Journal of
Environment
(JE)

Remote Sensing and Ensemble Machine Learning for Illegal Dumpsite Susceptibility Mapping: A Review



CARI Journals

Journal of Environment
ISSN 2789-3863 (Online)
Vol. 6, Issue No. 4, pp 35 – 55, 2026
www.carijournals.org

Remote Sensing and Ensemble Machine Learning for Illegal Dumpsite Susceptibility Mapping: A Review

Ijaware Victor Ayodele[1], Ogunlade Simeon Oluwole[2], Salifu Joshua Ojotule[3*]

[1,2,3]Department of Surveying and Geoinformatics, Federal University of Technology Akure

https://orcid.org/0009-0008-8367-6781

Accepted: 14th Oct, 2026, Received in Revised Form: 24th Oct, 2026, Published: 8th Nov, 2026

Abstract

Purpose: This review asks whether, and under what conditions, combining satellite remote sensing with machine learning, and ensemble learning in particular, improves the mapping of illegal-dumpsite susceptibility, and where the evidence for that claim is still missing, with emphasis on sub-Saharan Africa and Nigeria.

Methodology: A structured narrative review with a non-systematic, purposive selection of studies was carried out. Candidate studies published from 2000 to 2026 were identified through targeted keyword searches of scholarly databases and search engines (Google Scholar, Scopus-indexed journals and African Journals Online), combining dumping terms (illegal dump, illegal landfill, dumpsite) with remote-sensing, susceptibility and machine-learning terms, and through citation chasing from recent surveys. Empirical studies that detected dumpsites or mapped dumping susceptibility with remote-sensing or GIS predictors and reported a validation outcome were included, and each was appraised for source type and validation design. Twenty-one empirical studies (16 international detection and susceptibility studies and 5 Nigerian studies) were synthesised, supported by methodological literature.

Findings: Susceptibility studies outside Africa report strong discrimination with comparatively simple models (logistic regression, overall accuracy 92–94%; discriminant analysis, AUC 0.97–0.98), and the largest head-to-head comparison (seven classifiers on the same data) found AUC values within a narrow range (0.86–0.89). The two African susceptibility studies (Dakar, Blantyre) used expert-weighted multicriteria analysis rather than machine learning. Only one study used spatial cross-validation, none used a stacking ensemble, and no Nigerian study has modelled susceptibility predictively.

Unique Contribution to Theory, Policy and Practice: Unlike recent surveys that focus on detecting waste in imagery, this review compares susceptibility-mapping methods on their reported performance and validation practice, maps the regional evidence gap for Nigeria, and sets out minimum standards (simple-model baselines, spatial validation and treatment of pseudo-absences) that future ensemble studies must meet before ensembles can be recommended to waste-management authorities.

Keywords: *Illegal Dumping, Susceptibility Mapping, Remote Sensing, Ensemble Learning, Stacking, SVM, Random Forest, XGBoost*

Journal of Environment
ISSN 2789-3863 (Online)
Vol. 6, Issue No. 4, pp 35 – 55, 2026
www.carijournals.org

1. Introduction

Solid waste is one of the most persistent by-products of human activity, and its improper disposal has become an escalating environmental challenge in low- and middle-income countries. Rapid urbanization, population growth, changing consumption patterns and weak waste governance have combined to increase both the volume of waste generated and the frequency with which it is deposited in unregulated locations (Kaza, Yao, Bhada-Tata, & Van Woerden, 2018; United Nations Environment Programme [UNEP], 2024). Where collection systems are inadequate or enforcement is weak, waste is routinely discarded along roadsides, drainage channels, vacant plots and riverbanks, creating illegal dumpsites that degrade soil and water quality, contribute to air pollution through open burning and create breeding grounds for disease vectors (Ferronato & Torretta, 2019; Giusti, 2009; Vaverková, 2019).

Conventional monitoring approaches—manual inspection, patrols and complaint-driven reporting—are costly, spatially limited and reactive. Satellite remote sensing, particularly freely available medium-resolution platforms such as Sentinel-2 and Landsat, combined with geospatial modelling, has emerged as a lower-cost complement to manual surveillance (Fraternali et al., 2024). A second line of work goes beyond finding existing dumpsites and asks where dumping is likely to occur, producing susceptibility maps that can be used for prevention (Glanville & Chang, 2015; Quesada-Ruiz, Rodriguez-Galiano, & Jordá-Borrell, 2019).

Machine learning, and ensemble learning in particular, is increasingly proposed for this second task. Whether ensembles actually improve susceptibility maps, by how much, and in which settings has not been examined systematically. The existing literature is uneven: many studies are descriptive, are confined to single cities, rely on a single model, or report accuracy without a validation design that tests transfer to new places. A review that weighs this evidence is therefore needed before any particular framework can be recommended for operational use in Nigeria or elsewhere in West Africa.

This review addresses four questions:

- **RQ1.** What remote-sensing data and predictors have been used to detect illegal dumpsites and to map dumping susceptibility, and what do they contribute?
- **RQ2.** Which modelling approaches—expert multicriteria analysis, statistical models, machine-learning classifiers and ensembles—have been applied, and how do their reported performances compare?
- **RQ3.** How have these models been validated, and how well do studies address pseudo-absences, class imbalance, spatial autocorrelation, data leakage and interpretability?
- **RQ4.** What is the state of this evidence in Nigeria and comparable African settings, and what research is needed to close the gaps?

Section 2 describes the review method. Sections 3–5 address RQ1 and RQ2, Section 6 examines ensemble learning, Section 7 addresses RQ3, Section 8 addresses RQ4, and Sections 9–12 set out the research gap, policy implications, research priorities and conclusions.

2. Review Methodology

2.1 Design

The study is a structured narrative review with a non-systematic, purposive selection of studies. A systematic review was not attempted for three reasons. First, the literature on illegal-dumping susceptibility is small and dispersed across remote sensing, waste management, geography and computer-science venues, and it uses inconsistent terms (illegal landfill, open dump, dumpsite, waste pile, potential illegal dump site), so that fixed Boolean strings applied to one or two databases miss relevant studies while returning many irrelevant ones. Second, much of the Nigerian and African evidence appears in regional journals and theses that are not indexed in Scopus or Web of Science. Third, the included studies report non-comparable outcomes (overall accuracy, area under the ROC curve [AUC], F1-score, success rates and capture rates) on different units (pixels, grid cells, sites and image scenes), so a meta-analysis, the main reason for an exhaustive systematic search, would not be possible. The aim was therefore to assemble the evidence needed to answer RQ1–RQ4 and to appraise it transparently, rather than to enumerate every record.

2.2 Scope

The literature scope covered three topics: (i) remote-sensing-based detection of illegal dumpsites and uncontrolled landfills; (ii) susceptibility, risk or probability mapping of illegal dumping; and (iii) the classifiers and ensemble methods used for these tasks. Topics (i) and (ii) were searched globally, with targeted coverage of sub-Saharan Africa and Nigeria. Methodological sources on classifiers, ensembles and validation were not restricted by domain and are cited for definitions and methodological standards only, not as evidence of performance in dumpsite mapping.

2.3 Information sources and search terms

Candidate studies were identified through targeted keyword searches of Google Scholar, Scopus-indexed journals and African Journals Online, covering publications from 2000 to 2026 and last updated in November 2026. Backward and forward citation searching was carried out from two anchor reviews (Fraternali et al., 2024; Glanville & Chang, 2015) and from each included study. The following combinations of terms guided the searches:

- S1 (detection): (“illegal dump*” OR “illegal landfill*” OR “open dump*” OR dumpsite* OR “dump site*”) AND (“remote sensing” OR satellite OR Sentinel OR Landsat OR aerial)

- S2 (susceptibility): ("illegal dump*" OR "illegal landfill*") AND (susceptib* OR risk OR probabilit* OR potential OR predict*) AND (GIS OR "machine learning" OR "random forest" OR "support vector" OR XGBoost OR "logistic regression" OR AHP)
- S3 (Nigeria): (dumpsite* OR "dump site*" OR "solid waste") AND (GIS OR "remote sensing" OR geospatial) AND Nigeria

2.4 Eligibility criteria

Studies were included if they were empirical, addressed illegal or uncontrolled dumping (detection or susceptibility), used remote-sensing and/or GIS-derived predictors, and reported a method together with at least one validation outcome. Studies that explicitly reported no independent validation were retained only where they were among the few African susceptibility studies, so that the validation gap could be documented. Studies were excluded if they addressed only sanctioned landfill siting, marine or floating debris, or waste-item recognition in ground-level photographs. For the Nigerian evidence base (Table 2), siting and descriptive mapping studies were retained because they are the only geospatial dumpsite studies available nationally; they are labelled as such and are not used to support claims about predictive performance. Only English-language records were considered.

2.5 Quality appraisal

Each included study was appraised on four criteria: (a) source type (international peer-reviewed journal, national or regional peer-reviewed journal, or grey literature such as a thesis); (b) whether the number of verified dumpsites used for training or testing was reported; (c) validation design (none, random split or internal cross-validation, or spatially or temporally independent test data); and (d) whether a quantitative performance metric was reported. Grey literature was retained only for the Nigerian context and is flagged in Table 2.

2.6 Study selection

Twenty-one empirical studies met the criteria: 16 international detection and susceptibility studies (Table 1) and 5 Nigerian studies (Table 2). Because the selection was purposive, the number of records retrieved and screened is not reported, and the review cannot claim to include every eligible study. Two steps were taken to limit selection bias. First, studies were included on the eligibility criteria above regardless of their findings, so that studies reporting weak or no validation (e.g. Scharf et al., 2025) and studies favouring simple models (e.g. Quesada-Ruiz et al., 2018, 2019) are represented alongside machine-learning studies. Second, searching continued until new searches and citation chasing returned no further eligible studies. Readers should treat the synthesis as a structured overview of the main evidence rather than an exhaustive census.

3. Remote Sensing in Solid-Waste and Illegal-Dumping Monitoring

Remote sensing has become central to solid-waste research because it allows repeated, synoptic and relatively inexpensive observation of large areas. A recent survey identified the 50 most relevant studies on detecting, monitoring and mapping solid waste in remote-sensing images and reviewed 23 Earth-observation satellites and four public datasets used for these tasks (Fraternali et al., 2024). Sentinel-2 and Landsat are attractive in developing-country contexts because they are free, revisit regularly and cover large areas without the cost of commercial very-high-resolution imagery; free access has been a major driver of Sentinel-2 use in developing countries (Phiri et al., 2020).

Detecting illegal dumping directly from imagery remains difficult. Dumpsites are often small, irregular, short-lived and spectrally similar to bare soil, construction debris and other disturbed peri-urban surfaces. Glanville and Chang (2015) concluded that medium-resolution imagery alone rarely resolves small domestic dumps, and susceptibility studies consistently find that non-spectral, contextual variables distance to roads, drains and rivers, land-use transitions and industrial activity carry most of the predictive information (Das & Morshed, 2026; Mvula et al., 2025; Quesada-Ruiz, Rodriguez-Galiano, & Jordá-Borrell, 2018; Seror & Portnov, 2018). This is a key reason for the shift from direct detection toward susceptibility modelling.

Sensor and band choice still matter. Sentinel-2's Multispectral Instrument provides 10 m visible and near-infrared bands and a five-day combined revisit, whereas Landsat's reflective bands are 30 m; reviews of land-cover mapping report accuracies above 80% for Sentinel-2 with SVM and RF classifiers (Phiri et al., 2020). The resolution advantage is smaller than it first appears for waste applications, however, because Sentinel-2's short-wave infrared (SWIR) bands (B11 and B12) are recorded at 20 m. SWIR is useful because plastics and other synthetic hydrocarbons have characteristic absorption features in this region (Garaba & Dierssen, 2018), but at 20 m most dumps occupy only a few mixed pixels, so SWIR evidence is usually indirect. Vegetation indices such as NDVI (Rouse, Haas, Schell, & Deering, 1974) flag the vegetation suppression that often surrounds dumps. For surface moisture, the relevant index is the NIR–SWIR normalised difference water index of Gao (1996); the green–NIR index of McFeeters (1996) delineates open water and is better suited to mapping proximity to water bodies than to detecting waste. Landsat's thermal band and archive extending back to the 1970s support multi-temporal analysis; thermal anomalies have been used to locate active dumping within landfills (Gill, Faisal, Shaker, & Yan, 2019), and land surface temperature was a predictor in both African susceptibility studies (Mvula et al., 2025; Scharf et al., 2025). Grey-level co-occurrence matrix texture (Haralick, Shanmugam, & Dinstein, 1973) can capture the heterogeneous surface pattern of waste accumulations.

Where performance has been reported for medium-resolution detection, it varies with the target and the reference data. A Sentinel-2 random forest classification in Oaxaca, Mexico reported an overall accuracy of about 95% (Gómez Maturano, Mendoza Santana, Aguilar García, & Serna

Hernández, 2024), and neural networks applied to Sentinel-2 time series found more than twice as many waste sites in Indonesia as were listed in public databases (Kruse et al., 2023). Very-high-resolution imagery with deep learning gives finer results (Sun et al., 2023; Torres & Fraternali, 2021) but at higher data cost (Table 1).

4. Susceptibility Mapping as a Preventive Geospatial Approach

Rather than asking only where dumpsites already exist, susceptibility mapping asks where the landscape is more favourable to illegal dumping, based on accessibility, land use, settlement, terrain and opportunity. This framing is useful where no complete inventory of dumpsites exists or where dumping locations shift over time. Dumping is rarely random: it tends to cluster in accessible but weakly monitored spaces such as roadside corridors, drainage margins and peri-urban vacant land, which is consistent with Tobler's (1970) first law of geography and with the significant road, ravine and river effects reported in several studies (Mvula et al., 2025; Seror & Portnov, 2018).

Susceptibility mapping has a longer history outside Africa than the original version of this review acknowledged. In Japan, Tasaki et al. (2007) zoned illegal-dumping potential to make surveillance more efficient. In Italy, Biotto et al. (2009) combined multicriteria and multi-factor GIS analysis to estimate the probability of illegal landfills. In Andalusia, Spain, factor analysis and geostatistics placed 63.6% of 518 verified illegal landfills in the highest-probability zones (Jordá-Borrell, Ruiz-Rodríguez, & Lucendo-Monedero, 2014), and logistic regression showed that punitive policies, supervision, recycling facilities and awareness campaigns reduced the likelihood of illegal landfills (Lucendo-Monedero, Jordá-Borrell, & Ruiz-Rodríguez, 2015). In the Canary Islands, logistic regression achieved overall accuracies of 92.5–93.5% and discriminant analysis achieved AUC values of 0.97–0.98 (Quesada-Ruiz et al., 2018, 2019). In Australia, GIS data integration placed 32.9% of known sites in a very-high class that covered 6.9% of the Sunshine Coast (Glanville & Chang, 2015), and a machine-learning model of road segments in South Australia reached 85% classification accuracy (Du, Zuo, Vanzo, Chang, & Zillante, 2023). In Canada, night-time light and other remote-sensing indices were combined in a multicriteria framework to map probable dumping sites over more than 31,000 km² (Karimi, Ng, & Richter, 2022). Machine-learning susceptibility studies have since appeared in China (Geng et al., 2024), Slovenia (Hojnik, Horvat, Mongus, Brumen, & Kamnik, 2025) and Bangladesh (Das & Morshed, 2026). The search found no machine-learning susceptibility study from Latin America; the Latin American evidence located is detection-oriented (Gómez Maturano et al., 2024).

The two African susceptibility studies are relevant because their settings resemble Nigerian cities, but neither uses machine learning. In Dakar, Senegal, Scharf, Ducry, Sy, Djim and Lacroix (2025) combined remote-sensing and GIS indicators with citizen-science perceptions in an analytic hierarchy process (AHP) with ten criteria; the authors state that no independent field validation was possible. In Blantyre, Malawi—a low-resource urban setting broadly comparable to many

Nigerian cities—Mvula et al. (2025) combined MODIS land surface temperature and vegetation index, Sentinel-5P formaldehyde and distances to highways, rivers and official dumps using AHP and fuzzy overlay, and reported that about 89% of field-located illegal dumpsites fell within the predicted susceptible zones. These studies show that susceptibility mapping is feasible and useful in data-scarce African cities. They do not show that machine learning, or ensembles, would do better than expert-weighted overlay in those settings; that remains an open question.

5. Modelling Approaches and Their Reported Performance

The approaches used for dumpsite susceptibility and detection fall into five families. Their in-domain performance is summarised in Table 1.

Expert-driven multicriteria analysis. Criteria weights are set by experts or stakeholders, most often through AHP (Saaty, 1980), and layers are combined by weighted overlay. The approach needs no inventory of dumpsites, which explains its use in Dakar and Blantyre, but its weights cannot be estimated or tested from data, and validation is often limited (Mvula et al., 2025; Scharf et al., 2025).

Statistical models. Bivariate methods such as frequency ratio (Lee & Pradhan, 2007), and multivariate methods such as logistic regression, discriminant analysis and factor analysis, estimate the relationship between predictors and known dumpsites. They are interpretable and, in the Spanish studies, accurate (Jordá-Borrell et al., 2014; Quesada-Ruiz et al., 2018, 2019). Presence-only methods such as maximum entropy modelling (MaxEnt; Phillips, Anderson, & Schapire, 2006) are standard for the analogous problem of species distribution, where only presences are known; the search found no dumpsite application of MaxEnt, which is itself a gap.

Machine-learning classifiers. Support Vector Machine (SVM) defines nonlinear class boundaries in high-dimensional feature spaces through kernel functions (Hearst, Dumais, Osuna, Platt, & Schölkopf, 1998; Mountrakis, Im, & Ogole, 2011). Random Forest (RF) is an ensemble of decision trees built through bootstrap aggregation and random feature selection; it is robust to noise and provides variable-importance measures (Belgiu & Drăguţ, 2016; Breiman, 2001). Extreme Gradient Boosting (XGBoost) builds trees sequentially with regularisation and often gives strong predictive performance on tabular data (Chen & Guestrin, 2016). RF and XGBoost are therefore already ensembles of trees.

Positive–unlabelled (PU) learning. Because confirmed absences of dumping are rarely available, several recent studies treat unsampled locations as unlabelled rather than as true negatives and train repeated classifiers on random unlabelled subsets (Elkan & Noto, 2008). This approach was used in Jiangsu, China (Geng et al., 2024), Maribor, Slovenia (Hojnik et al., 2025) and Khulna, Bangladesh (Das & Morshed, 2026).

Deep learning. Convolutional neural networks dominate image-based detection, particularly with very-high-resolution or aerial imagery (Sun et al., 2023; Torres & Fraternali, 2021), and have been

applied to Sentinel-2 time series at regional scale (Kruse et al., 2023). They have not yet been used for susceptibility mapping from tabular predictors in the studies reviewed.

Table 1. Empirical studies of illegal-dumpsite detection and susceptibility mapping and their reported performance

Study	Location	Task; data and predictors	Method(s)	Validation design	Reported performance
Jordá-Borrell et al. (2014)	Andalusia, Spain	Susceptibility; 518 verified illegal landfills; geographic factors	Factor analysis + geostatistical model in GIS	Overlay of verified landfills on probability zones	63.6% of landfills in highest-probability zones
Glanville & Chang (2015)	Sunshine Coast, Australia	Susceptibility; predictive spatial layers	GIS data integration; class intervals	Known sites compared with classes	32.9% of known sites in very-high class covering 6.9% of area
Seror & Portnov (2018)	Haifa district, Israel	Susceptibility (construction and demolition waste); road distance, ravine depth, forest proximity	Geostatistical regression in GIS	Significance of predictors; no independent test	Road distance and ravine depth ($p < 0.01$), forest proximity ($p < 0.05$) significant
Quesada-Ruiz et al. (2018)	La Palma and Gran Canaria, Spain	Susceptibility; 153 and 286 field-verified landfills; 177 candidate features	PCA + binary logistic regression	Classification of presences and absences	Overall accuracy 93.5% (La Palma), 92.5% (Gran Canaria)
Quesada-Ruiz et al. (2019)	La Palma and Gran Canaria, Spain	Susceptibility; as above, including NDVI and slope	Discriminant analysis	ROC curve; success-rate curve	AUC 0.973 and 0.979; 81.6% and 87.3% of landfills in about 22% and 20% of area
Zhou et al. (2021)	China	Detection of construction-waste dumps; Sentinel-2 in Google Earth Engine	CART, RF, SVM (tuned)	Accuracy assessment with ground verification	Accuracy for the waste class: RF 98.05%, SVM 85.62%, CART 73.12%

Study	Location	Task; data and predictors	Method(s)	Validation design	Reported performance
Torres & Fraternali (2021)	Italy	Detection; about 3,000 aerial images at 20 cm	CNN scene classifier (ResNet50 + FPN)	Held-out test set	F1 88.2%; precision 88.6%; recall 87.7%
Du et al. (2023)	South Australia	Susceptibility of road sections; dumping records and road characteristics	Machine-learning classifier	Classification accuracy	Accuracy up to 85%
Kruse et al. (2023)	Indonesia and Southeast Asia	Detection of terrestrial waste sites; Sentinel-2 time series	Neural-network system	Comparison with public databases; confirmation of detections	374 sites in Indonesia (>2× public records); 996 confirmed sites region-wide
Sun et al. (2023)	28 cities worldwide	Detection; high-resolution optical imagery	Deep CNN detector	Detections in sampled city areas	About 1,000 dumpsites detected; >96.8% less investigation time than manual search
Geng et al. (2024)	Jiangsu, China	Susceptibility (hazardous waste); 214 training and 185 test sites; 7 predictors; 1 km grid	PU-bagging ensembles (KNN, RF, MLP, LR, DT) vs. discriminant analysis	Temporal hold-out (later-year cases)	AUC 0.65–0.73; top 30% risk area held 68.1% of new sites (PU-RF) vs. 53% (DA)
Gómez Maturano et al. (2024)	Oaxaca, Mexico	Detection; Sentinel-2 bands, NDVI, MNDWI, SAVI, NDBI, BSI, slope	RF	Confusion matrix	Overall accuracy 95.2%
Mvula et al. (2025)	Blantyre, Malawi	Susceptibility; MODIS LST and EVI, Sentinel-5P HCHO, distances to highways, rivers and official dumps	AHP + fuzzy weighted overlay (no ML)	Field-located dumpsites	About 89% of illegal sites identified; 10.3% of area "very high"

Study	Location	Task; data and predictors	Method(s)	Validation design	Reported performance
Hojnik et al. (2025)	Maribor, Slovenia	Susceptibility; 150 to 463 field sites over three iterations; UAV, LiDAR and land-use layers	Isolation Forest, One-Class SVM and PU classifier; majority vote	Bootstrap recall; K-fold quasi-AUC	Recall and quasi-AUC reported; high-risk area shrank as the inventory grew
Scharf et al. (2025)	Dakar, Senegal	Susceptibility; 10 criteria including LST and citizen-science perception	AHP (no ML)	No independent field validation	Sensitivity analysis only
Das & Morshed (2026)	Khulna, Bangladesh	Susceptibility; 341 sites; 12 predictors; 10 m grid	LR, SVM, KNN, MLP, RF, XGBoost, LightGBM within PU bagging	Spatial block cross-validation + hold-out	AUC 0.859–0.893 across models; RF F1 0.820, AUC 0.883; LightGBM best hold-out AUC 0.893

Note. Metrics are reported as given by the authors and are not directly comparable across studies because they differ in unit of analysis, reference data and validation design. AUC = area under the ROC curve; CART = classification and regression tree; CNN = convolutional neural network; DA = discriminant analysis; DT = decision tree; FPN = feature pyramid network; KNN = k-nearest neighbours; LR = logistic regression; LST = land surface temperature; MLP = multilayer perceptron; PCA = principal component analysis; PU = positive–unlabelled.

5.1 What the in-domain evidence shows

Three patterns emerge from Table 1. First, simple models perform well when they are given good predictors. Logistic regression and discriminant analysis achieved some of the highest reported values in the table (Quesada-Ruiz et al., 2018, 2019), although these were not tested on spatially independent data. Second, where several classifiers were compared on the same data, differences were small. In Khulna, seven classifiers fell within an AUC range of about 0.03, and the best model depended on whether cross-validation or hold-out results were used (Das & Morshed, 2026). In Jiangsu, the PU variants differed by less than 0.10 AUC, and their main advantage was over a non-ML baseline (Geng et al., 2024). Only in image-based detection did one classifier clearly dominate, with RF outperforming SVM by about 12 percentage points for construction-waste dumps (Zhou et al., 2021). Third, contextual predictors such as roads, drains, rivers and industrial land repeatedly carried the most importance (Das & Morshed, 2026; Mvula et al., 2025; Quesada-Ruiz et al., 2018;

Seror & Portnov, 2018). Together, these findings suggest that predictor engineering and validation design matter at least as much as the choice of classifier.

6. Ensemble Learning: Rationale and Evidence

A recurring argument in the remote-sensing and hazard-mapping literature is that no single classifier performs best across all conditions, because performance depends on study scale, imagery, feature engineering and landscape heterogeneity (Merghadi et al., 2020). Landscapes that combine dense urban cores, peri-urban fringes, farmland and savanna within one study area, as is common in Nigerian states, may expose this problem: a model calibrated in one part of the landscape may generalise poorly to another. Ensemble learning combines several models to reduce variance, bias or both. Wolpert's (1992) stacked generalisation trains a meta-learner on the out-of-fold predictions of several base learners, and Džeroski and Ženko (2004) showed that stacking can outperform selecting the single best classifier when no model dominates across the feature space.

Two cautions apply. First, ensembles gain most when their members make different errors (Kuncheva & Whitaker, 2003). RF and XGBoost are both tree ensembles, trained on the same predictors, and are likely to make correlated errors; a stack of SVM, RF and XGBoost therefore adds less diversity than its three names suggest. Members from different families, such as a regularised logistic regression or a presence-only model, would add more diversity. Second, the in-domain evidence for ensembles is limited. The ensembles that have been applied to dumping—PU bagging in Jiangsu and Khulna and majority voting of three one-class or PU models in Maribor (Das & Morshed, 2026; Geng et al., 2024; Hojnik et al., 2025)—were used mainly to handle unlabelled data, not to combine heterogeneous classifiers, and none was benchmarked against a stacked model. The search found no study that applied stacking of SVM, RF and XGBoost to illegal-dumping susceptibility. Evidence from adjacent hazards is mixed: in landslide susceptibility, tree-based ensembles often rank highly, but the best algorithm varies between study areas and validation schemes (Merghadi et al., 2020).

The case for stacking in dumpsite susceptibility is therefore a testable hypothesis rather than an established result. It is plausible in heterogeneous landscapes for the reasons given above, but it has to be demonstrated against simpler baselines under spatially independent validation.

7. Validation, Uncertainty and Interpretability

The reviewed studies are weakest in how models are validated. Five issues recur.

Pseudo-absences. Confirmed non-dumping locations are rarely available, so most studies generate absences from unsampled locations. How many absences are drawn, and where, changes model outputs; work on species distribution models recommends drawing pseudo-absences with deliberate rules on number and distance from presences, and reporting those rules (Barbet-Massin, Jiguet, Albert, & Thuiller, 2012). PU learning makes the problem explicit (Elkan & Noto, 2008),

and three of the most recent dumping studies adopted it (Das & Morshed, 2026; Geng et al., 2024; Hojnik et al., 2025).

Class imbalance. Dumpsites occupy a small fraction of any study area. Overall accuracy is then inflated by the majority class, and precision–recall measures, F1-score and capture rates in the highest-risk area are more informative (He & Garcia, 2009). The capture-rate measures reported in Andalusia, Queensland, the Canary Islands and Jiangsu (Table 1) are useful because they translate directly into how much area inspectors would need to patrol.

Spatial cross-validation. Dumpsites are spatially clustered, so random train–test splits place test points close to training points and overstate performance. Spatial or block cross-validation gives a more honest estimate of performance in new areas (Ploton et al., 2020; Roberts et al., 2017). Of the 16 international studies in Table 1, only Das and Morshed (2026) used spatial blocks, and only Geng et al. (2024) used a temporally independent test set.

Data leakage. Leakage occurs when information from the test data enters model training, for example when predictors are derived from the dumpsite inventory itself, when several points from the same dumpsite appear in both training and test sets, or when the meta-learner in a stacking model is trained on in-sample predictions of the base learners. Leakage has been identified as a widespread cause of over-optimistic results in machine-learning-based science (Kapoor & Narayanan, 2023). For stacking, base-learner predictions passed to the meta-learner must be generated out of fold (Wolpert, 1992).

Interpretability and uncertainty. Waste authorities need to know why an area is flagged. RF impurity-based importance is biased toward continuous and high-cardinality predictors (Strobl, Boulesteix, Zeileis, & Hothorn, 2007), so permutation importance or Shapley additive explanations (SHAP; Lundberg & Lee, 2017) are preferable, particularly for stacked models whose internal logic is otherwise opaque. None of the studies in Table 1 used SHAP. Few studies reported uncertainty, such as confidence intervals across resamples or maps of prediction variance, even though these would show where a susceptibility map is least reliable.

8. Regional and Nigerian Evidence

Nigerian scholarship has established the relevance of geospatial methods to waste management, but the published geospatial dumpsite studies located by the search are siting, descriptive mapping or impact studies rather than predictive susceptibility models (Table 2). Aderoju, Dias and Gonçalves (2020) used GIS to identify candidate sanitary landfill sites in Abuja and found that none of the existing disposal sites met the standards considered. Ogunlade, Afolabi, Akorede and Odupe (2021) applied spatial multicriteria analysis to dumpsite suitability in Ido Local Government Area, Oyo State. Ndoma, Songu and Buba (2018) mapped existing dumpsites in Kaduna South Local Government Area relative to settlements and drainage, and Yusuf (2018) analysed the spatial distribution and perceived risks of illegal dumpsites in Minna in an

unpublished master's thesis. In Lagos, Daramola and Makinde (2024) modelled air pollution around the Olusosun and Solous dumpsites using geospatial methods.

Table 2. Nigerian geospatial studies of waste-disposal sites

Study	Location (scale)	Method	Study type	Source type	Key finding
Aderoju, Dias, & Gonçalves (2020)	Abuja, FCT (city)	GIS multicriteria landfill siting	Siting	International peer-reviewed journal	Six candidate landfill sites identified; none of the existing disposal sites met the standards considered
Daramola & Makinde (2024)	Lagos (Olusosun and Solous dumpsites)	Geospatial modelling of air pollutants around dumpsites	Impact assessment	International peer-reviewed journal	Elevated particulate matter near the dumpsites; carbon monoxide within WHO guideline levels
Ndoma, Songu, & Buba (2018)	Kaduna South LGA (LGA)	GPS survey and GIS mapping	Descriptive mapping	National peer-reviewed journal	Mapped existing dumpsites relative to settlements and drainage
Ogunlade, Afolabi, Akorede, & Odupe (2021)†	Ido LGA, Oyo State (LGA)	GIS spatial multicriteria site-suitability analysis	Siting	Regional peer-reviewed journal	Identified suitable, as opposed to illegal, dumpsite locations
Yusuf (2018)	Minna, Niger State (city)	Spatial distribution and perception analysis	Descriptive mapping	Grey literature (master's thesis)	Documented spatial pattern and community-perceived risks of illegal dumpsites

Note. † Co-authored by S. O. Ogunlade, a co-author of the present review (see Declarations). Grey literature is included for national context only and is not used to support claims about model performance.

All five studies are confined to a single city or local government area. None models dumping susceptibility predictively, none reports a quantitative validation of a predictive map, and none applies machine learning. Within Africa more broadly, the only susceptibility studies located are the AHP-based studies in Dakar and Blantyre (Section 4). The Nigerian evidence base therefore establishes that geospatial methods are feasible and relevant, but it cannot yet show which modelling approach works best in Nigeria's varied landscapes.

9. Research Gap

Synthesising the evidence for RQ1–RQ4, the literature establishes that:

- contextual and terrain predictors carry much of the information needed to map dumping, and spectral data alone are insufficient at medium resolution (Sections 3 and 5);
- susceptibility mapping is operationally useful and has been applied in Europe, Asia, Australia and North America, and in two African cities using expert-weighted methods (Section 4);
- in-domain comparisons show small performance differences among classifiers, and simple statistical models can perform well (Section 5); and
- ensemble learning is theoretically motivated but has not been tested in stacked form for dumping susceptibility, and validation practice is generally weak (Sections 6 and 7).

The gap is therefore best expressed as a set of questions rather than as a case for one framework. Does ensembling, and stacking in particular, improve illegal-dumpsite susceptibility maps over well-specified simpler models? If it does, is the gain largest in heterogeneous landscapes, such as those combining urban, peri-urban, farmland and savanna zones, and does it survive spatially independent validation? Can such models be built from free medium-resolution data in a data-scarce Nigerian setting and translated into maps that waste authorities use? No study identified by this review has answered these questions for Nigeria or, with machine learning, for any African setting.

10. Policy and Decision-Making Implications

A susceptibility map has limited value unless it informs how waste-management authorities allocate resources. The reviewed literature points to four pathways.

First, susceptibility classes can be used to prioritise inspection. Tasaki et al. (2007) designed illegal-dumping zoning explicitly to make surveillance more efficient, and in Jiangsu the 30% of the area with the highest predicted risk contained 68.1% of newly reported dumping sites (Geng et al., 2024). Second, the maps can inform the siting of legal collection points and transfer stations: where formal disposal is far away or unaffordable, informal dumping fills the gap, and in Ibadan only 23% of surveyed residents reported government waste collection, while 17% reported dumping waste in gutters and 22% reported burning it (Jazat, Akande, & Ogunbode, 2023). Third, the maps can support targeted enforcement. Logistic-regression evidence from Andalusia associated supervision, punitive policies, recycling facilities and awareness campaigns with lower likelihood of illegal landfills (Lucendo-Monedero et al., 2015), and in Israel vehicle impoundment significantly increased the share of construction waste delivered to authorised sites whereas fines and criminal indictment did not (Seror & Portnov, 2020). Fourth, repeated mapping can serve as a monitoring instrument. In Maribor, field inspections guided by the model were fed back into later

model runs, so the inventory of known dumpsites grew from 150 to 463 sites over three iterations (Hojnik et al., 2025).

Susceptibility maps prioritise effort; they do not replace investment in collection infrastructure. Where collection coverage is low, as the Ibadan survey evidence suggests (Jazat et al., 2023), a susceptibility map can direct scarce enforcement resources more efficiently but cannot by itself close the service gap that drives dumping (Kaza et al., 2018; UNEP, 2024).

11. Future Research Priorities

Building on the gap identified in Section 9, seven priorities stand out:

1. **Benchmarking against simpler models.** Any ensemble should be compared on the same data with logistic regression, a single RF or XGBoost model and, where no inventory exists, an AHP or frequency-ratio baseline, so that the added value of complexity is measured rather than assumed.
2. **Spatially explicit validation and uncertainty.** Studies should use spatial block or leave-one-region-out cross-validation, a temporally independent test set where possible, and capture-rate and precision–recall metrics in addition to AUC, and should report uncertainty across resamples.
3. **Regionally calibrated feature engineering.** Studies should test which predictor combinations (SWIR bands, GLCM texture, vegetation and moisture indices, terrain and accessibility variables) contribute most in tropical, mixed land-cover settings, using permutation importance or SHAP rather than impurity-based importance alone.
4. **Transferability across landscape types.** Performance should be reported separately for dense urban, peri-urban, agricultural and savanna zones rather than as a single pooled figure, to reveal where ensemble gains, if any, are largest.
5. **Temporal and change-detection extensions.** Most studies use single-date or single-season imagery. Multi-temporal analysis that tracks the emergence, persistence and clearance of dumpsites would turn a static map into a monitoring tool, and Landsat's archive is well suited to this.
6. **Operational validation with waste-management authorities.** Studies should test whether outputs are usable within agency workflows, and identify the classification threshold and update frequency that are practically actionable, following iterative field-feedback designs such as that of Hojnik et al. (2025).
7. **Cross-country replication in West Africa.** A comparative study across several West African cities using a common protocol would show which predictors and model configurations generalise and which are location-specific, building on the Dakar and Blantyre work (Mvula et al., 2025; Scharf et al., 2025).

12. Conclusion

The reviewed literature shows a clear trajectory from descriptive uses of remote sensing for waste monitoring toward preventive susceptibility mapping and, more recently, machine learning and ensemble methods. The in-domain evidence is more modest than the methodological literature might suggest: simple statistical models perform well when given good contextual predictors, classifiers compared on the same data differ by small margins, and stacking has not yet been tested for dumping susceptibility. Validation is the weakest part of the evidence base, with spatial cross-validation and explicit treatment of pseudo-absences still rare. In Nigeria, geospatial waste studies remain siting-based or descriptive, and no predictive susceptibility model has been published. Stacking-ensemble susceptibility mapping with freely available satellite data is therefore a reasonable direction to test in environmentally heterogeneous, data-scarce settings such as southwestern Nigeria, but its value should be judged against simpler baselines under spatially independent validation before it is recommended to waste-management authorities.

Declarations

Conflict of interest and self-citation. Ogunlade et al. (2021) is co-authored by S. O. Ogunlade, a co-author of this review. The study is cited as part of the Nigerian evidence base and was appraised with the same criteria as the other included studies. The authors declare no other competing interests.

Data availability. No new data were generated. The search strings and inclusion criteria are reported in Section 2, and the extracted study characteristics are given in Tables 1 and 2.

References

Aderoju, O. M., Dias, G. A., & Gonçalves, A. J. (2020). A GIS-based analysis for sanitary landfill sites in Abuja, Nigeria. *Environment, Development and Sustainability*, *22*(1), 551–574. https://doi.org/10.1007/s10668-018-0206-z

Barbet-Massin, M., Jiguet, F., Albert, C. H., & Thuiller, W. (2012). Selecting pseudo-absences for species distribution models: How, where and how many? *Methods in Ecology and Evolution, 3*(2), 327–338.

Belgiu, M., & Drăguț, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS Journal of Photogrammetry and Remote Sensing, 114*, 24–31.

Biotto, G., Silvestri, S., Gobbo, L., Furlan, E., Valenti, S., & Rosselli, R. (2009). GIS, multi-criteria and multi-factor spatial analysis for the probability assessment of the existence of illegal landfills. *International Journal of Geographical Information Science, 23*(10), 1233–1244.

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32.

Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 785–794). ACM.

Daramola, S. O., & Makinde, E. O. (2024). Modeling air pollution around major dumpsites in Lagos State using geospatial methods with solutions. *Environmental Challenges, 16*, 100969.

Das, S., & Morshed, M. M. (2026). A GeoAI framework for detecting risk zones from illegal dumping sites in Khulna, Bangladesh. *PLOS ONE, 21*(3), e0345178. https://doi.org/10.1371/journal.pone.0345178

Du, L., Zuo, J., Vanzo, J., Chang, R., & Zillante, G. (2023). Assessing and predicting the illegal dumping risks in relation to road characteristics. *Waste Management, 169*, 332–341.

Džeroski, S., & Ženko, B. (2004). Is combining classifiers with stacking better than selecting the best one? *Machine Learning, 54*(3), 255–273.

Elkan, C., & Noto, K. (2008). Learning classifiers from only positive and unlabeled data. In *Proceedings of the 14th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 213–220). ACM.

Ferronato, N., & Torretta, V. (2019). Waste mismanagement in developing countries: A review of global issues. *International Journal of Environmental Research and Public Health, 16*(6), 1060.

Fraternali, P., Morandini, L., & Herrera González, S. L. (2024). Solid waste detection, monitoring and mapping in remote sensing images: A survey. *Waste Management, 189*, 88–102. https://doi.org/10.1016/j.wasman.2024.08.003

Gao, B.-C. (1996). NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment, 58*(3), 257–266.

Garaba, S. P., & Dierssen, H. M. (2018). An airborne remote sensing case study of synthetic hydrocarbon detection using short wave infrared absorption features identified from marine-harvested macro- and microplastics. *Remote Sensing of Environment, 205*, 224–235.

Geng, J., Ding, Y., Xie, W., Fang, W., Liu, M., Ma, Z., Yang, J., & Bi, J. (2024). An ensemble machine learning model to uncover potential sites of hazardous waste illegal dumping based on limited supervision experience. *Fundamental Research, 4*(4), 972–978. https://doi.org/10.1016/j.fmre.2023.06.010

Gill, J., Faisal, K., Shaker, A., & Yan, W. Y. (2019). Detection of waste dumping locations in landfill using multi-temporal Landsat thermal images. *Waste Management & Research, 37*(4), 386–393.

Giusti, L. (2009). A review of waste management practices and their impact on human health. *Waste Management, 29*(8), 2227–2239.

Glanville, K., & Chang, H.-C. (2015). Mapping illegal domestic waste disposal potential to support waste management efforts in Queensland, Australia. *International Journal of Geographical Information Science, 29*(6), 1042–1058. https://doi.org/10.1080/13658816.2015.1008002

Gómez Maturano, J., Mendoza Santana, J. D., Aguilar García, A. L., & Serna Hernández, M. (2024). Remote sensing of illegal dumps through supervised classification of satellite images: Application in Oaxaca, Mexico. *Cuadernos de Investigación Geográfica, 50*(2), 157–177. https://doi.org/10.18172/cig.6273

Haralick, R. M., Shanmugam, K., & Dinstein, I. (1973). Textural features for image classification. *IEEE Transactions on Systems, Man, and Cybernetics, 3*(6), 610–621.

He, H., & Garcia, E. A. (2009). Learning from imbalanced data. *IEEE Transactions on Knowledge and Data Engineering, 21*(9), 1263–1284.

Hearst, M. A., Dumais, S. T., Osuna, E., Platt, J., & Schölkopf, B. (1998). Support vector machines. *IEEE Intelligent Systems and Their Applications, 13*(4), 18–28.

Hojnik, B., Horvat, G., Mongus, D., Brumen, M., & Kamnik, R. (2025). Towards sustainable waste management: Predictive modelling of illegal dumping risk zones using circular data loops and remote sensing. *Sustainability, 17*(18), 8280. https://doi.org/10.3390/su17188280

Jazat, J. P., Akande, J. A., & Ogunbode, T. O. (2023). State of solid waste disposal and suggested fixes for Iwo and Ibadan Metropolis, Nigeria. *Frontiers in Sustainability, 3*, 1022519. https://doi.org/10.3389/frsus.2022.1022519

Jordá-Borrell, R., Ruiz-Rodríguez, F., & Lucendo-Monedero, Á. L. (2014). Factor analysis and geographic information system for determining probability areas of presence of illegal landfills. *Ecological Indicators, 37*, 151–160. https://doi.org/10.1016/j.ecolind.2013.10.001

Kapoor, S., & Narayanan, A. (2023). Leakage and the reproducibility crisis in machine-learning-based science. *Patterns, 4*(9), 100804.

Karimi, N., Ng, K. T. W., & Richter, A. (2022). Development and application of an analytical framework for mapping probable illegal dumping sites using nighttime light imagery and various remote sensing indices. *Waste Management, 143*, 195–205.

Kaza, S., Yao, L., Bhada-Tata, P., & Van Woerden, F. (2018). *What a waste 2.0: A global snapshot of solid waste management to 2050*. World Bank.

Kruse, C., Boyda, E., Chen, S., Karra, K., Bou-Nahra, T., Hammer, D., Mathis, J., Maddalene, T., Jambeck, J., & Laurier, F. (2023). Satellite monitoring of terrestrial plastic waste. *PLOS ONE, 18*(1), e0278997. https://doi.org/10.1371/journal.pone.0278997

Kuncheva, L. I., & Whitaker, C. J. (2003). Measures of diversity in classifier ensembles and their relationship with the ensemble accuracy. *Machine Learning, 51*(2), 181–207.

Lee, S., & Pradhan, B. (2007). Landslide hazard mapping at Selangor, Malaysia using frequency ratio and logistic regression models. *Landslides, 4*(1), 33–41.

Lucendo-Monedero, A. L., Jordá-Borrell, R., & Ruiz-Rodríguez, F. (2015). Predictive model for areas with illegal landfills using logistic regression. *Journal of Environmental Planning and Management, 58*(7), 1309–1326. https://doi.org/10.1080/09640568.2014.993751

Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. In *Advances in Neural Information Processing Systems 30* (pp. 4765–4774).

McFeeters, S. K. (1996). The use of the normalized difference water index (NDWI) in the delineation of open water features. *International Journal of Remote Sensing, 17*(7), 1425–1432.

Merghadi, A., Yunus, A. P., Dou, J., Whiteley, J., ThaiPham, B., Bui, D. T., Avtar, R., & Abderrahmane, B. (2020). Machine learning methods for landslide susceptibility studies: A comparative overview of algorithm performance. *Earth-Science Reviews, 207*, 103225.

Mountrakis, G., Im, J., & Ogole, C. (2011). Support vector machines in remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing, 66*(3), 247–259.

Mvula, R. L. S., Banda, Y. M., Njunju, M. A., Tholo, H. M., Chisenga, C., Nyengere, J., Njalam'mano, J., Eregno, F. E., & Kadewa, W. (2025). Mapping illegal dumping sites in a low-resource region using GIS and remote sensing: The case of Blantyre City, Malawi. *Urban Science, 9*(7), 254. https://doi.org/10.3390/urbansci9070254

Ndoma, E. E., Songu, G., & Buba, S. (2018). Mapping of existing solid waste dumpsites using geographic information system in Kaduna South Local Government Area. *Jalingo Journal of Social and Management Sciences, 1*(1).

Ogunlade, S. O., Afolabi, O. O., Akorede, S. A., & Odupe, S. O. (2021). Geospatial assessment of site suitability for solid waste dump sites in Ido Local Government Area, Oyo State, Nigeria. *European Modern Studies Journal, 5*(5), 95–107.

Phillips, S. J., Anderson, R. P., & Schapire, R. E. (2006). Maximum entropy modeling of species geographic distributions. *Ecological Modelling, 190*(3–4), 231–259.

Phiri, D., Simwanda, M., Salekin, S., Nyirenda, V. R., Murayama, Y., & Ranagalage, M. (2020). Sentinel-2 data for land cover/use mapping: A review. *Remote Sensing, 12*(14), 2291.

Ploton, P., Mortier, F., Réjou-Méchain, M., Barbier, N., Picard, N., Rossi, V., Dormann, C., Cornu, G., Viennois, G., Bayol, N., Lyapustin, A., Gourlet-Fleury, S., & Pélissier, R. (2020). Spatial

validation reveals poor predictive performance of large-scale ecological mapping models. *Nature Communications, 11*, 4540.

Quesada-Ruiz, L. C., Rodriguez-Galiano, V., & Jordá-Borrell, R. (2018). Identifying the main physical and socioeconomic drivers of illegal landfills in the Canary Islands. *Waste Management & Research, 36*(11), 1049–1060. https://doi.org/10.1177/0734242X18804031

Quesada-Ruiz, L. C., Rodriguez-Galiano, V., & Jordá-Borrell, R. (2019). Characterization and mapping of illegal landfill potential occurrence in the Canary Islands. *Waste Management, 85*, 506–518. https://doi.org/10.1016/j.wasman.2019.01.015

Roberts, D. R., Bahn, V., Ciuti, S., Boyce, M. S., Elith, J., Guillera-Arroita, G., Hauenstein, S., Lahoz-Monfort, J. J., Schröder, B., Thuiller, W., Warton, D. I., Wintle, B. A., Hartig, F., & Dormann, C. F. (2017). Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. *Ecography, 40*(8), 913–929.

Rouse, J. W., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring vegetation systems in the Great Plains with ERTS. In *Proceedings of the Third Earth Resources Technology Satellite-1 Symposium*. NASA.

Saaty, T. L. (1980). *The analytic hierarchy process*. McGraw-Hill.

Scharf, N., Ducry, B., Sy, B., Djim, A., & Lacroix, P. (2025). Integrating remote sensing, GIS, and citizen science to map illegal waste dumping susceptibility in Dakar, Senegal. *Sustainability, 17*(24), 11137. https://doi.org/10.3390/su172411137

Seror, N., & Portnov, B. A. (2018). Identifying areas under potential risk of illegal construction and demolition waste dumping using GIS tools. *Waste Management, 75*, 22–29.

Seror, N., & Portnov, B. A. (2020). Estimating the effectiveness of different environmental law enforcement policies on illegal C&D waste dumping in Israel. *Waste Management, 102*, 241–248.

Strobl, C., Boulesteix, A.-L., Zeileis, A., & Hothorn, T. (2007). Bias in random forest variable importance measures: Illustrations, sources and a solution. *BMC Bioinformatics, 8*, 25.

Sun, X., Yin, D., Qin, F., Yu, H., Lu, W., Yao, F., He, Q., Huang, X., Yan, Z., Wang, P., Deng, C., Liu, N., Yang, Y., Liang, W., Wang, R., Wang, C., Yokoya, N., Hänsch, R., & Fu, K. (2023). Revealing influencing factors on global waste distribution via deep-learning based dumpsite detection from satellite imagery. *Nature Communications, 14*, 1444. https://doi.org/10.1038/s41467-023-37136-1

Tasaki, T., Kawahata, T., Osako, M., Matsui, Y., Takagishi, S., Morita, A., & Akishima, S. (2007). A GIS-based zoning of illegal dumping potential for efficient surveillance. *Waste Management, 27*(2), 256–267.

Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. *Economic Geography, 46*(Suppl.), 234–240.

Torres, R. N., & Fraternali, P. (2021). Learning to identify illegal landfills through scene classification in aerial images. *Remote Sensing, 13*(22), 4520. https://doi.org/10.3390/rs13224520

United Nations Environment Programme. (2024). *Global waste management outlook 2024: Beyond an age of waste – Turning rubbish into a resource*. UNEP. https://doi.org/10.59117/20.500.11822/44939

Vaverková, M. D. (2019). Landfill impacts on the environment—Review. *Geosciences, 9*(10), 431.

Wolpert, D. H. (1992). Stacked generalization. *Neural Networks, 5*(2), 241–259.

Yusuf, T. (2018). *Analysis of spatial distribution and perception of the risks of illegal solid waste dumpsites in Minna, Niger State, Nigeria* [Unpublished master's thesis]. Ahmadu Bello University.

Zhou, L., Luo, T., Du, M., Chen, Q., Liu, Y., Zhu, Y., He, C., Wang, S., & Yang, K. (2021). Machine learning comparison and parameter setting methods for the detection of dump sites for construction and demolition waste using the Google Earth Engine. *Remote Sensing, 13*(4), 787. https://doi.org/10.3390/rs13040787

2026 by the Authors. This Article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/)