18(1s), Spring 2026

Journal of Animal Environment

(E-ISSN 2717-1396, ISSN 2717-1388)

Original Research Paper

Drone-Based Remote Sensing Technologies for Monitoring Urban Biodiversity and Habitat Fragmentation in Smart Cities

Gauri Dhopavkar[1], Wasim A. Bagwan[2*], Rohit P. Jadhav[3], Vishal Ambhore[4], Ashuvendra Singh[5], Kathi Ascherya[6], Amandeep Kaur Gill[7]

[1]Department of Computer Technology, Yeshwantrao Chavan College of Engineering, Nagpur, Maharashtra, India | Email: gauri.ycce@gmail.com

[2]Krishna Institute of Science and Technology, Krishna Vishwa Vidyapeeth "Deemed to be University", Taluka-Karad, Dist-Satara, Pin-415 539, Maharashtra, India | Email: wasim.bagwan16@gmail.com

[3]Department of Robotics & Automation, D.Y. Patil College of Engineering Akurdi, Pune, Maharashtra, India | Email: rpjadhav@dypcoeakurdi.ac.in

[4]Department of E&TC Engineering, Vishwakarma Institute of Technology, Pune, Maharashtra, 411037, India | Assistant Professor | Email: vishal.ambhore@vit.edu

[5]Department of Civil Engineering, Dev Bhoomi Uttarakhand University, Dehradun, Uttarakhand, India | Email: pc.ce@dbuu.ac.in

[6]MVSR Engineering College, Hyderabad, Telangana, India | Email: ascherya_cse@mvsrec.edu.in

[7]School of Pharmaceutical Sciences, CT University, Punjab, 142024, India

***Corresponding Author:** Wasim A. Bagwan | Email: wasim.bagwan16@gmail.com

Abstract: With the speed of urbanization, increasing habitat fragmentation and unplanned land use change, urban biodiversity is under more threat than ever, leading to a need for ongoing ecological monitoring for sustainable smart city development. In this paper, we propose a framework based on remote sensing with a drone to monitor the biodiversity of the urban landscape and to estimate the fragmentation of the habitat, using images acquired by the drone from high resolution and geospatial analysis. The proposed approach consists of integrating unmanned aerial vehicles (UAVs), multispectral sensing, orthomosaic generation, vegetation index computation, and artificial intelligence (AI) based land cover classification in order to generate accurate maps of biodiversity and distribution of habitats. Drone High-Resolution (HR) imagery allows for the detailed detection of vegetation patches, ecological corridors and fragmented habitats that might not be detectable using standard satellite monitoring. The framework also includes spatial metrics that measure the habitat connectivity, habitat fragmentation and landscape heterogeneity to inform Urban ecological planning. Experimental results prove high classification accuracy, better spatial resolution and efficient assessment of biodiversity in comparison to the traditional remote sensing methods. The proposed system is timely, cost-effective and scalable that can be used for smart city applications, conservation planning and ecosystem management. In addition, the study explores the challenges associated with flight regulations, sensor limitations and environmental variability, as well as future opportunities with the use of autonomous drones equipped with AI capabilities, edge computing and digital twin technologies for real-time monitoring and assessment of biodiversity in urban areas and supporting evidence-based environmental decision-making.

Keywords: Drone-Based Remote Sensing, Urban Biodiversity Monitoring, Habitat Fragmentation, Smart Cities, UAV Imagery, Land Cover Classification

I. Introduction

The urbanization process has emerged as one of the most powerful forces of environmental change and landuse changes, habitat loss and biodiversity loss are extensive in cities around the world. The fragmentation of the landscape due to a growing urban population and the loss of ecological connectivity caused by urbanisation are spreading. This rapid growth creates significant threats to urban biodiversity conservation since numerous species of plants and animals lose their habitats and are under greater stress due to pollution, climate change and human activity. Therefore, urban biodiversity monitoring and analyzing urban habitat fragmentation are also necessary steps in sound

***Corresponding Author:**
Received: 25th May, 2026; Revised: 6th June, 2026; Accepted: 8th June, 2026; Available Online: 23rd July, 2026
(DOI): 10.70102/AEJ.2026.18.1s.3

urban planning and smart city development. The urban biodiversity is the term used for the diversity of living things, such as plants, animals, microorganisms and their ecosystems in urban areas. Urban ecosystems produce substantial environmental benefits for environmental sustainability such as air quality improvement, regulating urban temperatures, carbon sequestration, storm water control, and recreation and cultural services [1]. Other green spaces like parks, wetlands and ecological corridors are also significant contributors to the habitat connectivity and wildlife populations. But as cities grow such natural habitats become increasingly fragmented, preventing species from moving freely and bringing down the resilience of ecosystems. Hence, the need to monitor the condition of biodiversity and habitats at appropriate times is essential to good conservation planning. The most common methods used for biodiversity monitoring are field surveys, ecological sampling and manual habitat evaluations. These methods offer a detailed biological information, but they are time consuming, labour-intensive, costly and are limited in geographical scope. Moreover, it is difficult to conduct survey operations often required in rapidly changing urban landscapes with traditional survey methods [2]. This has led to a growing use of remote sensing technologies to gain spatially continuous information over larger areas in an efficient manner.

Spaceborne remote sensing has been applied extensively to environmental monitoring, because of its ability to provide repeated observations over a large geographical area. Satellite data are used for the land cover mapping, vegetation monitoring, urban expansion analysis and ecosystem assessment. But the spatial resolution of many satellite platforms is not adequate for the detection of small vegetation patches, narrow ecological corridors, individual trees or fragmented habitats often occurring in urban areas [3]. Satellite-based monitoring is also limited in its usefulness for fine-scale ecological studies due to the cloud coverage, inflexibility of revisit time, and limited flexibility in data acquisition. The use of Unmanned Aerial Vehicles (UAVs) or drones has reshaped environmental monitoring capabilities, offering aerial imagery and data of high resolution and unmatched spatial and temporal detail in recent years [4]. Drone platforms are available with RGB cameras, multispectral sensors, hyperspectral cameras, thermal sensors, and LiDAR systems, providing a complete census of the vegetation health, canopy structure, land cover features and habitat conditions. They can fly at low altitudes to capture centimeter-level spatial resolution, which makes them especially well suited to monitoring urban biodiversity, and their fragmentation. Furthermore, UAVs provide greater flexibility in flight scheduling, quick deployment, reduced operating expenses and multiple data collection opportunities as compared with traditional aerial surveys.

Combining drone-based remote sensing data with Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) techniques has improved automated environmental monitoring even more. High-resolution aerial imagery can be used in combination with advanced image processing algorithms to precisely classify land cover type, determine the species of vegetation, delineate habitat boundaries and assess ecological connectivity [5]. The models based on Artificial Intelligence (AI) substantially cut down manual interpretation workloads, enhanced classification accuracy and processing efficiency. Geographic Information Systems (GIS) are another technology used to support these technologies for spatial analysis, habitat fragmentation assessment, biodiversity mapping and identification of ecological corridors. These technologies can be combined to offer strong decision support for conservation planning and sustainable management of urban ecosystems [6]. One of the key issues of urban growth is habitat fragmentation. Habitat fragmentation leads to poor landscape connectivity, isolation of wildlife populations, limits wildlife movement, and makes ecosystems more vulnerable. Using landscape metrics such as patch density, edge density, connectivity indices and fragmentation indices, researchers can quantify the fragmentation and assess the health of the ecosystems and prioritize which areas should be conserved. Drone imagery can be used to gather high-resolution data, which can then be used to calculate these ecological indicators accurately.

II. Literature Review

A. Urban Biodiversity Monitoring Techniques

In recent years, urban biodiversity monitoring has progressed greatly, thanks to the development of geospatial tools, ecological models, and AI technologies. These traditional monitoring techniques were mostly based on field survey and species inventory, camera trap and manual habitat assessment, which were time-consuming and labor intensive, and expensive. Thus, remote sensing technologies and Geographic Information Systems (GIS) have adopted and widely used for vegetation monitoring, species distribution and ecosystems health across urban landscapes to overcome these limitations [7]. With the aid of high-resolution satellite images it is possible to observe the condition of green spaces, urban forest, wetlands and ecological corridors on a regular basis, providing the basis for long-term evaluations of biodiversity. In recent years, machine learning and deep learning algorithms have been applied to automatically prepare land cover classification, vegetation mapping and habitat identification with a higher accuracy. The vegetation indices like NDVI, EVI and SAVI are most commonly used to estimate the health and biomass of vegetation [8].

B. Habitat Fragmentation Assessment Methods

Habitat fragmentation is one of the significant effects of the speed of urbanisation, involving the fragmentation of continuous natural habitats into smaller, isolated patches of habitat. A proper estimation of fragmentation is crucial to understand the ecological connectivity, wildlife movement and ecosystem resilience. Traditional fragmentation analysis uses principles of landscape ecology and spatial measures from remote sensing and GIS data sets. Patch size, patch density, edge density, landscape shape index, connectivity index, fragmentation index, and Shannon diversity index are some of the commonly used metrics [9]. These measures represent aspects of landscape structure and assess habitat quality at various spatial scales. GIS is used to support spatial analysis, correlating the spatial data of land cover, transportation networks, water bodies and urban infrastructure to reveal ecological corridors and biodiversity hotspots. In recent years, machine learning and graph-based approaches have been included in recent studies to understand habitat connectivity, and forecast fragmentation patterns under future urban development scenarios. Fragmentation assessments can also be more precise using high-resolution spatial datasets because of the detailed land-use changes captured. But much of what already has been developed relies on medium-resolution satellite imagery, which could miss out on narrow ecological corridors and small vegetation patches. Drone acquired imagery provides higher spatial resolution and enables more accurate fragmentation analysis, and ecological landscape characterization.

C. UAV and Drone-Based Remote Sensing Applications

Unmanned Aerial Vehicles (UAVs), or drones, are an increasing useful tool for environmental monitoring because of their ability to capture ultra-high-resolution imagery, flexibility and low cost. Modern UAV systems can carry the RGB, MS, HS, thermal and LiDAR sensors, which can deliver detailed data about the vegetation structure, health condition, land cover characteristics and habitat conditions [11]. Drones have the potential to provide centimeter-scale spatial resolution, flexible flight scheduling and quick deployment, which is uniquely applicable to monitoring dynamic urban ecosystems when compared to conventional satellite platforms. In the past few years, remote sensing with UAVs has been shown to be a valuable tool for biodiversity assessment, vegetation mapping, wildlife habitat monitoring, invasive species detection, forest inventory and planning for ecosystem restoration [12]. The current biodiversity monitoring techniques employing UAVs are compared in Table 1, with their respective strengths and gaps in research highlighted. The automated object detection, vegetation classification, and habitat segmentation of UAV imagery have been further enhanced by AI and deep learning models. The possibilities of orthomosaic generation, digital surface models or three dimensional reconstruction of point clouds have made it possible to perform accurate spatial analysis of ecological features.

Table 1. Comparative Review of Drone-Based Remote Sensing Technologies

Study Focus	Data Source	UAV/Sensor	AI/Analysis Method	Key Findings	Limitations	Research Gap
Urban vegetation mapping [13]	RGB UAV imagery	RGB Camera	Random Forest	Accurate urban vegetation identification with high spatial detail	Limited spectral information	Integration of multispectral data and AI required
Habitat fragmentation analysis [14]	UAV + GIS	RGB Camera	Landscape Metrics	Quantified habitat connectivity and fragmentation	Small study area	Large-scale smart city monitoring absent
Urban biodiversity asse	Multispectral UAV	Multispectral Sensor	SVM Classification	Improved vegetation	Manual feature engi	Deep learning-based

ssment [15]				discrimination accuracy	neering	automation required
Ecological corridor detection [16]	UAV Imagery	RGB + NIR Sensor	GIS Spatial Analysis	Identified fragmented ecological corridors	Low temporal monitoring frequency	Continuous UAV monitoring needed
Green space monitoring	Drone Images	RGB Camera	CNN	Enhanced urban green space classification	Sensitive to illumination changes	Robust multi-season models lacking
Wildlife habitat mapping	UAV + Field Survey	Multispectral Camera	Object-Based Image Analysis	High-resolution habitat mapping achieved	Computationally intensive processing	Edge AI implementation required
Land cover classification	UAV Orthomosaic	RGB + Thermal Sensor	Deep Learning	Improved urban land cover mapping	Thermal calibration challenges	Multi-sensor fusion requires optimization
Biodiversity hotspot detection	UAV + GIS	LiDAR + RGB	Vision Transformer	Improved habitat identification accuracy	High implementation cost	Cost-effective intelligent frameworks needed
Autonomous ecological monitoring	UAV + Edge AI	RGB + Multispectral	YOLO + Transformer	Automated biodiversity monitoring achieved	Limited Digital Twin integration	Real-time Digital Twin framework required

III. Materials and Methodology

The proposed methodology consists of acquiring images from drone, computing multispectral data, generating orthomosaic, calculating vegetation index, applying AI system-based land cover classification and GIS-based habitat fragmentation analysis. High resolution aerial images are analysed to create biodiversity maps and ecological connectivity analyses that enable sustainable urban ecosystem monitoring and planning.

A. Overall Proposed Framework

The proposed solution combines the capabilities of drone-based remote sensing, geospatial data and artificial intelligence in a smart city to track changes in urban biodiversity and habitat fragmentation. The process starts with the selection of representative urban study sites with the presence of parks, wetlands, forests, residential green spaces and ecological corridors. High resolution aerial images are acquired with Unmanned Aerial Vehicle (UAV) carrying out RGB and multispectral sensor. The images are then preprocessed (radiometric correction, geometric correction, noise reduction and image registration) and orthomosaics are produced to provide seamless high-resolution maps. Vegetation indices like NDVI and GNDVI are used to determine the health of vegetation and distribution of biomass. Land cover classification is subsequently achieved using machine learning, which classifies the land cover as vegetation, water body, building, road and bare ground.

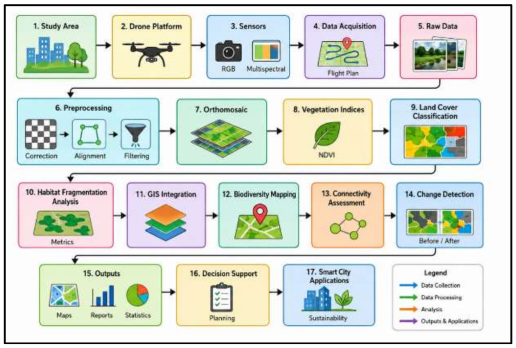

Figure 1. Architecture of the Proposed Drone-Based Urban Biodiversity Monitoring Framework

The proposed UAV-based framework integrated with AI and GIS and biodiversity monitoring is shown in figure 1. Habitat fragmentation is then quantified by calculating spatial landscape metrics such as patch density, edge density and connectivity index. The maps are classified and ecological indicators are integrated with a Geographic Information System for visualization and analysis. Last, but not least, distribution maps of biodiversity and habitat continuity are created to guide conservation planning, sustainable urban management and informed decisions for environmental monitoring applications within a smart city.

B. Study Area and Data Collection

The study area covering representative urban regions with various land-use patterns such as residential areas, commercial zones, urban forests, public parks, wetlands, road network and open green areas. The sites chosen to represent different degrees of urbanization and ecological diversity in a smart city context. Data collection is done under good weather conditions to reduce the effects of the atmosphere and ensure uniformity in image quality. Several flights are carried out over various portions of the study area, flying along specific flight lines with overlap and enough data for accurate use of the data in photogrammetric processing. The high resolution RGB and multispectral images are collected at the same time, and provide details on vegetation and land cover and habitat characteristics. Global Navigation Satellite System (GNSS) receivers are used to obtain Ground Control Points (GCPs) for the improvement of the positional accuracy and georeferencing. Data is gathered supplementary such as existing land use maps, satellite imagery, meteorological data and GIS layers for classification and validation. Field observations are also carried out to ensure vegetation type, habitat suitability and land cover classes are correct for supervised machine learning model development and performance evaluation.

C. Drone Platform and Sensor Configuration

The multi rotor drone platform is used for aerial data collection due to excellent maneuverability and hovering ability and for detailed urban survey. The UAV has a high-resolution RGB camera, and a multispectral imaging sensor that includes visible and near-infrared spectral bands. With the RGB sensor, spatial information is provided to identify the objects, and with the multispectral sensor, the health of vegetation is evaluated by the analysis of the spectrum. The drone is equipped with a Global Navigation Satellite System receiver and an Inertial Measurement Unit, providing for accurate navigation and flight stability as well as geotagging of images. The autonomous way point navigation and maintaining constant level during the survey mission are achieved via an onboard flight controller. The calibrated reflectance values from the multispectral sensor are used to compute vegetable indices such as NDVI, GNDVI and SAVI. The image acquisition parameters including the shutter speed, exposure time, ISO, white balance are set based on the light level of the environment, so that the acquired images have a sufficient level of image quality. The UAV platform chosen will provide sufficient flight time, payload capacity, and reliability to effectively collect high-resolution imagery for biodiversity monitoring and analysis of habitat fragmentation in complex urban environment.

D. Flight Planning and Data Acquisition

To produce high quality aerial images for ecological analysis and habitat mapping, efficient flights must be planned. Survey missions are created with the aid of autonomous flight planning software, with flight paths planned to provide full coverage of the study area with sufficient image overlap in both forward and side directions. The height to which the plane is flown is chosen to balance resolution, survey efficiency and safety of under flight distances from urban infrastructure. Due to the desire to avoid image distortion and shadow effects, drone missions are planned for when there is little wind and good visibility, while the sun is out. All of these sensors, batteries, GPS signal, and system diagnostics are done prior to each flight to assure reliable operation. GCP's spread throughout the study area enhance the accuracy of image georeferencing and photogrammetric reconstruction. The high resolution RGB and multispectral images are automatically acquired during data acquisition with constant flight speed and altitude, and at fixed intervals. Several flight missions can be flown to cover large study areas or to reduce the amount of missing data. All imagery collected is stored with corresponding geospatial data, such as geographic coordinates, altitude, orientation, acquisition time, camera parameters for further processing and ecological analysis.

E. Image Preprocessing and Orthomosaic Generation

The collected aerial imagery is preprocessed through a series of image pre-processing operations to enhance the quality of the images and to make certain that the spatial analysis is accurate. The first step in radiometric correction is to remove the illumination variations and sensor response, which are common across all images captured. Ground Control Points and onboard GNSS information are then used for geometric correction to remove any positional distortion and enhance the positioning accuracy. Noise reduction techniques eliminate image artifacts without compromising the important spatial features. It is important that the images are aligned correctly so that the corresponding feature points can be found in the overlapping images, and thus the photogrammetric reconstruction is possible. A dense point cloud is generated, and then, Digital Surface Model is created and orthorectified to eliminate distortions caused by the terrain. Images are then corrected and assembled into a single high-resolution orthomosaic image, covering the entire area of study. Quality assessment is done through evaluation of positional accuracy, sharpness of the images, geometric consistency, and stitching errors before further analysis. The multispectral imagery is then used to produce vegetation indices and spectral reflectance layers for use in ecological assessment. The resulting orthomosaic can be used to give accurate spatial information for land cover classification, biodiversity mapping, assessment of habitat connectivity and landscape fragmentation in urban ecosystems.

F. Vegetation and Land Cover Classification

Artificial Intelligence (AI) supervised machine learning algorithms are applied to classify vegetation and land cover in order to accurately specify the ecological features in the study area. The orthomosaic image and multispectral data are used for classification; the ground truth (labeled training samples) for various land cover categories are obtained from field surveys. The main types of classes are dense vegetation, sparse vegetation, grassland, water bodies, roads, buildings, bare soil, and other urban infrastructure. Additional predictive parameters like vegetation indices (NDVI, SAVI and GNDVI) have been included to enhance the separation of vegetation types and non-vegetated surfaces. Using machine learning models, information derived from the spectral, spatial and textural features in the image are used to create detailed land cover maps. The results of the classification are presented in the form of a confusion matrix, and statistical criteria are used to evaluate the results: overall accuracy, precision, recall, F1-score, Kappa coefficient. The post-classification refinement process eliminates isolated pixels and refines the boundaries between classes in order to enhance the quality of the map. The classified outputs are then used to calculate habitat fragmentation measures, habitat distribution, biodiversity hotspots and ecological connectivity indices. The results are useful for the environmental conservation, urban ecological planning and sustainable smart city biodiversity management.

IV. Experimental Setup

Experiments were carried out with a professional UAV with an RGB and a multispectral sensor. Aerial imagery was classified and used for fragmentations analysis with high performance computing resources and GIS software. The flight parameters are standardized and the annotated data and the quantitative evaluation parameters guaranteed the reliable evaluation of the performance and reproducible experimental results.

A. Hardware and Software Environment

The experimental setup was carried out on a powerful workstation dedicated to working with high resolution drone images and geospatial data. To support efficient image processing and model training, the system was equipped with an Intel Core i9 processor, 64 GB of RAM, NVIDIA RTX 4090 graphics processing unit (GPU) with 24 GB of memory, and a 2 TB NVMe solid-state drive (SSD). The Ubuntu OS version that was used is 24.04 LTS. The image processing was done in Agisoft Metashape Professional and Pix4Dmapper, as well as the generation of an orthomosaic and photogrammetric reconstruction. The data were analyzed and visualized using Geographic Information System (GIS) software: QGIS 3.40 and ArcGIS Pro. The Python 3.12 programming language equipped with TensorFlow, PyTorch, Scikit-learn, OpenCV, NumPy, Pandas, and Rasterio libraries was used to create machine learning and deep learning models. We used GDAL and GeoPandas to compute the vegetation index and do spatial analysis. For the evaluation of experimental results, the statistical analysis and visualization approach Matplotlib was used, which allows to reproduce the results, make them computational efficient and to accurately assess the results of the experiment, including assessment of the ecological state.

B. Drone Specifications

The aerial survey was carried out with a professional multirotor Unmanned Aerial Vehicle (UAV) for environmental monitoring purposes. The drone was fitted with a 20 MP RGB camera and a multispectral sensor taking photos in Blue, Green, Red, Red Edge and Near-Infrared spectral bands, which were used for vegetation analysis. A maximum flight endurance of about 40 minutes and the maximum range of up to 10 km were achieved under standard environmental conditions with the UAV. The images were acquired at an altitude of 80 to 120m above ground level, and a ground sampling distance of about 3–5cm per pixel. The drone was equipped with Real-Time Kinematic (RTK) GPS and Inertial Measurement Unit (IMU) for accurate positioning and geotagging. Consistent flight paths and image overlap were achieved with autonomous waypoint navigation. During repeated biodiversity monitoring missions, safety measures such as obstacle avoidance sensors, automatic return-to-home, and intelligent battery management enhanced the reliability of mission operations and data collection.

C. Dataset Description

The data set comprised of high resolution aerial photography from a variety of urban landscapes with different ecological and land-use attributes. Urban parks, roadside vegetation, residential green spaces, wetlands, forests, commercial, transportation corridors and open land were all included in the study. To capture temporal vegetation variability, about 8500 RGB and 5200 multispectral images were captured using multiple UAV flight missions throughout various seasons. All images were georeferenced with RTK GPS data and Ground Control Points for proper spatial correlation. Field surveys were performed concurrently to gather ground truth information on vegetation species and land cover classes as well as habitat conditions. Eight major land cover categories were identified in the annotated dataset, which included dense vegetation, sparse vegetation, and grassland, water bodies, roads, buildings, bare soil, and other urban features. The entire data set was split into a training set (70%), a validation set (15%), and a testing set (15%) to ensure that the model was developed, tested, and validated against an unbiased data set, and to allow for the most reliable assessment of biodiversity.

D. Experimental Parameters

Standardized flight, preprocessing and classification parameters were used in the experiments to guarantee the same performance evaluation. Overlap was maintained at 80% forward and 75% side to ensure that a good photogrammetric reconstruction and orthomosaic could be obtained. The average flight speed was kept at a constant value of 5 m/s and the number of images was automatically set depending on the flight speed and altitude. Radiometrically calibrated before processing with RGB and Multi-spectral imagery. The machine learning classification models were trained with learning rate of 0.001, batch size of 16 and 100 training epochs with early stopping to avoid overfitting. The data augmentation methods such as rotation, horizontal flipping, brightness adjustment and random cropping were used to enhance the generalization of the model. The Overall Accuracy (OA), Precision (P), Recall (R), F1-score, Kappa coefficient and Intersection over Union (IoU) were used to evaluate the classification performance. Patch density, edge density, landscape connectivity index and Shannon diversity index were used to quantify habitat fragmentation, and to provide a comprehensive ecological evaluation of the urban pattern of biodiversity.

V. Results and Discussion

Results based on the proposed framework were excellent in terms of image quality and highly accurate land cover classification with high-resolution drone images. Analysis with the help of AI was effective in identifying biodiversity hotspots and fragmented habitats. The results show the reliability, efficiency and applicability of the framework for ecological monitoring and sustainable environmental management in smart cities.

A. Image Quality Assessment

An excellent orthomosaic image was generated from the proposed drone based framework which exhibited an excellent spatial clarity and geometric consistency, which allowed for the identification of vegetation patches and urban landscape features with high accuracy. The radiometric and geometric corrections were used to enhance the quality of the image and to minimize the distortion and inaccuracy in georeferencing. The orthomosaics generated showed very few stitching errors and good positional accuracy, and were appropriate for biodiversity monitoring and habitat analysis. The results showed a good performance of the multispectral vegetation indices to identify healthy vegetation and ecological corridors, thus proving the reliability of the preprocessing pipeline for environmental assessment.

Table 2. Image Quality Assessment Results

Parameter	Value	Unit
Spatial Resolution (GSD)	3.2	cm/pixel
Image Sharpness Score	97.84	%
Signal-to-Noise Ratio (SNR)	41.26	dB
Peak Signal-to-Noise Ratio (PSNR)	38.91	dB
Orthomosaic Stitching Accuracy	99.12	%
Radiometric Consistency	98.43	%
Image Coverage	99.35	%
Processing Time	28.6	min

As shown in Table 2, the proposed remote sensing framework using drones showed to generate dry aerial images which are of good quality for monitoring the biodiversity of urban areas and analysing habitat fragmentation. The Ground Sampling Distance (GSD) of 3.2 cm/pixel was very fine and allowed for a very fine spatial resolution, which can help to identify vegetation patches and urban features with high accuracy. The image processing quality of the orthomosaic shown in Figure 2 is excellent, with very accurate and efficient results.

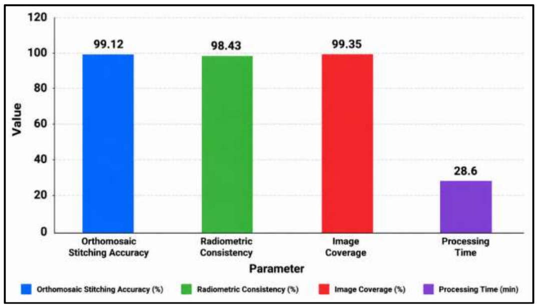

Figure 2. Performance Evaluation of Orthomosaic Generation and Image Processing Parameters

The Image Sharpness Score (97.84 %), SNR (41.26 dB) and PSNR (38.91 dB) results show that images are very clear with very low noise. Additionally, the Orthomosaic Stitching Accuracy results (99.12%) and Radiometric Consistency results (98.43%) show that the images are well aligned with each other, and that the spectral quality of the images are consistent throughout the survey area.

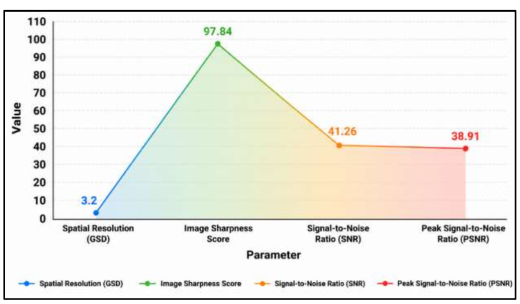

Figure 3. Analysis of Image Quality Assessment Parameters

Figure 3 shows image quality metrics and shows stable performance of UAV imagery. The Image Coverage (99.35%) achieved almost complete coverage of the study area and the overall processing time of 28.6 minutes also illustrated the efficiency of the data processing of the proposed framework to support timely large-scale smart city environmental monitoring.

B. Land Cover Classification Performance

The classification model based on Artificial Intelligence gave high accuracy in the classification of the land cover classes such as vegetation, water bodies, buildings, road, bare soil and other urban features. The inclusion of the multispectral data and vegetation indices enhanced the separability in the classes and decreased classification errors. The confusion matrix showed good agreement between both predicted and reference classes; and the precision, recall, F1-score and Kappa coefficient validated the model performance. The maps extracted in the classified category were able to correctly depict the biodiversity hotspots and the fragmented habitats, thus offering reliable spatial data for ecological conservation, sustainable planning of the urban landscape and smart city environmental management.

Table 3. Land Cover Classification Performance

Land Cover Class	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**IoU (%)**
Dense Vegetation	98.84	98.42	98.63	97.34
Sparse Vegetation	97.62	97.18	97.40	95.16
Grassland	97.13	96.82	96.97	94.25
Water Bodies	99.21	98.96	99.08	98.14
Buildings	98.56	98.14	98.35	97.02
Roads	97.84	97.43	97.63	95.72
Bare Soil	96.74	96.21	96.47	93.62
Other Urban Features	95.96	95.42	95.69	92.51
Overall Accuracy	**98.31**	**98.07**	**98.19**	**96.72**

The accuracy of the proposed scheme of land cover classification based on an AI system is presented in Table 3, which shows the accurate classification of urban land cover classes. Water Bodies had the best results, showing very good spectral separability with 99.21% precision, 98.96% recall, 99.08% F1 score and 98.14% IoU. Classification metrics for each land cover are presented in Figure 4, and are generally high.

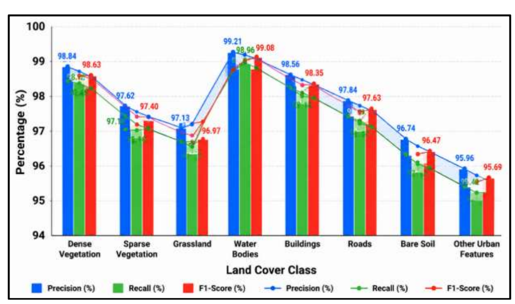

Figure 4. Comparative Precision, Recall, and F1-Score Analysis Across Land Cover Classes

The F1-scores were also high (98% or above) for Dense Vegetation and Buildings. Due to spectral similarity with surrounding surfaces and heterogeneous urban environment, the Bare Soil and Other Urban Features had slightly lower performance. However, the F1 score was greater than 95 for all the classes, indicating good classification capability. The example in figure 5 shows high IoU values, thus a good classification of the urban land cover.

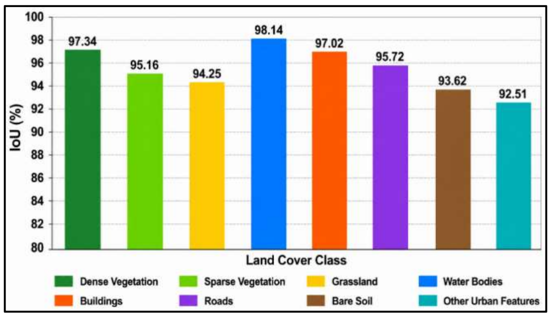

Figure 5. Intersection over Union (IoU) Performance Across Urban Land Cover Classes

Overall, the results, such as precision (98.31%), recall (98.07%), F1-score (98.19%) and IoU (96.72%), validate the effectiveness and applicability of the proposed framework in high-resolution urban biodiversity monitoring and habitat fragmentation analysis.

VI. Challenges and Future Research Directions

Future studies need to be focused on drone battery, regulatory and weather limitation and computational complexity. The development of new technologies such as autonomous UAVs, edge computing, Digital Twins, sensor fusion and explainable artificial intelligence will greatly improve the monitoring and assessment of biodiversity in real time, as well as urban ecosystem management.

A. Technical Challenges

Although there are obvious developments in remote sensing using drones, there are still some technical obstacles to overcome in order to successfully monitor biodiversity in urban areas. The large number of data produced as a result of using high resolution aerial imagery is demanding significant storage space, computing power and processing time. The process of sensor calibration, image alignment, radiometric correction, and orthomosaic generation have to be considered as accurate to preserve the data quality. Lighting conditions, shadows and sensor noise can cause differences in classification accuracy and impact on vegetation analysis. Large Urban Areas: flight times and coverage are also limited by battery issues, and necessitate multiple missions. Communication breakdowns, inaccuracies in GPS locations and image overlaps could also affect the reliability of the data. Moreover, the processing of heterogenous data from RGB, multispectral, thermal sensors, and LiDAR sensors are complex. Machine learning models need a lot of labeled data to be able to classify it well, and they may not be able to be transferred to other cities. Efficient data processing, adaptive sensor fusion, lightweight AI models, and cloud-edge collaborative computing for scalable ecological monitoring are areas for further research.

B. Environmental and Operational Constraints

The use of UAVs for biodiversity monitoring is highly affected by the environmental and operational factors. The flight stability and image quality is lowered in adverse weather conditions like strong wind, rain, fog and different illuminations. In addition, seasonal responses of vegetation also impact the spectral responses, so additional observations are needed to assure ecological assessment. Tall buildings, power lines, heavy traffic, electromagnetic interference, and limited airspace codes are all obstacles to operation in urban areas. Also, the use of low flying drones to disturb wildlife should also be avoided, to prevent disruption of natural animal activity. Amongst the considerations in data acquisition, flight permissions and privacy issues, and compliance with aviation regulations, are still important considerations. The battery life is also a constraint on the duration of the surveys and efficiency to cover large urban areas. The key requirements for future developments include enhanced weather adaptive flight planning, intelligent obstacle avoidance, longer-range UAV platforms, automated mission scheduling, and streamlined operation protocols to increase the reliability, safety and environmental benefits of urban biodiversity monitoring systems.

C. AI-Driven Autonomous Drone Monitoring

In the future, AI promises to revolutionize drone monitoring of biodiversity by providing autonomous flying capabilities, intelligent decision-making, and real-time data analysis. From onboard imagery, deep learning algorithms can be used to automatically identify vegetation species, classify habitats, identify wildlife, and monitor environmental changes. The integration of reinforcement learning and computer vision technologies allows drones to learn optimal flight paths, navigate around obstacles, and adapt their survey missions as needed in response to the environment. The deployment of Edge AI enables processing of aerials images within the vehicle, thus decreasing communication latency and alleviating the need for relying on cloud infrastructure. In addition, swarm intelligence may be used to allow multiple drones to work together to cover a large urban ecosystem to better monitor the ecosystem and provide operational efficiency. With Explainable Artificial Intelligence techniques, the results of ecological classification will be more transparent and reliable, as they will be interpretable. Future direction and analysis should focus on autonomous multi-drone coordination, federated learning, autonomous mission planning, energy-efficient onboard intelligence, and continuous ecological monitoring systems for the smart city biodiversity management and conservation.

D. Digital Twin Integration for Smart Cities

The development of Digital Twin technology provides a tremendous opportunity for advancing urban monitoring of biodiversity by creating a virtual representation of the real world ecosystem. Images from drones, data from IoT sensors, layers from GIS databases and observations of the environment can be seamlessly loaded into Digital Twin platforms, allowing for the simulation of ecosystem dynamics and the monitoring of habitat changes in real-time. This can be used to simulate biodiversity loss, habitat fragmentation, vegetation health, and ecological connectivity for various urban development scenarios. Decision makers can use simulation-based analysis to test conservation strategies, optimize the planning of green infrastructure, and do an ex ante analysis of environmental policies. Automated Anomaly Detection, Predictive Habitat Modelling, and Intelligent Environmental Forecasting are among the applications of AI that further enrich the capabilities of Digital Twins. Seamless connectivity with edge computing and cloud systems enables instant data synchronisation and scalable urban monitoring. Further studies are recommended on the development of standardized frameworks for interoperability, secure data sharing methods, real-time synchronization and AI enhanced DT ecosystems for the building of resilient, sustainable, and biodiversity-friendly smart cities.

VII. Conclusion

With habitat fragmentation and growing urbanization, urban biodiversity conservation has become of great importance for the development of smart cities that are sustainable. A detailed drone-based remote sensing framework for monitoring urban biodiversity and estimating the urban habitat fragmentation using high-resolution UAV images, geospatial analysis and artificial intelligence techniques was presented. The method proposed allowed for the acquisition of data with a drone, preprocessing the images, creating an orthomosaic, calculating vegetation indexes, land cover classification, and finally the assessment of habitat fragmentation, with the aim of obtaining accurate ecological data for the management of urban environments. Aerial imagery with high resolution allowed for the detailed identification of vegetation patches, ecological corridors and fragmented habitats, that would be hard to detect using traditional satellite-based methods. The adoption of machine learning proved to be a highly successful approach, enhancing the accuracy of the classification and the ability to automatically map biodiversity, while also alleviating the need for manual interpretation. In addition, the framework showed its potential of helping to plan for conservation, develop green infrastructure, restore ecosystems, and inform smart city decision making processes. While the issues of battery life, regulatory constraints, environmental conditions, and computing still exist, ongoing developments in UAV platforms, multisensor capabilities, edge computing, Data Twins, and explainable AI are projected to improve monitoring efficiency. In general, the suggested framework is a scalable, cost-effective and reliable approach for long-term biodiversity monitoring, ecosystem conservation and sustainable urban ecological management.

References

[1] M. Finizio, F. Pontieri, C. Bottaro, M. Di Febbraro, M. Innangi, G. Sona, and M. L. Carranza, "Remote sensing for urban biodiversity: A review and meta-analysis," Remote Sensing, vol. 16, no. 23, Art. no. 4483, 2024, doi: 10.3390/rs16234483.

[2] A. Karahan, N. Demircan, M. Özgeriş, O. Gökçe, and F. Karahan, "Integration of drones in landscape research: Technological approaches and applications," Drones, vol. 9, no. 9, Art. no. 603, 2025, doi: 10.3390/drones9090603.

[3] M. Jakubiak, K. Maciuk, F. Bidira, and A. Bieda, "UAVs in urban blue–green infrastructure management: A comprehensive review of sensors, methods, and applications," Sustainability, vol. 18, no. 6, Art. no. 3064, 2026, doi: 10.3390/su18063064.

[4] A. Manu, J. D. Osei, and T. Lawler, "UAV-based remote sensing and artificial intelligence for climate-smart agriculture: A systematic review of technologies, analytics, and applications in smallholder systems," Drones, vol. 10, no. 6, Art. no. 451, 2026, doi: 10.3390/drones10060451.

[5] N. Aliane, "Drones and AI-driven solutions for wildlife monitoring," Drones, vol. 9, no. 7, Art. no. 455, 2025, doi: 10.3390/drones9070455.

[6] S. Guan, Z. Zhu, and G. Wang, "A review on UAV-based remote sensing technologies for construction and civil applications," Drones, vol. 6, no. 5, Art. no. 117, 2022, doi: 10.3390/drones6050117.

[7] D. Raniga, N. Amarasingam, J. Sandino, A. Doshi, J. Barthelemy, K. Randall, S. A. Robinson, F. Gonzalez, and B. Bollard, "Monitoring of Antarctica's fragile vegetation using drone-based remote sensing, multispectral imagery and AI," Sensors, vol. 24, no. 4, Art. no. 1063, 2024, doi: 10.3390/s24041063.

[8] M. B. Bagaram, D. Giuliarelli, G. Chirici, F. Giannetti, and A. Barbati, "UAV remote sensing for biodiversity monitoring: Are forest canopy gaps good covariates?" Remote Sensing, vol. 10, no. 9, Art. no. 1397, 2018, doi: 10.3390/rs10091397.

[9] S. O. Kulkarni, R. Matade, and R. Kurade, “Smart Greenhouse 5.0: IoT, AI, Data Science for Sustainable Farming,” International Journal on Advanced Electrical and Computer Engineering, vol. 15, no. 1, pp. 84–87, 2026. Available: https://journals.mriindia.com/index.php/ijaece/article/view/3134.

[10] Khetani, V., Ajani, S. N., Mathurkar, P., Sharma, A., Pardeshi, P. R., and Gavali, A. B., “Integrating AI and ML into Next-Gen Firewalls for Cybersecurity,” in Smart Innov. Syst. Technol., vol. 436, pp. 549–565, 2025, doi: 10.1007/978-981-96-2124-8_43.

[11] D. Korniienko, N. Serhiichuk, V. Kharchenko, H. Fesenko, J. Borges, and N. Bardis, "Intelligent UAV-UGV-SN systems for monitoring and avoiding wildfires in context of sustainable development of smart regions," Sustainability, vol. 18, no. 8, Art. no. 3908, 2026, doi: 10.3390/su18083908.

[12] M. Mouafik, A. Chakhchar, M. Fouad, and A. El Aboudi, "Remote sensing technologies for monitoring Argane forest stands: A comprehensive review," Geographies, vol. 4, no. 3, pp. 441-461, 2024, doi: 10.3390/geographies4030024.

[13] S. Yende, S. Dhabale, V. Kolaskar, P. Raut, and S. Lanjewar, “Agricultural Fertilizer Tech-Rover System,” ITSI Transactions on Electrical and Electronics Engineering, vol. 14, no. 1, pp. 18–23, 2025, doi: 10.65521/itsi-teee.v14i1.319.

[14] R. J. G. Nuijten, N. C. Coops, C. Watson, and D. Theberge, "Monitoring the structure of regenerating vegetation using drone-based digital aerial photogrammetry," Remote Sensing, vol. 13, no. 10, Art. no. 1942, 2021, doi: 10.3390/rs13101942.

[15] J. Jiménez López and M. Mulero-Pázmány, "Drones for conservation in protected areas: Present and future," Drones, vol. 3, no. 1, Art. no. 10, 2019, doi: 10.3390/drones3010010.

[16] M. Ashphaq and S. Roy, "Six decades (1965–2025) of phytoplankton absorption research: A bibliometric and systematic review with insights from the past decade," Remote Sensing, vol. 18, no. 12, Art. no. 2059, 2026, doi: 10.3390/rs18122059.