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Perfecting the accuracy of digital map production from satellite imagery using application geomatics techniques

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ABSTRACT

Challenges remain in data retrieval and mapping development when compared to other land objects, despite the dependability of remote sensing technology in assessing land use and land cover distribution. The fuzzy ARTMAP model is an ART-based neural network (FAM). The goal of this study is to use satellite imagery and advanced geomatics methods to create accurate digital maps. Field coordinates were matched with satellite imagery to increase spatial accuracy as part of a series of geomatic correction processes that also included geographic correction using GPS coordinates. The fuzzy ARTMAP method was used to assess the quality of the data classification. This algorithm has already shown its efficacy in distinguishing between farmlands, urban structures, and arid lands. The algorithm's kappa value of 0.83 and overall accuracy of 89% indicate a very reliable data classification process. Further, extensive evaluations of the accuracy of geographical measures were carried out, specifically focussing on areas and distances. The findings indicated an overall error of 0.73% for distances and a mere 0.03% for areas. These results indicate that the methods used to get very high degrees of spatial accuracy while simultaneously decreasing spatial deviations work. The findings show that state-of-the-art georectification methods coupled with current classification algorithms may significantly enhance digital map quality, making them more reliable for applications such as environmental change monitoring, urban planning, and natural resource management. The research reinforces the importance of integrating low- and medium-resolution satellite imagery with modern geomatics techniques to achieve high-resolution digital maps.

Keywords: georectification, spatial deviations, natural resource management, monitoring, land use.

INTRODUCTION

Many different types of maps serve different functions, but most end up in one of three places: records of land division, engineering, planning, or design tools or as part of a geographic information system (GIS) with a wide range of applications. The maps serve as a digital basis for all of the presented intangible data, including but not limited to market statistics, land appraisals, and assessment comparisons. Imagery has high values when removing all distortions; it is connected to the main geodetic network, can serve as a base map, and meets the measurement tolerances with cadastral maps for the construction of the cadaster (Jasim, Al-Saedi, et al., 2024). Geographical, cultural, and physical aspects, as well as administrative and planning borders, should be included on large-scale base maps created for urban development plans (Jasim, Jasim, et al., 2024). Depending on the field of study, the phrase "low-resolution", "medium-resolution" or "high-resolution" might refer to pictures, digital elevation models (DEMs), or point clouds, depending on the platform and sensors used. In terms of geometric resolution, data classified as low-resolution has a size more than 30 m GSD, data classified as medium-resolution falls between 30 and 5 m GSD, data classified as high-resolution falls between 5 and 1 m GSD, and data classified as very high-resolution displays a spatial resolution less than 1 m (Backes and Teferle, 2020). Professionals have created a number of trustworthy classification algorithms that use remote-sensing images for mapping purposes (Nandika et al., 2023). Regarding the availability of comprehensive results, each algorithm has its advantages and disadvantages. It is possible to classify input patterns into hyper-rectangular clusters using supervised learning neural networks like fuzzy ARTMAP (FAM) (Carpenter et al., 1991).

This paper presents a comprehensive strategy for enhancing the precision of digital maps generated from medium-resolution satellite images via the use of cutting-edge geomatics methods. By closing the gap between freely available data and the necessary high-quality standards, we want to solve the problems related to guaranteeing the correctness of spatial data collected from free satellite images. Digital maps are essential in urban planning, resource management, and environmental monitoring; this study aims to improve their quality and reliability by integrating GIS with advanced image processing and geospatial analysis methods.

MATERIALS AND METHOD

Study area

This research focuses on a small area situated inside the municipal limits of Al-Hindiyah. The region offers a combination of residential and business purposes, and it is defined by its closeness to important infrastructure, including urban services and local roadways. It may be found around the coordinates of 32°32'10" North and 32°32'40" North and between the longitudes of 44°15'30" East and 44°16'20" East, as shown in Figure 1. Residential neighborhoods and commercial areas are forming in the study area, which is undergoing urban development as part of Hindiyah's urban expansion. There is a basic infrastructure present in the study region, including roads, public buildings, schools, and health facilities. Its proximity to the city center makes it eligible for easy access to public services.

Database

For this investigation, satellite data was used. Sentinal-2B image for the year 2024 was collected from the USGS (https://earth explorer. USGS.gov/). Before conducting the geo-special analysis, the images were adjusted using radiometric calibration and atmospheric correction. There are no clouds in the study area, and the image has a resolution of 10 meters. In addition, ground control points (GCPs) 15 monitoring stations use the field navigation device for ground monitoring. The data used for training accounted for 70% of the total, with 30% reserved for testing. The classification process may be reasonably balanced with a 70/30 train/test dividing ratio, which is ideal for cross-validation (Al-Saedi et al., 2023, Vrigazova, 2021).

Figure 2 shows the locations of the ground control stations (GCPs) that were used to correct the georeference of the study area. The 15 GPS stations were strategically distributed to

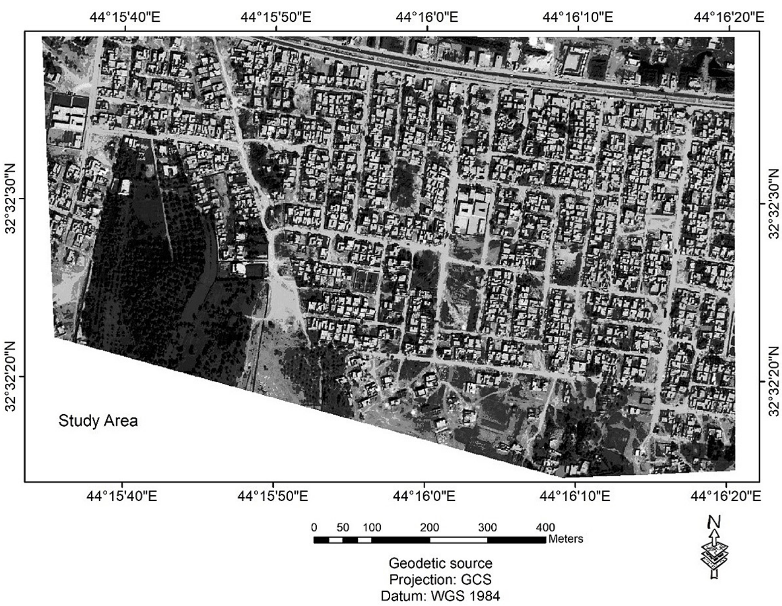

Figure 1. Location and geography of the study area

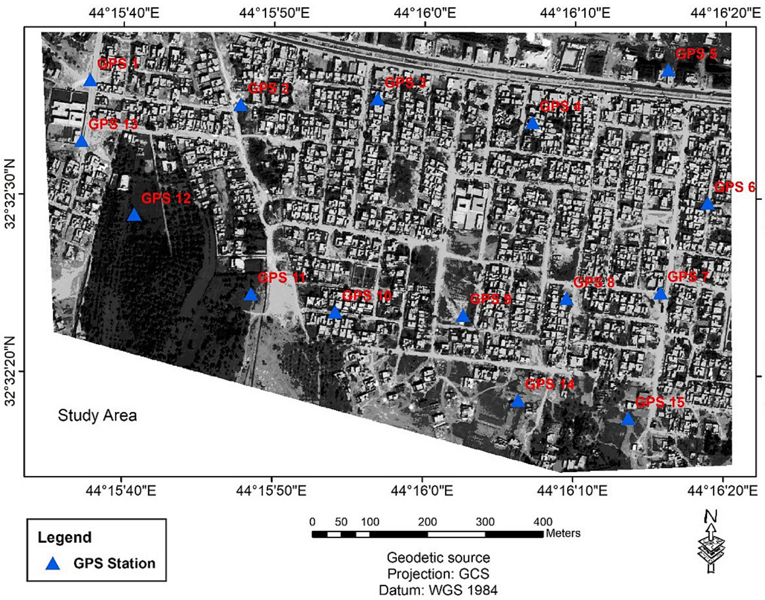

Figure 2. GPS stations in the study area

ensure comprehensive coverage of the area, which contributes to improving the spatial reference accuracy of the satellite images. Optimal distribution among the different urban, rural, and industrial sectors was achieved by carefully selecting the placements of the GPS stations. Data used to create the digital maps is more accurate because of this distribution, which aids in reducing mistakes caused by spatial distortions in the original images.

The accuracy of digital map-making depends heavily on the locating technique. As shown in Table 1, 15 ground control points (GCPs) were used to correct the georeferencing in the present study. The coordinates were obtained using very accurate GPS equipment with the goal of reducing positional errors. Reducing the possibility of spatial distortions and boosting the reliability of the georeferencing procedure, the research area was thoroughly covered by strategically placing the GPS stations.

Method

Fuzzy ARTMAP

Since its inception in 1992, the fuzzy ARTMAP (FAM) neural network (NN) has piqued the attention of researchers due to its status as a fast, accurate, offline, and online pattern classifier (Lerner and Guterman, 2008). Typically, while establishing the issue and site selection criteria, fuzzy logic is used as the typical approach (Al-Hameedawi, 2022). In image processing, image classification techniques are crucial for determining the location of objects that correspond to a given class that is specified in the image (Kadhum et al., 2023). In remote sensing, supervised and unsupervised classification are the two primary approaches. Neural network architectures belonging to the ARTMAP class allow for the random presentation of input vectors that cause incremental supervised learning of recognition classes and multidimensional maps (Systems, 1991). Medium- and low-resolution satellite data have a number of spectral and geographical restrictions that

Table 1. Coordinates are recorded for georeference fixing

No.	GPS Station	Easting (m)	Northing (m)
1	GPS1	430565	3600918
2	GPS2	430826	3600875
3	GPS3	431064	3600885
4	GPS4	431332	3600844
5	GPS5	431568	3600936
6	GPS6	431636	3600704
7	GPS7	431554	3600548
8	GPS8	431391	3600539
9	GPS9	431211	3600509
10	GPS10	430990	3600515
11	GPS11	430844	3600546
12	GPS12	430641	3600685
13	GPS13	430550	3600813
14	GPS14	431307	3600362
15	GPS15	431498	3600330

impact the accuracy of LULC categorization, according to many studies (Pal and Talukdar, 2020) (Yang et al., 2017, Latifovic and Olthof, 2004).

A streamlined version of the fuzzy ARTMAP algorithm is implemented using the Terrset program, drawing on extensive research into fuzzy ARTMAP and the features of remote-sensing data. The direct method of mapping, terrestrial mapping (sometimes called a field survey), allows for maps to be created at multiple sizes using information with varying degrees of accuracy; yet, it is a labor-intensive, time-and resource-intensive method of mapping vast regions (Langat et al., 2021). Fuzzy ARTMAP is a simplified way to classify (Lerner and Guterman, 2008, Carpenter et al., 1991, Matias et al., 2021):

$$T_j = \frac{\|I \wedge w_j\|}{\alpha + \|w_j\|} \tag{1}$$

where: I – is the input (image pixel), w_j – is the weight of the category j, $\wedge$ – represents the fuzzy intersection process (calculating the minimum between values I and w_j). α – a small parameter to avoid division by zero. This equation is used to calculate the similarity score between the input (such as a pixel in a satellite image) and the stored class weights.

$$\frac{\|I \wedge w_J\|}{\|I\|} \geq \rho \tag{2}$$

where: ρ – a vigilance parameter that determines the degree of similarity required. This equation checks whether the similarity score between the input (pixel) and the class is higher than the required threshold.

$$w_J^{\text{new}} = \beta\left(I \wedge w_J^{\text{old}}\right) + (1-\beta)w_J^{\text{old}} \tag{3}$$

where: β – the learning coefficient, which determines how much the new input affects the weight update. To classify a new image, the selection score is calculated for each class, and the class with the highest selection score is selected.

Accuracy assessment

Accuracy evaluation of fuzzy ARTMAP segment-based classified maps needs LULC. The Confusion Matrix in ArcGIS 10.8 is used to validate the division classification by means of the ground truth points (Jasim et al., 2024). For this reason, we calculated the kappa coefficient and overall accuracy of the LULC maps that were classified (Leta et al., 2021, Zabihi et al., 2020):

$$OA = \frac{\sum_{i=1}^{r} D_{ii}}{N} \tag{4}$$

$$K = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r}(X_{i+} * X_{+i})}{N^2 - \sum_{i=1}^{r}(X_{i+} * X_{+i})} \tag{5}$$

where: N – total number of values, r – number of rows, D_{ii} – number of total correct values, D_{ij} – number of correct values in row i, D_{ij} – number of correct values in column j, X_{ii} – number of values in row i and column i, X_{+i} and X_{i+} – the column total and row total, respectively.

Validation

1. Calculate the absolute difference between the two values (the difference without a negative sign) (Jasim, Al-Saedi, et al., 2024):

$$\Delta Distance = |Distance\ (Map) - Distance\ (Field)| \tag{6}$$

$$\Delta Area = |Area\ (Map) - Area(Field)| \tag{7}$$

2. Divide the absolute difference by the true value (field):

$$Length = \frac{|\Delta Distance|}{Distance\ (Field)} \tag{8}$$

$$Area = \frac{|\Delta Area|}{Area\ (Field)} \tag{9}$$

3. Multiply the result by 100 to get the percentage relative error:

$$PRE = \left(\frac{|Measured\ Value - True\ Value|}{|True\ Value|}\right) \times 100 \tag{10}$$

where: PRE – percentage relative error

Methodology

1. Data acquisition
- Download low-resolution satellite imagery (such as Landsat or Sentinel).
- Collect ground reference data (Ground Control Points - GCPs) to increase the accuracy of the results.

2. Preprocessing
- Radiometric correction.
- Geometric correction.
- Noise reduction using filtering techniques.

3. Image processing
- Apply image enhancement techniques such as contrast enhancement or radiometric correction.
- Image classification: Classification can include either supervising or unsupervising.
- Layer extraction: Use band analysis to select important features.

4. Data analysis
- Use spatial analysis tools in ArcGIS.

- Analyze spatial and numerical errors.
- Compare results with reference maps to assess accuracy.

5. Digital map production
- Generate final digital maps using GIS.
- Prepare maps for interpretation and evaluation (map layout).

6. Accuracy assessment
- Calculate the confusion matrix to assess classification accuracy.
- Compare results with reference data to determine the error rate.

7. Validation and compare results, as in Figure 3.

RESULTS AND DISCUSSION

Results of Fuzzy ARTMAP

Georeferencing is a fundamental step in the production of digital maps. By applying observed coordinates, spatial inconsistencies in raw satellite imagery are corrected, improving positional accuracy. This process is essential to ensure the integration of satellite data with other geographic datasets, contributing to spatial consistency in future geographic analyses. For this research, the supervised classification method was used to classify the objects as specified. Image processing supervised classification involves building a training area from which the class signature is used to generate the classification criteria.

The classified map, as shown in Figure 4, shows the spatial distribution of land cover patterns in the study area, which are classified into three main categories: Farmlands, Urban Structure, and Arid Lands. This map was produced using the Fuzzy ARTMAP algorithm, which is particularly effective in dealing with complex and overlapping spectral data. The findings show that the Urban Structure (red areas) is dominant in the

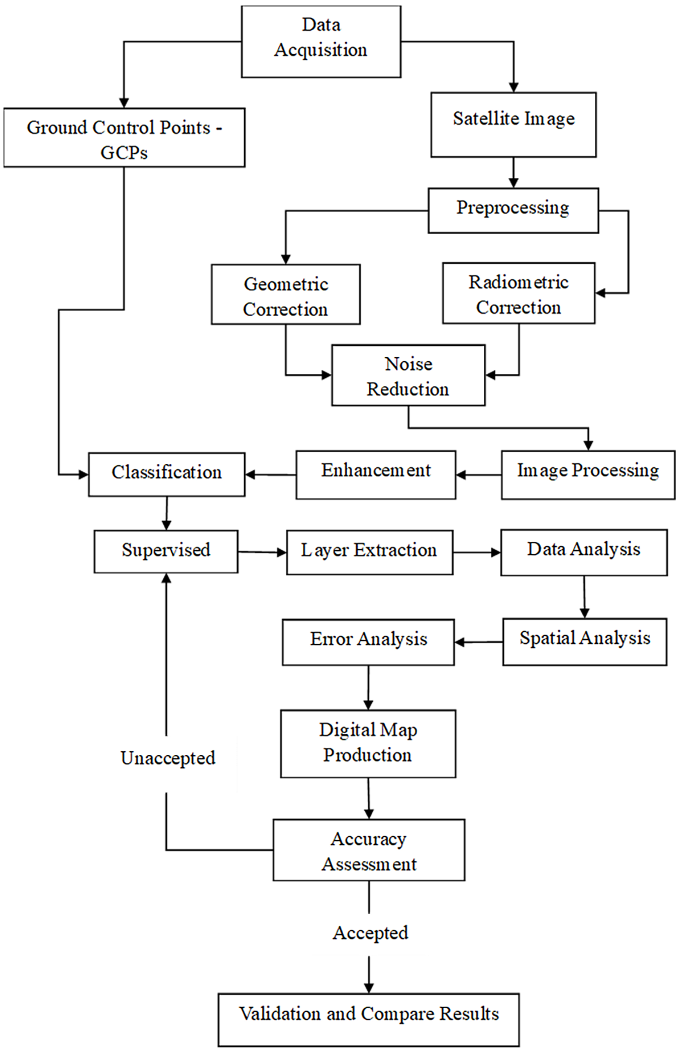

Figure 3. Methodology based on flowcharts

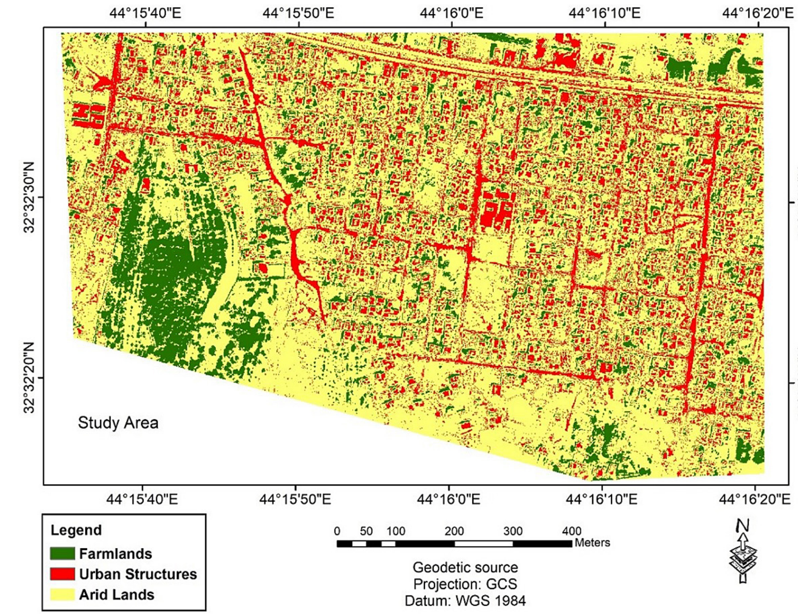

Figure 4. The finalization of the digital map.

northern and central parts of the research area, which is consistent with the tendencies of urban growth. The southern portion is mainly composed of Farmlands, which are green regions, while the outlying portions are mostly Arid Lands, which are yellow places. An issue with satellite image classification is the correct identification of transition areas between classes; this highlights the algorithm's capability to deal with mixed pixels.

This technique was able to decrease classification errors in regions with substantial spectral overlap, in contrast to conventional methods. There was an improvement in the separation between rural and urban regions, which are commonly misclassified because of similarities in spectral reflectance characteristics within particular spectral bands, thanks to its capacity to dynamically modify the learning rate. These findings highlight the promising future of digital maps created from medium-resolution satellite images by merging the Fuzzy ARTMAP algorithm with advanced geomatics methods.

Classification accuracy evaluation

Table 2 displays the results of the evaluation of classification accuracy using the Fuzzy ARTMAP method. This technique was used to classify satellite imagery into three primary classifications: Farmlands, Urban Structures, and Arid Lands. The overall accuracy and kappa coefficient show that this method performs well in the results. There was a great deal of agreement between the reference data and the classification findings since the overall accuracy was 89%. A very consistent and reliable classification method was shown by the computed kappa coefficient of 0.83.

Farmlands: With a 93% class accuracy, the system properly classified 28 out of 30 reference locations. A few errors occurred, including the classification of two points into various categories. With 25 out of 30 points properly classified, the classification accuracy for Urban Structures was 83%. There were several minor errors in the classification, and there was minimal overlap

Table 2. The outcomes of the accuracy assessment of the classification technique using the Fuzzy ARTMAP algorithm

Classifiers	Classes	Farmlands	Urban structures	Arid lands	Total	Overall accuracy %	Kappa coefficient
Fuzzy ARTMAP algorithm	Farmlands	28	2	2	32	89	0.83
	Urban structures	1	25	1	27		
	Arid lands	1	3	27	31		
	Total	30	30	30	90		
Class accuracy %		93	83	90			

between Farmlands and Arid Lands. The algorithm accurately classified 27 out of 30 points in the Arid Lands class, indicating 90% accuracy in understanding this classification. There were some minor errors, mainly with urban structures.

Farmlands, Urban Structures, and Arid Lands are shown in Figure 5 as histograms illustrating the distribution of accurate and incorrect classifications for each class. The visualization provides a thorough study of the class-level performance of the Fuzzy ARTMAP algorithm. There were 4 errors in the Farmlands classification, with two points classified as Urban Structures and one as Arid Lands. Urban Structures had 5 errors, the highest number of errors among the classes, indicating the spectral overlap between this class and the other two classes. In the Arid Lands class, only 3 errors were recorded, highlighting the robustness of the algorithm in dealing with this class. The issues of spectral similarity across classes are reflected in the discrepancy in the number of mistakes between them, especially between Arid Lands and Urban Structures.

Validation

Distance

Figure 6 shows the finished digital map that was created using sophisticated geomatics methods. This map displays precise measurements of distances between key points, highlighting the significant improvement in the accuracy of geographic data compared to traditional maps. The map demonstrates the ability of modern techniques, such as geometric displacement correction and integration with topographic data, to

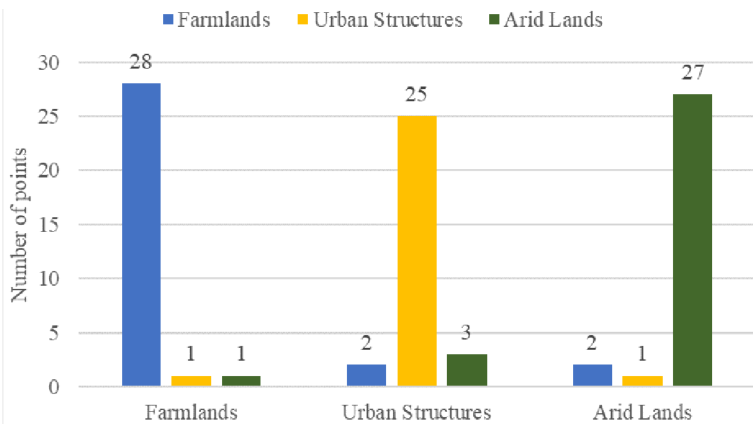

Figure 5. Evaluation of the Fuzzy ARTMAP algorithm's classification accuracy

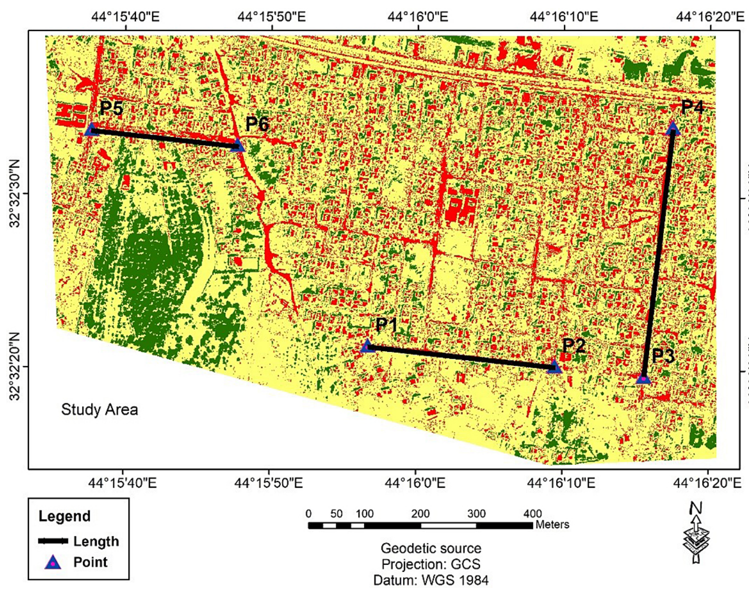

Figure 6. Distance measurements on the final digital map

improve location accuracy to within a few meters, which is critical for demanding applications such as urban planning and natural resource management. Distance measurements were used to analyze the efficiency of the correlation between the different elements on the map and to identify factors that influence the improvement of data quality. The results showed a high agreement between the values actually measured and those calculated on the digital map, confirming the effectiveness of the methods used to produce the map.

Table 3 shows measurements of three sets of points (Pair ID) with the differences between map distances and field distances for each pair. The data showed slight variation in distances, as the difference between distances (Δ Distance) ranged from 1.94 m to 3.46 m. At the level of individual measurements, the relative errors were low, ranging between 0.41% and 1.04%. This reflects a good convergence between digital data and field measurements, indicating high accuracy in producing digital maps using satellite images. The average of the differences between distances was calculated, which amounted to 2.41 m. The fact that the differences between the map values and the field values are so minimal is supported by this average. Also, the overall error was 0.73%, which means that the geomatics procedures helped keep the discrepancies to a minimum. The results prove that advanced geomatics methods are capable of creating digital maps with exceptional detail. Quality procedures, such as spatial processing and image analysis, are evident from the few discrepancies in the results. Applications, including urban planning, infrastructure construction, and management of natural resources, need this kind of study due to the high degree of spatial accuracy it provides. Time and effort saved compared to conventional field measurements and improved planning and implementation efficiency are both brought about by the capacity to receive correct findings from digital maps.

Area

The computed spatial measures in Figure 7 are based on the final digital map that was created by using advanced geomatics methods. The data derived from this map is more reliable for many applications since it demonstrates substantial increases in spatial accuracy when compared

Table 3. Evaluation of distance accuracy

Pair ID	Location description	Distance (Map) (m)	Distance (field/GPS) (m)	Δ Distance (m)	Avg. Δ distance (m)	Relative error (%)	Overall error (%)
1	(P_1-P_2)	336.65	333.19	3.46	2.41	1.04	0.73
2	(P_3-P_4)	449.45	447.62	1.83		0.41	
3	(P_5-P_6)	263.44	265.38	1.94		0.73	

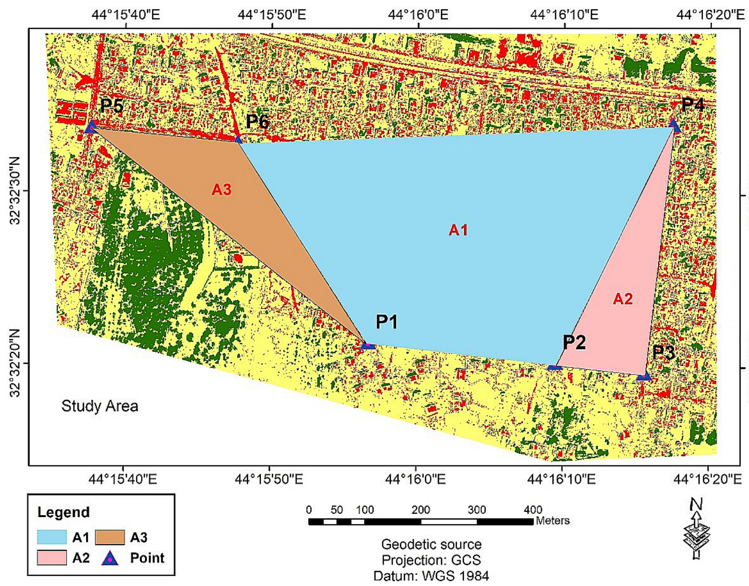

Figure 7. The finished digital map's area measurements

Table 4. Evaluation of area accuracy

Polygon ID	Region name	Area (map) (m^2)	Area (field/GPS) (m^2)	Δ Area (m^2)	Avg. Δ Area (m^2)	Relative error (%)	Overall error (%)
A1	(P_1-P_2-P_4-P_6)	217290.51	217275.6	14.88	15.70	0.01	0.03
A2	(P_2-P_3-P_4)	35480.98	35501.08	20.1		0.06	
A3	(P_1-P_5-P_6)	43601.67	43589.54	12.13		0.03	

to conventional maps. The correctness of the map was confirmed by comparing the produced spatial measures with reference data. The computed values converged closely to the reference values, and the error rate was minimal, according to the findings. This proves that the approaches used are successful in making digital maps more accurate, particularly when applied to medium-resolution satellite images using advanced correction procedures such as geometric and spectral correction.

Table 4 compares the areas assessed in the field using GPS methods to those measured using satellite imagery across many geographies. Displayed as well are the discrepancies between the computed areas, as well as the relative and overall errors for these areas. The results show that the relative error is often rather modest, which is a reflection of how accurate the digital maps made from satellite images appear. In region A1, for instance, a discrepancy of 14.88 m^2 was noted between field areas and satellite imagery, with a relative error of 0.01%; this demonstrates the superior accuracy of digital map generation.

The researcher's experience with the area's terrain and climate enables them to choose the location of the study because of their familiarity with the region's geographical characteristics. Although this study relied only on data collected by GIS and RS methods, the findings were boosted by including field data sources that used GPS and topographical maps. There was a strong correlation between the statistical outputs and the captured field reality, which indicated that the analysis was accurate when compared to field data.

Although digital map accuracy has been considerably improved using geomatics strategies, there are still certain limits and challenges that need to be taken into regard, such as:

1. Image captured by a satellite: Information may be lost in low-resolution images. Clouds and spectral distortions are two examples of external variables that might impact the accuracy of the analysis.
2. Not enough field verification: This could generally result in less exact results.

The use of high-resolution images, field evidence, and the development of advanced algorithms to lessen the probability of errors are all suggested responses to these problems.

CONCLUSIONS

The study's findings confirm the validity of geomatics methods for creating accurate maps that agree well with collected data. These findings provide validity to digital maps and satellite imagery as vital resources in a variety of industries, and they pave the path for more studies to refine and advance these methods. Urban planning, natural resource management, and the monitoring of spatial changes are just a few of the many applications that benefit greatly from the higher accuracy of spatial data made possible by contemporary geomatics technology. These technologies, when combined with satellite images, provide the groundwork for creating accurate geographic solutions that can fulfill the demands of contemporary spatial analysis. Furthermore, the image emphasizes how these strategies effectively decrease errors, which boosts trust in judgments that rely on geographic data. The confusion matrix was used to assess the classification accuracy; the results indicated a kappa coefficient of 0.83 and an overall accuracy of 89%. These results show that the Fuzzy ARTMAP algorithm is reliable and can withstand difficult situations.

REFERENCES

1. Al-Hameedawi, A. N. M. (2022). Fuzzy logic approach based on geomatics and remote sensing for siting a petroleum warehouse in the metropolitan area of Baghdad. *Journal of the Indian Society of Remote Sensing, 50*(7), 1211–1225.
2. Al-Saedi, A. S. J., Kadhum, Z. M., & Jasim, B. S. (2023). Land Use and land cover analysis using geomatics techniques in Amara City. *Ecol. Eng, 9*, 161–169.
3. Backes, D. J., & Teferle, F. N. (2020). Multiscale integration of high-resolution spaceborne and

drone-based imagery for a high-accuracy digital elevation model over Tristan da Cunha. *Frontiers in Earth Science, 8*, 319.

4. Carpenter, G. A., Grossberg, S., Markuzon, N., & Reynolds, J. H. (1991). Fuzzy ARTMAP: A neural network architecture for incremental supervised learning of analog multidimensional maps. Boston University Center for Adaptive Systems and Department of Cognitive ….
5. Jasim, B., Jasim, O. Z., & AL-Hameedawi, A. N. (2024). Monitoring change detection of vegetation vulnerability using hotspots analysis. *IIUM Engineering Journal, 25*(2), 116–129.
6. Jasim, B. S., Al-Saedi, A. S. J., & Kadhum, Z. M. (2024). Using remote sensing application for verification of thematic maps produced based on high-resolution satellite images. *AIP Conference Proceedings,* 3092(1).
7. Jasim, B. S., Jasim, O. Z., & AL-Hameedawi, A. N. (2024). A review for vegetation vulnerability using artificial intelligent (AI) techniques. *AIP Conference Proceedings*, 3092(1).
8. Kadhum, Z. M., Jasim, B. S., & Al-Saedi, A. S. J. (2023). Improving the spectral and spatial resolution of satellite image using geomatics techniques. *AIP Conference Proceedings*, 2776(1).
9. Langat, P. K., Kumar, L., Koech, R., & Ghosh, M. K. (2021). Monitoring of land use/land-cover dynamics using remote sensing: a case of Tana River Basin, Kenya. *Geocarto International, 36*(13), 1470–1488.
10. Latifovic, R., & Olthof, I. (2004). Accuracy assessment using sub-pixel fractional error matrices of global land cover products derived from satellite data. *Remote Sensing of Environment, 90*(2), 153–165.
11. Lerner, B., & Guterman, H. (2008). Advanced developments and applications of the fuzzy ARTMAP neural network in pattern classification. In Computational Intelligence Paradigms: Innovative Applications 77–107. *Springer.*
12. Leta, M. K., Demissie, T. A., & Tränckner, J. (2021). Modeling and prediction of land use land cover change dynamics based on land change modeler (Lcm) in nashe watershed, upper blue nile basin, Ethiopia. *Sustainability, 13*(7), 3740.
13. Matias, A. L. S., Neto, A. R. R., Mattos, C. L. C., & Gomes, J. P. P. (2021). A novel fuzzy ARTMAP with area of influence. *Neurocomputing, 432*, 80–90.
14. Nandika, M. R., Ulfa, A., Ibrahim, A., & Purwanto, A. D. (2023). Assessing the Shallow Water Habitat Mapping Extracted from High-Resolution Satellite Image with Multi Classification Algorithms. 17(2), 69–87.
15. Pal, S., & Talukdar, S. (2020). Assessing the role of hydrological modifications on land use/land cover dynamics in Punarbhaba river basin of Indo-Bangladesh. *Environment, Development and Sustainability, 22*, 363–382.
16. Systems, N. (1991). Fuzzy ARTMAP : A Neural Network Architecture for Incremental Supervised Learning of Analog Multidimensional Maps.
17. Vrigazova, B. (2021). The proportion for splitting data into training and test set for the bootstrap in classification problems. Business Systems Research: *International Journal of the Society for Advancing Innovation and Research in Economy, 12*(1), 228–242.
18. Yang, C., Wu, G., Ding, K., Shi, T., Li, Q., & Wang, J. (2017). Improving land use/land cover classification by integrating pixel unmixing and decision tree methods. *Remote Sensing, 9*(12), 1222.
19. Zabihi, M., Moradi, H., Gholamalifard, M., Khaledi Darvishan, A., & Fürst, C. (2020). Landscape management through change processes monitoring in Iran. *Sustainability, 12*(5), 1753.