Evaluating Multivariate Adaptive Regression Splines (MARS) for Modelling Observed Heights Above Mean Sea Level: A Case Study of the Tarkwa Local Geodetic Reference Network in Ghana

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Abstract: This study examines the potential of Multivariate Adaptive Regression Splines (MARS) in predicting recorded heights above mean sea level within the Tarkwa Local Geodetic Reference Network in Ghana. Logistical and computational constraints of conventional techniques, such as spirit levelling and geostatistical interpolation, drive the assessment of MARS as a strong soft computing substitute. The MARS model was trained and verified using field-measured data gathered using a Total Station DTM 122A, and its performance was compared against the Polynomial Regression model (PRM) and Kriging models. Each model technique was assessed based on statistical models such as arithmetic mean absolute error (A*MAE*), arithmetic mean squared error (*AMSE*), arithmetic root mean squared error (A*RMSE*), arithmetic standard deviation (*ASD*), correlation coefficient (*R*), and coefficient of determination (R^2). Statistical measures showed MARS's better accuracy utilizing near-perfect correlation (*AMAE*: 1.7963E-06 m; *AMSE*: 8.6775E-12 m) and low error margins. The results show MARS to be a possible, high-precision solution for orthometric height calculation, hence improving Ghana's geodetic network uses in environmental management, building, and surveying. This work not only confirms the effectiveness of MARS but also provides a basis for improving height measurement methods in local geodetic systems.

Keywords: Data Mining Model, Reference System, Multivariate Adaptive Regression Splines, Regression Model, Model Evaluation and Validation

1. Introduction

A basic issue in geodetic research is the calculation of orthometric heights, which has notable consequences for national height reference systems, surveying, engineering, and GIS applications (Peprah et al., 2017). 3D modelling, topography mapping, GIS applications, and satellite image corrections all depend on these heights (Konakoglu & Cakir, 2018; Falchi et al., 2018). It is difficult to obtain an accurate estimate because traditional methods like spirit levelling, trigonometric levelling, and GNSS-based technologies have their limits (Al-Krargy et al., 2017; Herbert & Ono, 2018). Polynomial Regression, Least Squares Collocation, and Kriging are some of the most common methods used, but they are not very efficient when it comes to computing. This is because the aforementioned models are sensitive to noise and have problems with scalability when used on a large scale (Ophaug & Gerlach, 2017; Erol & Celik, 2005).
As a result, multivariate adaptive regression splines (MARS), particularly machine learning (ML) techniques, have emerged as promising alternatives for height modelling. Friedman (1991) introduced MARS, a supervised learning method that maintains interpretability (Yakubu et al., 2018) and effectively captures complex nonlinear interactions. Prior studies have demonstrated its efficacy in geodetic applications, including the enhancement of DGPS data (Yakubu et al., 2018), the estimation of orthometric height (Najeeb, 2017), and geoid modelling (Kaloop et al., 2019). However, its use in Ghana, especially for small geodetic networks, is still not very well known.
Benchmarking MARS's performance against Polynomial Regression and Kriging, this work models observed heights above mean sea level (MSL) in Ghana's Tarkwa Local Geodetic Reference Network. Numerical models such as AMAE, AMSE, R, R^2, and ASD can be used to assess if a model is correct by comparing its results to measured datasets. The study addresses significant deficiencies in Ghana's height reference system, which currently relies on MSL-based standards without comprehensive geoid adjustments. This study provides empirical evidence regarding the suitability of MARS for vertical height modelling in Ghana, through a comparative analysis with conventional methods under identical conditions. The results support ongoing efforts to modernize geodetic infrastructure by offering a scalable, data-driven approach for calculating height in environmental monitoring, construction, and surveying.

This study also establishes a basis for future work on AI-enhanced geodetic solutions in underdeveloped countries.

2. Study Area

Focusing on Tarkwa, a mining center in Ghana's Western Region characterized by undulating terrain with heights average 387 m above Mean Sea Level (MSL), this paper

Geographically, the region is between 5° 0'–5° 20' N and 1° 50'–2° 10' W, spanning over 905 km² (Boye et al., 2018). Major mining activities in the area include Goldfields Ghana Limited (Tarkwa Mine), AngloGold Ashanti (Iduapriem Mine), and Ghana Manganese Company Limited (Nsuta Mine), all of which significantly influence the local economy. Geodetic System Based on the War Office 1926 ellipsoid, with coordinates projected on the Ghana National Grid (Transverse Mercator, central meridian 1° W). Ghana now lacks a geoid-based orthometric system; so, heights are MSL referenced (Peprah et al., 2017). For better accuracy, effort is still being made to match the national geodetic network with the International Terrestrial Reference System (ITRS) (Poku-Gyamfi & Schuder, 2008). Following a north-south rock strike, the topography shows sharp slopes (Joe-Asare et al., 2018). From a climatic standpoint, Tarkwa has a South-Western Equatorial climate with:

- Annual rainfall: ~1500 mm (peaking at 1700 mm in June/October).
- Temperature: Average of 25°C, with high humidity (61–80%) (Peprah & Mensah, 2017).

2.1 Data Gathering & Verification

Comprising 521 control points surveyed using a Total Station DTM 122A, field data recorded eastings (E), northings (N), and orthometric heights (H). Pre-processing (Z-score removal of 13 outliers) left 508 points. Control points SGW D904 13-25, GCG/WP/15E/35, AFGO 1/10 verified benchmark stability with a little coordinate difference of 0.002 m, hence validating data dependability (see Table 1 for sample data). Figures 1–2 show the research region and data distribution, hence stressing the geographic variation of elevations important for modelling.

3. Methods Used

3.1 Application of the Multivariate Adaptive Regression Splines (MARS)

This study utilized a comprehensive methodological framework to assess the efficacy of Multivariate Adaptive Regression Splines (MARS) in modelling observed heights within Ghana's Tarkwa Local Geodetic Reference Network. The strategy ensured comprehensive investigation and validation by integrating advanced machine learning technologies with traditional geodetic methodologies.

Friedman (1991) created the MARS model, which was the main analytical tool, because it had been shown to work well with complicated non-linear connections in geographic data (Najeeb, 2017). This supervised learning method works by splitting the input space into separate areas with adaptive spline functions. It then creates a piecewise regression model that combines many basis functions (Yakubu et al., 2018). The model uses an intercept term (α_0) and a weighted sum of basis functions to predict orthometric height ($\tilde{y}$). Each basis function's contribution is defined by its coefficient (β_n). This flexible framework allows MARS to capture complex patterns in elevation data while keeping computing efficiency (Friedman, 1991).

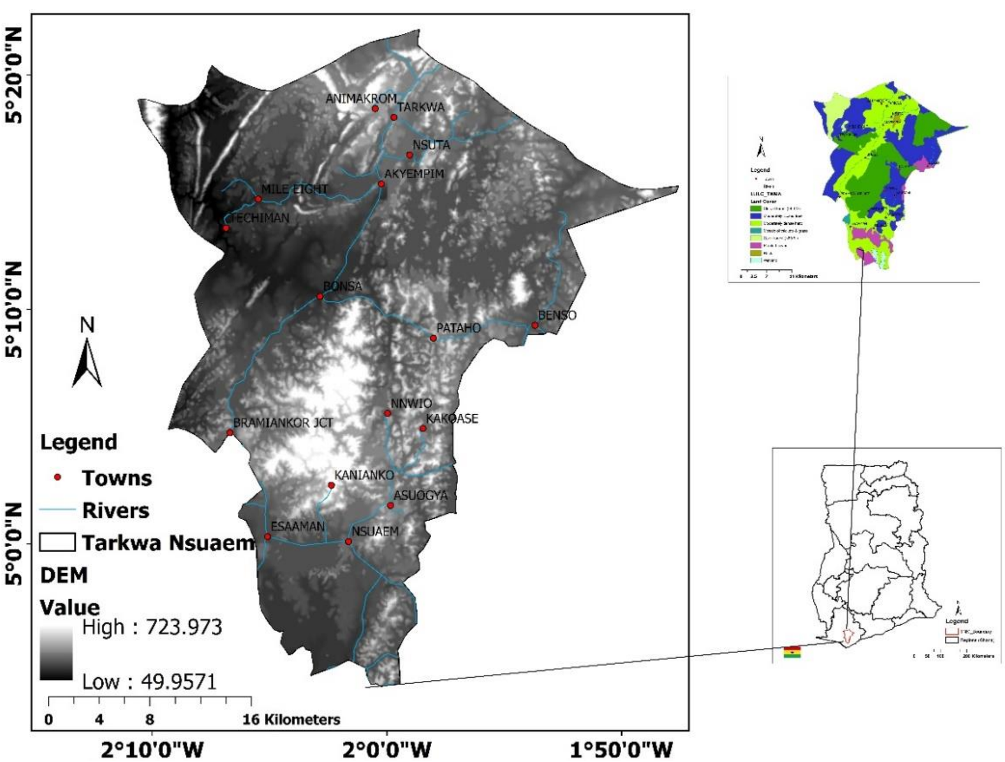

Figure 1. Map of the Study Area

Table 1. Example Data for Model Development (Units: meters)

POINT ID	E	N	H
GCP 1	163282.5	69761.99	70.19
GCP 2	163286.9	69756.31	70.224
GCP 3	163277.1	69759.25	70.036
GCP 4	163288.5	69745.97	70.382
GCP 5	163254.8	69743.19	69.845
GCP 6	163262.1	69736.02	69.883
GCP 7	163260.2	69729.12	69.846
GCP 8	163248.7	69739.03	69.735
GCP 9	163248.9	69729.08	69.724
GCP 10	163241.2	69733.04	69.636
GCP 11	163237.1	69721.75	69.749
GCP 12	163232.2	69729.85	69.687
GCP 13	163233.3	69723.5	69.741
GCP 14	163227.3	69725.96	69.279
GCP 15	163226.8	69717.75	69.671
GCP 16	163234.1	69716.32	69.669
GCP 17	163215.6	69718.49	69.176
GCP 18	163227	69711.45	69.541
GCP 19	163204.9	69712.29	68.937
GCP 20	163219.9	69706.23	69.351

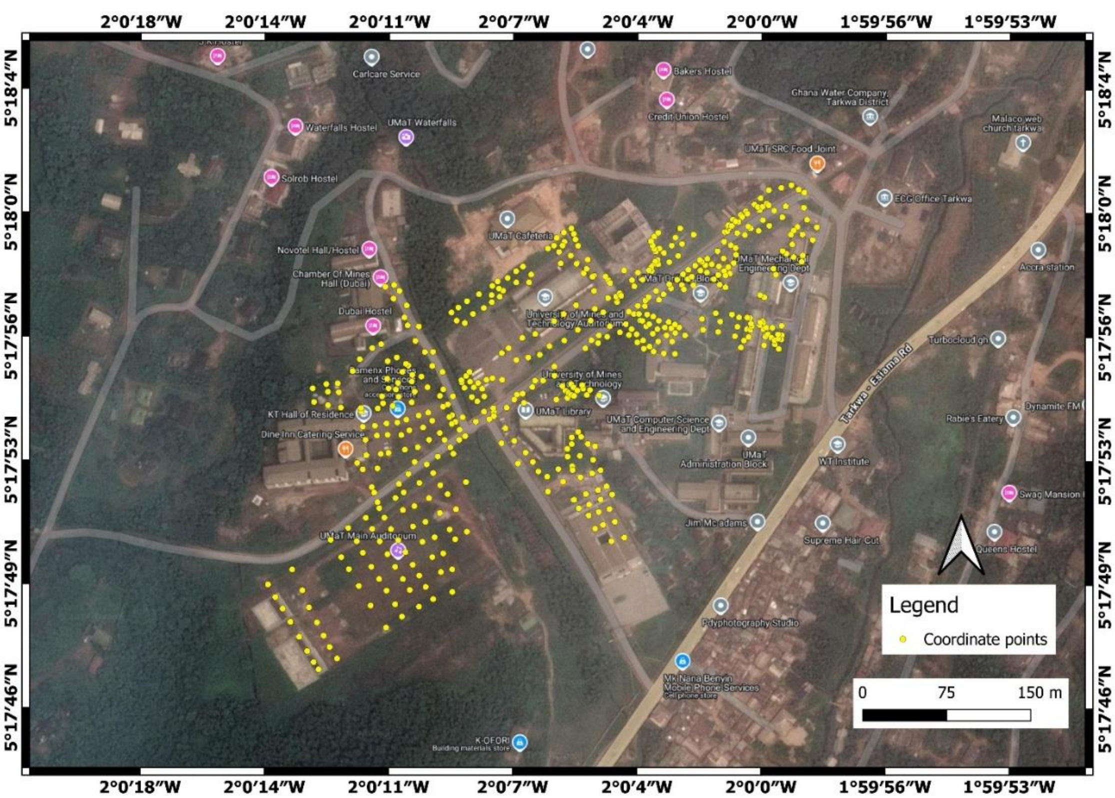

Figure 2. Distribution map of the Study area

It relates the input variables to the output variable through the summation of spline basis functions (Najeeb, 2017), as represented in Equations (1) and (2):

$$[-(x-r]_+^z = \{^{(r-x)^z}_{0,otherwise}, if x < r \quad (1)$$

$$[+(x-r]_+^z = \{^{(r-x)^z}_{0,otherwise}, if x \geq r \quad (2)$$

where z is the power and r is the knot. The final MARS model used in the orthometric heights prediction has the general form given by Equation (3) as:

$$\tilde{y} = f(x) = \alpha_0 + \sum_{n=1}^{n} \alpha_n \beta_n(x) \quad (3)$$

where, $\tilde{y}$ is the output variable (orthometric heights), α_0 is the coefficient a constant term determined by a least squares approach, n is the number of spline functions and β_n and α_n are the n_{th} spline function and its coefficient, respectively.
The model-building technique was methodical and two-phase. The algorithm in the forward selection phase repeatedly found the best knot sites and used basis functions to make the predictions more accurate (Najeeb, 2017). Yakubu et al. (2018) reported that this was made stronger by a backward pruning step that used Generalized Cross-Validation (GCV) to cut down on duplicate basis functions and stop overfitting.

With the complexity penalty term $C(\beta)$, the GCV criteria guaranteed parsimony in the final model, balancing model complexity against predictive performance. Chosen for its shown computing efficiency in geodetic applications, the implementation used the Salford Predictive Modeler (SPM V8.0) (Yakubu et al., 2018). The last optimized model kept six basis functions, striking the best compromise between simplicity and accuracy.

$$GCV = \frac{\frac{1}{N}\sum_{\tau}^{N}\left[y_t - f(x_t)\right]^2}{\left[1-\frac{C(\beta)}{N}\right]^2} \quad (4)$$

Here, N is the number of data points and $C(\beta)$ is a complexity penalty that increases with the number of basis functions introduced into the model, defined by Equation (5) (Najeeb, 2017):

$$C(\beta) = (\beta+1) + \delta\beta \quad (5)$$

In this equation, δ represents a penalty for each basis function introduced into the model, and β indicates the number of basis functions in Equation (3).

A key component of the approach was data preparation. The first dataset of 521 control points, which were gathered using exact Total Station DTM 122A measurements, passed quality control because the processes were followed exactly. The Z-score method found and removed thirteen statistical outliers, resulting in a corrected dataset of 508 points that better showed the actual elevation distribution. After Min-Max normalization, all input variables were put on the same scale, which made the model more stable and helped it converge (Yakubu et al., 2018). The processed data was meticulously partitioned into training (70%) and testing (30%) subsets; 10-fold cross-validation was employed during model training to ensure robust generalization performance (Kumi-Boateng & Peprah, 2020).

The research employed two established geodetic modelling techniques as benchmarks to contextualize the performance of MARS. Ordinary Kriging, a geostatistical interpolation method, was chosen because it can take into account spatial autocorrelation through semi-variogram analysis (Erol & Celik, 2005). This method generates theoretically unbiased predictions with diminished variance, albeit at a high computational cost, and has been widely employed in geodetic research (Falchi et al., 2018).
Practitioners, on the other hand, have to give their sensitivity to data clustering and the stationarity assumption much thought (Doganalp & Selvi, 2015). Second and third-degree polynomials were used to show the relationship between coordinates and height, but polynomial regression used a different method (Erol, 2011). This straightforward deterministic method is computationally efficient but risks overfitting with higher-order polynomials and may struggle with complex spatial patterns (Poku-Gyamfi, 2009; Soycan, 2014).

Performance assessment employed numerous supplementary metrics to comprehensively assess model accuracy and reliability. The Arithmetic Mean Squared Error (AMSE) squared the errors to make them seem bigger, while the Arithmetic Mean Absolute Error (AMAE) gave a good idea of how big the average prediction error was.
The Arithmetic Standard Deviation (*ASD*) assessed forecast consistency, while the coefficient of determination (R^2) defined the percentage of variation each model accounted for. Calculated equally for all three modelling methods, these measures allowed direct, quantitative evaluation of their relative performance in the Tarkwa geodetic network.

The strategy's strengths lie in its comprehensive methodology for model development and verification. The MARS implementation included tested strategies for managing complexity (Friedman, 1991; Erol & Celik, 2005), even though the use of well-known geodetic methods set important performance standards. Strict rules for preparing and dividing data made sure that the results were reliable. The different ways of judging model performance gave a more in-depth look at how well it worked (Kumi-Boateng & Peprah, 2020). This systematic approach not only facilitated a thorough evaluation of MARS for height prediction but also established methodologies that can be replicated in subsequent geodetic research. The method's careful balance between new ideas and old ones makes it a big step forward in the ongoing evolution of geospatial modelling methods.

3.2 Model Evaluation and Validation

The evaluation of the MARS optimal model entails assessing its predictive performance on independent validation datasets and comparing its forecasting against the measured orthometric observations for the area. The validation process involves calculating evaluation metrics such as the arithmetic minimum error value (Ar_{min}), arithmetic maximum error value (Ar_{max}), arithmetic mean absolute error (*AMAE*), arithmetic mean square error (*AMSE*), correlation coefficient (*R*), correlation coefficient of determination (R^2) and arithmetic standard deviation (*ASD*). Their mathematical expressions are given by Equation (6) to Equation (12) as:

$$Ar_{\min} = \alpha_i - \beta_i \tag{6}$$

$$Ar_{\max} = \alpha_i - \beta_i \tag{7}$$

$$AMAE = \frac{1}{n}\sum_{i=1}^{n}\left|\alpha_i - \beta_i\right| \tag{8}$$

$$AMSE = \frac{1}{n}\sum_{i=1}^{n}\left|\alpha_i - \beta_i\right|^2 \tag{9}$$

$$R = \left(\frac{\sum_{i=1}^{n}\left(\alpha_i - \bar{\alpha}_i\right)\left(\beta_i - \bar{\beta}_i\right)}{\sqrt{\sum_{i=1}^{n}\left(\alpha_i - \bar{\alpha}_i\right)}\sqrt{\sum_{i=1}^{n}\left(\beta_i - \bar{\beta}_i\right)}}\right) \tag{10}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}\left(\alpha_i - \bar{\alpha}_i\right)\left(\beta_i - \bar{\beta}_i\right)}{\sqrt{\sum_{i=1}^{n}\left(\alpha_i - \bar{\alpha}_i\right)}\sqrt{\sum_{i=1}^{n}\left(\beta_i - \bar{\beta}_i\right)}}\right)^2 \tag{11}$$

$$ASD = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(\mu - \bar{\mu}\right)^2} \tag{12}$$

where *n* represents the total number of test examples presented to the MARS learning algorithms. α_i and β_i denote the measured and predicted orthometric height values, respectively, derived from the MARS learning algorithms. $\bar{\alpha}_i$ and $\bar{\beta}_i$ are the mean values of the measured and predicted heights. The term μ signifies the residuals between the measured and predicted height data, while $\bar{\mu}$ represents the mean of these residuals. The integer *i* can be any number from 1 to n. These metrics together show how strong the model is at accurately predicting orthometric heights.

The findings corroborate previous research that highlights the advantages of adaptive regression models over traditional methods, particularly in complex geospatial contexts where non-linear relationships are prevalent.

4. Results and Discussion

Utilizing the Multivariate Adaptive Regression Splines (MARS) model for predicting orthometric heights has yielded significant insights regarding its effectiveness and reliability. This section goes into more detail about the findings and debate by including relevant information from current research, especially about the methodology, statistical analyses, and effects on geodetic practices in Ghana.

4.1. Model Performance Overview

The MARS model formulation first used 21 basis functions to forecast observed orthometric height data. During training, 15 basis functions were taken out because of overfitting. This left the final model with 6 basis functions. This change is important because it makes the model more generalizable and accurate at making predictions. Table 2 shows the model's performance indicators by showing the results of the training and testing. The statistical analysis showed that the MARS model did a great job of estimating orthometric heights because the test results showed an arithmetic minimum error value (Ar_{min}) of -5.5000E-06 m and an arithmetic maximum error value (Ar_{max}) of 2.5600E-06 m. The arithmetic root mean squared error (AMSE) was 8.0698E-12 m, and the arithmetic mean absolute error (AMAE) was 1.5364E-06 m. These results demonstrate a high level of accuracy in the forecasts, thereby corroborating findings from previous studies that emphasize the application of soft computing techniques in geospatial modelling.

The best model equation produced by the MARS model for forecasting the orthometric heights is Equation (13). Table 3 lists the basis function count in the last model formulation.

$$y(i) = 80.78 + 1 \times BF1 - 1 \times BF2 + 8.39911e - 009 \times BF3 - 1.79776e - 006 \times BF12 + 1.23724e - 006 \times BF16 - 7.12755e - 009 \times BF18 \tag{13}$$

Line graphs and box plots in Figures 2 and 3 visually depict the performance of the MARS model. The line graphs depict the expected vs recorded orthometric heights, highlighting how well the model's forecasts match actual measurements. Box plots show little outliers and validate the consistency of forecasts over several data points, hence stressing the distribution of mistakes.

Table 2. Performance Evaluation of the MARS model results (Unit: meters)

TRAINING							
PCI	Ar_{min}	Ar_{max}	**AMAE**	**AMSE**	**ASD**	R	R^2
MARS	-5.9000E-06	2.3800E-06	1.9073E-06	8.9372E-12	1.4700E-06	1	1
TESTING							
PCI	Ar_{min}	Ar_{max}	**AMAE**	**AMSE**	**ASD**	R	R^2
MARS	-5.5000E-06	2.5600E-06	1.5364E-06	8.0698E-12	1.5700-08	1	1

Table 3. Basis Functions Equations for the MARS Model

Basis Functions	Equations
$BF1$	$\max(0, Z_i - 80.78)$;
$BF2$	$\max(0,80.78 - Z_i)$;
$BF3$	$\max(0, N_i - 69546.3)$;
$BF12$	$\max(0, Z_i - 81.815)$;
$BF16$	$\max(0, Z_i - 81.26)$;
$BF18$	$\max(0, N_i - 69639)$;

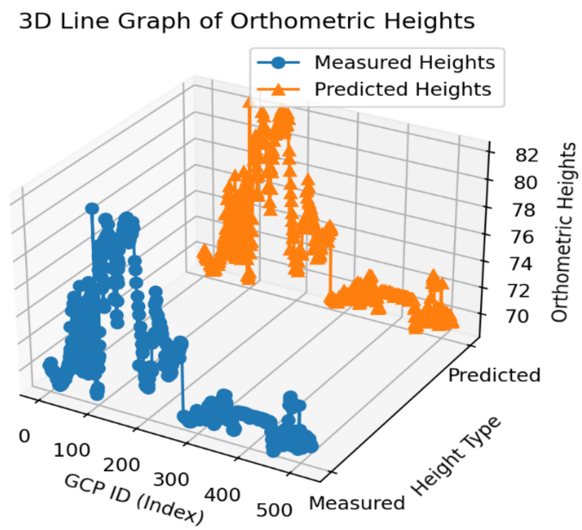

Figure 2. 3D Line Graph of Measured and MARS predicted Orthometric Heights.

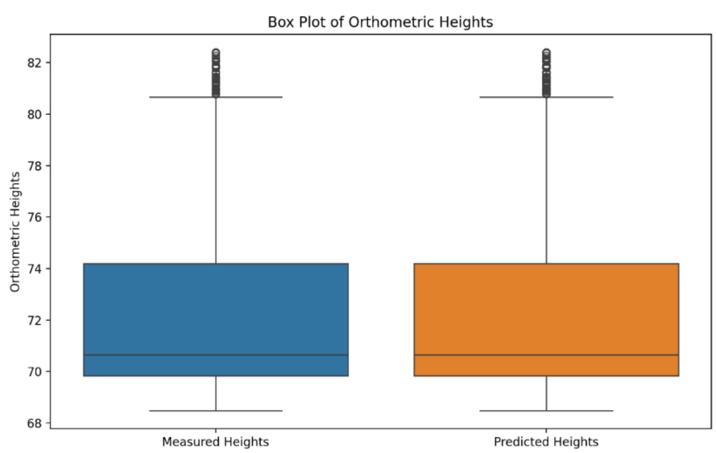

Figure 3. Box Plot of Measured and MARS Predicted Orthometric Heights

The produced numbers offer an analysis of the estimated and observed orthometric heights for many Ground Control Points (GCPs). Measured and projected orthometric heights across many GCP IDs are depicted in Figure 2. One line depicts the measured heights; the other shows the projected heights. This indicates the accuracy of the forecasts by showing how closely the projected values match the measured ones. Figure 3 shows the spread of both expected and measured heights. It reveals the median, quartiles, and possible outliers for every dataset. This graphic shows the difference in height and central tendency, as well as any big differences between the projected and actual values.

4.2 Implications for Geodetic Practices in Ghana

The successful application of the MARS model for predicting orthometric heights has significant implications for geodetic methodologies in Ghana. As Peprah et al. (2017) point out, it is very important to set a consistent vertical datum for a number of purposes, such as building, mining, and environmental monitoring. Models like MARS give better accuracy, which can help with more accurate geodetic measurements. This can help with building infrastructure and managing resources. Furthermore, incorporating advanced modelling techniques such as MARS would assist Ghana in establishing its national geodetic framework by addressing existing challenges related to height definition and spatial data accuracy. This aligns with ongoing efforts to modernize surveying methods through technological advancements (Yakubu et al., 2018; Kumi and Peprah, 2020; Peprah and Kumi, 2017). The study demonstrates that, within the geographical context of Ghana, the MARS model serves as an effective instrument for the precise prediction of orthometric heights. The statistical measures obtained validate its superiority over traditional methods, thereby providing a robust foundation for future geodetic applications. Researchers are looking for new ways to solve height determination problems, and using soft computing technologies like MARS will be very important for improving geodetic capabilities and making sure that measurements are correct for many different uses in many different fields.

The whole dataset-based MARS model statistical analysis is shown in Table 4.

Table 4. Statistical Analysis of the MARS Model Predictions (Units: meters)

PCI	Ar_{min}	Ar_{max}	AMAE	AMSE	ASD	R	R^2
MARS	-5.5900E-06	2.5600E-06	1.7963E-06	8.6775E-12	1.2400-08	1	1

The statistical analysis of Table 4 indicated that the MARS model showed better efficiency in calculating orthometric heights for the study region. The performance metrics showed that (Ar_{min}) was -5.9000E-06 m, (Ar_{max}) was 2.5600E-06 m, AMAE was 1.7963E-06 m, AMSE was 8.6775E-12 m, ARMSE was 2.9458E-06 m, and ASD was 1.2400E-09 m. Both the R and R^2 values were found to be 1, indicating that the input variables and the output variable are highly correlated. These results suggest that the MARS model is quite effective in predicting orthometric heights with enhanced precision in the research area.

4.3 Comparing MARS with the Classical Models

Its performance was contrasted with two commonly used alternative modelling techniques, Polynomial Regression and Kriging, to assess the robustness of the Multivariate Adaptive Regression Splines (MARS) model. This comparison study, which is summarized in Table 5, shows that the MARS model is much better than the other two methods on all important statistical measures. MARS has the lowest Arithmetic Mean Absolute Error (AMAE) of 1.7963E-06 meters, which means that its predictions are the closest to actual orthometric heights. Its Arithmetic Mean Squared Error (AMSE) of 8.6775E-12 m^2 and Arithmetic Root Mean Squared Error (ARMSE) of 2.9458E-06 meters, respectively, indicate that the model is even more accurate and can reduce both small and large errors in predictions.

In contrast, Polynomial Regression had higher error values: 4.2312E-05 meters AMAE and 5.4280E-05 meters RMSE. Kriging did better than Polynomial Regression with intermediate values (AMAE = 2.3189E-05 m; ARMSE = 3.2279E-05 m), but it was still behind MARS. The correlation coefficient (R) and the coefficient of determination (R^2), both of which have perfect values of 1.0000, show how well MARS can predict things. These numbers show that Polynomial Regression (R = 0.9945, R^2 = 0.9890) or Kriging (R = 0.9961, R^2 = 0.9922) did not perform as well as expected. They show a perfect linear connection and a full explanation of the difference between projected and actual values.

These results, when considered collectively, validate that the MARS model is not only a statistically superior method for predicting orthometric heights but also a highly reliable tool for geodetic modelling in regions with complex terrain such as Tarkwa. The combination of small errors and perfect correlation makes MARS a good alternative to traditional methods for estimating vertical height in geospatial applications.

Table 5. Comparative Performance of MARS, Polynomial Regression, and Kriging Models

Model	AMAE (m)	AMSE (m²)	ARMSE (m)	R	R^2
MARS	1.80E-06	8.68E-12	2.95E-06	1	1
Polynomial Reg.	4.23E-05	2.95E-09	5.43E-05	0.9945	0.989
Kriging	2.32E-05	1.04E-09	3.23E-05	0.9961	0.9922

5. Conclusion and Recommendations

This study demonstrates that Multivariate Adaptive Regression Splines (MARS), an advanced modelling technique for computing orthometric heights within Ghana's Tarkwa Local Geodetic Reference Network, has achieved considerable success. Our results show that MARS is better than traditional geodetic methods because it has an arithmetic mean absolute error of 1.7963E-06 m and a mean squared error of 8.6775E-12 m. These findings demonstrate that MARS is a transformative instrument for height estimation in Ghana, effectively mitigating the drawbacks of traditional surveying methods, which are typically hindered by elevated costs, labour intensity, and technical challenges associated with the nation's existing mean sea level-based reference system.

The work makes several important contributions to the field of geodesy. First, it shows that machine learning can be used to solve hard geographical problems in developing countries, where traditional methods may not work or cost a lot. The second thing it does is show how advanced analytics could make current surveying activities better by giving geodetic procedures a repeatable way to use soft computing techniques. Third, the study provides empirical data advocating for the enhancement of Ghana's vertical reference systems, especially as the country progresses towards the implementation of more complex geodetic infrastructures.

Based on these results, we suggest that Ghana's national geodetic operations make strategic use of MARS modelling. The first uses could be in important fields like mining zones, where knowing the exact height is important for keeping an eye on the environment and managing resources. These methods could be very helpful for the mining industry, where they could be used for everything from figuring out how much space to design a pit to optimizing its design. Also, urban planning officials in Ghana's rapidly growing cities may use this tool to model flood risk and plan for the growth of infrastructure.

We pinpoint three primary topics for forthcoming research initiatives. First, research on hybrid modelling methods that combine MARS with evolving deep learning architectures could lead to even more accurate results for large-scale applications. Second, research should investigate quality assurance methodologies in the integration of machine learning outputs with conventional surveying techniques, along with the propagation of errors. Research should also look into how MARS-derived heights can be made to work with Ghana's changing geodetic reference systems as the country moves toward more complex coordinate systems.
To make these ideas work well, there needs to be parallel investments in building capacity. Ghanaian colleges should update their geomatics curriculum to include machine learning methods so that the next generation of surveying professionals has the right information. Collaborative initiatives among universities, government entities, and private sector stakeholders may expedite practical adoption and technology transfer.

This work lays a solid groundwork for changing Ghana's geodetic practices through the use of new computational techniques. Ghana could greatly improve the accuracy and efficiency of its geographical data system by using these new technologies and following strict scientific standards. These kinds of progress would be very helpful in many areas of the country's development goals, from managing natural resources to planning cities and adapting to climate change. Combining machine learning with traditional geodesy is not just a technical advance; it's also a change in the way we think about collecting and analyzing geographical data in developing countries.

Declaration of generative AI and AI-assisted technologies in the writing process
During the preparation of this work, the author(s) used Quillbot and Grammarly tools to paraphrase text to enhance the readability of the work. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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