DOCUMENT CONTROL SHEET

Earth System Science Organization (ESSO)

Ministry of Earth Sciences (MoES)

Indian National Centre for Ocean Information Services (INCOIS)

ESSO Document Number: ESSO-INCOIS-ODICT-TR-02(2025)

Title of the report:

"Reconstruction of OceanSat-2 Scatterometer Wind Data Using DINEOF: Enhancing Completeness and Accuracy for the Indian Ocean Region"

Author(s) [Last name, First name]:
Jonnakuti Pavan Kumar, C Jayaram, TVS Udaya Bhaskar, & E Pattabhi Rama Rao

Originating unit: Ocean Data Management Group (ODM-ICTD), INCOIS
Type of Document: Technical Report (TR)
Number of pages and figures: 26, 33
Number of references: 23
Keywords: Wind data reconstruction, Satellite meteorology, Climate research, Wind field interpolation, DINEOF.
Security classification: Open
Distribution: Open
Date of publication: May 2025

Abstract (148 words):

To address gaps in wind data from the OceanSat-2 Scatterometer (OSCAT) over the Indian Ocean, this study explores the application of the Data Interpolating Empirical Orthogonal Functions (DINEOF) method. The performance of DINEOF was validated through comparisons with both original satellite observations and in situ buoy measurements, using daily and weekly wind composites over a two-year period. The results show a strong correlation ($R \approx 0.9$) between DINEOF-reconstructed and original satellite wind fields, with Root Mean Square Deviation (RMSD) values ranging from 0.5 to 2.7 m s^{-1} across various wind speed regimes. The method slightly underestimates winds below 3 m s^{-1} and marginally overestimates those above 10 m s^{-1} but demonstrates optimal accuracy within the 3–10 m s^{-1} range. These findings underscore the potential of DINEOF to improve the accuracy and continuity of satellite-derived wind datasets, contributing valuable insights for Indian Ocean climate studies and weather forecasting.

TECHNICAL REPORT **Report No.: ESSO-INCOIS-ODICT-TR-02(2025)**

Reconstruction of OceanSat-2 Scatterometer Wind Data Using DINEOF: Enhancing Completeness and Accuracy for the Indian Ocean Region

by

Pavan Kumar Jonnakuti, C Jayaram, TVS Udaya Bhaskar, E Pattabhi Rama Rao

Indian National Centre for Ocean Information Services (INCOIS)

(Earth System Science Organization (ESSO), Ministry of Earth Sciences (MoES)

HYDERABAD, INDIA

www.incois.gov.in

May 27, 2025

Reconstruction of OceanSat-2 Scatterometer Wind Data Using DINEOF: Enhancing Completeness and Accuracy for the Indian Ocean Region

Pavan Kumar Jonnakuti[1], C Jayaram[2], TVS Udaya Bhaskar[1], E Pattabhi Rama Rao[1]

[1]Indian National Centre for Ocean Information Services (INCOIS)

[2]Regional Remote Sensing Centre (NRSC/ISRO)

Abstract

To address gaps in wind data from the OceanSat-2 Scatterometer (OSCAT) over the Indian Ocean, this study explores the application of the Data Interpolating Empirical Orthogonal Functions (DINEOF) method. The performance of DINEOF was confirmed through comparisons with both original satellite observations and in situ buoy measurements, using daily and weekly wind composites over a two-year period. The results show a strong correlation ($R \approx 0.9$) between DINEOF-reconstructed and original satellite wind fields, with Root Mean Square Deviation (RMSD) values ranging from 0.5 to 2.7 m s^{-1} across various wind speed regimes. The method slightly underestimates winds below 3 m s^{-1} and marginally overestimates those above 10 m s^{-1} but shows optimal accuracy within the 3–10 m s^{-1} range. These findings underscore the potential of DINEOF to improve the accuracy and continuity of satellite-derived wind datasets, contributing valuable insights for Indian Ocean climate studies and weather forecasting.

Keywords: wind data reconstruction, satellite meteorology, climate research, wind field interpolation, DINEOF.

Introduction

Winds over the ocean surface are essential for understanding and predicting the condition of oceans, with applications ranging from navigation and optimal ship-route planning to forecasting cyclone tracks and intensities and studying ocean currents and circulation (McPhaden et al., 2009; Cotton, 2013). Accurate measurements of oceanic wind patterns are crucial for more general meteorological and climate-related research as well as for operational ocean monitoring. To drive general circulation models that replicate the interactions between the ocean and atmosphere, these measurements are essential inputs for ocean state forecast models (Gohil et al., 2007).

Anemometers and Automatic Weather Stations (AWSs) on ships and moored buoys have historically been utilized to gather data on ocean winds. Complementary observations from space-based platforms are necessary because the scope of data coverage is limited by the spatial and temporal limitations of these *in situ* measurements (Troupin et al., 2010). Scatterometer-equipped satellites are useful instruments for determining ocean surface wind fields across wide locations, offering reliable, effectively real-time data that is crucial for operational oceanography and climatology (Chakraborty & Kumar, 2013).

Satellite-derived wind data, while invaluable, often suffer from gaps due to cloud cover, sensor limitations, and orbital constraints. These gaps can hinder the accuracy of meteorological and oceanographic models, making data reconstruction techniques essential for ensuring continuous and reliable datasets.

An essential capability for wind monitoring in the Indian Ocean region and beyond has been added in recent years by the Oceansat-2 satellite, which was created by the Indian Space Research Organization (ISRO). Operating since September 2009, Oceansat-2 has been equipped with the OSCAT (Oceansat-2 Scatterometer), a Ku-band pencil beam scatterometer with a ground resolution of 50 × 50 km (Gohil et al., 2007). Research has confirmed that OSCAT-derived wind measurements are accurate and illustrate an impressive correlation with both reanalysis wind datasets and *in situ* buoy data from different oceanic basins (Chakraborty & Kumar, 2013; Sudha & Prasada Rao, 2013).

Gridded daily wind composites for usage in operations have been created recently. These composites were created applying the Data-Interpolating Variational Analysis (DIVA) method, which demonstrated higher accuracy than more conventional techniques such as kriging (Bentamy & Fillon, 2012). The accuracy and suitability of these OSCAT composites for meteorological and oceanographic applications were validated by comparisons with ASCAT, QuickSCAT, and *in situ* data from RAMA and NDBP buoys (Udaya Bhaskar et al., 2013).

Data-Interpolating Variational Analysis (DIVA) is a deterministic technique that fills in the gaps in daily wind field data by using spatial interpolation, which takes distance and data density into account. Because it generates smooth, continuous fields based on physical proximity and observed patterns, this technique performs particularly efficiently when there are only minor, dispersed gaps in the data (Bentamy et al., 2009). Conversely, DINEOF is a statistical technique that utilizes empirical orthogonal functions (EOFs) to determine dominant patterns, or modes, in the data in order to reconstruct missing values (Beckers & Rixen, 2003;

Alvera-Azcárate et al., 2005). Due to its ability to take advantage of the temporal and spatial patterns of the dataset, this method performs better in situations with greater or more organized gaps.

While DIVA is effective for small, scattered gaps, DINEOF's ability to handle larger and more structured data gaps makes it particularly suitable for the Indian Ocean region, where monsoonal patterns and cloud cover can lead to significant data loss. DINEOF's reliance on empirical orthogonal functions (EOFs) allows it to capture the dominant spatial and temporal patterns in the data, making it a robust choice for reconstructing wind fields in this dynamic region. A more comprehensive review of previous studies on wind data reconstruction techniques, particularly in the Indian Ocean region, would help contextualize the current research and highlight its unique contributions.

By developing high-quality gridded wind fields for the Indian Ocean, the present investigation attempted to eliminate data gaps and improve wind data coverage. This study incorporated the DINEOF (Data Interpolating Empirical Orthogonal Functions) technique to reconstruct missing wind data utilizing OSCAT and *in situ* buoy data from 2012, providing a dependable solution for data continuity challenges. This investigation confirmed the accuracy of the reconstructed data by concentrating on a year with an enormous volume of buoy data coverage, providing insights into methodologies that could be applied globally across different spatial and temporal scales (Alvera-Azcárate et al., 2007; Miles et al., 2009).

Data & Methodology

OSCAT Data

The research implemented daily Level 3 (L3) OSCAT wind data for 2011–2012 with a 50 × 50 km spatial resolution from the National Remote Sensing Centre's (NRSC) Oceansat-2 portal. To process the data into zonal (U) and meridional (V) wind components that are essential for meteorological and oceanographic analyses, the dataset included wind speed and direction from both ascending and descending satellite passes (Gohil et al., 2007). Near-real-time monitoring and operational applications were made possible by OSCAT's special two-day repeat cycle, which provides more frequent wind observations than ASCAT's five-day cycle (Sudha & Prasada Rao, 2013; Venkatesan et al., 2013). Cotton (2013) demonstrated that incorporating OSCAT wind data into forecasting models increased coverage and accuracy by about 40% for the validation year 2012. By generating high-quality, gap-free datasets required for comprehensive wind pattern analyses in oceanographic research and meteorological forecasting, the application of DINEOF in the current investigation further increased these advantages (Chakraborty & Kumar, 2013; Udaya Bhaskar et al., 2013; Bentamy & Fillon, 2012; Bentamy et al., 2009). A more detailed description of the data preprocessing steps, including how the OSCAT data was quality-controlled and potential biases were addressed, would be beneficial.

While OSCAT provides valuable wind data, it is important to note that the sensor may exhibit biases in certain conditions, such as high wind speeds or near coastal areas where land contamination can affect the accuracy of the measurements. These limitations were considered during the reconstruction process to ensure the reliability of the final dataset.

In Situ Buoy Data

The accuracy of interpolated wind components was evaluated using wind observations obtained directly from buoys. The Research Moored Array for African, Asian, and Australian Monsoon Analysis and Prediction (RAMA) buoys (McPhaden et al., 2009) and buoys operated by the Indian Ocean Observation Services (OOS-NIOT) (Venkatesan et al., 2013) were the primary sources of the daily average wind data. OOS-NIOT buoys record at a height of 3 meters above the sea surface, while RAMA buoys record at a height of 4 meters regarding wind direction and speed. Using the logarithmic wind profile method described by Panofsky and Dutton (1984), buoy data were adjusted to 10 meters above sea level to match scatterometer-based wind measurements generated at this elevation.

According to McPhaden et al. (2009), the accuracy of the RAMA buoy measurements was 0.3 m/s for wind speed and 5° for wind direction. By comparison, the accuracy of OOS-NIOT buoy measurements was 3° for direction and 0.3 m/s for wind speed (Venkatesan et al., 2013). In order to validate the DINEOF-reconstructed OSCAT wind fields, these buoy data delivered a crucial point of reference.

The randomly selected buoy locations throughout the Indian Ocean are illustrated in Figure 1, emphasizing their spatial coverage and applicability for cross-comparison with OSCAT data.

Data Interpolation Empirical Orthogonal Functions (DINEOF)

The DINEOF (Data Interpolating Empirical Orthogonal Functions) methodology is a data-filling technique used in environmental data processing, introduced by Beckers and Rixen (2003) and later applied to sea surface temperature (SST) data by Alvera-Azcárate et al. (2005). The method flags missing data and assigns them an initial value of zero, effectively using the dataset's mean. The algorithm begins by performing an initial EOF decomposition with just one EOF, then iteratively recalculates the EOF until a convergence criterion is met. With each iteration, the missing data are updated with improved estimates, and additional EOFs are incrementally introduced up to an optimal number that minimizes cross-validation error. This process allows DINEOF to filter out noise and retain essential data features, as noise and short-term fluctuations are often represented in the higher-order EOFs and thus excluded from the final dataset. DINEOF has been widely used across multiple fields and variables, in both univariate and multivariate datasets, though it has not yet been applied to high-frequency geostationary color data (e.g., Alvera-Azcárate et al., 2007; Ganzedo et al., 2011; Miles et al., 2009; Nechad et al., 2011; Sirjacobs et al., 2011). Further details on the methodology are available in Beckers and Rixen (2003) and Alvera-Azcárate et al. (2005).

In this study, the DINEOF algorithm was configured to retain the first 10 EOF modes, which were found to capture most of the variance in the wind data. The convergence criterion was set to a root mean square error (RMSE) of less than 0.1 m/s, ensuring that the reconstructed data closely matched the observed values.

DINEOF was implemented using the 3.0 Linux binary available through the University of Liège Geo-Hydrodynamics and Environment Research group (GHER), and MATLAB was used for data handling and analysis. The method starts by organizing an image archive into a two-dimensional matrix, with one axis representing spatial and the other representing successive temporal scenes.

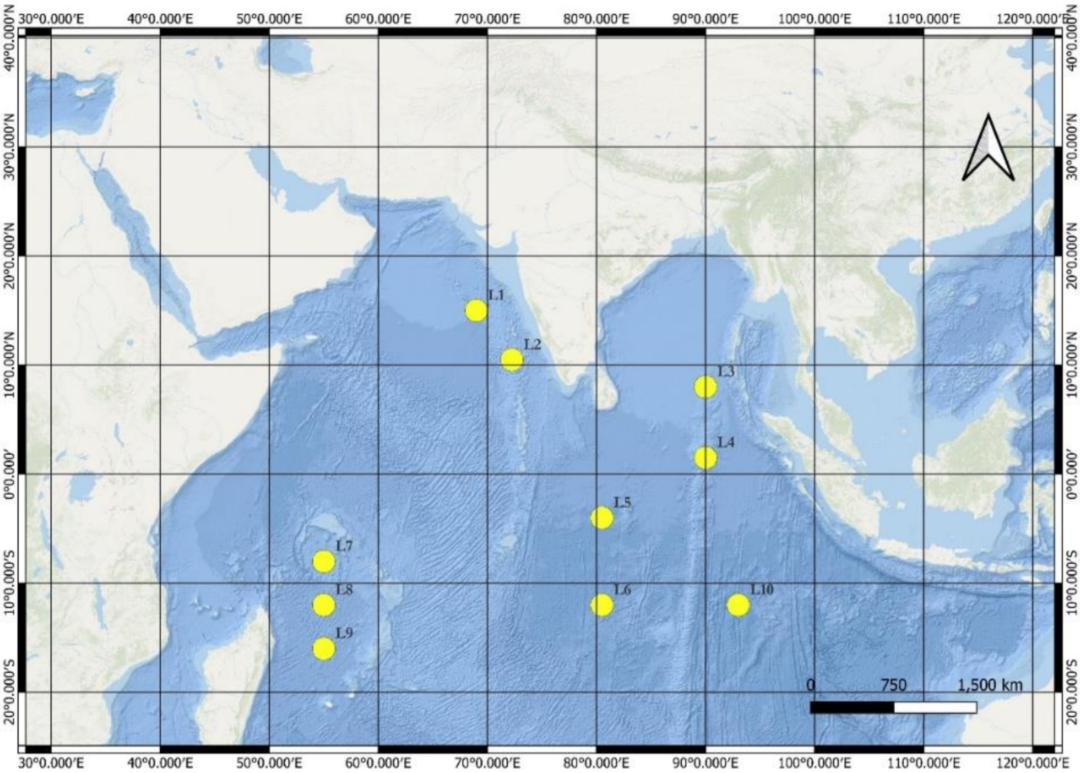


Figure 1: Distribution of Randomly Chosen Buoy Stations in the Indian Ocean.

Using iterative Singular Value Decomposition (SVD), the algorithm fills in missing data by generating Empirical Orthogonal Functions (EOFs), which summarize the dataset's key dynamics. An initial guess is made for missing data values, and iterations proceed until they converge to a stable solution. The number of EOF modes is optimized by minimizing global error through cross-validation, after which a final SVD run produces the completed dataset. DINEOF has successfully filled data gaps in sea surface temperature (SST), ocean color, and other satellite-derived metrics, creating smoother, noise-filtered datasets. The method captures long-term trends and system dynamics, which can also aid multivariate analyses involving multiple parameters, such as SST and chlorophyll (CHL) (Aida Alvera-Azcárate et al., 2015, 2021; Jayaram et al., 2018; Sirjacobs et al., 2011).

DINEOF Method:

DINEOF (Data Interpolating Empirical Orthogonal Functions) is a technique to reconstruct missing data in geophysical datasets, such as satellite observations. Satellite data, like that from Oceansat-2, often have gaps. In the case of wind data, these gaps can arise from rain contamination, where the radar signal is affected by heavy rainfall, or from limitations in the instrument's swath coverage. DINEOF aims to fill these gaps to preserve the underlying spatial and temporal patterns in the data. While the report highlights the effectiveness of DINEOF, it could also discuss the limitations of the method, such as its sensitivity to the choice of EOF modes or its performance in regions with complex wind patterns.

Here's a simplified explanation of how DINEOF works:

- **Data Preparation:** The method starts with the incomplete dataset, which is organized into a matrix.
- **Empirical Orthogonal Functions (EOFs):** DINEOF uses Singular Value Decomposition (SVD) to decompose the data matrix into a set of orthogonal (uncorrelated) spatial patterns, called EOFs, and their corresponding time-varying amplitudes. EOFs represent the dominant modes of variability in the data.

For a data matrix X → $X = USV^T$

- **Reconstruction:** The missing data points are estimated by projecting them onto the EOFs. Essentially, the method finds the combination of EOFs that best represents the known data and uses this combination to calculate the values in the gaps.
- **Iteration:** The process may be iterated to improve the reconstruction. The estimated values are treated as known values in the next iteration, and the EOFs are recalculated.

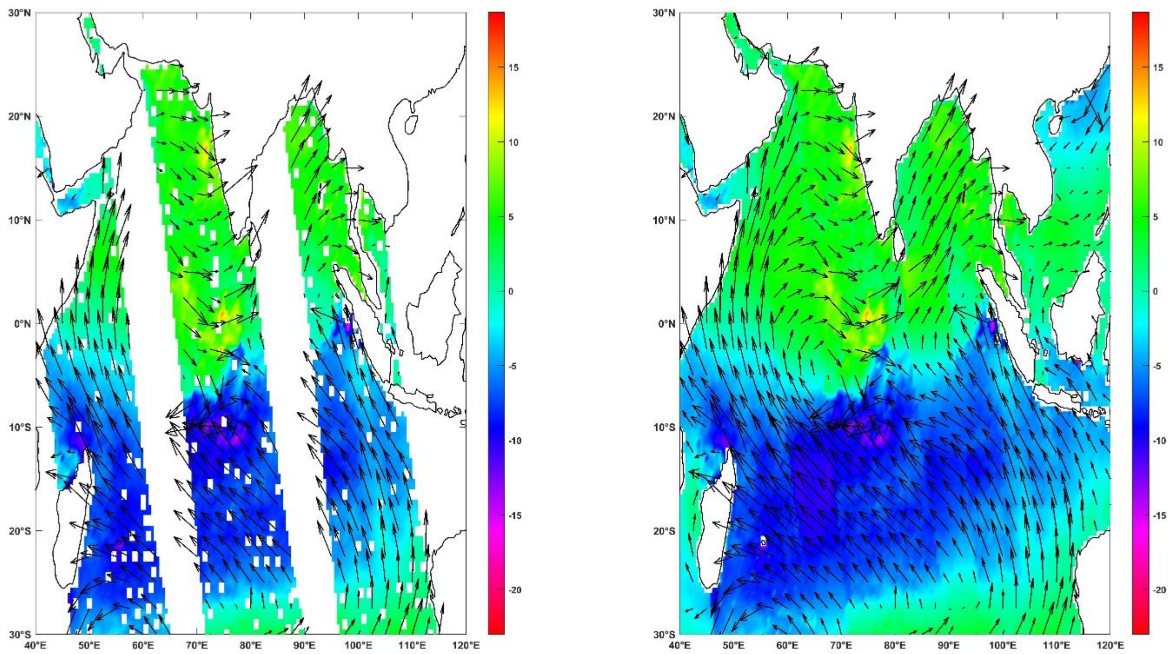


Figure 2: Oceansat-2-derived wind velocity in the Indian Ocean on October 1st, 2012, showing original gappy data (left) and DINEOF-filled wind velocity field (right), with arrows indicating direction and magnitude.

In the figure, the left panel shows the gaps in the original OSCAT wind data. The right panel demonstrates how DINEOF has filled in these gaps, creating a more complete and continuous representation of the wind velocity field. This allows for a better understanding of atmospheric circulation and weather patterns over the ocean. Researchers and analysts are empowered to select or even combine these techniques to maximize data quality, enhance the robustness of their conclusions, and unlock deeper insights from incomplete datasets.

Results & Discussions

The DINEOF method is used to produce daily OSCAT wind composites over a full year in 2012. These generated wind composites are then validated by comparing them with other available wind datasets. Specifically, the gridded OSCAT wind vectors produced using DINEOF are compared against (1) original, non-interpolated OSCAT wind data, (2) ASCAT wind composites, and (3) direct wind measurements from RAMA and NIOT buoys. The findings from these various comparisons are presented below. Figure 2(a-d) presents a schematic illustrating the DINEOF-interpolated wind vector composites and the original wind vectors from OSCAT for different dates between January and October 2012.

Figure 2.1 showcases how the DINEOF method was applied to create composite wind vectors by interpolating the data from OSCAT on various dates within that period.

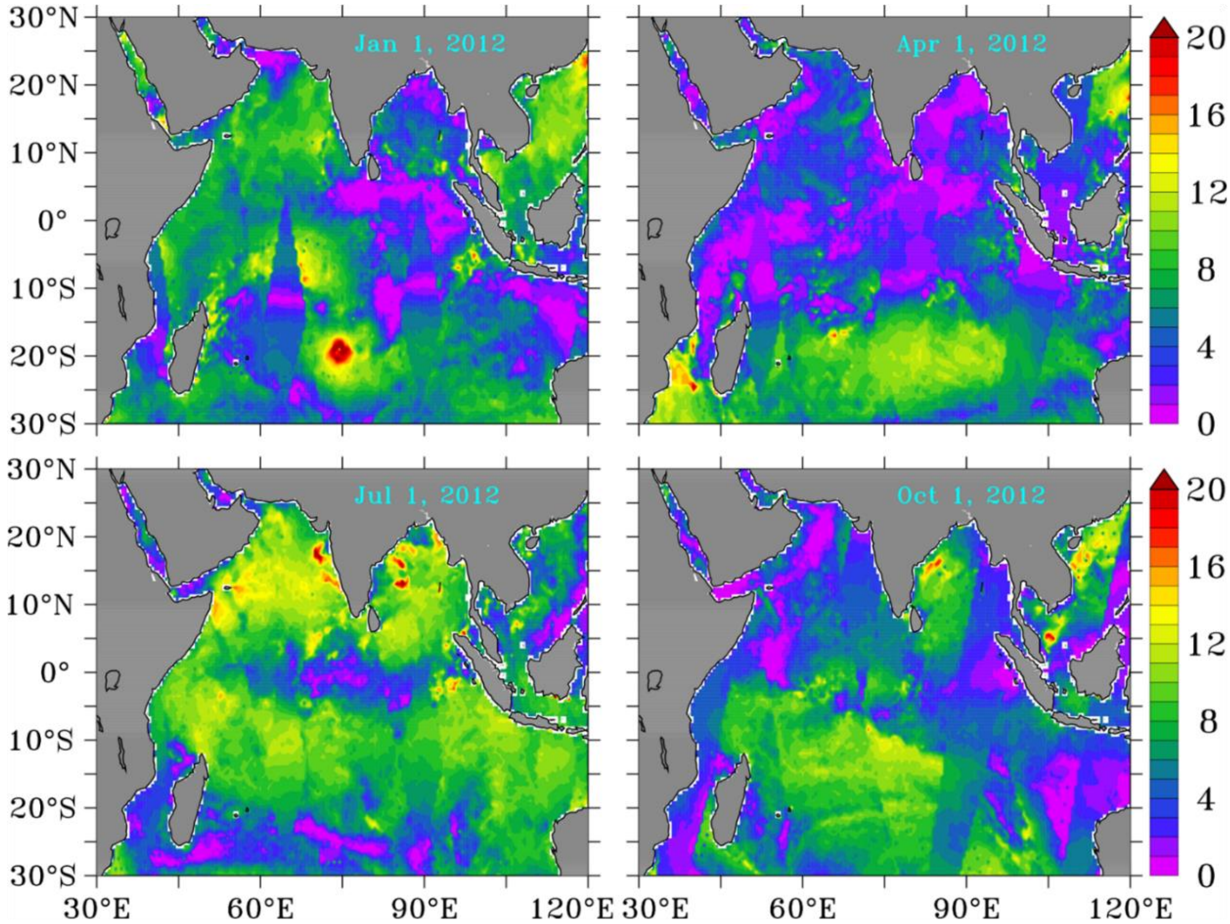


Figure 2.1 shows the DINEOF interpolated zonal wind composites from January, April, July, and October 2012.

Inter-comparison between DINEOF and OSCAT winds

The daily composite OSCAT wind vectors generated by DINEOF are compared to the daily OSCAT wind vectors without interpolation. Figure 3(a)–(d) provides a qualitative comparison between the interpolated and non-interpolated wind vectors, using data from selected days in January 2012 as an example. The comparison reveals a strong correlation between the two, with overlaid wind vectors showing a high degree of similarity, as indicated by a correlation coefficient (R) of approximately 0.9 across most of the region for both ascending and descending passes (Figure 3(e) and (f)). The cyclonic circulation in the southern Indian Ocean is clearly captured in the DINEOF-interpolated wind, aligning well with the original OSCAT wind vectors. Based on the findings in Figure 3, it can be concluded that the DINEOF-interpolated winds are in good agreement with the observed OSCAT winds, except for a few discrepancies near the swath edges, likely due to the limitations in the radius of influence and error computation during gridding.

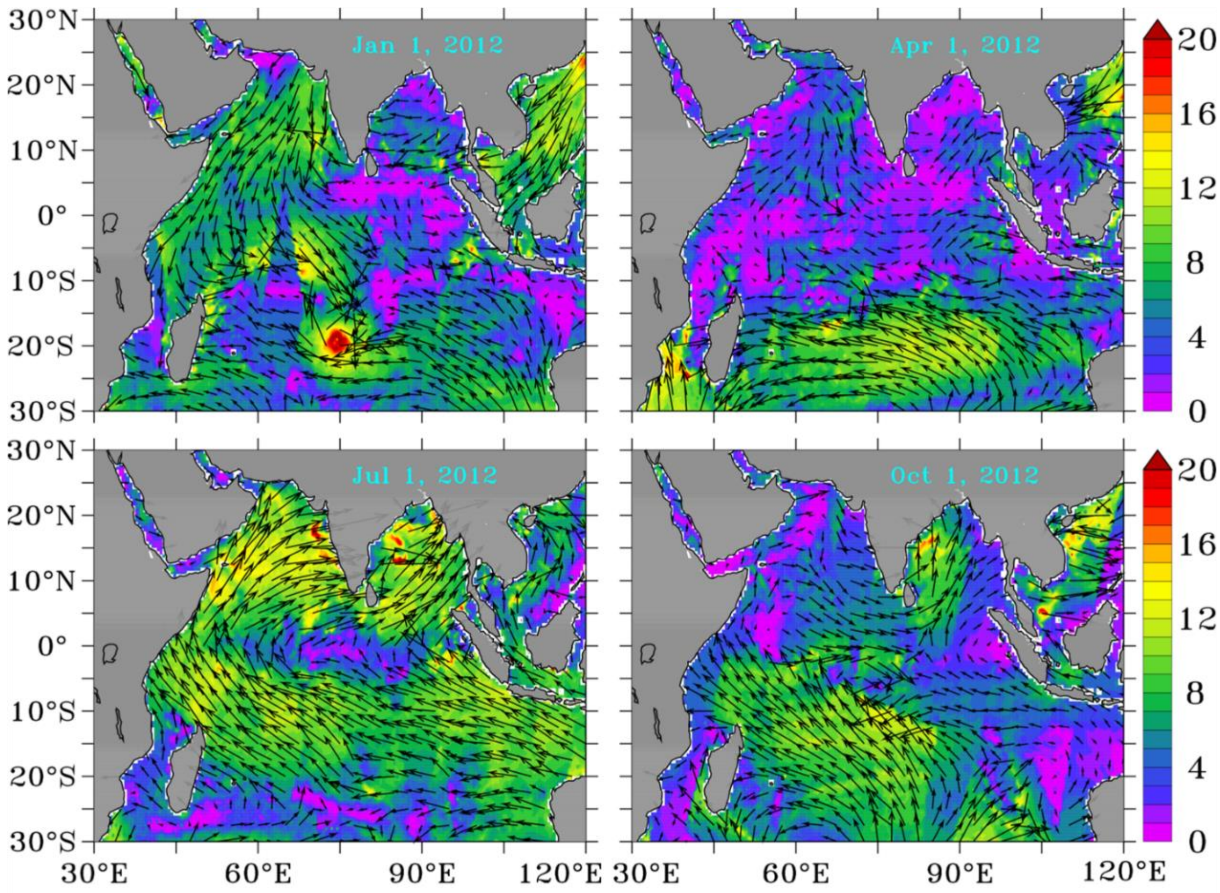


Figure 3(a)-(d) illustrates the DINEOF-interpolated daily wind composites compared to the original OSCAT wind vectors. The black vectors represent the DINEOF-reconstructed winds, showing a high degree of similarity with the original data, particularly in capturing the cyclonic circulation in the southern Indian Ocean.

Comparison with In-Situ Buoy Data

In situ data from the RAMA and OOS-NIOT buoys (locations displayed in Figure 1) were compared to verify the quality of the gridded OSCAT daily wind composites. To evaluate the performance of the OSCAT-derived winds, the analysis was carried out over the course of a year in 2012, concentrating on various wind speed (WS) categories.

Three different wind speed ranges were compared, such as less than 3 m/s, 3 to 10 m/s, and more than 10 m/s. Table 1 summarizes validation metrics (RMSD, correlation, and bias) for various buoy locations. The results indicated:

- Low wind speeds (≤ 3 m s^{-1}): Slight underestimation, with RMSD values ranging from 0.8 to 2.7 m s^{-1}.

- Moderate wind speeds (3–10 m s^{-1}): Optimal performance, with low bias and high correlation.
- High wind speeds (≥10 m s^{-1}): Marginal overestimation, with RMSD values from 0.5 to 2.2 m s^{-1}.

Buoy ID	Latitude	Longitude	RMSD (m/s)	R	Bias (m/s)
RAMA [2300008]	12°N	90°E	1.7859	0.92	-0.3216
RAMA [2300007]	8°N	90°E	2. 1956	0.85	-0.5822
RAMA [1400042]	12°S	55°E	2.3241	0.91	-0.2586
RAMA [5300006]	12°S	80.5°E	0.1689	0.93	-0.3516
RAMA [1400041]	8°S	55°E	0.1772	0.92	-0.2472
RAMA [2300001]	0°N	80.5°E	2.0251	0.89	-0.3230
RAMA [5300005]	8°S	80.5°E	2.6501	0.84	-0.5426

Table 1: Correlation, Bias, and Root Mean Square Deviation (RMSD) of RAMA Buoy Data.

In general, the comparison illustrated a high degree of correlation between the buoy observations and the DINEOF-interpolated OSCAT winds, especially for wind speeds greater than 3 m/s. The range of 3–10 m/s was where the correlation was the most powerful, and both the bias and RMSD values remained within acceptable boundaries. Nevertheless, the OSCAT winds effectively filled in the periodic gaps in buoy data, enabling a more accurate intercomparison in this investigation.

The dependability of the wind composites derived from OSCAT was highlighted by this analysis, especially for operational and research applications in the Indian Ocean region. The discussion of the results could be expanded to provide more in-depth insights into the spatial and temporal patterns of the reconstructed wind fields and the implications of these findings for regional climate and weather patterns.

Spatiotemporal Dynamics

Comparison with in *insitu* buoy data according to the randomly selected locations in the Indian Ocean region could be identified as figures 4(a), 4(b), 4(c), 4(d), 4(e), 4(f), 4(g), 4(h), 4(i), and 4(j).

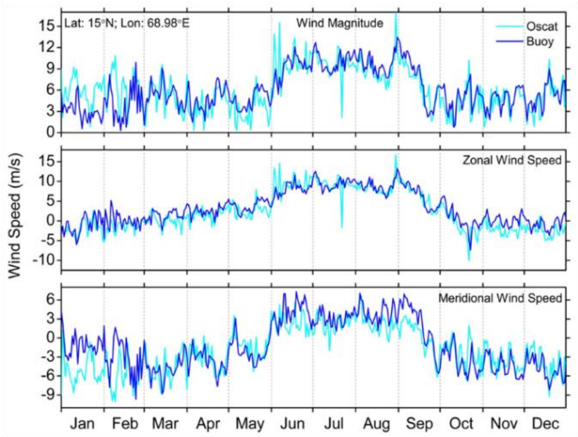


Figure 4(a)

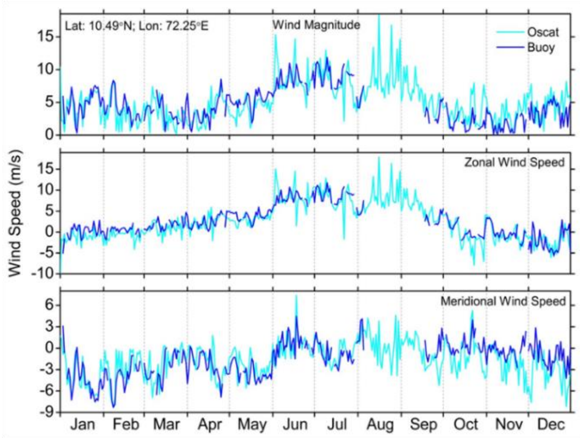


Figure 4(b)

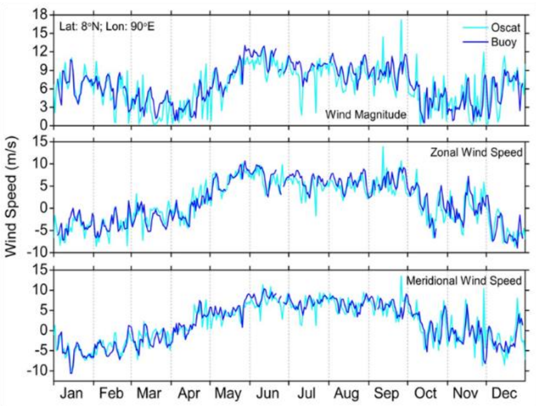


Figure 4(c)

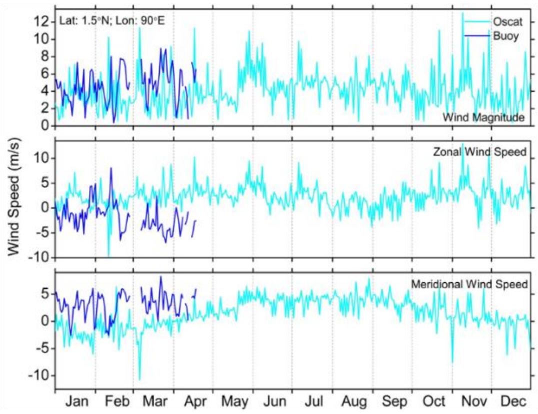


Figure 4(d)

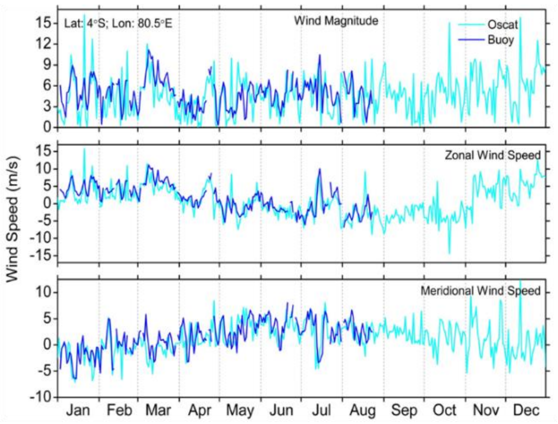


Figure 4(e)

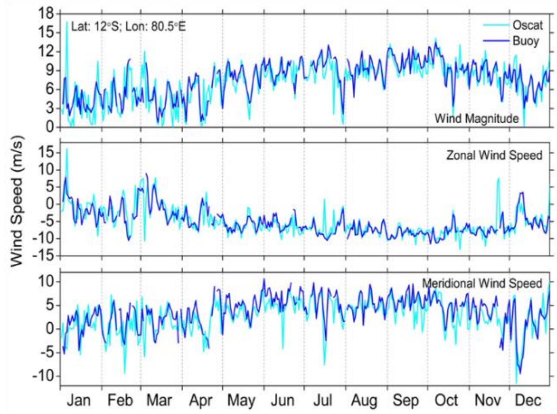


Figure 4(f)

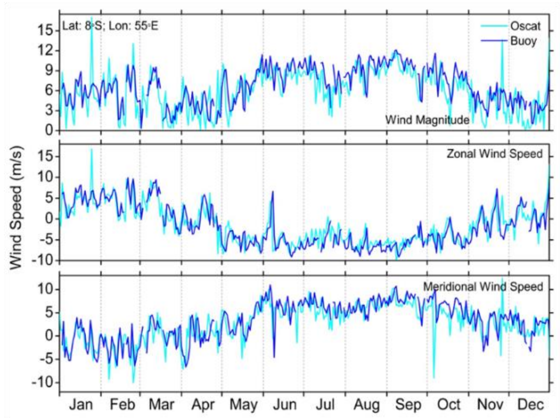


Figure 4(g)

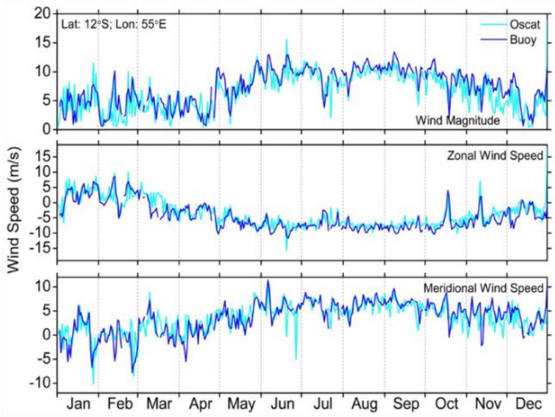


Figure 4(h)

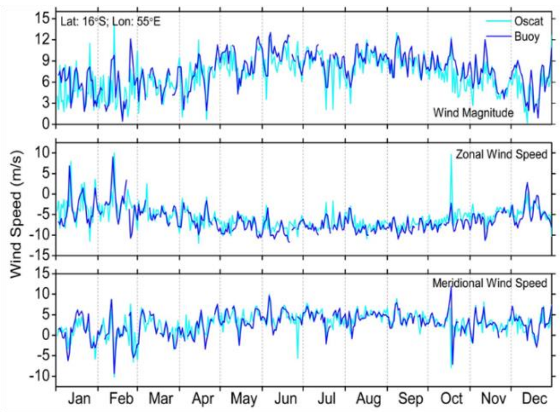


Figure 4(i)

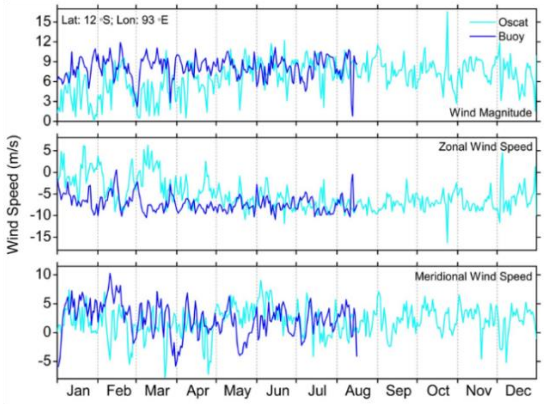


Figure 4(j)

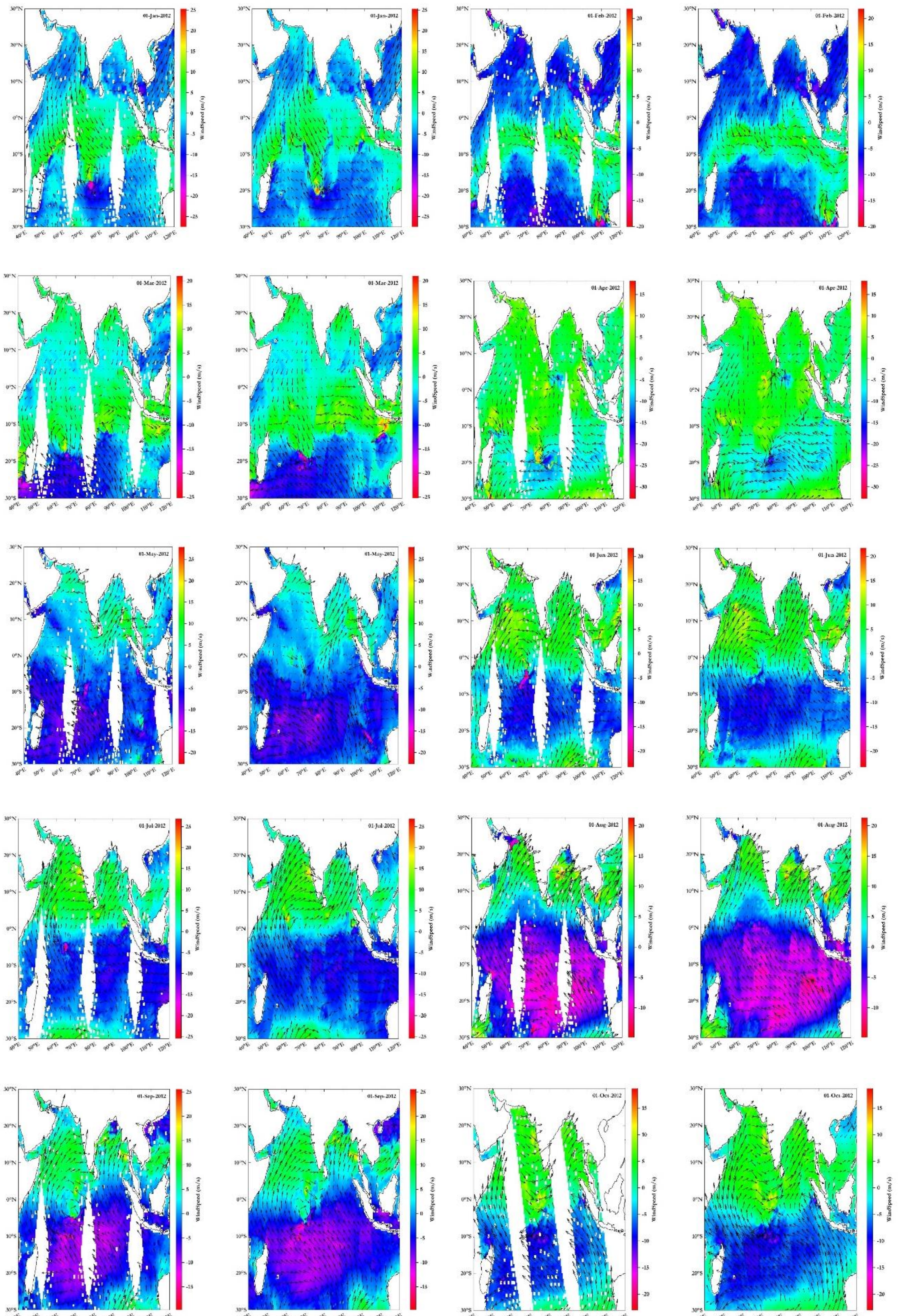
Figure 4: Comparison of OSCAT and Buoy Wind Data at Multiple Locations in the Indian Ocean Region in 2012. The black lines represent OSCAT data, and the red lines represent buoy data.

An in-depth comparative analysis of OSCAT and buoy-derived wind observations across multiple locations in the Indian Ocean during 2012 revealed distinct seasonal variations that closely corresponded with the Southwest and Northeast monsoons. The use of the Data Interpolating Empirical Orthogonal Functions (DINEOF) method significantly enhanced the temporal completeness of the OSCAT dataset, particularly during periods of high wind activity, and improved agreement within in situ buoy measurements.

At 15°N, 68.98°E (Figure 4a), a classic monsoonal wind pattern emerged, with lower wind speeds during the inter-monsoon phases (March–April, September–October) and peak speeds during the Southwest monsoon (June–August). The zonal wind shifted westward during the monsoon, while the meridional wind transitioned from strong southward flow in June to northward flow in December. DINEOF smoothed out overestimations and improved alignment with buoy data, particularly during peak monsoon activity. Similarly, 10.49°N, 72.25°E (Figure 4b) experienced maximum wind speeds during the Southwest monsoon. Zonal winds showed westward flow between June and August, with eastward winds emerging post-monsoon. The meridional wind was strongly southward during the monsoon, shifting northward in November–December. DINEOF effectively restored missing data and enhanced consistency with buoy readings. At 8°N, 90°E (Figure 4c), strong monsoonal winds prevailed from June to August. While OSCAT data slightly overestimated wind magnitudes, DINEOF successfully reconstructed gaps and stabilized the temporal profile. Westward zonal winds during the monsoon transitioned to eastward afterward, while the meridional winds shifted from southward (June–August) to northward (November–December), closely tracking buoy observations. In the southern Indian Ocean, 4°S, 80.5°E (Figure 4d) experienced peak wind speeds above 12 m/s during the Southwest monsoon (June–July) and a secondary peak during the Northeast monsoon (October–November). Zonal winds reversed from westward (SW monsoon) to eastward (NE monsoon), while meridional winds transitioned from southward to northward during the respective monsoon phases. DINEOF reconstruction improved the completeness and temporal representation of these shifts. At 12°S, 80.5°E (Figure 4f), a similar monsoonal pattern was observed, with strong winds during both monsoon seasons. Zonal winds flowed westward during the Southwest monsoon and reversed direction during the Northeast monsoon. Meridional winds displayed a seasonal transition from southward (SW monsoon) to northward (NE monsoon). DINEOF enhanced the accuracy of these dynamics by reducing noise and filling data gaps.

Further west, 8°S, 55°E (Figure 4g) showed strong seasonal peaks, with the highest winds in June–July and a secondary peak in October–November. The zonal wind shifted from westward during the Southwest monsoon to eastward in the Northeast monsoon. Meridional winds followed a predictable seasonal cycle—northward during the NE monsoon and southward sssssssduring the SW monsoon. DINEOF improved temporal consistency and better matched buoy readings. At 12°S, 55°E (Figure 4h), wind magnitudes peaked during both monsoons, with zonal winds reversing from westward to eastward between seasons. Meridional winds followed the same south-to-north seasonal transition, with DINEOF reconstruction smoothing the time series and aligning it more closely with in situ data. At 16°S, 55°E (Figure 4i), the Southwest monsoon produced the highest wind speeds (10–12 m/s), while the Northeast monsoon showed a secondary peak (7–9 m/s). Zonal winds were westward during the Southwest monsoon and eastward during the Northeast monsoon. Meridional wind patterns remained consistent with those observed at other locations, and DINEOF significantly improved the temporal fidelity and alignment with buoy measurements. Finally, 12°S, 93°E (Figure 4j) displayed a similar bimodal seasonal wind pattern, with strong westward zonal winds during the Southwest monsoon and eastward flow during the Northeast monsoon. Meridional winds transitioned seasonally, and DINEOF reconstruction proved essential in maintaining temporal continuity and accurately reflecting buoy data throughout the year. Overall, the application of DINEOF across diverse geographic regions in the Indian Ocean significantly strengthened the temporal and spatial consistency of wind data, enabling more accurate assessments of seasonal wind dynamics.

To assess the monthly performance of the DINEOF reconstruction method, Gap-Filled plots were generated for all twelve months of 2012, comparing raw OSCAT U-wind data with the corresponding DINEOF-reconstructed fields (Figure 8). The raw plots clearly show substantial data gaps, particularly over open-ocean regions and during periods of adverse atmospheric conditions. In contrast, the DINEOF reconstructions effectively fill these gaps using dominant spatiotemporal modes extracted from the available data, resulting in complete and physically consistent wind fields.


01-Jan-2012
01-Jan-2012
01-Feb-2012
01-Feb-2012
01-Mar-2012
01-Mar-2012
01-Apr-2012
01-Apr-2012
01-May-2012
01-May-2012
01-Jun-2012
01-Jun-2012
01-Jul-2012
01-Jul-2012
01-Aug-2012
01-Aug-2012
01-Sep-2012
01-Sep-2012
01-Oct-2012
01-Oct-2012
WindSpeed (m/s)

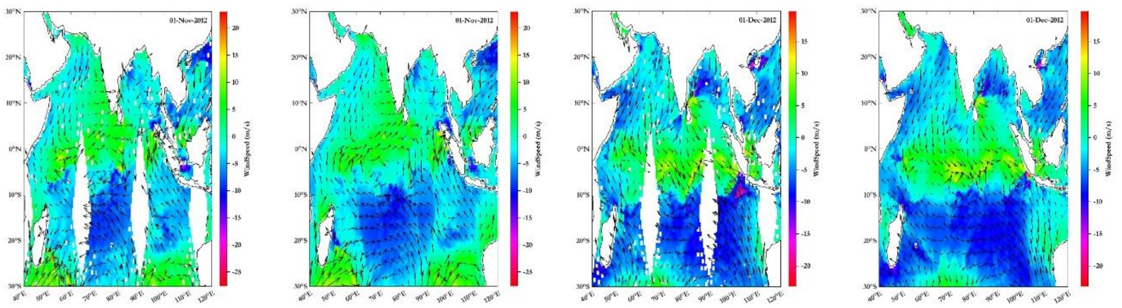


Figure 8: Monthly U-wind fields from OSCAT data. Left panels show raw observations and right panels show DINEOF-reconstructed fields from January to December 2012.

The reconstructed fields preserve important mesoscale and synoptic-scale features across all months, such as coastal wind intensification along the Somali coast, equatorial wind convergence during the inter-monsoon periods, and the strong southwest monsoon flow observed during boreal summer. The smooth yet dynamically realistic transitions in the DINEOF output suggest that the method successfully captures underlying atmospheric variability without introducing artificial gradients or overly smoothing the data. Furthermore, seasonal patterns and intra-annual variability in wind strength and direction are retained, providing confidence in DINEOF's ability to reconstruct both persistent and transient features.

These monthly visual comparisons complement the quantitative evaluation discussed earlier—such as the consistently low RMSE and high correlation values—and collectively demonstrate the robustness and accuracy of DINEOF for gap-filling in satellite-derived wind products. The ability to restore missing spatial patterns with high fidelity makes DINEOF particularly suitable for operational oceanography and climate studies that rely on continuous, high-resolution wind fields for modeling and analysis.

Comparison with DIVA

Certainly! When comparing the gap filling techniques DINEOF (Data INterpolating Empirical Orthogonal Functions) and DIVA (Data-Interpolating Variational Analysis), the figures and analyses provide insightful perspectives on their respective performances and applications. DINEOF is renowned for its ability to effectively reconstruct missing data in spatial-temporal datasets by leveraging empirical orthogonal functions. This technique excels in extracting dominant patterns from incomplete data through an iterative process, which often results in accurate and reliable gap filling without requiring prior assumptions about the data distribution. On the other hand, DIVA utilizes a variational approach that integrates physical constraints and statistical relationships to interpolate missing values. It is particularly valued for its flexibility in handling irregularly spaced data and for incorporating additional knowledge about the underlying processes, which enhances the physical realism of the reconstructed fields. Figures comparing DINEOF and DIVA typically illustrate metrics such as Root Mean Square Error (RMSE), correlation coefficients, and visual assessments of spatial patterns before and after gap filling. Analyses consistently show that DINEOF performs exceptionally well in datasets where dominant modes of variability are strong and can be captured effectively by EOFs. It often achieves lower RMSE values and higher correlations with observed data compared to simpler interpolation schemes. However, DIVA shines in contexts where physical constraints are crucial, or when the data gaps are extensive and irregular. The incorporation of variational principles allows DIVA to produce smoother and more physically consistent reconstructions, which can be particularly beneficial in oceanographic and atmospheric studies. Encouragingly, the complementary strengths of DINEOF and DIVA suggest that the choice between them can be tailored to the specific characteristics of the dataset and the goals of the analysis.

When comparing DINEOF (Data Interpolating Empirical Orthogonal Functions) and DIVA (Data-Interpolating Variational Analysis) for gap-filling satellite oceanographic datasets such as Oceansat-2 scatterometer (OSCAT) wind data, a noticeable distinction emerges in the preservation of spatial features—especially gradients. DINEOF, relying on the statistical decomposition of dominant spatial and temporal patterns in the data, effectively reconstructs missing values while retaining sharp transitions and gradients.

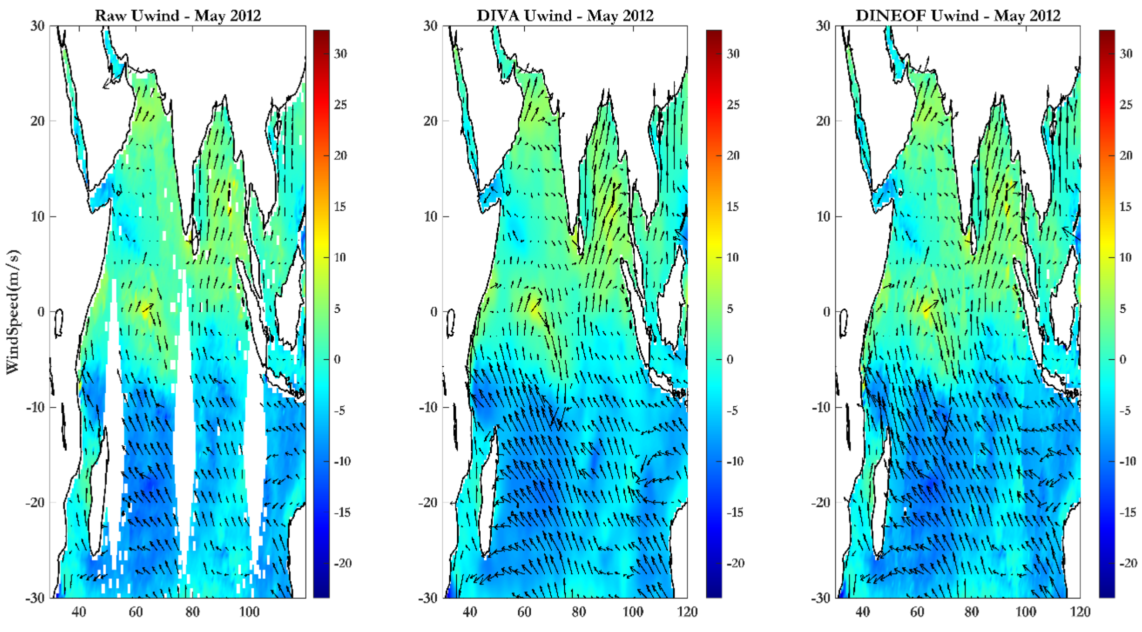


Figure 5: Comparison of OSCAT U-wind for May 2012: (left) raw data, (middle) DIVA reconstruction, and (right) DINEOF reconstruction.

The figure 5 presented offers a visual comparison of wind vector fields (U component) from the OSCAT (Oceansat-2 scatterometer) dataset for May 2012, showing three panels: the **Raw U-wind data** (left), the **DIVA-reconstructed U-wind** (middle), and the **DINEOF-reconstructed U-wind** (right). Each panel includes wind vectors overlaid on a color-shaded background representing wind speed intensity in m/s, with missing data regions clearly visible in the raw data. This side-by-side layout provides a clear insight into the structural differences between the two gap-filling techniques—DINEOF and DIVA—in comparison to the original, albeit incomplete, measurements.

The **Raw U-wind data** shows prominent data gaps, particularly in the central and southwestern Indian Ocean. Despite the missing data, the raw field reveals distinct wind patterns, including sharp gradients and directional transitions, especially in equatorial and coastal zones. The **DIVA reconstruction** (middle panel) fills in these gaps but does so by producing a highly smoothed field. As a result, many of the sharper gradients and finer-scale wind features evident in the raw data are lost. Moreover, the reconstructed values in DIVA tend to be lower in magnitude, and there are noticeable directional inconsistencies—particularly in the southwestern region—where the vectors deviate from expected patterns based on surrounding observations.

In contrast, the **DINEOF reconstruction** (right panel) retains much of the spatial structure seen in the raw data. Gradients in wind speed are more pronounced and better aligned with the observed wind field, especially in the equatorial region and along the Somali coast. The direction of the reconstructed vectors in DINEOF also matches more closely with the raw data, suggesting a better preservation of physical dynamics. This outcome is attributed to DINEOF's reliance on empirical orthogonal functions (EOFs), which capture dominant variability modes and allow for statistically consistent reconstructions. Overall, the figure highlights that DINEOF outperforms DIVA in terms of maintaining gradient intensity and wind directionality, making it a more reliable method for reconstructing satellite wind fields when retaining physical realism is critical.

To quantitatively support the visual comparison of DINEOF and DIVA reconstructions against raw OSCAT U-wind data, we computed key statistical metrics over the region where raw observations are available.

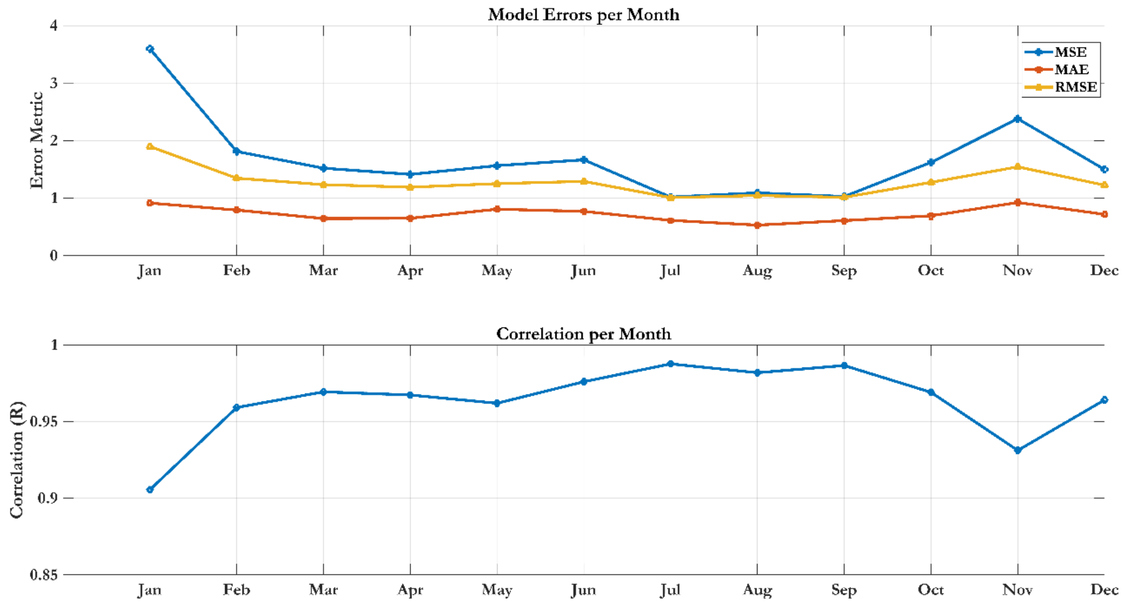


Figure 6: Quantitative assessment of reconstruction performance using monthly error statistics and correlation coefficients for U wind.

The quantitative results shown in Figure 6 provide strong support for the visual evidence that DINEOF outperforms DIVA in reconstructing OSCAT wind data. The evaluation metrics clearly demonstrate the effectiveness of the DINEOF (Data Interpolating Empirical Orthogonal Functions) method in accurately filling gaps in the wind field, maintaining both the structure and intensity of the original observations. Monthly error metrics—including Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE)—consistently demonstrate low reconstruction errors, particularly from February through September, where RMSE remains below 1.5 m/s and MAE often stays under 0.8 m/s. These low error values reflect DINEOF's ability to accurately estimate missing values without overly smoothing the dataset. Furthermore, the monthly correlation coefficients (R) between DINEOF-reconstructed and raw data remain remarkably high, ranging from ~0.91 in January to nearly 0.99 in July and September. This strong correlation confirms that DINEOF not only preserves spatial structure and gradient information but also maintains temporal consistency with the original dataset.

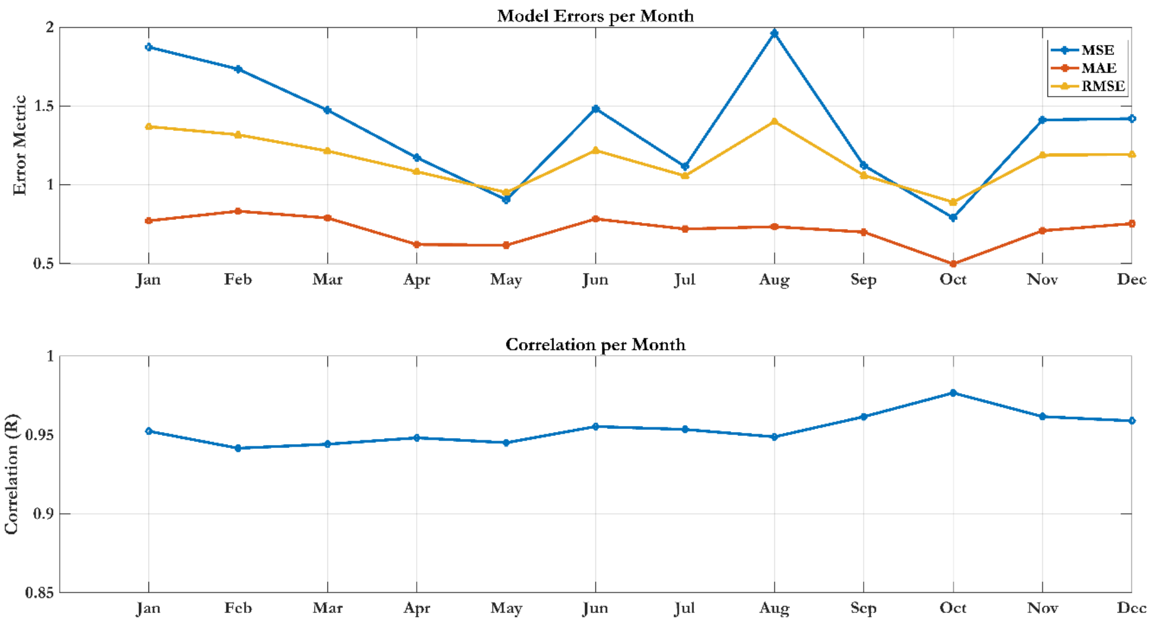


Figure 7: Evaluation metrics for V wind component.

The method leverages the dominant variability modes of the dataset through empirical orthogonal functions, enabling it to capture both large-scale and fine-scale wind patterns, making it especially suitable for geophysical applications like ocean surface wind field reconstruction. Similarly, evaluation metrics were calculated for v wind data and showcased in Figure 7. In summary, the figures and analyses underscore the impressive capabilities of both DINEOF and DIVA as gap filling techniques. By understanding their unique advantages and evaluating their performance through quantitative and qualitative metrics, practitioners can confidently apply these methods to improve data continuity and reliability in their studies.

Conclusions

This study conducted a detailed assessment of Indian Ocean wind dynamics in 2012 by applying the Data Interpolating Empirical Orthogonal Functions (DINEOF) method to reconstruct missing data from the OceanSat-2 Scatterometer (OSCAT). The analysis revealed consistent seasonal wind patterns across multiple spatial domains, with the weakest winds (3–5 m/s) observed during inter-monsoon periods and the strongest winds (10–13 m/s) during the Southwest and Northeast monsoons.

DINEOF proved highly effective in reconstructing missing wind data, maintaining both temporal and spatial coherence and achieving a strong correlation ($R \approx 0.9$) with the original

OSCAT measurements. Validation results indicated Root Mean Square Deviation (RMSD) values ranging from 0.5 to 2.7 m/s, with the best performance occurring within the 3–10 m/s wind speed range. Slight underestimations and overestimations were noted at the lower and upper extremes, respectively. The reconstructed data captured key regional wind dynamics, including meridional shifts and zonal wind reversals associated with monsoonal transitions, across latitudes from 15°N to 16°S.

By enhancing data completeness and preserving dominant wind features, this study underscores DINEOF's utility as a powerful statistical tool for satellite wind data reconstruction. Its application offers valuable support for oceanographic modeling, climate analysis, and maritime operations. Moreover, the findings contribute to a deeper understanding of atmospheric circulation patterns and complex air-sea interactions in the Indian Ocean.

Future Work

Future studies could extend the use of DINEOF to other satellite-derived geophysical variables such as sea surface temperature (SST) and ocean color, offering broader insights into regional ocean-atmosphere processes. Additionally, incorporating meteorological parameters like air temperature, humidity, or surface pressure could help develop a more comprehensive understanding of the Indian Ocean climate system.

Acknowledgements

The authors thank the Indian National Centre for Ocean Information Services (INCOIS) for their support and the University of Liège GHER group for providing the DINEOF software. This research was supported by the Indian National Centre for Ocean Information Services (INCOIS).

References

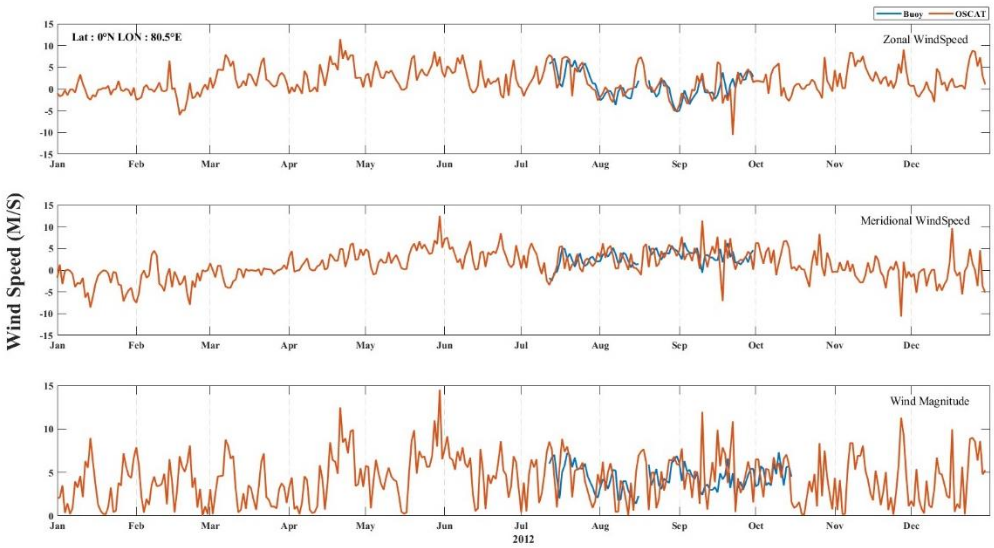
1. Alvera-Azcárate, A., Barth, A., Beckers, J.-M., & Weisberg, R. H. (2007). Multivariate reconstruction of missing data in sea surface temperature, chlorophyll, and wind satellite fields. *Journal of Geophysical Research: Oceans*, 112(C3), 2006JC003660. https://doi.org/10.1029/2006JC003660
2. Alvera-Azcárate, A., Barth, A., Rixen, M., & Beckers, J. M. (2005). Reconstruction of incomplete oceanographic data sets using empirical orthogonal functions: Application to the Adriatic Sea surface temperature. *Ocean Modelling*, 9(4), 325–346. https://doi.org/10.1016/j.ocemod.2004.08.001
3. Alvera-Azcárate, Aida, Van Der Zande, D., Barth, A., Troupin, C., Martin, S., & Beckers, J.-M. (2021). Analysis of 23 years of daily cloud-free chlorophyll and suspended particulate matter in the Greater North Sea. *Frontiers in Marine Science*, 8, 707632. https://doi.org/10.3389/fmars.2021.707632
4. Alvera-Azcárate, Aida, Vanhellemont, Q., Ruddick, K., Barth, A., & Beckers, J.-M. (2015). Analysis of high-frequency geostationary ocean color data using DINEOF. *Estuarine, Coastal and Shelf Science*, 159, 28–36. https://doi.org/10.1016/j.ecss.2015.03.026
5. Beckers, J. M., & Rixen, M. (2003). EOF calculations and data filling from incomplete oceanographic datasets. *Journal of Atmospheric and Oceanic Technology*, 20(12), 1839–1856. https://doi.org/10.1175/1520-0426(2003) 020<1839:ECADFF>2.0.CO;2
6. Bentamy, A., Croize-Fillon, D., Queffeulou, P., Liu, C., & Roquet, H. (2009). Evaluation of high-resolution surface wind products at global and regional scales. *Journal of Operational Oceanography*, 2(2), 15–27. https://doi.org/10.1080/1755876X.2009.12027738
7. Bentamy, A., & Fillon, D. C. (2012). Gridded surface wind fields from Metop/ASCAT measurements. *International Journal of Remote Sensing*, 33(6), 1729–1754. https://doi.org/10.1080/01431161.2011.600348
8. Chakraborty, A., & Kumar, R. (2013). Generation and validation of analysed wind vectors over the global oceans. *Remote Sensing Letters*, 4(2), 114–122. https://doi.org/10.1080/2150704X.2012.701344
9. Cotton, J. (2013). Assimilation of scatterometer winds from Oceansat-2: Impact on Met Office analyses and forecasts. Forecasting Research Technical Report, No. 572. Exeter: Met Office.

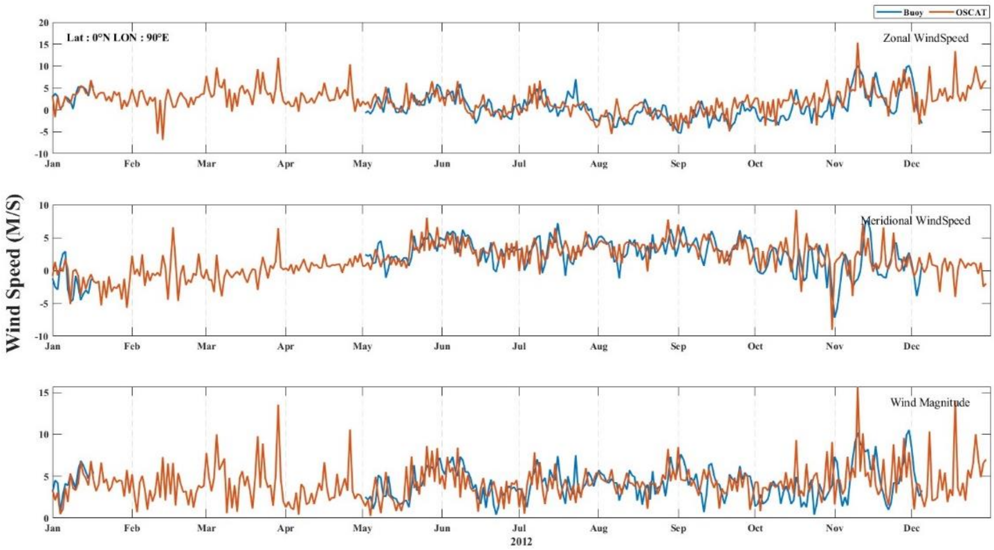
10. Ganzedo, U., Alvera-Azcárate, A., Esnaola, G., Ezcurra, A., & Sáenz, J. (2011). Reconstruction of sea surface temperature by means of DINEOF: A case study during the fishing season in the Bay of Biscay. *International Journal of Remote Sensing*, 32(4), 933–950. https://doi.org/10.1080/01431160903491420
11. Gohil, B., K., S., & Varma, A. (2007). Algorithm theoretical basis document (ATBD): Wind vector retrieval algorithms for Oceansat-2 scatterometer, version 1, SAC/ISRO I. Internal Report #OCEANSAT-II-UP/SCATT-1/SAC-2007.
12. Gohil B., et al. (2007). Algorithm theoretical basis document (ATBD): Wind vector retrieval algorithms for Oceansat-2 scatterometer. SAC/ISRO Internal Report.
13. Jayaram, C., Priyadarshi, N., Pavan Kumar, J., Udaya Bhaskar, T. V. S., Raju, D., & Kochuparampil, A. J. (2018). Analysis of gap-free chlorophyll-a data from MODIS in Arabian Sea, reconstructed using DINEOF. *International Journal of Remote Sensing*, 39(21), 7506–7522. https://doi.org/10.1080/01431161.2018.1471540
14. Jayaram, C., Pavan Kumar, J., Udaya Bhaskar, T.V.S. *et al.* Reconstruction of Gap-Free OCM-2 Chlorophyll-a Concentration Using DINEOF. *J Indian Soc Remote Sens* **49**, 1419–1425 (2021). https://doi.org/10.1007/s12524-021-01317-6.
15. McPhaden, M. J., Meyers, G., Ando, K., Masumoto, Y., Murty, V. S. N., Ravichandran, M., et al. (2009). RAMA: The Research Moored Array for African–Asian–Australian Monsoon Analysis and Prediction. *Bulletin of the American Meteorological Society*, 90(4), 459–480. https://doi.org/10.1175/2008BAMS2608.1
16. Miles, T. N., He, R., & Li, M. (2009). Characterizing the South Atlantic Bight seasonal variability and cold-water event in 2003 using a daily cloud-free SST and chlorophyll analysis. *Geophysical Research Letters*, 36(2), 2008GL036396. https://doi.org/10.1029/2008GL036396
17. Nechad, B., Alvera-Azcárate, A., Ruddick, K., & Greenwood, N. (2011). Reconstruction of MODIS total suspended matter time series maps by DINEOF and validation with autonomous platform data. *Ocean Dynamics*, 61(8), 1205–1214. https://doi.org/10.1007/s10236-011-0425-4
18. Panofsky, H. A., & Dutton, J. A. (1984). *Atmospheric turbulence: Models and methods for engineering applications*. New York: Wiley.
19. Sirjacobs, D., Alvera-Azcárate, A., Barth, A., Lacroix, G., Park, Y., Nechad, B., et al. (2011). Cloud filling of ocean colour and sea surface temperature remote sensing products over the Southern North Sea by the Data Interpolating Empirical Orthogonal

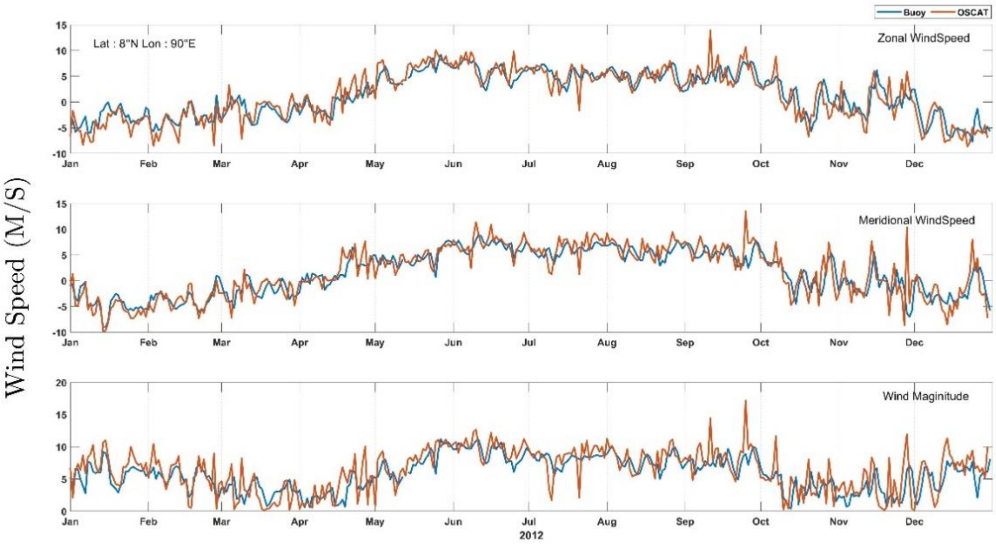
Functions methodology. *Journal of Sea Research*, 65(1), 114–130. https://doi.org/10.1016/j.seares.2010.08.002

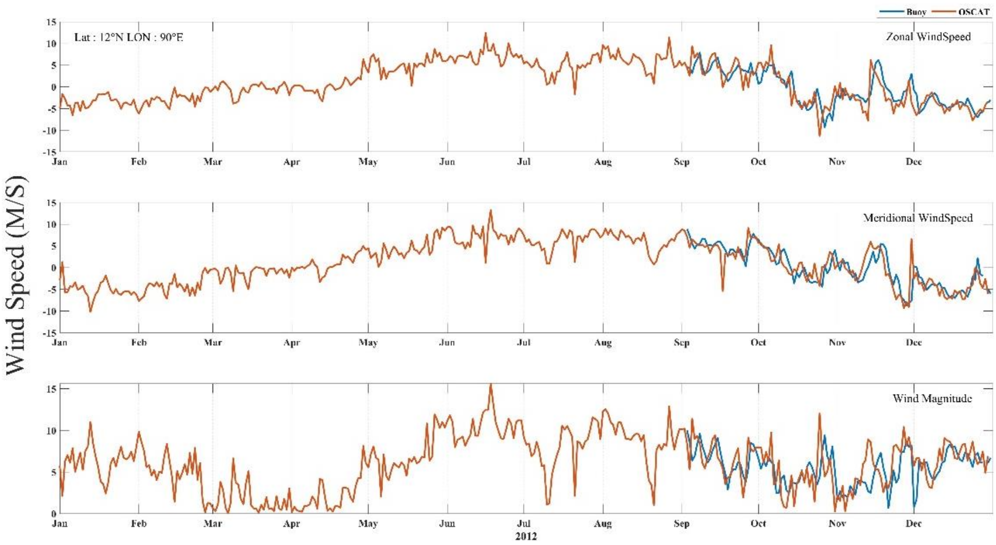
20. Sudha, A. K., & Prasada Rao, C. V. K. (2013). Comparison of Oceansat-2 scatterometer winds with buoy observations over the Indian Ocean and the Pacific Ocean. *Remote Sensing Letters*, 4(2), 171–179. https://doi.org/10.1080/2150704X.2012.713140
21. Troupin, C., Machín, F., Ouberdous, M., Sirjacobs, D., Barth, A., & Beckers, J.-M. (2010). High-resolution climatology of the northeast Atlantic using Data-Interpolating Variational Analysis (DIVA). *Journal of Geophysical Research: Oceans*, 115(C8), 2009JC005512. https://doi.org/10.1029/2009JC005512
22. Udaya Bhaskar, T. V. S., Jayaram, C., & Rama Rao, E. P. (2013). Comparison between Argo-derived sea surface temperature and microwave sea surface temperature in tropical Indian Ocean. *Remote Sensing Letters*, 4(2), 141–150. https://doi.org/10.1080/2150704X.2012.711955
23. Venkatesan, R., Shamji, V. R., Latha, G., Mathew, S., Rao, R. R., Muthiah, A., & Atmanand, M. A. (2013). *In situ* ocean subsurface time-series measurements from OMNI buoy network in the Bay of Bengal. *Current Science*, 104(9), 1166–1177.

Appendix




Buoy
OSCAT
Lat : 0°N LON : 90°E
Zonal WindSpeed
Meridional WindSpeed
Wind Magnitude
Wind Speed (M/S)
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
2012


Buoy
OSCAT
Lat : 8°N Lon : 90°E
Zonal WindSpeed
Meridional WindSpeed
Wind Maginitude
Wind Speed (M/S)
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
2012


Buoy
OSCAT
Lat : 12°N LON : 90°E
Zonal WindSpeed
Meridional WindSpeed
Wind Magnitude
Wind Speed (M/S)
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
2012