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Optimal Selection of Agricultural Lands Using Remote Sensing Techniques in the Analysis of Climate Data, Wasit Province, Iraq

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Abstract

Determining the optimal location for crop cultivation is a challenging task, as agriculture plays a significant role in economic development and efficient land use. Therefore, remote sensing techniques using satellite imagery have proven to be an excellent method for helping researchers make this choice. To achieve the goal of optimal selection, climate data, including temperature and rainfall, for the study area were collected. The city of Kut, located in central Iraq, was identified as a study area due to its geographical importance, distinguished administrative location, and the vast agricultural areas that can be exploited. These data were projected onto high-resolution satellite images obtained by Sentinel-2 (10 m). The spline interpolation technique was applied to a climatic data set to estimate the other missing points. Supervised classification using the support vector machine technique was performed to exclude agricultural areas from urban projects. Some important indices related to plant health and water content were implemented, which help illustrate soil suitability and quality of cultivated plants. These indices include the normalized difference vegetation index (NDVI), which provides a good indication of reach (0.6), and the normalized difference water index (NDWI), which yields a value of 0.34, considered a good value. Slope computation was applied to show the rate of ground gradient. The research results successfully estimate the optimal area for growing various types of crops.

Keywords: remote sensing, interpolation, NDVI, NDWI, classification, slope.

الاختيار الأمثل للأراضي الزراعية باستخدام تقنيات الاستشعار عن بعد في تحليل البيانات المناخية محافظة واسط العراق

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الخلاصة

إن تحديد الموقع المناسب لزراعة المحاصيل ليس بالمهمة السهلة، حيث تساهم الزراعة بشكل كبير في التنمية الاقتصادية والاستخدام الأمثل للأراضي. لذلك، أثبتت تقنيات الاستشعار عن بعد باستخدام صور

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الأقمار الصناعية أنها طريقة ممتازة لمساعدة الباحثين على اتخاذ هذا الاختيار. ولتحقيق هدف الاختيار الأمثل، تم التقاط بيانات المناخ مثل درجة الحرارة وهطول الأمطار لمنطقة الدراسة. حيث تم تحديد مدينة الكوت، الواقعة في وسط العراق، كمنطقة دراسة نظرًا لأهميتها الجغرافية وموقعها الإداري المتميز والمساحات الشاسعة التي يمكن استغلالها للزراعة. تم إسقاط هذه البيانات على صور أقمار صناعية عالية الدقة تم الحصول عليها بواسطة سننيتل 2- (10 م). تم تطبيق تقنية الاستيفاء المنحني على مجموعة بيانات مناخية لتقدير النقاط المفقودة الأخرى. تم إجراء التصنيف الخاضع للإشراف باستخدام تقنية آلة المتجهات الداعمة لاستبعاد المناطق الزراعية من المشاريع الحضرية. تم تنفيذ بعض المؤشرات المهمة المتعلقة بصحة النبات ومحتوى الماء، والتي تساعد في توضيح ملائمة التربة وجودة النباتات المزروعة. تشمل هذه المؤشرات مؤشر الغطاء النباتي الموحد (NDVI) الذي يُعطي مدًى جيدًا (0.6)، ومؤشر الماء الموحد (NDWI) الذي يُعطي (0.34)، وهي قيمة تُعتبر جيدة. وقد طُبّق حساب المنحدرات لإظهار معدل انحدار الأرض. وقد نجحت نتائج البحث في تقدير المساحة المثلى لزراعة أنواع مختلفة من المحاصيل.

1. Introduction

With the rapid expansion of agricultural areas, there is an urgent need to adopt modern technologies to inform smart site selection and enhance productivity. As the demand for food continues to rise, it is more important than ever to produce more with fewer resources—all while reducing the harmful impact of climate change. In response to these challenges, a global movement is gaining momentum toward the adoption of precision agriculture. At the heart of this approach is remote sensing technology, which plays a key role in identifying suitable locations and making data-driven decisions that support sustainable farming [1].

Choosing an appropriate area for agriculture is a critical initial step that not only helps propel economic growth but also affirms valuable future investment opportunities. Additionally, select areas have been designated for future housing projects, which are being periodically planned. Until recently, the selection of arable land was entirely dependent on manual and personal surveys, in addition to accumulated and inherited data. However, as science advances towards progress, the field of selecting and evaluating arable land has undergone significant changes with the development of modern programs used in remote sensing technologies. This technology allows one to use systematic and periodic surveying of the land from satellites, aerial photographs, and digital sensor data for accurate and very important analysis of large-scale land areas. Interestingly enough, the technologies provide the required information to form an informed land-use decision on soil, crop health, water, and other climate-related considerations. These are necessary prerequisites for land suitability for agriculture and increased agricultural production. [2-4].

Provide important crops. Land use and land cover play a crucial role in mitigating climate change and addressing global environmental issues. Therefore, it has become necessary to utilize modern technology to support the decision-making process in identifying land and land cover suitable for agriculture. For planning and management at the local, regional, and macro levels, the optimal use of land cover, aided by Remote Sensing (RS) and Geographic Information System (GIS) technologies, is a crucial matter that enhances the realism and practicality of the planning and decision-making process [5,6]. Numerous previous research studies have been conducted in this field, including the study presented by Elias Bojago et al. (2024), which focuses on understanding measures. The study utilized machine learning and simulation methods to address missing data. The results revealed significant variability in rainfall between agricultural areas, with annual rates ranging from 969.03 mm in lowland regions to 1,648.75 mm in highland regions, alongside seasonal differences in rainfall trends and distribution. This analysis aims to identify areas most affected by climate change and to plan adaptive measures for both wet and dry periods. The study recommended further

research on the impacts of climate change, including temperature and evaporation, and the development of localized strategies to enhance farmers' resilience to changing climatic conditions [7].

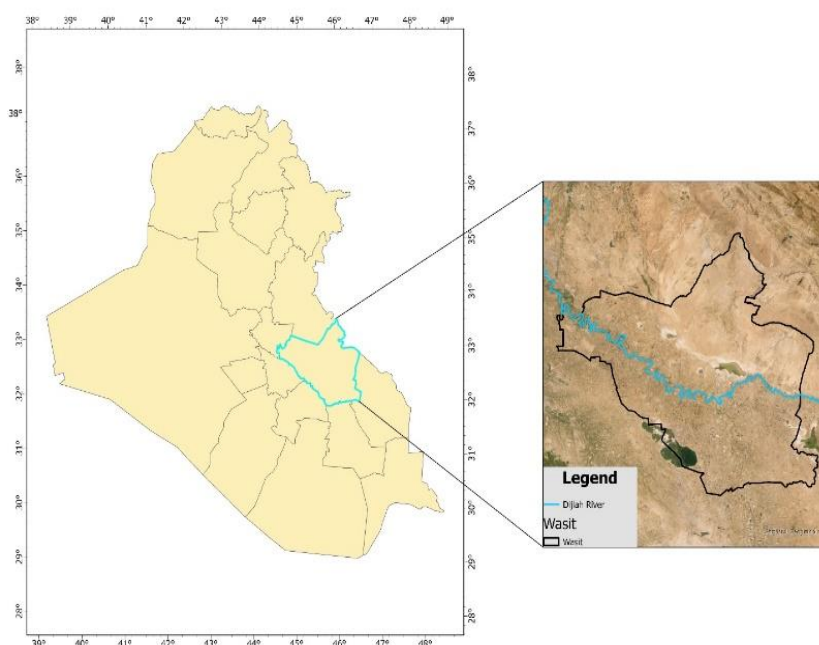
According to the research by Rinali Patel and Anant Patel (2024), an innovative approach for drought risk assessment has been employed, utilizing multiple data sources, including Digital Elevation Models (DEM), Landsat satellite data, and other climatic and rainfall data compiled into thematic layers. The Analytic Hierarchy Process AHP was then used to assign relative weightings to climate, soil, vegetation, and land use as influencing factors under which GIS was used to generate risk maps and analyze environmental indicators such as NDVI, NDWI, SMI, and VCI. Results showed that most of the basin area was classified as having a very low drought risk, while sparse locations were identified as high-risk zones. Thus, they provided guidelines for setting criteria to assess drought risk, using AHP as the primary method for assigning weightage factors to inform adaptive strategies that mitigate drought impacts in semi-arid areas. In this study, the key climatic parameters, temperature and annual precipitation, were considered for the study area. Climate data spatially corresponded with high-resolution satellite imagery, enabling the correlation of environmental conditions with geographic coordinates and the localization of suitable sites for agricultural development and regional economic uplift. Given that the selected area is not designated for residential, industrial, or institutional infrastructure, it presents potential for sustainable land use planning. To support temporal analysis and monitor land surface dynamics, Sentinel-2 satellite imagery was acquired for two distinct periods: 2016 and 2024. The primary objective of this study is to support sustainable agriculture in Kut, Iraq, by identifying the most suitable areas for crop cultivation. To achieve this, the research combines climate data, such as temperature and rainfall, with satellite imagery from Sentinel-2. It uses vegetation and water indices (NDVI and NDWI) to assess land health and filters out urban areas through supervised classification. By applying these modern geospatial techniques, the study aims to enhance land-use planning and support agricultural development in the region.

Studied Area

Wasit Governorate is located between two Latitude ($33^{\circ} 30' 15'' - 31^{\circ} 54' 15''$) North and Longitude ($46^{\circ} 34' 51'' - 44^{\circ} 31' 50''$) East, in the central part of Iraq and is bordered by Diyala and Baghdad Governorates to the north, Maysan and Dhi Qar to the south, Qadisiyah and Babylon to the west, and the international border with Iran to the east. The cultivation of wheat, barley, and rice is characteristic of Wasit Governorate. The Statistical Center of the Iraqi Ministry of Planning provided statistics on the annual average production of these crops. For more information, Table 1. Wasit Governorate contains large unused areas that can be selected as ideal areas to increase agricultural production and diversify crops to include other fruit trees. Therefore, this research aims to utilize remote sensing techniques, apply processing methods, and analyze climate data to select the optimal site for agriculture. A desert climate characterizes the climate of Wasit governorate, as it is located in the semi-tropical region and is characterized by middle to high temperatures and a level of dryness in the summer, with moderate temperatures in the winter. The amount of rainfall is characterized by scarcity and fluctuation, and its amounts increase in the eastern parts of the governorate.

Table 1 : average yield per dunum of crop production [9].

year	crop	Total cultivated area (dunum)	Average yield per dunum (kg/dunum)	Production (ton)
2015	Wheat	980011	782.0	766406
	Barley	78538	308,8	24254
	Rice	-	-	-
2016	Wheat	713224	884.9	631107
	Barley	82275	413.7	34038
	Rice	-	-	-
2017	Wheat	1057664	757.0	800652
	Barley	82824	433.0	35861
	Rice	-	-	-
2018	Wheat	947658	772.2	731767
	Barley	34508	375.4	12956

**Figure 1** : Wasit Study Area

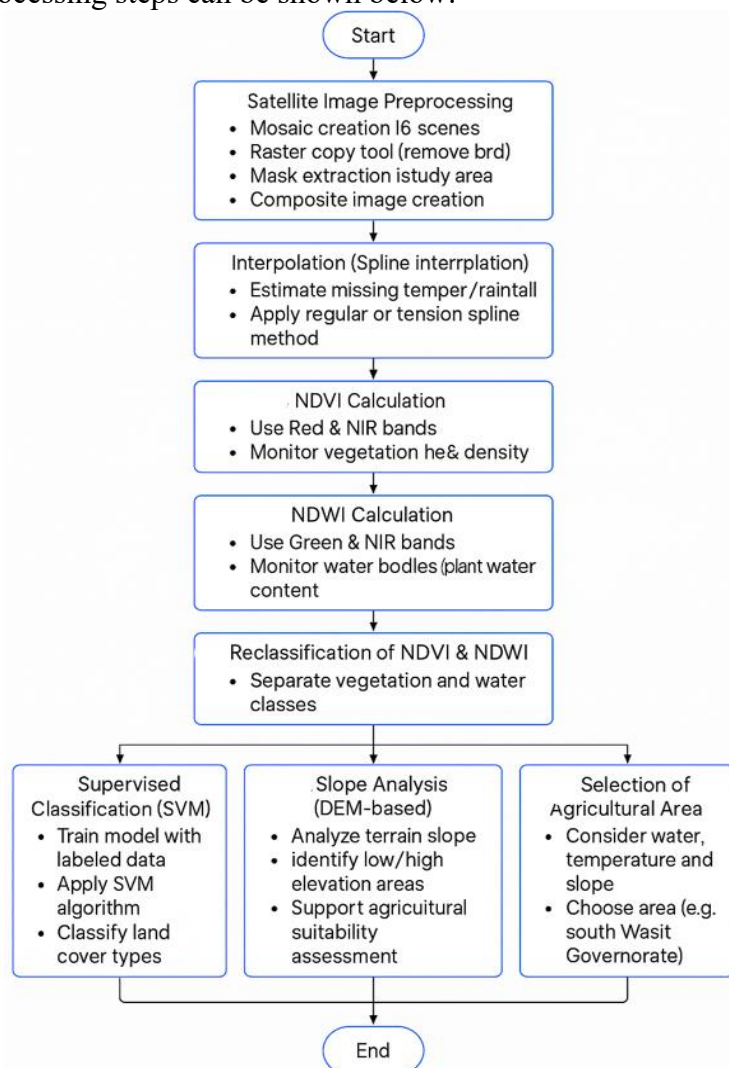
2. Data collection:

Before starting any work, the necessary data must be collected. Climate data, including rainfall and temperature, for the period 2016-2024, were collected from the Iraqi Meteorological Authority and NASA. This data covers all seasons for the mentioned years. Digital Elevation Models (DEMs) and high-resolution images were collected from the Sentinel-2 satellite data on the Copernicus Dataspace website, where six scenes were uploaded to cover the study area.

3. Methodology

Several techniques were used to conduct this research. The first step was to preprocess the satellite images, where a mosaic was made of the six scenes collected for the study area. A raster copy tool was used to remove the background, and subsequently, a mask extraction technique was employed to isolate the exact study area. All the satellite image bands were processed similarly, and finally, a composite image was created for all the bands used in

classification techniques. The second step involved integrating the satellite images with the collected rainfall and land temperature data to enhance the spatial resolution and coverage. The collected climate data were georeferenced and overlaid on the satellite images. The flowchart of the processing steps can be shown below:



Flowchart 1: The main steps of research performance

Interpolation Techniques: interpolation methods were used to estimate the values of missing data in the study area. Climate data, such as temperature and rainfall, were collected from specialized government institutions; however, this data may not be comprehensive for all points in the study area. Therefore, the researcher must apply interpolation techniques to estimate the remaining points. In this research, the Spline interpolation technique was used to carry out this process.

3.1 : Spline Interpolation

Spline interpolation is an essential technique that utilizes mathematical functions to create a smooth surface that precisely passes through the specified input data while minimizing surface curvature [9,10]. Regular interpolation and tension interpolation are the two types. The regular interpolation method, as given by the formula below, is an example of this study [10,11].

$$Z = \sum_{i=1}^n \lambda_i R(\gamma_i) + T(x, y) \quad \dots\dots\dots (1)$$

Where: Z is the estimated value, n is the number of points,

λ is the parameter that is identified by a series of linear equations, ($R(\gamma_i)$ and), ($T(x, y)$ are as follows)

Z = Estimated value

n = the number of points, i

λ = the parameter that is identified by a series of linear equations, ($R(\gamma_i)$ and), ($T(x, y)$ are as follows)

$$R(\gamma_i) = \frac{\frac{\gamma^2}{4} \left[\ln\left(\frac{\gamma}{2\pi}\right) + c - 1 \right] + \tau^2 \left[k_0\left(\frac{\gamma}{\tau}\right) \right] + c + \ln\left(\frac{r}{2\pi}\right)}{2\pi} \dots\dots\dots (2)$$

$$T(x, y) = a_1 + a_2x + a_3y \dots\dots\dots (3)$$

Where, τ^2 is the weighted parameter, r is the distance between the sample points and the estimated point, c is a constant equal to 0.577215, k_0 and is the modified Bessel function.

The results of applying Spline interpolation of the rainfall amount for summer and winter seasons can be shown in Figure (2), and the interpolation of temperature degrees can be shown in Figure (3) for the 2016 and 2024 period.

3.2 Normalized Difference Vegetation Index (NDVI)

The second step is to perform NDVI calculations: this index is widely used to monitor plant health, density, and viability. The natural vegetation index was derived from satellite imagery. It uses light reflectance in the red (visible) and near-infrared (NIR) spectral ranges, which depend on the biological composition of plants and the amount of chlorophyll, in addition to the purity of the color in which the plant appears, which affects the spectral signature reflected and recorded by the sensor in the satellite [12-14].

$$NDVI = \frac{(NIR-RED)}{(NIR+RED)} \dots\dots\dots (4)$$

Where:

NIR = Near-Infrared band

RED = Red band

The result of applying NDVI can be shown in Figure (4).

3.3 Normalized Difference Water Index (NDWI)

NDWI is a remote sensing-based index designed and developed to monitor and evaluate water bodies and water content in plants. It uses reflectance values of specific wavelengths sensitive to water content to highlight areas containing water and suppress features such as soil or plants. NDWI is widely employed in agriculture and environmental studies. Moreover, it can be written as the following formula [15,16]:

$$NDWI = \frac{(Green-NIR)}{(Green+NIR)} \dots\dots\dots (5)$$

Where:

$Green$ = Green band

NIR = Near-Infrared band

The results of applying NDWI can be shown in Figure (4).

The next step is to reclassify the NDVI and NDWI results to separate the vegetation class and water class. The results of applying this reclassification can be illustrated in Figure (5).

3.4 Supervised classification using a support vector machine.

Support Vector Machines (SVM) a technique of supervised machine learning algorithms widely used in image classification and regression. The technique was implemented by

finding the hyperplane that best separates data points belonging to different classes in the feature space. It performs well in processing high-dimensional data and is robust against overfitting, especially in cases where the number of dimensions exceeds the number of samples allocated to the study area. [17-20]. The SVM optimization problem is defined as:

$$\min_{w,b} \frac{1}{2} \|w\|^2 \dots\dots\dots (6)$$

Subject to:

$$y_i(w \cdot x_i + b) \geq 1 \quad \forall_i$$

Where:

w : weight vector defining the hyperplane.

b : Bias term.

w_i : input data points.

y_i : Labels (+1 or -1)

$w \cdot x_i + b = 0$: Equation of the hyperplane.

For non-linearly separable data, the optimization problem includes a slack variable. ξ_i to allow for some misclassifications:

$$\min_{w,b,\xi} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^N \xi_i \dots\dots\dots (7)$$

Subject to:

$$y_i(w \cdot x_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 0$$

Here, C is the regularization parameter that controls the trade-off between maximizing the margin and minimizing classification errors.

After applying the SVM supervised technique on the image, the results can be shown in Figure (6), and the area of each class can be listed in Tables (2) and (3).

3.5 Slope

Digital elevation models (DEMs) are currently one of the most important data sources used for geospatial analysis, as subsequent information for various applications can be easily derived from them. [18], where each cell in the image represents an elevation value relative to sea level. DEM images are widely used in geospatial analysis to identify topographic features. When slope analysis was applied to DEM images, the degree of slope for each cell was calculated based on the change in elevation between adjacent cells, helping to identify low and high areas. Slope analysis is a crucial tool for understanding water flow, identifying suitable agricultural sites, and assessing natural hazards such as landslides [21, 22]. The slope of the studied area was implemented, and the result can be illustrated in Figure (7).

$$S = \arctan \left(\sqrt{\left(\frac{\Delta Z}{\Delta X}\right)^2 + \left(\frac{\Delta Z}{\Delta Y}\right)^2} \right) \dots\dots\dots (8)$$

Where:

S =slope

ΔZ =Change in elevation between cells.

ΔX =Horizontal distance between cells (on the X-axis).

ΔY =vertical distance between cells (on the Y-axis).

Based on the results, the best agricultural area can be identified in this research. This is due to the availability of most elements for thriving agriculture, such as moderate temperatures, abundant water, and fertile soil. The proposed area is located south of Wasit governorate and is towards Amara. See Figure 8, which shows the proposed part for agriculture in Wasit governorate.

5. Results and Discussion

In this research, remote sensing techniques commonly used in monitoring and data analysis were applied to a set of satellite images captured by the Sentinel-2 satellite to identify the best agricultural areas in Wasit Governorate. In recent years, the area has undergone pronounced urban development, with agricultural areas giving way to residential areas. There are agricultural areas with fertile soil and all the necessary climatic elements, such as temperature and rainfall, which must be utilized to increase crop yields and improve the economic situation. Therefore, this research aims to select the best agricultural area in the governorate using remote sensing techniques.

Based on the results obtained from using climatic factors in the optimal selection of agricultural areas in Wasit City, the application of the interpolation method using the spline technique yielded significant findings regarding an increase in rainfall in 2024 compared to 2016 (Figure 2). The eastern regions adjacent to the Iranian border, as well as the southeastern regions adjacent to Maysan Governorate, experienced heavy rainfall. This indicates that the second region has been selected as a promising area for agriculture, due to its proximity to water reservoirs, represented by the southern marshes, and its vastness compared to the eastern region, which is adjacent to the Iranian border and lacks water reservoirs due to its higher elevation compared to other regions. The results of the interpolation calculations for the temperature distribution indicated that the southeastern regions experience moderate temperatures, as illustrated in Figure 3. The NDVI and NDWI calculations shown in Figure 4 indicated good values for both indices (0.6 NDVI and 0.32 NDWI) in 2024 compared to 2016. The NDVI results for May 2024, as shown in Figure 5, indicate that the study area as a whole is suitable for agriculture and contains abundant trees and green plants, characterized by a high percentage of chlorophyll and high greenness. The identification and calculation of green areas were done using the support vector machine (SVM) classification method. To view the classification results, refer to the calculated areas for each type in Figure 6, Tables 2 and 3. The classification results revealed the presence of large green areas adjacent to the Tigris River, which cannot be widely exploited for agriculture, as they are located in the city center and contain numerous government institutions, departments, universities, and residential areas. The results revealed the presence of extensive green spaces in the southeastern region adjacent to Maysan Governorate, which could be considered a promising area for developing the agricultural economy and achieving self-sufficiency (Figure 8). The results of applying the slope as shown in Figure 7 showed that the study area is a flat area suitable for agriculture, and that flood irrigation methods could be successful there.

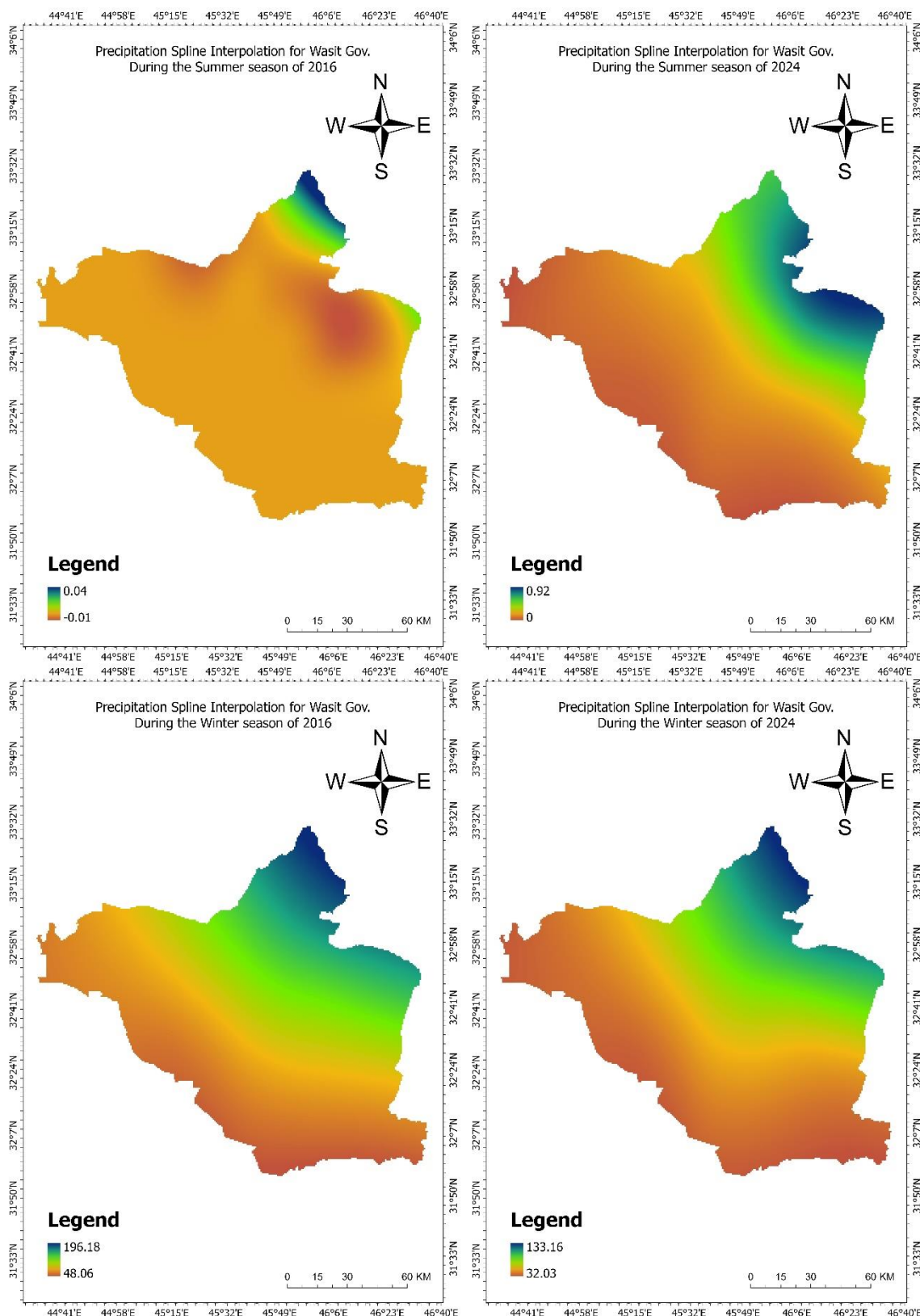


Figure 2: Spline interpolation for the amount of rainfall in the 2016,2024 period into summer and winter seasons.

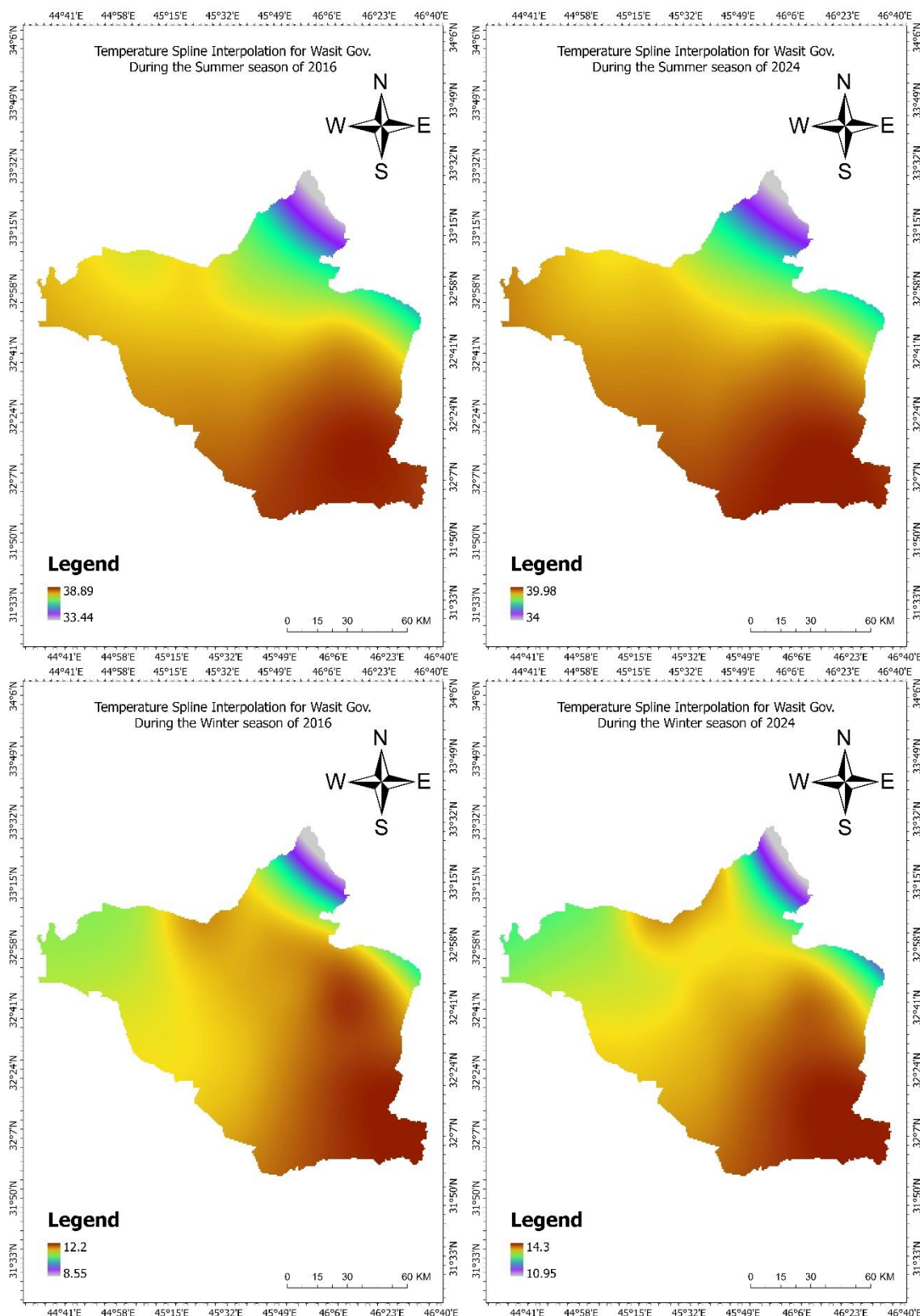


Figure 3: Spline interpolation for the temperature degree in the 2016,2024 period into summer and winter seasons.

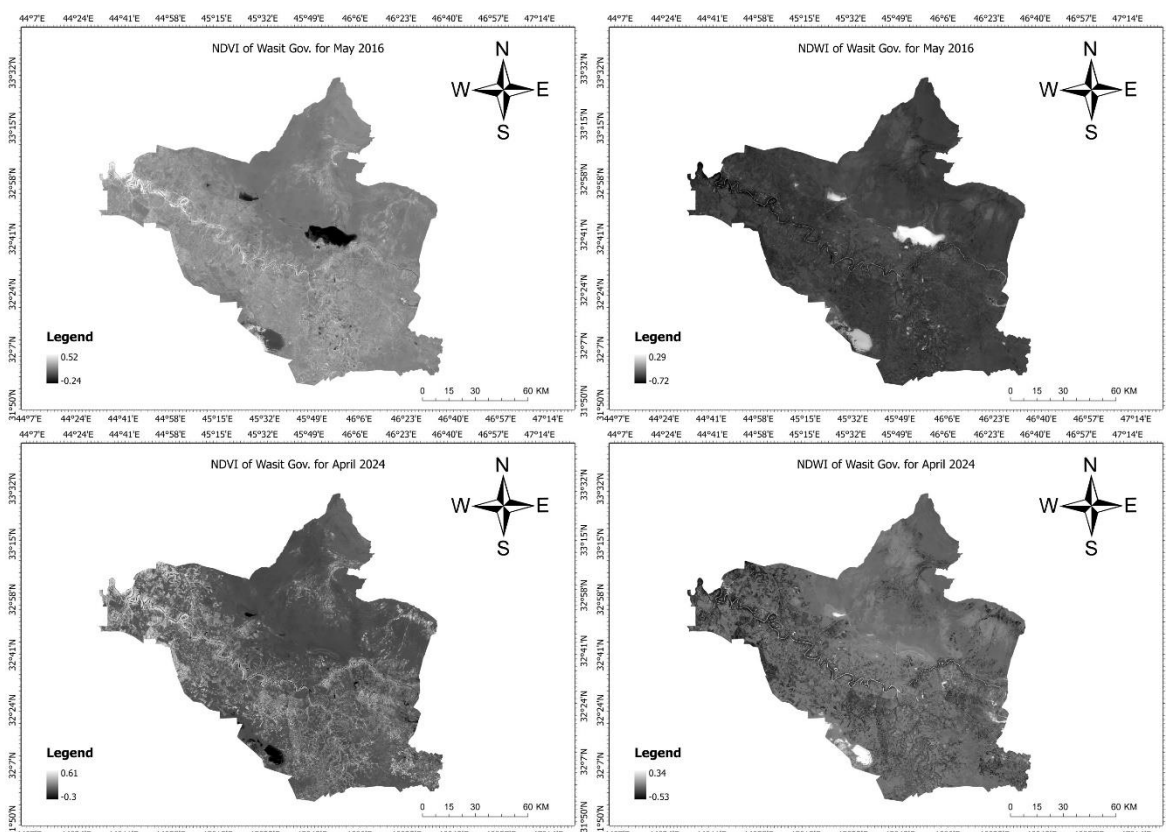


Figure 4: The result of applying NDVI and NDWI for two periods 2016,2024.

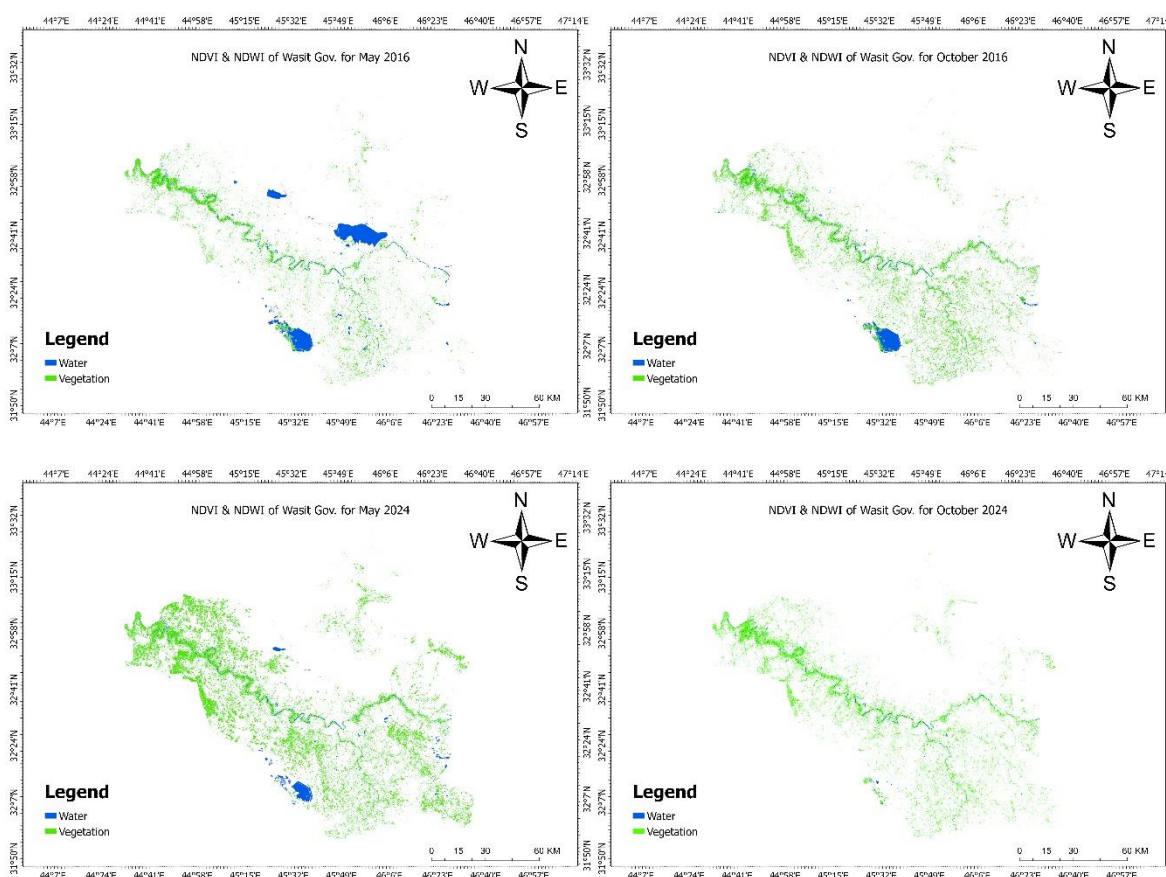


Figure 5: The results of applying the application of merging the vegetation cover with the water for the periods 2016 and 2024.

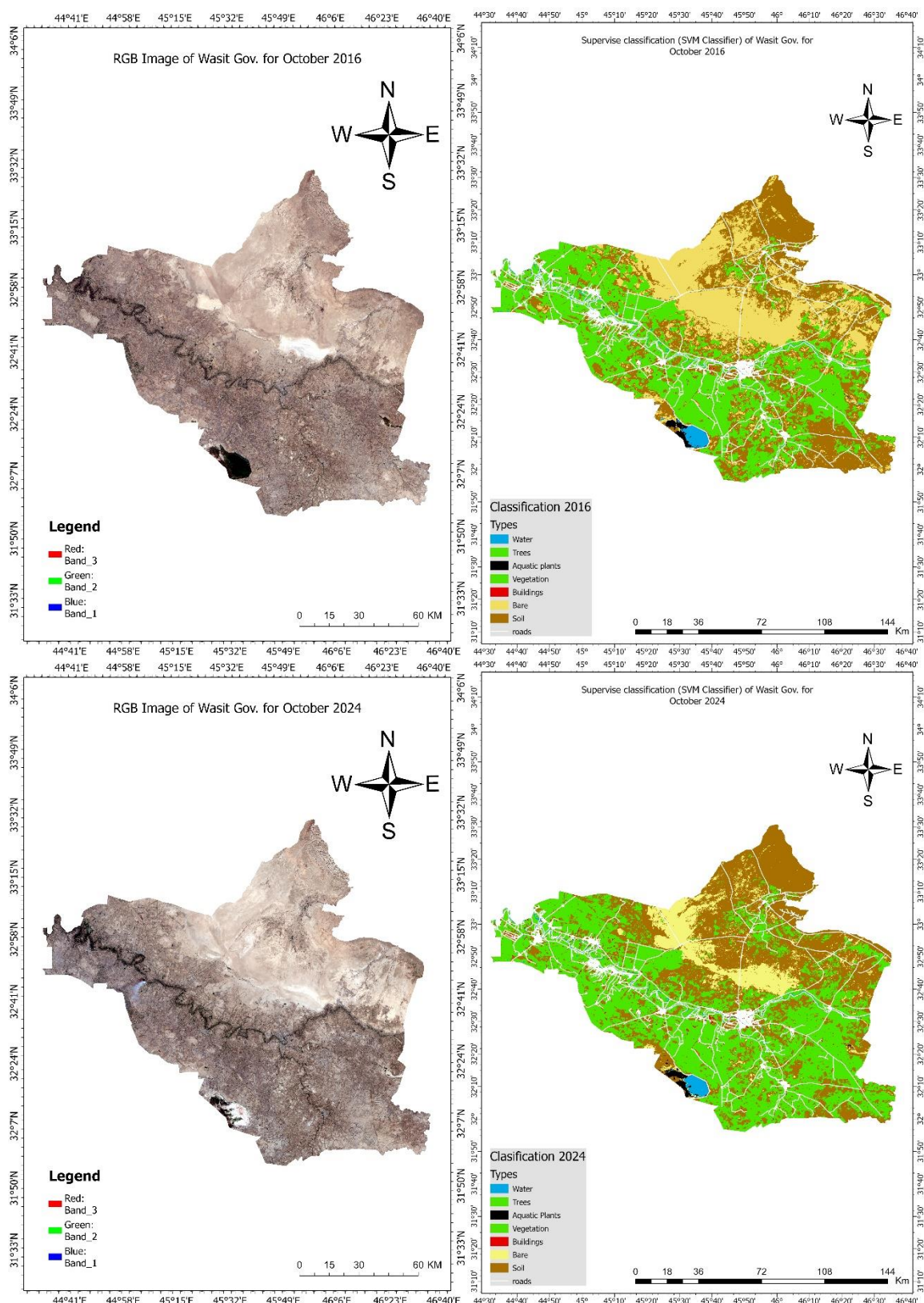


Figure 6: The results of applying Supervised classification (SVM) for the two periods 2016,2024.

Table 2: Area and percentage of classification results for 2016.

Name	Area (Km ²)	Percentage (%)
Water	248.159	1.397
Trees	16.1638	0.091025
Aquatic plants	65.3828	0.3682
Vegetation	7099.5912	39.98
Buildings	305.8929	1.722599
Bare	4034.852	22.7218
Soil	5987.5921	33.7184

Table 3:Area and percentage of classification results for 2024.

Name	Area (Km ²)	Percentage (%)
Water	212.3119	1.196
Trees	18.4722	0.104
Aquatic plants	72.1455	0.406279
Vegetation	8805.8559	49.589
Buildings	541.9011	3.0516
Bare	1491.568	8.399
Soil	6615.3761	37.254

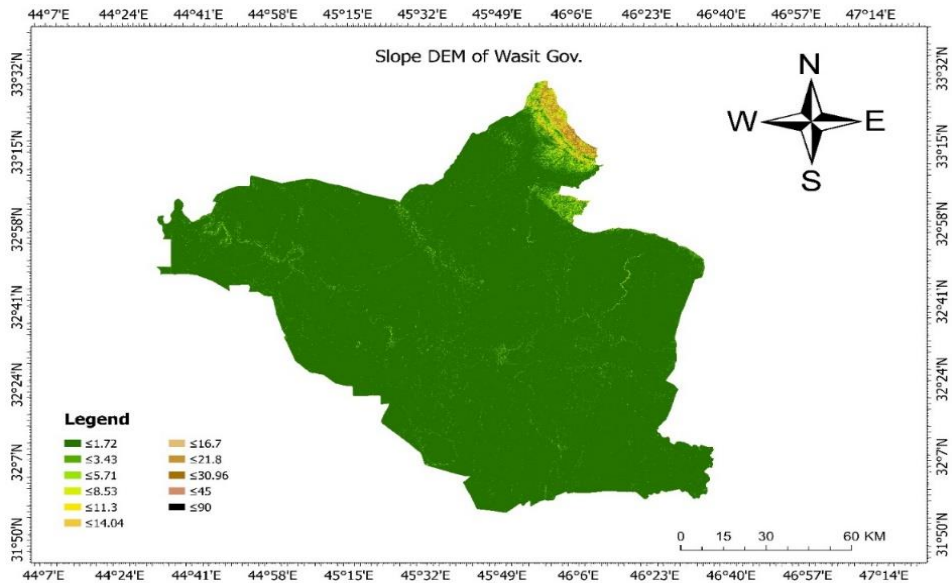


Figure 7: Classified slope results from digital elevation images

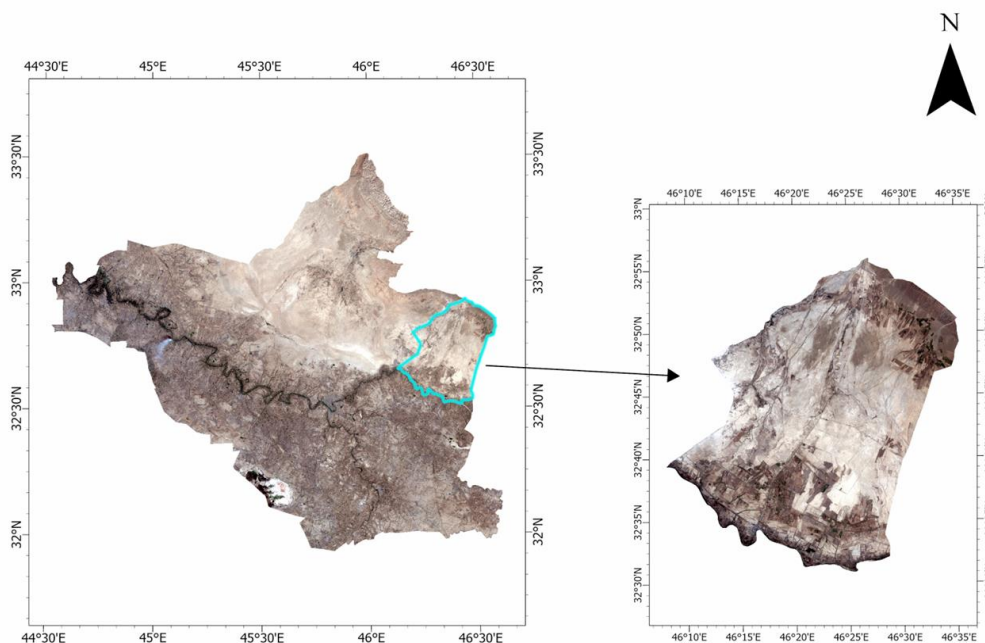


Figure 8 : The appropriate area for agricultural purposes.

6. Conclusion

Kut is a fertile city with good soil and a mild climate characterized by high temperatures in the summer and low temperatures in the winter. The prevailing climate is hot and dry, but the eastern regions bordering Iran experience significant rainfall. However, being highly sloping, these areas are difficult to store water, as shown by slope calculations. Therefore, they are not recommended as a promising area for agriculture. The central regions and those adjacent to the Tigris River are fertile and suitable for agriculture; however, due to the urban expansion of the governorate, they have been occupied by government institutions, departments, and residential complexes. The results showed that the region adjacent to Maysan Governorate is promising for agriculture, as the supervised classification revealed a large area with reasonable water reserves. It may represent a good option for growing crops such as rice, wheat, and barley to achieve self-sufficiency in these crops. Therefore, through the remote sensing applications in this research, it is possible to successfully select the best agricultural area based on the obtained values of the normalized vegetation index (NDVI) and the normalized water index (NDWI), which gives us a reasonable estimate for selecting this area according to the vegetation health rate and water content.

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