

Article

A Machine Learning-Based Long-Term Dataset of Blowing Snow Properties over Antarctica

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Abstract

A long-term, consistent dataset of blowing snow (BLSN), a common phenomenon over Antarctica, is essential for ice sheet mass balance analysis. While space-borne lidar missions such as Cloud–Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO) and Ice, Cloud, and Land Elevation Satellite (ICESat-2) have provided valuable continental-scale BLSN observations, their temporal resolutions and spatial reaches present notable limitations. Using CALIPSOs for training, a machine learning approach has been developed to generate hourly Antarctic BLSN data on the Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2) grid, extending back to the 1980s. ICESat-2 observations are used to assess the post-CALIPSO period; the results demonstrate greater bias with BLSN layer heights and better agreement with BLSN fraction and optical depth. When compared with ground-based observations, MERRA-2 exhibits a comparable and lower BLSN fraction and lower layer heights than those recorded by ceilometers. This data record represents the longest continuous BLSN data record to date. This study provides an overview of key BLSN properties, including occurrence, height, and optical depth. The results highlight strong seasonal patterns: BLSN occurrence peaks during Antarctic winter, while both height and optical depth are higher in summer with no statistically significant trend. Spatially, East Antarctica exhibits higher BLSN occurrence than West Antarctica.

Keywords: blowing snow; MERRA-2; climatology

1. Introduction

Blowing Snow (BLSN) refers to snow that is lifted from the surface by the wind, a process commonly observed in polar regions and during the winter season in cold midlatitude areas [1]. BLSN has a wide range of effects, from influencing daily weather conditions to having long-term climatic impacts. It is one of the severe weather conditions that can directly impact daily life by reducing visibility [2].

BLSN occurrence is common in Antarctica. Although wind speed is the primary driver of BLSN initiation and distribution, its occurrence results from the complex interaction of multiple atmospheric and surface factors. These include wind shear, surface snow cohesion and bonding, modulated by topography, vegetation cover, snow crystal morphology, temperature, snow age, etc. [3,4]. BLSN significantly impacts the surface mass balance (SMB) [5–13], near-surface atmospheric thermodynamics [14,15], the regional radiation budget, and satellite lidar altimetry [16–18]. The Antarctic ice sheet (AIS) serves as both



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a critical indicator of climate change and a potential major contributor to global sea-level rise [19,20]. While BLSN influences SMB through sublimation and transport, large uncertainties in these effects still exist due to a lack of long-term BLSN datasets with adequate temporal and spatial resolution and coverage.

Acquiring long-term BLSN data over Antarctica is challenging due to the harsh weather conditions and the geographical remoteness. Nevertheless, studies on various aspects of BLSN over Antarctica have been conducted since the early 20th century [21]. Records show the occurrence of BLSN observed during several Antarctic study field campaigns. Most early studies were stationed at various locations such as Cap Denison, Port Martin, Dumont D'Urville, Charcot Station, Byrd Station, Mizuho Station, Amundsen–Scott, etc. [7,13,22–30]. These studies were seasonal and spanned several years, using various instruments. More recently, BLSN studies have been further enhanced through combined observational and model-based analyses (e.g., [25,26]), with additional enhancement provided by satellite remote sensing techniques (e.g., [27,28]). A few studies have investigated BLSN at the continental scale, using satellite missions such as Cloud–Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO) and Ice, Cloud, and Land Elevation Satellite (ICESat-2) [1,31–33]. However, due to their orbital characteristics, these satellites have limited spatial and temporal coverage and do not reach south of 88°S, resulting in data gaps [33].

Modern technologies such as artificial intelligence (AI) and machine learning (ML) have demonstrated strong capabilities in pattern recognition and determining data-driven thresholds to classify events and quantify their magnitudes [34–40]. Incorporating domain-specific inputs and selecting appropriate ML models further enhance predictive accuracy and improve understanding of the key factors influencing these predictions. Using this approach, an hourly BLSN dataset has been generated over Antarctica on the same grid as the MERRA-2 reanalysis, spanning from the 1980s onward [4,35,38] (details are provided in the next section). The present study focuses on analyzing this long-term dataset of BLSN properties. It further explores the long-term spatiotemporal properties of BLSN on the standard MERRA-2 grid.

2. Data

Operational machine learning models have been developed to diagnose BLSN properties, such as occurrence, height, and optical depth [4,38,40]. For BLSN detection, the model uses CALIPSO BLSN observations from 2007 to 2016 [1] with a horizontal resolution of 333 m as the “truth” and MERRA-2 data as input features [41]. To create the BLSN training dataset, CALIPSO observations were categorized into two scene types: BLSN and non-BLSN. These scenes were then collocated with the nearest MERRA-2 grid (0.5° latitude by 0.625° longitude) points to set up training and testing datasets. For operational use, various machine learning models were tested, and the Extreme Gradient Boosting (XGBoost) classification model [42], which demonstrated the best performance, was selected. XGBoost is a tree-based boosting model [43]. Its adaptability comes from learning from poor predictions and strengthening them to produce a robust model. The strength of the model lies in its ability to optimize the loss function by sequentially fitting new trees to the negative gradients of the loss function, thereby minimizing the residual errors of preceding models [44]. This iterative and additive process enables the model to refine its predictions and achieve superior generalization performance. The model was trained using input features derived from MERRA-2 over Antarctic land ice and sea ice.

A thorough feature selection process was conducted, and the model was rigorously validated to ensure its reliability in producing long-term BLSN datasets. Temperature and wind speeds at different levels play a decisive role in BLSN diagnosis. The complete set of

selected input variables for BLSN diagnosis include temperature (2 M) and temperatures at model levels 70 and 68; zonal wind (U) at 10 M and levels 71, 70, and 68; meridional wind (V) at 10 M and levels 71, 70, 69, and 68; specific humidity at 2 M and levels 71 and 68; geopotential height; snow age; and surface pressure, including atmospheric pressure at levels 71 and 69. Here, MERRA-2 model layers refer to a hybrid vertical coordinate system (eta levels), resulting in variable above-ground heights for model levels based on surface pressure. MERRA-2 uses terrain-following vertical coordinates, which are dynamically derived from the surface and regions. The physical heights are surface pressure-dependent. In Antarctica, the first model level from the bottom is typically 45–60 m above ground, and the second level ranges from 120 to 170 m. In the lower atmosphere, the vertical layers have a resolution of 15 hPa per layer (up to layer 62), relative to a nominal baseline surface pressure of 1000 hPa. The horizontal resolution is roughly 56 km $\times$ 24 km around 70° latitude due to meridional convergence.

The complete list of variables used to train the model is provided in Table 1. The resulting dataset spans from 1980 to 2024 with the potential for future extensions. This approach consistently generates hourly BLSN data over Antarctica on the standard MERRA-2 grid, effectively filling spatial gaps near the poles where space-borne lidars have limited coverage.

Table 1. List of MERRA-2 inputs for classification model.

Surface Pressure	Wind Speed (U10 M)	Wind Speed (V10 M)	Sp. Humidity (2 M)	Temperature (2 M)	Geo. Potential Height	Wind Speed (U71)
Wind Speed (U70)	Wind Speed (U69)	Wind Speed (U68)	Wind Speed (V71)	Wind Speed (V70)	Wind Speed (V69)	Wind Speed (V68)
Temperature (70)	Temperature (68)	Sp. Humidity (71)	Sp. Humidity (68)	Pressure Level (71)	Pressure Level (69)	Snow age

Similarly, for estimating BLSN height and optical depth, CALIPSO BLSN layer heights and optical depth values were used and matched to the nearest MERRA-2 grid points to prepare training and testing data [38]. A combination of input features was applied to identify the most effective predictors. Model inputs consist of surface pressure; 10 M zonal and meridional winds; surface geopotential height; sensible and latent heat fluxes; temperature, specific humidity, and omega vertical velocity (at 2 M and levels 70 and 71); zonal and meridional winds at levels 70 and 71; pressures at model levels 70 and 71; the temperature gradient; and vertical wind shear (U70–U10 M and V70–V10 M). The complete list is provided in Table 2. Various regression models were tested, and the XGBoost regressor performed best for both height and optical depth estimation. The selected inputs were for each scene diagnosed as BLSN by the classification model; the selected regression model was utilized to estimate BLSN layer height and optical depth [40]. The resulting estimates are provided at the same spatial and temporal resolution as the MERRA-2 data [45].

Several cautions regarding the dataset must be noted. As the training labels are derived from CALIPSO, inherent lidar limitations such as signal attenuation under thick cloud cover are inevitably propagated to the model. In these high-attenuation regimes, positive blowing snow (BLSN) labels are often unavailable for training. While the model generates predictions under such conditions, they have not been independently validated and may introduce uncertainties into surface mass balance (SMB) calculations. Specifically, the lack of training labels during heavy snowfall or low-wind events increases the risk of false negatives and heightened predictive uncertainty in these specific meteorological regimes. Although these specific high-attenuation events lacked positive labels in the training dataset, the underlying meteorological drivers such as humidity, pressure, temperature, and wind

speed are represented within the MERRA-2 input fields. Consequently, the model may still produce predictions for these regimes based on the physical signatures captured in the reanalysis data, even if direct lidar validation was precluded during training. The algorithms used to generate the long-term BLSN dataset in this study are fully documented in [4,40].

Table 2. List of MERRA-2 inputs for Height and Optical depth regressor.

Total Latent Energy Flux	Vertical Pressure Velocity (71)	Pressure Level (71)	Sp. Humidity (70)	Temperature (70)	Wind Speed (U70)	Wind Speed (V70)
Sensible Heat Flux from Turbulence	Geo Potential Height	Pressure	Sp. Humidity (71)	Temperature (71)	Wind Speed (U71)	Wind Speed (V71)
Vertical pressure velocity (70)	Pressure Level (70)	Sp. Humidity (2 M)	Temperature (T2 M)	Wind Speed (U10 M)	Wind Speed (V10 M)	Temperature Gradient

The Ice, Cloud, and Land Elevation Satellite-2 (ICESat-2), the successor to the ICESat mission, is a high-precision altimeter that also measures atmospheric backscatter at 532 nm [46–48]. Palm et al. (2021) [33] implemented a slightly modified version of the CALIOP algorithm [1] to retrieve blowing-snow properties over Antarctica. The publicly available ATL09 data product contains BLSN detection over snow-covered surfaces using wind speed and laser backscatter measurements, as well as BLSN height and optical depth. It provides blowing snow layers at both high (25 Hz or 280 m) and low (1 Hz or 7 km) resolution [33]. It reaches 88° S, improving the coverage of CALIPSO and leaving a small hole at the South Pole. This data product is used to validate the ML BLSN product within MERRA-2.

At Zhongshan Station (69°22′24.76″ S, 76°22′14.28″ E) in Antarctica, using a C12 Ceilometer [49], a BLSN detection algorithm uses raw backscatter signals to mitigate range correction scaling issues. By applying a 3σ thresholding approach, the algorithm effectively distinguishes among clear sky, snowfall, and blowing snow events using both near-surface intensity and vertical gradient analysis. The method also provides automated detection of the BLSN layer top, maintaining accuracy even in the presence of overhead cloud cover [49]. We utilized data measured at Zhongshan Station in Antarctica as independent, ground-based data for validation [49]. The blowing snow classification and height detection data [50] were used for comparison with ML data. Python versions 2.7 and 3.1 are used to create the following figures.

3. Results

3.1. MERRA-2 BLSN Properties

The data described in the previous section, including model-diagnosed BLSN occurrence, height, and optical depth, are available at an hourly resolution on a uniform grid of $0.5^\circ \times 0.625^\circ$ [45]. This study provides an overview and analysis of these datasets. To derive the monthly BLSN occurrence over Antarctica, the number of BLSN events in each month was summed and divided by the total number of data points in each grid. This is presented in Figure 1a. The time series shows a periodic fluctuation in the monthly BLSN occurrence, indicating clear seasonality (discussed later in the section). The fraction also shows considerable interannual variability. The monthly BLSN fractions occasionally exceed 35% during peak cold periods, while dropping well below 5% during low-activity months.

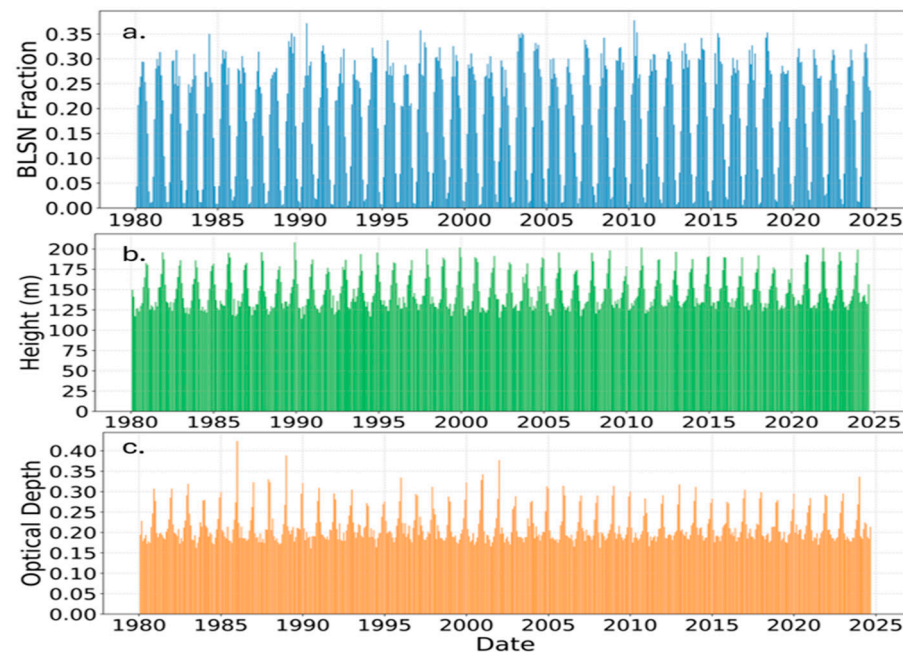


Figure 1. MERRA-2 Monthly blowing snow; (a) occurrence, (b) height, and (c) optical depth time series over Antarctica (1980 February to 2024 October).

Similarly, monthly BLSN height was calculated following the same approach. For each month, the total BLSN height was summed and then divided by the total number of BLSN events, resulting in an average BLSN height for that month. The monthly average BLSN height is shown in Figure 1b. The figure shows considerable variability, with heights occasionally reaching up to 200 m and dropping below 120 m during lows, indicating seasonality.

Furthermore, the same analysis was applied to BLSN optical depth. For each month, the total BLSN optical depth was summed and divided by the number of BLSN optical depths, yielding the monthly average optical depth. The results also exhibit a periodic pattern, with values occasionally reaching or exceeding 0.30 during peak months and dropping to around 0.20 during low-activity periods, as shown in Figure 1c. The standard Mann–Kendall test was applied to evaluate the long-term monotonic trends in blowing snow occurrence, height, and optical depth. While this test does not explicitly decompose the strong seasonal cycle, it provides an assessment of the overall directional trend of these variables over the study period. Our analysis indicates no statistically significant monotonic trend, suggesting that any year-to-year variations in blowing snow properties were not associated with a sustained long-term increase or decrease.

To investigate the seasonality in monthly BLSN occurrence, height, and optical depth, we aggregated all BLSN observations for each calendar month over the period from February 1980 to October 2024. These totals were then divided by the corresponding number of observations for each month, yielding an average monthly occurrence rate over the entire period. As shown in Figure 2a, the results further reinforce a clearly distinct seasonal cycle. BLSN occurrence is notably higher during the Antarctic winter months (April to September), with peak values in May, June, and July—each close to 30%. This seasonal increase is largely driven by the combination of persistently low temperatures, strong winds, and the widespread presence of loosely bound snow particles that together create ideal conditions for blowing snow events. The findings of this study are in good qualitative agreement with previous studies by Palm et al. (2018) [51] and Mahesh et al. (2003) [52]. Furthermore, East and West Antarctica were separated using the -45° and 171° longitudes [53]. The analysis reveals a clear contrast in BLSN occurrence between the two regions. East

Antarctica exhibits significantly higher frequencies, reaching over 35% in July, whereas West Antarctica shows comparatively lower values (<25% in winter months). This disparity is primarily attributed to the strong katabatic winds that descend from the high Antarctic Plateau, causing more prolific BLSN occurrence due to downslope winds that are more frequent in East Antarctica [38]. In contrast, during the summer months, both regions experience similar infrequent occurrences of BLSN.

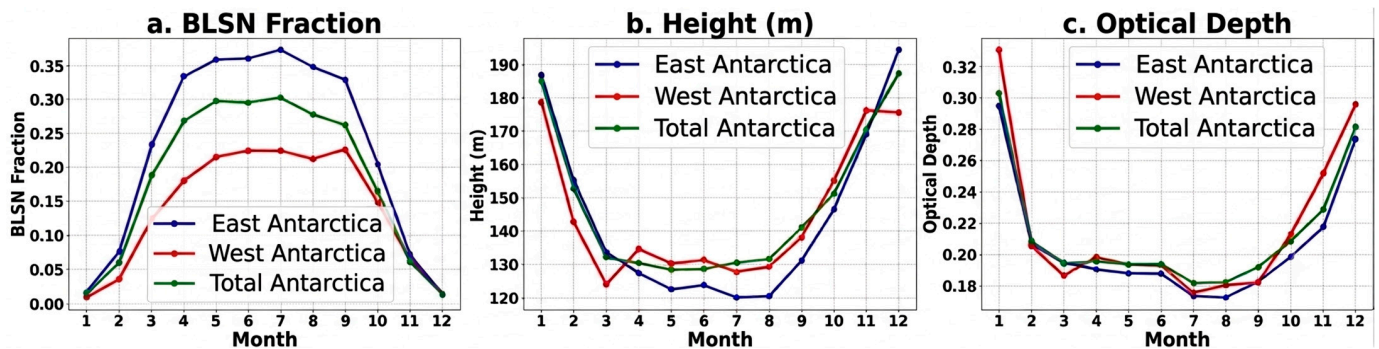
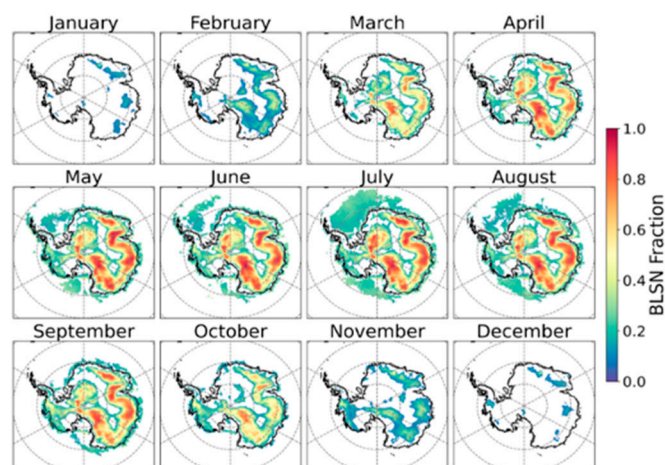


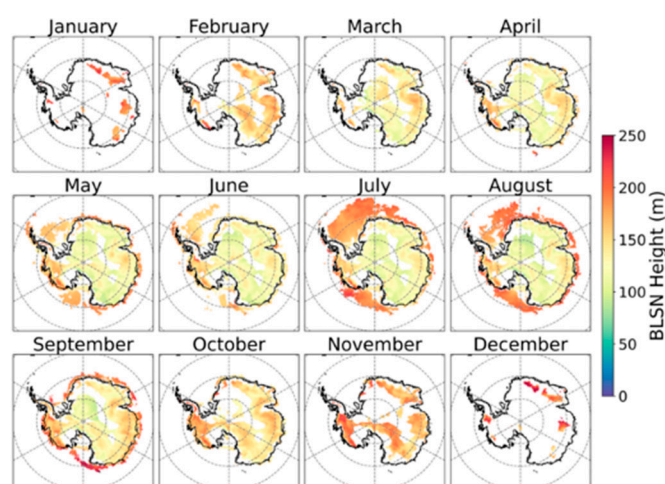
Figure 2. Monthly BLSN (a) occurrence, (b) height, and (c) optical depth, aggregated across all BLSN observations for each calendar month from February 1980 to October 2024.

Similarly, Figure 2b,c, present monthly averaged BLSN height and optical depth. Both show seasonally higher values, with BLSN height exceeding 180 m during the summer months, whereas it remains limited to ~130 m during the winter months. The Antarctic boundary layer exhibits extreme thermal stability during the winter months, characterized by strong surface-based temperature inversions. During the summer, this stability is reduced as increased solar radiation warms the ice surface, weakening the positive temperature gradient and promoting more frequent neutral or convective conditions [14,53,54]. Such a weakened temperature inversion can contribute to a higher BLSN height, as observed in the summer months. While this seasonal shift physically supports the occurrence of higher BLSN heights, it is important to note that these heights are overestimated when compared to ICESat-2 data and underestimated when compared to surface-based measurements (discussed further in Section 3.2). On the other hand, during winter, due to colder surface temperatures, the near-surface air remains denser than the layer above it, creating greater stability and restricting turbulence and vertical mixing [14]. A similar pattern is observed in BLSN optical depth, which reaches 0.30 in summer and remains slightly below 0.18 in July and August (winter months). Optical depth is a vertically integrated value, so a higher BLSN layer generally has a higher optical depth. Also, the lower optical depth in winter is likely from a volume- and moisture-limited regime because the extreme thermal stability of the winter ABL imposes a physical lid that confines blowing snow to a shallow vertical column [15]. Simultaneously, the dry air from the overlying inversion accelerates sublimation, further lowering particle concentrations and ensuring these frequent layers remain optically thin. In fact, the BLSN optical depth and turbulent layer height have been shown to be positively correlated over Dome C [14]. The smaller optical depth observed during the winter season is most likely linked to reduced turbulence in the stable boundary layer. Moreover, the observed seasonality may be affected by a smaller sample size (shown later in Figure 3) during the summer months.

a. Blowing Snow Fraction



b. Blowing Snow Height



c. Blowing Snow optical depth

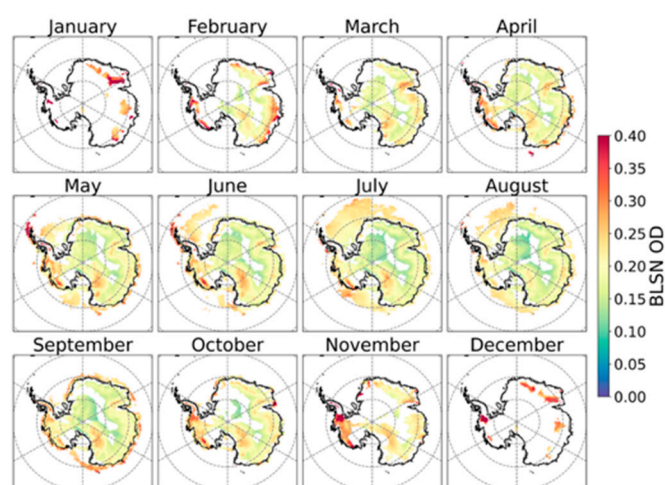


Figure 3. Monthly grid-averaged values for each MERRA-2 grid cell from February 1980 to October 2024: (a) BLSN occurrence, (b) BLSN height, and (c) BLSN optical depth.

A spatial average helps to identify regions of high and low BLSN occurrence, height, and optical depth over Antarctica. Figure 3a–c shows the average values over the MERRA-2 grid from February 1980 to October 2024. Occurrence is computed by counting the total number of BLSN events in each grid and dividing by the total number of data points. For height and optical depth, the sum of height and optical depth is divided by the total number of BLSN events in the respective grids. Because accurate estimation of BLSN height and optical depth depends on adequate sampling, a threshold of 15% of the maximum observed BLSN occurrence is used to define valid grid cells. Only grids meeting this criterion are included in the analysis, thereby ensuring a sufficient sample size and reducing uncertainties associated with sparse observations. A sensitivity analysis of this threshold is provided in Table 3 using the entire data. There are more grid cells with sporadic BLSN; this occurrence fraction is physically anticipated. The spatial patterns continue to be highly correlated across all thresholds, demonstrating that changes in the selected threshold, either 10%, 15%, or 20%, result in domain-averaged differences of less than 2% for height and optical depth. This confirms that our selection of the threshold for the distribution of blowing snow over Antarctica is not skewed.

Table 3. Sensitivity analysis of Antarctic BLSN statistics to the chosen occurrence threshold.

Threshold	Mean Height (m)	Mean Optical Depth
10%	150.36	0.216
15% (Baseline)	148.04	0.2120
20%	146.29	0.2124

Figure 3a shows monthly BLSN occurrences. It is evident that winter months exhibit high BLSN frequency, with parts of coastal East Antarctica experiencing over 70% occurrence. Conversely, the summer months and high-altitude interior regions maintain significantly lower frequencies due to lower surface wind speeds and lower temperatures. Antarctica’s interior region is the high polar plateau region with continuously cold and dense air above it. The cold, dense air flows from the high plateau to lower-lying surfaces, favoring turbulent mixing and blowing snow occurrences along the slopes and near the coastal regions [55]. Results obtained from this data agree with Mahesh et al. (2003) [52] and Palm et al. (2011 and 2018) [1,51]. BLSN heights and optical depths are slightly higher in sea ice regions and coastal regions.

3.2. Comparison with ICESat-2 and Ground-Based Measurement

To make a direct comparison and validation with independent BLSN data, we used ICESat-2 data [33] from 2023. First, we calculated BLSN occurrence, optical depth, and height from ICESat-2 BLSN data on the MERRA-2 grid for all of Antarctica, including sea ice and land. Then, corresponding grids were identified to make a grid-by-grid comparison. The statistics were calculated by taking the average of the difference for each grid value of fraction, layer height, and optical depth for 2023 and are listed in Table 4.

A comparative analysis of statistical performance metrics is shown in Table 4. The sample size varies seasonally, reaching a minimum during the summer months. For instance, the total number of blowing snow (BLSN) occurrence samples drops from approximately 19,000 in the winter months to 5000 in the summer months. Similarly, samples for BLSN height and optical depth decrease from approximately 15,000 in winter to 3000 in summer. Table 4 reveals that the MERRA-2 model’s accuracy varies significantly by parameter. The biases in fraction are generally small (e.g., 0.010 in February, 0.007 in June), suggesting that MERRA-2 is relatively well aligned with ICESat-2 regarding the frequency of blowing

snow events. Most months have positive fraction biases, except for slight underestimations in January (-0.068) and September (-0.044). The BLSN fraction standard deviations of MERRA-2 and ICESat-2 observations are the same in August. Across all other months, the standard deviations are minimal, showing the same degree of variability. Overall, BLSN occurrences are in statistically good agreement.

Table 4. Blowing Snow properties comparison of MERRA-2 and ICESat-2 for 2023.

Months	Variable	Bias	RMSE	SD (MERRA2)	SD (ICESat-2)
Jan	Fraction	-0.068	0.118	0.044	0.091
	Optical Depth	0.131	0.210	0.128	0.127
	Height (m)	83.800	99.221	45.708	27.218
Feb	Fraction	0.010	0.179	0.148	0.138
	Optical Depth	0.074	0.169	0.072	0.152
	Height (m)	51.347	64.703	29.047	31.157
March	Fraction	0.013	0.221	0.229	0.227
	Optical Depth	0.054	0.162	0.062	0.146
	Height (m)	40.680	61.318	34.943	29.873
April	Fraction	-0.052	0.278	0.273	0.286
	Optical Depth	-0.004	0.182	0.059	0.182
	Height (m)	27.685	52.827	28.354	39.484
May	Fraction	0.032	0.263	0.285	0.275
	Optical Depth	0.022	0.176	0.043	0.178
	Height (m)	43.410	73.168	25.297	55.426
June	Fraction	0.007	0.262	0.253	0.281
	Optical Depth	-0.018	0.174	0.051	0.180
	Height (m)	17.738	50.663	23.999	46.675
July	Fraction	0.049	0.273	0.256	0.267
	Optical Depth	-0.034	0.194	0.071	0.195
	Height (m)	12.540	57.127	38.493	53.261
August	Fraction	0.056	0.260	0.271	0.271
	Optical Depth	0.014	0.172	0.052	0.176
	Height (m)	24.111	55.058	31.245	48.616
September	Fraction	-0.044	0.247	0.248	0.278
	Optical Depth	0.079	0.173	0.061	0.154
	Height (m)	72.366	87.259	37.985	34.823
October	Fraction	0.039	0.203	0.229	0.185
	Optical Depth	0.075	0.154	0.065	0.132
	Height (m)	53.566	67.696	30.818	32.013
November	Fraction	0.017	0.141	0.134	0.095
	Optical Depth	0.129	0.212	0.103	0.142
	Height (m)	77.605	88.224	35.407	24.383
December	Fraction	-0.071	0.130	0.066	0.097
	Optical Depth	0.124	0.206	0.081	0.148
	Height (m)	91.502	111.007	56.355	28.810

For optical depth, MERRA-2 shows a consistent positive bias for most months, with a few exceptions in April, June, and July, with RMSE values ranging approximately from 0.15 to 0.21. Although MERRA-2 and ICESat-2 show occasional divergence in standard deviation, overall MERRA-2 optical depth estimates are reasonable. On the other hand, the BLSN layer heights display substantially higher variability. The RMSE for height ranges from a minimum of 50.66 m in June to a peak of 99.22 m in January, highlighting a persistent challenge in the summer months. Furthermore, the notable discrepancies between the SDs (averaging 12.61 m) suggest that the MERRA-2 model frequently struggles to replicate the vertical structure observed by ICESat-2. This could be due to the lower sample sizes in the summer months, as fewer BLSN events are detected then. On the other hand, BLSN events are more frequent in winter and provide a large sample size for robust statistical comparisons. Thus, the MERRA-2 BLSN layer height shows better agreement with ICESat-2 in the winter months such as June, July, and August, with biases of 17.74 m, 12.54 m, and 24.11 m, respectively. Overall, these mixed performance gaps are likely driven by the model's two-stage process: the initial classification of BLSN events followed by height prediction. The potential contributors to height discrepancies are attributed to false-positive classifications, where the model incorrectly identifies BLSN conditions, leading to the height estimates. These classification errors, combined with limitations in grid resolution, explain the divergence from ICESat-2's BLSN height estimates.

To further evaluate and observe grid-wise comparison, we arbitrarily selected May of 2023, as shown in Figure 4.

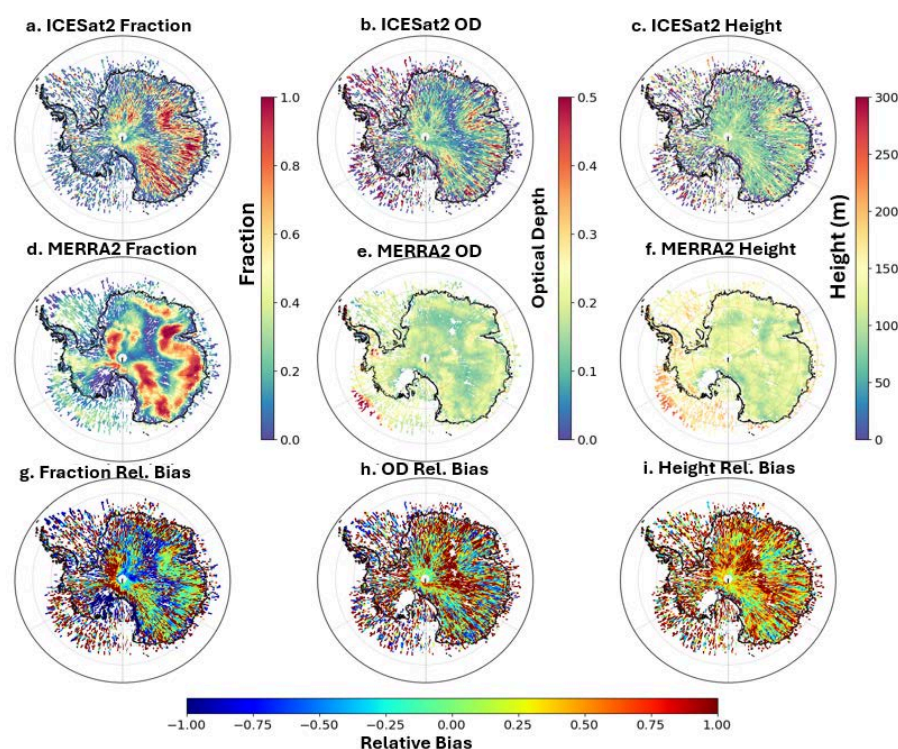


Figure 4. Spatial comparison of BLSN properties between ICESat-2 and MERRA-2 for May 2023. Panels (a–c) show ICESat-2 BLSN fraction, optical depth, and height. Panels (d–f) correspond to MERRA-2 variables masked to monthly aggregated masked to ICESat-2 orbital tracks. Panels (g–i) illustrate the grid-based relative bias (MERRA-2– ICESat2) over Antarctica.

As illustrated in Figure 4, panels a through c display ICESat-2 blowing snow (BLSN) fraction, optical depth, and height, while panels d through f show the corresponding MERRA-2 data on the same grid. Panels g through i provide grid-based bias comparisons.

Spatially, MERRA-2 BLSN properties show good agreement with nearby grids and successfully identify BLSN hot spots. Statistically, the MERRA-2 BLSN fraction aligns well with ICESat-2, with a low mean bias of +0.032 (relative bias < 10%) and an RMSE of 0.26. This suggests that MERRA-2 accounts well for overall BLSN occurrence, despite slight spatial misalignments seen in Figure 4. Table 4 summarizes these comparisons. For optical depth (panels b, e, and h), MERRA-2 shows a small positive bias of +0.022 (14.3%) with a good spatial distribution. This indicates that MERRA-2 BLSN layers are slightly denser than those observed by ICESat-2. For height, MERRA-2 tends to overestimate the vertical extent with a mean bias of +43.41 m (51.3%), but this is only slightly larger than ICESat-2's vertical resolution (30 m). As shown in Table 4, the standard deviation (SD) for the BLSN fraction is very similar between MERRA-2 (0.285) and ICESat-2 (0.275). However, the SD for optical depth and height differs more significantly. MERRA-2 is very reliable for identifying average values, though it is less sensitive than ICESat-2 to extreme highs and lows. Overall, MERRA-2 successfully identifies BLSN events, even though it overestimates their height. It is important to note that the sample sizes differ; MERRA-2 provides hourly estimates, while ICESat-2 data are limited to its orbital paths, cloud-free and penetrable conditions only.

To further validate the results with ground-based data, we used ceilometer measurements from Zhongshan Station ($69^{\circ}22'24.76''$ S, $76^{\circ}22'14.28''$ E) in coastal East Antarctica during 2022. This dataset provides blowing snow classification and layer-top measurements at nearly 1 min temporal resolution. We compared these observations with MERRA-2 blowing snow (BLSN) reanalysis data by identifying the nearest grid point and extracting hourly values. We conducted a monthly time-series comparison between the two datasets to avoid the sensitivity involved in applying arbitrary binary criteria to the ceilometer data. This method offers a more reliable evaluation of long-term variability as shown in Figure 5.

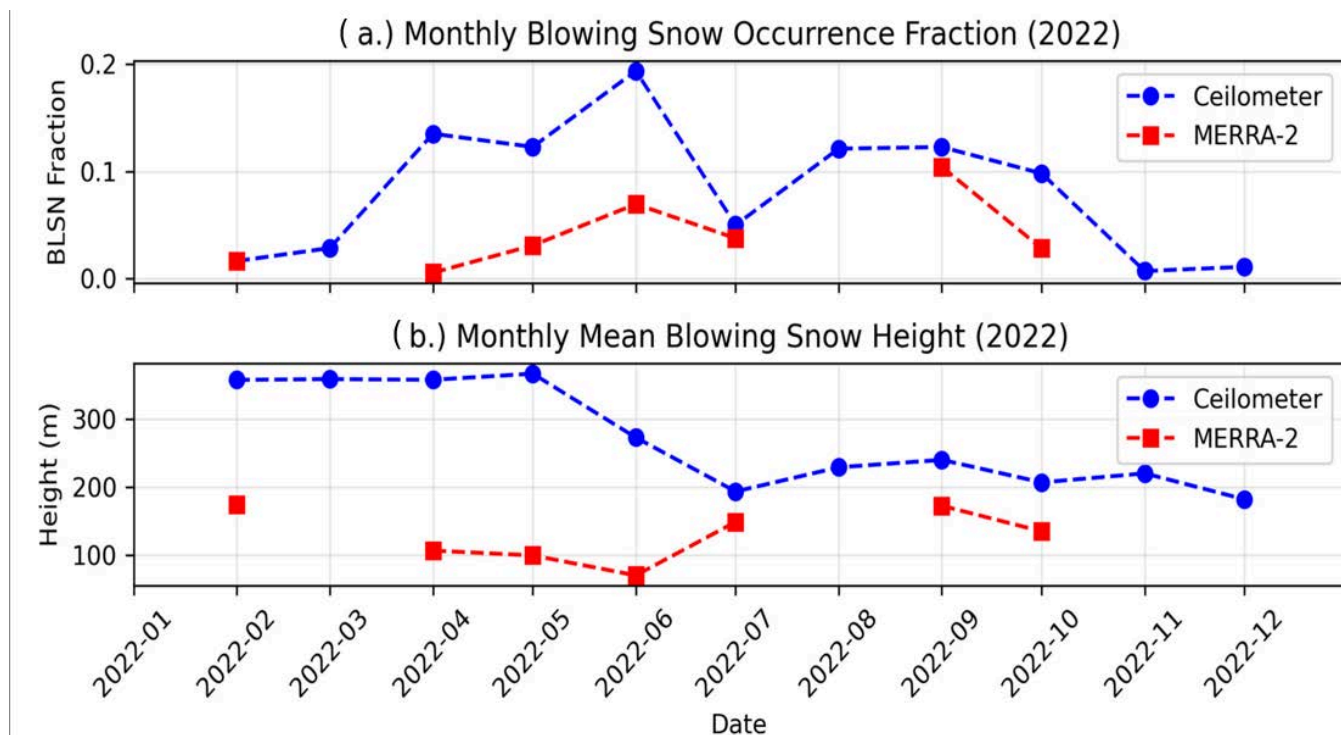


Figure 5. Comparison of monthly BLSN (a) fraction and (b) mean height between MERRA-2 and ceilometer data at Zhongshan Station for 2022.

The upper panel in Figure 5a shows the BLSN fraction from both the ceilometer and MERRA-2. Overall, BLSN fractions are comparable, with the ceilometer showing a higher

occurrence. The ceilometer occurrences are generally around 10%, with the exception of June, which is close to 20%. MERRA-2 fractions are mostly less than 10%, with some months where no BLSN is identified. Some months have very similar occurrences, as seen in February, July, and October. Both show a similar trend in BLSN occurrences. Similarly, the lower panel in Figure 5b shows the average BLSN height. The ceilometer consistently reports a higher height than MERRA-2, especially in the summer months. October and November show very similar heights for both. Some months, such as February, March, and September, in MERRA-2 do not have heights because no BLSN are identified for the given grid. The absence of BLSN events in MERRA-2 data during those months may result from a lack of sufficient training samples under heavy cloud cover or high snowfall conditions. It can be an artifact of the ML model, as the ceilometer observations demonstrate that the vast majority of BLSN events occur during or immediately following heavy snowfall. A noticeable discrepancy in both occurrence and BLSN layer height is expected because the ML model is a simplified representation of the atmosphere, whereas the instrument is a localized point observation. Also, the ceilometer data are from the coastal region, so they certainly do not represent more inland regions of Antarctica. This comparison is for a single grid; still, the collocated data provide a comparative analysis.

It is important to note that several inherent limitations of the Zhongshan Station blowing snow detection algorithm must be considered when using the ceilometer. High attenuation of the laser beam due to high concentrations of snow particles affects the estimation of the BLSN layer top. Secondly, the measurement and algorithm methods have a 15-m vertical blind zone where the ceilometer does not effectively capture signals. Additionally, the wind speed threshold for blowing snow depends on snow age, increasing after snowfall, while the blowing snow layer becomes shallower over time as loose snow is depleted, regardless of high wind speeds.

3.3. Regional and Surface-Type Variations in BLSN Properties

Figure 6 presents the BLSN properties for different regions and surface types over Antarctica. It shows the time series of monthly blowing snow (BLSN) occurrences across different surface types, including the total Antarctic region, land ice, sea ice, East Antarctica, and West Antarctica. Panel (a) shows the BLSN occurrence fractions for these regions from top to bottom, respectively. A strong seasonal pattern is evident across all surface types. We used MERRA-2 ice masks to identify valid ice-covered grid cells. A grid cell was included if the combined fraction of the dynamic sea-ice and land-ice masks was near-complete (>90%). Within these selected grid cells, we used the MERRA-2 static land-ice mask to separate land ice and sea ice. Grid cells with a non-zero land-ice fraction were classified as land ice, while the remaining ice-covered cells were categorized as sea ice.

In the comparison between land and sea ice, land ice exhibits a higher frequency of BLSN occurrences. Likewise, East Antarctica experiences more frequent BLSN events than West Antarctica, although both regions display similar seasonal patterns. Panels (b) and (c) depict the monthly averages of BLSN layer height and optical depth, respectively, for the same surface types shown in panel (a). The distributions of BLSN layer height and optical depth differ slightly over sea ice, where both variables tend to be lower compared with land ice. Such variations may result from small sample sizes when isolating sea ice data from land ice, particularly during the Antarctic summer months when sea ice samples are limited. While there is considerable interannual variability, no evident trends in BLSN properties are observed over the years.

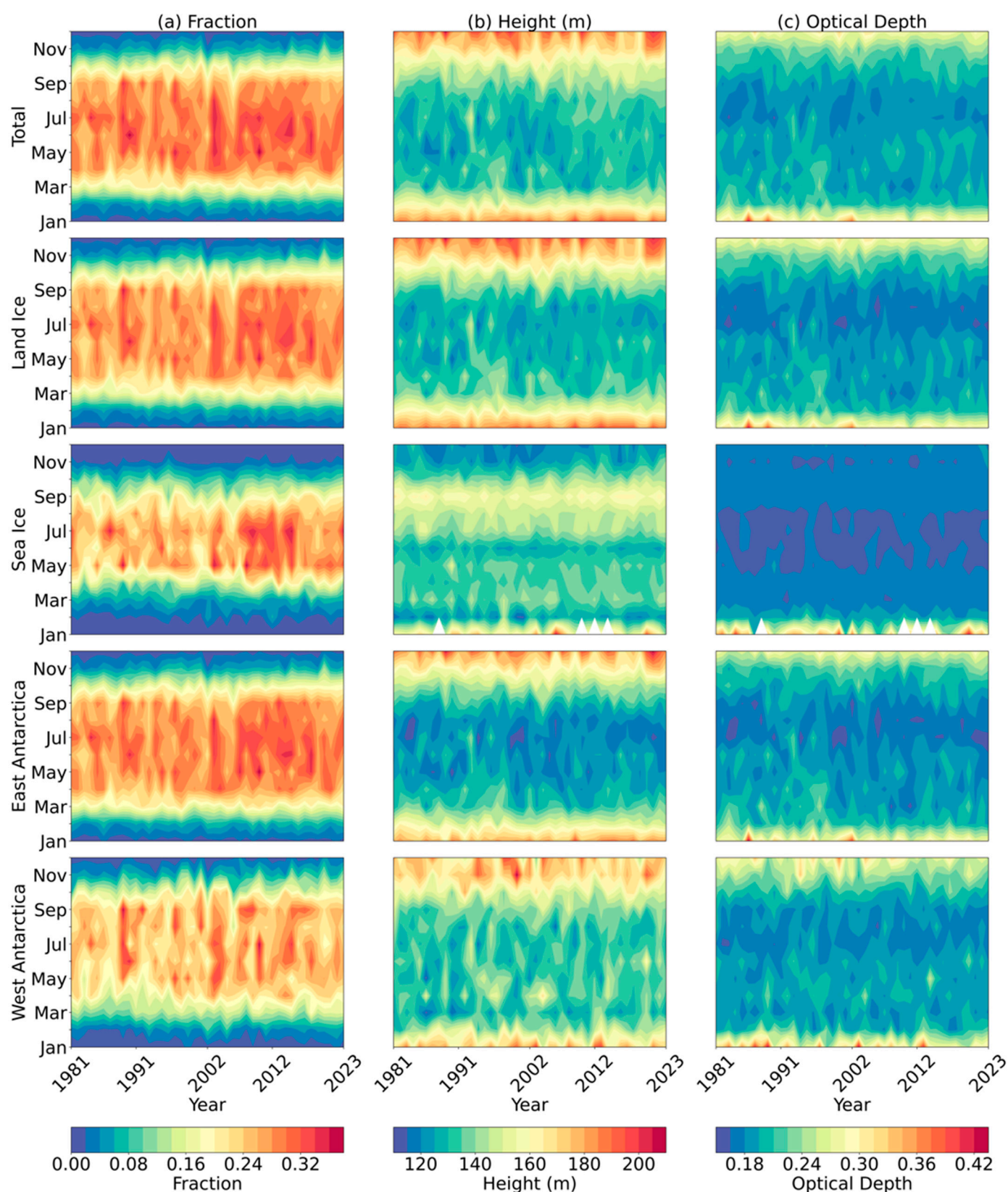


Figure 6. Temporal distribution of monthly MERRA-2 blowing snow (BLSN) properties across Antarctic regions and surface types. Shown are (a) BLSN occurrence fraction, (b) mean BLSN layer height, and (c) mean BLSN optical depth for the entire Antarctic domain, and separately over land ice, sea ice, and East and West Antarctica.

4. Discussion

Blowing Snow (BLSN) is wind-driven snow lifted from the surface, occurring most frequently in cold, particularly polar, regions. It results from the interplay of multiple atmospheric conditions and parameters such as wind speed, snow cohesion, bonding, topography, vegetation, temperature, and snow age. BLSN plays a significant role in the surface mass balance (SMB) of the Antarctic ice sheet through sublimation and transport, as well as in atmospheric thermodynamics, the radiation and moisture budgets, and satellite altimetry. Despite its considerable impact, the scarcity of long-term data has hindered accurate estimation of its contribution to atmospheric processes and a comprehensive climatological overview of BLSN properties. Nevertheless, research on BLSN has been conducted through ground-based observations, model-based approaches, satellite remote sensing, and, most recently, artificial intelligence (AI) and machine learning (ML) methods.

In this study, we used recently generated ML-produced BLSN data available from 1980 to the present on the existing MERRA-2 grid ($0.5^\circ \times 0.625^\circ$). The data were generated using the XGBoost classifier and regressor. The models use temperature, wind speed, relative humidity, pressure, etc., as inputs to estimate BLSN occurrence, optical depth, and height.

We analyzed the period from February 1980 to October 2024. The monthly time series of BLSN occurrence, height, and optical depth show clear seasonality. BLSN occurrence peaks in the winter months (April to September), reaching up to an average of 30% across Antarctica, while large areas of East Antarctica exhibit BLSN occurrence frequencies of 70%. The high frequency in wintertime is attributed to strong katabatic winds. In contrast, occurrence drops abruptly to below 5% during the summer months (November to February). These results are qualitatively consistent with previously reported studies.

Statistical comparisons with ICESat-2 for May 2023 indicate agreement in BLSN occurrence between MERRA-2 and ICESat-2, with a low mean bias error of +0.032 (<10%) and an RMSE of 0.26, suggesting minor grid misalignment. Optical depth shows a positive bias of +0.022 (14.3%), while BLSN height is overestimated, with a mean bias of +43.4 m (51.3%). The standard deviation comparison for MERRA-2 and ICESat-2, at 0.285 and 0.275, respectively, for BLSN occurrence, indicates high statistical agreement. For blowing snow height and optical depth, MERRA-2 consistently shows a lower standard deviation than ICESat-2. This suggests that while the model captures the overall distribution, it tends to smooth out the higher-frequency variability detected by the satellite sensors. Throughout the annual cycle of 2023, the model shows different levels of metrics for each of the three variables. With bias metrics typically staying low (e.g., 0.010 in February and 0.007 in June), the BLSN fraction is the most reliable performer, showing strong agreement with ICESat-2. Additionally, optical depth exhibits monthly bias values ranging between -0.034 and 0.131 . Larger variability is seen in height; the RMSE peaks considerably in January (99.221 m) compared to the seasonal minimum in June (50.663 m), indicating a greater sensitivity to sample size and the complex boundary layer stability of the Antarctic summer. MERRA-2 BLSN layer heights have a consistent positive bias across all months. Consequently, a systematic correction is possible for future versions of the layer height data by incorporating the ICESat-2 BLSN layer height.

With some exceptions, MERRA-2 displays a comparable BLSN fraction when compared with ground-based observations from ceilometers obtained at Zhongshan Station ($69^\circ 22' 24.76''$ S, $76^\circ 22' 14.28''$ E) in Antarctica during 2022 for the given collocated grid. Additionally, MERRA-2 BLSN layer height is consistently lower than ceilometer measurements.

Spatially, East Antarctica and land ice exhibit higher occurrence rates compared with West Antarctica and sea ice, respectively. However, BLSN heights and optical depths are greater during the summer months—reaching about 190 m and 0.30, respectively—and

are comparatively lower in the winter months, averaging around 130 m and 0.18. This seasonal variation is linked to differences in the Antarctic boundary layer, which is more stable in winter and less so in summer. The East–West Antarctica differences in BLSN height and optical depth are not as pronounced as those observed for BLSN occurrence. Neither occurrence, height, nor optical depth shows statistically significant monotonic trends over the period analyzed. The long-term BLSN data do not show a trend over the years, but they do show inter-annual variability. Such variability provides the foundation for analyzing other large-scale activities over Antarctica. In the future, a detailed analysis of this variability, along with the El Niño–South Oscillation or the Southern Annular Mode (SAM), will further clarify the role of these events in BLSN transport and, ultimately, their impact on SMB.

These results represent the longest available BLSN dataset to date, providing a comprehensive overview of BLSN properties over more than four decades. The dataset serves as a valuable resource for investigating additional characteristics of BLSN. As one of the major drivers of snow sublimation and transport in polar regions, BLSN plays a critical role in surface processes. Integrating BLSN data into MERRA-2 grids alongside other ancillary datasets enables grid-based calculations of these components. This approach has strong potential for advancing modeling efforts and can contribute to more accurate estimates of surface mass balance over Antarctic sea ice. While the current BLSN dataset demonstrates valuable potential for understanding blowing snow over Antarctica, future refinements will focus on optimizing retrieval accuracy under challenging cloudy and extreme conditions to further enhance the precision of height, optical depth, and SMB estimations.

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