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Selecting the reliability classification approach based on remote sensing data and GIS

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Abstract
This study investigates land use and land cover (LULC) changes in the western region of Iraq and neighboring countries within Sections 24 and 37, utilizing satellite remote sensing data and geographic information system (GIS) techniques. Landsat-9 imagery for the year 2025 was processed through geometric correction, image fusion, and digital classification methods to generate thematic maps of the study area. Two classification approaches were employed: Decision Tree (DT) and Support Vector Machine (SVM). Comparative evaluation of the two methods demonstrated that the SVM approach consistently produced results closer to the real field data than the DT method. Specifically, the integration of mathematical linear equations with GIS analysis showed that the SVM classification achieved a correlation coefficient of $R^2 = 0.97$, reflecting superior accuracy and lower standard error in estimating LULC elements. By contrast, the DT method recorded a slightly lower performance with $R^2 = 0.96$, highlighting its limitations in capturing spatial variability in arid and semi-arid environments. The findings recommend the adoption of SVM classification for environmental monitoring, as it offers higher reliability and precision.

Keywords: Image Classification, Support Vector Machine, Decision Tree, GIS

Introduction

Recent advancement in remote sensing technique has added an impetus to the accurate and efficient access of information about any object on earth. Using this approach together with empirical modelling it is possible to interpret and analyse any object on ground or water body without any physical contact. This information about an object or phenomenon on earth is acquired by means of the propagated electromagnetic signals, where the reflected or emitted radiances by the target is recorded and processed using computerized data acquisition systems to unravel the scientific truth [1, 2, 3, 4]. Remote sensing techniques are intensively used for monitoring and mapping the classification on earth [3, 4, 5]. Following remote sensing various inherent parameters can be used or retrieved for water and land depending on their surface spectral reflectance. This information corresponds to detected materials conditions and their chemical as well as physiological makeup. These lead to the varying spectral reflectance of the materials from different surfaces. Actually, the proportion of these materials with the remotely sensed pixel causes spatial variation in the grassed or weeds reflectance measurement [5, 6]. Several image classification techniques can be used to classify the satellite images such as Maximum Likelihood (ML), Minimum Distance (MD), Artificial Neural Network (ANN), Support Vector Machine (SVM) and Decision Tree (DT) [6, 7, 8]. This method of image classification is accurate and efficient for remote sensing. SVM needs small amounts of training data that is located in area of feature space near to interclass boundaries. Although SVM classification needs only sample per class but the sample must be close to the boundary of the class. Moreover, maximum likelihood (ML) classification requires a large training sample size especially when the data occurs in high dimensional feature space. The major advantage of SVM is will not consume time for collection data during the training. The main disadvantage of SVM is the need to specify a kernel function as well as the slow relation development of multiclass [6, 7, 8, 9]. Decision Tree (DT) is an advanced approach for image classification, which depends on the layered or stratified approach to solve the problems of distinguishes between the spectral classes [6, 7]. DT uses data from many different sources and files together to make a single decision tree classifier. This performs multistage classifications using a series of binary decisions to place pixels into classes. Input data can be obtained from various sources and data types. The results of the decisions are as classes can be saved as the trees to apply them for other datasets [8, 9, 10]. GIS tools are useful for database management for the geo-reference spatial data and automated maps production [9, 10, 11]. GIS is used to store and analyse large amount of spatial and temporal data, which is otherwise difficult to interpret. It allows the integration of diverse types of information into a form to select different approaches to environmental problems and land management before taking any decision [11, 12, 13,14], [15, 16]. The integration equation with the spatial capacity of geographical information system (GIS) as well as the spatial and temporal capabilities of remote sensing applications can be exploited as a powerful tool to manage and assess the earth's surface elements [3, 11, 17, 31]. This study investigates land use and land cover (LULC) dynamics in the western region of Iraq and neighboring countries across Sections 24 and 37, employing satellite remote sensing data in conjunction with geographic information system (GIS) techniques. By integrating mathematical equations with the spatial analytical capacity of GIS and leveraging the spatial and temporal capabilities of remote sensing, a powerful framework was established to classify imagery and generate thematic maps of the study area. Two classification methods were applied: Decision Tree (DT) and Support Vector Machine (SVM). The comparative analysis demonstrated that SVM consistently produced results more closely aligned with field observations, outperforming the DT method in accuracy and reliability.

Materials and methods

This section covers the processes of data collection and analysis, including the acquisition of ancillary data and satellite imagery, such as Landsat-9 images. The images underwent various processing steps, including geometric correction and image fusion, combined with the integration of mathematical equations for the study area in the year 2025, as illustrated in Figure 1. Further details are explained in the sections below:

Study Area

The study area lies between two geographical sections, 24 and 37. Section 24 covers central and western Iraq, eastern Syria, Jordan, and northern Saudi Arabia, while Section 37 encompasses the Arabian Gulf region, including southern Iraq, western Iran, and Kuwait, as illustrated in satellite imagery shown in Figure 2. This location falls within the southern part of the commercial latitudes, positioned at the edge of the desert. Its proximity to the Persian Gulf creates a transitional zone between the Mediterranean climate characterized by moderate temperatures and winter rainfall and the arid desert climate. This part of Iraq was selected due to its vast barren and decertified areas, as well as its exposure to strong air currents influenced by the regional climate. The study aims to predict, monitor, estimate, and classify surface areas in Iraq for the year 2025 by using the SVM classification approach as it provides more reliable and accurate results than the DT classification.

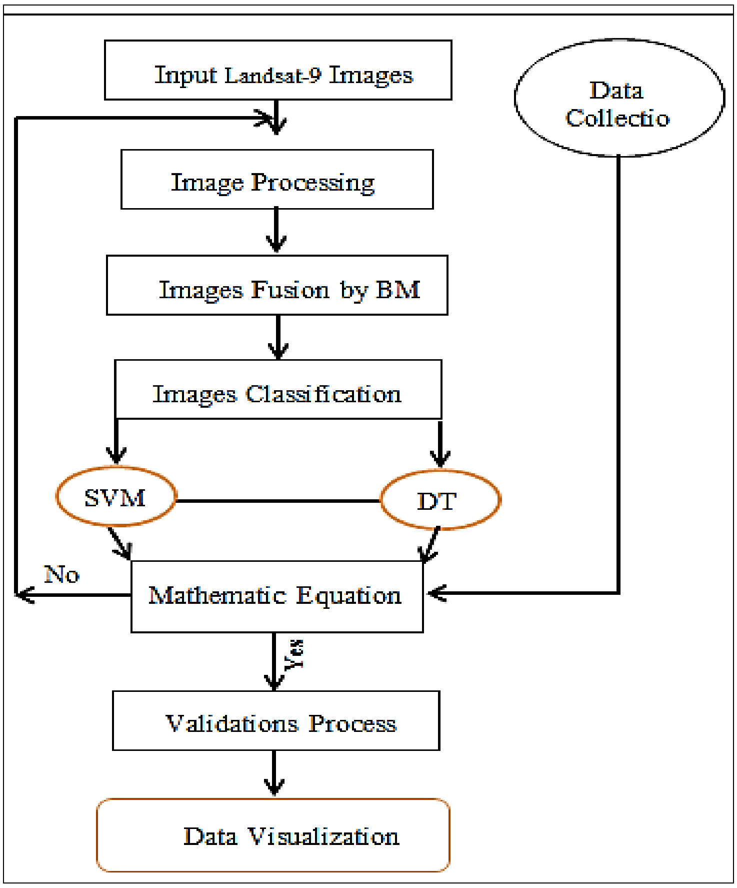

Fig 1: Flowchart of research methodology.

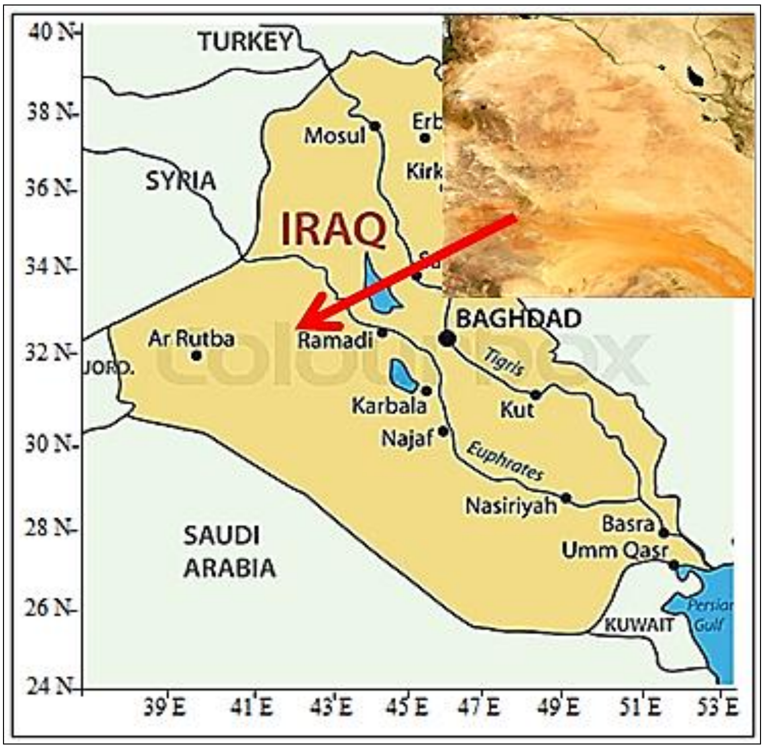

Fig 2: Location of study area.

Ancillary data

Ancillary data included field measurements collected on-site, such as the surface area of (water bodies, vegetation cover and desertified land as Soil A, Soil B, Soil C, Soil D, Soil E, and Soil F) during the summer season of 2025 were (19879, 55123, 62012, 13562, 15876, 12015, 77630 and 86123) respectively, While remote sensing data consisted of Landsat-9 imagery acquired from the TM and OLI sensors.

Image processing

Image processing is including the atmospheric corrections as the first important step of the research methodology. This process involves the steps such as radiometric calibration, dark subtraction, and Internal Average Reflectance (IAR) reflectance calibration, layer stacking, georeferencing, image enhancement, and Region of Interest (ROI) findings. The output of this process provides suitable images, which must be fused depending on (BM) band math methods [8].

Images Fusion

This process combines the multiple image layers into a single composite image and displays two datasets of the same area together in one RGB color composite. Commonly, it is used to enhance the spatial resolution of multispectral datasets of higher spatial resolution panchromatic data or single band SAR data. In the image fusion, the dataset files must be georeferenced, covering the same geographic area with same pixel size, identical image size, and similar orientation [6, 12, 13, 18, 19]. Band Math expression produces a result with the same spatial dimensions in samples and lines as the input bands. It is a flexible image-processing method with many capabilities and the power of the Band Math (BM) routine provided by the power, speed, and flexibility of IDL (Interactive Data Language) [8, 20, 21, 32, 33, 34]. Thus, the present study used the BM in data fusion for combining multiple image layers into a single composite image.

Images Classification

Several image classification techniques can be used to classify the satellite images such as Maximum Likelihood (ML), Minimum Distance (MD), Artificial Neural Network (ANN), Support Vector Machine (SVM) and Decision Tree (DT) [2, 6, 22, 23, 31]. The present study classified the surface area of water bodies, vegetation cover, and desertified land during the summer season of 2025 depending on the output results of data fusion. Two types of images classifications are used in this study such as SVM and DT as explained below.

Support Vector Machine (SVM)

This method of image classification is accurate and efficient for remote sensing. SVM needs small amounts of training data that is located in area of feature space near to interclass boundaries. Although SVM classification needs only sample per class but the sample must be close to the boundary of the class. Moreover, maximum likelihood (ML) classification requires a large training sample size especially when the data occurs in high dimensional feature space. The major advantage of SVM is will not consume time for collection data during the training. The main disadvantage of SVM is the need to specify a kernel function as well as the slow relation development of multiclass [6, 24, 25, 26]. This article uses SVM approach for ground features classification based on remote sensing data of 2025. It is based on the output results of data fusion for satellite images. The output of SVM classification results for ground features are water, vegetation and soil in one image. It implies that the output results of SVM are similar to the inputted data at the band math (BM) section but in single band.

Decision Tree (DT)

It is an advanced approach for image classification, which depends on the layered or stratified approach to solve the problems of distinguishes between the spectral classes [2, 6, 7, 27, 28, 36, 37]. DT uses data from many different sources and files together to make a single decision tree classifier. This performs multistage classifications using a series of binary decisions to place pixels into classes. Input data can be obtained from various sources and data types. The results of the decisions are as classes can be saved as the trees to apply them for other datasets [8, 28, 29, 30, 31, 34, 35]. In this article, the decision tree classification depended on the output results of data fusion. This classification refers to all the surface area of water bodies, vegetation cover, and desertified land during the summer season of 2025. The output of DT classification results can display all the surface area of water bodies, vegetation cover, and desertified land in one image. Thus, DT is considered as the advance approach than SVM.

Results and discussion

Remote sensing and Geographic Information Systems (GIS) techniques were employed to generate maps with basic classifications for the study area in 2025. Landsat-9 satellite imagery, with a spatial resolution of 30 m, was processed using specialized software (ERDAS IMAGINE 13) and GIS tools to identify and map the surface areas of water bodies, vegetation cover, and desertified land during the summer season of 2025. In this study used two types of the classifications (SVM & DT) classifictions as illustrated below:

Support Vector Machine (SVM)

The image classification process involved sorting each pixel in the satellite imagery based on its spectral reflectance. Each pixel was assigned a unique spectral class within the classification area, distinct from other elements. This process resulted in a thematic map illustrating the geographic classifications and the percentage composition of Earth's surface features, such as land cover types in the western region of Iraq and neighboring countries within Sections (24 & 37). The satellite images of the study area were classified according to the spectral reflectance of the identified classes using the Support Vector Machine (SVM) method.

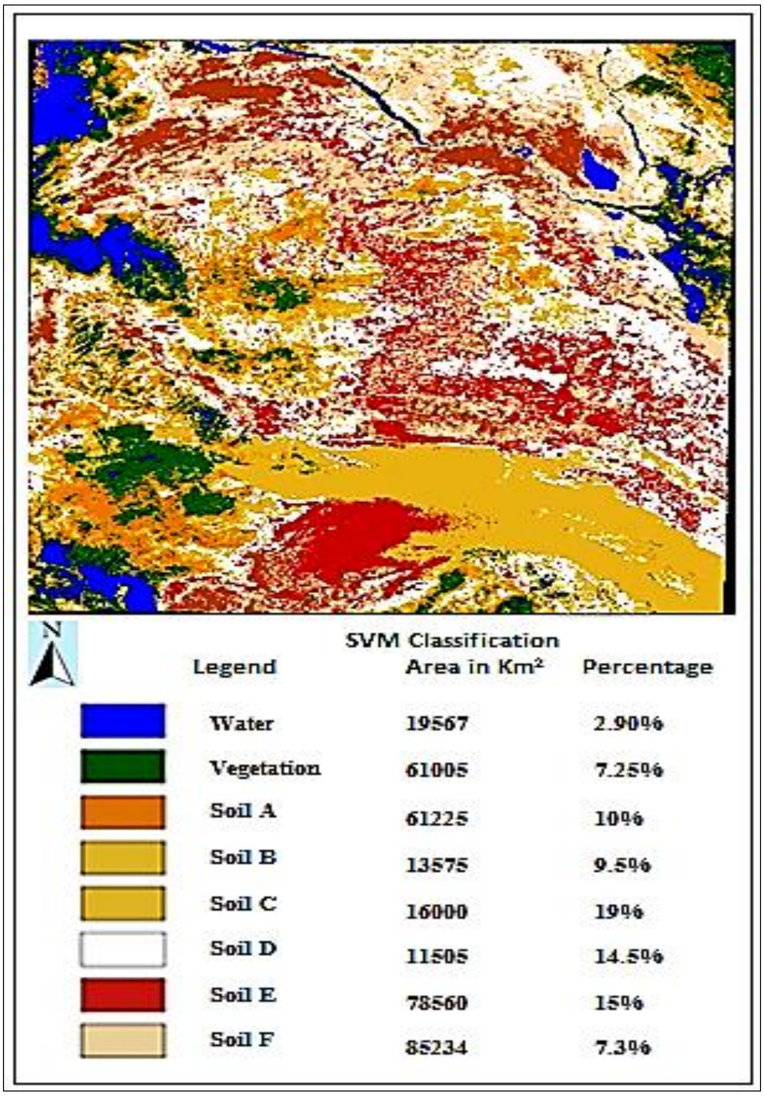

Fig 3: Shows SVM classification of the study area.

The surface areas of water bodies, vegetation cover, and desertified land (classified as Soil A, Soil B, Soil C, Soil D, Soil E, and Soil F) were measured as (19567, 61005, 61225, 13575, 130015, 16000, 11505, 78560 and 85234) km², respectively. The corresponding percentages of the total classified area were calculated as (2.9%, 7.2%, 10%, 9.5%, 19%, 14.5%, 15% and 7.3%) respectively, as illustrated in Figure 3. These results indicate that soil and dryland areas occupy a substantially larger proportion of the region compared to water bodies and vegetation cover.

Decision Tree (DT)

While, the satellite images of the study area were classified depending on disassion tree (DT) classification were measured as (19312, 81573, 60405, 14242, 18077, 15254, 84844 and 88578) km² for water bodies, vegetation cover, and desertified land (classified as Soil A, Soil B, Soil C, Soil D, Soil E, and Soil F) respectively. The corresponding percentages of the total classified area were calculated as (2.87%, 7.35%, 9%, 10%, 21%, 17%, 16% and 7.5%) respectively, as illustrated in Figure 4. These results indicate that soil and dryland areas occupy a substantially larger proportion of the region compared to water bodies and vegetation cover.

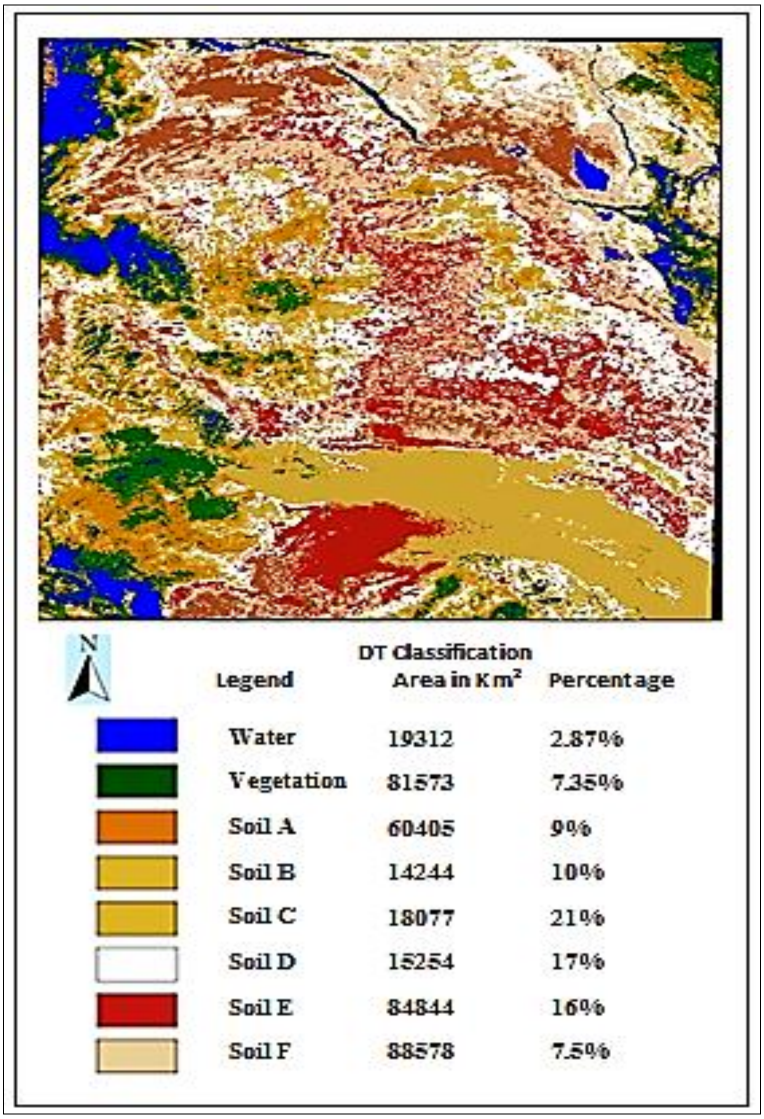

Fig 4: Shows DT classification of the study area.

Data validation and accuracy

This section explains the classification accuracy for the summer season of 2025. Table 1 summarizes the correlation accuracy between the real field data, Decision Tree (DT), and Support Vector Machine (SVM) classification results, based on the linear equation described in Equation 1. Figure 5 presents the SVM classification accuracy for water bodies, vegetation cover, and desertified land within the study area, while Figure 6 shows the corresponding DT classification results. The results indicate that the SVM classification achieved a correlation coefficient of (R^2 = 0.97) for estimating land cover elements, demonstrating superior accuracy with a lower standard error compared to the DT classification. In contrast, the DT method achieved a correlation coefficient of (R^2 = 0.96) using the same equation. This difference is attributed to the advanced capabilities of the SVM approach, which provides more precise and efficient classification of remote sensing data, thereby delivering a more accurate representation of land cover content than the DT method.

Linear Equation is [y = a x - b] (1)

Correlation coefficient is = [R^2= 0.97 & 0.90]

Where: (y) is representing of water bodies areas, which are required from satellite image. (x) is representing of water indexes values from satellite image based on the output results of linear equation. While (a and b) are constants depend on the nature of ground data.

Table 1: The correlation accuracy

classify	Area (km^2)	SVM	DT
Water	19879	19567	19312
Vegetation	55123	61005	81573
Soil A	62012	61225	60405
Soil B	13562	13575	14244
Soil C	15876	16000	18077
Soil D	12015	11505	15254
Soil E	77630	78560	84844
Soil F	86123	85234	88578
R^2	0.00	0.97	0.90

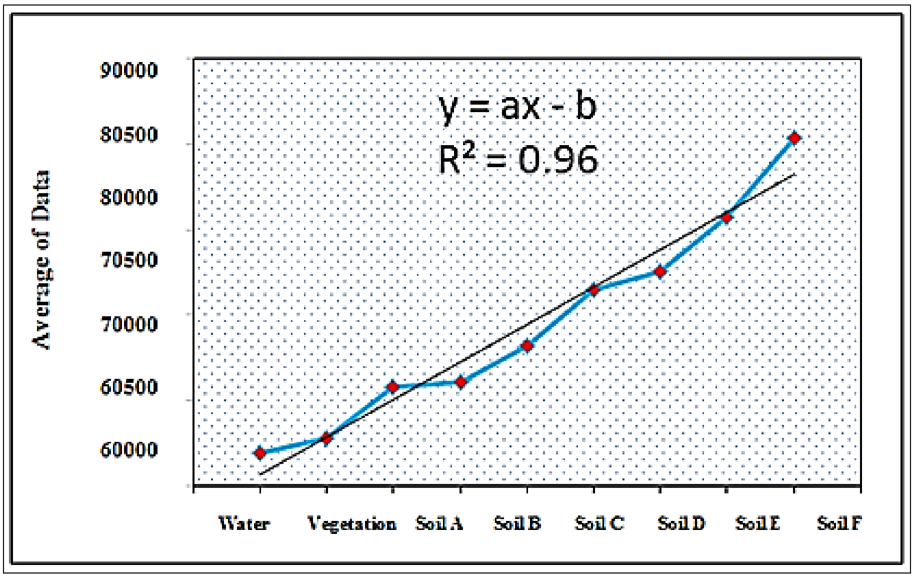

Fig 5: Presents the SVM classification accuracy.

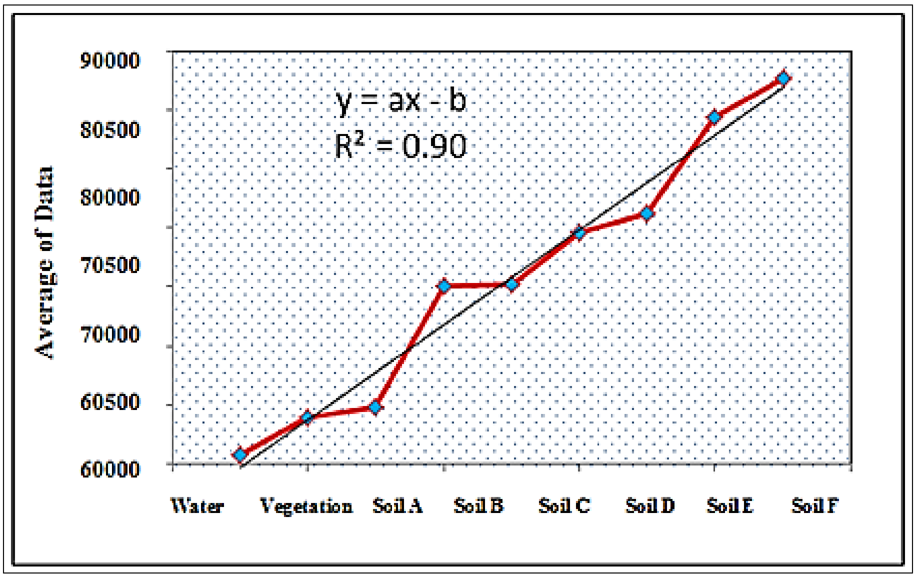

Fig 6: Presents the DT classification accuracy.

Conclusions and recommendation

This study produced a thematic map illustrating the geographic classifications and percentages of Earth's surface components, such as land use and land cover maps, in the western region of Iraq and neighboring countries within sections (24 and 37). Two classification methods were applied: Decision Tree (DT) and Support Vector Machine (SVM). The results showed that the SVM classification data were closer to the real data, while the DT classification data deviated further. By integrating the mathematical linear equation with GIS, the SVM classification yielded more accurate results than the DT classification. Specifically, the SVM method achieved a correlation coefficient of (R^2 = 0.97) for estimating land cover elements, indicating superior accuracy and a lower standard error compared to the DT method, which achieved a correlation coefficient of (R^2 = 0.96). Therefore, this study recommends using the SVM classification approach as it provides more reliable and accurate results than the DT classification.

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