A snow and glacier hydrological model for large catchments - case study for the Naryn River, Central Asia.

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Abstract. In this paper we implement a degree day snow and glacier melt model into the Dynamic fluxEs and ConnectIvity for Predictions of HydRology (DECIPHeR) model. The purpose is to develop a hydrological model that can be applied to large glaciated and snow-fed catchments, yet is computationally efficient enough to include model uncertainty in streamflow predictions. The model is evaluated by simulating monthly discharge at six gauging stations in the Naryn River catchment, (57,833 km^2) in Central Asia over the period 1951 to a variable end date between 1980 and 1995 depending on the availability of discharge observations. The spatial distribution of simulated snow cover is validated against MODIS weekly snow extent for the years 2001-2007. Discharge is calibrated by selecting parameter sets using Latin Hypercube sampling and assessing the model performance using six evaluation metrics.

The model shows good performance at simulating monthly discharge for the calibration period (NSE is $0.74 < NSE < 0.87$) and validation period ($0.7 < NSE < 0.9$) where the range of NSE values represent the 5th - 95th percentile prediction limits across the gauging stations. The exception is the Uch-Kurgan station which exhibits a reduction in model performance during the validation period attributed to commissioning of the Toktogul reservoir in 1975 which impacted the observations. The model reproduces the spatial extent in seasonal snow cover well, when evaluated against MODIS snow extent. 86% of the snow extent is captured (mean 2001-2007) for the median ensemble member of the best 0.5% calibration simulations.

We establish the present-day contributions of glacier melt, snow melt and rainfall to the total annual runoff and the timing of when these components dominate river flow. The model predicts the observed increase in discharge during the spring (April-May) associated with the onset of snow melting and peak discharge during the summer (June, July and August) associated with glacier melting well. Snow melting is the largest component of the annual runoff (89%), followed by the rainfall (9%) and the glacier melt component (2%), where the values refer to the 50th percentile estimates at the catchment outlet gauging station Uch-Kurgan. In August, glacier melting can contribute up to 66% of the total runoff at the highly glacierised Naryn headwater sub-catchment. The glaciated area predicted by the best 0.5% calibration simulations overlap the Landsat observations for the late 1990s and mid-2000s. Despite good predictions for discharge, the model produces a large range of estimates for the

glaciated area (680km^2 - $1,196\text{km}^2$) (5th - 95th percentile limits) at the end of the simulation period. To constrain these estimates further, additional observations such as glacier mass balance, snow depth or snow extent should be used directly to constrain model simulations.

1 Introduction

In high mountain Asia, large populations rely on glacier and snow-fed river systems for their fresh water supply (Lutz et al., 2014; Armstrong et al., 2019). These 'water towers', which provide essential streamflow during the summer and a buffer against drought, are under threat as glaciers melt in response to warming temperatures (Kraaijenbrink et al., 2017; Immerzeel et al., 2013, 2010, 2020). The Aral Sea basin in Central Asia has been identified as the region with the greatest human dependence on glacier melt water (Kaser et al., 2010). Streamflow in the Syr Darya river, the second largest river in Central Asia, is supplied by snow and glacier melt from the Tien Shan mountains during the spring and summer (Sorg et al., 2012). This water is crucial for hydro-production in upstream Kyrgyzstan and for irrigation downstream in the semi-arid low lands of Kazakhstan and Uzbekistan.

Glaciers in the Tien Shan have reduced in mass by approximately 27 % during the past 50 years (Pieczonka and Bolch, 2015). In the Naryn basin, the upstream tributary of the Syr Darya, satellite observations show a 23 % reduction in glacier area since the mid-1970s (Kriegel et al., 2013) and a similar reduction in the upper Naryn basin since the 1940s (Hagg et al., 2013). The shrinkage in glacier area has coincided with an increase in discharge in the upper reaches of the Syr Darya river caused by accelerated glacier melting (Zou et al., 2019). There has also been a shift in the precipitation regime with more precipitation falling as rain and less falling as snow, leading to enhanced melting and less snow accumulation. Chen et al. (2016) showed that in the Tien Shan Mountains the snowfall fraction decreased every decade, from 27% in 1960–1969 to 25% in 2005–2014.

As glaciers retreat, river runoff is expected to temporally increase, reaching a maximum known as 'peak water', after which flow is reduced as glaciers recede and disappear completely. There is a compelling need to predict the timing of 'peak water' in order to understand when to implement adaption strategies to reduced river flow. Projections of future streamflow in the upper reaches of the Syr Darya river show a decrease during the summer and an increase in the spring as the hydrological regime shifts from one of glacier melting to seasonal snow melting (Radchenko et al., 2017). The reduction in summer streamflow will have direct impacts on water availability in the Ferghana valley (Kyrgyzstan, Tajikistan) and further downstream in the Syr Darya river in Uzbekistan.

To estimate the timing of 'peak water', models which couple a representation of glacier processes to catchment hydrology are required. van Tiel et al. (2020) reviewed the many glacio-hydrological models in the literature and highlighted that one of the major challenges is uncertainty in the input data. Observations are generally sparse in mountainous regions. For example, meteorological stations are generally clustered at low altitudes meaning that the derivation of the precipitation and temperature lapse rates can be very uncertain. Furthermore, observations of solid precipitation can be underestimated by 20%-50% due to windiness at high elevations (Rasmussen et al., 2012) which redistributes snow. The accuracy of streamflow predictions will also be affected by model structural uncertainty and uncertainty in model parameters that cannot be directly observed. Further-

more, the quality of discharge observations used to evaluate models is often difficult to determine. Incorporating uncertainty analysis in streamflow predictions means that the models we use need to be computationally efficient.

The treatment of snow and glacier melting in glacio-hydrological models can vary in complexity, from simple temperature index models (Neitsch et al., 2005; Zhang et al., 2013; Lindstrom et al., 1997), enhanced temperature index models (Ragettli and Pellicciotti, 2012; Mayr et al., 2013), to full energy balance models (Ren et al., 2018). A benefit of using a simple temperature-index model is that only temperature is used to calculate melting, whilst energy balance models require observations of the radiation components, temperature, wind speed and humidity. This makes temperature-index models a pragmatic choice for data sparse regions, although it does mean that processes such as sublimation (important on glacier surfaces in areas of low humidity) might be overlooked. Furthermore, Magnusson et al. (2015) showed that for hydrological applications a temperature-index model can predict daily snowpack mass and runoff as well as a more complex energy balance model.

In this study, a degree day snow and glacier melt scheme is incorporated into the Dynamic fluxEs and ConnectIvity for Predictions of HydRology (DECIPHeR) (Coxon et al., 2019) model. The aim is to develop a glacio-hydrological model that can be applied to very large glaciated catchments, yet still retains computationally efficiency. This means parametric uncertainty in streamflow predictions can be explored while retaining a high spatial resolution to allow orographic variability in the climate to be represented. Many glacio-hydrological models already exist in the literature (van Tiel et al., 2020; Horton et al., 2022), however, we integrate a snow and glacier melt model into DECIPHeR for the following three reasons. Firstly, DECIPHeR uses hydrological response units (HRUs) to model water flow in hydrologically similar parts of the catchment and has a flexible model structure which allows the model to be run as a fully distributed (HRU for every single grid point), semi-distributed (multiple HRUs) or as a lumped model (1HRU). Depending on user requirements and the corresponding degree of complexity, topographic, land use, geology, soils, anthropogenic and climate attributes as well as points of interest (any gauged or ungauged point on the river network), can be supplied to define the spatially connected topology and thus differences in model inputs, structure and parameterization (Coxon et al., 2019). Other HRU based glacio-hydrological models exist, for instance, SWAT (Omani et al., 2017), PREVAH (Koboltschnig et al., 2008) and HBV (Finger et al., 2015) but they don't offer this level of flexibility within a single modelling framework. Secondly, DECIPHeR is computationally efficient, which makes it suitable for modelling very large catchments. Many of the glacio-hydrological models in the literature are distributed (grid point based) for example, TOPKAPI (Pellicciotti et al., 2012), DHSVM (Frans et al., 2018), VIC (Schaner et al., 2012), GERM (Farinotti et al., 2012). The computational expense of modelling processes with adjacent grid points makes distributed models more suited to studying small catchments. Furthermore, computationally efficiency makes it possible to quantify uncertainties and run large ensembles which is important for understanding the uncertainties in future predictions. Thirdly, the DECIPHeR code is open source which allows opportunities for further community development. In contrast, the glacier enhanced version of SWAT (Omani et al., 2017; Luo et al., 2013b) is not open source.

The model performance is assessed by simulating discharge in the Naryn river catchment in Central Asia for the period 1951-2007. Simulated snow cover is evaluated against MODIS remote sensing snow extent for the period 2001-2007. Simulated catchment-wide glaciated area is compared to glaciated areas derived from Landsat observations for time periods during the 1970s, 1990s and mid-2000s. This evaluation is used to establish the extent to which the model can reproduce past changes in

river discharge, snow extent and catchment-wide glaciated area, in order to have confidence in the model's predictive ability when applied to future scenarios. The model is used to quantify the present-day relative contributions of rain, snow and glacier melting to the total discharge and to determine the timing of when these components dominate river flow. Determining these baseline conditions for the present-day is important because these will change in the future as the seasonal snow pack reduces

95 and glaciers retreat. The paper is structured as follows; Section 2 gives an overview of the DECIPHeR model and describes the changes made to include and snow and glacier model. Section 3 describes the calibration and validation of discharge. Section 3.9 describes the validation of snow extent against MODIS observations. Section 4 describes the model limitations and proposes several avenues for further development.

2 Method

2.1 Study region

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The Naryn River (Fig. 1) originates in the Tien Shan mountains in Kyrgyzstan and flows west through the Ferghana Valley into Uzbekistan where it merges with the Kara Darya River to form the Syr Darya. The river is an important source of fresh water for agriculture downstream in the heavily irrigated Ferghana valley (Radchenko et al., 2017). According to the Randolph Glacier Inventory Version 6 (RGI, 2017) there are currently 1,784 glaciers in the catchment. Glaciers are found at elevations

105 ranging between 2,815m to 5,125m and are predominantly located in the east of the catchment and to a lesser extent in the north west. Rock glaciers are also common above around 3000m, especially downslope of contemporary glacier termini, and these represent considerable (if unquantified) ice and future water resources. The catchment has an area of 57,833 km^2 of which 1,060 km^2 or 1.8% is glaciated. The monthly temperature climatology (1951-1970) averaged over the catchment varies between -13°C in January and +11°C in August and the majority of the annual precipitation falls in spring and early summer

110 (April – July) (See Fig. 2d). There are six gauging stations with long term monthly observations commencing in 1951 and terminating between 1980 and 1995 (see Section 3.1). Discharge at the six stations peaks in the summer (June-August) due to glacier melting, with the exception of Aflatun which is un-glaciated and peaks in sooner in spring (May) due to snow melting (Fig. 2).

For the purposes of this study, we assume that streamflow at the gauging stations has a natural signal. The exception is Uch-

115 Kurgan station where streamflow after 1975 is impacted by the management of the Toktogul reservoir (Bernauer and Siegfried, 2012). A high-resolution irrigation map of the catchment derived from normalized difference vegetation index (NDVI) (Meier et al., 2018) shows that the irrigated area is low (3% area is irrigated), in contrast to the Ferghana valley downstream (Fig. S1). Irrigation is predominately clustered in the south eastern part of the Naryn catchment.

2.2 DECIPHeR model

120 DECIPHeR is a flexible hydrological modelling framework (Coxon et al., 2019) which is based on dynamic TOPMODEL (Beven and Freer, 2001; Metcalfe et al., 2015; Freer et al., 2004; Peters et al., 2003). The model can be spatially configured in

any form, providing a distributed mosaic of interacting and spatially connected hydrological response units (HRU's) that allow different representations of water fluxes due to local conditions (i.e. geology, soils, slopes, vegetation) via different inputs (i.e. precipitation/evaporation), model structures and parameterisations. HRUs group together similar parts of the landscape to minimise run times of the model. This enables the user to run large ensembles of event data and climate simulations and provide probabilistic flow simulations essential for risk analysis. The user can use DECIPHeR to test different spatial configurations, from a fully gridded model to a lumped model setups. Each HRU can be assigned its own processes and parameters, which allows for a more complex representation of spatially variable processes across the catchment. The capability to include spatially varying processes is particularly useful for modelling glaciers because the equations used to describe water storage and release from glaciated locations in the catchment will be different to unglaciated regions.

DECIPHeR simulates water storage, hydrologic partitioning, and surface/subsurface flow for steeper shallow soils and/or groundwater-dominated watersheds. The model structure (as implemented in Coxon et al. (2019) consists of three stores defining the soil profile (root zone, unsaturated and saturated storage), which are implemented as lumped stores for each HRU. Moisture is added to the soil root zone by rainfall input and removed only by evapotranspiration. Any excess precipitation is added to the unsaturated zone where it is either routed directly as overland flow or added to the saturated zone. Changes to storage deficits in the saturated zone are dependent on this recharge from the unsaturated zone, fluxes from upslope HRUs and downslope flow out of each HRU. Subsurface flows for each HRU are distributed according to a flux distribution matrix based on accumulated area and slope. Channel flow routing is modelled using a set of time delay histograms. For more detailed discussion of the original DECIPHeR model structure please see Coxon et al. (2019).

While DECIPHeR has been applied catchments in the UK (Coxon et al., 2019; Lane et al., 2021), it has not been used for glacier or snow-fed rivers because cryospheric processes have not yet been included in the model. TOPMODEL, the forerunner of dynamic TOPMODEL did have a snow melt scheme, however, seasonal variations in the degree day melt factor and snow sublimation were not included (Ambroise et al., 1996). DECIPHeR is implemented in two steps; 1) a digital terrain analysis (DTA) to setup and define the spatial complexity of the model domain and 2) ensemble simulation of that domain. The DTA is critical to define the model complexity, landscape features that will separate HRU's, their equations, function types and parameterisation. The DTA procedures also calculate the river network, routing path, catchment areas for each gauge and the connectivity between the HRUs and HRU's to the stream network. More details on the DTA can be found in Coxon et al. (2019).

2.3 Modifications to the DECIPHeR model

The following sections describe the modifications made to the DECIPHeR model to include snow and glacier processes (for a full description of the hydrology included in DECIPHeR, see Coxon et al. (2019)). We have altered the model to include a simple degree day snow and glacier melt scheme. The degree day approach is a well established method to calculate glacier and snow melting (Marzeion et al., 2020) and only requires air temperature as an input. The equations implemented in DECIPHeR for snow and ice melt are similar to those in the SWAT model (Luo et al., 2013a). SWAT is one of the most widely used community hydrological models which been applied to many snow-fed catchments (van Tiel et al., 2020). The evolution of

the snow and glacier depths are calculated every time step using the snow accumulation, melt and sublimation components. Temperature and precipitation are calculated at the HRU level by adjusting the gridded surface climate for elevation using a temperature lapse rate and a precipitation gradient. Glacier and snow melt are added to the precipitation fields every time step and are then routed through the catchment. Fig. 3 shows a conceptual diagram of the snow and glacier scheme added to the DECIPHeR model. All model parameters are sampled using Latin Hypercube sampling.

2.4 Modifications to the digital terrain analysis

The code is modified to read in two additional inputs; 1.) air temperature which is used for the degree day melting of ice and snow and to estimate the fraction of precipitation falling as rain or snow and 2.) the elevation of the forcing data which is used to apply a lapse rate correction to the surface temperature and precipitation fields. To reduce the number of HRUs we do not classify glaciated regions as a function of accumulated area or slope unlike in other parts of the catchment. HRUs located inside glaciers are only classified as a function of elevation, spatially varying climate and a unique ID that identifies the glacier. The spatial distribution of HRUs in the upper part of the catchment is shown in Fig S2 of the Supplementary Material.

2.5 Modifications to the hydrological model

2.5.1 Snow pack model

The daily snow pack depth is calculated as

$$S_{depth} = S0_{depth} + S_{accum} - S_{melt} - S_{sublim} \tag{1}$$

where S_{accum}, S_{melt}, and S_{sublim} are the snow accumulation, melt and sublimation components at time step t and $S0_{depth}$ is the snow depth at the previous time step. The snow pack components are described below.

2.5.2 Snowpack melting

Melting is related to the snowpack temperature using a degree day factor for snow. The degree day factor accounts for a variety of different processes that control melting, such as the presence of debris cover or the darkening of snow through the snow aging process. The potential snow melt S_{melt} (m w.e.day^{-1}) is

$$S_{melt} = \begin{cases} ddf_{snow} \left(T_{snow} - T_{melt} \right), & \text{if } T_{snow} > T_{melt}. \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

where T_{snow} is the snowpack temperature (°C), ddf_{snow} is the degree day factor for snow melting (m w.e.°C^{-1}day^{-1}) and T_{melt} is the melt temperature. To reduce the number of parameters required to calibrate the model we assume that $T_{melt} = 0°C$. A criteria is enforced such that the melting depth can not exceed the depth of snow that exists.

A seasonally varying degree day factor is calculated which has a maximum snow melt on the 21st of June (ddf_{max}) and a minimum snow melt on the 21st of December (ddf_{min}). The reason to use seasonally varying degree day factor rather than a

constant one, is because the degree day factor is a simplification of processes that can be more correctly described by the energy balance, i.e. inward and outward longwave and shortwave radiation, albedo, latent and sensible heat which vary throughout the year and are not solely a function of temperature. The degree day factor is represented as a sinusoidal curve,

$$ddf_{snow} = \left(\frac{ddf_{max} + ddf_{min}}{2}\right) + \left(\frac{ddf_{max} - ddf_{min}}{2}\right) sin\left(\frac{2\pi}{365}.(j - 81)\right) \tag{3}$$

where j is the day of the year.

The ddf_{min} is calculated by multiplying the maximum value by a scale factor ddf_{mult}.

$$ddf_{min} = ddf_{max}ddf_{mult} \tag{4}$$

The scale factor can vary between 0 and 1 and ensures melt rates are lower in the winter than in the summer.

The temperature of the snowpack T_{snow} is calculated from the air temperature using a lag factor l_{snow}. The lag factor can vary from 0 to 1, where a value of 1 sets the snowpack temperature equal to the air temperature. A value less than 1 sets the snowpack temperature lower than the air temperature. Using a temperature lag factor is a simple way to approximate the snow pack temperature without doing more complex heat transfer modelling of the temperature flux from the air into the snow pack. The lag factor accounts for affects of snow depth and density on the snowpack temperature.

$$T_{snow} = T0_{snow}(1 - l_{snow}) + T_{hru}l_{snow} \tag{5}$$

where $T0_{snow}$ is the snowpack temperature at the previous time step.

The daily HRU temperature T_{hru} (°C) is calculated by adjusting the forcing temperature T_0 (°C) using a lapse rate λ_{temp} (°Cm^{-1}).

$$T_{hru} = T_0 + \lambda_{temp}(E_{hru} - E_{climate}) \tag{6}$$

where E_{hru} is the elevation of the HRU (m) derived from a DEM and $E_{climate}$ is the elevation of the forcing data (m). Calculating temperature at the HRU level allows us to downscale the gridded climate data, allowing for high resolution spatial variability in temperature as a function of elevation.

2.5.3 Snowpack accumulation

Snow accumulates in the snowpack when precipitation falls in the form of snow.

$$S_{accum} = \begin{cases} P_{solid}, & \text{if } T_{hru} <= T_c. \\ 0, & \text{otherwise.} \end{cases} \tag{7}$$

where S_{accum} is the snow accumulation (m w.e.day^{-1}), P_{solid} is the solid precipitation falling on the HRU (m w.e.day^{-1}) and T_c is the threshold temperature for the conversion of rain to snow (°C).

A spatially uniform rainfall and snowfall correction factor is applied to the precipitation based on the equations used in the HBV-ETH model (Mayr et al., 2013). The correction is applied because gridded datasets often underestimate precipitation in mountainous regions due to the lack of meteorological stations at high elevations and the fact that observations of solid precipitation are susceptible to under catch due to windy conditions (Rasmussen et al., 2012). Wortmann et al. (2019) demonstrated

215 using the Soil and Water Integrated Model–Glacier Dynamics (SWIM-G) model that the APHRODITE precipitation (used in this study) needed to be increased by a factor of 1.5–4.3 to maintain observed glacier area and mass balances. Solid and liquid precipitation are scaled separately

$$P_s = P_0.S_c \quad T_{hru} <= T_c$$
$$P_l = P_0.R_c \quad T_{hru} > T_c$$

220 where P_s and P_l is the scaled solid and liquid precipitation (m day^{-1}), P_0 is the forcing precipitation (m day^{-1}), S_c and R_c are dimensionless snowfall and rainfall correction factors. Solid and liquid precipitation are lapse rate corrected for elevation using a linear precipitation gradient. The solid precipitation P_{solid} falling on the HRU (m day^{-1}) is

$$P_{solid} = P_s + P_s\lambda_{precip}(E_{hru} - E_{climate}) \tag{8}$$

where λ_{precip} is the precipitation lapse rate (%m^{-1}). The liquid precipitation falling on the HRU P_{liquid} (m day^{-1})

225 $$P_{liquid} = P_l + P_l\lambda_{precip}(E_{hru} - E_{climate}). \tag{9}$$

Rain falling on a snow or ice covered HRU is passed to the root zone.

2.5.4 Snowpack sublimation

The quantity of snow sublimated is calculated using the potential evapotranspiration which is provided as an input forcing dataset. The parameter E_{sub} is used to reduce the potential evapotranspiration over snow surfaces. Sublimation is then set

230 equal to the reduced PET and no PET_{hru} is passed to the root zone.

$$S_{sublim} = \begin{cases} PET_{hru}E_{sub}, & \text{if } S_{depth} > 0. \\ 0, & \text{otherwise.} \end{cases} \tag{10}$$

S_{sublim} is the snow sublimation (m w.e.day^{-1}), PET_{hru} is the forcing data potential evapotranspiration (m day^{-1}) and E_{sub} is a parameter to be calibrated that reduces the evapotranspiration over snow covered HRUs. Using PET to approximate snow sublimation has also been implemented in the SWAT model (Fontaine et al., 2002).

235 ### 2.5.5 Glacier model

The daily glacier depth is

$$G_{depth} = G0_{depth} + G_{accum} - G_{melt} - G_{sublim} \tag{11}$$

where G_{accum}, G_{melt}, and G_{sublim} are the glacier accumulation, melt and sublimation components at time step t and $G0_{depth}$ is the glacier depth at the previous time step.

2.5.6 Glacier melting

When the snow pack has melted and the glacier ice is exposed melting can occur. The amount of glacier ice melted G_{melt} (m w.e.day^{-1}) is

$$G_{melt} = \begin{cases} ddf_{ice}\left(T_{glacier} - T_{melt}\right), & \text{if } T_{glacier} > T_{melt}. \\ 0, & \text{otherwise.} \end{cases} \tag{12}$$

where ddf_{ice} is the degree day factor for ice melting (m w.e.°C^{-1}day^{-1}), $T_{glacier}$ is the temperature of the glacier ice (°C), T_{melt} is the melt temperature which is set to 0 °C.

The degree day factor for ice is calculated from the degree day factor for snow by multiplying by a scaling parameter ice_{mult}. The scaling parameter increases the degree day factor for ice relative to snow. Ice generally melts more per degree day than snow because it has a lower albedo.

$$ddf_{ice} = ddf_{snow}ice_{mult} \tag{13}$$

Glacier temperature is related to the air temperature using a lag factor

$$T_{glacier} = T0_{glacier}(1 - l_{glacier}) + T_{hru}l_{glacier} \tag{14}$$

where $T_{glacier}$ is the glacier temperature (°C), T_0 is the glacier temperature at the previous time step (°C), T_{hru} is the lapse rate corrected temperature of the HRU (°C), $l_{glacier}$ is the dimensionless lag factor for ice. The lag factor for glacier ice is found by multiplying the lag factor for snow by a scale factor $l_{ice_{mult}}$. This reduces the temperature lag factor for ice relative to snow, because ice responds more slowly to the air temperature than snow.

$$l_{glacier} = l_{snow}l_{ice_{mult}} \tag{15}$$

2.5.7 Glacier accumulation

Glacier accumulation is calculated by transforming a fraction of the snowpack into glacier ice. This is a simple way to convert snow into ice without including more complex processes such as the densification and compaction of snow grains under the force of gravity. Glacier accumulation is

$$G_{accum} = \beta S_{depth} \tag{16}$$

where (β) is the basal turnover coefficient (day^{-1}). This represents the fraction of snow that is removed from the snow pack and converted into ice every time step. The minimum parameter range for β is 1 year (2.74 x 10^{-3} day^{-1}), which means that it takes 1 year for all of the snowpack to be converted into ice. The upper bound is 100 years (2.74 x 10^{-4} day^{-1}). The upper range is based on observations of the age of ice at the firn-ice transition depth for different glaciers (Paterson, 1994).

2.5.8 Glacier sublimation

Sublimation occurs when the snowpack has disappeared and the glacier ice is exposed. We assume that the reduction in PET over snow and ice surfaces is the same.

$$G_{sublim} = \begin{cases} PET_{hru}E_{sub}, & \text{if } S_{depth} = 0. \\ 0, & \text{otherwise.} \end{cases} \tag{17}$$

270 where E_{sub} is used to reduce the potential evapotranspiration over ice and snow HRUs. Sublimation is set to the reduced potential evapotranspiration value.

2.5.9 Snow and glacier melt contributions to streamflow

Water from snow and glacier melting are added to the precipitation field and routed through the model to simulate river discharge.

275 $$P_{total} = P_{liquid} + S_{melt} + G_{melt} \tag{18}$$

where P_{total} is the total water input to the catchment, P_{liquid} is the liquid precipitation on the HRU, S_{melt} is the snow melt contribution and G_{melt}, each with units (m w.e.day^{-1}). See Table 3 for a list of the model parameters that are calibrated.

3 Model evaluation

3.1 Input data for DECIPHeR

280 DECIPHeR requires a digital elevation model and information of the location of gauging stations. Catchment elevation data are provided by the Multi-Error-Removed Improved-Terrain Digital Elevation Model (MERIT) (Yamazaki et al., 2017). The DEM has a spatial resolution of 3 arc seconds ($\sim$ 90 m at the equator) and pre-processed to remove any sinks or flat areas. Therefore we assume that all the catchment area flows to the gauging outlets.

The location of the gauging stations and monthly discharge observations come from the Global Runoff Data Centre (GRDC).
285 There are six gauging stations located the Naryn river catchment : Djumgol, Kekirim, Naryn, Toktogul Reservoir, Aflatun, Uch-Kurgan. The Toktogul Reservoir gauging station is located immediately upstream of the reservoir dam, so is not affected by water abstraction. Discharge at the Uch-Kurgan station after at 1975 is impacted by the reservoir management. Table 1 contains a list of the input and evaluation datasets used in this study.

3.2 Glacier area and thickness

290 Glacier outlines are used in the model to identify glaciated/non-glaciated HRUs and initial glacier thicknesses for each HRU. These are calculated using glacier outlines derived from Landsat Multispectral Scanner imagery for the 1970's (Kriegel et al., 2013). According to the Landsat data 1,472 glaciers existed in the catchment during the 1970s. Determining glacier thicknesses

at the start of the simulation is problematic due to the lack of long term observations. Therefore, we infer glacier thickness using the Glacier bed Topography (GlabTop2) method (Frey et al., 2013) where the glacier outlines from the 1970s and the MERIT DEM are used as input. Freely available python code to implement the GlabTop2 method was obtained from https://pypi.org/project/GlabTop2-py. Glacier thicknesses are converted to units of mw.e. using an ice density of 917 $\mathrm{kgm^{-3}}$.

GlabTop2 is a useful technique to infer glacier thicknesses in the absence of observations, however, the method has some limitations that should be acknowledged. Firstly, the method uses a simple parameterisation for the basal shear stress based on the elevation difference within a glacier. This can introduce a source of uncertainty in the initial ice thicknesses. Secondly, the method can produce very high ice thicknesses for locations with low slopes. Low slopes can appear in the MERIT DEM if a glacier has retreated and a glacier lake is formed or an existing lake expands. Two glaciers in the upper part of the catchment have very low slopes (flat) at the terminus and large ice thicknesses. The larger of these is Petrov glacier which drains into the Petrov glacial lake. Observations show that Petrov glacier has experienced accelerated retreat since the 1970s (Engel et al., 2012) and the lake area has more than doubled since 1980 (Janský et al., 2010). To correct for this, we take the mean thickness of a 5 x 5 pixel buffer upstream of the terminus for each of the two glaciers and replace the large thickness values with the fill value. Ice thicknesses before and after the fill values have been applied can be seen in the Supplementary Material (Fig. S3 and Fig S4. respectively. A third limitation is that the thickness estimate uses 1970s outlines but our model simulations commence in 1951. In situ mass balance observations show that glaciers in the Tien Shan were in a quasi-stable state between the 1950s and the 1970s but experienced accelerated mass loss in the years that followed (Barandun et al., 2020; Liu and Liu, 2016). The glaciers in the aforementioned studies were located outside of the Naryn catchment, however we assume the mass balance trends are representative of our study region.

3.3 Input climate

Daily precipitation data are provided by the Asian Precipitation Highly-Resolved Observational Data Integration Towards Evaluation of Water Resources (APHRODITE) Russia and Monsoon Asia V1101 daily precipitation (Yatagai et al., 2012). This data has been shown to outperform other gridded precipitation datasets for hydrological modelling applications in Central Asia (Malsy et al., 2015). The APHRODITE data are constructed from a network of rain gauges across Asia which are interpolated onto a 0.25 °grid. Daily air temperature, potential evaporation and elevation of the climate data comes from the ERA5 back extension (ERA5 BE) 1950-1978 and ERA5 1979-2007 (Copernicus, 2017). This data has a spatial resolution of 0.25°x 0.25°.

3.4 Calculation of Hydrological Response Units

HRU's are calculated by categorising the catchment according to the following;

- 81 elevation ranges consisting of; 0m-2000m in increments of 100m and 2000m-5,200m in increments of 50m. These elevation bands are selected to downscale the temperature and precipitation which is used for snow and glacier model.

The finer 50m bands are used between elevations 2000m-5,200m because glaciers are located within these elevation ranges in the catchment.

 – dividing the non-glacierised parts of the catchment into three equally sized surface slope and accumulated area fractions. This results in HRUs that cascade down to the valley bottom.

 – spatially varying precipitation, temperature and potential evapotranspiration. This provides the model with a regionally varying climate forcing.

 – glacier mask which is used to determine if a HRU is initially glacierised or un-glacierised.

This categorisation results in the following variable spatial resolution characteristics: A mean area of 0.94km^2, median 0.27km^2, minimum 0.0055km^2 and maximum 259.93km^2 per HRU. (See Fig. S5 in the Supplementary Material for a histogram of the areal distribution of the HRUs). The total number of HRUs in the catchment is 61,481.

3.5   Initialisation and spin up

The initial snowpack depth is set to 0 m w.e. and its temperature is set to 0°C. The initial glacier temperature is set to -5°C. The calculation of the initial glacier thicknesses using the GlabTop2 method is described in Section 3.2. The model is spun up by repeating the first simulation year 1951 for 10 years. The spin-up time period is found by performing an idealised experiment in which precipitation forcing is kept constant through time and the temperature forcing is set to less than 0°C to ensure there is no snow or ice melting. Under these conditions the discharge reaches an equilibrium in approximately 10 years.

3.6   Calibration and validation of discharge

The model is calibrated for the period 1951–1970 to determine behavioural parameter sets and then these are validated for the period 1971 to a variable end date between 1980 and 1995 depending on the availability of discharge observations at each gauging station. The calibration period is prior to the commissioning of the Toktogul reservoir in 1976 which affected the discharge at Uch-Kurgan. The model is run on a daily time step and monthly simulated discharge is calculated from daily values. Twelve additional parameters are added to DECIPHeR for the snow and glacier scheme. The parameters and their minimum and maximum sampling ranges are listed in Table 3. In total 150,100 simulations using parameter combinations selected using Latin Hypercube sampling are run (McKay et al., 1979). This form of stratified sampling is a more efficient and structured approach to generating a 'near random' sample for large multi-dimensional problems such as this. Model performance is assessed using six evaluation metrics described in Section 3.7 below. The best 0.5% performing simulations (see section below for the methods) in the calibration period are used in the validation.

3.7   Generalised Likelihood Uncertainty Estimation (GLUE)

The Generalised Likelihood Uncertainty Estimation (GLUE) is a technique used to identify parameter sets which provide a good representation of the system (Beven and Binley, 1992; Freer et al., 1996; Beven, 2006). The approach assumes that there is

no single optimum parameter that can be considered correct but instead there are a set of 'behavioural models' that describe the system equally well. In this study, we want to select models that perform well at simulating seasonal changes in discharge. The onset of snow melting affects the discharge during the spring, whereas peak discharge during the summer is affected by glacier melting. It is equally important, to ensure that the model performs well during the autumn and winter. Station observations show that the warming in the Naryn basin over the period 1960–2007 occurred primarily during the autumn and winter (Kriegel et al., 2013). Warming winter temperatures causes a reduction in snowpack accumulation when more precipitation falls in the form of rain rather than snow. This has an impact on the autumn and winter hydrograph. Therefore we use the following metrics to assess the model performance:

The Nash–Sutcliffe efficiency (NSE) is used to evaluate high flows and the timing of peak discharge, particularly from glacier melting during the summer. NSE values range between $-\infty$ and 1 where $NSE = 1$ is the optimal value.

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n} \left(Q_i^{obs} - Q_i^{sim} \right)^2}{\sum_{i=1}^{n} \left(Q_i^{obs} - Q_i^{\hat{obs}} \right)^2} \right] \tag{19}$$

Q_i^{obs} and Q_i^{sim} is observed and simulated monthly discharge, $Q_i^{\hat{obs}}$ is the mean observed monthly discharge and n is the number of observations.

The bias in runoff ratio $PBIAS$ is a measures of the tendency of the simulated data to be larger or smaller than the observations (Yilmaz et al., 2008). A negative $PBIAS$ indicates the model underestimates the discharge and a positive bias indicates the model overestimates the discharge. $PBIAS$ close to zero indicates better model performance.

$$PBIAS = \frac{\sum_{i=1}^{n} \left(Q_i^{sim} - Q_i^{obs} \right)}{\sum_{i=1}^{n} Q_i^{obs}} .100 \tag{20}$$

The ratio of the root mean square error to the standard deviation of the observations (RSR) (Moriasi et al., 2007) is used to evaluate the model performance for the four seasons, therefore this provides 4 separate evaluation metrics (bringing the total to 6).

$$RSR_{season} = \frac{RMSE}{STDEV_{obs}} = \frac{\sum_{i=1}^{n} \sqrt{\left(Q_i^{obs} - Q_i^{sim} \right)^2}}{\sum_{i=1}^{n} \sqrt{\left(Q_i^{obs} - Q_i^{\hat{obs}} \right)^2}} \tag{21}$$

where i is discharge for the months of spring (March, April, May), summer (June, July, August), autumn (September, October, November) and winter (December, January, February). $Q_i^{\hat{obs}}$ is the mean of the observed discharge. Better parameter sets have lower values of RSR. The units of RSR are dimensionless which makes it useful for comparing the model performance between the sub-catchments and with other studies.

In this study two different calibration techniques are tested:

1. ISC: individual-site calibration to find parameter sets best suited to individual sub-catchments. This approach parametrises areas upstream of a gauge in a lumped way. This is different to the step-wise approach where each upstream to downstream catchment is calibrated sequentially, resulting in spatial differences between upstream-downstream parameters. Nonetheless, the ISC method allows us to identify the spatial variability in parameters across the catchment.

2. MSC: multi-site calibration to find global parameters sets suited to the entire catchment.

385 The purpose of using two approaches is to investigate if there are parts of the catchment that behave differently to the entire catchment. The results of ISC are included in the main body of the paper and the results of MSC are detailed in the supplementary material.

Model performance is assessed by calculating conditional probabilities from the six metrics described above. The final conditional probability values are combined with an equal weighting to give overall model performance, where higher conditional

390 probability values (after all the normalisation steps) indicate better model performance. Prior to calculating the conditional probability values, NSE values less than zero are set to zero. By doing so, we reject these simulations because they will have a zero conditional probability. The NSE is adjusted such that

$$NSE_{rev} = 1 - NSE \tag{22}$$

This ensures that NSE values closer to zero represent good model performance and values closer to 1 represents poorer model

395 performance. The absolute value of $PBIAS$ is also calculated $|PBIAS|$. No prior adjustments are required for RSR_{season} because values close to zero are already considered good.

The metrics NSE_{rev}, $|PBIAS|$ and RSR_{season} are normalised so that values vary from 0 (good performance) to 1 (poor performance). This is to account for the difference in units between the metrics and the fact that the upper bounds values for the metrics are different. $PBIAS$ has units of percent and RSR_{season} and NSE_{rev} have dimensionless units. The upper bound

400 value for NSE_{rev} and RSR_{season} is 1, whilst $PBIAS$ can have an upper bound value exceeding 1. The above metrics are then normalised so that they are all on a scale of 0 to 1

$$O_{c,i,m} = \frac{(M_{c,i,m} - min\,(M_{c,I,m}))}{(max\,(M_{c,I,m}) - min\,(M_{c,I,m}))} \tag{23}$$

where $M_{c,i,m}$ is the metric m at catchment c for simulation i and $I = (1, 2, ..., n)$ are the vector of simulations from 1 to the

405 number of simulations n. $max\,(M_{c,I,m})$ and $min\,(M_{c,I,m})$ are the maximum and minimum values of the metrics across all simulations for each catchment.

Once normalised the values for each simulation, for each metric, and for each catchment is then calculated as

$$L_{c,i,m} = 1 - O_{c,i,m} \tag{24}$$

So that a higher value (between 0 and 1) reflects a better simulation for that metric Finally the conditional probability values

410 are then calculated so that for each metric and for each catchment all the simulations sum to 1.

$$L_{c,i,m} = \frac{L_{c,i,m}}{\sum_{i=1}^{n} L_{c,i,m}} \tag{25}$$

where n is the number of simulations. For the ISC method, a combined conditional probability measure is calculated for each sub-catchment ($\Theta_{c,i}$) by multiplying the conditional probability measures derived from the six metrics. We assume the metrics

contribute equally to the overall model performance.

$$\Theta_{c,i} = \prod_{m=1}^{6} L_{c,i,m} \tag{26}$$

For the MSC method, catchment wide conditional probability measures are calculated by multiplying $\Theta_{c,i}$ for each sub-catchment. We assume that the sub-catchments contribute equally to model performance.

$$\Theta_i = \prod_{c=1}^{6} \Theta_{c,i} \tag{27}$$

Simulations are ranked in order of descending conditional probability measure, where maximum values indicate good model performance. The best performing 0.5% calibration simulations (n=751) are extracted and used to validate the discharge and spatial snow extent.

3.7.1 Individual-site calibration and validation

Figures 4 and 5 show the simulated and observed discharge for the calibration and validation periods using the best 0.5% simulations. The range of values for the performance metrics are listed in Table 4. For the calibration period the model is able to capture the seasonal peaks in discharge well with NSE values $0.74 < NSE < 0.87$ for the 5th - 95th prediction limits and $PBIAS$ values lower than 11.36% at all each gauging stations. RSR values can be considered 'satisfactory' ($RSR< 0.7$) during the winter, spring and autumn, however some RSR values exceed 0.7 in the summer (June, July, August) indicating poorer model performance when glacier melting is active.

For the validation period the model also performs well NSE values $0.7 < NSE < 0.9$ for the 5th - 95th prediction limits, with the notable exception of the Uch-Kurgan station where discharge is overestimated by up to 32%. The discrepancy is most noticeable during the summers of 1987 and 1988. The model simulates the observed peak discharge during these years well at the Toktogul reservoir gauging station which is located upstream of the reservoir, however, downstream of the reservoir at Uch-Kurgan discharge is overestimated. Observations from the Central Asian Waterinfo Database shows that the reservoir inflow was very high during these two years, which coincided with a sharp increase in the reservoir volume by 7253 M m^3 from August 1987 to August 1988 (Fig. S6 in the supplementary material). Initial and calibrated parameter ranges for each sub-catchment for the best 0.5% of ensemble are listed in Table S3.

3.7.2 Multi-site calibration and validation

Simulated discharge for the calibration and validation periods are shown in the Supplementary Material Fig. S7 and Fig. S8 and performance metrics are listed in Table S1. There is a degradation in model performance when the MSC method is used to calibrate the model (See Table S1). The reduction in model performance is most noticeable for the Naryn sub-catchment where the best NSE is 0.91 for the ISC method and 0.59 for the MSC method. Furthermore, the summer peaks in discharge at the Naryn sub-catchment are under predicted when using the MSC method to select global parameters (Fig. S8). This suggests that the global catchment parameters are not well suited to the Naryn sub-catchment. Dotty plots showing the conditional

probability values for the model parameters are shown in the Supplementary material Fig. S9 (MSC method) and Figs. S10-S15 (ISC method). The top 10 best simulations are shown in red triangles.

Simulations that perform well in the sub-catchments (Figs. S10-S15) favour higher values for the precipitation lapse rates, in contrast to the global catchment parameters which range from $1\%100\mathrm{m}^{-1} - 10\%100\mathrm{m}^{-1}$ (Fig. S9). This is visible in Table S2 which summarises the range of precipitation lapse rates for the 10 best performing simulations for each sub-catchment. The upper values for the precipitation lapse varies between 16 and $24\%100\mathrm{m}^{-1}$ depending on the sub-catchment, which is higher than the global catchment upper bound of $10\%100\mathrm{m}^{-1}$. Simulations also perform better in the sub-catchments when higher values for the sublimation factor E_{sub} are used, in contrast to the global values (0.005 - 0.2). The 10 best E_{sub} parameter ranges are also listed in Table S2. The upper bound values for E_{sub} vary between 0.6 - 1.0, depending on the sub-catchment, which is higher than 0.2 predicted by the global catchment values. E_{sub} controls the reduction in PET over snow and ice surfaces. This indicates that discharge in the Naryn is predicted better when PET is reduced. The PET has not been adjusted for elevation, unlike the air temperature and precipitation. The ERA5 PET has a $0.25°$ spatial resolution which is much larger than the HRU areas. In mountainous regions PET should decrease with height as a consequence of decreasing temperatures (Lambert and Chitrakar, 1989).

We used wide parameter ranges to calibrate the model because this is the first time applying DECIPHeR in a mountainous region, with snow and glacier melt processes included. The dotty plots (see Fig. S9) show that the sampled parameter ranges could be further reduced for two of the parameters; the lateral saturated transmissivity ($ln(T0)$) and the rainfall correction factor (R_c). The $ln(T0)$ calibration range is -20 to 20 $\ln(\mathrm{m}^2\mathrm{hr}^{-1})$, however best simulations have values that are predominately clustered around -7 and 0. R_c is calibrated between 0.8-3, but best simulations have values less than 2. To explore whether any of the parameters are correlated, a plot of the coefficient of determination (r^2) for parameter pairs is shown in Fig S16 for the best 0.5% calibration experiments. The strongest correlation is found between the precipitation lapse rate and the snowfall correction factor ($r^2 = 0.46$) which both control the quantity of snow accumulation. The correlation indicates that good simulations can be produced with higher values of snowfall correction factor combined with lower precipitation lapse rates or vice versa.

3.8 Validation of glaciated area against Landsat observations

The simulated catchment wide glaciated area is compared to Landsat derived glaciated area (Kriegel et al., 2013) for the best 0.5% calibration simulations. The Landsat glaciated area is available for three time periods; the 1970's (1972-1977) which was used to calculate initial glacier thicknesses using GlabTop2, late 1990s (1998-2000) and mid-2000s (2002-2007). The observations have an uncertainty bound associated with the delineation process which was calculated by placing a buffer of approximately a pixel wide (for example 79 m for observations in the 1970s) around the glacier polygons. The uncertainty is the difference between the glaciated area and the area extended by the buffer. Figure 6 shows the simulated glaciated area for the top 0.5% simulations in the calibration overlaid with the Landsat observations. The simulated glaciated area overlaps the Landsat observations in the late 1990s and mid-2000. The model produces a large range of estimates for the glaciated area ($680\mathrm{km}^2 - 1,196\mathrm{km}^2$) ($5^{th}$ -95th percentile limits) at the end of the simulation period. This range is larger than the observed

uncertainty range of $903\text{km}^2 - 948\text{km}^2$. The uncertainty range in the model is 516km^2 (in 2007) which is more than 10 times greater than the uncertainty in the observed glaciated area (46km^2).

480   Figure 7 shows the initial glacier thickness and the mean annual thickness at the end of the simulation period in 2007 for a region in the upper part of the catchment. A thinning of the glaciers and retreat of the terminus from the initial glacier outlines in 1970 is evident. The plots show the median ensemble member of the best 0.5% calibration simulations.

3.9   Validation of modelled snow extent against MODIS observations

We evaluate the simulated spatial distribution of snow extent against MODIS 500m resolution 8-day snow cover extent
485   MOD10A2 version 6 (Hall and Riggs, 2016) for the period 2001-2007. Snow extent is an (internal) hydrological variable, that was not used in the calibration and is complementary to the discharge time series, which is spatially integrated. MODIS snow extent does not contain information on the snow water equivalent, however, it is spatially distributed, which makes it particularly useful for the evaluation of distributed models (Duethmann et al., 2014; Finger et al., 2011).

Daily simulated snow depth for each HRU is output for three simulations from the best 0.5% calibration simulations; 50th
490   (median), 5th and 95th ensemble members. It was not feasible to output daily HRU snow depth for all 751 simulations due to the size of the data. Snow depth is converted from meters of water equivalent to meters using a density of 300 kgm^{-3}, which is the mean density of settled snow. A spatial map of snow depth is generated by converting the snow depths on HRUs to a spatial grid using a map of HRU locations which was generated by the digital terrain analysis.

The MODIS sensor detects snow in a pixel if there is any snow present within an 8-day period. To compare this to the
495   model output we assume snow is present in the model if the snow depth exceeds 1cm on any day within the 8-day MODIS observational period. This threshold is used because MODIS can begin to detect snow with an accuracy 40% (Pu et al., 2007) at this depth. Modelled snow extent is interpolated onto a 500m grid for direct comparison with the MODIS data. Pixels where the MODIS data detects cloud cover are excluded from the analysis. Seasonal MODIS and simulated snow extent is calculated from the weekly data by selecting all the weeks that occur during a season and finding the most frequent state (i.e. snow or
500   no-snow) for each pixel.

For each season, a binary classification scheme is used to enable a comparison between the MODIS and modelled seasonal snow extent. The classification scheme has been used in flood hazard modelling to validate simulated and observed flood hazard area maps (Wing et al., 2017). Four metrics of fit are used, which categorise the relative number of pixels which conform to one of the states in the contingency table (Table 5).
505   The first is the hit rate (H) which is the proportion of snow pixels in the MODIS data that were reproduced by the model.

$$H = \frac{M_1 O_1}{(M_1 O_1 + M_0 O_1)} \tag{28}$$

H can range from 0 (none of the snow pixels in the MODIS data are snow pixels in the model data) to 1 (all of the snow pixels in the MODIS data are snow pixels in the model data).

The second metric is false alarm ratio (F) which indicates the proportion of snow pixels in the modeled that are not snow in

 the MODIS data.

$$F = \frac{M_1 O_0}{(M_1 O_0 + M_1 O_1)} \tag{29}$$

F can have values ranging from 0 (no false alarms) to 1 (all false alarms). F evaluates the tendency of the model to over predict the snow extent.

The third is the Critical Success Index (C) which evaluates both over prediction and under prediction in the model and can range from 0 (no match between modeled and MODIS data) to 1 (perfect match between modeled and MODIS data).

$$C = \frac{M_1 O_1}{(M_1 O_1 + M_1 O_0 + M_0 O_1)} \tag{30}$$

The fourth is the error bias (E) which evaluates the tendency of the model to under predict or over predict snow extent.

$$E = \frac{M_1 O_0}{M_0 O_1} \tag{31}$$

$E = 1$ indicates no bias, $0 \leq E < 1$ indicates a tendency toward under prediction, and $1 < E \leq \infty$ indicates a tendency toward over prediction.

The spatial distribution of the hit rates, misses and false alarms are shown in Fig. 8 for the median (50th percentile simulation) of the best 0.5% calibration runs. (See Figs. S17 and S18 of the supplementary material for the 5th and 95th percentile limit simulations). Seasonal hit rates, misses and false alarms averaged over the years of MODIS observations 2001-2007 are summarised in Table 6. Seasonal snow extent is predicted reasonably well with mean hit rates exceeding 0.86 (median ensemble member). The model captures the complete snow cover observed in winter and the snow that persists at high elevations in the upper part of the catchment in the summer. Most noticeable is the poorer model performance in Autumn, where there is a large positive bias (33.53% median ensemble member) and a high number of false alarms (0.42 median ensemble member). This indicates that the model is over predicting the snow extent in Autumn. The best 0.5% calibration simulations produce good estimates for discharge but at the same time predicts a range of snow extent values. This can be seen in the fraction of the catchment covered in snow (Fig. 9) where NSE values range from 0.78 - 0.89 (95th - 5th percentile limits simulations) with most of the model uncertainty occurring in the winter.

3.10   Discharge components and timing

Adding the snow and glacier model to DECIPHeR makes it possible to disentangle the relative contributions of snow melting, glacier melting and rainfall to the total runoff and to determine the timing of when each component influences river flow. It is important to establish these present-day baseline conditions because these will change under future climate change scenarios. Figure 10 shows the percentage contribution of snow melting, glacier melting and rainfall to the total annual runoff averaged over the years 1951-2007. The discharge components are calculated using the 0.5% best calibration parameters for the Uch-Kurgan station located the outlet of the catchment. Snow melting is the largest contributor consisting of 41-91%, followed by the rain component 8-43% and the glacier component 0-15%, where the ranges represent the $5^{th} - 95^{th}$ percentile simulations across all gauging stations. The glacier melt contribution is largest for the Naryn sub-catchment comprising of 4%-15% of the

annual discharge. This is the headwater sub-catchment located in the Tien Shan mountains and has the largest glaciated area. In contrast, the glacier melting contribution at Aflatun is zero because this sub-catchment contains no glaciers. Figure 10 shows that the rainfall component is larger at the 95th percentile simulations than at the 5th and 50th percentile simulations. This is because the lapse rate at the 95th percentile simulations is higher ($22\%100\mathrm{m}^{-1}$) than at the 5th ($1\%100\mathrm{m}^{-1}$) and the 50th
545 ($6\%100\mathrm{m}^{-1}$) percentile simulations.

To determine if there have been any statistically significant changes in the simulated discharge components since 1951, we do a trend detection analysis using a Mann-Kendall test and Sen's slope estimator with a significance level of 5% on the 50th percentile discharge predictions (Black line in Fig. 11). A trend detection is also run on the annual mean air temperature, potential evapotranspiration, precipitation and observed annual mean discharge. The trends are listed in Table 7. Despite a
550 warming of 0.12-0.2 °/decade we only see a statistically significant trend in the observed discharge at Uch-Kurgan which is affected by the management of the Toktogul reservoir and at Ust Kekirim. There are no statistically significant trends in the glacier melt fraction and only small positive trends in the snow melt and negative trends in the rainfall fractions of less than 1% per decade at some of the gauging stations. The glacier and snow melt fractions exhibit an anti-correlation which happens because the glacier melting occurs when the snowpack is depleted and the ice is exposed (11).

555 Monthly hydrographs averaged over the period 1951-2007 show that discharge from snow melting peaks in the spring (April and May) (Fig. 12). Peak discharge from glacier melting happens later during the summer (June, July, August and September) after the snowpack has melted and glacier surfaces are exposed. This seasonal signal is seen at all the gauging stations except for Aflatun where there are no glaciers. The glacier melt contribution is very high in August where the upper range is 66% for the Naryn sub-catchment and 41% for Ust Kekirim. The percentage contributions of snow melt, glacier melt and precipitation
560 to the monthly runoff are listed in Table S4 of the supplementary material.

4 Discussion

In this paper we added a snow and glacier melt model to the DECIPHeR hydrological model and demonstrated that the model performs well at predicting discharge and the spatial distribution of snow cover when compared to MODIS observed snow extent. This updated version of the DECIPHeR model is suitable for simulating discharge in large glacier and snow-fed
565 catchments at a high spatial resolution whilst maintaining the ability to include model uncertainty in the simulated discharge. Snow and glacier melting are modeled using the degree day approach which requires only air temperature as an additional forcing input.

We used the model to calculate the relative contributions of snow, rain and glacier melt to the annual runoff. We found spatial variability in the relative contributions of each of the components. For the entire catchment (gauging station at Uch-Kurgan)
570 the 50th percentile contributions are snow (89%), rain (9%) and glacier melting (2%). These estimates are broadly consistent with Armstrong et al. (2019) who used MODIS imagery and degree day melt modelling to partition the runoff components in the Syr Darya river. Armstrong et al. (2019) found the runoff comprised of snow (74%), rain (23%) and glacier melting (2%).

Our estimates are slightly higher for the snow melt contribution; however, our study focuses on the upper reaches of the Syr Darya river where the snow melt is more likely to dominate the discharge.

575   Snow melting is the dominate component of the runoff at the six gauging stations. Throughout the Tien Shan long-term hydrological records of the former USSR show that snow melt is the dominant source of runoff (Aizen et al., 1995). Further upstream in the Naryn sub-catchment the glacial melt contribution to the annual discharge is higher (4% - 15%) than at Uch-Kurgan. Our upper estimate (15%) is slightly lower than a study by Saks et al. (2022) who calculated that 23% of the runoff originates from glacier melting in upper Naryn river. A possible explanation for why our estimate is lower, is that our simulation
580   period starts 30 years earlier (1951) than the study by Saks et al. (2022) which started in 1981.

     In this study we set the behavioural models to the best 0.5% simulations in the ensemble. This is an unconventional way to select behavioural models, however, it was important in our analysis to rank models according to their ability to capture seasonal discharge, particularly from spring snow melt and summer glacier melt. Often behavioural models are selected using threshold values for guidelines metrics. These metrics are calculated over the complete discharge timeseries, rather than for individual
585   seasons. For example, metrics from Moriasi et al. (2007) are commonly used in the literature to categorise 'acceptable', 'good', or 'very good' simulations based on threshold values for NSE, PBIAS and RSR. Metrics calculated over the complete discharge time series are not a strong test of the model's ability to predict seasonal discharge. To our knowledge, there are no standardised guideline thresholds in the literature for seasonal metrics, therefore we selected the best 0.5% of the ensemble. If we decided to define the behavioural models using a threshold for the seasonal RSR, then this would also be based on an arbitrary choice of
590   value. A high threshold for seasonal RSR would be required to categorise the behavioural models because the summer values are high (See RSR_{JJA} in Table 4).

     We explored the impact of selecting alternative threshold values (1%, 2.5%, 5% and 10%) on the calibrated NSE values (Fig. S24). To obtain NSE values > 0.7 at all the gauging stations requires a threshold smaller than 1%. This is notable at the Alfatun station where the NSE value at the 0.5% threshold is 0.74 but reduces to 0.63 at the 1% threshold (95th percentile
595   limit values). Fig S24 also shows how the uncertainty in the NSE values increases for higher threshold values. At the 10% threshold the uncertainties in the NSE values are much larger than at the 0.5% threshold.

     In the Naryn sub-catchment which is the most upstream catchment located at elevations predominately exceeding 3000m, the model performed best when the E_{sub} parameter values are high. E_{sub} reduces PET over snow and ice surfaces. This suggests that to improve the model at high elevations an orographic adjustment for PET is required. Currently the model
600   uses surface values for PET, however in practice PET decreases with elevation because of temperature cooling with height. Future work would calculate PET at the HRU level using an empirically derived relationship with temperature (Xie and Wang, 2020; Oudin et al., 2005). This type of parameterisation would use the lapse rate adjusted HRU temperature calculated in the model. Alternatively PET could be calculated using the Penman-Monteith (PM) method recommended by the Food and Agriculture Organization (Allen et al., 1998). This would require additional inputs such as solar radiation, wind speed and
605   humidity. Nevertheless, the Penman-Monteith approach could potentially be more appropriate for high mountainous regions if the orographic increase in wind speed is also included.

Our simulated discharge and glaciated areas are presented with uncertainty bounds because many processes in the model are represented in a simplified way leading to uncertainty in the predictions. Likewise, forcing data in mountainous regions is often very sparse. We can see for example, that the location of the gauging stations, used to derive the APHRODITE precipitation, are sparsely located and not homogeneously distributed across the catchment (see Fig. S19 in the supplementary material). This leads to the requirement to calibrate snowfall and rainfall correction factors as they may vary across the catchment.

We found that when calibrating the discharge, the RSR values were higher in the summer than during the other seasons, suggesting that improvements to the glacier model may improve the simulated summer discharge. One of the key missing processes, is the role of permafrost which affects the upper part of the Naryn catchment. Barandun et al. (2020) showed that permafrost is the Western Tien Shan is continuous above 3800m, discontinuous between 3800m–3600m and sporadic between 3600–3000m and this can influence the runoff regime in three different ways. Firstly, the impermeable (or partially) frozen surface acts as a barrier over which water flows and this increases the speed of the runoff from snow and ice melting during the spring and summer. Secondly, every summer the thawing of ice-rich permafrost releases water that contributes to the streamflow. Thirdly, the degradation of ice-rich permafrost due to climate warming releases additional water. Permafrost responds more slowly to climate change than snow and glacier ice due to the insulating effect of the overlying land layer. This hidden water source could provide a buffer to water loss from glacier and snow melting.

We see from the comparison with MODIS data that snow extent is over predicted in the Autumn, as evidenced by a higher false alarm ratio. This may explain why the catchment wide glaciated area predicted by the model is higher than the Landsat observation at the end of the simulation period (median value in Fig. 6 is $988\mathrm{km}^2$ and observation is $926 \pm 23\%\mathrm{km}^2$). It is open to question whether the overestimate in snow extent is caused by an overestimate in accumulation or an underestimate in melting. The simple degree day melt model does not account for all the complex processes that contribute to melting. Terrain aspect can have a large impact on the quantity of solar energy available for melting. Snow and glaciers on south facing slopes receive more sunlight than north facing slopes in the Northern hemisphere. The effect of aspect could be included by modifying the degree day factor as a function of the slope (Immerzeel et al., 2012, 2013). Another improvement to the melt scheme would involve calibrating the temperature thresholds for glacier and snow melting. Currently the threshold temperatures for melting ice and snow are set to 0 $^\circ$. Alternative methods to calculate melting, such as using an enhanced temperature index model or full energy balance in scheme may help to improve the predictions of snow extent in the autumn.

Future versions of the model could also consider the impact of debris cover on glacier surfaces and its effect on glacier melt. While thin debris layers decrease albedo and enhance local melt rates, once the debris layer exceeds a few centimeters, it insulates the glacier which reduces melt rates (Fyffe et al., 2019). In addition, some debris covered glaciers in High Mountain Asia and elsewhere undergo a transition to form rock glaciers; these contain large ice volumes and appear to be more resilient to warming than ice glaciers (Jones et al., 2021). As a result, the degree day melt and temperature lag factors could be modified in regions where debris covered glaciers and rock glaciers are present. Information on the present day distribution of debris covered glaciers derived from remote sensing is available to implement this (Herreid and Pellicciotti, 2020; Scherler et al., 2018). However, similar information on rock glaciers is not yet available, and the climate and hydrological response of rock glaciers differs from that of debris-covered glaciers.

Additional developments would improve the representation of water flow through the ice and snow. Currently, when rain falls on a HRU the water goes straight to the root zone, so we do not consider the percolation of water through the ice and snow. This would require a more complex model that includes the density and pore space of the snow pack and ice. We have not included the re-freezing of melt water which would increase the snow pack or ice depth. Neither have we included the process by which rainfall adds warmth to the snow pack or ice which enhances melting.

Glacier flow has not been included in the model. To estimate catchment wide glaciated area an arbitrary threshold of 1mm is used to identify the presence of ice. Figure S20 shows the impact of using alternative thresholds of $1e^{-6}\text{m}$, 1cm and 1m. We see that the catchment wide glaciated area is sensitive to the choice of threshold value. Including ice flow and constraining this using mass balance observations in the calibration procedure would enable us to select a realistic threshold over an arbitrary one.

Glacier ice is not allowed to advance beyond the perimeter of the initial glacier outlines meaning the model is unsuitable for applications where glaciers are surging. Globally glaciers have been in a state of retreat (Zemp et al., 2019), however, this has not been the case in the Pamir-Karakorum region where observations show glaciers have advanced (Hewitt, 2005; Gardelle et al., 2012, 2013). Nevertheless, a more recent study by Hugonnet et al. (2021) shows that this anomalous mass gain appears to have ended. It is reasonable to assume that glaciers will only retreat for applications where the model is driven by future climate scenarios.

A future study would explore the sensitivity of the model to the initial glacier and snow conditions. Glacier ice is initialised with a fixed temperature of -5 °C and snow temperature was set to 0 °C. The GlabTop2 method (Frey et al., 2013) used to calculate the initial glacier thickness contains uncertainty due to empirically derived parameterisation to estimate basal shear stress. A sensitivity study would test alternative parameterisations or explore other methods. For example, the Volume and Topography Automation (VOLTA) model (Gharehchahi et al., 2020) which includes the effect of side drag on glacier thicknesses could be used.

The model does not include snow redistribution by wind and avalanches so multi-year accumulation of snow at high elevations leads to well known problem of isolated 'snow towers'. Disregarding snow redistribution in models can not only lead to the formation of these 'snow towers', but also have an impact on timing and magnitude of the snowmelt runoff (Freudiger et al., 2017). At the end of the simulations in 2007, 55 of the total 61,481 HRUs have daily snow depths exceeding 100m. This might eventually have a significant impact on river discharge if the model were run over longer simulation periods. 'Snow towers' were found predominately in a small region located in the western part of the catchment. This can be seen in the supplementary material Fig. S21 showing snow depths and Fig. S22 showing a 'snow tower'.

Future work should focus on improving the calibration method to include additional observations. In this study, it was not possible to include glacier mass balance observations in the calibration because of the lack of historical observations during the period 1951-1970. The large range of glaciated areas predicted by the model at the end of the simulation period, in 2007 shows that the model can make good predictions in discharge (Fig. 5) whilst simultaneously predicting a large range of estimates for glacier area (Fig. 6). This highlights the importance of including ancillary observations, such as glacier mass balance, snow depth or snow extent, in the calibration to help constrain the predictions. Currently, the model performance is not sensitive to

many of the calibration parameter values (Fig S15). It is possible that some parameter combinations compensate each other. For example, a high snowfall correction factor may be compensated for by a lower precipitation lapse rate. More analysis needs to be conducted on the sensitivity of the new snow and ice parameters added to DECIPHeR as part of this study, both in time and space, and the types of data that may help to constrain these parameters. Remote sensing snow products have been used to calibrate models and studies indicated that the integration of data such as MODIS snow cover into hydrological models can improve the simulated snow cover while maintaining model performance with respect to runoff (Parajka and Bloschl, 2008). For example, Hong et al. (2015) integrated glacier annual mass balance observations in the calibration of a glacio-hydrological model to simulate discharge for catchments in Norway and the Himalaya. Glacier mass balance was considered so relevant that an annual mass balance observation was given a weighting 10,000 times more then a discharge observation.

We have not included the impact of water abstraction for irrigation or water storage from reservoirs in the model. The results show that a reservoir model is required to improve estimates of discharge at the Uch-Kurgan station. Our assumption is that water abstraction for irrigation is minimal compared to natural streamflow. This assumption is supported by observations of flow intake at irrigation channels which is very small compared to the flow measured at the gauging stations. Observations of monthly flow intake for the major irrigation channels in Kyrgyzstan are archived in the Central Asian Waterinfo database. Three channel are located in the Naryn basin; Kulanak, Aryk Chegirtke and Alfatun. (See Fig. S1 of the supplementary material for the location of these irrigation head intakes). The Kulanak channel is the longest (40km) and irrigates an area of $45km^2$ in the Kulanak Valley. The maximum monthly flow intake at the head of the channel is approximately 3.6 m^3s^{-1} (Fig. S22 in the supplementary material) which is significantly lower than the peak flow observed at Ust. Kekirim and Naryn stations. Nonetheless, excluding the impact of irrigation will result in a small uncertainty in the prediction of the snow and glacier melt contributions to streamflow because the majority of the water abstraction takes place during in spring and summer (April to August).

The model evaluation presented here is an essential prerequisite for running future simulations to predict how river flow will change as glaciers lose mass and the seasonal snow pack disappears. We showed that for the period 1951-2007 discharge increases in the spring (April-May) when the snowpack melts and peaks in the summer (June, July, August and September) when glacier melting commences. Under future climate change scenarios we may expect the timing of the peak snow and glacier melt contributions to happen sooner in the year (Gan et al., 2015). These changes will have implications for water supply in the Ferghana valley and downstream in the Syr Darya River.

5 Conclusions

In this study we implemented a degree day snow and glacier melt model into the DECIPHeR model. The motivation for this work was to develop hydrological model that can be used to simulate discharge in very large glaciated and snow-fed catchments, at a high spatial resolutions, whilst maintaining the ability to explore model uncertainty. The overarching aim is to develop a tool for predicting changes in river flow under future climate change scenarios.

We describe the snow and glacier model and its application to the Naryn River catchment, Central Asia. The model is evaluated using discharge observations, MODIS snow extent and catchment wide glaciated area derived from Landsat observations. The model is found to be robust a predicting monthly discharge at six gauging stations over the period 1951 to variable end date between 1980 and 1995 depending on the availability of discharge observations. The validation with MODIS snow extent shows the model can reproduce the spatial extent in seasonal snow cover reasonably well in winter, summer and spring with mean hit rates exceeding 0.86 (median ensemble member of the best 0.5% calibration simulations), but overestimates snow extent in Autumn as reflected by a high false alarm ratio and a positive bias. The best 0.5% calibration simulations using 6 different and equally weighted metrics reproduce catchment wide glaciated area consistent with Landsat observations in the late 1990s and mid-2000s. There is, however, a large range of glaciated area estimates within this ensemble. This means that good predictions of discharge can be made concurrently with a large range of glacier area estimates. This strengthens the case that, to make robust predictions, additional observations such as glacier mass balance, snow depth or snow extent should be included in the model calibration.

Code availability. The DECIPHeR model code is freely available under the terms of the GNU General Public License version 3.0. The model code is written in FORTRAN 90 and can be downloaded from the Github repository https://github.com/sarahshannon/DECIPHeR-glacier

Author contributions. The paper was prepared by SS with contributions from all co-authors. SS wrote the snow and glacier models with contributions from GC and MK. SS generated the model output and performed the analysis. JF, TP, GC, MK and SH assisted with the experimental design, analysis and interpretation of results. DK provided the Landsat glacier outlines.

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Appendix A: Definitions of symbols. ts denotes the model timestep

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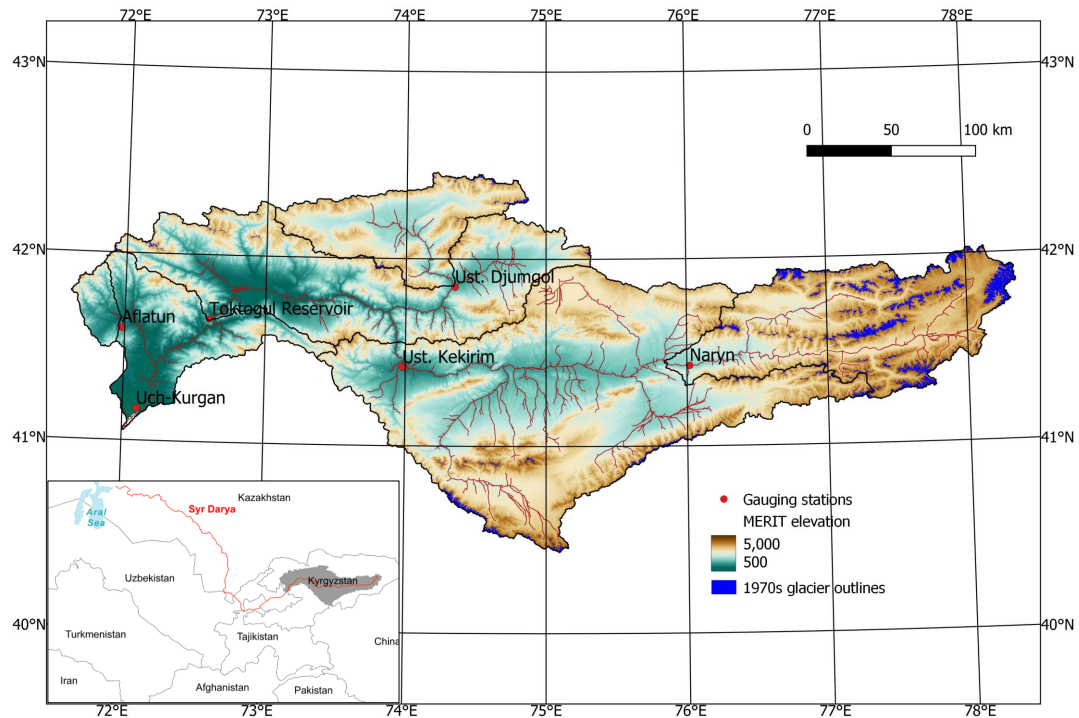
Figure 1. The location of Naryn catchment and gauging stations. The MERIT DEM elevation and 1970s Landsat derived glacier outlines used in this study are also displayed. The sub-catchment boundaries (black) and river path (red) calculated using DECIPHeR are shown. The Naryn River is a tributary of the Syr Darya River which flows across Central Asia from the Tien Shan mountains to the remains of the Aral Sea (bottom left inset figure).
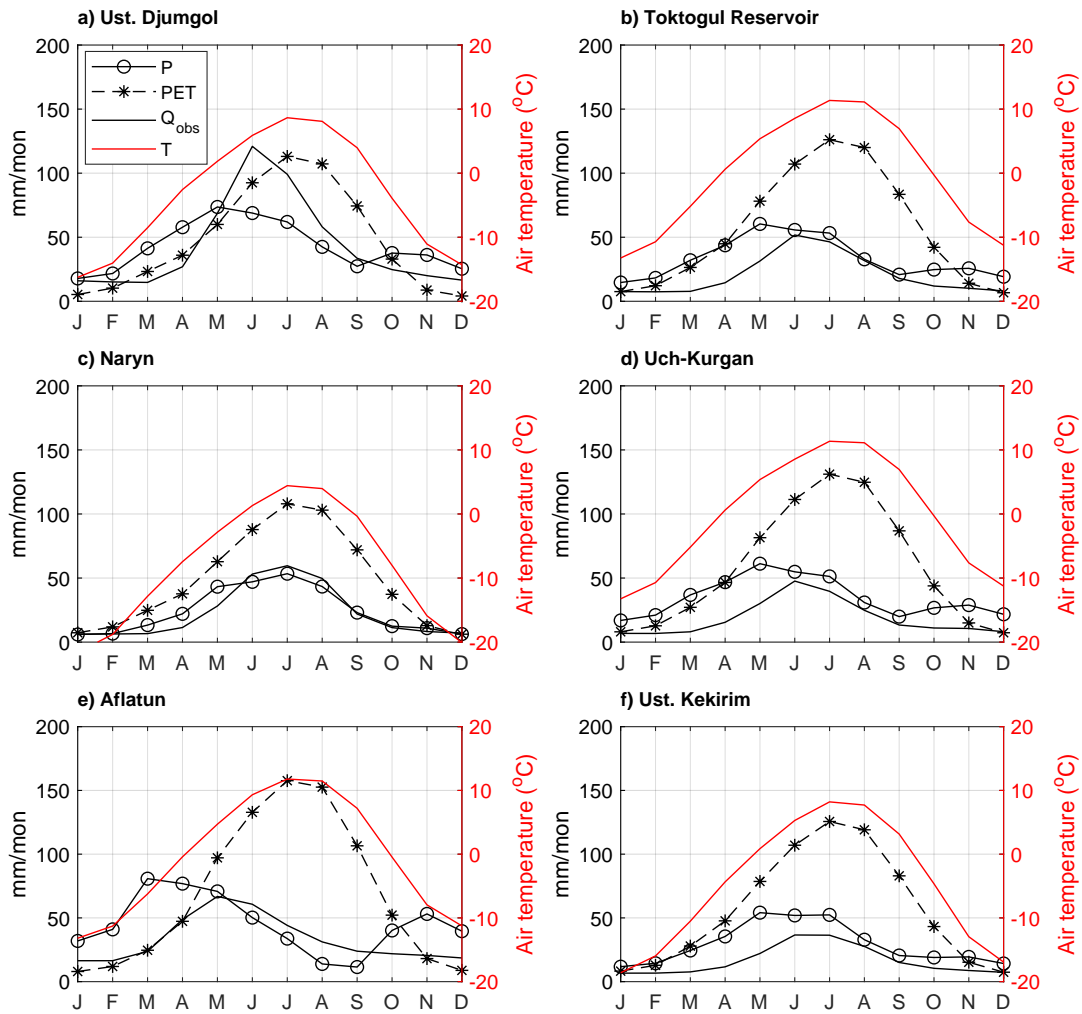
Figure 2. Climatology of monthly mean temperature (T), potential evaporation (PET), precipitation (P) and observed discharge (Q_{obs}) averaged for each sub-catchment for the calibration period 1951-1970. Temperature and PET are from the ERA5 and ERA5 back extension dataset, precipitation is from the APHRODITE dataset and observed discharge is from the Global Runoff Data Centre.
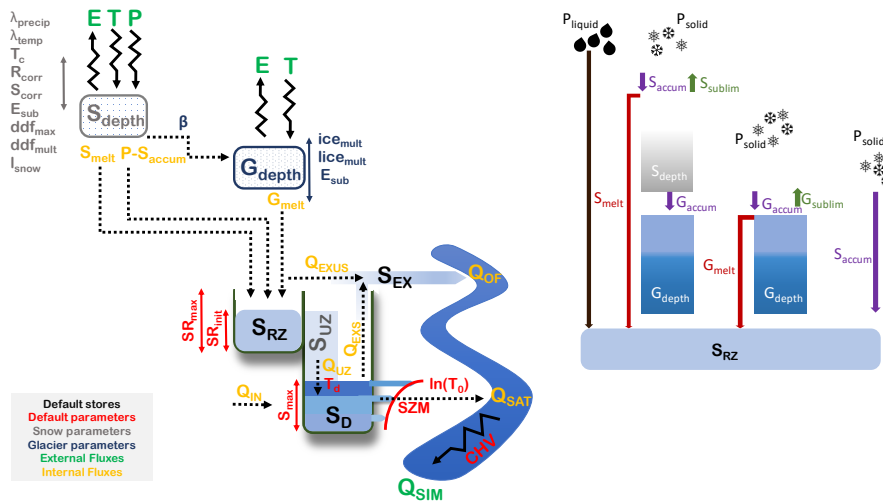
Figure 3. Conceptual diagram of the model adapted from Coxon et al. (2019) to show snow and glacier stores and model parameters (left). Glacier ice is situated beneath the snowpack or can be exposed if no snowpack exits (right). The snowpack accumulates when precipitation falls in solid form. Liquid precipitation, snow melt and glacier melt are transported to the root zone.
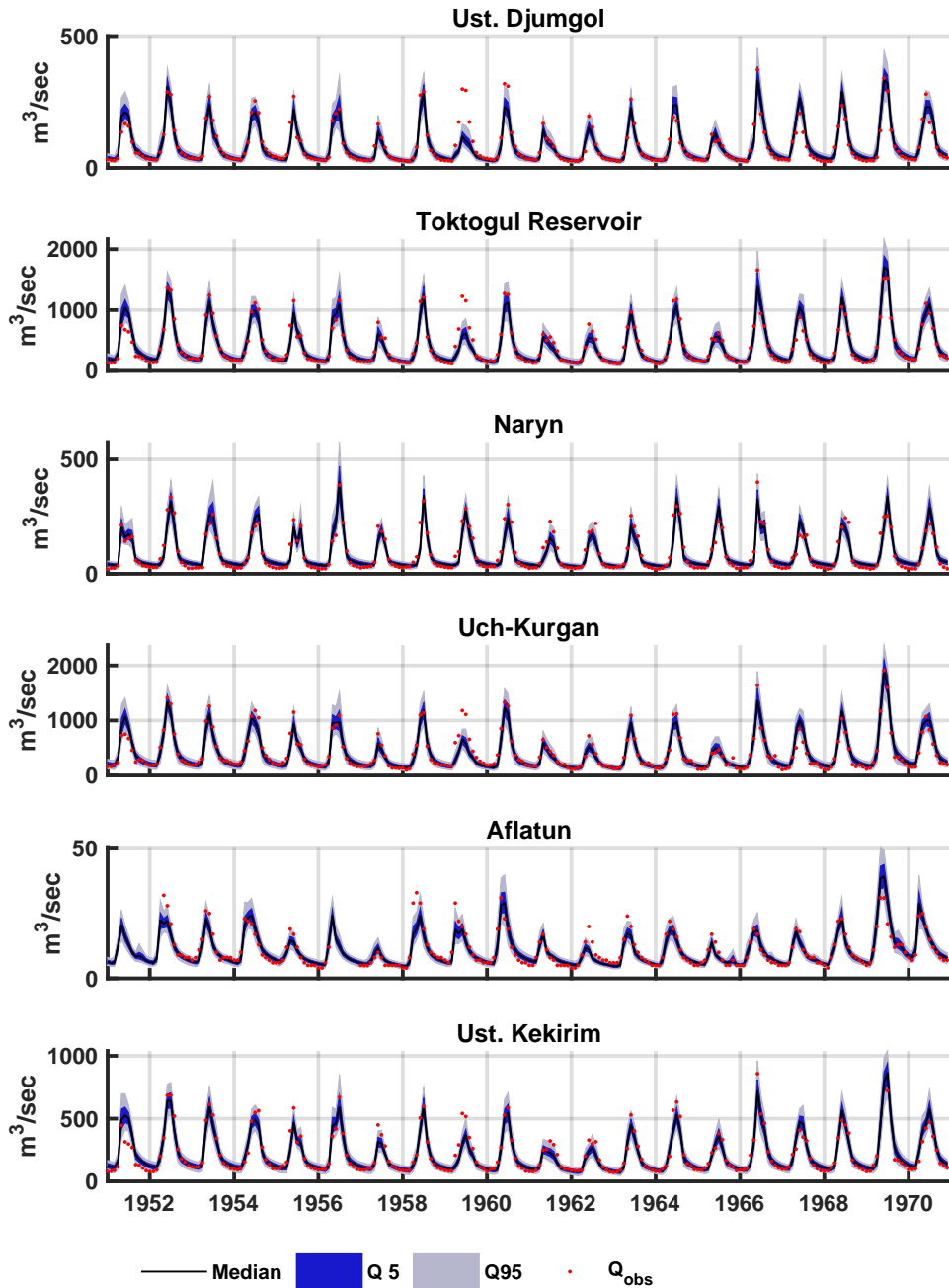
Figure 4. Observed and simulated discharge for the calibration period when parameters are selected for individual sub-catchments (MSC method). The shaded envelopes show the 5% and 95% percentile ranges and the black line show the 50th percentile of the best 0.5%
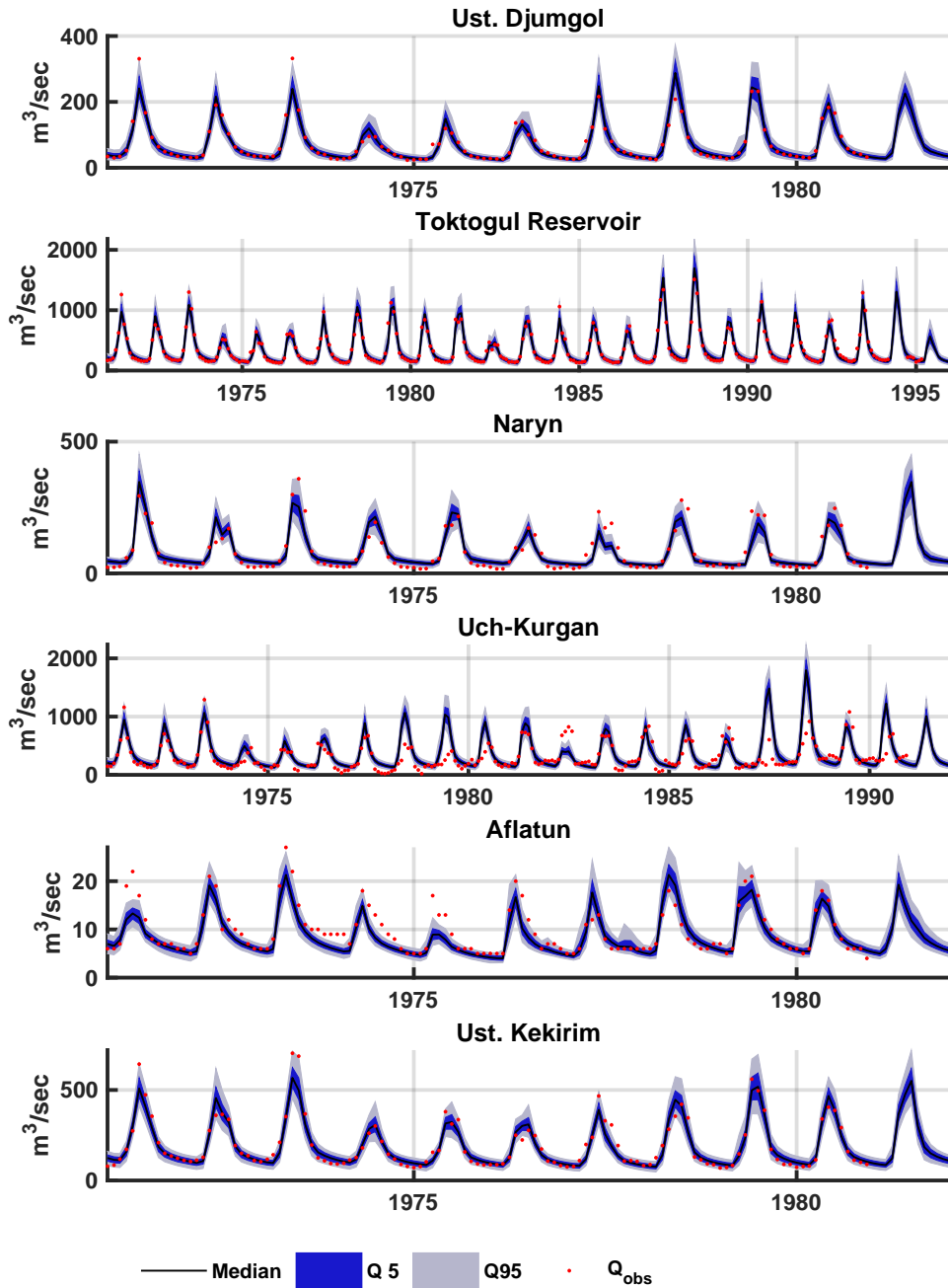
Figure 5. Observed and simulated discharge for the validation period when parameters are selected for individual sub-catchments (MSC method). The shaded envelope shows the 5th - 95th percentile ranges and the black line shows the 50th percentile of the best 0.5% simula-
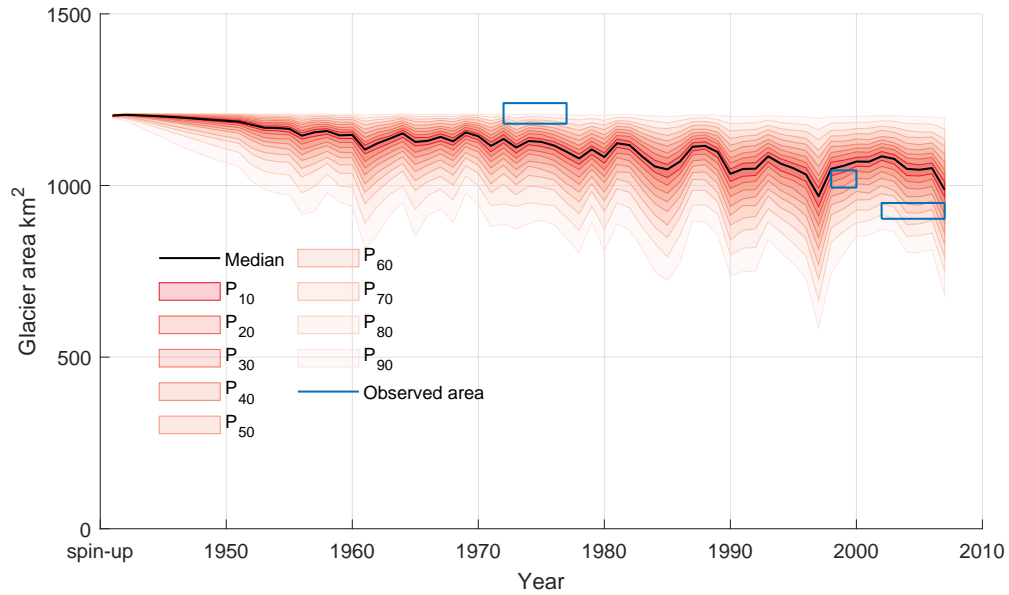
Figure 6. Simulated (top 0.5%, n = 751) catchment wide glaciated area using parameters for the Ust. Kurgan station which is located at the outlet of the catchment. Landsat observed glaciated area (Kriegel et al., 2013) is shown in blue boxes where the error on the time axis relates to the years when satellite imagery was used to calculate area. The Landsat glaciated area uses satellite imagery from; 1970's (1972-1977), late 1990s (1998-2000) and mid-2000s (2002-2007). A simulated threshold glacier depth of 1mm is used to identify the presence of glacier ice. The figure shows the spread of the glaciated areas predicted by the model, but the simulations are not sorted by conditional probability values.
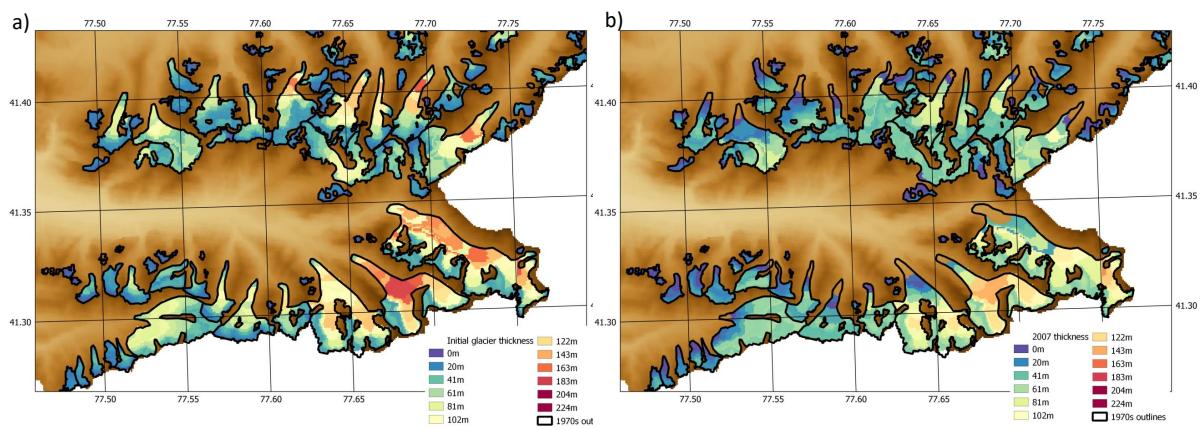
Figure 7. Panel a) shows initial glacier thicknesses on HRUs calculated using GlabTop2 in the upper part of the Naryn catchment. 1970s glacier outlines are shown in black. Panel b) shows the annual mean thickness for the year 2007 for the median ensemble member in the top 0.5% calibration simulations.
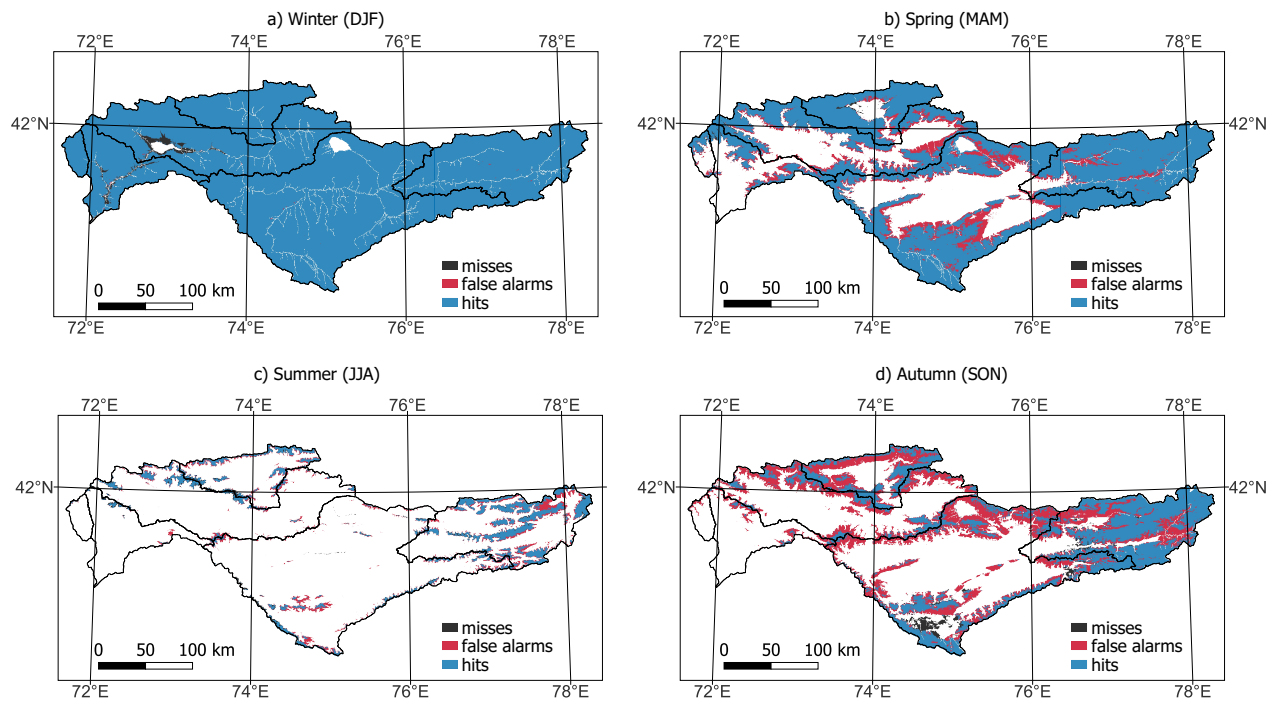
Figure 8. Spatial distribution of the hits, misses and false alarms between the simulated snow extent (median 50th percentile simulation) and MODIS snow extent for the year 2002. Hits, misses and false alarms are defined in Table 5.
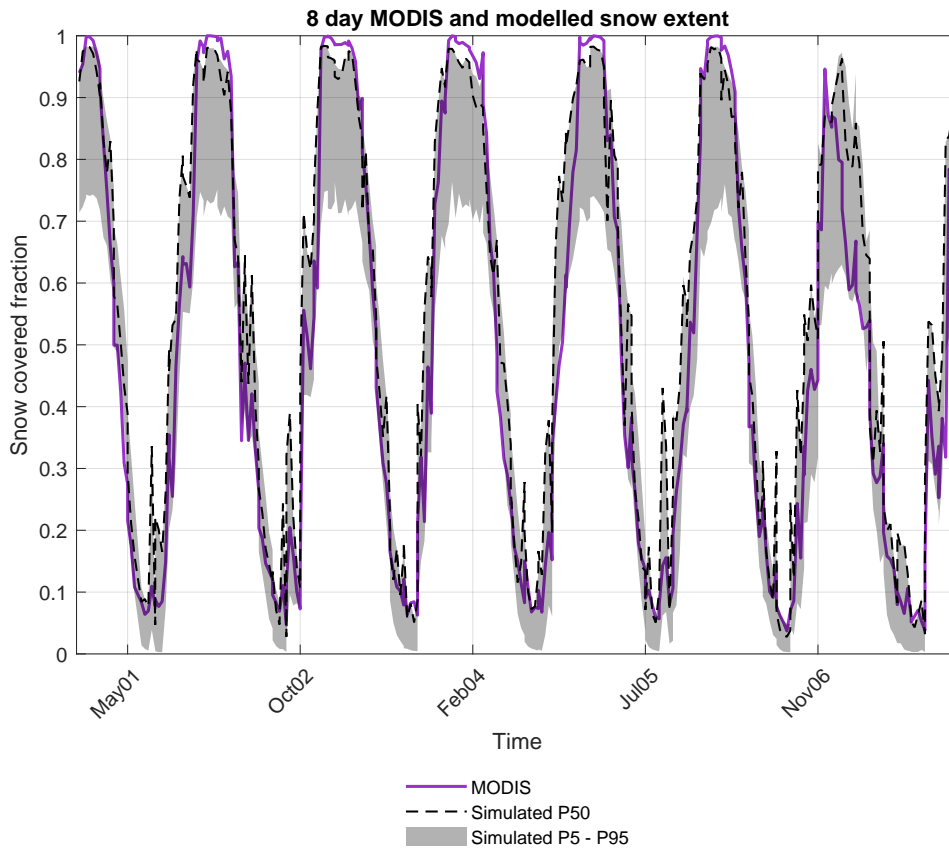
Figure 9. MODIS and simulated weekly fraction of the basin covered in snow. The grey shaded envelope shows the the 5th - 95th percentile range of the best 0.5% calibration runs.
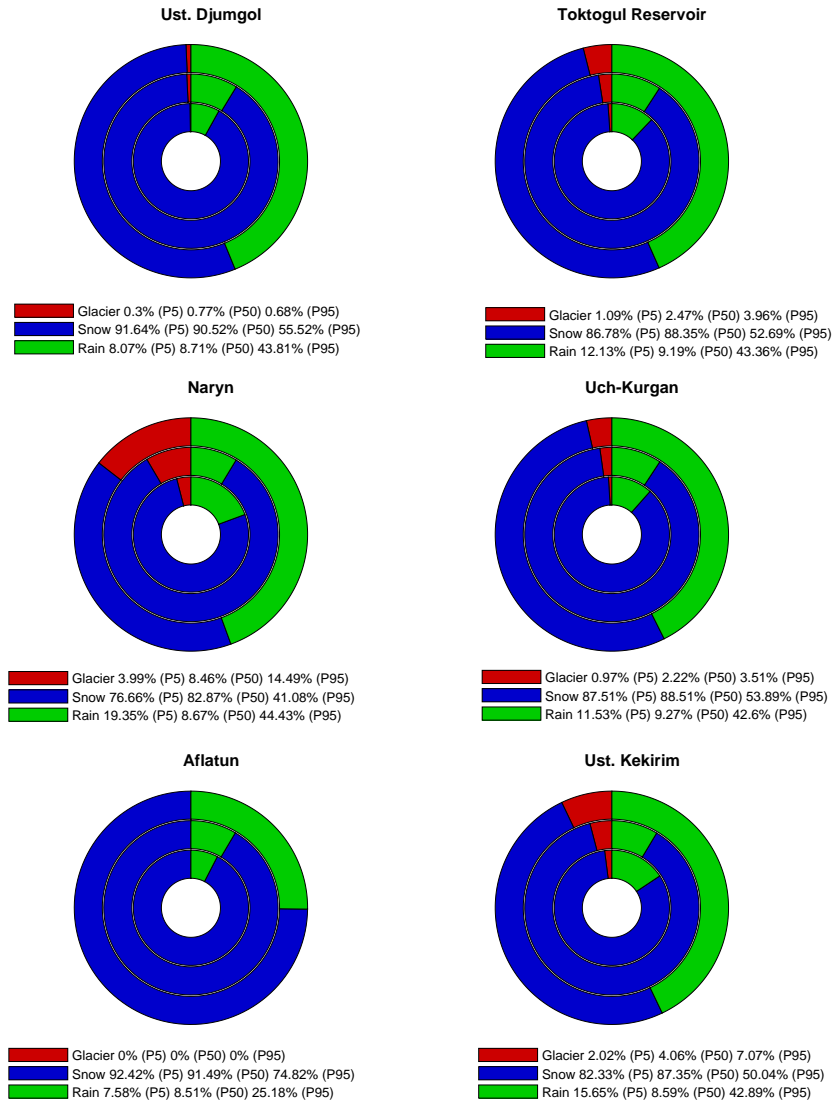
Figure 10. Simulated fraction of annual runoff from snow melting, glacier melting and rain averaged for the years 1951-2007. The inner ring shows the 5th percentile, the middle is the 50th percentile and the outer ring is the 95th percentile simulations.
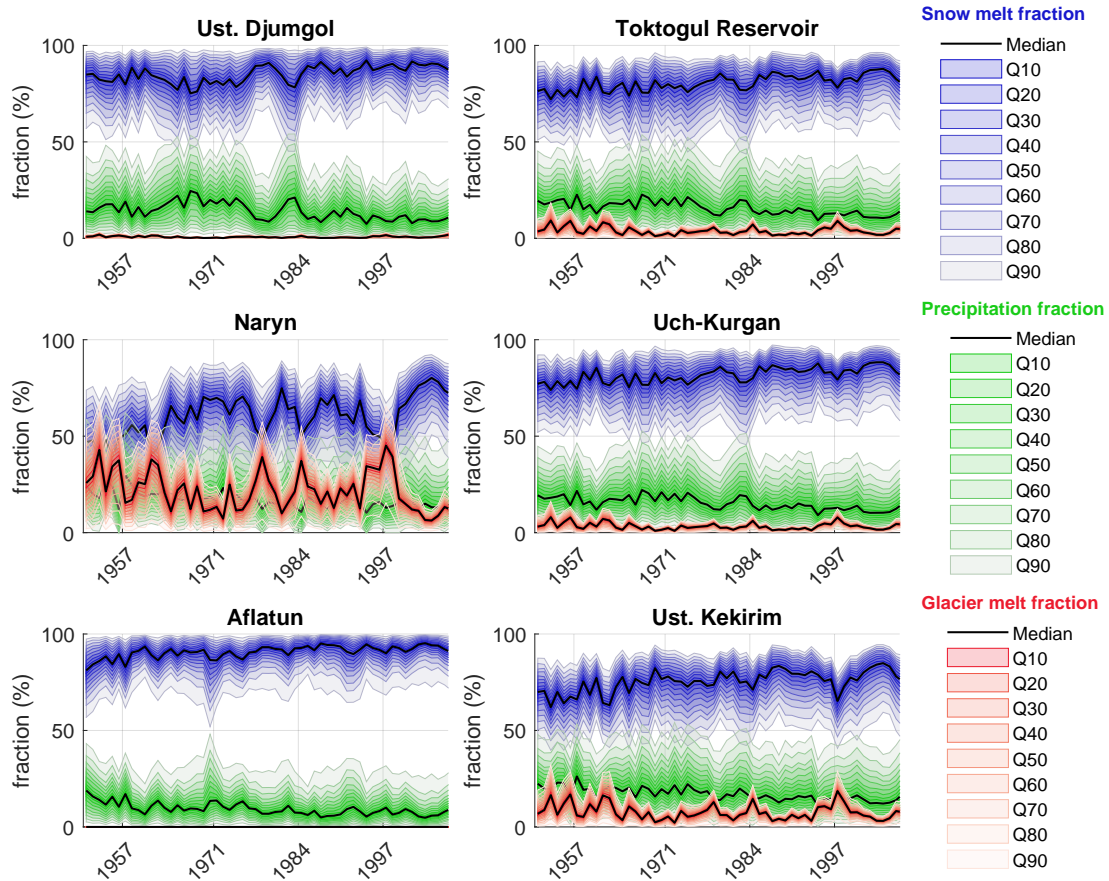
Figure 11. Annual percentage contribution of rain (green), snow melt (blue) and glacier melt (red) to the total runoff for the period 1951-2007. The coloured envelopes show the 10%-interval increasing percentile limits and the 50th percentile lines are shown in black.
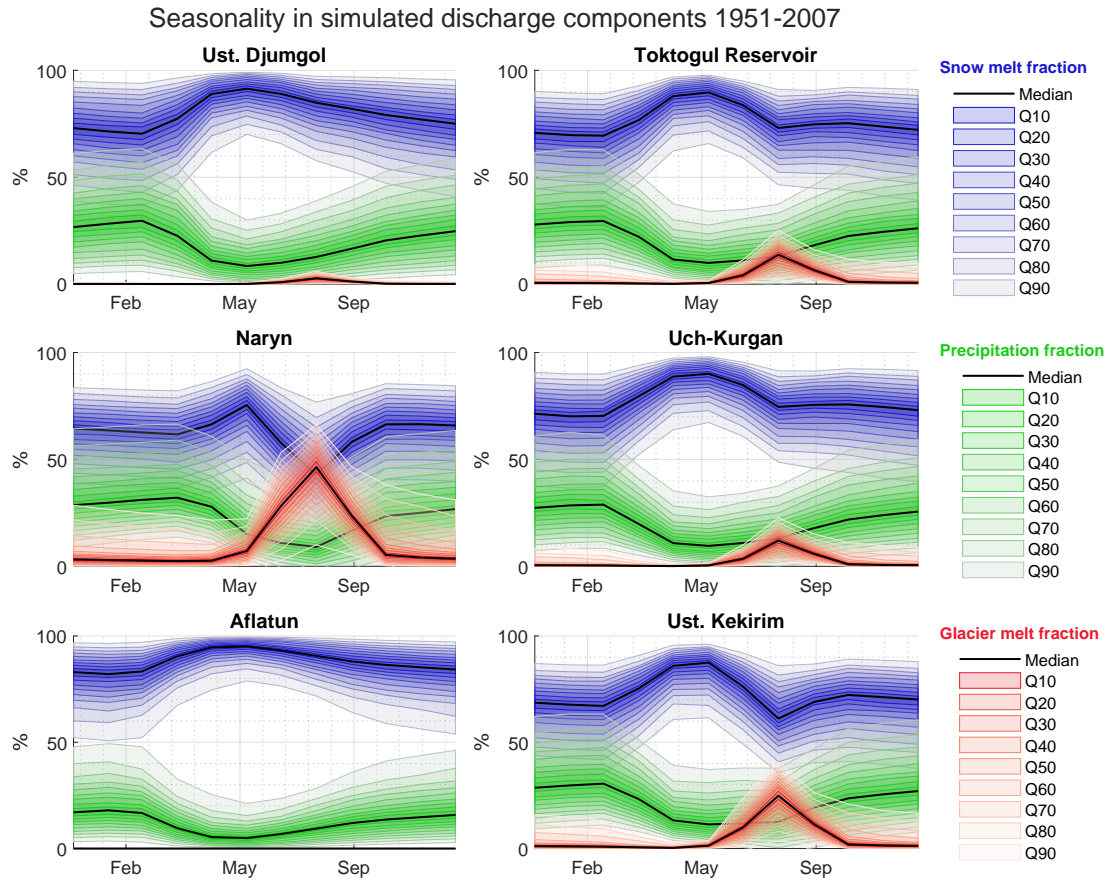
Figure 12. Monthly simulated runoff components averaged over the period 1951-2007 for the top 0.5% calibration simulations (n = 751). The coloured envelope shows the $5^{th} - 95^{th}$ percentile ranges.

Table 1. Summary of datasets used for this study.

Dataset	Temporal and spatial resolution	Time period
APHRODITE precipitation	Daily 0.25 °x 0.25 °	1951-2007
2m air temperature ERA5BE (ERA5)	Daily 0.25 °x 0.25 °	1951-1978 (1979-2007)
Potential evaporation ERA5BE (ERA5)	Daily 0.25 °x 0.25 °	1951-1978 (1979-2007)
Global Runoff Data Centre discharge	Monthly 6 stations	1951-1980 to 1995
ERA5 gridbox mean elevation	0.25 °x 0.25 °	-
MERIT digital elevation model	3 arcsecond	-
Landsat glacier outlines	polygons	1970s
MODIS weekly snow extent	500m	2001-2007

Table 2. The location, catchment area and elevation of the gauging stations from the Global Runoff Data Centre. Also listed are the annual mean climatology's (1951-1970) for; APHRODITE precipitation (P), ERA5 potential evapotranspiration (PET), ERA5 air temperature (T) and observed discharge Q_{obs}.

Station	Area (km^2)	Latitude	Longitude	Elevation (m)	P (mmyr^{-1})	PET (mmyr^{-1})	Q_{ob} (mmyr^{-1})	T (°C)
Ust. Djumgol	5,100	41.85	74.35	1,488	512	568	514	-4
Toktogul Reservoir	52,037	41.66	72.6	not provided	401	669	247	0
Naryn	10,474	41.43	76.02	2,039	288	572	270	-8
Uch-Kurgan	57,833	41.17	72.10	498	417	696	222	0
Aflatun	730	41.60	71.98	2,000	544	818	393	-1
Ust. Kekirim	34,430	41.42	73.98	1,234	350	676	197	-5

Table 3. List of parameters and ranges. Default parameters are described in detail in Coxon et al. (2019). The glacier and snow parameters have been added to the model for this study

Parameter	Symbol	Units	Minimum	Maximum
Default parameters				
Form of the exponential decline in conductivity	SZM	m	0.001	1.0
Maximum root zone storage	SR_{max}	m	0.001	1.0
Initial root zone storage	SR_{init}	m	0.0	0.1
Unsaturated time zone delay	T_d	mhr^{-1}	0.1	100
Channel routing velocity	CHV	mhr^{-1}	1.0	10000
Lateral saturated transmissivity	$ln(T0)$	$\ln(\mathrm{m^2hr^{-1}})$	-20	20
Max effective deficit of subsurface saturated zone	S_{max}	m	0.1	10
Snow parameters				
Temperature lapse rate	λ_{temp}	$^{\circ}\mathrm{C\,km}^{-1}$	-10	-2
Precipitation lapse rate	λ_{precip}	$\%\ 100\ \mathrm{m}^{-1}$	0	25
Maximum degree day factor snow	ddf_{max}	$\mathrm{mmw.e.^{\circ}C^{-1}d^{-1}}$	0	10
Minimum degree day factor snow scale factor	ddf_{mult}	–	0.1	0.95
Snow temperature lag factor	l_{snow}	–	0.01	1
Rain to snow conversion temperature	T_c	$^{\circ}\mathrm{C}$	-3	3
Snow and ice sublimation factor	E_{sub}	–	0.0	1.0
Rainfall correction factor	R_c	–	0.8	3
Snowfall correction factor	S_c	–	0.8	3
Glacier parameters				
Multiplication factor for ice melt	ice_{mult}	–	1	2
Multiplication factor for ice temperature lag factor	$l_{ice_{mult}}$	–	0.1	0.95
Basal turnover coefficient	β	day^{-1}	2.74 x 10^{-5}	2.74 x 10^{-3}

Table 4. Calibration and validation performance metrics for the best 0.5% of ensemble (751 simulations) when parameters are selected for individual sub-catchments. The table lists the metrics for the best simulation and the 5th, 50th and 95th percentiles limits.

Station	Best NSE	NSE			$PBIAS$			RSR_{MAM}			RSR_{JJA}			RSR_{SON}			RSR_{DJF}		
		5th	50th	95th	5th	50th	95th	5th	50th	95th	5th	50th	95th	5th	50th	95th	5th	50th	95th
Calibration																			
Djumgol	0.86	0.84	0.76	0.75	-7.27	-2.12	-3.78	0.41	0.52	0.64	0.66	0.81	0.69	0.20	0.19	0.28	0.07	0.06	0.13
Toktogul	0.91	0.87	0.81	0.79	-5.41	-2.41	4.17	0.36	0.43	0.35	0.58	0.74	0.83	0.20	0.17	0.16	0.06	0.09	0.16
Naryn	0.91	0.85	0.83	0.79	1.75	11.36	0.23	0.29	0.27	0.45	0.62	0.63	0.68	0.21	0.33	0.30	0.26	0.31	0.28
Uch-Kurgan	0.91	0.87	0.82	0.79	2.75	8.44	-8.05	0.44	0.31	0.40	0.53	0.68	0.76	0.17	0.37	0.23	0.13	0.11	0.19
Aflatun	0.84	0.80	0.73	0.74	-8.58	-2.36	6.05	0.65	0.82	0.69	0.58	0.51	0.50	0.17	0.32	0.42	0.13	0.21	0.37
Ust. Kekirim	0.90	0.87	0.80	0.79	-5.66	-9.03	7.54	0.31	0.26	0.38	0.63	0.80	0.67	0.17	0.21	0.42	0.13	0.20	0.25
Validation																			
Djumgol	0.83	0.82	0.79	0.70	-5.53	-0.22	-3.16	0.33	0.35	0.62	0.75	0.82	0.83	0.22	0.15	0.31	0.08	0.06	0.16
Toktogul	0.93	0.90	0.90	0.86	-4.07	-2.86	5.37	0.35	0.35	0.31	0.50	0.50	0.66	0.18	0.14	0.14	0.05	0.08	0.15
Naryn	0.87	0.68	0.74	0.81	-7.84	13.02	7.31	0.29	0.27	0.41	1.01	0.84	0.60	0.24	0.37	0.35	0.28	0.33	0.31
Uch-Kurgan	-0.16	-0.01	-0.28	0.39	21.54	32.06	8.60	1.04	0.89	0.64	1.64	1.87	1.26	0.36	0.81	0.56	0.29	0.30	0.30
Aflatun	0.77	0.61	0.73	0.72	-18.14	-8.27	1.58	0.75	0.78	0.72	0.88	0.58	0.60	0.38	0.25	0.36	0.30	0.22	0.35
Ust. Kekirim	0.91	0.87	0.82	0.83	-7.83	-7.70	5.64	0.31	0.23	0.31	0.62	0.76	0.60	0.16	0.20	0.39	0.14	0.20	0.25

Table 5. Table of possible pixel states in a binary classification scheme for the validation of seasonal MODIS (O) and modelled (M) snow extent.

	Snow in MODIS	No snow in MODIS
Snow in model	M_1O_1	M_1O_0
No snow in model	M_0M_1	M_0O_0

Table 6. Seasonal validation metrics for MODIS and modelled snow extent for the 5th, median and 95th percentile prediction limits of the best 0.5% calibration runs). Metrics for each season are calculated by averaging annual metrics over the years 2001-2007. Annual metrics are listed in Table S4 of the Supplementary Material.

	Winter (DJF)			Spring (MAM)			Summer (JJA)			Autumn (SON)		
	P5	**P50**	P95	P5	**P50**	P95	P5	**P50**	P95	P5	**P50**	P95
Error Bias E	0.03	**1.11**	3.03	0.47	**5.84**	41.00	0.04	**10.51**	8.96	0.30	**33.53**	12.47
Hit Rate (H)	0.72	**0.97**	0.98	0.85	**0.96**	0.99	0.26	**0.86**	0.89	0.62	**0.95**	0.90
Critical Success Index	0.72	**0.94**	0.95	0.80	**0.83**	0.80	0.25	**0.47**	0.46	0.56	**0.56**	0.59
False Alarm Ratio (F)	0.01	**0.03**	0.03	0.07	**0.14**	0.19	0.11	**0.48**	0.51	0.14	**0.42**	0.37

Table 7. Trends in annual air temperature, PET and precipitation and the fraction of annual runoff from snow melt, glacier melt and rainfall for the period 1951-2007. Trends are derived for the 50th percentile experiment using a Mann-Kendal test with Sen's slope estimator. Bold font indicates statistically significant trends with pValues $\leq$ 0.05. Trends in annual simulated and observed discharge is also shown for the period 1951 to a variable end date which is dependent on the available observations.

Station	T	PET	P	Glacier melt	Snow melt	Rain	Q_{sim}	Q_{obs}	Observations
	$^\circ$C/dec	mm/dec	mm/dec	%/dec	%/dec	%/dec	$m^3 s^{-1}/dec$	$m^3 s^{-1}/dec$	end
Ust. Djumgol	**0.19**	-0.01	**-0.07**	0.05	**0.74**	**-0.85**	-2.02	-5.24	1981
Toktogul Reservoir	**0.20**	-0.01	**-0.04**	0.06	**0.74**	**-0.79**	-9.76	-14.09	1995
Naryn	**0.18**	0.00	0.00	-0.12	0.66	**-0.82**	-2.84	-3.81	1981
Uch-Kurgan	**0.20**	-0.01	**-0.04**	0.05	**0.62**	**-0.69**	-9.61	**-33.31**	1991
Aflatun	**0.19**	**-0.03**	**-0.06**	0.00	0.02	-0.02	-0.45	-0.68	1981
Ust Kekirim	**0.12**	0.00	-0.02	0.00	**0.69**	**-0.69**	-11.98	**-14.18**	1981

Symbol	unit	Definition
Q_{sim}	$\mathrm{mts^{-1}}$	Simulated flow
Internal fluxes		
Q_{IN}	$\mathrm{mts^{-1}}$	Upslope input flow
Q_{OF}	$\mathrm{mts^{-1}}$	Overland flow (sum of S_{EXS} and S_{EXUS})
Q_{SAT}	$\mathrm{mts^{-1}}$	Saturated flow
Q_{EXUS}	$\mathrm{mts^{-1}}$	Precipitation excess flow
Q_{EXS}	$\mathrm{mts^{-1}}$	Saturation excess flow
Stores		
S_D	m	Saturated storage deficit
S_{RZ}	m	Root zone storage
S_{EX}	m	Saturation excess storage
S_{UZ}	m	Unsaturated storage
Forcing climate		
E	$\mathrm{mts^{-1}}$	Evapotranspiration
P	$\mathrm{mts^{-1}}$	Precipitation
T	$^{\circ}\mathrm{C}$	Temperature
Hydrology parameters		
SZM	m	Form of the exponential decline in conductivity
SR_{max}	m	Maximum root zone storage
SR_{init}	m	Initial root zone storage
T_d	$\mathrm{mts^{-1}}$	Unsaturated time zone delay
CHV	$\mathrm{mts^{-1}}$	Channel routing velocity
$ln(T0)$	$\ln(\mathrm{m^2 ts^{-1}})$	Lateral saturated transmissivity
S_{max}	m	Max effective deficit of subsurface saturated zone
Snow parameters		
S_{depth}	m w.e.	Snow depth
S_{melt}	$\mathrm{m\ w.e.ts^{-1}}$	Snow melt rate
S_{accum}	$\mathrm{m\ w.e.ts^{-1}}$	Snow accumulation
S_{sublim}	$\mathrm{m\ w.e.ts^{-1}}$	Snow sublimation
P_{liquid}	$\mathrm{mts^{-1}}$	Liquid precipitation
P_{solid}	$\mathrm{mts^{-1}}$	Solid precipitation
λ_{temp}	$^{\circ}\mathrm{C\ km^{-1}}$	Temperature lapse rate
λ_{precip}	$\%\ 100\,\mathrm{m^{-1}}$	Precipitation lapse rate

ddf_{max}	mmw.e.$°C^{-1}ts^{-1}$	Maximum degree day factor snow
ddf_{mult}	−	Minimum degree day factor snow scale factor
l_{snow}	−	Snow temperature lag factor
T_c	$°C$	Rain to snow conversion temperature
E_{sub}	−	Snow and ice sublimation factor
R_c	−	Rainfall correction factor
S_c	−	Snowfall correction factor

Glacier parameters

G_{depth}	m w.e.	Glacier depth
G_{melt}	m w.e.ts^{-1}	Glacier melt
G_{accum}	m w.e.ts^{-1}	Glacier accumulation
G_{sublim}	m w.e.ts^{-1}	Glacier sublimination
ice_{mult}	−	Multiplication factor for ice melt
$l_{ice_{mult}}$	−	Multiplication factor for ice temperature lag factor
β	ts^{-1}	Basal turnover coefficient

Table A1: Definition of symbols shown in Fig. 3