Understanding Informal Settlement Transformation through Google's 2.5D Dataset and Street View based Validation

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Abstract

Monitoring change in informal settlements remains a critical challenge, particularly in data-scarce contexts across the Global South. While satellite remote sensing provides strong temporal coverage, conventional approaches for mapping the built environment often rely on very high-resolution imagery or LiDAR, which lack consistent temporal availability and are costly to scale especially for capturing vertical growth. This study leverages Google's Open Buildings 2.5D Temporal Dataset (2016-2023), which offers annual estimates of building presence, count, and height, to detect structural change in Nairobi, Kenya. By analysing differences in building count and average height across 100-meter grid cells, we developed a rule-based framework to identify four key transformation types: vertical densification, horizontal densification, combined densification (increase in both count and height), and decline. To our knowledge, this is the first study to use this dataset to assess vertical change within informal settlements. Validation was conducted through a two-source approach using historical satellite imagery (Google Earth Pro) and archival street-level imagery (Google Street View). A total of 154 grid cells across 13 slum areas were manually assessed, yielding an overall accuracy of 96.75%. Horizontal and combined densification showed perfect agreement, while vertical densification and decline categories had over 80% accuracy. Spatial analysis across slums, adjacent buffer areas, and the broader city revealed horizontal densification as the dominant trend within informal settlements, while vertical and combined growth were more prominent in surrounding zones. These results demonstrate the potential of Google's 2.5D dataset for scalable, interpretable urban monitoring in rapidly changing environments.

1. Introduction

Rapid urbanization is transforming cities across globe, with the most dramatic growth in the Global South. By 2050, the world's urban population is projected to increase by 2.5 billion people, and nearly 90% of this growth will occur in cities in Asia and Africa (Sirko et al., 2023). This surge has strained the capacity of cities to provide adequate housing and infrastructure. In many countries, formal housing production cannot keep up, leading to a proliferation of informal settlements. As of 2018, over one billion people lived in slums or informal settlements worldwide (Aboulnaga et al., 2021). Such settlements often expand rapidly and organically, outpacing official data collection. Planners and policymakers require up-to-date information on these changes to guide sustainable urban development, but many regions in the Global South lack access to reliable data on building stocks and their evolution (Sirko et al., 2023). This data gap hampers effective planning, disaster risk management, and service provision in the very places experiencing the fastest urban growth.

Informal settlements present unique challenges for urban monitoring. They are typically high-density, self-built environments, growing incrementally in ways that defy formal planning regulations. Their ever-changing nature is a defining feature: structures are continually added or modified, sometimes expanding vertically when no more land is available (Georganos et al., 2021; Samper et al., 2020). Yet these communities are often under-mapped – at present, there is no comprehensive global inventory of informal settlement footprints or morphologies. The lack of consistent, longitudinal data on informal urban growth is problematic. Variation over time in the extent and density of these settlements creates challenges for city management and humanitarian response (Samper et al., 2020). Understanding not just where informal settlements are, but how they are changing – including vertical densification (additional floors or taller structures) is critical for addressing issues from overcrowding to infrastructure delivery. Tracking such change, however, is inherently difficult: informal construction is usually unpermitted and often falls outside official surveys and censuses.

Earth Observation data offer a promising avenue to close this information gap. Satellite imagery has long been used to detect urban expansion, but traditionally this required very high-resolution images or LiDAR to identify individual buildings. Such data can be prohibitively expensive and infrequent for large-scale analyses in the Global South. In practice, the scarcity of up-to-date very high-resolution imagery has limited our ability to systematically study urban changes over time – especially in informal settlements where change is continuous (Sirko et al., 2023). Recent advances in remote sensing analytics, however, are overcoming these hurdles. Google's Open Buildings initiative has provided new data resources for mapping urban areas even in data-sparse regions. In 2021, the first Open Buildings dataset was released, mapping millions of building footprints across Africa and later parts of Asia and Latin America (Sirko et al., 2021). This effort significantly increased public knowledge of built-up structures in those regions and has been used by UN agencies and NGOs for applications such as electrification planning and disaster response. However, this initial dataset was essentially a static snapshot. Users quickly identified the need for temporal data – information on how building patterns change year by year and for approximate building heights to estimate densities. Both aspects are crucial for understanding urban dynamics but were lacking in existing open datasets.

To address these gaps, Google recently introduced the Open Buildings 2.5D Temporal dataset, a novel source of multi-

This contribution has been peer-reviewed.

temporal building information. This dataset provides annual maps of building presence, counts, and estimated heights from 2016 to 2023 across roughly 58 million square kilometres of the Global South. It leverages the high revisit frequency of the ESA's Sentinel-2 satellite (with ~5-day coverage at 10m resolution) to derive building data at an effective spatial resolution of about 4 meters (Sirko et al., 2023). In essence, machine learning models aggregate numerous low-resolution images to produce a sharper view of urban development over time. The result is a first-of-its-kind open dataset capturing both where buildings are appearing and how tall they are growing, year by year. This represents a significant advance for urban remote sensing: it adds a vertical dimension (2.5D) to temporal change detection at large scale. With this data, researchers and practitioners can, for the first time, systematically track vertical growth in informal settlements alongside horizontal expansion. Such capabilities can improve population estimates (by accounting for multi-storey housing), enhance disaster impact models (tall, crowded structures can exacerbate risks), and inform upgrading interventions by pinpointing areas of rapid densification.

Despite the promise of the Open Buildings 2.5D dataset, its application to real-world urban challenges is still being explored. In particular, no prior studies have systematically assessed its potential to detect different forms of densification – especially vertical change within informal settlements. This study addresses that gap by applying the dataset to Nairobi, Kenya, a city where over 60% of the population lives in informal settlements with limited infrastructure and fast-changing built environments (Georganos et al., 2021). By focusing on both horizontal and vertical transformation patterns, and validating these patterns using satellite and Google Street View imagery, we offer one of the first empirical demonstrations of the dataset's utility for scalable urban change monitoring in data-scarce informal contexts.

1.1 Research Aim & Objectives

The overarching aim of this study is to assess the potential of Google's 2.5D building dataset for detecting and validating urban change within informal settlements in Nairobi, with a focus on leveraging both building count and height information for scalable, interpretable analysis. The two research objectives are:

1. To develop a grid-based framework for classifying urban change using building count and height differences derived from Google 2.5D dataset (2016-2023), focusing on key categories such as vertical densification, horizontal densification, high densification, and decline.
2. To validate the classified urban change patterns within informal settlement regions using satellite and street view imagery, and to analyse the spatial distribution of these patterns across informal settlements, surrounding buffer zones, and other city regions to assess the potential of the dataset for broader urban monitoring.

2. Material and Methods

2.1 Data Sources

This study relies on four key datasets: Google's 2.5D building dataset, slum boundaries from IDEAtlas, the Nairobi administrative boundary from the Humanitarian Data Exchange (HDX), and historical imagery from Google Earth and Google Street View platforms. These datasets enable temporal urban change detection and spatial validation of patterns within informal settlement contexts.

The Google Open Buildings 2.5D Temporal Dataset provides annual building footprint and height estimates from 2016 to 2023 across Africa, South Asia, South-East Asia, Latin America, and the Caribbean. It is generated using open-source, Sentinel-2 imagery and offers building presence, fractional count, and average building height at an effective resolution of 4 meters (distributed at 0.5-meter raster resolution) (Sirko et al., 2023). For this study, only the data from 2016 and 2023 were used, focusing on the earliest and most recent temporal snapshots to assess structural changes. The dataset was accessed and downloaded from Google Earth Engine at 0.5-meter resolution.

The slum boundary data were obtained from the IDEAtlas platform and the IDEAMAPS Network (Thomson et al., 2020), which provide curated reference datasets of informal settlements across multiple cities. The slum boundaries for Nairobi serve as a reliable spatial reference for identifying and analysing patterns of urban change specific to informal settlements. To define broader urban context, the administrative boundary for Nairobi was sourced from the Kenya Administrative Level 0-2 Boundaries (COD-AB) dataset, hosted on the HDX platform (https://data.humdata.org/dataset/cod-ab-ken).

For ground-truth validation, this study used historical imagery from Google Earth Pro (for satellite views) and Google Street View (for panoramic, ground-level images). These tools enabled manual inspection of physical changes in building presence and structure over time, supporting the qualitative verification of urban change categories.

2.2 Urban Change Classification

To detect and classify urban change across Nairobi, a 100 x 100 meter reference grid provided by IDEAtlas was used as the analytical unit. Using Google's 2.5D building dataset, zonal statistics were computed to extract the total building count and average building height within each grid cell for the years 2016 and 2023. The raster layers representing building presence and height were processed using spatial masking, and statistical summaries were assigned to each grid polygon. These statistics formed the foundation for identifying structural changes over time.

Following this, the difference in building count and average height between 2016 and 2023 was calculated for each grid. To interpret the changes meaningfully, each difference metric was categorized into one of the three classes: decrease, stable, or increase. For building count, thresholds were derived using the interquartile range (IQR) method, with a minor adjustment to the lower bound to account for noise associated with the synthetic nature of the dataset. The resulting classification was as follows:

- Decrease: count difference < -1.0
- Stable: $-1.0 <$ count difference < 6.34
- Increase: count difference > 6.34

For average building height, a fixed threshold of ± 1.8 meters was applied, informed by literature suggesting that one floor in informal settlements typically equates to approximately 1.8 meters in height (Kraff et al., 2019). Accordingly:

- Decrease: height difference < -1.8 meters
- Stable: -1.8 meters $<$ height difference < 1.8 meters
- Increase: height difference > 1.8 meters

By combining the classified changes in both metrics, each grid cell was assigned to one of the eight urban change categories, capturing diverse patterns of growth or decline. These include stable areas, various forms of densification (horizontal, vertical, and high), decline, and mixed trends (e.g., more buildings but shorter structures). Table 1 summarizes the rule-based logic used to derive these categories.

This study focuses on four categories of particular interest due to their relevance in the context of informal settlements and urban transformation: Vertical Densification, Horizontal Densification, High Densification, and Decline. These categories capture the most salient patterns of upward and outward growth, as well as declining or structural loss, within the city's built environment.

Urban change category	Building count change	Average height change	Description
Stable	Stable	Stable	No major change
Vertical densification	Stable	Increase	Taller buildings added
Horizontal densification	Increase	Stable	More buildings added
Combined (High) densification	Increase	Increase	Taller and more buildings
Decline	Decrease	Decrease	Fewer and shorter buildings
Mixed Trend 1	Increase	Decrease	More buildings but shorter structures
Mixed Trend 2	Decrease	Increase	Fewer buildings but taller structures
Partial Decline	Stable / Decrease	Decrease / Stable	Partial loss in structures

Table 1. Rule-based classification logic for urban change categories

2.3 Spatial Zone Delineation

To contextualize the spatial distribution of urban change across different parts of the city, three distinct spatial zones were delineated: slum areas, a 100-meter buffer ring surrounding slums, and the remaining urban areas within the city boundary (Friesen et al., 2018). These zones provide a comparative framework to assess the concentration and nature of change across informal and formal urban contexts.

The Nairobi city boundary, sourced from the HDX platform, served as the outer boundary encompassing all slum and buffer regions. The informal settlement boundaries were clipped to this city boundary to include only those portions of slums that fall within the administrative limits of Nairobi. To represent regions adjacent to informal settlements, a 100-meter buffer was generated around the slum boundaries. These buffer polygons were dissolved into a single contiguous geometry. To avoid double counting, areas overlapping with the original slum boundaries were subtracted from the buffer. The resulting buffer ring captures areas immediately surrounding the slums, excluding those already designated as slum areas.

Finally, the remaining city regions were derived by subtracting both the clipped slum boundaries and the clipped buffer ring from the Nairobi city boundary. This step ensured that all three spatial zones – slums, buffer ring, and other regions – were mutually exclusive and entirely contained within the city.

All subsequent area calculations and visualizations of the four urban change categories were performed across these three spatial zones.

2.4 Validation process

To assess the reliability of the urban change classifications, a manual validation procedure was conducted at the grid level, focusing exclusively on grid cells located within informal settlement boundaries. For each of the four targeted change categories – Vertical densification, Horizontal densification, High densification, and decline – the five slums with the largest area of corresponding classified grids were selected for validation.

Validation was carried out through visual interpretation of historical satellite imagery accessed via Google Earth Pro and street-level imagery accessed via Google Street View, depending on availability. Both tools allowed for a comparison of building presence and structural characteristics between 2016 and 2023, the two temporal endpoints used in this study.

The validation involved comparing the predicted urban change category with the observed change based on visual inspection, for a selected set of grids within each slum. This comparison formed the basis for constructing a confusion matrix, from which accuracy metrics such as overall accuracy, user's accuracy, and producer's accuracy were derived.

It is important to note that the validation of the classification model in this study is limited to four change categories and does not include validation of a 'Stable' class. However, the validation process allowed for the inclusion of 'Stable' as a reference class to capture potential overclassifications.

3. Results and Discussion

3.1 Building count and height change patterns

As illustrated in Figure 1, the majority of grid cells across Nairobi remained stable between 2016 and 2023, with 67.9% showing no significant change in building count and 82.1% remaining stable in average building height. This suggests that a large portion of the city's built environment has not undergone substantial structural transformation during this period, at least not while using a spatial resolution of 100 x 100 meters.

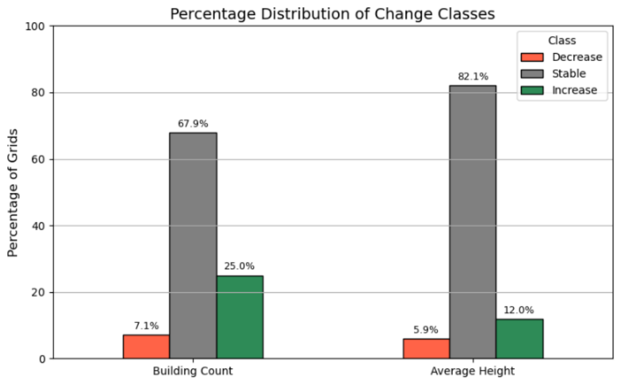


Figure 1. Distribution of change classes for building count and average height (2016-2023).

Notably, 25% of the grids showed an increase in building count, indicating a clear trend of horizontal expansion through the addition of new structures. In contrast, only 12% of grids exhibited an increase in average building height, pointing to a more limited extent of vertical growth. This disparity implies that horizontal densification is more prevalent than vertical densification during the study period.

The share of grids exhibiting a decrease in either indicator was relatively small – 7.1% for building count and 5.9% which may reflect localized processes of demolition or gradual structural decline. However, such decreases must be interpreted with caution, as they could also result from artefacts in the synthetic dataset or from noise along grid boundaries.

These underlying trends highlight the dominant spatial logic of change across Nairobi, where growth is occurring more frequently through increased footprint coverage rather than upward vertical extension. These patterns provide the structural basis for the more nuanced urban change typology discussed in the following section.

3.2 Urban change categories: Citywide and within Informal settlements

Figure 2 presents the citywide distribution of grid cells across all eight defined urban change categories. A majority of the city's grid cells (57.9%) were classified as stable, indicating limited or no detectable change in both building count and average height between 2016 and 2023.

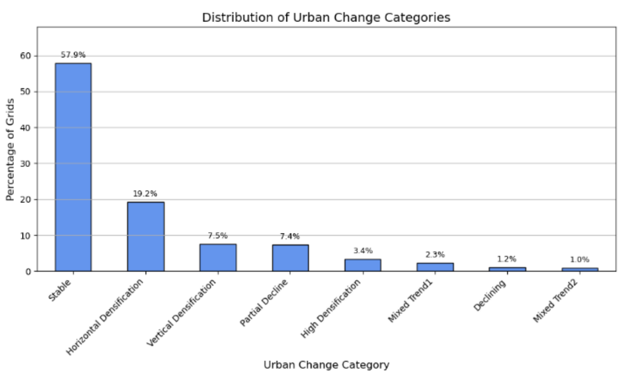


Figure 2. Distribution of classified urban change categories across all 100m grid cells in Nairobi (2016-2023).

Among the changing categories, horizontal densification is the most prevalent, observed in 19.2% grids. This reflects the city's dominant mode of urban growth through the addition of new structures without significant increases in building height. Vertical densification and partial decline are observed in 7.5% and 7.4% of grids respectively, indicating moderate levels of structural transformation through vertical extension or partial loss of built volume.

More intensive forms of change, such as high densification – an increase in both count and height are relatively limited, making up 3.4% of the grid cells. The declining category is even less common, accounting for only 1.2% while mixed categories are rare, each constituting less than 2.5% of the total.

Figure 3 focuses specifically on grid cells located within informal settlements. In contrast to the citywide pattern of broad structural stability, horizontal densification emerges as the overwhelmingly dominant category in slums, accounting for 52.2% of all classified grids. Stability, by comparison, accounts for only 20.9%, while partial decline and other categories appear in lower proportions. This suggests that while much of the broader urban fabric remains unchanged, informal settlements are experiencing significant physical transformation – primarily through lateral expansion of built structures. These findings reinforce the need for localized analysis of urban change processes, especially in informal areas where citywide summaries may obscure underlying dynamics.

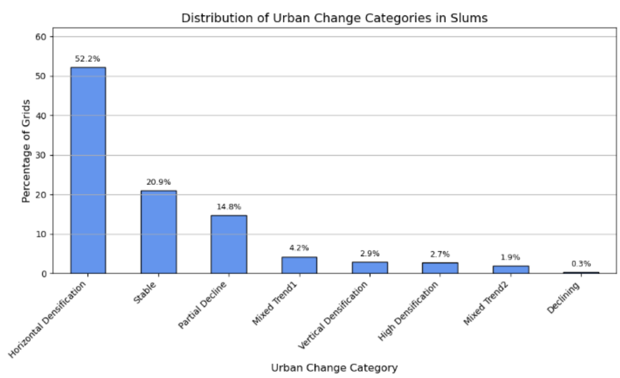
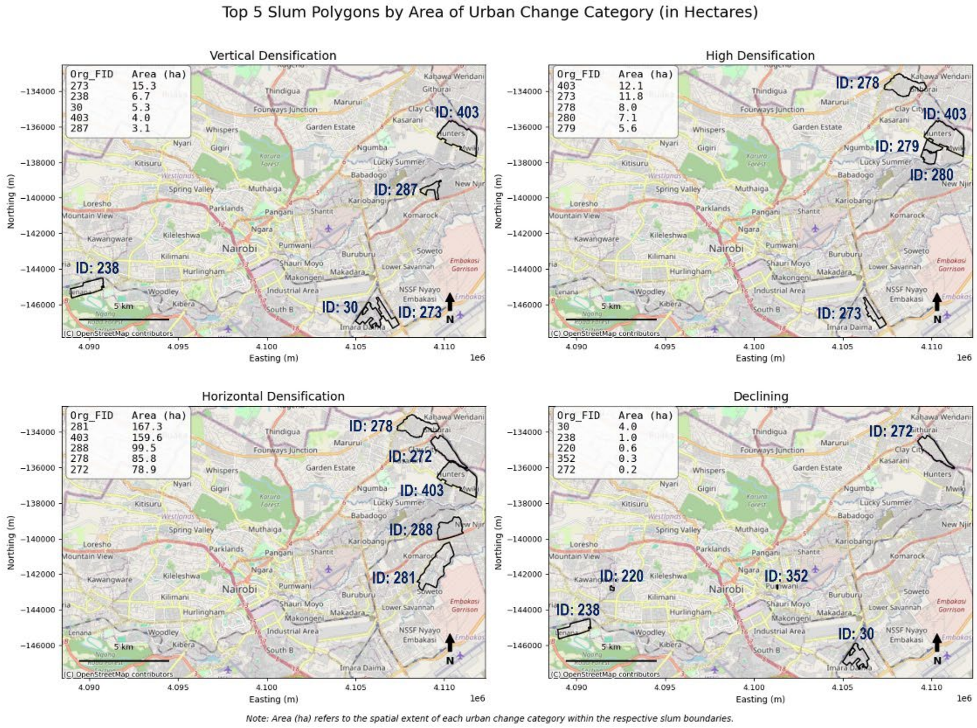


Figure 3. Distribution of classified urban change categories within informal settlements of Nairobi (2016-2023)

3.3 Validation in selected slum areas

To assess the reliability of the urban change classifications, a structured validation was conducted across a subset of slum areas. For each of the four focus categories – vertical densification (VD), horizontal densification (HorD), high densification (HigD), and decline (Dec) – the five slum boundaries with the largest area of classified grids were selected for manual inspection. This selection resulted in 13 unique slum polygons, many of which exhibited multiple categories simultaneously (Figure 4).

Validation was performed at the grid-cell level using two complementary sources: historical satellite imagery (via Google Earth Pro) and archival street-level imagery (via Google Street View). This dual-source approach enabled verification of both horizontal and vertical changes. Google Street View proved indispensable for confirming the addition of new floors or structural extensions that are often difficult to discern from satellite imagery. While the reference years for analysis were 2016 and 2023, the available street view imagery varied by location, with the actual timestamps ranging from 2016 to 2024.



ID	Category
30	De/VD
238	De/VD
220	De
352	De
272	De/HorD
273	VD/HigD
287	VD
403	VD/HigD/HorD
278	HigD/HorD
279	HigD
280	HigD
288	HorD
281	HorD

Total 13 slum boundaries

De: Declining; VD: Vertical Densification; HorD: Horizontal Densification; HigD: High Densification

Figure 4: Top five slums per urban change category (by area), showing spatial overlap and diversity of change types across 13 slum boundaries in Nairobi.

Figure 5 presents representative before-and-after snapshots from selected locations, annotated with their respective capture dates.

	Stable	Dec	VD	HigD	HorD	Sum	UA (%)
Stable	0	0	0	0	0	0	NaN
Dec	1	5	0	0	0	6	83.33
VD	4	0	19	0	0	23	82.61
HigD	0	0	0	26	0	26	100
HorD	0	0	0	0	99	99	100
Sum	5	5	19	26	99	154	NaN
PA (%)	0	100	100	100	100	NaN	96.75

Table 2. Confusion matrix comparing predicted and validated urban change categories.

Notes: Rows represent the predicted class (model output), and columns represent the validated classes from imagery interpretation. UA: Users Accuracy (commission error). PA: Producers Accuracy (omission error).

Of the 154 grid cells evaluated, 149 were found to be correctly classified, yielding an overall accuracy of 96.75% (Table 2). Both horizontal and high densification categories showed perfect validation agreement (100%), while decline and vertical densification exhibited slightly lower agreement rates of 83.3% and 82.6% respectively. Misclassifications observed in the decline and vertical densification categories highlight the inherent difficulty to confirming subtle structural changes using satellite and street-level imagery. These cases may reflect actual limitations in the classification model, uncertainty in the visual evidence, or a combination of both – underscoring the need for cautious interpretation and more systematic validation protocols. For decline, satellite imagery did not show any noticeable change in structure presence between 2016 and 2023, suggesting those grid cells may have remained stable. In the case of vertical densification, validation was impeded by the absence of Google Street View imagery, particularly in core slum regions where vertical changes were expected. Without ground-level views, it was difficult to verify subtle height increases, leading to a few instances where predicted VD grids were found to be stable upon satellite inspection. These errors, while few, highlight the importance of incorporating a 'Stable' reference class in confusion matrix even when it is not a direct focus of the classification.

Figure 6 summarizes the breakdown of validation sources used across categories. Notably, the reliance on Google Street View imagery increased for categories involving vertical growth (VD, HigD), whereas decline validations relied solely on satellite imagery due to the absence of street-level data in core slum regions.

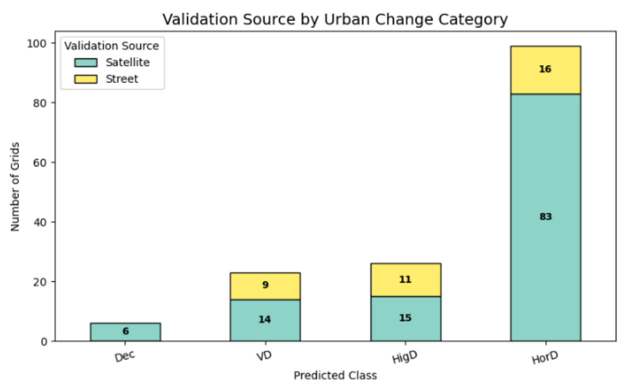


Figure 6. Validation sources by urban change category, showing grid counts validated using satellite and street view imagery.

Together, these results not only confirm the feasibility of using Google's 2.5D dataset for change detection in informal settlements, but also underscore the unique value of street-level

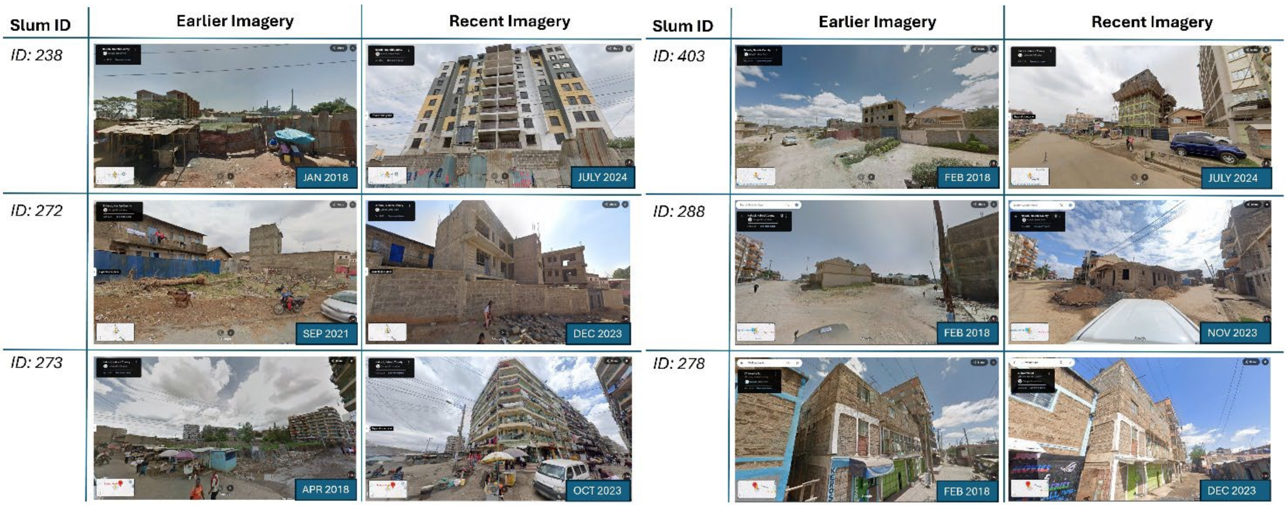


Figure 5: Example pairs of earlier and recent Google Street View imagery used for validation across different slum locations. The images illustrate observable structural changes such as building additions or vertical extensions. (© Google 2025, Used here for academic research under fair use)

imagery as a supplementary validation source for vertical transformations.

3.4 Spatial distribution across zones

The spatial distribution of the four focus urban change categories reveals distinct patterns across three delineated zones: slum boundaries, buffer ring around slums, and other regions within the city. As shown in Figure 7, horizontal densification is the dominant form of urban change within slums, accounting for 25.4% (2,741 hectares) of the total horizontal densification area. This indicates widespread infill development and structural expansion in already dense informal environments.

In contrast, vertical densification and high densification categories involving building height increase are less prevalent (though not negligible) in slums, accounting for 1.8% (80 hectares) and 6.0% (114 hectares) of their total area respectively. These findings suggest structural limitations within slum areas that constrain vertical expansion, such as informal construction practices, lack of materials, or regulatory restrictions.

The buffer zone surrounding slums, however, exhibits a more balanced pattern across densification categories, particularly for vertical densification (5.8%, 256 hectares) and high densification (8.7%, 166 hectares), indicating a spillover effect of growth into adjacent areas. This ring may represent transitional zones with more flexibility in development patterns, infrastructure upgrades, or informal-to-formal conversion processes.

Meanwhile, the vast majority of urban change for all categories occurs in other city regions outside the slum and buffer zones. For example, over 85% of both vertical and high densification occurs in these areas, which reflects the broader urban intensification trends in Nairobi beyond informal settlements.

While areas classified as ‘Declining’ represent the smallest share across all zones, their notably low presence within slums (1.0%, 7 hectares) and buffer zones (5.3%, 34 hectares) warrants careful interpretation. These patterns may point to actual instances of structural decay or demolition but could also stem from the synthetic nature of the dataset or subtle classification noise. As such, declining areas should be examined cautiously, especially in low-density or transitional zones where minor temporal inconsistencies may be amplified.

4. Conclusion and Limitations

This study explored the use of Google’s 2.5D temporal building dataset to detect and validate urban change patterns in Nairobi, focusing on informal settlements. By combining changes in building count and height across 100-meter grid cells, we developed a classification framework capable of capturing diverse transformation types – most notably vertical densification, horizontal densification, high (combined) densification, and decline. The results demonstrate the utility of this approach for tracking both footprint expansion and vertical growth in resource-constrained urban settings.

Validation conducted through a combination of historical satellite imagery and Google Street View confirmed strong agreement between predicted and observed change types, with an overall accuracy of 96.75%. This underscores the value of fusing remote sensing and street-level perspectives, particularly for verifying vertical changes that are otherwise difficult to capture. Spatial analysis across slum boundaries, adjacent buffer zones, and other urban areas revealed that while horizontal densification is dominant in informal settlements, vertical and high-density are transformations are more prevalent in surrounding zones and across the broader city.

While this study presents a robust first step in validating urban change patterns using Google’s 2.5D dataset, it does not adopt a formal sampling strategy such as random or stratified sampling. Instead, the validation focused on top-ranking slum areas for each category, prioritizing interpretability and feasibility given the exploratory nature of the work. This may introduce bias by favouring grids that are more readily interpretable, potentially inflating reported accuracy values. Future studies will incorporate systematic sampling to support broader generalizability and statistical rigor. Additionally, the lack of Google Street View coverage in dense core slum regions limited the ability to validate some vertical changes – a challenge that remains inherent to current data availability.

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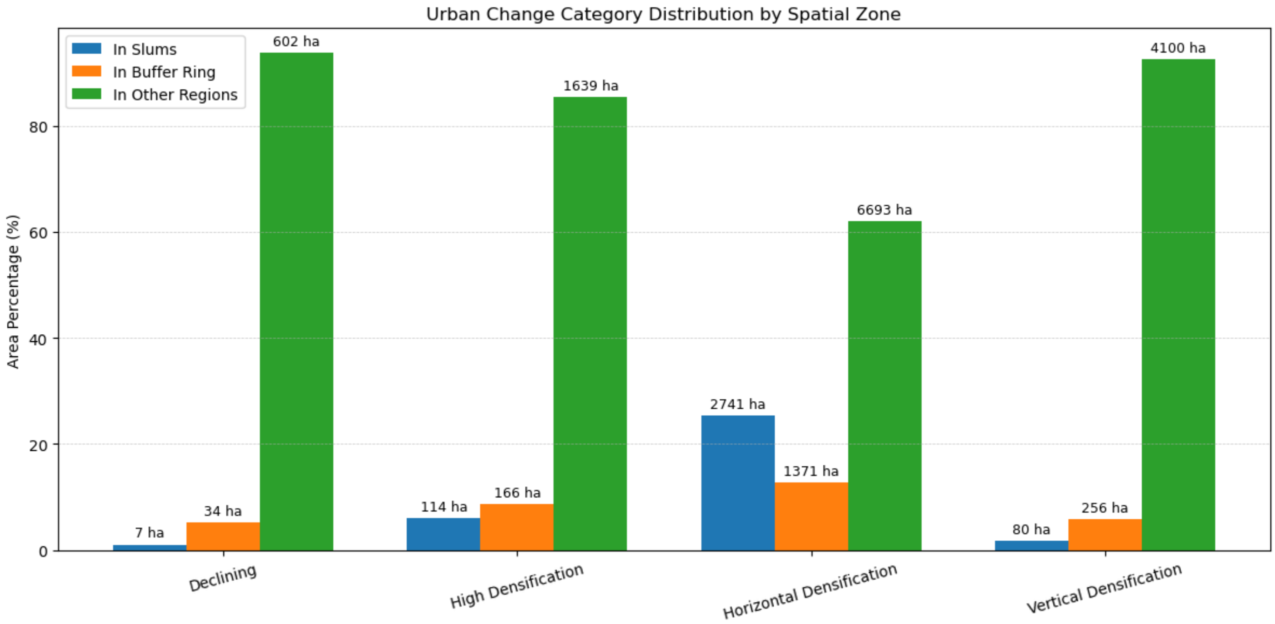

Figure 7: Urban change category distribution by spatial zone, represented as percentage of total area for each category

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Appendix

The full codebase developed for this study is publicly available on GitHub and archived on Zenodo: https://doi.org/10.5281/zenodo.15203081