International Journal of *Geo-Information*

MDPI

Article

From the Sky to the Garden: A Top-Down and Bottom-Up Methodology for Estimating Population Trends in Port Moresby's Informal Settlements

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Abstract

Papua New Guinea's capital, Port Moresby, is growing rapidly, and housing development has not kept pace. Thousands arrive in the city each year from rural villages, and many come to live in the city's sprawling urban squatter settlements. The National Capital District Commission lacks reliable population data for these so-called "self-help" settlements, posing a challenge for urban planning and the allocation of scarce development resources in a fast-growing city. Utilizing publicly accessible geospatial data gathered from 18 years of aerial imagery (top-down) alongside insights from on-the-ground interviews (bottom-up), this project establishes a low-cost, mixed-methods approach for estimating population and change within a large informal settlement. The findings show how manual rooftop identification, combined with local qualitative validation, can produce robust settlement-level population estimates in data-scarce environments and illustrate context-specific limitations of automated Earth Observation-based population models in Melanesian cities. This approach is applied to 8-Mile: a well-established 2.5km^2 settlement northeast of Port Moresby's city center. Results demonstrate the practicality of this method and reveal that, despite evictions and commercial rezoning, the settlement is growing at close to double the national average and is currently home to at least 27,000 people. Overall, the study highlights the value of combining spatial analysis with community-level knowledge to support evidence-based urban governance in rapidly growing cities.

Keywords: ArcGIS; Google Earth; 8-Mile; self-help housing; remote sensing; census

Academic Editors: Wolfgang Kainz, Shivanand Balram, Eric Vaz and Suzana Dragicevic

Received: 21 April 2026
Revised: 30 June 2026
Accepted: 2 July 2026
Published: 13 July 2026

1. Introduction

Rapid urbanization in Port Moresby, Papua New Guinea (PNG)'s capital, has generated extensive and politically contentious informal settlements. Each year, thousands of people arrive from rural areas, and many settle in what the National Capital District Commission (NCDC) terms "self-help housing" [1], the international community occasionally calls slums [2,3], and in PNG are referred to as 'settlements' [4,5]. These settlements are characterized by unplanned, sprawling residential areas with inadequate access to basic services such as electricity, water, and sewerage [6]. They emerged in response to high rural-urban migration and an insufficient supply of affordable housing [7].

Despite their scale and significance, reliable population and demographic data for Port Moresby's informal settlements are nonexistent. In 2010, the United Nations Office of the High Commissioner for Human Rights (UN-OHCHR) estimated that settlements housed approximately 45% of the city's population, increasing to more than 50% as of 2020 [1]. No other evidence-based settlement population estimates exist for PNG. The capacity of urban planners to collect settlement data in PNG's capital remains extremely limited by fiscal resources as well as a lack of training, personnel, security, and basic services. The absence of settlement-level population data poses a major challenge for urban planning and the allocation of scarce development resources in a rapidly growing city.

Settlement residents face multiple forms of marginalization that exacerbate the effects of data scarcity. Most have limited access to formal employment and rely primarily on informal economic activities and subsistence gardening [1,7]. Their economic vulnerability is exacerbated by media portrayals that associate settlements with lawlessness and criminality: a characterization that has deepened the societal divide between settlers and formal residential dwellers [4,8,9]. Settlers also face significant housing insecurity through state-sponsored forced evictions [4,10], often advertised as development and settlement-to-suburb upgrades [1]. These serve as a control mechanism for settlement growth [4,8]. Evictees have little recourse, as PNG law lacks anti-eviction legislation, adequate tenant protections, price controls, and legal frameworks for addressing housing disputes [6]. Research by Rooney (2021) documented the forced eviction of at least 18,791 people from 20 settlements between 2012 and 2021, with only six cases including resettlement provisions [4].

The lack of reliable demographic data compounds these challenges. Accurate mapping of deprived urban areas is widely recognized as vital for monitoring progress toward the Sustainable Development Goals (SDGs), particularly Goal 11: Sustainable Cities and Communities [11–14]. While a variety of remote sensing methods to estimate population have been trialed globally to meet this challenge, none have yet reached widespread adoption. Few techniques have been trialed in Melanesia, despite PNG's formal commitment to the SDGs [15] and the growing need for reliable urban demographics to inform governance.

Census-taking has long been challenging in PNG. Since independence, the country has undertaken five censuses in 1980, 1990, 2000, 2011, and 2024. Of these, only the 1980 and 2000 censuses are considered generally accurate [16–18]. The 2024 census results have been called into question by a former head of the PNG National Research Institute due to ongoing administration issues and limited reach [19,20]. Census-taking faces multiple obstacles, including dispersed rural populations with limited transport infrastructure, skills shortages among census staff, limited state finances, and a lack of government services [16,21]. Census results are also politically sensitive, as higher national population figures undermine key development metrics [22,23].

PNG's population has been estimated at the regional and national levels by several organizations using varied methodologies, all of which rely to some extent on projecting population data from past censuses [16,17,21,24–26]. Without data to work from, these models cannot be used to map informal settlements, nor can their regionally and nationally focused methodologies be readily transferred to a distinct settlement urban morphology. Earth Observation (EO)-based approaches have proven effective for mapping informal settlements in comparable urban environments in Africa, India, and South America [12,27–29]. These focused, small-scale techniques have yet to be applied in PNG, despite similarities between Port Moresby's urban morphology and that of successfully mapped cities such as Kinshasa in the DR Congo [30,31] and Surat in India [32]. Moreover, these methods generally focus on mapping slums at the municipal level—detecting slum areas as a percentage of the whole city—rather than mapping a single settlement at the residential level.

While the NCDC has precise municipal-level settlement data as a percentage of land cover for Port Moresby collected directly by officials, identifying urban settlements as covering 15% of the city as of 2020 [1], it possesses limited data at the settlement and sub-settlement scales. Such data on settlement area, density, and population is critical to inform urban policy and planning decisions in a city where land access, infrastructure provision, and service delivery are increasingly contested [4,7].

This study responds to these limitations through a detailed case study of the contiguous informal settlement known as 8-Mile. Selected due to its size, established boundaries, and documentation in successive NCDC development plans [1,33,34], 8-Mile is also currently the subject of an NCDC settlement-to-suburb upgrade plan and commercial development pressures [1]. Ethnographic data, notably Barber's [5] work with the Bugiau community, is also available to contextualize the findings of this study. Drawing on 18 years of freely available aerial imagery (providing a top-down 'sky view') and recent qualitative fieldwork (a bottom-up grounded perspective), this paper presents a mixed-methods approach for estimating settlement population, area, and density by measuring structural changes between August 2006 and January 2024. It addresses the extent to which population data can be estimated from a simple, accessible methodology combining manual structure counting and on-the-ground interviews, and the insights which can be derived from the resultant dataset for data-scarce urban environments.

2. Materials and Methods

2.1. Study Area

The area for this study is the informal settlement of 8-Mile located in the northern segment of Port Moresby within PNG's National Capital District (NCD) (Figure 1). The settlement was established in 1987, roughly eight miles from the city Center [5]. The name has since become official, featuring on NCDC maps and road signs (pers. obs. BD).

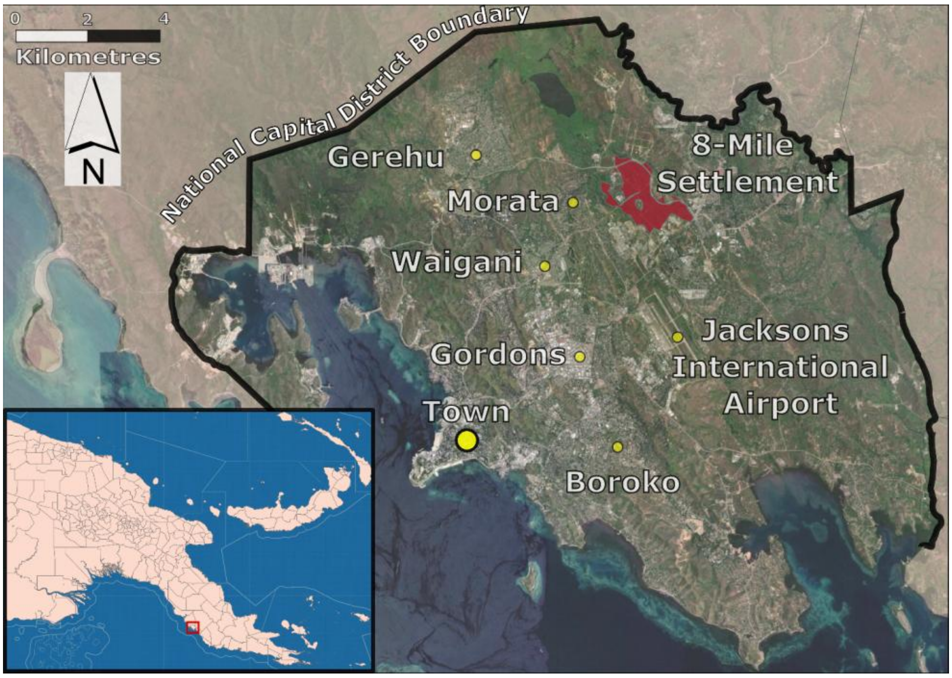

Figure 1. Location of the National Capital District (NCD)—the administrative boundary of Port Moresby—in Central Province, Papua New Guinea. 8-Mile settlement is highlighted in red. Major urban areas within the NCD [7] are shown as yellow dots. The inset shows the NCD (red square) on a district map of Papua New Guinea [35]. Scale is indicative only. Created by the author (see ArcGIS Projections S1.6).

8-Mile is defined here as an area of contiguous housing bounded by geographical and administrative boundaries (Figure 2): the Public Institutional Housing Area to the north, including its access road and drainage channel to Waigani swamp (Northern Drainage Channel); the Jacksons International Airport-Waigani swamp drainage channel to the south and west, separating 8-Mile from Morata; and the Hubert Murray Highway to the east. Parts of the settlement to the north and east, separated by the construction of the 8-Mile Highway in 2015, are retained within the study area. Moitaka Power Station, its attached residential area, and the central hilltop communications installation within 8-Mile were excluded from this study as they are managed by government authorities separately from the surrounding settlement (Figure 2: black polygons).

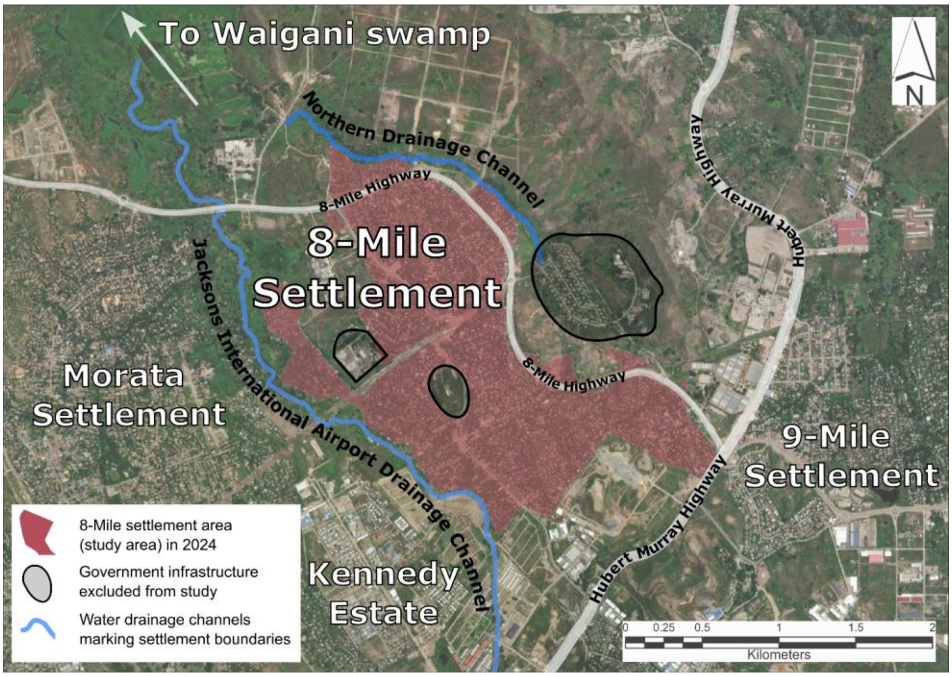

Figure 2. 8-Mile with associated boundary landmarks. Red shaded area created from 2024 point aggregate polygon (see Section 2.6.2) [33]. Satellite imagery captured from Google Earth Pro v.7.3.6 [36]. Geographic coordinate system WGS84 (EPSG:4326); displayed in WGS 1984 Web Mercator Auxiliary Sphere (EPSG:3857) (see ArcGIS Projections S1.6).

2.2. Methodology

The research methodology builds on a preliminary geospatial study of a representative 15% sample area within 8-Mile, previously published by Dare (Preliminary Study S1.3 and Preliminary Sample Dataset S2.7) [37]. Dare used historical aerial and satellite imagery sourced from Google Earth Pro v.7.3.4 to manually identify and count changing rooftop density with a 0.36 km^2 section of the settlement [37]. Here, the methodology and spatial extent are expanded to document the entirety of 8-Mile to improve the reliability of population estimates and to test the suitability of the 15% subsample approach and methodology for future applications. This comprehensive study of 8-Mile was thus carried out in two distinct phases. Qualitative data was first collected through semi-structured group interviews with 8-Mile residents to guide and contextualize the quantitative analysis. The quantitative phase then comprised a systematic spatiotemporal analysis of structural changes across 8-Mile using EO data.

Automated approaches, including artificial intelligence and machine learning, are increasingly used to map slums and informal settlements globally, often relying on digital surface models to extract individual building footprints with varying degrees of accuracy [25,38]. Active contour modeling has been used to extract structures within slums, with accuracy values ranging from 62% [29] to 94% [39] when extracting rooftop shapes from very-high resolution imagery. This method is dependent on elevation variance; however, it may not be suitable in 8-Mile, which has a significant canopy of shade and fruit trees. Additionally, the extraction of population data from EO requires training data, which is largely unavailable in Melanesia [16]. This is a distinct benefit of this study and method: it produces data that can be used for training and comparison with machine learning tools. These limitations highlight the importance of selecting context-appropriate methods when estimating population in informal urban environments [11].

Given the relatively small size of the 8-Mile settlement (2.75 km^2), manual identification of residential structures within the study area was both practical and able to deliver a high degree of accuracy. In addition to supporting reliable population estimation at the settlement scale, this methodology generates datasets that could be used to inform or train future machine learning tools, expanding their capabilities in this region.

2.3. Qualitative Phase: Local Stakeholder Engagement

The preliminary findings (Preliminary Study S1.3) [37] underwent qualitative validation through a series of semi-structured interviews with 8-Mile residents during a visit to the settlement in September 2024. Interviewees were selected based on their willingness to discuss local issues and comprised working-age men and women self-describing as gardeners, laborers, market stallholders, and employment seekers. All lived in family groups within 8-Mile.

Given the recent and historical context of state-sponsored evictions, interviews were conducted using culturally sensitive methodology: utilizing public spaces and informal engagement strategies. No digital recordings were made. Handwritten notes were compiled by the author after each interview. Interviews consisted of a targeted set of questions ($n \leq 5$) focusing on residential history, housing conditions, and observed temporal changes within the settlement. Upon establishing the research's independence from the PNG government, participants demonstrated high levels of engagement and transparency in their responses.

2.4. Quantitative Phase: Image Acquisition and Georeferencing

Ultra-high-resolution imagery mosaics (8192 × 5866 pixels) encompassing a 1.8 km × 3.4 km rectangular area over 8-Mile were captured from Google Earth Pro v.7.3.6 [36]. Seventeen 'time slice' images were selected from August 2006 to January 2024 (Figure 3, Historical Imagery S1.1), representing the earliest and latest ultra-high-resolution imagery available from Google Earth Pro (except 2008 and 2012—no suitable imagery was available). As ultra-high-resolution (0.5 m) imagery was required to accurately identify rooftops, Google Earth Pro proved to have the highest-definition, freely accessible, aerial and satellite composite images over time for 8-Mile (see Table 1, Other Imagery Sources S1.2). Other sources of EO imagery, such as NASA/USGS Landsat [40] and Maxar [41] satellites, were trialed but found to have too small a repository of historical imagery or were too low-resolution to identify required features.

Images were chosen for minimal cloud cover and maximum clarity as close as possible to one year after the previous image (Figure 3, Historical Imagery S1.1). These were then imported into the ArcGIS Pro software platform (v.3.3.5) and georeferenced in reverse-chronological order using a first-order polynomial transformation. Permanent (extant prior to 2006) structures around the settlement were used as control points and referenced to ESRI's satellite imagery basemap. These included gantries and outbuildings associated with the Moitaka Power Station, roundabouts and features of the Hubert Murray Highway, and a collection of churches scattered within the settlement extant in 2024. Con-

https://doi.org/10.3390/ijgi15070320

trol points were strategically distributed across the study area to optimize local spatial accuracy and mitigate distortions inherent in oblique aerial imagery within the mosaics.

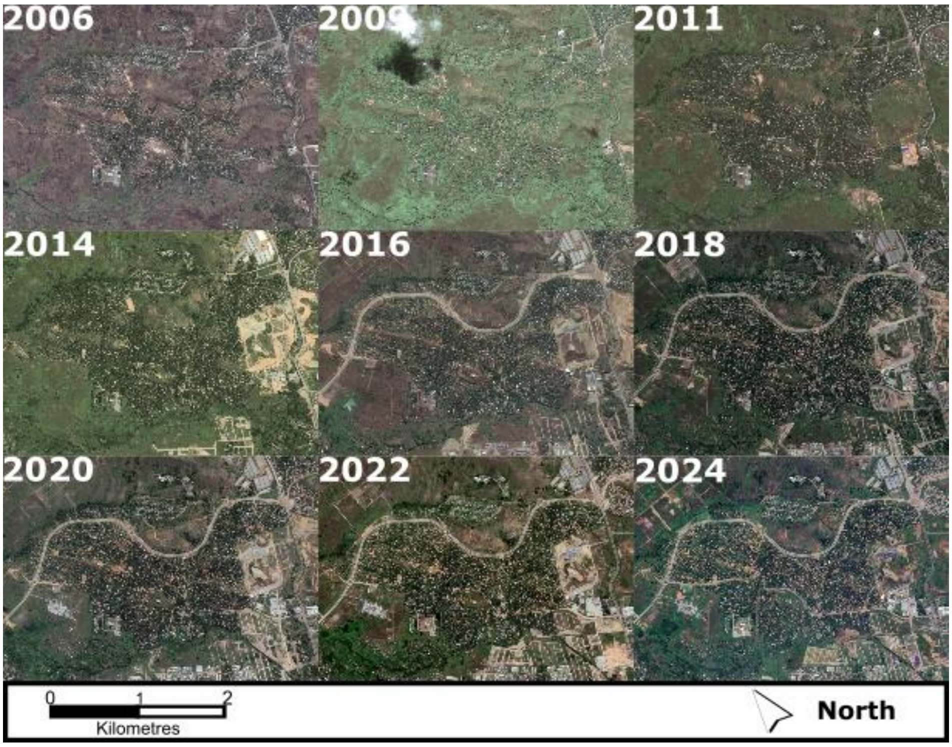

Figure 3. 8-Mile between 2006 and 2024. Showing every second aerial image time slice of 8-Mile used in this study (see also Historical Imagery S1.1). Imagery captured from Google Earth Pro historical imagery database [36]. Scale is indicative only (see ArcGIS Projections S1.6).

2.5. Dataset Compilation

2.5.1. Full Dataset Compilation

Orthorectified imagery from Google Earth was georeferenced in ArcGIS v.3.3.5 using a first-order polynomial transformation, with ground control points referenced to the WGS84 geographic coordinate system (GCS; EPSG:4326). Layers were displayed within a WGS 1984 Web Mercator Auxiliary Sphere projected coordinate system (PCS; EPSG:3857) data frame, enabling scale representation in meters and kilometers. As the study area is located 9° south of the equator, the distortion introduced by the Web Mercator projection is negligible (~35 m across the entire study area) at this scale. Following this, a comprehensive structural database was established through point feature digitization of visible rooftops. Each point feature was attributed with temporal and typological metadata, including construction date (set to August 2006 as the baseline), demolition date (arbitrarily set to January 2030 as a null indicator for structures extant as of Jan 2024), structure type, and binary residential status (Structure Dataset Table S2.1).

Structure types were differentiated by manual identification and organized into four categories: houses, complexes, churches, and businesses (as per Table 1). The "complex" structure type was added as a result of interviews conducted during the qualitative data collection. 8-Mile residents described the increasing number of residential complexes with internal subdivisions housing multiple family units. Business refers here to the structure, not commercial enterprises. Non-residential, non-church buildings were categorized as businesses, and therefore, business data reported here should not be used to draw significant conclusions about the nature of commercial enterprise within 8-Mile.

Table 1. Structure identification guide. In example images, the main/central structure corresponds to the structure type.

Structure Type	Example	Identifying Features
House		Comprised the vast majority of buildings. Attributed to structures larger than 5 × 5 m. Highly varied construction features.
Complex		Very large rectilinear or conglomerated house structures. Significant structural variety.
Church		Commonly very large structures with gabled roofs. Uniform shape. Commonly associated with cleared buffer zones. Often surrounded by housing.
Business		Other large structures—not complexes nor churches. Often associated with heavy vehicles and/or machinery. Always built adjacent to roads or vehicle access routes.

Given the significant socio-cultural role of churches in PNG, churches are often documented on crowd-sourced mapping platforms. Within the study area, ten churches are reg-

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istered in Google Maps, four of which were independently verified during the qualitative stage. These verified structures subsequently served as architectural reference points for the identification and classification of additional churches within 8-Mile (Table 1).

Small structures (defined as those with footprints < 5 × 5 m) that were either physically adjoined to or situated within the same parcel boundaries as primary structures were classified as non-residential outbuildings and excluded (Figure 4). Distinctly identifiable school buildings were also excluded from the dataset.

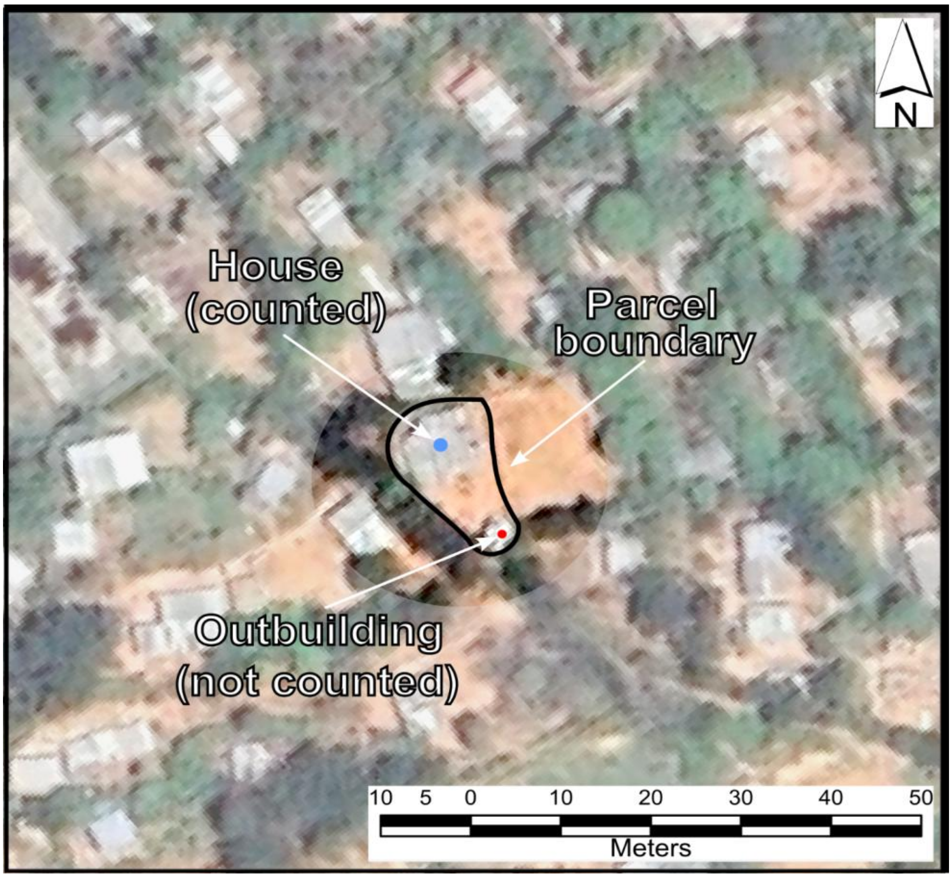

Figure 4. Aerial image showing a house (one data point), an outbuilding (not included in the dataset), and the parcel boundary. Parcel boundaries were used to assist in identifying outbuildings to exclude [36].

The inclusion of binary residential status attributes for each point feature prevented statistical distortion from non-residential structures in later analyses, as residences incorporated both houses and complexes. Due to a lack of data on household compositions of complexes, these structures proxied single, rather than multiple, households.

2.5.2. Time Slice Construction

Utilizing the dataset from 2006 as a baseline, successive chronological images of the settlement were overlaid, and a comprehensive spatial survey of 8-Mile was conducted for each year. The absence of recorded structures was interpreted as demolition events, and new structures were added as point features. Relocated structures, defined as those displaced within parcel boundaries, were recorded as concurrent demolition and construction events. To ensure consistency and minimize classification errors, the spatial coordinates of all recorded structural changes were cross-referenced against imagery from preceding temporal intervals.

Following complete data compilation, temporal cross-sections ('time slices') plotting all extant structures were created at annual intervals. This represented the extant structural composition of the settlement for each year. All subsequent analyses were built upon this complete dataset and its temporal derivatives (Structures Summary Table S2.2).

2.6. Analysis

2.6.1. Population Modeling

Population estimates for 8-Mile were derived by counting single residential structures (including complexes, as few were positively identified) as proxies for discrete households. These were then multiplied by 18 possible household density coefficients (5.3–10.0 persons per household) to establish minimum and maximum population models based on available data (Population Projections Table S2.3).

The lowest household density coefficient (5.3 people) was derived from the 2011 National Census [24], representing the national mean household size. In this same census, the Laloki/Napanapa Local Level Government (LLG) area within the NCD (which encompassed 8-Mile and other smaller formal and informal settlements at this time) recorded a mean household size of 7.2 people. Ethnographic research conducted by Barber [5] within a specific ethnic enclave of 8-Mile documented a mean household size of 8.0, a finding corroborated during this study's qualitative data collection. The upper boundary coefficient (10.0) was established based on the maximum reported household size during qualitative field interviews (see also PNG NSO Data Collection S1.4).

To account for the non-uniform temporal distribution of imagery, particularly pre-2017, population growth rates were adjusted. The absence of data for 2008 and 2012 necessitated compensation for doubled growth values in subsequent years (2009 and 2013). The adjusted growth rate was calculated using the following formula:

$$\boldsymbol{Adjusted\ Growth\ Rate} = \frac{\boldsymbol{Newly\ built\ residences - Demolished\ residences}}{\boldsymbol{Time\ between\ current\ and\ preceding\ imagery}\ (\mathbf{months})} \times \mathbf{12}$$

As all EO imagery was dated in month–year format, months were used as the shortest temporal increment to adjust growth rates. Unless otherwise specified, all growth rates presented are adjusted according to this methodology.

2.6.2. Area: Point Aggregate Polygons

The settlement's extent and its temporal evolution were quantified using polygons generated via point feature aggregation applied to each time slice dataset. Aggregation distance was 200 m—the minimum threshold distance required to generate a contiguous settlement boundary. Areas excluded from the residential study (Moitaka Power Station, its attached residential area, the central hilltop communications installation, and the 8-Mile Highway) were manually cut from the polygons (Figure 5).

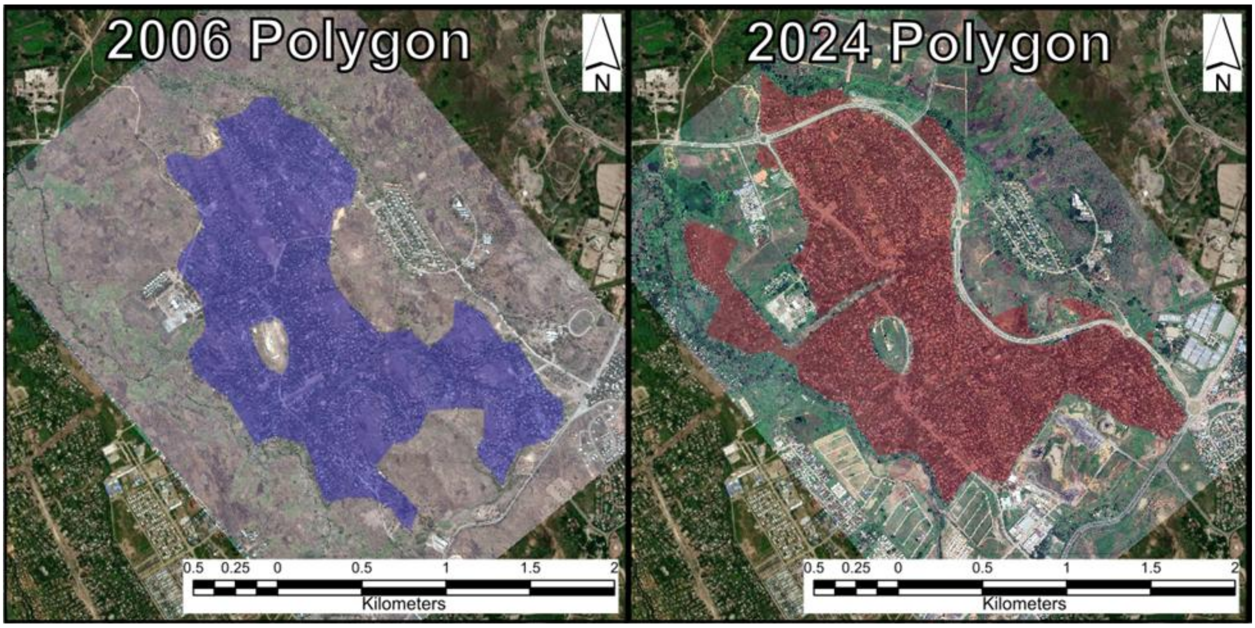

Figure 5. Comparison between 2006 (blue—**left**) and 2024 (red—**right**) point aggregate polygons created from residential time slices. Polygons overlie image mosaics captured from Google Earth Pro and georeferenced using static points onto the ESRI satellite basemap (created post-Jan 2024). Geographic coordinate system WGS84 (EPSG:4326); displayed in WGS 1984 Web Mercator Auxiliary Sphere (EPSG:3857) (ArcGIS Projections S1.6).

2.6.3. Density: Nearest Neighbor Analysis

Residential and therefore population density was modeled annually using a nearest neighbor analysis (Average Nearest Neighbor Table S2.4). The ArcGIS Pro Average Nearest Neighbor tool was used to measure the distance between each point feature and its neighbors (i.e., structure), averaging this distance over area values calculated from each year's point aggregate polygon. This distribution was then compared to a hypothetical random distribution over the same area to determine the extent of feature clustering or dispersal. For more detailed statistical information, including formulae, see ESRI's Nearest Neighbor statistics [42,43].

3. Results

3.1. Qualitative Data Collection

Qualitative data obtained through informal interviews revealed several significant findings regarding land use, housing patterns, and demographic characteristics. Land access emerged as a primary concern, particularly regarding the establishment of households for the newly married children of settlers within the context of ongoing evictions, commercial zoning, and land clearances.

Multi-household structures, locally termed "big houses" or "long houses" (referred to as "complexes" in this study), have proliferated over the past 10–15 years. These structures typically accommodate multiple small households (3–5 individuals, including children) in subdivided single-room dwellings with shared kitchen and bathroom facilities. Owners often live on site to manage their properties, which serve as initial accommodation for rural-urban migrants. Field observations indicated these structures were frequently indistinguishable from older, larger homes (pers. obs. BD). Interviewees consistently reported minimum occupancy rates of 20–30 residents per complex, with a high proportion of children (pers. obs. BD).

Gardening for subsistence and to fulfill community obligations significantly influenced land-use patterns, with areas under cultivation extending to the Waigani swamp sewage ponds (2.25 km north of Moitaka Power Station, outside the study area) and on the surface of all accessible waterways, particularly the northwest swamp fed by the Jacksons International Airport drainage channel. Gardens associated with a house increased its value, as did proximity to churches and some topographical features (pers. obs. BD; [5]). Valleys and level terrain beneath hills were considered easier to build on compared to hillsides and were therefore more highly valued (pers. obs. BD).

Field observations revealed several limitations in EO-based population estimation. Many structures were obscured completely by vegetation or existing buildings, while internal subdivision created many 'invisible' households. These findings strongly suggest that population estimates derived from EO methodologies return conservative minimum values.

3.2. Quantitative Data Collection and Analysis

Quantitative analysis identified 4653 discrete point features within 8-Mile, comprising 4560 houses, 10 complexes, 29 churches, and 54 businesses (Structure Dataset Table S2.1). Longitudinal analysis demonstrated consistent growth across all structure types since 2006 (Structures Summary Table S2.2). While significant demolition occurred during infrastructure development projects, such as the construction of the 8-Mile Highway in 2015 [44], these were consistently offset by new residential construction. The total number of structures grew continuously between August 2006 and January 2024, reaching a total of 3390 residences recorded for the beginning of 2024 (Table 2).

Table 2. Table showing population projections calculated using four population density coefficients, with reference to the time slice and number of residences identified during quantitative data collection. Adjusted growth rate was calculated to account for temporal discrepancies between time slices using the formula in Section 2.6.1. (See also Population Projections Table S2.3).

Time Slice	Number of Residences	Extrapolated Persons Per Household				Adjusted Growth Rate
		5.3	7.2	8.0	10.0	
Aug 2006	1463	7754	10,534	11,704	14,630	-
May 2007	1516	8035	10,915	12,128	15,160	5%
May 2009	1670	8851	12,024	13,360	16,700	5%
May 2010	1773	9397	12,766	14,184	17,730	6%
Feb 2011	1787	9471	12,866	14,296	17,870	1%
Feb 2013	1974	10,462	14,213	15,792	19,740	5%
Jan 2014	2045	10,839	14,724	16,360	20,450	4%
Aug 2015	2173	11,517	15,646	17,384	21,730	4%
Jun 2016	2455	13,012	17,676	19,640	24,550	16%
May 2017	2567	13,605	18,482	20,536	25,670	5%
Feb 2018	2780	14,734	20,016	22,240	27,800	11%
Feb 2019	2920	15,476	21,024	23,360	29,200	5%
Jan 2020	3038	16,101	21,874	24,304	30,380	4%
Jan 2021	3138	16,631	22,594	25,104	31,380	3%
Jan 2022	3205	16,987	23,076	25,640	32,050	2%
Apr 2023	3358	17,797	24,178	26,864	33,580	4%
Jan 2024	3390	17,967	24,408	27,120	33,900	1%

3.2.1. Population

Population projections reveal consistent growth concurrent with new residential construction, persisting despite periodic demolition for infrastructure development (Population Projections Table S2.3). Annual growth rates fluctuated between 16% (2016) and 1% (2011 and 2024). Five-year intervals yielded average annual growth rates of 4% (2007–2013), 8% (2014–2018), and 4% (2019–2023), with an overall mean annual growth rate of 5% (Table 2). Population estimates based on average household occupancy are presented in Table 2, alongside adjusted annual growth rates.

The number of structures identified as complexes also increased from two in 2006 to ten in 2024. However, methodological limitations in complex identification using roof morphology and land-use indicators suggest a significant underestimation of this figure (see Section 4.2). Qualitative data strongly indicates that the actual number of complexes substantially exceeds ten over the whole settlement area.

3.2.2. Area

Spatial analysis of point aggregate polygons demonstrates general expansion between 2006 and 2022, primarily concentrated in the settlement's northern and western sectors that were, in 2006, most distant from public institutional and commercial zones (Figure 5). Settlement expansion patterns show periodic constraint due to zoning and infrastructure development, evidenced by area reductions in 2011, 2015, 2017, and 2022 observed in satellite imagery. The settlement reached its maximum spatial extent in 2022, after which it has been increasingly constrained by commercial developments on its fringes and transport infrastructure (roadbuilding) through its Center (Figure 6).

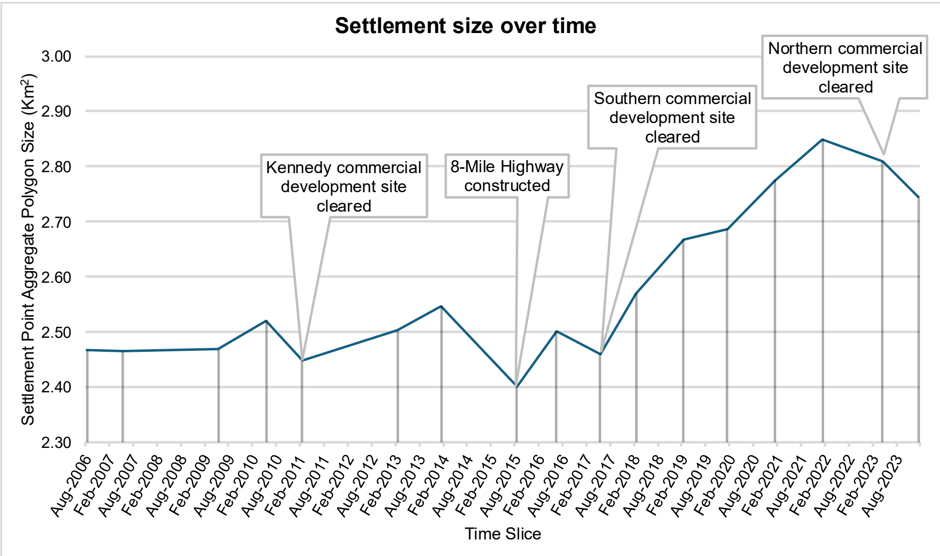

Figure 6. Graph showing the size of 8-Mile calculated from point aggregate polygons over time (Average Nearest Neighbor Table S2.4, Density Table S2.5). Labels indicate the first image mosaics where large-scale (30+ demolitions in a contiguous area) development projects were identified [33,42].

3.2.3. Density

Structural density within the settlement increased steadily between 2006 and 2024. Average Nearest Neighbor analysis revealed a steady reduction in Observed Mean Distances between residences, from 23.72 m (2006) to 17.42 m (2024), with a single anomalous 0.59 m increase in 2014 corresponding to settlement expansion incorporating <5 new structures at the northern extreme (Figure 7; Density Table S2.5).

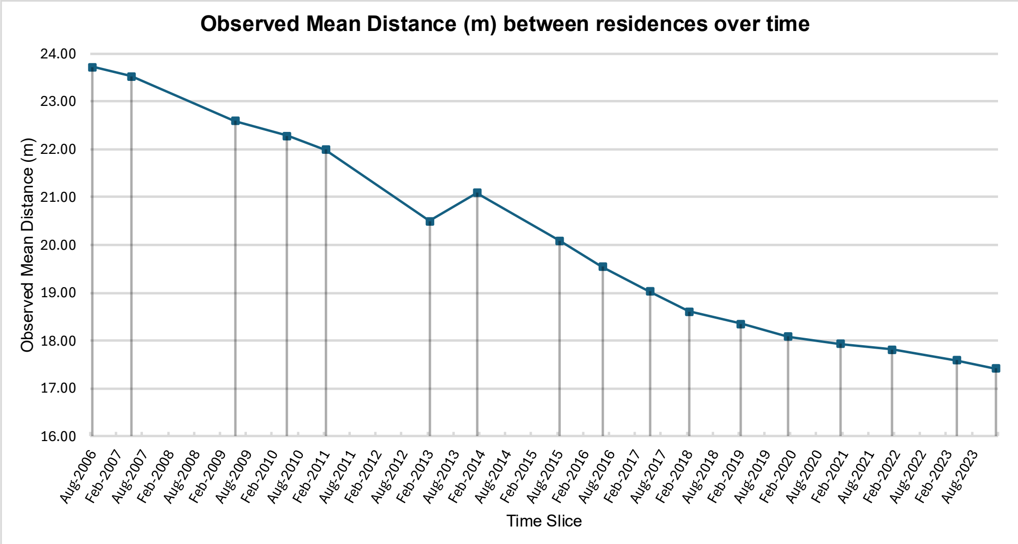

Figure 7. Graph showing the decreasing trend of Observed Mean Distances in meters between residences from Aug 2006 to Jan 2024 (Average Nearest Neighbor Table S2.4, Density Table S2.5). The mean increase in 2014 is due to expansion and demolition (in 2015) of the settlement buildings in the far north and east, temporarily increasing point aggregate polygon size and therefore the mean. Observed Mean Distances were calculated as part of ESRI's nearest neighbor analysis tool [42].

Structural dispersal patterns, quantified using Average Nearest Neighbor ratios, indicate consistently dispersed morphology, which increases progressively throughout the study period (Average Nearest Neighbor Table S2.4). This movement away from clustered or random structure distribution is particularly evident on the settlement's fringes.

Analysis of the relationship between Observed Mean Distances between residences and the number of residences using Pearson's correlation coefficient revealed a strong negative correlation, r(17) = 0.98, $p < 0.001$, demonstrating an inverse relationship between the number of residences and the mean distance between residences (Average Nearest Neighbor Table S2.4). However, the prevalence of internal subdivision within structures presents a significant limitation in producing a comprehensive household or population density assessment.

3.2.4. Non-Residential Structures

Non-residential structure growth paralleled residential development between 2006 and 2024 (Figure 8). This is supported by very strong correlations between the number of residences and the number of businesses over time, r(17) = 0.97, $p < 0.001$, and between the number of residences and the number of churches over time, r(17) = 0.93, $p < 0.001$ (Correlations Table S2.8).

Demolition was minimal (two churches and three businesses) and exclusively associated with infrastructure development or commercial land clearance affecting entire blocks (Figure 6). The spatial configuration of non-residential structures demonstrated remarkable temporal stability, with no instances of church or business relocations during the research period.

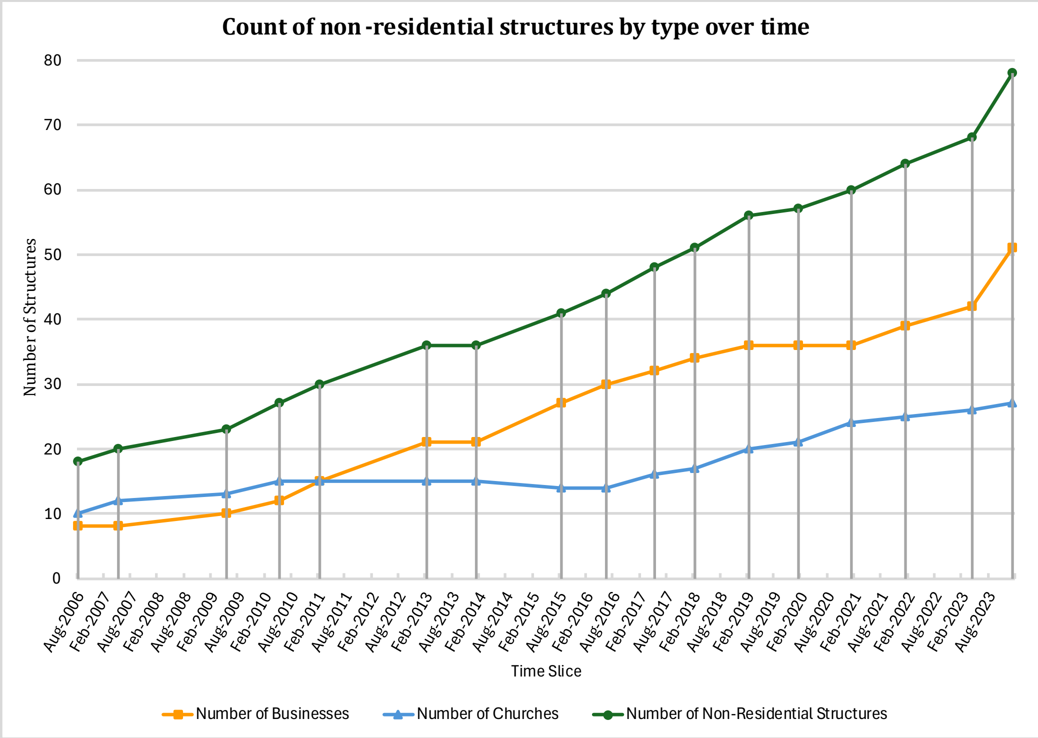

Figure 8. Graph showing the numbers of non-residential structures at temporal intervals.

Spatial analysis revealed consistent patterns in non-residential structure distribution: churches were positioned centrally within housing clusters, with a mean dispersal of 217 m across the settlement, while businesses were preferentially located along established roads on settlement peripheries (Figure 9).

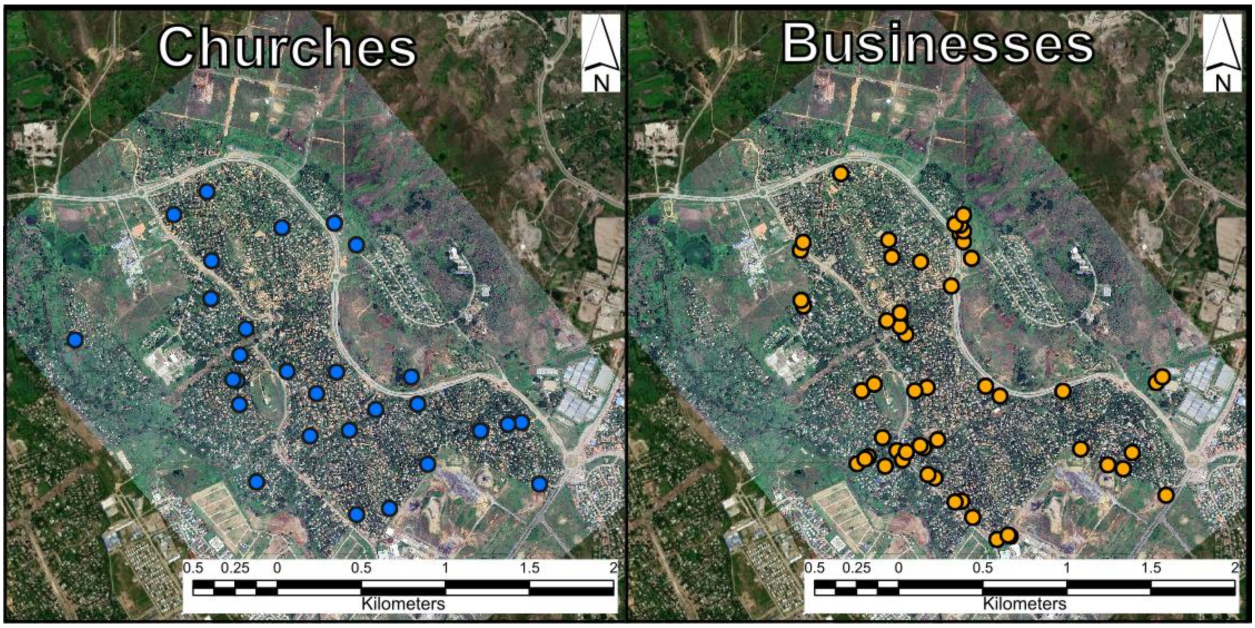

Figure 9. Comparison between the distribution of churches (blue circles—**left**) and businesses (orange circles—**right**) within 8-Mile over the study period (2006–2024). Circles include both demolished and extant structures. Churches exhibit dispersed distribution in core residential areas, while businesses are clustered along transport routes and on the settlement's periphery. Geographic coordinate system WGS84 (EPSG:4326); displayed in WGS 1984 Web Mercator Auxiliary Sphere (EPSG:3857) (ArcGIS Projections 1.6).

4. Discussion

4.1. Demographics and Significance

The most significant finding of this study is that the number of residential structures within 8-Mile has increased consistently each year, despite the recent shrinking of the settlement's total area. This pattern is strongly indicative of consistent population growth: a trend repeatedly attested to by residents during the interviews. Structural growth has therefore occurred not through spatial expansion, but through increasing residential density within an increasingly constrained settlement footprint.

To quantify this growth, population estimates derived from residential structure proxies rely on the selection of an appropriate household density coefficient. As this cannot be derived from EO data alone, qualitative assessment is essential prior to quantitative analysis of settlement structural morphology. The 2011 PNG national average household size (density coefficient) of 5.3 is significantly lower than household sizes observed within settlements in the NCD, as shown by the NCD census data [24], ethnographic studies [5], and qualitative findings of this study (pers. obs. BD). Based on these converging data sources, a density coefficient of 8 is considered the most representative mean household size for 8-Mile. Even this rate is still likely to underestimate the total population, particularly due to the increasing prevalence of 'invisible' households created from internal subdivision of existing houses and complexes. Field observations indicate that internal subdivision is increasingly common (pers. obs. BD), underscoring the need for further research regarding their prevalence across Port Moresby's informal settlements.

When contextualized with macro-population data, these findings provide vital insights for urban planning. During the 2011 census, which was declared a failure due to logistics and resourcing issues most pronounced in rural areas [21], 8-Mile was located within the Laloki/Napanapa LLG area [24]. This large administrative region incorporated disparate areas on Port Moresby's northern and western peripheries. Within this LLG area, 8-Mile constituted the largest residential area, with 21,404 residents across 2978 households in 2013, yielding a mean of 7.2 persons-per-household [24]. Applied to this study's 2013 time slice, this coefficient suggests 8-Mile housed 12,866 residents (Table 2), constituting approximately 60% of Laloki/Napanapa LLG area's population within just 3.42% of its total area (see Census Comparisons Table S1.6). At a minimum, this implies 8-Mile housed 6% of the NCD's total population. However, given the extent to which 8-Mile dominates housing within the LLG area (shown in Figure 10), these results indicate the real population of 8-Mile was likely underestimated.

The 2021 United Nations Population Fund (UNFPA) population estimate [25] used machine learning extraction of building footprints from EO imagery, a technique applied successfully in other low-income countries [12,27,28]. In PNG, however, this approach has been criticized for rural areas where rooftops cannot be accurately proxied for households, and dense vegetation often obscures structures entirely [45]. While this limitation is most consequential at the national scale due to PNG's large rural population [46], it also highlights broader risks associated with applying automated EO-based population models without local contextual validation. In the case of 8-Mile, modest vegetation cover and variability in construction necessitate manual rooftop identification as a critical first step, rather than reliance on machine learning tools built on foreign urban morphology. The combined use of manual counts and qualitative, on-the-ground investigation is shown as a necessary step to confirming household boundaries and complexes, and for producing more reliable population estimates for this urban context.

Uncertainty surrounding national population estimates further illustrates the stakes of these methodological choices. A report leaked to the press in December 2022 revealed a UNFPA national population estimate of 17 million [47], conflicting sharply with the official figure of approximately 9 million [48] and prompting the PNG government to withdraw support from the project [47]. Revised modeled population estimates released in July 2023, produced in collaboration with the PNG National Statistical Office (NSO) [26], combined multiple data sources (malaria bed net campaign data, urban structural listings, and geospatial covariates) within a Bayesian statistical hierarchical model to estimate a national population of 11.8 million [26]. These outcomes underscore the sensitivity of population modeling in PNG and reinforce the value of settlement-scale empirical data for grounding broader demographic estimates.

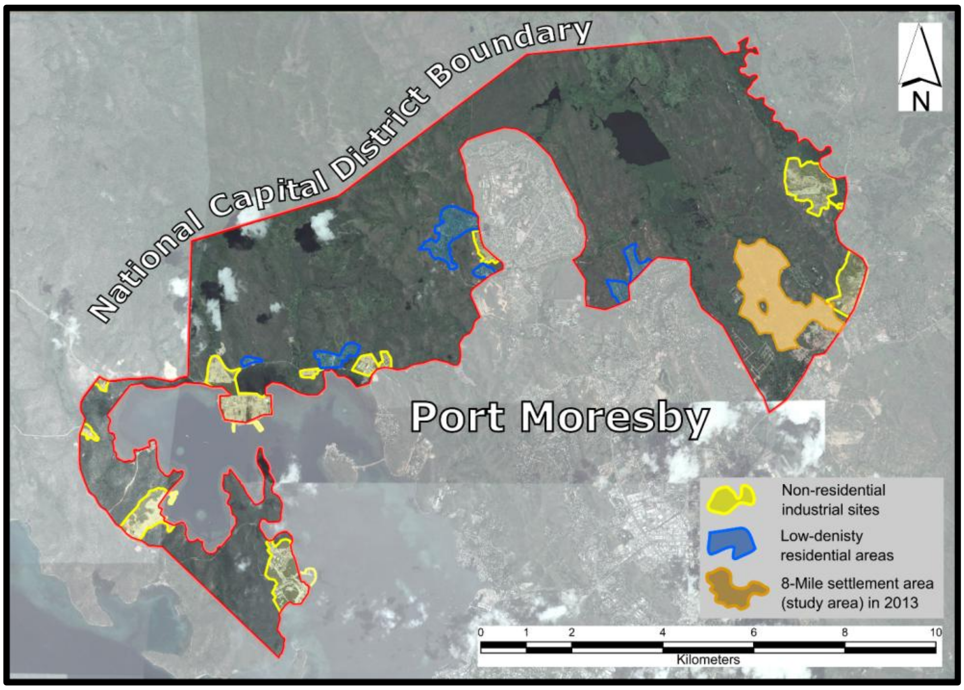

Figure 10. The extent of Laloki/Napanapa Local Level Government area (LLG) within Port Moresby is shown in red (total area ~70 km^2). Blue areas (1–2 km^2) denote low-density residential areas, and yellow areas (4–5 km^2) non-residential industrial sites. 8-Mile (high-density residential) is marked in orange (2–3 km^2), and its significantly greater size and residential density indicate it housed the majority of Laloki/Napanapa LLG area's population in 2013. Map created by author with 2013 historical data from Google Earth Pro [36] and boundaries from the PNG NSO [24]. Areas calculated from polygons digitized in WGS 1984 Web Mercator Auxiliary Sphere (EPSG:3857); ranges given to account for distortion (ArcGIS Projections S1.6). Scale is indicative only.

At the municipal scale, aggregation effects further obscure extreme population densities within individual settlements. For the purposes of the 2021 UNFPA estimate, 8-Mile was located within Ward 12, the largest NCD ward, covering 67 km^2. This ward contains the larger settlements of 9-Mile and Air Transport Squadron (ATS), as well as at least 21 smaller settlements, alongside Port Moresby's formal residential and commercial districts to the north and east of Jacksons International Airport. The results of this study demonstrate that 8-Mile occupies 4% of the land in Ward 12 and, as of 2021, 1% of the total land in the NCD. UNFPA and NSO estimated Ward 12's population at 86,011 [25]. Using mean density coefficients of 7.2 and 8, this study suggests 8-Mile alone accounted for between 26% and 29% of the ward's total population in 2021, equivalent to 4–5% of the NCD's total population. Such a high percentage of the ward's population residing within a comparatively small (2.75 km^2 of 67.00 km^2) area highlights the vast difference in density between Port Moresby's formal and informal residential zones. Additionally, the collocation of ATS and 9-Mile settlements—which are very similar in urban morphology to 8-Mile—

within Ward 12 is strongly indicative of the averaged density values being substantially lower than the actual population.

Looking forward, 8-Mile's mean annual growth rate of 5% exceeds both national (3.1%) and NCD (3.3%) averages, as well as the NCDC's highest projected growth scenario for 2030 (4.6%) [1]. The combination of high existing density and continued population growth within the settlement has significant implications for government service provision: placing particular pressure on water, energy, and sanitation [6,7]. Substantial investment in these services is needed not just to meet PNG's commitment to the SDGs [14], but to prevent a decline in urban living standards for the majority of Port Moresby's inhabitants.

In response, the NCDC has increasingly relied on commercial development to regulate settlement growth. Since 2022, 8-Mile has decreased in extent as state-sponsored development, commercial rezoning, evictions, and demolition of residences have constrained the settlement and intensified internal subdivision (Figure 6). The construction of the 8-Mile highway in 2015 exemplifies this policy; the road effectively cut the settlement's northeastern expansion, serving as a hard border beyond which residential structures are demolished.

The NCDC's 2020 Urban Development Plan Review "Towards 2030" designated a 0.23 km^2 eastern portion of 8-Mile, currently housing at least 3000 residents across 420 dwellings, as a "strategic site" for commercial investment [1]. For the planned development to proceed, these sites must be cleared, displacing thousands of residents. Warnings and threats have circulated to this effect in Port Moresby since 2012 [4], but residents, who do not necessarily share the state's understanding or interpretation of legal land ownership—a fact stated by the NCDC in its voluntary review of housing development policy [15] and corroborated in the field interviews—are usually forcibly evicted [4]. Public promises by politicians to issue "1000 permanent land titles" to settlers across the NCD before PNG's 50th Independence Day have failed to materialize [49,50]. Furthermore, 1000 land titles are insufficient to house those displaced from 8-Mile alone, discounting the thousands of evictees from other settlements across Port Moresby [4,50]. This exemplifies the use of commercial development by the state to exert control over the settlement [4], a policy supported by the popular media narrative proclaiming informal settlements and rural-urban migration as challenging social order [8,46].

Critically, the evictions, demolitions, and reduction in settlement size have not reduced settlement population (Table 2). Further rezoning and development are therefore unlikely to lead to an increase in living standards or the disappearance of the urban settler population. To genuinely make progress towards SDG 11, municipal service delivery must be improved universally in Port Moresby, with particular emphasis on high-density residential zones where investment can benefit the largest number of people [11,14]. A shift toward evidence-based, settlement-scale planning would enable the NCDC to better address urban settlement population growth, rural-urban migration, and housing policies more effectively, delivering broader societal benefits than current development initiatives such as those aimed at high-income first home buyers [15].

To meet this challenge, the NCDC and its development partners need accurate population and demographic data, such as those produced by this study. The historic absence of up-to-date demographic data has led to global underestimations of slum populations by at least an order of magnitude [51,52]. This has consequently led to increased pressure on scant development resources, poor urban planning outcomes, and poses severe risks for disaster response. In Port Moresby, the perceived unequal allocation of government resources has led, in part, to the "self-help" housing movement and the expansion of urban settlements [4]. Exclusion from government services is compounded by exclusion from the formal economy, and the parallel structures created by communities in their absence (illegal/unregulated water and power connections, informal street marketing) pose a challenge to social order [4,8].

4.2. Methodology Discussion

Data produced by studies such as this can reveal temporal trends affecting urban morphology, providing valuable insights for urban planners and authorities allocating government services. The effectiveness of this approach stems from its simplicity and its integration of quantitative spatial analysis with ground-level qualitative insights. This combination makes it particularly suitable for resource-constrained urban contexts, such as PNG.

Data collection for data-driven urban development in PNG faces significant challenges in terms of accuracy, reliability, and longitudinal consistency, limiting the capacity of state authorities and their development partners to implement evidence-based interventions [21]. In this context, small-scale longitudinal studies such as this offer a practical means of generating reliable population insights where conventional data collection approaches are infeasible. The methodology's reliance on free, publicly available imagery, rather than expensive licensed or bespoke data, makes it particularly well-suited to fiscally constrained environments while still enabling accurate, reliable, and timely analysis of urban structural changes over extended time periods.

Manual identification of settlement structures, whilst more labor-intensive than automated approaches, offers several advantages when applied at the settlement scale. Significantly, this study's comprehensive (100%) mapping of 8-Mile demonstrates the reliability of this approach in bounded urban areas. When compared with results from the 15% preliminary subsample [37], total population estimates differed by an average absolute error of just 8%. An overall accuracy of 92% is comparable to, and in some cases exceeds, reported accuracies for machine learning techniques for building footprint identification [12,28,29,52]. Crucially, a 15% subsample can be manually analyzed by a single operator in under a day (pers. obs. BD), making this a practical option for rapid assessment of settlements in resource-constrained scenarios. This methodology's high accessibility and replicability, and minimal training, software, and fiscal requirements are another key advantage.

Manual structure identification also enables direct integration of qualitative insights derived from stakeholder interviews and ground-level observations, facilitating verification of household boundaries, residential complexes, and construction practices (although potential exists for biases in reporting). This form of contextual validation is not necessarily possible or cost-effective using automated methods alone. Furthermore, manually created datasets can serve as training data for future machine learning projects (Specific Location Data S1.5), representing a valuable by-product in contexts such as PNG and Melanesia, where EO-based mapping of deprived urban areas remains unexplored.

The methodology nonetheless has clear limitations. Manual structure identification restricts the scale of analysis to discrete urban areas such as individual settlements. It is unsuitable for large municipal areas or places lacking recent high-resolution EO imagery. The methodology aims to provide minimum population estimations in places where the preferable option of conducting a census is impracticable, rather than precise population counts or demographic details. Within these bounds, however, it provides a transparent and adaptable framework for producing settlement-level population data to support urban planning and governance in data-scarce environments.

5. Conclusions

This study demonstrates that combining quantitative Earth Observation (EO) data (top-down) with qualitative stakeholder engagement (bottom-up) can produce reliable population estimates for informal settlements in Papua New Guinea. Applied to the urban settlement known as 8-Mile, the analysis revealed consistent population growth averaging 5% annually since 2006, exceeding both the national and National Capital District (NCD) averages, despite increasing pressure from commercial land clearance, infrastructure development, and forced evictions.

The results show that population growth within 8-Mile has occurred primarily through increasing residential density rather than spatial expansion. Even when conservative household density coefficients are applied, population estimates are likely to understate true settlement size due to widespread internal subdivision of dwellings. These findings highlight the limitations of automated EO-based population models when applied without local contextual validation, particularly in informal urban environments.

Methodologically, the study demonstrates that accurate population estimates can be achieved using manual rooftop identification and a relatively small subsample of structures. A 15% subsample produced estimates within 92% of those derived from full-coverage mapping, indicating that this approach is both feasible and practical for rapid assessment in resource-constrained environments, where full enumeration may be impractical. The methodology's reliance on freely available imagery and manual structure identification not only supports accurate and timely assessments but also enables integration with local knowledge, a feature often lacking in automated approaches. While not intended to replace censuses or provide detailed demographic profiles, the method offers a transparent and adaptable framework for generating minimum population estimates where conventional data collection is impracticable.

As Port Moresby continues to grow and informal settlements house an increasing proportion of its population, settlement-scale population data are critical for effective urban governance. The evidence presented here suggests that continued reliance on rezoning and commercial development to manage settlement growth is unlikely to reduce informal populations or improve living standards. Instead, progress toward Sustainable Development Goal 11 requires greater emphasis on evidence-based planning and service provision in high-density residential areas, where investment can benefit the largest number of residents.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/ijgi15070320/s1. S1.1-Historical Imagery; S1.2-Other Imagery Sources; S1.3-The Preliminary Study; S1.4-PNG NSO Data Collection; S1.5-Specific Location Data; S1.6-ArcGIS Projections; S2.1-Structure Dataset Table; S2.2-Structures Summary; S2.3-Population Projections Table; S2.4-Average Nearest Neighbor Table; S2.5-Density Table; S2.6-Census Comparisons Table; S2.7-Preliminary Sample Dataset Table; S2.8-Correlations Table.

Author Contributions: Bradley Dare: methodology, conceptualization, analysis, validation, visualization, and writing the original draft; Shimona Kealy: supervision, project administration, writing the review, and editing. All authors have read and agreed to the published version of the manuscript.

Funding: Funding for open access publication costs was covered by Australian Research Council (ARC) Early Career Industry Fellowship awarded to Kealy (IE250100071) and ANU discretionary research funds generously provided by Professor Sue O'Connor for which we are grateful.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author, Bradley Dare, upon request.

Acknowledgments: We would like to acknowledge Clifford, a local undergraduate student from the University of Papua New Guinea, who was instrumental in organizing access in 8-Mile and translation. We would also like to thank the 8-Mile community for their welcome and helpfulness in facilitating the ground-truthing efforts. Our acknowledgments also go to Bethwyn Evans for her advice and assistance with this project. We would also like to thank two anonymous reviewers as well as the editor for their suggestions to improve this paper's quality.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

GIS	Geographic Information System
EO	Earth Observation
PNG	Papua New Guinea
NCD	National Capital District
NCDC	National Capital District Commission
NSO	National Statistical Office (of PNG)
UN-OHCHR	United Nations Office of the High Commissioner for Human Rights
UN-HABITAT	United Nations Human Settlements Program
UNFPA	United Nations Population Fund
UN-OCHA	United Nations Office for the Coordination of Humanitarian Affairs
DFAT	Department of Foreign Affairs and Trade (Australia)
ESRI	Environmental Systems Research Institute
NASA	National Aeronautics and Space Administration
USGS	United States Geological Survey
ATS	Air Transport Squadron (settlement)
LLG	Local Level Government
SDG(s)	Sustainable Development Goal(s)
ISPRS	International Society for Photogrammetry and Remote Sensing

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