Surface energy and mass balance of Mera Glacier (Nepal, Central Himalaya) and their sensitivity to 1 2 temperature and precipitation Arbindra Khadka^{1,2,3}, Fanny Brun¹, Patrick Wagnon¹, Dibas Shrestha³, Tenzing Chogyal Sherpa² 3 4 5 **Affiliations** 6 ¹University Grenoble Alpes, CNRS, IRD, IGE, Grenoble, France 7 ²International Centre for Integrated Mountain Development, Kathmandu, Nepal 8 ³Central Department of Hydrology and Meteorology, Tribhuvan University, Kirtipur, Nepal 9 10 This manuscript has been submitted for publication in the Journal of Glaciology. The manuscript has been accepted for publication in May 2024. The published version might slightly differ, due 11 12 to the copy-editing process. 13

14 Abstract

The sensitivity of glacier mass balance to temperature and precipitation variations is crucial for informing models that simulate glaciers' response to climate change. In this study, we simulate the glacier-wide mass balance of Mera Glacier with a surface energy balance model, driven by in-situ meteorological data, from 2016 to 2020. The analysis of the share of the energy fluxes of the glacier shows the radiative fluxes account for almost all the energy available during the melt season (May to October). However, turbulent fluxes are significant outside the monsoon (June to September). On an annual scale, melt is the dominant mass flux at all elevations, but 44 % of the melt refreezes across the glacier. By reshuffling the available observations, we create 180 synthetic series of hourly meteorological forcings to force the model over a wide range of plausible climate conditions. A +1 (-1)°C change in temperature results in a -0.75 \pm 0.17 (+0.93 \pm 0.18) m w.e. change in glacier-wide mass balance and a +20 (-20)% change in precipitation results in a +0.52 \pm 0.10 (-0.60 \pm 0.11) m w.e. change. Our study highlights the need for physically based approaches to produce consistent forcing datasets, and calls for more meteorological and glaciological measurements in High Mountain Asia.

1. INTRODUCTION

The pace of climate warming in High Mountain Asia (HMA) is accelerating (Pepin and others, 2015) and precipitation in these regions exhibits significant heterogeneity and remains insufficiently comprehended (Lutz and others, 2014). Furthermore, the intricate relationship between precipitation and temperature variations proves to be a formidable puzzle. This connection, intricately intertwined with glacier mass balance, poses a challenge for understanding the recent evolution of glaciers in HMA (Oerlemans and Reichert, 2000). While multi-year satellite-based estimates of mass changes allow to map the heterogeneity of glacier mass balance across large scales (e.g., Hugonnet and others, 2021), they need to be complemented by other approaches to further elucidate these patterns of contrasted mass losses. One possible approach is to consider that glacier mass changes are the combination of a change in climate conditions modulated by a glacier sensitivity to these changes (e.g., Oerlemans and Reichert, 2000; Marzeion and others, 2012). Following this approach, Sakai and Fujita (2017) demonstrated that regionally different sensitivity to temperature changes could be the main driver of observed mass losses across Asia. They found that the glacier mass balance sensitivity to temperature was determined by the general climatology, and in particular, by the summer temperature, the annual range of temperature and the ratio between summer and annual precipitation. However, their approach relies on a number of simplifying

assumptions that consider only the climate at the equilibrium line altitude (Ohmura and others, 1992) and the climate data they used has a coarse spatial resolution. There is thus room to improve the methodology they applied, in particular through a better representation of processes responsible for glacier mass losses and gains.

These processes controlling the glacier mass are determined by the surface energy balance (SEB), which is commonly modelled to investigate how glacial mass balance is governed and how sensitive it is to climatic variables (Fujita, 2008; Azam and others, 2014; Fugger and others, 2022). There is a long history of studies that investigated the glacier SEB at various locations and at various temporal and spatial scales to relate atmospheric variables to glacier mass changes (e.g., Oerlemans and Knap, 1998; Favier and others, 2004). Specifically, in Hindu Kush Himalaya (HKH), a number of studies investigated the SEB of glaciers in different climate contexts (Mölg and others, 2012; Zhu and others, 2015, 2018, 2021; Huintjes and others, 2015; Fugger and others, 2022; Arndt and Schneider, 2023). They highlight the different sensitivities to temperature and precipitation in different climate conditions, with the dry and cold (continental) climate that prevails in the north west margin of HKH being associated to low sensitivities of glacier mass balance to temperature, and the warmer and wetter (oceanic) climate of south east HKH corresponding to larger sensitivities (e.g., Arndt and Schneider, 2023). The larger sensitivities are associated to the prevalence of surface melt in the surface mass balance. Surface energy based studies find highly non linear sensitivity of the mass balance to precipitation, unlike studies based on empirical approaches, such as degree-day modeling (e.g., Wang and others, 2019). This is due to the highly non linear response of glacier surface mass balance to the albedo effect (e.g., Arndt and Schneider, 2023).

However, in HKH most of the SEB studies have two main limitations: either they were done at point scale (Kayastha and others, 1999; Azam and others, 2014; Acharya and Kayastha, 2019; Litt and others, 2019; Mandal and others, 2022), or they used meteorological data from reanalysis products (Arndt and Schneider, 2023). The point-scale modelling of the SEB is limited because the SEB is very sensitive to the surface state of the glacier (ice, snow or debris), and to the distribution of meteorological variables (precipitation, temperature, radiative fluxes, etc.) that vary across the glacier area (Oerlemans and others, 1999). Modelling the SEB of a glacier across its entire area requires distributed measurements of meteorological variables, and measurements of the glacier surface mass balance at multiple locations, including the accumulation area. Unfortunately, such data are seldom available in HKH (Huintjes and others, 2015; Arndt and others, 2021; Srivastava and Azam, 2022; Oulkar and others, 2022). Meteorological variables obtained from reanalysis can be heavily biased, especially if they are not

downscaled with local measurements (e.g., Hamm and others, 2020; Khadka and others, 2022). When meteorological variables from reanalysis are used to force a glacier mass balance model, they first need to be debiased, which is often done by tuning a precipitation correction factor until the glacier mass balance matches observations. While there is usually no alternative, this method is known to be subject of equifinality (e.g., Rounce and others, 2020).

This article presents a glacier-wide SEB analysis of Mera Glacier in the eastern part of Central Himalaya. We applied the 'COupled Snowpack and Ice surface energy and mass balance model in PYthon' (COSIPY: Sauter and others, 2020) which has been optimised and evaluated using site specific measurements (Fig. S1 in supplementary material). Among Nepal's monitored glaciers, Mera Glacier stands out for its extensive and continuous meteorological and mass balance data, making it one of the most comprehensively observed glaciers in the region (Wagnon and others, 2021; Khadka and others, 2022). By integrating field measurements, in-situ meteorological data, and the SEB model, we aim to enhance our understanding of (1) the physical processes governing the seasonal and spatial variability of the glacier mass balance, and (2) the sensitivity of the mass balance to meteorological variables. The findings from this comprehensive study will give us a better understanding of the impact of the on-going climate change on Himalayan glaciers.

2. STUDY AREA AND CLIMATE

2.1 Mera Glacier

Mera Glacier, situated in the eastern part of the Central Himalaya within the Upper Dudh Koshi basin, is a plateau-type debris free glacier. Encompassing an area of 4.84 km² in 2018, the glacier stretches from an altitude of 6390 m a.s.l. to a minimum of 4910 m a.s.l. (Fig. 1). This north-facing glacier features a gentle slope with a mean inclination of around 16 degrees. At an elevation of approximately 5900 m a.s.l., the glacier separates into two distinct branches, the Mera branch and the Naulek branch. The Mera branch initially heads north and then curves westward, while the Naulek branch extends ~2 km towards the northeast. The Mera branch is the largest of the two branches and accounts for about 80 % of the glacier's total area.

"Figure 1 near here"

2.2 Climate

Like other glaciers in Nepal, Mera Glacier is a summer accumulation type glacier, gaining mass mainly from the summer monsoon (June to September) snowfalls brought by the South Asian monsoon system (Wagnon and others, 2013; Thakuri and others, 2014; Shea and others, 2015). The glacier experiences most of its accumulation and ablation during the monsoon, which makes it a key season to understand the climatic regime of the glacier (Ageta and Higuchi, 1984). From June to September, the average air temperature measured between 2012 and 2020 at 5360 m a.s.l. on Naulek branch is 0.3 °C, and the average precipitation recorded at 4888 m a.s.l. is equal to 570 mm, with an annual precipitation of 818 mm (Khadka and others, 2022). During this season, warm air masses flow from the Bay of Bengal and bring moisture and precipitation in the Himalaya (Perry and others, 2020). In just a few days, marking the start of the post-monsoon (October-November), generally at the beginning of October, meteorological conditions change abruptly to become dry, sunny and increasingly cold and windy. Very occasionally, this season is marked by the intrusion of typhoons in the Himalaya, which bring large amounts of snowfalls above ~4000 m a.s.l. in just a few days, like in October 2013 and 2014 (Shea and others, 2015). The winter (December-February) is similar but harsher than the post-monsoon with constantly cold, dry, and very windy conditions. At Naulek (5360 m a.s.l.), the average air temperature during this season is -10.4 °C. The pre-monsoon starts in March and is characterized by progressively warmer, wetter and less windy conditions until the monsoon is totally installed at the beginning of June. The pre-monsoon is then the second wettest season after the monsoon with approximately one quarter of the annual precipitation on the glacier (Khadka and others, 2022).

3. DATA

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3.1 Meteorological Data

A network of automatic weather stations (AWSs) has been installed and gradually expanded since 2012 in Mera Glacier catchment at different elevations and on various surfaces (Fig. 1). In this present study, we mainly use data from two on-glacier AWSs, one located in the ablation area on Naulek branch at 5360 m a.s.l., AWS-Low (hereafter referred as AWS-L; 4 years of data between November 2016 and October 2020), and one located in the accumulation area at 5770 m a.s.l., AWS-High (hereafter referred as AWS-H; 3 years of data between November 2017 and November 2020; Fig. S2). Both AWSs record air temperature (T), relative humidity (RH), wind speed (u), incoming and outgoing longwave (LWin and LWout, respectively) and shortwave (SWin and SWout, respectively) radiation (Table 1).

"Table 1 near here"

There are numerous data gaps in both records, due to AWS failure, power shortage during occasional abundant snowfalls covering the solar panels for instance or sensor breakdowns (Table 1; Fig. 2 and see https://glacioclim.osug.fr/). The largest data gap occurred at AWS-L, when the station fell down from 12 December 2017 to 24 November 2018. To fill these gaps, data from the off-glacier Mera La AWS was used. Linear correlation relationships were established each month between the same variables from the two stations from November 2016 to October 2020, at an hourly time step (Fig. S3 and Table S1). The atmospheric pressure (Pa) measured at Mera La AWS is used at AWS-L without any interpolation, as both AWSs are located less than 2 km apart at almost the same elevation (Table 1; Fig. 1).

The Khare Geonor station (4888 m a.s.l.) has been installed on 24-25 November 2016, 472 m lower in elevation and ~3 km northwest of AWS-L. In Mera catchment, this is the only station of the network recording all-weather precipitation, thanks to a weighing device. The precipitation data have been corrected for undercatch following the method by Førland and others (1996) as a function of wind speed and precipitation phase (liquid or solid) depending on air temperature (See the details in the supplement of Khadka and others, 2022).

"Figure 2 near here"

3.2 Spatial distribution of meteorological forcings

Given the complexity and heterogeneity of the local climate and terrain, it is a challenging task to distribute point data spatially. For air temperature, relative humidity and incoming longwave radiation, we derived empirical linear relationships from the respective measurements of the two on-glacier AWSs installed with a 410 m difference in altitude. To take advantage of the longest data series without gaps at AWS-H, we calculate the gradients between 01 March 2018 and 28 February 2019, even though a major part of the data from AWS-L is reconstructed over this period. Since AWS-L has a relatively longer and more consistent dataset than AWS-H, we distribute meteorological data from this lower station across the glacier using observed altitudinal gradients of air temperature, relative humidity, and incoming longwave radiation (Table S2; Fig. S4). In meteorology, the dew-point temperature gradient is more commonly encountered than the relative humidity gradient. However, in this particular study, the relative humidity gradient is utilised because the COSIPY model is developed based on relative humidity input data. For completeness, we also compute the dew-point temperature gradient from data collected at both stations, which we subsequently convert into a relative humidity gradient. This converted gradient is comparable to the one

directly obtained from relative humidity measurements at AWS-L and AWS-H, that we use in our study (Fig. S5 and corresponding supplementary text).

The incoming solar radiation has been distributed for each grid following the methods of Sauter and others (2020), already tested and applied on Himalayan glaciers (e.g., Arndt and Schneider, 2023). First the fraction of diffuse radiation (F_{diff}) is calculated based on Wohlfahrt and others (2016):

$$F_{diff} = e^{-e^{p_1 - (p_2 - p_3CI)}} * (1 - p_4) * p_4$$
 (1)

Where p1 = 0.1001, p2 = 4.7930, p3 = 9.4758, p4 = 0.2465 are parameters from Wohlfahrt and others (2016) and CI, for clearness index, is the ratio of incoming solar radiation to maximum incoming solar radiation. F_{diff} may vary from 0 to 1. Second, the measured incoming shortwave radiation is splited into beam (Rb = SWin * (1 - F_{diff})) and diffuse (Rd = SWin * F_{diff}) radiation. Then, the corrected solar radiation (Rc) is calculated on each grid based on Ham (2005).

$$Rc = Rb * cf + Rd \tag{2}$$

Where cf is the correction factor calculated based on the azimuth and the slope of each grid following Ham (2005).

As our network does not allow to assess precipitation variations with elevation over Mera Glacier catchment, precipitation amounts are assumed constant all over the catchment and equal to Khare Geonor records. Similarly, wind speed is likely spatially variable due to terrain aspect, roughness and heterogeneity but in first approximation, we had no choice but to consider the wind as constant over Mera Glacier and equal to that at AWS-L. These first-order approximations are discussed in section 6.3.

3.3 Mass balance data

Mera Glacier has been monitored since 2007 at least once a year in November and its mass balance series is one of the longest continuous field-based series of the Himalaya. Its glacier-wide mass balance is obtained annually using the glaciological method based on a network of 16 ablation stakes and five accumulation sites on average (Fig. 1). This glacier-wide mass balance series has been calibrated with the 2012-2018 geodetic mass balance (Wagnon and others, 2021). Over the period 2007-2023, the mean corrected glacier-wide mass balance is equal to -0.42 ± 0.23 m w.e. a^{-1} , with only four positive mass balance years out of 16. Our study period 2016-20 was characterized by constantly negative mass balance years

with a mean glacier-wide value of -0.74 \pm 0.18 m w.e. a^{-1} , 2017-2018 being the most negative year (-0.92 \pm 0.16 m w.e. a^{-1}) and 2019-2020 being the least negative (-0.49 \pm 0.22 m w.e. a^{-1}) (Table 2). Between 2007 and 2023, the glacier has lost around 10 % of its surface area.

Point mass balances measured at each stake or at each accumulation site can exhibit significant spatial variability depending on factors such as elevation, slope, aspect, and wind redistribution. Table 2 provides the annual and mean values of point mass balances over the study period 2016-20 at the two on-glacier AWSs. For AWS-L, it is computed by using all stake measurements available on Naulek branch between 5300 and 5380 m a.s.l., using a mean measured snow density of 370 kg m⁻³ and an ice density of 900 kg m⁻³. For AWS-H, point mass balances measured at sites located between 5750 and 5790 m a.s.l. in the vicinity of the station are averaged, using depth averaged snow densities measured during each field campaign (from 380 to 430 kg m⁻³).

"Table 2 near here"

4. METHODS

4.1 Model Description (COSIPY)

In this study, we use COSIPY model, which is a python-based coupled snowpack and ice SEB model (Sauter and others, 2020). The model is a one-dimensional multi-layer discretisation of the snowpack/ice column that resolves the energy and mass conservation, and calculates the surface energy fluxes using input meteorological variables as forcings. For spatially distributed simulations, the point model is run independently at each point of the glacier domain, neglecting the lateral mass and energy fluxes. The model's reliability has been validated across distinct contexts and geographical regions (Sauter and others, 2020; Blau and others, 2021; Arndt and others, 2021). COSIPY model calculates the energy available for melt (QM) for each time step and is expressed as:

$$QM = SWnet + LWnet + QS + QL + QC + QR$$
(3)

where *SWnet* is the remaining net shortwave radiation at the surface after penetration inside the snow/ice surface, *LWnet* is net longwave radiation and Q denotes the other heat fluxes of different subsequent scripts S: sensible, L: latent, C: sub-surface (called ground-heat flux in Sauter and others, 2020), and R: rain in W m⁻². All the fluxes are positive when directed towards the surface and negative away from the surface.

When the surface temperature is at the melting point and QM > 0, the excess energy is used to melt. Additionally, COSIPY calculates a subsurface melt, that is calculated from the penetration of the incoming shortwave radiation (Sauter and others, 2020). For the rest of the analysis, we refer to total melt as the sum of surface and subsurface melt.

4.1.1 Model settings

The COSIPY model is used in its default configuration. The turbulent fluxes, QS and QL, are calculated as:

$$QS = \rho_{air}C_PC_Su(T - T_S) \tag{4}$$

$$QL = \rho_{air} L_V C_l u(q - q_S) \tag{5}$$

where ρ_{air} is air density (in kg m⁻³); C_P is the specific heat of air at constant pressure (in J kg⁻¹ K⁻¹) and L_V is the latent heat of sublimation/vaporization (in J kg⁻¹). C_S and C_l are the dimensionless transport coefficients calculated using the bulk method with initial roughness lengths taken from Mölg and others (2012) and further calibrated (see section 4.2), q is the specific humidity of air (in g kg⁻¹), T_S and T_S are the temperature (in °C) and specific humidity at the surface, respectively. The bulk Richardson number has been used to assess the stability correction.

The snowfall is distinguished from liquid precipitation using a logistic transfer function based on Hantel and others (2000) (Fig. S6):

$$n = \frac{1}{2} \left\{ \tanh \left[((T - T_0) - T_{00}) s_0 \right] + 1 \right\}$$
 (6)

where n is the fraction of snowfall (1 when it is only snow, 0 if only rain and in between 0 and 1 if this is mixed rain and snow), T_0 is the melting point (0 °C), T_{00} is the center for snow transfer function (in °C) and s_0 is spread snow transfer function. The aging/decay of the snowpack's albedo is then based on Oerlemans and Knap (1998), where it depends on the number of days after the last snowfall. Snow density is another important property of snow, particularly for its liquid water content or thermal conductivity. It is obtained by following Essery and others (2013). The default albedo and densification parameterizations used in this study are described in the supplementary material (see additional text related to the method section p. 9-10).

4.1.2 Model description and initialisation

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We run COSIPY at point scale at AWS-L and in a distributed way over 51 glacierized grid points of 0.003°x0.003° (0.0984 km²) resolution (corresponding to a total glacier-covered area of 5.01 km²), resampled from Copernicus GLO-30 DEM (https://doi.org/10.5270/ESA-c5d3d65) using the glacier outlines in 2012 (5.10 km²) from Wagnon and others (2021). Additionally, the grid elevations were adjusted downward by 19 meters to align with the elevation of AWS-L. The selection of this particular resolution is a compromise between the computational time and a reasonable representation of the topography. The model is run at an hourly time scale, independently for the four years of data, from 1 November of one year until 31 October of the following year over 2016-20, without spin-up time. We impose a temperature of 265.16 K at the glacier sole because the glacier is cold-based (Wagnon and others, 2013). The model is initialised with 600 layers of glacier ice topped by a snowpack whose profile is specified by the user. In our case, this profile is determined by the snow depth (Table 2), with each layer having an optimal snow layer height of 0.1 m. The initial snow depth in the ablation zone is kept closest to the observations made every November, corresponding to the snow depth measurement at AWS-L. Above 5750 m a.s.l., the model is initialised with a snow depth that increases by 20 cm per 100 m with altitude, starting at 50 cm on 1 November at 5750 m a.s.l. (Table 2). This assumption is essential because it ensures that there is always snow in the accumulation zone for the simulations. Even though annual observations in November show that the snow line is always lower than 5750 m a.s.l., which is in line with this assumption, the altitudinal gradient is not verifiable in the field. The snow depth in the accumulation zone is probably greater than that used for the initialisation, as the firn-ice interface is several metres below the glacier surface. However, for modelling purposes, the initial snow depth within this zone is of minimal concern as accumulation consistently outweighs ablation, and the snow depth gradually synchronises with the ongoing snowfall.

4.2 Optimisation

SEB models are sensitive to the choice of parameter sets (e.g., Zolles and others, 2019). Consequently, model parameters need to be calibrated, and the model's ability to reproduce the glacier surface mass balance needs to be evaluated. We optimise the model following a multi-objective optimisation procedure using forcing data measured at AWS-L between 1 November 2018 and 31 October 2019, the mass balance year with the least gaps and the most reliable dataset. The optimisation is performed based on the maximum amount of data available i.e., observed albedo, surface temperature calculated from LWout

using the Stefan-Boltzmann equation with a surface emissivity of 0.99 (Blau and others, 2021), and point mass balance at AWS-L (Table 2).

4.2.1 Parameters

There are many parameters in COSIPY and the eight important ones are listed in Table 3. To identify the most sensitive ones among this set, we conducted 108 manual model runs at a point-scale, specifically at AWS-L. In these runs, we alternatively and randomly explored various values for selected sensitive parameters, focusing on five parameters related to albedo and three associated with roughness lengths. This rigorous testing encompassed a plausible range of values, allowing us to qualitatively assess their impact on the model's outcomes. These ranges of albedo parameters and roughness lengths are taken from Mölg and others (2012). As we only have one level of wind speed measurement at AWS-L, roughness lengths cannot be directly calculated at this site. Notably, the roughness lengths exhibited lower sensitivity compared to the albedo parameters, which were identified as the most sensitive (in bold in Table 3). These albedo parameters are known sensitive parameters for energy balance studies (e.g., Zolles and others, 2019). We then optimise these five parameters following the procedure described in section 4.2.2 starting from a plausible range of values taken from the literature (Mölg and others, 2012; Zolles and others, 2019). All other parameters are taken from the default settings, except those listed in bold in Table 3, that are optimised.

282 "Table 3 near here"

4.2.2 Multi-objective optimisation

Multi-objective optimisation is a calibration method that enables the possibility of more than one optimal solution and provides a way to evaluate a variety of parameter sets (Yapo and others, 1998; Rye and others, 2012; Zolles and others, 2019). The multi-objective approach can be expressed as:

minimise
$$\{f_1(\theta), f_2(\theta), \dots, f_n(\theta)\}\$$
 (7)

where $f_1(\theta), f_2(\theta), ..., f_n(\theta)$ are n objective functions of model realisations of parameter sets θ . The optimisation process combines multiple objectives into a single ideal through scalar aggregation. For this, a weighted sum $(f_{agg}(\theta))$ is applied to find the minimum aggregate of different single objectives (Rye and others, 2012):

minimise
$$f_{aaa}(\theta) = \{w_1 f_1(\theta), w_2 f_2(\theta), \dots, w_n f_n(\theta)\}$$
 (8)

where w is the weight applied to all single objectives based on their performance and the arguments of the aggregating functions to obtain the Pareto solution (Pareto, 1971). With the multiple single objective, the selection of Pareto solution and multi-objective is more precise. Here, the multi-optimisation is done based on three objective metrics that compare the observation at AWS-L and model outputs:

$$f_1(\theta) = \left[\frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \right]^2$$
(9)

$$f_2(\theta) = \frac{1}{N} \left| \sum_{i=1}^{N} (y_i - x_i) \right|$$
 (10)

$$f_3(\theta) = |(MB_{obs} - MB_{mod})| \tag{11}$$

where f_1 is the coefficient of determination (r^2) between the observed (x_i) and modelled (y_i) values of albedo and surface temperature (T_s), f_2 is the mean absolute error (MAE) between the observed (x_i) and modelled (y_i) values of both variables and f_3 is the absolute error (AE) between observed (MB_{obs}) and modelled (MB_{mod}) point mass balances.

"Figure 3 near here"

The simplest way to calibrate the model is to optimise the different objective functions for four study periods (4 years x 3 objective functions = 12 performances). This approach results in a large range of uncertainty with many sensitive parameters for different mass balance years. Similarly, the set of parameters optimised for one period may not perform better in another period, resulting in higher uncertainty (Soon and Madsen, 2005). However, by simulating Pareto solutions for individual mass balance years and evaluating the objective functions over the other years, it is possible to select the best set of parameters.

4.3 Evaluation of the model at point and distributed scale

First, we optimise the five sensitive model parameters highlighted in Table 3 at AWS-L for the 2018/19 period. Second, we evaluate the model performance at point scale at AWS-L site for the other three mass balance years, systematically comparing measured and simulated albedo, surface temperature and point mass balance. Third, we run the model in a spatially distributed way and similarly evaluate it at point scale

at AWS-H site, over the three years of available data (2017-20). Finally, we also compare simulated mass balance to measured surface mass balance at glacier-wide scale for each year between 2016 and 2020. This allows us to test both the spatial and the temporal transferability of the model optimised parameters.

4.4 Sensitivity analysis

Our study aims to evaluate the sensitivity of the surface mass balance to changes in meteorological forcings. In previous studies, the sensitivity to temperature or precipitation is usually assessed by a constant change in temperature (e.g., \pm 1-2 °C) or a relative change in precipitation (e.g., \pm 10-30 %), keeping all other meteorological variables unchanged at the same time (Kayastha and others, 1999; Mölg and others, 2012; Sunako and others, 2019; Arndt and others, 2021; Srivastava and Azam, 2022; Gurung and others, 2022; Arndt and Schneider, 2023). The main disadvantage of this method, hereafter referred to as the classical method, is that perturbing a single meteorological variable breaks the physical links between the meteorological variables, which is detrimental to the simulation of surface mass balance (e.g., Prinz and others, 2016; Clauzel and others, 2023). To overcome this issue, a number of methods were developed to perturb meteorological data while preserving the link between variables (Sicart and others, 2010; Prinz and others, 2016; Autin and others, 2022). Here we both perturb the meteorological forcings in a classical way and we produce synthetic scenarios, described below (see also Fig. S7 for a flow chart explaining how scenarios are obtained).

4.4.1 Classical scenarios

For the classical sensitivity analysis method, the scenarios are developed by varying temperature by \pm 1°C and precipitation amount by \pm 20 % for four mass balance years without changing the other meteorological variables. In total, we produce 16 runs (+ 1°C, - 1°C, + 20 % and – 20 % for each of the four years) between 2016 and 2020. In order to determine the sensitivity of the mass balance to temperature or precipitation, it is then simply necessary to calculate the average anomaly in the mass balance over the four-year period for each corresponding perturbation.

4.4.2 Synthetic scenarios

Utilising the initial four-year dataset, we performed a cyclic selection process, systematically considering each month of the year commencing with November and concluding in October of the subsequent year. During each cycle, we alternately chose data from the unaltered original dataset and data from the warmest, coldest, wettest, or driest month within the four-year period (2016-20). This process allowed us

to generate synthetic annual datasets at an hourly resolution. By this way, we create 180 one-year-long synthetic meteorological series, exploring a wide range of climatic variability from very warm to very cold conditions, and from very dry to very wet conditions (see details below). For each scenario, for each month, we keep original hourly data and we only shuffle the months from different years with each other. In this way, both the physical integrity between meteorological variables and the weather conditions with respect to the time of the year are preserved.

First, the four most extreme synthetic scenarios are developed by making one-year long series of hourly forcing data that contain the most extreme months among the four years of data. For instance, the wet scenario (hereafter referred as We_We) is obtained by combining the wettest (We) months: if November 2017 is the month with the maximum monthly amount of precipitation among the four months of November of the 2016-20 series, all hourly forcing data from November 2017 are selected in scenario We_We; then if December 2019 is the wettest of the four December months, then hourly data from December 2019 will be selected as the second month of scenario We_We; etc. until October. In this way the wet scenario We_We combining the hourly data of all meteorological variables from the 12 months with the maximum monthly amount of precipitation is created. Similarly, we combine the hourly data of all meteorological variables from the 12 driest months to create the dry scenario (D_D), or from the 12 warmest months to create the warm scenario (Wa_Wa), or from the 12 coldest months to create the cold scenario (C_C).

Second, starting from these four extreme scenarios referred hereafter as baseline conditions, we also create 48 additional scenarios by modifying some specific seasons. For instance, we keep the conditions of the wet scenario We, except during one season, let's say the monsoon, where we decide to take the conditions of the warm scenario Wa. The four considered seasons are winter (win), pre-monsoon (pre), monsoon (mon), and melting season (melt). We decide not to consider the post-monsoon which is not critical for the glacier mass balance because there is usually neither any large precipitation nor any large melt but we prefer to introduce a six-month long melting season which we suspect to be more critical to control the glacier mass balance. This melting season covers half of the year from May to October, the only months where significant melt is observed in the field. The synthetic scenarios follow the naming convention AB_x, where A is the climate baseline coming from the four extreme scenarios, so A is either We, D, C, or Wa, B characterizes the conditions of the modified season i.e., B is also either We, D, C, or Wa and X refers to the season that has been modified to create the additional scenario, so X is either win, pre, mon, or melt. In case of the specific example described above, the scenario is named We_Wa_{mon} which

means that the dataset is one year long, using hourly forcing data from the wet scenario except during the monsoon where the warmest months are selected. A can take 4 values, B can take 3 values and X can take 4 values (the number of values for B cannot be similar to that of A, otherwise we define one of the extreme scenario), resulting in a total of $4\times3\times4=48$ scenarios.

Similarly, we also mix the original unshuffled data (U) from each year of the study period with extreme months. U can be alternatively 2016/17, 2017/18, 2018/19 or 2019/20 respectively referred as 2017, 2018, 2019 or 2020. These scenarios follow the same naming convention, with U being an additional value for A and B. For example, the scenario 2018_{Wamon} corresponds to the unchanged original data of the year 2017/18, except during the monsoon where data from the warmest months are selected. We obtain here 4x4x4 = 64 scenarios. Similarly, D_{Wamon} corresponds to the driest months, where months of the melting season have been replaced by the original 2019/20 data. Again, we obtain here 4x4x4 = 64 scenarios. In total, we have 4 + 48 + 64 + 64 = 180 scenarios.

For each of these 180 synthetic annual datasets, we calculate the glacier-wide annual mass balance of Mera Glacier using COSIPY and calculate the difference from the mean annual glacier-wide mass balance simulated by COSIPY using the original 2016-20 dataset. We call this difference the mass balance anomaly. Similarly, we have an anomaly for each forcing meteorological variable. We can now derive the mass balance sensitivity to each meteorological variable by fitting a linear regression between the mass balance anomaly and the anomaly of the variable under consideration. The slope of this linear relationship gives the mass balance sensitivity to the given variable. The error bars on these sensitivities for ±1 °C temperature and ±20 % precipitation variation have been calculated using the 99 % confidence interval, given by three standard deviations, of this linear regression.

5. RESULTS

5.1 Optimisation and evaluation

5.1.1 Optimisation

The point-scale optimisation strategy at AWS-L results in a well identified group of parameter sets (Pareto solutions) that minimise multiple objective functions simultaneously (Fig. 3). The objective functions of each set of original parameters are largely scattered with the range of r^2 and MAE of albedo being 0.06-0.54 and 0.11-0.25, respectively (Fig. 3a). Similarly for surface temperature, r^2 and MAE are in-between 0.81-0.92, and 1.37-3.24 °C, respectively (Fig. 3d). The range of AE is 0-3.92 m w.e. for the point mass

balance at AWS-L (Fig. 3b,c,e,f). The 200 solutions closest to the utopia point in terms of how well they perform across all objective functions represent the Pareto solutions (Fig. 3: bold black dots). All these multiple Pareto solutions are almost equally good and plausible. The metrics of the Pareto solutions are less scattered than the original ensemble, with the range of r^2 and MAE of albedo being 0.31-0.54 and 0.11-0.15 (Fig. 3a), and the range of r^2 and MAE of surface temperature being 0.87-0.92 and 1.58-2.33 °C (Table 4). The range AE is 0-1.28 m w.e. for the point mass balance at AWS-L (Table 4).

Since Pareto solutions perform well over all time and space ranges, the best parameter set among these Pareto solutions is then chosen as the optimised set (Table 3). The r² and MAE between the observed albedo and that resulting from the selected optimised parameter set are 0.48 and 0.12, respectively; similarly, for surface temperature r² and MAE are 0.91 and 1.92 °C, respectively (Fig. 4), and AE for the point mass balance is 0.17 m w.e. This final optimised set of parameters corresponds to a time scaling factor of three days and a depth scaling factor of four centimetres for the albedo model (Oerlemans and Knap, 1998) as well as values of albedo of snow (0.85), firn (0.55) and ice (0.30) similar to the default values used in COSIPY (Table 3).

415 "Table 4 near here"

- 416 "Figure 4 near here"
- 417 5.1.2 Glacier-wide simulation of COSIPY

The good performance of COSIPY simulations at point scale with the optimal set of parameters does not guarantee the good performance of the distributed simulations that rely on additional hypotheses, such as the meteorological forcing distribution that changes the meteorological forcings even at AWS-L location, because for instance SWin is re-computed at AWS-L based on the slope and the aspect of the considered grid cell. We thus evaluate the distributed COSIPY simulations over the period 2016-20 with the albedo and surface temperature at AWS-L and AWS-H, and with the glacier-wide mass balance. r^2 (MAE) for albedo is 0.32 (0.15) and 0.16 (0.14) for the 2016/17 and 2019/20 years at AWS-L, respectively (Fig. S8). At AWS-H, over the three-year period 2017-20, r^2 for albedo and surface temperature are 0.50 and 0.92 respectively, and the mean AE for 2016-20 at AWS-H is only 0.15 \pm 0.14 m w.e.. The surface temperature is always highly correlated with a low bias in both sites (Fig. S8). These metrics are close to the ones from point-scale simulations.

"Figure 5 near here"

Additionally, we compare the observed and simulated surface point and glacier-wide mass balances. The simulated point surface mass balances match well with the in-situ measurements obtained at stakes for all the four years (Fig. 5 and 6). The location of the equilibrium line altitude is well represented in COSIPY simulations and the general shape of the dependency of the surface point mass balance on elevation is satisfyingly reproduced (Fig. 5). The glacier-wide mass balance from the model is the mean value from all 51 individual grid cells and it is compared to the in-situ glacier-wide mass balance taken from Wagnon and others (2021). Over the four year period, the mean observed glacier-wide in-situ mass balance is -0.74 \pm 0.18 m w.e. a^{-1} (Table 2) and the simulated mass balance is -0.66 m w.e. a^{-1} with a standard deviation of \pm 0.26 m w.e. a^{-1} . The largest difference between the observed and modelled glacier-wide mass balance happens in 2019/20, with the simulated mass balance being 0.22 m w.e. less negative than the observed one (Fig. 5).

441 "Figure 6 near here"

5.2 SEB and mass balance components

5.2.1 Seasonal and annual energy balance components

Fig. 7 shows the monthly glacier-wide surface energy and mass balance components at Mera Glacier for the period 2016-20, and Fig. S9-S16 are maps of the glacier, showing the distributed annual energy and mass fluxes for each year of the study period. SWnet is the primary energy source available at the surface throughout the year, the second energy source being the QS, that is significant only between November and March. Along the year, SWin is controlled by the position of the sun responsible for the potential SWin and also by cloudiness, explaining why it decreases from 274 W m⁻² in the pre-monsoon to 195 W m⁻² during the monsoon (Table 5). Similarly, SWnet decreases from 83 W m⁻² during the pre-monsoon to 61 W m⁻² during the monsoon because of SWin reduction rather than change in albedo (glacier-wide values of 0.71 during the pre-monsoon and 0.70 during the monsoon). The change in air temperature and water vapour (moisture) is responsible for a strong increase of LWin from the pre-monsoon (217 W m⁻²) to the monsoon (296 W m⁻²), the only season when LWin nearly counterbalances the LWout.

The total energy intake at the surface is highest and almost similar during the pre-monsoon (496 W m⁻²) and the monsoon (491 W m⁻²) (Table 5). However, the net all-wave radiation, calculated as the sum of SWnet and LWnet, is 32 W m⁻² during the pre-monsoon and 20 W m⁻² higher during the monsoon. This indicates that the change in cloud cover and atmospheric condition has a relatively minor effect on the

total energy absorbed at the glacier surface, but does impact the net all-wave radiation. In the premonsoon, this net all-wave radiation is equally compensated by QL and QM (\sim -16 W m $^{-2}$ each). During the monsoon, LWnet and QL are both reduced or close to zero leaving all the energy available for melt with an average energy value of -43 W m $^{-2}$. The contributions of QS and QC are always low during the premonsoon and the monsoon, while the QR is negligible all the time.

The energy balance components vary across different glacier areas; they are analysed in the ablation area at AWS-L and in the accumulation area at AWS-H. When considering the annual means, the magnitudes of SWnet and QM are higher at AWS-L (93 and -34 W m⁻², respectively) than at AWS-H (61 and -15 W m⁻², respectively). LWnet, QL, and QS exhibit similar annual means throughout the year at both sites. At AWS-L, SWnet remains similar during the pre-monsoon (87 W m⁻²) and the monsoon (88 W m⁻²) because the decrease in SWin (287 W m⁻² in the pre-monsoon and 201 W m⁻² in the monsoon) is compensated by a decrease in albedo (0.70 in the pre-monsoon and 0.56 in the monsoon). The albedo remains high at AWS-H during the whole year, and there is thus a decrease of SWnet in the monsoon (43 W m⁻²) compared to the pre-monsoon (76 W m⁻²). The variation of LWnet at AWS-L and AWS-H is rather small as the difference between LWin and LWout remains similar. Comparing both sites, QL remains rather similar during all seasons. QM dominates QL all year round except during the winter at AWS-L, but at AWS-H, QL always dominates QM, except during the monsoon. QS is significant only during the cold months of the winter and the post-monsoon, with a similar magnitude whichever the location. QC is positive and rather small (<5 W m⁻², slightly higher during the post-monsoon) all year round except during the monsoon at AWS-L where it is slightly negative (Table 5).

479 "Table 5 near here"

- 480 "Figure 7 near here"
- 481 5.2.2 Seasonal and annual mass balance components

Table 6 lists the annual and seasonal mass balance components of Mera Glacier. After the direct accumulation (through snowfalls) and surface melt on Mera Glacier, annual refreezing and sublimation are two major mass balance components, refreezing being even higher than snowfalls. Indeed, at glacier scale, 44 % of the total (surface + sub-surface) melt refreezes annually. The glacier-wide sublimation is -0.15 m w.e. and therefore contributes 23 % of the total mass balance or 6 % of the ablation terms (total melt + sublimation).

Looking at seasonal scale, pre-monsoon and monsoon are important seasons in terms of mass balance processes, as more than 86 % of solid precipitation falls and 84 % of annual melt happens from March to September. However, post-monsoon is not completely negligible in terms of melt (-0.30 m w.e. or 14 % of the annual melt). This melt is almost equal to the surface mass balance (-0.17 m w.e.) due to the limited magnitude of the other processes, and in particular the limited refreezing in the snow free areas of the glacier. The winter is characterized by limited mass balance processes, with approximately 11 % of the annual solid precipitation and 2 % of the annual total melt (Table 6).

At glacier scale, the total melt (-0.42 m w.e.) and sublimation (-0.05 m w.e.) during the pre-monsoon are balanced by the refreezing (0.30 m w.e.) and snowfall (0.14 m w.e.), leading to a near zero surface mass balance (Table 6). The glacier-wide total melt during the monsoon is -1.42 m w.e., which is higher at AWS-L (-2.15 m w.e.) and lower at AWS-H (-0.99 m w.e.). Depending on the presence and the state of a snowpack (snow depth, density and temperature), melt water refreezes below the surface. Glacier-wide refreezing is 0.49 m w.e. during the monsoon, it is lower at AWS-L (0.19 m w.e.) where ice is often exposed at the surface, and higher at AWS-H (0.70 m w.e.) where there is always a snowpack with negative temperature. The refreezing preserves 35 % (0.49 m w.e) of the total glacier-wide melt during the monsoon; its relative contribution is higher at AWS-H (71 %) than at AWS-L (9 %).

The annual glacier-wide sublimation is -0.15 m w.e. and is nearly identical at both AWSs (-0.16 and -0.15 mm w.e. at AWS-L and AWS-H, respectively; Fig. S6). Most of the sublimation (93 % glacier-wide) happens outside the monsoon, when cold, dry and windy conditions prevail. Wind is not spatially distributed in our simulations, leading to rather homogeneous sublimation across the glacier. There are few exceptions, like a slightly higher sublimation in winter at AWS-L (-0.07 m w.e.) than at AWS-H (-0.05 m w.e.) due to higher roughness length linked to the surface state (exposed ice at AWS-L versus snow at AWS-H) and to the mixing ratio that depends on the air temperature. Due to the lower wind speed, sublimation is insignificant at both AWS sites during the monsoon (Table 6).

"Table 6 near here"

5.3 Mass balance sensitivity to meteorological forcings

5.3.1 Link between meteorological forcing anomalies and mass balance anomalies

In order to analyse the link between the different input meteorological variables and the outputs from the simulations, we calculate anomalies of each variable from the 180 scenarios by subtracting the mean of

the original unshuffled 2016-20 simulations (Fig. 8). From all synthetic scenarios, the magnitude of variation of air temperature is nearly ± 1 °C, whereas for precipitation, it varies from -35 to +55 % annually. The anomalies of relative humidity (± 5 %) and incoming radiations (± 10 W m⁻²) are rather narrow. There are many significant correlations (p<0.001) between the anomalies of the different variables, suggesting that they are likely to be physically related to each other. On an annual scale, the anomaly of air temperature correlates significantly and positively with the wind speed and the air pressure anomalies, and negatively with the precipitation and relative humidity anomalies. Regarding radiations that are expected to have an impact on the mass balance, the SWin anomaly correlates significantly and negatively with the relative humidity, the precipitation and the LWin anomalies. The LWin anomaly correlates significantly and positively with the relative humidity and the precipitation anomalies, and negatively with the SWin and wind speed anomalies.

The mass balance anomaly correlates significantly with the anomalies of every meteorological variables except SWin (Fig. 8). The correlations between mass balance anomalies and those of LWin, atmospheric pressure, or wind speed are moderate but significant, positive in case of LWin, and negative for the other variables. The correlation between mass balance anomalies and air temperature is significant and highly negative (r = -0.79). Mass balance anomalies are highly and positively correlated with those of precipitation (r = 0.87) and relative humidity (r = 0.84; Fig. 8).

"Table 7 near here"

- 535 "Figure 8 near here"
- 536 5.3.2 Mass balance sensitivity to air temperature and precipitation

From the classical method, we find that perturbing the temperature by +1 (-1) °C leads to a change in glacier-wide mass balance of -0.61 (+0.41) m w.e. (Table 7). A -20 (+20) % change in precipitation leads to a -0.79 (+0.48) m w.e change in glacier-wide mass balance (Table 7). With the synthetic scenario method, we find that a temperature change of +1 (-1) °C leads to a glacier-wide mass balance change of -0.75 \pm 0.17 (+0.93 \pm 0.18) m w.e., and a -20 (+20) % change in precipitation results in a mass balance change of -0.60 \pm 0.11 (+0.52 \pm 0.10) m w.e. Due to the physical link between variables, and in particular the negative correlation between temperature and precipitation, we find that the sensitivity of mass balance to temperature is significantly higher when calculated from synthetic scenarios than from the classical

method, especially in case of cooling. For precipitation, it is significantly reduced in case of a precipitation deficit but almost unchanged in case of an increase.

This synthetic scenario approach allows to derive mass balance sensitivities to any meteorological variable, as long as a significant correlation exists between the anomalies of mass balance and the variable under consideration. In particular, as we find a high correlation between mass balance and relative humidity anomalies, we can assess also the mass balance sensitivity to this variable: a -4 (+4) % change in RH corresponds to a -1.02 (+1.38) m w.e. change in mass balance. However, we caution on the interpretation of these correlations, as most of the input meteorological variables covary, the correlations may be significant, but they do not show a causal ralationship, that needs to be discussed in the light of the knowledge of the processes (see discussion section).

"Figure 9 near here"

556 5.3.3 Specific meteorological conditions leading to the most positive/negative mass balances

From the synthetic scenarios, the annual glacier-wide mass balances range from -1.76 to 0.54 m w.e. (Fig. 9 and Fig. S17), which is a wider range than the historically measured glaciological mass balance since 2007 (min = -0.92 m w.e. in 2017/18 and max = 0.26 m w.e. in 2010/11; Wagnon and others, 2021). The simulated annual mass balances are compared with the original mean annual glacier-wide mass balance of -0.66 m w.e. (Table 6) over the 2016-20 study period, referred hereafter as the reference year. Most of scenarios that have warm or dry conditions as a baseline correspond to the first category of scenarios characterised with negative mass balances ranging from -1.76 to -0.81 m w.e. They have a positive SWnet anomaly compared to the reference year (+2 to +17 W m⁻²), associated either with a change in air temperature toward a warming (-0.71 to +1.13 °C) or to a decrease in snowfall (0 to -0.29 m w.e.) or to both, resulting in a low glacier-wide albedo (0.53 to 0.64). With more energy intake, melting is enhanced, and due to the reduced snowfalls, ice is more exposed at the glacier surface favoring runoff, and in turn less than 46 % of this meltwater refreezes, ultimately leading to the most negative glacier-wide mass balances (Fig. S17).

The second category of scenarios corresponds to glacier-wide mass balances from -0.80 to -0.25 m w.e. close to that of the reference year. Here, we find scenarios combining a baseline and a seasonal component that would normally lead to opposite mass balance responses such as dry with wet conditions or warm with cold conditions (e.g., Wa_We_{mon}, D_We_{mon}, Wa_We_{win}, D_C_{win}). We also find the majority of

scenarios that have the unperturbed data as baseline (Fig. 9 and Fig. S17). The mass balance is affected equally but in an opposite direction by the temperature anomalies (-0.97 and +1.02 $^{\circ}$ C) and the precipitation anomalies (-0.16 to +0.23 m w.e.). In this category, the refreezing ranges from 37 to 56 % of total melt, which is close to that of the reference year (44 %), and the ranges of SWnet (-8 to +6 W m⁻²) and LWnet (-4 to +3 W m⁻²) anomalies are small (Fig. 8).

The third category corresponds to positive or near-balanced glacier-wide mass balances (> -0.25 m w.e.) mostly produced by scenarios with wet or cold baselines. They have temperature anomalies between -1.00 and +0.52°C and precipitation anomalies between -0.04 and +0.45 m w.e. (Fig. 9 and Fig. S17). The higher amount of snowfall increases the accumulation, increases the albedo, and in turn decreases the SWnet (-19 to -4 W m⁻²). In addition, the refreezing is high (46-71 % of total melt). Overall, the scenarios with a wet year baseline always create a mass balance that is close to balance, and specifically, the highest positive mass balance is produced by the wettest conditions all year round (scenario WeWe) (Fig. 9 and Fig. S17).

For all scenarios, we find that the mass balance is primarily influenced by the baseline conditions, and not by the seasonal variation. We do not find any season that has an influence larger than the other ones (Fig. S17). In particular, when we look at the scenarios of unperturbed data with seasonal variations, we find that winter seems to have as much influence, if not even more influence, than the other seasons on the mass balance (Fig. S17). This result is rather counter intuitive, as most of the mass balance processes happen in monsoon and pre-monsoon (e.g., Fig. 8).

Regarding the classical scenarios, as expected, both -20 % and +1 $^{\circ}$ C scenarios produce negative mass balances, but less extreme than the dry and warm synthetic scenarios. In contrast, both +20 % and -1 $^{\circ}$ C classical scenarios are characterised by near-balanced mass balances, far from the positive glacier-wide mass balances obtained with the wet and cold scenarios. The energy and mass fluxes in the classical scenarios are also comparable to those of the synthetic scenarios. The LWnet is similar in all classical scenarios. However, SWnet is 13 W m⁻² higher and refreezing is 25 % lower in the -20 % precipitation and +1 $^{\circ}$ C scenarios than those in the +20 % and -1 $^{\circ}$ C scenarios.

6. DISCUSSION

6.1 Surface energy and mass balance components of Mera Glacier, and comparison with other similar studies in HKH

It is difficult to compare different glacier surface energy and mass balance analyses rigorously across the same region because study periods are never similar. Moreover, temporal (multi-annual, annual, or seasonal) and spatial (point scale or glacier-wide) resolutions are often different and not comparable (Table 8). In HKH region, the seasonality of precipitation has a strong impact on the energy and mass balance components. In the western Himalaya, the winter precipitation dominates the annual accumulation, and sublimation strongly contributes to the ablation processes (Mandal and others, 2022; Srivastava and Azam, 2022; Oulkar and others, 2022). In the Central Himalaya, the glaciers are summer accumulation type with significant longitudinal variability in mean summer temperature, which has the strongest impact on mass balance sensitivity (Sakai and Fujita, 2017). Still, precipitation, which depends on the monsoon intensity and duration, is a key variable governing the energy and mass balance of glaciers through the albedo effect and its control on the refreezing (Shaw and others, 2022).

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The pattern of surface energy and mass balance over the whole Mera Glacier confirms what has already been observed on other glaciers of HKH (Table 8, which is an update of Table 4 of Azam and others, 2014, with the location of glaciers given in Fig. S18). Overall, the radiative fluxes strongly dominate the SEB, and control the amount of energy available for melt (Fig. 7). Between the pre-monsoon and the monsoon, with the gradual establishment of the dense cloud cover typical of this latter wet and warm season, incoming shortwave radiation gradually loses intensity, replaced at the same time by increasing incoming longwave radiation, resulting in a constantly high amount of radiative energy available for the glacier. This amount of energy decreases with elevation mainly because albedo is higher in the accumulation zone, where ice is never exposed at the surface. Turbulent fluxes are only significant out of the monsoon, contributing to bring additional energy toward the surface by sensible heat flux (Fig. 7). Contrary to glaciers in the western Himalaya where resublimation occasionally occurs during the monsoon (Azam and others, 2014), on Mera Glacier, the latent heat flux is always negative which means that sublimation is a non-negligible process of mass loss, especially during seasons with strong wind (winter and post-monsoon), like on Zhadang and Parlung No 4 glaciers on the southeast Tibetan Plateau (Mölg and others, 2012; Sun and others, 2014; Zhu and others, 2018). On Mera Glacier, glacier-wide sublimation accounts for 23 % of the glacier-wide mass balance (Table 6), in agreement with previously published values in the Himalaya (e.g., Gurung and others, 2022; Srivastava and Azam, 2022) or lower than that of Shruti Dhaka Glacier in the western Himalaya (55 %; Oulkar and others 2022). However, this value on Mera Glacier is under-estimated because wind speed strongly increases with elevation (Khadka and others, 2022), an effect that has not been taken into account in our study. Refreezing is also an important process, because at annual and glacier-wide scales, as much as 44 % of meltwater refreezes on Mera Glacier, with a clear increase of this percentage with elevation (Table 6). This finding is again in agreement with other studies in the region (Stigter and others, 2018; Kirkham and others, 2019; Bonekamp and others, 2019; Veldhuijsen and others, 2022; Arndt and Schneider, 2023). It is noteworthy mentioning that sublimation and refreezing are two important processes for glaciers in this region but they are not included in empirical degree-day models (Litt and others, 2019). Moreover, refreezing is always parameterised in a more or less sophisticated way in physical snowpack models, but field experiments are crucially missing to evaluate the accuracy of such parameterisations.

"Table 8 near here"

6.2 Mass balance sensitivity to different meteorological variables and comparison with other studies in

HKH

6.2.1 Mass balance sensitivity of Mera Glacier to meteorological variables

Estimating the sensitivity of glacier mass balance to a change in temperature and/or precipitation is a classical problem in glaciology (e.g., Ohmura and others, 1992). Different approaches have been implemented in HKH to assess the glacier mass balance sensitivity at different scales (e.g., Sakai and Fujita, 2017; Wang and others, 2019; Arndt and others, 2021; Gurung and others, 2022). However, the classical approach (perturbing temperature and precipitation by certain values or percentages), which involves perturbing individual meteorological variables while keeping others unchanged, has been criticised due to the interconnectedness of these variables (Nicholson and others, 2013; Prinz and others, 2016). For example, changing air temperature directly impacts the water vapor ratio of the atmosphere, which can ultimately affect the turbulent heat fluxes.

For Mera Glacier, we find strong correlations among the meteorological variables, which makes difficult to decipher their individual effects on mass balance. Notably, the negative correlation between temperature and precipitation anomalies (r = -0.56; slope of the linear relationship: -0.16 m w.e. °C⁻¹) leads to larger mass balance sensitivities to temperature when this relationship is preserved (Table 7). The mass balance sensitivity to SWin is unexpectedly limited (-0.06 m w.e. a^{-1} (W m⁻²)⁻¹; r = -0.22) due to the role of albedo. Indeed, the correlation between albedo anomalies and mass balance anomalies is very high (r = 0.97) showing that the surface state, that depends primarily from the amount of snowfalls, is more important than the actual incoming shortwave radiative flux. Despite its direct contribution to the SEB, LWin correlates positively with mass balance due to its strong correlation with precipitation. One limitation

of our approach is that we can virtually find sensitivities of the mass balance to any input variable, as long as a correlation exists. For instance, the strong sensitivity to the relative humidity shown in Fig. 8 should not be interpreted as an expected change in mass balance due to a change in relative humidity. Instead it shows that the relative humidity is closely tied to the other meteorological variables, and that meteorological conditions that favor high relative humidity also favor positive mass balances.

Another interesting feature is the asymmetry towards negative values in the sensitivities to temperature with the classical method (Table 7). While continental and sub-continental glaciers typically exhibit less sensitivity to negative temperature changes (e.g., Arndt and Schneider, 2023; Wang and others, 2019), maritime glaciers tend to have symmetrical sensitivity, especially when estimated with degree-day models (Wang and others, 2019). However, with the synthetic scenario approach, we find the opposite asymmetry for temperature sensitivity (Table 7), likely due to the correlations between precipitation and temperature. This leads to higher negative mass balances than the simple +1 °C perturbation (Fig. 8), indicative of the maritime climate setting for Mera Glacier. Regarding precipitation, its sensitivity is asymmetric towards negative values with both methods (Table 7). It is clearly due to albedo feedback effects in the model, which are poorly represented in degree-day models that predict a symmetric sensitivity to precipitation (e.g., Wang and others, 2019).

6.2.2 Mass balance sensitivity comparison with other studies in HKH

The impact of temperature and precipitation changes on mass balance depends on the climate of the region, but it can be attenuated or exacerbated depending on the glacier's morphology and topography (Brun and others, 2019). Contrary to glaciers located in arid cold climates less sensitive to temperature changes (Ohmura and others, 1992), those affected by the Indian summer monsoon, such as Mera Glacier, are sensitive to both temperature and precipitation (Fujita, 2008; Johnson and Rupper, 2020; Arndt and others, 2021). With higher temperature, first less precipitation falls as snow and in turn accumulation is reduced, and second and more important, more shortwave radiation is absorbed through lower albedo leading to enhanced melt (Fujita, 2008). Still the mass balance sensitivity to temperature and precipitation varies among different glaciers. The glacier-wide sensitivity of Mera Glacier to changes in temperature and precipitation is of the same order of magnitude as other glaciers in HKH, even though it is noteworthy to mention that these glacier sensitivities have been assessed through the classical method and in turn are not directly comparable (Fig. 10, Table S3).

For instance, on Mera Glacier, with the synthetic scenarios approach, a ±1 °C temperature perturbation has greater impact than that of a ±20 % precipitation change, which is mostly the case for glaciers on Fig. 10, especially those located in Nepal. However, this pattern differs for glaciers in the Indian western Himalaya, which mostly exhibit lower sensitivities, sometimes higher for precipitation than for temperature like Shruti Dhaka Glacier (Oulkar and others, 2022). Surprisingly, Arndt and Schneider (2023) find extreme sensitivities of glacier-wide mass balances to warming or to increase in precipitation for glaciers in the Central Himalaya (Yala and Halji glaciers) or Nyainqentanglha Range (Zhadang Glacier) compared to what we observe on Mera Glacier, although all these glaciers are submitted to rather humid monsoon dominated conditions.

Our approach with the synthetic scenarios does not allow to investigate whether the sensitivity changes linearly. It is well established that the sensitivity to temperature is nonlinear and much higher for larger temperature changes (e.g., Arndt and Schneider, 2023). As we rely only on existing observations, we cannot assess what would be the other meteorological variables in a +2 or +3 °C climate setting. Directions to overcome this issue could be to investigate the links between glaciers' response to synoptic variables (e.g., Mölg and others, 2012; Zhu and others, 2022), to investigate specific monsoon characteristics and their impacts on the mass balance (e.g., Shaw and others, 2022), or to force glacier mass balance models with downscaled global circulation model outputs that preserve the physical relationships between variables (e.g., Bonekamp and others, 2019; Clauzel and others, 2023). Furthermore, the size of the glacier plays a role on its mass balance sensitivity. Glaciers with a higher accumulation area, such as Shruti Dhaka, Trambau, and Mera glaciers, exhibit a lower sensitivity than glaciers whose accumulation zone is strongly reduced, such as Zhadang and Halji glaciers (Zhu and others, 2018; Sunako and others, 2019; Arndt and others, 2021; Srivastava and Azam, 2022).

"Figure 10 near here"

6.3 Limitations of our approach

Simulating the distributed surface energy and mass balance of a glacier presents numerous challenges and limitations. One striking example is the relatively large difference between the simulated and observed glacier-wide mass balances for the year 2019/20, where COSIPY simulated mass balance is 0.22 m w.e. larger than the observed one. While we do not have a definitive explanation for such a discrepancy, we can list a number of sources of errors in our approach. Uncertainties arise primarily from (i) the model's

process representation, (ii) in-situ data, (iii) their spatial distribution over the glacier area, and (iv) the model's initial conditions.

One crucial process in snowpack modelling is the decay of snow albedo over time. COSIPY implements the Oerlemans parameterisation (Oerlemans and Knap, 1998), which has known limitations in certain climate contexts (e.g. Voordendag and others, 2021; Wang and others, 2022). Typically, albedo parameters are fixed or adopted from previous studies using COSIPY or any other energy balance model. However, here, we optimised these parameters at AWS-L before distributing the meteorological forcings. The snow aging and depth scaling factors used in this study fall within the range of commonly used factors (Sauter and others, 2020; Arndt and others, 2021; Wang and others, 2022; Sherpa and others, 2023), but differ slightly from those used in other studies (Sauter and others, 2020; Arndt and others, 2021; Potocki and others, 2022). Although the model can accurately predict albedo at a point scale, it is sometimes misrepresented (Fig. S8). The lack of robust parameterisation and uncertainties surrounding the amount of snow deposited on the glacier surface and its redistribution by the wind contribute to this issue.

Additionally, refreezing is another poorly constrained process. In HKH region, refreezing has primarily been assessed using models (Steiner and others, 2018; Kirkham and others, 2019; Saloranta and others, 2019; Veldhuijsen and others, 2022), rather than snowpack temperature and density measurements, as is done in the seasonal snowpack (e.g. Pfeffer and Humphrey, 1996). Specific experiments should be conducted to evaluate the effects of refreezing on glaciers, particularly to determine whether meltwater percolates below the previous year's horizon and contributes to internal accumulation. Additionally, COSIPY lacks certain processes, such as wind erosion and wind-driven snow densification. These processes can be very important, particularly during the post-monsoon and winter seasons due to the strong winds at high elevations (Litt and others, 2019; Brun and others, 2023; Sherpa and others, 2023). During November field campaigns, wind erosion features such as sastrugis are frequently observed in the accumulation area of Mera Glacier.

Distributing meteorological data over a rough terrain is one of the most challenging task. The spatial distribution of the meteorological data based on a single vertical gradient throughout the year is somehow questionable (section 3.2). Additionally, applying a vertical gradient to distribute meteorological variables weakens the physical links between them, as already discussed in the sensitivity analysis. For the study period and the range of elevation of Mera Glacier, the vertical gradients for temperature, relative humidity, and LWin exhibit high variability (Fig. S3). To derive the gradients, we selected the year with the

minimum gaps at AWS-H despite a large portion of the data at AWS-L being reconstructed at that time. Additionally, the T/RH sensor was not artificially ventilated at AWS-H, which introduces some measurement uncertainty. Therefore, we tested a range of gradients to distribute T [-6.5 to -4.2 °C km⁻¹] and RH [-25 to 0 % km⁻¹]. In alpine environments, LWin provides large amounts of melt energy, especially in the ablation area (through valley side walls) and can dominate the energy balance of snow or glacier surfaces. LWin is highly sensitive to surface melt when the atmosphere is saturated, particularly during the monsoon (Sicart and others, 2010). On Mera Glacier, the daily LWin gradient as a function of elevation varies greatly from day to day and season to season, with a minimum of -41 W m⁻² km⁻¹ observed during the monsoon. Various LWin gradients have been tested within the [-40 to 0 W m⁻² km⁻¹] range and optimised to -25 W m⁻² km⁻¹ (Table S2). In conclusion, there is no ideal method for spatially distributing meteorological variables on a complex glacier surface that extends over a large altitudinal range. On Mera Glacier, two on-glacier AWSs enable us to provide reasonable vertical gradients of temperature, relative humidity, and longwave incoming radiation. These gradients are highly variable in time and likely in space as well. To maintain simplicity in our modelling approach, we prefer to use a single gradient for these variables instead of using temporally or spatially variable gradients. The use of variable gradients would require a denser observation network than the two AWSs we currently have. Additionally, using different gradients would alter the set of optimised parameters without necessarily affecting the final results.

The depletion of precipitation as a function of elevation in the upper Khumbu region is still a matter of debate due to the lack of reliable data at high elevations, difficulties in correcting the undercatch of snow, and comparing precipitation records obtained with different devices (Salerno and others, 2015; Perry and others, 2020). On the Mera catchment, there is only one all-weather rain gauge located at 4888 m a.s.l., just below the glacier. The precipitation recorded at this station is considered constant across the glacier surface. The distribution of precipitation is clearly more complex due to the rough topography (Immerzeel and others, 2014) and snow redistribution by wind. We prefer not to apply any vertical precipitation gradient, as it would complicate the modelling and increase equifinality issues, as with other meteorological variables. Similarly, applying a vertical gradient of wind speed based on records at AWS-L and AWS-H is not recommended due to the site-specific nature of the records (Shea et al., 2015). Therefore, like precipitation, wind speed is assumed to be constant and equal to the wind velocity at AWS-L across the glacier. Given that wind speed mainly affects turbulent fluxes, which are of secondary importance compared to radiative fluxes, any assumptions made only impact the total sublimation and its spatial distribution.

To initialise the model, the snow depth on each grid cell at the start of the simulation, specifically on 1 November, must be known. As field trips typically occur around mid-November each year, and November is a relatively dry month with minimal melting, snow depth initialisation is based on direct observations performed around 15 days later than the initialisation date. However, this method is not entirely error-free as not all grid cells are surveyed and precipitation or wind drift may have occurred between 1 November and the survey date. Such error may have large impacts over the entire simulation period when a surface is initially recognized snow free although it is not, or vice versa.

In COSIPY, between 10 and 20 % of SWnet penetrates below the surface and is partly reflected at different depths within the snowpack or the ice (van den Broeke and Bintanja, 1995). This amount of shortwave radiation is not accounted for in the outtake term Qout of Table 5, which explains why Qin and Qout do not exactly compensate each other. Therefore, the energy balance is not perfectly closed in the COSPIY model (e.g., Arndt and others, 2021).

7. CONCLUSION

The COSIPY energy and mass balance model was applied to Mera Glacier in the Central Himalaya, Nepal. In-situ meteorological datasets were used, recorded both on and off the glacier at different elevations ranging from 4888 m a.s.l. (for precipitation) to 5770 m a.s.l. The data was collected from 1 November 2016 to 31 October 2020 at an hourly time step. The model parameters were optimised at the point scale using data from AWS-L at 5360 m a.s.l. over the year 2018/19. A multi-objective optimisation was employed, and the albedo aging and snow depth factors were selected as the most sensitive parameters and then calibrated. The model was validated both at the point scale with multiple AWS measurements (albedo and surface temperature recorded at 5360 and 5770 m a.s.l.) and at the glacier scale with annual point mass balance measurements obtained at various elevations. The validation indicates that the model effectively simulates the annual glacier-wide mass balance of Mera Glacier, with a simulated mean value of -0.66 m w.e. a⁻¹ for 2016-20 compared to the observed value of -0.74 m w.e. a⁻¹.

The SEB over Mera Glacier is dominated by radiative fluxes, which are responsible for almost all the energy available during the monsoon, the main melting season. From the pre-monsoon to the monsoon, with the increasing cloudiness, incoming shortwave radiation gradually decreases in intensity in favor of incoming longwave radiation thus maintaining a large amount of energy available for melt. Turbulent fluxes are only significant outside the monsoon. The sensible heat is an energy source at the surface whereas the latent heat flux is always negative. Sublimation is therefore an important ablation process, especially during the

windy months of the post-monsoon and winter. Annually and at glacier scale, refreezing is a crucial process, because on average 44 % of meltwater refreezes, with a large positive gradient with altitude.

To investigate the sensitivity of glacier mass balance to changes in temperature and precipitation, we generated 180 different scenarios by shuffling our four-year dataset. We aggregated warm, cold, dry, or wet months alternatively, depending on the seasons. These scenarios allowed us to explore a wide range of conditions, from very dry and warm to very cold and wet. As a result, the glacier-wide mass balances of Mera Glacier ranged from -1.76 to +0.54 m w.e. a^{-1} . The mass balance sensitivity to meteorological variables can be quantified from these synthetic scenarios. A temperature change of +1 °C(-1 °C) results in a change of -0.75 \pm 0.17 (+0.93 \pm 0.18) m w.e. in glacier-wide mass balance, while a precipitation change of +20 % (-20 %) results in a change of +0.52 \pm 0.10 (-0.60 \pm 0.11) m w.e. in mass balance. Compared to the classical approach, the sensitivity of the mass balance is more pronounced with temperature, but not significantly different with precipitation. Similar to other glaciers with summer accumulation, Mera Glacier is highly sensitive to both temperature and precipitation.

To evaluate the mass balance sensitivity to any meteorological variables, it is advantageous to generate scenarios based on real in-situ data. This not only helps to quantify these sensitivities more accurately but also to explore the inter-relationships between variables. Our study demonstrates, for instance, that temperature has a negative correlation with precipitation. Therefore, classical sensitivity approaches that alter temperature and precipitation independently are likely to be biased. It is worth noting that long-term high-quality datasets are necessary to apply such synthetic method approach. We are lucky enough to have a long-term dataset on Mera Glacier, but we encourage to maintain and develop similar observational networks on other glaciers in HKH, in order to compare glaciers and to assess whether sensitivities obtain locally on a glacier can be extrapolated regionally. Currently, we cannot be certain that this sensitivity is not specific to Mera Glacier.

Like any modelling, our approach has limitations inherent to the model used, the quality of input data, their spatial distribution, and the choice of initial conditions. These limitations are difficult to quantify, but our method allows us to provide an accuracy range for the results based on a 99 % confidence interval. A potential next step in this study would be to conduct an uncertainty analysis to assess the weight of all potential errors related to the model and data, as well as to evaluate the equifinality of the results. However, this is beyond the scope of the present study. Nonetheless, such an analysis would be valuable, as many modelling approaches encounter similar issues.

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Author contribution

PW initiated and DS supported the monitoring program on Mera Glacier. PW, FB and AK jointly designed the study. AK performed the analysis, under the supervision of FB and PW, with the support of TS. AK prepared all the figures and wrote the first draft of the manuscript. AK, FB and PW jointly developed the discussion and interpretation of the results. All authors participated in some field campaigns, and contributed to the analysis and to the paper writing.

Data availability

- 864 The data utilised in this study accessible through the GLACIOCLIM database are 865 (https://glacioclim.osug.fr/Donnees-himalaya). The model available outputs are at 866 https://doi.org/10.5281/zenodo.10053093.
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1051	
1052	List of figure captions
1053	Fig. 1. Map of Mera Glacier showing the network of ablation stakes (blue dots) and accumulation pits (cyar
1054	diamonds). The stake location and number are taken from November 2020. The number of stakes vary
1055	from year to year, due to total excavation, reinstallation at the original location, snow hurial or destruction

The pink stars represent the locations of different AWSs with their respective photos and dates (a. Khare Geonor, b. Mera La AWS, c. AWS-H, and d. AWS-L). The outline of Mera Glacier is from 2018 with a total area of 4.84 km², and the background image was acquired by Sentinel-2 on 24 November 2018. Elevation lines are extracted from the 2012 Pléiades DEM (Wagnon and others, 2021). The inset map gives the location of Mera Glacier in Nepal (black square) and the glacierised areas from RGI6 (shaded blue areas).

- Fig. 2. Hourly data from 1 November 2016 to 31 October 2020 of (a) air temperature (T), (b) relative humidity (RH), (c) wind speed (u), (d) incoming shortwave radiation (SWin), (e) incoming longwave radiation (LWin) at AWS-L, (f) atmospheric pressure (P_a) at Mera La AWS and (g) precipitation (P) at Khare Geonor. Orange shaded areas indicate data gaps at AWS-L, which have been filled by Mera La AWS data using linear interpolation, and the light blue shaded areas in panel (g) visualise the monsoons.
 - **Fig. 3.** Solution space for the multi-objective optimisation for the period 1 November 2018 31 October 2019. One dot represents results obtained with one set of parameters, and bold black and red dots define the Pareto solution space and optimised solution, respectively. Plots show the scatter plot between a) 1- r^2 and MAE from albedo comparison, b) MAE from albedo comparison and AE from mass balance comparison, c) AE of mass balance comparison vs 1- r^2 from albedo, d) 1- r^2 and MAE from surface temperature comparison and AE from mass balance and f) AE of mass balance vs 1- r^2 from surface temperature comparison.
 - **Fig. 4.** Mean daily snow albedo (top) and surface temperature (bottom) from observation (Obs., black line) and simulated with COSIPY between 1 November 2018 and 31 October 2019 at AWS-L. r² and MAE represent the correlation coefficient and mean absolute error between the observed and simulated variables, respectively. The red thick line and the brown thin lines represent the simulated variables using the final optimised parameter set and using all other solution spaces, respectively.
 - **Fig. 5.** In-situ (blue dots) and simulated at each grid cell (red dots) point mass balances as a function of elevation on Mera Glacier for each year of the 2016-20 period. MB is the glacier-wide mass balance obtained from field measurements (blue text) (Wagnon and others, 2021) and simulated with COSIPY (red text). Also shown are the hypsometries of Mera Glacier used for in-situ glacier-wide mass balance calculations (light blue histograms) and for COSIPY (light brown histograms).
 - **Fig. 6.** Distributed simulated annual mass balance (MB, in m w.e.) for each year of the study period. Also shown as white circles are the point mass balance observations (ablation stakes and accumulation pits)

with the inside colour corresponding to the respective annual measurement. The glacier outlines (black) is from Wagnon and others (2021).

- Fig. 7. Glacier-wide monthly (a) energy fluxes, (b) mass fluxes and (c) mass balance from November 2016 to October 2020 on Mera Glacier (left panels) and mean monthly annual cycle (right panels). SWnet = net shortwave radiation, LWnet = net longwave radiation, QL = latent heat flux, QS = sensible heat flux, QC = subsurface heat flux, QR = rain heat flux, QM = available melt energy at the surface, SnowF. = solid precipitation, Subl. = sublimation, Surf. M. = melt at surface, Sub S. M. = subsurface melt and Refr. = refreezing. Blue shaded areas visualise the monsoons.
- Fig. 8. Scatter plot between anomalies of different input variables and glacier-wide mass balance anomalies for the 180 synthetic runs. Also shown are the Pearson correlation coefficients between the series of annual anomalies. The black lines represent the linear regressions and the grey shaded areas indicate the standard error. The anomalies of each variable are calculated by subtracting the mean of the original unshuffled 2016-20 simulation. (stars represent significance levels, accordingly: * = 0.05, ** = 0.01, *** = 0.001).
 - **Fig. 9.** Glacier-wide (a) energy fluxes, (b) mass flux components, and (c) mass balance (MB) from (left panels) 12 selected synthetic scenarios (in red, grey, and blue, on the x-axis), as well as (right panels) from the four mean classical scenarios (in black) and the reference year (RY, in green, on the x-axis). The results from the classical scenarios or the reference year have been averaged over the four years 2016-20. Based on the MB results, 12 synthetic scenarios are selected (four corresponding to the most negative MBs, four from the middle of the MB set with moderately negative MBs, and four most positive MBs) out of the 180 scenarios (all visible in Fig S17). The colour code of synthetic scenarios visualises the MB range, from the most negative (red), to the most positive (blue), grey being intermediate and moderately negative. 2019 and 2020 represent the 2018/19 and 2019/20 mass balance years, respectively. SWnet = net shortwave radiation, LWnet = net longwave radiation, QL = latent heat flux, QS = sensible heat flux, QC = subsurface heat flux, QR = rain heat flux, QM = available melt energy at the surface, SnowF. = solid precipitation, Subl. = sublimation, Surf. M. = melt at surface Sub S. M. = subsurface melt and Refr. = refreezing.
 - **Fig. 10**. Location of glaciers where studies of mass balance sensitivities have been conducted in the Himalaya and Tibetan Plateau regions. Each panel gives the mass balance sensitivity to temperature and precipitation of each glacier, with the associated reference. Table S3 lists all these glaciers, and provides additional information.

List of tables

Table 1. List of the different AWSs operating on Mera Glacier, or in its vicinity, with their elevations, operating periods, list of sensors and associated meteorological variables used as forcing, optimisation or validation data of the SEB model. T = air temperature, RH = relative humidity, u = wind speed, SWin = incoming shortwave radiation, SWout = outgoing shortwave radiation, LWin = incoming longwave radiation, LWout = outgoing longwave radiation, $P_a = atmospheric$ pressure and P = precipitation). The numbers in brackets indicate the data gap of the variables (second column) or the uncertainty of each sensor provided by the manufacturer (third column).

Station	Variables (gap % during the study period)	Sensors (uncertainty)
Khare Geonor	P (0)	GEONOR T-200BM
4888 m a.s.l.		(±15%)
25 Nov 2016 – 18 Nov 2020		
Off-glacier, on a grassy surface		
Mera La AWS	T (0), RH (0)	Vaisala-HMP45C* (±0.2°C; ±2%)
5350 m a.s.l.	u (1)	Young 05103-5 (±0.3 m/s)
01 Nov 2016 – 31 Oct 2020	SWin (0)	Kipp&Zonen CNR4 (±3%)
Off-glacier, on a rocky surface	LWin (0)	
	P _a (0)	CS100 (±2.0 hPa)
AWS-L	T (23.2), RH (23.2)	Vaisala-HMP45C* (±0.2°C; ±2%)
5360 m a.s.l.	u (25.8)	Young 05103-5 (±0.3 m/s)
01 Nov 2016 – 31 Oct 2020	SWin (23.8), SWout (24.0)	Kipp&Zonen CNR4 (±3%)
On-glacier (ablation area)	LWin (24.0), LWout (24.0)	
AWS-H	T (17.1), RH (17.1)	Vaisala-HMP45C (±0.2°C; ±2%)
5770 m a.s.l.	u (17.1)	Young 05103-5 (±0.3 m/s)
11 Nov 2017 – 18 Nov 2020	SWin (17.2), SWout (17.2)	Kipp&Zonen CNR4 (±3%)
On-glacier (accumulation area)	LWin (17.1), LWout (27.8)	

* artificially aspired during daytime

Table 2. Glacier-wide mass balance for Mera Glacier, point mass balance at AWS-L (obtained by averaging all stake measurements on Naulek branch between 5300 and 5380 m a.s.l.) and at AWS-H (obtained by averaging stake measurements close to AWS-H, from 5750 to 5790 m a.s. l.), as well as snow depths in the ablation area (annually measured during field campaigns in November) and in the accumulation area (assumed for the model). An ice density of 900 kg m^{-3} and measured snow densities were used to compute point mass balances (370 kg m^{-3} for Naulek, and 380 to 430 kg m^{-3} for the accumulation area). The error range for point mass balances is the standard deviation of all measurements.

Glaciological mass balance of Mera Glacier											
	2016/17	2017/18	2018/19	2019/20	2016-20						
Glacier-wide mass	-0.76 ±	-0.92 ±	-0.80 ± 0.19	-0.49 ± 0.22	-0.74 ± 0.18						
balance* (m w.e. a-1)	0.16	0.16									

Mean point mass	-2.26 ±	-2.34 ±	-2.27 ± 0.10	-2.10 ± 0.24	-2.24 ± 0.09
balance around AWS-	0.12	0.19			
L (m w.e. a ⁻¹)					
Mean point mass	0.16 ± 0.01	-0.08 ±	0.12 ± 0.13	0.35 ± 0.12	0.14 ± 0.15
balance around AWS-		0.07			
H (m w.e. a ⁻¹)					
Snow depth in the	0.50	0.12	0	0.20	
ablation zone (< 5750					
m a.s.l.) used for the					
model initialisation					
(m)					
Snow depth in the	0.50 m at 57	50 m a.s.l. and	d an additional 0.2	0 m for each 100 m increase	in altitude
accumulation zone (>					
5750 m a.s.l.) used for					
the model					
initialisation (m)					

* updated from Wagnon and others (2021)

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Table 3. List of selected parameters used in COSIPY, and manually tested before running our optimisation procedure. In bold are
 the 5 most sensitive parameters that are optimised from a plausible range of values (Min-Max range, taken from the Mölg and
 others (2012) and used in this present study). The investigated range of max-min values for the roughness lengths is also shown.

Parameters	Min	Max	Optimised/ default
Fresh snow albedo	0.82	0.88	0.85
Firn Albedo	0.50	0.60	0.55
Ice albedo	0.25	0.35	0.30
Albedo time scaling factor (days)	3	9	3
Albedo depth scaling factor (cm)	2	14	4
Roughness length for fresh snow (mm)	0.19	0.29	0.24
Roughness length for firn (mm)	1.5	6.5	4
Roughness length for ice (mm)	0.7	2.7	1.7

1133 **Table 4.** The range of different objective function values in the first 200 Pareto solution space for 2018/19 period at AWS-L.

Objective function	Albedo	Surface temperature	Mass balance
$f_1(\theta)$	0.31-0.54	0.87-0.92	
$f_2(\theta)$	0.11-0.15	1.58-2.33 °C	
$f_3(\theta)$			0-1.28 m w.e.

Table 5. Annual and seasonal surface energy fluxes (W m⁻²) and their contribution to the total energy intake (Qin) and outtake (Qout) over the whole Mera Glacier area, at AWS-L and at AWS-H. The annual values are calculated between 1 November to 31

October of the following year, using all data over the study period. The negative (-) sign indicates the energy loss from the surface.

Winter = Dec-Feb, Pre-monsoon = Mar-May, Monsoon = Jun-Sep, Post-monsoon = Oct-Nov.

	SWin	SWout	SWnet	albedo	LWin	LWout	LWnet	QL	QS	QC	QR	QM	Qin	Qout
Annual values (W m ⁻²)														
Glacier-wide mean	215	-139	76	0.65	229	-273	-43	-13	4	4	0	-22	453	-447
AWS-L	227	-134	93	0.59	235	-278	-43	-14	4	3	0	-34	470	-460
AWS-H	218	-157	61	0.72	225	-269	-44	-13	4	5	0	-15	453	-454
Seasonal Glacier-wide (W m ⁻²)														1
Winter	183	-107	76	0.59	172	-237	-66	-22	13	4	0	-2	372	-368
Pre-monsoon	274	-191	83	0.71	217	-268	-51	-16	1	4	0	-17	496	-491
Monsoon	195	-133	61	0.70	296	-306	-10	-2	0	2	0	-43	491	-485
Post-monsoon	217	-121	96	0.56	199	-265	-66	-15	4	9	0	-18	429	-420
Seasonal AWS-L	. (W m ⁻²)							I	1				l	
Winter	196	-113	83	0.58	178	-247	-69	-26	13	5	0	-2	392	-388
Pre-monsoon	287	-200	87	0.70	223	-275	-52	-16	1	5	0	-22	517	-513
Monsoon	201	-113	88	0.56	302	-307	-5	-1	1	-3	0	-66	504	-490
Post-monsoon	235	-108	127	0.46	205	-273	-68	-18	4	6	0	-33	450	-432
Seasonal AWS-H	I (W m ⁻²)						<u>I</u>	l				l	
Winter	183	-120	63	0.66	167	-231	-63	-19	15	3	0	0	368	-369
Pre-monsoon	280	-204	76	0.73	212	-265	-52	-17	1	4	0	-13	496	-498
Monsoon	198	-155	43	0.78	291	-305	-13	-4	-1	5	0	-29	494	-493
Post-monsoon	221	-146	75	0.66	195	-261	-66	-15	4	10	0	-12	430	-433

Table 6. Glacier-wide annual and seasonal mass balance components (mm w.e.) over the total glacier area and at point scale at
 AWS-L and AWS-H using all data over the study period 2016-20. The negative (-) sign indicates a mass loss from the surface.

	Snowfall	Sublimation	Surface melt	Subsurface melt	Total melt	Refreezing	Mass balance					
Annual means (mm w.e.)												
Glacier-wide mean	718	-150	-2095	-88	-2183	956	-656					
AWS-L	641	-164	-3194	-88	-3282	659	-2144					
AWS-H	792	-149	-1434	-88	-1522	1174	297					
Seasonal Glacier-wi	de (mm w.e	2.)		1	1		1					
Winter	77	-62	-43	-4	-47	27	-4					
Pre-monsoon	137	-48	-395	-20	-415	298	-27					
Monsoon	479	-10	-1366	-53	-1419	489	-461					
Post-monsoon	25	-30	-291	-11	-302	142	-165					
Seasonal AWS-L (mr	Seasonal AWS-L (mm w.e.)											
Winter	77	-74	-51	-6	-57	41	-12					

Pre-monsoon	136	-50	-519	-29	-548	368	-94				
Monsoon	403	-4	-2098	-47	-2145	191	-1554				
Post-monsoon	25	-36	-526	-6	-532	58	-485				
Seasonal AWS-H (mm w.e.)											
Winter	77	-54	-11	-1	-12	11	22				
Pre-monsoon	138	-51	-309	-17	-326	275	37				
Monsoon	551	-15	-929	-57	-986	701	251				
Post-monsoon	26	-29	-185	-12	-197	187	-13				

1140 Table 7. Mass balance anomalies as compared to the mean of the four 2016-20 years from the classical and synthetic scenarios'1141 methods.

Sensitivity	Classical method (m w.e.)	Synthetic scenarios (m w.e.)
-1 °C T	+0.41	+0.93 ± 0.18
+1 °C T	-0.61	-0.75 ± 0.17
+20 % P	+0.48	+0.52 ± 0.10
-20 % P	-0.79	-0.60 ± 0.11

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Table 8. Comparison of SEB components on different glaciers in HMA, whose location is visible in Fig. S18. The various studies already included in Azam and others (2014) are not reported in this table. (All the fluxes are in W m^{-2})

Glacier	Study	Altitude	Region	Study	SW	LW	QS	QL	QC	QM	Reference
Name	type	(m a.s.l.)	(ISM	Period	net	net					
			dominat								
			ed, Y or								
			N)								
Parlung No.	Point/	4657-	southea	1 Oct	77	-46	11	-	1	-22	Zhu and others
4	annual	5937	st	2008 to				21			(2018)
			Tibetan	21 Sept							
			Plateau,	2013							
			China								
			(N)								
Zhandang	Point/	5515-	western	1 Oct	69	-49	14	-	-1	-20	Zhu and others
	annual	5947	Nyainqe	2008 to				13			(2018)
			ntanglh	21 Sept							
			a Range,	2013							
			China								
			(Y)								
Purogangri	Glacie	5350-	Tibetan	Oct	36	-39	28	-	-	-2	Huintjes and
ice cap	r-	6370	Plateau,	2000 to				22	1.3		others (2015)

r-	
No.1 annual Tibetan Plateau, Oct China (Y) 2012 to Plateau, Oct China (Y) 15 (2018) Rikha Samba Glacie G5427- Gentral (Y) Oct DCT Tr-G515 Himalay (Y) 1974 to Sept (Y) 20 NA -12 Gurung Others (2022) Naimona'nyi Glacie G16cie (Y) S545- Western (Y) Oct	
Plateau, Oct China 2016	
China	
Rikha Samba Glacie 5427- Central Oct 105 -74 -	
Rikha Samba Glacie 5427- Central Oct 105 -74 - NA -12 Gurung others (2022)	
T-	
wide/ annual x	ind
Naimona'nyi Glacie 5545- western Oct 77 -69 12 - 2 6 Zhu and oth (2021) wide/ annual (Y) 2018	
Naimona'nyi Glacie 5545- western Oct 77 -69 12 - 2 6 Zhu and oth (2021) r- 7262 Himalay 2010 to 16 16 (2021) wide/ annual (Y) 2018 -35 9 - NA -10 Srivastava r- 6632 Himalay 2020 32 32 Azam (2022) wide/ annual (Y) (Y) Azam (2022) -	
r- vide/ annual (Y) 2010 to a, China Sept (Y) 2018	
wide/ annual a, China (Y) Sept 2018	ers
Dokriani Glacie 4050- western 1979 to 68 -35 9 - NA -10 Srivastava 7- 6632 Himalay 2020 a, India annual (Y)	
Dokriani Glacie 4050- western 1979 to 68 -35 9 - NA -10 Srivastava 1979 to 68 -35 9 - NA -10 Srivastava 1979 to 68 -35 9 - NA -10 Srivastava 1979 to 68 -35 9 - NA -10 Srivastava 1979 to 68 -35 9 - NA -10 Srivastava 1979 to 68 -35 9 - NA -10 Srivastava 1979 to 68 -35 9 - NA -10 Srivastava 1979 to 68 -35 9 - NA -10 Srivastava 1979 to 68 -35 9 - NA -10 Srivastava 1979 to 1979 to	
r- 6632 Himalay 2020 32 Azam (2022) wide/ annual (Y)	
wide/ a, India (Y)	and
annual (Y)	
Chhota Point/ 4670 western 8 Jul to 5 202 -14 31 11 4 - Azam,	and
Shigri monso Himalay Sept 233 others (2014)	
on a, India 2013	
(Y)	
Chhota Glacie 4070- western 1979 to 77 -57 15 - NA -10 Srivastava	and
Shigri r- 5850 Himalay 2020 25 Azam (2022)	
wide/ a, India	
annual (Y)	
Srutri Dhaka Glacie 4500- western Oct 157 -85 7 -5 -3 -71 Oulkar	and
r- 6000 Himalay 2015 to others (2022)	
wide/ a, India Sept	
annual (Y) 2017	
Muztag Ata Point/ 5237- eastern 1 Oct 69 -61 18 - 0 -2 Zhu and oth	
No. 15 annual 5935 Pamir, 2008 to 24 (2018)	 ers
China 21 Sept	ers
(N) 2013	ers

^{*}corresponding to QS+QL here

Supplementary material of "Surface energy and mass balance of Mera Glacier (Nepal, Central Himalaya) and their sensitivity to temperature and precipitation" by Arbindra Khadka, Fanny Brun, Patrick Wagnon, Dibas Shrestha, Tenzing Chogyal Sherpa

Table S1. Monthly correlation coefficients (r^2) between the Mera La AWS and AWS-L hourly data with parameters used to linearly extrapolate the Mera La AWS data to AWS-L (y = mx + c). For SWin, the c value is 0 i.e., the correlation is forced to the origin, in order to keep night values at 0 W m^{-2} .

Variables	Т			RH			u			SWin			LWin		
Time frame	r ²	m	С	r ²	m	С	r ²	m	С	r ²	m	С	r ²	m	С
all	0.92	0.90	-2.09	0.91	0.94	5.47	0.51	0.94	0.70	0.90	1.10	0	0.93	0.92	12.77
Jan	0.86	0.86	-3.07	0.82	0.86	4.94	0.41	0.80	1.62	0.95	0.93	0	0.77	0.77	37.72
Feb	0.90	0.86	-2.82	0.85	0.89	3.60	0.45	0.69	1.88	0.97	0.98	0	0.88	0.84	27.90
Mar	0.88	0.82	-2.83	0.79	0.87	3.28	0.37	0.79	1.61	0.96	1.08	0	0.82	0.78	38.44
Apr	0.81	0.72	-3.06	0.81	0.91	3.98	0.34	0.79	1.16	0.91	1.23	0	0.71	0.76	44.96
May	0.73	0.66	-2.19	0.78	0.93	3.73	0.22	0.64	1.31	0.87	1.26	0	0.73	0.81	37.50
Jun	0.65	0.59	-0.90	0.72	0.84	15.59	0.26	0.69	0.53	0.83	1.32	0	0.76	0.88	29.04
Jul	0.65	0.45	-0.10	0.31	0.45	53.71	0.09	0.49	0.55	0.83	1.27	0	0.61	0.78	64.50
Aug	0.64	0.44	-0.14	0.42	0.54	44.88	0.15	0.61	0.48	0.81	1.22	0	0.76	0.86	37.92
Sep	0.70	0.61	-1.03	0.64	0.72	28.11	0.15	0.45	0.55	0.84	1.15	0	0.78	0.97	1.67
Oct	0.80	0.79	-2.95	0.81	0.89	10.95	0.19	0.61	1.05	0.91	1.05	0	0.86	0.86	26.36
Nov	0.79	0.77	-3.53	0.74	0.81	10.53	0.25	0.59	1.75	0.95	0.96	0	0.83	0.80	35.77
Dec	0.89	0.84	-3.12	0.77	0.85	8.55	0.47	0.77	1.59	0.96	0.93	0	0.85	0.84	26.40

Table S2. Tested range and final values of the altitudinal gradients of air temperature, relative humidity, incoming longwave radiation and precipitation used to spatially distribute the meteorological forcing data

SN	Parameters	Max	Min	final value
1	Temperature gradient (°C km ⁻¹)	-4.2	-6.5	-5.7
2	Relative humidity gradient (% km ⁻¹)	0	-20	-15
3	LWin gradient (W m ⁻² km ⁻¹)	0	-41	-25
4	Precipitation gradient (mm km ⁻¹ or % km ⁻¹)			0

Table S3. Glacier-wide annual mass balance perturbations (m w.e.) with different magnitudes of meteorological variables from various studies done on HMA glaciers, always using the classical method, except our present study using the synthetic scenario approach. (* refers to the sensitivities obtained from the literature, but multiplied or divided by a factor to make it comparable with other studies. For example, the mass balance sensitivity to a -10 % change in precipitation is multiplied by a factor 2, to make it comparable with a mass balance sensitivity to a -20 % change in precipitation.)

Glacier Name,	Region (ISM	Study Period	T (-1 °C)	T (+1	P (-20	P (+20	Reference
region	dominated, Y or			°C)	%)	%)	
	N)						
Parlung No 4	southeast	1 Oct 2008 to	+1.28	-1.28	-0.29	+0.29	Zhu and others (2018)
	Tibetan Plateau,	21 Sept 2013					
	China (N)						
Parlung No 4	southeast	Oct 2000 to					Arndt and Schneider
	Tibetan Plateau,	Sept 2018	+0.44	-0.55	-0.86	+0.51	(2023)
	China (N)						
Parlung No 94	southeast	Oct 2000 to					Arndt and Schneider
	Tibetan Plateau,	Sept 2018	+1.03	-1.14	-1.56	+0.89	(2023)
	China (N)						
Zhadang	western	1 Oct 2008 to	+1.30	-1.30	-0.52	+0.52	Zhu and others (2018)
	NyainqentangIh	21 Sept 2013					
	a Range, China						
	(Y)						
Zhadang	western	Oct 2000 to					Arndt and Schneider
	NyainqentangIh	Sept 2018	+1.68	-2.96	-2.34	+1.57	(2023)
	a Range, China		11.00	2.30	2.54	11.57	
	(Y)						
Mera	Central	Nov 2016 to	+0.93	-0.75	-0.60	+0.52	Present study
	Himalaya, Nepal	Oct 2020					
	(Y)						
Trambau	Central	May 2016 to	NA	-0.90*	NA	+0.36*	Sunako and others (2019)
	Himalaya, Nepal	Oct 2018					
	(Y)						
Yala	Central	Oct 2000 to					Arndt and Schneider
	Himalaya, Nepal	Sept 2018	+1.65	-3.18	-2.19	+1.25	(2023)
	(Y)						
Rikha Samba	Central	Oct 1974 to	+0.54	-0.69	-0.44	+0.35	Gurung and others
	Himalaya, Nepal	Sept 2021					(2022)
	(Y)						

Halji	Central	Oct 2000 to	+1.22	-1.33	-1.53	+1.07	Arndt and Schneider
	Himalaya, Nepal	Sept 2018					(2023)
	(Y)						
Halji	Central	Jan 1982 to	+0.99	-1.43	-1.29	+0.76	Arndt and others (2021)
	Himalaya, Nepal	Apr 2019					
	(Y)						
Naimona'nyi	Central	Oct 2000 to	+0.47	-1.8	-1.46	+0.49	Arndt and Schneider
	Himalaya, Nepal	Sept 2018					(2023)
	(Y)						
Naimona'nyi	western	Oct 2010 to	+0.37	-0.37	-0.20*	+0.20*	Zhu and others (2021)
	Himalaya, India	Sept 2018					
	(Y)						
Dokriani	western	Nov 1979 to	+0.50	-0.50	-0.46	+0.46*	Srivastava and Azam
	Himalaya, India	Oct 2020					(2022)
	(Y)						
Chhota Shigri	western	Nov 1979 to	+0.30	-0.30	-0.26	+0.26*	Srivastava and Azam
	Himalaya, India	Oct 2020					(2022)
	(Y)						
Chhota Shigri	western	Oct 2000 to	+0.49	-0.53	-0.67	+0.53	Arndt and Schneider
	Himalaya, India	Sept 2018					(2023)
	(Y)						
Shruti Dhaka	western	Oct 2015 to	+0.15	-0.25	-0.34*	+0.42*	Oulkar and others (2022)
	Himalaya, India	Sept 2017					
	(Y)						

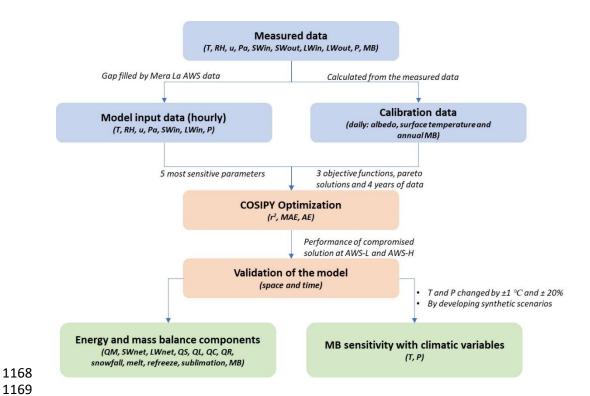


Figure S1. Flow chart describing the simplified sequential approach used in this study.

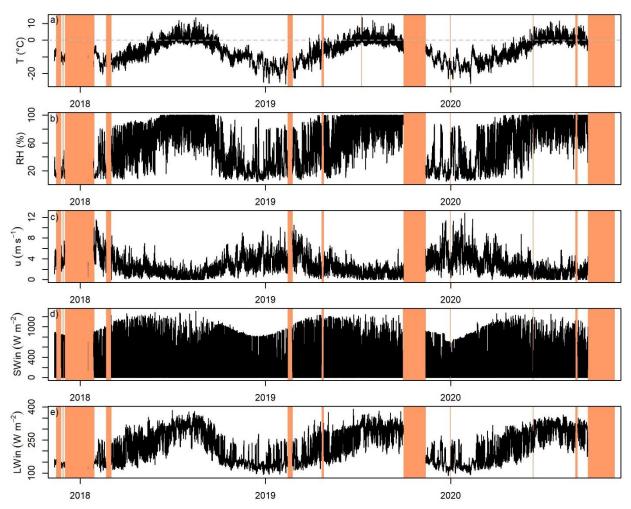


Figure S2. Hourly data of (a) air temperature (T), (b) relative humidity (RH), (c) wind speed (u), (d) incoming shortwave radiation (SWin), and (e) incoming longwave radiation (LWin) at AWS-H, from 10 November 2017 to 27 September 2020. Orange shaded areas indicate data gaps.

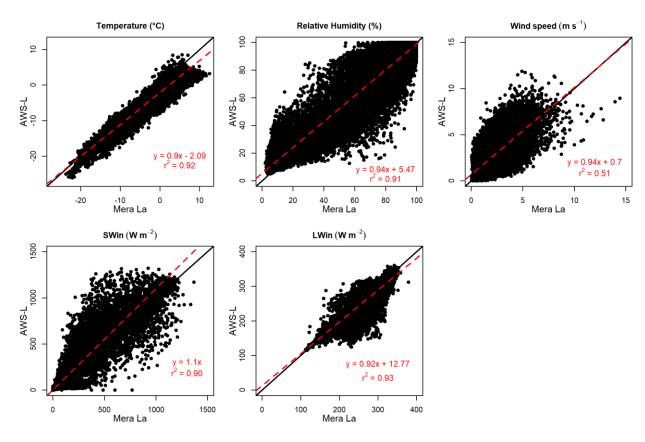


Figure S3. Hourly data comparison between Mera La and AWS-L. The red lines and equations are overall linear relationships between the two observed data, r^2 is the correlation coefficient, where the p-value is always significant (p < 0.01). Also shown in black the 1:1 line.

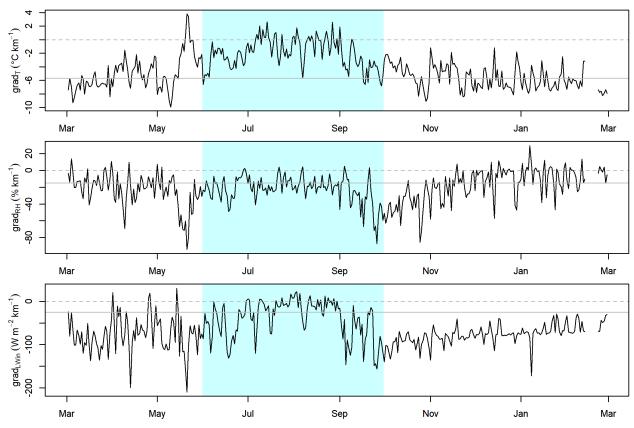


Figure S4. Mean daily altitudinal gradients of air temperature (grad_T), relative humidity (grad_{RH}), and longwave incoming radiation (grad_{LWin}), calculated from AWS-L and AWS-H data from 1 March 2018 to 28 February 2019. The horizontal grey lines represent the different values of altitudinal gradients used for the data distribution. The blue shaded area corresponds to the monsoon period.

Additional text related to fig. S4: Pressure data distribution method, altitudinal gradients of air temperature, relative humidity and incoming longwave radiation used in this study

The atmospheric pressure (Pa) has been interpolated using the barometric formula (eq. S1, S2):

$$SLP = \frac{Pa}{\left(1 - \frac{(0.0065 * Z_{AWS-L})}{288.15}\right)^{5.255}}$$

$$Pa_{elv} = SLP * \left(1 - \frac{0.0065 * Z_{elv}}{288.15}\right)^{5.255}$$
 (52)

Where SLP is the sea level pressure, Pa is the atmospheric pressure at the elevation of the AWS-L (Z_{AWS-L}) , and Pa_{elv} is the pressure at any grid elevation (Z_{elv}) .

The altitudinal gradients of air temperature, relative humidity and incoming longwave radiation are calculated using the data from AWS-L and AWS-H between 01 March 2018 and 28 February 2019. This particular period is chosen because there are almost no gaps at AWS-H (Fig. S1) and because it covers one full year, allowing to compute annual and seasonal gradients. However, it is worth noting that during this period, a large portion of data at AWS-L (from 01 March 2018 to 24 November 2018) has been reconstructed with Mera La AWS. Using reconstructed data does not alter our analysis since we explore different gradients over a wide range of values. For air temperature, this range goes from the environmental lapse rate (-6.5 °C km⁻¹) to the mean annual temperature gradient observed from both AWSs (-0.42 °C km⁻¹). For the other variables, the range goes from the mean monsoonal observed gradient (-22 % km⁻¹ and -41 Wm⁻² km⁻¹ for RH and LWin gradients, respectively) to 0 (no gradient) (Fig. S3). Deriving dew point temperature gradients between AWS and converting dew point temperature to relative humidity at any glacier grid cell is more physical than directly using relative humidity gradients, but both approaches provide the same range of RH gradients (Fig. S4). Twelve tests were conducted with different sets of gradients to ultimately determine the optimal set, which is -5.7 °C km⁻¹ for air temperature, -15 % km⁻¹ for relative humidity and -25 W m⁻² km⁻¹ for incoming longwave radiation (Table S2).

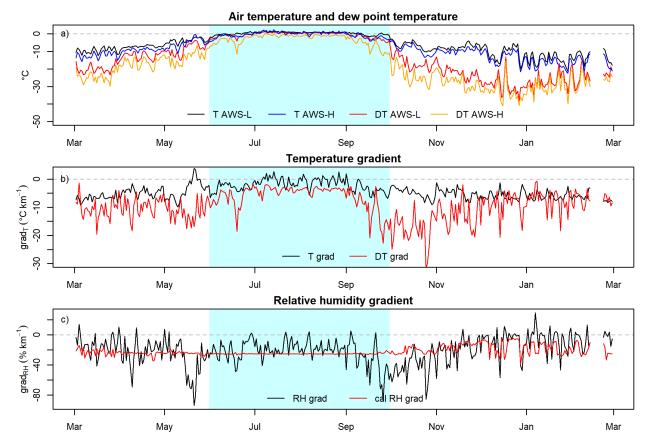


Figure S5. Mean daily temperature (T) and dew point temperature (DT) at AWS-L and AWS-H (top), calculated temperature and dew point temperature gradient (middle) and calculated relative humidity gradient from observation and dew point temperature (bottom) from the AWS-L and AWS-H from 1 March 2018 to 28 February 2019.

Additional text related to the method section

Albedo

In COSIPY, the albedo (α) of the snow surface is calculated by the Oerlemans and Knap (1998) method. The albedo of snow (α_{sn}) depends upon how fast $(t^*$ expressed in days) the fresh snow albedo (α_s) drops to firn albedo (α_f) after the last snowfall.

$$\alpha_{sn} = \alpha_f + (\alpha_s - \alpha_f) exp\left(\frac{s}{t^*}\right)$$
 (S3)

where s is the age of the snow layer from the last snowfall (in days). The overall snowpack thickness (d in m) impacts the albedo; if the snowpack is thin, the albedo must tend towards the albedo of ice (α_i). The full albedo can be written by introducing a characteristic snow depth scale d^* (in m) as

$$\alpha = \alpha_{sn} + (\alpha_i - \alpha_{sn})exp\left(\frac{-d}{d^*}\right)$$
(54)

1224 Densification

The snow volumetric mass (ρ_{sn} in kg m⁻³) is a key characteristic of the snowpack. Following Essery and others (2013), COSIPY calculates the snow volumetric mass to derive important snow properties such as thermal conductivity and liquid water content. Assuming that a rapid settlement of fresh snow occurs simultaneously with slow compaction by the load resisted by the viscosity (η), the rate of change in the volumetric mass as a function of time t, $\frac{d\rho_{sn}}{dt}$, of a snow layer with temperature T_{sn} and overlying mass M_{sn} is given by:

$$\frac{1}{\rho_{sn}} \frac{d\rho_{sn}}{dt} = \frac{M_{sn}g}{\eta} + c_1 exp[-c_2(T_0 - T_{sn}) - c_3 max(0, \rho_{sn} - \rho_0)]$$
 (S5)

1231 And the viscosity:

$$\eta = \eta_0 exp[c_4(T_0 - T_{sn}) + c_5 \rho_{sn}] \tag{S6}$$

Values for the two physical constants and six parameters in equations (S3) and (S4) are given in Table S4 below.

Table S4. Physical constants and parameter values for snow compaction parameterisations

equation	Parameters	Sources
S5	$c_1 = 2.8 \times 10^{-6} \text{ s}^{-1}, c_2 = 0.042 \text{ K}^{-1},$	(Anderson, 1976; Boone, 2002;
	$c_3 = 0.046 \text{ m}^3 \text{ kg}^{-1}$	Essery and others, 2013; Sauter
	ρ_0 = 150 kg m ⁻³	and others, 2020)
	T_0 = 273.15 K melting point	
	temperature	
	g = 9.81 m s ⁻² acceleration due	
	to gravity	
S6	c_4 = 0.081 K ⁻¹ c_5 = 0.018 m ³ kg ⁻¹	
	$\eta_0 = 3.7 \times 10^7 \text{ kg m}^{-1} \text{ s}^{-1}$	

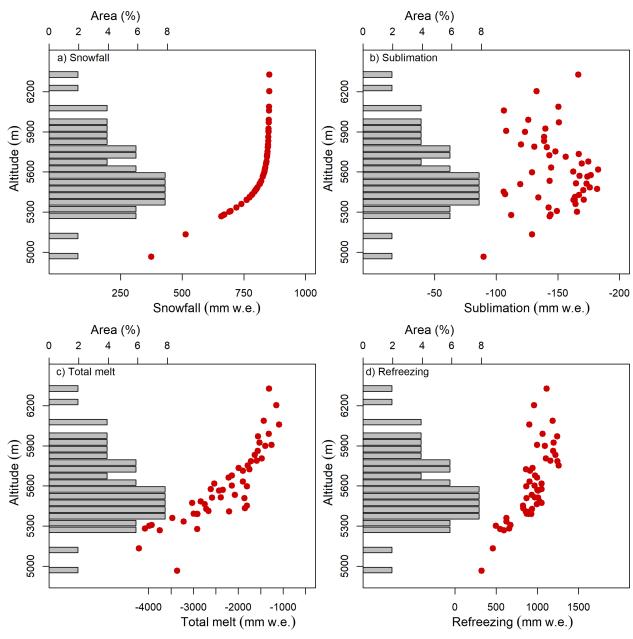
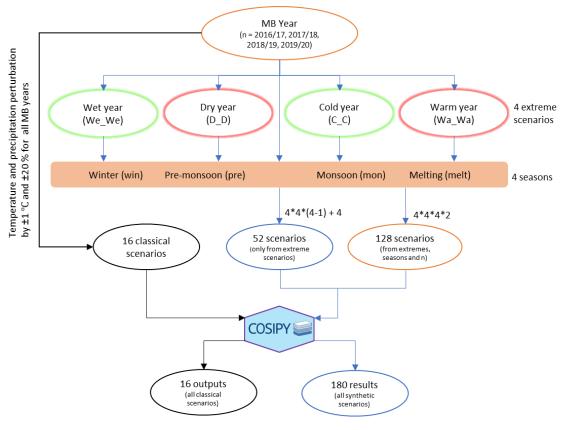


Figure S6. Total (a) snowfall, (b) sublimation, (c) melt and (d) refreezing (red dots) for each grid cell simulated by COSIPY for the 2018/19 period. Also shown is the glacier hypsometry (grey histograms) used in the model.



With mean, 4 results from classical scenarios, 180 results from synthetic scenarios

Figure S7. Flow chart illustrating the sequential approach used to develop and analyse mass balance sensitivity by both classical and synthetic methods.

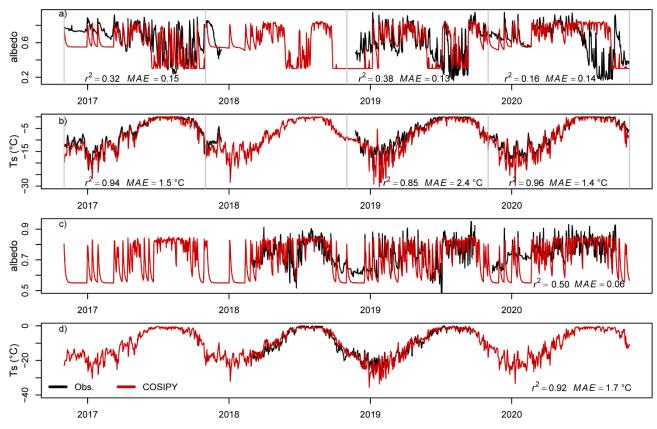


Figure S8. Mean daily observed and modelled albedo and surface temperature at AWS-L (a and b) and AWS-H (c and d) for the 2016-20 period. The metrics r^2 and MAE are calculated for each year at AWS-L (except 2017/18, because the data gap is too long) and for the 3-year 2017-20 period at AWS-H.

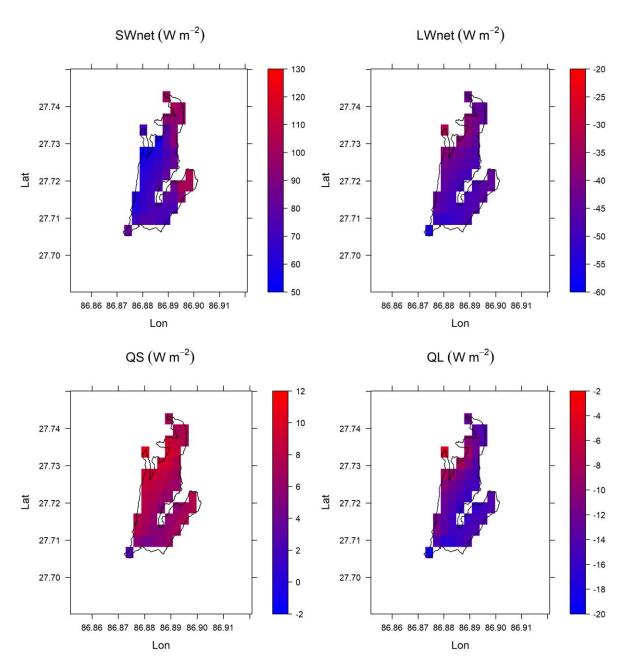


Figure S9. Distributed annual net shortwave radiation (SWnet), net longwave radiation (LWnet), sensible heat flux (QS), and latent heat flux (QL) in W m^{-2} for the year 2016/17. The glacier outilnes (black) is from Wangno and others (2021).

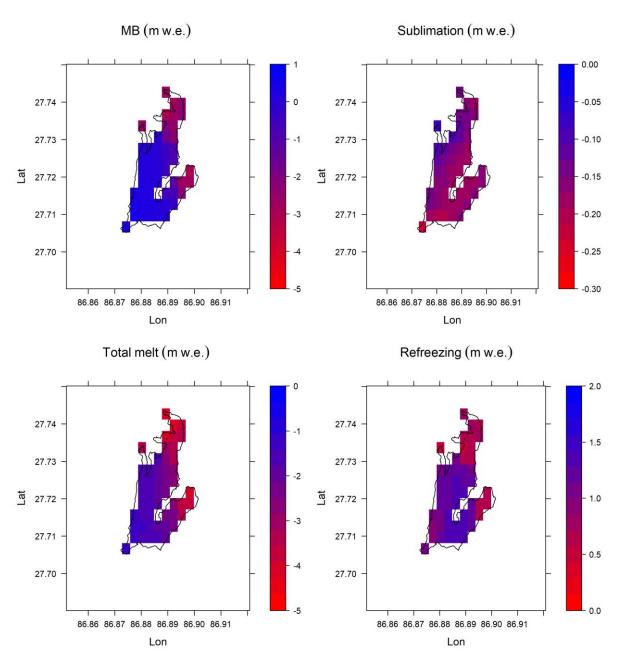


Figure S10. Distributed annual mass balance (MB), sublimation, total melt and refreezing in m w.e. for the year 2016/17. The glacier outilnes (black) is from Wangno and others (2021).

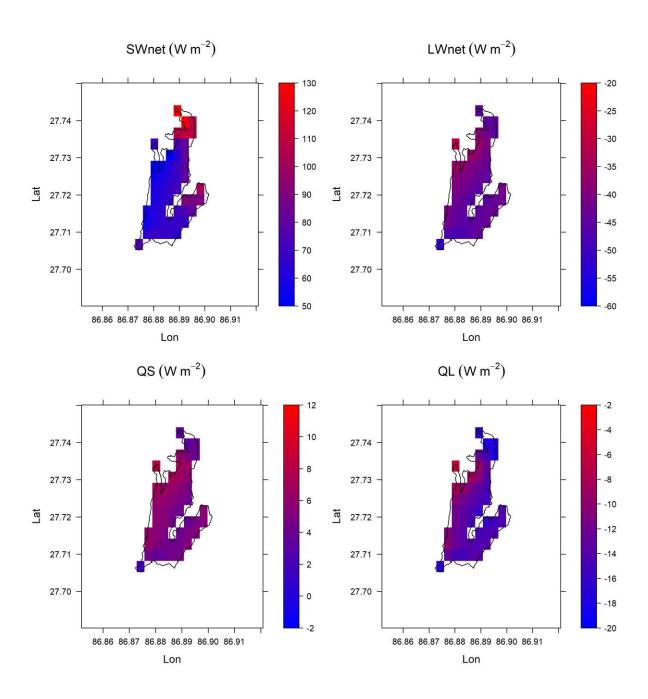


Figure S11. Same as Fig. S9 for the year 2017/18

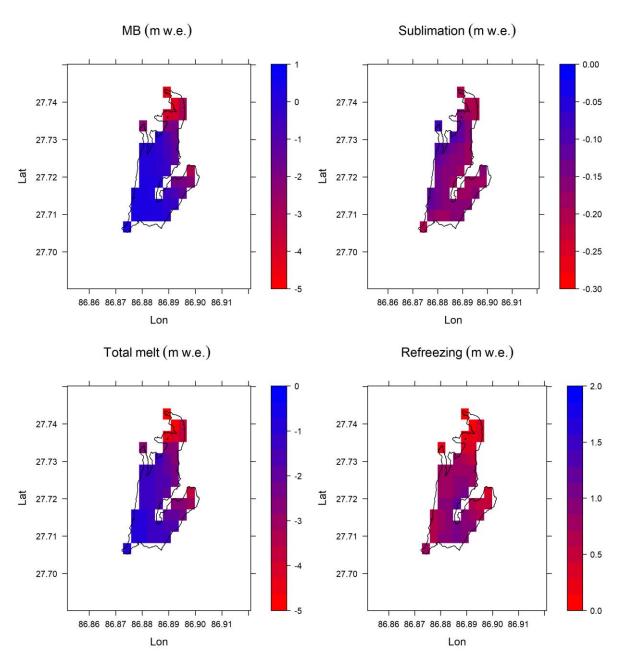


Figure S12. Same as Fig. S10 for the year 2017/18

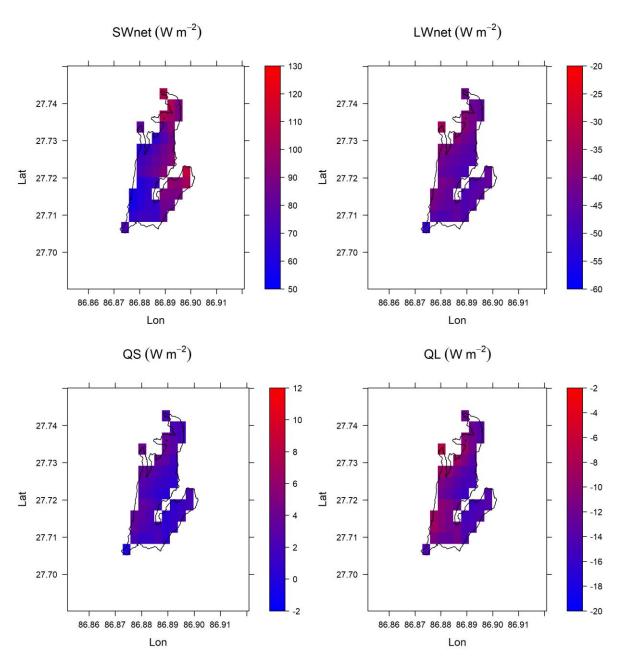


Figure S13. Same as Fig. S9 for the year 2018/19

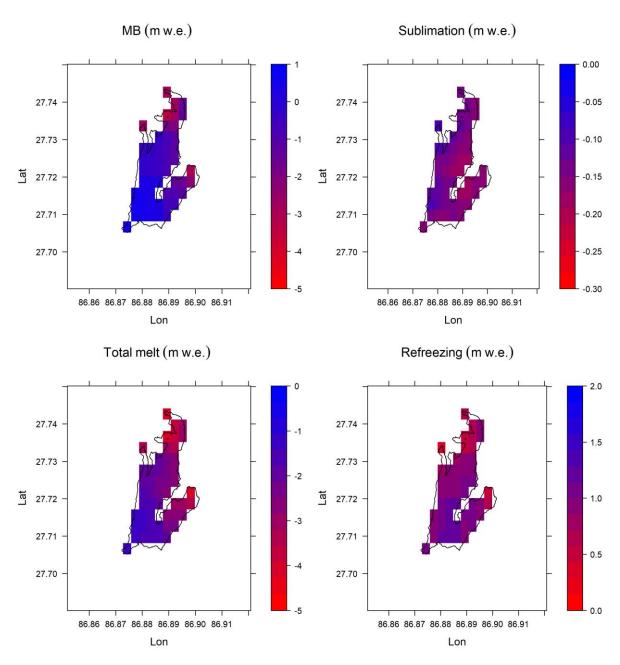


Figure S14. Same as Fig. S10 for the year 2018/19

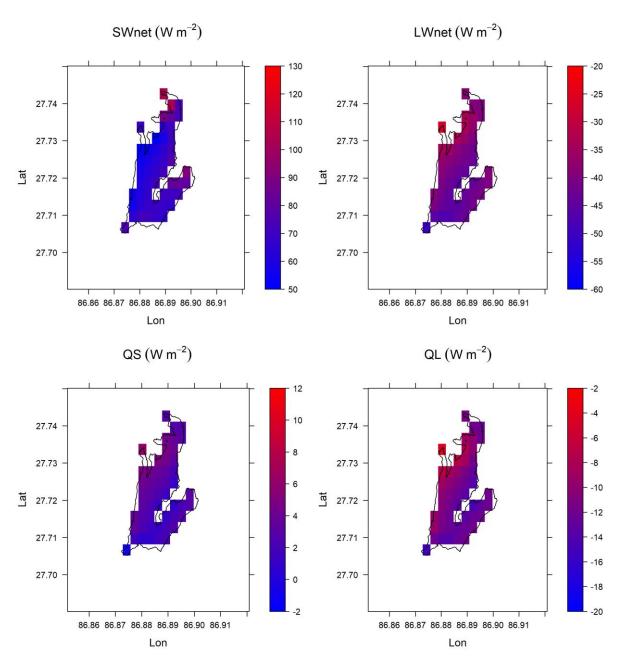


Figure S15. Same as Fig. S9 for the year 2019/20

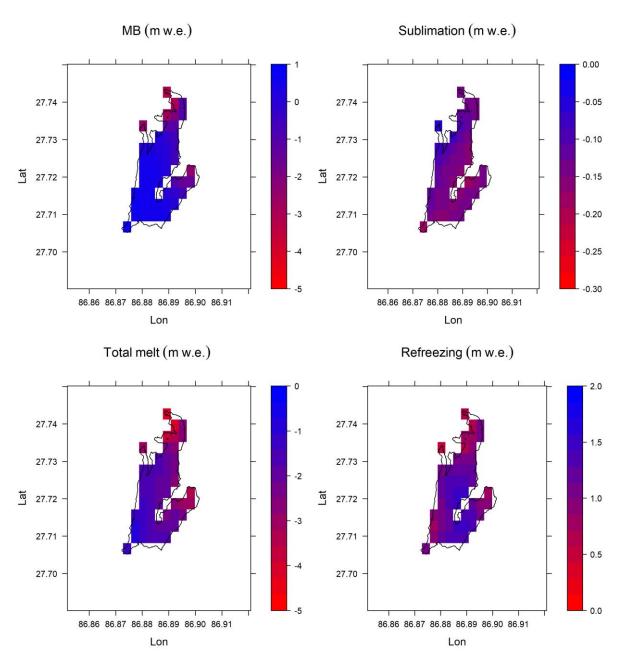


Figure S16. Same as Fig. S10 for the year 2019/20

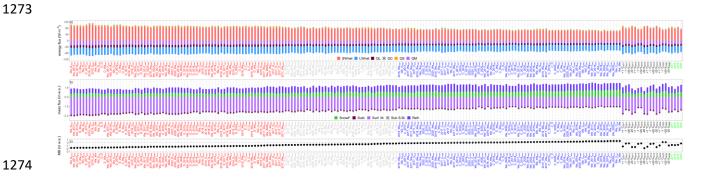


Figure S17. Glacier-wide (a) energy fluxes, (b) mass flux components, and (c) mass balance from the reference year (RY, in green on the x-axis) as well as all classical (in black) and synthetic (in red, grey and blue) scenarios. Synthetic scenarios are sorted in ascending order of glacier-wide mass balance, from the most negative (-1.76 m w.e.) to the most positive mass balance (0.54 m w.e.). The colour code of synthetic scenarios visualises the mass balance range: MB < -0.80 m w.e. (red); -0.80 m w.e. $\leq MB \leq -0.25$ m w.e. (grey) and -0.25 m w.e. $\leq MB$ (blue). SWnet = net shortwave radiation, LWnet = net longwave radiation, QL = latent heat flux, QS = sensible heat flux, QC = subsurface heat flux, QR = rain heat flux, QM = available melt energy at the surface, SnowF. = solid precipitation, Subl. = sublimation, Surf. M. = melt at surface Sub S. M. = subsurface melt and Refr. = refreezing. 2017, 2018, 2019 and 2020 are the mass balance years 2016/17, 2017/18, 2018/19 and 2019/20, respectively.

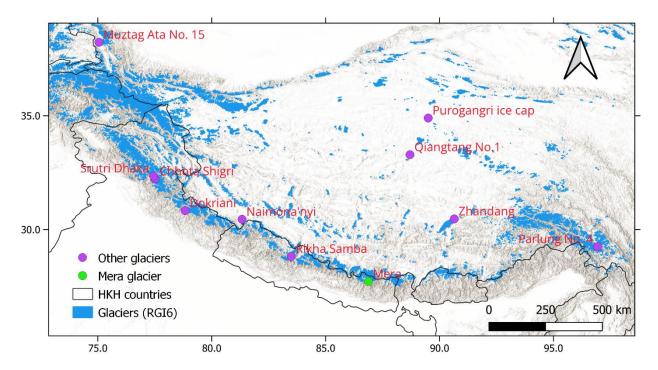


Figure S18. Location of glaciers where SEB studies have been conducted in HMA after 2014, and listed in Table 8.

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