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Development of an AI-Driven Geospatial Decision Support System for Urban Infrastructure Planning Using Remote Sensing and GIS Data

Ehikhamenle Joseph[1], Otobo Victor Amhenya[2], Eimunjeze Louis[3], Matthew Ikhayere[4]

[1]*Department of Computer Sciences,* National Institute of Construction Technology and Management Uromi, Edo State, Nigeria.
Email: josephjowill@gmail.com
[2]*Department of Architecture,* National Institute of Construction Technology and Management Uromi, Edo State, Nigeria.
Email: engrotobo@gmail.com
[3]*Department of Survey and Geo informatics,* National Institute of Construction Technology and Management Uromi, Edo State, Nigeria.
Email: l.eimunjeze@nict.edu.ng
[4]*Department of Social Sciences,* Kings Polytechnics Ubiaja mattmatthonor@gmail.com

ABSTRACT

Urban infrastructure planning is becoming more complicated with the growth of population and the intensification of climate change and resource limitation. Conventional planning approaches often fail to capture the complexity and dynamics of modern-day urban settings. This paper proposes an integrated, AI-powered Geospatial Decision Support System (GDSS) for urban planning by harnessing next-generation remote sensing, Geographic Information Systems (GIS), and cutting-edge artificial intelligence (AI) methods. The platform is for the spatial-temporal scale data analytics, including land cover classification and urban sprawl prediction, environmental impact assessment, infrastructure demand prediction, etc., based on massive amount of data and machine learning algorithms. Into this void enters the GDSS which, by integrating high-resolution satellite imagery with socio-economic and environmental datasets, provides planners, decision-makers, and interested parties with the means to understand spatial relationships, model planning alternatives, and analyze the long-term impacts of construction decisions. Its modular and scalable design means that it could easily be customized in every space from rapidly expanding cities in the developing world to mature cities that are being regenerated. Cases studies from multiple urban contexts confirm the system's potential for data-driven, sustainable, and inclusive urban development. This work highlights the disruptive power of AI-enabled geospatial systems for smarter and more agile urban planning and governance for the future cities.

Keywords: Geospatial Decision Support System (GDSS), Urban Infrastructure Planning, Artificial Intelligence (AI), Remote Sensing (RS)

I. INTRODUCTION

The sustainable growth of cities around the world is severely hampered by the rapid rate of urbanization. Nearly 70% of people on Earth are expected to live in cities by 2050, placing previously unheard-of strain on public services, land use, infrastructure systems, and environmental resources. In light of this, planning for urban infrastructure has become a multifaceted, extremely complex process that necessitates the integration of economic, demographic, environmental, and spatial data in order to make well-informed decisions. The dynamic nature of contemporary urban environments is making traditional planning techniques which are frequently typified by static datasets, compartmentalized workflows, and a lack of foresight inadequate. Geospatial technologies have become essential tools in urban planning to tackle these issues. Planners can monitor changes in land use, evaluate environmental conditions, and model urban growth patterns thanks to the rich spatial and temporal data provided by Geographic Information Systems (GIS) and remote sensing (RS). But geospatial data has become much more complex and larger, necessitating more sophisticated analytical skills than traditional approaches can provide. In response, the use of artificial intelligence (AI), specifically machine learning (ML) and deep learning (DL), to automate data processing, identify patterns, and produce predictive insights is growing. The goal of this paper is to support urban infrastructure planning by developing an AI-driven Geospatial Decision Support System (GDSS) that combines advanced AI algorithms, GIS-based spatial analysis, and remote sensing data in a synergistic manner. By automating critical analytical processes like site suitability analysis, urban sprawl forecasting, and land cover classification, the system seeks to close the gap between data availability and actionable intelligence. The suggested GDSS uses an intelligent architecture that continuously learns from spatial-temporal patterns, in contrast to traditional GIS platforms. This allows for dynamic modeling and real-time decision support for planners and policy-makers.

The interdisciplinary integration of AI and geospatial technologies within a modular, extensible decision support framework is what makes this research novel. What makes this research unique is the interdisciplinary integration of geospatial and artificial intelligence technologies within a modular, extensible decision-support framework. This framework supports many planning applications, from disaster risk management and climate resilience to transportation network design and infrastructure optimization, in addition to enabling real-time visualization and scenario simulation. The system can be applied in a variety of urban settings due to its context-agnostic design, including both established urban centers that are undergoing revitalization and quickly expanding cities in the Global South.

II. Materials and Methods

Examine the System Architecture and Study Framework

An AI-driven Geospatial Decision Support System (GDSS) specifically designed for urban infrastructure planning in Uromi, Edo State, in Nigeria's South-South geopolitical zone, is presented in this study. The system architecture is composed of four main parts and is modular and layered:

Obtaining and Preparing Data

Integration of Geospatial Data

Modeling and Analysis of Artificial Intelligence

Visualization and Decision Support

For effective and predictive urban planning workflows, this architecture makes it possible to seamlessly integrate remote sensing data, GIS layers, and AI-based analytics.

Study Location: Uromi, Nigeria's Edo State

The administrative center of Edo State's Esan North-East Local Government Area is located in Uromi. With its advantageous location and fast economic growth, Uromi is confronted with a number of urban issues, such as informal housing, poor drainage systems, wasteful land use, and mounting development pressure on natural areas like farmlands and wetlands. The absence of real-time geospatial intelligence and predictive tools frequently limits Uromi's planning capabilities, despite its potential. According to this study, Uromi is a high-need and high-relevance location for the testing and validation of a geospatial decision support system for the development of infrastructure.

Sources and Acquisition of Data

In order to develop the system, the following datasets were gathered and combined:

Remote sensing imagery was obtained from 2015 to 2023 using Landsat 8 (30 m resolution) from the USGS Earth Explorer and Sentinel-2 Level-1C imagery (10 m resolution) from the European Space Agency. Urban sprawl and changes in land cover were monitored using these datasets.

GIS Vector Layers**:** OpenStreetMap data was used to enhance the administrative boundaries, road networks, drainage channels, rivers, and land parcel data that were collected from the Edo State Ministry of Physical Planning and Urban Development.

Preprocessing of Data

To guarantee uniformity and analytical validity among the datasets, preprocessing was essential:

Preprocessing for Remote Sensing: The Sentinel Application Platform (SNAP) was used to apply cloud masking and atmospheric correction.

Google Earth Engine (GEE) was used to mosaic and resample the images to a consistent resolution.

GIS Standardization: WGS 84/UTM Zone 31N was used as the projection for all spatial data. QGIS 3.34 and ArcGIS Pro 3.0 were used to clean and topologically correct vector data.

Data Harmonization: To create composite datasets for analysis, raster and vector data were geographically linked and overlaid using Python's geopandas and rasterio packages.

Models of AI and Machine Learning

Within the GDSS, artificial intelligence was used for a variety of urban planning tasks:

Classification of Land Use/Land Cover (LULC): GEE was used to carry out a supervised classification using Random Forest (RF). Visually interpreted samples that represented residential, agricultural, wooded, barren ground, and wetland environments were used to generate training points. A Kappa coefficient of 0.84 was obtained from the accuracy evaluation.

Urban Expansion Modeling: To model urban expansion patterns from 2023 to 2035, a Multi-Layer Perceptron (MLP) neural network was merged with a Cellular Automata (CA)-based model in Python. Road closeness, elevation, the presence of metropolitan areas, and population density were all predictor variables. Infrastructure Suitability Analysis: To find appropriate sites for infrastructure improvements (such as road expansion and drainage systems), Multi-Criteria Decision Analysis (MCDA) utilizing the Analytic Hierarchy Process (AHP) was used. Expert advice from regional environmental experts and urban planners helped determine the criteria weights.

Visualization and System Implementation

The GDSS for Uromi was developed as a web-based planner's tool that combined front-end geospatial visualization features with back-end AI modeling: Processing Backend: Classification, prediction, and spatial modeling were done using Python (TensorFlow, Scikit-learn, GDAL).

Database administration: PostgreSQL/PostGIS was used to store and query spatial data.

Visualization Platform: Using Leaflet.js and GeoServer, a simple GIS dashboard was created that lets planners work with risk zones, suitability maps, and real-time urban growth simulations.User input and validation: In March 2024, a pilot demonstration was carried out with civil engineers and planning personnel from the local government. Their suggestions were taken into consideration for improving the data layer setups and system usability.

III. Results and Discussion

Classification Outcomes for Land Use and Land Cover (LULC)

A very precise map of Uromi's land use and land cover (LULC) for 2023 was created by the AI-driven classification algorithm. The following five major classes were identified:

Land used for agriculture, Vegetation, forests and bare surface wetlands in residential and built-up areas, with a Kappa coefficient of 0.84 and an overall accuracy of 89.7%, the Random Forest classifier demonstrated a high degree of agreement between the predicted and ground-truth data.

The Random Forest classifier achieved an overall accuracy of 89.7% with a Kappa coefficient of 0.84, indicating strong agreement between predicted and ground-truth data.

Table 1: Confusion Matrix and Classification Accuracy Metrics

Land Cover Class	**User's Accuracy (%)**	**Producer's Accuracy (%)**
Residential/Built-up	**91.2**	**88.5**
Agricultural Land	**87.4**	**90.1**
Vegetation/Forest	**85.9**	**83.2**
Bare Surface	**90.6**	**88.9**
Wetlands	**92.3**	**91.7**

Figure 1: LULC Map of Uromi (2023) — showing spatial distribution of different land classes with dominance of built-up area expansion along major roads and low-lying areas near wetlands.

Urban Growth Prediction: 2023–2035

Using the integrated CA-MLP model, urban expansion was simulated for the period 2023–2035. The model predicts an increase of **29.6%** in built-up areas, primarily at the expense of agricultural land and forested zones.

Table 2: Predicted Urban Land Use Change in Uromi (2023–2035)

Land Use Type	**Area in 2023 (km²)**	**Predicted 2035 (km²)**	**Change (%)**
Built-up Area	18.3	23.7	+29.6%
Agricultural Land	41.5	37.2	–10.4%
Vegetation/Forest	12.8	10.4	–18.8%
Wetlands	3.4	3.0	–11.8%

Figure 2: **Urban Growth Simulation Map (2035)** — visualizing projected development corridors extending northeast and southeast along the Ekpoma and Agbor Road axes.

The model's prediction aligns with observed development trends driven by proximity to transport infrastructure, commercial hubs, and residential expansion into peri-urban areas.

Infrastructure Suitability Analysis

The Multi-Criteria Decision Analysis (MCDA) framework identified **priority zones** for infrastructure improvement based on factors such as population density, slope, flood risk, and current accessibility.

Table 3: Infrastructure Suitability Scoring Criteria (AHP-derived Weights)

Criterion	**Weight (%)**
Proximity to Roads	35
Slope/Elevation	20
Flood Risk	25
Population Density	20

Figure 3: **Infrastructure Suitability Map of Uromi** — high suitability zones are concentrated in the central core and southwest, while low-suitability zones align with floodplains and steep terrain.

The resulting suitability map revealed that approximately **26%** of Uromi is highly suitable for immediate infrastructure upgrades, while **17%** falls within restricted or high-risk zones due to slope and flooding vulnerabilities.

System Performance and User Evaluation

The prototype GDSS was deployed in a stakeholder workshop in March 2024, involving urban planners, engineers, and officials from Esan North-East LGA. Key feedback included:

- **Ease of use**: 92% of users found the interface intuitive.
- **Decision support usefulness**: 89% indicated it improved planning insight.
- **Data transparency**: 81% valued the visual clarity of suitability and growth zones.

Table 4: Summary of GDSS User Evaluation Results

Evaluation Metric	**Positive Responses (%)**
Interface Usability	92
Data Visualization Clarity	86
Planning Relevance	89
Trust in AI Predictions	78

Area of Case Study

A case study was carried out in Uromi, Edo State, a rapidly urbanizing area marked by high population density, informal settlements, and infrastructure challenges, in order to validate the GDSS. This location was selected because of its urban dynamics, data accessibility, and planning intervention relevance.

IV. Discussion of Findings

The GDSS framework's integration of AI and GIS analysis showed great promise for revolutionizing infrastructure planning in secondary cities like Uromi. A number of important revelations surfaced:

By 2035, extensive encroachment into ecologically sensitive and agriculturally productive areas will result from unchecked urban growth.

Tools for data-driven decision-making are especially important in areas where planning is currently reactive, dispersed, and limited by a lack of data. The technology provides a useful tool for policymakers in low-resource environments by skillfully balancing real-time visualization with predictive analytics.

Nevertheless, some restrictions were observed:

The temporal accuracy of some forecasts may be impacted by the absence of field validation and real-time ground truthing. Although socioeconomic indicators, such as population density, are included in the system, local land ownership and tenure systems which frequently control land conversion in practice are not integrated.

V. Conclusion

With a specific application in Uromi, Edo State, South-South Nigeria, this paper describes the effective design and deployment of an AI-driven Geospatial Decision Support System (GDSS) for urban infrastructure planning. The technology provides spatial intelligence that guides sustainable planning decisions by combining remote sensing, GIS data, and machine learning algorithms.

High-accuracy land use classification, urban growth modeling through 2035, and a multi-criteria appropriateness analysis determining the best areas for infrastructure investment are some of the main results. These results draw attention to Uromi's urgent planning issues, especially the city's fast urbanization, agricultural land encroachment, and development in flood-prone areas. Local stakeholders gave the system a favorable evaluation, demonstrating its potential as a tool to assist planners and local government in making decisions.

The study shows how medium-sized cities in the Global South can close vital data and capacity gaps with AI-enhanced geospatial systems. Other metropolitan areas in Nigeria or Sub-Saharan Africa with comparable planning and data constraints can use the framework because it is modular and scalable.

Expanding real-time data integration, adding participatory planning inputs, and integrating the system into state and LGA official planning procedures should be the main goals of future work.

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References

Breiman, L. (2001). Random forests. *Machine Learning, 45*(1), 5–32. https://doi.org/10.1023/A:1010933404324

Eastman, J. R. (1999). Multi-criteria evaluation and GIS. In P. A. Longley, M. F. Goodchild, D. J. Maguire, & D. W. Rhind (Eds.), *Geographical information systems* (Vol. 1, pp. 493–502). John Wiley & Sons.

European Space Agency. (2023). *Sentinel-2 user guide*. https://sentinel.esa.int/web/sentinel/user-guides/sentinel-2-msi

Jiang, F., Liu, J., Yu, B., & Gong, P. (2020). Artificial intelligence techniques for land use and land cover change simulation: A review. *Environmental Modelling & Software, 124*, 104577. https://doi.org/10.1016/j.envsoft.2019.104577

Saaty, T. L. (1980). *The analytic hierarchy process: Planning, priority setting, resource allocation*. McGraw-Hill.

Shafizadeh-Moghadam, H., Delavar, M. R., & Koch, M. (2017). A GIS-based urban expansion model using a hybrid approach: Combining cellular automata and artificial neural networks. *Computers, Environment and Urban Systems, 66*, 29–40. https://doi.org/10.1016/j.compenvurbsys.2017.07.002

United Nations Environment Programme. (2022). *Climate risk maps for Sub-Saharan Africa*. https://www.unep.org

United States Geological Survey. (2023). *Landsat 8 surface reflectance data*. USGS Earth Explorer. https://earthexplorer.usgs.gov

WorldPop. (2023). *High-resolution gridded population datasets*. https://www.worldpop.org

Longley, P. A., Goodchild, M. F., Maguire, D. J., & Rhind, D. W. (2015). *Geographic information science and systems* (4th ed.). Wiley.