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COMMENTARY

Space-air-ground integrated system for illegal waste dumping sites monitoring

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Received: June 2, 2025; Accepted: September 29, 2025; Published Online: October 9, 2025; https://doi.org/10.59717/j.xinn-geo.2026.100182

Citation: Zhao R., Deng L., Zhou X., et al. (2025). Space-air-ground integrated system for illegal waste dumping sites monitoring. *The Innovation Geoscience* 3:100182.

The rapid increase in solid waste generation, coupled with uneven disposal capacity, has intensified the challenges of managing illegal waste dumping sites (IWDs). Globally, IWDs affect over 4 billion people and account for approximately 40% of the total solid waste, posing potential hazards to human and ecosystem health.[1] IWDs exhibit dispersed distributions that are delineated based on visual features such as color, tone, shape, and texture.[2] Traditional monitoring primarily relies on ground-based inspections and manual interpretation of aerial photographs, which are labor-intensive and time-consuming and have limitations in multi-scale and dynamic monitoring.

With improvements in the spatial and temporal resolutions of remote sensing imagery, intelligent interpretation methods have emerged for the detection of IWDs. By leveraging rich spectral and textural information, machine learning-based target detection models, including single-shot multi-box detectors (SSD), region-based convolutional neural network (R-CNN), and faster R-CNN, have enhanced the visual distinctions between ground objects. SSD enables the detection of IWDs at various scales, from scattered fragments to large stockpiles, using multi-scale anchor boxes on feature maps. The R-CNN extracts subtle features by generating region proposals and enabling the precise localization of irregular or partially occluded IWDs. Faster R-CNN shares convolutional feature extraction, accelerating the detection speed tenfold compared to R-CNN while reducing manual interpretation biases.

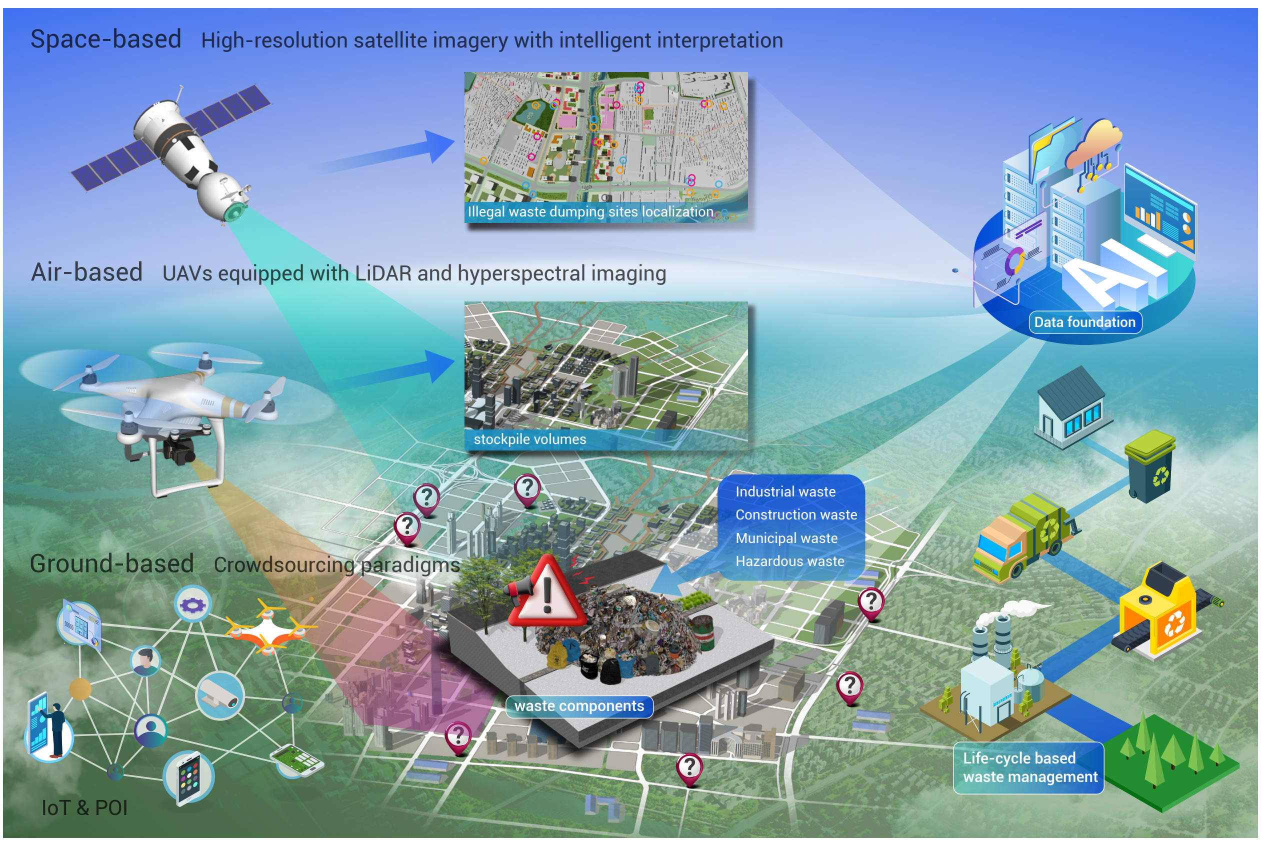

Figure 1. Space-air-ground integrated system for IWDs monitoring.

However, the performance of these methods may be constrained by challenges such as insufficiently labeled data and ambiguous category discrimination when applied in dense and complex urban environments. For instance, many IWDs are intentionally camouflaged with soil, and optical remote sensing technology cannot accurately identify the specific composition of waste, such as hazardous waste, plastics, and organic waste. This requires a transformative pathway for efficient and dynamic IWDs monitoring. This commentary proposes a space-air-ground integrated monitoring system for the quantification and characterization (i.e., generation, accumulation, and composition) of IWDs (Figure 1) and discusses the challenges and future prospects for sustainable municipal waste management.

SPACE-AIR-GROUND INTEGRATED SYSTEM FOR IWDs MONITORING

The space-air-ground integrated monitoring system achieves comprehensive and precise waste management through the synergistic combination of three-layered technologies, including space-based detection, air-based quantification, and ground-based validation. Space-based detection uses high-resolution satellite imagery with intelligent interpretation to achieve precise IWDs localization. Air-based quantification employs unmanned aerial vehicles (UAVs) equipped with light detection and ranging (LiDAR) and hyperspectral imaging to measure stockpile volumes and discriminate waste composition. Ground-based validation leverages crowdsourcing paradigms (IoT and POI) to verify spatial and aerial monitoring results through coordinate and area feedback, aiding in the detection of hidden waste components. Characterized by multi-technology synergy and real-time response, this system facilitates governance from detection to disposal and is essential for advancing smart municipal waste management.

Space-based localization. The precise localization of IWDs is a prerequisite for their governance. However, the hidden locations and widespread distribution of IWDs often cause incomplete image feature representations, manifesting as the ambiguity of "the same object with different spectra" or "the same spectrum with different objects", lowering detection accuracy. Global inference units address these issues by integrating prior constraint knowledge into target detection models and refining detection boundaries. By leveraging scene-level spatial relationships (e.g., waste stockpile clustering) and geographic context (e.g., waste-generating entities), this approach improves accuracy and reduces false positives/negatives.[3] For instance, a prior knowledge-integrated fast R-CNN model achieved 98.6% accuracy on 28 global landfill samples.[1]

Air-based quantification and characterization. After locating the IWDs, the stockpile volumes and waste compositions were intelligently interpreted using time-series UAV data. UAV-borne LiDAR with multi-echo detection and submeter vertical penetration resolution enables high-precision 3D spatial modeling. For IWDs monitoring, high-density point cloud data efficiently construct 3D geometries of solid waste stockpiles for volume estimation.[4] In the applications of mixed municipal/industrial waste landfill monitoring, UAV-derived point cloud models achieved a volume error of less than 5% compared to on-site total station measurements. Drone-borne hyperspectral imaging discriminates surface waste composition by leveraging reflectance differences across spectral bands.

Ground-based validation and enhancement. Crowdsourcing platforms (i.e., IoT, POI, and mobile apps) are deployed not only to verify the localization of IWDs by remote sensing imagery interpretation but also to address the limitations of UAV monitoring in capturing the internal details of waste stockpiles and the insufficient characterization of hidden waste components. Real-time uploads of stockpile images via mobile devices (37,000 monthly) enrich the spatiotemporal characteristics of the dataset, improving the solid waste component recognition accuracy by 5% compared with using UAV data alone.[5]

CHALLENGES

Multi-source data fusion barriers. Data from satellites, UAVs, and crowdsourcing lack standardization in terms of formats, coordinate systems, timestamps, and frequencies. These inconsistencies necessitate extensive preprocessing, such as data cleaning, format conversion, calibration, and spatiotemporal alignment. The dynamic characteristics of IWDs (e.g., fluctuations in waste stockpiles) require real-time response capabilities and consume substantial computational resources.

Limitations in monitoring accuracy and reliability. The absence of standardized multi-scenario IWDs sample databases presents a significant obstacle to target detection model training because these targets exhibit substantial variations in scale (from less than 10 m^2 to over 1,000 m^2). Environmental factors, such as terrain, vegetation, and weather, severely degrade optical imaging quality, leading to the obstruction of IWDs feature information. Spectral shifts and medium interference (e.g., irregular shapes and blending with surroundings) further cause misclassification and reduce detection accuracy.

Technical adaptability and application limitations. Monitoring techniques face challenges in complex environments. For example, fixed-size image windows in classic object detection algorithms fail to accommodate targets of varying scales, resulting in incomplete target segmentation. There is a lack of risk assessment for waste stockpiles in monitoring protocols, and the main concern stems from the accumulation of methane gas during the decomposition of organic solid waste.

FUTURE DIRECTIONS

Multimodal data fusion. The heterogeneity of monitoring data presents challenges and opportunities for integration. High-resolution satellite imagery offers macro-level context, UAV LiDAR reveals detailed meso-scale structures, and ground sensors provide high-frequency localized information. Future research should focus on sophisticated multimodal fusion techniques, such as Bayesian hierarchical modeling, graph neural networks, and spatiotemporal data assimilation, rather than simple data stitching. These methods can bridge resolution gaps across data scales, coordinate uncertainties, and construct the spatio-temporal data foundation and multidimensional IWDs digital twins. This will enable the descriptive and predictive monitoring of complex urban environments.

Integrated monitoring system optimization. System optimization is demonstrated not only in terms of expanded coverage but also in terms of adaptability, resilience, and scalable architecture. Future research will focus on hierarchical coordination among satellites, drones, and ground sensors, with each layer offering complementary spatiotemporal resolutions. This will aid in the identification of emerging pollutants, such as microplastics, at the molecular level. By leveraging edge computing and distributed sensor networks, data latency can be reduced, enabling near-real-time monitoring and response. Optimization mechanisms based on spatiotemporal configuration models and dynamic resource-scheduling algorithms empower the system to adapt to the dynamic characteristics of waste generation and stock. This improves localization accuracy, minimizes redundancies, eliminates blind spots, and facilitates the efficient monitoring of illegal dumping behavior.

AI-driven decision-making support. Artificial intelligence is the main driver of the transition of monitoring systems from passive to proactive modes. Future research should emphasize the development of AI-powered decision-support systems to achieve the chain management of IWDs (monitoring-warning-governance). Deep learning can enhance the accuracy of IWDs identification and waste classification in complex urban environments, whereas reinforcement learning optimizes drone path planning and sensor deployment under resource constraints. Hybrid models that combine physical mechanisms with deep learning models not only support the early warning of illegal dumping hotspots and the simulation of accumulation trends, but also improve the interpretability and transparency of predictions.

Integrated sustainable waste management. The merits of IWDs monitoring are ultimately reflected in its deep integration with life-cycle-based municipal waste management. Future research should consider developing technical standards that encompass unified specifications for the collection, processing, and sharing of monitoring data to support intelligent operations across waste generation, collection, transportation, and disposal processes. These standards are expected to promote the expansion of monitoring applications by measuring methane emission fluxes and leachate generation from IWDs, thereby providing a basis for regulatory mechanisms for pollution prevention and carbon emission reduction.

REFERENCES

1. Sun X., Yin D., Qin F., et al. (2023). Revealing influencing factors on global waste distribution via deep-learning based dumpsite detection from satellite imagery. *Nat. Commun.* **14**:1444. DOI:10.1038/s41467-023-37136-1
2. Fraternali P., Morandini L. and Herrera Gonzalez S.L. (2024). Solid waste detection, monitoring and mapping in remote sensing images: A survey. *Waste Manag.* **189**:88–102. DOI:10.1016/j.wasman.2024.08.003
3. Zhang S., Ma J. and Jiang F. (2025). Monitoring street-level improper dumpsites via a multi-modal and LLM-based framework. *Resour. Conserv. Recy.* **218**. DOI:10.1016/j.resconrec.2025.108227
4. Filkin T., Sliusar N., Huber-Humer M., et al. (2022). Estimation of dump and landfill waste volumes using unmanned aerial systems. *Waste Manag.* **139**:301–308. DOI:10.1016/j.wasman.2021.12.029
5. Kako S., Muroya R., Matsuoka D., et al. (2024). Quantification of litter in cities using a smartphone application and citizen science in conjunction with deep learning-based image processing. *Waste Manag.* **186**:271–279. DOI:10.1016/j.wasman.2024.06.026

FUNDING AND ACKNOWLEDGMENTS

This study is funded by the National Key Plan for Research and Development of China (2019YFC1905600), the National Natural Science Foundation of China (52222007, 52388101, 41571520), Sichuan Youth Science and Technology Innovation Team Funding (2022JDTD0005), and Fundamental Research Funds for the Central Universities (2682021ZTPY088). The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.