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Using remote sensing techniques to track environmental changes in the southern part of Iraq

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Abstract
Remote sensing allows us to track Earth's surface, research changes, and study pollution's impact on humans and other species. Classification Envi program was used to compare the results of several classification methods for the smoke from the Muthanna brick manufacturers in Muthanna province, the Nasiriyah thermal station, the brick stations (*al'islah*) in Dhi-Qar governorate, and the southern oil refinery in Basra governorate .This study aims to analyze pollution and classification techniques to identify the extent and effects of plant and refinery smoke on reserve areas and other communities. The maximum probability technique delivers more accurate, distinct, and apparent findings than the other three. In the Muthanna brick factory, the percentage of smoke is 1.365%, whereas, in the al'islah brick factories, the rate of smoke is 4.961%. At the thermal power station in Nasiriyah, the proportion of white smoke from the chimneys and spread is around 4.605%, whereas the percentage of smoke from the South Refinery in. max is 18.927%. max is the best way to discern the image, and the other method (*ISODATA, K-Means, Minimum Distance Classifier*).

Keywords: Remote Sensing, Pollution, Image Sensor, Image Classification for Pollution

1. Introduction
Using Remote Sensing to Monitor Environmental Pollution (Air Pollution from Smoke) One of the most important topics that society cares about is the environment [1]. Because of this imbalance, major environmental issues arise that endanger both human health and the existence of other living things, making air pollution one of the most hazardous forms of environmental pollution [2, 3]. It is crucial to protect the environment's elements from pollution and deterioration and to maintain their balance, which necessitates utilizing various strategies of limitation. To study the change in air pollution caused by smoking, cement plants, oil refineries, and brick manufacturers, satellite images will be used at various time intervals. [4, 5]. employing satellite-based research' captured images. Via the application of high-capacity remote sensing methods. It is possible to effectively identify and classify different water bodies and polluted areas while studying natural resources [6, 7]. The goal of this research is to investigate the use of systems software to access, store, and analyze data, information, maps, geographic information extraction, findings, and indications that forecast the use of GIS tools to map air pollutants and disperse their geographical distribution on the Muthanna brick and repair enterprises and thermal power generation units. The oil refinery south can be used as a foundation for distributing adequate air pollution monitoring stations as air pollution maps.

2. Remote sensing
using Remote sensing involves gathering information about the Earth's surface by detecting and recording reflected or emitted energy and processing, interpreting, and applying that information [4, 8]. Remote sensing images are obtained by capturing reflected or emitted electromagnetic radiation and analyzing then using the data. Multi-spectrum or over-spectrum data is collected on several wavelength bands [9]. Since the launch of the Landsat satellite in July 1972, remote sensing has been used to identify and monitor land surfaces and environmental conditions. [10, 11] The production of a taxonomy map of particular features with measurable or relevant categories of environmental contamination in Mashhad is the most critical use of remotely sensed data, which will be the subject of our research. One of the primary end products produced from remote sensing data is a classification image, which may be created in one of two ways: unsupervised or supervised [12, 13, 15].

3. Images Classification
Classification is one of the data extraction methods used to classify an object or phenomenon in a predefined set [6]. Most

image classification is based solely on detecting spectral signatures (i.e., spectral response patterns) for land cover categories [14]. In other cases, classification can only be an intermediate step in more complex and difficult analyzes. [16] Digital Image Classification uses spectral information represented by digital numbers in a spectrum or more to allocate pixels or base units of the image separately to this spectral information. Thus, groups of identical pixels in remotely sensed data are grouped into categories that match or match categories of information that interest users by comparing the pixels of each unit with each other and with available units [17]. To get a distinction from multiple objects from one another inside the image called the layer level, The classification problem occurs when an object needs to assign a predefined group or class based on several observed attributes related to that object or phenomenon. Classification plays a critical role in remote sensing and satellite image classification. Classification can be done in two ways: (1) Unsupervised Classification, which aims to automatically divide the image into natural groups without prior knowledge of categories, including (ISODATA and K-Means). (2) The Supervised Classification that operates from the knowledge of each category identified by a probabilistic approach (Maximum Likelihood, Minimum Distance, Mahalanobis Distance, Parallelepiped, Spectral Angle Mapper (SAM), Spectral Information Divergence (SID), The binary encoding, the Neural Net, Support Vector Machine(SVM)) [18].

4. Materials and methods

4.1 Study Area

The studied areas are located in central and southern Iraq. Fig 1 illustrates a digital map of Iraq showing the location of the studied regions; For example, the Eastern / Muthanna brick factories in the south-eastern part of the city of Samawah are at a distance of 20 km (31◦11′14. 26″ N) and the width (45◦26′ 56.71″ E) with an area of 250 km ². While the brick factory (000 repairs) in the province of DhiQar, which is far from the city of Nasiriyah, 28.24 km between long lines (31◦09′ 38. 4″ N) and latitude (46◦ 30′ 43.0″ E) and area of .4299 km ², The Nasiriyah thermal power station is located on the outskirts of Nasiriyah, at a distance of 2 km north of the coast (31°02′ 09. 3″ N) and latitude (46°11′ 34.3″ E) with an area of 7.513 km ².

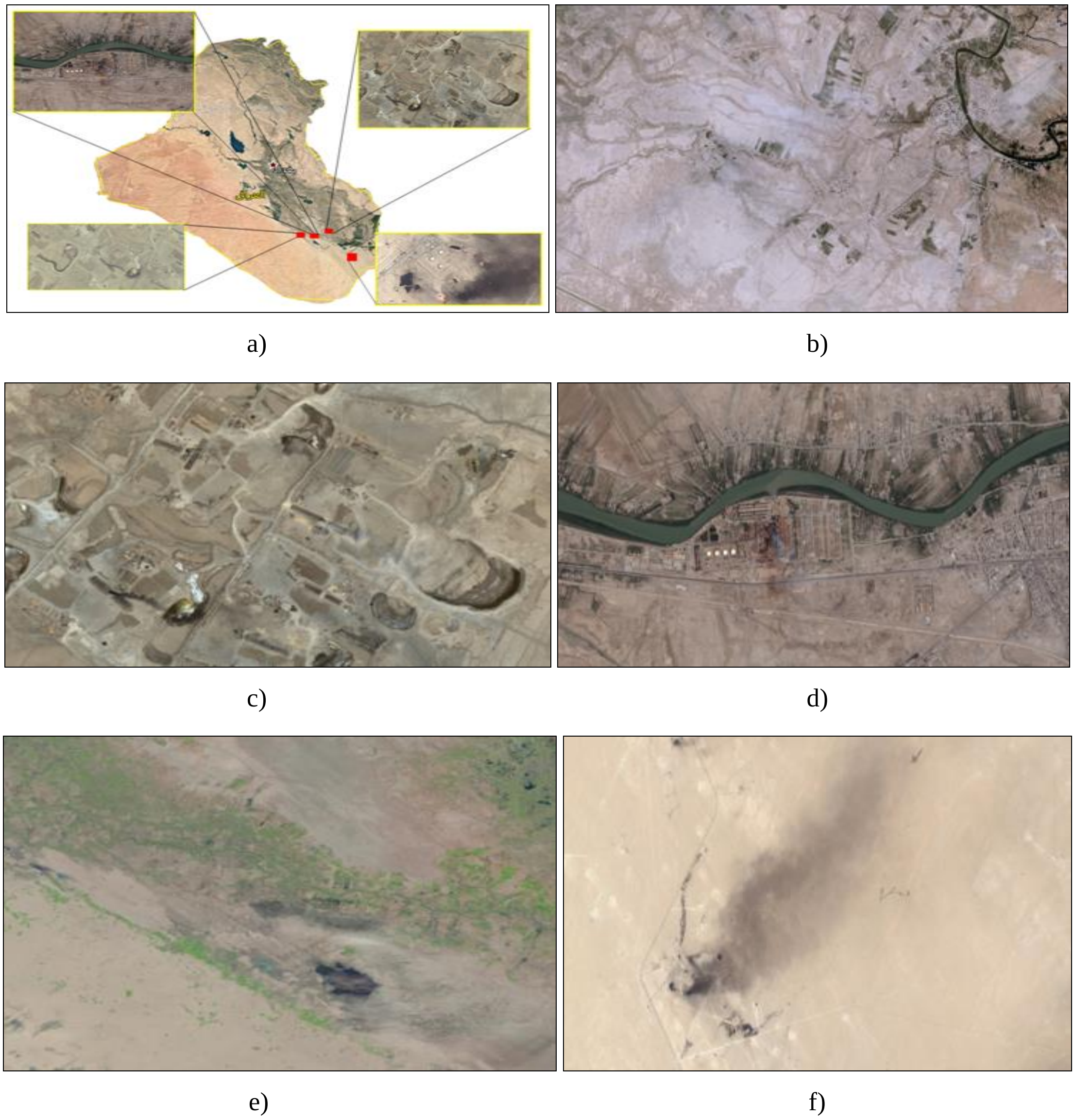

Fig 1: (a) Digital map of Iraq showing the location of the studied areas. (b) The satellite image of the suburbs of Al-Muthanna Governorate showing the Muthanna brick factories. (c) Satellite image of al'iislah brick factories in DhiQar governorate. (d) The satellite image of Nasiriyah thermal power plant in the outskirts of DhiQar Governorate. (e) Satellite image of the South Refinery in Basrah Governorate. (f) The satellite image of Muthanna province and DhiQar shows the dense smoke of Muthanna brick factories.

4.2 Satellite Image Classification

The classification methods which applied in this section are(unsupervised and supervised)classification methods. Unsupervised classification methods which were used ISODATA and K-Means classification methods. The supervised classification methods which were used(Maximum likelihood Classifier, Minimum distance classifier).

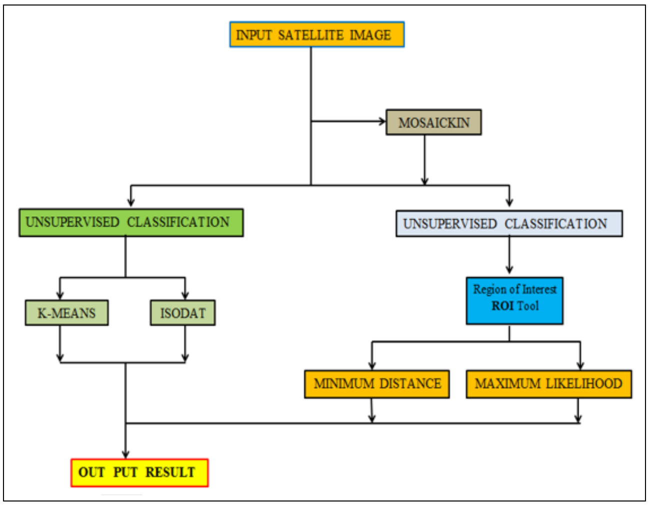

Fig 2: Block diagram of the classification methods using ENVI 4.5

We will then give a Maximum Likelihood rating for both Muthanna brick factories, repair brick factories, Nasiriyah thermal power plant, and South Oil refinery as follows from Fig 3-7*.*

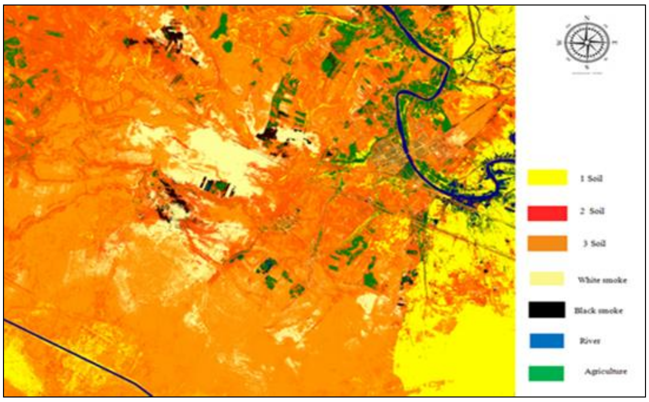

Fig 3: The results of the process (MLC) for the coefficient of brick Muthanna, where distinguish smoke coefficient black color

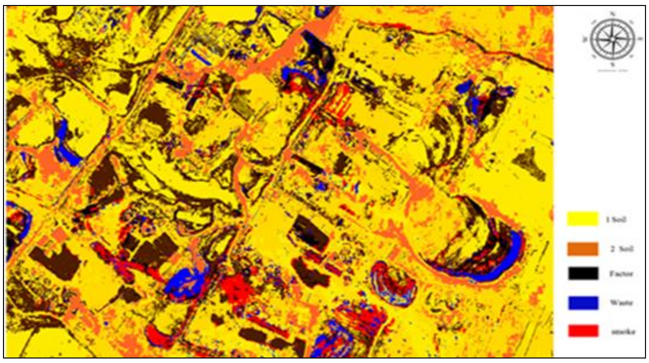

Fig 4: The results of the process (MLC) for the brick lab alaslah, where the laboratory smoke is characterized by red color

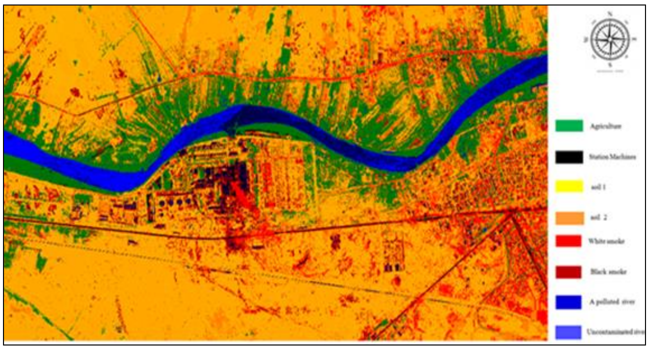

Fig 5: The results of the process (MLC) Nasseria thermal power station, where the red smoke smoke and red soil contaminated with black smoke from the product classification

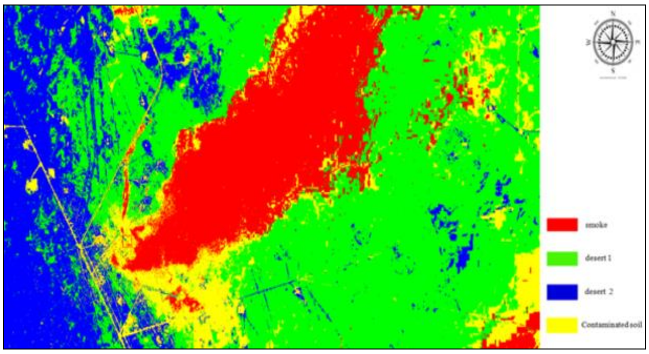

Fig 6: The results of the process (MLC) oil refinery south, where the smoke is characterized by red color

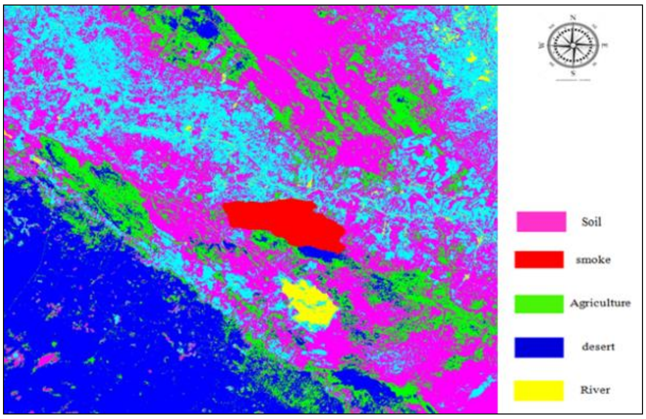

Fig 7: The results of the MLC (MLC) 2017 process, where smoke is distinguished by red color classification

5. Areas with and surrounding pollution sources

Economic and industrial growth in the last century has been the leading cause of the dramatic increase in emissions of air pollutants, leading to a significant environmental problem worldwide. The urban environment emphasizes several common issues, such as population, industrial and commercial growth, and increasing demand for energy and transportation. Pollution from fossil fuel combustion is largely emitted in the open air, but human exposure occurs at home and abroad. Air pollution can be classified as primary air pollutants entering the atmosphere and are known to be harmful in sufficient concentration. A secondary air pollutant is harmful at good concentration and is composed of primary pollutants due to the chemical reaction of two or more elements.

6. Results

The results of the classification process and the methods of different ways differ from each other in the same area studied, the results are the selection of results for the southern oil refinery (Basra),We conclude from the process of Supervised Classification and Unsuccessful Classification for the studied area of the southern refinery and in the ways of Maximum Likelihood, Minimum Distance, ISODATA and K-Means, which produces very good results and is more accurate, distinct and clear.

6.1 Maximum Likelihood Classification results

Note that the process of Supervised Classification and Maximum Likelihood method gave different results to the classification process refined oil South, characterized by the classification of the most accurate and accurate classification and the reason for the accuracy of the high image and the clarity of smoke in the image taken from the moon, where the smoke rate 18.927% of the total classification, while desert 1 and 2 in the form are characterized by 49.921% and 19.425%, respectively, as in Fig 8 and as shown in the following Table 1.

Table 1: Results of the Southern Oil Refinery classification in a way Likelyhood Maximum

classes	No. pixels	Ratio classification	Classified area/ km^2
smoke	57089296	18.927 %	**17.18155206**
Desert 1	150576641	49.921 %	**45.31728538**
Desert 2	58589809	19.425 %	**17.6336265**
Contaminated soil	35371865	11.727 %	**10.64553606**
			Total area = 90.7789 km^2

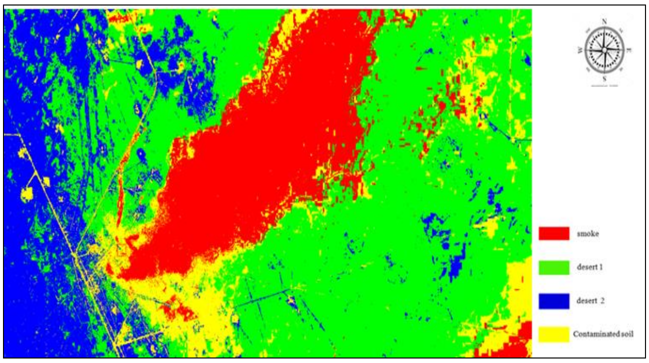

Fig 8: Represents the results of the Maximum Likelihood Classification process

6.2 Minimum Distance Classification results

Note that the process of Supervised Classification and Minimum Distance method gave different results to the classification process refined oil South, characterized by the classification of the most accurate and accurate classification and the reason for the accuracy of high image and clarity of smoke in the image taken from the satellite. Where the smoke rate 12.278%, while the percentage of desert 1 and 2 is characterized by 45.660% and 23.466%, respectively as in Fig 9, and Table 2.

Table 2: Results of the Southern Oil Refinery classification in a way Minimum Distance

Classes	No. pixels	Ratio classification	Classified area/ km^2
Smoke	37035219	12.278 %	**11.14572284**
Desert 1	137723669	45.660 %	**41.4492348**
Desert 2	70781075	23.466 %	**21.30196548**
Contaminated soil	56087648	18.595 %	**16.8801691**
			Total area = 90.7789 km^2

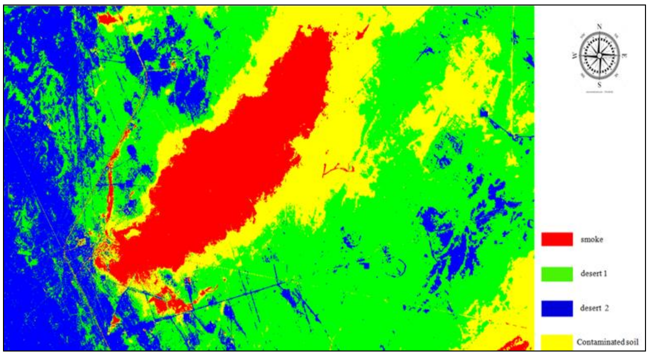

Fig 9: Represents the results of the Minimum Distance Classification process

6.3 ISODATA Classification results

The process of classification Unsupervised Classification and Isodata is no different from the previous method of classification of the southern oil refinery, which gives results close to the previous classification methods, where we find the results of the classification of Isodata gives three results of the classification is Class 1, 2.3 respectively (18.85%), 49.839% and 31.357%, respectively, as shown in Fig 10, The following Table 3.

Table 3: Results of the Southern Oil Refinery classification in a way ISODATA

Classes	No. pixels	Ratio classification	Classified area/ km^2
Class 1	56719595	18.805 %	**17.0708029**
Class 2	150326714	49.839 %	**45.24284742**
Class 3	94581302	31.357 %	**28.46525746**
			Total area = 90.7789 km^2

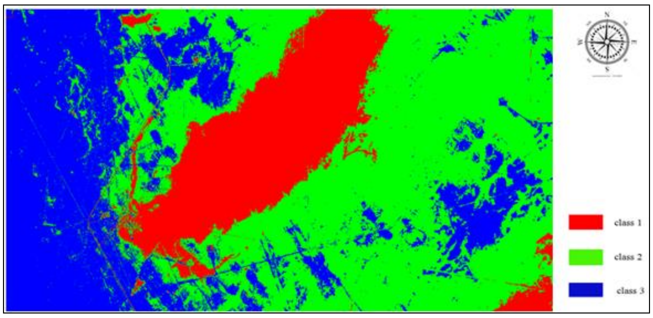

Fig 10: Represents the results of the ISODATA Classification process

6.4 K-Means Classification results

Classification method gave K-Means percentage of oil refinery and in different proportions where the percentage of classification in Fig 11 class 5,6 and by 28.066% and 10.998% respectively and as in the following Table 4.

Table 4: Results of the Southern Oil Refinery classification in a way K-Means

classes	No. pixels	Ratio classification	Classified area/ km^2
Class 1	46759230	15.502 %	**14.07240556**
Class 2	15200813	5.040 %	**4.5752112**
Class 3	34627509	11.480 %	**10.4213144**
Class 4	87212126	28.914 %	**26.24755092**
Class 5	84653862	28.066 %	**25.47775348**
Class 5	33174071	10.998 %	**9.98376444**
			Total area = 90.7789 km^2

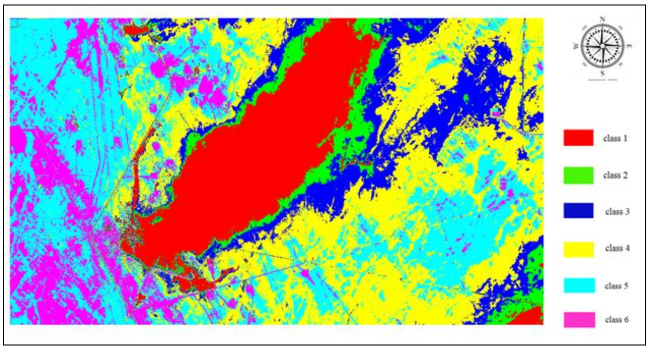

Fig 11: Represents the results of the K-Means Classification process

7. Conclusions

The results show that the process (supervised classification) depends on the methods of classification mainly on the user experience because the user who chooses the area to study (ROI) The results show the Maximum Likelihood Classification method, the smoke ratio of Muthanna brick factories is 1.365% and the area of 3.4125 km^2 for the year 2008, while the percentage of smoke bricks (al'iislah) reaches 4.961% and the area of 0.2693 km^2 of the total area and the year 2010, Thermal The ratio of white smoke out of the flue and diffuse is about 4.605% And the amount of smoke generated by the South Oil Refinery in .max method is 18.927% and 17.18155206 km^2 area of the area surrounding the refinery, while we conclude that the smoke ratio of the Muthanna brick factories for 2017 is about 4.914% and an area of 582.35814 km^2. Thus, we conclude that the max. method is the best and most accurate method of distinguishing between the picture and the other. It also distinguishes between smoke, agriculture and other parameters from the classification process in the manner of Minimum Distance Classification, ISODATA and K-Means.

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