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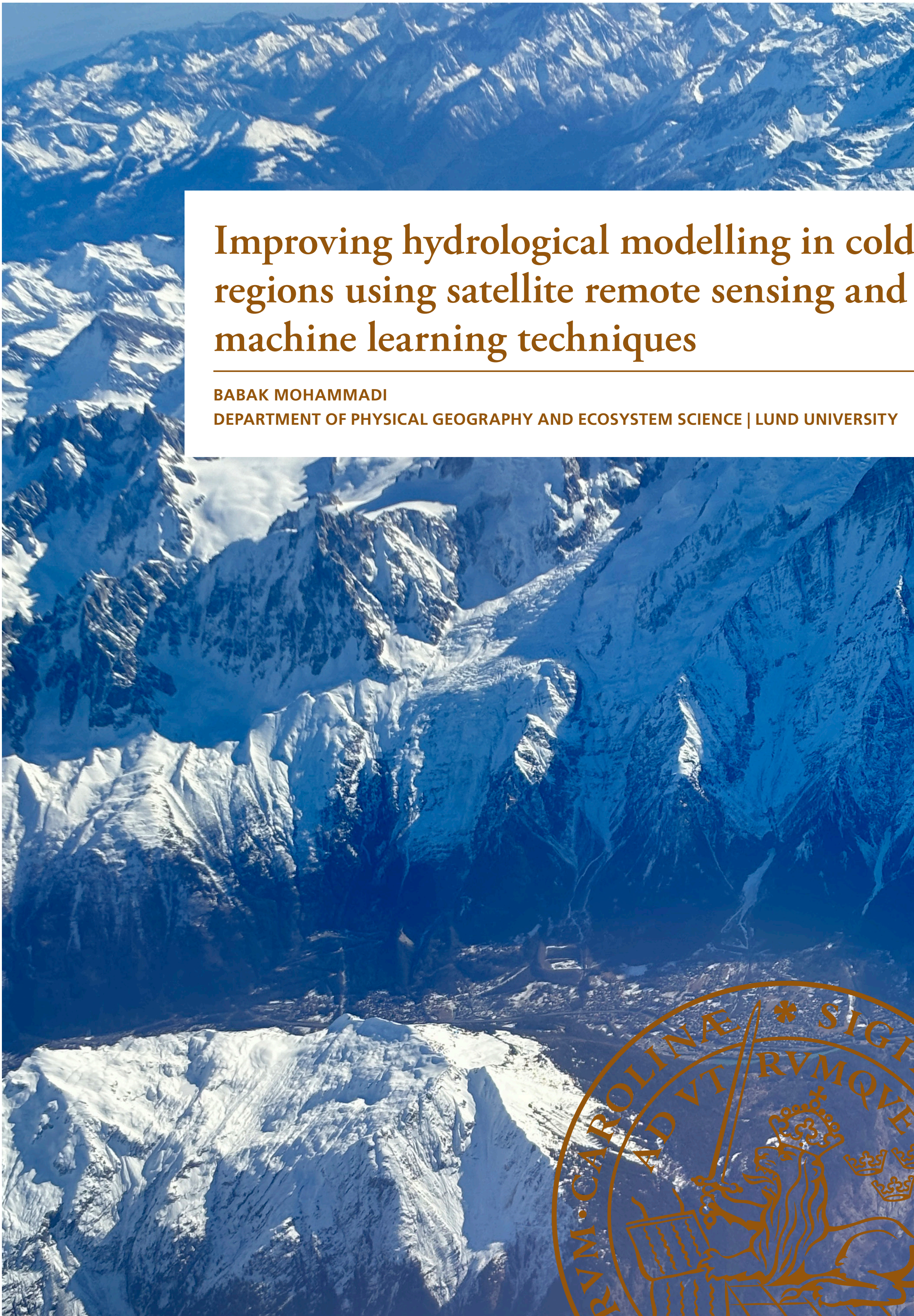

Improving hydrological modelling in cold regions using satellite remote sensing and machine learning techniques

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LUND UNIVERSITY

DOCTORAL DISSERTATION

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Abstract:

Water resources are fundamental to life, ecosystems, and human development. In an era of climate change and increasing water scarcity, effective management of these resources is crucial, particularly in cold regions where glaciers and snow play vital roles in hydrological cycles. Understanding and accurately modelling these complex systems is essential for sustainable water resource management, climate change adaptation, and ecological preservation. The aim of this PhD research was to enhance hydrological modelling in cold regions by developing and applying advanced techniques that address the complex interactions between snow, glaciers, and runoff processes. This research was divided into four subprojects. Subproject-1 focused on implementing and evaluating the FLEX^G model for glacio-hydrological modelling in the Torne River basin, northern Sweden, for the first time. The results demonstrated that the FLEX^G model performed very well in runoff simulation. Subproject-2 developed the Adjusted Normalized Difference Snow Index (ANDSI) for improved glacier mapping using Sentinel-2 imagery. This index, combined with machine learning (ML) algorithms, showed enhanced accuracy in differentiating glaciers from water bodies compared to existing methods across various glacierized regions. Subproject-3 aimed to develop and evaluate a multi-variable calibration approach by using satellite-derived snow cover area data to enhance hydrological simulation accuracy and realism. Subproject-4 investigated hybrid modelling frameworks that combine ML algorithms with the FLEX^G model for improving hydrological simulations in cold regions. The results indicated that the hybrid modelling framework, which incorporated precipitation, temperature, evapotranspiration, glacier mass balance, snow cover area, relative humidity, sunshine hours, solar radiation, and wind speed as inputs of the ML model, shows excellent performance in runoff simulation, especially in detecting peak flows. The proposed methods demonstrate the potential for improving our understanding of the complex interactions within glacierized catchments and enhancing the accuracy of hydrological predictions in these sensitive environments. This research supports the use of advanced modelling techniques and reliable data integration for the sustainable management of water resources and environmental protection in cold regions.

Key words: Hydrological modelling, hydroinformatics, remote sensing, machine learning, snow hydrology, water resources

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Abstract

Water resources are fundamental to life, ecosystems, and human development. In an era of climate change and increasing water scarcity, effective management of these resources is crucial, particularly in cold regions where glaciers and snow play vital roles in hydrological cycles. Understanding and accurately modelling these complex systems is essential for sustainable water resource management, climate change adaptation, and ecological preservation. The aim of this PhD research was to enhance hydrological modelling in cold regions by developing and applying advanced techniques that address the complex interactions between snow, glaciers, and runoff processes. This research was divided into four subprojects. Subproject-1 focused on implementing and evaluating the $FLEX^G$ model for glacio-hydrological modelling in the Torne River basin, northern Sweden, for the first time. The results demonstrated that the $FLEX^G$ model performed very well in runoff simulation. Subproject-2 developed the Adjusted Normalized Difference Snow Index (ANDSI) for improved glacier mapping using Sentinel-2 imagery. This index, combined with machine learning (ML) algorithms, showed enhanced accuracy in differentiating glaciers from water bodies compared to existing methods across various glacierized regions. Subproject-3 aimed to develop and evaluate a multi-variable calibration approach by using satellite-derived snow cover area data to enhance hydrological simulation accuracy and realism. Subproject-4 investigated hybrid modelling frameworks that combine ML algorithms with the $FLEX^G$ model for improving hydrological simulations in cold regions. The results indicated that the hybrid modelling framework, which incorporated precipitation, temperature, evapotranspiration, glacier mass balance, snow cover area, relative humidity, sunshine hours, solar radiation, and wind speed as inputs of the ML model, shows excellent performance in runoff simulation, especially in detecting peak flows. The proposed methods demonstrate the potential for improving our understanding of the complex interactions within glacierized catchments and enhancing the accuracy of hydrological predictions in these sensitive environments. This research supports the use of advanced modelling techniques and reliable data integration for the sustainable management of water resources and environmental protection in cold regions.

Popular summary

This study advances our understanding of cold regions hydrology, exploring glacier melt dynamics, their influence on water availability, improvements in glacier mapping, and the enhancement of predictive models. Glaciers, acting as massive freshwater reservoirs, are crucial in regulating water flow in rivers and streams by gradually releasing water as they melt. Using the $FLEX^G$ model, my research simulates the complex process of glacier mass balance and runoff in northern Sweden, incorporating landscape features like elevation and slope to improve the accuracy of our understanding. A key innovation in this study is the development of a new glacier mapping technique, the Adjusted Normalized Difference Snow Index (ANDSI). This method uses satellite data to create detailed and precise glacier maps, outperforming traditional approaches in accuracy. Also, my research employs a multi-variable approach, combining both streamflow and satellite-derived snow cover area data to produce more realistic simulations and enhance our understanding of how glaciers respond to environmental changes. Additionally, the study investigates the potential of artificial intelligence (AI) to enhance predictive modelling. By integrating AI's learning capabilities with the $FLEX^G$ model, I developed hybrid frameworks that combine AI with the conceptual hydrological model to enhance runoff simulation accuracy. These frameworks can address weaknesses in conceptual hydrological models, such as difficulties in accurately predicting peak flow events. This PhD research contributes to our understanding of catchment-scale hydrological modelling in cold regions, simulating glacier mass balance and its contribution to runoff, introducing an innovative satellite-based glacier mapping technique, and exploring AI's promising role in runoff modelling. This comprehensive approach paves the way for a more detailed and thorough appreciation of these vital natural resources.

Populärvetenskaplig sammanfattning

Denna studie främjar vår förståelse av hydrologi i kalla regioner, utforskar glaciärsmältningsdynamik, deras inverkan på vattentillgänglighet, förbättringar av glaciärkartläggning och förbättring av prediktiva modeller. Glaciärer, som fungerar som massiva sötvattenreservoarer, är avgörande för att reglera vattenflödet i floder och bäckar genom att gradvis släppa ut vatten när de smälter. Med hjälp av FLEX^{G}-modellen simulerar min forskning den komplexa processen med glaciärmassbalans och avrinning i norra Sverige, och inkluderar landskapsegenskaper som höjd och lutning för att förbättra noggrannheten i vår förståelse. En viktig innovation i denna studie är utvecklingen av en ny glaciärkartläggningsteknik, Adjusted Normalized Difference Snow Index (ANDSI). Denna metod använder satellitdata för att skapa detaljerade och exakta glaciärkartor, som överträffar traditionella tillvägagångssätt i noggrannhet. Min forskning använder också ett tillvägagångssätt med flera variabler, som kombinerar både vattenflöde och satellit-härledd snötäckesområdesdata för att producera mer realistiska simuleringar och förbättra vår förståelse för hur glaciärer reagerar på miljöförändringar. Dessutom undersöker studien potentialen hos artificiell intelligens (AI) för att förbättra prediktiv modellering. Genom att integrera AI:s inlärningsförmåga med FLEX^{G}-modellen utvecklade jag hybrida ramverk som kombinerar AI med den konceptuella hydrologiska modellen för att förbättra avrinningssimuleringsnoggrannheten. Dessa ramverk kan ta itu med svagheter i konceptuella hydrologiska modeller, såsom svårigheter att exakt förutsäga toppflödeshändelser. Denna doktorandforskning bidrar till vår förståelse av hydrologisk modellering av avrinningsområden i kalla regioner, simulerar glaciärmassbalansen och dess bidrag till avrinning, introducerar en innovativ satellitbaserad glaciärkartläggningsteknik och utforskar AI:s lovande roll i avrinningsmodellering. Detta övergripande tillvägagångssätt banar väg för en mer detaljerad och grundlig uppskattning av dessa viktiga naturresurser.

List of papers

Paper I

Mohammadi, B., Gao, H., Feng, Z., Pilesjö, P., Cheraghalizadeh, M., Duan, Z. (2023). Simulating glacier mass balance and its contribution to runoff in Northern Sweden. Journal of Hydrology, 620, 129404.

Paper II

Mohammadi, B., Pilesjö, P., Duan, Z. (2023). The superiority of the Adjusted Normalized Difference Snow Index (ANDSI) for mapping glaciers using Sentinel-2 multispectral satellite imagery. GIScience & Remote Sensing, 60(1), 2257978.

Paper III

Mohammadi, B., Gao, H., Pilesjö, P., Duan, Z. (2024). Improving glacio-hydrological model calibration and model performance in cold regions using satellite snow cover data. Applied Water Science, 14(3), 55.

Paper IV

Mohammadi, B., Gao, H., Pilesjö, P., Tuo, Y., Guo, R., Duan, Z. (2024). Integrating machine learning with process-based glacio-hydrological model for improving the performance of runoff simulation in cold regions. Manuscript under review.

Author's contribution to the papers

Paper I

Babak Mohammadi: conceptualization, data curation, formal analysis, investigation, methodology, resources, software, validation, visualization, writing – original draft. Hongkai Gao: methodology, resources, validation, writing – review & editing. Zijing Feng: methodology, software. Petter Pilesjö: supervision, writing – review & editing. Majid Cheraghalizadeh: methodology, visualization. Zheng Duan: conceptualization, formal analysis, funding acquisition, project administration, supervision, validation, methodology, resources, writing - review & editing.

Paper II

Babak Mohammadi: conceptualization, data curation, formal analysis, investigation, methodology, resources, software, validation, visualization, writing – original draft. Petter Pilesjö: supervision, writing – review & editing. Zheng Duan: conceptualization, formal analysis, funding acquisition, project administration, supervision, validation, writing – review & editing.

Paper III

Babak Mohammadi: conceptualization, data curation, formal analysis, investigation, methodology, resources, software, validation, visualization, writing – original draft. Hongkai Gao: methodology, resources, validation, writing – review & editing. Petter Pilesjö: supervision, writing – review & editing. Zheng Duan: conceptualization, formal analysis, funding acquisition, project administration, supervision, validation, writing – review & editing.

Paper IV

Babak Mohammadi: conceptualization, data curation, formal analysis, investigation, methodology, resources, software, validation, visualization, writing – original draft. Hongkai Gao: methodology, validation, writing – review & editing. Petter Pilesjö: supervision, writing – review & editing. Ye Tuo: validation, writing – review & editing. Renkui Guo: writing – review & editing. Zheng Duan: conceptualization, formal analysis, funding acquisition, project administration, supervision, validation, writing – review & editing.

Abbreviations

ANDSI	Adjusted Normalized Difference Snow Index
AI	Artificial Intelligence
AVHRR	Advanced Very High Resolution Radiometer
CGF	Cloud Gap Filled
CSI	Char Soil Index
ET	Evapotranspiration
GMB	Glacier Mass Balance
HBV	Hydrologiska Byråns Vattenbalansavdelning
KGE	Kling-Gupta Efficiency
Ln	Natural Logarithm
ML	Machine Learning
MAE	Mean Absolute Error
mm.w.e.	millimeter water equivalent
MODIS	Moderate Resolution Imaging Spectroradiometer
NDSI	Normalized Difference Snow Index
NSE	Nash-Sutcliffe Efficiency
SCA	Snow Cover Area
SWE	Snow Water Equivalent
TOA	Top Of the Atmosphere
R^2	Coefficient of determination
RF	Random Forest
RMSE	Root Mean Square Error
RSR	Ratio of root mean square error to the standard deviation of the observations

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Completing this PhD thesis has been a long journey, and it would not have been possible without the support, guidance, and encouragement of many individuals and institutions.

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Introduction

Importance of water resources and cryosphere in cold regions

Water is an essential factor on the Earth, and there are interactions between water and human, animal, and plants life; also, it has a key role in ecosystem health and sustainable development goals. The growing population of the world in the 20th century increased the water demand rapidly, and this huge water demand is expected to continue into the next generation (Ashley & Cashman, 2006). Then, understanding the amount of available water has been identified as the most critical global environmental issue of the 21st century (Gleick, 2000; Lall et al., 2008). Both surface and groundwater resources, including rivers, lakes, and glaciers, serve as principal sources of water for human use and environmental sustainability. This reality accentuates the necessity for a detailed analysis and assessment of water resources across diverse climates, emphasizing the need for integrated water management strategies to address this pressing global issue.

The cryosphere constitutes a critical component of Earth's climate system and hydrological cycle, encompassing all water in its frozen state. This landscape is characterized by the presence of snow, ice caps, glaciers, ice sheets, permafrost, and frozen ground (Barry & Gan, 2022; Qin et al., 2018). The cryosphere plays an essential role in affecting sea levels, atmospheric circulation patterns, and the availability of freshwater.

Approximately 70% of the world's freshwater is stored in glaciers and ice sheets, positioning the cryosphere as the planet's most significant freshwater reservoir (Hood et al., 2015). The interaction between the cryosphere and the hydrosphere is pivotal for understanding climate dynamics and Earth's systems (Yongjian et al., 2020). This interaction encompasses the transition of liquid water across various cryospheric components, including glaciers, ice sheets, snow cover, permafrost, river ice, lake ice, and sea ice. Such interactions exert profound impacts on hydrology, water resources, ecology, and the overall environment. Hydrological processes in cold regions are intricate and involve the movement, distribution, and quality of water in environments dominated by snow, ice, and frozen ground. These processes are important for assessing water availability, ecosystem health, and climate dynamics in these regions. Notably, cold region hydrology features distinctive phenomena such as snow accumulation and melt, permafrost thawing, ice formation, and glacier dynamics. These phenomena significantly affect water flow and storage, highlighting their importance in the study of hydrology (Bibi et al., 2018; Gao et al., 2021). The cryosphere plays an essential role in the global climate system and hydrology by encapsulating all Earth's frozen water and snow-covered areas, including glaciers, ice caps, ice sheets, sea ice, snow cover, permafrost, and frozen ground. The cryosphere significantly influences the global climate through its high albedo effect, which relates to the reflectivity of the Earth's surface (Barry, 2002; Barry, 1985). Surfaces blanketed by snow and ice reflect a larger proportion of solar radiation back into space compared to darker surfaces, contributing to the cooling of the Earth. This regulatory effect plays an essential role in maintaining the energy balance and temperature stability of our planet. In addition, release of meltwater from glaciers is of particular significance in several regions, including the Himalayas, Andes, and specific areas of Central Asia, where it constitutes a crucial water source during the dry seasons (Ragettli et al., 2016; Nie et al., 2021). The timing and quantity of glacier meltwater are vital for sustaining river flows that support agricultural activities, provide drinking water, and enable energy production. This emphasizes the significance of comprehending and observing the dynamics of the cryosphere, due to cryosphere role in cold regions' water management.

Snow and glacier melt play a pivotal role in modulating river flow patterns throughout the year, with particularly significant impacts during spring and summer. Along with groundwater, they serve as vital water resources across seasons, including during periods of low precipitation or high demand. The water derived from the melting of snow and glaciers is critical for sustaining the livelihoods of millions; specifically, it provides sufficient water for 38 million people to maintain a balanced diet (Biemans et al., 2019). Snow's contribution is especially significant in augmenting streamflow in numerous highland and cold regions worldwide. Furthermore, the melting of seasonal snow cover and permafrost has a notable impact on the annual water volume in rivers located downstream (Tong et al., 2020). This dynamic significantly influences water availability and supports various ecological systems, and also human populations that depend on these water resources for agriculture, drinking, and other uses. Therefore, understanding the complexities of snow and glacier melt processes is essential for predicting and managing water resources in the cold regions. In addition, permafrost represents a critical component of the cryosphere, influencing hydrological processes through its interaction with snow and glaciers (Chang et al., 2023). As a perennially frozen layer of soil, permafrost acts as a storage for significant amounts of groundwater, which contributes to baseflow in river systems.

Approximately 338 million people live in regions that are regularly covered in snow during the winter months in the Northern Hemisphere (Järvi et al., 2017). Population growth, food scarcity, and global warming have led researchers to pay more attention to these areas in recent years. There are cold regions on earth where snow and ice are present at least part of the year. The definition of cold regions is given first, followed by their key characteristics, such as snow, ice, permafrost, and glaciers. Despite being sparsely populated, the polar and cold regions play a key role in terms of climate change, sea-level rise, and water availability. During the winter, snow covers up to 50% of the Northern Hemisphere, but short-term weather anomalies as well as long-term effects of climate change influence snow cover distribution, duration, and amount. The boundaries of the Northern Hemisphere's cold regions are determined using parameters such as air temperature, snow depth, ice cover, and frozen ground. From a hydrological perspective, cold regions are areas of the world that have at least seasonal snow and ice (Gelfan & Motovilov, 2009). Cryosphere has a preponderant influence on hydrology in these regions, and the complex interactions between the cryosphere and hydrological processes result in unique hydrological responses to climate change, which are marked by spatial and temporal heterogeneity. Hydrological conditions in cold regions are controlled by the seasonal accumulation of snow and ice, and subsequently by their melting. When the snowpack melts, the accumulated water in the snowpack makes a significant contribution to total streamflow, which often represents an important water resource in many parts of the world (Barnett et al., 2005).

In a cold region, glaciers, snow cover, permafrost, and all components of freezing water are also essential components of the water balance in the cold region watershed system. Changing climatic factors can affect changes in hydrology in cold regions, such as frozen soils, snowfall/rainfall ratio, snow cover, river ice, glaciation, and vegetation. A cold region watershed water ecosystem is controlled by a hierarchical set of climatic, hydrological, and glacial variables. Hydrological studies in a cold region mainly focus on four distinguishing factors, including snow, permafrost, glaciers, and lake and river ice (Hock et al., 2019). While snowmelt is the primary contributor to both surface and subsurface flows, seasonally frozen soil also influences how meltwater and rain are partitioned between these flows (Aygün et al., 2020). Existing glaciers in cold regions add more importance to cold regions' hydrological studies. As we know, glaciers are the main resource of freshwater in the cold regions, and they play a critical role in cold regions' water resources management (Woo, 2008). Then knowing about the behavior of glaciers requires knowing about cold regions' hydrology, in addition, the different climates in the cold regions will add more complexity to water resources management in cold regions (Freitag & McFadden, 1997). In regions where sub-freezing temperatures persist for most of the year, hydrological models need to take into consideration the effects of snow, below-zero temperatures, and the presence of frozen water bodies. This emphasizes the need for specialized approaches in hydrological research and water resource management in cold areas.

Aims and objectives

This study aims to enhance our understanding of glacio-hydrological processes within cold regions and to improve the performance of glacio-hydrological modelling through the integration of process-based hydrological model, satellite remote sensing (RS) data, and machine learning (ML) techniques. The key objectives are:

1. To evaluate the performance of the semi-distributed glacio-hydrological conceptual model (FLEX^G) in simulating glacio-hydrological variables in the Torne River basin, northern Sweden.
2. To develop and assess the efficacy of a new satellite-based index, the Adjusted Normalized Difference Snow Index (ANDSI), in conjunction with ML algorithms, for improving the accuracy of glacier mapping in snow-covered regions. The aim is to demonstrate the superiority of ANDSI over the traditional Normalized Difference Snow Index (NDSI) across various glacierized regions in Canada, China, Sweden, and Switzerland-Italy.
3. To investigate the benefits of employing a multi-variable calibration framework in reducing model uncertainty and enhancing the realism of hydrological modelling in a glacierized catchment in northern Sweden. This includes comparing the calibration performance of the FLEX^G model using different combinations of gauged streamflow and satellite-derived snow cover area (SCA) data.
4. To explore the potential of ML frameworks in improving the performance of the FLEX^G model for glacio-hydrological simulations in northern Sweden. This involves assessing the efficacy of three different hybrid approaches to combine the FLEX^G model with the Random Forest (RF) algorithm via a physics-aware approach, integrating residuals with meteorological and glacio-hydrological variables, and coupling these variables in a sequential RF model for enhancing runoff modelling accuracy and detecting peak flow events.

To achieve the stated goals, four papers (I, II, III, and IV) have been developed. Each paper tackles one or several of the outlined objectives, together creating the structure of the current study (Figure 1).

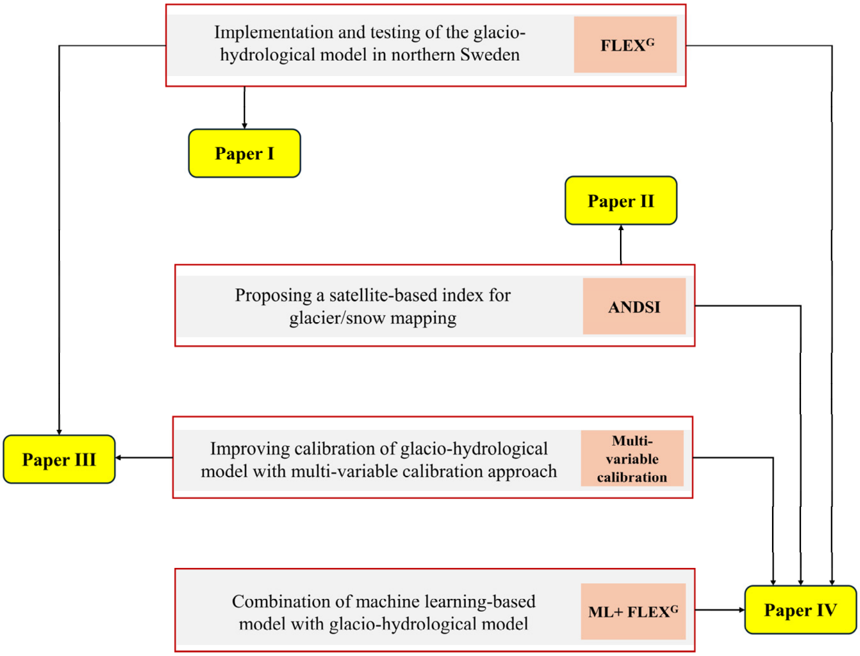

Figure 1. Illustration of this study's workflow that highlights relationships and correspondence among the papers included in the study.

Structure of the thesis

This PhD thesis begins with an introduction section, outlining the aims and objectives of the research and providing an overview of the thesis structure. The second chapter discusses the concepts of hydrological modelling in cold regions, the critical role of snow and glaciers in the hydrological processes of these regions, the challenges posed by the lack of in-situ measurements, and various hydrological modelling approaches. This chapter also explores the use of ML models and RS technology to enhance hydrological simulations. The materials and methods chapter details the methodologies used in the four key studies (Papers I-IV) that form the core of this research. Following this, the results and discussion chapter presents the findings from these studies, including the performance of the FLEX^G model in simulating glacio-hydrological processes (Paper I), the development and application of ANDSI for glacier mapping (Paper II), the benefits of multi-variable calibration for hydrological models (Paper III), and the integration of hydrological models with ML algorithms (Paper IV). Finally, the conclusions and recommendations chapter summarizes the key findings and provides recommendations for future research.

Enhancing hydrological modelling in cold regions: challenges, approaches, and advanced techniques

Role of snow and glacier in hydrological processes of cold regions

In modelling snow processes, various factors are considered to enhance accuracy, including the non-uniform temperature distribution within snow cover and the impact of snow and ice on radiation and albedo. An essential aspect of glacial modelling is determining the thickness of snow cover and ice, as this information is vital for calculating the snow water equivalent (SWE). SWE refers to the quantity of water stored in the snowpack (Taheri & Mohammadian, 2022), and SWE plays an indispensable role in the hydrological cycle, acting as a major freshwater reservoir that releases water into rivers and groundwater systems during warmer months.

In mountainous regions, a comprehensive understanding of snow cover characteristics is instrumental in forecasting avalanches and floods, highlighting the critical nature of snow in disaster risk management. Also, snow cover is essential for sustaining local water supplies, facilitating river runoff, and contributing to groundwater recharge, particularly in mid to high latitudes (Dumont & Gascoin, 2016). The modification of albedo in snow-covered basins is another significant effect of snow cover, which in turn affects solar radiation absorption, and the rate of evapotranspiration (ET) within glacierized or snow-covered basins (Jain et al., 2008). These multifaceted impacts of snow on the environment underscore its vital role in climate regulation, water cycle processes, and ecosystem health, making the accurate parameterization of snow processes in models essential for predicting and managing water resources effectively.

In regions with cold climates, the production of runoff is greatly affected by factors such as temperature, precipitation, snow and glacier variations, and additionally, the melting rate of snow and glaciers. This is because these areas are characterized by the presence of substantial amounts of frozen water and often experience negative air temperatures (Hagg et al., 2013). The quantification of changes in glaciers and the processes of snowmelt are crucial for hydrological research in these cold environments (Barnhart et al., 2016). The meltwater from glaciers and snow plays a pivotal role in regulating river flow patterns throughout the year, with significant contributions during spring and summer melt periods. It also contributes to replenishing groundwater supplies, which is particularly important during periods of low rainfall.

With climate change leading to warmer temperatures, snowmelt patterns are shifting, often resulting in earlier and more rapid melting. This shift can disrupt the traditional balance of water availability, leading to potential water scarcity when demand is high during the warmer months, and increasing flood risks during peak melt periods. These challenges underscore the importance of accurately predicting and managing the impacts of snowmelt on runoff. Efficient water resource management in these contexts demands a deep understanding of the hydrological processes involved in snow and glacier melt. Moreover, it requires the use of advanced hydrological models capable of accounting for the nature of snowmelt and glacier dynamics. Such models are indispensable tools for predicting water availability, planning for water resource allocation, and devising strategies to mitigate the adverse effects of climate change on water systems in cold regions. Through research efforts, we can aim to secure water resources for future generations, preserve ecosystems, and sustain human development even in the face of evolving climatic conditions.

The effect of glacier melting is manifested in many nonlinear hydrological processes in cold region ecosystems, resulting in a multitude of systems consisting of natural hydrological interactions between snow and glacier on all aspects of the ecosystem in cold regions (Frezzotti & Polizzi, 2002; Ferrigno et al., 1998). Changes in the glacier area, volume, surface properties, and physical properties (i.e., albedo, snow cover, ice sheet) reflect changes in air temperature, precipitation, and geomorphology (Haeberli et al., 2000). The catchment surfaces can be covered with varying snow/ice/glacier thicknesses, which significantly affects the surface energy balance and changes the state of the surface boundaries (Collier et al., 2015). The meltwater from glaciers feeds large river basins, and it supplies water resources for millions of people in different places of the world. In addition, the melting rates of glaciers in the high mountains can change the frequency and extent of flash floods from glacial lakes, and it can have a significant effect on downstream communities (Vaughan et al., 2013; Liu & Jezek, 2004). The snowmelt runoff is vital for hydroelectric power generation, irrigation, and water supply in cold regions. Quantifying and improving our understanding of the glacier mass balance (GMB) and dynamic of glaciers in the high mountains are critical to effectively predicting and mitigating the effects of changes in these water resources. Snow packs in mountain areas are highly sensitive to air temperature and precipitation phase, both of which significantly influence their formation and persistence. Due to the observed increase in air temperature, the proportion of snowfall relative to total precipitation has decreased over the given period in some regions (Knowles et al., 2006). This decrease leads to a generally decreasing snow cover, subsequent snow accumulation, and earlier thawing (Fyfe et al., 2017).

Referring to the above-mentioned, it is important to have access to long-term and reliable datasets for investigating the impact of snow and glaciers on water resources. Hydrologists utilize a variety of technologies to gather hydrological data, ranging from manual observation gauges at flow measurement points to advanced automatic data recorders employing synoptic station technology. However, these methods are often costly, labor-intensive, and time-consuming, especially in harsh, high-altitude environments like cold regions, snow-covered terrains, and glaciers, where severe conditions significantly hinder hydrological data collection. The dearth of data in glacial-hydrology systems within glacierized catchments represents a considerable challenge for hydrologists. In order to overcome these challenges, hydrologists are often turning to indirect approaches, such as utilizing RS techniques.

Lack of in-situ measurements in cold regions

Hydrologic data are at the core of our understanding of physical hydrologic processes, and it is necessary for towering our knowledge about hydrology (McMillan et al., 2018). Ideally, hydrological studies need to have long-term in-situ measurements of hydrological variables such as streamflow, snow cover, and glacier extents. Also, for water resources management and policymaking, we need to understand the hydrological process, and that requires long time series of hydrological variables. It is very important to obtain reliable and qualified in-situ measurements in cold regions for water resources management. A wide range of hydrologic data exists, from raw data, such as depths to groundwater at a well, to highly processed data, such as rainfall totals derived from radar. Perhaps one of the biggest challenges for researchers who are working in the fields of water resources management, climatology, and physical geography is access to up-to-date and long-term data. For collecting hydrological data, hydrologists use various technologies, ranging from observing gauges installed at flow measuring points to automatic data recorders and synoptic station technology. But these methods are costly, and they need human resources, and also they require a long time to collect data. Hydrological data collection faces significant challenges in cold regions, snow-covered areas, and glacier areas. The presence of snow, ice, and glaciers introduces additional complexities to data gathering processes. Furthermore, snow and glacier regions are often located in high-altitude areas with harsh environments, making data measurement particularly difficult. Lack of data measurement in the glacial-hydrology system in the glacierized catchment areas is a challenge for hydrologists, and therefore hydrologists have been trying to use other indirect technologies, such as RS approaches, for overcoming this limitation.

The processes of change in cold regions are numerous and complex, and forecasting future change is fraught with uncertainty. Then, for handling this complexity, we consider hydrological modelling and RS technology as a powerful tool for this aim. Hydrological modelling for reproducing required hydrological data has been proved as a capable approach in case of a lack of hydrological datasets (Wang et al., 2023). Therefore, we need to modify and test hydrological models for improving our understanding and making hydrological simulations (particularly for the cold regions). Satellite-based RS applications have improved our knowledge about snow cover and glacier mapping, and it helps us to have a better view and monitoring of glacier behavior (Wang et al., 2018; Kumar & Venkataraman, 2011; Fayad et al., 2017). Researchers have been monitoring snow and glacier behavior via RS technology in different climates of the world (Baumhoer et al., 2018).

Hydrological modelling approaches in cold regions

A hydrologic basin is defined by its natural topographic boundaries and its hydrological waterway system, serving as a water-based ecosystem where all precipitation and melted snow are collected through streamflow at the basin's outlet (Chen et al., 2020; Wagener et al., 2007). The regulation of surface and groundwater flows, as well as the overall water balance within the basin, are influenced by river shapes, land topography, wetlands, and coastal regions. These factors are determined by precipitation, evaporation, infiltration, runoff, groundwater recharge, and erosion (Wang et al., 2021). Mankin et al. (2015) highlight that snowmelt runoff supplies water to approximately two billion people in the Northern Hemisphere. Specifically, in the western United States, snowmelt accounts for 53% of total runoff, a figure that increases to around 70% in mountainous regions (Li et al., 2017). Moreover, seasonally frozen ground plays a crucial role in water infiltration, significantly contributing to the hydrology of cold regions (Lundberg et al., 2016). During snowmelt periods, completely frozen ground can prevent water infiltration entirely, leading to surface runoff and potentially causing larger and more frequent floods. The hydrology of cold regions is distinctively shaped by the cryosphere and specific hydrological processes. Snowmelt primarily contributes to runoff, while the presence of seasonally frozen soils affects the distribution of meltwater. Climate change has notably impacted the cold regions of the Northern Hemisphere's midlatitudes. Thus, assessing the effects of climate change on the hydrology of this region is crucial, as it supports a significant population that depends on hydrological services and faces evolving hydrological risks.

The hydrological cycle of the Earth encompasses all processes that move water from the land and ocean surfaces to the atmosphere and back in the form of precipitation, and a hydrological model tries to simulate this process (Gelfan & Motovilov, 2009). The characterization of hydrologic features and systems using small-scale physical models, mathematical analogs, and computer simulations is known as hydrological modelling (Renard et al., 2010). During the hydrological modelling process, a modeler tries to provide a simplification of a real-world water system for monitoring, predicting, understanding, and managing water resources systems (Yang et al., 2020). The goal of hydrological modelling is to concentrate on individual flows in a hydrological system, with various parameters controlling the intensity of the flows as well as soil, land, climate, and river properties. As a result, the accuracy of modelling is primarily determined by the number of parameters and the used way for their implementation, and also the functions used in the model (Anees et al., 2016).

Catchment scale hydrological models are applied for a wide range of aims, including water resource management, flood risk assessment, climate change impact studies, and environmental protection. Despite their utility, catchment scale hydrological models face several challenges. Some of the most common challenges are (i) data availability: the presence of high-quality, long-term hydrological and meteorological data is required for the calibration and validation of models; however, it is often lacking or non-existent in numerous regions. (ii) parameter uncertainty: many models have parameters that are difficult to measure directly in the field, and this results in uncertainties in model outputs.

Within the field of catchment scale hydrological modelling, there are three main methods that have been developed to study and understand how water moves within a catchment area. These methods are known as distributed, semi-distributed, and lumped models (Khakbaz et al., 2012; El-Nasr et al., 2005). Distributed models provide a detailed representation of hydrological processes by considering spatial variability. However, they require a large amount of data and computational power due to their complexity. Semi-distributed models offer a compromise by dividing the catchment into separate units according to specific characteristics. This approach streamlines the representation within each unit, striking a balance between providing detailed information and ensuring efficiency. In contrast, lumped models simplify the catchment into a single, uniform entity, giving priority to simplicity and reduced data needs rather than spatial intricacies. Each approach possesses distinct strengths and limitations, addressing varying research requirements, data accessibility, and modelling goals. Figure 2 illustrates schematic definitions of these three approaches.

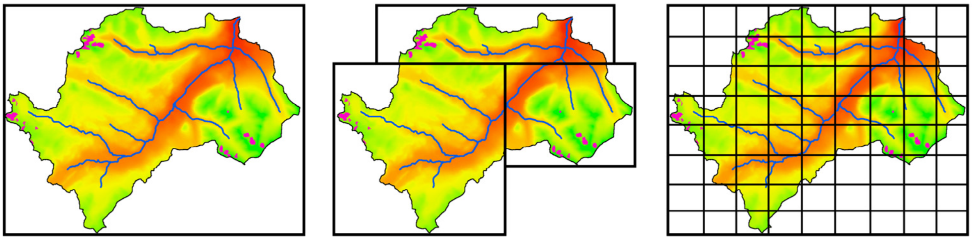

Figure 2. Comparison of hydrological models at the basin scale: this schematically illustrates three types of hydrological modelling approaches. (1) Lumped model, where the basin is represented as a single unit, capturing average responses without spatial differentiation. (2) Semi-distributed model, which segments the basin into multiple sub-units to address spatial variability in parameters and hydrological processes. (3) Fully distributed model, depicting the basin with high spatial resolution where parameters and hydrological processes are varied continuously across the entire area.

Hydrological models are typically utilized for individual river basins and incorporate various parameters that require calibration specific to each case study. Examples include the Xinanjiang model (Zhao, 1992), the Hydrologiska Byråns Vattenbalansavdelning (HBV) model (Bergström, 1995), and the Soil and Water Assessment Tool (SWAT) (Arnold et al., 2012). These models are categorized based on several aspects of process description, such as parameterization schemes, time scales, and the spatial resolution of simulations (Hrachowitz & Clark, 2017; Paniconi & Putti, 2015). Essential hydrological and meteorological components required by these models to understand hydrological processes include precipitation, air temperature, ET, SCA, snow depth, and GMB (Wang et al., 2018; Gao et al., 2020; Lamačová et al., 2014). A notable degree-day factor (DDF)-based model for cold regions (glacierized basins) is the Glacio-hydrological Degree-day Model (GDM), offering a window into the dynamics of the hydrological system by offering information on snowmelt, ice melt, rain, and baseflow (Kayastha & Kayastha, 2020). Generally, distributed models are capable of considering each point within a basin, offering a comprehensive view of hydrological variables; however, they require extensive information and numerous parameters to operate effectively. In contrast, lumped models, which operate with fewer variables and parameters, do not provide detailed insights across all points of a basin.

The influence of changes in climate indices, particularly snowfall, on the seasonal water balance and runoff process is well-documented (Dierauer et al., 2018). Mountain areas function as complex systems, necessitating a comprehensive analysis that integrates all climatic and geographic data. Previous research has underscored the critical role of snow in generating runoff (Jenicek & Ledvinka, 2020; Barnhart et al., 2016). The topics of snow storage, snowmelt, and runoff changes across various regions have garnered significant attention in glacial-hydrological studies (Dierauer et al., 2018; Van Loon et al., 2015). The rates of runoff are influenced by the quantities of snow and glaciers within a snow-covered basin, highlighting the importance of understanding the glacier's contribution to the runoff generation process (Godsey et al., 2014). For the understanding effect of the glacier in the runoff process, a comprehensive glacio-hydrological model requires by conserving all snow changes in each elevation zone (Jenicek & Ledvinka, 2020). The current study employed a recently developed glacio-hydrological model, the FLEX^G model (Gao et al., 2017), to address this complexity. The literature review indicates that the FLEX^G model, unlike other hydrological models, can accurately simulate runoff amounts for both glacier and non-glacier parts of a basin separately. Furthermore, it offers insights into GMB changes under various topographic conditions by incorporating elevation zone data. These capabilities distinguish the FLEX^G model as a uniquely effective tool for hydrological modelling in glacierized basins.

Machine learning models for improving hydrological simulations

ML techniques are considered state-of-the-art methodologies in water resources management, particularly for hydrological modelling tasks. ML has the capability to discover patterns and connections within extensive datasets in order to improve the prediction of hydrological responses or enhance the parameterization of models (Xu & Liang, 2021; Kratzert et al., 2019). The application of these methodologies proves highly advantageous for continuously refining models with real-time data inputs. This offers a robust tool for effectively managing water resources in regions with cold climates that experience rapid changes.

The incorporation of ML models into hydrological simulations signifies a substantial advancement in the realm of the hydrological sciences. ML provides robust tools for enhancing the accuracy and efficiency of hydrological models through its capacity to learn from data, identify patterns, and make predictions. The integration of hydrological models with ML techniques combines the process-based understanding of hydrological systems from conventional models with the data-driven insights provided by ML (Yang et al., 2020; Mekonnen et al., 2015). The combination of hydrological and ML models results in a suite of benefits that significantly enhance the capabilities of hydrological simulations (Konapala et al., 2020). Furthermore, the integration of ML aids in quantifying and mitigating the inherent uncertainties present in hydrological modelling, thus yielding more dependable predictions and risk assessments. The importance of this aspect is paramount in fields such as water resource management and climate change studies, where accurate predictions can influence policy decisions and planning strategies. Additionally, ML algorithms contribute to boosting computational efficiency, and this increased efficiency makes complex hydrological simulations more feasible and also supports the investigation and modelling of hydrological processes at scales and complexities previously deemed unattainable.

The main objective of integrating hydrological models with ML is to improve the accuracy and efficiency of hydrological simulations. Hydrological models, which are based on fundamental physical principles, demonstrate exceptional proficiency in capturing the fundamental processes of the hydrologic cycle. However, they may encounter challenges when dealing with intricate nonlinear interactions and uncertainties associated with parameters. In contrast, ML models exhibit exceptional aptitude in detecting patterns and correlations within vast datasets; nevertheless, they lack the inherent capability to comprehend the underlying processes behind these patterns. The aim of some researchers is to integrate these two components in order to establish models that are both informed by physical principles and optimized through data analysis. The outcome will be an enhanced and all-encompassing tool for hydrological forecasting and analysis.

The integration of ML and a process-based hydrological (PBH) model can be achieved through various ways, depending on factors like data accessibility, the design of the ML model, and the capabilities of the hydrological model. The categorization of ML-PBH models includes four commonly utilized implementations, including: (1) parallel combination of ML- PBH: in this approach, an ML model and a PBH model run simultaneously, and their results are combined through averaging or ensemble modelling to produce a final prediction (Gelete et al., 2023; Mohammadi et al., 2021). For example, the ML model might predict variables like rainfall-runoff relationships, while the PBH model simulates physical processes related to rainfall-runoff. The final prediction is then a blend of both models' outputs. (2) Nested ML-PBH: this involves using the output of one model as the input to another. For instance, a PBH model might predict certain hydrological variables, which are then used as inputs to an ML model to simulate runoff amounts (Chen et al., 2023; Yu et al., 2023). (3) ML-assisted PBH: in this case, an ML model enhances the performance of a PBH model (Boucher et al., 2020; Sezen & Partal, 2022). The ML model can be trained to predict certain variables (e.g., soil moisture, ET, etc.), and it can be used as boosting technique during PBH calibration or can be used for updating specific parts of the PBH (e.g., parameters of PBH), and the PBH can then simulate the physical processes related to hydrology. (4) PBH-assisted ML: in this scenario, a PBH (or hydrological principles) is used to improve the performance of an ML model. The PBH model might simulate physical hydrological processes or incorporate physically-based equations like water balance equations into the ML model. The enhanced ML model can then predict variables such as streamflow or groundwater recharge (Bhasme et al., 2022; Zhong et al., 2023).

Use of remote sensing technology to improve hydrological modelling in cold regions

The definition of remotely sensed information is the acquisition of information without making physical contact with an object, as opposed to in situ or on-site observations. Specifically, this term applies to acquiring information about the Earth through RS techniques (Lillesand et al., 2015). Using satellite RS instruments, we can gain a better understanding of human influence in the biosphere, enabling us to determine the spatial scale and extent of human direct interaction with land cover. In satellite RS, a machine orbiting the Earth collects radiation reflected from the Earth's surface. RS approach can be used as a technique to observe the Earth’s surface or the atmosphere from out of space using satellites (space-borne) or from the air using aircraft (airborne). RS uses a part or several parts of the electromagnetic spectrum (Lillesand et al., 2015). Images from the RS can be used to map land use and cover as well as agriculture, soils, forests, city planning, archaeological investigations, military observation, geomorphology, vegetation dynamics, water quality dynamics, urban growth, etc.

The process of RS involves measuring reflected and/or emitted radiation at a distance (typically from a satellite or aircraft) in order to detect and monitor the physical characteristics of an area (Ali et al., 2016). Remotely sensed images are collected by special cameras, which allow scientists to discover more about the Earth. Sensors can be classified into two primary types: Active sensors provide their own power to illuminate the objects they observe, and passive sensors use the external power to illuminate the objects they observe. Sensors that detect natural energy (radiation) emitted by or reflected by an object or scene, on the other hand, are passive. In satellite imageries, spatial resolution refers to the smallest feature that can be detected or displayed by a satellite sensor (Roy et al., 2017). Usually, it is presented as a single value representing the length of one side of a square. The spectral resolution of a satellite sensor refers to its ability to measure specific wavelengths of the electromagnetic spectrum. Temporal resolution refers to the time between images.

Nowadays, RS technology provides multispectral optical and microwave data for natural resource mapping of the Earth’s surface, and it can aid Earth observation across various disciplines. Snow and glacier mapping are critical for checking the availability of water resources on the Earth’s cryosphere and quantifying the impact of climate change on these cryosphere components. Retreating glaciers can cause environmental changes, such as changes in the number and timing of freshwater supplies for plant and animal species that require freshwater to survive (Meshesha et al., 2020). Satellite RS has been used in monitoring snow and glacier components, and the following subsection will focus on the application of RS in snow cover and glacier extents issues.

Timely and accurate monitoring of glaciers' extents and their spatiotemporal variability are critical for many applications (Kneib et al., 2021; Paul et al., 2004; Redpath et al., 2013) such as water resources management (Bolch et al., 2009; Huss, 2011; Rangecroft et al., 2015), hydrological modelling, and impacts assessments of climate and environmental changes in cold regions (Bindschadler et al., 2001; Bishop et al., 2004; Che et al., 2008; Kargel et al., 2005). Since the 1970s, numerous studies have employed band ratios and indices across various satellite imagery platforms, capitalizing on the distinct spectral signatures of snow and ice across visible, near-infrared (NIR), and shortwave infrared (SWIR) wavelengths (Foster et al., 2009; Wang et al., 2019). These efforts aim to map glacier and snow-covered areas by integrating satellite band ratios, particularly SWIR and NIR (Hall et al., 1995; Dozier, 1989).

Band ratios and indices facilitate the mapping of snow- and glacier-covered areas using satellite data by enabling the differentiation of surface features through the reflectance properties of distinct spectral bands. The unique spectral signatures of snow and ice in the visible, NIR, and SWIR bands are instrumental in their identification within satellite imagery. The Normalized Difference Snow Index (NDSI) (Hall et al.,1995) exemplifies this approach and has been applied to delineate glacier and snow cover extents across multiple multispectral satellite image platforms, including the Moderate Resolution Imaging Spectroradiometer (MODIS), Landsat, and Sentinel-2 (Cayo et al., 2022; Xie et al., 2020; Singh et al., 2021; Zhang et al., 2019).

The NDSI is calculated according to Equation 1, a formulation that has been employed and validated in numerous studies (Wang et al., 2022; Kuter et al., 2018; Mityók et al., 2018; Sood et al., 2020; Ali et al., 2020; Luo et al., 2022):

$$NDSI = (Green - SWIR1)/(Green + SWIR1) \qquad (1)$$

where Green represents the reflectance of the green band, and SWIR1 represents the reflectance of the shortwave infrared band. NDSI values range from -1 to 1, where higher values indicate a greater likelihood of snow presence. A common threshold to identify snow is an NDSI value of 0.4 or above (Lu et al., 2022; Burns & Nolin, 2014; Hall et al., 1998), although this threshold can be adjusted based on the specific requirements of a study or the characteristics of the area being analyzed.

Materials and methods

Paper I

Glaciers play a vital role as a primary freshwater source in cold regions. The process of glacier melting has a profound impact on the GMB and leads to a substantial amount of runoff in these areas. The primary objective of paper 1 is to utilize the newly developed semi-distributed glacio-hydrological conceptual model (FLEX^G) in order to understand the process of glacier melting and the impact of topography on the GMB within the Torne River basin (Figure 3), located in northern Sweden.

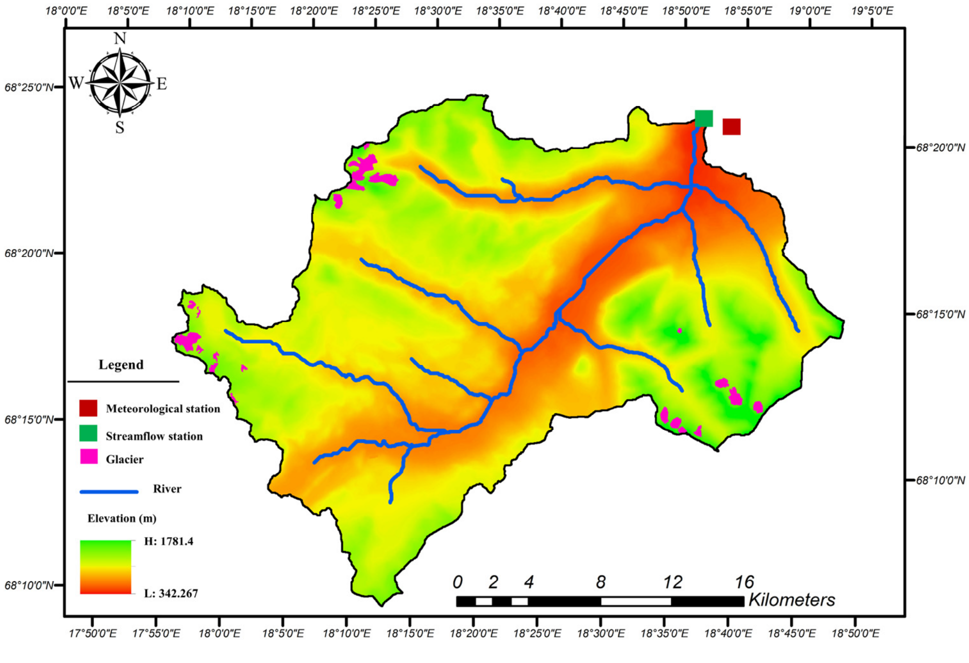

Figure 3. DEM and boundary of the Torne River basin including location of glaciers, meteorological and streamflow stations.

The study employed the FLEX^G model to simulate glacier and snow accumulation, ablation, as well as runoff from both glacier and non-glacier regions of the basin for the periods of 1985 to 1988 (for warm up), 1989 to 2003 (for calibration), and 2004 to 2018 (for validation). The FLEX^G model takes into account the impact of topography on runoff generation. In this study, the basin was divided into 143 zones based on elevation and aspect. To obtain a thorough understanding of the FLEX^G model's performance, the classical lumped hydrological model HBV was employed and compared to the FLEX^G model in simulating total streamflow and peak runoff at the basin outlet. The FLEX^G model utilizes the temperature index method, distributed by topographical data, to partition the entire basin into glacial and non-glacial regions. This enables the accurate estimation of runoff in the glacier areas. The FLEX^G model utilized the Xinanjiang storage capacity curve to compute runoff formation in the non-glacier region (Gao et al., 2017).

The modules for snow and glaciers are designed to simulate the processes of snow and glacier accumulation and ablation. These modules take into account factors such as air temperature (T) and its threshold (Tt) to determine the separation of snowfall and rainfall. The modules also simulate snowmelt processes, including the refreezing water from liquid storage (Rrf) and solid snowpack (Sw). This can be achieved using the degree-day factor (Fdd), while also considering the liquid water content in the snowpack. If there is no snow cover, then ice begins to melt, generating glacier runoff (Mg). For calculating the released runoff from glacier areas, the FLEX^G model also requires an assumed linear reservoir (Sf,g) and a parameter for recession (Kf,g). The mathematical representation of the snow and glacier module can be described by Equations 2 to 5.

$$R_{rf} = \begin{cases} F_{dd}F_{rr}(T_t - T); & T_t > T \\ 0; & T_t \leq T \end{cases} \tag{2}$$

$$M_g = \begin{cases} F_{dd}C_g(T - T_t); & T > T_t \; and \; S_w = 0 \\ 0; & T \leq T_t \; or \; S_w > 0 \end{cases} \tag{3}$$

$$\frac{dS_{f,g}}{dt} = P_l + M_g - Q_{f,g} \tag{4}$$

$$Q_g = \frac{S_{f,g}}{K_{f,g}} \tag{5}$$

where Cg is a factor for ice melt, Frr is a refreezing factor, Pl indicates liquid precipitation (particularly rain), Qg represents streamflow for the glacier part of the basin, and Qf,g represents glacier subsurface flow.

In the non-glacier area, the rainfall-runoff module of the model incorporates an unsaturated reservoir that accounts for infiltration and evaporation. To capture the flow dynamics, the module includes fast recession parameter (Kf) and slow recession parameter (Ks). The surplus water replenishes two linear reservoirs, denoted as Sf and Ss, which symbolize the dynamic processes associated with subsurface flow (Qf) and groundwater runoff (Qs). Equations 6 to 9 express the rainfall-runoff module in the non-glacial area.

$$\frac{dS_f}{dt} = R_f - Q_f \tag{6}$$

$$\frac{dS_s}{dt} = R_s - Q_s \tag{7}$$

$$Q_f = \frac{S_f}{K_f} \tag{8}$$

$$Q_s = \frac{S_s}{K_s} \tag{9}$$

where Rf is the recharge into the fast response reservoir and Rs is the recharge into the slow response reservoir.

In the calibration of the $FLEX^G$ model parameters, a total of 13 parameters were considered. The calibration process utilized the generalized likelihood uncertainty estimation (GLUE) technique (Beven & Binley, 1992; Gao et al., 2017). The implementation of a Monte Carlo sampling strategy involved 10000 homogeneous distribution parameters. The Kling-Gupta Efficiency (KGE) was used as the objective function during the calibration phase. The calibration process involved determining the range of $FLEX^G$ model parameters, as listed in Table 1.

Table 1. The selected range of $FLEX^G$ parameters for the calibration phase.

Parameter	Unit	Statement of parameters	Selected range
β	-	Shape parameter	[0, 5]
$S_{u,max}$	mm	Root zone storage capacity	[0, 100]
C_e	-	The threshold value for evaporation	[0, 1]
D	-	Splitter	[0, 1]
K_f	days	A coefficient for recession of reservoir fast response	[0, 15]
Ks	days	A coefficient for recession of reservoir slow response	[15, 200]
Tt	°C	Threshold temperature for ramification snowfall and rainfall	[-6, 4]
F_{dd}	mm (°C day)$^{-1}$	A degree day factor for snow	[0, 10]
C_g	-	Ice melt factor	[0, 5]
C_a	-	A factor for effect of aspect on melting process	[0, 3]
C_{wh}	-	Capacity of snow water holding	[0, 3]
F_{rr}	-	Refreezing factor	[0, 3]
$K_{f,g}$	days	A coefficient for recession of glacier runoff	[0, 8]

Paper II

The precise and timely monitoring of glacier extents and their spatiotemporal variations is crucial for a wide range of applications. Previous research has explored mapping glacier and snow-covered areas by integrating satellite band ratios, such as SWIR and NIR bands (Hall et al., 1995). Band ratios and indices are commonly used to map snow- and glacier-covered areas using satellite data. These methods enable the differentiation of surface features based on their reflectance properties across various spectral bands. Snow and ice have distinctive spectral signatures in the visible, near-infrared, and shortwave infrared regions, which can be used to identify them in satellite imagery.

Besides NDSI, this study also utilizes the Char Soil Index (CSI) (Sparks et al., 2014) as a satellite index, demonstrating its effectiveness in detecting specific surface features for the development of a novel index (Equation 10).

$$\mathrm{CSI} = \frac{\mathrm{NIR}}{\mathrm{SWIR2}} \tag{10}$$

Nonetheless, the utilization of NDSI for glacier mapping is subject to certain limitations. For example, the NDSI may struggle to differentiate between snow and ice, as well as accurately identify water pixels. In order to overcome these limitations, the current study introduces a novel approach known as the Adjusted Normalized Difference Snow Index (ANDSI). The ANDSI can be calculated using Equation 11.

$$\mathrm{ANDSI} = \frac{\mathrm{CSI} - \mathrm{NDSI}}{\mathrm{CSI} + \mathrm{NDSI}} = \frac{\mathrm{NIR}(\mathrm{Green} + \mathrm{SWIR1}) - \mathrm{SWIR2}(\mathrm{Green} - \mathrm{SWIR1})}{\mathrm{NIR}(\mathrm{Green} + \mathrm{SWIR1}) + \mathrm{SWIR2}(\mathrm{Green} - \mathrm{SWIR1})} \tag{11}$$

where, *Green* is band 3, *NIR* (Near Infrared) indicates band 8, *SWIR1* represents a short wave infrared spectral band (band 11), and *SWIR2* is band 12 of Sentinel-2 data.

The inclusion of both the NDSI and CSI in the ANDSI is necessary to encompass a broader range of spectral response. By utilizing ANDSI, the differentiation between inland water- and glacier-covered pixels in satellite images can be significantly improved. This eliminates the necessity of removing water-covered pixels in NDSI-based classifications. The current study incorporated glacier mapping through the application of thresholds in order to compare ANDSI with the original NDSI. For this aim, NDSI$\geqslant$0.42 was used as a threshold for glacier mapping via NDSI. To explore a potential thresholding approach for mapping glaciers using the ANDSI, we tested threshold values of -0.25 ≤ Ln (ANDSI) < 0 in order to reach a maximum differentiation between glacier and non-glacier regions for ANDSI.

Additionally, this study aims to evaluate the effectiveness of integrating ML algorithms with satellite indices for accurate glacier mapping, which may further address the limitations of traditional methods. This study selected four different regions to provide a diverse representation of glacierized areas with variations in geographic location, located in Canada (CAN), China (CHI), Sweden (SWE), and Switzerland-Italy (SWIT). Table 2 lists the location of these study areas and the used satellite images. Sentinel-2 satellite images were selected between August and October because the snow cover generally would be in its minimum coverage and high-quality satellite images are easier to obtain due to less cloud coverage during these months. The MSI Level-1C data of Sentinel-2, which is radiometrically and geometrically corrected, has been used for glacier mapping (Yan et al., 2021; Veettil, 2018; Alifu et al., 2020; Zhang et al., 2019), thus the current study also used this data.

Table 2. Location of the four study areas and the date of used Sentinel-2 satellite imagery data.

No.	ID	Country	Latitude	Longitude	Date (dd/mm/yyyy)	Approximate location
1	CAN	Canada	57° 36' 40.68" 57° 36' 14.44"	-132° 31' 50.92" -132° 32' 35.92"	05/10/2021	
2	CHI	China	36° 13' 26.52" 35° 41' 23.39"	90° 25' 48.58" 91° 10' 52.92"	16/10/2021	
3	SWE	Sweden	68° 18' 45.52" 68° 06' 1.780"	18° 12' 6.25" 18° 47' 52.56"	19/09/2021	
4	SWIT	Switzerland-Italy	45° 56' 39.56" 45° 54' 53.31"	07° 40' 43.95" 07° 44' 30.16"	23/09/2021	

Paper III

Hydrological modelling commonly depends on streamflow data for calibration, which might not adequately represent and simulate all internal hydrological processes. To overcome this constraint, RS data have been utilized as an alternative information source in hydrological investigations (Xu et al., 2014). Relying solely on measured runoff data for calibrating hydrological models may not guarantee adequate simulation of internal hydrological processes, potentially introducing uncertainties in hydrological modelling tasks. Therefore, the current study used multi-variable calibration strategy to calibrate the hydrological model.

The $FLEX^G$ model was run for the time periods: warm-up period (1995-1999), calibration period (2000-2009), and validation period (2010-2018) within the Torne River basin. The $FLEX^G$ model was calibrated using three schemes: scheme 1, where the $FLEX^G$ model was calibrated by gauged streamflow as reference data; scheme 2, where the $FLEX^G$ model was calibrated using satellite-derived SCA data (MODIS snow cover product) as reference data; and scheme 3, where the $FLEX^G$ model was calibrated by both gauged streamflow and satellite-derived SCA dataset (MODIS) as reference data at the same time.

This study employed different objective functions depending on the calibration scheme during the $FLEX^G$ model calibration procedure. For scheme 1, the KGE was employed as the objective function. The KGE is a comprehensive hydrological metric that considers the correlation, variability, and timing of the simulated and observed hydrographs. KGE can capture different aspects of hydrological processes and has been widely used in hydrological model calibration (Gupta et al., 2009). For scheme 2, the objective function included integrated weight of the coefficient of determination (R^2) and the ratio of root mean square error (RMSE) to the standard deviation of the observations (RSR). In scheme 2, a combination of R^2 and RSR was used to improve the calibration performance. In this scheme, R^2 was used for explaining proportion of variance by the model, while RSR was used to indicate the goodness of fit between measured and simulated values. Finally, for scheme 3, a combination of KGE, R^2, and RSR was used as the integrated weight of the objective function. This approach can consider the strengths of each metric and make a balance in their contributions. Similar integrated objective functions have been used in other studies to improve the model calibration performance (Blasone et al., 2007, Blasone et al., 2008; Drisya & Sathish Kumar, 2018). The prior parameters' ranges were subjected to a Monte Carlo sampling strategy with 10000 samples drawn from a homogeneous distribution, and then parameter sets that meet the predefined criteria were selected for further analysis. The predefined criteria in this study were based on the model's performance, selecting the best iteration according to the objective function for each defined scheme (Table 3).

Table 3. Applied objective functions based on three defined calibration schemes for calibrating the FLEX^G.

Calibration strategy	Objective function
Scheme 1	KGE_Q
Scheme 2	$(1 - R^2_{SCA(MODIS)}) + RSR_{SCA(MODIS)}$
Scheme 3	$KGE_Q/((1 - R^2_{SCA(MODIS)}) + RSR_{SCA(MODIS)})$

Paper IV

In this study, three hybrid modelling methodologies were applied to improve runoff simulation in the Torne River basin. The hybrid 1 approach integrates the FLEX^G model with the RF algorithm, using the hydrological concept in glacierized catchments (where total runoff is the sum of runoff from the glacier and non-glacier parts of the basin) to train the RF algorithm. To this end, the RF model uses refined total runoff (Q*), precipitation (P), temperature (T), ET, GMB, SCA, relative humidity (RH), sunshine hours (SSH), solar radiation (Rs), and wind speed (WS) to simulate runoff. Hybrid 2 focuses on residual simulation, where the RF model corrects the biases of the FLEX^G model by using residuals (the differences between observed and FLEX^G-simulated runoff). This approach uses a variety of meteorological and glacio-hydrological inputs to refine the runoff predictions, namely P, T, ET, GMB, SCA, RH, SSH, Rs, and WS. Hybrid 3 employs a sequential modelling technique, using FLEX^G-simulated glacio-hydrological variables (GMB and SCA) combined with meteorological data (P, T, ET, RH, SSH, Rs, and WS) to simulate runoff. This method starts with basic meteorological inputs and incrementally adds more variables to improve prediction accuracy. Each methodology leverages the strengths of both process-based and ML models to achieve robust and reliable runoff simulations. Figure 4 shows schematic diagrams of three applied hybrid frameworks.

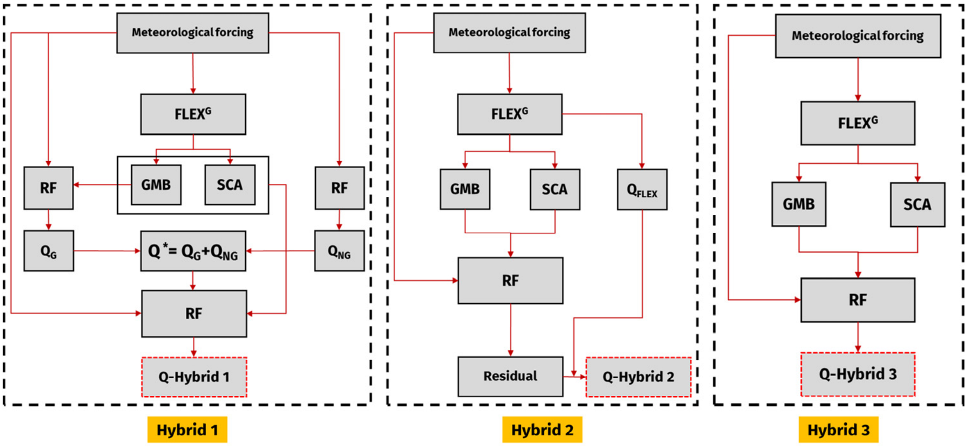

Figure 4. Schematic diagram of three applied hybrid models.

Results and discussion

Glacio-hydrological simulation through hydrological process-based models (Paper I)

Streamflow simulation using process-based models can be significantly challenging due to the complex physical hydrological processes that may not be fully understood in terms of some hydrological phenomena (Li et al., 2020; Swift et al., 2005). Given the importance of glacier regions as stable water resources for water resource systems, simulating streamflow values in snow-covered regions using suitable approaches is essential. Therefore, this study investigated the capability of the $FLEX^G$ model in simulating runoff related to both glacier and non-glacier parts of the studied basin. Figure 5 presents a comparison of the daily runoff simulated by the $FLEX^G$ model with the observed total runoff in the basin for the calibration (1989-2003) and validation (2004-2018) periods. The $FLEX^G$ model demonstrated satisfactory results for the calibration period, with metrics approximately at KGE = 0.80, NSE = 0.64, and R^2 = 0.65. During the validation period, the $FLEX^G$ model effectively simulated the pattern of streamflow with acceptable accuracy. However, the statistical metrics indicated a marginally weaker performance during the validation period, with metrics approximately at KGE = 0.71, NSE = 0.47, and R^2 = 0.58. Despite this decrease in metrics of the validation phase, the $FLEX^G$ model's overall performance in simulating runoff behavior in the glacierized catchment proved acceptable, aligning with the results previously reported by Gao et al. (2017).

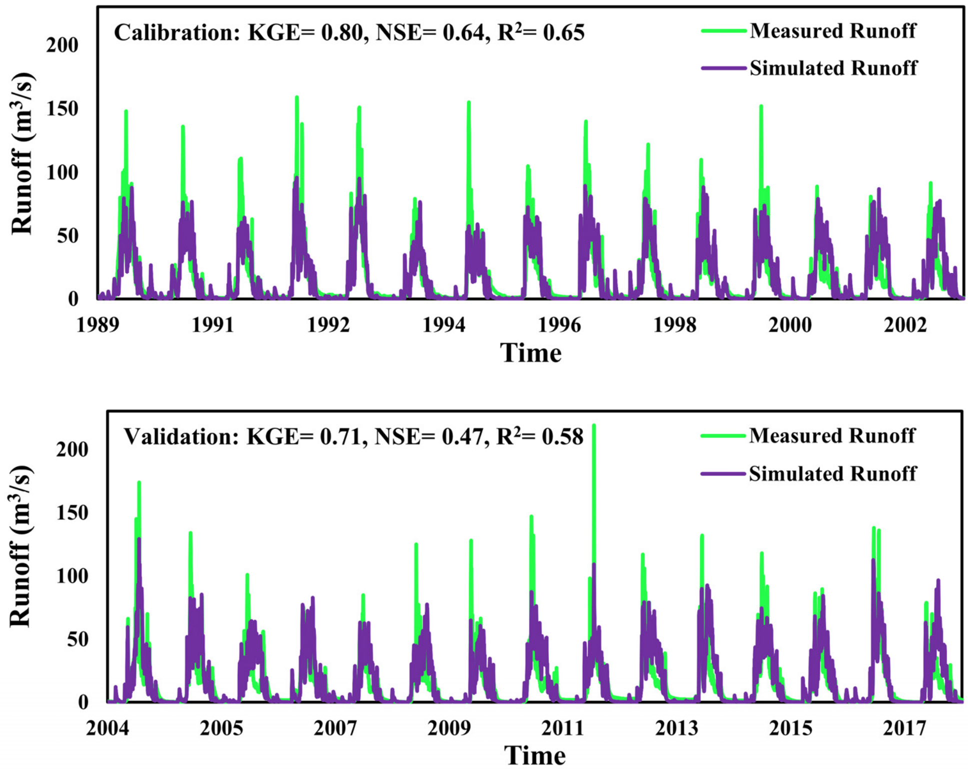

Figure 5. Time series of simulated daily total runoff by the FLEX^G model against measured runoff during the calibration (1989-2003) and validation period (2004-2018).

While the current study mainly focused on understanding the dynamics of snow and glaciers in cold regions, and the results also demonstrated the capability of the FLEX^G model in glacio-hydrological simulations, it is important to acknowledge a limitation regarding the exclusion of frozen soils (permafrost) in the modelling framework. Frozen soils can play a crucial role in the hydrological cycle by influencing soil moisture dynamics, groundwater flow, and surface runoff. The presence of permafrost can affect the timing and magnitude of streamflow, particularly during thawing and freezing periods. Therefore, integrating permafrost processes into hydrological models can provide a more comprehensive understanding and improve the accuracy of streamflow simulations in cold regions.

Figure 6 displays the simulated GMB in the glacierized basin using the FLEX^G model. Throughout the entire study period, the most significant change in GMB occurred in 2013, with a decrease of -204.06 (mm.w.e.), while the smallest change was observed in 1993, with a decrease of -113.05 (mm.w.e.). Over the 30-year span, the overall simulated GMB indicates a decreasing trend in the rate of GMB changes, as illustrated by the blue trend line in Figure 6. Gao et al. (2018) reported similar results in other regions of China. Their study of Urumqi Glacier showed a decrease in GMB from 1959 to 2007. Our study similarly demonstrated a negative rate of glacier mass volume change in northern Sweden. These findings are also consistent with Hugonnet et al. (2021), who reported negative glacier mass changes across Scandinavia.

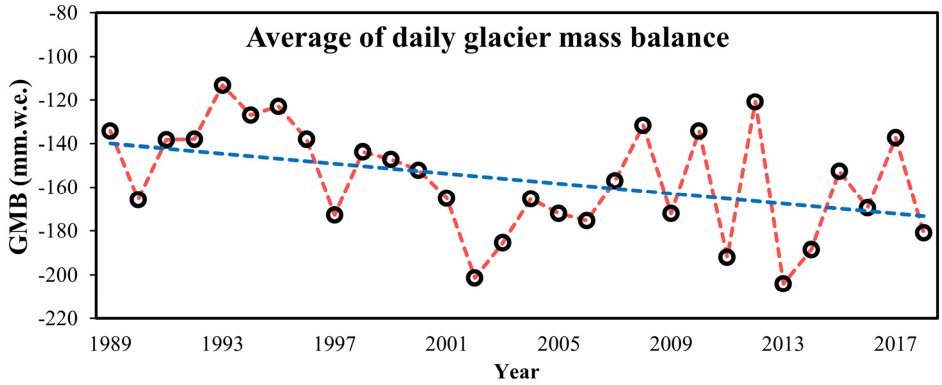

Figure 6. The average of daily simulated glacier mass balance by the FLEX^G model. The blue line shows the average trend during the study period (1989-2018).

The performance of the FLEX^G model in simulating SCA was assessed using daily available SCA data from the MODIS/Terra Cloud Gap Filled (CGF) (MOD10A1F version 61) product. Figure 7 demonstrates that the SCA simulated by the FLEX^G model closely matches the satellite-derived SCA data, especially in capturing the seasonal variations. The R^2 and the RMSE were found to be 0.61 and 28.04%, respectively. These results align with those of a previous study by Gao et al. (2020), which focused on SCA simulation in the Yigong Zangbu river basin in China. In their study, the simulated SCA achieved a higher R^2 (between 0.82 and 0.86) and a comparable RMSE (ranging from 18% to 29%) when compared against satellite-derived SCA.

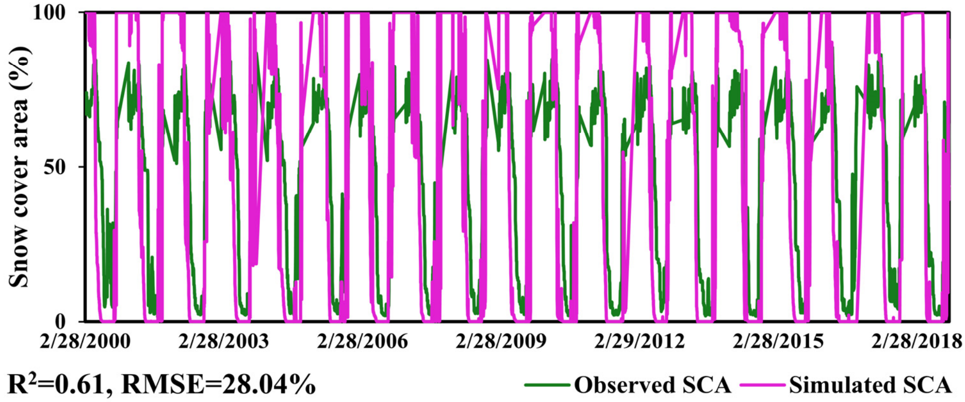

Figure 7. The simulated and satellite observed daily snow cover area percentage from 2000 to 2018.

Glacier mapping with ANDSI (Paper II)

Based on the previous studies, we selected a threshold value of 0.42 for NDSI to compare the ability of ML classifiers and threshold-based approaches for glacier mapping. Thus, we evaluated the ability of NDSI with thresholds and ML classifiers for glacier detection in the four studied regions of our study. Figure 8 shows the comparisons of detected glaciers from different methods. The limitations of using NDSI with a threshold are apparent from Figure 8, indicating that many glaciers remain undetected in the CAN when a threshold is applied. Also, water bodies are misclassified as glaciers in CHI when NDSI is applied using a threshold. Applying NDSI with a threshold (NDSI≥0.42) could not detect the difference between water bodies and glacier regions, and it recognized water pixels as glacier pixels. In contrast, applying a threshold ($-0.25 \leq \text{Ln (ANDSI)} < 0$) on ANDSI (based on the differentiation of glacier and non-glacier boundary on the images) can detect glacier pixels well, and it yielded much better results than using NDSI with a threshold. Using an ML classifier (C5.0) with NDSI is more accurate than using NDSI with a threshold. Therefore, applying the proposed ANDSI using a threshold is more reliable than NDSI with a threshold, and using an ML classifier (C5.0) with ANDSI is even better than using NDSI with ML classifiers.

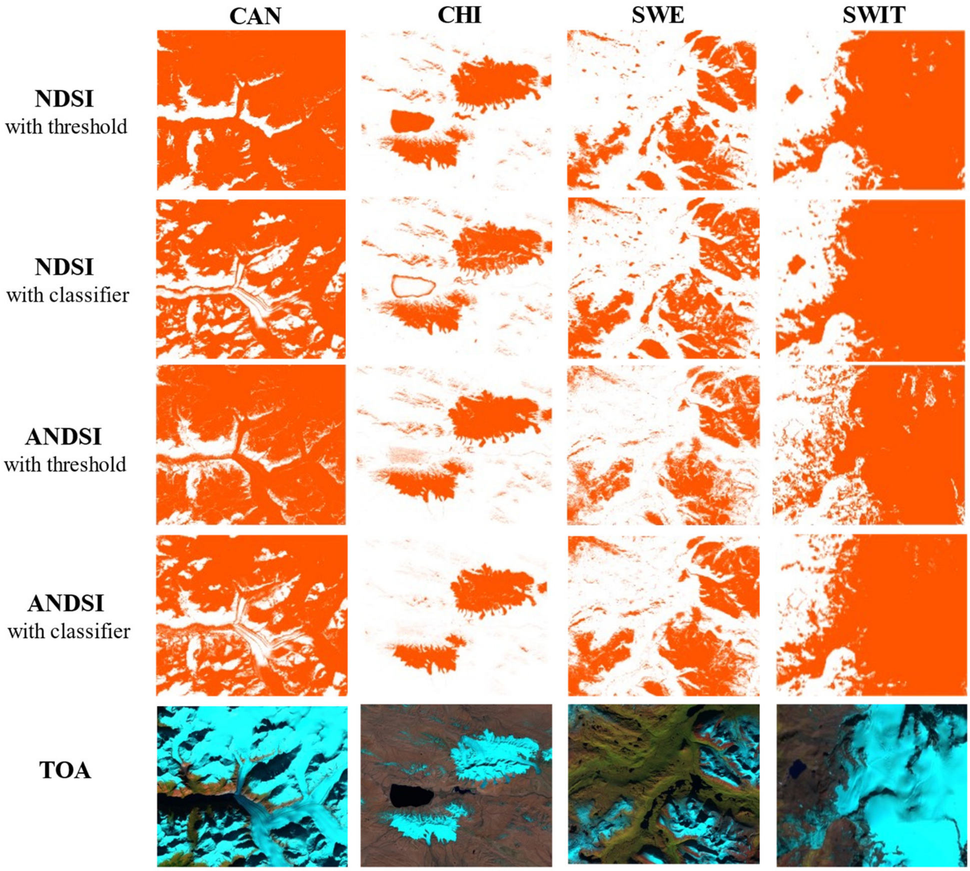

Figure 8. Glacier detection by: (i) considering NDS ≥ 0.42 as a threshold for NDSI to detect glacier regions; (ii) applying a machine learning classifier (C5.0) on original NDSI; (iii) considering -0.25 ≤ Ln (ANDSI) <0 as a threshold for ANDSI to detect glacier regions; (iv) applying a machine learning classifier (C5.0) on proposed ANDSI. These methods are compared with Top Of the Atmosphere (TOA) images.

Employing the ANDSI for glacier mapping offers several advantages over traditional methods, such as NDSI. First, ANDSI enhances the distinction between glacier and water pixels by reducing spectral overlap with snow-free areas, leading to more precise delineations of glacier boundaries. This improvement in differentiation was evident in our study, where ANDSI's performance in mapping glaciers surpassed that of NDSI and other methodologies, demonstrating its superior accuracy. Furthermore, when ANDSI is combined with Sentinel-2 imagery, it facilitates glacier mapping at a higher spatial resolution than is achievable with other commonly used satellite data. This detailed resolution provides richer information on glacier features and changes, facilitating a more thorough understanding of glacier dynamics over time. Additionally, the integration of ML techniques with

ANDSI enhances the glacier mapping process, making it more efficient and suitable for accurate glacier monitoring programs.

Multi-variable calibration of the hydrological process-based model (Paper III)

This study aimed to model runoff within a glacierized basin by employing a glacio-hydrological model (FLEX^G) which was calibrated using three distinct schemes. The calibration utilized observed streamflow data (scheme 1), satellite-derived SCA data (scheme 2), and a combination of both streamflow and SCA data (scheme 3) as references for calibration of the FLEX^G model. Table 4 details the performance metrics of the FLEX^G model under these calibration scenarios. Scheme 1 demonstrated the highest accuracy in runoff prediction, achieving a Mean Absolute Error (MAE) of 7.25 m^3/s and a KGE of 0.75 during the validation phase. Scheme 3 also performed well, with a MAE of 7.43 m^3/s and a KGE of 0.70 for the same period. Conversely, scheme 2 failed to simulate runoff accurately, recording a MAE of 9.73 m^3/s and a negligible KGE of 0.01 during validation. Overall, while all calibration approaches yielded acceptable errors in terms of MAE, RMSE, and RSR, only schemes 1 and 3 produced satisfactory KGE values for the simulation of runoff across both the calibration and validation phases.

Table 4. The evaluation of the FLEX^G for simulating runoff using three calibration schemes on daily scales. Note: Cal.: calibration period (2000–2009); Val.: validation period (2010–2018).

	Scheme 1		Scheme 2		Scheme 3	
Metrics (unit)	Cal.	Val.	Cal.	Val.	Cal.	Val.
MAE (m^3/s)	7.39	7.25	8.94	9.73	7.42	7.43
RMSE (m^3/s)	13.88	13.61	17.41	19.55	13.82	14.03
RSR	0.74	0.64	0.93	0.92	0.74	0.66
R^2	0.53	0.62	0.44	0.53	0.52	0.58
KGE	0.73	0.75	0.03	0.01	0.71	0.70

Table 5 presents the evaluation of the FLEX^G model's ability to simulate the SCA as compared to the SCA data derived from MODIS satellite observations. The evaluation results indicate that scheme 2 achieved the best accuracy in SCA simulation, characterized by the lowest RMSE of 22.19%, the highest R^2 of 0.87, and the lowest RSR of 0.76 among the schemes. Scheme 3 also outperformed scheme 1 in terms of SCA simulation, achieving an RMSE of 23.85%, an R^2 of 0.79, and an RSR of 0.82 during the validation phase. Conversely, scheme 1 exhibited the least accurate performance, with the highest RMSE of 26.05%, the lowest R^2 of 0.78, and the highest RSR of 0.89 during the validation phase. This analysis demonstrates that scheme 2 outperformed the other schemes, and that employing a multi-variable calibration strategy enhances the $FLEX^G$ model's accuracy in SCA simulations.

Table 5. The evaluation of the $FLEX^G$ for simulating SCA using three calibration schemes. Note: Cal.: calibration period (2000–2009); Val.: validation period (2010–2018).

	Scheme 1		Scheme 2		Scheme 3	
Metrics (unit)	Cal.	Val.	Cal.	Val.	Cal.	Val.
MAE (%)	22.16	21.41	17.56	17.37	19.67	19.42
RMSE (%)	27.03	26.05	22.22	22.19	24.21	23.85
RSR	0.96	0.89	0.79	0.76	0.86	0.82
R^2	0.73	0.78	0.86	0.87	0.75	0.79
KGE	0.38	0.39	0.45	0.46	0.45	0.45

This study also utilized MODIS-derived SCA data to calibrate the $FLEX^G$ model and compared this with SCA data obtained from the Advanced Very High Resolution Radiometer (AVHRR) and Landsat-8 satellite imagery. A notable discrepancy exists in the $FLEX^G$ model's simulation of SCA, which ranges from 0 to 100%, indicating the potential for the entire basin to be snow-covered. Conversely, the peak SCA values derived from MODIS never exceed 90%, suggesting that the basin is never fully snow-covered. This discrepancy prompted further examination of the applicability of MODIS SCA in the Torne River basin, validated against other satellite SCA datasets. MODIS SCA values were found to align more closely with Landsat-8 than with AVHRR, likely due to MODIS's superior spatial resolution (~ 500 m) compared to AVHRR (~ 1 km), allowing for more precise differentiation of snow cover.

Coupling hydrological process-based models with machine learning algorithms (Paper IV)

Figure 9 presents a time series comparison of measured runoff against simulated runoff produced by the $FLEX^G$ model and the best results from three hybrid modelling frameworks (hybrids 1-3). The $FLEX^G$ model's simulated runoff is displayed alongside the measured runoff, providing a baseline for comparison. Among hybrid types 1, 2, and 3, the scenario incorporating all available variables as input features for the RF model yielded the most accurate results. For hybrid 1, the variables Q*, P, T, ET, GMB, SCA, RH, SSH, Rs, and WS were considered as input features. For hybrid 2 and 3, the variables P, T, ET, GMB, SCA, RH, SSH, Rs, and WS were used as input features. The best results from hybrid 1 demonstrate how integrating RF with physical processes of glaciated and non-glaciated runoff dynamics improves simulation accuracy, particularly during periods of significant runoff variation. Hybrid 2 (residual simulation) shows enhanced performance by using RF to correct biases in the FLEX^G model through residuals, capturing the observed runoff more closely during both high and low runoff periods. Hybrid 3 (sequential hybrid model) combines FLEX^G-simulated glacio-hydrological variables with meteorological data, yielding the accurate result of runoff simulation.

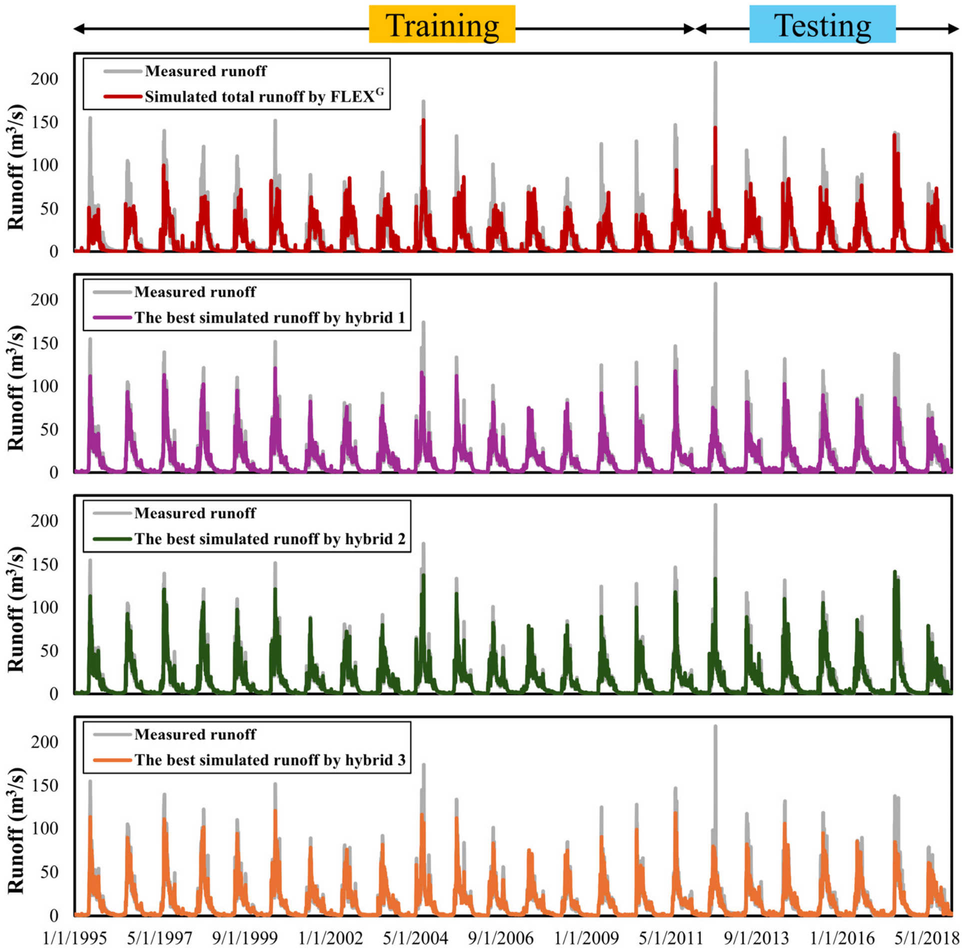

Figure 9. Measured runoff vs. simulated runoff by FLEX^G, hybrids 1, 2, and 3 during the training and testing phases.

Table 6 lists the performance of the FLEX^G model compared to the best scenarios in each hybrid type. For hybrid 1, the scenario includes Q* along with P, T, ET, GMB, SCA, RH, SSH, Rs, and WS as inputs to the RF model. In comparison, hybrids 2 and 3 include P, T, ET, GMB, SCA, RH, SSH, Rs, and WS as input features. During the training period, hybrid 2 achieved the lowest RMSE (3.62 m^3/s) and highest NSE (0.97), R^2 (0.97), and KGE (0.94), indicating its robustness in capturing runoff dynamics. Hybrids 1 and 3 also performed well, with RMSE values of 3.83 m^3/s and 3.95 m^3/s, respectively during the training period. Both hybrids 1 and 3 achieved NSE and R^2 values of 0.96 and 0.97 during the training period. In the test period, hybrid 2 continued to outperform the others with an RMSE of 8.07 m^3/s, NSE of 0.86, R^2 of 0.86, and KGE of 0.90, demonstrating its superior generalization capability. Both hybrid 1 and hybrid 3 exhibited strong performance but were slightly less accurate than hybrid 2, with RMSE values of 9.17 m^3/s and 9.18 m^3/s, and NSE, R^2, and KGE values of 0.82 during test section. Overall, hybrid 2 showed the best results, closely followed by hybrid 1 and hybrid 3, with all three hybrid models significantly outperforming the $FLEX^G$ model in both training and testing periods. This comparison demonstrates the enhanced predictive capability and reliability of the hybrid models, particularly hybrid 2, in simulating runoff dynamics in the studied catchment.

Table 6. Performance of $FLEX^G$ model vs. the best scenario of hybrids 1, 2, and 3 for runoff simulation during training (1995–2011) and testing (2012–2018) periods.

Period	Metrics	$FLEX^G$	Hybrid 1	Hybrid 2	Hybrid 3
Train	RMSE	13.91	3.83	3.62	3.95
	NSE	0.52	0.96	0.97	0.96
	R^2	0.55	0.97	0.97	0.97
	KGE	0.65	0.92	0.94	0.92
Test	RMSE	14	9.17	8.07	9.18
	NSE	0.58	0.82	0.86	0.82
	R^2	0.59	0.82	0.86	0.82
	KGE	0.68	0.82	0.90	0.82

Conclusions and recommendations

Conclusions

This thesis aims to enhance hydrological modelling in cold regions, where the hydrological cycles are influenced by snow and glaciers. Because of the complexity of this non-linear behavior, advanced techniques such as ML and satellite RS data can help hydrological models perform better. By increasing the performance of hydrological simulations, the interaction and impact of glacier and snow on a hydrological model can be understood more deeply. The following summaries present the main findings for each goal and the papers associated with them:

1. The FLEX^G model was utilized in this study to simulate the processes of glaciers and snow, as well as the GMB and generation of runoff from glacier and non-glacier parts of the Torne River basin located in northern Sweden. The FLEX^G model demonstrated an acceptable performance in terms of simulating the runoff and SCA. It also effectively captured the influence of topography on various hydrological variables. The FLEX^G model outperformed the classical HBV model in simulating both runoff and peak flows during the studied period. The findings of this study have provided evidence for the practicality of the FLEX^G model in glacio-hydrological modelling in regions with high latitudes. The model can also help to understand the interactions and feedbacks between the glacier, snow, and runoff processes in different spatial and temporal scales.

2. The Adjusted Normalized Difference Snow Index (ANDSI) was proposed and tested for mapping glaciers using Sentinel-2 multispectral satellite imagery. The ANDSI was designed to improve the differentiation between glaciers and water bodies, which is a challenging task for existing indices such as the Normalized Difference Snow Index (NDSI). The ANDSI was tested on four glacierized regions in the Northern Hemisphere, including Canada, China, Sweden, and Switzerland-Italy. The ANDSI was also mapped with ML algorithms to provide a more robust and efficient approach to glacier classification. The results indicated that the ANDSI and ML achieved higher accuracy and reliability than the ANDSI with threshold and NDSI with ML algorithms and threshold methods in various glacierized environments. The proposed index (ANDSI) can be used as a useful tool for glacier monitoring and cryosphere studies, especially in regions with complex glacier (snow)-covered landscapes.

3. The multi-variable calibration approach, utilizing satellite-derived SCA data, has shown to enhance the calibration and performance of the FLEX^G model for glacio-hydrological simulations in the Torne River basin, northern Sweden. This approach reduces model uncertainty, thereby improving the model's performance in terms of both streamflow and SCA, as opposed to focusing on a single variable. Furthermore, a comparison of various SCA products (MODIS, AVHRR, and Landsat-8) with those simulated by FLEX^G for the studied catchment indicated that MODIS SCA data are reliable for this investigation.

4. Various combinations of ML and hydrological models were investigated to improve performance of hydrological modelling in the Torne River basin, northern Sweden. To this end outputs of the FLEX^G model, including the SCA and GMB, along with meteorological variables were used for training RF algorithm to simulate runoff. The three proposed hybrid frameworks showed excellent performance compared to the standalone FLEX^G model. The framework which simulated runoff residual based on P, T, ET, GMB, SCA, RH, SSH, Rs, and WS showed the highest accuracy. The findings suggest that including every meteorological and glacio-hydrological variable improves the models' accuracy while also adding more complexity to the modelling procedure. The proposed hybrid framework also enhanced the detection of peak flows in runoff simulation compared with the standalone FLEX^G model.

Recommendations

Several recommendations for further research can be proposed to enhance the hydrological modelling in cold regions:

- This study focused on the snow and glaciers within cold regions, without addressing the role of frozen soils (permafrost). Future research should integrate the modelling of permafrost dynamics to provide a more comprehensive understanding of the hydrological processes in cold regions. Including frozen soils in the model will help to capture the interactions between snow, glaciers, and permafrost, thereby improving the accuracy and applicability of the hydrological simulations.
- Future studies should further refine and validate the ANDIS across diverse glacierized regions and under varying climatic conditions. This could involve integrating ANDIS with other RS indices and exploring its application with different ML techniques to enhance its robustness and accuracy in differentiating glaciers from other landscape features. Additionally, long-term monitoring using ANDIS can help track changes in glacier dynamics and contribute to more effective cryosphere studies.

- Multi-variable calibration in this study relies on streamflow and SCA data. Due to the important role of glaciers in cold regions, future potential studies can consider glacial variables (e.g., GMB) as one potential variable for calibrating hydrological models.
- The current study integrated glacio-hydrological variables (GMB and SCA) with meteorological variables to augment the efficacy of hydrological models using ML techniques. While this approach has shown improvements, it is recommended that future studies investigate the impact of including soil variables, such as soil moisture, within the proposed frameworks. Incorporating soil moisture and other relevant soil properties could provide a more comprehensive understanding of the hydrological processes, especially in regions where soil conditions significantly influence water flow and storage. Additionally, incorporating soil data could help to identify potential interactions between soil, snow, and glaciers, leading to a more holistic approach in glacio-hydrological modelling.
- Since the output of the hydrological model heavily depends on the objective function, future studies can consider an integrated objective function. This integrated function should incorporate multiple metrics, such as error, bias, correlation, and overall model accuracy, to enhance the reliability and performance of the model outputs.
- Future studies could explore feature selection algorithms to identify the most impactful meteorological and glacio-hydrological variables for inclusion in hybrid frameworks. This approach would optimize the training of ML algorithms for enhanced hydrological forecasting accuracy.
- Future work can also apply climate change scenario data to the model to understand glacierized basins under different climate change conditions and their interaction within the framework of climate change.

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