow accumulation, leading to an earlier onset of the snowmelt season that is not compensated by a strong enough warming trend in the melt season. This is illustrated in Figure 3.32a. However, here we show that slower snowmelt can also occur where snow accumulation is increasing. This occurs if warming snow season temperatures lead to earlier snowmelt, despite increasing snow accumulation, and the snowmelt season temperature does not significantly warm. This is possible as warming impacts are clearer for a longer period like the whole snow season, compared to a shorter period like melt season (Figure 3.25). This slower snowmelt mechanism is illustrated in Figure 3.32b, and to the best of our knowledge has not previously been demonstrated in the literature.

Musselman et al. (2017) suggested melt rates might actually be faster in the future if there is a strong enough increase in warming during the melt season. We show that this mechanism is more likely to occur only for snowpacks with declining trends in snow accumulation less than -10% per decade, meaning increases in melt season temperature can more easily compensate for a small reduction in melt season average daily shortwave radiation, making melt rates faster as illustrated in Figure 3.32c. Importantly, we demonstrate that

faster snowmelt is a more widespread response than previously recognised, and that this is actually mostly occurring where snow accumulation is increasing. While previous literature suggested that more snowfall and warmer temperatures could double melt rates even without a later snowmelt onset (Krogh & Pomeroy, 2019), we show that increasing snowfall is mostly delaying the snowmelt season to a later time with higher daily shortwave radiation and much warmer temperatures, significantly increasing the melt rates, as simulated by López-Moreno et al. (2013b), and illustrated in Figure 3.32d. Our results also highlight that trends in melt rate need to be contextualised to the conditions they started from. We show that climates with a typically early melt season and low melt rates are becoming faster, and climates with a typically late melt season and high melt rates are becoming slower. In other words, snowpacks that used to melt fast now melt slower than snowpacks that used to melt slowly and now melt fast, as illustrated in Figure 3.27b.

Moreover, we show that the response of melt rates to a warming climate can be seen in terms of probability. Our generalised results and findings, based on mean trends and groups, explain the average outcome given a series of combined changing drivers, but this does not mean that another trend than expected given those conditions may not occur. For example, even for the most likely conditions for slower snowmelt trends (as illustrated in Figure 3.28), which is for strong reductions in peak SWE, we show there is still a probability of 30% to find faster snowmelt trends. This highlights that melt rate trends depend on a fine balance between the different drivers described in this study, and this balance can easily shift over a relatively small spatial due to factors not explored in this study, such as land use and topography, resulting in the fairly high spatial variability observed. In fact, when broken into regions, it is clear no trends or drivers occur exclusively (Figure 3.30), rather it is the dominance of certain drivers that differ per region.

In summary, slower snowmelt trends are more likely in temperate climates with deeper snowpacks, such as the European Alps, Scandinavia, and mountains of western North America. Faster snowmelt trends are more likely in temperate climates with shallower and early season melting snowpacks, which may occur in every region except Eurasia. Faster snowmelt

is very likely in cold climates with increasing snow accumulation due to increased precipitation and a delayed onset of snowmelt, such as is occurring in Eurasia and continental North America. Regions with a high spatial variability, such as eastern North America, show consistency in drivers but no spatial consistency in melt rate change, suggesting local climatic and geographic factors are shifting the fine balance in melt rate drivers described above.

Our study sheds light on the drivers behind the large spatial variability of the snowmelt rate response to a warming world, which has not previously been addressed (Musselman et al., 2017; Harpold & Brooks, 2018; Wu et al., 2018). The interplay between changing snow accumulation, the length of the snowmelt season, the timing of snowmelt, and warming temperatures conspire to affect snowmelt rates in a way that is complicated to generalise, as it varies by climates, regions and initial conditions. We explain differences between climates based on the response of the snowpack to warming temperatures. Our results suggest the probability of changing melt rates based on simple climatic drivers such as snow accumulation, temperature, and shortwave radiation, but melt rate variability at smaller scales should be addressed in a more detailed analysis considering detailed snow processes and physics based modelling, such as those performed by Krogh and Pomeroy (2019). The sensitivity of the snowmelt rate response to climate should be investigated with detailed climate simulations, as different magnitudes of warming trends at different times of the season, as shown also by Essery et al. (2020), can affect the melt rate in more complex ways than simply shifting the mean temperature of a reference period by a fixed number of degrees celsius, as many studies currently do.

### **3.5.4 Implications**

Our results have a wide range of implications for climate, water resources, and ecosystems. The widespread decline in snow cover duration, regardless of the snow accumulation trend, implies an enhanced snow-albedo feedback, which can affect the climate (Thackeray & Fletcher, 2016) and enhance evaporation, potentially reducing streamflow (Milly & Dunne,

2020).

Furthermore, our results show varying snow trends across climates. The driest and coldest climates are experiencing little change or increasing snow resources. Although this may be good for water resources in those regions, the absolute increasing snow accumulation is still minor as snowpacks are shallow over these colder climates that receive low total precipitation in the winter months. Over higher elevations, however, increasing snow may provide resilience for glaciers (Colucci et al., 2021). In contrast, wetter and warmer climates show the most substantial declines in snow resources, with implications for water resources (Siirila-Woodburn et al., 2021) and for low flows (Jenicek & Ledvinka, 2020). As these regions may heavily rely on snow resources, relative reductions of 10% to 30% per decade in snow accumulation may be critical for water management strategies.

Increasing snow may delay flowering of tundra plants (Bjorkman et al., 2015), and given the spatial extent of increasing snow accumulation climates, this may have important ecological implications despite relatively lower water resource implications. In contrast, snow loss may enhance plant productivity (Rumpf et al., 2022) over the warmer climates, but much earlier snowmelt may be detrimental for grassland greening (Revuelto et al., 2022). The increase in snow ephemerality observed here aligns with observations made by Petersky et al. (2019) and has the potential to impact vegetation through longer and drier growing seasons (Petersky & Harpold, 2018). This shows that snow loss or snow gains, in combination with earlier or delayed snowmelt, have strong implications that need to be considered at smaller scales based on local biogeographic factors.

Our insights into changing snowmelt rates in response to warming contribute to the ongoing research on the hydrological response to changing melt rates (Berghuijs et al., 2014; Barnhart et al., 2016, 2020). We show that the response of snowmelt rate to warming is highly heterogeneous and spatially variable, even at the basin scale, which poses greater challenges for hydrological and land surface models (Fisher & Koven, 2020). In particular, our findings show a strong shift in several snow indicators. Shallow snowpacks in cold climates may become deeper than deep snowpacks that are thinning, as outlined in Figure 3.27a.

Snowpacks that used to melt slowly may now melt faster than snowpacks that used to melt faster and are melting slower, as outlined in Figure 3.27b. This may have severe implications for hydrological modelling applications, as assumptions and model parameterisations that are valid in the current climate may become invalid in future warmer climates.

### 3.5.5 Limitations

Despite the robustness of our results and interpretations, a few limitations and assumptions need to be emphasised.

First, we use the NH-SWE dataset, which provides time series of snow water equivalent based on actual snow observations, but they are not direct observations of snowmelt. The modelling approach, or the quality of the snow depth dataset used to generate the NH-SWE dataset, might still have inaccuracies or biases. However, given the amount of data available and the robustness of the evaluation exercises both in Fontrodona-Bach et al. (2023a) and in Section 3.3.2, we do not expect erratic data to be significantly large or to affect the results. Another data-related limitation is the length of the time series available for trend analysis. We calculate trends from 1980 if more than 20 years of data are available, which do not need to be continuous. Although the trends are computed under the assumption of widespread warming, which is backed up by the temperature trends, the diverse trend periods availability at each station might introduce some uncertainty in the results.

We rely on temperature and precipitation data to analyse trends and drivers. While these are statistically and spatially robust, we rely on observational gridded products for these variables in contrast to the point-scale time series of snow water equivalent. This means some stations may have an inaccurate or biased time series of temperature because the gridded data may not be representative of the point scale, and we do not apply a lapse rate correction. Note that a lapse rate correction, however, would not affect the values of trends. For precipitation, gridded datasets are known to have systematic biases (Adam & Lettenmaier, 2003), especially for complex terrain. However, our analysis focuses on

seasonal precipitation and is therefore more robust than if we would use daily precipitation data to extract conclusions. Although some stations do have observed temperature and precipitation time series available (see Chapter 4), gridded datasets have a longer, gap-free and quality controlled record, which reduces the amount of data processing to do. Based on the robustness of temperature and seasonal precipitation trends, and because temperature and precipitation are only used to infer drivers of snow trends, we assume the results would not change by using point-scale observations.

Regarding radiation data used, we assume radiation does not change year to year for one same day. This is different in reality because of interannual variability, and might even change in the long term because of changing cloud coverage due to changes in atmospheric circulation (Sfîcă et al., 2021). Some results might change when using varying radiation, or when using a full energy balance model, but this would increase the complexity of the analysis, reduce the spatial coverage of the study, and is out of the scope for this chapter. A more detailed analysis of radiation and energy balance would provide deeper insights into observed changes and complement this study, but would likely not change the conclusions drawn here.

Limitation are also present in our snowmelt rate trend analysis. Previous studies have found differences in melt rates between different land uses (Pomeroy et al., 2015; Mazzotti et al., 2023), but here we did not focus on factors such as land use or topography. The vast collection of station data from different sources complicates keeping track of such metadata information, and coordinates might not be accurate enough to extract station locations at the resolution that would be needed for land use information such as forest or clearings. However, the analysis focuses on main different between climates and regions. More detailed, small scale analysis are needed to infer other conclusions including land use and topographic factors. Rain-on-snow events have also been hypothesised to affect the melt rate (López-Moreno et al., 2021), but we are not able to investigate this because of the limitations outlined above about precipitation data. Finally, because of limitations in the NH-SWE dataset time series, we are not able to include midwinter melt events in the analysis of snowmelt rate

change, which have been found to be increasing due to warming temperatures (Musselman et al., 2021). While other studies have investigated the average melt rate considering all yearly melt, here we gain insights on the melt season slope of melt, which determines how quickly or slowly the snowpack melts, with its subsequent implications.

## 3.6 Conclusion

In this study, we examine the response of key snowmelt variables to warming using a novel Northern Hemisphere snow water equivalent dataset. Our approach provides the first analysis of changing Northern Hemisphere snowmelt patterns based on actual ground observations of snow.

We observe a wide range of trends in most snow variables. Decreasing snow accumulation dominates over warmer and wetter climates, while colder and drier climates show smaller changes or increasing snow accumulation. Changes in the duration of snow cover are more homogeneous, driven by unequivocal warming trends affecting the beginning and the end of the snow season regardless of snow accumulation trends. Negative trends in precipitation and warming can enhance snow accumulation losses, while increasing precipitation can compensate for warming, leading to no change or increasing snow accumulation.

We demonstrate that slower snowmelt in a warmer world occurs under certain conditions and climates, but this is not the only response of snowmelt rates to rising temperatures. While slower snowmelt is observed for heavily thinned snowpacks that melt significantly earlier in the season, faster snowmelt is observed if warming in the melt season compensates for the decrease in solar radiation. Moreover, increasing snow accumulation likely delays the snowmelt season, with higher temperatures and higher radiation making melt rates faster. However, high spatial variability is observed across climates, regions, and even at the basin scale.

We show that the response of snowmelt to warming is complex to generalise across

climates. Further work is needed to improve our understanding of the response of snowmelt to warming. Detailed analyses, including processes driving snow accumulation and melt, need to be considered when assessing the impact of climate change at smaller regional or catchment scales.



## Chapter Four

# Estimating robust degree-day factors and temperature thresholds for snow modelling across climates

*This chapter is being prepared for submission to a peer-reviewed scientific journal*

Josh Larsen, Bettina Schaepli and Ross Woods have all contributed to the supervision of this PhD chapter.

## Abstract

There are two main limitations to understanding large-scale impacts of environmental change on snow resources, 1) observational snow data at the point scale is highly limited, and 2) extrapolation using models can be challenging due to data availability and performance. This paper seeks to address these limitations using widely available climate network data combined with a temperature-index snow model to derive large-scale estimates of mean snow water equivalent conditions across the Northern Hemisphere. Temperature-index modelling is a common approach for simulating snow accumulation and melt in hydrological models. Many studies use this method because of its simplicity, efficiency, and generally good performance if properly calibrated. The approach relies on three assumptions and parameters, namely the snowfall and snowmelt temperature thresholds and the degree-day factor. At scales beyond single gauged catchments, the estimation of these parameters was difficult to date due to a lack of observations on snowmelt. Using the new Northern Hemisphere snow water equivalent dataset (NH-SWE) presented in this thesis and co-located climate network observations of temperature and precipitation, this work provides the first large-scale evaluation of temperature-index melt model assumptions and parameters across a diverse range of snow climates. Our study reveals the  $0^{\circ}\text{C}$  as snowfall air temperature threshold captures most snowfall events, especially in cold climates, but risks missing 13% of snowfall events, especially in climates hovering at near-freezing temperatures. Similarly, a snowmelt air temperature threshold of  $0^{\circ}\text{C}$  performs well for most daily snowmelt observations but may incorrectly identify the onset of the melt season too early. Estimated degree-day factors converge towards  $3\text{--}5 \text{ mm }^{\circ}\text{C}^{-1} \text{ day}^{-1}$  for deeper snowpack climates ( $> 300 \text{ mm}$ ), but their estimation may be more challenging for colder climates with shallower snowpacks ( $< 300 \text{ mm}$ ), conditions where the degree-day factors have much higher interannual variability. For estimating mean values of seasonal snow onset and snowmelt season onset and mean snow accumulation at a given location, the temperature-index melt model performs consistently well on average despite its simplicity, but challenges may arise due to warm biases in temperature records or solid precipitation undercatch, mainly over higher elevation areas. This study pro-

vides valuable insights into temperature-index melt modelling for large-scale applications, and the results should help refine modelling approaches to enhance our understanding of snowpack responses to global warming.

## 4.1 Introduction

The sensitivity of snow accumulation and melt to warming temperatures is crucial for predicting global hydrological responses to climate change (Nijssen et al., 2001; López-Moreno et al., 2020a). Our understanding of snowpack sensitivity to rising temperatures can be improved by analysing trends in historical observations of snowpacks and climate variables (Fontrodona Bach et al., 2018; Luomaranta et al., 2019; Matiu et al., 2021a), as done in Chapter 3, but direct snow measurements may be limited in time and space (Chapter 1, Chapter 2). Improved spatial and temporal representation of snowpack processes can be obtained by simulating the response of snow accumulation and melt under warming scenarios using models, where we have sufficient information to inform them (Pomeroy et al., 2015; López-Moreno et al., 2021).

There are two main approaches to modelling snow accumulation and melt, 1) solving the full energy balance, or 2) using simpler approaches that relate snowmelt directly to more readily available climate variables such as temperature and potential incoming radiation. The first approach is more physics-based and requires a swathe of meteorological variables as forcing data, such as temperature, precipitation, relative humidity, wind speed, incoming and outgoing short/long-wave radiation, and often information on the snowpack itself (Bartelt & Lehning, 2002; Lehning et al., 2002b, 2002a; Magnusson et al., 2017). The physics-based models use these data to calculate turbulent and sensible heat fluxes at the snow-air interface, which drive the overall energy balance and, therefore, the magnitude of snow accumulation and melt. Although they may be more easily transferable and rely less on calibration, some physical parameters may introduce uncertainty in model simulations (Günther et al., 2020). Physics-based modelling is computationally expensive and feasible at the catchment or hillslope scale if high-resolution observations of the required meteorological forcing are available. However, application at larger spatial scales comes with a reduction in resolution and, therefore a reduction in model performance (Magnusson et al., 2019). This is because coarse, gridded meteorological observations smooth out the effect of topographical complexity on variables such as temperature and precipitation. For snow, the spatial variability on the

ground can be even more significant because of different land use, topography, and snow redistribution processes (Clark et al., 2011; López-Moreno et al., 2013a), which increase the uncertainty of gridded snow products (Mudryk et al., 2015; Liu et al., 2022).

Contrasting with the complexity of physics-based models, temperature-index melt modelling (Lang & Braun, 1990; Rango & Martinec, 1995; Hock, 2003) requires only air temperature and precipitation data as forcing. However, this approach relies on the key assumption that the precipitation phase and snowmelt can uniquely be related to air temperatures. Accordingly, any temperature-index model has at least three parameters: a threshold temperature to separate rainfall from snowfall, a threshold temperature for the onset of snowmelt, and a melt factor to link the amount of melt to the air temperature, generally called the degree-day factor (DDF). In principle, effective values for the threshold temperatures and the degree-day factor need to be estimated or calibrated to achieve comparable performance as physics-based snow models (Essery et al., 2013; Kumar et al., 2013). There are also models of intermediate complexity, known as extended temperature-index models, which include a radiation index based on potential incoming solar radiation in order to better capture the diurnal melt cycles (Hock, 1999; Pellicciotti et al., 2005).

Most snowfall events occur below 0°C (Rohrer & Braun, 1994). However, most contemporary studies derive the rainfall/snowfall threshold from precipitation phase observations or set it to some generally accepted value, which may differ from 0°C. In fact, rain-snow partitioning depends on wet-bulb temperature, and in alpine climates it is well known that snowfall events regularly occur at air temperatures above the freezing point, depending on relative humidity and surface pressure (Jennings et al., 2018b). Inclusion of humidity and wet-bulb temperature to estimate the rain-snow transition has shown improved snow and runoff simulations (Tobin et al., 2012; Zhang et al., 2015; Harpold et al., 2017; Wang et al., 2019), and it has been shown that the choice of precipitation phase method is important for snow modelling performance, especially in the warmer snow climates (Jennings & Molotch, 2019). As the actual precipitation freezing elevation may lie 300-400 metres above the snowfall limit (Fabry & Zawadzki, 1995), a temperature range between 0°C and 2°C is often used

for hydrological modelling over mountain areas (Tobin et al., 2012). However, it is noteworthy that a wide range of studies still use the  $0^{\circ}\text{C}$  threshold for rainfall/snowfall separation. Although it is clear that snowfall can occur above freezing temperatures, how much snowfall occurs above freezing is key to judging the significance of this threshold.

The initiation of snowmelt first depends on cold content, or the energy required for a unit of snowpack to reach  $0^{\circ}\text{C}$ , at which point the latent heat of fusion then needs to be overcome to trigger melt. Deeper snowpacks and colder winters result in a larger energy deficit and, therefore, a later snowmelt onset (Molotch et al., 2009), while warmer climates lead to earlier peak snow water equivalent (SWE) and snowmelt onset (Kapnick & Hall, 2012). Parajuli et al. (2021) found a weak correlation between cumulative air temperature and snowmelt initiation. Instead, Parajuli et al. (2021) observed a strong correlation between snowpack cold content and air temperature. They observed the initiation of the snowmelt season when air temperatures crossed the freezing point. Persistent spring snowfall (around the time of peak snow water equivalent) has also been shown to substantially increase the energy deficit of the snowpack and delay snowmelt (Seligman et al., 2014; Jennings et al., 2018a). At sub-seasonal timescales, larger cold content was linked to a couple of hours delay in the onset of daily snowmelt and a reduction in the daily melt rate, but this had no significant effect on the initiation of the seasonal snowmelt onset (Jennings et al., 2018a). Therefore, an air temperature of  $0^{\circ}\text{C}$  is commonly used as a threshold temperature for snowmelt.

The degree-day factor (DDF), or melt factor (with units  $\text{mm } ^{\circ}\text{C}^{-1} \text{ day}^{-1}$ ), is a lumped linear parameter designed to capture how much melt should be produced per positive degree day. Thus, it combines many factors that could modify the conversion of melt energy and the relationship with air temperature. Although this risks mixing melt mechanisms, degree-day factors have been shown to give good results for mostly the right reasons, namely because in many snow climates, snowmelt is dominated by some combination of incoming short and long-wave radiation (Sicart et al., 2006), as well as heat advected by wind, with average daily air temperatures usually correlating well with these melt energy sources (Ohmura, 2001).

The interpretation and meaning of the DDF also fundamentally depend on the integration period being considered, with the literature varying widely from days to months to multiple years. Degree-day factors vary daily and seasonally with the daily and seasonal variations of incoming radiation (Ismail et al., 2023). This has motivated efforts to include radiation as a component of the degree-day factor (Pellicciotti et al., 2005), but this adds complexity to an otherwise simple approach that is known to work well over longer timescales (Hock, 1999). Lower DDF values indicate that snowmelt magnitude is less sensitive to a change in temperature and the sensible heat flux drives a larger fraction of snowmelt. In comparison, higher DDF values indicate that melt needs to be amplified above what can be explained by the temperature relation alone, usually due to incoming shortwave radiation playing a larger role in driving snowmelt compared to longwave radiation and the sensible heat flux (Hock, 2003; Ismail et al., 2023).

The degree-day factor also varies significantly in space. Reported DDF values for snow in the literature range between 0.5- and 20-mm degree<sup>-1</sup> day<sup>-1</sup>, but typical values range between 2- and 6- mm degree<sup>-1</sup> day<sup>-1</sup> (Braithwaite, 1995; Kane et al., 1997; Lefebvre et al., 2002; Hock, 2003; Braithwaite, 2008; Shea et al., 2009; Asaoka & Kominami, 2013). Spatially, degree-day factors may vary due to slope, aspect, and mountain shading affecting the solar irradiance (Marsh et al., 2012). However, the degree-day factor has been designed and is known to work for larger spatial scales, as more minor scale effects average out (Comola et al., 2015; Ismail et al., 2023).

Temperature-index models are computationally efficient and can be used at larger scales. However, global-scale distributed observations of temperature and precipitation are not available at resolutions higher than 10km, limiting the applications of these models at the global scale for snow research. Furthermore, these models rely heavily on the parameterisation of the temperature thresholds and the degree-day factor. The degree-day factor is typically calibrated to match streamflow observations at the catchment scale (Schaeffli et al., 2005; Bogacki & Ismail, 2016; Riboust et al., 2019). Hingray et al. (2010) calibrated the degree-day factor using the signals of the precipitation phase and timing of snowmelt-

induced runoff. For large-scale studies or use in ungauged catchments, degree-day factors can also be calibrated against snow observations. However, in situ snowmelt observations are usually unavailable, and estimated DDF values can vary depending on the method used to estimate it (Bormann et al., 2014). Calculation of the degree-day factor has only been done at the catchment and glacier scale, with estimations of snow and ice melt (Braithwaite, 1995; Lefebvre et al., 2002; Shea et al., 2009). However, the transferability of a calibrated degree-day factor may be problematic, as it depends on local catchment characteristics.

Empirical estimation of temperature-index model parameters at the global scale is complex and has not been done to date because snow accumulation and melt observations are scarce. However, the availability of recently published station-based snow water equivalent time series over the Northern Hemisphere (Fontrodona-Bach et al., 2023a; Fontrodona-Bach et al., 2023b) now provides the possibility to gain insights into the global variability of the temperature-index melt model parameterisations. In addition, the novel NH-SWE dataset offers the opportunity to test whether a temperature-index model can be robustly used across diverse snow climates.

Here, we use the station-based snow water equivalent time series from the NH-SWE dataset and corresponding co-located climate network station observations of temperature and precipitation to gain insights into the variability of snowfall and snowmelt processes and parameterisations across climates. We then use a temperature-index model to estimate snow water equivalent time series from the point-scale observations of temperature and precipitation, and we evaluate the performance of our temperature-index modelling approach against the NH-SWE dataset. Specifically, we answer the following questions: (i) How do temperature-index model parameters vary across climates? (ii) When and where can we use temperature-index models at the global scale to investigate changing snow resources?

## 4.2 Data

### 4.2.1 Temperature and precipitation data

We use global daily time series of precipitation and temperature from the global historical climatology network dataset (GHCN-Daily, version 3.30-upd-2023080717) (Menne et al., 2012), the European Climate Assessment and Dataset (ECA&D, last access: July 3rd 2023) (Klein Tank et al., 2002), and from the MeteoSwiss data portal IDAWEB (last access: August 17th 2023) (MeteoSwiss, 2023). If the mean daily temperature is unavailable, we use the daily minimum and maximum to compute the daily mean as the middle point between the two. A total of 34,536 stations are initially available.

We apply a simple gap-filling and quality control procedure for the temperature time series, similar to Serreze et al. (1999). For each station, an average daily climatology is calculated, and we remove values that are more or less than three times the standard deviation of the daily temperature climatology, which is a conservative estimate. We also remove temperatures above or below  $\pm 55$  °C. For gap sizes of one day, we use linear interpolation. For gap sizes of two, we fill the gap with the corresponding neighbour. For larger gap sizes, we fill the gap with the climatological mean. We only fill gaps if they represent less than 20% of the climatological winter. The climatological winter is defined as the period with temperatures lower than the mean temperature minus two times the standard deviation of daily temperatures. We do not gap-fill the precipitation time series, but we remove daily precipitation values higher than 176 mm, considered outliers. This value corresponds to the 99.99th percentile of all daily precipitation observations over all gathered precipitation time series. We select stations with at least 7 years of gap-free data from 1950 to 2023, although the time period available does not need to be continuous. A total of 14,881 stations with temperature and precipitation time series are still available.

## 4.2.2 Snow water equivalent data

We use the Northern Hemisphere daily snow water equivalent time series from the NH-SWE dataset (Fontrodona-Bach et al., 2023a; Fontrodona-Bach et al., 2023b). A total of 11,071 quality-controlled and gap-filled stations are initially available in the dataset. We match the locations of the stations in the NH-SWE dataset with the locations of the stations with temperature and precipitation time series. We select those that are closer than  $0.01^\circ$  latitude and  $0.01^\circ$  longitude (ca. 1 km distance) between one another, with an elevation difference not larger than 10 meters, and which contain at least 7 years of overlapping gap-free data with the temperature and precipitation time series. A total of 5,366 stations from the NH-SWE dataset are matched with 4,731 stations from the GHCN-d, 601 stations from ECA&D, and 34 stations from MeteoSwiss (Figure C.1). This results in a large range of stations across elevation, latitude and longitude gradients in the Northern Hemisphere (Figure 4.1). As the NH-SWE data contains only stations with at least 40 days of continuous snow cover on average, warmer climates and ephemeral snow climates are filtered out.

## 4.3 Methods

### 4.3.1 Snow season and climate indices

We use the same snow season definitions as in Chapter 2 (Figure 2.3) (Fontrodona-Bach et al., 2023a): namely that the snow season is the longest period with continuous snow cover in a year; the onset of the accumulation season is the starting day of the snow season and lasts until the date of peak SWE; the peak snow water equivalent (peak SWE) is the highest snow water equivalent value in the snow season; the onset of the melt season is the first day with a decrease in snow water equivalent after peak SWE; the melt season lasts until the end of the snow season, which is the first day with zero snow water equivalent after peak SWE; snowmelt days are defined as those days with a decrease in SWE; the snowmelt rate is the

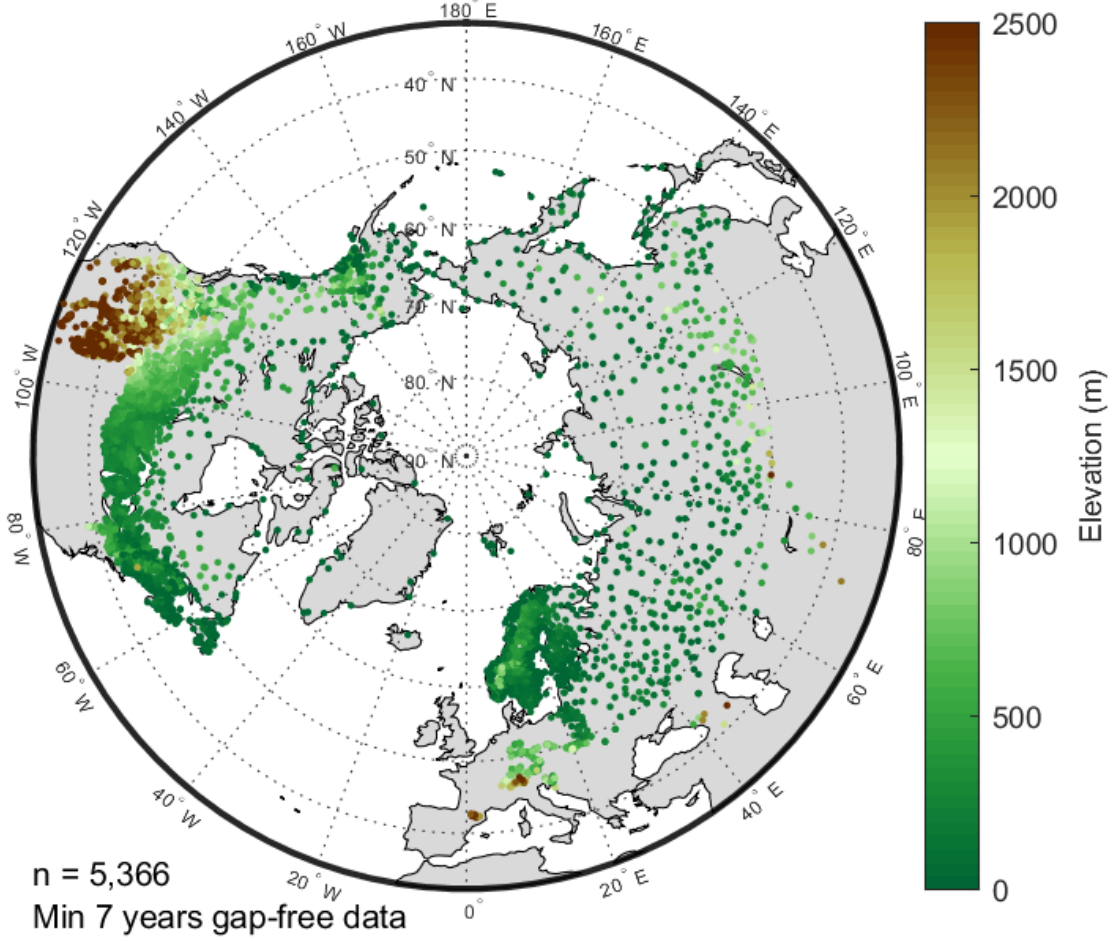


**Figure 4.1:** Matched NH-SWE stations with GHCNd/ECA&D/MeteoSwiss stations, and their elevation.

sum of all SWE decreases in the melt season divided by the number of snowmelt days.

We use two temperature-based indices from Woods (2009) to define the characteristic temperature climate of the stations, namely the mean annual temperature ( $\bar{T}$ ) and the amplitude of the annual cycle of temperature ( $\Delta T$ ), which is a measure for continentality. We also define the melt season temperature as the mean temperature in the snowmelt season. Additionally, we compute for each station the mean annual sum of precipitation occurring during temperatures below  $0^{\circ}\text{C}$ .

### 4.3.2 Estimating temperature-index model parameters

We estimate values for the three key parameters of a minimum temperature-index model for all snow stations in our study: the snowfall temperature threshold, the snowmelt temperature threshold, and the degree-day factor. However, the snow water equivalent time series from the NH-SWE dataset are modelled based on snow depth observations. Therefore, they are not able to distinguish whether an increase in SWE was actual snowfall, or whether a decrease in SWE was actual snowmelt or an alternative loss mechanism such as sublimation or snow redistribution by wind. Therefore, from here on, we refer to SWE increases and SWE decreases whenever there is a change in daily SWE ( $\Delta\text{SWE}_d$ ) (and not about snowfall or snowmelt).

For each weather station, we compute the distribution of daily temperatures on days when there is an increase in daily SWE and set the snowfall temperature threshold equal to the 80th percentile (i.e. 80% of SWE increases occur at or below this temperature threshold). Based on these snowfall thresholds derived from observed data, we build a simple multilinear regression model that predicts the snowfall threshold based on climate variables. We use these predicted parameters to run the third set of temperature-index model simulations (see section 4.3.3).

In analogy, the snowmelt temperature threshold could be estimated based on the distribution of observed daily temperatures on days when there is a decrease in SWE. However, such distribution is not useful to robustly estimate a minimum threshold temperature for snowmelt, since as already mentioned, other loss mechanisms could occur. Therefore, we do not predict the snowmelt temperature threshold based on climate variables and focus our analysis on the temperatures at the time of SWE decrease and the processes they may represent. This analysis does not provide an alternative method to estimate the snowmelt temperature threshold but is useful to gain insights into temperature-index modelling limitations (e.g. where we can apply the 0°C threshold with confidence and where not), as well as NH-SWE data limitations (e.g. not being able to distinguish between snowmelt and

sublimation).

To estimate the degree-day factor, we divide the daily absolute magnitude of SWE decreases by the corresponding observed daily temperature to obtain a daily degree-day factor in  $\text{mm } ^\circ\text{C}^{-1} \text{ day}^{-1}$ . Given the high variability in this value and the focus on integrating over longer timescales, we define the annual degree-day factor as the median of all daily degree-day factors. We also compute the median degree-day factor for SWE decreases during the snowmelt season only (called melt season DDF). We define the interannual variability of the degree-day factors as the standard deviation of the annual melt season degree-day factors. We build a simple multilinear regression model that predicts the median DDF based on climate variables. We use these predicted DDF parameters to run the third set of temperature-index model simulations (see section 4.3.3).

### 4.3.3 Temperature-index model simulations and performance

To assess the performance of the estimated parameters, we simulate daily time series of snow water equivalent using the daily time series of temperature and precipitation alone, without assimilating any NH-SWE data. We use a simple temperature-index model, where SWE (denoted as  $H$ ) at time step  $t$  is as follows:

$$\frac{dH(t)}{dt} = A(t) - M(t) \quad (4.1)$$

which is implemented with an explicit scheme, i.e.:

$$H_t = H_{t-1} + A_{t-1} - M_{t-1} \quad (4.2)$$

where  $A_{t-1}$  is the snow accumulation and  $M_{t-1}$  the snow melt of the preceding day. The snow accumulation (denoted as  $A$ ) at time  $t$  is computed as follows:

$$A_t = \begin{cases} P_t & \text{if } T_t \leq T_a \\ 0 & \text{if } T_t > T_a \end{cases} \quad (4.3)$$

where  $P_t$  is the daily sum of precipitation,  $T_a$  is the threshold temperature for snowfall, and  $T_t$  is the daily temperature. The snowmelt (denoted as  $M$ ) at time  $t$  is computed as follows:

$$M_t = \begin{cases} \alpha \times (T_t - T_m) & \text{if } T_t \geq T_m \\ 0 & \text{if } T_t < T_m \end{cases} \quad (4.4)$$

where  $\alpha$  is the degree-day factor, which we assume to be constant in time, and  $T_m$  is the threshold temperature for snowmelt. Snowmelt  $M_t$  cannot exceed available snow, i.e.  $M_t \leq H_t + A_t$ ;

We simulate three daily snow water equivalent time series for each available station, with three different parameter sets. An overview of the workflow to obtain the three parameter sets and to set up the model simulations is shown in Figure 4.2, and the parameter values used are shown in Table 4.1. The first simulation is run with a unique parameter set for all stations across the Northern Hemisphere, where the unique degree-day factor corresponds to the median of all estimated DDFs across the Northern Hemisphere, and the unique snowfall temperature threshold is set to 0.5°C. The second simulation is run with the estimated parameters based on the NH-SWE station time series, for each station individually, as described in section 4.3.2. The third simulation is run with the simulated parameters based on the multiple linear regression models built for snowfall threshold and degree-day factor (see sections 4.4.1 and 4.4.1). For all three simulations, the threshold temperature for snowmelt is set to 0°C.

We evaluate the performance of the model for the following snow variables: accumulation season onset, snowmelt season onset, end of the snow season, peak SWE, number of snowmelt days and snowmelt rate. For snow season timing variables, we evaluate the per-

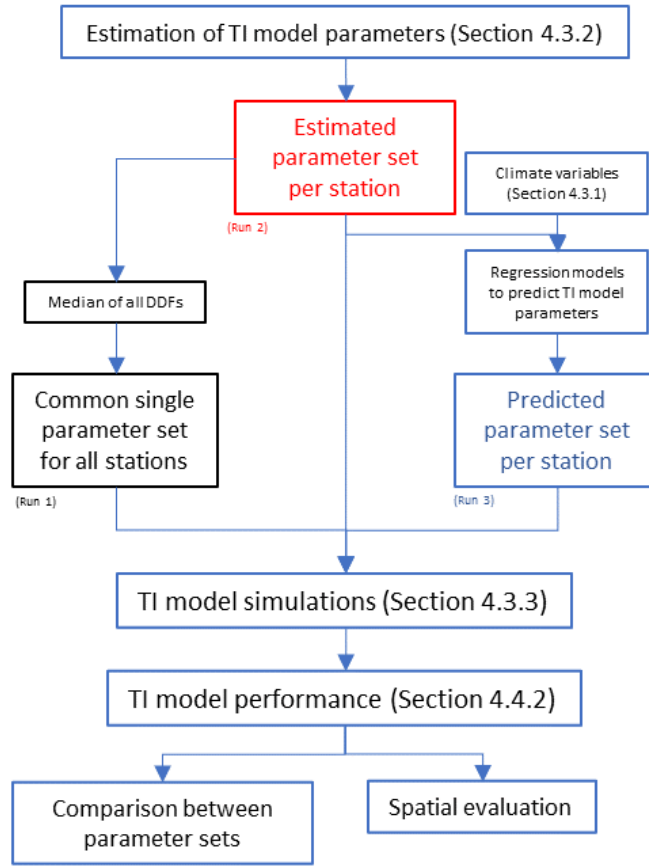


**Figure 4.2:** Flow diagram describing the temperature-index model simulations and the parameter sets used.

**Table 4.1:** Parameter values used for the three sets temperature-index model simulations.

| Parameter set                               | Snowfall threshold ( $^{\circ}\text{C}$ )            | Snowmelt threshold ( $^{\circ}\text{C}$ ) | DDF ( $\text{mm } ^{\circ}\text{C}^{-1} \text{ day}^{-1}$ ) |
|---------------------------------------------|------------------------------------------------------|-------------------------------------------|-------------------------------------------------------------|
| Single common parameter set (run 1)         | 0.5                                                  | 0                                         | 3.57                                                        |
| Estimated parameter set per station (run 2) | 80th percentile of snowfall temperature observations | 0                                         | Median DDF at each station                                  |
| Simulated parameter set per station (run 3) | Equation 4.5                                         | 0                                         | Equation 4.6                                                |

formance based on the error in days, where a negative value means too early, and a positive value means too late. For snow season magnitude variables, we compute the relative percent error by subtracting observed from modelled and dividing by the observed value. Instead of typically used performance metrics such as the root-mean-square error or the bias, we use these variables because they quantify features relevant to our understanding of snow hydrology and provide a more comprehensive analysis of SWE time series performance.

## 4.4 Results

### 4.4.1 Estimating temperature index model parameters

#### Snowfall temperature threshold

For interpreting snowfall temperature thresholds, we find 87% of all days with an increase in SWE (daily  $\Delta\text{SWE} > 0$ ) occur at temperatures below freezing ( $0^\circ\text{C}$ ), while only 13% occur at temperatures above freezing (Figure 4.3a). There is a minor tail of data at or above  $5^\circ\text{C}$ , which may be feasible in extreme cases where the daily temperature cycle with negative excursions still has a positive daily mean, or where humidity is extremely low, or some combination of both. If we filter out small SWE increases ( $> 5$  mm), the range of snowfall temperature contracts considerably, with a large decrease in the frequency of SWE increases at very cold temperatures, suggesting small events dominate these very low temperatures. This is supported by Figure 4.3b, which shows the magnitude of events is also limited at very low temperatures ( $< -20^\circ\text{C}$ ), physically consistent with a considerably diminished moisture-carrying capacity for the atmosphere at such low temperatures. Assuming SWE increases are a good proxy for snowfall, the largest snowfall events occur between  $-7^\circ\text{C}$  and  $-2^\circ\text{C}$ . Snowfall events may still be large at  $+1^\circ\text{C}$ , but they quickly diminish for temperatures above this. In Figure 4.3c, we compare observed precipitation events above and below  $0^\circ\text{C}$  from the climate network stations with the daily changes in the SWE time series from the NH-SWE dataset.

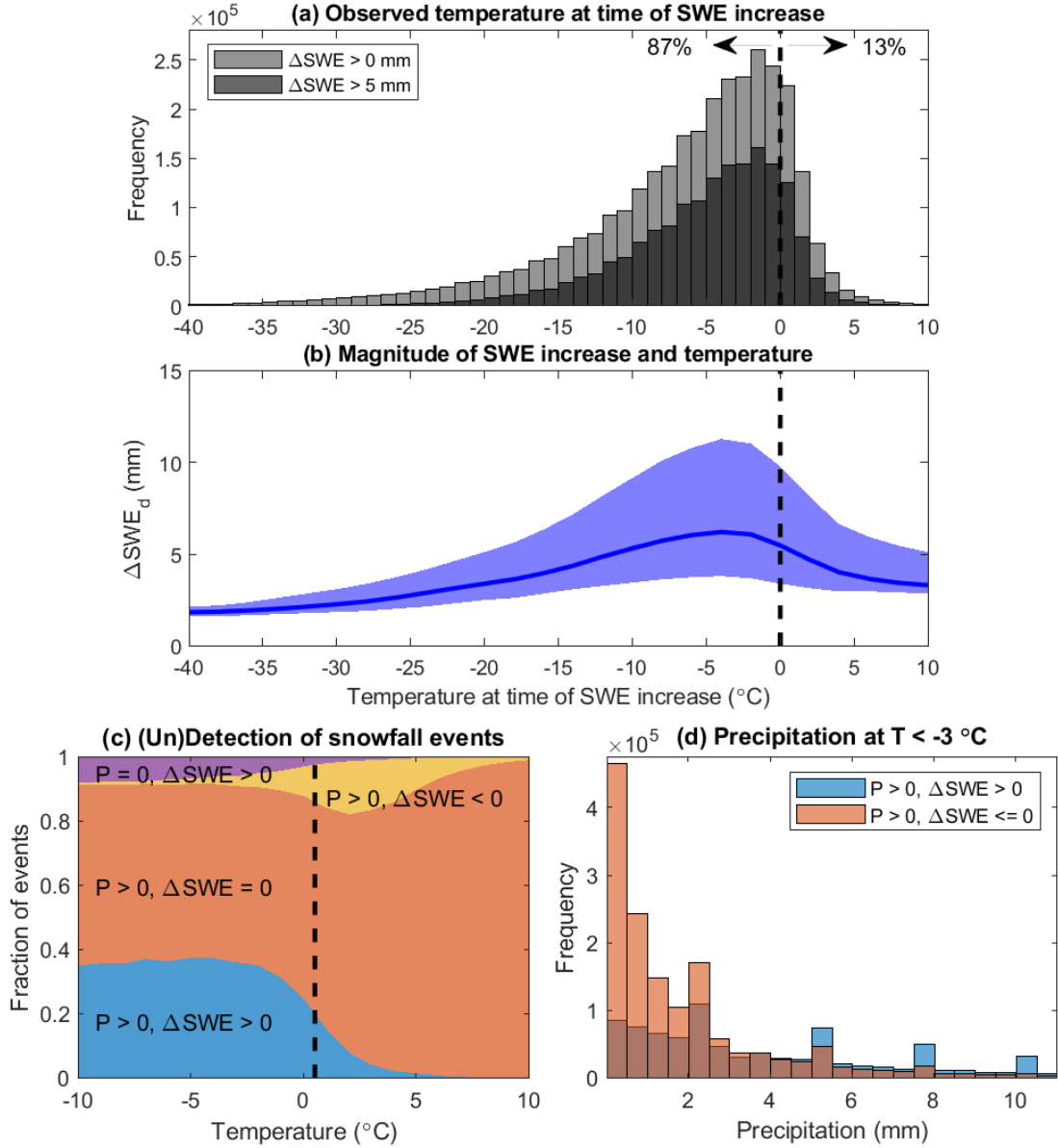


**Figure 4.3:** Analysis of observed temperatures at the time of observed SWE increases. (a) Distribution of daily temperatures at the time of an increase in daily SWE in the NH-SWE dataset for all increases and for increases higher than 5 mm only. (b) The magnitude of SWE increases and daily temperatures. Solid line shows the median, and shaded area the interquartile range, for each  $2^{\circ}\text{C}$  bin between  $-40^{\circ}\text{C}$  and  $+14^{\circ}\text{C}$ . (c) Distribution of events linking precipitation, snow accumulation and temperatures. For each  $1^{\circ}\text{C}$  bin between  $-10^{\circ}\text{C}$  and  $+10^{\circ}\text{C}$ , each event is coloured based on its fraction of occurrence. (d) Distribution of snowfall magnitudes (precipitation at a temperature below  $-3^{\circ}\text{C}$ ) detected (blue) and not detected (orange) by the NH-SWE time series.

A summary of this detailed comparison is provided in Table 4.2:

**Table 4.2:** Summary and description of causes of events shown in Figure 4.3c. Note that P refers to precipitation observed from the weather station time series, while  $\Delta\text{SWE}$  refers to the snow water equivalent time series from the NH-SWE dataset. Colours in event column refer to Figure 4.3c

| Event                                           | Meaning                                           | Suggested cause at $T < 0^\circ\text{C}$                                                                                                                                    | Suggested cause at $T > 0^\circ\text{C}$                                                                                                |
|-------------------------------------------------|---------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------|
| $P = 0$ ,<br>$\Delta\text{SWE} > 0$<br>(purple) | No recorded precipitation, but an increase in SWE | It occurs at low temperatures and decreases at higher temperatures. Possibly precipitation undercatch                                                                       | Occurrence uncommon. Possibly precipitation undercatch                                                                                  |
| $P > 0$ ,<br>$\Delta\text{SWE} < 0$<br>(yellow) | Precipitation recorded, but a decrease in SWE     | Occurrence uncommon at low T, increases close to $0^\circ\text{C}$ . Likely rain on snow                                                                                    | Highest occurrence at $1^\circ\text{C}$ to $4^\circ\text{C}$ . Very likely rain on snow                                                 |
| $P > 0$ ,<br>$\Delta\text{SWE} = 0$<br>(orange) | Precipitation recorded, but no change in SWE      | Largest fractions of events. Possibly insufficient precipitation to record an increase in snow depth (Fig. 4.3c). Likely liquid precipitation if close to $0^\circ\text{C}$ | Becomes 100% of events at $T = 10^\circ\text{C}$ . Very likely liquid precipitation or insufficient to record an increase in snow depth |
| $P > 0$ ,<br>$\Delta\text{SWE} > 0$<br>(blue)   | Precipitation recorded, and an increase in SWE    | Very likely actual snowfall events                                                                                                                                          | Very likely actual snowfall events. Becomes marginal as temperature increases                                                           |

In summary, Figure 4.3c suggests some mismatches between what should be expected based on temperature and precipitation data and what is observed on snow water equivalent time series from the NH-SWE dataset. At  $0^\circ\text{C}$ , around 45% of precipitation events do not record an increase in SWE, and only around 37% of precipitation events have a corresponding increase in SWE. Figure 4.3d suggests that precipitation events  $< 0^\circ\text{C}$  that do not record an increase in SWE are small events (mostly  $< 3\text{ mm}$ ) and thus are probably insufficient to

record an increase in snow depth and SWE. In contrast, precipitation events below  $0^{\circ}\text{C}$  that do record an increase in SWE are more uniformly distributed, with fewer small precipitation events and more large precipitation events (Figure 4.3d). It is also noteworthy that 5 to 10% of events  $< 0^{\circ}\text{C}$  record no precipitation but have an increase in SWE, suggesting precipitation undercatch. Close to 20% of events between  $1^{\circ}\text{C}$  and  $4^{\circ}\text{C}$  suggest a large fraction of rain on snow events that drive a decrease in SWE.

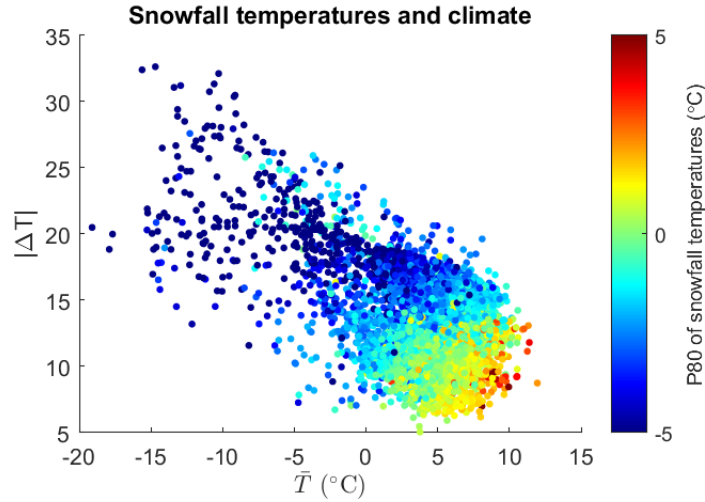


**Figure 4.4:** Snowfall temperature thresholds and climate variables (one point per station).  $\Delta T$  is the temperature amplitude of the climate (see section 4.3.1), and  $\bar{T}$  is the mean temperature climate. Colours show the 80th percentile of snowfall temperatures at each of the sites.

The snowfall temperature threshold also varies across climates (Figure 4.4). Very cold climates (high  $\Delta T$  and low  $\bar{T}$ ) have most snowfall events at temperatures well below  $0^{\circ}\text{C}$ , but more temperate climates have a larger fraction of snowfall events at daily temperatures between  $0^{\circ}\text{C}$  and  $5^{\circ}\text{C}$ . While increasing the temperature threshold for snowfall might capture more of those above-freezing snowfall events, it also increases the false positive rate, i.e. recording actual liquid precipitation as snowfall.

We build a multilinear regression model (Equation 4.5) to predict the threshold temperature for snowfall based on  $\bar{T}$  and  $\Delta T$  (as in Figure 4.4), which explains 70% of the variability in the threshold. The model equation reads as follows:

$$T_a = 0.199 \times \bar{T} - 0.361 \times A_t + 2.512 \quad (4.5)$$

where  $T_a$  is the temperature threshold for snowfall,  $\bar{T}$  is the mean annual temperature of a station, and  $A_t$  ( $\Delta T$ ) is the amplitude of the annual temperature cycle at a station. We use these predicted snowfall thresholds for the third set of temperature-index model simulations (see Figure 4.2). However, we set the minimum threshold value to  $0^\circ\text{C}$ , as the model predicts snowfall thresholds below  $0^\circ\text{C}$  for the colder climates. This is because the 80th percentile of the distribution of snowfall temperatures is below  $0^\circ\text{C}$  for the colder climates, which receive a larger fraction of snowfall below  $0^\circ\text{C}$ . Note that the correlation between  $\bar{T}$  and  $\Delta T$  in Figure 4.4 holds across latitudes and longitudes but does not hold across elevation gradients in the European Alps (Figure C.2).

### **Snowmelt temperature threshold**

Figure 4.5a shows that 77% of daily SWE decreases in the NH-SWE dataset occur at daily temperatures above  $0^\circ\text{C}$  and 23% at temperatures below  $0^\circ\text{C}$ . While snowmelt should only be expected above freezing, it is not unreasonable that snowmelt may occur at temperatures close to but below  $0^\circ\text{C}$ , as the mean daily temperature may not capture parts of the day that could be  $> 0^\circ\text{C}$ . Figure 4.5b shows that the magnitude of SWE decreases is increasing with temperatures  $> 0^\circ\text{C}$ . However, below freezing, SWE decreases have both low frequency and magnitude. This suggests that  $< 0^\circ\text{C}$ , SWE decreases might not be snowmelt but other processes like sublimation, snow redistribution, and errors in either the temperature data or errors in the NH-SWE dataset. Melt simulation errors in the NH-SWE dataset can occur if a sharp decrease in snow depth caused by snow compaction, densification, or even sublimation is larger than the model parameterisation for these processes and is, therefore, incorrectly interpreted by the model as snowmelt. However, Figure 4.5c shows the frequency of days with decreasing SWE events is rare below  $-5^\circ\text{C}$  compared to the frequency of days with SWE increasing or no change in SWE. Furthermore, between  $-5^\circ\text{C}$  and  $-1^\circ\text{C}$  it is around 6 times more likely to observe no change in SWE than a decrease in SWE. For temperatures higher

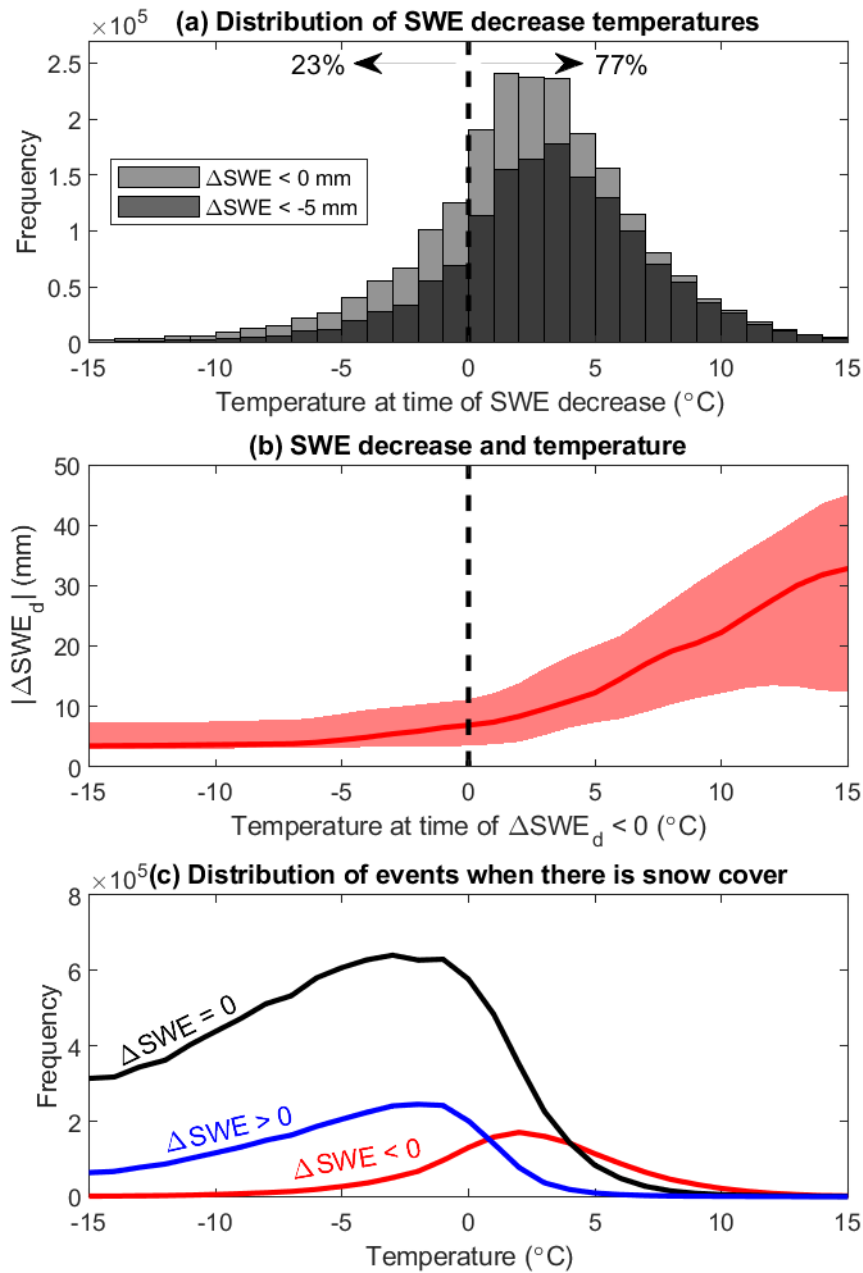


**Figure 4.5:** Analysis of observed temperatures at the time of observed SWE decreases. (a) Distribution of daily temperatures at the time of a decrease in daily SWE in the NH-SWE dataset for all daily decreases and for decreases higher than 5 mm only. (b) The magnitude of SWE decrease and daily temperatures. Solid line shows the median, and shading shows the interquartile range, for each 1°C bin between -15°C and +15°C. (c) Distribution of daily change in SWE events (increase, decrease, or no change) linked to temperature. Distribution lines based on histogram bins every 1°C bin between -15°C and +15°C.

than  $-1^{\circ}\text{C}$ , the frequency of decreasing SWE increases as the frequency of no change in SWE decreases sharply, suggesting it is very likely to have a decrease in SWE for temperatures at or above freezing. Despite the limitations, if we make the broad assumption that SWE increases are overall a good proxy for snowfall and that SWE decreases are overall a good proxy for snowmelt, it is interesting to note that the distribution of the daily frequency of these events with respect to temperature is largely consistent with what one would expect if this broad assumption were accurate (Fig 4c). Specifically, the frequency of daily SWE decreases begins to dominate over SWE increases at a temperature of  $1^{\circ}\text{C}$ , showing that at  $0^{\circ}\text{C}$  it is more likely to have snowfall events or no change in SWE, and at  $1^{\circ}\text{C}$  it is more likely to have snowmelt events.

### Degree day factor

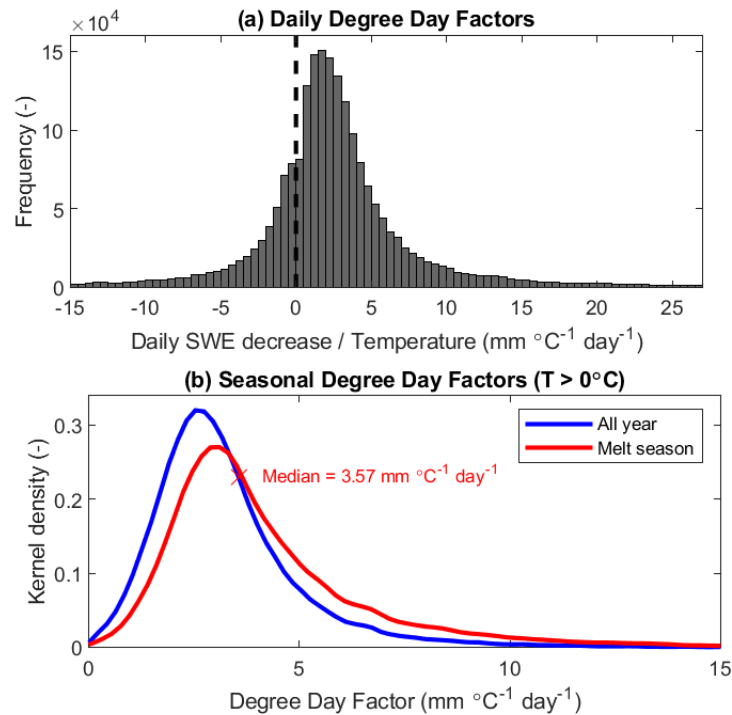


**Figure 4.6:** Estimated degree-day factors. (a) Distribution of all DDFs observed (all daily data considered). (b) Median of daily DDFs for all year and for the melt season only (one value per station-year), considering only days with positive temperatures.

Daily degree-day factors (DDFs) show a wide distribution of possible values but show

a peak in a heavy-tailed distribution between 1 and 3 mm °C<sup>-1</sup> day<sup>-1</sup> (Figure 4.6a). Two considerations are important to make: 1) the possibility of having SWE decreases at daily temperatures very close to 0°C (as explained in section 4.1.2) means that computed daily DDFs may become very large, up to infinite, due to dividing by zero. 2) SWE decreases during negative temperatures observed in Figure 4.5 result in the estimation of negative degree-day factors, which are not physically plausible. We therefore remove values higher than 20 mm °C<sup>-1</sup> day<sup>-1</sup> (4% of all data), as these are rare in the literature (Asaoka & Kominami, 2013), and we remove negative values (23% of all data). After removing these values, we compute the median of all daily DDFs for each station and year, and for each station and melt season (Figure 4.6b). The median of all annual DDFs (2.93 mm °C<sup>-1</sup> day<sup>-1</sup>) is slightly lower than for the melt season only (3.57 mm °C<sup>-1</sup> day<sup>-1</sup>). This is likely because SWE decrease during the accumulation season typically occurs at lower radiation, and therefore degree-day factors (and melt rates) are lower. We use the median melt season DDF value for the first set of model simulations with a single common parameter set for all stations (see section 3.3).

Degree day factors and their variability vary with melt season temperatures (Figure 4.7). When comparing the median melt season degree-day factor for each year with the mean melt season temperature for each year, we can see that the range of possible degree-day factors is very large at mean melt season temperatures close to 0°C (Figure 4.7a). It is also important to note the low density of points below freezing, and the very high density of points between 0°C and 5°C, and between 3 and 5 mm °C<sup>-1</sup> day<sup>-1</sup>. The DDF range converges towards values between 3 and 5 mm °C<sup>-1</sup> day<sup>-1</sup> with increasing melt season temperature. In Figure 4.7b, a mean value for each station is shown, with the colour indicating interannual variability. Only 17% of stations have mean melt season temperatures below freezing. For these stations, shortwave radiation is likely a bigger component of the energy balance and therefore DDFs are higher. Higher DDFs occur mainly for the shallower (< 300 mm) snowpacks (Figure 4.8a). Their interannual variability is also very high, further limiting the predictive capacity of temperature-index models for these conditions. In contrast, 83% of stations have positive mean melt season temperatures and lower DDFs, converging

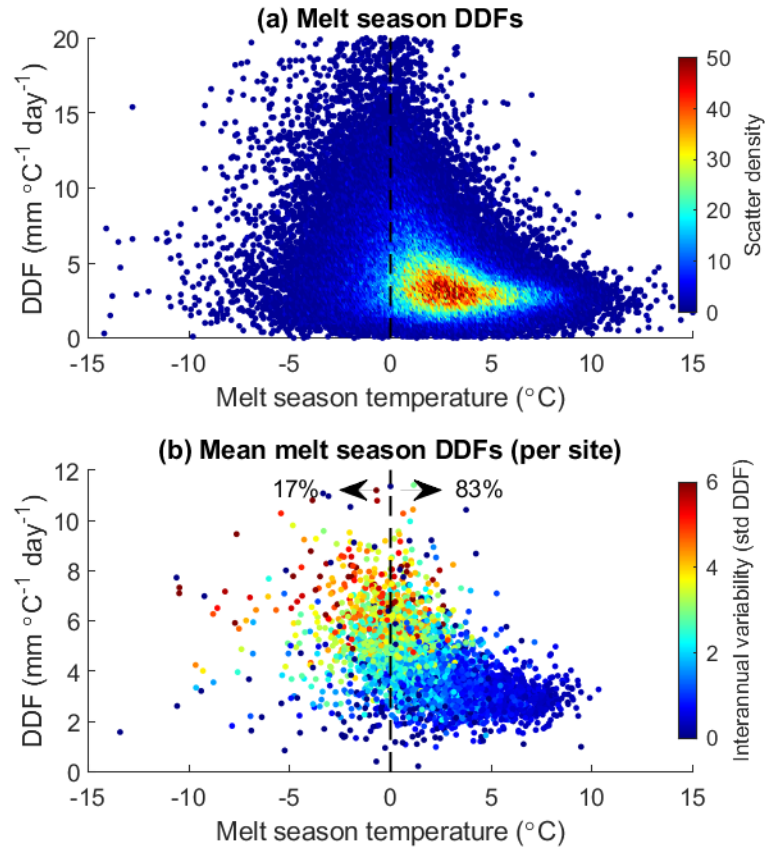


**Figure 4.7:** Degree day factors, temperature, and variability. (a) Median melt season DDF and mean melt season temperatures (all station-years). (b) Per station, mean DDF, mean melt season temperature, and interannual variability of the DDF.

towards 3 and 5 mm °C<sup>-1</sup> day<sup>-1</sup> and with far lower interannual variability.

We explore the variability across stations and across years in the mean melt season degree-day factor alongside climate variables in Figure 4.8. The range of possible DDFs is very wide, from 1 to 12 mm °C<sup>-1</sup> day<sup>-1</sup>, for climates with low annual snowfall (< 200 mm) but converges towards 3-4.5 mm °C<sup>-1</sup> day<sup>-1</sup> for stations with annual snowfall above 400 mm/y (Figure 4.8a). This convergence is also observed when comparing the DDF and elevation (Figure C.4), as these deeper snowpacks are usually located in higher elevation regions. Figure 4.8b shows that the mean DDF and its interannual variability both increase weakly with  $\Delta T$ ; this is mostly driven by colder, more continental climates, with low precipitation, shallow snow, and late melt onset having higher DDF values, likely due to the dominance of sublimation losses over melt.

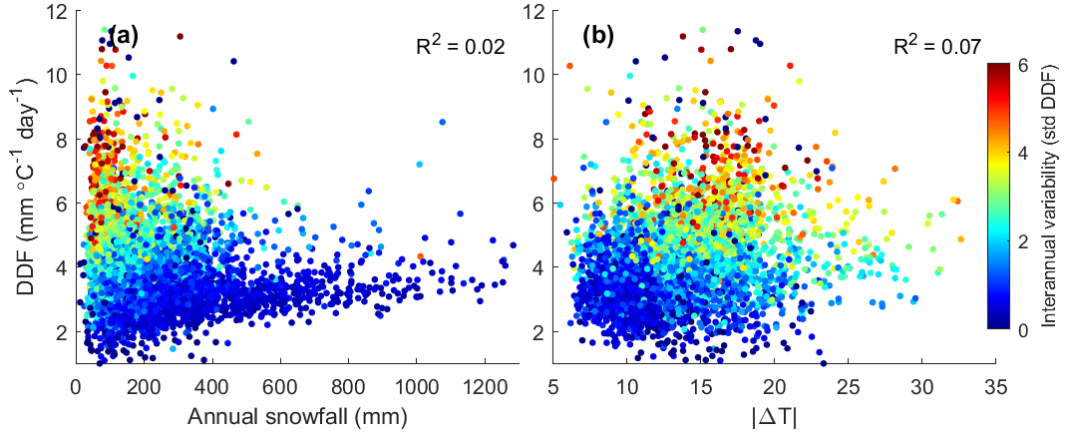


**Figure 4.8:** Climatic variability of the mean melt season DDF. (a) Melt season DDF and mean annual snowfall for each station; (b) Melt season DDF and yearly amplitude of the temperature cycle. Both a and b are coloured by the interannual variability of the melt season DDF.

In Figure 4.9, we show the spatial variability of mean annual DDFs and their interannual variability compared to annual snowfall and  $\Delta T$ . The convergence of DDF values to  $3\text{--}4 \text{ mm } ^\circ\text{C}^{-1} \text{ day}^{-1}$  (Figure 4.9a) clearly occurs over the areas with higher annual snowfall (Figure 4.9b), and the more maritime and temperate climates (Figure 4.9d), namely the mountain areas of Western North America, the European Alps, the Pyrenees and Scandinavia, which also show the lowest interannual variability values (Figure 4.9b). Outside these deeper snowpack areas, over colder climates with shallower snowpacks such as continental North America and Eurasia (Figure 4.9c,d), it is clear that degree-day factors are higher, spatially more variable (Figure 4.9a), and show a higher interannual variability (Figure 4.9b).

Because of the clear difference in DDF ranges between shallow and deeper snowpacks, we analyse the variability of the degree-day factor separately for stations with annual snowfall below and above 300 mm, as this is the value above which DDFs converge in Figure 4.10. It is noteworthy that for shallower snowpacks the interannual variability of the DDF is higher than the spatial variability of the DDF across climates (Figure 4.10a). In contrast, for the deeper snowpacks the variabilities are lower in general, and the interannual variability is slightly lower than spatial variability (Figure 4.10b).

Even though considerable spread exists between DDFs and climate variables (Figure

4.8), this does not include explicit spatial information. Therefore, we build a multiple linear regression model to estimate the degree-day factor based on latitude, elevation, and  $\bar{T}$  ( $R^2 = 0.16$ ) (Equation 4.6). The model equation reads as follows:

$$\alpha = 9.6 - 0.00083 \times e - 0.0868 \times L - 0.117 \times \bar{T} \quad (4.6)$$

where  $\alpha$  is the degree-day factor in  $^{\circ}\text{C}^{-1} \text{ day}^{-1}$ ,  $e$  the elevation in metres,  $L$  the latitude in decimal degrees, and  $\bar{T}$  the mean annual temperature in  $^{\circ}\text{C}$ . Our degree-day factor simulation model shows that degree-day factors decrease with elevation, opposite to what Hock (2003) suggested, probably because of the convergence towards lower DDF values ( $3\text{--}5 \text{ }^{\circ}\text{C}^{-1} \text{ day}^{-1}$ ) that our results show for deeper snowpacks, which are typical at higher elevations. Similarly, the degree-day factor also decreases with increasing latitude. The simulated degree-day factor increases with lower mean temperatures as the shortwave radiation component for melt becomes more important. We use these predicted degree-day factors, together with the predicted snowfall thresholds from Equation 4.5 for the third set of temperature-index model simulations (see Figure 4.2).

#### 4.4.2 Temperature-index model performance

The performance of the temperature-index model is very good considering the simplicity of the model and that parameters were estimated (see Figure 4.2) but not calibrated to improve performance (Figure 4.11). Importantly, all snow season timing variables show median errors close to zero days, and interquartile ranges do not exceed a 15 day error (Figure 4.11a,b,c). Especially excellent is the performance of the timing of the accumulation season onset, where even the whiskers do not exceed a 15 day error for any of the three sets of model simulations. Regarding the snowmelt season onset, all three simulations show a median of 4 days too early in timing. However, it must be noted that the validation data (the NH-SWE dataset) showed an average model delay of 2 days in the onset of the melt season (Fontrodona-Bach et al., 2023a) (Figure 2.6 in Chapter 2), which suggests that on balance, the median error in Figure

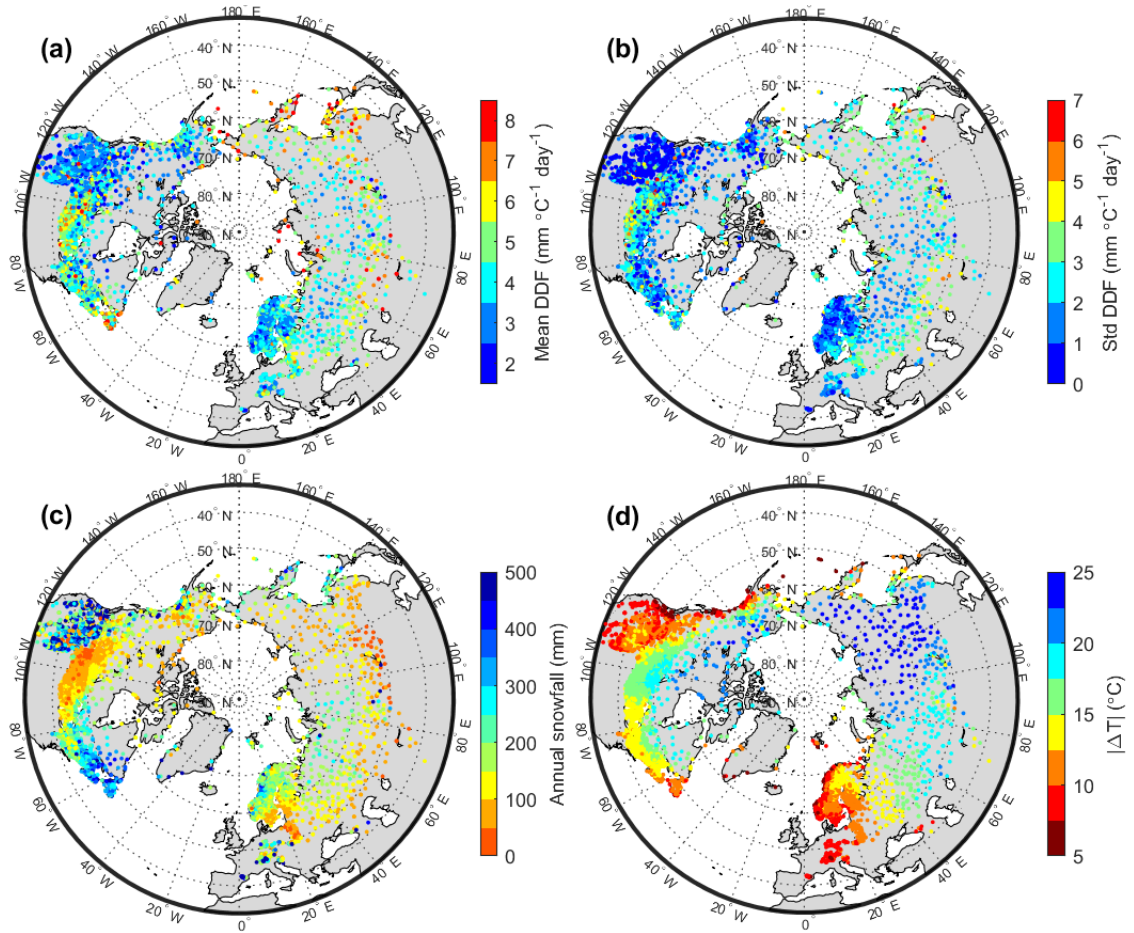


**Figure 4.9:** Spatial distribution of the DDF (a), its interannual variability (b), annual snowfall (c), and the amplitude of temperature  $\Delta T$  (d).

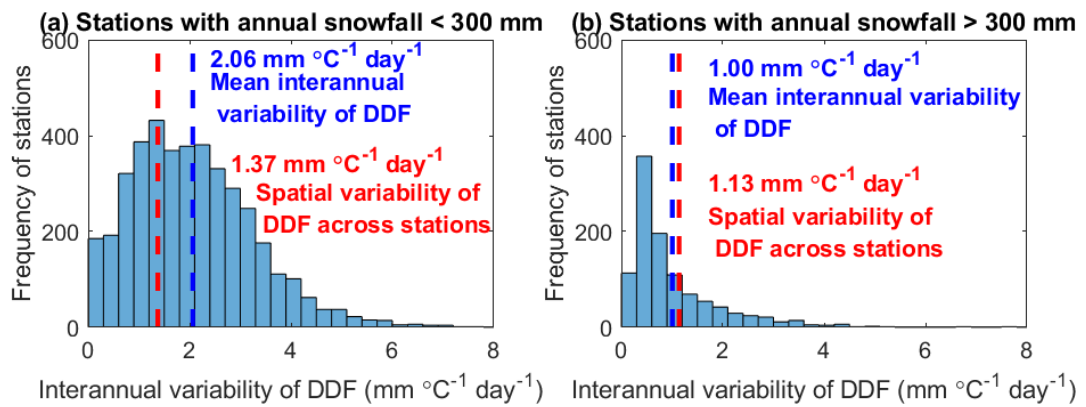


**Figure 4.10:** Distribution of the interannual variability and spatial variability of the degree-day factor. For (a) shallow ( $< 300$  mm) and (b) deep ( $> 300$  mm) snow climates.

4.11b may actually be closer to zero. Given the snowmelt season onset depends mostly on the snowmelt threshold temperature, which is the same for all simulations, it is unsurprising that all three simulations show an almost equal performance. Differences between the simulations are more visible but still minor for the end of the snow season performance. This is because of the dependence on the degree-day factor, which is estimated differently in all three sets of simulations. The unique parameter set has a better median error, likely because the degree-day factor used is the median of all stations. The estimated parameter set has a narrower IQR, as values are estimated from observations at each station individually. Nevertheless, the predicted parameter set has a comparable, only slightly worse performance.

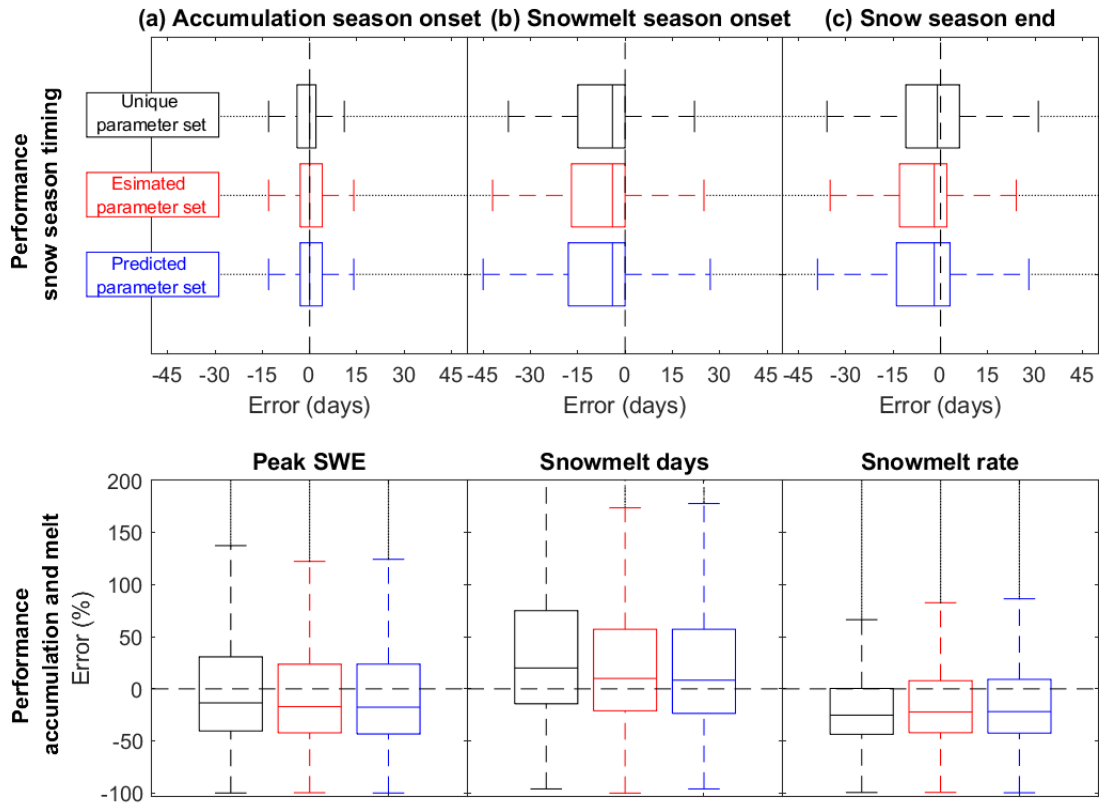


**Figure 4.11:** Temperature index model performance. The three sets of model simulations are shown in each boxplot, namely the unique parameter set for all stations, the estimated parameter set for each station, and the predicted parameter set for each station (see section 3.3). Boxes are built with all station-years in the analysis. Top row: performance of the three snow variables related to timing of the snow season. Bottom row: performance of the three snow variables related to magnitudes of the snow season. Note that outliers are shown as points outside the box whiskers.

Regarding snow season magnitude variables, the temperature-index model shows good median errors across variables and parameter sets, but also has large interquartile ranges and whiskers, and many outliers (Figure 4.11d,e,f). Interquartile ranges for peak SWE are within 45% error, and medians are around -10% error, showing a negative bias in the peak of snow accumulation. No significant differences arise between parameters sets for peak SWE, given this is mostly dependent on the snowfall threshold temperature. For snowmelt days, the estimated and predicted parameter sets have a similar median of 10% and 8% error, while the unique parameter set performs slightly worse with a median 20% error overestimation of the number of snowmelt days. For snowmelt rate, the unique parameter set also performs slightly worse (-25% error) than the estimated and predicted ones (-22% error), but they all underestimate the snowmelt rate. However, Figure 3.6 in Chapter 3 of this thesis (validation of snowmelt rate) shows that the NH-SWE dataset slightly overestimates snowmelt rates, which indicates that the error of the temperature-index model for snowmelt rate may be closer to zero.

The spatial distribution of the model performance across the Northern Hemisphere for these same six variables (as in Figure 4.11) is shown in Figure 4.12. The median error for the simulations with the predicted parameter set is displayed for each station. Spatial differences in model performance are clearly visible. For snow season timing variables (Figure 4.12a,c,e), the mountain areas of Western North America have poorer performance with late accumulation season onset, early melt season onset, and early end of the snow season. The spatial consistency suggests a potential warm bias in the measured daily temperatures for those stations. Figure 4.13a supports that high elevation North American stations have larger melt onset errors than lower elevation stations, and higher errors than European stations, suggesting a warm bias is more apparent for mountain stations in western North America. An example of a station with a marked warm temperature bias is shown in Figure C.5. Performance is much better over the rest of the Northern Hemisphere and for all three timing variables with timing errors generally not exceeding 10 days except for some stations in Scandinavia and the European Alps.

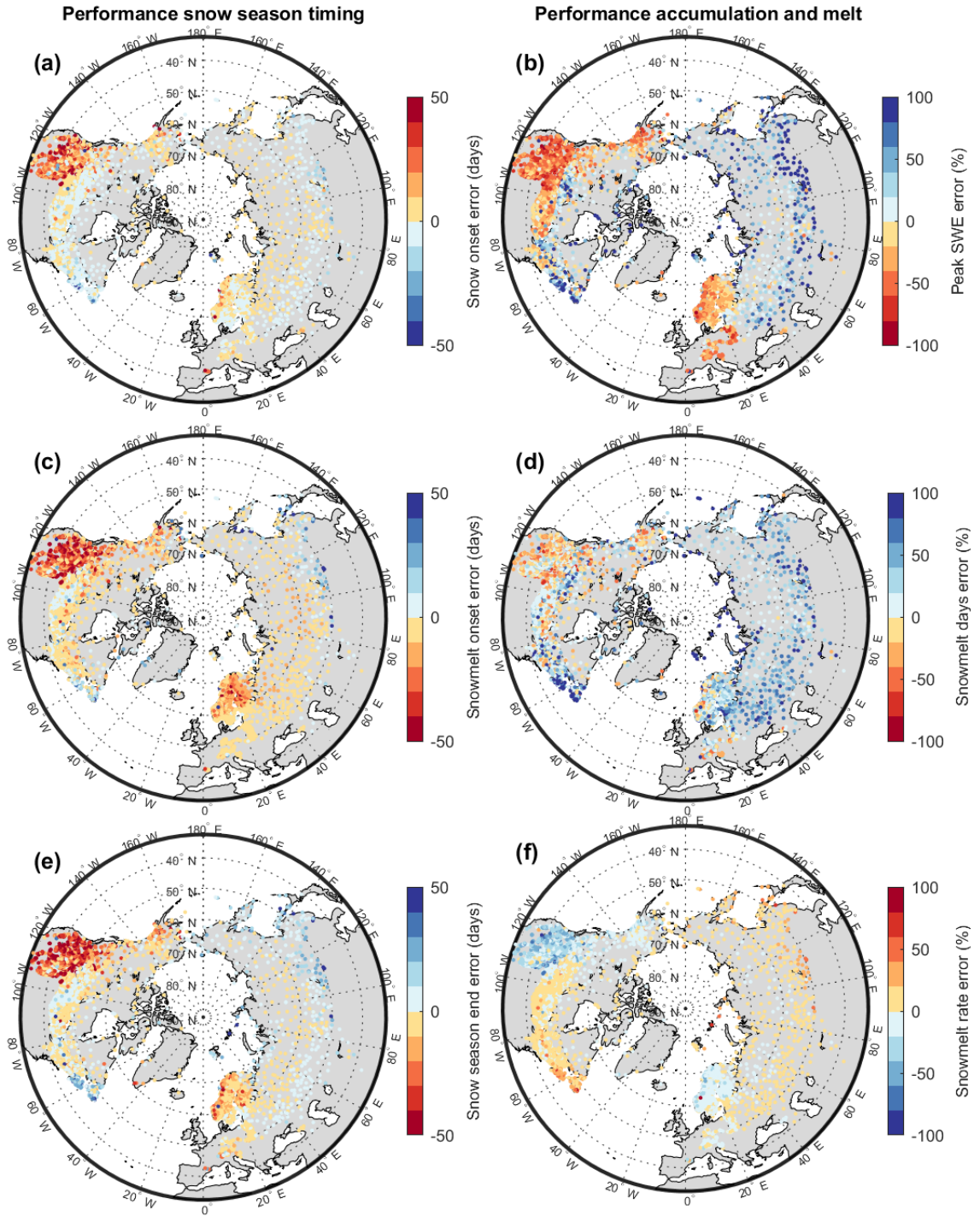


**Figure 4.12:** Spatial distribution of temperature-index model performance. Left column (a,c,e) for snow season timing variables, and right column (b,d,f) for snow season magnitude variables. The median error for each station is shown for the simulation using the predicted parameter set.

Performances of snow accumulation and melt magnitudes show marked differences between Northern Hemisphere regions (Figure 4.12b,d,f). Many stations underestimate peak SWE over the United States and over Europe, while overestimates are observed over Canada and Eurasia (Figure 4.12b). This suggests the potential for warm bias and/or precipitation undercatch in data from stations from the United States, as this is observed also in Alaska but not in adjacent Canadian stations. Figure 4.13b suggests the underestimation of peak SWE is more pronounced for higher elevation areas than lower elevation areas for all regions. Modelled stations in western North America also underestimate the number of melt days, probably because of the underestimate in peak SWE, which inherently leads to fewer snowmelt days as there is less snow to melt. In contrast, data from stations across the rest of the Northern Hemisphere mostly overestimate the number of melt days (Figure 4.11), suggesting that the melt temperature threshold might not be accurate for these stations, or the DDF values are too low. Figure C.3 suggests melt onset initiation peaks at temperatures between 1°C and 3°C, which also explains the negative bias in the timing of melt onset. Finally, melt rates show the smallest relative errors of all three variables (Figure 4.12f), generally not exceeding 10% over any regions, even over regions with a high inter-annual variability of the DDF. The melt rate errors also have some spatial structure, with underestimation generally occurring over regions with deeper snowpacks, such as Western North America, Scandinavia, and the European Alps, and overestimation over regions with shallower snowpacks, such as continental Canada and Eurasia.

Overall, the simple temperature-index model performs remarkably well for most input data and stations, but there can also be large variance, and it occasionally performs poorly. Examples of this range in performance are provided as time series in Figure 4.14, which shows two example time series with excellent performances in all variables (Figure 4.14a,b), one with good performance in timing but an underestimation of peak SWE (Figure 4.14c), one with acceptable performance on timing but overestimation of peak SWE (Figure 4.14d), and one with a poor performance in all variables (Figure 4.14e). Figure C.5 shows the likely reason for the very poor performance in Figure 4.14e is a likely too warm temperature record. While the SWE time series from the NH-SWE dataset shows long and persistent

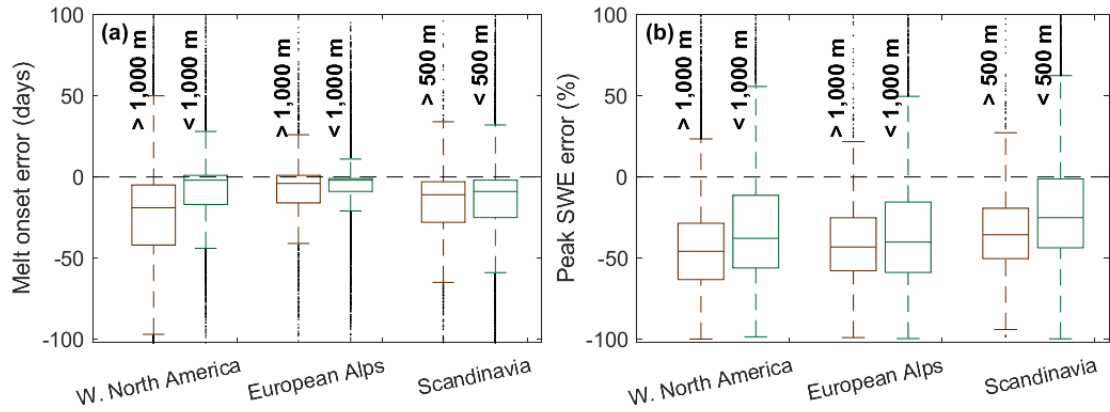


**Figure 4.13:** Error, regions, and elevation. (a) Peak SWE error and (b) melt onset error over three different NH regions for higher and lower elevation stations.

accumulation seasons, the temperature time series has many winter days above freezing. The temperature-index model, therefore, simulates more rain than snow and a lot of accumulation season snowmelt.

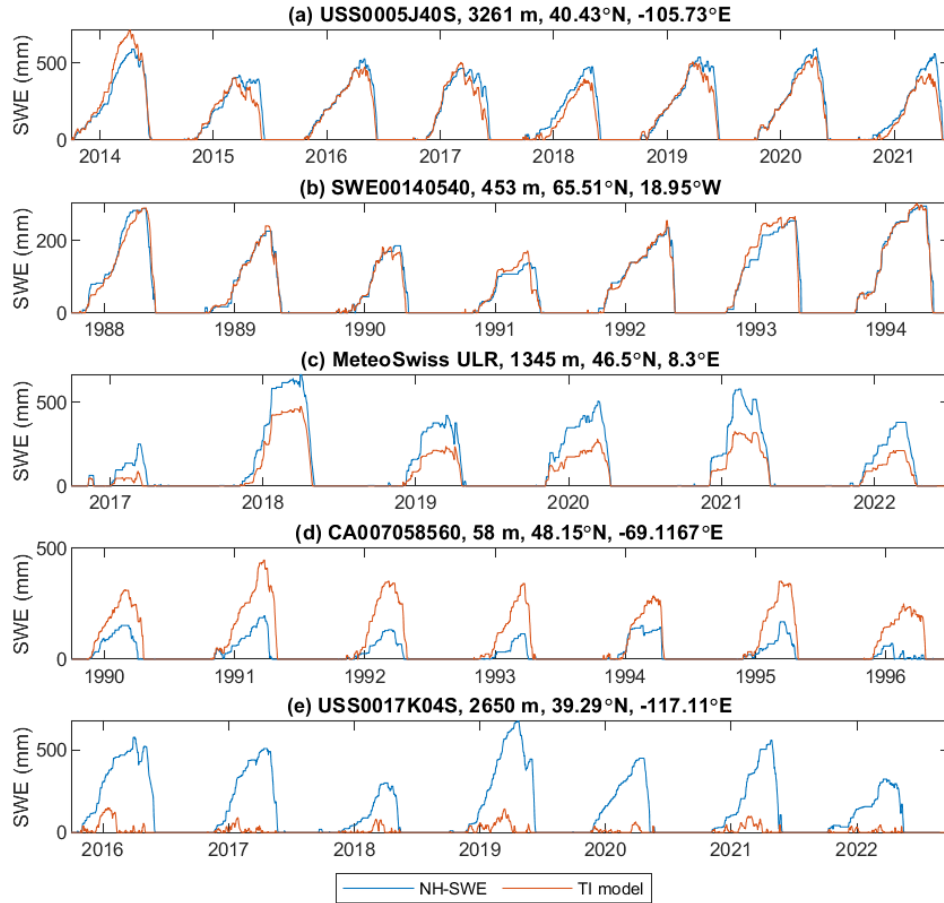


**Figure 4.14:** Example SWE time series comparisons of NH-SWE vs temperature-index model simulations with the predicted parameter set. Good (a,b), medium (c) and poor (d,e) performances across different regions. Title of each subpanel shows the station ID, elevation in metres, latitude and longitude.

## 4.5 Discussion

The results presented in this study provide valuable insights into the performance and limitations of a simple temperature-index snowmelt model applied to climate station locations across the Northern Hemisphere, thus capturing different climatic conditions and snow processes. The discussion below highlights key findings, implications, and areas for further research.

We first tested the range of temperatures over which snowfall occurs and showed that most snowfall events occur at daily average temperatures below freezing. This is broadly in accordance with previous studies (Rohrer & Braun, 1994) but now provides this evidence at a much larger spatial and temporal scale. This highlights the potential of a simple snowfall threshold to capture most snowfall events successfully. For cold, continental climates with shallow snowpacks (e.g., Eurasia, continental Canada), we can robustly capture most snowfall events as these mainly occur below freezing. However, our results also highlight that some relatively large snowfall events at temperatures close to, but just above freezing temperatures as a daily average, will be difficult to capture, even though the frequency of these events is relatively small (13%). Using a simple temperature threshold, the risk of missing some snowfall events can be high, especially over warmer maritime climates with deeper snowpacks (e.g. western North American mountains, the European Alps, or Scandinavia) when these occur near freezing temperatures. Therefore, where snowfall events above freezing temperatures are critical to capture, we emphasise the importance of using a different precipitation phase method, such as the use of wet bulb temperature (Jennings & Molotch, 2019), if available.

Where more accurate methods for precipitation phase partitioning are unavailable, such as including humidity or wet bulb temperature, our results suggest that the assimilation of snow data into modelling efforts (Alonso-González et al., 2022) may provide a useful complement to precipitation and temperature data. Snowfall events above freezing are well captured by snow observations (such as the NH-SWE time series, which are based

on snow depth observations) but may be missed by a temperature-based precipitation phase threshold. For warmer climates receiving most of their snowfall near freezing temperatures, assimilating snow depth observations can be beneficial to simulate the precipitation phase and enhance model performance at the catchment scale, for instance to simulate the snow cover elevation limit. Conversely, snowfall events are well captured at temperatures well below the snowfall threshold but may be missed by snow observations if the precipitation events are small ( $< 3$  mm), which is typical of cold climates, such as Eurasia and continental Canada. Additionally, our efforts to combine snow and precipitation observations from different sources also suggest that rain-on-snow events during the melt season are more frequent and widespread than previously recognised.

Overall, we show the NH-SWE time series provide a good framework for assimilating snow data into models to aid in reaching the required accuracy for diverse modelling applications (Giroto et al., 2020), especially for mountain areas where accurate weather station observations are increasingly challenging. Our results highlight that undercatch of solid precipitation in rain gauges is likely (ca. 10% of fraction of precipitation events below freezing), which has been previously reported at smaller scales in the literature (Adam & Lettenmaier, 2003; Kochendorfer et al., 2020; Pan et al., 2020). Additionally, our results show a poorer overall performance of the temperature-index model over higher elevation areas, probably linked to an increased complexity of temperature and precipitation processes and their measurements over alpine areas (Collados-Lara et al., 2018).

We have tested the validity of a simple temperature threshold of  $0^{\circ}\text{C}$  to capture snowmelt using an observation dataset at the largest spatial and temporal scale to date. The data clearly indicate that snowmelt occurs almost exclusively at daily average temperatures above  $0^{\circ}\text{C}$ , as evidenced by the sharp decrease in the frequency of days with no change in SWE as temperatures rise above this value and the linear increase of snowmelt magnitude with temperature. Overall, our results highlight snowfall and snowmelt events reach an equal frequency of occurrence at a temperature between  $0^{\circ}\text{C}$  and  $1^{\circ}\text{C}$ , suggesting an appropriate temperature threshold for most data in a large-scale study. However, the onset

of the snowmelt season may require a slightly higher temperature threshold as the snowpack needs to overcome the energy deficit to initiate snowmelt.

We have shown degree-day factors (DDFs) vary substantially across spatial and temporal scales. Seasonal scale degree-day factors across the Northern Hemisphere ranged from 1 to 12 mm °C<sup>-1</sup> day<sup>-1</sup>, in accordance with ranges estimated in the literature at smaller spatial scales (Braithwaite, 1995; Kane et al., 1997; Lefebvre et al., 2002; Hock, 2003; Braithwaite, 2008; Shea et al., 2009; Asaoka & Kominami, 2013). We have demonstrated a convergence of DDF values to between 3 and 5 mm °C<sup>-1</sup> day<sup>-1</sup>, particularly in regions with deeper snowpacks and more temperate climates. This key finding suggests that DDFs tend to stabilise within these specific climatic conditions, which also tend to have warmer melt seasons. Furthermore, the low interannual variability of these DDF values suggests they are conditions well suited to the assumptions of simple temperature-index models. In contrast, it may be harder to robustly estimate DDFs for colder, continental climates with shallower snowpacks, as they typically exhibit larger DDFs with higher interannual variability. In addition, our results suggest other loss mechanisms, such as sublimation or snow redistribution by wind, may often dominate over melt in these colder, shallower snowpack climates. As a result, temperature-index melt modelling will likely provide a poorer representation of SWE dynamics under these conditions, which are more typical during the accumulation season.

After evaluating the validity of temperature thresholds and seasonal degree-day factors, we were able to assess the performance of a simple temperature-index model at the largest spatial and temporal scale to date. The median performance of the temperature-index model across various indicator variables for a wide range of climate conditions across the Northern Hemisphere is surprisingly good given the model’s simplicity and that parameters were only estimated but not calibrated. Evaluation of snow season timing variables showed a median error of 0 days for the snow season onset, 4 days early for the snowmelt onset, and 1-2 days early for the end of the snow season. This shows the time series dynamics are, on average, well-modelled by the temperature-index approach. Regarding snow magnitude variables, a median relative error of -10% was found for peak SWE, a median

relative error of +10% for the number of snowmelt days, and a median relative error of -22% for the snowmelt rate. Example time series highlight the excellent performance that the temperature-index models can achieve if the input data is of high quality and at least 80% of snowfall events occur at temperatures below 0°C.

Despite good performance when considering median errors, performance ranges are large, with clear outliers. The snowmelt season onset is often estimated to be a couple of days too early when using a threshold of 0°C for melt, especially for regions with deeper snowpacks. This aligns with the findings of Molotch et al. (2009) and suggests that deeper snowpacks may need a couple of days of positive temperatures to initiate snowmelt. However, it must be noted the NH-SWE time series used for validation exhibited a slight delay on average in snowmelt season onset (Fontrodona-Bach et al., 2023a), thus it is possible to speculate this could reduce the overall uncertainty in snowmelt onset for the temperature-index model results presented here.

The temperature-index model, on average, underestimates peak SWE for all parameter sets used (see Figure 4.2), and especially over deeper snow climates (e.g. western North American mountains, the European Alps, and Scandinavia), where a negative bias is observed for up to 75% of stations. This is consistent with our analysis above, highlighting the undercatch of solid precipitation, the inability of the temperature threshold to capture snowfall events above freezing, and the potential underestimation of the snowmelt initiation temperature threshold. Our results show the worst performances are located over SNOTEL monitoring stations in the United States. However, this is likely due to known data collection errors such as a warm bias and underestimating precipitation that are restricted to SNOTEL sites (Avanzi et al., 2014; Oyler et al., 2015). Nevertheless, for all other regions, it is challenging to point out the exact cause of smaller errors on peak SWE, as they may be a combination of interacting uncertainties from temperature thresholds, weather station measurement errors, or residual uncertainties with the validation dataset. For instance, a temperature-index model underestimation of peak SWE may, in turn, result in an underestimation of the number of melt days, but an underestimation of the snowmelt threshold

temperature may overestimate the number of days with melting conditions and compensate for the underestimation of melt days.

Lastly, the temperature-index model performance analysis suggests the estimated degree-day factors are relatively robust, as snowmelt rates, which is the model performance indicator most sensitive to DDF accuracy, display smaller relative errors than peak SWE and the number of melt days. However, it may also suggest that despite the challenges in estimating degree-day factors for colder and shallower snowpacks (as outlined above), melt rate model performance is not overly sensitive to DDF accuracy, as performance remains good even under conditions where the DDF experiences high interannual variability. In any case, the important implication is that melt rates can be more confidently estimated using temperature-index models than some of the other key variables (such as peak SWE and snowmelt onset) evaluated here. However, the impact of climate change on snowmelt may complicate the robust estimation of degree-day factors (Raleigh & Clark, 2014). Faster snowmelt rates in a warmer climate are generally associated with increased temperatures in the melt season (Chapter 3), and these might be well modelled in the future climate with a temperature-index model. However, slower snowmelt rates due to earlier melt and reduced radiation (Chapter 3) might require a reduced degree-day factor to avoid overestimating melt rates (Raleigh & Clark, 2014).

## 4.6 Conclusions

This study comprehensively examines temperature-index model parameters, their performance, and their limitations across diverse climatic conditions. The results underscore the interplay between temperature, snow processes, and modelling accuracy.

The findings highlight the significance of temperature thresholds in governing snowfall and snowmelt events. While a temperature-based precipitation phase threshold captures most snowfall events, the risk of missing substantial snowfall events, particularly in climates receiving precipitation near freezing temperatures, must be considered. The assimilation of snow data, such as the NH-SWE dataset, into modelling efforts emerges as a future line of research, owing to its ability to capture snowfall events above freezing temperatures or rain-on-snow events.

Evidence is clear that most snowmelt occurs at daily temperatures above freezing, and that SWE decreases below freezing in the NH-SWE dataset are likely not snowmelt runoff but sublimation or snow redistribution processes. The study highlights the equal frequency of snowfall and snowmelt events occurring at a temperature of 0°C, making this a suitable threshold for large-scale studies. However, our results also suggest the potential need for a positive temperature duration before significant snowmelt initiation.

The investigation into degree-day factors (DDFs) offers insights into their variability across climatic conditions. DDF values largely converge (3-5 mm °C<sup>-1</sup> day<sup>-1</sup>) in regions with deeper snowpacks and temperate climates. Our study highlights challenges in estimating DDFs for colder, continental climates with shallower snowpacks due to higher interannual variabilities, but the model performance was nonetheless not worse over those regions.

The temperature-index model exhibits consistent performance in capturing snow season timing variables, although minor deviations in melt season initiation and end are noted. Our results highlight the model's challenges in estimating peak SWE and the number of melt days, particularly in regions with deeper snow climates, attributed to factors including un-

dercatch of solid precipitation, temperature thresholds, and potential data errors. However, the robustness of estimated degree-day factors yields more accurate melt rate predictions compared to other variables.

In summary, this study provides valuable insights into temperature-index modelling for global snow applications. Our results should help refine modelling approaches by acknowledging the interplay of temperature thresholds, the potential for snow data assimilation, and the robust degree-day factor estimations. Further research could advance our understanding of snowpack responses to global warming by applying the temperature-index melt model on a global scale, using globally available weather station data, and assessing the sensitivity of various snow climates to warming scenarios.

# Chapter Five

## Conclusions and outlook

### 5.1 Key research outcomes

#### **Outcome from research objective 1: the open access NH-SWE dataset**

The first key outcome of this thesis is the production and publication of the NH-SWE dataset (Fontrodona-Bach et al., 2023a; Fontrodona-Bach et al., 2023b). This is the first pan-Northern Hemisphere compilation of historical snow depth time series from ground observations converted to snow water equivalent. The dataset features 11,071 historical time series (1950-2022) of daily snow water equivalent, which are published and publicly available. The production of the dataset involved an extensive data collection of available historical snow depth time series from different sources across the Northern Hemisphere, as well as a long process of data curation, gap filling, quality control, data mining and modelling. The established  $\Delta$ SNOW model from Winkler et al. (2021) was used to convert snow depth to snow water equivalent time series. Another outcome of this chapter was the regionalisation of the  $\Delta$ SNOW model parameters suitable for climates across the Northern Hemisphere, which generally outperformed the original model parameters, which were developed on data only from the European Alps. Furthermore, Chapter 2 demonstrated an excellent performance of the  $\Delta$ SNOW model from Winkler et al. (2021) for a range of snow season variables that are sometimes overlooked or not assessed when evaluating snow water equivalent time series, such

as the timing of onset of the melt season and the number of snowmelt days, which quantify features that are relevant to our understanding of snow hydrology. This comprehensive model performance and evaluation, together with an extensive data usage and limitations section in Chapter 2, provide the scientific community with enough information to evaluate whether the data can be used for their research needs and applications. The dataset is also used for Chapters 3 and 4 of this thesis and has already received considerable attention from the scientific community, with 1,968 article views, 641 dataset views, and 421 dataset downloads from January 24th 2023 to September 3rd 2023 (Figure 5.1).

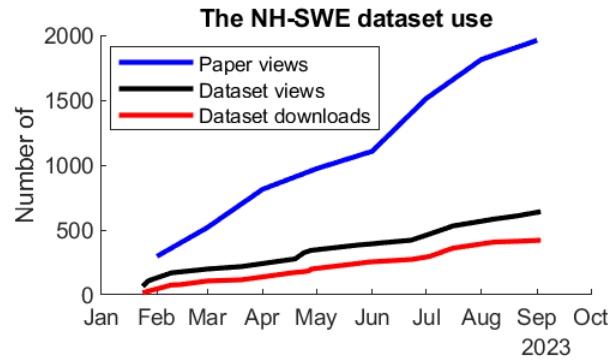


**Figure 5.1:** NH-SWE dataset views and downloads.

## **Outcome from research objective 2: Unveiling the diversity of snowmelt responses to global warming**

The second key outcome of this thesis is the first analysis of Northern Hemisphere snowmelt rate patterns based on observed snow information. Chapter 3 highlights the potential of the NH-SWE dataset, developed in Chapter 2, for use in wider climate research, particularly to leverage the long time series available for trend analysis. Decreasing snow accumulation was observed over most of the Northern Hemisphere, especially for the warmer and wetter climates, while increasing snow accumulation was observed over the colder climates, consistent with many previous studies that have been regionally focused (Bulygina et al., 2011; Fontrodona Bach et al., 2018; Brown et al., 2019; Matiu et al., 2021a). An in-depth analysis provides robust evidence of the effect of warming temperatures and changing precipitation on changing snow accumulation and melt patterns. Rising temperatures heavily affect the beginning and end of the snow season, as well as the number of snow-

fall days and the intensity of snowfall, leading to decreased peak snow accumulation and a shorter overall snow season. However, weak yet consistent trends towards more precipitation in the coldest climates lead to more snow accumulation. The increased temperature facilitates higher moisture transport but remains cold enough to precipitate as snow. Generally, snowmelt season durations are primarily controlled by snow accumulation trends. Previously influential findings that snowmelt may be slower in a warmer world (Musselman et al., 2017) are shown to only manifest under specific circumstances characterised by deeper snowpacks that experience significantly earlier melting due to reduced snow accumulation. In these cases, the reduced accumulation results in a much earlier onset of the melt season during a period with far lower incoming radiation and, thus, slower melt rates. Conversely, faster snowmelt emerges in situations where either the warming trend or the reduction in negative degree-days frequency in the melt season is sufficiently large to compensate for any reduction in incoming radiation. Faster snowmelt also clearly emerges where the melt occurs later due to increased snow accumulation. This chapter highlights the complicated interplay between changing temperatures, precipitation, and radiation on snowmelt dynamics, producing a spectrum of responses across the Northern Hemisphere that vary by climate and region and even at very small scales with high topographic or land use variability. The diverse trends and drivers identified across the Northern Hemisphere carry significant implications for climate, water resources, and ecosystems. While declining snow resources in warmer and wetter regions may impact water availability and low flows, increasing snow accumulation in colder climates underscores the complexity of snowmelt responses to a changing climate, emphasizing the need for detailed climate simulations and further research to better understand and model these processes at various scales.

### **Outcome from research objective 3: Insights and evaluation of a modelling approach for the global scale**

The third key outcome of this thesis is an in-depth exploration of the potential of a simple temperature-index snowmelt model for application at the global scale and its performance across diverse climatic conditions. The outcome of this chapter also demonstrates

the potential of the NH-SWE dataset to aid modelling efforts as an unprecedentedly large evaluation dataset and to gain insights into model parameters and snowfall and snowmelt threshold validity. The analysis of this chapter represents to date the most extensive assessment of temperature thresholds for snowfall and snowmelt events and thus provides the most comprehensive assessment of their accuracy and limitations. It also suggests the potential for integrating snow data, such as the NH-SWE dataset, into modelling efforts to capture events like snowfall above-freezing temperatures or rain-on-snow events, whilst retaining the benefits of a simple modelling approach. Research findings show most snowfall occurs at temperatures below  $0^{\circ}\text{C}$ , and most snowmelt occurs at temperatures above  $0^{\circ}\text{C}$ , supporting its potential applicability as a valid threshold for large-scale studies, but also hinting at the need for accumulated positive temperature duration before significant snowmelt initiation. Furthermore, Chapter 4 has provided novel insights into the variability of degree-day factors (DDFs) across different climate conditions, highlighting the robustness of long-term average DDF values in regions with deeper snowpacks and temperate climates, evaluated from a large dataset of long time series. While the temperature index model demonstrates consistent performance in capturing snow season timing variables, challenges persist in accurately estimating peak SWE and the number of melt days, particularly for locations with deeper snowpacks. These challenges arise mainly from either inaccuracies or errors in the forcing data from climate networks or the inability of the model to capture loss dynamics beyond melting. Overall, this research contributes valuable insights for refining temperature index melt modelling on a global scale and assessing snowpack responses to global warming under various scenarios.

## 5.2 Potential future research directions

Numerous further lines of research arise from this PhD thesis. Some potential research directions expand on topics covered by this thesis, and some appear as new ideas emerging from its discussions and conclusions.

The publication of the NH-SWE dataset is in itself a future challenge. While this thesis has demonstrated its value and potential for current and future research, maintaining the dataset with up-to-date time series requires constant data curation, quality control, data storage, and computing power. Expanding the dataset with more time series of snow depth as they become available would also be a promising development. This would be especially the case for areas not well covered by the NH-SWE dataset, such as High Mountain Asia (Yao et al., 2022), or even locations from the Southern Hemisphere snow despite its lower seasonal snow coverage compared to the Northern Hemisphere. Furthermore, conversion models from snow depth to snow water equivalent will continue to be in development, and improved methods could outperform the ones used to produce the dataset. In fact, Winkler and Schellander (2022) are working on an improved  $\Delta$ SNOW model, with varying new-snow density parameters based on the amount of freshly fallen depth of snow, and varying maximum snow density parameters based on the age of each layer and the weight of overlying snow. Exploring an improved model could be beneficial for the snow water equivalent time series at the expense of increased complexity. However, maintaining and improving the NH-SWE dataset beyond the lifetime of this PhD will be challenging.

The production of the NH-SWE data also involved a novel gap-filling method for snow depth records based on artificial neural networks. This method was only a small step in producing the NH-SWE dataset but nonetheless showed excellent performance and demonstrated a huge potential for further research with snow time series and machine learning algorithms. Artificial neural networks have already been explored to directly estimate snow water equivalent based on snow depth (Ntokas et al., 2021). However, continuous time series of SWE are yet to be explored.

This thesis has shed light on trends and drivers of Northern Hemisphere snow accumulation and snowmelt dynamics, especially snowmelt rates, with a focus on identifying similarities and differences between climatic regions at the Northern Hemisphere-scale. However, the amount of data in the NH-SWE dataset would also allow for comprehensive regional studies within the Northern Hemisphere, such as the mountains and prairies of North Amer-

ica, the European Alps, Scandinavia or Eurasia. These include various subclimates that may provide additional insights into this thesis’s analysis and research outcomes. A high spatial variability, especially for snowmelt rate trends, is evident across most Northern Hemisphere regions. Although the first-order drivers were the focus, further analysis could explore the influence of additional variables on snowmelt rates that might be important at more local scales, such as elevation, slope, aspect, or land use, all of which have shown to influence melt rates (Mazzotti et al., 2023) but have been unexplored for differing trends at larger scales.

Furthermore, this thesis has focused on trends at the seasonal scale, but higher resolution time scales might also provide further insights into changing snowmelt rates. For instance, melt rates could indeed be slower for the earlier parts of the season, but faster for the later parts of the season, depending on different warming trends during different months (Essery et al., 2020). This could result in a non-significant change in the seasonal melt rate, but might still have implications for water resources and for ecosystems, with snow melting slowly at the beginning and accelerating as the melt season progresses.

This thesis has not directly evaluated the impacts of the changing snow patterns on aspects such as streamflow or ecological responses, but the NH-SWE dataset and the findings of this thesis have the potential to be used directly in other studies in combination with other hydrological or ecological data, and to infer direct impacts of the observed historical changes.

The outcome of Chapter 4 has also laid the grounds for future research directions. First, it has become clear that the NH-SWE dataset has potential for aiding modelling efforts, demonstrated by the agreement between the snow water equivalent time series and the temperature and precipitation time series regarding snowfall and snowmelt thresholds. Assimilating snow water equivalent time series into models, as proposed by Giroto et al. (2020), could minimise uncertainty in seasonal snow estimates and be easily achieved with the NH-SWE dataset. Improvements to the  $\Delta$ SNOW model could be performed by introducing temperature and precipitation data as forcing for the model, which would, however, increase the model complexity.

The occurrence and identification of a relatively high frequency of rain-on-snow events in Chapter 4 calls for a further analysis of the frequency of these events and their links with warming trends, an important process whose response to climate change remains unclear (Brandt et al., 2022).

Finally, the successful evaluation of the temperature-index melt modelling approach at the Northern Hemisphere-scale calls for an analysis of the sensitivity of global snowpacks to warming scenarios. This research direction could be based on globally available time series of temperature and precipitation. While this method will not achieve high spatial and temporal resolutions, it would still inform important seasonal and climatic scale impacts of warming on global snow accumulation and melt patterns.

## 5.3 Overall conclusion and final remarks

This thesis has embarked on a comprehensive exploration of the diversity of snow accumulation and melt responses to a warming climate, investigating the challenges of studying such responses due to data limitations and presenting methods to overcome these challenges through three interconnected chapters. By developing and introducing the NH-SWE dataset, exploring historical trends, and evaluating modelling approaches it has enhanced our understanding of snow hydrology and its response to climate change.

There is a key element of novelty in each of the three research chapters of this thesis. Chapter 2 has identified the need for reliable and publicly accessible snow water equivalent data, and it has provided an open-access dataset which is available for the research community. Chapter 3 of this thesis has then explored its potential for climate research by studying snowmelt rates at the Northern Hemisphere scale based on actual snow observations on the ground, with novel findings in terms of processes and scale. As a final novel step, Chapter 4 of this thesis has provided insights into the utility of temperature-index melt modelling at the global scale for research into snow accumulation and melt in response to warming.

The research outcomes of this thesis open up numerous lines of potential research directions, both following up on key findings and on the potential of the NH-SWE dataset for a variety of applications. The publication of new data, new findings, and exploration of future research at the global scale, as well as the integration of ground observations, modelling, and climate data, open up prospects for a better and broader comprehension of the Earth's hydrological systems. In the face of ongoing climate change, the findings of this thesis will hopefully contribute to better-informed decisions and policies for a sustainable future.

# Appendix A

## Appendix Chapter 2

### A.1 Snow depth data gap-filling and quality control

The  $\Delta$ SNOW model (Winkler et al., 2021) requires a continuous record of daily observations of snow depth to estimate daily SWE. Our compilation of snow depth time series contains a large variability in time series length, number and size of gaps (Fig. A.1). Many time series have missing data during the summer period when there is no snow (e.g. most MeteoSwiss stations). This is easy to visually identify and manually fill with zeros, but it is complicated to fill all the series in an automated way with high confidence. Gaps also occur often in the middle of the snow season. Over 90% of the gaps in the dataset are less than 50 days long, and 80% of the gaps are less than 10 days long (Fig. A.2).

The high autocorrelation of daily snow depth time series (i.e. the correlation of snow depth at time  $t$  to snow depth at time  $t-i$ ) motivates us to use a *non-linear autoregressive neural network with external input (NARX)* technique to fill the time series of snow depth. Neural networks have been used by Silva et al., 2018 and Vieira et al., 2020 to fill environmental time series of sea surface wind speeds and ocean waves, but have to date not been applied to snow depth time series. We use the `narxnet` function from the MATLAB Deep Learning Toolbox (“MATLAB Deep Learning Toolbox”, 2021). The NARX neural network uses snow depth at time steps up to  $i$  days before time  $t$  as input to estimate snow depth at time  $t$ . The delay parameter  $i$  must be estimated. We found  $i = 4$  days to be the best estimation of the delay parameter. This means that the snow depth at time  $t$  is mostly

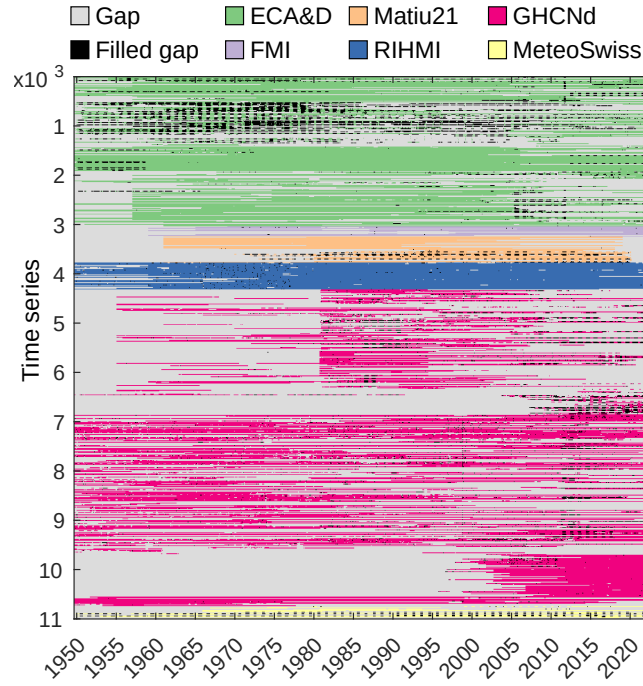


**Figure A.1:** Final modelled NH-SWE dataset matrix. Each row corresponds to one of the 11,071 time series in the dataset at daily resolution. Colours indicate data sources, gaps, and filled gaps.

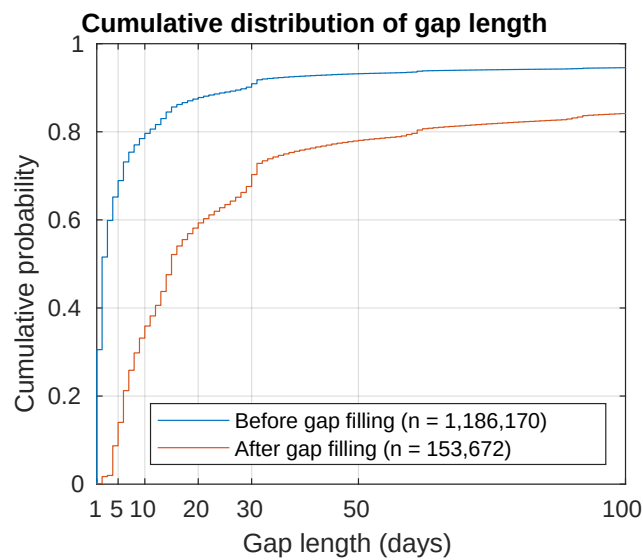


**Figure A.2:** Cumulative distribution of dataset gap length before and after gap-filling.  $n$  is the total number of data gaps.

influenced by snow depth at 1, 2, 3 and 4 days before time  $t$ .

External inputs are used to help the NARX simulation. We tested a few NARX network architectures and inputs and found that including precipitation and temperature data as input to the NARX network showed promising results for filling the snow depth time series. We obtain daily precipitation and temperature data from DAYMET (Thornton et al., 2020) for the stations in North America and from E-OBS (Cornes et al., 2018) for the European stations. For the stations in Eurasia not covered by E-OBS we use temperature and precipitation station data from RIHMI-WDC, 2022 stations. For stations where precipitation and temperature data cannot be obtained (i.e. locations not covered by gridded data and no station data available) we do not gap-fill the snow depth data with NARX. For stations that were not gap-filled, we only modelled SWE for those years with continuous (gap-free) daily measurements of snow depth.

Neural network models require enough data to be trained. We train one model for each snow depth station in the dataset because the training of the network could differ per site. During training, the data are divided into a training, a validation and a testing set. The division is made by blocks with a ratio of 60/20/20, meaning that for every 5 years, 3 are used for training, 1 for validation and 1 for testing. For snow depth stations with more than 20 years of data where the trained model yields an r-squared performance higher than 0.9, we further test the performance of the NARX network gap-filling technique by creating synthetic gaps of 1, 3, 7, 15, 30 and 50 days in the time series, at different times of the year. We then run the NARX network gap-filling and compute the absolute error (in centimetres) of the filled snow depth compared to the real observed snow depth. We also compute the percentage error dividing by the observed snow depth value. For each site we repeat this procedure 50 times so that the gaps are randomly tested at different times of the year, for various years and for various gap lengths. The overall performance of the gap-filling can be visualised in Fig. A.3, where the mean absolute error and mean percentage error of the 50 simulations is plotted for each time of the year and gap length. At the beginning of the year (September-October) and at the end (June to August), the mean absolute error is zero,

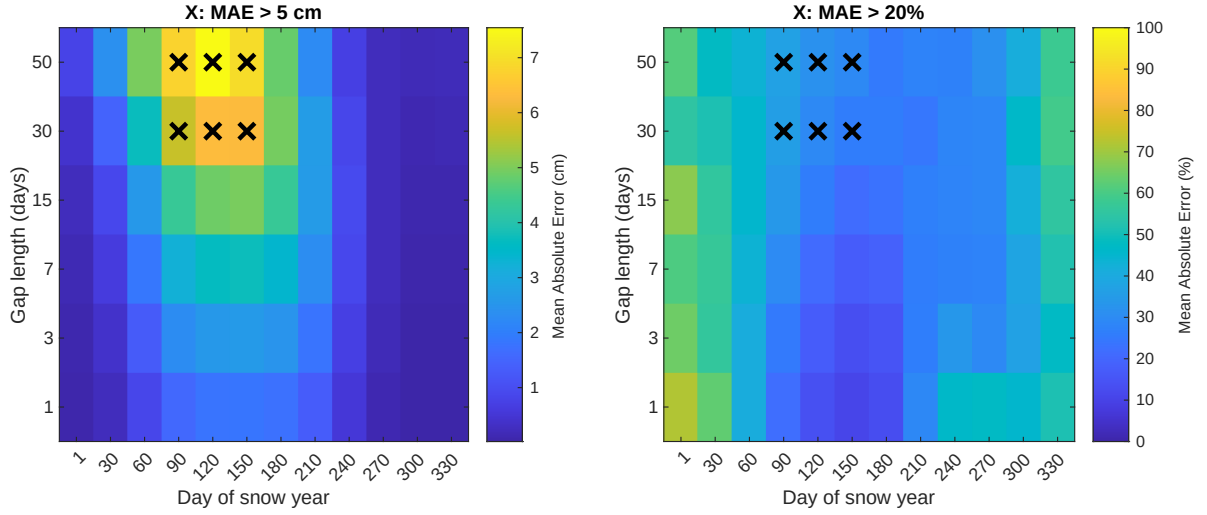


**Figure A.3:** Mean performance of NARX gap-filling routine. Left panel shows absolute error in centimetres of the snow depth filled gaps at different times of the year and for different gap lengths. Right panel shows the same but in percentage error. A cross is displayed if the absolute error is higher than 5 cm and the percentage error is higher than 20%.

indicating that the NARX neural network performs very well during the summer periods when there is no snow. This allows for filling the gaps in summer with high confidence. During the snow season (November to May), the errors are higher the longer the gap. In percentage terms, the error also becomes larger the longer the gap. We consider an acceptable error to be less than 5 cm or less than 20%. For gaps equal to or under 15 days the error of the NARX network gap-filling is consistently under those thresholds. Figure A.3 shows the mean over all sites where the performance is tested, but the procedure is applied to each site independently because the training of the network could differ per site.

For each gap in each time series we decide whether or not to fill the gap based on a series of conditions. For stations with a minimum of 20 years of data where the performance is tested as explained above, we fill all the gaps under 16 days long because of the high confidence on filling them (Fig. A.3). For gaps longer than 15 days and shorter than 70, we decide based on the performance according to the decision matrix (as in A.3, where an acceptable error is less than 5 cm or less than 20%) for that specific station. For long gaps between 70 and 365 days, we fill the gaps if the performance for gaps of 50 days is acceptable

and at least 80% of the filled values are under 2 cm of snow depth, which means snow-cover-free periods are being filled. For stations with less than 20 but more than 5 years of data where the training of the NARX model yields an r-squared performance of at least 0.95, we also fill all gaps under 16 days long. For those stations, we also fill longer gaps if at least 80% of the filled values are under 2 cm, indicating that snow-cover-free summer is being filled. For stations where less than 5 years of daily snow depth data are available but where the NARX model still yields an r-squared performance higher than 0.95, we fill all gaps shorter than 7 days and only fill gaps longer than 7 days if 90% of the filled values are under 2 cm.

After the NARX neural network gap-filling, we also fill all gaps in the dataset that are equal to or shorter than 3 days by linear interpolation. If a station has more than 20 years of data but the NARX neural network model does not perform well, or no precipitation and temperature data are available, we compute the average main snow cover season and we fill with zeros any gaps outside the average snow cover season. If after all the gap-filling routine, 1 snow year at any station has only a gap of 7 days or shorter, we also fill the gap by linear interpolation. We do not fill gaps if any of the conditions above are not met.

Overall, 94.8% of the filled gaps are filled by the NARX neural network models, while only 5.2% are linearly interpolated or filled with zeros.

Finally, we apply an extra quality control to the gap-filled time series of snow depth before running the  $\Delta$ SNOW model. We remove those years where the annual snow season (see Fig. 2.3) contains more than 75% of filled gaps. We remove any snow cover period of less than 8 days that is fully gap-filled. We remove those years that are fully snow cover free, given that it is an unlikely event after our selection based on a minimum of 40 days of snow cover on average (see Section 2.2.3). We remove unrealistic daily snow depth increases of more than 150 cm in one day or decreases of more than 45 cm in one day. These values are based on the 99.99 percentile of all observed daily snow depth increases and snow depth decreases of the entire SNOTEL dataset (see Section 2.2.1). We remove years with perennial snow cover, since the  $\Delta$ SNOW model is developed over seasonal snowpacks. We remove all snow depth values that are higher than 4 times the median absolute deviation of the average

yearly peak of snow depth.

Figure A.4 shows example time series where the gap-filling is successfully filling the summer zeroes and small gaps during the snow season.

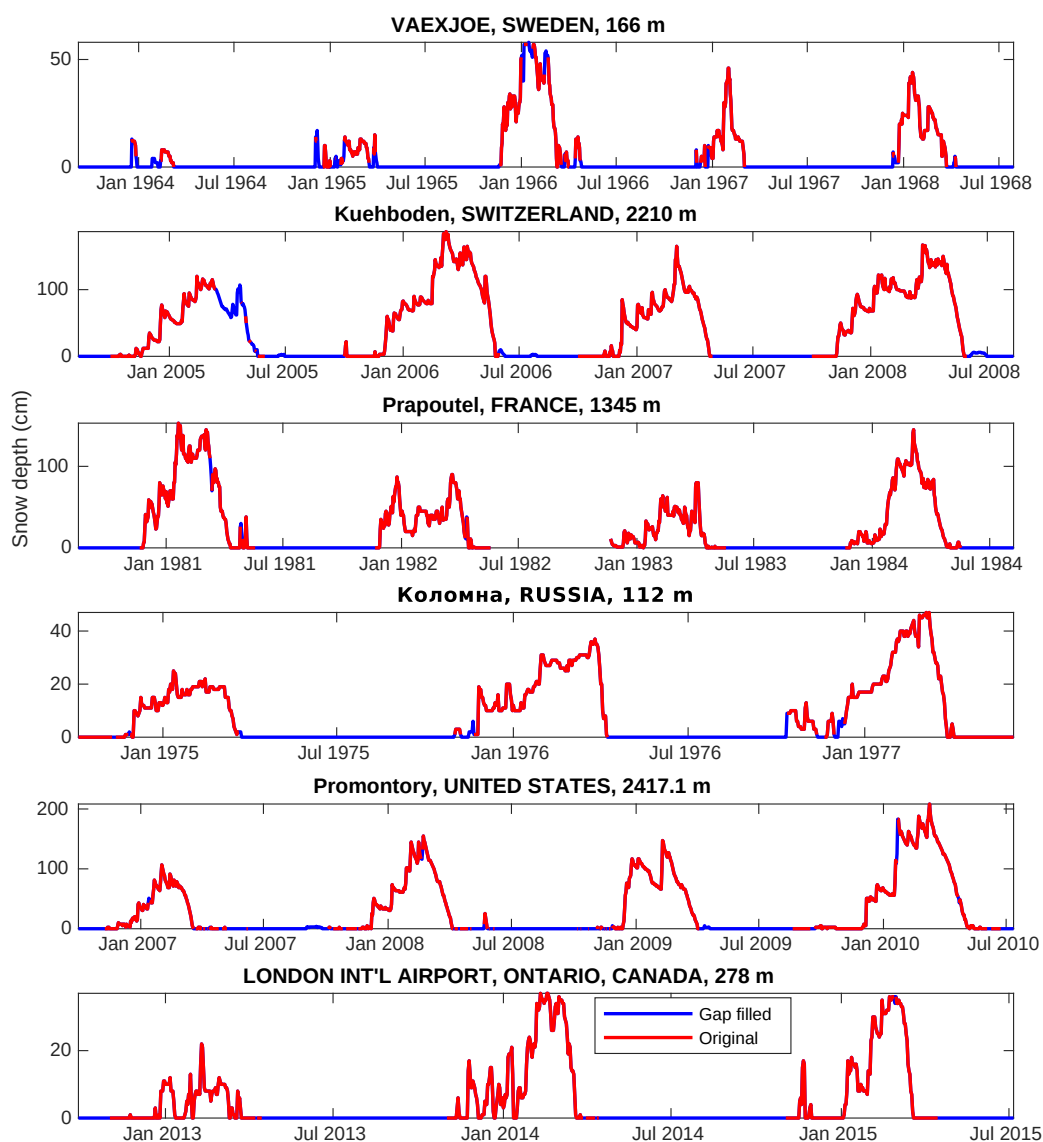


**Figure A.4:** Example gap-filled snow depth time series. The title of each subplot corresponds to the station name, the country, and the elevation in metres above sea level.

## A.2 Climate variables for parameter regionalisation

We test a few climate variables to regionalise the  $\Delta$ SNOW model parameters in Section 2.3.4. All the climate variables are obtained from the WorldClim2 dataset of monthly climate variables (Fick & Hijmans, 2017). We complete the set of climate variables with snow climatology variables (i.e. climate variables based on snow depth data). The variables that were computed and tested are the following:

- $\overline{T}_Y$ : mean yearly temperature
- $\overline{T}_{DJF}$ : mean December-January-February temperature
- $\overline{T}_{NDJFM}$ : mean November-December-January-February-March temperature
- $\overline{P}_{DJF}$ : mean December-January-February cumulative precipitation
- $\overline{P}_{NDJFM}$ : mean November-December-January-February-March cumulative precipitation
- $\overline{P}_{snow}$ : precipitation as snow computed as the sum of monthly precipitation when temperature is below zero
- $\overline{T}^*$ : dimensionless temperature index from Woods, 2009 defined as the ratio between mean annual temperature and the amplitude of the annual temperature cycle
- $\overline{P}^*$ : dimensionless precipitation index from Woods, 2009 comparing the average precipitation rate and melt rate for a site
- $P_{V,DJF}$ : mean December-January-February Vapour Pressure in the atmosphere.
- $P_{V,NDJFM}$ : mean November-December-January-February-March vapour pressure in the atmosphere
- $S_{R,DJF}$ : mean December-January-February shortwave Radiation
- $P_{R,NDJFM}$ : mean November-December-January-February-March shortwave Radiation

- $\overline{H}$ : mean snow depth
- $\overline{H}_{max}$ : mean maximum snow depth (i.e. peak of snow accumulation)

### A.3 Extended model performance and evaluation

Table A.1 extends the model performance summary of Section 2.4, showing the mean model performance for each of the datasets separately for three model scenarios ( $\Delta$ SNOW original,  $\Delta$ SNOW regionalised, and Hill model) and for the six evaluation metrics from Table 2.3.

**Table A.1:** Extended model performance and evaluation. Here the performances are shown for all the datasets separately.  $\Delta\text{SNOW}_{\text{Orig}}$  refers to the original model parameters by Winkler et al., 2021,  $\Delta\text{SNOW}_{\text{Regio}}$  refers to our regional parameterisation (see Section 2.3.4) and Hill model refers to the regression model from Winkler et al., 2021. Where a value is not shown, it means that performance variable is not possible to compute for that dataset due to a lack of appropriate observed SWE records to compute that metric. The  $\Delta\text{SNOW}_{\text{Regio}}$  is better than  $\Delta\text{SNOW}_{\text{Orig}}$  on 77% of all datasets and metrics, and better than the Hill model on 61% of all datasets and metrics.

|                 | SWE <sub>daily</sub>              |                                    |            |                                   |                                    |              |
|-----------------|-----------------------------------|------------------------------------|------------|-----------------------------------|------------------------------------|--------------|
|                 | RMSE (mm)                         |                                    |            | Bias (mm)                         |                                    |              |
|                 | $\Delta\text{SNOW}_{\text{Orig}}$ | $\Delta\text{SNOW}_{\text{Regio}}$ | Hill model | $\Delta\text{SNOW}_{\text{Orig}}$ | $\Delta\text{SNOW}_{\text{Regio}}$ | Hill model   |
| SNOTEL          | 26.0                              | 25.0                               | 35.9       | −11.6                             | 1.0                                | 2.5          |
| CanSWE          | 58.5                              | 52.8                               | 51.9       | −41.6                             | −34.0                              | −11.2        |
| GCOS-CH         | 38.3                              | 53.4                               | 44.0       | −28.5                             | −0.6                               | −15.0        |
| RIHMI-WDC       | 16.1                              | 14.5                               | 11.1       | −18.9                             | −16.9                              | −7.8         |
| NVE             | 44.5                              | 39.4                               | 38.4       | −27.5                             | −15.3                              | 3.5          |
| Kuhtai-AT       | 23.2                              | 37.3                               | 42.8       | −8.3                              | 7.5                                | 8.9          |
| Sodankyla-FI    | 19.1                              | 16.8                               | 21.9       | −15.1                             | −15.4                              | 7.5          |
| Col-de-Porte-FR | 66.1                              | 34.7                               | 48.8       | −79.4                             | −28.8                              | −49.4        |
| Alptal-CH       | 39.9                              | 33.3                               | 41.7       | −49.8                             | −33.0                              | −33.1        |
|                 | SWE <sub>peak</sub>               |                                    |            |                                   |                                    |              |
|                 | RMSE (mm)                         |                                    |            | Bias (mm), Rel. Bias (%)          |                                    |              |
|                 | $\Delta\text{SNOW}_{\text{Orig}}$ | $\Delta\text{SNOW}_{\text{Regio}}$ | Hill model | $\Delta\text{SNOW}_{\text{Orig}}$ | $\Delta\text{SNOW}_{\text{Regio}}$ | Hill model   |
| SNOTEL          | 42.3                              | 36.5                               | 60.9       | −22.4 (−6.7%)                     | 3.4 (1.0%)                         | 33.3 (9.4%)  |
| CanSWE          | 86.3                              | 73.0                               | 59.4       | −68.6 (−16.1%)                    | −56.4 (−11.3%)                     | 3.9 (1.0%)   |
| GCOS-CH         | 56.0                              | 76.9                               | 89.7       | −3.0 (−0.6%)                      | 50.9 (17.2%)                       | 48.8 (15.4%) |
| RIHMI-WDC       | 26.6                              | 23.0                               | 17.7       | −21.4 (−26.7%)                    | −16.2 (−14.6%)                     | 7.1 (13.7%)  |
| NVE             | 60.6                              | 68.3                               | 61.2       | −53.3 (−10.0%)                    | −32.5 (−5.9%)                      | 45.0 (13.1%) |
| Kuhtai-AT       | 36.9                              | 58.5                               | 86.9       | 19.2 (5.1%)                       | 47.7 (12.7%)                       | 73.3 (19.5%) |
| Sodankyla-FI    | 30.8                              | 30.5                               | 29.0       | −29.6 (−14.9%)                    | −29.8 (−15.0%)                     | 26.6 (13.4%) |
| Col-de-Porte-FR | 88.2                              | 40.6                               | 61.5       | −81.4 (−20.8%)                    | 9.7 (2.5%)                         | 30.8 (7.9%)  |
| Alptal-CH       | -                                 | -                                  | -          | -                                 | -                                  | -            |
|                 | Snowmelt onset bias (days)        |                                    |            | SWE time-series NSE (-)           |                                    |              |
|                 | $\Delta\text{SNOW}_{\text{Orig}}$ | $\Delta\text{SNOW}_{\text{Regio}}$ | Hill model | $\Delta\text{SNOW}_{\text{Orig}}$ | $\Delta\text{SNOW}_{\text{Regio}}$ | Hill model   |
|                 | $\Delta\text{SNOW}_{\text{Orig}}$ | $\Delta\text{SNOW}_{\text{Regio}}$ | Hill model | $\Delta\text{SNOW}_{\text{Orig}}$ | $\Delta\text{SNOW}_{\text{Regio}}$ | Hill model   |
| SNOTEL          | 6.1                               | 1.6                                | −14.7      | 0.93                              | 0.94                               | 0.89         |
| CanSWE          | 6.0                               | 3.0                                | −17.1      | 0.85                              | 0.91                               | 0.88         |
| GCOS-CH         | -                                 | -                                  | -          | -                                 | -                                  | -            |
| RIHMI-WDC       | -                                 | -                                  | -          | -                                 | -                                  | -            |
| NVE             | 9.1                               | −1.3                               | −12.9      | 0.81                              | 0.84                               | 0.85         |
| Kuhtai-AT       | 2.2                               | −7.3                               | −22.5      | 0.94                              | 0.89                               | 0.84         |
| Sodankyla-FI    | -                                 | -                                  | -          | -                                 | -                                  | -            |
| Col-de-Porte-FR | -                                 | -                                  | -          | -                                 | -                                  | -            |
| Alptal-CH       | -                                 | -                                  | -          | -                                 | -                                  | -            |
|                 | Snowmelt total bias (mm)          |                                    |            | Snowmelt duration bias (days)     |                                    |              |
|                 | $\Delta\text{SNOW}_{\text{Orig}}$ | $\Delta\text{SNOW}_{\text{Regio}}$ | Hill model | $\Delta\text{SNOW}_{\text{Orig}}$ | $\Delta\text{SNOW}_{\text{Regio}}$ | Hill model   |
|                 | $\Delta\text{SNOW}_{\text{Orig}}$ | $\Delta\text{SNOW}_{\text{Regio}}$ | Hill model | $\Delta\text{SNOW}_{\text{Orig}}$ | $\Delta\text{SNOW}_{\text{Regio}}$ | Hill model   |
| SNOTEL          | −37.4                             | −4.0                               | 138.0      | −7.6                              | −5.1                               | 8.0          |
| CanSWE          | −125.4                            | −83.6                              | 62.8       | −5.5                              | −4.0                               | 11.5         |
| GCOS-CH         | -                                 | -                                  | -          | -                                 | -                                  | -            |
| RIHMI-WDC       | -                                 | -                                  | -          | -                                 | -                                  | -            |
| NVE             | −116.2                            | −63.5                              | 31.8       | −8.5                              | −2.5                               | 10.0         |
| Kuhtai-AT       | -                                 | -                                  | -          | -                                 | -                                  | -            |
| Sodankyla-FI    | -                                 | -                                  | -          | -                                 | -                                  | -            |
| Col-de-Porte-FR | -                                 | -                                  | -          | -                                 | -                                  | -            |
| Alptal-CH       | -                                 | -                                  | -          | -                                 | -                                  | -            |

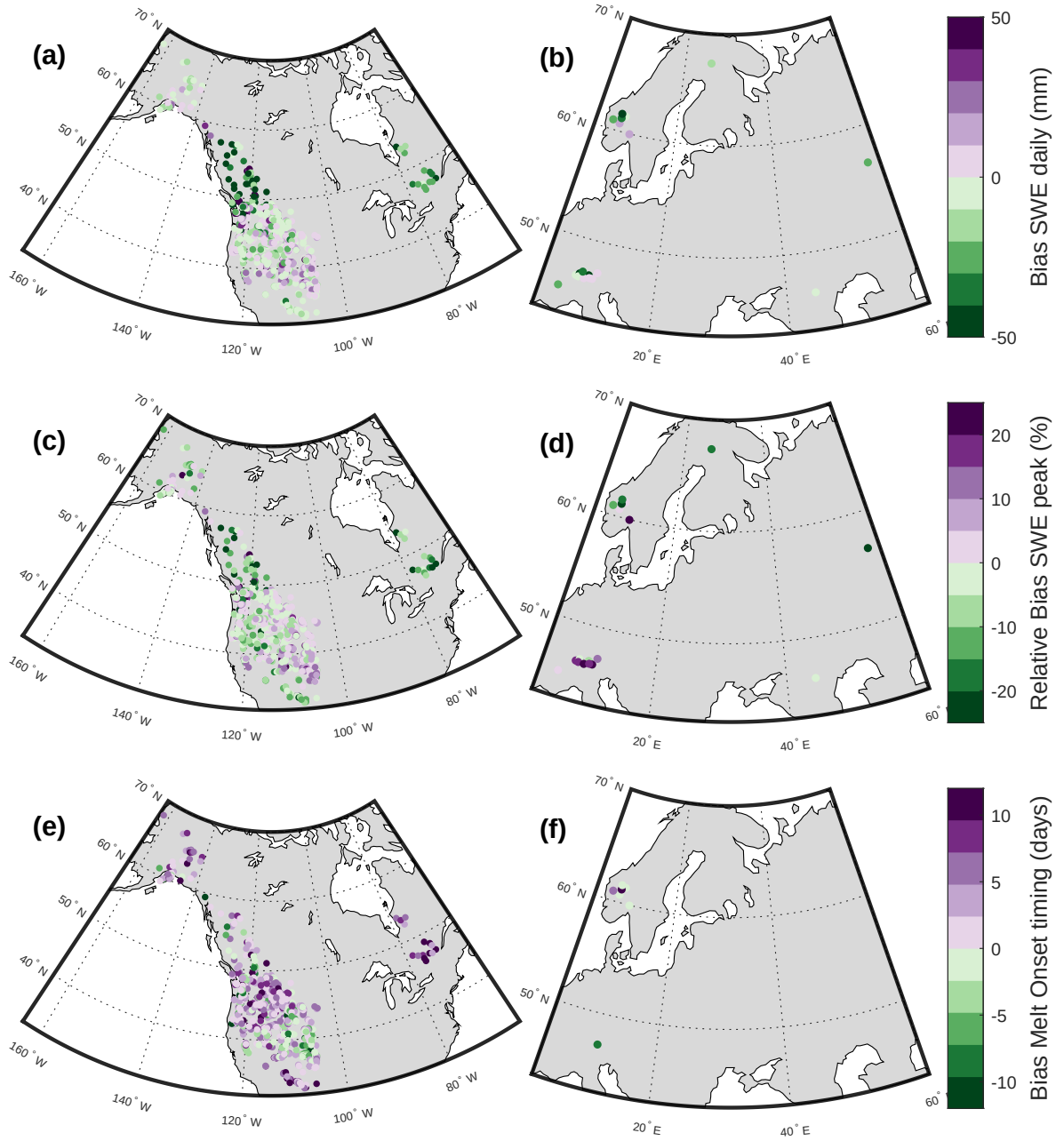


**Figure A.5:** Spatial distribution of model performance. The variables shown are the same as in Table 2.4: Panels (a) and (b) for bias of daily SWE, panels (c) and (d) for relative bias of peak SWE, and panels (e) and (f) for bias of snowmelt onset timing. All sites displayed are from regionalisation and evaluation datasets.



# Appendix B

## Appendix Chapter 3

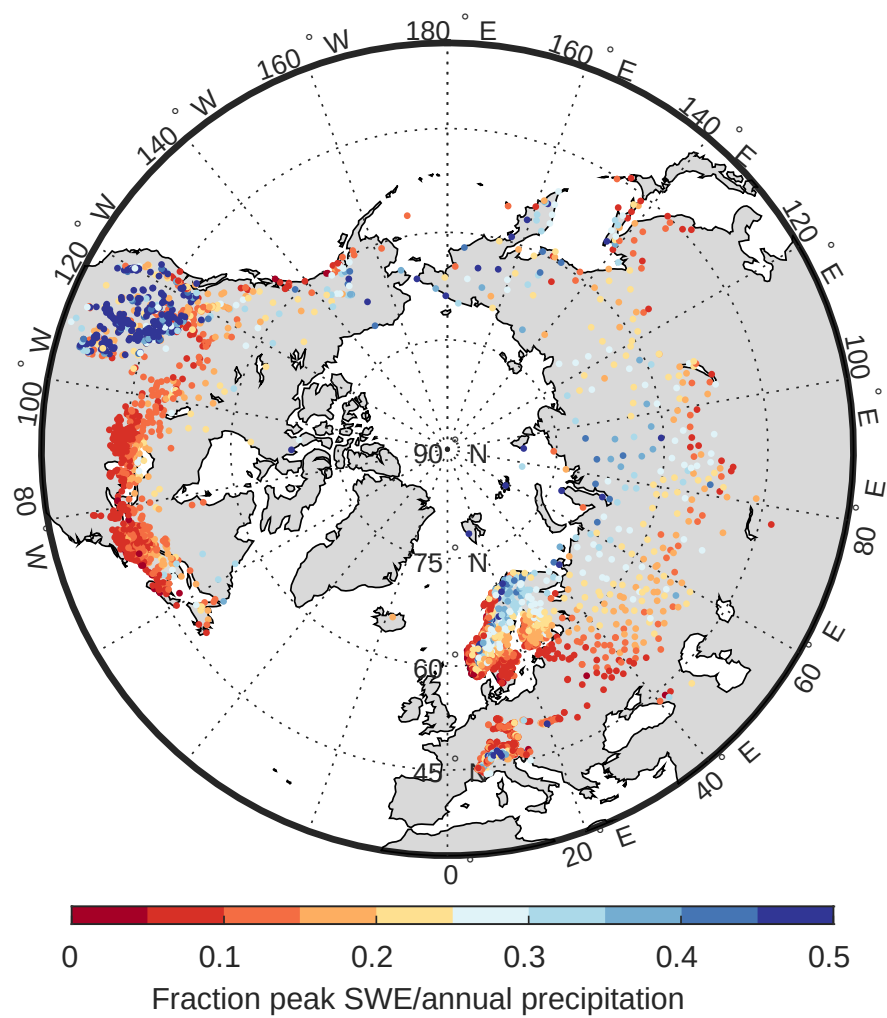


**Figure B.1:** Fraction of peak SWE to total annual precipitation.

## Central Europe trends (1980-2022)

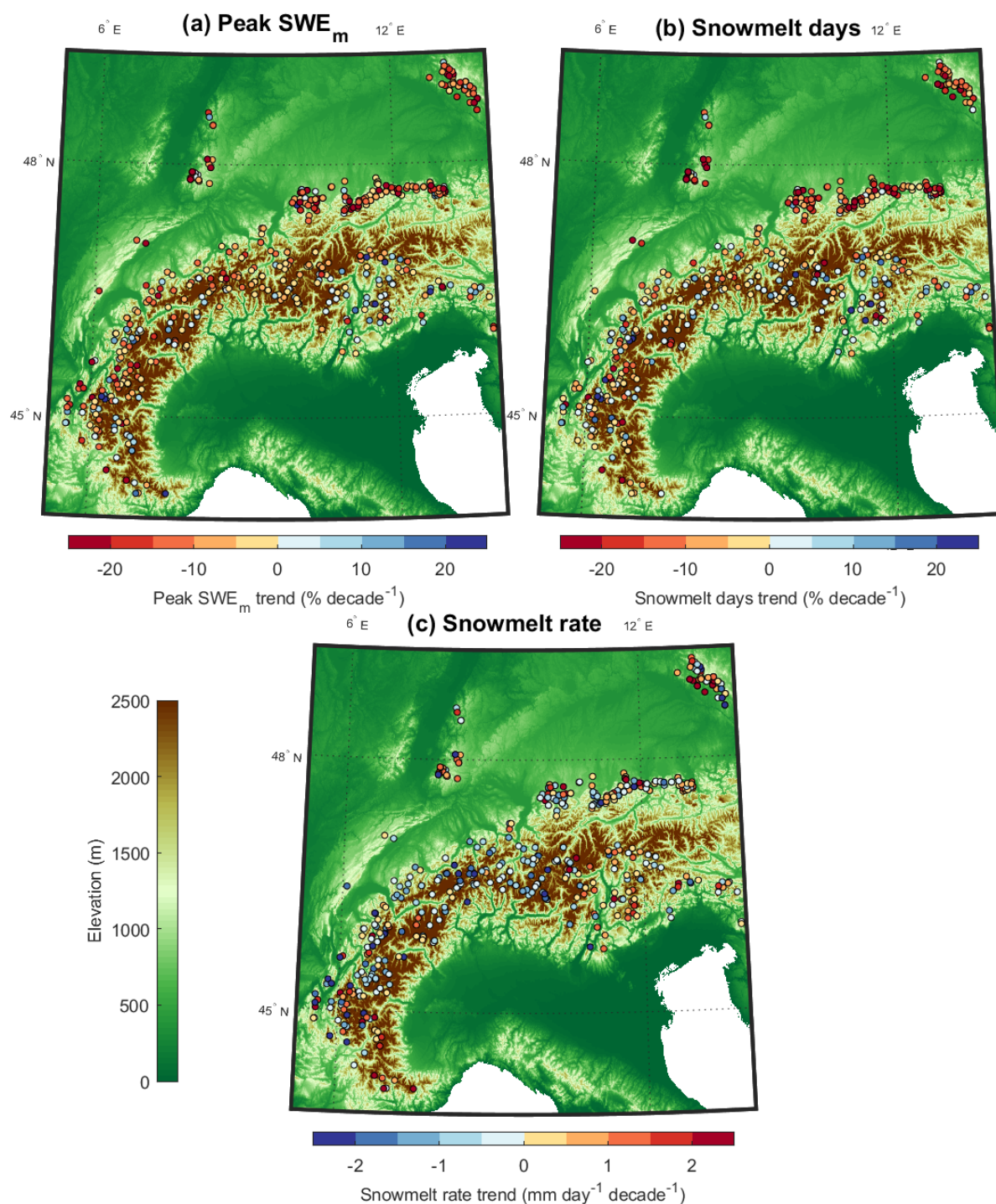


**Figure B.2:** Spatial variability of peak SWE, snowmelt days, and snowmelt rate trends in Central Europe.

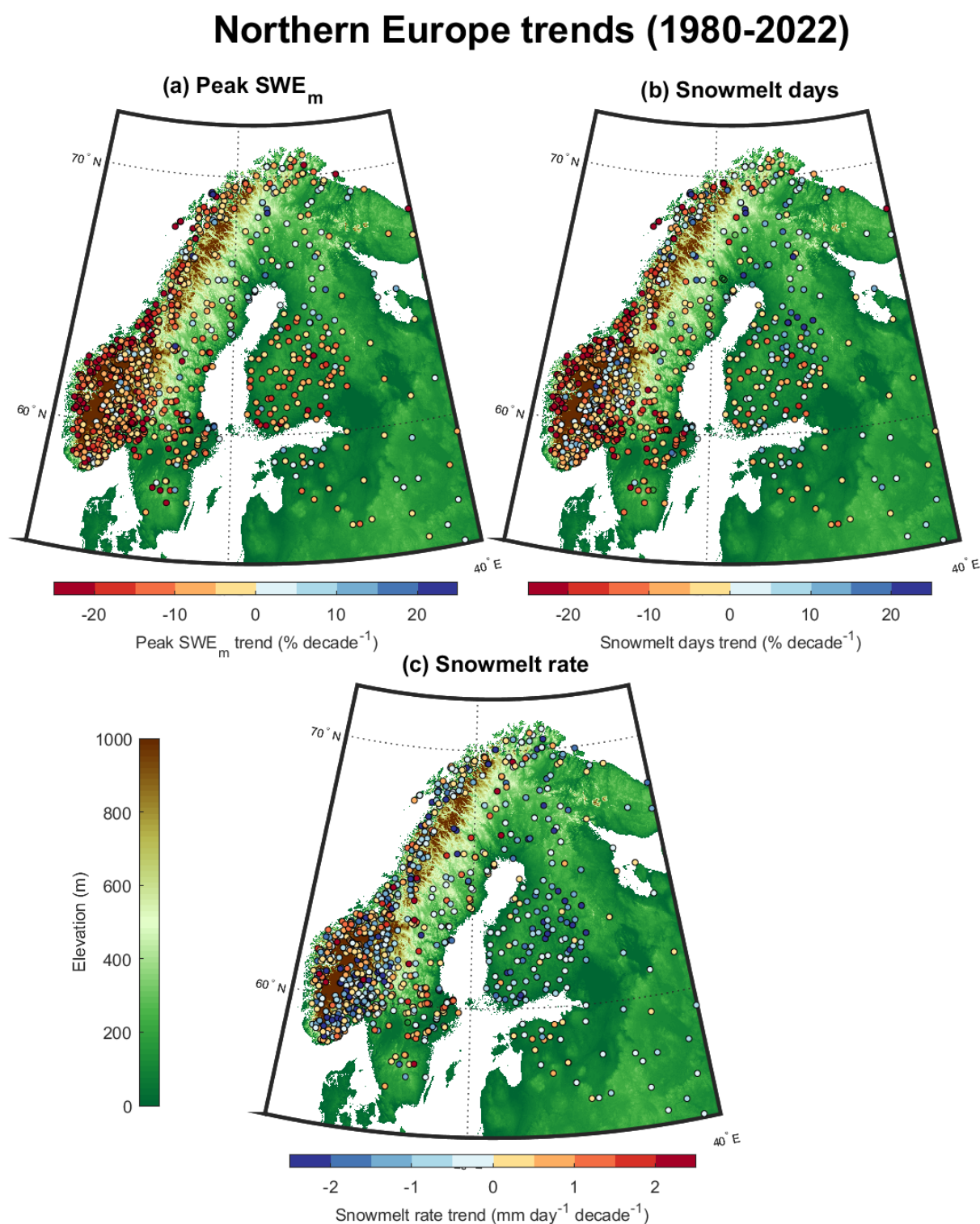


**Figure B.3:** Spatial variability of peak SWE, snowmelt days and snowmelt rate trends in Northern Europe.

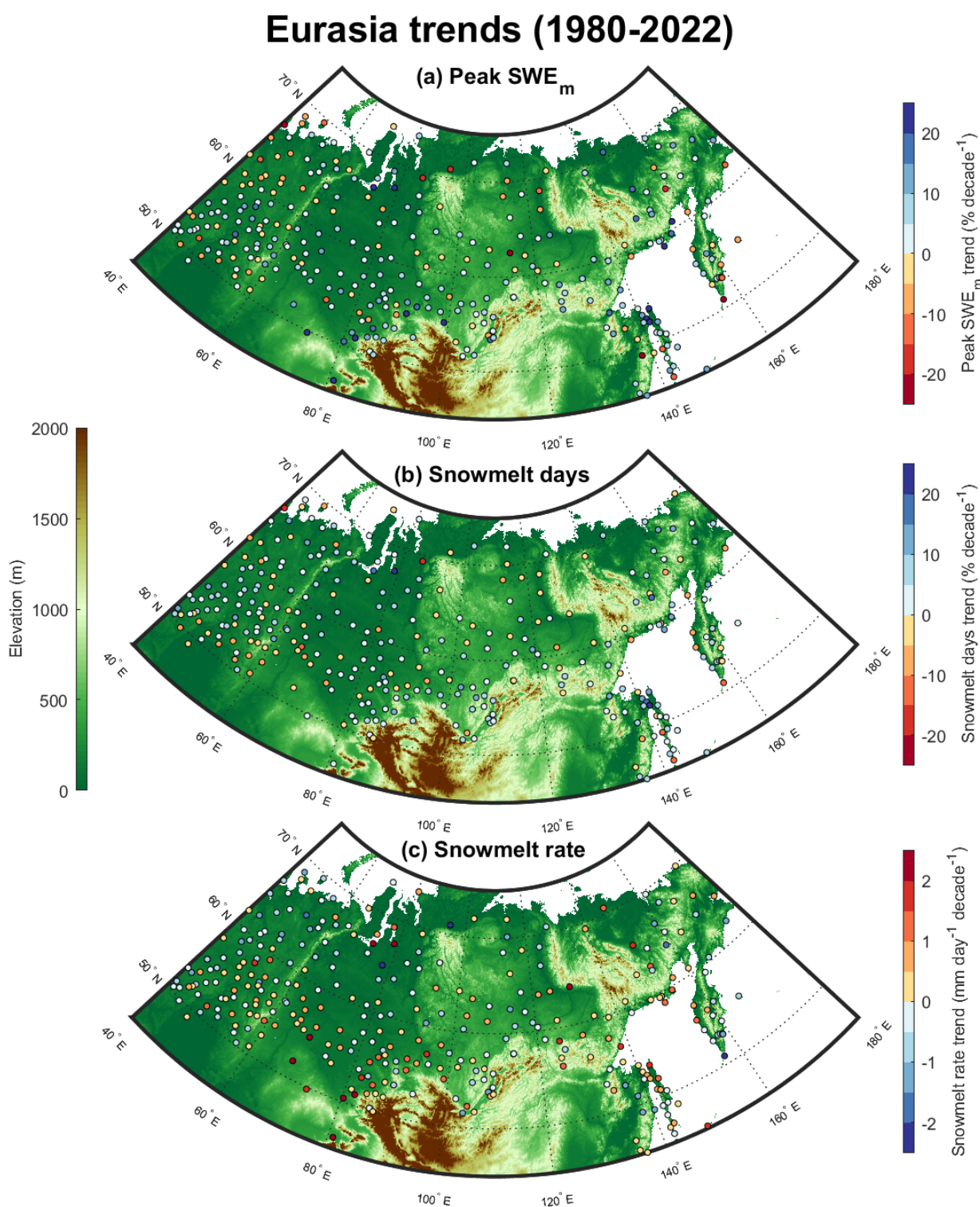


**Figure B.4:** Spatial variability of peak SWE, snowmelt days and snowmelt rate trends trends in Eurasia.

## Western North America trends (1980-2022)

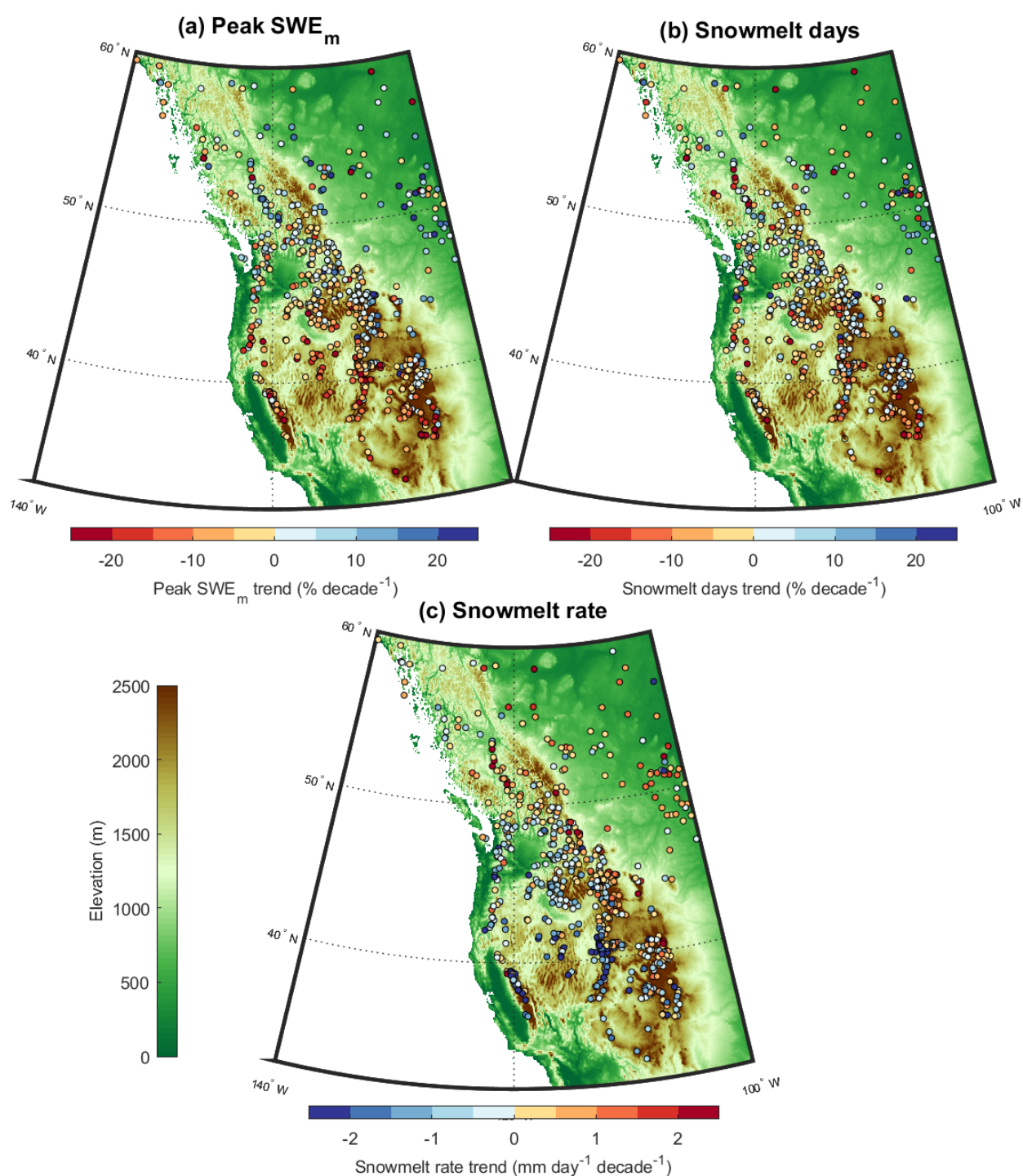


**Figure B.5:** Spatial variability of peak SWE, snowmelt days and snowmelt rate trends trends in Western North America.

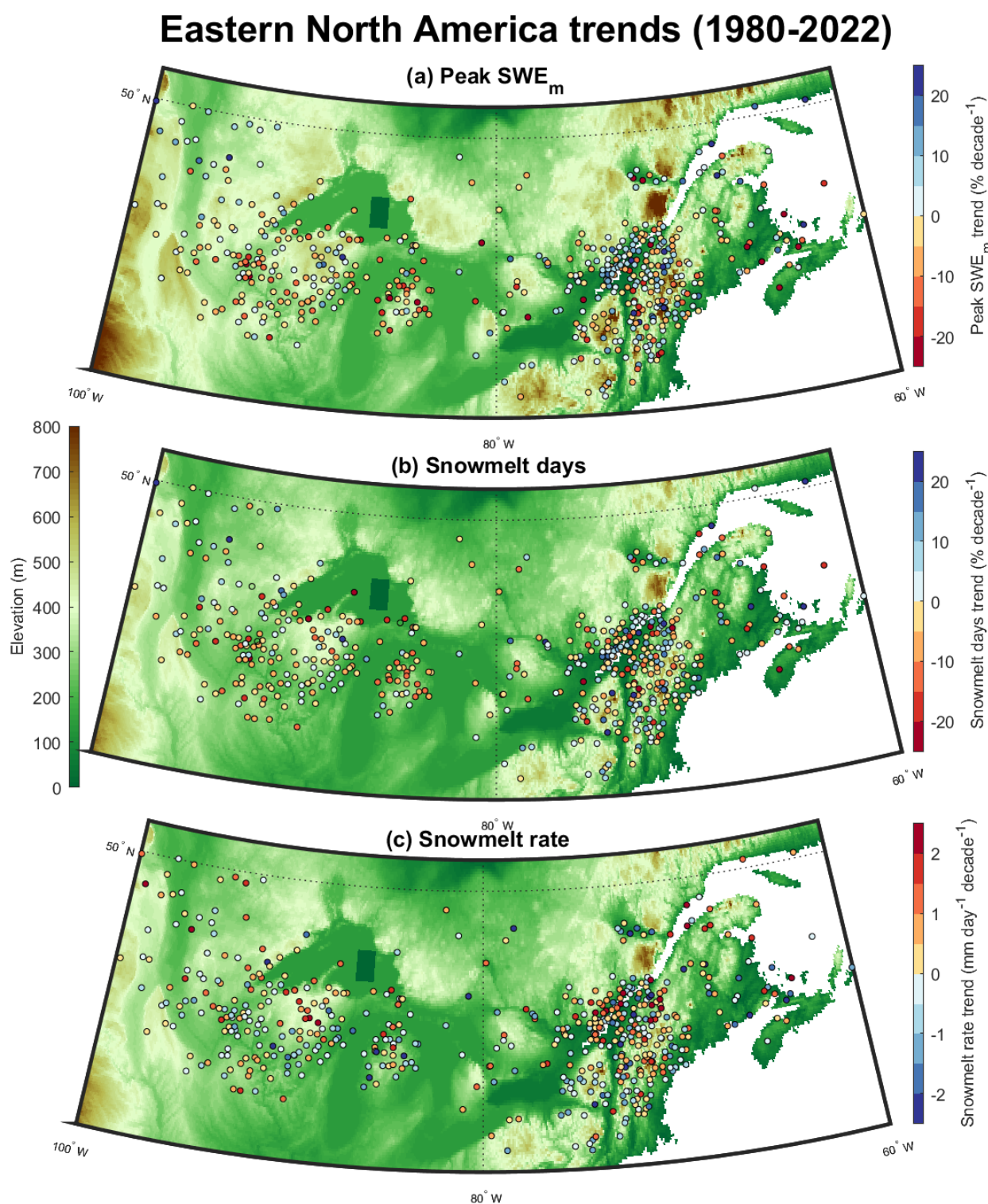


**Figure B.6:** Spatial variability of peak SWE, snowmelt days and snowmelt rate trends in Eastern North America.

# Appendix C

## Appendix Chapter 4

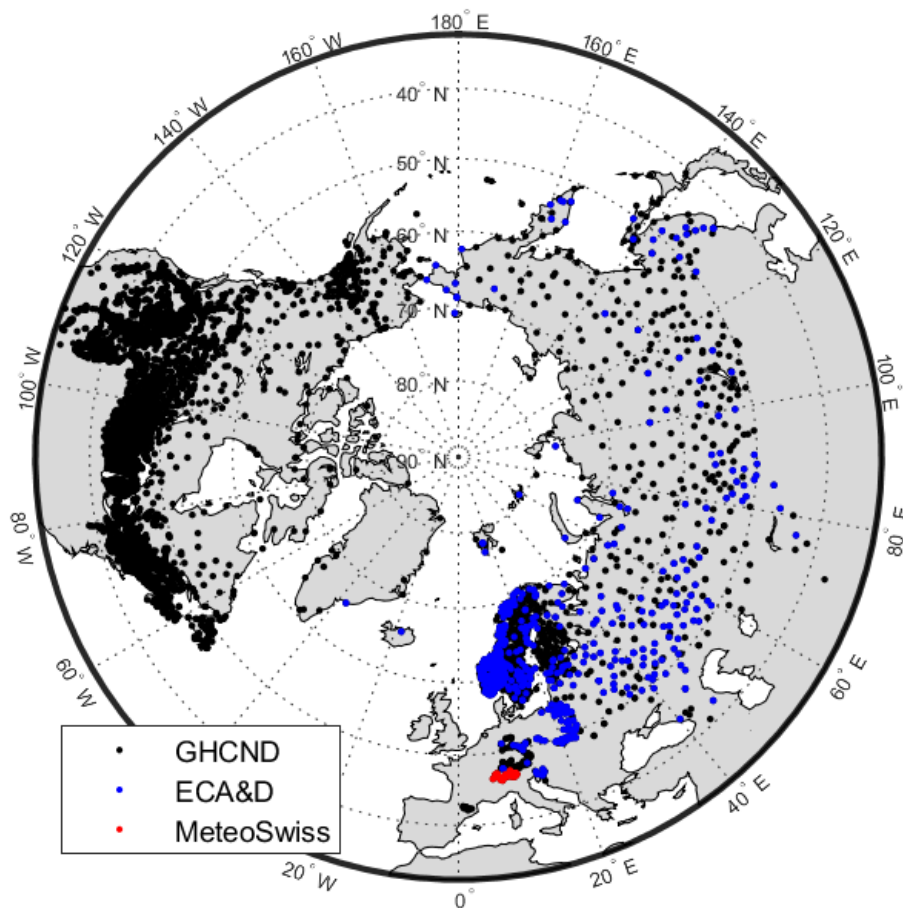


**Figure C.1:** Matched NH-SWE stations with GHCNd/ECA&D/MeteoSwiss stations, and their source.

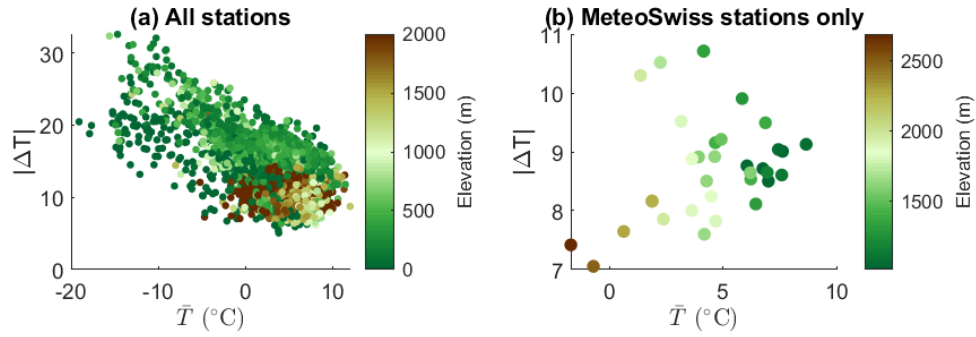


**Figure C.2:**  $\Delta T$  vs  $\bar{T}$  and elevation, for all stations (a), and for MeteoSwiss stations only (b).

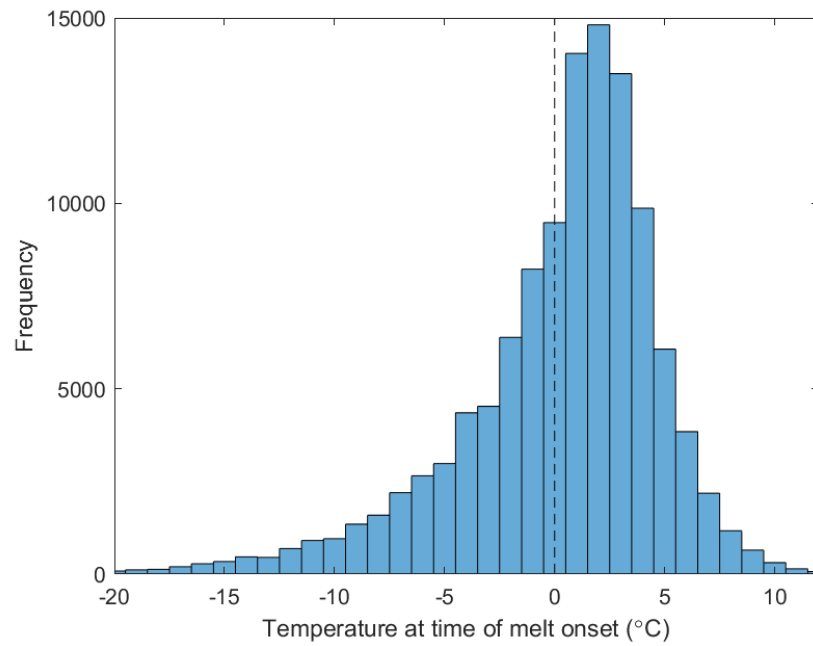


**Figure C.3:** Distribution of daily temperatures at the time of snowmelt season onset. Median is +1.10  $^{\circ}\text{C}$

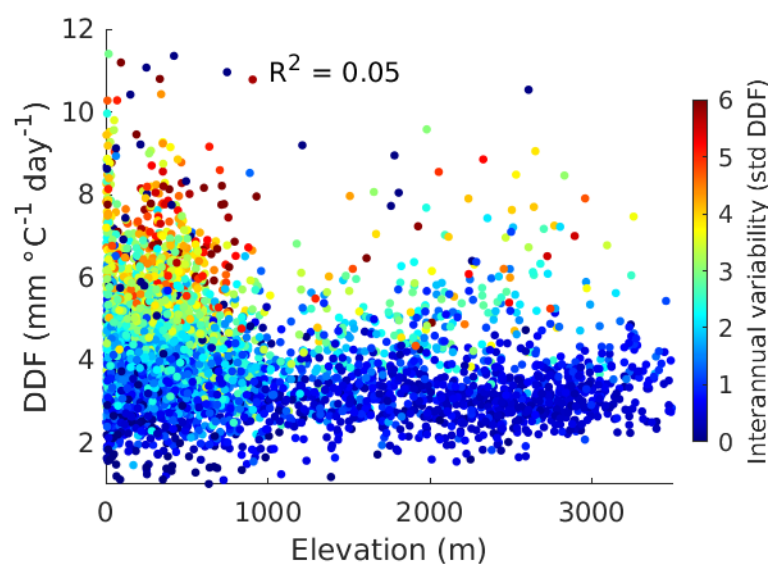


**Figure C.4:** Median DDF and elevation, coloured by its interannual variability.

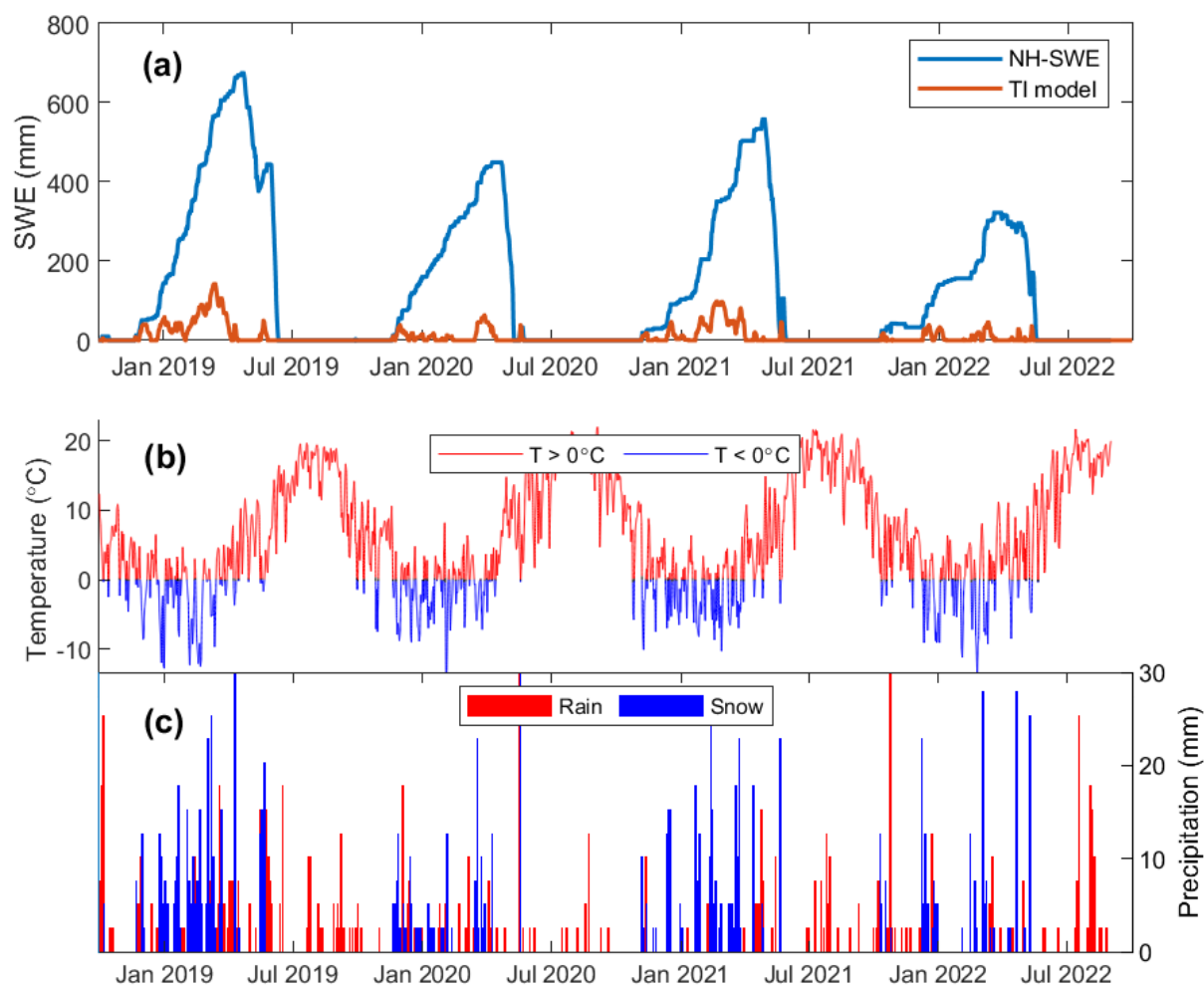


**Figure C.5:** Extended Figure 4.14. (a) SWE time series, (b) Temperature time series, (c) Precipitation time series. Station from GHCNd station ID USS0017K04S.

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