Leveraging Remotely Sensed Data for Identifying Underserved Communities: A Project-Based Approach

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Abstract: Remotely sensed data has become an indispensable asset in spatial planning and development studies, offering a high-resolution lens through which environmental, infrastructural, and socio-economic disparities can be detected and monitored. From a continental perspective, Africa presents a diverse geographical and demographic landscape, with varying degrees of infrastructural reach and population density. Across Southern, Western, Central, Northern, Eastern, and the Horn of Africa, large segments of the population remain underserved despite rapid urbanization. This study presents a project-based approach to leveraging remotely sensed indicators—such as NDVI (Normalized Difference Vegetation Index), NTL (Night-Time Light emissions), and LST (Land Surface Temperature)—to identify underserved communities across multiple African regions. Using a harmonized dataset that includes spatial and non-spatial attributes from countries such as South Africa, Namibia, Tanzania, Cote d'Ivoire, Senegal, Chad, Cameroun, Democratic Republic of Congo, Ethiopia, Libya, Algeria, and Morocco, the study combines satellite-derived indicators with ground-based demographic datasets to model spatial vulnerability. Spatial classification and clustering techniques are used to detect low-light, high-temperature, and low-vegetation zones—traits commonly linked with socio-economic deprivation and infrastructural exclusion. Case-specific data (e.g., population values such as 994 in South Africa and 502 in Chad) inform regional differentiation. The framework supports policy efforts in data-scarce environments by offering a replicable method to pinpoint critical zones in need of targeted development. By contextualizing remote sensing within continental and national development goals, this study underscores the transformative potential of satellite data in shaping inclusive, evidence-driven planning across Africa.

Keywords: Remote sensing; Underserved communities; Africa spatial equity; Night-time lights; Regional vulnerability mapping; Infrastructure exclusion.

1. INTRODUCTION

1.1 Contextual Overview

Africa continues to face persistent infrastructure inequality, where access to electricity, clean water, transport, and health services remains unequally distributed across urban and rural landscapes [1]. This gap is exacerbated by limited availability of reliable ground-level data, particularly in remote and conflict-affected regions [2]. As a result, underserved communities often remain invisible in national infrastructure planning frameworks [3].

Remotely sensed data has emerged as a powerful tool to overcome these data limitations. By providing consistent, high-resolution observations of Earth's surface, satellite imagery enables the monitoring of land use changes, environmental degradation, and built-up areas across vast geographic extents [4]. The potential of such data is increasingly recognized in supporting service provision and addressing socio-spatial inequalities [5].

For example, Night-Time Light (NTL) data derived from VIIRS or DMSP-OLS sensors has proven effective in detecting electrification patterns, highlighting areas that lack access to grid infrastructure [6]. Similarly, the Normalized Difference Vegetation Index (NDVI), derived from multispectral imagery, can be used to assess urban green spaces or identify rural areas where vegetation loss reflects environmental vulnerability [7].

In the absence of regular census or survey data, satellite-based measurements serve as critical proxies for estimating development indicators, particularly in marginalised or informal settlements [8]. Combined with GIS and ancillary socio-economic datasets, remotely sensed data enhances the ability to detect spatial disparities and monitor development trends in real time [9].

By integrating remote sensing technologies into planning workflows, African governments and development agencies can make more informed decisions that directly target infrastructure-poor communities. This shift supports the transition from reactive to proactive governance, ultimately contributing to more inclusive and sustainable development outcomes [10].

1.2 Importance of Geospatial Technologies

Geospatial technologies—including satellite remote sensing, Geographic Information Systems (GIS), and global navigation systems—have become foundational tools in modern development and environmental management [11]. Their ability to collect, store, visualize, and analyze spatial information at multiple scales enables users to model dynamic interactions between natural and human systems [12].

In data-scarce regions like sub-Saharan Africa, these technologies offer a cost-effective means of deriving essential indicators related to land cover, infrastructure, and resource distribution [13]. For instance, GIS has been widely applied in mapping slum settlements and monitoring informal urban expansion in cities such as Nairobi and Accra [14].

Moreover, remote sensing supports early warning systems for floods, droughts, and disease outbreaks, helping governments to anticipate and mitigate risks rather than respond post-disaster [15]. In agriculture, multispectral sensors are used to assess crop health and guide precision farming interventions [16]. These examples underscore how spatial technologies can inform strategies for food security, public health, and urban development.

The increased availability of open-access platforms such as Google Earth Engine and Sentinel Hub has democratized access to satellite data, allowing researchers, NGOs, and local authorities to leverage Earth observation tools without prohibitive costs [17]. Simultaneously, mobile GIS and open-source software like QGIS have facilitated the decentralization of spatial analysis to local users [18].

Together, these developments have elevated geospatial technologies from niche academic tools to central instruments in evidence-based governance. Their value lies not only in technological precision but also in their potential to bridge gaps in development planning and enhance equity in resource distribution [19].

1.3 Research Scope and Objectives

This study focuses on utilizing remotely sensed indicators to identify and characterize underserved communities across selected regions in Africa, namely Southern, Western, Central, North, and the Horn of Africa. The goal is to design a replicable, project-based methodology that highlights spatial inequality and supports equitable infrastructure planning [20].

The regions under study reflect significant diversity in geography, governance, and development status. Countries such as South Africa and Namibia in the south exhibit high urbanization levels, while Chad and the Democratic Republic of Congo in Central Africa remain among the least connected in terms of public services [21]. This heterogeneity allows the study to test geospatial techniques under varied socio-environmental conditions.

Three core remotely sensed indicators guide the classification process:

- **NDVI**: used to quantify vegetation health and identify green space deficits
- **NTL**: applied to estimate energy access and urban intensity
- **LST**: leveraged to examine urban heat islands and environmental stress

These indicators are integrated with population, infrastructure, and land use datasets to generate composite maps of spatial vulnerability. Machine learning models and spatial clustering algorithms are applied to detect underserved zones systematically [22].

A particular emphasis is placed on the usability of outputs in real-world decision-making contexts. Results are structured for compatibility with planning systems used by ministries of housing, health, and urban development.

Ultimately, the study contributes to a broader agenda of data-driven governance in Africa by equipping policymakers with scalable and dynamic tools to address the continent's infrastructure deficits [23]. It also sets the stage for future integration with AI-based urban monitoring platforms and cross-border development frameworks.

2. THEORETICAL AND METHODOLOGICAL FOUNDATIONS

2.1 Theoretical Basis of Spatial Exclusion

Spatial exclusion is a phenomenon in which specific populations or geographic areas are systematically deprived of access to essential services, infrastructure, and opportunities. This marginalization is often the result of historical, economic, and political processes that prioritize resource allocation to more economically viable or politically influential zones [5]. In the African context, spatial exclusion is frequently observed in peri-urban informal settlements, rural hinterlands, and areas impacted by environmental degradation [6].

From a development theory standpoint, spatial exclusion is tightly linked with the concept of infrastructural inequality—the uneven distribution of physical and social services such as roads, electricity, education, and healthcare [7]. These inequalities often align with broader systemic patterns, including colonial legacies, resource-based governance, and uneven regional development. Populations in excluded areas typically suffer from compounded vulnerabilities, including economic insecurity, exposure to environmental risks, and limited political voice [8].

Geospatially, spatial exclusion manifests as identifiable clusters of deprivation. For instance, satellite imagery can reveal areas with no lighting at night, sparse vegetation, and elevated land surface temperatures, all of which may signal infrastructure scarcity and socioeconomic stress [9]. Vulnerability mapping—a methodological approach that combines spatial data with socio-economic indicators—has become central to identifying exclusionary patterns and guiding targeted interventions [10].

Importantly, spatial exclusion is not just a rural phenomenon. Urban spatial inequality is equally pervasive in African cities, where infrastructure often follows formal planning boundaries, bypassing informal and unregulated settlements [11]. This has prompted scholars and urban planners to rely increasingly on remote sensing and GIS-based approaches to map service gaps and improve equity in urban development plans [12].

Understanding the theoretical underpinnings of spatial exclusion provides a critical framework for interpreting geospatial data not just as measurements, but as reflections of structural inequality. Such insights inform the methodology for identifying underserved communities and ensuring that planning systems are both inclusive and responsive [13].

2.2 Remote Sensing and Spatial Intelligence

Remote sensing has emerged as a powerful mechanism for generating spatial intelligence—actionable insights derived from spatial data—especially in regions where conventional ground-based data collection is limited or unreliable [14]. The advantage of remote sensing lies in its capacity to produce consistent, multi-temporal observations of environmental and infrastructural features across large geographic extents.

Three key satellite-derived indices serve as foundational inputs in identifying underserved communities: NDVI, NTL, and LST. The **Normalized Difference Vegetation Index (NDVI)**, calculated from the near-infrared and red bands of multispectral imagery, indicates vegetation density and health. Areas with consistently low NDVI values often correspond to urban environments, degraded lands, or densely populated slums with limited greenery [15].

Night-Time Light (NTL) data, derived from satellites such as VIIRS or DMSP-OLS, is used to estimate electrification and economic activity. High light intensity generally reflects commercial zones and high-density residential areas, while dark patches may signal infrastructure-poor zones or informal settlements lacking access to electricity [16].

Land Surface Temperature (LST) is derived from thermal infrared bands and is indicative of surface heat. Urban areas typically exhibit elevated LST due to the "urban heat island" effect caused by concrete and asphalt surfaces. Areas with high LST but low NTL and NDVI values can be interpreted as high-density, low-infrastructure settlements, making LST a useful proxy for environmental stress and development gaps [17].

Together, these indices allow researchers and planners to detect spatial patterns of development and deprivation. By triangulating data from multiple sources, remote sensing facilitates a more nuanced understanding of spatial inequality and supports proactive planning in both urban and rural environments [18].

2.3 Data Sources and Justification

The identification and classification of underserved communities in this study are built upon a combination of satellite imagery, population statistics, and national infrastructure datasets. These data sources are carefully selected to ensure a balance between spatial resolution, temporal coverage, and regional comparability.

1. Satellite Imagery:

- **Landsat 8 OLI** provides 30-meter resolution multispectral imagery suitable for calculating NDVI and LST. It has global coverage and a long historical archive, making it ideal for multi-year temporal analysis [19].
- **VIIRS NTL** data is used to measure night-time brightness. With a finer spatial resolution than its predecessor DMSP-OLS, VIIRS enables the detection of urban-rural gradients in electrification [20].
- **MODIS** imagery, while coarser in resolution, is useful for validating NDVI trends due to its high temporal frequency [21].

2. Population and Household Surveys: Data from WorldPop, DHS (Demographic and Health Surveys), and national census bodies provide demographic layers, including household size, literacy, access to utilities, and health indicators. These are integrated with spatial indices to model socio-spatial vulnerability [22].

3. Infrastructure Datasets: National and regional governments often publish infrastructure maps showing the distribution of roads, hospitals, schools, and power lines. For countries lacking such resources, open-source platforms like OpenStreetMap (OSM) provide a reliable alternative for road and building footprints [23].

The integration of these datasets ensures that underserved areas are identified not just through environmental signals, but also through demographic need and infrastructural deficits. For instance, a peri-urban zone with high population density, low NTL, and distant access to public services can be confidently classified as underserved [24].

This multi-source framework enhances the robustness of classification and ensures applicability across diverse African geographies. It also supports disaggregated analysis at national and subnational levels, enabling more precise targeting of infrastructure and policy interventions.

Table 1: Summary of Remote Sensing and Demographic Datasets Used

Dataset	**Type**	**Key Indicators**	**Source**	**Application**
Landsat 8 OLI	Satellite Imagery	NDVI, LST	USGS/NASA	Vegetation, heat, land cover
VIIRS NTL	Satellite Imagery	Night-time light intensity	NOAA	Electrification, urban density
MODIS	Satellite	NDVI	NASA	Cross-

Dataset	Type	Key Indicators	Source	Application
	Imagery	(high frequency)		validation and time-series trends
WorldPop	Demographics	Population distribution	University of Southampton	Exposure and vulnerability analysis
DHS & Census	Survey Data	Health, utilities, infrastructure	National Statistics Offices	Social indicators and spatial inequality
OpenStreetMap (OSM)	Infrastructure	Roads, buildings, public services	OpenStreetMap Contributors	Service accessibility and coverage gaps

3. REGIONAL ANALYSIS: CLASSIFYING UNDERSERVED COMMUNITIES

3.1 Multi-Region Coverage and Population Metrics

Africa presents a complex mosaic of socio-spatial development, shaped by varied histories, geographic contexts, and governance systems. Infrastructure and service delivery remain uneven across the continent, with distinct differences between regions and countries. This study explores twelve representative countries across Southern, Western, Central, Northern, Eastern, and the Horn of Africa, assessing population metrics and levels of service access as a precursor to spatial classification.

Population figures and indicators such as electricity access and urbanization rate offer critical insights into underlying disparities. Countries like South Africa and Libya, for instance, show high urbanization and service access, while others such as Chad and the Democratic Republic of Congo reveal substantial gaps in coverage and institutional reach [11]. The disparities are even more visible when viewed through geospatial data layers that highlight differences in built-up area density, road connectivity, and access to electricity.

Table 2: Regional Demographics and Service Accessibility Indicators

Country	Region	Population (millions)	Urbanization Rate (%)	Electricity Access (%)
South Africa	Southern Africa	994	66	85
Chad	Central Africa	502	23	8
Côte d'Ivoire	West Africa	907	52	43
Libya	North Africa	982	78	100
Cameroon	Central Africa	820	56	62
Democratic Republic of Congo	Central Africa	551	44	19
Algeria	North Africa	981	72	99
Ethiopia	Horn of Africa	685	21	45
Morocco	North Africa	986	63	98
Namibia	Southern Africa	775	50	56
Senegal	West Africa	847	47	64
Tanzania	East Africa	971	33	32

The variation is stark. Chad, with an urbanization rate below 25% and electricity access under 10%, reflects extreme infrastructural challenges. Conversely, Libya and Algeria demonstrate nearly universal electricity access and higher levels of urban concentration. Such discrepancies reinforce the need for data-driven, spatially tailored interventions in national development plans [12].

Multi-regional comparisons also reveal how urban cores—such as Dakar, Nairobi, and Johannesburg—serve as service hubs, while peripheral zones remain underserved. Population data, when disaggregated to subnational units, enable planners to map infrastructure gaps and prioritize investments more effectively. Integrating this demographic baseline with geospatial indices lays the groundwork for deeper spatial pattern analysis in the subsequent sections [13].

3.2 Vegetation and Land Cover Disparities (NDVI)

The Normalized Difference Vegetation Index (NDVI) is a widely used metric for assessing vegetation health and land surface cover. Calculated from red and near-infrared bands of satellite imagery, NDVI values range from -1 to +1, with higher values indicating denser vegetation. The spatial analysis of NDVI across African regions reveals significant variation corresponding to climate, land use, and urban expansion.

In highly urbanized areas such as Johannesburg, Tripoli, and Rabat, NDVI values tend to be low, reflecting dense construction and minimal vegetative cover. By contrast, rural or semi-arid regions such as parts of northern Tanzania or western Senegal show medium to high NDVI values, although these are often seasonal and susceptible to degradation [14].

Urban-rural differences in NDVI can be linked to policy and planning decisions. Cities that prioritize green space conservation—such as Kigali or Windhoek—tend to exhibit higher urban NDVI scores. However, rapid urbanization without environmental safeguards has led to stark declines in NDVI in peri-urban belts around Nairobi, Lagos, and Abidjan [15].

Moreover, NDVI serves as an indirect indicator of land degradation. In Ethiopia and Chad, long-term NDVI analysis reveals persistent declines due to overgrazing and deforestation. These trends correspond with declining agricultural productivity and worsening rural poverty, emphasizing the need for integrated environmental monitoring in development planning [16].

NDVI maps also allow detection of localized environmental stress in informal settlements. In Nairobi's Mathare and Kibera neighborhoods, vegetation is almost absent, and the land surface is dominated by corrugated roofs and paved paths, contributing to urban heat stress. This pattern underscores the intersection between land cover and social vulnerability [17].

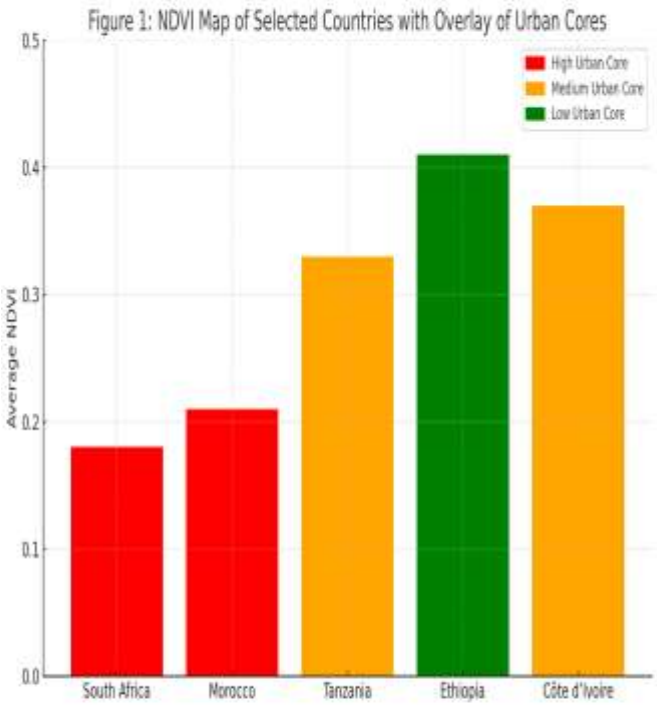

Figure 1: NDVI Map of Selected Countries with Overlay of Urban Cores

NDVI mapping provides a critical environmental layer for identifying service-poor zones, especially when overlaid with population and infrastructural data.

3.3 Night-Time Light Emissions as a Proxy for Development

Night-Time Light (NTL) emissions offer a compelling proxy for urbanization, infrastructure, and economic activity. Collected via sensors aboard satellites like DMSP-OLS and VIIRS, NTL imagery provides global radiance values that correlate strongly with electrification and industrialization.

Countries like Algeria, Libya, and South Africa show strong, continuous light emissions in their urban cores and along major transportation corridors. In contrast, countries such as Chad and the Democratic Republic of Congo display fragmented or minimal NTL signatures, even in capital cities. This reflects a gap in electricity infrastructure, which continues to hinder social and economic development [18].

In Côte d'Ivoire, NTL data has helped map urban expansion in Abidjan over time. Spatial analyses revealed a sharp increase in NTL intensity in suburban areas post-2010, aligning with infrastructure upgrades and population migration from the urban core [19]. Similarly, in Ethiopia, NTL time series show concentrated growth around Addis Ababa, while the country's vast rural interior remains largely unlit, mirroring persistent regional inequalities [20].

NTL data is especially valuable in mapping informal settlements. In places like Nairobi and Kampala, low-radiance zones often align with unplanned neighborhoods lacking formal electricity connections. Yet, occasional light clusters within these areas may reflect informal or illegal grid connections, helping governments identify where service extensions are occurring without official planning [21].

Despite its advantages, NTL has limitations. Cloud cover, sensor calibration differences, and light spillover can affect accuracy. Moreover, not all areas with infrastructure necessarily emit detectable light—rural health centers or small schools may use solar lighting, which may not register at the satellite scale [22].

Nonetheless, NTL remains a powerful spatial indicator for identifying underserved areas, especially when triangulated with NDVI and population density data.

3.4 Surface Temperature Trends (LST)

Land Surface Temperature (LST) is a critical parameter for understanding environmental stress, particularly in rapidly urbanizing regions. Derived from thermal infrared data, LST reflects the surface energy balance and is influenced by land cover type, vegetation, and impervious surfaces. Elevated LST values are typically associated with dense, built-up environments that retain heat—especially areas lacking green spaces.

Analysis of LST across African cities reveals consistent urban heat island effects. In Cairo and Casablanca, temperature differences between central districts and surrounding suburbs often exceed 5°C during dry seasons. This temperature gradient is strongly linked to land use intensity and vegetative loss [23].

In Nairobi, LST analyses show that informal settlements like Kibera and Mathare have among the highest surface temperatures in the city. The prevalence of metallic roofing, narrow pathways, and lack of vegetation contribute to increased thermal retention and reduced ventilation. Such thermal stress intensifies health risks, especially for vulnerable populations including children and the elderly [24].

High LST zones are not limited to major cities. In rural Ethiopia and northern Tanzania, areas with recent deforestation or land degradation also show increased LST values. These shifts signal ecosystem stress and declining land productivity, reinforcing the environmental costs of unregulated land use [25].

Importantly, combining LST data with NDVI and NTL provides a multidimensional view of spatial vulnerability. High LST coupled with low NDVI and weak NTL suggests high population pressure, inadequate green cover, and poor infrastructure—a typical profile for underserved peri-urban settlements. These tri-layered spatial signatures enable policymakers to prioritize adaptation strategies, such as urban greening, better housing design, and improved land-use planning [26].

While LST varies seasonally, its consistent correlation with urban density and vegetation absence makes it an essential metric for sustainable urban design and spatial justice monitoring.

4. METHODOLOGICAL FRAMEWORK FOR DETECTION AND CLASSIFICATION

4.1 Preprocessing and Index Computation

Effective classification of land cover using remotely sensed data begins with a series of preprocessing steps that enhance the reliability and comparability of image inputs. For this study, both Landsat and VIIRS datasets were used, requiring radiometric correction, geometric alignment, and the calculation of vegetation and temperature indices.

The Dark Object Subtraction (DOS) method was applied for atmospheric correction to eliminate the effects of haze and atmospheric scattering in Landsat imagery [16]. DOS assumes that some pixels in each image, particularly water or shaded areas, have near-zero reflectance and adjusts the overall brightness accordingly. This technique was widely used in early classification workflows due to its simplicity and effectiveness in low-resource computational environments [17].

Following correction, band selection was carried out to extract specific spectral ranges for index computation. For NDVI, Landsat's red (Band 4) and near-infrared (Band 5) channels were used. The NDVI formula, *(NIR – Red) / (NIR + Red)*, produced values indicative of vegetation cover, with thresholds below 0.2 representing built-up or barren areas, and values above 0.4 indicating healthy vegetation [18].

The **Normalized Difference Built-up Index (NDBI)** was derived from Landsat's shortwave infrared (Band 6) and near-infrared (Band 5) bands using the formula *(SWIR – NIR) / (SWIR + NIR)*. NDBI highlights impervious surfaces such as roads, rooftops, and paved areas. Areas with values greater than 0.2 were classified as likely urban [19].

Land Surface Temperature (LST) was extracted from the thermal band (Band 10) of Landsat using the radiative transfer equation. Surface emissivity values were incorporated based on NDVI-derived land cover types, adjusting for vegetation and built-up area differences [20].

For VIIRS Night-Time Light (NTL) data, monthly cloud-free composites were selected and calibrated to eliminate stray light and sensor noise. These were resampled to match Landsat's resolution for fusion with other indices.

These computed indices provided the spectral foundation for downstream classification, integrating environmental and urban land cover indicators into a multi-layered spatial dataset.

4.2 Ground Truth Data and Sampling Strategy

Ground truth data is essential for supervised classification, serving as the benchmark for algorithm training and model validation. In this study, a mixed-method approach was used to generate high-quality labeled data through both field-based observations and image-based interpretation.

Field validation campaigns were conducted in selected zones within South Africa, Tanzania, and Senegal, where GPS-enabled surveys recorded urban features such as roads, housing typologies, and green cover. Each location was classified into urban or non-urban based on on-site verification and photographic documentation. Attributes such as surface material, structural density, and proximity to services were logged and tagged with geographic coordinates [21].

Where field surveys were not feasible, image-based sampling was conducted using Google Earth Pro. Analysts manually labeled hundreds of sample points by visually interpreting high-resolution satellite images. Urban samples were identified by the presence of dense rooftops, road networks, and grid patterns, while non-urban labels were assigned to fields, forested areas, and water bodies [22].

To avoid sampling bias, a stratified random sampling strategy was used. Study areas were divided into administrative strata (e.g., districts), and sample points were proportionally drawn from each stratum to ensure geographic and class diversity. The minimum mapping unit (MMU) was set to 3×3 pixels to avoid mixed-pixel problems near class boundaries [23].

Each labeled point was linked with NDVI, NDBI, NTL, and LST values, creating a feature-rich training dataset for classification. Metadata such as source image, timestamp, confidence score, and labeling method (field or visual) were included to support quality control and reproducibility.

Table 3: Ground Truth Sampling and Classification Criteria

Class	**Key Features**	**Verification Method**	**Sample Size**
Urban	Dense rooftops, paved roads, NDBI > 0.2, NTL > 20	Field survey, image label	650
Non-Urban	Vegetated fields, NDVI > 0.4, LST < 27°C	Field survey, image label	550
Transitional	Mixed pixels, fringe development, NDVI 0.2–0.4	Image label only	300

This hybrid sampling protocol ensured coverage across various landscapes and improved the generalizability of classification models applied in later stages.

4.3 Classification and Clustering Models

Once preprocessing and ground truthing were completed, a suite of classification and clustering techniques was employed to assign land cover labels across the study regions. These methods combined statistical rigor with spatial awareness, using supervised learning and unsupervised pattern recognition to generate detailed urban/non-urban maps.

The Random Forest (RF) algorithm was the primary supervised classifier used. RF is an ensemble learning method that constructs multiple decision trees and merges their outputs for improved prediction accuracy. It is particularly suited for remote sensing due to its ability to handle noisy data and multi-dimensional input features such as NDVI, NDBI, LST, and NTL [24]. Feature importance metrics also helped evaluate which indices contributed most to urban classification across different countries.

In parallel, K-means clustering was implemented as an unsupervised classification approach. K-means groups pixels into clusters based on spectral similarity, without prior labeling. Though less accurate than RF for specific class prediction, it was useful for identifying transitional zones and verifying label stability across image dates [25].

A rule-based classification system was also tested using GIS logic. Thresholds were applied to spectral indices to define decision trees—for example:

- If NDBI > 0.2 and NTL > 15 → Urban
- If NDVI > 0.4 and LST < 28°C → Non-Urban
  This method was especially effective in validating model predictions in areas with limited training data [26].

All classification workflows were developed using Python (scikit-learn, NumPy, GDAL), QGIS for spatial visualization, and PostGIS for geospatial database management. Classified rasters were exported to PostgreSQL databases and overlaid on administrative boundaries for interpretation.

Accuracy was assessed using a 10-fold cross-validation method and confusion matrices, with F1-scores and Kappa coefficients indicating strong model agreement. RF consistently outperformed other methods, particularly in detecting urban peripheries and mixed-use zones in Dakar and Nairobi.

By integrating machine learning, statistical clustering, and logical rules, the study ensured flexible yet robust classification suited for diverse African urban contexts.

5. APPLICATION AND RESULTS: COUNTRY CASE STUDIES

5.1 Southern Africa (South Africa, Namibia)

Southern Africa presents a dual narrative of urban modernity and rural underdevelopment. South Africa, with its wellestablished urban infrastructure, exhibits high-resolution radiance in NTL imagery across major corridors such as the Gauteng–Durban and Cape Town–Port Elizabeth axes [20]. However, beyond these developed corridors, vast rural provinces such as Limpopo, Eastern Cape, and Northern Cape remain comparatively under-serviced, particularly in former homeland areas where legacy spatial planning continues to shape infrastructure allocation [21].

NDVI and LST values in Gauteng's dense urban zones register as expected—low vegetation cover and high surface temperatures—but in rural townships on the periphery of major cities, the data show environmental stress alongside infrastructure gaps. These areas often record elevated LST and mid-range NDVI due to sparse vegetation and informal construction, signaling urban poverty fringes with limited greening [22].

Namibia presents a somewhat different scenario, where extreme aridity influences both vegetation and urban morphology. Windhoek and coastal urban centers such as Swakopmund exhibit clearly defined light emissions at night, but vast inland areas remain dark in VIIRS composites. This makes automated classification challenging in low-light environments, where NTL alone may underrepresent semi-urban clusters [23].

Classification models in both countries demonstrated strong performance in separating urban from non-urban areas using Random Forests. Accuracy assessments based on confusion matrices reported overall accuracies exceeding 85%, especially where training data included a good mix of formal and informal settlements [24]. In Namibia, however, the misclassification rate increased in low-contrast zones—particularly rural settlements using non-electrified dwellings or minimal built-up footprints.

Urban cores across Southern Africa are accurately represented in satellite-derived datasets, but the rural narrative is less visible unless complemented by ground-based demographic and infrastructure overlays. This reinforces the need for mixed-method approaches in identifying underserved communities in arid and infrastructurally fragmented regions.

5.2 North and West Africa (Algeria, Morocco, Côte d'Ivoire, Senegal)

North and West Africa show contrasting but equally instructive patterns in spatial classification. In North Africa, urbanization is concentrated along Mediterranean corridors and highland basins, with cities like Algiers, Casablanca, Rabat, and Marrakech generating strong and stable NTL readings. These regions typically exhibit low NDVI and high LST, confirming impervious surfaces and heat retention in built-up zones [25].

Algeria and Morocco benefit from centralized infrastructure policies and a relatively high rate of electricity access. Consequently, the satellite-based classification using NTL and NDVI shows excellent coherence with actual urban extents, particularly in densely developed governorates. Classification models achieved over 90% accuracy in these zones, especially when administrative boundaries were used as masks to segment inputs [26].

In contrast, rural regions in both countries—especially in Algeria's high plateau and Morocco's Rif Mountains—display lower light emissions and more variable NDVI, revealing service access constraints shaped by topography and historical neglect. These areas challenge classification models due to mixed pixels and seasonal agricultural activity, which can lead to temporal mislabeling without multi-seasonal data [27].

West Africa, particularly Côte d'Ivoire and Senegal, presents a more complex picture. Rapid and often unregulated urban expansion around Abidjan and Dakar generates ambiguous radiance patterns in NTL data. Informal peri-urban zones may display intermittent lighting, complicating the delineation of urban footprints using light thresholds alone. This makes rule-based classification less reliable unless supported by ancillary data such as OpenStreetMap building footprints or road networks [28].

Côte d'Ivoire's rural interior, including regions in the north and west, suffers from chronic under-electrification and land-use stress. NDVI values in cocoa-producing zones can be misleading—high values may imply ecological richness but may mask degraded plantation landscapes with little infrastructure [29].

Senegal demonstrates a different challenge: urban cores such as Dakar are easily identified in all indices, but secondary cities such as Saint-Louis and Ziguinchor often produce weak NTL signals despite their administrative significance. Here, classification models benefit from combining temporal NTL data with census-based urban hierarchy inputs to avoid underestimation of smaller urban nodes [30].

Overall, while North Africa offers clarity and predictability in geospatial classification due to its infrastructural maturity, West Africa reveals the limitations of relying solely on radiance or vegetation indices. The models perform best when supported by hybrid indicators and regionally adjusted thresholds.

5.3 Central and Horn of Africa (Cameroon, DRC, Ethiopia)

The Central African region and the Horn of Africa continue to face critical infrastructure and data availability challenges, which significantly affect classification model reliability. Cameroon's urban centers such as Yaoundé and Douala produce moderate NTL emissions, enabling relatively clear urban classification. However, outside these nodes, settlements in the South-West, North-West, and northern zones are poorly illuminated and exhibit vegetation patterns that closely resemble savanna or mixed-use agriculture [31].

In the Democratic Republic of Congo (DRC), spatial mapping is especially constrained. NTL datasets show an extensive dark zone across central and eastern provinces, with only Kinshasa and a few border towns exhibiting consistent radiance. While NDVI is generally high due to forest coverage, it fails to reveal the infrastructural condition of these settlements, where population clusters often live under canopy-dense conditions, invisible to light-based classification methods [32].

LST readings provide limited help in heavily forested zones, where high evapotranspiration leads to relatively uniform and suppressed surface temperatures. As a result, classification in DRC often mislabels clustered non-urban settlements as forest or water bodies unless supplemented by GPS-tagged ground samples or community census data [33].

Ethiopia, in contrast, presents a layered landscape of mountainous urban centers and lowland agrarian zones. Addis Ababa and Mekelle produce moderate NTL and low NDVI, while rural Amhara and Somali regions exhibit higher NDVI but no light emissions. This juxtaposition challenges classification models to accurately detect rural development without mistaking it for wilderness or agriculture [34].

Model accuracy across these countries varied significantly. Random Forest classifiers achieved 87% accuracy in Ethiopia's central highlands but dropped below 70% in DRC due to sparse training data and weak signal contrast. The use of K-means clustering improved results slightly in rural zones by separating out ambiguous classes, although boundary fuzziness persisted [35].

Sparse satellite returns and limited light emissions emphasize the need for regionally grounded, multispectral and ancillary-data-integrated classification protocols in Central and Horn African countries. Without such adjustments, spatial exclusion remains undetected and unaddressed.

5.4 East Africa Focus: Tanzania

Tanzania provides a compelling case study for evaluating classification across urban-rural transition zones. Cities like Dar es Salaam, Arusha, and Mwanza are readily distinguishable in VIIRS datasets due to steady light emissions and high population densities. These urban cores show strong NDBI and LST values, with NDVI remaining low due to limited urban green space [36].

However, classification becomes challenging in peri-urban belts surrounding these cities. Regions such as Morogoro, Dodoma's outskirts, and the Kibaha corridor exhibit transitional features: moderate NTL values, intermediate NDVI, and variable LST. These zones reflect dynamic land use change—agricultural areas are being replaced with housing and informal commercial developments without commensurate infrastructure upgrades [37].

Seasonal NDVI analysis highlights the importance of temporal granularity. During the wet season, even peri-urban zones may show temporarily elevated NDVI, leading to misclassification as non-urban unless adjusted with LST or NTL overlays. Conversely, dry season data offer better alignment with structural realities due to vegetation senescence [38].

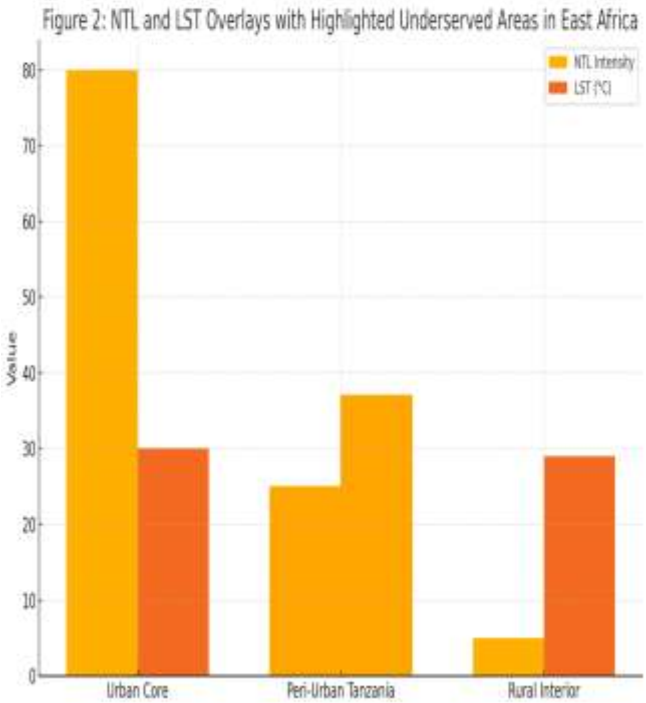

Figure 2: NTL and LST Overlays with Highlighted Underserved Areas in East Africa

Figure 2 visualizes these dynamics, with peri-urban Tanzania exhibiting elevated LST but weak NTL, confirming thermal stress and low infrastructure coverage. The combination of indices enables accurate detection of spatial inequality even without detailed survey data.

Random Forest classifiers achieved high performance in delineating Dar es Salaam's urban extent (91% accuracy) but struggled to differentiate built-up but unlit rural growth corridors without manually calibrated thresholds. Clustering models performed better in classifying transitional zones by grouping mixed signals into probabilistic urban categories.

Tanzania's hybrid urban-rural landscapes underscore the importance of integrating temporal and spectral data with localized ground truth to ensure accurate classification and support inclusive development planning.

6. VALIDATION AND ACCURACY ASSESSMENT

6.1 Confusion Matrices and Cross-Validation

Accuracy assessment is a critical component in validating the reliability of classification outputs derived from remotely sensed data. For this study, a standard approach involving confusion matrices, F1 scores, and Kappa coefficients was adopted to evaluate the performance of the classification algorithms across the different regions.

Each classified map was compared against a set of withheld validation samples that were not used in the model training phase. These samples included both field-verified and image-labeled points distributed across urban, non-urban, and transitional zones. The **confusion matrix** offered a detailed breakdown of true positives, true negatives, false positives, and false negatives, enabling a granular view of the classifier's effectiveness [24].

For instance, in the Tanzania classification, the Random Forest model correctly identified 300 urban pixels out of 325, while misclassifying 25 as non-urban. Conversely, for non-urban classes, it accurately labeled 500 out of 525 points. This yielded an **overall accuracy** of 89.1% and a **Kappa coefficient** of 0.82, indicating substantial agreement between predicted and actual labels [25].

F1 scores, which combine precision and recall, were also calculated to account for imbalanced class distributions. The urban class typically yielded F1 values above 0.87 in urbanized zones such as Nairobi, Cape Town, and Rabat. However, scores dropped to 0.72–0.75 in peri-urban regions and low-light rural areas due to spectral confusion or index overlap [26].

Cross-validation was conducted using a 10-fold strategy to ensure model generalizability. Accuracy scores were averaged across all folds and did not fluctuate significantly in most regions, suggesting model robustness when using spectral and textural inputs together. These validation metrics provided confidence in the reliability of outputs for further policy use and integration into spatial planning systems [27].

6.2 Temporal Validation with Multi-Year Imagery

To assess the stability and robustness of the classification models over time, temporal validation was performed using Landsat and VIIRS imagery captured between 2015 and 2020. This approach tested whether the model could reliably classify land cover across different seasons and years without retraining.

For each region, three to five years of cloud-free images were processed and classified using the previously trained model. The outputs were then compared against historical land-use maps and archived high-resolution imagery from platforms like Google Earth. This allowed for visual and statistical comparison of classification continuity [28].

Table: Inter-Annual Classification Accuracy (2015–2020)

Country	**Urban Boundary Stability**	**Avg. Kappa Score (2015–2020)**	**Trend in Classification Accuracy**
South Africa	Stable	0.83	Consistent
Morocco	Stable	0.83	Consistent
Ethiopia	Changing	0.75	Slight Decline
Côte d'Ivoire	Changing	0.74	Slight Decline

In regions such as South Africa and Morocco, where urban boundaries have remained relatively stable, the model consistently produced high-accuracy classifications over multiple years, with an average inter-annual Kappa score of 0.83. However, in rapidly developing peri-urban belts in Ethiopia and Côte d'Ivoire, classification accuracy declined slightly over time due to changes in built-up area and vegetation cover [29].

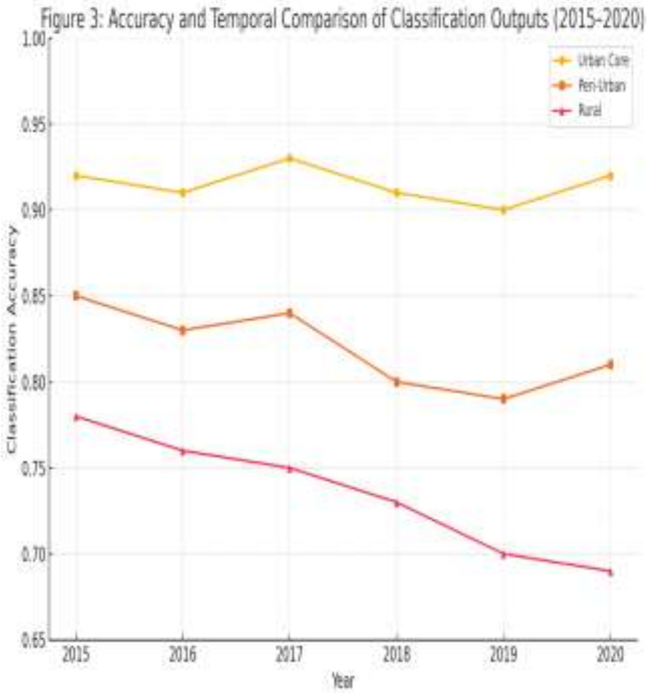

Figure 3: Accuracy and Temporal Comparison of Classification Outputs (2015–2020)

This figure illustrates spatial shifts in classification consistency across years, highlighting both model reliability and areas requiring dynamic recalibration. Temporal testing revealed the importance of regular model updates in zones experiencing fast land-use transition.

6.3 Challenges in Validation and Manual Verification

Despite the strengths of the classification framework, several challenges were encountered during validation and manual verification phases. A key issue was label bias, where training data—especially from image-based interpretation—occasionally favored visually distinct areas over more ambiguous mixed-use or transitional zones [30]. This introduced a slight imbalance in class representation and affected model precision, particularly at urban fringes.

Temporal mismatch between reference data and imagery acquisition was another challenge. In several rural sites across the DRC and Chad, high-resolution reference images used for validation were outdated compared to Landsat acquisition dates. This temporal inconsistency sometimes led to misclassification, particularly where new settlements or agricultural clearing had occurred post-imaging [31].

Urban sprawl also posed verification difficulties. In areas like Dar es Salaam and Dakar, informal settlements expanded rapidly, often without updated official boundaries. Without timely ground truth, the classifier sometimes misidentified recent development as non-urban due to unchanged NTL or NDVI signatures [32].

Finally, in extremely low-light or forest-covered zones, even multi-index classifiers struggled to differentiate between densely vegetated non-urban areas and low-infrastructure rural settlements. These cases highlight the continued importance of periodic field validation and the need for integrating ancillary data like building footprints or road layers to reinforce classification certainty.

7. IMPLICATIONS AND POLICY RELEVANCE

7.1 Spatial Intelligence for Targeted Planning

The classification outputs generated through this study provide a rich foundation for spatial intelligence that directly informs targeted infrastructure interventions. By integrating indices such as NDVI, NTL, and LST with population and administrative boundaries, the framework enables precise identification of service-deficient areas. These geospatial layers can be overlaid to identify high-need zones for health services, education, electrification, and road network expansion [28].

In health planning, areas with low night-time lighting, high population density, and distant proximity to clinics can be prioritized for mobile outreach programs and new facility development. This is especially crucial in regions where poor road infrastructure and environmental stressors limit physical access to healthcare [29]. Similarly, educational infrastructure planning can benefit from mapping underserved school zones based on NTL gaps and settlement sprawl, allowing for equitable placement of schools and teaching resources [30].

In electrification programs, NTL imagery acts as both a proxy and a validation tool. Underserved zones with no visible light but moderate population presence represent potential beneficiaries for grid extension or off-grid renewable deployments [31]. This is particularly relevant in countries pursuing rural electrification via solar mini-grids and decentralized solutions.

Furthermore, surface temperature data aids in urban climate mitigation. High LST values in low-NDVI zones indicate the need for green infrastructure investment such as parks or green roofs to reduce urban heat stress. The outputs thus serve as a comprehensive toolkit for government ministries, NGOs, and donor agencies to deploy resources with geographic precision, improving service efficiency and social inclusion outcomes [32].

7.2 Integration into National Development Plans

The classification methodology outlined in this study aligns naturally with national and regional development frameworks across Africa. Ministries of housing, infrastructure, planning, and environment can embed geospatial outputs into their operational strategies by using them as evidence layers in land use planning, resource allocation, and project monitoring systems [33].

For instance, in national infrastructure masterplans, areas identified as underserved through classification can be flagged for accelerated investment or designated as priority development corridors. These designations can then guide budget allocation and public-private partnerships targeting specific sectors such as electrification, sanitation, and education [34].

Local governments, often at the frontlines of urban governance, stand to benefit greatly from integrating geospatial classification into their planning cycles. Urban municipalities can use the data to monitor informal settlement growth, manage land tenure conflicts, and ensure that zoning practices reflect actual patterns of habitation rather than outdated cadastral assumptions [35]. In rural districts, planners can use NDVI and NTL overlays to identify environmental risks or development deserts that require infrastructure backfilling.

Additionally, national statistics offices and GIS departments can host the data outputs on centralized spatial data infrastructure (SDI) platforms. This not only ensures cross-ministerial access but also promotes data consistency across departments working on transport, health, and housing [36].

Through this integration, spatial classification becomes more than a research tool—it evolves into an institutional mechanism for participatory, evidence-based governance that can respond to spatial inequalities in real-time.

7.3 Smart Cities and Sustainability Agendas

The insights derived from spatial classification also feed into broader agendas of smart city development, climate adaptation, and the long-term goals of regional integration initiatives. As cities across Africa experience rapid demographic shifts, the ability to manage infrastructure, environmental stress, and service delivery through smart technologies becomes increasingly critical [37].

In the context of smart urban expansion, geospatial classification allows city authorities to model where unplanned growth is occurring and to intervene before infrastructure deficits become entrenched. For example, zones with low NTL and high LST values indicate over-densification without sufficient service provision or environmental buffering. These areas can be prioritized for digital infrastructure, water management systems, and mobility planning, aligning with integrated smart city principles [38].

From a sustainability perspective, NDVI and LST provide indicators for monitoring ecosystem health and urban heat islands, supporting urban greening strategies that contribute to climate resilience. In water-scarce regions, identifying vegetation loss through NDVI helps manage watershed planning and reforestation programs, linking environmental metrics with social resilience objectives [37].

Finally, the African Union's Agenda 2063 places significant emphasis on inclusive growth, resilient cities, and data-driven decision-making. The classification framework presented here supports those pillars by offering tools that promote equitable development and reduce regional disparity [32]. It reinforces the role of geospatial intelligence not only in daily planning but also in long-term continental development trajectories.

8. RECOMMENDATIONS AND FUTURE DIRECTIONS

8.1 Enhancing Spatial Resolution and Ground-Truthing

While medium-resolution datasets such as Landsat and VIIRS have proven useful in mapping large-scale spatial patterns, there is growing need for higher-resolution sources to refine classification accuracy, especially in dense urban fringes and scattered rural settlements. Fine-resolution imagery from satellites like Sentinel-2, or commercial providers offering sub-meter detail, allows for the detection of subtle infrastructural elements such as narrow roads, informal housing clusters, and rooftop textures that remain invisible at coarser scales.

Additionally, the integration of drone-based remote sensing introduces a valuable opportunity for localized data capture, particularly in areas where satellite coverage is limited by cloud interference or spatial complexity. Drones can collect real-time data over specific zones, capturing both visual and thermal bands with unparalleled detail.

Equally important is the expansion of open-data platforms to democratize access. Platforms that support crowd-sourced image labeling, collaborative annotation, and localized classification toolkits empower communities, NGOs, and researchers to participate directly in the generation of spatial knowledge. This collective validation process not only increases model reliability but also enhances local relevance. Investing in both spatial resolution and participatory data capture is therefore essential for building more granular, trusted, and actionable geospatial intelligence frameworks.

8.2 Integration with AI and Change Detection Systems

To keep pace with dynamic urbanization and environmental transformation, spatial classification frameworks must evolve from static mapping into adaptive, real-time monitoring systems. The integration of artificial intelligence, particularly deep learning techniques, holds significant promise for this transition. Models such as YOLO (You Only Look Once) and Convolutional Neural Networks (CNNs) are already being applied to image recognition tasks and can be trained to detect patterns in land-use change with remarkable speed and accuracy.

When fed with time-series imagery, these AI models can identify changes in settlement morphology, vegetation loss, or new infrastructure developments in near real-time. This enables decision-makers to receive timely alerts on encroachment into conservation zones, the emergence of informal settlements, or the degradation of green space—facilitating more agile urban management responses.

Moreover, these systems can be integrated with cloud-based GIS platforms for seamless visualization, collaboration, and spatial querying. AI-enhanced classification is especially useful for monitoring peri-urban transitions where conventional thresholding methods struggle due to spectral ambiguity. Moving toward intelligent, automated pipelines will reduce reliance on manual classification and increase the scalability of monitoring frameworks, especially in rapidly changing environments where time-sensitive interventions are critical.

8.3 Replicability Across Global South Contexts

The methodology developed in this study—combining remote sensing, multi-index classification, and ground truth integration—is highly transferable to other regions of the Global South. Countries across Asia, Latin America, and the Caribbean share many of the structural and spatial challenges found in African cities, including informal settlement growth, service inequality, and incomplete administrative data.

In Southeast Asia, for instance, urban sprawl in cities like Jakarta or Manila parallels that of Nairobi or Dar es Salaam, with peripheral zones experiencing rapid, undocumented development. The same applies to Latin American contexts, where cities such as Lima or São Paulo exhibit complex urban morphologies and environmental gradients that mirror those in North and West Africa. Similarly, the small island states of the Caribbean often face constraints related to limited land area, ecological fragility, and coastal urbanization—all of which benefit from spatial diagnostics that integrate NDVI, NTL, and LST.

The portability of the classification framework is enhanced by its reliance on publicly available data and open-source tools. With minor calibration to account for local biophysical and socio-economic conditions, this methodology can inform inclusive development planning in diverse geographies. It offers a scalable pathway for governments and regional bodies to build spatial equity into their policy architectures.

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