32/2021
Lee, R.D. (2021) „Potential applications of publicly available remote sensing data to solid waste management in developing countries", In: Proceedings "Sardinia 2021, 18th International symposium on waste management and sustainable landfilling", E-paper, CISA Publisher, Forte Village, S.M. Di Pula, Sardinia, Oct. 11th-15th 2021.

SARDINIA2021 HYBRID EVENT / 11-15 OCTOBER 2021 / CAGLIARI / ITALY
18TH INTERNATIONAL SYMPOSIUM ON WASTE MANAGEMENT AND SUSTAINABLE LANDFILLING

Potential applications of publicly available remote sensing data to solid waste management in developing countries

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ABSTRACT: In the context of many developing countries, if there is no concerted effort made to gather vital waste-related data, or there is simply a lack of resources for this purpose, then solid waste becomes ever more difficult to manage sufficiently. Where there is a dearth of data, or where there is considerable uncertainty surrounding available data, remote sensing (RS) may offer waste and environmental authorities at all levels of governance some solace, by providing them with valuable tools to fill information gaps and verify data collected in-situ. This paper then attempts to identify already established methods for monitoring solid waste using Earth observation (EO) technologies, and suggests additional applications of publicly available RS resources to solid waste management (SWM), especially within a developing country context. Ultimately, emphasis is placed on the potential of utilizing RS in this way to encourage additional research collaborations between waste experts and geoinformatics institutes, and to preliminarily expose local governments to a new dimension of cost-effective tools for effective solid waste management via open access RS products.

Keywords: Remote sensing, solid waste management, developing countries, space-borne data acquisition, Earth observation technologies, open access platforms, in-situ data verification

1. INTRODUCTION

Remote sensing (RS) has long been established and heralded as an indispensable tool to improve upon the exactitude and sheer quantity of data available for environmental monitoring and environmental management purposes (Moore, 1979). Its contributions to climate science, meteorology, oceanography, glaciology, soil science, urban planning, forestry, hydrology, land tenure policy and enforcement, agricultural sciences, disaster risk management and mitigation, and so many others, cannot be underestimated (NASA, 2021c). With the passage of time, not only has the magnitude of Earth observation (EO) satellites placed into orbit steadily increased (e.g., see Figure 1), so has the quality of the data they produce (UNOOSA, 2021). This is due to the continuous refinement of the detection instruments that each subsequent satellite is equipped with, leading to both a finer spectral resolution (i.e., additional electromagnetic radiation (EMR) bands and finer detection ranges) and a finer spatial resolution (i.e., smaller pixels in recorded images and data) (NASA, 2021c). What's more, instead of individual satellites being placed up in orbit, there has been a trend towards linking up multiple satellites, forming constellations that collectively provide data with a much higher temporal resolution (i.e., the amount of time between successive recordings of the same point on planet Earth) (NASA, 2021c). Last but not least, the number of space agencies, state actors, and private companies making their data and

data products available for purchase or open access has also steadily increased.

Figure 1: Quantity of European Space Agency EO satellites in orbit increasing over time (ESA, 2021a)

That means, not only has the body of data being gathered, and its associated quality, improved continuously, but also because of its partial democratization much of it has been made available to anyone with research and/or regulatory purposes. This has massive implications and benefits for authorities working on the management of natural resources and the environment at all levels of governance, especially in developing countries. No longer is this field reserved exclusively for intelligence agencies and reconnaissance purposes. Instead satellite imagery made public can now be processed and form-fitted to a myriad of purposes, including solid waste management (SWM).

Historically, attempts to apply remote sensing data and techniques to SWM have been hindered by the fact that many phenomena occurring within SWM were too small to be adequately discerned and described by sensors with low or moderate spectral and spatial resolutions (see Table 1 for spatial resolution ranges). Furthermore, while most EO technologies were designed to monitor broad global phenomena that occur slowly over time (e.g., climate patterns, deforestation, urbanization rates, land use changes, sea surface temperature fluctuations, and so on), many SWM phenomena occur on much smaller timescales. But as the field has expanded, so has the possibility for utilizing it in a solid waste management context. To illustrate this, the following section describes examples from the literature.

Table 1: Satellite sensor spatial resolution grades (Glanville & Chang, 2015)

Spatial Resolution Grade	Pixel Size
LOW	> 50 m
MODERATE	12-50 m
MEDIUM	4-12 m
HIGH	1-4 m
VERY HIGH	< 1 m

2. Established remote sensing techniques as applied to SWM

Probably the most well-established applications of remote sensing within solid waste management as observed in the literature, include landfill management—especially the siting of landfills—and a wide variety of attempts to systematically identify illegal dumpsites. RS-integrated SWM examples are provided below and partially summarized in Table 2.

2.1 Landfill siting and expansion

Landfill studies that have attempted to utilize RS data and techniques have become increasingly more frequent over the past 10 years. Although many satellite sensors produce images with too low a spatial resolution for some SWM applications, in the case of landfill siting and expansion, large swaths of land need to be evaluated based on many different environmental and anthropogenic criteria to determine the optimal position for the new sites. Given the aptness of many sensors for this application, it comes as no surprise that multiple research teams have developed techniques that employ RS data to reinforce the effectiveness of more traditional landfill siting criteria and methodologies.

For example, a study in Crete, Greece derived a detailed landfill suitability map for the Chania prefecture (western part of the island) using 17 predetermined criteria (Alexakis & Sarris, 2013). This was done by weighting each criterion using a fuzzy logic algorithm and an analytical hierarchy process (AHP), and then manually applying five suitability classes ("extremely appropriate" to "extremely inappropriate") to the subsequent map (Alexakis & Sarris, 2013). One of the 17 criteria was based on an NDVI[1] map averaged from two Landsat 7 ETM+ images acquired in 2003 and 2011. This helped to avoid siting in areas with healthy vegetative growth and (presumably) high soil moisture content (Alexakis & Sarris, 2013). Ultimately, only 0.8% of the study area (about 19 of 2,343 km^2) was determined to be "extremely appropriate" for a new landfill site (Alexakis & Sarris, 2013).

Somewhat similarly, Richter, Ng, and Karimi (2019) devised a method for landfill expansion suitability in Saskatchewan, Canada, by combining remote sensing and vector data taken from LANDSAT 8 and governmental sources, respectively, paving the way for a decision-making tool that policy makers might use without the prior consultation with experts (Richter et al., 2019). It ranked 38 landfills across a 36,766 km^2 area based on multiple geospatial factors for their suitability for expansion. This was done, in part, by dividing the study area into 39 Thiessen polygons and utilizing five remote sensing indices (NDVI[1], NDBI[2], NDSI[3], NDMI[4], and NTL[5]) argued to be contextually significant to landfill expansion suitability in the study area. Then a novel ranking algorithm was applied to the polygons based on the normalized index and vector values (Richter et al., 2019).

Additional siting studies have also been carried out in a number of lower income countries, to include: Mohammedia, Morocco (El Maguiri, Kissi, Idrissi, & Souabi, 2016); Gulu Municipality, Uganda (Okot, Ogao, & Abandu, 2019); and four municipalities in the state of Bihar, India (Kumar, Singh, Mishra, & Kumar, 2021). Almost every example makes use of publicly available satellite imagery and integrates it with a geographic information system (GIS) and a decision-making model, like an Analytical Hierarchical Process (AHP), a Weighted Linear Combination (WLC), or a Multi-Criteria Decision Analysis (MCDA) (Richter et al., 2019). For example, in the case of Mohammedia, Morocco, a Landsat 7 ETM+-derived land use map was layered against other maps in a GIS to determine 3 optimal sites that satisfy 6 criteria (El Maguiri et al., 2016). Similarly, Kumar et al. (2021) used Landsat 7 ETM+ and Landsat-TM data to derive coarse land coverage maps and compare them against official topographical maps, for more precise satisfaction of landfill placement criteria.

[1] Normalized Difference Vegetation Index (NDVI)
[2] Normalized Difference Built-up Index (NDBI)
[3] Normalized Difference Snow Index (NDSI)
[4] Normalized Difference Moisture Index (NDMI)
[5] Night Time Light (NTL)

2.2 Unauthorized dumpsite detection

Multiple research groups have employed RS techniques in an attempt to detect illegal dumpsites with varying degrees of success. Glanville and Chang (2015) precisely described a number of these methodologies and analyzed their effectiveness and efficiency for suitability of application to Queensland, Australia. Their review primarily showed that using high resolution satellite imagery (<4 m pixel size) and a mixed-method approach, especially when analyzed RS data is combined with other spatial data and then analyzed in a GIS, yields the most accurate results (Glanville & Chang, 2015). The use of a GIS introduces new criteria not available in the RS data, and significantly reduces down the overestimation of potential illegal dumpsites identified exclusively by any given RS analysis technique (Glanville & Chang, 2015).

To cite some examples:

Notarnicola, Angiulli, and Giasi (2004) used LANDSAT-TM data to show that when one enhances spectral differences with a principal component transformation, and then applies an unsupervised classification algorithm to the data, that illegal dumpsites can be identified based on the indirect land changes resulting from the illegal disposal. The technique relies on areas with primarily homogenous land cover, and would require overlays of additional images and spectral bands to be refined and/or suited to more heterogeneous landscapes (Glanville & Chang, 2015).

Silvestri and Omri (2008) used high-resolution satellite imagery from IKONOS-2 to first identify spectral characteristics of 7 known illegal dumpsites in a so-called “training zone”, based on stressed vegetation deemed to be linked to buried hazardous waste. They then used this spectral library in conjunction with a maximum likelihood (ML) algorithm to identify other potential old illegal dumpsites in the 1,969 km^2 study area, and then refined the search further, by comparing the sites against historic aerial photography, vector data (e.g., road access), and other information provided by local authorities in a GIS (Silvestri & Omri, 2008). The final result was supplied to authorities for further verification. Ultimately, only 81 of the 633 sites (~13%) identified were shown to contain hazardous waste (Silvestri & Omri, 2008).

Visual classification of aerial photography (aircraft and drones) proved to be pretty successful, due to its high spatial resolution, but a very low efficiency level, as the work was primarily done manually by experts and proved to be very time intensive (Glanville & Chang, 2015). By comparison, visual classification of illegal disposal sites using data from medium spatial resolution sensors, proved to not be possible, given that most of the disposal sites were smaller than the predefined 10-meter spatial resolution (Glanville & Chang, 2015). All the same, Yonezawa (2009) was able to use Quickbird’s panchromatic band (0.61 m GSD[6]) to successfully identify illegal industrial dumpsites larger than 2 square meters surrounded by vegetation, by utilizing the differences in spectral characteristics, and then confirming with field observations. The multispectral (2.44 m) data was then able to successfully classify the materials at the dumpsites larger than 6x4 meters, given that the panchromatic band could not always differentiate between scrap iron and plastic, and soil (Glanville & Chang, 2015; Yonezawa, 2009).

Ferrara et al. (2010) used aerial infrared thermography from a drone to show, among other things, that the thermal distributions observed in managed landfills as compared to uncontrolled dumpsites differ enough to potentially identify uncontrolled dumpsites over larger land areas.

Zhang, Du, and Guo (2013) devised a “multiresolution” method using Quickbird imagery to identify MSW dumpsites. They used average MSW characteristics to define a “low heterogeneity” identity standard as observed in resampled satellite images with a lower resolution, and then used an automated classification process to identify sites that likely contain MSW. Then, the author presumes[7], the high-resolution originals were then used to help verify the presence of waste in the predicted sites to increase accuracy of the analysis.

More recently, Azmi, Mohamad Sharom, Md Zin, Numpang, and Sipit (2020) visually classified pan-

[6] GSD = Ground Sample Distance. Otherwise known as the spatial resolution.

[7] This publication was originally published in the Chinese language, and the author therefore did not have full access to its original contents.

sharpened high-resolution satellite imagery from SPOT-7 and the Pleiades constellation to initially identify potential dumping grounds and using a loose set of criteria (to include some known vector data) to increase the likelihood of the identified locales (Azmi et al., 2020). Then 10 of the identified sites were selected at random for verification of illegal activities via video from an unmanned drone. Ultimately, nine of the ten sites were confirmed to be sites with illegal disposal activities and additional evidence incriminating perpetrators was recorded for authorities (Azmi et al., 2020).

2.3 Landfill thermal detection

Where MSW is not separated or treated before final disposal, the landfill sites function as bio-reactors as organic material biochemically degrades over time. This process leads to a temperature increase within the landfill, and oftentimes to an increase in land surface temperature (LST), too, depending on the final land coverage.

Mahmood, Batool, and Chaudhry (2016) used bands 10 and 11 of Landsat 8 imagery to map the fluctuating thermal zone surrounding the primary dumping site near Faisalabad, Pakistan, to determine its breadth and the effects of observed elevated surface temperatures on the surrounding vegetation (indirect indicator of air and soil pollution from the decomposing waste). For a disposal site that is about 141,000 m^2 with about 120,000 tonnes of landfilled MSW, a thermal zone that averaged a 700 m radius (500-1,100 m range) and a maximum temperature elevation of 4.67 °C in spring were determined (Mahmood et al., 2016). Using Landsat Surface Reflectance High Level Data Products (i.e., NDVI, SAVI, and MSAVI, specifically), they were then able to confirm that the seasonal changes of the thermal zone, both in temperature and extent, were indeed having a negative effect on the surrounding agriculture, and concluded that wheat was most resistant to the higher levels of pollution (Mahmood et al., 2016).

A year later, a follow-up study using very similar techniques was carried out by Mahmood et al. (2017), comparing the Faisalabad site to the Mahmood Booti dumpsite in Lahore. Mahmood Booti has a lot more heterogeneity in the land cover surrounding it (Mahmood et al., 2017). Their ultimate conclusion was that a concrete distance of 1,000 m from agricultural land should be adopted as a criterion for landfill siting (Mahmood et al., 2017).

2.4 Landfill methane point source detection

Cusworth et al. (2020) utilized the Next Generation Airborne Visible/Infrared Imaging Spectrometer (AVIRIS-NG) to quantify strong point source methane emissions at active faces of landfill sites that are otherwise difficult to measure with in situ techniques, or are by and large unaccounted for in the LandGEM model (Landfill Gas Emissions Model) employed as the standard for operators to estimate emissions. Their RS measurements showed that active face methane emissions can comprise 11-21% of a given landfill's total emissions, and that methane emission estimates from landfills, as documented under the California Methane Survey, are typically grossly underestimated (Cusworth et al., 2020).

They used the same technique to show that landfill infrastructure insufficiencies and/or degradations can also lead to unintentional methane plumes, proving the value of continuous RS monitoring of even well-engineered landfill sites (Cusworth et al., 2020). Finally, they observed two facilities intended to process organic waste to reduce methane emissions and found that methane plumes were forming over specific areas of each facility. These plumes implied, as stated by Cusworth et al. (2020), seal or valve failure and/or unintentional anaerobic conditions due to process insufficiencies. The resulting methane estimates for both facilities were well above the reporting threshold for landfills of the State of California (Cusworth et al., 2020).

Table 2: Examples of SWM using data and techniques derived from remote sensing instruments

Waste Management Application	Location of Study	Remote Sensing Instrument(s)	Sample Period	Method of Analysis	Study Outcome(s)	Source
Landfill siting	Crete, Greece	ETM+ (Landsat 7)	5/6/2003 and 5/20/2011	Analytical hierarchy process (AHP) enhanced with fuzzy logic techniques	Only 0.8% of total study area deemed “extremely appropriate” for new landfills; 73% of existing landfills situated in “extremely inappropriate” areas	Alexakis and Sarris (2013)
Landfill expansion	Saskatchewan, Canada	OLI/TIRS (Landsat 8); VIIRS (Suomi NPP)	6/15/2018, 4/3/2018; 4/1/2012 – 10/30/2012	Novel ranking algorithm applied to GIS using RS index data, vector data, and Thiessen polygons	38 landfills within a 36,800 km^2 area mapped, analyzed, and ranked for expansion suitability	Richter et al. (2019)
Landfill methane point source detection	California, USA	AVIRIS-NG (airborne; 3-4 km above ground)	2016-2018; n = 436 Californian landfills and organic waste facilities	Integrated Mass Enhancement (IME) flux quantification method	32 sites w/ persistent methane plumes; constituting 41.3% of the state-wide point source emissions	Cusworth et al. (2020)
Landfill thermal zone detection	Faisalabad, Pakistan	TIRS (Landsat 8); Quickbird high-resolution imagery	April 2013-Oct 2015; 30 images	Zonal statistic operation of valid temperature observations (Band 10 of TIRS); polygon digitization of varying land cover (Quickbird and ENVI 5.1; seasonal analysis of vegetation indices	Dumpsite thermal zone range of 500-1,100 m (avg. 700 m); agricultural lands in radius affected by resultant pollution; wheat determined to have most vigor	Mahmood et al. (2016)
Historic illegal dumpsite identification	Veneto region, Italy	OSA (IKONOS-2); Historic aerial photography	6/26/2001; 7/2/2001; 8 data points total 1955, 1978, and 1987	Maximum likelihood (ML) algorithm; manual digitization of detected sites; integration of RS and auxiliary data in a GIS	Generated spectral library based on vegetation stress at known historic dumpsites and applied the results to a 1,969 km^2 area to identify 633 additional candidate sites	Silvestri and Omri (2008)
Illegal dumpsite identification (industrial waste)	Sendai, Japan	Quickbird panchromatic and multispectral	6/5/2003; 8/5/2005; 9/21/2006	Visual interpretation of pan-sharpened imagery	Successfully identified illegal industrial waste dumpsites 2 m^2 and larger (PAN); material classification at dumpsites larger than 6x4 m (MS)	Yonezawa (2009)

3. Accessing remote sensing data

Many platforms have been developed to make remote sensing imagery and data accessible to wider groups of people with varying levels of expertise. Table 3 provides a number of examples.

Table 3: Open access sources of satellite imagery and remote sensing data products

Platform	URL	Operator	Remote sensing data employed	Noteworthy features
EarthExplorer	https://earthexplorer.usgs.gov/	USGS	Landsat Missions (all) Terra and Aqua MODIS and ASTER Suomi VIIRS Resourcesat-1 and -2 Sentinel-2 IKONOS-2 OrbView-3 SPOT (historic)	- 40 years of available data - Level 1, 2, and 3 data products available (sensor-dependent) - Hyperspectral imagery available - Access to free high-res imagery - Image preview and download, but in-program analysis capabilities limited
EOSDIS Worldview	https://worldview.earthdata.nasa.gov/	NASA	Global Image Browse Services (GIBS) Data from many different satellite sensors	- Diverse selection of scientific data products (incl. Level 4) provided by NASA - Imagery upload is almost real-time (3-5 hours after recovery from sensor) - Many in-program analysis options
Land Viewer	https://eos.com/landviewer/	EOS Data Analytics	Landsat Missions (4-5, 7, 8) Sentinel-1 and -2 CBERS-4 Terra and Aqua MODIS NAIP (aerial imagery) SPOT 5-7 Pleaiades-1 Kompsat-2, 3, 3A SuperView-1	- Program has its own cloud storage - High-res imagery can be previewed, but must be purchased for download - In-program analytics: 20+ default band combinations, indices like NDVI, NBR, and SAVI, custom index builder, time series analysis, etc. - Good for beginners/non-experts
Sentinel Hub	https://www.sentinel-hub.com/	Synergise Laboratory for GIS, Ltd. (Slovenia)	Sentinel-1 Sentinel-2 Sentinel-3 Sentinel-5P Landsat Missions (4-5, 7, 8) Terra and Aqua MODIS Envisat MERIS Proba-V GIBS PlanetScope Pleiades-1 SPOT 6 and 7 WorldView (1, 2, 3) and GeoEye-1	- Two services: EO Browser and Sentinel Playground - EO Browser analytics: 8 band combinations, indices, custom index builder, time series analysis, etc. - Upload of other datasets possible - High-res imagery must be purchased
Google Earth Engine	https://earthengine.google.com/	Google LLC	Combines publicly available geospatial data and imagery from many sources (EO and met sensors, aircraft, etc.). Examples include: Landsat Missions (all) Terra and Aqua MODIS Sentinel-1 CHIRPS NAIP (aerial imagery) Planet SkySat	- Very versatile platform - Combines immense variety of datasets and scientific data products with customizable layering and analysis options - Option to upload external files and save work in Google Cloud Storage - Requires coding abilities (JavaScript) and deeper understanding of RS data handling
Global Visualization Viewer (GloVis)	https://glovis.usgs.gov/app	USGS	Landsat Missions (all) Terra ASTER EO-1 ALI and Hyperion Resourcesat-1 and -2 Sentinel-2 SRTM (aerial radar) DOQ's (aerial photography) OrbView-3	- Primarily for image search, preview, and download (no in-program analysis) - Offers some free high-res imagery - Easy to use/good for non-experts

Platform	URL	Operator	Remote sensing data employed	Noteworthy features
UNAVCO	https://www.unavco.org/	University NAVSTAR Consortium	ESA/ERS/Envisat Sentinel-1 RadarSat-1 and -2 ALOS-PALSAR TerraSAR-X UAVSAR (aerial)	- Access to diverse sources of SAR data and derived data products (Seamless SAR Archive) - Provides access to separate programs for analysis of downloaded data
INPE Image Catalogue	http://www2.dgi.inpe.br/catalogo/explore	National Institute for Space Research (Brazil)	Landsat Missions (all) Terra and Aqua Suomi-NPP CBERS-2 CBERS-2B CBERS-4 ResourceSat-1 and -2 UK-DMC-2 DEIMOS-2	- Primarily for image search, preview, and download (no in-program analysis) - Offers some free high-res imagery - Limited to Central and South America and the African continent - Easily translated Portuguese interface

***Green backdrop = Sensor with high or very spatial resolution

Even with broad access to the data, selecting the appropriate sensor, time frame, coordinates, and type of data can be tricky. As was stated earlier, imagery with a higher spatial resolution is probably better suited for applications in SWM (see Table 5 below for a list of these satellites). Secondly, RS data can be processed to varying degrees, depending on its source. Seeking out higher data processing levels (Level 3 or higher) provides data that is easier to work with and is more "analysis-ready" after retrieval. See Table 4 below for a description of each level.

Table 4: Satellite data processing levels. Adapted from NASA (2021a)

Processing Level	Definition	Clarification
Level 0	Raw instrument data	Unusable to most. Usually not distributed. Full sensor resolution.
Level 1A	Geometric distortion and radiometric correction	Accounts for differences between satellite's multiple sensors (i.e., instrument calibration). Adjusts misaligned scan lines and non-uniform pixel size due to detection angle differences. Data is full resolution and time-referenced.
Level 1B	Sensor unit processing	Not all instruments have units. As such, not every instrument has L1B data.
Level 2A	Geo-referencing	Geophysical variables derived at the same resolution and sites as Level 1 data. That is, data is matched up with the actual physical locations on the planet.
Level 2B	Sensor unit processing	Not all instruments have units. As such, not every instrument has L2B data.
Level 3	Final orthorectification	Data gridded uniformly in space and time to eliminate inconsistencies and account for elevation variability (i.e., topographic relief). Ready for GIS upload.
Level 4	Derived data products	Combines multiple measurements of lower level data to develop a model output or perform some form of analysis (e.g., vegetation indices).

Once specific datasets and imagery have been identified in one of the platforms mentioned above, then it can either be analyzed within the platform itself, or exported in a typical RS file format (e.g., GeoTIFF) to another program better equipped for the intended analysis (e.g., ArcGIS).

Table 5: Non-exhaustive list of high and very high spatial resolution satellite sensors (ESA, 2021b; Satellite Imaging Corporation, 2021)

Satellite Name	Operator	Spectral Range	Temporal Resolution	Spatial Resolution
Dove CubeSats (ESA)	Planet Labs, Inc. (USA)	420-900 nm	1 day	2.7-4.9 m
CARTOSAT-1 (ESA)	ISRO (India)	500-850 nm (PAN)	5 days	2.5 m (PAN)
SPOT 5 (ESA)	CNES (France); AIRBUS	480-890 nm (MS); 1580-1750 nm (SWIR)	2-3 days	2.5 m (PAN); 10 m (MS); 20 m (SWIR)
ALOS (ESA)	JAXA (Japan)	420-890 nm (MS); L band at 1.3 GHz	46 days	2.5 m (PAN); 10 m (MS); 10-100 m (SAR)
Tianhui 1 Constellation	CNSA and PLA (China)	430-900 nm	5 days	2 m (PAN); 10 m (MS)
FORMOSAT-2	NSO (Taiwan)	450-900 nm	1 day	2 m (PAN); 8 m (MS)
SPOT 6 and SPOT 7 (ESA)	AIRBUS Defence and Space	455-890 nm	1-3 days	1.5 m (PAN); 6 m (MS)
RADARSAT-2 (ESA)	CSA (Canada)	C band at 5.405 GHz (5.55 cm)	24 days	1 x 3 m (spotlight)
ALOS-2	JAXA (Japan)	L band at 1.2 GHz (25 cm)	14 days	1 x 3 m (spotlight); 3 x 10 m (strip map)
KOMPSAT-2 (ESA)	KARI (South Korea)	450-900 nm	14 days	1 m (PAN); 4 m (MS)
OrbView-3	GeoEye Inc. (USA)	450-900 nm	3 days	1 m (PAN); 4 m (MS)
COSMO-Sky Med Series (ESA)	ASI (Italy)	X band at 9.6 GHz (3.12 cm)	3-4 hours	1 m (spotlight); 3 m (strip); 30 m (scan)
TerraSAR-X / TanDEM-X (ESA)	DLR (Germany); AIRBUS	X band at 9.65 GHz (3.1 cm)	11 days	<1 m (spotlight); 3 m (strip map)
PAZ (ESA)	Hisdesat (Spain)	X band at 9.65 GHz (3.1 cm)	1 day	<1 m (spotlight); 3 m (strip); 15 m (scan)
IKONOS-2 (ESA)	DigitalGlobe, Inc. (USA)	450-900 nm	1-3 days	0.82 m (PAN); 3.28 m (MS)
Gaofen-2	CNSA (China)	450-890 nm	5 days	0.8 m (PAN); 3.2 m (MS)
TripleSat Constellation	21AT, Ltd. (China)	440-910 nm	1 day	0.8 m (PAN); 3.2 (MS)
Deimos-2 (ESA)	Deimos Imaging (Spain)	420-900 nm	2 days	0.75 m (PAN); 4 m (MS)
Jilin-1 Optical Constellation	Chang Guang Satellite Tech Co.	457-800 nm	3.3 days	0.72 (PAN); 2.88 m (MS)
KOMPSAT-3	KARI (South Korea)	450-900 nm	1.4 days	0.7 m (PAN); 2.8 m (MS)
QuickBird-2 (ESA)	DigitalGlobe, Inc. (USA)	450-900 nm	1-3.5 days	0.61 m (PAN); 2.4 m (MS)
SkySat-C Constellation (ESA)	Planet Labs, Inc. (USA)	450-900 nm	6-7x daily	0.57 m (PAN); 0.75 (MS)
KOMPSAT-3A	KARI (South Korea)	450-900 nm (PAN); 3.3-5.2 µm (MWIR)	1.4 days	0.55 m (PAN); 2.2 m (MS); 5.5 m (IR)
SuperView-1	Beijing Space View Tech Co.	450-890 nm	2 days	0.5 m (PAN); 2 m (MS)
Pleiades-1A / Pleiades-1B (ESA)	AIRBUS Defence and Space	430-950 nm	1 day	0.5 m (PAN); 2 m (MS)
WorldView-1 (ESA)	DigitalGlobe, Inc. (USA)	400-900 nm	1.7 days	0.5 m (PAN)
WorldView-2 (ESA)	DigitalGlobe, Inc. (USA)	400-1040 nm	1.1 days	0.46 m (PAN); 1.84 m (MS)
GeoEye-1 (ESA)	DigitalGlobe, Inc. (USA)	450-920 nm	2.6 days	0.41 m (PAN); 1.65 (MS)
WorldView-3 (ESA)	DigitalGlobe, Inc. (USA)	400-1040 nm (MS); 8 SWIR bands; 12 CAVIS bands	<1 day	0.31 m (PAN); 1.24 m (MS); 3.7 m (SWIR); 30 m (CAVIS)
WorldView-4 (ESA)	DigitalGlobe, Inc. (USA)	450-920 nm	<1 day	0.31 m (PAN); 1.24 m (MS)
Pleiades Neo 3	AIRBUS Defence and Space	N/A	1 day	0.3 m
ICEYE Constellation (ESA)	ICEYE (Finland)	X band at 9.65 GHz (3.1 cm)	20 hours	0.25 m (spotlight); 3 m (strip); 15 m (scan)

***LEGEND: Red text = Decommissioned satellite; Purple backdrop = Private company; Yellow backdrop = National space agency; Green backdrop intensity = Increasing spatial resolution; (ESA) = Partial or full archive of sensor's data available through the European Space Agency, oftentimes with a project proposal

4. Proposed additional applications of RS to SWM in developing countries

4.1 Broad context of SWM in developing countries

It has been observed time and time again that insufficient resource availability, in the form of human capital, financial capital, and technological solutions, continually lead to poorly managed solid waste. Where waste is left unmanaged in large quantities it is dumped indiscriminately and openly burned, exposing vulnerable groups (generally, marginalized and impoverished individuals) to pollution and pathogens that damage their health and quality of life. The same holds true for the consequences of poor SWM on the surrounding natural environment. While the particularities vary from nation to nation, these outcomes are commonplace in many developing nations in Sub-Saharan Africa, Southeast Asia, and Latin America.

4.2 Landfill fire detection

Due to a high proportion of organic waste deposition and a lack of daily cover and/or final cover, high temperatures resulting from rapid biodegradation tend to ignite landfill gas at poorly managed landfill sites in developing countries. These surface landfill fires ignite frequently and pose dangers to informal waste pickers at the sites, via physical harm (i.e., burns, shifting waste) and inhalation of toxic emissions (e.g., carbon monoxide, heavy metals, and unintentional persistent organic pollutants (uPOP's)).

Wildfire detection is a well-established, ongoing task employed by the MODIS sensor aboard NASA's Terra and Aqua satellites, as well as the VIIRS sensor aboard the Suomi-NPP satellite (NASA, 2021b). Both sensors use bands in the mid-wavelength infrared (MWIR) range (3-8 μm) to detect thermal anomalies across the entire globe on a broad scale (1 km and 375 m spatial resolution, respectively) (NASA, 2021b). Those anomalies are then fed into a contextual algorithm and a hybrid thresholding and contextual algorithm, respectively, to verify the presence of an active fire (NASA, 2021b).

To detect landfill fires, which are typically much smaller and burn at lower temperatures than wildfires to be registered adequately by MODIS and VIIRS, selection of another sensor with MWIR bands and a higher spatial resolution would be necessary. As can be seen in Table 5, KOMPSAT-3A might be a viable candidate to detect landfill fires using similar techniques, given its 5.5 m spatial resolution in the MWIR range. EOS's "Land Viewer" open source data platform (see Table 3) even provides access to KOMPSAT-3A's imagery. If the extent and intensity of the fire can be determined this way, then it might be possible to estimate the mass of waste burned and the ultimate uPOP emissions for reporting under the Stockholm Convention.

4.3 Identification of additional points of integration, verification of data collected in-situ, and validation of implemented interventions

Sustainable waste management practices include integrating multiple systems that intersect and then deriving synergies from them. This includes considering how SWM fits into concepts like the water-energy-food security nexus. For example, a state government might utilize satellite data to help them identify depleted agricultural soils (i.e., erosion, moisture content, nutrient levels) on large commercial farms, to help generate the market for fertilizers and soil conditioners derived from organic waste, thereby increasing circularity, reducing the need for synthetic (water-polluting) fertilizers, and supporting sustainable food production.

Composting is also adopted to adequately process organic waste and avoid methane emissions. Where composting schemes are implemented by local governments, publicly available vegetation indices (e.g., NDVI, NDMI, SAVI) could be employed to track agricultural improvements over time in fields where composts are applied and then use that data for verification of yield improvements and educational campaigns aimed at increasing compost adoption by local farmers.

Finally, there are many waste-related development projects aimed at reducing CO_2 emissions by installing facilities like composting and biogasification plants. Projects contracted specifically under the Clean Development Mechanism (CDM) of the Kyoto Protocol, generate tradable Certified Emission Reduction (CER) credits (1 tonne of CO_2 per credit) to quantify these reductions. Not only do facility maintenance standards tend to degrade over time once funding has ended, but as was shown by Cusworth et al. (2020), models for estimating emissions (at landfills) can be flawed and underestimate the actual emissions, even where in-situ measurements are carried out. As such, it might also be valuable to use similar point source methane detection techniques to help ensure the validity of generated CER credits as a result of CDM projects like the "Uganda Municipal Compost Programme" (Tumuhairwe & Kakeeto, 2015), and the "Kinshasa Landfill Gas Recovery and Flaring Project" (Decq, Evercooren, & Goorden, 2011).

4.4 Landfill destabilization detection

Poorly managed disposal sites experience myriad problems. Where waste is haphazardly placed in the site and stacked up over time, there is a much higher risk of physical instability, eventually leading to catastrophic landslide events. Of course, better landfill management should be made the main priority for longer-term prevention, but at sites where there is a long legacy of poor disposal practices and a high volume of waste deposition, monitoring of subtle elevation changes using, for example, interferograms derived from synthetic aperture radar (SAR) sensors, could potentially reveal the first signs of instability before forthcoming events occur. This could, in turn, prevent unnecessary loss of life and costly damages to neighboring communities and/or infrastructure. UNAVCO manages a "Seamless SAR Archive" (see Table 3) filled with publicly available SAR data. Given that many waste disposal sites cover relatively small areas of land, data with the appropriate spatial resolution should be selected for effective analysis. Some high-resolution SAR sensors include (see Table 5): RADARSAT-2, ALOS-2, and TerraSAR-X.

5. Conclusions, limitations, and recommendations for future research efforts

As the literature has shown, for many applications of RS-techniques to SWM, a necessity of high-resolution sensors and imagery need to be employed. This imposes some limits on these applications (both described in the literature and as suggested here in this paper) in developing countries, because as has been shown by the various open access platforms listed in Table 3, only in few cases is high resolution imagery available free of charge. Such financial provisions for high-res satellite imagery may be unavailable or deemed frivolous and unnecessary by local authorities, especially if the full potential of their use might not be possible. As such, it may be some time before some of these techniques can truly benefit a wider swath of individuals working outside of specialized institutions with access to substantial funding.

Additionally, although the democratization of satellite imagery has made a massive volume of data available to almost anyone, the ability to utilize said data for the applications described in this paper is probably not likely without some prior knowledge of remote sensing, big data processing, and the specific software packages available to integrate different types of data (e.g., vector data in a GIS). That is to say, it is unlikely that an RS layman will be able to duplicate some of the methods observed in the literature without additional technical training. Making matters worse, layering and rendering of RS maps requires a lot of processing power and storage capacity, potentially excluding even more individuals without the necessary computer hardware.

All that said, the author believes these difficulties present a number of unique research opportunities. First and foremost, it would be beneficial for a higher quantity of researchers working in the area of SWM to become familiar with RS to then seek out collaborative studies between their research efforts and those of geo-informatics institutes. These collaborations might help refine the body of work already established,

yield new techniques and data products for solid waste monitoring and management, and potentially even provide the first software that can be used “off-the-shelf” for waste managers in developed and developing countries alike.

Secondly, where foreign aid and development grants are highly sought after sources of research funding in the global north, RS presents an opportunity to apply a new type of expertise and set of analytical tools to solid waste problems that pose a massive threat to human health and the local environment in many developing countries. Collaborative efforts undertaken by, for example, universities, research institutes, international organizations, state aid agencies, and NGO’s in the global north, and local waste/environmental authorities, community-based organizations, state governments, NGO’s, and researchers from developing countries, might yield appropriate solutions to otherwise difficult, systemic problems. In this vein, instead of claiming that RS is simply a fix-all, where any lack of technical training would undoubtedly guarantee inaction and a lack of adoption by potential beneficiaries, groups working on the ground in a given developing country can provide all of the necessary in-situ measurements and local context that strengthen the application of RS techniques provided by EO experts (and vice versa).

Finally, in addition to arguing for collaborative projects between diverse groups of specialists (within and outside of a given country), as EO analysis techniques are steadily improved upon, made more accessible, and even become more user-friendly, advocating for educational opportunities in remote sensing as applied to SWM for waste managers at different levels of governance would also be a potentially fruitful application of foreign aid. Through such training opportunities more sustainable outcomes might be achieved, as a reliance on outside sources of expertise can be eliminated slowly over time.

The use of remote sensing techniques to facilitate improved solid waste management is, by and large, incomplete, but the potential for its further development and its tailoring to a developing country context is extremely promising. Awareness of moving in this direction simply needs to be emphasized in the appropriate fields and research areas, and then actively sought after.

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