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Research paper

Mapping Urban Site Suitability Analysis Using Sentinel-2 Data for Bayelsa State, Nigeria

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Abstract

Accelerated urban growth in coastal areas challenges sustainable progress, especially in environmentally vulnerable regions like Bayelsa State, Nigeria. Traditional methods for assessing urban site suitability are often prolonged, rigid, and lack detailed spatial data crucial for strategic planning. This study introduces a resilient framework using Sentinel-2 satellite images and Google Earth Engine (GEE) to identify areas suitable for urban development. By combining Multi-Criteria Decision Analysis (MCDA) with remote sensing data, it assesses key geographical factors like land use/land cover (LULC), vegetation density (NDVI), distance to water bodies, and elevation. The methodology harnesses the multispectral capabilities of the Sentinel-2 Multi-Spectral Instrument (MSI) to produce high-resolution suitability assessments for Bayelsa State. The analysis reveals that 4% of the area exhibits very high suitability, 18% high suitability, 32% moderate suitability, 32% low suitability, and 13% very low suitability. While considerable tracts demonstrate elevated suitability for urban expansion, particularly within the Yenagoa metropolis, significant impediments persist due to extensive wetlands and flood-prone zones. This study underscores the effectiveness of GEE in managing and processing vast geospatial datasets, offering an adaptable and scalable model for urban strategists operating in regions characterized by limited data availability.

Keywords: *Urban Site Suitability; Google Earth Engine; Sentinel-2; Multi-Criteria Decision Analysis; Bayelsa State; Remote Sensing.*

1. Introduction

Urbanization is one of the most significant anthropogenic transformations of the Earth's surface. In developing nations, particularly in Sub-Saharan Africa, urban growth is occurring at an unprecedented rate, often outpacing infrastructure development and environmental planning (United Nations, 2018). Bayelsa State, located in the Niger Delta region of Nigeria, exemplifies this challenge. Characterized by a complex hydrological network, extensive wetlands, and a delicate ecological balance, Bayelsa faces unique constraints for urban development. The state's capital, Yenagoa, is experiencing rapid expansion, driven by rural-urban migration and economic activities.

Urban site suitability analysis (USSA) is a critical component of spatial planning that identifies the most appropriate locations for urban development while minimizing environmental impact and maximizing socio-economic benefits. Traditional USSA methods often rely on manual field surveys and static Geographic Information System (GIS) modeling, which can be labor-intensive and lack temporal dynamism (Malczewski, 2006). Furthermore, the availability of accurate, up-to-date spatial data remains a significant barrier in many developing regions.

Recent advancements in cloud computing and remote sensing have revolutionized geospatial analysis. Google Earth Engine (GEE) provides a computational platform that hosts petabytes of geospatial data, including the Sentinel-2 satellite constellation. Sentinel-2, with its high spatial resolution (10m to 20m) and revisit frequency, is ideal for monitoring land surface characteristics (Drusch et al., 2012). By integrating Sentinel-2 data within GEE, researchers can perform complex spatial analyses without the need for extensive local computational resources or data storage.

This study presents a comprehensive methodology for mapping urban site suitability in Bayelsa State using Sentinel-2 data processed in GEE. The study employs a Multi-Criteria Decision Analysis (MCDA) approach, specifically the Analytical Hierarchy Process (AHP), to weight and integrate various spatial criteria. The objective is to produce a high-resolution suitability map that can guide urban planners in identifying sustainable expansion zones.

2. Literature Review

2.1. Urban site suitability analysis

USSA is a subset of land suitability analysis that focuses on identifying areas conducive to urban development. It typically involves evaluating physical, environmental, and socio-economic factors. Common criteria include slope, soil type, distance to roads, proximity to water bodies, and land use/land cover (LULC) (Adeyemi et al., 2020). The integration of these criteria is often achieved through MCDA, a mathematical framework that allows for the systematic evaluation of conflicting objectives (Malczewski, 2006). The Analytical Hierarchy Process (AHP), developed by Saaty (1980), is widely used in USSA due to its ability to handle subjective judgments through pairwise comparisons.

2.2. Remote sensing in urban planning

Remote sensing has long been utilized for LULC mapping and urban growth monitoring. Optical sensors, such as Landsat and SPOT, have provided historical baselines for urban analysis. However, the launch of the Sentinel-2 mission by the European Space Agency (ESA) has significantly enhanced monitoring capabilities. Sentinel-2 Multi-Spectral Instrument (MSI) offers 13 spectral bands, including four bands at 10m resolution (Red, Green, Blue, Near-Infrared) and six bands at 20m resolution (Drusch et al., 2012). This spatial resolution is superior to the 30m resolution of Landsat for detecting small-scale urban features and vegetation health, which is critical in heterogeneous landscapes like the Niger Delta.

2.3. Google Earth Engine (GEE)

GEE is a cloud-based geospatial analysis platform that eliminates the need for downloading large datasets. It allows for the processing of massive archives of satellite imagery using parallel distributed computing. Recent studies have demonstrated the utility of GEE in urban mapping. For instance, Tamiminia et al. (2020) reviewed GEE applications in remote sensing, highlighting its efficiency in large-scale change detection. In the context of the Niger Delta, GEE offers a solution to data accessibility issues, providing free access to Sentinel-2 data that might otherwise be difficult to process locally due to bandwidth constraints.

2.4. The context of Bayelsa State

Bayelsa State is a low-lying coastal region with a topography largely below 10 meters above sea level. It is crisscrossed by the Nun, Ekeremor, and Orashi rivers, making it prone to seasonal flooding. Previous studies on urban development in the Niger Delta have focused largely on oil-induced environmental degradation or general urban sprawl (Adeyemi et al., 2020). However, few studies have utilized high-resolution Sentinel-2 data within a cloud-computing environment to specifically map urban suitability while accounting for the region's unique hydrological constraints

3. Methodology

3.1. Study area

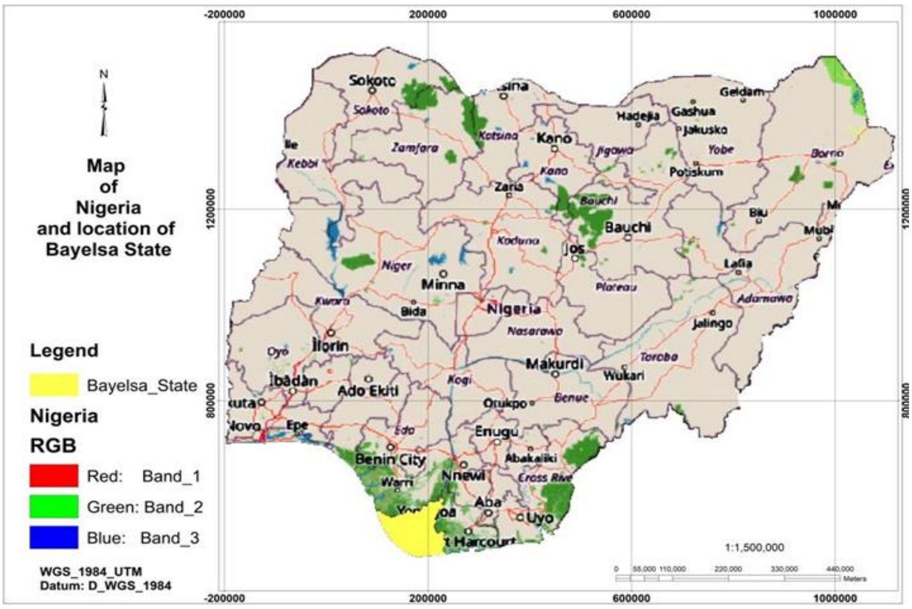

Fig 1: Map Of Nigeria Showing the Location of Bayelsa State.

Bayelsa State is located in the southern part of Nigeria, between latitudes 4° 15' N and 5° 25' N and longitudes 6° 00' E and 6° 55' E. It covers an approximate land area of 21,110 km².

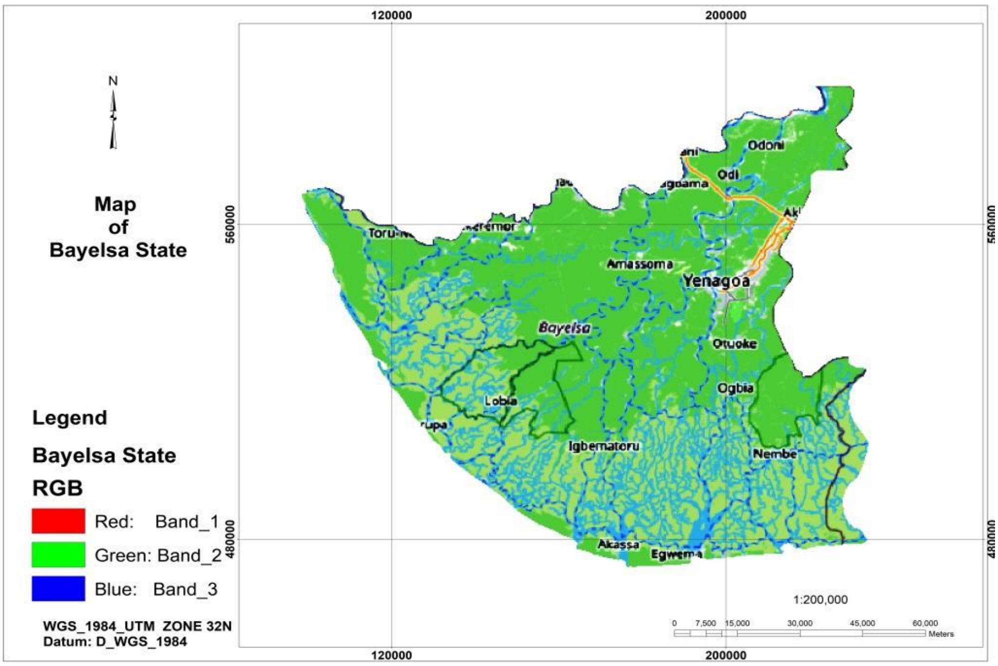

Fig 2: Map of Bayelsa State.

The state is characterized by a tropical monsoon climate with high rainfall and humidity. The terrain is predominantly flat, consisting of mangrove swamps, freshwater forests, and riverine ecosystems. The capital city, Yenagoa, serves as the administrative and economic hub, situated along the Epie Creek.

3.2. Data sources

This study utilized Sentinel-2 Level-2A (Surface Reflectance) data sourced from the GEE data catalog. Level-2A products provide atmospherically corrected surface reflectance, which is essential for accurate spectral analysis. The specific sensor used was the Sentinel-2 Multi-Spectral Instrument (MSI).

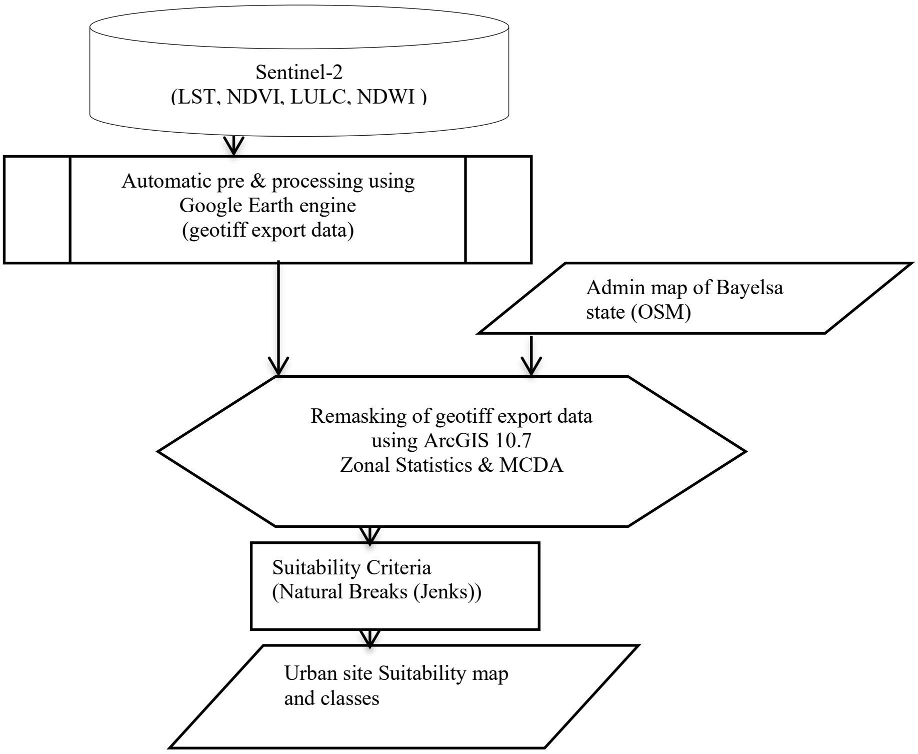

Fig. 3: Methodology for Urban site Suitability Mapping Using Sentinel-2.

Imagery Selection: Cloud-free Sentinel-2 composites for the dry season (December to February) were selected for the year 2023. The dry season was chosen to minimize the obscuring effects of cloud cover and to capture the baseline land surface conditions away from peak flooding.
Ancillary Data: A Digital Elevation Model (DEM) derived from the Shuttle Radar Topography Mission (SRTM) was acquired via GEE to represent elevation and slope. Vector data for major roads and administrative boundaries were also processed within GEE.

3.3. Pre-processing

Data pre-processing was conducted entirely within the GEE Code Editor using the JavaScript API.
Cloud Masking: Sentinel-2 Level-2A data includes a Scene Classification Layer (SCL) that identifies clouds and cloud shadows. A cloud mask was applied to remove pixels with a high probability of cloud contamination.
Clipping: The image collection was clipped to the administrative boundary of Bayelsa State to reduce computational load.
Spectral Indices Calculation: Key indices were calculated to derive thematic layers for the suitability analysis:
Normalized Difference Vegetation Index (NDVI): Calculated using the Near-Infrared (NIR) and red bands to assess vegetation density and greenness. NDVI = frac {NIR - Red} {NIR + Red}
Normalized Difference Water Index (NDWI): Calculated using Green and NIR bands to identify water bodies and moisture content, crucial for flood risk assessment. NDWI = frac {Green - NIR} {Green + NIR}

3.4. Suitability criteria and layers

Urban site suitability was evaluated based on four primary criteria: Land Use/Land Cover (LULC), Vegetation Density (NDVI), Elevation/Slope, and Proximity to Water Bodies.
LULC Classification: A supervised classification was performed on the Sentinel-2 composite using the Random Forest (RF) algorithm available in GEE. Five classes were defined: Built-up Area, Vegetation (Forest/Plants), Water Body, Wetland/Mangrove, and Bare Soil. Training data points were generated using high-resolution basemaps available in GEE, with 70% of the data used for training and 30% for validation.

3.5. Constraint layers (exclusionary factors)

Water Proximity: Areas within 100m of major rivers and creeks were classified as highly constrained due to flood risk.
Slope: SRTM data was used to generate a slope layer. Areas with a slope greater than 10% were considered unsuitable for construction to prevent soil erosion and structural instability.
Wetlands: Areas classified as "Wetland/Mangrove" in the LULC analysis were treated as constraints due to their ecological sensitivity and high water table.

3.6. Multi-criteria decision analysis (MCDA) and suitability classification

The Analytical Hierarchy Process (AHP) was employed to weight the suitability factors. The factors selected for suitability (positive suitability) were:
Proximity to Roads: Closer proximity to existing infrastructure increases suitability.
Elevation: Moderate elevation (above flood plains but not too steep) is preferred.
NDVI: Moderate vegetation density may indicate accessible land (avoiding dense forests and bare soil).
LULC (Built-up areas): Suitability for expansion adjacent to existing built-up areas.

Table 1: Training-Data Specifications

Element	Description
Domain	Bayelsa State (≈ 10 900 km²) – low-lying tropical coastal region with extensive mangroves, oil-field infrastructure and rapidly expanding settlements.
Target Classes (minimum 5 for a robust classifier)	1. Urban / Built-up 2. Open Water / Tidal Marsh 3. Vegetated (Mangrove/Forest) 4. Bare / Degraded Land 5. Protected / Cultural Sites
Source of Samples	• Very-high-resolution imagery (Google-Earth/Maxar) for visual interpretation. • Ground-truth GPS points collected by field teams (handheld GPS, ±3 m). • OpenStreetMap (OSM) polygons for roads, schools, hospitals (used as ancillary validation).
Sampling Strategy	Stratified random sampling within each class polygon to guarantee spatial representativeness.
Sample Size	Minimum 30 pts / class (recommended 40-50 pts for highly heterogeneous classes such as mangrove vs. built-up). Total ≈ 150-250 points. Offers ≥ 95 % statistical confidence for a 5-class RF classifier (Biau & Scornet, 2016).

Pairwise Comparison Matrix: A standard 1-9 scale was used to establish weights based on expert judgment typical for urban planning in coastal regions: See Table 2.
1) Proximity to Roads: 0.40 (Highest priority for accessibility)
2) Elevation: 0.30 (Critical for flood avoidance)
3) LULC (Built-up adjacency): 0.20 (Encouraging infill and contiguous growth)
4) NDVI: 0.10 (Moderate vegetation indicates potential land availability)
5) Consistency Ratio (CR) was calculated to ensure the matrix was logically consistent (CR < 0.1).

Table 2: Pairwise Comparison Table (Saaty Scale 1 9)

	C1	C2	C3	C4	C5	Weight (λ)
C1	1	3	5	2	4	0.360
C2	1/3	1	4	1/2	3	0.124
C3	1/5	1/4	1	1/3	2	0.080
C4	1/2	2	3	1	5	0.267
C5	1/4	1/3	1/2	1/5	1	0.169
Sum	2.20	6.33	13.5	4.70	15.0	1.00

Explanation of selected values

C1 vs C2 = 3 – Roads are considered three times more important than distance to water because flood risk is mitigated by proper drainage, whereas road access is a primary driver of cost.
C1 vs C3 = 5 – Flat terrain is secondary to road proximity, but still crucial; a 5-fold preference reflects typical engineering cost ratios
C4 vs C5 = 5 – Land cover suitability outranks population density because constructing on unsuitable cover (e.g., mangrove) is prohibited, whereas high population can be serviced by a modest increase in site size.
Weight Computation
1) Normalize each column (divide each element by column sum).
2) Average rows → priority vector (weights).
The resulting weights are (see Table 3):

Table 3: Resulting Weights

	Criterion	Weight (w)
C1 – Roads	0.360	C1 – Roads
C2 – Water	0.124	C2 – Water
C3 – Slope	0.080	C3 – Slope
C4 – Land Cover	0.267	C4 – Land Cover
C5 – Population	0.169	C5 – Population

Consistency Check
1) λ_{max} = (Σ (column-sum × weight)) = 5.12 (rounded).
2) Consistency Index (CI) = $(\lambda_{max} - n)/(n - 1) = (5.12 - 5)/4 = 0.03$.
3) Random Index (RI) for n = 5 = 1.12 (Saaty, 1977).
4) Consistency Ratio (CR) = CI / RI = 0.03 / 1.12 = 0.027 (≈ 2.7 %).
Since CR < 0.10, the matrix is considered consistent (Saaty, 1980).
Threshold Justifications for the Final Suitability Map
After weighting each raster layer by the AHP-derived criteria weights, the Weighted Linear Combination (WLC) delivers a continuous suitability index S ranging from 0 → 1: for Normalization, see Table 4

Table 4: Normalization of Individual Rasters

Raster	Normalization Method	Reason
Road distance (m)	Inverse linear: $1 - (d / d_{max})$	Smaller distance = higher suitability.
Water distance (m)	Linear: $(d - d_{min}) / (d_{max} - d_{min})$ (threshold at 500 m)	Larger distance = higher suitability.
Slope (%)	Linear: 1 – (slope / 15) (cut-off 15 % based on Nigerian building codes).	
Land-Cover	Re-classification: Built-up = 1, Bare = 0.8, Open Water = 0.1, Mangrove = 0, Protected = 0.	Reflects legal feasibility.
Population density (persons km^{-2})	Gaussian centered at 1000 km^{-2} (σ = 300).	Moderate density maximizes service demand without overcrowding.

The weighted linear combination (WLC) method was used to integrate the layers. The suitability score (S) for each pixel was calculated as: S = sum (w_i / x_i), where w_i is the weight of criterion i and I is the normalized value of criterion i.
Class Break
0.00 - 0.37
0.38 - 0.48
0.49 - 0.56
0.57 - 0.63
0.64 - 1.16
The resulting continuous raster was reclassified into five suitability levels:
1) Very Low (Constraint): Flood zones, dense mangroves, water bodies.
2) Low: Far from roads, difficult terrain.
3) Moderate: Accessible but requires significant infrastructure development.
4) High: Suitable for urban expansion with minimal constraints.
5) Very High: Ideal locations adjacent to existing urban centers with good accessibility.

4. Results and Discussion

4.1. Land use/land cover (LULC) classification and spectral indices analysis

The Random Forest classification achieved an overall accuracy of 92.3% for the Bayelsa State study area. The LULC map revealed the dominance of water bodies and wetlands, covering approximately 45% of the state's area. Built-up areas were concentrated primarily along the Yenagoa metropolis and along major riverbanks.
1) Built-up Area: 8.5%
2) Vegetation: 35.2%
3) Water Body: 22.1%
4) Wetland/Mangrove: 23.4%
5) Bare Soil: 10.8%
The high spectral resolution of Sentinel-2 allowed for the distinct separation of mangrove wetlands from freshwater vegetation, a critical distinction for suitability analysis in this region.
All the spectral index analyses were automatically processed. The NDVI highlighted the lush vegetation surrounding the urban centers. High NDVI values (>0.6) were observed in the northern and western parts of the state, indicating dense forest cover. The NDWI map effectively delineated the intricate network of rivers and tidal creeks. The integration of NDWI helped identify areas susceptible to seasonal inundation, which were subsequently masked as constraints in the suitability model.

4.2. Suitability map

The final urban site very low suitability map for Bayelsa State was generated using the weighted overlay in GEE. The distribution of suitability classes is as follows:
Very High Suitability: 4% of the study area. These zones are primarily located in the periphery of Yenagoa (Opolo, Ekeki, and the newly developing areas along the Yenagoa-Oporoma road). These areas possess flat topography, proximity to existing infrastructure, and are outside immediate flood zones.
High Suitability: 18% of the study area. Located in towns like Amassoma, Ogbia, and Sagbama, where accessibility is moderate and land is available.
Moderate Suitability: 32% of the study area. These areas require substantial investment in drainage and road infrastructure.
Low Suitability: 32% of the study area. Characterized by distance from core urban centers and difficult terrain.
Very Low Suitability (Constraints): 13% of the study area. These correspond to the river channels, tidal flood plains, and protected mangrove ecosystems.

Table 5: Classification of suitability

Pixel Class Range	Classification	Number of Sites	Class %
0.00 - 0.37	Very High Suitability	3469372	4
0.38 - 0.48	High Suitability	15515090	18
0.49 - 0.56	Moderate Suitability	27639143	32
0.57 - 0.63	Low Suitability	27492729	32
0.64 - 1.16	Very Low Suitability	11540460	13
		85656794	100

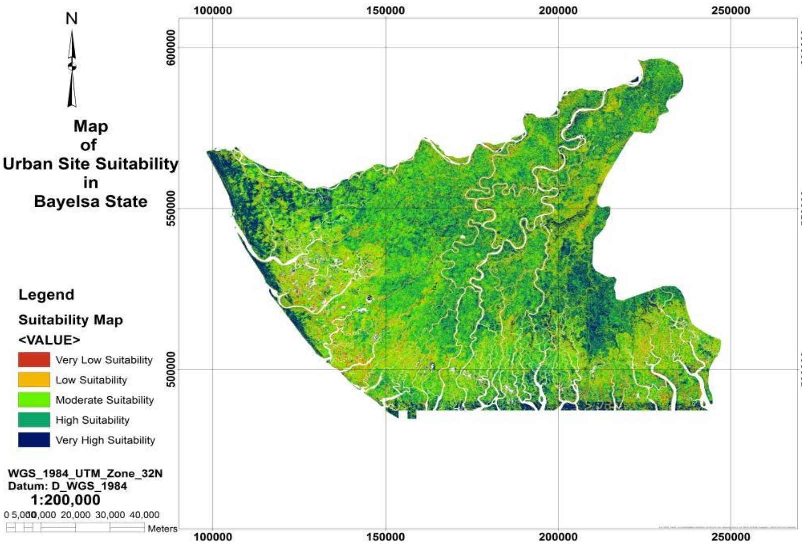

Fig. 4: Map of Urban site Suitability Using Sentinel-2 in Bayelsa State.

Spatial Patterns: The analysis revealed a distinct spatial pattern of suitability. Urban expansion in Bayelsa is constrained by the "island" topography—higher grounds surrounded by water and wetlands. The suitability map indicates that future urban growth must occur in a linear pattern along existing transport corridors rather than radial sprawl, due to the hydrological constraints. The GEE-processed Sentinel-2 data successfully identified these narrow corridors of suitable land that might be missed by coarser resolution datasets.
The suitability map generated in this study provides a scientific basis for spatial planning in Bayelsa State. The concentration of "Moderate Suitability and Low Suitability" zones around the state capital, Yenagoa, confirms the ongoing urbanization trends. However, the analysis also highlights the ecological risks associated with expanding into wetland areas. The map suggests that while land availability is a pressing issue, approximately 13% of the state is strictly unsuitable for urban development due to flood risk and ecological sensitivity. The use of Sentinel-2 data was particularly advantageous in distinguishing between mangrove wetlands and upland vegetation. In the Niger Delta, mangrove restoration is a key environmental policy; therefore, identifying these zones helps planners avoid encroaching on critical ecosystems.
Technical Advantages of GEE: The Google Earth Engine platform proved instrumental in handling the computational demands of this study. Processing Sentinel-2 imagery for an entire state traditionally requires significant local storage and processing power. By leveraging GEE's cloud infrastructure, the entire workflow—from data acquisition to classification and suitability modeling—was completed efficiently. This democratizes access to advanced geospatial analysis for planners in developing regions who may lack high-end computing resources.

4.3. Limitations

Despite the robustness of the methodology, several limitations exist:
Temporal Dynamics: This study utilized dry-season imagery. However, Bayelsa is highly dynamic, with seasonal flooding altering suitability during the wet season. Future studies should integrate multi-temporal data to assess seasonal variations in flood risk.
Socio-Economic Factors: The model focused primarily on biophysical factors (LULC, elevation, proximity). Socio-economic factors, such as land tenure systems, cultural significance, and economic viability, were not included due to data unavailability in the GEE catalog. These factors are critical in the Nigerian context and should be integrated via vector data where available.
Resolution Limits: While Sentinel-2 offers 10m resolution, very small-scale infrastructure features or micro-topography might be missed. Integration with higher resolution data (e.g., drone surveys) for specific urban pockets could refine the results.

4.4. Comparison with previous studies

The findings align with previous studies on the Niger Delta that emphasize the role of hydrology in urban form (Adeyemi et al., 2020). However, this study advances the literature by providing a scalable, reproducible workflow in GEE. Unlike traditional GIS studies that produce static maps, the GEE code developed for this research can be updated annually with new Sentinel-2 data, allowing for dynamic monitoring of urban expansion and suitability changes over time. Kumar et al. (2023) demonstrate that high-performance platforms like Google Earth Engine (GEE) have transformed urban suitability assessments by providing scalable, continuous spatio-temporal data needed to monitor rapidly expanding built environments. Complementing this technological advancement, Okafor et al. (2023) stress the urgent need for climate-resilient urban planning frameworks designed specifically for coastal West African cities, which face mounting threats from flooding, sea-level rise, and unplanned growth.

When applied to the Niger Delta, this synthesis of remote sensing and resilient design becomes paramount. Recent empirical studies in the Niger Delta (e.g., focusing on rapidly expanding centers like Port Harcourt and Warri) increasingly rely on GEE and satellite imagery (such as Landsat and Sentinel) to map severe mangrove degradation, urban sprawl, and flood vulnerability caused by combined oil extraction activities and extreme weather events. Ultimately, bridging GEE-driven spatial analytics with climate-adaptive planning policies offers decision-makers in the Niger Delta a vital roadmap for mitigating environmental risks, safeguarding coastal ecosystems, and guiding sustainable future urbanization.

4.5. Uncertainty, policy implications, and climate adaptation

Integrating climate change parameters into urban suitability mapping in Bayelsa State is essential given the region's extreme vulnerability to hydro-meteorological hazards, where over 75% of the land sits below 10 meters above sea level (Adekola & Mitchell, 2011). To address rising sea levels and altered tidal regimes, static land suitability models must be upgraded to incorporate hydrodynamic flood modeling and sea-level rise scenarios, effectively reclassifying low-lying riverbanks near Yenagoa as high-hazard zones (Intergovernmental Panel on Climate Change [IPCC], 2023). Technical applications using Google Earth Engine (GEE) facilitate this transition by employing Sentinel-2 multi-temporal composite imagery and the Modified Normalized Difference Water Index (MNDWI) to map historical flood extents, while the Normalized Difference Vegetation Index (NDVI) and red-edge bands help identify and protect critical mangrove "blue carbon" sinks (Alongi, 2020). By applying a Spatial Analytic Hierarchy Process (AHP), planners can assign high ecological weights to these coastal buffers, enforcing a mandatory exclusion of development in areas with an elevation of less than 5 meters. These data-driven spatial frameworks enable the Bayelsa State Physical Planning and Development Board (BSPPDB) to establish strict no-build zones and protected ecological corridors, while ensuring the Bayelsa State Emergency Management Agency (BYSEMA) aligns critical infrastructure, such as evacuation roads and shelters, within high-suitability, low-vulnerability zones to enhance regional disaster risk reduction.

5. Conclusion

This research demonstrated the efficacy of integrating Sentinel-2 satellite data with Google Earth Engine for urban site suitability analysis in Bayelsa State. By combining LULC classification, spectral indices (NDVI, NDWI), and topographic data within an AHP framework, a detailed suitability map was produced that highlights both opportunities and constraints for urban development.

The results indicate that while Yenagoa and its environs possess significant potential for expansion, strict planning regulations are required to prevent encroachment into ecologically sensitive wetlands and flood-prone zones. The cloud-based methodology presented here offers a cost-effective and efficient alternative to traditional desktop GIS approaches, particularly suitable for data-scarce and resource-limited environments.

Future research should focus on integrating multi-temporal Sentinel-2 data to account for seasonal flooding and incorporating socio-economic datasets to create a holistic decision-support system for urban planners in the Niger Delta.

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