CLIMATE MIGRATION AND SUSTAINABLE URBAN GROWTH IN THE LAKE VICTORIA BASIN SITE SUITABILITY MODELING AND STAKEHOLDER PREFERENCES

by

Huong Giang Duong

A thesis submitted

in partial fulfillment of the requirements

for the degree of

Master of Science

(Environment and Sustainability)

in the University of Michigan

April 2026

Thesis Committee:

Associate Professor Derek Van Berkel, Chair

Professor. Emerita Maria Carmen Lemos

Abstract

Global South cities are likely to receive large volumes of climate-induced migration, putting additional strain on existing urban areas by pushing up housing prices and overloading infrastructure systems. Nevertheless, spatial data gaps continue to limit planning in these cities. This study develops a geospatial decision-support approach for Kampala (Uganda), Eldoret (Kenya), and Mwanza (Tanzania) in the Lake Victoria Basin. We integrated multi-source open and remotely sensed datasets, including building footprints, population density, residential built-up areas, impervious surface products, transport networks, and terrain-hydrological variables, aggregated into 1-km hexagonal units. Urban development is defined as a binary outcome based on impervious-surface change, to create a site-suitability model that captures the status quo of urban expansion over the past 25 years. Logistic regression is used to model the probability of development. Results show strong predictive performance (AUC: 0.911-0.990) and are used to map development potential for scenario analysis. Across cities, development is more likely in areas with greater developable land and lower density, while avoiding flood-prone zones, indicating outward expansion rather than infill. Stakeholder engagement through participatory GIS, in general, substantiates these findings while also raising context-specific considerations, such as socio-demographic dynamics, land-use planning, and institutional constraints.

Acknowledgements

I would like to express my sincere gratitude to my advisors, Associate Professor Derek Van Berkel and Professor Emerita Maria Carmen Lemos, for their guidance and support throughout this research. I am especially grateful to Derek for his patience, excellent guidance, and continuous support throughout the development of this thesis. His expertise and encouragement have been instrumental in shaping both the direction and quality of this research.

This research has been conducted in the context of the Climate Adaptation and Resilience Strategies (CLARS): Socio-Economic Vulnerabilities among Urban Migrants in the Lake Victoria Basin and Great Lakes Region Project. I would like to thank people in my laboratory, Lisa, David, Yixin, and Xiaohao, for their support, discussions, and shared experiences, which have enriched my graduate journey. I would also like to thank all those who took part in the survey.

My appreciation also extends to the faculty and staff of the Environment and Sustainability program at the University of Michigan for providing a stimulating academic environment and the resources necessary to complete this research.

Finally, I am grateful to have had the people who have appeared in my life: my mom, my family, my best friends, and my significant other for their love, unwavering support, and encouragement throughout my studies. Their belief in me has been a constant source of strength, shaping and transforming my life time and time again.

This thesis is dedicated to all those who strive for sustainable and equitable solutions in the face of climate change.

Table of Contents

Abstract..... *ii*

Acknowledgements..... *iii*

I. Introduction..... **1**

II. Methodology..... **3**

2.1. Background..... **3**

2.2. Data acquisition..... **4**

2.3. Modeling/statistical modeling..... **6**

2.4. Stakeholder engagement and field meetings (PPGIS)..... **8**

III. Results..... **9**

3.1. Model estimation and overall fit..... **9**

3.2. Associations between covariates and development probability..... **9**

3.3. Spatial outputs: predicted development probability and classified potential..... **11**

3.4. Stakeholder Engagement: Survey Results..... **11**

IV. Discussion..... **13**

V. Conclusions..... **15**

Appendix..... *16*

Bibliography..... *18*

I. Introduction

Cities around the world are facing increasingly complex challenges due to the impacts of climate change, environmental degradation, and potentially population increases. In this context, urban adaptation and sustainability has become critical, particularly in light of projected large-scale climate migration. Climate migration is generally defined as the movement of individuals or groups, either voluntarily or involuntarily, within or across national boundaries, primarily in response to environmental changes associated with anthropogenic climate change (IMO, 2019).

Migration has long been perceived as a form of adaptation enabling individuals and families to adjust to changing environmental and socioeconomic conditions (Blocher et al., 2024; Chegere & Mrosso, 2022; McLeman et al., 2021). Increasingly, climate-induced mobility is projected to increase in response to the rising occurrence and unpredictability of extreme weather events (IPCC, 2022). A number of studies identify disasters as a principal driver of migration, which is already underway and projected to intensify in the coming years (IDMC, 2023). By 2050, an estimated 216 million people will experience internal displacement due to climate change, with that number potentially rising to 2 billion by 2100 under extreme scenarios, among which Sub-Saharan Africa is expected to bear the largest burden, with approximately 86 million people affected (Clement et al., 2021). To address this challenge, it is essential to assess not only the conditions of migrants themselves but also those of people in both the origin and destination communities (Blocher et al., 2024).

While there has been substantial research on migrants, and regions suffering from population loss, little has been done on potential receiving cities that will need to adapt to these potential new residents. Migration and development researchers emphasize that the arrival of migrants does not solely lead to disorder or overcrowding. On the contrary, cities experiencing population growth often benefit economically through filling labour and demographic gaps (Lee, 1966; Taylor, 1999; Foresight, 2011), and generating increased demand for goods and services (Blocher et al., 2024). In line with this emerging dynamic, particular attention should be paid to approach climate migration as an opportunity to develop comprehensive and anticipatory plans for sustainable and inclusive adaptation, rather than merely treating it as a hazard (Van Berkel et al., 2022)

Nowhere are these challenges and opportunities more emergent than in the cities of the Global South, where rates of urbanization are among the fastest in the world (Mahendra & Seto, 2019). By 2050, nearly 900 million more people are expected to live in cities across the continent, mostly in informal and peri-urban areas (Forget et al., 2021). Many of these cities are growing faster than their infrastructure and planning systems can handle. Rapid population growth from climate-driven migration is intensifying pressure on African cities. Many informal settlements within these cities struggle with inadequate or absent infrastructure services (Tietjen et al., 2023). Infrastructure disparities are widening most rapidly in urbanizing cities of the Global South, where uneven growth is making it harder to provide fair access to services (Pandey et al., 2025). The combination of these factors creates a serious challenge for urban planners, particularly amid multiple overlapping pressures.

The Lake Victoria region in East Africa is expected to receive climate migrants. It is home to the largest tropical freshwater lake in Africa, supporting the largest inland fishery in the world - yielding over one million tons of fish per year (Reviving Lake Victoria, n.d.). Cities around the lake are increasingly becoming destinations for climate-induced migration (World Bank, 2021a). Their abundant freshwater resources, fertile land, and economic opportunities make them attractive to displaced populations (Reviving Lake Victoria, n.d.). These cities are experiencing rapid population changes due to natural growth and climate-driven migration from nearby rural areas affected by water scarcity, declining agricultural productivity, and climate-induced flooding (World Bank, 2021b). Between April and July 2020, over 29,000 people were affected by floods in the basin, causing many rural residents to move to nearby urban and peri-urban areas for better opportunities (Pietroiusti et al., 2024; Tietjen et al., 2023). Moreover, climate change impacts, such as shifting hydrological cycles, extreme heat, and rising floods, are adding further pressure on these rapidly growing urban areas.

A major barrier to effective urban planning in fast-growing East African cities is their enduring colonial legacies, which still cause spatial segregation and unequal infrastructure (Baruah et al., 2021), especially in Anglophone cities. Under the British dual mandate, colonial governments planned only for European settler zones, leaving indigenous areas without formal planning. This approach created long-lasting spatial fragmentation (Baruah et al., 2021; Home, 2015). Unlike Francophone cities, which were laid out using grid structures, British colonies evolved with disconnected and irregular urban forms, often lacking integrated land use planning (Baruah et al., 2021; Bigon & Ross, 2020). As a result, these cities tend to be less compact and more spatially dispersed, making coordinated urban planning more difficult. Furthermore, the lasting effects of colonialism in these cities is apparent in inherited planning norms that perpetuate fragmented and inefficient urban development, namely dual land tenure systems, informal settlements, and Institutional Stickiness (Baruah et al., 2021).

The lack of coordinated urban development in African cities, shaped by colonial legacies and exacerbated by rapid urban growth, and the scenarios of climate-migration in the foreseen future (including the possible significant in-migration to urban centers) raise the critical question – under current planning policies, where would new settlements be formed if the area were to receive climate migrants? If approximately 300,000 people were to arrive over the next 30 years, what locations could accommodate this influx, infill or outward expansion, and which areas should be avoided due to environmental constraints or infrastructure-related risks? Changes in urban form and development trajectories under the pressures of climate-induced migration are not purely spontaneous within pre-existing inner-city systems; rather, they are continuously shaped by the influence of a multiplicity of interdependent factors (Van Berkel et al., 2022). Some of these are relatively fixed structuring conditions, such as accessibility and environmental constraints, waterway networks and associated distance surfaces, and topographic and hydrological settings. Others are path-dependent urban features that have accumulated over time, including the built environment (e.g., building footprints) and transport infrastructure (e.g., road networks). Still others are dynamic and evolving, such as population density and surface (e.g., residential land layers and impervious-surface estimates derived from remotely sensed data). In this context, there is a critical need to synthesize citywide data on environmental conditions, constraints, risks, and infrastructural capacity, and to visualize these indicators, use exploratory modeling and mapping to examine neighborhood-scale patterns relevant to climate risk, urban development, and informal

settlement dynamics to inform scenario-based discussions of where growth could be accommodated and where it should be avoided, and support decision making. However, many cities continue to face critical data deficiencies, including the absence of disaggregated urban data (Osuteye et al., 2017), up-to-date census data, digitized city plans, coherent spatial boundaries, and mapping datasets (Agyemang et al., 2024). These data gaps significantly hinder local governments' ability to plan inclusively, especially for increasingly diverse urban populations that now include climate migrants with distinct needs.

Recent developments in remote sensing and open-source geospatial data offer new ways to fill data gaps in urban planning. High-resolution satellite images and machine learning now make it possible to use building footprints to map up-to-date population distribution or planning resource distribution campaigns in much greater detail - something that was difficult before due to outdated surveys and limited census data (Chamberlain et al., 2024; Jochem & Tatem, 2021). These innovations facilitate spatially explicit analyses of urban morphology and growth patterns, offering new insights into settlement structures, informal neighborhoods, and peri-urban expansion (Prieto-Curiel et al., 2023). Nonetheless, these datasets are often disaggregated and not easily usable by local governments in their current form. There remains a critical need for comprehensive approaches that consolidate heterogeneous citywide datasets and operationalize them through scenario development and exploratory modeling, thereby reflecting the practical constraints and realities faced on the ground to support context-specific urban planning and decision-making.

This paper introduces a novel decision support approach designed specifically for Eldoret, Kampala and Mwanza city in the Lake Victoria Basin. We compiled an extensive set of spatial data for these African cities and their surrounding regions by integrating building footprint data, population estimates, accessibility metrics, residential and impervious surface datasets. These data allow users to visualize and explore urban density and settlement patterns within each city, improving understanding of where people are settling, what types of infrastructure are needed, and how to anticipate future change. The core component of the approach is a model that describes site suitability based on development patterns and is used as input to a public participatory GIS (PPGIS) stakeholder engagement. Specifically, the paper aims to: 1) to characterize urban development in receiving communities around Lake Victoria over the last 20 years to understand status quo planning and trends, 2) to collect preferences for development from key stakeholders, and 3) to compare these to understand key planning goals.

II. Methodology

2.1. Background

Cities around Lake Victoria in East Africa, including Kampala (Uganda), Eldoret (Kenya), and Mwanza (Tanzania) have been identified as future climate-migration destinations, which project that climate-related in- and out-migration hotspots will begin to emerge as early as 2030 and will intensify and expand geographically in subsequent decades (World Bank, 2021a). Population movements are predicted to shift away from areas where the ecosystems have become less viable (e.g., water scarcity and dwindling crop products) (Cai et al., 2016; Suhrke, n.d.; Warner et al., 2010) to inland urban and peri-urban areas (Marchiori et al., 2012), including the cities mentioned above (World Bank, 2021). It is predicted that

in-migration pressures in these destinations will shape housing demand, infrastructure needs, and the trajectory of urbanization (Alhalalmeh & Al-Tarawneh, 2025; Tacoli, 2009). To better understand and project potential expansion driven by climate migration, we estimated site suitability for development across these cities by assembling novel geospatial datasets and conducting a multi-stage spatial analysis. Specifically, we fitted statistical models using a set of explanatory variables likely to influence urban growth and produced site suitability maps for each city. We then presented maps of site suitability to experts and stakeholders familiar with local development processes and solicited feedback, as well as preferences for future development, using a public participatory GIS (PPGIS) approach. These inputs were integrated into the model outputs and compared with stakeholder preference maps to generate management-relevant insights for future urban planning (Lemos et al., 2018).

We compiled spatial datasets for the three cities and the surrounding region to characterize population distribution, urban form, infrastructure, and environmental conditions, including high-resolution population density estimates, building footprint datasets (Yang, 2025), mapped informal housing, road and waterway networks, and derived distance surfaces (e.g., Euclidean distance to the CBD). Land-use and surface characteristics are represented by residential layers at 100 m resolution (2005 - 2025, 5-year intervals) (*Global Human Settlement - Direct Download - European Commission*, n.d.) and by impervious surface estimates (2005 - 2025, annual) derived from remote sensing. Topographic and hydrological conditions are captured using DEMs and flow-direction products. To integrate inputs with differing spatial resolutions, formats (raster and vector), and temporal coverage, we aggregated and appended variables into the building-footprint and then into hexagons. Zonal statistics were performed to summarize raster-based variables and aggregated vector data on housing and infrastructure within each grid cell, compiling the results into a single spatial dataset.

In this research, we use historical development patterns as an empirical indicator of how these factors have interacted over time. By analyzing where growth has occurred and the conditions under which it took place, we assess how comparable pressures could shape future settlement outcomes. All data processing, spatial analysis, and aggregation were conducted in R, utilizing packages including **sf, terra, exactextractr, gdistance**, and **dplyr**

2.2. Data acquisition

2.2.1. Building footprint level

Building footprints and height attributes were derived from the 3D-GloBFP dataset (Suhrke, n.d.; Warner et al., 2010) with data acquisition and processing performed in R using the gloBFPr package (Yang, 2025). As building height should be considered to understand the city's population density, we retained vector building footprints containing building geometry and height. Building height rasters were masked by footprint polygons. Building volume was calculated by footprint area and mean height, in cubic meters.

Raster datasets (population, residential built-up, and impervious surface) were aggregated to building footprints via area-weighted extraction (exactextractr). Population distribution was derived from the 30 m High Resolution Population Density Maps produced by Facebook Data for Good (2020). Population per

building was estimated by allocating population counts proportionally to the share of each footprint's area within raster pixels. Residential built-up surface data were obtained from the Global Human Settlement Layer (GHSL), spanning 2005 - 2025 at 5-year intervals with a spatial resolution of 100 m. Values represent the residential built-up area (m^2) per cell (Figure 1). Area-weighted sums were computed within each footprint. Annual impervious surface data for 2005 - 2025 were compiled from satellite-derived products accessed through Google Earth Engine, using GAIA (2005 - 2018, 30 m) and Dynamic World (2019 - 2025, 10 m), quantified as area-weighted impervious surface fractions.

Road and waterway data were obtained from OpenStreetMap (HOTOSM) and rasterized to generate a composite cost surface, in which road cells were assigned low costs, waterway cells were assigned high costs, and all remaining cells were assigned moderate costs. Cost-distance modelling was performed at 30 m spatial resolution and implemented using a tiled (chunk-based) processing with **gdistance** package to compute the cost distances from centroids to roads.

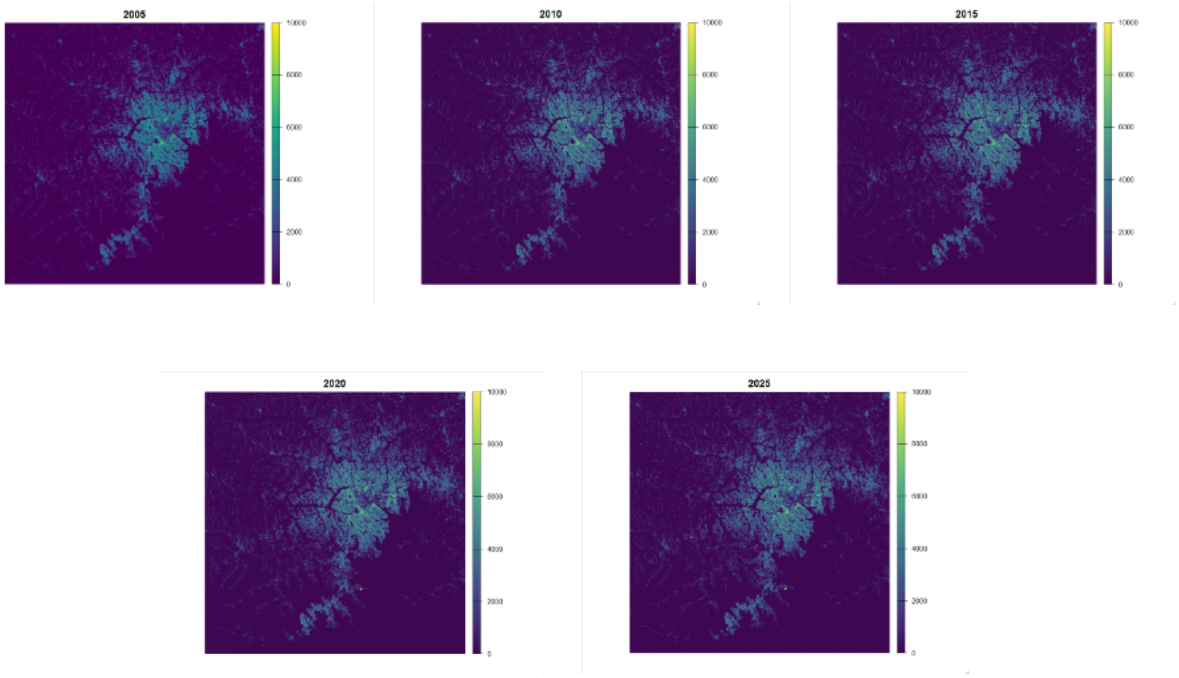


Figure 1. Residential built-up surface data were obtained from the Global Human Settlement Layer, 100m spatial resolution.

2.2.2. Hexagon aggregation

As no formal zoning or census tract data were available, each city was divided into hexagons with 1-km side lengths. This provided a consistent spatial framework for analysis across cities and enabled disaggregation of data to better capture neighborhood-level variation. Building footprints were spatially joined to hexagons and building-level metrics (building volume, height, area, population, residential built-up area, accessibility, and impervious change) were aggregated to hexagons using spatial joins and

group-by operations in R. Average people per building was computed at the hexagon level by first summing the population values of all buildings located within each hexagon, then dividing by the number of buildings in the same hexagon. The CBD was defined as the centroid of the hexagon with the greatest building volume and mean height, and Euclidean distances from each building to the CBD centroid were computed.

Digital elevation model (DEM) and flow direction (FD) were obtained from the Hydrologic Derivatives for Modeling and Analysis database for Africa (Kristine L Verdin, 2017). Elevation was aggregated as the median DEM value within each hexagon (terra), and FD (categorical) was summarized as the majority (modal) pixel value within each hexagon using the exactextractr package.

2.3. Modeling/statistical modeling

To characterize and evaluate site suitability for urban development, we adopt an exploratory modeling approach that relates observed development to multiple spatial datasets. Although urban change occurs through diverse processes (Angel et al., 2011; Seto et al., 2012), our analysis focuses on correlates of past built-up growth over the study period (Dutta et al., 2020). Impervious surfaces are widely used as indicators to assess and identify the level and density of urban development; therefore, we simplify the analysis by adopting a binary definition of development. Specifically, for each spatial unit we classify an area as developed if it exhibits a measurable increase in impervious surface over the study period, and as not developed otherwise. For each hexagon, we computed (i) the minimum imperviousness across all available epochs (2005 - 2025), and (ii) the net change in imperviousness between 2005 and 2025. We then used rule-based thresholds to classify each hexagon into one of four land-change categories to generate a city-wide overview of where and how urban change has occurred. All remaining cells not meeting the above criteria were classified as No Development (Figure 2).

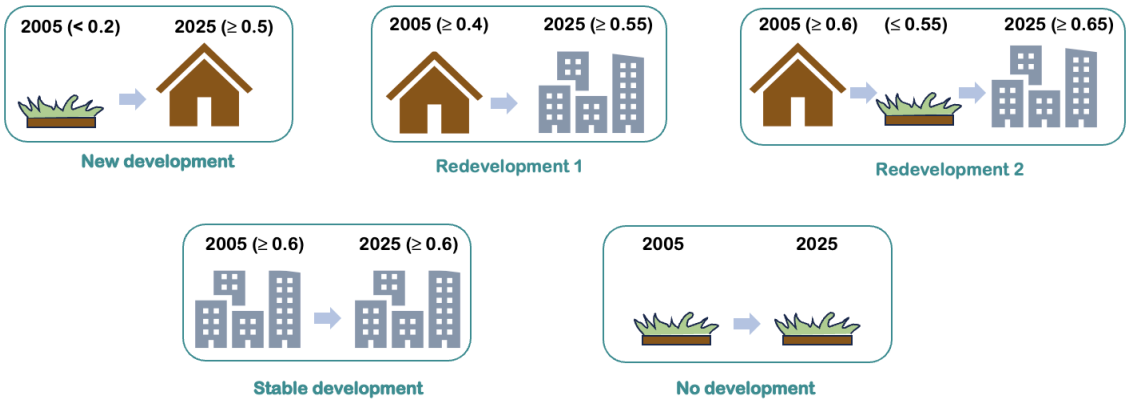


Figure 2. Development classification categories

This multi-class mapping summarizes the spatial distribution of development patterns and provides an interpretable baseline for stakeholders, including a consistent “development map” for each city. However, because the objective of this study is to characterize urban development in order to understand status quo planning and trends, and to support the elicitation of preferences for future development, we focus

the subsequent modeling and suitability assessment on the dominant category - New Development. For subsequent probability modeling, we focused on the New Development by converting the categorical outcome into a binary response variable (1 for “New Development”, 0 otherwise) (Figure 3 & 4).

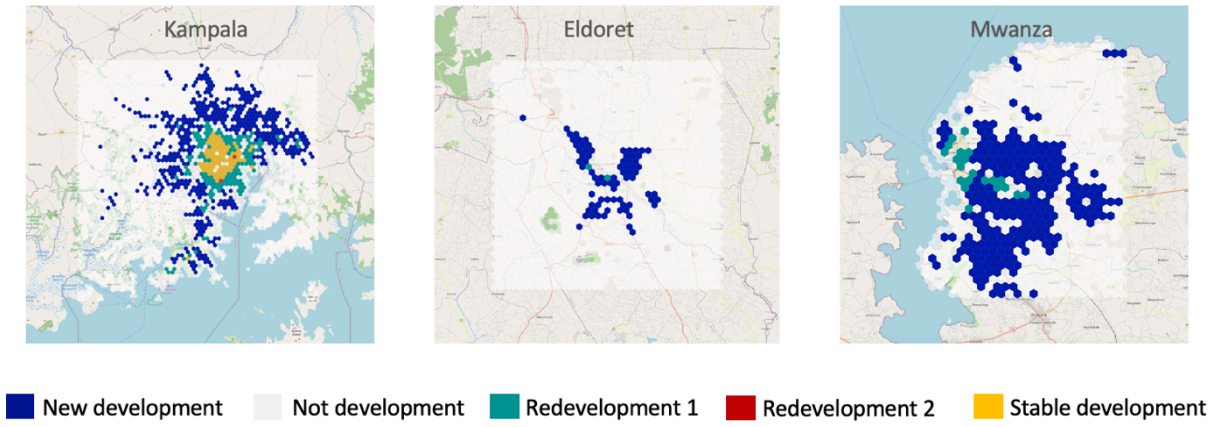


Figure 3. Development classification maps



Figure 4. Development classification counts by city

To model where development is likely to occur, we compiled environmental, accessibility, and built-environment predictors at the hexagon level and applied light transformations to improve interpretability and numerical stability. We log-transformed variables to reduce right-skewness and stabilize variance, defining log_Area = log(Area + 1), log_flood = log (flood_area + 1), and population growth as the log-difference pop_growth = log(residential_2020 + 1) − log(residential_2005 + 1); and

treated flow_direction as a categorical factor. Continuous predictors (distance to the CBD and roads, elevation, slope, average people per building, flood exposure, and growth terms) were standardized (z-scored) to place coefficients on comparable scales. Development probability was then estimated using a binomial logistic regression, with a binary response indicating whether a hexagon was newly developed between 2005 and 2025. Covariates captured (i) accessibility (distance to CBD and roads), (ii) topographic and hazard conditions (DEM, slope, flood area, flow direction), and (iii) baseline built environment and growth signals (log_Area, avg_people_per_building, pop_growth); distance to the CBD was modeled using a second-order polynomial to allow non-linear distance decay. Data were split into training (70%) and testing (30%) subsets using stratified sampling on the outcome, multicollinearity was assessed using variance inflation factors (VIF), and predictive performance was evaluated on the held-out test (%) set using the Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC), where higher AUC values indicate better ability to distinguish between developed and non-developed locations.

The Area Under the Curve (AUC) summarizes how well the model distinguishes between developed and non-developed locations. An AUC of 0.5 indicates no discriminative power, while values of 0.6 - 0.7 suggest limited performance. AUC values between 0.7 and 0.8 are considered acceptable, 0.8 - 0.9 indicate strong performance, and values above 0.9 reflect excellent discrimination, though they should be interpreted with caution due to potential overfitting. In applied planning contexts, AUC values above 0.7 are generally considered useful (Fawcett, 2006).

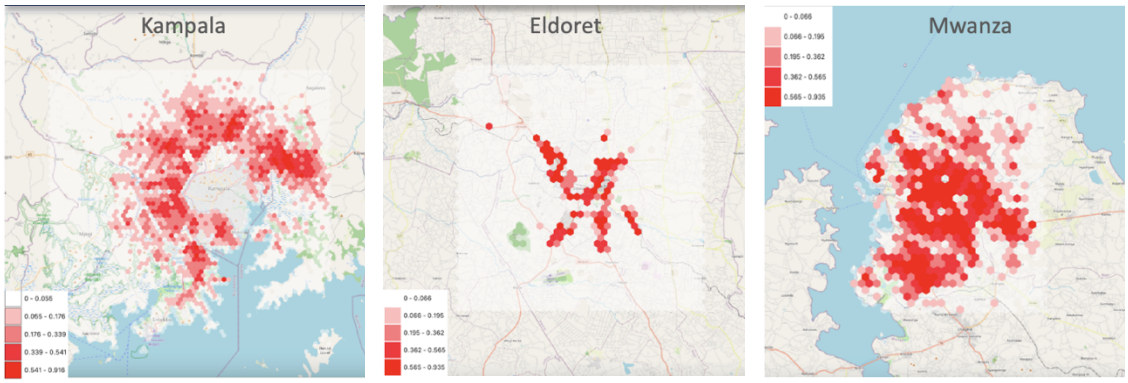


Figure 5. Predicted Probability of Development Maps

For each city, predicted probabilities were computed for all complete-case hexagons and mapped to visualize spatial variation in development likelihood. These probability surfaces are interpreted as relative likelihoods, locations more similar to those that developed during 2005 - 2025 under the included covariates rather than deterministic forecasts. For scenario communication, probabilities were also grouped into three ordinal classes: Low (0 - 0.33), Medium (0.33 - 0.66), and High (0.66 - 1.00) development potential (Figure 5).

2.4. Stakeholder engagement and field meetings (PPGIS)

To compare observed patterns of urban development with stakeholders' preferences, we implemented a stakeholder engagement process using a public participatory GIS (PPGIS) approach (Van Berkel et al.,

2023). Instead of asking participants to make explicit zoning decisions, the study invited them to express their views on the relative importance of key factors influencing urban development in their local context after being shown model-derived site-suitability outputs for each study city. This approach is grounded in evidence that co-production enhances the uptake and practical application of knowledge in decision-making by fostering mutual learning and engagement (Lemos et al., 2018) as reflected in the iterative comparison between model outputs and stakeholder perspectives. By structuring engagement around model-informed spatial information, the process enabled participants to reflect on how different environmental, infrastructural, and socio-economic factors shape urban development dynamics. Prior to consultations, we conducted a train-the-trainer day in each country/city to prepare facilitators (students and faculty) on site-suitability concepts, interpretation of model outputs, and the use of the mapping interface to support consistent facilitation across cities. We then held in-person meetings in each study city with experts and stakeholders familiar with local development processes, including NGOs and local planners. Site-suitability maps, developed above and representing status quo development suitability, were presented via ShinyApps through structured individual and group mapping activities (with additional layers introduced in a second round). Using these outputs as a reference point, participants completed structured individual and group exercises in which they expressed their preferences for key development-related factors.

III. Results.

3.1. Model estimation and overall fit

City-specific binomial logistic regression models showed good fit across all cities, effectively explaining the probability that a hexagon experienced development (New Development = 1; all other classes = 0) based on the available explanatory variables. In Kampala, the fitted model substantially improved upon the null model (null deviance = 1901.8; residual deviance = 1232.5), with an AIC of 1266.5, indicating strong explanatory power relative to an intercept-only specification. Eldoret and Mwanza models also showed large reductions in deviance relative to their null models (Eldoret: null deviance 406.700, residual deviance 84.769, AIC 116.77; Mwanza: null deviance 665.47, residual deviance 362.04, AIC 394.04), consistent with meaningful covariate signal. However, Eldoret fitted probabilities indicated (quasi-)separation due to the relatively small number of developed hexagons and warranting cautious interpretation of coefficient magnitudes. Variance inflation diagnostics indicated no problematic multicollinearity. Adjusted GVIF values were modest across cities (Kampala ≈ 1.01 - 1.81; Eldoret ≈ 1.06 - 2.43; Mwanza ≈ 1.03 - 2.12), supporting coefficient stability and interpretability. Model generalization was evaluated, holding-out test sets of 30% of observations, showing that discrimination was excellent in all three cities: AUC = 0.911 in Kampala, AUC = 0.99 in Eldoret, and AUC = 0.92 in Mwanza. While the Eldoret AUC indicates near-perfect separation in the test split, the combination of class imbalance and separation warnings suggests performance should be interpreted conservatively and validated with robustness checks in future work.

3.2. Associations between covariates and development probability

Across 3 cities, area (log transformed) was the strongest positive predictor, meaning that areas with larger built-up land area are likely to have higher development potential (Kampala log_Area: $\beta = 2.068$, $p < 2\times10^{-16}$; Eldoret: $\beta = 6.877$, $p = 1.03\times10^{-8}$; Mwanza: $\beta = 1.032$, $p = 3.04\times10^{-11}$). Accessibility to the CBD was

strongly associated with development in all cities. Modeled as a second-order polynomial, distance to the CBD exhibited a pronounced nonlinear relationship with development probability, indicating that the likelihood of development varies in more complex ways than a simple distance-decay assumption would imply. This means it is not simply that the closer a location is to the city center, the higher its development potential. In cases where the urban core is already densely developed, moving closer to the inner core beyond a certain point can actually reduce development potential. Particularly, in Kampala, both polynomial terms were significant ($\beta = -109.683$, $p < 2\times10^{-16}$; $\beta = -78.651$, $p = 3.23\times10^{-10}$). In Eldoret, the second polynomial term was significant ($\beta = -57.26$, $p = 0.015$), while the first term was marginal ($p = 0.089$). In Mwanza, the first polynomial term was significant ($\beta = -19.23$, $p = 0.00197$).

In contrast, higher occupancy intensity (avg_people_per_building) was associated with a lower probability of development in all three cities (Kampala: $\beta = -1.212$, $p = 1.10\times10^{-10}$; Eldoret: $\beta = -3.454$, $p = 5.71\times10^{-4}$; Mwanza: $\beta = -3.682$, $p = 3.74\times10^{-6}$) (Table 1).

Table 1. Translated variable direction for the model estimate. The full model result can be found in the supplemental material.

Variable	Eldoret	Kampala	Mwanza
Area	+***	+***	+***
Flood		-**	
People per building	-***	-***	-***
Distance to road	-	-	-*
DEM	-	+	+***
Slope	+	-	+
Residential (Population growth)	+	+	-
Distance to CBD	second-order polynomial (term1 −.; term2 −*)	second-order polynomial (term1 −; term2 −)	second-order polynomial (term1 −**; term2 −)

***** Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$;

In Kampala, flood exposure(log_flood) likewise showed a negative association ($\beta = -0.290$, $p = 0.00435$), suggesting that development is less likely in flood-prone areas, even after accounting for accessibility and terrain characteristics. Other variables, including population growth proxy (pop_growth), distance to roads (dist_road_30m), slope, and elevation (DEM) were not statistically significant at conventional thresholds (all $p > 0.10$). Flow-direction categories were generally not significant, though several levels showed marginal evidence ($p \approx 0.06$ - 0.10), suggesting hydrologic routing may contribute a limited additional signal beyond flood-area exposure.

In Eldoret, population growth proxy, distance to road, slope, and elevation were not statistically significant. Flow-direction levels were mostly not significant, with some marginal effects.

In Mwanza, road accessibility was significant: distance to road was negative ($\beta = -2.118\times10^{-4}$, $p = 0.015$), consistent with higher development likelihood in better-connected locations. Unlike Kampala and Eldoret, elevation (DEM) was positive and significant ($\beta = 0.0193$, $p = 9.05\times10^{-8}$). Several flow-direction categories were also significant (e.g., flow_direction2: $\beta = 1.552$, $p = 0.028$; flow_direction128: $\beta = 1.253$, $p = 0.024$), suggesting hydrologic structure captured additional spatial heterogeneity in development patterns.

3.3. Spatial outputs: predicted development probability and classified potential

All three cities classify hexagons into three categories: high potential, medium potential, and low potential (Figure 6). It is evident that Kampala, the capital city of Uganda, with a long history of development (*Kampala - ACRC*, 2021; Vermeiren et al., 2012), has a densely developed urban core where land for new development is nearly exhausted, resulting in low development potential in the central areas. In contrast, areas near the urban fringe (old town), which are not too far from the center and have less dense existing development, exhibit the highest development potential. Meanwhile, the relatively younger cities of Mwanza and Eldoret still retain significant development potential in their central areas, where many hexagons with high development potential are concentrated. These are also aligned along major road corridors, with medium-potential hexagons interspersed as they extend outward. In particular, as Mwanza is located along the shores of Lake Victoria, areas near the Lake also show high development potential.

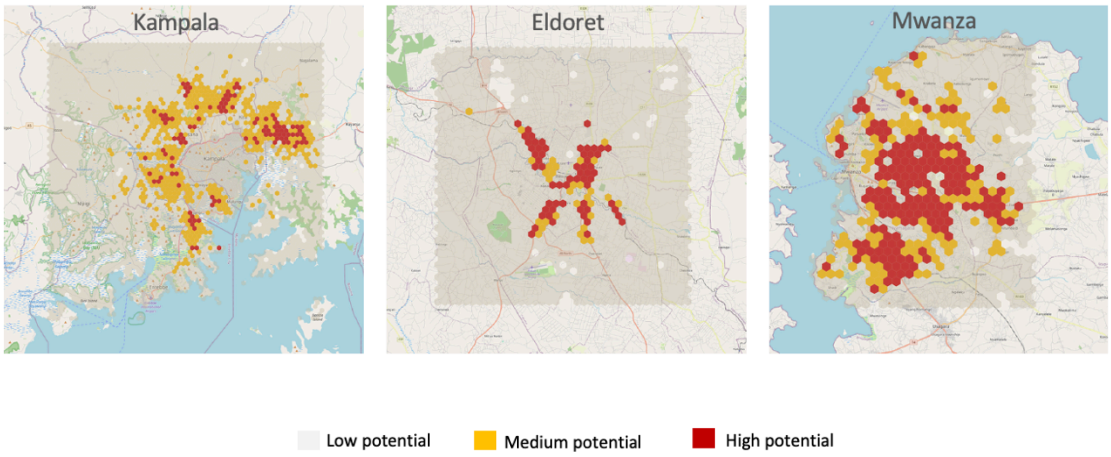


Figure 6. Classified potential maps

3.4. Stakeholder Engagement: Survey Results

In Kampala, responses are relatively concentrated around environmental and service-related constraints. The most dominant factor is exposure to climate risks, with 13 respondents indicating “a lot” when asked how much they considered each factor in their decision-making, clearly positioning climate-related concerns as the most salient issue. This is followed by access to water and sanitation (7 “a lot”) and infrastructure capacity (7 “a lot”), suggesting that basic service provision remains important but not uniformly dominant across respondents. In Eldoret, responses are more evenly distributed and generally less extreme. The most notable pattern is that infrastructure capacity receives 18 “somewhat”

responses and 6 “a lot”, suggesting that infrastructure is widely acknowledged but not perceived as an acute constraint. In Mwanza, the factors most strongly preferred by respondents are infrastructure capacity (12 “a lot”), climate risk exposure (10 “a lot”), and land availability (10 “a lot”), indicating that these considerations are perceived as having the strongest influence on stakeholders’ development decisions.

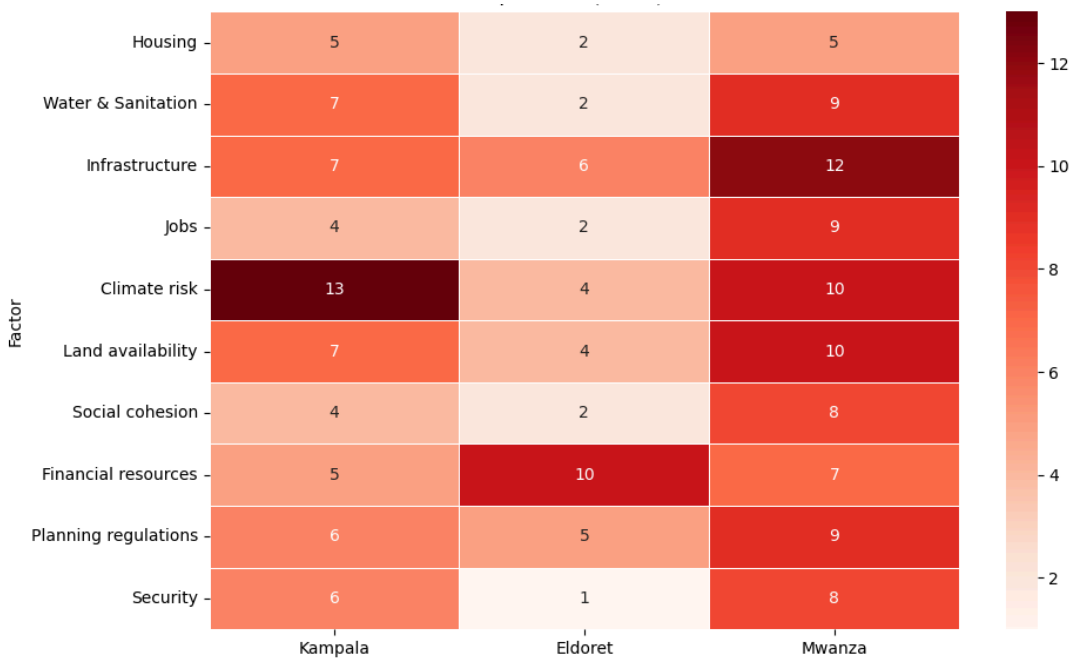


Figure 7. Stakeholders’ preferences (‘A lot’ responses) for key urban development factors across three cities.

First, the model shows that built-up area is the strongest positive predictor of development across all cities, which aligns closely with survey responses where infrastructure capacity is consistently rated highly important, particularly in Mwanza and Kampala. This suggests that respondents are implicitly recognizing the role of spatial concentration and existing urban form in shaping development potential. Second, the model finds that distance to CBD is strongly and nonlinearly associated with development probability in all cities, which corresponds with the high perceived importance of accessibility-related factors such as infrastructure and services, especially in Kampala (7 “a lot” for infrastructure and 7 for water services). This supports the idea that centrality remains a key organizing principle in urban development decisions. Moreover, participants consistently emphasized the importance of service provision, including access to healthcare, education, and public green spaces, as these amenities are perceived to strongly influence an area’s development potential Third, the model indicates that population density (people per building) is negatively associated with development in all cities, reflecting pressure and congestion effects. This is consistent with survey results where respondents in all cities assign relatively high importance to land availability and housing constraints, particularly in Mwanza (10 “a lot” for land availability), suggesting awareness of spatial saturation effects.

However, some mismatches are also observed. For example, although road accessibility is significant only in Mwanza in the model, respondents across all cities still report moderate to high importance of infrastructure access, suggesting that perception may be broader than what is captured in spatial regression outputs. The model identifies flood exposure as statistically significant in Kampala. This finding is consistent with stakeholder preferences and is particularly relevant given Kampala's low-lying topography, which makes it more prone to flooding and related impacts. However, for Eldoret and Mwanza, disaster-related layers could not be included in the model due to data unavailability. Despite this limitation, respondents in both cities still rate climate risks as highly important (with 10 and 12 combined "somewhat/a lot" responses in Eldoret). Notably, stakeholder engagement in Eldoret also highlighted landslides as a key local hazard, reinforcing the relevance of climate-related risks even where they are not explicitly captured in the spatial model.

In addition, respondents also referred to environmental (e.g., air and noise pollution) and ecological considerations, highlighting the importance of environmental quality and land-use planning constraints in shaping development preferences, which could be incorporated in the model. Importantly, results from the engagement also highlight data gaps in many African urban contexts, where several locally salient factors are not readily available in open-source spatial datasets, such as wetland encroachment in Kampala, mining-related pressures in Mwanza, agricultural land-use dynamics, and landslide risk in Eldoret. These examples underscore the importance of integrating locally grounded knowledge to complement spatial datasets and improve the representation of real-world development constraints.

Overall, while the model captures structural determinants of urban development such as area, accessibility, and density, the perception data highlight that respondents tend to generalize infrastructure and climate-related constraints more broadly across cities than what is statistically observed in spatial variation.

IV. Discussion

In this study, we have developed a site-suitability model that captures the urban status quo over the past 25 years and a site-suitability model for future development in Kampala, Eldoret, and Mwanza, alongside stakeholders' preferences regarding priority factors. This overview picture of receiving cities in Africa in the context of climate-induced migration is rarely combined due to limited data that is often outdated, unavailable, or inconsistent, especially at the neighborhood level (Agyemang et al., 2024; Osuteye et al., 2017). By integrating novel open-source geospatial datasets, we were able to integrate historical urban growth patterns with stakeholder-defined priorities in a unified spatial framework. This allows us to visualize these dynamics in a way that supports effective planning for future urban growth and identifies areas where observed development aligns with planning preferences and those where it does not, thereby providing a more grounded basis for understanding urban expansion and planning decisions.

Limitations

First, development in this study is operationalized as a binary outcome based on changes in the built-up surface. While this definition allows us to focus on identifying broad associations between development and environmental, infrastructural, and demographic conditions, rather than attempting to model the full complexity of urban changes, it collapses heterogeneous urbanization processes into a single class and

therefore cannot differentiate among infill, redevelopment, edge expansion, or incremental/informal growth (Brooks et al., 2011; Mustafa et al., 2018). As a result, the modeled relationships could be interpreted as correlates of net built-up change.

Second, the analysis is primarily driven by spatially explicit biophysical and land-cover proxies and does not directly represent economic, social, political, or institutional determinants of urban development. Factors not available to us, such as land tenure regimes, land-use plans, infrastructure governance, market dynamics, and local political economy, are important determinants of the location of development (McDonald et al., 2020), even when physical suitability is low.

Third, the hazard and constraint representation is not yet comprehensive. The current hazard layers do not explicitly incorporate several locally relevant constraints and risks, such as wetlands (in Kampala), urban heat, landslide susceptibility (in Eldoret), and conservation priorities nor do they account for infrastructure capacity or the presence of industrial/extractive land uses that can alter both feasibility and desirability of development (e.g., mining activity in Mwanza).

Regardless of these constraints, the results illustrate the practicality of a geospatially explicit and replicable suitability model. This model can effectively describe where built-up growth is more likely to occur under observed land-cover change patterns. Various development processes are responsive to different drivers and constraints, such as including formal subdivision, peri-urban conversion, self-built expansion, and redevelopment (Angel et al., 2011). However, within the simplified binary definition of development in the scope of this study, future work should move beyond a single binary outcome by distinguishing development typologies, particularly separating formal and informal processes. Doing so would improve both interpretability and policy relevance, enabling process-specific recommendations (e.g., infrastructure-led upgrading for informal growth versus reform for infill).

The second finding is the reinforcement of the hazard and constraint layers to represent more closely the multi-risk and multi-objective planning. The inclusion of wetlands (*GWO 2018*, n.d.), heat exposure, landslide-prone areas, and conservation areas would enhance the suitability outputs' ability to facilitate risk-sensitive and environmentally friendly urban development (de Sherbinin et al., 2019). The inclusion of infrastructure capacity would further transform the model from determining where development can take place without going beyond service limits, which is the key to sustainable urban growth management. It is also important to explicitly represent industrial or extractive land uses (e.g., mining) in places like Mwanza, since these activities may produce exclusion zones, conflicting land uses, and localized environmental impacts that alter urbanization trajectories (Niu et al., 2023; Zheng et al., 2025).

Third, a formal comparison between model-derived suitability maps and stakeholder preference maps should be further conducted. An alignment/misalignment evaluation can show where the technical suitability aligns with the community priorities. These comparisons can also help identify discrepancies between the two types of maps, such as missing variables in the model (e.g., land-use planning, industrial activities, or hazards) or variables that reflect differences in value systems or priority criteria (e.g., livelihoods or cultural landscapes). In turn, these insights can guide necessary model refinements and support the development of participatory scenarios.

Lastly, with the enhancement of hazard layers, infrastructure constraints, and typology of development, and the inclusion of stakeholder preferences in the process, resulting evidence can support more specific

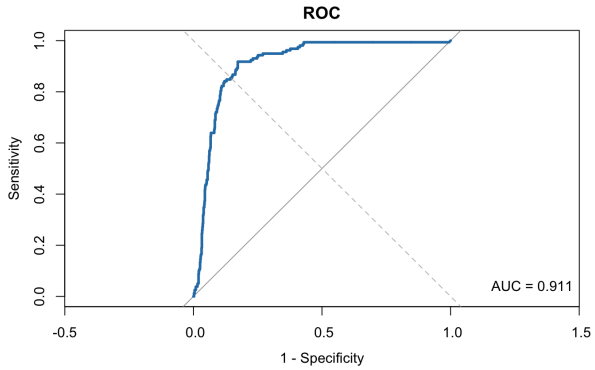
recommendations regarding sustainable and context-sensitive planning, including focusing on the development of serviced growth corridors, the protection of high value conservation and wetland systems, avoiding multi-hazard zones and interventions tailored to both formal and informal development dynamics. Overall, these results highlight the importance of merging data-driven site-suitability evaluations grounded in observed development patterns with a stakeholder-informed account of preferred future directions (Van Berkel et al., 2023).

V. Conclusions

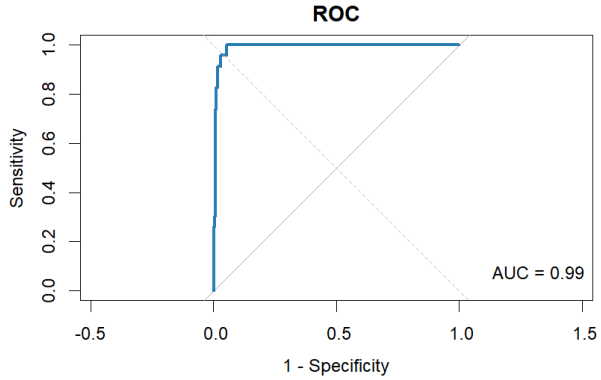
The future of cities in the Lake Victoria Basin is becoming increasingly uncertain, as both climate-induced migration and long-standing socio-economic and environmental constraints continue to shape urban development trajectories. By assembling novel open-source geospatial datasets, this study develops a site-suitability model that captures the status quo logic of urban expansion over the past 25 years, alongside stakeholders' preferences regarding priority factors for urban development. The analysis shows that current urban growth is strongly influenced by historical development patterns, while stakeholder perspectives provide complementary insights that, when compared with these spatial patterns, help clarify key planning priorities and goals.

Appendix

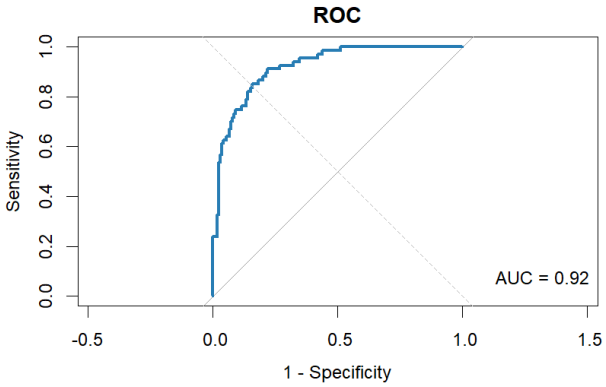
Kampala



Eldoret



Mwanza



Kampala

```
Call:
glm(formula = is_developed ~ log_Area + pop_growth + poly(euclidean_CBD,
    2) + dist_road_30m + slope + avg_people_per_building + DEM +
    log_flood + flow_direction, family = binomial, data = train_data)

Coefficients:
                          Estimate Std. Error z value Pr(>|z|)
(Intercept)               -4.17334    0.32048 -13.022  < 2e-16 ***
log_Area                   2.06809    0.17462  11.843  < 2e-16 ***
pop_growth                 0.08942    0.10959   0.816  0.41450
poly(euclidean_CBD, 2)1 -109.68301   11.78598  -9.306  < 2e-16 ***
poly(euclidean_CBD, 2)2  -78.65104   12.50957  -6.287 3.23e-10 ***
dist_road_30m             -3.14686    1.92999  -1.631  0.10299
slope                     -0.24139    0.15930  -1.515  0.12970
avg_people_per_building   -1.21155    0.18777  -6.452 1.10e-10 ***
DEM                        0.25157    0.13870   1.814  0.06970 .
log_flood                 -0.29017    0.10176  -2.852  0.00435 **
flow_direction2            0.23320    0.33617   0.694  0.48787
flow_direction4            0.19774    0.24384   0.811  0.41741
flow_direction8            0.26149    0.28743   0.910  0.36295
flow_direction16          -0.08409    0.21382  -0.393  0.69412
flow_direction32          -0.41180    0.43876  -0.939  0.34795
flow_direction64           0.02707    0.26049   0.104  0.91724
flow_direction128          0.16969    0.27402   0.619  0.53575
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Eldoret

```
Call:
glm(formula = is_developed ~ log_Area + pop_growth + poly(dist_t
    2) + dist_to_road + slope_median + avg_people_per_building +
    DEM + flow_direction, family = binomial, data = train_data)

Coefficients:
                            Estimate Std. Error z value Pr(>|z|)
(Intercept)               -6.176e+01  1.719e+01  -3.593 0.000327 *
log_Area                   6.877e+00  1.201e+00   5.726 1.03e-08 *
pop_growth                 5.718e-01  5.033e-01   1.136 0.255909
poly(dist_to_CBD, 2)1     -8.121e+01  4.772e+01  -1.702 0.088779 .
poly(dist_to_CBD, 2)2     -5.726e+01  2.358e+01  -2.428 0.015187 *
dist_to_road              -3.998e-05  1.073e-04  -0.372 0.709531
slope_median               3.189e-01  3.749e-01   0.851 0.394961
avg_people_per_building -3.454e+00  1.003e+00  -3.445 0.000571 *
DEM                       -7.875e-03  6.877e-03  -1.145 0.252156
flow_direction2           -3.786e+00  1.665e+03  -0.002 0.998186
flow_direction4            1.745e+00  1.992e+00   0.876 0.381147
flow_direction8            1.500e+00  1.705e+00   0.880 0.379036
flow_direction16           2.933e+00  1.677e+00   1.749 0.080273 .
flow_direction32           3.535e+00  1.817e+00   1.945 0.051720 .
flow_direction64           1.493e+00  1.887e+00   0.791 0.428871
flow_direction128          2.574e+00  2.306e+00   1.116 0.264215
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)
```

Mwanza

```
Call:
glm(formula = logit_formula, family = binomial, data = train_data)

Coefficients:
                            Estimate Std. Error z value Pr(>|z|)
(Intercept)               -3.195e+01  4.875e+00  -6.554 5.61e-11 ***
log_Area                   1.032e+00  1.553e-01   6.645 3.04e-11 ***
pop_growth                -2.899e-01  2.807e-01  -1.033  0.30174
poly(dist_CBD, 2)1        -1.923e+01  6.214e+00  -3.094  0.00197 **
poly(dist_CBD, 2)2        -6.885e+00  5.076e+00  -1.356  0.17501
dist_road                 -2.118e-04  8.743e-05  -2.422  0.01543 *
slope_median               1.851e-02  1.018e-01   0.182  0.85570
avg_people_per_building -3.682e+00  7.961e-01  -4.625 3.74e-06 ***
DEM                        1.931e-02  3.613e-03   5.345 9.05e-08 ***
flow_direction2            1.552e+00  7.079e-01   2.192  0.02838 *
flow_direction4            5.554e-01  5.498e-01   1.010  0.31243
flow_direction8           -2.575e-01  5.120e-01  -0.503  0.61500
flow_direction16          -3.188e-01  4.929e-01  -0.647  0.51780
flow_direction32          -3.411e-01  6.447e-01  -0.529  0.59674
flow_direction64          -1.714e-01  5.295e-01  -0.324  0.74615
flow_direction128          1.253e+00  5.568e-01   2.251  0.02439 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)
```

Bibliography

Baruah, N. G., Henderson, J. V., & Peng, C. (2021). Colonial legacies: Shaping African cities. *Journal of Economic Geography*, *21*(1), 29–65. https://doi.org/10.1093/JEG/LBAA026

Bigon, L., & Ross, E. (2020). Grid Planning in the Urban Design Practices of Senegal. *Grid Planning in the Urban Design Practices of Senegal*, 1–210. https://doi.org/10.1007/978-3-030-29526-4/COVER

Chamberlain, H. R., Darin, E., Adewole, W. A., Jochem, W. C., Lazar, A. N., & Tatem, A. J. (2024). Building footprint data for countries in Africa: To what extent are existing data products comparable? *Computers, Environment and Urban Systems*, *110*, 102104. https://doi.org/10.1016/J.COMPENVURBSYS.2024.102104

Clement, V., Rigaud, K. K., de Sherbinin, A., Jones, B., Adamo, S., Schewe, J., Sadiq, N., & Shabahat, E. (2021). *Groundswell Part 2: Acting on Internal Climate Migration*. World Bank, Washington, DC. https://hdl.handle.net/10986/36248

Forget, Y., Shimoni, M., Gilbert, M., & Linard, C. (2021). Mapping 20 Years of Urban Expansion in 45 Urban Areas of Sub-Saharan Africa. *Remote Sensing 2021, Vol. 13, Page 525*, *13*(3), 525. https://doi.org/10.3390/RS13030525

Home, Robert. (2015). *Colonial Urban Planning in Anglophone Africa*. 53–66. https://doi.org/10.4324/9781315797311-4

IDMC. (2023). *IDMC | GRID 2023 | 2023 Global Report on Internal Displacement*. https://www.internal-displacement.org/global-report/grid2023/

Jochem, W. C., & Tatem, A. J. (2021). Tools for mapping multi-scale settlement patterns of building footprints: An introduction to the R package foot. *PLOS ONE*, *16*(2), e0247535. https://doi.org/10.1371/JOURNAL.PONE.0247535

Mahendra, A., & Seto, K. C. (2019). *Upward and Outward Growth: Managing Urban Expansion for More Equitable Cities in the Global South*. https://www.wri.org/research/upward-and-outward-growth-managing-urban-expansion-more-equitable-cities-global-south

Pandey, B., Brelsford, C., & Seto, K. C. (2025). Rising infrastructure inequalities accompany urbanization and economic development. *Nature Communications 2025 16:1*, *16*(1), 1–12. https://doi.org/10.1038/s41467-025-56539-w

Pietroiusti, R., Vanderkelen, I., Otto, F. E. L., Barnes, C., Temple, L., Akurut, M., Bally, P., Van Lipzig, N. P. M., & Thiery, W. (2024). Possible role of anthropogenic climate change in the record-breaking 2020 Lake Victoria levels and floods. *Earth System Dynamics*, *15*(2), 225–264. https://doi.org/10.5194/ESD-15-225-2024

Prieto-Curiel, R., Patino, J. E., & Anderson, B. (2023). Scaling of the morphology of African cities. *Proceedings of the National Academy of Sciences of the United States of America*, *120*(9). https://doi.org/10.1073/PNAS.2214254120/FORMAT/EPUB

Tietjen, B., Jacobsen, K., & Hollander, J. (2023). Climate Change and Urban Migration in Sub-Saharan African Cities: Impacts and Governance Challenges. *Journal of Climate Resilience and Justice*, *1*, 20–32. https://doi.org/10.1162/CRCJ_A_00009

Alhalalmeh, A.-H., & Al-Tarawneh, A. (2025). Immigration and Infrastructure: Navigating the Impact on Transportation, Housing, and Healthcare. In A. Hannoon & A. Mahmood (Eds.), Intelligence-Driven Circular Economy: Regeneration Towards Sustainability and Social Responsibility—Volume 2 (pp. 563–574). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-74220-0_44

Angel, S., Parent, J., Civco, D. L., Blei, A., & Potere, D. (2011). The dimensions of global urban expansion: Estimates and projections for all countries, 2000–2050. Progress in Planning, The Dimensions of Global Urban Expansion: Estimates and Projections for All Countries, 2000–2050, 75(2), 53–107. https://doi.org/10.1016/j.progress.2011.04.001

Billbillbilly. (2025). gloBFPr/README.md at main · billbillbilly/gloBFPr. GitHub. https://github.com/billbillbilly/gloBFPr/blob/main/README.md

Brooks, N., Donaghy, K., & Knaap, G.-J. (2011). The Oxford Handbook of Urban Economics and Planning. Oxford University Press.

Cai, R., Feng, S., Oppenheimer, M., & Pytlikova, M. (2016). Climate variability and international migration: The importance of the agricultural linkage. Journal of Environmental Economics and Management, 79, 135–151. https://doi.org/10.1016/j.jeem.2016.06.005

de Sherbinin, A., Bukvic, A., Rohat, G., Gall, M., McCusker, B., Preston, B., Apotsos, A., Fish, C., Kienberger, S., Muhonda, P., Wilhelmi, O., Macharia, D., Shubert, W., Sliuzas, R., Tomaszewski, B., & Zhang, S. (2019). Climate vulnerability mapping: A systematic review and future prospects. WIREs Climate Change, 10(5), e600. https://doi.org/10.1002/wcc.600

Dutta, D., Rahman, A., Paul, S. K., & Kundu, A. (2020). Estimating urban growth in peri-urban areas and its interrelationships with built-up density using earth observation datasets. The Annals of Regional Science, 65(1), 67–82. https://doi.org/10.1007/s00168-020-00974-8

Global Human Settlement—Direct download—European Commission. (n.d.). Retrieved April 19, 2026, from https://human-settlement.emergency.copernicus.eu/download.php

GWO 2018. (n.d.). Global Wetland Outlook. Retrieved April 19, 2026, from https://www.global-wetland-outlook.ramsar.org/gwo-2018

Lemos, M. C., Arnott, J. C., Ardoin, N. M., Baja, K., Bednarek, A. T., Dewulf, A., Fieseler, C., Goodrich, K. A., Jagannathan, K., Klenk, N., Mach, K. J., Meadow, A. M., Meyer, R., Moss, R., Nichols, L., Sjostrom, K. D., Stults, M., Turnhout, E., Vaughan, C., … Wyborn, C. (2018). To co-produce or not to co-produce. Nature Sustainability, 1(12), 722–724. https://doi.org/10.1038/s41893-018-0191-0

Marchiori, L., Maystadt, J.-F., & Schumacher, I. (2012). The impact of weather anomalies on migration in sub-Saharan Africa. Journal of Environmental Economics and Management, 63(3), 355–374. https://doi.org/10.1016/j.jeem.2012.02.001

McDonald, R. I., Mansur, A. V., Ascensão, F., Colbert, M., Crossman, K., Elmqvist, T., Gonzalez, A., Güneralp, B., Haase, D., Hamann, M., Hillel, O., Huang, K., Kahnt, B., Maddox, D., Pacheco, A., Pereira, H. M., Seto, K. C., Simkin, R., Walsh, B., … Ziter, C. (2020). Research gaps in knowledge of the impact of urban growth on biodiversity. Nature Sustainability, 3(1), 16–24. https://doi.org/10.1038/s41893-019-0436-6

Mustafa, A., Van Rompaey, A., Cools, M., Saadi, I., & Teller, J. (2018). Addressing the determinants of built-up expansion and densification processes at the regional scale. Urban Studies, 55(15), 3279–3298. https://doi.org/10.1177/0042098017749176

Niu, H., Wang, J., Jing, Z., & Liu, B. (2023). Identification and management of land use conflicts in mining cities: A case study of Shuozhou in China. Resources Policy, 81, 103301. https://doi.org/10.1016/j.resourpol.2023.103301

Norström, A. V., Cvitanovic, C., Löf, M. F., West, S., Wyborn, C., Balvanera, P., Bednarek, A. T., Bennett, E. M., Biggs, R., de Bremond, A., Campbell, B. M., Canadell, J. G., Carpenter, S. R., Folke, C., Fulton, E. A., Gaffney, O., Gelcich, S., Jouffray, J.-B., Leach, M., … Österblom, H. (2020). Principles for knowledge co-production in sustainability research. Nature Sustainability, 3(3), 182–190. https://doi.org/10.1038/s41893-019-0448-2

Suhrke, A. (n.d.). Pressure Points: Environmental Degradation, Migration and Conflict.

Tacoli, C. (2009). Crisis or adaptation? Migration and climate change in a context of high mobility. Environment and Urbanization - ENVIRON URBAN, 21, 513–525. https://doi.org/10.1177/0956247809342182

Van Berkel, D., Estabrook, T., Fox, N., Bejarano, R. A., Maillard, L., Gill, D., Goto, E. A., & Lemos, M. C. (2023). PPGISr: An R package for Public Participatory GIS. SoftwareX, 22, 101389. https://doi.org/10.1016/j.softx.2023.101389

Van Berkel, D., Kalafatis, S., Gibbons, B., Naud, M., & Lemos, M. C. (2022). Planning for Climate Migration in Great Lake Legacy Cities. Earth's Future, 10(10), e2022EF002942. https://doi.org/10.1029/2022EF002942

Warner, K., Hamza, M., Oliver-Smith, A., Renaud, F., & Julca, A. (2010). Climate change, environmental degradation and migration. Natural Hazards, 55(3), 689–715. https://doi.org/10.1007/s11069-009-9419-7

World Bank. (2021). Groundswell Africa: A Deep Dive Into Internal Climate Migration in Uganda [Text/HTML]. World Bank. https://documentos.bancomundial.org/es/publication/documents-reports/documentdetail/en/101161634533716676

Yang, X. (2025). gloBFPr: Access Global Building Height Datasets (Version 0.1.3) [Computer software]. https://cran.r-project.org/web/packages/gloBFPr/index.html

Zheng, Y., Wang, K., & Hao, R. (2025). Dynamic mechanisms of land use spatial conflicts in mining cities: A case study of Xintai City, China. Resources, Environment and Sustainability, 19, 100197. https://doi.org/10.1016/j.resenv.2025.100197