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Analysis and quality control of tide gauge data: Case studies on cyclone and swell surge events over the Indian ocean

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Abstract

The present study focuses on the Quality Control (QC) and analysis of tide gauge water-level data collected along the Indian coastline. A network of 36 state-of-the-art tide gauge stations was established by the Indian National Centre for Ocean Information Services (INCOIS) at strategic coastal locations to monitor tsunami wave propagation, validate ocean model outputs, and assess long-term sea-level trends. These gauges continuously record sea level, providing essential inputs for operational oceanography and improving our understanding of coastal ocean dynamics. The present work details the data processing and QC procedures implemented for the entire 36-station network, ensuring the accuracy and reliability of the observations. Multiple QC tests including spike detection, out-of-control checks, outlier identification, buddy or neighbourhood comparison, and time-sequence checks were developed and applied. As a case study, the QC methodology was evaluated for two representative stations, Visakhapatnam (east coast) and Cochin (west coast) covering the period (2011–2024) and is intended for implementation across the full network. Using the quality-controlled dataset, 96% of observations passed QC tests, 4% were flagged, and 29.2% of records were missing across the network. Further analyses were conducted to investigate major oceanographic events, including cyclones and swell surges, particularly at the Cochin station. The results reveal significant water-level variations during cyclone periods, evident in both observed and residual components, providing valuable insights into storm-surge dynamics. Additionally, abrupt residual changes corresponding to tsunami and swell-surge signals demonstrate the importance of tide gauge observations in early warning systems and operational oceanography.

Keywords Tide gauge · Observation · Quality control · Cyclone · Residual · Swell surge

1 Introduction

The global sea-level record derived from tide gauge observations is a crucial indicator for assessing the evolution and impacts of climate change. The recent Global Sea Level Observing System (GLOSS) implementation plan encourages coastal nations to upgrade their tide gauge networks to meet the new requirements of modern early-warning systems (IOC 2012). Tide gauge data not only provide long-term sea-level trends but also capture a broad spectrum of local and regional oceanographic phenomena, including decadal variability, tides, storm surges, tsunamis, swell events, and other coastal processes. These observations also play a vital role in validating ocean circulation models and detecting drifts or biases in satellite altimetry. Although tsunami warning systems are a well-known application, real-time or near-real-time tide gauge data are equally critical for storm surge warnings, particularly in regions such as the North Sea (Holgate et al. 2008; Woodworth et al. 2009a, b).

Tide gauge observations further support operational oceanography, including numerical model validation (e.g., Flather et al. 2000; Alvarez Fanjul et al. 2000; Pérez et al. 2012; Maraldi et al. 2013), satellite altimeter calibration (Mitchum 2000), and local applications such as harbor operations and navigation safety. These local applications are especially important because high-resolution tide gauge data enhance harbor safety, optimize vessel movement, and guide coastal infrastructure development. Compared

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to satellite observations, tide gauges offer higher temporal resolution and longer historical records, although their spatial coverage is more limited. Computing a global mean sea level from tide gauge data remains challenging due to regional circulation effects, atmospheric pressure variability, limited long-term continuous records, and the absence of a unified vertical datum across stations (Ponte 2006; Peltier et al. 2015). Tide gauges provide direct measurements of sea level and are essential for detecting tsunamis and monitoring coastal sea-level dynamics (Thompson et al. 2014; Ray and Mitchum, 1996; Titov et al. 2005). Their real-time data significantly enhance our understanding of ocean atmosphere interactions and their impacts on coastal regions. Tide gauge records capture diverse events such as storm surges, tsunamis, and long-term sea-level trends, making them indispensable tools for operational oceanography, disaster preparedness, and model validation. Tide gauge observations may be delivered as real-time (RT), near-real-time (NRT) or delayed-mode (DM) products with each mode corresponding to different levels of quality control (Pouliquen et al. 2011). Previous studies have underscored the importance of high-quality data for monitoring sea-level variations and extreme events. For example, Unnikrishnan et al. (2006) analyzed storm surge patterns along the Indian coastline emphasizing the need for real-time observations for improved forecasting. Similarly, Menéndez and Woodworth (2010) highlighted the importance of robust QC for reliable extreme sea-level assessments. Building on these insights, the present study uses quality-controlled (QCed) data and applies refined QC procedures to examine cyclone and swell surge related sea-level variations. The analysis successfully captures major cyclone events and swell surges recorded at tide gauge stations along both the east and west coasts of India.

The tide gauge network operated by INCOIS consists of 36 stations equipped with three types of sensors: Radar (RAD), Pressure (PRS), and Shaft Encoder (ENC). Among these, 21 stations contain all three sensors, while the remaining 15 operate solely with Radar sensors, which provide high-accuracy water-level measurements. The spatial distribution of these stations is shown in Fig. 1(a) and (b). Figure 2 provides a comprehensive visualization of monthly real-time data availability for the 36 tide gauge stations from 2010 to 2024. Presented as a heatmap, the X-axis represents years and the Y-axis corresponds to stations, with each colored block indicating monthly data availability. Green blocks denote “Available” data, while red blocks indicate “Missing” data. This figure provides immediate insight into overall data coverage, revealing that stations such as Visakhapatnam and Veraval show consistently high availability, while others exhibit varying degrees of data gaps, including prolonged outages such as the multi-year gap at Jakhau from 2017 to 2020.

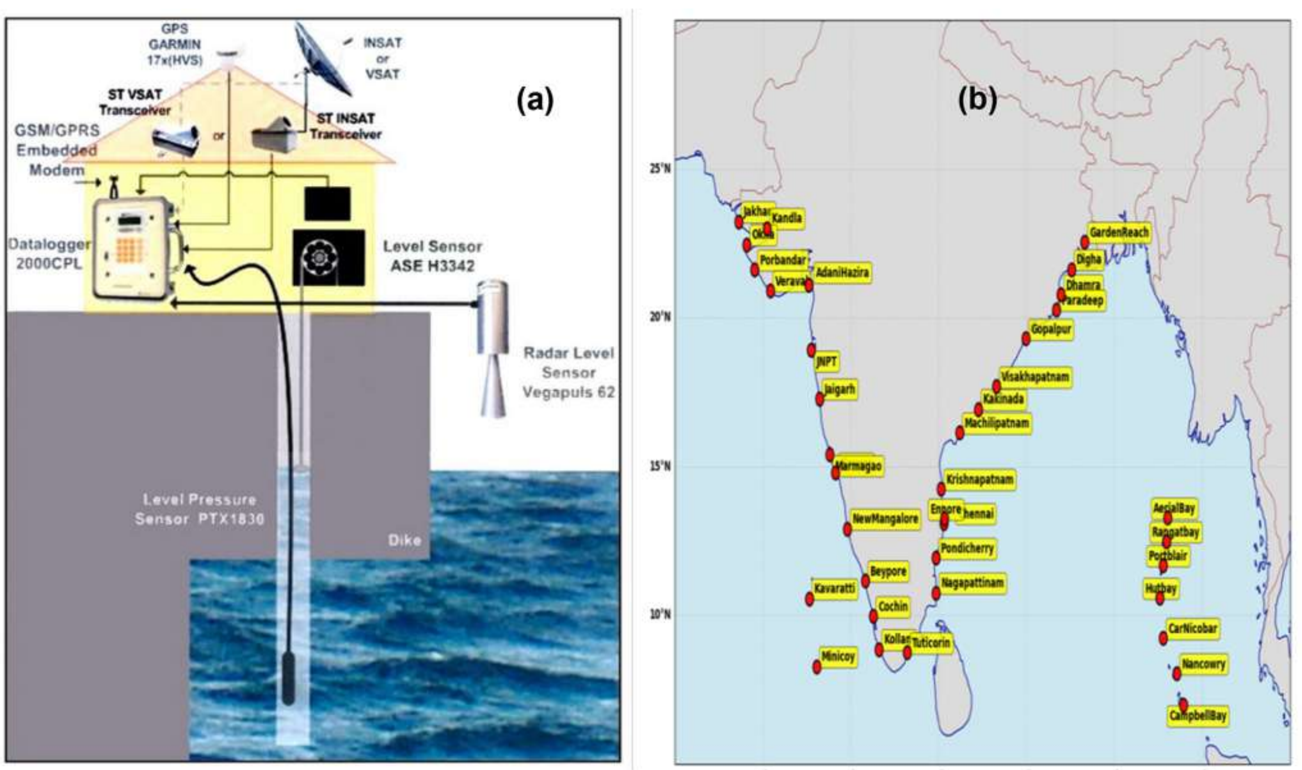

Fig. 1 (**a**) A Schematic diagram of Tide gauge sensors (**b**) Network of 36-Tide gauge stations installed by INCOIS along the Indian coast

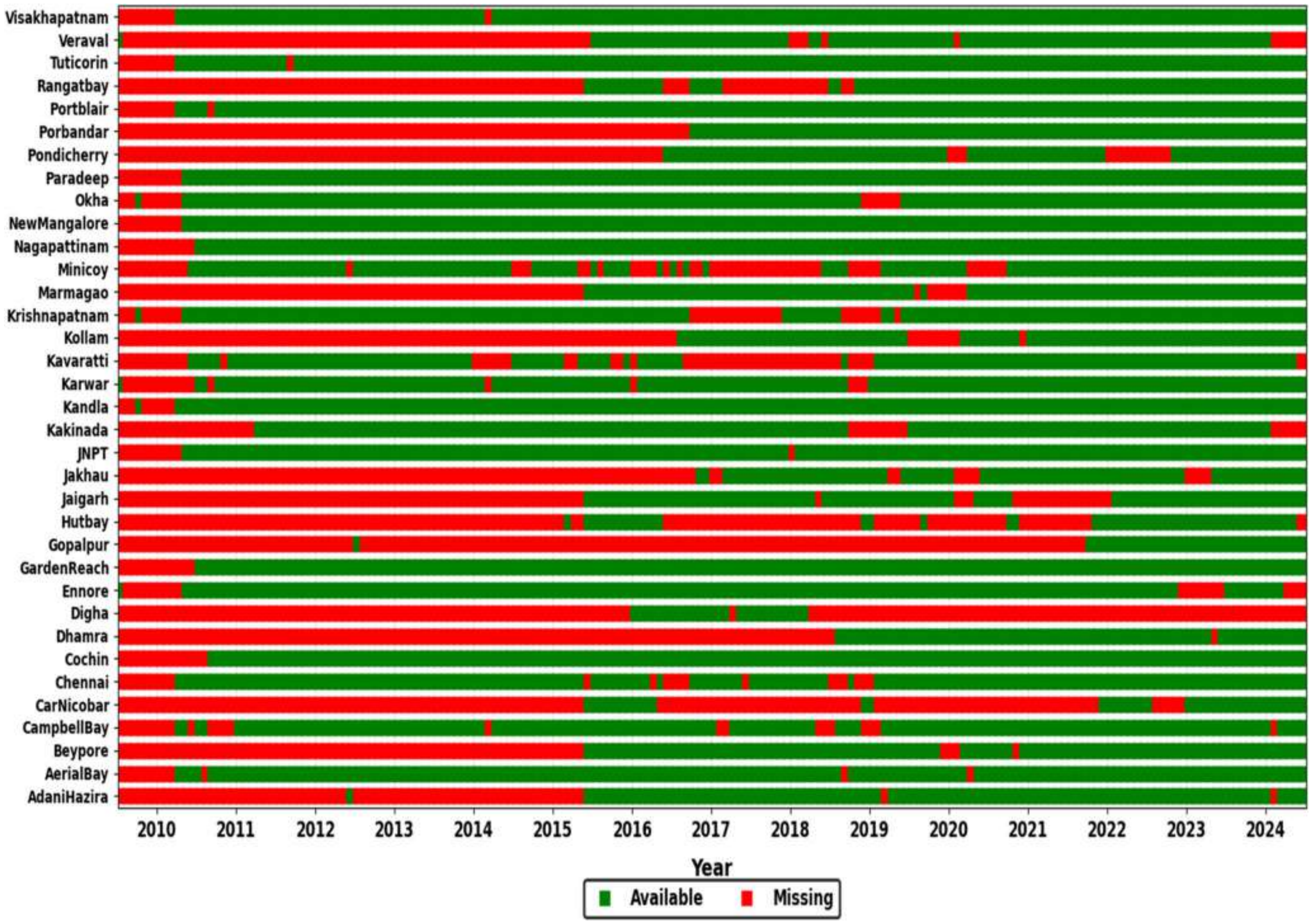

Fig. 2 Monthly data availability at each station from period (2010–2024) green horizontal line available and red missing data

This paper provides a comprehensive evaluation of the methodologies employed in tide gauge QC, including validation and correction techniques. It details the identification and correction of data issues using QCed data through range tests, spike detection, out-of-range value checks, outlier filters, Buddy/Neighbour tests, time-sequence checks, and systematic handling of missing data clearly distinguishing pre- and post-QC conditions. The study further presents detailed case studies of extreme events, including the impacts of cyclones such as Maha, Nivar, Burevi, Tauktae, and Yaas on water levels near the Cochin station, and Titli, Fani, Amphan, and Asani in the Visakhapatnam region. Swell surges and their effects on water levels are also examined. By analyzing cyclone-induced water-level changes and swell events, the paper demonstrates the critical importance of tide gauge observations in understanding sea-level variability and its response to severe meteorological phenomena. The detailed QC procedures, results, and their implications for cyclone and swell-surge-related sea-level variations are discussed in the following sections.

2 Data and methodology

Real-time tide gauge data, sampled at one-minute intervals, are transmitted via a robust, multi-modal communication system that includes both Indian National Satellite System (INSAT) satellite communication and General Packet Radio Service (GPRS), ensuring critical redundancy and reliability. The INSAT system provides indispensable satellite-based connectivity, particularly vital for remote and island stations, while GPRS serves as a complementary link for nearshore installations. INCOIS is equipped with a dedicated INSAT satellite communication hub as described by Harikumar et al. (2013), alongside state-of-the-art computing infrastructure and advanced real-time data processing and visualization systems. These comprehensive facilities expedite the seamless reception, immediate display, and systematic archiving of tide gauge data, which are crucial for operational tsunami monitoring, early warning services (e.g., Pugh and Woodworth 2014), operational oceanographyandcoastalmanagement.

The importance of accurately capturing tidal extremes for robust early-warning systems and precise storm-surge predictions, often addressed through harmonic tidal analysis (Cartwright and Tayler, 1971; Foreman, 1977; Zong and Li, 2013) and considering long-term postglacial sea-level variations (Peltier, 1998), has been emphasized by studies such as Woodworth et al. (2009a, 2009b) and Haigh et al. (2011).

For the present study, the one-minute interval data were converted to hourly averages to facilitate analysis. QC methodology employed is bifurcated into a primary QC procedure and a more complex secondary QC procedure. Table 1, as presented in this study, meticulously lists the various QC protocols categorized under both procedures. A QC flag, indicating the outcome of each test applied to a given datum is assigned. The primary QC flag is designed to provide an immediate status of the data's reliability. It primarily adopts three values: '1' signifies that all primary QC tests have been successfully passed indicating high-quality and reliable data; '9' denotes missing values. As elaborated in Table 2 which provides a detailed description of the primary QC tests specific flagged data points receive distinct classifications. For instance certain designated tests assign a QC flag of '2' when data are identified as an outlier. Other issues trigger different QC flags: '3' for detected spikes and '4' for values determined to be out-of-range. Furthermore, QC tests pertaining to the time of observation, location and temporal sequence directly influence the assignment of the primary QC flag. If a datum successfully passes any of these critical tests the primary QC flag is automatically set to '1', thereby confirming the data's acceptable quality for subsequent analyses.

Table 1 Primary QC procedures employed for flagging the data

Primary QC Tests
Range check
Spike test
Outliers check
Out of Range
Missing values check
Buddy or Neighbor test
Time sequence check

Table 2 Binary numbers used in defining the secondary QC flag

Binary number	Detail
1	Good data
2	Outliers
3	Spikes
4	Out of control
9	Missing values

2.1 Individual QC tests for tide gauge stations

Missing Values:
The observed data are first checked for missing values. Positions containing missing values are flagged with **1**, while all valid data points receive a flag of **9**. This facilitates the identification and handling of data gaps in subsequent processing steps.

Range Test:
The range test evaluates whether the tide gauge measurements fall within acceptable physical limits. These limits follow international standards from the Permanent Service for Mean Sea Level (PSMSL) and the International Hydrographic Organization (IHO) (PSMSL,2019; IHO, 2020). For this study, the upper threshold was set to 1000 cm, based on analyses of Indian tide gauge records from 2010 to 2024, where water levels did not exceed 950 cm. Any value above this threshold representing the maximum realistic limit for Indian coastal conditions is flagged with **4**. This ensures consistency with global best practices while preventing unrealistic extremes.

Spike Test:
Spikes are detected by comparing the absolute difference between consecutive data points against a threshold of **three times the standard deviation**. Values identified as spikes are flagged with **3**.

Out-of-Control Test:
Data points falling below the lower limit or above the upper limit are flagged with **4**.

Outliers:
Outliers calculate the z-score for each element in the variable extending the functionally to identify outliers in addition to handling missing values. The quality flags will now have the value 2 for the outliers 0 for the rest of the data position in variables.

$$Z = (x - \mu) / \sigma$$

Where μ is the mean of the data and σ is the standard deviation of the data. The data with Z-values beyond 3 are considered as outliers.

Buddy or Neighbour Test:
In this test, water levels recorded at one station are compared with a neighbouring station or with a second sensor at the same site. This helps detect inconsistencies and ensures that spatially coherent events such as surges or tides are represented accurately along the coastline.

Time Sequence Check:
Time-series consistency is assessed to examine long-term trends and temporal continuity. This test ensures the

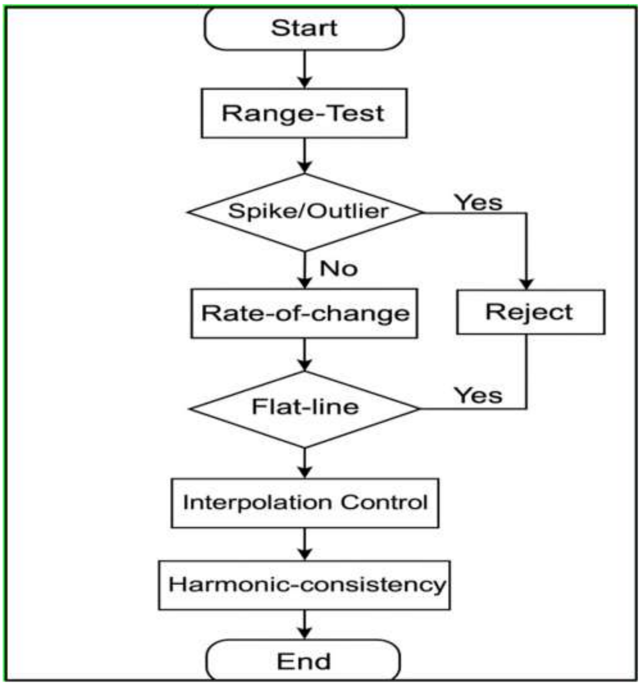

Fig. 3 Overview of the Automated QC Workflow for Tide Gauge Data

integrity of the sequence, prevents incorrect time ordering, and supports the detection of abnormal jumps in sea level. The complete QC workflow applied to the tide gauge dataset is summarised in the flowchart shown in Fig. 3.

To minimise limitations associated with globally fixed thresholds, a station-specific QC approach was adopted for range and spike detection. Historical records from each station were analysed to estimate physically realistic extremes, with statistical limits determined using the mean ± 3σ method. These limits were then cross-validated using known extreme events such as storm surges and high tides to ensure that genuine extremes were not inadvertently removed. This station-tailored strategy reduces false positives and false negatives and provides a QC framework that aligns with local oceanographic variability and instrument behaviour.

High-quality, long-term tide gauge observations from Visakhapatnam (East Coast) and Cochin (West Coast) play an important role in monitoring sea-level variability along the Indian coastline. Figures 4 and 5 indicate that Cochin exhibits more anomalies spikes (382), outliers (66), and out-of-range values (283) than Visakhapatnam, reflecting a more error-prone sensor environment. The broader spread of unfiltered values, with a mean of 109.92 cm and mean ± 3σ range of 207.49 cm, further highlights the necessity of effective QC. Despite the removal of major anomalies, both stations show substantial data gaps particularly during 2016–2019 (Figs. 6 and 7), which limits the robustness of long-term trend assessments. While the QC procedures significantly improve the reliability of individual station records, it is important to emphasise that data availability is not uniform

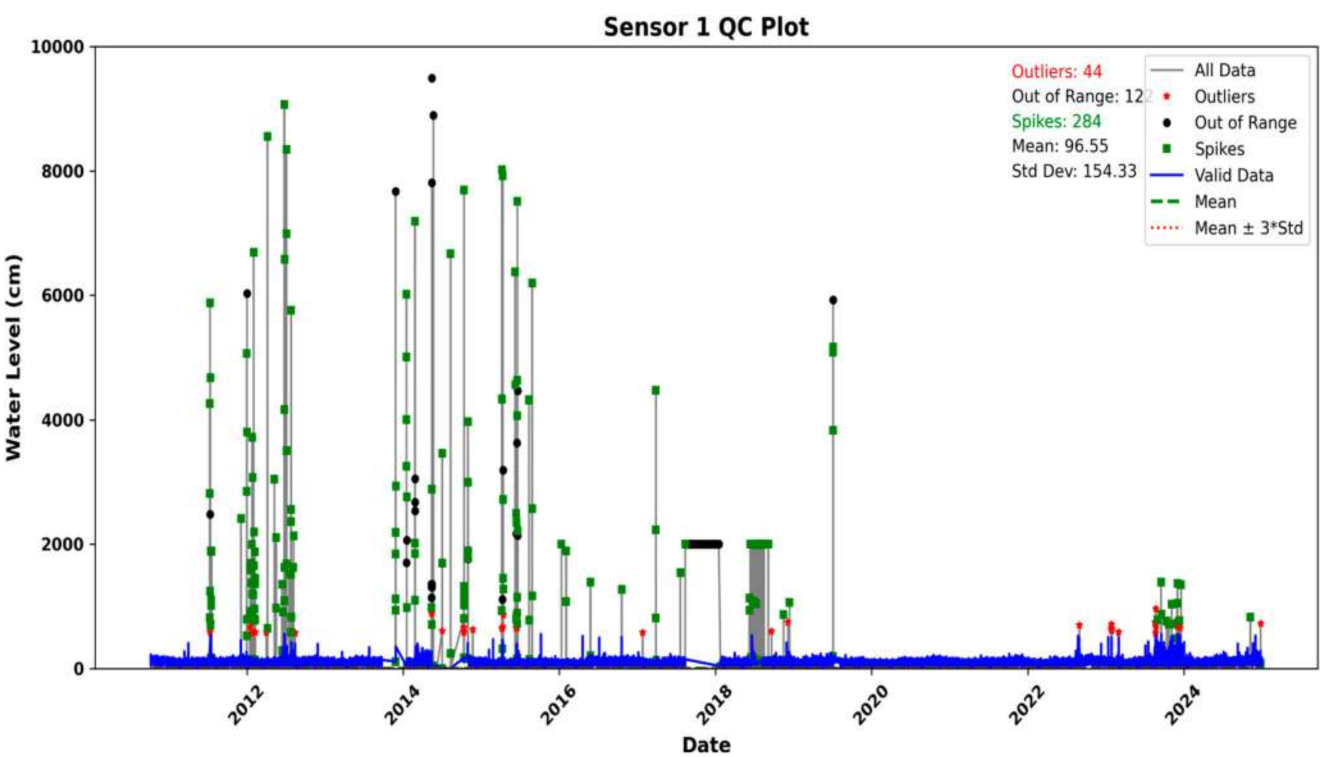

Fig. 4 Water level flagged data before QC at the Visakhapatnam tide gauge location from the 2011 to 2024

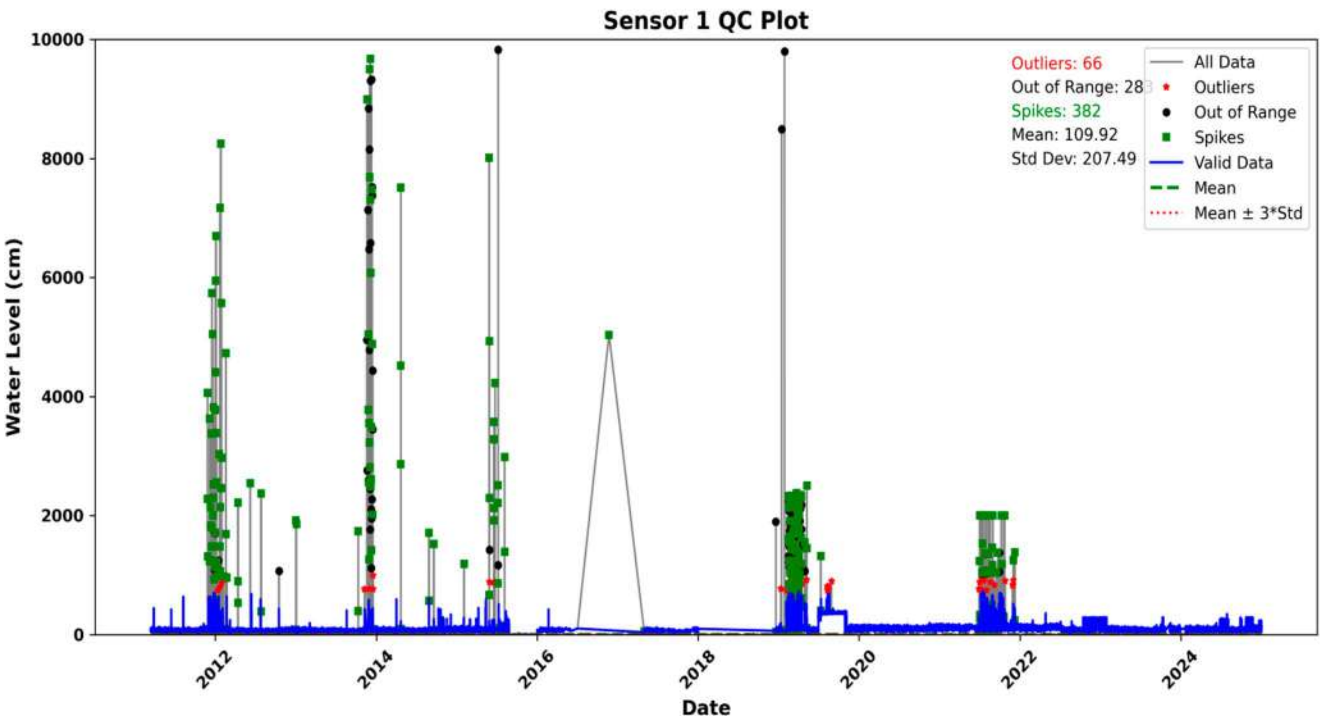

Fig. 5 Water level flagged data before QC at the Cochin tide gauge location from the 2011 to 2024

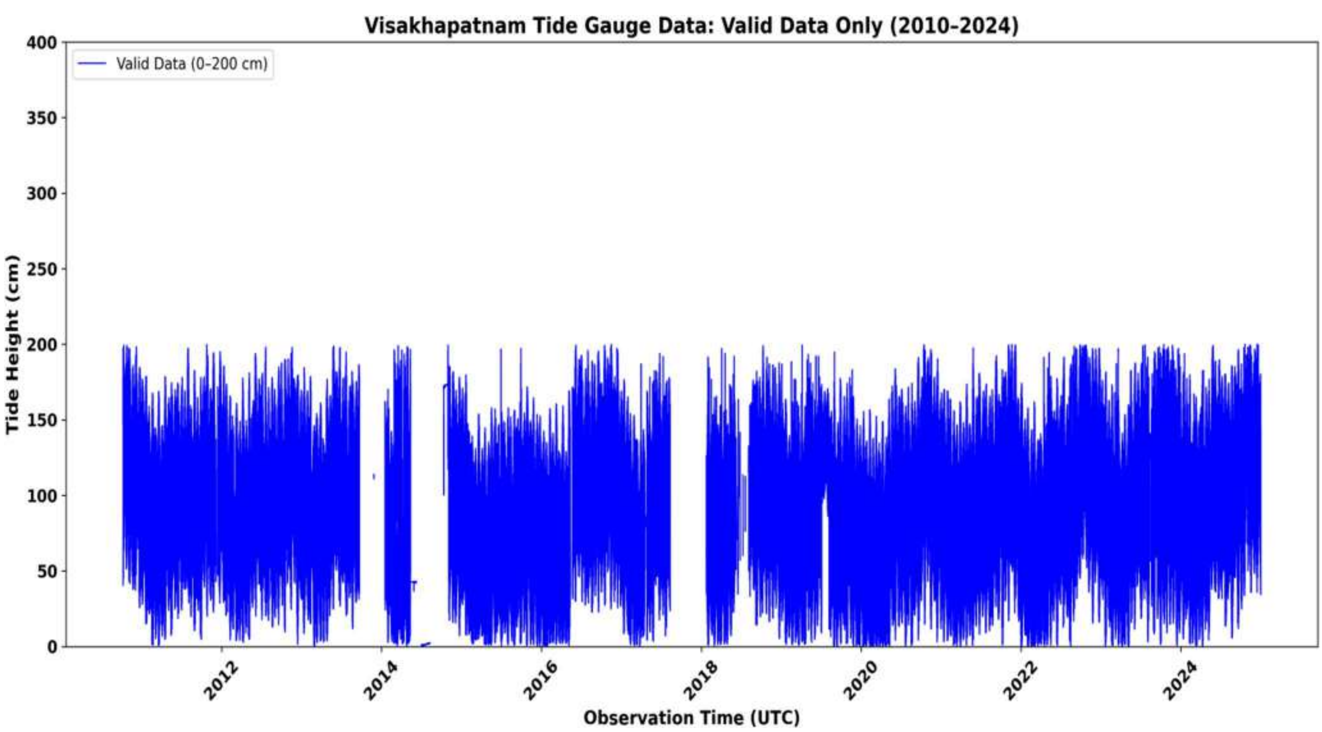

Fig. 6 Water level valid data after QC from the period 2011–2024 at Visakhapatnam tide gauge location

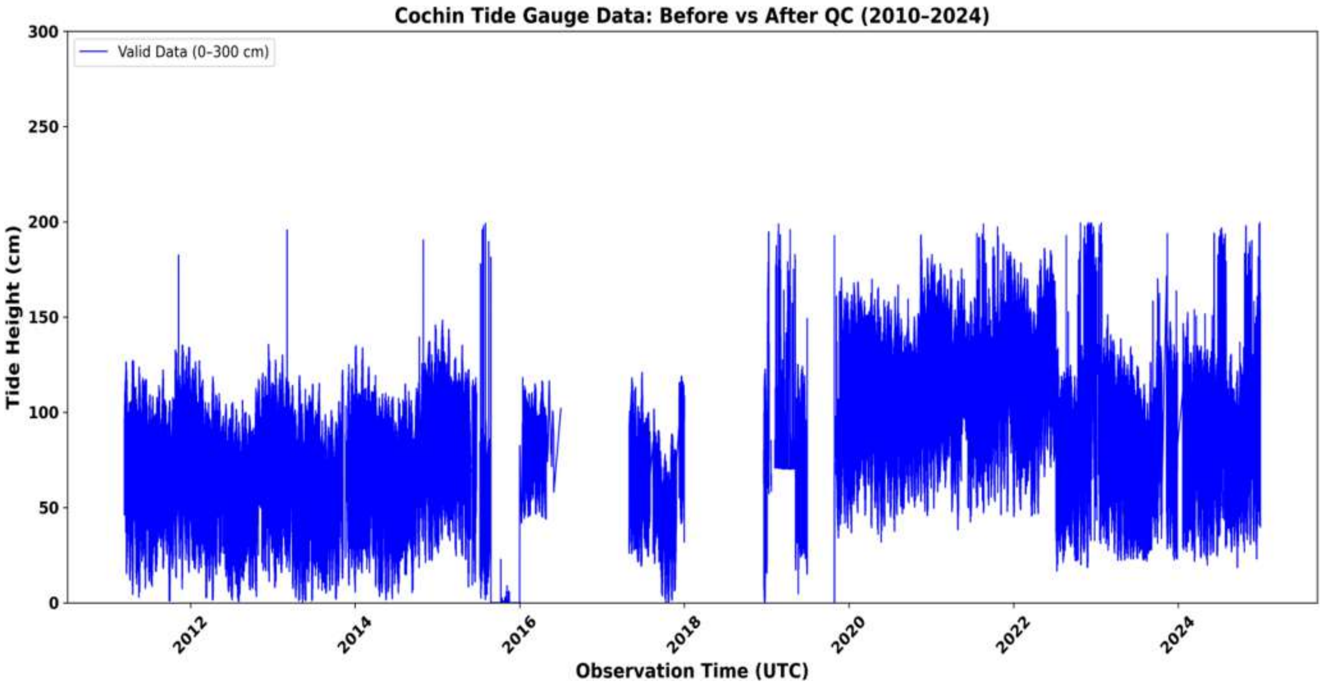

Fig. 7 Water level valid data from the period 2011–2024 at Cochin tide gauge location

across the entire INCOIS tide gauge network. Several stations exhibit prolonged data gaps due to sensor downtime, communication failures, or maintenance interruptions, as evident in Figs. 2, 6 and 7. Therefore, any reference in this study to "reliable QCed data" pertains to improvements at the station level after QC application and should not be interpreted as implying uniform reliability across the network. This clarification ensures that network performance is interpreted in accordance with the observed spatial variability in data continuity.

Regional tidal characteristics also influence how each station responds to extreme events. Visakhapatnam exhibits a semi-diurnal tidal regime with a moderate tidal range (100–200 cm), making it more sensitive to cyclone-driven storm surges. In contrast, Cochin displays a mixed semi-diurnal regime with a larger tidal range (400–600 cm) and is more strongly affected by monsoon-generated swells. After QC, the cleaned datasets display physically consistent oscillations and accurately capture tidal cycles and surge events, transforming noisy raw measurements into coherent water-level records. To avoid over-stating robustness, we acknowledge that the present QC implementation relies on fixed parameter settings such as the moving-window length and z-score thresholds for spike and outlier removal. These values follow INCOIS operational practice and were selected based on preliminary tuning. A full sensitivity analysis of these parameters, which is essential for formal robustness claims, is beyond the scope of this study. Future work will include systematic parameter sensitivity testing to optimise QC performance across the broader INCOIS network.

Finally, this study incorporates several methodological advances over previously documented INCOIS and international QC approaches. In contrast to earlier publications that describe QC checks individually, the present work integrates all QC components range tests, spike detection, rate-of-change limits, flat-line screening, interpolation control, and harmonic-consistency evaluation into a single automated pipeline applied uniformly to all stations. The introduction of a harmonic-consistency check, which compares observed sea level with tidal predictions derived from harmonic analysis, represents a key refinement. This step enables the detection of datum shifts, long-term sensor drift, and low-frequency inconsistencies that conventional filters may miss. Furthermore, the workflow quantifies QC performance using pre- and post-QC gap statistics, annual data-coverage maps and station-wise retention metrics, offering an objective assessment of data reliability. Event-based validation using major cyclone and swell cases further demonstrates how QC-refined records improve the detection and interpretation of storm surges and meteorological anomalies. Together, these advances provide a more comprehensive and operationally relevant QC system for long-term tide gauge observations along the Indian coastline.

2.2 Methodological innovation

In this study, we introduce several methodological advancements that extend beyond previously documented INCOIS and international QC practices. First, all QC procedures range tests, spike and outlier detection, rate-of-change limits, flat-line checks, interpolation control, and harmonic-consistency evaluation are integrated into a single automated QC pipeline, allowing uniform and reproducible processing across the entire network. Second, unlike earlier methods that relied on globally fixed limits, we implement station-specific statistical thresholds based on historical distributions (mean ± 3σ), which are cross-validated with known extreme events to ensure that genuine surges are retained while erroneous values are removed. Third, we introduce a harmonic-consistency test, in which observed water levels are compared with tidal predictions derived from harmonic analysis to identify datum shifts, long-term sensor drift, and low-frequency inconsistencies that conventional QC tests may not detect. Additionally, the workflow includes quantitative QC impact diagnostics, such as pre- and post-QC gap statistics, annual data-coverage maps, and retention metrics, enabling an objective evaluation of QC performance. Finally, the pipeline is designed to be compatible with operational INCOIS workflows and is validated using multiple cyclone and swell events, demonstrating the improved ability of QC-refined data to capture storm surges and meteorological anomalies. These innovations collectively represent a significant methodological refinement over existing INCOIS QC procedures.

The QC framework implemented in this study is fully aligned with the core principles of EuroGOOS (2020) and GLOSS/PSMSL (2019), both of which prescribe a structured sequence of checks for missing data, range limits, spike detection, temporal consistency, and metadata verification. However, these international standards primarily recommend the use of globally fixed thresholds and generic tolerance limits for identifying anomalous values. In contrast, the present study advances beyond these guidelines by introducing station-specific statistical thresholds derived from long-term historical distributions (mean ± 3σ), allowing physically meaningful extremes to be preserved in regions with large tidal variability such as the Indian coastline. Furthermore, this work incorporates a harmonic-consistency test comparing observed water levels with model-derived tidal predictions computed using in-house harmonic analysis codes which is not explicitly required in EuroGOOS or GLOSS protocols but is essential for detecting datum shifts and long-term sensor drift. The inclusion of quantitative QC diagnostics (gap percentages, retention ratios, and station-wise anomaly statistics) provides a level of performance evaluation that exceeds the descriptive emphasis of existing international frameworks. Together, these refinements position the INCOIS QC workflow as a more adaptive and operationally robust system relative to current EuroGOOS and GLOSS practices.

3 Results and discussion

This section presents an analysis of the QCed water level data from 36 tide gauge stations maintained by INCOIS. It assesses data quality and quantity, provides statistical summaries, and demonstrates the effectiveness of the QC process. Figure 8 shows the mean and standard deviation of tide heights (2010–2024) across all 36 stations. The X-axis represents individual stations (from Adani Hazira to Visakhapatnam), while the Y-axis indicates tide height in centimeters. Each station has two bars: blue for mean tide height and green for standard deviation. This visualization allows a straightforward comparison of average tidal levels and tidal variability. For example, Adani Hazira exhibits one of the highest mean tide heights with a large standard deviation, indicating substantial tidal fluctuations. In contrast, Veraval and Tuticorin have lower mean tide heights and smaller variability, suggesting more consistent tidal patterns. Stations with higher standard deviations likely reflect greater tidal variability influenced by storm surges, coastal topography or atmospheric conditions. This overview provides a baseline for identifying vulnerable coastal zones and supports further analysis of extreme sea-level events and cyclone impacts.

Table 3 summarizes QC outcomes across the 36 stations, categorizing data points into different flag types and providing overall statistics. Flags include "Out of control" (Flag 4), "Outliers" (Flag 2), "Spikes" (Flag 3), and "Quality data" (Flag 1), along with missing data (Flag 9) and total flagged data. Adani Hazira, for instance, shows 0.75% flagged data, contributed by spikes, outliers, and out-of-control values. Chennai has 1.72% flagged data, while Veraval exhibits the highest at 3.60%, primarily due to out-of-control readings. Stations such as Digha, Marmagao, and Porbandar report 0% flagged data, reflecting exceptional data quality. The table also highlights variability in total data collected, ranging from 19,546 points at Car Nicobar to 131,496 at several other stations, which affects overall percentages. Figure 9 presents data return performance for all 36 stations (2010–2024). The X-axis shows the Percentage of Total Data Return (PTDR), and the Y-axis shows the Percentage of Quality Data Return (PQDR). Cochin (TG7), Kandla (TG35), and Paradeep (TG28) perform excellently, with both PTDR and PQDR above 90%. In contrast, Car Nicobar (TG5) and Digha (TG9) have PTDR below 20% and PQDR below 30%, reflecting significant gaps and quality issues.

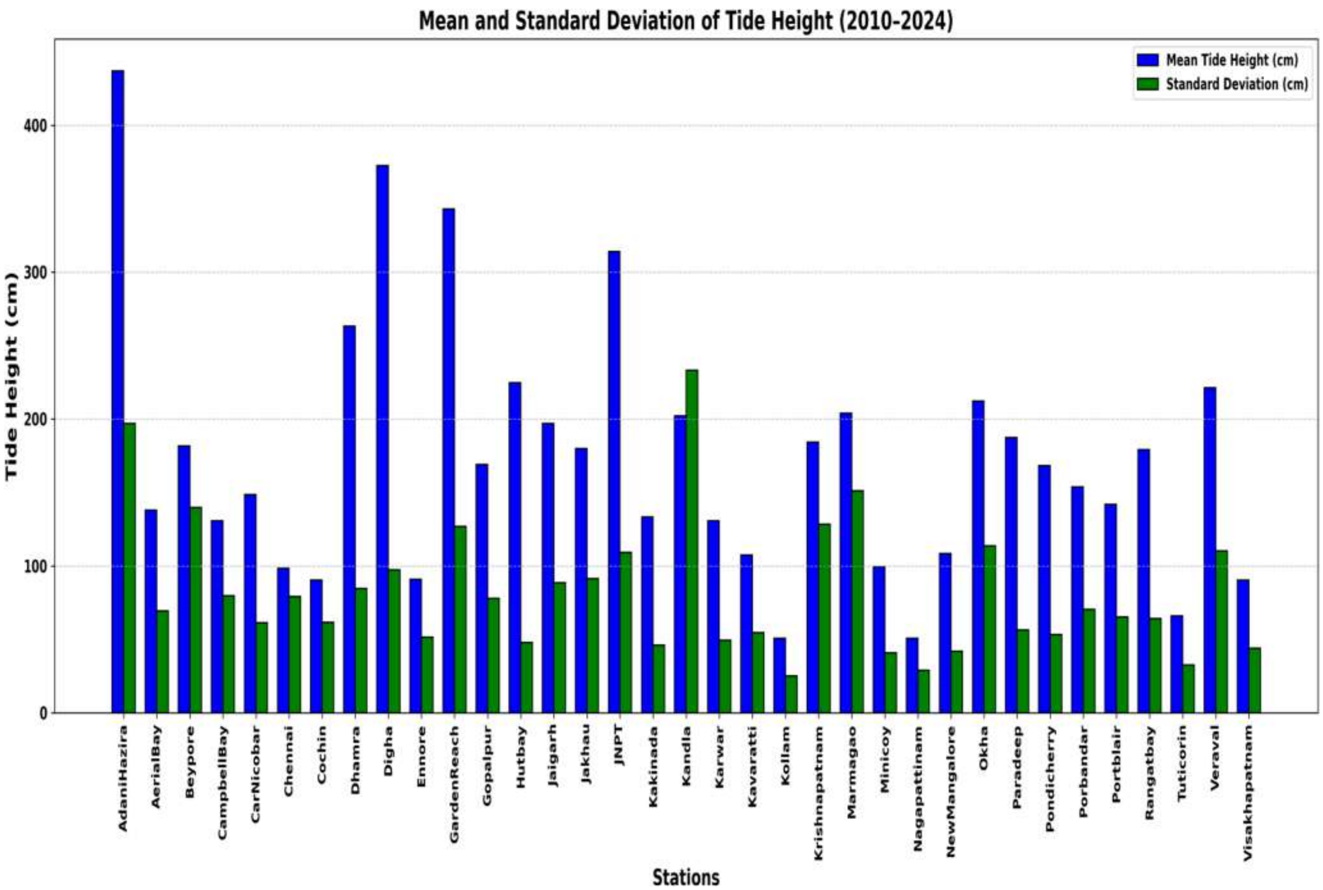

Fig. 8 Mean and standard deviation of tide height (2010–2024) for all 36 tide gauge stations

These results highlight variability across the network and underscore the need for continuous maintenance and QC to ensure reliable tide gauge records for coastal studies, sea-level monitoring, and early warning systems.

3.1 Analysis of cyclone events near Visakhapatnam and Cochin tide gauge location

QC is critical for filtering erroneous spikes and isolating storm surge signals, particularly at cyclone-prone stations like Visakhapatnam and Cochin. Several major cyclones from 2011 to 2024 show distinct water level anomalies corresponding to landfall times. Comparison of tide gauge data before and after QC demonstrates that extreme events, including cyclones and swell surges, are more reliably identified once spurious data are removed. At Visakhapatnam, raw data contained unrealistic spikes exceeding 600 cm due to sensor errors. Post-QC, water levels generally remain within 0–200 cm, with occasional peaks of 400–500 cm, aligning with realistic tidal and storm surge patterns. Cyclones like Phailin, Hudhud, and Fani are clearly visible in the cleaned data as shown in Figs. 10 (Visakhapatnam) and 11 (Cochin).

Similarly, Cochin shows more contamination in raw data, with frequent spikes above 600 cm. Post-QC, data reveal a tidal range of 400–600 cm, consistent with local conditions. Cyclones such as Ockhi, Tauktae, and Yaas are annotated, highlighting storm surge influence. Data gaps, especially from 2016 to 2019, remain a challenge. Figures 12 and 14 illustrate observed tide and residual heights at Visakhapatnam and Cochin during selected cyclones (2018–2022). Residuals, obtained using a 12-hour moving average, isolate meteorological contributions by removing predictable tidal components. At Visakhapatnam, cyclones Titli, Fani, Amphan, and Asani produce noticeable residual peaks corresponding to nearby or regional landfall effects. At Cochin, cyclones Tauktae, Burevi, and Nivar induce residual surges, with even distant events (e.g., Yaas) showing measurable effects.

A detailed comparison of the Visakhapatnam tide gauge data before and after QC, incorporating inset panels for high-resolution analysis, reveals the robustness of the applied methodology (see Figs. 13). The analysis of cyclone events like Asani (2022) and Fani (2019) clearly demonstrates the procedure's effectiveness in identifying and removing significant, non-physical spikes and data

Table 3 Quality control and assurance summary for all 36 tide gauge stations

Station Name	Out of control Flag (4)	Outliers Flag (2)	Spikes Flag (3)	Quality data Flag (1)	Total Flagged Data	Missing data Flag (9)	Percentage of flagged data	Total data
AdaniHazaria	250	193	219	64,210	662	23,462	0.75%	87,672
Aerial Bay	48	607	184	116,180	839	15,316	0.64%	131,496
Bay pore	1	2	3	71,722	6	15,950	0.01%	87,672
Campbell Bay	66	747	129	74,678	942	56,818	0.72%	131,496
CarNicobar	2	2	3	21,214	7	66,458	0.03%	19,546
Chennai	632	1360	265	87,028	2257	87,028	1.72%	131,496
Cochin	483	551	370	99,021	1404	23,715	1.14%	122,712
Dhamra	51	51	6	45,913	108	6695	0.21%	52,608
Digha	0	0	0	14,244	0	64,668	0.00%	78,912
Ennore	149	165	192	107,262	506	24,234	0.39%	131,496
GardenReach	326	316	188	111,273	830	11,463	0.68%	122,736
Gopalpur	6	449	15	22,330	470	3974	1.79%	26,304
Hutbay	0	83	6	31,505	89	56,167	0.10%	87,672
Jaigarh	549	83	70	59,794	702	27,878	0.80%	87,672
Jakhau	172	173	5	52,944	350	17,184	0.50%	70,128
JNPT	8	229	230	113,888	467	17,608	0.36%	131,496
Kakinada	154	133	132	89,398	419	33,338	0.34%	122,736
Kandla	103	117	123	79,333	343	52,163	0.26%	131,496
Karwar	247	316	142	100,055	705	22,681	0.57%	122,736
Kavaratti	38	153	103	74,635	294	56,861	0.22%	131,496
Kollam	0	113	3	48,982	116	21,146	0.17%	70,128
Krishnapattnam	578	403	236	85,701	1217	45,795	0.93%	131,496
Machilipattnam	3	43	9	52,379	55	35,293	0.06%	87,672
Marmagao	0	0	0	74,209	0	13,463	0.00%	87,672
Minocoy	8	229	230	61,350	467	70,146	0.36%	131,496
Nagapattnam	66	156	190	112,867	412	9869	0.34%	122,736
Nancowry	133	140	123	70,994	396	51,742	0.32%	122,736
NewMangalore	49	159	178	117,308	386	14,188	0.29%	131,496
Okha	112	295	138	108,793	545	22,703	0.41%	131,496
Paradeep	75	177	150	117,813	402	13,683	0.31%	131,496
Pondicherry	0	9	5	48,733	14	30,179	0.02%	78,912
Porbandar	0	0	0	64,611	0	5517	0.00%	70,128
Portblair	221	288	238	100,810	747	30,686	0.57%	131,496
Rangatbay	3	427	11	59,477	441	28,195	0.50%	87,672
Tuticorin	281	253	108	110,378	642	21,118	0.49%	131,496
Veraval	1898	647	297	64,882	2842	14,030	3.60%	78,912
Visakhapatnam	332	252	284	113,604	868	17,892	0.66%	131,496

drops from the raw sensor readings. Conversely, the case of Cyclone Amphan (2020) serves as a critical validation, showing that the 'Before' and 'After' data are nearly identical. This confirms that the QC algorithm does not arbitrarily alter the record and correctly preserves high-quality, genuine data. This ability to distinguish between error and event is further highlighted during Cyclone Titli (2018), where high-frequency noise was filtered out while the integrity of the peak cyclone-induced surge signal was fully maintained. Taken together, these examples confirm the QC process is a critical and reliable step, ensuring non-physical errors are removed while preserving the fidelity of true extreme water level events.

The effectiveness of the QC procedure is further demonstrated by the analysis of the Cochin tide gauge data during multiple cyclone events (see Fig. 14). The plots for Cyclone Yaas (2021) and Cyclone Tauktae (2021) are clear examples of robust error correction. In both cases, the raw 'Before QC' data (red lines) were heavily contaminated with high-frequency noise and numerous spurious, sharp data drops. The 'After QC' data (blue lines) show these erratic points and noise have been effectively filtered out, revealing a physically consistent and much cleaner time series that preserves the underlying tidal and surge patterns. Conversely, the comparisons for Cyclone Nivar (2020) and Cyclone Burevi (2020) serve as critical validation cases (Fig. 15).

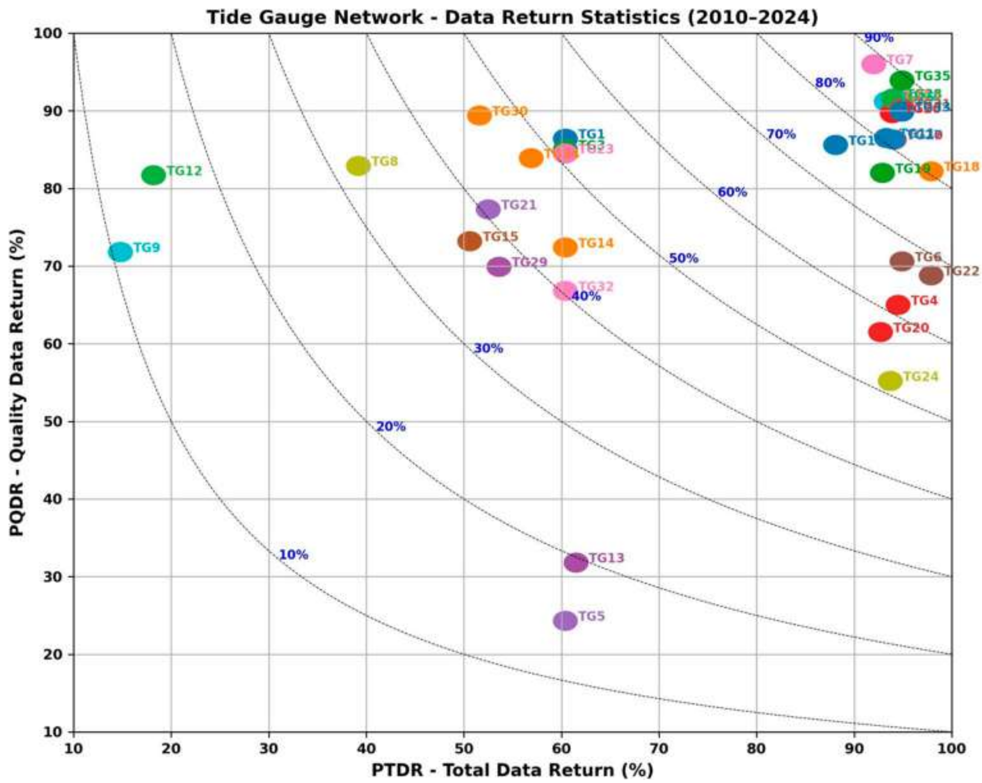

Fig. 9 Performance of Tide Gauge Stations (2010–2024): Data return and quality assessment across 36 Locations

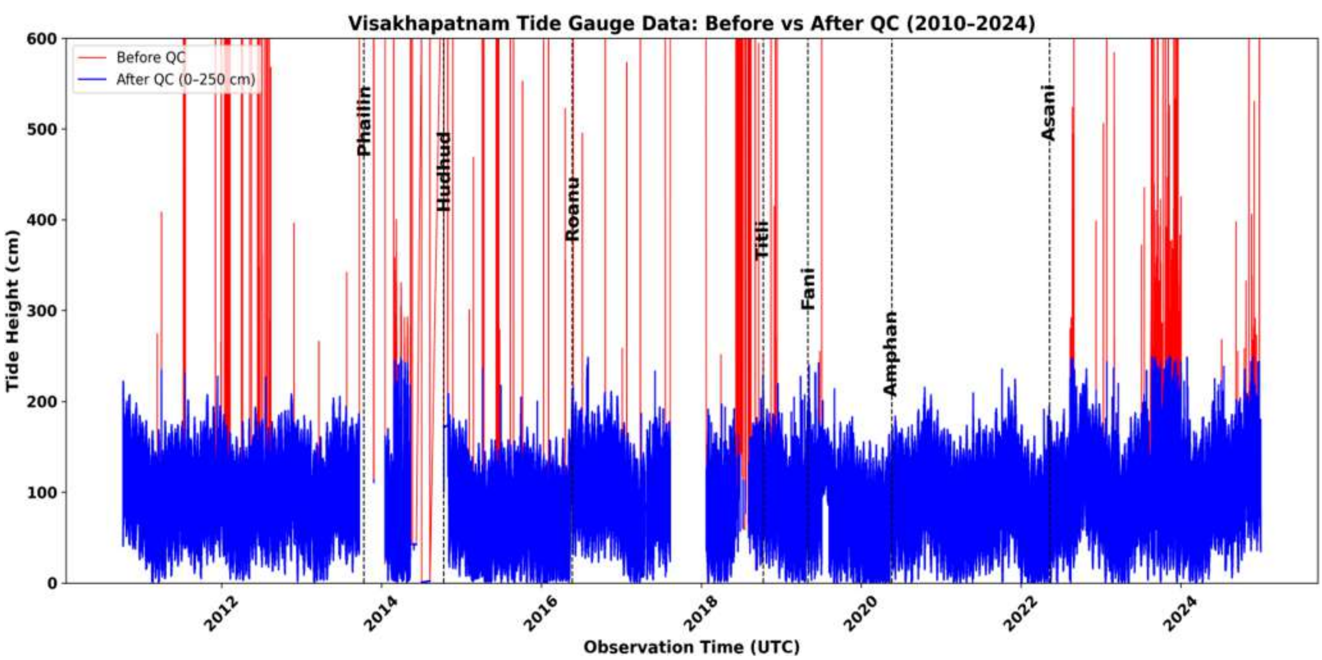

Fig. 10 Visakhapatnam Tide Gauge Data (2011–2024): Comparison of raw and quality-controlled water levels during major cyclone time

For these events, the 'Before' and 'After' plots are nearly identical, indicating the raw sensor data was already of high quality. This confirms the QC algorithm is not overly aggressive, successfully validating and passing clean data without distortion, while still being rigorous in removing noise and errors when they are present.

These analyses confirm the value of tide gauge stations in monitoring storm surge impacts. Visakhapatnam responds

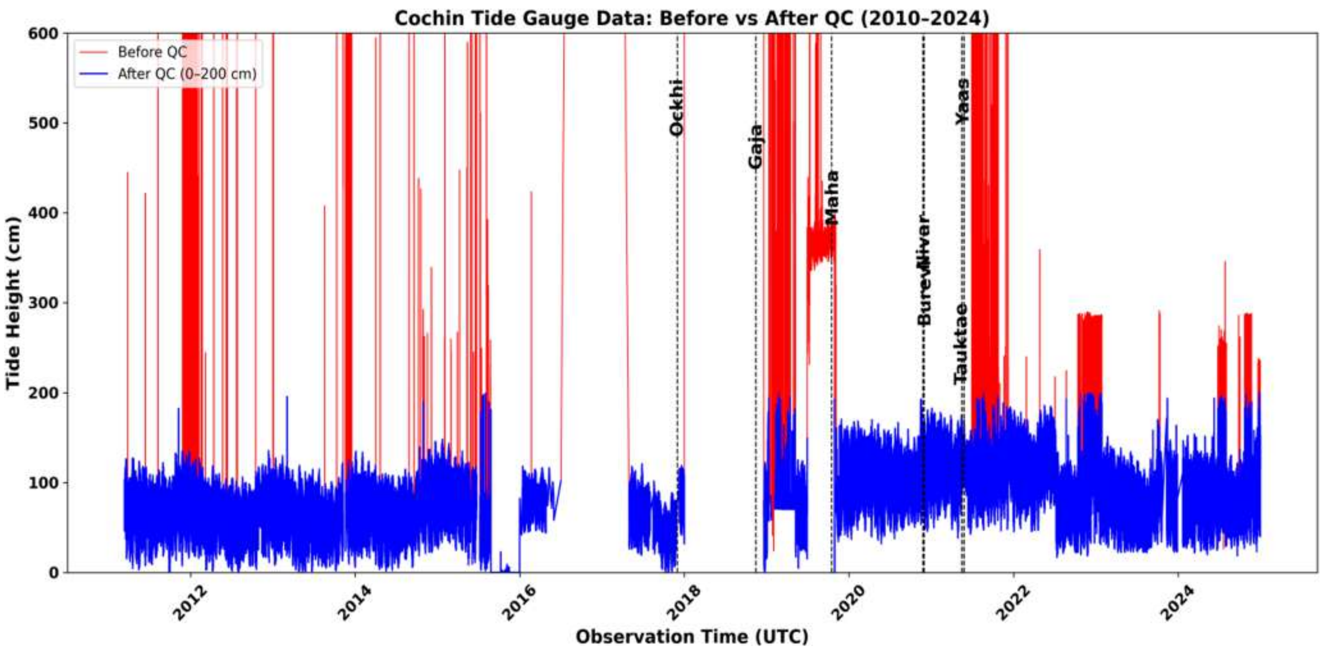

Fig. 11 Cochin Tide Gauge Data (2011–2024): Comparison of raw and quality-controlled water levels during major cyclone time

primarily to Bay of Bengal cyclones, while Cochin captures Arabian Sea cyclones and occasionally distant events. Residual peaks coincide consistently with cyclone landfalls, highlighting the reliability of residual analysis for identifying cyclone-induced sea level anomalies. A 12-hour moving average is used only for illustrative residuals. While it can attenuate semidiurnal tides and short-period disturbances, QC diagnostics and event detection rely on the cleaned water-level time series. Future work will implement harmonic predictions for precise surge quantification. All cyclones recorded at Visakhapatnam (Phailin, Hudhud, Roanu, Titli, Fani, Amphan, Asani) and Cochin (Ockhi, Gaja, Maha, Burevi, Nivar, Tauktae, Yaas) were analyzed to ensure comprehensive QC assessment, including moderate events and near-misses.

3.2 Analysis of swell surge events near to Cochin tide gauge location

Figures 16 and 17 show two 2024 Kallakadal events near Cochin (March 28–31 and October 10–20). These were characterized by elevated water levels without local storms. Residuals were extracted by removing tidal components via a semi-diurnal moving average. Wave parameters (significant wave height, swell height, wave direction) were obtained from INCOIS WaveWatch III (WW3) outputs to support attribution of non-tidal anomalies. In the March event, residuals and observed water levels sharply increased on March 28–29, coinciding with swell heights ~ 160 cm and wave heights ~ 100 cm. In October, prolonged elevated residuals were observed from October 14–18, with long wave periods above 18 s. Vertical shaded lines mark the onset of swell-induced rises corresponding to peak wave conditions. Although WW3 outputs support the analysis, formal uncertainty propagation was not performed. Therefore, model-derived parameters should be interpreted qualitatively rather than quantitatively. Peak wave period (PWP) time series was used as a proxy for swell-dominated conditions, showing consistency with observed residuals. Future work will incorporate full spectral diagnostics and offshore model validation to improve robustness. These cases demonstrate that Kallakadal events are driven by long-period swells from distant storms, capable of causing significant coastal water level anomalies even in calm weather. Integration of tide gauge and wave data provides valuable insights for monitoring and predicting such low-visibility, high-impact events along India's southwest coast.

The enhanced analysis for the October 2024 swell event provides a robust and physically consistent demonstration of the swell-surge relationship, directly addressing the reviewer's need for spectral wave parameters. The Fig. 18 uses a two-panel structure: the top panel displays the Observed Tide and the Surge Component (residual), while the bottom panel focuses on the wave forcing, and showing Wave Height, Swell Height, and the Peak Wave Period (PWP). The key scientific improvement lies in the PWP line, which demonstrates clear variability throughout the event, rising

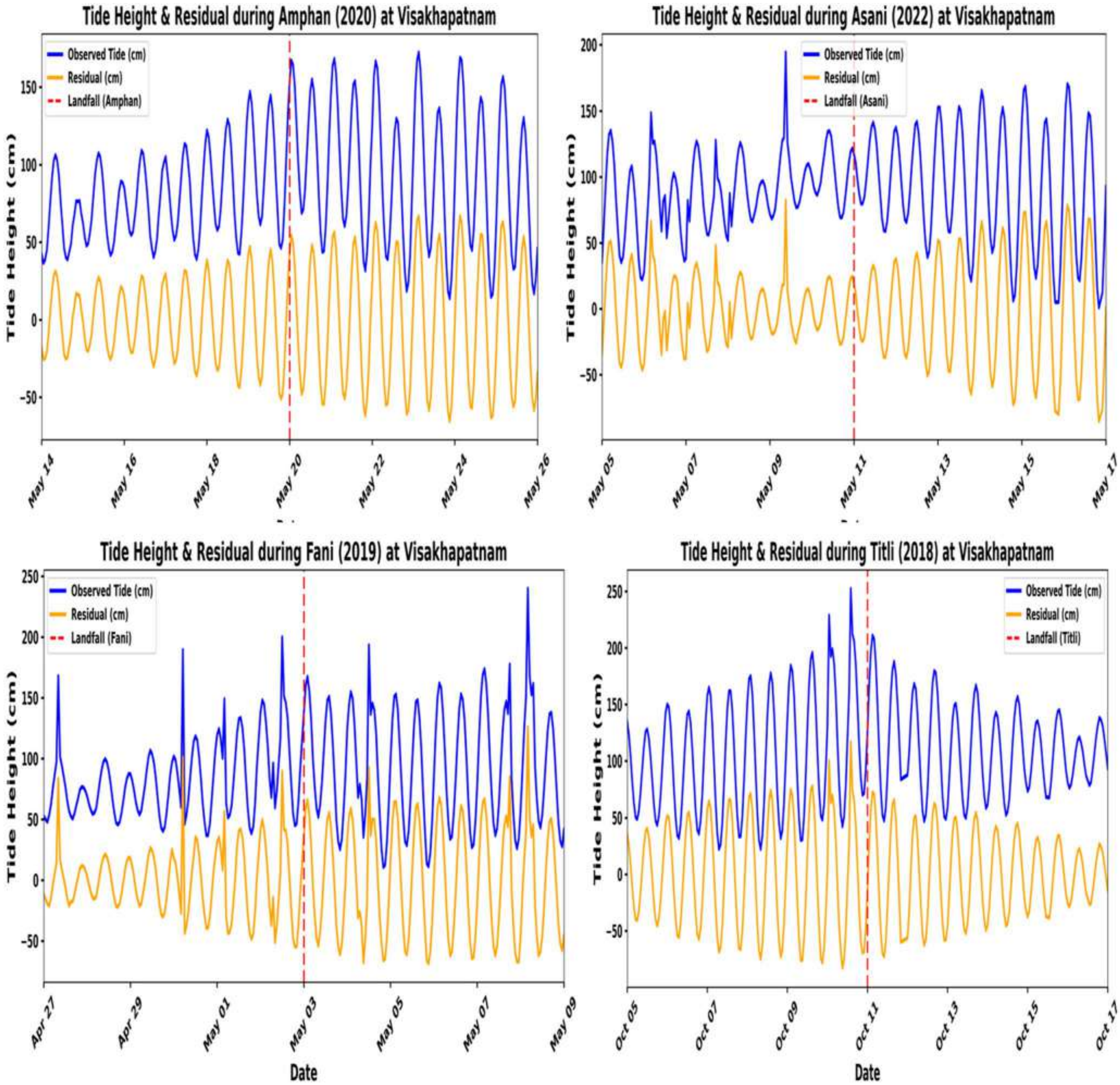

Fig. 12 Tide Height & residual during Amphan, Asani, Fani and Title at Visakhapatnam tide gauge location

sharply from a baseline to a peak near 20 s around October 15th-16th. This extreme period is characteristic of the long-period energy associated with Kallakadal-like events. This increase in PWP, combined with the rise in Swell Height, confirms the arrival of significant long-period swell energy, thereby fulfilling the request for spectral analysis. Critically, the peak wave energy period (shaded red and yellow boxes) coincides with the highest values of the positive Surge Component in the top panel. This temporal correlation provides strong evidence that the long-period swell forcing is the mechanism driving the observed water level anomaly.

4 Limitations

This study has several limitations that should be acknowledged. The QC procedures rely on fixed parameter settings such as moving-window lengths and z-score thresholds that follow current operational practice. A full sensitivity analysis for optimizing these parameters across all stations is planned for future work. Data availability is not uniform across the INCOIS network, and several stations exhibit extended gaps due to sensor downtime or communication interruptions, meaning that the reliability of QC-processed

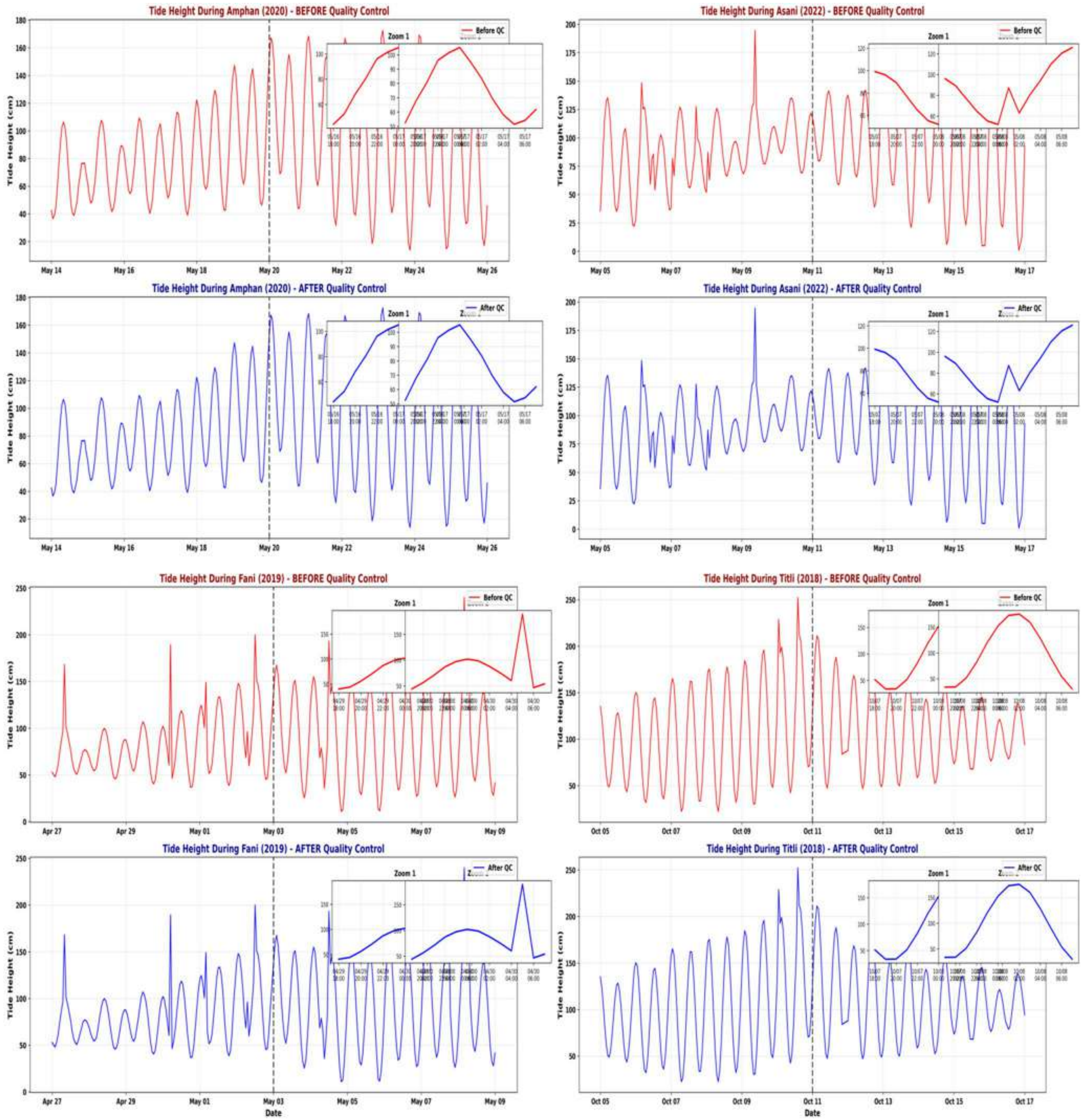

Fig. 13 Comparison of Visakhapatnam tide gauge data before and after QC during major cyclone events, with zoom-in panels

data varies spatially. While cyclone and swell events were used to demonstrate the effectiveness of the QC workflow, a comprehensive statistical validation across a wider range of oceanographic conditions remains to be conducted. Limitations in the available WW3 outputs prevented the inclusion of spectral wave-energy diagnostics for swell attribution; instead, peak wave period was used as a practical proxy. Additionally, the harmonic-consistency test depends on the accuracy of tidal predictions derived from locally calibrated harmonic constituents, which may introduce uncertainty in detecting low-frequency inconsistencies. Initially, the manuscript did not include flowcharts or pseudocode for the QC sequence, which the reviewers noted as a limitation. In the revised version, both the QC flowchart and the pseudocode have now been incorporated to enhance procedural transparency. These additions strengthen the clarity and reproducibility of the QC methodology. Despite earlier constraints, the present framework still represents a significant advance

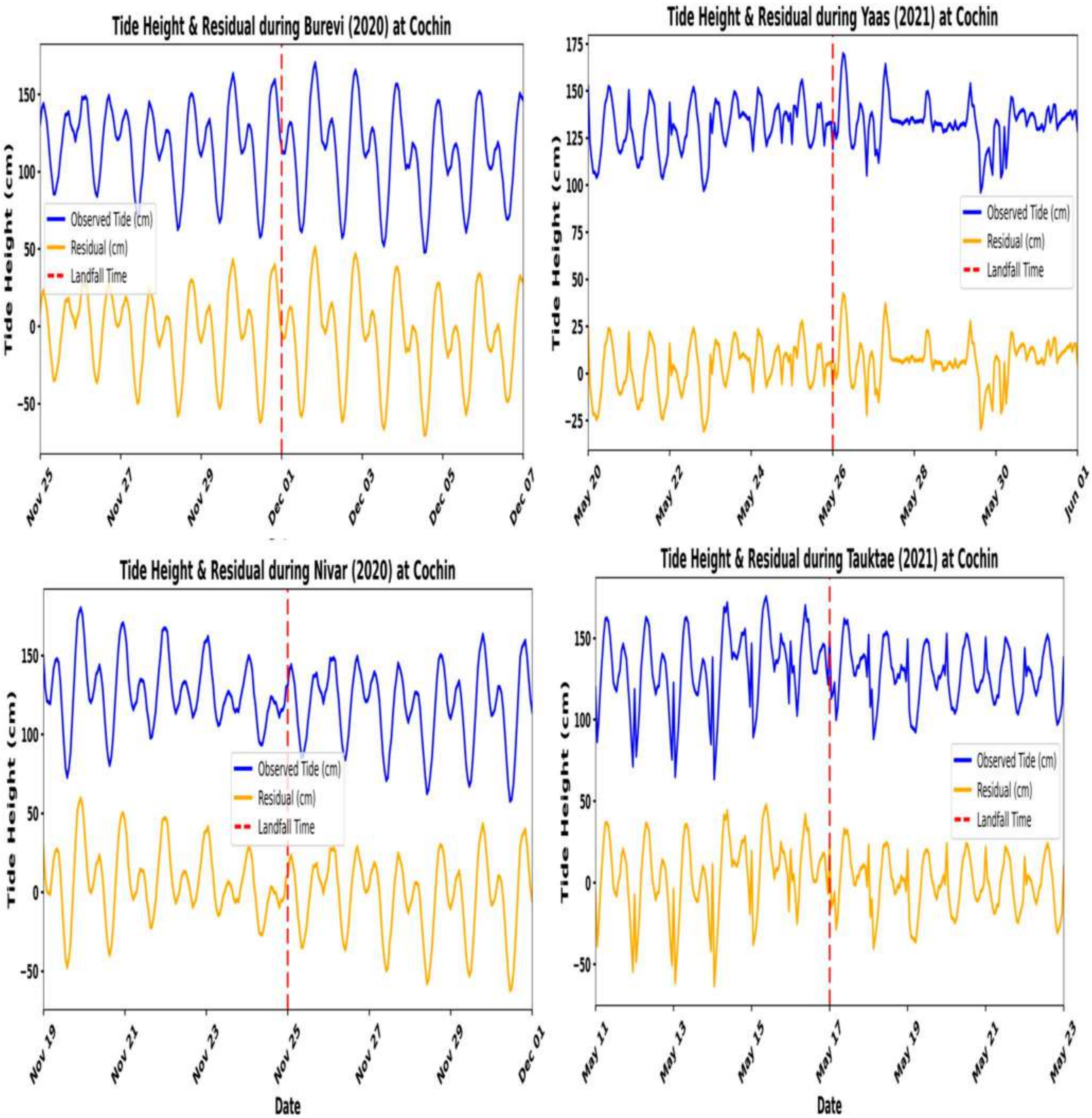

Fig. 14 Tide height & residual during Buevi, Yaas, Nivar and Tauktae at Cochin tide gauge location

toward an integrated and operationally scalable QC system for tide gauge observations along the Indian coastline.

5 Conclusions and future scope

The assessment of tide gauge data from 36 stations along the Indian coastline for the period 2010–2024 underscores the critical role of rigorous QC in ensuring reliable sea level observations. The QC process substantially improves the usability of tide gauge records by removing spurious spikes, outliers, and sensor-related anomalies, especially at stations such as Cochin and Visakhapatnam. These corrections transform erratic raw datasets into coherent records that accurately reflect tidal cycles and genuine storm surge events, enabling meaningful scientific analysis. Analysis of mean tide heights and standard deviations across the network reveals considerable variability. Stations such as Adani

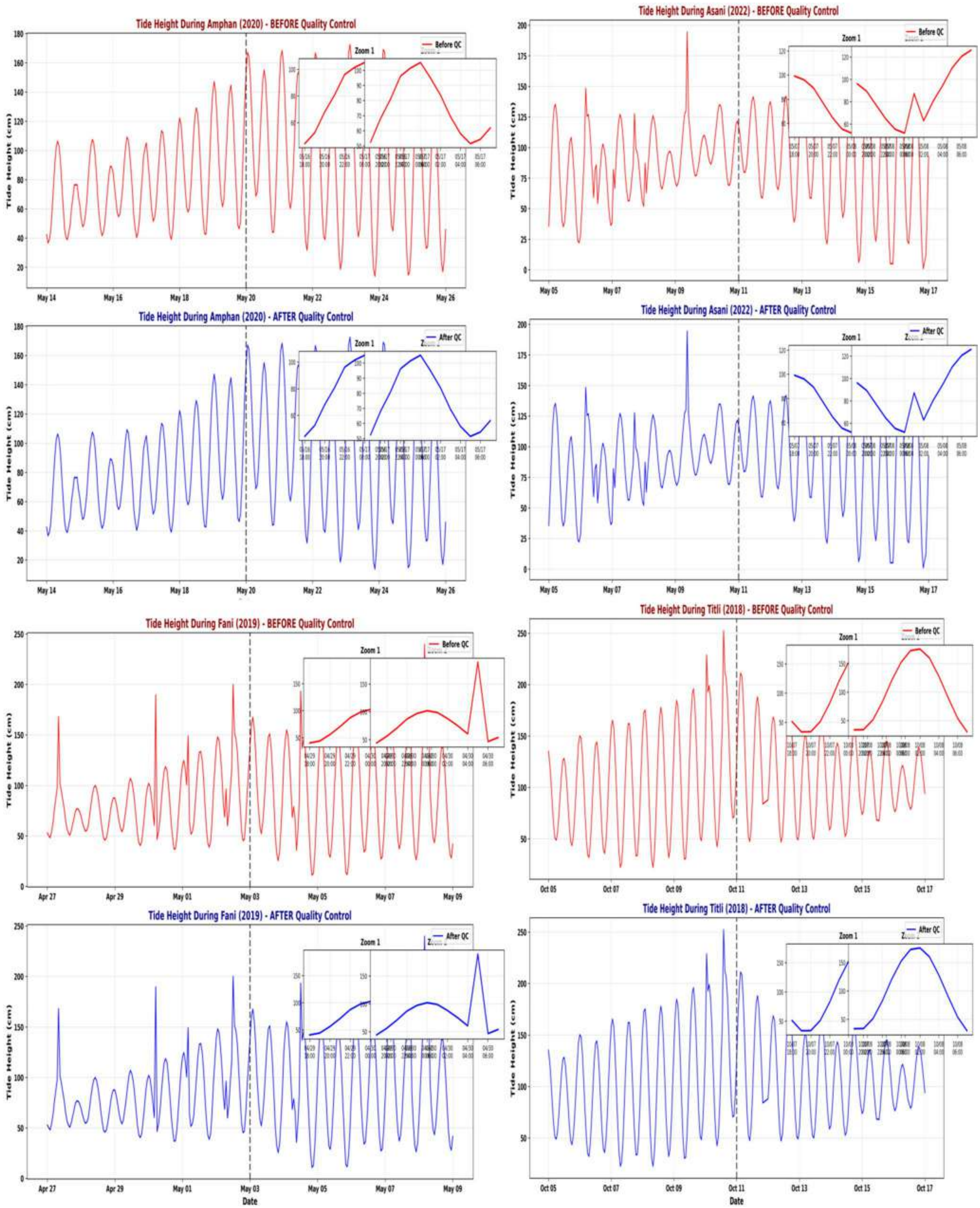

Fig. 15 Comparison of Cochin tide gauge data before and after QC during Cyclones Yaas (2021), Tauktae (2021), Nivar (2020), and Burevi (2020), with zoom-in panels

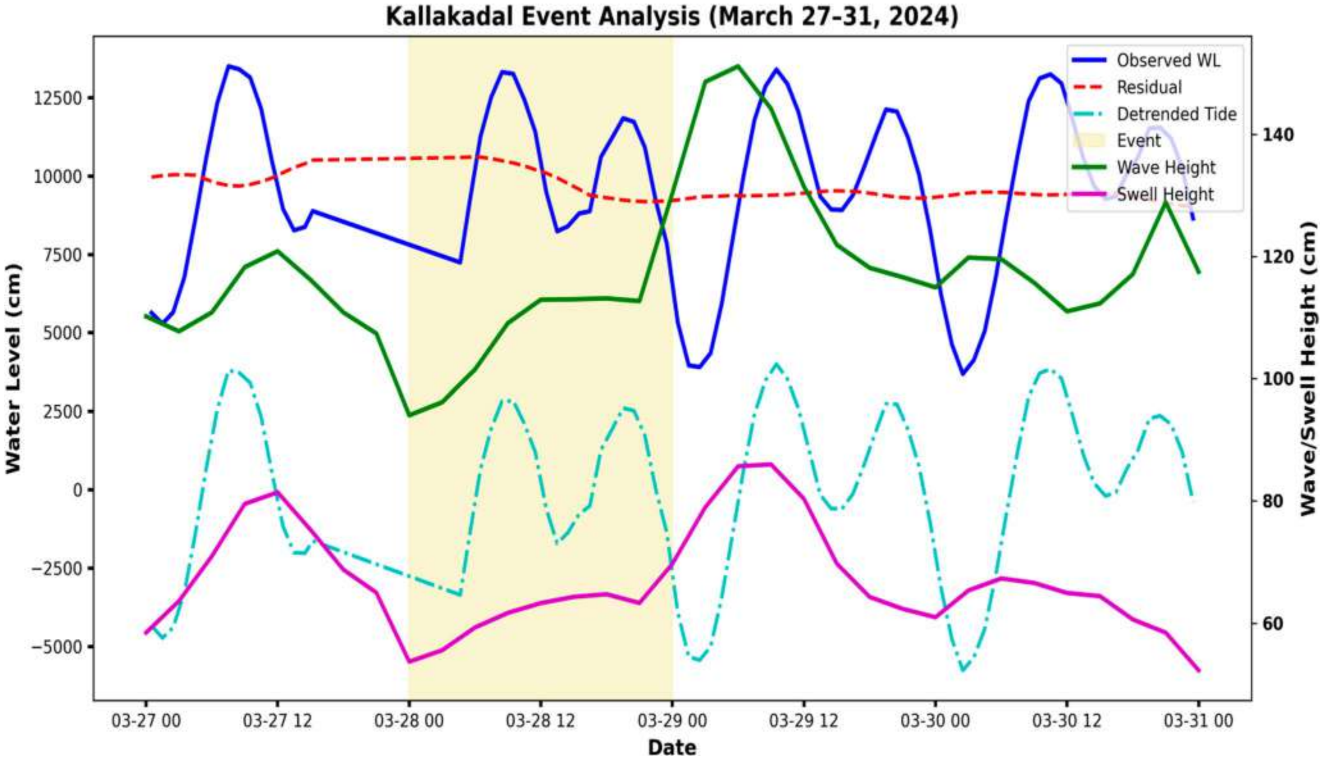

Fig. 16 Swell surge event at Cochin tide gauge location (March 28-31, 2024)

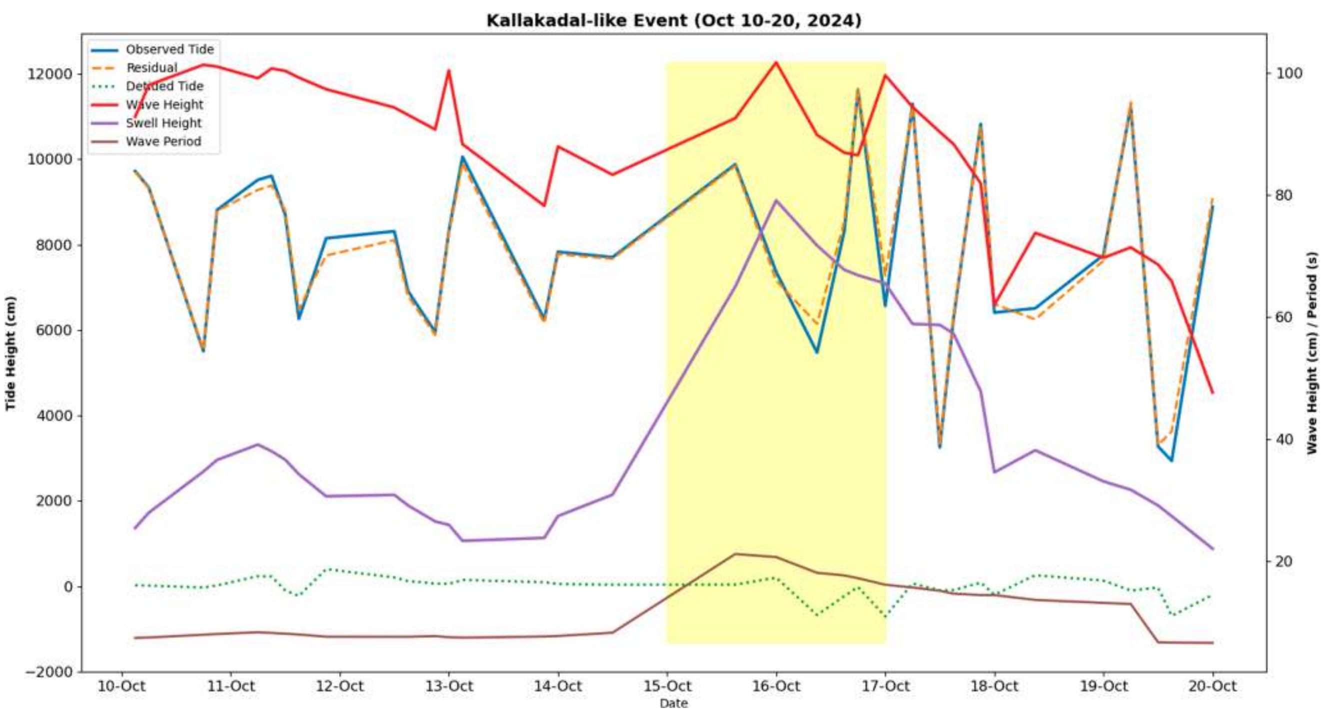

Fig. 17 Swell surge event at Cochin tide gauge location (October 10-20, 2024)

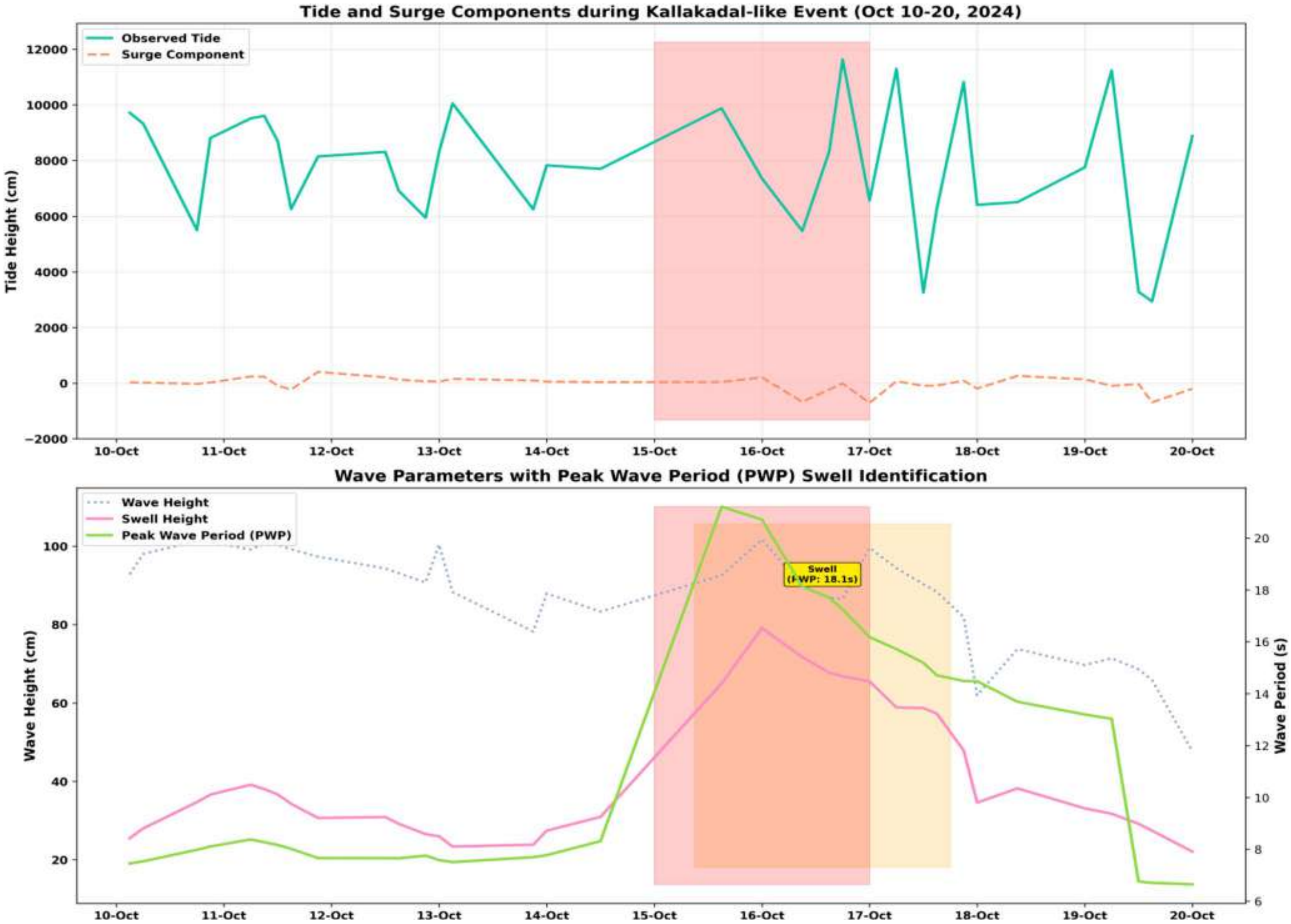

Fig. 18 Swell–surge relationship during the October 2024 swell event, highlighting long-period wave forcing and associated water level response

Hazira exhibit high tidal amplitudes coupled with significant fluctuations, while stations like Veraval and Tuticorin display more stable and consistent tidal behavior. These differences are closely linked to regional oceanographic and meteorological conditions, including the influence of the Bay of Bengal and Arabian Sea dynamics. QC and assurance statistics further highlight disparities in data integrity across stations. While stations like Digha, Marmagao, and Porbandar exhibit exemplary data quality with virtually no flagged data, others such as Veraval, Chennai, and Adani Hazira present higher proportions of flagged or missing data, often due to persistent "out of control" measurements and sensor spikes. Variability in PTDR and PQDR across the network emphasizes the importance of consistent maintenance, timely calibration, and sensor upgrades. Cyclone case studies demonstrate the operational value of tide gauges in capturing storm surge events. Post-QC data at Visakhapatnam and Cochin revealed clear residual signatures during major cyclonic systems such as Titli, Fani, and Tauktae. Residual analysis using moving averages effectively isolated meteorological influences from tidal signals, confirming that these stations can reliably monitor both local and distant cyclone impacts.

Additionally, non-cyclonic swell surge events, such as the Kallakadal events near Cochin in 2024, were successfully detected by integrating tide gauge and wave data, highlighting the utility of these stations for tracking long-period swells and associated coastal flooding. In summary, while the Indian tide gauge network provides a foundational dataset for sea level trend analysis, storm surge detection, and operational oceanography, its effectiveness depends heavily on sustained data quality and coverage. Enhancing station performance through regular maintenance, robust QC protocols, and integration with wave and atmospheric datasets will significantly improve early warning capabilities and long-term climate monitoring along the Indian coastline.

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

Declarations

Competing interests The authors declare no competing interests.

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