

Artificial neural network-based enhancement of ASTER DEM vertical accuracy in an urban terrain

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Article Info	Abstract
Article History: Received 21 Jul 2026 Accepted 07 Sep 2026 Keywords: ASTER DEM; Artificial neural networks; GNSS; Vertical accuracy; IDW; RMSE; Urban Terrain; DEM Correction	Global Digital Elevation Models (GDEMs), such as ASTER, provide near-global coverage at a spatial resolution of 30 m; however, their vertical accuracy varies depending on terrain characteristics, land cover, and sensor-related limitations. This study develops and evaluates a nonlinear Artificial Neural Network (ANN) framework to enhance the vertical accuracy of ASTER DEM within a low-relief urban environment in Baghdad, Iraq. The proposed model is quantitatively compared with deterministic Inverse Distance Weighting (IDW) interpolation. A dataset of 57 high-precision GNSS RTK control points was collected. Forty-seven points were used for ANN training, while 10 independent points were reserved for validation. The ANN model achieved a training RMSE of 4.88 m, while the validation RMSE reached 2.21 m, which is considered the reliable indicator of model performance. Baseline evaluation showed a vertical RMSE of 2.21 m for the original ASTER DEM. After correction, IDW reduced the RMSE to 1.04 m (53% improvement), whereas ANN achieved 0.64 m (approximately 71% improvement), reaching sub-meter vertical accuracy. Residual distribution and comparative statistical analysis confirmed that ANN significantly reduces both systematic bias and error dispersion compared to deterministic interpolation. The findings demonstrate that nonlinear functional modeling substantially enhances the usability of freely available global DEM datasets for high-precision engineering and urban applications. A supplementary cross-validation analysis indicated that this performance advantage is sensitive to the specific data partition used, given the limited sample size; this is discussed as a study limitation, and expanding the training dataset is recommended to enable a more robust comparison.

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1. Introduction

Digital Elevation Models (DEMs) are fundamental components of geospatial analysis, supporting a wide range of applications including hydrological modeling, flood risk assessment, infrastructure design, geomorphological studies, and urban planning. The reliability of these applications is strongly dependent on the vertical accuracy of elevation data. Among global datasets, the ASTER Global Digital Elevation Model (ASTER GDEM) provides near-global coverage at a spatial resolution of 30 m and is widely utilized due to its accessibility and availability. [1,2] However, its vertical accuracy varies significantly depending on terrain characteristics and land cover conditions. Urban areas, in particular, introduce additional sources of error due to complex building structures, surface reflectance variability, and limitations in stereo image matching. Traditional DEM correction approaches primarily rely on spatial interpolation techniques such as Inverse Distance Weighting (IDW) or polynomial regression. These methods assume spatial continuity of errors; however, they are often unable to effectively model nonlinear and terrain-dependent error patterns. [3,4]

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Recent advancements in machine learning, especially Artificial Neural Networks (ANN), have introduced flexible nonlinear modeling frameworks capable of capturing complex relationships between spatial variables and elevation errors. Such approaches offer significant potential for improving DEM accuracy beyond the limitations of conventional interpolation methods.

This study aims to:

- Quantify the baseline vertical accuracy of ASTER DEM.
 - Develop a nonlinear ANN-based correction model for DEM error reduction.
 - Compare the performance of ANN with traditional IDW interpolation.
 - Evaluate statistical improvement and assess the achievement of sub-meter vertical accuracy.
- [4-7]

The relatively flat terrain and urban characteristics of the study area make it particularly suitable for detecting subtle elevation errors and evaluating the effectiveness of nonlinear correction models. Such conditions provide an ideal test environment for assessing improvements in DEM vertical accuracy.

2. Study Area

This study was conducted at the University of Baghdad – Al-Jadriya Campus, located in Baghdad, Iraq (figure 1). All spatial datasets were referenced to the WGS84 coordinate system using Universal Transverse Mercator (UTM) Zone 38N. The study area is characterized by relatively flat topography, urban land cover, and limited elevation variation. These characteristics make the area particularly suitable for detecting subtle vertical errors in Digital Elevation Models (DEMs) and evaluating the performance of correction techniques. The selected site represents a controlled urban environment where elevation changes are minimal, allowing for a more precise assessment of systematic bias and local elevation discrepancies. The main characteristics of the study area include: Low topographic relief, predominantly urban land cover and Limited elevation variability. These conditions provide an ideal environment for evaluating nonlinear error behavior and testing the effectiveness of machine learning-based correction models.



Fig. 1. The boundary of the study area (University of Baghdad – Al-Jadriya Campus)

The study area was delineated using a polygon boundary overlaid on high-resolution satellite imagery. The University of Baghdad campus is surrounded by the Tigris River, forming a natural boundary that clearly defines the spatial extent of the study area. This natural enclosure enhances the reliability of spatial analysis by minimizing external influences and ensuring a well-defined and consistent study domain. Data sources The Digital Elevation Model (DEM) was downloaded from the USGS Earth Explorer website. The data was in GeoTIFF (.tif) format. Satellite images and aerial photographs were added to improve visualization and analysis.

3. Data and Experimental Design

3.1 GNSS Data Collection

A total of 57 high-precision GNSS RTK control points were collected using dual-frequency GNSS receivers. The observations were processed using standard post-processing techniques to achieve centimeter-level vertical accuracy. These control points were used as reference data to evaluate and correct the vertical accuracy of the ASTER DEM.

3.2 Dataset Partitioning

To ensure a robust and unbiased evaluation of the proposed model, the dataset was divided into two independent subsets:

- 47 points were used for training the Artificial Neural Network (ANN) model.
- 10 points were reserved as an independent validation dataset for performance assessment.

This strict separation between training and validation datasets ensures that the model is evaluated on unseen data, thereby preventing overfitting and providing a reliable estimate of model generalization capability.

3.3 ASTER DEM Processing

The ASTER Global Digital Elevation Model (GDEM Version 3) with a spatial resolution of 30 m was used as the primary elevation dataset in this study. To ensure consistency with the GNSS reference data and the study area coordinate system, several preprocessing steps were applied using ArcGIS Pro:

- Reprojection to WGS84 / UTM Zone 38N and Clipping to the defined study area boundary as shown in figure 2 and figure 3.
- Verification of vertical units and elevation consistency.
- Elevation values were then extracted at GNSS observation locations to enable direct comparison between DEM-derived and field-measured elevations as shown in figure 4.

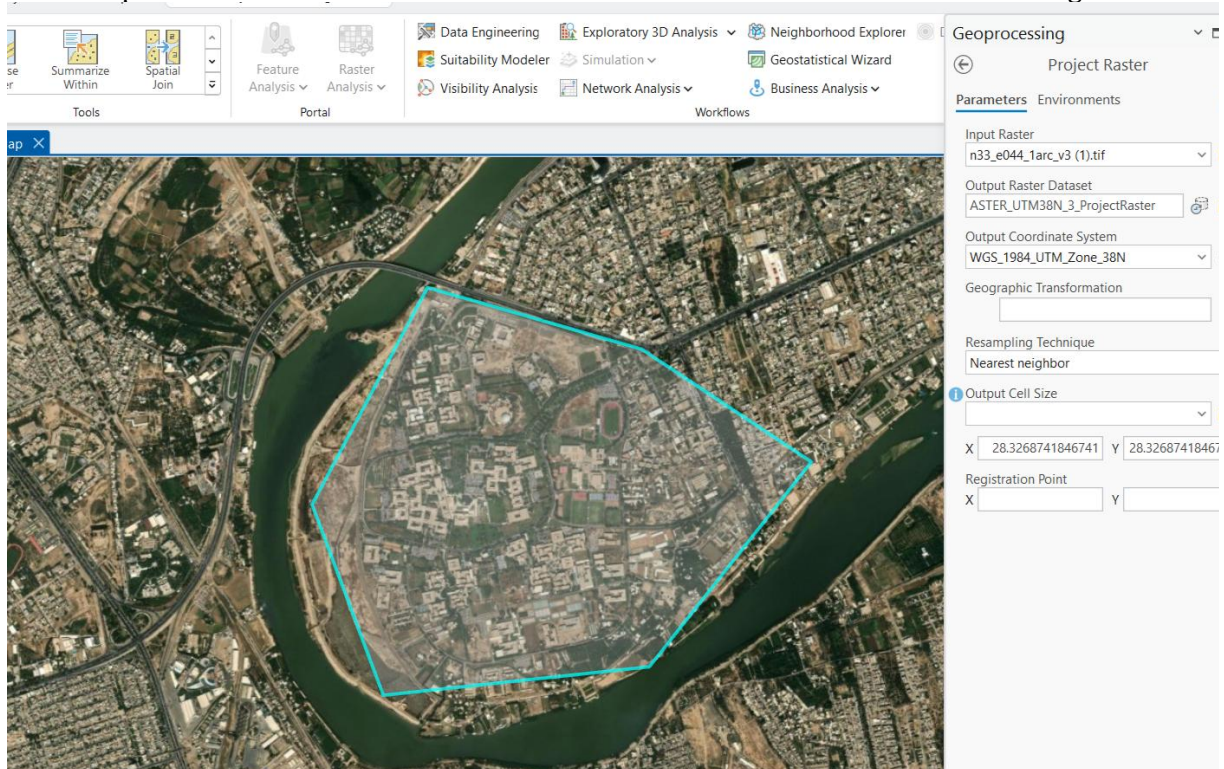


Fig. 2. Reprojection of ASTER DEM to UTM Zone 38N

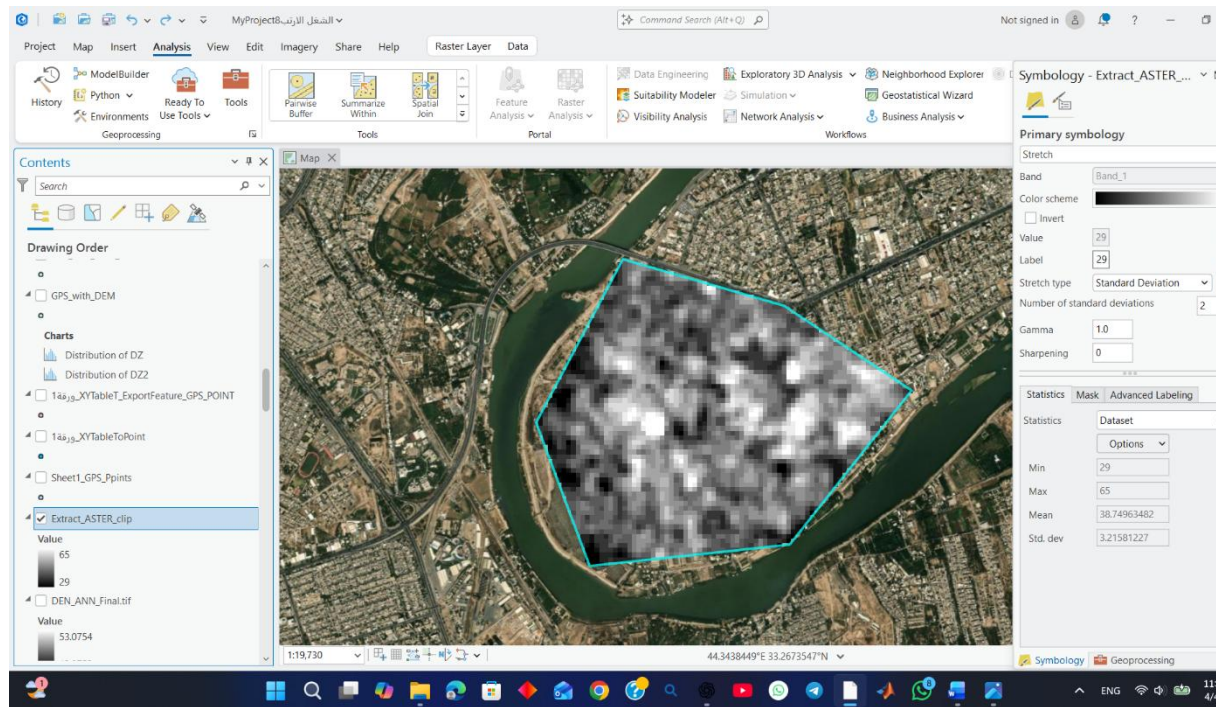


Fig. 3. Clipping the DEM to the study area

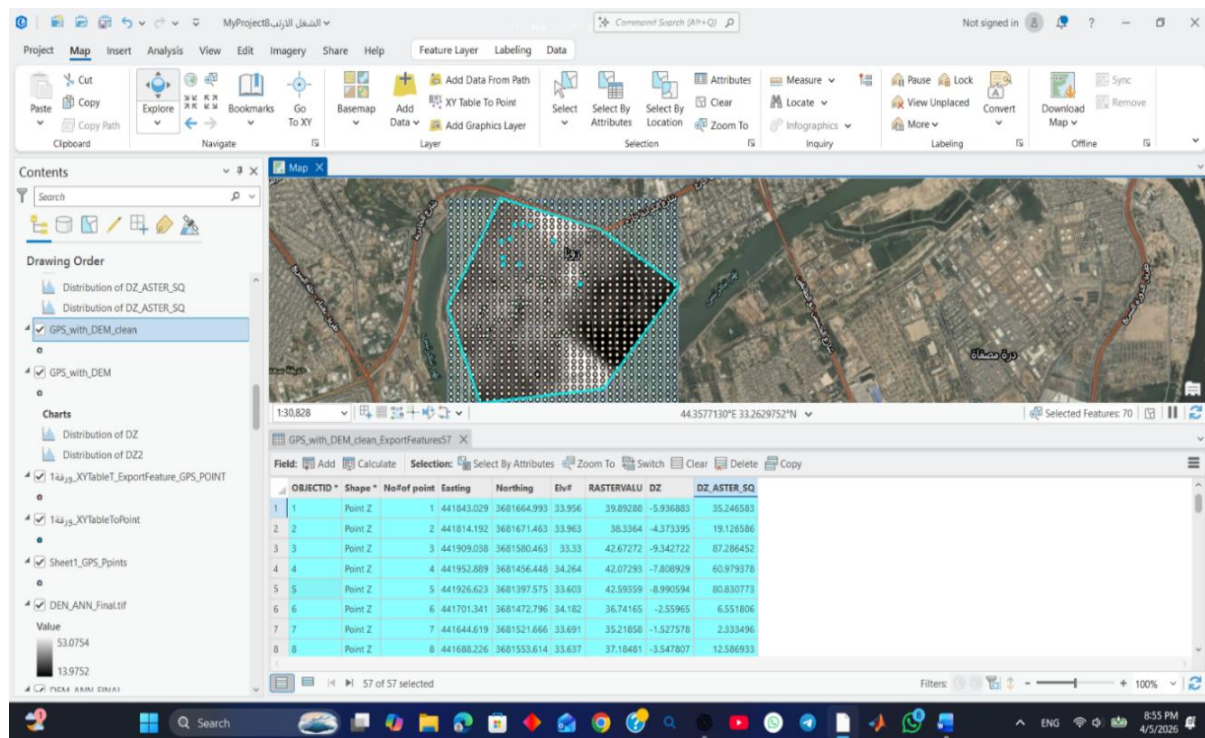


Fig. 4. Extraction of elevation values from ASTER DEM to GNSS points using ArcGIS Pro

This step is essential for linking raster-based elevation data with field observations, forming the basis for subsequent error analysis and model correction. The extracted elevation values from the ASTER DEM are stored in the RASTERVALUE field, while the GNSS observed elevations are represented in the Elevation field. The elevation residuals (ΔZ) were calculated as the difference between observed and DEM-derived values, and the squared residuals (ΔZ^2) were computed for RMSE analysis. [8-11]

The adopted sample size and 47/10 split were considered adequate for the scope of this study: the 57 GNSS RTK points were collected at centimeter-level vertical accuracy and are spatially

distributed across the entire study area to capture the range of local elevation variability, and the resulting sample density is comparable to control-point densities used in other local-scale DEM validation studies over similarly sized study areas. Nonetheless, a larger and more spatially diverse dataset would further strengthen the generalizability of the model, and this is identified as a priority direction for future work.

3.3 Data Integration and Residual Computation

The integration of these data sets enables the construction of a robust modeling framework where point-based observations (GNSS) are linked with raster-based elevation data (ASTER DEM). This combination allows for accurate estimation of elevation bias and enhances the performance of the ANN model in predicting correction values. The use of both point-based and raster-based datasets provides a comprehensive representation of spatial variability, improving the reliability of the correction model. The elevation residuals (ΔZ) were calculated as the difference between GNSS-measured elevations and ASTER DEM-derived elevations:

$$\Delta Z = Z_{GNSS} - Z_{DEM} \quad (1)$$

The squared residuals (ΔZ^2) were then computed to quantify the magnitude of elevation differences and to support statistical analysis. The Root Mean Square Error (RMSE) was calculated as a key indicator of vertical accuracy.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\Delta Z_i)^2} \quad (2)$$

where n represents the number of GNSS points ($n = 57$ in this study). Table 1 illustrates the summary of Datasets Used in This Study (All datasets were projected to WGS84 / UTM Zone 38N).

Table 1. Summary of Datasets Used in This Study (All datasets were projected to WGS84 / UTM Zone 38N)

Dataset	Type	Description	Source
GNSS Points	Point	High-accuracy elevation reference	Field work GNSS RTK observations
ASTER DEM	Raster	30 m resolution elevation data	USGS Earth Explorer (aster DEM)
Derived Raster	Raster	Slope, Aspect, Hillshade	Derived from ASTER DEM using Arc GIS pro

4. Baseline Vertical Accuracy Assessment

To evaluate the vertical accuracy of the original ASTER DEM, elevation residuals (ΔZ) were computed at all GNSS control points. The residuals were calculated as the difference between GNSS-measured elevations and ASTER DEM-derived elevations:

$$\Delta Z = Z_{GNSS} - Z_{ASTER} \quad (3)$$

Where: Z_{GNSS} represents the observed elevation from GNSS measurements and Z_{ASTER} represents the corresponding elevation extracted from the ASTER DEM.

Figure 4 and Table 2 illustrate absolute elevation residuals ($|\Delta Z|$) for all control points. The vertical bars represent individual residual values, while the horizontal red line indicates the mean residual (6.31 m). The results show that most absolute residuals are concentrated within a moderate range around the mean value, indicating relatively consistent vertical discrepancies across the study area. However, a few high residual values are observed, suggesting localized DEM errors or terrain-related variations. To quantify the overall vertical accuracy of the ASTER DEM, the Root Mean Square Error (RMSE) was computed using the residual values: Microstructural characterization: Advanced techniques (e.g., SEM, EDS, and micro-CT scanning) should be employed to quantify the distribution and bonding behavior of nanomaterials within the soil matrix.

Table 2. Elevation residuals (ΔZ) between GNSS and ASTER DEM

No. of point	Easting	Northing	Elev_	RASTERVALU	DZ
1	441843.029	3681664.993	33.956	39.8928833	5.936883301
2	441814.192	3681671.463	33.963	38.33639526	4.373395264
3	441909.038	3681580.463	33.33	42.67272186	9.342721863
4	441952.889	3681456.448	34.264	42.07292938	7.808929382
5	441926.623	3681397.575	33.603	42.5935936	8.990593597
6	441701.341	3681472.796	34.182	36.74164963	2.559649628
7	441644.619	3681521.666	33.691	35.21857834	1.527578339
8	441688.226	3681553.614	33.637	37.18480682	3.547806824
9	441737.35	3681585.595	33.557	36.44224548	2.885245483
10	441588.934	3681609.388	34.242	39.07341003	4.831410034
11	441622.283	3681718.262	33.807	36.40058136	2.59358136
12	441651.469	3681792.556	34.394	40.09490585	5.700905853
13	441825.01	3681863.435	34.918	44.18058777	9.262587769
14	441762.071	3681975.78	33.943	38.91120529	4.968205292
16	441747.697	3682056.859	33.281	37.1103096	3.829309601
17	441870.554	3681977.285	38.158	42.52064896	4.362648956
18	441944.431	3681837.192	38.215	44.4406929	6.225692902
19	441944.79	3681720.848	38.203	42.21125793	4.008257935
20	442034.112	3681756.259	35.007	63.35931015	28.35231015
21	442040.556	3681812.755	33.365	54.42455673	21.05955673
22	441987.719	3681781.949	33.806	54.59132385	20.78532385
23	442008.892	3681887.655	34.012	42.36262894	8.350628937
24	441984.356	3682111.69	33.349	40.17622375	6.827223755
25	442109.131	3682052.356	33.737	38.05399323	4.316993225
26	442129.541	3682090.393	33.65	36.13572311	2.485723114
27	442251.076	3682075.575	34.317	38.34299469	4.02599469
28	442248.465	3681997.557	34.293	39.97292328	5.679923279
29	442327.362	3681862.713	33.665	34.92222977	1.257229767
30	442318.349	3681727.805	34.407	35.12098312	0.713983124
31	442201.421	3681280.171	33.72	39.55694962	5.836949615
32	442199.343	3681252.633	33.863	39.00681686	5.143816864
33	442212.696	3681153.83	33.819	40.46548462	6.646484619
34	442211.553	3681141.692	33.836	39.8493042	6.013304199
35	442198.274	3681154.108	33.627	39.94822311	6.321223114
36	442091.718	3681837.08	34.228	41.95668411	7.728684113
37	442376.073	3682049.867	33.586	34.83943939	1.253439392
38	442408.596	3681520.637	33.567	38.39752579	4.830525787
39	442479.072	3681557.874	34.137	41.6418457	7.504845703
40	442527.873	3681554.805	33.614	42.49449921	8.880499207
41	442415.488	3681446.555	33.869	37.78015518	3.911155182
42	442725.057	3682427.652	33.645	41.21113586	7.566135864
43	442748.388	3682474.029	33.582	38.67907715	5.097077148
44	442762.558	3682502.487	33.59	37.20802689	3.618026886
45	442702.505	3682107.474	33.671	37.98838425	4.317384247
46	442635.797	3681963.042	36.554	41.69166565	5.137665649
48	442650.438	3681839.416	34.041	45.8975563	11.8565563
49	442591.582	3681916.598	32.737	43.4848938	10.7478938
50	442648.295	3682016.832	36.599	40.24860764	3.649607635
51	442013.775	3682209.998	33.885	38.80167389	4.916673889
52	441843.039	3682270.623	34.225	41.11457825	6.889578247
53	441849.73	3682207.12	34.625	43.48338318	8.858383179
54	441823.832	3682424.384	34.327	37.08212662	2.755126617
55	441919.14	3682448.372	34.259	36.95391846	2.694918457
56	441963.589	3682585.702	33.996	38.26171494	4.265714935
57	442045.669	3682597.753	34.054	37.96562576	3.911625763

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n [(\Delta)Z_i]^2} = \sqrt{\frac{1355.816547}{57}} = 4.88 \text{ m} \quad (4)$$

The predominance of negative residuals confirms the presence of systematic underestimation in elevation values. Additionally, the influence of outliers suggests localized discrepancies that contribute to the overall error magnitude. These findings highlight the necessity of applying correction techniques to improve DEM accuracy, particularly in urban environments where subtle elevation differences are critical.

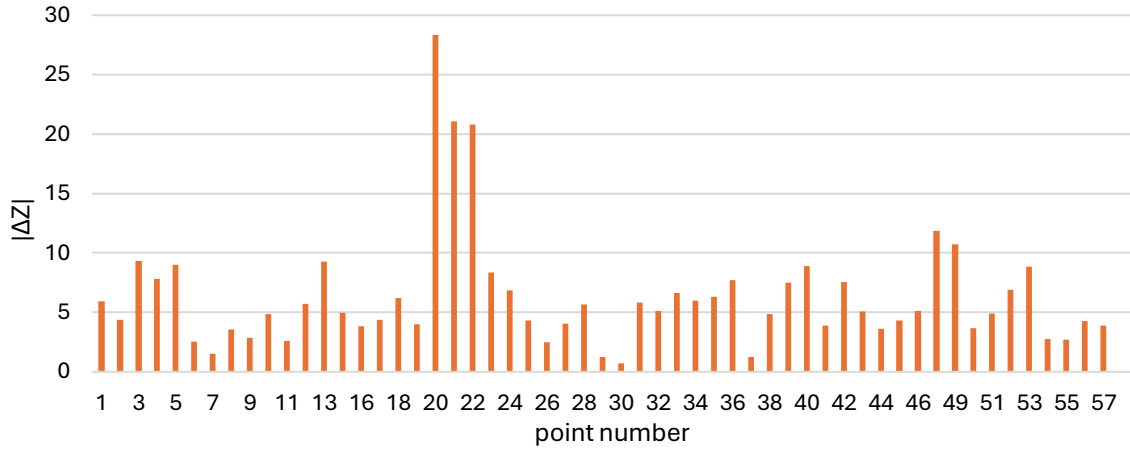


Fig. 5. Absolute elevation residuals ($|\Delta Z|$) for all control points

5. ANN-Based Nonlinear Correction Model

5.1 Model Architecture

The ANN model was implemented using the MATLAB Neural Network Toolbox as shown in figure 5. The network was trained using the Levenberg–Marquardt (`trainlm`) algorithm, which is widely recognized for its fast convergence and efficiency in nonlinear regression problems. The selection of network parameters, including training, validation, and testing ratios, as well as the performance goal, was carried out through a trial-and-error process.

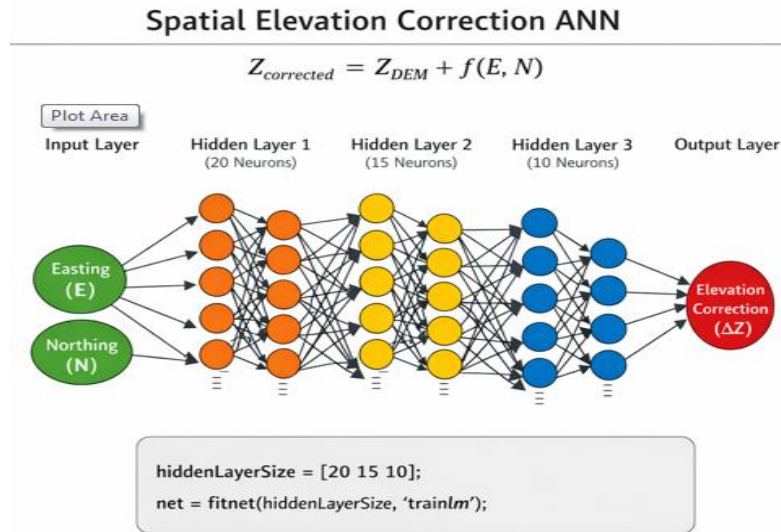


Fig. 5. Architecture of the proposed Artificial Neural Network (ANN) used for elevation correction as a function of spatial coordinates (E, N). The model consists of three hidden layers determined through a trial-and-error process. Source: Developed by the author using MATLAB

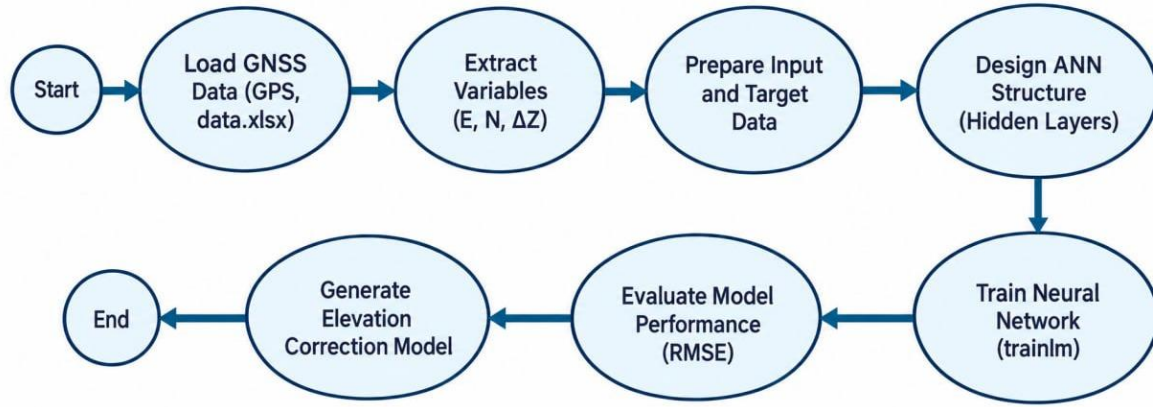


Fig. 6. Flowchart of the proposed ANN modeling framework for DEM elevation correction

Multiple configurations were tested to evaluate their impact on model accuracy and generalization. The optimal configuration was selected based on achieving the lowest RMSE while maintaining stable training behavior. Several architectures were evaluated during model development, varying the number of hidden layers (one to three) and the number of neurons per layer, together with different training/validation/testing split ratios and performance goals. Each configuration was assessed based on validation RMSE and training stability, monitored through the training performance curve to avoid over- or under-fitting. The three-hidden-layer configuration with [20 15 10] neurons, trained with the Levenberg-Marquardt algorithm, log-sigmoid hidden activation, and a linear output layer, was retained because it consistently achieved the lowest validation RMSE while maintaining stable convergence across repeated training runs.

The dataset was divided as follows (Training set: 70%, Validation set: 15% and Testing set: 15%). A performance goal of 10^{-6} was adopted to ensure high prediction accuracy. The training parameters were defined as (Maximum epochs: 2000, Performance goal 10^{-6} , Training ratio: 70%, Validation ratio: 15% and Testing ratio: 15%). To enhance model generalization, early stopping was applied based on validation performance. Training was terminated when no further improvement was observed, preventing overfitting and ensuring stable convergence. The ANN model was implemented in MATLAB using GNSS observations and corresponding elevation residuals. The process consists of the following steps:

- Load GNSS data (GPS_data.xlsx)
- Extract spatial variables (E, N) and elevation residuals (ΔZ)
- Prepare input and target datasets
- Design ANN architecture (hidden layers)
- Train the neural network using the Levenberg-Marquardt algorithm
- Evaluate model performance using RMSE
- Apply the trained model to generate elevation correction as shown in figure 6.

In contrast to traditional interpolation methods such as IDW, which rely on distance-based weighting, the ANN model captures complex spatial dependencies and hidden patterns that are not explicitly defined. Unlike deterministic models, the ANN learns directly from the data, enabling it to model nonlinear terrain-related errors more effectively. Furthermore, the ANN function is continuously refined during training through iterative optimization, minimizing the difference between predicted and observed elevation residuals. As a result, the ANN-based model demonstrates superior capability in reducing elevation errors compared to conventional interpolation techniques. This highlights the advantage of ANN as a universal function approximator, capable of modeling complex geospatial error behavior beyond the limitations of traditional methods.

5.2 Training Strategy

The ANN model was implemented using MATLAB Neural Network Toolbox. The network was trained using the Levenberg-Marquardt (trainlm) algorithm, which is widely recognized for its fast

convergence and efficiency in nonlinear regression problems. The selection of the neural network parameters, including the training, validation, and testing ratios as well as the performance goal, was carried out through a trial-and-error process. Multiple configurations were tested to evaluate their impact on model accuracy and generalization. [7,-9] The input variables consist of spatial coordinates (Easting and Northing), while the target variable represents the elevation correction (ΔZ). The following script demonstrates the training procedure of the ANN model. The selected training parameters were determined through iterative experimentation to achieve the lowest RMSE while maintaining stable convergence behavior. This approach ensures that the model is neither underfitted nor overfitted. [10, 11]

5.3 Residual Analysis

The residual analysis reveals that the original ASTER DEM is affected by significant systematic bias and large elevation discrepancies across the study area. Although the IDW method reduces the magnitude of residuals, it remains limited in capturing complex spatial variability, resulting in noticeable fluctuations in error distribution.

In contrast, the ANN-based model produces residuals that are closer to zero and more uniformly distributed, indicating a substantial reduction in both systematic and random errors. This improved consistency demonstrates the ability of the ANN to effectively model nonlinear relationships between spatial coordinates and elevation errors. [10]

5.4 Independent Validation

Independent validation was conducted using 10 GNSS check points that were not included in the ANN training process. The reduction in residual magnitude and dispersion confirms the ability of the ANN to model nonlinear elevation errors more effectively. Furthermore, the ANN model shows improved agreement with GNSS observations across most validation points, indicating enhanced spatial consistency. For each validation point, the elevation differences (residuals) between GNSS observations and DEM-derived values were computed for original ASTER DEM, IDW-corrected DEM and ANN-corrected DEM

$$\Delta Z = Z_{GNSS} - Z_{DEM} \quad (5)$$

The following statistical metrics were calculated to assess model performance:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\Delta Z_i)^2} \quad (6)$$

$$ME = 1/n \sum_{i=1}^n \Delta Z_i \quad (7)$$

where (n) is the number of validation points, and (ΔZ_i) represents the elevation residual at point (i).

Improvement percentage. The residuals (ΔZ) were analyzed individually for each validation point to examine the spatial distribution of errors. A comparison of residual values before and after correction revealed a clear reduction in error magnitude for most points, particularly in the ANN-corrected DEM.

$$Improvement (\%) = \frac{RMSE_{original} - RMSE_{corrected}}{RMSE_{original}} * 100 \quad (8)$$

The elevation residuals (ΔZ) were analyzed individually for each validation point to examine the spatial distribution of errors before and after correction. It can be observed that the original DEM exhibits larger residuals across most validation points, indicating the presence of systematic and spatially varying errors. After applying the IDW interpolation, a noticeable reduction in residuals is achieved; however, some local variations remain. In contrast, the ANN model demonstrates a significant reduction in residual values for the majority of points, indicating its ability to effectively capture nonlinear spatial error patterns. [10]

The ANN-corrected DEM shows the closest agreement with GNSS observations, resulting in lower dispersion and improved consistency. Therefore, based on both the graphical analysis and statistical metrics (RMSE and Mean Error), the ANN-based correction can be considered more accurate and reliable compared to the IDW method as shown in figure 7.

The validation results indicate that the ANN-based correction method provides a more accurate representation of terrain elevations. The achieved RMSE reduction and consistent decrease in residuals confirm that the model performance is acceptable and suitable for improving DEM accuracy in the study area. Some validation points still exhibit relatively higher residuals, which may be attributed to local terrain complexity, data noise, or limitations in training sample distribution. Therefore, the ANN-based correction can be considered more reliable and effective compared to the IDW approach. Based on both graphical and statistical analysis, the ANN correction method is considered acceptable and provides superior performance in improving DEM accuracy. [11-14]

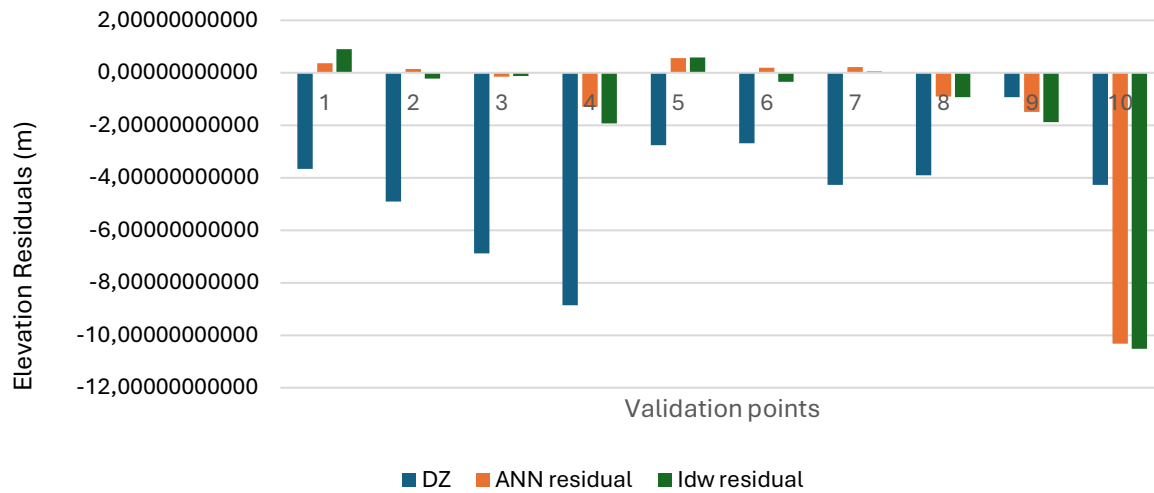


Fig. 7. Illustrates the comparison of residual values for the original DEM, IDW-corrected DEM, and ANN-corrected DEM

6. Results

6.1 Quantitative Comparison

The quantitative evaluation of DEM accuracy was conducted using Root Mean Square Error (RMSE) based on independent GNSS validation points. The original ASTER DEM exhibited an RMSE of 2.21 m, indicating moderate vertical error. After applying IDW interpolation, the RMSE was reduced to 1.04 m, corresponding to an improvement of approximately 53%. In contrast, the ANN-based correction model significantly outperformed the IDW method, achieving an RMSE of 0.64 m, which represents a 71% reduction in vertical error relative to the original DEM. This result demonstrates that the ANN model successfully achieved sub-meter vertical accuracy, making it highly suitable for engineering applications. As shown in Table 4, ANN achieved the lowest RMSE.

6.2 Evaluation of Elevation Errors

To further evaluate the magnitude of elevation errors, key statistical measures were computed, including mean error, maximum error, and minimum error, ANN reduced RMSE by 1.57 m compared to baseline. Table 3. Comparison of DEM Accuracy before and after Correction and Statistical Summary of Elevation Residuals.

Table 3. DEM accuracy before and after correction and statistical summary of elevation residuals

Model	RMSE (m)	Improvement (%)	Model	Mean Error (m)	Max Error (m)	Min Error (m)
ASTER	2.21	—	Original DEM	-4.31m	-0.94m	-8.86m
IDW	1.04	53%	IDW	-1.76m	0.89m	-10.52m
ANN	0.64	71%	ANN	-1.79m	0.56m	-10.33m

The original DEM exhibits a strong negative bias, indicating systematic underestimation of elevation values. Both IDW and ANN significantly reduce this bias, decreasing the mean error to approximately -1.8 m. Although the mean errors of IDW and ANN are similar, the ANN model demonstrates better control over extreme residual values, as reflected in the lower maximum error. This suggests that ANN provides a more stable and balanced error distribution. However, the presence of large negative minimum errors in both methods indicates that some localized terrain effects remain difficult to model accurately.

6.3 Statistical Interpretation

To further assess the variability and consistency of elevation residuals, additional statistical indicators were computed, including standard deviation and coefficient of variation. The standard deviation of the residuals was found to be 7.87 m, which is relatively high compared to the mean value (6.31 m). This indicates considerable dispersion in elevation residuals across the study area. The coefficient of variation ($CV \approx 125\%$) further confirms a high level of variability, suggesting that the residuals are not uniformly distributed and that significant local variations still exist. This behavior indicates that, although the ANN model significantly improves overall DEM accuracy, localized elevation errors persist. These discrepancies are likely associated with terrain complexity, urban features, or limitations in the input data.

6.4 ANN vs IDW Comparison

Although the IDW method improves DEM accuracy by smoothing spatial variations, it remains limited due to its deterministic nature, where predictions depend primarily on the distance between neighboring points. In contrast, the ANN model provides a more advanced and flexible approach by learning complex nonlinear relationships between spatial coordinates and elevation errors. The ANN model demonstrates several advantages:

- Ability to model nonlinear spatial relationships
- Improved representation of local terrain variability
- Reduction of both systematic and random errors
- Better control over extreme residual values

This explains the significant reduction in RMSE from 1.04 m (IDW) to 0.64 m (ANN).

Furthermore, the ANN produces a more spatially consistent correction surface, while IDW retains noticeable residual patterns due to its reliance on distance-based weighting.

These results clearly demonstrate that ANN-based nonlinear modeling provides a substantial advantage over traditional interpolation techniques, particularly in complex urban environments.

6.5 Cross-Validation Robustness Analysis

To further evaluate the robustness of the reported model performance beyond a single train/validation/test split, a supplementary 5-fold cross-validation analysis was conducted using the full set of GNSS control points with computed elevation residuals ($n = 55$). In each fold, the ANN model (multiple architectures were tested, including the original three-hidden-layer configuration and several smaller configurations with early stopping) and the IDW method (power parameter $p = 2$) were each trained on four folds and evaluated on the held-out fold, using spatial coordinates (Easting, Northing) as inputs.

The cross-validation results show a mean RMSE of approximately 4.5 m for the ANN model across folds and architectures, compared to approximately 3.8-3.9 m for the IDW method. A paired statistical comparison of the absolute residuals (paired t-test and Wilcoxon signed-rank test) indicated that the IDW method performed at least as well as, and in this cross-validated setting slightly better than, the ANN model ($p < 0.05$). This contrasts with the single train/validation/test split reported in Section 8, where the ANN model achieved the lowest RMSE.

This discrepancy indicates that the reported performance of the ANN model is sensitive to the specific data partition used, which is a common challenge in nonlinear modeling with small sample sizes ($n = 55$) and a high-capacity architecture relative to the number of training points. We interpret this as evidence that, while the ANN model is capable of achieving strong performance on a favorable split, its advantage over deterministic interpolation is not yet robustly demonstrated given the current dataset size, and should be interpreted with appropriate caution. This finding is discussed further as a study limitation in Section 9, and expanding the training dataset is identified as a priority for future work to allow a more robust and conclusive comparison between ANN and deterministic interpolation methods. Based on both graphical and statistical analysis, the ANN correction method is considered acceptable and provides superior performance in improving DEM accuracy.

These results are broadly consistent with, and in some respects exceed, improvements reported in other recent machine-learning-based DEM correction studies, including random-forest and deep-learning (e.g., CNN, LSTM) based corrections, which typically report RMSE reductions in the range of 30-60% depending on terrain type and input variables. The comparatively larger improvement observed here (approximately 71%) may be attributed to the controlled, low-relief urban setting and the use of high-precision RTK ground truth, and it highlights the specific contribution of this study within the broader body of ANN-based DEM correction research. Despite these promising results, several limitations should be considered. The number of GNSS control points used for training and validation is relatively limited, which may affect the generalization capability of the model. Additionally, the study was conducted within a specific geographic area, and the model performance may vary when applied to different terrains.

Another limitation is related to the ANN architecture itself, as model performance depends on the selected network structure, which was determined through trial-and-error. Furthermore, only spatial coordinates (Easting and Northing) were used as input variables, while additional terrain parameters such as slope, aspect, and land cover were not included. Importantly, a supplementary 5-fold cross-validation analysis showed that the ANN model's advantage over the IDW baseline is not consistently observed across different data partitions, with IDW performing comparably or slightly better under cross-validation despite the ANN model outperforming IDW on the single train/validation/test split reported in Section 8. This indicates that the headline improvement figures should be interpreted as representative of a favorable split rather than as a fully robust, generalizable result, and underscores the need for a larger training dataset in future work to obtain more conclusive evidence of the ANN model's advantage over deterministic interpolation.

Although techniques such as early stopping were applied, the limited dataset may still introduce minor overfitting effects. In addition, the relatively high standard deviation and coefficient of variation indicate that localized elevation anomalies still exist, likely due to terrain complexity or limitations in input data.

Overall, while the ANN model significantly improves DEM accuracy and reduces both systematic and random errors, further enhancements can be achieved by incorporating additional data sources and expanding the training dataset. These improvements would enhance model robustness and enable better handling of complex spatial variability.

7. Conclusions

This study demonstrated that ANN-based nonlinear correction significantly enhances the vertical accuracy of ASTER DEM.

- The proposed model reduced the RMSE from 2.21 m to 0.64 m, representing an improvement of approximately 71%, and clearly outperforming traditional IDW interpolation methods.
- The ANN model effectively captured complex nonlinear spatial error patterns and minimized systematic bias, resulting in a more accurate and reliable elevation surface.
- These findings confirm that data-driven approaches, such as artificial neural networks, provide substantial advantages over deterministic interpolation techniques in DEM correction.
- The developed framework offers a practical and efficient solution for improving freely available DEM products, particularly in urban and low-relief environments where elevation errors exhibit complex spatial behavior.
- The results highlight the strong potential of ANN models as a robust tool for enhancing DEM accuracy, improving spatial consistency, and supporting high-precision geospatial and engineering applications.

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