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ORIGINAL ARTICLE

# Evaluation of Wind Speed Accuracy Enhancement in South Asia Through Terrain-Modified Wind Speed ($W_t$) Adjustments of High-Resolution Regional Climate Modeling

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**Abstract**
Due to the complex interactions between terrain and atmospheric processes, climate modeling can be challenging in regions with complex topography, such as South Asia. This research examines a critical gap in the added value of high-resolution climate simulations for daily wind speed in South Asia, focusing on the innovative terrain-modified wind speed ($W_t$) adjustment method. By applying distribution added value (DAV) and upper-tail PDF (95th percentile) analyses, we systematically evaluate the performance of regional climate models (RCMs) and global climate models (GCMs) pre- and post-$W_t$. The comparison of DAV results before and after applying the $W_t$ method revealed the impact of the $W_t$ adjustment on the performance of the regional climate models. In several models, such as IPSL-RCA, NorESM1-RCA, and CanESM2-RCA, the incorporation of $W_t$ led to substantial improvement, as shown by positive DAV values. In the Upper-tail PDF analysis, improvements were more consistent, indicating that $W_t$ adjustment generally enhanced the representation of extreme wind events. However, some models such as NorESM1-RCA and CanESM2-RCA consistently perform well before and after $W_t$ adjustment by depicting positive DAV values. Overall, the results show that the $W_t$ is effective in improving the representation of wind speed for most climate models. According to the DAV analysis, high-resolution models have a positive added value of 15% on average over lower-resolution models. The contribution of this study is bridging the gap between the observed wind speed patterns in South Asia and climate model outputs. As a result of this research, tailored approaches to evaluating and adjusting models are revealed, emphasizing the complexity of model behavior. In the subcontinent research domain, the results of this study provide crucial insights for climate-related decision-making, risk assessment, and infrastructure development.

**Keywords** Terrain-modified wind speed ($W_t$) · Distributions added value (DAV) · Regional climate modeling · CORDEX-SA (South Asia) · Probability density function (PDF)

## 1 Introduction

Wind speed stands as a paramount meteorological parameter, evoking profound interest not solely within the realms of meteorology and climatology, but also reverberating across diverse domains of applied sciences and engineering disciplines (Zeng et al. 2018; Li et al. 2019, 2020; Fan et al. 2021; Molina et al. 2021; Libanda and Paeth 2023; Marsh et al. 2023). Nonetheless, comprehending wind speed through modeling endeavors is full of challenges. These challenges stem from its inherently localized nature, its intricate interplay with the terrain's topographical features (Brinckmann et al. 2016; Khan et al. 2019; Khan and Dairaku 2024), and the deficiency of comprehensively observed data. This coming together of factors complicatedly weaves a complex array that researchers and practitioners must navigate to unravel the dynamics of this crucial meteorological phenomenon. The accurate wind speed representation is crucial for climate change obtaining an evaluation, impact modeling, and many applications from wind energy to ocean modeling. Global climate models (GCMs) provide valuable insights into climate variability and change on a broad scale. However, their coarse resolution limits their accuracy in representing

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regional and local climate phenomena (IPCC 2014; Khan and Pilz 2019; Akinsanola et al. 2021; Ayodele et al. 2022). Therefore, to overcome this limitation, regional climate models (RCMs) are commonly utilized (Giorgi 2019) due to being more appropriate for wind research work, presenting more detailed research (Laprise 2008), as well as regional simulation (Rummukainen 2010). In the last few years, international projects have concentrated on advancing Regional Climate Models (RCMs) to enhance their resolution, extend model durations, and amplify model ensembles. These coordinated initiatives range from PRUDENCE (Christensen et al. 2007), ENSEMBLES (van der Linden et al. 2009), and the World Climate Research Program Coordinated Regional Downscaling Experiment (CORDEX) (Giorgi 2019) at 50 km, 25 km, and spanning 50–12 km resolution, respectively. Nonetheless, RCMs exhibit limitations, including an inclination to overestimate the frequencies of low winds and underestimate the highest ones (Larsén and Mann 2009; Cannon et al. 2015). According to Niermann et al. (2019) this bias arises partly due to the discretization of dynamic equations on grids, leading to the smoothing of complex orography. Based on these studies (Liston and Sturm 1998; Cannon et al. 2015; Molina et al. 2023; Marsh et al. 2023), model parameterizations can also mischaracterize extreme events due to atmospheric mechanism representation constraints. Previous research (Pryor et al. 2012) demonstrated that the subgrid-scale depiction of surface inhomogeneities also introduces uncertainty, making increased model resolution beneficial for capturing surface features and dynamical processes vital to wind speed.

Several pieces of research evidence suggest that wind speeds simulated by global and regional climate models often contain substantial biases compared to the observed values. To overcome this problem, bias adjustment methods have been developed to adjust GCM outputs and RCM simulations to match observational data. Michelangeli et al. (2009) developed a method to obtain local CDFs from large-scale fields of surface climate variables. Theoretical Weibull distribution demonstrated by Haas et al. (2014). While quantile mapping based on the Weibull distribution has demonstrated robustness in rectifying simulated wind biases across two different CORDEX domains (Moemken et al. 2018; Li et al. 2019), however, it is critical to understand its limitations. This approach effectively corrects the time series of univariate wind speeds. However, it needs to include consideration of the interdependence between the zonal flow and meridional flow wind components, consequently failing to address wind direction corrections. Further, examples of cumulative distribution function-based quantile mapping fall into Statistical methodology (Rahman et al. 2018; Ali et al. 2019). On the other hand, the multivariate bias adjustment (MBA) mechanism developed by Cannon (2018), while offering the advantage of correcting multiple variables simultaneously (Li et al. 2020), may fall short of capturing the full mechanical impact of terrain on wind flow. This is attributed to their lack of explicit consideration of terrain effects, which have been observed to be significant.

The present study follows the "Terrain-Modified Wind Speed ($W_t$) method" which considers the influence of terrain characteristics on wind speed biases. This method modifies wind speed and directions by integrating terrain slope, terrain slope azimuth, and curvature information, accounting for physical interactions between wind patterns and topographical features (Liston and Elder 2006). In contrast to other methods that lack a sound physical basis, the "Terrain-Modified Wind Speed ($W_t$) method" suggests an innovative approach to bias correction. For instance, statistical techniques that as linear scaling, variance scaling, MBA method, and quantile mapping correct biases by adjusting the statistical properties of the modeled wind speed distribution to match observations without considering physical processes. During the past few years, climate models have received a topic of significant research attention for their ability to predict regional winds, particularly for regions with complex topography like South Asia (Moemken et al. 2018; Li et al. 2019, 2020). Despite being effective to a certain extent, traditional bias correction techniques tend to miss the nuanced interactions between terrain and atmospheric dynamics. It has not been extensively used in climate models for enhancing wind speed using terrain-modified wind speed ($W_t$) method, which is a good method for modifying wind speed in hydrology (Liston and Elder 2006). With the work presented in this study, new improvements to the $W_t$method are introduced, which are integrated into high-resolution models (RCMs) and coarser-resolution models (GCMs), ultimately enhancing their predictive accuracy. In addition to correcting biases, the approach provides a robust framework for future climate studies in similar regions by improving the representation of temporal trends in wind speed.

As a result of the approach, spatially distributed hydrological models have gained considerable attention, especially in complex terrain scenarios. Noteworthy instances of its application include works. I.e., to develop that as statistical correlations, see for example (Pohl et al. 2006). "SnowTran-3D" was developed by Liston et al. (2007) as a model for the distribution of the weather. Bernhardt et al. (2012) investigated the "lateral snow redistribution". Musselman et al. (2015) stated that physical wind flow models can reduce uncertainty. Ravazzani et al. (2020) can increase the accuracy of wind flow for topographical regions. The last instance is the development of "Windmapper" by Marsh et al. (2023). This research aimed to evaluate the added value of RCM resolution climate simulations for diurnal wind flow over South Asia, a region characterized by diverse topography and meteorological conditions. We employed the $W_t$technique, inspired by Liston and Elder (2006), to


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account for the influence of topography on wind flow patterns. By comparing the distribution added values (DAV) (full PDF) and the upper-tail PDF (95th percentile; $DAV_{P95}$) of wind speed before and after the application of $W_t$, we seek to identify the extent to which high-resolution simulations enhance wind speed representation and extreme wind events in the region (the explanation of DAV evaluation is presented in Sect. 2.4).

Overall, the $W_t$ method stands as a robust terrain-based approach for estimating wind fields. By intricately combining the effects of terrain slope and curvature, it provides a comprehensive understanding of wind dynamics. This sets it apart from conventional methods, offering enhanced accuracy in capturing wind speed and direction patterns. As research evolves, the $W_t$algorithm's integration with advanced computational fluid dynamics models can be promising for further refining its accuracy and expanding its applications. As a tool for unraveling the complexities of wind flow in intricate terrains, $W_t$ is poised to contribute significantly to the realm of environmental modeling. This method has significant advantages over other methods, such as considering physical processes, improving accuracy in complex terrain, and enhancing understanding of wind dynamics (Liston and Elder 2006). Further, this method adjusts the climate model output based on the local topographical influence, while the conventional method does not consider the physical impact of terrain on wind fields. The $W_t$ method could adjust future projection experiments. Conventional approaches, such as linear scaling, variance scaling, quantile mapping, and cumulative distribution function transformation, only consider static properties (Li et al. 2019). Meanwhile, long-term high spatial resolution historical observation wind data records are needed for conventional applications (Li et al. 2019). The $W_t$ method is a valuable and effective tool for estimating wind speed in challenging terrain conditions. Climate change has become one of the most important concerns regarding regional weather patterns and their effects in recent years. Making informed decisions regarding climate change mitigation and adaptation strategies requires a thorough understanding of the accuracy and reliability of climate model simulations. Climate model performance is evaluated by their ability to capture regional-scale climate features that are not adequately captured at coarser resolutions. However, the 'Added Value' concept is emerging as a valuable tool for assessing climate model performance (Soares and Cardoso 2018; Lloyd et al. 2021; Cardoso and Soares 2022; Molina et al. 2023).

Although numerous studies have investigated the added value of high-resolution climate simulations for various climate variables over different regions, the specific assessment of daily wind speed over South Asia remains relatively understudied. Furthermore, the incorporation of terrain-modified wind speed ($W_t$) from MicroMet, as described in Liston and Elder (2006), presents a novel opportunity to refine the evaluation of added value for this region. Thus, this study explores how the use $W_t$ can enhance the accuracy of wind speed simulations and improve the understanding of regional wind patterns in South Asia.

This research's novelty lies in its incorporation of the Terrain-Modified Wind Speed ($W_t$) technique and the DAV metric to assess the added value of high-resolution climate simulations for daily wind speed in South Asia. By explicitly accounting for topographic influences on wind flow, our study seeks to bridge the gap between climate model outputs and regional-scale wind speed variations observed in South Asia. Furthermore, this research contributes to understanding climate model performance in capturing extreme wind events in the energy sector, infrastructure development, and risk management, which is crucial for making decisions.

Subsequently, the present manuscript unfolds: Sect. 2 delineates the compendium of data sets from observations and models alongside the methodological apparatus harnessed in this inquiry. The ensuing section, Sect. 3, provides the empirical outcomes garnered through this investigative endeavor. In Sect. 4, the conclusions of this study are presented.

## 2 Data and Methods

### 2.1 CORDEX-SA

The dataset offered through the Coordinated Regional Climate Downscaling Experiment (CORDEX) within the framework of the World Climate Research Program (WCRP), tailored specifically for the South Asian region, serves as a pivotal resource for the scientific community. Its primary purpose is to facilitate intelligent investigations of the ramifications of climate change on regional dynamics. By catering to analyses conducted at localized extents, this dataset engenders a more transparent comprehension of potential shifts in future climate patterns within homogenous geographical realms, thus engendering broader public awareness (CORDEX; http://www.cordex.org/). Table 1 for the research domain contains a concise data enclosure (CORDEX-SA) of the simulations employed.

### 2.2 Integrated Earth Science Datasets

#### 2.2.1 Observation Datasets

To validate the simulations and gauge the added values of the CORDEX-SA models, a comparative analysis was performed against their respective forcing counterparts (GCM) and Regional Climate Model (RCM) resolutions. This assessment considers observed wind speed data as a

**Table 1** The salient feature of the CORDEX-SA regional climate model (RCM) simulations with daily wind speed (m/s) at 0.44° resolution, has been used for the subcontinental region at an altitude of 10 m

| Acronym | Institute | RCM | GCM | Resolution | Period | Reference |
|---|---|---|---|---|---|---|
| IPSL-RCA | SMHI | RCA4 | IPSL-CM5A-MR | 0.44° × 0.44° | 1973–2005 | https://doi.org/10.1111/j.1600-0870.2010.00478.x |
| CanESM2-RCA | SMHI | RCA4 | CanESM2 | | | |
| CSIRO-RCA | SMHI | RCA4 | CSIRO-Mk3-6–0 | | | |
| GFDL-RCA | SMHI | RCA4 | GFDL-ESM2M | | | |
| HadGEM2-RCA | SMHI | RCA4 | HadGEM2-ES | | | |
| MIROC5-RCA | SMHI | RCA4 | MIROC5 | | | |
| MPI-RCA | SMHI | RCA4 | MPI-ESM-LR | | | |
| NorESM1-RCA | SMHI | RCA4 | NorESM1-M | | | |
| MPI-REMO | MPI-CSC | REMO2009 | MPI-ESM-LR | | | https://doi.org/10.3390/atmos4020214 |

baseline. The evaluation employs the distribution added value (DAV) metric, which casts a comprehensive spotlight not only on the entire Probability Density Function (PDF) but also on its extremities (P95). To obviate the smoothing effects engendered by gridded datasets, which can impact the tails of PDFs, the utilization of local observations becomes imperative (Boberg et al. 2009). Within the scope of this study, the meteorological observations are culled from the Met Office Hadley Centre's Integrated Surface Database (HadISD), specifically version 3.3.0.2022f. This global sub-daily dataset is based on the dataset of the NOAA Integrated Surface Database (ISD), provided by the UK Met Office Hadley Centre (Dunn et al. 2019, 2022).

The selection of stations adhered to stringent criteria, warranting the presence of valid values of no less than 90% (Molina et al. 2023) of diurnal means (derived using hourly datasets) from 1973 to 2005, within the contours of the CORDEX-SA domain. This criterion surpassed the standards employed in previous investigations, signifying a rigorous approach (Zeng et al. 2018; Fan et al. 2021). Consequently, the stations' results demonstrated daily averaged wind speed series at 10 m altitude (refer to Fig. 1 for

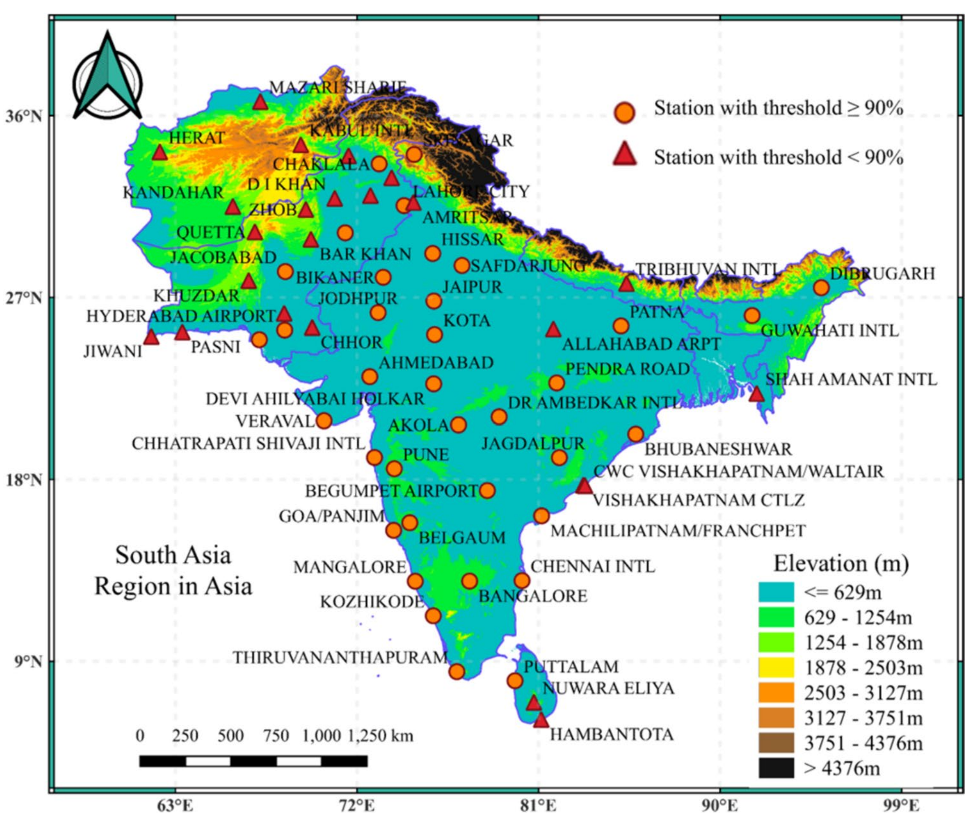


**Fig. 1** Shows the locations of WMO (World Meteorological Organization) stations for wind intensity from the Hadley Integrate Surface Database (HadISD) in the South Asia domain along with orography. The 90% threshold criteria for all the wind stations in the subcontinent domain is selected

detailed insights regarding the distribution of meteorological stations). The quality control steps assessed the validity of daily data at each station and considered only valid stations for model assessment. Figure S1 displays the missing and non-missing wind at each monitoring station in the South Asia study domain. As shown in Equation S1, wind data availability (WDA; %) is calculated at each monitoring station by dividing the available aggregate count of observed wind days by the total number of days sampled. Further, Table S1 depicts the WMO stations with ID and wind station names in more detail.

#### 2.2.2 Digital Elevation Models (DEMs) and Climate Model Outputs

Terrain or topographic characteristics on the land surface significantly affect the earth's surface dynamics and associated atmospheric processes. Accurately representing terrain and topographic characteristics is essential to understanding many environmental processes in analytical and subjective terms (Salekin et al. 2023). In a digital elevation model (DEM), the elevation values are represented as box cells (pixels), which are associated with the continuous variation of relief over space (Mahesh et al. 2021). Table 2 lists the insights regarding the DEM and HadISD datasets.

The data extracted from each general circulation model (GCM) and regional climate model (RCM) were explicitly drawn from the nearest neighboring grid point for each wind station, as well as digital elevation model (DEM) data. Regridded by the bilinear (bill) interpolation method at a lat-lon (latitude and longitude) grid spacing of 0.1 degrees. If multiple stations find themselves encompassed within the confines of a solitary model grid cell, their respective observations are amalgamated to construct the Probability Density Function (PDF). To address temporal discrepancies, instances in which the observational dataset bears missing values lead to their corresponding time steps being expunged across all models. By adopting this approach, despite the asynchronous nature of the data, a uniform count of valid time steps is upheld in the construction of PDFs, thus supporting the computation of added value. Elaboration for PDF analysis is provided in the 2.4 section.

### 2.3 Estimation of Terrain-Modified Wind Speed ($W_t$)

In the domain of climate modeling, the accurate estimation of near-surface wind fields is of paramount importance for various applications, ranging from hydrology to ecology. However, the complexity of terrains, particularly in mountainous regions, presents challenges in capturing the intricate interplay between topography and wind flow patterns. We explore its fundamental principles, advantages over conventional methods, and its potential to enhance our understanding of wind dynamics in intricate terrains (Liston and Elder 2006). There is an overview of the terrain-modified wind speed equations depicted in the flow chart found in Fig. 2 for an overview of the equations. The wind speed adjustment equations described by Liston and Elder (2006) were applied (illustrated in the following section). We used high-resolution DEM data specific to South Asia to capture the region's unique terrain and climatic conditions and enhance the accuracy of RCMs and GCMs. The methodology used to calculate wind speed accuracy has never been applied before to South Asia's diverse topographic features. Hence the method provides new insights into how accurate wind speed measurements can be made in this complex region.

#### 2.3.1 Equations for Wind Speed and Direction Modification

$$\text{Wind speed (W)} = \sqrt{u^2 + v^2} \quad (1)$$

$$\text{Wind direction } (\theta) = \frac{3\pi}{2} - \tan^{-1}\left(\frac{v}{u}\right) \quad (2)$$

**Table 2** The meteorological observations are obtained from the Met Office Hadley Centre's Integrated Surface Database (HadISD), specifically, version 3.3.0.2022f, and in a digital elevation model (DEM), the elevation values are represented as box cells (pixels), which are associated with the continuous variation of relief over space

| Datasets | | | Time resolution | Variable | Period | Coordinates | URL |
|---|---|---|---|---|---|---|---|
| Name | Full Name | Institution | | | | | |
| HadISD | Hadley Integrated Surface Database (HadISD) | Met Office Hadley Centre | Sub-daily (3, 6, 12-h) | Wind Speed (10-m) | 1973–2005 | Surface Meteorological Station | https://www.metoffice.gov.uk/hadobs/ |
| DEM | Digital Elevation Model | United States Geological Survey (USGS) | 30 Arc-Second Resolution | Elevation (meter) | | Vertical Coordinates: Surface | https://search.earthdata.nasa.gov/search |

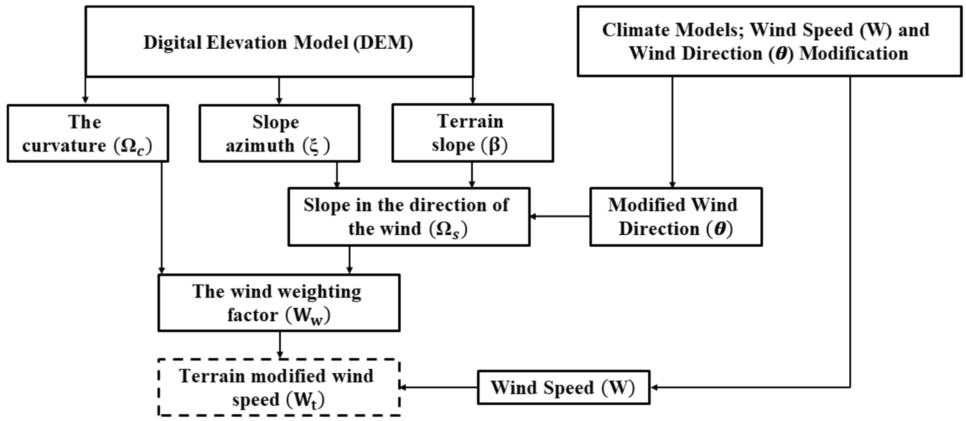


**Fig. 2** Flow chart of a terrain-modified wind speed ($W_t$)

The wind speed ($W$) from the zonal ($u$) and meridional ($\upsilon$) wind components were obtained by interpolation ( bilinear). The wind speed is the magnitude of the vector formed by the $u$ and $\upsilon$ components. Wind direction ($\theta$) from zonal ($u$) and meridional ($\upsilon$) wind components. The wind direction is the angle between the wind vector and reference direction (e.g., north).

### 2.3.2 Modification of Wind Speed with Topographic Influence

$$\text{Terrain slope}\,(\beta) = \tan^{-1}\left[\sqrt{\left(\frac{\partial z}{\partial x}\right)^2 + \left(\frac{\partial z}{\partial y}\right)^2}\right] \quad (3)$$

The terrain slope ($\beta$) is based on the topographic height ($z$; $m$) and its partial derivatives with respect to horizontal coordinates $x$ *(m)* and $y$ *(m)*. The terrain slope represents the steepest slope of each grid cell.

$$\text{Slope azimuth}\,(\xi) = \frac{3\pi}{2} - \tan^{-1}\left(\frac{\partial z/\partial y}{\partial z/\partial x}\right) \quad (4)$$

The terrain slope azimuth ($\xi$) was determined by considering the partial derivatives of topographic height ($z$) with respect to x and y. The slope azimuth represents the steepest slope direction.

$$\text{The curvature}\left(\Omega_c\right) = \frac{1}{4}\left[\frac{z - 1/2\left(z_W + z_E\right)}{2\eta} + \frac{z - 1/2\left(z_S + z_N\right)}{2\eta} + \frac{z - 1/2\left(z_{SW} + z_{NE}\right)}{2\sqrt{2}\eta} + \frac{z - 1/2\left(z_{NW} + z_{SE}\right)}{2\sqrt{2}\eta}\right] \quad (5)$$

The curvature ($\Omega_c$) at each model grid cell is determined by considering elevation differences between the grid cell and its neighboring cells at a curvature length scale ($\eta$). The curvature represents the local concavity or convexity of the terrain.

To facilitate the application of the topographic weighting function described below, the calculated curvature ($\Omega_c$) is then scaled to ensure that its values lie within the range of −0.5 to 0.5 over the entire simulation domain.

$$\text{The scaled curvature}\,(\Omega_c) = -0.5 \le \Omega_c \le 0.5 \quad (6)$$

By scaling the curvature values, we ensure that they are suitable for use in the subsequent topographic weighting function, allowing for effective adjustments to the wind speed and direction based on the terrain characteristics.

$$\text{Slope in the direction of the wind}\,(\Omega_s) = \beta\cos(\theta - \xi) \quad (7)$$

The slope in the wind direction ($\Omega_s$) is based on elevation differences between neighboring grid cells along the wind direction. The slope ($\Omega_s$) represents the local slope aligned with the wind direction. In addition, scaled such that $-0.5 \le \Omega_s \le 0.5$, over the simulation domain.

$$\text{Curvature weights}\left(\gamma_c\right) = \frac{C - \left(\frac{C_{max}+C_{min}}{2}\right)}{C_{max} - C_{min}} \quad (8)$$

whereas C is the local terrain curvature. $C_{max}$ and $C_{min}$ are the maximum and minimum curvature values, respectively.

$$\text{Slope weight}\left(\gamma_s\right) = \frac{S - \left(\frac{S_{max}+S_{min}}{2}\right)}{S_{max} - S_{min}} \quad (9)$$

whereas S is the local slope in the direction of the wind. $S_{max}$ and $S_{min}$ are the maximum and minimum slopes in the direction of the wind values, respectively.

$$\text{The wind weighting factor}\left(W_w\right) = 1 + \gamma_s\Omega_s + \gamma_c\Omega_c \quad (10)$$

The wind weighting factor $\left(W_w\right)$ used to modify the wind speed. The wind weighting factor accounts for the influence of topography on the wind speed by considering both the slope ($\Omega_s$) and curvature ($\Omega_c$) deviations from slope ($\gamma_s$) and curvature weights ($\gamma_c$), respectively. For the subregions domain values ($\gamma_c, \gamma_s$) are tabulated in Table S1.

$$\text{Terrain-modified wind speed}\left(\mathrm{W_t;m/s}\right) = W_w \times \mathrm{W} \tag{11}$$

By multiplying the original wind speed (W) through the weighting factor ($W_w$), the terrain-modified wind speed was calculated ($\mathrm{W_t}$) by multiplying the original wind speed (W) along with the weighting factor ($W_w$). Wind speed is modified by terrain to account for topographic effects.

This process generally corresponds to converting wind speed and direction into zonal and meridional components, interpolating these components to the model grid, and modifying these components following topography. With this approach, the model can be used to more accurately model high-resolution terrestrial winds by accounting for the effects of terrain on wind patterns (Liston and Elder 2006).

### 2.4 Distribution Added Value (DAV) Metric

Lately, there has been increasing concern about the impact of climate change on regional weather patterns. To make informed decisions regarding mitigation and adaptation strategies for climate change, it is essential to comprehend the accuracy and reliability of climate model simulations. Climate models are evaluated in this context based on their ability to capture regional characteristics that may be difficult to capture at coarser resolutions, a concept known as "Added Value". Despite the extensive efforts in added value assessments, quantifying and objectively characterizing the real added value of high-resolution simulations remains challenging (Di Luca et al. 2013; Dosio et al. 2015; Rummukainen 2016; Lloyd et al. 2021; Careto et al. 2022a, b; Cardoso and Soares 2022; Molina et al. 2023). Many studies in the literature refer to added value, but few provide a rigorous and objective quantification of this improvement. Comparisons are often made based on error measures, which only provide a crude added-value description.

To quantify and characterize the added value of high-resolution simulations defined by Soares and Cardoso (2018) and PDF skill score (Perkins et al. 2007) provides a comprehensive approach to evaluate the skill of high-resolution climate simulations in reproducing observed climate distributions over specific regions. This study's PDF matching score method has several relative advantages compared to other metrics. It is a normalized measure that quantitatively assesses the discrepancy between the common area enclosed by validation and high-resolution Probability Density Functions (PDFs) and the PDF common area contained by validation and low-resolution GCM. It is particularly useful for analyzing sections of the PDF due to the potentially high socio-economic and health implications associated with the extreme tails (95 percentile) of these documents. DAV can be used to analyze the entire PDF, not just specific points, or moments. Moreover, it provides a robust assessment of distribution added value (DAV) that can be utilized to determine whether dynamical downscaling of coarser resolution models will result in benefits or losses. By comparing the full probability density function (PDF) and the upper-tail PDF (95th percentile; P95) of climate variables before and after adjustments, researchers can quantitatively assess whether high-resolution RCMs improve the characterization of regional climate conditions compared to their forcing GCMs.

Adopting the DAV metric, as delineated by Soares and Cardoso (2018), the discernment of the enhanced attributed to employing simulations at higher resolutions, in contrast to their lower-resolution counterparts and relative to observational data, becomes attainable. This methodology utilizes the Perkins skill score to assess the semblance similarity of two distinct PDFs. Wind observation stations and their corresponding model cells are systematically calculated for the Probability Density Function (PDF). This computation is based on both the higher-resolution and lower-resolution models. Perkins skill score (PDF skill score) is expressed by Perkins et al. (2007). Calculated the diurnal wind speed DAV for the entire PDF by comparing the scores of the RCM (higher resolution) and GCM (lower resolution) with respect to validating data (HadISD). DAV is defined as follows (Soares and Cardoso 2018). A positive DAV value indicates added values associated with RCM, while a negative DAV value suggests lost value compared to lower resolutions.

Mentioned here are the steps involved in calculating $S_{HR}$ and $S_{LR}$ scores. Divide the total number of occurrences by the frequency of each bin to normalize the wind speed data. The PDF skill score (S) is calculated using the overlap between model PDFs and observed PDFs for both high-resolution (HR) and low-resolution (LR) models. Determine the $S_{HR}$ (score for high-resolution model) by summing the minimum values of corresponding bins between HR and observations dataset. Compute the $S_{LR}$ (score for low-resolution model) by summing the minimum values of corresponding bins between LR and observations dataset. Finally, determine the DAV metric by calculating the relative difference between $S_{HR}$ and $S_{LR}$, normalized by $S_{LR}$.

$$\text{Distribution added values (DAV)} = \frac{\sum_1^n \min\left(Z_{RCM}, Z_{validate}\right) - \sum_1^n \min\left(Z_{GCM}, Z_{validate}\right)}{\sum_1^n \min\left(Z_{GCM}, Z_{validate}\right)} \times 100 \tag{12}$$

$$= \frac{S_{HR} - S_{LR}}{S_{LR}} \times 100 \quad (13)$$

whereas $S_{HR}$ (Score for high-resolution model) = $\sum_1^n \min\left(Z_{RCM}, Z_{validate}\right)$, $S_{LR}$ (Score for low-resolution model) = $\sum_1^n \min\left(Z_{GCM}, Z_{validate}\right)$, DAV is bounded between 100 and − 100 when multiplied by 100 (Soares and Cardoso 2018). DAV Score = 100 − > Perfect overlap of PDFs (*gained added value; DAV = 100*), DAV Score = 0 − > No significance between PDFs (*negligible; 0 < DAV < 100*), DAV Score = -100 − > Not perfect overlap of PDFs (*lost added value; DAV < 100*).

Additional analysis is conducted while evaluating the DAV in the context of extreme wind speed. This assessment involves computing added value for the section of the PDF that lies above the 95th percentile of the observational dataset. This quantification, termed, closely adheres to the methodologies laid out by Soares and Cardoso (2018), as well as Cardoso and Soares (2022) and Molina et al. (2023).

Finally, the grid-to-point scale of the research domain is executed, entailing the amalgamation of all data emanating from individual cells within the general circulation model (GCM), and regional climate model (RCM). This process culminates in the computation of comprehensive or partial Probability Density Functions (PDFs) for each of these cells. The scrutiny of the model's capacity to accurately depict the spatial dispersion of wind speed unfolds focused explicitly on the geographical expanse of the South Asia region. All these methodologies are consistently employed both yearly and across various seasonal scales.

## 3 Results

### 3.1 Evaluation Before and After Terrain-Modified Wind Speed ($W_t$) Daily m/s

This section compared the Percent Bias (PBIAS) calculations before and after applying the Terrain-Modified Wind Speed ($W_t$) approach for various GCMs and RCMs over the South Asia region. The PBIAS values represent the percentage deviation of model-simulated wind speed from the observed data (HadISD) before and after adjusting for terrain effects using the Terrain-Modified Wind Speed ($W_t$) method. Positive PBIAS indicates an overestimation of wind speed, while negative values indicate underestimation. The comparison aims to evaluate the impact of the Terrain-Modified Wind Speed ($W_t$) method on the accuracy of wind speed representation over the South Asia region. Figure 3 Percent bias (PBIAS) for RCMs and GCMs, and reference measure is HadISD (in-situ) in the research domain of South Asia for daily wind speed (m/s). PBIAS values are presented in each corresponding model name in the graph. E-S2 presents the Percent Bias (PBIAS) equation.

In the analysis of various GCMs and RCMs, the effectiveness of the Terrain-Modified Wind Speed ($W_t$) approach in enhancing wind speed representation was examined. Notable improvements were observed across multiple models after the application of $W_t$. For instance, IPSL-CM5A-MR initially exhibited an optimistic Percent Bias (PBIAS) of 20.16%, indicating overestimated wind speeds. However, this PBIAS decreased significantly after $W_t$ adjustments to − 13.41%, showcasing substantial enhancement. Similarly, CanESM2 displayed a high positive PBIAS of 111.34% before $W_t$, which decreased to 22.41% after $W_t$, indicating a remarkable improvement in wind speed representation. This trend was consistent across other models such as CSIRO-Mk3-6-0, GFDL-ESM2M, HadGEM2-ES, MIROC5, MPI-ESM-LR, NorESM1-M, and the multi-model ensemble (MME), where PBIAS values were significantly reduced post-$W_t$, signifying enhanced accuracy in wind speed simulation.

Moreover, the Regional Climate Models (RCMs) demonstrated similar patterns. IPSL-RCA, CanESM2-RCA, CSIRO-RCA, GFDL-RCA, HadGEM2-RCA, MIROC5-RCA, MPI-RCA, NorESM1-RCA, and MPI-REMO all displayed substantial improvements in wind speed representation following $W_t$ adjustments. The multi-model ensemble (MME) also exhibited a noteworthy decrease in PBIAS, highlighting the method's consistent effectiveness in enhancing wind speed accuracy. This evaluation underscores the significance of the Terrain-Modified Wind Speed ($W_t$) approach in addressing terrain-related biases and enhancing wind speed simulations across various models, with potential implications for climate assessments, risk management, and infrastructure planning.

Overall, the results show that the Terrain-Modified Wind Speed ($W_t$) method has effectively improved the representation of wind speed for most GCMs and RCMs over South Asia. The multi-model ensemble (MME) also exhibited a noteworthy decrease in PBIAS, highlighting the method's consistent effectiveness in enhancing wind speed accuracy. Consequently, the positive PBIAS values observed before applying $W_t$ indicate that the original simulations overestimated the wind speed, which was drastically reduced after applying $W_t$. $W_t$. enhanced accuracy in wind speed simulations in complex terrains is demonstrated here (added value of the $W_t$ approach) by accounting for terrain effects. The mechanism behind these enhancements is rooted in the $W_t$method's ability to correct wind speed simulations based on terrain effects. The approach effectively addressed biases induced by complex topography and terrain-related factors, resulting in closer alignment with observed wind patterns.

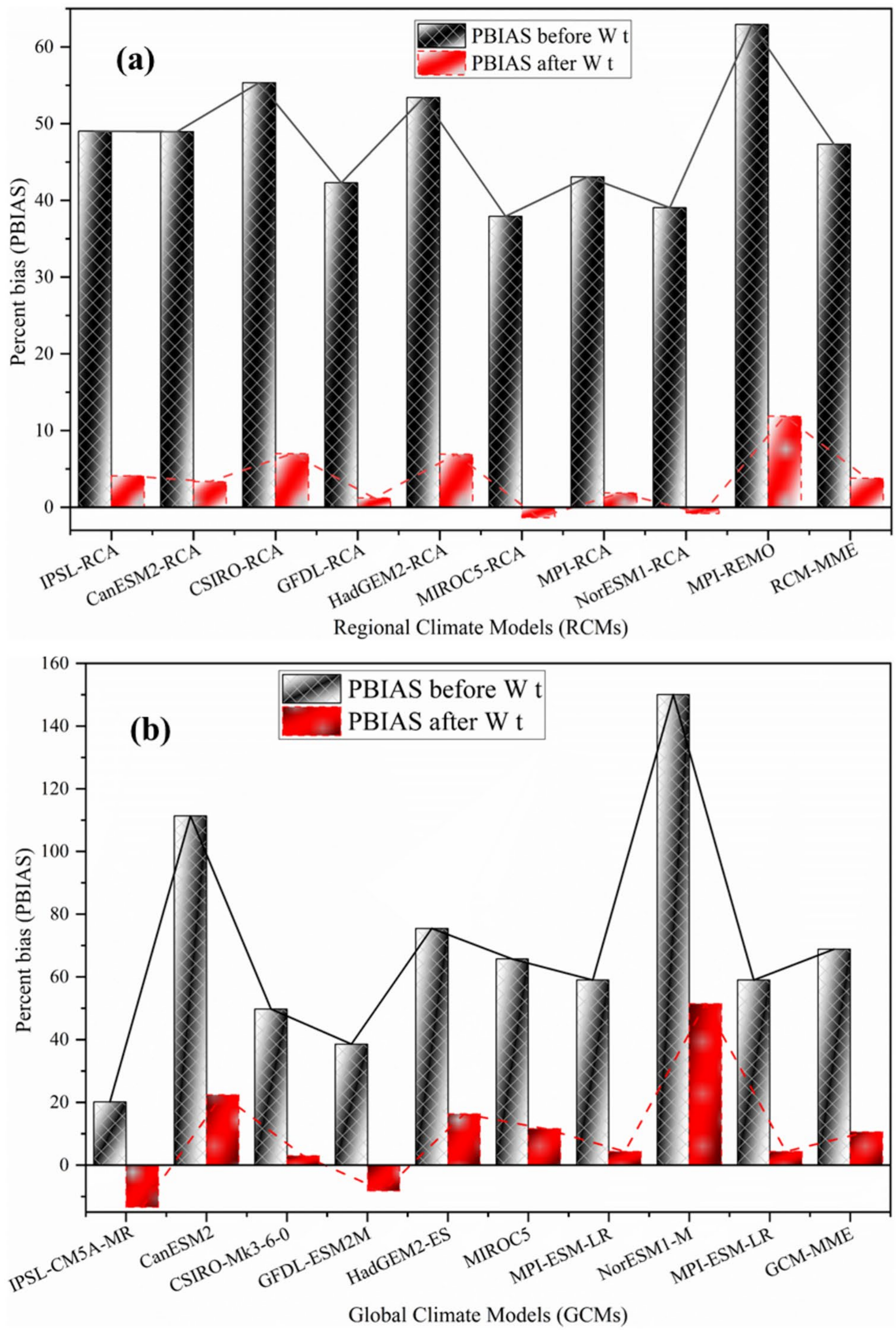


**Fig. 3** Percent bias (PBIAS) for RCMs and GCMs, and reference measure is HadISD (in-situ) in the research domain of South Asia for daily wind speed (m/s)

#### 3.1.1 Taylor Diagram Analysis for Climate Models Wind Speeds

Climate modeling at high resolution in South Asia is enhanced by terrain-modified wind speed ($W_t$) adjustments, which are crucial for improving the accuracy of both Regional Climate Models (RCMs) and Global Climate Models (GCMs). The Taylor diagram (Fig. 4) identifies the nuanced dynamics inherent in model performance using meticulous daily wind speed data analysis from 1973 to 2005. This diagram provides a visual representation of the standard deviation, correlation coefficient, and root mean square error (RMSE) of wind speed predictions from both GCMs and RCMs before and after the $W_t$ adjustment is applied.

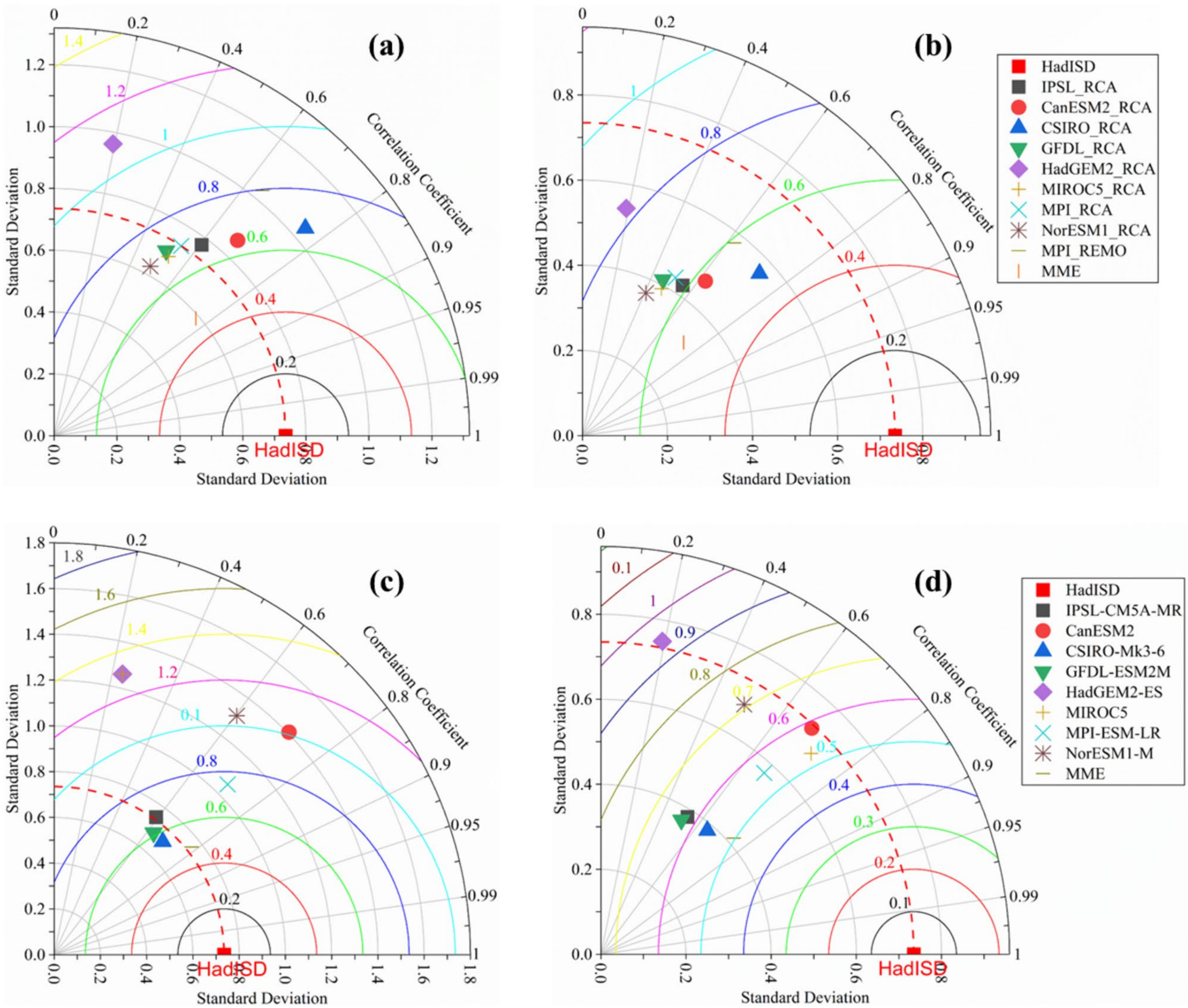


**Fig. 4** Taylor Diagram demonstrates the RCM models before applying the $W_t$ adjustment method in graphs (**a**, **b**) depict the RCM models after applying the $W_t$ adjustment method, **c** illustrate the GCM models before applying the $W_t$ adjustment method, and **d** present the GCM models after applying the $W_t$ adjustment method

Figure 4a result reveals a pre-adjustment panorama for RCMs in the form of elevated standard deviations and centered RMS differences for some models, including CanESM2-RCA and IPSL-RCA, indicating that the models' observed values are inconsistent. Nevertheless, when $W_t$ adjustments are implemented, and a consistent trend is observed across models, characterized by a reduction in standard deviations and RMS differences, indicating that the models are more closely aligned with observed behaviors in Fig. 4b. A significant finding is that correlation coefficients post-adjustment varies indicating the nuanced impact of the $W_t$ method on correlation coefficients. The CSIRO-RCA and MPI-REMO models are exemplary in terms of demonstrating substantial improvements in correlation. Using $W_t$ adjustments consistently improve model outputs and harmonize them with observed wind dynamics in the multi-model ensemble.

In the context of global climate models depicted in Fig. 4c, the Taylor diagram reveals pre-adjustment disparities, particularly in models such as CanESM2 and HadGEM2-ES, which are reflected in elevated standard deviations and centered RMS differences. Observed patterns converge because of post-adjustment in Fig. 4d, as demonstrated by reduced standard deviations and RMS differences between multiple models post-adjustment. Increasing correlation coefficients lead to greater improvements, with models such as MIROCS exhibiting significant improvements after adjustment while CanESM2 and MPI-ESM-LR display stables correlation observed. Based on the visualization results, the multi-model ensemble consistently aligns GCM outputs with observed wind dynamics due to $W_t$ adjustments.

Using Taylor diagrams as a keystone to educate climatologists about the nuanced impact of $W_t$ adjustments on enhancing regional as well as global climate representation, this study provides a robust framework for understanding the nuanced impacts of $W_t$ adjustments in South Asia. With the $W_t$ method, model outputs can be refined, and regional climate dynamics can be more nuanced, which makes climate modeling more accurate.

### 3.2 Full PDF Analysis for Annual and Seasonal Before and After $W_t$

The present section demonstrates the results and comparison of the Distributions Added Value (DAV) calculations for simulating daily wind speed over South Asia pre- and post-applying the Terrain-Modified Wind Speed ($W_t$) method on enhancing the performance of regional climate models (RCMs). The DAV methodology proves to be exceptionally versatile. The current study approach fits the profound concept of capturing wind Probability Density Functions (PDFs) as presented by models, with the observational PDF serving as a standard of reference. The graphical depictions of these distributions can be found in Fig. 5 for the yearly analysis and Fig. S5.1–4, which offers a glimpse into the seasonal PDFs. In addition, graphics show the yearly GCM PDF before and after $W_t$ in Fig. 5c, d to distinguish the performance compared to Fig. 5a, b.

According to a Weibull distribution, wind speed distributions are skewed. Over the entire Subcontinent, the highest frequency was recorded for wind speeds between 1.83 and 2.33 m/s, it's rare to get winds that high. Hence, despite the significant differences among the highest wind frequencies, it has a relatively limited effect on the outcomes of the DAVs for the PDF. Since they're not a big part of the PDF, their frequency contribution is small. RCMs tend to underestimate the low winds and overestimate the high winds in historical experiments, despite the substantial spread. It is possible that the model was underestimated or overestimated in terms of terrain elevation within the grid cells of the model (Carvalho et al. 2014). As a result, if the model assumes that the simulation point is higher or lower than it is, the computed wind speed could likewise be greater or lower than that Molina et al. (2023).

The examination is focused on the DAV calculations, indicating the change in the added value of RCMs and global climate models (GCMs) before and after the incorporation of

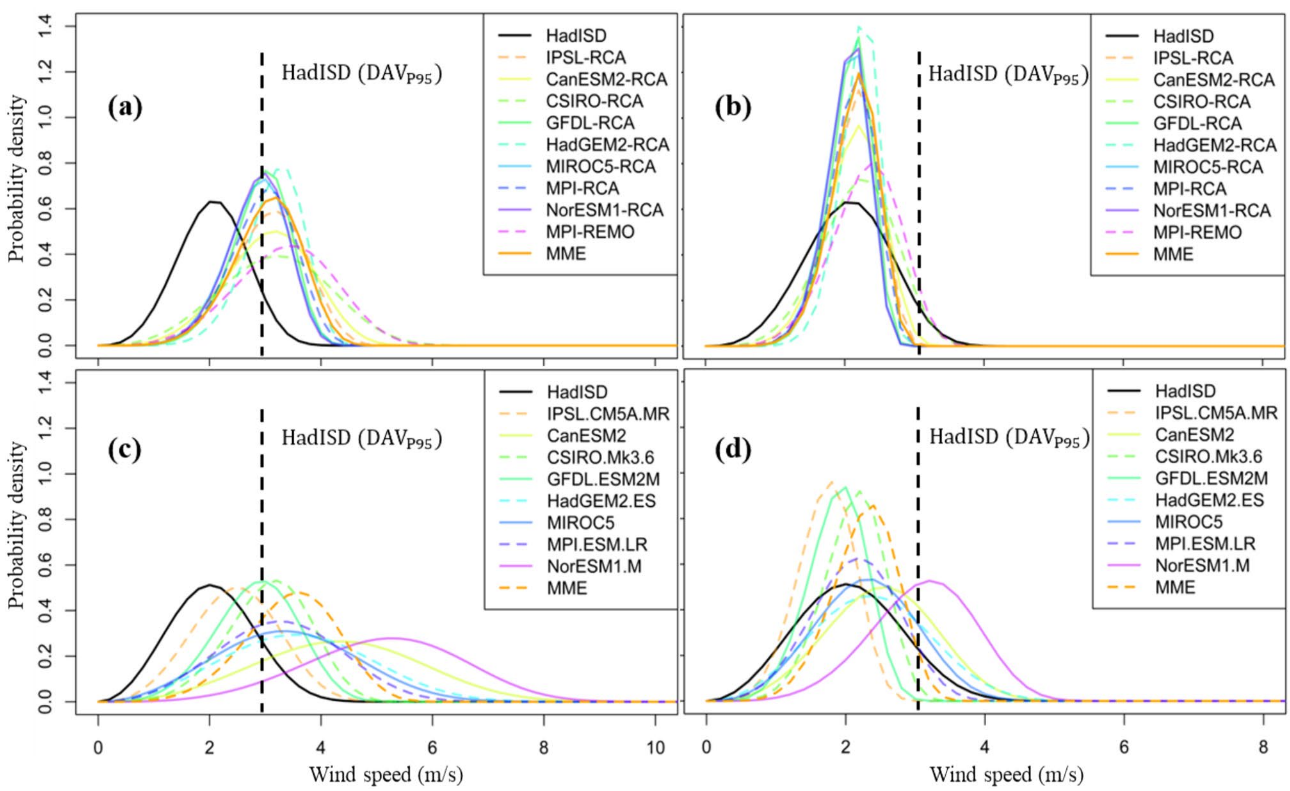


**Fig. 5** Yearly probability density functions (PDFs) of the CORDEX—South Asia RCM and HadISD for the subcontinent CORDEX domain. PDFs concerning pre- and post-$W_t$ are demonstrated in graphs A and B, respectively. The numerical values indicated the black dashed lines correspond to the 95th percentile of the data observations (HadISD = > P95 = 3.03 m/s)

$W_t$ adjustments. We delve into these adjustments' underlying mechanisms and implications, addressing model performance variations. The DAV values are presented as percentages, indicating the gain or loss of added value associated with the regional climate models (RCMs) and global climate models (GCMs) relative to the observation data (HadISD). The positive DAV values represent added value, indicating that the RCMs outperform the GCMs in representing the wind speed distribution, while negative DAV values imply losses, suggesting that the GCMs perform better than the RCMs even after $W_t$ adjustments. The present study provides a comprehensive analysis of the effects of integrating the Terrain-Modified Wind Speed ($W_t$) technique on the performance of regional climate models in simulating daily wind speed patterns over South Asia. Through an evaluation of the Distributions Added Value (DAV) pre- and post-applying $W_t$ adjustment, key insights have emerged for Fig. 6.

Among the RCMs examined, before applying $W_t$ adjustments, IPSL-RCA exhibited negative DAV values, indicating poor performance in representing wind speed over South Asia. However, post-adjustments, the model shows significant improvement, with positive DAV values for all seasons and the annual period. This suggests that the $W_t$ adjustments have enhanced the model's ability to capture wind speed variations. Similarly, CanESM2-RCA demonstrated relatively high positive DAV values before $W_t$adjustments, indicating good performance in representing wind speed. After incorporating $W_t$ adjustments, the model's DAV values

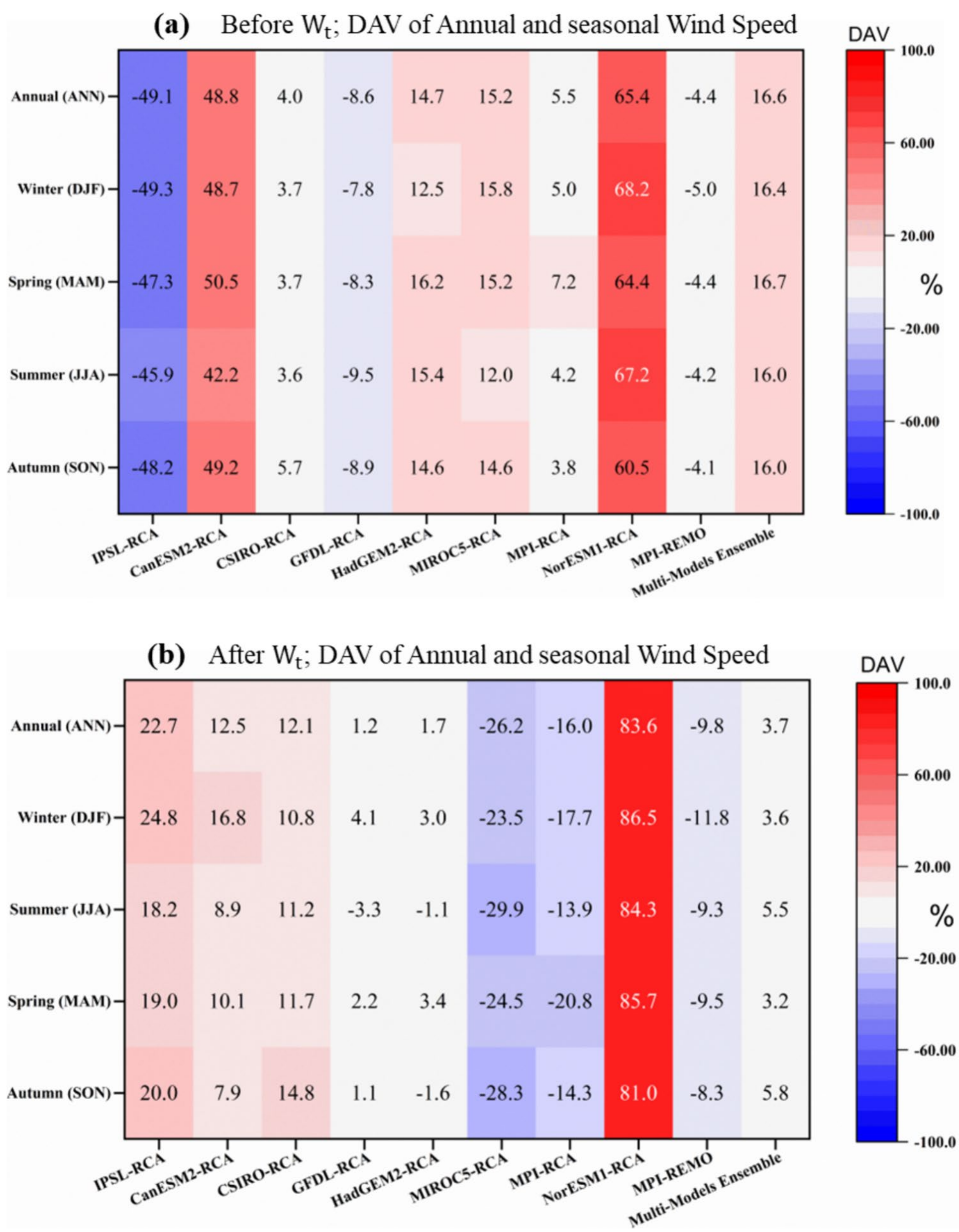


**Fig. 6** Annual and seasonal distribution added values (DAV) for diurnal wind speed PDFs of the CORDEX-South Asia simulation. The DAV is measured before and after $W_t$ of the model's simulations. RCM simulations at 0.44° resolution, forcing GCMs data (CMIP5), and the reference for measures is HadISD (observation)

remain optimistic, but there is a decrease in added value. Despite this, CanESM2-RCA still performs well in capturing wind speed variations over the region while CSIROL-RCA increases the performance as positive DAV indicates. On the other hand, the impact of $W_t$ adjustments varied across models. While MIROC5-RCA, HadGEM2-RCA, and MPI-RCA exhibited promising wind speed simulation initially, the introduction of $W_t$ adjustments resulted in a decline in performance with negative DAV values, except two seasons (spring; 3.4% and winter; 3.0%) showed positive DAV in the case of HadGEM2-RCA, implying that the $W_t$ adjustment may not have been beneficial for these specifically in representing wind speed over South Asia. Additionally, models like GFDL-RCA and MPI-REMO faced challenges in accurately capturing wind speed patterns, as indicated by negative DAV values before adjustments and while some improvements were observed post-adjustments, overall performance remained suboptimal.

In the case of moderately positive DAV values before $W_t$ adjustments, they indicated added value in wind speed representation for HadGEM2-RCA and MIROC5-RCA. Post-adjustments, the model's performance showed slight enhancement, maintaining positive DAV values across seasons and the annual period. Also, the mixed DAV results for HadGEM2-RCA indicated no significant DAV values for summer and autumn. The post-adjustments have affected HadGEM2-RCA's performance variably. Notably, NorESM1-RCA displayed remarkably high positive DAV values, indicating superior wind speed representation even before $W_t$ adjustments. Post-adjustments, the model's performance remained outstanding, reflecting extremely high positive DAV values for all seasons and the annual period. Finally, the Multi-Models Ensemble (MME) exhibited positive DAV values before $W_t$ adjustments, signifying added value in wind speed representation. After post-$W_t$ adjustment, the MME's performance improved further, reinforcing its capacity to capture wind speed patterns across seasons and the annual period. Overall, the impact of Terrain-Modified Wind Speed ($W_t$) adjustment is model-specific, enhancing some RCMs' performance while potentially not benefiting others. This highlights the complexity of accounting for terrain effects and the need for careful consideration in enhancing wind speed simulation capabilities within regional climate models. Additionally, tests have been conducted to know the objective quantification of the results by adding two more sets of DAVs (GCM-$W_t$ vs. GCM and RCM-$W_t$ vs. RCM) revealed in Figs. S8 and S9.

### 3.3 Upper-Tail PDF Analysis for Annual and Seasonal Before and After $W_t$

In this phase of research, the focus is on analyzing the Upper-tail Probability Density Function (PDF) at the 95th percentile (P95) and its associated Distributions Added Value ($DAV_{P95}$) pre- and after $W_t$ method. The assessment aims to elucidate the impact of $W_t$ adjustment on the model's ability to capture extreme wind events above the 95th percentile, using HadISD observation data (refer to Fig. 7).

Examining the $DAV_{P95}$ values before applying $W_t$ adjustments, varying performance across different models was observed. This is evident in the case of IPSL-RCA, which displayed limitations in representing wind speed patterns, as evidenced by negative DAV values. However, post-adjustments, the model exhibited remarkable improvement, as indicated by positive DAV values, demonstrating the potential of $W_t$ adjustments to enhance IPSL-RCA's wind speed simulation. Also, HadGEM2-RC showcased favorable wind speed representation before adjustments, with positive DAV values. Post-incorporating $W_t$ adjustments, the model's performance trend persisted, indicating the reliability of the model.

Interestingly, the impact of $W_t$ adjustments were diverse among models. While models like CSIRO-RCA and GFDL-RCA exhibited increased DAV values after adjustments, indicating enhancement, others such as MPI-RCA and MPI-REMO continued to face challenges in capturing extreme wind events. However, CanESM2-RCA presents a mixed DAV by indicating positive and negative performance. Notably, NorESM1-RCA demonstrated exceptional performance even before adjustments, with high positive DAV values remaining outstanding even after applying $W_t$ adjustments.

Following the $W_t$ adjustments for CSIRO-RCA, improvements were evident ($DAV_{P95}$ ranging from approximately 17.9–22.4%), as compared to prior displayed mixed results with limited added value ($DAV_{P95}$ ranging from approximately −5.57 to 1.51%). Further, following the $W_t$, i.e., MIROC5-RCA and Multi-Models Ensemble (MME) declined the performance $DAV_{P95}$ranging from approximately −60.1 to −46.7% and −16.3 to −23.2%, respectively.

Our results emphasize the significance of model-specific responses to $W_t$ adjustments, underlining the complexities of accurately representing extreme wind events in regional climate models. These findings contribute to a comprehensive understanding of the effectiveness of the $W_t$ application in improving the simulation of $DAV_{P95}$ in the South Asia region, which is essential for enhancing climate modeling accuracy and impact assessment.

## 4 Discussion

This research endeavors to unravel the underlying mechanisms behind the disparities observed in wind speed simulations over South Asia's diverse and complex region. We employed the "Terrain-Modified Wind Speed ($W_t$)" method,

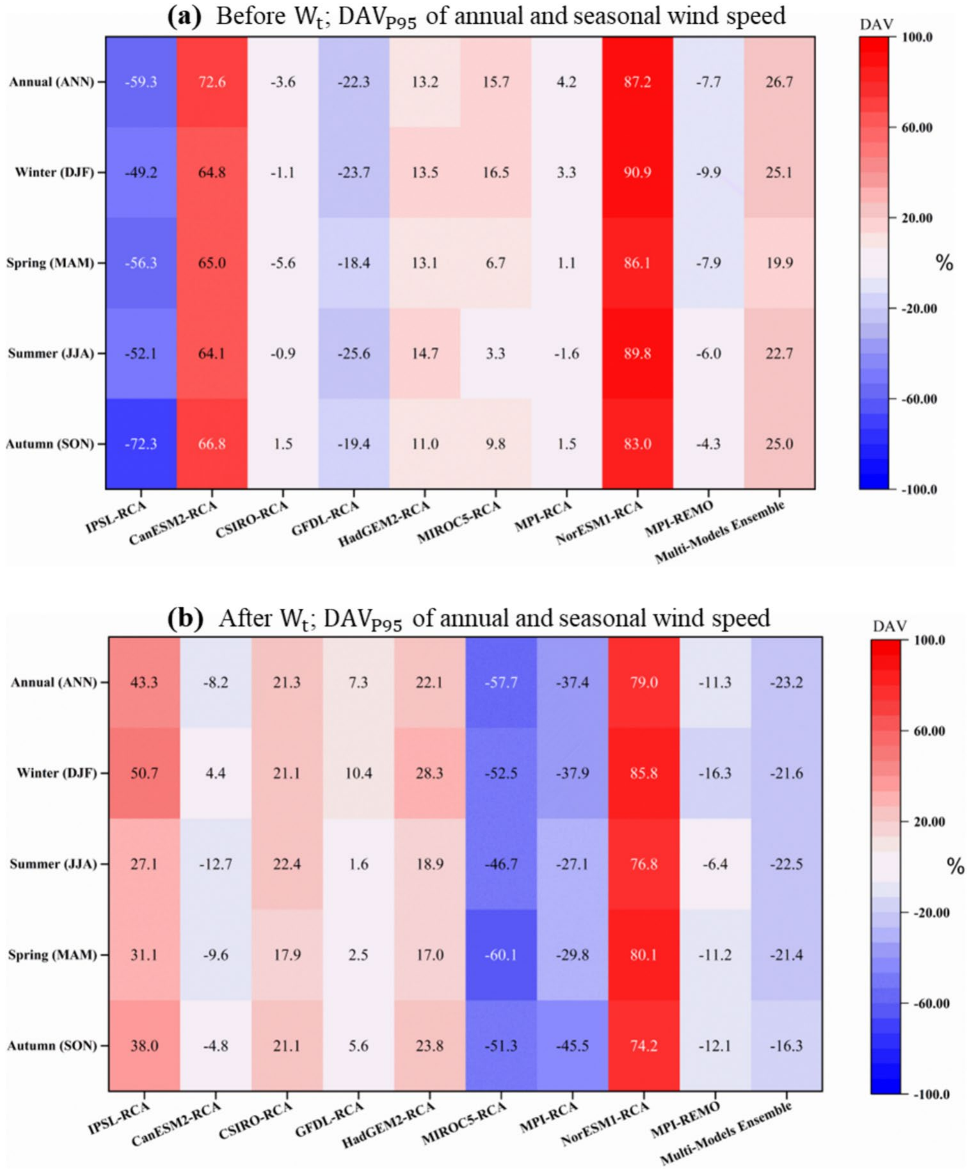


**Fig. 7** As illustrated in Fig. 5, examined the partial Probability Density Function (PDF) of wind speed, specifically focusing on wind speed bins situated above the 95th percentile

submitted by Liston and Elder (2006), as a crucial tool to account for the complex influence of topography on wind flow patterns. The added value is evaluated through the DAV metric introduced by Soares and Cardoso (2018), for full Probability Density Function (PDF) and the upper-tail PDF, represented by the 95th percentile ($DAV_{P95}$), pre-and post-$W_t$ bias adjustment, we delve into the complexity of regional climate modeling in South Asia.

In the analysis of various general circulation models (GCMs) and regional climate models (RCMs), the effectiveness of the Terrain-Modified Wind Speed ($W_t$) approach in enhancing wind speed representation was examined. Notable improvements were observed across multiple models after the application of $W_t$. For instance, GCM (IPSL-CM5A-MR) initially exhibited an optimistic Percent Bias (PBIAS) of 20.16%, indicating overestimated wind speeds. However, after $W_t$ adjustments, this PBIAS decreased significantly (in the negative direction) to − 13.41%, showcasing substantial enhancement, etc. Furthermore, the Regional Climate Models (RCMs) demonstrated similar patterns. These results agree with Li et al. (2020) and Khan and Dairaku (2024) findings which showed significantly improved wind speed representation. However, this study did not follow the terrain-based algorithm $W_t$.

The comparison of DAV results before and after applying the Terrain-Modified Wind Speed ($W_t$) method revealed the impact of the $W_t$ adjustments on the performance of the regional climate models (RCMs). In several cases, the incorporation of $W_t$ led to improved model performance, as evidenced by positive DAV values after adjustments i.e., IPSL-RCA. This suggests that accounting for topographic influences through $W_t$ has enhanced the accuracy of wind speed simulations in some RCMs. Notably, NorESM1-RCA stands out as the model with the highest added value both before and after $W_t$ adjustments. The model consistently performs well in representing wind speed variations over South Asia, and the $W_t$ adjustments further enhance its performance. However, it is essential to acknowledge that not all models benefited from the $W_t$ adjustments. Some RCMs, such as MIROCS5-RCA and MPI-RCA, demonstrated a decline in performance after incorporating $W_t$ adjustments, resulting in negative DAV values. This indicates that the $W_t$ adjustments may not be universally effective in improving wind speed simulations, and their impact varies depending on the model configurations and interactions between the RCM and GCM. Although variables like wind are often dependent upon synoptic low-pressure systems, storm track representation also contributes to the added value of a GCM. The downscaled products are not able to correct misrepresentations made by GCMs, for example, if GCMs do not correctly represent storm tracks. As a result, DAV values can be close to neutral in this situation. On the contrary, when a Global Climate Model accurately predicts the storm track, the downscaled Regional Climate Models can provide more relevant values, indicating either a gain or a loss in value. In this context, the adequate performance of the input data for the primary variables within the lateral boundary forcing region (Jury et al. 2015) assumes paramount significance.

Related to the Upper-tail PDF ($DAV_{P95}$) analysis focused on extreme wind events above the 95th percentile. It assessed the model's ability to accurately capture these events, which are crucial for understanding the impacts of extreme weather. It is observable that some models consistently perform well in both aspects (pre-and post-$W_t$), such as NorESM1-RCA and CanESM2-RCA, while others face challenges, namely GFDL-RCA and MPI-REMO. These variations highlight the complex nature of climate modeling over the Subcontinent region. The impact of $W_t$ adjustments is diverse. In the Full PDF analysis, $W_t$ adjustments improved performance for models like IPSL-RCA but negatively affected models like MIROCS5-RCA and MPI-RCA. In the Upper-tail PDF analysis, improvements were more consistent, indicating that $W_t$ adjustments generally enhanced the representation of extreme wind events. It is observed that models demonstrate specificity in their responses. This is exemplified in the work undertaken by GFDL-RCA, which struggles with extreme wind events yet sees slight improvements, whereas MPI-REMO experiences a decline in performance in both analyses (DAV and $DAV_{P95}$). These dissimilarities emphasize the need for tailored approaches to model evaluation and adjustment.

These results reflect those of Cardoso and Soares (2022), Molina et al. (2023) and Soares and Cardoso (2018) who also found that compared to the full PDF, RCMs generally produce better results in representing extreme wind speed than do the full PDFs, indicating an improvement in their representation before $W_t$ adjustment. By improving the resolution, an added value can be gained or lost in terms of the land-sea contrast and small-scale topography. In EURO-CORDEX models, especially over the sea, the daily maximum wind speed variable has a clear added value compared to coarser resolution counterparts, as demonstrated by Outten and Sobolowski (2021), without $W_t$. In coastal and mountainous regions, extreme winds are underestimated because of their structure and intensity (Cardoso and Soares 2022; Molina et al. 2023; Outten and Sobolowski 2021). In low-resolution models, the performance of the drag generated by unresolved terrain is improved, and the flow over mountains is possibly to be speeded up as a result (Molina et al. 2023). Moreover, the better representation of the main orographic structures produced a greater spatial variability of gusts over complex terrain (Cardoso and Soares 2022; Molina et al. 2023; Soares and Cardoso 2018).

It is necessary to recognize that the Taylor Diagram and DAV analyses evaluate different aspects of model performance to reconcile the results. DAV measures the added value that high-resolution modeling provides in capturing detailed wind speed distributions, while the Taylor Diagram focuses on the overall accuracy of patterns, variability, and correlation of wind speeds. However, as shown in the Taylor Diagram, the adjustment may introduce biases that affect the wind speed distributions, as reflected in the DAV analysis, even though it generally improves pattern accuracy and reduces RMSE. It is evident from this discrepancy that model performance evaluation can be quite complex and emphasizes the importance of obtaining a comprehensive assessment by utilizing a variety of metrics. Overall, the integration of PBIAS, Taylor Diagram, PDF, and DAV metrics offers a robust framework for assessing the nuanced impact of $W_t$ adjustments on wind speed forecasting in South Asia. As a result, a thorough and balanced analysis of the model performance can be achieved by capturing the strengths and limitations of the adjustments.

The present work comprehensively assesses the climate model's performance in representing wind speed variations and extreme events over the Subcontinent region. The study's novelty lies in the application of the DAV metric and the Terrain-Modified Wind Speed ($W_t$) technique for assessing the added value of high-resolution climate simulations for daily wind speed in South Asia. The incorporation of $W_t$adjustments address topographic influences and enhances the accuracy of wind speed simulations in some RCMs. However, the impact of $W_t$ adjustments on different models varies, and some models may not benefit from these adjustments. The research contributes to understanding climate model performance in capturing wind speed variations, providing valuable insights for decision-making in risk management, infrastructure development, and the energy sector in South Asia. The study's unknown aspects involve exploring how the use of $W_t$ can enhance wind speed simulations and improve our understanding of regional wind patterns in the region. Overall, this research adds to the body of knowledge on climate modeling in South Asia and advances our understanding of wind speed variability in the region. The findings pave the way for future research to refine climate model performance further and enhance the accuracy of wind speed simulations, thereby improving regional climate assessments.

Furthermore, it could be possible for future directions to use terrain-adjusted wind speed for wind energy generation yield estimates based on the power classified stations according to the international standard for future projections. The $W_t$ adjustment methodology should also be refined in the future to make it more easily applicable to different regions and climates. Further improvements in the accuracy and reliability of climate models for historical and future projections could be achieved by integrating high-resolution observational data and advanced machine-learning techniques. Our understanding of wind dynamics and their implications for climate change impact assessments would be advanced through collaborative efforts between climate scientists, meteorologists, and data scientists.

## 5 Conclusions

This study reveals the significant impact of terrain-modified wind speed ($W_t$) based on terrain topographic characteristics and the DAV metric. It assesses the enhancements in accuracy by the added value of high-resolution climate simulations for daily wind speed, which have been rigorously evaluated throughout South Asia. The metric of distribution-added value using high-resolution models (RCM) and coarser-resolution models (GCM) for evaluations has led to significant insights. These findings underscore the profound influence that terrain considerations have on wind speed simulations, instilling confidence in the study's method. The key findings are as follows.

- **Model Performance Enhanced:** The incorporation of terrain-modified wind speed ($W_t$) adjustments have significantly improved the accuracy of wind speed simulations. The model's enhancement performance is rigorously validated by statistical metrics such as PBIAS, Taylor diagram, probability density functions, and DAV. This thorough validation process underscores the effectiveness of the $W_t$ technique in generating more accurate and reliable model output.
- **Performance of RCMs versus GCMs:** In this study, we found that both RCMs and GCMs benefited from the adjustments, but RCMs demonstrated notably superior performance. This was due to their superior spatial resolution, enabling a more detailed representation of complex terrain features. The present study reaffirms the importance of high-resolution modeling in accurately capturing the effects of terrain on wind patterns, providing a clear direction for future research in this field.
- **Regional Effectiveness in South Asia**: This method has demonstrated considerable effectiveness in South Asia's diverse and topographically complex regions. Accurate wind speed forecasts are particularly important in this region for applications such as wind energy potential assessments, improving weather forecasting accuracy, and better-understanding climate projections.
- **Research Implications for Climate Modeling:** This study provides a solid foundation for advancing climate modeling. Terrain-modifying methods can be refined and validated in a variety of geographic regions and climate conditions. Accordingly, terrain characteristics can be incorporated into climate models to enhance their accuracy.
- **Limitations and Future Work:** The study has limitations, such as the specific models and regional focus. As part of future research, it is recommended that the $W_t$ method be validated in other regions and that more sophisticated terrain representations be explored to further improve the accuracy of wind speed predictions.

In summary, high-resolution climate models benefit significantly from terrain-modified wind speed ($W_t$) adjustments. Ultimately, improved climate predictions will lead to more informed environmental policy and resource management decisions as we refine our approaches and integrate more detailed terrain data.

**Supplementary Information** The online version contains supplementary material available at https://doi.org/10.1007/s41748-024-00453-6.

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**Data Availability** The observation data are achieved by Met Office Hadley Centre (https://www.metoffice.gov.uk/hadobs/index.html), Digital

Elevation Model through United States Geological Survey (https://search.earthdata.nasa.gov/search), and simulation model outputs from CORDEX (https://cordex.org/data-access/esgf/).

## Declarations

**Conflict of interest** All authors declare that they have no conflict of interest.

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