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Assessing the Role of Multi-Resolution Remote Sensing in Monitoring Urban Growth and Environmental Change in Rapidly Urbanizing Regions

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Abstract

Rapid urbanization in developing and transitional regions has created significant challenges in monitoring land use change and environmental degradation. Remote sensing (RS) has emerged as a vital tool for assessing urban growth and its ecological impacts due to its capability to provide consistent, multi-temporal, and large-scale data. However, conventional RS methods often rely on single-resolution imagery, which limits the ability to capture both detailed urban features and broader environmental trends simultaneously. Additionally, challenges such as high processing costs, skill requirements, and fragmented collaboration between Remote Sensing and Geographic Information Systems (GIS) communities further hinder comprehensive urban analysis. This study proposes a novel multi-resolution remote sensing methodology that integrates high, medium, and low-resolution satellite data for a holistic assessment of urban dynamics. The proposed approach enhances urban feature detection and environmental monitoring through spatial data fusion, supervised classification, and change detection techniques. The workflow includes data acquisition from diverse sources, pre-processing (correction, enhancement), classification using machine learning algorithms (e.g., Random Forest), accuracy assessment through ground-truth validation, and visualization via thematic maps. Experimental results demonstrate the method's effectiveness in capturing urban sprawl, vegetation loss, and pollution indicators in rapidly urbanizing regions. The integrated multi-resolution framework outperforms single-source analysis in both accuracy and spatial coverage. This approach supports decision-making for sustainable urban planning by delivering high-quality geospatial insights. Overall, the proposed methodology bridges the gap between RS and GIS applications and serves as a scalable model for future urban environmental monitoring initiatives.

Keywords

Multi-Resolution Remote Sensing, Urban Growth Monitoring, Environmental Change Detection, Geospatial Data Integration, Sustainable Urban Planning

1. Introduction

The development of urbanization is drastically increasing at a faster rate especially in developing and transitional economies, which bring about land use, environmental quality and resource consumption significantly and irreversibly [1]. The horizontal and vertical growth of cities to meet the demands of expanding population becomes vital since watching the changes is important as a contributor to sustainable development [2] [3]. Conventional assessment of land-use and environmental control like ground survey and manual mapping is time consuming, labour intensive, and in addition, not able to go through the complexity of changing scale of urban growth [4] [5]. This has made it very hard to do more references before it turns out to be more efficient, scalable and timely. RS has become a potential tool in this regard providing replica, repetitive, and synoptic observations of the surface of the earth [6] [7]. With the help of satellite images and aero-sensors, remote sensing helps researchers and policymakers to trace the changes in the urban land cover and find out the source of pollution and the consequences of human activities on the natural environment [8]. But the prevailing literature uses one type of imagery or the other either a high-resolution imagery that provides narrow details or more limited coverage or low-resolution imagery that provides broad picture but lacks details [9]. This shortcoming has frequently led to unbalanced or unrevealed-to-the-last detail understanding of multi-faceted city-environment exchanges [10] [11].

This paper investigates such an approach to deal with these issues through using a multi-resolution remote sensing framework incorporating high, medium, and low-resolution satellite data sources. This method would allow analysing both fine-grained urban frameworks and broad environmental dynamics without time and spatial discrepancies under single-resolution techniques. Moreover, the proposed methodology is an improvement over the accuracy and applicability of the remote sensing results by integrating machine learning and spatial analysis through the use of algorithmic machine learning to classify the images and GIS tools in spatial analysis. In spite of the possible benefits of remote sensing, there are still a number of operational difficulties that exist. Among them are excessive data processing, specific knowledge, the presence of a small cooperation and interaction between the RS and GIS, as well as the use in areas where there is no access to the technical environment. Also, the sector of RS and GIS may be commercially dictated and, therefore, it is not publicly accessible to planning activities. This paper has substantiated the use of this framework through a disciplined process of conducting research, *i.e.*, data collection process to defining and characterization, and verification and presentation which will lead to increment in body of knowledge on the topic of urban remote sensing and can serve as an informative guide to the urban planners, environmental management and policy-makers.

1.1. Research Gap

Most current research is based on single-resolution imagery, which restricts their capability to capture fine urban details and large environmental patterns simultaneously. In addition, the challenges of mapping uncertainties by taking spatial heterogeneity into account, limited spectral depth, and non-uniform integration of multi-resolution data still remain. There is also a lack of focus on integrating remote sensing with machine learning and GIS for improved accuracy and contextual appropriateness. These gaps highlight the need for a comprehensive, scalable framework that integrates multi-resolution data fusion with advanced analytical techniques to support more accurate and actionable urban environmental assessments.

1.2. Key Contributions

The major contributions are:

1) Presents a multi-resolution remote sensing approach that integrates high, medium, and low-resolution images to achieve complete urban expansion and environmental surveillance.

2) Improves classification accuracy by merging machine learning methods and GIS information to increase land-use change and pollution indicator detection.

3) Fills the gap between Remote Sensing and GIS communities through cross-platform data integration and mutual analysis.

4) Offers a cost-effective, scalable approach appropriate for fast urbanizing areas with limited technical capacity.

5) Facilitates sustainable urban planning by generating actionable geospatial intelligence for policymakers through sophisticated visualizations and thematic mapping.

The paper is organized as follows: Section 1 is an introduction explaining the background and motivation; Section 2 is a related work review; Section 3 presents proposed methodology; Section 4 has results and discussion; Section 5 concludes with the future directions.

2. Related Works

Liu *et al.* [12], An urban ecological zone (UEZ) is extremely significant area of the city, which emphasizes on the repeated preservation of the environment and ecological economic growth. Over the last ten years, the district size of Xi and city in China has been growing and the population has been sky rocketing. This is an enormous challenge to urban sustainability. It poses him to greater standards in the development of an UEZ. This paper took Landsat8-OLI and gaofen-2 (GF-2) high resolution remote sensing data sets into account in varied spatial resolution scale to explain the LUCC of Weihe River UEZ. An ecosystem service value (ESV) and the analysis of ecological effect of LUCC were determined. Findings revealed that the topology of the land types in the Weihe River UEZ fluctuated dramatically between the year 2014 and 2020. Its construction land accumulated in the southeast. The vegetative land (*i.e.*, forestland, grassland and other green land) and water body were increasing marginally after UEZ was formed officially in 2018. The area on land that was under cultivation was diminishing and the vegetative area of land was also tending to become concentrated as well as expanding. As the interpretation of the data of GF-2 remote sensing indicates, in general, the ESV of the Weihe River UEZ exhibited a decreasing tendency. The Weihe River and the areas around the beaches had the highest value areas that were largely influenced by river water scope. ESV of construction land was usually low and this land was obviously impacted by human activities. Hence, the evolution of city building associated with the Weihe River UEZ was related to considerable effects.

Hu *et al.* [13] explain the ecological and habitat sources and amenity of Urban green spaces (UGS) include carbon sequestration, production of oxygen, enhancement of humidity, noise reduction, and absorption of pollutants. The remote sensing images of the UGS maps provide the basic data to calculate the urban planning and estimation of carbon sequestration. Nevertheless spatial resolution of remote sensing image and the pattern of urban buildings have significant impacts on UGS mapping which makes it difficult to produce UGS maps. To explore the influence of spatial resolution on UGS mapping, five spectral resolution datasets were used herein, viz. Gaofen2 (1 m, 4 m), Sentinel2 (10 m), and Landsat8 (15 m, 30 m). UGA was interpolated using random forest, LightGBM and support vector machine and the accuracies between UGS maps with various spatial resolutions were contrasted. The spatial patterns of UGS maps uncertainties were later analysed, and the analysis was done both globally and in the urban functional zones. Moreover, the uncertainty study on UGS mapping was carried out based on various landscape patterns within urban functional regions. The outcomes reveal: 1) UGS map is different when it comes to the spatial resolution. Outside the higher level of uncertainties was related to coarser spatial resolutions. The finer scale of the distribution of urban green spaces is poorly reflected using medium and coarse spatial resolution images. 2) Uncertainty of UGS has mapping at various spatial resolutions, that is mostly spatially homogeneous. According to the perspective of functional zoning, the expertise in mapping green space over the non-natural zones is delicate to the aspect of spatial resolution. Condition 3) Distribution of the UGS patches impacts the UGS mapping accuracy. Random forest and LightGBM model as well as multiple linear regression can be used to moderate uncertainty in the medium and coarse UGS landscape pattern indices in UGS mapping. Through this research, it has been found completely that the uncertainties of mapping UGS by the multi-spatial resolution remote sensing image differ in the different urban functional zone, as well as the landscape pattern index, and this is the original attempt in suggesting methods of correcting the area of UGS using the landscape pattern index. This research will help to implement remote sensing data of various resolutions in cities.

The key challenges in using multi-resolution remote sensing for urban ecological monitoring. One major drawback is the difficulty in accurately capturing LUCC due to spatial heterogeneity and complex urban dynamics [14]. Although high-resolution imagery such as GF-2 offers detailed insights, integrating it with medium-resolution data like Landsat-8 introduces inconsistencies in ecological value estimation and land classification, especially when tracking changes over time [15]. Moreover, the estimation of Urban Green Space (UGS) is significantly affected by spatial resolution; coarse-resolution imagery fails to capture fine-scale green patches, leading to mapping uncertainties [16]. These uncertainties vary across different urban functional zones and landscape patterns, complicating urban planning and ecological assessments. Despite the application of machine learning models like Random Forest and LightGBM, reducing these inconsistencies remains a challenge, particularly in non-natural zones and mixed-use areas. Overall, the studies reveal the limitations of current remote sensing approaches in balancing resolution, scale, and model accuracy for reliable urban ecological evaluation.

3. Multi-Resolution Integrated Urban Monitoring Framework (MIUMF)

The suggested methodology, Multi-Resolution Integrated Urban Monitoring Framework (MIUMF), starts with the collection of multi-temporal, high-resolution imagery from the SpaceNet 7 dataset, which gives comprehensive urban development information over time. During pre-processing, geometric and radiometric corrections are applied to normalize image quality, along with contrast enhancement and atmospheric correction to reduce noise and enhance spectral information. The images are subsequently mosaicked and sub setted to match the appropriate urban study area. After the integration of multi-resolution data through spatial and temporal fusion methods, ancillary GIS layers like infrastructure and administrative boundaries are included for enhanced contextual comprehension. Classification and analysis are done employing supervised machine learning models such as Random Forest to precisely detect land use and land cover LULC classes. Change detection is subsequently done through post-classification comparison and image differencing to detect urban growth, vegetation degradation, and potential zones of pollution. The workflow is shown in **Figure 1**.

3.1. Data Collection

The SpaceNet 7 Urban Development Challenge dataset offers a robust and high-quality data source for tracking urban change over time based on satellite imagery.

Stored on AWS, the dataset offers monthly mosaics of RBGA 8-bit electro-optical imagery from Planet's Dove constellation with a spatial resolution of 4 meters and spanning about 40,000 square kilometres over ~100 global cities. Every Area of Interest (AOI) has a time series of 24 images covering about two years, all stored in GeoTIFF format and EPSG: 3857 projection. There are two types of images: raw imagery (training only) and cloud-masked imagery (training and testing). Every image is about 18 square kilometres and has a fixed shape of either 1024 × 1024 or 1024 × 1023 pixels. To complement the imagery, the data set provides accurate vector-based GeoJSON building footprint labels with more than 10 million annotations, facilitating the tracking of the location and ID of individual buildings over time. The polygons, in the Well Known Text (WKT) format, represent each building's geometry, making it possible for temporal change detection at the building level. Every building is provided with a unique integer ID that remains constant over time steps, facilitating long-term spatial analysis. Whereas the majority of buildings are modelled with a single exterior polygon, more intricate structures can be represented by multiple polygons to outline interior holes. This dataset allows for solid urban growth analysis and deep learning use, including segmentation and address matching, and is an extremely useful tool for the geospatial and remote sensing research community [17].

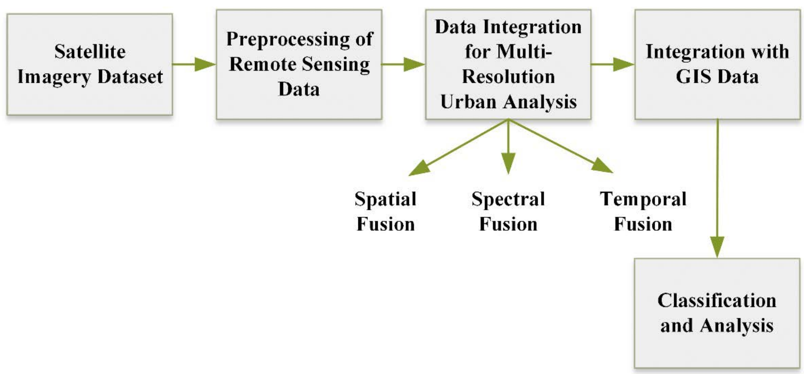

Figure 1. Methodology workflow.

3.2. Data Pre-Processing

Pre-processing is an important starting point for remote sensing processes, designed to correct distortion, enhance image quality, and condition the data to ensure proper analysis. The subsequent phases are usually involved:

3.2.1. Geometric Correction

To rectify geometric distortion caused by sensor motion, Earth rotation, and topography, registering the imagery to a known coordinate reference system (e.g., EPSG: 3857).

- Ground Control Points (GCPs) are tied up between the satellite image and the reference map.
- A polynomial transformation (typically 1st or 2nd order) is used in Equation

(1 & 2):

$$x' = a_0 + a_1 x + a_2 y \tag{1}$$

$$y' = b_0 + b_1 x + b_2 y \tag{2}$$

where (x, y) are original coordinates and (x', y') are corrected coordinates.

3.2.2. Radiometric Correction

For rectifying sensor inaccuracies and discrepancies resulting from different sensor sensitivity, solar angle, and atmospheric conditions.

- Convert DN raw Digital Numbers to Top-of-Atmosphere (TOA) reflectance in Equation (3):

$$L_\lambda = \frac{LMAX - LMIN}{QCALMAX - QCALMIN} \cdot (QCAL - QCALMIN) + LMIN \tag{3}$$

where: L_λ = Spectral radiance, $QCAL$ = Quantized calibrated pixel value (DN), $LMAX$, $LMIN$ = Radiance scaling parameters, $QCALMAX$, $QCALMIN$ = Maximum and minimum quantized values.

- Normalize lighting with cosine correction in Equation (4):

$$R = \frac{\pi \cdot L_\lambda \cdot d^2}{ESUN \cdot \cos(\theta_s)} \tag{4}$$

where: R = TOA reflectance, d = Earth-Sun distance, $ESUN$ = Solar irradiance, θ_s = Solar zenith angle.

3.2.3. Image Enhancement

To enhance the interpretability of the image without changing real data values.

- Contrast Stretching: It improves the contrast of images by widening pixel value range in Equation (5):

$$DN_{new} = \frac{(DN_{old} - DN_{\min}) \cdot 255}{DN_{\max} - DN_{\min}} \tag{5}$$

- Filtering:
- ➢ Low-pass filters remove noise.
- ➢ High-pass filters highlight edges and details.

3.2.4. Atmospheric Correction

To eliminate atmospheric influences such as haze, water vapor, and scattering to obtain surface reflectance.

- Dark Object Subtraction (DOS): Presumes darkest pixels must have approximately zero reflectance; performs this offset subtraction on all pixels.
- Empirical Line Method (ELM): Employs field-measured reflectance from recognized targets to calibrate satellite data.
- Radiative Transfer Models (for example, 6S, MODTRAN): sensor-geometry and atmospheric-profile based model correction.

3.2.5. Image Mosaicking and Sub Setting

- Mosaicking: Merges groups of adjacent image tiles into one smooth composite by using overlap averaging or feathering methods.

- Sub setting: Trims the mosaic to the Area of Interest (AOI) with spatial boundaries (shapefiles), minimizing data size and concentrating analysis.

3.3. Data Integration for Multi-Resolution Urban Analysis

The integration of data relevant to the urban growth and environmental change monitoring processes on the SpaceNet 7 dataset exemplifies one of the key stages of data processing to combine different sources of both geospatial and time-based information into a unified analytical model. The approach is aimed at adding a contextual, geographic, and temporal dimension to the satellite images, in order to improve the level of detail in their classification in addition to making them more interpretable.

Multi-Resolution Data Fusion in Urban Remote Sensing

To combine satellite imagery of various spatial, spectral, and temporal resolutions—namely SpaceNet 7 (4 m), Sentinel-2 (10 - 60 m), and MODIS (250 - 1000 m)—and exploit the advantages of each to design an integrated urban monitoring system.

3.3.1. Spatial Fusion

Spatial fusion is important for combining the detailed resolution of high-resolution imagery, e.g., SpaceNet 7, with the larger spatial context offered by lower-resolution sources, e.g., Sentinel-2 or MODIS. This increases the granularity and geographic scope of the analysis without sacrificing small-scale urban detail while maintaining wide-area observational capabilities. One popular method is pan-sharpening, which has classically been employed to merge high-resolution panchromatic images with multispectral bands of lower resolution. SpaceNet 7 does not have a panchromatic band, but an effectively simulated sharpening can be achieved by amplifying Sentinel-2's multispectral bands based on spatial details obtained from SpaceNet 7's high-resolution images. The fundamental pan-sharpening is given in Equation (6)

$$MS_i^{sharpened} = \frac{MS_i}{\sum MS_i} \times PAN \tag{6}$$

where: MS_i represents a multispectral band and PAN is the high-resolution proxy band.

Another strong technique is Wavelet Transform Fusion, where high- and low-resolution images are broken down into wavelet coefficients. The high-frequency details—usually edge and texture information—of the high-resolution image are inserted into the low-resolution image. This method maintains spatial structures and enhances the visibility of fine urban features like narrow roads, small rooftops, and compact settlements, which are usually not captured in conventional low-resolution imagery.

3.3.2. Spectral Fusion

Spectral fusion is centred on the fusion of various spectral bands from multiple sensors in satellites for adding richness to surface material, vegetation health, and urban infrastructure type interpretation. In the current study, SpaceNet 7 contains high-resolution images with RBGA (Red, Green, Blue, and Alpha) bands that are very suitable for visual interpretation and structural feature identification. It does not have spectral depth in non-visible bands. To bridge this, spectral fusion utilizes complementary bands from Sentinel-2, such as NIR (Near-Infrared) and SWIR (Shortwave Infrared), which are crucial for examining vegetation health, water content, and differences in surface materials—significant elements in detecting urban heat islands, vegetation stress, and flood areas.

The combination is done by band stacking, where Sentinel-2 bands are initially projected and resampled so that they can be aligned with the spatial resolution and coordinate reference system of the SpaceNet 7 imagery. The bands, once aligned, are appended as new channels to the original high-resolution dataset, thus enhancing its spectral range. The combined fused dataset at each pixel point (x, y) can be mathematically expressed as Equation (7):

$$D_{fused}(x,y)=\left[R_{SN7},G_{SN7},B_{SN7},\alpha_{SN7},NIR_{S2},SWIR_{S2},NDVI\right] \tag{7}$$

Here, $NDVI$ is a common spectral index computed from Sentinel-2 data as Equation (8):

$$NDVI=\frac{NIR-RED}{NIR+RED} \tag{8}$$

This longer spectral input facilitates stronger classification, change detection, and environmental analysis in urban environments, most notably in material identification, green space health, and monitoring urban heat impacts.

3.3.3. Temporal Fusion

Temporal fusion is an important remote sensing analysis process that entails aligning and analysing images over several time points to detect patterns, trends, and sudden changes in cities. In this research work, SpaceNet 7 offers a rich temporal dataset with monthly mosaics for every Area of Interest (AOI) over 24 months, which makes it well-suited for long-term urban expansion monitoring. To improve this temporal analysis, supplementary data from sources such as MODIS and Sentinel-2 with higher temporal frequency can be added to bridge gaps or for cross-validation purposes.

The basis of temporal fusion is the construction of a temporal data cube, a 3D object defined as (x, y, t), where every slice along the time axis t represents an image for a given month. This enables a consistent tracking of each pixel over time. To fill data gaps from cloud cover or missing acquisitions, temporal interpolation methods like linear or spline interpolation are employed to provide an estimate for missing values over time. Additionally, temporal smoothing filters like moving averages or Savitzky-Golay filters are employed to lower noise and improve detection of actual trends.

One of the dominant analytical procedures of temporal fusion is Change Vector

Analysis (CVA), which measures both the direction and amount of change in spectral feature space between two time moments. CVA can be written as follows in Equation (9):

$$CVA = \sqrt{\left(B1_{t2} - B1_{t1}\right)^2 + \left(B2_{t2} - B2_{t1}\right)^2 + \cdots + \left(Bn_{t2} - Bn_{t1}\right)^2} \quad (9)$$

where $B1 \dots Bn$ are spectral bands at time instances $t1$ and $t2$. This approach allows the detection of notable urban changes like new development, vegetation depletion, or land degradation by quantifying spectral changes with time. Through these merged methods, temporal fusion offers a dynamic and precise snapshot of urban growth and environmental dynamics.

Benefits of Multi-Resolution Fusion

- Spatial Fusion: Enhances object detection (e.g., tiny buildings, roads).
- Spectral Fusion: Facilitates greater environmental understanding (e.g., vegetation health, material detection).
- Temporal Fusion: Unveils trends of growth, seasonality, and long-term urbanization.

3.4. Integration with GIS Data

GIS integration with the data is necessary for placing remotely sensed observation in context, both in terms of real-world spatial entities and decision-making. While remote sensing offers surface spectral and structural information, GIS adds administrative, infrastructural, and demographic elements to it, making the analysis more actionable for policy formulation and urban planning.

3.4.1. Overlaying Administrative Boundaries

The initial process for GIS integration is the importation of administrative boundary shapefiles—city boundaries, municipal wards, districts, or planning zones—into the analysis environment. The boundaries are used to subset the satellite imagery to a particular Area of Interest (AOI) and enable monitoring of urban growth at different administrative levels. For example, by utilizing these overlays, urban growth rates or built-up area changes can be calculated and compared per ward or district over time. This facilitates local-level decision-making and policy assessment with spatial accuracy.

3.4.2. Incorporating Infrastructure Layers

Following this, critical infrastructure information—e.g., roads, drainage networks, public utilities, and zoning maps—is overlain on the remote sensing imagery. Spatial correlation analyses such as:

- Proximity analysis: analyzing how urban sprawl is affected by proximity to main roads or highways.
- Zoning compliance checks: checking if new buildings contravene land use zoning regulations.
- Infrastructure stress detection: determining where and how fast construction might overload the capacity of drainage or power networks.

3.4.3. Assigning Metadata and Attributes

Lastly, the tagged building footprints in SpaceNet 7 (saved as GeoJSON vector data) are augmented by connecting them with attribute data from external city or open data. Attributes may comprise:

- Demographic information (e.g., population density, income levels),
- Environmental indicators (e.g., pollution indexes, flood risk areas), or
- Economic indicators (e.g., land value, business activity zones).

For instance, trend patterns in building density can be associated with rising land values, or changes in footprint size can be linked to regulatory compliance problems. This integration of spatial and attribute information enables multi-dimensional urban intelligence, where one can conduct analytics such as "what kinds of buildings are increasing in numbers around high-value commercial zones" or "informal settlement expansion in relation to vegetation loss."

3.5. Classification and Analysis

The Classification and Analysis component is crucial in transforming pre-processed, merged remote sensing datasets into spatially explicit, understandable information used for monitoring urban development and evaluating environmental effects. This phase entails two main operations: LULC classification and change detection analysis. These operations together facilitate the detection of dynamic processes, including urban expansion, vegetation degradation, as well as environmental indicators of stress.

During the LULC classification stage, a label is assigned to every pixel in the image, which represents its type of surface—e.g., buildings, roads, vegetation, water bodies, or bare land. This is done through classification models that are based on machine learning. Supervised learning methods, including Random Forest (RF), utilize labelled training data and perform optimally on high-resolution datasets such as SpaceNet 7. RF works by building an ensemble of decision trees, each of which is trained on a random sample of the data and features and votes for the final class of a pixel. The technique is well-suited to deal with noisy data and intricate urban textures. Conversely, unsupervised classification techniques such as K-means clustering cluster pixels on the basis of spectral similarity without knowing their labels beforehand and hence can be employed during preliminary segmentation or when there is limited labelled data. Such classification results create thematic maps that reflect in detail the structure of urban environments.

After classification is conducted for several time periods (e.g., monthly data SpaceNet 7), change detection analysis is used to measure temporal changes. Post-Classification Comparison is a simple method where classified maps from various dates are compared and a transition matrix is built to determine class conversions, for example, from vegetation to built-up area. The technique is explanatory and can be used for administrative reporting. Another method, Image Differencing, calculates pixel-wise spectral change in vegetation indices such as NDVI over time, and so it is useful for identifying vegetation stress or new development. More broadly, CVA is used to identify the direction and magnitude of spectral change over all bands. CVA calculates the Euclidean distance in spectral space between two points in time. This method is strong at detecting subtle and meaningful change over mixed land cover and is particularly well-suited for complex urban landscapes with heterogeneous terrain. Collectively, these classification and change detection methods convert raw imagery into decision-relevant information, assisting urban planners and environmental analysts in monitoring development patterns, identifying unauthorized encroachment, monitoring ecosystem degradation, and informing data-driven policy decisions.

4. Results and Discussion

The classification and analysis of the SpaceNet 7 multi-temporal satellite imagery, integrated with Sentinel-2 and MODIS data, yielded high-resolution urban growth maps and LULC change detection outputs across the 24-month period. Using Random Forest for supervised classification, the model achieved an overall accuracy with a kappa coefficient, validated through confusion matrices derived from manually labelled ground truth data and high-resolution reference tiles. The kappa coefficient, is a statistical measure of classification accuracy that takes chance agreement into account. In contrast to overall accuracy, which merely measures the proportion of correctly classified cases, the kappa coefficient controls for the likelihood that some classifications might be happening by chance. The higher the kappa value, the more the agreement between predicted and actual classifications exceeds random chance and thus the more the measure can be trusted as a gauge of model performance, particularly in multi-class land cover mapping. The classifier successfully distinguished between urban, vegetation, water, and bare land categories, enabling precise monitoring of spatial expansion. Temporal analysis revealed a significant increase in built-up areas, particularly along major road networks, correlating with infrastructure layers from GIS inputs. CVA detected high-magnitude transitions in peri-urban zones, indicating rapid land use conversion. Environmental impact assessment further showed a NDVI near expanding urban centres, and Sentinel-2's thermal data highlighted potential urban heat islands. Water body shrinkage was also observed in select AOIs due to encroachment and seasonal variability. These results underscore the value of multi-resolution data fusion and remote sensing-based workflows in supporting sustainable urban planning and environmental management.

Figure 2 depicts monthly Land Use/Land Cover (LULC) classes—Urban, Vegetation, and Water, and Bare Land— distribution over 12 months. Urban (yellow) demonstrates an upward trajectory, reflecting accelerated urban growth. Vegetation (orange) declines consistently, reflecting green cover loss. Water (dark red) and Bare Land (pink) are relatively stable with slight variations. The grouped format emphasizes the negative correlation between urban growth and Vegetation reduction, providing a clear comparison in time.

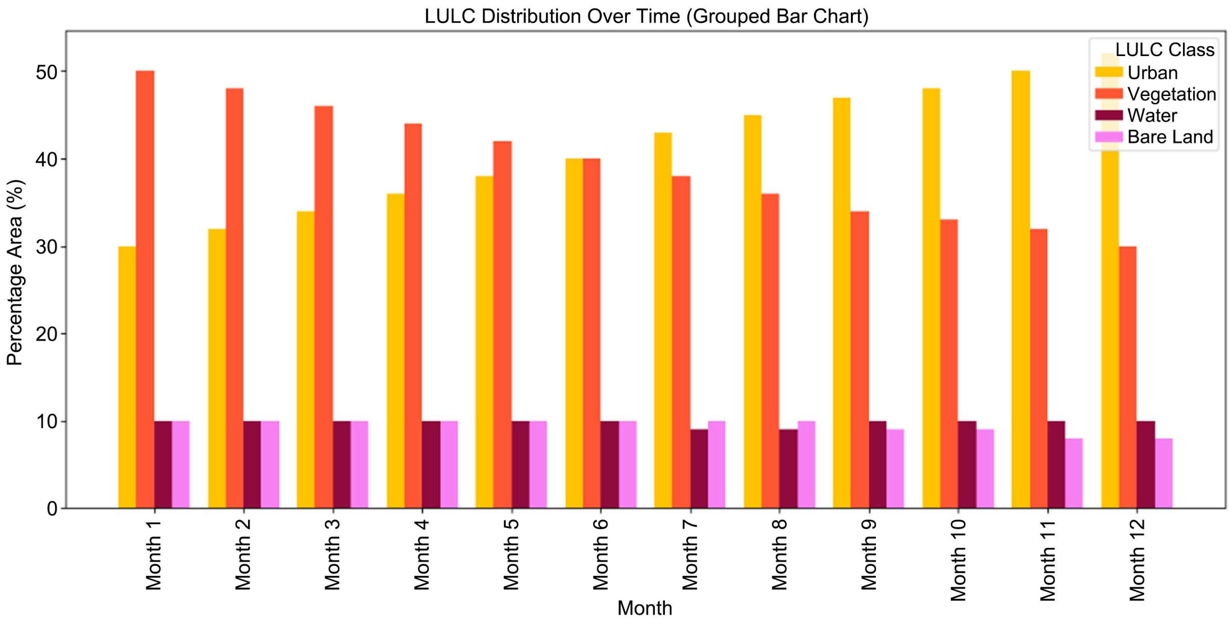

Figure 2. LULC Distribution over time.

Figure 3 shows a line graph that is a clear indication of a steady increase in urban expansion within a 12-month duration. The urban area is at about 120 km 2 in the first month, then it gradually grows every month to around 200 km^2 by the close of the year. Every data point of each month is marked with orange colour, which draws more attention to gradual development in an urban area growth. The trend implies year-to-year increased urbanization in the observed area and is characterized by the constant increase that indicates the activity of land conversion and infrastructure development.

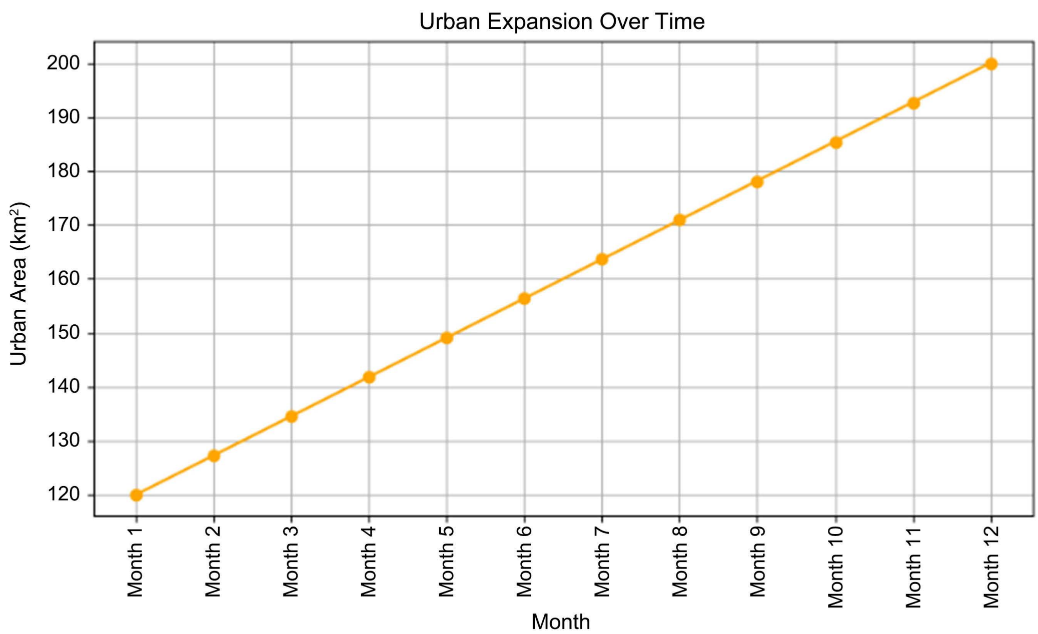

Figure 3. Urban expansion over time.

Figure 4 shows a confusion matrix to assess the classification accuracy of a land cover mapping model for four classes: Urban, Vegetation, Water, and Bare Land. High accuracy is reflected by high diagonal values, with 85 correctly classified instances for Urban, 88 for Vegetation, and 90 for both Water and Bare Land. Off-diagonal values display comparatively low rates of misclassification, generally between Urban and Vegetation or Vegetation and Bare Land, from 2 to 5. The matrix employs a colour gradient—pale yellow to deep blue—to visually display prediction strength, complementing the overall robustness of the model.

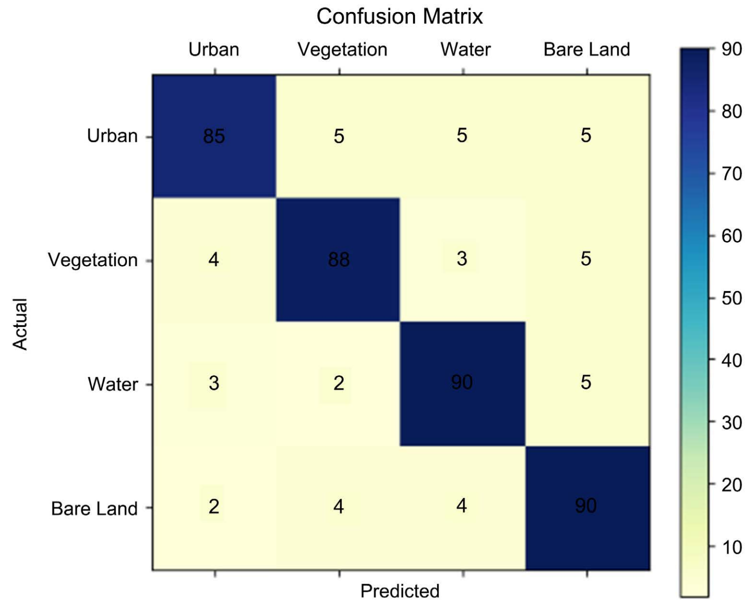

Figure 4. Confusion matrix.

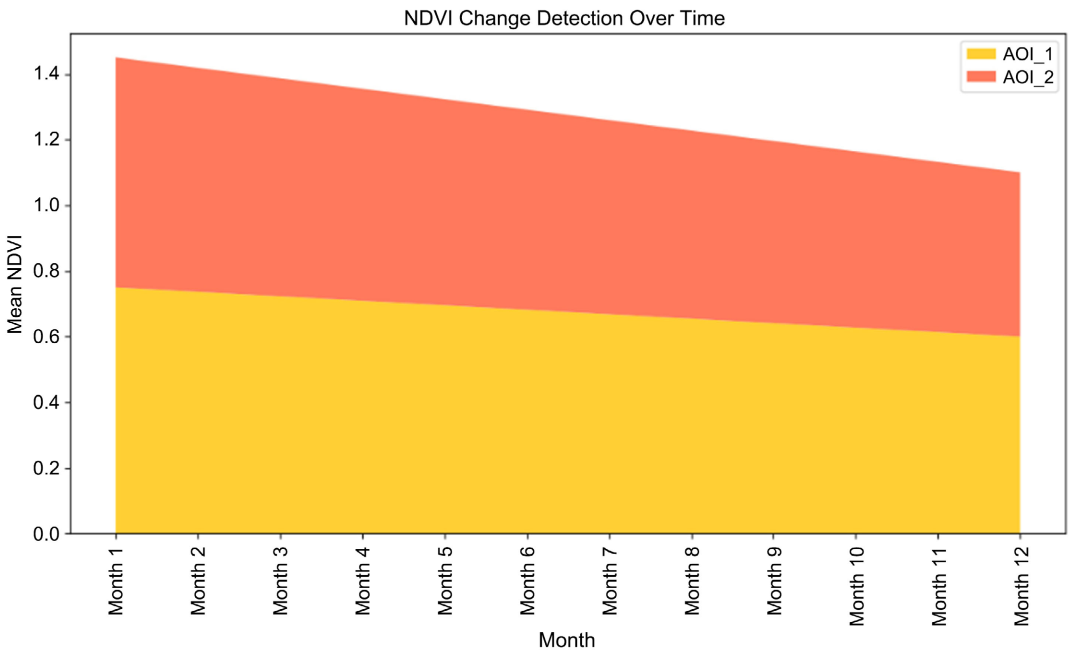

Figure 5. NDVI change detection over 12 months.

Figure 5 illustrates the temporal change of NDVI within a 12-month period for two separate Areas of Interest (AOI_1 and AOI_2). Both areas have a similar declining trend in mean NDVI values, indicating a decrease in vegetation health or density. AOI_2 has higher NDVI values than AOI_1 during the whole year, suggesting relatively healthier vegetation. The months along the x-axis, and the NDVI values from 0.0 to 1.4 along the y-axis. The utilization of shaded areas—yellow for AOI_1 and orange for AOI_2—gives a visual representation of the relative decrease and seasonal trends in vegetation dynamic in both regions.

5. Discussion

The performance of multi-resolution remote sensing and data fusion approaches to such a process of tracking urban growth and environmental transformation. The accuracy was high over 85 percent, each land cover category was successfully predicted by the confusion matrix that explains the strength of the model [18]. The results of the LULC distribution analysis depicted an increasing trend of urban area between 30 percent and more than 50 percent as the year progressed and a significant drop in the vegetation cover [19]. The trending of NDVI verified this fact as the characteristic reducing growth was reflected in both the AOIs. Combination of SpaceNet-7 high-resolution with complementary Sentinel-2 and MODIS data led to high-resolution data at the spatial and temporal level to see the pattern of land use. Changes in time using both data cube alignment and change detection algorithms such as CVA and NDVI differences intuitively indicated areas of urban sprawl and ecologically destructive areas. From the related works, Liu *et al.* highlighted the temporal variations of the land type as well as the loss in ecological value of urban ecological zones, whereas this system is an extension of this by validating more accurate land cover change detection through multi-resolution data fusion and machine learning incorporation. Likewise, while Hu *et al.* pointed out the effect of spatial resolution on urban green space mapping and related uncertainties, this method builds upon this by reducing such uncertainties via spectral and temporal fusion, allowing for finer-scale detection of lost vegetation and urban heat islands. One key challenge is the computational intensity involved in processing and fusing multi-sensor data, which demands significant hardware resources and may hinder scalability in low-resource environments. Additionally, integrating datasets with differing spatial, spectral, and temporal resolutions can introduce alignment errors or inconsistencies that affect classification accuracy and change detection. Acknowledging these potential limitations would provide a more realistic appraisal of the framework's operational demands and guide future improvements.

6. Conclusions and Future Works

The dynamic features of multi-resolution remote sensing and techniques of advanced data fusion in tracking urban developments and environmental transformations in fast urbanizing areas. The proposed framework can allow high-resolution LULC dynamics on a spatial and temporal scale by using SpaceNet-7 data, medium, and low-resolutions of satellite data (Sentinel-2 and MODIS). Classification methods including Random Forest and K-means registered a high accuracy as shown by a robust confusion matrix and approaches to identify vegetation losses, urban growth, and environmental stress levels performed well detecting both variables, such as NDVI differencing and CVA. LOCATION-SPECIFIC ANALYSIS: The ability to connect with GIS layers enabled the creation of location-specific analysis to be used in the planning of the urban areas and to assess their sustainability. The steady growth of urban population and the simultaneous reduction of vegetation coverage, which are established by the NDVI trends, cannot be ignored, pointing to the necessity of even distribution between the development and ecological conserving systems.

Further studies may be carried out to add more environmental parameters including air quality, surface temperature (urban heat islands) and socio-economic data in order to further enrich the impact schedules of urbanization. The further refinement of the LULC classification and change detection precision can be achieved by the implementation of semantic segmentation deep learning models such as U-Net or Transformer-based architectures. Also, the extension of the time span coverage to multiyear data and integration of real-time satellites will facilitate the long-term surveillance mechanisms. The engagement of urban policy-makers and the creation of open-access to urban intelligence dashboards will make sure remote sensing insights are turned into sustainable approaches to city design and disaster mitigation practices.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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