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An Investigation of PlanetScope and UAV Imagery for Automated Plastic Waste Detection in Vientiane

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Statement of Originality

I declare that this dissertation represents my own work, and that where the work of others has been used it has been duly accredited. I further declare that the length of the components of this dissertation is **5000** words for the Research Paper and **6106** words for the Technical Report.

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Signed: 10/08/2024

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Part 1 - Research Paper

Abstract

Effective monitoring of urban plastic pollution is crucial for sustainable waste management, especially in rapidly urbanising regions. This study, conducted in Vientiane, Laos, focuses on four key components: (1) characterising urban plastic waste using spectral and textural features, (2) evaluating the effectiveness of PlanetScope and UAV imagery (RGB) for plastic waste detection, (3) assessing the accuracy of Random Forest (RF) and Support Vector Machine (SVM) algorithms in classifying plastic, and (4) examining the operability and scalability of these methodologies for urban waste management.

The study identified mean saturation and standard deviation of RGB values as critical spectral features, while contrast and dissimilarity were key textural features for accurately classifying plastic. PlanetScope's 3-meter resolution was found to be inadequate for detecting urban plastic waste accumulations, whereas UAV imagery (~5 cm resolution) provided more precise data for identifying plastic across the city. The RF and SVM models achieved 86% and 96% accuracy, respectively, during training but experienced significant accuracy drops in real-world applications, with 38% for RF and 28% for SVM, due to misclassification errors, particularly between buildings and plastics. Consequently, this study recommends several improvements for future research.

To enhance waste management practices, this study proposes integrating these methodologies with GIS to optimise plastic waste monitoring and collection strategies. This approach shows promise for scaling across Vientiane, provided that model improvements and increased computational efficiency are achieved. This study offers a foundational framework for advancing urban environmental monitoring and addressing plastic pollution in rapidly developing cities.

1. Background & Literature Review

1.1 The Urgency for Improved Plastic monitoring

The exponential increase in plastic production since the 1950s has resulted in plastics becoming one of the most pervasive materials in the modern world (Geyer et al., 2017). The proliferation of plastic is affecting all ecosystems, driving biodiversity loss, ecosystem degradation, and posing risks to human health.

The primary sources of plastic pollution are land-based, originating from urban runoff, littering, industrial activity, and inadequate waste management services. However, there is a distinct lack of data on accumulations of plastic waste in urban environments compared to marine and riverine environments (Lavender, 2022). Effective monitoring and environmental surveillance are key to address this environmental threat. Despite global mitigation strategies by legal regulators (UNEP, 2018; OECD, 2001; Tanaka et al., 2019), plastic pollution is expected to nearly triple by 2040 if significant actions are not taken (UNEP, 2021).

To effectively inform mitigation strategies, environmental monitoring is essential to understand the sources, pathways, and spatiotemporal distribution of plastic waste. Estimates suggest that 70-80% of plastic pollution originates from land-based sources and that 91% of ocean plastic pollution occurs via watersheds. The top 10 rivers transporting plastic waste are located in South or Southeast Asia, where dumpsites are commonly used for disposal (Kruse et al., 2023).

Vientiane, the capital of Laos, is one of many cities along the Mekong River that urgently requires monitoring for plastic pollution. The city faces significant waste disposal challenges due to rapid urbanisation, economic development, population growth, and modernising lifestyles, leading to increased volumes and new types of waste (Switch Asia, 2022). In Laos, the producers of plastic remain largely unaccountable. This may change with the initiative of the Global Plastic Treaty (UNEP, 2022) and support of international organisations, local movements, and advocacy groups like Green Vientiane (Laotian Times, 2024). However currently, addressing plastic pollution hinges on improving waste management practices. In 2022, Vientiane's Sustainable Solid Waste Management Strategy and Action Plan was published to tackle waste disposal. The city government urges immediate action against illegal dumping and open burning (VCOMS, 2021).

One key issue for addressing plastic waste is the lack of comprehensive data on its movement and distribution across the city. This data is crucial for evidence-based policy development and effectively tackling plastic pollution. Therefore, identifying the distribution of plastic waste across the city is an important first step (AIT, 2024).

Current efforts to identify sources and distribution have used modelling through geospatial proxy indicators and field survey methods. However, significant challenges remain, including the limited accuracy of such geospatial models and the resource-intensive nature of field surveys. As a result, there is a growing consensus on the need for an innovative methodology, with the AIT emphasising the pivotal role of remote sensing technologies in the future of plastic waste management strategies.

1.2 Remote Sensing Techniques for Plastic Detection and Monitoring

Satellite imagery has emerged as a potential tool for detecting plastic pollution in various environments, providing near continuous environmental surveillance. Several studies have identified the capability of spectral reflectance information to effectively discriminate plastic from other land classes (Aoyama, 2016; Topouzelis et al., 2019). Tasserson et al., (2021) used a hyperspectral camera in a laboratory to reveal absorption peaks of plastic at (1215nm and 1410nm), highlighting the importance of SWIR and NIR bands when detecting plastic. This research is consistent with Topouzelis et al., (2019) who emphasised the need for hyperspectral measurements when detecting plastic, specifically for matching objects to spectral reference libraries of known plastics. However, in reality, the spectral signature of plastics is highly variable (Karakus, 2023). Plastic type, variations in colour, transparency and additives, weathering processes and presence of other materials in the surrounding environment, complicate the detection of plastic in natural environments.

Despite challenges, many studies are currently exploring space-borne remote sensing to monitor ocean plastic and detect floating plastic litter in rivers, achieving varying levels of success *(Table 1).* Sentinel-2 imagery combined with machine learning techniques has been effective in identifying some forms of plastic waste, as highlighted by Biermann et al., (2020), Mifdal et al., (2021), and Gomez et al., (2022). However, there is still significant debate in the academic community regarding the validity and effectiveness of these methods (Karkus, 2023; Hu et al., 2021).

Detecting plastic waste within terrestrial or built environments presents a unique challenge due to the complex background settings. A notable study by Hasituya et al. (2017) used Landsat-8 imagery with 30-meter multispectral and 15-meter panchromatic spatial resolutions to monitor plastic-mulched farmland, using high-resolution GaoFen-1 images as reference data. This study employed Support Vector Machine (SVM) and Random Forest (RF) models, achieving high accuracy in classifying plastic among various land classes. However, the accuracy results were derived solely from training process statistics, not ground validation, leaving the model's real-world effectiveness uncertain. Conversely, Lavender (2022) demonstrated the potential of combining Sentinel-1 and Sentinel-2 data at a 10-meter spatial resolution to map significant accumulations of plastics, including greenhouses, plastic, tires, and waste sites. Focusing on known plastic accumulation sites such as landfills and dam areas, the study used an Artificial Neural Network (ANN) model, which performed well during training. Despite extensive training data, the model's accuracy reduced when applied to validation sites. Model accuracy decreased to 58% and 83% for plastic and waste sites respectively. This discrepancy suggests that a 10-meter spatial resolution may be too coarse to detect smaller plastic accumulations effectively, highlighting the need for higher spatial resolution data or alternative methodologies to enhance detection accuracy.

Both studies indicate that higher spatial resolution significantly enhances the detection of plastic. Therefore, alternative approaches, such as UAV-based methods, may be necessary. Although the use of UAVs for waste management is not yet widespread, recognition of their potential is growing (Sliusar et al., 2022). Table 2 provides a review of current literature using UAVs to detect, classify, and map plastic in riverine and terrestrial environments. Many current studies utilise RGB cameras to detect plastic but recognise the potential of multispectral cameras in improving classification. Small-scale studies with low drone heights achieve precise detection of plastics; however, their scalability, which is necessary for improving waste management strategies, is limited (Wolf et al., 2020; Han et al., 2022; Iordache et al., 2022). Greater flying heights providing wider areal coverage, are better suited for city-wide waste management applications, but classification accuracies are often reduced, and many types of plastics cannot be differentiated.

Machine learning techniques are commonly used to enhance and automate detection processes from UAV and satellite imagery. In the case of UAV imagery, deep learning techniques, such as Convolutional Neural Networks (CNNs), have been previously employed to improve plastic detection accuracy, particularly in complex environments like rivers and urban areas (Wolf et al., 2020; Jakovljevic et al., 2020; Kelm et al., 2021; Han et al., 2022; Maharjan et al., 2022). In contrast, machine learning algorithms like Random Forest are often used when the input data is limited or when more control over model features is desired, providing reliable classification capabilities (Iordache et al., 2022; Kalonde et al., 2022).

1.4 Study Justification

Recognising the necessity for a remote sensing method capable of extensive coverage to support municipal waste management strategies, this paper explores a method for detecting and mapping plastic waste in Vientiane. To assess current capabilities, this study will use primarily publicly available datasets, supplemented by some local data sources. These include PlanetScope imagery, plastic litter surveys, and UAV imagery provided by a World Bank project.

Reviewing the literature, it is evident that there have been limited studies based in complex urban environments. Therefore, several challenges are anticipated. Notably, the classification of plastic against varied backgrounds, the trade-off between sufficient areal coverage and spatial resolution, and relying solely on RGB data from the drone imagery. Nevertheless, this research is justified, as it seeks to advance the understanding of the practical application of these techniques and their potential efficacy in supporting ground-level waste management operations.

Name of Study	Author	Year	Location of Study	Sensor	Spectral Range	Bands Used	Spatial Resolution	Indices Used	Image Target	Image Classification Technique
Mapping Plastic-Mulched Farmland with Multi-Temporal Landsat-8 Data	Hasituya and Chen	2017	China	Landsat-8 OLI	VIS-NIR; SWIR; TIR	L8: All bands	L8: 30m (multispectral); 15m (panchromatic)	NDVI; NDBI	Plastic mulched farmland	SVM; RF
On Thermal Infrared Remote Sensing of Plastic Pollution in Natural Waters	Goddijn-Murphy and Williamson	2019	Global Oceans	ECMWF; ERA5 Thermal Infrared	TIR	3-5µm; 8-14µm	ERA5: 27km x 27km	N/A	Floating plastic in seawater	Temperature difference between plastic and water
Detection of Floating Plastics from Satellite and Unmanned Aerial Systems (Plastic Litter Project 2018)	Topouzelis et al.	2019	Greece	Sentinel-2; Sentinel-1; UAV	VIS-NIR; SWIR; microwave	S2: All bands; UAV: RGB; multispectral; thermal	S2: 10m; 20m; 60m; S1: 5m x 20m; UAV: various	NDVI; FDI	Floating plastic in seawater	Image interpretation; spectral analysis; pixel coverage estimation
Remotely Sensing the Source and Transport of Marine Plastic Debris in Bay Islands of Honduras (Caribbean Sea)	Kikaki et al.	2020	Honduras	PlanetScope; Sentinel-2; Landsat 8	VIS-NIR; SWIR	PS: All bands; L8: All bands; S2: All bands (except 9;10)	PS: 5m; S2: 10m; L8: 30m	N/A	Floating and submerged plastic in coastal waters	Image interpretation
Finding Plastic Patches in Coastal Waters using Optical Satellite Data	Biermann et al.	2020	Ghana; Vietnam; Canada; UK	Sentinel-2	VIS-NIR; SWIR	S2: 4; 6; 8; 11; 12	S2: 10m (B4-8); 20m (B11;12)	FDI; NDVI	Floating plastic in coastal waters	Supervised Naïve Bayes
Towards Detecting Floating Objects on a Global Scale with Learned Spatial Features Using Sentinel-2	Mifdal et al.	2021	Global	Sentinel-2	VIS-NIR; SWIR	S2: All bands	S2: 60m (B1;9); 20m (B5;6;7;8A;11;12); 10m (B2;3;4;8)	FDI; NDVI	Floating objects in marine environment	SVM; RF; Naïve Bayes; CNN-U-Net
A Learning Approach for River Debris Detection	Gomez et al.	2022	Balkans; USA; China	Sentinel-2	VIS-NIR; SWIR	S2: All bands	S2: 60m (B1;9); 20m (B5;6;7;8A;11;12); 10m (B2;3;4;8)	N/A	Floating plastic in riverine environment	Neural Networks (U-Net; U-Net3DE; DV3M; DV3X)
Detection of Waste Plastics in the Environment: Application of Copernicus Earth Observation Data	Lavender	2022	Global	Sentinel-1; Sentinel-2	VIS-NIR; SWIR; microwave	S1: All bands; S2: All bands	S2: 60m (B1;9); 20m (B5;6;7;8A;11;12); 10m (B2;3;4;8); S1: 5m x 20m	NDVI; SAVI; NDWI2; NDBI	Waste plastic detection on land and water	Spectral Index; supervised classification
Identification of Illegally Dumped Plastic Waste in a Highly Polluted River in Indonesia Using Sentinel-2 Satellite Imagery	Satki et al.	2023	Indonesia	Sentinel-2A; Pleiades 1a/1b; UAV imagery	VIS-NIR; SWIR	S2: 10-60m; Pleiades: 0.5-2m; UAV: 0.05m	S2: 10-60m; Pleiades: 0.5-2m; UAV: 0.05m	PI; NDVI; NDBI	Floating plastic in riverine environment	Random Forest; Mahalanobis distance
Investigating Detection of Floating Plastic Litter from Space Using Sentinel-2 Imagery	Themistocleous et al.	2023	Cyprus	Sentinel-2	VIS-NIR; SWIR	S2: All bands	60m (B1;9); 20m (B5;6;7;8A;11;12); 10m (B2;3;4;8)	NDWI; WRI; NDVI; AWEI; MNDWI; NDMI; SR; PI; RNDVI	Floating plastic in marine environment	Image interpretation

Table 1- Extended Review of satellite based studies for detecting plastic waste in marine, riverine and terrestrial settings.

Name of Study	Author	Year	Location of Study	Sensor	ML Techniques	Drone Height	Focus	Success	Limitations
Illegal dumping investigation: a new challenge for forensic environmental engineering	Lega et al.	2014	Italy	RGB Camera, IR Camera	N/A	Not Specified	Detection of illegal environmental dumping (land)	Integrated data from multiple platforms; high-quality 3D models generated allowing precise measures of volume of illegal landfills	Cost and resource-intensive; limited ground truthing; weather dependency of surveying using drones
Riverine Plastic Litter Monitoring Using Unmanned Aerial Vehicles (UAVs)	Geraeds et al.	2019	Malaysia	RGB Camera	Various (Deep Learning)	~60 m	Identifying and quantifying the amount of floating plastic on rivers	Novel study for identifying and quantifying plastics on rivers; effective in inaccessible areas; high accuracy quantification values closely matching field survey quantifications	Application dependent on weather conditions; manual labeling of plastic debris from aerial images can introduce observer bias
Machine Learning for Aquatic Plastic Litter Detection, Classification, and Quantification (APLASTIC-Q)	Wolf et al.	2020	Cambodia	RGB Camera	CNNs	6m	Classifying and quantifying floating and wash ashore plastic	Capable of identifying and quantifying various types of floating and washed ashore plastic litter objects with high precision. Precision much higher than using satellite imagery	Shadows introduce bias; results could be improved with multispectral imagery; small-scale study; scalability and real-world effectiveness uncertain
A Deep Learning Model for Automatic Plastic Mapping Using UAV Data	Jakovljevic et al.	2020	Bosnia and Herzegovina, Serbia, Spain	RGB Camera	CNNs (U-Net, ResUNet50)	12-90m	Detection, classification, and mapping of floating plastics: nylon, oriented polystyrene, and PET	High classification accuracy; effective differentiation between different types of plastic; good generalization classifying plastics in shallow waters and on land	Small spatial coverage; scalability; dependence on quality of training data which was subject to errors; model overestimation
Evaluation of the Accuracy of WDS Mapping Using UAV	Bhatsada et al.	2020	Thailand	RGB Camera	N/A	~115m	Photogrammetric accuracies when mapping open dumpsites	Demonstrated that UAV photogrammetry can achieve high accuracy in mapping open dump sites; safety and accessibility reduce risks to surveyors; detailed spatial data produced	Dependence on weather conditions; complexity in data processing; technical limitations of UAV used (low cost therefore lower sensor quality)
Applying FFP Approach to Wider Land Management Functions	Kelm et al.	2021	Cambodia	RGB Camera	CNNs	Not Specified	Detection of plastic in polluted rivers, beaches, and urban canals	Detection of plastic in polluted rivers, beaches, and urban canals. The drone imagery resolution is compatible with other land administration tasks, making research more practical for operations	Results have not been verified through ground truthing to ensure accuracy; results could be improved with a hyperspectral camera
A Deep Learning Model for Automatic Plastic Waste Monitoring Using UAV Data	Han et al.	2022	China	RGB Camera	EfficientNet, YOLOv5	7m	Real-time detection of plastics on rivers	Algorithm successful for floating plastic detection (bags, foam, and bottles) with real-time performance	Despite high accuracy in controlled experiments, challenges to assess models' performance in real-world conditions; varied environmental conditions affect model effectiveness; small-scale study - scalability
Targeting Plastics: Machine Learning Applied to Litter Detection in Aerial Multispectral Images	Iordache et al.	2022	Belgium	Multispectral	Random Forest	7m	Classification of plastic materials on both land and water	Plastic materials spotted with high accuracy in both test and validation data. Detected plastic on both land and water - high versatility of detection methods	Confusion between plastic and painted surfaces; shadows caused classification inaccuracies; small-scale study - scalability
Detection of River Plastic Using UAV Sensor Data and Deep Learning	Maharjan et al.	2022	Laos and Thailand	RGB Camera	CNNs (YOLOv3, YOLOv4, YOLOv5)	30m	Real-time detection of plastics on rivers	YOLOv5 model suitable for real-time detection of plastics floating on rivers. High mean precision	Model performance varies with environmental conditions; field validation limited, performance in varied real-world settings uncertain
Geospatial Methods for Mapping Domestic Waste Piles and Macro Plastics	Kalonde et al.	2022	Malawi	RGB Camera	Random Forest	15 to 90m	Detection and classification of terrestrial waste piles and plastic	High classification accuracy from training data; evaluation of best spatial resolution for mapping smaller plastics (GSD of 1.17 cm); demonstrated practicality of mapped plastics near river in Blantyre	Heterogeneous nature of urban landscapes leads to misclassifications; environmental variability impacted classification accuracy; GSD of 2.5 cm too coarse for mapping plastics smaller than 10 cm

Table 2 – Extended Review of UAV based studies for detecting, monitoring and mapping plastic.

2. Research Aims and Objectives

2.1 Aims

This study aimed to develop a remote sensing methodology for detecting plastic waste piles throughout Vientiane by comparing PlanetScope and drone imagery to determine the most effective approach for monitoring and mapping plastic waste. The study sought to enhance waste management practices in the locality by assessing a novel method to map the distribution of plastic across different parts of the city.

Using publicly available plastic survey data, this research assessed the ability of these two platforms to detect plastic. Random Forest (RF) and Support Vector Machine (SVM) algorithms were applied to the imagery to create an automated method for detecting plastic waste. The results were compared to manually assessed plastic detection, accompanied by a critical analysis of the benefits and limitations of developing this automated process.

2.2 Objectives

To meet this aim, the following objectives were formulated:

1. Characterise the nature of urban plastic waste in Vientiane by assessing its defining features that are pertinent for classification.
2. Evaluate the suitability of PlanetScope Super Dove imagery and RGB drone imagery, classified using RF and SVM algorithms, to detect various forms of urban plastic waste in Vientiane.
3. Assess the overall accuracy of the classification technique, including a detailed analysis of omission and commission errors made by the classifier.
4. Assess the method's operability by developing exemplary maps for local authorities and evaluating the feasibility of scaling the methodology across Vientiane.

3. Data Sources

3.1 Available Data Sources

3.1.1 Planet Imagery

This study utilised imagery from Planet's Super-Dove satellites, selected for their 3-meter spatial resolution and 8 spectral bands (*Technical Report (TR) 2.2*). These satellites offer frequent near-daily updates, ideal for environmental surveillance. Imagery was downloaded from Planet Explorer, covering the regions corresponding to the drone data, corrected for surface reflectance, specifically for November 23, 2021.

Satellite imagery was first visually inspected in QGIS. Following this, two indices were calculated to support plastic detection: NDVI (Equation 1) and the Plastic Index (PI) (Equation 2). While NDVI is traditionally used for vegetation density, Biermann et al. (2020) and Tasserson et al. (2021) demonstrated its effectiveness in distinguishing plastic from organic materials. Themistocleous et al. (2020) introduced the Plastic Index for detecting plastic on water surfaces. This study assesses the ability of these indices to differentiate vegetation from plastics on land in urban environments.

Equation 1. $$NDVI = (NIR - R)/(NIR + R)$$

Equation 2. $$PI = NIR/(NIR + R)$$

3.1.2. Aerial survey

The drone imagery used in this research was collected as part of a World Bank Project aimed at mitigating flood risk. This project sourced imagery over Vientiane City and Luang Prabang from September to November 2021. A fixed-wing VTOL drone, the JOUAV CW-007, was flown at an altitude of 400 meters above ground level (AGL), with a cruising speed of approximately 60-70 kph. Images were captured using a SONY CA102 camera with a resolution of 42 megapixels.

Post-processing of the drone imagery involved several steps to ensure high-quality orthophoto mapping. Initially, images underwent density and contrast adjustments to even out appearances affected by monsoon skies. Following this, images were processed in Agisoft Metashape in three stages: image and data acceptance, placement of Ground Control Points for triangulation and photogrammetry, and the creation and editing of point clouds. The imagery used in this study is a corrected orthophoto map produced with a Ground Sample Distance (GSD) of 5.19 cm.

To manage the extensive data, the imagery was clipped to three regions in Vientiane City: Thatluang Lake Economic Zone, Saphanthong and Watsop, and the Ban Hom agricultural area. Due to limitations in data transfer capacity, this selection of regions was deemed sufficient to assess the distribution of plastic waste across different parts of the city (Figure 1c).

3.1.3 Ground Survey

Ground data from two field surveys in Vientiane were utilised for this study (Figure 1b). The data from the first survey, was conducted as part of the PLitter project were used to classify plastic waste piles from the drone and satellite imagery (GIC-AIT, 2022). This survey provided a visual interpretation of plastic materials in Vientiane using a mobile application and was conducted during the wet and dry seasons from April 2021 to December 2021. The data was downloaded from the specified source and subset to Vientiane in November 2021 to align with the UAV imagery dates.

A second field survey was conducted in June 2024 with assistance from the National University of Laos and local advocacy group Green Vientiane. This survey gathered further data on the types and characteristics of plastic waste in Vientiane, providing locational information and pictures of plastic waste piles located in the Ban Hom agricultural area.

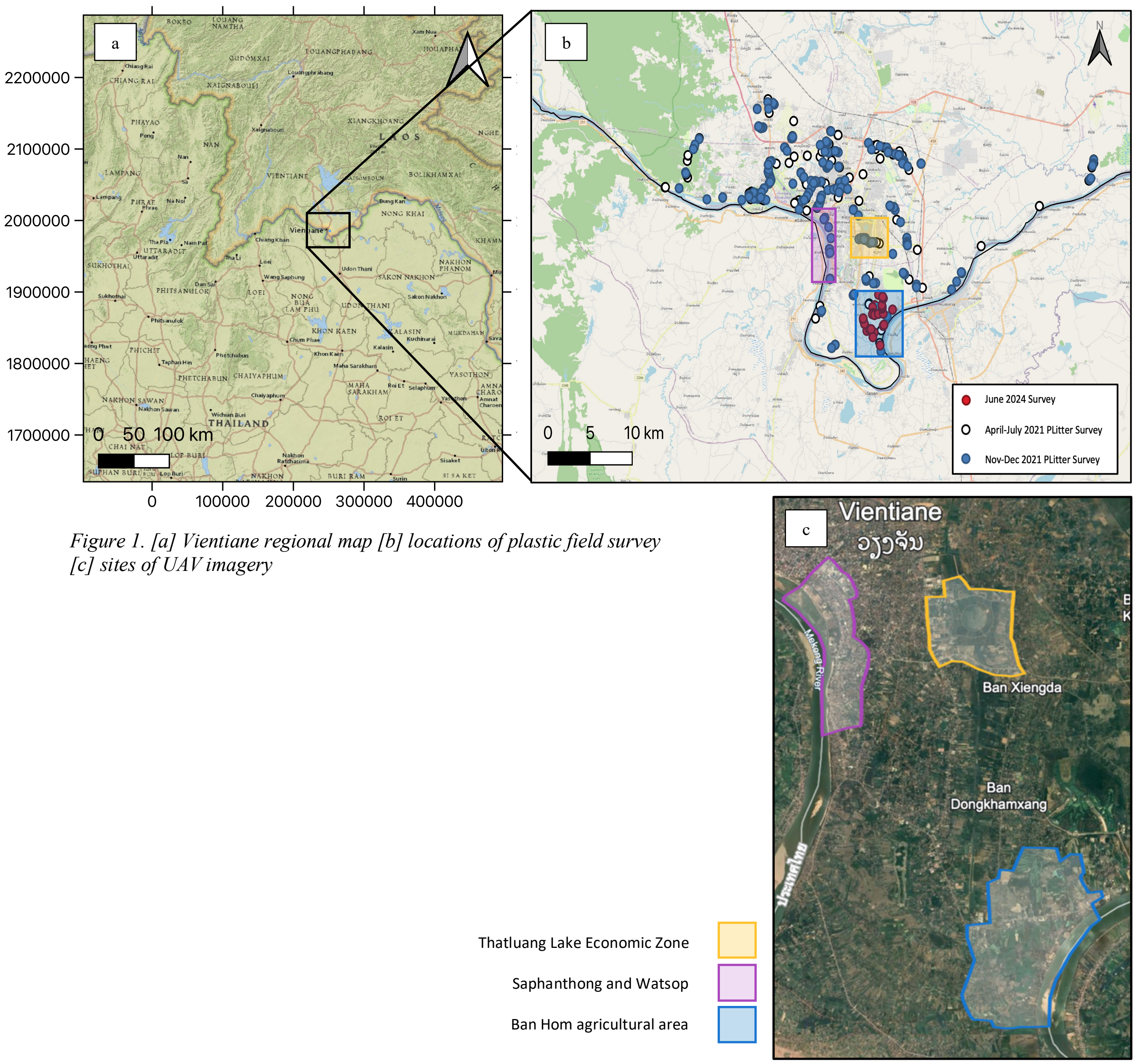


Figure 1. [a] Vientiane regional map [b] locations of plastic field survey [c] sites of UAV imagery

4. Methodology

4.1 PlanetScope Methods

Planet imagery from November 23rd, 2021, were downloaded from Planet Explorer and processed using the raster calculator in QGIS to derive the NDVI and PI indices (Planet Labs, 2024). Given the anticipated challenges in identifying urban plastic waste using this imagery, an initial visual analysis was conducted, with comparative assessment against the UAV imagery and PLitter survey locations. Refer to *TR Section 3.2.1* for the download of PlanetScope imagery.

Based on the results of this initial exploration, it was confirmed whether to proceed with further analysis using the UAV methodological framework outlined in Figure 2.

4.2 UAV Methods

Feature selection plays a key role in Machine Learning (ML) classifiers significantly improving model accuracy. Figure 2 shows the methodological framework. It can be broken down into 5 key steps: developing training data, feature analysis and selection, model training, model application and selection and generation of key model outputs.

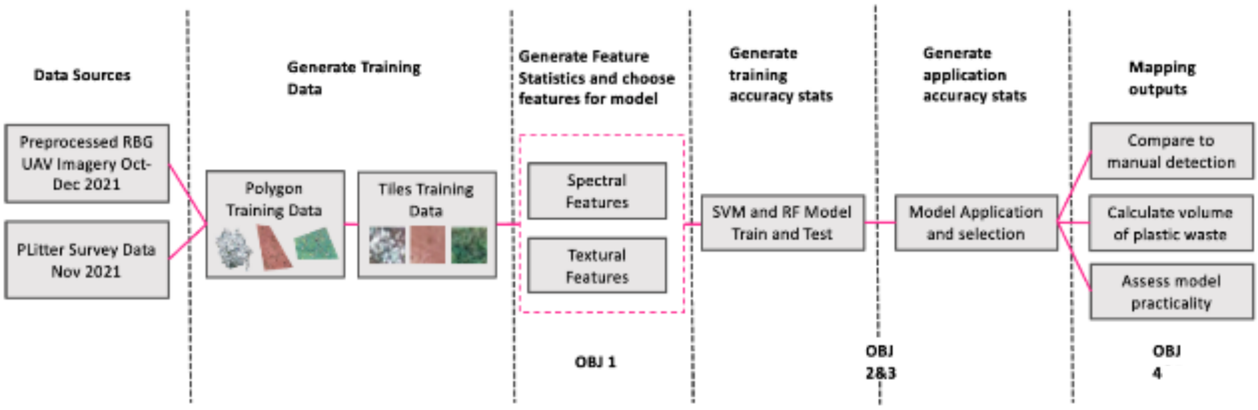


Figure 2. Methodological Framework, with steps, processes, and objectives

4.2.1 Developing training data

This research employs a multi-class classification approach instead of a binary 'plastic versus non-plastic' method. This strategy usually enables a more comprehensive and accurate classification (Gall et al., 2012). Consequently, alongside plastic, five other land classes were identified: vegetation, road, earth, building, and water. These classes were determined by observing key land features in the available drone imagery.

In QGIS, training data was created from the drone imagery using the PLitter survey data as a ground reference for the plastic class. This process involved digitising polygons for each land class and extracting the underlying UAV pixels to create a series of .tif files for training data (*TR Section 4.2.1*).

Following this, the training images were split into tiles of equal dimension (~1.4 m^2) for the feature extraction process. This resulted in a total of 394 training tiles, which were nearly evenly distributed across the different classes.

4.2.2 Feature Selection

Using Python, several image statistics were extracted from the training tiles. These included the reflectance of optical bands and textural characteristics as defined by Haralick et al. (1973). The predictor features considered in this study are listed in Table 3. Box plots were generated to understand the distribution of all feature characteristics across the target classes (*TR Section 5*), and the Feature Importance tool within the RF Classifier was utilised to identify the most significant features.

Feature Type	Feature Name
Optical Properties	RGB Mean, RGB Std, HSV Mean, HSV Std
Haralick Texture Features	Contrast, Dissimilarity, Homogeneity, ASM (Angular Second Moment), Energy, Correlation, Entropy, Inverse Difference Moment, Inertia, Cluster Shade, Cluster Prominence, Haralick Correlation

Table 3. A list of the features explored to characterise plastic and other land classes. Optical features explored Red, Green, Blue (RGB) characteristics and Hue, Saturation, Value (HSV) characteristics. Several Haralick features were explored for texture. Refer to TR Section 5 for explanation behind the chosen features.

4.2.3 Model Development

Random Forest (RF) and Support Vector Machine (SVM) algorithms were chosen for land classification due to the limited training data available. These algorithms are effective with multiple classes and small datasets, producing results comparable to CNNs (Skeyhmousa et al., 2020). Model development was done in Python3, using an 80:20 training-testing split. The RF and SVM models were fine-tuned via a cartesian grid search (*TR Section 6.1-2*), with the optimal hyperparameters selected based on the highest accuracy during training. Accuracy statistics, including overall accuracy (OA), precision, recall, Kappa coefficient, and confusion matrices were calculated to assess model performance. Refer to the TR Section 7 for further details on the accuracy statistics.

4.2.4 Model Application

To evaluate the ability of the SVM and RF land classifier models on real-world imagery, a 'validation site' region was subset from the drone imagery (*TR Section 7*). Human land class predictions were generated for 1000 points across the site and used to generate accuracy statistics to assess model performance for a range of application techniques. It was determined that dividing this region into tiles sized 14x14 pixels, representing 0.7 m^2, was the best application technique for model performance (*TR Section 8*). During this process, the SVM and RF models generated a prediction for each tile, and then the tiles were mosaicked back together to create a final classified map. Classified maps were visually analysed to identify patterns and trends in commission and omission errors. Based on these analyses, the superior model was chosen for generating the final outputs.

4.2.5 Model Outputs

1. **Comparison of Human and Model Predictions:** Manually developed a series of polygons identifying the presence of plastic in drone imagery, with varying confidence levels. Compared this against model predictions, to assess discrepancies between human and ML predictions.
2. **Volume Calculation of Plastic Waste**: Using statistics on waste dimensions from the June 2024 Field Survey, developed a method to calculate the volume of plastic waste in two areas of the city: a riverside residential area in Watsop and an open ground region near ThatLuang Lake.
3. **Method Evaluation for Waste Management:** Assessed the scalability of ML-based plastic classification for waste management by integrating information from field surveys, UAV collection times, and model processing durations.

5. Results

5.1 Detecting Plastic from Planet Imagery

The comparison between UAV and Planet Super Dove imagery, along with two spectral indices maps (PI and NDVI), revealed significant insights (Figure 3). The 3-meter spatial resolution provided by the Planet Super Dove imagery proved insufficient for detecting plastic waste piles, as no spectral changes were observed in areas of plastic waste identified by PLitter survey and UAV imagery analysis.

The NDVI index, designed for vegetation analysis, successfully differentiated denser vegetation, illustrated by the darker green regions on the map. The PI index exhibited characteristics similar to NDVI, with darker red regions indicating denser vegetation. However, it did not show significant capability for detecting plastic waste. This outcome suggests that both indices, in their current form, are not suitable for plastic detection in terrestrial settings. Given these findings, further analysis using Planet imagery was deemed unnecessary, as no statistical technique would likely overcome the limitations imposed by the 3-meter spatial resolution for plastic detection.

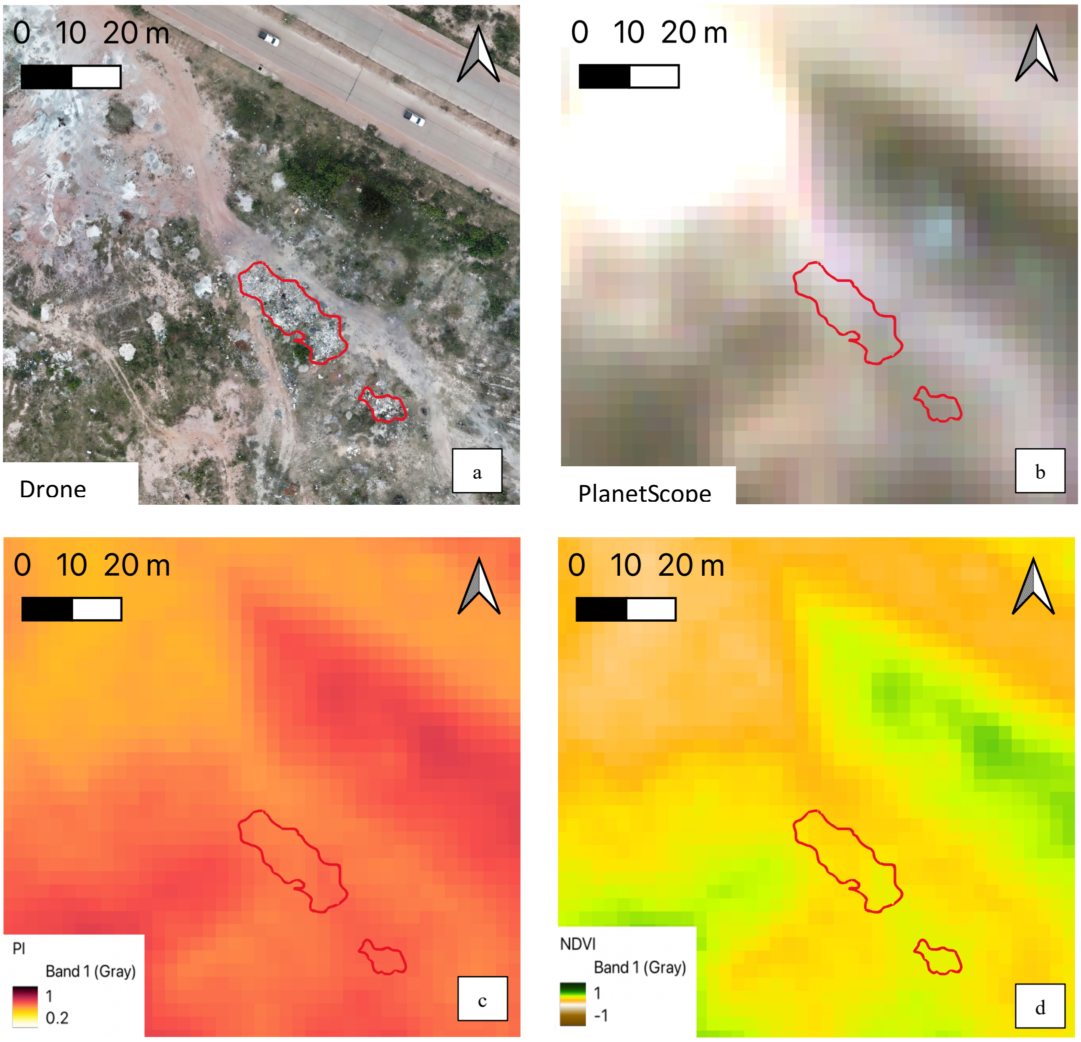


Figure 3. A comparison between UAV imagery [a] with true colour Planet Scope Super Dove imagery [b] with Plastic Index generated from satellite imagery [c], and Normalised Vegetation Index [d]

5.2 Detecting Plastic from UAV

4.2.1 Plastic Characteristics

The analysis of feature importance from the random forest classifier, coupled with box plot analysis, highlights key features for distinguishing plastic waste from other land classes and the overall feature importance for land classification.

'Mean saturation' emerged as the most significant feature for predicting plastic, with an importance score of 0.13. Figure 4 illustrates that the plastic training data have a lower median saturation compared to the other classes, with a relatively narrow interquartile range. This lower saturation is indicative of the less vibrant colours typical of the transparent, black, and white plastic objects commonly found across the city. This feature differentiates plastics from other materials such as vegetation and buildings, which tend to have higher saturation levels.

Furthermore, the standard deviation of RGB values, with importance scores of 0.10, 0.13, and 0.13 for red, green, and blue respectively, represents the colour variability within plastic regions. The high variability in RGB channels, as depicted in the box plots, underscores the heterogeneity in the colour intensity of plastic waste. This higher variability distinguishes plastics from more uniformly coloured land classes such as earth, roads, and water.

Additionally, the high importance of average contrast values, 0.10, indicates the presence of sharp changes in pixel intensity, likely due to the variability in colours of the plastic. This contrasts with the more homogeneous textures of other land classes, making average contrast another important indicator of plastic.

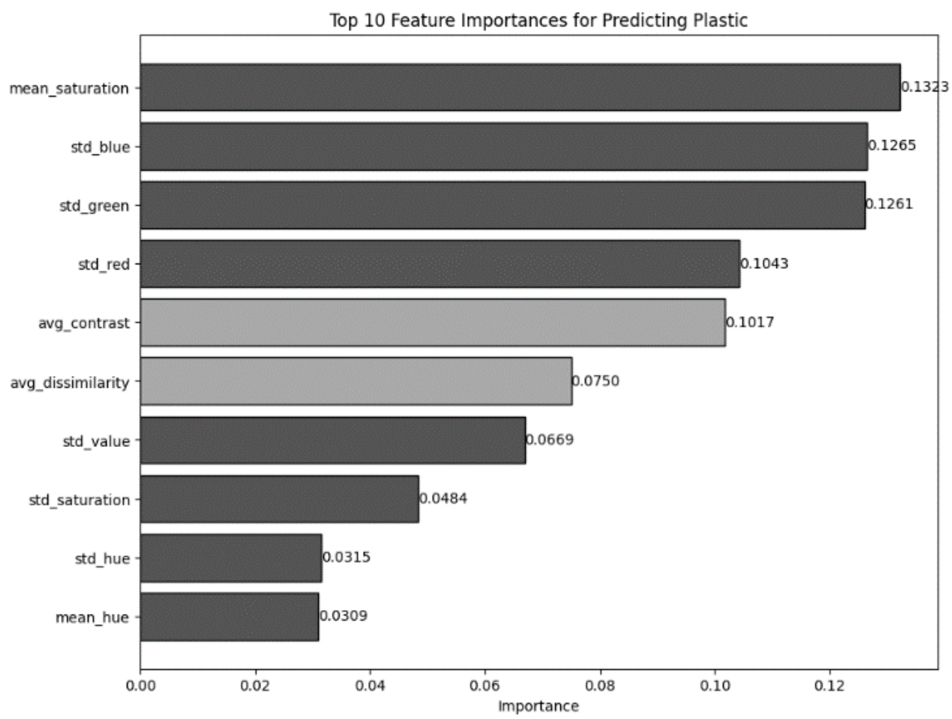


Figure 4. Feature Importance obtained from Random Forest classifier. Represents the relative importance of each feature to the overall classification. Light grey bars represent texture features and dark grey represents spectral features. Importance values across all input features sum to 1.

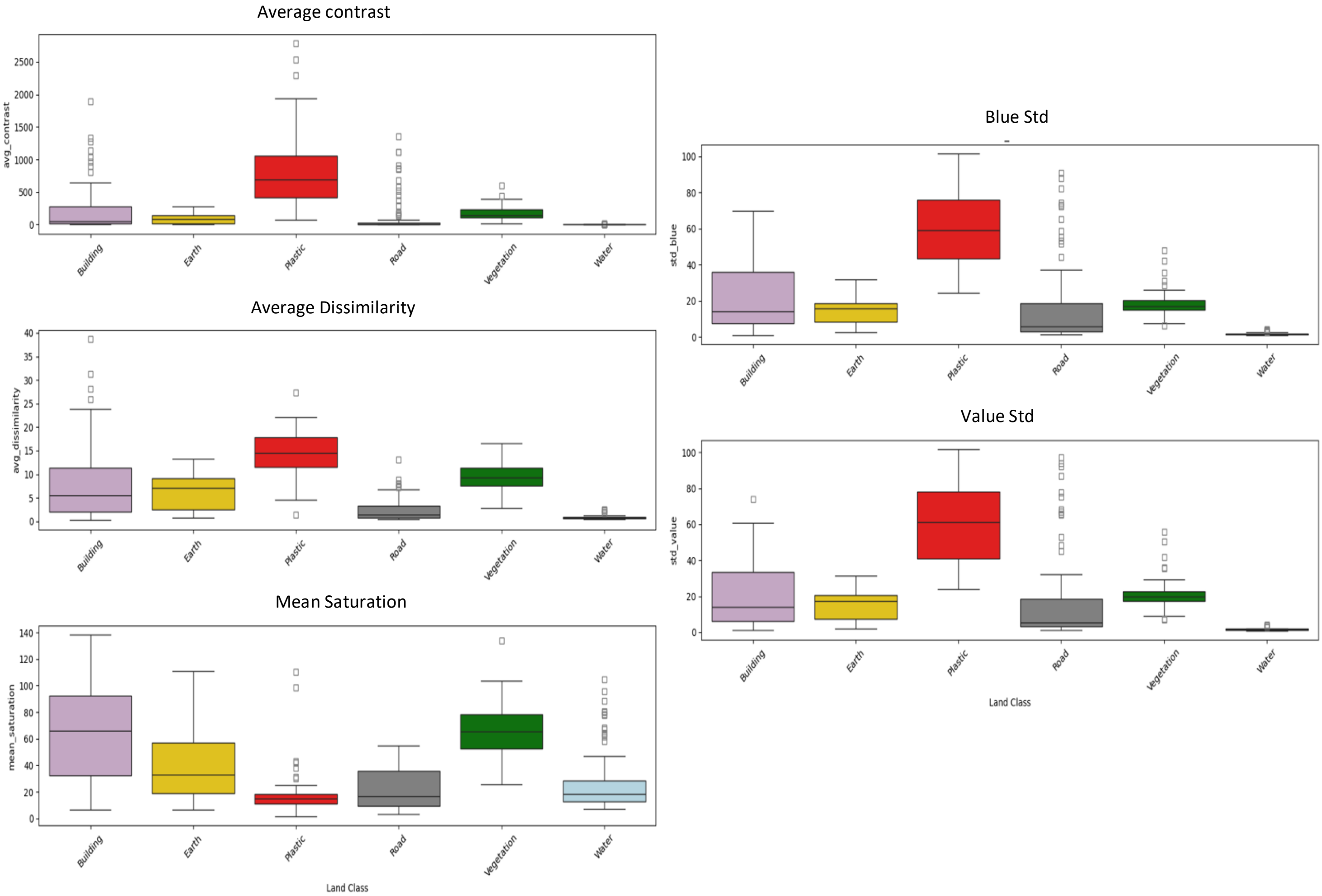


Figure 5- Boxplots generated to show feature distribution across land classes. Wider boxes indicate greater variability in the characteritics of the training data for a given class. These features demostrate where plastic (red) is most distinct from other land classes, building (purple), earth (yellow), road(grey), vegetation (green) and water (blue)

5.2.2.1 Accuracy statistics generated from training process

The RF model demonstrated an OA of 87%, while the SVM model showed slightly higher overall accuracy of 89%. Both models were highly effective at correctly identifying water occurrences (Table 4). The SVM model also performed exceptionally well in identifying plastic instances with a precision and recall of 0.94, compared to the RF model which had a lower precision of 0.79 but high recall 0.94, indicating a higher rate of false positives. The building class proved challenging for both models, potentially indicating the need for more training data for this class. See *TR Section 8* for confusion matrices.

SVM Model	Precision	Recall	F1-score	RF Model	Precision	Recall	F1-score
Building	0.79	0.73	0.76	Building	0.85	0.73	0.79
Earth	0.87	0.76	0.81	Earth	0.88	0.82	0.85
Plastic	0.94	0.94	0.94	Plastic	0.79	0.94	0.86
Road	0.93	0.93	0.93	Road	0.87	0.87	0.87
Vegetation	0.88	1.00	0.93	Vegetation	0.92	0.86	0.89
Water	0.95	1.00	0.97	Water	0.95	1.00	0.97

Table 4 – Precision, recall and f1-score statistics generated for each land class during the training process for the SVM model (right) and RF model (left).

5.2.2.2 Accuracy statistics generated from application process

The RF model achieved an overall accuracy of 0.54 and a Cohen's Kappa score of 0.424, while the SVM model demonstrated an overall accuracy of 0.23 and a Kappa score of 0.037. Additional accuracy measures are highlighted in Table 5, with the confusion matrices detailed in the *TR Section 9.*

SVM Model	Precision	Recall	F1-score	RF Model	Precision	Recall	F1-score
Building	0.00	0.00	0.00	Building	0.24	0.57	0.41
Earth	0.23	0.77	0.36	Earth	0.41	0.57	0.49
Plastic	0.18	0.50	0.28	Plastic	0.35	0.4	0.38
Road	0.30	0.46	0.37	Road	0.42	0.55	0.49
Vegetation	0.00	0.00	0.00	Vegetation	0.94	0.69	0.82
Water	0.00	0.00	0.00	Water	0.71	0.76	0.74

Table 5. Precision, recall and f1-score statistics generated for each land class during the application process for the SVM model (right) and RF model (left). Statistics were generated through comparison of manual validation sites.

A closer examination of the accuracy metrics and prediction maps (Table 5, Figure 7) reveals the SVM model's significant shortcomings in practical applications. The SVM model failed to correctly predict the building, vegetation, and water classes. Although it correctly identified 50% of plastic instances, its low precision score of 18% indicates substantial overprediction, particularly in areas characterised by earth and vegetation. This issue is evident in Figure 7, where the SVM model accurately maps plastic along roadsides but misclassifies large regions of earth and shrubland. This misclassification likely stems from the heterogeneous texture and colour of these regions, which closely resemble plastic, confusing the model.

In contrast, the RF model demonstrated better performance, especially with vegetation and water classes. It provided a more balanced performance in plastic identification, with a precision of 35% and a recall of 40%, resulting in half the false positives compared to the SVM model. Despite these advantages, plastics were still often misclassified as buildings and earth, and false positives occurred over regions of earth. Nevertheless, the overprediction was less severe than with the SVM model.

While both models exhibit suboptimal performance in plastic classification, the RF model offers an advantage due to its more conservative approach. Conservative models are preferred in waste management services, as overprediction can lead to inefficient resource allocation and increased costs (Lavender, 2022). Although further refinement is needed, the RF model will be used to demonstrate how such models could be applied to optimise waste management services.

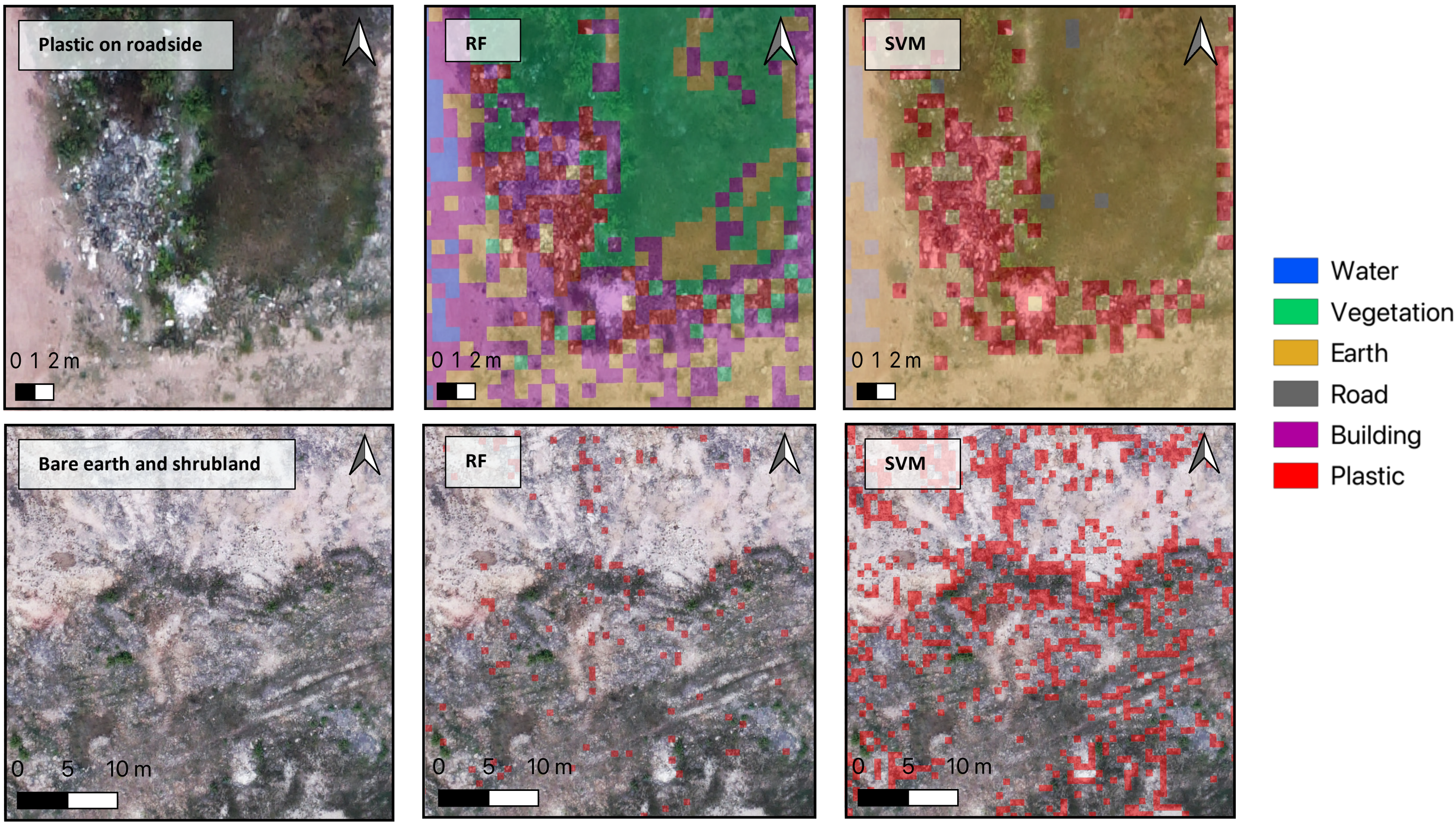


Figure 6. Visual assessment of RF and SVM classification maps. Comparison of drone imagery (left) to the RF model predictions (center) and SVM model prediction (Right). The bare earth and shrubland was compared with plastic predicted only, to highlight the number of false positives in the region.

5.2.3 Comparison of RF Model Results with Human Prediction

In the ThatLuang Lake region, plastic waste was manually classified along a dirt track and subsequently compared to the RF classification results (Figure 7). Figure 8 illustrates that the RF classifier performed reasonably well in areas manually identified as 'Very Likely' to contain plastic. However, the classifier's accuracy diminished in regions where human confidence in classification was lower. This indicates that while the model is more effective in clear-cut cases, it struggles with ambiguous regions, highlighting the value of using human classification in these instances.

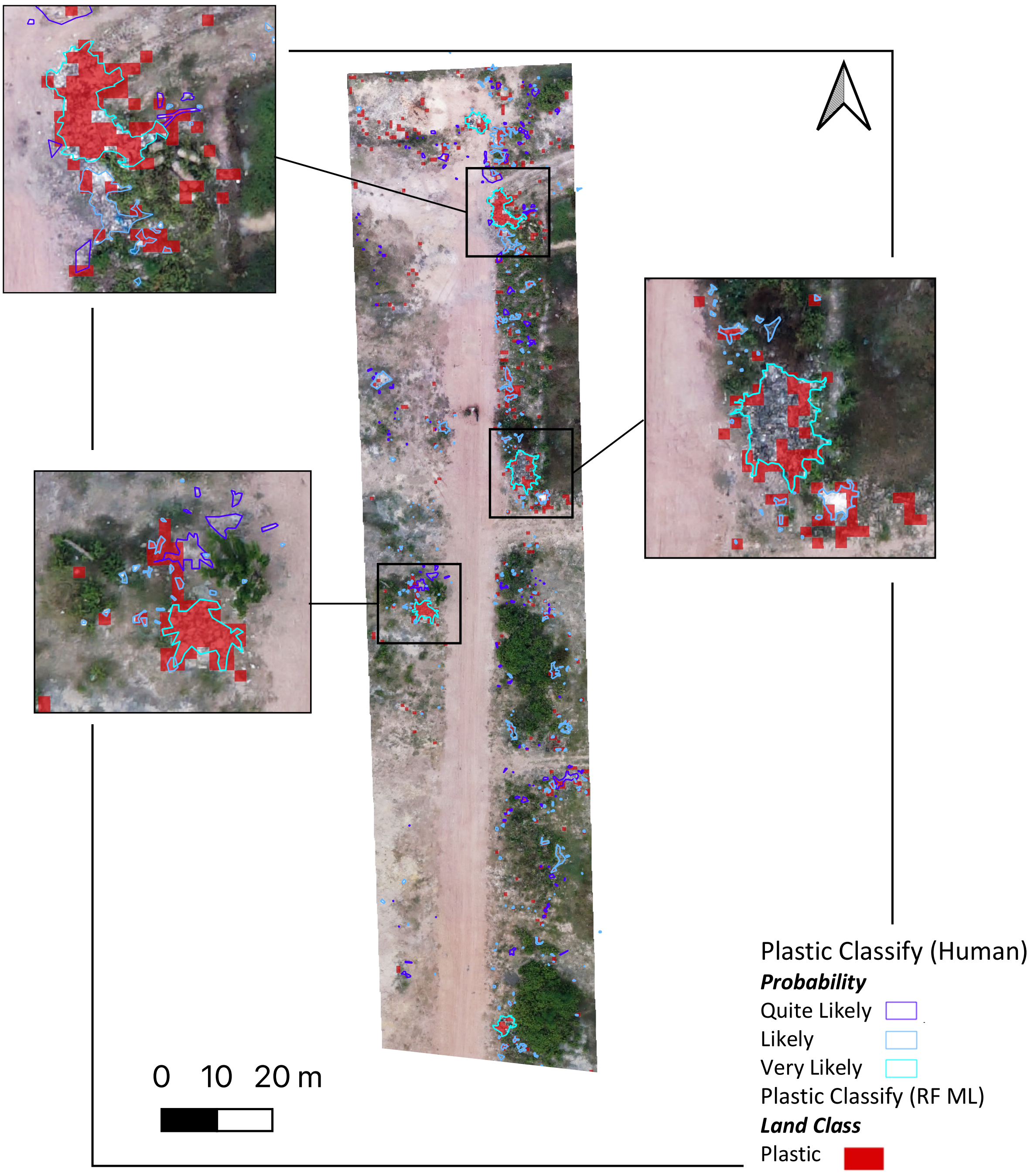


Figure 7- Comparison of human and RF model prediction. Subset maps highlight the model's performance in the regions labelled 'Very Likely' to be plastic.

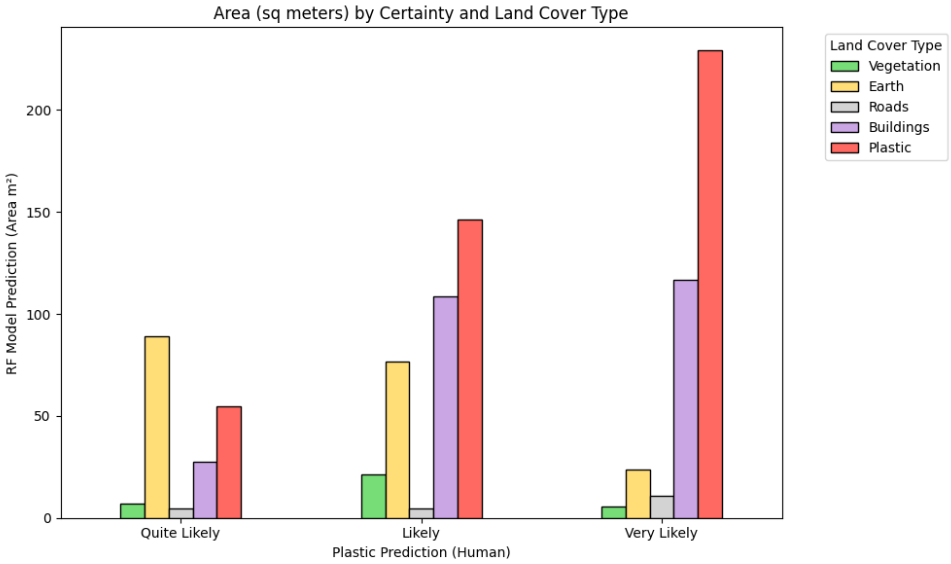
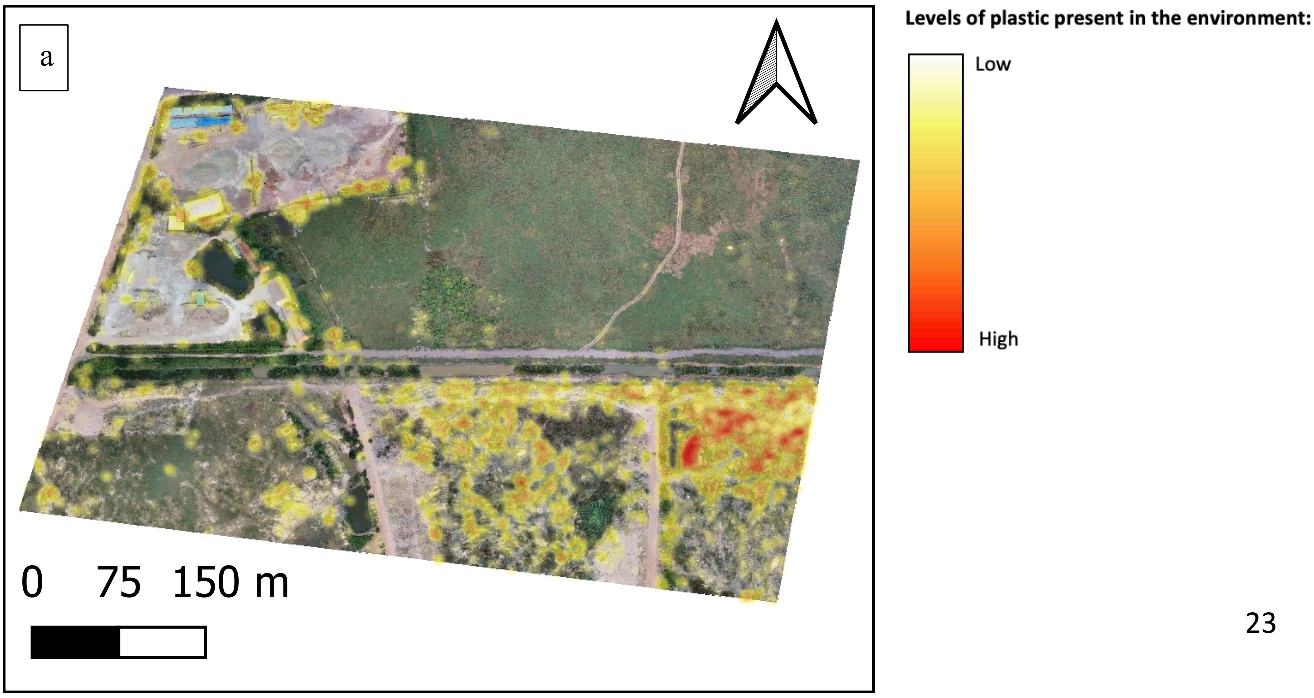


Figure 8. Comparison of RF model land class prediction with human labelled plastic prediction across 3 levels of certainty. The bar height represents the area predicted for all land cover types.

5.2.4 Mapping for enhanced plastic waste management

Heatmaps were generated to identify plastic accumulation hotspots near Thatluang Lake and Watsop. In the Thatluang Lake region (Figure. 8a), the greatest plastic accumulation was observed in the southwest, particularly in vegetation and shrubland areas parallel to roads and around the periphery of a building site, with no significant plastic in grassland. In Watsop (Figure. 8b), key accumulation areas were found in vegetative zones near the river and smaller hotspots along residential roads.

Based on the number of plastic pixels present in the study region and the average plastic height dimensions obtained from the field survey, the total plastic volumes across these regions were estimated. This resulted in approximations of 4,310 m³ in the Watsop region and 614 m³ in the Thatluang Lake region, respectively.



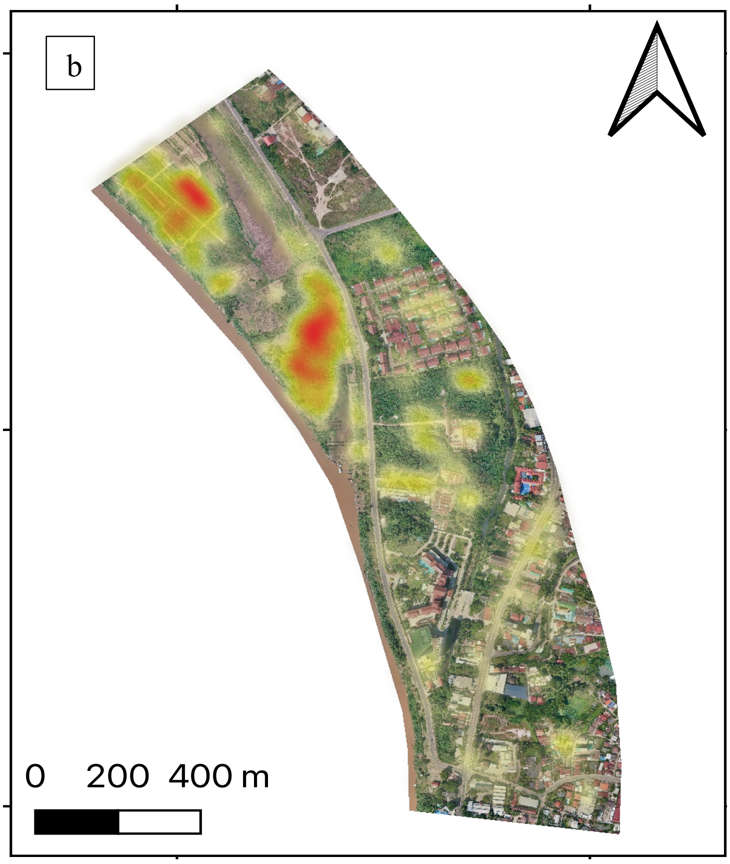


Figure 9. Identifying key locations of plastic waste accumulation in [a] open ground near Thatluang Lake and [b] Residential area in Watsop.

6. Discussion

6.1 Characterising Urban Plastic Waste in Vientiane

Despite the heterogeneity of plastics in Vientiane, this study emphasised the importance of spectral over textural characteristics. Results from the random forest classifier indicate only two of the top ten important features were textural, highlighting the need for high-quality spectral data for accurate classification. These findings align with the study by Illehag et al., (2020), which focused on classifying urban materials, that found 75% of most important features were spectral. However, the variability in spectral reflectance due to different plastic types, colours, and weathering conditions often complicated classification. Collecting multispectral and hyperspectral data alongside RGB may resolve such issues. Features like near infrared (NIR) reflectance (Iordache, 2022) and shortwave infrared absorption (Aoyama, 2016; Toupuzelis et al., 2019) may provide more reliable indicators for plastic waste, though the cost and complexity of hyperspectral sensors limit their widespread application.

Consistent and unique indicators for plastic waste are crucial for successful classification. Misclassification occurs when plastic characteristics closely resemble those of other materials, as seen in the building and plastic classes in Figure 5. For example, the overlap in dissimilarity values and standard deviations between plastic and building materials may explain the confusion in the RF classifier.

To address this issue, future studies could follow the approach of Ulloa-Torrealba et al. (2023), who also found that similar spectral signatures between rooftops and certain waste classes led to numerous false positives in their RF model. By excluding building rooftops from their analysis, they improved classification accuracy from 73.95% to 95.76%. Applying a similar method could potentially enhance the accuracy of the model presented in this study.

6.2 Evaluation of imagery and classification techniques

6.2.1 Satellite versus UAV

This study indicated that PlanetScope Super Dove satellite data is unsuitable for detecting plastic waste piles. While its spatial resolution of 3-4 meters is relatively high, it is still insufficient for detecting very small features or highly heterogeneous areas (Cui et al., 2022), such as plastic waste piles in urban environments.

Although Kikaki (2020) utilised PlanetScope data to map observed marine plastic in Honduras, these were dense masses of plastic on a relatively uniform background. For instance, the study mentions plastic masses of 6 km in length with varying widths from 1 to 40 meters. Furthermore, despite their extensive size, it was still challenging to discriminate plastics from other floating materials like algae or organic matter. This demonstrates the challenge of using PlanetScope imagery to detect urban plastic waste piles, where the largest piles identified were approximately 30m by 10m.

UAV imagery largely addresses the issue of spatial resolution found in satellite images. Despite the relatively coarse UAV imagery used in the study, it was still possible to manually map plastic with varying confidence, depending on plastic waste size and background settings (Figure 7). Kalonde (2022) suggested that individual plastic pieces are only visible when drone imagery is collected at a height of 20 meters. However, this study indicates that detection of individual plastic bags is possible at higher altitudes. Nonetheless, without extensive ground truth data, there are regions where plastics are difficult to differentiate from their surroundings. This challenge underscores why all studies reviewed in *Section 2* utilised drone heights of 120m or less. Therefore, it is recommended future studies use higher resolution imagery, closer to 100m despite the increased data processing this will require.

6.2.2 Model Performance and Insights

The initial employment of the ML models, particularly SVM, did not achieve the anticipated results, providing valuable insights for further optimisation. As D'Amour et al. (2022) highlighted, ML models often underperform in real-world settings due to under-specification and mismatches between training and deployment data. This study supports the importance of thorough testing on application-specific tasks.

Many studies focus on accuracy statistics generated during the training process, which limits direct comparisons with this study's results. However, Lavender (2022) noted the reduction in accuracy from training to application data, particularly in the plastic category. This highlights the difficulty of training a classifier to be sufficiently generalised to handle plastics occurring in various environments, which have different spectral signatures and varying background characteristics. Furthermore, plastic waste often coexists with other types of waste, such as plastic litter covered by tires, which further complicates classification (Lavender, 2022). In both the SVM and RF models in this study, other types of waste, such as construction debris, were often misidentified as plastic. Therefore, it is essential to build suitable training datasets with sufficient flexibility to cope with real-world settings while adhering to strict class boundaries (FAO, 2023). Future work should employ a greater number of land classes when training models, as explored by Lavender (2022) and Hasituya (2017).

Additionally, alternative ML algorithms could be considered. Astorayme (2024) suggests that DL models, especially CNN-based architectures, outperform classical ML models in detecting macro-plastics due to their ability to learn complex patterns. However, classic ML models like RF and SVM are more interpretable and well-suited for small datasets, making them ideal for exploratory studies. Furthermore, the significant computational resources required for DL techniques might not be accessible to all researchers or the stakeholders this research aims to support

6.3 Evaluation of operability and scalability

This initial exploration shows promise for the future implementation of automated classification of plastic from UAVs for waste management initiatives, provided the suggested model improvements are made. Accurate maps of plastic waste can enable local authorities in Vientiane to enhance planning and resource allocation by identifying hotspots and trends in waste generation (Sakshi et al., 2023). Integrating these results with GIS can optimise waste collection routes or locate areas most at risk of leakage into the Mekong River (Trahn-Than et al., 2022). Moreover, these maps can support policy development and enforcement by providing evidence-based recommendations, ultimately benefiting waste management services, public health and the environment (Cicala, 2024).

Considering the scalability of the presented methodology, is essential to understand the time required to run model processes, conduct drone flights, and collect field data for validation. Upscaling to a 20 km² area of the city using a powerful GPU is estimated to take 2.4 weeks, with upscaling the entire city taking 3.4 months. Computational improvements, such as cloud computing or parallel processing, could further reduce this time by distributing tasks across multiple virtual machines (Buyaa et al., 2009). A substantial number of high-quality ground truth samples are necessary to validate the training data and generating these samples can be labour-intensive over large urban areas. However, once trained, plastic classification models can be easily transferred to other urban areas using similar high-resolution datasets (Zhang, 2018).

Notably, drone technology faces challenges, including dependence on weather conditions and airspace regulations (Mager and Blass, 2022), which can further delay implementation, particularly during the wet season. Despite these limitations, advancements in ML-based classification and UAV imagery hold significant promise for improving waste management and supporting environmental sustainability in urban settings.

	0.5 km² Standard Laptop (Apple M2, 8GB RAM)	20 km² Standard Laptop (Apple M2, 8GB RAM)	20 km² Powerful GPU (e.g., NVIDIA RTX 3080)	(130 km²) Powerful GPU (e.g., NVIDIA RTX 3080)
Drone Imagery Collection	N/A (1 day)	~1 day	~1 day	~7day
Drone Postprocessing	N/A (72 hours)	~3 days	~3 days	~21 days
Field Survey Ground Data	N/A (1 day)	~1 day	~1 day	~7 days
Prepare Drone Imagery for Model	12 hours	~21 days	~2.1 days	~13.65 days
Apply Classification Model	20 hours	~34 days	~3.4 days	~22.1 days
Stitch Tiles with Classification	30 hours	~50 days	~5 days	~32.5 days
TOTAL	**~2.6 days**	**~3.7 months**	**~2.4 weeks**	**~3.4 months**

Table 6. Estimated time requirements for various stages of UAV imagery processing and classification across different computing setups and project scales. Refer to the TR Section 10 for details of calculations.

7. Conclusion

This study developed and evaluated a remote sensing methodology for detecting and mapping plastic waste piles in Vientiane, with the broader objective of enhancing urban waste management practices. By comparing PlanetScope satellite and UAV imagery and applying Random Forest (RF) and Support Vector Machine (SVM) classifiers, it sought to determine the most effective approach for monitoring plastic pollution in urban environments.

The analysis indicated that while PlanetScope imagery offers broad spatiotemporal coverage, its 3-meter resolution is inadequate for detecting plastic waste in complex urban environments, making it unsuitable for automated detection. In contrast, the UAV imagery, provided sufficient resolution for identifying plastic waste. However, challenges remain due to the spectral variability of plastic and the heterogeneous nature of urban landscapes. Both classifiers achieved high accuracy during training but experienced significant performance drops during application, particularly SVM, highlighting the need for thorough testing on application-specific tasks. The RF model, while superior due to its more conservative predictions, still faced misclassifications, particularly between plastic and the earth and building classes.

The proposed methodology shows promise for enhancing waste management in Vientiane, offering the potential to improve plastic waste mapping, optimise resource allocation, and support policy development aimed at reducing illegal dumping. Integrating these methodologies into GIS frameworks could also improve city-wide planning and environmental monitoring.

Future research should focus on improving the accuracy and scalability of these methods through higher-resolution imagery, additional spectral bands, or advanced machine learning techniques like deep learning. Expanding the study to diverse urban areas will help validate and refine the methodology, ensuring its broader applicability. While challenges remain, this research is a key step towards leveraging remote sensing and machine learning technologies for urban environmental management, providing valuable insights into addressing plastic pollution in rapidly urbanising regions like Vientiane.

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