

Benchmarking Snow Products under Imperfect Observational Constraints: The Case of ERA5-Land across Canada and Alaska

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25 S1. ERA5-Land snow variables

The snowpack in HTESSEL model is treated as a single layer cover over the soil, with thermal insulation, density and albedo properties. The model allows for the interception of liquid water into the snowpack and aging processes (see Dutra et al., 2010; Balsamo et al., 2011). SD, SC, and SWE are modelled using a detailed representation of snow accumulation, compaction, and melting processes driven by coupling mass and energy balance equations at the snow layer. SWE is modelled by mass balance
 30 equation, in which snowfall is accumulated in the snow layer, and depleted by snowmelt, sublimation and snowmelt runoff:

$$SWE(t) = SWE(t - 1) + P_{snow}(t) - M_{snow}(t) - S_{snow}(t) - R_{snow}(t) \quad (1)$$

In which $P_{snow}(t)$, $M_{snow}(t)$, $S_{snow}(t)$, and R_{snow} are snowfall, snowmelt, sublimation and runoff from melting snow, respectively. The snowmelt and sublimation are derived from the energy balance equation:

$$Q_{net}(t) = Q_{SW}(t) + Q_{LW}(t) + Q_{sens}(t) + Q_{latent}(t) - Q_{ground}(t) \quad (2)$$

In which Q_{SW} , Q_{LW} , Q_{sens} , Q_{latent} , and Q_{ground} are incoming shortwave and longwave radiations, as well as sensible, latent and ground heat fluxes. Within this representation, snowmelt occurs when Q_{net} is positive and calculated as:

$$M_{snow}(t) = \frac{Q_{net}(t)}{L_f} \quad (3)$$

35 In which L_f is the latent heat of fusion. Similarly, sublimation is derived from Q_{latent} and the latent heat of sublimation, L_s :

$$S_{snow}(t) = \frac{Q_{latent}(t)}{L_s} \quad (4)$$

SD can be inferred from SWE, given the knowledge of snow density:

$$SD(t) = \frac{SWE(t)}{\rho_{snow}(t)} \quad (5)$$

In which $\rho_{snow}(t)$ is snow density. Freshly fallen snow has a low density, however it evolves in time due to metamorphism, compaction and melt:

$$\frac{\rho_{snow}(t + 1) - \rho_{snow}(t)}{\Delta t} = C_1 \rho_{snow}(t) \times (T_{snow}(t) - T_{ref}) + C_2 P_{snow}(t) \cdot \frac{\rho_{snow}(t)}{\rho_{ice}} - C_3 M_{snow}(t) \quad (6)$$

In which, C_1 , C_2 , and C_3 are parameters that quantify rates of snow metamorphism, compaction and melt, respectively. C_1 represents sensitivity of snow density to temperature changes, derived from physical principles related to snow grain metamorphism and bonding. C_2 is a coefficient related to the compaction of snow under pressure, based on the mechanical properties of snow and its response to overburden weight; and, C_3 is a coefficient that quantifies the impact of melting on snow density, derived from the energy required for phase changes and the dynamics of liquid water movement through the snowpack. $T_{snow}(t)$ and T_{ref} are temperature of snowpack and reference temperature and ρ_{ice} is the density of ice. Within ERA5L framework, snow density is constrained to remain within $[50\ 450]$ kg m^{-3} (ECMWF, 2018).

By having $SD(t)$, SC at the time t can be determined as:

$$SC(t) = \min \left(1, \frac{SD(t)}{0.1} \right) \quad (7)$$

S2. CMC snow depth and snow water equivalent

The CMC's analysis of SD and SWE starts with collecting the in-situ SD, as well as precipitation and temperature data from the forecast model, with which a simple snowpack model is forced. The simulation results of the snowpack model provide a first-guess estimate for SD based on the calculated SWE according to the mass balance as well as the estimated snow density (see Equations 1 and 5). The assumption for mass balance equation is that the entire precipitation occurs at temperature 0°C or less is snowfall. This proportion is decreases linearly up to $+2^\circ\text{C}$, where all the precipitation will be in rain. Also, sublimation is not modelled directly but is taken out as a landscape-dependent proportion of SWE at each timestep. The density of new snowfall is assumed to be a function of air temperature after Hedstrom and Pomeroy (1998):

$$\rho_{snowfall}(t) = \begin{cases} 67.9 + 51.3 \exp\left(\frac{T_{air}(t)}{2.6}\right) & T_{air}(t) \leq 0^\circ\text{C} \\ 119.2 + 20T_{air}(t) & T_{air}(t) > 0^\circ\text{C} \end{cases} \quad (8)$$

The increase in snow density at each time step is calculated using empirical function for snow aging for cold and warm snow, which are discriminated based on temperature threshold of -1°C . The hourly settling rate for cold snow (i.e., $T_{air}(t) < T_{melt}$) is based on Anderson (1976) as:

$$\rho_{snow}(t+1) - \rho_{snow}(t) = 600C_1 \exp[-0.08(T_{melt} - T_{snow}(t))] \times SWE(t) \times \exp(C_2\rho_{snow}(t)) \quad (9)$$

In which C_1 is the snow setting rate at T_{melt} ; $T_{snow}(t)$ is the temperature of snow at time t ; and C_2 is an empirically derived constant. For warm snow (i.e., $T_{air}(t) > T_{melt}$), the snow density is recursively calculated as (Tabler et al., 1990):

$$\rho_{snow}(t+1) = \rho^*(t+1) - 200 \exp \left[\frac{\log(\rho^*(t+1) - \rho_{snow}(t))}{200} \right] - 0.01 \quad (10)$$

60 In which $\rho^*(t+1)$ is the upper bound, given the snow density at $SD(t)$:

$$\rho^*(t+1) = 700 - \left(\frac{20470}{SD(t)} \right) \left[1 - \exp \left(\frac{-SD(t)}{67.3} \right) \right] \quad (11)$$

The density starts from a low density and increases as it ages. As new snow falls, the density declines. The density in CMC analysis is bounded in $[100 \ 550]$ kg m^{-3} (Brown and Brasnett, 2010).

Snowmelt is calculated using a variable degree-day melt factor, which is a function of snowpack density and vegetation cover following Kuusisto (1984):

$$\gamma(t) = \begin{cases} 0.0104\rho_{snow}(t) - 0.70 & \text{if forested area} \\ 0.0196\rho_{snow}(t) - 2.39 & \text{if open area} \end{cases} \quad (12)$$

65 In which $\gamma(t)$ is the melt factor at time t . Accordingly the snowmelt can be calculated as:

$$M_{snow}(t) = \gamma(t)[T_{air}(t) - T_{melt}] + \frac{C_w Rain(t) T_{air}(t)}{L_f \rho_{ice}} \quad (13)$$

The first term refers to the melt driven by temperature and the second term denotes to the melt contributed by rainfall in which C_w is the heat capacity of water and $Rain(t)$ is rainfall at time t .

Equations 8 to 14 together provide a basis to calculate the first-guess estimate of SD. These estimates are then blended with the in-situ observation of SD and corrected using the Optimum Interpolation scheme, described by Brasnett (1999):

$$SD^*(t) = SD(t) + \sum_{i \in I} w_i (SD_{i,obs}(t) - SD_i(t)) \quad (14)$$

70 In which $SD_{i,obs}(t) - SD_i(t)$ is the difference between in-situ observation and the first-guess estimate at station i that is within 600 km from the center of the grid in which $SD(t)$ is calculated. w_i is the optimum weight for station i . The vector of weights $\mathbf{w}$ for all neighbouring stations I can be calculated as:

$$\mathbf{w} = (\mathbf{P} + \mathbf{O})^{-1} \mathbf{q} \quad (15)$$

Where $\mathbf{P}$ is the correlation coefficient matrix of first-guess error between all pairs of observation, $\mathbf{O}$ is the normalized covariance matrix of observational errors between all pairs of observations and $\mathbf{q}$ is the vector of correlation coefficients of the first-guess error between the observation and the grid in which $SD(t)$ is calculated. $\mathbf{P}$ and $\mathbf{q}$ are selected in a way that the spatial correlation depends only on horizontal and vertical separation with a distance of respectively 120 km and 800 m.

S3. Unified AMSR-E/AMSR2 snow water equivalent data

The retrieval procedure of unified AMSR-E/AMSR2 SWE product starts by combining climatological information, with the Helsinki University of Technology (HUT/TKK) electromagnetic snow-emission model, and Artificial Neural Networks (ANNs) to estimate snow depth. A synthetic ANN training dataset is generated using the TKK model and consists of simulated brightness temperatures paired with snow depth, snow density, and near-surface temperature (Pulliainen, 2006; Tedesco and Jeyaratnam, 2016). The ANN formulation builds on the microwave snow-retrieval approach of Tedesco et al. (2004). Two feed-forward ANNs are used to estimate microwave-effective snow grain size, based on 36.5-GHz brightness temperatures alone, as well as both 18.7- and 36.5-GHz brightness temperatures with horizontal and vertical polarizations included. The two grain-size estimates account for differences in microwave penetration depth and vertical snowpack structure. These estimates are then used to calculate spatially and temporally varying retrieval coefficients that relate multifrequency brightness-temperature differences to snow depth (Tedesco and Jeyaratnam, 2016).

Retrieved snow depth is then converted to SWE using spatially and temporally varying bulk snow-density estimates based on snow depth, day of year, and snow-climate class following Sturm et al. (2010). After retrieval, SWE estimates from multiple overpasses within a grid cell are screened for consistency. When more than one valid estimate is available in a grid cell on a given day, the maximum is retained. The distributed 5-day SWE field is then formed by retaining the maximum daily SWE within each 5-day window (Tedesco and Jeyaratnam, 2019). Thus, the native value is a 5-day maximum rather than a 5-day mean. During leap years, the final February interval comprises six days.

S4. MODIS snow cover data

The MODIS detects snow cover based on the distinct spectral reflectance characteristics of snow (Riggs et al., 2019). Snow strongly reflects in the visible part of the spectrum but absorbs the shortwave infrared radiation, making it easily distinguishable from other land surfaces. This classification is made using the Normalized Difference Snow Index (NDSI; Hall et al., 1995), derived from MODIS instrument on NASA's Terra satellite. NDSI in a given day t can be calculated as (Wang et al., 2022):

$$NDSI(t) = \frac{R_{green}(t) - R_{SWIR}(t)}{R_{green}(t) + R_{SWIR}(t)} \quad (16)$$

In which R_{green} and R_{SWIR} are the reflectance in the green and shortwave infrared bands respectively (Dozier, 1989). The pixel is classified as snow-covered if both the NSDI and reflectance in the visible band exceed specific thresholds. One key challenge here is that NSDI cannot distinguish between clouds and snow cover; therefore, there is a need for resolving clouds (see also Gafurov and Bárdossy, 2009). The cloud masking in MODIS snow cover products involves multiple spectral tests and uses data from the MODIS Cloud Mask Product (MOD35; Ackerman et al., 2010), which assesses the presence of clouds using a combination of visible, infrared, and near-infrared bands (Ricciardelli et al., 2009). The results of these individual tests are combined to categorize the state of cloudiness. The snow cover algorithm integrates this cloud information to ensure only clear-sky observations are considered. If a pixel is flagged as cloud-covered, no snow cover is determined for that pixel in that day, and the area is marked accordingly (Riggs et al., 2019). Accordingly, the Fraction of Snow Cover (FSC) over a grid cell in a given day t can be calculated as (Salomonson and Appel, 2004, 2006; Masson et al., 2018; Yan et al., 2022):

$$FSC(t) = -0.001 + 1.45NSDI(t) \quad (17)$$

To upscale daily data to monthly, grids with low FSC or high cloud cover are eliminated. In addition, a daily data must have a cloud cover less than 30% to be included in the averaging. The contribution of daily observation to the monthly averaging is based on its fractions of clouds. If there is no day within a month that satisfies this criterion then the monthly averaging is not calculated and the data is tagged as missing (see Riggs et al., 2019).

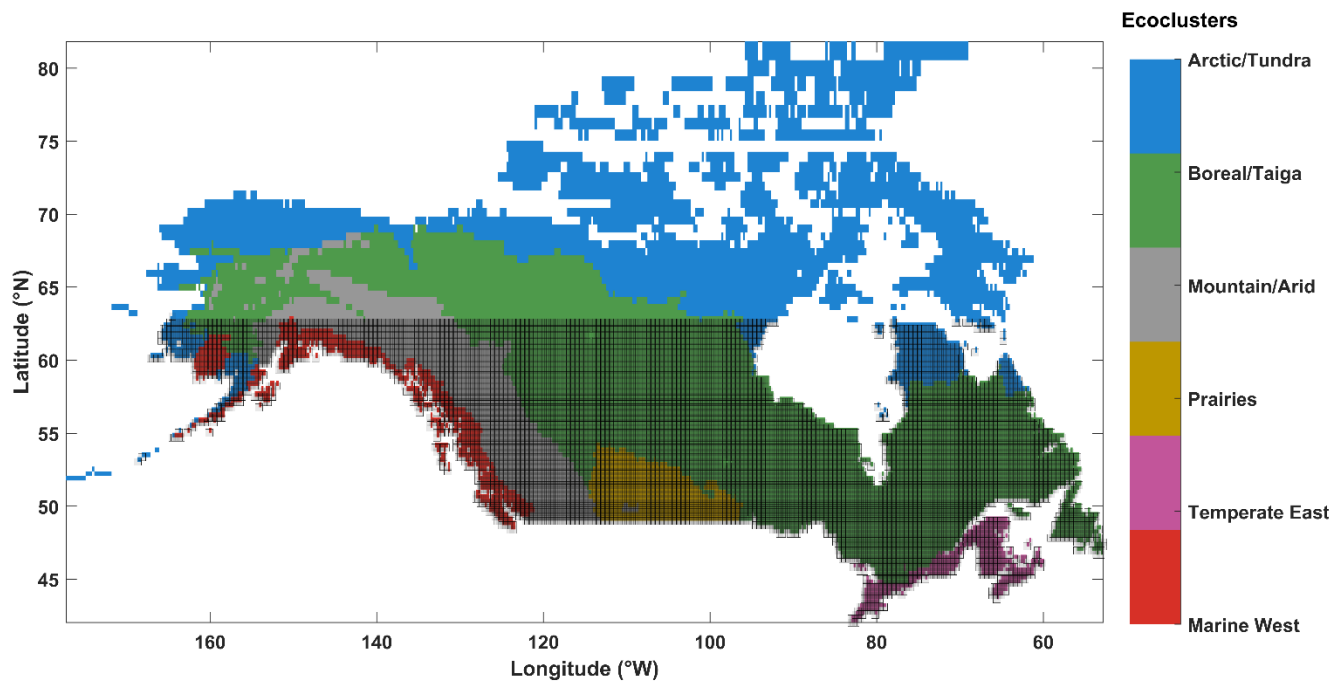


Figure S1: The geographic extents of complete MODIS data coverage across eco-clusters in the study domain during the benchmarking period (hatched). Due to polar nights, latitudes above ~64°N do not include complete data and are excluded from benchmarking.

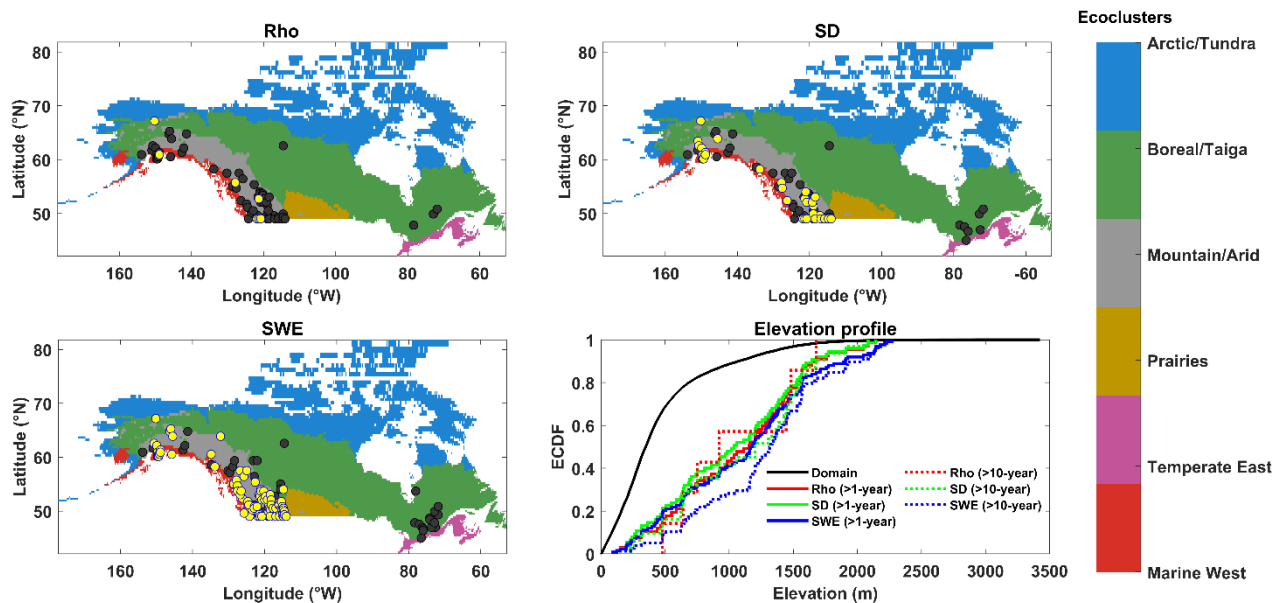
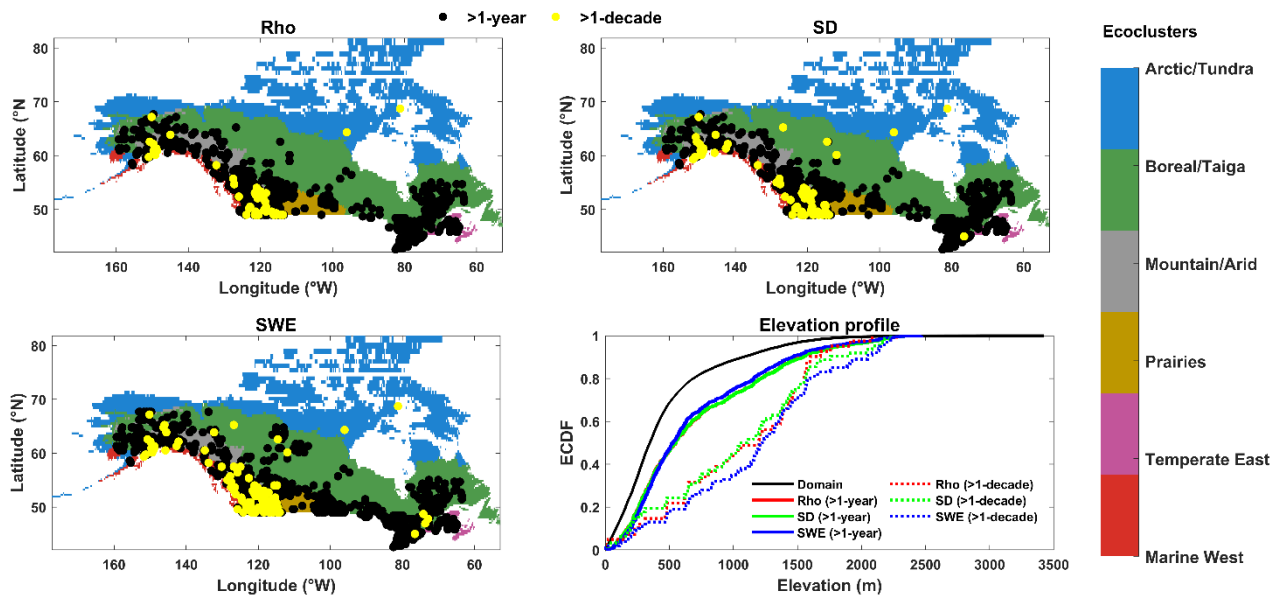


Figure S2: Selected in-situ stations for benchmarking gridded data at the daily timescale. Stations with more than 1-year worth of data (black dots) are used for evaluating the goodness-of-fit of gridded data, whereas stations with more than 10-year worth of data (yellow dots) are also used for evaluating how snow characteristics are reconstructed by the gridded data. Bottom right panel shows the elevation profiles of selected stations, characterized by Empirical Cumulative Distribution Function (ECDFs), for Rho (red lines), SD (green lines) and SWE (blue lines). Solid and dotted coloured lines are respectively related to the stations with more than 1-year and more than 10-year worth of data during the benchmarking period of 2002-2016. Solid black line shows the elevation profile of the domain, revealing how the selected in-situ stations have a tendency toward higher elevations.



130 Figure S3: Selected in-situ stations for benchmarking gridded data at the monthly timescale. Stations with more than
 1-year worth of data (black dots) are used for evaluating the goodness-of-fit of gridded data, whereas stations with
 more than 10-year worth of data (yellow dots) are also used for evaluating how snow characteristics are reconstructed
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 135 coloured lines are respectively related to the stations with more than 1-year and more than 10-year worth of data during
 the benchmarking period of 2002-2016. Solid black line shows the elevation profile of the domain, revealing how the
 selected in-situ stations have a tendency toward higher elevations.

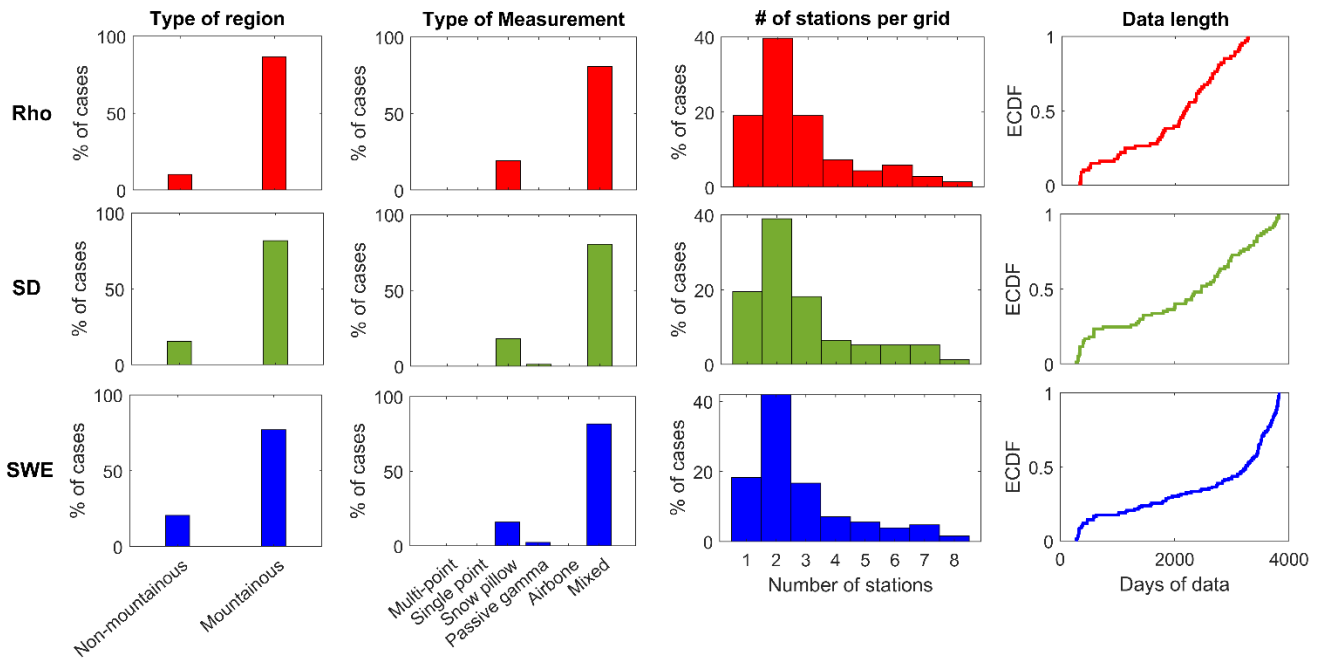
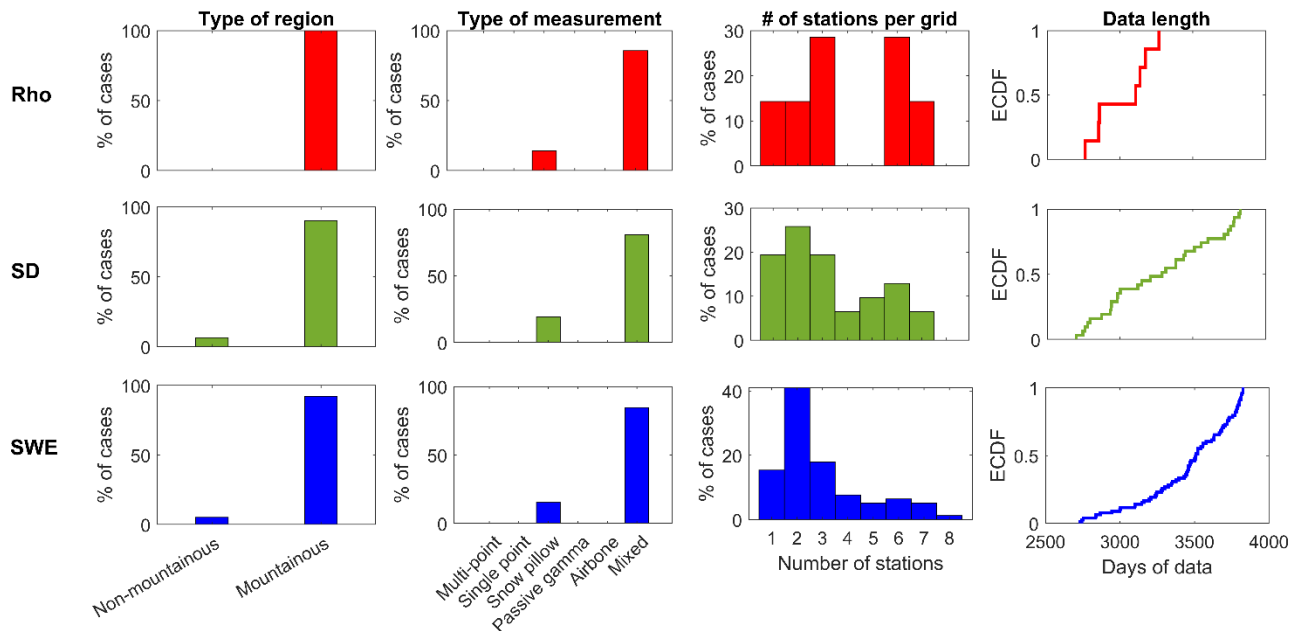


Figure S4: Characteristics of in-situ stations considered for weak conditioning of gridded data at the daily time scale. From top to bottom rows are related to snow variables, i.e. Rho, SD, and SWE, respectively. From left to right, columns are related to type of region and measurement, as well as number of stations per grid cell, and the data length. For type of region, type of measurement, and number of stations per grid, percentage of cases are reported, whereas for data length, the Empirical Cumulative Distribution Functions (ECDFs) of data lengths in selected stations are shown.



145 **Figure S5: Characteristics of in-situ stations considered for strong conditioning of gridded data at the daily time scale. From top to bottom rows are related to snow variables, i.e. Rho, SD, and SWE, respectively. From left to right, columns are related to type of region and measurement, as well as number of stations per grid cell, and the data length. For type of region, type of measurement, and number of stations per grid, percentage of cases are reported, whereas for data length, the Empirical Cumulative Distribution Functions (ECDFs) of data lengths in selected stations are shown.**

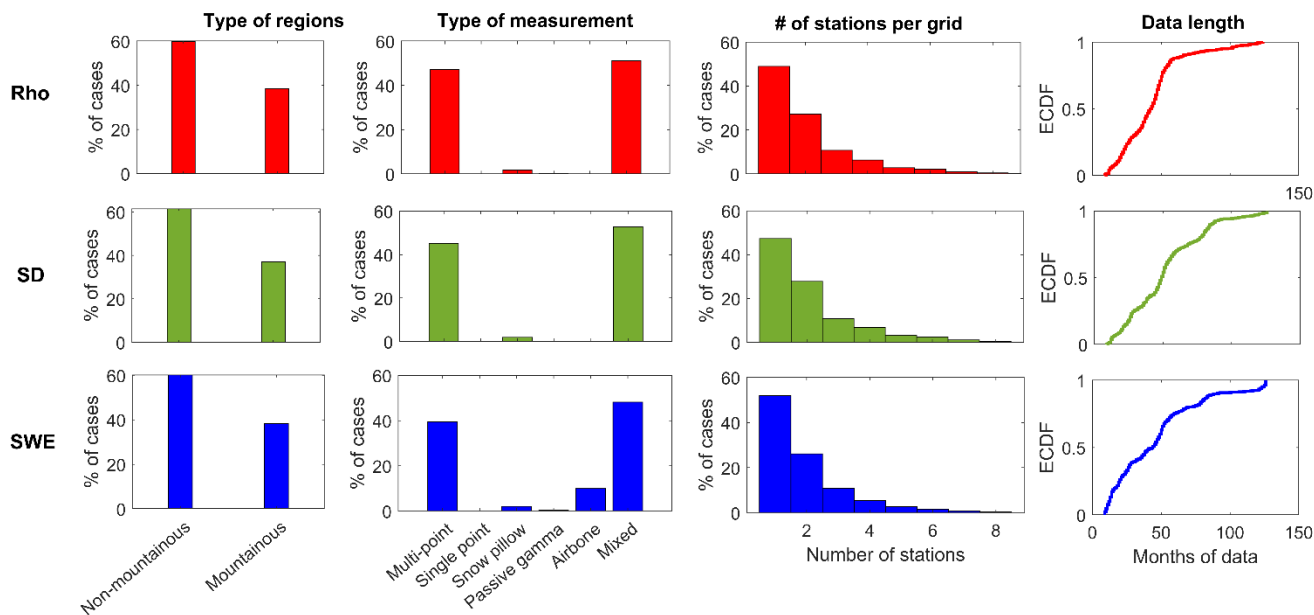


Figure S6: Characteristics of in-situ stations considered for weak conditioning of gridded data at the monthly time scale. From top to bottom rows are related to snow variables, i.e. Rho, SD, and SWE, respectively. From left to right, columns are related to type of region and measurement, as well as number of stations per grid cell, and the data length. For type of region, type of measurement, and number of stations per grid, percentage of cases are reported, whereas for data length, the Empirical Cumulative Distribution Functions (ECDFs) of data lengths in selected stations are shown.

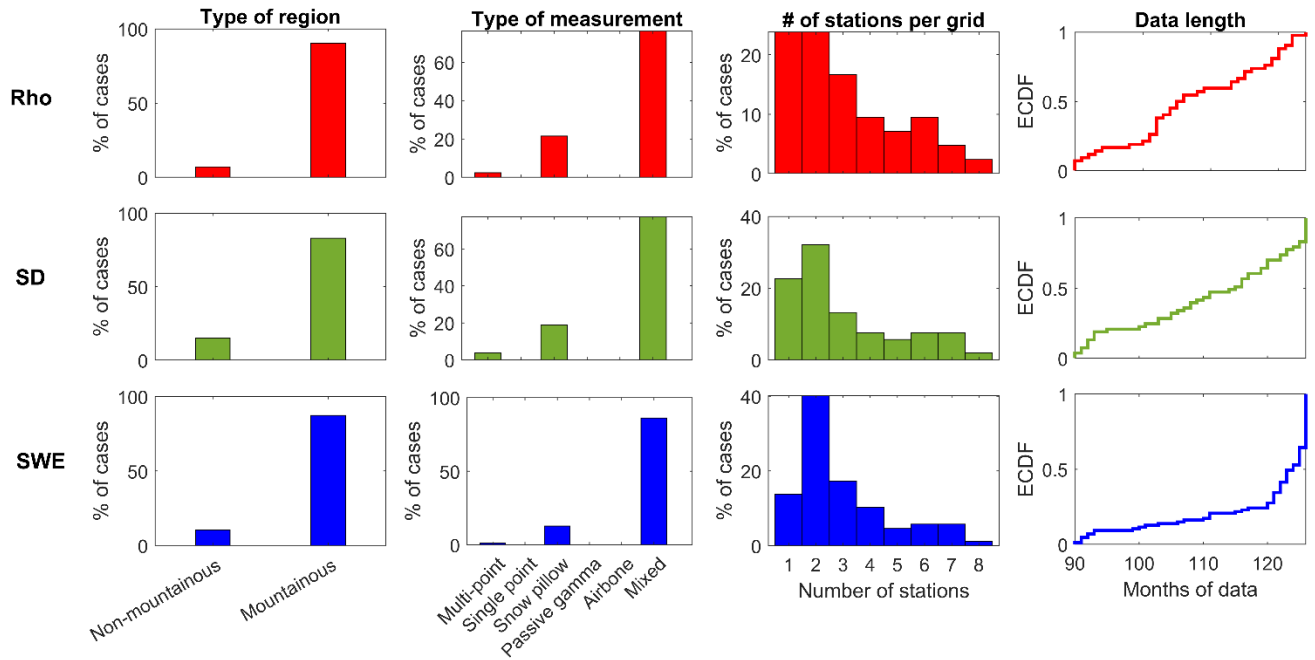
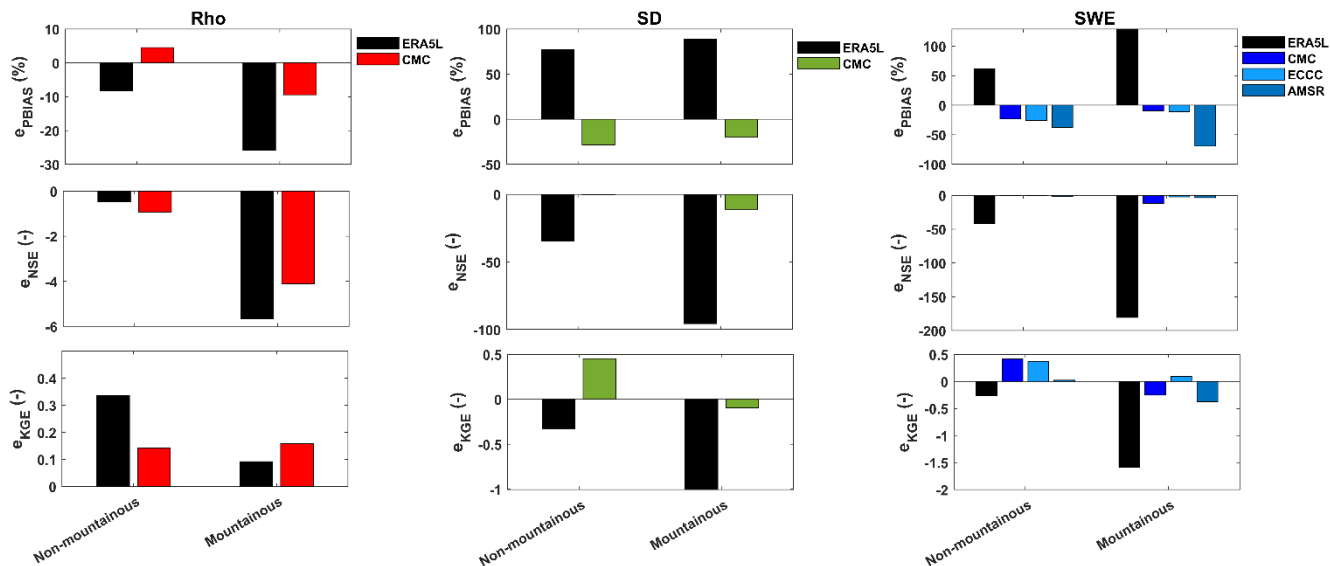


Figure S7: Characteristics of in-situ stations considered for strong conditioning of gridded data at the monthly time scale. From top to bottom rows are related to snow variables, i.e. Rho, SD, and SWE, respectively. From left to right, columns are related to type of region and measurement, as well as number of stations per grid cell, and the data length. For type of region, type of measurement, and number of stations per grid, percentage of cases are reported, whereas for data length, the Empirical Cumulative Distribution Functions (ECDFs) of data lengths in selected stations are shown.



165 **Figure S8: Expected GoFs of ERA5L and competing gridded product(s) in tracking monthly dynamics of Rho (left column), SD (middle column), and SWE (right column) across non-mountainous and mountainous grids. From top to bottom, rows correspond to PBIAS, NSE, and KGE respectively. In all panels, black and coloured bars are related to ERA5L and associated competing product(s) respectively.**

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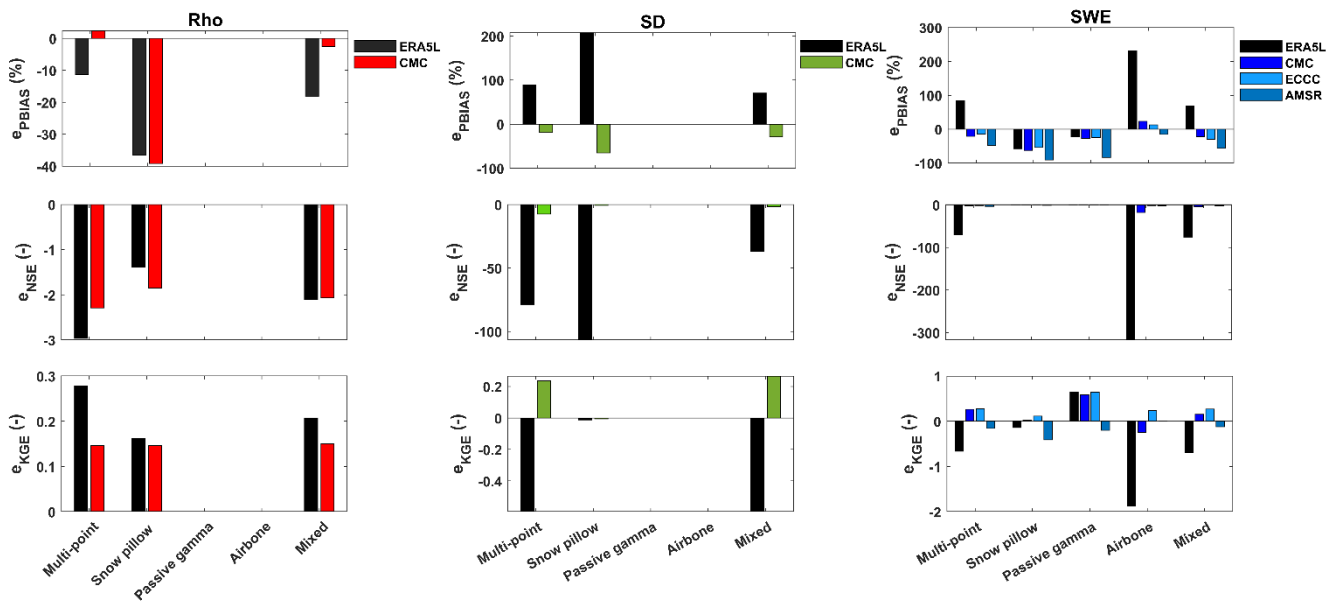


Figure S9: Expected GoFs of ERA5L and competing gridded product(s) in tracking monthly dynamics of Rho (left column), SD (middle column), and SWE (right column) across various measurement techniques. From top to bottom, rows correspond to PBIAS, NSE, and KGE respectively. In all panels, black and coloured bars are related to ERA5L and associated competing product(s) respectively.

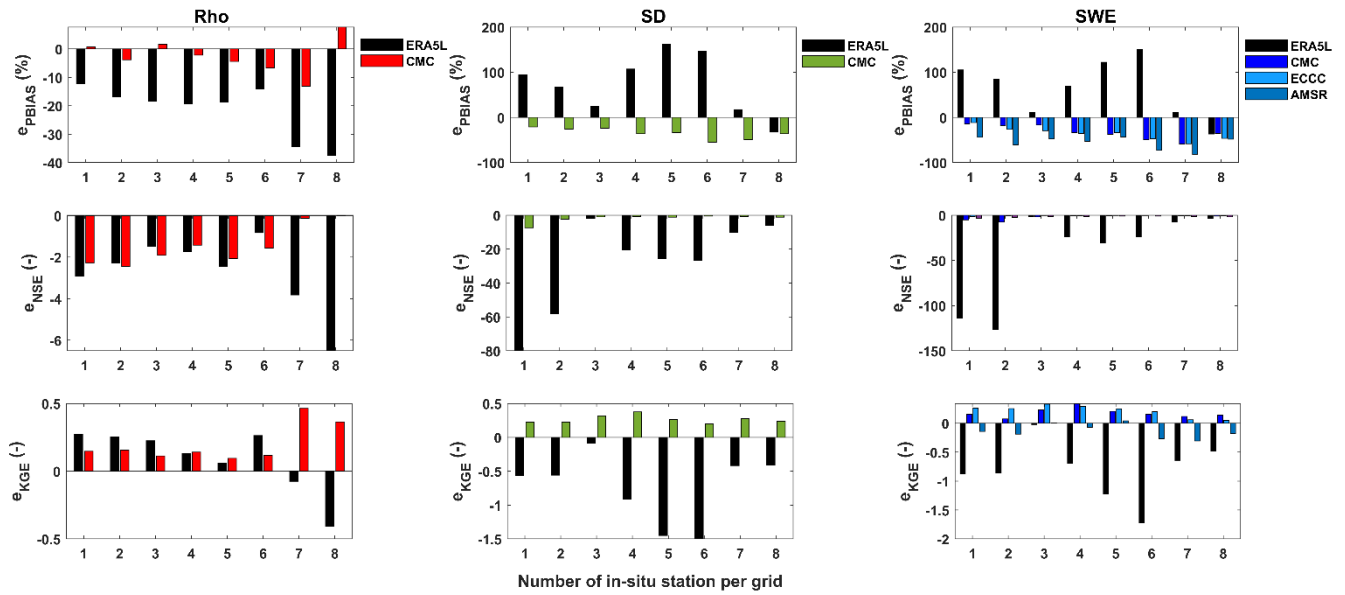
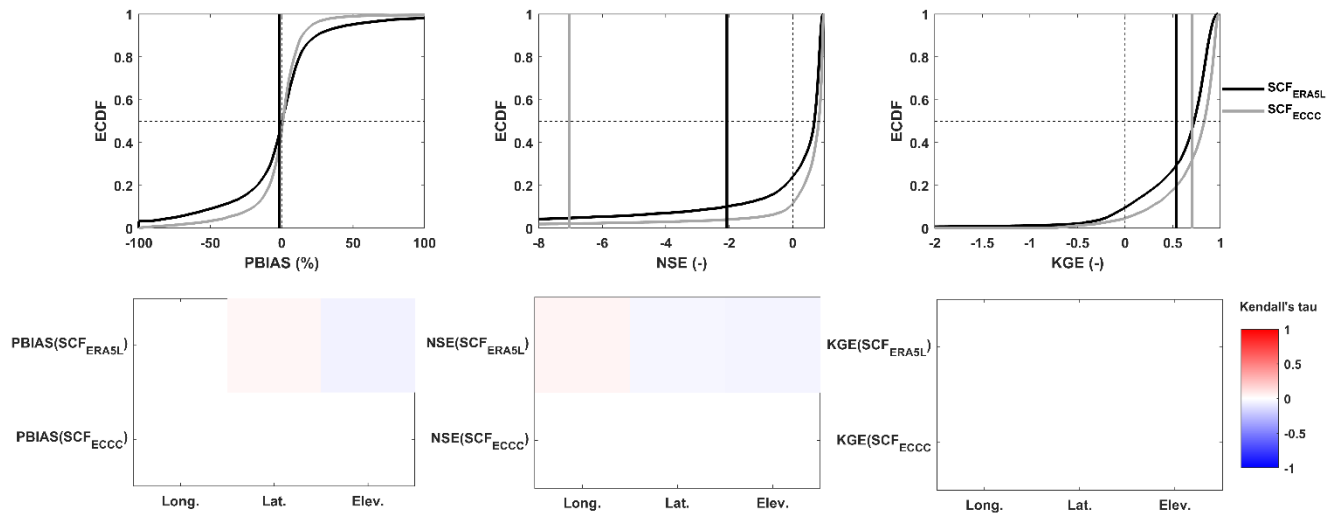
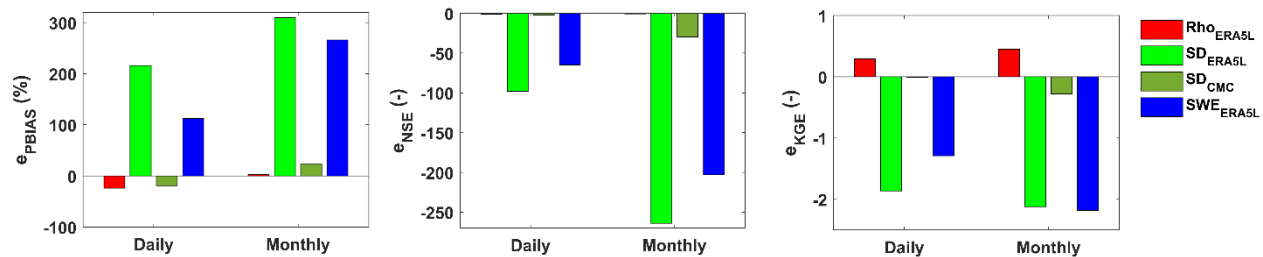


Figure S10: Expected GoFs of ERA5L and competing gridded product(s) in tracking monthly dynamics of Rho (left column), SD (middle column), and SWE (right column) across different levels of observational density, i.e. from 1 to 8 in-situ stations per grid. From top to bottom, rows correspond to PBIAS, NSE, and KGE respectively. In all panels, black and coloured bars are related to ERA5L and associated competing product(s) respectively.



185 **Figure S11: Spatial variability in ERA5L's and ECCO's GoFs in representing gridded monthly SCFs observed by MODIS (top row), and the significant spatial dependencies in GoFs (bottom row). From left to right columns are related to PBIAS, NSE and KGE.**



190 **Figure S12: Variations in the expected GoFs of ERA5L's Rho (red bars), SD (light green bars), and SWE (blue bars) across daily and monthly time scales. Dark green bars show the expected GoFs of CMC's SD. From left to right, panels show expected PBIAS, expected NSE, and expected KGE respectively.**

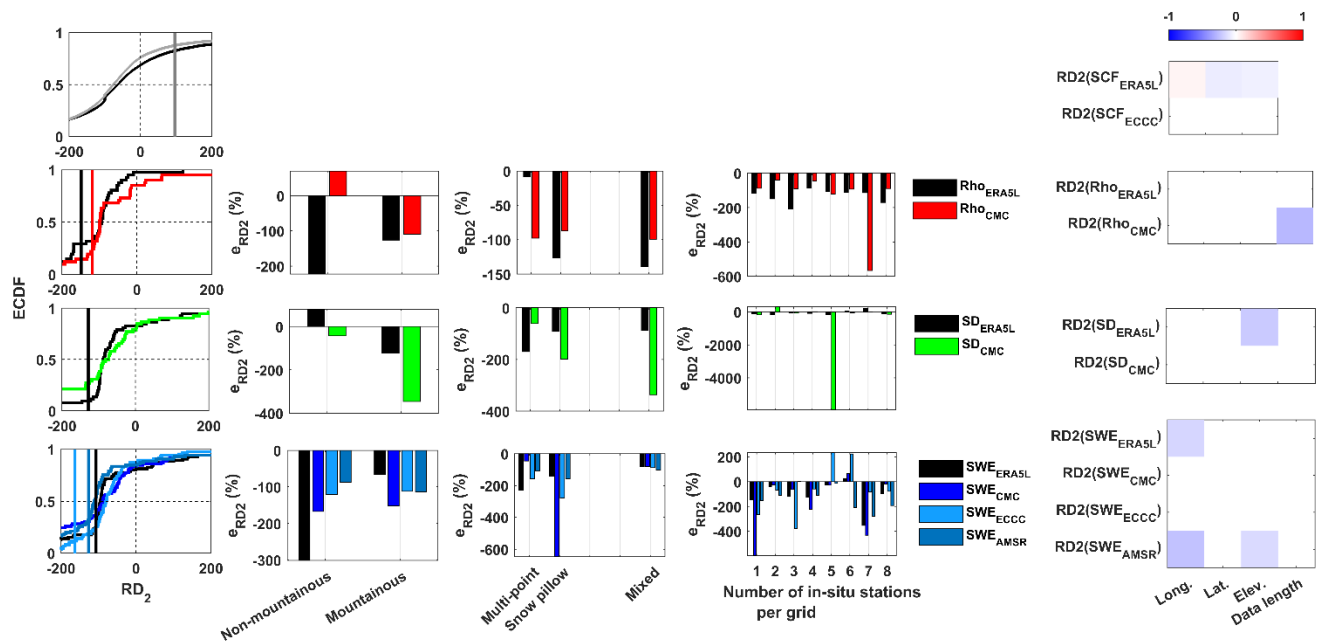


Figure S13: Evaluating the performance of ERA5L in reconstructing the annual trend of SCF (top row), Rho (second row from the top), SD (third row from the top), and SWE (bottom row). Left column shows ECDFs of RDs across benchmarking grids, where vertical lines represent the expected RDs. The three middle columns respectively from left to right show sensitivities of RDs to regions, measurement type, and density of in-situ observations, where black and colour bars represent the expected RDs of ERA5L and competing product(s). The right column depicts significant dependencies of RDs on longitude, latitude, elevation, and reference data length (p -value ≤ 0.05). Positive and negative significant dependencies are shown with shades of red and blue colours respectively.

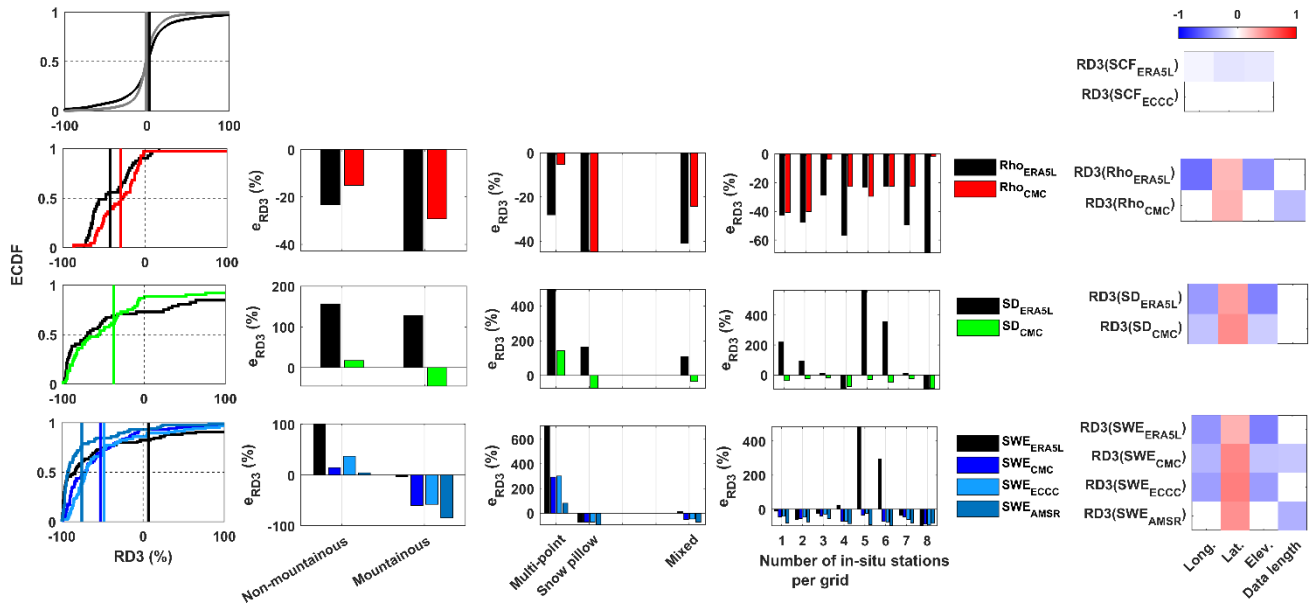
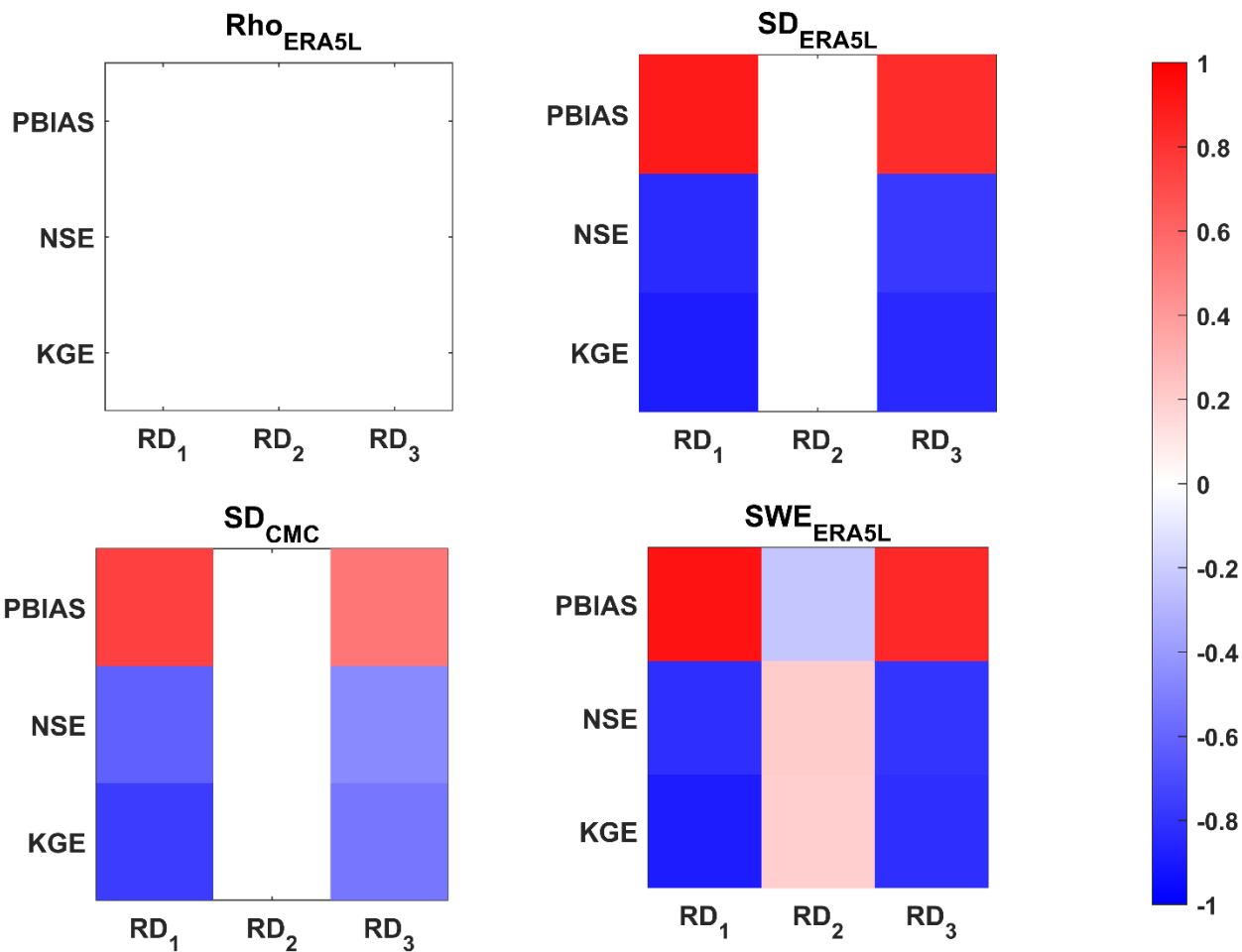
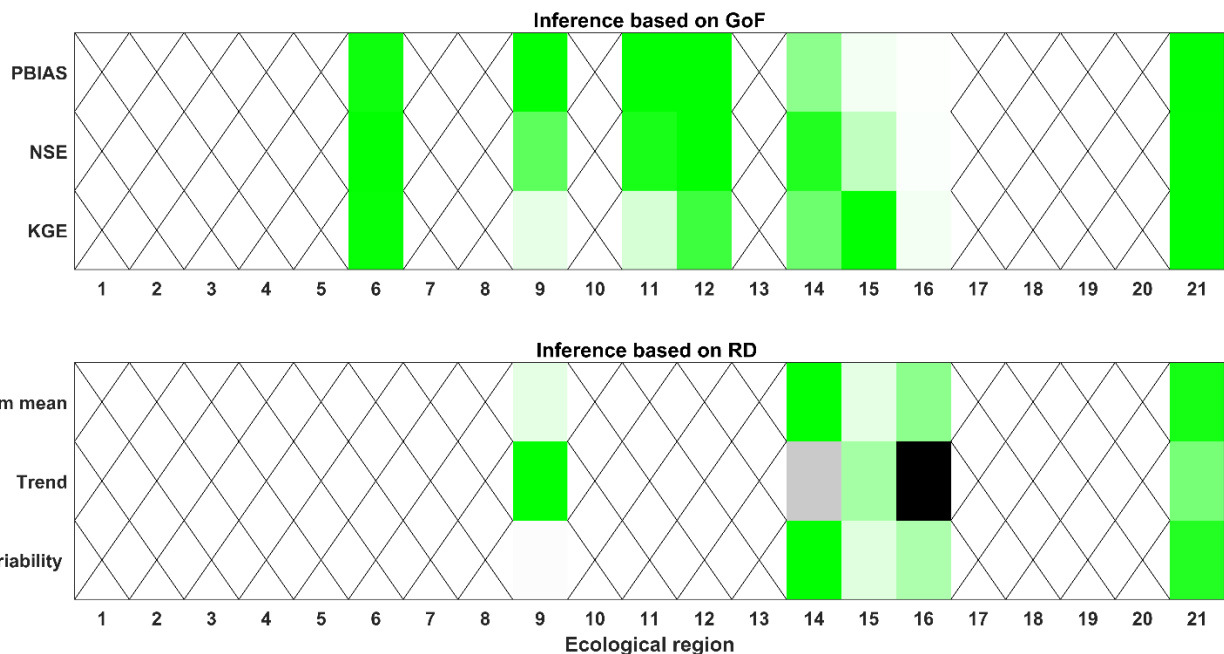


Figure S14: Evaluating the performance of ERA5L in reconstructing the interannual variability of SCF (top row), Rho (second row from the top), SD (third row from the top), and SWE (bottom row). Left column shows ECDFs of RDs across benchmarking grids, where vertical lines represent the expected RDs. The three middle columns respectively from left to right show sensitivities of RDs to regions, measurement type, and density of in-situ observations, where black and colour bars represent the expected RDs of ERA5L and competing product(s). The right column depicts significant dependencies of RDs on longitude, latitude, elevation, and reference data length (p -value ≤ 0.05). Positive and negative significant dependencies are shown with shades of red and blue colours respectively.



210 **Figure S15: Joint significant dependencies between discrepancies in daily time series match and annual maximum snow characteristics. Top row is related to ERA5L's Rho (left) and SD (right). Bottom row is related to CMC's SD (left) and ERA5L's SWE (right). In each panel, x axis is related to Relative Differences (RDs) in long-term mean (RD₁), trend (RD₂), and standard deviation (RD₃) of annual maximum snow variables from left to right. From top to bottom, y axis show PBIAS, NSE, and KGE Significant joint dependencies are identified at $p\text{-value} \leq 0.05$.**



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Figure S16: Inference on the relative fidelity of ERA5L and CMC daily SD based on observational constraints across ecological regions. The top and bottom rows show the inference based on GoF in matching daily time series and RDs in reconstruction of annual maxima characteristics, respectively. Green cells indicate ecological regions where CMC exhibits better agreement with the observational constraints than ERA5L, whereas grey cells indicate regions where ERA5L exhibits better agreement than CMC. Colour saturation is proportional to the magnitude of the difference in fidelity between ERA5L and CMC; consequently, white cells indicate regions where the two products have indistinguishable fidelity given the observational constraints. Hatched cells denote ecological regions for which observational constraints are unavailable.

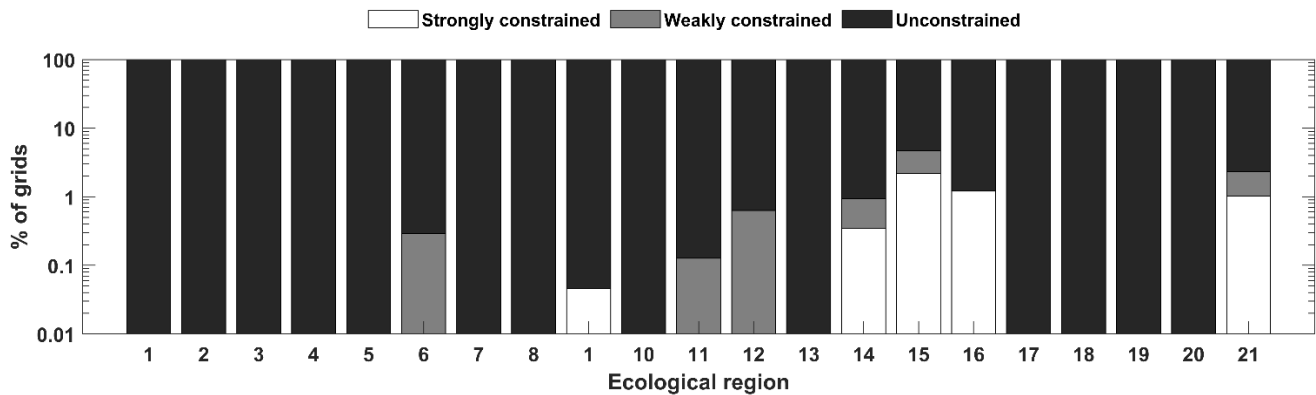


Figure S17: Level of observational conditioning for daily SD across ecological regions. Each bar shows the proportion of land area within an ecological region that is strongly conditioned (white), weakly conditioned (grey), or unconstrained (black) by the available observations.

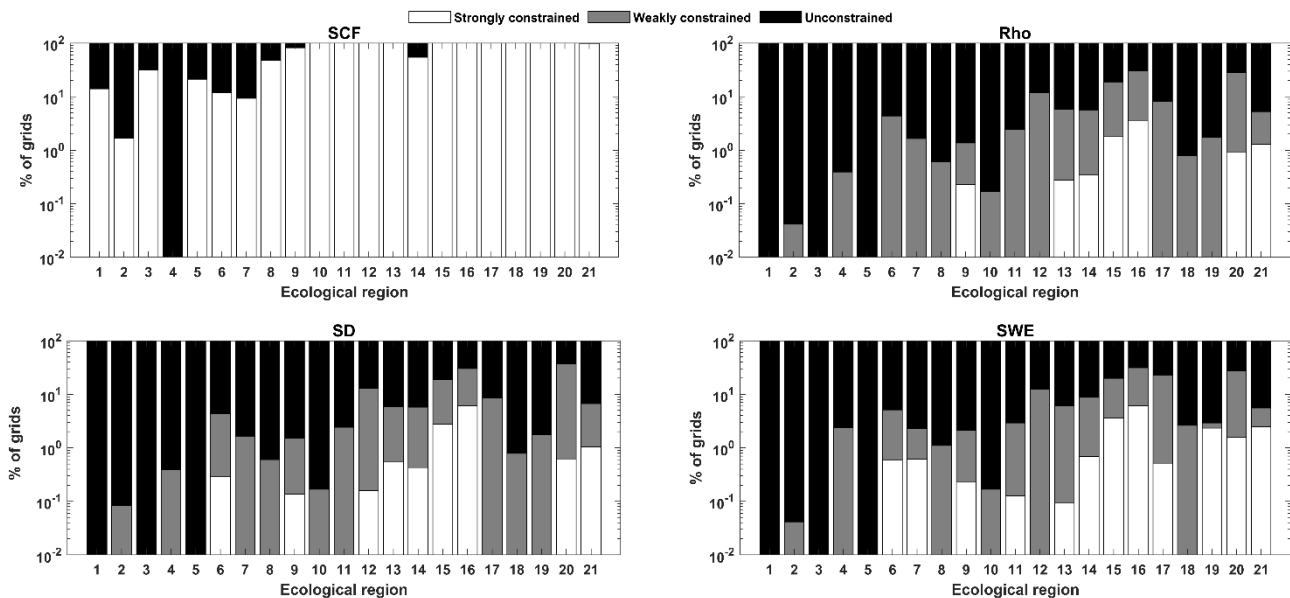


Figure S18: Level of observational conditioning for monthly SCF, Rho, SD, and SWE across ecological regions. Each bar shows the proportion of land area within an ecological region that is strongly conditioned (white), weakly conditioned (grey), or unconstrained (black) by the available observations.

S6. Supplementary table

Table S1. Selected number of stations for conditioning Rho, SD, and SWE at daily and monthly scales across ecological regions of Canada and Alaska

Eco-cluster	Ecological region ID	Name	Number of daily in-situ stations considered*			Number of monthly in-situ stations considered*		
			Rho	SD	SWE	Rho	SD	SWE
Arctic/Tundra	1	Arctic Cordillera	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
	2	Northern Arctic	0 (0)	0 (0)	0 (0)	1 (0)	2 (0)	1 (0)
	3	Alaska Tundra	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
	4	Brooks Range Tundra	0 (0)	0 (0)	0 (0)	1 (0)	1 (0)	6 (0)
	5	Southern Arctic	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Boreal/Taiga	6	Alaska Boreal Interior	2 (0)	2 (0)	2 (1)	30 (0)	30 (2)	35 (4)
	7	Taiga Cordillera	0 (0)	0 (0)	1 (0)	8 (0)	8 (0)	11 (3)
	8	Taiga Plains	0 (0)	0 (0)	2 (1)	6 (0)	6 (0)	11 (0)
	9	Taiga Shield	1 (0)	1 (1)	2 (0)	30 (5)	33 (3)	47 (5)
	10	Hudson Plains	0 (0)	0 (0)	0 (0)	1 (0)	1 (0)	1 (0)
	11	Softwood Shield	3 (0)	3 (0)	4 (0)	57 (0)	57 (0)	69 (3)
	12	Mixed Wood Shield	0 (0)	4 (0)	10 (0)	75 (0)	82 (1)	79 (0)
	13	Boreal Plains	0 (0)	0 (0)	4 (4)	62 (3)	64 (6)	65 (1)
Mountain/Arid	14	Boreal Cordillera	9 (0)	11 (4)	13 (7)	66 (4)	67 (5)	102 (8)
	15	Western Cordillera	33 (4)	34 (16)	56 (38)	137 (13)	137 (20)	145 (26)
	16	Cold Deserts	1 (0)	1 (1)	5 (2)	25 (3)	25 (5)	26 (5)
Prairies	17	Temperate Prairies	0 (0)	0 (0)	0 (0)	32 (0)	33 (0)	89 (2)
	18	West Central Semiarid Prairies	0 (0)	0 (0)	0 (0)	3 (0)	3 (0)	10 (0)
Temperate East	19	Atlantic Highlands	0 (0)	0 (0)	0 (0)	3 (0)	3 (0)	5 (4)
	20	Mixed Wood Plains	0 (0)	0 (0)	0 (0)	89 (3)	119 (2)	87 (5)
Marine West	21	Marine West Coast Forest	17 (3)	18 (8)	23 (23)	41 (10)	52 (8)	43 (19)
Whole domain			66 (7)	74 (30)	122 (76)	667 (41)	723 (52)	832 (85)

* Figures inside the parenthesis show the number of stations that have 10-year or more data and used to evaluate the ability of gridded data to capture the observed annual snow characteristics

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