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TitleOpen-Data GeoAI for Short-Term Urban Land-Use/Land-Cover Forecasting in Rapidly Growing African Cities: A Reproducible Workflow and the Kinshasa (DRC) Case Study

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1 BACKGROUND, GAP AND OBJECTIVE

- Rapid urbanisation in African cities often outpaces official mapping, zoning control and serviced-land delivery.
- Operational planning needs short-term spatial foresight, not only retrospective monitoring.
- Objective: develop a reproducible open-data Geospatial Artificial Intelligence (GeoAI) workflow for Land Use/Land Cover (LULC) forecasting, using Kinshasa as a transferable case study.

2 STUDY AREA

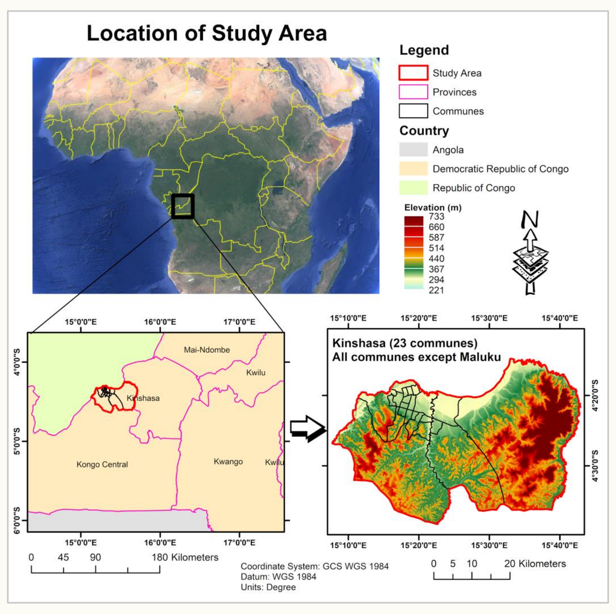

Figure 1. Kinshasa: 23 communes, excluding Maluku; strong urban–rural gradient and fast peri-urban growth.

3 METHODS: OPEN-DATA GEOAI WORKFLOW

1	**Data sources**	Dynamic World v1 / Sentinel-2; NASADEM; OpenStreetMap
2	**Pre-processing**	Google Earth Engine and GIS harmonisation
3	**Change analysis**	TerrSet Land Change Modeler
4	**Transition modelling**	Multilayer Perceptron and Support Vector Machine
5	**Validation**	Receiver Operating Characteristic – Area Under the Curve and Kappa indices
6	**Forecasting**	Markov allocation for 2028 and 2031

Abbreviations: MLP = Multilayer Perceptron; SVM = Support Vector Machine; ROC–AUC = Receiver Operating Characteristic–Area Under the Curve; GEE = Google Earth Engine; OSM = OpenStreetMap; LCM = Land Change Modeler; DEM = Digital Elevation Model.

Figure 2. Reproducible methodological chain from open data to forecast maps.

4 DATASETS AND TOOLS

Table 1. Main open datasets and modelling tools used in the workflow.

Dataset / tool	Role in the study
Dynamic World v1 (10 m)	Annual LULC labels from Sentinel-2 imagery
NASADEM	Elevation and slope drivers
OpenStreetMap	Road and river proximity drivers
TerrSet LCM	Transition modelling and Markov allocation
ArcGIS Pro / GEE	GIS processing and cloud-based mapping

5 OBSERVED LAND-COVER STRUCTURE

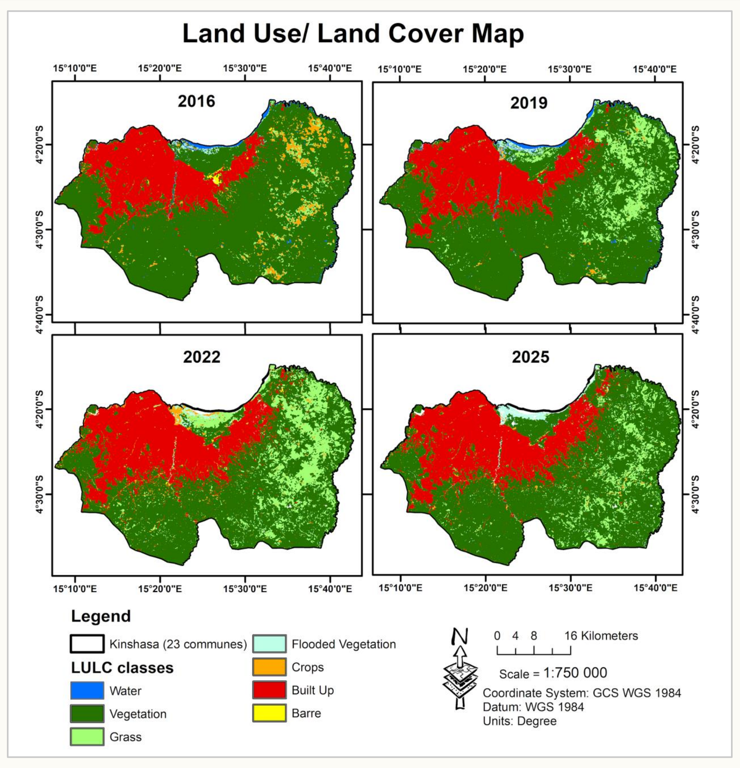

Figure 3. Land Use/Land Cover maps for 2016, 2019, 2022 and 2025 derived from Dynamic World v1 at 10 m resolution.

6 MAIN QUANTIFIED CHANGES (2016–2025)

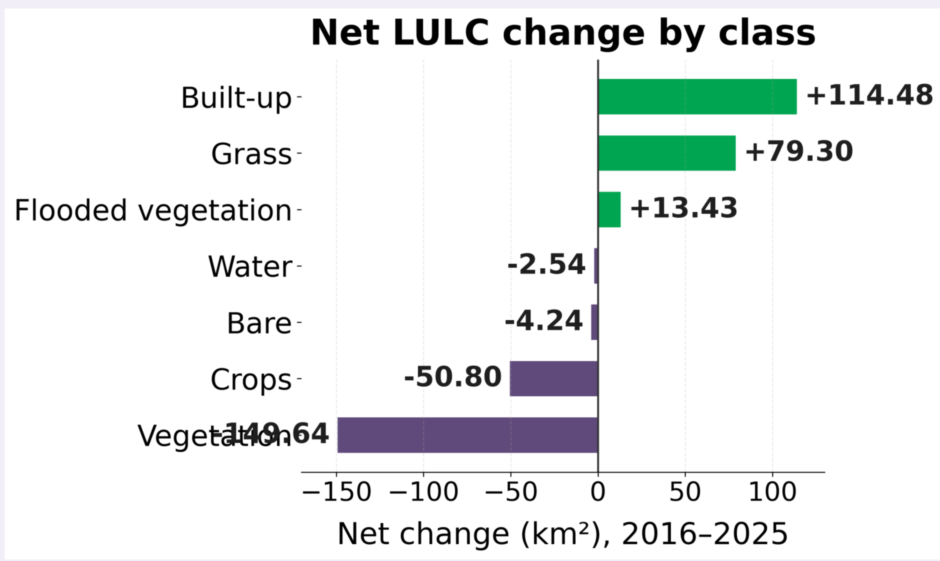

Figure 4. Net change by LULC class. Positive values indicate gains and negative values indicate losses.

Table 2. Planning-relevant net changes (km²).

Class / transition	Magnitude	Planning meaning
Built-up	+114.48 km²	Large urban expansion
Vegetation	−149.64 km²	Green-cover loss
Cropland	−50.80 km²	Pressure on peri-urban food land
Vegetation → built-up	~110.65 km²	Dominant urbanisation pathway

7 SPATIAL TRANSITION HOTSPOTS

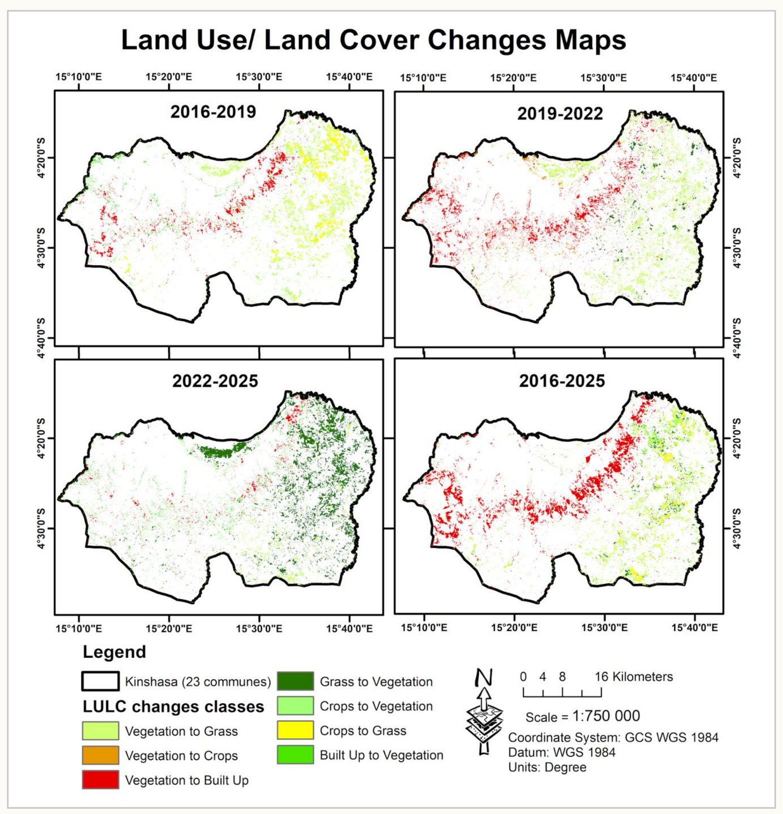

Figure 5. Major transition hotspots between 2016 and 2025, showing concentration along peri-urban belts and accessibility corridors.

8 KEY FINDINGS FOR URBAN PLANNING

- Built-up land expanded strongly between 2016 and 2025, mainly at the urban fringe.
- Vegetation and cropland acted as the main donor classes, highlighting environmental and food-system pressures.
- The 2019–2022 interval showed the most pronounced wave of built-up gains and vegetation losses.
- Hotspots identify areas where zoning, serviced-land provision and green buffers should be prioritised.

9 MODEL PERFORMANCE AND VALIDATION

Table 3. Validation evidence used to assess short-term predictive skill.

Metric	Result	Interpretation
ROC–AUC	0.81–0.92	Strong discrimination for vegetation → built-up
ROC–AUC	0.74–0.89	Moderate to strong vegetation → grass signal
Kappa 2022	0.8226	Substantial map agreement
Kappa 2025	0.7568–0.7778	Reliable short-term backcast

10 FORECAST SCENARIOS (2028 AND 2031)

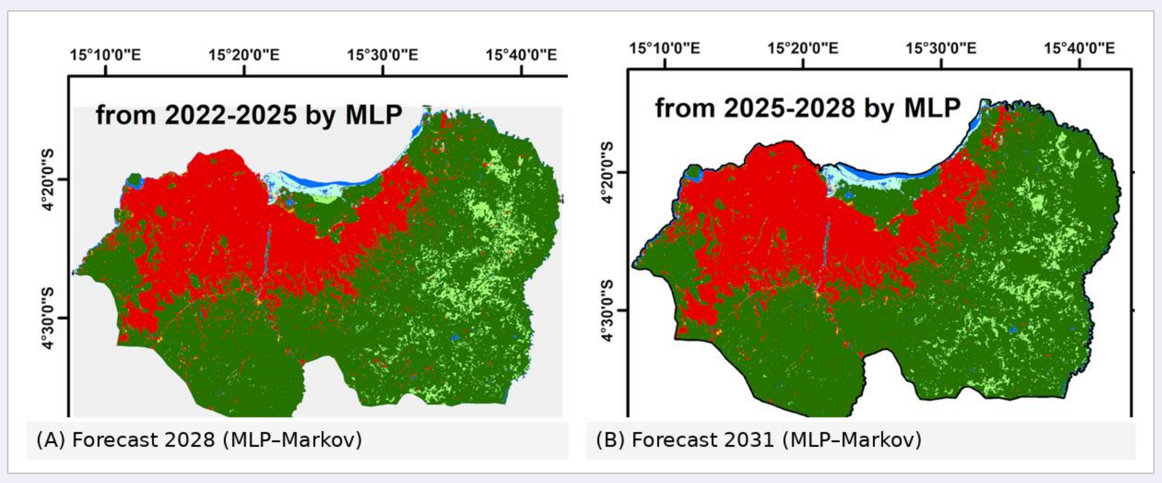

Figure 7. Forecast LULC maps produced by the MLP–Markov workflow; both scenarios indicate continued peri-urban expansion and vegetation fragmentation.

11 DISCUSSION: URBAN PLANNING AND DESIGN

- Open-data forecasting turns monitoring into proactive spatial foresight for data-scarce planning contexts.
- Forecast maps help locate future growth corridors and areas of pressure on vegetation and cropland.
- Outputs can support zoning, green infrastructure protection, road hierarchy design, drainage planning and serviced-land prioritisation.
- The workflow is transferable to other rapidly growing African cities after local calibration of drivers and transition classes.

12 CONCLUSIONS

- A reproducible open-data GeoAI workflow successfully captured recent urban expansion in Kinshasa.
- Built-up growth was mainly associated with vegetation and cropland conversion.
- The method provides actionable spatial evidence for short-term urban planning, peri-urban design and green-cover protection.

13 SELECTED REFERENCES

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