

**ASSESSMENT OF OPEN WASTE DUMPING SITES
IN TWO CITIES IN THE EASTERN PROVINCE,
SAUDI ARABIA: REMOTE SENSING AND IMAGE
PROCESSING APPROACH**

BY

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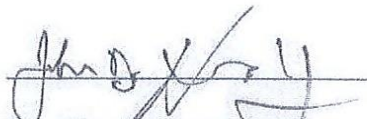
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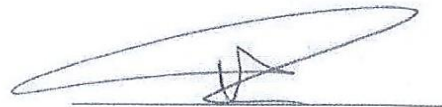
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[To my family for their support and patience |

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LIST OF ABBREVIATIONS

C&DW - Construction and Demolition Waste

GEE - Google Earth Engine

GIS - Geographic Information System

LULC - Land Use and Land Cover

NDWI - Normalized Difference Water Index

NIR - Near Infrared

NVDI - Normalized Difference Vegetation Index

RS – Remote Sensing

SAR - Synthetic Aperture Radar

SAVI - Soil Adjusted Vegetation Index

SPOT - French acronym for a commercial Earth-imaging satellite system

USGS - United States Geological Survey

VIS - Visible Spectrum

ABSTRACT

Full Name : Mohammed Hajjaj Alharbi

Thesis Title : Assessment of Open Waste Dumping Sites in two cities in the Eastern Province, Saudi Arabia: Remote Sensing and Image Processing Approach

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Due to increased urbanization and the construction of new houses and buildings, open dumpsite is becoming a challenge facing local authorities in Saudi Arabia. Open dumpsites pose health risks to the public and potentially deteriorate the environment around them. Local municipalities rely on field surveys and citizens' reports. This can be inefficient as dumpsites are often discovered too late, and remediating them can be costly. This research assessed open dumpsites in two cities in the Eastern Province of Saudi Arabia using satellite images classifications assessment techniques. The assessment included mapping the open dumpsite locations and studying the spectral reflectance of materials found in these dumpsites. The environmental impact on the soil is assessed as well in the selected dumpsite. The research provided a mapping of the 62 open dumpsite locations. The quality of the soil was within the normal ranges found in the nearby soil, indicating no impact on the soil. Also, the spectral reflectance of 21 common materials was studied, and a spectral library was created for these materials.

ملخص الرسالة

الاسم الكامل: محمد هجاج محمد الحربي

عنوان الرسالة: تقييم مواقع تفريغ النفايات المفتوحة في مدينتين في المنطقة الشرقية ، المملكة العربية السعودية: نهج الاستشعار عن بعد ومعالجة الصور

التخصص: علوم بيئة

تاريخ الدرجة العلمية: ماجستير

بسبب زيادة التحضر وبناء المنازل والمباني الجديدة ، أصبح المكب المفتوح يمثل تحديًا يواجه السلطات المحلية في المملكة العربية السعودية. تشكل المكبات المفتوحة مخاطر صحية على السكان ومن المحتمل أن تؤدي إلى تدهور البيئة المحيطة بها. تعتمد البلديات المحلية على المسوح الميدانية وعلى تقارير المواطنين. قد يكون هذا غير فعال لأن مكبات النفايات غالبًا ما يتم اكتشافها بعد فوات الأوان ومعالجتها قد تكون مكلفة. قيم هذا البحث المكبات المفتوحة في مدينتين في المنطقة الشرقية في المملكة العربية السعودية باستخدام تقنيات تقييم تصنيفات صور الأقمار الصناعية. وشمل التقييم رسم خرائط مواقع المكبات المفتوحة ودراسة الانعكاس الطيفي للمواد الموجودة في هذه المكبات. يتم أيضًا تقييم التأثير البيئي على التربة في مكب النفايات المختارة. قدم البحث خريطة لمواقع المكبات المفتوحة البالغ عددها 62. وجدت جودة التربة ضمن النطاقات الطبيعية الموجودة في التربة المجاورة مما يشير إلى عدم وجود تأثير على التربة. أيضًا ، تمت دراسة الانعكاس الطيفي لـ 21 مادة شائعة وإنشاء مكتبة طيفية لهذه المواد.

CHAPTER 1

INTRODUCTION

1.1 Overview of Waste Management

Waste is defined as substances or objects that are discarded or intended to be discarded, referring to unwanted byproducts of human activity. In general, waste can be categorized based on its origin, composition, hazard characteristics, management techniques, or a combination of these factors. For regulatory purposes, waste is often categorized depending on the risk posed to the environment and the general public. The term "solid waste" refers to any non-soluble substance, such as agricultural trash, industrial waste, mining leftovers, demolition debris, municipal garbage, or even sewage sludge (Pichtel, 2006). These types of waste are all considered to fall under the category of "solid waste." An example of solid waste commonly generated in large quantities is Construction and Demolition (C&D) waste. This type of waste generated by the construction industry which includes waste generated from construction, demolition, renovation, roadwork, and excavation work. The materials found in C&D are concrete, wood, asphalt, metals, bricks, glass and rocks.

Solid waste management (SWM) involves the regulation of waste creation, its storage, collection, transfer and transport, processing and disposal in line with the best principles of public health, economics, engineering, conservation, aesthetics, public opinion, and other environmental factors (Pichtel, 2006).

Proper waste management is essential for public and environmental health. However, this is becoming a challenging effort due to high rates of waste generation. It is estimated that 2.01 billion tons of Solid Waste (SW) are generated annually around the world (Kaza, et al. 2018). There are several factors that lead to the increase in waste generation rates in a country that mainly include population growth, rapid urbanization, and standard of living. These factors are making waste collection and disposal more difficult and costly, which may lead to improper waste disposal.

1.2 Sustainable Solid Waste Management Practices

The goal of sustainable waste management is to treat waste in a way that respects the environment and does not deplete its resources. It adopts the waste hierarchy idea, which begins with the best approach—waste prevention—and concludes with the worst approach—landfill disposal or, even worse, illegal dumping. To limit the quantity of solid waste transferred to landfills or illegally disposed of, a sustainable strategy should reduce waste at its source by keeping resources in use for as long as practicable. Innovative solutions allow for the reduction of waste. For example, C&D can be minimized by utilizing smart building solutions (Blaisi, 2019).

If waste generation cannot be avoided, items should be reused or recycled in accordance with the waste hierarchy. Construction and demolition debris might be repurposed and utilized as concrete and masonry. According to the findings of researchers, C&D waste may be used as an effective road building material (Blaisi, 2019). The next stage in the waste hierarchy is recovery, which entails extracting valuable materials or energy from waste and utilising them as inputs for the production of new, valuable goods.

The dumping of waste in landfills is the final and least desirable option for waste management. This is because of the severe environmental effects, which include the possible contamination of groundwater and air, as well as the aftercare requirements spanning many years (David Turner, 2016).

1.3 Challenges to Waste Management in Saudi Arabia

Saudi Arabia is not an exception to this global issue as it has witnessed highly accelerated urban expansion due to population growth, rural movement to urban centres and immigration (Alahmadi & Atkinson, 2019). With a population of around 35 million people (The World Bank, 2021), Saudi Arabia produces more than 15 million tons of solid waste each year (Neyara Radwan, 2021). Such an amount of waste illustrates the magnitude of the challenge faced by local municipalities (Zafar, 2020).

As a consequence of this, there was an increase in waste in general, and in particular, the generation of C&D waste has seen a significant increase and is now regarded as the main component of the stream of solid waste generation in Saudi Arabia. Some studies indicate that 30% to 40% of the total solid waste is construction and demolition(C&D) waste (Abdullah F. Alqurashi, 2016). Some statistics suggest that for every ten thousand (10,000) m², around 500 to 600 tons of C&D waste are generated, while around 7,000 to 12,000 tons of C&D waste are generated when demolishing and constructing the same area (10,000 m²) (Al-Ghamdi, et al., 2017). This means huge waste is generated considering the high rate of building houses.

It is becoming more common to see pile of waste, old furniture, and C&D waste left by the roadside, or in the desert, vacant lot or undesignated sites. This behaviour is on the rise and is becoming a concern to both authorities and communities. While local authorities are devising and enforcing regulations to protect the environment, violators dump waste illegally in areas not designated for disposal. One dump after another until the waste accumulates.

Key actors in Saudi Arabia's waste management industry include: the Ministry of Environment, Water, and Agriculture (MEWA), National Center for Waste Management (MWAN), National Center for Environmental Compliance (NCEC). MEWA is in charge of applying and carrying out all parts of national policies for the agricultural, water, and environmental sectors. In order to realize its aims for sustainable development, MWAN regulates, monitors, and advocates waste management operations that adhere to the circular economy idea. The NCEC is in charge of granting accreditation and licensing to businesses that provide environmental services. Additionally, it issues and renews service facilities and activities that could have an effect on the environment.

1.4 Remote Sensing in Environmental Applications and Waste Management

In simple terms, Remote Sensing (RS) means acquiring data about something without physically being there. It usually refers to the process of sensing reflected and emitted

radiation from a distance to identify and monitor an area's physical attributes, this is usually performed with sensors attached to satellites or aircrafts (USGS, n.d.).

Many applications of this technology have been enabled as result of the continuous developments in the remote sensing field. It has a wide range of environmental uses, including disaster mapping, surveying, and solid waste management. The value of remote sensing in waste management is clear since waste management requires data about the location and distribution of waste in an area. This data is traditionally obtained by field observations, but this could be labor-intensive in nature. Field data cannot be easily aggregated to regional or global scales, and the field studies cannot be extended to a greater geographic scale (Rhodes¹, et al., 2015). Therefore, remote sensing is very useful in gathering data over large areas.

1.5 Illegal Dumping

Illegal dumping is defined as large deposit of waste in unauthorized sites (BEHM, 2019). The types of waste found at illegal dumping sites range from organic waste to C&D waste to household furnishings (Hadidi, et al., 2020). Improper waste management could contaminate water bodies, soil and air (Kaza, et al. 2018). Approximately 100 million tons are dumped illegally each year, according to some estimates (BEHM, 2019). Observations indicate that C&D waste are frequently composed of a mixture of elements, including bricks, steel, and plastics, making it hard to separate and recycle these components. In spite of that fact, 50–80 percent of C&D waste is recoverable or recyclable, improper management of C&D waste leads in the loss of significant economic resources and is a leading cause of resource depletion. (Kofoworola O.F., 2009).

1.5.1 Causes of Illegal Dumping

There is a wide range of motivations behind illegal dumping. It might be as simple as not taking the time to drive to the local landfill, or it could be economic drivers behind it, or a lack of information on the many disposal options that are currently available.

One of the main reasons are disposal fee avoidance at waste management facilities. Residents are disposing of large quantities of waste themselves to avoid paying disposal fees as they believe fees are expensive. Sometimes residents pay third parties for services

to pick up waste but then the third parties engage in illegal dumping to maximize their profits (Rinkesh, 2019). Countries around world apply progressive taxes to combat waste generation and ban landfills, but this nature of taxation should be carefully enforced, otherwise it may unintentionally increase illegal dumping. There is a risk that a landfill expensive fee would simply raise disposal costs, and that landfill prohibitions, in the lack of acceptable alternatives, would encourage an increase in more illegal dumping. For example, it was noted that countries that introduced increased landfill fees to tackle waste generation witnessed an increase in illegal dumping as a result of this (Blaisi, 2019).

Another reason for illegal dumping is poor waste collection which can result in enormous piles along the roadways and even in residential areas. In certain instances, illegal dumpsites may arise (SinghNagpure, 2019).

Furthermore, there is a lack of adherence to different waste management policies, categorization, and tracking systems. In addition, uncertainty about disposal places makes effective waste management legislation difficult in many areas. The non-compliance is not faced by hefty fines for violators; instead, violators receive few, modest fines for which do not deter their illegal dumping activities.

1.5.2 Environmental Pollution from Illegal Dumping

Illegal dumpsites have serious potential health risks to humans and the surrounding environment. Illegal dumping may cause a number of environmental issues related to degradation of the quality of the soil, water and air in the areas around the dumpsites (BEHM, 2019). As this type of dumping does not go through any treatment, any type of material can be dumped including hazardous waste. Chemicals in the waste can be leached into the groundwater, also can be washed over by rain and spread to surrounding places. The effect of the open dumpsites can reach the marine environment, a study shows that around 80% of marine litter (mostly plastic waste) is generated on the mainland and pushed by rivers that drain into the seas (Andrady A., 2015).

There is a risk of fire within illegal dumpsites since these sites include combustible items like wood and tyres; thus, there is a risk of air pollution as a result of these fires. Open dumpsites have the potential to have a negative effect on the surrounding soil. The soil is

very necessary for the continuation of life on Earth, including human life. As a consequence of this, heavy metals can make their way into the food chain as well as groundwater if the land is polluted. In addition to these detrimental effects, illegal dumping sites also have an unfavourable visual impact on the people who live nearby and on those who pass by them. These landfills often serve as a breeding ground for rodents and other pests that can be hazardous to human health.

It is expected that these dumping could lead to soil contamination with organic material and heavy metals. The determination of Total Organic Carbon (TOC) is an important part of any site assessment because its presence in large quantities can be an indicator of soil contamination with organic materials (Oluseyi, et al., 2014). Carbon may be found in a wide variety of states, the most common of which are elemental, inorganic, and organic. The presence of organic carbon in the soil may be an indication that it has been contaminated as a result of pollution induced by human activities. It's possible that dumping waste could cause the release of toxins into the environment, which will lead to an increase in the total carbon content of the soil.

1.6 Statement of the problem

Illegal dumping is a growing environmental issue in urban areas in Saudi Arabia. Local authorities are facing challenges in locating illegal dumpsites on a timely basis and identifying the type and amount of waste in these dumping sites. The timely identification of these dumpsites will help in planning the remediation efforts to contain the negative effect on the environment. If these open dumpsites are not remediated on time, there is a possibility that more waste will be dumped as violators perceive this as a potential dumping site. However, this is ineffective as dumping sites were discovered too late or after the area deteriorated. Remote Sensing (RS) techniques, specifically satellite image analysis, can potentially provide more effective waste management at these sites (Glanville & Chang, 2015).

This study aims to (1) evaluate the effectiveness of using remote sensing techniques in identifying illegal dumpsites, (2) map the existing uncontrolled dumpsites in the study area,

(3) identify and quantify the composition (waste type) of these illegal dumping in a selected dumpsite, (4) to assess the impacts of a selected dumpsite on the surrounding soil quality. This study is important as it will create an inventory of unauthorized dumpsites, provide a decision support system to monitor illegal dumping to help protect the environment, plan remediation, and promote the use of Remote Sensing in Environmental applications.

CHAPTER 2

LITERATURE REVIEW

This section examined the literature review of research related to thesis objectives: evaluating the effectiveness of remote sensing in identifying dumping sites, characterization of waste materials in the dumpsites, and assessing the impact of dumpsites on the surrounding soil quality.

2.1 Illegal Dumpsite Detection using Remote Sensing

Using remote sensing (RS) to identify illegal dumping sites is not new. The many published papers in scientific journals about the RS techniques have varying results. Some achieved higher accuracy (more than 95%) with high-resolution images. In addition, multi-factor analysis is used to identify potential dumping sites; this is supported by solid literature. An overview of the previous studies is presented in this chapter.

Previous studies have indicated potential benefits of using remote sensing in mapping unauthorized dumpsites. However, most studies focused on identifying and mapping site's locations, but only a few focused on identifying certain types of waste (tyres and plastics) (Page & Lavender, 2020).

One of the early studies in Saudi Arabia was conducted in Riyadh in 1996. The study used four sub-scenes from SPOT satellites to map dumping sites on the fringe of Riyadh. The result was encouraging and proved valuable for registering and monitoring dumpsites (Ali, 1997).

A common approach in the literature is using satellite images as they are multi-temporal and cover large areas, which is an advantage in LULC classification. The classification of images using machine-learning algorithms can be of two types: supervised or unsupervised. Supervised classification uses a training set to learn to classify the given area. In contrast, the unsupervised classification uses image clustering and cluster grouping based on features and patterns to classify land cover.

Another study in Rajmahal in India investigated six machine-learning algorithms in terms of the accuracy of the classification. These algorithms are namely: random forest (RF), support vector machine (SVM), artificial neural network (ANN), fuzzy adaptive resonance theory-supervised predictive mapping (Fuzzy ARTMAP), spectral angle mapper (SAM) and Mahalanobis distance (MD). This study aimed at classifying land cover in general. The results reveal that all the classifiers have a comparable degree of accuracy with little variance, with the RF algorithm having the highest accuracy of 0.89 and the MD algorithm (parametric classifier) having the lowest accuracy of 0.82. The study used the Kappa coefficient to investigate accuracy assessment; this coefficient is the most popular technique used to analyse accuracy (Talukdar, et al., 2020).

In one of the studies, various visual indices were considered to indicate vegetation, soil, water and biophysical cross-sectional groups. These indices were reviewed, and additional groups were used as classification layers; these indices include NDVI, SAVI, and NDWI. The indices were loaded into a file with satellite bands used for landcover classification (Dimitrios D. Alexakis, 2015).

In another study, an algorithm of the high-resolution multispectral satellite was developed to detect tyre waste. Generally, tire dumps looked as darker in color but were similar to other dark features like shadows, asphalt, etc. Therefore, the researchers used SAR and multispectral data to differentiate smooth dark surfaces from tire waste (Page & Lavender, 2020).

A study in Greece developed a novel detection index to identify olive oil mill waste (OOMW) by testing different spectral vegetation indices to improve the accuracy of satellite imageries of medium resolution. This is done in combination with spatial analysis in the GIS environment and investigation of temporal changes in their respective spectral signatures (Dimitrios D. Alexakis, 2015).

In the literature review, researchers used data from In-situ measurements as reference data. In-situ measurements use a spectrometer to study the reflectance of the different materials and store them in a library to compare the spectral reflectance acquired by satellite sensors. For example, USGS has developed a library of spectral signatures of different materials,

including minerals, soils, rocks, plants, and different materials. Etc. This can be used to detect similar materials found in the study area (Kokaly, 2017).

Landfills, especially municipal ones that contain organic waste, can generate heat during the aerobic and anaerobic processes. Such "heat generating" phenomena can provide useful information for discovering illegal landfill activities and tracing unrecorded dumping areas where the waste surface temperature is usually higher than the surrounding areas. The spatial distribution of waste buried beneath the ground can be discovered and reported by measuring the ground surface heat variation. This approach is used in a study conducted in Kuwait to locate landfills after their records went missing after the Gulf War. The approach adopted is the use of thermal anomalies in LANDSAT Thematic Mapper is recorded to detect illegal waste (Jasravia Gill1, 2019). As a result, the probable dumping areas were identified, and then these locations were validated with data from the EPA of Kuwait. The maximum accuracy assessment reached was 72%.

2.2 Spectroscopic Remote Sensing for Material Identification

Measurement and evaluation of reflectance spectra to identify materials has been a major part of analytical chemistry for decades. The same concept can be applied for spectra collected by satellite or airborne sensors.

The objective of the in-situ measurements is to understand the interaction of the materials of interest with electromagnetic radiation, be it VIS or NIR, under conditions better than

those available for satellite sensors. In-situ measurements (see Figure 1) are used to calibrate and validate remote-sensing sensors.



Figure 1 collection of in-situ measurements for the USGS spectral library. Photographs from the USGS website.

One of the early studies that was widely cited was conducted in Santa Barbara, CA, US (Herold M. 2004). A spectral library of roofs, roads, parking lots, vegetation, and bare soil was built and analyzed. This library included the range of 350 to 2400 nanometers and adopted the classification of buildings and roofs that are often seen in the research region. (Santa Barbara, CA, US), taking into consideration a variety of materials and colors, the primary objective of the survey was to identify the spectral characteristics shared by urban materials. The survey found several difficulties in abstracting urban materials, prompting the authors to recommend more research into the use of hyperspectral data in urban area mapping.

Another similar study conducted in Italy to investigate the spectrum reflectance of asphalts in highways, roads, and parking lots, using various satellite images and field spectra (Alessandro Mei, 2014). This study examined asphalt spectral signatures in the field and in the lab in order to improve its differentiation and correlation with hyperspectral and multispectral imaging. Data from an airborne spectrometer and satellite images from the Quickbird and Ikonos satellites were used in the investigation. With an overall accuracy of

95% for Ikonos, 98% for Quickbird, it was possible to distinguish different types of asphalt surfaces on the photos and categorize them based on asphalt distress levels. To have more effective road asphalt stress monitoring, the study advised using more modern technology like drones with ad hoc sensors to identify asphalt from the collected wavelengths.

A study in Poland used remote sensing images to distinguish Asbestos cement roofing from other types of roofing. It also included further investigation of other types of roofing material. For wavelengths between 350 nm and 2500 nm, a spectral library of 43 roofing materials was developed and studied. Using statistical software, the curves of these reflectances were grouped into six clusters based on their similarity in reflectance shape. A technique called Spectral Angle Mapper (SAM) is used to evaluate spectral signature similarity by treating them as vectors in an n-dimensional space. Smaller angles are a representation of closer spectral matching to the reference spectrum. Different materials, coatings, and colors were considered in each group during the clustering. Due to the fact that roof coverings are made of many composite materials, the shapes of spectral curves vary greatly. Metal sheets had spectral curves that were easily recognizable. The study indicated that the entire spectral spectrum should be investigated in order to distinguish asbestos from all other roofing materials.

The reviewed research often integrates the outcome of RS with spatial analysis in GIS software. This is to further study the factors that led to illegal dumping. These factors include demographics, availability and affordability of waste services, law enforcement effectiveness, road access and distance from residential areas. The correlation between population density and illegal dumping occurrences was examined and found to be relevant. Also, the income of people living in the area directly affects the probability of illegal dumping; therefore, lower-income areas have a high probability of illegal dumping. The areas with a high probability of illegal dumping are identified to have better surveillance and monitoring systems to prevent it from happening in the first place (Jordá-Borrell, et al., 2014).

The literature review proves the benefit and future potential of Remote Sensing in Waste Management and detecting and preventing illegal dumping. However, the result depends on the spectral, spatial and temporal resolution of the satellite sensors. Therefore, studies suggest ground-truthing as a validation mechanism, especially for low- to medium-resolution images, to confirm illegal dumpsites and land cover classes.

2.3 Dumpsites Soil Pollution Assessment

A study was conducted to evaluate the heavy metal contamination in soil from a municipal solid waste dumpsite in Khamees-Mushait, Saudi Arabia (Ismat H. Ali, 2018). The study used an combined approach of statistical analysis, geochemical indexes and human risk indices to assess the status of heavy metal contamination levels and distribution patterns, as well as the potential risk of heavy metal exposure in soil. The Igeo results indicate that Cu, Cr, Mn, and Zn are extremely polluted, whereas Co, Ni, and Pb are moderately polluted. Co, Ni, and Zn exposure through inhalation was below acceptable limits, whereas Cr indicated hazardous cancer risk levels in both children and adults.

A similar study was conducted in Yenagoa, Nigeria d to determine the levels of heavy metals in soils taken from an open dumpsite in, as well as some physicochemical parameters (AMOS-TAUTUA, 2014). At the dump field and control site, top soil samples were randomly collected at two depths (0-10 and 10-20 cm) and taken to laboratory for analysis of heavy metal contamination. It was found that Pb levels in the dump varied from 14.750 to 16.140 ppm, while those in the control ranged from 8.35 to 8.78 ppm. Cr levels in the dump soil ranged from 0.05 to 0.06 ppm, which is somewhat higher than the control (0.005), whereas Cd was discovered in trace amounts (0.0001 ppm). These values are all well below the FAO and WHO maximum acceptable levels for agricultural soil. It is proposed that the dumpsite and control area, which have appropriate soil nutrients and low metal levels, be turned to agricultural lands in the future. At this time, no remediation is required.

Research was conducted in Al Jubail, Saudi Arabia to assess the contamination level of metals in the study area by measuring uranium and trace metal concentrations in topsoil

from various zones around the Industrial Area (Alshahri, 2019). The levels of uranium and nine different trace elements were analyzed in 116 topsoil samples that were collected from six different areas in Al Jubail, the most significant and oldest industrial city in Saudi Arabia. Gamma ray spectrometry and a plasma atomic emission spectrometer were used to determine the amounts of heavy metals. The data revealed that the mean uranium values in all zones were below or similar to the global average and the soil background value. With the exception of U and Cu, the calculated values of the geo-accumulation index (Igeo) indicated elevated levels of Cd, Co,

Cr, Mn, Ni, Sr, and Zn in the topsoil of the study area. Furthermore, the topsoil in all zones around the industrial city is heavily contaminated by Pb. Furthermore, the pollution load index (PLI) data revealed that the area is heavily contaminated by metals.

2.4 Research Gap

There is no research of this type for the selected study areas. This study area is in Dammam and Hafer Al-Batin, which are considered arid environments. This environment needs to be researched further to better understand remote sensing performance in detecting dumpsites in arid environments. Bare soil is a common form of land cover in an arid environment and can create noise in the image classification process. Much of the research was conducted in areas where vegetation is common, and vegetation stress is often used to indicate the presence of illegal dumping.

CHAPTER 3

Methodology

3.1 Study Area

This research identifies illegal dumping in Dammam and Hafer Al-Batin in Eastern of Saudi Arabia as a case study, as shown in Figures 2. These two cities experienced rapid population growth and increased housing and commercial buildings. Once the approach is established, it could be extended to other cities.

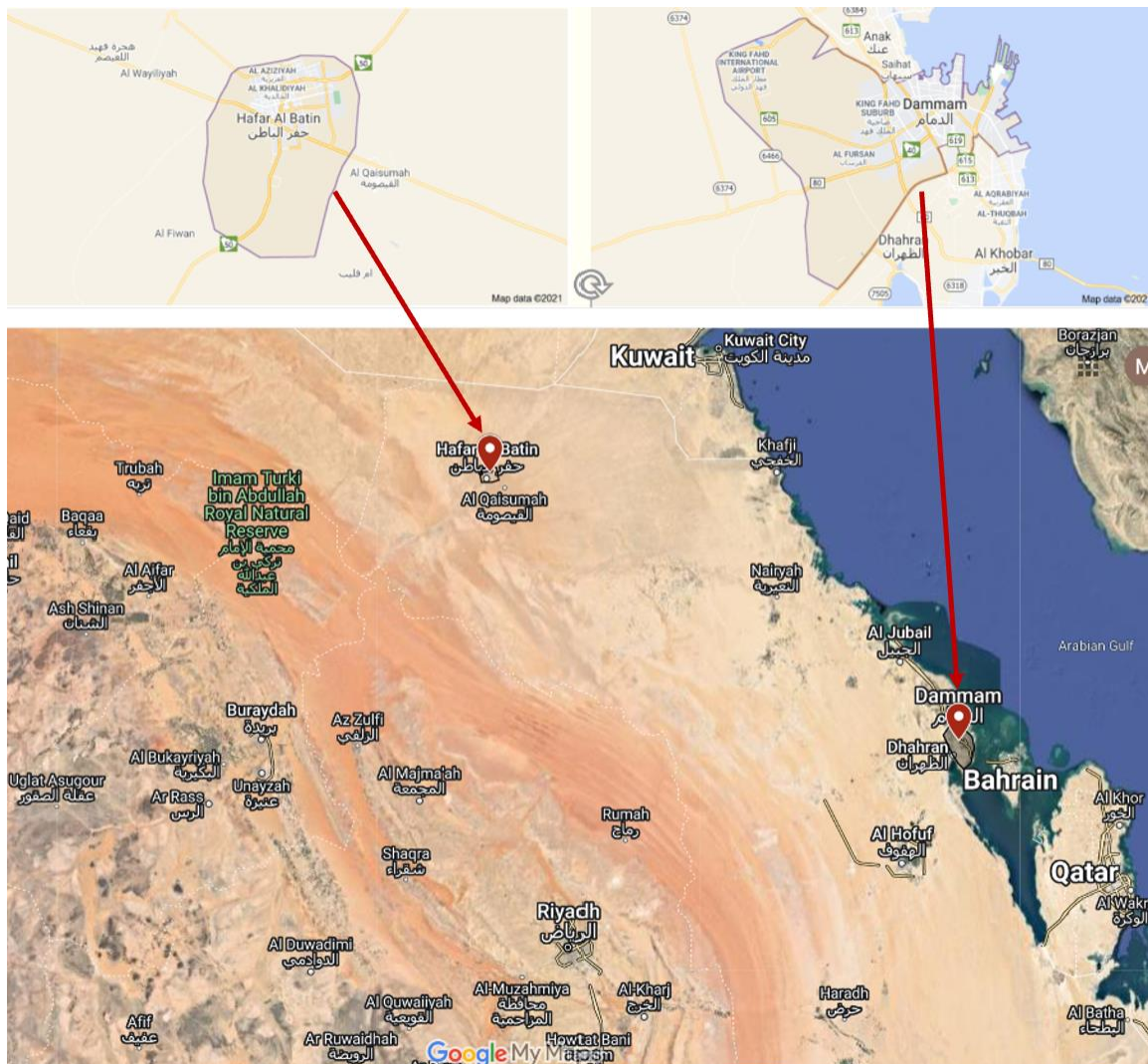


Figure 2 The study was conducted in two areas: Dammam and Hafer Al-Batin Cities, Eastern Saudi Arabia.

The methods used in this study can be categorized into two types: 1) Remote sensing-based methodologies to identify dumpsites and map them and 2) lab-based methodologies to study the impact of the dumpsites on the underneath soil.

3.2 Remote Sensing Based Methodologies:

Satellite images are the main dataset for this study. Due to the heterogeneity of the illegal dumping sites, two methods must be examined on known sites to find the most accurate ones and then try these methods on the whole study areas. These methods can be directly related to the spectral characteristics of the dumping sites, like spectral signatures or indirectly related to temporal changes in the spectral signatures on the surface due to the dumpsites. The analysis was conducted on satellite imageries obtained from open access providers like Google Earth Engine (GEE) or USGS.

The accuracy of the classification is assessed by comparing the classified images to a reference dataset considered to be validated by ground truth. The ground-truthing is conducted in the field for randomly selected sites.

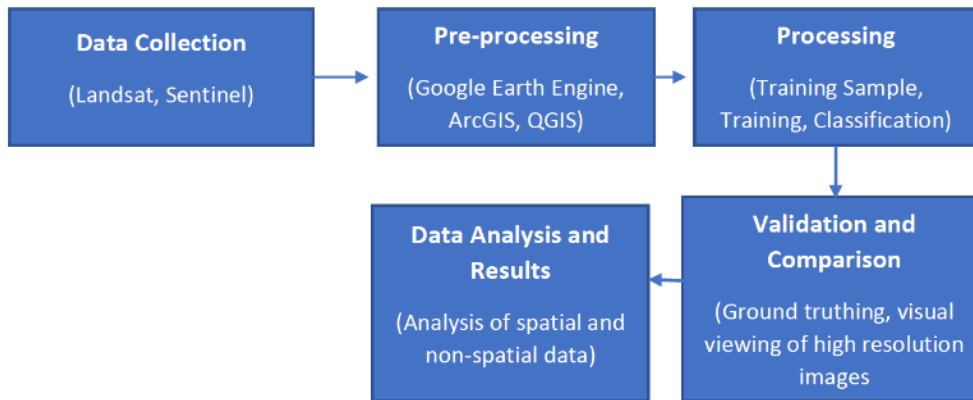


Figure 3 Image classification Methodology flowchart

The satellite image classification methodology (see Figure 3) consists of five phases. The first phase is data collection; satellite images can be collected from various sources. Some are open access to all public, while sources are commercial, and one has to buy them at a cost. The open access images are usually of low resolution compared to the commercial satellites. One of the top

open providers is USGS Earth Explorer and the European Space Agency (ESA) (System, 2019). Once the images are acquired, they may need to be pre-processed to correct or minimize image distortions caused by, for example, imaging equipment, sensors, and observation conditions. Examples of common pre-processing activities include, but are not limited to: radiometric, atmospheric and geometric corrections (Glanville & Chang, 2015). It is noted that all satellite images require pre-processing, as some image providers perform this step on raw images. After the images are pre-processed, they would be ready for the processing phase, where the classification activities are performed.

Class Name	Class Description	Example
Urban (Built up area)	Area covered by buildings and roads	
Water	Areas covered by water	
Vegetation	Area covered by farms, gardens	
Bare Soil	area without vegetation	
Dumpsite	Areas covered by dumps	

Figure 4 description of Land Cover/land use classes

This technique assigns land cover classifications (urban, water, see Figure 4) to image pixels. The classification can be unsupervised, supervised, or object-based image analysis (GISGeography, 2021). After the land cover is classified, the next phase is accuracy assessment. Any image classification project has to include an assessment of accuracy. It compares the classified land cover image

to data from a trusted or ground-truth source. This can be done in the field, where ground truth can be acquired, but it is time-consuming and costly. Ground truth data can also be obtained by visually inspecting high-resolution images different from the ones used for classification. Finally, the analysis and results are shared, where decisions can be made based on the results.

Below is the high-level summary of the methods to be used:

3.2.1 In Field Spectral Measurements

During the field survey, a ground-based spectroradiometer was used to measure the spectral reflectance of materials found in a selected dumpsite. The site was selected because it was accessible and near the main roads. This type of survey is sometimes called terrestrial remote sensing. This method studied surface reflectance for its reflectance properties. The reflectance process can be analysed as a function of the incident electromagnetic radiation's wavelength/frequency and polarization. Therefore, reflectance spectroscopy would be useful for investigating the nature of the material found in dumpsites, which reflect sunlight into the atmosphere.



Figure 5 spectroradiometer for in-situ measurements of reflectance

The spectroradiometer (see Figure 5) was from SPECTRAL EVOLUTION. It covers the UV/VIS/NIR range from 350-2500 nanometres. Before use, it was calibrated at the site with a whiteboard to ensure accurate reading of the samples.

3.2.2 Satellite Images Classification:

Various image classification algorithms were applied to the study area, beginning with an unsupervised approach to test the algorithm's ability to distinguish between land cover types. Then a supervised machine learning classification method was applied to the dataset.

The landcover is classified into five categories: urban, water, vegetation, bare soil and potential dumpsite. The classification model was trained using 300 samples from the five landcover categories and then executed for the rest of the study area. A simple Machine Learning (ML) algorithm called Random Forest was used for the classification. This algorithm is based on the development of decision trees iteratively and randomly. The result was visually inspected using high-resolution images provided by KFUPM-Remote Sensing Laboratory. As a result, many new dumpsites were discovered on the outskirts of the two cities (see Figures 6 & 7). The supervised classification process was iterated several times to improve accuracy assessment based on validation from site visits.

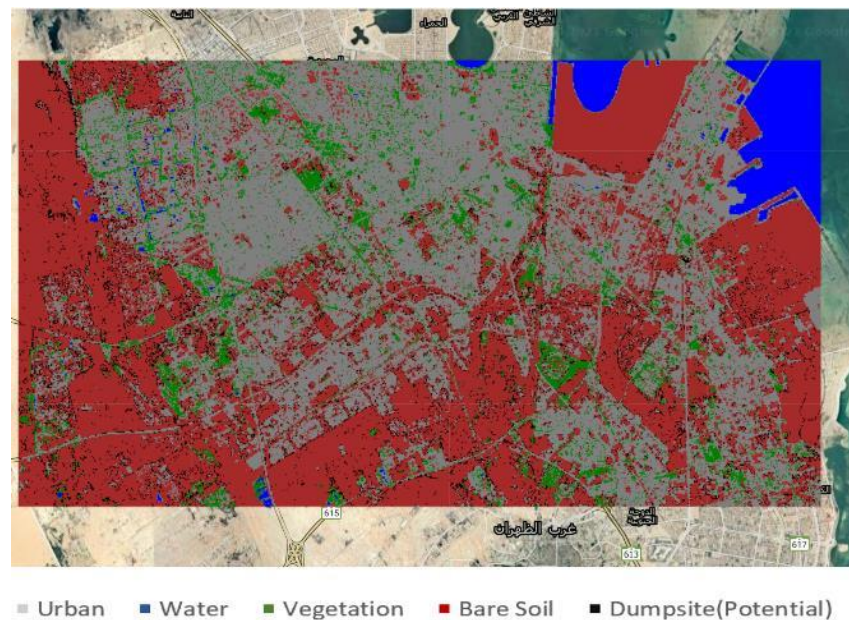


Figure 6 Supervised classification result in Dammam area (black indicate potential dumping area)

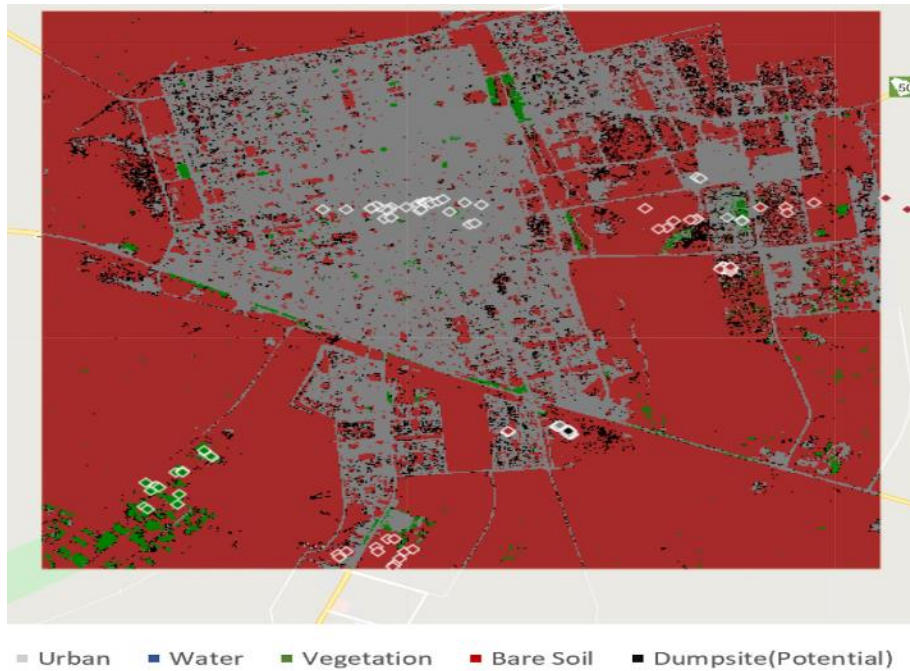


Figure 7 Supervised classification result in Hafer Al-Batin area (black indicates potential dumping area)

The in-situ measurements data were co-related with spectral signatures of satellite images from known dumpsites for possible matching. The spectral signature is a function of the pixel contents and the wavelength. The spectral values of the identified dumpsites were used to scan the area again for possible unique spectral signatures that would indicate the presence of similar sites in the study area.

From a mapping perspective, it was assumed that each map pixel corresponds to a single map cover type. However, this was not the case with satellite images because the reflected pixels are a mixture of spectral reflectance of all the pixel contents. Each image pixel contains more than one type of land cover; therefore, spectral unmixing is employed to classify the images based on the pixel contents. Spectral unmixing is used to extract the pure spectral signature for the land cover of interest in the pixel to indicate the presentence of an illegal dump.

The research involved conducting a field survey for ground-truthing for satellite image classification. Ten identified sites were visited to perform grounding truthing. Eight of

these sites were confirmed as dumpsites (two of them were shown in Figure 8. These sites mostly consisted of construction and demolition waste.



Figure 8 Ground truthing of two dumpsites (on the right satellite image, left ground image)

3.2.3 Temporal Analysis and Change Detection

Change detection implies identifying differences in scenes taken at different periods of the same location. The current scene was compared with another scene for the same area taken one year back; then, the process was iterated to compare with two years, etc. The reported changes were further studied to identify whether there were natural or anthropogenic changes. The anthropogenic changes were studied to identify which ones were dumpsites. The process was tedious but could capture dumpsites that were missed in the classification algorithms.

The Image Differencing technique was employed in this study. The technique finds the difference between each pixel in each image and then produces a new image based on the result. The two images must first be aligned so that corresponding points coincide, and their photometric values must be compatible. The resulting images can be displayed on a

grey scale where the darkest pixels show no change and the brightest pixels indicate the highest change (see Figure 9).



Figure 9 The result of comparison between two images to detect the change (brighter pixels indicate in the area)

3.2.4 Waste types and Volume Estimation for a selected site Method

This objective could not be achieved due to a lack of hyperspectral data(images) for the study area. It was not possible to use Arial remote sensing to obtain such data. The method I was trying to use was from research conducted in the US, where Google Earth Engine has 3D images constructed from Arial remote sensing. However, the study area in Dammam and Hafer Al-Batin have only 2D satellite images available.

In addition, the dumpsites have heterogeneous mixtures of waste materials that cannot be separated from the available data. Also, the identified dumpsite has a small surface area; the biggest one is around 3 km². I realized that a large area is required in order to be able to identify and separate materials based on their signatures. In my case, the area is small, and the waste is a heterogeneous mixture of all types—Figure 10 shows the attempts to identify the materials.

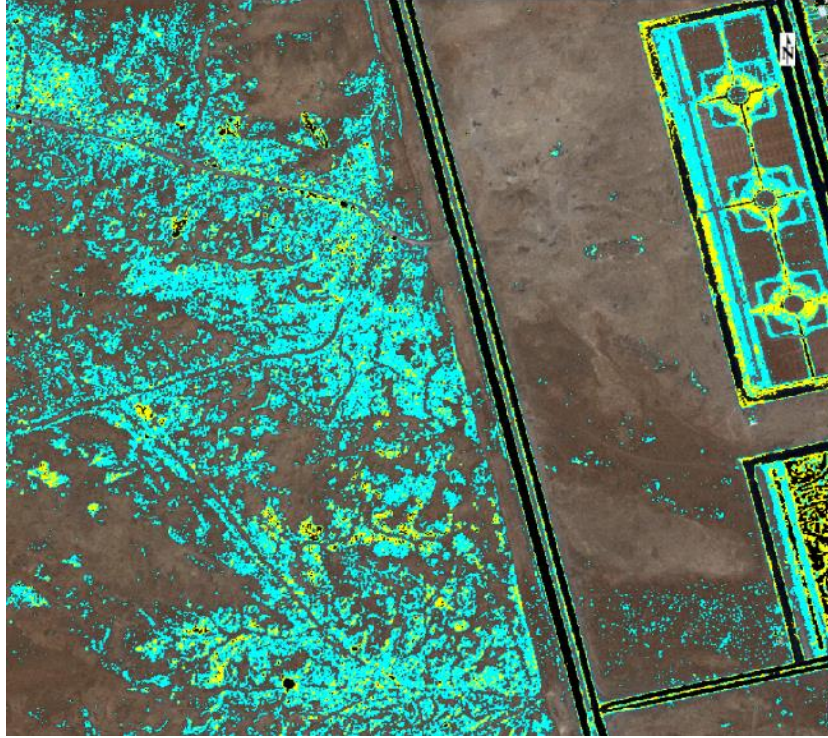


Figure 10 Materials in dumpsite could not be separated from built-up surroundings

3.3 Soil Quality Assessment

3.3.1 Sampling:

The study was conducted for two open dumping sites in two cities in the Eastern province of Saudi Arabia. The first dumping site selected was in Dammam; it was selected because of its accessibility, and it also resembled many other discovered sites in the area. At this site, five soil samples were collected to explore the impact of the dumping in the soil. However, these samples were just experimental samples, and since no significant anomalies were found, another site was selected in a different area. The second dumping site was in Hafer Al-Batin city, which was selected as the largest site discovered in this area. At this site, thirty-one (31) samples were collected to represent the investigated site and assess the impact of dumping activities on the soil.

A cell sampling strategy was used, a sampling method where the field was divided into a grid of evenly sized cells (four quadrants), and samples were collected from each cell randomly.



Figure 11 The auger digs a hole to 5 cm depth, and then the sample is collected.

The soil samples were collected from the topsoil surface (0-5cm) using a soil sampling auger (see Figure 11). A small amount of surface scraping was done to remove transported soil from nearby locations. To avoid contamination, the soil samples were kept in sealed polyethylene bags. The soil samples were already dry, which is one of the methods for soil preservation; however, the samples were refrigerated while waiting to be transferred to the laboratory.

3.3.2 Method of Measuring pH and Conductivity

A glass electrode was used to measure the soil pH in a solution containing twenty (20) g of soil sample and twenty (20) ml of deionized water. The suspension was sonicated for 10 minutes. The conductivity was also measured from the soil suspension. The conductivity was measured by a hand-held CyberScan PCD 650 with pH electrode and conductivity probe; this device was manufactured by Eutech Star.

3.3.3 Method of Measuring TOC and TC

The following steps are included in carbon analysis for TOC and TC with a dry combustion analyzer called Elementar (from the Analytical Instrumentation Dept. of the Heraeus): weighing the sample (50 mg of soil sample was added to a crucible, adding 30 mg of standard (glucose) after every four samples, then the analyzer burned the sample in an oxygen stream, and measuring of the combustion gases, using infrared cells. The method is called DIN 19539. According to this method, samples are placed at various heights in the combustion furnace; the temperature varies depending on the

height. The TOC400 value is measured at 400 degrees Celsius, the ROC (residual oxidizable carbon) value is measured at 600 degrees Celsius, and the TIC900 value is measured at 900 degrees Celsius.

3.3.4 Method of Measuring Heavy Metals

To measure the heavy metals content of the soil sample, these samples were prepared using microwave-assisted acid digestion. This method to prepare the sample is known as EPA 3051 and is intended to resemble extraction using nitric acid heating (HNO₃). However, as this approach is not intended to accomplish complete sample decomposition, the extracted analyte concentration may not accurately reflect the sample's total content (EPA, 2007). For example, it is known that silicates do not decompose using this method. Therefore, its goal is to provide a quick analysis of the level of soil contamination so that clean-up activities can be determined (EPA, 2007). Then Inductively Coupled Plasma Mass Spectrometry (ICP-MS) was used to analyse heavy metals in the prepared samples.

In this study, 0.25 g of each soil sample was digested using concentrated nitric acid and heated to 175 using a microwave. After cooling down, the digested solutions were raised to a total volume of 100 mL with deionized water in a volumetric flask. Then, 10 ml was taken from the flask into a vile for each soil sample. An internal standard was added to each vile to calibrate the ICP-MS. Finally, the samples were put in the ICP-MS to measure the heavy metal contents.

A high-temperature ICP source is combined with a mass spectrometer in an ICP-MS. The elements in the sample are atomized and ionized by the ICP-MS source. Therefore, the masses of the elements can be used to identify them. The soil test findings are expressed in parts per million (ppm) of the pollutant being detected. A ppm value of 1 means that there is 1 part of the pollutant in every million "parts" of soil by dry weight. Metal levels are measured in "mg/kg" (milligrams of pollutant per kilogram of soil) units, equivalent to ppm.

To better comprehend the soil assessment results, it is necessary to distinguish between the natural concentration of heavy metals resulting from the earth's crust's weathering effect and those resulting from anthropogenic activities. Therefore, there are methods

to evaluate soil contamination using indexes. One of these methods is Geoaccumulation Index (I_{geo}), which will be used to assess the soil contamination in the Result chapter. This index is calculated using the below formula (Barbieri, 2016):

$$I_{geo} = \text{Log}_2 [C_i / (1.5 C_{ri})]$$

where:

C_i is the concentration of heavy metals in soil (mg kg^{-1} or ppm);

C_{ri} is the reference value of the heavy metal in undisturbed soil;

In this study, the average and maximum heavy metal concentrations were used to derive the I_{geo} index. In addition, the reference (control) sample was used as a reference (background value). The equation result is a designated class of soil based on I_{geo} value; see Table 1 for details.

Table 1 Heavy metals soil contamination based on Geo-accumulation (I_{geo}) index

I_{geo} value		Class	Soil Quality
$I_{geo} \leq 0$		0	Unpolluted
$0 \leq I_{geo} \leq 1$		1	Unpolluted to moderately polluted
$1 \leq I_{geo} \leq 2$		2	Moderately polluted
$2 \leq I_{geo} \leq 3$		3	Moderately to strongly polluted
$3 \leq I_{geo} \leq 4$		4	Strongly polluted
$4 \leq I_{geo} \leq 5$		5	Strongly to extremely polluted
$I_{geo} > 6$		6	Extremely polluted

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Remote Sensing Assessment Results

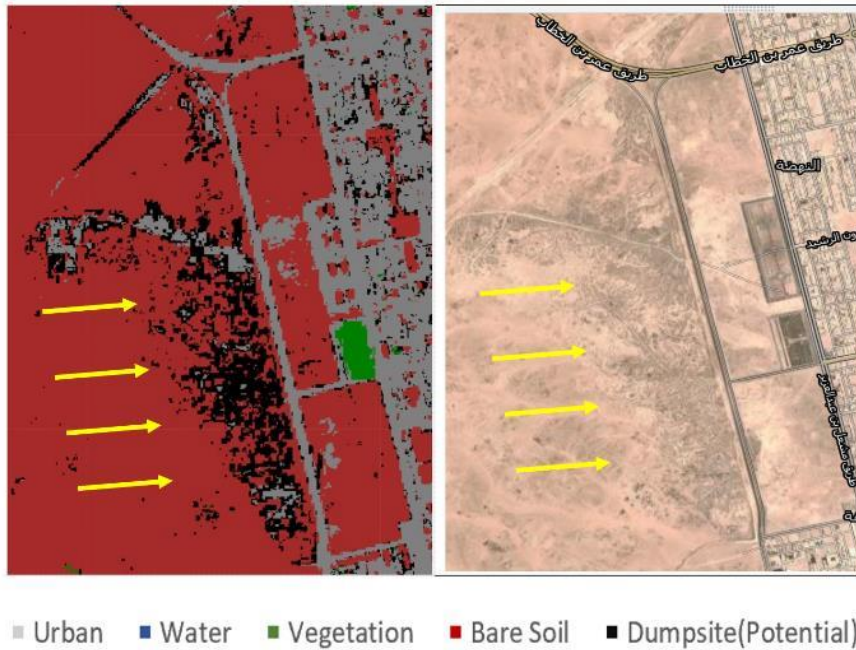


Figure 12 from the left shows the image classification results and the corresponding true color image

Unsupervised is used to understand how dumpsites appear compared to the surrounding. Results varied from one area to another; several false positive sites appeared as dump sites in the classification, but when closely visually inspected, they were not. This could be due to the similarity between the content of the open dumpsites and the building materials. The unsupervised classification was useful to group spectral classes or clusters that shared the same characteristics for better understanding and to conduct further analysis for the identified categories. It was very effective as an exploratory technique, showing how landcover can be separated from each other, see Figure 12.



Figure 13 Map of open dumpsites in the Dammam area



Figure 14 Map of open dumpsites in the Hafer Al-Batin area



Figure 15 Sample of satellite images of some of the identified dumpsites

After several iterations of supervised classification, the outcome was satisfactory as more dumpsites were discovered by this method. However, construction debris is sometimes classified as 'urban' due to the similarity between construction debris and built-up areas. More training samples and refinement of the model improved the classification accuracy. A total of 64 dumpsites were discovered in the two cities. Table

2 shows the breakdown by discovery method, and Table 3 lists the coordinates and areas of the discovered sites. See Figures 13, 14, and 15 to illustrate the findings.

Table 2 Number of identified dumpsites per method

	No. of Findings per Method			
City	Supervised Classification	Change Detection	Visual Inspection of Images	Total
Dammam	14	5	9	28
Hafer Al-Batin	17	12	7	36

Table 3 Discovered sites coordinates and their areas in km²

Site Number	Latitude (Decimals)	Longitude (Decimals)	Area (km ²)
1	26.167361	49.950764	0.53
2	26.175715	49.916998	0.09
3	26.181796	49.966628	0.69
4	26.189960	49.984653	0.08
5	26.192883	50.137017	0.12
6	26.201114	50.112586	0.01
7	26.207138	49.885069	0.45
8	26.212900	50.111023	0.02
9	26.213103	50.135881	0.08
10	26.221314	50.102361	0.28
11	26.246525	50.032625	1.50
12	26.251590	50.087775	0.27
13	26.273891	49.751973	0.05
14	26.277589	50.045933	0.80
15	26.279073	50.027149	0.13
16	26.285050	49.799050	0.20

17	26.290949	50.035035	0.12
18	26.302283	50.039158	0.28
19	26.328760	50.077882	0.01
20	26.345106	49.917537	0.10
21	26.347994	49.952233	0.10
22	26.355832	49.754065	0.01
23	26.376533	49.930333	0.11
24	26.385056	50.052115	0.02
25	26.469867	49.832554	0.64
26	26.479089	49.861425	0.06
27	26.483555	49.846604	0.03
28	26.507900	49.594800	0.02
29	28.272515	45.963717	0.02
30	28.281269	45.965708	0.10
31	28.301042	45.970586	0.15
32	28.308079	45.980338	0.05
33	28.314533	45.943256	0.09
34	28.325228	46.086084	0.20
35	28.326416	45.951501	0.02
36	28.326792	45.947930	0.10
37	28.329794	45.951134	0.01
38	28.333170	46.066116	0.50
39	28.333493	45.952129	0.01
40	28.337563	45.947975	0.07
41	28.354393	46.044382	0.09
42	28.355046	46.011919	0.10
43	28.356245	45.999983	0.04
44	28.379674	46.035663	0.02
45	28.381088	46.050483	0.17
46	28.381812	45.928467	0.02
47	28.384063	45.926233	0.01
48	28.389311	46.071316	0.15
49	28.395305	45.912914	0.70

50	28.396605	46.028277	0.30
51	28.407143	45.908285	0.01
52	28.408374	46.023090	0.27
53	28.411706	46.007945	0.17
54	28.422753	46.007229	0.38
55	28.433460	45.907750	1.50
56	28.438644	46.009895	0.20
57	28.441161	45.909511	0.30
58	28.446559	45.912082	0.05
59	28.453401	45.920542	0.07
60	28.454728	45.928637	0.04
61	28.458670	45.931359	0.08
62	28.466165	45.952940	0.10
63	28.467409	46.032737	0.07
64	28.468450	45.973314	0.06
Total Area:			13.01 KM ²

The identification and quantification of waste type in a dumpsite could not be achieved due to two reasons:

1. Lack of required data. High spatial and hyperspectral imaging data is needed to accurately characterize a dumpsite in terms of waste types and quantities. The hyperspectral gathers hundreds of photos at various wavelengths across the spectrum for the same area. Each substance has a unique spectral signature that could be used as a "fingerprint" for identification. This type of data is currently not available for the study area.
2. Dumpsites are a heterogeneous mix of materials and occupy a small area. This makes it very difficult for the current algorithms to unmix the spectral mixture of these materials. Therefore, a large area is required to obtain material comparable to the actual soil.

4.1.1 In Field Spectral Measurements

Twenty types of materials were studied at the site by taking their spectral reflectance. See Figure 16 for the materials list and Figure 17 for their reflectance responses curve.

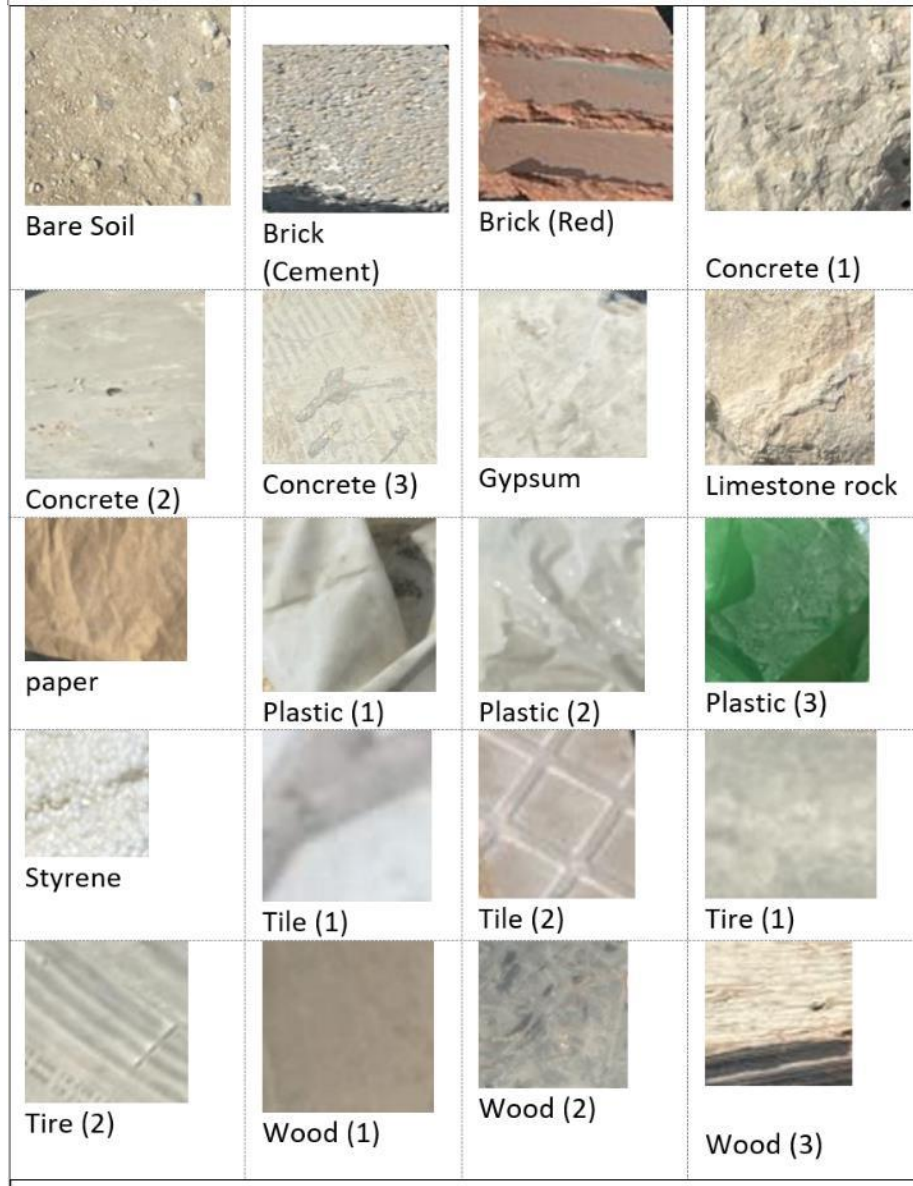


Figure 16 Common materials found in construction dumpsite

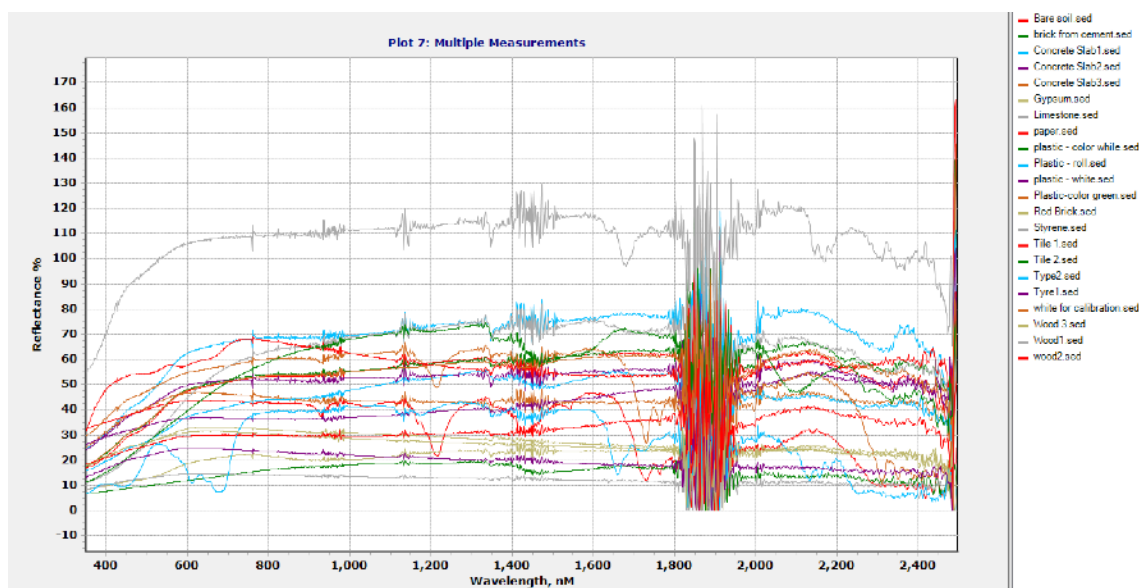


Figure 17 Reflectance readings from some sample materials found in dumpsites (the first one is for calibration)

After examining the reflectance responses for the same material, it was noted that although the overall shape of the curve may be similar for some of them, changes in reflectance occur through variations in the amplitudes of the curve. This could be due to the materials coming from different sources and purity issues. See Figures 18 and 19 for examples of different reflectance for the same materials (concrete and wood). It was also noted that the different materials overlap; therefore, a single absorption could not be identified and directly connected to the chemical abundance of particular material composition.

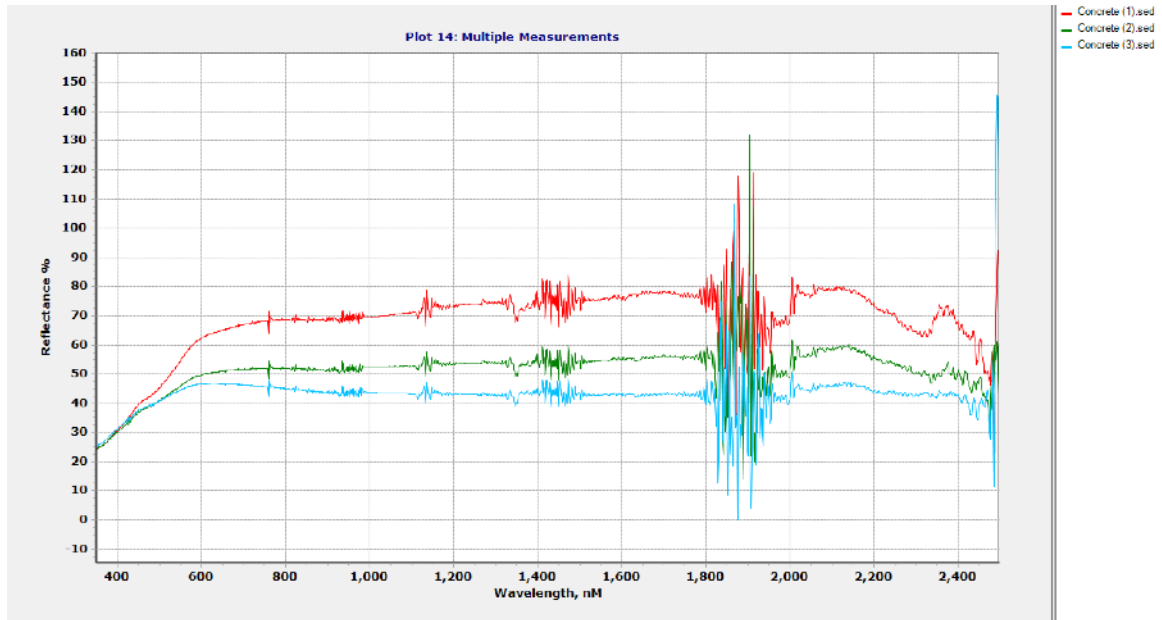


Figure 18 concrete samples have a similar shape curve

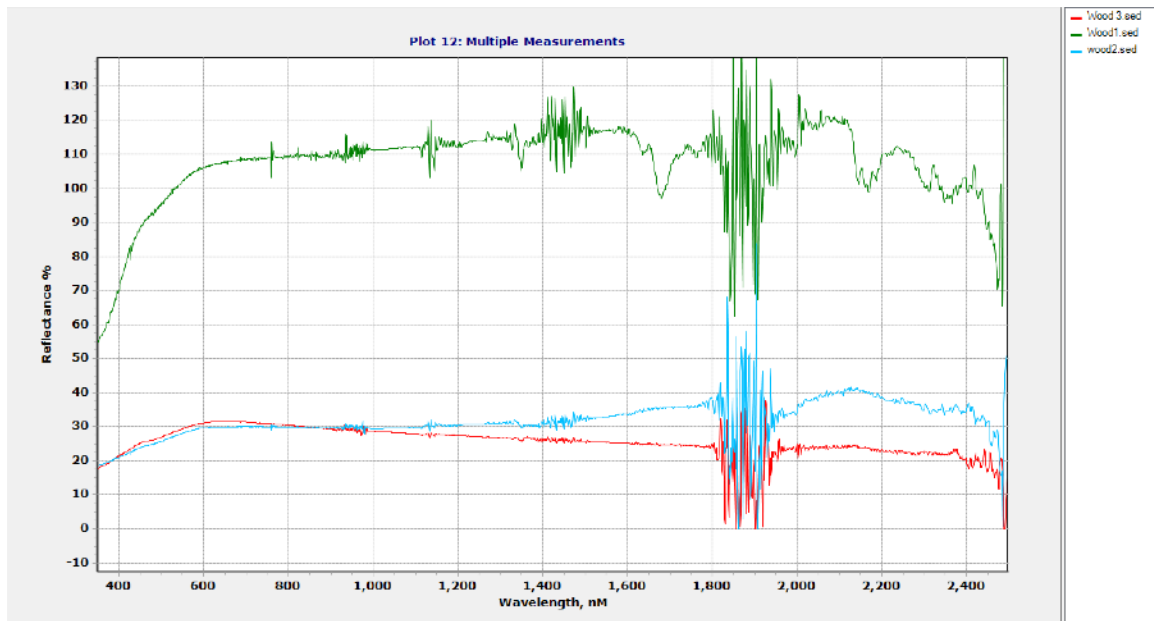


Figure 19 Wood samples have different shape curve

These readings can serve as a spectral library that provides a set of standards for materials of known composition as a reference for spectral analysis. The library includes spectral

reflectances of different materials including plastics, construction materials, processed wood, paint, and other artificial materials

4.2 Soil Assessment Results

Table 4 Samples results from a dumpsite in Dammam

Sample No.	%TOC	%TC
1	1.154	9.897
2	0.344	17.643
3	0.547	6.436
5	0.179	11.783
6	0.461	7.017

Table 5 Samples results from a dumpsite in Hafer Al-Batin

Sample No.	%TOC	%TC
1	0.208	2.770
2	0.304	3.226
3	0.151	2.621
4	0.253	1.810
5	0.206	0.885
6	0.215	1.657
7	0.289	0.962
8	0.266	4.421
9	0.193	1.154
10	0.099	0.451
11	0.464	1.808
12	0.118	1.452
13	0.178	1.484
14	0.111	0.965
15	0.093	1.667
16	0.303	1.754
17	0.096	0.766

18	0.296	3.901
19	0.231	1.822
20	0.282	1.998
21	0.225	1.737
22	0.552	2.929
23	0.399	2.114
24	0.235	1.190
25	0.295	1.659
26	0.346	2.273
27	0.318	1.767
28	0.316	1.705
29	0.291	1.419
30	0.295	1.700
31	0.224	1.188

4.2.1 TOC and TC

The result shows that the open dump site in Hafer Al-Batin has an average organic carbon level of 0.25%, whereas the total carbon level is 1.8% (see Tables 4 & 5). This is within the normal range of soil. The open site in Dammam has a similar average organic carbon level of 0.5%, whereas the total carbon is considered elevated at 10%. The normal organic carbon content for the two open dumpsites could be due to waste type, which is mostly construction and demolition waste. On the other hand, the higher total carbon content in the open dumpsite in Dammam could be because of inorganic carbonates. The soil may have a higher concentration of inorganic carbon in arid regions. Tables 6 and 7 summarise TOC, TC, PH and EC for both dumpsites.

Table 6 The Dumpsite in Dammam Results

	%TOC	%TC	PH	EC (μS/cm)
Min	0.179	6.436	8.03	396.00
Max	1.154	17.643	9.09	4194.00
Mean	0.537	10.555	8.27	1931.00
STD	0.332	4.041	0.41	1362.33

Table 7 The Dumpsite in Hafer Al-Batin Results

	%TOC	%TC	PH	EC(μS/cm)
Min	0.093	0.451	7.60	309.00
Max	0.552	4.421	8.48	4331.00
Mean	0.253	1.847	8.13	2200.00
STD	0.104	0.880	0.19	910.68

4.2.2 Result of pH and EC

The pH values at an average of 8.2 for both dumpsites indicated slightly alkaline soil; this could be due to the presence of calcium carbonates in the soil samples.

Both sites' average electrical conductivity (EC) was around 2000 (μS/cm). According to the literature, this level is considered moderately high compared to the natural level of 1000 μS/cm. The soil electrical conductivity (EC) measures the number of salts in the soil and is proportional to the ion concentration in the water. Therefore, it is an important parameter for determining the health of the soil. Elevated EC could be caused by soluble salts accumulating and remaining near the soil surface.

4.2.3 Heavy Metals

Table 8 Heavy metals result from Dammam

Sample/Concentration (PPM)	AI	CR	Ni	Co	Cu	As	Cd	Hg	Pb
1	4519.1	22.8	38.5	3.8	8.8	3.8	0.3	0.11	10.9
2	1622.1	19.3	46.0	1.8	4.2	1.8	0.4	0.03	4.3
3	2531.6	16.1	33.2	2.3	6.8	1.4	0.2	0.01	6.1
4	2220.1	16.8	38.9	2.3	4.4	2.3	0.1	0.01	2.5
5 (Control Sample)	2351.5	12.5	25.3	2.2	5.3	1.3	0.1	0.03	4.9

Table 9 Heavy metals result from Hafer Al-Batin

Sample/Concentration (PPM)	AI	CR	Ni	Co	Cu	As	Cd	Hg	Pb
1	6279.21	24.17	36.00	5.15	8.56	4.31	0.07	0.01	2.77
2	1119.36	3.25	5.97	0.81	1.38	0.56	0.02	ND	0.71
3	4709.52	20.38	37.31	4.82	4.44	5.10	0.06	ND	2.24
4	4943.80	14.87	22.80	2.99	4.50	1.73	0.07	0.02	2.80
5	3842.66	14.66	25.19	3.71	4.52	3.21	0.05	ND	2.46
6	3440.08	10.61	14.91	2.24	2.97	1.25	0.04	ND	1.46
7	5024.45	19.66	16.21	5.36	5.90	3.31	0.09	ND	2.10
8	4970.62	12.84	27.83	4.28	4.52	2.42	0.09	ND	2.81
9	318.72	1.25	2.12	0.16	0.60	0.20	0.01	ND	0.42
10	5550.75	18.72	21.55	3.19	4.50	2.77	0.06	ND	2.49
11	3533.39	12.94	14.94	2.46	3.89	1.51	0.06	ND	4.46
12	4549.68	18.99	22.66	3.75	4.80	2.38	0.07	0.12	2.93
13	2954.94	9.87	11.20	1.90	2.10	1.45	0.02	ND	1.14
14	2506.88	13.37	15.04	3.05	10.83	1.45	0.05	ND	2.86
15	1442.91	6.46	8.84	1.38	1.74	0.81	0.03	ND	1.03
16	5512.08	18.52	21.00	4.60	5.86	3.16	0.08	0.01	2.95

17	2798.42	10.56	11.89	2.25	2.81	1.73	0.04	ND	1.73
18	4860.05	13.20	24.60	4.92	4.59	3.08	0.11	ND	2.80
19	4897.24	18.40	20.65	4.25	5.58	2.37	0.09	ND	2.99
20	6111.33	21.80	27.61	5.41	7.44	3.02	0.09	0.02	2.29
21	2524.77	9.50	14.11	2.16	3.37	1.67	0.05	0.02	1.65
22	4682.40	17.13	21.84	3.90	7.33	2.36	0.11	0.05	3.10
23	5918.82	22.79	23.48	5.43	6.67	3.34	0.09	0.05	4.88
24	3129.15	13.68	19.14	3.97	5.19	3.24	0.05	0.04	1.68
25	3415.79	13.86	18.43	3.60	4.12	2.16	0.08	0.05	2.49
26	8160.90	20.31	18.61	4.13	5.09	2.41	0.07	0.06	3.35
27	5372.31	19.77	23.76	5.45	8.09	2.48	0.11	0.05	6.72
28	5527.16	19.49	20.47	4.74	6.40	2.25	0.09	0.05	4.86
29	3550.29	13.85	16.14	3.39	263.43	1.64	6.67	0.05	4.93
30	4611.46	18.04	20.42	4.10	5.26	2.54	0.08	0.04	3.43
31 (Control Sample)	5248.99	18.81	26.61	5.32	7.35	2.90	0.09	0.03	2.30

Table 10 Heavy metal summary of a Dumpsite in Dammam

(In ppm)	Co	Al	Cr	Pb	Ni	As	Cu	Cd	Hg
Min	1.8	1622.1	12.5	2.5	25.3	1.3	4.2	0.1	0.01
Max	3.8	4519.1	22.8	10.9	46.0	3.8	8.8	0.4	0.11
Mean	2.5	2648.9	17.5	5.8	36.4	2.1	5.9	0.2	0.04
STD	0.68	983.7	3.4	2.8	6.9	0.9	1.7	0.1	0.04

Table 11 Heavy metal summary of a Dumpsite in Hafer Al-Batin

(In ppm)	Co	Al	Cr	Pb	Ni	As	Cu	Cd	Hg
Min	0.16	318.72	1.25	0.42	2.12	0.20	0.60	0.01	ND
Max	5.5	8160.9	24.2	6.7	37.3	5.1	263.4	6.7	0.119
Mean	3.6	4242.2	15.2	2.7	19.7	2.3	13.3	0.3	0.040
STD	1.4	1658.9	5.5	1.4	7.6	1.0	46.5	1.2	0.026

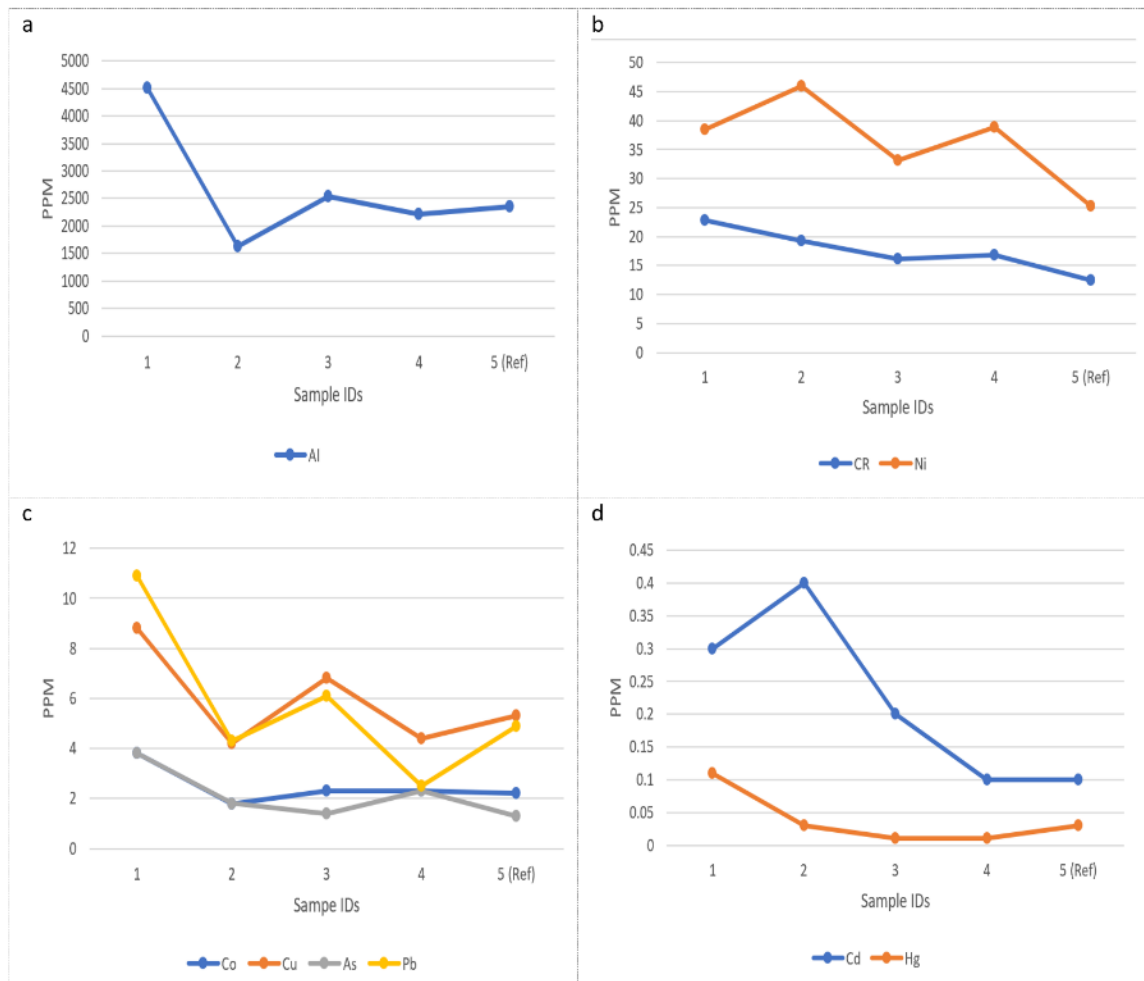


Figure 20 heavy metals results in Dammam

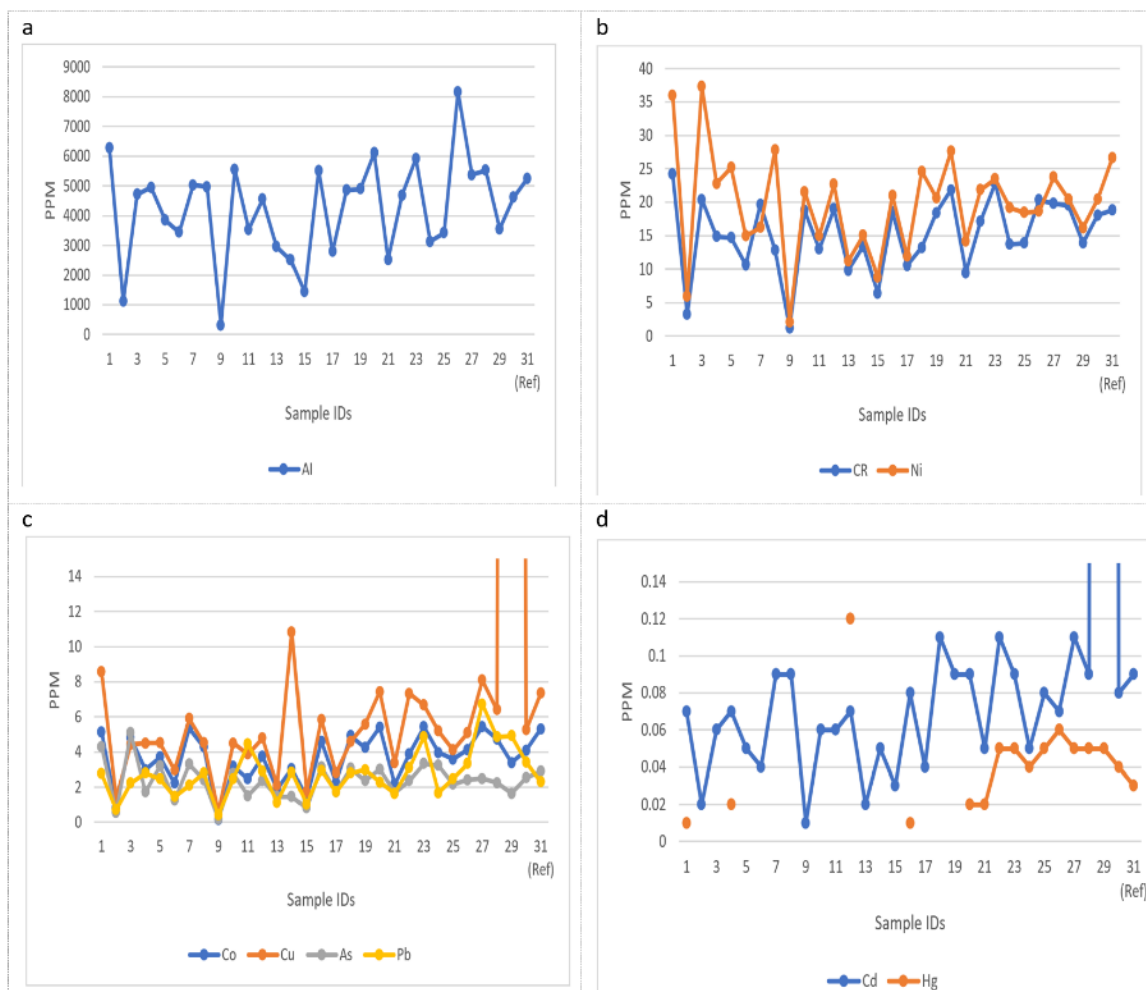


Figure 21 heavy metals results in Hafer Al-Batin

The results revealed the presence of toxic following heavy metals in the samples taken from the two dumpsites: Co, Al, Cr, Pb, Ni, As, Cu, Cd and Hg (see Tables 8 & 9). Heavy metal concentrations were within the normal ranges compared to previous studies and EPA standard limits. Heavy metal concentrations in the reference soil did not consistently show lower levels than those in the dumpsite area. However, some samples showed slightly higher concentrations than the reference sample due to anthropogenic activities. See Tables 9, 10 and 11 for a summary of the heavy metals results. For a graphical representation of the result, see Figure 20 and Figure 21.

The Geoaccumulation index (Igeo) is used to further assess soil pollution. After calculating Igeo (see Table 12) based on the average sample concentration for the dumpsite in Dammam, it is noted that all the values for Co, Al, Cr, Pb, Ni, Cu, and Hg are below zero (0), which means unpolluted based on Table 1. On the other hand, Igeo values for As and Cd are between 0 and 1, which means “Unpolluted to moderately polluted”.

Table 12 Geoaccumulation index calculation for Dammam

Dammam	Co	Al	Cr	Pb	Ni	As	Cu	Cd	Hg
Igeo (Based on the mean value of samples)	-0.12	-0.12	-0.03	-0.10	-0.02	0.03	-0.13	0.1	-0.05
Igeo (Based on the max value of samples)	0.22	0.36	0.11	-0.04	-0.01	0.42	1.52	1.65	0.42

Geoaccumulation index (Igeo) analysis based on the mean value for samples collected from the dumpsite in Hafer Al-Batin (see Table 13) shows that the values for Co, Al, Cr, Pb, Ni, As and Hg are below zero (0), which corresponds to “Class 0” which means “Unpolluted” based on Table 1, while Igeo values for Cu and Cd are between 0 and 1 which falls under “Class 1” that means “Unpolluted to moderately polluted”. However, if the index is calculated based on the maximum value of samples, then Cu and Cd fall under Class 2, which means “Moderately polluted”.

Table 13 Geoaccumulation index calculation for Hafer Al-Batin

Hafer Al-Batin	Co	Al	Cr	Pb	Ni	As	Cu	Cd	Hg
Igeo (Based on the mean value of samples)	-0.35	-0.27	-0.27	-0.11	-0.31	-0.28	0.08	0.35	-0.05
Igeo (Based on the max value of samples)	-0.16	0.02	-0.07	0.29	-0.03	0.07	1.38	1.70	0.42

CHAPTER 5

Conclusion

In the thesis, a practical approach was tried to treat a challenging local environmental issue that opens dumpsites around two cities in Saudi Arabia. The goal was to use a combination of remote sensing, machine learning and soil assessments to study open dumpsites in two major cities in the Eastern Province. Open dumpsites pose health risks to both people and the environment. The use of remote sensing to map the locations of unlawful dumpsites has been shown to have potential advantages in previous studies. The study included identifying dumpsites' locations around the cities, building a spectral library of common materials found in these dumpsites and assessing the impact of two dumpsites on soil quality. This was achieved by acquiring satellite images for the study area and then studying these images by running a combination of unsupervised, supervised and change detection methods. Then the spectral characteristics of common materials were studied using a spectrometer, and a spectral library of twenty-one (21) was documented after those two selected dumpsites were studied further to assess the soil quality in terms of heavy metals, TOC, pH and conductivity.

As a result, 62 confirmed dumpsites were discovered in the two cities using these methods. The result of the TOC and TC soil assessment for the two sites were within normal ranges. Both dumpsites had mildly alkaline soil, with pH values averaging 8.2. Both locations have an average electrical conductivity (EC) of roughly 2000 (S/cm), which is substantially high when compared to the normal level of 1000 S/cm. The heavy metal concentration was within normal ranges compared to EPA standards.

In conclusion, remote sensing effectively maps open dumpsites but requires a combination of few methods and multiple iterations to produce satisfactory results. The construction and demolition dumpsites do not seem to significantly impact the soil quality. Removing the waste from the dumping sites should be enough, and no further soil remediation is required. To better protect the environment from illegal dumping, it is recommended to develop more comprehensive waste management regulations, raise

awareness of waste management regulations and to be stricter in enforcing these regulations. The penalties for illegal dumping need to be severe, and if there is a new "hotspot" for illegal dumping to develop in the region, it has to be checked on a regular basis, and those who break the law need to be penalized. In addition, practices, use sustainable building materials and technologies, and invest more in research and development related to waste management sustainable practices.

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