The Data Behind AI Coastal Forecasting: Inputs, Sources, and Preprocessing Approaches

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Abstract

Coastal zones, shaped by marine and terrestrial processes, are home to over 40% of the global population and contribute significantly to the global economy. However, their attractiveness also makes them vulnerable to extreme coastal water levels (ECWLs), which can lead to catastrophic flooding. ECWLs, driven by sea-level changes, waves, and tidal variations, have become more frequent and severe due to climate change, resulting in significant loss of life and economic damage. Artificial intelligence (AI) has emerged as a powerful tool for forecasting oceanographic processes, leveraging its ability to capture the complex, non-linear relationships. However, the performance of AI models depends heavily on the availability, quality, and preparation of oceanographic data, which are often heterogeneous. This study reviews the data types, input features, spatial and temporal resolutions, data coverage, and pre-processing methods used in AI-driven forecasting of ECWL drivers, i.e., waves, tides, and sea level anomaly. The findings highlight the importance of in-situ measurements, remote sensing, numerical simulations, laboratory experiments, and reanalysis data in capturing different aspects of wave dynamics, while emphasising the need for improved data accessibility, integration, and longer datasets. The review also highlights research imbalances, such as limited attention to certain wave dynamics (e.g., wave spectra, wave energy flux), as well as data scarcity in less-resourced regions.

1 Introduction

Coastal zones occupy a narrow fraction of the Earth's surface, yet they support an exceptionally large share of the world's population and economic activity. More than 40% of people live near the coast (Kummu et al., 2016), and in some countries almost the entire population resides within 100 km of the shoreline (Martínez et al., 2007). These areas accommodate major cities and infrastructure, and their economic importance continues to draw people toward them. Their exposure, however, makes them especially vulnerable to extreme coastal water levels (ECWLs).

ECWLs arise from unusual combinations of sea-level variability, tides, and wave conditions (Gregory et al., 2019). When these forces coincide with storms or high tides, they can exceed the capacity of natural or engineered coastal defences and produce severe flooding. The frequency and scale of such events have increased in recent decades, a trend widely linked to climate change (Golnaraghi, 2012; Mayo & Lin, 2022). Historical records show their human toll is substantial: storm-surge-related flooding alone has caused hundreds of thousands of deaths over the past century (Siegel, 2020). Modern events remain destructive, as seen recently in Spain, where an ECWL event in 2024 resulted in heavy loss of life and widespread damage (Manez & Latona, 2024; Wise, 2024).

Accurate and timely flood forecasts are therefore essential for coastal communities. Early warning systems have proven effective—studies estimate that they can cut flood-related casualties nearly in half (Perera et al., 2019). Their performance, however, depends on how well the underlying oceanic processes can be predicted. Waves, tides, and sea level anomalies (SLAs) are central to these processes (Brempong et al., 2023; Green et al., 2025; Gregory et al., 2019; Jafarzadegan et al., 2023), yet each is influenced by multiple drivers and exhibits substantial spatial and temporal variability. This complexity makes forecasting difficult.

Artificial intelligence (AI) has become an important tool in this setting because it can learn patterns from large, multi-source datasets that are challenging to handle using traditional approaches. AI methods are increasingly used in oceanography for tasks ranging from detecting eddies to tracking marine pollution (Dong et al., 2022). Their growing adoption in ocean forecasting reflects both methodological advances and the expanding availability of oceanographic data. Nevertheless, the performance of AI models is shaped as much by their inputs as by their architecture. Issues such as sparse measurements, data gaps, inconsistent resolution, and noise remain limiting factors across many coastal regions.

Oceanographic data relevant to ECWL forecasting come from several sources, including in-situ instruments, satellite missions, numerical models, reanalysis products, and laboratory experiments. Each source captures different aspects of the marine environment. For example, satellite altimetry provides wide-area SLA observations, while wave buoys resolve local sea-state conditions at high temporal resolution. Laboratory experiments reproduce specific wave behaviours that are difficult to isolate in the field. These differences mean that the suitability of a dataset depends on the process being forecast and the spatial or temporal scales involved.

The characteristics of the data also influence model performance. Many studies rely on short or discontinuous records; others combine datasets with mismatched resolutions. Pre-processing choices such as resampling, normalisation, gap-filling, and decomposition can therefore have a substantial effect on the behaviour of AI models. Despite this, existing reviews tend to emphasise modelling techniques and comparative performance, while the data foundations of those models receive comparatively little attention.

This review addresses this knowledge gap by examining the data used in AI-based forecasting of waves, tides, and SLAs. It focuses on the types of data employed, the input features selected, the spatial and temporal resolutions reported, the length of the records, and the pre-processing methods applied before modelling. By bringing together these elements, the review highlights current practices, regional and methodological patterns, and areas where data limitations continue to constrain ECWL forecasting.

The remainder of the paper is structured as follows: section 2 outlines key concepts and definitions related to ocean data, waves, tides, and SLAs. section 3 describes the approach used to identify relevant literature. section 4 presents the findings, including the geographic distribution of studies, the distribution of data types, data coverage, temporal and spatial resolutions of input features, and the pre-processing methods identified. Finally, section 5 discusses major insights and persistent challenges in the field.

2 Concepts and Definitions

2.1 Data

Ocean data is vast and heterogeneous, sourced from satellite imagery, sensor networks, and historical records. This data often contains uncertainties, inconsistencies, and gaps. AI is particularly suited for handling such data. It thrives on large datasets, can integrate data from multiple sources, and manages varying levels of uncertainty and incompleteness. However, the performance of AI in oceanography depends heavily on the quality, diversity, and accuracy of the input data (Dong et al., 2022).

Given these dependencies, understanding the sources and characteristics of ocean data is crucial. Temporal resolution refers to the frequency of data collection. A finer (or higher) temporal resolution involves short intervals, such as hourly or minute-based recordings, capturing short-term fluctuations. Conversely, a lower (or coarser) temporal resolution, with longer intervals like six hours, daily, or monthly, smooths out short-term variability while emphasising broader trends.

Spatial resolution defines the level of geographic detail but varies depending on the data source. In images, a finer spatial resolution means more pixels per unit area, capturing small-scale features with high detail, while a coarser spatial resolution consists of fewer pixels per unit area, resulting in less detailed representations (Athanasiou et al., 2017). In numerical models, spatial resolution is determined by grid spacing, which defines the distance between two consecutive grid points. A higher spatial resolution in numerical models employs smaller grid spacing to capture finer-scale processes, while a coarser resolution uses larger grid spacing, representing broader patterns but missing localised details (Collins et al., 2013). In this study, the term spatial resolution is used in an all-encompassing manner.

Both temporal and spatial resolution are often resampled to a higher or lower resolution, depending on the objective of the study, data availability, data uniformity (Shahabi & Tahvildari, 2024) or computational constraint. The final data characteristic is the data coverage period, which describes the duration of historical records. It refers to the number of days, months, or years over which the data is collected.

2.2 Sea Level Anomaly

Sea level refers to the average height of the surface of the ocean. Sea level rise, driven by human and natural processes, is increasing the risk of coastal inundation worldwide. Changes in sea level vary across regions and over time due to factors like thermal expansion, land subsidence or uplift, and wind shifts. While mean sea level rise is the main driver of increased flood risk, other oceanic processes like tides and waves amplify or reduce this risk (Wahl & Dangendorf, 2022).

SLA is the difference between the observed sea surface height and the average sea surface height. It reflects variations in sea levels caused by factors such as oceanic processes, regional geography, precipitation, evaporation, water salinity, air and water temperature, and local topographical features (Imani et al., 2013; Sarsito et al., 2018). Given the significant threat sea level rise poses to millions living in coastal areas, accurate forecasting of sea level variations is essential for effective coastal engineering and hydrological planning (Imani et al., 2017). Predicting SLA is also needed for global and regional sea level studies, enabling more accurate forecasting, risk assessment, and management of sea level change impacts (J. Zhao, Fan, et al., 2019).

2.3 Tides

Tides are the regular, periodic rise and fall of sea levels caused by astronomical and meteorological forces (Komar, 2018). They influence the depth of floods and the behaviour of waves nearshore, as tides regulate where waves break and how wave set-up occurs (Ramakrishnan et al., 2022). High tides create higher baseline water levels, which intensify the impact of storm surges. They influence the timing, duration, and magnitude of flooding events.

When tidal levels interact with storm surges, they often create prolonged and complex flood scenarios (H. Liang & Zhou, 2022). Tides predictably modulate extreme sea levels, raising the likelihood and severity of floods during peak phases (Enríquez et al., 2022).

Tidal level forecasting is the process of predicting the height of water levels at a specific location and time, taking into consideration the periodic (astronomical) and non-periodic (meteorological) forces that affect tides.

2.4 Waves and Their Characteristics

Waves, which are primarily caused by wind blowing over the ocean's surface, interact with atmospheric and other oceanic forces in ways that exacerbate flooding. They amplify storm surge levels and elevate water levels, particularly in shallow coastal areas (Staneva et al., 2016).

Wave forecasting involves estimating wave evolution under dynamic environmental conditions, including wind fields and bathymetry. The inherent complexity of this process arises from factors such as spectrum variability, the development process, frequency and duration dependencies, and intricate energy dynamics (Kumar et al., 2017), all of which make precise forecasting challenging. Given these complexities and the broad impact of waves across various sectors, researchers have dedicated extensive efforts to forecasting diverse wave dynamics.

2.4.1 Multiple Parameters in Wave Forecasting

SLAs and tides manifest primarily as vertical displacements of water, making water level the dominant characteristic that effectively captures their behaviour and impact.

Ocean waves, in contrast, have a more complex behaviour that cannot be fully characterised by a single parameter. Instead, multiple interrelated variables describe different aspects of wave motion. Wave height refers to the vertical distance between a wave crest and the adjacent trough, while wavelength is the horizontal distance between two successive crests or troughs (Dean & Dalrymple, 1991). Additionally, several secondary parameters provide further insight into wave dynamics. For example, wave energy flux, which represents the rate of energy transfer per unit wave crest length, is a function of both wave height and wave period.

Waves also interact with coastlines and coastal structures. Wave run-up is the maximum vertical extent of wave uprush on a beach or structure, which plays a role in coastal flooding and erosion.

Given the complexities of wave dynamics and their broad impacts across various domains, numerous studies aim to forecast different wave parameters. However, this review homes in on specific aspects of wave dynamics. Consequently, wave dynamics, as used in this review, include fundamental wave characteristics, wave energy parameters, and coastal impacts.

3 Literature Identification and Review Approach

This review was developed as a narrative synthesis of the literature on AI-based forecasting of wave dynamics, tidal levels, and SLAs, with a particular emphasis on the oceanographic data that underpin these models. The aim was to compile and interpret current practices in data selection, data preparation, and feature engineering, and to describe the range of datasets and preprocessing techniques used across the field.

Relevant publications were identified through searches of major scientific databases, including the ACM Digital Library, IEEE Xplore, ScienceDirect, and Scopus. Search terms combined expressions related to coastal water level forecasting, with terms associated with artificial intelligence and machine learning. The search process was exploratory rather than exhaustive, allowing additional studies to be incorporated through citation tracing and references within key papers. This approach ensured broad coverage of work published across ocean engineering, marine science, climate research, and data-driven modelling.

The review focuses on peer-reviewed studies that apply AI or statistical learning techniques to forecast wave characteristics, tidal fluctuations, or SLAs. Across these studies, attention was directed to the nature of the datasets employed, including their origin, spatial and temporal resolution, duration, and the physical variables measured. Emphasis was placed on understanding how input features were selected, how datasets were pre-processed or transformed before modelling, and how heterogeneous data sources were integrated.

All studies included in the review were examined in full. Information relevant to data types, input variables, and preprocessing methodologies was extracted descriptively and then organised thematically. This qualitative synthesis forms the basis of the results presented in subsequent sections, which outline dominant data practices, common modelling inputs, and recurring strategies for preparing oceanographic time series for AI-based forecasting.

4 Results

4.1.1 Geographic Distribution

The literature covers work conducted in at least 28 countries, across 11 different seas, and several major regional water bodies such as the Gulf of Mexico and the Caspian Sea (Figure 1). There is also at least one study with global coverage (Upreti et al., 2023). The United States appears most frequently as a study location, followed by China, India, and Taiwan. This pattern aligns with trends reported in other reviews, which similarly identify the USA, China, and India as leading contributors to AI-driven coastal forecasting research (Byaruhanga et al., 2024; Hakim et al., 2023).

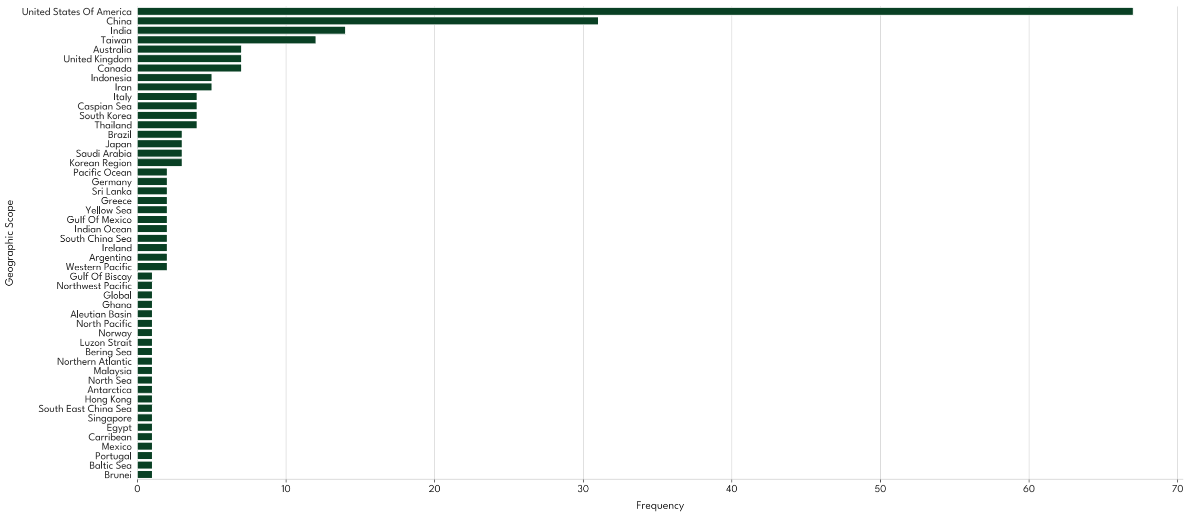


Figure 1 Most frequent study areas.

4.1.2 Publication Distribution

The body of literature on AI-based forecasting of water-level-related ocean processes has expanded rapidly, especially after 2020. A substantial portion of recent work focuses on wave dynamics, which dominate the research landscape. Wave-related forecasting studies form the largest group, followed by studies on tidal levels, while SLAs forecasting represents a much smaller fraction. These patterns suggest that wave prediction remains the primary focus within the field, with tides receiving steady attention and SLA forecasting still emerging as a niche area.

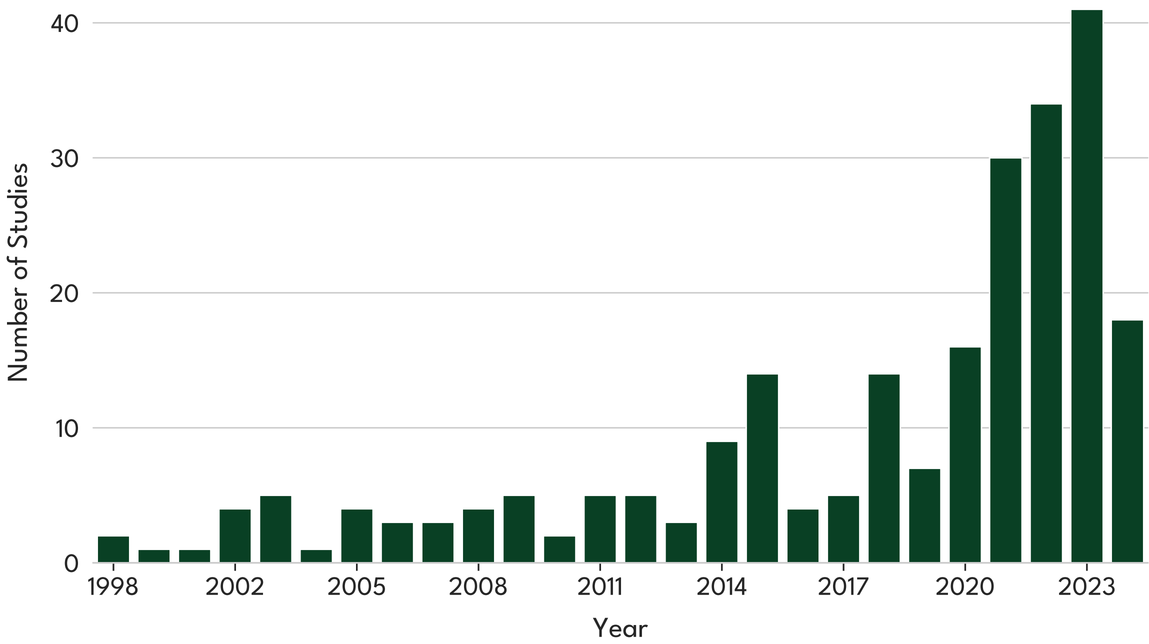


Figure 2 Yearly trends of publications focused on forecasting waves, tides, and SLAs.

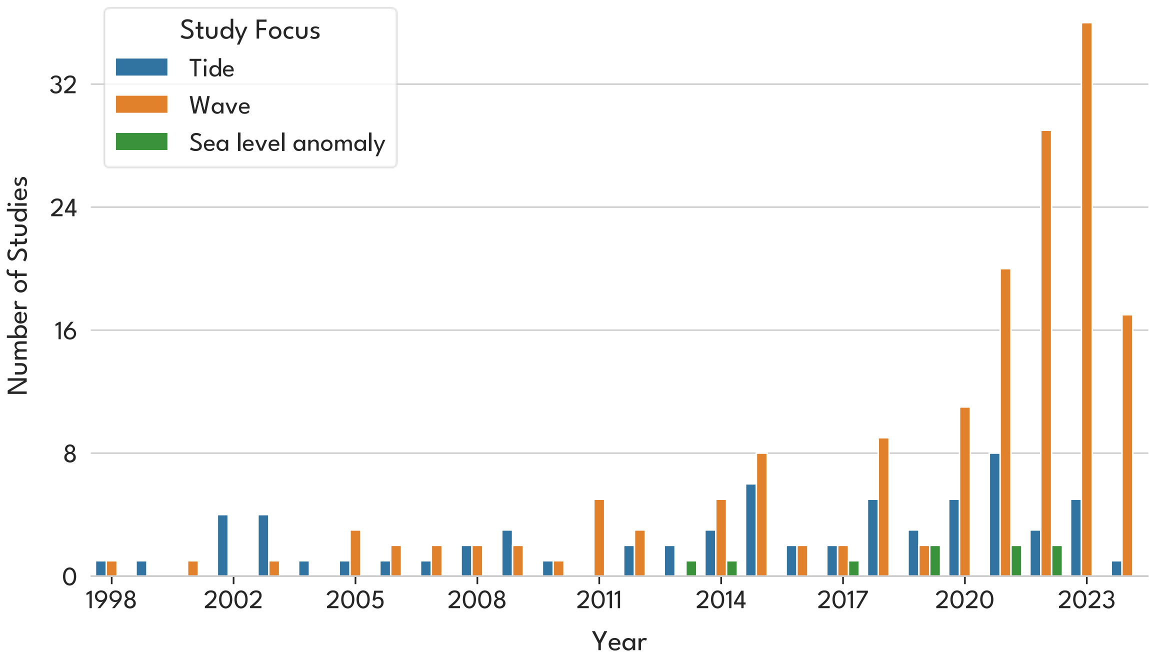


Figure 3 Yearly distribution of studies by focus area.

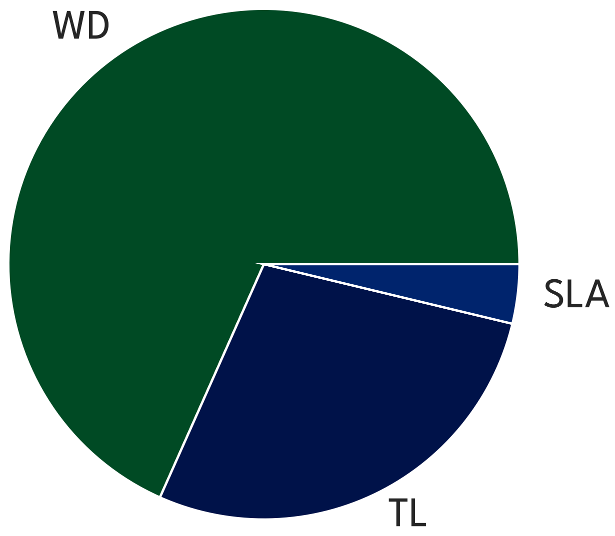


Figure 4 Distribution of studies by focus area. WD = Waves dynamics, TL = Tidal level, SLA = Sea level anomaly.

4.2 Data Type

The accuracy and reliability of oceanographic forecasting models are fundamentally dependent on the data sources used for their training and evaluation. Different ocean processes can adequately be captured by specific data collection devices or methods, each with its strengths and limitations. For instance, satellite altimetry provides broad-scale SLAs measurements that in-situ tide gauges cannot, while the detailed analysis of certain wave dynamics often necessitates controlled wave tank experiments rather than field-deployed wave buoys.

Five types of data were identified across the reviewed studies: in-situ data (e.g., tide gauge and wave buoy), remote sensing (e.g., satellite altimetry and synthetic aperture radar), numerical model simulations(e.g., Simulating WAves Nearshore (SWAN) and WaveWatchIII), laboratory experiments (e.g., wave tanks), and reanalysis data (e.g., ERA5). These represent a spectrum from direct, real-world observations (in-situ measurements) to indirect, simulated data (numerical models), with remote sensing providing indirect real-world observations and laboratory experiments offering direct simulated measurements. Reanalysis data bridges these categories by assimilating simulated data with real-world observations.

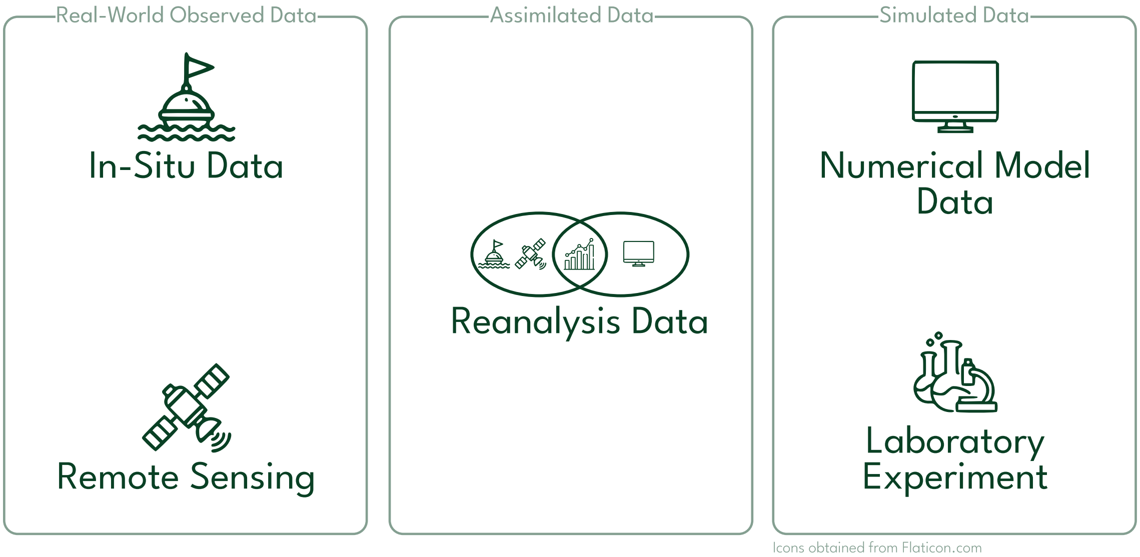


Figure 5 Types of data.

In-situ Data

In-situ data refers to measurements collected directly from the natural environment using various instruments and sensors. Devices used for acquiring in-situ data include wave-buoys, tide gauges, weather stations, and oceanographic vessels. In-situ measurements are highly accurate and reliable and are often considered ground truth data against which other types of data are validated (Feng et al., 2020; Shao et al., 2024; Yue & Wu, 2024).

Nevertheless, they face several challenges. The most notable challenge is their restricted spatial coverage, which does not capture the details of ocean processes across larger areas and is only representative of wave conditions at their specific locations (P. Han et al., 2023; N. Wang et al., 2023). This limitation is compounded by the high costs associated with purchasing, deploying and maintaining in-situ devices, which makes establishing dense measurement networks impractical (Bai et al., 2022; Govindan et al., 2011).

Data quality and continuity present additional challenges. In-situ devices are vulnerable to harsh ocean environments and can experience measurement problems during severe weather, maintenance periods, or navigation incidents (Rao & Mandal, 2005). This results in data gaps that may limit their usefulness as training data.

These factors necessitate the use of data borne from other complementary technologies such as remote sensing and numerical models.

Remote Sensing

Remote sensing data is obtained through satellite and aerial platforms, offering a bird's-eye view of atmospheric and oceanic conditions. They provide extensive spatial coverage and synoptic views that far exceed the capabilities of point-based in-situ measurements (Fang et al., 2024). Satellites can consistently collect data across vast ocean regions, including remote areas where deploying in-situ data collection devices would be impractical (Ardhuin et al., 2024). Remote sensing data enables climate-related research, particularly sea level rise, to be examined extensively on spatial and temporal scales (Ahmad Affandi et al., 2024). Moreover, combining remote sensing data with in-situ data provides a more comprehensive sea condition assessment (Tapoglou et al., 2021).

Whilst remote sensing data offers broad coverage, it is generally considered less accurate than in-situ measurements (Yu et al., 2024) as they do not directly measure the physical variable of interest but infer them from proxies, which can introduce errors and uncertainties (Paciorek & Liu, 2009). As such, they are normally validated against in-situ measurements. Furthermore, this category of data is subject to random, environmental, and representative errors, arising from sensor limitations, environmental conditions, and the spatial-temporal differences between remote sensing and in-situ observations (Jiang, 2023)

Numerical Model Simulation

Numerical models are essential sources of metocean data. The volume of data from this category is expected to outpace all other data sources (Overpeck et al., 2011). These models simulate atmospheric and oceanic processes computationally, rather than through physical experiments as done in a laboratory.

Numerical models allow researchers to simulate vast oceanic areas and long-term processes that would be impractical to measure in the field (Bell et al., 2024). These models can be adjusted to incorporate new data, test various scenarios, and integrate multiple data sources, including remote sensing and in-situ data, providing continuous data across time and space (Bell et al., 2024). Additionally, numerical models are used in validating remote sensing data and optimising oceanic observation strategies (Jiang, 2020; K. Zhang et al., 2020).

The considerable computational resources required for traditional numerical simulations can impede real-time applications and scalability, especially for long-term or high-resolution simulations (Saviz Naeini & Snaiki, 2024). Furthermore, model accuracy heavily depends on the parameterisation of physical processes and the quality of forcing fields. This becomes particularly challenging in coastal environments, where complex shorelines, local wind seas, and bottom friction complicate model adaptation across different regions (Alday et al., 2022). Numerical mixing, an artefact of advection discretisation, poses problems in estuarine and coastal models, potentially overestimation mixing processes in areas with sharp, energetic fronts (Schlichting et al., 2023).

Reanalysis Data

Reanalysis data, such as the Climate Forecast System Reanalysis, is a combination of two types of data: observational data from the environment, such as in-situ and satellite data, and numerical model simulation data (Overpeck et al., 2011). The data are combined through a data assimilation process where observations are integrated into numerical models to improve the predictions of these models. Reanalysis data often cover long periods and are essential data sources in climate research because they offer detailed and comprehensive insights into how the climate system has evolved (Overpeck et al., 2011). Their high spatial and temporal resolution capabilities allow researchers to detect fine-scale ocean features like mesoscale eddies (Korabel et al., 2023).

Model and data assimilation errors present significant challenges, with some reanalysis data showing regional biases (Rahman & Rahaman, 2024). Additionally, this category of data tends to struggle with extreme event prediction (Mcilvenny et al., 2023). Resolution constraints and physical model limitations can impair the accurate representation of oceanic processes. While certain assimilation techniques help reduce biases, they may still introduce inconsistencies with independent data due to insufficient model physics and resolution (Fujii et al., 2023). Moreover, the choice of data assimilation scheme significantly impacts performance, leading to varying levels of accuracy in representing oceanic processes, as evidenced by mixed performance in seasonal excitation budgets (Börger et al., 2023).

Laboratory Experiments

Controlled laboratory experiments, such as those conducted by Liu et al. (2022), generate high-resolution data essential for modelling metocean variables. These experiments offer notable advantages in ocean research through their controlled environments and high-precision measurements. Researchers can isolate specific variables and study them without external interference, achieving resolution levels that would be impossible in field studies (Galmiche et al., 2007). Additionally, lab experiments provide valuable benchmarks for calibrating and validating numerical models, especially in scenarios where field data is sparse or incomplete (McClimans & Johannessen, 1998).

The primary challenge of laboratory experiments is the lack of realism. Lab conditions often fail to capture the full complexity of natural marine environments (Favretto-Cristini et al., 2019). This simplification, while necessary for controlled study, can lead to discrepancies when results are extrapolated to real-world scenarios. Scale limitations are an added challenge. Reduced-scale models may not adequately represent all dynamics present in larger systems, potentially introducing errors when findings are scaled up to full-size applications (Favretto-Cristini et al., 2019)

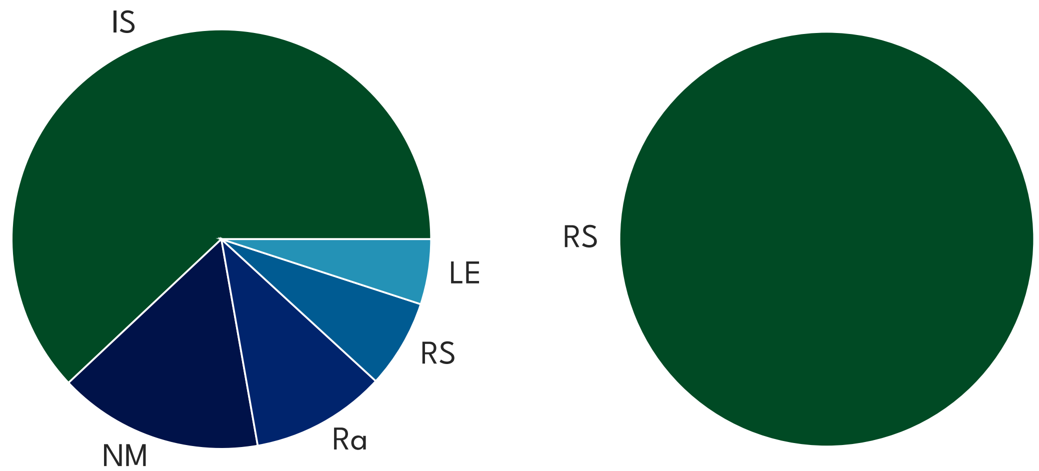
Distribution Analysis of Data Types

In-situ measurements were the most frequently used data category, utilised in 62.4% of the eligible studies, followed by numerical model simulations (15.8%), reanalysis data (10.0%), remote sensing data (6.8%), and laboratory experiments (5.0%) (Figure 6a).

The preference for data types varied across different study domains. In tide prediction studies, in-situ data were the predominant category by a vast margin (97.1%) (Figure 6c). Remote sensing was used to estimate tides in regions without tidal gauges (Alarcon, 2019), while reanalysis data provided meteorological information (X. Zhang et al., 2023).

SLA studies relied on only remote sensing data (Figure 6b) while wave studies, in contrast, utilised a diverse range of data sources, drawing from all five identified categories (Figure 6d). In-situ measurements were the primary choice, appearing in 53.2% of wave studies, while numerical model simulations (21.9%) and reanalysis data (13.4%) also played significant roles. Laboratory experiments (7.0%) and remote sensing data (4.5%) were used less frequently. This broader distribution of data types suggests that wave studies benefit from complementary data types to capture the complex nature of wave behaviour.

(a) (b)



(c) (d)

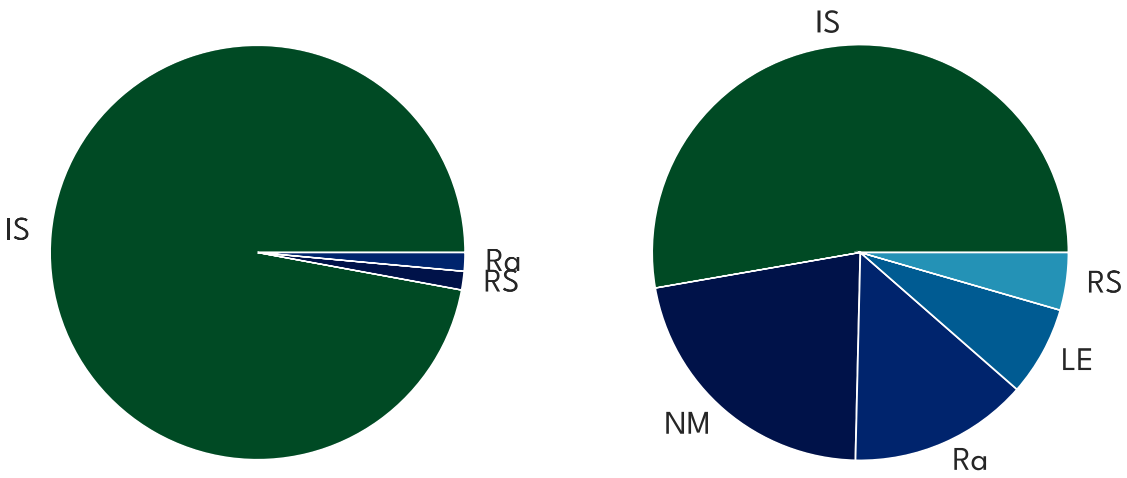


Figure 6 Distribution of data types used. (a) Overall distribution, (b) Distribution for SLAs studies, (c) Distribution for tide studies, and (d) Distribution for wave studies. IS = In-situ, NM = Numerical Models, Ra = Reanalysis, RS = Remote Sensing, LE = Lab Experiments.

4.3 Input Features and Data Characteristics

This section presents a detailed analysis of features used in AI-based forecasting of SLA, tides, and wave dynamics. Features are the data variables fed into AI models to predict specified outcomes, such as tidal levels or wave heights. This analysis examines the frequency of these variables across studies, identifying the most used features for each forecasting target. However, in several cases, obtaining a complete list of features was challenging, as some studies use broad terms, such as “wave set-up data” or “wave run-up data” (Iuppa et al., 2021), without specifying the individual variables included.

In addition to features, the section analyses the spatial and temporal resolutions adopted in these studies. Notably, a significant proportion of studies do not explicitly state their temporal resolution. Likewise, among the few that use spatial data, only a small number reported their spatial resolution.

4.3.1 Sea Level Anomaly Input Features

Three climate features were used in forecasting SLA across studies, with SLA data serving as the main input feature (Figure 7). More than 70% of studies used SLA data from Archival Verification and Interpretation of Satellite Oceanographic Data (AVISO), a French altimetric data distribution service managed by the Centre National d'Etudes Spatiales (CNES).

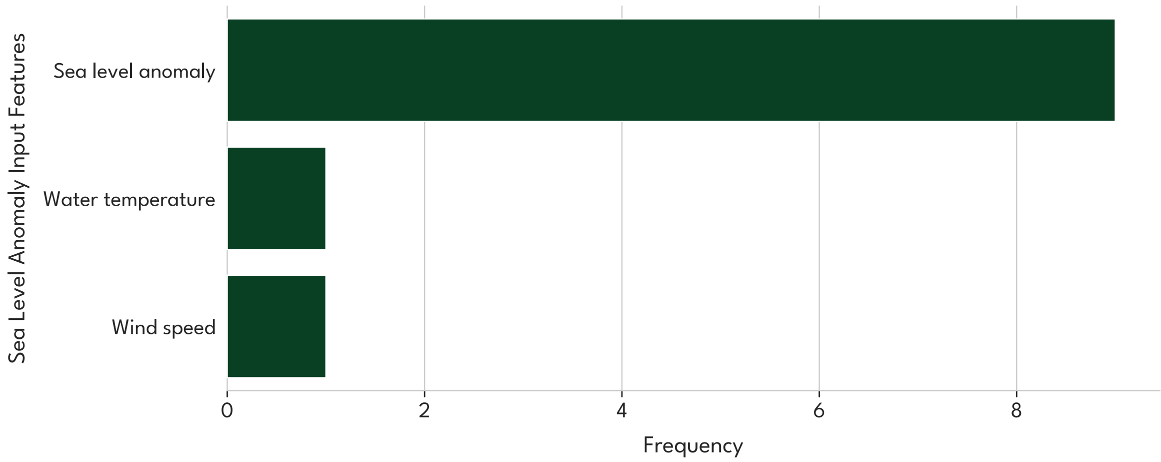


Figure 7 Input Parameters for SLAs forecasting models.

Input Data Characteristics

The length of data records ranged from 15 years (Imani et al., 2013) to 26 years (G. Wang et al., 2022), with a median of 23 years and a mean of 22 years, indicating a need for long-term data records to capture the full range of sea level variations and patterns.

The temporal resolution of SLA data varied significantly, ranging from 1 hour to 720 hours (30 days), with a median of 168 hours and a mean of 197.6 hours.

Among studies that explicitly reported spatial resolution, the most common value was 0.25° × 0.25°, which was expressed in different formats such as "1/4° × 1/4°" and "25 km".

4.3.2 Tidal Level Input Features

A total of 36 distinct features were identified for tide-focused studies (Figure 8). Among these, observed tidal levels emerged as the most frequently used parameter. It was often represented with time lags, incorporating both current and past tidal levels. Some studies used HA or wavelet analysis to decompose tidal components (B.-F. Chen et al., 2007; Filippo et al., 2012; T.-L. Lee, 2004), while others included the residuals (differences between observed and predicted tidal levels) to improve model accuracy (X. Wang et al., 2020; J.-C. Yin et al., 2015; Z.-G. Zhang et al., 2018).

There is a consensus among tide studies that the astronomical component of tides is effectively predicted using HA, with discrepancies between HA predictions and observed tidal levels attributed to meteorological influences. Consequently, meteorological variables were integrated into AI models to capture the tidal level variations not caused by astronomical factors. These include wind-related factors like wind speed and direction, as well as atmospheric conditions such as atmospheric pressure and air temperature. Additionally, typhoon-specific parameters, such as typhoon speed, pressure, coordinates, and distance from observation points, were incorporated to model the effects of extreme weather events on tides, commonly referred to as storm tides.

A few studies incorporated astronomical factors such as the moon-earth distance, solar declination, and lunar azimuth angle, alongside oceanographic variables such as SLA. Rainfall and cumulative rainfall were also included as key parameters, as well as a time feature, which is important given that it correlates with tidal forces.

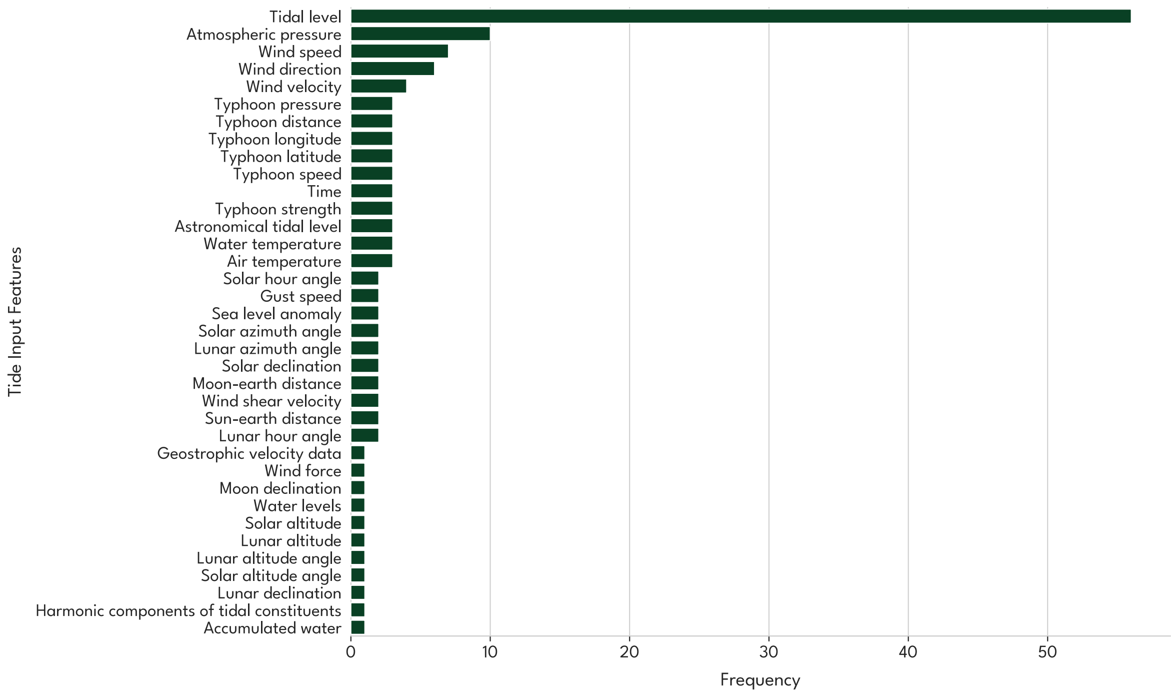


Figure 8 Input Parameters for tidal level forecasting models.

Input Data Characteristics

The data lengths used in tidal-level forecasting studies range from 7 days (Z. Zhang et al., 2016) to 38 years (X. Zhang et al., 2023), with a median of 219.5 days and a mean of 2.4 years. Shorter data durations were often employed to demonstrate that AI models require less data than HA to accurately forecast tidal levels. Notably, a few studies used exceptionally extensive datasets over 20 years. For example, Shahabi & Tahvildari (2024) and C.-Hong. Yang et al. 2020 (2020) used datasets exceeding 20 years, while the dataset used by X. Zhang et al. (2023) exceeded 38 years.

Temporal resolutions spanned from 1 minute (Meena & Agrawal, 2015) to 10 days (Rizkina et al., 2019), with a median of 1 hour and a mean of 5.8 hours. For temporal resolution, 72.4% of the datasets had an interval of one hour. 18.6% featured finer resolutions, such as 15 and 30-minute intervals (Deo & Chaudhari, 1998). The remaining datasets had coarser resolutions of 3 (1.7%), 6 (1.7%), 24 hours (3.4%) and 10 days (1.7%), often derived as averages of hourly tidal levels.

Spatial resolution is typically not needed in tide studies as tidal data come from tide gauges. Reported resolutions usually refer to climate data, such as meteorological data (0.30°, 0.205°, 0.1°, 0.25°) (Shahabi & Tahvildari, 2024; X. Zhang et al., 2023) or sea surface height (0.25°) (Alarcon, 2019).

4.3.3 Waves Characteristics Input Parameters

Unlike SLA and tidal studies, which primarily water level variation, wave studies have explored multiple wave dynamics in their forecasting efforts. Fourteen wave dynamics were identified.

It is important to note that not all parameters identified as forecasted in wave studies are inherent characteristics of waves. Some represent the impacts or effects of waves on coastal environments. These parameters have been included in the analysis because the broader research focus is on understanding and forecasting ECWLs, where waves play a significant role.

These dynamics are categorised into three groups: Wave Characteristics (WC), which describe the primary physical properties of waves, including size, timing, direction, and shape; Wave Energy Metrics, which pertain to the energy carried by waves and their potential for power generation; and Coastal Impacts, which examine how waves interact with the coastline.

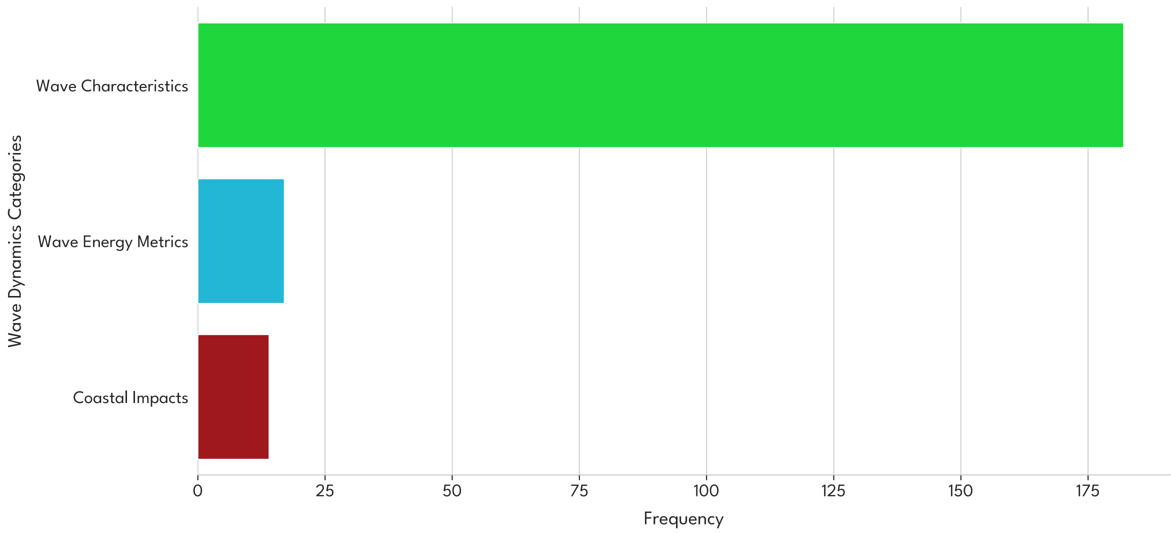


Figure 9 Distribution of wave dynamic categories.

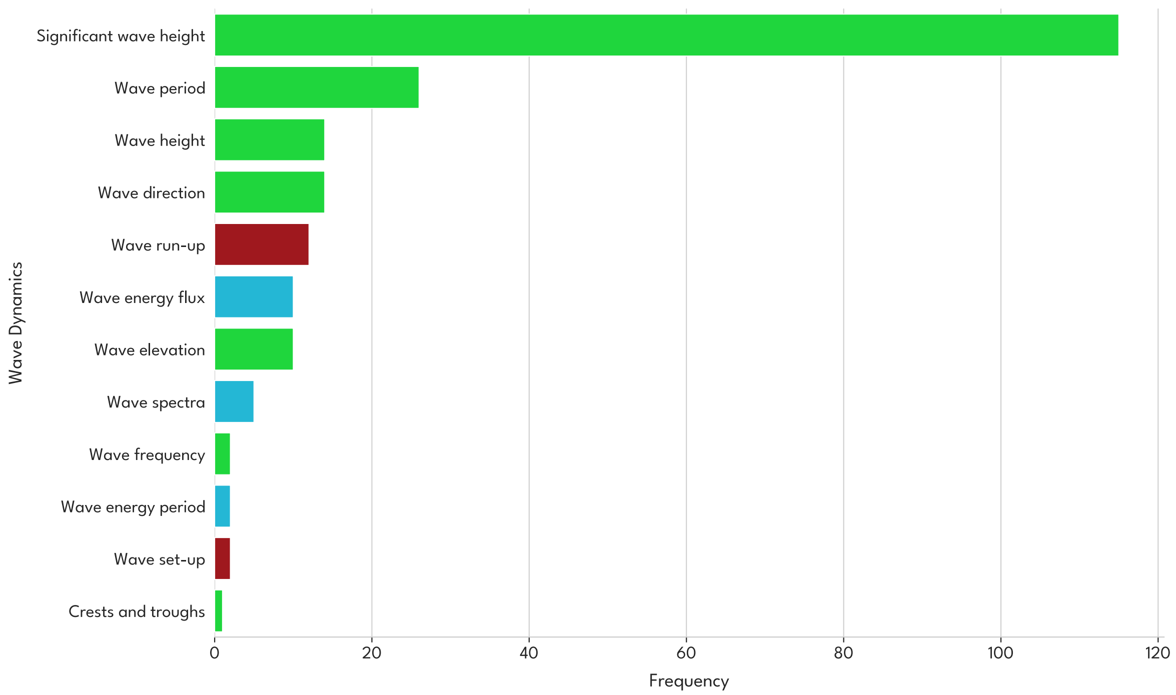


Figure 10 Wave dynamics forecasted in research studies.

Figure 9 and Figure 10 illustrate the frequency distribution of wave dynamics categories and individual wave dynamics, respectively. WC dominated the other two categories by a significant margin, accounting for 85.4 % of all forecasted wave dynamics. Among these, SWH was the most prominent, representing 63.2 % of WC and 54% of all forecasted wave dynamics. Wave Energy Metrics and Coastal Impacts followed, accounting for 8% and 6.6%, respectively.

This subsection provides a detailed analysis of input data and its characteristics, examining the frequency of input features, their attributes, and their sources for each wave dynamic (Figure 10).

Significant Wave Height

SWH is the most important wave parameter, defined as the average height of the highest one-third of waves in a given sea state. SWH forecasts take various forms, including general height forecasts over time, peak values (Nitsure et al., 2012), maximum values (Sinha et al., 2023; H. Wu et al., 2024), monthly averages (H. Wang et al., 2019), and space-time series (J. Kim et al., 2022). While most AI models forecast in-situ measurements, some studies use AI to forecast SWH values produced by numerical models (James et al., 2018; Kordatos et al., 2024).

Input Features

In total, 60 distinct features were used in forecasting SWH (Figure 11). Researchers have explored various approaches, with one study even using seismic data to estimate SWH (Donne et al., 2014). Notably, SWH itself was the most often used feature in its forecasting. SWH input time lags ranged from the earlier hour to the past seven days. One study incorporated statistical values of SWH as inputs (Penalba et al., 2022). In some cases, SWH was decomposed using methods such as wavelet analysis and empirical decomposition techniques (Ji et al., 2023; Lv et al., 2023; Tan et al., 2022). Other commonly used wave features included wave period, wave height, and wave direction, which were incorporated in various forms such as mean wave period, dominant wave period, peak wave period, zero-up crossing wave period, and peak wave height.

Wind-related variables, including wind speed, wind direction, and wind velocity, are prominently used as input features, highlighting the influence of atmospheric conditions on wave formation and dynamics. In some cases, numerical models were used to forecast these wind variables instead of relying on historical data. Additionally, other metocean factors, including atmospheric pressure and water and air temperature, are also key contributors.

Less frequently used input features include bathymetric and seafloor characteristics, such as seafloor slope and sandbank morphology, as well as typhoon attributes like typhoon speed and radius. Wave energy features, including wave power flux and wave energy flux, also appear occasionally. This is because studies that incorporate these energy-related features often forecast SWH alongside wave power or wave energy.

Temporal variables, including the day of the year, weather season, date, and hour, emphasise the consideration of time-dependent factors in the studies.

Figure 12 displays the data types for wave height forecasting. Notably, lab experiments are not included.

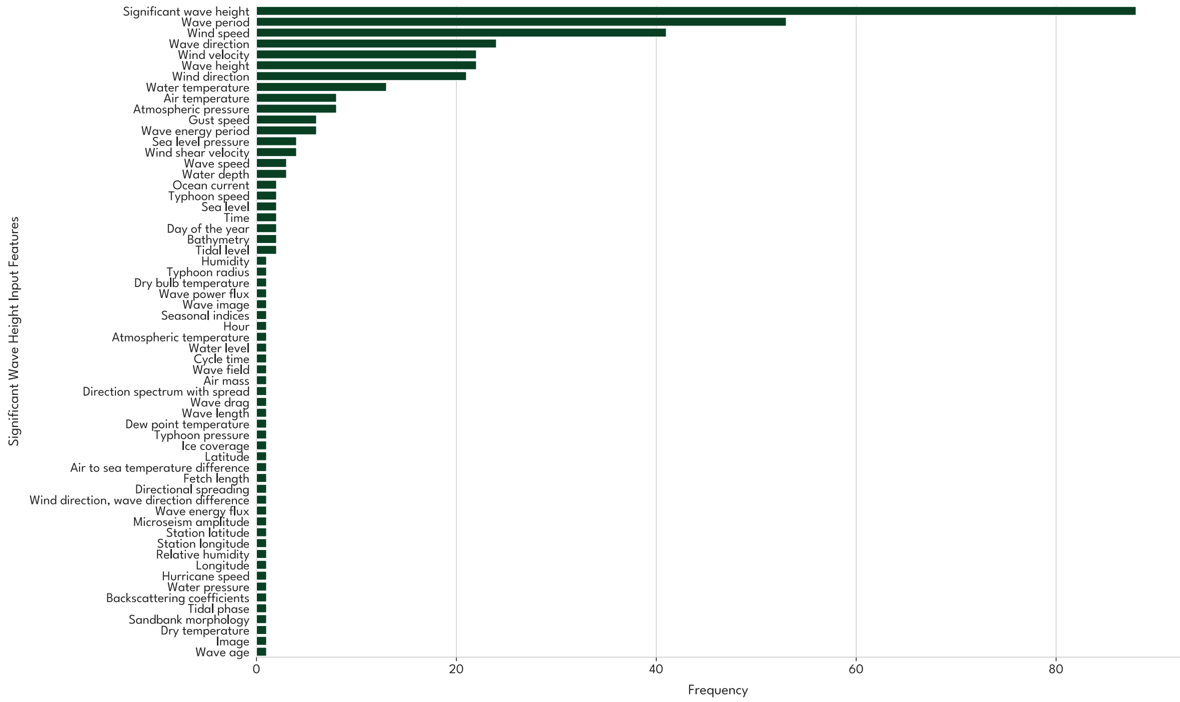


Figure 11 Input parameters used in significant wave height forecasting models.

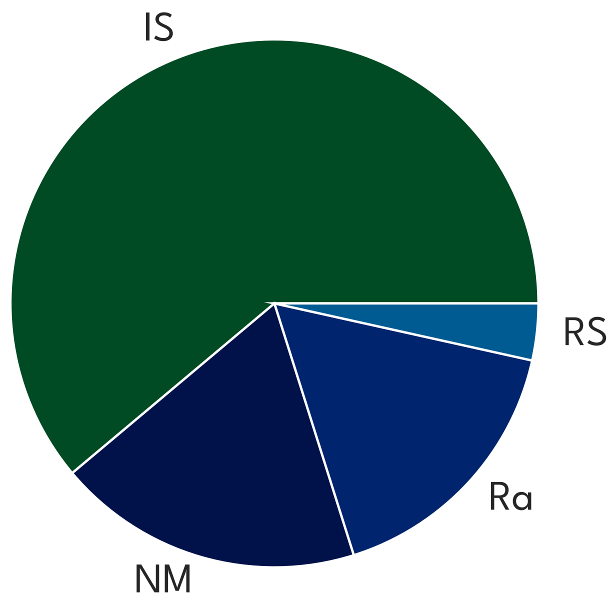


Figure 12 Data types for significant wave height forecasting.

Input Data Characteristics

The data coverage period for SWH forecasting datasets ranges from 18 days (Deo et al., 2001) to 62 years (Penalba et al., 2022), with a median duration of 3 years and a mean of 7 years.

The temporal resolution of datasets used in SWH forecasting ranged from 1.43 seconds (Kwon et al., 2023) to 7 days (Deo et al., 2001), with a median of 1 hour and an average of 3.4 hours. 52.4% of datasets had a resolution of 1 hour, while 18.1% featured finer resolutions of less than 1 hour. Coarser resolutions are less common, with 17.1% at 3 hours, 10.5% at 6 hours, and only 1% each at 12 hours and 168 hours. These coarser resolutions are typically derived as averages of hourly data.

The spatial resolution of datasets used in SWH forecasting varied widely depending on the data source and measurement approach. Some datasets utilise predefined grid structures, such as the T62 Gaussian grid for wind speed data, which corresponds to approximately 220 km in the u-direction and 280 km in the v-direction (Oh & Suh, 2018). A 2.5° × 2.5° grid is also a commonly used resolution. Higher-resolution datasets include grids with 0.25° × 0.25° and 0.125° (~13.7 km) in both longitude and latitude (M. Wu et al., 2020), as well as a 0.5° × 0.5° resolution (Ahn et al., 2022; J. Kim et al., 2022). Some datasets offer finer resolutions, such as 1 km × 1 km (J. Chen et al., 2021), 5 km × 5 km (Zeng et al., 2022), and 0.1° (Yu et al., 2024). These variations highlight the diversity in dataset granularity, with finer resolutions capturing localised SWH variations, while coarser resolutions provide broader spatial coverage.

Wave Period

Wave period is a critical wave parameter, defined as the time interval between successive wave crests passing a fixed point in the ocean. It is the second most forecasted wave dynamic. Wave period forecasts are provided in various forms, including single representative value or more detailed statistical measures such as mean wave period (Y. Liu et al., 2024; Yu et al., 2024), zero-up crossing wave period (Makarynskyy, 2007), peak wave period (J. Huang et al., 2023), peak spectral wave period (Elbisy, 2015), dominant wave period (Dogan et al., 2021), mean zero-crossing wave period (J. Chen et al., 2021), and mean peak wave period (Iqbal & Mehran, 2023).

Input Parameters

A total of 23 unique input parameters were identified, with wave period being the most frequently used, followed closely by SWH and wave direction. Meteorological factors such as wind velocity, wind speed, and wind direction are also commonly incorporated, emphasising the strong influence of wind forcing on wave dynamics. Additionally, some studies have explored less conventional parameters, including wave energy flux, wave energy period, wave age, ocean currents, and directional spreading.

These input parameters have been utilised in various forms, including weekly wind speed, zero-up crossing wave period, peak wave period, mean energy wave period, forecasted wind speed, decomposed wave periods, decomposed SWH, and dominant wave period.

Figure 14 displays the distribution of data types for wave period forecasting, which closely resembles the data type distribution for SWH (Figure 12).

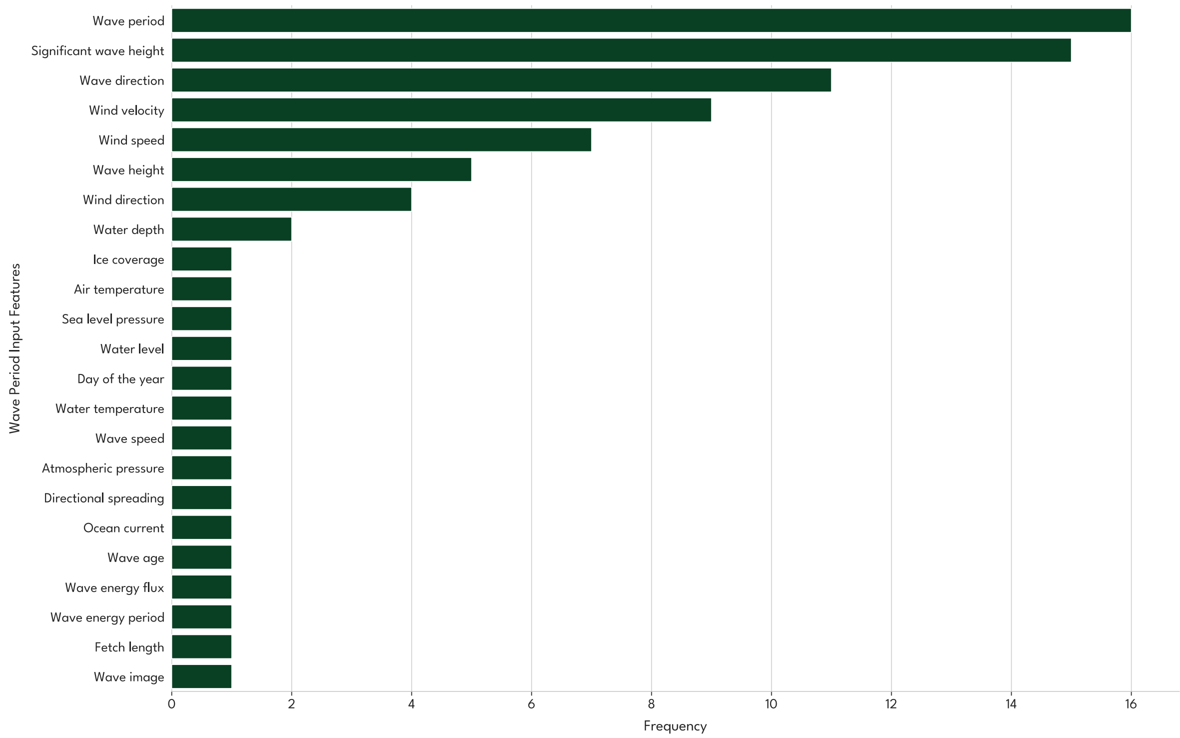


Figure 13 Input parameters used in wave period forecasting models.

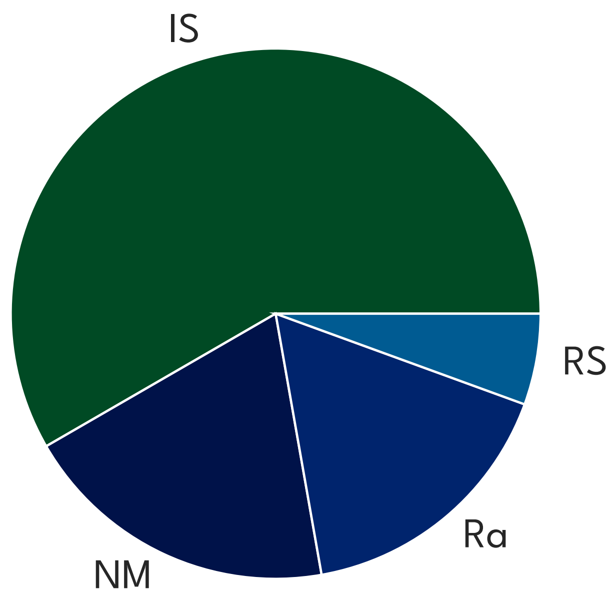


Figure 14 Data types for wave period forecasting.

Input Data Characteristics

The duration of data used in studies ranges from a minimum of 18 days (Deo et al., 2001) to a maximum of 42 years (J. Kim et al., 2022), with a median of 2 years and an average of 5.5 years.

The temporal resolution ranges from 20 minutes (Dogan et al., 2021) to 7 days (Deo et al., 2001). The median resolution is 3 hours, with a mean of 9.3 hours, indicating that most studies rely on sub-daily data granularity. Analysing the distribution of temporal resolutions, 3-hour and 1-hour intervals are the most frequently used, each accounting for 30.8%. These are followed by 6-hour intervals, which make up 19.2% of the datasets. Higher-resolution data sub-hourly datasets account for 11.5%, while coarser resolutions of 12-hour and 168-hour intervals each contribute 3.8%.

Reported spatial resolutions range from as fine as 0.001° (James et al., 2018) to coarser grids of 0.5° × 0.5° (J. Kim et al., 2022). High-resolution datasets include grids of 0.25°, 0.1°, and 0.125° (approximately 13.7 km) in both longitude and latitude, as well as a 3 km grid (James et al., 2018; Yu et al., 2024).

Wave Height

Wave height is defined as the vertical distance between the crest and trough of a wave. It is the third most forecasted characteristic in the reviewed studies. Wave height forecasts take various forms, including predictions of the breaking wave height (Robertson et al., 2015) and low-frequency wave height (Zheng et al., 2020).

Input Parameters

A total of 24 distinct input parameters were identified (Figure 15). Wave height is the most frequently used input feature for forecasting wave heights, followed by wave period and wind speed. Other wind-related factors, such as wind direction and wind velocity, also feature prominently. Additionally, atmospheric pressure, air temperature, and water temperature are commonly used, highlighting the significant influence of atmospheric conditions on wave dynamics.

These input parameters are used in various forms, including weekly mean wind speed, mean wind speed, peak wave period, spatial wind velocity, zero-moment wave height, zero-up crossing wave period, dominant wave period, and mean wave period. Figure 16 displays the data types for wave height forecasting.

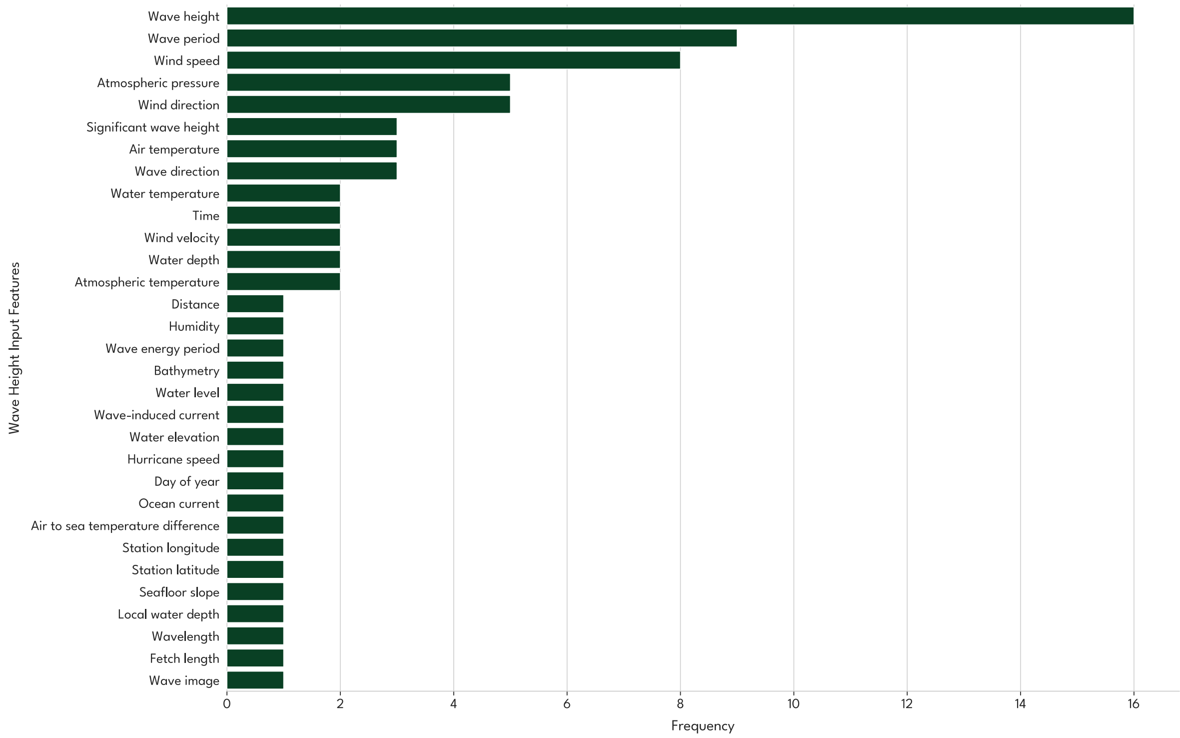


Figure 15 Input parameters for wave height forecasting models.

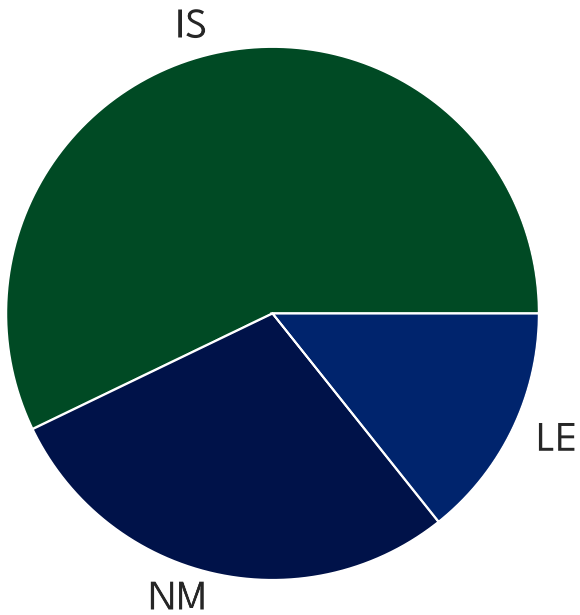


Figure 16 Data types for wave height forecasting.

Input Data Characteristics

Datasets used in wave height forecasting span from a minimum of 47 days (Zheng et al., 2020) to a maximum of 15 years (Upreti et al., 2023), with a median duration of 3 years and an average of 4.5 years.

The temporal resolution of wave height data varies from 10 minutes (Kar et al., 2024) to 6 hours, with a median of 1 hour and an average of 85 minutes. The most used resolution is 1 hour (42.9%), followed by finer resolutions of less than 1 hour (42.9%). Six-hour resolution represents 14.3%.

Wave Direction

Wave direction is defined as the direction from which waves originate, typically measured in degrees, with North as 0° and increasing clockwise (Xie et al., 2015).

Wave direction forecasts take three forms: single representative values, mean wave direction (Dogan et al., 2021; Ouyang et al., 2023), and mean wave direction at peak wave period (Makarynskyy, 2007).

Input Features

A total of 19 distinct input features were identified across wave direction forecasting studies (Figure 17). Wave direction is the most frequently used parameter, followed by wave period and SWH. These inputs were used in various forms, including zero-up crossing, peak, dominant wave period, and mean wave direction.

Meteorological factors, such as wind velocity, wind direction, and wind speed, also contribute to model accuracy as wind plays a significant role in wave generation and propagation.

There is a predominant reliance on core wave parameters, supplemented by wind conditions and occasional environmental factors.

Figure 18 shows that only three data types were used in wave forecasting studies: in-situ measurements, numerical models, and reanalysis datasets.

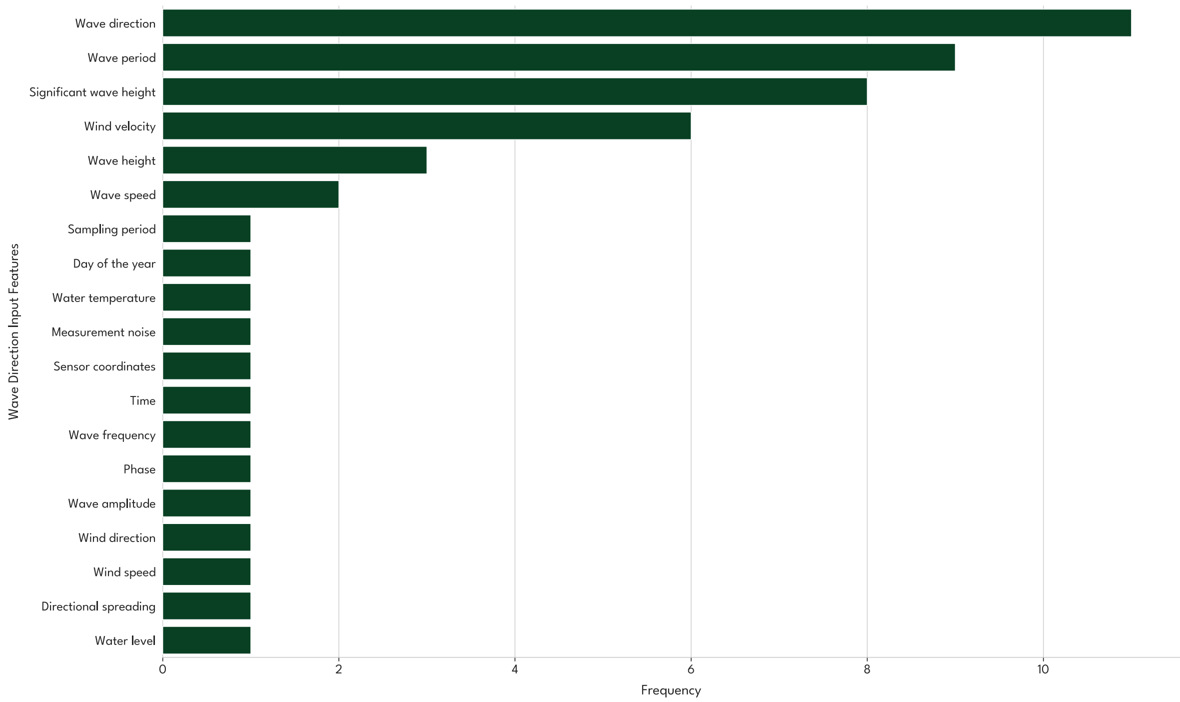


Figure 17 Input parameters for wave direction forecasting models.

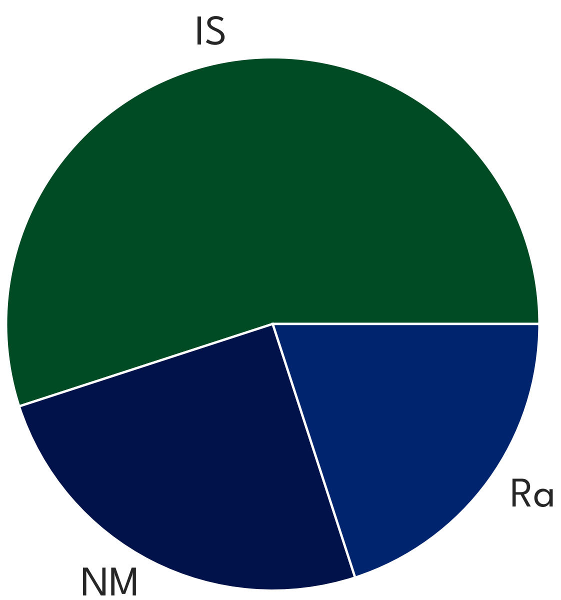


Figure 18 Data types for wave direction forecasting.

Input Data Characteristics

The datasets used across studies range from a minimum of 59 days (Makarynskyy, 2007) to a maximum of 41 years (J. Kim et al., 2022), with a median duration of 3 years and a mean of 13 years.

The temporal resolution for data used for wave direction forecast spans from high-frequency measurements every 12 minutes (Lawal et al., 2024) to half-daily observations (J. Chen et al., 2021). The median resolution is 1 hour, with an average of 2.6 hours. Hourly and sub-hourly resolutions are the most common, each accounting for 30.8% of the datasets, followed by 3-hour and 6-hour resolutions at 15.4% each, and 12-hour resolutions at 7.7%.

Two spatial resolutions were reported: 1 × 1 km^2 (J. Chen et al., 2021) and 0.5° × 0.5° (J. Kim et al., 2022; Y. Liu et al., 2024).

Wave Run-Up

Wave run-up refers to the fluctuating height reached by waves as they move up the shore before receding. Extreme run-up is defined as the elevation that is exceeded by only the highest 2% of wave swash events over a given period (Holman, 1986; Stockdon et al., 2006). Wave run-up has been predicted in single representative values, solitary wave run-up (Wei et al., 2010), and relative wave run-up (Elbisy, 2015; Tarwidi et al., 2023).

Input Features

A total of 38 unique parameters were identified (Figure 19). Unlike other wave dynamics, where the variable being forecasted is also the most frequently used input feature, wave run-up forecasts typically rely on wave height and wave period rather than wave run-up itself as the primary input. Additionally, water depth and the wave height-to-depth ratio influence wave transformation as it approaches the shore.

Other parameters include wave set-up, wave amplitude, and significant wave height, all of which contribute to estimating run-up levels. Some models also incorporate specialised parameters, such as deep-water wave steepness, relative depth, and slope cotangent, to improve accuracy in site-specific conditions.

Figure 20 indicates that wave run-up studies rely exclusively on data from laboratory experiments and numerical models, with no reported use of observational field data.

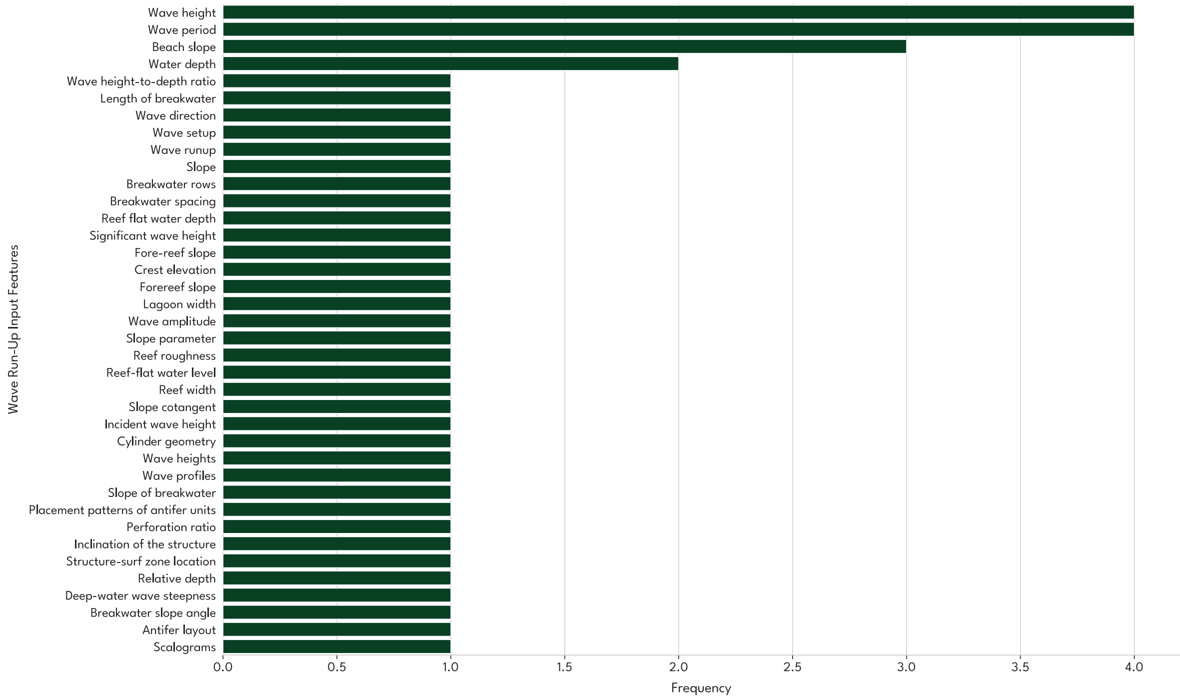


Figure 19 Input parameters for wave run-up forecasting models.

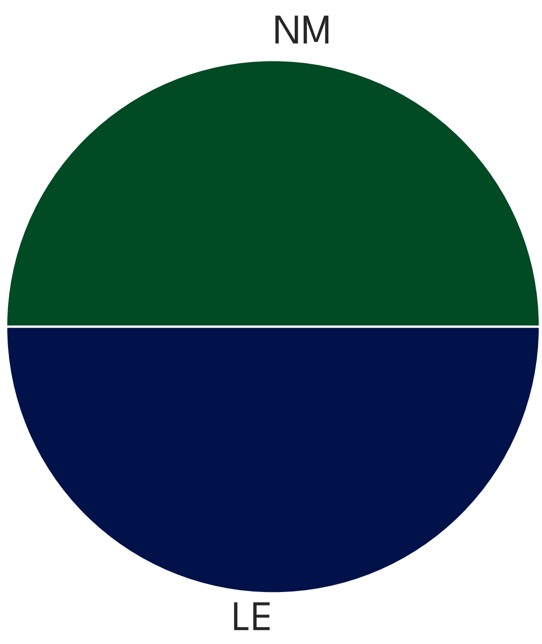


Figure 20 Data types for wave run-up forecasting.

Wave Elevation

Wave elevation is a fundamental concept in ocean studies, but its definition varies depending on the context and application in the literature. Generally, wave elevation refers to the vertical displacement of the water surface from the mean water level at a given point in space and time (Luhar et al., 2010). In the context of wave diffraction by a fixed body, wave elevation can be expressed as a perturbation series, with first and second-order components contributing to the overall free surface elevation (Olivieri & Penna, 1999). Additionally, for applications involving wave measurement, wave elevation is described as a function of position, with the orientation of the water surface and the direction to a measurement device defined in terms of the wave elevation at that local place (Fucile et al., 2016).

Input Features

Across the reviewed studies, four input features were identified for forecasting wave elevation, all of which were wave-related; No meteorological variables were used in these studies (Figure 21).

The primary data types for training wave elevation forecasting models are laboratory experiments and numerical models (Figure 22). In-situ data was used in only one instance (Shi et al., 2018), while remote sensing data was not directly used for training AI models. Instead, it was utilised to set the parameters of a numerical model, which then generated the data for AI model training (R. Li et al., 2023).

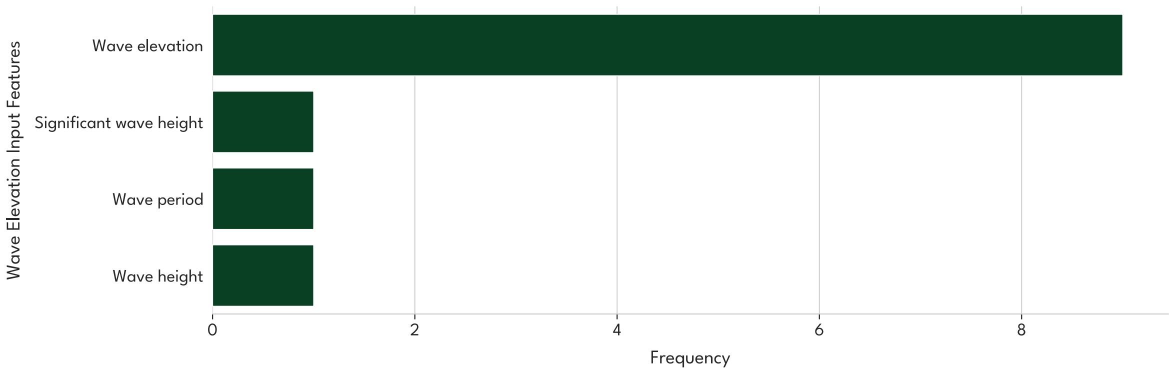


Figure 21 Input parameters for wave elevation forecasting models.

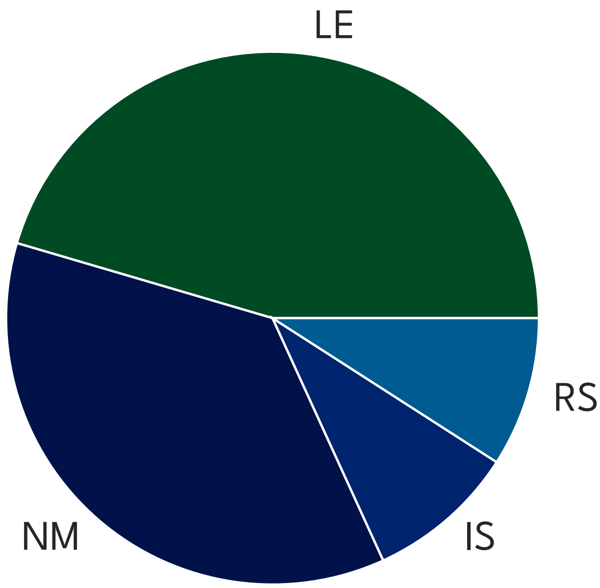


Figure 22 Data types for wave elevation forecasting.

Input Data Characteristics

Only one study provided a data coverage period of 247 days and a temporal resolution of one hour (R. Li et al., 2023).

Wave Energy Flux

Wave energy flux represents the mean rate at which wave energy is transferred through a vertical plane of unit width, oriented parallel to the wave crest (Farrok & Islam, 2024). It is measured in kilowatts per meter (kW/m).

Input Parameters

A total of 17 unique parameters were identified (Figure 23). Similar to wave run-up, the variable being forecasted in wave energy flux studies is not wave energy flux itself. Instead, SWH and wave period are the most frequently used input features, followed by wave energy period and wind speed. SWH and wave period are the most commonly used because wave energy flux is a function of these two parameters. (Ibarra-Berastegi et al., 2015). Less commonly used inputs include wave and wind direction, time of day (hour), and, in rare cases, factors such as gust speed and weather seasons.

Figure 24 illustrates the distribution of data types used in wave energy flux studies. Notably, reanalysis data were used only once, specifically for sea level pressure and wind data (Ibarra-Berastegi et al., 2015).

Wave energy flux forecasting studies relied exclusively on data from in situ devices, reanalysis datasets, and numerical models (Figure 24).

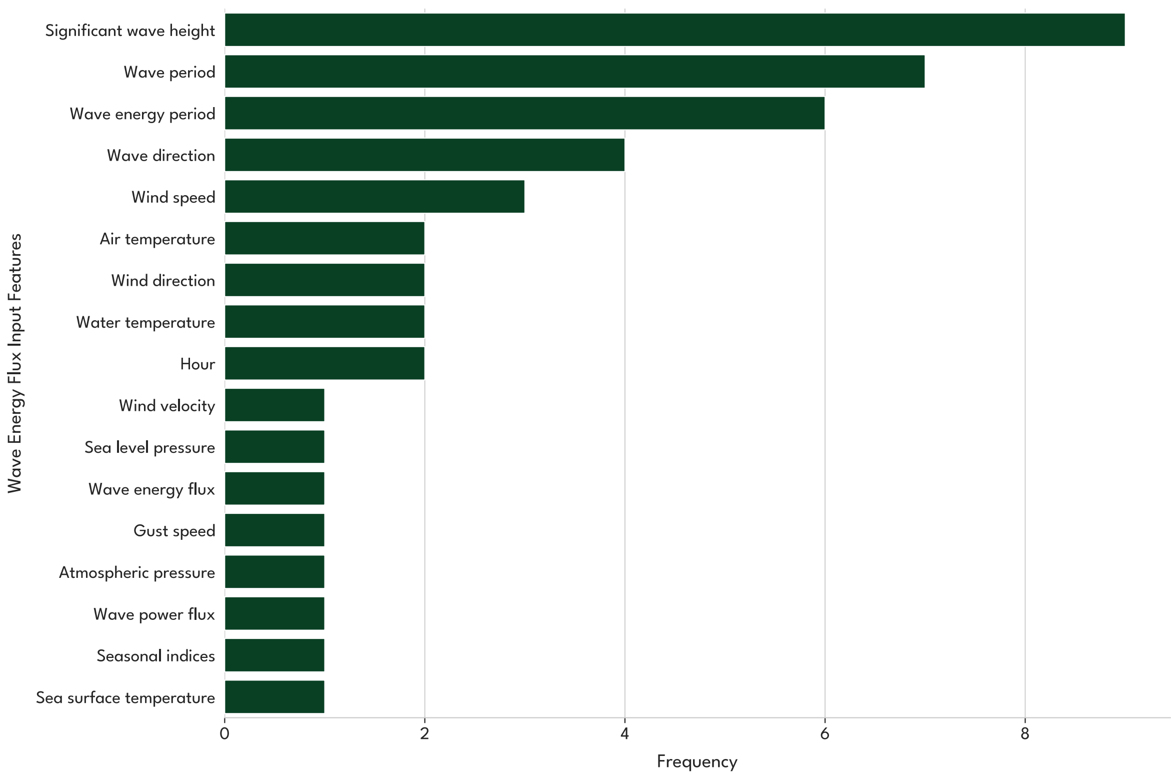


Figure 23 Input parameters for wave energy flux forecasting models.

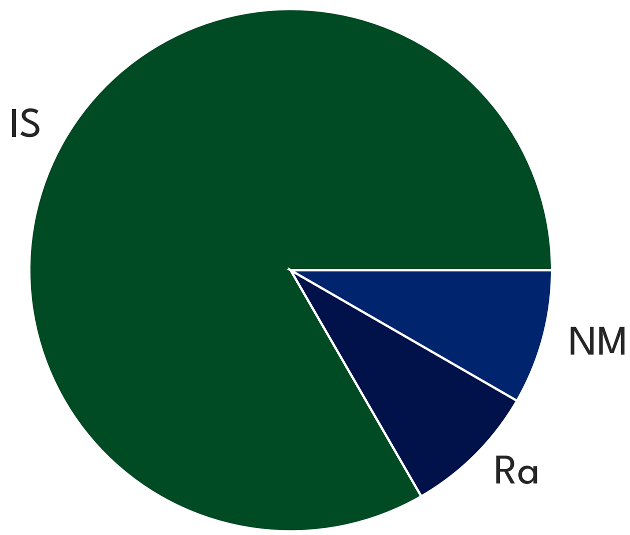


Figure 24 Data types for wave energy flux forecasting.

Input Data Characteristics

The datasets spanned from 1 year to 40 years (Pirhooshyaran & Snyder, 2020), with a median of 2 years and a mean of 7.4 years. Reported temporal resolutions included 1-hour, which accounted for 88.9%, and 6-hour, which accounted for 11.1%.

Wave Spectra

An ocean wave spectrum represents the distribution of wave energy across different frequencies and directions, forming energy clusters known as wave systems. These systems can originate from local wind forcing (wind sea) or distant meteorological events (swell), with distinct spectral characteristics (Portilla-Yandún et al., 2016)

Input Features

Six distinct input parameters were identified (Figure 25). The most used are wave spectra and wind velocity. Other inputs, used in single studies, include acceleration data, water level, wave height, and wave images.

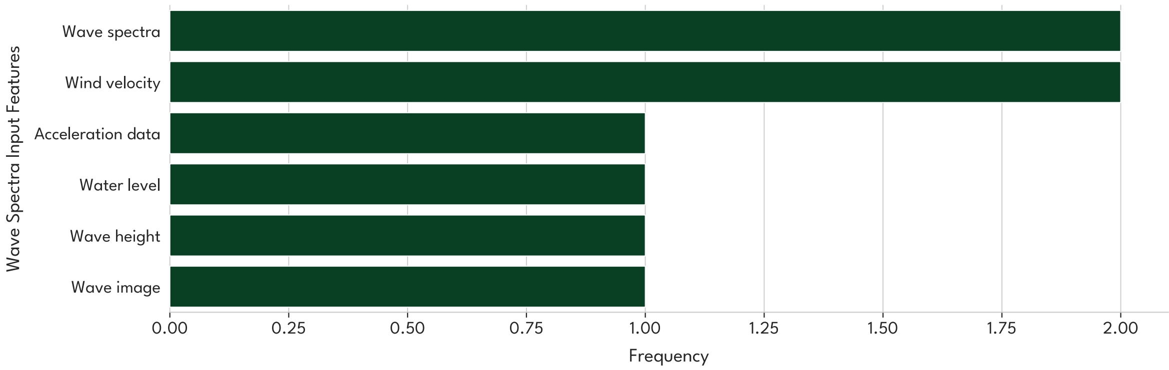


Figure 25 Input parameters for wave spectra forecasting models.

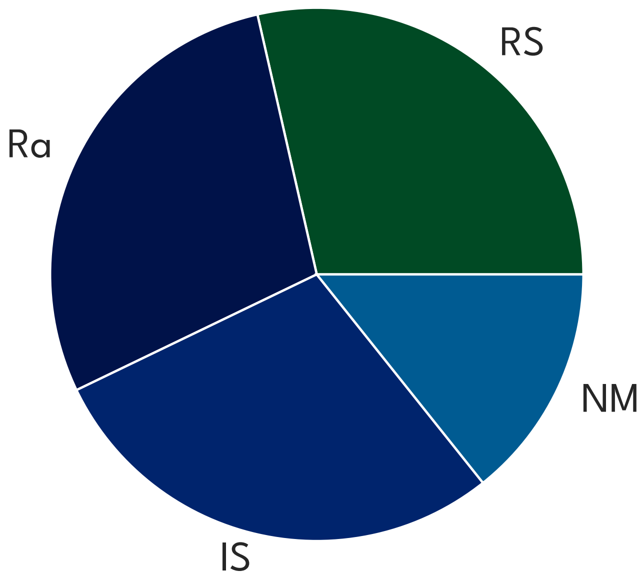


Figure 26 Data types for wave spectra forecasting.

Input Data Characteristics

The data coverage period for wave spectra studies ranges from 30 days (X. Y. Zhang et al., 2014) to 5 years (Fang et al., 2024). The median duration is 76 days, while the mean is 1.25 years. Reported temporal resolutions were 1 hour (N. Wang et al., 2023) and 3 hours (Fang et al., 2024). The only spatial resolution reported was for the synthetic aperture radar (SAR) data, which had a spatial resolution of 5 meters in the azimuth direction and 3.4 meters in the range direction (Fang et al., 2024).

Wave Frequency

Wave frequency refers to the number of wave crests that pass a fixed point within a given time, typically measured in cycles per second (Hertz), and is the inverse of the wave period.

Input Features

Ten input features were identified, with wave direction being the most frequently used (Figure 27). Numerical simulations were the only type of data used in wave energy forecasting (Figure 28)

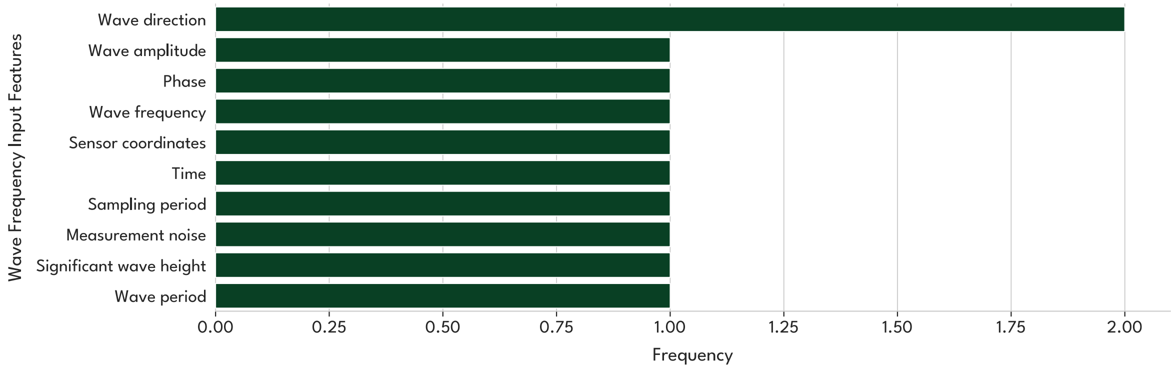


Figure 27 Input parameters for wave frequency forecasting models.

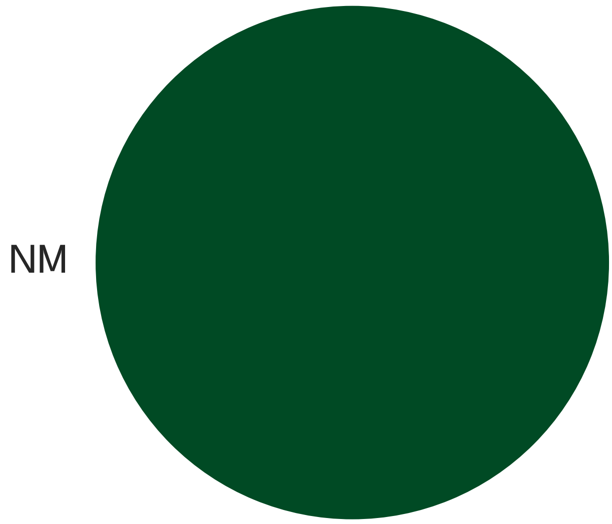


Figure 28 Data types for wave frequency forecasting.

Wave Energy Period

The wave energy period is defined as the ratio of the first negative moment of the wave spectrum to the zeroth moment of the spectrum. This parameter is particularly useful in wave energy calculations, as it characterises the distribution of wave energy across different frequencies (Folley, 2017).

Input Features

Eight unique input features were identified, with wave period being the most used feature (Figure 29). Wave energy period studies only used in-situ measurements for training the AI models (Figure 30).

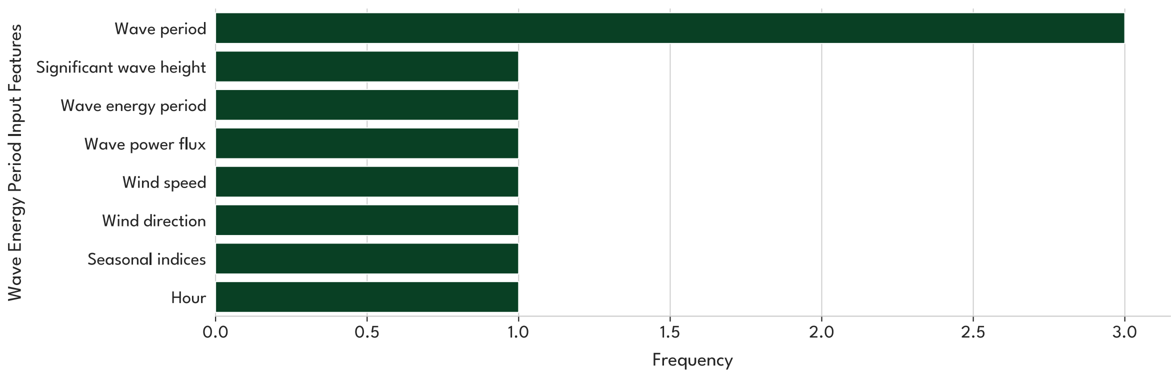


Figure 29 Input parameters for wave energy period forecasting models.

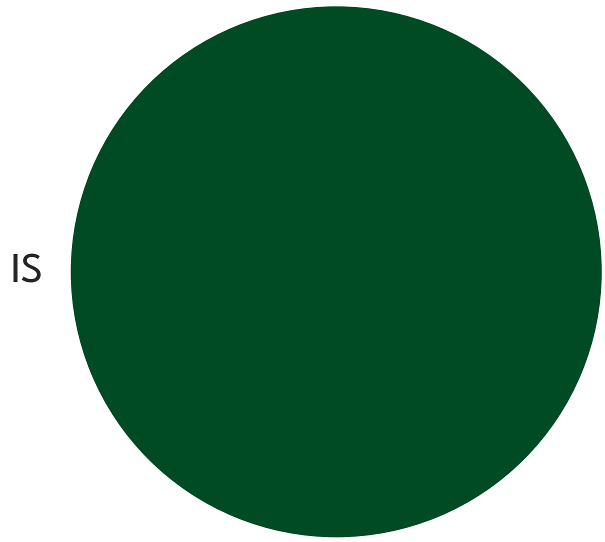


Figure 30 Data types for wave energy period forecasting.

Input Data Characteristics

One study reported a data coverage period of 6 years (Ali et al., 2021). Reported temporal resolutions were 30 minutes (Ali et al., 2021) and 1 hour (Bento et al., 2021).

Wave Set-up

Wave set-up is the increase in the mean water level within the surf zone caused by the transfer of momentum from breaking waves (Gourlay, 2011). As waves break and dissipate energy, the reduction in wave thrust results in a shoreward increase in water level. This setup contributes to coastal flooding and influences nearshore currents.

Input Features

Seven unique input features were identified across the reviewed studies, with each being used only once (Figure 31).

Wave set-up studies only used numerical models for training the AI models (Figure 32).

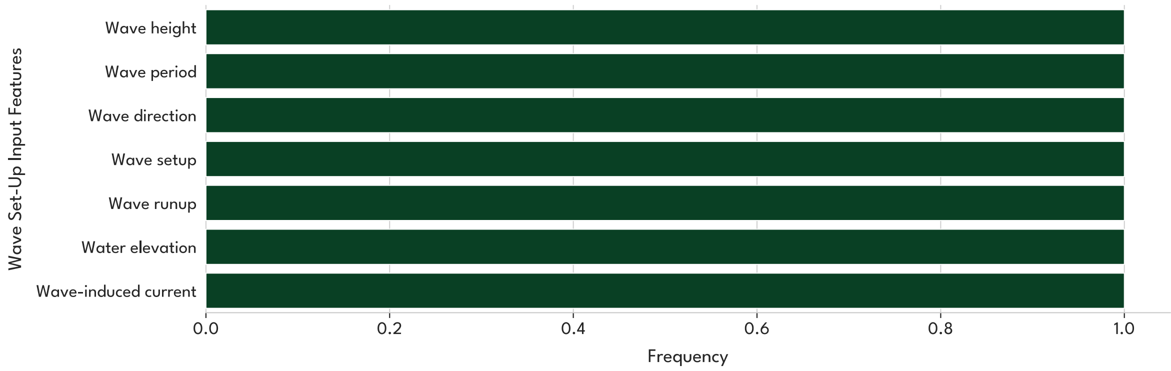


Figure 31 Input parameters for wave set-up forecasting models.

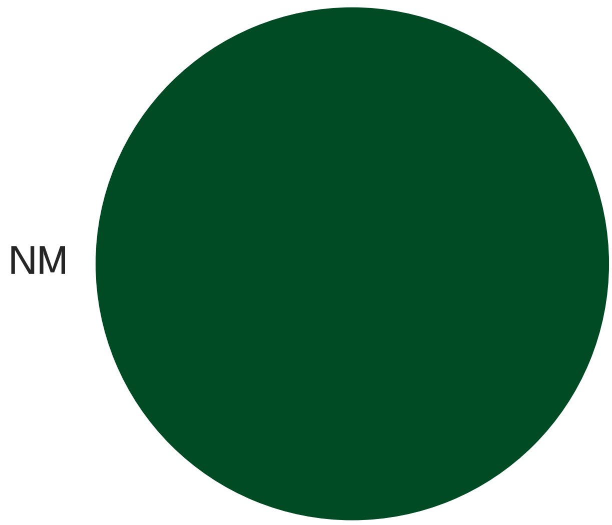


Figure 32 Data types for wave set-up forecasting.

Wave Crests and Troughs

A crest is the highest point of an ocean wave, representing the maximum upward displacement of the water surface, while a trough is the lowest point, representing the maximum downward displacement. These two points define the vertical range of a wave, with wave height being the vertical distance between the crest and the trough.

Input Features

The input parameters were slow-varying amplitudes derived from lab experiments. The in-situ measurements used in the study served to fit the wave model, which then provided the processed amplitudes as inputs to the AI model (Breunung & Balachandran, 2023).

Input Data Characteristics

The reported data duration was 389 days (Breunung & Balachandran, 2023).

4.4 Pre-processing Techniques for AI-Based Forecasting of Sea Level Anomaly, Waves, and Tidal Levels

Accurate AI-based forecasting of SLA, waves, and tidal levels relies on effective pre-processing techniques to enhance data quality, remove noise, and extract meaningful patterns. These methods are necessary for optimising AI algorithms by ensuring clean, consistent, and well-structured input data (Bala & Behal, 2024; García et al., 2015). While some pre-processing approaches are broadly applied across all three focus areas, others are specific to one or two focus areas (Figure 33).

Data pre-processing is so integral to AI-based forecasting that it is sometimes presented as a core component of the AI model itself. Some studies propose AI frameworks where pre-processing plays a fundamental role alongside the forecasting algorithm. For instance, in the MVMD-BXGB-CFNN model, CFNN is responsible for forecasting, while MVMD and BXGB handle preprocessing (Jamei et al., 2022). Similarly, CEEMDAN-LSTM (L. Zhao et al., 2023), EEMD-LSTM (G. Wang et al., 2022), and SVD-Fuzzy (Çelik, 2022) integrate pre-processing as a crucial component. These are often termed "improved" or "hybrid" models because they outperform traditional approaches that lack pre-processing.

Given the diverse role of preprocessing in AI forecasting, this section categorises these techniques based on their application in AI-driven wave, tide, and SLA studies.

Pre-processing	Sea Level Anomaly	Tidal Level	Wave Dynamics
Normalisation & Standardisation	✓	✓	✓
Decomposition	✓	✓	✓
Chronological Data Splitting	✓	✓	✓
Determining Relevant Input Lags	✓	✓	✓
Resampling	✓	✓	✓
Feature Selection	✓	✓	✓
Addressing Data Gaps		✓	✓
Location Data Splitting		✓	✓
Stationarity Testing		✓	✓
Outlier Removal		✓	✓
Wind Data Processing		✓	✓
Seasonal Data Division		✓	✓
Signal Filtering		✓	✓
Frequency Domain Analysis		✓	✓
Sliding Window	✓	✓	
Calculation of SLA and Correction of Satellite Altimetry Data	✓		
Periodic Component Extraction	✓		
Tidal Data Refinement		✓	
Period Analysis		✓	
Adaptive Temporal Segmentation		✓	
Condition-Based Data Filtering			✓
Binocular Image Processing			✓
Synthetic Aperture Rader Image Processing			✓
Continuous Variable Categorisation			✓
Encoding Seasonal Patterns			✓
Data Assimilation			✓
Wave Energy Calculations			✓
Temporal Sampling			✓
Integrating Ice and Bathymetry Data			✓
Addressing Data Imbalance			✓

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Figure 33 Pre-processing methods identified in reviewed studies.

4.4.1 Wave, Tide, and Sea Level Anomaly Studies

Normalisation and Standardisation

Data normalisation and standardisation are essential pre-processing techniques that scale data to a standard range, typically between -1 and 1 or 0 and 1. These methods enhance comparability between variables, improve the learning efficiency of deep neural networks, and ensure more consistent performance during training. As a result, they contribute to greater accuracy and reliability in predictions. Various normalisation approaches have been successfully utilised in the reviewed studies. Common methods include Min-Max normalisation, z-score standardisation, zero-mean standardisation, and domain-specific methods that account for the natural range of oceanographic variables (L. Huang, 2022; Kar et al., 2024; Su & Jiang, 2023; Supharatid, 2003; G. Wang et al., 2022).

Decomposition

Decomposing data involves breaking it into simpler components to reveal underlying patterns. In oceanographic studies, this often means separating time series data into intrinsic mode functions (IMFs), which capture distinct frequency components for AI models. This enhances model performance by isolating non-linear trends.

Studies have employed different decomposition approaches. IMFs generated by the Empirical Mode Decomposition method were used to augment the input data (Tan et al., 2022). In another study, the input data was decomposed at multiple levels using the wavelet transform (Dixit et al., 2015). Wavelet transforms were also used to convert data into scalograms, which served as input to AI models (Saviz Naeini & Snaiki, 2024). One study trained AI models on denoised data reconstructed from IMFs (Bao & Bin, 2019). Some methods, like Seasonal Trend Regression, smooth data by isolating season and long-term variations. Table 1 presents a list of decomposition methods identified in the studies.

Table 1 Data decomposition tools identified in studies.

Decomposition Methods
Harmonic Wave Model (Breunung & Balachandran, 2023)
Seasonal-Trend Regression (H. Yang et al., 2022)
Singular Value Decomposition (Çelik, 2022, p. 202)
Singular Spectrum Analysis (J. Zhao et al., 2021)
Empirical Mode Decomposition (B.-X. Liang et al., 2021; J. Yin et al., 2023)
Ensemble Empirical Mode Decomposition (B.-X. Liang et al., 2021; G. Wang et al., 2022)
Variational Mode Decomposition (Ban et al., 2023)
Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (Ban et al., 2023)
Discrete Wavelet Analysis (Dixit & Londhe, 2016)
Maximum Overlap Discrete Wavelet Transform (Altunkaynak et al., 2024)
Multivariate Variational Mode Decomposition (Raj & Prakash, 2024)
Nelder-Mead variational mode decomposition (Neshat et al., 2022)
Improved Complete Ensemble Empirical Mode Decomposition With Adaptive Noise (Y. Yang et al., 2024)

Determining Relevant Input Lags

Input lags are the past time steps used as predictors in time-series forecasts. Selecting appropriate input lags ensures the models capture meaningful temporal dependencies and patterns.

Autocorrelation and Partial Autocorrelation analysis are commonly used to identify the most relevant time lags by measuring the relationships between past and future values. These techniques have been applied to determine optimal time steps for SLA forecasting (Imani et al., 2014), tidal predictions (Kareem et al., 2022; Supharatid, 2003; J.-C. Yin et al., 2018), and wave forecasting (Ali et al., 2021; Bento et al., 2021; H. Wu et al., 2023).

Beyond autocorrelation, other methods have been used to refine input lag selection. Power spectrum analysis (G. Han & Shi, 2008) detects dominant cycles, while Bayesian optimisation (H. Yang et al., 2022) systematically searches for optimal time lags. Correlation-based approaches, including correlation coefficients (Çelik, 2022), correlation matrices (Zheng et al., 2023), and cross-correlation analysis (Jamei et al., 2022), assess dependencies between time steps.

Additionally, the vector autoregressive model (Kar et al., 2024) captures multivariate relationships.

Chronological Data Splitting

Before deployment, AI models undergo training, validation, and testing, each requiring a distinct dataset. A common approach in the studies reviewed is chronological splitting, where data is divided based on time order. The most widely used method involves using the earliest period for training while reserving later periods for validation and testing. Few studies, however, use the middle period for training and the earlier period for testing (El-Rabbany & El-Diasty, 2003), while others just shuffle the entire dataset and randomly split the datasets (Kwon et al., 2023).

Resampling

Resampling as a pre-processing technique alters the resolution of a dataset to better align with analytical needs. It involves either downsampling, which reduces resolution by aggregating data, or upsampling, which increases the resolution through interpolation. Resampling helps smooth noise, improve computational efficiency, and align datasets from multiple sources.

Hourly temporal resolutions were downsampled to 10-day means (Rizkina et al., 2019). Cubic spline interpolation was applied to upsample 3-hour wind data to a 1-hour resolution, aligning it with hourly tidal levels (Filippo et al., 2012). Similarly, wave data collected at 15 and 10-minute intervals were resampled to a uniform 1-hour resolution to ensure consistency in modelling (Kar et al., 2022).

Spatial datasets were averaged into equidistant grids (Imani et al., 2017) or interpolated into coarser grids (Feng et al., 2020). Bilinear interpolation was employed to downsample high-resolution SWAN data to a lower-resolution grid (J. Chen et al., 2021).

Feature Selection

Feature selection is a crucial pre-processing step in AI modelling, ensuring that only the most relevant input variables are used to improve model performance and interpretability. Additionally, it plays a key role in reducing the dimensionality of the input data. Various statistical and AI-based methods were employed in identifying optimal features (Table 2).

Table 2 Feature selection methods identified in studies.

Statistical Methods	**AI-Based Methods**
Sensitivity analysis (Deo et al., 2001; Paplińska-Swerpel & Paszke, 2006),	Grouping Genetic Algorithm (James et al., 2018)
Correlograms (Jörges et al., 2021)	Multilayer Perceptron (T.-L. Lee, 2004; Malekmohamadi et al., 2011)
Pearson correlation coefficient (Minuzzi & Farina, 2023),	Recursive Feature Elimination (Penalba et al., 2022)
Mutual information (W. Huang & Dong, 2021; Zamani et al., 2008)	Random Forest (Tan et al., 2022)
Variance inflation factor (Costa et al., 2023)	Boruta-Extreme Gradient Boosting (Jamei et al., 2022)
Sequential forward selection (Costa et al., 2023)	
Gini impurity index (Upreti et al., 2023)	

Method of trials (Nitsure et al., 2012)	
Principal component analysis (Kong et al., 2022; Ni & Ma, 2020)	

4.4.2 Wave and Tide Studies

Addressing Data Gaps

The handling of missing data in wave and tide forecasting studies followed several distinct methodological approaches.

Gap-Based Classifications Approaches

Several studies employed duration-based criteria to determine treatment methods. A four-hour threshold was established, filling shorter gaps while removing longer ones from analysis (Bao & Bin, 2019; Nitsure et al., 2014). Similarly, a sequential approach was implemented where up to two consecutive missing points were interpolated using quadratic methods, but three or more consecutive missing points led to the exclusion of affected sub-sequences (Yevnin et al., 2023). More complex strategies have been developed, using interpolation for gaps under 24 hours while filling longer gaps with historical data or model predictions, followed by outlier detection and handling (Zhou et al., 2021)

Interpolation Methods

Interpolation techniques represent the most common approach to addressing data gaps. These techniques have been frequently employed to replace missing or unrealistic values (G. Han & Shi, 2008; Su & Jiang, 2023; Zheng et al., 2020). Cubic spline, linear, and quadratic interpolation methods were identified across studies. Adaptive methods have been applied, selecting between linear and quadratic interpolation based on the number of consecutive missing values (B.-X. Liang et al., 2021). Forward padding methods have been utilised for interpolation (Q. Huang & Cui, 2023), while context-sensitive interpolation approaches have been developed based on data characteristics and missing data patterns (Lv et al., 2023).

Advanced Statistical and Computation Methods

More sophisticated approaches include harmonic analysis (HA) to fill missing data (B.-F. Chen et al., 2007), Fast Fourier analysis to interpolate missing values (Filippo et al., 2012), and linear regression to reconstruct data gaps (Bao & Bin, 2019). Neural networks have been employed to predict missing values(T. L. Lee et al., 2002; Pierini & Gómez, 2009).

Exclusion Approaches

Some studies simply excluded records with missing data from their analysis (Donne et al., 2014; Jörges et al., 2021; C.-H. Yang et al., 2020; L. Zhao et al., 2023).

Location Data Splitting

Location-based division involves training an AI model on data from one site and applying it to predict wave or tide parameters at a different location. This approach is particularly useful when the target location has insufficient data, contains gaps, or requires an analysis of spatial relationships between different sites (Alarcon, 2019; B.-F. Chen et al., 2007; Law et al., 2020; S. X. Liang et al., 2008; Özger, 2009).

Stationarity Testing

Stationarity is a key characteristic of a time series, indicating that its statistical properties remain constant over time, which is essential for reliable forecasting. Before applying AI models, some studies evaluated the stationarity of tidal and wave time series. If the data were found to be non-stationary using tests such as the Augmented Dickey-Fuller test, differencing was applied to stabilise the series. (Dixit & Londhe, 2016; Raj & Prakash, 2024; Zhou et al., 2021).

Outlier Removal

Outlier removal is a crucial step in ensuring data quality. Statistical measures, such as the 25th and 75th percentiles, help identify and eliminate unrealistic values. Another method, including threshold-guided decomposition (Kar et al., 2022) and rigorous quality control checks (Reikard et al., 2011), further refines the dataset by detecting and removing anomalies. These methods enhance data reliability and improve overall analysis accuracy (Filippo et al., 2012; Mo et al., 2023; Rizkina et al., 2019).

Wind Data Processing

Wind data is often processed in tidal and wave studies, as it influences the two ocean parameters. Various pre-processing techniques are applied to refine wind data for oceanographic modelling. These include resampling wind data to be consistent with tide and wave data (Filippo et al., 2012; Kamranzad et al., 2011) and calculating wind shear velocities to better capture wind-driven forces acting on waves (Bao & Bin, 2019; Nitsure et al., 2012; B. Wang et al., 2020).

Other studies transformed wind speed by squaring it to reflect its nonlinear relationship with wave height (Paplińska-Swerpel & Paszke, 2006) or adjusted wind speeds to a standardised 10-meter height to ensure consistency across datasets (Reikard et al., 2011). Additionally, wind direction has been converted from degrees to a 16-point compass scale (Kar et al., 2022)

Seasonal Data Division

Studies divided data into seasons or specific date intervals to account for seasonal variations and temporal patterns. This approach helps in capturing seasonal patterns and improving the accuracy of AI models, especially in regions with strong seasonal influences (Cox et al., 2002; Deo et al., 2001).

Signal Filtering

Signal filtering techniques are used to improve the quality of tidal and wave data by smoothing fluctuations and removing discontinuous points. These techniques enhance the learning efficiency of AI models and help prevent overfitting to noise (Guodong & Zhongxian, 2023; G. Han & Shi, 2008).

Butterworth filter (Guodong & Zhongxian, 2023), median filter (Donne et al., 2014), and Gaussian filter (Zhan et al., 2023) were identified in the reviewed studies.

Frequency Domain Analysis

The Fast Fourier Transform (FFT) is widely used to convert time series into the frequency domain, allowing researchers to identify dominant frequencies within the dataset. These frequency components can then be used as inputs for AI models (Filippo et al., 2012; W. Huang & Dong, 2021; Jain et al., 2011; Q. Liu et al., 2022). Furthermore, some studies applied FFT to derive wave parameters and generate height fields for real-time wave simulations (Y. Li et al., 2022).

4.4.3 Tide and Sea-Level Anomaly

Sliding Window

To enhance time-series forecasting, studies segmented data into smaller sequences using a sliding window approach. This method involves dividing the dataset into overlapping windows, where a portion of the frames serves as input while the remaining frames are used for prediction. For example, some studies applied a 30-frame window, using the first 15 frames as inputs and the next 15 frames as targets (Bao & Bin, 2019; G. Wang et al., 2022).

4.4.4 Sea Level Anomaly Studies Only

Calculation of SLA and Correction of Satellite Altimetry Data

The calculation of SLA is a fundamental pre-processing step. SLA is typically derived by subtracting a reference sea level (such as the mean sea level or a geoid model) from the observed sea surface heights. Some studies also applied corrections for tides, atmospheric pressure, and wind stress to obtain more accurate SLA values (Imani et al., 2013, 2014; J. Zhao, Cai, et al., 2019; J. Zhao, Fan, et al., 2019).

Periodic Component Extraction

The least squares method was employed to separate deterministic components from stochastic residuals (J. Zhao, Fan, et al., 2019).

4.4.5 Tide Studies Only

Tidal Data Refinement

Various methods have been used to refine tidal-level data by separating periodic components from external influences. Harmonic analysis (HA) is commonly applied to decompose tidal signals into their harmonic constituents, isolating the periodic (astronomical) part from the overall tidal variations. This process enables the extraction of the non-periodic components of tides (W. Wu et al., 2021; Z.-G. Zhang et al., 2018). This non-periodic component is also referred to as residuals, SLAs, meteorological part, or typhoon-influenced levels (W. Wang & Yuan, 2018; Yuan et al., 2015), depending on the aim of the study. In some cases, these residuals were further decomposed into simpler sub-series (Bao & Bin, 2019; J.-C. Yin et al., 2018). To further refine tidal levels, some studies removed external influences, such as atmospheric pressure (Molino-Minero-Re et al., 2014; C.-H. Yang et al., 2020).

Typically, AI models are trained on residuals, allowing them to focus on the non-periodic components that traditional methods cannot capture. However, some studies incorporated the tidal constituents as input data (T.-L. Lee, 2004) and assessed the impact of different tidal constituents on model performance (Pierini & Gómez, 2009).

Period Analysis

Determining the periodicity of tidal data is important as it improves prediction precision, particularly in handling the periodic nature of tidal records (S. X. Liang et al., 2008).

Adaptive Temporal Segmentation

Adaptive temporal segmentation uses the Improved Gath-Geva (IGG) fuzzy algorithm to dynamically partition time series data based on changing system dynamics, ensuring that each segment contains data with similar characteristics (J. Yin & Wang, 2016).

4.4.6 Wave Studies Only

Condition-Based Data Filtering

Some studies applied data filtering techniques to include only measurements taken under specific conditions. For instance, data was restricted to open ocean depths greater than 50 meters (Govindan et al., 2011), while other studies focused exclusively on storm surge events (Jörges et al., 2023). Some researchers filtered data based on high kurtosis values of SWH (Nitsure et al., 2012), while others selected only deep-sea waves and tidal levels within a specified range (D. H. Kim et al., 2014). Additionally, the k-means algorithm was employed to classify data into different sea states, allowing for more targeted model training (R. Li et al., 2023).

Binocular Image Processing

Binocular wave images underwent stereo rectification to align them geometrically, ensuring consistency between the left and right images. These images were then resized and cropped to prevent memory overflow (J. Huang et al., 2023).

Synthetic Aperture Radar Image Processing

Pre-processing SAR images involved deburtsting to merge sub-swaths, geometric-terrain ellipsoid correction to convert data to the WGS 1984 coordinate system, and topographic correction using the Range-Doppler approach with SRTM DEM data to address distortions like shadowing, layover, and foreshortening. Finally, the images were subsetted to extract the area of interest, and the VH and VV bands were exported in NET-CDF4 CF format for ANN use (Tapoglou et al., 2021). SAR cross-spectra calculation is used to remove noise for SAR images (Fang et al., 2024)

Continuous Variable Categorisation

Continuous variables, such as SWH, were transformed into ordered categories to aid classification (Fernández et al., 2015).

Encoding Seasonal Patterns

Some studies have modified temporal data to better capture seasonal variations. For instance, the day of the year was converted into a fuzzy value to represent seasonal changes more effectively (Donne et al., 2014).

Data Assimilation

Optimal interpolation was employed as a pre-processing step to enhance wave height estimates before training predictive models. This method integrated numerical model outputs with real observations to correct biases and fill data gaps, generating pseudo-observations at locations without direct measurements (Ozaki et al., 2023).

Wave Energy Calculations

In studies focusing on wave energy, wave energy flux was calculated from SWH and wave energy period (Bento et al., 2021; Fernández et al., 2015). Another approach involved extracting SWH and mean wave energy period directly from wave spectra (Reikard et al., 2011).

Temporal Sampling

Selective sampling of SWH at predefined intervals ranging from 4 to 24 hours across different days was applied (Londhe & Panchang, 2006). Previous wave heights at fixed 6-hour intervals were selected (Dixit & Londhe, 2016), while wave height values at 30 minutes past each hour by averaging observations taken at 20 and 40 minutes past the hour have been calculated (Oh & Suh, 2018).

Integrating Ice and Bathymetry Data

An ice-mask matrix was created by combining ice coverage and bathymetry data, enhancing the analysis of ice-related oceanographic conditions (Feng et al., 2020).

Addressing Data Imbalance

To mitigate data imbalance, a stratified random sampling method was applied to balance the distribution of wave heights in the training data (Kwon et al., 2023). Additionally, to address seasonal imbalances, a randomised sampling approach—combined with bootstrapping—was employed (Asma et al., 2012). This ensured that the training, validation, and evaluation datasets included representative data points from all seasons, without altering the temporal resolution of the data.

5 Discussion

5.1 Data Types and Methodological Approaches

The distinct data preferences across ocean domains suggest standardised methodological approaches. Tide forecasts rely heavily on in-situ data, emphasising the importance of local measurements, while SLA studies depend exclusively on remote sensing for large-scale spatial coverage. In contrast, wave forecasting utilises diverse data sources due to the complexity of wave behaviour and its broad range of applications.

In-situ data remains the backbone of ocean research, valued for its reliability and accuracy. However, its limited spatial coverage and high cost restrict data collection in remote and resource-poor regions. To address these challenges, AI offers a promising solution. AI can approximate complex functions (Augustine, 2024; Lu & Lu, 2020), enabling researchers to establish relationships between large-scale, spatially abundant datasets (e.g., remote sensing) and in-situ measurements. Integrating AI to infer in-situ parameters from remote sensing could significantly improve forecasting in data-scarce areas (Alarcon, 2019).

The reliance on multiple data sources, particularly in wave forecasting, underscores the importance of improved data accessibility and sharing. While open-access datasets from agencies like ECMWF, NOAA, and Copernicus have facilitated many studies, data simulated by labs and collected in less-resourced regions (often by national meteorological services, port authorities, and disaster management agencies) must be standardised and made accessible to the broader research community. Doing so would enhance the integration of diverse data sources collected from multiple locations under different conditions and improve forecasting studies.

5.2 The Dominance of Significant Wave Height

SWH is the most forecasted wave dynamic, accounting for 54.0% of all forecasted wave parameters. Its dominance reflects its fundamental role in wave research, as it directly relates to wave energy and its impacts on coastal structures, navigation, offshore operations, and extreme events. Additionally, the high frequency of SWH studies suggests that it is easier to observe, measure, and model compared to other wave dynamics.

In contrast, wave spectra, wave energy flux, and wave set-up are rarely studied despite their importance for advanced wave modelling, renewable energy, and coastal hazard assessment.

5.3 Complementary Use of Data Sources in Wave Forecasting

This review demonstrates that no single data source can fully capture the complexity of wave behaviour. Instead, different data sources are better suited for modelling specific wave dynamics. For example, wave run-up and wave set-up were primarily studied using numerical models and laboratory experiments, while wave energy flux relied heavily on in-situ measurements. SWH and wave period were analysed without the use of laboratory experiments, whereas wave spectra studies exhibited an even distribution of remote sensing, reanalysis, numerical model and in-situ data.

Each data source contributes unique insights that are essential for understanding different aspects of wave behaviour. In-situ measurements provide high-resolution, localised data, while remote sensing offers broad spatial coverage. Numerical models simulate complex wave dynamics, while laboratory experiments allow for controlled testing of specific hypotheses.

5.4 Inputs Features for Wave Forecasting

The results indicate that some wave dynamics exhibit strong temporal autocorrelation and can be predicted using their historical values. For example, SWH, wave period, wave direction and wave elevation (all in the WC category) are frequently forecasted using their historical values.

In contrast, for secondary wave dynamics such as wave run-up, wave energy flux, and wave energy period, the most frequently used input features were not the respective wave dynamics themselves but rather primary WCs. Wave run-up was most predicted using wave height, reflecting its physical dependence on wave height (Synolakis, 1987). Similarly, SWH and wave period were the most frequently used input features for forecasting wave energy flux, as wave energy flux is derived from these WCs. Finally, the most used input feature for predicting wave energy period was the wave period itself.

Not all primary WCs had their historical values as the most frequently used input feature. Wave direction was the most used input feature for forecasting wave frequency. Similarly, wave crests and troughs were forecasted using slow-varying amplitude (Breunung & Balachandran, 2023) rather than their historical values. However, wave crest, trough, and frequency are inherently captured by WCs. Wave height, defined as the vertical distance between the crest and trough, and wave frequency, which is the inverse of the wave period (Geng et al., 2016; Nguyen et al., 2019), are more practical and sufficient for forecasting purposes. Explicitly predicting wave crest, trough, and frequency may therefore be redundant in many applications.

A compelling example to support this point is SWH, which is the average of the highest one-third of all wave heights. SWH is more practical and widely used in applications because it provides a statistically robust and practical measure of wave conditions (Komar, 2018). SWH forecasting offers a more representative and efficient metric for real-world use while individual, thus it is more studied and forecasted compared to individual wave heights.

5.5 Data Coverage Periods

Longer data periods are preferred, especially for SWH, wave direction, and SLA studies. Wave direction spanned a median of 13 years, while SLA had a median of 23 years. Longer data records are favoured because they capture more seasonal variability and extreme events, which is important for developing a robust AI model.

Tidal-level studies, on the other hand, tended to use shorter datasets, with a median data coverage of 219.5 days. This preference may be attributed to research demonstrating that AI models can achieve accurate tidal-level predictions with smaller datasets compared to HA.

Additionally, five wave dynamics (run-up, elevation, frequency, set-up, and crests and troughs) had limited or no data coverage as they relied heavily on numerical simulations and laboratory experiments. This indicates a lack of observational data on these identified parameters, limiting the capacity of AI models to train on empirical data.

6 Conclusion

Ocean processes play a crucial role in shaping coastal water levels, posing risks to human lives, livelihoods, and infrastructure. To better predict and understand these dynamics, artificial intelligence (AI) has been increasingly utilised for modelling and forecasting. However, the accuracy of AI-driven models depends heavily on the quality, coverage, and suitability of the data used. This review evaluates the types and characteristics of data employed in forecasting three key drivers of extreme coastal water level (ECWL) variations: waves, tides, and SLA.

The analysis reveals that in-situ measurements remain the most widely used data source in ocean studies, valued for their reliability and accuracy. However, deviations exist at a more detailed level. For instance, SLA studies rely exclusively on remote sensing data, while wave run-up studies depend heavily on numerical simulations and laboratory experiments. Among wave parameters, significant wave height (SWH) is the most forecasted, underscoring its importance in ocean research. Nevertheless, no single data source can fully capture the complexity of wave behaviour, as specific data types are better suited for modelling certain wave dynamics. Additionally, longer data coverage is preferred to improve the robustness of forecasting models.

The findings highlight the need for advancing ECWL forecasting. Improved accessibility and standardisation of datasets, particularly from less-resourced regions, are essential for enhancing data integration and model accuracy. Establishing relationships between large-scale remote sensing data and localised in-situ measurements can address data scarcity in remote areas and improve forecasting capabilities. Additionally, extending the temporal coverage of datasets will enhance the reliability of forecasting models, particularly for extreme events.

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