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Guidelines for Glacio-hydrological Modelling in High Mountain Asia

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AUTHORS **S. Khanal, N. Faezeh, J. Fiddes, P. Kraaijenbrink, W. Immerzeel, P. Droogers, P. van Ravesteyn, T. Schults, J.E. Hunink**

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Authors
Dr. Sonu Khanal
Dr. Faezeh Nick
Dr. Joel Fiddes
Dr. Philip Kraaijenbrink
Prof. Dr. Walter Immerzeel
Dr. Peter Droogers
Pepijn van Ravesteyn
Tijmen Schults
Dr. Johannes Hunink (j.hunink@futurewater.es)

Date
July 2025

FutureWater

ADDRESS FutureWater B.V.
Costerweg 1V
6702 AA Wageningen
The Netherlands

TELEPHONE +31 317 460 050
WEBSITE www.futurewater.eu

Summary

High Mountain Asia (HMA) contains the world's largest ice and snow reserves outside the polar regions. It serves as a crucial source of water for Asia's major river systems, which sustain the livelihoods of more than a billion people, a rapidly increasing population. As the global climate warms, glaciers and snow cover are changing rapidly, affecting water availability throughout the year and changing the risks of floods and droughts. Due to the topography, multiple climate zones, large elevation differences, and the presence of snow and glaciers, river discharge in the HMA region originates from a combination of glaciers, snowmelt, rainfall, and groundwater. This creates complex hydrological regimes that are difficult to model.

Glacio-hydrological models (GHM) are important for water management as they help in understanding and predicting the complex interactions between glaciers, snowmelt, and surface and groundwater in mountainous regions. These models are critical in regions such as the Himalayas, where a considerable proportion of the population depends on water supplied by snowmelt and glacier melt. GHMs can provide valuable information to water managers and policymakers to make informed decisions regarding water allocation, infrastructure development, and environmental regulations. These models also help assess the impact of climate change on the water cycle. This is especially important in mountainous regions, where the effects of global warming are often more severe than in other regions.

This report offers practical, step-by-step guidelines for setting up and applying the glacio-hydrological model SPHY (Spatial Processes in Hydrology) in the HMA region. This document covers model configuration, data requirements, calibration approaches, and applications for assessing the impacts of climate change on water resources. It also explains how GHM outputs can be integrated into water allocation planning frameworks to promote sustainable water management. This manual was created to support researchers, practitioners, and policymakers working on water resource management and climate adaptation in high-mountain regions.

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List of abbreviations

APHRODITE	Asian Precipitation – Highly Resolved Observational Data Integration Towards Evaluation
ASI	Agricultural Stress Index
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
CCI	Climate Change Initiative
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station data
CMORPH	Climate Prediction Center Morphing Technique
CWC	Central Water Commission (India)
DDFS	Degree Day Factor for Snow
DDFDG	Degree Day Factor for Debris-Covered Glacier
DDFG	Degree Day Factor for Glacier Snow
DEM	Digital Elevation Model
ECMWF	European Centre for Medium-Range Weather Forecasts
ERA5	ECMWF Reanalysis 5th Generation
ERA5-Land	Land surface component of ERA5 reanalysis
ESA	European Space Agency
GCM	Global Climate Model
GHM	Glacio-hydrological Model
GLIMS	Global Land Ice Measurements from Space
GRACE	Gravity Recovery and Climate Experiment
GRDC	Global Runoff Data Centre
HAR	High Asia Refined analysis
HiHydroSoil	High-resolution Hydrological Soil Dataset by FutureWater
HKH	Hindu Kush Himalaya
HMA	High Mountain Asia
HM	Hydrological Model
ICESat	Ice, Cloud, and land Elevation Satellite
ICIMOD	International Centre for Integrated Mountain Development
IHR	Indian Himalayan Region
LAI	Leaf Area Index
MODIS	Moderate Resolution Imaging Spectroradiometer
MSWEP	Multi-Source Weighted-Ensemble Precipitation
NDVI	Normalized Difference Vegetation Index
PET	Potential Evapotranspiration
PERSIANN	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Network
RCP	Representative Concentration Pathway
RGI	Randolph Glacier Inventory
SCA	Strengthening Climate Change Adaptation

SDC	Swiss Agency for Development and Cooperation
SPHY	Spatial Processes in Hydrology
SRTM	Shuttle Radar Topography Mission
TERI	The Energy and Resources Institute
TOA	Top of Atmosphere
TopoSCALE	Topographic Downscaling Model for Atmospheric Data
TRMM	Tropical Rainfall Measuring Mission
WEAP	Water Evaluation and Planning System
WMO	World Meteorological Organization
WRF	Weather Research and Forecasting model

1 About these guidelines

1.1 Background

High Mountain Asia (HMA) contains the world's largest ice and snow reserves outside the polar regions and serves as an important source of water for the major river systems in Asia, providing water for a population of more than a billion people, which is increasing rapidly (Immerzeel, 2010; Immerzeel et al., 2020; Kraaijenbrink et al., 2021; Stocker et al., 2013). As the global climate warms, glaciers and snow cover are changing rapidly, impacting water availability throughout the year and altering the risks of flooding and droughts. Owing to the region's topography, multiple climate zones, significant elevation differences, and the presence of snow and glaciers, river discharge in the HMA region is a result of a combination of glacier melt, snowmelt, rainfall, and groundwater. This creates complex hydrological regimes that are difficult to model. HMA encompasses a vast region that includes the Hindu Kush, Karakoram, and Himalayan Mountain ranges.

To address these challenges, glacio-hydrological models (GHMs) have become essential tools for understanding and predicting the intricate interactions between glaciers, snowmelt, and surface and groundwater in mountainous regions. These models are particularly important in regions such as the Himalayas, where a significant proportion of the population depends on water supplied by snowmelt and glacier melt. GHMs can provide valuable information to water managers and policymakers to make informed decisions regarding water allocation, infrastructure development, and environmental regulation. These models also help in assessing the impact of climate change on the water cycle. This is especially important in mountainous regions, where the effects of global warming are often more severe than in other regions.

This guidelines report was prepared as part of the project *Development of a Glacio-Hydrological Model and Integrated Water Resources Management Plan for the Uttarakhand Subbasin*, commissioned by the Swiss Agency for Development and Cooperation (SDC) under the *Strengthening Climate Change Adaptation in Himalayas (SCA-Himalayas)* Program. The project was implemented between 2021 and 2023 by a consortium comprising FutureWater, Utrecht University, the University of Geneva, and the Energy and Resources Institute (TERI) in India. This report was the final deliverable for this project. The guideline uses a study performed in the Bhagirathi Basin in northern India (see Section 4.7) as a case study for setting up a GHM (*Present-day and future changes in the hydrology of the Bhagirathi Basin* (Khanal et al., 2022)).

1.2 Scope

This guideline report is designed to assist researchers, practitioners, and policymakers engaged in water resource planning, climate impact analysis, and catchment management within the glaciated and snow-fed basins of HMA. It provides practical, step-by-step instructions for setting up and utilizing the Spatial Processes in Hydrology (SPHY) model in the HMA region. The report covers the sourcing and preparation of model input data, calibration of essential processes such as snow and glacier melt, climate impact assessments, and integration of hydrological simulations with water allocation models.

1.3 Reading guide

The document is structured to be both a reference and practical manual.

- **Chapter 2** introduces glacio-hydrological modelling concepts, types of GHMs, key processes, and the challenges associated with setting up GHMs.
- **Chapter 3** provides information on the modelling of key glacio-hydrological processes and their overall implementation within the SPHY model.
- **Chapter 4** offers guidance on retrieving model input data and setting up and calibrating a SPHY model.
- **Chapter 5** describes the assessment of climate change impacts and provides information on sourcing and processing climate projections.

Readers can follow the chapters sequentially or consult specific sections as needed for project-specific tasks.

2 Introduction to glacio-hydrological modelling

2.1 Introduction to glacio-hydrological modelling

A model is a simplified replica of a real system in which knowledge of the system is condensed into mathematical equations (Beven, 2012). Hydro-meteorological processes are often complicated to model because of limited information on catchment characteristics, system states, boundary conditions, governing equations, and underlying heterogeneity (Beven, 2012; Blöschl and Sivapalan, 1995). Hydrological models (HMs) represent intricate relationships between input and output signals, through intermediate fluxes and states, satisfying mass, energy, and momentum balances. Hydrological fluxes and storage, such as evaporation, groundwater, soil moisture, snow, and riverine storage, are often associated with memory and dependence at various spatiotemporal scales, and these complex interactions are represented by HMs.

A Glacio-hydrological model (GHM) typically integrates data and processes related to glaciology, hydrology, meteorology, and other relevant disciplines to simulate the behavior of glaciers and their influence on the hydrological cycle. A GHM falls under the broad category of HMs and mainly focuses on snow and glacier processes and their influence on the overall hydrological cycle. Thus, HMs and GHMs are used interchangeably in the hydrological modelling community.

GHMs can simulate various processes such as snow accumulation and ablation, ice melt, glacier movement, and runoff generation. GHMs are valuable tools for studying glacier dynamics and hydrological processes in glacierized regions and for assessing the impact of climate change on water resources. GHMs are often used by glaciologists, hydrologists, climatologists, and other scientists to improve our understanding of glacier behavior and its influence on hydrological systems, which can have significant implications for water management, ecosystem dynamics, and human livelihoods in glacierized regions.

A well-configured and calibrated GHM model serves as a robust and reliable tool for estimating the magnitude and frequency of extreme hydro-meteorological events for both current and future climates. It can also be used to assess climate adaptation options by integrating potential interventions in the model set-up, serving as a “digital twin” a tool to evaluate how decisions play out in a possible future. The propagation of uncertainty in magnitude, spatial extent, and time from climate and non-climate drivers to hydrological response and impact can also be estimated well with GHMs.

2.2 Types of GHMs

HMs and GHMs can be defined in terms of processes and spatial complexity across model elements (Clark et al., 2017; Hrachowitz and Clark, 2017). HMs can be categorized into two broad categories: conceptual and physically based models. A conceptual HM is based on the understanding of processes, their interactions, and overall system behavior (Arnold et al., 1998; Bergström, 1992; Martinec and Rango, 1986). These HMs (and GHMs) require calibration and validation to comply with the purpose of use, and if the model does not meet its objective, it should be revised and amended. Thus, conceptual GHMs represent a top-down approach in which the uncertainty of the processes in a catchment is defined a priori.

On the other hand, physically based GHMs are based on a bottom-up approach, which assumes that the overall performance is the result of a combination of all small-scale processes, where each of these processes is defined based on physical laws and equations (Ragettli and Pellicciotti, 2012; Schulla, 2017). Physically based HMs incorporate the space-time variability of precipitation, radiation, and variation in physiographic characteristics, and resolve spatial heterogeneity issues (Fatichi et al., 2016).

GHMs can also be categorized based on their ability to model processes at different spatial scales, that is, lumped and distributed (also semi-distributed). Lumped HMs consider the entire system (or catchment) as a single entity. In contrast, distributed HMs are lumped models applied at the grid scale and account for distributed forcing and catchment characteristics (Kampf and Burges, 2007). Distributed HMs provide a better understanding of the spatial variability in system behavior and thus provide additional information on the spatiotemporal processes of the system (Reed et al., 2004; Smith et al., 2004b). Based on data availability, the parameters in distributed HMs (and GHMs) can vary spatially (Beven, 2001). The lack of spatial observations limits the application of distributed HMs (Grayson et al., 2002). Often, physically based distributed HMs have many parameters and are associated with higher computational times and costs (Koch et al., 2016).

2.3 Key processes for glacio-hydrological modelling

The cryosphere (the portion of the Earth's surface where water exists in a solid form as snow, ice, lakes, glaciers, and permafrost) plays a key role in the global water cycle and affects water availability, weather, energy, and agriculture (Hock et al., 2017; Huggel et al., 2015). Each of these components is associated with a different response and spatiotemporal scale. A change in the state of these variables affects the overall water cycle differently (both in space and time) and thus requires a proper understanding of the process and its current and future states. The following are the key processes relevant to the HMA region.

2.3.1 Melt modelling

Melt estimation, from snow-covered or glaciated areas, is a key element in the assessment of river runoff, flood risk, water resources and cryosphere-related changes associated with climate change in high mountains (Hock, 2003). A robust river runoff simulation, in a mountainous environment such as HMA, requires proper representation of snow and ice melting processes in GHMs (Pellicciotti et al., 2012). The degree-day approach (also known as the temperature index model), which is based on the empirical assumption between near-surface air temperature and melt rates, is commonly used in HMs to simulate snow and ice (Braithwaite and Zhang, 2000; Hock, 2003). This approach has been widely used because of its simplicity and parsimony in terms of data requirements (Pellicciotti et al., 2005). However, this method is sensitive to the time integration process of daily mean temperatures (use of different periods and time frames used to calculate the average) and is unable to capture diurnal changes. For instance, the daily mean temperature could be zero or negative, indicating no melt, but the melt conditions may fluctuate throughout the day (Tobin et al., 2013). GHMs generally assume a constant degree-day factor over the entire spatial modelling domain. Spatiotemporal variability, due to changes in seasons, topographic characteristics (slope, aspect and shading), albedo changes, and atmospheric conditions should be considered while calculating the melt rates (Hock, 2003). The other approach to calculating melt requires the estimation of all relevant fluxes based on physical equations, which often require numerous input data at fine spatial and temporal scales (Cazorzi and Dalla Fontana, 1996; Che et al., 2019; Hock, 2005; Hock and Holmgren, 2005). Energy balance models can resolve the complex interactions between the fluxes and internal states that cannot be resolved by temperature index models (Cazorzi and Dalla Fontana, 1996; Hock, 2005).

However, the implementation of an energy balance scheme in GHMs is a cumbersome and computationally expensive task. Moreover, many variables in energy balance models are still abstract, far from being easy to identify from measurements, and indirectly estimated, thus increasing the uncertainty in the results (Essery et al., 2013; Günther et al., 2019; Hock, 2005).

2.3.2 Snow sublimation

Snow sublimation is an important component of the water cycle in the high-altitude HMA region and thus requires proper representation in GHMs (Lv and Pomeroy, 2020; Sexstone et al., 2018; Stigter et al., 2018; Strasser et al., 2008). Studies have reported that snow sublimation in mountainous areas is highly variable, ranging from 10% to 90% of winter snowfall (Groot Zwaaftink et al., 2011; Lv and Pomeroy, 2020; MacDonald et al., 2010; Montesi et al., 2004; Pomeroy and Gray, 1995; Reba et al., 2012; Sexstone et al., 2016, 2018; Stigter et al., 2018; Strasser et al., 2008). Snow sublimation is a local-scale process that depends on the available energy for the turbulent flux, vapor pressure gradient between the snow and the atmosphere, wind speed, and solar exposure (MacDonald et al., 2010; Sexstone et al., 2018). The direct measurement of sublimation is a difficult task and only provides an estimate at a point scale (Bowling et al., 2004). Sublimation of snow is categorized into surface sublimation (representing water vapor fluxes between the atmosphere and the snowpack surface), canopy sublimation (representing intercepted snow held within the forest canopy), and blowing sublimation (representing snow that is transported by wind) (Groot Zwaaftink et al., 2011; Sexstone et al., 2018; Strasser et al., 2008). The degree-day approach, often used by GHMs, is representative only when surface melt is the only dominant ablation component as ablation represents the ensemble of the processes such as melt, evaporation, wind and gravity-driven transport and sublimation (Litt et al., 2019; Mott et al., 2018; Saloranta et al., 2019; Stigter et al., 2018; Wagnon et al., 2013). The empirical relationship between sublimation and meteorological variables is generally used to scale sublimation processes from the point level to the catchment scale (Stigter et al., 2018). However, these empirical relationships are often region-specific and thus require a more sophisticated energy balance approach (Clark et al., 2015a; Knowles et al., 2012). The lack of data (e.g., albedo decay time scale and aerodynamic roughness length) and the difficulty in measuring parameters, hinder the implementation of energy balance schemes and models in HMs (Bowling et al., 2004; Günther et al., 2019).

2.3.3 Permafrost

Permafrost constitutes any type of ground (soil, sediment, or rock that extends vertically from a few feet to a few miles beneath the ground) that has been frozen (< 0 °C) continuously for a minimum of two years (Dobinski, 2011). A quarter of the Northern Hemisphere and 17% of the Earth's land surface (exposed) are covered by permafrost (Biskaborn et al., 2019). Hydrological processes, such as quick surface runoff, movement of water in soil layers, and storage and exchange of surface and subsurface water, are affected by the low hydraulic conductivity of permafrost (Dobinski, 2011; McNamara et al., 1998; Woo and Winter, 1993). The increasing warming rates, which are significantly higher in polar and high-elevation regions than the global average, impact permafrost and associated hydrological processes (Lafrenière and Lamoureux, 2019; Pepin et al., 2015; Quinton and Baltzer, 2013). Degradation in permafrost (or thawing), either from climate or human-induced changes, can change surface drainage patterns by generating ponding and inducing soil skin flow and gully effects (Lafrenière and Lamoureux, 2019; Walvoord and Kurylyk, 2016). Understanding hydrologic changes and permafrost-carbon feedback mechanisms in response to permafrost degradation and climate change is critical for ecosystems (Lawrence et al., 2015; Schuur et al., 2015; Walvoord and Kurylyk, 2016). Permafrost processes are associated with diurnal changes, microclimates, physiographic characteristics, and spatial heterogeneity (Gao et al., 2021). Permafrost processes are difficult to implement in GHMs because they require sophisticated energy balance and phase transformation schemes (Walvoord and Kurylyk, 2016). Although some models include permafrost processes, the uncertainty in representing permafrost dynamics remains high because of the complex local conditions and limited observational data.

2.3.4 Evapotranspiration

Evapotranspiration is an important component of the water and energy balance. It affects weather and climate through its influence on boundary layer and thermal dynamics (Clark et al., 2015b). Globally, only

30-35% of the total inland precipitation ends up in rivers (or river systems), and the remainder evaporates (Rodell et al., 2015). Evapotranspiration, which constitutes surface evaporation, transpiration, evaporation from interception, and open-water evaporation, strongly influences hydrological conditions (Savenije, 2004). Evapotranspiration is not only affected by meteorological conditions (radiation, wind speed, atmospheric humidity and air temperature), but also depends on hydrological (soil moisture availability) and biological factors (such as type and growing stage of vegetation). Most HMs and GHMs use potential evapotranspiration (or actual evapotranspiration if available) to calculate the water balance (Zhao et al., 2013). Spatially distributed HMs and GHMs often require evapotranspiration information at the grid level, which is not available as it is measured at the point scale. Also, the relative contributions of various sources and processes that make up evapotranspiration are not well understood (Coenders-Gerrits et al., 2014; Nelson et al., 2020; Sutanto et al., 2014). Thus, more data measurement efforts are required to improve our understanding of evaporation processes (Harrigan and Berghuijs, 2016). It is found that the hydrological simulations that include explicit biological processes, such as vegetation dynamics, tend to predict lower future droughts and small evapotranspiration changes in a warmer climate than models not include them (Prudhomme et al., 2014). This highlights that evapotranspiration should not be separated from the physical and biological processes it is connected to. There are vast arrays of methods and equations available, differing in complexity and data requirements, to estimate potential evapotranspiration (Oudin et al., 2005). Potential evapotranspiration estimation methods can be divided into three categories: energy-based, temperature-based, and mass-transfer-based. The energy-based implementation of evapotranspiration processes in GHMs is difficult to implement because it requires a large amount of input data compared with the other two methods.

2.3.5 Groundwater

Groundwater is an essential component of GHMs and HMs and plays a critical role in the hydrological cycle and water availability (Taylor et al., 2013). It acts as a vast storage reservoir, interacting with surface water bodies and influencing their flow dynamics, water quality, and ecological processes. Accurate modelling of groundwater flow is crucial for assessing sustainable pumping rates, impacts on water availability and quality, and human water use. Groundwater flow is particularly important in regions where surface water availability is limited and groundwater is the primary source of water for domestic, agricultural, and industrial purposes. By incorporating groundwater flow in GHMs and HMs, a comprehensive understanding of water storage and release dynamics, surface water interactions, human water use, and climate change impacts can be obtained, providing valuable insights into water resource management, planning, and adaptation strategies.

GHMs and HMs that exclude groundwater processes may underestimate water availability, overestimate human water use, and fail to capture the impact of climate change on water resources. Therefore, it is crucial to include groundwater flow in GHMs to obtain accurate and reliable estimates of water availability, water use, and the impact of climate change on water resources. This information can help policymakers make informed decisions regarding water allocation, water management, and adaptation strategies, ensuring the sustainable and equitable use of water resources for both present and future generations.

2.3.6 Flow routing

Flow routing, i.e., transport of water from upstream cells (source) to downstream cells (sink) through a river network, in physically based distributed HMs is a difficult task as it requires solving the Saint-Venant equations (Beven, 2012; Chaudhry, 2007; Te Chow, 2010). This physical method requires solving complex partial differential equations (i.e., continuity and momentum), and often has high data requirements related to river geometry, morphology and floodplain, which are often not available for large spatial scales (Singh and Woolhiser, 2002). Several simple numerical approximations of these complex partial differential equations have been proposed and implemented in several HMs (and GHMs) in the past (Beven, 2012; Chanson, 2004; Cunge, 1969). The choice of routing scheme has a significant influence on the timing of simulated river discharge and its peak values (Hattermann et al., 2017; Zaherpour et al., 2018; Zhao et al., 2017).

2.4 Typical challenges in setting up GHMs

2.4.1 Data availability

The availability and quality of spatial ground-based information are crucial for selecting HM and GHM types (Clark et al., 2017). Over the past decades, many efforts have been made to improve the technology, quantity, and quality of data required for HMs and GHMs (Singh, 2018). Advancements in remote sensing technology, such as satellites and radars, have made it easier to model the hydrological characteristics of ungauged or data-scarce regions such as HMA. However, for most hydrological processes, such as snow sublimation, avalanching, glacier melt and characteristics (debris, ponds, and cliffs), permafrost, groundwater processes, and routing processes, such spatial data do not exist (Beniston et al., 2018; Dobinski, 2011). The use of GHMs, especially in high mountains where the hydrological processes vary considerably with altitude, is hampered by the limited qualitative data availability in higher and remote regions.

It is extremely challenging to perform reliable streamflow simulations, particularly for ungauged catchments and data-scarce regions such as HMA (Immerzeel et al., 2015a; Wortmann et al., 2018). Existing hydrometeorological stations, mostly located in valleys lower than 4000m, are sparsely and unequally distributed in the region (Palazzi et al., 2013; Qin et al., 2009). The point-based station data are not representative of the complex surrounding HMA. The low quality and limited availability of data at high altitudes impose difficulties in spatial interpolation and often lead to a strong underestimation of HMA precipitation (Immerzeel et al., 2015a; Li et al., 2017; Palazzi et al., 2015).

To address these data scarcity issues, GHMs either use a calibration parameter or an approximation based on limited data obtained from location-specific studies (e.g., glacier mass balance, snow sublimation, and hydraulic conductivity). Most processes are often measured or modelled at a small scale (time and space). However, real applications require the estimation of these processes over long periods and large regions (such as the lifetime of hydraulic structures). Conversely, some local studies use regional and global-scale coarse data and parameters. The use of these approximations renders the outcome of HMs (and GHMs) uncertain (Bierkens et al., 2001; Blöschl and Sivapalan, 1995; Peters-Lidard et al., 2017; Seyfried et al., 2009).

Remote sensing and satellite data provide better geographical coverage compared to sparse point-based station data and have been extensively used in the past decades to provide a better understanding of the states and variables related to the hydrological cycle and water resources (Wagner et al., 2009; Xu et al., 2014). The integration of remote sensing information into HMs provides a better uncertainty assessment of water resources and water-related issues; and therefore, an in-depth exploration of the accuracy of such data is required (Emery and Camps, 2017).

2.4.2 Spatiotemporal resolution

The response time of hydrological processes varies from a few minutes (snow melt, snow avalanche) to multiple decades (glacier dynamics, groundwater flow in aquifers) (Hock, 2003, 2005; Koutsoyiannis, 2005; Marshak, 2008). The choice of an appropriate modelling time step for hydrological simulation depends on the availability of the data (temporal resolution of the forcing), dominant hydro-meteorological processes, geophysical characteristics of the catchments and objective of the study (Bastola and Murphy, 2013; Littlewood and Croke, 2008; Ostrowski et al., 2010; Smith et al., 2004; Syed et al., 2003). For urban drainage processes, a sub-hourly resolution time step is recommended, whereas for irrigation, a monthly resolution is sufficient (Blöschl and Sivapalan, 1995). For the simulation of highly dynamic processes, such as floods, a sub-daily time step is required to represent the high intermittency of convective precipitation and fast catchment response time which depends on basin physiographic characteristics such as the size, drainage network, steepness, and percentage of impervious area (Ochoa-Rodriguez et al., 2015). The spatial resolution of GHMs can vary from less than a meter (for unsaturated flow processes) to a few hundred kilometers (monsoon circulation). The coarse spatial resolution of GHMs could be an important source of error in the HMA region because of the missing interactions between the topography and atmospheric processes required for small-scale processes (Beniston et al., 2018; Blöschl and Sivapalan, 1995; Sillmann et al., 2013).

2.4.3 Computational time

The use of physically based HMs and GHMs is limited because of their high computational requirements (Huintjes et al., 2015; Koch et al., 2016; North, 1975; Paul and Kotlarski, 2010; Reid and Brock, 2010). Conversely, conceptual HMs are becoming popular because they require less data and computational resources (Koch et al., 2016). Advances in computational capacity in recent decades have made it possible to model the desired system and keep track of the state and fluxes of a system at any given time and spatial scale (Fatichi et al., 2016). However, computing remains a present-day challenge as expectations have increased beyond the limits (Bierkens et al., 2015; Clark et al., 2017). Issues related to the trade-off between the process complexity, spatial complexity, domain size, ensemble size, the time period of simulation, single deterministic simulation and model inter-comparisons persist (Clark et al., 2017; Wood et al., 2011).

2.4.4 Model uncertainty

Communicating predictive uncertainties with hydrological predictions is essential for water resources and other relevant decision-making processes (Georgakakos et al., 2004; Liu and Gupta, 2007). GHMs and HMs involve many processes, and each component introduces uncertainty, which ultimately contributes to the total uncertainty. Uncertainties in GHMs and HMs stem from parameters, model structure, input data, initial conditions, and calibration (Lindenschmidt et al., 2007; Papacharalampous et al., 2019; Renard et al., 2010; Sudheer et al., 2011; Troin et al., 2016; Wilby, 2005). Parameter uncertainty in GHMs (and HMs) is a result of conceptual simplification which arises due to inadequate process understanding, over-approximations, limited data, inability to measure or estimate a process (e.g. hydraulic conductivity can be measured at point scale but varies considerably for catchment scale), natural process variability, and observational errors (Beven, 2012). Structural uncertainty, sometimes referred to as “model uncertainty”, in GHMs and HMs mainly arises due to the simplified representation of hydrological processes (Lindenschmidt et al., 2007; Moges et al., 2021; Troin et al., 2016). HMs structural uncertainty also includes alternative conceptualizations related to surface and subsurface processes (Refsgaard et al., 2012). The input uncertainty in GHMs and HMs is governed by uncertainty in forcing (sampling and measurement error in rainfall and temperature, large variability among the reanalysis, satellite-derived, and merged products), elevation, soil characteristics, and other catchment-related information. GHMs and HMs require the calibration of different parameters (including snow, glaciers, and rainfall-runoff) and states based on the availability of ground-based observations. Errors arising from unsatisfactory calibration and imperfect observations (for e.g., systematic error in stage and runoff measurements, rating curve extrapolations and hysteresis errors), contribute to the calibration and observational uncertainty of GHMs and HMs (Domeneghetti et al., 2012; Kiang et al., 2018). Parameters calibrated to a stationary climate also add uncertainty to hydrological predictions used to assess climate change impacts (Brigode et al., 2013; Wilby, 2005). Model structural uncertainty is the dominant source of predictive uncertainty in GHMs and HMs under both stationary and non-stationary climates (Højberg and Refsgaard, 2005; Mendoza et al., 2015; Rojas et al., 2008). The input uncertainty, especially in data-scarce mountain environments where the data involve interpolation, scaling and derivation from other measurements, constitutes approximately 10 to 40% of the predictive uncertainty (McMillan et al., 2018). To adequately assess and reduce the uncertainty from GHMs and HMs, it is important to understand and quantify them (Liu and Gupta, 2007).

3 Introduction to the SPHY model

Despite the proliferation of hydrological models in recent decades, only a limited number incorporate snow and glacier processes in a manner that is both physically realistic and coherent with the available data. This is particularly critical for HMA, where snow and ice dynamics play dominant roles in seasonal water availability and long-term hydrological trends. Rivers originating in the HMA region are the most meltwater-dependent river systems on Earth (Schaner et al., 2012). In the regions surrounding the Himalayas and the Tibetan Plateau, large human populations depend on the water supplied by these rivers (Immerzeel, 2010).

However, the dependency on meltwater differs strongly between river basins within the HMA region, as a result of differences in climate and basin topography (Immerzeel et al., 2012). Only by using a distributed hydrological modelling approach that includes the simulation of key hydrological and cryospheric processes, and the inclusion of transient changes in climate, snow cover, glaciers, and runoff, appropriate adaptation and mitigation options can be developed for this region (Sorosg et al., 2014). The SPHY model is highly suitable for this approach and has therefore been widely applied in the region (Khanal et al., 2021).

3.1 Overall approach of the SPHY model

SPHY is suitable for a wide range of water resource management applications. Therefore, SPHY is a state-of-the-art, easy-to-use, and robust tool that can be applied for operational as well as strategic decision support. The SPHY modelling toolbox is available in the public domain and uses only open-source software. SPHY is developed by FutureWater in cooperation with partners across the world, and several in the HMA region, including ICIMOD (visit https://sphymodel.com/ for more information).

SPHY is a spatially distributed leaky bucket-type model that is applied on a cell-by-cell basis. To minimize the number of input parameters and avoid complexity and long model runtimes, SPHY does not include energy balance calculations and is therefore a water-balance-based model. The main terrestrial hydrological processes are described in a physically consistent manner so that changes in storage and fluxes can be assessed adequately over time and space. The model is designed for both large- and small-scale cryospheric-hydrological studies and integrates different hydrological processes, including (a) rainfall-runoff, (b) cryospheric processes, (c) evapotranspiration, and (d) soil hydrological processes. SPHY can operate at flexible spatial scales (glaciers, sub-basins, basins, and regions). A schematic visualization of the key processes included in the SPHY model is shown in Figure 1.

SPHY enables the user to turn on/off modules that are not required. This concept is very useful if the user is studying hydrological processes in regions where not all hydrological processes are relevant. For example, a user may be interested in studying irrigation water requirements in central Africa. For this region, glacier and snowmelt processes are irrelevant and can thus be switched off. Another user may only be interested in simulating moisture conditions in the first soil layer, allowing the possibility of switching off the routing and groundwater modules. The advantages of turning off irrelevant modules are two-fold: (i) decrease the model run-time and (ii) decrease the amount of required model input data.

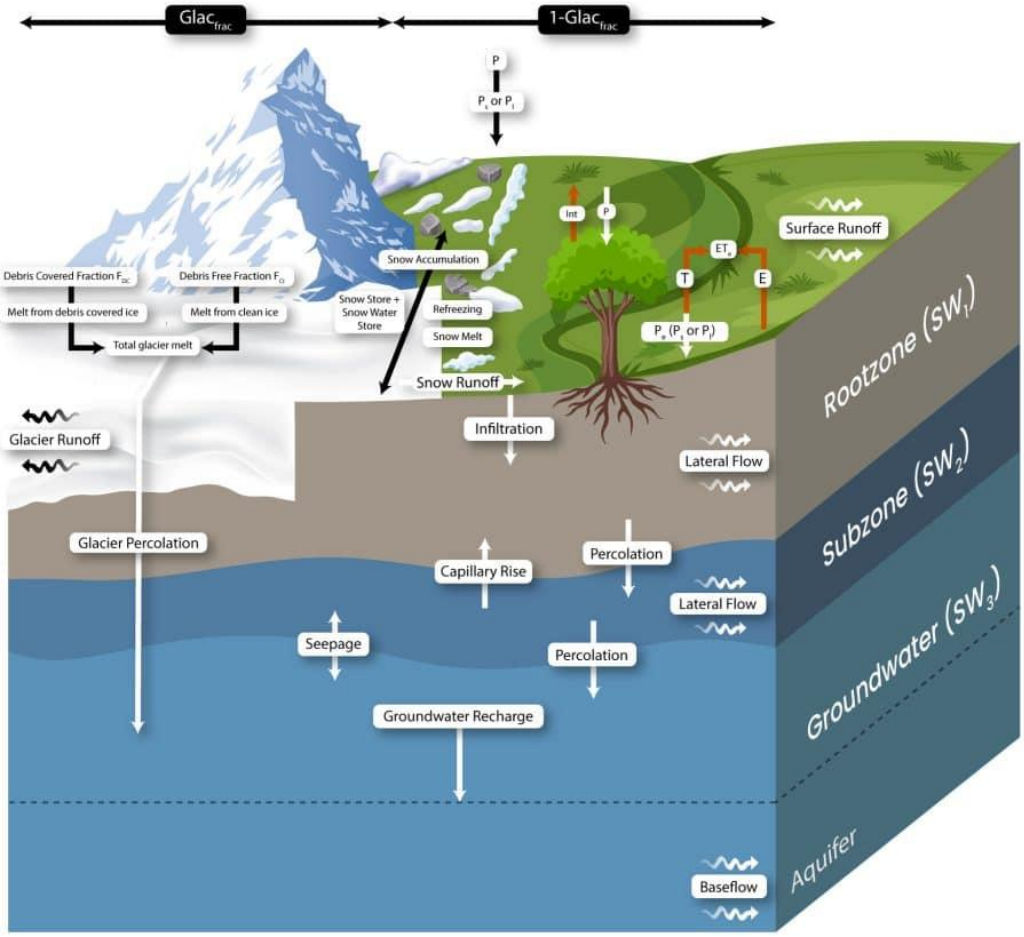

Figure 1. A schematic visualization of the key processes included in the SPHY glacio-hydrological model (source: https://sphymodel.com/concept/)

3.2 Snow processes

Snowmelt is an important source of runoff in mountainous catchments. To obtain a realistic estimate of snowmelt, several processes must be considered. Processes such as snow precipitation rates, meltwater refreezing in the snowpack, sublimation, and evaporation. The SPHY model simulates dynamic snow storage at a daily time step, adopted from the model presented by (Kokkonen et al., 2006).

The model tracks snow storage, which is fed by precipitation and generates runoff from snowmelt. Refreezing of snowmelt and rainfall within the snowpack is simulated as well. Depending on the temperature threshold, precipitation is defined as either a solid or liquid. To simulate snowmelt, a well-established and widely used degree-day melt modelling approach is used (Hock, 2003). Runoff from snow is generated when the air temperature is above the melting point and no more meltwater can be refrozen within the snowpack (for more information, read the SPHY manual[1]).

[1] https://sphymodel.com/publications/

3.3 Glacier processes

Mountain glaciers are typical features found in high-mountain environments. These features, which are also referred to as 'rivers of ice', flow from high-altitude areas to valleys due to gravitational forces. Glaciers are typically formed when accumulated snow at higher altitudes is transformed into ice and flows down under the force of gravity to lower altitudes. The mass balance of a glacier is determined by the sum of all processes that add mass to a glacier (accumulation) and remove mass from a glacier (ablation), and can be considered to be in equilibrium when accumulation equals ablation (Haeberli, 2011). When accumulation is higher than ablation due to increased snowfall or a decrease in melt, a glacier advances/thickens, and when ablation is higher than accumulation due to decreased snowfall or an increase in the melt, a glacier retreats/thins.

In addition to precipitation and temperature, variables such as sublimation, wind-blown transport of snow, and avalanching also influence the rate of ablation and accumulation on glaciers. Melting of glacier ice contributes to river discharge through slow and fast components: (i) percolation to the groundwater reservoir that eventually becomes base flow and (ii) direct runoff. The dynamic behavior of glaciers can be considered by incorporating key processes such as accumulation, ablation, and ice mass transfer from the accumulation to the ablation zone. Changes in glacier fraction in response to the precipitation and temperature are considered by using a mass-conserving ice distribution approach.

The accumulated snow in the accumulation zone is transformed into ice and distributed downwards to the ablation area at the end of each melting season (1st of October). The redistribution is proportional to the initial total volume of ice so glacier parts with a larger initial ice volume will receive a large volume of accumulated ice from the accumulation zone to the ablation zone (Khanal et al., 2021 for further details). Ice redistribution is performed once a year (1st of October) at the end of the hydrological year (1st October to 30th September next year).

The SPHY model usually operates at a spatial resolution that is too large to include the ice flow and dynamics of glaciers. Therefore, glaciers in SPHY are considered melting surfaces that can completely or partially cover a grid cell (Khanal et al., 2021). Glacier melt is calculated with a degree-day modelling approach as well. Because glaciers covered with debris melt at different rates than debris-free glaciers, a distinction can be made between the different degree-day factors for both types. When SPHY is run for future scenarios, the fractional glacier cover in a grid cell changes according to a parameterization of glacier changes at the river basin scale. This parameterization estimates the changes in a river basin's glacier extent as a function of the glacier size distribution in the basin and the projected temperature and precipitation.

3.4 Soil processes

Soil water storage properties can determine the amount of rainfall-runoff and infiltration into groundwater. The soil water processes in SPHY are modelled for three soil compartments: (i) the first soil layer (root zone), (ii) the second soil layer (sub-soil), and (iii) the third soil layer (groundwater store).

The lateral flow of water in the soil between cells, the exchange of water between soil layers and the groundwater reservoir through percolation and capillary rise, as well as the release of baseflow from the groundwater reservoir, are calculated in the model.

3.5 Lake or reservoir processes

Lakes or reservoirs present within a catchment act as natural buffers, resulting in a delayed release of water from these water bodies. SPHY allows the user to choose a more complex routing scheme if lakes or reservoirs are located in their basin of interest. The use of this more advanced routing scheme requires a known relationship between lake outflow and lake level height (Q(h)-relation) or lake storage.

4 Setting up a glacio-hydrological model

4.1 Spatial resolution

Among many other factors, the choice of the spatial resolution of the model depends on the objectives of the study, time to conduct the study, computational resources, and data availability. For instance, if the objective of the study is to assess the impact of climate change on a regional scale or large basin scale (such as the Ganges or the Brahmaputra), a spatial resolution ranging from 1 to 5 km would be favorable (Khanal et al., 2021; Lutz et al., 2014b; Wijngaard et al., 2017). Conversely, if the objective of the study is to assess the impact of climate change on a glacier or smaller sub-basin, a spatial resolution of 30m–1000m would be favorable.

The choice of spatial resolution also depends on data availability. If there are fewer observed stations where meteorological variables (such as snow, temperature, and precipitation) are available within the region of interest, then it is advisable to use a coarser spatial resolution compared to the scenario with a dense meteorological station network. Cryospheric processes are associated with different responses and spatiotemporal scales. For instance, glacier and snowmelt processes are localized and dominant processes in the higher mountains compared to large-scale rainfall-runoff processes, which are dominant in the lower plain regions. Thus, snow and glacier melt processes require finer-scale spatial discretization than large-scale rainfall-runoff processes.

Because SPHY considers sub-grid variability, it is possible to run the glacier processes at fine resolution (50 x 50m) and downstream rainfall-runoff processes at a coarser resolution (5 x 5 km) (Khanal et al., 2021). The larger the geographical extent (or the number of cells in the model), the longer it will take to simulate the hydrological characteristics. Therefore, it is advisable to have a total number of cells less than 1 million for faster computation.

4.2 Model timestep and time-horizon

Similar to spatial resolution, the selection of an appropriate temporal resolution and time horizon depends on several factors. For instance, if the objective is to simulate a particular glacier-specific extreme event, then it is advisable to run the model on a sub-daily scale (sub-hourly, hourly, 3-6 hourly time steps). The choice of time step is highly dependent on data availability. If meteorological forcings are available only on a daily timescale, then it is advisable to run the model on a daily time step.

However, if the objective of the model is to understand the impact of climate change on water availability at a large scale at longer time horizons in the future (mid-century and end of century, or centennial time scale), then it is advisable to run the SPHY model on daily time steps and aggregate the outputs as per need. In the hydrological realm, it is a widely accepted practice to employ a limited set of observed discharge data for fine-tuning GHMs (Khanal et al., 2021; Lutz et al., 2014b; Wijngaard et al., 2017).

However, to attain a comprehensive understanding of the hydrological regime and flow characteristics exhibited by a given basin, it is strongly recommended to subject the calibrated GHM to an extensive simulation period spanning 20–30 years. This extended duration allows for a more robust analysis of the model's performance and its ability to capture long-term hydrological patterns. It is recommended that the baseline scenario used for this simulation incorporates the most recent and up-to-date data.

4.3 Data requirement for SPHY model setup

SPHY requires both static and dynamic data. The most relevant static data are topography, land use type, glacier cover, lakes/reservoirs, and soil characteristics. For dynamic data, SPHY uses climate data such as precipitation, temperature, vegetation, snow cover, snow depth, snow water equivalent, glacier mass balance, and streamflow. Because SPHY is a grid-based model, the flexible integration of different remote sensing and global data sources can be easily performed. For example, the Normalized Difference Vegetation Index (NDVI) *(Myneni and Williams, 1994)* can be used to determine the leaf area index to estimate the growth stage of land cover.

Streamflow data are not required to set up the model. However, flow data are required to perform proper calibration and validation procedures. The model can also be calibrated using actual evapotranspiration, soil moisture content, and/or snow-covered areas. The data required to set up the SPHY model are described in the following subsections.

4.3.1 Digital Elevation Model (DEM)

A Digital Elevation Model (DEM) is a representation of the bare ground (bare earth) topographic surface of the Earth , excluding trees, buildings, and any other surface objects. A DEM is required to calculate the slope, aspect, flow direction, and flow accumulation in the SPHY model. The DEM can be downloaded from the following sources:

- Shuttle Radar Topography Mission (SRTM): This DEM has a spatial resolution of 30m (1-arc second global digital elevation) and covers the entire globe. This DEM is freely available in the public domain. The data can be downloaded via the USGS Earth Explorer[1], Google Earth Engine[2], or any other source.
- Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER): This DEM has a resolution of 90m (3 arc-seconds) and is also available at the global scale. The data can be downloaded via the USGS Earth Explorer[1], Google Earth Engine[2], or any other source.
- HydroSHEDS: HydroSHEDS, an open-source data available at 3, 15, and 30 arc-seconds as well as 5 and 6 arc-minutes, provides hydrographic information in a consistent and comprehensive format for regional and global-scale applications. It offers a suite of geo-referenced datasets (vector and raster), including stream networks, watershed boundaries, drainage directions, and ancillary data layers, such as flow accumulations, distances, and river topology information. The data can be downloaded from HydroSHEDS[3].

4.3.2 Soil properties

The SPHY model requires soil properties as inputs for hydrological simulations. Soil information is the basis for all environmental research. Because local soil maps of good quality are often unavailable, global soil maps with low resolution are used. FutureWater has developed HiHydroSoil v2.0, a freely available high-resolution dataset (250m), with soil properties and classes on a global scale that can be easily used for hydrological, erosion, and crop modelling. This can be downloaded from FutureWater[4]. It is also possible to use the observed soil properties values or maps (read the SPHY manual for more description).

4.3.3 Land use data

Land use maps represent spatial information on different types (classes) of physical coverage of the Earth's surface, such as forests, grasslands, croplands, lakes, wetlands, snow, and glaciers. Land use data are an important input for the SPHY model. There are several free sources to acquire land use data at the country, regional, and global scales. For glacier-scale studies, it is recommended to generate detailed land use data using Sentinel2 images (2015–present coverage). The raw images can be

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[1] https://earthexplorer.usgs.gov/
[2] https://developers.google.com/earth-engine/datasets/catalog/CGIAR_SRTM90_V4
[3] https://www.hydrosheds.org/
[4] https://www.futurewater.eu/projects/hihydrosoil/

accessed via SCI Hub Copernicus[1]. Similarly, any available observed land use data can be used in the SPHY model. For large-scale applications, land use data can be derived from:

- Esri Land Cover: The Esri Land Cover provides a very high resolution (10m) land cover from 2017–2022 generated using Sentinel-2. This 10m resolution data source is open-source and available on a global scale. Visit Esri Living Atlas[2] to download and for more information.
- European Space Agency Climate Change Initiative (CCI) Land Cover V2: This data is available at a 300m resolution for 1992–2018. The data can be downloaded from ESA Land Cover CCI[3]
- MCD12Q10.5 km MODIS: The Terra and Aqua combined Moderate Resolution Imaging Spectroradiometer (MODIS) Land Cover Type (MCD12Q1) Version 6 data product provides global land cover types at yearly intervals (2001–2020), derived from six different classification schemes. The MCD12Q1 Version 6 data product is derived using supervised classifications of MODIS Terra and Aqua reflectance data. The data can be downloaded from USGS Earth Data – MCD12Q1[4].

4.3.4 Glacier outlines

Glacier outlines are required to prepare the inputs required for simulating the glacier module in SPHY. The observed glacier outlines, if available, can be easily used with the SPHY model. Otherwise, the most recent version of the Randolph Glacier Inventory (RGI 6.0) is preferred. RGI 6.0 is freely available on a global scale. The dataset can be downloaded from GLIMS[5].

Moreover, the SPHY glacier module can distinguish glacier melt from clean ice and debris-covered glaciers. However, this requires the pre-distinction of the glacier surface into clean ice and debris. The ablation characteristics of debris-covered glaciers differ from those of clean-ice glaciers. On this type of glacier, the amount of ablation depends on several factors, such as debris thickness and the presence of ice cliffs and supraglacial ponds (Pellicciotti et al., 2015; Ragettli et al., 2016; Reid and Brock, 2010; Steiner et al., 2015). The magnitude of ablation depends on the thickness of the debris on the glacier. Very thin layers of debris (<2 cm) enhance melt rates due to the lower albedos, whereas thicker layers of debris reduce melt rates due to the insulation of the surface (Kraaijenbrink et al., 2017; Nicholson and Benn, 2006; Østrem, 1959; Reid and Brock, 2010; Rowan et al., 2015).

4.3.5 Glacier ice thickness

Glacier ice thickness is required to prepare the inputs required for simulating the glacier module in SPHY. The observed glacier ice thickness, if available, can be easily used with the SPHY. Otherwise, the following data sources are preferred:

- Farinotti et al. (2019): present a dataset containing an ensemble of up to five models to provide a consensus estimate for the ice thickness distribution of 215,000 glaciers outside the Greenland and Antarctic ice sheets. The models use principles of ice flow dynamics to invert ice thickness from surface characteristics. The dataset is freely available at ETH Zurich Research Collection[6].
- Millan et al. (2022): The authors present a comprehensive high-resolution mapping of ice motion for 98% of the world's total glacier area during the period 2017–2018. We use this mapping of glacier flow to generate an estimate of global ice volume that reconciles ice thickness distribution with glacier dynamics and surface topography. The dataset is freely available through nature.com[7].

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[1] https://www.copernicus.eu/en/access-data/conventional-data-access-hubs
[2] https://livingatlas.arcgis.com/landcover/
[3] https://www.esa-landcover-cci.org/
[4] https://lpdaac.usgs.gov/products/mcd12q1v006/
[5] https://www.glims.org/RGI/
[6] https://www.research-collection.ethz.ch/handle/20.500.11850/315707
[7] https://www.nature.com/articles/s41561-021-00885-z

4.3.6 Meteorological forcings

SPHY requires spatial daily maps of precipitation and temperature (minimum, maximum, and mean). The most preferred option is to use observed station data (or gridded data) if available for hydrological simulations. Existing hydrometeorological stations, mostly located in valleys lower than 4000m, are sparsely distributed in the mountains. The complex topography and harsh conditions in the mountains make it difficult to manage ground stations. Usually, in HMA, such datasets are not available. In such cases, satellite-derived and remotely sensed products can be used.

Remotely sensed satellite measurements from geostationary thermal infrared and polar-orbiting passive microwave sensors are useful for deriving precipitation measurements based on cloud-top brightness temperature and spectral scattering caused by large ice particles. However, the uncertainty is high because of the limitations in sensor signals to penetrate clouds and correctly estimating the precipitation falling as snow at high altitudes (Immerzeel et al., 2015a). Nevertheless, remotely sensed products, in recent decades, have proven to be a cost-effective and reliable tool to understand precipitation patterns and trends at various spatial and temporal scales (Gehne et al., 2016).

Several reanalyses and remotely sensed options available for the HMA region are as follows:

- European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5: The ERA5 is an improved (atmosphere, ozone, land, and ocean waves component) and high-resolution successor of the ERA-Interim (Dee et al., 2011). The ERA5 uses observations from over 200 satellite instruments or conventional data types, including ground-based radar–gauge observations, PILOT, radiosonde, dropsonde, buoys, and aircraft. The ERA5 data are available at an hourly time scale and 31 × 31 km spatial resolution for 137 vertical pressure levels. Surface or single-level data are also available, containing two-dimensional parameters such as precipitation, 2m temperature, top-of-atmosphere radiation, and vertical integrals over the entire atmosphere. ERA5 is a freely available dataset that covers the period from 1950 to 2023 (present). The dataset can be accessed from Copernicus Climate Data Store[1]. This dataset has been extensively used for hydrological applications in the region and globally (Khanal et al., 2021). However, the data need to be bias-adjusted and downscaled for hydrological applications. The ERA-5 data were bias-adjusted and downscaled at 1 km resolution for the entire HMA using the topography-based downscaling scheme TopoSCALE (Fiddes and Gruber, 2014). TopoSCALE downscales atmospheric fields available on pressure levels to a high-resolution digital elevation model. The bias adjusted and downscaled ERA5 datasets can be accessed freely via the SPHY model website[2].
- ERA5-Land: ERA5-Land is a reanalysis dataset that provides a consistent view of the evolution of land variables over several decades at an enhanced resolution compared to ERA5. It is available as hourly data from 1950 to the present. The data can be accessed from the Copernicus Climate Data Store[1].
- High Asia Refined analysis version 2 (HAR v2): The High Asia Refined analysis version 2 (HAR v2) is an atmospheric dataset generated by dynamical downscaling using the Weather Research and Forecasting model (WRF) version 4.1 and freely available for the Tibetan Plateau and surrounding mountains. It is available for the period 1980–2020 at hourly, daily, monthly, and yearly time scales.
- Other remotely sensed products commonly used in the HMA region are the Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation (APHRODITE), Tropical Rainfall Measuring Mission (TRMM), Climate Hazard group Infrared Precipitation (CHIRPS), Multi-Source Weighted-Ensemble Precipitation (MSWEP), Climate Prediction Center

[1] https://cds.climate.copernicus.eu/
[2] https://sphymodel.com/downloads/

MORPHing product (CMORPH), and Precipitation Estimation from Remotely Sensed Information using Artificial Neural Network (PERSIANN).

The direct use of such products to derive climatological and hydrological trends often requires validation and correction based on in situ observations (Gebregiorgis and Hossain, 2015; Gehne et al., 2016). Such corrections for meteorological forcings involve adjusting meteorological data to account for the effects of terrain elevation on atmospheric variables. The process consists of several steps aimed at ensuring accurate representation of meteorological conditions in areas influenced by topography. The meteorological variables (temperature, precipitation, wind speed, and solar radiation) serve as the foundation for subsequent correction procedures.

High-resolution elevation data, such as DEMs, is essential for accurately characterizing the terrain of the study area. This elevation data provides information on the elevation profile and the presence of mountains, valleys, and other topographic features. Statistical analysis, regression models, and empirical relationships can be used to investigate and quantify the effects of elevation on temperature, precipitation, solar radiation, and other variables of interest. Based on the findings of this analysis, correction techniques can be applied to account for the topographic effects on meteorological variables. These correction techniques may vary depending on the variables being corrected.

For temperature, adjustments can be made by considering the lapse rate, which describes the decrease in temperature with increasing elevation. Precipitation correction involves accounting for the orographic effects caused by mountains or hills, which result in increased precipitation at higher elevations. Solar radiation correction addresses the shading effects caused by terrain features by incorporating models that account for shadowing and terrain slope. After the correction procedures are implemented, the corrected meteorological data is validated to ensure its accuracy and reliability. Validation involves comparing the corrected data with observed data or independent validation datasets. This step verifies the effectiveness of the topographical correction methods applied and helps assess the quality of the resulting data. It is important to note that the specific techniques and algorithms for topographical correction may vary depending on the available data, study area, and atmospheric variables of interest.

4.4 Data required for SPHY model calibration

Datasets are used throughout model delineation, parameterization, calibration, and validation, and are essential and integral parts of glacio-hydrological modelling, which will later influence model performance and may limit model applications. Traditionally, only observed streamflow datasets have been used to calibrate GHMs.

However, parameterizing the GHM along with stream flow induces uncertainties (especially in snow and glacier processes). Thus, it is necessary to ensure that snow and glacier-related processes are well parameterized in GHMs. The SPHY model can use a large array of observed data sources (to the extent available). Here, we provide a list of data that could be useful for parameterizing snow and glacier processes in a GHM.

4.4.1 Snow cover

Snow is a significant component of ecosystems and water resources. Snow cover information is required to ensure that snow-related processes and model parameters are well-calibrated in the SPHY model. Unfortunately, snow cover data sources are limited in this region.

- Moderate Resolution Imaging Spectroradiometer (MODIS) snow cover data were used for this project. The most recent version of MODIS snow cover (MOD10CM006) can be downloaded from NSIDC[1]. This is a global, 0.05° resolution monthly mean snow cover extent derived from the MODIS daily snow cover extent product (MOD10C1). The dataset is available from 2000 to the present for the entire globe on a monthly timescale.

- International Centre for Integrated Mountain and Development (ICIMOD) has developed a new method to improve the interpretation of snow cover data in the region using Terra and Aqua MODIS snow cover data. The improved snow data for HMA covered the MODIS observation period between 2002 and 2018. The product is available for free on ICIMOD's Regional Database System[2].

4.4.2 Glacier mass balance

Region-wide observed glacier mass balance data are not available in most cases. However, for specific glaciers, some information is available in the public domain (e.g., published scientific articles, reports and websites). SPHY is sufficiently flexible to incorporate data at both the individual glacier and large basin level aggregation. For instance, if information is available on the glacier mass balance for multiple glaciers in a basin, different glacier mass balances could be used to parameterize the glaciers. However, if such information is not available, only one glacier mass balance for the entire basin can be used to parameterize the glacier processes. Some regional databases are available for the HMA region.

- Shean et al. (2020): This database consists of 5,797 high-resolution DEM) from available sub-meter commercial stereo imagery (DigitalGlobe WorldView-1/2/3 and GeoEye-1) acquired over HMA glaciers from 2007 to 2018 (primarily 2013–2017). The project reprocessed 28,278 ASTER DEMs over HMA from 2000 to 2018 and combined these observations to generate robust elevation change trend maps and geodetic mass balance estimates for 99% of HMA glaciers between 2000 and 2018. The dataset is freely available through Frontiers in Earth Science[3].
- Brun et al. (2017): This database provides the mass balance for approximately 92% of the glacierized area of HMA using time series of digital elevation models derived from satellite stereo-imagery between 2000 and 2016. The dataset is freely available on Nature.com[4].
- Wang et al. (2021): This database provides the recent status of HMA glaciers based on the first analysis of Ice, Cloud, and Land Elevation Satellite-2 (ICESat-2) data between 2003 and 2019. This database uses the Gravity Recovery and Climate Experiment (GRACE) and GRACE Follow-On (FO) data to complement ICESat-1,2 data and validate them independently. The dataset is freely available from Advancing Earth and Space Sciences[5].

4.4.3 Discharge

Discharge is the most crucial variable required to correctly parameterize the GHM and is important for water resource projects, such as energy production, irrigation planning, water quality improvements, and waterway transport. However, discharge data in the HMA region are often considered confidential, and there are many restrictions on their open use. Lack of observed data most of the time becomes a big barrier to parametrizing the qualitative GHM and its further use for estimation and prediction purposes. It is advisable to use the observed discharge data if available; however, such information is not readily available in the remote regions of HMA.

For example, in the IHR, the Central Water Commission (CWC) has the mandate to monitor, collect, and collate information regarding hydro-meteorological data. It is advisable to check with the CWC for location-specific discharge data. However, in some cases, the discharge data are also available from

[1] https://nsidc.org/data/mod10_l2/versions/61
[2] https://rds.icimod.org/
[3] https://www.frontiersin.org/journals/earth-science/articles/10.3389/feart.2019.00363/full
[4] https://www.nature.com/articles/ngeo2999
[5] https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2020GL090954

educational institutes such as universities, research institutes, and agencies such as the department of forestry, hydropower/irrigation development corporation, and disaster management authority.

If data are not available at the local scale, a few global datasets are available. However, the quality and quantity of these global datasets are limited. The following databases are available on a global scale:

- Global Runoff Data Centre (GRDC): The GRDC is an international archive, operating under WMO, of data up to 200 years old, and fosters multinational and global long-term hydrological studies. This database consists of information on long-term daily flow data (mean daily and monthly) and catchment information from more than 10,000 river gauging stations across 159 countries and regions. To date, this is the largest river discharge time series database. The GRDC station locations are available on Google Earth Engine. The datasets are freely available at the Global Runoff Data Centre[1].
- Global Monthly River Discharge dataset: The Global River Discharge (RivDIS) dataset contains monthly discharge measurements for 1018 stations worldwide. The period of record varies widely from station to station, with a mean of 21.5 years. The datasets are freely available at PANGAEA[2].

It is advisable to use the observed discharge data at daily (or sub-daily) time steps, but if the data are not available at this temporal resolution, then monthly (or even annual) average values are still very useful for calibrating and validating the GHMs.

4.4.4 Optional complementary data and challenges

Hydrometeorological measurements in high mountains pose unique challenges owing to the inaccessible terrain, harsh weather conditions, and complex environmental factors. Establishing and maintaining measurement stations in remote locations can be difficult, and extreme weather conditions can damage instruments and hinder data collection. The significant elevation changes and orographic effects in mountainous regions necessitate the installation of sensors at different heights.

Additionally, snow and glacial processes, limited data transmission and power supply, and environmental considerations further complicate the measurements. Overcoming these challenges requires specialized equipment, sensors, innovative techniques, and collaboration among multidisciplinary teams. Despite these difficulties, accurate high-mountain measurements are crucial for understanding hydrological processes, managing water resources, and mitigating natural hazards.

Various sensors are used to collect hydrometeorological data, capturing information on different aspects of the water cycle and meteorological variables. The choice of sensors depends on the specific research or monitoring objectives, variables of interest, and environmental conditions of the study area. The following common types of sensors are used in hydrometeorological monitoring:

- Rain gauges: Rain gauges are used to measure precipitation, including rainfall and snow. They come in various designs, such as tipping bucket gauges, weighing gauges, disdrometers, pluviographs, and optical sensors, and are used to record the amount and intensity of precipitation over specific periods. Importantly, the effectiveness of rain gauge monitoring can be significantly enhanced by integrating data from multiple gauges within a network. This approach facilitates the consideration of spatial variability in rainfall patterns, thereby enabling a comprehensive understanding of precipitation distribution across a given area.
- Temperature sensors: Thermocouples, which generate a voltage based on temperature differences, are commonly employed because of their ruggedness and wide temperature range. Resistance Temperature Detectors offer high accuracy and stability over a broad temperature

[1] https://grdc.bafg.de/
[2] https://grdc.bafg.de/

span, making them suitable for mountainous regions. Thermistors provide good sensitivity and accuracy, although they have a limited temperature range. Infrared thermometers offer non-contact temperature measurements, making them useful in inaccessible or hazardous mountain locations. Data loggers integrated with temperature sensors provide convenient solutions for continuous monitoring. Considering factors such as accuracy, temperature range, and ruggedness, along with sensor placement at different elevations, ensures comprehensive temperature measurements in high mountain environments.

- Discharge: Traditional area-volume, rated structure, current meters, acoustic Doppler current profilers, tracer methods, stage-discharge rating curves, and remote sensing techniques are available to measure discharge. These methods involve the use of instruments, data analysis, and modelling techniques to estimate streamflow. Combining multiple approaches, ongoing monitoring, technological advancements, and interdisciplinary collaborations are vital for improving the precision and reliability of discharge measurements in high mountain regions.
- Other sensors, such as water level, snow depth, soil moisture, evapotranspiration, and water quality sensors, would help improve our understanding of mountain hydrology, assess water resources, and mitigate natural hazards in these critical regions.

4.5 Model parameter sensitivity analysis

In glacio-hydrological modelling, it is important to conduct a sensitivity analysis of model parameters to determine the possible values to be assigned to the parameters and the qualitative and/or quantitative variations (McCuen, 1973). Model parameter sensitivity analysis is a critical step in glacio-hydrological modelling that involves evaluating how changes in model parameters influence model outputs and performance.

GHMs typically have a large number of parameters (more than 100) that represent various physical and process-related characteristics of the hydrological system, such as precipitation, evapotranspiration, glaciers, snow, infiltration, runoff, and storage parameters (Table 1). These parameters need to be fine-tuned based on the climate and catchment characteristics (Khanal et al., 2021; Lutz et al., 2014c; Wijngaard et al., 2017). Such a task is practically impossible and highly resource-intensive.

Sensitivity analysis quantifies the effects of parameter variations on model outputs, such as streamflow, groundwater levels, and water balance components. This helps us understand how changes in parameter values affect model performance and whether the model is sensitive or robust to parameter changes. Sensitivity analysis reveals which parameters have a significant impact on the model results and which parameters have negligible effects, allowing for the prioritization of parameter estimation efforts and model calibration. Therefore, sensitivity analysis helps identify which parameters are most influential in determining model behavior and outputs.

Sensitivity analysis is typically done through techniques such as one-at-a-time sensitivity analysis, where individual parameters are varied while others are held constant, or global sensitivity analysis methods that evaluate the combined influence of multiple parameters (Khanal et al., 2021; Song et al., 2015; Wijngaard et al., 2017). The most sensitive parameters, along with the calibrated values and plausible range, identified for the Bhagirathi case study are presented in
Table 2. Overall, parameter sensitivity analysis enhances the understanding and applicability of hydrological models, making them more reliable tools for water resource management, planning, and decision-making.?

Table 1 Overview of the SPHY model parameters. The last column indicates whether the parameter is observable or can be determined by calibration ('free').

Acronym	Description	Units	Parameter determination
Kc	Crop coefficient	–	Free
Kc_{max}	Maximum crop coefficient	–	Free
Kc_{min}	Minimum crop coefficient	–	Free
$NDVI_{max}$	Maximum NDVI	–	Observable
$NDVI_{min}$	Minimum NDVI	–	Observable
$FPAR_{max}$	Maximum fraction of absorbed photosynthetically active radiation	–	Free
$FPAR_{min}$	Minimum fraction of absorbed photosynthetically active radiation	–	Free
T_{crit}	Temperature threshold for precipitation to fall as snow	°C	Free
DDF_s	Degree-day factor for snow	mm °C^{-1} day^{-1}	Free
SSC	Water storage capacity of snowpack	mm mm^{-1}	Free
GlacF	Glacier fraction of grid cell	–	Observable
DDF_{CI}	Degree-day factor for debris-free glaciers	mm °C^{-1} day^{-1}	Free
DDF_{DC}	Degree-day factor for debris-covered glaciers	mm °C^{-1} day^{-1}	Free
F_{CI}	Fraction of GlacF that is debris free	–	Observable
F_{DC}	Fraction of GlacF that is covered with debris	–	Observable
GlacROF	Fraction of glacier melt that becomes glacier runoff	–	Free
$SW_{1,sat}$	Saturated soil water content of first soil layer	mm	Observable
$SW_{1,fc}$	Field capacity of first soil layer	mm	Observable
$SW_{1,pF3}$	Wilting point of first soil layer	mm	Observable
$SW_{1,pF4.2}$	Permanent wilting point of first soil layer	mm	Observable
$K_{sat,1}$	Saturated hydraulic conductivity of first soil layer	mm day^{-1}	Observable
$SW_{2,sat}$	Saturated soil water content of second soil layer	mm	Observable
$SW_{2,fc}$	Field capacity of second soil layer	mm	Observable
$K_{sat,2}$	Saturated hydraulic conductivity of second soil layer	mm day^{-1}	Observable
$SW_{3,sat}$	Saturated soil water content of groundwater layer	mm	Observable
slp	Slope of grid cell	m m^{-1}	Observable
δ_{gw}	Groundwater recharge delay time	day	Free
α_{gw}	Baseflow recession coefficient	day^{-1}	Free
BF_{tresh}	Threshold for baseflow to occur	mm	Free
kx	Flow recession coefficient	–	Free

Table 2 Calibrated SPHY model parameters for the Bhagirathi case study along with description units and plausible range

Parameters	Description	Units	Range	Calibrated value
DDFS	Degree day factor for snow	mm °C-1 day-1	2 – 11	6.1
DDFDG	Degree day factor for debris cover glacier	mm °C-1 day-1	2 – 11	4.8
DDFG	Degree day factor for Snow for glacier	mm °C-1 day-1	2 – 11	7.7
Tcrit	Critical temperature	°C-1	-1 – 3	0.7
SnowSC	Water storage capacity of snowpack	- -	0 – 1	0.5
Kx	Routing recession coefficient	- -	0 – 1	0.9
RootDepthFlat	Thickness of root zone	Mm	50 – 1500	300
SubDepthFlat	Thickness of subsoil	Mm	50 – 1500	150
alphaGw	Baseflow recession coefficient	- -	0 – 1	0.5
YieldGw	Specific aquifer yield	- -	0.01 – 0.5	0.05

4.6 Model calibration approach

GHM calibration can suffer from 'equifinality'. Equifinality is a phenomenon in which different parameter combinations can lead to the same simulated discharge pattern. For example, a shortage in snowmelt can be compensated for by excess glacier melt, and underestimating precipitation input can be compensated for by melting extra water from the glacier; however, this results in incorrect melt estimates and estimations of glacier geometry changes.

To avoid such internal error compensation effects and to better constrain the parameter, a multi-data or multi-signal calibration is highly recommended by several other studies (He et al., 2018; van Tiel et al., 2020). To overcome equifinality problems, we suggest using a three-step modelling strategy to calibrate the snow, glaciers, and rainfall-runoff processes in the model (Immerzeel, 2010; Khanal et al., 2021; Lutz et al., 2014c; Pellicciotti et al., 2012).

4.6.1 Snow

The first step is to parameterize the snow and snowmelt-related processes. Parameters related to snow storage and melt (degree-day factor snow, water storage capacity of snowpack, minimum slope for gravitational snow transport, minimum snow holding depth, and sublimation factor) can be calibrated independently by comparing observed snow flow with modelled snow flow from GHM. In most cases, observed snow runoff is difficult to obtain. Therefore, alternative methods, such as snow cover comparison, as mentioned in Section 0, could be used to calibrate the snow module of a GHM.

Remotely sensed (or observed) data can be used to calculate indicators such as snow cover area, snow seasonality, and snow persistence (i.e., the percentage of the time a pixel is covered with snow). These indicators can be simulated with a GHM and thus help to fine-tune the snow parameters[1]. Depending on the need and data availability, other snow parameters, such as critical temperature, snow water equivalent, snow cover threshold, and snow depth, can also be parameterized.

4.6.2 Glaciers

The second step is to parameterize glacier-related processes without altering snowmelt-related processes. Parameters related to glacier processes are calibrated to observe (or geodetic) glacier mass balance data. To calibrate the SPHY model, the geodetic mass balance data mentioned in Section 0 could be used. Users can simulate the glacier mass balance in SPHY and compare it with the observed mass balance. The parameters related to glacier mass balance in the SPHY model are the degree-day factor for clean ice, degree-day factor for debris-covered glaciers, glacier fraction, lapse rate for glaciers, and temperature and precipitation, which can be fine-tuned.

4.6.3 Rainfall-runoff and groundwater

The last step is to calibrate the rainfall-runoff-related processes without altering the snow and glacier melt-related parameters. After calibrating the model parameters related to snow and glacier melt, the remaining parameters related to soil, infiltration, groundwater, and routing (root depth, capillary rise, seepage, infiltration excess, groundwater depth, saturated water content, baseflow recession constant, and routing coefficient) can be calibrated to the observed discharge at the existing station.

4.7 Typical outputs of the SPHY and their application

SPHY includes a large number of processes from which outputs can be generated. SPHY allows the user to output the variable as (a) time-series data at specified locations and (b) spatial maps for the model domain. The spatial maps outputs can be aggregated for the user-specified time. In a separate CSV file, that is, “reporting.csv”, the user can decide how the output should be generated for over 50 model variables (Figure 2). The CSV file has six columns. The first column refers to the variable name in the model, which should not change. In the second column, the user can decide the frequency at which the map output should be generated, with Y (yearly), M (monthly), and D (daily) aggregations. The option MS (Monthly Sum) results in 12 output maps with a long-term monthly average sum. In the third column, the average per year (Y) and month (M) can be determined, which is most suitable for storage

[1] Khanal, S., Nick, F., Fiddes, J., Kraaijenbrink, P., Immerzeel, W., Hunink, J. 2022. Present-day and future changes in the hydrology of the Bhagirathi Basin. FutureWater Report 252

components such as soil water storage and groundwater storage. The option MA (Monthly Average) results in 12 output maps with the long-term monthly average. In the second and third columns, more than one output frequency can be selected, which should be separated with a “+” symbol. For example, when the user wants to obtain the yearly and average monthly outputs the following combination should be provided: “Y+MA”. In the fourth column, time series can be generated at the stations, for instance, for discharge and sediment yield. In the fifth column, the user can define the file name (prefix), with a maximum of six characters. The sixth column provides information on each model variable. Furthermore, SPHY is sufficiently flexible to output any intermediate flux or variable used in the model.

The aggregated time series and spatial map outputs from SPHY help understand hydrological cycle processes such as evapotranspiration, infiltration, snow or glacier melt, runoff and groundwater flow, flood and drought risk assessment, environmental impact assessment, water availability, and water management through water allocation planning. These outputs can provide valuable information to support IWRM planning, which is a framework for the coordinated and sustainable development and management of water resources. For instance, the time-series outputs of snow, glaciers, rainfall-runoff, and baseflow can be used to understand the flow contribution of each component to the overall flow (Figure 3). Such analysis would provide the basin aggregated flow contribution analysis which helps water managers to plan water resources in the basin. Moreover, SPHY outputs in the form of spatial maps can be used to understand the spatial variation of the fluxes across the basin (Figure 4). Spatial maps would help water managers assess the sources and contributions of water, its availability, and variability (floods and droughts) across different units/subunits of the catchment.

These outputs would also help in understanding the trends of different components of flow across the subunits of the basin. These outputs, together with water quality, land use, socioeconomic, institutional, and infrastructure data, can be further used to simulate various water allocation scenarios, considering different priorities for water use. This information is essential for developing plans that balance the competing demands for water resources of various stakeholders. Therefore, the outputs of SPHY can provide valuable information for formulating an IWRM plan by assessing water availability, identifying flood and drought risks, evaluating environmental impacts, and developing water allocation plans that balance competing demands.

Name	Map	Avg	Timeseries	Filename	Description
wbal	NONE	NONE	NONE	wbal	WATER BALANCE (Can only select daily output)
# ONLY FOR LAKE AND/OR RESERVOIR MODULE					
TotStor	NONE	NONE	NONE	TotS	REPORT TOTAL STORAGE (only D or F options are logical)
RainStor	NONE	NONE	NONE	RainS	REPORT STORAGE FROM RAINFALL (only D or F options are logical)
SnowStor	NONE	NONE	NONE	SnowS	REPORT STORAGE FROM SNOW RUNOFF (only D or F options are logical)
GlacStor	NONE	NONE	NONE	GlacS	REPORT STORAGE FROM GLACIER RUNOFF (only D or F options are logical)
BaseStor	NONE	NONE	NONE	BaseS	REPORT STORAGE FROM BASEFLOW RUNOFF (only D or F options are logical)
# FLUXES IN MM					
TotPrec	Y	NONE	NONE	Prec	PREC
TotPrecF	NONE	NONE	NONE	PrecF	PREC; CORRECTED FOR FRACTION
TotPrecEF	Y	NONE	NONE	PrecEF	EFFECTIVE PRECIPITATION; CORRECTED FOR FRACTION
LAI	NONE	NONE	NONE	LAI	LEAF AREA INDEX
TotIntF	Y	NONE	NONE	IntF	INTERCEPTION; CORRECTED FOR FRACTION
TotRain	NONE	NONE	NONE	Rain	RAIN
TotRainF	NONE	NONE	NONE	RainF	RAIN; CORRECTED FOR FRACTION
TotETref	NONE	NONE	NONE	ETr	ETREF
TotETrefF	NONE	NONE	NONE	ETrF	ETREF; CORRECTED FOR FRACTION
TotETpot	Y	NONE	NONE	ETp	ETPOT
TotETpotF	NONE	NONE	NONE	ETpF	ETPOT; CORRECTED FOR FRACTION
TotETact	Y	NONE	NONE	ETa	ETACT
TotETactF	NONE	NONE	NONE	ETaF	ETACT; CORRECTED FOR FRACTION
PlantStress	NONE	MA	NONE	Pws	PLANT WATER STRESS

Figure 2 A snippet of the reporting.csv file, which allows the user to output the desired variables from SPHY

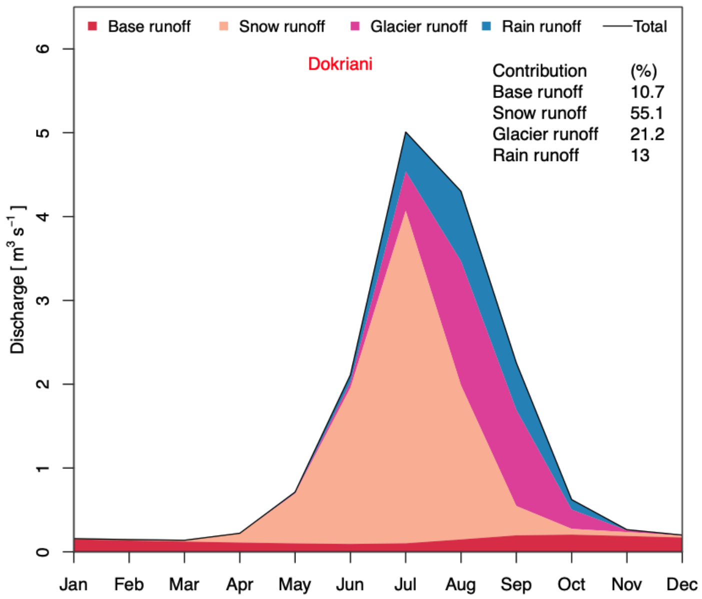

Figure 3 Baseline-averaged monthly runoff with the distinction of flow components (base, snow, glacier, and rain-runoff) at the Dokriani outlet for 1991-2020. The top right part of the figure shows the contribution of stream flow contributors to the total flow (expressed in %) (Khanal et al., 2022)

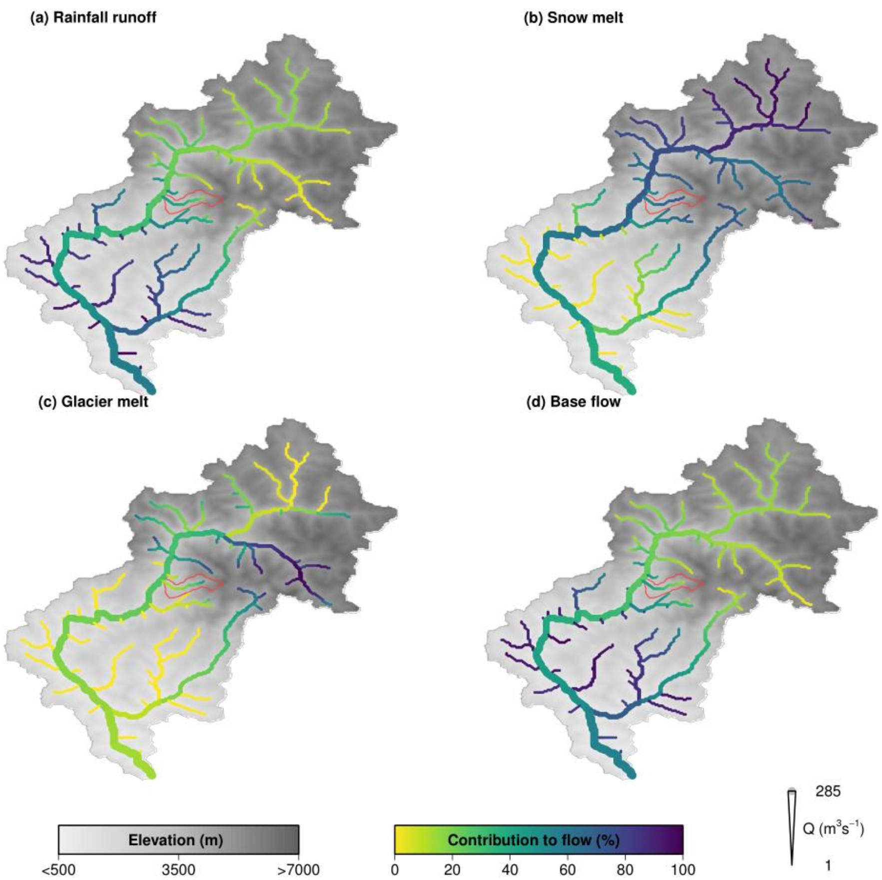

Figure 4 Spatial patterns of the flow components (base, snow, glacier, and rain-runoff) at the outlet of the Bhagirathi Basin (just before the confluence of the Alaknanda River) for 1991-2020. The gray and red boundaries represent the Bhagirathi and Din Gad catchments, respectively (Khanal et al., 2022).

4.8 Scaling up and transferring a model to another HMA river basin

Scaling up GHMs refers to the process of extending or adapting existing GHMs to larger spatial and temporal scales. Scaling up GHMs is necessary to address various challenges, such as studying regional or global water resource management, understanding the impacts of climate change on hydrological processes, and supporting decision-making for water-related infrastructure projects. Scaling up hydrological models can be challenging because of the complexities and uncertainties associated with hydrological processes at larger scales, the availability and quality of data, and the computational requirements of larger models. SPHY was developed with the explicit aim of simulating terrestrial hydrology at flexible scales under various land use and climate conditions. Because the input data required to set up the SPHY model are mostly available for the entire HMA region (as described in Sections 0 and 0), the SPHY model can be easily scaled up or applied to different regions of HMA.

Basins adjacent to each other with similar climatic and physiographic characteristics tend to hydrologically behave in a similar manner (Merz and Blöschl, 2004; Patil and Stieglitz, 2014). Thus, the calibrated parameters (Table 2) can be transferred to hydrologically similar basins in HMA. A parameter regionalization approach, in which the replica of the parameters from the gauged catchment can be transferred to the ungauged catchment, can be used for basins in the HMA region (e.g. Bárdossy, 2007). This approach has been widely used for regional SPHY studies in which discharge data are unavailable (Khanal et al., 2021; Lutz et al., 2014c; Wijngaard et al., 2017).

However, proper validation and verification of scaled-up and regionalized models are essential to ensure their reliability and accuracy. Even if no discharge data are available, some validation can be performed using remote sensing-based snow cover data in ungauged catchments. The regionalized parameters can then be re-adjusted based on the discrepancy between the simulated and observed snow cover, as explained in Section 0.

Satellite-based observations of surface water elevation and extent are a promising new source of discharge data that can be useful for calibrating and validating larger-scale models. One of its new groundbreaking applications is the remote estimation of river discharge, especially in ungauged or poorly gauged basins. The SWOT (Surface Water and Ocean Topography) mission is a satellite mission led by NASA and CNES (French Space Agency), which currently provides the most state-of-the-art datasets for this purpose. Currently, testing is taking place in several regions of the world by FutureWater, within the Europe-funded SOS-Water project[1]. It is expected that in the near future, the availability of this type of data in terms of spatial and temporal coverage will expand, and that it has great potential to improve glacio-hydrological modelling in the HMA region.

[1] https://sos-water.eu/

4.9 The Bhagirathi river basin case study

A glacio-hydrological model was developed to inform an Integrated Water Resources Management (IWRM) plan for the Bhagirathi sub-basin in Uttarakhand, India. The project was led by FutureWater in collaboration with Utrecht University, TERI, the University of Geneva, and the Swiss Agency for Development and Cooperation (SDC), as part of the 3SCA Phase II program under SCA-Himalayas. The initiative ran from 2020 to 2023 and aimed to enhance water resource management in a glacier-fed Himalayan basin under current and future climate scenarios.

The main objectives were to model the present and future hydrological dynamics of the Dokriani glacier catchment and the broader Bhagirathi sub-basin, to support IWRM decision-making with a dedicated Decision Support System (DSS), and to strengthen local technical capacity through training and knowledge exchange. The modeling approach was structured in multiple scales. At the headwater level, the Dokriani glacier catchment was simulated using a high-resolution SPHY (Spatial Processes in HYdrology) model. This allowed for detailed process-based simulation of snow and glacier melt. At the sub-basin scale, a second SPHY model was used to integrate upstream dynamics with broader basin hydrology. In addition, the WEAP–PODIUMSim framework was used to simulate water allocation and demand scenarios for downstream users under changing climatic and socioeconomic conditions.

The models were forced using downscaled and bias-corrected data from four CMIP6 global climate models, under two emission scenarios: SSP2-4.5 and SSP3-7.0. Simulations were run for both mid-century and end-century periods, using a baseline period of 1991–2020 for calibration and validation. This setup enabled the team to assess not only long-term water availability, but also seasonal variations and the risk of extreme events such as flood waves.

Stakeholder engagement was central to the project's success. Consultations held in Dehradun in November 2022 brought together government agencies, researchers, and local stakeholders to co-design adaptation strategies. These strategies were integrated into the IWRM plan, which addresses both short- and long-term needs in terms of water security, disaster risk reduction, and ecosystem protection. Capacity building was achieved through a combination of virtual and in-person training sessions for Central Water Commission staff, ensuring knowledge transfer and local ownership of the modeling tools.

The project revealed several critical insights. While total water availability is expected to remain relatively stable or even increase slightly under future climate scenarios, significant shifts in the seasonality of flows are anticipated. Reduced snowfall and increased meltwater could lead to more intense and earlier peak flows, thereby heightening the risk of downstream flooding. Infrastructure such as hydropower facilities, irrigation canals, and roads may be particularly vulnerable. The IWRM plan therefore includes policy recommendations such as improved early warning systems, ecotourism controls, bans on non-biodegradable waste, and promotion of electric transport in sensitive zones.

Several lessons can be drawn from this experience. First, the use of nested SPHY models allowed for a comprehensive understanding of both localized glacial processes and basin-wide water dynamics. Second, integrating climate projections from multiple models provided robust scenario planning. Third, involving stakeholders from the outset ensured that the modeling outcomes were aligned with local priorities and institutional capacities. Finally, building capacity through targeted training has laid the groundwork for replicating this approach in other Himalayan sub-basins.

The Uttarakhand case provides a strong example of how physically realistic, stakeholder-informed glacio-hydrological modeling can directly inform water policy and climate adaptation strategies. The workflow established in this project—including multi-scale modeling, climate scenario integration, stakeholder engagement, and DSS application—offers a transferable model for data-scarce mountain regions confronting similar climate and water management challenges.

For more information, please refer to the report on “Present-day and future changes in the hydrology of the Bhagirathi Basin” by Khanal et al. (2022 and “Water Allocation Modeling for the Bhagirathi Basin”, by Droogers et al., (2022).

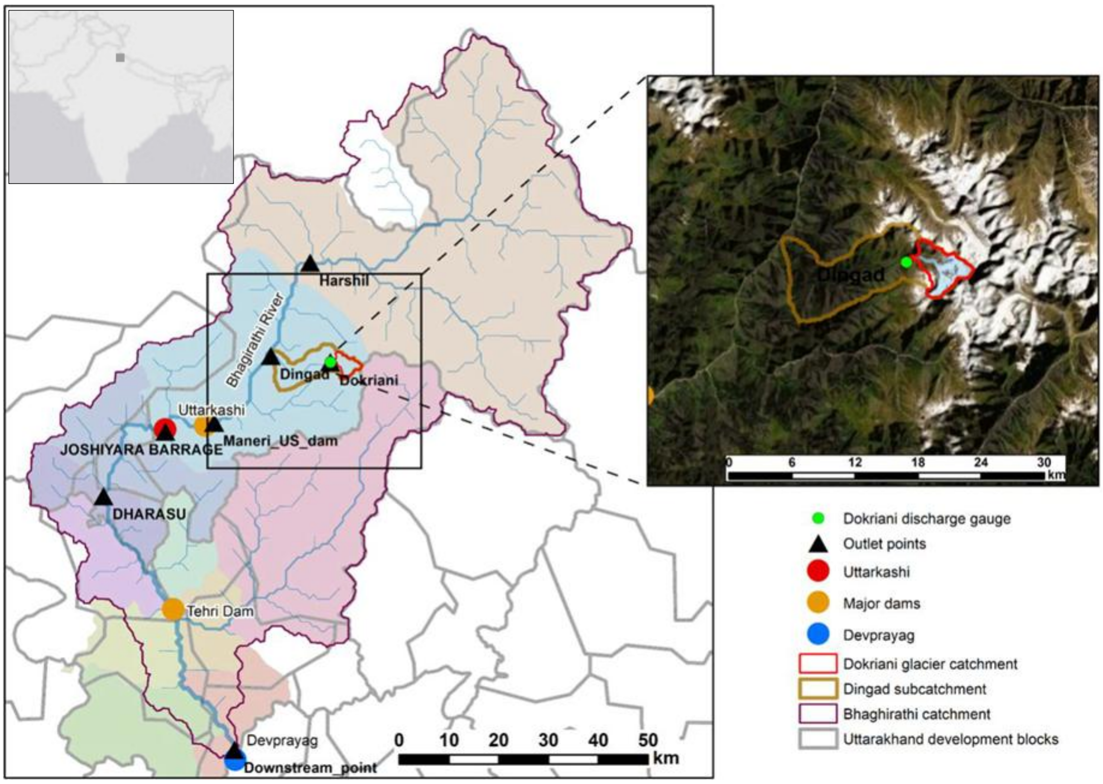

Figure 5 The Bhagirathi river basin and the Dingad sub-catchment (FutureWater, 2024).

5 Climate change impact assessment

Mountains are highly significant regions in the context of climate change and sustainable development. Over the past few decades, the HMA region has experienced many climatic changes. Past climate change has led to changes in the cryosphere and hydrological cycle. These changes include rapid glacier shrinkage, reduction in snow cover, permafrost degradation, changes in the area of seasonally frozen grounds, and increases in the frequency of snow and ice avalanches (Ballesteros-Cánovas et al., 2018; Bolch et al., 2012; Kang et al., 2010). Changes in climate and cryosphere lead to shifts in the timing and magnitude of river discharge (Immerzeel, 2010; Khanal et al., 2021; Lutz et al., 2014b; Maurer et al., 2019). Furthermore, climate change has led to increases in the area and volume of glacial lakes further exacerbating the risk of glacial lake outburst floods (King et al., 2019). The impacts of climate change on the cryosphere and water resources in mountains are typically assessed using GHM.

Climate change assessments serve as important syntheses of the science associated with biophysical characteristics, ecosystems, and socio-economic conditions, and provide useful information and context for management and policy decisions. Climate change assessments usually focus on understanding the what, why, where, and how of climate change, its consequences, and the options for responding to it. Climate change assessment usually depends on the location, context, objectives, and type of information needed.

5.1 Assessing climate change impact

This manual focuses on the impact of climate change on the cryosphere and water resources in the mountainous regions of HMA. Usually, climate change impact studies identify and quantify the expected impacts of climate change for decades to centuries on different sectors, such as water, agriculture, energy, and transportation. The impact assessment begins by understanding the changes in the magnitude, frequency, and patterns of hydro-meteorological variables, such as temperature, rainfall, snow, and streamflow, for the historical period. The observed station data, gridded data, and remotely sensed satellite-based information provided in Section 0 can be used to derive changes in the historical hydroclimate of a region or sector.

For the future, climate information is obtained from ‘climate projections’. Climate projections are simulations of the Earth’s climate in future decades (typically until 2100) based on assumed ‘scenarios’ for the concentrations of greenhouse gases, aerosols, and other atmospheric constituents that affect the planet’s radiative balance. Climate projections are obtained by running numerical models of the Earth’s climate. These numerical models are used to simulate the fundamental processes driving weather and climate, which may cover either the entire globe or a specific region, such as Asia. These models are referred to as Global Climate Models (GCMs), also known as General Circulation Models. A GCM combines a series of models of the Earth’s atmosphere, ocean, and land surface. GCMs divide the Earth into many layers and thousands of three-dimensional gridded spaces (100–400 km spatial resolution and ~30–50 vertical layers between the surface and the top of the atmosphere). A Regional Climate Model (RCM) is similar to a GCM, but it is run at a higher resolution over a smaller domain (e.g., Asia) to generate higher-resolution data. RCM are used to downscale GCM information to regional or local scales, and they require boundary information from a GCM. These models are skilled at replicating past and current climates.

Many research institutions worldwide develop and maintain GCM/RCM. Currently, there are more than 100 climate models available. To streamline activities between different institutions worldwide, a collaborative framework was designed to improve knowledge of climate change by the World Climate Research Programme (WCRP) in 1995. This framework is known as the Coupled Model Intercomparison Project (CMIP). The CMIP was developed in phases to foster climate model improvements and support national and international assessments of climate change. The objective of CMIP is to better understand past, present, and future climate changes arising from natural, unforced variability or in response to changes in radiative forcing in a multi-model context. The number of climate models in CMIP has increased over time: CMIP1-2 (1996, 18 GCMs), CMIP3 (2005-2006, 20 GCMs), CMIP5 (2010-2014, 34 GCMs), and CMIP6 (2016-present, >100 GCMs). CMIP6 is the most recent CMIP and includes over 100 models from more than 50 modelling centers worldwide.

The Intergovernmental Panel on Climate Change (IPCC) reviews and assesses the latest scientific, technical, and socio-economic climate change information. These modelling groups around the world coordinate their updates with the IPCC assessment reports. The 2013 IPCC fifth assessment report (AR5) featured climate models from CMIP5, while the 2021 IPCC sixth assessment report (AR6) features the new state-of-the-art CMIP6 models. CMIP6 uses Shared Socio-economic Pathways (SSPs) scenarios, which are the most complex created to date and span a range from very ambitious mitigation to ongoing growth in emissions. The SSPs use narratives about future societal development (the SSPs) in conjunction with Representative Concentration Pathways (RPCs), which describe trajectories of change in atmospheric GHG and aerosol concentrations (and corresponding changes in radiative forcing) over time. SSPs provide storylines regarding global societal developments and narratives about how the world might develop over the coming century in the presence and absence of climate change mitigation and adaptation policies. The most ambitious mitigation scenario suggested by the Paris Agreement, that is, holding the increase in global temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit the increase to 1.5°C, are included in the SSPs. Five SSPs were created, with varying assumptions about human developments, including population, education, urbanization, gross domestic product (GDP), economic growth, rate of technological developments, greenhouse gas (GHG) and aerosol emissions, energy supply and demand, and land-use changes. The following SSPs were defined:

- SSP1 - Sustainability - Taking the green road (low challenges to mitigation and adaptation)
- SSP2 - Middle of the road - (medium challenges to mitigation and adaptation)
- SSP3 - Regional rivalry - A rocky road (high challenges to mitigation and adaptation)
- SSP4 - Inequality - A road divided (low challenges to mitigation, high challenges to adaptation)
- SSP5 - Fossil-fueled development - Taking the highway (high challenges to mitigation, low challenges to adaptation)

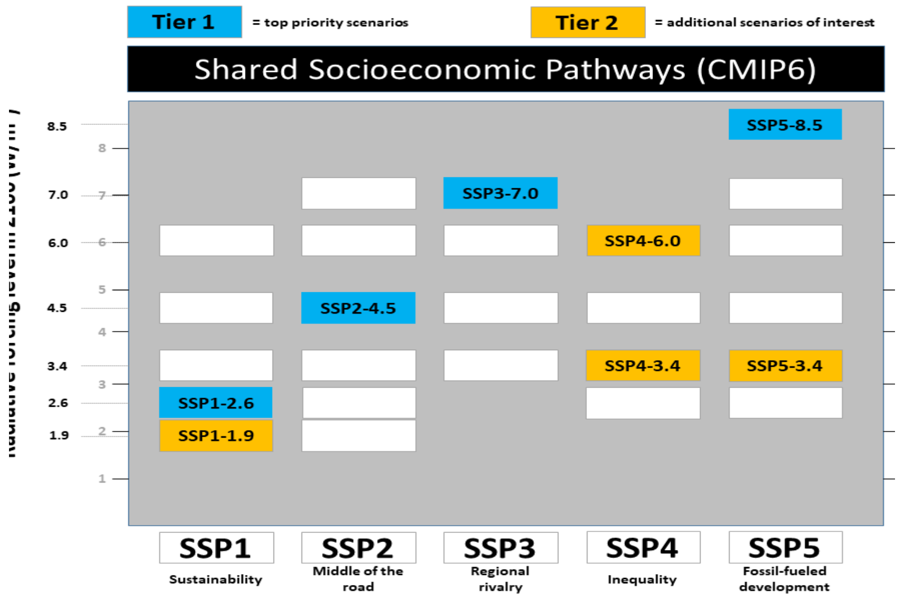

Figure 6 Shared Socio-economic Pathways and year 2100 radiative forcing combinations

The different levels of radiative forcing (a measure of the extent to which GHGs in the atmosphere warm or cool the climate, measured in watts per meter squared (Wm^{-2})) by the year 2100 range from 1.9 to 8.5 Wm-2, with higher values representing stronger climate warming effects, and are used in conjunction with SSPs (Figure 6).

5.2 Download climate change projections

Downloading and working with CMIP6 GCM data can be complex and require specialized programming software and expertise. These data are usually available in the Network Common Data Form (netCDF) and Hierarchical Data Format (HDF) formats. There are different ways to access the raw GCM variables, which can be downloaded from the following:

- National Centers for Environmental Information (NCEI): The NCEI is the world's largest repository of climate and weather data. The CMIP6 GCM data can be downloaded from the NCEI website.
- The Program for Climate Model Diagnosis and Intercomparison (PCMDI) is a research organization that works to improve our understanding of climate variability and change. The CMIP6 GCM data can be downloaded from the PCMDI website (https://pcmdi.llnl.gov/CMIP6/).
- DKRZ: The DKRZ acts as a "laboratory" for all German climate researchers working with climate models. DKRZ's hardware and services of DKRZ are specifically tailored for complex simulations using numerical models of the climate system. You can download CMIP6 GCM data from the DKRZ website[1].
- Climate Data Store (CDS): The CDS is a service provided by the European Center for Medium-Range Weather Forecasts (ECMWF) that provides access to a wide range of climate data sets. You can download CMIP6 GCM data from the Copernicus Climate Data Store[2]

Of the above, Copernicus' Climate Data Store (CDS) is the preferred platform, as it contains the most comprehensive and harmonized set of climate data. The data can also be accessed freely through an API, and there are numerous existing scripts and guiding materials to get started.

5.3 Selection of GCMs

The selection of GCMs is important because not all models perform equally well in representing the climatology of HMA. Additionally, it is a cumbersome and resource-intensive task to process all GCM (>100 models). Therefore, a selection of representative GCMs should be made for use in hydrological models. The selection of climate models is not straightforward and can be performed using different strategies. An approach explained by Lutz et al. (2016) is to select climate models by combining the envelope and past-performance approaches, which have been widely adopted in different studies in HMA. The goal is to select an ensemble consisting of a manageable number of climate model runs, which still represents all possible futures in terms of future mean air temperature and annual precipitation sums, and only includes models with acceptable performance in simulating the historical climate. The following steps are recommended for sub-selection of models:

1. *Determine the research question or application*: The first step in selecting a climate model is to define the research question or application. For example, how will global warming impact a particular region, or how will extreme precipitation and temperature patterns change in the coming years?

2. *Identify the relevant variables and time horizons*: The second step is the identification of climate variables, such as temperature, precipitation, wind patterns, or other variables, for the analysis. The timeframe used for climate change impact assessment can vary depending on the specific

[1] https://esgf-metagrid.cloud.dkrz.de/search/cmip6-dkrz/
[2] https://cds.climate.copernicus.eu/datasets/projections-cmip6?tab=overview

research question or application. For example, some studies may focus on analyzing climate data for a specific year or season, while others may focus on analyzing decadal or centennial trends in climate data. In many cases, climate change impact assessment focuses on a baseline period, which is typically a 20- or 30-year period used as a reference for assessing changes in climate over time. The baseline period is often chosen to represent a period of relatively stable climatic conditions. Climate models simulate future climate conditions by dividing the future into discrete time slices or periods that typically span several decades. These periods are often referred to as "time slices" or "time horizons," and are used to assess how climate conditions may change over time. The most commonly used time slices for future climate change projections are 20-year or 30-year periods, such as 2036–2065 (mid-century) or 2071–2100 (end-of-the-century). These time slices are often used to provide projections of climate conditions that can be compared to historical data and used to assess the magnitude of climate change that is likely to occur over different periods of time.

3. *Changes in climatic means* were calculated based on the range of projections of changes in the mean state of the variable. For instance, changes in air temperature (ΔT) and annual precipitation sum (ΔP) between historical (1985–2014) and future time horizons (mid-century and end-of-the-century). For the model runs included in the SSP-RCP combination, low (5th or 10th) and high (95th or 90th) percentiles of ΔT and ΔP were determined (to exclude outliers). These values represent the four corners of the spectrum of projections for temperature and precipitation changes. For instance, the 10th percentile value for ΔT and the 10th percentile value for ΔP are in the 'cold, dry' corner of the spectrum. The 10th percentile value for ΔT and the 90th percentile values for ΔP are in the 'cold, wet' corner of the spectrum. The 90th percentile value for ΔT and the 10th percentile value for ΔP are in the 'warm, dry' corner of the spectrum. The 90th percentile value for ΔT and the 90th percentile value for ΔP are in the 'warm, wet' corner of the spectrum. The proximity of the model runs to these low/high quantiles is then calculated. Few models (5–10) close to each of these corner are selected for each SSP-RCP scenario.

4. *Refining the selection by evaluating the performance of the selected models*: The next step is to evaluate the performance of each model in simulating the relevant climate variables. In this step, the model runs are evaluated for their projected changes in climatic extremes with the help of extreme climate change indicators[1]. A score (from 1 to the number of initially selected models), based on the ranking (or largest change), is assigned to each climate model. Based on the final score, a few models (2-3) with the highest scores are selected.

5. *Final selection based on past performance*: The ability or criteria, or skill of the models in reproducing historical climate conditions, is assessed in this step. The skill assessment is done for the historical period from GCM and observations. These criteria might include choosing models that perform well in simulating a particular variable, models that have shown consistency across different scenarios, and models that have been widely used in previous studies. There are several skill functions available for different variables in the literature (see Lutz et al., 2016, for details).

Overall, the sub-selection of climate models requires careful consideration of the research question, relevant variables, and model performance. It is important to note that no single model can fully capture the complexity of the Earth's climate system, and the use of multiple models can help account for uncertainty and variability in the results.

[1] http://etccdi.pacificclimate.org/list_27_indices.shtml

For the Bhagirathi case study, two scenarios, namely the " middle of the road" (SSP2-RCP4.5) and a more extreme one (SSP3-RCP7.0), were used to select four GCMs representing each of the four corners of the envelope (cold, wet/cold, dry/warm, wet/warm, and dry). For this study, only GCM runs with daily mean air temperature, daily maximum air temperature, daily minimum air temperature, and daily precipitation were selected.

5.4 Bias-correction

Bias correction in climate refers to the process of adjusting climate model outputs or observational data to remove systematic errors or biases. These biases can arise from various factors, such as errors in the underlying physics of the model, inadequate spatial or temporal resolution, or incomplete or inaccurate data input. In climate modelling, bias correction techniques are commonly used to improve the accuracy of model simulations by matching the model output with observed data. This can help reduce uncertainties in future climate projections and improve our understanding of how the climate system is likely to change under different scenarios.

Bias correction can be applied to a wide range of climate variables, including temperature, precipitation, and atmospheric circulation. Various methods for bias correction exist, including statistical methods such as quantile mapping and distribution-based scaling, as well as more complex techniques that involve the use of machine learning or data assimilation approaches. The choice of method and quality of the input data can significantly affect the effectiveness of the correction. Therefore, careful evaluation and validation of the results are essential to ensure that the corrected data are appropriate for the intended use. For more information regarding bias correction, readers are referred to the detailed climate change report of the Bhagirathi case study.

5.5 Downscaling

Downscaling is a technique used in climate science to provide more detailed and localized information on climate variables, such as temperature and precipitation, than that typically provided by global climate models. Global climate models (GCMs) simulate the behavior of the Earth's climate system at a coarse resolution, typically spanning hundreds of kilometers. However, for many applications, such as water resource management and agriculture, more localized and detailed information is required.

Downscaling is the process of taking the coarse-resolution output from a global climate model and using statistical or dynamical methods to generate higher-resolution climate data that are more relevant to specific regions or locations. In some countries or regions, Regional Climate Models (RCMs) have been developed, and downscaled products are available; however, these datasets are often not open access or can be difficult to obtain and validate. Consequently, the choice of downscaling approach and data sources depends strongly on the geographical focus and data availability in the study area. Downscaling can be performed in two ways:

- *Statistical downscaling*: Statistical downscaling uses statistical relationships between large-scale climate variables (such as atmospheric pressure patterns) and local-scale climate variables (such as precipitation or temperature) to produce more detailed information. This method is typically applied when there is a strong relationship between large- and local-scale climate variables.
- *Dynamical downscaling*: Dynamical downscaling uses regional climate models (RCMs) to simulate the behavior of the Earth's climate system at a finer resolution, typically between 10 and 50 km. RCMs are driven by the boundary conditions provided by GCMs and can provide more detailed information on climate variables over specific regions or locations.

Downscaled climate data can be used to assess the impact of climate change on specific regions or sectors, such as agriculture or water resources. It can also be used to develop adaptation strategies and inform decision-making in sectors that are particularly vulnerable to climate variability and change effects.

For the Bhagirathi case study, a monthly delta change approach was adopted. The following procedure for downscaling using monthly deltas was implemented:

- The GCM data were resampled to the model grid (50m and 500m) using bilinear interpolation.
- Monthly climatological means (temperature) and sums (precipitation) were calculated for both the historical GCM data and the baseline series from 1991 to 2020.
- Monthly climatological differences, that is, deltas, between the historical GCMs and the baseline data were determined using subtraction (temperature) and division (precipitation).
- Future GCM series were downscaled by adding (temperature) or multiplying (precipitation) the resampled daily values with the offsets and using scaling factors determined using the delta values (Section 5.3, step 3) monthly. In other words, all daily values corresponding to a specific calendar month were multiplied by the same bias correction factor. The output of the monthly delta change bias correction includes leap days.

Several recent initiatives and projects have focused on downscaled climate change projections for the HMA region. These projects utilize various climate models and observational data to provide detailed insights into the future climatic conditions of these ecologically and culturally significant regions. However, it is crucial to validate these data before application. These validation efforts include the following:

- High Mountain Asia Daily 5 km Downscaled SPEAR Precipitation and Air Temperature Projections, Version 1: This dataset provides daily precipitation and air temperature projections for HMA from 2015 to 2100. These projections were based on 0.5° resolution model data from the GFDL SPEAR model. It includes two Shared Socioeconomic Pathways (SSP2-4.5 and SSP5-8.5) and historical data from 01-01-1990 to 31-12-2014. The data is in netCDF-4 format, with a 5 km spatial resolution, and the spatial coverage ranges between latitudes 20.025°N to 45.975°N and longitudes 60.025°E to 110.975°E. For more information, you can access the dataset on the National Snow and Ice Data Center's website[1].
- NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP-CMIP6): This dataset comprises global downscaled climate scenarios from CMIP6 GCM runs, supporting the IPCC AR6. It includes downscaled projections for all four Tier 1 greenhouse gas emission scenarios (SSPs). The dataset aims to provide high-resolution, bias-corrected climate change projections for evaluating the impacts of local-scale climate gradients and topographic effects. Data are accessible via AWS and NCCS THREDDS, with a spatial subset feature for custom data retrieval. The dataset, in netCDF4 format, covers a global scale with a daily temporal and 25 km spatial resolution. For more details, visit the NASA NEX-GDDP-CMIP6 page[2].

5.6 Future hydrological impact assessment

After bias correction and downscaling of the GCMs, the selected climate models and emission scenarios are used to generate future climate projections, such as changes in temperature, precipitation, and evapotranspiration. These future forcings are then used in conjunction with the calibrated and validated GHM. Thus, the GHM simulates the effects of climate change on variables such as river flow, groundwater recharge, and soil moisture. Evaluation of the GHM results to assess the potential impacts of climate change on water resources is further required. This process can involve comparing future hydrological variables with historical baseline conditions and assessing the sensitivity of the results to

[1] https://nsidc.org/data/hma2_dspat/versions/1
[2] https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp-cmip6

different model assumptions and uncertainties. It is important to note that assessing future hydrological changes due to climate change involves a high degree of uncertainty because it is not possible to predict future climate conditions with complete accuracy. Therefore, it is important to account for this uncertainty in the assessment and use multiple models and scenarios to generate a range of possible outcomes. The results of the impact assessment are used to inform decision-making and planning for water resources management. This may involve identifying areas that are particularly vulnerable to changes in water availability, exploring different adaptation strategies, and evaluating the costs and benefits of various options.

5.7 Links to water allocation and downstream demand

Hydrological models and water allocation models are interconnected and play a crucial role in effective water management. Hydrological models estimate the amount of water available in an area by simulating the physical processes of the water cycle. Water allocation models use hydrological data to determine the amount of water that can be allocated to different users while considering factors such as water quality, environmental regulations and competing demands. Hydrological models provide input data to water allocation models, which in turn make informed decisions regarding water allocation.

Linkages between these models are essential for providing critical information for sustainable water management, such as infrastructure development, dam construction, reservoirs, and irrigation systems. These models can also inform decision-making processes to ensure the social, economic, and environmental well-being of the community. Effective linkages between hydrological and water allocation models are necessary to ensure sustainable water management, which is vital for community well-being.

These water allocation modelling exercises should be participatory and involve stakeholders from different sectors, including government agencies, local communities and private sector actors. This will ensure that the models reflect the diverse perspectives and needs of stakeholders and are relevant to their decision-making processes.

For water allocation assessments, models that can incorporate natural hydrological processes and scenario analyses to assist decision-makers are necessary. The selection of the most suitable model for this purpose involves evaluating the strengths and weaknesses of different, well-known, and established models. The various models were scored based on the following criteria and functionalities:

- Drought
- Floods
- Allocation
- Crops
- Complexity
- Scalable
- Scenarios

Figure 7 provides an overview of the various models, each scored based on its various functionalities.

	Drought	Floods	Allocation	Crops	Complexity	Scalable	Scenarios
HEC-HMS	2	3	1	1	3	3	3
HEC-RAS	1	5	2	1	4	2	2
SPHY	3	4	2	2	2	4	4
WEAP	5	4	5	5	1	5	5
SWAT	4	3	3	3	2	4	3
SOURCE	4	4	4	2	4	5	4
SWMM	2	5	2	1	2	3	2
SOBEK	1	5	2	2	3	2	2
MIKE BASIN	4	3	4	2	2	4	4
MIKE SHE	3	3	3	3	5	2	1

Figure 7 Qualitative (expert-based) assessment of catchment-scale models that might be used for the project. Scores ranged from 1 (=limited) to 5 (=well suited). Note that the color scale for "Complexity" is reversed to maintain green for "better" and red for "worse."

The Water Evaluation and Planning (WEAP) model[1] is particularly suitable for water allocation and scenario analysis, and its scalability is a significant advantage. With its low level of complexity and user-friendly interface, the WEAP model is suitable for training purposes.

Other strengths of WEAP not covered by these seven functionalities are as follows:

- WEAP is used in over 180 countries and has many active users in India.
- WEAP can be automated and coupled with other models to enhance its capabilities. Coupling with SPHY (also used in the Bhagirathi Basin case study) has been successfully performed in many other projects.
- WEAP has excellent (and free) training modules.
- WEAP is tailored to start in an explorative way and gradually include other components for a more detailed analysis.
- WEAP is the de facto standard for many developing and funding agencies to make investment decisions in the water sector.
- WEAP is freely available.

Glacio-hydrological impacts on water allocation can be studied using a water allocation model, such as WEAP (Figure 8 and Figure 9). Within the SDC-funded project presented earlier in section 4.9, for the Bhagirathi river basin, the WEAP model has been enhanced by the addition of "virtual tracers," which is an innovative approach to monitoring the various sources and reuse of water (Simons et al., 2020). This involves adding user-specific virtual tracers to different sources of water in the model to assess the mixing of return flows from each water user in the sources of water supply to subsequent users. The use of virtual tracers in the WEAP model is an innovative approach for better understanding water allocation and management. For more information on how this approach was implemented for the Bhagirathi river basin, please refer to Droogers et al. (2022).

[1] https://www.weap21.org/

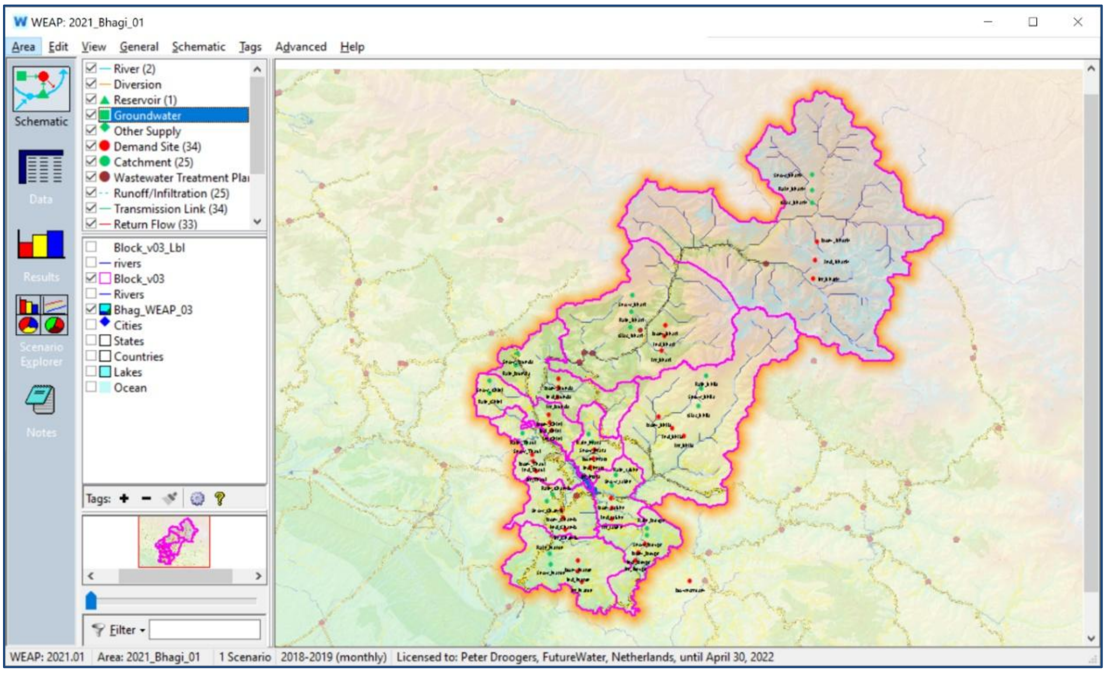

Figure 8 Screenshot of the WEAP model as developed for the Bhagirathi Basin to analyse water allocation scenarios (source: Droogers et al., 2022)

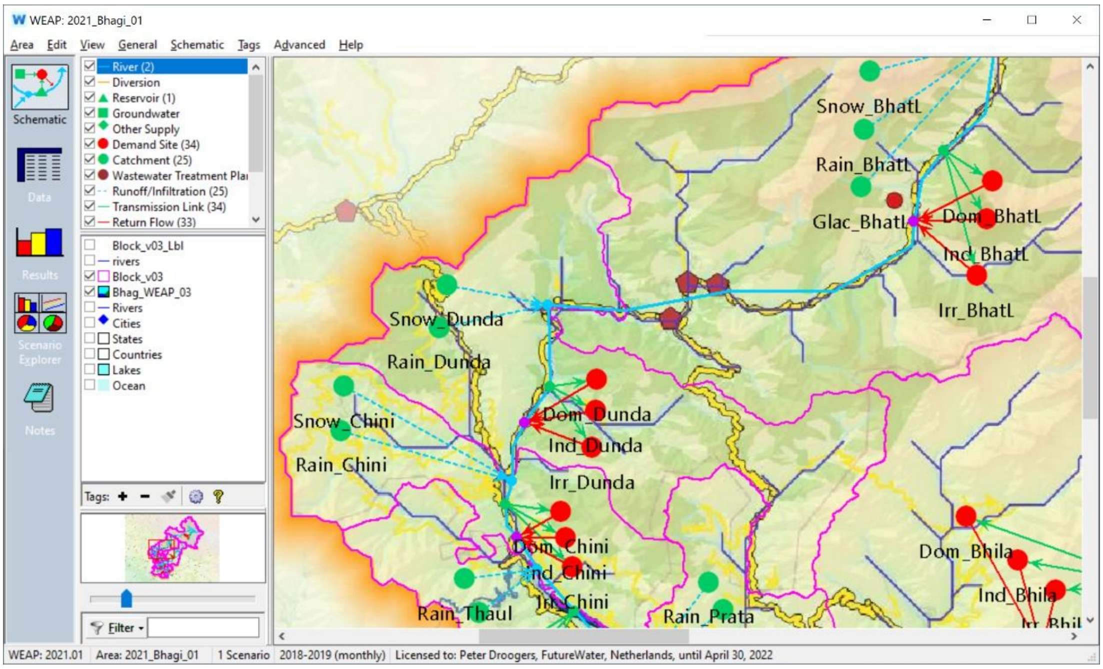

Figure 9 Same as the figure above, zoomed in on the western part of the Bhagirathi Basin.

Some typical examples of analyses that can be performed with the WEAP model in terms of tracing different water sources are presented below (Figure 10). Note that the WEAP model simulations also consider water use and return flows to the river, whereas a model like SPHY does not consider water withdrawals and returns.

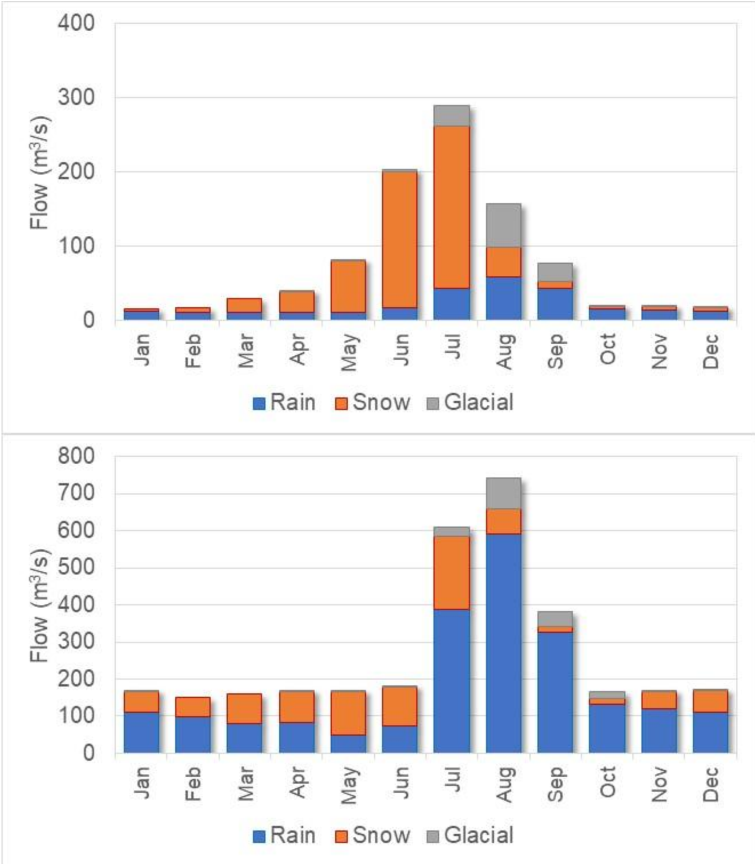

Figure 10 shows the origin of the water. Mean monthly 2001-2020. Top: upstream users Bhatwari_H; bottom inflow Tehri Reservoir

For more details on water allocation modelling and other inputs required beyond the glacio-hydrological modelling outputs, please refer to the WEAP manual or the manuals of related software.

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