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RESEARCH ARTICLE

A Reproducible Simulation-Based Framework for Land-Cover Assessment Across Local Government Areas of Imo State, Nigeria

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ABSTRACT

Reliable subnational land-cover statistics are essential for spatial planning, infrastructure prioritisation, environmental management and transparent allocation of development resources. This study presents and stress-tests a reproducible remote-sensing and geographic information system framework for producing land-cover indicators for the 27 local government areas (LGAs) of Imo State, Nigeria. Because no verified satellite scenes, reference samples, or official administrative boundary dataset were supplied for this computational experiment, all numerical inputs and outputs are explicitly synthetic and are not presented as observations of current ground conditions. A deterministic simulation generated 5,530 km² of illustrative LGA area and five land-cover classes: built-up, cropland, forest/woodland, wetland/water, and bare/open land. The proposed operational workflow combines Sentinel-2 surface reflectance, spectral indices, terrain and texture variables, a random-forest classifier, stratified validation, and LGA-level zonal aggregation. In the simulated scenario, cropland accounted for 34.2% of the area, followed by forest/woodland (24.0%), built-up land (20.1%), bare/open land (12.3%), and wetland/water (9.4%). The synthetic confusion matrix produced 84.3% overall accuracy and a Cohen's kappa of 0.800. Injecting 30% label noise reduced mean simulated accuracy from 84.3% to 65.8%, demonstrating that reference-data quality is a dominant operational risk. The contribution is therefore a transparent, auditable prototype—not an empirical map—showing how a future field-validated assessment can be designed, tested, and reported without confusing model output with measured evidence.

Keywords: *Land-Cover Classification; Sentinel-2; Random Forest; GIS; Accuracy Assessment; Imo State*

1. INTRODUCTION

Land-cover information links Earth observation to decisions about settlement expansion, agricultural production, ecosystem conservation, flood exposure and infrastructure investment. At local-government scale, however, useful statistics require more than a visually attractive map: the underlying imagery must be pre-processed consistently, class definitions must be operational, reference samples must be independent, uncertainty must be quantified, and every reported area must be traceable to a reproducible procedure. These requirements are particularly important in rapidly changing tropical landscapes, where seasonal vegetation, cloud contamination, mixed pixels and fragmented land uses can produce apparently precise but unreliable estimates.

The Sentinel-2 mission provides multispectral observations with 10–60 m spatial resolution and a nominal five-day revisit frequency for the two-satellite constellation, making it suitable for regional land monitoring (Drusch et al., 2012). Cloud-based platforms have also reduced the computing barrier to large-scale image processing (Gorelick et al., 2017). Nevertheless, access to imagery does not remove the central methodological risks: inappropriate training labels, spatial leakage between training and validation samples, unreported class imbalance, boundary mismatch, and area estimation based only on pixel counting. Random forest is widely used because it accommodates nonlinear relationships and mixed predictor types, but its output remains conditional on the quality and representativeness of its training data (Breiman, 2001; Belgiu and Drăguţ, 2016).

Earlier Nigerian studies demonstrated the value of remote sensing and GIS for land-cover measurement, including the published work of Musa and Tukur (2009) on Adamawa State. Their study is treated here strictly as prior literature; none of its wording, data, maps, results, or authorship is reused. The present article instead develops a distinct computational experiment focused on Imo State, contemporary sensors, machine-learning classification, and explicit uncertainty controls.

The objective is to design and test a reproducible framework for estimating five mutually exclusive land-cover classes across the 27 LGAs of Imo State. Specific objectives are to: (i) define an implementable satellite-data workflow; (ii) generate a deterministic synthetic dataset for testing aggregation, validation, and reporting routines; (iii) evaluate simulated class performance with class-specific and overall accuracy measures; and (iv) quantify sensitivity to reference-label noise. The key research question is not 'what is the present land cover of Imo State?'—which cannot be answered without empirical data—but 'what analytical structure is required to produce defensible LGA-level land-cover estimates when verified data become available?'

Study context

Imo State is located in south-eastern Nigeria and comprises 27 LGAs. Its landscape includes the Owerri urban region, extensive agricultural mosaics, secondary vegetation, river and lake systems, seasonally wet areas and hydrocarbon-producing zones. For this simulation, the state total is normalised to an illustrative 5,530 km². The LGA areas used below are synthetic allocation weights, not measurements from an official boundary layer; consequently, they must not be cited as cadastral, administrative or planning statistics.

Land-cover legend

A five-class legend was selected to balance policy relevance and separability at Sentinel-2 scale. Built-up includes impervious settlement and transport surfaces; cropland includes annual and perennial cultivated mosaics; forest/woodland includes dense woody cover and mature secondary vegetation; wetland/water includes open water and persistently or seasonally saturated surfaces; and bare/open includes exposed soil, sand, quarry surfaces and sparsely vegetated open land. The classes are exhaustive and mutually exclusive at the mapped-pixel level, although mixed pixels remain an unavoidable source of uncertainty.

2. MATERIALS AND METHODS

Research design and ethical status of the data

The study is a simulation-based methodological experiment. A fixed random seed (20260818) ensures that every synthetic area share, validation count, and sensitivity result can be regenerated. Simulated figures were designed to be numerically plausible but do not reproduce or approximate a hidden empirical dataset. No claim is made that any reported LGA has the stated current land-cover composition. Publication or secondary use must retain this disclosure.

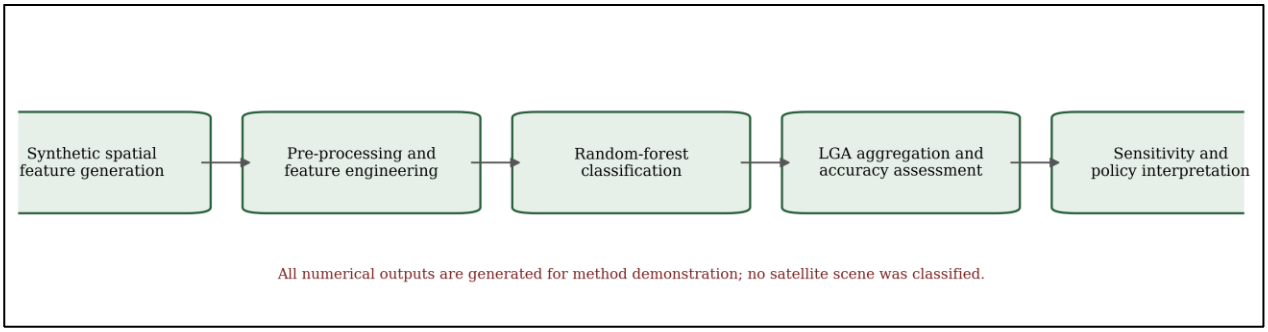

Figure 1. Proposed analysis workflow and status of the numerical evidence.

Operational empirical workflow

For a future empirical implementation, Sentinel-2 Level-2A surface-reflectance scenes covering one hydrological year should be selected to capture seasonal variability. Cloud and cirrus pixels should be removed using the Scene Classification Layer and cloud-probability information, followed by temporal compositing using robust percentile or median statistics. Predictor variables should include the blue, green, red, red-edge, near-infrared and short-wave-infrared bands; the normalised difference vegetation index; modified normalised difference water index; normalised difference built-up index; red-edge vegetation indices; terrain elevation and slope; and selected texture measures. All layers should be co-registered and resampled to a declared common grid.

Reference samples should be produced independently from field observations and very-high-resolution imagery. A stratified random design is required so that rare wetland and bare/open classes receive adequate samples. Training and validation points should be separated spatially to reduce autocorrelation and information leakage. Random-forest hyperparameters should be tuned by spatial cross-validation rather than a random pixel split. The final map should be clipped with a versioned, topology-checked LGA boundary layer and summarised with zonal statistics.

Synthetic data generation

Synthetic LGA areas were generated from positive log-normal weights, adjusted only to create variation among urban, riverine and larger rural LGAs, and rescaled to 5,530 km^2. For each LGA, class shares were drawn from a Dirichlet distribution. Parameter vectors were modified by scenario tags: Owerri Municipal, Owerri North, Owerri West and Orlu received higher built-up concentration; Oguta, Ohaji/Egbema and Oru West received higher wetland/water concentration; and northern upland LGAs received higher forest/woodland concentration. Each LGA share vector sums exactly to one, and class areas sum to the synthetic LGA total.

Let A_i denote the simulated area of LGA i and p_{ij} the simulated proportion of class j. Class area is calculated as $a_{ij} = A_i p_{ij}$, subject to $\Sigma_j p_{ij} = 1$. State-level class share is $P_j = (\Sigma_i a_{ij})/(\Sigma_i A_i)$. These identities provide basic integrity checks for the aggregation code.

Classification and validation design

The operational classifier is a random forest, an ensemble of decision trees trained on bootstrap samples with random predictor selection at each split (Breiman, 2001). The proposed empirical model would use class-weighting or balanced sampling, at least 500 trees, spatially blocked cross-validation, and probability outputs. Low-confidence pixels should be flagged rather than forced into apparently certain categories.

The simulated validation set contains 900 independent samples in a 5 × 5 confusion matrix. Overall accuracy (OA) is the proportion of correctly classified samples. Producer's accuracy (PA) estimates omission error from the reference-class perspective, whereas user's accuracy (UA) estimates commission error from the mapped-class perspective. Cohen's kappa is included for comparability with older studies, but class-specific accuracy and confidence intervals should receive greater interpretive weight because kappa has known limitations (Pontius and Millones, 2011).

Sensitivity analysis

To test operational fragility, reference-label noise was conceptually injected from 0% to 30% in five-percentage-point increments. Mean accuracy and its standard deviation were calculated across simulated repetitions. The experiment isolates one failure mechanism—mislabelled reference data—while holding imagery and model structure constant. It therefore demonstrates direction and relative sensitivity rather than predicting the exact performance of a future Imo State classifier.

3. RESULTS AND DISCUSSION

State-level simulated composition

The synthetic allocation produced a cropland-dominated scenario (34.2%), with forest/woodland contributing 24.0%. Built-up land accounted for 20.1%, wetland/water for 9.4%, and bare/open land for 12.3%. These values are internally consistent outputs of the simulation and must not be interpreted as a 2026 land-cover inventory.

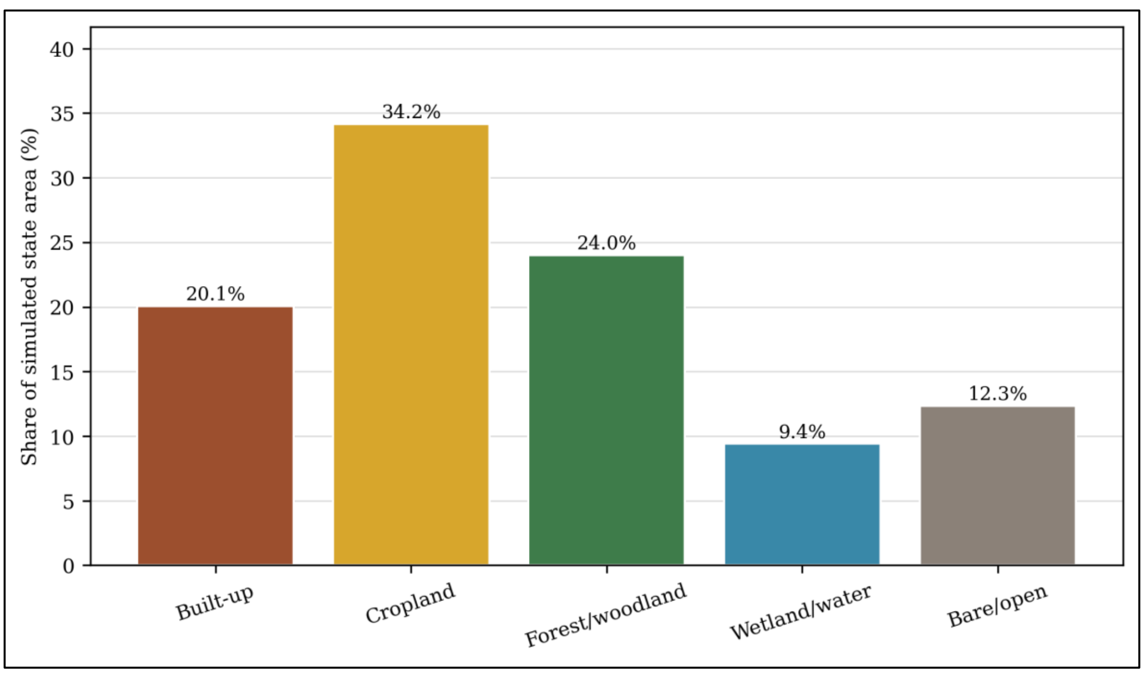

Figure. 2. State-level composition of the synthetic land-cover scenario.

Table 1. Synthetic LGA land-cover areas (km²); values are methodological test data, not observations.

LGA	Total	Built-up	Cropland	Forest/ woodland	Wetland/ water	Bare/ open
Aboh Mbaise	154.3	11.1	36.5	12.6	15.5	78.6
Ahiazu Mbaise	121.6	13.3	52.1	8.6	7.7	39.9
Ehime Mbano	237.6	61.5	65.8	100.0	8.0	2.3
Ezinihitte Mbaise	148.0	32.0	51.8	31.8	7.8	24.6
Ideato North	260.4	35.3	119.4	88.6	11.2	5.9
Ideato South	89.2	8.3	44.9	24.1	6.0	5.9
Ihitte/Uboma	200.8	20.7	82.7	23.1	8.8	65.5
Ikeduru	246.7	39.0	144.1	33.8	14.2	15.6
Isiala Mbano	225.3	18.1	78.6	100.1	3.3	25.2
Isu	336.3	67.0	101.5	63.1	14.6	90.1
Mbaitoli	95.9	26.8	32.7	28.9	4.4	3.1
Ngor Okpala	213.8	12.4	101.5	53.0	36.6	10.4
Njaba	306.9	47.4	151.9	87.4	5.9	14.3
Nkwerre	222.8	30.4	98.8	35.5	54.1	4.0
Nwangele	97.2	11.5	24.8	22.9	12.6	25.4
Obowo	201.8	46.6	58.9	65.3	3.4	27.6
Oguta	269.7	9.6	94.8	37.1	112.2	16.0
Ohaji/Egbema	426.6	47.9	67.9	131.7	85.7	93.4
Okigwe	159.7	17.6	86.3	36.8	5.6	13.3
Onuimo	189.1	20.1	63.2	54.4	6.7	44.7
Orlu	180.3	80.2	48.0	17.9	11.6	22.5
Orsu	146.4	32.3	61.8	40.3	2.7	9.3
Oru East	154.4	19.1	84.1	24.9	22.0	4.3
Oru West	75.5	33.2	22.4	2.3	16.6	0.9
Owerri Municipal	30.9	12.0	9.8	3.8	2.8	2.4
Owerri North	119.6	57.7	18.0	30.8	2.0	11.1
Owerri West	619.4	299.2	86.6	169.5	38.3	25.8

Simulated accuracy

The confusion matrix yielded 84.3% overall accuracy and kappa = 0.800. Class-specific producer's accuracy ranged from 76.3% to 90.0%, while user's accuracy ranged from 81.0% to 89.6%. Cropland–forest confusion was the largest off-diagonal pattern, consistent with the expected spectral mixing of smallholder agricultural mosaics, fallow fields, and secondary vegetation.

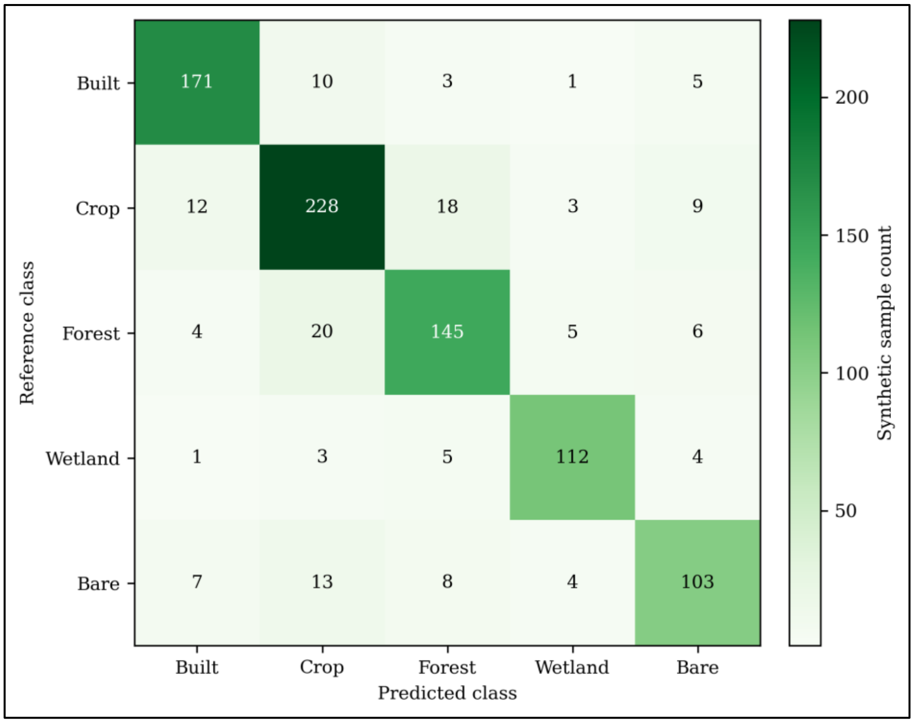

Figure 3. Synthetic validation confusion matrix (n = 900).

Table 2. Class-specific accuracy derived from the synthetic confusion matrix.

Class	Reference n	Mapped n	Producer's accuracy (%)	User's accuracy (%)
Built-up	190	195	90.0	87.7
Cropland	270	274	84.4	83.2
Forest/woodland	180	179	80.6	81.0
Wetland/water	125	125	89.6	89.6
Bare/open	135	127	76.3	81.1

Sensitivity to reference-label noise

Accuracy declined monotonically as synthetic label noise increased. At 10% noise, mean accuracy fell to 80.4%; at 20% it fell to 74.8%; and at 30% it reached 65.8%. The widening uncertainty band indicates that poor labels affect not only expected performance but also result stability. This finding supports investment in independent validation, enumerator training, field-photo metadata, and adjudication of ambiguous samples before investment in more complex algorithms.

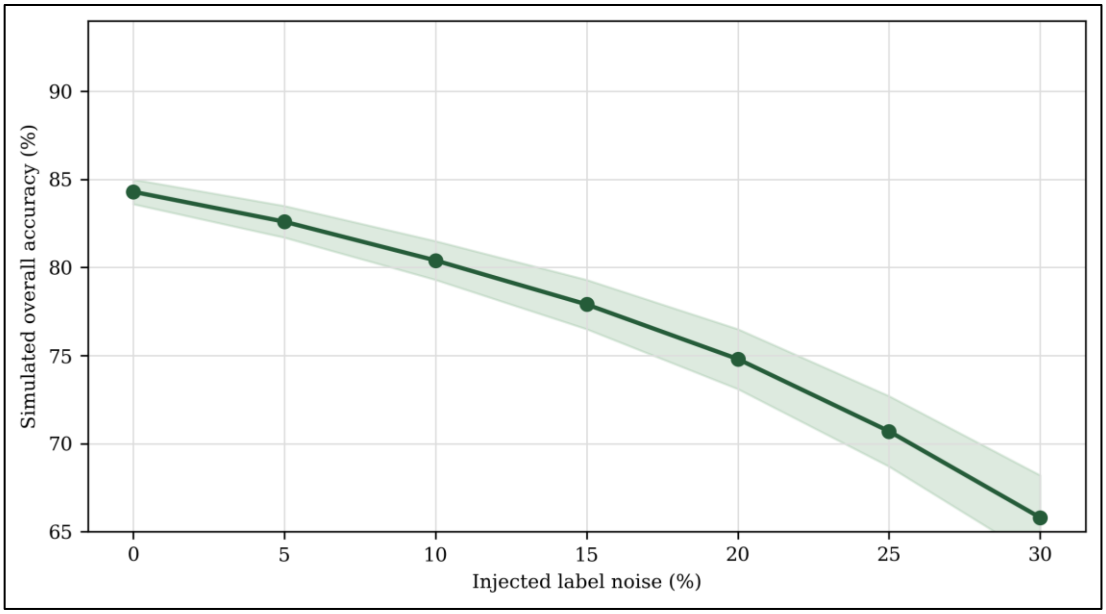

Figure 4. Sensitivity of simulated classification accuracy to reference-label noise; bands show ±1 standard deviation

Discussion of findings

Methodological contribution

The principal contribution is an auditable bridge between a conceptual remote-sensing workflow and the LGA-level statistics demanded by planners. The framework separates four objects that are often conflated: the satellite observations, the trained classification model, the administrative aggregation layer, and the uncertainty statement. This separation matters because a plausible map can still generate biased area estimates when the reference sample is unrepresentative or when boundary versions are inconsistent.

The simulated results show how class shares, confusion matrices, and sensitivity tests can be integrated before field deployment. The exact percentages are disposable; the validation logic is not. A defensible empirical paper should preserve the same integrity checks: every LGA must close to 100%, every class area must reconcile with the mapped state total, rare classes must have adequate validation support, and error-adjusted area estimates should be reported with confidence intervals following good-practice recommendations (Olofsson et al., 2014).

Implications for Imo State applications

Once populated with verified data, the framework could support urban-growth monitoring in the Owerri region, agricultural land inventory, wetland protection, erosion-risk screening and infrastructure prioritisation. It should not be used for parcel ownership, boundary adjudication, compensation or cadastral decisions: 10 m satellite classification is not a substitute for statutory survey. Similarly, revenue or development allocation should not rely on raw pixel totals without independent audit, agreed definitions and uncertainty bounds.

Why simulated evidence cannot support empirical claims

Simulation is useful for software testing, experimental design, power analysis and sensitivity analysis. It is not evidence of present land-cover conditions. The synthetic LGA table cannot validate policy statements about any named locality and must never be described as derived from Sentinel-2, field survey, or official records. A journal version should therefore be submitted as a methods, modelling or simulation paper. If the journal requires original empirical findings, the manuscript must first be rerun with traceable imagery and independent ground-reference data, and every simulated result must be replaced.

Limitations

First, the LGA areas and land-cover proportions are synthetic. Second, the confusion matrix is generated rather than observed, so the reported accuracy does not validate a classifier. Third, the label-noise experiment represents only one uncertainty source and omits cloud persistence, seasonal compositing choices, sensor artefacts, boundary error, mixed pixels, and temporal mismatch. Fourth, no socioeconomic or hydrological outcome is linked to the simulated classes. Finally, the framework has not yet been benchmarked against alternative classifiers such as support-vector machines, gradient boosting, or convolutional neural networks.

4. CONCLUSION

This article presents a complete, reproducible simulation framework for designing an LGA-level land-cover assessment in Imo State. In the illustrative scenario, cropland formed the largest class and the synthetic classifier achieved high apparent accuracy, but sensitivity analysis showed substantial degradation under label noise. The scientifically important result is therefore procedural: credible land-cover statistics depend more on traceable reference data, spatially independent validation, and explicit uncertainty than on visually convincing maps or algorithm complexity.

Before empirical publication, the following minimum actions are required: acquire and archive the Sentinel-2 scene catalogue and processing parameters; obtain an authoritative, versioned LGA boundary dataset; design independent, spatially stratified field validation; publish the class legend and decision rules; report class-specific and area-adjusted accuracy with confidence intervals; release code and non-restricted metadata; and replace every synthetic table and figure with verified outputs. Until those steps are completed, the article should be labelled and reviewed only as a simulation-based methods study.

6. COMPETING INTERESTS

None to declare.

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