

# Supplementary material for “Contrasted climatologies in Pamir and Central Himalaya highlighted from MAR high-resolution atmospheric reanalysis over 1950-2025”

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## S1. Tuning of the MAR model

15 Model calibration is conducted using a classical tuning approach, often referred to as expert tuning, whereby simulations with different sets of parameters are iteratively compared against available observations, and parameters are subsequently adjusted accordingly. However, we aim to refine this approach toward a more objective calibration strategy by following the recommendations of Bellprat et al. (2012, 2016): (1) ensuring transparency and reproducibility, (2) focusing on a limited number of key tunable parameters, (3) targeting predefined diagnostics that account for observational uncertainty and model  
20 predictability, (4) relying on objective sensitivity experiments, and (5) clearly separating calibration and validation periods. As the ultimate objective is to apply MAR over the full High Mountain Asia (HMA) domain (Figure 1a), sensitivity experiments are first performed over two smaller subdomains representing contrasting climatic regimes: the Pamir (dry, continental, westerly-dominated precipitation) and the Central Himalaya (monsoon-dominated, with intense summer precipitation) (Figure 1b,c). This approach facilitates the identification of a robust and transferable model configuration while  
25 reducing computational cost.

One of the main deficiencies identified in the model is the underestimation of precipitation over the lowland plains, particularly pronounced over the Nepal region (Figure 2b). Consequently, the model tuning focuses primarily on sensitivity experiments to explore the impact of key atmospheric parameters controlling moisture availability and precipitation-related processes  
30 (Table S1). In particular, we vary i) the humidity diffusion parameter (parameter humidity\_magic), which regulates the strength of moisture diffusion and thereby influences cloud formation and thus, temperature, (ii) the cloud reversion parameter (cloud\_magic), which controls the fraction of precipitation converted back into cloud condensate and thus affects cloud persistence and the timing of precipitation, and (iii) the parameter governing the sedimentation velocity of snow particles (cnos), which impacts the spatial distribution of snowfall since snow particles are advected as they fall into the atmosphere of

35 MAR and (iv) the lateral boundary specific humidity through a multiplicative correction allowing to alter the condition prescribed from the ERA5 forcing field (humid\_corr). The humid\_magic parameter is varied around 1-5, with higher values promoting stronger diffusion and increased cloudiness, while cloud\_magic is tested within its recommended range (0–0.2). The cnos parameter is scaled by factors of 1/10 and 1/100 relative to its default value to assess its impact on the spatial redistribution of precipitation. Additional experiments examine the sensitivity to different precipitation fall velocity  
40 formulations ('ur' vs. 'up'), which modify, in addition to the parameter cnos, the sedimentation speed of hydrometeors within the microphysics scheme. The 'up' formulation is expected to enhance precipitation near topographic barriers by favouring a more rapid fallout of moisture along mountain slopes.

The experiments are organized into two sets, starting from a reference configuration and progressively modifying one  
45 parameter at a time to isolate its effect (Table S1). Initial tests (set 1) primarily investigate the role of moisture availability and diffusion, while the second set selects the most suitable combinations from set 1 and further adjusts them by combining reduced boundary humidity (–5%) with modifications of the diffusion coefficient parameter (cnos). The analysis focuses on the vertical profile of precipitation during the accumulation period for a representative year (2016).

50 In the Pamir region (Figure S1a), observed precipitation from CHIRPS remains relatively low, generally below  $\sim 1.5 \text{ mm} \cdot \text{day}^{-1}$  at low elevations, increasing to  $\sim 2 \text{ mm} \cdot \text{day}^{-1}$  around 3000 m a.s.l., and decreasing again above 4000 m a.s.l. However, CHIRPS is known to be less reliable for solid precipitation, and thus particularly in high-elevation regions such as the Pamir, and caution is therefore required when interpreting values at high elevations. In contrast, the coarser-resolution datasets GPCP and CRU show values below  $\sim 1 \text{ mm} \cdot \text{day}^{-1}$  across all elevations, likely reflecting their inability to capture the vertical structure  
55 of orographic precipitation at resolutions of  $0.5^\circ$  and  $1^\circ$ , respectively. The reference simulation (set1\_ref\_00) reproduces slightly lower precipitation rates compared to CHIRPS at lower elevations ( $\sim 0.5\text{--}1 \text{ mm} \cdot \text{day}^{-1}$  vs.  $\sim 1\text{--}2 \text{ mm} \cdot \text{day}^{-1}$ ) and exhibits a stronger vertical gradient. The subset of sensitivity experiments highlights the dominant influence of moisture availability and diffusion processes: decreasing diffusion, and therefore increasing moisture availability leads to a systematic increase in precipitation across elevations, with the strongest impact at high elevations, where the other simulations display lower  
60 precipitation values. In contrast, reducing the precipitation spatial redistribution parameter primarily affects the vertical redistribution of precipitation with lower precipitation values around  $\sim 4000 \text{ m}$  while maintaining a similar overall vertical evolution as set1. Changes in precipitation fall velocity and cloud reversion have a comparatively smaller impact on the vertical profile of precipitation. The parameter exerting the strongest control is the humidity correction at the boundaries, which reduces precipitation by approximately  $0.5 \text{ mm} \cdot \text{day}^{-1}$  throughout the elevation profile. The final configurations (set 2)  
65 identified as the most suitable for the Pamir, combining moderate moisture enhancement with reduced diffusion, provide the best overall agreement with observations, although uncertainties in observed high-elevation precipitation remain substantial. Nevertheless, configurations 07–08 appear more realistic, as they remain closer to the observational estimates. In parallel, the final model selection was further constrained by the evaluation over the Central Himalaya domain.

70 The Central Himalaya region (Figure S1b) exhibits much higher precipitation amounts associated with monsoonal dynamics. Observational datasets indicate values of  $\sim 10\text{--}15 \text{ mm}\cdot\text{day}^{-1}$  at low elevations, increasing to  $\sim 25\text{--}35 \text{ mm}\cdot\text{day}^{-1}$  at mid-elevations ( $\sim 2000\text{--}3500 \text{ m a.s.l.}$ ). The initial simulation (set1\_ref\_00) underestimates lowland precipitation ( $\sim 5\text{--}10 \text{ mm}\cdot\text{day}^{-1}$ ), confirming a pronounced dry bias over the plains. Sensitivity experiments reveal that reducing diffusion of precipitation and cloud conversion (set1\_huimd\_magic\_04 and set1\_cloudmagic\_06) slightly reduces this low-elevation deficit, but often leads  
75 to excessive precipitation at mid-elevations (set1\_except set1\_humid\_cor\_01). Similarly to the Pamir, configurations combining increased moisture availability with reduced diffusion tend to produce excessive precipitation at mid-elevations ( $\sim 2000\text{--}4000 \text{ m a.s.l.}$ ), locally exceeding  $\sim 35 \text{ mm}\cdot\text{day}^{-1}$ . Conversely, reducing spatial distribution of precipitation (cnos/10 or cnos/100) helps redistribute precipitation more evenly across elevation bands, but does not fully resolve the lowland dry bias. The final configuration (final\_07) provides the best compromise, with precipitation reaching  $\sim 20\text{--}30 \text{ mm}\cdot\text{day}^{-1}$  at mid-  
80 elevations while limiting excessive peaks, although a residual underestimation persists below  $2000 \text{ m a.s.l.}$

Overall, decreasing diffusion and cloud conversion lead to higher precipitation amounts across elevations, whereas modifications to the diffusion parameter strongly influence the vertical redistribution of precipitation, particularly at mid- to high elevations. Changes in the vertical fall precipitation velocity formulation have a secondary impact on precipitation  
85 intensity and vertical gradients. All in all, the consistent behaviour of the sensitivity experiments across both subdomains demonstrates that a single configuration can adequately capture the dominant processes in contrasting climatic regimes. We therefore select configuration 07 as the optimal compromise for both domains, and it is used for all subsequent analyses in this study.

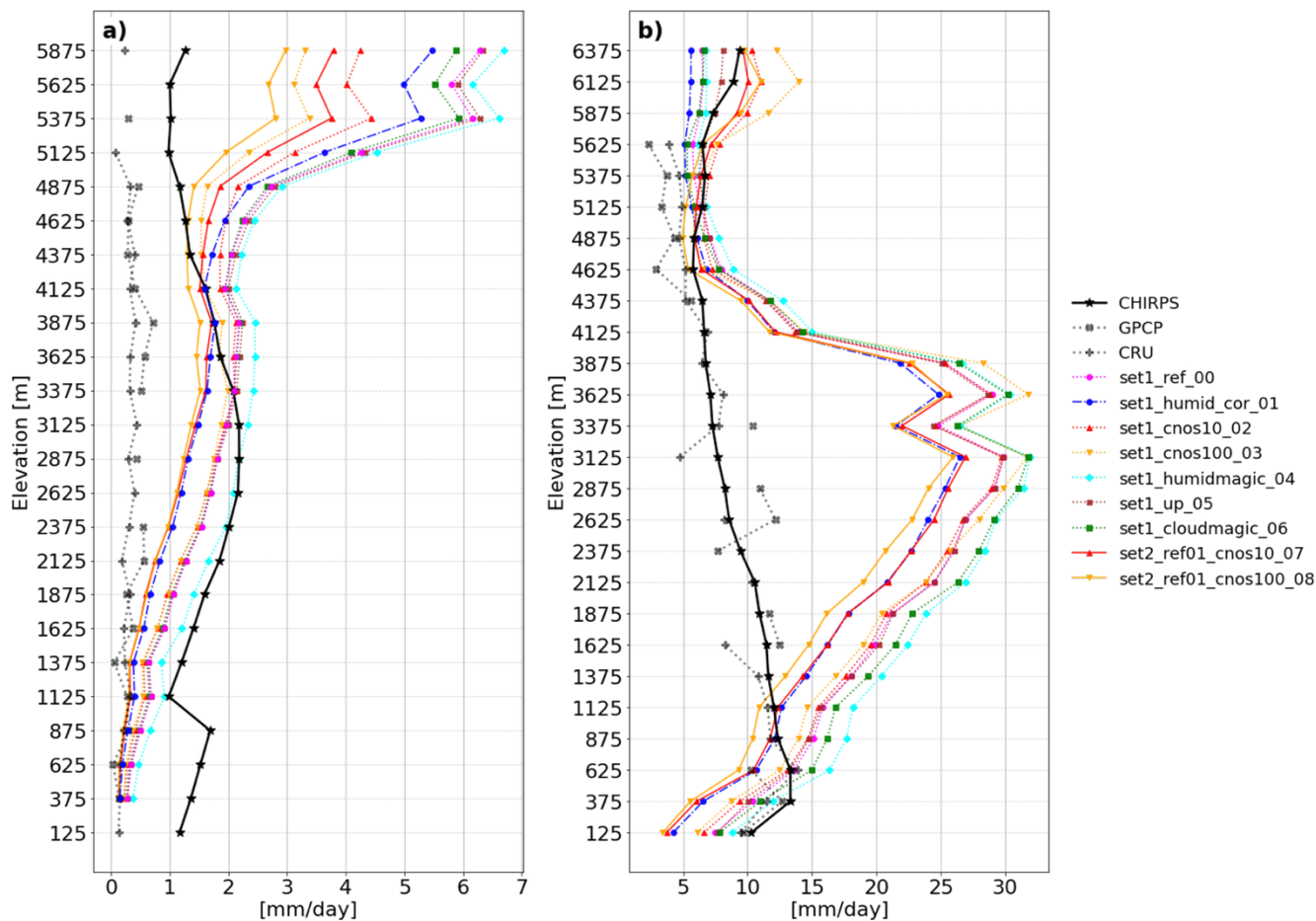


**Figure S1: Vertical profile of precipitation as a function of elevation during the accumulation season in Pamir (March–April–May; a) and Nepal (June–July–August–September; b) for the year 2016, for the different sensitivity experiments. Dashed lines correspond to Set 1 and solid lines to Set 2 (see text for details). The gridded observational products CHIRPS, GPCP, and CRU are shown in black.**

| Simulation        | humid magic <sup>a</sup> | cloud magic <sup>b</sup> | cnos <sup>c</sup> | humid_corr <sup>d</sup> | up <sup>e</sup> |
|-------------------|--------------------------|--------------------------|-------------------|-------------------------|-----------------|
| Set 1             |                          |                          |                   |                         |                 |
| set1_ref_00       | 5                        | 0                        | cnos              | 0%                      | ur              |
| set1_humid_cor_01 | 5                        | 0                        | cnos              | -5%                     | ur              |
| set1_cnos10_02    | 5                        | 0                        | cnos/10           | 0%                      | ur              |

|                           |   |     |          |      |    |
|---------------------------|---|-----|----------|------|----|
| set1_cnos100_03           | 5 | 0   | cnos/100 | 0%   | ur |
| set1_humidmagic_04        | 1 | 0   | cnos     | 0%   | ur |
| set1_up_05                | 5 | 0   | cnos     | 0%   | up |
| set1_cloudmagic_06        | 5 | 0.1 | cnos     | 0%   | ur |
| Set 2                     |   |     |          |      |    |
| set1_up_05<br>(ref set 2) | 5 | 0   | cnos     | -5 % | ur |
| set2_ref01_cnos10_07      | 5 | 0   | cnos/10  | -5%  | ur |
| set2_ref01_cnos100_08     | 5 | 0   | cnos/100 | -5%  | ur |

<sup>a</sup>humidity magic: Controls humidity diffusion; The larger this value, the greater the diffusion, which results in more clouds and warmer conditions. A value of 10 is considered the median.

<sup>b</sup>cloud magic: Controls reconversion of precipitation to cloud condensate; The larger it is, the more rain/snow precipitation is converted back to cloud rain/ice, leads to more clouds and delayed precipitation. To bet set between 0 and 0.2 max.

<sup>c</sup>cnos: Parameter adjusting the spatial distribution of precipitation.

<sup>d</sup>humidity corr: Correction applied at humidity boundaries.

<sup>e</sup>up/ur: fall velocity of precipitation.

**Table S1: Model parameters used to calibrate the MAR model.**

**S2. Methodology snowline**

The snowline is estimated from monthly climatologies as the transition between snow-covered and snow-free areas. For snow depth products (MAR, HMA-SR, HARv2 and ERA5-Land), a snow-covered pixel is defined using a snow depth threshold of 10 cm, whereas for ESA-CCI a snow cover fraction threshold of 10% is adopted. For each monthly climatology, the highest snow-free pixels and the lowest snow-covered pixels are identified, and the snowline elevation is defined as the mean elevation between these two elevations.

Because the different datasets have markedly different spatial resolutions and therefore different numbers of grid cells within each study domain, using a fixed number of pixels would lead to inconsistent estimates of the snowline. Instead, the number of pixels used for each dataset was scaled according to the total number of grid cells in each domain, while maintaining a comparable pixel-to-domain ratio (Table S2). This approach provides a homogeneous estimate of the snowline across datasets while limiting the influence of differences in spatial resolution.

Figure S2 shows the monthly climatology of snow cover fraction from snow ESACCI over the Pamir, highlighting the progressive seasonal migration of the snow-covered area from low to high elevations. However, snow cover spans a broad elevation range, particularly in the northeastern part of the domain where snow persists throughout the year at relatively low elevations. Consequently, the estimated snowline is sensitive to both the snow cover threshold and the number of pixels retained for its calculation.

Figure S3 evaluates the sensitivity of the snowline estimate to both the snow cover fraction threshold (1%, 10% and 50%) and the number of pixels considered. This sensitivity analysis was performed using ESACCI because it exhibits substantially lower snowline elevations than the other datasets in Figure 7, raising the question of whether this behaviour results from the methodology used to define the snowline. However, even when applying a much more restrictive snow cover threshold of 50%, the estimated snowline remains relatively low during winter, particularly in January. As illustrated in Figure S2, this behaviour is mainly explained by the persistence of snow cover in the northeastern part of the Pamir, where snow-covered pixels remain present at low elevations throughout the cold season. The results show that the snow cover fraction threshold primarily affects the absolute snowline elevation, whereas the number of pixels mainly controls the smoothness and representativeness of the annual cycle. Using too few pixels produces a noisy estimate that is strongly influenced by local variability, while too many pixels artificially broaden the transition zone. Overall, a 10% snow cover fraction threshold provides the best compromise between preserving the seasonal snow signal and avoiding the inclusion of isolated snow patches or very thin snowpacks in the corresponding snow depth products. Combined with a dataset-dependent number of pixels that preserves a similar pixel-to-domain ratio, it yields a physically consistent and stable estimate of the annual snowline cycle. This criterion was therefore adopted for all datasets.

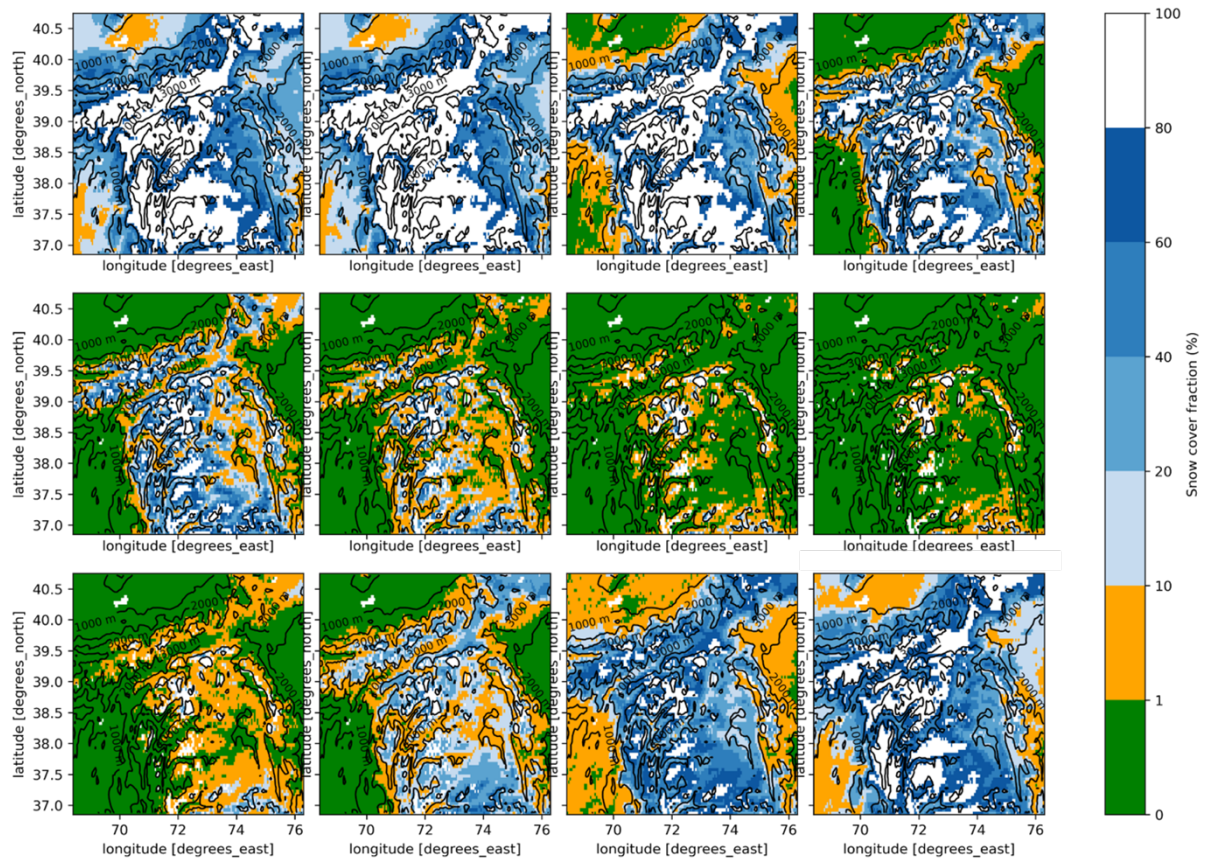


**Figure S2: Climatology of snow cover fraction in ESACCI during 2000-2016 over the Pamir. Black contour lines indicate topography (1000 m interval). Snow cover fraction is classified to illustrate different snow/no snow threshold: 0–1% (green), 1–10% (orange), 10–100% (blues).**

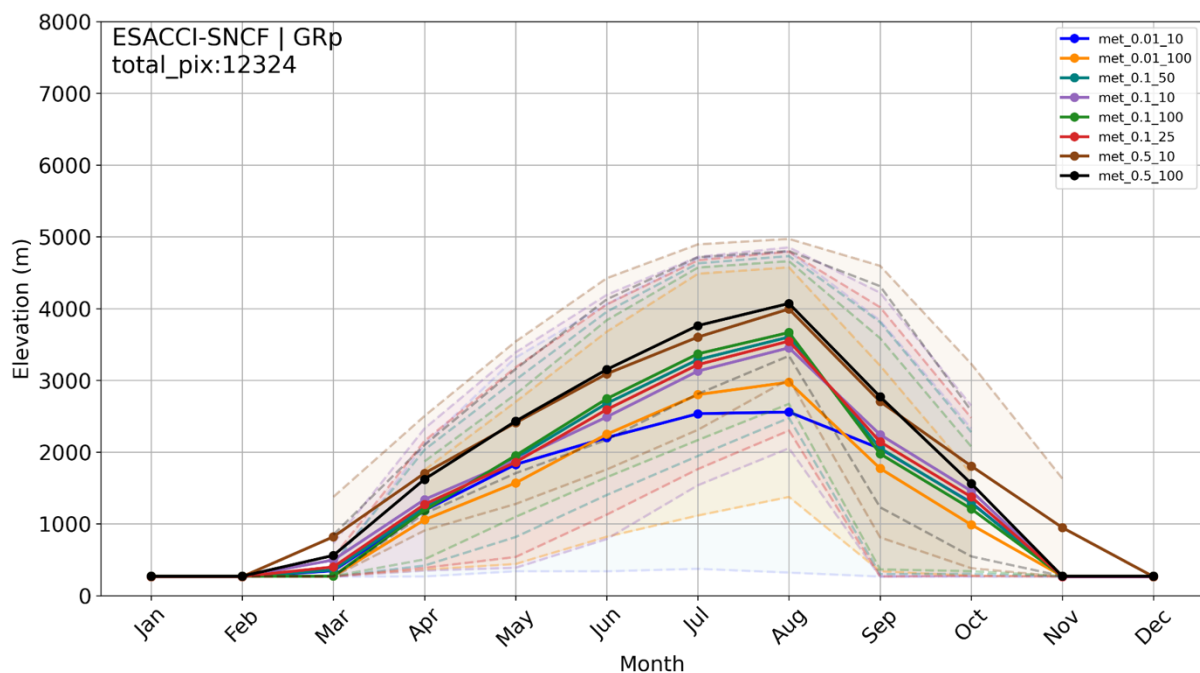


**Figure S3: Sensitivity of the annual snowline cycle derived from ESA-CCI over the Pamir domain to the snow cover fraction(SNCF) threshold and the number of pixels used to define the snowline.** The legend indicates the snow cover fraction threshold (first number, expressed as a fraction of 1; e.g. 0.1 = 10%) and the number of pixels considered (second number). Dashed envelopes indicate the elevation range between the highest snow-free and the lowest snow-covered pixels used to compute the monthly snowline.

| Domain                  | Dataset   | Total grid cells | Pixels used for snowline | Pixel-to-domain ratio |
|-------------------------|-----------|------------------|--------------------------|-----------------------|
| <b>Pamir</b>            | MAR       | 5,952            | 50                       | 119.0                 |
|                         | HMA-SR    | 6,844            | 50                       | 136.9                 |
|                         | ESA-CCI   | 12,324           | 100                      | 123.2                 |
|                         | ERA5-Land | 3,081            | 25                       | 123.2                 |
|                         | HARv2     | 3,600            | 25                       | 144.0                 |
| <b>Central Himalaya</b> | MAR       | 5,952            | 50                       | 119.0                 |

|  |           |        |     |       |
|--|-----------|--------|-----|-------|
|  | HMA-SR    | 5,408  | 50  | 108.2 |
|  | ESA-CCI   | 10,842 | 100 | 108.4 |
|  | ERA5-Land | 2,691  | 25  | 107.6 |
|  | HARv2     | 3,220  | 25  | 128.8 |

160 **Table S2. Total number of grid cells within each study domain, number of pixels retained to estimate the snowline, and corresponding pixel-to-domain ratio used for each dataset.**

**S3. In situ comparison**

165 This section presents the complete daily time series of 2 m air temperature and precipitation at all stations used in the Khumbu region (Table 2). For temperature, both the original MAR output and the lapse-rate-corrected temperature are shown. The lapse-rate correction is computed daily from the MAR temperature–elevation relationship over the Khumbu region and applied according to the elevation difference ( $\Delta z = z_{\text{MAR}} - z_{\text{station}}$ ) between each station and its corresponding MAR grid cell. Each figure also reports the station elevation, the elevation of the corresponding MAR grid cell, and  $\Delta z$ . The available  
170 observation periods differ among stations and some records contain temporal gaps; therefore, the bias and correlation coefficients presented in Figure 8 were computed only over the overlapping periods between observations and MAR simulations.

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# Daily Mean Air Temperature (TTZ) - Glacioclim AWS vs Model

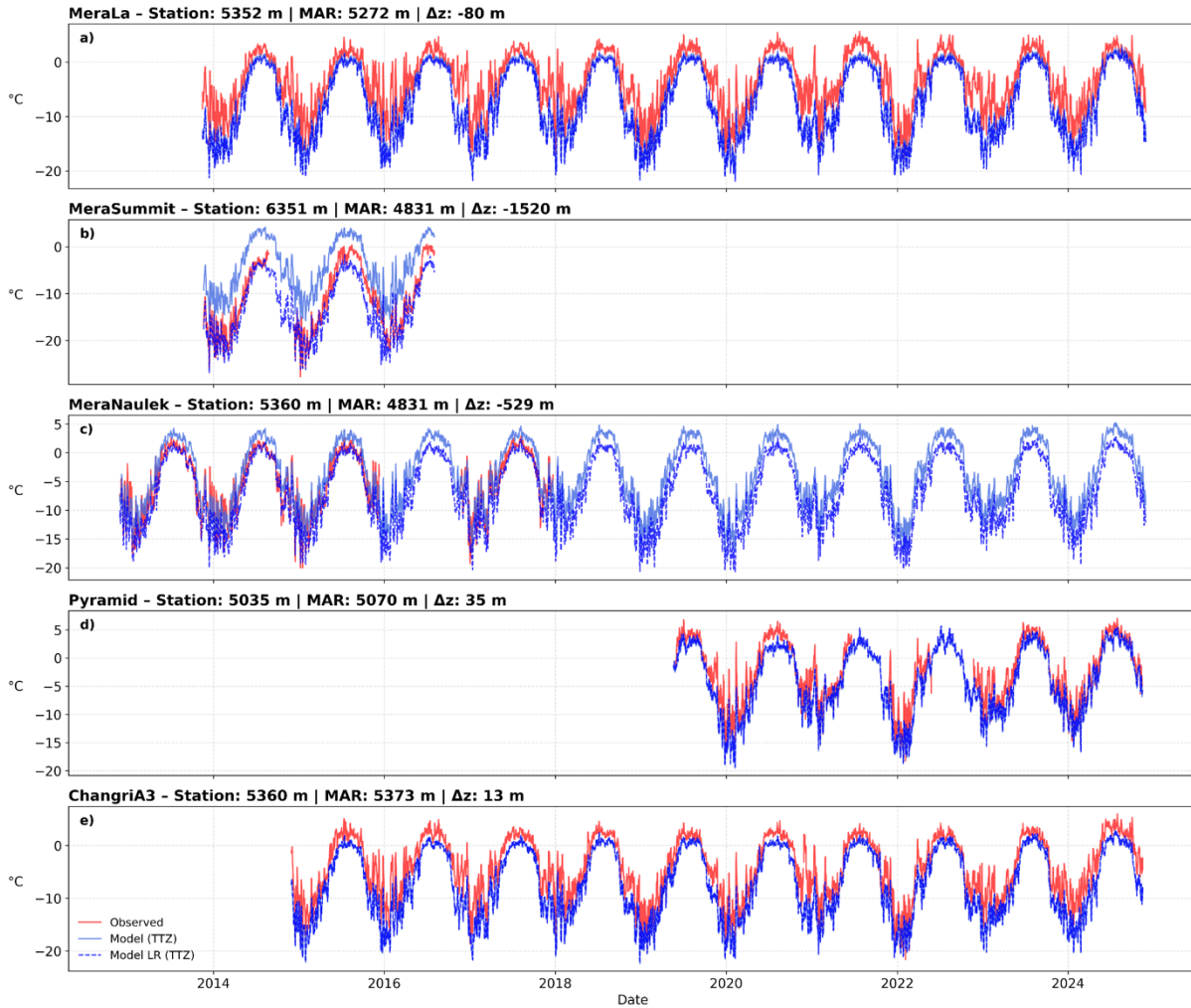
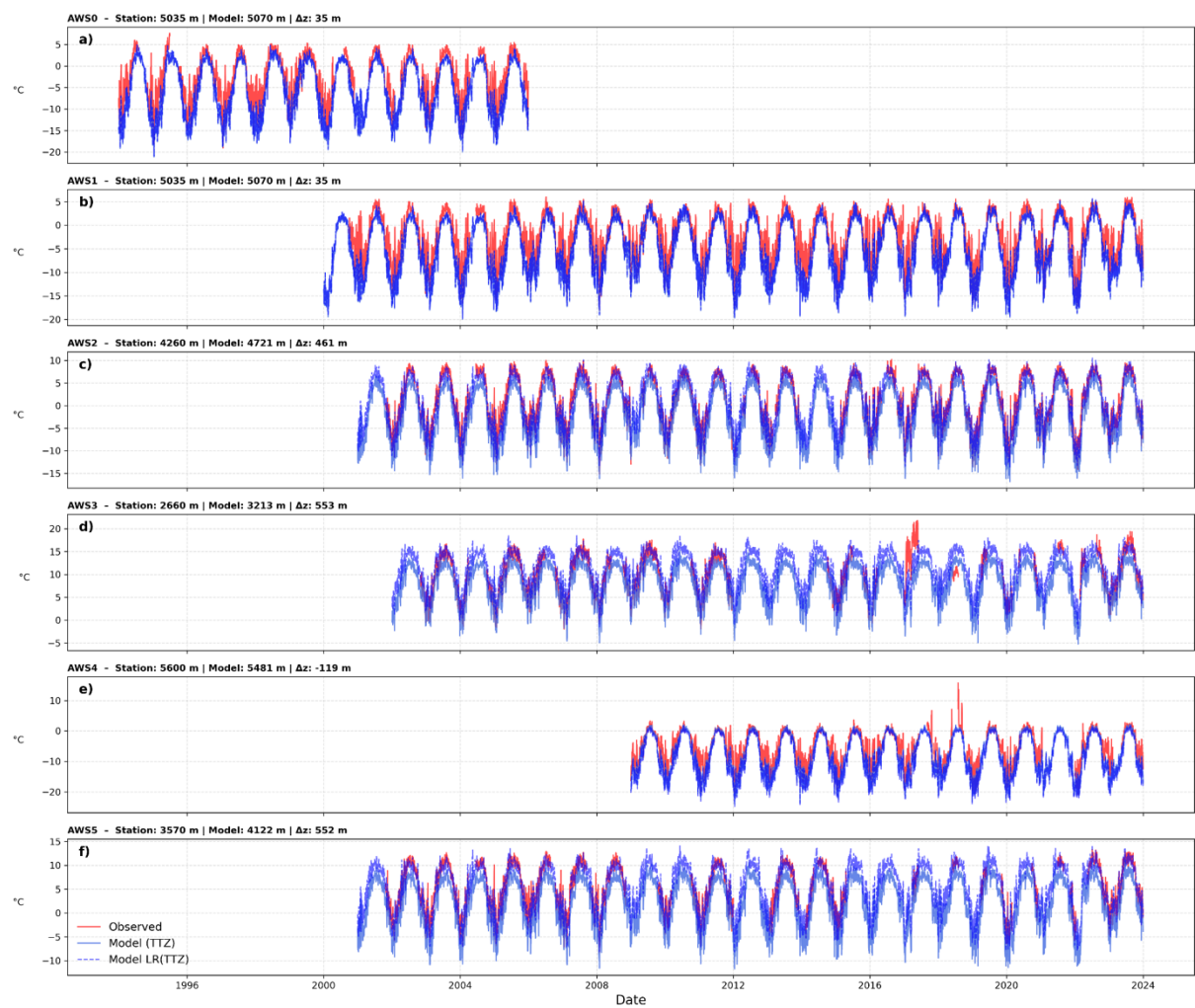


**Figure S4.** Time series of air temperature at the GLACIOCLIM stations (see Table 2 in the main text) over the available observation period for each station. Observations are shown in red, while MAR simulations at the station locations are shown in blue: raw model output (solid line) and daily lapse-rate-corrected temperature. The lapse rate is derived daily from the MAR temperature–elevation relationship over the entire Khumbu region and applied according to the elevation difference ( $\Delta z = z_{\text{MAR}} - z_{\text{Station}}$ ) between each station and its corresponding MAR grid cell.

Daily Mean Air Temperature (TTZ) - Ev-K2-CNR AWS vs Model



185 Figure S5. Same as Figure S4 but for Ev-K2-CNR stations.

## Daily Mean Air Temperature (TTZ) - Ev-K2-CNR AWS vs Model

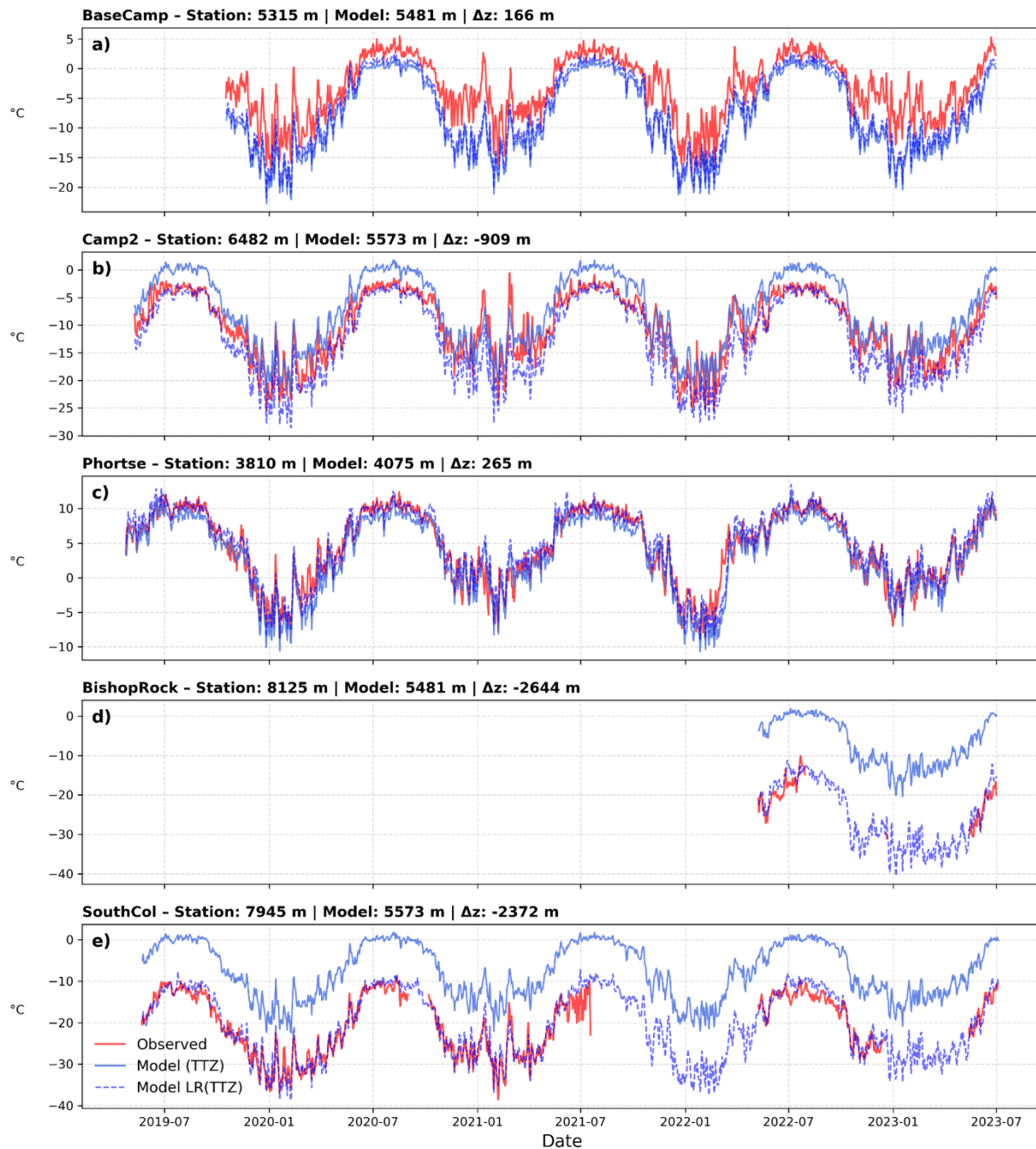


Figure S6. Same as Figure S4 but for NatGeo stations.

# **Daily Total Precipitation - Glacioclim AWS vs Model (RF+SF)**

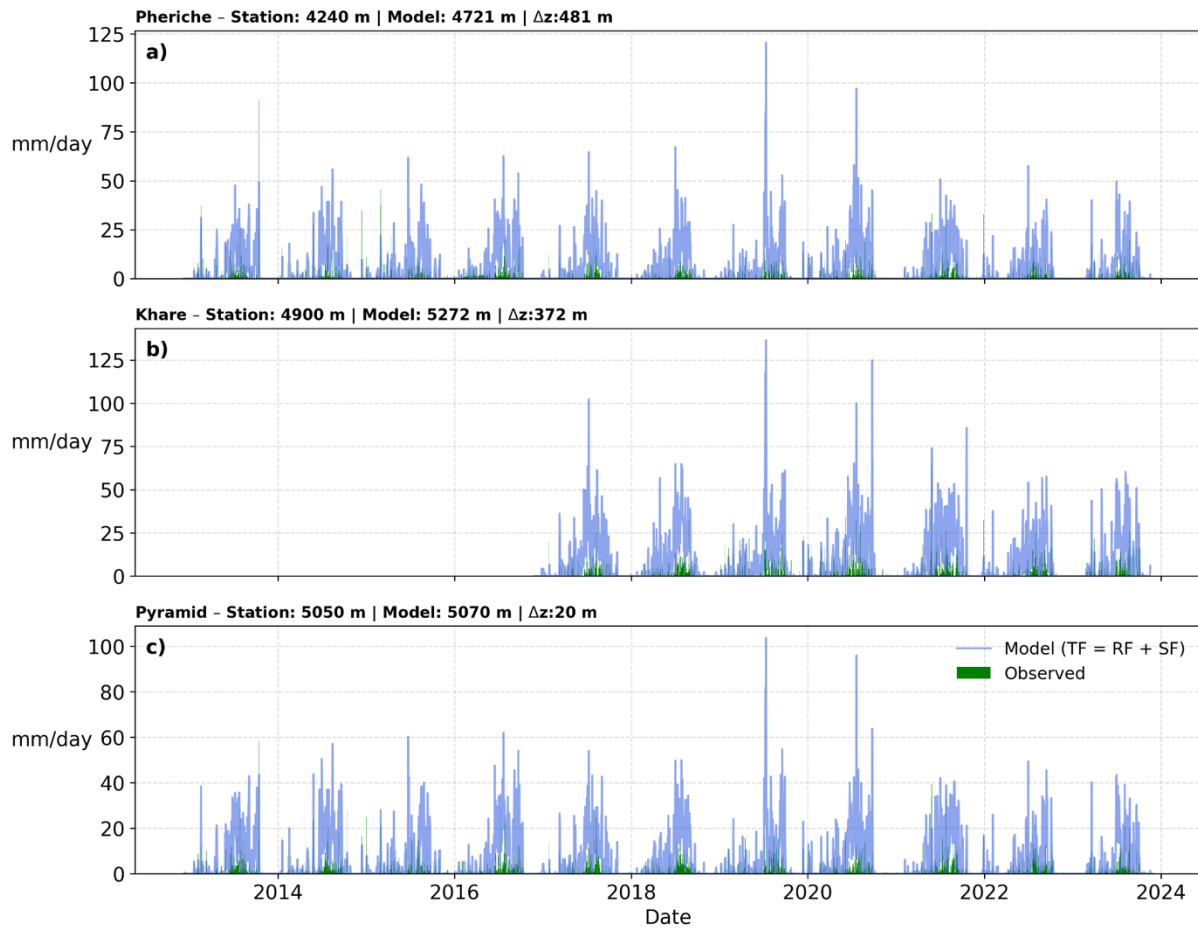


**Figure S7. Time series of precipitation at the GLACIOCLIM stations (see Table 2 in the main text) over the available observation period for each station. Observations are shown in red, while MAR simulations at the station locations are shown in blue.**

### Daily Total Precipitation - Ev-K2-CNR AWS vs Model (RF+SF)

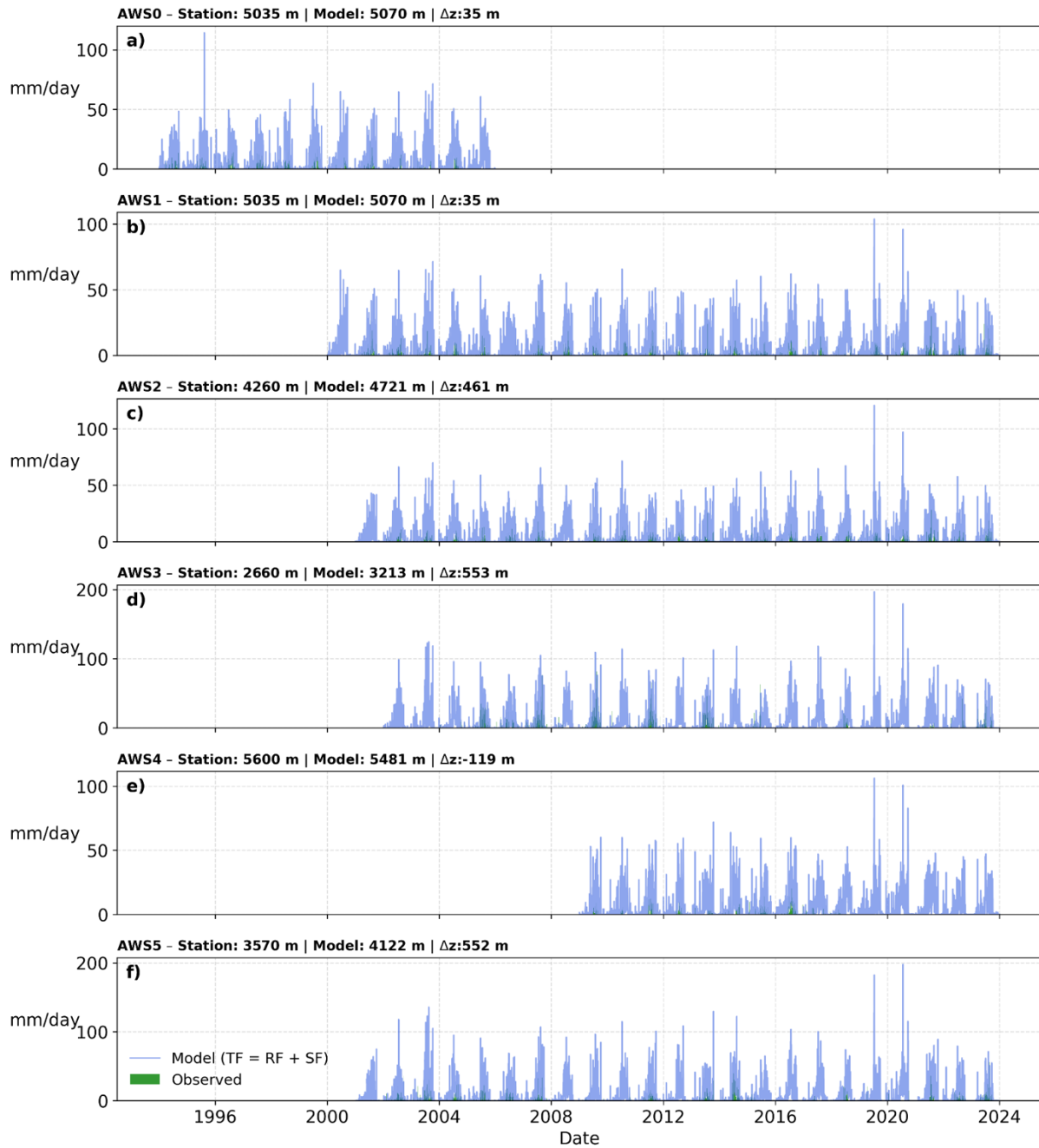


Figure S8. Same as Figure S6 but for Ev-K2-CNR stations.

## Daily Total Precipitation - NatGeo AWS vs Model (RF+SF)

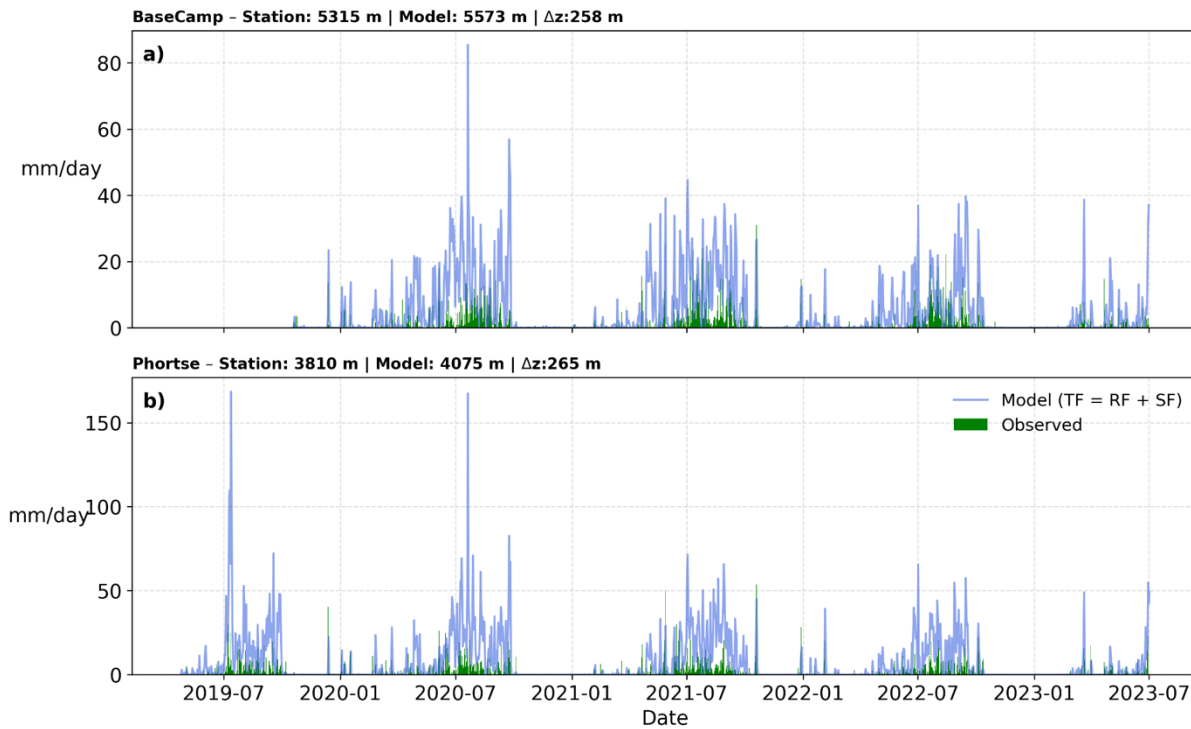


**Figure S9. Same as Figure S6 but for NatGeo stations.**

## References

Bellprat, O., Kotlarski, S., Lüthi, D., & Schär, C. (2012). Exploring perturbed physics ensembles in a regional climate model.

Journal of Climate, 25(13), 4582–4599. <https://doi.org/10.1175/JCLI-D-11-00275.1>

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