

Article

Evaluating the Impacts of Climate Change on Irrigation Water Requirements

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Abstract: Climate change and its impact on agriculture and water resources have become a global concern. The implications of extreme weather events on food production and water resource availability are starting to have social and economic effects worldwide. The present research aims at integrating the analysis of the atmospheric parameters with remote sensing, geographic information systems, and CROPWAT 8 model to evaluate the impacts of climate change on the irrigation water requirements estimates in a selected area in El-Beheira governorate, Egypt. Remote sensing and GIS are incorporated to produce land-use/land-cover maps and soil properties maps. On the other hand, the atmospheric parameters were analyzed using python analytical coding. The study utilized the Land-use/Land-cover (LU/LC) map produced from Sentinel-2 data. The agricultural area covered about 89% of the studied area and was occupied by seven crops. Wheat and berseem were the major crops in the area and covered about 67% of the studied area; therefore, their irrigation water requirements were calculated utilizing the CROPWAT 8 model. Furthermore, citrus irrigation water requirements were also included in this research, even though it only covered 10% of the studied area because it had the highest amount of irrigation water requirements. Forecasting the potential climate changes under the best-case scenario for the next thirty years revealed that the studied area will have no rain and a slight decrease in the average temperature. Accordingly, the irrigation water requirements will increase by almost 4% under current practices, and the increase will reach about 13% under no-field loss practices.

Keywords: GIS; remote sensing; irrigation water requirements; CROPWAT model; climate change



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1. Introduction

Climate change and global warming have become the main concern of studies in the field of water resources, agriculture, ecology, and other disciplines [1]. Global warming promoted shifts in the climatic zones of various parts of the world, causing expansion in arid zones and reduction of glacial areas—consequently resulting in changes in the abundance and seasonal activities of various plant and animal species. Climate change also caused changes in rainfall intensity, drought frequency and severity, wind speed, and rise in sea level [2]. An example of these changes was reported by [3]. They stated that the mean surface temperature in the Himachal Pradesh state of the Himalayan Mountains has increased by almost 0.5 °C from 2000 to 2014. These changes were directly related to global warming, caused a reduction in apple production in low altitudinal regions of the state, and created new opportunities for apple cultivation in higher regions where the growth conditions became more favorable for apples.

Irrigated agriculture depends on freshwater from rivers, lakes, and aquifers and it consumes about 70% of the total renewable water resources [4]. Agriculture is directly

affected by climatic conditions and changes, and it is essential to understand the impact of climate change on agricultural water resources for sustainable agriculture and to minimize the negative effects caused by such changes [1]. According to [5], lack of rainfall, soil moisture, and persistent above-normal temperatures are found to be the important factors in cases of severe loss in rice productivity in Bihar state, India. Furthermore, food security has been affected by climate change due to warming, changing precipitation patterns, and increasing frequency of extreme events [2]. Therefore, careful planning of water use by crops is of strategic importance from farm to the global level [6].

Remote sensing data have been excessively used in mapping the agriculture area and detecting their change as well as mapping water resources and their changes, which is vital for evaluating water availability and usability. Furthermore, the capability of GIS to analyze and visualize spatial information can be very important in water resources management. Considering their data collection and analysis capability, they are viewed as efficient and effective tools for irrigation water management. For example, remote sensing can be used in improving agricultural irrigation water accounting, both independently and in combination with in situ monitoring [7].

On the other hand, other studies utilized available models, such as CROPWAT, to develop sound water management strategies. The model was used to calculate the crop water requirements of selected crops under different environmental conditions, such as humid tropical areas [8] and Hungarian conditions [9]. The model was also utilized to study the crop water requirements when intercropping maize with rice, as well as intercropping maize with soybeans [10]. The model was also used to improve water management in selected on-farms in Egypt, and scenarios were suggested which could lead to saving irrigation water [11].

Moreover, remote sensing and GIS have been coupled with CROPWAT to simplify the water management process. CROPWAT was used to estimate the irrigation water requirements for selected crops and to compare the results with the farmer irrigation practices [12]. The author could verify that the irrigation practices exceeded the irrigation water requirement by 30%. The spatial distribution of irrigation water requirements in the study area derived by the GIS technique could be a good management tool for planners and decision-makers to minimize the overexploitation of the water resources. An integrated approach of remote sensing, GIS, and CROPWAT model was used to determine the irrigation requirements of rice crops on different soils [13]. Satellite data were used to estimate the rice and fallow lands, and climate and soil data were integrated into the GIS platform. On the other hand, the CROPWAT model was used to determine crop evapotranspiration. Utilizing this approach, water deficiency and excess could be detected and could, thereafter, allow for better management in the studied area. The use of CROPWAT and GIS was studied to estimate crop water requirements in a selected area, and the results could be used for irrigation management of the different crops in the study area [14].

Moreover, CROPWAT was utilized in addition to climate models and under different scenarios to study the impact of climate change on crop water demand and irrigation requirements [6]. The results showed that under climatic changes in Serbia, irrigation water requirements will increase for sugar beet and potato to keep the actual quantity and quality of crop yield. A similar approach was followed, and the results revealed that there will be both rise and fall in crop water requirement for future scenarios when compared with baseline conditions depending on the crop [15].

The objective of the current work is to integrate the atmospheric data analysis remote sensing, GIS, and CROPWAT model to estimate the potential impacts of climate change on the irrigation water requirements of selected crops in a study area located in El-Beheira governorate, Egypt.

2. Materials and Methods

Figure 1 demonstrates the methodology and materials used in this study.

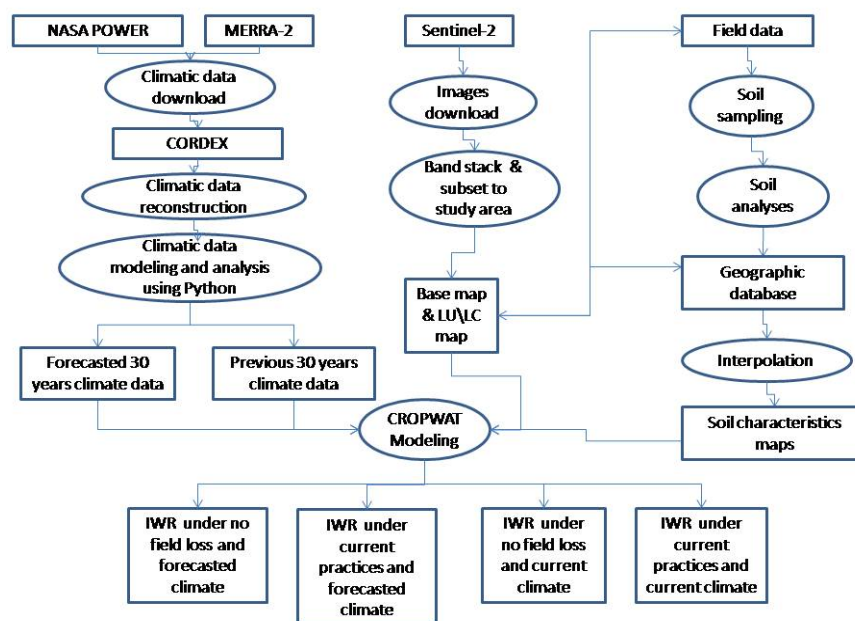


Figure 1. Methodology flowchart.

2.1. Study Area

The study area is located about 45 km south of Alexandria City and is considered part of El-Beheira governorate. The area is bounded by latitudes $30^{\circ}41'55''$ and $30^{\circ}53'20''$ N and longitudes $29^{\circ}58'40''$ and $30^{\circ}11'20''$ E. It extends to cover a total acreage of about 175 km². It is surrounded by three irrigation canals: Nubariyah Canal to the east, Al-Hidayah Canal to the north, and Al-Nasr Canal to the south, while Cairo–Alexandria Desert Road outlined its western boundary (Figure 2). The area is irrigated from An-Nasr canal via various small branches. Nevertheless, the area is characterized by shortage of irrigation water [16].

The land use/land cover map produced by [16] was used in this study. This map was produced from four Sentinel-2 (S2) images acquired on 18 October 2020, 27 December 2020, 17 March 2021, and 6 April 2021. The images used covered most of the winter growing season, which extended from October 2020 to May 2021. The overall classification accuracy was 86.8% (Figure 3). According to the same authors, wheat and berseem were the major crops in the study area and covered about 67% of the study area. Green beans, potato, and citrus covered about 21%, while guava and strawberry covered less than one percent each (Table 1).

Table 1. Acreage of the Land use/Land cover units.

Class	km ²	%
Wheat	60.08	34.19
Berseem	57.27	32.59
Green beans	21.00	11.95
Potato	6.32	3.60
Citrus	10.00	5.69
Strawberry	0.87	0.50
Guava	0.80	0.46
Fish ponds	3.48	1.98
Settlements	15.89	9.04
Total	175.71	100.00

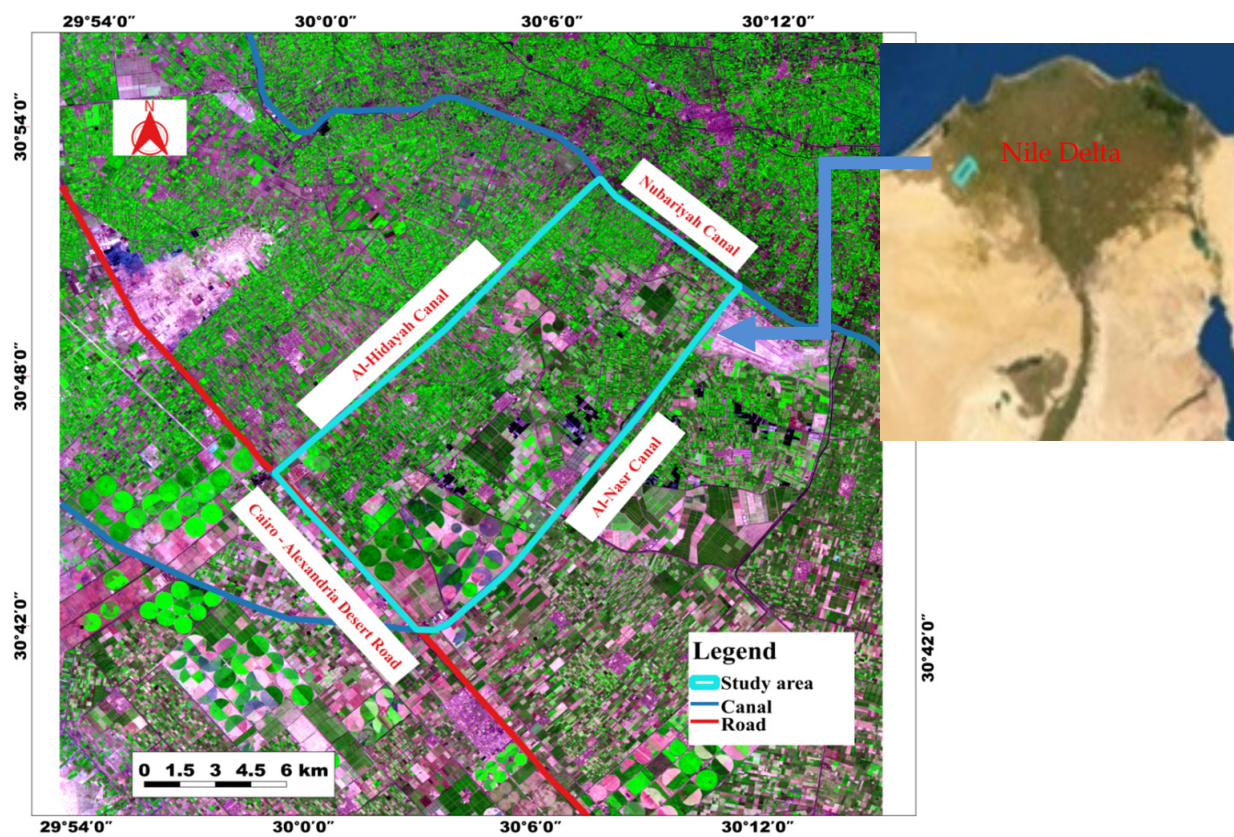


Figure 2. Location map of the study area (modified after [16]).

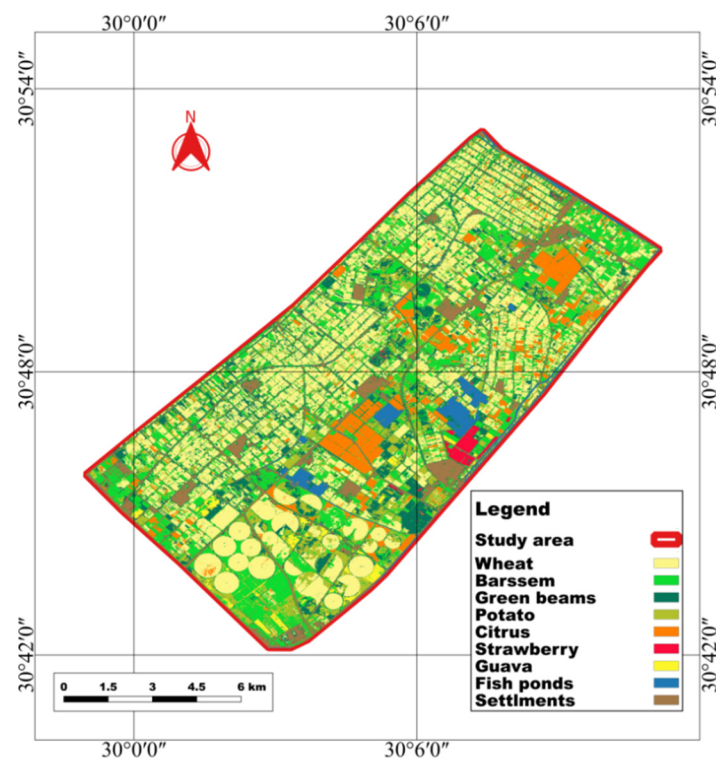


Figure 3. Land use/Land cover classification map of the study area (Modified after [16]).

2.2. Fieldwork

Fieldwork was carried out from December 2020 to March 2021. Soil sampling was designed along a grid system (1 observation per 1 km²), and samples were collected using an auger. A total of 167 soil observations were planned for analyses, but only 149 samples were collected due to the inaccessibility of sample locations (Figure 4). Samples were geo-referenced using a GPS utility. For orchards, three soil samples were collected to 120 cm, while for other crops, two samples were collected to 75 cm depth. For each location, the weighted average of each measured soil characteristic was calculated [17].

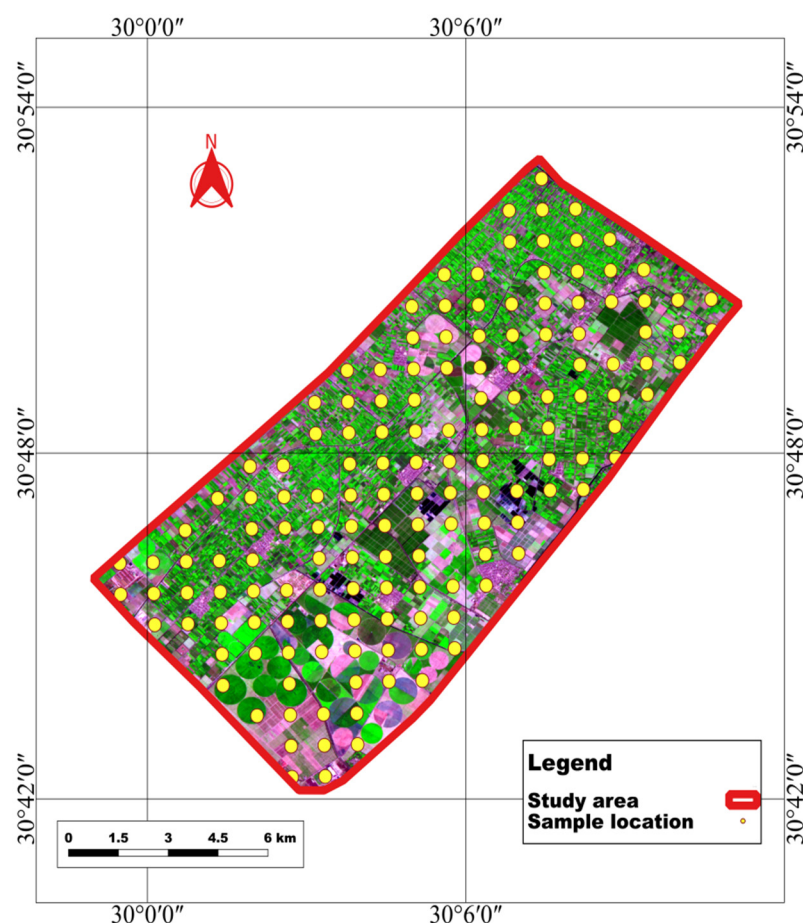


Figure 4. Location map of the soil samples.

2.3. Laboratory Analysis

The collected soil samples were air-dried, ground gently, and sieved through a 2 mm sieve. They were analyzed concerning the soil's physical properties. Determining the sample's particle size distribution was according to [18]. Other soil physical properties, including wilting point, field capacity, bulk density, hydraulic conductivity, and available water, were determined according to [19].

2.4. Geostatistical Analysis

After the average weight values calculated to the designated depths were calculated for each soil characteristic, these data were added to the QGIS software to produce a detailed soil database.

Spatial interpolation is the process of using a set of point data to create surface data [20]. Spatial interpolation has been widely and commonly used in many studies on a set of sampled points, such as soil properties, temperature, and precipitation, to produce a continuous representation of the phenomenon in question [21].

The inverse distance weighting (IDW) was developed by the U.S. National Weather Service in 1972. IDW is considered one of the most frequently used deterministic models in spatial interpolation. It is relatively fast and easy to compute, and straightforward to interpret. Its general idea is based on the assumption that the attribute value of an unsampled point is the weighted average of known values within the neighborhood, and the weights are inversely related to the distances between the prediction location and the sampled locations [22].

2.5. The CROPWAT Model

The crop water requirement refers to the total amount of water required by the crop from the time of cultivation to the time of harvest. On the other hand, the irrigation water requirement refers to the difference between the evapotranspiration of the crop under ideal conditions and the effective rainfall throughout the growing season. It is a measure of the excess quantity of water added through irrigation to guarantee optimum crop growth conditions [15].

The CROPWAT 8.0 is an empirical process-based crop model [23]. It provides an opportunity for automation of all the necessary calculations for evapotranspiration determination. The model uses the Penman–Monteith method as a base for calculations of evapotranspiration, crop water requirements, irrigation water requirements for separate crops and crop rotations, building of the irrigation schedules, etc. [24]. The Penman–Monteith methodology is recommended for estimating crop water requirements, especially for planning purposes [25]. The advantage of CROPWAT is its simplicity and easiness to use. Furthermore, the program requires less intense data. The model analyzes complex relationships of on-farm parameters, including crop, climate, and soil, for assisting in irrigation management and planning [9]. Its main functions are to calculate reference evapotranspiration, crop water requirements, and crop irrigation requirements to develop irrigation schedules under various management conditions, scheme water supply, and evaluate the efficiency of irrigation practices [26].

2.6. Climate Data Processing

2.6.1. Climate Data Download and Extraction

The climatic data used and analyzed in this study were obtained from NASA's POWER (Prediction Of Worldwide Energy Resource) and The Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2). NASA POWER is available for download from <https://power.larc.nasa.gov/data-access-viewer> (accessed on 1 January 2021). The data available from this site are in grid resolution 0.5×0.5 degrees [27]. On the other hand, MERRA-2 is the latest atmospheric reanalysis of the modern satellite era produced by NASA's Global Modeling and Assimilation Office (GMAO), and has a spatial resolution of 0.5×0.67 degrees (latitude $\times$ longitude) [28]. MERRA-2 data are available at <https://giovanni.gsfc.nasa.gov/giovanni> (accessed on 1 January 2021).

The data collected and processed for the studied area included only: Day Length (sunshine hours), Precipitation (mm/month), Temperature at 2 m ($^{\circ}\text{C}$), Maximum Temperature at 2 m ($^{\circ}\text{C}$), Minimum Temperature at 2 m ($^{\circ}\text{C}$), Wind Speed at 10 m (m/s), and Relative Humidity at 2 m (%). The temperature at 2 m, maximum and minimum temperatures were available at hourly time step and were used to deliver daily values, while the other variables were daily values already, and the data were continuous with no missing values. All the data were downloaded from MERRA-2, except the sunshine hours which were downloaded from NASA's POWER.

The Coordinated Regional Climate Downscaling Experiment (CORDEX), a framework sponsored by the World Climate Research Program, which is responsible for the global coordination of regional climate downscaling to improve regional climate change adaptation and impact assessment, was used in this study [29]. Both Weather Research and Forecasting model (WRF) and Regional Climate Model (RegCM) within the CORDEX were used to determine which could provide the necessary climate variables to reconstruct a

weather file that will be used as an input for at least one future scenario (temperature, solar radiation, relative humidity, atmospheric pressure, cloud cover, and wind speed) [30,31]. The reconstructed weather data were available in the popular NetCDF4 format.

2.6.2. Climate Data Analysis

The daily maximum and minimum temperature data were quality controlled for the period from 1991 to 2020 (i.e., outliers were checked and verified with metadata and corrected where applicable). Climate data analysis included checking and analyzing the temperatures over the historical period (1991–2020) as a reference period and carrying out a future run for the period 2021–2050; considering thirty years is standard in climatology to eliminate the uncertainty related to the internal climate variability. These historical periods are usually used in the literature and are the least referenced periods that are available on the platform. According to the literature, it is generally accepted that the 21st century can be divided into three equal future periods: The short-future (2011–2040), medium-future (2041–2070), and long-future (2071–2100) [30]. The data were processed using Python analytical coding.

3. Results and Discussion

3.1. Climatic Data Processing

The monthly meteorological data for the last thirty years (1991–2020) revealed that the maximum temperature ranged from 23.4 to 41.1 °C, while the minimum temperature ranged from 12.0 to 23.9 °C. The maximum temperature was recorded in June, whereas the minimum was recorded in January. The average minimum and maximum temperatures were 18.4 and 33.8 °C, respectively. The maximum relative humidity was 64.7%, while the minimum was 47.1%. The wind speed ranged from 229 to 286 km/day, with an average of 254 km/day. The average sunshine period was 10.5 h. There was no rain during August and almost no rain in May, June, July, and September. The highest amount of rain was in April and reached 7.6 mm/month. The total annual rain throughout the year was 39.4 mm (Table 2).

Table 2. Meteorological data of the studied area from 1991–2020.

Month	Temperature °C		Humidity (%)	Wind (km/Day)	Sunshine (Hours)	Precipitation (mm)	ET _o mm/Day
	Tmax	Tmin					
Jan.	23.4	12.0	64.7	240	10.4	6.1	3.01
Feb.	26.8	12.1	60.8	243	10.4	5.4	3.94
Mar.	31.9	14.8	55.8	256	10.5	6.9	5.51
Apr.	37.1	18.3	48.9	269	10.5	7.6	7.45
May	33.5	16.0	53.5	259	10.5	0.5	6.79
Jun.	41.1	22.4	47.1	286	10.5	0.5	8.74
Jul.	40.9	23.7	49.7	280	10.5	0.2	8.58
Aug.	39.8	23.9	52.1	259	10.6	0.0	7.80
Sep.	38.8	23.1	53.9	253	10.6	0.2	7.10
Oct.	36.1	21.4	57.6	237	10.6	2.4	5.71
Nov.	30.7	17.9	61.5	229	10.6	6.3	4.41
Dec.	25.4	14.5	64.5	237	10.7	3.3	3.14
Average/ Total	33.8	18.4	55.9	254	10.5	39.4	5.99

The monthly meteorological data for the next thirty years (2021–2050) are shown in Table 3. The data revealed that the maximum temperature ranged from 19.6 to 38.9 °C, while the minimum temperature ranged from 8.5 to 24.5 °C. The maximum temperature was recorded in August, whereas the minimum was recorded in January. The relative humidity ranged from 37.0% to 58.0%, with an average of 46.0%. The wind speed ranged from 250 to 379 km/day. The average sunshine hours were 12.2. There was no rain throughout the year.

Table 3. Meteorological forecasted data of the studied area from 2021 to 2050.

Month	Temperature °C		Humidity (%)	Wind (km/Day)	Sunshine Hours	Precipitation (mm)	ET _o mm/Day
	Tmax	Tmin					
Jan.	19.6	8.5	54.6	279	10.4	0.00	3.14
Feb.	21.6	9.2	48.0	309	11.1	0.00	4.20
Mar.	25.5	12.0	41.8	350	12.0	0.00	5.94
Apr.	29.4	15.2	37.8	379	12.9	0.00	7.76
May	33.3	19.0	37.0	354	13.7	0.00	8.92
Jun.	36.8	22.8	37.2	364	14.1	0.00	10.05
Jul.	38.8	24.5	39.7	367	13.9	0.00	10.36
Aug.	38.9	24.4	41.2	344	13.2	0.00	9.71
Sep.	36.4	22.8	45.4	327	12.4	0.00	8.17
Oct.	30.8	19.4	51.8	275	11.4	0.00	5.67
Nov.	25.6	14.3	54.6	250	10.7	0.00	3.95
Dec.	20.7	9.9	58.0	252	10.2	0.00	2.94
Average/ Total	29.8	16.8	46.0	321	12.2	0.00	6.73

The data revealed that compared to the previous thirty years, there will be a noticeable decrease in the total amount of rain and an increase in the sunshine hours as well as wind speed. The ET_o was calculated using the CROPWAT model and ranged from 3.01 to 8.74 mm/day, with an average of 5.99 mm/day in the previous thirty years. On the other hand, the ET_o for the next thirty years ranged from 2.94 to 10.36 mm/day, averaging 6.73 mm/day. The observed difference between the monthly precipitation and ET_o ensures that there is a need for efficient irrigation throughout the year, especially in the upcoming thirty years under such forecasted conditions.

3.2. Processing of the Soil Data for the CROPWAT Model

The results of the soil physical analyses were used to develop a geographic database of the studied area. Nevertheless, the data were in the form of a point database. To convert these point data into spatially continuous data, spatial interpolation using IDW was employed utilizing the QGIS software. The IDW was performed using the power of two, a minimum of four points, and a maximum of 16. The accuracy of results was obtained using the cross-validation procedure as described by [17] for all the studied soil properties. Twenty-two samples, representing about 15% of the samples, were used for validation, while the rest of the samples were used for IDW. The performance evaluation was applied using the root mean square error (RMSE) [17]. The results revealed that the RMSE was 9.77, 7.55, and 7.78 for sand, silt, and clay, respectively. On the other hand, the RMSE for available moisture content (AMC) and infiltration rate (IR) was 15.03 and 4.84, respectively.

Utilizing the raster calculator, a model was developed to classify the soils based on their content into different soil texture classes. The resulting data revealed that the study area could be classified into four texture classes; sandy loam, clay loam, silty loam, and loam (Figure 5). Most of the studied area was classified as loamy soils covering about 71.0% of the studied area. The sandy and silty loam covered almost similar areas of about 6% and 6.5%, respectively, while the clay loam soils covered about 16.5% of the studied area.

To determine the vegetation cover in each soil texture class, the cross-operation of the Integrated Land and Watershed Management Information System “ILWIS” software was used. Only the agriculture area, which covered about 89% of the studied area (156.34 km²), was used in this operation, and the fish ponds and the settlements were excluded. The results of the cross-operation revealed that most berseem and wheat were cultivated in loamy soils, covering about 76.6 and 69.7% of the total area cultivated for each crop. For potatoes and citrus, about half of the crops were cultivated in loamy soils as well (Table 4).

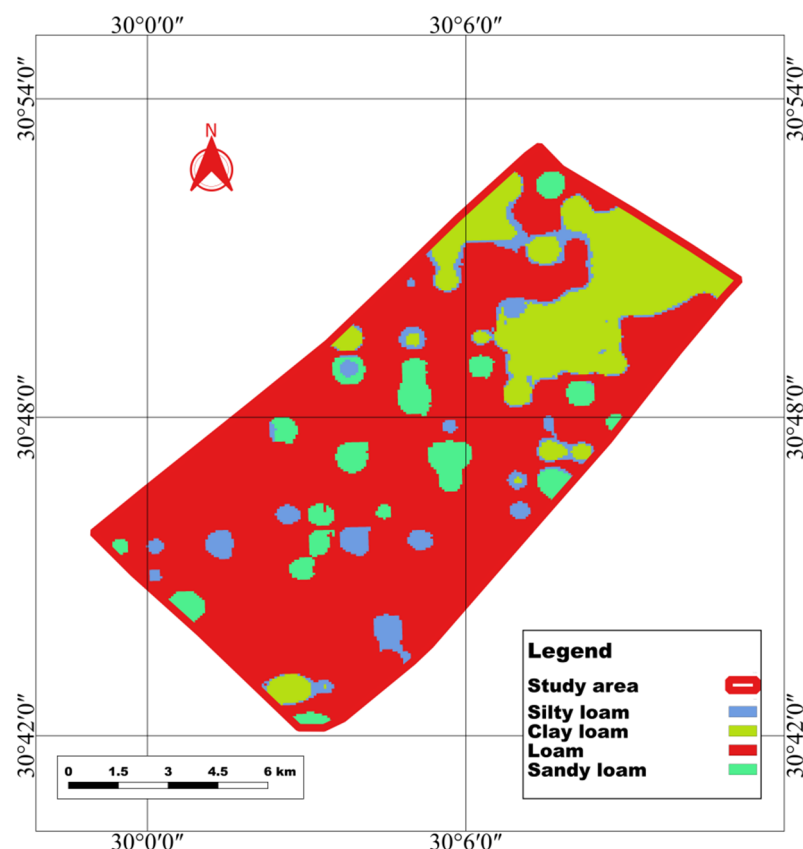


Figure 5. Soil texture class map of the studied area.

Table 4. Land cover classification within each soil texture class.

Class	Sandy Loam		Loam		Clay Loam		Silty Loam		Total	
	km ²	%	km ²	%	km ²	%	km ²	%	km ²	%
Wheat	2.11	3.51	45.99	76.55	9.05	15.06	2.93	4.88	60.08	10.00
Berseem	4.63	8.08	39.90	69.67	9.77	17.06	2.97	5.19	57.27	100.00
Green beans	1.43	6.81	14.75	70.24	2.46	11.71	2.36	11.24	21.00	100.00
Potato	0.89	14.08	3.21	50.79	1.15	18.20	1.07	16.93	6.32	100.00
Citrus	0.84	8.40	5.55	55.50	3.09	30.90	0.52	5.20	10.00	100.00
Strawberry	0.11	12.64	0.34	39.08	0.33	37.93	0.09	10.34	0.87	100.00
Guava	0.17	21.25	0.21	26.25	0.32	40.00	0.10	12.50	0.80	100.00

The interpolated AMC and IR are presented in Figure 6A,B, respectively. Utilizing the raster zonal statistics of the QGIS software, the average values of each soil texture class within the study area could be calculated. The silty loam soils had the highest average AMC within this study area, reaching 149.9 mm/m, while the lowest was the sandy loam soils, with an average of 124.7 mm/m. Concerning the infiltration rate, the lowest rate was for the clay loam soils, with an average of 7.8 mm/h, and the highest was for the sandy loam soils, with an average of 20.1 mm/h.

3.3. Crop Water Requirement (CWR)

As concluded from the LU/LC map, the agricultural area covered about 156 km². Citrus, wheat, and berseem were considered when determining the irrigation water requirements. While wheat and berseem were considered because they covered most of the agricultural area (about 75%), citrus was also considered because it is a permanent crop and is expected to consume the largest amount of irrigation water and covered about 6.4% of the agricultural area. The rooting depth, crop coefficient, critical depletion, and yield

response factor parameters were according to [32,33]. The crop growth stages and planting dates for seasonal crops were adapted according to the field conditions.

According to the CROPWAT model, the CWR was 746.2 and 587.5 mm/season for wheat and berseem, respectively. On the other hand, the highest amount of CWR was for citrus, reaching about 1653.5 mm per year. On the other hand, under the forecasted climate conditions, the CWR increased to 809.7 and 636.1 mm/season for wheat and berseem, respectively, while citrus reached about 1926 mm/year (Figure 7). Compared to the previous thirty years, there is an increase in the crop water requirements, which could be rendered to the lack of rain throughout the year, which decreased from about 40 mm/year to none, in addition to changes in the other climatic conditions. That increase ranged from 3 to 3.9% in the case of the field crops but reached about 14% in the case of citrus.

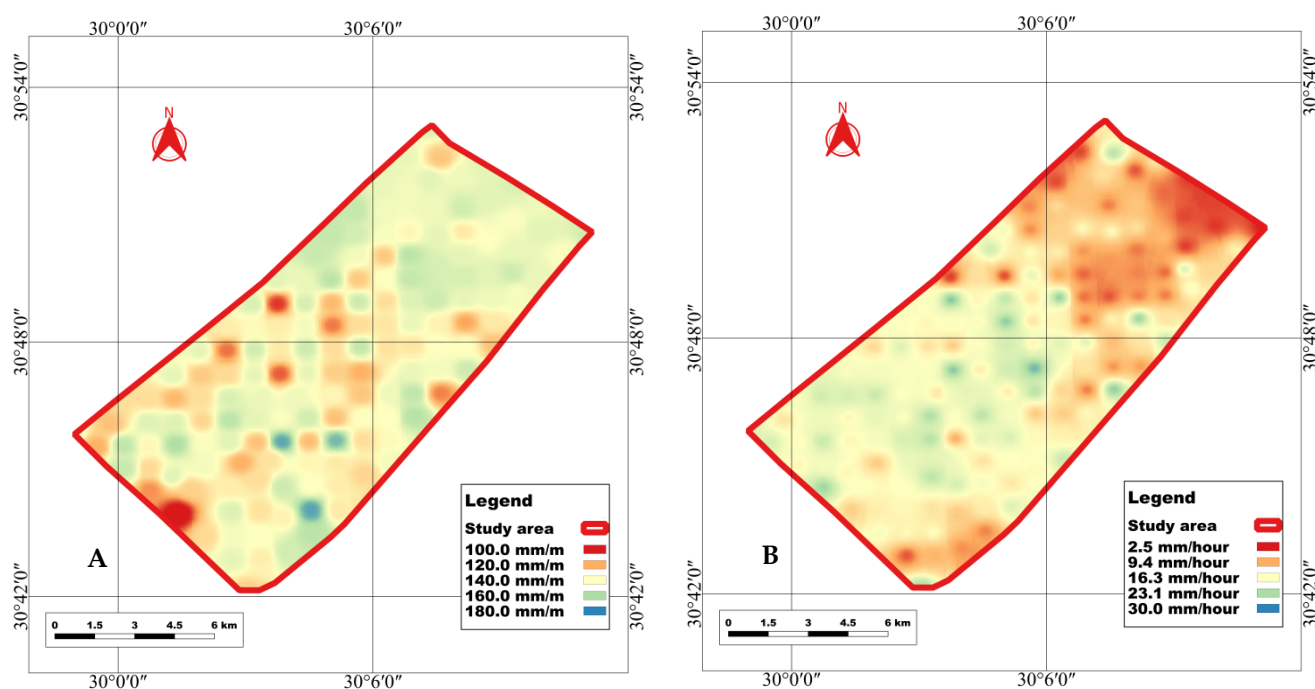


Figure 6. Interpolated soil properties maps, (A) available moisture content (AMC), (B) infiltration rate (IR).

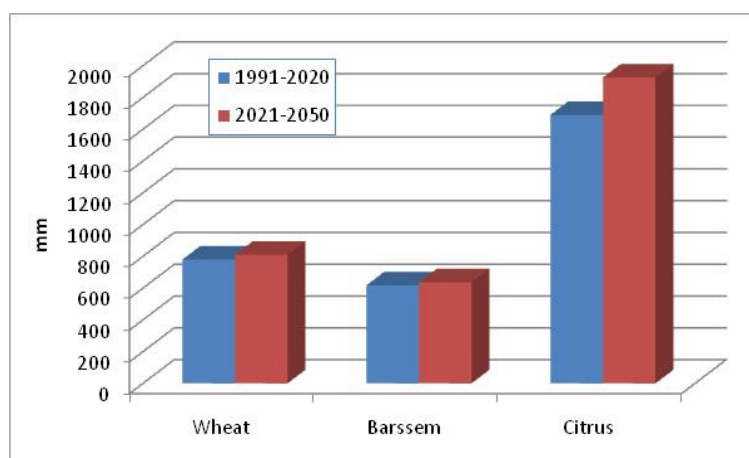


Figure 7. Crop water requirements under current and forecasted climate conditions.

3.4. Irrigation Water Requirements (IWR)

In the study area, the loamy soils were the dominant soils. Therefore, the loamy soils were considered when calculating the IWR. Furthermore, utilizing CROPWAT, the management practice that ensures no yield loss due to water deficiency was compared to current practices under current and forecasted climate conditions for the selected crops.

Wheat is mostly irrigated using sprinkle irrigation, whether fixed or movable. In loamy soils, the current irrigation practices include the application of irrigation water once almost every week, and adjustments are made when there is no irrigation water available in the irrigation canals. These practices should result in the reduction of the crop yield to 2.5%, according to CROPWAT.

Nevertheless, the decrease in crop yield reached about 10–20%, according to a field survey, which could be rendered to soil properties and/or management. Berseem is also irrigated using sprinkle irrigation and, in loamy soils, is irrigated almost once every two weeks, and adjustments are made when there is no irrigation water available in the irrigation canals. These practices should result in a reduction in crop yield reaching 10%, which matches the field survey. Under current practices, the amount of irrigation water required for wheat per feddan will increase by about $160 \text{ m}^3/\text{feddan}$ under climate forecast conditions, while this increase will reach $288.6 \text{ m}^3/\text{feddan}$ under the no-yield loss practices (Figure 8A).

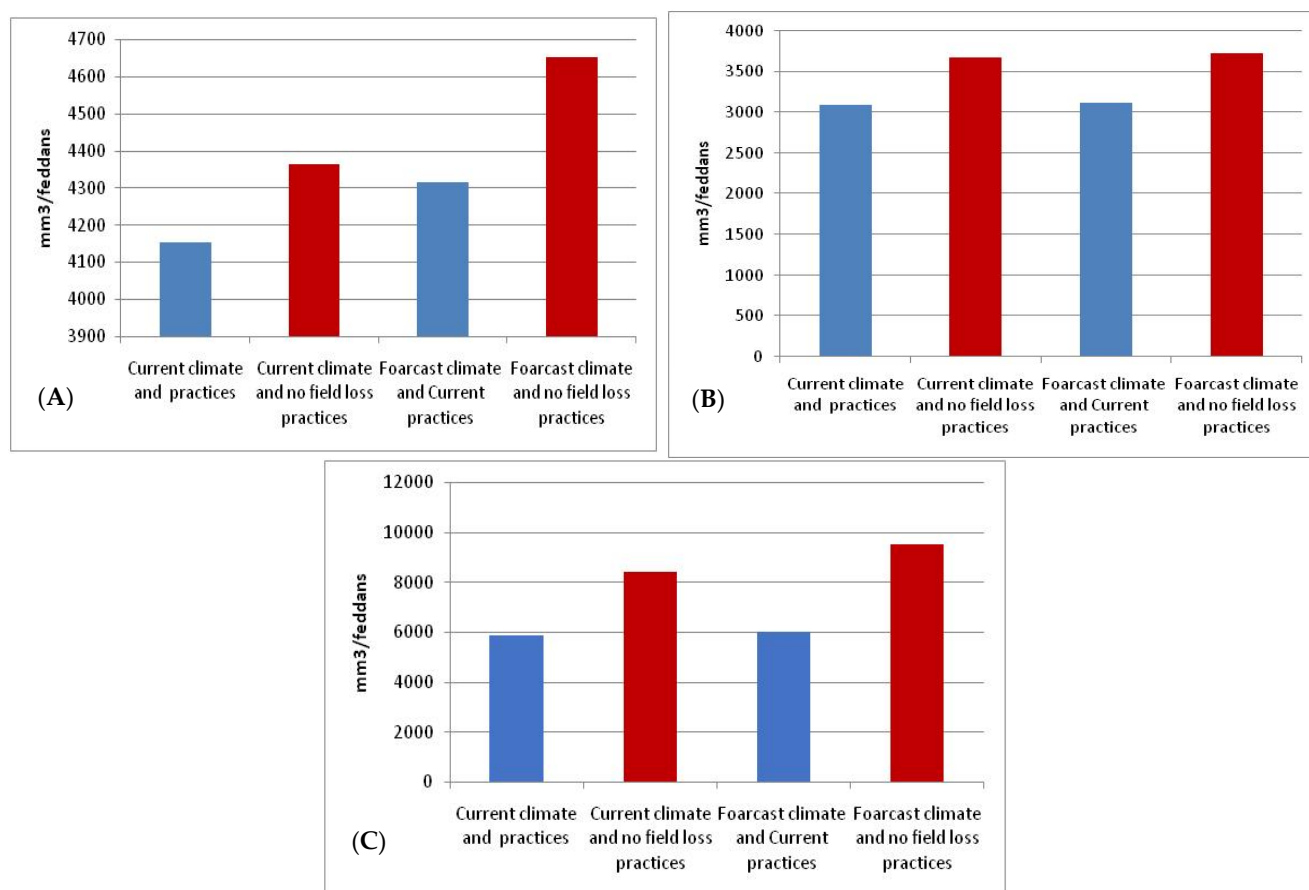


Figure 8. IWR of the studied crops under current and predicted climate, (A) wheat, (B) berseem, (C) citrus.

On the other hand, under the current practices, there will be an increase of the irrigation water for berseem by $22 \text{ m}^3/\text{feddan}$ under forecast conditions, and under the no yield loss practices, there be an increase of about $50 \text{ m}^3/\text{feddan}$ (Figure 8B).

Moreover, citrus is irrigated every day using drip irrigation. It is irrigated throughout the study area in almost a uniform application daily which accounts for about $125 \text{ m}^3/\text{feddan}$

per week of irrigation water from mid-May to mid-September and about 65 m³/feddan per week from December to January and the in the remaining months is irrigated using about 85 m³/feddan per week, which accounted for about 5871.2 m³/feddan/year irrigation water under field conditions.

Nevertheless, the expected crop yield loss reached about 25%, which matched the field survey. Citrus irrigation water requirements will increase by about 146 m³/feddans under current practices, while under no yield loss, the irrigation requirements increase will be about 1095 m³/feddans (Figure 8C).

4. Conclusions

The crop water requirements of major crops in a selected area in El-Beheira governorate were computed using CROPWAT 8.0 model and supported by remote sensing, GIS, and atmospheric data analysis. The major cultivated crops in the study area were wheat and berseem, while citrus was the major orchard. The study area is irrigated from El-Nasr Canal, and there is a problem with water availability in the study area, which is considered a major problem, especially in the initial growth stages.

The crop water requirements and irrigation requirements for the various crops grown in loamy soils have been computed using CROPWAT 8. Citrus had the largest amount of irrigation water requirements. The irrigation water requirements calculated according to the model based on the current practices showed an expected decrease in yield for the three studied crops.

The research results revealed that there will be an increase in CWR due to the expected climate change in the next thirty years under the best-case scenario. The IWR will increase to reach almost 3.9, 0.7, and 2.5% for wheat, berseem, and citrus, respectively, under the current irrigation practices. The increase will reach about 6.6, 1.4, and 13% for wheat, berseem, and citrus under no field loss practices.

The proposed approach took advantage of various sources of information, especially the freely available remote sensing data, whether related to LU/LC or climatic data, as well as various tools such as climatic models, CROPWAT, GIS, and remote sensing software. The application of such an approach will facilitate setting up an efficient irrigation management strategy by the decision makers and releasing the right amount of water in irrigation canals at the right time to avoid any wastage or shortage in the water supply. It also provides decision-makers with an insight into the expected changes in irrigation water requirements and, therefore, helps to change or adjust the forthcoming land use plans accordingly, especially since the climate models provide the forecasting conditions that may not be appropriate for the current land uses.

The proposed approach is applicable at any administrative level where enough soil and LU/LC data are available. Nevertheless, in Egypt, its application is recommended on the sub-administrative level, where updated soil and LU/LC data could be collected more easily. Furthermore, it is worth mentioning that unless such data are available, the approach will be somewhat time-consuming, and processing the climatic model is time-consuming as well.

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References

1. Liu, Q.; Yan, C.; Yang, J.; Mei, X.; Hao, W.; Ju, H. Impacts of climate change on crop water requirements in Huang-Huai-Hai Plain, China. In *CABI Climate Change Series, Climate Change and Agricultural Water Management in Developing Countries*; CABI International: Wallingford, UK, 2016; pp. 48–62. Available online: https://www.researchgate.net/profile/Qin-Liu-4/publication/315729544_Climate_Change_and_Agricultural_Water_Management_in_Developing_Countries/links/58dfe024585153bfe97e008/Climate-Change-and-Agricultural-Water-Management-in-Developing-Countries.pdf (accessed on 1 May 2022).
2. Intergovernmental Panel on Climate Change (IPCC). Summary for policymakers. In *Climate Change and Land: An IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems*; Shukla, P.R., Skea, J., Calvo Buendia, E., Masson-Delmotte, V., Pörtner, H.O., Roberts, D.C., Zhai, P., Slade, R., Connors, S., van Diemen, R., et al., Eds.; IPCC: Geneva, Switzerland, 2020. Available online: https://www.ipcc.ch/site/assets/uploads/sites/4/2020/02/SPM_Updated-Jan20.pdf (accessed on 1 May 2022).
3. Sahu, N.; Saini, A.; Behera, S.K.; Sayama, T.; Sahu, L.; Nguyen, V.T.; Takara, K. Why apple orchards are shifting to the higher altitudes of the Himalayas? *PLoS ONE* **2020**, *15*, e0235041. [CrossRef] [PubMed]
4. FAO. *The State of Food and Agriculture. Overcoming Water Challenges in Agriculture*; FAO: Rome, Italy, 2020. [CrossRef]
5. Sahu, N.; Saini, A.; Behera, S.; Sayama, T.; Nayak, S.; Sahu, L.; Duan, W.; Avtar, R.; Yamada, M.; Singh, R.; et al. Impact of Indo-Pacific climate variability on rice productivity in Bihar, India. *Sustainability* **2020**, *12*, 7023. [CrossRef]
6. Lalic, B.; Francia, M.; Jacimovic, G. Assessment of climate change impact on crop water requirements in Serbia in 2030 using CROPWAT model. In *Proceedings of the International Scientific Conference on Environmental changes and adaptation strategies* Skalica, Slovakia, 9–11 September 2013.
7. Foster, T.; Mieno, T.; Brozovic, N. Satellite-based monitoring of irrigation water use: Assessing measurement errors and their implications for agricultural water management policy. *Water Resour. Res.* **2020**, *56*, e2020WR028378. [CrossRef]
8. Surendran, U.; Sushanth, C.M.; Mammen, G.; Joseph, E.J. Modeling the crop water requirement using FAO-CROPWAT and assessment of water resources for sustainable water resource management: A case study in Palakkad district of humid tropical Kerala, India. *Aquat. Procedia* **2015**, *4*, 1211–1219. [CrossRef]
9. Halimi, A.H.; Tefera, A.H. Application of cropwat model for estimation of irrigation scheduling of tomato in changing climate of eastern Europe: The case study of Godollo, Hungary. *SSRG Int. J. Agric. Environ. Sci.* **2019**, *6*, 1–11. [CrossRef]
10. Suryadi, E.; Ruswandi, D.; Dwiratna, S.; Prawiranegara, B.M.P. Crop water requirements analysis using Cropwat 8.0 Software in maize intercropping with rice and soybean. *Int. J. Adv. Sci. Eng. Inf. Technol.* **2019**, *9*, 1364–1370. [CrossRef]
11. Swelam, A.; El-Marsafawy, S.; Elbana, M. Effective management of on-farm irrigation for some major crops in Egypt using CROPWAT model. *Misr J. Agric. Eng.* **2019**, *36*, 105–122. [CrossRef]
12. Al-Najar, H. The integration of FAO-CropWat Model and GIS techniques for estimating irrigation water requirement and its application in the Gaza strip. *Nat. Resour.* **2011**, *2*, 146–154. [CrossRef]
13. Naidu, C.; Giridhar, M. Irrigation demand vs supply-remote sensing and GIS approach. *J. Geosci. Environ. Prot.* **2016**, *4*, 43–49. [CrossRef]
14. Meena, S.K.; Punjabi, S.T.; Dadhich, P.N. Crop water estimation for Chaksu Tehsil of Jaipur using CROPWAT and GIS. *Int. J. Adv. Sci. Technol.* **2020**, *29*, 3540–3551. Available online: <http://sersc.org/journals/index.php/IJAST/article/view/20887> (accessed on 1 May 2022).
15. Manasa, H.G.; Shivapur, A.V. Implications of climate change on crop water requirements in Hukkeri Taluk of Belagavi district, Karnataka, India. *Int. J. Res. Eng. Technol.* **2016**, *5*, 236–241. Available online: <https://ijret.org/volumes/2016v05/i06/IJRET20160506044.pdf> (accessed on 1 May 2022).
16. Makar, R.S.; Shahin, S.A.; El-Nazer, M.; Wheida, A. Development of a PCA-based land use/land cover classification utilizing Sentinel-2-time series. *Middle East J. Agric. Res.* **2022**, *11*, 630–637. [CrossRef]
17. Morgan, R.S.; Abd El-Hady, M.; Rahim, I.S.; Silva, J.; Ribeiro, S. Evaluation of various interpolation techniques for estimation of selected soil properties. *Int. J. GEOMATE* **2017**, *13*, 23–30. [CrossRef]
18. Gee, G.W.; Bauder, J.W. Particle size analysis. In *Methods of Soil Analysis, Part A*, 2nd ed.; Klute, A., Ed.; American Society of Agronomy/Soil Science Society of America: Madison, WI, USA, 1986; Volume 9, pp. 383–411.
19. Saxton, K.E.; Rawls, W.J.; Romberger, J.S.; Papendick, R.I. Estimating generalized soil-water characteristics from texture. *Soil Sci. Soc. Amer. J.* **1986**, *50*, 1031–1036. [CrossRef]
20. Longley, P.A.; Goodchild, M.F.; Maguire, D.J.; Rhind, D.W. *Geographic Information Systems and Sciences*, 2nd ed.; John Wiley & Sons Ltd.: West Sussex, UK, 2005.

21. Achilleos, G.A. The inverse distance weighted interpolation method and error propagation mechanism-creating a DEM from an analogue topographical map. *J. Spat. Sci.* **2011**, *56*, 283–304. [[CrossRef](#)]
22. Lu, G.Y.; Wong, D.W. An adaptive inverse-distance weighting spatial interpolation technique. *Comput. Geosci.* **2008**, *34*, 1044–1055. [[CrossRef](#)]
23. Food and Agriculture Organization (FAO). *CROPWAT 8.0*; Land and Water Development Division, Ed.; FAO: Rome, Italy, 2009.
24. Vozhehova, R.A.; Lavrynenko, Y.O.; Kokovikhin, S.V.; Lykhovyd, P.V.; Biliaieva, I.M.; Drobitko, A.V.; Nesterchuk, V.V. Assessment of the CROPWAT 8.0 software reliability for evapotranspiration and crop water requirements calculations. *J. Water Land Dev.* **2018**, *39*, 147–152. [[CrossRef](#)]
25. El-Magd, I.A.; Tanton, T. Remote sensing and GIS for estimation of irrigation crop water demand. *Int. J. Remote Sens.* **2005**, *26*, 2359–2370. [[CrossRef](#)]
26. Karuku, G.N.; Gachene, C.K.K.; Karanja, N.; Cornelis, W.; Verplancke, H. Use of CROPWAT model to predict water use in irrigated tomato production at Kabete, Kenya. *E. Afr. Agric. For. J.* **2014**, *80*, 175–183.
27. Sparks, A.H. NASAPOWER: A nasa power global meteorology, surface solar energy and climatology data client for R. *J. Open Source Softw.* **2018**, *3*, 1035. [[CrossRef](#)]
28. Gelaro, R.; McCarty, W.; Suárez, M.J.; Todling, R.; Molod, A.; Takacs, L.; Randles, C.A.; Darmenov, A.; Bosilovich, M.G.; Reichle, R.; et al. The modern-era retrospective analysis for research and applications, version 2 (MERRA-2). *J. Clim.* **2017**, *30*, 5419–5454. Available online: <https://journals.ametsoc.org/view/journals/clim/30/14/jcli-d-16-0758.1.xml> (accessed on 1 May 2022). [[CrossRef](#)] [[PubMed](#)]
29. Chen, W.; Castruccio, S.; Genton, M.G.; Crippa, P. Current and future estimates of wind energy potential over Saudi Arabia. *J. Geophys. Res. Atmos.* **2018**, *123*, 6443–6459. [[CrossRef](#)]
30. Mostafa, A.N.; Wheida, A.; El Nazer, M.; Adel, M.; El Leithy, L.; Siour, G.; Coman, A.; Borbon, A.; Magdy, A.; Omar, M.; et al. Past (1950–2017) and future –2100) temperature and precipitation trends in Egypt. *Weather. Clim. Extrem.* **2019**, *26*, 100225. [[CrossRef](#)]
31. Tyagi, N.; Jayal, T.; Singh, M.; Mandwal, V.; Saini, A.; Nirbhav; Sahu, N.; Nayak, S. Evaluation of observed and future climate change projection for Uttarakhand, India, using CORDEX-SA. *Atmosphere* **2022**, *13*, 947. [[CrossRef](#)]
32. Allen, R.G.; Pereira, L.S.; Raes, D.; Smith, M. Crop evapotranspiration-guidelines for computing crop water requirements. In *FAO Irrigation and Drainage Paper 56*; FAO: Rome, Italy, 1998.
33. Pereira, L.S.; Allen, R.G.; Smith, M.; Raes, D. Crop evapotranspiration estimation with FAO 56: Past and future. *Agric. Water Manag.* **2015**, *147*, 4–20. [[CrossRef](#)]