Ocean Dynamics (2026) 76:16
https://doi.org/10.1007/s10236-026-01772-0

Quality control of wave rider buoy data and its applications to cyclones and swell surges in the Indian ocean

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Received: 29 September 2025 / Accepted: 12 January 2026

Abstract

Long-term wave observations are crucial for ocean forecasting, coastal hazard assessment, and climate studies, but their utility depends on rigorous quality control (QC). The present study discusses a comprehensive QC framework applied to 14 years (2009–2023) of Wave Rider Buoy (WRB) data obtained from the Wave Monitoring Nearshore Network (WAMAN), operated by the Indian National Centre for Ocean Information Services (INCOIS). The network comprises 17 WRBs deployed along the Indian coastline and islands to support wave monitoring, validation and assimilation into operational wave models. The QC framework includes tests for checking ranges, spikes, persistence, data gaps, issues with timestamps, location consistency, and extreme wave heights. From the analysis it is observed that approximately 90% of the observations passed all QC tests, while 10% were flagged as erroneous. Although the dataset exhibits a 28% overall data gap rate, extreme events associated with major cyclones (e.g., Phailin, Hudhud, Roanu, Titli, Fani, Amphan, Asani) were successfully retained, demonstrating the robustness of the approach in preserving high-impact conditions. Applications of the QC dataset highlight its scientific and operational value. Regional analysis revealed higher mean significant wave heights (SWH) and variability along the west coast and island stations, driven by southwest monsoon winds and long-period swells, in contrast to calmer east coast conditions. Additionally, WAMAN buoys proved critical for monitoring swell surges, with the Seychelles buoy detecting high-period waves two days before their arrival along the Indian coast, enhancing the accuracy of INCOIS swell surge alerts. This quality-controlled dataset establishes a reliable foundation for advancing research and improving operational ocean forecasting and coastal risk management.

Keywords WAMAN · Significant Wave Height (SWH) · Quality control · Cyclone wave activity · Swell surge · Indian monsoon

1 Introduction

The Indian Ocean (IO) is a uniquely dynamic ocean basin, strongly influenced by the Asian landmass to its north, which drives pronounced seasonal variability through the monsoon system. Unlike the Pacific and Atlantic Oceans, the IO exhibits a marked seasonal reversal of winds, resulting in complex patterns of circulation and wave generation. In addition to monsoonal forcing, interannual climate modes such as the Indian Ocean Dipole (IOD) and the El Niño–Southern Oscillation (ENSO) modulate regional wind and wave conditions, contributing to substantial variability in wave climate across the basin (Ashok et al. 2001; Schott et al. 2009; Anoop et al. 2016; Srinivas et al. 2021; Ham et al. 2017; Ding et al. 2025). The IO is also frequently affected by intense tropical cyclones, particularly in the Arabian Sea and the Bay of Bengal, which generate extreme waves and long-period swells that can propagate far from their generation regions. These combined influences make the IO one of the most complex and hazard-prone ocean basins, with significant implications for maritime safety, coastal infrastructure, and densely populated coastal communities. In this context, reliable coastal and offshore wave observations are of critical importance, as they provide essential

Responsible Editor: Jay Kumar Seelam

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Published online: 30 January 2026

ground-truth data for understanding ocean–atmosphere interactions, validating numerical wave and circulation models, and improving operational forecasting systems. High-quality wave measurements are essential for a wide range of applications, including climate research, marine resource management, safe navigation, and disaster mitigation. In particular, in situ observations play a vital role in evaluating satellite products and numerical model outputs, especially in regions where observational coverage remains sparse (Rusu 2011; Ardhuin et al. 2019; Centurioni et al. 2019). Given the strong influence of monsoons, cyclones, and large-scale climate variability on wave conditions in the IO, the accuracy and reliability of buoy-based wave observations are fundamental to advancing both scientific understanding and operational services in this region. Wave dynamics in the IO are strongly influenced by seasonal monsoon winds and frequent cyclonic disturbances, making accurate and high-quality wave observations essential for coastal resilience, navigation safety, and hazard preparedness (Kumar et al. 2006). Coastal wave buoy data are widely used to assess vulnerability to extreme wave events (Cunha et al. 2021; Rezaie et al. 2020), evaluate wave energy potential (Yang et al. 2024), and validate satellite altimetry and numerical weather prediction models, particularly in data-sparse regions (Young et al. 2013; Bidlot et al. 2020). Reliable estimates of key wave parameters such as significant wave height (SWH), period, and direction are essential for storm surge prediction, coastal erosion studies, and marine operations, and are critical for the design of offshore and coastal infrastructure (Marone et al. 2017; Luo et al. 2021; Thai et al. 2017; Murthy et al. 2020). In addition, long-term, quality-controlled wave datasets are essential for climate variability studies, enabling robust assessments of interannual to decadal variability and long-term trends in extreme wave conditions. Multi-decadal buoy and reanalysis records have been used to document regional increases in extreme SWH and wave energy linked to changes in wind patterns and large-scale climate modes (Young et al. 2011; Montefusco et al. 2019). These datasets also facilitate analyses of climate-driven changes in wave directionality and swell dominance, with important implications for coastal erosion and marine infrastructure (Morim et al. 2019). Moreover, quality-controlled wave climatologies support assessments of renewable ocean energy potential at both global and regional scales. Globally, long-term wave observations and reanalysis products have been used to characterize the variability and climate sensitivity of wave energy resources (Ardhuin et al. 2017; Morim et al. 2019). In the Indian context, observationally constrained wave climatologies and model-based studies have evaluated wave energy potential along the Indian coast, highlighting its seasonal and interannual variability relevant for site selection and feasibility analysis (Mithun et al. 2025). However, in situ wave observations are often affected by sensor drift, biofouling, mooring movement, or transmission errors, which can introduce significant uncertainties into downstream applications (Bender et al. 2010). The harsh marine environment poses continuous challenges to instrumentation, with degradation of sensor performance being common over long period post deployments. Errors can also arise from data telemetry issues, processing algorithms, or environmental interference such as high sea states and bio-organic growth on sensors. If left uncorrected, such errors can propagate into wave model calibration, validation, and data assimilation systems, leading to biased estimates of SWH, wave period, and spectral energy, and ultimately degrade the reliability of operational forecasts and climate analyses. Consequently, rigorous quality control (QC) procedures are essential to ensure the integrity of wave observations before their use in scientific research, operational forecasting, and climate assessments. The importance of robust QC frameworks has been increasingly recognized in the oceanographic community. In recent years, dedicated initiatives have emerged to establish standardized QC practices across different observational platforms. For example, the Quality Assurance of Real-Time Ocean Data (QARTOD) manuals developed by the U.S. Integrated Ocean Observing System (IOOS) have set widely accepted guidelines for evaluating oceanographic data streams. Similar efforts have been carried out by international programs such as the Global Ocean Observing System (GOOS), which stresses the need for harmonized data quality procedures to enable interoperability between datasets. These frameworks are particularly important for regions such as the IO, where observations remain sparse compared to the Pacific and Atlantic basins, and where reliable QC procedures are vital for filling observational gaps and ensuring the utility of available data. In recent years, increasing attention has been directed toward the development of QC frameworks for ocean in situ datasets (Tan et al. 2021; Good et al. 2013; Gomez-Lopez et al. 2014). Building on this progress, the present study focuses on establishing a dedicated QC framework for WRB observations in the North Indian Ocean (NIO), with an emphasis on SWH — a key indicator of sea state. SWH is not only a critical parameter for marine meteorology but also serves as a proxy for understanding wind–wave interactions and energy transfer processes between the atmosphere and ocean. Given its direct implications for safety of navigation and coastal hazard assessment, ensuring the reliability of SWH data is of paramount importance.

The work presented here represents the first systematic attempt to implement QC procedures tailored to the

WAMAN data, an observational program that provides continuous wave measurements along the Indian coastline. By creating a comprehensive QC framework for these buoy observations, this study addresses a critical gap in the current observational and forecasting systems of the region. The framework integrates both range-based checks and contextual validation steps, thereby ensuring that flagged anomalies are effectively identified without discarding valuable extreme-event observations that are particularly important in the cyclone-prone NIO. The broader impact of this work extends beyond technical validation. High-quality, QC-processed datasets will strengthen operational forecasting systems, support climate assessments, and improve confidence in regional and global wave reanalysis. The methods implemented here also provide a reference for similar observational networks, where context-specific adaptations of QC protocols are required to account for regional variability in oceanographic conditions.

The paper is structured as follows: Sect. 2 provides an overview of the WAMAN buoy network, including instrumentation and data characteristics. Section 3 details the datasets and methodology. Section 4 presents the QC framework and validation results, including an analysis of SWH during cyclonic events and a case study on wave frequency characteristics. Section 5 concludes with a summary and future perspectives.

2 WAMAN network

The WAMAN, established and maintained by the Earth System Science Organization – Indian National Centre for Ocean Information Services (ESSO–INCOIS), provides continuous in situ wave observations along the Indian coastline. The network comprises Datawell Directional Waverider buoy models MKIII (hereafter Mk3) and MKIV (hereafter Mk4), deployed at 17 locations since 2009 to support research, forecasting, and operational applications (Balakrishnan Nair et al. 2025). The Mk3 buoys measure wave height, wave direction, sea surface temperature (SST), whereas the Mk4 buoys extend these observations by measuring near-surface currents additionally (Peach et al. 2017), enabling a more comprehensive characterization of sea state variability. Among the deployed stations, Gopalpur, Visakhapatnam, Krishnapatnam, Kanyakumari, Karwar, and Kollam have Mk4 buoys (shown as blue colored filled circles in Fig. 1b), while the remaining sites are equipped with Mk3 buoys (shown as red colored filled circles in Fig. 1b).

A typical Mk4 directional buoy (Fig. 1a) is designed to provide precise measurements of key wave parameters, including SWH, wave period, and wave direction. The buoy is moored to the seafloor with a site-specific system that allows free response to wave motion while maintaining

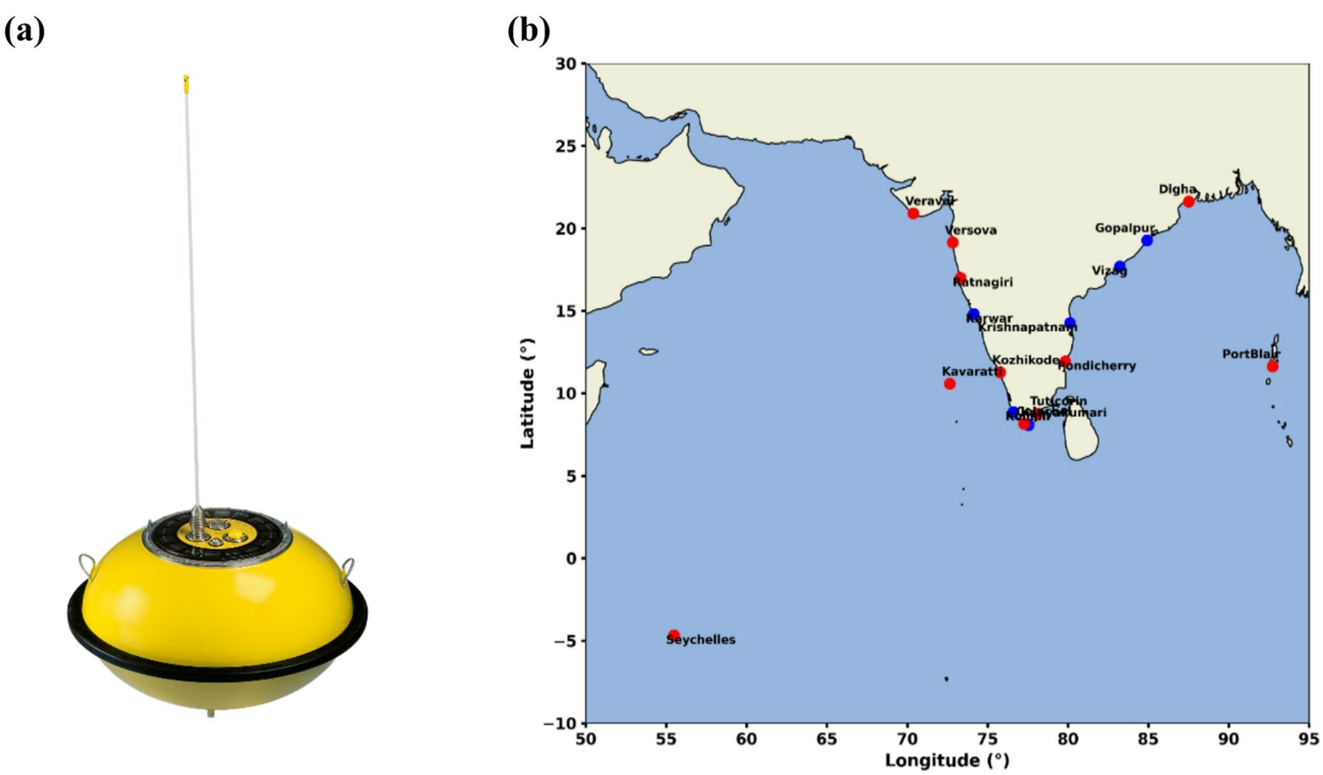

Fig. 1 (**a**) Datawell Directional WRB (Datawell BV, The Netherlands). Source: Datawell (https://datawell.nl/products/directional-waverider-4/). (**b**) Network of WAMAN buoy locations in the Indian Ocean. The Red colored filled circles represent locations of Mk3 buoys and blue colored filled circles represent Mk4 buoys

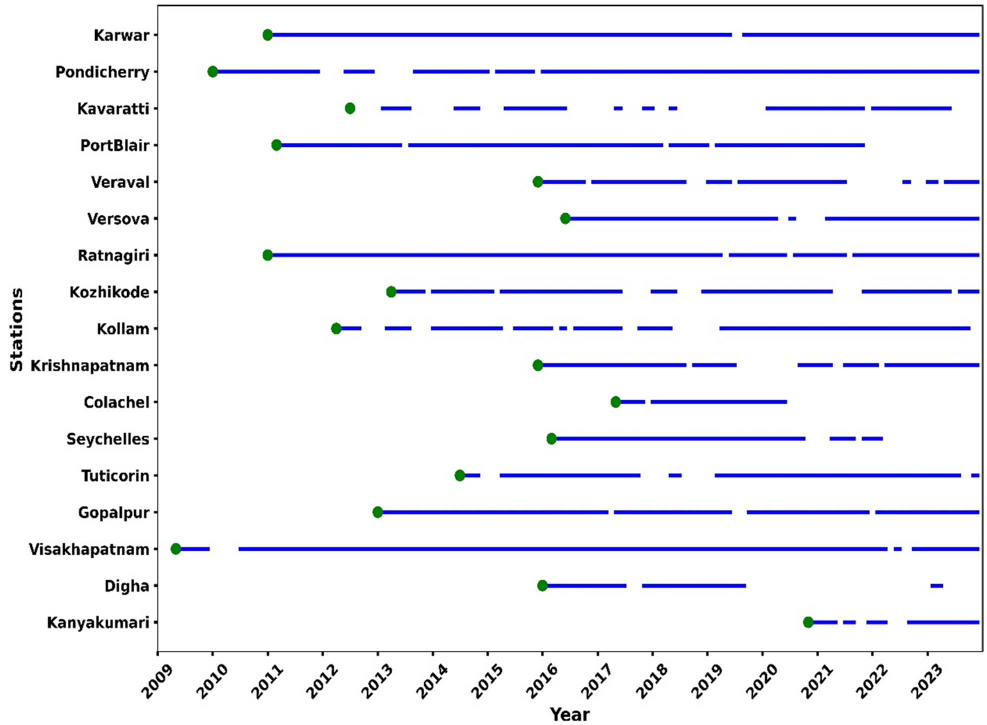

Fig. 2 Data availability at each WRB station from 2009 to 2023. The green colored filled circle indicates the deployment date and beginning of the buoy data reception

position, ensuring accurate wave measurements (Datawell 2024). The sensors are high-precision accelerometers housed within a sealed casing, which measure three-dimensional buoy motion induced by waves. Vertical accelerations are double-integrated to derive surface displacement for calculating SWH and wave period, while horizontal accelerations combined with an internal magnetic compass provide wave direction.

The buoys record data at 1.28 Hz for 17 min every half hour, providing consistent temporal coverage, and the motion signals are processed using Fast Fourier Transform (FFT) techniques with a high-frequency cut-off of 0.58 Hz (Balakrishnan Nair et al. 2013; Sirisha et al. 2023; Sajiv et al. 2012). Key wave parameters derived from the wave spectrum include SWH, swell wave height, wind-sea wave height, maximum wave height, peak wave period, and peak wave direction (Sirisha et al. 2019; Sajiv et al. 2012). Data are stored onboard at 30-minute intervals for delayed-mode retrieval, while real-time transmission every three hours is provided via INSAT satellite communication for operational monitoring.

The spatial distribution of WAMAN buoys are shown in Fig. 1b. Monthly data availability for each buoy ever since they were deployed is illustrated in Fig. 2. Continuous long-term records are maintained at Visakhapatnam and Pondicherry (since 2010) on the east coast, and at Ratnagiri and Karwar (since 2011) on the west coast. Several new stations, including Krishnapatnam, Veraval, Seychelles, Versova, and Digha, were added in 2015–2016, while data gaps at Digha, Colachel, and Kavaratti reflect maintenance and logistical challenges.

Table 1 Upper and lower thresholds of WRB variables (Anuradha et al. 2024) applied in the QC range check, derived from all available data

S. No	Parameter	Range	Units
1.	Significant Wave Height	0.1–12	meters
2.	Wave Direction	0–360	deg
3.	Wave Period	1.7–30	seconds
4.	Sea Surface Temperature	0–35	centigrade
5.	Current Speed	0–4.1	meter/second

3 Data and methods

The primary datasets used in this study are from WRBs deployed across the NIO by ESSO-INCOIS, India. Details of the key parameters measured by Mk3 and Mk4 buoys are given in Table 1. These long-term time series are used to demonstrate the applicability of the QC procedures. For this purpose, WRBs deployed off Visakhapatnam on the east coast and Ratnagiri on the west coast were selected, as both provide continuous records with minimal data gaps at 30-minute intervals. The raw SWH time series from Visakhapatnam (Fig. 3a) and Ratnagiri (Fig. 3b) contain numerous spurious spikes, underscoring the necessity of rigorous QC prior to scientific analysis.

The quality control procedure is an iterative process; continuous monitoring and improvement of QC methods are essential for maintaining data integrity. Documentation of QC procedures and flagged data are crucial for transparency and data interpretation. The QC framework applied in this study builds upon the procedure we earlier summarized

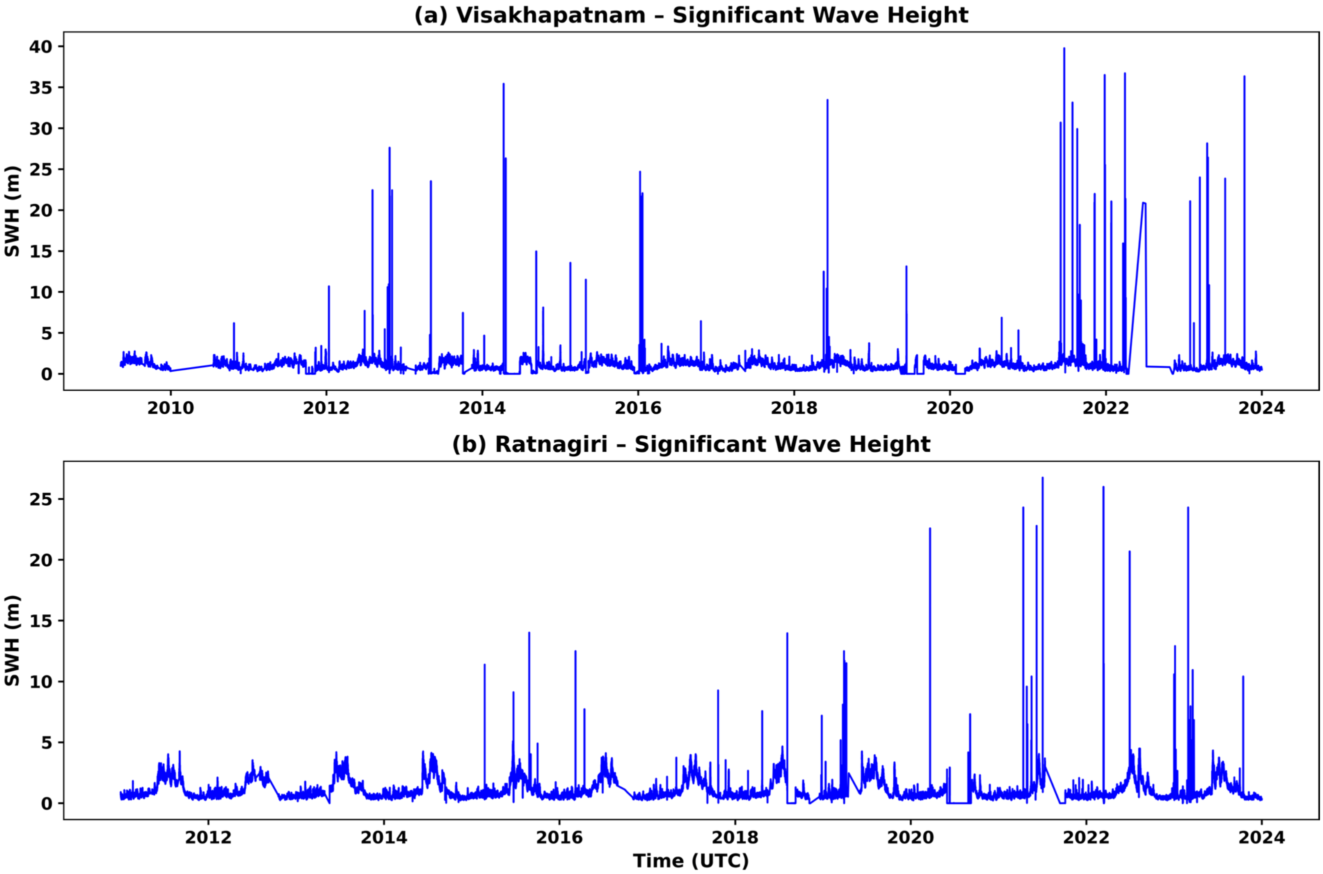

Fig. 3 Time series of SWH (m) before QC from WRB: (**a**) Visakhapatnam during 2009–2023, and (**b**) Ratnagiri during 2011–2023

in the IIOE-2 Newsletter (Anuradha et al. 2024), but has been substantially extended to cover the complete 2009–2023 buoy records from both the east and west coasts. The framework integrates a series of checks grouped into three broad categories: (i) plausibility checks, which verify temporal consistency, location stability, and continuity of the time series; (ii) physical consistency checks, which ensure that SWH values remain within realistic basin-specific ranges and below the maximum allowable wave heights; and (iii) statistical outlier detection, designed to identify short-term anomalies such as spikes and persistence errors. Thresholds were empirically derived from long-term WRB observations (Table 1) in the IO and adjusted to reflect regional climatology, allowing the procedure to retain genuine extreme events, including cyclone-driven high waves on the east coast and monsoon-dominated swell waves on the west coast.

This systematic grouping and regional customization represent the first basin-wide adaptation of international QC protocols for Indian WRB data. The complete set of flag definitions and codes used to identify different error types is summarized in Tables 2 and 3.

Table 2 Details of quality flags assigned based on the QC tests that the data failed

Flag meaning	Flag Value
Good data	1
Timestamp and Location Consistency	2
Range	3
Spikes	4
Persistence value	5
Maximum wave height	6

Table 3 Final QC flags assigned at the end of QC procedure, adapted from Anuradha et al. (2024)

Flag Value	Meaning
1	Good data
4	Bad data
9	Data Gap

Although the QC framework follows internationally accepted guidelines such as QARTOD and NOAA (2018), all tests were regionally customized for the Indian Ocean WRB data. Range thresholds were based on long-term historical records (2009–2023); spike detection employed a 7-point moving window with a 4× standard deviation threshold validated during cyclone events; persistence errors were identified using six consecutive identical values, reflecting the operational behaviour of Indian WRBs; and spatial consistency was defined using a ± 0.5° window around known buoy positions. These refinements ensured reliable error detection while preserving true extremes. For cyclone applications, track data were obtained from the Regional Specialized Meteorological Centre (RSMC), New Delhi, the official agency responsible for monitoring tropical cyclones over the North Indian Ocean. The dataset provides cyclone position, central pressure, and maximum sustained winds at 3-hour intervals (Kotal et al. 2019), and was used to analyse cyclone tracks and intensity evolution during the study period.

The QC framework implemented in this study is designed to flag suspect observations rather than delete them. Data points flagged as bad are excluded from statistical analyses, climatological calculations, and validation metrics to prevent biases in results. For downstream applications, QC-processed data with only "good" flags are recommended for routine model validation and data assimilation, while flagged data may be selectively examined for diagnostic purposes or detailed case studies. This approach ensures data integrity while preserving valuable information on rare high-impact events.

4 Results and discussion

This section demonstrates the effectiveness of the QC methods applied in improving the reliability and accuracy of WRB data. Detailed analyses, including before-and-after comparisons, statistical assessments, and case studies, highlight the substantial improvements in data quality achieved by applying these QC methods. The proposed QC methods are demonstrated using the SWH data from WRB installed at Visakhapatnam and Ratnagiri, at 30-minute intervals.

The SWH data were organized into 1 m bins to examine the distribution of occurrences at each interval. Figure 4 presents the histograms derived from the raw (pre-QC) buoy observations for (a) Visakhapatnam and (b) Ratnagiri, with the x-axis showing SWH (0–37 m) and the y-axis indicating the number of data points on a logarithmic scale.

At both sites, the highest frequency of observations is concentrated in the 0–3 m range, underscoring the prevalence of calm sea states. For Visakhapatnam, approximately 56% fall within the 0–1 m range, 40% in the 1–2 m range, and about 3% in the 2–3 m range. Ratnagiri also shows a strong clustering in the lower wave height range, though with relatively more occurrences of SWH in the 3–4 m bin. Beyond 3 m, the frequency of observations decreases sharply at both locations, with only a few scattered data points extending into the 3–38 m range. The very high counts in the lower bins (on the order of 10^5 for the 1–2 m range) reflect the dominance of calm to moderate sea states for most of the year. Conversely, the sparse distribution beyond 5 m corresponds to extreme wave events such as storms or cyclones, which occur infrequently but contribute to the higher-end tail of the distribution. The Ratnagiri buoy on the west coast shows a broader spread into the 3–4 m range compared to Visakhapatnam, a pattern attributable to the southwest monsoon, which generates stronger and more persistent wind seas and swells along the Arabian Sea. In contrast, the east coast (Visakhapatnam) is relatively sheltered from the direct influence of southwest monsoon waves, resulting in fewer occurrences of SWH above 3 m.

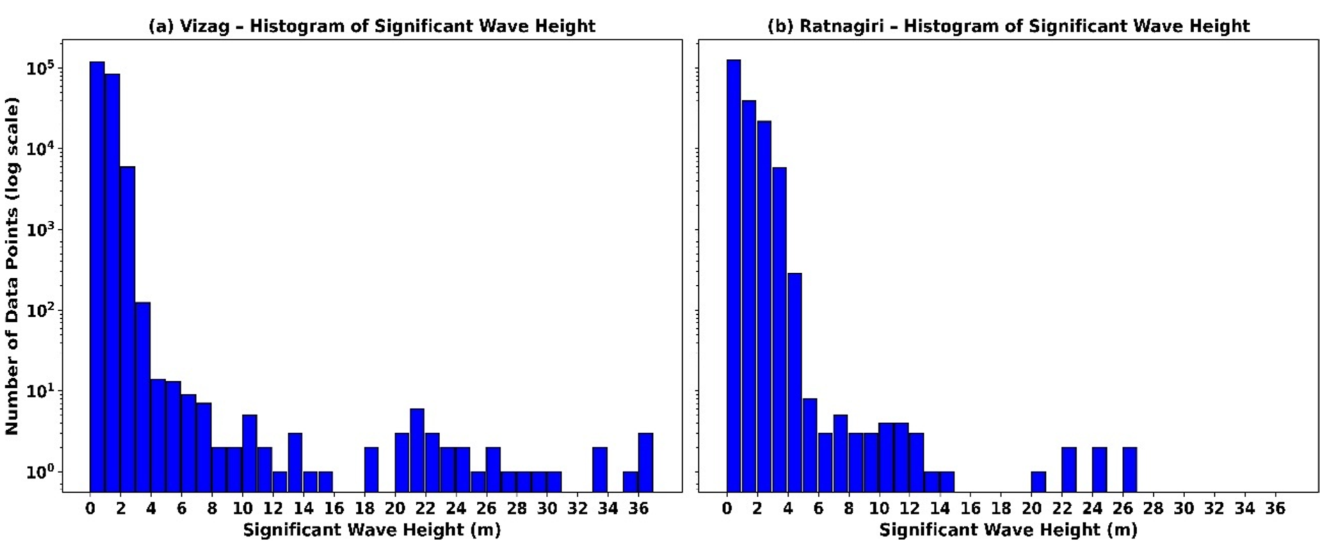

Fig. 4 Histograms of SWH at (**a**) Visakhapatnam and (**b**) Ratnagiri derived from raw (pre-QC) WRB observations, using 1 m bin interval

Overall, the histograms highlight the contrasting wave regimes of the two coasts: the west coast exhibits enhanced monsoon-driven wave activity, while the east coast remains dominated by calmer sea states. These differences are consistent with the established seasonal wave climate of the Indian subcontinent.

4.1 Implementation of quality control procedures for SWH data

The application of QC procedures to the SWH time series from Visakhapatnam (east coast) and Ratnagiri (west coast) buoys effectively identified and flagged a range of anomalies, including outliers, spikes, persistence errors, location inconsistencies, and missing records (Fig. 5). For the Visakhapatnam buoy, approximately 4% of the data points were flagged for time-location inconsistencies. These were identified by comparing the reported buoy positions with the deployed mooring coordinates and flagging records that exceeded a predefined spatial deviation threshold. Such deviations are typically attributed to GPS dropouts, transmission errors, or temporary buoy displacement caused by strong currents or increased mooring tension during energetic sea states. In addition, only 0.03% of the records were marked as spikes, which are generally associated with short-duration sensor malfunctions, electronic noise, or physical impacts on the buoy or sensor housing, particularly during storms. Persistence (flat-line) errors accounted for approximately 4.7% of the dataset and are commonly associated with sensor freezing, power interruptions, or telemetry failures that result in repeated transmission of identical values over extended periods. All reported percentages represent fraction of records failing the respective QC tests relative to the total number of observations. Although the raw dataset contained spurious SWH values exceeding 30–40 m, none of the values surpassed the upper threshold of 12 m after QC application, confirming that the extreme anomalies were effectively detected and flagged. Around 16% of the time series was identified with gaps, which were preserved with NaN placeholders to ensure continuity in temporal indexing and facilitate downstream analyses. At Ratnagiri, a similar pattern emerged, though the anomalies were less frequent compared to Visakhapatnam. The QC overlays revealed fewer extreme spikes and persistence errors, but data gaps were still a notable issue. The west coast buoy also recorded relatively more moderate wave heights (3–4 m) linked to the southwest monsoon, which were retained as valid after passing QC checks.

The implementation of the QC procedures effectively removed unrealistic values such as spurious spikes, flat-line sequences, and missing segments, while retaining genuine extreme events like monsoon-driven high waves.

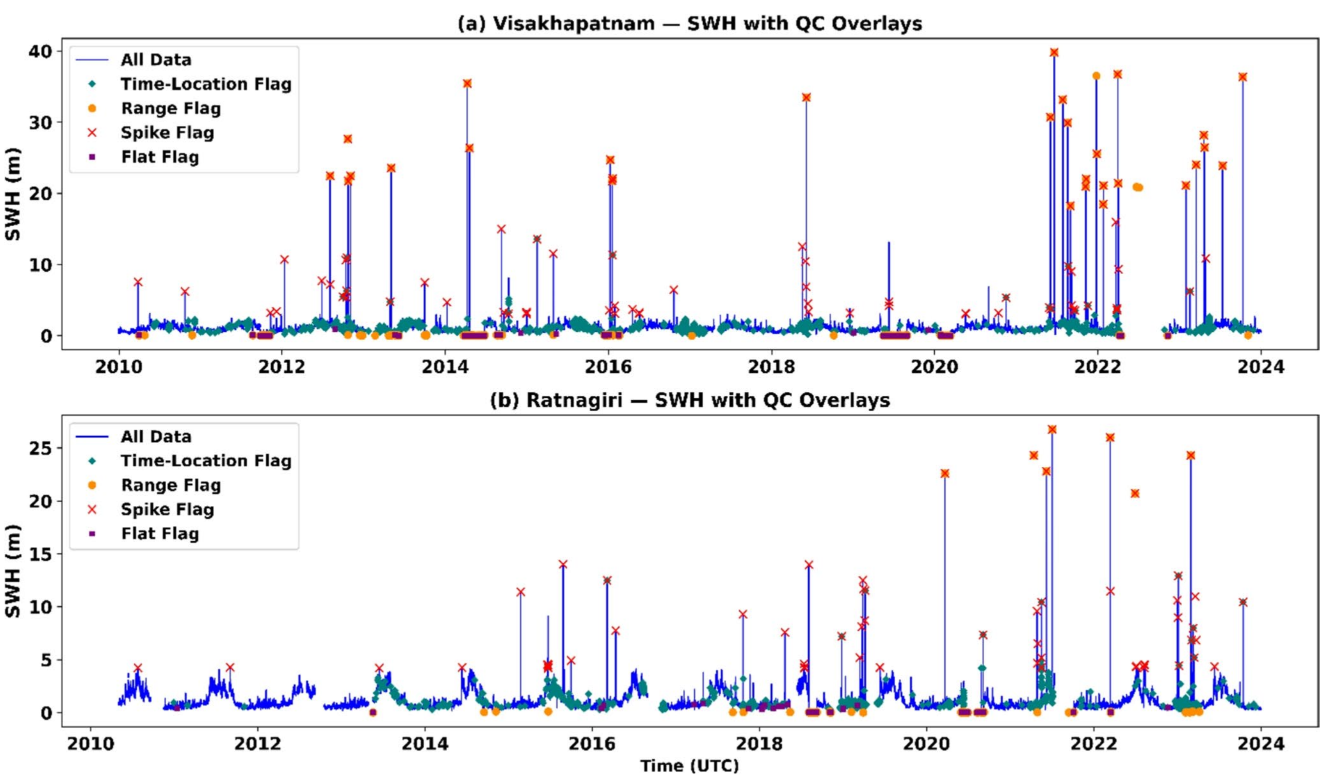

Fig. 5 Time series of SWH with QC flags overlays at (**a**) Visakhapatnam and (**b**) Ratnagiri. The raw dataset (blue) is overlaid with QC flags: time-location (green), range (orange), spike (red), and flat (purple)

The resulting cleaned datasets provide a reliable long-term record of SWH variability at both sites, making them suitable for scientific studies and model validation. After the complete QC process, the time series was thoroughly screened to ensure reliability, and only valid observations were preserved.

The final quality-controlled 30-min time-series dataset (Fig. 6) shows SWH within a realistic range of 0–9 m at Visakhapatnam and 0–6 m at Ratnagiri, consistent with the climatology of the Indian coastal region. The post-QC time series reveal smooth and continuous records with realistic seasonal and interannual variability. At Visakhapatnam (east coast), SWH generally remains below 4 m but reaches higher peaks during cyclone events. Notably, the Hudhud cyclone in October 2014 is clearly retained after QC, demonstrating that genuine extreme events are preserved while spurious anomalies are removed. This highlights the east coast's greater exposure to cyclone-driven high waves. In contrast, Ratnagiri (west coast) exhibits more frequent moderate wave heights in the 2–4 m range, with variability strongly tied to the southwest monsoon and swell waves arriving from the Arabian Sea. The absence of anomalous spikes (> 10 m) and the preservation of consistent seasonal cycles at both sites confirm the robustness of the QC process in producing reliable datasets suitable for long-term wave climate analysis.

4.2 Quality assessment and analysis of significant wave height data

Quality control procedures were applied to all WRB data collected during the period 2009–2023. Data quality was evaluated based on the percentages of good, bad, and missing records. These percentages were computed as the ratio of each category to the total (or expected) number of data points, expressed as a percentage. The quality statistics for each buoy location are summarized in Table 4. High-quality data were recorded in stations such as Pondicherry and Karwar, with 95% good data, while Kanyakumari exhibited an outstanding 99% good data with minimal bad data (~1%) and only 26% gap data. Gopalpur and Tuticorin also show strong data integrity, with 93% of received data marked as

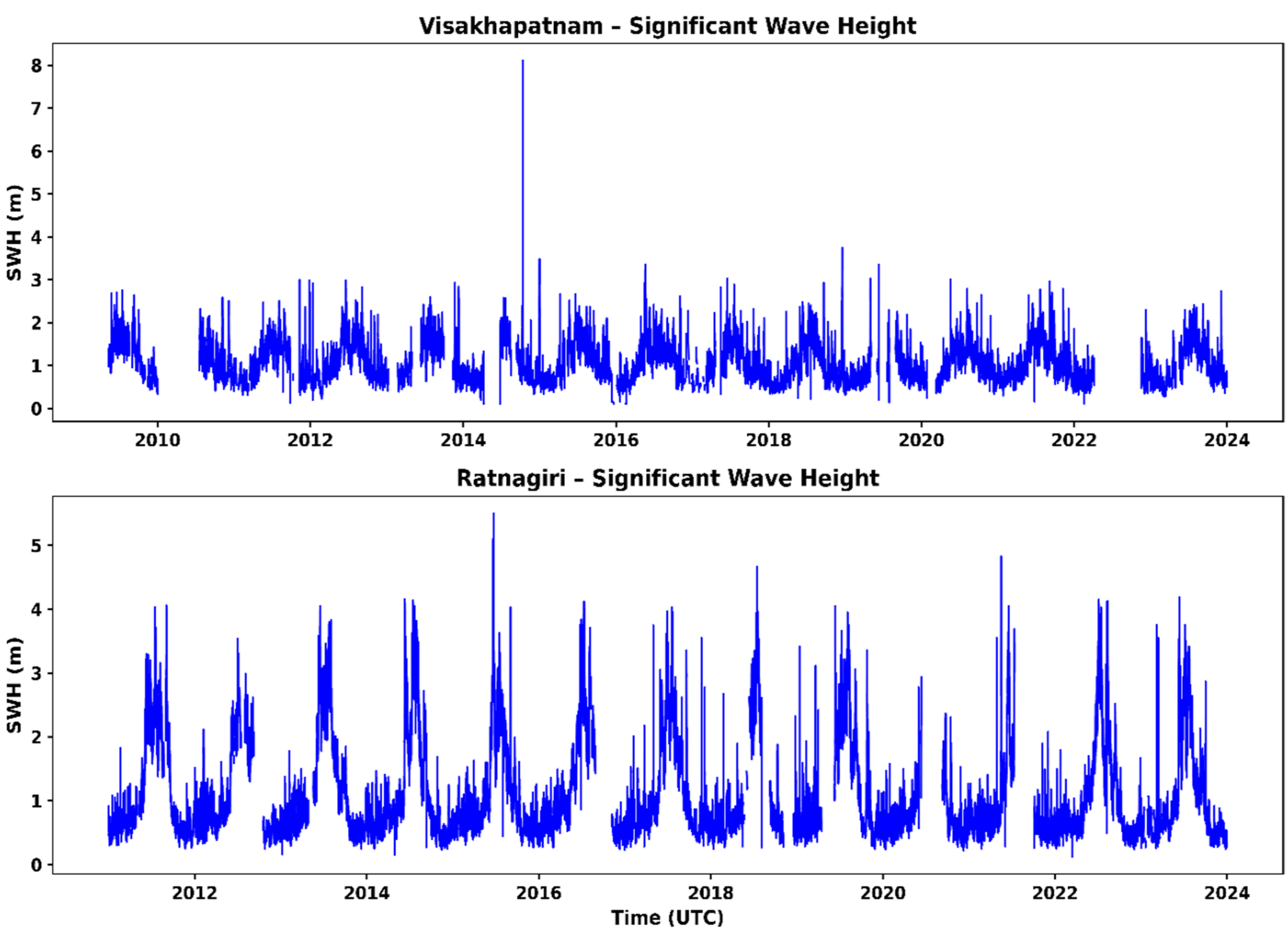

Fig. 6 Quality-controlled 30-minute time series of SWH from WRBs at Visakhapatnam (top) and Ratnagiri (bottom)

Table 4 Summary of QC-processed WRB data (2009–2023) for each station

Station	Expected Data Points	Data Received	Good Data Points (Good %)	Bad Data Points (Bad %)	Data Gap Points (Missing %)
Digha	139,288	51,394	45,215 (88%)	6179 (12%)	87,894 (63%)
Gopalpur	190,023	163,771	152,252 (93%)	11,519 (7%)	26,252 (13%)
Visakhapatnam	245,422	210,024	188,499 (90%)	21,525 (10%)	35,398 (14%)
Krishnapatnam	140,860	94,101	84,052 (90%)	10,049 (10%)	46,759 (33%)
Pondicherry	245,422	201,892	191,593 (95%)	10,299 (5%)	43,530 (17%)
Tuticorin	166,596	117,860	108,811 (93%)	9049 (7%)	48,736 (29%)
Port Blair	220,695	135,083	130,121 (97%)	4962 (3%)	85,612 (38%)
Kanyakumari	54,222	39,745	39,496 (99%)	249 (1%)	14,477 (26%)
Colachel	53,818	36,047	32,218 (90%)	3829 (10%)	17,771 (33%)
Kollam	205,568	122,629	105,549 (87%)	17,080 (13%)	82,939 (40%)
Kozhikode	187,285	131,794	102,679 (78%)	29,115 (22%)	55,491 (29%)
Karwar	243,934	198,150	198,150 (95%)	11,041 (5%)	34,743 (14%)
Ratnagiri	239,456	198,436	193,766 (98%)	4670 (2%)	41,020 (17%)
Versova	132,515	112,026	109,621 (98%)	2405 (2%)	20,489 (15%)
Veraval	133,890	72,666	56,218 (78%)	16,548 (21%)	61,124 (44%)
Seychelles	105,050	76,270	65,317 (86%)	10,953 (14%)	28,780 (27%)
Kavaratti	167,656	73,772	65,882(88%)	7920 (12%)	93,884 (50%)

good and relatively low bad data percentages (7%). Stations like Digha and Kollam have significant data gaps, with 63% and 40% data, respectively, despite maintaining a high percentage of good data among received records (88% and 87%). Veraval and Kavaratti recorded notable gap data rates at 44% and 50%, respectively, with good data points at 78% and 88% of received data. Meanwhile, Seychelles and Krishnapatnam exhibit reasonable data quality at 86% and 90%, though gap data is more about 27% and 33%.

The large data gaps observed at some locations primarily reflect operational and long-term mooring-related challenges rather than persistent sensor malfunction. The WRBs are deployed using elastic mooring systems designed to maintain buoy position while allowing compliance during energetic sea states. Over extended deployments, strong currents, cyclonic conditions, and repeated high-wave loading can increase mooring tension, occasionally leading to buoy drift, partial mooring failure, or loss. In addition, accidental damage or cutting of mooring lines during fishing activities, temporary unavailability of local logistical support for redeployment, and delays due to limited availability of spare parts contribute to prolonged data gaps. These same factors can also influence short-duration anomalies such as spurious spikes or flat-line sequences through altered buoy motion or sensor response. Consequently, while the proportion of good-quality data among recovered observations remains high at most stations, data completeness varies spatially and temporally across the network, underscoring the need for improved maintenance logistics and rapid redeployment strategies to enhance long-term data continuity.

Figure 7 represents the SWH data return percentages for various WRBs, with the x-axis showing the total data return (%) and the y-axis indicating the quality data return (%). Buoys like Ratnagiri, Versova, Gopalpur, and Visakhapatnam are clustered near the top-right corner, demonstrating high total and quality data returns, which reflect robust data collection and QC. In contrast, buoys such as Digha and Kavaratti exhibit relatively lower percentages, indicating potential issues with data availability. The hyperbolic lines serve as reference guides, illustrating the ratio of quality data to total data, where buoys closer to higher percentage lines (e.g., 90%) have most of their collected data in good quality. This visualization provides insights into the performance and reliability of the buoys, helping prioritize maintenance efforts and refine data analysis strategies (Satish et al., 2022).

After performing QC, using the good-quality data, the mean and the standard deviation are calculated for all the buoys and shown in Fig. 8. The analysis of mean and standard deviation of SWH at different locations revealed significant variations along the Indian coastline and the surrounding islands. On the west coast, buoys at locations such as Veraval (1.05 m), Ratnagiri (1.08 m), Karwar (1.12 m), Kollam (1.07 m), and Kanyakumari (1.12 m) exhibit relatively high mean SWH values. These elevated wave heights reflect the combined influence of strong southwest monsoon winds over the Arabian Sea, longer fetch conditions, and exposure to energetic swells propagating from the open ocean, modulated by regional bathymetry and shelf width (Sajiv et al. 2012).

In contrast, the east coast buoys, such as Pondicherry (0.77 m), Tuticorin (0.85 m), and Krishnapatnam (0.77 m), exhibit lower mean SWH values. This reflects relatively weaker local wind forcing, shorter fetch, partial sheltering by landmasses such as Sri Lanka, and the influence of a broader continental shelf, which together limit wave growth and nearshore wave energy. In the Island WRBs mean of

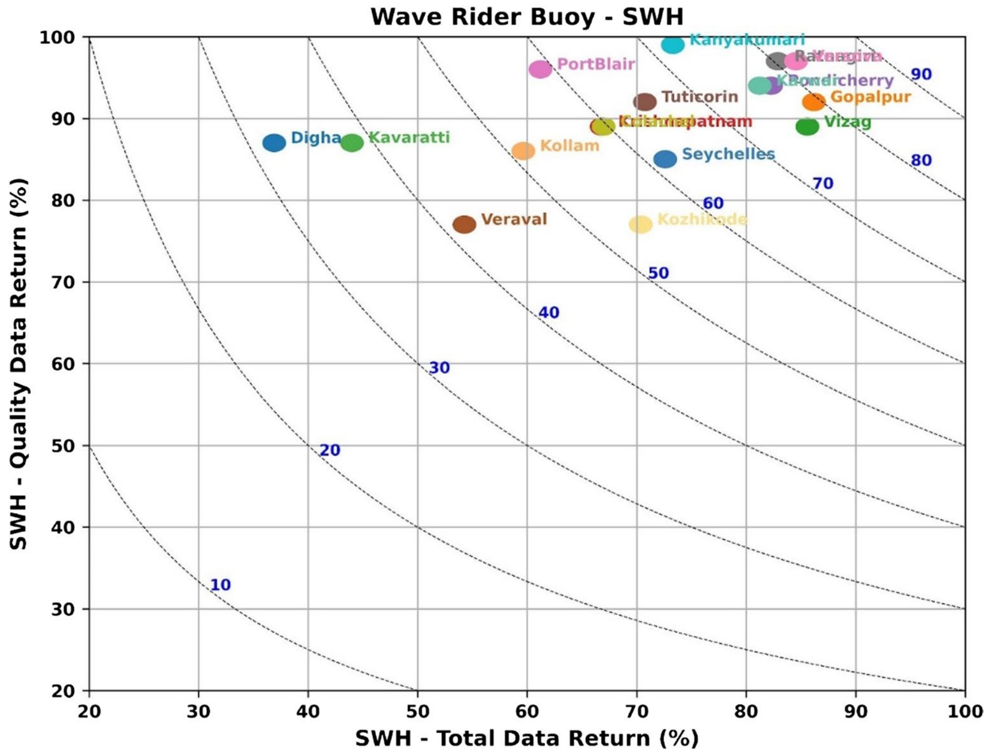

Fig. 7 Percentage of Total data return and Quality data return from WAMAN buoys for the period of 2009–2023

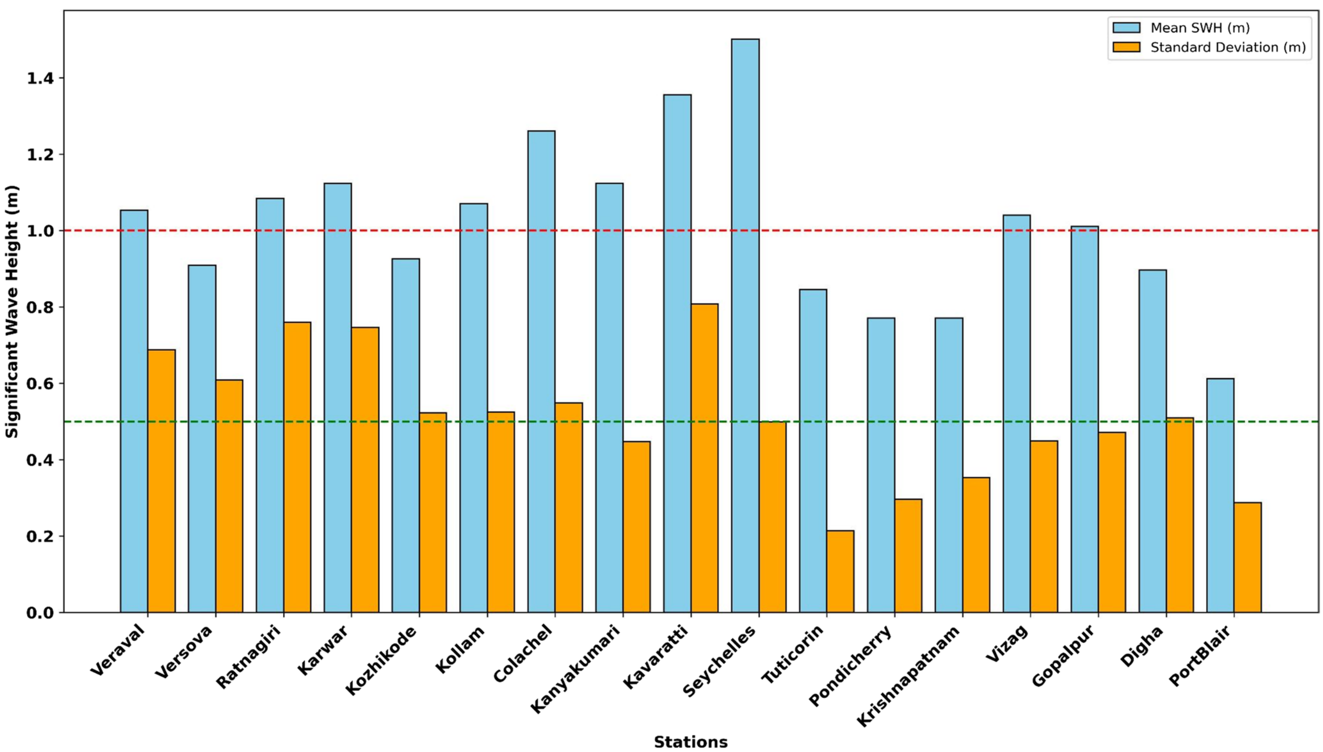

Fig. 8 Mean and Standard deviation (2009–2023) of SWH (m) at each WRB station

SWH varies significantly, from a minimum of 0.61 m at Port Blair to a maximum of 1.5 m at Seychelles, 1.35 at Kavaratti, consistent with their greater exposure to deep-water swell systems and minimal coastal attenuation.

The standard deviation of SWH reveal variability in wave conditions, with notably higher values at west coast buoys compared to east coast buoys, indicating stronger temporal variability associated with monsoon-driven wind seas, episodic storm activity, and swell interactions. Conversely, the east coast buoys show low standard deviations, suggesting more consistent wave conditions with less fluctuation in wave height. Overall, these regional patterns in mean SWH and variability reflect the interplay of atmospheric forcing, water depth, bathymetric characteristics, shelf geometry, and exposure to open-ocean swell, which collectively govern wave height and wave energy distribution across the Indian coastal and island regions (Remya et al. 2022; Sandhya et al. 2024; Mithun et al. 2025).

4.3 QC performance during cyclonic events

Having established the effectiveness of the QC framework through statistical assessment and internal consistency checks, its performance during extreme cyclonic conditions is examined. Cyclone Hudhud intensified into a very severe cyclonic storm, with reported maximum sustained surface wind speeds of approximately 50–55 m s^{-1} during its peak phase (India Meteorological Department 2015; Nadimpalli et al. 2016). The high wave heights observed during cyclone Hudhud (12 Oct 2014) are not flagged as bad data during quality assignment process, demonstrating that the QC framework successfully retains physically realistic extremes. Genuine cyclone-generated extreme waves were distinguished from erroneous spikes based on temporal coherence, with cyclone-induced SWH showing gradual growth over consecutive records, while spikes appear as isolated anomalies. Accordingly, spike detection was performed using a 7-point moving window with a 4× standard deviation threshold, which effectively flagged abrupt instrumental artifacts without removing sustained, cyclone-driven extreme wave conditions. The wave spectra and wave direction during Cyclone Hudhud at 12:00 UTC on October 10, 2014, are shown in Fig. 9, representing the peak-intensity phase of the cyclone when energetic wave conditions affected the Visakhapatnam buoy. This figure presents the detailed wave characteristics observed during this cyclone, including the spectral distribution of wave energy and the directional spread. The energy density shows a prominent peak at lower frequencies (~0.1 Hz), indicative of long-period, high-energy waves generated by the cyclone's strong and sustained winds. These waves dominate the spectrum and signify the powerful young swells associated with the event. At higher frequencies (>0.3 Hz), the energy density drops significantly, representing shorter, less energetic waves likely influenced by local wind conditions. The wave direction, shown on the secondary y-axis, indicates that the high-energy wave components in the 0.1–0.15 Hz band are predominantly aligned between 90° and 120°, consistent with east to east-southeast propagation. This directional alignment reflects the influence of strong easterly winds associated with the westward-moving track of Cyclone Hudhud over the Bay of Bengal, which generated organized, cyclone-driven wave systems impacting the buoy location. Overall, this directional behavior highlights the strong coupling between cyclone track, wind forcing, and wave generation, demonstrating how Cyclone Hudhud produced organized, high-energy wave systems with significant implications for coastal hazards such as storm surge, coastal flooding, and erosion.

Figure 10 shows the time series of SWH from the Gopalpur WRB between 2012 and 2023, both before and after QC. The red lines represent the unfiltered data, while the blue lines indicate the data after applying QC procedures. It is evident that the raw data contains numerous spurious spikes, with unrealistically high SWH values exceeding 20 m. These erroneous peaks are effectively removed in the post-QC dataset, which displays more consistent and physically realistic wave height values. The plot highlights several cyclone events, including Phailin (2013), Hudhud (2014), Roanu (2016), Titli (2018), Fani (2019), Amphan (2020), Depression (2021), and Asani (2022). Each cyclone event corresponds to a sharp peak in SWH, indicating high wave activity due to the cyclone's impact. It is worth noting that the QC methods successfully retained these high waves

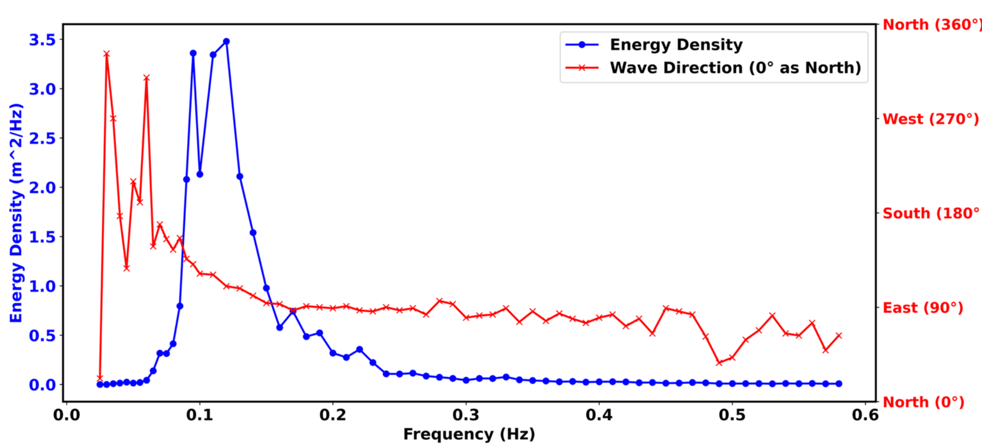

Fig. 9 The one-dimensional wave energy spectra (m^2/Hz) and direction of Visakhapatnam buoy observation during cyclone Hudhud (12:00 UTC on 10 October 2014)

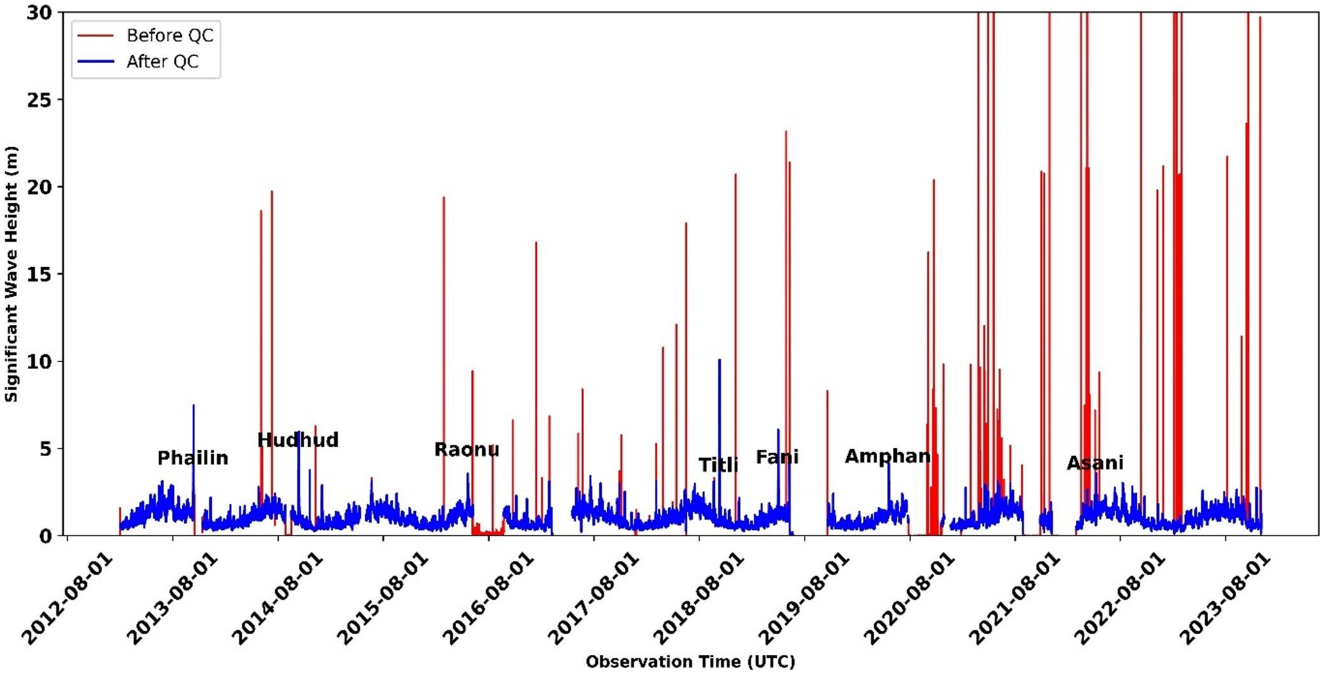

Fig. 10 Time series of SWH (m) before and after QC from Gopalpur WRB during 2009–2023

during cyclones, ensuring that true events are accurately identified and not mistaken for erroneous spikes. Previous studies have also documented extreme wave heights during cyclones such as Phailin (2013) and Hudhud (2014), which were observed at Gopalpur (Samiksha et al. 2021; Amarendra et al. 2015; Balakrishnan Nair et al. 2014).

The full time series of SWH at Gopalpur after QC from 2012 to 2023 (Fig. 10) shows sharp peaks corresponding to cyclone events, the detailed individual time series and cyclone tracks presented in Fig. 11. While the full time series shows prominent sharp peaks during cyclone occurrences, these individual plots reveal that the increase in SWH is not abrupt but rather characterized by a gradual rise over several days preceding the cyclone's landfall. For example, cyclones such as Phailin (2013), Hudhud (2014), and Titli (2018) exhibit a steady escalation in SWH, reaching peaks of 6–7 m as the storms approached the coast. Similar trends are observed for Fani (2019), Amphan (2020), and Asani (2022), where wave heights build up progressively, reflecting the intensification and proximity of the cyclones. Even relatively weaker systems like Roanu (2016) show distinct wave responses, although with lower peak values. The inclusion of cyclone tracks overlaid with the buoy location further supports the spatial coherence between the storm path and the observed wave activity. These results affirm the effectiveness of the applied QC procedures in retaining physically realistic wave responses while eliminating spurious spikes. The QC-processed data successfully captures the gradual buildup and peak wave activity associated with cyclonic forcing, demonstrating the reliability of the buoy observations.

A special case occurred during Cyclone Phailin (2013), when the buoy drifted from its mooring after 13 October due to extreme winds and waves. Because the buoy no longer represented the fixed Gopalpur location, the QC procedure flagged all subsequent records as invalid, causing the "after QC" series (blue) to truncate on that date while the raw data (red dashed) in Fig. 11 (Phailin) continue beyond this period. This behavior is consistent with documented observations of buoy displacement during Phailin, where extreme conditions led to mooring failure and buoy drift (Balakrishnan Nair et al. 2014). This case demonstrates the effectiveness of the QC system, which preserves realistic storm-driven wave growth prior to drift while removing measurements rendered unrepresentative by buoy displacement, ensuring the reliability of the final dataset.

In contrast, Cyclone Asani (2022) provides an example of short-duration instrumental anomalies rather than buoy displacement. During this event, a spurious spike present in the raw SWH time series was successfully identified and removed by the QC procedure. The resulting QC-processed series exhibits a smoother and physically consistent evolution of wave height, better representing the storm-driven wave growth. Together, these cases demonstrate that the QC framework effectively handles both buoy displacement during extreme events and isolated instrumental spikes, while preserving the physical evolution of cyclone-induced wave signals.

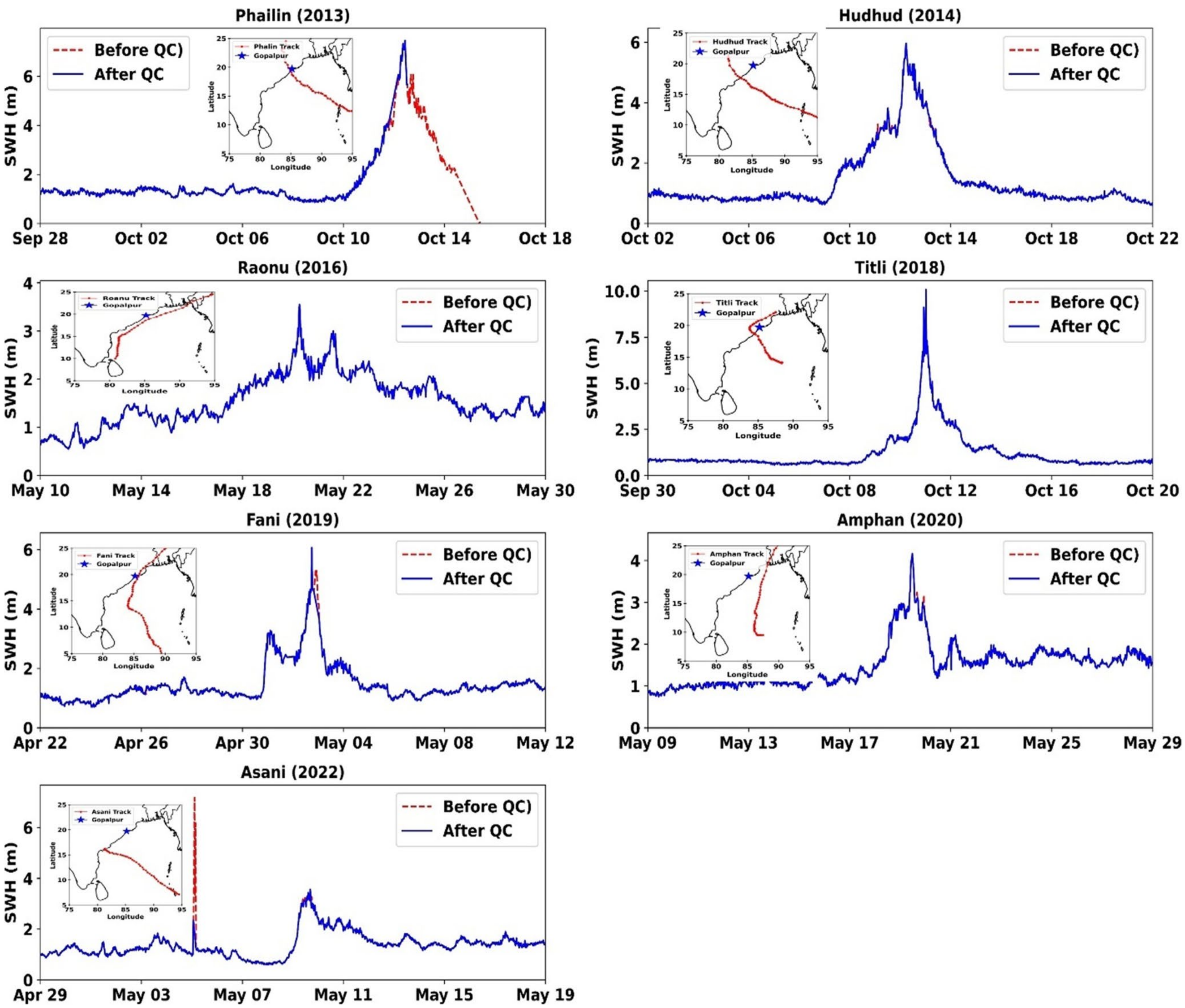

Fig. 11 Time series of SWH observed by Gopalpur WRB location during seven major cyclones along with the cyclone track

4.4 QC performance during swell surge events

Beyond cyclone-driven extremes, the QC framework is further evaluated using a long-period swell surge event to assess its ability to retain physically realistic remote swell signals. Swell surges, locally referred to as Kallakkadal, are sudden coastal flooding events driven by incoming swells without associated local wind activity or clear precursors, which makes prediction and early warning especially challenging (Remya et al. 2016). INCOIS plays an important role in issuing swell surge alerts based on its advanced multi-model operational ocean forecasting system to safeguard coastal populations. One such significant event occurred during 21–24 April 2018, when INCOIS issued a swell surge Alert for the Indian coastal regions. This event was triggered by high-energy swell waves originating approximately 10,000 km away in the southern Indian Ocean (around 45°S and 60°E) on 18 April 2018. The swell, characterized by a long peak wave period (~23 s), propagated northward towards the Indian Ocean, caused flash flooding along the coast. Coastal flooding happened in the low-lying areas of south Kerala, South Tamil Nadu, and Lakshadweep islands which were under swell surge warning. WRB data played a pivotal role in monitoring this event, providing critical insights into the energy density, wave height, and direction of the swell as it approached the Indian coast. This demonstrates the importance of real-time WRB observations in validating and refining swell surge forecasts issued by INCOIS.

The progression of a swell originating from the southern Indian Ocean and propagating northward through the Indian Ocean, as evident from buoy data at Seychelles and Colachel buoys is shown in Fig. 12. At Seychelles, the swell is observed around April 19–20, 2018, with a marked increase in both SWH and peak period, indicating its arrival at this location. Subsequently, the impact of the swell is seen at Colachel around April 21–22, showing a temporal lag consistent with northward propagation. The increase in wave height and peak period at these two locations highlights the typical energy transfer and long-period characteristics of swells originating in the southern Indian Ocean. The Seychelles buoy recorded high-period waves two days before they reached the Indian coastline, provided valuable confidence in predicting and issuing alerts for these swell waves.

Figure 13 represents the spectral analysis of data from the Seychelles buoy during 20 h of April 19, 2018, capturing energy density (blue) and wave direction (red). The high energy (~6 m^2/Hz) density peaks prominently at a low frequency (~0.05 Hz), indicating the presence of long-period swell waves. The corresponding wave direction, marked near 180° (south), confirms that these swell waves originated from the southern sector. The consistent alignment of wave direction around south throughout the spectrum supports the observation of a well-defined swell system approaching Seychelles from the southern direction. This aligns with the typical characteristics of energy propagation from a distant storm system in the southern Indian Ocean.

The effectiveness of the quality control procedure for wave parameters is illustrated in Fig. 14, which presents the time series of peak wave period from the Visakhapatnam WRB during 2010–2023. The raw dataset contains numerous unrealistic spikes exceeding 30–40 s and noisy fluctuations that are inconsistent with expected ocean wave conditions. After QC application, the peak period time series

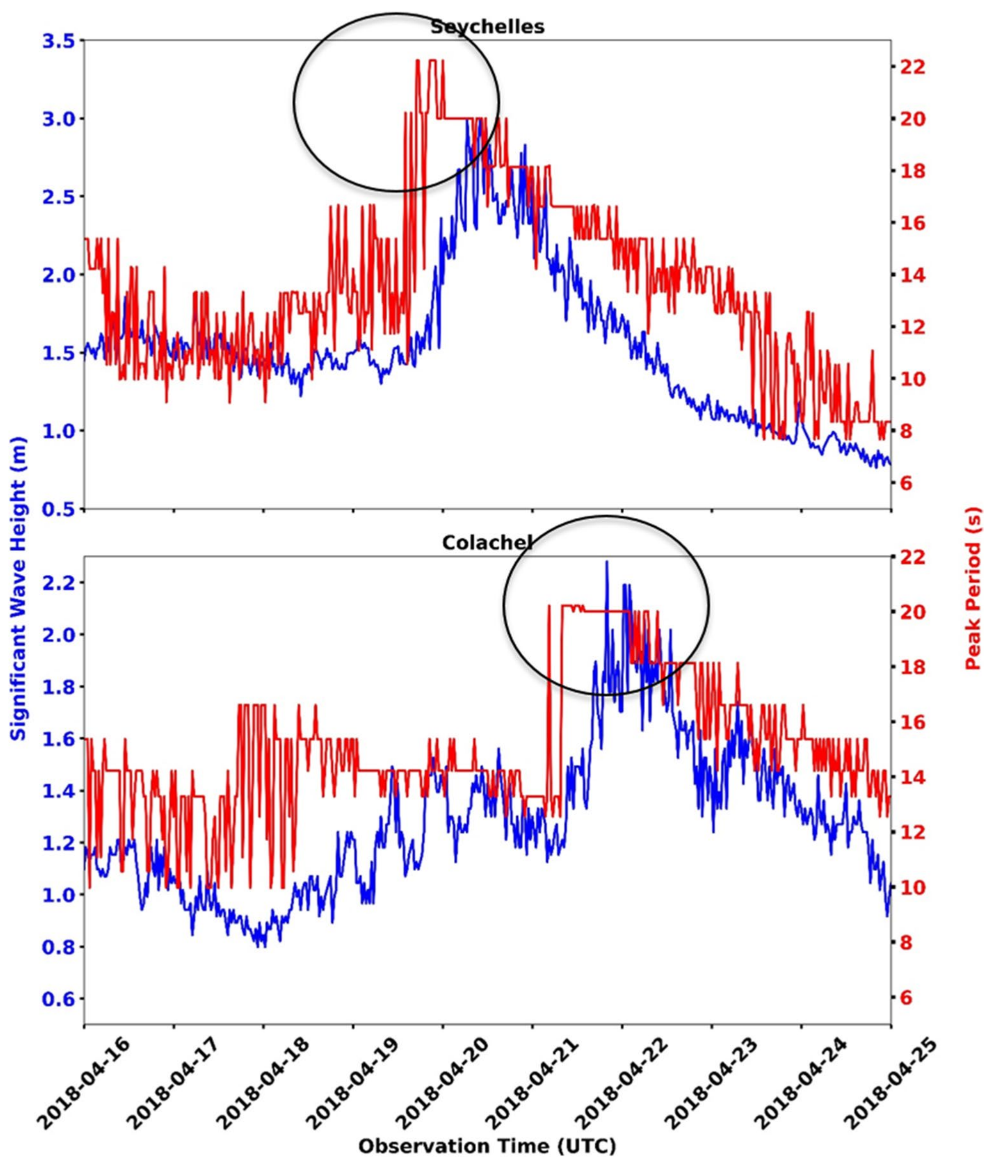

Fig. 12 Time series of SWH (blue) and peak wave period (red) at the Seychelles and Colachel buoys from April 16 to April 25, 2018

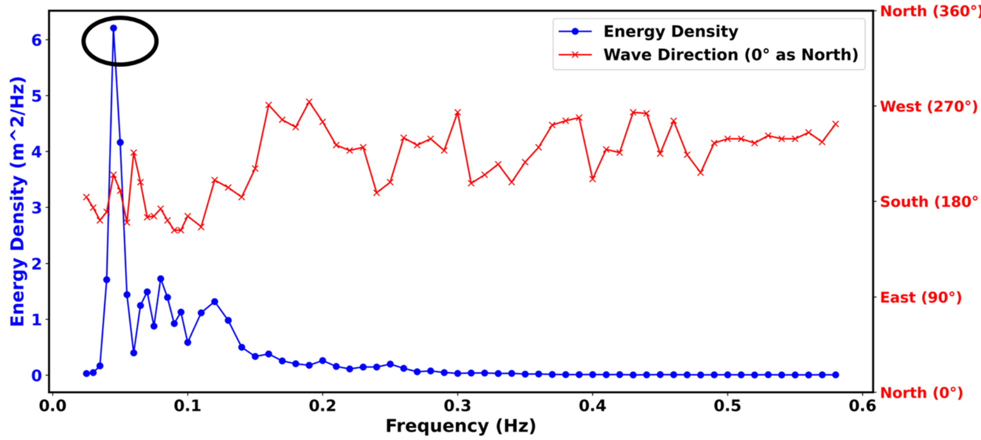

Fig. 13 Spectrum of Seychelles WRB, energy density (blue) and wave direction (red) as a function of frequency during a 20 h April 19, 2018

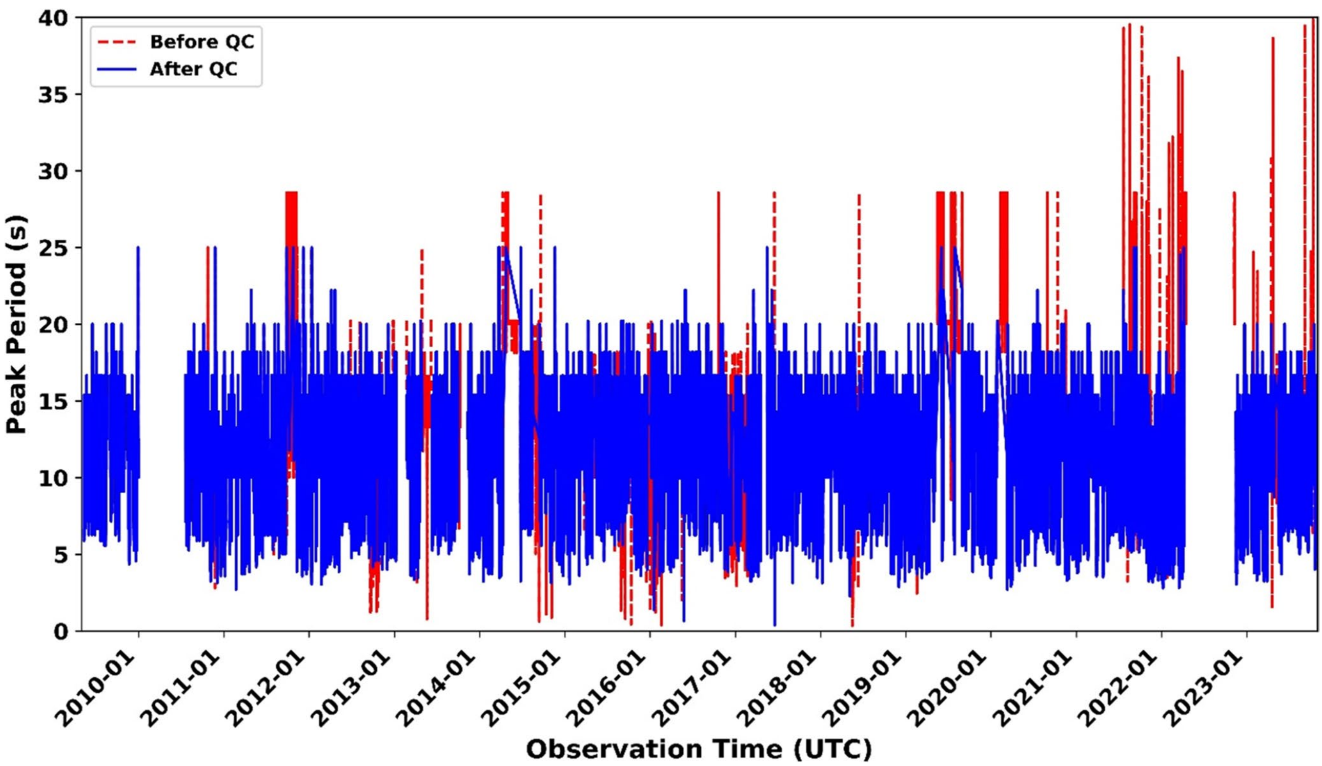

Fig. 14 Time series of Peak Wave Period (s) before and after QC from Visakhapatnam WRB during 2010–2023

is substantially cleaner, with values predominantly within the physically realistic range of 5–20 s for the study region.

The QC procedure effectively removes spurious outliers while preserving natural temporal variability, including elevated peak periods during energetic events such as storms and cyclones. Although some data gaps remain due to missing observations, the overall temporal structure and variability of the time series are retained without distortion. These results demonstrate the importance of QC in ensuring the reliability of buoy-derived wave parameters, making the dataset suitable for climatological analyses, event-based studies, and model validation.

5 Summary and future scope

The INCOIS Wave Rider Buoy data sets from 2009 to 2023 are extracted, processed, and quality controlled. This is the one of the first systematic basin-scale QC approach implemented to remove erroneous data from 14 years of WRB data. Visakhapatnam and Ratnagiri WRB data are selected for explaining the detailed QC procedures applied. The QC methods like Range, Spike, Persistence, Gap, Timestamp and Location Consistency and maximum wave height tests are applied to SWH data. The average number of observations that passed the QC test is about 90%. About 10% of the observations were flagged as bad during the QC process. Among the 14 years (2009–2023), 30 min interval data, the data gap is about 28% of the total expected data. After QC, high wave heights during cyclones (Phailin, Hudhud, Roanu, Titli, Fani, Amphan, and Asani) are not flagged as bad data. Each cyclone event is characterized by a sharp peak in SWH, reflecting the intense wave activity caused by the cyclone. The QC methods applied effectively capture these high waves, ensuring they are correctly identified as genuine events, rather than being mistaken for false peaks or spikes.

The observed mean and standard deviation of SWH reveal complex wave dynamics across the Arabian Sea, the Bay of Bengal, and surrounding island regions. The Arabian Sea stations, located along the west coast, exhibit higher mean SWH values and greater variability, driven primarily by the energetic southwest monsoon winds. In contrast, the Bay of Bengal stations on the east coast experience calmer wave conditions, with lower mean SWH values and less variability, partly due to the sheltering effect of Sri Lanka. The island buoys display mixed characteristics, with Seychelles recording the highest mean SWH and variability, influenced by its exposure to open ocean swells, while Kavaratti and Port Blair exhibit conditions intermediate between the west and east coasts. These regional differences underscore the importance of accounting for varying wave climates in coastal planning and management.

The buoy observations from Seychelles and Colachel effectively captured the northward propagation of long-period swell waves originating from the southern Indian Ocean, demonstrating their critical role in monitoring and validating swell surge events. The timely recording of high-period waves by the Seychelles buoy, two days before their impact on the Indian coastline, underscores the importance of WRB data in enhancing the accuracy and reliability of swell surge forecasts issued by INCOIS.

Future work will focus on quantitative validation of QC-processed buoy data using collocated satellite altimeter and numerical model datasets. The demonstrated reliability of the quality-controlled dataset enables WRB observations to be effectively utilized for a wide range of applications, including validation and assimilation in wave forecasting models, calibrating and validating satellite wave sensors, monitoring climate conditions, designing ships and offshore installations, and supporting efficient sea operations. Furthermore, this data is invaluable for climate studies, enabling researchers to analyze long-term wave trends, assess the impact of climate change on oceanic processes, and improve our understanding of variability in the marine environment. Researchers and stakeholders can confidently rely on this data for informed decision-making, scientific advancements, and deeper insights into oceanic and climatic phenomena in this critical region.

Acknowledgements The authors are grateful to the Director, INCOIS, Ministry of Earth Sciences (MoES), for providing the necessary facilities. Secretary, MoES, is thanked for the support and encouragement. This is INCOIS contribution 604.

Author contributions Anuradha Modi: Conceptualization, Visualization, Validation, Software, Methodology, Investigation, Formal Analysis, Data Curation, Writing – Original Draft, Review & Editing. TVS Udaya Bhaskar: Conceptualization, Formal Analysis, Investigation, Writing – Review & Editing, Supervision. PG Remya: Formal Analysis, Writing – Review & Editing. Venkat R Shesu: Resources, Data Curation. P Suneeta: Formal Analysis, Writing – Review & Editing. M Mahender: Data Curation. S Shivaprasad, N Arun, C Jeyakumar, and R Bharat Kumar: Deployment and Maintenance of WRBs. E Pattabhi Rama Rao: Formal Analysis, Writing – Review & Editing. TM Balakrishnan Nair: Investigation, Writing – Review & Editing.

Funding This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability Data is available from INCOIS on request. Contact details can be found at https://incois.gov.in/site/contactus.jsp.

Declarations

Clinical trial number Not applicable.

Competing interests The authors declare no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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