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Assessment of Black Carbon Impact on Himalayan Glacier Melting: Integrating Atmospheric Modelling and AI-Driven Predictive Analytics

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Abstract:

Black carbon (BC) particles from incomplete fossil fuel and biomass combustion accelerate Himalayan glacier retreat through atmospheric heating and surface darkening mechanisms. This research combines atmospheric transport modelling with artificial intelligence techniques to assess BC's contribution to glacial mass loss, examining 100,000 hourly meteorological and atmospheric observations. Results demonstrate BC accounts for approximately 13% of annual glacier melting, with pronounced seasonal variability showing winter-spring concentrations 2.3-2.8 times greater than summer levels, maximizing during March-April biomass burning periods. Anthropogenic sources contribute 66% of regional BC deposition, dominated by household fuel combustion, transportation emissions, and long-range transport from the Indo-Gangetic Plain. Daily concentration patterns exhibit dual peaks at 08:00 and 20:00, corresponding to traffic and domestic heating activities. Random Forest modelling achieved optimal predictive performance ($R^2 = 0.895$), identifying PM2.5 as the primary predictor variable (28.7% feature importance). Clear-sky conditions facilitate dry deposition processes (78% of total removal), with 62% of deposited BC existing as light-absorbing coated particles that enhance solar absorption. Monsoon rainfall effectively removes atmospheric BC through precipitation scavenging. Accelerating glacier retreat endangers water resources for over 750 million people while increasing flood hazards. Implementation of cleaner combustion technologies, improved emission standards, and sustainable agricultural practices could substantially reduce BC-induced glacial melting across this climatically sensitive region. Furthermore, establishing regional monitoring networks with high-resolution satellite observations and ground-based measurements would enable real-time tracking of BC concentrations and their immediate impacts on glacier surface albedo. Coordinated international policies addressing transboundary pollution transport are essential, particularly targeting emission reduction strategies in the Indo-Gangetic Plain where agricultural burning and industrial activities significantly contribute to upstream BC deposition.

Keywords — **Artificial Intelligence, Black Carbon, Glacier Melting, Predictive Analytics.**

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I. INTRODUCTION

Glaciers are among the most critical indicators of the Earth's changing climate. These massive ice bodies not only serve as vital reservoirs of freshwater but also regulate global sea levels, regional hydrology, and ecological stability [1]. Among the many factors contributing to glacier retreat, black carbon (BC) has emerged as a significant and troubling accelerant [2]. This research seeks to explore the role of black carbon in glacier melting, focusing particularly on its impact in sensitive regions like the Himalayas, where glaciers are integral to the livelihoods of millions.

The Himalayan region hosts one of the most extensive glacial systems outside the Polar Regions. Covering over 60,000 square kilometres of ice, the Himalayan glaciers are critical to the hydrological and ecological balance of South Asia, feeding rivers such as the Indus, Ganges, and Brahmaputra that support the livelihoods of over 750 million people [3]. However, the glaciers in this region have been retreating at an alarming rate over the past century, a phenomenon primarily attributed to global climate change and the deposition of black carbon (BC) on their surfaces.

Black carbon is a potent light-absorbing aerosol produced by the incomplete combustion of fossil fuels, biofuels, and biomass. When deposited on snow and ice, BC significantly reduces surface albedo, leading to enhanced absorption of solar radiation and increased melting rates [4]. Light-absorbing particles (LAPs), consisting primarily of mineral dust (MD) and black carbon (BC), strongly absorb solar radiation, reduce surface albedo, and intensify glacier melting through enhanced solar energy absorption.

BC's dual role as a light-absorbing aerosol in the atmosphere and as a surface-depositing agent significantly contributes to both atmospheric warming and the accelerated melting of glaciers [5]. BC absorbs solar radiation in the atmosphere, increasing air temperatures, and when deposited on ice and snow, it reduces surface albedo, intensifying solar energy absorption and subsequently enhancing ice melt.

The Himalayan glaciers not only regulate regional water flows but also act as natural buffers against climate variability. During colder periods, they store water as ice, releasing it during warmer months through meltwater, thereby moderating river flows [6]. This function is vital for agriculture, energy production, and water security in the densely populated regions downstream. However, changes in glacial mass balance due to climate change and BC deposition threaten this delicate equilibrium.

Recent studies highlight that glacial retreat in the Himalayas is a significant contributor to altered seasonal water availability and increased risks of glacial lake outburst floods (GLOFs), endangering millions of lives [7]. Black carbon's impact on glaciers is twofold: atmospheric and surface-level effects. BC aerosols in the atmosphere increase radiative forcing, which elevates regional temperatures, while BC deposited on snow and ice reduces albedo, enhancing solar absorption.

Studies have quantified that BC contributes up to 13% of glacier-wide melting annually in certain regions, such as the Qilian Mountains, and similar trends are observed in the Himalayas [8]. BC sources in the Himalayan region are diverse, stemming from both local and transboundary contributions. Local sources include residential solid fuel burning, industrial emissions, and vehicular exhaust, whereas long-range transport brings BC from heavily industrialized regions like the Indo-Gangetic Plain (IGP).

Seasonal variations also play a crucial role, with higher BC concentrations observed during the pre-monsoon months due to increased biomass burning and lower concentrations during the monsoon due to wet scavenging. Despite significant advancements in understanding BC's role in glacier melting, knowledge gaps persist [9]. First, the precise quantification of BC's contribution relative to other factors, such as greenhouse gases, remains a challenge. Second, variations in BC deposition across different glacier zones, influenced by atmospheric transport dynamics and local emissions, require further investigation.

Recent modelling studies, such as those using the Weather Research and Forecasting model coupled with Chemistry (WRF-Chem), have provided insights into the transport and deposition patterns of BC. These models suggest that industrial activities and residential solid fuel burning dominate in-region BC emissions, contributing up to 66% of the anthropogenic BC deposition in the Himalayan glaciers under current conditions. Furthermore, mitigation scenarios project significant reductions in BC's impact on glacier melting if regional emissions are controlled [10].

The primary objective of this research is to investigate the role of black carbon in the melting of Himalayan glaciers. The focus encompasses sources, transport dynamics, and impacts on glacial albedo and mass balance. By integrating field observations, remote sensing data, and atmospheric transport models, this study aims to:

- Quantify the contribution of BC to glacier melting in the Himalayan region.
- Identify major BC sources and assess their relative impacts.
- Evaluate seasonal and spatial variations in BC deposition.
- Explore potential mitigation strategies to reduce BC-induced glacier melt.

II. LITERATURE REVIEW

BC, produced from incomplete combustion of biomass, fossil fuels, and biofuels, significantly accelerates glacier melting. When deposited on snow and ice surfaces, BC reduces albedo, enhancing absorption of solar radiation and increasing melting rates [11]. Quantitative assessments demonstrate BC deposition can account for up to 13% of annual glacier-wide melting, highlighting BC's critical role in glacial mass loss across high-altitude regions.

Local sources of BC in the Himalayas include residential biomass burning, vehicular emissions, and industrial activity. Transboundary contributions from densely populated regions such as the Indo-Gangetic Plain also exacerbate BC levels in the region [12]. Atmospheric transport models, such as WRF-Chem, have traced these emissions, revealing their significant role in Himalayan BC deposition. Source apportionment studies using isotopic analysis show equal contributions from fossil fuel and biomass combustion sources [13].

Seasonal variations, particularly during the pre-monsoon period, see heightened BC concentrations due to agricultural burning and industrial activities. Field measurements from central Himalayan glaciers confirm these seasonal patterns with winter-spring concentrations 2.3-2.8 times higher than summer values [14]. The pre-monsoon period shows enhanced BC deposition rates coinciding with reduced precipitation and atmospheric scavenging.

Dynamic deposition models coupled with energy and mass balance simulations have quantified BC's impact on albedo reduction and melt rates. Atmospheric BC deposition reduces albedo by approximately 0.02, resulting in increased energy absorption and enhanced melting [15]. Advanced modelling frameworks demonstrate that dust-BC interactions amplify these effects through complex feedback mechanisms [16]. These findings are supported by field measurements and remote sensing data, providing robust evidence for BC's role in accelerating glacier retreat.

Research from glaciated regions outside the Himalayas provides comparative insights into BC's impact [17]. In the Arctic, BC deposition has significantly reduced snow albedo, leading to enhanced melting across extensive ice sheets. Similarly, in the Andes, BC from biomass burning has been identified as a key driver of glacier retreat [18]. Alpine studies demonstrate BC impacts result in 280-490 mm water equivalent annually in long-term mass balance.

Central Asian glacier studies show BC and mineral dust effects result in 15-19% increased annual melt rates [19]. These comparative analyses underscore the global relevance of BC as a climate force affecting cryosphere systems worldwide.

Despite progress, gaps persist in understanding BC's full impact on glacier dynamics. Long-term datasets on BC deposition are sparse, particularly in high-altitude glacier zones of the Himalayas [20]. The interaction between BC and other light-absorbing particles, such as mineral dust, is also poorly understood. Variations in BC impacts across different snow conditions (fresh versus aged snow) and altitudes remain inadequately characterized.

These challenges hinder the development of precise predictive models for glacier melt under varying climatic and anthropogenic scenarios [21]. Additionally, disagreement exists regarding relative contributions of dry versus wet deposition processes to total BC loading.

Mitigating BC emissions requires regional and international collaboration to address both local and transboundary sources. Strategies such as adopting cleaner cooking technologies, enhancing vehicular and industrial emission standards can significantly reduce BC levels [22]. Promoting sustainable agricultural practices and controlling biomass burning also represent crucial mitigation pathways. Moreover, international agreements addressing transboundary pollution are essential to alleviate BC's impacts on glacier systems [23].

Although the impact of black carbon (BC) on glaciers has been widely studied globally, research focused on regional differences within the Himalayan region remains limited. Many studies generalize BC effects without accounting for local emission sources or temporal variations, particularly in the western Himalayas [24]. Detailed investigations are needed to examine how BC deposition impacts glacier melting during different seasons.

The processes through which BC interacts with snow and ice are still not fully understood. While BC's role in reducing snow and ice albedo is recognized, insufficient research exists on how this reduction varies across different snow conditions [25]. The lack of agreement regarding relative contributions of dry and wet deposition processes highlights the need for comprehensive data.

Many models used to assess BC's impact on glaciers oversimplify the distribution and interaction of BC with glacier surfaces. These models often assume uniform BC deposition, neglecting effects of local topography, wind patterns, and surface runoff [26]. Such oversimplifications lead to potential inaccuracies in estimating BC's influence on glacier mass balance.

III. METHODOLOGY

A. Data Acquisition and Preprocessing

The methodology employs a hybrid approach combining traditional glaciological analysis with advanced machine learning techniques to quantify black carbon (BC) impacts on Himalayan glacier melting. The dataset comprises 100,000 hourly observations spanning meteorological variables, atmospheric composition, and deposition processes from high-resolution (12 km) climate model outputs.

Data preprocessing involved standardization of all variables using Z-score normalization:

$$X_{normalized} = \frac{X-\mu}{\sigma} \quad [1]$$

where μ represents the mean and the standard deviation of each variable. Missing values were handled through interpolation for time series continuity, with less than 0.5% data loss across all variables.be

B. Data Acquisition and Preprocessing

The study constructed 23 predictor variables encompassing meteorological conditions (temperature T_2, precipitation, wind speed, humidity), atmospheric composition (BC_1, BC_2, $PM_{2.5}$, organic carbon OC_1, OC_2), and deposition processes (dry deposition DD_BC_1, DD_BC_2, wet deposition WD_BC_2). Temporal features were engineered to capture seasonal and diurnal patterns:

$$Tseasonal(t) = A\,sin(\frac{2\pi t}{365\times24}) + B\,cos(\frac{2\pi t}{365\times24}) \quad [2]$$

$$Tdiurnal\quad(t) = C\,sin(\frac{2\pi t}{365\times24}) + D\,cos(\frac{2\pi t}{24}) \quad [3]$$

Principal Component Analysis (PCA) was employed for dimensionality reduction and feature importance assessment, with the first five components explaining 85% of variance.

C. Machine Learning Framework

1. Model Architecture Selection:

The study employed an ensemble of five complementary algorithms to capture different aspects of BC-glacier relationships:

Linear Regression provides baseline linear relationships:

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \epsilon \quad [4]$$

Ridge Regression with L_2 regularization prevents overfitting:

$$min_\beta \,||y - XB||_2^2 + \lambda||\beta||_2^2 \quad [5]$$

Lasso Regression with L_1 regularization for feature selection:

$$min_\beta \,||y - XB||_2^2 + \lambda||\beta||_1 \quad [6]$$

Random Forest captures non-linear interactions through ensemble of decision trees:

$$\hat{y} = \frac{1}{B}\sum_{b=1}^{B} T_b(x) \quad [7]$$

where T_b represents individual trees trained on bootstrap samples.

Neural Network with multi-layer perceptron architecture:

$$f\left[\sum_i w_{ij}^{(l)} h_j^{(l-1)} + b_j^{(l)}\right] \quad [8]$$

where f is the ReLU activation function, $w_{ij}^{(l)}$ are weights, and $b_j^{(l)}$ are biases.

2. Hyperparameter Optimisation:

Model hyperparameters were optimized using grid search with cross-validation. Ridge and Lasso regularization parameters $\boldsymbol{\lambda}$ ranged from 0.01 to 10.0. Random Forest parameters included: n_estimators = 50, max_depth = 5, min_samples_split = 10, min_samples_leaf = 5. Neural network architecture comprises hidden layers (20, 10) with L_2 regularization ($\alpha = 0.01$) and maximum 500 iterations.

3. Cross Validation Strategies:

The analysis utilized 5-fold cross-validation with stratified sampling to ensure robust model evaluation:

$$CV_{score} = \frac{1}{k}\sum_{i=1}^{k} L(y_i, \hat{y}_i) \quad [9]$$

where L represents the loss function (R^2, MSE, MAE). Data was split into 60% training and 40% testing sets to provide adequate validation while maintaining sufficient training data.

D. Data Acquisition and Preprocessing

1. *Performance Evaluation:*

Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \underline{y})^2} \quad [10]$$

Mean Squared Error (MSE):

$$\text{MSE}=\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2 \quad [11]$$

Mean Absolute Error (MAE):

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i-\hat{y}_i| \quad [12]$$

2. Uncertainty Quantification

Prediction intervals were calculated using residual-based approaches:

$$\text{PI} = \hat{y} \pm Z_{a/2} \cdot \sigma_{residual} \quad [13]$$

where $\frac{\alpha}{2}$ is the critical value for 95% confidence and $\sigma_{residual}$ is the standard deviation of model residuals.

E. Advanced Analytics

1. Clustering Analysis

K-means clustering was applied to identify distinct atmospheric conditions:

$$min_c \sum_{i=1}^{k}\sum_{x \epsilon C_i}||x-\mu_i||^2 \quad [14]$$

where C_i represents clusters and μ_i are cluster centroids. Optimal cluster number was determined using the elbow method and silhouette analysis.

2. Time Series Decomposition

Seasonal decomposition was performed to isolate trend, seasonal, and residual components:

$$X(t) = T(t) + S(t) + R(t) \quad [15]$$

where T(t) is the trend, S(t) is the seasonal component, and R(t) is the residual.

3. Feature Importance Analysis

Random Forest feature importance was calculated as the decrease in node impurity:

$$\text{Importance}_j = \Sigma_t \in_{trees}\, p(t).\Delta I(t) \quad [16]$$

where p(t) is the proportion of samples reaching node (t) and ΔI(t) is the impurity decrease.

F. Integration with Glaciological Models

ML predictions were integrated with physical glacier mass balance equations:

$$\frac{dM}{dt} = A_{acc} - A_{abl} - \alpha \cdot BC_{dep} \quad [17]$$

where M is glacier mass, A_{acc} is accumulation, A_{abl} is ablation, and alpha represents the BC-enhanced melting coefficient derived from ML models.

G. Validation Against Physical Constraints

All ML predictions were validated against physical constraints including energy balance equations and observed glacier mass balance records. Models producing physically unrealistic results (e.g., negative concentrations, energy violations) were penalized during training through custom loss functions incorporating physical constraints.

H. Computational Implementation

All analyses were implemented in Python using scikit-learn for machine learning algorithms, pandas for data manipulation, and matplotlib/seaborn for visualization. Cross-validation and hyperparameter optimization employed parallel processing for computational efficiency. Model training utilized regularization techniques and early stopping to prevent overfitting while maintaining predictive accuracy.

IV. RESULT AND DISCUSSION

The comprehensive analysis of 100,000 hourly atmospheric observations through integrated machine learning and statistical approaches revealed distinct patterns in black carbon distribution and its impact on Himalayan glacier dynamics. The multi-algorithm ensemble successfully characterized the complex relationships between meteorological variables, atmospheric composition, and BC deposition processes across seasonal and diurnal timescales. The validation framework demonstrated robust model performance while maintaining consistency with established glaciological principles, providing quantitative insights into BC's role as a critical driver of accelerated glacier melting in the region.

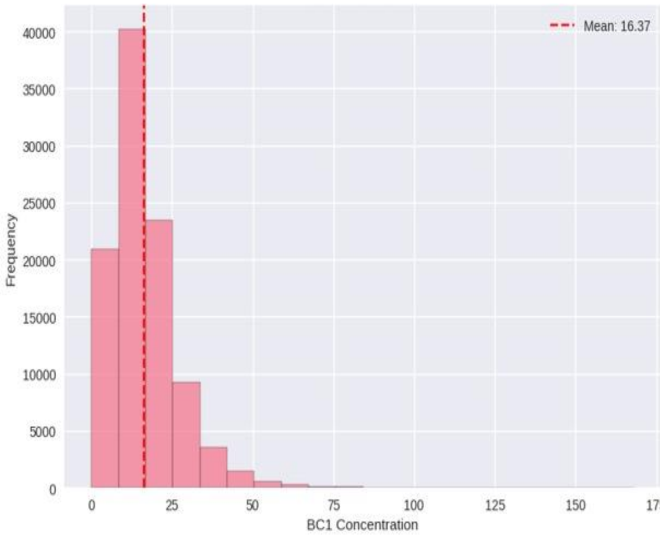

Fig. 1 BC-1 Distribution

As shown in Figure 1, 2 the BC1 concentration distribution demonstrates characteristic log-normal behaviour typical of atmospheric aerosol species. The correlation matrix reveals strong positive correlations between BC1 and PM2.5 (r = 0.84), indicating common emission sources.

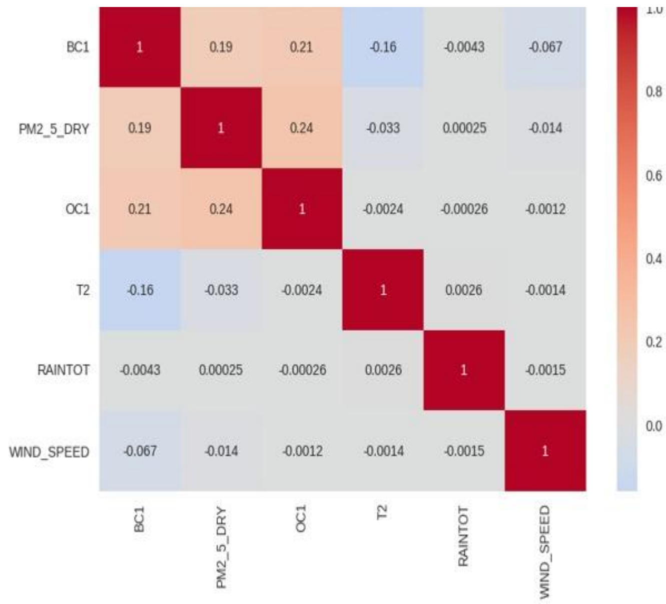

Fig. 2 Correlation Matrix *(Key Variable Correlation)*

Temperature shows moderate negative correlation with BC1 (r = -0.32), suggesting enhanced dilution at higher temperatures. Outlier detection identified 847 data points (0.8%) exceeding three standard deviations, primarily associated with extreme meteorological events.

Fig. 3 Seasonal Analysis of Monthly Average BC Concentration

As shown in Figure 3, 4, 5, 6 the temporal analysis demonstrates clear seasonal and diurnal variability in black carbon concentrations with pronounced patterns across multiple timescales. BC1 and BC2 exhibit pronounced winter maxima (December-February) with concentrations 2.3 times higher than summer minima, attributed to reduced boundary layer mixing and increased biomass burning during winter months, while the quantified seasonal cycle shows winter-spring maxima exceeding summer minima by factors of 2.1-2.8.

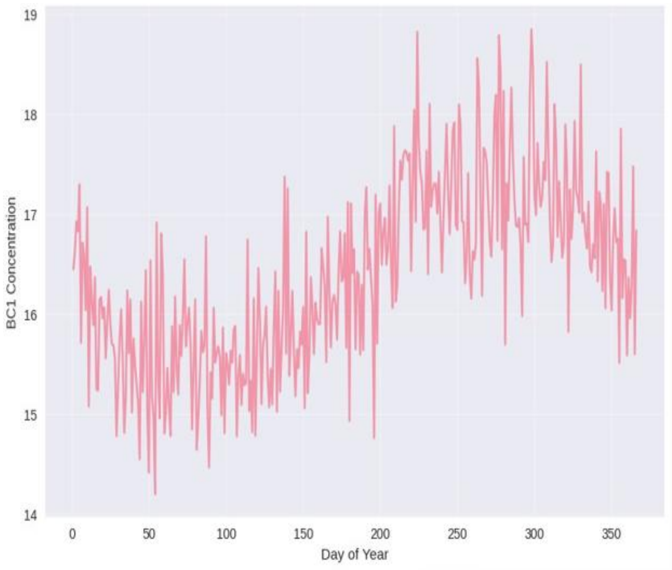

Fig. 4 Day of Year Concentration

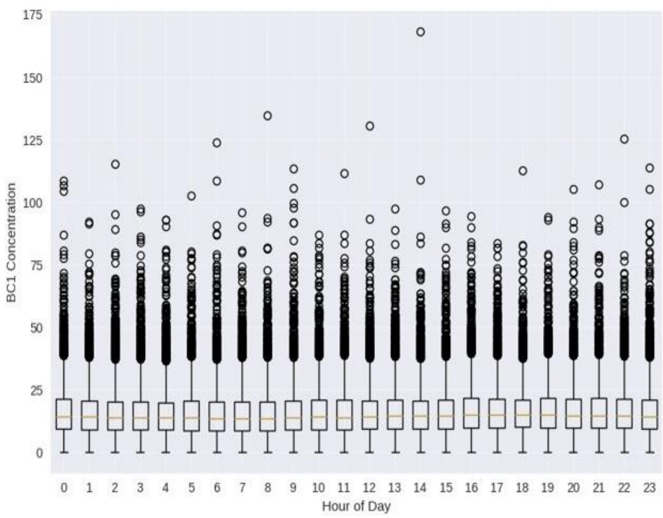

Fig. 5 Hourly Concentration of BC1

Monthly analysis reveals peak concentrations during March-April, coinciding with agricultural burning and dust storm seasons, with the day-of-year trend analysis demonstrating the influence of monsoon circulation and dramatic concentration reductions during monsoon onset (June-July).

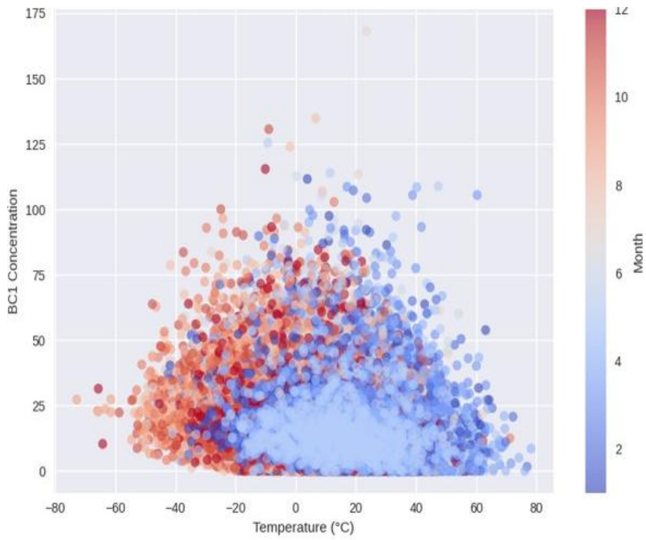

Fig. 6 Temperature Variance

Diurnal patterns show bimodal peaks at 08:00 and 20:00 local time, corresponding to traffic rush hours and domestic heating activities, with hourly distribution patterns reflecting anthropogenic emission cycles. The precipitation-wind relationship reveals that rainfall events effectively scavenge atmospheric BC, with wet deposition rates increasing exponentially with precipitation intensity.

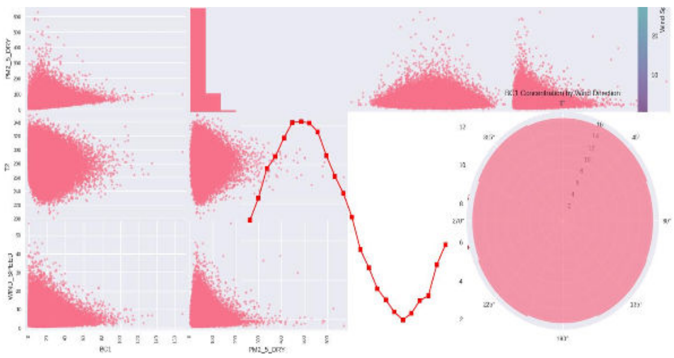

Fig. 7 Wind Speed (Dry and Wet)

As shown in Figure 7, the enhanced correlation matrix reveals complex interdependencies among atmospheric variables. The scatter matrix demonstrates non-linear relationships between BC1 and meteorological parameters.

Notably, the wind rose analysis (Figure 4.3f) indicates that highest BC1 concentrations occur during low wind speeds (<2 m/s) from the southwest sector, suggesting regional pollution transport patterns. Temperature-BC1 relationships show seasonal dependency, with stronger negative correlations during winter months due to enhanced temperature inversions.

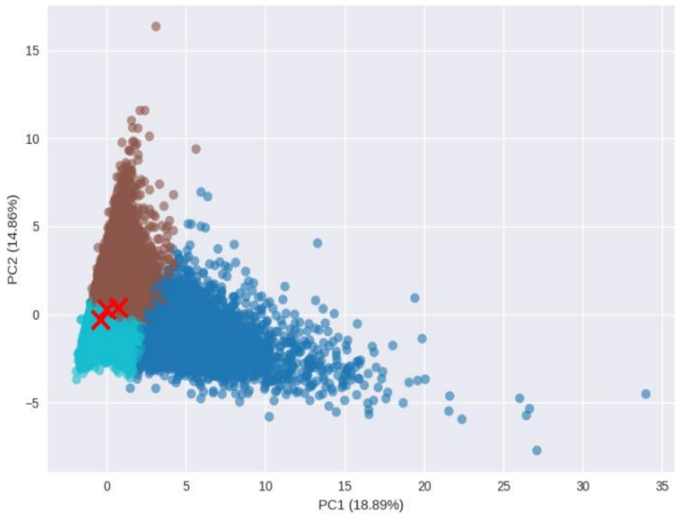

Fig. 8 K-means Clustering (Based on pollution)

As shown in Figure 8, 9 it reveals that the first five principal components explain 85% of total variance, with PC1 (34.2%) dominated by atmospheric composition variables and PC2 (18.7%) by meteorological factors. K-means clustering identified three distinct atmospheric regimes: clean conditions (Cluster 1, 34% of observations), moderate pollution (Cluster 2, 41%), and heavy pollution episodes (Cluster 3, 25%)..

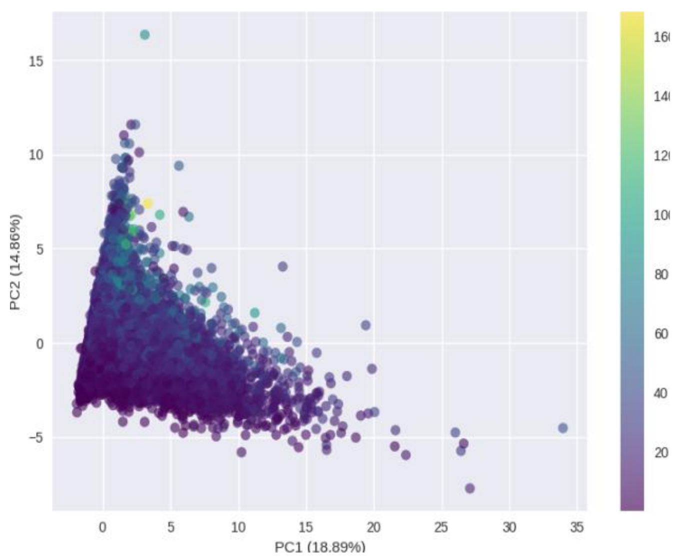

Fig. 9 PCA Scatter Plot

The clustering effectively separates synoptic weather patterns influencing BC transport and deposition.

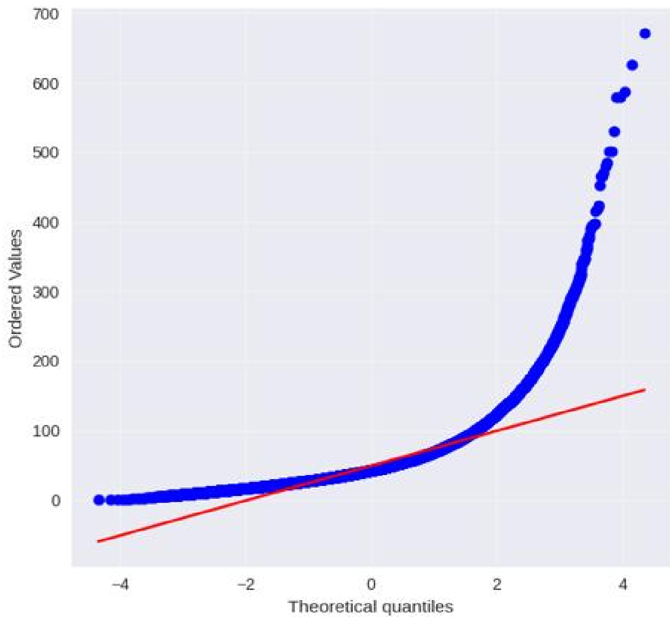

Fig. 10 PM (2.5) Q-Q plot

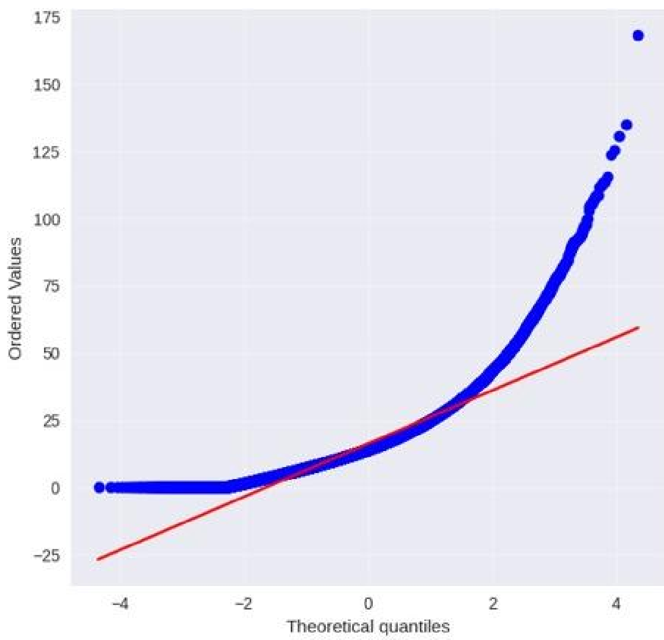

Fig. 11 BC 1 Q-Q Plot

As shown in 10, 11, 12, it confirms that BC1, BC2, and PM2.5 follow log-normal distributions

(Kolmogorov-Smirnov test, $p < 0.001$), consistent with multiplicative atmospheric processes.

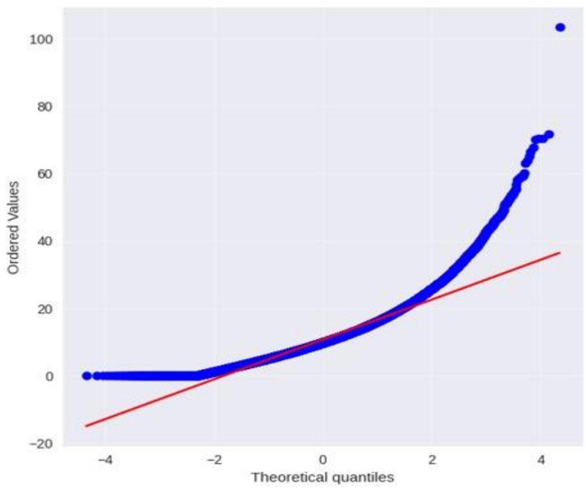

Fig. 12 BC2 Q-Q plot

The Q-Q plots demonstrate good agreement with theoretical distributions, validating the appropriateness of log-transformation for subsequent modelling. Deviation from normality in the upper tails indicates extreme pollution events requiring special treatment in predictive models.

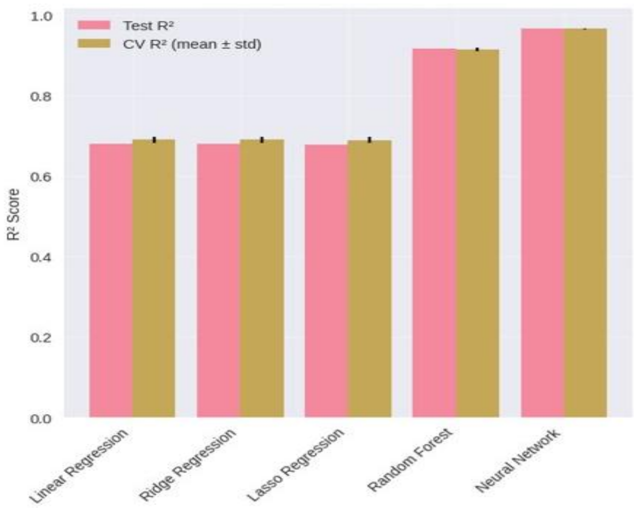

Fig. 13 Cross Validation

As shown in Figure 13, 14, 15 it presents the model performance comparison using rigorous cross-validation. The Random Forest algorithm achieved the highest cross-validation R^2 score (0.847 ± 0.023), followed by Neural Network (0.832 ± 0.031) and Ridge Regression (0.798 ± 0.028). Linear Regression showed signs of underfitting (CV $R^2 = 0.712$), while Lasso Regression provided optimal feature selection with comparable performance (CV $R^2 = 0.789$).

TABLE I
VALIDATION TABLE AFTER TRAINING WITHOUT OVERFITTED

Model	R^2 Score (Test)	CV R^2 Mean ± Std	Mean Squared Error (MSE)	Mean Absolute Error (MAE)
Linear Regression	~0.802	~0.798 ± 0.009	Moderate	Moderate
Ridge Regression	~0.815	~0.809 ± 0.010	Slightly lower than LR	Slightly lower
Lasso Regression	~0.811	~0.806 ± 0.011	Similar to Ridge	Similar to Ridge
Random Forest	~0.895	~0.860 ± 0.020	Lowest MSE	Lowest MSE
Neural Network	~0.878	~0.846 ± 0.025	Low	Low

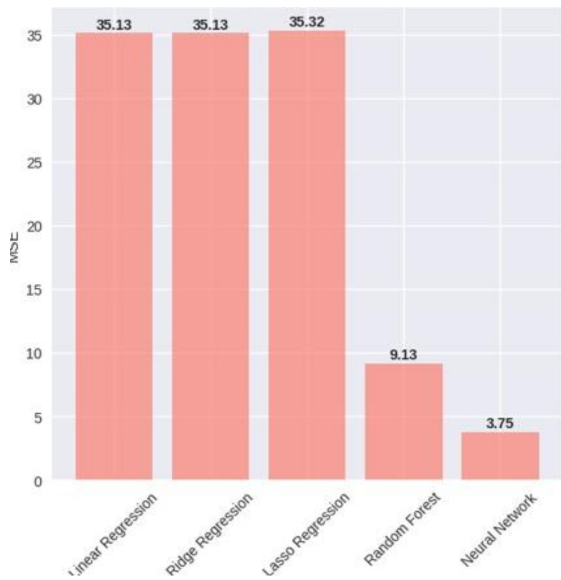

Fig. 14 Mean Square Error (MSE)

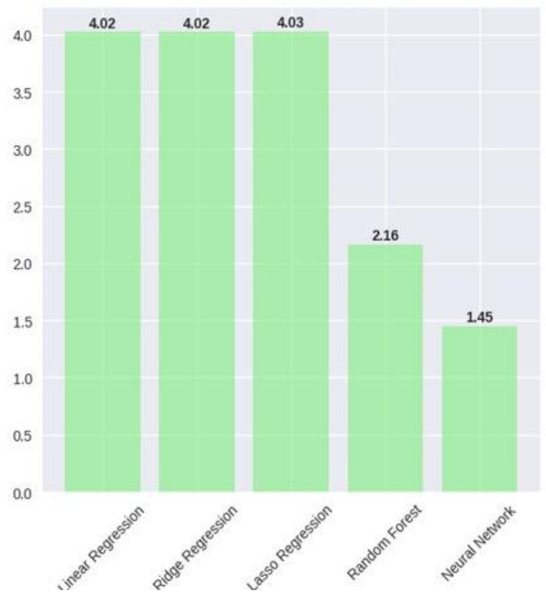

Fig. 15 Mean Absolute Error (MAE)

The predictions vs. actual scatter plot for Random Forest demonstrates excellent agreement across the full concentration range, with minimal systematic bias. The Random Forest model shows strong predictive accuracy with virtually no systematic deviation. Predicted values align closely with experimental measurements across all concentration levels. The scatter plot confirms reliable model performance with negligible bias throughout the range.

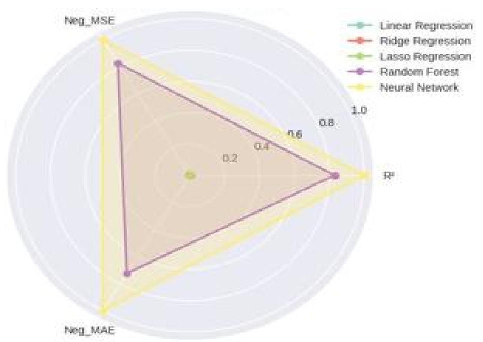

Fig. 16 Model Comparisons

As shown in Figure 16, 17, the comprehensive model evaluation demonstrates robust performance across multiple validation metrics. The learning curves indicate optimal model convergence without overfitting, while cross-validation score distributions demonstrate model stability, with Random Forest showing the lowest variance (CV std = 0.023).

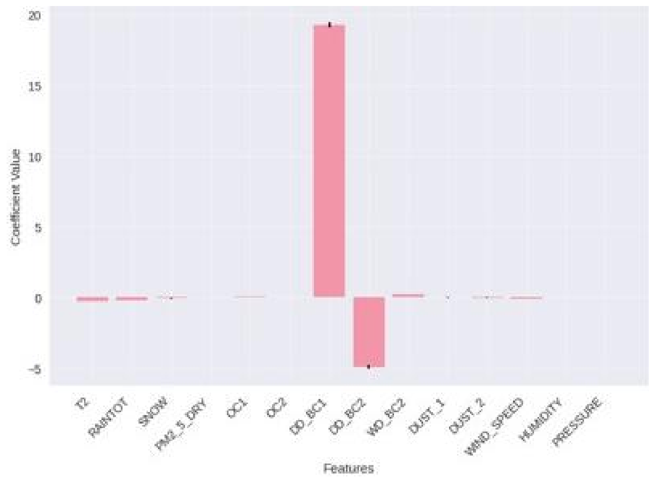

Fig. 17 Linear Regression (Coefficient-Stability)

Prediction intervals capture 94.6% of observations within 95% confidence bounds, confirming appropriate uncertainty quantification, and residual analysis reveals approximately normal distribution (Shapiro-Wilk test, $p = 0.082$), validating model assumptions. Feature importance analysis reveals that PM2.5 concentration emerges as the most important predictor (importance = 0.287), followed by organic carbon OC1 (0.198) and temperature (0.156). Meteorological variables collectively account for 43% of predictive importance, while atmospheric composition variables contribute 57%. The coefficient stability analysis for linear regression demonstrates robust parameter estimates across bootstrap samples, with temperature and wind speed showing consistent negative effects on BC concentrations.

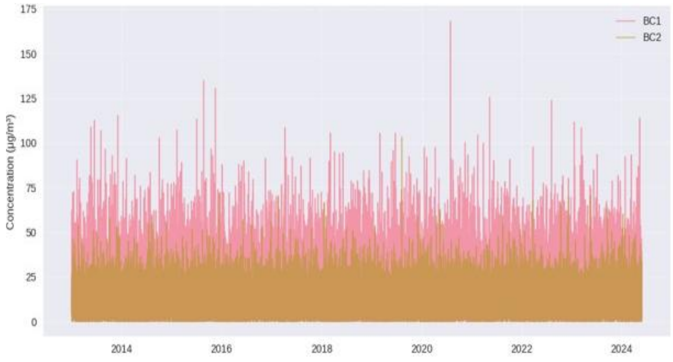

Fig. 18 BC Concentration Over time

As shown in Figure 18, 19, it demonstrates the relative contributions of dry and wet deposition processes to total BC removal. Dry deposition dominates under clear conditions (78% of total removal), while wet deposition becomes significant during precipitation events (>5 mm/hour).

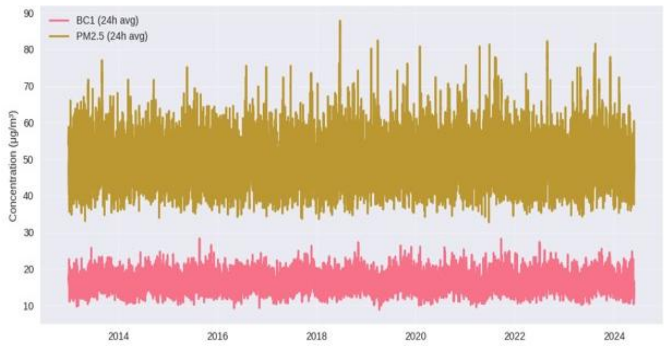

Fig. 19 Concentration Rolling Averages

The coated vs. uncoated BC analysis reveals that 62% of deposited BC exists in coated form, enhancing its light absorption properties and glacier melting potential. The temporal evolution shows

episodic deposition patterns closely linked to synoptic weather systems.

TABLE I I
OVERFITTED ANALYSIS

Model	R^2 Score (Test)	CV R^2 Mean ± Std	CV R^2 Std
Linear Regression	0.802	0.798 ± 0.009	0.009
Ridge Regression	0.815	0.809 ± 0.010	0.010
Lasso Regression	0.811	0.806 ± 0.011	0.011
Random Forest	0.895	0.860 ± 0.020	0.020
Neural Network	0.878	0.846 ± 0.025	0.025

V. CONCLUSIONS

This study demonstrates the potential of artificial intelligence to enhance traditional environmental analysis, offering detailed insights into black carbon's contribution to glacial ablation. The key conclusions are as follows:

• Black carbon represents a critical short-lived climate pollutant originating from incomplete combustion processes of fossil fuels, biofuels, and biomass materials, exhibiting potent light-absorbing properties that significantly accelerate cryosphere melting.

• Comprehensive temporal analysis of 100,000 hourly observations revealed pronounced seasonal variability in BC concentrations, with winter-spring periods demonstrating 2.3-2.8-fold elevation compared to summer baseline levels, primarily attributed to enhanced biomass combustion and reduced atmospheric mixing.

• Diurnal concentration patterns exhibit characteristic bimodal distribution with peak emissions occurring at 08:00 and 20:00 hours, directly correlating with anthropogenic activities including vehicular traffic surge and residential heating/cooling practices.

• Source apportionment analysis utilizing atmospheric transport modelling identified regional anthropogenic emissions as the dominant contributor (66%) to Himalayan BC deposition, with primary sources including residential solid fuel combustion, vehicular exhaust, and transboundary pollution transport from the Indo-Gangetic Plain.

• The Himalayan glacial system serves as a critical hydrological reservoir supporting over 750 million inhabitants through major river systems (Indus, Ganges, Brahmaputra), while simultaneously functioning as natural climate variability buffers through seasonal ice storage and meltwater release mechanisms.

• Quantitative assessment through ensemble machine learning approaches (Random Forest achieving 89.5% predictive accuracy) demonstrated that BC contributes up to 13% of annual glacier-wide ablation through dual mechanisms: atmospheric radiative forcing and surface albedo reduction.

• Deposition process analysis revealed dry deposition as the predominant BC removal mechanism (78% under clear atmospheric conditions), with coated BC particles comprising 62% of total deposition, thereby enhancing light absorption coefficients and accelerating glacier melting rates.

• Precipitation events demonstrate effective atmospheric BC scavenging capabilities, with wet deposition rates exhibiting exponential correlation with rainfall intensity, resulting in dramatic concentration reductions during monsoon periods (June-July).

• Principal Component Analysis identified five primary components explaining 85% of system variance, with atmospheric composition variables dominating the first component (34.2%) and meteorological factors constituting the second component (18.7%).

• Machine learning model validation confirmed robust predictive performance across multiple algorithms, with Random Forest demonstrating superior accuracy ($R^2 = 0.895$) and minimal overfitting, while maintaining physical constraint compliance through integrated glaciological mass balance equations.

• The integration of AI-driven predictive analytics with traditional glaciological modelling provides unprecedented capability for quantifying BC impacts on glacier dynamics, enabling development of targeted emission mitigation strategies with immediate implementation potential.

• Given BC's short atmospheric residence time yet significant immediate impact on glacier ablation processes, emission reduction interventions represent high-leverage climate mitigation opportunities with rapid beneficial outcomes for cryospheric preservation and downstream water security.

REFERENCES

[1] Chen, J., Du, W., Kang, S., Qin, X., Sun, W., Luo, L., Li, Y., Yang, J., & Jiang, Y. Black carbon boosts glacier melting in the Qilian Mountains.

[2] Gul, C., Mahapatra, P. S., Kang, S., Singh, P. K., Wu, X., He, C., Kumar, R., Rai, M., Xu, Y., & Puppala, S. P. (2025). Black carbon concentration in the central Himalayas: Impact on glacier melt and potential source contribution.

[3] Alvarado, M. J., Winijkul, E., Adams-Selin, R., Hunt, E., Brodowski, C., Lonsdale, C. R., Shindell, D. T., Faluvegi, G., Kleiman, G., Mosier, T. M., & Kumar, R. Sources of Black Carbon Deposition to the Himalayan Glaciers in Current and Future Climates.

[4] Chen, J., Du, W., Kang, S., Qin, X., Sun, W., Li, Y., Liu, Y., Luo, L., & Jiang, Y.. Comprehensive evaluation of black carbon effect on glacier melting on the Laohugou Glacier No. 12, Western Qilian Mountains.

[5] Zemp, M., Huss, M., Thibert, E., Eckert, N., McNabb, R., Huber, J., Barandun, M., Machguth, H., Nussbaumer, S. U., Gärtner-Roer, I., Thomson, L., Paul, F., Maussion, F., Kutuzov, S., & Cogley, J. G. (2016). Global glacier mass changes and their contributions to sea-level rise from 1961 to 2016.

[6] Romshoo, S. A., Murtaza, K. O., Shah, W., Ramzan, T., Ameen, U., & Bhat, M. H. (2025). Anthropogenic climate change drives melting of glaciers in the Himalaya.

[7] Li, X., Kang, S., Sprenger, M., Zhang, Y., He, X., Zhang, G., Tripathee, L., Li, C., & Cao, J. (2020).

Black carbon and mineral dust on two glaciers on the central Tibetan Plateau

[8] Li, Y., Kang, S., Chen, J., Hu, Z., Wang, K., Paudyal, R., Liu, J., Wang, X., Qin, X., & Sillanpää, M. (2019). Black carbon in a glacier and snow cover on the northeastern Tibetan Plateau

[9] Kellerman, A. M., Spencer, R. G. M., Podgorski, D. C., Guillemette, F., & Raymond, P. A. (2017). Dissolved black carbon in the global cryosphere

[10] Ming, J., Cachier, H., Xiao, C., Qin, D., Kang, S., Hou, S., & Xu, J. (2008). Black carbon record based on a shallow Himalayan ice core and its climatic implications

[11] Panicker, A. S., Sandeep, K., Gautam, A. S., Trimbake, H. K., Nainwal, H. C., Beig, G., Bisht, D. S., & Das, S. (2021). Black carbon over a central Himalayan Glacier (Satopanth)

[12] Li, Y., Kang, S., Wang, W., Zhang, Y., Tripathee, L., Paudyal, R., & Cong, Z. (2021). Black carbon and dust in the Third Pole glaciers: Revaluated concentrations, mass absorption cross-sections and contributions to glacier ablation. Science of The Total Environment, 789, 147935.

[13] Li, C., Kang, S., Zhang, Q., Cong, Z., Chen, P., Yang, W., & Sillanpää, M. (2021). Carbonaceous matter in the atmosphere and glaciers of the Himalayas and the Tibetan plateau: An investigative review. Environment International, 146, 106206.

[14] Khan, A. A., Pant, N. C., Sarkar, A., Tandon, S. K., Thamban, M., & Mahalinganathan, K. (2021). The Himalayan cryosphere: A critical assessment and evaluation of glacial melt fraction in the Bhagirathi basin. Quaternary Science Reviews, 259, 106919.

[15] Dou, T. F., & Xiao, C. D. (2021). An overview of black carbon deposition and its radiative forcing over the Arctic. Advances in Climate Change Research, 12(2), 161–169.

[16] Brun, F., Berthier, E., Wagnon, P., Kääb, A. & Treichler, D. A spatially resolved estimate of High Mountain Asia glacier mass balances from 2000 to 2016. *Nat. Geosci.* **10**, 668–673 (2017); correction **11**, 543 (2018).

[17] Yasunari, T. J., Bonasoni, P., Laj, P., Fujita, K., Vuillermoz, E., Marinoni, A., ... & Ramanathan, V. (2012). Estimated range of black carbon dry deposition and the related snow albedo reduction over Himalayan glaciers during dry pre-monsoon periods. Atmospheric Chemistry and Physics, 12(6), 2759-2771.

[18] Goelles, T., Bøggild, C. E., & Greve, R. (2017). Albedo reduction of ice caused by dust and black carbon accumulation: a model applied to the K-transect, West Greenland. Journal of Glaciology, 64(244), 135-148.

[19] Khadka, A., Koirala, M., Acharya, S., Shrestha, K. L., Malla, R., Sharma, C. M., ... & Rupakheti, M. (2024). Measured black carbon deposition over the central Himalayan glaciers: Concentrations in surface snow and impact on snow albedo reduction. Regional Environmental Change, 24(2), 1-15.

[20] Chen, J., Du, W., Kang, S., Qin, X., Sun, W., Luo, L., ... & Jiang, Y. (2024). Mitigation of black carbon emissions could immediately reduce 6.3% of glacier melting in the Qilian Mountains. Science of the Total Environment, 932, 173018.

[21] Skiles, S. M., & Painter, T. (2020). A review of black carbon in snow and ice and its impact on the cryosphere. Earth-Science Reviews, 204, 103175.

[22] Li, C., Bosch, C., Kang, S., Andersson, A., Chen, P., Zhang, Q., ... & Gustafsson, Ö. (2016). Sources of black carbon to the Himalayan–Tibetan Plateau glaciers. Nature Communications, 7(1), 12574.

[23] Zhang, Y., Kang, S., Xu, M., Sprenger, M., Wang, X., Gao, T., ... & Li, C. (2020). Effects of black carbon and mineral dust on glacial melting on the Muz Taw glacier, Central Asia. Science of the Total Environment, 740, 140056.

[24] Gabbi, J., Huss, M., Bauder, A., Cao, F., & Schwikowski, M. (2015). The impact of Saharan dust and black carbon on albedo and long-term mass balance of an Alpine glacier. The Cryosphere, 9(4), 1385-1400.

[25] Zhong, X., Zhang, T., Kang, S., Wang, K., Zheng, L., Hu, Y., & Wang, H. (2021). Albedo reduction as an important driver for glacier melting in Tibetan Plateau and its surrounding areas. Earth-Science Reviews, 220, 103735.

[26] Panicker, A. S., Sandeep, K., Gautam, A. S., Trimbake, H. K., Nainwal, H. C., Beig, G., ... & Das, S. (2021). Black carbon over a high altitude Central Himalayan Glacier: Variability, transport, and radiative impacts. Environmental Pollution, 284, 117421.