GIS Odyssey Journal

2026 • Volume 6 • Number 2

https://doi.org/10.57599/gisoj.2026.6.2.53

Suman Chatterjee[1], Anwesha Chattopadhyay[2]

ASSESSING TEMPORAL DYNAMICS, GEOMETRY, AND COMPOSITION OF KATWA MUNICIPALITY LANDFILL SITE USING HIGH-RESOLUTION MULTISPECTRAL DATA AND MACHINE LEARNING-BASED SPECTRAL ANALYSIS

Abstract: This study attempts to assess and characterize landfill site under Katwa Municipality in Purba Burdwan district, West Bengal, India. The landfill site has grown rapidly in recent years, in an unmanageable manner. The majority of the municipal solid waste is dumped here. Areal and geometric changes over time (from 2017 to 2025) have been assessed and characterized by digitizing the site for the present day and at two other points in the past (2017 and 2021) using Google Earth and its History tool. Existing geometric properties have also been characterized using different indices, including the Shape Index (SI), Compactness (C), Fractal Dimension, and Elongation Ratio (ER). The composition of the waste has been characterized using remotely sensed data by comparing two advanced techniques: Linear Spectral Unmixing and Random Forest-refined Spectral Unmixing. Field visits were conducted, and the materials of composition were identified as follows 1. Plastic, 2. Raw and decomposed organic material, humus, and barren soil and 3. Thin and sparse vegetation cover. The landfill site has grown in size, possibly because more waste is being made. The evaluation of site geometry reveals a deterioration in compactness and regularity, indicating potential deficiencies in planning and waste management oversight. It is clear from what we see that there is too much plastic, either in the form of fully plastic parts or materials that are covered in plastic. The combination of RF and LSU worked better for finding plastic and plants. But LSU by itself might work better for the soil. The results provide important decision-making aid to municipal authorities in improving their landfill practices and waste management activities through remediating waste.

Keywords: landfill expansion, spatial assessment, random forest (RF), waste composition, spectral assessment

Received: 6 March 2026; accepted: 9 July 2026; revised: 30 July 2026

[1] Loreto College, Department of Geography, Kolkata, India, ORCID ID: http://orcid.org/ 0000-0002-3512-0016, email: suman.chatterjee27@yahoo.in

[2] Sree Chaitanya Mahavidyalaya, Department of Microbiology, Habra, India, email: achat.mcb@gmail.com

Introduction

With the increasing availability of high-resolution open-access satellite data, along with advancements in spatial analysis techniques and the parallel development of machine learning methods, the relevance of using remote sensing and advanced spatial analysis techniques for many unconventional applications has become unquestionable. There are examples of using remote sensing and GIS techniques for characterizing dumping site and waste management (Theres B et al., 2023; Tripathi et al., 2022). Majority of those studies are conducted to identify the suitable place for dumping and dumping site selection (Theres B et al., 2023; Tripathi et al., 2022). Many of them have used overlay, weighted overlay integrating it with multicriteria decision analysis techniques (Reddy & Asadi, 2024; Tripathi et al., 2022). Some studies have been conducted to highlight the efficiency and cost-effectiveness of these methods (Mohammedshum et al., 2014). Few studies have also used this method to assess disparities in waste collection systems due to rapid population growth. (Nyachiro & Mgala, 2024). But this study takes this approach to an advanced level by incorporating advanced techniques such as spectral unmixing, machine learning algorithms, and integrating change and geometric analysis, giving it a holistic evaluation for such a small-scale study. Another encouraging element in this study is that open-access data have been used here, which is not of moderate resolution but of satisfactorily high resolution, encouraging researchers to adopt such methodologies with ease for such rarely applied scenarios.

Geometric characterization establishes an important basis for all future applications of geophysical surveying and other fieldwork investigating the environmental risks associated with landfill sites. The precise location of landfill limits, thickness, volume, and surface morphology will improve the understanding of subsurface conditions, stability, and possible contamination of the environment. By combining the use of historical topographic mapping, complete aerial photography, digital photogrammetry, and airborne LiDAR, G. Esposito et al. presented an integrated methodology for the detection and geometric characterization of a buried landfill in Italy (Esposito et al., 2018). The research data were utilized to reconstruct the morphological history of the landfill between 1956 and 2008, during which the average thickness of waste in the landfill had grown to approximately 8 m and the total estimated volume of waste in the landfill was almost 100,000 m3. The authors stressed that the combination of qualitative history with elevation datasets is an extremely effective means for the identification and geometric characterization of buried landfill deposits. Although it did not explicitly study geometric measures of stability and the potential for slope failure, structural failure and slope failure mitigation strategies discussed in the study feel relevant to landfill geometry in that the morphology of the site and the thickness of the waste both are significant determinants of stability conditions.

A geo-environmental assessment used satellite images and drainage analysis to evaluate a landfill site southeast of Riyadh (Hussein et al., 2008). The results of this investigation provide significant information regarding the development of the landfill footprint, modification of the drainage network, and physical characteristics of the site. These findings create an understanding of the geometric development of the site and its environmental impacts.

The use of spatial analysis, such as GIS and remote sensing, to evaluate proposed landfill sites in Kirkuk (Mitab et al., 2023) demonstrates the significance of geometric parameters, including slope, elevation, spatial extent, and proximity factors, as they relate to determining landfill suitability. Overall, these studies suggest that the integration of historical data, remote sensing data, and spatial analysis methodologies must be utilized together to provide an accurate geometric depiction of a landfill site and the environmental impact of the site. Research demonstrates that Linear Spectral Unmixing (LSU) has successfully been used for classifying land cover in cities using multispectral remote sensing (Segl & Roessner, 1999), and has shown that using endmembers chosen from pixel-based rather than area-based locations yields improved reliability of classifications when using stochastic modelling methods (Small, 2001). Further research has also demonstrated that LSU produces stable and repeatable estimates of vegetation within urban areas, with validated results using high-resolution imagery (Small, 2001). Preliminary work using Landsat data has also indicated that LSU methods can be used for mapping land cover in urban areas, primarily for estimating the amount of vegetation (Segl & Roessner, 1999).

The literature reports that the traditional techniques used for the unmixing of hyperspectral imaging can also be utilized for multispectral data. Jizhen Cai et al. (2021) did an experiment testing the efficiency of three key unmixing algorithms: VCA, NMF and N-FINDR, using synthetic samples of multispectral data obtained from hyperspectral images. The practical implementation of unmixing techniques substantiates their effectiveness: an example of study conducted by Siliuk et al. (2020) involved an application of unmixing on 4-channel multispectral images (10-meter resolution) in the task of monitoring forests' health which received "high agreement" with the results produced by air measurements. In addition, in the work of Ronay et al. (2025) demonstrate good results of using four approaches of spectral mixture analysis for multispectral field data. The latter techniques managed to achieve the mean absolute error of estimation of weed coverage lower than 12% after using the advanced technologies of SUnSAL-TV and VPGDU.

The above evidence indicates that caution should be exercised when utilizing LSU methods for urban land cover mapping due to possible differences in the results reported by different researchers; for example, Small et al. (Small, 2001) report that three-component linear mixing models applied to Landsat TM data in New York City provide stable and consistent estimates of the fractional amount of vegetation with a difference of no more than 0.1 between the estimates and the results of validation when the fractional amount of vegetation is greater than 0.2.

Nonetheless, despite the widespread adoption of remote sensing technology for monitoring landfills, various gaps remain in the existing literature. Research has often concentrated on metropolitan landfills (Altarez et al., 2026), focusing on landfills situated in relatively smaller regions such as Katwa. Besides, most papers do not address the integration of spatio-temporal dynamics, geometric indices, and waste composition into a single framework. Furthermore, the implementation of machine learning-based spectral unmixing is still in its emergence (Papale et al., 2023; Sharma & Rajendra, 2025). It is worth mentioning that no comprehensive geospatial analysis of Katwa landfill has been conducted before. This article fills gaps in the research highlighted above through integrating time-related analysis, geometric indices, and machine learning based spectral analysis.

Katwa Municipality lies within Purba Burdwan District of West Bengal (Figure 1). The municipality covers an area of 7.93 sq. km with a population of 81,615 as per recent census. There is total 17,200 houses where non-residential premises are 1,050. In the municipality, door-to-door collection is practiced along with segregated transport. A total of eight tractors and one compactor are operational. However, no other vehicles such as refuse collectors or tipping trucks are in operation. There are no sanitary landfills; instead, there is an open dump site with 32 MT/day of waste being landfilled, while the overall solid waste generation amount is 40 tons per day (TPD). An estimated 392.08 grammes of waste are generated daily per person. The municipality is still assessing how much land is needed for proper waste disposal. Composting/Vermicomposting is not practiced, and the total number of waste storage depots is 16. The only and most prominent open landfill dumping site of Katwa Municipality is located over an area of 29,628 square meters as of 2025. The landfill site has been expanding since 2017, covering 18,185.83 square meters in 2017, 21,604.35 square meters in 2021, and 29,628 square meters in 2025. The growth rate has been evidently very high over this period, and if it continues without proper management, it is certain to affect the entire urban planning and sustainability aspects of the town. There are no formal waste management by-laws in place yet. Regarding sewage treatment, the existing STP (Sewage Treatment Plant) capacity is 4.36 million liters per day (MLD), of which 2.36 MLD is being utilized. There is one proposed Common Biomedical Waste Treatment Facility (CBWTF) being reconsidered for development in Purba Bardhaman, West Bengal, at Plot Nos. 125 & 128, Mouza Khirgram. This project aims to establish a centralized facility for the safe and compliant treatment of biomedical wastes, such as those collected from hospitals and healthcare facilities (State Environment Plan 2021).

Objectives of the study.

I. To assess the temporal expansion of the Katwa landfill site from 2017 to 2025.
II. To evaluate changes in the geometric characteristics of the landfill site over time using spatial shape metrics.
III. To characterize landfill waste composition and evaluate the effectiveness of Linear Spectral Unmixing (LSU) and Random Forest-refined LSU (RF-LSU) for mapping waste materials.

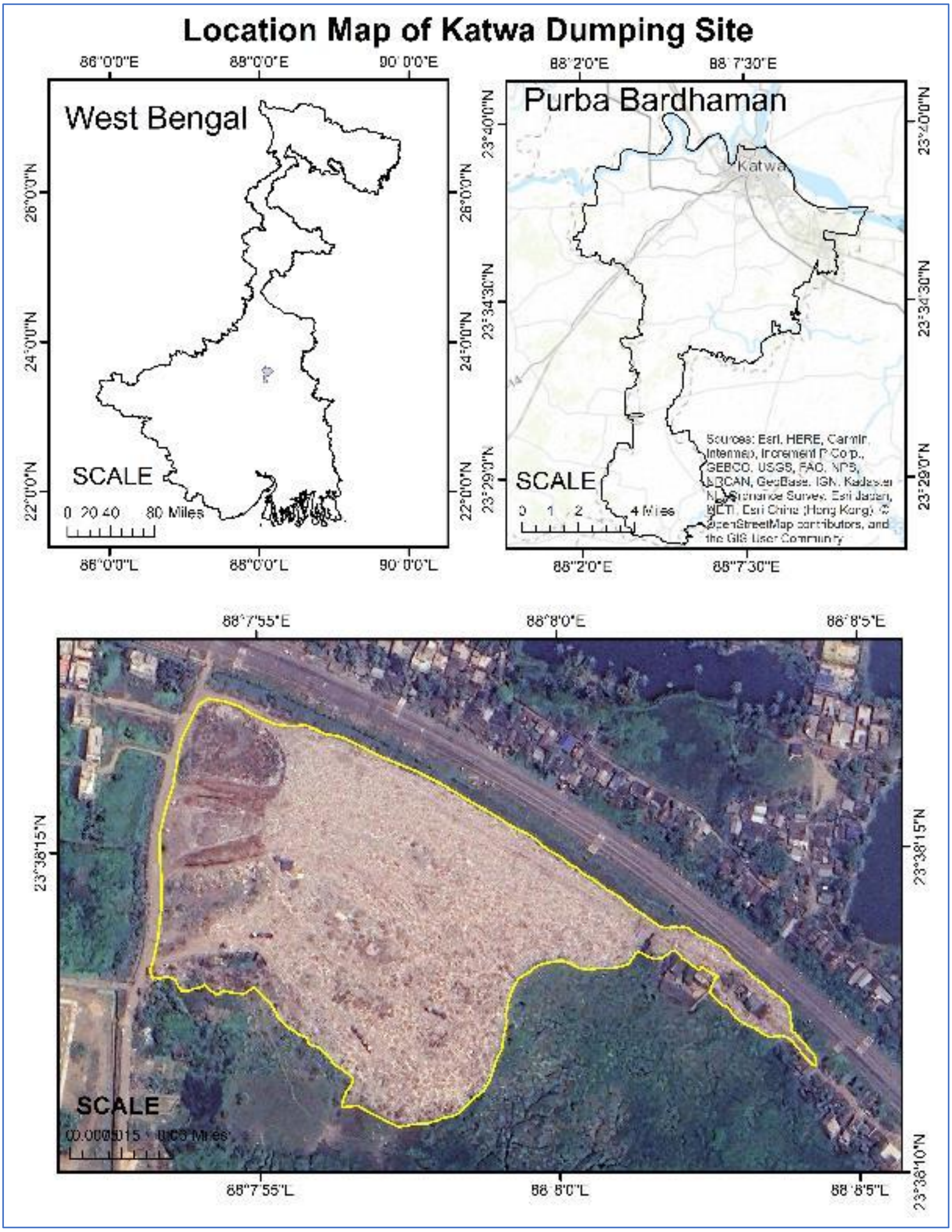

Figure 1. Location map of the study area (Katwa dumping site)
Source: Survey of India Administrative Boundary Database
and Google Earth Satellite image

The rapid growth of the generation of municipal solid waste across the globe can be attributed to urbanization, population growth, and consumption trends, hence scientific management of landfills has become a global environmental need. As per World Bank report, the generation of municipal solid waste in the world has surpassed 2.01 billion metrics every year (Bhajantri et al., 2026) and it is expected to reach around 3.88 billion metrics annually by the end of 2050 if the present trend stays unchanged. India is the third largest producer of municipal solid waste in the whole world with more than 62 metrics being produced every year (Ravish, 2025), with a significant amount being mixed with the open dumps or landfills with poor engineering (Ravish, 2025). Katwa Municipality follows these trends. The municipality produces around 32.95 metric tons of waste per day with a population of ~81615 and a high growth rate of 13.68% from 2001 to 2011 (Ghosh & Pal, 2017). In addition, monitoring of the growth of the landfill sites is required to estimate the land consumption and define the uncontrolled growth (Sharma & Rajendra, 2025; Shevchuk et al., 2021), while geometric characteristics provide information about the efficiency and sustainable development of the landfills thanks to changes in shape, compactness and complexity of the borders (Esposito et al., 2018; Mello et al., 2022). Furthermore, waste compositional analysis is critical for identifying dominant waste fractions, assessing recycling and resource recovery potential, and supporting the design of appropriate treatment and remediation strategies (Götze et al., 2016; Zorpas et al., 2015). In the present study, the temporal expansion of the Katwa landfill site from 2017 to 2025, the geometric characteristics of the site over time using spatial shape metrics, and the characterization of landfill waste composition have been assessed. The findings of this study will be helpful for evidence-based landfill monitoring and scientific management. The integration of multi-temporal geospatial analysis, geometric indices, and advanced spectral unmixing techniques provides a practical framework for supporting municipal authorities in landfill planning, legacy waste remediation, environmental risk assessment, and the implementation of sustainable solid waste management practices consistent with the Swachh Bharat Mission, Solid Waste Management Rules, 2016, and the Waste Wise Cities framework.

Material and methods

The whole work employs different methods based on the objectives mentioned earlier. For the change detection analysis, simple digitization in Google earth and Google earth history tool have been used. Mainly three years have been selected based on the commencement of the usage of the dumping site as per the literature and visual interpretation of the satellite imageries. The initial time stamp has been selected as 2017. Subsequent timestamps are 2021 and current that is 2025 with an interval of four years. Which is a decent and optimum interval for such small-scaled change detection studies. Finally, the landfill areas visibly identified in Google Earth historical imagery as having been utilized for waste disposal in 2017, 2021, and 2025 have been digitized in Google Earth and subsequently three shapefiles have been generated.

For geometric analysis, the same shapefile digitized in the previous process was used, and those three shapefiles were used for the consecutive geometric characterization. Firstly, the fundamental properties, i.e., Area, Perimeter, etc., have been calculated. Subsequently, certain popular indices been utilized for the same, i.e., Perimeter, Area, Shape Index (SI), Compactness (C), Fractal Dimension (FD), and Elongation Ratio (ER), to understand the expansion and dynamics of the site and its relation to the impact upon the environment and surrounding settlement (Table 1). These indices are important morphometric measures that are commonly used across diverse disciplines such as medicine, urban planning, and geometry Following table summarizes the constructions of these indices.

Table 1. Geometric shape indices used for landfill site characterization, including their interpretation, equations, and literature references

Indices	Interpretation	Equation	Reference
Shape Index (SI)	The shape index reflects shape complexity—higher values mean more complex, irregular shapes	$P/2\sqrt{\pi a}$ Where: P = Perimeter (m) A = Area (m^2)	(Patton, 1975; Ruiz del Portal & Salazar, 2003)
Compactness (C)	Compactness is inverse of shape irregularity—higher values suggest more circular or regular shapes	$C = 4\pi a/A^2$ P = Perimeter (m) A = Area (m^2)	(Yan-guang, 2006)
Fractal Dimension (FD)	Fractal dimension measures shape complexity and boundary detail	$FD = 2 \times \log(0.25 \times P)/\log(A)$ P = Perimeter (m) A = Area (m^2)	(Yan-guang, 2006)
Elongation Ratio (ER)	Elongation ratio indicates how stretched or elongated the shape is (values closer to 1 = compact, values >1 = more elongated)	$Major\ Axis\ Length/Minor\ Axis\ Length$	(Liu et al., 2020)

Source: own elaboration, based on Karmakar et al., 2021; Lv et al., 2009; Powell & Roberts, 2008; Priem et al., 2016

Waste compositional analysis: For compositional analysis and for characterization of the waste materials in the site in current timestamp (2025) multispectral (Eight Analytic bands) atmospherically corrected surface reflectance images captured by PSB SD (SuperDove) Sensor have been used. The data have 3-meter spatial resolution. The bands used here are, Coastal Blue 431-452 nm, Blue: 465-515 nm, Green I: 513. – 549 nm, Green II: 547 – 583 nm, Yellow: 600-620 nm, Red: 650 – 680 nm, Red-Edge: 697 – 713 nm, and NIR: 845 – 885 nm.

For compositional and characterization analysis first, a field visit was conducted to identify and categorize the material of composition. The field visits were carried out, and the materials of composition were identified as follows:

1. Plastic;
2. Raw and decomposed organic material, humus, and barren soil;
3. Thin and sparse vegetation cover.

Based on this identification, three major materials of interest – or endmembers – were determined:

1. Plastic, representing all plastic and plastic-covered materials;
2. Soil, denoting raw and decomposed organic material, humus, contaminants and soil materials;
3. Vegetation, representing sparse and thin vegetation such as grass or shrubs.

The spectral patterns and the unsupervised clusters of the multiband images were also assessed to aid in the selection of training samples. Additionally, 30 ground-truthing data points were collected during the field visit to validate the results of the material composition classification.

After identifying and categorizing the endmembers, two different methods were employed: one traditional Linear Spectral Unmixing (LSU) method, and another method, which is the same as LSU but refined by a popular machine learning algorithm, i.e., Random Forest-refined Spectral Unmixing. These two advanced techniques were compared. In the table below, the comparison of outputs and their interpretations is highlighted. The process of breaking down the recorded spectrum of a mixed target into pure component spectra, called endmembers, and their fractional abundances is called spectral unmixing. It is a very common sub-pixel analysis applied in hyper-spectral data analysis (Cohen & Gillis, 2018). For LSU every pixel in the image is thought to have a reflectance that is a linear combination of the reflectance of all the materials (or end-members) that are present in that pixel. For instance, the spectrum for a pixel is a weighted average of 0.25 times the spectrum of material A, plus 0.25 times the spectrum of material B, plus 0.5 times the spectrum of material C if 25% of the pixel contains material A, 25% of the pixel contains material B, and 50% of the pixel contains material C (Pour et al., 2023). On the other hand, Random Forest Refined Linear Spectral Unmixing is a hybrid approach that combines traditional physical unmixing (LSU) with Random Forest, a popular machine learning algorithm, to refine abundance estimates or assign classes based on endmember spectra (Li et al., 2023).

The combination of Random Forest classifiers with Linear Spectral Unmixing techniques, as explored in the studies mentioned, offers a robust framework for advanced remote sensing applications. While the specific term "Random Forest Refined Linear Spectral Unmixing" is not commonly used, the underlying concept aligns with current research trends in the field. Random Forest Refined Linear Spectral Unmixing is not a specific established technique, but rather refers to the application of Random

Forest algorithms to enhance traditional linear spectral unmixing methods in hyperspectral image analysis. Random Forest improves unmixing by providing robust classification, handling high-dimensional data, and incorporating spatial-spectral information more effectively than conventional approaches (Ghasemi et al., 2024; Kathirvelu et al., 2023).

Random Forest (RF) has been extensively applied to hyperspectral image classification and analysis tasks. The algorithm's ensemble nature makes it particularly suitable for handling the high-dimensional, noisy characteristics of hyperspectral data. In the context of spectral unmixing, RF can be employed in several ways i.e. RF can classify pixels into material categories before unmixing, providing spatial constraints that improve abundance estimation (Belgiu & Drăgu, 2016; Joelsson et al., 2005; Poona & Ismail, 2013). When LSU produces continuous fractional abundance with pixel values ranging from 0 to 1, RF probability represents the per-class probability, also ranging from 0 to 1. In this study for each endmember (e.g., soil, vegetation, water), a Random Forest (RF) classifier has been trained using the extracted spectral signatures. Each RF model has been trained as a binary classification problem (one-vs-rest), where the target class has been labeled as 1 and all others as 0. The RF models have been trained with training samples using the random Forest package in R. Model performance was evaluated using standard metrics to ensure robustness.

Validation of the composition. 30 field samples have been collected and employed for accuracy assessment for each of the methods applied here separately. Accuracy, Kappa Coefficient, Sensitivity Analysis have been performed here.

Results

Result section has been discussed with respect to three different assessment that have been performed here i.e. Temporal Change assessment, Site's Geometric characterization over time and Waste Compositional Analysis.

Temporal changes. In the temporal change detection analysis, it has been found that the area of the landfill site was 18,185.83 square meters in 2017, 21,604.35 in 2021, and 29,628 in 2025. Over time, the landfill's area has steadily increased. This suggests that the landfill site has expanded spatially, perhaps as a result of rising waste production and disposal requirements.

Site's geometric characterization over time (2017 to 2025). The perimeter and area have changed very rapidly over the time. The perimeter has decreased between 2017 and 2021, however again it increased again by 2025 (Figure 2).

The Shape Index for Katwa exhibits its trends in complexity over the years. In 2017, it clocked a value of 2.027, which is the index's highest for irregularity and complexity. By 2021, the site shape index had stricken down to 1.453 which hints the shape became more regular in form. Nevertheless, by 2025 it rose again to 1.878, which could be due to uneven growth in the region's perimeter and surfaced area.

Figure 2. Katwa Landfill Site's Geometric characterization (2017 to 2025)
Source: Google Earth Historical Images

*The Compactness Index***,** which instead presents an opposite picture of what a shape's true nature is at play, that is, the higher the value the more round or regular the shape, shows a mixed report for the site. In 2017, a value of 0.243 was computed. That improved by 2021 to 0.474, which indicates a change toward more ordered growth. But then, by 2025, it is seen that the trend broke and the index went down to 0.283, which in turn points back to less ordered or outreaching growth. *The Fractal Dimension* for Katwa landfill site which quantifies the detail and complexity of a shape, exhibits slight variation within the range of 2017 to 2025. The landfill tends to show moderate complexity because of its range of 1.051 and 1.119. Significantly, the lowest fractal dimension of 1.051 in 2021 corresponds with the more regular shape that was observed for that year. The *Elongation Ratio* for Katwa landfill site provides understanding as to how compact or stretched the area's shape was throughout time. As in most of the cases, the value closer to 1 indicates more compact shape and greater than 1 indicates elongation, in this area, the data augurs an interesting story. In 2017, the ratio was 1.289 suggesting it was more elongated. This went down to 1.205 in 2021 indicating the area became more compact or rounded. The ratio went up again by 2025 to 1.252 suggesting return to more elongated form.

Waste Compositional Analysis: Linear Spectral unmixing. By comparing the results of LSU and RF-LSU outputs it is observed that there is a clear difference in the estimation of endmember abundance. LSU has identified greater number of pixels with plastic (13,658.81 sqm, −6.57%) and soil (13,825.89 sqm, +181.15%) (Figure 3) in comparison with the estimation from RF-LSU output (Figure 4). It indicates that LSU might overestimate the concerned endmembers due to spectral confusion and misclassification of mixed pixels. On the contrary LSU output has underestimated the area covered by the vegetation (2,143.30 sqm, −78.76%) in comparison with the RF-LSU output, which might be due to difficulty in distinguishing vegetation signatures from soil and plastic in the spectral space (Table 2).

Table 2. Comparison of Outputs of LSU and RF: Abundance of Endmembers

Class	RF-LSU (sqm)	LSU (sqm)	Difference (sqm)	% of Change (LSU vs RF-LSU)
Plastic	14,619.67	13,658.81	−960.86	−6.57% (less)
Soil	4,917.54	13,825.89	+8,908.35	+181.15% (more)
Vegetation	10,090.79	2,143.30	−7,947.49	−78.76% (less)

Source: own study based on PlanetScope SuperDove 8-band satellite imagery

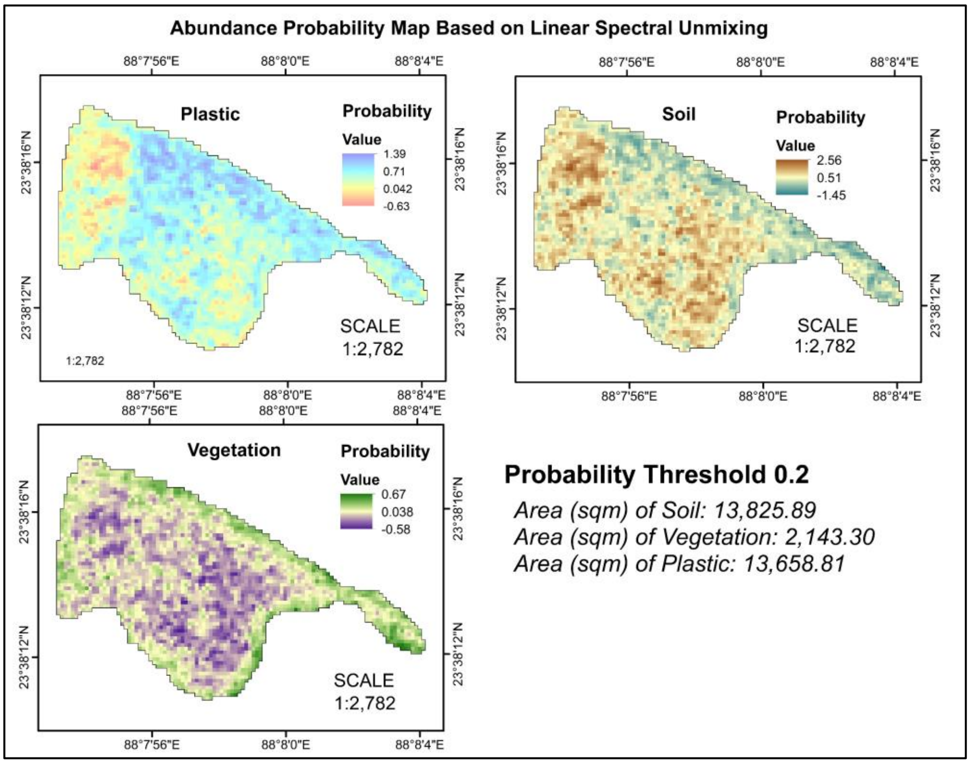

Figure 3. Abundance probability map of Katwa landfill site based on linear spectral unmixing (LSU) method
Source: own study based on PlanetScope SuperDove 8-band satellite imagery

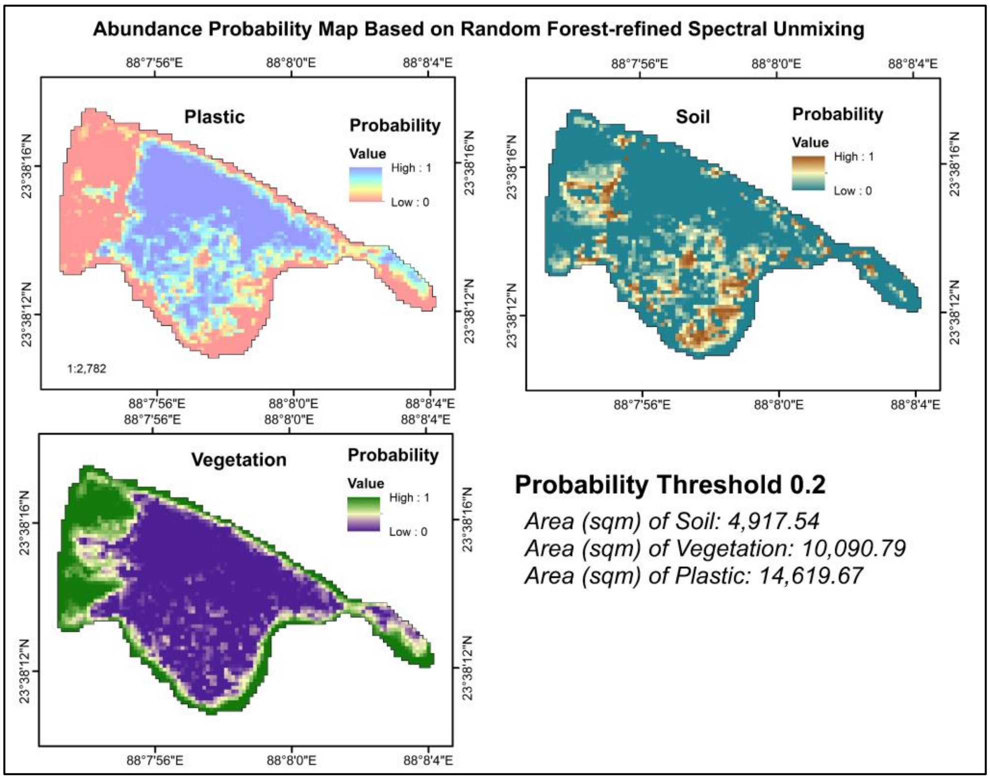

Figure 4. Abundance probability map of Katwa landfill site based on random forest refined-linear spectral unmixing method
Source: own study based on PlanetScope SuperDove 8-band satellite imagery

With the LSU method, an overestimation of soil and plastic materials, and an underestimation of vegetation cover, can be noticed. On the other hand, RF-LSU has produced comparatively reliable and ecologically realistic class proportions. Because of the predominant characteristics of linear mixing and spectral confusion, the refinement helped in producing better results (Table 3).

Table 3: Comparison of validation outputs of LSU and RF

Layer	Method	Accuracy	Kappa	Sensitivity	Specificity	Balanced Accuracy
Plastic	RF + LSU	0.9667	0.9315	1.0000	0.9444	0.9722
Plastic	LSU only	0.7000	0.4444	1.0000	0.5000	0.7500
Vegetation	RF + LSU	0.7000	0.4444	1.0000	0.5714	0.7857
Vegetation	LSU only	0.6333	0.0000	NA	0.6333	NA
Soil	RF + LSU	0.7333	0.1489	0.1111	1.0000	0.5556
Soil	LSU only	0.7667	0.4928	0.7778	0.7619	0.7698

Source: own study based on PlanetScope SuperDove 8-band satellite imagery and field survey, 2025

Random forest refinement method helped to reduce spectral confusion, especially between Plastic and Vegetation, where the sole LSU method misclassified the mixed pixels. It also improves accuracy by cutting down on false positives, though sometimes it may reduce sensitivity when class signals are weak, as seen in Soil. The LSU method on its own is simpler, but it often overestimates class presence in mixed pixels. It does not perform well for Vegetation, probably because of spectral overlap with Soil or Plastic, though it works moderately well for Soil detection.

The combined RF + LSU approach has been observed to be effective when the classes have distinct spectral signatures, such as Plastic, while LSU alone works better for the classes with mixed or continuous spectral responses, such as Soil. However, Vegetation detection tends to suffer without RF, likely because LSU assigns lower and more spread-out probabilities, which leads to missed detections at a fixed threshold.

Discussion

The analysis of the landfill site shows that area expansion over time is continuous. The shape of the landfill, however, has undergone more compact and regular forms in 2021 but more complex and irregular shapes in both 2017 and 2025. This is supported by the compactness metric, which suggests more regulated management during that period, considering it was highest in 2021. The fractal dimension and elongation ratio showed constant moderate shape complexity with time. This suggests that landfill management peaked around 2021 and was regulated, but by 2025 some inefficient expansion, or suboptimal waste management practices, caused irregular growth.

The analysis of waste composition confirms the relevance of taking into account the issue of spectral mixing in the assessment of inhomogeneous landfill surfaces based on multispectral remote sensing. The results of comparing traditional linear spectral unmixing and random forest-aided linear spectral unmixing methods yielded significant estimates of plastic, soil, and vegetation. LSU calculated the area covered with plastic in the amount of 13658.81 m^2, soil of 13825.89 m^2, and vegetation being only 2143.30 m^2, while RF-LSU produced a more precise and detailed estimate of composition of waste materials. The considerable difference in the estimates of vegetative cover and soil suggests that it is very challenging to segregate the materials that overlap spectrally. Results indicate that LSU might overestimate the concerned endmembers due to spectral confusion and misclassification of mixed pixels. These findings show that the RF-LSU approach offers a more accurate and balanced depiction of land cover in complex landfill environments, whereas LSU alone overstates plastic and soil cover at the expense of vegetation (Table 3).

Because of the predominant characteristics of linear mixing and spectral confusion, the refinement helped in producing better results (Table 3). Upon comparing with prior studies, it becomes evident that landfill development is mainly influenced by the rise in municipal solid waste production and the lack of efficient waste management methods (Sharma & Rajendra, 2025). Moreover, recent research has shown that by using remote sensing and combining it with machine learning methods, waste composition and landfill characterization can be vastly improved (Papale et al., 2023). However, the Katwa Municipality landfill has not been subject to such thorough evaluation. Thus, this research seeks to investigate this problem by performing the first integrated evaluation of the landfill's changes, geometry, and composition through multispectral imagery and machine learning methods in order to offer certain evidence for effective landfill management.

Conclusions

From the site-specific assessment of change over the time it can be concluded that the site has rapidly expanded over short span of time from 18,185.83 m^2 in 2017 to 29,628 m^2 in 2025 and will continue to grow, hence relocation of new site or treatment plant might be required. The rapid growth indicates the exponential increment of waste generation and demand for disposal. Which further aggravated by lack of sanitary landfills and over dependencies upon open waste dumping. Although there was a temporary improvement noticed in the site in the year of 2021 which can be assumed from better geometric regularity at that time, but by 2025, the site expanded irregularly, indicating possible lapses in planning and waste disposal control. Although the pattern of geometric change is somewhat fluctuated over time, the overall pattern indicating towards mismanagement, losing compactness and regularity.

From both the analysis linear spectral unmixing, LSU refined with random forest method and field observation it is pretty much evident that the amount of plastic material is overwhelming in different manner whether the material is fully composed of the plastic or only covered by the plastic it has a great environmental and public health implications through plastic and microplastic pollutions in different environmental mediums and among the organisms. Since plastic materials have a lower density than other waste components, they tend to remain or resurface in the upper layers of dumpsites, particularly after rainfall-induced leachate flow and waste rearrangement. On the contrary very limited vegetation or natural cover has been observed which indicate a low site restoration potential for future, and low mitigation efficiency of this natural cover from the impact of this pollution upon the environment. The mixed pixel effects in the LSU show that various material classes may overlap in space, but the fact that soil class and plastic class are the most common means that we need systems for separating, recycling, and composting these materials right away. For the detection of plastic and vegetation, the combination of RF and LSU performed better because it increases the reliability of the results and lowers misclassification. On the other hand, LSU alone may work better for Soil, but this came with the problem of producing more false positives in other classes. Therefore, the choice of method should depend on the characteristics of each class and whether it is more acceptable for the application to deal with overprediction or underprediction.

Acknowledgements

The author(s) gratefully acknowledge the Department of Geography, Adamas University, for their valuable support and for providing access to departmental facilities, which greatly assisted in the preparation of this manuscript. The authors would like to thank Planet Labs for providing the PlanetScope SuperDove 8-band satellite imagery used in this study.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The work was not sponsored by any organization.

Data Availability

The datasets generated during the current study are available from the corresponding author on reasonable request.

Use of generative AI and AI-assisted technologies

Generative AI tools were used only for language editing and grammar improvement during the preparation of this manuscript. The authors reviewed and approved all final content.

References

Altarez R.D., Zulkarnain N.A., Rusmi H. (2026). The potential of GIS and multi-platform remote sensing for dynamic landfill airspace monitoring: A systematic review of trends, applications and opportunities. Multimedia Tools and Applications, 85(6), 526. https://doi.org/10.1007/s11042-026-21481-6.

Belgiu M., Drăgu L. (2016). Random forest in remote sensing: A review of applications and future directions. ISPRS Journal of Photogrammetry and Remote Sensing, 114, 24–31. https://doi.org/10.1016/j.isprsjprs.2016.01.011.

Bhajantri V.N., Das S., Mandpe A. (2026). Towards sustainable waste management: A systematic PRISMA review of environmentally responsible landfill siting. Waste Management & Research: The Journal for a Sustainable Circular Economy. https://doi.org/10.1177/0734242X261438670.

Cohen J.E., Gillis N. (2018). Spectral Unmixing With Multiple Dictionaries. IEEE Geoscience and Remote Sensing Letters, 15(2), 187–191. https://doi.org/10.1109/LGRS.2017.2779477.

Esposito G., Matano F., Sacchi M. (2018). Detection and Geometrical Characterization of a Buried Landfill Site by Integrating Land Use Historical Analysis, Digital Photogrammetry and Airborne Lidar Data. Geosciences, 8(9), 348. https://doi.org/10.3390/geosciences8090348.

Ghasemi M., Latifi H., Shafeian E., Naghavi H., Pourhashemi M. (2024). A novel linear spectral unmixing-based method for tree decline monitoring by fusing UAV-RGB and optical space-borne data. International Journal of Remote Sensing, 45(4), 1079–1109. https://doi.org/10.1080/01431161.2024.2305630.

Ghosh C., Pal S.C. (2017). Municipal solid waste management scenario and its mitigation measures of Katwa municipality, Bardhaman, West Bengal. Asian Journal of Research in Social Sciences and Humanities, 7(7), 303. https://doi.org/10.5958/2249-7315.2017.00388.4.

Götze R., Pivnenko K., Boldrin A., Scheutz C., Astrup T.F. (2016). Physico-chemical characterisation of material fractions in residual and source-segregated household waste in Denmark. Waste Management, 54, 13–26. https://doi.org/10.1016/j.wasman.2016.05.009.

Hussein M.T., Loni O.A., Alrehaili A.M. (2008). Geo-Environmental Assessment of a Landfill Site Southeast of Riyadh, Saudi Arabia. The 3rd International Conference on Water Resources and Arid Environments (2008) and the 1st Arab Water Forum. https://icwrae-psipw.org/papers/2008/Environment/16.pdf.

Joelsson S.R., Benediktsson J.A., Sveinsson J.R. (2005). Random forest classifiers for hyperspectral data. International Geoscience and Remote Sensing Symposium (IGARSS), 1, 4. https://doi.org/10.1109/IGARSS.2005.1526129.

Karmakar N.C., Ballav J., Hazra A. (2021). Roadside Vegetation in and Around the Megacity of Kolkata Along an Urbanisation Gradient. Acta Botanica Hungarica, 63(1–2), 77–86. https://doi.org/10.1556/034.63.2021.1-2.6.

Kathirvelu K., Yesudhas A.V.P., Ramanathan S. (2023). Spectral unmixing based random forest classifier for detecting surface water changes in multitemporal pansharpened Landsat image. Expert Systems with Applications, 224, 120072. https://doi.org/10.1016/J.ESWA.2023.120072.

Li X., Wang Y., Zhang Y., Hou S., Zhou P., Wang X., Du Y., Foody G.M. (2023). Unmixing-Based Spatiotemporal Image Fusion Based on the Self-Trained Random Forest Regression and Residual Compensation. IEEE Transactions on Geoscience and Remote Sensing, 61. https://doi.org/10.1109/TGRS.2023.3308902.

Liu Y., Chen X., Liu D. (2020). How Does Urban Spatial Structure Affect Economic Growth? Evidence from Landsat Data in China. Journal of Economic Issues, 54(3), 798–812. https://doi.org/10.1080/00213624.2020.1787062.

Lv Y., Sun L., Tang H. M. (2009). Extracting impervious surface distribution and changing information of Shenyang. 2009 Joint Urban Remote Sensing Event, 1–5. https://doi.org/10.1109/URS.2009.5137599.

Mello C.C. de S., Salim D.H.C., Simões G.F. (2022). UAV-based landfill operation monitoring: A year of volume and topographic measurements. Waste Management, 137, 253–263. https://doi.org/10.1016/j.wasman.2021.11.020.

Mitab B.T., Hamdoon R.M., Sayl K.N. (2023). Assessing Potential Landfill Sites Using GIS and Remote Sensing Techniques: A Case Study in Kirkuk, Iraq. International Journal of Design & Nature and Ecodynamics, 18(3), 643–652. https://doi.org/10.18280/ijdne.180316.

Mohammedshum A.A., Gebresilassie M.A., Rulinda C.M., Kahsay G.H., Tesfay M.S. (2014). Application of geographic information system and remotesensing in effective solid waste disposal sites selection in Wukro Town, Tigray, Ethiopia. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences – ISPRS Archives, 40(2), 115–119. https://doi.org/10.5194/ISPRSARCHIVES-XL-2-115-2014.

Nyachiro A., Mgala M. (2024). Mapping Population Densities and Waste Management Systems in Mombasa County: A Literature Review of GIS and Remote Sensing Techniques. International Journal of Innovative Research and Development. https://doi.org/10.24940/IJIRD/2024/V13/I6/JUN24050.

Papale L.G., Guerrisi G., De Santis D., Schiavon G., Del Frate F. (2023). Satellite Data Potentialities in Solid Waste Landfill Monitoring: Review and Case Studies. Sensors, 23(8), 3917. https://doi.org/10.3390/s23083917.

Patton D.R. (1975). A Diversity Index for Quantifying Habitat "Edge" on JSTOR. Wildlife Society Bulletin (JSTOR), 3(4), 171–173. https://www.jstor.org/stable/3781151.

Poona N.K., Ismail R. (2013). Reducing hyperspectral data dimensionality using random forest based wrappers. 2013 IEEE International Geoscience and Remote Sensing Symposium – IGARSS, 1470–1473. https://doi.org/10.1109/IGARSS.2013.6723063.

Pour A.B., Ranjbar H., Sekandari M., Abd El-Wahed M., Hossain M. S., Hashim M., Yousefi M., Zoheir B., Wambo J.D.T., Muslim A.M. (2023). Remote sensing for mineral exploration. In: Geospatial Analysis Applied to Mineral Exploration, pp. 17–149. Elsevier. https://doi.org/10.1016/B978-0-323-95608-6.00002-0.

Powell R.L., Roberts D.A. (2008). Characterizing Variability of the Urban Physical Environment for a Suite of Cities in Rondônia, Brazil. Earth Interactions, 12(13), 1–32. https://doi.org/10.1175/2008EI246.1.

Priem F., Okujeni A., van der Linden S., Canters F. (2016). Use of multispectral satellite imagery and hyperspectral endmember libraries for urban land cover mapping at the metropolitan scale. Remote Sensing Technologies and Applications in Urban Environments, 10008, 13. https://doi.org/10.1117/12.2240929.

Ravish P. (2025). Sustainable Management of Landfill Sites in India: Addressing Environmental, Health, and Socioeconomic Challenges. Current World Environment, 20(1), 19–34. https://doi.org/10.12944/CWE.20.1.3.

Reddy C.M., Asadi S.S. (2024). Solid Waste Disposal Site Selection Using Geospatial Technology: A Comprehensive Study. Advances in Environmental Sustainability, Energy and Earth Science, 187–200. https://doi.org/10.1007/978-3-031-73820-3_14.

Ruiz del Portal F.R., Salazar J.M. (2003). Shape index in metric spaces. Fundamenta Mathematicae, 176(1), 47–62. https://doi.org/10.4064/FM176-1-4.

Segl K., Roessner S. (1999). Pixel-oriented selection of endmember combinations for linear stochastic spectral unmixing applied to urban environments. In: M.R. Descour, S.S. Shen (ed.), International Journal of Remote Sensing, 22(7), 327–338. https://doi.org/10.1117/12.366295.

Sharma K., Rajendra A. (2025). Remote-Sensing Applications for Monitoring and Analysis of Waste Disposal Sites Using Satellite Images: A Review. Transactions in GIS, 29(8). https://doi.org/10.1111/tgis.70175.

Shevchuk O.V., Azimov O.T., Tomchenko O.V. (2021). Remote sensing monitoring of the landfill sites as a factor of adverse environmental impact. Geoinformatics, 1–7. https://doi.org/10.3997/2214-4609.20215521054.

Small C. (2001). Multiresolution analysis of urban reflectance. IEEE/ISPRS Joint Workshop on Remote Sensing and Data Fusion over Urban Areas (Cat. No.01EX482), 15–19. https://doi.org/10.1109/DFUA.2001.985717.

State Environment Plan 2021, West Bengal Based on District Environment Plans 2021. (n.d.).

Theres B.L., Karuppusamy B., Salvakumar R. (2023). GIS based solid waste management – a case study of Nagercoil municipality, Tamil Nadu. https://doi.org/10.3390/IECG2022-14144.

Tripathi D.K., Kumar M., Biswas V. (2022). Spatial Modelling for Municipal Solid Waste Management Using Remote Sensing and Geographic Information System. Advances in Geographical and Environmental Sciences, 483–497. https://doi.org/10.1007/978-981-16-7731-1_25.

Yan-guang C. (2006). Fractal measurement of urban boundaries and compactness or circularity ratios of cities (2006). Journal of Northeast Normal University, 126–131. https://scispace.com/papers/fractal-measurement-of-urban-boundaries-and-compactness-or-5jmpniaca8.

Zorpas A.A., Lasaridi K., Voukkali I., Loizia P., Chroni C. (2015). Household waste compositional analysis variation from insular communities in the framework of waste prevention strategy plans. Waste Management, 38, 3–11. https://doi.org/10.1016/j.wasman.2015.01.030.