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Identifying and Mapping Municipal Solid Waste Disposal Sites in Kenya Using Remote Sensing and GIS—A Case Study of Juja and Dandora Areas

Joy Priscah Akinyi, Eunice Nduati

Department of Geomatic Engineering and Geospatial Information Systems (GEGIS), Jomo Kenyatta University of Agriculture and Technology, Kiambu, Kenya
Email: joypriscah@gmail.com

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Abstract

Waste generation in Kenya has been increasing with the rapid urbanization (Haregu et al., 2017; Okot-Okumu, 2012). Almost 50% of the waste is generated in urban centers, and 0.5 kg per capita waste per day is produced, estimated to increase three-fold by 2030. The management of solid waste in Kenya is complicated by various factors. While the national sustainable waste management policy highlights the need for timely inventories and integrated monitoring of waste disposal, there is currently no comprehensive system in place for mapping or monitoring waste disposal sites, both legal and illegal (Ministry of Environment and Forestry, 2021). This study aims to identify waste disposal sites in Dandora in 2021 to 2024 through supervised classification, identify MSW spectral interpretation marks from multispectral satellite imagery and map the spatial distribution of MSW disposal sites using Mobile GIS in Juja in 2022. Supervised classification of the multispectral imagery was performed using training data points from planet imagery, resulting in LULC maps for 2021 to 2024. Spectral reflectance curve charts were generated. Post-classification and location of smaller dumpsites in Juja were collected using mobile GIS. The distribution characteristic of waste disposal sites is associated with densely populated areas of Juja such as areas around Gates A, B and C. Classification results show a high degree of accuracy in identifying and mapping disposal sites across all epochs. In conclusion, high LULC classification accuracy and the other results, indicates that these remote sensing techniques, combined with other GIS and field data, can significantly enhance waste management in Kenya.

Keywords

LULC, Solid Waste, Geographic Information Systems, Remote Sensing, Waste Management, Circularity, Environmental Management

1. Introduction

Waste is a substance or an object, which is unnecessary or unusable. Solid waste is waste in a solid state. Municipal Solid Waste is nonhazardous disposable materials generated by households, institutions, industries, agriculture, and sewage. It is made up of organic and recyclable materials, such as product packaging, grass clippings, furniture, clothing, bottles, food scraps, newspapers, and appliances. (Du et al., 2021; U.S. Environmental Protection Agency, 2016).

Waste generation in Kenya has been increasing with rapid urbanization (Haregu et al., 2017; Okot-Okumu, 2012). For instance, almost 50% of the waste is generated in urban centers, and that 0.5 kg per capita waste per day is produced, and this is estimated to increase three-fold by 2030. According to Okot-Okumu (2012), waste in urban centers like Nairobi consists of 65% biowaste and 12% plastics. Solid waste generates leachate and emits toxic gases (Kumar et al., 2019).

Solid waste management is a challenge for the cities' authorities in developing countries mainly due to the increasing generation of waste, the burden posed on the municipal budget because of the high costs associated with its management, the lack of understanding over a diversity of factors that affect the different stages of waste management and linkages necessary to enable the entire handling system functioning (Guerrero et al., 2013). The current waste management efforts in most urban centers in Kenya are characterized by low coverage of solid waste collection, pollution from uncontrolled dumping of waste, inefficient public services, unregulated and uncoordinated private sector activities, and lack of infrastructure to process key solid waste (Okot-Okumu, 2012; Haregu et al., 2017).

Waste management is a major public health and environmental concern in the urban areas and emerging towns of developing countries (Haregu et al., 2017; Okot-Okumu, 2012). Due to improper solid waste management, waste has become one of the pollution sources that has caused diverse environmental impacts as well as detrimental towards human health and safety (Gupta et al., 2015: p. 102). Therefore, the understanding and utilization of both these wastes will remove about 77% of the total waste in such centers, thereby significantly mitigating the negative environmental impacts posed by these wastes (Biswas et al., 2010; Gbanie et al., 2013; Şener et al., 2010). Municipal solid waste (MSW) fate lies in its disposal by piling it up. Moreover, the disposal of waste by piling it up is the most used method and neglecting the indirect costs is the cheapest of all the waste management techniques.

Poorly managed waste has an enormous impact on health, local and global environment, and economy; improperly managed waste usually results in higher downstream costs than what it would have cost to manage the waste properly in the first place. With the increasing urban population in Kenya, which is estimated to be growing at a rate higher than that of the country's general population, waste generation and management will be a major challenge (Haregu et al., 2017: p. 1). The three most important challenges facing the world in the 21st Century are food shortage, energy deficiency and environmental degradation (Haregu et al., 2017). This is supported by (Hou, Al-Tabbaa, Guthrie, & Watanabe, 2012), who found that waste generation and resource shortages have long been recognized as two of the greatest challenges human society is facing.

Illegal waste presents governments with a wide range of risks that have prompted demands for cost-effective, efficient monitoring and mapping solutions to support improved management outcomes. Remote sensing has the potential to provide critical information about the location of illegal waste to inform targeted active surveillance operations and cost-effective remediation activities. SWM has a cross-cutting outlook with its impacts affecting several sectors which are vital for sustainable development (Ogutu et al., 2019). The Sustainable Development Goals (SDGs), more specifically SDG 13 and their relevant targets, are linked to SWM which defines the priority warranted for proper SWM. SDG 11 is aimed at making cities safe, resilient and sustainable, which can be attained by effectively addressing the challenges of SWM (Ogutu et al., 2021).

Kenya generates an estimated 22,000 tons of waste per day translating to eight million tonnes annually. Management of solid waste in Kenya is characterized by a range of factors, including inadequate policies, poor enforcement of existing regulations, and a lack of reliable data on waste generation and disposal. While the national sustainable waste management policy highlights the need for timely inventories and integrated monitoring of waste disposal, there is currently no comprehensive system for mapping or monitoring waste disposal sites, both legal and illegal (Ministry of Environment and Forestry, 2021). This observation reinforces (Shekdar, 2009) research on data on solid waste generation being typically collected through surveys that are only deployed for a brief time and may be limited to certain cities. This gap hampers efforts to formulate and implement effective waste management strategies, ultimately affecting the quality of life of urban residents and the sustainability of the environment (National Environment Management Authority, 2025). Therefore, there is a need for an improved understanding of the distribution of illegal waste disposal and its potential to support improvements to the cost-effectiveness and efficiency of waste management efforts. (Glanville & Chang, 2015) and to regularly gather and organize already existing data while generating additional knowledge and information using technologies such as GIS and Remote sensing to inform planning and decision-making for integrated and sustainable waste management.

Waste management service providers are reliant on the public sector for enforcement and therefore mountains of garbage are still a common feature in most residential areas, marketplaces and by the roadsides. In addition, the private sector waste management companies involved in collection of waste often are accused of illegal disposal of waste in rivers, by the roadsides, quarries or even dispose illegally disposal at the dumpsites (Ministry of Environment and Forestry, 2021).

The primary target of MSWM is to protect the health of the population, promote environmental quality, develop sustainability, and provide support to economic productivity. To meet these goals, sustainable solid waste management systems must be embraced fully by local authorities in collaboration with both the public and private sectors (Henry, Yongsheng, & Jun, 2006).

Local authorities need to implement strategies to effectively deal with their waste in a sustainable, cost-effective, self-sufficient, and environmentally acceptable manner. However, there are several technical and economic aspects concerning the management of municipal solid waste. To take decisions that consider all such issues, it is necessary to accurately model the system, analyzing material recovery versus disposal, and representing the solid waste flows, as well as their cost and environmental impact (Mitropoulos et al., 2009: p. 2).

Effective waste management will reduce emissions of greenhouse gases, especially methane, from the waste sector, contributing to the achievement of Kenya's Paris Agreement commitments, and reducing industrial waste, non-point run off and sewage waste to Kenya's water bodies. (Ministry of Environment and Forestry, 2021).

Kenya aims to transition the waste sector in every county away from low collection rates, illegal dumping and uncontrolled dumpsites to affordable waste collection, recycling and composting, and minimize waste fractions that are finally disposed to a well-engineered and regulated landfill (Ministry of Environment and Forestry, 2021). There is an underutilization of remote sensing despite remote sensing having the potential to monitor and map illegal waste disposal and provide critical information about the location of illegal waste to inform targeted active surveillance operations and cost-effective remediation activities (Glanville & Chang, 2015). Satellite imagery can be used to monitor the usage and extent of private and illegal dumping sites that have already been identified. Visual interpretation of satellite data is a practical method for local governments to manage waste disposal sites, with spectral characteristics of satellite data being useful for identifying the illegal dumping of waste (Yonezawa, 2009).

Research Objectives:

1) To identify MSW disposal sites in Dandora from 2021 to 2024 through supervised LULC mapping.

2) To identify MSW spectral interpretation marks from multispectral satellite imagery.

3) To map the spatial distribution of MSW disposal sites using Mobile GIS in Juja in 2022.

Previous research on waste disposal in Kenya has primarily focused on waste types, opportunities, and challenges and while these studies have contributed to our understanding of the environmental consequences of improper waste management, there remains a critical gap in the spatial identification and mapping of

MSW waste disposal sites in Kenya. Addressing this gap is important for improving the efficiency of waste management practices and reducing adverse environmental impacts of improper waste disposal.

Remote sensing and Geographic Information Systems (GIS) emerged as powerful tools for environmental monitoring and management, offering innovative solutions for detecting and mapping waste disposal sites. Remote sensing technology involves the use of satellite imagery or aerial photographs to observe and analyze various features on the earth's surface without direct contact, while GIS provides the capability to capture, store, manipulate, and analyze spatial data (Campbell & Wynne, 2011).

Satellite imagery can be used to monitor the usage and extent of dumping sites that have already been identified. Visual interpretation of satellite data is a practical method for local governments to manage waste disposal sites, with spectral characteristics of satellite data being useful for identifying the illegal dumping of waste (Yonezawa, 2009).

Land use/land cover (LULC) classification provides a better understanding of land use land cover (LULC) change and may pave the way to unravel urban growth dynamics. It is a crucial tool for sustainable LULC planning and management (Gaur & Singh, 2023). Using RS for LULC classification, it is possible to identify areas that have been used for MSW dumping, which may not be accessible through field surveys. This information could be useful for guiding waste collection and disposal efforts, as well as to monitor changes in land use over time.

This research aims to identify MSW disposal sites in Dandora area of Kenya through supervised LULC mapping, identify MSW spectral interpretation marks that could be used to characterize MSW sites in the future from multispectral satellite imagery and map the spatial distribution of MSW disposal sites in Juja using Mobile GIS. By combining different approaches for large, known dumpsite and smaller, unknown dumpsites to MSW disposal site identification and mapping, this research seeks to address the gap in spatial monitoring and inventory of waste disposal sites, thereby contributing to the development of more sustainable waste management practices in Kenya.

2. Literature Review

2.1. Overview of Municipal Solid Waste Management

According to University of Michigan's center for sustainable systems, Municipal Solid Waste (MSW), commonly called "trash" or "garbage", includes wastes such as durable goods (e.g., tires, furniture), nondurable goods (e.g., newspapers, plastic plates/cups), containers and packaging (e.g., milk cartons, plastic wrap), and other wastes (e.g., yard waste, food). This category of waste refers to common household waste, as well as office and retail waste, but excludes industrial, hazardous, and construction waste. Municipal solid waste management (MSWM) encompasses the functions of collection, transfer, resource recovery, recycling, and treatment (Henry, Yongsheng, & Jun, 2006). (Kimwatu & Ndiritu,

2016) in their study n applications of GIS and remote sensing in solid waste management defined municipal solid waste as a heterogeneous collection of wastes produced in urban areas, the nature of which varies from region to region.

In developing countries, although open dumping is common, there is also a realization that this is inadequate (Shekdar, 2009). Despite dumps being the most common method according to waste management hierarchy, it is the final and least recommended solution (Faitli et al., 2015). Globally, sustainable waste management has been a major challenge. Waste degradation in the dumps lead to generation of emissions. They are the most significant contributors of GHG emissions (Kumar et al., 2019). Currently, more than half, 55%, of the world's population resides in cities. The urban share of the world's population is projected to increase to 68% by 2050 (United Nations Department of Economics and Social Affairs, UN DESA). This has led to the increase in generation of municipal solid waste due to the increased urbanization levels and increase in income levels. This makes waste management one of the most important priorities for governments. The East African Community (EAC), Kenya, Uganda and Tanzania have attempted to address proper waste management through the East African Community (2016). Illegal waste management is a critical issue for contemporary governments. Locally, poor waste management hinders the delivery of the constitutional right to a clean and healthy environment. Most communities across Kenya do not receive proper waste management and disposal services. This leads to the rise of informal and illegal dumpsites. This is a challenge in proper waste management (Ministry of Environment and Forestry, 2021).

2.2. Waste Management in Kenya

Kenya's national waste policy envisions transition from low collection, illegal dumping and uncontrolled dumpsites to affordable waste collection, recycling, and composting, and waste minimization. The continued growth of Kenya's economy and cities due to devolution has compounded its waste management challenges. The policy emphasizes the necessity to develop new and innovative solutions that include research and development in emerging technologies to help map, collect, segregate, quantify and utilize waste. It also encourages engagement with all the stakeholders at all levels of waste management. It is on the realization of these objectives that this project is formulated. NEMA's national solid waste management strategy is being implemented through five key objectives that include formulation of policies, legislations, and economic instruments to reduce waste quantities, inculcating responsible public behaviour on waste management, promoting waste segregation at source and resource recovery for materials and energy generation, establishing environmentally sound infrastructure and systems for waste management. To meet the five key objectives, it is imperative that solid waste dumps are identified and mapped.

Reliable data on waste generation are recorded and are available. Data is collected daily and provides a rational basis for planning and executing waste management operations. By contrast, in developing economies the data on solid waste generation is collected through surveys that are only deployed for a brief time and may be limited to certain cities. Moreover, the data related to solid waste that is transported by the system, which may not be equivalent to the quantity of waste generated (Shekdar, 2009).

Currently no comprehensive and integrated monitoring or mapping of illegal and legal waste is undertaken in Kenya and the national sustainable waste management policy categorizes the inculcation of timely inventories on quantities and types of waste generated as a gap that needs to be addressed.

2.3. Environmental Impact of Improper Waste Disposal

The illegal dumping of waste materials presents a significant challenge for environmental conservation efforts due to the potential risks it poses to human health and natural habitats (Helvoort, 2023). Poor disposal of municipal solid waste has major adverse effects on health and the environment. The bi products resulting from the waste mass could infiltrate the local environment posing serious threats that degrade the quality of the environment as well as the human health (Slonecker et al., 2010). Organic waste products degrade and produce toxic substances, such as biogas, leachate, and heat. The other biproducts produced due to waste decomposition, biogas and leachate, have an injurious effect on the surrounding vegetation. Dumping of MSW not only damages aesthetic beauty but also causes air pollution and groundwater contamination (Kumar et al., 2019).

Previous studies have assessed the impact of heat generation of dumpsites and the leachate leakage on the surrounding vegetation and while that has been a noble contribution to the scientific body of work, an improved understanding of the distribution of illegal waste disposal can support improvements to the cost-effectiveness and efficiency of waste management efforts (Glanville & Chang, 2015).

2.4. Applications of Remote Sensing and GIS in Waste Management

Waste disposal into landfill and dumps is the most adopted technique of waste management in many countries, despite being the least recommended waste management solution (Gill et al., 2019). Dumps are significant air and soil pollution sources especially when they are not sanctioned and not controlled (Notarnicola, 2004). The lack of proper waste treatment facilities has also majorly contributed to the problem of many informal garbage dumps. Existence of a proper waste monitoring and characterization system is one of the most important requirements in waste management.

The first analysis on the application of remote sensing for waste management was published by Garofalo in 1974. This study discusses the utilization of aerial photographs to support estimation techniques of solid waste distribution and production. The methodology is based on the visual interpretation of land use and the incorporation of these data into solid waste production models (Ottavianelli et al., 2005). Yonezwa investigated the usefulness of monitoring waste on land areas using data from the currently operated earth observation satellites ALOS (Advanced Land Observing Satellite) and Quickbird (Yonezawa, 2009).

BJ-1 micro-satellite remote sensing images can provide support to open-air solid waste dumps management, and it has potential to reduce the operational costs, so it can meet the challenges of the solid waste management agenda (Yalana, et al., 2008), while (Richter et al., 2019) gathered and combined vector data with RS indices (vegetation, built-up area, and moisture) in a GIS, ranked and assessed Nova Scotia's seven waste management regions based on a normalized ranking classification. In another study, the researchers used from the sensor Thematic Mapper on Landsat 5 in collaboration with digital ortho-photos (1:10000) and land cover map Corine 1990 data to identify degraded lands with a high environmental hazard in the Apulia Region in Southern Italy. They monitored and identified dump presence by the spectral signature specificity and individuated areas characterized by the same spectral properties (Notarnicola, 2004). In his study, results revealed that the efficiency of waste management systems can be maximized by the proper use of remote sensing and GIS techniques. The study also revealed that these techniques were most used for sitting the landfill and waste bin for waste disposal and evaluation of environmental impact of buried waste (Singh, 2019).

In their study, (Mahmood et al., 2019) compare the suitability of different satellite-based vegetation indices (VIs) for environmental hazard assessment of municipal solid waste (MSW) open dumps. The compared VIs, as bio-indicators of vegetation health, are normalized by different vegetation index (NDVI), soil adjusted vegetation index (SAVI), and modified soil adjusted vegetation index (MSAVI) that have been subject to spatial-temporal analysis. (Ottavianelli et al., 2005) sought to identify practical ways in which EO data can support landfill management and monitoring, providing quantitative data where possible. (Jasravia Gill et al., n.d.) in their paper on detection of waste dumping locations demonstrated how to utilize thermal remote sensing techniques to measure the land surface temperature (LST), which can aid in outlining the waste dumping regions within a landfill.

(Elsadiq Ali et al., 2009) used Radarsat to assess the potential of spaceborne SAR systems for mapping waste-disposal sites. The results showed that high resolution SAR imagery from space platforms could be a viable tool for the inventory of waste-disposal sites. An inventory that if monitored regularly can mitigate waste impacts on the environment while (Glanville & Chang, 2015) analyzed existing remote sensing methods and sensors used to monitor and map illegal waste disposal sites to support the evaluation of existing remote sensing methods for mapping illegal domestic waste sites in Queensland, Australia. The informal garbage dumps in Beijing were monitored by SPOT-6 image and identified by the establishment of the interpretation key using multivariate data; and then classified by the established interpretation key (Cheng & Sun, 2021). The geography of illegal waste disposal sites is not random, but a complex pattern influenced by a multitude of economic, environmental, and social factors such as demographics, availability of waste facilities or services, affordability of legal waste facilities or services, effectiveness of law, site access, remoteness of illegal waste disposal location, sociocultural acceptability of illegal waste disposal (Glanville & Chang, 2015) while (Yalan et al., n.d.) in their study to detect the location of the open-air solid waste dumps in Beijing based on BJ-1 image found that the output and distribution of solid wastes has correlation with the quantity and density of the permanent population.

In their studies, (Dabija et al., 2021) address the need for a comparative analysis of SVM and RF algorithms across different European regions using the same datasets to determine regional accuracy variations in land cover mapping. Their results informed the choice of support vector machine as a classifier of choice for land use and landcover mapping in this study. (Cheng & Sun, 2021) detected and classified informal garbage dumps, particularly smaller, irregular sites that were not previously well-monitored using remote sensing due to cost and resolution constraints, which builds on this study's utilization of various image interpretation techniques for identification of MSW dumping sites. It also informed the application of high-resolution satellite imagery for accurate mapping and identification. (Glanville & Chang, 2015) focused on the limited use of RS in Australia for detecting waste disposal in Australia, a situation like Kenya's application of RS and GIS in solid waste management.

Several studies have successfully demonstrated the application of remote sensing and GIS in waste management. For example, (Dabija et al., 2021) in their study, they employed machine learning algorithms—specifically, Support Vector Machines (SVM) and Random Forests (RF) to classify land cover based on Sentinel-2 and Landsat 8 satellite images. The minimal mapping unit of 500 x 500 m used in the Corine program reduced the image's informational potential.

In addition, (Notarnicola, 2004) study used a remote sensing-based observational design to detect illegal dumps through spectral signature analysis. Cloud cover interference affected data quality for the February 1995 image and identification of small, heterogeneous areas like dumps was less accurate due to spectral variability.

2.5. Mobile GIS and Community Participation

Mobile GIS refers to an integrated software/hardware framework for the access of geospatial data and services through mobile devices via wireline or wireless networks (Tsou, 2004). Mobile computing systems and hardware are changing the way mobile mapping technology is being used by moving GIS from the desktop into the user's hands, providing flexibility in data acquisition, data accuracy and integrity, validation in real-time reducing errors and process costs, providing more information with much less time and effort, faster communication protocols, and high productivity, making the mobility an enticing aspect of GIS (de Abreu Freire & Painho, 2014). Mobile GIS has emerged as a significant advancement in waste management, enabling real-time data collection and community engagement (Kumar et al., 2019). By providing citizens with tools to participate in mapping and reporting MSW dumping sites, mobile GIS enables communities to play an active role in the circular economy. This participatory approach is important for cultivating ownership and responsibility among communities, hence resulting in improved waste management.

Waste management is a shared responsibility. Unmanaged waste can be a threat to public health, and community participation is essential in waste management. Community participation in waste management can be implemented through active involvement in the process of disposal, transportation, and waste management, with a sense of awareness and responsibility to create a clean and healthy environment (Tarigan, Rogaleli, & Waangsir, 2020). Successful case studies demonstrate that integrating mobile GIS with community participation can lead to significant improvements in waste management systems, as communities are more likely to adhere to waste management guidelines when actively involved in the process (Kumar et al., 2019).

In the prior years, waste was viewed only as a problem and not as a resource and economic opportunity. This can only be achieved through proper waste management (Ministry of Environment and Forestry, 2021). An improved understanding of the distribution of illegal waste disposal sites is critical to enhance the cost-effectiveness and efficiency of waste management efforts. However, there has been limited use of remote sensing for monitoring and mapping illegal waste disposal despite its potential to address this knowledge gap. Remote sensed images provide effective, efficient monitoring and mapping which support improved management outcomes (Glanville & Chang, 2015). The critical information provided by remote sensed images is important in meeting targets for proper solid waste management.

3. Materials and Methods

This study employed Support Vector Machines (SVM) machine learning algorithms for LULC mapping of Planet satellite images, together with remote sensing and GIS-based exploratory design to evaluate the potential of remote sensing techniques in identifying and mapping solid waste disposal sites. The design focused on field surveys, reviewing and analyzing multi-temporal archive remote sensing imagery, spectral characteristics and their applicability for identifying and mapping municipal solid waste sites in Juja and Dandora Areas of Kiambu and Nairobi Counties, respectively. This included the formerly unidentified municipal waste disposal sites for administrative and environmental action.

This research design focuses on LULC classification of Dandora as a large, known dumpsite, by comparing remote sensing data over multiple years, using established LULC classification methods with high resolution imagery. This is aligned with this study's goal to identify waste disposal sites through changes in land cover, spectral signature analysis for extracting spectral characteristics and identifying waste sites through interpretation of these patterns while the field survey focuses on spatial mapping of waste disposal sites using Mobile GIS.

3.1. Study Area

Juja Ward is an administrative unit in Kiambu County with an area of approximately 326.6 square kilometers. Juja town is located about thirty kilometers north of Nairobi between Thika and Ruiru town as shown in **Figure 1**, and it is under the Nairobi metropolitan authority as envisaged in the vision 2030 of Kenya. Estimated population is 272,737 people (National Government Constituencies Development Fund [NG-CDF] Juja, n.d.).

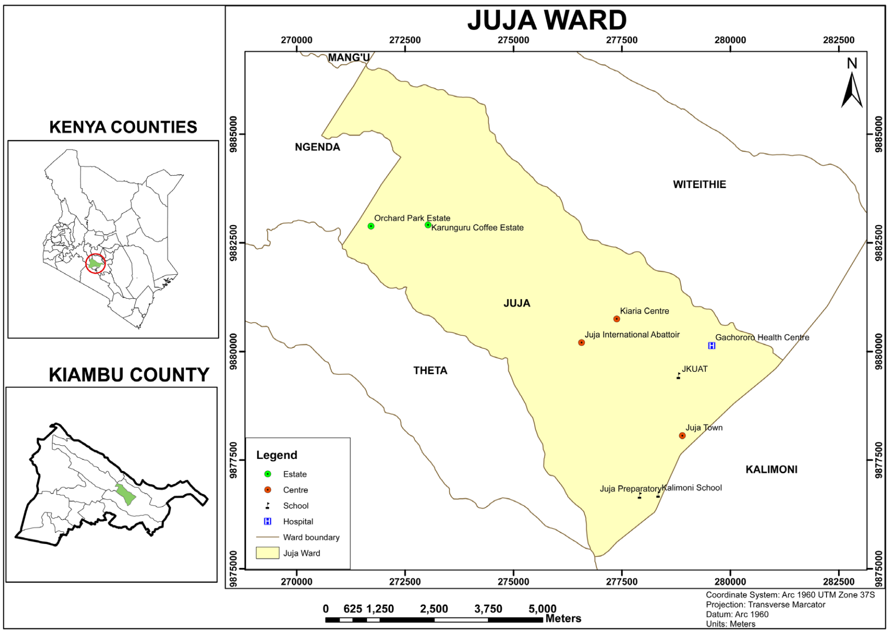


Figure 1. Juja ward.

Dandora area is in Embakasi North and Ruaraka Constituencies as shown in **Figure 2**, respectively. As reported by UNEP in 2018, Dandora dumpsite covered approximately thirty acres and is the destination for approximately 850 tonnes of solid waste daily from Nairobi. This location was chosen due to its elevated levels of illegal dumping and insufficient waste management services, making it an ideal case study for examining the application of remote sensing and GIS technologies in waste management (Kumar et al., 2019). Juja area has smaller, irregularly distributed dumpsites while the Dandora area of interest contains a well-known, large dumpsite and therefore its identification through classification and the extraction of the spectral reflectance curves of the dumpsite and of the other land use/cover classes zones will provide a benchmark for identifying and validating areas characterized by the same spectral properties in Juja area.

3.2. Data Collection

Data collection for this study involved various sources as shown in **Table 1**, that ensured comprehensive identification of MSW disposal sites. The software used for this practical was ArcGIS to design the forms and collection of dumpsite data for analysis.

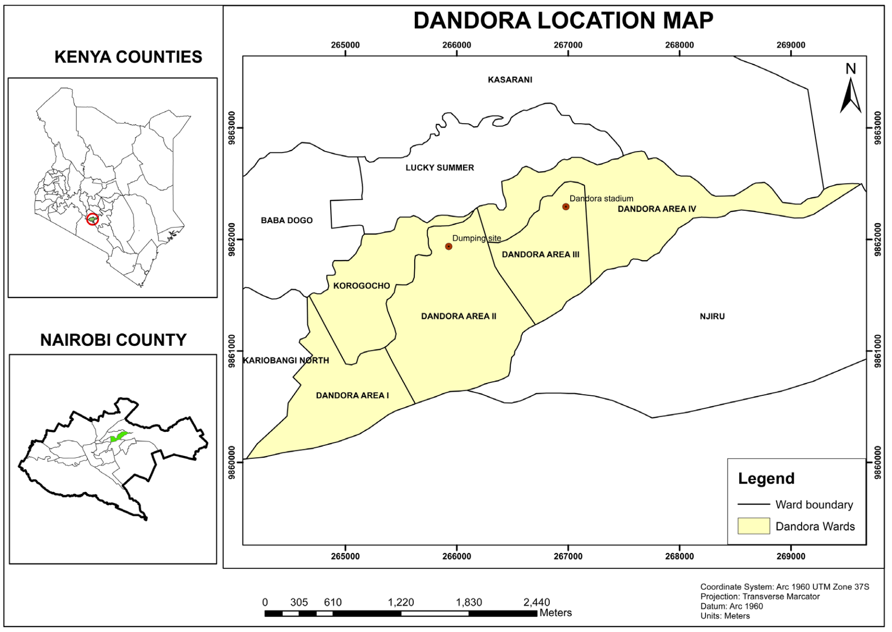


Figure 2. Dandora and korogocho areas.

Table 1. Summary of data types, resolution, sources and uses.

Data	Type	Temporal and Spatial Resolution	Purpose	Source
PlanetScope Ortho Imagery	Raster	1 day, 3 m	Detection municipal solid waste interpretation key/spectral signatures	http://www.planet.com/
Dumpsite locations	Vector	Collected in January 2022	Spatial distribution	Field Survey
Administrative Boundaries Data	Vector	2019 Census by Kenya National Bureau of Statistics	Defining area of interest	Independent Electoral Boundaries Commission
Waste type, dumpsite type	Attribute	Collected in January 2022	MSW characteristics	Field Survey

Field data collection involved the collection of solid waste dump characteristics listed in Table 2 as generator name, waste type, location, ownership and whether the dumpsite is active or not. A total of 171 random points were collected in ArcGIS online within the administrative boundary of Juja Ward. An ArcGIS online project group was constituted which contained the data collection form and an Esri base map for reference. Data Collection form was created in Survey123 desktop. This was in the form of an editable xlsx with the following attributes:

Six enumerators with smartphones running android operating systems were used for data collection. Survey123 android application was downloaded from google Play Store and installed on each of the phones. Six named users were assigned using the enumerator's email addresses and unique login details for each generated. Five of the enumerators were assigned fieldworker user type while one was the administrator with publishing privileges. The form was published to the

ArcGIS online group android phone from Google play store. The enumerators logged in to the Survey123 mobile app and downloaded the published dumpsite survey form ready for field data collection.

Table 2. Juja ward field survey attributes.

Attribute	Description
Dumpsite Code	A unique identifier for each sampling point
Generator Name	Unique Sampling Name for the sampling point
Street	Along which point was sampled
Location	Within which the dumpsite lies
Dumpsite status	Whether the dumpsite is active or inactive
Waste types	Whether the waste is durable, non-durable, containers and packaging and other waste
Dumpsite type	Whether the dumpsite is designated or illegal
Garbage collection method	If by vehicles/trucks, not collected, decomposition or individuals
Waste source	From markets, households, or farms
Ownership	Municipal council or other (to be specified)
Waste is	A list of items at the dumpsite

Data collection involved spreading out within Juja Ward starting at Jkuat on day one and spreading outward in all directions on days two and three interviewing household members and recording the answers and taking pictures of the dumped waste. This was repeated until the sampling size of 180 was slightly surpassed. The data collected was automatically syncing into ArcGIS online cloud database. Downloaded data was cleaned for visualization and analysis. This included cleaning typos and re-coding the dumpsite code from 1 to 183. The data will be visualized on a dashboard and a web map created for ease of identification of the locations of dumping areas. A summary of the materials and methods is represented in **Figure 3** below.

This imagery was acquired from planet explorer portal. Planet offers two geometry types for PlanetScope imagery: Basic and Ortho. Basic Scene is not orthorectified or corrected for terrain distortions. The geometry used in this study is Ortho Scene, which is orthorectified with additional post processing applied. For ortho products, GeoTIFFs are resampled at 3 meters and are projected into the UTM projection using the WGS84 Datum (Planet Labs, n.d.). The 3m resolution planet imagery was preferred because moderate-resolution sensors like Sentinel, LANDSAT and ALOS had limited success in identifying smaller illegal waste sites due to their lower spatial resolution (4 - 50 meters) (Glanville & Chang, 2015). The analytic products are accompanied by a Usable Data Mask (UDM2) file. This is a raster file consisting of eight bands with information about each pixel quality in the scene. Each band provides context on whether a pixel is clear, cloudy, or shadowed, amongst other characteristics. These bands allow users to remove non-useful pixels post download of the image. UMD2 also compensates for effects due to vignetting, low signal-to-noise, or hot or cold pixels.

The PlanetScope Ortho Scene product is orthorectified and is designed for applications that require imagery with accurate geolocation and cartographic projection. These scenes have been processed to remove distortions caused by terrain. Ortho Scenes are delivered as Visual (RGB) and Analytic products. Ortho Scenes are radiometrically, sensor, and geometrically corrected products projected to a cartographic map projection (Planet Labs, n.d.).

Analysis-Ready PlanetScope combines data from the three available PlanetScope sensors (Dove Classic, Dove-R, and SuperDove) while enhancing temporal and spatial consistency with Landsat, Sentinel-2, MODIS, VIIRS). It delivers four surface reflectance bands: blue, green, red, and near infrared. The 4-band analytic product used for this study was delivered as Surface Reflectance (SR) (Planet Labs, n.d.).

Analysis-Ready PlanetScope band order:

The 4-band multispectral band order is:

- Band 1= Blue band (0.490 μm, bw: 0.065 μm)
- Band 2 = Green band (0.560 μm, bw: 0.035 μm)
- Band 3 = Red band (0.665 μm, bw: 0.030 μm)
- Band 4 = NIR band (0.865 μm, bw: 0.021 μm)

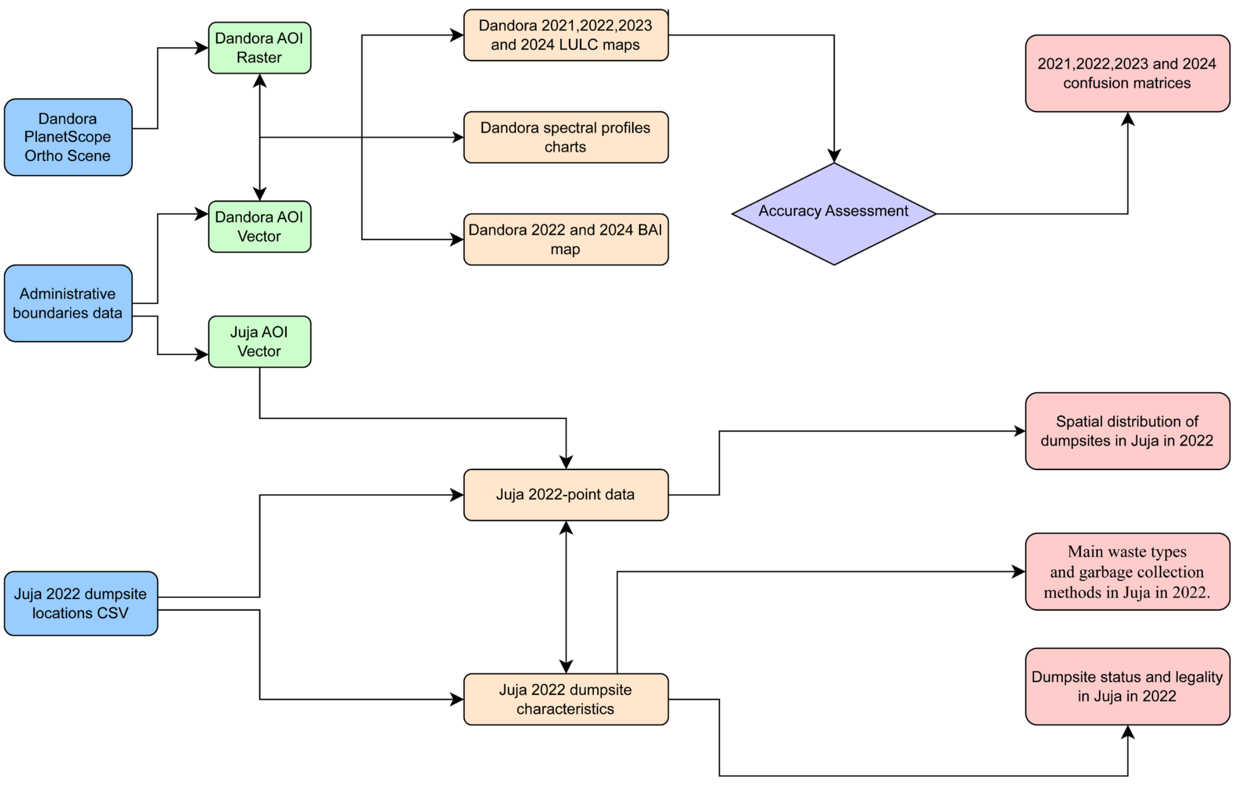


Figure 3. Summary of materials and methods.

3.3. Land Use Land Cover Mapping Using Supervised Image Classification

Planet's satellite imagery was acquired from planet explorer for purposes of LULC mapping. The RGB band combination was used for analysis and the raster was clipped to the area of interest in ArcGIS Pro. Training samples were then collected for five classes namely dumpsites, built up areas, water, bare land and vegetation by drawing polygons around known locations of each of the five classes and their definition in a classification schema. We then ran the imagery classification wizard on the support vector machine algorithm. The output was visualized a few times and the process refined, validated and compared. In their study to assess the automatic land classification accuracy according to Corine guidelines based on Sentinel-2 and Landsat 8 multitemporal images (Dabija et al., 2021). The Sentinel-2 satellite images allowed to classify land cover with better overall accuracy (8% - 10%) than the Landsat 8 data, and the Support Vector Machines algorithm with an RBF kernel function achieved the best results and obtained higher overall accuracy results (6% - 7%) than Random Forest.

Supervised classification is performed when an analyst defines the spectral characteristics of the classes by identifying training areas. It is a requirement for the analyst to be familiar with the area of interest, hence the inclusion of Dandora dumpsite, which is large, known and easily identifiable on high resolution satellite images. It will therefore be easier to identify sample areas of the unknown information class of a dumpsite (Lillesand, Kiefer, & Chipman, 2009). The choice of an SVM classifier was influenced by (Dabija et al., 2021), whose study employed machine learning algorithms, specifically, Support Vector Machines (SVM) and Random Forests (RF) to classify land cover based on Sentinel-2 and Landsat 8 satellite images. The landcover was classified into six classes namely water, vegetation/forests, dumpsite, bare land/grassland, built-up areas and roads. The design was aimed at comparing the performance of these algorithms in land cover mapping in various European regions. The research also focused on assessing classification accuracy for different land cover classes, considering regional and spatial variability across diverse geographic areas. For accuracy assessment, they calculated metrics like overall accuracy (OA), producer accuracy (PA), user accuracy (UA), F1-score, and Kappa coefficient. SVM was preferred due to the small training data sets, robustness to overfitting and its strength in modelling non-linear boundaries, which suits Dandora area's landscape of mixed and transitional landcover. Radial Basis Function (RBF) Kernel using a 2D grid with optimal parameter pairs (C, gamma) in ArcGIS Pro was used due to less susceptibility to noise, correlated bands, and an unbalanced number or size of training sites within each class (Esri, n.d.-a, n.d.-c).

3.4. Spectral Separability and Signatures

Several pixels were used to extract spectral reflectance curves in homogeneous regions to avoid a great variation of values, comparable to the class of interest.

The regions of interest are of different shapes. The dump in Dandora has a large and smooth continuous surface located in the North-Western side of the study area. Sensing in several spectral bands simultaneously allows one to relate properties that show up well in specific spectral bands, therefore enabling the discrimination of materials of interest like dumpsites and their various components based on their spectral reflectance curves. We can establish for each material type of interest a reflectance curve. Such a curve shows the portion of incident energy that is reflected as a function of wavelength (Lillesand, Kiefer, & Chipman, 2009).

3.5. Validation and Accuracy Assessment

Image classification results in a raster file in which the individual raster elements are class labeled. As image classification is based on samples of the classes, the actual quality of the result should be checked. This is usually done by a sampling approach in which several raster elements of the output are selected, and both the classification result and the true world results are compared. Comparison is done by creating an error/confusion matrix from which different accuracy measures can be calculated. The true world class is preferably derived from field observations (Lillesand, Kiefer, & Chipman, 2009). A total of 500 samples were collected for the purposes of accuracy assessment using ground truth data from the 2021 raster. Through equal stratified sampling 100 cases each of built-up areas, dumpsites, vegetation, water and bare land respectively were found in the real world for all four epochs. Sample points were created by dividing the study area into five distinct and contiguous raster region strata of built-up areas, dumpsites, water, bare land and vegetation, and performing simple random sampling separately within each stratum.

The measures of mapping accuracy used were the overall, user, producer accuracy and Kappa statistics. Overall accuracy is the number of correctly classified divided by the total number of pixels checked. The user accuracy is the probability that a certain reference class has also been labeled that class. The producer's accuracy is the probability that a sampled point on the map in that class is that class (Lillesand, Kiefer, & Chipman, 2009). The burn area index (BAI) uses the reflectance in the red and NIR portion of the spectrum to identify the areas of the terrain affected by fire. This index highlights burned land in the red to near-infrared spectrum by emphasizing the charcoal signal in post-fire images (Wu et al., 2022). In calculating the BAI of Juja and Dandora areas, we hypothesize that the field data collection points and the visual observation of the large and known Dandora dumpsite will overlay with high BAI results. Due to unavailability of training datasets for BAI, we automatically selected a threshold that minimizes intra-class variance, which created the new BAI raster that divided the data into two distinct classes, creating a low value class displayed with black pixels, and a high value class displayed with white pixels Esri (n.d.-b). BAI outputs were subsequently integrated with the SVM map by creating a burn mask.

3.6. Ethical Considerations

Informed consent was obtained from all participants involved in the study, ensuring their understanding of the research purpose and their right to withdraw at any time. Data confidentiality and privacy will also be maintained.

4. Results

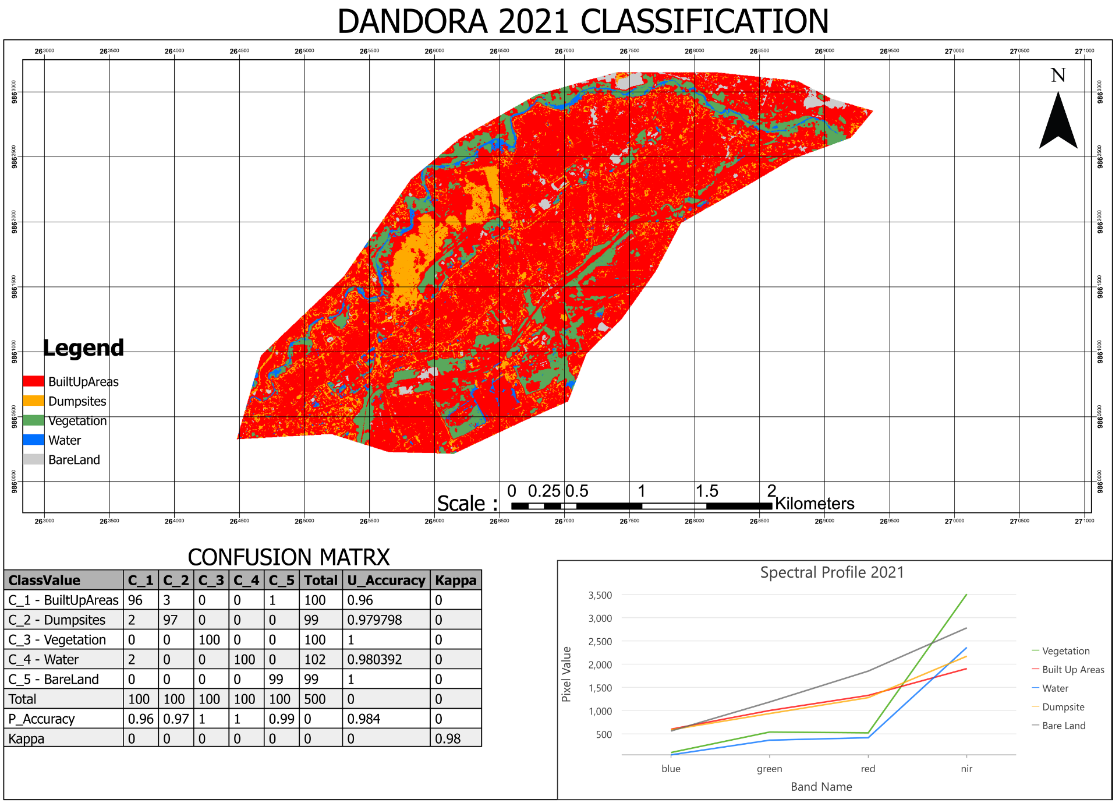
This section presents the results of the study on identifying and mapping MSW disposal sites using Remote Sensing and GIS. The analysis was guided by the following objectives:

- To identify MSW disposal sites in Dandora from 2021 to 2024 through supervised LULC mapping.
- To identify MSW spectral interpretation marks from multispectral satellite imagery.
- To map the spatial distribution of MSW disposal sites using Mobile GIS in Juja in 2022.

The findings will provide insights for improved waste management in Kenya by contributing to a better understanding of the current state of MSW disposal sites and subsequently offer scientifically backed recommendations for policy and practice.

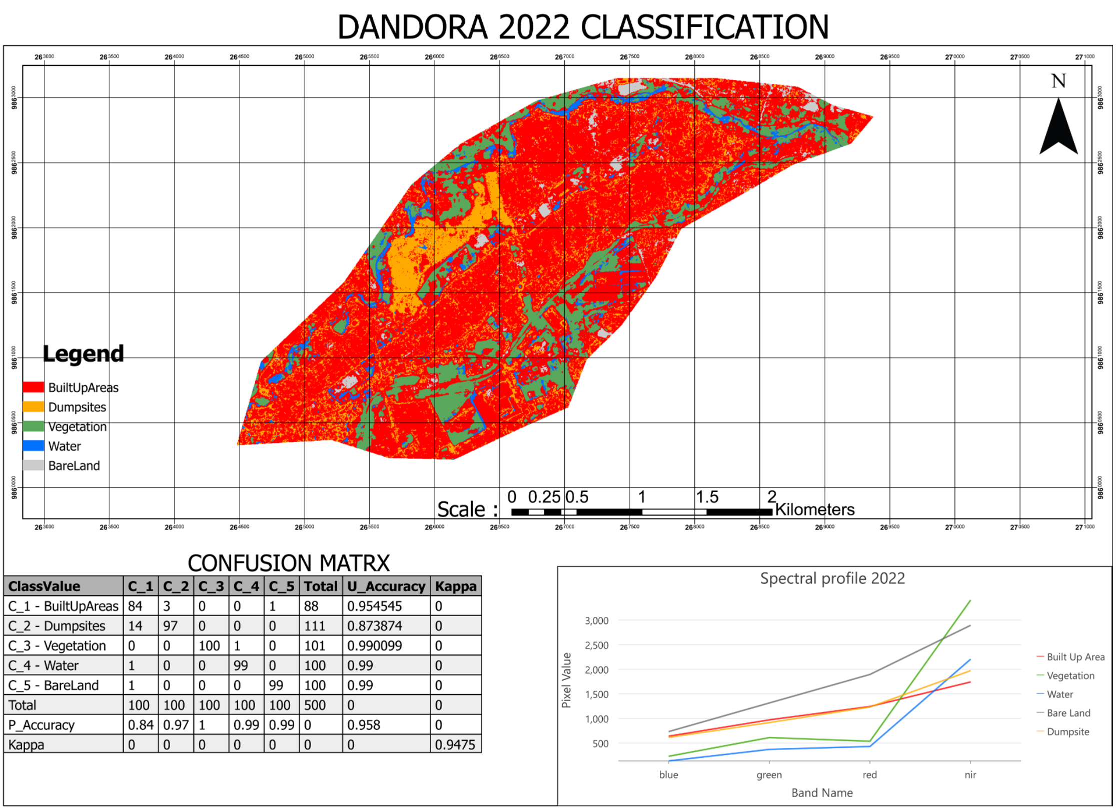
4.1. MSW Disposal Sites in Dandora from 2021 to 2024

This study's classification results from the SVM classifier resulted in a high degree of accuracy in identifying and mapping MSW disposal sites. Specifically, the SVM model was able to classify dumpsites, water, vegetation, bare land and built-up areas as shown in the LULC maps in **Figures 4-7** below. An overall accuracy of 98, 95,92, 95 % for years 2021, 2022, 2023 and 2024 respectively was achieved as measured through the confusion matrices comparing classifications to the training data collected from a high-resolution multispectral imagery. Kappa coefficients were found to be 0.98, 0.95, 0.9 and 0.94 for the four epochs, showing strong agreement between the classification and actual ground truth. In this table five classes brackets C_1, C_2, C_3, C_4, C_5 representing built up areas, dump sites vegetation, water and bare land are listed. A total of five hundred samples were collected. Through equal stratified sampling 100 cases each of built-up areas, dumpsites, vegetation, water and bare land respectively were found in the real world for all the four epochs, while classification results for 2021 yielded 100,99,100,102 and 99 cases of C_1, C_2, C_3, C_4, C_5; in 96, 97, 100,100, and 99 cases they agree, as shown in **Table 3**. In 2022, classification results yielded 88,111,101,100 and 100 cases of C_1, C_2, C_3, C_4, C_5; in 84, 97,100,99 and 99 cases they agree as shown in **Table 4**. In 2023, classification results yielded 69, 118,100,101 and 112 cases of C_1, C_2, C_3, C_4, C_5; in 65,96,100,100 and 99 cases they agree as shown in **Table 5**. Finally, classification results in 2024 yielded 94, 106, 101,99 and 100 cases of C_1, C_2, C_3, C_4, C_5 whereby in 85, 94,100, 100,99 and 97 cases they agreed as shown in **Table 6**.



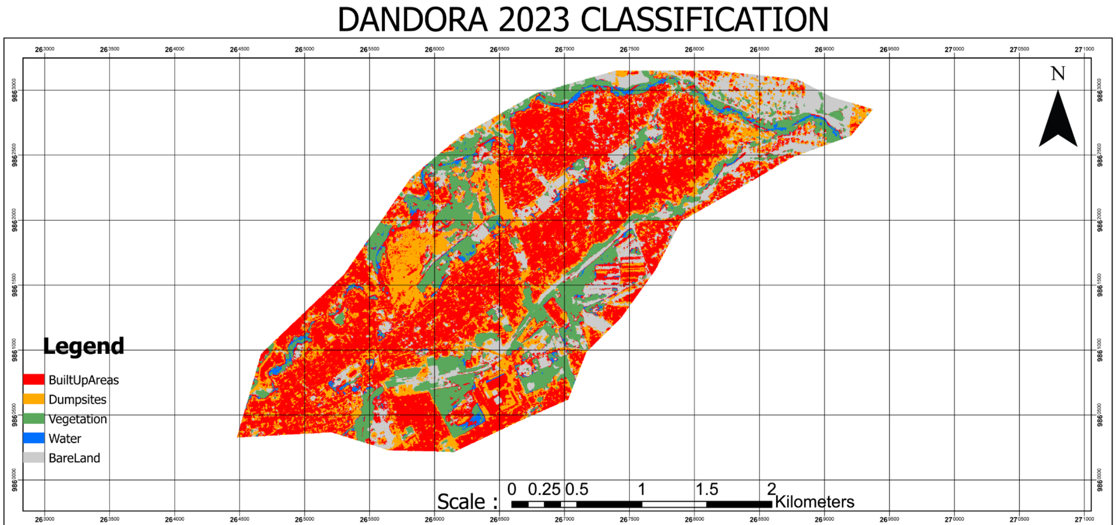
ClassValue	C_1	C_2	C_3	C_4	C_5	Total	U_Accuracy	Kappa
C_1 - BuiltUpAreas	96	3	0	0	1	100	0.96	0
C_2 - Dumpsites	2	97	0	0	0	99	0.979798	0
C_3 - Vegetation	0	0	100	0	0	100	1	0
C_4 - Water	2	0	0	100	0	102	0.980392	0
C_5 - BareLand	0	0	0	0	99	99	1	0
Total	100	100	100	100	100	500	0	0
P_Accuracy	0.96	0.97	1	1	0.99	0	0.984	0
Kappa	0	0	0	0	0	0	0	0.98

Figure 4. Dandora 2021 LULC map.



ClassValue	C_1	C_2	C_3	C_4	C_5	Total	U_Accuracy	Kappa
C_1 - BuiltUpAreas	84	3	0	0	1	88	0.954545	0
C_2 - Dumpsites	14	97	0	0	0	111	0.873874	0
C_3 - Vegetation	0	0	100	1	0	101	0.990099	0
C_4 - Water	1	0	0	99	0	100	0.99	0
C_5 - BareLand	1	0	0	0	99	100	0.99	0
Total	100	100	100	100	100	500	0	0
P_Accuracy	0.84	0.97	1	0.99	0.99	0	0.958	0
Kappa	0	0	0	0	0	0	0	0.9475

Figure 5. Dandora 2022 LULC map.



CONFUSION MATRX

ClassValue	C_1	C_2	C_3	C_4	C_5	Total	U_Accuracy	Kappa
C_1 - BuiltUpAreas	65	4	0	0	0	69	0.942029	0
C_2 - Dumpsites	21	96	0	0	1	118	0.813559	0
C_3 - Vegetation	0	0	100	0	0	100	1	0
C_4 - Water	1	0	0	100	0	101	0.990099	0
C_5 - BareLand	13	0	0	0	99	112	0.883929	0
Total	100	100	100	100	100	500	0	0
P_Accuracy	0.65	0.96	1	1	0.99	0	0.92	0
Kappa	0	0	0	0	0	0	0	0.9

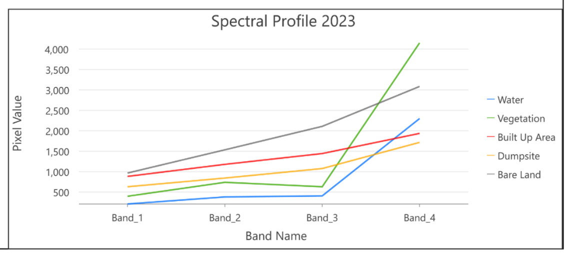
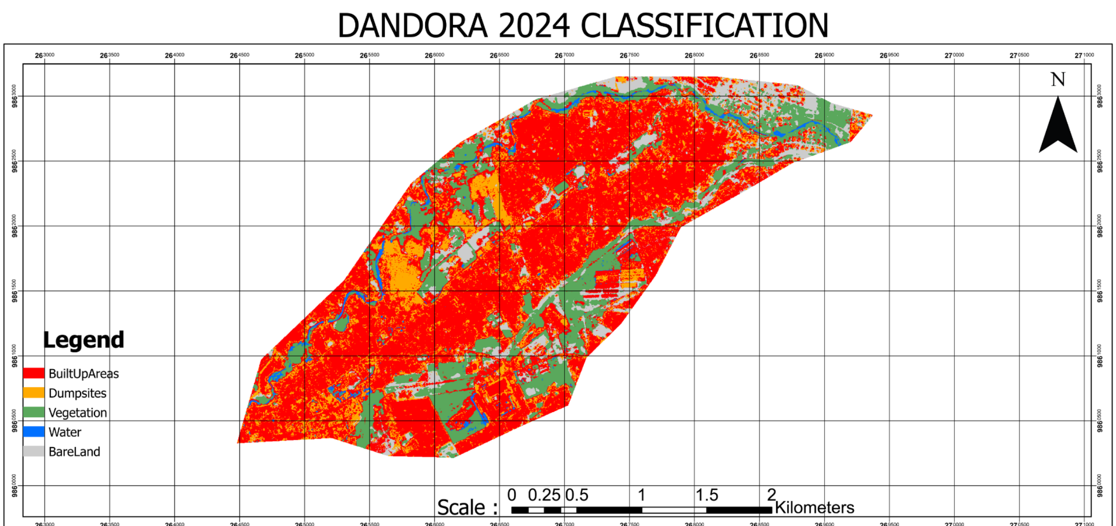


Figure 6. Dandora 2023 LULC map.



CONFUSION MATRX

ClassValue	C_1	C_2	C_3	C_4	C_5	Total	U_Accuracy	Kappa
C_1 - BuiltUpAreas	85	6	0	0	3	94	0.904255	0
C_2 - Dumpsites	12	94	0	0	0	106	0.886792	0
C_3 - Vegetation	0	0	100	1	0	101	0.990099	0
C_4 - Water	0	0	0	99	0	99	1	0
C_5 - BareLand	3	0	0	0	97	100	0.97	0
Total	100	100	100	100	100	500	0	0
P_Accuracy	0.85	0.94	1	0.99	0.97	0	0.95	0
Kappa	0	0	0	0	0	0	0	0.9375

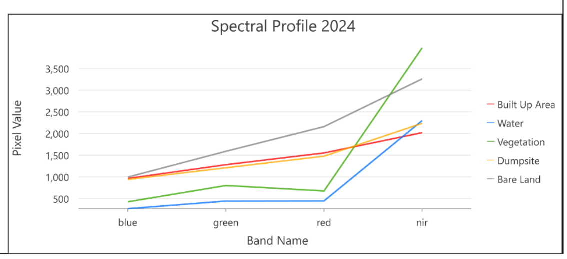


Figure 7. Dandora 2024 LULC map.

Table 3. 2021 Dandora confusion matrix.

2021	C_1	C_2	C_3	C_4	C_5	Total	User's Accuracy	Kappa	Commission Error
C_1 - Built Up Areas	96	3	0	0	1	100	96		4
C_2 - Dumpsites	2	97	0	0	0	99	98		2
C_3 - Vegetation	0	0	100	0	0	100	100		0
C_4 - Water	2	0	0	100	0	102	98		2
C_5 - Bare Land	0	0	0	0	99	99	100		0
Total	100	100	100	100	100	**500**			
Producer's Accuracy	96	97	100	100	99		**98**		
Kappa								**98**	
Omission Error	4	3	0	0	1				

Table 4. 2022 Dandora confusion matrix.

2022	C_1	C_2	C_3	C_4	C_5	Total	User's Accuracy	Kappa	Commission Error
C_1 - Built Up Areas	84	3	0	0	1	88	95		5
C_2 - Dumpsites	14	97	0	0	0	111	87		13
C_3 - Vegetation	0	0	100	1	0	101	99		1
C_4 - Water	1	0	0	99	0	100	99		1
C_5 - Bare Land	1	0	0	0	99	100	99		1
Total	100	100	100	100	100	**500**			
Producer's Accuracy	84	97	100	99	99		**96**		
Kappa								**95**	
Omission Error	16	3	0	1	1				

Table 5. 2023 Dandora confusion matrix.

2023	C_1	C_2	C_3	C_4	C_5	Total	User's Accuracy	Kappa	Commission Error
C_1 - Built Up Areas	65	4	0	0	0	69	94		6
C_2 - Dumpsites	21	96	0	0	1	118	81		19
C_3 - Vegetation	0	0	100	0	0	100	100		0
C_4 - Water	1	0	0	100	0	101	99		1
C_5 - Bare Land	13	0	0	0	99	112	88		12

Continued

Total	100	100	100	100	100	**500**			
Producer's Accuracy	65	96	100	100	99		**92**		
Kappa								**90**	
Omission Error	35	4	0	0	1				

Table 6. 2024 Dandora confusion matrix.

2024	C_1	C_2	C_3	C_4	C_5	Total	User's Accuracy	Kappa	Commission Error
C_1 - Built Up Areas	85	6	0	0	3	94	90		10
C_2 - Dumpsites	12	94	0	0	0	106	89		11
C_3 - Vegetation	0	0	100	1	0	101	99		1
C_4 - Water	0	0	0	99	0	99	100		0
C_5 - Bare Land	3	0	0	0	97	100	97		3
Total	100	100	100	100	100	**500**			
Producer's Accuracy	85	94	100	99	97		**95**		
Kappa								**94**	
Omission Error	15	6	0	1	3				

SVM accurately differentiated dumpsites from other land cover types in 2021, with 3 out of the 100 samples interpreted as the other classes, resulting in a 3% error of omission (Type 2 error) while 2 out of the 99 interpreted samples were incorrectly classified, hence leading to a 3% error of commission (Type 1). In 2022, SVM classifiers accurately differentiated dumpsites from other landcover types with 3 out of 100 samples interpreted as other classes, resulting in a 3% error of omission while fourteen out of 111 interpreted samples were wrongly classified, leading to a 13% error of commission. In 2023, 4 out of 100 samples were interpreted as other classes, resulting in a 4% error of omission while twenty-two out of 118 interpreted samples were incorrectly classified, leading to a 19% error of commission. Finally in 2024, 6 out of 100 samples were interpreted as other classes, resulting in a 6% error of omission while twelve out of 106 samples were incorrectly classified, leading to a 12% error of commission.

Dumping sites, especially those characterized by burning, were mapped with higher precision through the Burned Area Index (BAI) as a validation input in the classification process. The 2022 and 2024 BAI maps indicate a correlation between high BAI and location of Dandora dumpsite, as shown in Figure 15 and Figure 16. BAI provided additional differentiation between burned dumpsites and other LULC types in Dandora, hence improving the performance of RS techniques in mapping and identifying MSW disposal sites.

4.2. 2021, 2022, 2023 and 2024 MSW Spectral Interpretation Marks/Spectral Signatures

Spectral signatures of all the four epochs are shown in Figures 8-11. Vegetation (class 3), water (class 4), and bare land (class 5) show different and distinct spectral signatures. Wavelengths 0.865-0.021 μm indicate the peculiarities of dumpsites (class 2) with the spectral reflectance curves being stable. Although dumpsites (class 2) spectral signatures are well depicted, the maximum and minimum values are not as distant as they are in vegetation and water. This may be because Dandora dumpsite has heterogeneous materials. Built up areas (class1) exhibits spectral response similar to class 2 (dumpsites), with the most similarity being recorded in 2023. This could be the influence of seasonal/weather changes. The vegetation reflectance is low in the

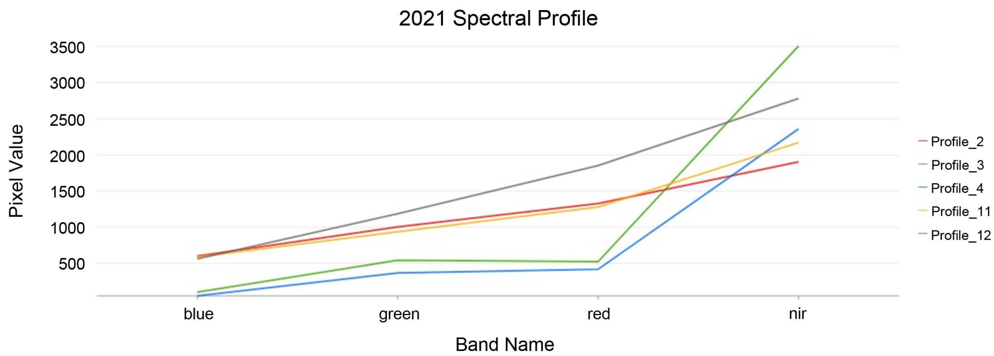


Figure 8. Dandora 2021 spectral profile.

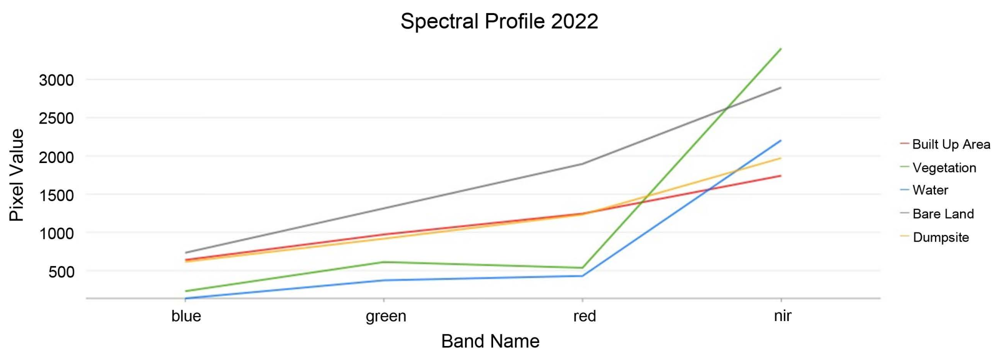


Figure 9. Dandora 2022 spectral profile.

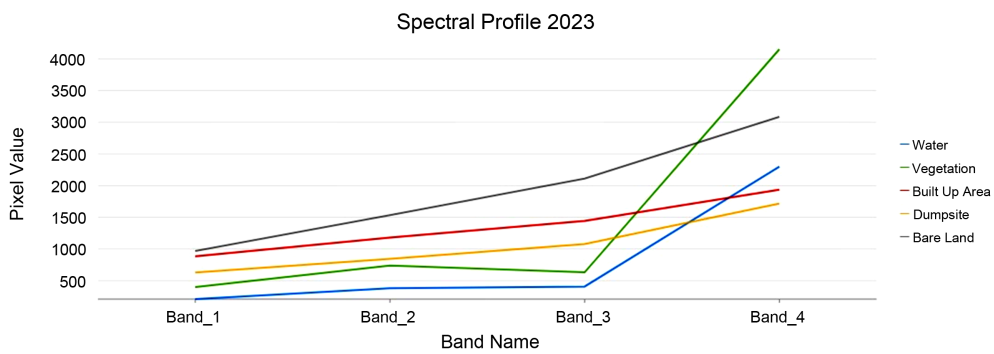


Figure 10. Dandora 2023 spectral profile.

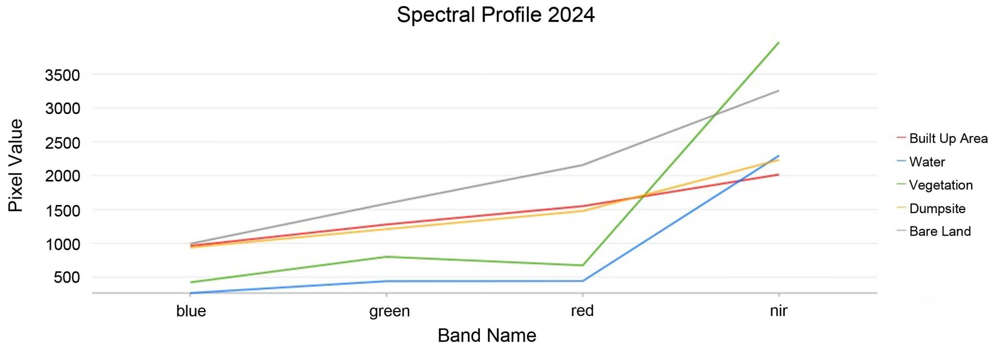


Figure 11. Dandora 2024 spectral profile.

visible spectrum and sharply rises in the NIR band. Water's reflectance is also low in the visible spectrum, and sharply rises in the NIR, but its maximum reflectance is lower that vegetation's across all epochs. Out of all the five classes, bare soil's reflectance is the highest in visible band, with a steady and gradual increase towards the blue band and NIR.

4.3. Spatial Distribution of MSW Disposal Sites Using Mobile GIS Technology in Juja in 2022

The data from the field survey exercise conducted in January 2022 recorded 183 dumpsites as shown in **Figure 12**, and 16 other attributes. 176 of the identified dumpsites are active while seven were inactive as shown in **Figure 14**, translating 96% of the dumpsites operational in January 2022, hence indicating a persisting and improperly managed waste disposal. 166 of the dumpsites were illegal while thirteen were designated as shown in **Figure 13**, showing that 91% of the dumpsites are unauthorized and pose safety, health, and environmental risks. Waste went uncollected in 119 of the sites, collection by individuals and vehicles/trucks was recorded at 27 and 10 dumpsites respectively while decomposition was used as a management method in nine of the sites. Waste went uncollected in 65% of the sites, hence manual and informal systems dominate. Containers and packaging, nondurable goods and household organic waste were the top waste types, an opportunity for single-use and organic waste recycling and composting, respectively. Finally, dumpsite ownership is formal and fragmented with limited institutional control. Eighty-one are community-based, thirty-three individuals while forty-three had unspecified ownership.

4.4. Case Studies

Some case studies involve the application of remote sensing to informal garbage dumps recognition in Beijing City (Cheng & Sun, 2021) and remote sensing analysis techniques and sensor requirements to support the mapping of illegal domestic waste disposal sites in Queensland, Australia (Glanville & Chang, 2015), which successfully identified informal garbage dumps using SPOT-6 satellite images, demonstrating an accuracy of over 90% in the interpretation of these sites and found that very high-resolution satellite data was most effective for detecting illegal waste disposal sites. Lower-resolution data was less useful for identifying smaller sites, respectively. The authors emphasized that the accuracy of remote sensing in detecting informal dumps shows great promise for future urban waste management, highlighting the efficiency and cost-effectiveness of using satellite data compared to traditional methods and suggested that the spatial resolution of satellite data is crucial for accurate waste detection and recommend combining GIS analysis with remote sensing to improve detection accuracy.

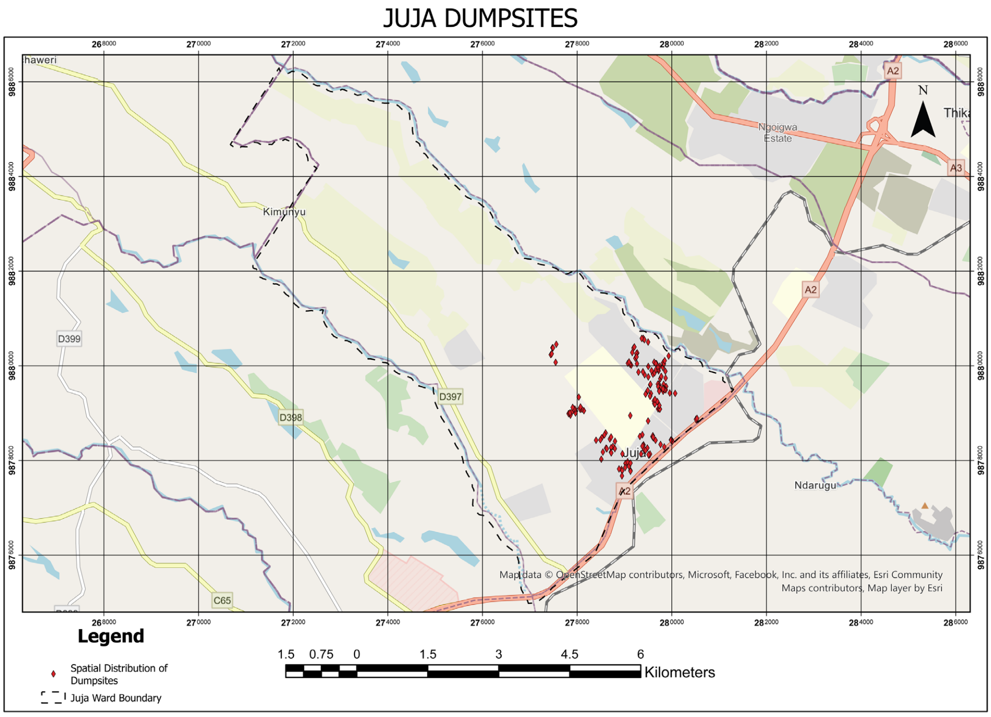


Figure 12. Juja dumpsites.

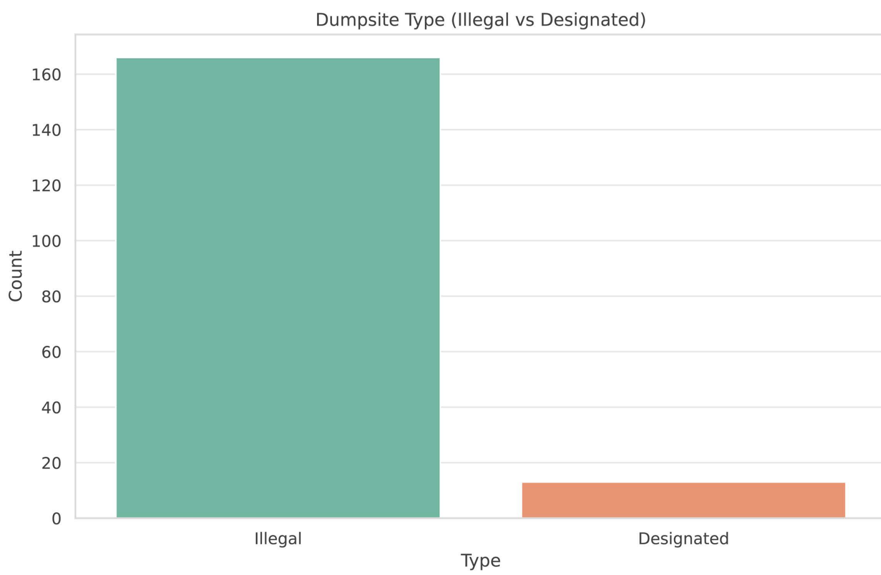


Figure 13. Juja dumpsites legality in 2022.

The results of this study illuminate on the critical issue of MSW disposal in Kenya, with significant implications for circularity, public health and sustainable development. Application of GIS and remote sensing techniques has demonstrated its ability and efficacy in identifying and mapping waste disposal sites, hence providing a cost-effective, valuable, and effective tool for national environmental authorities, circular economy entrepreneurs and policymakers. This study's findings contribute to the pressing and broader discourse on sustainable waste management while offering actionable insights for realization of SDG 11 on sustainable cities.

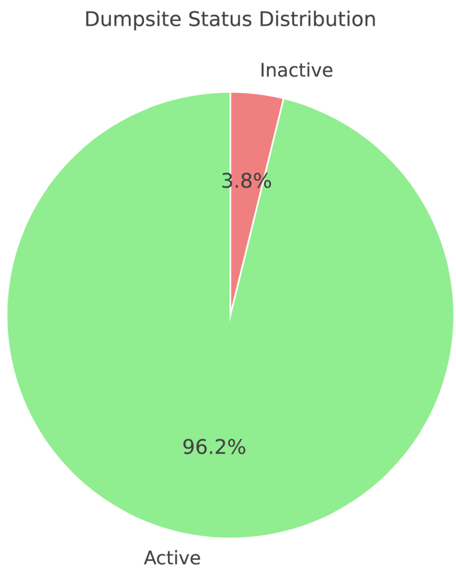


Figure 14. Juja dumpsite status in 2022.

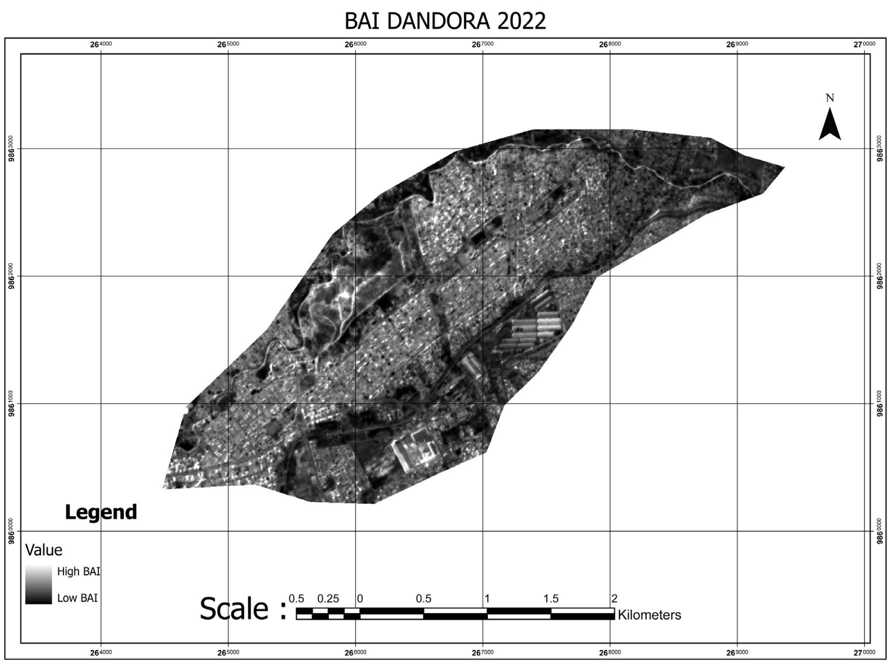


Figure 15. Dandora BAI 2022.

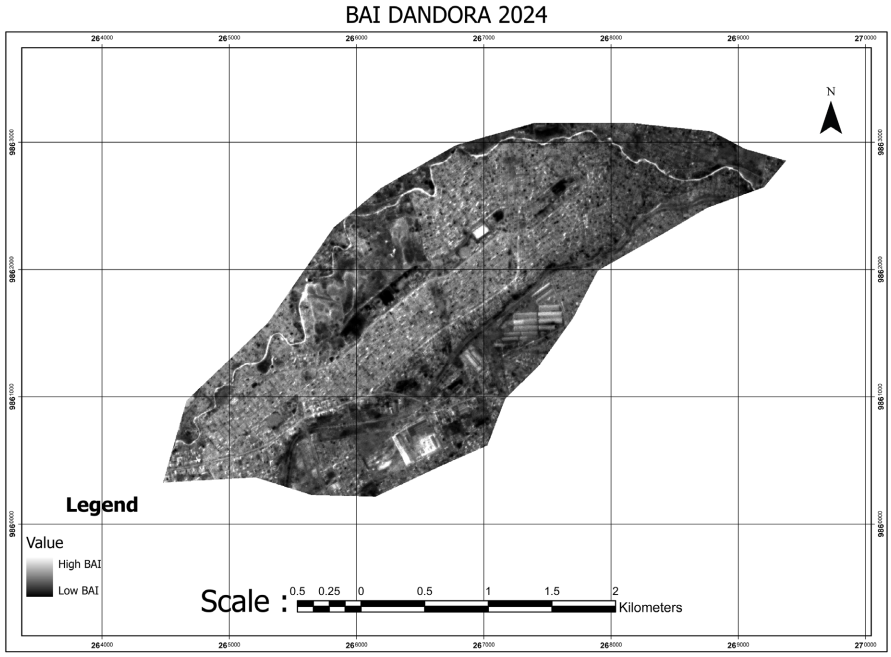


Figure 16. Dandora BAI 2024.

5. Discussion

The main objective of this research was to identify and map municipal solid waste disposal sites using remote sensing and GIS. Field data collection, spatial and digital image analysis conducted in this study resulted in the identification of 182 MSW disposal sites in Juja, 2021,2022,2023 and 2024 LULC maps for Dandora area, Juja and Dandora's 2022 BAI map and Dandora's spectral profile charts in the four epochs. The spatial distribution of MSW dumpsites in Juja represent the findings from a field survey exercise conducted in January 2022 with reported attributes of legal and illegality from the participants, while the BAI map represents a correlation between high BAI and location of dumps as shown in **Figure 15** and **Figure 16** above.

The LULC maps in **Figure 1** highlight the distribution of both MSW disposal sites. The concentration of MSW dumps is notably higher next to high-density neighborhood access roads, reflecting a pattern often associated with population density and industrial development (Yalana et al., 2008). Through Support Vector Machine (SVM) as the applied classifier, the study achieved an overall classification accuracy of 98, 95,92, 95 percent from 2021 through to 2024 for dumpsites, water, vegetation, bare land and built-up areas, with a Kappa coefficient of 0.98, 0.95, 0.9 and 0.94 for the four epochs, showing strong agreement between the classification and actual ground truth. The Burned Area Index (BAI) spectral index enhanced Remote Sensing's precision in identifying MSW dumpsites, particularly those managed by burning activities. There is a possibility that the high overall accuracy figures and Kappa could be overestimated in Dandora due to spatial autocorrelation of the classes as discussed by a study to critically assesses three high-resolution (10 m) global LULC products, finding overall accuracies between 73%

- 84%. Their findings highlight how high-resolution detail can mask thematic discrepancies, leading to inflated user confidence in certain classes without acknowledging their varying spatial reliability (Xu et al., 2024). The highest accuracy recorded for the 2021 results (98%), are likely because the training data utilized for 2022, 2023 and 2024 epochs were collected from the 2021 raster. The odds for overfitting were however, reduced in the epochs 2022-2024 by the SVM, RBF classifier that worked well with our small training datasets. Secondly, high-resolution built-up maps may show artificially high overall accuracies in denser urban areas; which Dandora is, but hide significantly reduced accuracy in rural and peri-urban zones (Uhl & Leyk, 2024).

The spectral reflectance showed consistent behaviour in dumpsites across all the years. However, similarities in reflectance to the built-up areas could pose a significant challenge in differentiating these two classes in the absence of more spectral bands that could provide more advanced interpretation marks. The reflectance curves were consistent throughout the epochs of 2021 to 2023. With the highest portion of incident energy reflected from the NIR band between 0.865 and 0.021 micrometers. Three spectral signature charts revealed that MSW dumping sites had unique reflective properties in each of the four bands, with the highest reflectance recorded in the NIR which allowed for their identification in satellite imagery.

The identification of garbage dumps requires the creation of appropriate interpretation marks, but this can be challenging and time-consuming to do through field investigations alone. The study by (Cheng & Sun, 2021) aimed to overcome this by utilizing the characteristics of informal garbage dumps in SPOT-6 satellite images and forming the interpretation marks based on their known distribution locations, field investigations, and aerial photographs. To map the rest of the study area, the unique spectral properties of the known waste disposal sites and other land cover types were used to train the classifier. Using BJ-1 satellite imagery, their study identified open-air dumps in Beijing with 90.3% accuracy. Dumps were located in suburban areas, correlating with population density and industrial development. In doing so, (Yalana et al., 2008) successfully mapped the distribution of open-air waste dumps and correlated their locations with socioeconomic factors.

The vegetation reflectance is low in the visible spectrum and sharply rises in the NIR band. Water's reflectance is also low in the visible spectrum and sharply rises in the NIR. The reflectance of these two classes is typical. Out of all the five classes, bare soil's reflectance is the highest in visible band, with a steady and gradual increase towards the blue band and NIR.

Dumpsites (class 2) spectral signatures are well depicted. The maximum and minimum values are as distant, which may be because Dandora dumpsite is composed of heterogeneous materials. Built up areas (class 1) exhibits spectral response similar to class 2 (dumpsites), with the most similarity being recorded in 2023. This could be the influence of seasonal/weather changes. Although built up areas (class1) depicts spectral curves similar to that of dumpsites, the difference in maximum reflectance in the NIR and visual analysis distinguishes between the two areas.

In Nairobi and its metropolitan areas, 0.64 kg per capita of municipal waste is generated daily. Recent data from UN Habitat (2019) indicates that the plastic portion of MSW composition ranges between 9 % to 15 %, due to varied income levels in Nairobi. Plastics account for the biggest share of MSW after organic waste and paper (Kenya Association of Manufacturers, 2019: p. 41). Higher spectral response in the NIR for dumpsites is consistent with (Francos et al., 2021) study where they applied controlled laboratory experimental design to artificial soil samples created by mixing dune sand with known quantities of five different organic matter composts. This allowed precise analysis into how organic matter composition affects spectral detectability and prediction accuracy with spectral measurements taken in the VIS-NIR-SWIR range and reflectance at multiple wavelengths between 400 - 2500 nm measured.

The spectral signatures of waste were compared against known references from the literature, and the results were consistent with previous findings from (Notarnicola, 2004), whose spectral analysis effectively detected illegal dumps in Southern Italy, with stable signatures across seasons enabling reliable identification despite smaller dumps and mixed-use areas presenting challenges that were addressed through spectral techniques. The researchers answered their research question by demonstrating the feasibility of using spectral data for detecting and mapping illegal dumps in diverse landscapes. In extracting spectral signatures, (Notarnicola, 2004) finds that the more bands the sensor has the more its feasibility in spectral behavior identification of various classes.

In a study using a remote sensing-based observational design to detect illegal dumps through spectral signature analysis, the key variables measured from Landsat 5 were spectral signatures of different land cover classes including dump areas, and the temporal stability of dump spectral signatures: where stability over time helped differentiate dumps from other land cover types (Notarnicola, 2004).

The collection rate of MSW in Nairobi City is as low as 33%, which leaves most of it uncollected. The total solid waste reuse and recycling in the city is about 100-150tons/day, which is approximately equivalent to 3.7% of total waste generated. With the assumption that collection of recyclables/reusables happens before final collection, uncollected waste reduces to 2,540 tonnes per day. This could be assumed to be disposed of inappropriate ways such as burning and illegal/indiscriminate dumping either by collectors or due to non-collection (Njoroge et al., 2014). (Dianati et al., 2021) characterized a dumpsite in Kisumu, Kenya with uncontrolled open dumping and open burning of waste contribute to the emission of climate altering GHGs such as methane (CH4), as well as carbon dioxide (CO2) and black carbon (BC).

SVM's performance and overall accuracy being above 70% indicates its potential for identification and mapping of MSW disposal sites while the BAI results offer an additional identifying characteristic for MSW, especially where management by burning is prevalent.

While SVM performed well, certain limitations were noted, differentiating dumpsites from built up areas. In these two classes, the classification accuracy slightly decreased, requiring further ground validation. This could be attributable to the heterogeneous nature of a MSW dumping site, that includes remnants of building materials used in surrounding buildings. In obtaining the spectral signature of dumpsites, a limitation in the number of bands in Planet's multispectral imagery limited the identification of characteristics only to the NIR, which was the longest wavelength available for this study. This points towards a need for more data types, such as LiDAR, to improve the robustness of the methodology.

Our findings concerning complement and extend the work by (Cheng & Sun, 2021) who successfully identified informal garbage dumps using SPOT-6 satellite images, demonstrating an accuracy of over 90% in the interpretation of these sites and Studies such as (Dabija et al., 2021) demonstrated that even though both algorithms showed regional variability in performance, SVM generally outperformed RF in classification accuracy, particularly in regions with complex land cover. These findings further align with (Notarnicola, 2004) results, whose spectral analysis effectively detected illegal dumps in Southern Italy, with stable signatures across seasons enabling reliable identification despite limitations on smaller dumps and mixed-use areas presenting challenges that were addressed through spectral techniques.

The research addresses a several gaps identified in previous studies, particularly with relation to MSW management in Kenya. The findings provide practical approaches to using multi-spectral, high resolution satellite imagery for MSW identification for larger dumpsites in Kenya. Secondly the findings add to the body of knowledge on classification for MSW identification and mapping, while reinforcing the application of spectral signature stability as a key parameter for identification of MSW sites.

Previous studies, such as those by (Glanville & Chang, 2015), focused on the environmental impacts of waste sites, such as heat generation and leachate leakage while others focused on identification of landfills, and application of individual GIS and remote sensing techniques. Others such as the ones by (Cheng & Sun, 2021; Yalana et al., 2008), demonstrated the efficacy of LULC classification in waste detection, achieving high accuracy results when high-resolution satellite imagery is used. This study builds on and provides a more targeted approach to identifying MSW sites by incorporating spectral indices and field data collection and validation to complement and supplement each other, hence improving the robustness of the application of GIS and RS techniques in the presence of limiting variables such as resolution, budgets and spatial extent, hence contributing to the improvement of Kenya's waste management system.

The ability to accurately identify and map waste sites is essential for improving waste management practices in Kenya, especially in the reality of an increasing population trend. The results and gaps identified from this study can be utilized by municipal authorities to identify areas of concern and target them for action. To exemplify, the identification of burned waste sites through spectral indices such as BAI can guide authorities in monitoring open dumps and discouraging harmful waste management practices.

Furthermore, the high LULC classification accuracy and the other results, indicates that these remote sensing techniques, combined with other GIS and field data, can significantly enhance waste management in Kenya. With accurate data on waste distribution, authorities can implement more targeted interventions, reduce environmental hazards, and ensure a clean and healthy environment for all Kenyans. The mapping and statistical outputs from this study further provide important data for environmental management and future urban planning, particularly in the identification of zones at risk of illegal dumping and ensuring circularity.

6. Conclusion and Future Work

The primary objective of this research was to identify and map municipal solid waste disposal Sites in Juja and Dandora areas of Kenya using Remote Sensing and GIS. Through the LULC classification of Planet satellite images and the two other remote sensing and GIS-based exploratory design, the findings were highly accurate. Our field survey mapped spatial distribution of MSW dumping sites while the spectral reflectance curves showed consistent behaviour in dumpsites across all the years. Despite the similarities in reflectance to the built-up areas, the results indicate that LULC mapping when combined with spectral characteristics provides a high-accuracy method for identifying MSW dumping sites. This study addresses a critical gap in the literature regarding the need for comprehensive mapping and monitoring of waste disposal sites, specifically in Kenya. While previous studies focused on one or two methodologies and were primarily outside the African continent, this research focuses on spatial analysis and mobile GIS data collection in Kenya, and findings from this study are meant to provide insights for improved waste management by contributing to a better understanding of the current state of MSW disposal sites and subsequently offer scientifically backed recommendations for policy and practice.

Kenya's aims to transition the waste sector from low collection rates, illegal and uncontrolled dumping to affordable waste collection, recycling and composting. The Ministry outlines the need for timely inventories and the minimization of illegal dumpsites (Ministry of Environment and Forestry, 2021). Accurate data on the extent, type and location of waste informs waste recovery strategies, particularly in the context of circularity, where waste is seen as a resource rather than a byproduct, while incorporating geospatial tools and techniques, and classifiers such as SVM, into MSW waste site identification and mapping also supports efforts for site identification for MRFs (material recovery facilities) and mapping waste collection coverage gaps.

Future research could benefit from the integration of real-time monitoring systems, such as drone-based imagery, to complement satellite data. The use of mobile GIS platforms to crowd-source waste disposal data from citizens and waste management personnel could further enhance the accuracy and timeliness of waste disposal site identification.

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Conflicts of Interest

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

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