



Contrasted climatologies in Pamir and Central Himalaya highlighted from MAR high-resolution atmospheric reanalysis over 1950-2025

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Abstract. High Mountain Asia (HMA) hosts the largest mass of terrestrial ice outside the polar regions, where combined glacier and snow melting with high precipitation rates supplies water to hundreds of millions of people. HMA hydroclimate is controlled by complex topography that shapes the contrasting atmospheric circulation patterns of the monsoon influence in the South and the westerly fluxes on the West, making particularly challenging the understanding of climate variability in this area. Despite its importance, large observational gaps persist, particularly at high elevation, while the coarse resolution of global climate products and the limited spatial or temporal coverage of existing high-resolution simulations hinder robust analyses of long-term climate variability and trends. Here, we present high-resolution (7 km) simulations performed with the regional climate model MARv3.14 over two climatically contrasted regions of HMA: the westerly-dominated Pamir and the monsoon-dominated Central Himalaya. Covering the 1950–2025 period, these experiments constitute, to our knowledge, one of the longest continuous high-resolution regional climate simulations available over these regions. Model skill is evaluated using multiple gridded observational and reanalysis datasets, satellite-derived snow products, and extensive in situ observations, with a particular focus on temperature, precipitation, snow cover, and strong precipitation events. MAR successfully reproduces the main hydroclimatic characteristics of both regions despite their contrasting climatic influences. It captures the seasonal evolution of temperature, ranging from nearly 30 °C in the lowlands to below –20 °C at the highest elevations, the winter–spring precipitation maximum in the Pamir (up to ~110 mm · month^{–1}), the summer monsoon peak in the Central Himalaya (up to ~550 mm · month^{–1}), and the seasonal migration of the snowline from ~3800 to ~4800 m in the Pamir and from ~4700 to ~5400 m in the Central Himalaya. The evaluation reveals an elevation-dependent precipitation bias, characterized by underestimated precipitation at low elevations (<40–60 mm · month^{–1}), and excessive snowfall accumulation at high elevations, which is associated with cold temperature bias (<2–4°C) and an excessive snow persistence. High-resolution



dynamical downscaling substantially improves the representation of orographic precipitation and its spatial distribution over the Khumbu area compared to the driving ERA5 reanalysis. These simulations provide a new long-term climatic reference for the Pamir and Central Himalaya and a validated modelling framework for investigating climate variability, cryosphere evolution, and natural hazards, as well as high-resolution atmospheric forcing for impact models such as glacier mass balance, snowpack, and hydrological models. The validated model configuration also provides a robust and transferable framework for extending the simulations to the entire High Mountain Asia domain.

1 Introduction

High Mountain Asia (HMA) comprises the major mountain ranges of the Himalaya, Karakoram, and Pamir, together with the extensive Tibetan Plateau. The region spans elevations from the low foothills to peaks exceeding 8000 m. Often referred to as the “Third Pole” or the “Asian Tower”, HMA represents the third-largest reservoir of glacier ice, outside the polar regions (e.g., Immerzeel et al., 2010), with nearly 100,000 km² of glacierized area (Pfeffer et al., 2014), making it a critical reservoir of frozen water for downstream societies (Immerzeel et al., 2010; Yao et al., 2012). Seasonal meltwater from snow and glaciers sustains freshwater supply, agriculture, irrigation and hydropower generation across large parts of Asia (Pritchard, 2019; Bolch et al., 2019; Biemans et al., 2019). The downstream lowlands of the major Asian river basins (Bookhagen and Burbank, 2010) - the Indus, Ganges, and Brahmaputra- are among the most densely populated regions on Earth and home to hundreds of millions of people who depend heavily on this meltwater, making hydrological stability a matter of critical socio-economic importance (Lutz et al., 2014; Wester et al., 2019). Over recent decades, glaciers across HMA have experienced widespread mass loss, although important regional contrasts persist, most notably in the Kunlun–Karakoram region where near-stable or slightly positive mass balances have been reported (e.g., Brun et al., 2017; Shean et al., 2020; Farinotti et al., 2020; Hugonnet et al., 2021). These changes have important implications for both regional water resources and global sea-level rise, and are projected to continue under future warming scenarios (Kraaijenbrink et al., 2017; Bolch et al., 2019).

HMA forms a vast and remote region shaped by diverse topographic and climatic regimes (e.g., Palazzi et al., 2013; Ménégoz et al., 2025). Its climate variability is primarily governed by the interplay between complex topography and large-scale atmospheric circulation patterns (Maussion et al., 2014; Schiemann et al., 2009), leading to pronounced longitudinal (west–east), latitudinal (north–south), and vertical climatic gradients (Yao et al., 2012). These gradients arise from the interaction of two dominant large-scale circulation systems: the mid-latitude westerly disturbances (WDs) and the Asian monsoon systems. The western and northwestern sectors, including the Pamir, Karakoram, and western Himalaya, are primarily influenced by WDs, which are extratropical cyclones originating over the Mediterranean and Caspian regions that bring winter and spring precipitation mainly in the form of snow (e.g., Dimri et al., 2015, 2023; Hunt et al., 2018, 2025). These synoptic-scale systems are crucial for glacier accumulation and snowpack maintenance, exerting a strong control on the hydrological regime of the upper Indus Basin (Cannon et al. 2016) and are projected to intensify, potentially increasing variability and the likelihood of



65 heavy precipitation events over the western Himalaya (Madhura et al. 2015). In contrast, the central and eastern Himalaya are
predominantly influenced by the South Asian summer monsoon, which supplies most of the annual precipitation through
intense convective rainfall between June and September (Maussion et al., 2014; Curio and Scherer, 2016). The eastern sector
is further modulated by interactions with the East Asian monsoon and by intraseasonal oscillations that affect the onset,
intensity, and withdrawal of the monsoon (Kapnick et al. 2014). These differing regimes need to be fully understood to
70 investigate how climate variability shapes cryospheric and hydrological processes across the subregions of HMA.

Despite the critical importance of HMA, large observational gaps persist, particularly at high elevations. In situ measurements
remain sparse and unevenly distributed, as harsh environmental conditions and logistical constraints hinder the establishment
and long-term maintenance of monitoring stations (Shea et al., 2015; Matthews et al., 2020). Most observations are
75 concentrated in valleys below ~4000 m, leading to an underrepresentation of high-altitude climate conditions (Palazzi et al.,
2013). This scarcity of high-elevation data limits the quantification of elevation-dependent warming, precipitation phase
transitions, and snow accumulation, thereby introducing substantial uncertainties in the assessment of historical variability and
climate trends (Lutz et al. 2014; Pepin et al., 2015; Bolch et al. 2019; Khanal et al., 2023). Although several field campaigns
and long-term high-altitude observatories –such as the Ev-K2-CNR Pyramid (e.g., Salerno et al., 2015), the GLACIOCLIM
80 network (Wagon et al., 2021), and recent expeditions on Mount Everest (Matthews et al., 2020)–have provided valuable
insights into local atmospheric and cryospheric processes, their spatial coverage remains limited and insufficient to capture the
full heterogeneity of the region. Satellite observations provide essential complementary information for monitoring cryospheric
and hydrological processes across HMA, but remain hampered by the challenges related to steep terrain. Recent advances in
multi-sensor remote sensing have substantially improved estimates of glacier mass balance (Hugonnet et al., 2021) and snow
85 cover (Liu et al., 2021b; Naegli et al., 2022) changes. Satellite-derived and gauge-merged precipitation products exhibit large
and spatially variable biases relative to in situ observations (Andermann et al., 2011; Cheema and Bastiaanssen, 2012; Guo et
al., 2015; Tong et al., 2014; You et al., 2015a), in part due to limitations in detecting solid precipitation and signal interference
from cloud cover (Immerzeel et al., 2015). In addition, the coarse spatial resolution of many observational and reanalysis
products limits their ability to resolve steep topographic gradients and localized processes (e.g., Orsolini et al., 2019; Khanal
90 et al., 2023). While these datasets provide a cost-effective and indispensable means to investigate regional climate variability
and trends (Gehne et al., 2016), their limitations represent a major source of uncertainty and a key constraint for studies aiming
to accurately characterize hydroclimatic variability in complex mountain environments.

The steep and heterogeneous terrain of HMA also poses significant challenges for climate modelling across scales, from global
95 to regional. Coarse-resolution global climate models, such as those participating in CMIP5 and CMIP6, often struggle to
capture steep orographic gradients and their influence on precipitation, temperature, and snow processes (Palazzi et al. 2013,
2015; Lalande et al. 2021). In particular, the inadequate representation of complex topography, snow dynamics, and glacier–
atmosphere interactions contributes to large uncertainties and substantial inter-model spread in simulated temperature and



precipitation over HMA (Immerzeel et al., 2010; Kapnick et al., 2014). Efforts within the CORDEX-South Asia framework (e.g., Krishnan et al., 2020) have improved regional climate representation through higher-resolution dynamical downscaling; however, significant challenges remain in reproducing snow cover and precipitation variability (Collier et al., 2024). Orographic effects generate strong spatial gradients in temperature, snowfall, and snow accumulation, requiring high-resolution simulations to accurately resolve processes over complex terrain. At the same time, the influence of mountain ranges on atmospheric circulation extends over large spatial scales, requiring sufficiently large model domains to capture upstream flow and orographic forcing. Summer precipitation in many basins is dominated by deep convection, which remains difficult to explicitly resolve and requires kilometre-scale resolution to be explicitly represented. Because achieving both large spatial domains and convection-permitting resolutions is computationally demanding, regional climate simulations generally involve a compromise between domain extent, horizontal resolution, and simulation length (e.g., Chow et al., 2019; Babaei et al., 2021).

Recent advances in convecting – permitting at kilometre-scale regional climate modelling have demonstrated substantial added value for the simulation of mountain hydroclimate (Prein et al 2022a, Collier et al 2024). Increasing horizontal resolution allows for a more realistic representation of steep topography and associated mesoscale processes, while also enabling explicit or partially explicit representation of deep convection in convection-permitting configurations (e.g., Ban et al., 2014; Prein et al., 2015; Collier et al., 2024). Such approaches have been shown to improve the simulation of orographic precipitation, cloud cover, snow cover and near-surface temperature variability over complex terrain (Rasmussen et al., 2011; Prein et al., 2013; Collier and Immerzeel, 2015). The finer resolution used in large eddy simulations, reaching values between 500m and 50m, allows an accurate representation of snow accumulation at the surface (Vionnet et al., 2017) and is appropriate to fully solve mesoscale circulation (Krieger et al., 2025) and convective processes (Panosetti et al., 2016). The computational cost of such numerical experiments limits their duration to days or weeks. Over HMA in particular, kilometre-scale simulations better reproduce precipitation intensity, seasonal cycles, and spatial variability compared to coarser regional and global models (Collier et al., 2024; Cannon et al., 2017; Gurung et al., 2026). Nevertheless, despite the clear added value of kilometre-scale and convection-permitting simulations over complex terrain, many existing studies over HMA remain limited to short simulation periods, seasonal experiments, individual extreme events, or relatively restricted spatial domains (e.g., Cai et al., 2021; Li et al., 2021; Sugimoto et al., 2021). As a result, important uncertainties remain regarding the robustness of simulated long-term hydroclimatic variability, while multi-decadal simulations are still needed to properly assess climate trends, extremes, and internal variability (e.g., Deser et al., 2012). Moreover, systematic biases in temperature, precipitation, and snow cover continue to affect even high-resolution simulations. This highlights the need for continued development of high-resolution modelling approaches, combined with robust observational evaluation, to improve both process understanding and the reliability of future climate projections. Such projections are critical for informing adaptation strategies related to water resources, agriculture, and ecosystem management across HMA (e.g., Pörtner et al., 2019, SROCC; Krishnan et al., 2019).



In this study, we address these gaps by presenting long-term simulations at 7 km resolution using the regional climate model MAR (for Modèle Atmosphérique Régional in French) over two contrasting sub-domains of HMA: the Pamir region, primarily influenced by westerly disturbances, and Central Himalaya, dominated by the South Asian monsoon. Covering the 1950–2025 period using the ERA5 reanalysis (Hersbach et al., 2020) as lateral boundary conditions, these experiments provide one of the longest continuous regional climate simulations currently available for these regions. Model performance is assessed against multiple gridded observational and reanalysis datasets, together with in situ measurements, with a particular focus on temperature, precipitation, and snow variability. By evaluating MAR across two strongly contrasting hydroclimatic regimes, we assess the robustness and transferability of a common model configuration prior to its extension to the broader HMA domain. The paper is organized as follows. Section 2 describes the MAR configuration, reference datasets, and in situ observations. Section 3 presents a comparison between model simulations and available observations, highlighting the climatological conditions in remote areas. This includes analyses of mean climatology, annual cycles, snowline variability, and several strong precipitation events over the Khumbu–Everest region. Finally, Section 4 summarizes the main findings, discusses remaining limitations and uncertainties, and outlines perspectives for future high-resolution climate simulations over HMA.

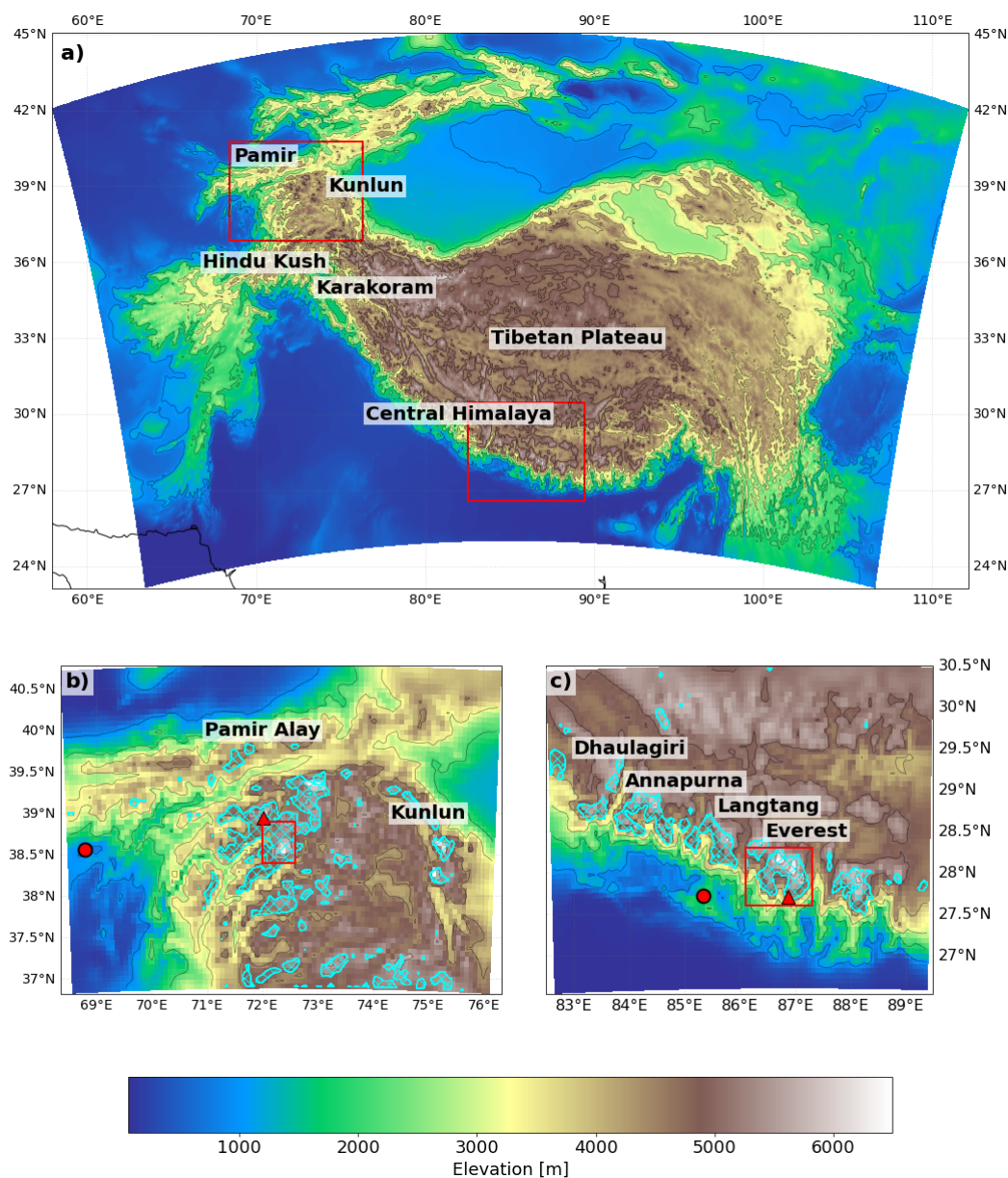


Figure 1: Topography in the MAR model (7km of resolution) over High Mountain Asia (a), and the subdomains of Pamir (b) and Central Himalaya (c). The red boxes in panel (a) indicate the locations of the Pamir and Central Himalaya subdomains. Red circles denote the major cities of Dushanbe (Tajikistan) and Kathmandu (Nepal), while red triangles mark Imeni Peak (7,649 m), near the Fedchenko Glacier (officially renamed Vanch-Yakh Glacier) in the Pamir, and Mera Peak (6,476 m), in the Khumbu region of the Central Himalaya. Cyan hatched areas represent glacierized surfaces in the MAR model with an ice fraction greater than 20%.



2 Data & Methods

2.1 MAR model

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The Modèle Atmosphérique Régional (MAR; Gallée and Schayes, 1994) is a hydrostatic regional climate model originally developed for polar areas (Gallée, 1995). Cloud microphysical processes and resulting precipitation are simulated by solving conservation equations for specific humidity, cloud droplets and ice crystals, raindrops, and snow particles (Gallée, 1995; Gallée et al., 2001). It has been widely used and evaluated in the Arctic (Maure et al., 2023), over Greenland (e.g., Fettweis et al., 2017; Delhasse et al. 2020; Maure et al., 2023) and Antarctic (e.g., Kittel et al. 2018; Agosta et al. 2019; Amory et al. 2021) ice sheets. MAR has been adapted to tropical regions by implementing the convective adjustment scheme of Bechtold et al. (2001). MAR has demonstrated also good skill in high-mountain environments, including the Himalayas (Ménégoz et al. 2013), the Alps (Ménégoz et al. 2020; Beaumet et al. 2021; Castellanos et al. 2026) and Patagonia (Noël et al., 2025; Collao-Barrios et al., 2026).

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MAR is coupled to the one-dimensional land surface scheme SISVAT (Soil Ice Snow Vegetation Atmosphere Transfer, De Ridder and Gallée, 1998; Gallée et al., 2001) in which water and energy budgets are solved independently for soil and vegetation. SISVAT explicitly represents snowpack evolution with a multi-layer snow cover scheme (Brun et al., 1992) and glacier surface mass balance (Gallée et al., 2001; Lefebvre et al., 2003). The grid cells are divided in different tiles, corresponding to the main surface conditions found locally, that can be vegetated areas or bare soils, as well as lakes or glaciers. In this study, two tiles are considered for each grid cell. The topography is derived from the ETOPO global relief model (version 2022, MacFerrin et al., 2022), and land-surface properties are prescribed from the GlobCover land-cover dataset (Arino et al., 2012) and translated into the corresponding SISVAT surface classes. The glacier mask was updated here using the Randolph Glacier Inventory (RGI 6.0; <https://doi.org/10.7265/N5-RGI-60>), and corrected to reduce an overestimation of glacierized areas caused by the misclassification of seasonal snow as permanent ice. Debris-covered glacier areas are represented as bare soil within the current model framework. This is justified by the fact that these areas feedback on the atmosphere as non-glacierized areas.

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The simulations were performed with the version 3.14 of MAR, coupled to the ecRad radiation scheme (Grailet et al., 2025). The model is driven by 6-hourly ERA5 reanalysis data, which provide lateral boundary conditions for pressure, wind, temperature, and specific humidity, as well as upper-tropospheric temperature and wind fields. Over the ocean, ERA5 sea-surface temperature and sea-ice concentration are prescribed as surface boundary conditions.

A 10km-resolution regional climate simulations have been performed already over HMA, using a forecast configuration (i.e. with daily re-initialisation from ERA5 reanalysis), a way to get accurate precipitation rates (HAR and HARv2, Maussion et



190 al. 2011, 2014; Wang et al., 2020). Such configuration is however affected by the systematic biases found in the atmospheric
 reanalysis, and in particular the strong snow cover overestimation found in ERA5, which requires a bias-correction in the
 initial surface conditions that limits the possibility to simulate a realistic and continuous snow cover evolution (Wang et al.,
 2020). Here, MAR is configured for continuous multi-decadal experiments, allowing a consistent evolution of the surface
 conditions, including soil moisture and snow cover.

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 The simulations were performed over two domains centred on the Pamir (68.4°E:76.3°E, 36.8°N:40.7°N) and Central
 Himalaya (82.5°E:89.4°E, 26.6°N:30.5°N) regions (Figure 1b, c), using a horizontal resolution of 7 km on a 116 × 82
 stereographic grid and a 20 s time step. In this study the snowpack is described with 30 snow or ice layers distributed over a
 maximum of 20 m thickness. The atmospheric column extends up to 20 km altitude and is discretized on a stretched grid into
 200 30 terrain-following vertical levels, including 8 levels within the lowest 100 m and a lowest model level at 2 m above the
 surface. This vertical configuration was designed to avoid excessive nudging close to the surface over the highest mountain
 peaks of the domains. To reduce the influence of the lateral boundary forcing on the model physics, the 10 grid cells closest
 to the domain boundaries (~70 km), i.e. the relaxation zone, were excluded from the analysis.

205 2.2 Reference gridded datasets

To evaluate the MAR simulations, we use a combination of global reanalyses, regional atmospheric products, and observation-
 based gridded datasets describing temperature, precipitation, snow cover, and topography across High Mountain Asia (Table
 1). These datasets differ in spatial resolution, temporal coverage and observational input.

210 2.2.1 Reanalysis

ERA5 reanalysis (ERA5; Herbach et al 2020) provides a global, physically consistent reconstruction of the atmosphere, land
 surface, and ocean waves from 1940 to present. It is produced using the ECMWF Integrated Forecasting System (IFS) at 0.25°
 x 0.25° spatial resolution and hourly temporal frequency, with atmospheric parameters on 37 pressure levels. It combines a
 modern data-assimilation scheme with an extensive set of in situ and satellite observations.

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 ERA5-Land (ERA5-L; Muñoz-Sabater et al. 2021) provides land-surface variables at 0.1° resolution for 1981–2020. It is
 produced by rerunning the land component of ERA5 at higher spatial resolution, improving the representation of soil and
 surface processes relative to the standard 0.25° ERA5 fields.

220 The High Asia Refined Analysis (HAR; Maussion et al. 2011, 2014) is a regional atmospheric dataset created using WRF-
 based dynamical downscaling in a forecast configuration (Section 2.1). The updated HAR v2 (Wang et al. 2020) provides 10
 km resolution meteorological fields for 1981–2020, using ERA5 as lateral boundary conditions. Its domain covers the Tibetan
 Plateau and surrounding high mountain regions.



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2.2.2 Observation-based gridded products

Temperature and precipitation datasets

230 The CRU TS4.05 dataset (Harris et al. 2014) provides monthly temperature and precipitation fields at 0.5° resolution from 1901 to 2020, based on quality-controlled station homogenised observations. This century-long record is particularly useful for long-term climate analyses, although uncertainties remain in regions with sparse observation networks such as over HMA.

235 CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data; Funk et al. 2015) offers rainfall estimates between 50°S and 50°N at 0.05° resolution for 1981–present, combining satellite infrared data with station observations. Its fine resolution and temporal coverage make it suitable for hydrological and drought monitoring, but the product does not include snowfall being less accurate in snow-dominated or highly complex terrain.

240 The APHRODITE dataset (Asian Precipitation – Highly-Resolved Observational Data Integration Towards Evaluation; Yatagai et al. 2012) provides daily precipitation fields based on an extensive network of Asian rain gauges. It is available from 1951 onward and here, we use the $0.25^\circ \times 0.25^\circ$ version. Although designed to improve spatial consistency where gauge density is high, it may underestimate precipitation in regions with limited observations or at high elevations, and might be affected by the varying number of available observations over time.

245 The GPCP (Global Precipitation Climatology Project; Adler et al. 2018) monthly product merges satellite retrievals, gauge observations, and sounding data to produce global precipitation fields at 1.0° resolution from 1979 onward. Its consistent global coverage is advantageous for climatological assessments, though the coarse resolution limits applications in areas with strong topographic gradients. These datasets have previously been evaluated in mountainous regions of South and Central Asia, including the Indus Basin (Baudouin et al. 2020).

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Snow datasets

255 The High Mountain Asia Snow Reanalysis (HMASR; Liu et al. 2021a) provides daily estimates of snow-covered fraction (SCF), snow water equivalent (SWE), and snow depth (SND) at 500 m resolution for water years 2000–2017. SWE is derived using a data assimilation approach that integrates Landsat and MODIS SCF (Margulis et al. 2019), supported by bias-corrected and downscaled meteorological forcings and ensemble-based uncertainty estimation (Durand et al. 2008, Girotto et al. 2014). HMASR focuses on seasonal snow and excludes semi-permanent snow and glacier ice (Liu et al. 2021a). It has been widely



used to study snow dynamics across High Mountain Asia (Liu et al. 2021a, 2022; Gascoin 2021). In this study, we use only the
 SND variable. Because the native spatial resolution of HMA SR (16 arcsec 500 m) is substantially finer than the other datasets
 260 considered here (7–25 km), the data were aggregated to 7 km using spatial averaging to ensure consistency across products.

The ESA Snow CCI SCFG v2.0 dataset provides daily snow cover fraction (SCFG) over global land areas, excluding
 permanent snow and ice regions such as Antarctica and Greenland. The product is derived from medium-resolution optical
 satellite observations from AVHRR (1982–2018; Naegeli et al. 2022) and MODIS (2000–2020; Nagler et al., 2022), at spatial
 265 resolutions of approximately 5 km and 1 km, respectively. SCFG provides snow cover fraction values ranging from 0 to 100%
 per pixel and includes a canopy transmissivity correction to improve snow detection in forested areas by representing snow on
 the ground beneath vegetation. Cloud-contaminated pixels are masked using the Cloud CCI v3.0 cloud mask product. In this
 study, we use the 5 km SCFG product and to reduce temporal gaps associated with cloud cover, a linear interpolation is applied
 along the time dimension using a maximum interpolation window of 10 days, while longer gaps are retained as missing values
 270 (Lalande et al., 2023).

Snow variables were converted into binary snow/no-snow values: grid cells with snow depth greater than 10 cm, and snow
 cover fraction greater than 10 %, were classified as snow-covered. Note that snow depth is used for HMASR, MAR, HARv2,
 and ERA5-Land, whereas ESA-CCI provides snow cover fraction (Table 1).

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2.2.3 Topography and glacier mask

Topography is represented using the GMTED2010 digital elevation model (Danielson and Gesch, 2011), originally available
 at 15 arc-second resolution. The elevation data were aggregated and bilinearly interpolated to match the native resolution of
 280 each dataset. The only exception is HAR v2, which includes its own topographic field derived from the WRF configuration.

To ensure a consistent treatment of glacierized and permanent snow areas across datasets with different spatial resolutions and
 snow representations, each dataset was analysed using its own glacier or permanent snow mask on its native grid. While most
 datasets provide a binary glacier mask, MAR represents the fraction of each grid cell covered by glacier ice. Likewise, although
 285 HMA-SR originally provides a binary glacier mask at 16 arcsec (~500 m) resolution, its aggregation to a coarse grid results in
 a fractional ice cover for each grid cell. For both MAR and the aggregated HMA-SR product, grid cells with an ice fraction
 greater than 50% were classified as glacier-covered, yielding a binary mask comparable to those provided by the other datasets.

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Dataset	Variable	Resolution	Period (Frequency)	Reference
Reanalysis				
HAR v2	t2m,pre,snd	10 km × 10 km	1980-2023 (daily)	Wang et al. (2021)
ERA5-Land	t2m,pre,snd	0.1° × 0.1°	1950-present (daily)	Muñoz-Sabater et al. (2021)
ERA5	t2m,pre,snd	0.25° × 0.25°	1950-present (daily)	Hersbach et al. (2020)
Gridded products				
CRU	t2m,pre	0.5° × 0.5°	1901–2020 (monthly)	Harris et al. (2014)
CHIRPS	pre	0.05° × 0.05°	1981–2025 (daily)	Funk et al. (2015)
APHRODITE	pre	0.25° × 0.25°	1951–2015 (daily)	Yatagai et al. (2012)
GPCP	pre	1.0° × 1.0°	1891–2019 (monthly)	Adler et al. (2018)
HMA SR V1	snd	16 arcsec × 16 arcsec (~500 m)	1999–2017 (daily)	Liu et al. (2021)
ESA CCI v2.0	snc	0.05° × 0.05°	1979–2022 (daily)	Naegeli et al. (2021)
In situ				
GLACIOCLIM	t2m,pre	Nepal; Khumbu Region	2012-2025 (<1h)	Wagnon et al. (2021)
Ev-K2-CNR	t2m,pre	Nepal; Everest's region	1995-2024 (<1h)	Salerno et al. (2025)
National Geographic	t2m,pre	Nepal; Everest's region	2019-2023 (<1h)	Matthews et al. (2020)
Central Asia Temperature and Precipitation Data, Version 1	t2m, pre	Pamir	1879-2003 (monthly)	Williams et al. (2008)

295 **Table 1: Reanalysis, observed-based gridded products and in situ networks used in this study. Acronyms are “t2m”**
 temperature at 2m, “pre” total precipitation, “snd” snow depth and “snc” snow cover extent.



2.3 In situ/AWS

2.3.1 Central Himalaya domain

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We use three different set of in situ observations over the Khumbu region (Table 2, Figure 7a):

- ‘GLACIOCLIM’ is the French National Observation Service dedicated to glacier monitoring (<https://glacioclim.osug.fr>). In addition to glacier mass-balance observations, GLACIOCLIM operates a network of automatic weather stations (AWS) in the Khumbu region. Over Mera Glacier, four AWS have been deployed and two additional AWS are installed on West and North Changri Nup glaciers, on- and off-ice. Three stations are located at Pyramid, Pheriche, and Khare (Table 2), where precipitation measurements are available at these three sites only. Precipitation data were corrected for undercatch following the methods of Førland et al. (1996) and Lejeune et al. (2007), as a function of wind speed and precipitation phase (liquid or solid) determined by air temperature (see Khadka et al., 2022, for a detailed description).

315 - ‘NatGeo’: The highest altitude automatic weather station (AWS) network was installed on the southern slopes of Mount Everest in 2019 and 2022 (Matthews et al., 2020b, Matthews et al., 2022). The network consists of five stations spanning elevations from 3,840 to 8,430 m a.s.l., providing unique in situ observations of meteorological conditions across extreme elevation gradients in the upper Khumbu region. These measurements have enabled improved characterization of temperature, humidity, radiation, and precipitation processes in the world’s highest mountain environment (Matthews et al., 2020a,b; Perry et al., 2020; www.nationalgeographic.org/projects/perpetual-planet/everest/weather-data/)

325 - ‘Ev-K2-CNR’: The Pyramid Meteorological Network, established by the Everest–K2–National Research Council (Ev-K2-CNR) Committee, operates on the southern slopes of Mount Everest, Nepal (Locci et al., 2014; Salerno et al., 2015, 2025). The network comprises seven meteorological stations spanning elevations from 2,660 to 7,986 m a.s.l. and has provided continuous climatic observations in the Khumbu region since the mid-1990s (1994–2023), representing one of the longest high-elevation meteorological records in the Himalaya. The data can be freely downloaded from <https://doi.org/10.5281/zenodo.15211352> (Salerno et al., 2025).

330 As with most in situ meteorological observations in high-mountain environments, several limitations must be acknowledged. Solid precipitation is often underestimated due to wind-induced undercatch, particularly during snowfall events (e.g., Buisán et al., 2017; Kochendorfer et al., 2020). Extreme precipitation episodes may also exceed gauge capacity, leading to additional measurement losses (e.g. the October 2025 event; Matthews, *personal communication*). Homogeneous comparison across stations is further complicated by changes in station location over time, even over short distances, which can introduce systematic biases in the recorded variables. In addition, variations in sensor height can lead to non-negligible differences in



the measured values, a common issue for stations installed on snow- or glacier-covered surfaces (Préaux et al., 2025). Finally, temporal data gaps are common, reflecting the logistical constraints of operating and maintaining instruments in remote, high-elevation terrain.

Station name (Acronym)	Variable	Lat (°N)	Lon (°E)	Elevation (m a.s.l)	Period	Sampling rate
GLACIOCLIM						
Mera Naulek (MK)	t2m (min,max)	27.72	86.90	5360	2012-11 to 2024-11	30min
Mera La (ML)	t2m	27.73	86.90	5352	2013-11 to 2024-11	30min
Mera Summit (MS)	t2m (min,max)	27.71	86.87	6351	2013-11 to 2016-08	30min
Mera Camp 5770 (M57)	t2m	27.72	86.88	5769	11-2017 to 02-2024	30min
Khare (KH)	t2m, pre	27.74	86.88	4888	11-2016 to 11-2023	30min
Pheriche (PHE)	t2m, pre	27.89	86.82	4260	12-2012 to 11-2023	30min
Pyramid (PY)	t2m, pre	27.96	86.81	5035	2019-05 to 2024-11	30min
CHA3 (CHA)	t2m	27.98	86.78	5360	2014-11 to 2024-11	30min
Ev-K2-CNR						
South Col (AWSSC)	t2m	27.98	86.76	7986	05-2008 to 09-2011	1h
Changri Nup (CNG_SNP)	t2m	27.96	86.93	5700	02-2010 to 12-2015	1h
Pyramid (AWS0)	t2m,pre	27.96	86.81	5035	01-1994 to 12-2005	1h
Pyramid (AWS1)	t2m,pre	27.96	86.81	5035	01-2000 to 12-2023	1h
Pheriche (AWS2)	t2m,pre	27.90	86.82	4260	01-2000 to 12-2023	1h
Lukla (AWS3)	t2m, pre	27.70	86.72	2660	01-2002 to 12-2023	1h
Kala Patthar (AWS4)	t2m, pre	27.99	86.83	5600	01-2009 to 12-2023	1h
Namche (AWS5)	t2m,pre	27.80	86.71	3570	01-2001 to 12-2023	1h
NatGeo						
Base Camp AWS (BC)	t2m, pre	27.99	86.84	5315	10-2019 to 06-2023	1h
Camp II AWS (C2)	t2m	27.98	86.90	6464	05-2019 to 07-2023	1h
Phortse AWS (PHO)	t2m, pre	27.84	86.75	3810	04-2019 to 07-2023	1h
Bishop Rock AWS (BIS)	t2m	27.97	86.93	8810	05-2022 to 07-2023	1h
South Col AWS (SC)	t2m	27.97	86.93	7945	05-2019 to 07-2023	1h

Table 2: List of meteorological stations used in this study from the GLACIOCLIM, Ev-K2-CNR, and NatGeo networks over the Khumbu–Everest region (Nepal). The ‘Period’ column indicates the available observation period for each station; some records contain temporal gaps and are therefore not continuous.



2.3.2 Pamir domain

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The Central Asia Temperature and Precipitation dataset is an expanded and updated subset of the NOAA Global Historical Climate Network (GHCN; Williams et al. 2008), providing quality-controlled monthly air temperature and precipitation records from 298 meteorological stations in the Northern Tien Shan and Pamir mountain ranges of Central Asia. The dataset is primarily based on observations from the National Hydrometeorological Services of Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan, with station records spanning variable periods between 1879 and 2003. Monthly precipitation totals are bias-corrected for gauge type, blowing snow and wetting losses, while temperature data consist of monthly means, with maximum and minimum temperatures available for many stations. All records underwent rigorous quality control and homogeneity assessment following GHCN procedures, and are accompanied by detailed station metadata, making this dataset a key resource for long-term climate variability and trend analyses in Central Asian Mountain regions

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Over the Pamir domain considered in this study, the dataset includes approximately 76 meteorological stations spanning elevations from 264 to 4169 m a.s.l., providing a representative vertical sampling of regional climate conditions. Temperature and precipitation are provided as separate records, and while not all stations report both variables, the majority correspond to the same station locations for temperature and precipitation, allowing consistent station-based analyses.

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3 Results

3.1 Climatology

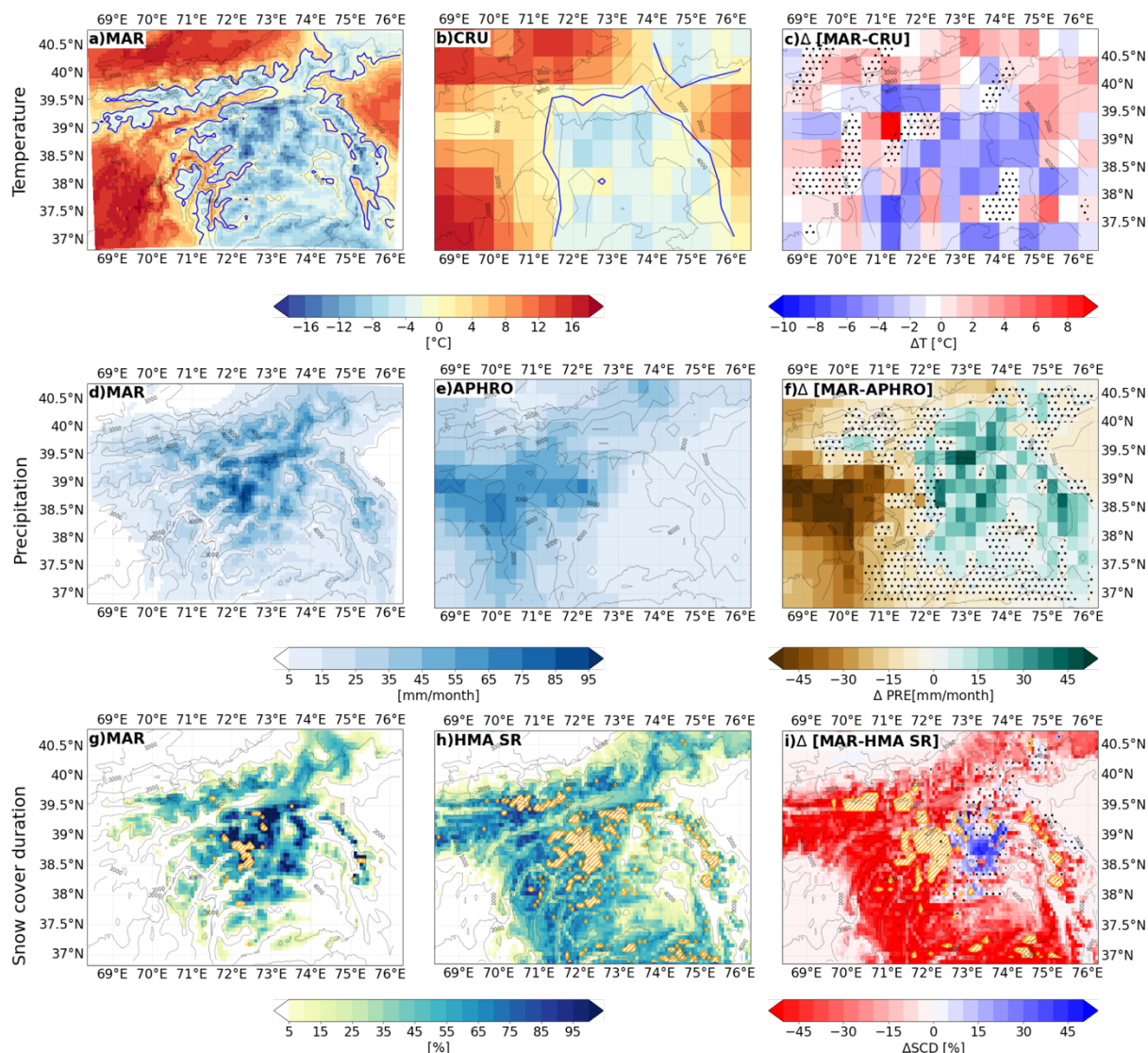


Figure 2: Annual climatology and bias of temperature (1980-2020; °C, top), precipitation (1981-2015; mm · month⁻¹), and snow cover duration (2000-2016; expressed as the percentage of days with snow cover during a year, %) over the Pamir domain. Biases are computed on the observational grid. Grey contour lines show the topography of each dataset (contour interval: 1000 m). Hatched areas indicate glacier-covered grid cells (glacier fraction >50%) based on the respective dataset mask (g-h) and the combined MAR/HMA-SR mask (i). Blue contours (top panel) represent the 0°C isotherm. Black dots indicate grid cells where the difference is not statistically significant, i.e., the bias is higher than the standard deviation of observation ($|\Delta| < \sigma_{\text{obs}}$).



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Figure 2a shows the annual mean temperature simulated by the MAR model. The 0°C isotherm is located at approximately 3000 m, with minimum temperatures reaching −18°C at the highest elevation, namely over the Fedchenko Glacier (Vanch-Yakh Glacier). Mean annual temperatures of −9 to −10°C extend over the Pamir Alay and the northeastern part of the domain. Lower-elevation regions (<2000 m) east of the Kunlun range exhibit warmer conditions, with mean temperatures of 10–12°C, while the lowest areas in the north and west of the domain (~800 m) reach maximum values close to 20°C. The CRU observational dataset (Figure 2b) reproduces the large-scale temperature pattern but with a substantially smoothed representation of the topography. In CRU, the 0°C isotherm is located at higher elevations (3500–4000 m), and mean temperatures over the central Pamir are around −3°C, with minimum values of approximately −6°C. Due to its coarse resolution, the Pamir Alay and deep, narrow valleys are not resolved, although the western extent of the Tien Shan is partially represented, with temperatures around −5°C. As shown in Figure 2c, MAR exhibits colder temperatures at high elevations and warmer temperatures at low elevations compared to CRU, with significant differences reaching up to 5°C, reflecting the role of unresolved topography in the observational dataset.

Annual mean precipitation simulated by MAR is depicted in Figure 2d. High precipitation amounts ($>50 \text{ mm} \cdot \text{month}^{-1}$), occur over the highest elevations, particularly over glacierized areas of the central Pamir, with maximum values reaching $149 \text{ mm} \cdot \text{month}^{-1}$, highlighting the importance of solid precipitation as a key contribution to glacier mass balance. Relatively high precipitation values ($60\text{--}70 \text{ mm} \cdot \text{month}^{-1}$) are also simulated over the Pamir Alay. In contrast, the lowland regions of the Pamir domain are comparatively dry, with annual mean monthly precipitation below 15 mm. The APHRODITE dataset (Figure 2e) exhibits considerably lower precipitation amounts, with maximum values of approximately $70 \text{ mm} \cdot \text{month}^{-1}$, roughly half of the maximum values simulated by MAR. Precipitation in APHRODITE displays a strong zonal gradient, with higher values primarily confined to the western flank of the domain and reduced amounts at high elevations over the east, likely reflecting gauge undercatch and the difficulty of measuring solid precipitation at these high elevation, as well as a lack of spatial coverage of rain gauges over the eastern part (Figure 8). These significant differences lead to a contrasting spatial bias pattern (Figure 2f), with MAR simulating higher precipitation over high-elevation regions, particularly in the eastern and central Pamir, and smaller or negative differences over parts of the western domain.

The differences in temperature and precipitation are reflected in the seasonal snow cover duration. Note that the analysis only considers seasonal snow-covered areas, with permanent snow and glacierized surfaces excluded from the comparison. The enhanced precipitation simulated by MAR leads to longer snow cover duration at the highest elevations (Figure 2g), where snow persists for 80–85% of the year, higher than in HMA-SR. However, at mid-elevations (~2000–3500 m), MAR simulates significantly less snow cover compared to HMA-SR (Figure 2h), which indicates snow persistence for approximately half of

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the year whereas HMA-SR exhibits values of 65 %. The bias pattern (Figure 2i) clearly highlights this elevation-dependent behaviour, with MAR overestimating snow cover at high elevations while underestimating it at mid- to low elevations, consistent with a cold and wet bias at high elevations and a slightly warm and dry bias at lower elevations.

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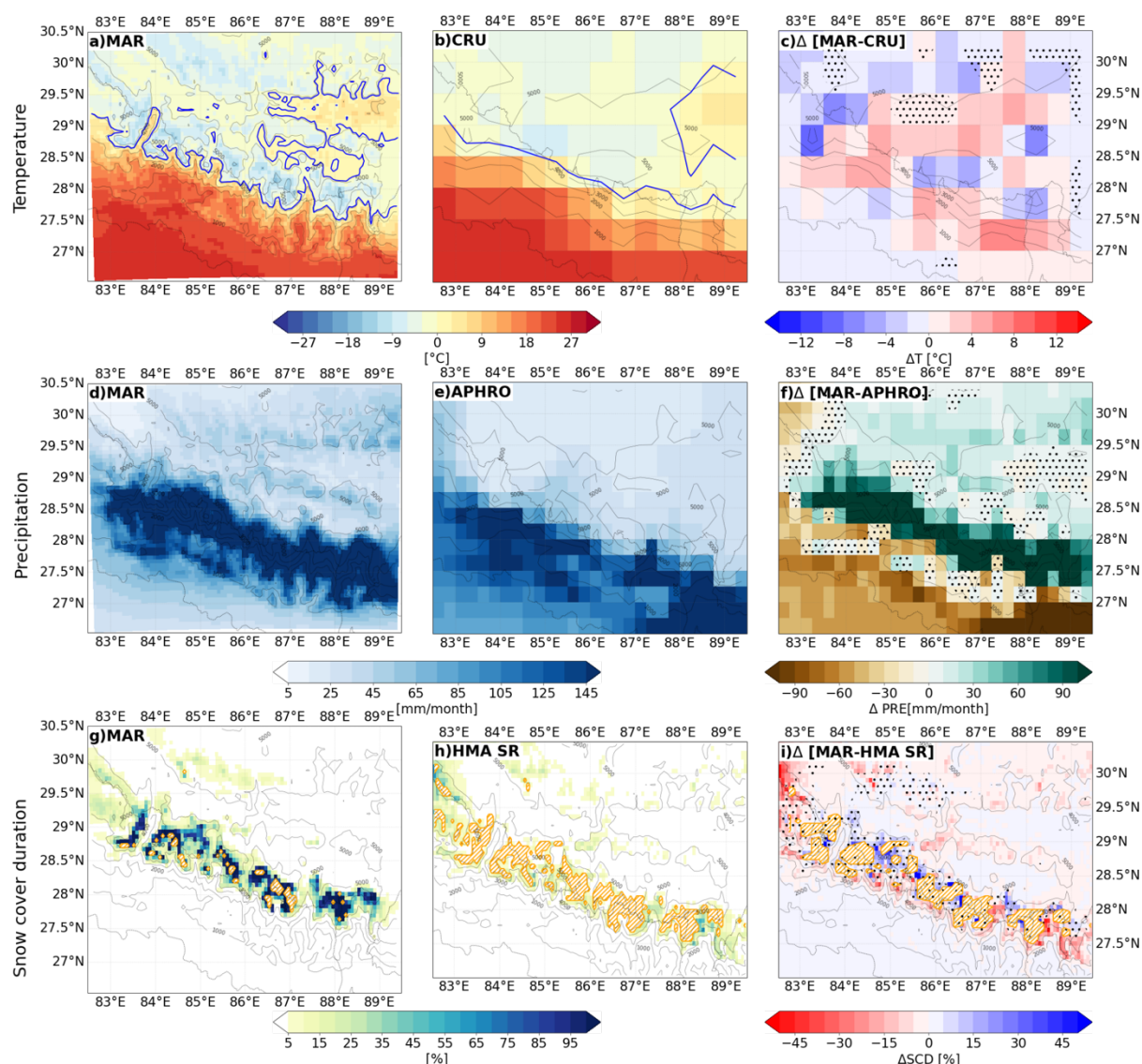


Figure 3: Annual climatology and bias of temperature (1980-2020; °C, top), precipitation (1981-2015; mm · month⁻¹, middle), and snow cover duration (2000-2016; expressed as the percentage of days with snow cover during a year, %, bottom) over Central Himalaya. Biases are computed on the observational grid. Grey contour lines show the topography of each dataset (contour interval: 1000 m). Hatched areas indicate glacier-covered grid cells (glacier fraction >50%) based on the respective dataset mask (g-h) and the combined MAR/HMA-SR mask (i). Blue contours (top panel) represent the 0°C isotherm. Black dots indicate grid cells where the difference is not statistically significant, i.e., the bias is higher than the standard deviation of observation ($|\Delta| < \sigma_{\text{obs}}$).



Annual mean temperature simulated by the MAR model over Central Himalaya is shown in Figure 3a. Over the southern flank of the Himalayas, MAR simulates warm conditions, with annual mean temperature ranging from 20 to 25°C. Following the pronounced meridional elevation gradient, temperature decreases steadily northward, with the 0°C isotherm located around 4500 m and locally reaching 5000 m in the central part of the domain. Over the Tibetan Plateau, mean annual temperatures range between -6 and -12°C in the highest-elevation areas. MAR also captures the orographic depression in the northeastern part of the domain, around the Namucuo Lake region (30.7°N, 90.7°E), where mean annual temperatures locally rise to values above 0°C, reaching approximately 8°C. The CRU observational dataset (Figure 3b) reproduces the large-scale meridional temperature gradient, with mean annual temperatures of around 25°C over the southern plains and minimum values of approximately -6°C over the highest elevations, which CRU represents at ~6000 m maximum due to its coarse resolution. In CRU, the 0°C isotherm is located at lower elevations (~4000 m) compared to MAR. The temperature bias pattern (Figure 3c) is spatially heterogeneous, reflecting the sharp elevation contrasts of the region. Notable significant differences are found in the Dhaulagiri region in the western Himalayas, where adjacent grid cells show strong significant negative biases (up to -12°C) and positive biases of around +4°C, highlighting MAR's ability to resolve the steep topographic gradients of the Kali Gandaki Gorge (28.7°N, 83.6°E) on the eastern slope of Dhaulagiri. In the Everest region, several grid cells exhibit negative biases, indicating colder temperatures simulated by MAR relative to CRU at high elevations, a feature that is also evident over the northern Tibetan Plateau above 5500 m. Along the southern Himalayan flank, MAR is slightly warmer than CRU (2–3°C), transitioning to a weak cold bias (<2°C) over the lowlands.

Figure 3d shows the annual mean monthly precipitation simulated by MAR. High precipitation amounts exceeding 150 mm · month⁻¹, are simulated at high elevations, with maximum values reaching 337 mm · month⁻¹ in the southeastern part of the domain. These spatial patterns are broadly consistent with the APHRODITE dataset (Figure 3e), although APHRODITE exhibits lower maximum values, until 294 mm · month⁻¹. However, as discussed in Section 2, MAR underestimates precipitation over flat and low-elevation regions where convective processes dominate. In these areas, MAR simulates values below 25 mm · month⁻¹, whereas APHRODITE shows precipitation exceeding 70 mm · month⁻¹ and locally reaching up to 140 mm · month⁻¹ in the southwestern part of the domain. This contrast results in a pronounced dipole structure in the precipitation bias (Figure 3f), characterized by strong negative significant biases exceeding -100 mm · month⁻¹ in the lowlands – more than twice the domain-mean annual precipitation and positive biases over the highest elevations. As for the Pamir, the latter is partly attributable to the underrepresentation of snowfall in observational datasets at high altitudes due to sparse station coverage and gauge undercatch associated with blowing snow.

Due to the extremely steep elevation gradient over the Central Himalaya domain, combined with its relatively southern location and consequently warmer conditions, seasonal snow cover is quite limited at lower elevations, as shown by the HMA-SR product (Figure 3h), where snow cover is present for less than 15% of the year in most non-glacierized areas. Permanent snow

and ice are masked and are therefore not represented. As a result, the snow cover duration differences (Figure 3i) indicate a significant overestimation of snow persistence by MAR at high elevations, for instance at 5000 m south of Tibetan Plateau, and a slight underestimation at intermediate elevations around 4500 m over the southern flank of the Himalayan range.

465 3.2 Annual Cycle

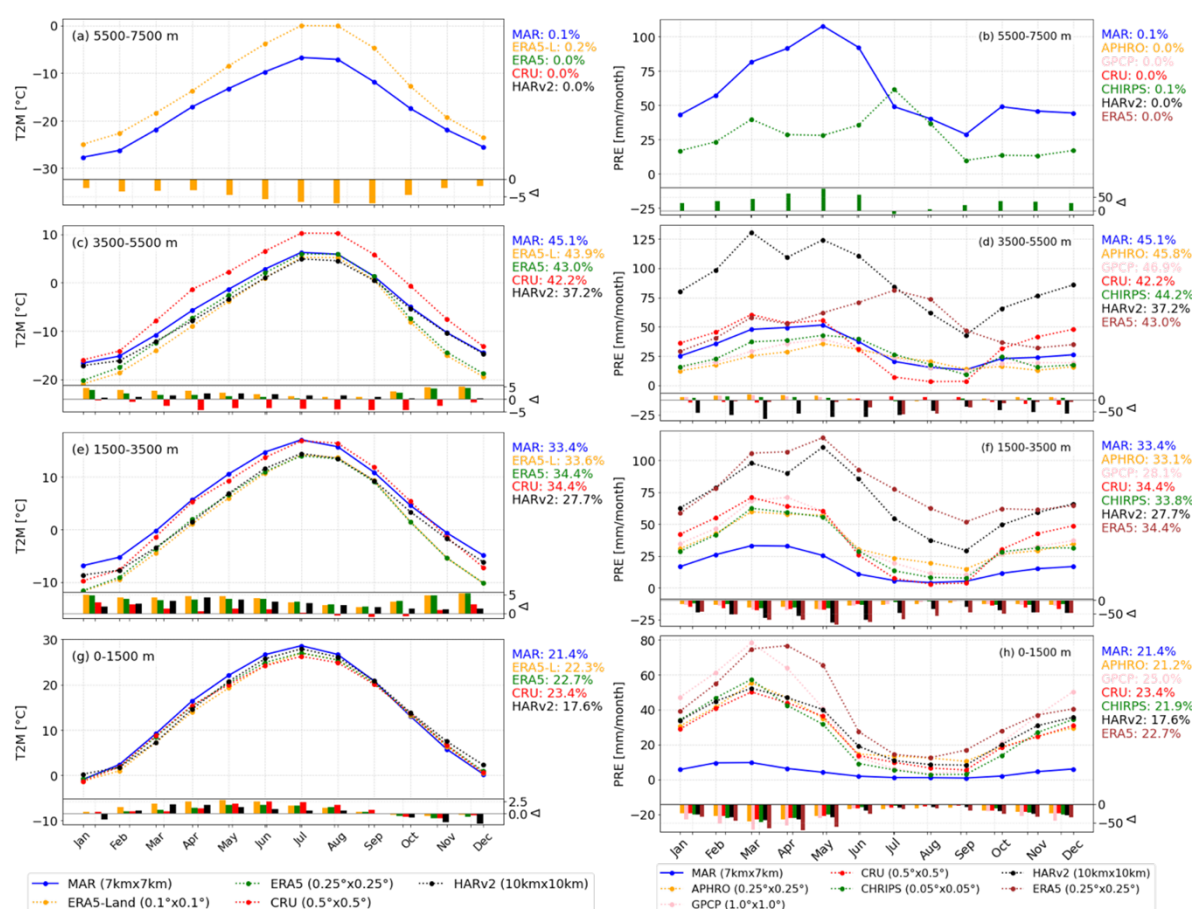


Figure 4: Annual cycle of air temperature (1980-2020; left) and monthly mean precipitation (1981-2015; right) of MAR simulation and different datasets (Table 1) for different elevation range 0-1500m, 1500-3500 m, 3500-5500 m and 5500-7500 m over the Pamir domain. Right side: percentage of pixels in each elevation range for the different datasets.

Figure 4 shows the annual cycle of temperature and precipitation for different elevation ranges over the Pamir domain. At the lowest elevations (Figure 4g), all datasets show a marked seasonal cycle, with temperatures close to 0 °C in winter and increasing to nearly 30 °C during the summer. MAR reproduces this annual evolution well, remaining within the spread of



475 the observational datasets throughout the year. Temperature differences are generally below 2°C, with MAR being slightly warmer during spring and summer and marginally colder during winter, although differences are below 1°C for most datasets, indicating an overall good agreement with the observations. Between 1500 and 3500 m, all products exhibit a pronounced seasonal cycle, with temperatures below freezing (up to -10°C) during winter and positive temperatures from spring to early autumn. MAR reproduces the timing of the seasonal cycle but is systematically warmer (~3 to 5 °C) than ERA5, ERA5-L, and 480 HARv2, while remaining close to CRU. This warm bias is more pronounced during the cold season which is likely associated with the underestimation of snow cover shown in Figure 2. At higher elevations (3500–5500 m), all datasets except CRU display a similar seasonal cycle, with temperatures close to 0°C in June and September and summer maxima around 5°C. MAR remains within the spread of these datasets, whereas CRU is systematically warmer by up to ~5°C, likely reflecting the smoothing of the topography associated with its coarse spatial resolution (0.5°), which smooths the topography. Similar to the 485 previous elevation band, MAR is slightly warmer than the ECMWF reanalysis during the cold season, likely related to the larger snow cover simulated by ERA5 and ERA5-L (Figure 6a). Above 5500m, the comparison becomes much more uncertain owing to the very limited sampling. MAR contains only 8 grid cells (0.1%) and ERA5-L contains only 5 (0.2%), while HARv2 does not reach these elevations, with a maximum elevation of 5446 m. Despite these limitations, ERA5-L is systematically warmer than MAR during summer by more than 5°C, reaching differences of up to ~7°C in July. This colder summer climate 490 in MAR is consistent with the larger precipitation amounts (Figures 2f and 4b) and longer snow cover duration simulated at the highest elevations, which maintain lower surface temperatures throughout the melt season.

Regarding precipitation, the seasonal cycle is strongly controlled by the winter–spring precipitation associated with westerly disturbances, with a pronounced accumulation season followed by a dry summer. At the lowest elevations (Figure 4h), all 495 datasets consistently capture this pattern. MAR reproduces the timing of the seasonal cycle but systematically underestimates precipitation during the accumulation season (~40 and 60 mm · month⁻¹). Most observational datasets are in relatively good agreement, although ERA5 and GPCP exhibit larger precipitation amounts in spring. At intermediate elevation (1500–3500 m; Figure 4f), precipitation increases and the seasonal cycle becomes more pronounced, with maxima reaching approximately 60 - 120 mm month⁻¹. MAR continues to reproduce the seasonal evolution but maintains the dry bias during accumulation 500 season, particularly relative to ERA5 and HARv2 (80-100 mm · month⁻¹), while remaining closer to CHIRPS and APHRODITE (differences below ~40 mm · month⁻¹). The spread among observational datasets also increases at these elevations, especially during the accumulation season from March to May. Between 3500 and 5500 m (Figure 4d), the agreement among most observational datasets remains relatively good. CHIRPS, APHRODITE, CRU and GPCP all exhibit a relatively consistent seasonal cycle, with precipitation peaking during spring and decreasing markedly during summer. MAR 505 reproduces both the timing and magnitude falling within the spread of observational products. In contrast, HARv2 diverges strongly, simulating substantially large precipitation throughout the year, particularly during the accumulation season, whereas ERA5 captures the accumulation season reasonably well but substantially overestimates precipitation during the summer dry season, showing values of ~75 mm · month⁻¹ in summer. At the highest elevations, as for temperature, the comparison is

limited by the small number of grid cells available, particularly in MAR (8 pixels,0.1%) and CHIRPS (18 pixels;0.1%). MAR
simulates larger precipitation amounts than CHIRPS (Figure 4b), but this comparison should be interpreted with caution
because CHIRPS does not adequately capture solid precipitation. This limitation is evident in the seasonal cycle, where
CHIRPS displays an unrealistic summer precipitation maximum, whereas precipitation is expected to peak during winter and
spring. Consequently, the apparent disagreement is likely dominated by observational limitations rather than model
deficiencies.

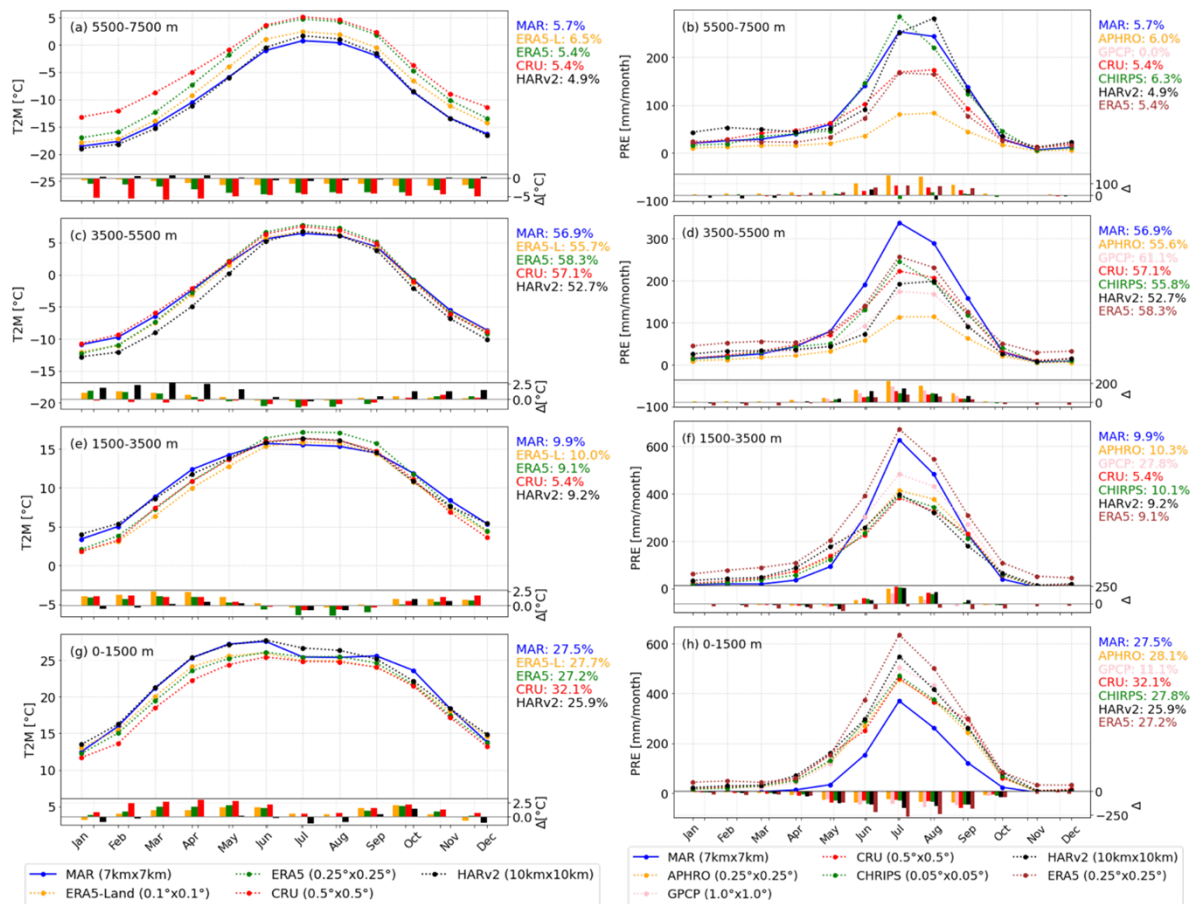


Figure 5: Annual cycle of air temperature (1980-2020; left) and monthly mean precipitation (1981-2015; right) of MAR simulation and different datasets (Table 1) for different elevation range 0-1500m, 1500-3500 m, 3500-5500 m and 5500-7500 m over the Central Himalaya domain. Right side: percentage of pixels in each elevation range for the different datasets.



Figure 5 shows the annual cycle of temperature and precipitation for different elevation ranges over Central Himalaya. In contrast to the Pamir domain, where precipitation is mainly controlled by westerly disturbances, Central Himalaya is dominated by the summer monsoon, resulting in a much stronger seasonal cycle and larger precipitation amounts from June to September.

525 At the lowest elevations (Figure 5g), all datasets exhibit a similar annual evolution, with temperature peaking before the onset of the summer monsoon and decreasing slightly during JJAS associated with precipitation. MAR reproduces this behaviour well but remains warmer than most datasets throughout the year. The warm bias reaches approximately 2°C relative to the ECMWF reanalyses and up to 2.5°C compared with CRU, although these differences become smaller during the monsoon season when agreement among all datasets improves. Between 1500 and 3500 m (Figure 5e) the seasonal cycle is also well

530 reproduced by MAR, but a clear seasonal bias emerges. MAR is warmer than ERA5, ERA5-L, and CRU during the cold season, whereas it becomes colder than all datasets during the monsoon season, with differences of around 2–3°C relative to its forcing (ERA5). This seasonal contrast persists at higher elevations (3500–5000 m; Figure 5c), MAR remains slightly warmer during the post-monsoon and winter season, but becomes up to ~2.5°C colder than HARv2 during summer, with the transition across the freezing point delayed by approximately one month. This behaviour is consistent with the enhanced

535 snowfall and longer snow cover duration simulated by MAR (Figure 3, Figure 6b). At the highest elevations (Figure 5a), the comparison is more robust than in the Pamir because a larger number of grid cells are available (~5–6 %) MAR reproduces the seasonal cycle well and, together with HARv2, simulates colder temperature than the coarser-resolution datasets, particularly CRU, with differences reaching up to ~5°C. ERA5 exhibits a pronounced warm bias during the warm season, exceeding ERA5-L by up to ~5°C, likely reflecting the smoothing of the topography associated with its coarser spatial

540 resolution. As in the Pamir the colder temperatures simulated in MAR are consistent with enhanced snowfall and longer snow cover duration at the highest elevations, suggesting a similar snow–temperature feedback.

Regarding precipitation, the annual cycle is dominated by the South Asian summer monsoon, with precipitation rapidly increasing from June, peaking in July, and decreasing after September. At the lowest elevations (Figure 5h), all datasets

545 consistently capture this evolution. MAR reproduces the timing of the monsoon onset, peak, and retreat but systematically underestimates precipitation over the plains. The observational products consistently indicate July maxima of around ~500 mm · month⁻¹, approximately 20% higher than MAR, whereas ERA5 exhibits a marked wet bias and HARv2 remains closer to the observations. At mid-to-low elevations (Figure 5f), precipitation remains strongly controlled by the summer monsoon, but the behaviour of MAR changes markedly. The dry bias observed over the plains disappears and is replaced by a wet bias

550 during JJAS, with MAR and ERA5 exceeding the observational products by up to 250 mm · month⁻¹ during the July maximum. As at lower elevations, MAR slightly delays the onset of the monsoon compared to the other datasets, but compensates through a more rapid increase in precipitation, ultimately reaching higher peak values. At higher elevations (3500–5000 m; Figure 5d), where approximately 45–55% of the grid cells fall within this elevation range for all datasets (Figure 5, right), the comparison becomes particularly robust. MAR simulates the largest precipitation amounts among all datasets, likely due to a better

555 representation of solid precipitation. In contrast, APHRODITE exhibits the lowest values (~100 mm · month⁻¹ during the



monsoon), probably reflecting the sparse in situ observational network and the undercatch of snowfall by rain gauges. The remaining datasets show relatively good agreement, with a maximum spread of $\sim 100 \text{ mm} \cdot \text{month}^{-1}$ during the monsoon season and much smaller differences ($< 50 \text{ mm} \cdot \text{month}^{-1}$) during the rest of the year. Because the different datasets sample this elevation band similarly, the spread is unlikely to result from differences in topographic sampling, instead, it mainly reflects differences in the representation of solid precipitation. Above 5500 m (Figure 5b), the Central Himalaya domain includes a larger proportion of high-elevation grid cells than the Pamir domain, providing greater confidence in the comparison. MAR shows good agreement with HARv2 and CHIRPS, the two highest-resolution datasets, in both timing of the monsoon and precipitation magnitude ($\sim 250 \text{ mm} \cdot \text{month}^{-1}$). In contrast, coarser-resolution datasets such as CRU and ERA5 exhibit lower precipitation, highlighting the limitations of representing steep topography. APHRODITE again displays the lowest precipitation amounts, less than half those simulated by MAR, further illustrating the limitations of gauge-based products for estimating solid precipitation at high elevations.

Overall, the annual cycles illustrate the strong hydroclimatic contrast between the Pamir and Central Himalaya domains, as well as a clear dependence on elevation on both temperature and precipitation. In the Pamir, temperature is generally well reproduced, with relatively small biases, while precipitation is characterized by a winter–spring maximum associated with westerly disturbances. MAR captures this seasonal cycle but exhibits a systematic dry bias at low elevations that progressively transitions to a wet bias at the highest elevations. In contrast, Central Himalaya is dominated by the summer monsoon, resulting in a much stronger seasonal cycle. Temperature biases display a marked seasonal dependence, with MAR tending to be warmer during winter and colder during monsoon season at mid-elevations; whereas precipitation shows the same elevation-dependent behaviour as in the Pamir, with underestimated monsoonal precipitation over the plains and overestimated precipitation at higher elevations.

Despite these systematic biases, MAR successfully reproduces the dominant seasonal hydroclimatic regimes of both regions, including the winter accumulation season in the Pamir and the onset, peak, and retreat of the South Asian monsoon in Central Himalaya.

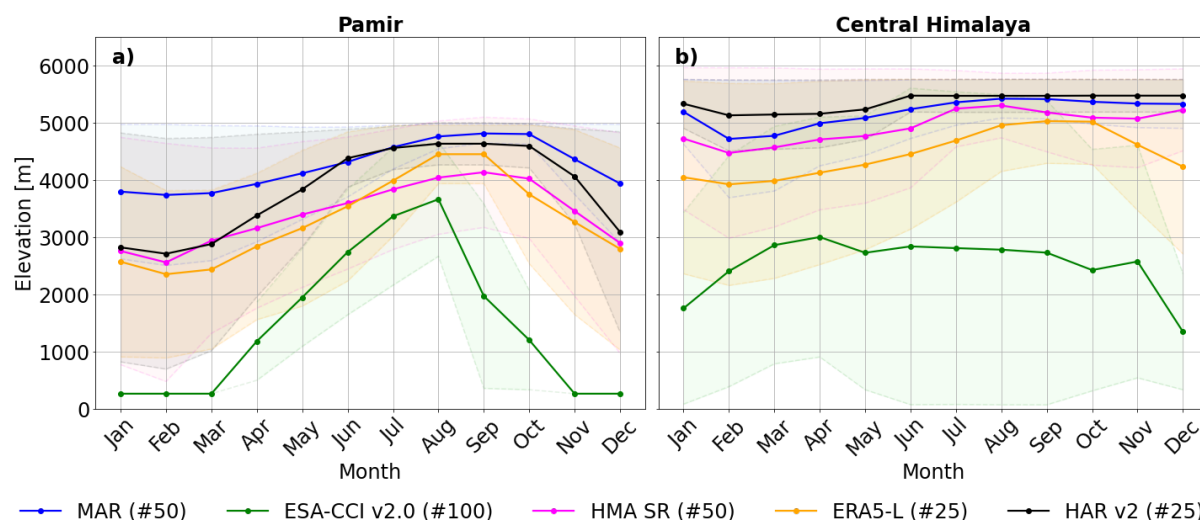


Figure 6: Annual cycle of snowline elevation over the Pamir (a) and Central Himalaya (b) domains for MAR and the different datasets (Table 1). The snowline is defined as the mean elevation between the highest snow-free pixels and the lowest snow-covered pixels, computed from monthly climatologies (2000–2016). Shaded areas represent the elevation range between the snow-free and snow-covered pixel groups. The numbers given in parentheses (#) in the legend indicate the number of pixels used to estimate the monthly snowline position for each dataset. Glacierized and permanent snow/ice areas are excluded from the analysis.

Figure 6 shows the annual cycle of snowline elevation over the Pamir and Central Himalaya domains. The snowline is defined here as an indicator of the transition between snow-free and snow-covered areas, following the definition of Castellanos et al. (2025). For each monthly climatology, we identify the highest snow-free pixels and the lowest snow-covered pixels, for snow depth we consider 10 cm and for snow cover 10%. Then, we define the snowline as the mean elevation between these two elevations. To ensure a comparable estimate across datasets with different spatial resolutions, the number of pixels used in the calculation is scaled according to the total number of grid cells in each domain while maintaining a similar pixel-to-domain ratio (see section 2 of Supplementary Material).

In the Pamir (Figure 6a), all datasets show a clear seasonal migration of the snowline, rising from winter to a maximum during late summer before descending again in autumn. MAR simulates the highest snowline throughout most of the year, increasing from approximately 3800 m in winter to around 4800 m in late summer. ERA5-L and HARv2 exhibit a similar evolution, although with generally lower snowline elevations and a more seasonal amplitude going from 2800 to almost 4800m. HMA-SR follows a similar annual cycle than MAR in terms of amplitude, but remains below it around 1000m throughout the year. ESA-CCI clearly differs from the other datasets, showing substantially lower snowline elevations and a much larger seasonal



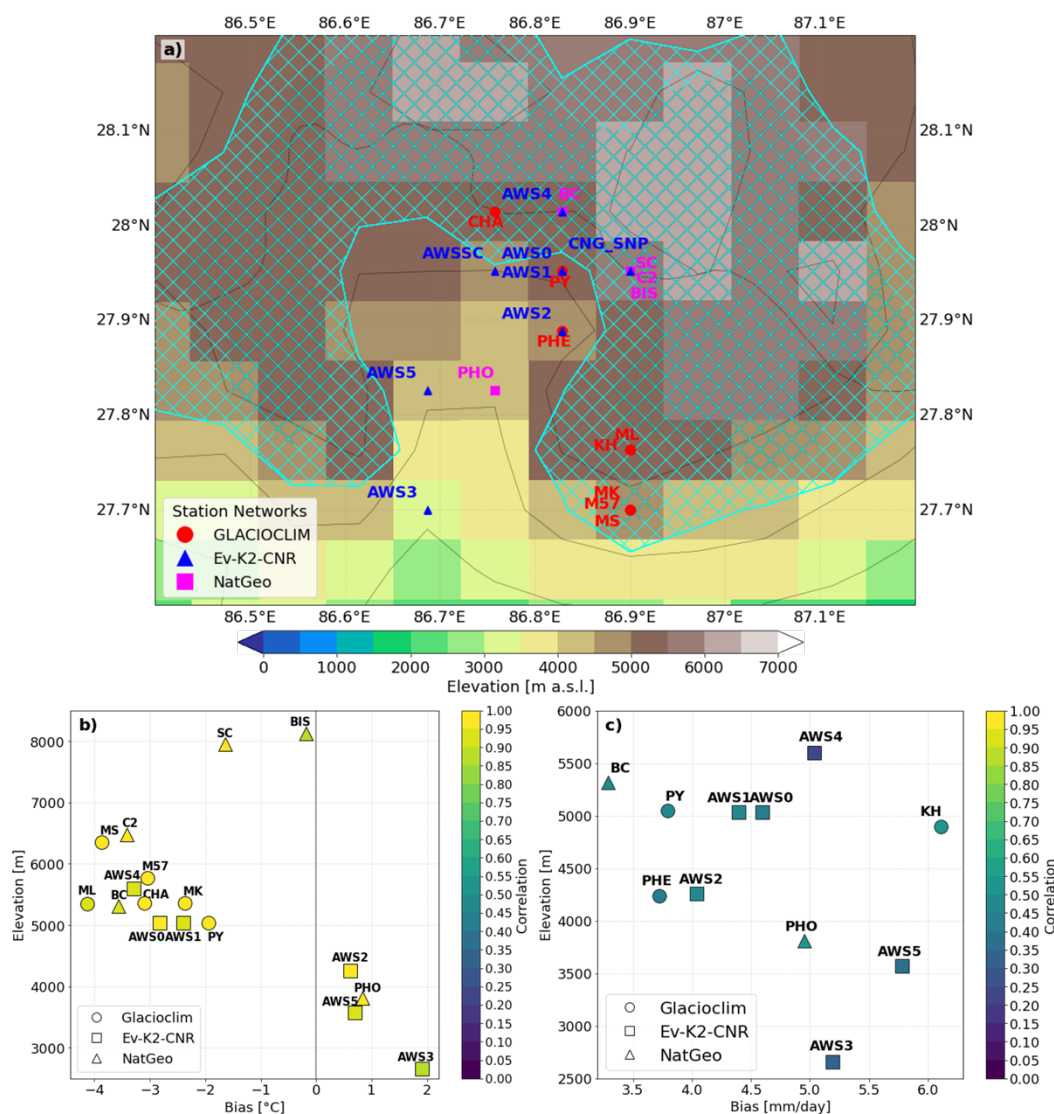
605 amplitude, particularly during late summer and autumn, owing to an extension of snow cover areas over the north east part of the domain (Figure S2).

In Central Himalaya (Figure 6b), all datasets show consistently higher snowline elevations and a smaller seasonal amplitude than in the Pamir, reflecting both the lower latitude of the region, which results in a warmer climate, and the strong topographic
610 barrier of the Himalaya that confines persistent snow cover to the highest elevations. MAR, HMA-SR and HARv2 show remarkably similar seasonal behaviour, with snowline elevations remaining close to 5000–5500 m throughout the year. ERA5-Land reproduces the general evolution but simulates lower snowline elevations up to 4000 m, particularly outside the monsoon season. ESA-CCI again differs from the other datasets, exhibiting much lower snowline elevations and a substantially larger snowline uncertainty, as reflected by the wider elevation range between the highest snow-free and lowest snow-covered pixels.

615 Overall, MAR reproduces the seasonal evolution of snowline elevation well in both domains and agrees best with the highest-resolution datasets (HMA-SR and HARv2). The largest discrepancies are found for ESA-CCI, which systematically simulates lower snowline elevations, particularly in the Pamir. ERA5-Land captures the general seasonal evolution but tends to underestimate snowline elevations compared with MAR and the highest-resolution products.

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3.3 In situ comparison



625 **Figure 7: (a) MAR topography (shading) over the Khumbu-Everest region (86.4°E:87.2°E, 27.6°N:28.2°N; Central**
Himalaya). Glacierized areas with more than 20% ice fraction are hatched in blue. In situ temperature and
precipitation observations are shown for the different station networks: GLACIOCLIM (circles), NatGeo (triangles),
and Ev-K2-CNR (squares). For temperature, MAR values are corrected using a daily lapse-rate adjustment to account
for elevation differences between the model grid and the station altitude (Table 2, Figures S4-9). Annual bias and
 630 **correlation for temperature (b) and precipitation (c). For each station, MAR is evaluated over the corresponding period**
of data availability (Table 2, Figures S4-9).



3.3.1 Central Himalaya

635 In this section, we compare the local 2m temperature and precipitation simulated by MAR with the in-situ observations of the
 dense network available in Nepal over the Khumbu area (Figure 7a; Table 2). For temperature, MAR outputs are corrected
 using a daily lapse-rate adjustment computed over the Khumbu–Everest region (86.4–87.2°E; 27.6–28.2°N) to account for the
 elevation difference between each station and the corresponding model grid cell. The stations span a wide range of elevations,
 from valley locations (e.g., AWS3) to the highest meteorological stations in the world (e.g., South Col and Bishop Rock), and
 640 include both glacierized and ice-free environments (Figure 7a, Table 2). The available records differ in temporal coverage
 (Table 2, Figures S4–9), but together provide a comprehensive evaluation of MAR across the elevation gradient.

Daily temperature is very well reproduced by MAR, with correlations exceeding 0.9 at all stations (Figure 7b), demonstrating
 that the model accurately captures day-to-day variability. However, systematic biases remain exhibiting a clear dependence
 on elevation consistently with Figure 5. Small biases (~ -0.2 to -1.8 °C) are found at the highest stations (e.g., South Col and
 645 Bishop Rock), whereas larger cold biases occur between approximately 5000 and 6000 m, reaching about -4 °C at Mera La.
 For most GLACIOCLIM stations, MAR is around 2 °C colder. In particular, at Mera La, this discrepancy is likely explained
 by the mismatch in surface type, as the station is located off-glacier while the corresponding MAR grid cell is glacier-covered
 (Figure 7a), enhancing snow–ice cooling in the model and potentially linked to an overestimation of snow cover (Figure 3g–
 650 i). Conversely, very small biases ($< +2$ °C) are found at AWS5, AWS2 (Ev-K2-CNR), and Phortse (NatGeo), which are located
 in topographic depressions, highlighting MAR’s ability to represent local climatic conditions in complex terrain.

In contrast, daily precipitation is less well reproduced, with correlations generally between 0.2 and 0.4. MAR exhibits a
 systematic wet bias in all stations, ranging from approximately $+1.5$ to $+3$ mm·day⁻¹, corresponding to a relative overestimation
 655 of ~ 200 –400%. This indicates that MAR tends to simulate more frequent and persistent precipitation events, including light
 precipitation (“drizzle”) even when no precipitation is recorded at the stations, which accumulates over time and contributes
 significantly to the bias (Figures S7–9). Note also that, even after the gauge-correction procedures applied in the observational
 datasets, snowfall is likely still systematically underestimated in the observations due to wind undercatch. In addition, during
 extreme events, precipitation amounts may exceed the capacity of the rain gauges, leading to an underestimation of the
 660 magnitude of intense snowfall and rainfall events in the station records.



3.3.2 Pamir

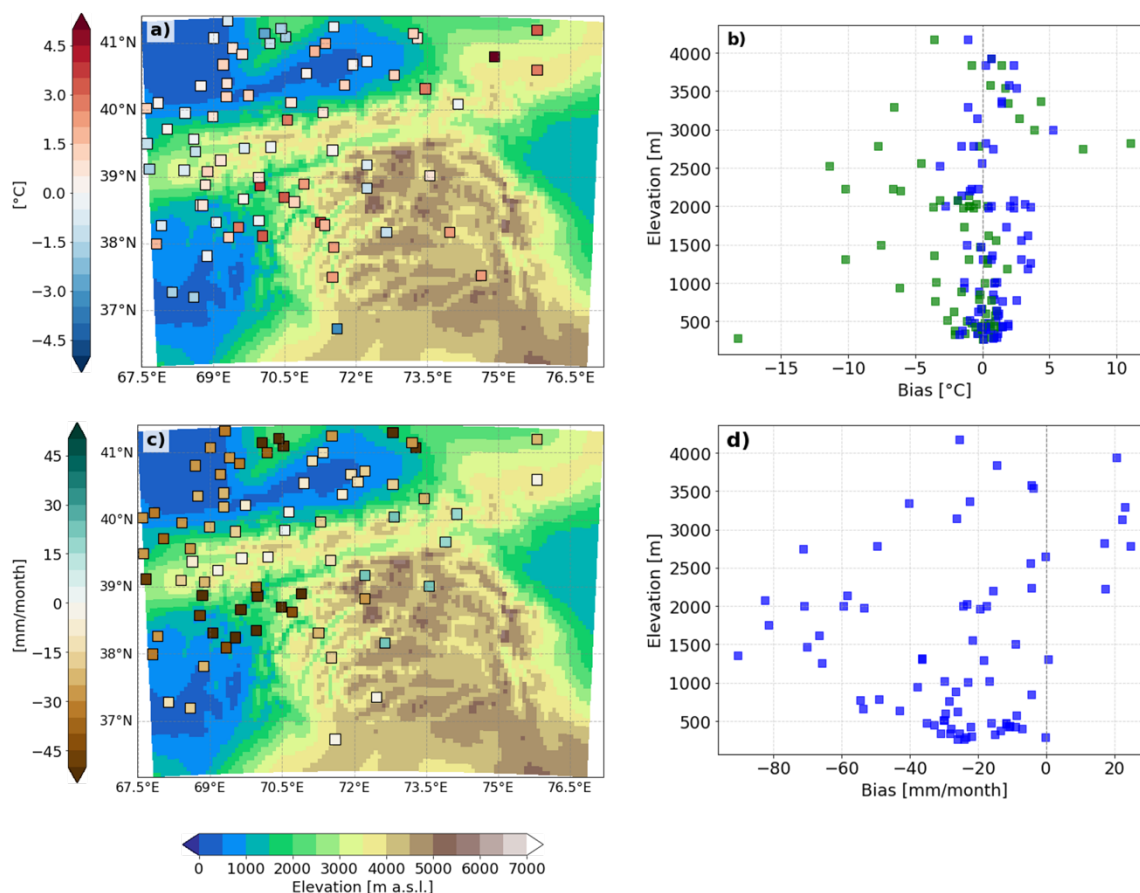


Figure 8: MAR topography (shading) over the Pamir region with the annual bias at each station location for temperature (a) and precipitation (c). Annual bias and correlation of temperature with (blue) and without (green) lapse rate correction (b) and precipitation (d) for each station elevation. For each station, the MAR simulation is evaluated over the corresponding period of observational data availability (see Figure 9).

We analyse 76 meteorological stations spanning elevations from 264 to 4169 m a.s.l. over different periods (see Williams et al., 2008, Figure 9 right) for monthly temperature and precipitation available over the Pamir domain (Figure 8a,c). Figure 8a,c shows the location of the stations and the annual bias of temperature (Figure 8b) and precipitation (Figure 8d) for each station. Note that, in order to retain the largest number of stations, we use the longest available period for each station; thus, MAR (1950–2025) is subsampled to match the period of each station.



MAR simulations have been corrected using a monthly lapse rate derived from the model, as for the Khumbu region. Green dots correspond to the raw MAR output, while blue dots indicate lapse-rate-corrected values highlighting the importance of applying a temperature correction when using regional climate models for comparison with in situ observations. We observe a consistent bias in MAR, which is colder at elevations between 2000–3000 m, particularly for stations located near the Fedchenko (Vanch-Yakh) Glacier and west of the Pamir Alay, with biases of around -3 – -5°C ; and warmer at lower elevations (<2000 m), extending toward the plains (Figure 8a,b). Some high-elevation stations (>3500 m) exhibit a warm bias of 1 – 3°C consistent with the spatial temperature patterns shown in Figure 2a–c.

Regarding precipitation (Figure 8c–d), there is a persistent dry bias at the lowest elevations, mainly in the northwest and southwest parts of the domain, corresponding to elevations below 2000 m with values ranging from -30 to -40 $\text{mm} \cdot \text{month}^{-1}$. From 0 to 1000 m, the bias is smaller, with values ranging from -15 to -30 $\text{mm} \cdot \text{month}^{-1}$, whereas between 1500 and 2200 m, a group of stations located within the Pamir Alay valley shows a stronger underestimation, with values reaching up to -60 $\text{mm} \cdot \text{month}^{-1}$, and even -80 $\text{mm} \cdot \text{month}^{-1}$. Conversely, some high-elevation stations in the central Pamir exhibit a wet bias of up to ~ 10 $\text{mm} \cdot \text{month}^{-1}$, which is consistent with the bias observed against the APHRODITE dataset in Figure 2f. Overall, these patterns are consistent with previous analyses, showing a dry bias over the western and lower-elevation regions of the domain and a wet bias over the central and highest elevations.

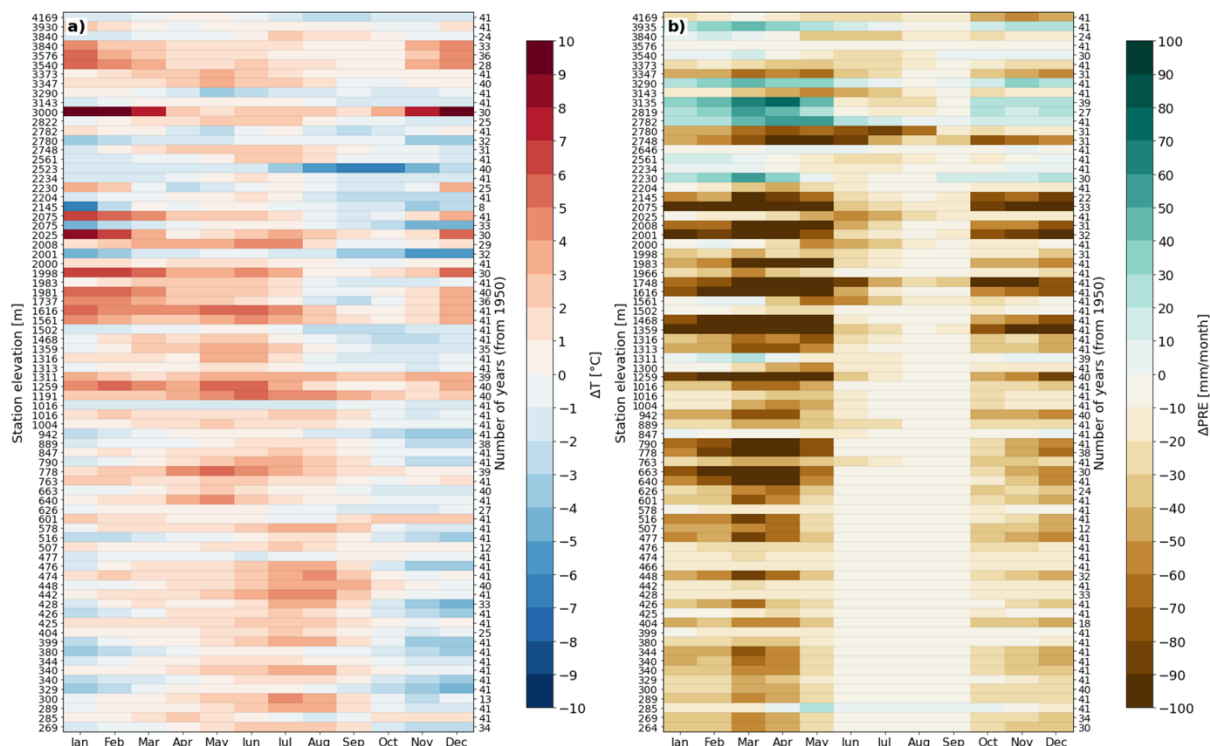


Figure 9: Annual cycle bias of temperature (a) and precipitation (b) for each station in the Pamir domain, ordered by elevation. The right-hand ticks at y-axis indicate the number of years available at the station records and thus considered in the MAR data (1950–1990).

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Figure 9 shows the annual cycle of the bias temperature and precipitation for each station, covering a wide range of elevations across the Pamir domain, which allows a robust characterization of both the seasonal and elevation dependence of the MAR biases. Most stations overlap with the simulation period for at least ~20 years, ensuring a meaningful comparison. The analysis is restricted to the 1950–1990 period because precipitation observations in Central Asia are considered less reliable after 1990, potentially introducing substantial biases into the evaluation (Brun et al., 2021)

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With respect to temperature, there is a clear seasonality in the bias, particularly below ~2000 m, showing that MAR tends to be warmer than observations during the summer months (by ~1 to 2°C) and colder during the cold season, with stronger biases in December–January reaching up to -4°C for some stations around 400 m. As seen in Figure 8, in the elevation band of 2000–2500 m there is a persistent cold bias of ~2 to 3°C, which may be related to the presence of snow at these elevations in the MAR model. At the highest elevations represented by the stations (3500–4200 m), the bias becomes more homogeneous, with a slight warm bias generally below 1°C.

710



Regarding precipitation, there is also a clear pattern of seasonality and elevation dependence. From the lowest stations (264 m) up to ~2145 m, and during the summer months (June–September), MAR slightly underestimates precipitation by less than ~10 mm · month⁻¹, indicating that MAR produces precipitation even during the driest period. In contrast, during the accumulation season, particularly in spring and for elevations between ~1350 and 2145 m, MAR shows a strong underestimation, reaching up to ~100 mm · month⁻¹, consistent with the dry bias over lowlands identified previously.

Between ~2000 and 4000 m, MAR shows a slight overestimation in precipitation, mainly during spring. This highlights a transition from a dry bias at low elevations to a slight wet bias at higher elevations. This behaviour may be partly explained by gauge undercatch of solid precipitation at these elevations, as snowfall is not fully captured by in situ measurements, which could lead to an apparent wet bias in the model when compared to observations. Overall, the consistency between spatial and seasonal diagnostics strengthens confidence in the identified bias structure of the MAR simulations in previous figures.

3.4 Strong post-monsoon precipitation events of October 2013, 2014 and 2021.

Strong precipitation events associated with tropical cyclones and monsoon disturbances represent major hydro-meteorological hazards across the Himalaya, producing floods, landslides, avalanches, and severe impacts on infrastructure and mountain communities (e.g., Ballesteros-Cánovas et al., 2018; David Raj, 2025). In Nepal, remnants of Bay of Bengal tropical cyclones can interact with Himalayan topography and mid-latitude circulation, generating intense orographic precipitation and extreme snowfall events at high elevation (e.g., Wang et al., 2015; Neckel et al., 2015). Such events are particularly important for glacier accumulation, snowpack variability, and downstream hydrological hazards.

Here, we evaluate the ability of MAR to reproduce three major strong post-monsoon precipitation events that affected Central Himalaya: the October 2013 event associated with Cyclone Phailin, the October 2014 event linked to Cyclone Hudhud, and the October 2021 extreme southerly moisture transport. Although MAR is not designed as a numerical weather prediction model, these experiments provide an opportunity to assess whether the model is able to realistically reproduce the large-scale circulation patterns, moisture transport and convergence, as well as associated precipitation structures at hourly scale when forced by ERA5 reanalysis as boundary conditions.

The October 2013 Phailin cyclone was among the strongest cyclones observed over the Bay of Bengal and generated widespread heavy precipitation over the Himalaya following landfall over eastern India (Mohanty et al., 2015; Osuri et al., 2016). In October 2014, the remnants of Cyclone Hudhud interacted with a mid-latitude disturbance, producing exceptional snowfall and deadly snowstorms across the central Himalaya (Wang et al., 2015; Neckel et al., 2015). The October 2021 event was characterized by intense late-monsoon rainfall and flooding associated with strong moisture transport from the Bay of Bengal and enhanced orographic uplift over Central Himalaya (Perry et al., 2020).

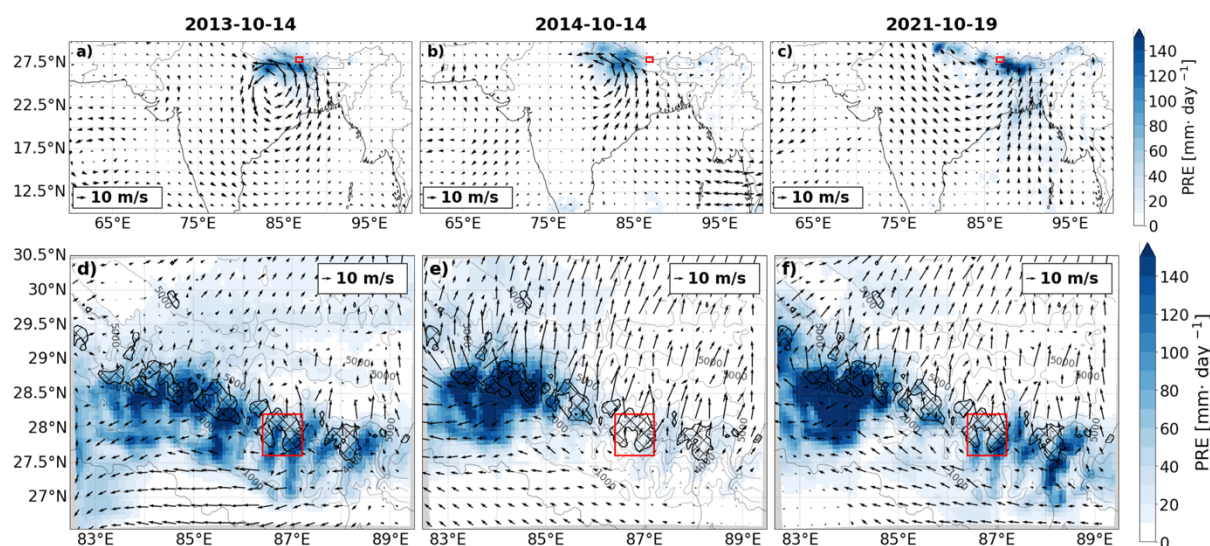


Figure 10: Wind vectors at a (arrows) and total cumulative precipitation (shading) for the peak day of October 2013, of October 2014 and of October 2021 strong precipitation events. Panels (a-c) show ERA5 850hPa winds and precipitation over Middle Asia, whereas panels (d-f) show MAR 100m wind and precipitation over Central Himalaya. The red box in panels (a–c) outlines the Khumbu region (86.4–87.2°E, 27.6–28.2°N).

Figure 10 shows the low-level winds, and precipitation associated with the three extreme events in ERA5 and MAR. In all cases, the events are characterized by strong south-easterly to southerly moisture transport from the Bay of Bengal toward the Himalayan barrier, producing intense orographic precipitation over central and eastern Nepal.

During the October 2013 event (Tropical Cyclone Phailin; Figure 10a,d), ERA5 shows a broad cyclonic circulation over northern India and the Bay of Bengal with enhanced low-level moisture transport toward the Himalaya and 24 h accumulated precipitation reaching approximately 130–140 mm over eastern and south-western Nepal. Although the precipitation maxima does not directly affect the Khumbu region in ERA5, MAR reproduces the overall circulation structure and associated precipitation band over the southern Himalayan slopes, with local precipitation maxima reaching ~140 mm in 24 h. Compared to ERA5, which shows lower precipitation amounts (~80 mm) over the Himalayan slopes, the higher-resolution MAR simulation enhances the representation of orographic precipitation associated with the Himalayan barrier.

The October 2014 Hudhud event (Figure 10b,e) exhibits a similar large-scale circulation pattern, but with a more localized precipitation structure over centred west of the Khumbu region., MAR captures the synoptic circulation and strengthens the low-level southerly flow along the eastern flank of the Himalayan barrier compared to ERA5, where winds remain weaker



over the complex topography. This enhanced channelling and uplift of moist southerly air increase moisture transport toward the mountains, resulting in stronger orographic precipitation. However, unlike the other two events, the precipitation maxima are displaced too far westward in MAR, leading to an overestimation over western Nepal and an underestimation over the Khumbu region.

The October 2021 event (Figure 10c,f) is associated with strong moisture convergence from the Bay of Bengal and widespread precipitation along the Himalayan front. As for the Phailin event, MAR provides added value by enhancing the interaction between moisture transport and topography. While ERA5 simulates precipitation amounts generally below 50 mm over the Khumbu region, MAR produces more intense precipitation reaching ~100 mm, particularly over the Mera Glacier area. Among the three events, this case is the best reproduced in terms of both the spatial distribution and intensity of precipitation.

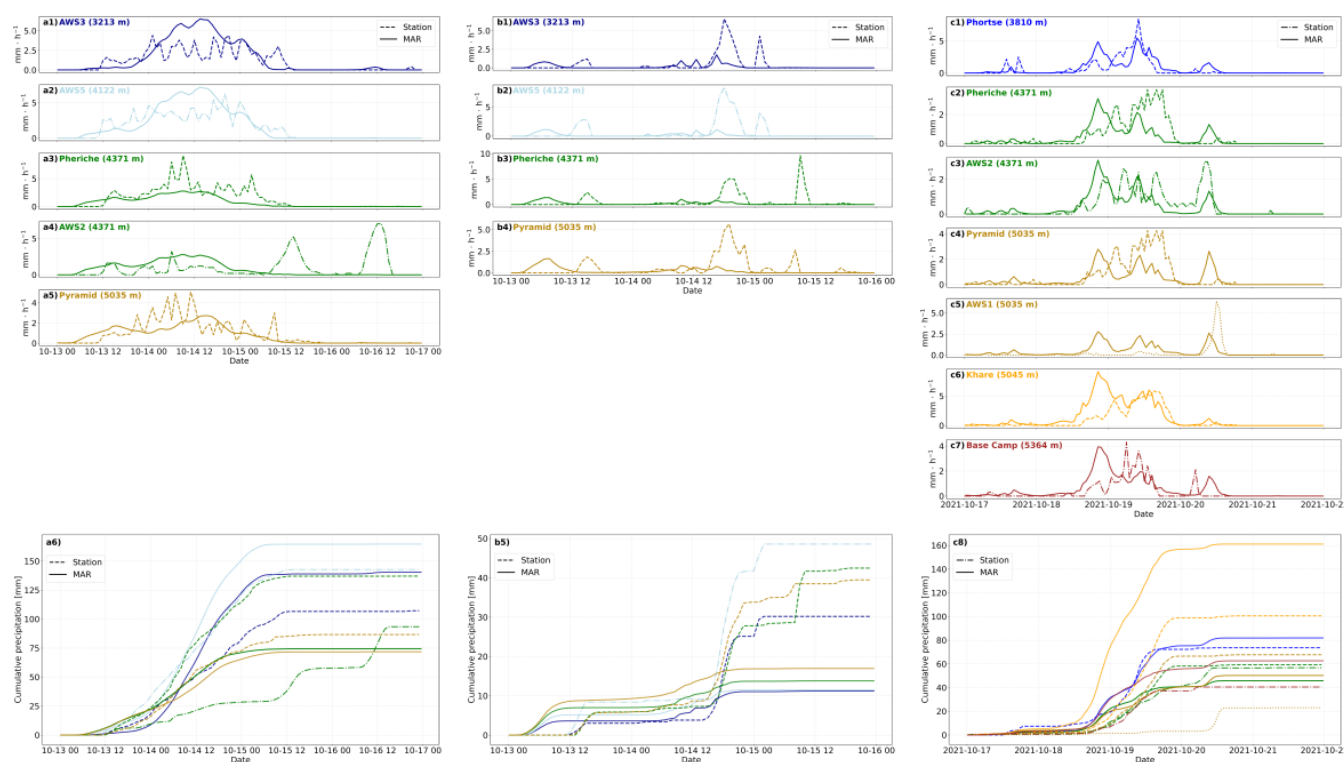


Figure 11: Hourly precipitation (a1-5, b1-4, c1-7) and cumulative precipitation (a6, b5, c8) recorded at the Khumbu stations during the October 2013 (a), October 2014 (b), and October 2021 (c) extreme precipitation events. Colored dashed lines represent observations at the different stations, while solid lines indicate MAR simulations extracted at the corresponding station grid cells. Station elevations are indicated in the legends.



Figure 11 compares hourly and cumulative precipitation recorded at the Khumbu station network with MAR simulations extracted at the corresponding model grid cells over these three events. For the October 2013 event (Figure 11a; left column),
790 MAR captures the general timing of the precipitation event, with precipitation intensifying during 14–15 October. However, it is not able to reproduce the hourly peaks recorded at the stations, and presents a smoother precipitation curve. For instance, at Pheriche and AWS2 (shared grid cell, Figure 7a), precipitation reaches 7–8 mm·h⁻¹ at Pheriche, while MAR simulates a steadier peak around 3 mm·h⁻¹ (Figure 11a3). AWS2 records lower values (<4 mm·h⁻¹) and precipitation does not peak on 16 October (Figure 11a4). MAR also reproduces Pyramid precipitation (Figure 11a5), although it does not simulate well the
795 magnitude of the peaks observed and instead simulates more persistent precipitation. Compared to the lowest stations, AWS3 and AWS5, MAR displays larger precipitation peaks, reaching up to 7 mm·h⁻¹ in AWS5, more than double the observed value (~2 mm·h⁻¹) at AWS3. In terms of cumulative precipitation (Figure 11a6), MAR generally overestimates precipitation and exhibits excessive persistence of precipitation once the event begins, resulting in larger cumulative totals than observed at most stations, for instance, by approximately 25 mm more than AWS5 and AWS3. What is particularly notable is that MAR remains
800 close to AWS2, differing by less than 15 mm, but overestimates totals by almost 50 mm relative to Pheriche. The most striking feature of this event is the strong spatial variability in cumulative precipitation over the Khumbu region, ranging from ~85 mm at the highest Pyramid station to ~145 mm at the lower-elevation AWS5 station.

For the October 2014 Hudhud event (Figure 11b; middle column), MAR captures the timing of the main precipitation
805 reasonably well, particularly between 14 and 15 October. However, as suggested by Figure 10, the westward displacement of precipitation maxima in MAR strongly affects the Khumbu stations. The model generally underestimates precipitation intensity compared to the observations, especially at stations located in the eastern part of the region. At Pheriche, observed hourly precipitation peaks reach ~9–10 mm·h⁻¹, whereas MAR simulates values below ~3–4 mm·h⁻¹. Similarly, the strong precipitation peaks observed at AWS3 and AWS5 during 15 October are only partially reproduced by the model. In terms of
810 cumulative precipitation (Figure 11b5), MAR underestimates total precipitation at most stations, consistent with the westward shift of the simulated precipitation band. The underestimation is particularly pronounced at Pheriche, where observed cumulative totals exceed almost 50 mm, while MAR remains below ~15 mm. Nevertheless, the model still reproduces the general temporal evolution of the event, including the abrupt increase in precipitation during the main phase of the storm.

815 The October 2021 event (Figure 11c; right column) is overall better reproduced by MAR, both in terms of timing and cumulative precipitation. Note that, for this event, three more stations are available (Phortse, Khare, and Base Camp). MAR successfully reproduces the timing of the main precipitation events, although it slightly underestimates or overestimates their intensity depending on the station. The initial precipitation peak, reaching ~2 mm·h⁻¹ at the lower-elevation stations (Phortse, Pheriche and AWS2; Figure 11c1-3), is reasonably well reproduced, while MAR simulates some precipitation at the highest
820 stations. MAR then reproduces the first major precipitation peak earlier on 19 October, with hourly intensities exceeding 7 mm·h⁻¹ at Khare (Figure 11c6). The secondary precipitation peak is also realistically captured, particularly at the highest



stations with similar values of less than $4 \text{ mm} \cdot \text{h}^{-1}$ and a good agreement with Khare of around $6 \text{ mm} \cdot \text{h}^{-1}$. The third peak, there is a general agreement with intensities of around $3 \text{ mm} \cdot \text{h}^{-1}$ the timing of the event is well represented by MAR, with observed and simulated precipitation peaks occurring nearly simultaneously. AWS1 appears as an outlier during this event (Figure 11c5), recording precipitation intensities above $6 \text{ mm} \cdot \text{h}^{-1}$, almost twice those observed at the surrounding stations.

In terms of cumulative precipitation (Figure 11c8), MAR overestimates precipitation at the lower-elevation stations and at Khare, mainly due to the excessive intensity of the second precipitation phase, with cumulative totals exceeding 150 mm and more than 50 mm higher than the observations at Khare. Apart from this, MAR captures the overall magnitude of the event reasonably well at the highest stations, although it underestimates precipitation at Pheriche and AWS2, where cumulative totals remain below $\sim 15 \text{ mm}$. MAR reproduces approximately 75–80 mm at Phortse and Base Camp. At Pyramid, MAR slightly underestimates precipitation by less than 20 mm, while precipitation at AWS2 is overestimated by more than 25 mm. This event also highlights the very strong spatial variability of cumulative precipitation across the Khumbu region, ranging from $\sim 25 \text{ mm}$ at AWS2 to nearly 1000 mm at Khare. The Base Camp station appears particularly robust during this event, successfully recording the large snowfall accumulation without apparent measurement failure.

4 Summary and conclusion

In this study, we presented new long-term high-resolution MARv3.14 simulations performed at 7 km resolution over two contrasting sub-domains of HMA, the Pamir and Central Himalaya regions, covering the 1950–2025 period. To our knowledge, these simulations represent the longest continuous high-resolution regional climate simulations currently available over these regions. The objective was twofold: first, to evaluate the ability of the MAR model to reproduce the hydroclimate of two strongly contrasting climatic regimes, namely the westerly-dominated Pamir and the monsoon-dominated Central Himalaya regions; and second, to identify a robust and transferable model configuration before extending the simulations to the broader HMA domain. The evaluation combined multiple independent observational and reanalysis datasets, snow products, and extensive in situ observations, with a particular focus on temperature, precipitation, snow cover, snowline variability, and extreme precipitation events over the Khumbu region.

One of the main systematic biases identified in MAR concerns the representation of precipitation across elevation gradients, a behaviour consistently found in both the Pamir and Central Himalaya domains. At high elevations, MAR tends to simulate excessive precipitation and snow accumulation, as highlighted by both the station observations and the gridded observational products, despite the substantial uncertainties affecting high-elevation precipitation measurements. The in situ observations additionally reveal a tendency toward overly persistent light precipitation (“drizzle”), suggesting that MAR maintains precipitation for too long once precipitation events are initiated. This behaviour is particularly visible during the extreme precipitation events and in the supplementary analyses over the Khumbu region, and likely reflects an excess of moisture



retained over high-elevation areas. Conversely, precipitation is generally underestimated at lower elevations, particularly over the plains of Central Himalaya. These elevation-dependent precipitation biases largely explain the remaining discrepancies in temperature and snow cover.

860 Regarding temperature, MAR generally reproduces the main spatial gradients associated with topography and elevation in both domains, particularly when compared to the highest-resolution datasets and the in situ observations. The model substantially improves the representation of temperature gradients relative to coarse-resolution products such as CRU and ERA5, which smooth the complex Central Himalaya and Pamir topography. However, systematic elevation-dependent biases remain. MAR tends to simulate slightly warmer conditions at low elevations and colder conditions at high elevations, 865 particularly over glacierized and snow-covered regions. This behaviour is consistent with the precipitation biases discussed previously, as enhanced snowfall and snow persistence at high elevations likely reinforce surface cooling through snow–albedo feedbacks. The station analysis additionally highlights the strong influence of elevation mismatches between model grid cells and observations, particularly in steep mountain environments. Applying a lapse-rate correction substantially improves the comparison with observations, emphasizing the importance of accounting for unresolved sub-grid elevation differences when 870 evaluating regional climate simulations or using them as forcing for impact studies. Notably, the Khumbu stations exhibit remarkably high correlations for daily temperature, evidencing the ability of MAR to realistically reproduce the temporal variability of near-surface temperature even in extremely complex high-mountain environments. Despite these remaining biases, MAR is able to reproduce the overall seasonal cycle and vertical structure of temperature reasonably well across both subregions.

875 Regarding snow cover, MAR is able to simulate the broad seasonal evolution of snow persistence and snowline elevation in both the Pamir and Central Himalaya domains, particularly when compared to the highest-resolution datasets such as HMA-SR. The model captures the snow distribution over complex topography areas and generally reproduces the transition between seasonal snow cover at mid-elevations and persistent snow conditions at higher elevations. The snowline analysis additionally 880 shows that MAR realistically represents the seasonal migration of the snowline throughout the year. However, consistent with the precipitation and temperature biases previously discussed, MAR tends to overestimate snow persistence at high elevations while underestimating snow cover at mid-elevations. This behaviour is particularly visible in the snow cover duration comparison, where excessive snowfall and colder temperatures at high elevations lead to long snow persistence in some glacierized regions, whereas lower and mid-elevation regions exhibit reduced snow duration.

885 Finally, to complete the evaluation of MAR performance, we selected three major events that strongly affected Nepal: the October 2013 event associated with Cyclone Phailin, the October 2014 event linked to Cyclone Hudhud, and the October 2021 precipitation event. The model is able to reproduce the main timing and large-scale evolution of these three extreme precipitation events affecting the Khumbu region, particularly the associated synoptic circulation and moisture transport from



the Bay of Bengal. Among them, the October 2021 event is the best reproduced in terms of both timing and cumulative precipitation. However, important spatial biases remain, with MAR tending to shift precipitation maxima westward along the Himalayan slopes, leading to underestimations over the eastern Khumbu stations, especially during the 2014 Hudhud event. Part of this displacement likely originates from biases already present in the ERA5 forcing itself, highlighting the importance of the large-scale forcing and how these biases can propagate through the dynamical downscaling. Nevertheless, the high-resolution dynamical downscaling substantially improves the representation of orographic precipitation compared to ERA5, enhancing both precipitation intensity and spatial structure over the complex Himalayan topography. The station observations additionally highlight the very strong spatial variability of precipitation within the Khumbu region during extreme events, with large differences in accumulated precipitation occurring over relatively short distances and elevation gradients.

5. Applications, limitations and future perspectives

Despite these encouraging results, several limitations remain and should be considered in future developments. First, although MAR realistically reproduces many aspects of the regional hydroclimate, the simulations were not coupled to a glacier model. Consequently, glacier evolution and ice-flow processes are not explicitly represented. Nevertheless, the high-resolution atmospheric forcing produced by MAR represents a valuable framework for future hydrological and glaciological applications, including estimates of snow accumulation, melt rates, and surface mass balance. These long-term simulations provide a robust base for future applications related to climate variability, hydrology, glaciology, and societal impacts, including water resources, natural hazards, and climate risk assessments across HMA. The continuous multi-decadal framework additionally opens important perspectives for trend analyses and the investigation of long-term elevation dependence warming. Future work should focus on extending the simulations to the full HMA, improving the representation of precipitation processes and snow–atmosphere interactions. Finally, all simulations produced in this study will be made publicly available through Zenodo to facilitate future interdisciplinary research and applications over High Mountain Asia.

Code and data availability

The scripts used to process the data, perform the analyses, and generate the figures presented in this study will be made publicly available in a GitHub repository. The MAR model simulations and associated outputs are permanently archived on Zenodo and are publicly available for the two study regions: Pamir (<https://doi.org/10.5281/zenodo.21739644> ; Santolaria-Otín et al., 2026a) and Central Himalaya (<https://doi.org/10.5281/zenodo.23263392> ; Santolaria-Otín et al., 2026b). The scripts used to process the data, perform the analyses, and generate the figures presented in this study will be made publicly available in the GitHub repository (https://github.com/msantolariaotin/MAR_HMA_evaluation_paper/ ; <https://doi.org/10.5281/zenodo.23344343>)



925 The observational and reanalysis datasets used in this study are publicly available from their respective repositories. ERA5
 and ERA5-Land reanalyses are available from the Copernicus Climate Data Store (<https://cds.climate.copernicus.eu/>). HAR
 v2 can be obtained from the High Asia Refined Analysis project website
 (<https://www.tu.berlin/klima/forschung/regionalklimatologie/hochasien/har>). CRU TS4.05 is distributed by the Climatic
 Research Unit (University of East Anglia; <https://crudata.uea.ac.uk/cru/data/hrg/>). CHIRPS precipitation data are available
 from the Climate Hazards Center (<https://www.chc.ucsb.edu/data/chirps>), APHRODITE precipitation data from the
 APHRODITE project (<http://aphrodite.st.hirosaki-u.ac.jp/download/>), and GPCP monthly precipitation data from the NOAA
 930 Physical Sciences Laboratory (<https://psl.noaa.gov/data/gridded/data.gpcp.html>). The High Mountain Asia Snow Reanalysis
 (HMA-SR, Version 1) is available from the NASA National Snow and Ice Data Center (NSIDC;
https://nsidc.org/data/hma_sr_d/versions/1), and the ESA Snow CCI SCFG v2.0 product is available through the ESA Climate
 Change Initiative data portal (<https://climate.esa.int/en/projects/snow/>). The GMTED2010 digital elevation model is available
 from the TEMIS data portal (<https://www.temis.nl/data/gmted2010/index.php>).

935 The in situ observations over the Khumbu region are publicly available from the GLACIOCLIM programme
 (<https://glacioclim.osug.fr>), the National Geographic Perpetual Planet Everest expedition
 (<https://www.nationalgeographic.org/projects/perpetual-planet/everest/weather-data/>; Matthews et al., 2020), and the Ev-K2-
 CNR project (<https://doi.org/10.5281/zenodo.15211352>; Salerno et al., 2025).

940 Supplement link

Find attached the Supplementary Material

Author contributions

945 MSO, CA, MM, and FB conceived and designed the study. MSO performed the data analysis, analyzed the model outputs,
 produced the figures, and wrote the first draft of the manuscript. CA configured the model, and CA and MM performed the
 simulations. MM made major contributions to the development and revision of the manuscript. CA, FB, and XF contributed
 to the scientific discussions and the interpretation of the results. XF provided methodological guidance on the model



950 configuration and the analysis of the model outputs. MC contributed to the technical aspects of the model computations. PW, DS, and AK contributed their expertise through field observations and data collection. All authors contributed to revising the manuscript and approved the final version.

Competing interests

The contact author has declared that neither they nor their co-authors have any competing interests.

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965 weather stations in the world, which greatly contributed to the evaluation of the MAR simulations.

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Review statement

975 The review statement will be added by Copernicus Publications listing the handling editor as well as all contributing referees according to their status anonymous or identified.

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