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Satellite and Model-Based Estimation of Crop Water Requirement of Major Irrigated Crops in the Koga Irrigation Scheme, Ethiopia

Alebachew Tiruye,[1] Pakorn Ditthakit,[1,*] Quoc Bao Pham,[2] Warit Wipulanusat,[3] Uruya Weesakul,[4] Suthira Thongkao,[5] Nand Lal Kushwaha[6]

Abstract

An adequate supply of water and nutrients is vital in crop cultivation to conserve water, prevent shortages, minimize production losses, and curb excessive utilization of water resources. This study aimed to estimate the water demand of major irrigated crops using open-access portals, such as satellite and reanalysis datasets within the Koga irrigation scheme. We collected climate data from the local weather station, WaPOR, and ERA5-Land open-source datasets. The Koga Irrigation Development Office provided the field data for the entire irrigation system. The Modified Penman-Monteith equation was employed to compute the reference evapotranspiration. The single-crop coefficient approach was applied to determine crop evapotranspiration (ET_C). The result indicated a strong correlation between the measured and predicted values. Additionally, it was also found that the ET_C tended to peak during the mid-stage of the crops, and a robust relationship between the measured and estimated values was examined on a monthly scale. The seasonal average water requirements for wheat were 532 mm, 510 mm, and 542 mm, whereas maize had mean values of 603 mm, 589 mm, and 636 mm. Potato water needs averaged 549 mm, 529 mm, and 564 mm, and for tomatoes, the water requirements were 540 mm, 532 mm, and 583mm based on observed, satellite, and model-based estimations, respectively. Remarkably, the maize crop consistently had the highest ETc value across all estimation scenarios, indicating that maize is more susceptible to water stress, has a longer growing season, a large leaf area index when mature, and transpires at a higher rate than wheat, potato, and tomato. According to our research, the model-based estimation was 5.9 to 8.7% and 1.9 to 7.4% higher than the satellite-based estimates and the measured values, respectively. In conclusion, our research highlights the importance of utilizing satellite and model-based data to calculate crop evapotranspiration in irrigation schemes and benefits decision-makers, water managers, agronomists, stakeholders, and irrigation operators.

Keywords: Crop evapotranspiration; ERA5-Land; WaPOR; Koga irrigation scheme.
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1. Introduction

Water is crucial for agricultural productivity and is necessary to ensure food security. Approximately 20 % of the world's cultivated land is used for irrigation agriculture, accounting for 40 % of global food production.[1] Over the past 20 years, there has been a noticeable decline in investments made in the growth of irrigated agriculture, mostly due to the depletion of freshwater and land resources (FAO, 2003). The rapacious and unethical exploitation of land and water resources also causes them to deplete more quickly. The growing global population has led to a worldwide increase in the demand for two critical resources (water and land) and pressing greater pressure on these essential assets. The depletion and improper handling of freshwater resources are also major concerns for researchers and decision-makers.[2,3] Estimates suggest that by 2025, due to the pressures that increasing urbanization is placing on nearby water sources, an estimated 1.8 billion people will experience acute water scarcity.[4] Sub-Saharan Africa (SSA) has the lowest proportion of irrigated land (4%) compared to the total amount of land cultivated[5] and thus for expanding irrigation production, proper management of water is needed.

[1] *Center of Excellence in Sustainable Disaster Management, School of Engineering and Technology, Walailak University, Nakhon Si Thammarat 80161, Thailand.*
[2] *Faculty of Natural Sciences, Institute of Earth Sciences, University of Silesia in Katowice, Będzińska Street 60, 41-200, Sosnowiec, Poland.*

Therefore, in arid and semiarid regions, water conservation has become a fundamental building block for sustainable water resource management and crop production. Currently, irrigation systems need to be modernized and managed by carefully analyzing the water requirements of agricultural production systems. Water serves as the medium through which nutrients are dissolved and transported within the plant, facilitating their movement through the stems and roots. Furthermore, at the end of the life cycle, water is a predominant component of valuable economic products such as leaves, stems, seeds, flowers, and fruits.[6] The promotion of irrigation is considered a strategy to alleviate poverty and stimulate economic progress in Ethiopia. Traditional irrigation systems cover over 138,000 ha, whereas modern small-scale irrigation covers an additional 48,000 ha of land[7] in Ethiopia. As expressed by Ref. [8], it is worth noting that approximately 10-12% of the total irrigable potential is actively cultivated through the utilization of both modern and traditional irrigation methods. In the future, it seems unlikely that the world water cycle will be able to cope with this demand.[6,9] Currently, irrigation accounts for approximately 87% of the water consumed and 70% of global water withdrawal.[10] Approximately 40–45% of the world's food supply is generated through irrigated agriculture, although it encompasses less than one-fifth of all cultivated lands. To meet this demand, it is essential to apply an appropriate amount of water based on the specific water requirements of each crop. In the future, the expansion of irrigated agriculture will be necessary to meet the food demands of the growing population. Thus, to ensure an ample food supply for the rapidly growing population, research on the water requirements of cultivated crops is paramount and a top priority. Given the global water shortage crisis, there is growing apprehension about integrating water conservation technologies owing to rising water demands and scarcity concerns on a worldwide scale.[11,12] Addressing the increasing water demand is a daily challenge, emphasizing the need for effective irrigation management: (a) to mitigate the adverse effects of both over- and under-utilization of water, and (b) to ensure a balance between crop water needs and available water. In Ethiopia, agriculture relies on rain-fed farming in areas with ample rainfall. Concurrently, irrigated agriculture is practiced in response to insufficient natural precipitation and to maintain production loss. However, the lack of affordable and practical scheduling methods, high costs, limited access to soil water monitoring tools, and absence of local climate data and soil water parameters have been identified as significant challenges to the sustainability of irrigation practices.[13] Long-term sustainability is affected by inappropriate watering schedules[14,15] in Ethiopia. The Koga irrigation scheme in Ethiopia faces several irrigation-related challenges, including inadequate irrigation scheduling, inconsistent water distribution within farms, incorrect durations of water application, and over-utilization of irrigation water. A stable water supply is essential for the growing production of common crops, such as wheat, maize, tomatoes, and potatoes, since they are important for satisfying the nation's food demands and for the economy's sustainability. To determine the water needs of crops, numerous studies have been conducted worldwide as well as in Ethiopia using various estimation methods and scenarios, for instance,[6,16,17], and the potential of remote sensing for the determination of crop water requirements was reported by Ref. [18]. Weather stations require a complete set of meteorological data, including air temperature, relative humidity, wind speed, solar radiation, and pressure.[16] Ground-based weather stations with a complete set of sensors are the main and ideal sources of climate data, but such stations are generally limited in number, not easily accessible, and do not offer complete climatic data in developing countries. The reanalysis data can be successfully exploited as a source of gridded weather data and used to estimate the water requirements of crops with minimum error.[16] Furthermore, designers need to estimate crop evapotranspiration using remotely sensed data to better understand the quantity of irrigation water required for different crops and to schedule irrigation.[19]

Previous simulation models, such as FAO CROPWAT and AQUACROP, did not provide historical and current climate data (input data) but relied on historical climate data obtained from weather stations and other databases to simulate crop water use under various environmental conditions. Additionally, AQUACROP was designed to predict yield at a single-field scale (point simulation), assuming a uniform field and only vertical incoming and outgoing water fluxes (https://www.fao.org/land-water/databases-and-software /cropwat/en/). Moreover, in developing countries such as Ethiopia, the number and accessibility of weather stations with a full set of sensors are typically restricted, making it difficult to get complete ground-based data. To overcome this problem, the application of currently developed open-access datasets is relevant for determining crop water needs in areas with limited ground information. In this research, the WaPOR portal and ERA5-Land reanalysis datasets are used for calculating the water demands of crops. This research focused on the determination of the water requirements of major irrigated crops in the Koga irrigation scheme with provided open-

[3] Research Unit in Data Science and Digital Transformation, Department of Civil Engineering, Faculty of Engineering, Thammasat School of Engineering, Thammasat University, Pathumthani, Thailand.

[4] Thammasat University Research Unit in Climate Change and Sustainability, Department of Civil Engineering, Faculty of Engineering, Thammasat School of Engineering, Thammasat University, Pathumthani 12120, Thailand.

[5] School of Languages and General Education, Walailak University, 222, Thaiburi, Thasala, Nakhon Si Thammarat 80160, Thailand.

[6] Division of Agricultural Engineering, ICAR-Indian Agricultural Research Institute, New Delhi, 110012, India.

**Email:* dpakorn@mail.wu.ac.th (P. Ditthakit)

access datasets. Additionally, we validated the application of remote-sensing and reanalysis portals in crop water need calculation by comparing it with observed values. In addition, this study can provide a feasible alternative way to calculate the water demand for various crops and contribute to water managers, policy-makers, irrigation scheme planners and designers, stakeholders, agronomists, and irrigation scheme operators.

2. Material and methods

2.1 Site description

The study was conducted at the Koga irrigation scheme, which lies in the Blue Nile basin located in the northwest of the Amhara Region, Tana Basin, Ethiopia (Fig. 1). Koga Dam is situated at an elevation of 1900 m above sea level, with geographic coordinates of 11.35° N latitude and 37.14° E longitude. The Koga irrigation scheme has 12 irrigation blocks and eleven-night storage reservoirs (NSR), which help to achieve the working time of each irrigation block properly based on the design of the scheme.

The full storage capacity of the main dam is 83.1 Mm^3 with an impounding area of 1750 ha and the useful storage is 73.4 Mm^3.[20] The irrigation scheme was designed to irrigate 7000 ha, with an estimated household size of 6500.[21] The primary and secondary canals are lined, whereas the tertiary and quaternary canals are unlined and exposed to damage.

2.2 Irrigation system and planting pattern

Information on the overall irrigation system and the cropping pattern was obtained from the Koga Irrigation Development Office implementation report, the research conducted on the dual impact of climate change on irrigation water and reservoir performance,[22] and the FAO-56 manual.[23] Due to the wide range of low degrees of mechanization in the irrigation scheme, the surface irrigation method, particularly furrow irrigation is the preferred irrigation practice in the Koga irrigation scheme.[24] Thus, the local farmers apply this method for delivering water into the fields. There are two crop growing seasons *i.e*. rainfed and irrigation with diverse crop production, in the Koga irrigation scheme. However, our investigation is focused on the irrigation season cropping patterns and considered major irrigated crops. The major irrigated crops were selected based on literature sources and survey information based on the Koga Irrigation Development Office (KIDO).

2.3 Data collection

The data used in this study was derived from open-access data portals, reanalysis datasets, and in situ observation data sources. The observational data was collected from the field, while open-access data were generated using the WaPOR and ERA5-Land datasets. Temporal and spatial variations in water needs were analyzed in the irrigation scheme. In this study, data on water, land, and climate at various spatial and temporal resolutions were used to determine crop water demands of irrigated crops. The climate data include reference evapotranspiration (ET_0), relative humidity, temperature, wind speed, net radiation, soil, and crop information, as shown in (Fig. 2).

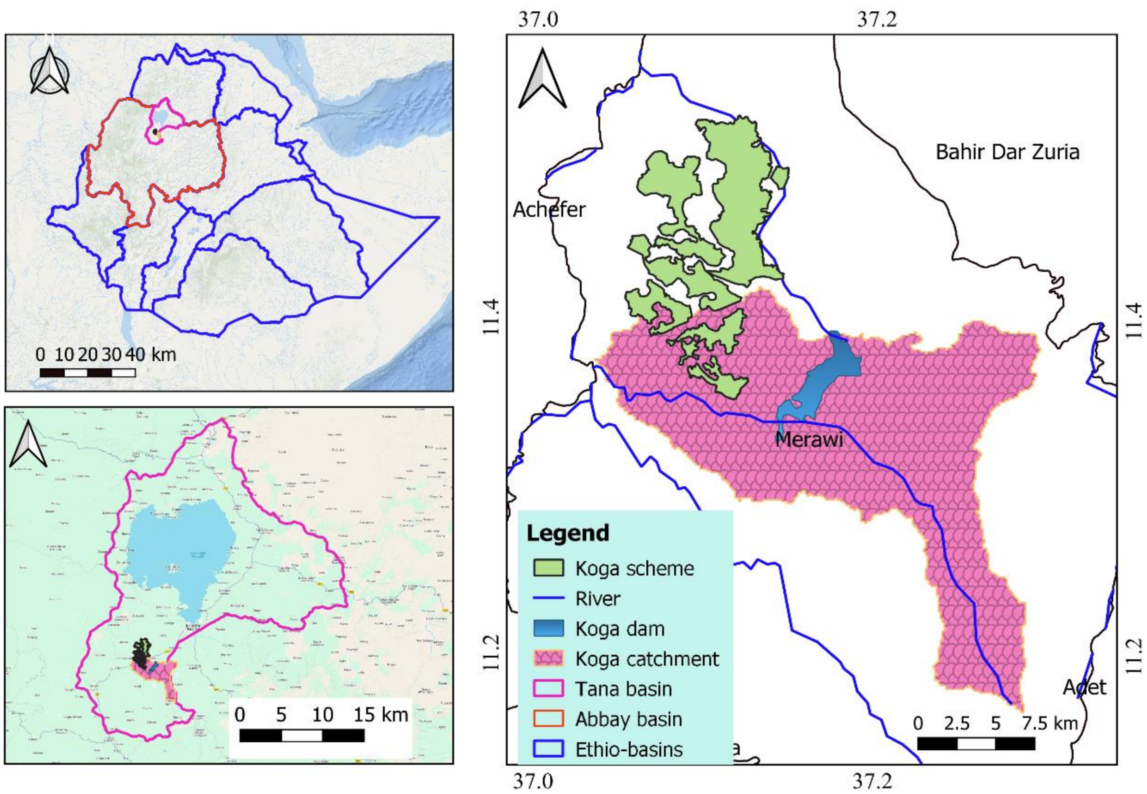

Fig. 1 Geographic map of the study area, located in the Amhara region, Tana basin.

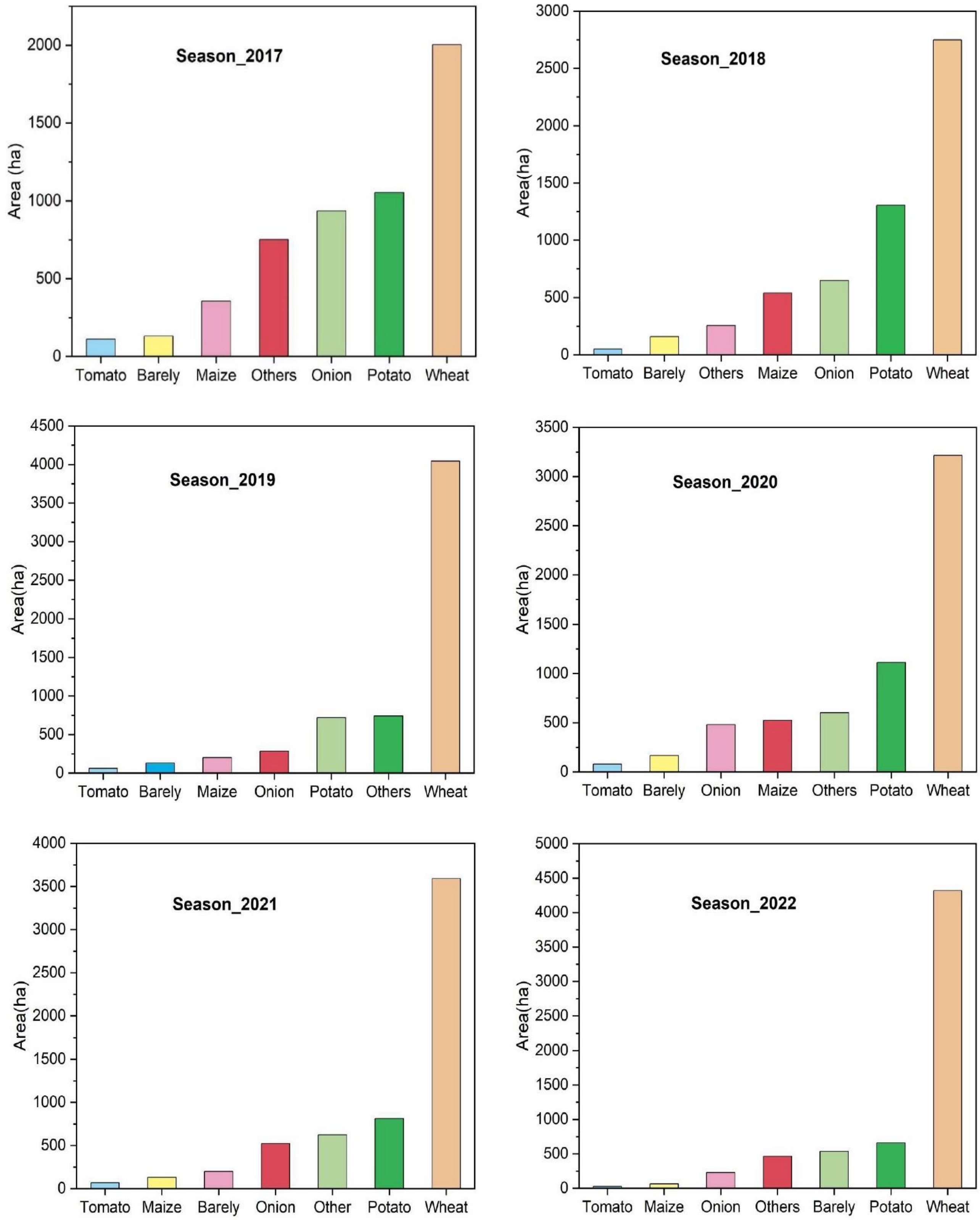

Fig. 2 The changes in area coverage of the irrigated crop across the irrigation seasons, spanning from 2017 to 2022.

2.3.1 Observation data

The observation data were collected from the Koga Irrigation Development (KID) office including information on the sowing date, major irrigated crops, coverage area, harvesting date, and the weather data from the Ethiopian National Metrological Agency, Bahir Dar branch (Table 1 and Table 4).

As presented in Fig. 2, the cropping patterns of the Koga irrigation scheme varied from year to year, based on market availability and market linkage. According to Ref. [25] direct interviews with farmers, irrigation managers, and survey data obtained from the Koga irrigation development office, the irrigated crop planting plan was ruled by market access and the irrigation water availability in the area of interest. Besides, water-stress-sensitive crops and crops that have less market demand were not cultivated in the scheme.

The bar graph shows that the wheat crop has a larger coverage area and has increased annually, followed by potatoes. On average, wheat covers 56% to 70% of the irrigated area. This growth is attributed to the Ethiopian government's strategy to enhance the production and productivity of wheat under irrigation, which aims to sustain farmers' livelihoods. Additionally, the government has developed a strategy to improve food security for local farmers and incentivize wheat cultivation within the irrigation scheme.

Table 1. The expression of the crop growing period and their date of operation.

Crop type	Growth period (days)				Sowing date
	Initial stage	Development stage	Mid-season	Late-season	
Wheat	15	25	50	30	November 15
Maize	30	45	50	35	November 01
Potato	30	35	40	25	November 05
Tomato	30	40	45	30	November 15

Typically, different crops are irrigated in the Koga irrigation scheme, leading to inconsistent planting and harvesting dates (Table 1). It is difficult to pinpoint the exact dates for planting and harvesting because the irrigation system is designed for a variety of crops, and users do not carry out farm operations simultaneously. The beginning and end of the irrigation season are regarded as crucial times when the majority of local farmers conduct their operations. In this research, these periods are assumed to calculate the crop factor of each crop and apply to all irrigation seasons.

Table 2. Crop coefficient based on the growth stage for each irrigated crop

List of crops	Initial stage	Development stage	Mid-season	Late-season
Wheat	0.70	0.93	1.15	0.32
Maize	0.50	0.85	1.20	0.50
Potato	0.70	0.93	1.15	0.75
Tomato	0.50	0.71	0.95	0.70

2.3.2 WaPOR portal

Water productivity through open access of Remotely Sensed derived data (WaPOR) is the most recent database that the Food and Agriculture Organization (FAO) has created to monitor water productivity and assess agricultural water management, with a focus on the idea of water productivity terms.[26] The WaPOR portal offers freely available real-time data on water, climate, and land (https://wapor.apps.fao.org/home/WAPOR_2/1).

The WaPOR data undergo a gap-filling and smoothing process, which ensures that all the produced products avoid data gaps.[27] In this study, the daily reference evapotranspiration was utilized at a spatial resolution of 20 km to compute the crop water requirements of major irrigated crops under standard conditions. The additional input data such as the crop coefficient (kc), crop operation calendar, and crop growth stage were incorporated into the estimation process. The detailed information can be found in Tables 1, 2, and 5.

2.3.3 ERA5-Land reanalysis

The European Climate Medium-Range Weather Forecasts (ECMWF) created a fifth dataset called ERA5 for the reanalysis of climatic data.[28] The land fields of the ERA5 atmospheric variables supplied atmospheric forcing in ERA5-Land. According to the lapse rate adjustment, the air temperature, air humidity, and pressure were adjusted to account for the elevation difference between the forcing grid and the higher-resolution grid of ERA5-Land.[29] This would make it possible to fill the gaps left by the lack of ground data in the study area and cover a large geographical extent. Starting from 2017 to 2022, the desired climate data used for our analysis were downloaded from the climate data store (CDS) at https://cds.climate.copernicus.eu/. To spatialize the meteorological data from ERA5-Land, a horizontal interpolation was performed. The objective analysis of the scheme was conducted based on Barnes techniques, which apply a Gaussian distance-dependent weighting function to interpolate the station data to the model grid resolution.[30] After processing and downscaling the climatic data, estimates of water and land production were made, along with the irrigation scheme. The downscaling steps to obtain the ERA5-Land data are explained in the CDS web interface, which is used to perform the downloading process.[31] This model-based dataset provides climatic information for past, present, and future periods of the globe. In this study, the ERA5-Land reanalysis dataset was used to generate agrometeorological and land surface information for the area of interest at an hourly temporal resolution. After retrieving the initial and boundary conditions from the ERA5-Land reanalysis dataset with 0.1-degree spatial resolution and hourly temporal resolution, the downscaling process was employed to fit the data consistency for the study area. Climate data (air temperature, dew point temperature, and surface net radiation at 2 m and the horizontal and vertical components of wind speed at 10 m) were used to calculate the reference evapotranspiration (Table 3). The wind-speed components measured at 10 m were converted to a wind speed measured at the height of 2 m using a mathematical approach Eq. (4).

2.3.4 Soil moisture status

To evaluate the soil moisture patterns under irrigation conditions, soil water volume data at depths of 0-7cm, 7-28 cm, and 28-100 cm were retrieved from the ERA5-Land reanalysis dataset. This enables to assessment of the soil moisture status in the study area. In this case, volumetric soil water is associated with soil texture, soil depth, and underlying groundwater level.[29] Hence, the soil moisture status was conveyed at a monthly temporal resolution, considering diverse soil depths and corresponding growing periods within the irrigation scheme. As shown in Fig. 3, the value of soil moisture at a soil depth of 28 cm was found between the lower and upper control lines for all irrigation seasons. This demonstrated the presence of available soil water in the root zone for crop growth. From December to March during the irrigation seasons of 2018 to 2022, the soil water content in the top layer (7cm depth) consistently fell below the lower control line. This suggests a recurring water scarcity issue during the crucial growth stages of cultivated crops within the irrigation scheme. However, an abrupt increase in soil water content was noted in February during the 2017 irrigation season, implying the possibility of rainfall and over-irrigation water application in that month. Conversely, the soil water content exceeded the upper control line at a depth of 100 cm in November and December in all irrigation seasons. This indicates that saturation occurs in the deeper soil layer, which is attributed to the influence of the wet season and groundwater recharge. Since November and December marked the conclusion of the wet period in the study area, moisture is expected. In general, the volumetric soil water increased as the soil depth increased for all irrigation seasons, leading to percolation, capillary rise, and an increase in groundwater level.

Table 3. Desired data components were downloaded from the ERA5-Land reanalysis model.

Parameters	Spatial extent	Spatial resolution	Temporal resolution
Dewpoint temperature	Global	9 km	Hourly
Air temperature	Global	9 km	Hourly
Soil information	Global	9 km	Hourly
Wind speed	Global	9 km	Hourly
Net solar radiation	Global	9 km	Hourly

As illustrated in Fig. 4, there was a notable increase in variability of soil water content during November and December, particularly in the middle and lower soil layers. This variability can be attributed to several factors, including changes in precipitation patterns, temperature fluctuations, and the influence of crop growth stages during these months.

In contrast, the upper soil layer exhibited a higher degree of moisture variability specifically in November. This phenomenon may be linked to unseen uncertainties, such as microclimatic conditions, surface evaporation rates, and the effects of human activities such as irrigation practices. These factors can create fluctuations in moisture levels that are not immediately observable, highlighting the complexity of soil water dynamics in agricultural settings. Understanding these variations is crucial for effective water management and optimizing crop irrigation strategies.

2.3.5 Preprocessing data components

Before estimating crop water requirements, a preprocessing step was conducted on the open-access datasets, which varied in spatial and temporal resolution. For this study, the ERA5-Land data were aggregated at a daily time step and the climatic variables were compared with ground-based observations. The wind speed was adjusted to the standard measurement height above the surface. The estimation of actual vapor pressure (e_a), saturated vapor pressure (e_s), vapor pressure deficit (VPD), and slope of the saturated vapor pressure curve (Δ) have proceeded using the dew point (T_d) and mean air temperature (T) according to the equations expressed below.[23,32]

$$e_a = 0.6108 \times \exp\left[\frac{17.27 \times T_d}{T_d + 237.3}\right] \tag{1}$$

$$e_s = 0.6108 \times \exp\left[\frac{17.27 \times T}{T + 237.3}\right] \tag{2}$$

$$\Delta = \frac{4098 \times (e_s)}{(T + 237.3)^2} \tag{3}$$

where exp […] = 2.7183 (base of natural logarithm)

The soil heat flux (G) was positive when the soil became warm and negative when it was cooled. Although the soil heat flux is small compared to the net radiation (R_n) and may not be considered, often neglected theoretically, the amount of energy gained or lost by the soil in this process should be subtracted or added to the net radiation (R_n) when estimating evapotranspiration.

To compensate for wind speed data gathered from instruments placed at nonstandard elevations, a logarithmic wind speed profile was employed when measuring above a surface with short grass. This profile was determined using the following equation.[23]

$$u_2 = u_z \times \frac{4.87}{\ln(67.8Z - 5.42)} \tag{4}$$

where u_2 is the wind speed at 2 m above the ground surface (m s^{-1}), u_z is the measured wind speed at z m above the ground surface (m s^{-1}), and z is the height of the measurement above the ground surface (m).

Atmospheric pressure is the pressure exerted by the weight of Earth's atmosphere and it is a function of elevation above sea level. Using atmospheric pressure (P), the psychometric constant is estimated by applying the following equations:[33, 34]

$$P = 101.3\left(\frac{293 - 0.0065z}{293}\right)^{5.26} \tag{5}$$

$$\gamma = 0.665 \times 10^{-3} P \tag{6}$$

where P is the atmospheric pressure (kPa), z is the elevation above sea level (m), and γ is a psychrometric constant (kPa °C^{-1}). Generally, R_s, R_n at a given location depends on latitude, Julian day, albedo (a), cloudiness and elevation (z), and the parameters Δ, γ, e_s-e_a are functions of T (temperature) and/or pressure (P).

The trends in both the observed and estimated values of the air temperature and relative humidity exhibited a strong degree of similarity. However, the ERA5-Land model showed

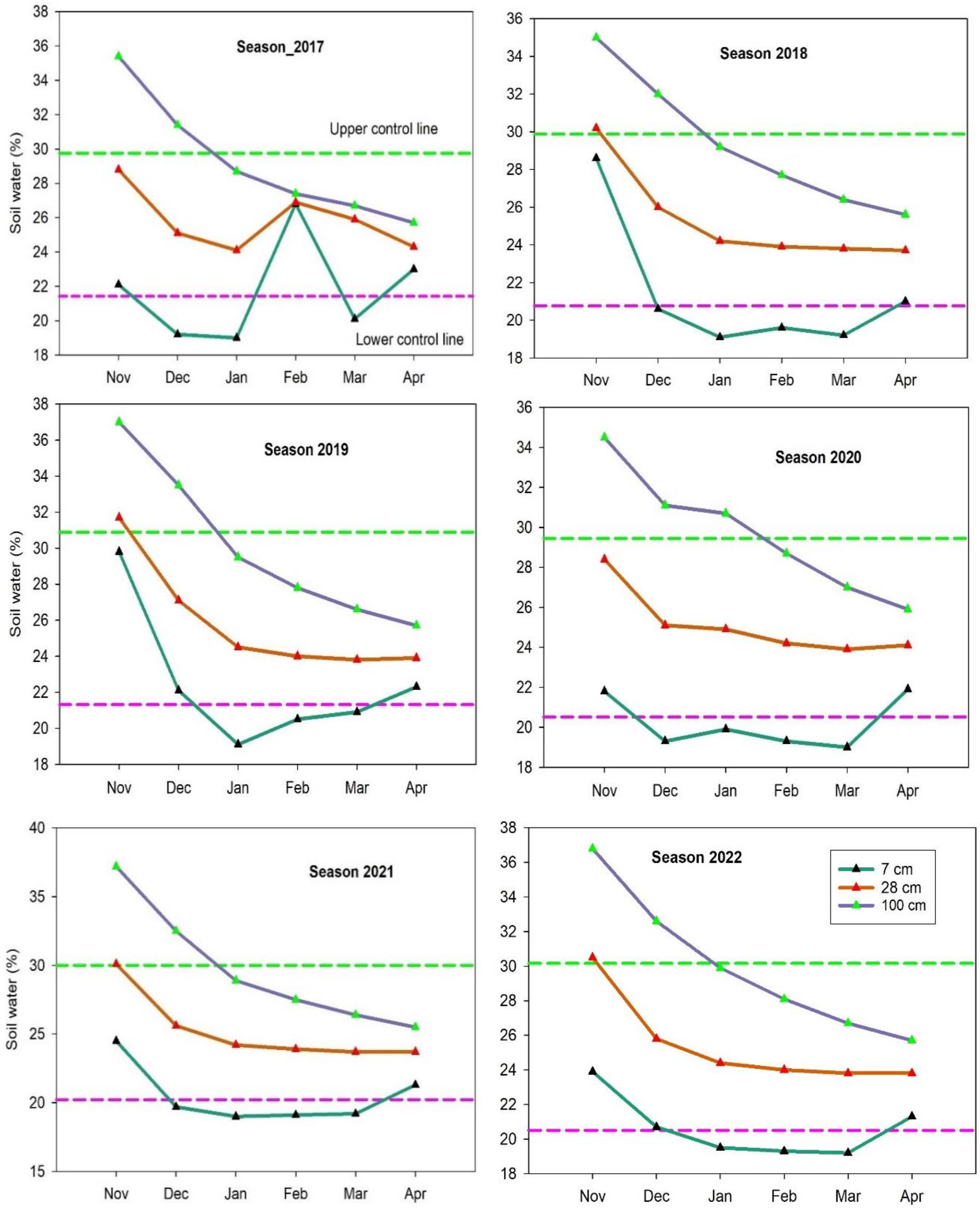

Fig. 3 The soil moisture status of irrigated fields over the six irrigation seasons using data from ERA5-Land surface information.

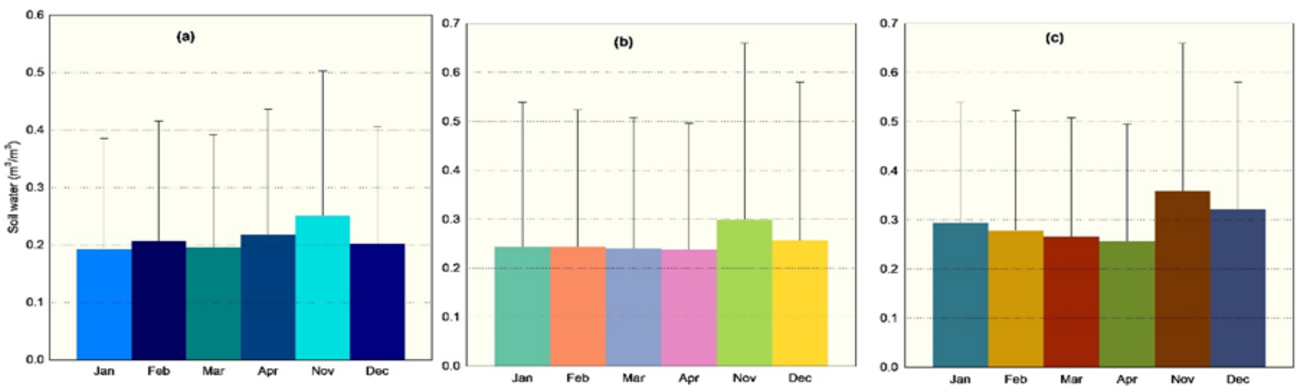

Fig. 4 The variability of soil moisture values for three soil depths (a) 7cm, (b) 28 cm, and (c) 100 cm along with six irrigation seasons.

a tendency to underestimate air temperature from July to November and overestimate it from January to May (Fig. 5a). Conversely, relative humidity was underestimated from January to May and overestimated from June to October (Fig. 5b). This overestimation and underestimation suggest a potential bias in the performance of the model owing to the uncertainties and the difference in height of measurement above the surface.

2.3.6 Reference evapotranspiration

A climate parameter known as the reference ET has been studied as a potential indicator of climate change.[35-37] The ET_0 is solely influenced by climatic parameters, such as air temperature, relative humidity, wind speed, sunshine hours, and net radiation. Reference crop evapotranspiration (ET_0), expressed as daily water use depth (mm day^{-1}), serves as a standard, even though it may not be practical to cultivate such a crop year-round. The ET_0 is one of the basic components to estimate crop evapotranspiration (ET_c). Due to difficulties in ET_0 measurement, various estimation methods have emerged, from basic empirical or physics-based models to advanced algorithms such as neuro-fuzzy or machine learning techniques.[38-40] Reference evapotranspiration (ET_0) represents the evaporation of a surface of green grass of constant height (0.12 m) growing with adequate water.[23] In this study, The climate data from the nearby weather station and ERA5-Land reanalysis were used for the estimation of ET_0 while WaPOR provided it directly from the portal. The Modified FAO Penman-Monteith equation was used for the calculation of reference evapotranspiration (ET_0). The reason for the selection of this method is that it demands available input parameters (from ground-based or open-access datasets) and this could be estimated via the available parameters according to FAO guidelines Eq. (7).

$$ET_0 = \frac{0.408\times\Delta\times(Rn-G)+\gamma\times\left(\frac{900}{T+273}\right)\times u_2\times(e_s-e_a)}{\Delta+\gamma(1+0.34u_2)} \tag{7}$$

where ET_0 is the reference evapotranspiration (mm day^{-1}), T is the mean air temperature (°c) at 2 m height, u_2 is the wind speed at 2 m height (ms^{-1}), Δ is the slope of the saturation vapor pressure curve (kPa◦C $^{-1}$), and e_s and e_a are the saturation and actual vapor pressures (kPa °C^{-1}), respectively.[41]

2.3.7 Crop water requirement

Crop water requirement represents the water necessary for a crop to attain its maximum yield potential under given environmental conditions, which is usually measured in in-depth units. The ET_0 is the main climatic parameter for estimating crop evapotranspiration.[42] In this study, the water demands of major irrigated crops were determined using reference evapotranspiration and crop coefficients. There are two methods used to compute evapotranspiration (ET): the potential ET from crop surfaces under standard and nonstandard conditions and single and dual crop coefficients.

Table 4. Monthly average values of ERA5-Land reanalysis climatic parameters: dew point temperature (T_d in °C), net surface radiation (Rn in MJ/m^2), wind speed at 2 m (u_2 in m/sec) and 10 m (u_{10} in m/sec), actual vapor pressure (e_a), saturated vapor pressure (e_s) in kPa/ °C, Vapor pressure deficit (VPD) and Δ is the slope of the saturation vapor pressure curve (kPa C $^{-1}$).

Month	T_d	Rn	u_{10}	u_2	e_a	e_s	VPD	delta (Δ)
Nov	9.09	11.20	0.40	0.30	1.17	2.09	0.92	0.13
Dec	6.70	8.70	0.30	0.22	1.00	2.15	1.15	0.13
Jan	4.38	11.33	0.47	0.35	0.85	2.18	1.33	0.14
Feb	6.43	11.43	0.45	0.33	0.98	2.39	1.41	0.15
Mar	4.36	12.71	0.55	0.41	0.85	2.67	1.81	0.16
Apr	6.75	12.99	0.59	0.44	1.02	2.73	1.71	0.17

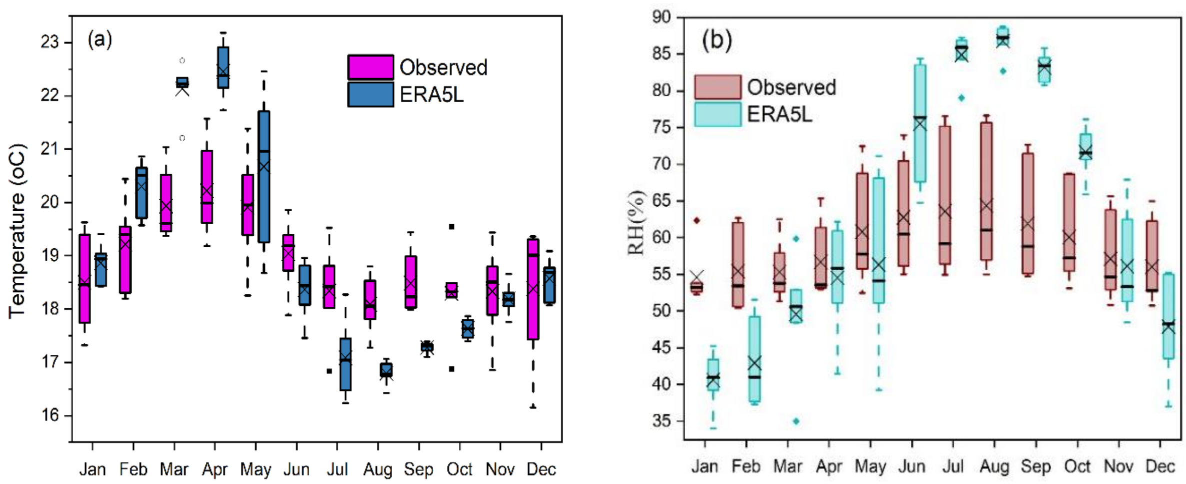

Fig. 5 The relationship between observed and ERA5-Land products (a) air temperature and (b)relative humidity, reflecting the overall average from 2017 to 2022.

The single crop coefficient (k_c) combines the impact of transpiration and soil evaporation, whereas the dual crop coefficient comprises a basal component (kc_b) and a soil evaporation coefficient (k_e), which relate ET_c to ET_0. The potential ET from crop surfaces under nonstandard conditions is adapted by employing a water stress coefficient (K_s) or adjusting the crop coefficient. In this research, the potential evapotranspiration was estimated using the meteorological data method and crop coefficient approach, and it was assumed that the area was under standard conditions. Thus, crop evapotranspiration was estimated by multiplying ET_0 by k_c, as follows:[43]

$$CWR = ET_c = ET_0 \times k_c \tag{8}$$

where; k_c is the cropping coefficients, ET_c is crop evapotranspiration (mm day^{-1}), and ET_0 is reference evapotranspiration (mm day^{-1}).

According to Ref. [44], crop-specific growth information categorizes the growing period into four phases (initial, crop development, mid-season, and late season), and assigns daily crop coefficients. As clarified by Ref. [23], the crop coefficient remained constant during the initial and mid-season stages. In the development stage, k_c increased linearly from the initial to the mid-season stages, whereas the kc values decreased linearly from the development stage to the late-season stage.

2.3.8 Calculation of kc for field crops

The timing of the crop growth stages did not align with the specific months. Consequently, this misalignment resulted in a lack of correspondence between the ETo and kc values. Therefore, it is necessary to determine kc on a monthly scale. The monthly crop factor (crop coefficient) and crop water requirement were computed based on the given crop factor and crop growth period in days according to the crop growth stage using local and open-source datasets (Table 2). The equation is formulated using FAO Irrigation and Drainage Paper No. 56[23] and the monthly crop coefficient was calculated using Eq. (9):

$$kc_m = \frac{N_{stage} \times kc_{stage}}{N\ total} \tag{9}$$

where kc_m is the monthly crop factor, N_{stage} is the number of days in a specific crop-growth stage, kc_{stage} is the crop factor in a specific crop-growth stage, and N_{total} is the number of days in a given month. After computing the monthly crop factor for each crop, the monthly and seasonal water requirements were estimated (Fig. 6).

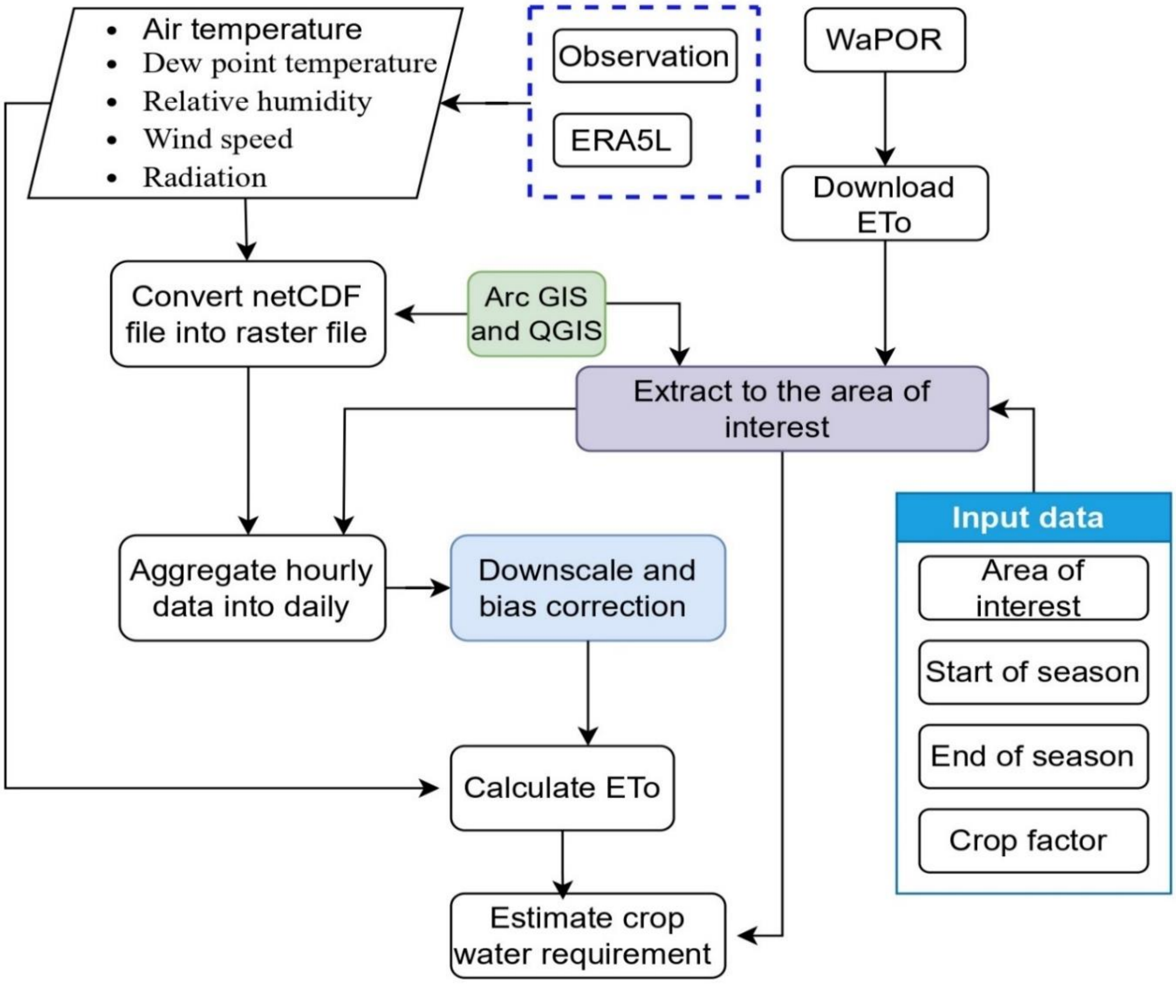

Fig. 6 Flowchart illustrating the comprehensive procedures in this study.

2.3.9 Weather data downscaling

Climate data, which include ERA5L reanalysis and WaPOR products, are accessible in the form of regularly spaced geographic grid points, each with varying resolutions. The process of transferring information from these points to a specific region of interest within the grid is referred to as downscaling, which is the method employed for this purpose.[45] This study utilized statistical downscaling techniques to extrapolate reanalysis and satellite-derived data from the original grids to a specific area of interest. Subsequently, the downscaled data were subjected to bias correction to eliminate systematic errors in the estimates. This hampers the accurate estimation of the downloaded parameters at the field scale. Higher spatial and temporal resolutions of the product parameters were obtained from two products of different resolutions using downscaling techniques.[46]

3. Results and discussion

3.1 Computation of ETo

To compute the reference evapotranspiration (ET_0), we used observed climate data, the ERA5-Land reanalysis model, and the WaPOR portal products. The ERA5-Land reanalysis provided climate data taken as the input to compute the reference evapotranspiration (Tables 3 and 4), while ET_0 was generated directly from the WaPOR portal. Time series analysis of the reference evapotranspiration (ET_0) showed that WaPOR and ERA5-Land had similar trends to the measured values (Fig. 7). However, the model-based estimated values were higher than those of the satellite products. Both WaPOR and ERA5-land reanalysis underestimated the ET_0 during the wet seasons (Fig. 7). ERA5-Land displayed higher values of reference evapotranspiration (ET0), although some deviations were observed in the reanalysis products. In contrast, the values estimated by WaPOR were found to be lower than the ground measurements. This discrepancy arises because model-based results typically offer finer resolution compared to satellite-based products.

Upon examining the line graph depicting reference evapotranspiration, it becomes evident that both the WaPOR and ERA5L estimated values are consistently lower than the observed ground data. Nevertheless, they displayed comparable trends when analyzed on both monthly and annual time scales (Fig. 7). Notably, despite the limited availability of actual climate data from the nearby weather station within the irrigation scheme, the observed ET_0 values significantly exceed those estimated using satellite and model-based methods.

The results presented in Table 5 indicate the ET_0 progressed through the crop growth stages, and there was a corresponding increase in the average monthly ET_0. This is primarily attributed to the elevated transpiration rates during crop growth, resulting in higher ET_0 as the growth of the crop increased, particularly during the mid-season growth stages of irrigated crops. In all three simulated scenarios, the outcome showed consistent trends for most months, except April, where some deviations were noted for the observed values (Table 5).

At each irrigation season, it is evident that the average daily reference evapotranspiration values, as simulated by the WaPOR dataset, consistently exhibited lower values than the observed and ERA5-Land estimated values (Fig. 8) This

Table 5. The mean monthly reference evapotranspiration of the three scenarios.

Month	Observed	WaPOR	ERA5L
November	5.55	3.70	5.44
December	5.30	3.84	5.01
January	5.61	4.42	5.80
February	6.19	4.81	5.62
March	6.85	5.68	6.60
April	7.07	5.54	6.61

Note: WaPOR is Water productivity through open access of Remotely Sensed derived data, and ERA5L denotes model-based land surface information for the estimation of reference evapotranspiration.

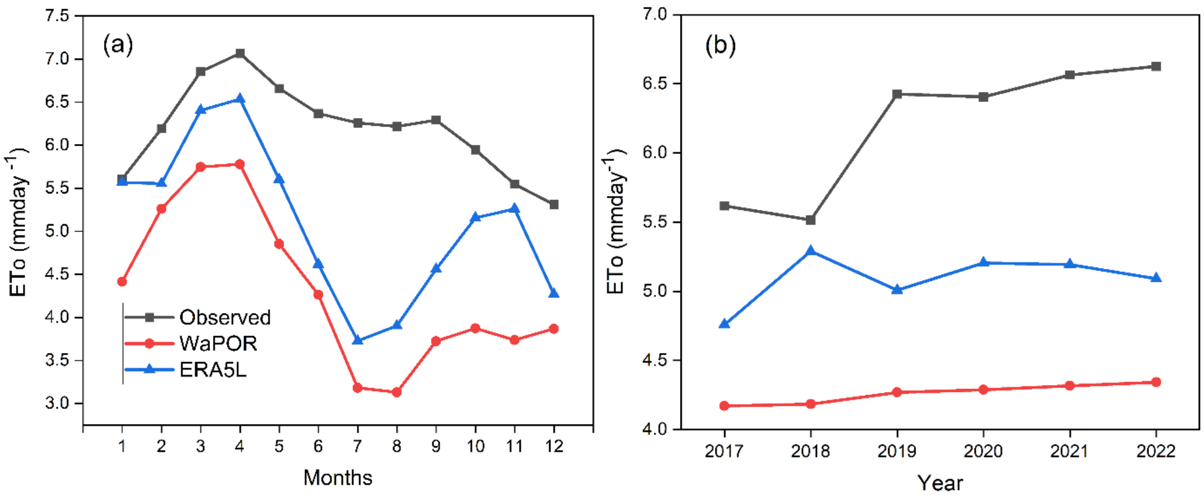

Fig. 7 The daily reference evapotranspiration for three estimation methods (a) monthly and (b) annually.

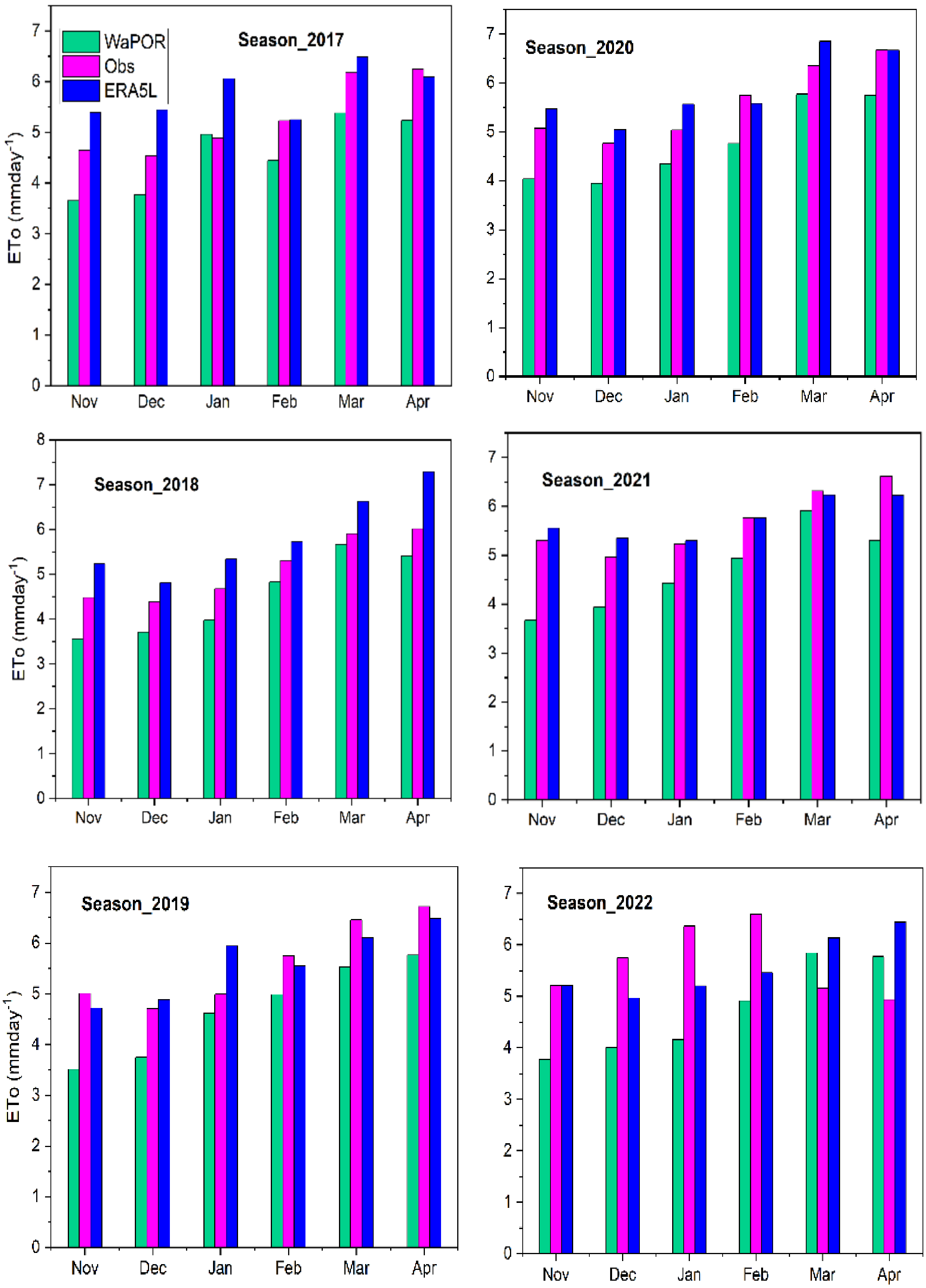

Fig. 8 The variation in daily reference evapotranspiration over the six-irrigation season.

discrepancy in estimated values can be attributed to a multitude of influencing factors, including but not limited to variations in the quality of climate data sources, differences in data analysis techniques, and limited availability of ground-based information. These factors collectively contribute to variations in the reference evapotranspiration estimations.

Additionally, we understand that the type of crop, soil, and water availability affects the reference evapotranspiration over the irrigation scheme. As shown in Fig. 8, the mean monthly ET0 increased from November to April across all irrigation seasons. This indicates that the rate of transpiration rises as the crop growth stage transitions from one cycle to the next.

The alteration in evapotranspiration throughout the irrigation growing seasons provided a visual representation of how the value of ET_0 gradually increased during each growing month. The increase in evaporation rates as crops progress through their growth stages under irrigation is primarily due to enhanced canopy development, the dominance of transpiration over soil evaporation, consistent soil moisture availability, and the creation of a favorable microclimate. These factors collectively contribute to higher rates of evapotranspiration, essential for optimal crop growth and yield. Furthermore, this underscores the fact that the presence of irrigated crops covering the land surface leads to a notable enhancement in evaporation levels, further amplifying the effects of climate change. Additionally, daily reference evapotranspiration exhibited fluctuations each month across all three estimators. These variations underscore issues related to inadequate irrigation water distribution and ineffective scheduling within the system

3.2 Correlation analysis

Pearson's correlation coefficient (r) was computed to understand the association between reference evapotranspiration estimators. The results of the correlation analysis indicated that both the reanalysis ($r = 0.66$ and $r = 0.93$) and satellite-based ($r = 0.86$ and $r = 0.98$) estimates were in good agreement with the observed values at a significant level ($P < 0.05$) concerning the daily and monthly time scales. However, the WaPOR outperformed the ERA5-Land on a daily and monthly basis and was suggested as the best estimator of ET_o in the study area and similar regions.

The preceding diagram illustrates that the relationship between the observed and ERA5L-estimated ETo exhibits a moderate correlation, while the observed and WaPOR_ETo showed a strong agreement when examined on a daily time scale (Fig. 9a). Conversely when the data were analyzed on a monthly timescale (Fig. 9b), both WaPOR and ERA5L revealed a robust correlation with the actual values.

3.3 Calculating the crop factor

The monthly crop coefficient is determined by utilizing the growth stage-specific crop coefficient sourced from the United States Food and Agriculture Organization (FAO), along with the number of days within each month and the sowing or planting date. As mentioned in Equation 10, the monthly crop factor was calculated by considering the crop coefficients, identifying crop growth stages, and determining the planting date. Finally, the monthly crop factor was computed. The growing season of wheat and potato crops was lower than that of the other crops, as described in Table 6. The results indicated that the value of the crop coefficient (kc) gradually decreased from February to April and increased from November to January, with the highest values occurring in February (Table 6) for irrigated crops, which is the developmental growth stage that requires frequent irrigation.

3.4 Crop evapotranspiration

This section emphasizes the main output of the model and satellite data portals that were used to verify field information to propose the water demands of major irrigated crops in the study of interest under dry conditions. Regression analysis of

Table 6. Monthly crop factor values of the irrigated crops during the irrigation season.

Crop type	Nov	Dec	Jan	Feb	Mar	Apr
Wheat	0.70	0.86	1.12	1.00	0.26	
Maize	0.50	0.84	1.03	1.12	0.64	0.17
Potato	0.70	0.89	1.09	1.01	0.36	
Tomato	0.50	0.61	0.76	0.95	0.78	0.21

Source: Own calculation based on growth stage and number of days during the growing season

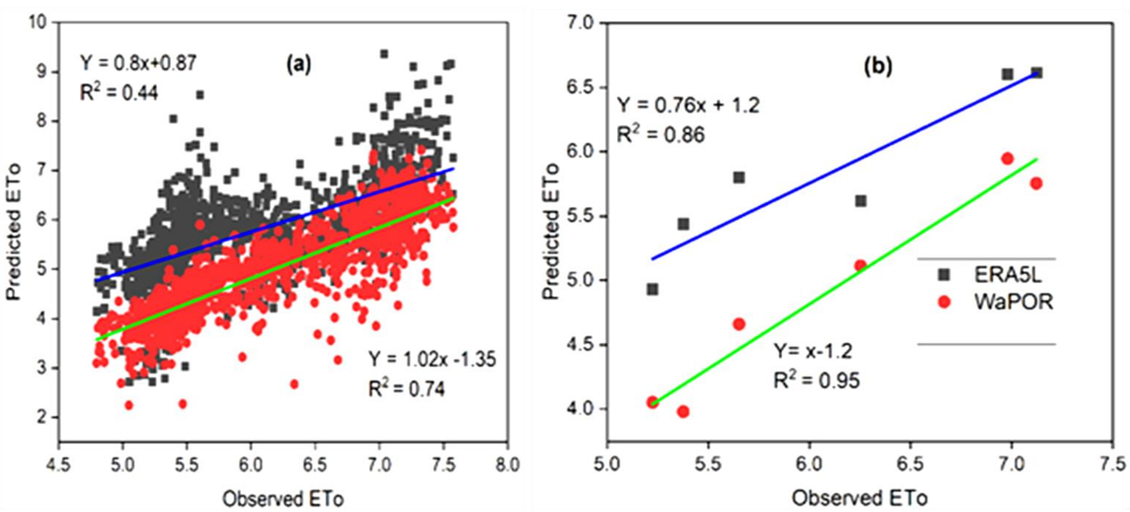

Fig. 9 The correlation between observation and estimated reference evapotranspiration (a) daily and (b) monthly.

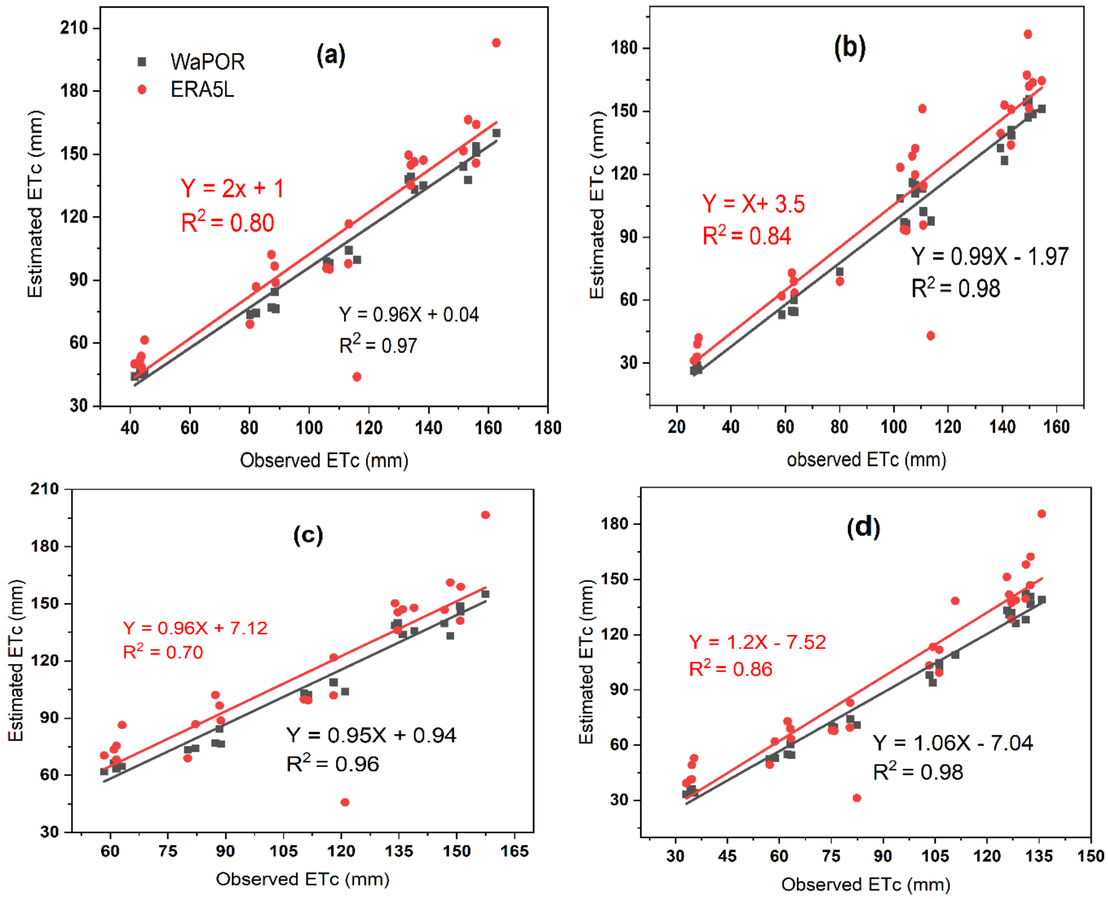

Fig. 10 Regression analysis of monthly crop water requirement (a) wheat, (b) maize, (c) potato, and (d) tomato for all irrigation seasons.

monthly crop water requirements, as depicted in the scatter plot (Fig. 10), revealed a robust correlation between the estimated and observed values for all irrigated crops considered in this study. This suggests that in situations where ground information is limited, both satellite and model-based datasets can effectively ascertain the crop water requirements. The research findings are comparable with those of other research conducted by Ref. [47] for calibration and validation analysis investigations to determine the crop evapotranspiration of wheat based on daily timescales.

3.5 Seasonal crop water needs

The evapotranspiration of the major irrigated crops was computed using the crop factor and the reference evapotranspiration. The seasonal crop water requirements of wheat varied from 522 to 540 mm, 494 to 528 mm, and 500 to 580 mm per season, with overall means of 532 mm, 510 mm, and 542 mm for the observed, WaPOR, and ERA5-Land analysis methods, respectively. This result is higher than the other findings conducted by Ref. [22] using climate change scenarios for all selected crops in this study; conversely,[48] found a greater value of wheat crop water requirement (573 mm) under field-level farmer irrigation practices. The differences are brought about by the models' different features and geographic resolutions and the results of climate change and other invisible factors in the study area. For maize crops, the seasonal amount of water needed varies from 593 mm to 616 mm, 568 mm to 600 mm, and 598 mm to 667 mm with mean values of 603 mm, 589 mm, and 636 mm for the observation, satellite-based (WaPOR), and model-based (ERA5L) products respectively. The outcomes of this discovery surpass the findings reported in [49] although the estimated value from WaPOR aligns favorably with this previous research. In this study, the water requirement of maize is lower than the previous studies reported by [50] and [42] using weather-based, remote sensing, and CROPWAT analysis approaches respectively. The seasonal crop water requirements of potatoes determined in this investigation ranged from 541 mm to 559 mm, 513 mm to 547 mm, and 519 to 599 mm with mean values of 549 mm, 529 mm, and 564 mm, respectively; for tomatoes, the seasonal crop water requirement varied from 533 mm to 549 mm, 518 mm to 546 mm, and 565 mm to 603 mm with mean values of 540 mm, 532 mm, and 583 mm for the observed, WaPOR, and ERA5-Land estimated methods, respectively (Fig. 11).

The estimated seasonal water requirements differed among the three scenarios and varied across different irrigation seasons and cultivated crops (Fig. 11). Notably, maize crops consistently demonstrated a greater water demand than other crops throughout all growing seasons due to factors including

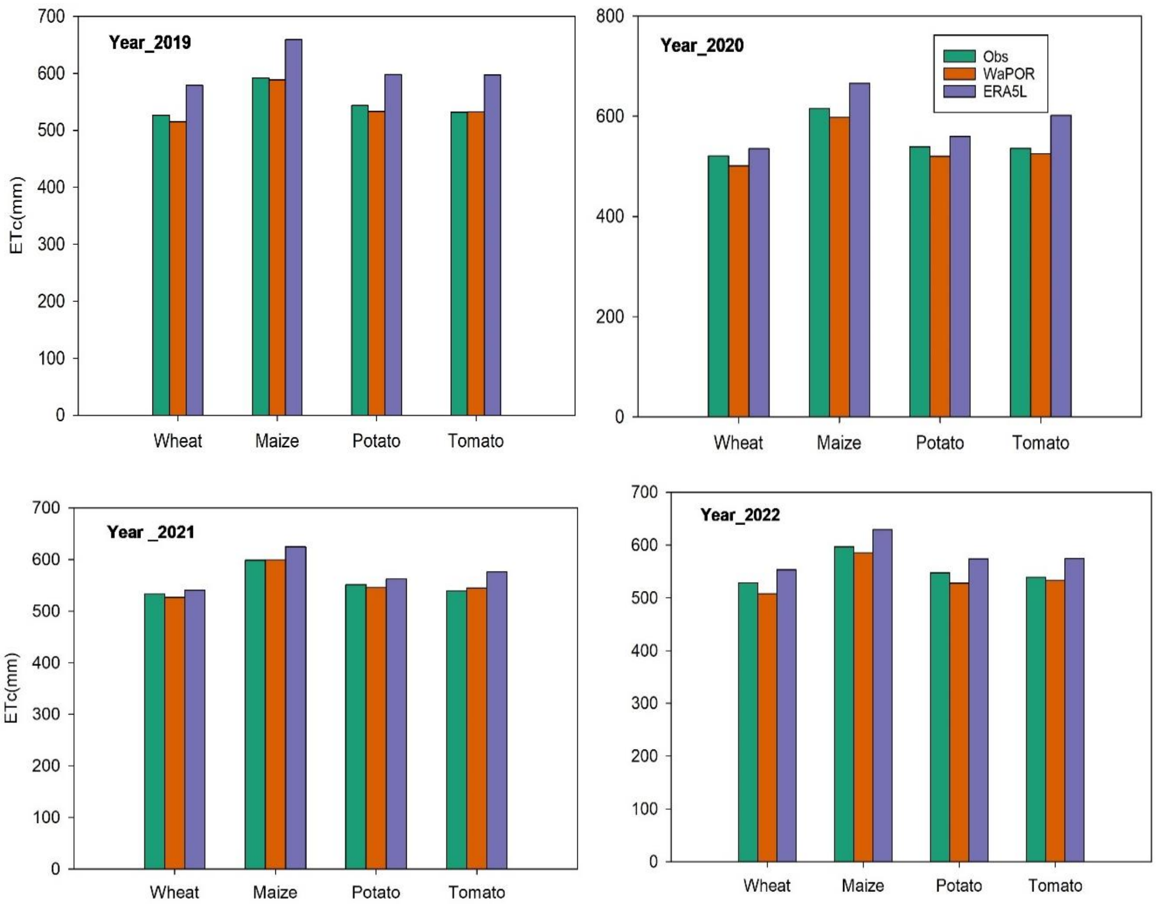

Fig. 11 Seasonal crop water requirement of irrigated crops within the scheme across four irrigation seasons.

leaf surface area, growth habitat (maize is a C4 crop and has a higher transpiration rate), and root depth resulting in an enhanced transpiration rate of maize compared to potato. The higher the ET value, the amount of water needed will be higher, and vice versa. As per FAO publications, the crop water requirements for wheat, maize, potato, and tomato fall within the indicative ranges of water needs for all relevant estimators.[51] However, it is worth noting that the ERA5-Land reanalysis product tends to overestimate the water requirements of maize and tomato.

3.6 Limitations of the study

This research focused on the determination of crop water needs using open-access datasets in ground data-limited regions and single crop coefficient approach estimation procedures were applied to compute the water demand of the crop. The coefficient integrates differences in the soil evaporation and crop transpiration rate between the crop and the grass reference surface. Due to fluctuations in soil evaporation caused by rainfall or irrigation, the single crop coefficient represents only the time-averaged (multi-day) impact of crop evapotranspiration. Therefore, the time-averaged single K_c is used for planning studies and irrigation system design where the averaged effects of soil wetting are acceptable and relevant in the case of surface and sprinkler irrigation systems where the time interval between successive irrigation is several days, often ten days or more. For typical irrigation management, single-time averaged k_c is valid. However, irrigation scheduling for high-frequency water applications, such as micro irrigation and automated sprinkler irrigation were not considered in this study. The dual coefficient approach (k_{cb}+k_e) is applicable for frequent irrigation application methods with a separate determination of evaporation and transpiration rather than the single coefficient approach.

4. Conclusion

In this research, we considered various factors while estimating crop water requirements and involved the calculation of reference evapotranspiration through three distinct methods including, weather-based, WaPOR, and ERA5-Land. The modified Penman-Monteith equation was employed to compute reference evapotranspiration and the crop factor of irrigated crops was determined based on FAO-56 guidelines. Finally, the water needs of each irrigated crop were calculated. Our analysis revealed a strong correlation between the measured and model-estimated reference evapotranspiration, evident across both daily and monthly temporal scales. However, it's noteworthy that the performance of the WaPOR model surpassed that of ERA5-Land in this regard. Similarly, a robust relationship between the measured and estimated crop evapotranspiration (ET_c)

values was found when examined on a monthly time scale. We also attained that the monthly crop evapotranspiration tends to peak during the mid-stage of the growing season for all irrigation seasons. Specifically, for wheat, the mean crop evapotranspiration was determined to be 532 mm, 510 mm, and 542 mm for observed, satellite-based, and model-based estimates, respectively. Meanwhile, for maize, the ET_c values were 603 mm, 589 mm, and 636 mm for the same respective categories. Moving on to potatoes, we found that the average crop evapotranspiration values were 549 mm, 529 mm, and 564 mm, while for tomatoes the mean crop water requirements were 540 mm, 532 mm, and 583 mm for the measured, WaPOR, and ERA5-Land estimations, respectively. Remarkably, the highest crop evapotranspiration (ET_c) value was consistently observed for maize crops across all estimation scenarios, suggesting their sensitivity to water stress in comparison to wheat, tomato, and potato. While our estimated ET_c values generally fell within the range of FAO-book recommendations, it is worth noting that the model-based estimates tend to be higher than the satellite-based and measured values. To sum up, our study emphasizes the significance of utilizing satellite and model-derived data to compute crop evapotranspiration for key irrigated crops within an irrigation system. This research offers insights for decision-makers, designers, water managers, agronomists, stakeholders, and irrigation operators. Additionally, further investigation into the dual crop coefficient approach is suggested.

Conflict of interest

This is to confirm that the authors have no conflict of interest.

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Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

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