Working paper UGA-25122

April 2026

Predicted property values for all buildings in Kampala

Thomas Pave Sohnesen
Peter Fisker
Flavia Zabali Musisi
Cornelious Bakaki
Cliff Edyegu
Maria Orjuela Pava

DIRECTED BY

FUNDED BY

Predicted Property Values For All Buildings in Kampala

IGC Working Paper

Thomas Pave Sohnesen* Peter Fisker* Flavia Zabali Musisi†
Cornelious Bakaki† Cliff Edyegu† Maria Orjuela Pava‡

April 2026

Abstract

Kampala, like many fast-growing African cities, lacks a complete picture of property values: the Kampala Capital City Authority (KCCA) holds official assessments for only a fraction of the city's 2.1 million buildings. We combine KCCA's property valuation roll with satellite and geospatial data (nighttime lights, building height and footprint, vegetation, elevation, distance to roads and amenities, population, and neighbourhood context) to train a gradient-boosted decision tree (LightGBM) that predicts the assessed annual property rate of any building. Validated by cross-validation on the 165,000 assessed buildings, the model explains more than half of the variation in property rates ($R^2 = 0.51$) and ranks buildings correctly in 72 of 100 cases (Spearman $\rho = 0.72$), outperforming a Random Forest benchmark. We apply the model to produce the first building-level property value map for the Greater Kampala Metropolitan Area, covering all 2.1 million buildings. The resulting surface supports tax-base expansion and equity, targeting of infrastructure investment, identification of low-value informal settlements, and temporal monitoring of urban change. We discuss limitations, including regression-to-the-mean compression and greater uncertainty outside the KCCA training area.

The challenge

Kampala is a fast-growing city of more than three million people. The Kampala Capital City Authority (KCCA) collects property rates (a form of annual tax based on the assessed value of buildings), but formal assessment records exist for only a small fraction of the city's **2.1 million buildings**. Without a complete picture of property values, it is difficult for the city to plan infrastructure, identify where investment is most needed, or ensure that the tax system is fair.

*Independent Consultant
†GIS Department, Kampala Capital City Authority (KCCA)
‡The International Growth Centre (IGC)

What we did

We combined KCCA's official property rate records with a rich set of satellite and geospatial data to build a machine-learning model that predicts the assessed value of any building in the city. This follows a growing body of work that uses satellite imagery and machine learning to predict economic outcomes where ground data are sparse (Jean et al., 2016).

The idea is straightforward: buildings in wealthier areas tend to be taller, sit closer to roads and shops, enjoy brighter nights (as captured by satellite nighttime light images), and are surrounded by larger, denser structures. By learning these patterns from the **165,000 buildings** that already have an official KCCA assessment, the model can make an informed prediction for the remaining buildings as well. The predictions extend beyond the KCCA area, which covers 527,487 buildings, to the full extent of the Kampala building agglomeration with 2.1 million buildings. Buildings with a footprint larger than 500 m^2 or a height above 6 metres are excluded from the predictions as these are assumed to be commercial buildings or apartment/multi-storey buildings. There is currently not enough training data to support an accurate prediction model for these building types.

The data ingredients include:

- **Satellite nighttime lights:** brighter areas signal more economic activity and better infrastructure.
- **Building height:** taller buildings are generally worth more.
- **Building footprint size and shape:** larger or more regularly shaped buildings tend to command higher values.
- **Vegetation cover (NDVI):** green, leafy neighbourhoods are often associated with higher incomes.
- **Distance to the city centre and amenities:** proximity to markets, schools, hospitals, and transport hubs adds value.
- **Neighbourhood context:** the average height, size, and lighting of the 100 nearest buildings captures the character of the immediate surroundings.
- **Electrical grid proximity:** distance to the nearest low-voltage (LV) and high-voltage (HV) distribution lines from the UMEME network, which closely tracks formal economic activity and household access to services.
- **Wetland and lake proximity:** distance to wetlands and lakes, which influence buildable land supply and local land values.

All of these data layers were extracted at the individual building level, giving each of the 2.1 million buildings in the dataset its own set of characteristics.

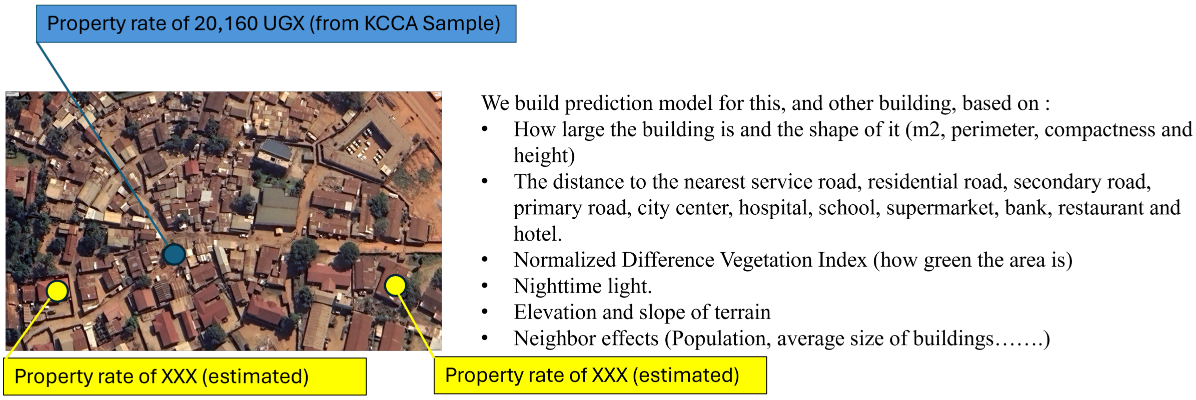


Figure 1: Illustration of the prediction method. The **blue** marker indicates a building with a known KCCA property assessment (here: 20,160 UGX). The **yellow** markers indicate neighbouring buildings without official records, which receive a model-estimated property value. By learning from the 165,000 assessed buildings across Kampala, the model infers values for the remaining 1.9 million unassessed structures.

How well does it work?

The model is a *gradient-boosted decision tree* (LightGBM; Ke et al., 2017), a state-of-the-art machine-learning method. It was chosen after comparing it against a Random Forest model (Breiman, 2001); LightGBM performed better on every metric.

To test how well the model generalises to new buildings, we used *cross-validation*: repeatedly training on part of the data and checking predictions on the remainder. The results show that the model correctly ranks buildings by value in **72 out of 100 cases** (Spearman rank correlation of 0.72), and explains more than half of the variation in assessed property rates ($R^2 = 0.51$).

What the map shows

The result is a **city-wide property value surface at the level of individual buildings**, the first of its kind for Kampala. The map reveals sharp contrasts between neighbourhoods: high-value commercial corridors and wealthy residential estates stand out clearly against the dense, lower-value informal settlements that characterise much of the city.

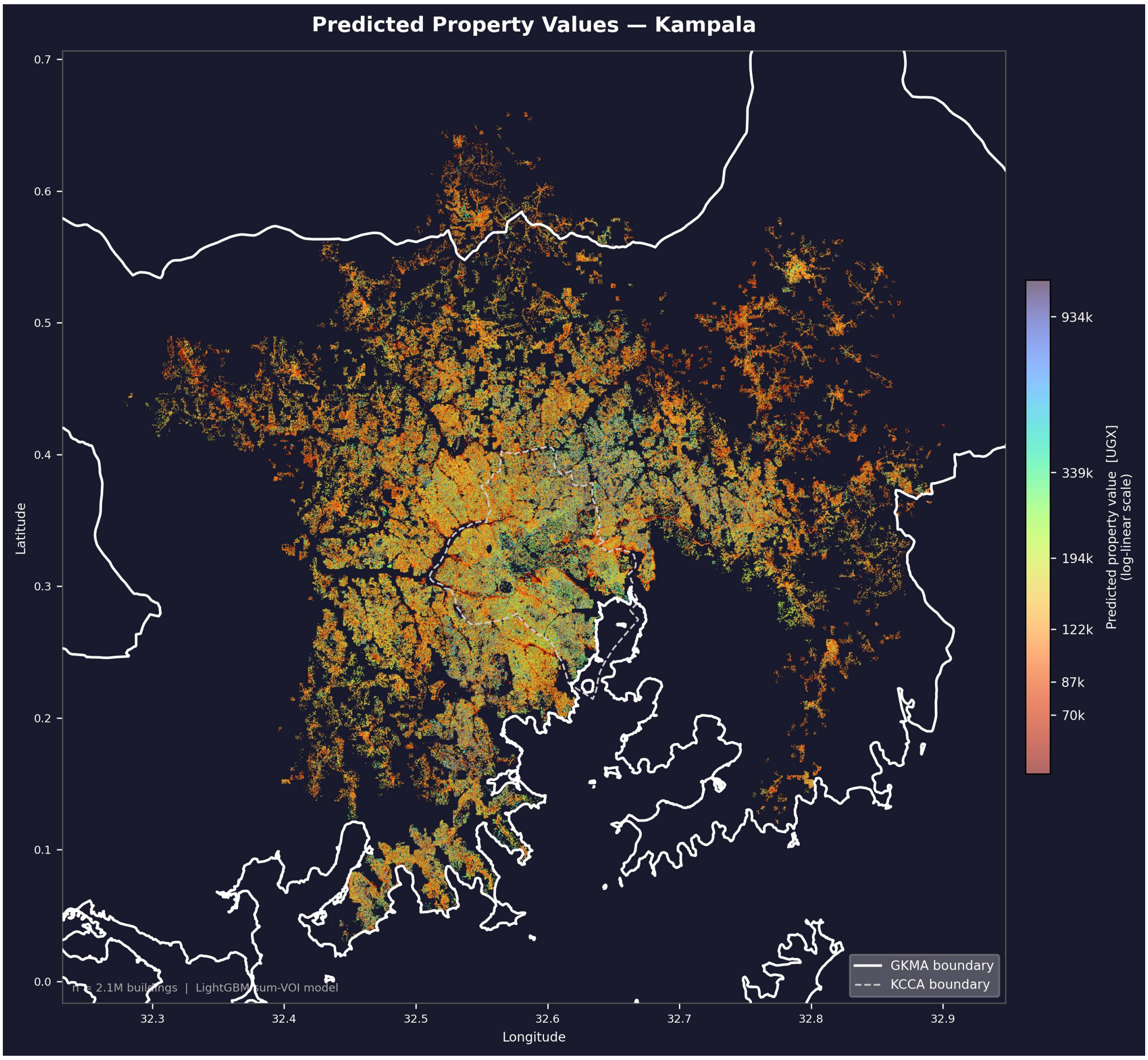


Figure 2: Predicted property values for all 2.1 million buildings in the Greater Kampala study area. Each dot represents one building, coloured from red (lower values) to yellow/green (higher values) using the turbo colour scale. The solid white line is the official GKMA boundary (5,143 km^2); the dashed line marks the KCCA administrative boundary (195 km^2). High-value buildings cluster along major road corridors and in the central business district; dense informal settlements appear in warmer colours throughout the city.

Some patterns are intuitive: the Kampala central business district and areas along major roads show the highest predicted values. Others are more surprising: pockets of relatively high value appear in areas far from the city centre, suggesting that local amenities and neighbourhood density matter almost as much as proximity to downtown.

A note on uncertainty: the model was trained and validated exclusively on buildings within the KCCA administrative boundary, where official assessments exist. Predictions *within* the KCCA area are therefore grounded in observed local data. The map extends predictions to the wider Greater Kampala Metropolitan Area (GKMA), covering municipalities such as Kira, Wakiso, and Entebbe, but these areas lie **outside**

the training sample. While the satellite and geospatial features used should generalise reasonably to similar urban environments, there is no local ground-truth to validate against, and predicted values in these zones carry greater uncertainty and should be interpreted with corresponding caution.

Policy implications

A complete building-level property value map has wide practical uses:

- **Increase tax revenue and equity.** These results allow the city to identify buildings that are currently unassessed or under-assessed, supporting expansion of the tax base and revenue collection as well as fairness of the tax system.
- **Targeting investment.** Development programmes (upgrading roads, extending water supply, improving drainage) can be directed to areas where the infrastructure gap is largest relative to underlying economic potential.
- **Urban planning.** Understanding how property values vary across the city helps planners anticipate where demand for services will grow and how land use is likely to change. As new data becomes available, these predictions can be updated to track change over time.
- **Poverty analysis.** Property value is a strong correlate of household wealth. The map complements household survey data by providing a high-resolution, continuously updated signal of economic conditions at the neighbourhood and street level.
- **Identification of poor housing and slums.** The approach can be used to identify areas with low property values, which are likely to correspond to informal settlements and slums. This information can help policymakers and urban planners to improve targeting of affordable housing programmes and slum upgrading initiatives. With further data, the model could be refined to predict not just property values but also housing quality indicators, enabling more precise identification of vulnerable housing conditions, ideal for targeted interventions against slums.
- **It's a first stepping stone in a powerful policy tool.** These results are a first stepping stone, but the approach of data collection combined with machine learning predictions is not perfect and it can be continuously improved. Currently there is not training data for properties outside of KCCA and there are not training data for large and multi-storey buildings. As the results are utilised and checked against observational data, more training data becomes available and the model can be retrained to improve accuracy and coverage, leading to continuous improvements in the map and its policy relevance. Further, expansion could also go beyond Kampala to other cities and eventually nationwide, providing a powerful tool for urban management across Uganda.
- **Temporal application would allow timely policy responses.** The model can be updated as new spatial data becomes available, allowing for tracking of city expansion and changes over time. This would enable policymakers to respond more quickly to emerging trends and shifts in the urban landscape, such as gentrification, infrastructure development, new construction (formal and informal), or economic shocks.

Conclusion

We have produced the first building-level property value map for Kampala, predicting the assessed annual property rate of all 2.1 million buildings in the Greater Kampala Metropolitan Area from satellite and geospatial features. The model is validated within the KCCA boundary, where it explains more than half of the variation in assessed rates ($R^2 = 0.51$) and preserves the relative ranking of buildings (Spearman $\rho = 0.72$), outperforming a Random Forest benchmark.

Several limitations should be borne in mind. First, like most regression models the predictions are compressed toward the mean: the lowest-value buildings are over-predicted and the highest-value buildings under-predicted, so the map is most reliable for ranking buildings and neighbourhoods rather than for absolute values at the extremes. Second, the model is trained only on buildings inside the KCCA boundary; predictions for the wider GKMA generalise the learned relationships but cannot be validated against local ground truth and carry greater uncertainty. Third, buildings with a footprint above 500 m^2 or a height above 6 metres are excluded, as there is not yet enough training data to predict values for commercial and multi-storey structures reliably.

These limitations also define the path forward. As predictions are used and checked against observed assessments, more training data become available, the model can be retrained to improve accuracy and extend coverage to large and multi-storey buildings and to areas beyond KCCA, and the approach can be applied over time to monitor urban change and replicated in other Ugandan cities.

Technical appendix: Model performance

Preferred model: sum-based property value

Table 1 summarises the performance of the preferred LightGBM model, which uses the *sum* of matched KCCA property rates as the target variable (see the aggregation discussion below). The model achieves a cross-validated R^2 of 0.51 and a Spearman rank correlation of 0.72, trained on 165,167 buildings and using only predictors that are available for the full city-wide building stock.

Distribution compression (regression to the mean). A diagnostic comparison of predicted and actual values across value deciles reveals a pattern typical of regression models: the model *compresses* the predicted distribution relative to the true one (predicted standard deviation 0.68 vs. actual 0.91 in log-UGX units). Concretely, the lowest-value buildings are over-predicted by roughly 0.72 log units on average (around $2\times$ in UGX), and the highest-value buildings are under-predicted by around 0.54 log units. Buildings in the middle four deciles are well calibrated (mean bias $|\beta| < 0.15$). This has two practical implications. First, the map is most reliable for ranking buildings and neighbourhoods (relative ordering is preserved with a Spearman correlation of 0.71), but absolute predicted values should be interpreted with caution, especially at the extremes. Second, the density of very-high-value commercial and institutional buildings may appear lower than reality, since their assessed values are partly compressed toward the mean.

Figure 3 shows the relationship between actual and predicted property values on the log scale.

Table 1: LightGBM Performance (Google Buildings) – Log Sum Property Rate - log(VOI sum)

Metric	In-sample	Cross-validation
RMSE	0.5573	0.6531
MSE	0.3106	0.4265
MAE	0.4097	0.4767
R^2	0.6474	0.5140
Spearman ρ	0.7970	0.7160
Best LightGBM parameters:		
learning_rate	0.05	
min_child_samples	50	
num_leaves	127	
best_iteration	484	

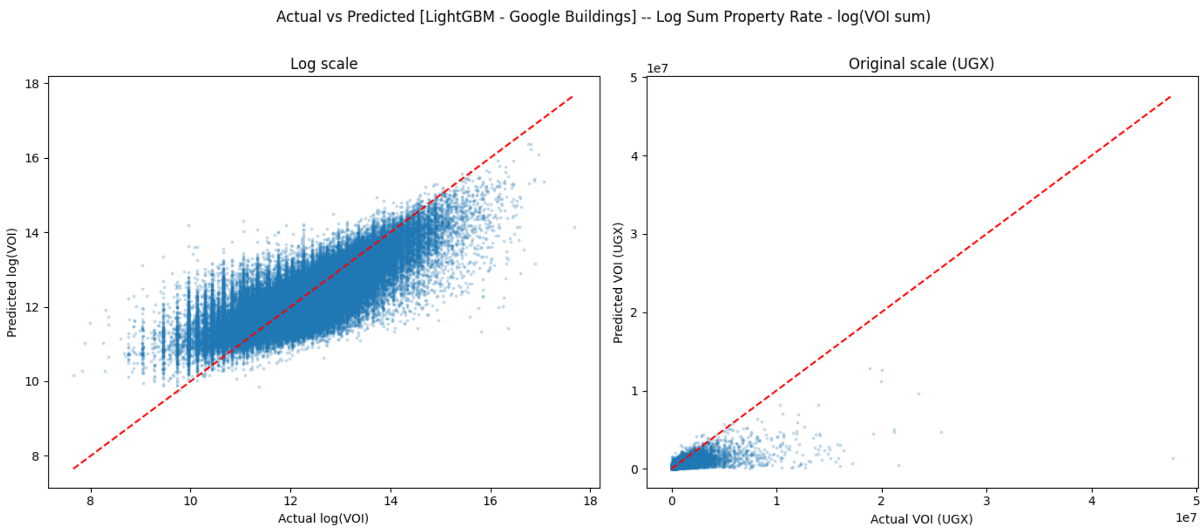


Figure 3: Actual vs predicted property values (preferred sum-based model).

Figure 4 shows the top 20 features ranked by gain importance.

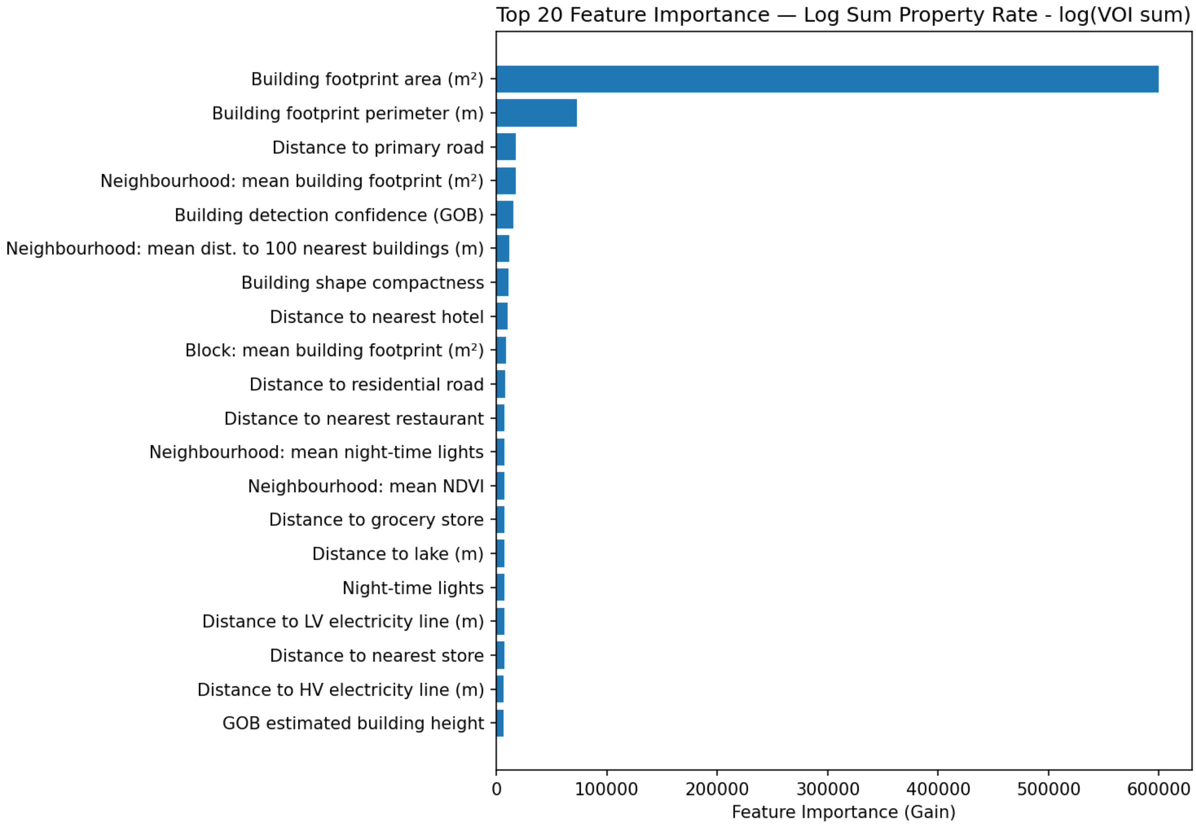


Figure 4: Feature importance (gain): preferred sum-based LightGBM model.

Robustness: multi-match diagnostic and mean vs. sum aggregation

When matching KCCA property rate records to Google building footprints, a two-step procedure is used. First, each property point is spatially joined to the building polygon it falls *inside* (68% of records); the remaining 32% are matched to the nearest building polygon boundary via a spatial nearest-neighbour join projected to a metric coordinate system (median distance: 1 m). This polygon-boundary matching is more accurate than centroid-based matching, particularly for large or irregularly shaped footprints. Of the 167,176 buildings with at least one match, 33,032 (19.8%) receive multiple property records. This raises the question of whether these multi-matches represent *distinct living units* within a single building (e.g. apartments) or *GPS measurement error* leading to ambiguity about which building a record belongs to.

The answer matters for aggregation: if multi-matches are distinct units, the correct building-level value is the **sum** of their property rates; if they are due to measurement error, the **mean** is appropriate.

Five diagnostics were conducted to distinguish between these explanations:

1. **Property identifiers.** 99.9% of multi-match buildings have all unique CAMV_IDs (KCCA's property identifier), ruling out duplicate records in the source data.
2. **Within-building value variation.** 73% of multi-match buildings have a coefficient of variation (CV) of at least 20% across their matched property values, indicating meaningfully different, not identical, assessments.

3. **Building size and height.** Correlations between the number of matches and building footprint area or height are near zero ($\rho \approx 0.00$), suggesting that multi-matches are not driven by physically larger or taller structures.

4. **Spatial spread.** The median maximum distance between property points within the same building is small (a few metres), consistent with GPS noise rather than spatially dispersed units.

5. **Duplicate CAMV_IDs.** Only 0.1% of multi-match buildings contain duplicate property identifiers.

The balance of evidence favours the *distinct properties* explanation: almost all multi-match records have unique identifiers and different assessed values. We therefore adopt the **sum** of property rates as the preferred target variable.

Table 2 reports the mean-based model for comparison. The mean and sum models perform very similarly (R^2: 0.52 vs 0.51; Spearman: 0.71 vs 0.72), which is consistent with the diagnostic evidence: the two aggregations differ only for the 19.8% of buildings with multiple matches, and the differences between the two approaches are modest in terms of prediction accuracy. We retain the sum as the preferred specification on conceptual grounds: it better reflects the total assessed value of all taxable properties associated with a building.

For comparison, a Random Forest model trained on the same data and predictors achieves a cross-validated R^2 of 0.49 and a Spearman rank correlation of 0.69, below the LightGBM results on both metrics, confirming the choice of gradient boosting as the preferred method.

Table 2: LightGBM Performance (Google Buildings) – Log Mean Property Rate - log(VOI)

Metric	In-sample	Cross-validation
RMSE	0.4927	0.6299
MSE	0.2427	0.3969
MAE	0.3645	0.4634
R^2	0.7053	0.5171
Spearman ρ	0.8293	0.7116
Best LightGBM parameters:		
learning_rate	0.05	
min_child_samples	50	
num_leaves	127	
best_iteration	803	

Technical appendix: Data sources

KCCA property valuation roll: data collection methodology

The official property rate records used as the training sample originate from the Kampala Capital City Authority (KCCA) Property Valuation Roll, generated through the City Address Model (CAM) and

Computer-Aided Mass Valuation (CAMV) project.

Background. KCCA implemented the CAM/CAMV project under the Second Kampala Institutional and Infrastructure Development Project (KIIDP 2), with funding from the World Bank (International Development Association). The initiative began in 2016 and ran through approximately 2020, with progressive roll-outs across Kampala's five divisions: Central (completed 2017), Nakawa (2018), and Kawempe, Lubaga, and Makindye (around 2019). The full system was formally launched in September 2021. The primary goal was to update the long-outdated city valuation roll (last major update around 2005/06), which had resulted in an incomplete tax base, revenue leakage, and inequities in property taxation.

Data collection. Data were gathered through intensive ground-based fieldwork involving teams of trained enumerators and valuation supervisors who conducted physical visits to every property across Kampala's divisions. Key activities included reconnaissance surveys, direct observation of buildings, interviews with owners and occupiers, GPS recording of exact coordinates, precise measurements of land and building footprints, and photographic documentation of building characteristics (size, shape, type, condition, and attributes relevant to value). All data were captured digitally via structured forms using the Survey 123 mobile data collection app, with immediate upload, cleaning, and quality control by supervisors.

Validation. Property attributes were cross-validated against 3D oblique aerial imagery captured specifically for the project. This high-resolution oblique photography allowed valuers to confirm building details, heights, and structures from multiple angles.

Valuation methodology. The actual property rates were computed using KCCA's Computer-Aided Mass Valuation (CAMV) system, in full compliance with the Local Governments (Rating) Act, 2005. Three quantities are computed for each property: (i) *Gross Annual Value*: the estimated market rent the property could reasonably command per year; (ii) *Ratable Value*: gross value minus a standard 22% conservancy allowance; and (iii) *Annual Property Rate*: typically 6% of the ratable value, producing the final annual tax obligation per building. In summary, the sampled property values represent KCCA's most comprehensive and up-to-date official valuation roll, a major reform achievement that transformed property tax administration in Kampala.

Table 3 lists every data layer used in the model, together with its provider, vintage, spatial resolution, and the features it contributes.

Table 3: Data sources

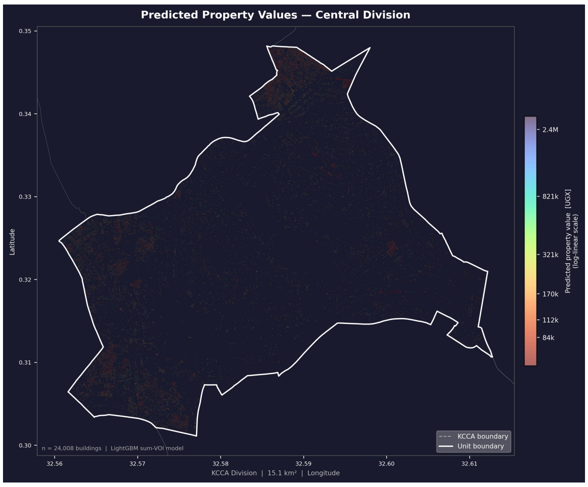
Dataset	**Provider**	**Year**	**Resolution**	**Features contributed**
Target variable				
KCCA Property Valuation Roll	Kampala Capital City Authority	2025	Point	Annual property rate (UGX) per building
Building footprints				
Google Open Buildings v3: polygons (Sirko et al., 2021)	Google Research	2023	Building	Footprint area (m^2), perimeter (m), compactness (Polsby–Popper), detection confidence
Google Open Buildings v3: raster (via GEE)	Google Research	2023	~4 m	Building height (m), fractional building count per pixel, building presence score
Satellite imagery				
VIIRS Nighttime Lights v2.2	NOAA / EOG	2022	~500 m	Annual average radiance at building location and mean over 100 nearest neighbours
NDVI (Landsat 8/9 composite, via GEE)	USGS / NASA	2023	30 m	Normalised Difference Vegetation Index at building location
SRTM Digital Elevation Model (via GEE)	NASA / USGS	2000	30 m	Ground elevation (m) at building location
Street network and points of interest				
OpenStreetMap	OpenStreetMap contributors	2024	Vector	Distance to primary and residential roads; distance to restaurants, hotels, stores, schools, supermarkets, grocery stores, bus stations, shopping malls, transport hubs; residential and industrial land-use flags; on/off network street length within block
Population				
LandScan Global	Oak Ridge National Laboratory (ORNL)	2022	1 km	Population count and density (per hectare, per building)
WorldPop	WorldPop, Univ. of Southampton	2020	100 m	Population count and density (per hectare, per building)
Urban classification				
Africapolis 2025	OECD / Sahel and West Africa Club	2025	Polygon	Urban agglomeration membership, urban hierarchy class
Neighbourhood and block features (derived)				
Neighbourhood aggregates	Derived from above	n/a	Building	Mean nighttime light, NDVI, footprint area, height, and distance to nearest neighbour over the 100 closest buildings
City block statistics	Derived from OSM	n/a	Block	Block area (ha), building count, built-up ratio
Infrastructure				
UMEME electricity distribution network	UMEME Ltd / Uganda Electricity Distribution Company	2024	Vector	Distance to nearest low-voltage (LV) line; distance to nearest high-voltage (HV) line (log-transformed)
Uganda wetlands	National Environment Management	2020	Polygon	Distance to nearest wetland; binary flag for buildings inside wetland area

Predicted property values by administrative area

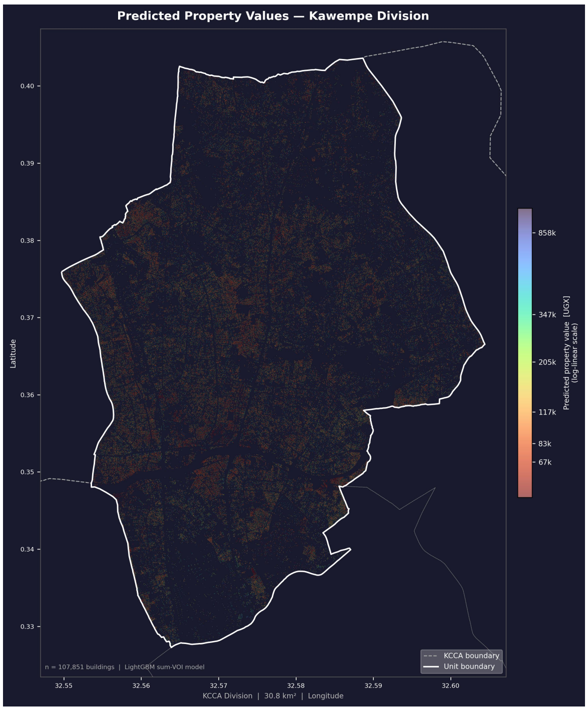
The following maps show predicted property values disaggregated by administrative unit. Each map uses the same colour scale as the city-wide map (turbo, clipped at the 0.5th and 99.5th percentiles of the unit's own distribution), allowing within-unit variation to be seen clearly. The white boundary outline marks the unit boundary; the dashed line (where shown) marks the KCCA outer boundary for reference.

A.1 KCCA divisions

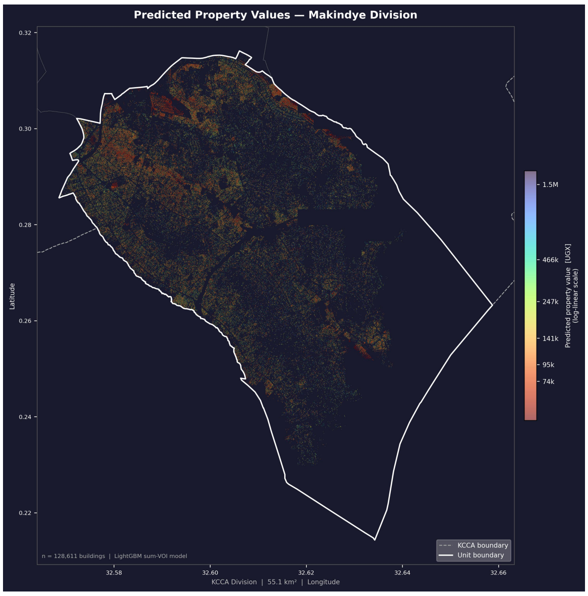
The five divisions of the Kampala Capital City Authority (KCCA) are the primary sub-district administrative units within the city boundary.



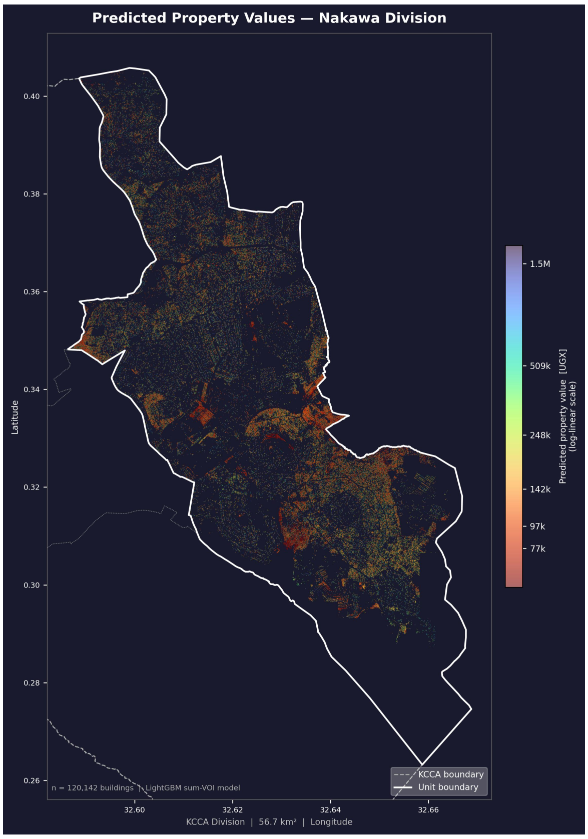
(a) Central Division (15 km^2, 24,008 buildings)



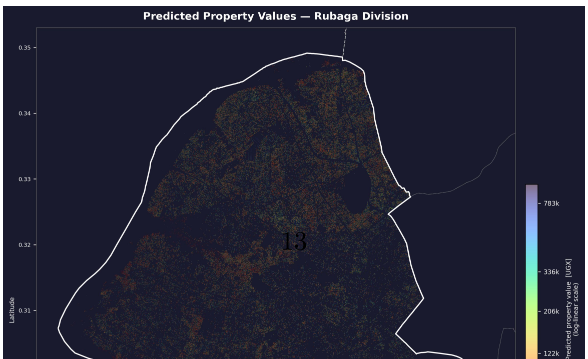
(b) Kawempe Division (31 km^2, 107,851 buildings)



(c) Makindye Division (55 km^2, 128,611 buildings)

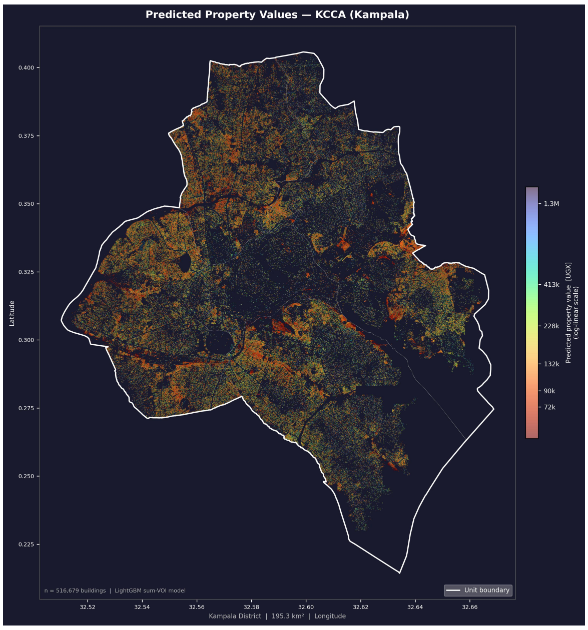


(d) Nakawa Division (57 km^2, 120,142 buildings)

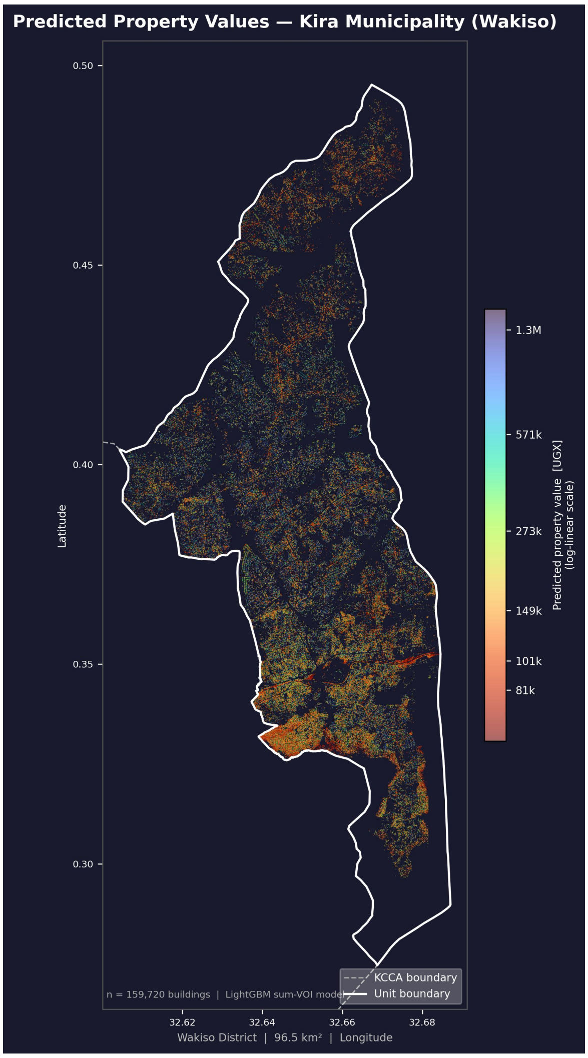


A.2 Municipalities and counties: Greater Kampala area

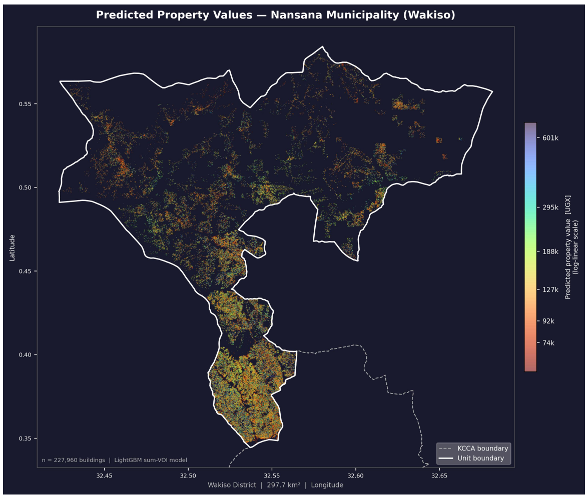
The following maps cover municipalities and counties within the greater Kampala metropolitan area, including the surrounding districts of Wakiso, Mukono, and Mpigi. Predictions are available wherever Google Open Buildings footprints exist, which extends well beyond the KCCA boundary.



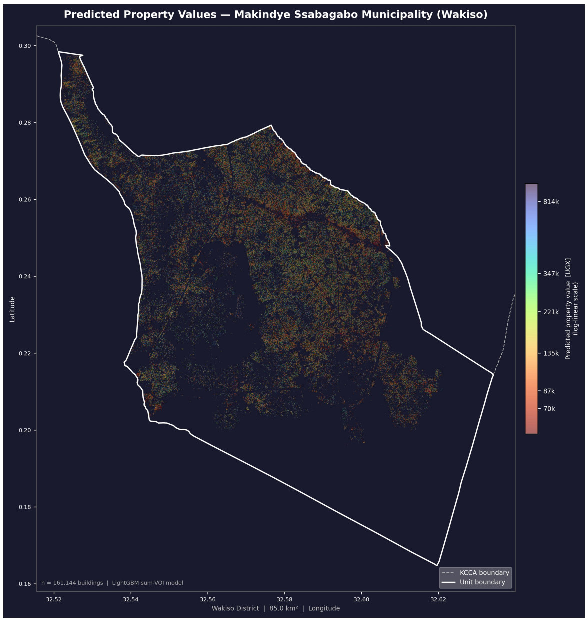
(a) KCCA: Kampala District (195 km^2, 516,679 buildings)



(b) Kira Municipality, Wakiso (97 km^2, 159,720 buildings)

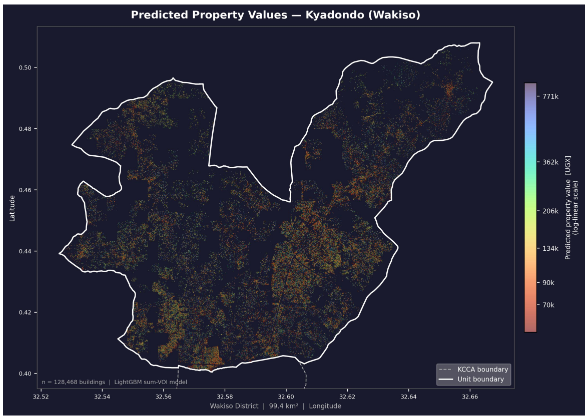


(c) Nansana Municipality, Wakiso (298 km^2, 227,960 buildings)

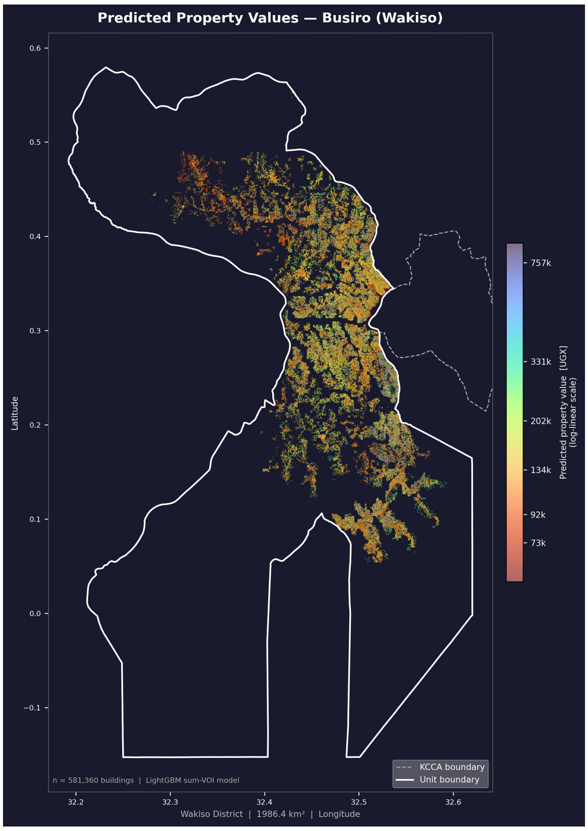


(d) Makindye Ssabagabo Municipality, Wakiso (85 km^2, 161,144 buildings)

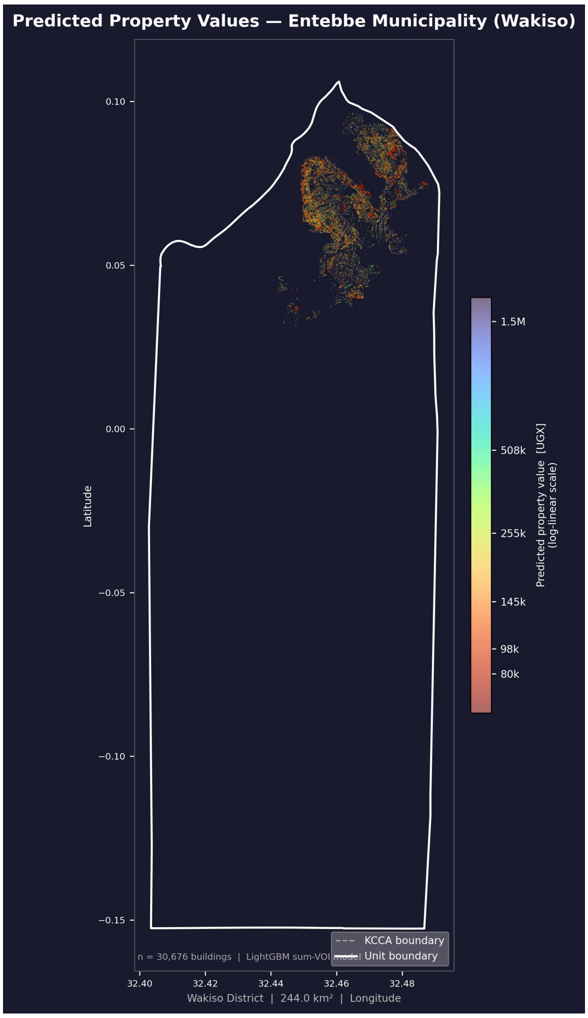
Figure 6: Predicted property values by municipality: KCCA and Wakiso (part 1). The dashed line shows the KCCA boundary for reference.



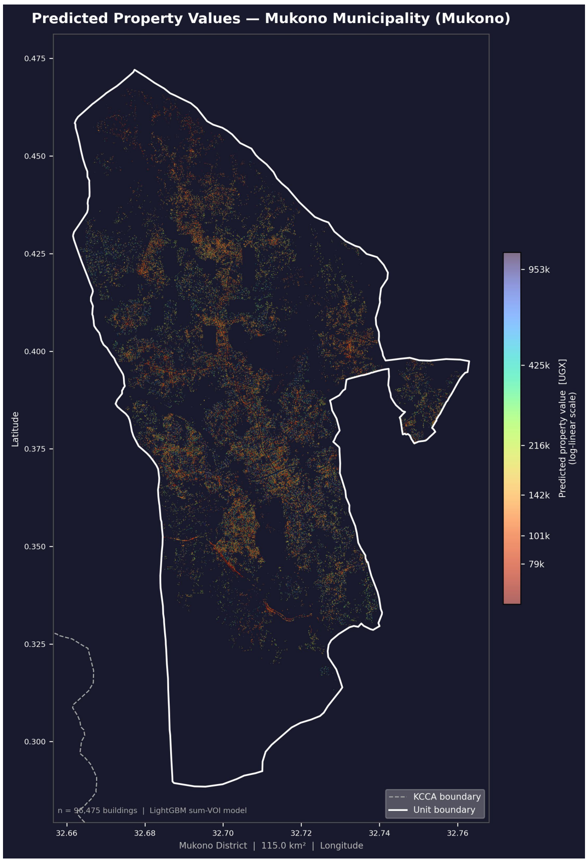
(a) Kyadondo, Wakiso (99 km^2, 128,468 buildings)



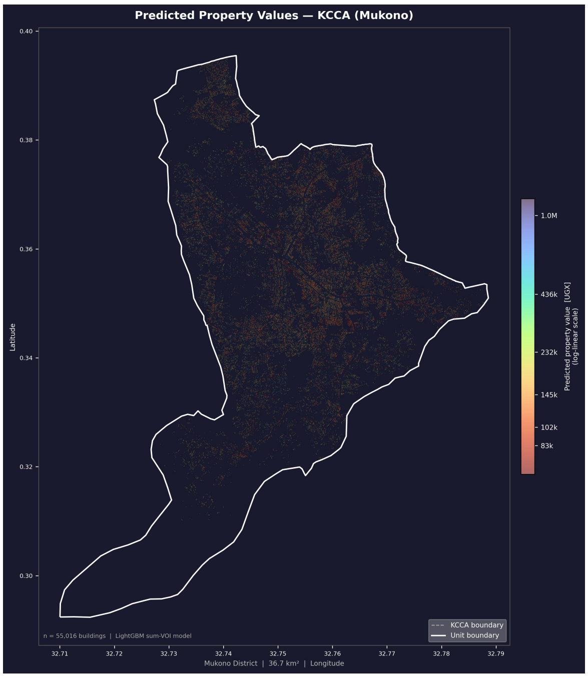
(b) Busiro, Wakiso (1,986 km^2, 581,360 buildings)



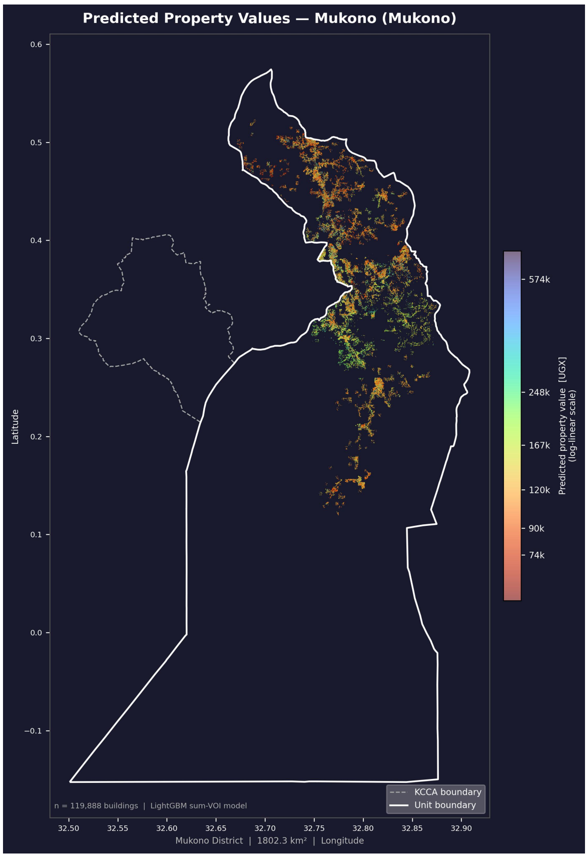
(c) Entebbe Municipality, Wakiso (244 km^2, 30,676 buildings)



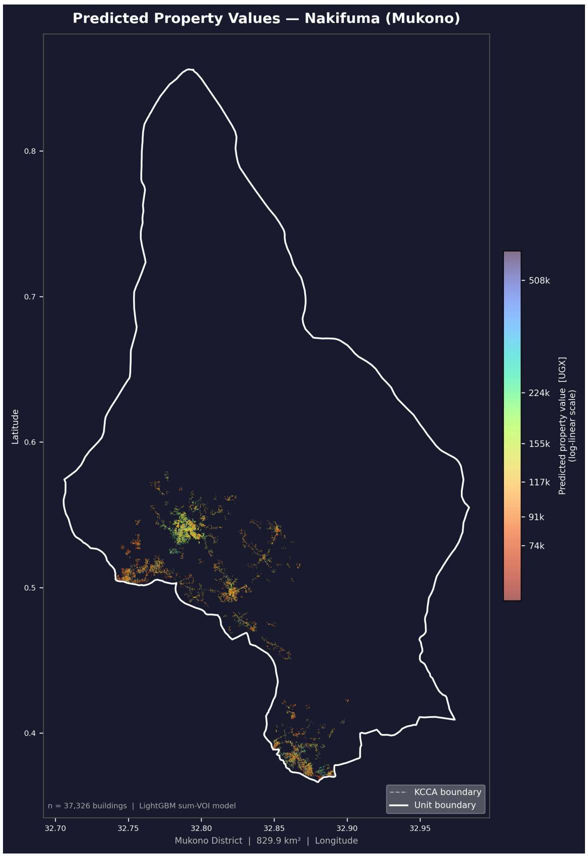
(d) Mukono Municipality, Mukono (115 km^2, 96,475 buildings)

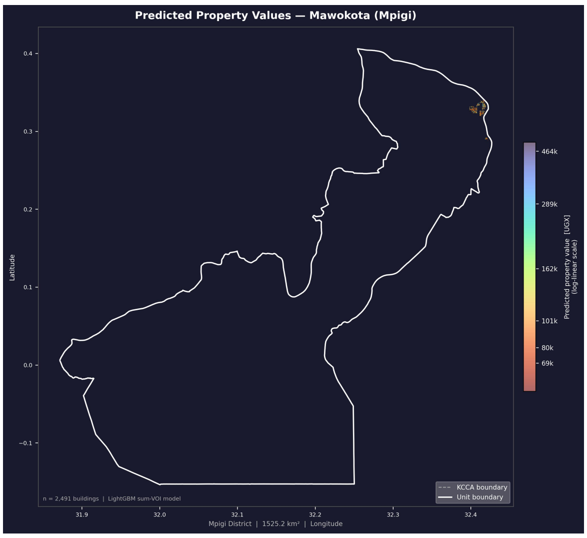


(a) KCCA: Mukono District (37 km^2, 55,016 buildings)



(b) Mukono County, Mukono (1,802 km^2, 119,888 buildings)





(c) Nakifuma, Mukono (830 km^2, 37,326 buildings)

(d) Mawokota, Mpigi (1,525 km^2, 2,491 buildings)

Figure 8: Predicted property values by county/municipality: Mukono and Mpigi. The dashed line shows the KCCA boundary for reference.

A.3 Parish-level choropleth: Greater Kampala Metropolitan Area

Each of the 379 parishes in the GKMA is shaded by the *median* predicted property value of the buildings it contains. This provides a neighbourhood-level summary of the spatial distribution of property wealth, at the finest officially demarcated administrative level available for the GKMA.

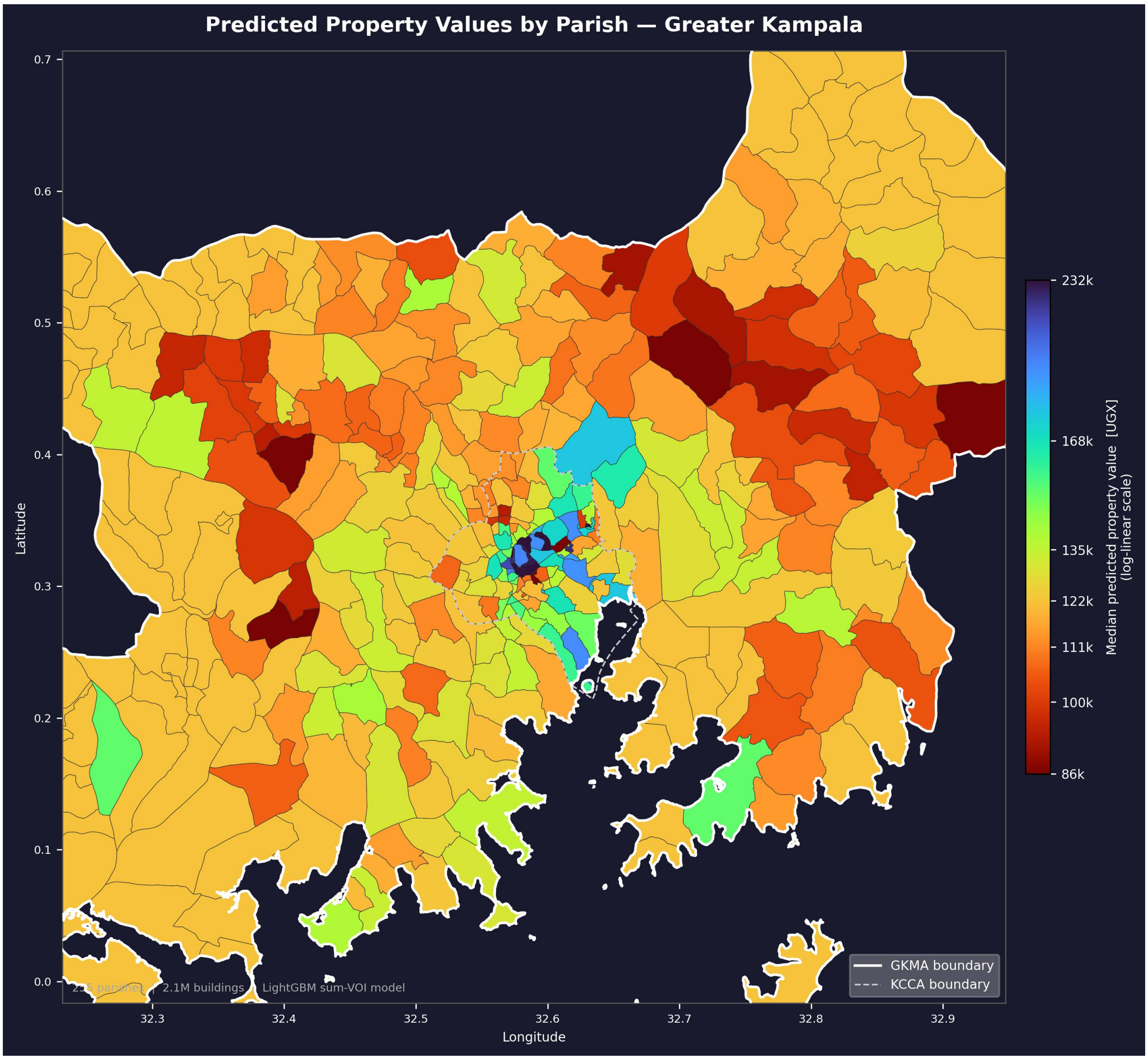


Figure 9: Median predicted property value by parish (379 parishes, GKMA 2023 boundaries). Parishes with no Google Open Buildings coverage are shown in dark grey. The solid white line is the GKMA boundary; the dashed line is the KCCA boundary.

A.4 KCCA training sample: assessed buildings

Figure 10 shows the spatial distribution of the 165,167 officially assessed buildings that form the training sample. Each dot represents one building coloured by its *actual* annual property rate from the KCCA valuation roll (the same colour scale as the prediction map). The sample is concentrated within the KCCA boundary (dashed line) but extends into the adjacent peri-urban area, reflecting the coverage of the CAM/CAMV fieldwork. The spatial clustering of high-value buildings along major road corridors and in the central business district is clearly visible, as are the dense pockets of lower-value buildings in the informal settlements ringing the city core.

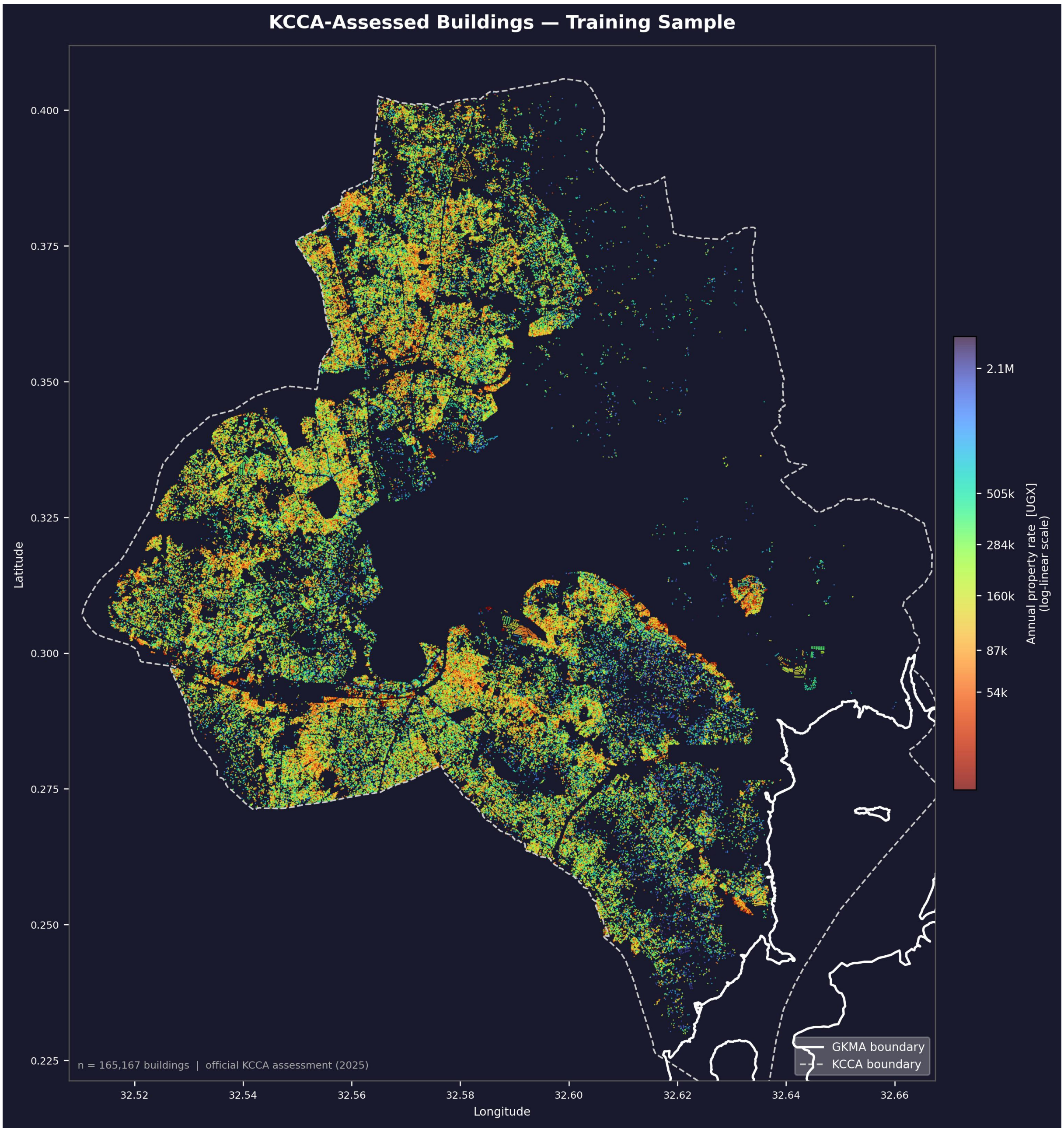


Figure 10: Actual annual property rates for the 165,167 KCCA-assessed buildings used to train the model. Colour scale is identical to the city-wide prediction map (turbo, clipped at the 0.5th and 99.5th percentiles). The solid white line is the GKMA boundary; the dashed line marks the KCCA boundary.

Acknowledgements

This work was funded by the International Growth Centre (IGC) under grant UGA-25122. The project was developed by Peter Fisker and Thomas Pave Sohnesen in partnership with Flavia Zabali and the GIS Department of the Kampala Capital City Authority (KCCA). The views expressed in this paper are those of the authors and do not necessarily reflect those of the IGC, the KCCA, or their funders.

Data sources. Property rate records are from the Kampala Capital City Authority (KCCA). Building footprints are from Google Open Buildings v3. Satellite data were sourced from VIIRS (NOAA/EOG), Landsat 8/9 (USGS/NASA), and SRTM (NASA/USGS), all processed via Google Earth Engine. Street network and amenity data are from OpenStreetMap contributors. Population data are from LandScan (ORNL) and WorldPop (University of Southampton). Urban classification uses the Africapolis 2025 dataset (OECD/SWAC). Administrative boundaries are from the Uganda Common Operational Datasets (COD), sourced via OCHA, and from the Greater Kampala Metropolitan Area (GKMA) 2023 dataset, sourced from KCCA.

References

Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5–32.

Google Research. (2023). *Open Buildings v3* [Data set].

Jean, N., Burke, M., Xie, M., Davis, W. M., Lobell, D. B., & Ermon, S. (2016). Combining satellite imagery and machine learning to predict poverty. *Science*, 353(6301), 790–794.

Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., Ye, Q., & Liu, T.-Y. (2017). LightGBM: A highly efficient gradient boosting decision tree. In *Advances in Neural Information Processing Systems 30* (pp. 3149–3157).

NASA/USGS. (2000). *Shuttle Radar Topography Mission (SRTM) 1 Arc-Second Global* [Data set].

NOAA Earth Observation Group. (2022). *VIIRS Nighttime Lights, Version 2.2* [Data set].

Oak Ridge National Laboratory. (2022). *LandScan Global* [Data set].

OECD/Sahel and West Africa Club. (2025). *Africapolis* [Data set]. `https://africapolis.org`

OpenStreetMap contributors. (2024). *OpenStreetMap* [Data set]. `https://www.openstreetmap.org`

Sirko, W., Kashubin, S., Ritter, M., Annkah, A., Bouchareb, Y. S. E., Dauphin, Y., Keysers, D., Neumann, M., Cisse, M., & Quinn, J. (2021). Continental-scale building detection from high-resolution satellite imagery. *arXiv preprint* arXiv:2107.12283.

USGS/NASA. (2023). *Landsat 8/9 surface reflectance composite* [Data set].

WorldPop. (2020). *Global high-resolution population data* [Data set]. University of Southampton. `https://www.worldpop.org`

theigc.org