A domain knowledge-augmented satellite image segmentation approach for global landfill detection

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Abstract

Landfills are the global primary solution for waste management but pose significant environmental and social challenges. Automated landfill detection is essential for cost-effective environmental management. However, existing methods typically focus on landfill presence detection within limited areas. This study developed a domain knowledge-augmented satellite image segmentation approach to recognize landfills' presence and areal extent globally. We harnessed satellite images of 1,380 representative landfills from various global regions to fine-tune a deep learning segmentation model; while five domain knowledge-informed features were defined and used to calibrate segmentation results. Our approach achieved a recall of 99.51% for landfill presence detection, an overall accuracy of 98.97%, a mean accuracy of 91.95%, and a mean intersection over union of 88.08% for landfill segmentation. This research surpasses existing studies by identifying landfill locations and areas worldwide and improving segmentation accuracy through domain knowledge. The approach can support global landfill mapping and illegal landfill detection.

Keywords: Waste Management; Landfill Detection; Satellite Image Segmentation; Deep Learning; Domain Knowledge

1. Introduction

Landfills are engineered sites designed for waste disposal, where various solid waste (e.g., municipal solid waste, construction waste, or commercial waste) is buried and isolated to limit environmental contamination of soil, water, and air, by using systems like liners, leachate collectors, and gas management infrastructure (Nanda & Berruti, 2021; Warith, 2003). Within the '3R' hierarchy (i.e., Reduce, Reuse, Recycle) for waste management, landfill ranks as the least favoured option, employed only when waste minimization, reuse, and recycling are unfeasible (World Bank, 2016; Yuan et al., 2024). However, landfills offer practical advantages, such as managing large waste volumes cost-effectively and, in advanced facilities, generating energy via methane capture (Frändegård et al., 2013; Mahmood et al., 2016). Therefore, despite its low priority, landfilling still dominates waste management, handling 69.6% of solid waste in 2016 compared to 13.5% recycled, 11.1% incinerated, and 5.5% composted (World Bank, 2016).

Nevertheless, landfilling causes numerous drawbacks. For example, they demand significant land, emit greenhouse gases like methane and carbon dioxide if mismanaged, risk groundwater pollution from leachate containing heavy metals, and produce odours and health hazards for nearby populations (Graupman et al., 2023; Limoli et al., 2019). These issues, compounded by their linear "end-of-life" nature, clash with circular economy goals (Dong et al., 2025; MacArthur, 2013), necessitating accurate detection of the landfill and stringent, long-term monitoring of air, soil, and water. Landfill detection and monitoring are thus well mandated by regulations in many regions, like the EU (European Union, 2018), US (USEPA, 2023), and Australia (EPA of Victoria, 2020).

Remote sensing data holds a great promise for automating landfill detection, as its increasing availability, spatial scalability, and relatively low data collection costs; consequently, current studies on landfill site detection increasingly develop and employ remote sensing-based methods to detect these sites. The data source of these methods includes airborne thematic maps (Jones & Elgy, 1994), LiDAR point cloud (Valjavec, 2014), land surface temperature images (Yan et al., 2014), satellite images (Manzo et al., 2017), unmanned aerial vehicle photographs (Wyard et al., 2021), and night-time light images (Karimi et al., 2022). Meanwhile, advanced artificial intelligence technologies, e.g., machine learning and deep learning, have been widely utilized to develop appropriate models for underpinning remote sensing-based automated landfill detection. These studies made significant contributions to automating landfill detection and monitoring.

However, weaknesses persist: Firstly, existing approaches were generally developed based on the sample data of a small case area, e.g., a region (Azmi et al., 2022; Karimi et al., 2022), city (Mahmood et al., 2016; Yan et al., 2014), or even a neighbourhood (Azmi et al., 2022; Wyard et al., 2021). Hence, the generalizability of these approaches is questionable, because the intrinsic regional heterogeneity unavoidably incurs differences in landfills' visual features (Manzo et al., 2017; Yalana et al., 2008). Secondly, almost all existing approaches focus only on detecting the presence of landfills, which transforms landfill detection to be a binary remote sensing data classification problem; while little research has probed into recognizing the areal extent of landfills, which means object segmentation in remote sensing data, differing from the classification problem. The landfill area is also an essential attribute for subsequent monitoring and management practice.

The primary aim of this study is to develop a domain knowledge-enhanced satellite image segmentation approach for recognizing global landfills, including presence detection and area extraction. High-resolution satellite images are selected as the input because they provide rich feature information and are easy to access. A proper image segmentation model will be trained to extract landfill objects from images. Moreover, landfill-related domain knowledge will be integrated to reinforce image segmentation, thereby improving the approach's performance. The paper is organized as follows: Section 2 provides a critical review of existing studies on landfill detection; Section 3 elaborates on the methodology, integrating the segmentation model with domain-specific knowledge derived from the literature; Section 4 presents the approach development and validation procedures, based on 1,380 landfills across diverse global regions; Section 5 offers a deeper discussion on the approach's strengths and limitations; and Section 6 concludes the study.

2. Literature review

Remote sensing data-based landfill detection has been a hot research topic for years. This research conducted a critical review of existing approaches, with a special focus on data inputs, outputs, spatial scale, and the use of domain knowledge. Table 1 summarizes the literature review results.

Table 1. A summary of existing remote sensing-based landfill recognition approaches

Reference	Approach input	Approach output	Spatial scale	Use of domain knowledge
(Salleh & Tsudagawa, 2002)	Airborne image	Presence of landfill	Province	No
(Silvestri & Omri, 2008)	Vegetation spectrum image and GIS data	Presence of landfill	Neighbourhood	Yes
(Yalana et al., 2008)	Satellite image	Presence of landfill	Region	No
(Valjavec, 2014)	LiDAR point cloud	Presence of landfill	Neighbourhood	No
(Gill et al., 2019)	Land surface temperature image	Presence of landfill	Neighbourhood	Yes
(Incekara et al., 2019)	LiDAR point cloud	Areal extent of landfill	Single landfill	No
(Vambol et al., 2019)	Satellite image and GIS data	Areal extent of landfill	Neighbourhood	No
(Azmi et al., 2022)	Satellite image and drone full-motion video	Presence of landfill	Neighbourhood	No
(Gao et al., 2022)	Unmanned aerial vehicle images	Areal extent of landfill	Neighbourhood	No
(Karimi et al., 2022)	Night-time light image	Probability of landfill occurrence	Region	No
(Quesada-Ruiz et al., 2022)	Satellite image, socioeconomic statistics, and GIS data	Probability of landfill occurrence	Region	No
(Zhang et al., 2022)	Satellite image	Areal extent of landfill	City	No
(Yong et al., 2023)	Satellite image	Areal extent of landfill	City	No
(Sun et al., 2023)	Satellite image	Presence of landfill	Globe	No
(Lin et al., 2024)	Satellite image	Areal extent of landfill	District	No

According to Table 1, the prevailing input of existing approaches is remote sensing data, including satellite images, airborne images, LiDAR point clouds, land surface temperature images, night-time light images, and so on. A few studies also combined Geographical Information System (GIS) data and socioeconomic statistics to enhance landfill identification (Quesada-Ruiz et al., 2022; Vambol et al., 2019). Basically, satellite images are most commonly utilized to map landfills in existing studies.

The dominant output is the presence of landfills, while little research engages in extracting landfill areas. Detecting the existence of landfills based on remote sensing images is equivalent to image classification. Benefitting from deep learning technologies, existing approaches have achieved high accuracy in identifying whether an image contains landfills (Yalana et al., 2008). Recognizing the areal extent of landfills, meanwhile, involves image segmentation, namely, partitioning the pixel region within a remote sensing image into landfill and non-landfill groups, which is a more complex and challenging task than image classification but provides essential areal information for landfill monitoring and management. The pre-trained models frequently selected by previous studies for landfill image segmentation include Pspnet, U-Net, DeepLab, and DeepLab V3+ (Gao et al., 2022; Yong et al., 2023), as they are relatively more robust and accurate in most cases. Also, a few studies proposed new deep learning models specified for certain landfill image segmentation contexts. For example, Zhang et al. (2022) established a trainable cross-channel multi-scale gated fusion network (termed “CCMGNet”), which can effectively fuse the RGB and NIR bands of high-resolution satellite images to obtain cross-channel information complementarity, thereby improving segmentation accuracy. Currently, the first and second highest landfill image segmentation accuracies were achieved by Lin et al. (2024) (IoU=82.08%) and Yong et al. (2023) (IoU=74.60%), based on the pre-trained DeepLab V3+ model.

Furthermore, previous studies focus primarily on neighbourhood-scale case regions. This can reduce data collection costs but may limit the generalizability of the developed methods, as the visual features of landfills often vary from region to region (Sun et al., 2023). A recent publication by (Sun et al., 2023) expands the spatial scale to a global scope by sampling landfill images from 28 cities around the world, establishing a highly generalizable approach. However, their research focuses only on identifying the presence of landfills, not segmenting landfill areas from images.

In addition, previous methods generally achieve landfill recognition based only on the visual features extracted from remote sensing data. Little research harnesses landfill-related domain knowledge to enhance landfill recognition. Gill et al. (2019) harnessed the land surface temperature differences between landfilling areas and non-landfilling areas as input features to detect the presence of landfills, based on domain knowledge that the decomposition of organic matter releases heat. This study exemplifies the potential of domain knowledge for landfill recognition, and indicates one of the common methods for integrating domain knowledge, i.e., utilizing domain knowledge for the post-processing of model segmentation.

3. Methodology

3.1 Research methods

To develop the model for recognizing global landfill presence and areal extent, this study adopted experimentation as the research method. The general procedure is to use the stratified sampling technique to collect satellite images of landfills from different regions around the world. Stratified sampling balances the sample's acquisition cost and representativeness (Lohr, 2021). Then, sample images are input into appropriate deep learning algorithms to train semantic segmentation models, which are applied to detect the presence and area of landfill instances in newly input images. Finally, landfill image segmentation results are calibrated using domain knowledge-based features defined based on a literature review.

The rationale behind the proposed approach is that waste landfills generally present some visual features (e.g., color, shape, texture) distinct from their surroundings (Chen et al., 2003). Deep learning algorithms are capable of quantifying and learning these features to produce task-specific models, which can then be applied to recognize landfill sites from new image inputs. Also, in the computer science community, incorporating domain knowledge, which refers to prior or tacit knowledge of a specific subject, is an increasingly used solution for enhancing deep learning-based image recognition performance (Dash et al., 2022; Xie et al., 2021), because deep learning-based object recognition still faces many challenges when training datasets are small or the object boundary is not clear (Dash et al., 2022; Xie et al., 2021). Moreover, the site selection, design, and construction of landfills are generally based on certain codes and principles, which contain prior knowledge that can produce informative features to support landfill instance segmentation.

3.2 Data sources

This research acquired the precise spatial locations (longitude and latitude) of landfill samples from four sources: (1) map platforms including Google Maps and Baidu Maps, which record a few landfills located near urban areas; (2) landfill catalogues published by governments, e.g., the

Landfill Methane Outreach Program (LMOP) of the United States Environmental Protection Agency (USEPA, 2024) and Permitted Waste Sites–Authorised Landfill Boundaries (PWS-ALB) data set issued by the Environment Agency (2023) of the United Kingdom, which record legally registered landfill information; (3) public environmental reports (Auckland Council, 2024; Muwaieh, 2015), which indicate the location of landfills uncatalogued in governments' databases; and (4) social media platforms, where the public post the photo and address of landfills affecting their lives and travel. In addition, high-resolution satellite images of landfill samples can be collected from multiple satellite optical imageries, e.g., Pléiades, WorldView Series and GeoEye.

4. Landfill detection approach development

4.1 Approach architecture

Figure 1 visualizes the architecture of the proposed landfill detection approach. Its input is high-resolution satellite images, and its output is the semantic segmentation result, which informs the pixel area of landfill and non-landfill objects in an image. When feeding a satellite image into the approach architecture, the deep learning-based image segmentation model will output the segmentation result, which will then be fed into the calibration procedure based on domain knowledge-enabled features. Finally, the calibrated landfill instance segmentation will be output as the ultimate recognition result. Detailed methods are presented in the subsequent sections.

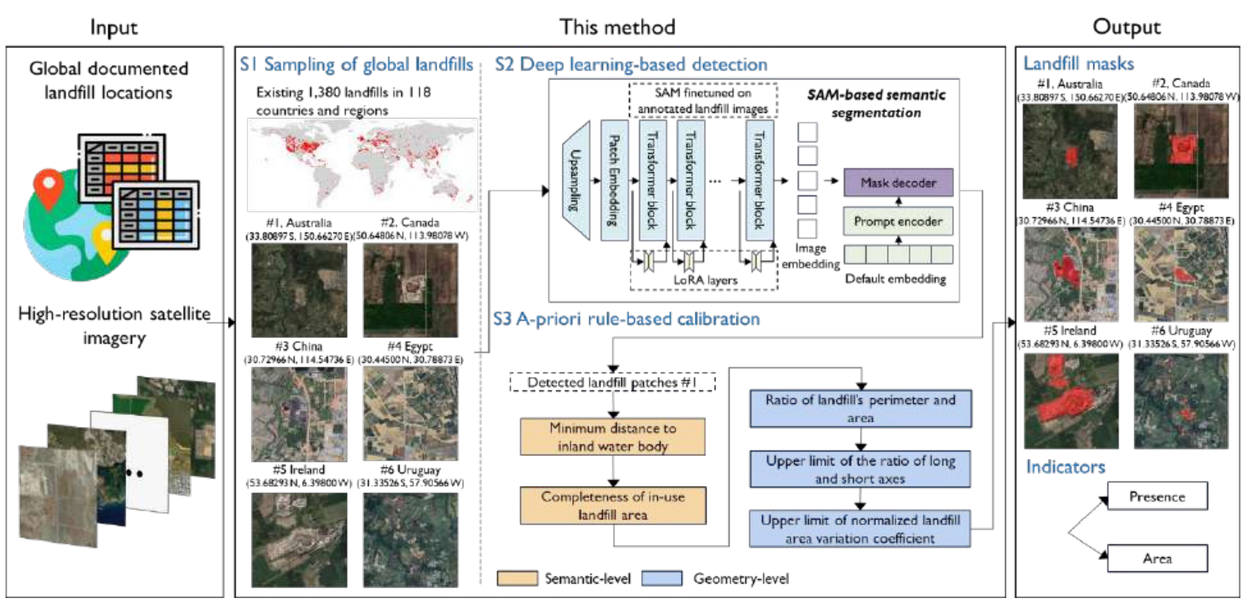

Figure 1. The architecture of domain knowledge-augmented landfill recognition approach

4.2 Stratified sampling of landfills

Ensuring that training samples represent global landfills is crucial for the model's global mapping capability. We identified the major factors influencing landfill visual feature diversity to determine the strata for stratified sampling, ensuring comprehensive sample coverage. Our review of existing publications identified five key factors affecting landfill visual features:

1) landfilling methods, including sanitary landfills and open-air dumpsites (Chen et al., 2003);
2) land cover type, which influences landfill surroundings (Mahmood et al., 2017);
3) terrain, including valley, step, slope, and flat landfills (Yalana et al., 2008; Yong et al., 2023);
4) waste composition, such as agricultural, construction, and domestic waste, with distinct material types and contents (Sun et al., 2023); and
5) economic level, affecting site selection (Sun et al., 2023).

In addition, seasonal change also affects visual features but can be mitigated by controlling image capture dates when conducting the landfill detection (Manzo et al., 2017); meanwhile, the seasonal difference between regions with different latitudes can also enhance the temporal diversity of samples for the model training in Section 4.3. We combined these factors to stratify the global landfill samples.

The stratified sampling procedure involved three main steps: (1) collecting geographic coordinates of in-use landfills from various sources; (2) cropping and extracting satellite images from Google Web Map Tile Service (WMTS); and (3) reviewing whether the samples cover all situations of each stratum, e.g., both sanitary and open-air landfills. We repeated these steps until the samples adequately represented each stratum. Notably, we only collected satellite images containing at least one landfill, resulting in a one-class dataset. The reason behind this decision is that constructing a globally representative dataset consisting of images without landfills is far more challenging, given the immense diversity of the sample population. Finally, 1,380 landfill samples were collected for model development.

This research acquired the satellite image of the 1,380 landfill samples from the mosaic optical imagery platform Google WMTS geocoded with the World Geodetic System 84/Pseudo-Mercator system (EPSG: 3857). The multi-source images of Google WMTS were cleansed (e.g., cloud removal), calibrated (e.g., the radiometric, atmospheric, and geometric), mosaiced, and updated since 2016. To appropriately represent global landfills of multifarious areal sizes, we determined each image covering 4,000 × 4,000 = 16 km^2 based on a balance of multiple factors (including the size range of global landfills, recognizability of objects in images, and computation load) and referring to (Đidelija et al., 2022). We saved the image at a size of 2,000 × 2,000 pixels, with a spatial resolution of 2 meters in the projected geospatial coordinate system. Benefiting from the high data quality of Google WMTS, apart from cropping satellite images to a size of 2000 × 2000 pixels, no other preprocessing procedure is required.

Figure 2 shows the characteristics of the gathered landfill samples. These samples come from 118 countries and regions across six continents. As shown in Figure 2a, the landfill samples are distributed in lands of 12 latitudinal zones (46° S to 65° N) and 34 longitudinal zones (157° W to 176° E), covering 85.71% of climate zones according to the the Köppen-Geiger Classification (Rubel et al., 2017). The other climate zones, e.g., polar frost, polar tundra, snow, and extremely continental, do not have conventional landfills due to less waste generation and environmental protection.

Figure 2(b) indicates that 755 samples are sanitary landfills, and 625 are open-air landfills. Figure 22(c) shows 659 landfills in forests, 242 in grasslands, 104 in barren lands, 138 in shrublands, 207 in croplands, and 30 in built-up areas. Figure 2(d) classifies the terrain as 276 valley landfills, 158 step landfills, 197 slope landfills, and 749 flat landfills. Although it was challenging to identify the waste composition for all samples, available official documents confirm at least 24 agricultural, 45 construction, and 128 domestic waste landfills, as shown in Figure 2(e). Figure 2(f) presents six examples of collected satellite images with different types of landfilling methods, land cover, terrain, and major waste composition.

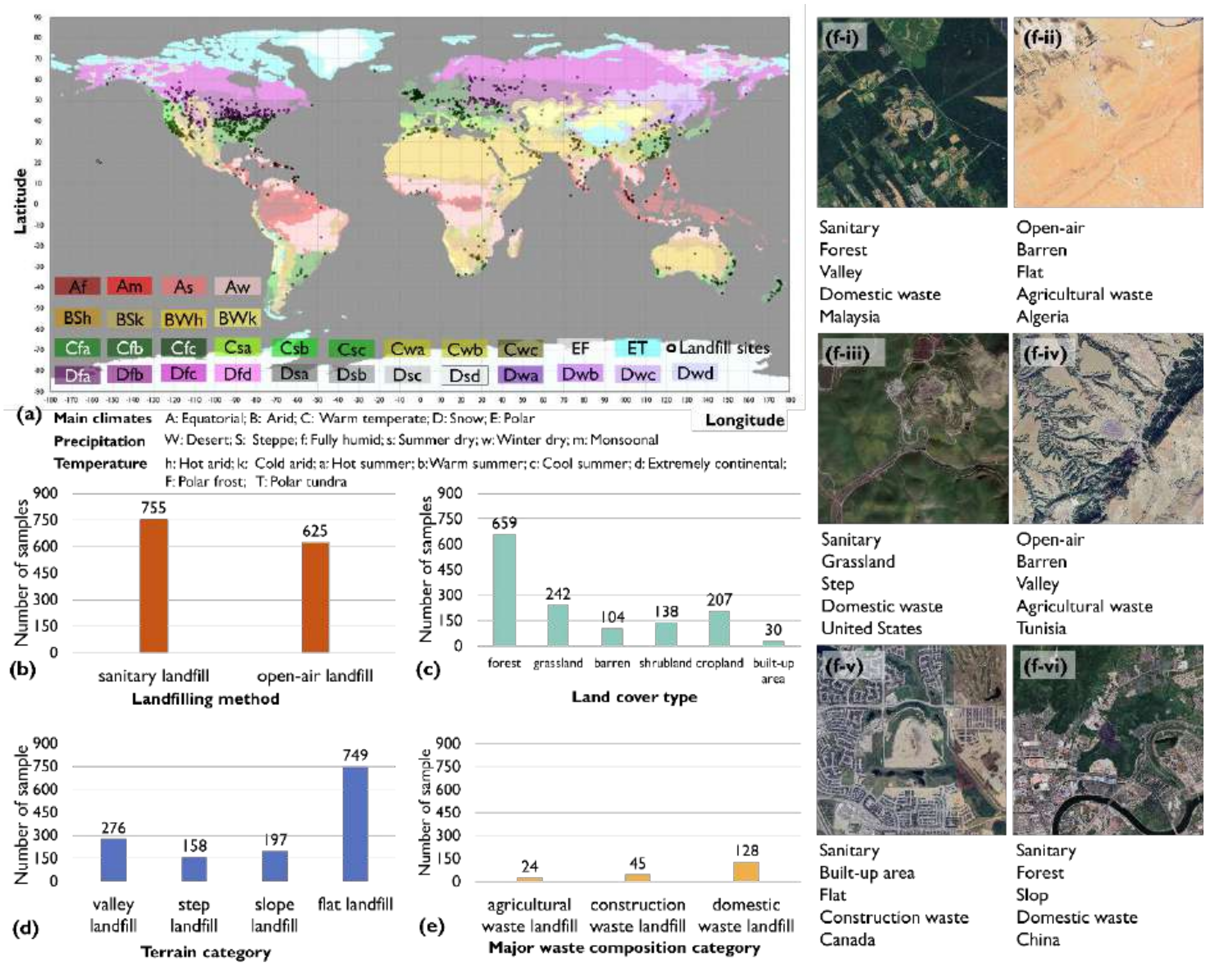

Figure 2. Characterization of the global landfill samples by (a) locations, (b) landfilling methods, (c) land cover types, (d) terrain categories, (e) major waste compositions, and (f) case images

Stratified sampling fully considered multiple factors (i.e., multiple strata) that have significant impacts on landfill recognition, while the 1,380 landfills cover all situations of each stratum; furthermore, we referred to the global sampling procedure used by Sun et al. (2023), who developed a model to identify the presence of open-air dumpsites at the global scale. On this basis, it is reasonable to justify that the sample dataset is a representative sample of global landfills.

4.3 Developing landfill segmentation models

Developing the proposed model involved four main stages. The first stage is image annotation. We annotated landfill images by using the LabelMe platform (CSAIL, 2023). Image annotation means labelling all pixel regions that belong to landfilling areas. When a satellite image contains more than one landfilling site, all sites are given the label “landfill” (namely, semantic segmentation label). Note that this study annotates only the in-use landfilling area, while regions that were originally landfill space but have been recovered as grassland or the like are not considered to be landfill objects. For consistency in annotation, one of the authors initially annotated all of the image samples. Subsequently, the other author reviewed each image and its corresponding annotation for double-checking. If any incorrect annotations were identified, the annotation masks were returned for correction. This process was repeated until all annotation results were validated, achieving a validation accuracy of 100%. Last, each annotated image will be an individual input in model training and validation.

The second stage is to select appropriate pre-trained models. Segment Anything Model (SAM) is an open-source pre-trained model proposed by Meta AI in 2023 and has made significant progress in breaking boundary segmentation (Zhang et al., 2023). A more detailed explanation about SAM’s structure and principles can refer to (Kirillov et al., 2023). Previous comparative experiments have demonstrated that SAM performs better in image segmentation than earlier popular models like FCN (Kirillov et al., 2023) and DeepLab V3 (Chen et al., 2018). Hence, this research selected it for landfill segmentation model development. Besides, DeepLab V3+ was also selected for comparative analysis, as the current first and second highest landfill image segmentation accuracy are achieved based on it (Lin et al., 2024; Yong et al., 2023).

The third stage is to determine proper metrics for measuring the model’s performance. IoU (intersection over union) and mIoU (mean intersection over union) were adopted, as they are the most widely adopted indicators for segmentation accuracy measurement. IoU measures the overlap between the predicted region and the ground-truth region (also called “Per-class IoU”); while mIoU represents the mean IoU computed across multiple instances (Rahman & Wang, 2016). Generally, an IoU and mIoU of ≥ 0.5 represent an acceptable segmentation accuracy (Zhou et al., 2019). To comprehensively assess the model’s segmentation performance, another two metrics, i.e., overall accuracy (OA) and mean accuracy (mAcc), were also adopted. OA measures the proportion of correctly classified pixels over the total number of pixels and presents a general sense of performance. mAcc characterizes the average accuracy across all classes, and provides a balanced view which is useful when classes are imbalanced. Additionally, for a more comprehensive approach comparison, this study also combined the metric "Recall" to measure the image classification performance of the new approach. Recall evaluates the ability of a model to correctly identify instances from all the samples.

The fourth stage is model training, validation, and testing. This research randomly splits the 1,380 satellite images into training, validation, and test datasets, with a proportion of 70%, 15%, and 15%. Specifically, we first classify the image samples into categories by spatial and climate zones. Then, in each category, the image samples are randomly selected into training, validation, and test sets according to the proportions of 70% : 15% : 15%. Last, we merge the subsets of training, validation, and test in each category for model training. Three SAM model variants and four DeepLab V3+ model variants were respectively fine-tuned for the model performance comparison. SAM variants are differentiated by the complexity level of the image encoder Vision Transfomer (ViT), including ViT-Base, ViT-Large, and ViT-Huge. The ViT-Base with 12 layers of the neural layers renders the SAM small for landfill detection through limited computation resources, while the SAM with the ViT-Large (24 layers) controls the balance of the detection speed and accuracy and the SAM with the ViT-Huge (36 layers) is often the most high-performance but resource-intensive. The three model variants were pre-trained on the Segment Anything 1 Billion (SA-1B) dataset (Kirillov et al., 2023).

We then fine-tuned them based on landfill satellite images. The fine-tuning process applied the low-rank-based (LoRA) strategy, which can reduce the number of trainable parameters and optimize the storage of large models for a satisfactory segmentation performance. The dice (Sudre et al., 2017) and focal losses (Lin et al., 2017) with the weight at 50% : 50% were applied for the three SAMs regarding the imbalanced area ratios of landfills and surrounding environments. Meanwhile, we fine-tuned the four DeepLab V3+ model variants differentiated by the backbone (Xception and MobileNet) and the output stride (8 and 16) based on the satellite image of sampled landfills. The cross-entropy loss was applied in fine-tuning the four variants. The entire fine-tuning process of both SAM and DeepLab V3+ was conducted in the same development environment of PyTorch (ver. 1.10) and Python (ver. 3.7). Specifically, we implemented the experiments on a high-performance computing cluster with 7 servers, each of which owns dual Intel Xeon 6226R (16 core) CPUs, 384GB RAM, 4 × NVIDIA V100 (32GB) SXM2 GPUs, and a CentOS 8 system.

We assigned each variant of SAM and DeepLab V3+ 24 core CPUs, 64GB RAM, and 4 NVIDIA V100 (32GB) SXM2 GPUs. Six key hyperparameters, i.e., the batch size, the combination of loss functions and their values, learning rate, momentum factor, and weight decay, were finetuned to achieve the optimal model performances. Detailed values of settings can be accessed through the mentioned the repository. The early-stop method was used to avoid overfitting, and we saved the checkpoint of each model with minimal validation loss for comparison.

4.4 Extracting and incorporating domain knowledge

We systematically reviewed many publications to gather landfill-related domain knowledge, and then analysed their universality in practice. Finally, five universally applicable features were defined based on domain knowledge to augment satellite image-based landfill recognition, as summarized in Table 2. Notably, several other domain knowledge-based features, e.g., soil type, pipeline network density, land cost, and flood vulnerability (Aslam et al., 2022; Rezaeisabzevar et al., 2020), were not included due to the availability limitation of the global-scale dataset.

Table 2. The domain knowledge-informed features for augmenting satellite image segmentation-based landfill recognition

No.	Feature name	Domain knowledge behind the feature	Threshold	Feature utilization
1.	Minimum distance to inland water body	A universally applicable rule is that landfills should be far away from large inland water bodies (natural lakes, manmade reservoirs, wetlands, and rivers) to prevent water pollution by landfill leachate (Karimi et al., 2020; Ya et al., 2019). This rule can be harnessed to exclude the detected landfill objects very close to inland water bodies. Notably, landfills may be adjacent to the ocean when it comes to coastal regions. Examples can be seen in Singapore’s landfills.	Distance <0.4 km	Removing segmented instances with a value of <0.4 km
2.	Completeness of in-use landfill area	In practice, it is almost impossible that an in-use landfill contains an inner non-landfilling area. Hence, we can fill the hole (unrecognized pixel region) inside a detected landfill pixel region.	N.A.	Filling the hole in segmented landfill instances
3.	Upper limit of the landfill’s perimeter and area ratio	To control construction costs and improve operation convenience, the edges of landfills are generally designed to be as regularly shaped as possible (Crawford	<0.1	Using Structuring Element (MathWorks, 2024) with a scaling coefficient of 4 to dilate the segmented object

No.	Feature name	Domain knowledge behind the feature	Threshold	Feature utilization
		& Smith, 2016). Hence, the ratio of the landfill perimeter to area should have an upper limit.		in an image with 2000*2000 pixels, so as to reduce the perimeter-area ratio (akin to antialiasing)
4.	Upper limit of the length ratio of long and short axes	The long and short axes refer to the two axes of the ellipse that have the same normalized second-order central moment as the segmented object. In practice, designing landfills in an elongated shape is generally not recommended, as it is not convenient for landfill construction and operation (Meegoda et al., 2016).	<5.5	Removing segmented instances with a value of >4.2
5.	Upper limit of normalized landfill area variation coefficient	Combining multiple small landfilling areas into one large site is the prioritized practice. Even for illegal dumping sites, offenders prefer existing sites over new ones to minimize risks, which could be explained by the Broken Windows Theory (Massa et al., 2023). Consequently, it is reasonable to believe that the normalized areal variation coefficient of multiple landfills within one image should be less than a certain threshold.	<0.40	Removing the smallest segmented instances until the value becomes less than 0.60

The specific methods for integrating domain knowledge are multifarious, as reviewed by (Dash et al., 2022) and (Xie et al., 2021). This study adopted post-processing (sometimes called "post hoc evaluation") as the integration method. Specifically, the domain knowledge-informed features are incorporated to calibrate the image segmentation results of the developed deep learning models in Section 4.3, thereby improving the final landfill segmentation accuracy. The quantitative threshold of each feature was from conservative estimation based on values given in existing literature (Djokanović et al., 2016; Karimi et al., 2020; Rezaeisabzevar et al., 2020) and statistical analysis of the collected landfill image samples. Meanwhile, sensitivity analyses (calibration performance difference when changing the feature threshold) were conducted to demonstrate the optimality of threshold selections. Notably, the global inland water body datasets used for Feature 1 are from (Yamazaki et al., 2015), (Feng et al., 2016), and (Klein et al., 2017), which provided the segmentation result of inland water bodies (including areal extent and location). The five domain knowledge-informed features are respectively encoded and then connected in a certain sequence as a whole. Its computational complexity is low as it involves the numerical calculation of the pixel matrix (2000×2000 pixels for each image input).

5. Result analysis and comparison

5.1 SAM model segmentation and domain knowledge-based calibration

Table 3 compares the model performance with and without the five domain knowledge-based features. Several findings were derived from the experiments:

- Firstly, it can be observed that the model shows the best performance in both detecting the presence of landfills and segmenting landfill instances when selecting the complexity level of the image encoder ViT-Huge, which uses a larger number of parameters than ViT-Base and ViT-Large to capture visual features for image segmentation.
- Secondly, comparing Row 1 of Table 3 to Rows 4~8, it can be found that with Feature 1, 2, 3, 4, or 5, the model's IoU respectively increased from 70.72% to 71.95%, 75.82%, 74.99%, 74.57%, or 74.59%, demonstrating that each of the five domain knowledge-based features can effectively calibrate the segmentation result by SAM.
- Thirdly, the last three rows of Table 3 indicate that combining the five features can further improve the SAM model's performance. With the ViT-Huge image encoder and calibration by the five features, the SAM can achieve a recall of 99.51% in detecting the presence of landfills, as well as an OA of 98.97%, mAcc of 91.95%, mIoU of 88.08%, and IoU of 77.21% in segmenting global landfill instances from satellite images.
- Fourthly, in comparison, combining the five features contributes to improving the OA from 98.90% to 98.97%, the mAcc from 91.86% to 91.95%, the mIoU from 86.33% to 88.08%, and the landfill segmentation IoU from 73.82% to 77.21%.
- Lastly, the experiments indicated that the optimal sequence of applying the five features is to calibrate segmentation results by "minimum distance to inland water body" firstly, then by "completeness of in-use landfill area", following by "ratio of landfill's perimeter and area"; next by "upper limit of the length ratio of long and short axes", and finally, "upper limit of normalized landfill area variation coefficient".

Table 3. Performance comparison of SAM models with and without segmentation calibration by domain knowledge-based features

Model and domain knowledge-based feature	Vit Type	Pretrained dataset	Presence detection	Segmentation of landfill's areal extent				
			Recall (%)	OA (%)	mAcc (%)	mIoU (%)	Per-class IoU (%)	
							Landfill	Others
SAM	Base	SA-1B	98.06	98.94	89.85	84.81	70.72	98.89
SAM	Large	SA-1B	99.03	98.89	90.64	85.59	72.34	98.83
SAM	Huge	SA-1B	99.51	98.90	91.86	86.33	73.82	98.84
SAM with Feature 1	Base	SA-1B	98.06	98.92	91.88	86.34	71.95	98.87
SAM with Feature 2	Base	SA-1B	98.06	98.94	90.71	87.36	75.82	98.90
SAM with Feature 3	Base	SA-1B	98.06	98.94	90.90	86.95	74.99	98.90
SAM with Feature 4	Base	SA-1B	98.06	98.95	89.84	86.74	74.57	98.91
SAM with Feature 5	Base	SA-1B	98.06	98.88	90.28	86.72	74.59	98.84
SAM with the five features	Base	SA-1B	98.06	98.96	91.44	87.62	76.32	98.91
SAM with the five features	Large	SA-1B	99.03	98.96	91.91	88.06	77.18	98.93
SAM with the five features	Huge	SA-1B	**99.51**	**98.97**	**91.95**	**88.08**	**77.21**	**98.94**

Notes: Referring to Table 2 for the feature number explanation.

Figure 3 illustrates the results of ablation experiments that aim to reveal how the three SAM model types and the five domain knowledge features respectively contribute to calibrating landfill segmentation results. As observed in Lines 2~4 of Figure 3, when employing the ViT-Larger image encoder or ViT-Huge image encoder, wrong segmentation instances can be reduced, improving the overall segmentation accuracy. But this improvement is limited. Further improvement is observed when introducing domain knowledge features, as presented in Line 5 of Figure 3. For satellite image-based landfill segmentation, the false positive instance may stem from polluted inland water bodies, empty construction sites, and the like. Integrating the domain knowledge-informed Features 1, 4, and 5 can significantly reduce false positive instances. While the false negative instance mostly originates from blurred landfill boundaries and significant differences in surface waste compositions. Features 2 and 3 can largely correct this kind of instance.

Figure 3. Ablation experiments of using distinct domain knowledge features and SAM segmentation models with different ViT types to calibrate SAM segmentation results

In addition, previous studies indicated that land cover type has a more significant impact on satellite image-based landfill recognition than other factors, e.g., terrain type and waste composition type (Sun et al., 2023; Yong et al., 2023). A segmentation accuracy comparison between different land cover types was conducted to further understand the proposed approach's performance, based on the test dataset. Finally, comparison analysis results indicated that the highest accuracy measured by mIoU occurs in forest land, while the lowest occurs in barren land;

nonetheless, their average accuracy gap is small (4.21%). This further reflects the superior generalizability of the proposed approach. Figure 4 exemplifies landfill detection results under different land cover types(areal extent is converted from the number of pixels).

Figure 4. Example of landfill detection under different land cover types by the developed approach

5.2 DeepLab V3+ model segmentation performance

As shown in Table 4, this research also conducted experiments to investigate landfill recognition performance using DeepLab V3+ model variants, in order to compare with the latest study by Yong et al. (2023) and Lin et al. (2024), who achieved a high accuracy in recognizing landfill areas based on DeepLab V3+ models. Connecting to Table 3, it can be found that the recall of DeepLab V3+ (95.63% to 98.54%) is basically lower than that of SAM (98.06% to 99.51%). This means that SAM has a better performance in detecting the presence of landfills. Similarly, according to Tables 3 and 4, the OA, mAcc, IoU, and mIoU of DeepLab V3+ also tend to be lower than the counterparts of SAM, meaning that SAM performs better in segmenting landfill instances from satellite images. Such results further demonstrate that SAM is a better pre-trained model choice for developing our global landfill recognition approach.

Table 4. Performance of the four DeepLab V3+ model variants in recognizing landfills

Model	Backbone	Pretrained dataset	Output stride	Presence detection	Segmentation for landfill extent				
				Recall (%)	OA (%)	mAcc (%)	mIoU (%)	Per-class IoU (%)	
								Landfill	Others
DeepLab V3+	Xception	PASCAL VOC	8	95.63	98.09	86.45	78.22	58.39	98.05
DeepLab V3+	Xception	PASCAL VOC	16	98.06	97.60	89.12	76.06	54.59	97.52
DeepLab V3+	MobileNet	PASCAL VOC	8	98.54	97.82	89.20	77.40	57.05	97.76
DeepLab V3+	MobileNet	PASCAL VOC	16	98.06	98.17	83.73	77.75	57.37	98.12

5.3 Comparison analysis

Compared to existing methods, the new approach shows multiple strengths. In terms of identifying the existence of landfill sites, Sun et al. (2023) achieved a recall of 98.0% at the global scale, which represents the highest recall performance among existing landfill identification methods. The second-highest recall is 85.6%, achieved by Yong et al. (2023) at the urban scale. In comparison, our approach reaches a recall of 99.51% at the global scale, a little higher than Sun's approach, demonstrating that in terms of detecting the presence of landfills, our approach performs better than existing approaches.

As for landfill object segmentation, the method developed by Gao et al. (2022) achieved a mIoU of 93.8% on the neighbouring scale, which is the highest mIoU among existing studies. The mIoU of our approach is 88.08%, which is high if compared with most existing studies (See Table 1). Despite a lower mIoU than Gao's method, our approach focuses on a far larger spatial scale, i.e., the global scale. Achieving a high segmentation accuracy at the global scale is far more challenging than at the neighboring scale, and in general, expanding the spatial scale will unavoidably reduce segmentation accuracy. A piece of indirect evidence is that Gao et al. achieved a mIoU of 85.24% and 79.12% by using DeepLab V3+, with an output stride of 16 and MobileNet and Xception as the backbone, respectively; however, according to Table 4, the corresponding mIoU decreases to 77.75% and 76.06% respectively, when the spatial scale increases to the globe.

Furthermore, Yong et al. (2023) reached a landfill image segmentation IoU of 74.6% at the city scale. By comparison, the newly proposed approach has a higher IoU (77.21%), meaning that the new approach is more accurate than Yong's method in segmenting landfill instances from remote sensing images. Lin et al. (2024) achieved a higher IoU (82.08%) than our study; however, their work focused only on the district scale. The IoU might largely decrease when expanding the application scope from the district level to the global level, as indicated in Table 4.

6. Discussions

6.1 Applicability of the developed approach

In the experiment, the trained model did not show a significant segmentation accuracy difference between distinct countries, demonstrating that the developed approach has a superior global applicability. The newly developed approach has multiple application scenarios. For example, it provides an efficient and cost-saving solution to trace uncatalogued landfills, supporting urban/regional/national landfill database creation. This is particularly important for landfill-related environmental management (Gill et al., 2019). Also, given that the approach was developed based on a diversified landfill sample dataset, it has the potential to automatically detect illegal/unauthorized landfills around the world. Such a detection task has been recognized as a major concern by the environmental protection departments of many governments (Quesada-Ruiz et al., 2019). According to the report by Watkins (2015), most European countries are affected by the presence of illegal landfills within their territory, and the total number of illegal landfilling and dumping events in the European Union reached 12,628 at the end of December 2014, involving around 2,871,186 tonnes of waste. The approach can also be used for global landfill mapping, which contributes fundamental data to further investigation, such as health risk assessment of residents near landfills, analysis of land occupation by waste landfilling, and landfill evolution-based waste recycling level inversion.

The proposed approach enables practitioners from environmental protection agencies and other institutions to automatically conduct large-scale landfill detection. The full automation of the detection process and the increasing availability of high-resolution satellite images facilitate the integration the approach into existing environmental monitoring systems. Compared to traditional methods for landfill detection in local areas, the scalable and accurate approach is cost-effective through global stratified sampling and domain knowledge integration. Using a workstation equipped with two Intel Xeon Gold 6226R (16-core) CPUs, 192 GB RAM, and an NVIDIA RTX6000 GPU (24 GB memory), the approach—based on SAM with the ViT-Base model—processes each image sample for segmentation in every 1.84 seconds. Nevertheless, when applied to global landfill mapping with over 8.4 million satellite images (each covering 16 km^2), the method remains relatively inefficient. To reduce processing time, parallel computing across multiple supercomputers can be applied in the future.

6.2 Research contributions

The major theoretical contribution of this research is in going beyond existing landfill recognition studies from three perspectives. Firstly, unlike previous studies concentrating mainly on neighbourhood and city scales, this work expands the spatial scale of landfill recognition to the globe, ensuring that the developed approach is more generalizable to different regions than existing approaches. Secondly, previous studies focused mainly on detecting the presence of landfills, which was treated as a binary classification problem. In contrast, this research delves further into extracting the areal extent of in-use landfills. This can not only inform us of the existence of landfills, but also provide more comprehensive information by giving the area information of in-use landfills. Thirdly, differing from existing studies that only harness the features extracted from remote sensing data to identify and segment landfill objects, this study innovatively integrates domain knowledge into the deep image learning process to enhance landfill recognition. Experimental results demonstrate that this strategy improves global landfill recognition accuracy and efficiency.

There are three main aspects to the practical significance of this study. First, the approach can be used to recognize landfills in various regions, assisting the public sector in automatic landfill inventory and monitoring. Second, with superior generalizability, the approach can be applied to the automatic detection of illegal landfills, thereby providing data support for illegal dumping governance. Like the data availability challenge faced by most computer vision application research (Khan et al., 2024; Li et al., 2024), illegal landfill detection is also limited by the availability of sufficient samples. Last, the approach can be utilized to map global landfills, producing the first comprehensive and reliable global landfill database to support further research and practice.

6.3 Shortcomings and recommendations

The major limitation of this research is that the domain knowledge-enhanced satellite image segmentation approach may be incapable of recognizing small waste dumpsites. As shown in Figure 2, the approach input is the satellite image with a size of 2000×2000 pixels (covering around 16 km^2 in reality), and the image size selection was based on the balance of multiple factors. Within such a satellite image, open-air landfills with a size of hundreds of square meters (generally termed "waste dumpsites") will not be very clear, reducing the approach's effectiveness in real world; moreover, these small dumpsite might be camouflaged or covered intentionally, further increasing recognition difficulty. Nonetheless, this kind of dumpsite accounts for only a small share of the global landfill community. Meanwhile, if necessary, the methodological architecture of the domain knowledge-enhanced satellite image segmentation approach can be easily generalized to address this issue, based on proper model retraining using a certain number of dumpsite images.

7. Conclusions

Focusing on the landfill detection and monitoring challenge faced by the public sector, this research proposed a domain knowledge-augmented satellite image segmentation approach to accurately recognize the presence and areal extent of landfill sites around the world. To this end, 1,380 landfills with distinct societal, geographical, topographical, and morphological characteristics were sampled from different countries around the world; then, their satellite images with a resolution of 2m were extracted and annotated to establish a landfill image dataset, which was utilized to fine-tune deep image learning models for accurately segmenting landfill instances from images. Three variants of the pre-trained SAM model and four variants of the pre-trained DeepLab V3+ model were selected as the backbone model and cross-compared in experiments, while five features defined based on landfill-related domain knowledge was incorporated to calibrate model segmentation results, thereby improving the recognition accuracy of global landfills.

Experimental results indicated that the five domain knowledge-informed features have a significant contribution to improve deep learning model-based landfill segmentation. Basically, the developed approach, based on the SAM model with ViT-Huge image encoder and augmenting by domain knowledge, reaches a recall of 99.51% in detecting the presence of landfills, while achieving an OA of 98.97%, mAcc of 91.95%, mIoU of 88.08%, and IoU of 77.21% in segmenting landfill instances from satellite images. This approach goes beyond existing landfill detection methods by expanding the spatial scale to the globe, focusing on both landfill presence detection and area extraction, and incorporating domain knowledge to achieve higher accurate landfill recognition. The developed approach can be applied to automate landfill cataloguing, detect illegal and uncatalogued landfills, and map global landfills. Future research is recommended to apply the approach for extracting landfills in different regions and to develop global landfill map databases for supporting further landfill management research.

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Data availability

Data and codes will be made available on request. The code can be found in the GitHub repository (https://github.com/Lanny107/Global-Landfill-Recognition.git).

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