Prediction of Tidal Effect in Crustal Deformation Monitoring: A Geodetic Perspective*

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Abstract

The gravitational force that arises by the pull from external objects varies from one part of the affected object to the other. These differential pulls produce what are known as tidal forces. This tidal force leads to deformation of the earth crust which can be in both the horizontal and vertical planes. It is quite agreeable that over the years there have been growing interest in crustal deformation monitoring and many geodetic techniques such as precise levelling measurements, angle and distance measurements, photogrammetric and Global Navigation Satellite System (GNSS) have been adopted for this purpose. However, literature has shown that tidal effects have not been given much consideration in crustal deformation and structural health monitoring studies. In the present study, three mathematical approaches namely Auto-Regressive Integrated Moving Average (ARIMA) Time Series, Non-Linear Auto-Regressive Neural Network (NARNET), and the Hybrid ARIMA and Neural Network model have been used to model and predict the tidal effect on the earth crust for geodetic deformation monitoring These models were developed from a set of quantified deformation values based on geographic locations of points found in five regions of Ghana on which a prediction of future trend was made. The average deformation values produced by ARIMA, NARNET and Hybrid model are 0. 002004, 0.001900, and 0.00242 m, respectively. The ARIMA, NARNET and hybrid models showed average over- and under-estimation values of 0.000033, 0.000310 and -0.00046 m corresponding to their mean residuals. In assessing the precision of the estimated tidal values, the Hybrid model performed slightly better than the NARNET and the ARIMA models with average standard deviation of 0.00039, 0.000780 and 0.000784 m respectively. As such, future tidal deformation values can best be predicted in deformation monitoring assessment by using the Hybrid ARIMA and Neural Network models.

K**eywords:** Tides, Auto-Regressive Integrated Moving Average, Time Series, Non-Linear Auto-Regressive

1 Introduction

Tide is the daily rising and falling of the sea level. There is a general understanding that it is due to the Moon's and the Sun's gravitational pull. The gravitational force that arises by the pull from external objects varies from one part of the affected object to the other. These differential pulls produce what are known as tidal forces. Whenever one touch a body, internal stresses are set up in the material in contact (Torge, 2001). Elastic materials can be deformed depending on the applied force and the properties of the material. In short time scales, the Earth can therefore be considered to be elastic and can be deformed by an external force, the tidal force (Torge, 2001). Specifically, the tidal force affect the Earth's hard outer layer (crust) which is made up of continental and oceanic. The continental crust is known to be thicker than the oceanic and both constitute different types of rocks: igneous, metamorphic, and sedimentary rocks (Schubert, 2001).

Several scholars have attributed the Earth crustal movement to natural or human activity (Yakubu *et al*., 2010 and references therein). Such movements can trigger displacement in the earth's crust thereby causing significant property loss and human life. Therefore, it is a well-established fact that the importance of deformation monitoring cannot be underestimated. There have been evidence of different scenarios in which structures collapse all over the world. In line with that, the study of crustal deformation is increasingly receiving much attention in civil engineering and the building profession (Uren and Price, 2010).

In continuance of that, several research works have gone into the mathematical modelling and prediction of crustal deformation over the years. In addition to that, owing to the importance of tidal deformation predictions, various techniques have been proposed over the years, such as linear and nonlinear regression based methods, time series based models, artificial neural networks, hybrid of time series model and artificial neural network, , Fuzzy logic, and Support Vector Machine (Yang and Chen, 2005; Badran and Abouelatta, 2011; Kandananond, 2012; Sheikh, 2012; He *et al*., 2012; Khandelwaal *et al*., 2015; Okwuashi and Ndehedehe, 2017).

Among the numerous deformation monitoring prediction techniques (Multiple Regression, Time series, Artificial Intelligence *etc*), tidal effects have not been given much consideration. This study considered five regions in Ghana to predict its tidal deformation using Auto-Regressive Integrated Moving Average (ARIMA) Time Series, Non-

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Linear Auto-Regressive Neural Network and Hybrid ARIMA and Neural Network procedure. Using quantified tidal effect data based on geographic locations of the study areas, it is possible for future predictions to be made.

2 Resources and Methods Used

2.1 Resources and Study Area

Ghana is positioned at the western part of Africa, and share boarders with Togo to the east, Burkina Faso to the north and Ivory Coast to the west. The country lies between latitudes 4^{o} and 12^{o} N and longitude 4^{o} E and 2^{o} W and covers a total land area of 239,460 sq. km. The topography is generally of low plains with divided plateau in the South-Central area and scattered areas of high relief (Baabereyir, 2009). The Greenwich Meridian runs through Tema near Accra which makes Ghana geographically contiguous to the center of the world, that is, the speculative point of intersection between the equator and longitude 0˚ located in the Atlantic Ocean is about 614 km from the southern direction of Accra ((Opoku, 2015).

There are ten regions in Ghana and this study focuses on five regions namely: Ashanti, Greater Accra, Western, Central and Eastern Regions (see Fig. 1). Ashanti Region is the third largest of the 10 regions in Ghana. This region has thick forests with no sea but have different rivers and lakes. The topology of the lands consists of both plain surfaces and steep ridges ((Opoku, 2015). Greater Accra is delimited on the north by the Eastern Region, on the east by the Lake Volta, on the south by the Gulf of Guinea, and on the west by the Central Region (Opoku, 2015). The topography of Accra consists of a low sandy shore behind which stretches the coastal plain. The lands are fairly low with no mountain ranges and less grassland as compared to the other regions. Western Region is enclosed on the east by the Central Region, to the west by Ivory Coast, to the north by Ashanti and Brong-Ahafo Regions, and to the south by the Gulf of Guinea. The southernmost part of Ghana lies in this region, at Cape Three points near Busua in the Ahanta West District (Opoku, 2015). The topography generally describes as a series of ridges and valleys parallel to one another with few low lands (Ziggah, 2007). The land is undulating with thick forests (Mohammed, 2015). Eastern Region is enclosed to the east by the Lake Volta, to the north by Brong -Ahafo Region, to the west by Ashanti region, to the south by Central region and Greater Accra Region. The Eastern Region has both high and low lands. The Kwahu scarp has an elevation of about 788 m above the mean sea level. There are inaccessible hills and mountains speckling the relatively low-lying plains to the south, notably the Krobo and the Yogaga Mountains (Mohammed, 2015). Central Region is encircled by Ashanti and Eastern Regions to the north, Western Region to the west, Greater Accra to the east, and to the south by the Gulf of Guinea (Opoku, 2015). The Central Region have equitably low lands with very less forest reserves. The region has a stretched land of coastal area with sandy shores (Mohammed, 2015). This study applies secondary data obtained from the Survey and Mapping Division in Ghana. The data was collected during a DGNSS campaign by the Survey and Mapping Division across the whole country. The data was denoised or cleaned using Kalman filter model and moving average filter.

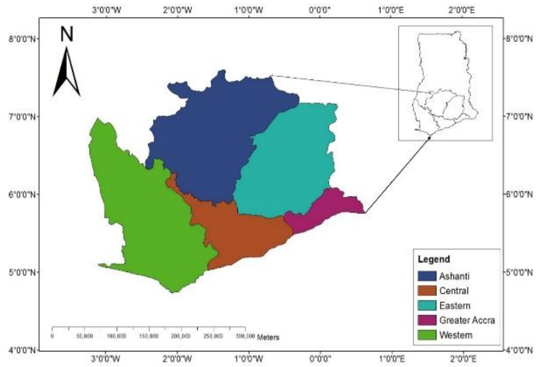

Fig.. 1 Map of Ghana showing the Selected Study Area

2.2 Methods

2.1.1 Auto-Regressive Integrated (ARIMA) Time Series

In practice, fitting a suitable model is essential because it provides a general understanding on the nature of the time series data which helps in future forecasting and in decision making. The ARIMA is one of the commonly used models applied in time series forecasting. This model has the capabilities to represent stationary as well as non-stationary time series and to produce accurate forecasts based on a description of historical data of single variable. The basic assumption made towards the implementation of this model is that, it is in most cases linear and follows the normal distribution (Raymond, 1997). The ARIMA model has subclass of other models. These are Autoregressive (AR) and Moving Average (MA) models respectively.

The AR(p) (Autoregressive of order p) model is a discrete time linear equation with noise as expressed in Equation (1).

$$X_t = \alpha_1 X_{t-1} + \dots + \alpha_p X_{t-p} + \varepsilon_t \quad (1)$$

Here, X_t is the current forecasted model, p is the order, $\alpha_1, \dots, \alpha_p$ are the parameters or coefficients (real numbers) of the model formed, X_{t-1}, X_{t-p} are the previous observations, ε_p is the error of the forecast , usually a white noise.

The MA(q) (Moving Average with orders p and q) model is an explicit formula for X_t in terms of noise given by Equation (2).

$$X_t = \varepsilon_t - \beta_1\varepsilon_{t-1} - \ \dots - \beta_p\varepsilon_{t-q} \qquad (2)$$

Difference operator. Integration:

The first difference operator, Δ, is defined as

$$\Delta X_t = X_t - X_{t-1} = (1-L)X_t. \qquad (3)$$

The ARIMA with orders (p, d, q) is defined in Equation (4).

$$\left(1-\sum_{k=1}^{p}\alpha_k L^k\right)(1-L)^d X_t = \left(1+\sum_{k=1}^{q}\beta_k L^k\right)\varepsilon_t \qquad (4)$$

Where L^k is the time lag operator, ε_t is an error term, d is the order of integration.

The basic steps in the Box-Jenkins methodology was adopted in this study to build the ARIMA model (Equation (4)). This include stationarity checks, model identification, parameter estimation and model selection, (3) diagnostic checking.

2.2.2 Artificial neural network (ANN)

A neural network consists of input layer, hidden layer and output layer as shown in Fig. 2.

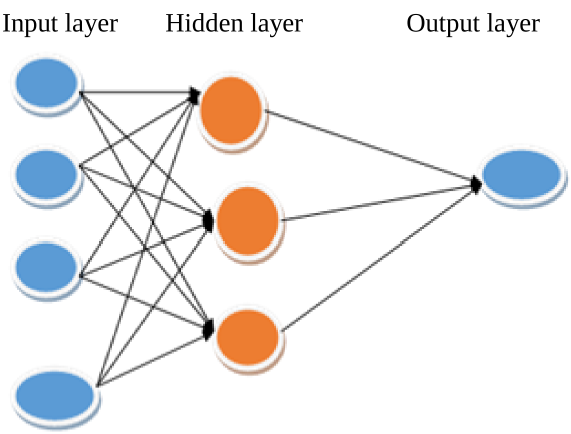

Fig. 2 ANN Structure

The input neuron from the input layer represents some independent variable that militate the output result. This study did not apply more than one hidden layer because it does not significantly contribute to the accuracy output result. In the hidden and output layers, the hyperbolic tangent and linear regressor activation functions were used. Processing of the data take place in the hidden layer before they finally arrive at the output layer.

2.1.3 Non-Linear Auto-Regressive Neural Network

The MATLAB neural network toolbox has a function NARNET for designing a neural network model for predicting future values of time series data. The NARNET can be trained to predict a time series from that series past values. The NARNET takes these arguments feedback delays, hidden sizes and training functions. These arguments are varied till it conforms to the data pattern which is then used to predict future values. The Levenberg-Marquardt training function was used in this study.

2.1.4 Hybrid ARIMA and Neural Network Models

In the hybrid ARIMA and Neural Network models, ARIMA is used to predict the linear component of the time series data whereas Neural Network is used to predict the nonlinear component. Zhang pointed out this important fact relating the total prediction as given in Equation (5).

$$Y_t = L_t + N_t \qquad (5)$$

where Y_t is the observation at time t and L_t, N_t denote linear and nonlinear components respectively.

The prediction is done in two steps; firstly, an ARIMA model is fitted to the linear component to get the corresponding forecast L_t*. The residual at time t is given by $e_t = Y_t^* - L_t^*$. According to Zhang, the residual dataset after fitting the ARIMA model contains only the nonlinear component which can be modelled through an ANN. Secondly, N_t* is predicted from the ANN model using the residuals, e_t:

$Y_t^* = L_t^* + N_t^*$ becomes the hybrid forecast at time t.

Through empirical analysis with three real-world time series, Zhang has found that his hybrid ARIMA-ANN method has achieved considerably better forecasting accuracies than separate application of ARIMA and ANN models.

2.1.5 Assessment of the Models

In order to know the validity of the models, the following statistical indicators were employed: Mean residuals (Mean), Root Mean Square (RMSE), Standard Deviation (SD), and Mean Absolute Error (MAE).

The mean residual which shows the average tidal displacement value was computed using Equation (6).

$$Mean(\bar{x}) = \frac{|\Sigma(x)|}{n} \tag{6}$$

The mean absolute error (MAE) indicating the mean squared variations was computed using Equation (7):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|x_{o_i} - x_{p_i}\right| \tag{7}$$

Root Mean Squared Error (RMSE), which gives a sense of the typical size of the value, was computed using Equation (8):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_{o_i} - x_{p_i})^2} \tag{8}$$

The standard deviation (SD) measures how closely the data are clustered about the mean. It was computed using Equation (9):

$$SD = \sqrt{\frac{\Sigma(x_{p_i} - \bar{x}_{p_i})^2}{n-1}} \tag{9}$$

where x_{o_i}, x_{p_i}, $\bar{x}_{p_i}$ are the observed, predicted and mean of the predicted tidal value. N denoted the number of sample points used.

3 Results and Discussion

The forecasted tidal displacement results from the ARIMA, ANN and hybrid-ANN models were categorised under three main groups; those close to the coast (COAST), those away from the coast

(INLAND) and those in between Coast and Inland (MIDDLE) for the next five years on a monthly observation basis.

From the ARIMA model, the average of the tidal displacements corresponding to the COAST, MIDDLE and INLAND were 0.001955, 0.002187 and 0.001869 m. The overall average displacement for the forecast is 0.002004. The maximum displacement value recorded was 0.002562 m and the minimum 0.001528 which is for MIDDLE and INLAND respectively. This suggest that those along the coast experience a great tidal displacement. Fig. 3 illustrate the ARIMA forecasted tidal displacement as well as its corresponding residuals. A summary statistics of the ARIMA model prediction performance are also presented in Table 1.

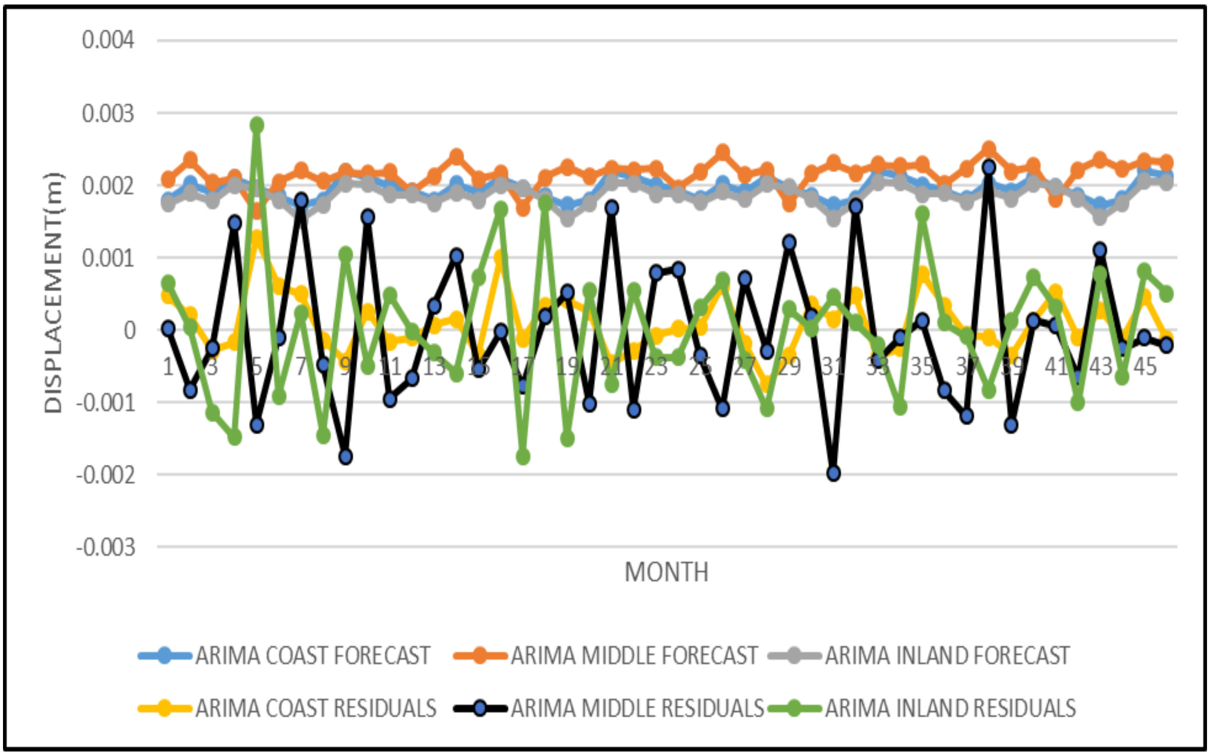

Fig. 3 ARIMA Forecast and Residuals Model

Table 1 Statistical Analysis on the ARIMA Model Residuals

STAT	COAST	MIDDLE	INLAND
MEAN	9.653E-05	-1.689E-05	1.993E-05
RMSE	4.034E-04	9.866E-04	9.343E-04
MAE	1.002E-20	-1.237E-20	0.00000
SD	4.079E-04	9.975E-04	9.447E-04

From the ANN model forecast, the average of the tidal displacements are: 0.001949, 0.001969 and 0.001783 m for the COAST, MIDDLE and INLAND respectively. The overall average displacement for the forecast is 0.001900 m. The largest displacement value recorded was 0.002248 m for the COAST and a minimum value of 0.001683 m was noticed for the MIDDLE respectively. This suggest that those along the coastal areas of Ghana experience great tidal displacement as compared to the MIDDLE and INLAND. The prediction performance of the ANN model are summarised in Table 2. Fig. 4 illustrate the ANN forecasted tidal displacement as well as its corresponding residuals.

Table 2 Statistical Analysis on the Artificial Neural Network Residuals

STAT	COAST	MIDDLE	INLAND
MEAN	0.00117	0.00120	-0.00144
RMSE	0.00064	0.00095	0.00072
MAE	-4.685E-19	1.549E-20	-1.510E-19
SD	0.00065	0.00096	0.00073

From the Hybrid ARIMA and Neural Network model, the average displacements are 0.00137 m, 0.00364 m and 0.00226 m for COAST, MIDDLE and INLAND respectively. The overall average displacement for the forecast is 0.00242 m. The peaked displacement value recorded was 0.00457 m and the minimum 0.00079 m which is for MIDDLE and COAST respectively. This suggest that those within the MIDDLE areas of Ghana experience a great tidal displacement based on the Hybrid ARIMA and Neural Network model results. Table 3 illustrates the hybrid model prediction performance. Fig. 5 illustrate the hybrid forecasted tidal displacement as well as its corresponding residuals.

Table 3 Statistical Analysis on the Hybrid ARIMA Neural Network Residuals

STAT	COAST	MIDDLE	INLAND
MEAN	0.00069	-0.00162	-0.00044
SD	0.00039	0.00066	0.00065
RMSE	3.809E-04	6.396E-04	6.288E-04
MSE	1.451E-07	4.091E-07	3.953E-07

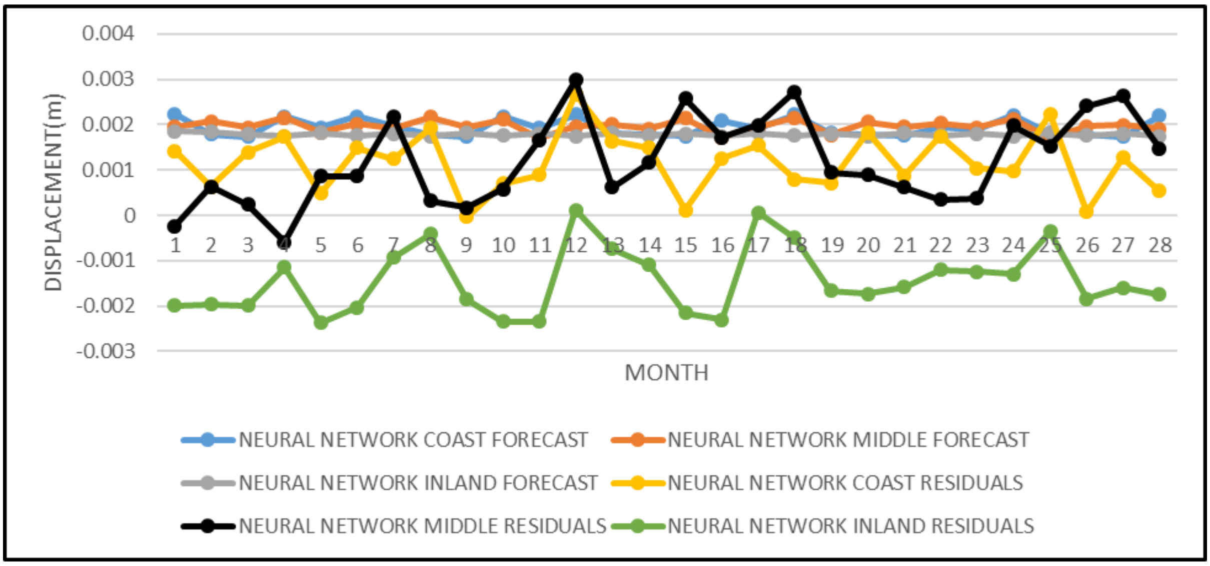

Fig. 4 Neural Network Forecast and Residuals Model

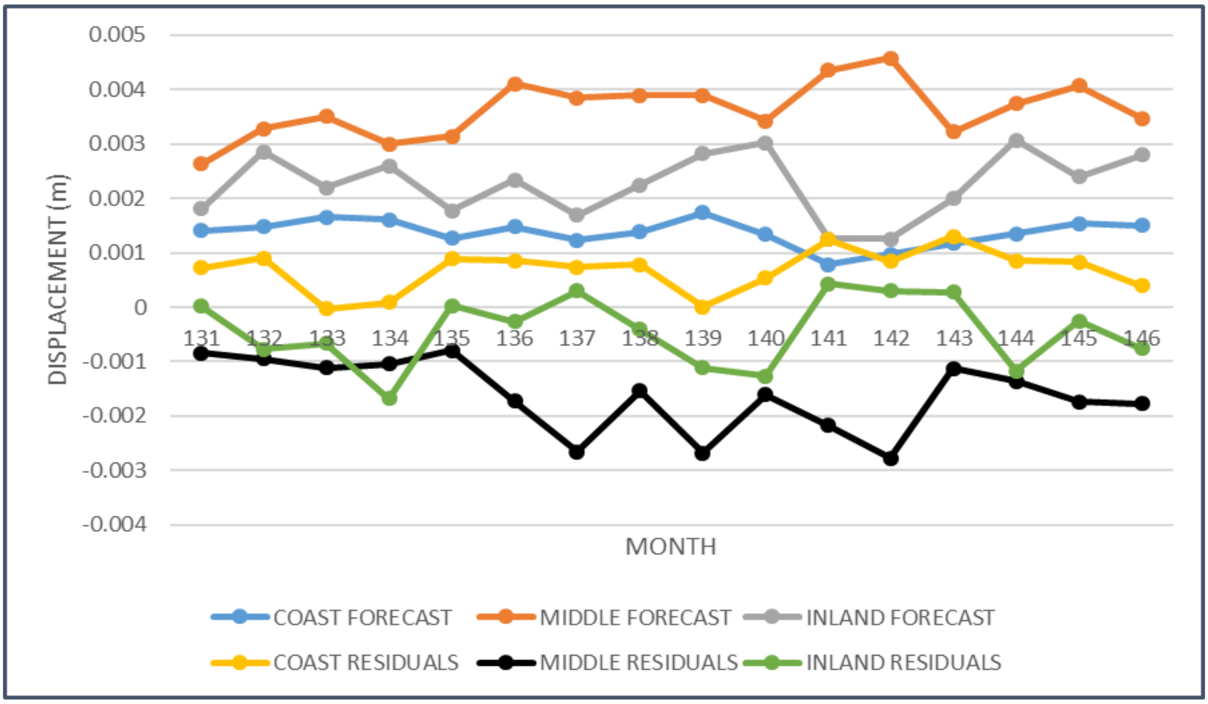

Fig. 5 Hybrid ARIMA-Neural Network Forecast and Residuals

4 Conclusions

Auto-Regressive Integrated Moving Average (ARIMA) time series model, Non-Linear Auto-Regressive Neural Network and hybrid of the two models have been successfully applied to predict future trends of the tidal deformation. It has been shown that the tidal deformation values follow a time series pattern. However, from the statistical analyses performed on the residuals of the three methods; the Hybrid model performed better than the Neural Network and the ARIMA model. The Hybrid model, ARIMA model and Neural Network had SDs of 0.00039, 0.000408 and 0.000650 m respectively in the COAST (see Tables 1, 2 and 3). This is an indication that the Hybrid model performed better. In the MIDDLE areas of Ghana, the hybrid model produced the best prediction results with approximate SD of 0.00066 m while, 0.000998 and 0.00095 m were achieved by the ARIMA and the ANN (see Tables 1, 2 and 3). With regards to the INLAND areas of Ghana, 0.00065, 0.000945 and 0.0. 00072 were the corresponding SDs obtained by the hybrid, ARIMA and the ANN respectively. It can be concluded that future tidal deformation values can best be predicted in Ghana by the Hybrid ARIMA and Neural Network model.

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