

Contrasting elevation-dependent warming and snowfall changes in the Karakoram and Central Himalaya

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Abstract

High Mountain Asia shows strong regional differences in climate and glacier change, yet how future warming and precipitation responses vary with elevation remains unclear. Here, we examine elevation-dependent changes in near-surface temperature, snowfall fraction, snowfall amount and rain–snow transition elevations across glacier-containing grid cells of the Karakoram–Himalaya. We analyse a future simulation with the dynamically coupled regional glacier–climate model REMO_{glacier} under RCP4.5, comparing 2021–2050 with 1980–2005 across 500-m elevation bands, with emphasis on the Karakoram and Central Himalaya. REMO_{glacier} reproduces the main precipitation seasonality and captures part of the interannual variability in the reference datasets, while annual spatial-mean 2-m temperature agrees more closely with ERA5 than standalone REMO. During June–September, warming increases with elevation in the Karakoram ($+0.23 \pm 0.04$ °C km⁻¹) but decreases slightly with elevation in the Central Himalaya (-0.05 ± 0.02 °C km⁻¹). Snowfall fraction decreases by 2.4% and 21.5%, respectively; however, snowfall increases across all analysed Karakoram elevations (+1.3% to +41.7%) but decreases across the Central Himalaya (−11.0% to −32.4%). Freezing-level

and rain–snow transition elevations generally shift upward, with the Central Himalayan summer transition frequently moving above the modelled terrain. Random Forest diagnostics identify downward longwave radiation as the variable most strongly associated with the contrasting summer warming gradients. These results show that future mountain snowfall depends on the vertical structure of warming, precipitation phase and moisture supply, rather than warming magnitude alone.

Introduction

Glaciers and seasonal snow in High Mountain Asia (HMA) store substantial freshwater and feed major Asian rivers, including the Indus, Ganges and Brahmaputra. Changes in this storage affect downstream water supply, agriculture, hydropower and ecosystems [1-3]. Across the Karakoram–Himalaya (KH), glacier accumulation is controlled by contrasting climatic regimes. The Karakoram (KR) and Western Himalaya (WH) receive much of their cold-season precipitation from Western Disturbances (WDs), whereas the South Asian summer monsoon becomes increasingly important toward the Central (CH) and Eastern Himalaya (EH) [4,5].

Most Himalayan glaciers have retreated and lost mass in recent decades, whereas parts of the KR have remained near balance or shown slightly positive mass budgets, commonly referred to as the Karakoram anomaly [6-8]. This contrast has been linked to differences in precipitation seasonality, winter snowfall, summer temperature and regional circulation [4,9-11].

Warming affects glacier accumulation partly by shifting precipitation from snow to rain. Such phase changes reduce solid precipitation and can intensify glacier mass loss [12]. Their sensitivity depends strongly on the background thermal state: cold regions can retain high snowfall fraction (SF), whereas regions near the rain–snow transition respond much more strongly to similar warming [13,14].

However, declining SF does not necessarily imply less snowfall. Snowfall may increase if total precipitation (T_p) rises sufficiently, whereas modest SF losses can produce substantial snowfall

reductions where T_p decreases. Rain–snow transition elevation (RSTE) and near-surface freezing-level elevation (NS-FLE) therefore provide complementary measures of how snow-favourable conditions shift vertically.

Mountain snow responses can also be influenced by elevation-dependent warming (EDW), in which warming varies with altitude. EDW is widely observed and simulated, but its magnitude and sign differ across regions and seasons [15–18]. Proposed mechanisms include changes in albedo, atmospheric moisture, clouds, longwave and shortwave radiation, and land–atmosphere energy exchange [16,19].

Previous studies have examined glacier mass balance (MB), snowfall variability, EDW and precipitation phase across HMA, but largely separately [11,14,17,20]. Consequently, how warming, precipitation phase and snowfall interact as a function of elevation across contrasting KH climates remains poorly constrained. In addition, many regional climate simulations do not explicitly represent dynamically evolving two-way glacier–atmosphere interactions, limiting their ability to capture feedbacks between changing glacier surfaces and the overlying atmosphere. REMO_{glacier} provides such a coupled framework by linking the regional climate model REMO with a dynamic glacier module [11,20,21].

Here, we extend previous REMOglacier hindcast applications by analysing what is, to our knowledge, the first future REMOglacier simulation driven by MPI-ESM-LR under RCP4.5 [23–25]. We first evaluate the coupled model against reference datasets and standalone REMO and then compare near-future (2021–2050) with historical (1980–2005) conditions across the KR, WH, CH and EH. Focusing on the contrasting KR and CH, we (i) quantify seasonal EDW; (ii) assess elevation-dependent changes in SF and snowfall amount; (iii) diagnose shifts in NS-FLE and RSTE and local SF–temperature sensitivity; and (iv) identify atmospheric and surface variables associated with EDW. Complementary WH and EH results are provided in the Supporting Information. Together, these analyses provide a

process-based framework for assessing how elevation-dependent warming, precipitation phase and moisture supply jointly shape future mountain snowfall across HMA.

Materials and methods

Study region

The study covers the glacier-containing grid cells of four climatically distinct sectors of the KH defined by Bolch et al. [2]: KR, WH, CH and EH (Fig 1a), spanning approximately 26.9-37.4°N and 72.6-95.4°E. Each sector was analysed separately because the sectors differ in topography, elevation distribution and precipitation regime [4,5].

We use the term glacier-containing grid cell because a $REMO_{glacier}$ cell may be only partly covered by glacier; the cell footprint is not the actual glacier area. The same historical cell mask was used for both periods, so that the diagnosed changes are not affected by changes in the mask.

Elevations of the selected cells range from approximately 262 to 5569 m. The KR is the highest sector (3376-5569 m; mean 4838 m). The WH spans 1503-5317 m (mean 4265 m), the CH 1495-5408 m (mean 4104 m, the lowest), and the EH 262-5481 m (mean 4253 m, the widest range) (Fig 1a).

In the KR, 41.3% of cells lie between 5000 and 5500 m and 29.3% between 4500 and 5000 m. The 4500-5000 m band is also the most common in the WH (35.3%), CH (34.5%) and EH (42.6%), but low-elevation cells become more frequent toward the CH and EH (Fig 1b). These different hypsometries give a wide vertical range for studying EDW and phase change, but they also mean that each sector samples a different part of the elevation profile.

Fig 1. Study region and elevation distribution of the glacier-containing $REMO_{glacier}$ grid cells.

(a) Spatial distribution of the grid cells across the KR, WH, CH, and EH from west to east. Shading

represents REMO_{glacier} model-grid topographic elevation. **(b)** Number and percentage contribution of glacier-containing grid cells within 500-m elevation bands for each region. Percentages denote the contribution of each elevation band to the total number of selected grid cells within that region.

88 REMO_{glacier} configuration and experimental design

89 REMO is a hydrostatic regional climate model based on the Europa Model dynamical core, with
 90 physics parameterisation derived from ECHAM4 and ECHAM5 [21,22]. REMO_{glacier} couples REMO
 91 with the Dynamic Glacier Module (DYNAMICE), which represents glacier fraction, surface energy
 92 and mass balance, runoff, soil heat diffusion and two-way glacier–atmosphere feedbacks [11,20,21].
 93 Grid cells may contain glacier, ice- and snow-free land and water, while glacier fraction evolves with
 94 accumulation and ablation (Fig 2a). REMO provides meteorological and surface-energy forcing to
 95 DYNAMICE, which returns updated glacier and surface properties to the atmosphere (Fig 2b).
 96 The model runs at $0.22^\circ \times 0.22^\circ$ horizontal resolution with 27 vertical levels. The historical simulation
 97 is driven by MPI-ESM-LR historical forcing [23,24] for 1980–2005, while the future simulation is
 98 driven by MPI-ESM-LR under RCP4.5 [25], with 2021–2050 analysed here. Separate ERA-Interim-
 99 forced hindcasts [26] are used for model evaluation over 1989–2016.

100 REMO_{glacier} provides a physically consistent coupled framework in which glacier-surface conditions
 101 interact with the atmosphere. A standalone REMO hindcast is additionally used to assess the added
 102 value of the coupled configuration for historical T_{2m} . Future-minus-historical changes are analysed
 103 only with REMO_{glacier} and therefore are not interpreted as the isolated effect of glacier coupling.

Fig 2. Schematic of the coupled REMO_{glacier} framework. (a) Sub-grid scale glacier representation within a model grid box containing glacier, land and water surfaces. Static and dynamic glacier masks illustrate fixed and evolving glacier fractions, respectively. **(b)** Two-way coupling between REMO and the Dynamic Glacier Module (DYNAMICE). REMO provides atmospheric and surface-energy forcing, while DYNAMICE calculates glacier fraction, energy and mass balance, runoff, soil heat diffusion and area adjustment, and feeds the updated surface properties back to REMO.

Model evaluation

REMO_{glacier} was evaluated for 1989–2016 using the seasonal cycle, interannual variability and grid-cell temporal agreement. The reference datasets were first conservatively remapped to the REMO_{glacier} grid, after which only collocated valid grid cells were retained for spatial comparisons. Monthly climatologies of T_p , rainfall and snowfall were computed over the full period. T_p was compared with ERA5 [27], MSWEP [28] and CRU [29], and rainfall and snowfall with ERA5 [27] (S1 Table). Interannual variability was assessed with the Spearman rank correlation between annual domain-mean model and reference values:

$$r_s = \text{corr}_{\text{Spearman}}(X_{\text{REMO}_{\text{glacier}}}, X_{\text{ref}})$$

where $X_{\text{REMO}_{\text{glacier}}}$ and X_{ref} represent corresponding annual model and reference values.

For the spatial evaluation, the same temporal correlation was calculated at each collocated grid location, and the share of cells with a significant positive correlation was computed as:

$$P_{\text{sig}} = \frac{N(r_s > 0, p < 0.05)}{N_{\text{valid}}}$$

where N_{valid} is the number of grid cells with sufficient overlapping observations. ERA5 and REMO_{glacier} hypsometries were also compared using common 500-m elevation bands to assess the consistency of the vertical sampling framework used in the elevation-dependent analyses.

T_{2m} was evaluated against ERA5 using $REMO_{glacier}$ and standalone REMO. Annual trends were estimated by ordinary least squares, while agreement was quantified using the squared Pearson correlation coefficient (R^2), root-mean-square error (RMSE) and mean absolute error (MAE). Grid-wise Pearson correlations were calculated from annual T_{2m} with significance at $p < 0.05$. Spatial trend differences were defined as model minus ERA5, and historical EDW was estimated from the elevation dependence of annual T_{2m} trends across 500-m bands.

Elevation-dependent warming

EDW was estimated from how the projected change in 2-m temperature (T_{2m}) varies with elevation. The change is:

$$\Delta T = T_{future} - T_{historical}$$

where T_{future} and $T_{historical}$ are the mean T_{2m} for the future and historical periods, respectively.

Grid cells were grouped into 500-m elevation bands, and only bands with at least three valid cells were kept. The elevation-band-mean ΔT was regressed against the mean elevation of each band using ordinary least squares:

$$\Delta T_j = \beta_0 + \beta_1 z_j + \varepsilon_j$$

where ΔT_j is the mean temperature change in elevation band j , z_j is the mean elevation of the band, β_0 is the regression intercept, β_1 is the fitted warming-elevation slope, and ε_j represents the regression residual.

The EDW is defined as:

$$EDW = \frac{d(\Delta T)}{dz} = \beta_1$$

expressed in °C km⁻¹. A positive value means that warming increases with elevation; a negative value means that warming decreases with elevation. This approach follows earlier mountain EDW studies [15-17,30,31]. For each regression, we report the slope, its standard error, the 95% confidence interval, R² and the p-value.

Snowfall fraction and area-integrated snowfall change

Precipitation phase was described by the snowfall fraction (SF), the share of T_p that falls as snow:

$$SF_j = \frac{Snow_j}{Rain_j + Snow_j}$$

SF ranges from 0 (all rain) to 1 (all snow).

The relative change in SF is:

$$\Delta SF_j(\%) = \frac{SF_{future,j} - SF_{historical,j}}{SF_{historical,j}} \times 100$$

Positive values mean a larger share of snow; negative values mean a shift toward rain.

Because SF does not show how much snow falls, the relative change in snowfall amount (S) was also calculated for each band:

$$\Delta S_j(\%) = \frac{S_{future,j} - S_{historical,j}}{S_{historical,j}} \times 100$$

This was computed only where historical snowfall was at least 0.1 mm, to avoid unstable percentages from near-zero values.

To combine the size of the snowfall change with the area that each band represents, an area-weighted diagnostic was calculated. The mean snowfall change in band *j* is:

$$\Delta S_j = S_{future,j} - S_{historical,j}$$

The area represented by each band is:

$$A_j = N_j A_{cell}$$

where N_j is the number of valid model cells within the elevation band, and a nominal model-cell area of $A_{cell} = 596.3364 \text{ km}^2$ was used in the present analysis.

The contribution of band j is:

$$\Delta S_{area,j} = \Delta S_j \times A_j$$

With units of $\text{mm km}^2 \text{ month}^{-1}$. The regional total is the sum over all bands:

$$\Delta S_{area,region} = \sum_j \Delta S_{area,j}$$

Expressed as a water volume in m^3 (1 mm over 1 km^2 equals 10^3 m^3):

$$\Delta V_{region} = 10^3 \sum_j \Delta S_{area,j}$$

Because a fixed nominal cell area is used, these totals are area-weighted diagnostics rather than exact area integrals.

Near-surface freezing-level and rain-snow transition elevation

Vertical shifts in the precipitation-phase transition were described with two thresholds: NS-FLE, the elevation where the band-mean T_{2m} profile crosses 0°C , and RSTE, the elevation where $\text{SF} = 0.5$ (equal snow and rain). These thresholds are used as operational climate diagnostics for comparing vertical changes between periods and are not interpreted as universal event-scale rain–snow thresholds.

As before, only bands with at least three valid cells were used. Each profile was first made monotonic with weighted isotonic regression (T_{2m} decreasing and SF increasing with elevation), using the number of valid cells in each band as the weight.

When the threshold fell between two adjacent bands, its elevation was found by linear interpolation:

$$z_{thr} = z_1 + \frac{X_{thr} - X_1}{X_2 - X_1} (z_2 - z_1)$$

where z_1 and z_2 are the elevations of the two adjacent bands, and X_1 and X_2 are their corresponding fitted T_{2m} or SF values.

For NS-FLE, $X = T$ and $X_{thr} = 0$ °C, whereas for RSTE, $X = SF$ and $X_{thr} = 0.5$.

Thresholds outside the represented terrain were kept as censored states. NS-FLE is ‘below range’ when T_{2m} is below 0 °C at all supported elevations and ‘above range’ when it is above 0 °C everywhere. RSTE is ‘below range’ when $SF > 0.5$ everywhere and ‘above range’ when $SF < 0.5$ everywhere.

For years with a valid in-range crossing, the period mean is:

$$\bar{z} = \frac{1}{N_v} \sum_{y=1}^{N_v} z_y$$

where N_v is the number of valid crossings.

Interannual variability is given by the standard deviation and the standard error:

$$SD = \sqrt{\frac{\sum_{y=1}^{N_v} (z_y - \bar{z})^2}{N_v - 1}}$$

and

$$SE = \frac{SD}{\sqrt{N_v}}$$

The shift between the two periods is:

$$\Delta z_{thr} = \bar{z}_{future} - \bar{z}_{historical}$$

where a positive value denotes an upward displacement.

Its standard error was estimated as

$$SE_{\Delta z} = \sqrt{SE_{historical}^2 + SE_{future}^2}$$

A 95% confidence interval for the difference was calculated using the corresponding t -distribution with Welch-type degrees of freedom.

The frequency of in-range crossings is:

$$F_{cross} = \frac{N_{valid}}{N_{total}} \times 100$$

where N_{valid} is the number of years in which the threshold occurred within the represented elevation range and N_{total} is the total number of complete years or season-years.

Local SF-temperature sensitivity near the RSTE

This analysis measures how quickly SF changes with temperature near the RSTE. Here, RSTE is diagnosed from the multi-year climatological SF profile and need not equal the mean annual RSTE as in the last section because threshold extraction is nonlinear and annual means include only valid in-range crossings.

A window of about ± 750 m (at least three bands) around the historical climatological RSTE was used for both periods. Keeping the same window lets us compare sensitivities without simply following the upward movement of the transition. Within the window, SF was regressed on band-mean T_{2m}

$$SF_j = \alpha + \beta T_j + \varepsilon_j$$

where SF_j is the SF in elevation band j , T_j is the corresponding mean T_{2m} , α is the intercept, and

$$\beta = \frac{d(SF)}{dT}$$

represents the local SF-temperature sensitivity in fraction $^{\circ}\text{C}^{-1}$. A negative value indicates decreasing SF with increasing temperature.

220 Elevation-dependent sensitivity profiles were built by repeating this regression in moving windows
221 centred on each supported band.

222 Finally, the relationship between SF change and warming across bands was fitted as:

$$223 \quad \Delta SF_j = a + \gamma \Delta T_j + \varepsilon_j$$

224 where

$$225 \quad \Delta SF_j = SF_{future,j} - SF_{historical,j}$$

226 and

$$227 \quad \Delta T_j = T_{future,j} - T_{historical,j}$$

228 The coefficient

$$229 \quad \gamma = \frac{\Delta(SF)}{\Delta T}$$

230 was expressed in fraction °C⁻¹, with R^2 and p -values reported as descriptive measures of the strength
231 of the relationship.

232 **Random Forest diagnosis of predictor contributions to EDW**

233 Random Forest (RF) regression was used to diagnose how projected changes in downward LW↓, net
234 SW_{net}, cloud cover (C), specific humidity (q) and surface albedo (α) are associated with the elevation
235 dependence of warming:

$$236 \quad \Delta T_i = f_{\text{RF}}(\Delta LW_{\downarrow,i}, \Delta SW_{\text{net},i}, \Delta C_i, \Delta q_i, \Delta \alpha_i) + \varepsilon_i.$$

237 where ΔT_i is the future-minus-historical T_{2m} change at grid cell i . Separate RF models were fitted for
238 each region and season using 500 trees, a minimum of three samples per terminal leaf, bootstrap
239 sampling and a fixed random seed of 42. Model skill was evaluated using grouped cross-validation
240 with up to five folds, where 500-m elevation classes were kept intact between training and validation

sets. Analyses required at least 30 valid grid cells and four elevation groups, and performance was assessed using R^2 , RMSE and MAE.

Predictor contributions were estimated using a reference-based decomposition. For each region and season, the regional median change of all predictors defined the reference state. Each predictor was varied individually while the others were held at their median values, and the resulting change in RF prediction was taken as its diagnostic contribution. The remaining difference from the full RF prediction was retained as an interaction remainder.

The resulting grid-cell contributions were averaged within 500-m elevation bands. For predictor j , its contribution to EDW was defined as the elevation gradient of its band-mean contribution:

$$s_j = \frac{d\bar{C}_j}{dz}$$

with units of $^{\circ}\text{C km}^{-1}$. Positive s_j values indicate that the corresponding predictor strengthens warming with elevation, whereas negative values indicate that it weakens warming with elevation or contributes toward negative EDW. The relative magnitude of each predictor was calculated as

$$P_j = 100 \frac{|s_j|}{\sum_{k=1}^5 |s_k|}$$

The normalised absolute contributions of the five predictors sum to 100%, while the sign of s_j retains the direction of the associated EDW response. Interaction and residual terms were retained separately and were not included in the normalised predictor percentages. These RF-derived contributions are interpreted as diagnostic associations within the selected predictor set rather than causal fractions of the physical surface-energy budget.

Statistical analysis and reproducibility

Statistical significance was assessed at $p < 0.05$ unless otherwise stated. Linear trends and EDW gradients were estimated using ordinary least-squares regression. Interannual precipitation variability

was evaluated using Spearman rank correlation, whereas T_{2m} agreement was assessed using Pearson correlation, R^2 , RMSE and MAE. Elevation-based analyses retained 500-m bands containing at least three valid grid cells. Transition-elevation uncertainty was represented using standard errors and 95% confidence intervals calculated with Welch-type degrees of freedom. Analyses were conducted using Python 3.13.2, with NumPy 2.2.3, pandas 2.2.3, xarray 2025.10.1, SciPy 1.16.0 and scikit-learn 1.8.0. Analysis scripts are archived at Zenodo ([doi:10.5281/zenodo.23105265](https://doi.org/10.5281/zenodo.23105265)).

Use of generative AI

A generative AI tool (ChatGPT) was used solely to improve the readability and grammar of the manuscript. No data generation, analysis, or scientific interpretation was performed using these tools. The authors reviewed and verified all content and take full responsibility for the work.

Results

Historical model evaluation

For 1989–2016, REMO_{glacier} reproduces the broad seasonal cycle of precipitation (Fig 3a-c), including the JJAS maxima in total precipitation (T_p) and rainfall and the winter-to-early-spring snowfall maximum. The seasonal timing is well represented, although REMO_{glacier} generally produces more snowfall and less monsoon rainfall than ERA5.

Interannual variability is reproduced with moderate skill. Domain-mean Spearman correlations for T_p are 0.48 with ERA5, 0.51 with MSWEP and 0.14 with CRU (Fig 3d). Against ERA5, correlations are higher for snowfall ($r_s = 0.70$; Fig 3f) than rainfall ($r_s = 0.50$; Fig 3e). Significant positive grid-cell correlations occur in 49%, 42% and 39% of cells for T_p against ERA5, MSWEP and CRU, respectively, and in 41% and 56% of cells for rainfall and snowfall against ERA5 (Fig 3g-i). ERA5 and REMO_{glacier} also show similar hypsometry over the common domain (Fig 3j).

The T_{2m} evaluation shows closer agreement of $REMO_{glacier}$ with ERA5 than standalone REMO (Fig 3k). ERA5 shows a warming trend of $+0.355\text{ }^{\circ}\text{C decade}^{-1}$, compared with $+0.379\text{ }^{\circ}\text{C decade}^{-1}$ in $REMO_{glacier}$ and $+0.249\text{ }^{\circ}\text{C decade}^{-1}$ in REMO. $REMO_{glacier}$ also shows closer agreement for annual spatial-mean T_{2m} ($R^2 = 0.907$, $RMSE = 0.173\text{ }^{\circ}\text{C}$, $MAE = 0.134\text{ }^{\circ}\text{C}$) than REMO ($R^2 = 0.627$, $RMSE = 0.979\text{ }^{\circ}\text{C}$, $MAE = 0.912\text{ }^{\circ}\text{C}$; S2 Table). Grid-wise annual T_{2m} correlations are significant over 98.7% of cells for $REMO_{glacier}$ and 96.5% for REMO. However, $REMO_{glacier}$ exhibits a stronger positive historical EDW than ERA5, indicating that some elevation-dependent temperature bias remains despite improved domain-mean performance (S1 Fig).

Fig 3. Historical evaluation of $REMO_{glacier}$ for 1989–2016. Climatological annual cycles of (a) T_p (b) rainfall and (c) snowfall compared with the available reference datasets. Domain-mean interannual Spearman correlations between $REMO_{glacier}$ and ERA5, MSWEP, and CRU for (d) T_p (e) rainfall, and (f) snowfall. Percentage of analysed grid cells exhibiting statistically significant positive temporal correlations for (g) T_p (h) rainfall, and (i) snowfall. (j) Distribution of glacier-containing grid cells across 500-m elevation bands from ERA5 and $REMO_{glacier}$. (k) Annual spatial-mean T_{2m} time series and linear trends from ERA5, $REMO_{glacier}$ and REMO.

Future EDW, precipitation-phase and snowfall responses

The near-future (2021–2050) climate is compared with the historical period (1980–2005) for the annual mean, winter (DJF) and summer (JJAS), using 500-m elevation bands.

Regional and seasonal EDW

Projected warming changes with elevation very differently in the KR and CH (Fig 4). In the KR, warming increases with elevation in all three seasons. The annual ($+0.132 \pm 0.059\text{ }^{\circ}\text{C km}^{-1}$; $R^2 = 0.552$, $p = 0.090$) and DJF ($+0.133 \pm 0.101\text{ }^{\circ}\text{C km}^{-1}$; $R^2 = 0.304$, $p = 0.257$) gradients are positive but

not significant. The JJAS gradient is the strongest and is significant ($+0.233 \pm 0.040$ °C km⁻¹; $R^2 = 0.893$, $p = 0.004$; 95% CI: 0.121-0.345 °C km⁻¹).

In the CH, the gradients are weaker and change sign with season. The annual ($+0.034 \pm 0.024$ °C km⁻¹; $R^2 = 0.259$, $p = 0.197$) and DJF ($+0.062 \pm 0.043$ °C km⁻¹; $R^2 = 0.259$, $p = 0.198$) gradients are small, positive and not significant. In JJAS, the sign reverses, and warming decreases significantly with elevation (-0.046 ± 0.017 °C km⁻¹; $R^2 = 0.549$, $p = 0.036$; 95% CI: -0.088 to -0.004 °C km⁻¹).

The two regions therefore differ most in JJAS, when EDW is significantly positive in the KR and significantly negative in the CH. This sets the thermal context for the snowfall and phase changes described below. Corresponding results for the WH and EH are provided in S2-S8 Figs.

Fig 4. Contrasting seasonal EDW in the KR and CH. Elevation dependence of projected T_{2m} change for Annual, DJF, and JJAS conditions in the KR (a–c) and CH (d–f). Blue profiles show mean warming within 500-m elevation bands for 2021–2050 relative to 1980–2005, and dashed lines show the linear EDW fit. Panel annotations report the EDW gradient $\pm$ standard error, R^2 , and p-value.

Elevation-dependent redistribution of snowfall fraction

SF shows a strong regional contrast in both its elevation structure and projected change (Fig 5). The KR remains predominantly snow-dominated. Annual mean SF decreases slightly from 0.962 to 0.954 (−0.78%), with the largest losses at lower and middle elevations. In DJF, SF remains close to unity and increases marginally from 0.977 to 0.980 (+0.33%). The largest KR decrease occurs in JJAS, when SF declines from 0.870 to 0.849 (−2.44%), with reductions across most elevation bands.

Changes are substantially larger in the CH. Annual mean SF decreases from 0.506 to 0.447 (−11.60%), with the largest relative reductions at low elevations. DJF SF decreases from 0.901 to

319 0.887 (−1.58%), mainly at low and middle elevations. The largest change occurs during JJAS, when
 320 SF declines from 0.265 to 0.208 (−21.46%) across nearly all supported elevation bands.

Fig 5. Elevation-dependent changes in SF. Elevation-dependent SF changes in the KR and CH for Annual, DJF and JJAS. **(a)** Historical and future SF profiles across 500-m elevation bands, with inset regional mean values and absolute changes. **(b)** Relative SF change between future and historical periods; blue bars indicate increases, red bars decreases, and the dashed line denotes no change.

321

322 **Contrasting snowfall changes across elevation**

323 Snowfall responses differ markedly between the KR and CH (Fig 6). In the KR, annual snowfall
 324 changes are small, shifting from losses below 4500 m (−0.3% to −2.9%) to gains above this elevation
 325 (+1.6% to +3.2%). DJF snowfall decreases across nearly all elevation bands, with the strongest
 326 reductions at lower elevations and progressively weaker losses upward.

327 In contrast, JJAS snowfall increases at every analysed KR elevation, ranging from +41.7% at 3250 m
 328 to +1.3% at 5750 m. This increase occurs despite the concurrent reduction in JJAS SF.

329 The CH shows widespread snowfall loss. Annual reductions range from approximately −13.6% to
 330 −50.8%, while DJF losses range from −14.2% to −52.3%. During JJAS, snowfall decreases by
 331 −11.0% to −32.4% between 2750 and 5250 m. Percentage changes are not reported for the two lowest
 332 bands because historical snowfall is <0.1 mm.

Fig 6. Contrasting elevation-dependent snowfall responses. Relative change in snowfall between the future period (2021–2050) and historical period (1980–2005) across 500-m elevation bands in the KR and CH for Annual, DJF, and JJAS. Panels **(a–c)** show the KR and panels **(d–f)** show CH.

Elevation-band contributions to regional snowfall change

The contribution of individual elevation bands further highlights the contrasting regional snowfall responses (Fig 7). In the KR, the annual total is positive ($+349.8 \text{ mm km}^2 \text{ month}^{-1}$), as lower-elevation losses are outweighed by gains above approximately 4500 m, particularly between 4750 and 5250 m. During DJF, the KR shows a net loss of $-929.5 \text{ mm km}^2 \text{ month}^{-1}$, with the largest negative contributions between approximately 3750 and 4750 m and a small positive contribution near 5250 m. In JJAS, the regional total becomes strongly positive ($+988.0 \text{ mm km}^2 \text{ month}^{-1}$), with gains across all supported elevation bands and the largest contributions around 4250–4750 m.

In the CH, snowfall contributions are negative in all three periods: $-3912.2 \text{ mm km}^2 \text{ month}^{-1}$ annually, $-6883.3 \text{ mm km}^2 \text{ month}^{-1}$ in DJF and $-4203.0 \text{ mm km}^2 \text{ month}^{-1}$ in JJAS. Annual and DJF losses occur across the full elevation range, whereas JJAS losses are concentrated mainly around 4750–5250 m.

Fig 7. Elevation-band contributions to regional snowfall change. Contributions of 500-m elevation bands to the future-minus-historical snowfall change in the KR and CH for Annual, DJF, and JJAS. Blue bars indicate positive contributions and red bars indicate negative contributions to the area-weighted snowfall change; the dashed vertical line denotes no change. Insets report the total contribution summed across elevation bands in $\text{mm km}^2 \text{ month}^{-1}$. Panels (a–c) represent the KR and panels (d–f) represent CH.

Upward migration of freezing and rain–snow transition elevations

Both NS-FLE and RSTE generally shift upward, although their behaviour differs by region and season (Fig 8).

In the KR, historical annual NS-FLE cannot be estimated because mean T_{2m} remains below 0°C across all sampled elevations. In the future, annual NS-FLE becomes identifiable at 3310 ± 10 m, although no period-to-period shift can be calculated. In DJF, NS-FLE remains below the terrain in both periods. During JJAS, NS-FLE rises from 4507 ± 14 m to 4745 ± 30 m, corresponding to an upward shift of $+238 \pm 33$ m.

In the CH, NS-FLE rises by $+202 \pm 22$ m annually, from 3554 ± 15 to 3757 ± 17 m, and by $+220 \pm 37$ m in DJF, from 2433 ± 27 to 2653 ± 25 m. In JJAS, NS-FLE lies above the represented terrain because T_{2m} exceeds 0°C across all sampled elevations.

The KR annual and DJF RSTE remain below the terrain because SF exceeds 0.5 at all elevations. In JJAS, RSTE rises from 3759 ± 56 m to 3972 ± 31 m ($+214 \pm 64$ m). In the CH, RSTE rises by $+337 \pm 85$ m annually, from 4060 ± 64 to 4397 ± 56 m, and by $+127 \pm 36$ m in DJF, from 2019 ± 29 to 2146 ± 22 m. The JJAS RSTE increases by $+85 \pm 35$ m, from 5087 ± 21 to 5171 ± 29 m.

However, CH JJAS RSTE lies above the sampled terrain in 4 of 26 historical years (15.4%) and 25 of 30 future years (83.3%). The conditional $+85$ m shift therefore represents only years with valid in-range crossings, whereas the strong increase in above-range occurrence indicates a more substantial transition toward increasingly rain-favouring conditions.

Fig 8. Upward migration of snow–rain transition elevations. Transition-elevation diagnostics for the KR and CH for Annual, DJF, and JJAS. **(a)** Historical and future temperature–elevation profiles with NS-FLE. **(b)** Historical and future SF–elevation profiles with RSTE. Blue lines denote historical conditions, and red lines denote future conditions. Horizontal dotted lines indicate the mean transition elevation, and annotations report the historical and future mean values and the future-minus-historical shift.

Temperature sensitivity of SF near the RSTE

The temperature sensitivity of SF is strongest near the rain–snow transition and differs markedly between the KR and CH (Fig 9). In the KR, annual and DJF SF remain above 0.5 across all elevations, preventing estimation of an RSTE-centred sensitivity. During JJAS, the climatological RSTE rises from 3737 to 3794 m (+57 m), while the local SF–temperature sensitivity weakens from -0.0507 to -0.0407 fraction $^{\circ}\text{C}^{-1}$.

In the CH, the annual climatological RSTE rises from 4013 to 4307 m (+294 m), while sensitivity weakens slightly from -0.0317 to -0.0285 fraction $^{\circ}\text{C}^{-1}$. During DJF, the RSTE increases from 2064 to 2197 m (+133 m), while the magnitude of the sensitivity strengthens from -0.0644 to -0.0755 fraction $^{\circ}\text{C}^{-1}$.

The strongest historical sensitivity occurs in CH JJAS, reaching -0.1425 fraction $^{\circ}\text{C}^{-1}$ near an RSTE of 5067 m. In the future, the climatological RSTE moves above the sampled terrain; at the historical RSTE elevation, the future sensitivity is -0.1174 fraction $^{\circ}\text{C}^{-1}$.

The $\Delta\text{SF}-\Delta\text{T}$ regressions across elevation bands are not significant for any region or season ($p > 0.05$). Nevertheless, the local analysis shows that SF is most temperature-sensitive near the transition zone, particularly during JJAS in the CH.

Fig 9. Temperature sensitivity of snowfall fraction near the transition zone. Temperature sensitivity of SF in the KR and CH for Annual, DJF, and JJAS. **(a)** Historical and future SF– T_{2m} relationships across elevation bands. Dashed segments indicate local linear fits around the RSTE, and the horizontal dotted line denotes SF = 0.5. Insets report the climatological RSTE and local $d(\text{SF})/dT$, where estimable. **(b)** Elevation profiles of local $d(\text{SF})/dT$ for historical and future conditions. The vertical dotted line denotes $d(\text{SF})/dT=0$, while horizontal dashed lines indicate historical and future RSTE.

Atmospheric and surface variables associated with EDW

The RF diagnostic reveals substantial regional and seasonal differences in the variables associated with EDW (Fig 10). In the KR, downward LW has the largest relative contribution annually (47.2%) and during DJF (64.8%), although its signed EDW slope is negative in both periods. During JJAS, downward LW accounts for 72.6% of the normalised contribution and has a strong positive slope (+0.214 °C km⁻¹), while cloud cover and specific humidity contribute negatively.

In the CH, annual EDW is associated primarily with downward LW (46.2%) and surface albedo (36.9%). During DJF, specific humidity (50.9%) and downward LW (44.6%) dominate. In JJAS, downward LW accounts for 67.7% of the normalised contribution and has a negative slope (−0.045 °C km⁻¹).

The clearest regional contrast therefore occurs during JJAS where downward LW is the leading associated variable in both regions, but its elevation-dependent contribution is positive in the KR and negative in the CH.

Fig 10. Atmospheric and surface variables associated with EDW. RF-based relative contributions of downward LW, net SW, cloud cover, specific humidity, and surface albedo to EDW in the KR (a–c) and CH (d–f) for Annual, DJF, and JJAS. Bar lengths show normalised absolute contribution magnitudes, while signed values indicate the corresponding EDW slopes in °C km⁻¹.

Discussion

The results reveal a strong seasonal and regional contrast in EDW, with the clearest divergence during JJAS, when warming increases with elevation in the KR but decreases slightly with elevation in the

399 CH. This is consistent with previous evidence that EDW varies substantially across regions and
400 seasons and can arise from different combinations of radiative, moisture and surface feedbacks [16-
401 19]. EDW is therefore not necessarily positive; its magnitude and sign depend on regional climate,
402 season and model configuration.

403 The KR summer response is consistent with its distinct climatic setting, where mid-latitude
404 circulation, WDs and the western edge of the South Asian monsoon interact. Earlier studies have
405 shown that snowfall seasonality and summer temperature variability in the KR differ from those of
406 the CH and EH and strongly influence glacier behaviour [4,9-11]. In contrast, the negative JJAS EDW
407 diagnosed in the CH does not indicate cooling at high elevations, but rather weaker warming aloft
408 than at lower elevations. The contrasting gradients therefore describe differences in the vertical
409 structure of warming rather than opposite signs of regional mean temperature change.

410 The RF diagnostic provides additional insight into these regional differences. During JJAS,
411 downward LW is the leading associated predictor in both regions, but its elevation-dependent
412 contribution is positive in the KR and negative in the CH. Downward LW, atmospheric moisture,
413 clouds and albedo have all been linked to EDW, although their relative importance varies substantially
414 among regions and models [19,32]. Because downward LW is itself influenced by lower-atmospheric
415 temperature, humidity and cloud conditions, its contribution cannot be interpreted as an independent
416 radiative forcing. The opposing LW gradients therefore indicate a strong statistical association with
417 the contrasting EDW patterns rather than a direct causal attribution.

418 The contrasting thermal structures are accompanied by markedly different precipitation-phase
419 responses. The KR remains strongly snow-dominated, with only modest changes in SF, whereas the
420 CH experiences substantially larger SF losses, particularly during JJAS. This agrees with the
421 expectation that precipitation phase is most sensitive to warming where background temperatures are
422 close to the RSTE, while persistently cold regions are less responsive [13,14]. The larger SF losses at

lower and middle elevations of the CH are therefore consistent with its warmer background climate and proximity to the RSTE. Similar behaviour has been reported in Central Asian mountain regions, where SF declines most strongly at elevations close to the phase-transition threshold [33].

Importantly, changes in SF are not equivalent to changes in snowfall amount. Because snowfall can be expressed as $S = SF \times T_p$, declining SF can coexist with increasing snowfall if total precipitation increases sufficiently. This is evident in the KR during JJAS, where snowfall increases across all analysed elevation bands despite a modest decline in SF. The response therefore reflects the combined effects of precipitation phase and moisture supply rather than a temperature-only mechanism. This is consistent with previous evidence that KR snowfall is comparatively less sensitive to warming because of its seasonal precipitation cycle and that changes in regional moisture supply can alter snowfall independently of temperature [9,34]. In the CH, by contrast, decreasing SF coincides with snowfall losses across most elevations. Although JJAS EDW is negative, the region still warms overall, and its background climate lies much closer to the rain–snow transition. The combination of warming, lower historical SF and reduced solid precipitation therefore produces a substantially stronger snowfall loss than in the colder KR.

The elevation-band analysis further shows that regional snowfall change depends not only on the percentage change within each elevation band but also on the amount of terrain represented by that band. The KR combines winter snowfall losses with summer gains, whereas the CH exhibits negative snowfall contributions across all analysed periods. This distinction is important because large percentage changes at sparsely represented elevations may contribute less to the regional signal than smaller changes occurring over extensive elevation ranges.

The upward migration of NS-FLE and RSTE provides an additional indicator of changing snow conditions. Where these thresholds remain within the represented terrain, both generally shift upward, consistent with warming displacing snow-favourable conditions to higher elevations [35]. However,

447 censored cases provide important information that mean transition elevations alone cannot capture.
 448 In the KR, annual and DJF RSTE remain below the terrain, reflecting a persistently snow-dominated
 449 regime. In the CH, the JJAS RSTE lies above the represented terrain in 15.4% of historical years but
 450 in 83.3% of future years. This strong increase in above-range occurrence indicates a more substantial
 451 regime shift than the conditional +85 m mean change calculated only from years with valid in-range
 452 crossings.

453 The local SF–temperature analysis also shows that phase sensitivity is strongest near the transition
 454 zone. The strongest historical sensitivity occurs in CH JJAS, where SF changes by -0.1425 fraction
 455 $^{\circ}\text{C}^{-1}$ near the RSTE, substantially more than in the KR. This behaviour is consistent with the
 456 transition-regime framework proposed by Li et al. [14]. However, precipitation phase is not controlled
 457 by near-surface temperature alone; humidity, pressure and local atmospheric conditions can shift the
 458 rain–snow threshold over a wide temperature range [13,36]. Accordingly, the absolute NS-FLE and
 459 RSTE values should be interpreted as operational climate diagnostics rather than universal
 460 precipitation-phase thresholds. The principal EDW, SF and snowfall changes, however, are calculated
 461 independently of these threshold definitions.

462 These contrasting responses imply different future snow-climate trajectories for the KR and CH. The
 463 KR maintains a high SF and gains JJAS snowfall despite strong summer EDW, whereas the CH loses
 464 both SF and snowfall and experiences an upward displacement of phase boundaries. This is consistent
 465 with the broader spatial heterogeneity of glacier change across the KH, where relatively stable KR
 466 glaciers contrast with widespread glacier mass loss farther east [7,8,10,37]. However, projected
 467 snowfall changes should not be interpreted directly as future glacier MB changes. Glacier MB also
 468 depends on ablation, radiation, snow and ice albedo, debris cover, glacier geometry, ice dynamics and
 469 the timing of accumulation and melt [37]. Increased summer snowfall may therefore partly offset
 470 accumulation losses without necessarily compensating for enhanced melt.

471 The upward movement of snow–rain transition zones also has implications for downstream
 472 hydrology. As snow-favourable conditions migrate upward, a smaller fraction of precipitation may
 473 be stored seasonally as snow, potentially altering the timing and magnitude of snowmelt runoff [3,35].
 474 Such changes are particularly relevant across the KH because snow and glacier melt contribute to
 475 major Asian river systems, although runoff responses were not explicitly analysed here.

476 Several uncertainties should be considered when interpreting these results. The projections are based
 477 on a single REMO_{glacier} simulation driven by MPI-ESM-LR under RCP4.5 and therefore represent
 478 one model realisation rather than a multi-model estimate. EDW and its associated processes may vary
 479 across models, scenarios and internal climate variability [17,18,32]. The 500-m elevation-band
 480 framework also simplifies complex mountain topography, while differences in the number and
 481 elevation range of supported bands may influence fitted EDW gradients. NS-FLE and RSTE are
 482 censored when thresholds fall outside the represented terrain, so mean shifts apply only to years with
 483 valid in-range crossings. In addition, the RF analysis is diagnostic rather than causal: predictor
 484 contributions describe relative statistical associations with EDW within the selected predictor set and
 485 should not be interpreted as independent physical fractions of total warming.

486 Overall, the study demonstrates that future snow-climate responses across the KH are controlled not
 487 simply by the magnitude of warming, but by how warming varies with elevation and interacts with
 488 precipitation phase and moisture supply. During JJAS, EDW is strongly positive in the KR but weakly
 489 negative in the CH, while snowfall fraction declines modestly in the KR and much more strongly in
 490 the CH. Despite the reduction in SF, snowfall increases across all analysed KR elevations but
 491 decreases across most of the CH, and transition elevations generally migrate upward. Downward LW
 492 shows the strongest statistical association with the contrasting summer EDW patterns, although this
 493 relationship is diagnostic rather than causal. These regional contrasts highlight the need to evaluate
 494 warming structure, precipitation phase and snowfall amount together when assessing future high-

495 mountain climate. Multi-model simulations and additional independent high-elevation observations
496 will be important for testing the robustness of these responses.

497 **Conclusion**

498 This study reveals a pronounced seasonal contrast in EDW and snow-climate response between the
499 KR and CH. During JJAS, warming increases with elevation in the KR ($+0.233\text{ }^{\circ}\text{C km}^{-1}$) but decreases
500 with elevation in the CH ($-0.046\text{ }^{\circ}\text{C km}^{-1}$). Over the same season, SF decreases by only 2.44% in the
501 KR, compared with 21.46% in the CH. Despite the modest SF decline, JJAS snowfall increases across
502 all analysed elevations in the KR, whereas the CH experiences snowfall losses across nearly the entire
503 supported elevation range. Where identifiable, the transition elevations generally shift upward, and
504 the CH JJAS rain–snow transition lies above the represented terrain in most future years. These results
505 show that changes in precipitation phase and snowfall amount should be considered separately, and
506 that snowfall response cannot be inferred from warming alone. Downward LW is the variable most
507 strongly associated with the contrasting JJAS EDW gradients, although this relationship is diagnostic
508 rather than causal. Future high-mountain snow conditions will depend on the elevation structure of
509 warming, precipitation phase, precipitation supply and surface–atmosphere feedbacks. Multi-model
510 simulations and additional independent high-elevation observations are needed to assess the
511 robustness of these regional contrasts.

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Data availability

ERA5 monthly averaged data on single levels used for model validation are publicly available from the Copernicus Climate Change Service (C3S) Climate Data Store (CDS) at <https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels-monthly-means>, with DOI <https://doi.org/10.24381/cds.fl7050d7>. CRU TS monthly gridded precipitation data used for model validation are publicly available from the Climatic Research Unit, University of East Anglia, at <https://crudata.uea.ac.uk/cru/data/hrg/>, and are described by Harris et al. [29], DOI <https://doi.org/10.1038/s41597-020-0453-3>. MSWEP V2 precipitation data used for model validation are available from GloH2O at <https://www.gloh2o.org/mswep/> and are described by Beck et al. [28], DOI <https://doi.org/10.1175/BAMS-D-17-0138.1>. REMO and REMO_{glacier} model outputs analysed in this study are available from the corresponding author upon reasonable request.

Code availability

All Python scripts used for data processing, statistical analysis, Random Forest diagnostics and figure generation in this study are publicly available through Zenodo at <https://doi.org/10.5281/zenodo.23105265>; Gupta, R. P., & Kumar, P. (2026).

Author contributions

P.K. conceived and supervised the study. R.P.G. and P.K. jointly developed the methodology and analysis framework. R.P.G. performed the data processing, model-output analysis, statistical analyses, Random Forest analysis and figure preparation. R.P.G. and P.K. interpreted the results and prepared the manuscript. Both authors reviewed and approved the final manuscript.

Competing interests

The authors declare no competing interests.

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Supporting Information

S1 Table. Datasets and variables used in the study. Summary of the observational/reanalysis datasets and model simulations used for model evaluation and future-change analysis, including period, spatial resolution and analysed variables.

686 **S1 Fig. Historical evaluation of REMO_{glacier} and REMO with ERA5 for 1989–2016.** Annual
687 T2m evaluation for 1989–2016. (a) Model-minus-ERA5 grid-wise trend differences, (b) annual EDW
688 across 500-m elevation bands, and (c) grid-wise annual T2m correlations, with statistically significant
689 cells stippled at $p < 0.05$.

690 **S2 Table. Annual T_{2m} performance of REMO_{glacier} and REMO relative to ERA5 for 1989–2016.**
691 R^2 denotes the squared Pearson correlation between model and ERA5 T_{2m} ; RMSE and MAE are
692 expressed in °C.

693 **S2 Fig. Contrasting seasonal EDW in the Western and Eastern Himalaya.** Elevation dependence
694 of projected T_{2m} change for annual, DJF and JJAS conditions in the WH (a–c) and EH (d–f). Blue
695 profiles show mean warming within 500-m elevation bands for 2021–2050 relative to 1980–2005,
696 and dashed lines show the linear EDW fit. Panel annotations report the EDW gradient $\pm$ standard
697 error, R^2 and p-value.

698 **S3 Fig. Elevation-dependent changes in snowfall fraction.** Elevation-dependent SF changes in the
699 WH and EH for annual, DJF and JJAS. (a) Historical and future SF profiles across 500-m elevation
700 bands, with inset regional mean values and absolute changes. (b) Relative SF change between future
701 and historical periods; blue bars indicate increases, red bars decreases, and the dashed line denotes no
702 change.

703 **S4 Fig. Contrasting elevation-dependent snowfall responses.** Relative change in snowfall between
704 the historical and future periods across 500-m elevation bands in the WH and EH for annual, DJF and
705 JJAS. Panels (a–c) show the WH and panels (d–f) show the EH.

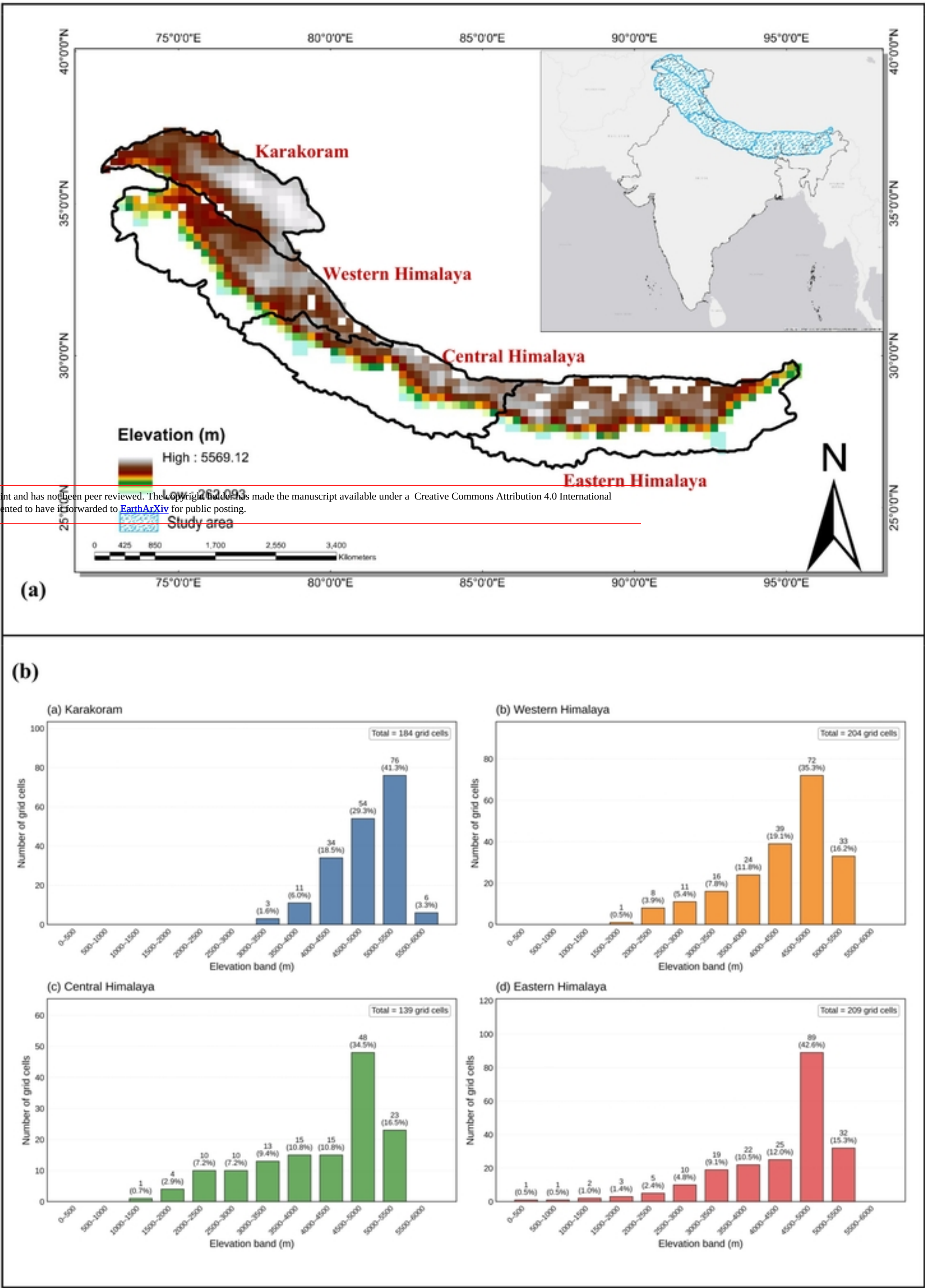
706 **S5 Fig. Elevation-band contributions to regional snowfall change.** Contributions of 500-m
707 elevation bands to the future-minus-historical snowfall change in the WH and EH for annual, DJF

and JJAS. Blue bars indicate positive contributions and red bars indicate negative contributions to the area-weighted snowfall change; the dashed vertical line denotes no change. Insets report the total contribution summed across elevation bands in $\text{mm km}^2 \text{ month}^{-1}$. Panels (a–c) represent the WH and panels (d–f) represent the EH.

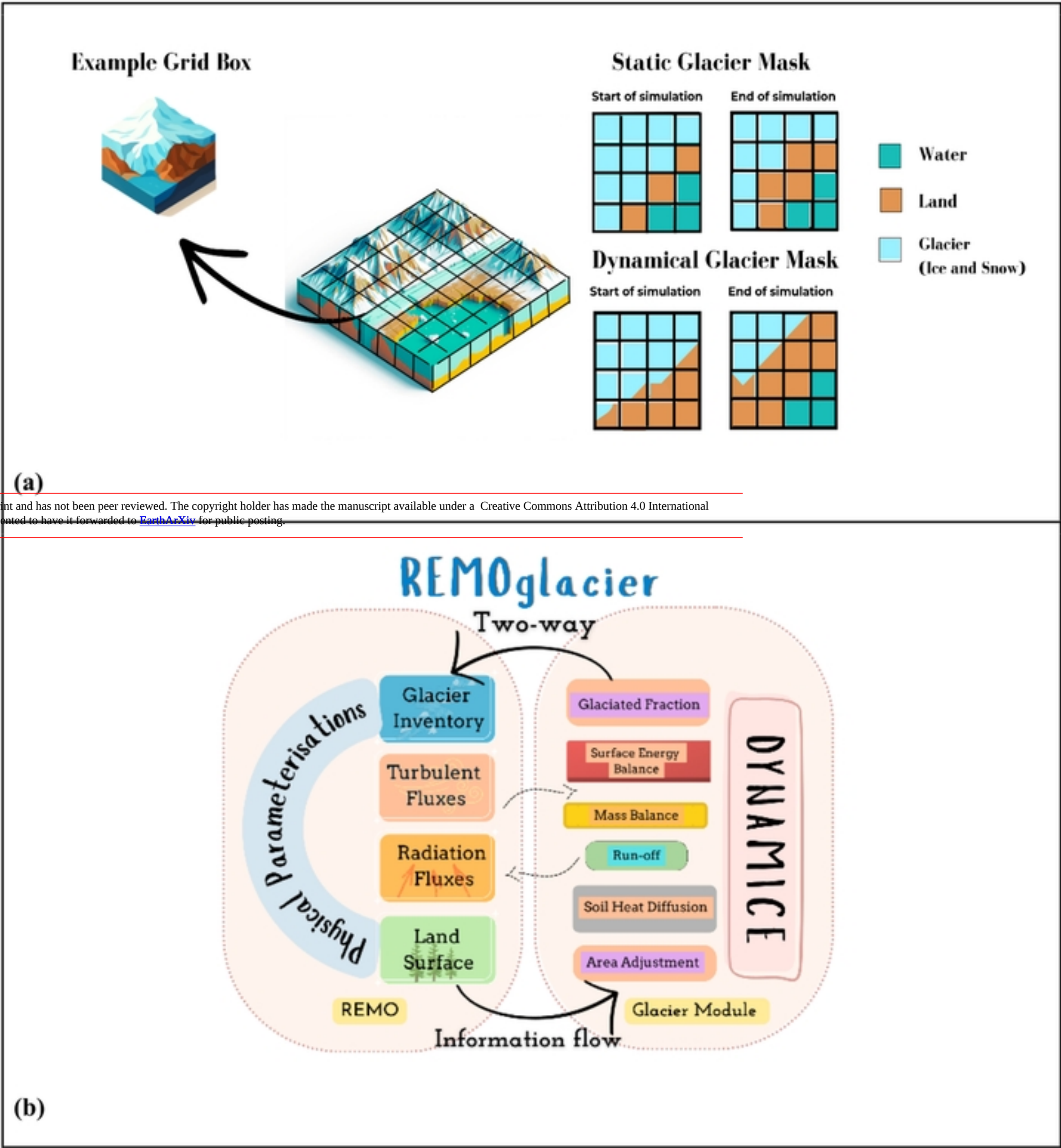
S6 Fig. Upward migration of snow–rain transition elevations. Transition-elevation diagnostics for the WH and EH for annual, DJF and JJAS. (a) Historical and future temperature–elevation profiles with NS-FLE. (b) Historical and future SF–elevation profiles with RSTE. Blue lines denote historical conditions and red lines denote future conditions. Horizontal dotted lines indicate the mean transition elevation, and annotations report historical and future mean values and the future-minus-historical shift.

S7 Fig. Temperature sensitivity of snowfall fraction near the transition zone. Temperature sensitivity of SF in the WH and EH for annual, DJF and JJAS. (a) Historical and future SF–T2m relationships across elevation bands. Dashed segments indicate local linear fits around the RSTE, and the horizontal dotted line denotes $\text{SF} = 0.5$. Insets report the climatological RSTE and local $d(\text{SF})/dT$, where estimable. (b) Elevation profiles of local $d(\text{SF})/dT$ for historical and future conditions. The vertical dotted line denotes $d(\text{SF})/dT = 0$, while horizontal dashed lines indicate historical and future RSTE.

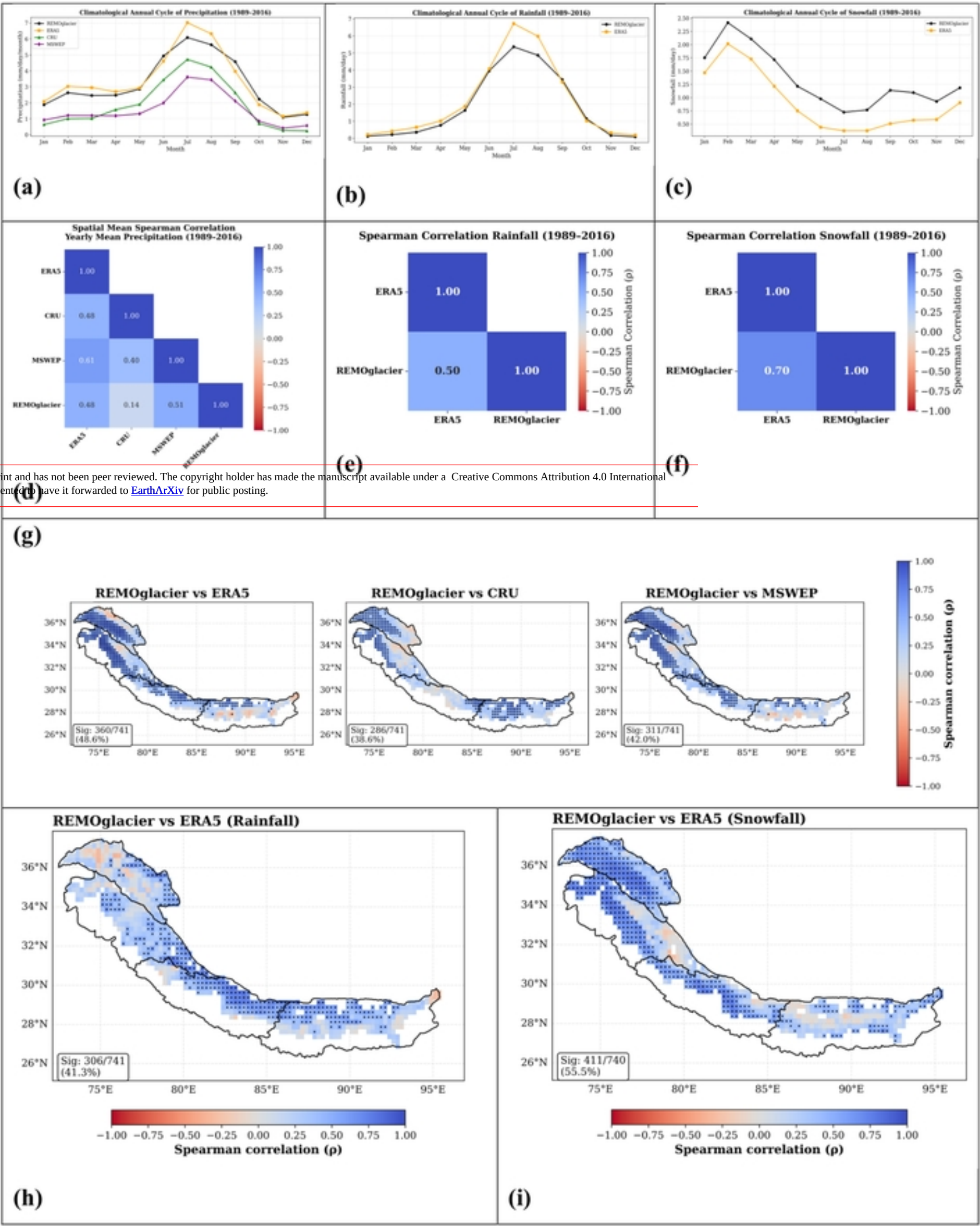
S8 Fig. Atmospheric and surface variables associated with EDW. RF-based relative contributions of downward LW, net SW, cloud cover, specific humidity and surface albedo to EDW in the WH (a–c) and EH (d–f) for annual, DJF and JJAS. Bar lengths show normalized contribution magnitudes, and signed values indicate the corresponding EDW slopes in $^{\circ}\text{C km}^{-1}$.



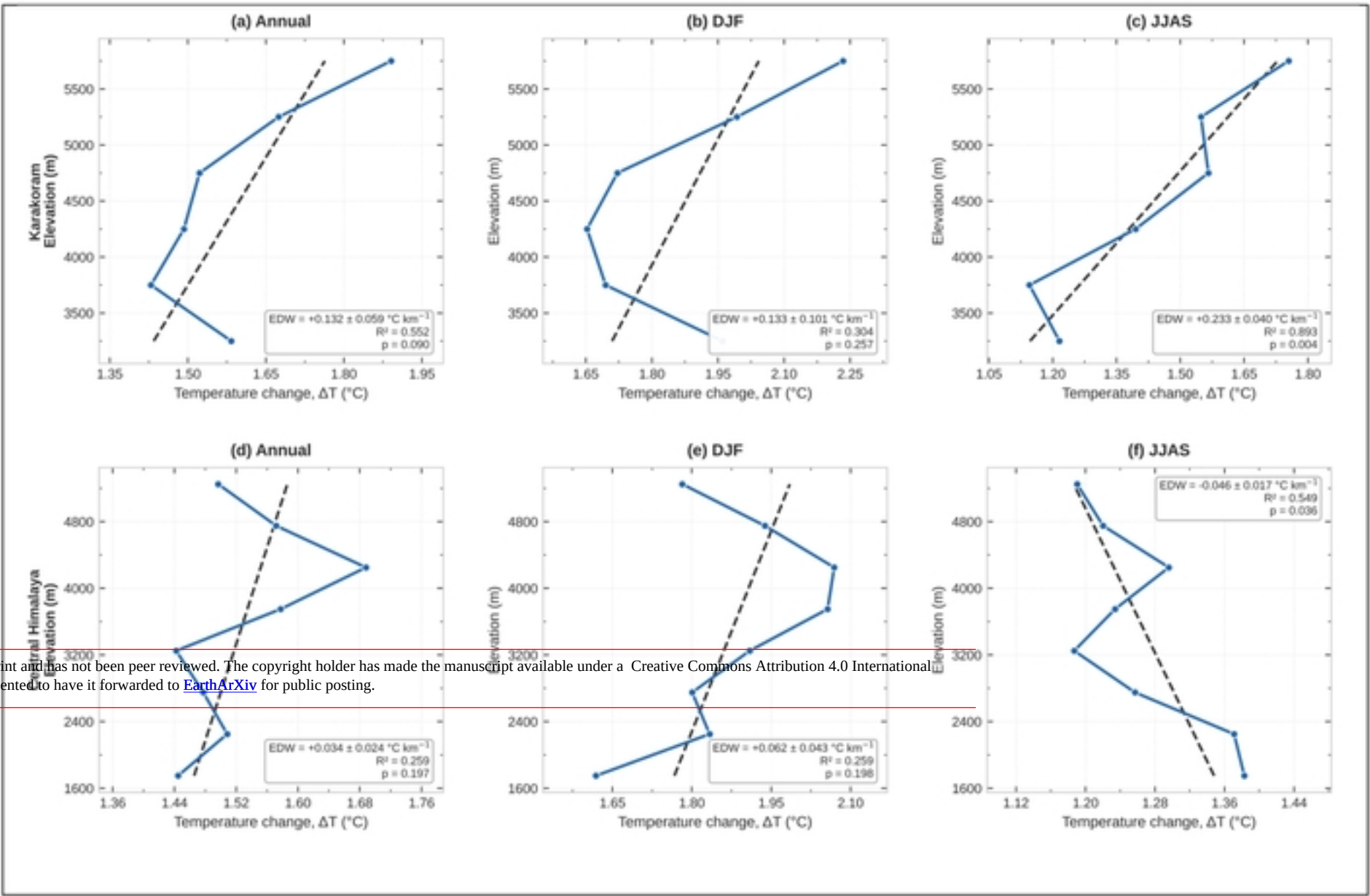
Figure



Figure

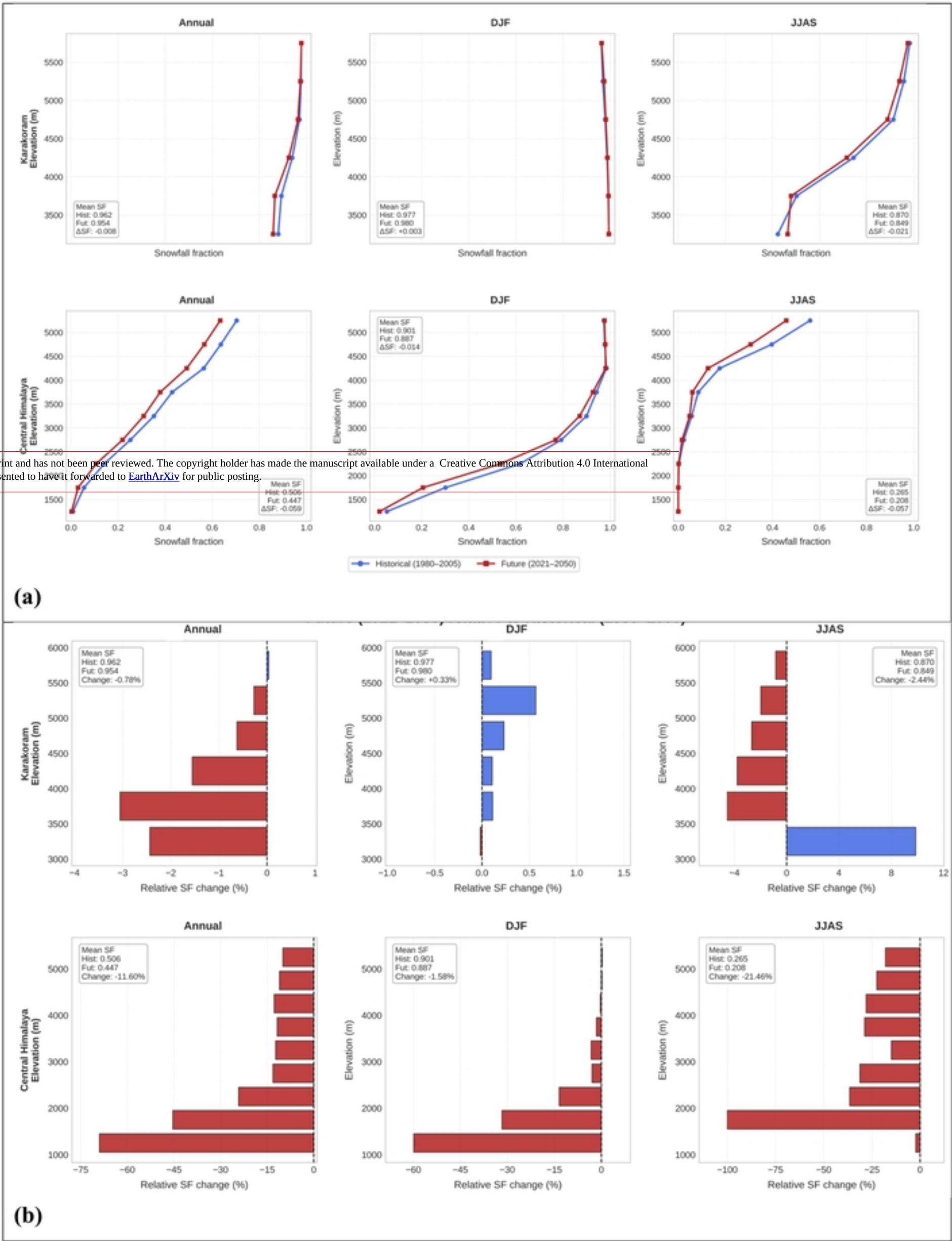


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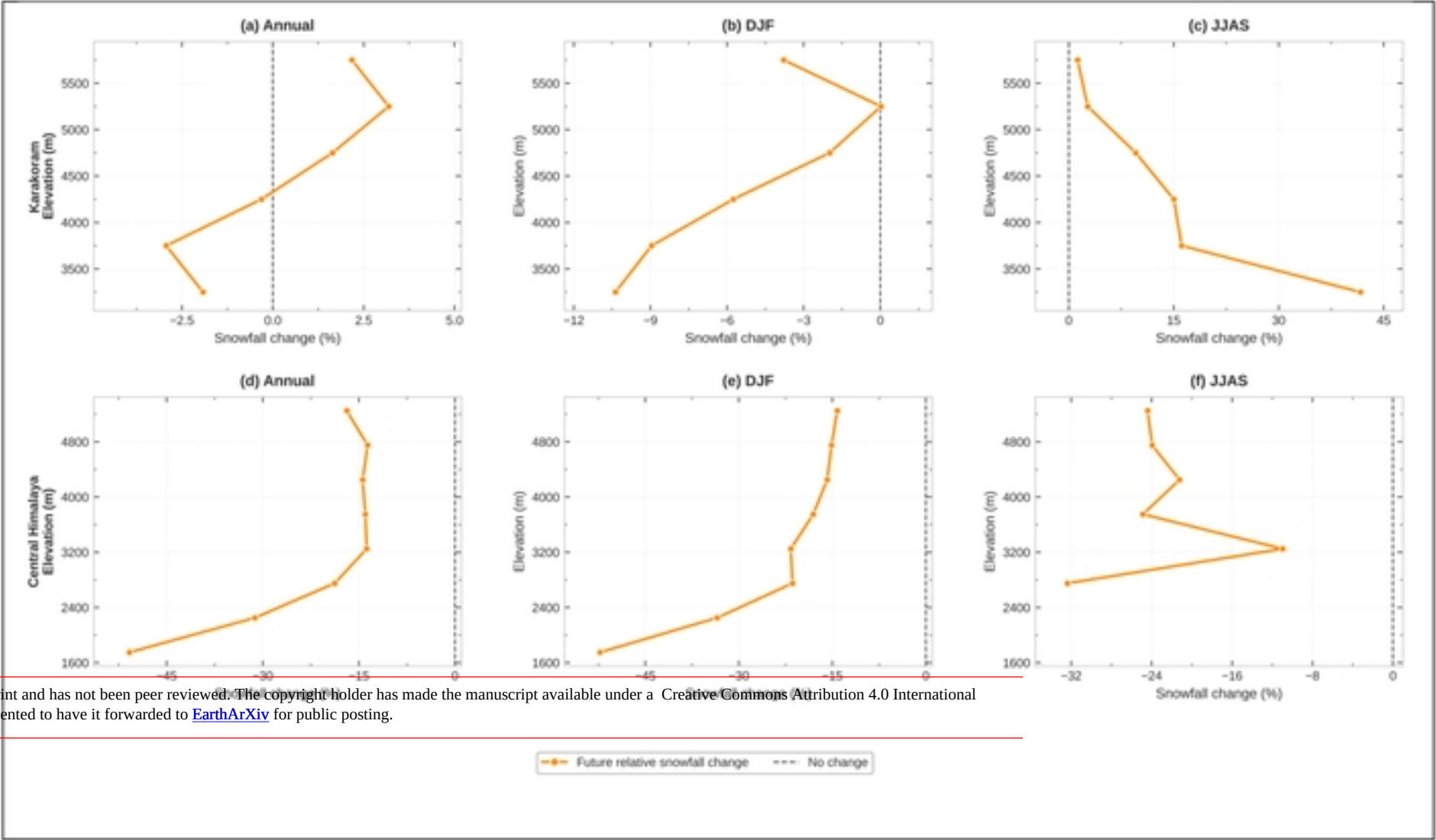


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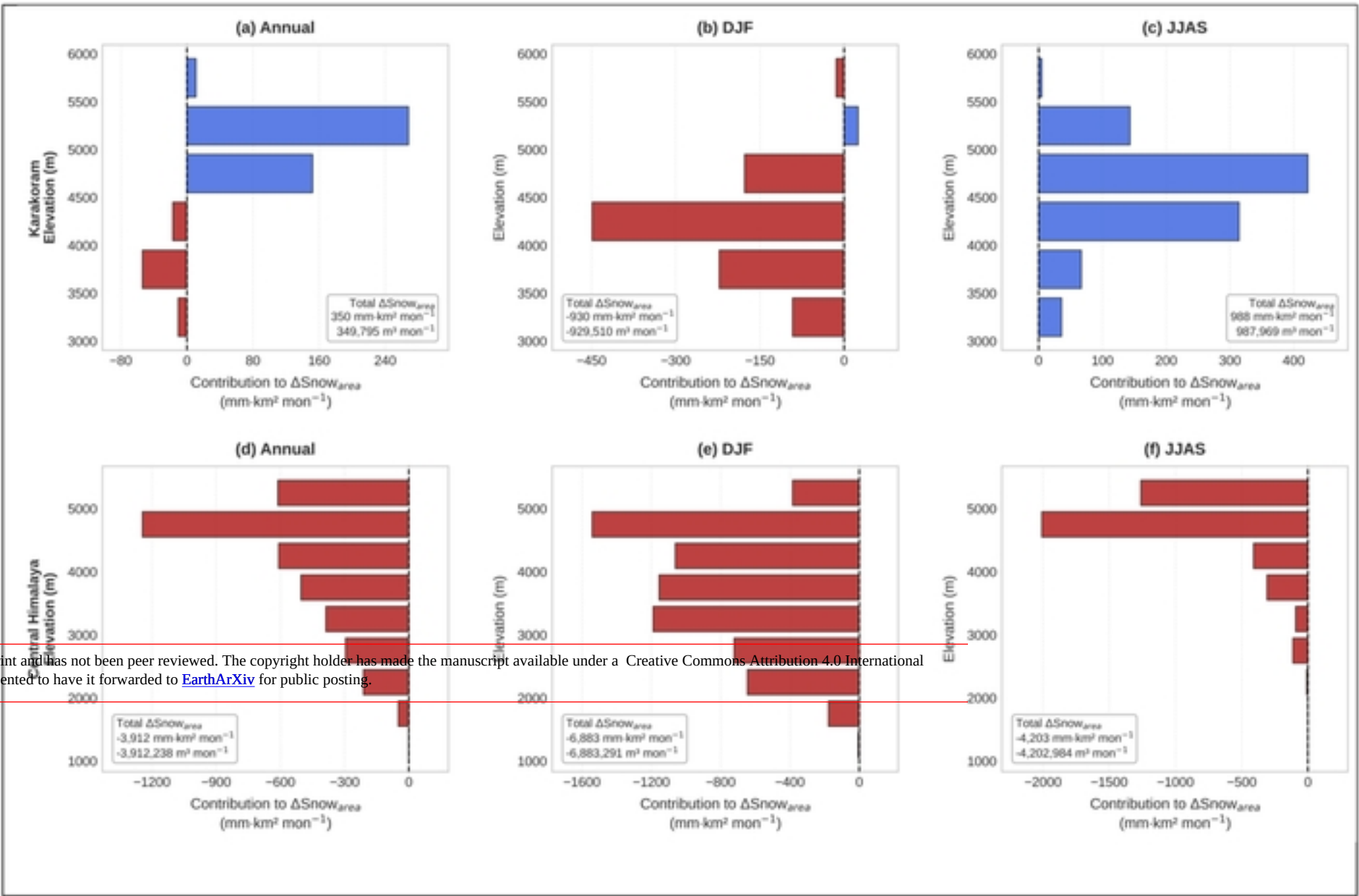
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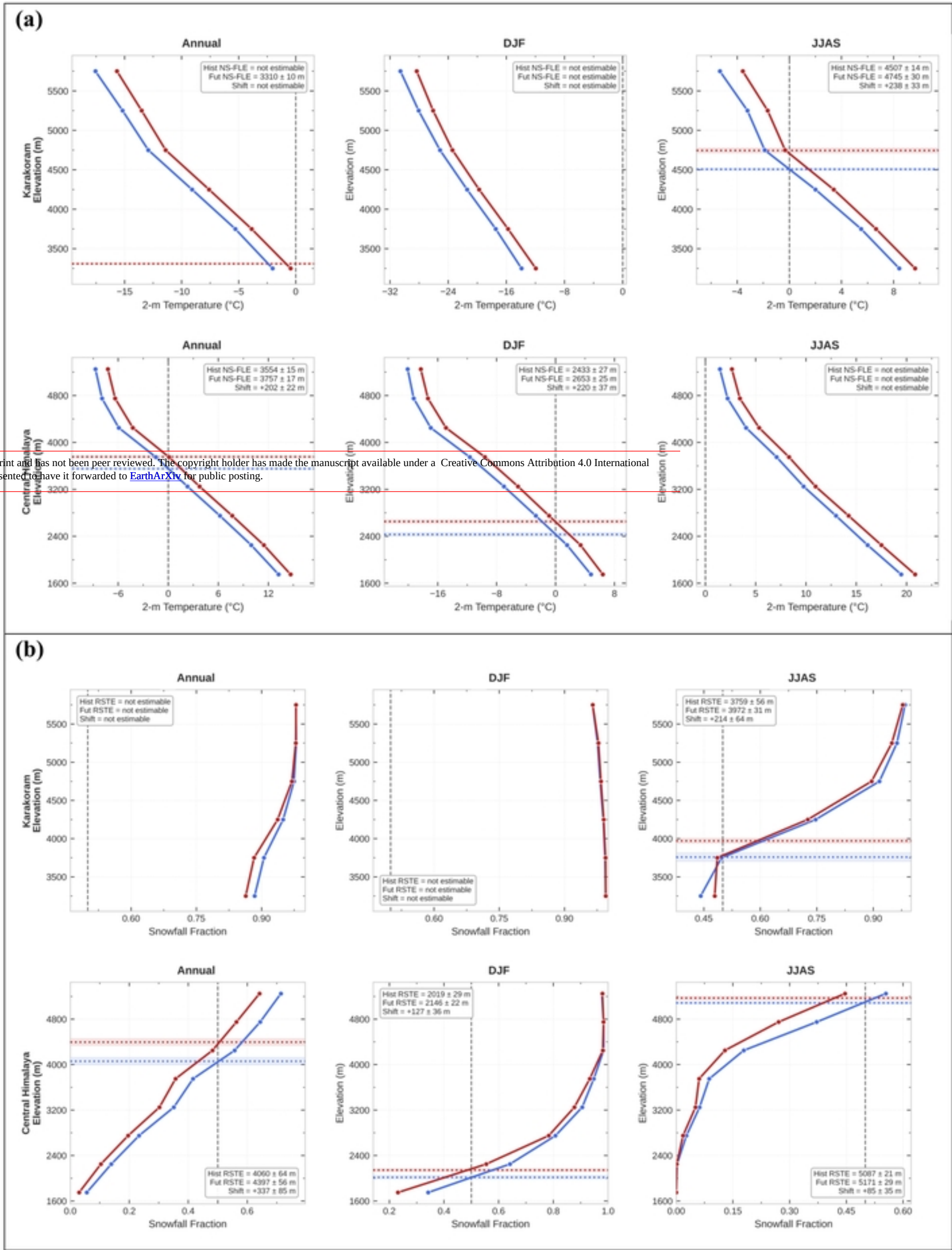
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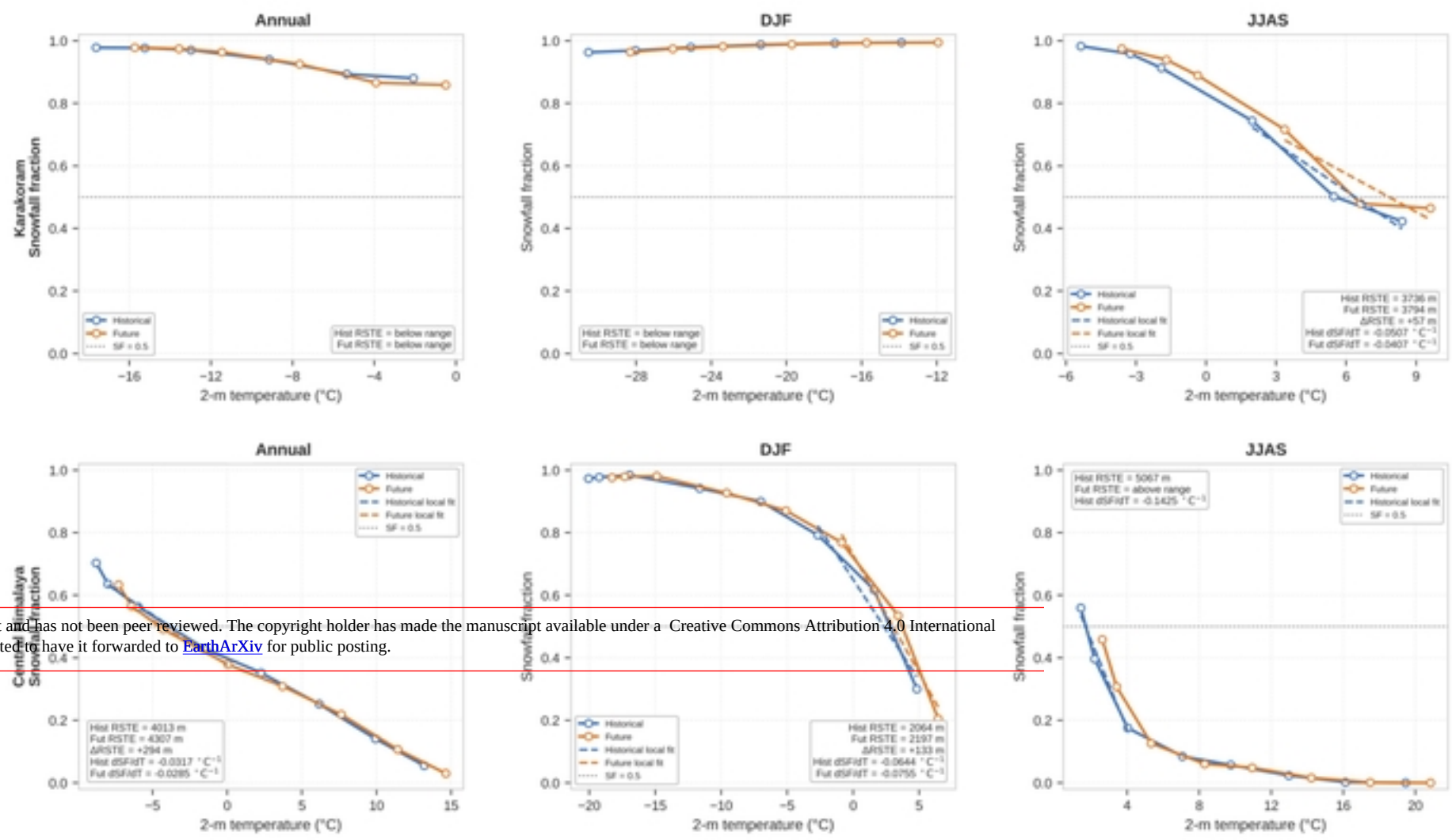
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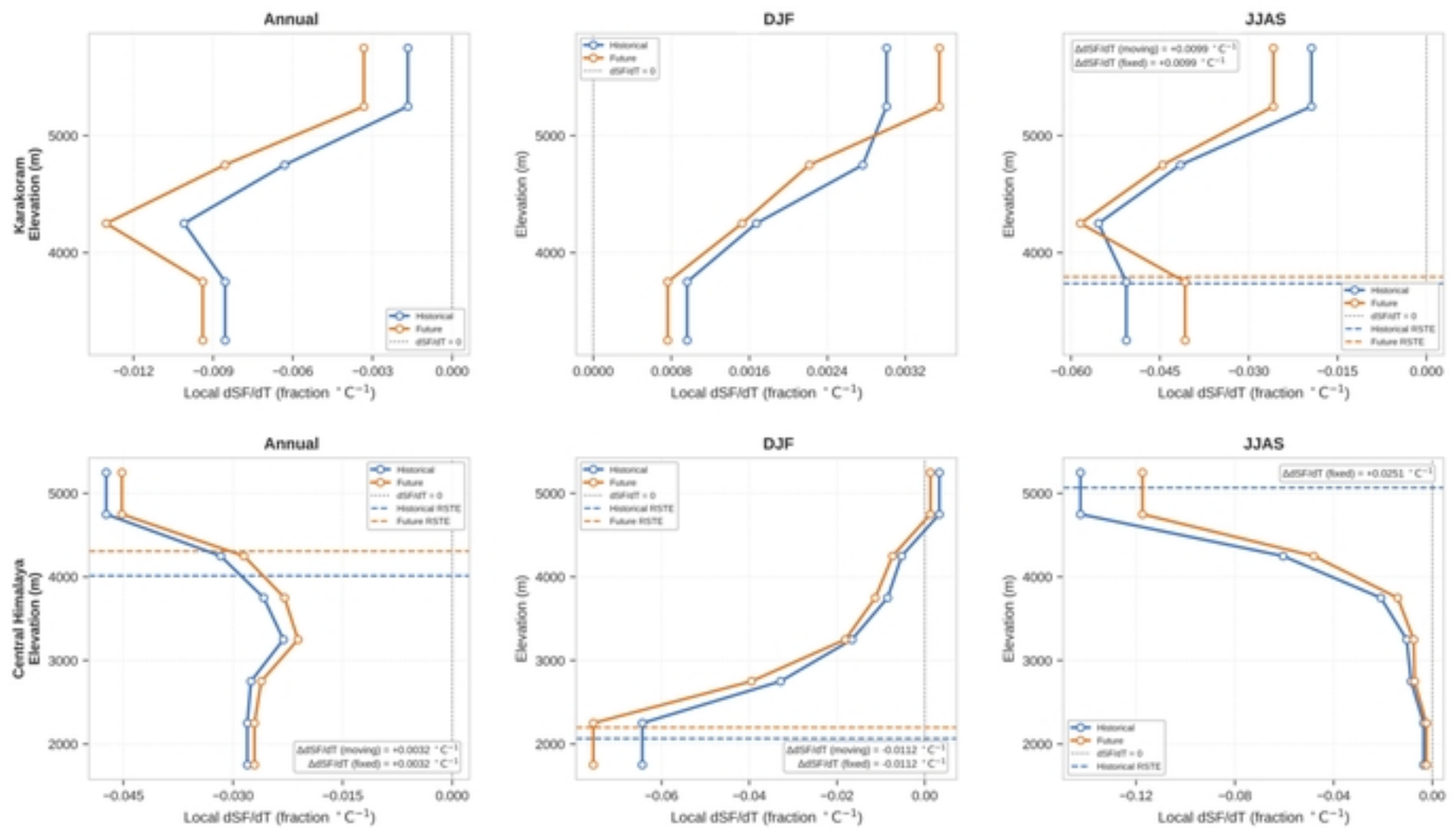


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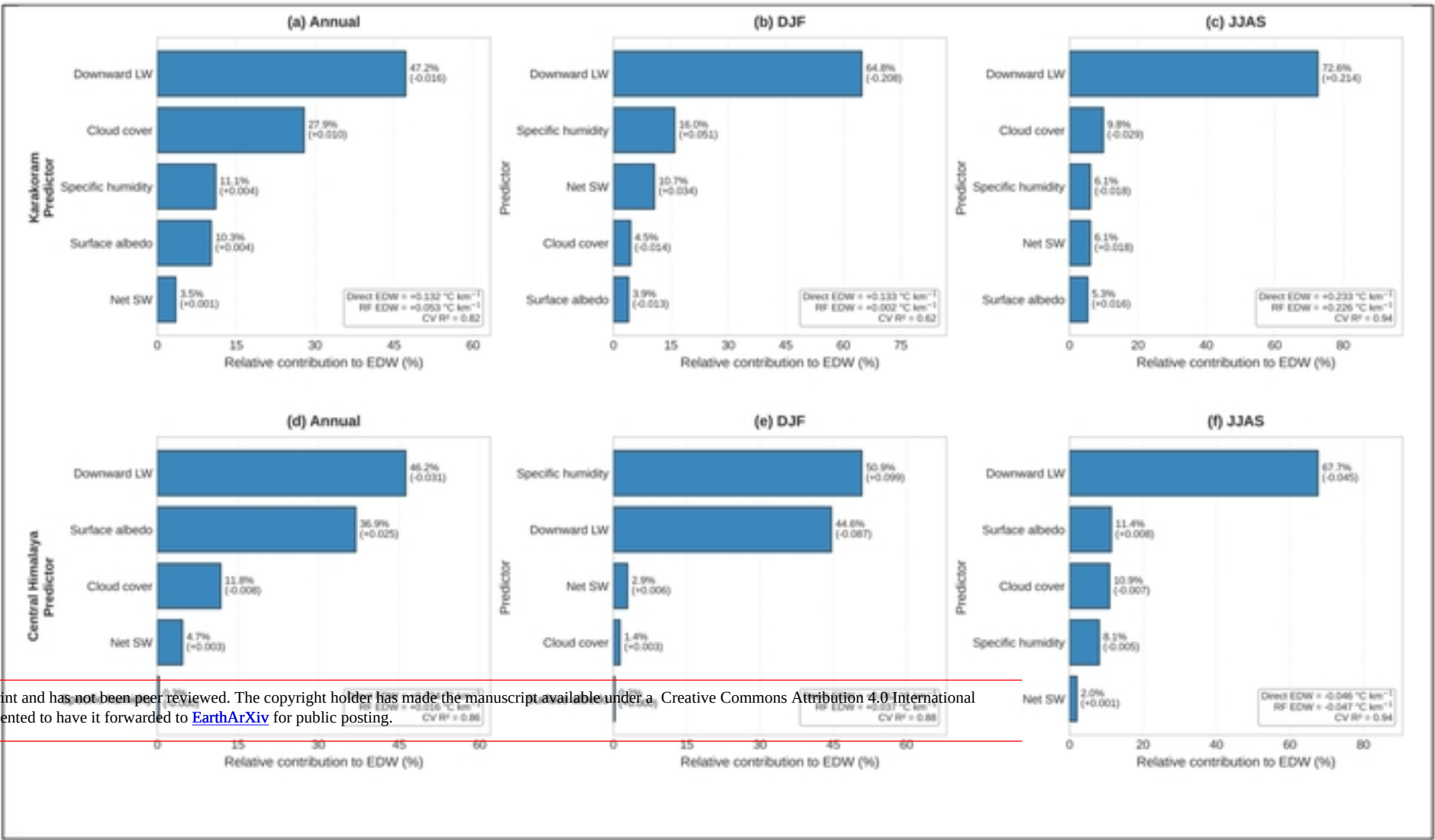
(a)



(b)



Figure



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Figure