Evapotranspiration and Vegetation Cover Classifications Maps Based on Cloud Computing at the Arab Countries Scale

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Abstract
According to the most recent Köppen–Geiger classification, Arab countries are divided into seven climate classes. Ground data availability is limited in developing countries, and ground meteorological data are scarce and concentrated in a few locations, rather than station maintenance capability being adequate for the responsibilities. The current study uses remote sensing and meteorological data to create regional classification maps of reference evapotranspiration (ETo), potential crop evapotranspiration, and vegetation cover in Arab countries from 2005 to 2020. The Stand-alone Remote Sensing Approach to Estimate Reference Evapotranspiration (SARE) was used to estimate ETo using satellite data from 2005 to 2020. The Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) were extracted from MODIS satellite data and used in the SARE model, in addition to elevation (E), Julian day (J), and Latitude (Lat). To validate the SARE model results, the FAO-Penman–Monteith model was applied to 35 ground meteorological stations distributed across Arab countries to cover all climate classes based on the most recent Köppen–Geiger climate classification. Google Earth Engine was used to create the classification. The statistical indices produced acceptable results, with average RMSE values ranging from 6.9 to 17.3 (mm/month), while correlation coefficient (r) and index of agreement (d) values are more significant than 0.9. To be included in the ETc calculation, the crop coefficient (Kc) was calculated using NDVI 250 m spatial resolution. The density of the vegetation cover is used to classify it (low to high). The average vegetation cover was calculated to be greater than 31.5 Mha. The minimum vegetation cover was 14.9 Mha, and the maximum vegetation cover was 49.2 Mha. 15.8 Mha can be cultivated without supplementary irrigation for at least one agricultural season, according to the rainfall classification map.

Keywords Reference evapotranspiration (ETo) · Potential crop evapotranspiration (ETc) · Vegetation cover density · Google Earth Engine (GEE) · SARE model

1 Introduction
Since Köppen based the scheme on his knowledge as a botanist, the primary climatic classes are based on the types of flora that grow in a given climate classification region. Aside from differentiating climates, the technique can also analyze habitat conditions and classify the essential types of plants within given climatic conditions. Because of its connection to that region’s plant life, the method aids in anticipating potential advances in plant life within a given location. The Köppen climatic classification is based on the scientific relationship between the atmosphere and vegetation. This concept offers a practical method for categorizing climatic conditions based on temperature and precipitation using a single metric. The Köppen definition has been widely used to depict the geographical distribution of long-term environmental and associated ecosystem conditions because it emphasizes biologically significant climatic variables (Chen and Chen 2013).

Agriculture yields in Arab countries are likely to suffer due to unprecedented changes in the climate system (Jarvis et al. 2010, Thornton et al. 2011). According to the IPCC, precipitation in arid and semi-arid areas may...
Precipitation is essential for rainfed cropping; even in the Mediterranean region, rainfed cropping accounts for 60% of cereal production (Parry et al. 2005). If precipitation decreases in the future, there will be a water shortage for agricultural water demand. As a result, there has been a surge in interest in using classification to identify temperature fluctuations, precipitation trends, and potential changes in vegetation over time (Chen and Chen 2017; Mohorji et al. 2017; Almazroui et al. 2020a, b). The Köppen climate classification is essential in ecology because it aids in predicting dominant plant types based on climatic data and vice versa (Crichtfield 1983). Between 1950 and 2010, roughly 5.7% of the world’s land area shifted from wetter and colder to drier and hotter conditions. Natural variability cannot account for the change, which is being driven by artificial factors (Chan and Wu 2015). Because of changes in land area and climate, there is a knowledge gap for Köppen classification based solely on temperature and precipitation.

Hot dry-summer climates (Csa) and cold dry-summer climates (Csb) are sometimes referred to as “Mediterranean.” The initial letter of the Köppen climate system designates the climatic party (in this case, temperate climates). “C” regions are frequently referred to as “temperate zones,” with surface temperatures ranging from 0 °C (or 3 °C) to less than 18 °C during their coldest months. The precipitation pattern is described in the second letter (“s” represents dry summers). Summers with less than 30 mm of precipitation are defined as dry, and little precipitation falls between April and September in the Northern Hemisphere and October to March in the Southern Hemisphere. A 40 mm level, on the other hand, can be used. An “a” denotes an average temperature greater than 22 °C in the hottest month, whereas a “b” denotes an average temperature less than 22 °C in the warmest month (Kottek et al. 2006; Peel et al. 2007).

The amount of ET produced by a large grassed field 8–15 cm tall, uniform, actively growing, completely covering the ground, and having enough water is defined as the reference evapotranspiration (ETo) (Doorenbos and Pruitt 1977). After that, Allen et al. (1998) expanded on the definition of ETo by referring to an ideal 18 cm tall crop with a set surface resistance of 70 sm⁻¹ and an albedo of 0.23. The NDVI measures plant density up to full coverage, biotic and abiotic stress conditions, and vegetation health parameters (Xue and Su 2017). Surface temperature, in addition to weather variables, reflects crop and soil water conditions (El-Shirbeny et al. 2014a, Holzman et al. 2018; El-Shirbeny and Abutalib 2018; Tolba et al. 2020, Mohamed et al. 2021).

According to El-Shirbeny and Abdellatif (2017), Häusler et al. (2018), Xiang et al. (2020), El-Shirbeny et al. (2021), and Abdelkhalik et al. (2020), the ETo is calculated using on-site meteorological data and multiplied by the crop coefficient (Kc) to estimate crop evapotranspiration (ETc), which is then multiplied by the stress coefficient (Ks) to obtain actual evapotranspiration (ETa).

ETa or ETc was the focus of remote sensing approaches. Although there have been few studies on ETo estimation using satellite data, it is primarily based on statistical correlations with vegetation indicators such as soil adjusted vegetation index (SAVI) and NDVI (Yin et al. 2008; Papadavid et al. 2011; Alblewi et al. 2015; Zhao et al. 2015).

The crop coefficient (Kc) is a scalar number (commonly varied from 0.3 to 1.2). Many articles use Kc and NDVI similarities to calculate Kc from satellite data (El-Shirbeny et al. 2014b, 2015, 2016, 2019, 2021a, b, El-Shirbeny and Saleh 2021).

The Normalized Difference Vegetation Index (NDVI) is a popular satellite data index that indicates the amount of plant growth. Aridity is determined using NDVI, a common standard for satellite imaging of the world’s land cover. Temperate and tropical rainforests can be found below 0.2, but only temperate rainforests exist above 0.3. (0.6–0.8). Chlorophyll absorbs visible light from 0.4 to 0.7 µm, supplying nutrition to plant leaves. The structure of plant cells reflects a significant amount of near-infrared light (from 0.7 to 1.1 m). Plants with more leaves receive a greater number of light wavelengths.

The treasure trove of archived satellite data from 1972 to the present, in addition to global meteorological data, enlarges the database daily on spatial and temporal resolutions. In the case of high-level data availability, which necessitates highly sophisticated processes, very high-efficiency processors are required; otherwise, processing becomes a massive problem. The Google Earth Engine (GEE) platform enables the processing of large amounts of data. GEE is a cloud-based platform for geospatial analysis on a global scale. It enables researchers to take advantage of Google’s massive computational power. Many topics benefit from intensive work on a global scale.

This study aims to use Google Earth Engine (GEE) to categorize vegetation density, reference evapotranspiration (ETo), crop evapotranspiration (ETc), and rainfall in Arab countries from 2005 to 2020.

2 Materials and Methods

2.1 Study Area Description

The Arab region is located in the center of the old world, between three continents (Africa, Asia, and Europe). Agriculture was established early in the area (thousands of years ago, i.e., in Old Egyptian and Iraqi civilizations), and crop diversification is influenced by climate and water scarcity. The soil and topography differ from place to place. The vast
majority of water resources are obtained from sources outside the country. Wheat and barley are common winter field crops, whereas corn and rice are critical summer field crops. The most common horticultural crops are palm trees, citrus, and olive trees.

The study area is located in the Arab countries region (Fig. 1). The Arab countries are located in two major classes in Köppen climate classification; Class B [Desert (BWh, BWk) and Semi-arid (BSh, BSk)] and Class C [Mediterranean (Csa, Csb, Csc)].

2.1.1 Köppen Climate Classification

Seasonal fluctuations in precipitation and temperature distinguish the five climatic classes of Köppen. Tropical, dry, temperate, continental, and polar are the five major categories (polar). Each category or subcategory is assigned a different letter. There is an essential category for each climate (the first letter). All climates have a seasonal precipitation subgroup, except for the E group (the second letter). Arid climates (sometimes known as desert climates) occur when evaporation exceeds precipitation. Since deserts are often barren, rocky, or sandy, little or no precipitation falls on the surface. The polar environment is the second most common, and dry desert climates cover 14.2% of the Earth’s land surface (Peel et al. 2007).

A semi-arid, semi-desert, or steppe climate gets less than potential evapotranspiration but not as little as a desert climate. Different biomes are born in semi-arid climates that are influenced by various factors such as temperature. Steppe climates (BSk and BSh) are classified as transitional conditions in the Köppen climatic classification between desert climates (BW) and humid climates (BS) (SH). Semi-arid zones are renowned for their shorter and scrappier vegetation.

A Mediterranean climate, often known as a dry-summer climate, has dry summers and slightly moist winters as the norm. It receives its name from the Mediterranean climatic zone, situated roughly 30°–45° north and south of the equator. Mediterranean climates may also be found in climatic zones of the Eastern Hemisphere. The subtropical ridge creates the warm, dry climate for which the Mediterranean is famous in the summer. The Mediterranean or dry-summer climate is influenced by subtropical ridge activity.

2.2 Data Availability

2.2.1 Climate Data

2.2.1.1 Ground Meteorological Data The ground meteorological data of the 35 ground meteorological stations were chosen for inclusion in the dataset. This research region is well covered with stations to cover all Köppen–Geiger climate classes (Fig. 2), and all of them are located closely together. The meteorological data covered 16 years (2005–2020), with every station covered for at least 7 years. The

![Figure 1](https://via.placeholder.com/150) Study area location and its climate classification based on updated Köppen–Geiger climate classification () source: Kottek et al. 2006

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data needed to calculate the ETo were drawn from the FPM model, and it was utilized to validate the SARE model.

2.2.1.2 TerraClimate Data TerraClimate’s monthly water balance parameters, which are a high-resolution (1/24°, 4 km) dataset globally since 1958, were made available for download on the TerraClimate website. The water balance model used in monthly surface water balance datasets contains the effects of ETo, rainfall, Tair, and interpolated vegetation extractable soil water capacity. The findings of TerraClimate were tested for the features of spatiotemporal scales using estimated ETo derived from ground stations. The global mean absolute error was improved, and accuracy and realism were enhanced using TerraClimate datasets (Abatzoglou et al. 2018). The simulated weather data were utilized to fill in the gaps in the ground meteorological data.

2.2.2 Satellite Data

2.2.2.1 Normalized Difference Vegetation Index (NDVI) The vegetation index (VI) measurement in the V6 product of the MYD13Q1 has two main layers: the continuity index to the current NDVI computed by the National Oceanic and Atmospheric Administration-Advanced Very High-Resolution Radiometer (NOAA-AVHRR). Atmospherically adjusted bi-directional surface reflectances are masked for water, clouds, heavy aerosols, and cloud shadows.

2.2.2.2 Land Surface Temperature (LST) A 1,200 km grid resolution and 1 km per pixel LST & E data are included in the MYD11A1 Version 6 package. Pixel temperature is estimated using the MYD11 L2 swath product. Specific pixels, when the prerequisites for a clear sky are achieved, may include numerous observations. The pixel value is calculated as the average of all qualifying observations. Quality control assessments, observation times, view zenith angles, and clear-sky coverages are additionally offered.

2.2.2.3 CHIRPS Rainfall Data Precise estimation of rainfall change is critical for drought warning and environmental monitoring. Since it is the beginning of a drier-than-normal season, it must be assessed in perspective. Satellite data produces region averages, but they may be skewed because of terrain, underestimating unusual precipitation. Station data-generated precipitation grids perform worse in regions without rain gauges. CHIRPS was created in cooperation with scientists from the EROS Center of the USGS to provide detailed, trusted, and up-to-date datasets for early warning objectives, including trend analysis and seasonal drought monitoring.

Early studies focused on combining precipitation enhancement models with interpolated data. Recently, grid-ded satellite-based precipitation estimates from NASA and NOAA have been utilized to build high-resolution (0.05°) gridded precipitation climatologies. Systematic bias, which was a successful technique in producing the 1981–present CHIRPS precipitation data, is eliminated using improved climatologies. CHIRPS’ creation helped the USAID Famine Early Warning Systems Network’s drought monitoring operations (FEWS NET).

2.3 Vegetation Cover Density

Several levels of vegetation cover density will be investigated over the research period, including maximum, minimum, mean, and medium vegetation cover density. MODIS NDVI measurements with a 250 × 250 have been taken every 16 days since 2000. The Max NDVI computes the maximum NDVI value inside each 250 × 250 m². As a result, Max NDVI maps may contain data from different periods.

The NDVI for the site is calculated using a minimum of 250 × 250 m². The Min NDVI calculates the lowest NDVI value for each 250 × 250 m² of the research area. That implies that the Min NDVI maps have data for the driest periods.

Fig. 2 Climatic classification of Arab countries with dispersed meteorological stations in the research region based on an updated Köppen–Geiger climate classification
The Mean NDVI computes the average NDVI value for each 250 × 250 m² during the research.

### 2.4 Reference Evapotranspiration (ETo)

#### 2.4.1 SARE Model

Three sources of input data were used to construct the SARE model. The first is the Spatial Variation Layer (SVL), which changes across locations but stays constant over time. The SVL data includes elevation and Latitude. The second kind of data is Temporal Variation Layer (TVL), which varies over time for the precise location. The Spatio-Temporal Variation Layer (STVL) is the third data type, reflecting the earth’s surface conditions as reflected in chemical, physical, and biophysical interactions reflected by space-borne sensors through received electromagnetic radiation. STVL data include thermal and vegetation conditions. The thermal relies on satellites produced by surface temperature, including topography, surface water, and wind, affecting ET rates directly or indirectly (Kerdiles et al. 1996).

#### 2.4.2 FAO-Penman–Monteith (FPM) Model

The FPM method relies on critical climatological data such as Rad (sunshine), Tair (Max and Min), RH (Max and Min), and U. Weather measurements should be collected at 2 m (or converted to that height) across a wide area of green grass that covers the ground and is well watered to guarantee the accuracy of calculations (Allen et al. 1998):

\[
\text{ETo} = \frac{0.408 \Delta (R_n - G) + \frac{900}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma (1 + 0.34 u_2)},
\]

where \( R_n \) is the net radiation [MJ m⁻² day⁻¹], \( G \) is the soil heat flux density [MJ m⁻² day⁻¹], \( T \) is the mean daily air temperature at 2 m height [°C], \( u_2 \) is the wind speed at 2 m height [ms⁻¹], \( e_s \) is the saturation vapor pressure [kPa], \( e_a \) is the actual vapor pressure [kPa], \( \Delta \) is the slope vapor pressure curve [kPa °C⁻¹], and \( \gamma \) is the psychrometric constant [kPa °C⁻¹].

### 2.5 Crop Coefficient (\( K_c \))

The \( K_c \) is a proportional number (commonly varied from 0.3 to 1.2). The equation expresses the relationship between \( K_c \) and NDVI (2). Driven \( K_c \) using satellite data is widespread, and several researchers employed NDVI to compute \( K_c \):

\[
K_c = \frac{0.9}{\text{NDVI}_{dv}} (\text{NDVI} - \text{NDVI}_{mv}) + 0.3,
\]

where 0.9 is the difference between the highest \( K_c \) rate in arid regions and the minimum number of \( K_c \) recommended by FAO 56 paper (Allen et al. 1998), \( \text{NDVI}_{dv} \) is the interval within the lowest and highest NDVI rate for plants, and \( \text{NDVI}_{mv} \) is the least NDVI rate for plants.

The \( K_c \) equation will be used for Max NDVI and Mean NDVI to calculate the potential and average \( K_c \) in the study region for the research period.

### 2.6 Potential Crop Evapotranspiration (ETc)

The key factor for determining ETc is ETo and \( K_c \), as the following equation reveals:

\[
\text{ETc} = K_c \times \text{ETo}.
\]

The crop coefficient (\( K_c \)) and reference evapotranspiration (ETo) are both dynamic parameters. They depend on microclimate, canopy volume, water, nutrient availability, and pest and disease-free conditions.

The ETc equation will be used to compute potential and average ETc in the study area during the research period using potential \( K_c \) and mean \( K_c \).

### 2.7 Validation

Three statistical factors were employed to test the model-related assumptions of the SARE, which pertains to the FPM. This parameter has the following definition:

\[
\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (X_i - X_{obs})^2}{n}},
\]

\[
d = 1 - \frac{\sum_{i=1}^{n} [(X_i - X_m) - (X_{obs} - X_m)]^2}{\sum_{i=1}^{n} [(X_i - X_m) + (X_{obs} - X_m)]^2},
\]

\[
r = \frac{(X_{obs} X_i) - (X_{obs})(X_i)}{\sqrt{(X^2_{obs}) - (X_{obs})^2} \sqrt{(X_i^2) - (X_i)^2}}.
\]

where RMSE is the root mean square error, \( d \) is the index of agreement, \( r \) is the correlation coefficient, variable \( n \) is the number of observations, \( X_{obs}, i \) is the observation of sample \( i, X_i \) is the simulated result for the sample \( i, \) and \( X_m \) is the average value.

The flowchart in Fig. 3 describes the framework for the approaches that were utilized in this paper, which serves as a summary of the methodologies.
3 Results and Discussion

3.1 Reference Evapotranspiration Classification

From 2005 to 2020, the annual ETo was estimated using the SARE model. MODIS data were utilized, with LST 1 km spatial resolution and NDVI 250 m. The average annual ETo data have been divided into five categories: Class 1 (less than 1200 mm/year), Class 2 (between 1200 and 1700 mm/year), Class 3 (between 1700 and 2300 mm/year), Class 4 (between 2300 and 2800 mm/year), and Class 5 (beyond 2800 mm/year).

Classes 1 and 2 are found in the northern region, particularly in high elevation areas. While the third class is prevalent in the eastern portion of the Red Sea, it is also abundant in the northern section of the Mediterranean Sea. Class 4 is prevalent in vast parts of the desert belt. The fifth class is located mainly in eastern Egypt and Sudan, as well as a significant region in the UAE, Sultanate of Oman, and south Saudi Arabia.

According to the comparison of Figs. 4 and 5, there are many differences between the ETo map and the K–G climate classification map, showing the need to regularly update the K–G climate classification map for the Arab region. The ETo map indicated more details in BWh climate class of the Köppen–Geiger climate classification map.

From 2005 to 2020, the average RMSE (mm/month) for the SARE model compared to the FAO-Penman–Monteith approach was classified into five classes: Class 1 (6.9–9.1, mm/month), Class 2 (9.1–11.1, mm/month), Class 3 (11.1–12.3, mm/month), Class 4 (12.3–14.1, mm/month), and Class 5 (14.1–17.3, mm/month). Class 1 is concentrated in the north, whereas the remaining classes show no discernible trend (Fig. 6).

3.2 Potential Crop Evapotranspiration Classification

The average of ETo and $K_c$ from 2005 to 2020 was used to compute the average potential crop evapotranspiration (ETc) shown in Fig. 6. The ETc for Arab nations was derived using the SARE model of ETo and $K_c$ calculated using NDVI 250 m data (Eq. 2). The average annual ETc data have been classified into five categories: Class 1 (less than 500 mm/year), Class 2 (between 500 and 800 mm/year), Class 3 (between 800 and 1200 mm/year), and Class 5 (above 1700 mm/year).

The most critical factors influencing ETc value in dry areas are vegetation cover density and growth period.
Fig. 4 The Arab countries’ yearly ETo categorization map based on satellite data from 2005 to 2020.

Fig. 5 The climatic classification of Arab countries based on an updated Köppen–Geiger climate classification.

Fig. 6 Distributed map of the average RMSE (mm/month) of SARE results compared to the FAO-Penman–Monteith from 2005 to 2020.
duration. According to Fig. 7, Class 1 is the default class in the region, occupying the main class as evident in arid settings, where precipitation is infrequent and, therefore, vegetation is few. The second class, in contrast to the first, has a low distribution. The third class is found in the northern and southern parts of the country, depending on the duration of the growing season and the reference values of ETo during the growing season. The fourth class is visible in multi-seasonally irrigated regions such as Egypt’s Nile delta and valley and the northwestern region along the Mediterranean Sea, and the southern portion of Sudan. The fifth class represents dense or medium vegetation values that accumulate high reference values of ETo throughout the growing season.

Figure 8 estimates the maximum potential evapotranspiration (ETc) based on the most excellent vegetation cover density recorded in the study area over the last 16 years and the mean ETo. This simulated figure represents the region’s potential water consumption for maximal vegetation cover throughout the study. The distribution of vegetation cover is determined by the quantity and distribution of rainfall beside irrigated areas. 49.152 Mha is the maximum quantity of vegetation area.

### 3.3 Vegetation Density Classification

Figure 9 shows a minimum vegetation cover classification map based on the minimum NDVI values recorded in the study area over the last 16 years. Four classes represent the region’s driest conditions. The dominant class is no vegetation, with NDVI values less than 0.17, and class 2 (low vegetation) with NDVI values ranging from 0.17 to 0.3. Class 3 (Medium vegetation) had NDVI values ranging from 0.3 to 0.5, while class 4 (Dense vegetation) had NDVI values greater than 0.5. This figure depicts the driest period for each pixel for the study. The minimum amount of vegetation is 14.930 Mha.
The minimum vegetation cover represents the region’s permanent vegetation over the last 16 years, implying the region’s lowest border of vegetation cover.

Figure 10 depicts a categorization map of average plant cover based on mean NDVI values measured in the research region during the past 16 years. The mean vegetation cover map reflects the region’s average vegetation density over the past 16 years. Four groups represent the average vegetation cover conditions. The dominating class was still no vegetation, with NDVI values less than 0.2, and class 2 (poor vegetation), with NDVI values ranging from 0.2 to 0.4. NDVI levels in Class 3 (Medium Vegetation) ranged from 0.4 to 0.6, whereas NDVI values in Class 4 (Dense Vegetation) exceeded 0.6. This figure shows the average period conditions for each pixel throughout the research. The average area of vegetation is 31.490 Mha.

The median vegetation cover reflects the region’s median value of vegetation density over the past 16 years. There are considerable variations in mean and median vegetation cover distribution, particularly in the southern portion of Arab nations (Mauritania, Sudan, and Somalia). Figure 11 depicts a categorization map of the highest vegetation cover based on median NDVI values obtained in the research region during the past 16 years. Four groups represent the median values of vegetation cover conditions. The dominating class was still no vegetation, with NDVI values less than 0.2, while class 2 (poor vegetation) had NDVI values ranging from 0.2 to 0.4. NDVI levels in Class 3 (medium vegetation) ranged from 0.4 to 0.6, whereas NDVI values in Class 4 (dense vegetation) exceeded 0.6. This graph shows the period’s median conditions for each pixel throughout the length of the research. The average area of vegetation is 29.84 Mha.

Figure 12 depicts a categorization map of the highest vegetation cover based on maximum NDVI values observed in the research region during the past 16 years. Four classes represent the potential vegetation cover of the area. The no vegetation class is still the dominating class, with NDVI
values less than 0.26, while class 2 (low vegetation) has NDVI values ranging from 0.26 to 0.54. Class 3 (Medium vegetation) had NDVI values ranging from 0.54 to 0.8, whereas class 4 (Dense vegetation) had NDVI values higher than 0.8. This figure shows the most vegetation expanding and density phase for each pixel throughout the research. The maximum quantity of vegetation is 49.152 Mha.

The maximum vegetation cover reflects the region's potential vegetation during the past 16 years, indicating the region's highest boundary of vegetation cover.

Comparing the maximum vegetation cover distribution for 2005 and 2020, there are some differences around the map. The maximum vegetation cover represents the potential value of vegetation density in the region during the years 2005 (Fig. 13) and 2020 (Fig. 14), which show a classification map of the maximum vegetation cover based on the maximum NDVI values recorded in the study area. Four classes represent the average vegetation cover conditions. The dominant class still indicated no vegetation, with NDVI values less than 0.26, and class 2 (low vegetation) with NDVI values ranging from 0.26 to 0.54. Class 3 (Medium vegetation) had NDVI values ranging from 0.54 to 0.8, while class 4 (Dense vegetation) had NDVI values greater than 0.8. This figure depicts the median conditions of the period for each pixel throughout the study. The potential amount of vegetation is 30.6 Mha and 31.7 Mha for 2005 and 2020, respectively.

### 3.4 Rainfall Classification

The quantity of rainfall is the most important driving element for the growth of vegetation cover in arid, semi-arid, and sub-humid environments. The rainfall map shows the most significant vegetation cover spreading as two boundaries, one in the north, near the Mediterranean Sea, and the other in the south, with barren soil desert in between save for a few areas that rely on irrigation systems.
Fig. 13  Maximum vegetation cover classification map based on the maximum NDVI values recorded in the study area in 2005

Fig. 14  Maximum vegetation cover classification map based on the maximum NDVI values recorded in the study area in 2020

Fig. 15  Average yearly rainfall classification map
Figure 15 depicts a yearly average rainfall classification map based on average precipitation values (mm/years) observed in the research region for 16 years. Five classifications represent the area's yearly average rainfall.

The first class is the driest section of the research region since the rainfall does not exceed 100 (mm/year), class 2 (100–200, mm/year), and class 3 (200–400, mm/year). The fourth class runs from 400 to 800 mm each year, whereas the fifth class goes from 800 to 1200 mm per year.

The fifth class, which may be suggested for rainy cultivation for at least one season, encompasses 4.997 Mha. The fourth class might potentially be suggested for rainy cultivation for at least one season, covering an area of 10.836 Mha. The third class, which covers 33.033 Mha, may be recommended for rainy agriculture for at least one season but requires supplementary irrigation. The second class is insufficient for agriculture in the southern portion but may be utilized in the northern section during the winter with supplementary irrigation for at least one season, covering 26.706 Mha.

4 Conclusion

This research was carried out in Arab nations throughout the preceding 16 years, from 2005 to 2020. The average vegetation cover was determined to be 31.5 Mha. The minimum and maximum vegetation densities in the region represent the significant changes in amount and space generated by the dry and wet seasons. The lowest vegetation cover was 14.9 Mha, while the greatest was 49.2 Mha. The 250 m spatial resolution NDVI MODIS data are sufficient for large-scale investigations like this one, but it might be enhanced using higher spatial resolution data such as the Landsat series with 30 m spatial resolution and Sentinel-2 with 10 m spatial resolution. Cloud computing can help with more significant resolution processing, and the authors may do a similar study in the future with a higher spatial resolution for more precise results.

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Declarations

Conflict of interest On behalf of all the authors, the corresponding author states that there is no conflict of interest.

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References

Abatzoglou JT, Dobrowski SZ, Parks SA, Hegewisch KC (2018) TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015. Sci Data 5:1–12. https://doi.org/10.1038/sdata.2017.191

Abdelkhaliq A, Pascual B, Näjera I, Domene MA, Baixauli C, Pascual-Seva N (2020) Effects of deficit irrigation on the yield and irrigation water use efficiency of drip-irrigated sweet pepper (Capsicum annuum L.) under Mediterranean conditions. Irrig Sci 38(1):89–104. https://doi.org/10.1007/s00227-019-00655-1

Albawi B, Gharabaghi B, Alazza AA, Mahboubi AA (2015) Evapotranspiration models assessment under hyper-arid environment. Arab J Geosci 8:9905–9912

Allen RG, Perrier LS, Raes D, Smith M (1998) Crop evapotranspiration: guidelines for computing crop requirements. FAO Irrigation and drainage. paper No. 56, Rome, Italy

Almazroui M, Saeed F, Saeed S, Islam MN, Ismail M, Klutse NAB, Siddiqui MH (2020a) Projected change in temperature and precipitation over Africa from CMIP6. Earth Syst Environ 4(3):455–475

Almazroui M, Saeed S, Saeed F, Islam MN, Ismail M (2020b) Projections of precipitation and temperature over the South Asian countries in CMIP6. Earth Syst Environ 4(2):297–320

Chan D, Wu Q (2015) Significant anthropogenic-induced changes of climate classes since 1950. Sci Rep 5(13487):13487

Chen D, Chen HW (2013) Using the Köppen classification to quantify climate variation and change: an example for 1901–2010. Environ EDev 6:69–79

Chen H, Chen D (2017) Köppen climate classification. hanschen.org. Archived from the original on 2017-08-14. Retrieved -08-04

Critchfield HJ (1983) General climatology, 4th edn. Prentice Hall, New Delhi, pp 154–161 (ISBN 978-81-203-0476-5)

Dooenbos J, Pruitt WO (1977) Crop water requirement: food and agriculture organization of the United Nations. FAO Irrigation and Drainage Paper 24, Rome, 144 pp

El-Shirbeny MA, Abdellatif B (2017) Reference evapotranspiration borders maps of Egypt based on Kriging spatial statistics method. Int J Geomat 13:1–8. https://doi.org/10.21660/2017.37.63048

El-Shirbeny MA, Abutaleb KA (2018) Monitoring of water-level fluctuation of Lake Nasser using altimetry satellite data. Earth Syst Environ 2(2):367–375

El-Shirbeny MA, Saleh SM (2021) Actual evapotranspiration evaluation based on multi-sensed data. J Aridland Agric 7:95–102. https://doi.org/10.25081/jaa.2021.v7.7.087

El-Shirbeny MA, Aboolghar MA, Arafat SM, El-Gindy AGM (2014a) Assessment of the mutual impact between climate and vegetation cover using NOAA-AVHRR and Landsat data in Egypt. Arab J Geosci 7(4):1287–1296

El-Shirbeny MA, Ali A, Saleh N (2014b) Crop water requirements in Egypt using remote sensing techniques. J Agric Chem Environ 3:57–65

El-Shirbeny MA, Alerssy MAM, Saleh NH, Abu-Taleb KA (2015) Changes in irrigation water consumption in the Nile

 Springer
Delta of Egypt assessed by remote sensing. Arab J Geosci 8(12):10509–10519
El-Shirbeny MA, Ali AM, Saleh NH (2016) Evaluation of Hargreaves based on remote sensing method to estimate potential crop evapotranspiration. Int J Geomat 11(23):2143–2149
El-Shirbeny MA, Mohamed ES, Negm A (2019) Estimation of crops water consumptions using remote sensing with case studies from Egypt. In: Conventional water resources and agriculture in Egypt, pp 161–186
El-Shirbeny MA, Ali AM, Savin I (2021a) Agricultural water monitoring for water management under pivot irrigation system using spatial techniques. Earth Syst Environ 5:341–351. https://doi.org/10.1007/s41748-020-00164-8
El-Shirbeny MA, Ali AM, Khedery GA, Saleh NH, Afify NM, Badr MA, Bauomy EM (2021b) Monitoring agricultural water in the desert environment of New Valley Governorate for sustainable agricultural development: a case study of Kharga. Euro-Mediterr J Environ Integr 6(2):1–15
Häusler M, Conceição N, Tezza L, Sánchez JM, Campagnolo ML, Häusler AJ, Ferreira MI et al (2018) Estimation and partitioning of actual daily evapotranspiration at an intensive olive grove using the STSEB model based on remote sensing. Agric Water Manag 201:188–198
Holzman ME, Carmona F, Rivas R, Nicolás R (2018) Early assessment of crop yield from pleaseremotely sensed water stress and solar radiation data. ISPRS J Photogramm Remote Sensing 145:297–308
Jarvis A, Ramírez J, Anderson B, Leibing C, Aggarwal P (2010) Scenarios of climate change within the context of agriculture. Climate change and crop production p 1
Kerdiles H, Groundena M, Rodrigues R, Seguin B (1996) Forest mapping using NOAA-AVHRR data in the Pampean region, Argentina. Agric for Meteorol 79:157–182
Kottek M, Grieser J, Beck C, Rudolf B, Rubel F (2006) World map of the Köppen–Geiger climate classification updated. Meteorol Z 15(3):259–263
Mohamed ES, Belal AA, Abd-Elmabod SK, El-Shirbeny MA, Gad A, Zahran MB (2021) Smart farming for improving agricultural management. Egypt J Remote Sens Space Sci (in press)
Mohorji AM, Şen Z, Almazroui M (2017) Trend analyses revision and global monthly temperature innovative multi-duration analysis. Earth Syst Environ 1(1):1–13
Papadavid G, Hadjimitsis D, Michaelides S, Nisantzi A (2011) Crop evapotranspiration estimation using remote sensing and the existing network of meteorological stations in Cyprus. Adv Geosci 30:39–44
Parry M, Rosenzweig C, Livermore M (2005) Climate change, global food supply and risk of hunger. Phil Trans Roy Soc B 360:2125–2138. https://doi.org/10.1098/rstb.2005.1751
Peel MC, Finlayson BL, McMahon TA (2007) Updated world map of the Köppen–Geiger climate classification. Hydrol Earth Syst Sci 4(2):439–473
Thornton PK, Jones PG, Ericksen PJ, Challinor AJ (2011) Agriculture and food systems in sub-saharan Africain a 4°C+ world. Philosophical transactions of the royal Society A: Mathematical, physical and engineering sciences 369:117–136
Tolba RA, El-Shirbeny MA, Abou-Shleel SM, El-Mohandes MA (2020) Rice acreage delineation in the Nile Delta based on thermal signature. Earth Syst Environ 4(1):287–296
Xiang K, Li Y, Horton R, Feng H (2020) Similarity and difference of potential evapotranspiration and reference crop evapotranspiration—a review. Agric Water Manag. https://doi.org/10.1016/j.agwat.2020.106043
Xue J, Su B (2017) Significant remote sensing vegetation indices: a review of developments and applications. J Sens 2017:17p
Yin Y, Wu S, Du Z, Yang O (2008) Radiation calibration of FAO56-Penman Monteith model to estimate reference crop evapotranspiration in China. Agric Water Manag 95:77–84
Zhao S, Yang Y, Zhang F, Sui X, Yao Y, Zhao N, Zhao Q, Li C (2015) Rapid evaluation of reference evapotranspiration in Northern China. Arab J Geosci 8:647–657