




Impact of Climate Change on Crops Productivity Using MODIS-NDVI Time Series

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Abstract

Climate change is the single biggest threat facing the global food system. Irrefutable impacts of climate change on the food systems are recently acknowledged. Therefore, extensive scientific efforts around the globe are dedicated to investigating and evaluating the short and long-term effects of climate change on the development of global food systems. In this study, an integrated approach of two methodologies, including Moderate Resolution Imaging Spectroradiometer (MODIS) Data and Normalized Difference Vegetation Index (NDVI), was employed to extrapolate the long-term changes in agronomic areas from 2000 to 2020 in the Dukan Dam Watershed (DDW), Northern Iraq. The link between agricultural areas and the primary production of essential crops (Wheat, Barley, Rice, Maize, and Sunflower) is proposed to be altered due to the impact of climate change. According to the Intergovernmental Panel on Climate Change (IPCC) report, Iraq is one of the semi-arid regions in the world that has recently been characterized by water scarcity and limited agronomic areas. Three independent variables (rainfall, temperature, and agriculture area) were used in the multiple regression analysis to understand the impact of the main drivers affecting the production of crops in DDW. Obtained results showed an increasing trend in crop production as a result of the frequent use of groundwater and surface water sources along with the implementation of greenhouse cultivation. Correlation analysis shows that the crop production was significantly related to the annual precipitation with a 59–63% in winter crops like wheat and barley, but was less sensitive to the temperature with a 20–40% in summer crops like rice, maize, and sunflower.

Keywords: Climate Change; NDVI; MODIS; Multiple Regression Analysis; Remote Sensing.

1. Introduction

In recent years, remote sensing techniques have been widely applied to provide new insights in the field of earth observation technology and a useful tool to interpret the complex interactions of environmental factors using sensors with multi-spectral signals. Satellite image processing can indicate a range of physical properties of the object, such as elements of the land cover and land use, including surface elevation and temperature [1-3]. Assessments of vegetative cover changes and processes have brought global attention and are topics of considerable societal relevance. Spectral vegetation indices are among the most widely used satellite data products, providing key measurements for a range of scientific fields such as climate, hydrologic, and biogeochemical studies; phenology; land cover and land cover change detection; natural resource management, and sustainable development [4].

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1.1. The Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI), one of the first remote sensing analysis applications, was signed to make multi-spectral imagery more understandable [5]. The NDVI Method was chosen as the most accurate indicator for difficult-to-access areas because it combines three (3) capturing vegetative change over time using remote sensing applications.

For agricultural land conservation and water resources restoration, the characteristics of land cover should be monitored, including water bodies, urban spaces, and agricultural land [2, 6–11]. This is particularly true in sub-humid to semi-arid environments, where the agricultural change in grazing areas may only be noticed over long periods. It is theoretically feasible to generate NDVI at a time by combining data from several sensors. NDVI is also used to classify the land in areas with different terrains, such as mountain forests and lowland plants. For example, these areas were monitored based on statistical information on the Mongolian plateau [2]. Another example, NDVI with high-resolution remote sensing data was applied to investigate the urban vegetation classes in Kuala Lumpur. The main types of urban vegetation were identified as low vegetation, high vegetation, and non-vegetation areas [12]. Because NDVI is one of the most extensively used categorization methods for detecting changes in land cover and land use, two Landsat TM images from 1990 to 2010 were used to generate NDVI values, which were obtained using the Natural Breaks (Jenks) method [13].

Ozyavuz et al. (2015) confirmed the validity of the use of satellite images with the NDVI method in detecting the change of the land cover, particularly the changes in vegetation in Tekirdag Province, Sarkoy in the short term (1987, 2002, and 2012) [14, 15]. Viana et al. (2019) have used Landsat satellite images with NDVI and NDWI to apply a long-term LULC analysis in a rural region characterized by a mixed agro-silvo-pastoral environment based on a Landsat time series for a period between 1995 and 2015 [16, 17]. Sahebjalal & Dashtekian (2013) have used NDVI classification to monitor the change in LC/LU with multiple thresholds in Ardakan, Iran for the period 1990–2006 [18]. Bhandaria et al. (2012) also improved the effectiveness of the NDVI method to classify LC/LU as a case study in the Jabalpur region, India. Multiple features were found from the NDVI Method classification, such as urban areas, agricultural land, and water resources [19]. Zaitunah et al. (2018) have used NDVI with remote sensing data to detect changes in land cover for the Besitang Watershed, in addition to determining the density of vegetation for multiple thresholds in areas for the period 2005–2015 [9]. Markov chain analysis and complex network methods were used to identify regimes of land-cover dynamics from land-cover maps (Terra Class) derived from high-resolution (30 m) satellite imagery in the Brazilian Amazon [20]. Overall, the NDVI time series has been shown to be an efficient index for long-term monitoring of vegetation changes. The goal of this chapter is to capture global vegetation change dynamics within the 10-day MODIS-NDVI time series by looking at April fluctuations during the long-term observation period (2000–2017) in Iraq [21].

One of the reasons for changing the land cover is the change in agricultural areas, which negatively affects the natural resources like grassland area, which has decreased as a result of the increase in irrigated agriculture in Aso Caldera, Japan. The NDVI with the GIS program indicated the areas of grassland that were affected by the change in agricultural patterns and water circulation in the study area as a result of the fluctuating groundwater recharge [22]. While a study in Vijayawada, Krishna district, Andhra Pradesh showed that the main activity of the main causes in the change of Land cover using NDVI technique and GIS tools to clarify Land cover for the period between 2014 and 2020 [17]. Foroumandi et al., (2022) claimed that one of the important limiting factors for vegetation cover is hydro climatological and is critical to the preservation of a region's characteristics to the current study (the watersheds of two rivers, Nazloo-Chay and Aji-Chay in Iran). NDVI was utilized as a remotely sensed indicator to investigate changes in vegetation's spatial-temporal pattern. Furthermore, ground measurements were used to collect temperature, precipitation, and stream flow time series in order to investigate the causes and consequences of changing plant cover [23].

Drought is generally caused by an imbalance between evaporation and precipitation during the growth cycle, which can be dangerous to the environment and human activities. The NDVI was considered an anomaly to observe the drought situation in Mongolia for about 20 years, the spatial correlation between the NDVI anomaly and two meteorological variables differed depending on the land cover type and plant growth [24]. To monitor drought in these areas, NDVI was used with temperature data from MODIS sensors to obtain a result of the extent to which crop production is affected by the increase in temperature [25].

The NDVI Method is not limited to indicate vegetation changes but also to quantify crop yield [10]. Borowik et al. (2013) compared the production from remote sensing and terrestrial NDVI. Their results showed that the correlation between theoretical NDVI and terrestrial NDVI, was applied within a seasonal range in an area in Eastern Poland [14]. NDVI Model with statistical approaches to develop corn and soybean yield prediction under water scarcity conditions was investigated [26]. The temperature and the amount of rain are inversely related to the production for agricultural lands, particularly in dry areas such as India, and with the lack of agricultural production of crops, the drought increases. Bellón et al. (2017) have developed an approach to monitor the full-scale agricultural land in Tocantins, Brazil. The approach was implemented in two stages, the first stage is MODIS data with NDVI time series; the second stage is classifying the agricultural land to crop agriculture domain land according to cropping systems [27].

1.2. Relationship of Crop Production with Changes in Temperature and Rainfall

Crop production depends on many external factors. These factors are climatic, biological, type of irrigation, and others. Climatic factors are denoted as temperature, rainfall, evaporation - transpiration, wind speed, and angle of solar radiation. Two elements intervene in this study, which is temperature and rainfall, and it will explain the extent of their impact on the crops in the study area. In the next section, the effect of rainfall, and the effect of temperature on crop production will be discussed.

Crop production in the Fanteakwa District is mostly rainfall-dependent, making field yield of this crop is highly vulnerable to the changes in precipitation patterns. Therefore, the net effect of precipitation patterns on agricultural output unavoidable. The rainfall variability within the major seasons in the three groups was smaller than in the minor seasons accordingly. These results have also revealed that the yields of three crops had decreased over time [28]. Croplands appear to be highly correlated to the annual average of precipitation. The accumulative annual precipitation and the croplands area have a strong link, which is attributed mostly to the irrigation type, where enormous swaths of farmland are irrigated [21]. Land use and land cover could be influenced by some environmental factors. This is also could be resulted from the combination effects of multi-factors including dry weather which is well known to cause a negative effects on vegetation areas. Therefore, primary production (e.g., wheat and barley in particular) are likely decreased when the agricultural areas that based on rainfall irrigation is decreased [29]. Pale and Antonio, 2015 explained the link between rainfall and agricultural productivity, who claimed that rain has a negative impact on maize production, particularly for rain-fed and small farmers. Nevertheless, there is conflict information concerning non-maize crop output and the influence of rainfall on family net income [30].

Modi et al. (2021) have explained that the impact of climate change on crop production until the year 2090 is reverse effects, as the study showed that the increase in temperature, as a consequence of global warming, makes the production of the corn crop decreased significantly ($p < 0.05$) as bioavailability of water in for plants is decreased [31]. According to a recent NASA research, climate change might influence maize (corn) and wheat productivity as early as 2030 if the recent scenario of high greenhouse gas emissions continued. Maize crop yields are expected to fall by 24%, while wheat yields are expected to increase by roughly 17%. The change in field yields is likely to be related to the increases in temperature, variations in rainfall patterns, and rising surface carbon dioxide concentrations from man-made greenhouse gas emissions. These alterations would make producing maize in the tropics more challenging, but they might increase wheat's growing area [32]. Between 2020 and 2029, the study investigates the influence of rising temperatures levels on agricultural yields in northern Thailand, notably rice and maize. According to the Representative Concentration Pathways 8.5 (RCP8.5) scenario, high temperatures are possible [33].

This study aims to evaluate the impact of rainfall and temperature on the crop production in the Dukan Dam Watershed (DDW) in the Kurdistan Region of Iraq using remote sensing techniques. The Dukan Dam Watershed (DDW) in the Kurdistan Region of Iraq was evaluated to distinguish the impact of climate change and agricultural area on the production of crops. Statistical approach will be implemented to understand the impact of agricultural areas on crop production using historical data of temperature and rain. The relationship between crop production and change in climatic elements will be investigated. Obtained results will be used to recommend for a further a research strategy future studies to improve plant production.

2. Materials and Methods

2.1. Study Area

The area of DDW is 6526 km² inside Iraq as it is regarded as a boundary watershed between Iraq and Iran, Figure 1. DDW is located between latitude 35° 25' 8" to 36° 54'15" N and longitude 44° 25' 35" to 46° 20' 53" E. On the north-west, it is bounded by the Great Zab River Tributary watershed while on the southeast it is adjoined by the watershed of Derbendi-Khan Dam reservoir [34]. DDW extends to Sulaymaniyah and Erbil governorates. DDW contains a group of irrigation projects shown in Table 1. The topography of the study area was simulated using Digital Elevation Model (DEM) which is provided by the Shuttle Radar Topography Mission (SRTM). The data is available in ARC GRID, ARC ASCII, and Geotiff formats, using decimal degrees and WGS84 datum. SRTM data are obtained from the USGS and NASA (USA). This data has been processed by CIAT to give an actual topography that is smooth surfaces areas where there was no data in the original SRTM data have been highlighted using interpolation methods described by Reuter et al. [35].

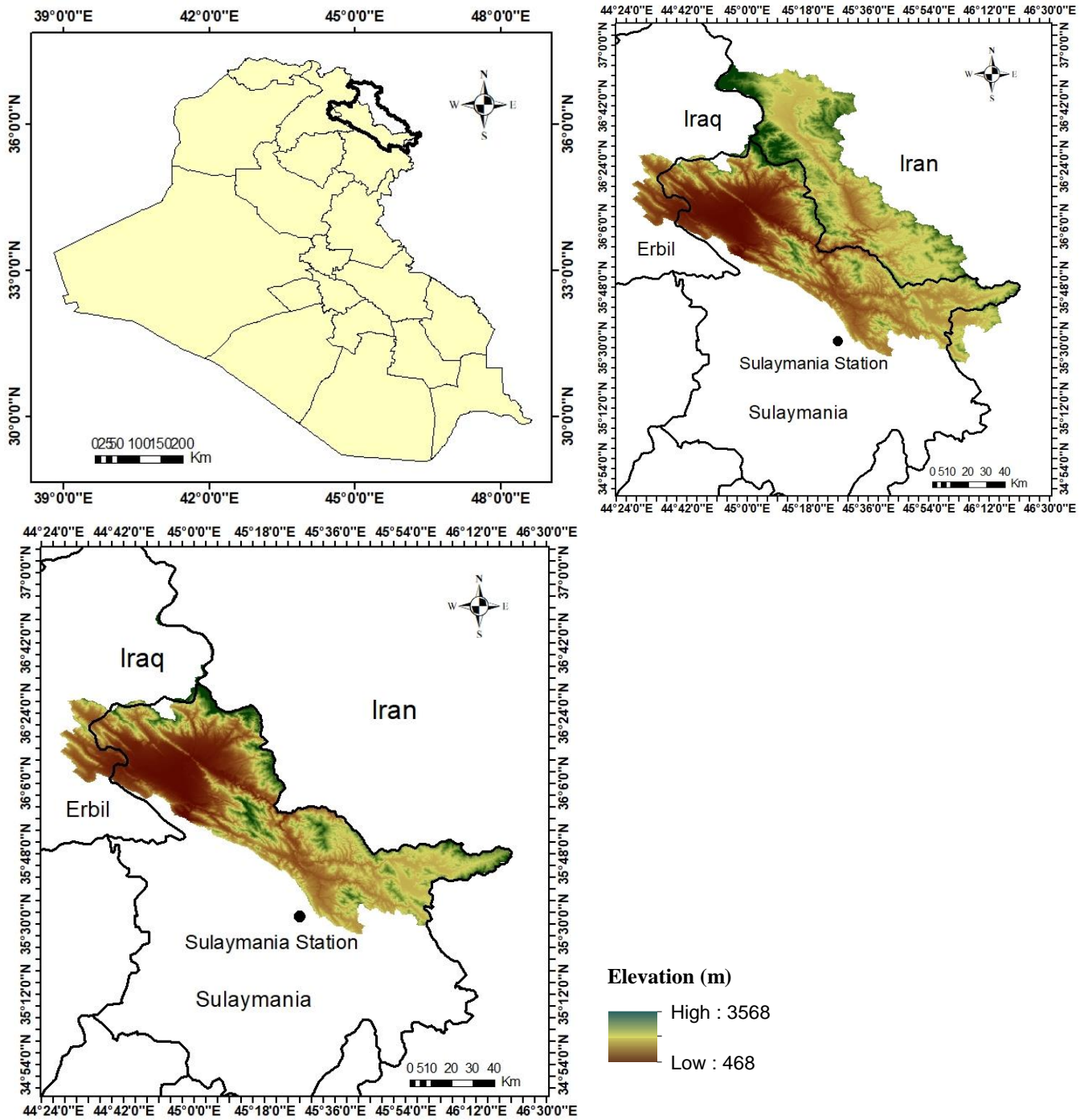


Figure 1. DDW Spatial location with the topography of the study area

Table 1. Irrigation Projects in DDW [36]

Watershed	Government	Irrigation Projects	Area (m ²)	Status Project
Dukan Dam	-	Kalar	50000	Partially Development
	-	Raniya – Sarujawa	215000	Partially Development
-	Erbil	-	-	-
-	Sulaymaniyah	Rain-fed fields (not Classified under Agricultural projects)	-	Partially Development

The irrigation methods of DDW are rained and irrigated, Most of the crops grown in the DDW are irrigated (rain-dependent) for their growth. The cropping pattern for DDW, planting time, harvest time and crop growth months were shown in the Table 2.

Table 2. Main crops in DDW [37-39]

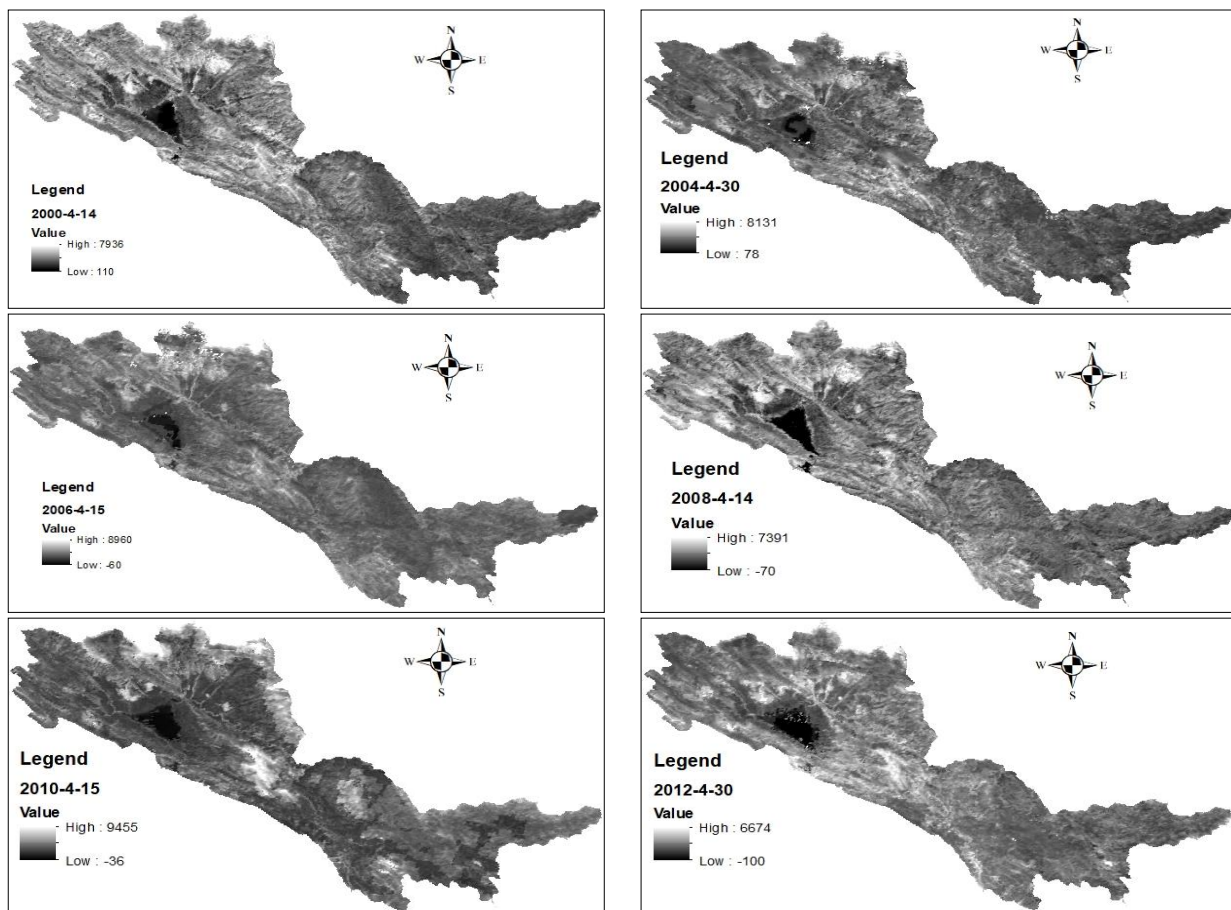
Crops	Plant Time	Harvest Time	Crop growth months
<i>Winter Crops</i>			
Wheat	a) The second half of October to the second half of November b) The second half of November to the second half of December	Beginning of May to the end of June	October, November, December, January, February, March, April and May.
Barley	Second half of November	May - to the beginning of June	October, November, December, January, February, March, April and May.
<i>Summer Crops</i>			
Rice	Second half of May	September to October	May, June, July and August
Maize	Mid-June to July	October to November	June, July, August and September.
Sunflower	Beginning of July	October	July, August, and September

2.2. Data Preparation

2.2.1. MODIS Data

A Moderate Resolution Imaging Spectroradiometer (MODIS) is a critical instrument aboard the Terra satellites (formerly EOS AM-1) and Aqua (formerly EOS PM-1). Terra's orbit around the Earth is timed so that it crosses the equator from north to south in the morning, whereas Aqua crosses the equator from south to north in the afternoon. Terra MODIS and Aqua MODIS are both looking at the same thing. The MODIS sensor offers virtually entire Earth coverage every day, because the clouds and aerosols are prevalent in daily global imaging sensors, so the cloud shadow effect is eliminated using temporal compositing of numerous data taken at predetermined time intervals [40]. Time-series data representing a cycle of vegetation phenology is required for the land cover monitoring. While a reliable time series of MODIS data is being developed to give the good applicable [41-44]. To get a high resolution and high NDVI resolution, Borowik et al. (2013) was used MODIS (MOD13Q1 V.5 dataset gathered at 250×250 m resolution) [45].

Satellite images have been provided from MODIS Terra's Surface Reflectance 8-Day L3 Global 250m sensor MOD09Q1 product [46]. Figures 2 and 3 explained satellite images for months (April and September) for each year of the period (2000-2020). All satellite images were implemented by NDVI Method in ArcGIS10.3 to get a set of vegetation images with area for the two months (April and September) of each year. These months were chosen according to the planting and harvesting of crops in DDW, Table 2.



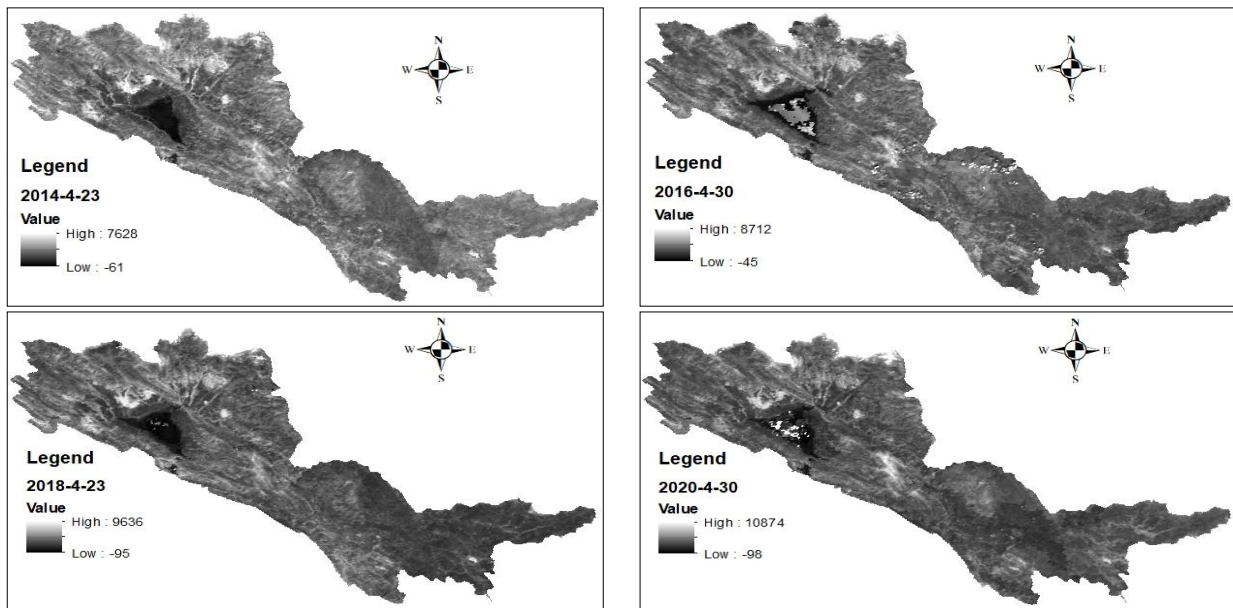
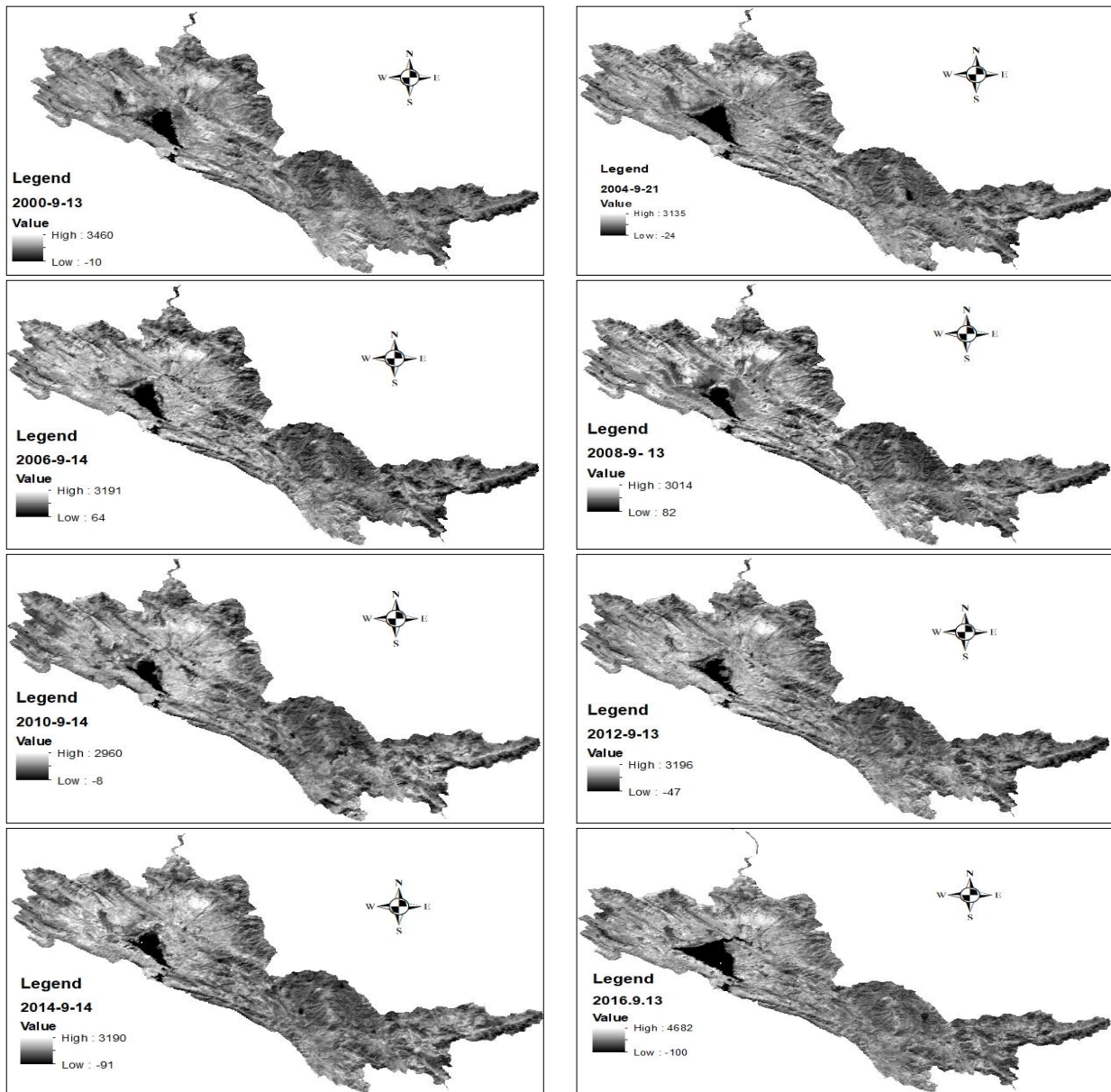


Figure 2. Satellite images for April month in DDW, MODIS Terra's Surface Reflectance 8-Day L3 Global 250m sensor MOD09Q1 Data (2000-2020)



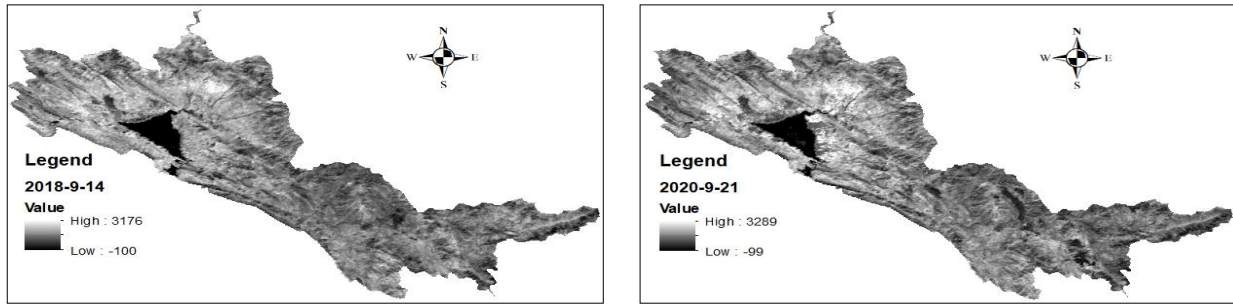


Figure 3. Satellite images for September month in DDW, MODIS Terra's Surface Reflectance 8-Day L3 Global 250m sensor MOD09Q1Data (2000-2020)

2.2.2. Climate Data

In Iraq, both continental and sub-tropical climates are present featuring cool and cold winter and hot to extremely hot and dry summer. The rainy season extends from October to March and the rainfall pattern is generally erratic. Iraq is divided into eight agro-ecological zones as a result of the natural changes in terrain [36, 47]. In the study area, DDW locates in Agro Climatic Zone1 (Upper Zagros Mountains Region) which describe is Sub-humid to humid, cold to cool winter, and mild to very warm summer [35]. The climate data used in the study was rainfall and temperature provided from Sulaymaniyah station for the period (2000-2020) [48] (Figures 4, and 5).

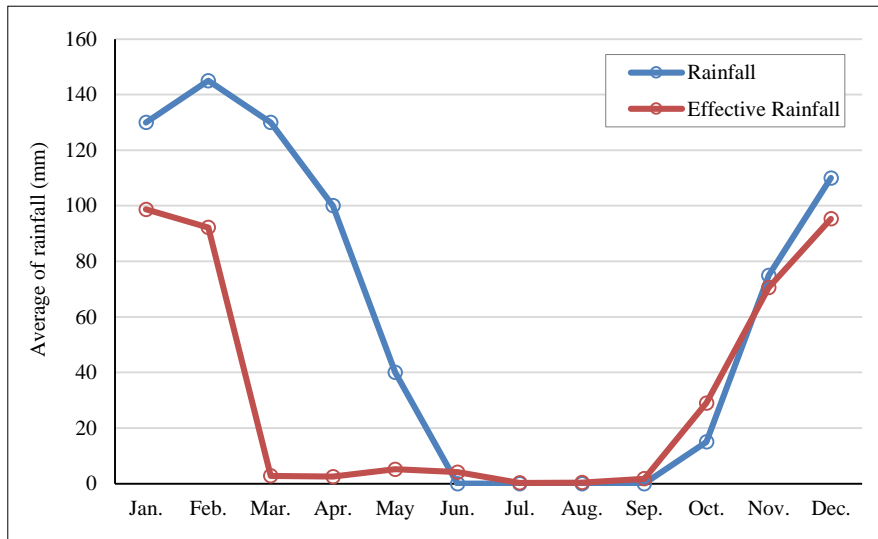


Figure 4. Average of rainfall for the period (2000-2020)

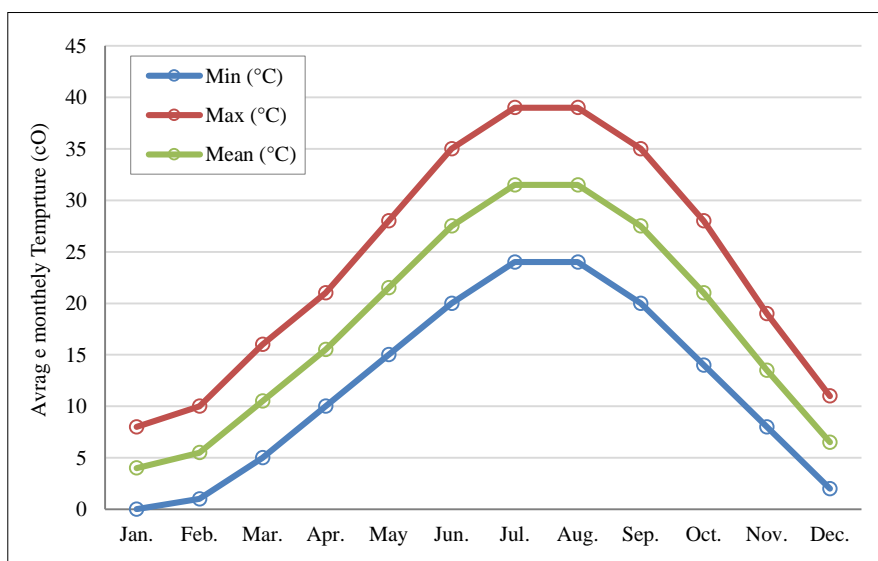


Figure 5. Average monthly of maximum, Minimum and Mean temperature for the period (2000-2020)

2.2.3. NDVI

The simplest metric of vegetation structure that can be obtained from remote sensing data is vegetation cover. Assigning a single class to each pixel is the most popular method for mapping plant cover from remotely sensed pictures. The percentage of pixels identified as vegetation can then be used to estimate vegetation cover. This method is based on the notion that each pixel reflects a uniform cover type. When the pixel size is much less than the typical plant patch size, this assumption may be plausible. This assumption, however, is rarely true for coarse-resolution remotely sensed imaging since coarse-resolution pixels are typically made up of a combination of cover types [49]. There are several methods for investigating seasonal changes in vegetation using satellite images, one of which is to use vegetation indices based on the extent of the greenness [50]. NDVI method is a metric methodology that measures the balance of energy received and released by the observable objects on Earth. This index sets a value for how green area is when applied to plant communities, that is, the quantity of vegetation present in a particular area and its condition of development. NDVI methods have been used to give a comprehensive view of land cover change, especially in the agricultural areas in the study area. It is calculated based on near-infrared (NIR) and red (RED) light reflectance assessments as in Equation 1, [6]:

$$NDVI = (NIR - red)/(NIR + red) \quad (1)$$

where NIR and RED are the amounts of light reflected by growing vegetation and captured by satellite sensor [6]. The NDVI threshold value varies from -1 to +1 (where the red and near-infrared bands of the NDVI were employed in this study. Table 3 explained the variability in thresholds NDVI values according to the results of researchers before. The NDVI values for each type of land cover vegetation are:

- NDVI values for water bodies and snow are less than 0 according to the elevation of water [51, 52]; 1-0.199; -0.35-0 [53], and described the NDVI value less than -0.5 is an index for No drought).
- NDVI values for no vegetation or urban area are (0-0.2) [18, 19, 51], 2013 represented the NDVI threshold (0-0.3).
- NDVI values for low vegetation or the natural grasses and herbs are (0.1-0.3) as low and medium Density vegetation [18]; 0.21-0.5 described as an agriculture area and Scuba area [9, 12, 51] described Lowest dense vegetation; Mašková et al. [54] clarified this range in meadows.
- NDVI values for high dense vegetation, urban agriculture area (cropland) and forest are (0.5-1) [9, 12, 18, 51, 52, 55].

Table 3. Comparison between many researchers for NDVI threshold values

Researchers	Thresholds	Descriptions
Gandhi et al. (2015) [51]	-0.8-0	Water body
	0-0.2	Open area
	0.21-0.4	Agriculture area
	0.41-0.5	Scuba area
	0.51-0.6	Thin Forest
Dagnachew et al. (2020) [52]	0.6-0.9	Thick forest
	-0.3-0.1	Cloud-Water-Snow
Ehsan and Kazem (2013) [18]	0.1-0.2	Forest in Humid Region
	0.1-0.2	Low Density vegetation
	0.2-0.3	Medium Density vegetation
	0.3-0.4	High Density vegetation
Nanzad et al. (2019) [53]	>0.4	Very High Density vegetation
	0.1-0.2	Urban Area
	0.2-0.3	Vegetation
	0.3-0.4	
Shareef & Abdulrazzaq (2021) [7]	0.4-0.5	Natural vegetation
	0-0.25	
Shimelis et al. (2015) [8]	0.25-0.5	Cropland
	-1-0.199	Non-Vegetation Barren areas, build up area, road network
	0.2-0.5	Low Vegetation Shrub and grassland
Hashim et al. (2019) [12]	0.501-1.0	High Vegetation Temperate and Tropical urban forest
	< -0.5	Non-drought
	-0.5 - -0.25	Mild drought
Javed et al. (2021) [24]	-0.25 - -0.1	Moderate drought
	-0.1 - 0	Severe drought
	>0	Very severe drought

	<0	Non vegetation
	0-0.15	Lowest dense vegetation
Zaitunah et al. (2018) [9]	0.15-0.3	Lower dense vegetation
	0.3-0.45	Dense vegetation
	0.45-0.6	Higher dense vegetation
	>0.6	Highest dense vegetation
Mašková et al. (2008) [54]	0.18-0.339	Mown meadow
	0.34-0.4	mulched meadow
Rawat and Biswas (2016) [55]	-0.35-0	Water bodies -
	0.01-0.6	dense green vegetation

Based on the values displayed in the Table 3, the threshold values for this search are deduced as shown in Table 4:

Table 4. NDVI Thresholds Values Range used in this study

Thresholds Values	Desecration
0 - 0.199	No Vegetation Area (Urban area)
0.2-0.499	Low Vegetation Area(Sharp and Grass Land)
0.5-1	High Vegetation Area(Urban Agricultural area)

2.2.4. Multiple Regression Analysis

Multiple regression analysis is a statistical technique for estimating the relationship between independent variables. Regression models with one dependent variable and more the one independent variable are called multilinear regression, Equation 2:

$$Y(c) = b_0 + b_1 X_1 + b_2 X_2 + b_3 X_3 \tag{2}$$

where: Y(c) is the production for each crop in tones (depended variable), x_1 is agricultural area for each crop (Km²), x_2 is annual accumulated effective rainfall for actual growth months (mm), and x_3 is average mean temperature for actual growth months (°C), b_0 is Y intercept (This is value of Y when all values of $x=0$); b_1 is Slope for agriculture area (when other independent variables do not change). b_2 is Slope for average mean temperature (for actual growth months) when other independent variables do not change. b_3 is Slope for effective rainfall (for actual growth months) when other independent variables do not change.

The multiple regression was interpreted by determine the coefficient of determination to test how well the model fits the dada. A correlation matrix was used to show correlation coefficient between the three independent variables with the crop production and to see which one of these variables has the highest correlation with the production of crops. Figure 6, shows the flowchart of the research methodology through which the objectives of this study were achieved.

3. Results

3.1. Trend Climate data in DDW

The climate data for ten years during the period (2000-2020) have been clarified in Figures 4 and 5 which represented the temperature, rainfall, effective rainfall, and effective temperature respectively. The actual climate data which affects the crop production was formed during the crop growth period and as shown in Table 2, the time of growth, and the time of harvest of each crop as shown in Table 2. Figure 7 showed that the observed annual accumulated rainfall at Sulaymaniyah station was significantly decreasing with time (negative trend). Figure 8 showed that there is a positive trend between the time and mean temperature for actual growth months of crops. The trend of annual rainfall has correlated with the average annual temperature. The reason is a result of the role of climate change in dry and semi-arid areas such as Iraq. As shown in the Figures 7 to 10, the rate of increase in average mean temperature between 2000 and 2020 is 37%, with an average of about 6 degrees. While a fluctuation was found in the annual rainfall for the period (2000-2020).The slope of annual average rainfall decrease in the direction of progress over the years. But the trend of effective annual rainfall (for actual growth months of the crop) was different from the trend of the annual rainfall because of the impact of climate change in Iraq. Which shows the change in the distribution of rain and its amounts in that time.

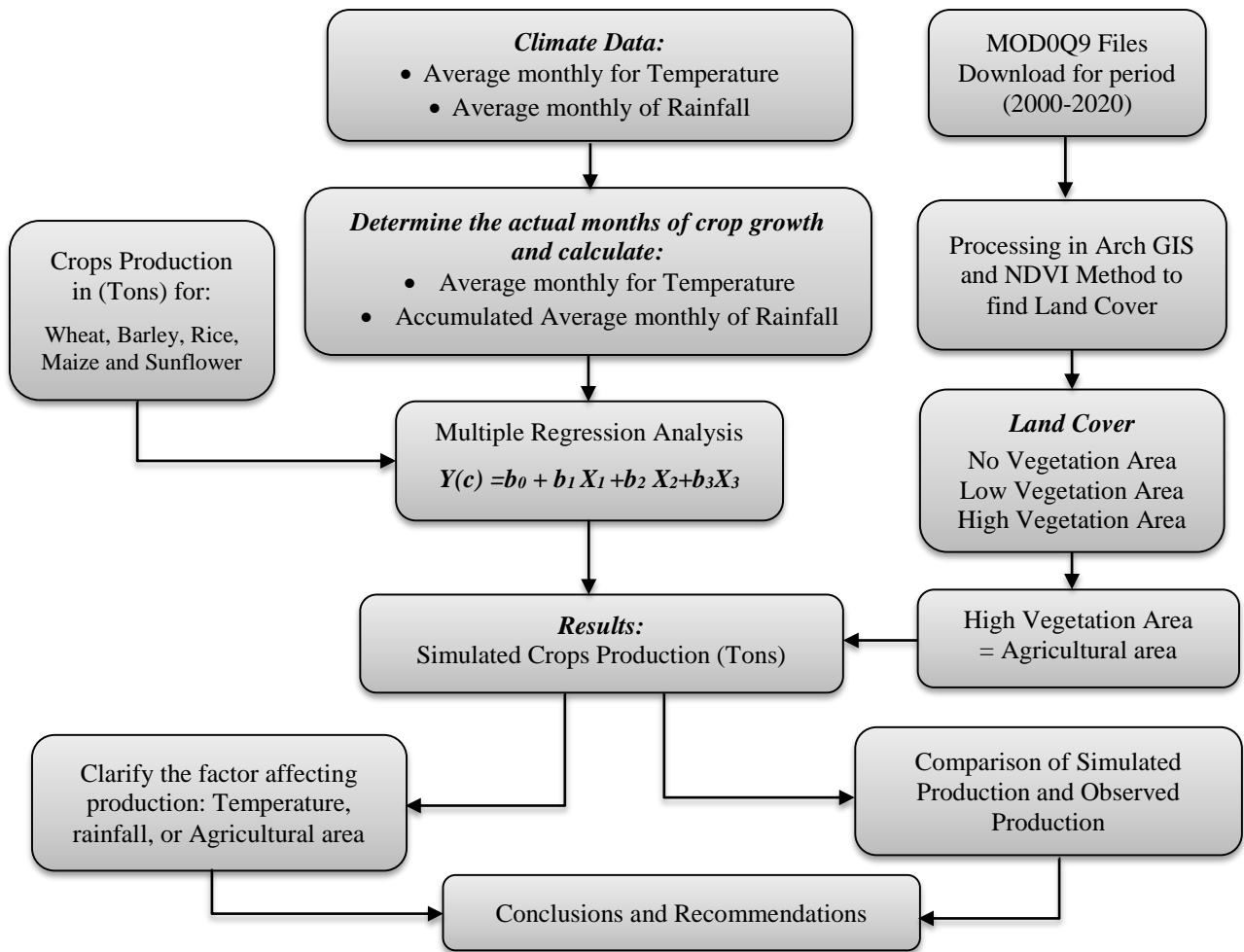


Figure 6. Flow chart for study methodology

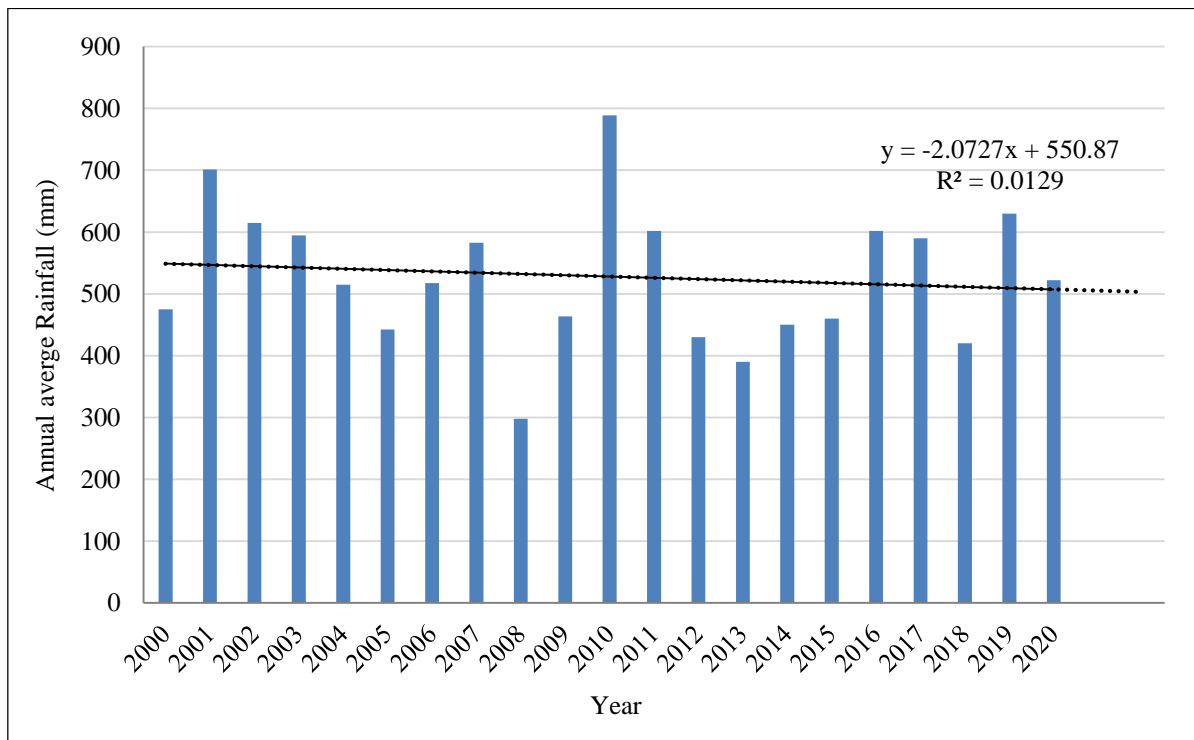


Figure 7. Annual average rainfall

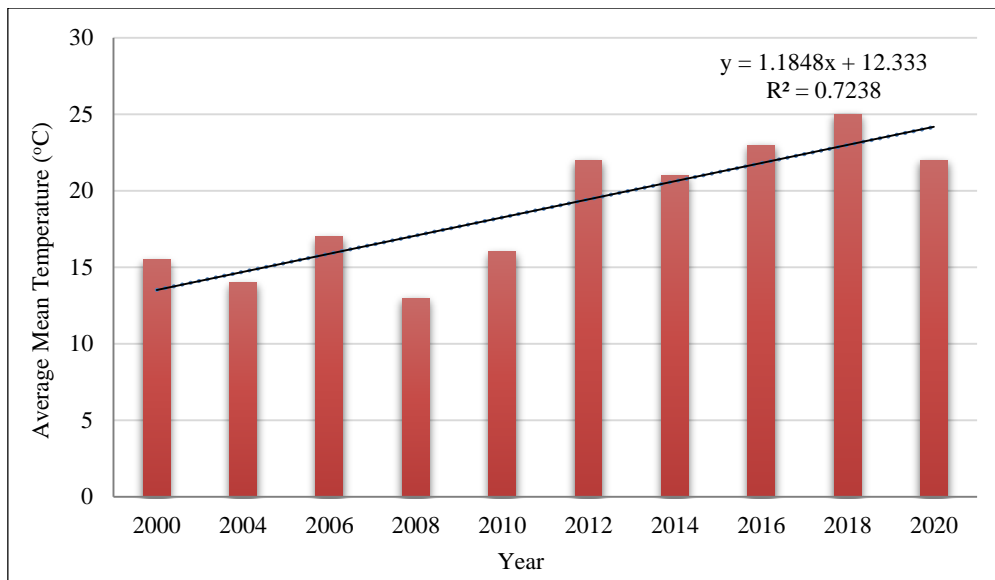


Figure 8. Average mean temperature

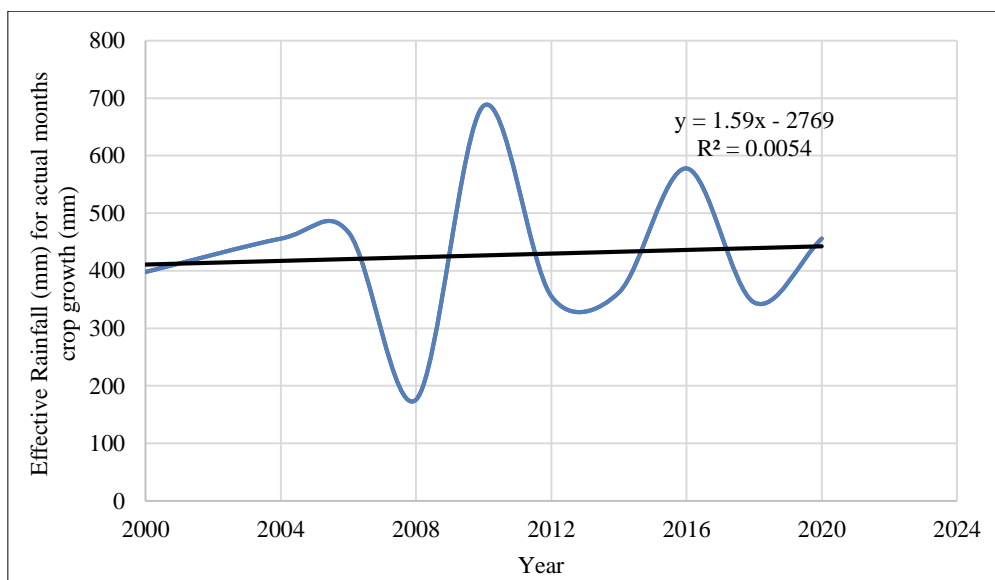


Figure 9. Annual average effective rainfall

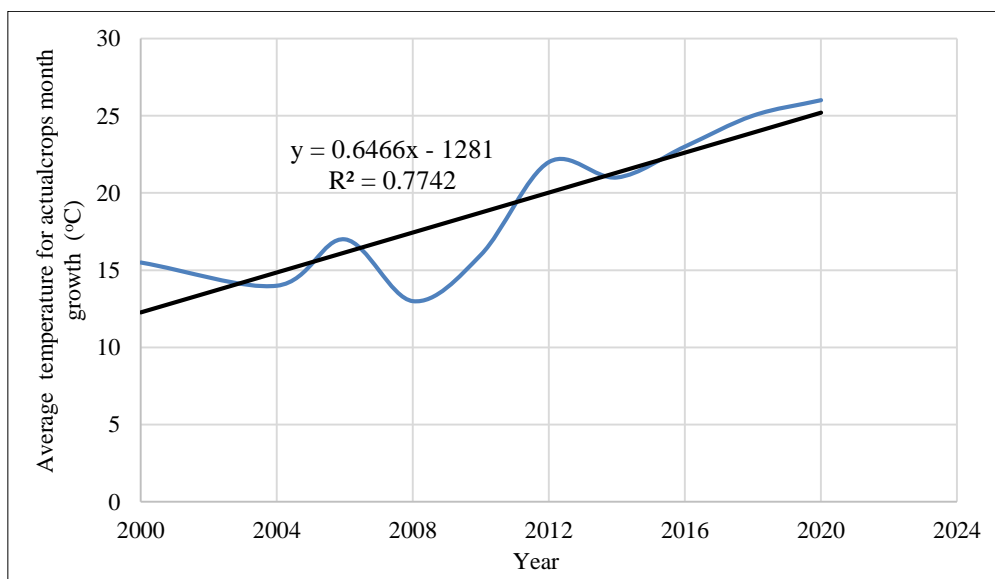
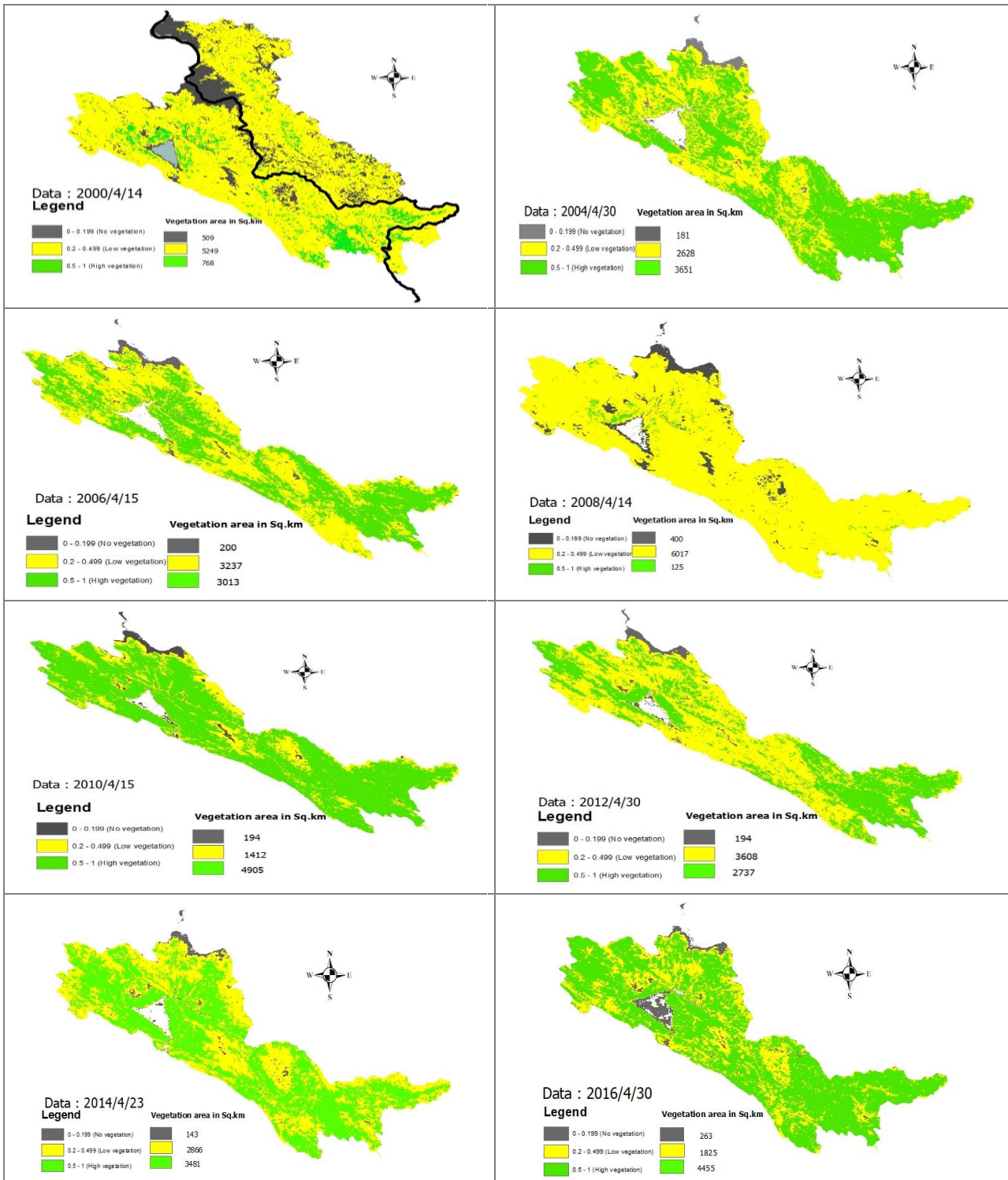


Figure 10. Average Mean effective Temperature

3.2. Land Cover Classification for Vegetation Region in DDW

The results of vegetation region change for each period can be visualized in Figures 11 and 12. These Figures illustrate the temporal and spatial change of agricultural areas in DDW for April and September. The study area is frequently cultivated with different agricultural patterns, where large areas of seasonal crops are occupied with natural vegetation and agroforestry area. Three classes of agriculture area are presented in Figure 12: No vegetation, Low vegetation area, and High vegetation area. The file produced by MOD0Q9 is an HDF-type and contains 4 layers, the following Science Data Set (SDS) for HDF file Layers (4) [56]:

- Surface Reflectance Band 1 (620-670 nm);
- Surface Reflectance Band 2 (841-87 nm);
- Reflectance State QA consists of cloud states;
- Reflectance Band Quality and atmospheric correction were performed.



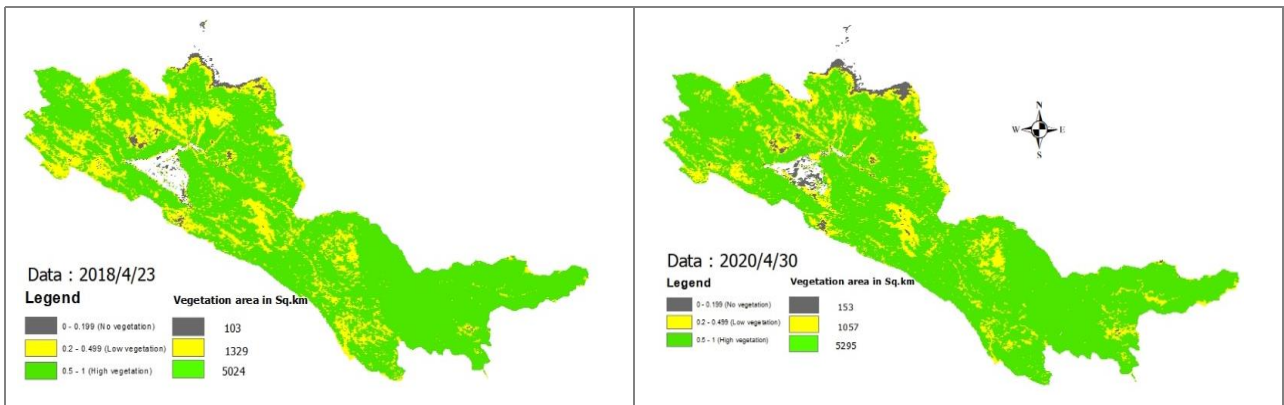
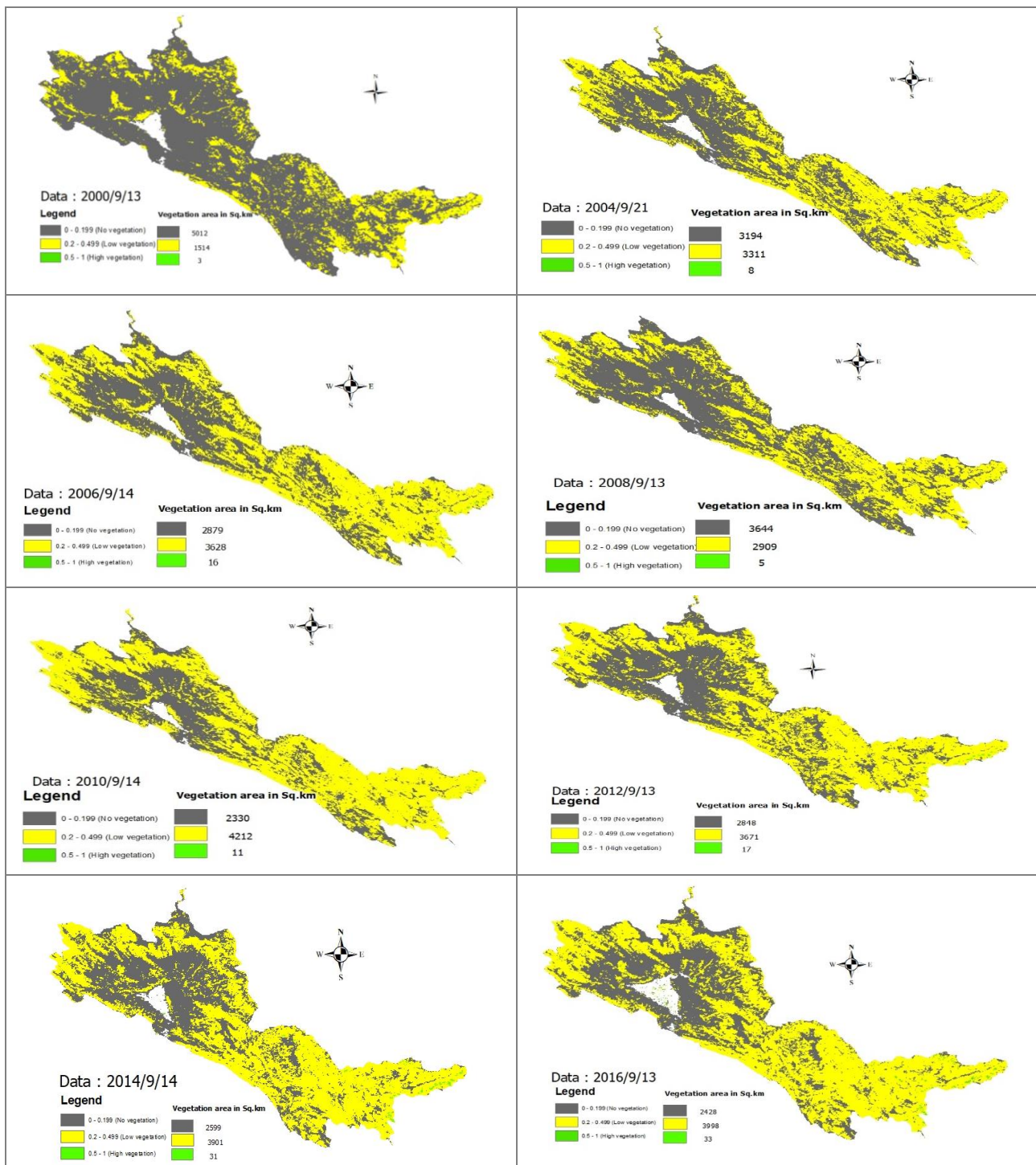


Figure 11. Land Cover classification for vegetation area in April month during the period (2000-2020)



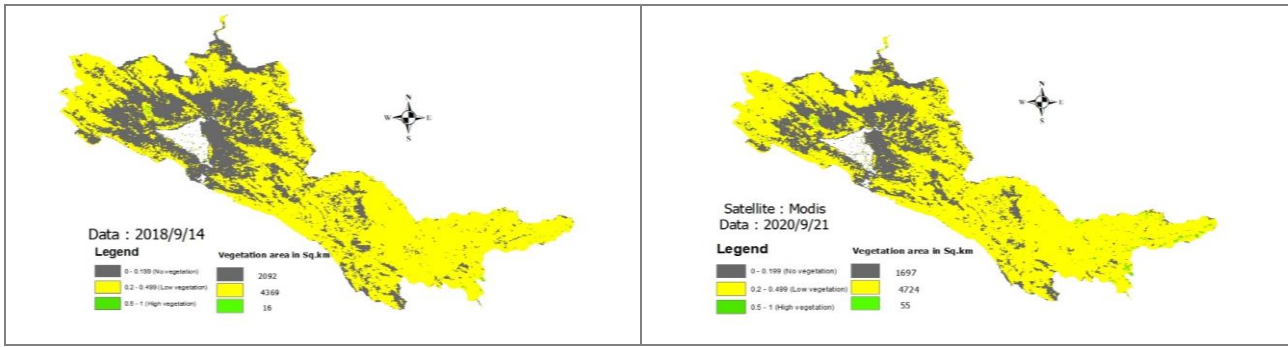


Figure 12. Land Cover classification for vegetation maps in September month during the period (2000-2020)

NDVI Method was used to get this classification according to the percentage of NDVI in equation (1). The near-infrared (NIR) represents Band 1 (620-670 nm) and RED light Band 2 (841-876 nm). In Figure 13, In April, the high agricultural area increases with time with position trend. A fluctuation in the values, of the areas during the period (2000-2020) occurred. The agricultural area decreases to a value of less than 250 square km in 2008 and increased to a large value in 2010, (5000 km²). While in the September months, a positive trend was observed without high fluctuation in the areas with a large value in the year 2020, which indicates the confirmation of the agricultural pattern used for agricultural projects and fields within the watershed. The high agricultural area represents the agricultural area within the agricultural season within the agricultural season in DDW.

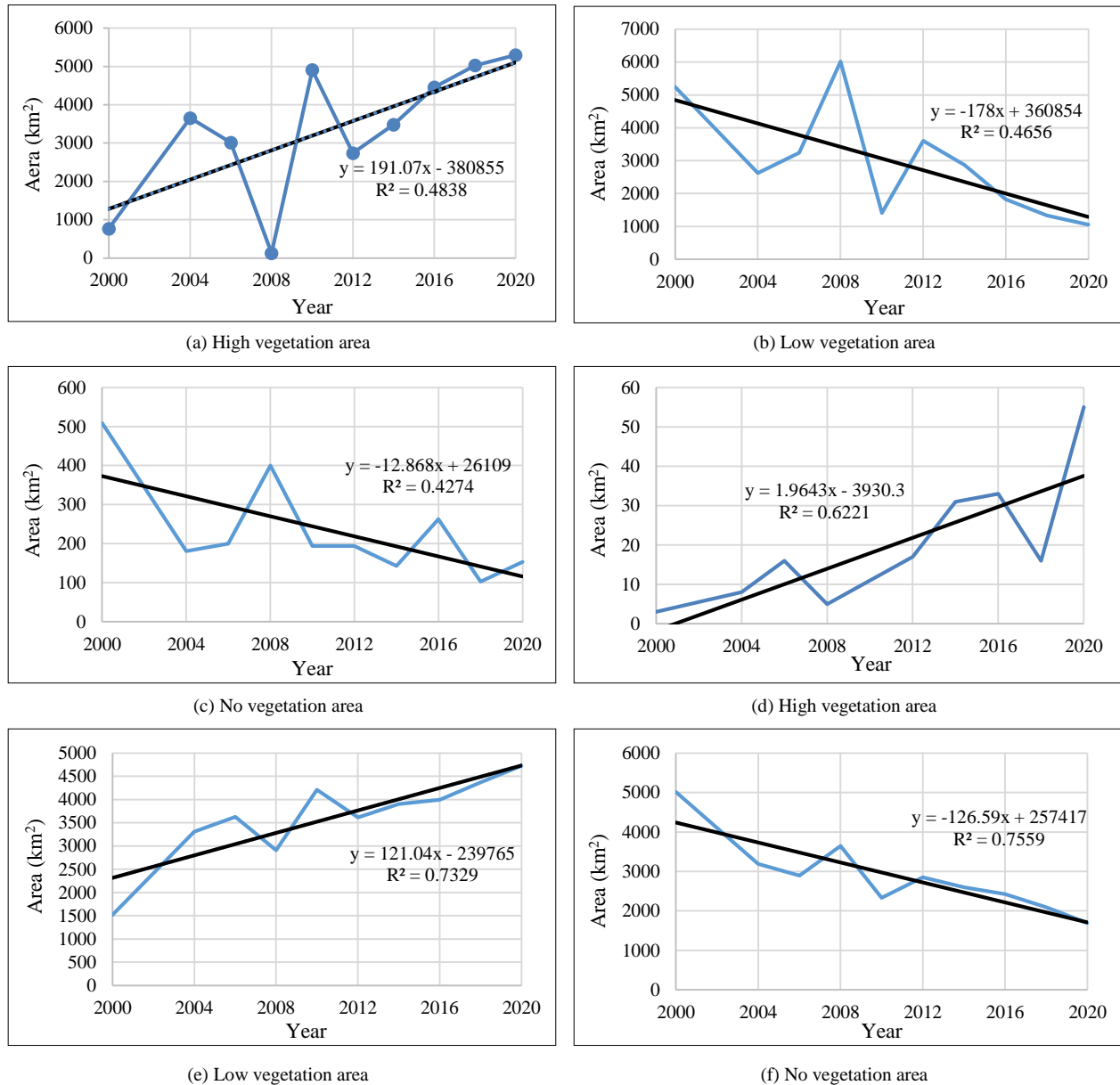


Figure 13. Land cover vegetation areas from DDW (a, b, c in April month and d, e and f in September month)

3.3. Crops Production in DDW

The crops found within the DDW for the period 2000 to 2020 are many, but the lack of data for these crops made the researcher take the available crops and their data, as shown in a Table 2. The studied crops within the summer and winter seasons of satellite images were observed in April month and September month. The crops are wheat and barley for the winter season; rice, maize, and sunflower for the summer season. Crop production data from the Ministry of Agriculture and the Statistics Division in the Kurdistan region. Figure 14 explain the change of production crops with time. The figures show a fluctuation in the values of crop production. For example, the production of all crops in the year 2008 decreased very significantly, except for the rice crop. The second decline is clear in 2012 for winter crops, but it did not affect much of the summer season's crops.

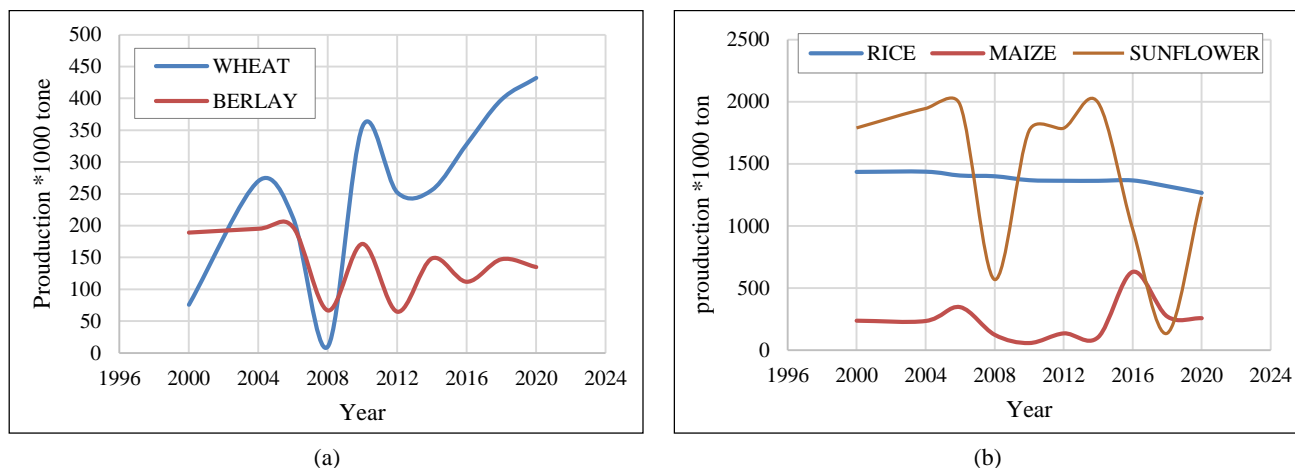


Figure 14. Change production crop for period (2000-2020): a) Winter crops; b) Summer crops

3.4. Multiple Regression Analysis Results

The results of linear multiple regression analysis between the dependent variable (crop production) and the independent variables (agricultural area temperature and rainfall by using the statistical analysis were shown in the following Tables.

Table 5. Linear equations resulting from multiple statistical analysis with R square for each crop and F significant

Crops	Correlation Coefficient Multiple R	R square	Significance F	Simulated Equations
Wheat	0.996	0.994	7.4884E-07	$422+135x_1+60x_2+47x_3$
Barley	0.56	0.32	47%	$1866+104x_1+99.8x_2+218x_3$
Rice	0.77	60	1%	$752.04+31.8x_1+32.8x_3$
Maize	0.52	0.27	38%	$213.2+3.05x_1+0.6 x_2$
Sunflower	0.47	0.22	3%	$3.2+ 2.34 x_1+14.12x_2$

The analysis of the linear multiple regression showed that the production of winter crops were significant and highly sensitive to (rainfall) effect. In addition, the sensitivity of wheat production in agricultural areas was 98%, in contrast to the barley crop, which was 22%, Table 6. Summer crops were significant and highly sensitive to temperature, especially in the sunflower crop, where the correlation to production ratio was 34%.

Table 6. Correlation Coefficients Matrices

Crops	Agricultural area %	Temperature %	Rainfall %	Highest Correlation coefficient
Wheat	98	-64	63	98
Barley	22	-29	59	59
Rice	-80	24	---	24
Maize	31	19	---	19
Sunflower	-7	34	---	34

The Production quantity and its effect on changing agricultural areas and climatic changes, where shown in Tables 7 to 11. Climate change will disrupt the crops production, the increase in temperature (+1.3), change in rainfall depth (+6%) changes in the area of agricultural will reduce the crops productivity.

Table 7. Variation of the dependent and independent variable for wheat yield (the reference year 2000)

Crops	Production change%	Agriculture area change%	Temperature change%	Rainfall change%
2000	-----	-----	-----	-----
2004	256.67	375.39	-14.29	8.42
2006	180.05	292.32	-19.05	8.95
2008	-86.79	-83.72	9.52	-37.26
2010	370.28	538.67	-23.81	66.11
2012	232.89	256.38	4.76	-9.47
2014	238.18	353.26	0.00	-5.26
2016	333.29	480.08	-42.86	26.74
2018	425.76	554.17	-38.10	-11.58
2020	470.67	589.45	9.52	9.89
Average	+484	+337	-13.33	+5.65

Table 8. Variation of the dependent and independent variable for Barely yield (the reference year 2000)

Crops	Production change%	Agriculture area change%	Temperature change%	Rainfall change%
2000	-----	-----	-----	0.00
2004	3.20	375.39	-14.29	8.42
2006	4.48	292.32	-19.05	8.95
2008	-64.74	-83.72	9.52	-37.26
2010	-9.40	538.67	-23.81	66.11
2012	-65.80	256.38	4.76	-9.47
2014	-21.44	353.26	0.00	-5.26
2016	-40.89	480.08	-42.86	26.74
2018	-22.16	554.17	-38.10	-11.58
2020	-28.69	589.45	-9.52	9.89
Average	-24.54	+337	-13.33	+5.65

Table 9. Variation of the dependent and independent variable for Rice yield (the reference year 2000)

Crops	Production change%	Agriculture area change	Temperature change	Rainfall change
2000	-----	-----	-----	-----
2004	0.12	166.67	-14.29	-----
2006	-2.01	433.33	-19.05	-----
2008	-2.41	66.67	9.52	-----
2010	-4.60	266.67	-23.81	-----
2012	-4.92	466.67	4.76	-----
2014	-4.95	933.33	0.00	-----
2016	-4.74	1000.00	-42.86	-----
2018	-7.94	433.33	-38.10	-----
2020	-11.65	1733.33	-9.52	-----
Average	-4.31	+611.11	-13.33	

Table 10. Variation of the dependent and independent variable for Maize yield (the reference year 2000)

Crops	Production change%	Agriculture area change	Temperature change	Rainfall change
2000	-----	-----	-----	-----
2004	-0.98	273.33	-14.29	-----
2006	46.03	646.67	-19.05	-----
2008	-47.86	133.33	9.52	-----
2010	-76.02	413.33	-23.81	-----
2012	-43.17	693.33	4.76	-----
2014	-56.08	1346.67	0.00	-----
2016	166.07	1440.00	-42.86	-----
2018	14.45	646.67	-38.10	-----
2020	8.45	2466.67	-9.52	-----
Average	+1.21	+806	-13.33	

Table 11. Variation of the dependent and independent variable for Sunflower yield (the reference year 2000)

Crops	Production change %	Agriculture area change %	Temperature change%	Rainfall change%
2000	8.75	-----	-----	-----
2004	10.48	0.00	-14.29	-----
2006	-68.26	166.67	-19.05	-----
2008	-1.32	433.33	9.52	-----
2010	-0.14	66.67	-23.81	-----
2012	11.46	266.67	4.76	-----
2014	-45.33	466.67	0.00	-----
2016	-92.51	933.33	-42.86	-----
2018	-31.02	1000.00	-38.10	-----
2020	-20.79	433.33	-9.52	-----
Average	8.75	+1733.33	-13.33	

To get an impression of crop production during the period (2000-2020), the relationship between Observed and Simulated production has been clarified from the equations of Table 5. Figure 15 shows the relationship between Observed and Simulated production.

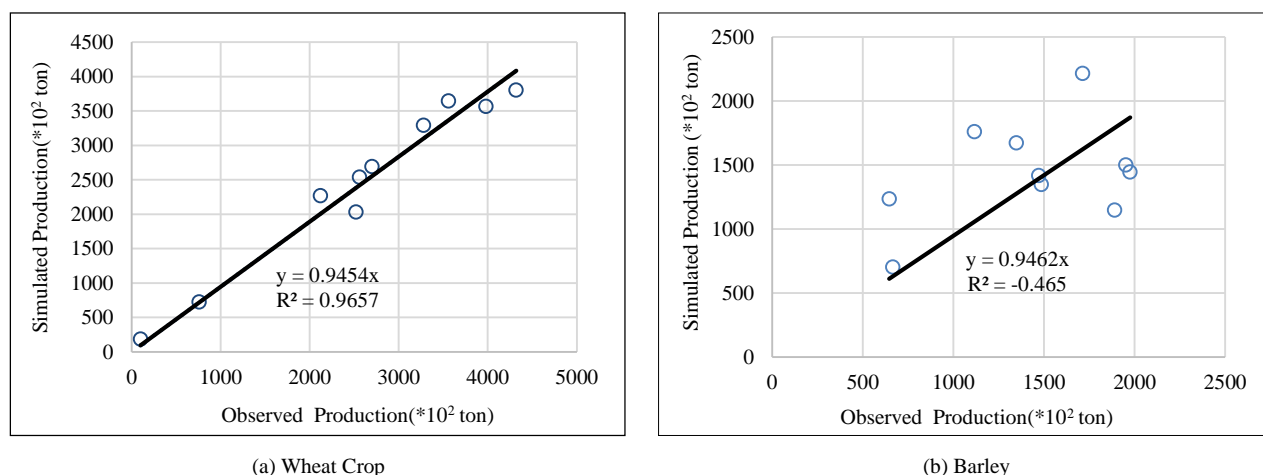


Figure 15. Relationship between Observed and Simulated Production for each crop in DDW

4. Conclusions

The impact of climate change on crop production shows a clear impact on food security, especially for arid and semi-arid areas such as Iraq. Climate change reduces agricultural productivity by 40–100% of the extra water required in the absence of global warming [57]. This percentage from the FAO corresponds to the two rates of production as a result of climatic change. There are two cases in this study, the first case is the change in the mean annual rainfall amount for the winter crops, which produces a negative change of 86% in the wheat crop in DDW during the year 2008. The negative

change in the production of the barley crop in DDW during the year 2008 reached 65%. The second case is the ratio in the production change for summer crops (the temperature is considered to be the critical factor because these crops depend on irrigation). Production of the rice crop in DDW during the year 2020 is to reach 11%. Maize production increased by 10% with an increase in temperature by 1.3% during a period of ten years, the reason is that maize is due to the high temperature that suits the ideal temperature, which is 30.

After comparing the agricultural areas from the results of remote sensing with the agricultural areas of the official agricultural projects, it turns out that there are many fields that are not classified within the official projects and that are dependent on rain-fed agriculture. The reason for the inconsistency of agricultural areas with the amount of production per crop is the reasons related to the methods of harvesting the crop. These reasons are the high humidity caused by the activity of fungi; damage caused by insect and animal pests; and many other factors for the fact that the methods of agriculture in Iraq are below the standard levels required to secure food security.

It is strongly thought that Iraq will not be able to become self-sufficient in food and fiber commodities, particularly when considering the expected population growth over the next twenty years in association with the diminishing available water for irrigation. Therefore, the Strategic Study for Water and Land Resources in Iraq recommends identifying the most suitable and sustainable agronomic approach to maximize plant productivity. The farming proportion between food staple crops and high-value (cash) crops has been carefully investigated by the consultant and diversified among the agro-ecological zones of the country, with the goal of addressing as much as possible the national food demand while ensuring satisfactory revenue for the farmers and the other actors of the concerned value chain.

The study provided a new insight into the changes in the land cover in the long term in one of the most important watersheds in Iraq (Dukan Dam). This change was seasonal for two months of the year, which coincides with the agricultural cycle that already exists in the study area. Clarification of the change in temperature and precipitation for a period of time (2000–2020). When observing this change, we deduce two cases: the first, the long-term average temperature and annual rainfall rates for the study area, which makes the study one of the first studies to justify a tendency in temperature and rain due to the lack of data and loss in the region, as the researcher was able to provide this type of data for the upcoming studies and show the type of climate change that is affecting the study area. The second case is knowing the direction of change in the temperature rates and the cumulative rate of the actual months of crop growth, and this case actually provides a real impression of the type of climatic change that occurs during these months, leading to the growth of the crop. The fluctuation of crop production was dependent on agricultural areas (extracted from NDVI average temperatures and rains for the months of crop growth) analyzed using multiple variable linear regression.

This study provides a useful strategic plan for improving rain-dependent agriculture as a result of changing rain and temperature. The goal is to improve food security, which is an essential element that is important to be researched and applied in our time. Among the strategies for the sustainability of crop production, making the outputs a useful reference to enrich discussions and policies on adaptive agricultural production methodologies for the region in the face of climate change.

5. Declarations

5.1. Author Contributions

Conceptualization, Z.-K.J., T.-S.K. and I.-A.A.; methodology, T.-S.K. and I.-A.A.; remote sensing data processing Z.-K.J. and I.-A.A.; climate data analysis, T.-S.K. and Z.-K.J.; regression analysis, Z.-K.J., T.-S.K. and I.-A.A.; writing—original draft preparation, Z.-K.J., T.-S.K. and I.-A.A.; writing—review and editing, Z.-K.J., T.-S.K. and I.-A.A.; visualization, I.-A.A. and T.-S.K.; supervision, Z.-K.J.; project administration, Z.-K.J.; All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available in the article.

5.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

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5.5. Conflicts of Interest

The authors declare no conflict of interest.

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