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Nilamoni Barman

neelspinor@gmail.com

Central Ground Water Board, Northeastern Region

Research Article

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Decoding the precipitation dynamics at an East Himalayan glacier using Spectral Bin Classification and Boosted Regression Trees

Nilamoni Barman^{*1,2}

¹ Central Ground Water Board, Northeastern Region, Guwahati, Assam, India

² Centre for Atmospheric Science and Hydrometeorology, (Research initiative) Nalbari, Assam, India

*e-mail: neelspinor@gmail.com, ORCID: 0000-0003-3288-8131

Abstract

The Himalayan high-altitude region exerts a crucial impact on downstream hydrology, where meteorological conditions decisively govern glacier mass balance at sites like the Yala glacier. Because glacier mass is highly dependent on precipitation type, snowfall enhancing accumulation and rainfall accelerating reduction which indicates that the understanding atmospheric drivers is critical. Across all four seasons, relative humidity (RH) acts as the most immediate and dominant driver of snowfall, requiring high-moisture states ($RH > 80\%$) and varying by temperature range: lower temperatures ($T1$: -18°C to -5.1°C) require a mean RH of $86.5 \pm 0.9\%$, while near-freezing temperatures ($T2$: -5°C to 0°C) demand a higher mean RH of $94.5 \pm 0.3\%$. While solar incoming radiation S_{inc} consistently suppresses snowfall due to daytime heating, dew point temperature (T_d) serves as a steady positive background predictor, and ambient temperature transitions from a negligible factor in winter to a strong inhibitor during the monsoon. Boosted Regression Trees (BRTs) modeling indicates that these temperature variations are overwhelmingly driven by outgoing longwave radiation (L_{out} , 65–80% importance), whereas RH dynamics are dictated by incoming longwave radiation (L_{inc}) and precipitation type, with L_{inc} becoming the solo dominant driver ($\approx 70\%$) during the monsoon and post-monsoon periods. Ultimately, seasonal snowfall distribution between the $T1$ and $T2$ ranges shifts from a $T2$ dominance in winter to a $T1$ dominance by post-monsoon, establishing a balance where normal days experience strong diurnal cycles that increase glacier mass, while anomalous "Special day" warming events shift temperatures above freezing and accelerate glacier mass reduction.

Key word: Spectral binl Classification, Boosted Regression Trees, Precipitation type, Normal day, Special day

Introduction:

Precipitation and its types (e.g., rain, snow, and sleet) have important impacts on hydrological processes in cold regions (Berghuijs et al., 2014; Gjertsen and Ødegaard 2005; Thériault et al., 2006). The glaciers, snow-capped

mountains, and snow-ice melting, referred to as a prime water storage, ensure equilibrium between the liquid and solid states of water resources and across different reservoirs, which is crucial for its reliability and sustainability (Yao et al., 2022). With the changing climate, the rain-to-snow ratio on the Himalaya has increased, significantly affecting hydrological processes, ecology, precision of runoff simulations, and snow water equivalent evaluation (Berghuijs et al., 2014; Behrangi et al., 2018). Precipitation types vary significantly across both space and time, and this variability is particularly pronounced in mountainous regions (Harder and Pomeroy 2013). In addition, accurately identifying precipitation types, especially during the early winter months, remains a challenge in weather prediction models (Qin et al., 2019; Ralph et al., 2005). Therefore, the precise identification of different precipitation forms is very important for hydrological processes and weather forecasting (Arnold et al., 1998; Huang et al., 2016; Wigmosta et al., 1994).

The global hydrological cycle is changing in response to global temperature rise. However, the hydrological manifestation of temperature rise in terms of variation in the timing and amount of precipitation is not homogenous worldwide (Houghton et al., 2001; Nageswararao et al., 2016; Trenberth, 2011; Vinnikov et al., 1990). This occurs because essential cloud processes e.g. including prominent updrafts, condensation, rainout history, moisture recycling, and the mixing of vapor masses, which are fundamentally governed by regional geographical features such as topography, land use/land cover, and surface water availability. Together, these processes and factors play essential roles in governing the precipitation patterns in various parts of the world (Liu and Liu, 2018; Montgomery et al., 2001; Smith, 1979). In the contemporary hydrological scenario, particularly in the water stress regions such as India, it is crucial to understand the characteristic hydrometeorological processes that determine the precipitation patterns and type sources for rainfall.

The Himalayan Mountain ranges (2400 km) (Fig. 1) that border India in the north is one such place with significant variability in all the above stated characteristics that impact the regional precipitation pattern (Dimri et al., 2013; Sinha et al., 2013). It is noteworthy that although there exists an understanding about the major rain-bearing systems in the Himalayas, however, it is yet unclear how the specific hydrometeorological processes differ throughout the Himalayas (Jeelani and Deshpande, 2017; Jeelani et al., 2018; Jeelani et al., 2017b). Because there are 19 prime rivers (rain and glacial-fed) that belong to three major river systems (Indus, Ganga, and Brahmaputra) that drain the Himalayas and feed the enormous population of over 50 million people living in the Himalayas and the Indo-Gangetic plains (400 million), a better understanding of the current hydrometeorological processes in the Himalayas is especially important.

At a high-altitude Himalayan glacier site, air temperature and relative humidity serve as the fundamental controls for precipitation partitioning and the resulting glacier mass balance. Air temperature dictates the thermal energy available for melting, yet the specific rain-snow threshold is highly variable, often occurring between -1°C and 2.5°C depending on local atmospheric conditions (Jennings et al., 2018). Relative humidity significantly modulates this threshold via the wet-bulb effect; under the dry, low-humidity conditions common in the pre-monsoon season, evaporative cooling allows snow to fall at air temperatures well above freezing (0°C) (Harpold et al., 2017). Conversely, during the Indian Summer Monsoon, the high humidity and near-saturation of the air column suppress evaporative cooling, causing a sharp rise in the freezing level and increasing the frequency of liquid rain on high-altitude ice (Tiwari & Bush, 2025). This shift toward rainfall is particularly critical for Himalayan glaciers, as it not only reduces seasonal snow accumulation but also lowers the surface albedo, triggering a feedback loop that accelerates glacial thinning and runoff (Luo et al., 2024; Tiwari & Bush, 2025).

The variation of air temperature and relative humidity is intricately linked to diverse meteorological parameters, including solar radiation, wind speed, atmospheric pressure, and topography. Solar radiation serves as the primary driver of the diurnal cycle, where air temperature typically shares a negative correlation with relative humidity as increasing temperatures expand the air's moisture-holding capacity (Duane et al., 2008; Vaishali et al., 2023). Furthermore, atmospheric pressure and wind speed play critical roles in regulating these variables; for instance, wind characteristics and vertical mixing significantly influence the transport and dispersion of air masses, which can stabilize localized temperature and humidity gradients (Yadav et al., 2023). In mountainous regions, topography further dictates these variations through adiabatic processes, where moisture availability typically decreases with elevation while seasonal and diurnal variability in relative humidity is often enhanced toward summits due to upslope moisture transport (Duane et al., 2008).

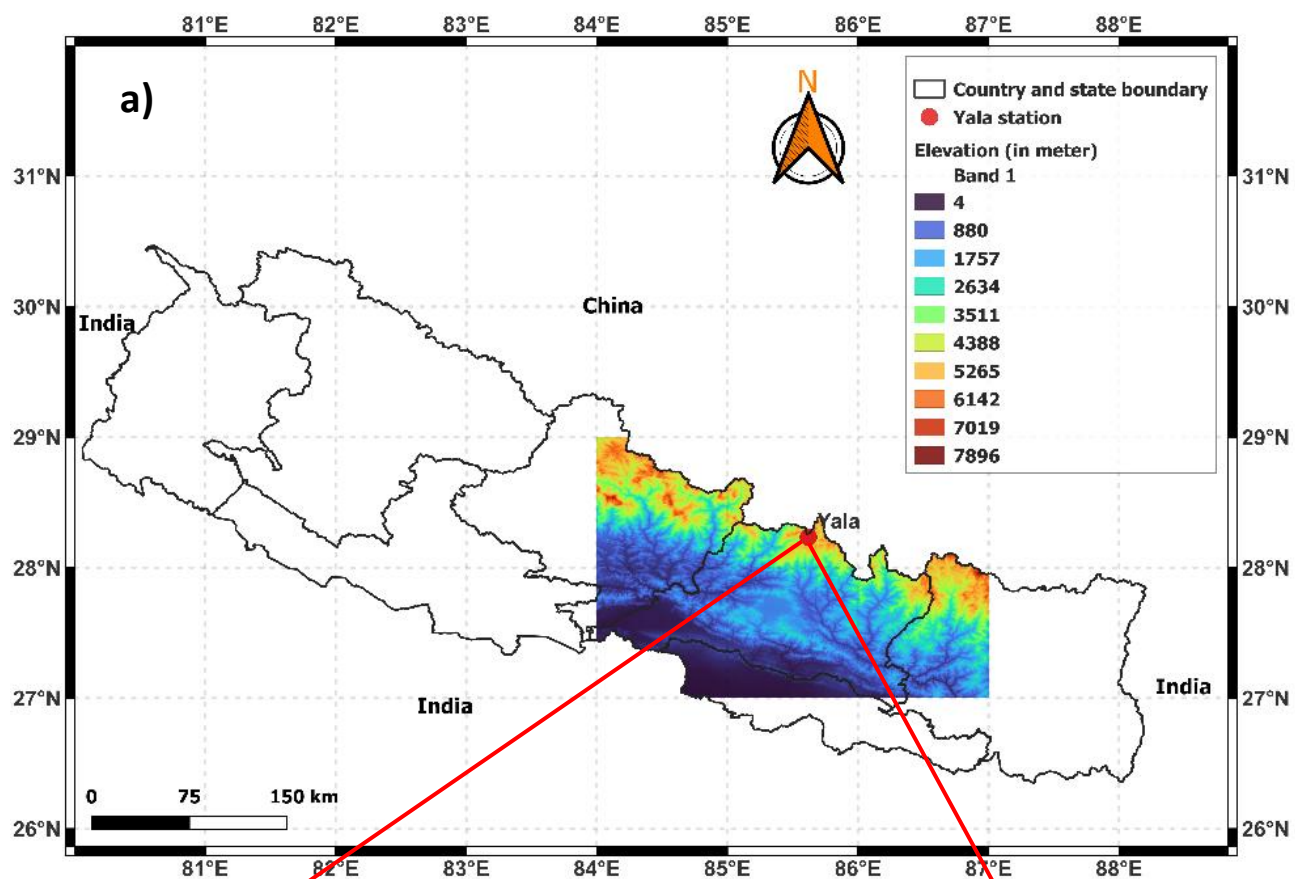
In meteorological modelling, Boosted Regression Trees (BRTs) are primarily utilized to predict continuous variables like precipitation intensity, temperature fluctuations, and glacial runoff. Unlike traditional linear models, BRTs do not assume a specific distribution of data; instead, they recursively partition the predictor space into regions with similar response values. This makes them exceptionally effective at capturing the "threshold effects" often seen in mountain meteorology e.g. the specific altitude or humidity level at which precipitation suddenly shifts from rain to snow (Elith et al., 2008; Luo et al., 2024). The primary advantage of the BRTs is its robustness against overfitting. By training multiple trees on random subsets of the data (the "bootstrap" samples) and averaging their predictions, the model reduces variance and provides more stable results in the face of "noisy" weather station data (Reichstein et al., 2019). Furthermore, BRTs provide a clear measure of relative

influence, allowing researchers to rank which meteorological parameters; like as solar radiation versus wind speed, which are the most significant drivers of a specific atmospheric phenomenon (Yadav et al., 2023). This provides a level of interpretability that is often missing in "black-box" deep learning models.

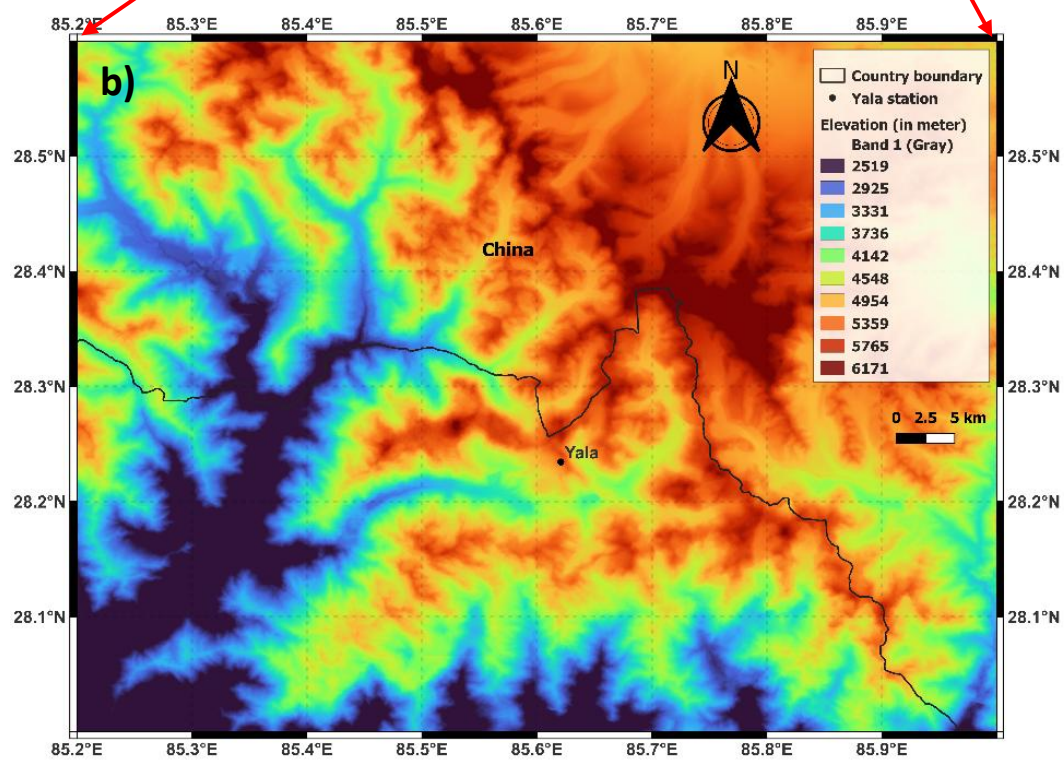
In this study, the prime objective is to decoding the precipitation types at a mountainous glacier site. To accomplish the work, spectral bin classifier is utilized for precipitation type identification. While the BRTs is utilized to find the influence of meteorological parameters on air temperature (T) and relative humidity (RH) and prediction. Besides, multi-variable lag analysis for snow events also investigated. In addition, the normal day ($T < 0^{\circ}$, $RH < 80\%$) and special day ($T > 0^{\circ}$, $RH > 80\%$) are considered for diurnal and seasonal analysis of meteorological parameter and energy fluxes.

2 Observation site

Yala Glacier (28.23436667° N, 85.62083333° E) is a debris-free glacier in the Gandaki watershed area and Trisuli River in Nepal (Rasuwa district), is located at an average altitude of 5330 meters above sea level. It is around 60 kilometres north of the capital city of Kathmandu and has a northern international border with Tibet. With a total area of 1.37 km^2 , the glacier's highest and lowest points are 5749 m and 5128 m, respectively and shown a CARTOSAT image in Fig.1 (Barman et al., 2024). The glacier is a plateau type, with a slope of 22° and a southwest orientation (Fujita et al. 1998). As a benchmark Central Himalayan glacier, this site is characterized by summer accumulation driven by the Indian Summer Monsoon, which introduces intense solar radiation and high atmospheric moisture (Immerzeel et al. 2014b). Monsoon circulation dominates the region from June to September, contributing 68–89% of the annual precipitation, while a distinct decline in temperature, humidity, and moisture levels typically occurs between the end of August and October (Fujita et al. 1998; Immerzeel et al. 2014b). Condensation and generally cloudy conditions in the afternoon are caused by the up-valley winds' tendency to carry moist air to higher altitudes. Surface temperatures rise much above air temperatures during the day because of the debris cover (Steiner and Pellicciotti 2016).



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Fig.1 a) Map of the study area in regional scale and red circle represent the station **b)** Topographical map (DEM) of the study area and the black circle indicates the station. Adopted from Barman et al., 2024

3 Materials and methodology

3.1 Instrumentation and data

In this study, three-years data of Automatic Weather Station (AWS) from 2017 to 2019 is utilized for the analysis. The data set is collected from the International Centre for Integrated Mountain Development (ICMOD) (<https://rds.icimod.org>), Kathmandu, Nepal. In this study, total 395 days data is analysed from the mentioned period. The days are classified as a normal and special day. This classification is implemented based on the air temperature (T), relative humidity (RH), incoming short wave (S_{inc}), and outgoing longwave radiation (L_{out}) profile at the station. There are 66, 66, 85 and 44 days are considered as a normal-days ($T < 0^\circ$, $RH < 80\%$), while 31, 37, 48, and 20 days are special days ($T > 0^\circ$, $RH > 80\%$) in winter, pre-monsoon, monsoon and post-monsoon, respectively. Hence, total 261 and 134 days are normal and special days are available for the analysis with in the study period.

The AWS is equipped with the various sensors e.g. Rotronic Hygroclip2, Switzerland (Temperature/RH; with radiation shield), CNR4 Campbell Scientific, UK (Radiation), Campbell data CR1000 data logger, Kipp and Zonen CNR4, Young anemometer 05103 etc. All the sensors are used to measure the concerned parameter at the site and the data quality check completed by ICMOD (ICMOD, 2021). The AWS measured the relative humidity, air temperature, wind speed at a height of 2.5 m (30-minute interval), and the incoming and outgoing shortwave and longwave radiation was also measured at a height of 1.6 m (ICMOD 2021). The details about the instrument and sensor can be found in ICMOD (2021).

3.2 Spectral Bin Classifier

Spectral Bin Classifier (SBC) a rule-based classifier that uses threshold bins of meteorological variables (e.g., temperature ranges, humidity levels, and dew point) to assign precipitation types based on known physical behaviours of atmospheric conditions (Ramer, 1993; Bourgouin, 2000; Dai, 2008; Harder and Pomeroy, 2013).

To classify 5 precipitation types using an SBC based on air temperature, relative humidity, and dew point, the following atmospheric conditions are considered. Here, R package has been used to implement the SBC on the observation data.

Table 1. Atmospheric conditions for 6 types of precipitation

Sl. No.	Class	Temperature (°C)	Relative Humidity (%)	Dew Point (°C)	Description
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1	Snow	≤ 0	≥ 80	≤ 0	Cold enough for snow formation, saturated air
2	Rain	> 2	≥ 80	> 1	Warm enough to remain liquid
3	Rain–Snow Mix	0 to 2	≥ 85	-1 to 1	Near melting point, with enough saturation
4	Freezing Rain	> 0 to 2	≥ 85	0 to 2	Rain that freezes on contact; T slightly above 0°C , surface below
5	Freezing Rain–Ice Pellet Mix	0 to 1	≥ 85	-1 to 1	Mixture of sleet and freezing rain, marginal freezing levels

3.3 Cross correlation function

The Cross-Correlation Function (CCF) is a statistical tool used to measure the degree of similarity between two different time series at various time lags. In fields like hydrogeology or signal processing, it is essential for identifying the lead-lag relationship between a "driving" variable (like rainfall) and a "response" variable (like groundwater levels).

For two stationary time series, x_t and y_t , the cross-covariance at lag k is defined as

$$\gamma_{xy}(k) = E[(x_{t-k} - \mu_x)(y_t - \mu_y)]$$

The CCF scales this covariance by the product of the individual standard deviations (σ_x, σ_y)

$$\rho_{xy}(k) = \frac{\gamma_{xy}(k)}{\sigma_x \sigma_y}$$

Where $k > 0$: Indicates the correlation of y_t with past values of x .

$k < 0$: Indicates the correlation of y_t with future values of x .

The time shift between the two series. If the highest correlation occurs at a positive lag (e.g., $k=3$ hours), it suggests that changes in x take three hours to manifest in y . Values range from -1 to +1. Positive CCF represents that the both variables move in the same direction. While negative CCF indicates that, the variables move in opposite directions. The software plots dashed lines representing the 95% confidence interval (usually $\pm 2\sqrt{n}$). Peaks extending beyond these lines are considered statistically significant.

The dashed red lines [95% Confidence Interval (CI)] represent the threshold for statistical significance.

Most variables are significant between Lag -10 and Lag +10. Values outside these lines are unlikely to be due to random noise. Negative Lags indicates that the predictor leads the target. When the highest correlation bars are on the left side of the zero line (negative values), it means the predictor variable (e.g., Rainfall or Humidity) happened first, and the target variable (e.g., snow) responded later. If it is a high peak at Lag -5, it means that

whatever happened to the predictor today will show up in the target variable 5 days/time units from now. Positive Lags indicates that the target leads the predictor. If a peak at Lag +3, it means the target changed at the very hour, and 3 hours later, the predictor variable responded. The center bar represents Lag, indicates that both variables are changing at exactly the same time.

3.4 Boosted Regression Trees

Boosted Regression Trees (BRTs) is a kind of regression methodology based on Machine Learning. In contrast to traditional regression techniques (GLMs, GAMs), BRTs improve predictive performance by combining many simple decision trees. BRTs are considered as a reliable method that can manage nonlinearity and outliers, as well as can manage intricate linkages and interactions between predictors (BRT 2023, <https://blog.devgenius.io/r-tutorial-boosted-regression-trees-9f243d88a921>). The variation in the predicted impacts can be estimated with the aid of bootstrap and resampling techniques. This is necessary because, a subset of the total population is used instead of the complete population. As a result, the projections from the model are estimates of the real population parameters. The model estimates would differ from the prior sample if the data came from a different sample. Within the sample, different data would yield different statistics. It is frequently impractical to gather several samples. As a result, bootstrap or resampling techniques aid in roughly gathering several samples from the target population (Elith et al., 2008). BRT integrates the advantages of regression trees with the boosting method, making it capable of handling diverse data types and accommodating missing data. When handling complex nonlinear interactions, its predictive power outperforms that of the majority of traditional modelling techniques (Luo et al., 2024).

There are four parameters that must be defined to perform a BRT: Learning rate (lr , determines the contribution of each tree to the growing model). Decreasing lr increases nt required. Tree complexity or interaction depth (tc , controls the interactions or controls how complex the interactions between predictors can be). Number of trees (nt , defined by lr and tc . Trees required for optimal prediction. Bag fraction (bf , proportion of data selected at each step). A cross-validation (CV) procedure can be used to estimate the optimal nt and lr . In *gbm*, stochasticity is controlled through a ‘bag fraction’ that specifies the proportion of data to be selected at each step. The default bf is 0.5, which means that 50% of the data are randomly selected from the entire training set at each iteration without replacement. By comparing prediction accuracy and model-to-model variability under various bf , optimal bf can be determined. This process uses the same dataset, which is useful in cases when you don’t have large amounts of data. The lr is used to shrink the contribution of each tree as it is added to the model. Decreasing (slowing) lr increases the number of trees required, and in general a smaller lr (and larger nt) are preferable,

conditional on the number of observations and time available for computation. The usual approach is to estimate optimal nt and lr with an independent test set or with CV, using deviance reduction as the measure of success.

In this study, the “*gbm*” package in the R software (version 4.3.1) is utilized to implement BRT model. BRT approach is used to evaluate the impact of various environmental parameters on T and RH . T and RH are the target variables and BRT used for different learning rate ($lr=0.001, 0.01, 0.05$, and 0.1) with constant number of trees ($nt=500$) and tree complexity ($tc=4$).

3.5 Performance Metrics

Nash-Sutcliffe Efficiency (Nash and Sutcliffe, 1970), Kling-Gupta Efficiency (Gupta et al., 2009) and r^2 (Krause et al., 2005) metrics were used to quantify the model performance. The main reason for using multiple metrics is to avoid individual bias that may occur from the metrics. The obtained performance results were ranked, and the model with relatively better performance was determined by the overall rank results. The R package "hydroGOF" (Zambrano-Bigiarini, 2024) is used for calculating performance metrics.

3.4.1 Mean squared error (MSE) and Nash–Sutcliffe efficiency (NSE)

The mean squared error (MSE) criterion and its related normalization, the Nash–Sutcliffe efficiency (NSE, defined by Nash and Sutcliffe, 1970) are the two criteria most widely used for calibration and evaluation of hydrological and hydrometeorological models with observed data. NSE is sensitive to large errors and outliers. In variables like rainfall (which can be sparse or skewed), NSE may not be robust. $NSE < 0$ indicates the model is worse than the mean which is often happens with poorly predicted meteorological data. May not be ideal for skewed or binary/threshold-based meteorological predictions. The value of MSE depends on the units of the predicted variable and varies on the interval $(0 \text{ to } \infty)$, whereas NSE is dimension less, being scaled onto the interval $(\infty \text{ to } 1)$. As a consequence, the NSE value– obtained by dividing MSE by the variance of the observations and subtracting that ratio from 1 (Eqs. (1) and (2)), and commonly the measure of choice for reporting (and comparing) model performance. Further, NSE can be interpreted as a classic skill score (Murphy, 1988), where skill is interpreted as the comparative ability of a model with regards to a baseline model, which in the case of NSE is taken to be the ‘mean of the observations’ (i.e., if NSE is 0, the model is no better than using the observed mean as a predictor). The equations are:

$$MSE = \frac{1}{n} \sum_{t=1}^n (x_{s,t} - x_{o,t})^2 \quad \dots\dots\dots 1$$

$$NSE = 1 - \frac{\sum_{t=1}^n (x_{s,t} - x_{o,t})^2}{\sum_{t=1}^n (x_{o,t} - \mu_o)^2} = 1 - \frac{MSE}{\sigma_o^2} \quad \dots\dots\dots 2$$

where n is the total number of time-steps, $x_{s,t}$ is the simulated value at time-step t , $x_{o,t}$ is the observed value at time-step t , and μ_o and σ_o are the mean and standard deviation of the observed values. In optimization, MSE is subject to minimization and NSE is subject to maximization. The range of NSE varies between 1 (perfect fit) and $-\infty$. An efficiency coefficient below zero indicates that the average value of the observed time series is a better predictor than the model.

3.4.2 Kling-Gupta Efficiency

KGE coefficient (Gupta et al., 2009) is a performance indicator that includes the correlation, the ratio of means and the ratio of distribution of two paired data sets. The KGE can be calculated using the formulas in equations 3, 4, and 5.

$$KGE = 1 - \sqrt{(1 - r)^2 + (\beta - 1)^2 + (\gamma - 1)^2} \quad \dots\dots\dots 3$$

$$\beta = \frac{\mu_p}{\mu_o} \quad \dots\dots\dots 4$$

$$\gamma = \frac{\frac{\sigma_p}{\mu_p}}{\frac{\sigma_o}{\mu_o}} \quad \dots\dots\dots 5$$

Where P is the modelled data and O is the observation data, r is the Pearson correlation coefficient between the models and benchmark, β is the deviation rate, γ is the variability rate, μ and σ are the mean and standard deviation of the observation data. The range of the coefficient varies between 1 and $-\infty$. A value of 1 represents a perfect fit.

4 Results and Discussion

4.1 Spectral bin classification of precipitation type

The plot is a stacked bar chart over 24 hours (0–23) is shown in **Fig.2**. Each bar represents percent frequency (0–100%), showing the distribution of categories (colour code) across the day. Dark Blue (dry condition) makes up 60% of the distribution for most hours. Indicates one major prevailing condition, likely stable winter atmosphere or a primary weather class. Strongest presence from midnight to early morning (0000–0800LT), indicates a stable atmosphere, one condition dominates (cold, saturated air). Transition Hours between 0900–1400LT, the dark blue area reduces slightly, and purple (snow) & magenta (freezing rain) increase, suggesting greater variability during daytime. The daytime heating of the surface leads wider dew point depression and multiple categories observed. Around 1000–1300LT, the contribution from orange (freezing rain-ice pellet)/ magenta (freezing rain) and yellow

(rain-snow mix) categories is noticeable (indicating rare but important events). Evening build-up (1500–2100LT), purple (snow) and magenta (freezing rain) fractions increase again, showing more variability owing to high *RH* and leads to more mixed conditions. This suggests late afternoon/evening disturbances, possibly linked to temperature-dew point spread reduction or humidity rise. At night (2200–2300LT), distribution stabilizes again, dark blue dominance returns ($\approx 75\%$). The Fig suggests that in winter, stable atmospheric conditions dominate at night, while daytime heating introduces variability, and evening shows transitional mixing before stabilizing again.

In pre-monsoon, dark blue (dry condition) dominates during 0000–0700 LT ($\approx 59\%$), showing stable conditions (similar to winter nights) (**Fig.S1a** in supplementary material). However, unlike winter, the purple (Snow) and magenta (Freezing rain) fractions are higher at night, suggesting more variability even in stable hours. Some yellow (rain-snow mix) spikes (rare conditions) appear even at night. During the transition hours (0800–1200 LT), a noticeable drop in dark blue dominance ($\approx 50\text{--}60\%$). Purple (snow) and magenta (freezing rain) layers increase, reflecting increasing atmospheric instability as daytime heating occurs. Yellow (snow-rain mixed) peaks appear more prominently between 1000–1200 LT, suggesting episodes of strong warming or dry intrusions. Afternoon & evening (1300–2000 LT), the strong rise in purple (snow) & magenta (freezing rain) dominance, especially around 1500–1900 LT. Dark blue is reduced significantly, showing that mixed/unstable ones replace stable atmospheric conditions. This reflects enhanced convective activity and variability in pre-monsoon afternoons/evenings. Late Evening (2100–2300 LT) dark blue strengthens again, but still lower than winter recovery levels. Purple (snow) and magenta (freezing rain) remain significant, showing lingering instability even at night in pre-monsoon. Strong night-time stability, reduced daytime variability, evening re-stabilization are observed in the winter. While in pre-monsoon, greater variability overall is observed (more purple/ magenta at all hours). Daytime heating causes stronger disturbances (yellow & orange peaks). Evenings remain unstable longer, unlike winter where stability returns quickly. Fig shows that the atmosphere is much more unstable compared to winter. Nights are less stable (more variability than in winter). Days show strong convective influence and humidity variations. Evening instability lingers, reflecting pre-monsoon heat-driven turbulence.

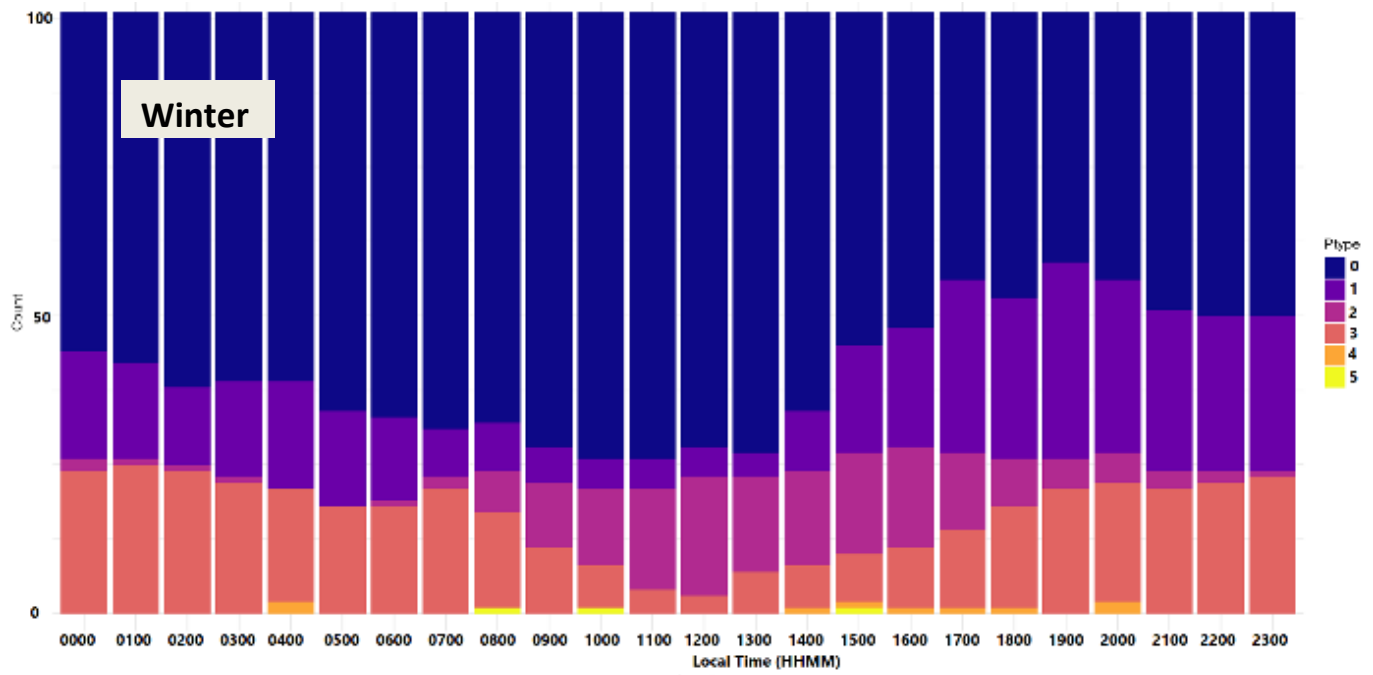


Fig. 2 The diurnal frequency distribution of *ptype* during the winter season. No precipitation (in dark blue, 0), Snow (in purple, 1), rain (salmon red, 2), freezing rain (in magenta, 3), orange freezing rain-ice pellet (in orange, 4), and rain-snow mixed (in yellow, 5)

In monsoon, night & early morning (0000–0600 LT) high proportion of purple (snow) and magenta (freezing rain) is observed (35–45%), compared to winter and pre-monsoon (**Fig.S1b**). Dark blue is still dominant ($\approx 60\%$), but not as overwhelming as in winter. Suggests humid, partially unstable conditions at night (consistent with monsoon cloud cover and moisture). During morning Transition hours (0700–1200 LT), dark blue increases around 0800–1000 LT, showing short-lived stability in the morning. While, instability rises again by 1100–1200 LT, with magenta (freezing rain)/orange (freezing rain-ice pellet)/yellow (rain-snow mixed) gaining share. This likely reflects daytime convection triggered by moisture and solar heating. Afternoon & Evening (1300–2000 LT) higher variability is observed and dark blue shrinks ($\approx 50\%$). Purple (snow) and magenta (freezing rain) expand ($\approx 40\text{--}45\%$). Noticeable that the yellow (rain-snow mixed) bands appear around 1400–1600 LT. This matches peak convective activity (showers, thunderstorms) in the monsoon afternoons. Late Evening (2100–2300 LT) dark blue regains ground ($\approx 60\text{--}70\%$). However, purple (snow) and magenta (freezing rain) remain significant, showing that instability lingers overnight in monsoon (unlike winter). In monsoon, higher instability is observed at all hours (purple (snow) / magenta (freezing rain) stronger). Daytime extremes (yellow (rain-snow mixed)) strongest among all seasons, reflecting frequent precipitation episodes. **Fig.S1b** shows an atmosphere that is consistently

unstable and moisture-laden. Afternoons show peak convective activity with extremes. Unlike other seasons, instability is spread across the entire day-night cycle, consistent with the dynamic monsoon environment.

In post-monsoon, dark blue dominates ($\approx 60\%$) dominates during 0000-0600 LT, showing stable, cooler, moisture-balanced conditions (**Fig.S1c**). Secondary bands (purple (snow) and magenta (freezing rain) $\approx 25\text{--}30\%$) are moderate, reflecting some variability but less than monsoon. Occasional thin yellow (rain-snow mixed) bands are occurred and considered a rare instability episodes even at night. This indicates calm/stable mornings, typical of post-monsoon clear skies after the humid season. The lowest instability levels appear around 1000–1100 LT. In afternoon (1200–1700 LT), variability rises gradually and Purple (snow) and magenta (freezing rain) expand to $\approx 30\text{--}35\%$. Yellow (rain-snow mixed) appears around 1400–1600 LT, but very thin compared to monsoon. Suggests localized convection or cloud build-up, but not as intense or widespread. Evening & night (1800–2300 LT), instability (purple (snow) and magenta (freezing rain)) grows again ($\approx 35\text{--}40\%$). Dark blue reduces ($\approx 60\%$), especially around 1800–2100 LT, showing evening convection. Overall, stability is restored towards late night. As the post-monsoon is the intermediate state between monsoon and winter. Nights and mornings are more stable (closer to winter). Afternoons show some convection, but less extreme than monsoon. A balance between stability (winter-like nights) and residual variability (monsoon-like afternoons) is visible.

4.2 Multi-variable lag analysis for snow

In a real atmospheric system, the snowfall is influenced by multiple interacting variables, each operating at different time lags.

In winter, RH shows the strongest statistical relationship with the snowfall. The correlation peaks at Lag 0 ($r \approx 0.38$) (**Fig.3a**). The correlation remains significant and relatively high across a broad window, from Lag -5 to Lag +5. The snow is highly synchronized with RH . Since the peak is at Lag 0, it suggests a near-instantaneous physical response or a shared diurnal cycle. S_{inc} exhibits a distinct and interesting flip in its relationship with the snow. Centered around Lag 1-2, S_{inc} shows a negative correlation ($r \approx -0.20$). This implies that higher solar radiation is associated with a decrease in the snowfall shortly thereafter. This phase shift often suggests a complex feedback loop or a delayed thermal response. In winter, as solar intensity increases, it triggers evaporation that inversely affects snowfall with a slight delay. T_d shows a moderate positive correlation that is most stable between Lag -3 and Lag 0. It mirrors the behaviour of RH but with lower intensity ($r \approx 0.18$). T shows the weakest overall correlation among the four variables. It is barely significant, hovering just above the 95% Confidence Interval (the dashed red lines) at negative lags and dipping below it at positive lags. The fact that RH and T_d are strongest at Lag 0 and slightly negative lags suggests they are excellent proximal drivers for the winter season. When the

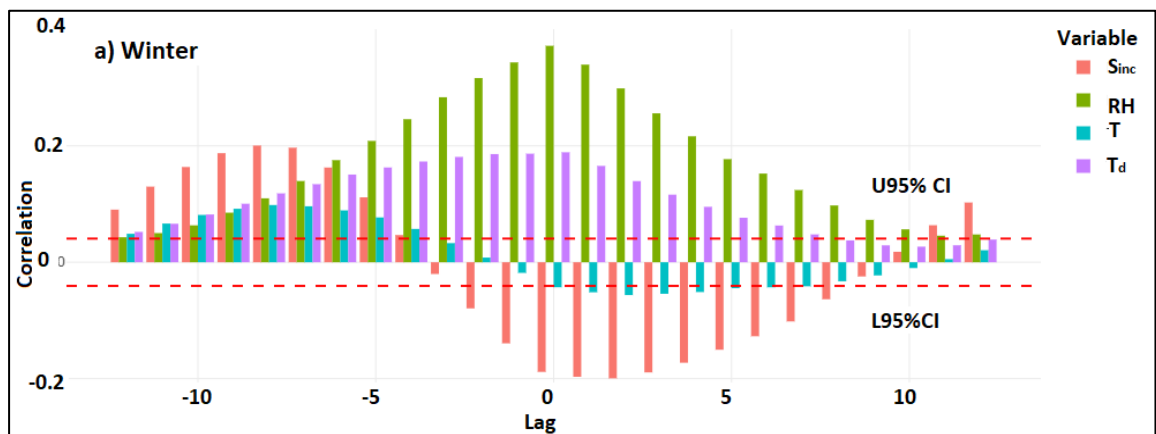
highest bars are on the right side of the zero line (positive values), it means the target variable changed first, and the predictor variable changed afterward.

In pre-monsoon, RH remains the most dominant variable, but its influence is even more pronounced. Hits a maximum of approximately $r \approx 0.40$ at Lag 0. The correlation follows a very clean, bell-shaped distribution (**Fig.3b**). It rises sharply from Lag -5 and decays symmetrically by Lag +5. This indicates that during the pre-monsoon heat, the snow is almost entirely governed by instantaneous moisture availability in the air. S_{inc} reaches its lowest point at Lag +2 ($r \approx -0.22$). The negative correlation is stronger here than in winter. In pre-monsoon, high solar radiation leads to a more rapid and significant decline in the snowfall about 2 hours of time later. This likely reflects intense evapotranspiration or thermal stress characteristic of this season. The positive correlation at Lag -8 to -10. This suggests that high solar energy a week or so prior might actually precede an increase in the snowfall before the immediate heat-effect (negative correlation) takes over. T_d shows a very stable positive correlation ($r \approx 0.20$) from Lag -2 to Lag +1. Unlike RH , T_d does not peak as sharply at zero; it stays consistently influential across a 3-lag window, suggesting it is a steadier predictor than the more volatile RH . T continues to be the weakest predictor. While it stays mostly within the significant zone (above the dashed red line) at negative lags, it remains close to the noise threshold. It interestingly becomes negatively correlated starting at Lag +1, following a similar trend to S_{inc} . The system is highly sensitive to the Heat-Moisture balance. The snow responds almost instantly to RH but shows a clear, delayed negative reaction to S_{inc} .

The monsoon season shows a very distinct and clean lag structure compared to the previous two seasons. The atmospheric saturation during this period results in very high correlation peaks, particularly for moisture-related variables (**Fig.3c**). During monsoon, RH remains the dominant predictor, reaching its highest seasonal intensity. It hits a definitive peak of $r = 0.40$ at Lag 0. The correlation is exceptionally stable. It stays above $r = 0.30$ from Lag -3 to Lag +2, indicating that RH has both a leading influence and a sustained contemporaneous relationship with the snowfall. In this environment, the snowfall is almost perfectly coupled with air saturation. The inverse relationship with S_{inc} is most symmetrical during the monsoon season. The strongest negative correlation occurs at Lag 0 and Lag +1 ($r \approx -0.23$) and a positive correlation at Lag -8 to -12. This suggests a very rapid transition: high solar radiation a week prior may drive the process upward, but the immediate effect (Lag 0) of solar radiation during the monsoon is strongly negative. This is likely due to the cloud-cover effect, the high solar radiation implies a lack of clouds/rain, which immediately drives the snowfall down in this specific seasonal context. T_d shows a very flat and consistent positive correlation ($r \approx 0.18$) across a wide window from Lag -5 to Lag +1. This suggests that while RH is a sharp, immediate driver, the overall moisture content provides a steady,

background floor for the target variable throughout the week. Interestingly, during the monsoon, T becomes significantly negative at Lag 0 and positive lags. It dips below the 95% CI (dashed red line) between Lag -1 and Lag +4. Unlike winter where T was mostly positive/neutral, in the monsoon, higher T is clearly associated with a decrease in the snowfall, mirroring the behavior of solar radiation.

The post-monsoon shows a transition where environmental variables begin to decouple compared to the high-intensity synchronization seen during the monsoon. The atmosphere is drier and more stable, which is reflected in the more gradual correlation curves (**Fig.3d**). RH remains most reliable variable, but the nature of its influence has shifted. Reaches approximately $r = 0.38$ at Lag 0. Unlike the sharp peaks of previous seasons, the green bars here form a very wide. It maintains significant correlation ($r > 0.20$) even at Lag +5. Changes in RH during the post-monsoon period have a more lingering effect on snowfall compared to the rapid turnover seen in the monsoon. The negative relationship with S_{inc} is noticeably less intense in the post-monsoon phase and minimum at Lag 0 ($r \approx -0.18$), which is weaker than the -0.23 seen in the monsoon. There is a clear positive lead at Lag -10 to -12. As the sun's angle shifts and intensity decreases post-monsoon, the thermal stress or evaporative pressure reduces. The system is less sensitive to solar heating than it was during the peak summer or monsoon months. One of the most interesting features of the post-monsoon plot is the behavior of T (blue bars). T is consistently negative and significant across the central window (Lag -2 to Lag +3). In the post-monsoon season, higher T are strongly associated with a decrease in the snowfall. Shows a moderate, stable positive correlation ($r \approx 0.17$) centered at Lag 0. It behaves similarly to RH but at a lower magnitude.



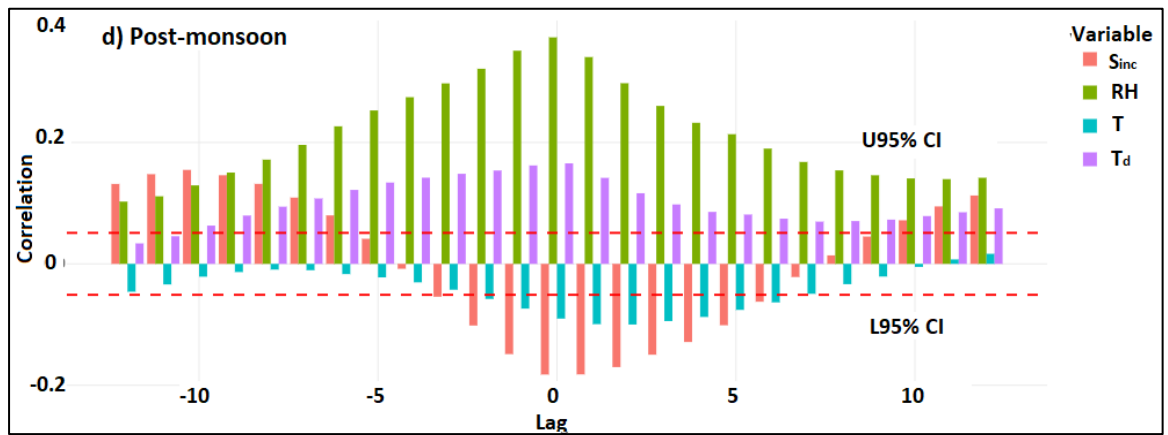
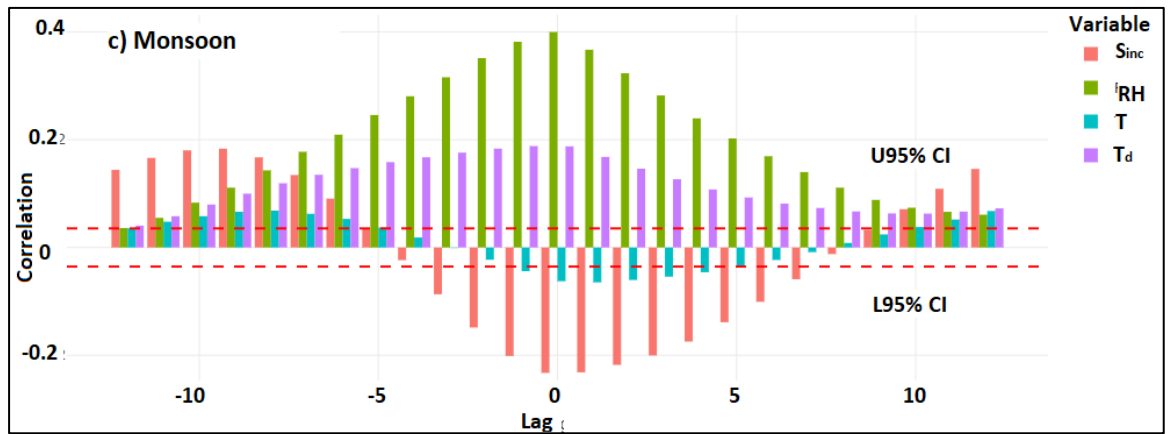
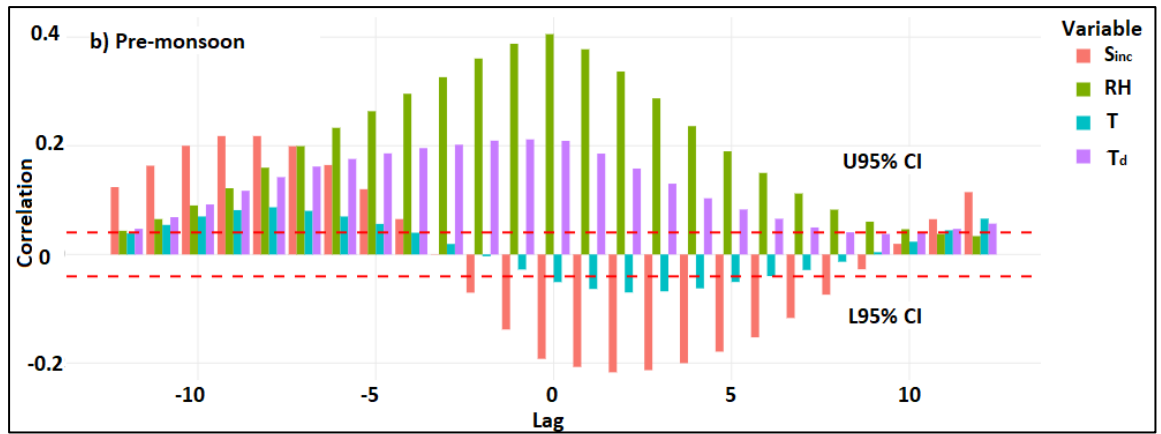


Fig.3 Multi-variable (S_{inc} , RH , T and T_d) lag analysis for snowfall **a)** winter, **b)** pre-monsoon, **c)** monsoon and **d)** post-monsoon. S_{inc} in salmon red, RH in green, T in teal, and T_d in lavender

4.3 Temperature vs Relative Humidity

In this section T and RH is plotted for different seasons (Fig). The four quadrant is shown in the plots Q1 ($T > 0$, $RH > 80\%$), Q2 ($T < 0$, $RH > 80\%$), Q3 ($T < 0$, $RH < 80\%$), and Q4 ($T > 0$, $RH < 80\%$). The precipitation takes place when atmosphere fulfil the Q1 and Q2 condition. Q1 represent the mixed precipitation (snow and rain) and rainfall, while Q2 represents the snowfall events.

In winter, at $RH > 80\%$ and $T < 0^{\circ}\text{C}$, most points are green. This indicates precipitation events (likely snow 14%) are clustered in this cold, moist region (**Fig.4a**). Near 0°C with high RH , a cluster of blue and green points appears close to 0°C at $RH > 90\%$. Suggests a mix of rain–snow transition or freezing precipitation events. Below 75% RH , most points are yellow means dry conditions (52%) or no precipitation events. Dry condition dominates across all temperatures, especially in $RH < 80\%$. Green points concentrated at high $RH (>80\%)$ and T between -10°C to 0°C indicates the snowfall events. Red point (rain-snow mix) and blue point (Freezing rain-ice pellet mix) are appearing at very high RH (90–100%) and T close to freezing (around 0°C) and can consider as a rare events. Freezing rain (Orange in colour, 13.7%) event also occurred near the freezing line. Dry condition dominates at low RH . Snow-related events dominate at sub-zero T with very high RH . Freezing rain (orange points) and freezing rain-ice pellet mix (blue points) occurs near 0°C with $RH > 90\%$.

In pre-monsoon, the dominance of Yellow Points (dry condition) and scattered across almost all RH values (10–100%) (**Fig.4b**). This indicates that dry conditions dominate during pre-monsoon. Green Cluster (snowfall), concentrated at $RH > 80\%$ and T between -10°C and 0°C , which indicates the cold but moist events, possibly snow or mixed events, but far fewer compared to winter. Freezing rain-ice pellet mix events appears at the upper-right corner at near 0°C , $RH \approx 95\text{--}100\%$. Likely a rare event type. In winter, snow/mixed precipitation classes were much more frequent. In pre-monsoon, dry condition clearly dominates, and only a few scattered cold-weather precipitation events remain. This shift is expected, as pre-monsoon has higher T and drier atmospheric conditions compared to winter, can considered as a transition period to the monsoon season. Only occasional moisture builds up at high RH leads to limited precipitation events. Near 0°C with high RH still produces rare freezing/mixed events. This is a major contrast with winter, where precipitation types (snow/mixed/freezing) were far more active.

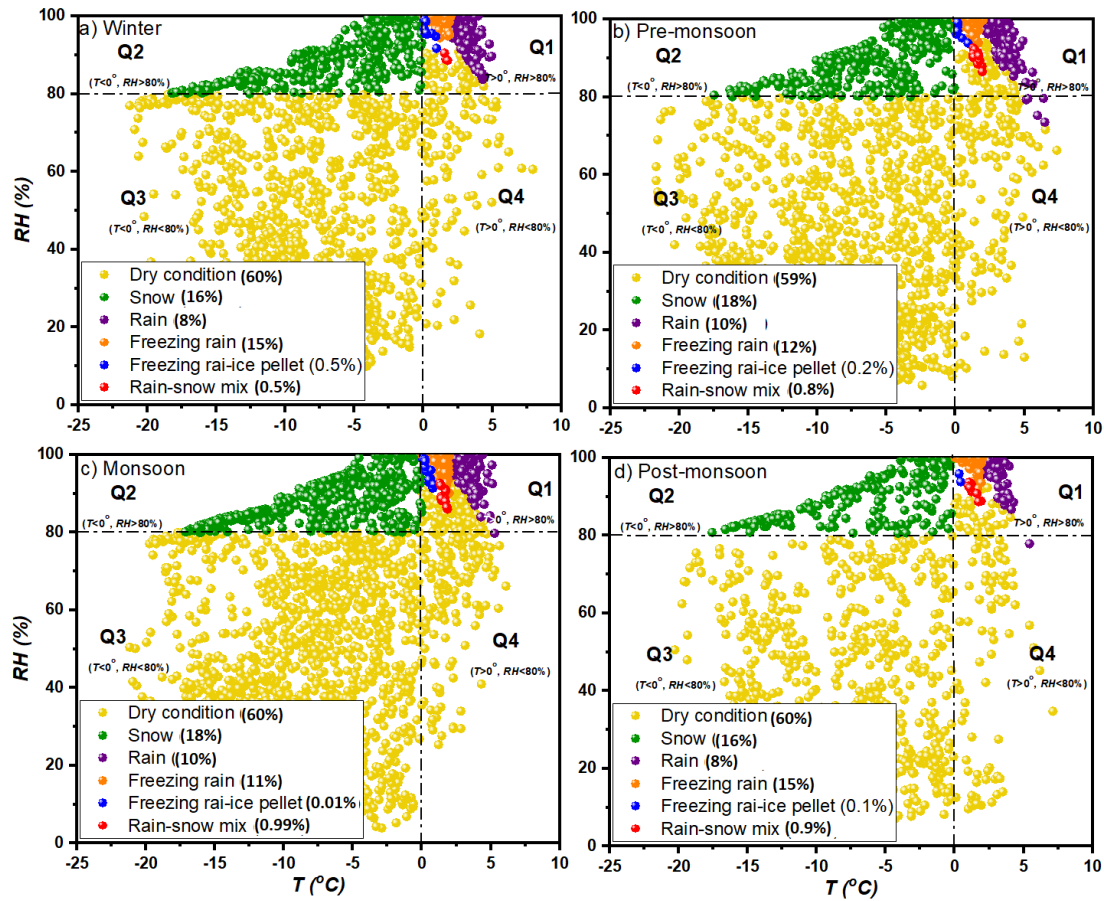


Fig.4 RH vs T in **a)** winter, **b)** pre-monsoon, **c)** monsoon and **d)** post-monsoon; Q1 ($T > 0$, $RH > 80\%$), Q2 ($T < 0$, $RH > 80\%$), Q3 ($T < 0$, $RH < 80\%$), and Q4 ($T > 0$, $RH < 80\%$)

In monsoon, dry condition is dominant, but compared to pre-monsoon, these are more concentrated at higher RH values (50–90%) (Fig.4c), which indicates the increased atmospheric moisture in monsoon, but many events remain non-precipitating. Green Cluster is located around -5°C to 0°C and $RH > 80\%$ and denser than pre-monsoon, indicating more frequent cold, moist events (possibly snow or wet-snow aloft). Blue and orange points are prominent at near 0°C and $RH \approx 90\text{--}100\%$. These represents the mixed/freezing precipitation, occurring more frequently than in pre-monsoon. Blue Cluster is appeared at highest RH (95–100%) near 0°C . Very rare, but more visible compared to winter. During monsoon, the atmosphere is much moister (many points above 70% RH). Shows more precipitation-supporting conditions than pre-monsoon. However, the persistence of many yellow points suggests periods of non-precipitation despite high humidity likely due to stratiform clouding or suppressed convection.

In post-monsoon, yellow Points (dry condition) are spread widely across $RH \approx 0\text{--}80\%$ and $T \approx -20^{\circ}\text{C}$ to $+5^{\circ}\text{C}$ (Fig.4d). Indicates that non-precipitating conditions dominate in post-monsoon, similar to pre-monsoon.

Green Cluster (snowfall) is present but slightly less dense compared to monsoon season. Blue points (rare, RH 95–100%, near 0°C) are only two, which suggests occasional saturation/precipitation near freezing point.

4.4 Temperature vs dew point

The seasonal T and Dew point is plotted for six (6) distinct clusters e.g. dry condition (Yellow in colour), snowfall (Green in colour), Freezing rain (Orange in colour), rain (Purple in colour), Freezing rain-ice pellet (blue in colour) and rain-snow mix (red in colour) represent different types of precipitation shown in **Fig.5**.

In all the seasons, the data points spread extends further down (dew points around -20 to -40°C), indicating extremely dry air masses. The slope of the data band is steeper, meaning large dew point depression is more common. Dry condition is dominant, very dry conditions, large temperature–dew point gap. Snowfall follows an inclined path and higher snowfall events accumulated between T range from -5°C to 0°C , indicating the rare periods of higher humidity (fog, cloud, or moisture intrusions). Rainfall & freezing rain events are in the top-right indicates the relatively humid and warmer episodes. Freezing rain-ice pellet events is the phase changing regime when solid and liquid phase of water occurs. Dew point depressions often exceed 20 – 30°C , showing low absolute humidity. Rare but important green cluster events likely correspond to foggy nights/mornings. All the snowfall events distributed in two T range i.e. T1 (-18°C – -5.1°C) and T2 (-5°C – 0°C). In T1, 40%, 49.9%, 50.5% and 60% of snowfall events are occurred during winter, pre-monsoon, monsoon and post-monsoon, respectively. Similarly, in T2, 60%, 50.1%, 49.5% and 40% snowfall events occurred during winter, pre-monsoon, monsoon and post-monsoon, respectively. It is observed that the mean RH $86.5\pm0.9\%$ and $94.5\pm0.3\%$ is required to occur snowfall in the T1 and T2 range, respectively. Similarly, L_{out} ($268\pm3\text{ Wm}^{-2}$ and $300\pm1\text{ Wm}^{-2}$) and T_d ($-12.7\pm0.9^{\circ}\text{C}$ and $-3.3\pm0.2^{\circ}\text{C}$) also varies in T1 and T2.

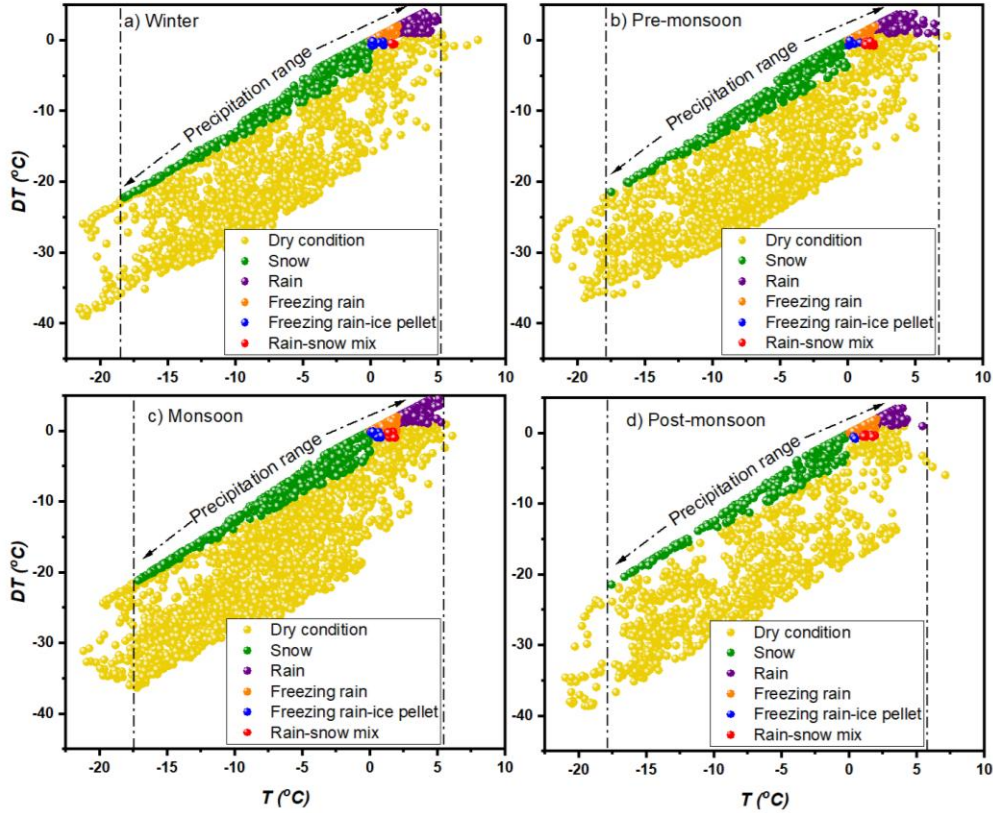


Fig.5 Dew temperature vs air temperature in **a)** winter, **b)** pre-monsoon, **c)** monsoon and **d)** post-monsoon

4.5 Variable impact on T and RH

BRT is utilized to investigate the impact of other meteorological parameters on T and RH (Fig.6). In all the seasons, the longwave outgoing Radiation (L_{out}) dominates with the highest importance score ($\approx 65\text{--}80\%$), means have higher influence on T . This suggests the model is heavily relying on this single variable. Longwave incoming radiation (L_{inc}) has the next highest importance ($\approx 5\text{--}15\%$), significantly lower than L_{out} but still relevant. RH and wind Direction come next with smaller contributions ($\approx 3\text{--}7\%$). Wind Speed, Shortwave outgoing radiation (S_{out}) Shortwave incoming radiation (S_{inc}) and precipitation type ($Ptype$) all have very low importance ($<5\%$). This indicates they contributed little to the T predictive power of the model.

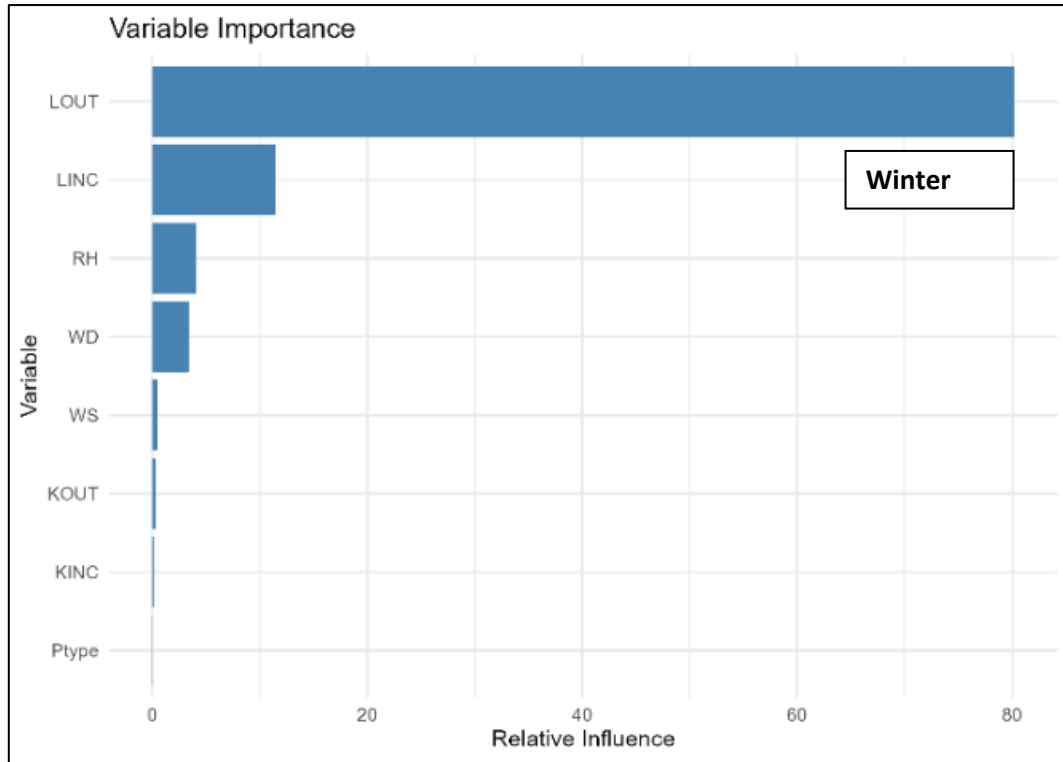


Fig.6 Relative influence of meteorological parameters on T during the winter season.

For RH , in winter and pre-monsoon seasons, L_{inc} has the highest importance (≈ 36 - 45%) and $Ptype$ is the second most influential parameter (≈ 41 - 46%). L_{inc} and $Ptype$ dominate the importance ranking, contributed the majority of the predictive capacity. T shows some significance ($\approx 6\%$), but far less than L_{inc} or $Ptype$. L_{out} , S_{inc} , S_{out} , wind direction, and wind speed all contribute very little (all $< 5\%$). These variables likely add minimal predictive value compared to the L_{inc} and $Ptype$. The model's predictions are driven mainly by L_{inc} and $Ptype$, meaning the target variable is strongly associated with radiation balance and $Ptype$. T still plays a role, but secondary. Other variables (wind speed, wind direction, outgoing radiation, etc.) are nearly negligible in terms of impact. The dataset may be heavily influenced by radiation and precipitation conditions, which could dominate the target (possibly precipitation intensity/type, evapotranspiration, or hydrological response). Less importance for wind and some radiation outputs suggests they are either collinear with the top variables or not strongly related to the modeled outcome.

With a significance score of $\approx 70\%$, L_{inc} dominates in the monsoon and post-monsoon seasons. This suggests that L_{inc} is the main factor influencing the model's prediction. $Ptype$ is the second most important (≈ 15 - 17%) and still relevant, it contributes far less than L_{inc} . T makes a small (≈ 4 - 5%) contribution. L_{out} , S_{inc} , S_{out} , wind speed, wind direction has very low relevance ($< 2\%$), indicating a negligible influence. It indicates that L_{inc} is the controlling driver of the process being modelled (likely related to surface energy balance or atmospheric

conditions). Since *Ptype*'s importance decreased here compared to winter and pre-monsoon, the aggregation to monthly values may be diluting the role of precipitation type, while radiation remains consistently influential. In the winter and pre-monsoon, both *L_{inc}* and *Ptype* were strong drivers (close to each other in importance). In this plot, *L_{inc}* dominates even more strongly, with *Ptype* and *T* dropping in relative significance. This change implies that *L_{inc}* the main explanatory factor when the model is trained/tested under this configuration. Other variables are almost negligible, meaning the model relies heavily on radiation balance rather than wind, temperature, or outgoing fluxes.

4.6 Comparison of Observed vs Predicted data

BRT is utilized to predict the *T* and *RH* at the station. The actual and predicted *T* and *RH* have been evaluated with the assistance of NSE, KGE and RMSE (Fig.7 & 8). The BRT has been run for different learning rate (*lr*) with constant Number of trees (*tn*=500) and Tree complexity(*tc*=4). The Fig. shows highest performance at higher value of *lr*. However, for low *lr*, the performance matrices are higher values. For *T*, the model has shown the perfect values for performance matrices at higher *lr*=0.05. While, for *RH*, modal reach the minimum performance matrices value when *lr* = 0.1. Temperature usually follows very strong diurnal and seasonal patterns with relatively smooth gradients. Because the relationship is more linear or predictable, a moderate *lr* (0.05) is sufficient for the 500 trees to map the pattern accurately without overcomplicating the model. *RH* is often more non-linear and sensitive to small changes in *T* and pressure. If *RH* required a higher *lr* (0.1) to reach peak performance, it suggests the model needed more aggressive updates to capture the sharper fluctuations or spikes in the *RH* data within the fixed limit of 500 trees.

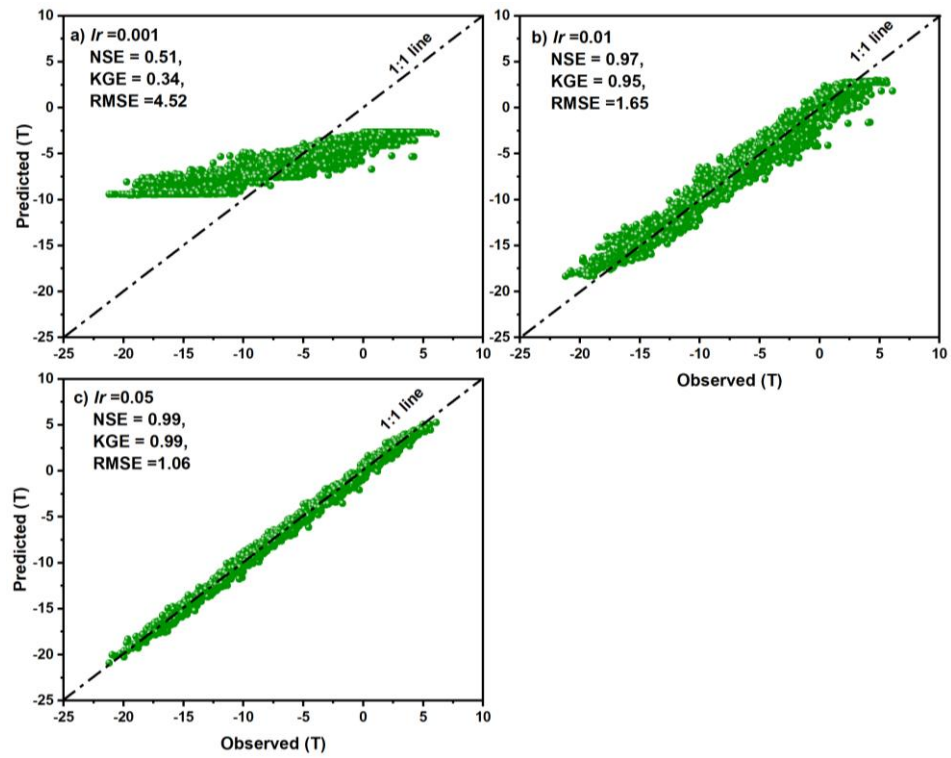


Fig.7 Comparison of observed and predicted T for **a)** $lr=0.001$, **b)** $lr=0.01$, and **c)** $lr=0.05$ for constant number of trees ($tn=500$) and tree complexity ($tc=4$)

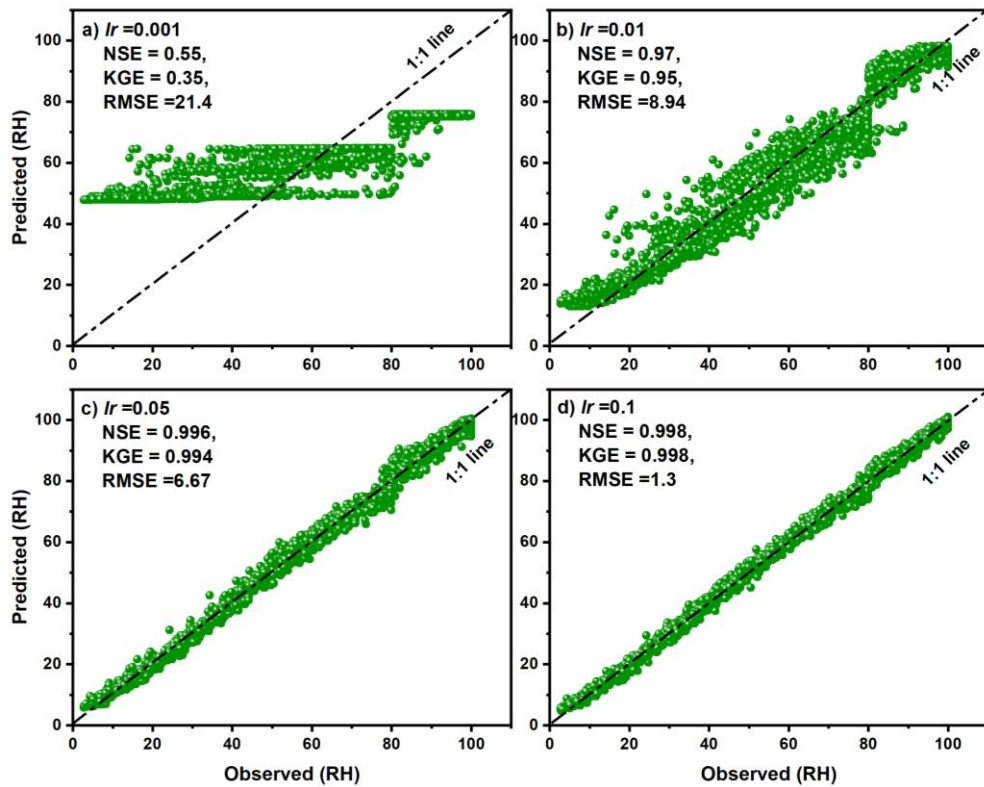


Fig.8 Comparison of observed and predicated RH for **a)** $lr=0.001$, **b)** $lr=0.01$, **c)** $lr=0.05$ and **d)** $lr=0.1$ for constant number of trees ($tn=500$) and tree complexity ($tc=4$)

4.7 Diurnal variation of meteorological parameters

The site has a glacier environment; the T is less than 0°C all the time and considered as a normal day (ND). However, there are occasions when the T increased above 0°C and these days are considered as a special day (SD). Here, the diurnal variation of T , RH and U represented for both ND and SD for better understating of the land atmosphere interaction at the site during different seasons (**Fig.9**). During ND, the T is below the 0°C throughout the day ($-8.6\pm 0.6^{\circ}\text{C}$). While in SD, T is above the 0 -degree and day mean $T\approx 1.3\pm 0.1^{\circ}\text{C}$. In ND, RH shows a variation of 20%-70%, while in SD, RH varies 80%-100%. The U shows a typical diurnal variation during ND, While, no typical pattern is manifested during SD. The wind speed is also less during SD compared to ND.

4.7.1 Diurnal T variation

For normal day, across all seasons, the T follows a diurnal cycle (**Fig.9a**). Lowest values during early morning hours (0000–0600 LT). Steady rise from ≈ 0700 LT, peaking between 1200–1400 LT. Gradual decrease after 1600 LT, returning to nighttime lows. Winter, generally warmer at night compared to other seasons (-10°C). Peak daytime temperature around -6°C . Pre-monsoon is slightly warmer than winter during the day. Peaks just above -6°C . Monsoon shows the highest daytime peak ($\approx -5^{\circ}\text{C}$). Clear warming trend relative to other seasons. Post-monsoon is the coldest, especially during night time ($\approx -12^{\circ}\text{C}$). Even at daytime peak, it stays cooler ($\approx -7^{\circ}\text{C}$). T variability is larger in monsoon and post-monsoon, especially around peak hours (1000–1600 LT). Winter and pre-monsoon show smaller variability, indicating more stable daily cycles. The diurnal warming pattern is consistent across all seasons, but absolute temperatures differ. Post-monsoon is the coldest season (both day and night). Monsoon is the warmest season during the day, likely due to higher cloud cover reducing nighttime cooling but allowing daytime warming. Winter nights are not as cold as post-monsoon nights, possibly due to atmospheric conditions such as stronger inversions or less radiative cooling. All seasons show a strong diurnal cycle.

Unlike the “Normal day”, in special day all temperatures are shifted upward (mostly above 0°C) (**Fig.9b**). This suggests a warmer background condition or event (possibly due to weather anomaly, heatwave, or external forcing). Early morning (0000–0600 LT), T remain near 0°C across all seasons. From ≈ 0700 LT, temperature rises sharply; reaching peak between 1100–1400 LT. Maximum T is about $3\text{--}3.5^{\circ}\text{C}$. After 1500 LT, gradual cooling occurs, returning close to 0°C by night. Pre-monsoon is the warmest among all seasons, with peak $\approx 3.5^{\circ}\text{C}$. Winter is slightly cooler than pre-monsoon but still above 2°C during peak hours. Monsoon has a lowest daytime peak ($\approx 2^{\circ}\text{C}$) among all, but still much warmer than its “normal day” counterpart. T variability is highest

around 1000–1400 LT in monsoon and pre-monsoon. Night (0000–0600 LT, 2000–2400 LT) show smaller variability, suggesting more stable conditions. In normal day scenario, all temperatures are below freezing (-12 to -5 °C range). Whereas, all temperatures are above freezing (0 to $+3.5$ °C range) in special day. This indicates that the “Special day” is likely influenced by an anomalous warming event. Oerlemans and Klok (2004b) reported a feedback factor of approximately four for the ablation zone of an alpine glacier, meaning the total impact on mass balance was about four times greater than the snowfall amount itself—primarily due to the high albedo of fresh snow, which reduces energy absorption and limits melt.

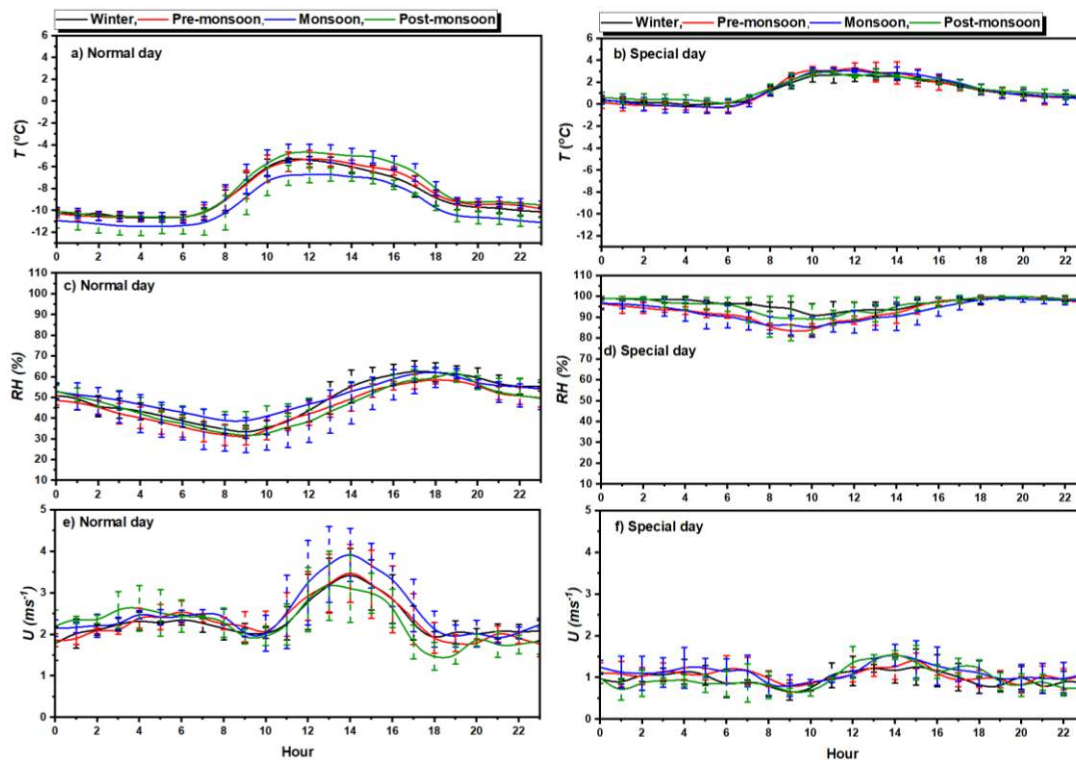


Fig.9 Normal and special day diurnal variation of T (a, b), RH (c, d), and U (e, f) for winter (in black), pre-monsoon (in red), monsoon (in blue) and post-monsoon (in green) and vertical bars represents the standard deviation.

4.7.2 Diurnal relative humidity

In **Fig.9c, d**, Seasonal diurnal RH variation is shown for normal and special day scenario. In night/early morning (0000–0600 LT), RH is relatively higher (≈ 45 – 55%). Morning to noon (0600–1000 LT), RH decreases steadily, reaching a minimum of ≈ 30 – 35% around 0900–1000 LT. Afternoon to evening (1200–2000 LT), RH increases again, peaking at ≈ 55 – 65% around 1700–1800 LT. Late evening/night (2000–2400 LT), slight decline or stabilization around 50 – 55% . This typical cycle reflects the inverse relation between T and RH : As temperature rises in the daytime, RH drops. As T falls in the evening, RH increases again. In monsoon, consistently highest

RH across the day (45–65%) and peak ~60–65% in evening. Winter shows a moderately high *RH*, closely following monsoon values (50–60%). Similarly, in post-monsoon, slightly lower than monsoon/winter during the day but still high. Pre-monsoon shows a lowest *RH* among all seasons (drops to ≈ 25 –30% at noon, peaks ≈ 50 %). Largest *RH* variation is observed in monsoon and winter evenings (1600–2000 LT). Pre-monsoon shows relatively tight error bars, suggesting more stable dry conditions. The diurnal *RH* cycle is strongly controlled by *T*; *RH* dips during daytime heating and recovers with evening cooling. Monsoon is most humid, as expected due to high rainfall and moisture. On a “Normal day,” *RH* varies between ~25% (minimum, noon, pre-monsoon) to ~65% (maximum, evening, monsoon). The diurnal cycle shows a midday dip and evening rise, directly tied to *T* variations. Seasonal contrasts are clear, with monsoon being most humid and pre-monsoon driest.

In Special day scenario, *RH* values are very high (80–100%) throughout the day, unlike the “Normal day” where values ranged 25–65%. Indicates extremely moist conditions, possibly during heavy rain, fog, or a moisture-laden system. Unlike the pronounced dip–rise diurnal cycle of the “Normal day,” the curve here is much flatter. Small dip between 0800–1200 h (*RH* ≈ 80 –85%), followed by recovery to near-saturation (≈ 95 –100%) in the evening and night. Suggests that *T* variations have limited impact on *RH* because the air is already near saturation. In winter and post-monsoon, remain consistently high (95–100%) with minimal fluctuation. Pre-monsoon shows a slightly lower midday *RH* (≈ 85 %), but rises back near 95% by night. Monsoon shows the lowest daytime dip (≈ 80 –82% around noon). Daytime (0800–1400 LT) shows larger *RH* variability, especially in monsoon and post-monsoon. Nighttime values are more stable, suggesting uniform near-saturation conditions. On a Special day, atmospheric conditions are exceptionally humid across all seasons. The near-saturation *RH* values (95–100%) suggest events like: Heavy rainfall or persistent cloud cover, fog formation, synoptic-scale moisture influx.

4.7.3 Diurnal Wind Speed (*U*)

Wind speed (*U*) remains relatively low and steady in the early morning (0000–0800 LT), hovering around 2–2.5 m/s. After 0900 LT, wind speed begins to rise gradually (**Fig.9e**). The peak is observed in the afternoon (1300–1600 LT), reaching up to 3.5–4 m/s depending on the line. Following 1700 LT, wind speed declines, returning to near the baseline (≈ 2 m/s) by 2000–2400 LT. Error bars represent variability/uncertainty in wind speed measurements. They are larger during the afternoon peak hours (1200–1600 LT), indicating higher variability or stronger turbulence when winds are stronger. In early morning and late night, error bars are smaller, indicates more stable wind conditions. All follow the same diurnal trend (morning low, afternoon peak, evening decline). The blue line shows the highest afternoon peak, while the green line remains slightly lower. Differences among

lines are most pronounced during the afternoon peak period, but minimal during nighttime. This is a diurnal wind speed cycle typical of boundary-layer meteorology: Morning low winds due to stable stratification. Afternoon peak driven by solar heating, convective mixing, and stronger momentum transfer. Evening decline with cooling and stabilization of the boundary layer. The higher variability in the afternoon suggests gusty or turbulent winds, possibly linked with convective activity.

Wind speeds are much lower on the special day compared to the normal day (**Fig.9f**). Range from ≈ 0.6 to 1.6 m/s, versus ≈ 2 to 4 m/s in the normal case. The diurnal variation is muted; no strong afternoon peak is observed. Wind speeds remain nearly flat throughout the day, with only a small bump around 1300–1500 LT (peaking just above 1.5 m/s). Error bars are present but smaller than in the normal day case. This indicates more stable conditions and less turbulent wind fluctuations. The absence of large error bars in the afternoon suggests reduced convective mixing. All lines (blue, red, green, black) track very closely with minimal separation. This suggests that under “special day” conditions, spatial or conditional differences among the compared cases are negligible. In contrast, on a normal day, different lines diverged more strongly in the afternoon. The “special day” appears to represent a low-wind and stable atmospheric condition indicates the cloudy or precipitation conditions suppressing solar heating causes weaker convective mixing. The boundary layer likely remains shallow and stable. On a “special day,” wind speeds are consistently weak (≈ 1 m/s), with little diurnal variation and low variability. This contrasts with the “normal day,” where wind speeds peak strongly in the afternoon ($3\text{--}4$ m/s) due to solar-driven boundary layer mixing.

4.8 Diurnal variation of energy flux

4.8.1 Incoming shortwave radiation (S_{inc})

S_{inc} at the site for two different atmospheric weather conditions is shown in **Fig. 10**. S_{inc} begins to rise around 0600–0700 LT and peaks at $\approx 1200\text{--}1300$ LT with $\approx 850\text{--}950$ W/m². Declines symmetrically, dropping to near zero by 1800 LT. The Highest peak radiation ≈ 950 W/m² is observed during the pre-monsoon season and indicates a clear-sky conditions and strong solar insolation. In monsoon, the S_{inc} peak is ≈ 900 W/m² and likely reduced by cloud cover and atmospheric moisture. In winter and post monsoon, the S_{inc} peak is varied from 850-900 W/m². Shorter day length also evident curve narrower compared to summer seasons. The largest variability in S_{inc} is observed around midday (1000–1400 LT) when solar input is highest and strongest. Pre-monsoon and monsoon show more variation, likely owing to the higher influence of cloud cover or atmospheric variability. Winter shows smaller variability, suggesting more stable clear-sky days. The S_{inc} cycle drives the diurnal T and RH patterns observed in **Fig.9a, c**. In pre-monsoon, the maximum S_{inc} leads to strong heating, driest conditions (Fig).

While, lower S_{inc} caused the clouds/haze, even though the day length is long. Variability is greatest during peak hours, linked to cloudiness and atmospheric disturbances.

Maximum solar radiation on special days is much lower ($\approx 500\text{--}600\text{ W/m}^2$) compared to normal days ($\approx 900\text{--}1000\text{ W/m}^2$). This suggests strong atmospheric attenuation – likely due to dense clouds, haze, fog, and precipitation events. Radiation begins rising around 0600 LT, peaks around 1200–1300 LT, and falls back to zero near 1800 LT. Shape is flatter and less symmetric than normal days, which indicates the interrupted sunlight due to clouds. Highest peak among special days ($\approx 550\text{ W/m}^2$), but with large variability (tall error bars). Reflects intermittent cloud breaks and precipitation events. In pre-monsoon, the lower peak of $S_{inc} \approx 500\text{ W/m}^2$, possibly due to cloud, fog, that are typical of this season. Similar magnitude ($\approx 480\text{--}500\text{ W/m}^2$), may represent fog events reducing radiation in winter. The Peak ($\approx 520\text{ W/m}^2$), slightly higher than winter and pre-monsoon, possibly linked to residual cloudiness or haze in post-monsoon. The higher variation is exhibited during midday (1000–1400 LT). Indicates that special days are highly variable due to transient clouds or weather events. Special days are characterized by suppressed solar radiation (only $\approx 50\text{--}60\%$ of normal day values). The reduction is linked to atmospheric disturbances like Fog events, thick cloud cover and precipitation. This directly impacts the energy balance, reducing heating and influencing the T and RH cycles seen in **Fig.9b, d**. Special days show flattened, weaker solar radiation curves across all seasons.

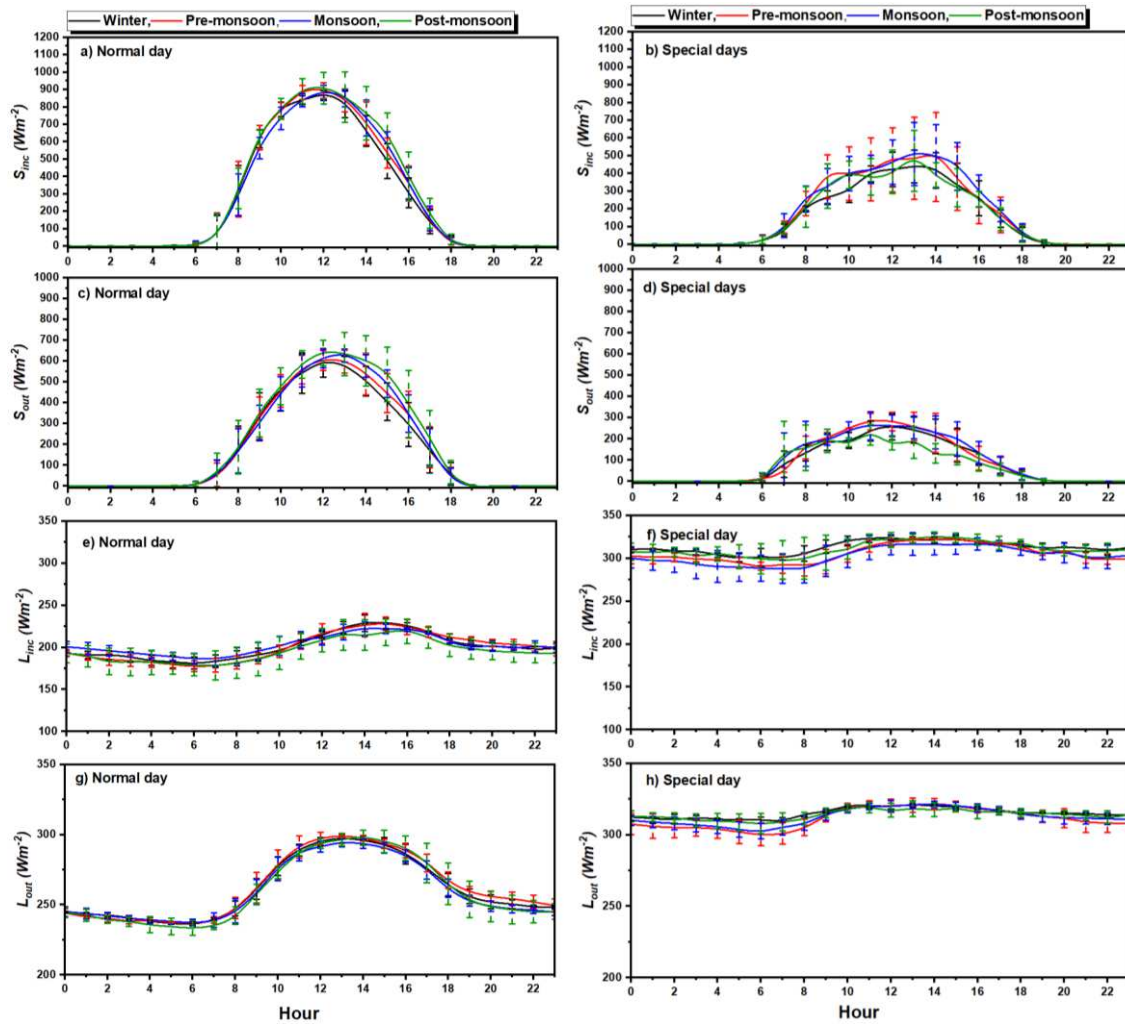


Fig.10 Normal and special day diurnal variation of S_{inc} (a, b), S_{out} (c, d), and L_{inc} (e, f) and L_{out} (g, h) for winter (in black), pre-monsoon (in red), monsoon (in blue) and post-monsoon (in green) and vertical bars represents the standard deviation.

4.8.2 Shortwave outgoing radiation (S_{out})

The curve follows a clear bell-shaped pattern, similar to S_{inc} . Rapid increase after sunrise, peaking around midday (1200–1400 LT), then decreasing towards sunset. High outgoing radiation due to stronger S_{inc} and higher surface heating is occurred in pre-monsoon. Peak slightly below post-monsoon but higher than winter. Outgoing radiation is somewhat lower, reflecting reduced S_{inc} due to cloud cover in monsoon. In post-monsoon, the highest peaks, suggesting clear-sky conditions and strong reflection from the surface owing to snow or ice surface. Larger variability (error bars wider), possibly due to mixed clear/cloudy days. Winter shows the lowest outgoing radiation due to weaker solar incidence and cooler surface conditions. Peak S_{out} is around 550–650 W/m² at noon. This is consistently lower than peak S_{inc} ($\approx$ 900–1000 W/m² on normal days), indicating partial absorption and retention of energy at the surface. S_{out} daytime variability, particularly in post-monsoon and monsoon seasons. Likely due

to fluctuations in sky conditions (cloudiness, haze, or moisture). On normal days, S_{out} shows a tight coupling with S_{inc} , but at a lower magnitude. Seasonal variation reflects surface–atmosphere energy exchange. In winter, a weaker radiation due to low solar angles. While in pre-monsoon, a strong heating and clear skies leads higher S_{out} . The suppressed S_{out} is observed due to cloud cover in monsoon. In post-monsoon, the clear sky conditions enhance outgoing radiation, sometimes exceeding pre-monsoon levels.

In special day scenario, the diurnal curve is present, but the magnitude is much lower than on normal days. Outgoing radiation rises after sunrise (≈ 0600 – 0700 LT), peaks between 1100 – 1300 LT, and drops back near zero after 1800 LT. Maximum peaks are only around 200 – 300 W/m^2 , compared to 550 – 650 W/m^2 on normal days. Pre-monsoon shows the highest peaks on special days (≈ 280 W/m^2). Suggests relatively clearer conditions than other seasons, though still reduced compared to normal days. In monsoon, peaks near 220 – 250 W/m^2 , but shows high variability (large error bars). Likely reflects dense cloud cover and intermittent clearing, reducing radiation escape. Post-monsoon shows the lowest outgoing values, with maxima <200 W/m^2 . Likely, due to persistent atmospheric moisture, haze, or cloud layers trapping radiation. Winter shows a peak around 200 – 230 W/m^2 , lower than pre-monsoon but comparable to monsoon. Stable pattern with relatively narrow error bars (consistent sky conditions). Large variability in monsoon and post-monsoon, reflecting unstable atmospheric conditions (cloud thickness, water vapor). Winter and pre-monsoon shows more consistent patterns. On special days, S_{out} is suppressed by ≈ 50 – 70% compared to normal days. This reduction indicates greater atmospheric scattering, absorption, or blocking by clouds and precipitation events. Special days show a drastic reduction in surface energy loss to the atmosphere, implying that cloud cover, or unusual weather events significantly alter the surface–atmosphere radiative balance compared to normal days.

4.8.3 Longwave incoming radiation (L_{inc})

Unlike solar radiation (S_{inc} and S_{out}), longwave radiation does not drop to zero at night because it is continuously emitted by the Earth–atmosphere system. The values remain relatively steady between 180 – 230 W/m^2 throughout the day. A small diurnal variation is observed, slight dip in the early morning (≈ 0500 – 0700 LT). Gradual increase after sunrise, peaking around 1400 – 1600 LT (≈ 220 – 230 W/m^2). Decline again during the night. Monsoon consistently higher L_{inc} across the day (≈ 200 – 230 W/m^2). Indicates higher atmospheric humidity and cloud cover, which enhance downward longwave emission. In Pre-monsoon, intermediate values (≈ 190 – 220 W/m^2). Stronger diurnal cycle than monsoon, consistent with clearer skies but higher surface heating. Lower values (≈ 185 – 210 W/m^2), but stable with narrow error bars during winter. Reflects dry and cooler atmospheric conditions with less water vapor. In post-monsoon, lowest values (≈ 170 – 210 W/m^2), especially during nighttime. Suggests relatively

dry air and less greenhouse trapping effect. L_{inc} is a function of atmospheric water vapor, cloud cover, and temperature. In normal days, monsoon season dominates with the highest incoming longwave due to moist/cloudy atmosphere. Post-monsoon & winter have the lowest, reflecting drier skies. The small diurnal cycle is driven by surface heating during the day, which warms the lower atmosphere and increases downward longwave flux. On normal days, incoming longwave radiation is highest during the monsoon due to moisture and clouds, and lowest during winter/post-monsoon due to dry conditions. The overall variation is much smaller than solar fluxes, highlighting the more stable role of atmospheric longwave radiation.

The diurnal curve is present, but the magnitude is much lower than on normal day. Outgoing radiation rises after sunrise (~0600–0700 LT), peaks between 1100–1300 LT, and drops back near zero after 1800 LT. Maximum peaks are only around 200–300 W/m², compared to 550–650 W/m² on normal days. Among the highest peaks on special days ($\approx$ 280 W/m²) during pre-monsoon. Suggests relatively clearer conditions than other seasons, though still reduced compared to normal days. In monsoon, peaks near 220–250 W/m², but shows high variability (large error bars). Likely reflects dense cloud cover and intermittent clearing, reducing radiation escape. Post-monsoon shows the lowest outgoing values, with maxima <200 W/m². Likely due to persistent atmospheric moisture, haze, or cloud layers trapping radiation.

4.8.4 Longwave outgoing radiation (L_{out})

Values range from about 230–300 W/m². Minimum in the early morning (~0500–0700 LT, ~230–240 W/m²). Maximum in the afternoon (~1200–1500 LT, ~295–300 W/m²). This pattern reflects the surface thermal emission cycle, strongly tied to surface temperature. During night/early morning, lowest values due to surface cooling. Rapid rise after 0800 LT, peaking at midday when land temperature is highest. Decline after sunset. Shape matches expected surface longwave emission. In pre-monsoon, slightly higher L_{out} during the day, reflecting hotter land surface. During monsoon, a bit lower daytime values due to cloud shading and soil moisture cooling. Winter and post-monsoon, closer to each other, generally lower than pre-monsoon but higher than monsoon in some hours. Small error Bars, small to moderate spread across seasons, especially in the afternoon. Suggests daily variability in surface heating efficiency (clouds, soil moisture, aerosols). On normal days, L_{out} is strongly temperature-driven. Maximum emission aligns with afternoon surface heating.

The flux is consistently higher than in normal days, ranging 300–320 Wm⁻², with smaller diurnal amplitude. Unlike the pronounced peak (~295 Wm⁻² around noon) in normal days, here the curve remains nearly flat, indicating suppressed daytime variation. In nighttime, values remain high (around 310–315 Wm⁻²), showing less nocturnal cooling compared to normal days. Small error bars, suggesting stable conditions across

measurements. This flattening pattern is typical of cloudy/overcast days, where longwave radiation dominates and shortwave exchange is suppressed. Clouds trap outgoing radiation, elevating nighttime fluxes and muting daytime peaks. Higher night-time values indicate the stronger greenhouse trapping effect. Daytime values suppressed compared to normal days. On special days, L_{out} is elevated and uniform, reflecting enhanced atmospheric back-radiation and reduced radiative cooling. On normal days, L_{out} follows solar forcing more closely, showing a clear diurnal cycle.

5 Conclusion

Across all four seasons, relative humidity (RH) stands out as the most dominant and immediate driver of snowfall, consistently peaking at Lag 0 ($r \approx 0.38$ to 0.40) to indicate a near-instantaneous response to air saturation, though its influence becomes more sustained during the monsoon and lingers longest into post-monsoon. Solar incoming radiation (S_{inc}) consistently displays an inverse relationship with snowfall due to daytime heating and evaporation, showing a delayed negative response (Lag +1 to +2) in winter and pre-monsoon, an immediate cloud-cover effect negative peak at Lag 0 in the monsoon, and a significantly weakened impact in the cooler post-monsoon phase. Dew point temperature (T_d) serves as a steady, positive background predictor across a multi-lag window in all seasons, while ambient temperature (T) transitions from the weakest, barely significant predictor in winter and pre-monsoon to a strongly negative, statistically significant inhibitor of snowfall during the monsoon and post-monsoon periods.

Seasonal quadrant analysis of temperature (T) and relative humidity (RH) demonstrates that precipitation is strictly confined to high-moisture states ($RH > 80\%$), where sub-zero temperatures (Quadrant 2) trigger green-coded snowfall events and near-freezing temperatures (Quadrant 1) yield mixed or freezing precipitation. Winter displays the most active precipitation signatures, with widespread snowfall clustered between -10°C and 0°C alongside rare freezing rain and ice-pellet mixes near the freezing line, while pre-monsoon transitions into a heavily dry-dominated state (yellow points) with only sparse, scattered cold-weather events due to rising temperatures. Moisture rebounds significantly during the monsoon, shifting non-precipitating yellow points to higher humidity levels (50%-90%) and creating a much denser, more active sub-zero green cluster alongside more frequent freezing precipitation near 0°C . Finally, the post-monsoon environment acts as a stabilizing phase, mimicking pre-monsoon's widespread dryness across lower humidity levels (0%-80%) while retaining a moderately dense but fading winter-like snowfall cluster. All the snowfall events distributed in two T range i.e. T1 ($-18^\circ\text{C} - -5.1^\circ\text{C}$) and T2 ($-5^\circ\text{C} - 0^\circ\text{C}$). In T1, 40%, 49.9%, 50.5% and 60% of snowfall events are occurred during winter, pre-monsoon, monsoon and post-monsoon, respectively. Similarly, in T2, 60%, 50.1%, 49.5% and

40% snowfall events occurred during winter, pre-monsoon, monsoon and post-monsoon, respectively. It is observed that the mean RH $86.5 \pm 0.9\%$ and $94.5 \pm 0.3\%$ is required to occur snowfall in the T1 and T2 range, respectively. Similarly, L_{out} (268 ± 3 Wm⁻² and 300 ± 1 Wm⁻²) and T_d ($-12.7 \pm 0.9^\circ\text{C}$ and $-3.3 \pm 0.2^\circ\text{C}$) also varies in T1 and T2.

Boosted Regression Tree (BRT) modeling reveals that temperature (T) variations are overwhelmingly driven by outgoing longwave radiation (L_{out}), which maintains an identical seasonal dominance with an importance score of ≈ 65 -80%, while relative humidity (RH) dynamics are primarily controlled by incoming longwave radiation (L_{inc}) and precipitation type ($Ptype$). The predictive structure for RH splits clearly by season: during winter and pre-monsoon, $Ptype$ (≈ 41 -46%) and L_{inc} (≈ 36 -45%) share near-equal dominance as primary drivers, whereas during the monsoon and post-monsoon periods, L_{inc} surges to solo dominance at approx. 70% while $Ptype$ drops to a secondary role (≈ 15 -17%). Across all modeled scenarios, ambient temperature (T) maintains only a minor influence (≈ 4 -6%), while factors like wind speed, wind direction, and shortwave radiation fluxes prove nearly negligible, indicating that the atmospheric system's thermal and moisture profiles are fundamentally tied to the longwave radiation balance and precipitation states.

In normal days, strong diurnal cycles are observed in T , S_{inc} , S_{out} , and L_{out} . Lower nighttime RH and radiation values, which shows a distinct heating/cooling contrast. Conversely, on Special days, an anomalous warming event shifts the entire seasonal background well above freezing point. And indicates that in the normal day snowfall depositing increases the glacier mass while the special day scenario contributes towards the glacier mass reduction.

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Nilamoni Barman: Conceptualization, Methodology, Software, Writing-Original draft preparation, all figures, Writing-Reviewing, and Editing; The author is agreed to submit it to the journal.

Data availability:

The data of meteorological data can be acquired from the International Centre for Integrated Mountain Development (ICMOD) (<https://rds.icimod.org>), Kathmandu, Nepal

Declarations

Ethics approval:

Not Applicable

Consent to participate:

753 Not Applicable

754 **Consent for publication:**

755 The author hereby grants permission for the above-mentioned manuscript to be published, collectively with any
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765 I declare that the author has no competing interests as defined by Springer, or other interests that might be
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767

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