ISSN: 2447-3359

REVISTA DE GEOCIÊNCIAS DO NORDESTE

Northeast Geosciences Journal

v. 11, nº 1 (2025)

https://doi.org/10.21680/2447-3359.2025v11n1ID38147

Predictive models for analyzing sea surface height variation using tide gauge records

Modelos preditivos para análise da variação da Altitude da Superfície do Mar utilizando leituras maregráficas

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Abstract: Evaluating Sea Surface Height (SSH) is fundamental for predicting the consequences that global warming may cause in coastal cities, in addition to being used for establishing an altimetric reference. Monitoring this altimetric component can be carried out through tide gauges or via Satellite Altimetry (ALTSAT). The objective of this research was to analyze the readings from the tide gauge in Fortaleza/CE to determine SSH and generate predictive models for the variation of this component, thereby conducting a general analysis of SSH variation over the period considered. Based on a sample of five years of readings, a linear regression was performed using the statistical software R. Starting in 2020, there was a change in the measurement pattern of the readings, which may have been caused by a change in the sensors' origin position or because of the Adjustment of the Altimetric Network with Geopotential Numbers (REALT-2018). This change in the measurement pattern significantly impacted the validation of the models. The average variation in SSH was 1.02 cm ± 0.09 cm, thus suggesting a rise in the local SSH.

Keywords: Tide gauge readings; Sea surface height (SSH); Predictive models.

Resumo: Avaliar a Altitude da Superfície do Mar (ASM) é fundamental para a predição das consequências que o aquecimento global pode ocasionar nas cidades litorâneas, além de poder ser utilizada para a determinação de um referencial altimétrico. O monitoramento desse componente altimétrico pode ser realizado por meio de marégrafos ou pela Altimetria por Satélites (ALTSAT). O objetivo desta pesquisa foi analisar as leituras do marégrafo de Fortaleza/CE para determinar a ASM e gerar modelos preditivos para a variação desse componente, a fim de realizar uma análise geral da variação da ASM no período considerado. Com base em uma amostra de cinco anos de leituras, foi realizada uma regressão linear utilizando o *software* estatístico R. A partir de 2020, houve uma mudança no padrão de medição das leituras, que pode ter sido causada por uma alteração na posição da origem dos sensores ou em decorrência do Reajustamento da Rede Altimétrica com Números Geopotenciais (REALT-2018). Essa mudança no padrão de medição impactou significativamente a validação dos modelos. A variação média da ASM foi de 1,02 cm ± 0,09 cm, sugerindo, portanto, uma elevação da ASM no local.

Palavras-chave: Leituras maregráficas; Altitude da superfície do mar (ASH); Modelos preditivos.

Received: 03/11/2024; Accepted: 10/01/2025; Published: 24/03/2025.

1. Introduction

Currently, the causes, scale, and impacts of global warming and sea level rise are topics of great concern for the future of humanity and they are the subject of numerous studies (FU et al., 2024; MANSOURMOGHADDAM et al., 2024; MCCULLOCH et al., 2024; ZAMRSKY, ESSINK, BIERKENS, 2024). In cartographic sciences, one application of studies on sea level variation is the use of these analyses to define an altimetric reference (TORGE, 2001).

Determining sea level variation is of great global importance, especially after observing the increase in sea level over the years (NICHOLLS and CAZENAVE, 2010). This implies that governments and countries need to make decisions on measures to mitigate future consequences.

One of the main reasons for this variation in ocean levels is polar ice melt (FREDERIKSE et al., 2020), in addition to other factors such as astronomical and meteorological effects (MESQUITA, 1997) and geophysical effects (ABREU, 2019). To quantify this variation, an altimetric component associated with a geodetic surface, called Sea Surface Height (SSH) (MELO, 2024), can be used.

Sea Level (SL) is a type of height measurement associated with the sensor's origin—or the tide gauge—and the ocean surface (MESQUITA, 1997). Sea level can be local, when it is obtained through readings from a set of equipment that make up tide gauges (tide readings), or global, when it is associated with variables derived from altimetric satellites.

The local mean sea level can also be determined by altimetry satellites; however, the data will be derived from an extrapolation process of global data to a specific region. This will depend on the objectives of the study.

The equipment that makes up the tide gauges, depending on the programmed time interval, performs readings of the sea surface height (tide gauge readings) and sends them to a designated storage and processing location (GIEHL, 2020). These devices may experience technical failures, which can result in gaps in the daily record of these readings.

The development of regression models capable of predicting values to fill gaps generated by technical failures in the tide gauges is an alternative that makes the use of this data feasible. These failures can be caused by power outages, lack of internet connection, or malfunctions in the equipment or sensors (IBGE, 2021).

This article aims to determine two predictive models: one capable of forecasting the average variation of ASM between 2018 and 2022, and another capable of predicting the daily average variation of ASM. Both models were developed using readings corrected for coastal influences.

This research analyzed the variation of ASM between 2018 and 2022. Readings from the Encoder sensor of the Fortaleza/CE tide gauge (EMFOR) were considered, since the Fortaleza station did not provide the readings taken by the Radar sensor for the period in question.

Routines were developed to facilitate the downloading, processing, and manipulation of these data, with the statistical analysis performed using R software. The linear regression models were implemented by applying the Least Squares Method (LSM) and were evaluated for quality using R-squared and cross-validation.

A change was observed in the location of the Encoder sensor's origin between 2019 and 2020, which affected the pattern of the tide gauge readings and influenced the regression models. Despite statistical inconsistencies in the models, the cross-validation of the data demonstrated errors within the standard deviation (± 23.36 cm). An average ASM value of 21.93 meters in absolute terms and a daily average ASM variation of 1.02 centimeters were obtained.

2. Methodological Procedures

The tide gauge readings from Fortaleza/CE were chosen because they did not have any missing records, that is, all tidal readings were available from the database during the considered interval solely for the Encoder sensor. This is of utmost importance, as the data needed to be consistent and intact to enable the analyzed simulations.

Figure 1 shows the flowchart of the steps performed.

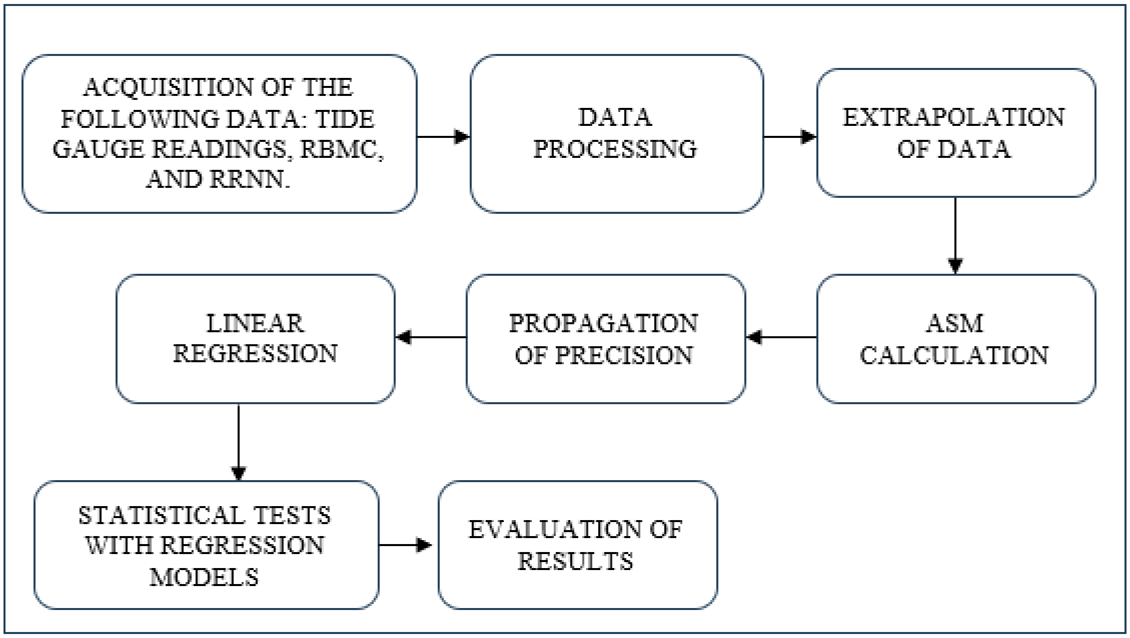

Figure 1 – Flowchart of steps.
Source: Authors (2025).

The readings were obtained through registration and access to the Geodetic Database (BDG) of the Brazilian Institute of Geography and Statistics (IBGE). All tide gauge readings from Fortaleza – CE, between January 2018 and December 2022, were collected in a single compressed file. Data consistency was verified based on the occurrence of technical failures.

Using the entire dataset available from 2018 to 2022, a systematic sampling was performed at a fifteen-day interval starting on January 1, 2018, resulting in a total of 122 days. This sampling was important because it simulated the absence of tide gauge readings due to technical failures, and based on that, a linear regression was conducted to model these missing readings.

The data from the Brazilian Continuous Monitoring Network (RBMC) station and the Level References (RRNN) were obtained through the BDG on the same days that the tide readings were taken, thus maintaining temporal correspondence between the data. The RBMC data provided consisted of a file with a RINEX extension and a descriptive file for each station, which included technical information about the antenna and the Global Navigation Satellite System (GNSS) receiver used, necessary for post-processing.

The RRNN data was obtained from the BDG and consisted of reports containing geodetic information of the level reference. The RRNN stations used to transfer precision were 4336T, 4336L, and 4336A. These RRNN stations were selected because they had the shortest distance between the tide station and the RBMC station compared to the other distances, effectively combining the RRNN stations around the tide station.

The data filtering process was carried out using R software on the .txt files. A routine was developed to select only the columns of interest from each file coming from the tide station—namely, just the date column and the Encoder sensor readings. The values recorded by the sensor were used to calculate the daily average of the tide readings. It was decided to eliminate data with empty spaces or incorrect tabulation during the calculation of the averages, as well as data affected by various tabulation arrangements.

The post-processing of the files obtained by RBMC was carried out on the IBGE portal, using the online service for GNSS data post-processing (Precise Point Positioning – PPP). For this research, only information on the ellipsoidal coordinate values pertaining to SIRGAS2000 and their uncertainties was used. Equation 1 shows the conversion between the altimetric reference surfaces (IBGE, 2023).

$$H^N = h \pm \xi \tag{1}$$

Being that: H^N is the normal height; h is the geometric height; ξ is the correction factor, composed of the height anomaly added to the intrinsic influences. For this purpose, the IBGE hgeoHNOR2020 height conversion model was used.

The daily averages of the tide gauge readings were referenced to the Brazilian Geodetic System (SGB), using the GRS80 ellipsoid—the basis for SIRGAS2000—in accordance with the considerations of IBGE (2021) and Giehl et al. (2022), as demonstrated in Equations 2 and 3.

$$ASM_{marégrafo} = L_{maregráfica} - S \quad (2)$$

$$S = A + B + C + J - T \quad (3)$$

Being that: $ASM_{marégrafo}$ is the observed height of the sea surface relative to the reference ellipsoid; $L_{maregráfica}$ is the observed height of the sea surface relative to the sensor's zero; A is the level difference between the zeros of the tide gauge and the sensors; B is the nominal reading of the staff's pin; C is the level difference between the staff's pin and the level reference; J is the stability of the station's Level References – RRNN; T is the ellipsoidal height of the adjacent RN.

The table 1 presents the values of the constants to be subtracted to reference the observations from the tide gauge in Fortaleza, Ceará, to SIRGAS2000. In this research, values for a mean tide system were used. This system was chosen because it considers the effects of tides (IBGE, 2023).

Table 1 – Correlation of Reference Levels for the Tide Gauge Station in Fortaleza, Ceará.

Tide Type / Sensor	Value of constant S (m)
Mean Tide / Radar Sensor	15,096 ± 0,036
Tide-Free / Radar Sensor	15,028 ± 0,036
Mean Tide / Encoder Sensor	13,849 ± 0,061
Tide-Free / Encoder Sensor	13,781 ± 0,061

Source: IBGE (2023).

After converting tide gauge readings into geometric heights, the MAPGEO2015 geoidal undulation model—as described in Equation 4—was considered using the latitude and longitude values provided for the EMFOR tide gauge station. This alternative was adopted because no geometric height information is available for EMFOR and due to financial constraints, it was not possible to perform GNSS positioning at the tide gauge location. The model provides the geoidal undulation and, theoretically, at the tide gauge, it is zero (IBGE, 2015).

$$H = h - N \quad (4)$$

Being that: H is the orthometric height, h is the geometric height and N is the geoid undulation.

The ASM variation was calculated as the difference between the geometric heights obtained from tide gauge readings and the tide gauge's geometric height. This allows for the determination of values for both daily variation and total variation, considering the entire sample of days on which the tide gauge readings were collected.

Tectonic activities modify the morphology and structure of the Earth's surface. "The construction and destruction of the Earth's crust is determined by tectonic processes that promote seismic, volcanic, metamorphic, orogenic, and isostatic movements" (FAUSTINON et al., 2016). According to Albarici et al. (2019), tidal loading is the alteration of the Earth's crust caused by the movement of the ocean mass over it, leading to vertical displacements that can result in up to ten centimeters of vertical shift in the positioning of a station.

Crustal uplift and crustal subsidence are two vertical movements that the Earth's crust undergoes. Consequently, it became necessary to propagate the precision of the RBMC to the tide gauge to analyze the effects on sea level.

The import of RBMC data into the R software was performed in a manner similar to that of importing tide gauge readings. A vector was created that stored the estimated geometric height values along with their respective Root Mean Square Error (RMSE). This research proposed the following methodology for precision propagation, considering Equations 5 to 7.

$$h_{maregrafo} = h_{RBMC} + \xi_{RBMC} + DN_{(RBMC-RN_1)} + DN_{(RN_1-RN_2)} + DN_{(RN_2-RN_3)} + DN_{(RN_3-maregrafo)} + \xi_{maregrafo} \quad (5)$$

Being that: $h_{maregrafo}$ is the geometric height of the tide gauge; h_{RBMC} is the geometric height of the RBMC station determined by PPP; DN is the level difference determined through geometric leveling; ξ_{RBMC} e $\xi_{maregrafo}$ are the height anomalies at the RBMC station and the tide gauge, respectively, determined using the hgeoHNOR2020 height conversion model.

The propagation of accuracies to obtain the uncertainty of $h_{maregrafo}$, considered the precision of the level difference determined by geometric leveling negligible compared to the precision of the RBMC's geometric height and the height anomaly (ξ).

$$EMQ_{DN_{(RBMC-RN_1)}} = EMQ_{DN_{(RN_1-RN_2)}} = EMQ_{DN_{(RN_2-RN_3)}} = EMQ_{DN_{(RN_3-maregrafo)}} \cong 0 \quad (6)$$

$$EMQ_{h_{maregrafo}} = \sqrt{(EMQ_{h_{RBMC}})^2 + (EMQ_{\xi_{RBMC}})^2 + (EMQ_{\xi_{maregrafo}})^2} \quad (7)$$

Being that: $EMQ_{h_{maregrafo}}$ is the precision of the tide gauge's geometric height obtained by propagating the precision in transferring the geometric height from the RBMC to the tide gauge; EMQ_{DN} is the precision of the geometric leveling between the leveling sections; $EMQ_{h_{RBMC}}$ is the precision of the geometric height determined through PPP; $EMQ_{\xi_{RBMC}}$ e $EMQ_{\xi_{maregrafo}}$ are the precisions of the height anomaly due to the uncertainty of the hgeoHNOR2020 height conversion model at the RBMC station and the tide gauge, respectively..

In linear regression models, the core lies in the dependence among the analyzed variables. The variables must be random and have a probability distribution. The simple linear regression model follows the form of the parametric equation, as shown by Equation 8 (CHEIN, 2019):

$$Y_i = \beta_0 + (\beta_1 * x_i) + \varepsilon_i \quad (8)$$

Being that: Y_i is the response variable; β_0 is the intercept of the line; β_1 is the slope of the line; ε_i s the error made when estimating Y as a function of x, and x_i is the regressor variable.

The error associated with estimating Y through X can be described as the difference between the observed value and that predicted by the model. The goal of the Least Squares Method (LSM) is to establish the best parameters for the regression model, which implies reducing the value of the error (ε) committed.

The statistical tests used to evaluate the regression models were the Shapiro-Wilk test to assess normality; the student's t-test to assess linearity; the Breusch-Godfrey test to assess autocorrelation; the Breusch-Pagan test to assess homoscedasticity; and the R-squared test to assess the quality of the models.

3. Results and Discussion

The normal heights were converted to geometric heights (Table 2). Since height anomaly values depend on the latitude and longitude of the RRNNs, variations were expected, as the shape of the Earth's surface is not uniform, even over shorter distances, as is the case with RRNNs 4336T, 4336L, and 4336A. The conversion to obtain the geometric height at the EMFOR tide gauge (03°42'52.55"S and 38°28'36.54"W) resulted in a geoid undulation of -8.94m.

Table 2 – Geometric Heights for RRNN 4336T, 4336L, and 4336A.

Points	Latitude	Longitude	Geometric height (m)	Normal height (m)	n(m)	Uncertainty (m)
4336T	3°42’45”S	38°28’29”O	-4,335	4,834	-9,17	0,05
4336L	3°42’50”S	38°28’34”O	-5,058	4,121	-9,18	0,05
4336A	3°42’51,84”S	38°28’36,12”O	-5,468	3,701	-9,17	0,05

Source: Authors (2025).

By obtaining the EMQ from the tide gauge and the geometric heights derived from the tide gauge readings, it was possible to observe a deviation from the standard in the values between 2019 and 2020 (Figure 2). This may have been caused by a change in the origin of the Encoder sensor, as there was no significant alteration in the position of the tide gauge.

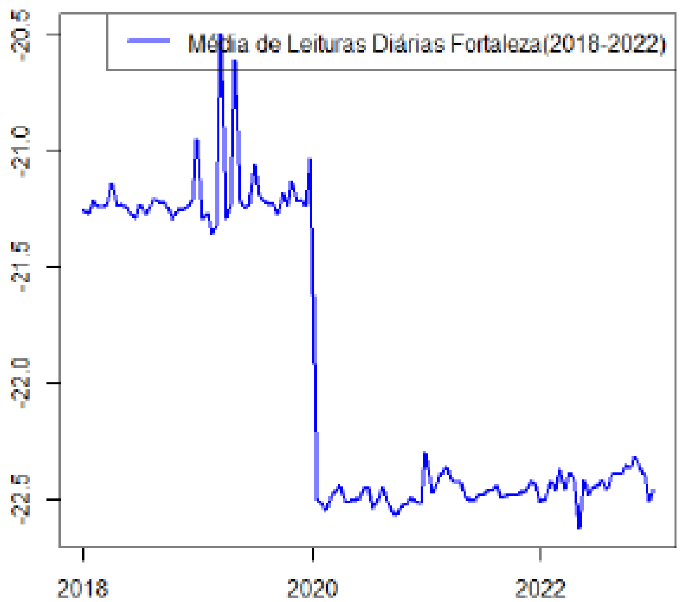

Figure 2 – Graph for the daily average of tidal readings, with daily average values on the vertical axis and years on the horizontal axis.
Source: Authors (2025).

After obtaining the daily averages for the sample days, the mean ASM, considering the SIRGAS2000 reference system and the influence of Earth's crust movement was -21.93 ± 0.23 meters. The variation in the daily mean ASM was 1.02 ± 0.09 cm.

The coefficients of the regression models are listed in Table 3.

Table 3 – Coefficients of the proposed regression models.

Model	x	y	β0	β1
1	Day	Variation of the Daily Average of ASM	-0,0943	0,00000456
2	Day	Daily ASM Average	-4,0419	-0,00097006

Source: Authors (2025).

The *p-value* for the normality test, considering the variables used in the models, were: $2{,}18*10^{-16}$ for the daily mean variation and $3{,}65*10^{-12}$ for the average ASM. At a significance level (α) of 0,05%, the null hypothesis was rejected, indicating that the distribution is not normal.

For each of the models, a statistical test was conducted to determine if there is a linear relationship between the regression model and the sample values. For Model 1, the variable's *p-value* indicated that there is no statistical evidence to reject the null hypothesis (no linear relationship). In other words, the sample used did not produce an adequate model to predict the variation in the daily average of the ASM, as evidenced by the adjusted R-squared value of -0.008473, where values closer to |1| indicate a better model fit. This suggests that the sample was impacted by the change in the origin of the Encoder sensor's scale.

For model 2, which indicates the average daily value for ASM, the p-value was less than the significance level, leading to the rejection of the null hypothesis of non-linearity. The adjusted R-squared value (0.6805) indicated a median model fit, considering that in an ideal model, the R-squared would be equal to 1 in absolute value.

After conducting statistical tests on regression models, it can be inferred that both exhibit autocorrelation of residuals and both have homoscedastic residuals. Only the regression model of the daily average of ASM (model 2) presented the normality of residuals.

The violation of statistical assumptions is for the most part not prohibitive for prediction (FIGUEIREDO FILHO et al., 2011; ZONATO et al., 2018). However, they compromise the quality of the model and the determination of confidence intervals.

4. Concluding remarks

The deviation in the average daily ASM value observed between 2019 and 2020 can be attributed to changes in the encoder sensor's zero point or the influence of the Altimetric Network Adjustment with Geopotential Numbers (REALT-2018). Although the ASM predictive models exhibited inconsistencies with expected statistical assumptions—such as normality, linearity, autocorrelation, and homoscedasticity—the ASM values obtained from these models were coherent and consistent when tested through cross-validation. In other words, despite statistical shortcomings in the models, the results remained reliable within the context of the analysis.

It's important to note that the uncertainty propagation from the PPP processing of the RBMC to the tide gauge (EMFOR) could be influenced by changes in level differences caused by crustal movements or subsidence at RRNN stations not anchored in rock. While geometric leveling doesn't enhance precision in transporting RRNNs, it remains relevant for minimizing uncertainties in local surveys. Additionally, an alternative was proposed for situations where field surveys are not feasible.

The sampling was limited due to the complexity of the study object, as tidal variations do not follow a fixed pattern between high and low tides. Therefore, for future investigations, it's recommended to use a sampling method that covers a broader temporal interval and incorporates all values obtained during that period. Even with gaps, a more extensive database will enable models to better capture the nuances of tide gauge data. The sampling period between 2018-2019 and 2020-2022 is a hypothesis to consider when working with the same data sample.

A sampling that ensures 90% confidence using 5 years (2018-2022) with a data population should have at least 200 sample units. Therefore, the systematic frequency interval should be smaller. Assuming all years have 365 days, an ideal frequency interval to obtain at least 200 days is every 9 days. However, to work with an even larger sample, collecting data from the RBMC and using the PPP becomes a more costly task.

Automating the PPP was an alternative to reduce computational costs and avoid gross errors. Selecting a set of dates for downloading RBMC data, rather than the interval between dates, can facilitate the process when the data volume is extensive and specific, as in the methodology used in this study.

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