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Remote Sensing for Sustainable Crop Water Management in a Changing Climate

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Abstract

Climate change is escalating, posing challenges that impact agricultural regions, including the Gharb irrigated area in North-Western Morocco. This paper explores the role of remote sensing as a powerful geospatial tool for identifying, characterizing, and landmarking resources in agriculture over a large surface area. It proposes adaptive strategies for sustainable agriculture amid dynamic climatic conditions, with a particular focus on addressing water management challenges. This research estimates the water requirements of different crop types in the Gharb Plain irrigated area by combining geospatial technological development, crop modeling, and multi-date data. Throughout the study, we address key challenges such as crop dynamics, data accuracy, and policy integration. The findings show that remote sensing plays a significant role in crop water management, promoting sustainability, and precision agriculture despite the challenges posed by climate change. Furthermore, the study emphasizes the necessity of continued research, technological advancement, and policy implementation to fully realize the potential of remote sensing in guiding agriculture toward a resilient and sustainable future.

Keywords:

Remote sensing; climate change; water requirement; Gharb Plain

1. Introduction

In recent years, remote sensing data has increasingly become valuable for various applications, serving as an essential analytical resource for monitoring crucial land cover changes in sustainable crop water management. Amidst climate change challenges, sustainable crop water management has emerged as a vital solution. By optimizing water use efficiency and enhancing resilience, it ensures the sustainability of agricultural practices, conserves resources and promotes economic viability for farmers worldwide. Projections indicate a 70% increase in global agricultural production required to meet the needs of an anticipated population of 9.8 billion by 2050. According to the United Nations Department of Economic and Social Affairs (2017), the global population is expected to grow from 7.6 billion currently to 8.6 billion by 2030, 9.8 billion by 2050, and 11.2 billion by 2100. These projections highlight the critical importance of adopting sustainable farming practices to meet the growing demand for food while safeguarding the environment.

The agricultural sector faces increasing challenges due to climate change's impact on crop productivity and essential production inputs (Ortiz-Bobea, 2021). Studies, such as those conducted by Porter et al. (2014), have extensively analyzed the effects of observed climate changes on crop yields over the past half-century. Amidst these challenges, satellite remote sensing has emerged as a critical tool for identifying crops and monitoring their conditions (Potgieter et al., 2021; Weiss et al., 2020). This technology allows the assessment of crop growth status and eventual production, providing valuable insights into agricultural sustainability and food security. Recent advancements in satellite technology, combined with cloud-computing platforms like Google Earth Engine (GEE) (Gorelick et al., 2017), have significantly enhanced our capacity to identify and monitor crops at high spatial and temporal resolutions, overcoming previous constraints in satellite data processing and information extraction.

The agriculture in the Gharb Plain faces significant challenges due to climate variability, characterized by unpredictable weather patterns, changing precipitation, and an increased frequency of extreme events. These variations disrupt traditional farming practices, affecting crop yields and water availability. To effectively address these challenges, advanced tools like remote sensing become imperative. Remote sensing offers a comprehensive and real-time assessment of the region's climatic conditions, enabling farmers to make informed decisions about water management, crop planning, and resource allocation in response to the dynamic climate of the Gharb Plain.

Previous studies have provided fundamental insights into the interplay between climate change, agricultural productivity, and the role of remote sensing in mitigating these challenges. For example, research by Parmar et al. (2023) highlighted the high correlation between NDVI and crop coefficient, while studies by Potgieter et al. (2021) and Weiss et al. (2020) emphasized the critical role of remote sensing in monitoring crop conditions. Additionally, a study conducted by Smith et al. (2023) investigated the impact of climate variability on agricultural productivity and highlighted the effectiveness of remote sensing techniques in assessing crop health and yield predictions. Furthermore, recent research by Cheikhaoui et al. (2024) provided insights into the estimation of water requirements. Building upon these findings, the present study aims to estimate the annual irrigation water requirements for different crops (rice, cereals, sunflower, sugarcane, and citrus) during their development stages between 2019 and 2022.

Based on prior research and through the employment of advanced remote sensing techniques, this research contributes to the advancement of sustainable agricultural practices in the face of climate change challenges, providing valuable insights into sustainable water management amidst changing climatic conditions. Addressing the necessity of sustainable food production while mitigating ecological disruption is a pressing concern in the irrigated area of the Gharb Plain. Accurate estimation of water requirements in irrigated areas is crucial for efficient water allocation and reducing ecological footprint.

2. Materials and Methods

2.1. Study area

The Gharb plain, situated at coordinates 34°15′N 6°35′W, occupies the northwestern region of Morocco as shown in Figure 1. Encompassing approximately 6160 square kilometers, it stretches approximately 80 kilometers along the

Atlantic coastline and extends inland for about 110 kilometers. This region experiences a Mediterranean climate, characterized by hot, arid summers and mild winters. However, there is notable local variation in climate, with semi-arid conditions prevailing inland and sub-humid conditions along the coast. Annual rainfall typically exceeds 400 millimeters across most of the plain, with average temperatures hovering around 18.62°C. The cooler, wetter season lasts seven months from October to April.

The boundaries of the Gharb plain are defined by natural features: the hills of Lalla Zohra to the north, the Prerifans hills to the east, the Maamora plateau to the south(which is part of the Moroccan Meseta), and the Atlantic Ocean to the west.

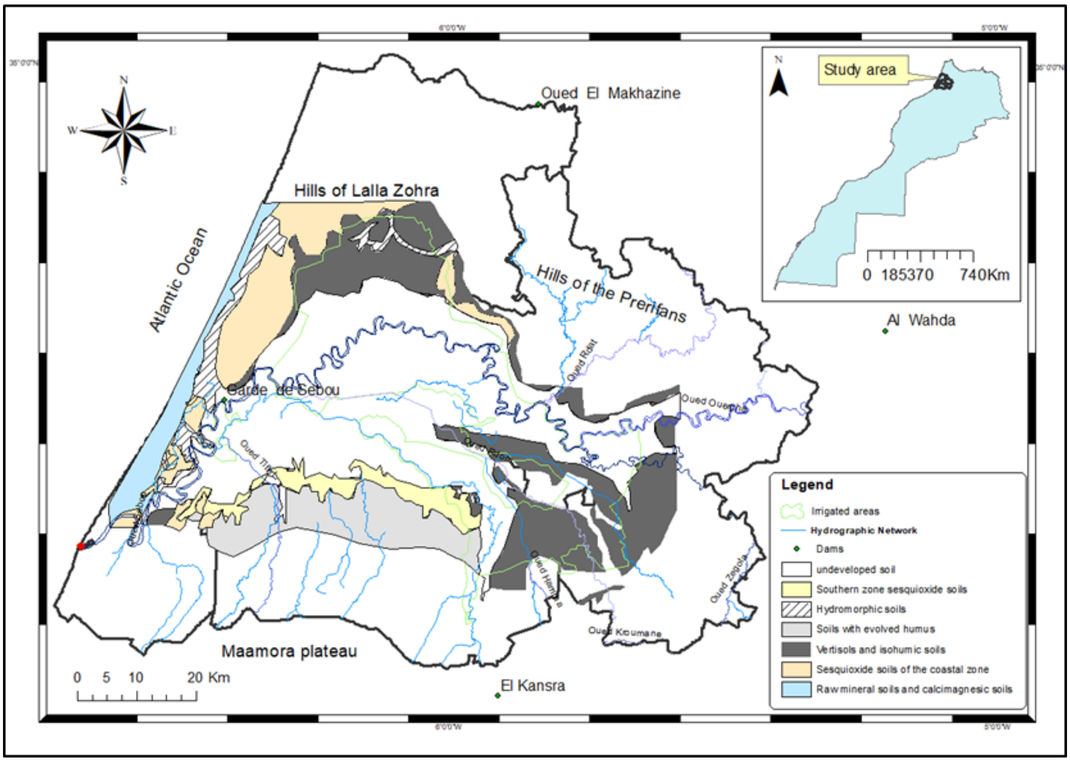

Figure 1: Location map of the study area (Cheikhaoui et al.2024)

The hydrographic network of the region is represented by the Sebou River, one of the major rivers in the kingdom, along with its tributaries including the Ouergha, Beht, Rdom, and Tiflet Rivers.

2.2. Data

The data processing encompasses several key components (Fig.2): Firstly, we computed vegetation indices such as NDVI (Normalized Difference Vegetation Index), NDWI (Normalized Difference Water Index), SAVI (Soil Adjusted Vegetation Index), EVI (Enhanced Vegetation Index), and GNDVI (Green Normalized Difference Vegetation Index) for Landsat images available within Google Earth Engine (GEE) Table 1. This process yielded annual maximum and minimum changes in vegetation indices from 2013 to 2023. Secondly, we leveraged growing season images from 2019 to 2022 to delineate various land cover types and crop characteristics. Finally, we determined the land cover types of crop areas by overlaying land cover classification with the distribution of vegetation types.

Table 1 : Formula and Source of Vegetation Indices

Vegetation Indice	Source	Temporal Resolution	Spatial Resolution	Reference	Formula
NDVI	Landsat 8 OLI/TIRS Collection 2 Tier 1	16 days	30 meters	USGS Earth Explorer	(NIR - RED) / (NIR + RED)

	TOA Reflectance				
NDWI	Landsat 8 OLI/TIRS Collection 2 Tier 1 TOA Reflectance	16 days	30 meters	USGS Earth Explorer	(GREEN - NIR) / (GREEN + NIR)
GNDVI	Landsat 8 OLI/TIRS Collection 2 Tier 1 TOA Reflectance	16 days	30 meters	USGS Earth Explorer	(NIR - GREEN) / (NIR + GREEN)
SAVI	Landsat 8 OLI/TIRS Collection 2 Tier 1 TOA Reflectance	16 days	30 meters	Huete, A. R., et al. (2002).	((NIR - RED) / (NIR + RED + L)) * (1 + L)
EVI	Landsat 8 OLI/TIRS Collection 2 Tier 1 TOA Reflectance	16 days	30 meters	Huete, A. R., et al. (2002).	2.5 * ((NIR - RED) / (NIR + 6 * RED - 7.5 * BLUE + 1))

Leveraging GEE's extensive library of analysis tools and computing resources, we implemented a workflow for calculating vegetation indices, and advanced image classification algorithms to identify and map different land cover classes, ensuring accuracy in our measurements. The following figure represents the workflow of the overall methodology of the study:

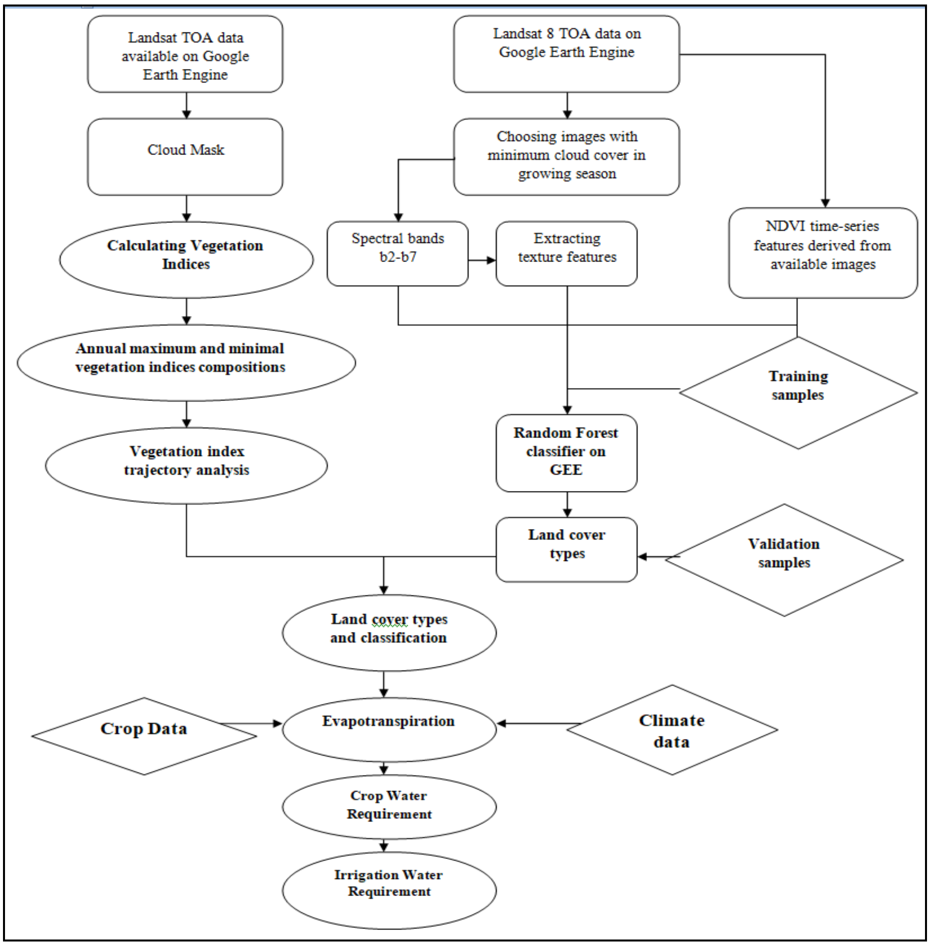

Figure 2: Methodology of the study

The Gharb Regional Development Office (ORMVAG) provided data socioeconomic for 2019/2020,2020/2021, and 2021/2022, which included details about crop types, areas, and production in the Gharb plain. These datasets were integrated with remote sensing, Google Earth engine platform, and meteorological data to analyze the spatial and temporal patterns of crop water consumption in the Gharb irrigated perimeter from 2019 to 2022. Solar and meteorological data obtained through Power Data Access Viewer (DAV)(power.Iarc.nasa.gov) from NASA were used in this study. Monthly and annual observed maximum and minimum air temperature, rainfall, wind speed measured at 2m height, relative humidity and daily sunshine duration data were available (Cheikhaoui et al. 2024).

To determine the irrigation water needs of crops such as rice, citrus, and sugarcane, factors such as evapotranspiration, crop coefficients, effective rainfall, crop water requirement, and irrigation coefficients are taken into account, using relevant meteorological data from studies by Allan (2003), Allen et al.(1998), and Cammarano et al. (2016).

2.3. Methodology

2.3.1. References evapotranspiration (ET0)

ET0 was calculated using the FAO-56 Penman-Monteith equation (Allen et al., 1998), which is a modified version of the original Penman-Monteith equation (Monteith,1965). The equation (1) is expressed as follows:

$$\text{ETo} = \frac{0{,}0048\ \Delta(Rn-G) + \gamma \frac{900}{T+273} u2\ (es-ea)}{\Delta + \gamma\ (1+0{,}34U2)} \qquad (1)$$

Where ET0 is the reference evapotranspiration (mm/d), T is the air temperature (°C),Rn(net surface radiation), G (soil heat flux density), u2(wind speed at 2m height),es(saturated vapor pressure),ea(actual vapor pressure), Δ (slope of vapor pressure curve), and γ (psychrometric constant).

2.3.2. Crop water requirement (CWR)

The rice, sugarcane and citrus CWR during the growth period in the study area were estimated using the crop coefficient method by the Food and Agriculture Organization (FAO), equation (2):

$$\text{ETc} = \text{ET0} \times \text{Kc} \qquad (2)$$

Where ETc is the crop evapotranspiration, ET0 is the reference evapotranspiration and Kc is the crop coefficient (Allen et al.,1998)

The water requirement for the three crops is calculated as follows, equation (3):

$$\text{CWR} = \text{ETc} - \text{Pe} \qquad (3)$$

Where CWR is the crop water requirement and Pe is the effective precipitation.

2.3.3. Crop coefficient (Kc)

Kc at different stages (Kcini, Kcmid and Kcend) where Rice, Sugarcane, Citrus, Sunflower, and Cereals were calculated using the FAO single crop coefficient method. These values are based on meteorological and soil conditions and are documented in the Food and Agriculture Organization (1977), which provides comprehensive data for various climates and locations.

In the early stage of crop growth, Kcini values are mainly based on FAO’s standard values at the initial stage multiplied by the fraction of surface wetted by irrigation or rain.

2.3.4. Effective precipitation

Effective rainfall is calculated using the Department of Soil and Water Conservation of the United States Department of Agriculture method according to the following equation(4):

$$\text{Peff} = \begin{cases} Pmonth \times \frac{(125-0.2 \times Pmonth)}{125} Pmonth \leq 250mm \\ 125 + 0.1 \times Pmonth \;\; Pmonth > 250mm \end{cases} \quad (4)$$

Where P_{month} is the actual monthly precipitation.

2.3.5. Irrigation efficiency (Ie)

Water use efficiency in irrigated agriculture is the ratio of estimated irrigation water requirements to the actual water withdrawal from river channels or reservoirs (FAO,2022).

The Ie values utilized in this study to calculate the irrigation water requirement (IWR) for different provinces in the Gharb region are obtained from the ORMVAG. These values, outlined in Table 2, take into account factors such as irrigation system management, water distribution characteristics, crop water use rates, as well as weather and soil conditions.

Table 2: Irrigation efficiency for the equipped area of the Gharb plain between 2019 and 2022.

Year	**2019**	**2020**	**2021**	**2022**
Ie	71%	73%	76%	75%

2.3.6. Irrigation water requirement (IWR)

The net irrigation water requirement (IWR) (5) can be calculated by (Li Y. and al., 2020):

$$IWR = A\ CWR / Ie \quad (5)$$

Where A is the planting area of the crop, and CWR is the crop water requirement.

3. Results

3.1. Vegetation Indices Changes

Our study utilized Landsat imagery, accessible through the cloud-computing platform Google Earth Engine (GEE), to analyze temporal trends in vegetation indices within the Gharb-irrigated perimeter from 2013 to 2023. The selection of vegetation indices, including the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Soil Adjusted Vegetation Index (SAVI), Enhanced Vegetation Index (EVI), and Green Normalized Difference Vegetation Index (GNDVI), reflects a comprehensive approach to understanding ecosystem dynamics. NDVI, a widely used indicator of vegetation health, assesses the presence and vigor of vegetation based on the contrast between near-infrared and red reflectance. NDWI, on the other hand, highlights water bodies by exploiting the contrast between green and near-infrared reflectance. SAVI incorporates a soil adjustment factor to better account for soil background effects in dense vegetation areas. EVI, developed to overcome some limitations of NDVI, provides enhanced sensitivity in regions with dense vegetation. GNDVI, similar to NDVI but using the green band instead of the red band, offers an alternative perspective on vegetation dynamics. By analyzing the temporal distribution of these indices, we gain insights into long-term vegetation dynamics, including seasonal variations, trends in vegetation health, and responses to environmental factors such as water availability and land management practices. The line graph illustrates the time series of various vegetation indices from 2013 to 2023 in the Gharb-irrigated perimeter. (Fig.3) The graph indicates similar trends for the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Green Normalized Difference Vegetation Index (GNDVI) in the Gharb-irrigated perimeter during the period. The mean values for these indices peaked in March 2017, with NDVI reaching 0.657, GNDVI reaching 0.568, and EVI reaching 0.651. Regarding minimum values, the NDVI reached a mean of 0.255 in July 2022, the GNDVI reached 0.237 in November 2013, and the EVI reached 0.212 in October 2021. Conversely, the minimum mean values for these indices occurred at different times. NDVI reached a minimum of 0.255 in July 2022, GNDVI reached 0.237 in November 2013, and EVI reached 0.212 in October 2021.

In contrast, the SAVI (Soil Adjusted Vegetation Index) indices displayed different fluctuations. SAVI peaked at 0.197 in March 2017 and reached a minimum of 0.064 in November 2013.

Furthermore, the NDWI (Normalized Difference Water Index) peaked in December 2016 at -0.244 and reached a minimum of -0.372 in May 2020.

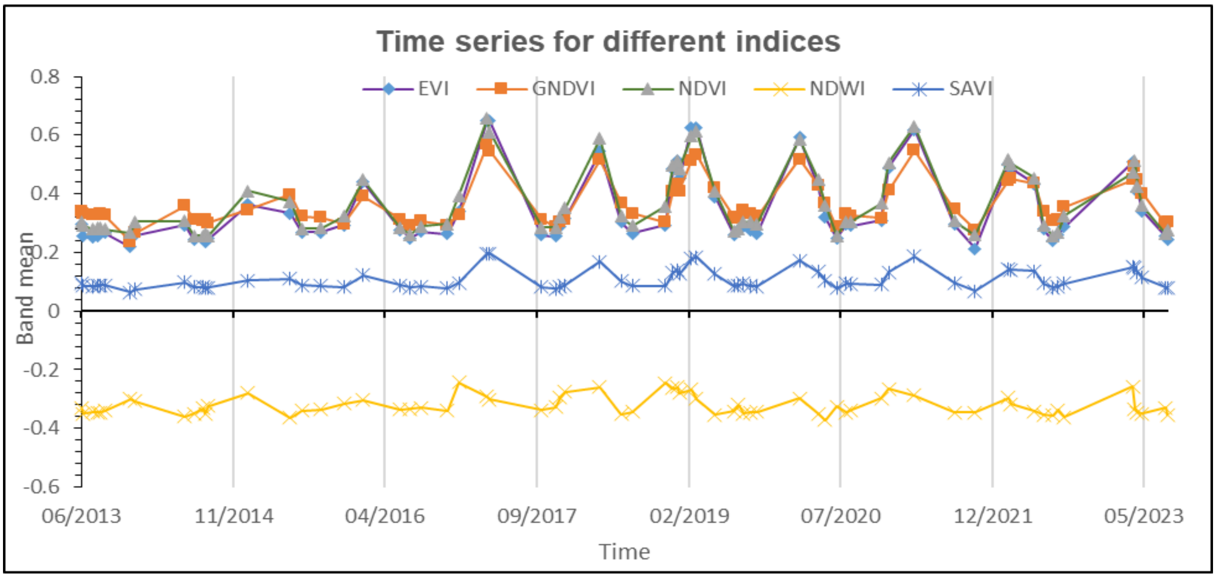

Figure 3: Time series for vegetation indices between 2013 and 2023(GEE Platform)

3.2. Google Earth Engine Crop Classification Analysis

Using Google Earth Engine, we conducted a classification analysis aimed at mapping crop types across the Gharb-irrigated perimeter (Fig.4). Leveraging the capabilities of this platform, we employed a classifier trained with Landsat imagery and ground-truth data. The result was a classification map boasting an impressive 100% accuracy rate, indicative of the reliability and precision of our approach. Our observations unveiled distinct spatial patterns where various crops, including Rice, Sugarcane, Citrus, Sunflower, and Cereals, flourished, each occupying specific geographic zones dictated by environmental and agronomic factors. The concentrated cultivation of Rice in the Northwest region of the irrigated perimeter, encompassing areas along the province of Kenitra and Sidi Kacem. In contrast, Sugarcane fields dominate the expansive plain flanking both banks of the Oued Sebou River, showcasing the suitability of these areas for this particular crop. Moving further, we noted the cultivation of Citrus orchards across the plain, especially prevalent within the three provinces of the Gharb. These orchards thrive in the region's mild climate and well-drained soils, forming a distinct feature of the agricultural landscape. Sunflower fields, characterized by their vibrant yellow blooms, were found scattered across the northern reaches of the study area. The abundant sunlight and nutrient-rich soils provide optimal conditions for Sunflower cultivation, contributing to the agricultural diversity of the region. Lastly, Cereal crops, including wheat and barley, make their mark in both the northern and southern parts of the perimeter. These crops benefit from cooler temperatures and seasonal rainfall, creating favorable conditions for their growth and contributing to the agricultural mosaic of the Gharb-irrigated perimeter. In summary, our classification analysis not only provides a detailed map of crop distribution but also offers valuable insights into the complex interplay of environmental factors and agricultural practices shaping the Plain of the Gharb-irrigated perimeter.

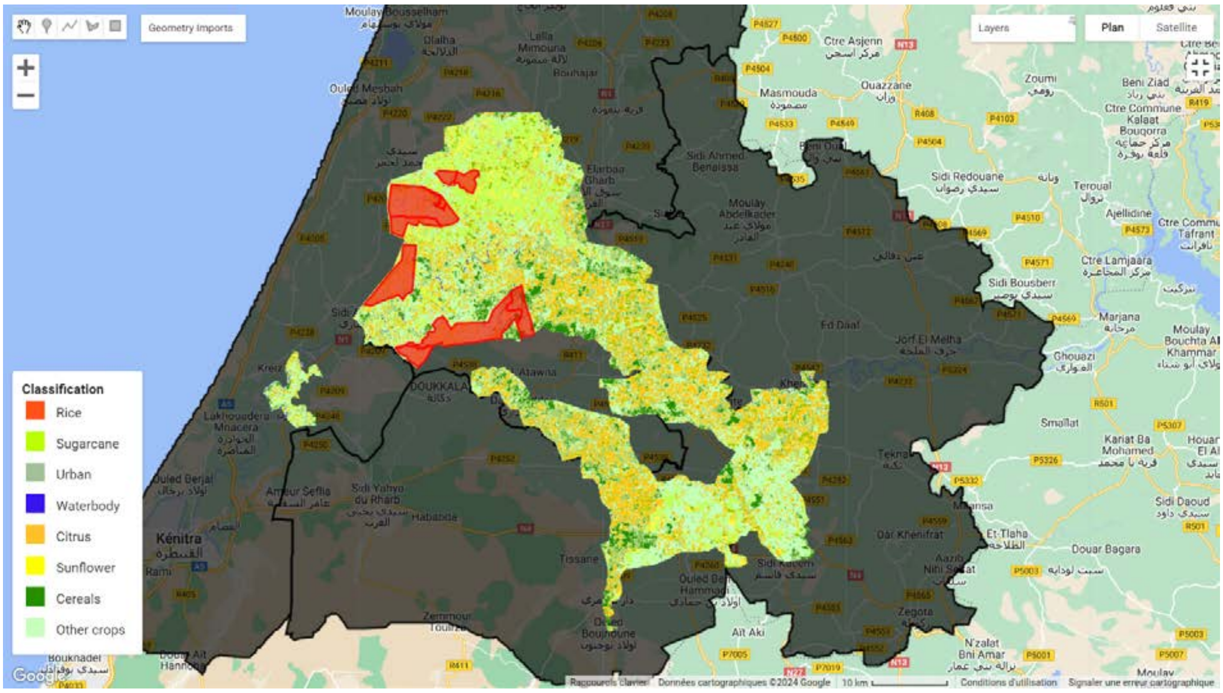

Figure 4: Classification map of crop types in the Gharb-irrigated perimeter (GEE, 2021)

3.3. Temporal Analysis of Crop Area Dynamics

The bar chart (Fig.5) illustrates the crop area evolution in the Gharb-irrigated perimeter from 2019 to 2022. Our analysis of this temporal crop area evolution within our study area reveals intriguing trends for Rice, Sugarcane, Citrus, Sunflower, and Cereals. Notably, Rice cultivation showed a fluctuation, increasing from 6101.38 hectares in 2019 to 6604 hectares in 2020, declining to 5827.33 hectares in 2021, then rebounding to 7349.56 hectares in 2022. Similarly, Cereals experienced fluctuations, increasing from 1011.76 hectares in 2019 to 9722 hectares in 2020, sharply decreasing in 2021, then rising again in 2022.In contrast, the Sugarcane cultivation saw a general trend of decrease, with areas of 7530.79 hectares in 2019, 6949 hectares in 2020, 5829.37 hectares in 2021, and 4082.92 hectares in 2022. Sugar beet cultivation area increased by 2677.74 hectares from 2019 to 2020 and by 1767.76 hectares from 2020 to 2021 but significantly decreased by 5309.42 hectares in 2022. Meanwhile, Sunflower cultivation area showed a gradual increase, reaching 3703.72 hectares in 2022, after fluctuations from 257.35 hectares in 2019 to 2307 hectares in 2021 and a notable decrease to 844.11 hectares in 2022. Citrus cultivation area remained relatively stable, starting at 12152.41 hectares in 2019, increasing slightly to 12192.57 hectares in 2020, decreasing to 9269 hectares in 2021, rebounding to 11707.43 hectares in 2022, then decreasing again to 8915.32 hectares.

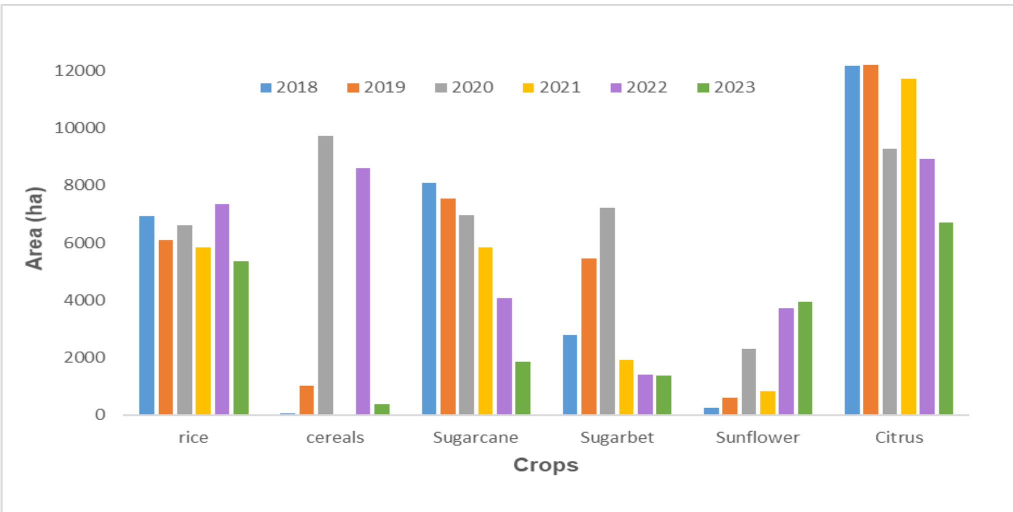

Figure 5: Crops area evolution between 2019 and 2022

3.4. Temporal Analysis of Evapotranspiration, Precipitation, and Temperature

The line graph (Fig.6) outlines Evapotranspiration (ET0), Temperature (T) and Precipitation (P) changes from 2019 to 2022 across the three provinces of the irrigated perimeter of the Gharb: Kenitra, Sidi Kacem, and Sidi Slimane. In Kenitra, precipitation started at 0.54(mm/day) in 2019 and experienced fluctuations over the years, while temperature gradually increased from 16.95°C to 18.66°C in 2022. Sidi Kacem exhibited a similar trend with a slight decrease in precipitation from 0.31 in 2019 to 0.15 in 2022, while temperature increased from 21.97°C to 23.22°C during the same period. Sidi Slimane demonstrated fluctuations as well, with precipitation decreasing from 0.45 in 2019 to 0.21 in 2022, and the temperature gradually rising from 22.07°C to 23.3°C. Evapotranspiration fluctuated, with an increase from 6.717 in 2019 to 8.390 in 2020, followed by a slight decrease to 6.970 in 2021 and a subsequent rise to 7.735 in 2022. Similarly, in Sidi Kacem, evapotranspiration decreased from 11.198 in 2019 to 10.438 in 2020, then increased slightly to 10.953 in 2021 before declining to 9.042 in 2022. In Sidi Slimane, evapotranspiration decreased from 11.554 in 2019 to 10.176 in 2020, increased slightly to 11.004 in 2021, then decreased to 9.310 in 2022. Fluctuations in evapotranspiration (ET0), temperature, and precipitation suggest diverse water demand and climatic conditions across locations. Understanding their relationship is crucial for managing water balance in ecosystems and agriculture, as temperature influences evapotranspiration rates while precipitation restores soil moisture.

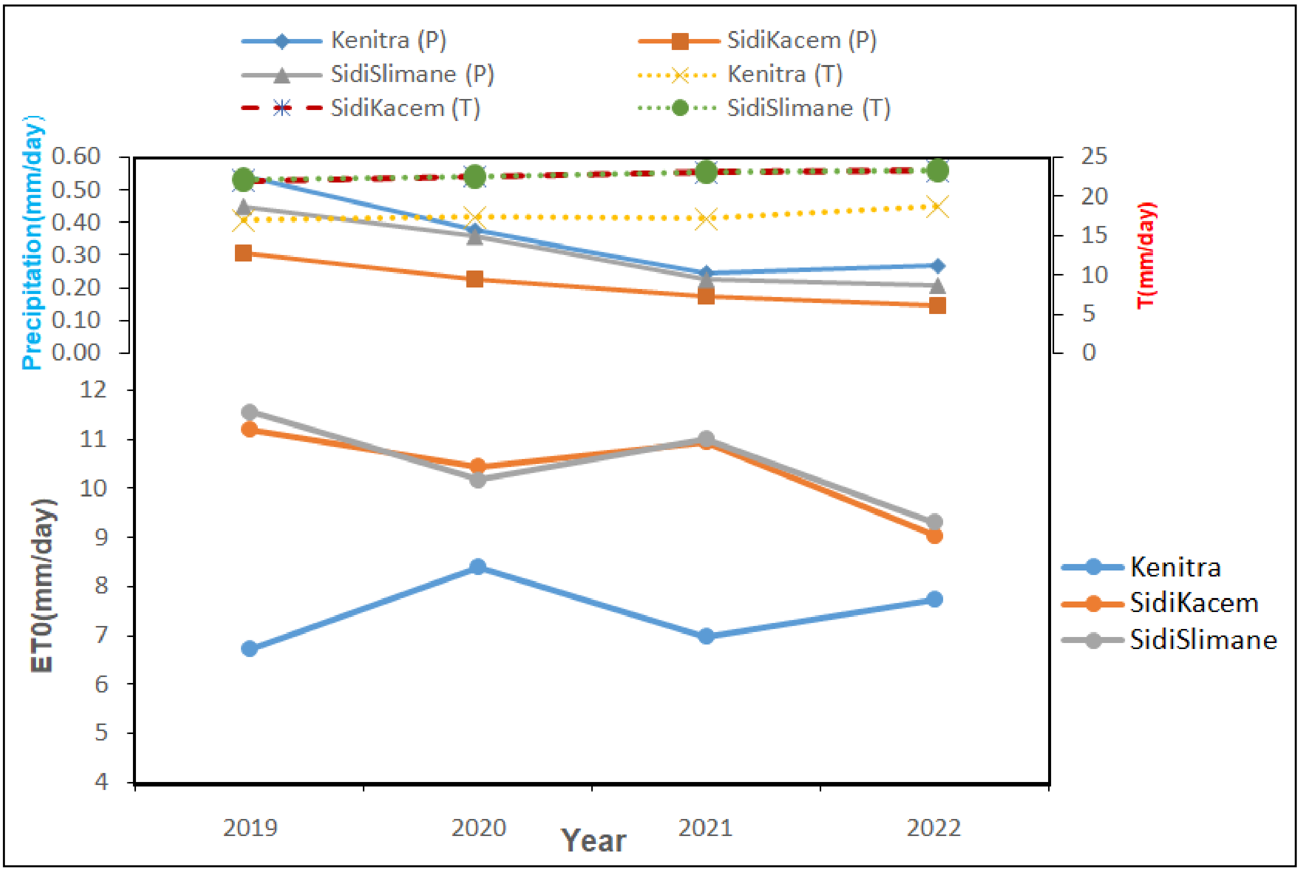

Figure 6: Temporal distribution of Evapotranspiration, Precipitation, and Temperature (2019-2022)

3.5. Crop Water Requirements

The bar graphs represent the crop water requirement (CWR) for different crops in the provinces of Kenitra, Sidi Kacem, and Sidi Slimane between 2019 and 2022.(Fig.7) For the CWR of rice crops in the provinces of Kenitra, Sidi Kacem, and Sidi Slimane over the four-year period. Sidi Slimane consistently shows the highest CWR, followed by Sidi Kacem and Kenitra. Additionally, there's a general decreasing trend in CWR from 2019 to 2022 across all provinces. In Kenitra, the highest CWR value was observed in 2019(3.942mm/day), while the lowest was recorded in 2021(1.828 mm/day), indicating a decrease over the years. Similarly, in Sidi Kacem, the highest CWR was noted in 2019(3.910 mm/day), with the lowest in 2022(1.489 mm/day), showing a consistent decrease over the period. Sidi Slimane exhibited the highest CWR in 2019(5.885) and the lowest in 2022(2.164), indicating a decreasing trend in CWR from 2019 to 2022 across all provinces. For cereals, in Kenitra, the Crop Water Requirement (CWR) was highest in 2019(4.306 mm/day) and lowest in 2021(1.998 mm/day), showing a decrease over the years. In Sidi Kacem, the highest CWR was observed in 2019(4.254 mm/day), while the lowest was recorded in 2022(1.622 mm/day), indicating a decrease over the period. Sidi Slimane exhibited the highest CWR in 2019(6.403 mm/day) and the lowest in 2022(2.358 mm/day), showing a decreasing trend in CWR from 2019 to 2022 across all provinces. Regarding Citrus crops, in Kenitra, the CWR decreased from 2.553 mm/day in 2019 to 1.519 mm/day in 2022. Similarly, in SidiKacem, the CWR decreased from 2.680 mm/day in 2019 to 1.010 mm/day in 2022. In Sidi Slimane, there was also a decrease in CWR from 4.046 mm/day in 2019 to 1.459 mm/day in 2022. Overall, there is a noticeable decline in the CWR for citrus crops across all three provinces over the four-year period. For sugarcane crops, the Crop Water Requirement (CWR) showed a decreasing trend across all three provinces from 2019 to 2022. In Kenitra, the CWR decreased from 4.718 mm/day in 2019 to 2.745 mm/day in 2022. Similarly, in Sidi Kacem, there was a decline in CWR from 4.712 mm/day in 2019 to 1.793 mm/day in 2022. In Sidi Slimane, the CWR also decreased from 7.096 mm/day in 2019 to 2.603 mm/day in 2022. Overall, there is a consistent reduction in the CWR for sugarcane. In summary, the analysis of CWR trends across different crop types and provinces highlights a complex interplay of factors impacting water demand in agricultural regions over time, underscoring the importance of adaptive water management strategies in response to evolving climatic and agricultural conditions.

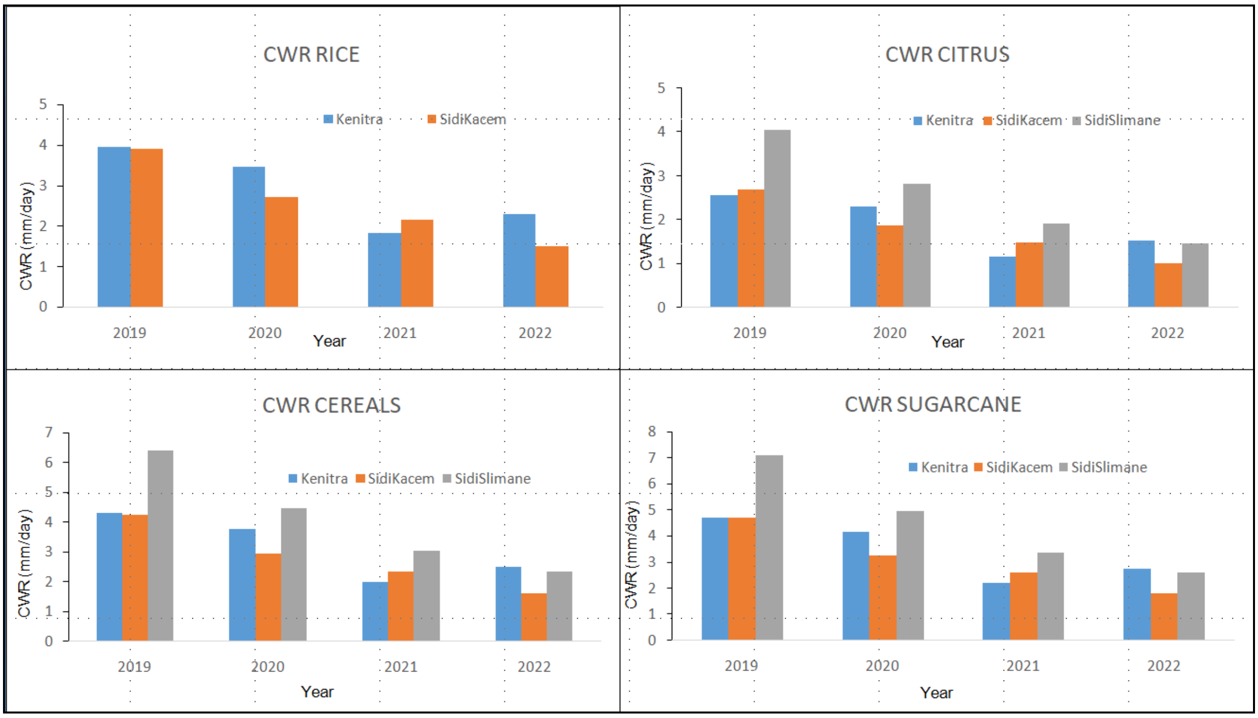

Figure 7: Crop Water Requirement (CWR) for Various Crops from 2019 to 2022

3.6. Irrigation Water Requirements

The bar graph represent the irrigation water requirement (IWR) in cubic meters (m^3) for various crops across different years shows distinct patterns (Fig.8). Specifically, for rice crops, a decrease in IWR is evident from 2019 to 2022, with the highest demand recorded in 2019(143,623,494.6 m^3) and the lowest in 2021(63,155,873.24 m^3) indicating a significant reduction over the period. Cereals, on the other hand, exhibit fluctuations, with a substantial increase in 2020 followed by a notable decrease in 2021, then a slight rise again in 2022, reflecting dynamic trend in water requirements for cereal cultivation. In contrast, sugarcane cultivation demonstrates a decline in IWR over the years, with the highest demand in 2019(213,268,574.7 m^3) and the lowest in 2022(47,296,741.61 m^3). Similarly, Citrus crops display a consistent decrease in IWR, with the highest demand in 2019(193,876,163.3 m^3) and the lowest in 2022(57,674,646.93 m^3) over the specified period. These observations underscore the dynamic nature of water demand across different crop types, highlighting potential shifts in agricultural practices, technological advancements, or environmental influences that may impact irrigation needs over time.

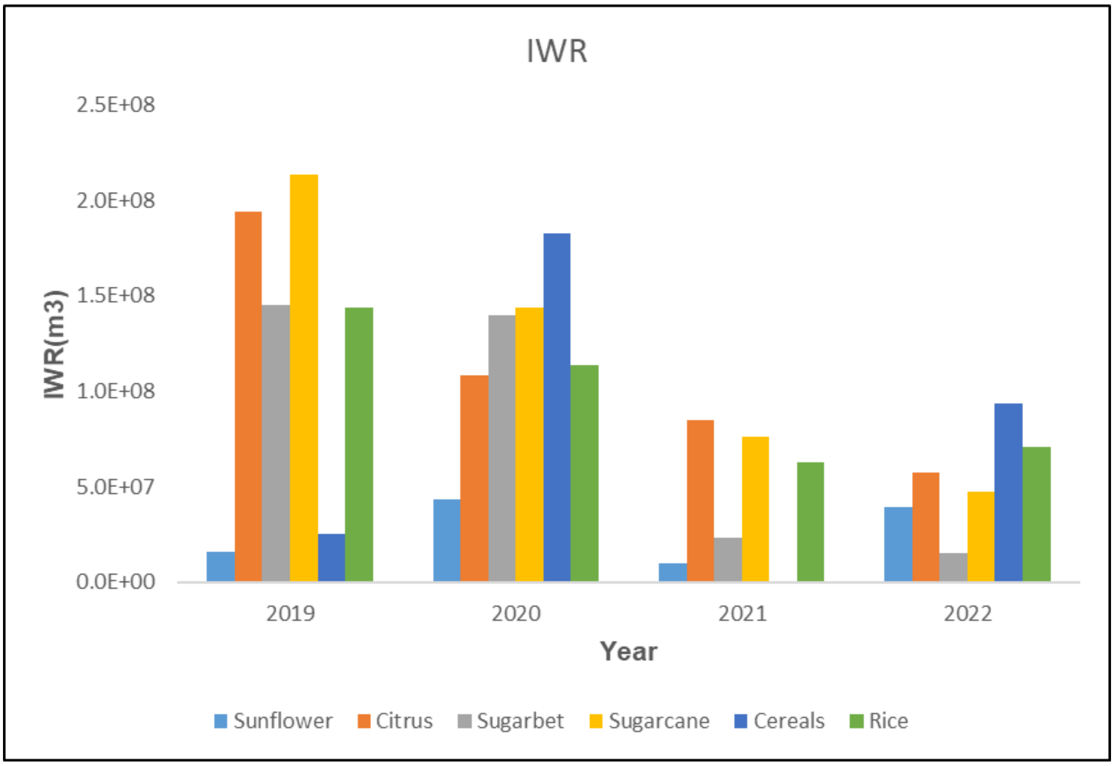

Figure 8: Irrigation Water Requirement (IWR) for Various Crops from 2019 to 2022

4. DISCUSSION

In the following discussion, we delve into the pivotal role of remote sensing technology in addressing water management challenges and promoting sustainable agriculture within the Gharb irrigated area of North-Western Morocco. Through the utilization of geospatial tools and multi-date data, this study estimates the water requirements of diverse crop types, emphasizing the significance of accurate Irrigation Water Requirement (IWR) estimation for resource allocation in semi-arid regions like the Gharb Plain (Cheikhaoui et al., 2024). By employing remote sensing techniques, such as satellite imagery and vegetation indices, this study contributes to the ongoing efforts in precision agriculture by providing detailed insights into water demand dynamics.

Analyzing the extremes of vegetation indices helps assess vegetation health, detect changes, and understand ecosystem resilience to environmental factors. The maximum and minimum values of vegetation indices provide insights into the health, dynamics, and environmental responses of vegetation over time (Pettorelli et al., 2005). Peak values indicate optimal growth conditions and vigor, while minimum values often signal stress or disturbance events. The integration of these indices, including the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Green Normalized Difference Vegetation Index (GNDVI), allows a comprehensive assessment of vegetation dynamics (Zhang et al., 2022; Rouse et al., 1974). The synchronized trends observed in NDVI, EVI, and GNDVI highlight consistent vegetation dynamics within the Gharb-irrigated perimeter, indicating periods of optimal growth and health with peak values. Fluctuations in SAVI suggest varying vegetation stress levels, while NDWI trends reflect changes in water availability (Guan et al., 2019; Jiang et al., 2020). These findings underscore the importance of monitoring vegetation indices for identifying crop types and provide crucial insights for effective land management by quantifying vegetation health and vigor through remote sensing technology (Wu et al., 2020). They facilitate informed decision-making in agricultural practices, enhancing productivity and sustainability across diverse landscapes.

The classification analysis conducted using Google Earth Engine(Gorelick et al. 2017) successfully identified various crop types within the Gharb-irrigated perimeter with a remarkable accuracy rate. The spatial distribution of crops, including Rice, Sugarcane, Citrus, Sunflower, and Cereals, underscores the diverse agricultural landscape of the region. This comprehensive understanding of crop distribution is invaluable for informed decision-making in land management, crop planning, and resource allocation, thereby promoting sustainable agricultural practices and enhancing productivity in the Gharb area.

The relationship between temperature, precipitation, and evapotranspiration (ET) is crucial in understanding water balance dynamics in an area (Feng et al., 2018; Allen et al., 1998). Generally, higher temperatures lead to increased evapotranspiration rates due to greater atmospheric demand for moisture. Conversely, higher precipitation levels can replenish soil moisture and potentially offset increased ET rates. Analyzing the results, we observe that in Kenitra, higher temperatures in 2022 coincided with an increase in evapotranspiration compared to the previous years, despite similar or slightly decreased precipitation levels. In Sidi Kacem and Sidi Slimane, higher evapotranspiration rates in 2019 corresponded with higher temperatures, followed by fluctuations in subsequent years that did not always align with precipitation trends. These observations suggest that while temperature plays a significant role in driving evapotranspiration, other factors such as soil moisture, humidity, and vegetation cover also influence ET rates. Additionally, the relationship between temperature, precipitation, and evapotranspiration can vary depending on the provinces climate conditions and landscape characteristics.

Regarding, the analysis of Crop Water Requirement (CWR) for various crops across Kenitra, Sidi Kacem, and Sidi Slimane provinces from 2019 to 2022 reveals significant trends. There is a consistent decreasing pattern in CWR observed across all provinces for rice, cereals, citrus, and sugarcane crops over the four years. This decline suggests potential shifts in agricultural water demand and emphasizes the need for efficient water management strategies to ensure sustainable crop production in the face of changing climatic conditions. These findings underscore the importance of ongoing monitoring and adaptation efforts to optimize water use efficiency and mitigate the impacts of water scarcity on agricultural productivity in the region.

The analysis of irrigation water requirements (IWR) of the various crops over different years reveals distinct patterns, with notable fluctuations observed. For rice crops, there's a decrease in IWR from 2019 to 2022, indicating potential improvements in water efficiency. Cereals show fluctuations, possibly influenced by factors like weather variability and market demand. Sugarcane crops demonstrate a decline in IWR, reflecting efficient water management practices. Similarly, Citrus crops show a decrease in IWR, suggesting optimized irrigation strategies.

The decrease in irrigated areas during the COVID-19 pandemic in 2021 may be attributed to labor shortages, supply chain disruptions, financial constraints, shifts in crop demand, government policies, and water availability challenges (Kumar et al., 2021). These multifaceted factors, alongside regional and agricultural-specific considerations, likely contributed to the observed changes in irrigated areas during the pandemic year, highlighting the complex interplay between external influences and agricultural practices.

While our study contributes valuable insights into water management and agriculture in the Gharb region, future research should integrate detailed ground-based observations, advanced modeling, and socioeconomic factors to improve water management strategies. Despite potential biases and challenges, such integration promises more tailored approaches. Furthermore, smart irrigation, offers a promising solution for conserving water while optimizing crop yield. However, challenges initial costs and technological expertise need addressing. Considering climate change, the imbalance between water demand and supply in the Gharb-irrigated perimeter underscores the need for adaptive management strategies to accurately mitigate future impacts

5. Conclusion

In conclusion, our research offers a comprehensive understanding of the interaction between environmental factors, technological advancements, and agricultural practices in the gharb irrigated area of north-western morocco. Through the utilization of remote sensing technology and geospatial tools, we have gained valuable insights into crop distribution, vegetation dynamics, and water management practices, which are essential for promoting sustainable agriculture in semi-arid regions. Our analysis of vegetation dynamics using vegetation indices such as ndvi, evi, and gndvi provided detailed insights into water demand dynamics and highlighted periods of optimal growth and health within the region. Furthermore, the classification analysis successfully identified various crop types, facilitating informed decision-making in land management and resource allocation. Additionally, our examination of the relationship between temperature, precipitation, and evapotranspiration (et) revealed the complex interplay of factors influencing water balance dynamics. The consistent decreasing pattern in crop water requirements (cwr) across all provinces suggests shifts in agricultural water demand, emphasizing the need for efficient water management strategies. Moreover, our analysis of irrigation water requirements (iwr) revealed distinct patterns, with fluctuations observed across different crops and through the years, indicating potential improvements in water efficiency and optimized irrigation strategies. Overall, our findings contribute to the ongoing efforts in precision agriculture and underscore the importance of monitoring and adapting to changing climatic conditions to ensure sustainable crop production and water resource management in semi-arid regions like the gharb plain. Moving forward, it is imperative to integrate these findings into policy frameworks and on-the-ground interventions to support resilient and sustainable agricultural development in the gharb region and beyond. By embracing innovation, collaboration, and advanced approaches, we can forge a path towards a more equitable, resilient, and environmentally sustainable agricultural future, not only in the gharb region but also across similar agroecological landscapes worldwide.

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The authors declare there is no conflict.

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