TIDAL HARMONIC ANALYSIS AND PREDICTION TO SUPPORT EARLY WARNING FOR COASTAL FLOODING

ANALISIS HARMONIK DAN PREDIKSI PASANG SURUT UNTUK MENDUKUNG PERINGATAN DINI BANJIR PESISIR

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ABSTRACT: The Indonesian Maritime Continent (IMC) is the largest archipelago that vulnerable to climate change especially sea level rise. Some coastal areas frequently experience coastal flooding affecting the activities and infrastructures. Thus, an accurate tide prediction in this region plays a pivotal role in providing the early warning, mitigation, and adaptation to frequent coastal flooding. BMKG, through the Center for Marine Meteorology has done undertaken efforts to provide an accurate tidal prediction information by developing the tidal information system call the Indonesian Tidal Information System (INATIS). Tidal harmonic analysis (THA) using the least-square method was applied to sea level data from 49 Marine Automatic Weather System (MAWS) stations collected between 2020-2021 to generate tidal predictions for the period of 2022-2023. Accuracy was assessed based on Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE). MAWS stations with prediction accuracy above 80% visualized on publicly accessible online platform of the BMKG website using the open-source Looker Studio. Verification of the tidal predictions showed an average prediction accuracy of 93.21% with a MAE of 0.11 m. The high accuracy of INATIS demonstrates its potential as a reference for coastal flood early warning systems.

Keywords: tidal prediction, tidal accuracy, Ina-TIS, least-square method

***ABSTRAK**: Benua Maritim Indonesia (BMI) merupakan kepulauan terbesar di dunia yang rentan terhadap perubahan iklim utamanya kenaikan tinggi muka laut. Beberapa wilayah pesisir secara reguler mengalami banjir pesisir (ROB) yang berdampak terhadap berbagai aktivitas dan infrastruktur pesisir. Sehingga informasi prediksi pasang surut yang akurat sebagai acuan peringatan dini banjir pesisir sangat diperlukan. BMKG melalui Pusat Meteorologi Maritim yang menurut Undang-Undang ditugaskan untuk menyampaikan informasi pasang surut telah melakukan berbagai upaya untuk memberikan informasi pasang surut yang akurat salah satunya melalui pengembangan sistem informasi yang diberi nama dengan INATIS (Indonesian Tidal Information System). Analisis harmonik pasang surut (THA) menggunakan metode kuadrat terkecil (least square) diterapkan pada data tinggi muka laut di 49 stasiun Marine Automatic Weather System (MAWS) pada periode 2020-2021 digunakan untuk menghasilkan prediksi pasang surut pada periode 2022-2023. Akurasi prediksi pasang surut dievaluasi menggunakan kriteria galat mutlak rata-rata (MAE) dan persentase akurasi galat mutlak rata-Rata (MAPE). Stasiun MAWS yang memiliki hasil akurasi prediksi >80% selanjutnya ditampilkan pada laman online menggunakan platform open-source looker studio yang bisa diakses publik pada laman BMKG. Hasil verifikasi prediksi pasang surut menunjukkan bahwa nilai persentase rata-rata akurasi prediksi sebesar 93,21% dan MAE sebesar 0,11 m. Nilai akurasi yang tinggi pada INATIS* *ini menunjukkan hasil prediksi yang bisa menjadi acuan dalam membuat peringatan dini banjir pesisir.*

Kata Kunci: *prediksi pasut, akurasi pasut, Ina-TIS, metode kuadrat terkecil*

INTRODUCTION

The sea level rise is regarded as a crucial indicator of climate change, exerting significant influence across various sectors of human life, particularly within coastal communities. Sea levels have experienced a substantial increase over the past decade, and projections indicate continued elevation in the future (Storto et al., 2019). Research conducted by Widlansky et al. (2020) has revealed that a 2°C rise in sea surface temperature can enhance the global variability of sea levels by 4-10%. Concurrently, studies by Frederikse et al. (2020) demonstrate that sea levels have been rising at a rate of 1.56 mm per year during the 20th century. This situation rise threatens approximately 23% of the world's population residing in vulnerable coastal regions, susceptible to extreme coastal flooding events (Small & Nicholls, 2003).

Climate change and land subsidence combine to cause coastal flooding, damaging infrastructure and threatening coastal livelihoods. Losses can reach millions of dollars (Dasgupta et al., 2009). Indonesian coastal regions, including the northern coast of Java and the eastern coast of Sumatra, routinely experience coastal flooding. According to Ward et al. (2011), extreme coastal flooding events in Jakarta with return periods of 100 and 1000 years could cause total losses of 4 and 5.2 million Euros, respectively.

Hence, the provision of tidal prediction information becomes paramount importance for early warning systems and coastal flooding mitigation efforts. Tidal prediction information also benefits maritime activities, facilitating ship loading and unloading operations, planning port construction, meeting recreational needs such as fishing and surfing, and indirectly enhancing the productivity of fisheries for local fishermen (Su & Jiang 2023). Sea level data is also utilized for verifying events such as tsunami waves, tropical cyclones, or meteo-tsunamis. Globally, observational data from tide gauges, in conjunction with satellite data, have been employed for projecting global sea level rise under various scenarios.

Tides, short-term sea level fluctuations, are primarily caused by the gravitational forces of the moon and sun interacting with the Earth's shape and bodies of water. This oceanographic phenomenon is relatively predictable due to the cyclical nature of these forces (Egbert & Ray, 2017). Various methods for predicting tides have been developed. The harmonic analysis method is one of the most common approaches, known for its accuracy in generating tidal predictions (Li et al., 2019). Other approaches are also frequently employed, such as numerical modeling (Haditiar et al., 2020), as well as the application of machine learning and artificial intelligence (Riazi, 2020; Granata & Di Nunno 2021).

According to Law No. 31 of 2009 on Meteorology, Climatology, and Geophysics, BMKG (Indonesia's Meteorology, Climatology, and Geophysics Agency) has the responsibility to conduct observations of tidal movements in the ocean. BMKG, through the Maritime Meteorological Center, has employed various approaches to provide tidal prediction information. Previously, BMKG developed the Coastal Flooding Prediction System, known as the Indonesian Coastal Inundation Forecasting Demonstration Project (INA-CIFDP), utilizing numerical methods (Riama et al. 2021). The expansion of weather and oceanography monitoring networks, including sea level sensors, has enable to the development of a tidal prediction system using harmonic analysis methods, making use of observational data known as the BMKG-Indonesian Tidal Information System (INATIS). This web-based system utilizes harmonic analysis and observational data to provide tidal predictions accessible to the public.

METHODS

The data used in this research comprises of sea level data collected over a period of two years (2021-2022), recorded by water level sensors within the Marine Automatic Weather Station (MAWS) instruments at 49 MAWS stations located in various locations (Figure 1). A MAWS is an automated observatory equipped with various of weather and ocean sensors. Typically, at each MAWS stations, there are at least two types of water level sensors, including bubbler sensors (pressure-based) and radar sensors. Additionally, tide staffs serve as reference points for the raw data (Figure 2).

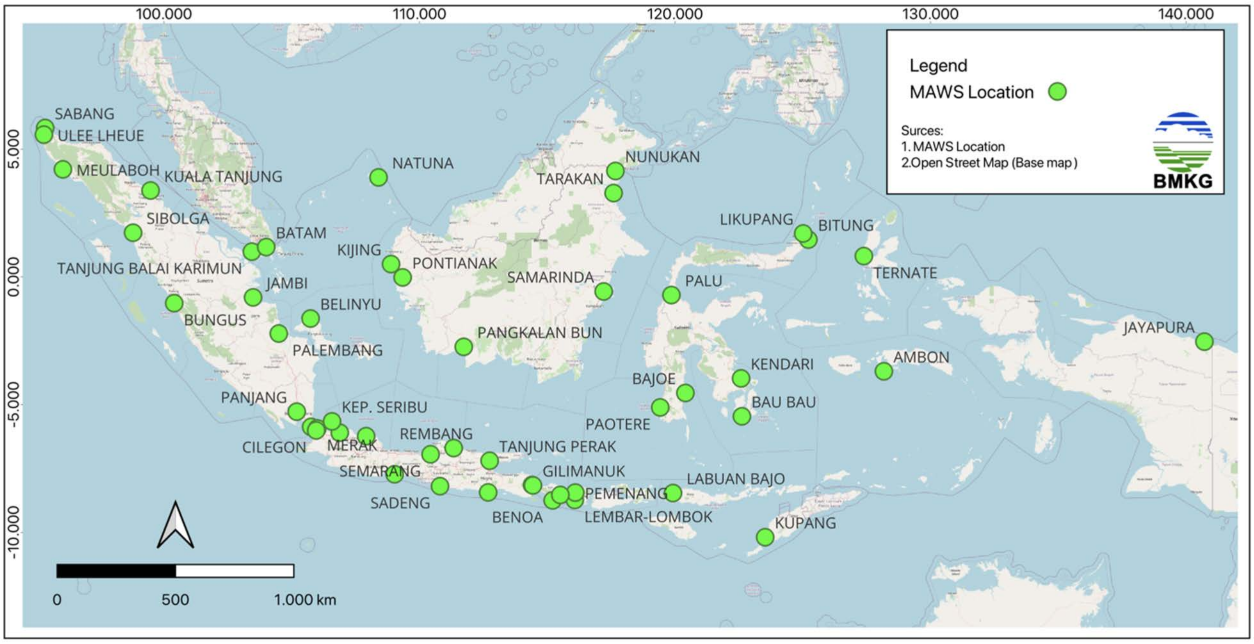

Figure 1. Study location (distribution of BMKG's Marine Automatic Weather Station for sea level

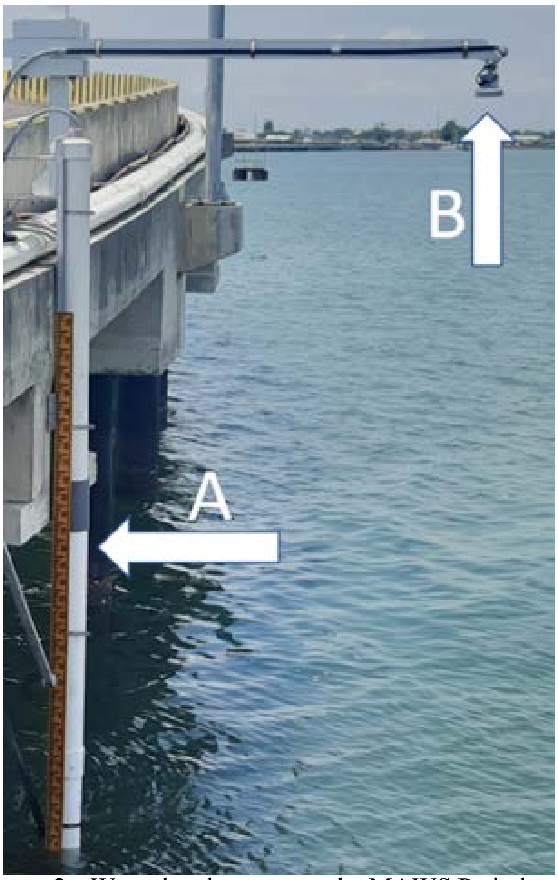

Figure 2. Water level sensors at the MAWS Patimban: a. bubler sensor, b. radar sensor

Water level data from MAWS stations was collected at either 1-minute or 10-minute intervals. The data has undergone a quality control (QC) process (IOOS, 2016) that is programmed into the MAWS system, as shown in Table 1. Despite the presence of the QC system, further data conditioning was conducted prior to harmonic analysis. Data conditioning includes the removal of noise and spikes through the application of high-frequency filtering, filtering data based on favorable QC flags (i.e., QC flag 1), and ensure consistent time intervals (without gaps).

Table 1. QC flag for MAWS

Flag	Description
0	No QC was performed
1	Good data
2	Probably good data
3	Probably bad data that are potentially correctable
4	Bad data
5	Value changed
6	Not used
7	Not used
8	Interpolated value
9	Missing value

Harmonic Analysis

The sea level recorded by MAWS water level sensors at any time represents a superposition (summation) of several waves with specific frequencies (referred to as tidal components), along with a residual component (Parker, 2007), as expressed by Equation (1).

$$h(t) = H_0 + \sum_{i=1}^{n} f_i H_i \cos\left(\alpha_i t + \{V_0 + u\}_i - \kappa_i\right) + h_r(t) \quad (1)$$

Here, in Equation (1), $h(t)$ represents the water surface elevation at time t with respect to a specific datum, n is the number of tidal components, H_0 is the mean sea level above the datum, H_i is the amplitude of the i-th tidal component, while $\alpha_i t + \{V_0 + u\}_i - \kappa_i$ represents the phase of the i-th tidal component, and h_r is the residual sea level component.

Tidal Harmonic Analysis (THA) employs the least-squares (LS) method to determine the amplitude and phase of predetermined tidal harmonic components with known frequencies (Thomson and Emery 2014). The LS method is employed to minimize the variance of time series data, and this can be expressed as Equation (2) (Pawlowicz *et al.* 2002).

$$E = \sum_{i=1}^{n} |x(t_i) - y(t_i)|^2 \qquad (2)$$

Equation (1) is substituted to Eq. (2), results in Equation 3 as follow.

$$e^2 = \sum_{i=1}^{n} {h_{r_i}}^2 = \sum_{i=1}^{n} \{h_i - [H_0 + \sum_{i=1}^{n} f_i H_i \cos\cos(\alpha_i t + \{V_0 + u\}_i - \kappa_i)]\}^2 \qquad (3)$$

The least-squares harmonic analysis method can be employed for the analysis of up to hundreds of tidal components. Harmonic analysis is conducted using the T_Tide software package in MATLAB, as provided by Pawlowicz et al. (2002).

We applied the THA to nearly two years of water level time series data. While Parker (2007) suggests a standard length of 369 days for THA, 365 days of data often sufficient for the least-square in practice. The amplitude and phase values obtained from THA can be utilized for tidal prediction throughout 2023 using Equation (1). This one-year prediction window is conducted due to the limitation of THA which only resolve two years tidal constituent for 2 years data.

An example of tidal components resulting from harmonic analysis at the MAWS Bajoe station is presented in Figure 3. With a length of data of about 400 days, it can result in about 70 tidal constituents in total, with 58 constituents being significant (the value of signal-to-noise (SNR) ratio> 1). Detailed information about the first 20 highest amplitude of significant harmonic constituent with its description is shown in Table 3. The five highest tidal amplitudes in Table 3 are M2, K1, O1, S2, and N2, with an amplitude (in m) of 0.57, 0.33, 0.20, 0.16, and 0.12, respectively. The next step is the 58 significant constituents (in this case) will be used to predict the tidal for the next one year.

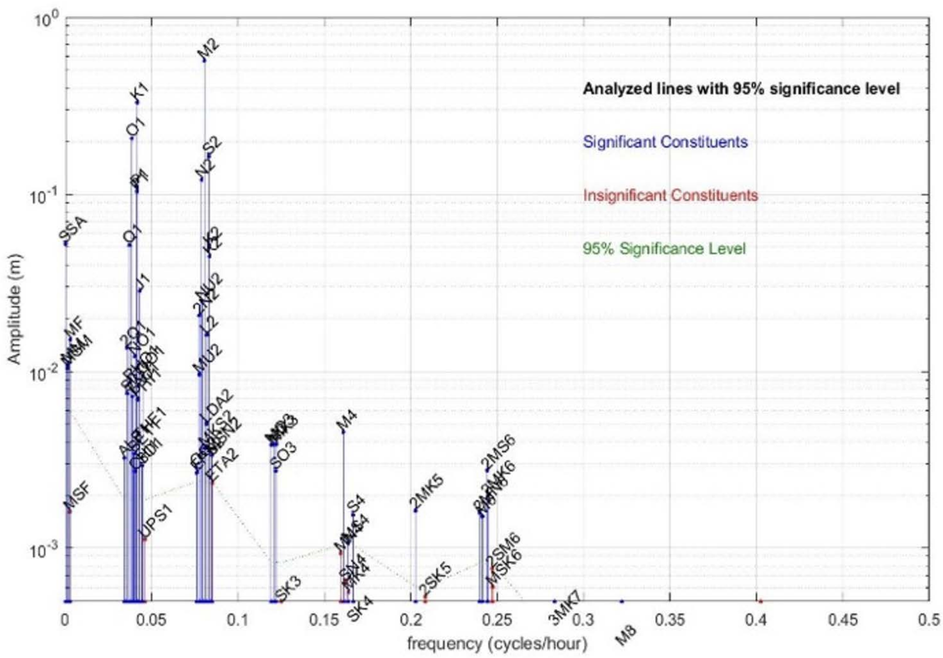

Figure 3. An Example of tidal harmonic analysis in Bajoe station. The significant harmonic constituents at significant level of 95% were note by the blue line.

Table 2. The first 20^{th} highest significant tidal constituent in Bajoe station for about 400 days harmonic analysis

No	Tidal Constituent	Amplitude (m)	Phase (degree)	SNR	Description
1	M2	0.5715	137.66	6.90E+04	Principal lunar semidiurnal
2	K1	0.3302	185.06	5.00E+04	Lunar diurnal
3	O1	0.2069	168.4	2.00E+04	Lunar diurnal
4	S2	0.1622	192.97	5.50E+03	Principal solar semidiurnal
5	N2	0.1216	114.99	3.10E+03	Larger lunar elliptic semidiurnal
6	P1	0.1093	192.13	5.40E+03	Solar diurnal
7	SA	0.0734	54.29	1.80E+02	Solar annual
8	Q1	0.051	166.44	1.20E+03	Larger lunar elliptic diurnal
9	K2	0.048	189.94	4.90E+02	Lunisolar semidiurnal
10	J1	0.0275	204.74	3.40E+02	Smaller lunar elliptic diurnal
11	NU2	0.0263	116.89	1.50E+02	Larger lunar evectional
12	S1	0.025	213.69	2.80E+02	Solar diurnal
13	2N2	0.0211	92.21	93	Lunar elliptical semidiurnal 2^{nd} order
14	L2	0.017	171.83	61	Smaller lunar elliptic semidiurnal
15	MF	0.0168	34.58	9.4	Lunisolar fortnightly
16	2Q1	0.0136	163.39	85	Larger elliptic diurnal
17	NO1	0.0133	154.88	80	Smaller lunar ellipti
18	SSA	0.0105	271.05	3.7	Solar semiannual
19	MM	0.0104	359.58	3.6	Lunar monthly
20	T2	0.0099	170.66	21	Larger solar elliptic

Tidal prediction verification

Verification of prediction results is conducted by comparing them with observational data. The criterion used for this verification is the Mean Absolute Percentage Error (MAPE) as defined in Equation (4) (Zhang et al., 2023).

$$MAPE = \left(\frac{\sum_{i=1}^{n}\frac{|h-h'|}{h}}{n}\right) \times 100\% \qquad (4)$$

Where h represents the observed water surface elevation, h' represents the predicted tidal elevation, and n is the number of data points used in the calculation.

Therefore, the accuracy percentage can be obtained from Equation (5).

$$Accuracy(\%) = 100\% - MAPE \qquad (5)$$

The accuracy criteria modified from MAPE criteria by Lewis (1962) is showed in Table 2.

Table 3. Prediction's accuracy criteria

Accuracy (%)	Interpretation
>90	Highly accurate
80-90	Good
50-80	Reasonable
<50	Weak and inaccurate

Verification is conducted monthly, allowing for an assessment of the variation in the performance of tidal predictions each month. Tidal prediction verification at one of the MAWS stations in Bajoe for January 2023 is illustrated in Figure 4.

Web-based visualization

MAWS stations with accuracy values exceeding 80% are visualized on the open-source web-based platform, Looker Studio (latest name from Google Data Studio). Looker Studio is primarily designed for creating interactive analytical reports, yet can also be utilized to create a user interface for tidal prediction with various data display options such as graphs, maps, tables, diagrams, and more (Snipes 2018). Looker Studio is an intuitive platform that does not require specific programming language skills in the implementation. In this study, the tide prediction data for the year 2023 is displayed on Looker Studio to avoid the heaviness of loading on the website. At the end of each year, the dashboard will be updated with prediction data for the following year. In general, the research flowchart is presented in Figure 5.

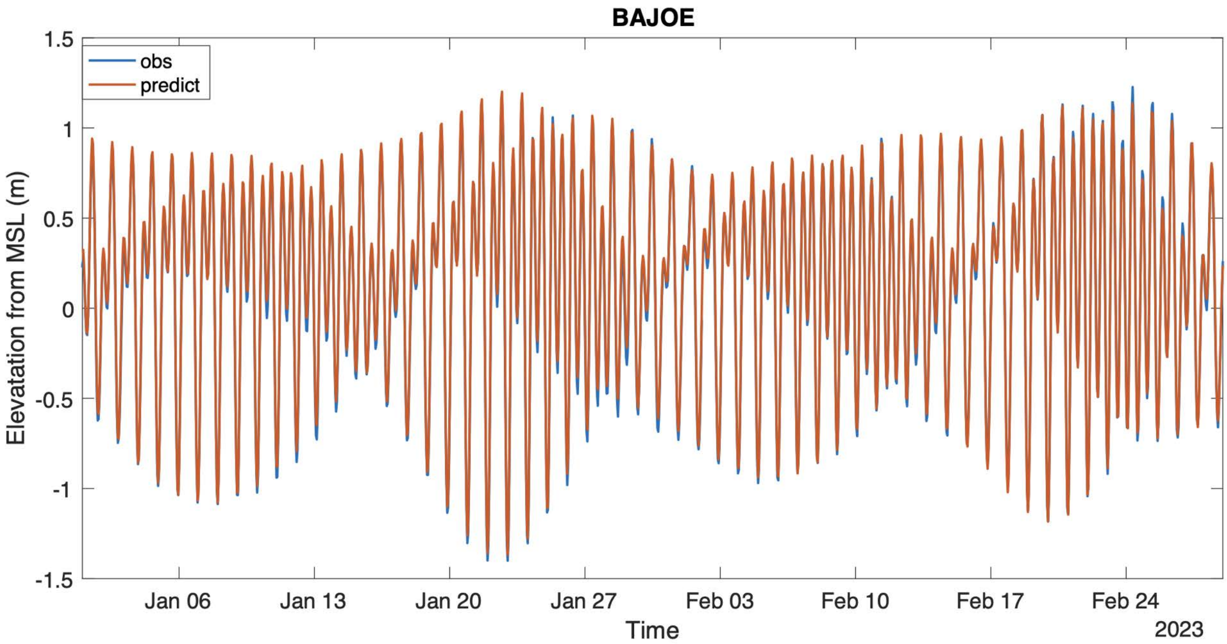

Figure 4. Verification of tidal prediction (red line) and observation (blue line) data in BAJOE station for January-February 2023.

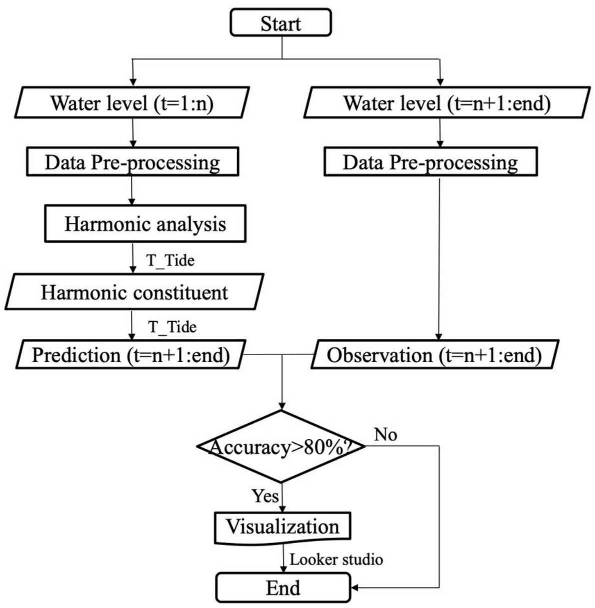

Figure 5. Research's flowchart

RESULTS AND DISCUSSIONS

Tidal prediction accuracy

The average accuracy percentage of tidal prediction results and the mean absolute bias (MA) against observational data from January 2022 to April 2023 is displayed in Figure 6. The average of accuracy percentage of tidal predictions during this period is 93.21%, with the highest percentage at the Bajoe station (98.26%) and the lowest at the Belinyu station (79.6%) (Figure 6). According to Lewis (1962) criteria, the overall accuracy percentage is classified as highly accurate, makes the predictions in a suitable reference for the early warning of coastal floods. The Mean Absolute Error (MAE) ranges from 0.049 to 0.43 m. A lower MAE signifies a more accurate prediction. The MAE values generally aligns with the Mean Absolute Percentage Error (MAPE). The highest MAE value is observed at the Belinyu station (0.43 m), whereas the lowest MAE value is recorded at the Bajoe station (0.049 m) (Figure 6). Some locations with accuracy values below 85% and high value of MAE (such as the Belinyu station) are associated with the observational data quality and data availability issues. Data at these locations often contain significant noise that can no longer be eliminated. Moreover, data availability also significantly impacts the accuracy percentage. In some of these locations, there are lengthy data gaps during certain periods. According to Pawlowicz et al. (2002), tidal analysis and prediction using the T_Tide toolbox are recommended to minimize data gaps. The length (duration) of water level data that analyze using THA absolutely affected the prediction accuracy. Research by Parker, 2007 demonstrated that longer water level time series allow for the analysis of more tidal constituents, leading to more accurate tidal predictions. It's important to note that in this study, the predictions only consider harmonic tidal components without adding non-tidal residual components or the sea level rise trend caused by climate change. Naturally, the predicted values over a long time period may slightly differ from the observations.

The histogram grouping of accuracy percentages in Figure 7 demonstrates variations in prediction accuracy over time. Generally, most months are dominated by predictions exceeding 90% accuracy. More than 60% of the 55 MAWS stations have accuracy exceeding 90% during the period from January 2022 to April 2023. Meanwhile, accuracy percentages between 70-90% are observed in less than 35% each month, and only about 10% of MAWS stations within the 50-70% accuracy range. Figure 7 also shows an increase in accuracy percentages exceeding 90% and a decrease in those within the 70-90% and 50-70%. This is due to the increasing number of MAWS station installations with improved water level sensor quality. Monthly variations in prediction accuracy are also related to variations in the quality of observational data over time. The variation in observational data quality is influenced by various factors such as communication systems, transmission, and the general electronic equipment conditions.

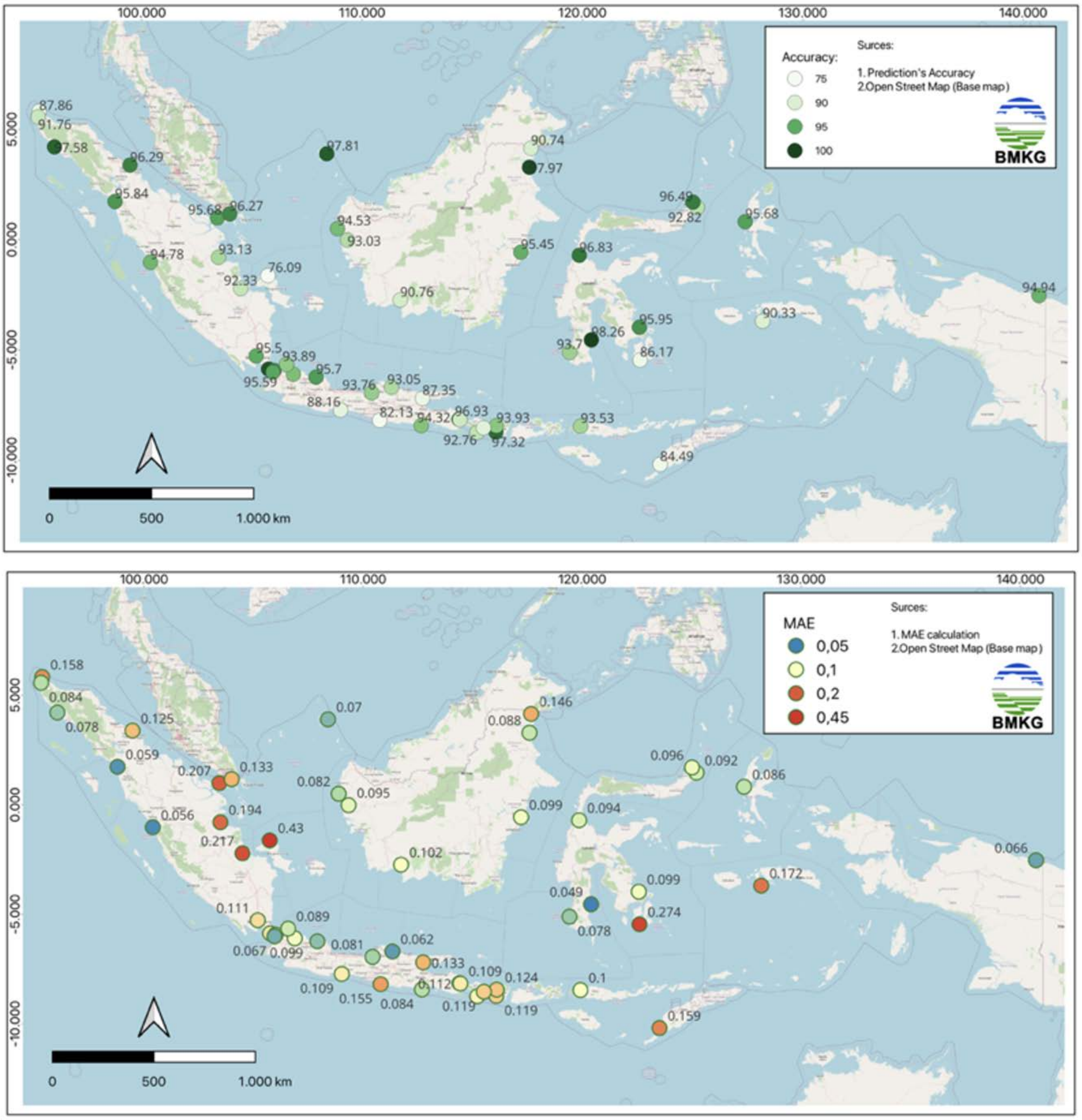

Figure 6. The average of accuracy percentage (MAPE, top) and Mean Absolute Bias (MAE, bottom) of tidal predictions for the period of January 2022 to April 2023.

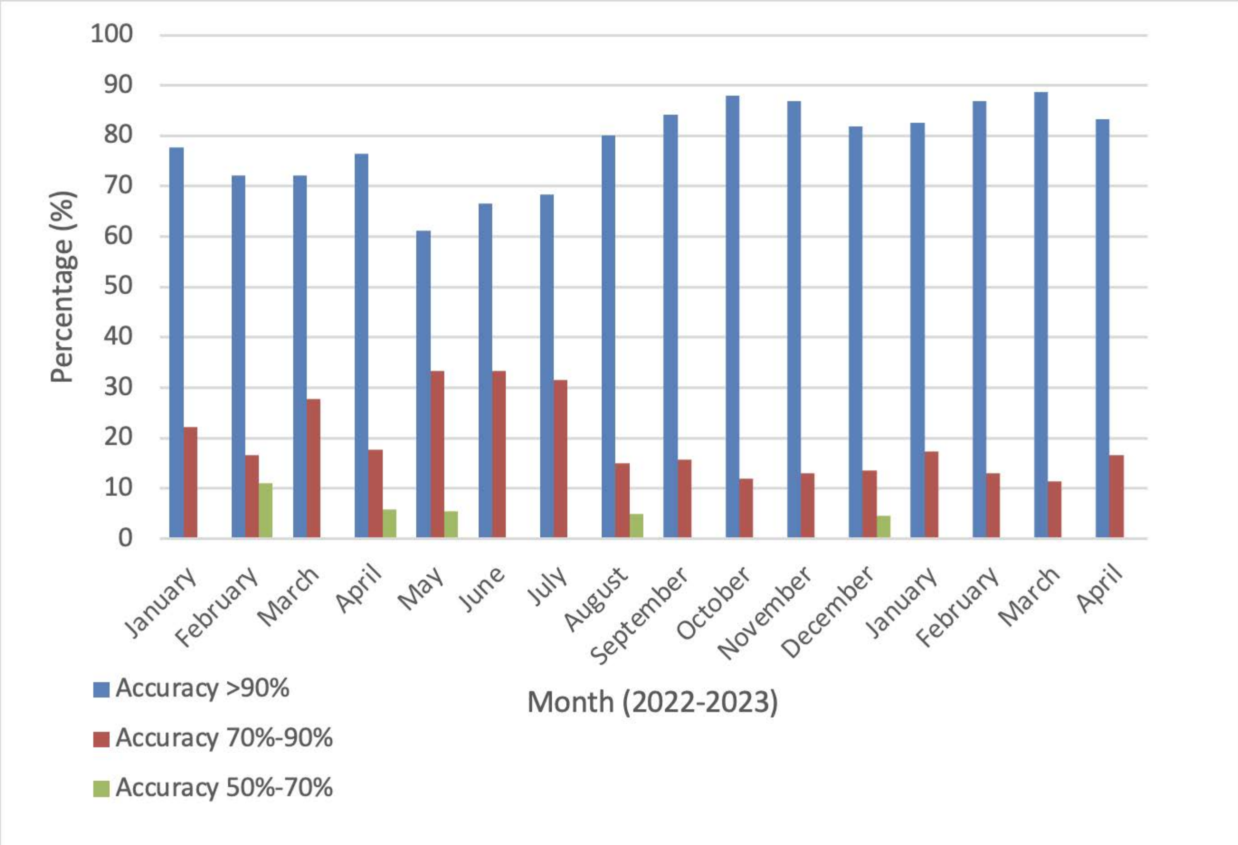

Figure 7. Histogram of accuracy percentage of tidal predictions for the period of January 2022 to April 2023.

Tidal prediction dashboard

Figure 8 displays the implemented tidal prediction dashboard. This tools consists of four sections, each section labelled A-D with different border color as shown in Figure 8. Part A (red border) serves as the control section, where users can select various controls, such as choosing the MAWS station to be displayed, the type of datum to be used, and the desired time range. In the datum section, two types of datum can be selected: Mean Sea Level (MSL) datum and Mean Lower Low Water (MLLW) datum, depending on the user's needs. MSL datum represents the average sea level observed over a specific period, while MLLW represents the average lowest tide within a day over a certain period. MLLW datum is also used by other institutions like National Oceanic and Atmospheric Administration (NOAA). In the time control section, users can select the desired time within a one-year range. Prediction values will be updated annually at the end of the year. Additionally, Part A contains a "User's Guide," link which serves as the manual for the conducted predictions, providing user instruction and scientific documentation for the dashboard. Finally, a map at the bottom displays the locations of the tidal prediction stations. This map dynamically updates to reflect the currently selected MAWS station.

Part B (blue circle) consists of a tidal elevation graph that adjusts its display based on the selected location and time. The bottom of the graph displays information about elevation units, datum, and the time zone used. The time zone utilized in this dashboard is Coordinated Universal Time (UTC) (WIB+7). Part C is a table of predicted elevation values that correspond to the chosen location and time in the control section in Part A. This table also offers an option to download the data by clicking the three dots in the upper right corner and selecting "export". Finally, Part D provides information about tidal elevation and time over a 12-hour period, which can serve as a reference for various maritime activities. Figure 9 illustrates an example of the dashboard display when customized to select the Bajoe station, MSL datum, and a prediction period in July 2023.

Websites built with Google Looker Studio can experience slower loading times due to large amounts of stored data. This can be further impacted by individual internet connection speeds. BMKG is commited certainly work on developing a more

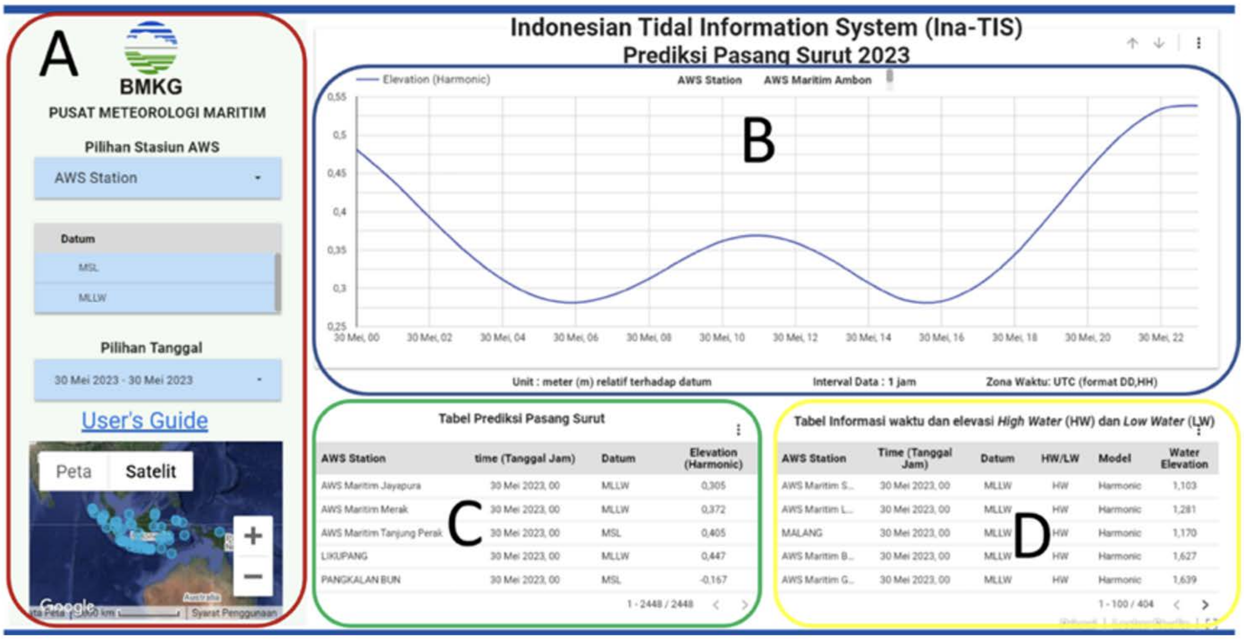

Figure 8. The initial display of the INATIS dashboard when first opened on the page https://maritim.bmkg.go.id/tide

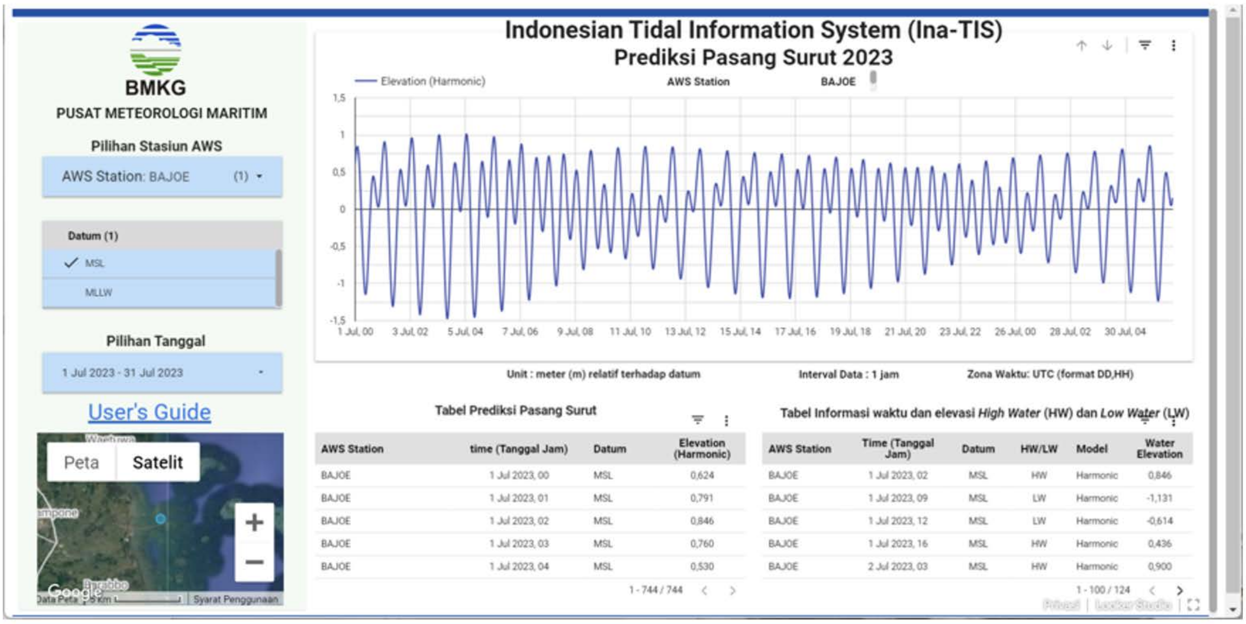

Figure 9. The display of the INATIS dashboard for Bajoe station with a MSL datum and prediction period in July 2023.

lightweight system to facilitate various users and improve loading efficiency.

CONCLUSIONS

Tidal predictions using classical harmonic analysis methods have demonstrated good accuracy, with an average accuracy reaching 93.21%. Monthly variations in prediction accuracy are influenced not only by the quality of data used for predictions but also by the quality of observational data used for verification. The tidal predictions have been successfully displayed on an open-source platform at https://maritim.bmkg.go.id/tide. This prediction information can serve as a reference for early warning systems for coastal flooding due to tidal influences. The prediction accuracy will continue to improve with the lengthening time series and availability of data to obtain more tidal components.

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