

A Local Geoid for Egypt's Mediterranean Coast: A Model Based on Artificial Neural Networks

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DOI: <https://doi.org/10.52939/ijg.v18i3.2193>

Abstract

The principal goals of this study are to assess five global geoid models, namely EGM2008, EIGEN-6C4, GECO, SGG-UGM-1, and XGM2019e_2159, as well as to create a centimeter-accurate local geoid model for Egypt's Mediterranean coast. To generate the geoid model for the Mediterranean coast, GNSS/leveling points were integrated with the best global geoid model in the region. This process is a cost-effective replacement for the more expensive conventional leveling technique. The Artificial Neural Network (ANN) was created and is now being utilized to do interpolation and statistical geoid height prediction. The findings show that XGM2019e_2159 is the best global model for modeling the geoid surface on the Mediterranean coast, with a Standard Deviation of 14 cm. The findings showed that using this model constructed with the aid of the ANN, it is feasible to determine the geoid height with a Standard Deviation of 3 cm in the Mediterranean coastal areas.

1. Introduction

The importance of Egypt's coastlines originates from the country's year-round mild temperature and vast landmass, which provide a perfect chance for expansion and the construction of a number of new towns employing cutting-edge planning and development techniques. The government has recently been more cognizant of the need for big projects along these coasts, as well as the creation of numerous new coastal cities, such as New Alamein and New Mansoura. In recent years, GNSS has become one of the most widely used practical geodesy techniques. The GNSS offers three-dimensional location, but it also provides height (geodetic height) above the ellipsoid, which is entirely mathematical and has no physical value (Mukesh et al., 2020). Orthometric height, or height above the geoid, is utilized in engineering projects. To fully use GNSS's potential, geoid modeling must be used to create a relationship between geodetic and orthometric height. Equation 1 describes the relation between orthometric height (H), geoid height (N), and geodetic height (h). The relation between geodetic, orthometric, and geoid heights is depicted in Figure 1.

$$N \approx h - H$$

Equation 1

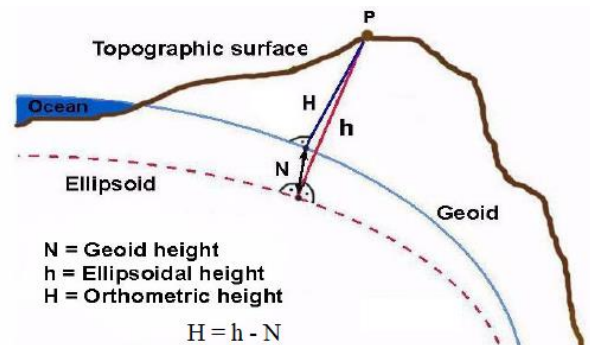


Figure 1: Relation between geodetic, orthometric, and geoid heights (Ylmaz et al., 2021)

Obtaining a one centimeter-level geoid is still a tremendous difficulty in geodetic research, and determining the geoid model with high precision is still a fundamental subject in physical geodesy that gets a lot of attention from the geodetic and geophysical communities. Many research and studies have been done on the geoid model all across the world (Arana et al., 2017 and Zaki and Mogren, 2021).

In recent years, several research in Egypt have concentrated on developing geoid models for the entire country or specific regions, for example (Sobh et al., 2019, Dawod and Abdel-Aziz, 2021, Ahmed et al., 2021 and Elshewy et al., 2021). To date, geoid modeling development in Egypt has remained a pressing concern.

Global Geoid Models (GGMs) are spherical harmonic coefficients that describe the gravitational field of the Earth at different wavelengths. These factors were calculated using satellite orbit deviation, altimeter data, gravimeter-gradiometer data, and gravimeter data. The recent CHAMP, GRACE, and GOCE satellite field missions have significantly improved our understanding of the longwave and mediumwave parts of the Earth's gravitational field, and hence the geoid (Doganalp, 2016). They give virtually comprehensive globe coverage of gravitational field data in a uniform and consistent manner. Five GGMs were chosen for this study based on numerous factors, including the greatest degree and order of each GGM, the range of data sources used in each GGM development, and current GGM development in recent years. EGM2008, EIGEN-6C4, GECO, SGG-UGM-1, and XGM2019e_2159 were chosen based on these criteria. In Egypt, for example, there are a lot of research dedicated to the evaluation of GGMs (Al-Karargy and Dawod, 2021 and Elwan et al., 2021). Many research on the assessment of GGMs have lately been undertaken at the worldwide level, for example (Kanushin et al., 2017 and Mosquera et al., 2021).

The geometric technique entails interpolating the geoid heights at each point based on N acquired from h and H at some points. To interpolate geoid heights at any place, interpolation methods such as polynomial regression model, least-squares collocation, spline interpolation, kriging, artificial neural networks, and others are utilized. The geometric technique for geoid modeling has the benefit of ensuring that GNSS heights are consistent with local orthometric heights, thereby absorbing any movement in the survey region. The geometric approach is one of the most important ways for creating geoid models, however it is largely reliant on the method for interpolating known geoid heights to generate a geoid model. There are several mathematical methods that connect the height of a geoid to its location in order to calculate the geoid's surface. ANN is a method for interpolating geoid heights that was shown to be more dependable than other methods (Ahmed et al., 2021).

ANN is a set of data processing algorithms inspired by the biological nervous system's

information processing mechanism. The ANN is built up of "neurons," which are parallel fundamental units, and "connections," which are the connections between these neurons. Neurons are connected by a vast network of weighted connections that send data. The neuron uses a non-linear process to mix the incoming input data and output the outcomes. By evaluating previously recorded data, ANN may determine the relationship between variables for input and output. The fundamental benefit of ANN is that they can solve issues for which no algorithmic solution exists or for which an algorithmic solution is extremely difficult to specify. Because of its computational efficiency, ANN is effectively used in a wide range of engineering, mathematics, and other subjects. According to the experimental results, the values of the ANN model closely mirror the real data, according to El-naggar (El-naggar, 2013). Elshambaky revealed that among the transformation strategies tested, a feed-forward multilayer neural network with only two neurons is particularly precise (Elshambaky, 2018). According to Albayrak et al., (2020), the model identified by the ANN looks to be more dependable than the model retrieved using classic interpolation approaches (Erol and Erol, 2021). ANN has recently been used to generate a geoid surface as a means of interpolation between known geoid heights at control points that are identified and distributed accurately on the ground (Akcin and Celik, 2013 and Erol and Erol, 2020).

In connection with the above, the purpose of the study is to assess the accuracy of five global geoid models, EGM2008, EIGEN-6C4, GECO, SGG-UGM-1, XGM2019e_2159, and then using the ANN to develop a geoid model for the Mediterranean coast by combining GNSS/leveling data with the data from best Global models in this region.

2. Materials and Methods

2.1 Study Area and Measurements

Figure 2 shows the research region in northern Egypt, which stretches from Sidi Barrani to North Sinai along the Mediterranean coast. Extends from latitude $30^{\circ} 49' 9.24''$ N to $31^{\circ} 35'58.78''$ N, and from longitude $26^{\circ} 36'18.81''$ E to $33^{\circ} 0'21.82''$ E. A total of 87 GNSS/leveling data points were used in the survey. By attaching the leveling loops to the Egyptian national vertical coordinate system, precise leveling data was gathered with a Leica NA2 precision level.

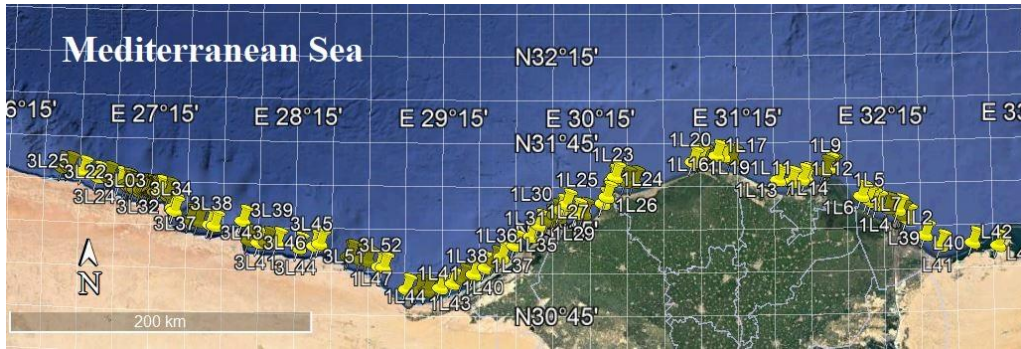


Figure 2: Map of the study area

The inaccuracy of orthometric heights in reference to the nearest points of the state levelling network is less than 1.0 cm. Furthermore, GNSS measurements were taken for 87 benchmarks in relation to the Egyptian National Geodetic Coordinate System. To observe each rover, the Trimble 5700 dual-frequency survey receivers were employed in static mode at the reference base station for 2 hours. Geodetic heights were determined with a maximum inaccuracy of 2.0 cm for each station in each session.

2.2 Research Methodology

GNSS/leveling points are merged with global geoid models to generate a geoid model for the Mediterranean coast. The purpose of this procedure is to use global geoid models in places where GNSS/leveling points are not available, as well as to increase model accuracy in local areas by minimizing long-wave geoid errors. This approach is a low-cost alternative to the more expensive traditional leveling technique. The geoid surface was simulated using ANN in this study. The following steps are included in the approach for creating a geoid model on Egypt's Mediterranean coast:

- First, the geoid heights ($N_{\text{GNSS/level}}$) of 87 reference points are calculated using Equation 1;
- Then, the ANN is used to interpolate these geoid heights for creating an initial geoid model. Based on this model, the geoid heights ($N_{\text{GNSS/level-ANN}}$) of 87 control points are calculated;
- After that, the geoid heights of the five global models (N_{GGM}) for 87 reference points are obtained using the latitude (φ) and longitude (λ) of the points in .txt format from the site of the International Centre for Global Earth Models (ICGEM), <http://icgem.gfz-potsdam.de/calcpoints>.

ICGEM is one of five services coordinated by the International Gravity Field Service (IGFS) of the International Association of Geodesy (IAG);

- Then, N_{GGM} from the different global models are assessed by comparing with $N_{\text{GNSS/level}}$ according to Equation 2:

$$\Delta N = N_{\text{GNSS/level}} - N_{\text{GGM}} \quad \text{Equation 2}$$

- From this evaluation, the best global model ($N_{\text{GGM-B}}$) on this territory is used in the next steps;
- The ANN is used to interpolate the discrepancies between the best global model and the initial geoid model to obtain (ΔN_{ANN}) as follows;

$$\Delta N_{\text{ANN}} = N_{\text{GNSS/level-ANN}} - N_{\text{GGM-B}} \quad \text{Equation 3}$$

- The final geoid height (N_{F}) at any point in this territory is calculated using Equation 4;

$$N_{\text{F}} = N_{\text{GGM-B}} + \Delta N_{\text{ANN}} \quad \text{Equation 4}$$

Figure 3 shows a flow chart for creating a geoid model based on the combination of data from GNSS/level points and data from the global geoid model.

2.3 Creating a Local Geoid Model by ANN

Artificial neural networks (ANNs) are computational models that mimic the human nervous system. Artificial neural networks exist in a range of forms and sizes, but they all compute their output using mathematical operations and a set of parameters.

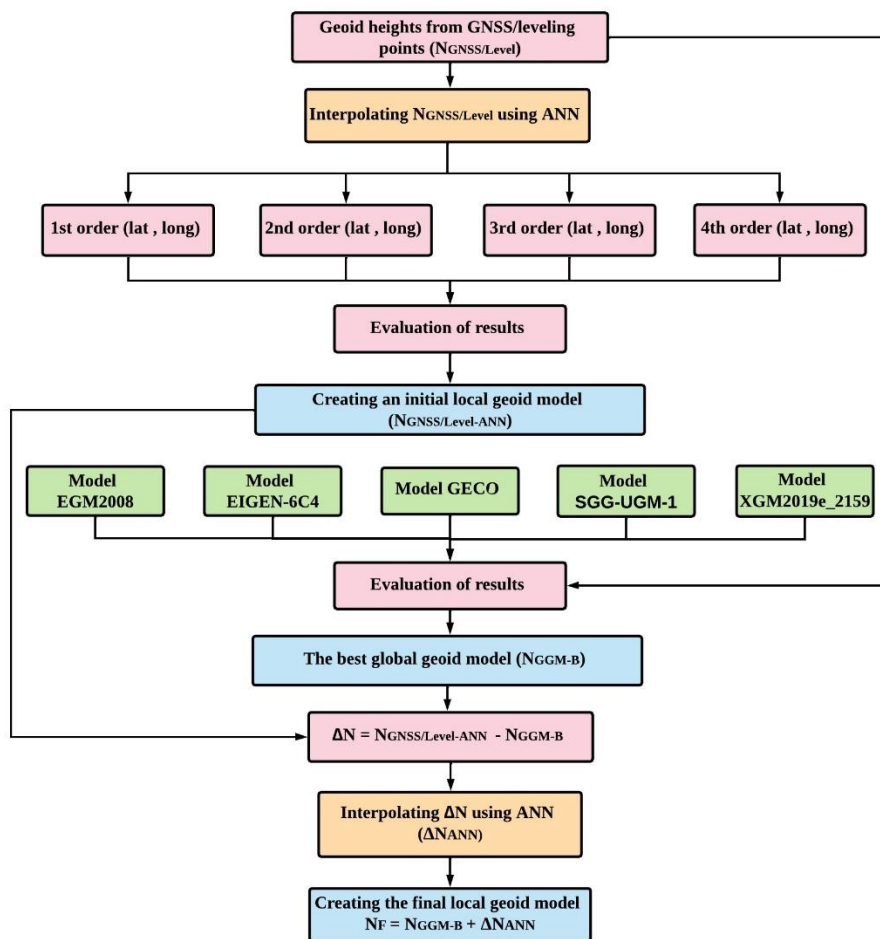


Figure 3: The flowchart of the methodology used

Cascade forward backprop, extended regression, recurrent layers, radial basis, and feed forward backprop are examples of neural networks. Because of its high representation capabilities, the feed-forward backprop network was employed to create a geoid model in this study. The data was randomly divided into three percentages in the training, validation and testing steps:

- In the training phase, 80% of the inputs were utilized; they were presented to the network during training, and the network was adjusted based on its error.
- The validation phase employed 10% of the inputs; they were used to test network generalization and to cease training when generalization stopped improving.
- In the testing procedure, 10% of the inputs were used; they have no effect on training and hence provide an independent measure

of network performance during and after training.

The Neural Network Toolbox program includes a variety of learning algorithms. Trainlm is generally the quickest training function, and it is the default training function for a direct distribution network. The trainbfg approach, which is quasi-Newtonian, is likewise fairly quick. For big networks (with thousands of weights), both of these strategies are often less efficient since they demand more memory and computation time. Furthermore, trainlm is better at identifying functions (nonlinear regression) than it is at solving pattern recognition issues. Traincg and trainrp are ideal solutions for training large networks as well as pattern recognition networks. They have a modest memory footprint, yet they are substantially quicker than typical gradient descent methods. The trainlm (Levenberg–Marquardt) algorithm was used in this study to reduce the error, and there were 20 hidden neurons.

This strategy frequently needs a greater amount of memory while requiring less time. When the generalization stops improving, as shown by an increase in the mean square error of the validation samples, the training is immediately ended. As performance measures, mean squared error and regression (R) are utilized. The average squared difference between outputs and objectives is known as Mean Squared Error (MSE), with smaller values indicating greater performance and zero indicating no mistake. The R-value measures the relationship between outputs and goals. The R-value of 1 indicates a close link, whereas the R-value of 0 indicates a random relationship. Equations 5 and 6 include the equivalent mathematical representations:

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (t_i - a_i)^2 \quad \text{Equation 5}$$

$$R = \left(\frac{\sum_{i=1}^n (t_i - \bar{t})(a_i - \bar{a})}{\sqrt{\sum_{i=1}^n (t_i - \bar{t})^2} \sqrt{\sum_{i=1}^n (a_i - \bar{a})^2}} \right) \quad \text{Equation 6}$$

Where n represents the number of points used in the processes, t_i and a_i are the network outputs and target outputs, \bar{t} is the average of the network outputs, \bar{a} is the average of the target outputs, respectively.

2.4 Testing the Significance of Differences between the Results from GGMs

The F-test was performed to determine if the two samples were drawn from the same normal population with equal variance or from two different normal populations with equal variance (Kaur, 2015). To find out whether the differences between the results from various global geoid models significant or not, F test was done between the differences between $N_{\text{GNSS/level}}$ and N_{GGM} from the global models with confidence level β equal 0.95. Five global geoid models, EGM2008, EIGEN-6C4, GECCO, SGG-UGM-1, and XGM2019e_2159, were selected in this study. The choice is mainly based on some criteria: the maximum degree and order of each GGM, the variety of data sources included in each development of the global geoid model, modern global geoid models in recent years. Using sample data, determine whether the difference between the population's standard deviations of two groups is significant:

Hypotheses: $H_0: \sigma_1 \leq \sigma_2$
 $H_1: \sigma_1 > \sigma_2$

F statistics:

$$F = \frac{S_1^2}{S_2^2}$$

Equation 7

Required Sample Data:

S_1, S_2 -Sample standard deviations of group1 and group2.

n_1, n_2 - Sample size of group1 and group2.

2.5 Influence of the Distance between Control Points on the Model's Accuracy

Four different instances were created to investigate the impact of the distance between control points on the accuracy of the geoid model and the average distance between control points was roughly 5, 10, 15, and 20 kilometers. In each of the four cases, a geoid model was created using the selected control points and using the rest of the points as checkpoints. ANN was used for interpolation between control points. Then the calculated N_{ANN} of the models were compared with $N_{\text{GNSS/level}}$ checkpoints. Furthermore, these models were produced first using only GNSS/leveling points and again using combining between GNSS/leveling points and global models to investigate the effects of incorporating global models on the accuracy of the geoid model.

3. Results and Discussion

3.1 Creating an Initial Local Geoid Model on the Mediterranean Coast

ANN was used to interpolate the geoid heights ($N_{\text{GNSS/level}}$) in this step to generate the initial geoid model. The ANN operations were done using the MATLAB program's neural network toolbox. As a transfer function, the TANSIG function was employed. The Levenberg-Marquardt method was used to adaptively adjust the unknown parameters (weights and biases) between gradient descent and Gaussian-Newton updating to minimize the error. Figure 4 shows the diagram of the architecture of ANN used. The interpolation operations for the latitude and longitude in four orders (four examples) were used to test the accuracy of the ANN methodology in generating a geoid model. 69 points were utilized at random in the training phase (about 80% of the data), whereas 9 points were used in both the validation and testing processes. In the three procedures, Figure 5 depicts the MSE assessment of ANN and the correlation function (R) between the output network and the target network. The training, validation, and testing techniques are all highly compatible with the MSE and R value, as can be observed.

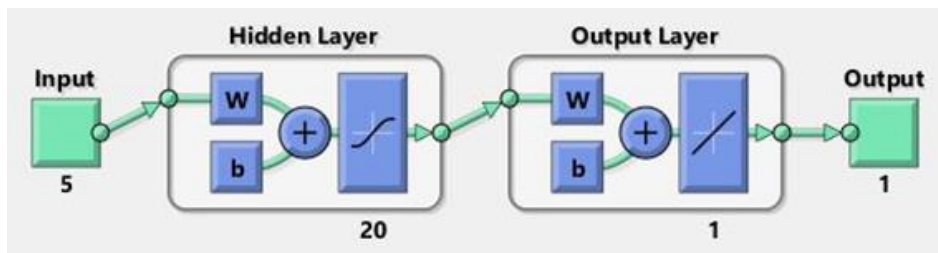


Figure 4: The diagram of the architecture of ANN used

Results			
	Samples	MSE	R
Training:	69	7.50498e-4	9.99512e-1
Validation:	9	1.05273e-3	9.99201e-1
Testing:	9	1.34645e-3	9.99542e-1

Results			
	Samples	MSE	R
Training:	69	5.41104e-4	9.99667e-1
Validation:	9	2.92330e-3	9.98284e-1
Testing:	9	1.54330e-3	9.99064e-1

Results			
	Samples	MSE	R
Training:	69	7.49249e-4	9.99544e-1
Validation:	9	4.51981e-4	9.99616e-1
Testing:	9	2.36363e-3	9.97929e-1

Results			
	Samples	MSE	R
Training:	69	5.18939e-4	9.99672e-1
Validation:	9	4.58024e-3	9.93666e-1
Testing:	9	1.83499e-2	9.85660e-1

Figure 5: The values of the MSE and R in the training, validation, and testing processes from the four cases

The error histogram of the trained neural network in training, validation, and testing for the four examples is also shown in Figure 6. The mistakes in data fitting are spread in a tolerable range around zero, as seen in this graph. The resilience and capacity to anticipate new values of the ANN structure are supported by these findings. The N_{ANN} values of geoid height from the four scenarios were then compared to $N_{GNSS/level}$ for the same 87 reference points.

Table 1 demonstrates that the outcomes of the second and fourth models are nearly identical, with the second model somewhat better. The accuracy of the first and third models was the lowest. With a mean of -0.001 m and a standard deviation of 0.032 m, the second model obtained a difference between -0.10 m and 0.08 m. The final geoid model was built using the geoid heights from this model ($N_{ANN-2nd}$).

3.2 Evaluating the GGMs on the Mediterranean Sea Coast

The geoid heights for all 87 reference points from the ICGEM computational service were obtained from these models (N_{GGM}) for the comparative evaluation of the accuracy of the five global models in the research region. The N_{GGM} was then compared to the $N_{GNSS/level}$ using Equation 2. Table 2 lists and illustrates the differences between N_{GGM} and $N_{GNSS/level}$.

Table 2 shows that the accuracy of the five global models in the Mediterranean coastline area is close, with the XGM2019e_2159 model being slightly distinguished. Figure 7 demonstrates that the average value of the discrepancy N for the worldwide models tested has a negative sign and ranges between -0.84 and -0.78 m, suggesting the presence of a systematic inaccuracy, probably related to the choice of the heights' datum. The search for the best GGM for the whole territory of Egypt, according to Essam Al-Karargy and Gomaa Dawod, concluded that XGM2019e_2159 had the best standard deviation of 0.13 m, while GECO had the lowest value of 0.16 m. (Al-Karargy and Dawod, 2021). These findings are consistent with those of this research.

3.3 Test the Significance of Differences between the Results from GGMs

To test if there are significant differences between the geoid heights of global models or not, ΔN from the XGM2019e_2159 was selected to compare ΔN from the other four global models because the minimum standard deviation of differences was obtained from the model XGM2019e_2159. From the F-table when the sample size (number of points) is 87, and with a confidence level of 95% the F-value = 1.4286. Table 3 shows the F test results for the global geoid models.

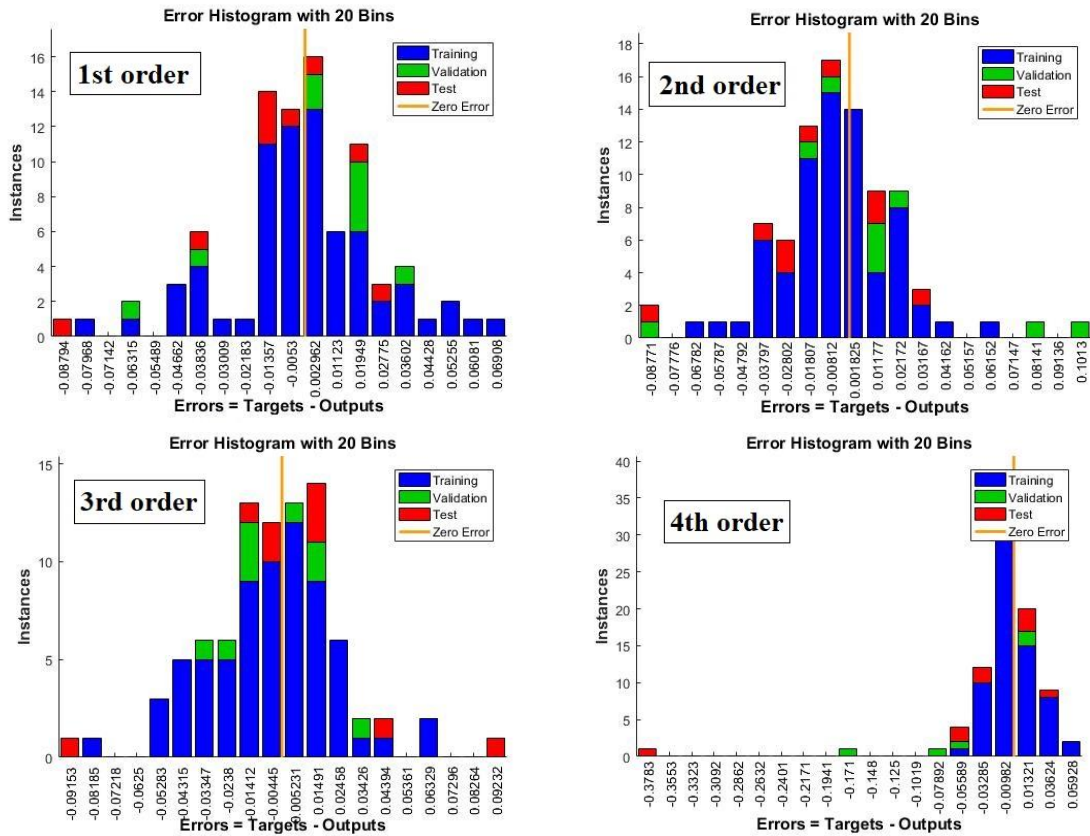


Figure 6: The error histogram for the four cases

Table 1: Descriptive statistics of discrepancies between N_{ANN} from ANN models and $N_{GNSS/level}$ for the reference points

	ANN Models			
	(φ & λ) 1 st order	(φ & λ) 2 nd order	(φ & λ) 3 rd order	(φ & λ) 4 th order
Mean (m)	0.007	-0.001	0.007	-0.002
Standard Deviation (m)	0.045	0.032	0.046	0.035
Range (m)	0.327	0.180	0.348	0.226
Minimum (m)	-0.070	-0.103	-0.079	-0.139
Maximum (m)	0.257	0.078	0.269	0.087

Table 2: Descriptive statistics of discrepancies between N_{GGM} and $N_{GNSS/level}$ on the Mediterranean Sea coast

	EGM2008	EIGEN-6C4	GECO	SGG-UGM-1	XGM2019e_2159
Mean (m)	-0.78	-0.81	-0.81	-0.84	-0.80
Standard Deviation (m)	0.20	0.15	0.15	0.18	0.14
Range (m)	0.88	0.82	0.82	0.79	0.72
Minimum (m)	-1.23	-1.24	-1.24	-1.22	-1.18
Maximum (m)	-0.40	-0.42	-0.43	-0.43	-0.47

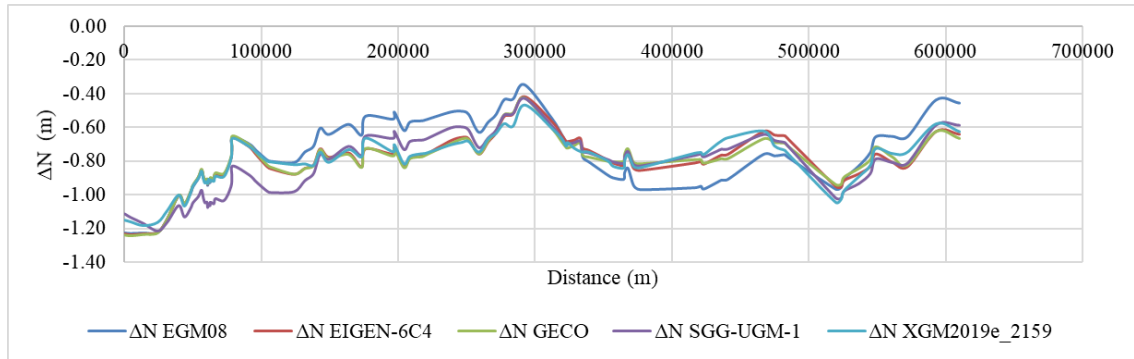


Figure 7: Discrepancies between geoid heights from the GGMs and geoid heights of the GNSS/levelling points on the Mediterranean Sea coast

Table 3: F test results for the global geoid models

The two tested model	The test statistic F	Result
XGM2019e_2159 and EGM2008	1.9006	significant difference
XGM2019e_2159 and EIGEN-6C4	1.1498	no significant difference
XGM2019e_2159 and GECO	1.0635	no significant difference
XGM2019e_2159 and SGG-UGM-1	1.6176	significant difference

Table 4: Descriptive statistics of discrepancies between N_{Fi} and $N_{GNSS/level}$ for the 87 reference points

Mean (m)	-0.002
Standard Deviation (m)	0.029
Range (m)	0.192
Minimum (m)	-0.095
Maximum (m)	0.096

Table 3 shows that the geoid heights derived from the XGM2019e 2159 model, as well as the EGM2008 and SGG-UGM-1 models, differ significantly. While the geoid heights obtained from the XGM2019e 2159 model and both EIGEN-6C4 and GECO models do not differ significantly.

3.4 Creating the Final Geoid Model on the Mediterranean Coast

In this phase, a combination of the best global model in this area, the XGM2019e_2159, and the initial geoid model ($N_{ANN-2nd}$) was built to create the final geoid model for the Mediterranean coast. First, ANN was used to interpolate the differences between the two models, resulting in a model that represented the differences. The final geoid height at any position might then be calculated using the equation:

$$N_{Fi} = N_{XGMi} - \Delta N_{ANNi}$$

Equation 8

Where: N_{XGMi} : the geoid height from the XGM2019e_2159 model at any points.

ΔN_{ANNi} : the difference value at any points from the model of discrepancies that created by ANN.

For the 87 reference points ($N_{GNSS/level}$), Table 4 shows the descriptive statistics of the discrepancies between the final model (N_{Fi}) geoid heights and the actual geoid heights. The final geoid model in the research region is also shown in Figure 8. The findings reveal that using ANN, a geoid model was built by combining GNSS/levelling data and the XGM2019e_2159 model with an accuracy of 2.9 cm, as shown in Table 4. Erol and Erol observed that when a geoid model was built for the Izmir metropolitan region, the wavelet neural network (WNN) model had an accuracy of 3.2 cm in RMSE at the test locations, which they compared to earlier research (Erol and Erol, 2021).

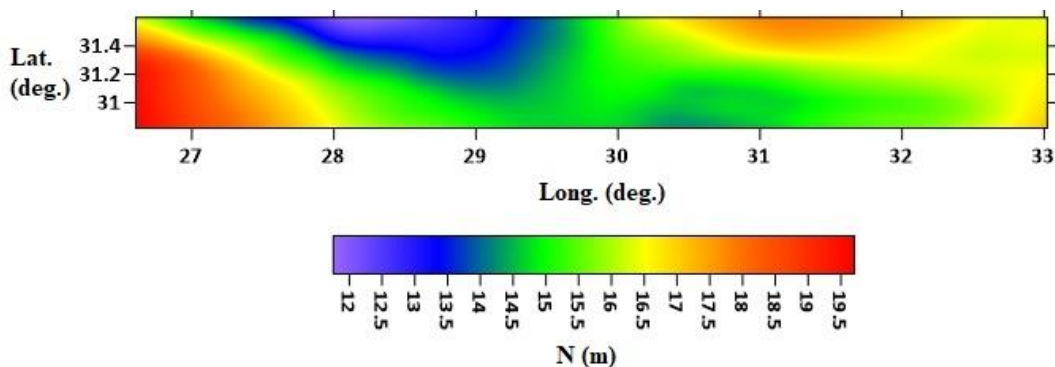


Figure 8: The final geoid model on the Mediterranean Sea coast

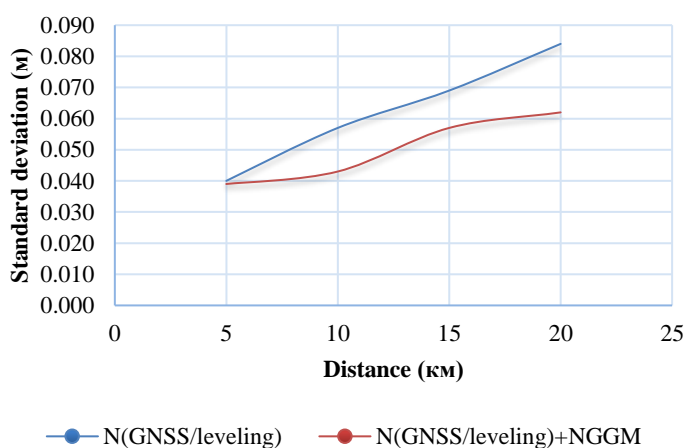


Figure 9: Relation between standard deviation values and distance between GNSS/leveling points

The accuracy of utilizing ANN to generate the geoid model for the Egyptian Red Sea coast was roughly 5.5 cm, according to Ahmed et al., (2021). These findings are consistent with the study's findings in terms of the distinction of ANN in interpolation and prediction of geoid heights and accuracy.

3.5 Effect of Distance between the GNSS/leveling Points on the Accuracy of the Geoid Model

The effect of the distance between GNSS/leveling points on the accuracy of the geoid model, as well as the effect of combining the reference points and the global geoid models on the accuracy of the geoid model, were investigated in four cases: The average distances between GNSS/leveling points were 5 kilometers, 10 kilometers, 15 kilometers, and 20 kilometers. A geoid model was built in each of the four situations utilizing the selected GNSS/leveling points and the remaining GNSS/levelling points as checkpoints. The interpolation between the control points was done using ANN. The calculated N_{ANN} of the models was then compared with $N_{GNSS/level}$ at checkpoints.

The standard deviation values from the four scenarios are shown in Figure 9.

Figure 9 demonstrates that when the distance between the points used to generate the model reduces, the accuracy of the geoid model formed by the geometric technique improves. The geoid model formed by integrating GNSS/leveling points with the global model XGM2019e_2159 is roughly 20% more accurate than models created just using GNSS/leveling points, as evidenced by the fact that the distance between points grows.

4. Conclusions

The increased use of the GNSS system in geodetic and engineering works necessitates the construction of a geoid model to convert geodetic heights into orthometric heights, particularly in coastal areas where new cities and national projects are springing up. The goal of the work is to compare and contrast five contemporary global geoid models, namely EGM2008, EIGEN-6C4, GECO, SGG-UGM-1, and XGM2019e_2159, as well as build a local geoid model for the Mediterranean coast with centimeter precision.

The geometric approach for creating a geoid model is one of the most significant. However, it is very dependent on the method employed to create the geoid model by interpolating the known geoid heights. To create a local model for the Mediterranean coast, 87 GNSS/leveling points were integrated with the best global model for the Mediterranean coast. The goal of this approach is to utilize the global geoid model in places without GNSS/leveling points, as well as to enhance the model's accuracy in local regions by minimizing long-wave geoid errors. The results showed that on the Mediterranean coast, the minimum standard deviation value was ± 14 cm with the XGM2019e_2159 model and the maximum standard deviation value was ± 20 cm with the EGM2008 model. The TANSIG function was used as a transfer function, and the Levenberg-Marquardt algorithm was used to minimize the error. This approach adaptively updates unknown parameters (weights and biases) between gradient descent update and Gaussian-Newton update. Combining the model generated by the ANN with the global model XGM2019e_2159, the Mediterranean coast geoid model was developed. The main search results can be listed as follows:

- 1- On the Mediterranean coast, the minimum standard deviation value was ± 14 cm with the XGM2019e_2159 model and the maximum standard deviation value was ± 20 cm with the EGM2008 model.
- 2- ANN is an excellent alternative to standard prediction methods in surveying and engineering applications.
- 3- The results showed that in the coastal areas of the Mediterranean, using this model built by ANN, it is able to predict the height of the geoid with an error of about 3 cm.
- 4- The geoid model created by combining between the GNSS/leveling points and the XGM2019e_2159 global model is about 20% more accurate than models created with GNSS/leveling points only, and this becomes apparent as the distance between the control points increases.
- 5- The final model for the study regions was a digital geoid model with a (5' x 5') point grid.

Acknowledgment

The author [Elshevy A. Mohamed] is funded by a scholarship under the joint executive program between the Arab Republic of Egypt and the Russian Federation.

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