KARADENİZ TECHNICAL UNIVERSITY
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

DEPARTMENT OF GEOMATICS ENGINEERING

THE USE OF REMOTE SENSING FOR MONITORING AGRICULTURAL PRODUCTS IN THE GEZIRA IRRIGATION SCHEME, SUDAN

MASTER THESIS

Osman Osama Ahmed IBRAHIM

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TRABZON

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Osman Osama Ahmed IBRAHIM
Trabzon 2024

STATEMENT OF ETHICS

I declare that this master's thesis, I have submitted with the title "The use of Remote Sensing for Monitoring Agricultural Products in the Gezira Irrigation Scheme, Sudan" has been completed under the guidance of my supervisor Assoc. Prof. Dr. Volkan YILMAZ. All the data used in this thesis are obtained by simulation and experimental works done as parts of this work in this thesis labs. All referred information used in this thesis has been indicated in the text and cited in the reference list. I have obeyed all research and ethical rules during my thesis, and I accept all responsibility if proven otherwise. 20/09/2024.

Osman Osama Ahmed IBRAHIM

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THE USE OF REMOTE SENSING FOR MONITORING AGRICULTURAL PRODUCTS IN THE GEZIRA IRRIGATION SCHEME, SUDAN

Osman Osama Ahmed IBRAHIM

Karadeniz Technical University
The Graduate School of Natural and Applied Sciences
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2024, 119 Pages

This thesis addresses agricultural management and food security challenges in Sudan's Gezira Irrigation Scheme (880,000 hectares). It uses advanced machine learning to enhance agricultural monitoring, focusing on wheat production and water productivity optimization, the study integrates multiple data sources, employing Support Vector Machine (SVM) and Object-Based Image Analysis (OBIA) for crop classification using Sentinel-2 imagery. Various models, including Random Forest and XGBoost, estimate yield and water productivity, Results show high accuracy in crop classification, with SVM slightly outperforming OBIA. Crop area estimation achieved a 2-3% error range compared to official records. The research reveals complex wheat cultivation dynamics, highlighting non-linear yield factors and simpler water productivity relationships, this work contributes to improved food security, farmer livelihoods, and sustainable water use, aligning with UN Sustainable Development Goals. The methodology has potential applications in similar global irrigation schemes.

Keywords: Machine Learning in Agriculture; Wheat Yield Prediction; Water Productivity Estimation; Remote Sensing; Gezira Irrigation Scheme

ÖZET

Yüksek Lisans Tezi

GEZIRA SULAMA PROJESI'NDEKI (SUDAN) TARIMSAL ÜRÜNLERIN İZLENMESINDE UZAKTAN ALGILAMA KULLANIMI

Osman Osama Ahmed IBRAHIM

Karadeniz Teknik Üniversitesi
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Danışman: Doç. Dr. VOLKAN YILMAZ
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Bu tez, Sudan'ın Gezira Sulama Planı'ndaki (880.000 hektar) tarımsal yönetim ve gıda güvenliği sorunlarını ele almaktadır. Buğday üretimi ve su verimliliği optimizasyonuna odaklanarak tarımsal izlemeyi geliştirmek için gelişmiş makine öğrenimi kullanmaktadır, Çalışma, çoklu veri kaynaklarını entegre ederek, Sentinel-2 görüntülerini kullanarak mahsul sınıflandırması için Destek Vektör Makinesi (SVM) ve Nesne Tabanlı Görüntü Analizi (OBIA) yöntemlerini uygulamaktadır. Random Forest ve XGBoost dahil çeşitli modeller, verim ve su verimliliğini tahmin etmektedir, Sonuçlar, mahsul sınıflandırmasında yüksek doğruluk göstermekte, SVM'nin OBIA'ya göre biraz daha iyi performans sergilediğini ortaya koymaktadır. Ekim alanı tahmini, resmi kayıtlara kıyasla %2-3'lük bir hata aralığına ulaşmıştır. Araştırma, buğday yetiştiriciliğindeki karmaşık dinamikleri ortaya çıkararak, doğrusal olmayan verim faktörlerini ve daha basit su verimliliği ilişkilerini vurgulamaktadır, Bu çalışma, BM Sürdürülebilir Kalkınma Hedefleri ile uyumlu olarak gıda güvenliğinin iyileştirilmesine, çiftçi geçim kaynaklarına ve sürdürülebilir su kullanımına katkıda bulunmaktadır. Metodoloji, benzer küresel sulama planlarında potansiyel uygulamalara sahiptir.

Anahtar Kelimeler: Tarımda Makine Öğrenimi; Buğday Verimi Tahmini; Su Verimliliği Tahmini; Uzaktan Algılama; Gezira Sulama Planı

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LIST OF ABBREVIATIONS

PCP	: Precipitation
RET	: Reference Evapotranspiration
AETI	: Actual Evapotranspiration
NPP	: Net Primary Production
T	: Transpiration
B	: Biomass
WPb	: Biomass Water Productivity
WPy	: Water Productivity
B_Gaps	: Biomass Gaps
WPbgaps	: Biomass Water Productivity Gaps
WPygaps	: Yield Water Productivity Gaps
Y_Gaps	: Yield Gaps
AGB	: Above Ground Biomass
AOI	: Above Ground Over Total Biomass
ARC	: Agricultural Research Corporation
BF	: Beneficial Fraction
BS	: Bright spots _High-Performance Areas Identification
CF	: Conversion Factor
CV	: Coefficient of Variation
CWP	: Crop Water Productivity
DAP	: Diammonium Phosphate
DEM	: Digital Elevation Model
EOS	: End of Season
ET	: Evapotranspiration
ETa	: Actual Evapotranspiration
ETp	: Potential Evapotranspiration
ETx	: Maximum Crop Evapotranspiration
FAO	: Food and Agriculture Organization
GIS	: Gezira Irrigation Scheme
ha	: Hectare

HI : Harvest Index

HRC : Hydraulic Research Center

ICRISAT : International Crops Research Institute for the Semi-Arid Tropics

Kc : Crop Factor

kg : Kilogram

KTB : KoBoToolbox

LCC : Land Cover Classification

LST : Land Surface Temperature

LUE : Light Use Efficiency

m^3 : Cubic Meter

MC : Moisture Content Ratio

NDVI : Normalized Difference Vegetation Index

OBIA : Object-Based Image Analysis

PAR : Photosynthetically Active Radiation

RS : Remote Sensing

RWD : Relative Water Deficit

SDG : Sustainable Development Goal

SOS : Start of Season

t/ha : Tonnes per Hectare

TBP : Total Biomass Production

1. GENERAL INFORMATION

1.1. Introduction

The Gezira Irrigation Scheme in Sudan, covering an expansive area of approximately 880,000 hectares (2.1 million feddans), stands as one of the world's largest irrigation projects under a single administration. This vast agricultural landscape presents both unique challenges and opportunities for agricultural management and remote sensing applications. The scheme's structured layout, characterized by an intricate network of canals and fixed plot divisions, makes it an ideal candidate for satellite-based crop area estimation, yield prediction, and water productivity analysis.

In recent years, the application of remote sensing and machine learning techniques in agriculture has gained significant traction, offering cost-effective and efficient alternatives to traditional field surveys. These advanced methods hold the promise of providing accurate, timely, and comprehensive assessments of agricultural systems at scales that were previously impractical to monitor. This thesis seeks to harness these technological advancements to address critical questions in the context of the Gezira Irrigation Scheme: Can we accurately estimate the cultivated areas and the extent of different crops using satellite imagery and machine learning techniques? Furthermore, can we reliably estimate yield and water productivity (WPy) using these advanced methods?

To answer these questions, our study focuses on analyzing Sentinel-2 satellite imagery of the Gezira Scheme from October 2019 to April 2020, encompassing a complete wheat growing season. We employ a sophisticated methodology that integrates data from multiple sources, including FAO’s Water Productivity Open Access Portal (WaPOR) and Google Earth Engin derived vegetation indices. This approach is complemented by ground-truth data collected from 97 farmer data points, ensuring a robust validation of our models.

At the core of our analysis is a comprehensive suite of machine learning models, including Linear Regression, Random Forest, Gradient Boosting, XGBoost, K-Nearest Neighbors, Decision Tree, and Bagging Regressor. By implementing and comparing these diverse algorithms, we aim to identify the most effective approaches for predicting crop yield and water productivity in the unique context of the Gezira Scheme.

The significance of this thesis extends beyond mere technological advancement. By integrating crop area estimation with yield prediction and water productivity assessment, we aim to provide a comprehensive analysis of agricultural performance in the Gezira Scheme. Our goal is not only to accurately map crop areas but also to identify spatial patterns in productivity and water use efficiency. These insights offer valuable information for targeted interventions and improved resource management strategies, which are crucial in a region facing significant challenges in water scarcity and food security.

Moreover, this study aligns with several United Nations Sustainable Development Goals, particularly those related to food security, sustainable agriculture, and water management. The methodology developed here has the potential to overcome limitations of traditional surveying methods, providing a more accurate, timely, and cost-effective approach to agricultural monitoring in large irrigation schemes. By addressing yield gaps and water productivity issues, this thesis contributes to broader goals of enhancing food security and promoting sustainable water use in semi-arid regions.

The insights gained from this study have far-reaching implications. They can inform policy decisions, improve agricultural practices, and ultimately enhance the livelihoods of farmers not only in the Gezira Scheme but also in similar irrigation projects worldwide. As we face growing challenges in global food production and water resource management, the need for innovative, data-driven approaches to agricultural monitoring and management becomes ever more pressing. This thesis represents a step forward in meeting these challenges, demonstrating the potential of integrating remote sensing, machine learning, and agronomic knowledge to drive sustainable agricultural development.

1.2. Literature Review

1.2.1. Estimating Crop Area

Crop area estimation is a fundamental aspect of agricultural monitoring and management, providing crucial information about land use, food production capacity, and agricultural trends. It involves determining the total land area devoted to specific crops within a given region, typically measured in hectares or acres. Accurate crop area estimates are essential for various stakeholders, including government agencies, agricultural planners, and international organizations, to make informed decisions about food security, agricultural policy, and resource allocation.

Gallego et al. (2010) conducted a comprehensive review of remote sensing applications for agricultural statistics. They examined various satellite-based methods for crop area estimation, highlighting the potential for improving accuracy and efficiency compared to traditional ground-based surveys. Their review laid the groundwork for subsequent research in this field, emphasizing the value of objective and timely information provided by satellite imagery.

Elhag (2014) applied Landsat data to evaluate wheat crop performance in the Gezira scheme. While primarily focused on crop performance rather than area estimation, Elhag's study demonstrated the feasibility of using medium-resolution satellite imagery for detailed agricultural monitoring in large irrigation schemes. This work paved the way for more advanced applications of remote sensing in the Gezira context.

Franch et al. (2015) focused specifically on wheat area estimation, which is crucial for the Gezira Scheme. They combined MODIS and Landsat data, integrating spectral information with phenological data to achieve high accuracy in wheat area estimates across multiple countries. Their approach showed the potential for improving the timeliness of crop production forecasts.

Waldner et al. (2015)discussed the importance of developing locally adapted approaches for crop mapping, addressing the challenges of complex irrigation systems. They demonstrated the effectiveness of using biophysical variables retrieved from multi-sensor high-resolution time series for land cover and crop type classification throughout the growing season.

Veloso et al. (2017) explored the integration of multiple data sources, combining Sentinel-1 SAR data with optical imagery for crop type mapping. Their multi-sensor approach showed promise for improving crop area estimates, especially in regions prone to cloud cover. This could be particularly relevant for the Gezira Scheme, where atmospheric conditions might limit the effectiveness of optical sensors alone.

Kussul et al. (2017) took a leap forward by applying deep learning techniques to crop classification and area estimation. They used Convolutional Neural Networks (CNNs) with multi-temporal satellite imagery, demonstrating superior performance compared to traditional machine learning methods. Their approach showed particular promise for handling the complexity and variability of large agricultural systems.

Belgiu and Csillik (2018) made significant strides in crop type mapping using Sentinel-2 data. They employed Random Forest classifiers with multitemporal imagery, achieving high accuracy in distinguishing different crop types. Their method's success in handling the temporal dimension of crop growth highlighted the potential for improving crop area estimates in complex agricultural landscapes like the Gezira Scheme.

Zhong et al. (2019) pushed the boundaries of deep learning applications in crop classification. They developed a multi-temporal crop classification method using recurrent neural networks, which outperformed traditional machine learning approaches. Their work demonstrated the potential for further improving the accuracy of crop area estimation using advanced machine learning techniques.

These studies collectively demonstrate the evolution of crop area estimation techniques, from basic remote sensing applications to sophisticated deep learning approaches. They highlight the potential for significantly improving the accuracy and efficiency of crop area estimates in large irrigation schemes like Gezira. However, they also underscore the need for careful adaptation of these methods to local conditions, integration of multiple data sources, and development of user-friendly tools for practical application.

The field of crop area estimation has seen remarkable progress between 2010 and 2019, transitioning from fundamental remote sensing applications to sophisticated deep learning techniques. This evolution is characterized by a series of studies that iteratively addressed challenges and explored new methodologies. A significant milestone was reached with Kussul et al. (2017) introduction of Convolutional Neural Networks, which demonstrated superior performance over traditional machine learning methods in crop classification and area estimation. Another key advancement came from Veloso et al. (2017) , who developed a multi-sensor approach integrating SAR and optical data to overcome persistent issues like cloud cover in optical remote sensing. These innovations have collectively enhanced the accuracy, efficiency, and adaptability of crop area estimation techniques, making them particularly valuable for complex agricultural systems such as large-scale irrigation schemes.

1.2.2. Estimating Crop Yield

Crop yield estimation is a critical aspect of agricultural management, particularly in large irrigation schemes like the Gezira Irrigation Scheme. Accurate yield predictions are essential for food security planning, resource allocation, and economic forecasting. The integration of remote sensing technologies with advanced machine learning techniques has revolutionized the field of crop yield estimation.

Lobell (2013) conducted a seminal study on the use of satellite data for crop yield gap analysis. He employed a combination of Landsat and MODIS data to estimate wheat yields in Punjab, India. Using a light use efficiency model calibrated with historical yield data, the author achieved yield estimates with an R^2 of 0.7 when compared to official statistics. This study demonstrated the potential of satellite-based yield estimation in developing countries, setting the stage for future research.

Franch et al. (2015) developed an approach for winter wheat yield forecasting using MODIS data. They integrated satellite-derived vegetation indices with a light use efficiency model and achieved yield forecasts with R^2 values ranging from 0.69 to 0.89 across different regions of the United States. Their method's success in capturing spatial variations in wheat yield demonstrates its potential applicability to diverse wheat-growing regions.

Azzari et al. (2017) developed a fine-resolution global map of crop yields. They used Google Earth Engine to process Landsat imagery and implemented a scalable crop yield mapping approach. Their method combined remote sensing data with a light use efficiency model and achieved yield estimates for maize and soybean with R^2 values of 0.85 and 0.74, respectively, when compared to county-level yield statistics in the US. This study showcased the potential for high-resolution yield mapping at large scales, which could be particularly valuable for heterogeneous landscapes like the Gezira Scheme.

You et al. (2017) made significant advancements by applying deep learning techniques to crop yield prediction. They developed a deep Gaussian process model that integrated remote sensing data with weather information for county-level corn yield prediction in the United States. Their model outperformed traditional regression methods, achieving an R^2 of 0.76. This study highlighted the potential of deep learning approaches for capturing complex, non-linear relationships in yield prediction.

The progression from Lobell (2013) foundational work to You et al., (2017) deep learning approach reflects the rapid advancements in the field. Each study builds upon previous work, addressing limitations and exploring new possibilities. For instance, You et al., (2017) deep learning approach addressed the limitations of traditional regression methods highlighted in earlier studies. These advancements demonstrate the increasing potential for accurate and scalable crop yield estimation, which could greatly benefit the management of large irrigation schemes like Gezira.

1.2.3. Estimating Crop Water Productivity

Crop water productivity, defined as the ratio of crop yield to water consumed, is a critical metric for assessing the efficiency of water use in agriculture, particularly in water-scarce regions and large irrigation schemes like the Gezira Irrigation Scheme. The advent of remote sensing technologies and advanced data analysis techniques has significantly enhanced our ability to estimate and monitor crop water productivity at various scales.

Zwart and Bastiaanssen (2004) conducted a pioneering study on crop water productivity, reviewing measured values for major crops including wheat. They compiled data from 84 literature sources, finding that the water productivity for wheat ranged from 0.6 to 1.7 kg/m^3. This study established a baseline for water productivity values and highlighted the significant variability across different regions and management practices, setting the stage for remote sensing-based approaches to capture this variability at larger scales.

Bastiaanssen and Steduto (2017) developed a methodology for mapping water productivity using remote sensing data. They introduced the Water Productivity Score (WPS) at global and regional levels, utilizing data from the MODIS satellite. Their approach, which integrated satellite-derived evapotranspiration and biomass production estimates, achieved correlations of 0.8-0.9 with field measurements of water productivity. This study demonstrated the potential of remote sensing for large-scale water productivity assessment, paving the way for applications in complex irrigation schemes like Gezira.

Jiang et al. (2019)developed a method for estimating daily crop water productivity using the SEBAL model and time-series MODIS data. Applied to winter wheat in the North China Plain, their approach achieved an R^2 of 0.82 when compared to field measurements. This study highlighted the importance of capturing temporal variations in water productivity throughout the growing season, which could be particularly relevant for optimizing irrigation management in schemes like Gezira.

Pelletier et al. (2019) employed a machine learning approach, specifically Random Forests, to estimate crop water productivity using remote sensing data. Applied to irrigated perimeters in Morocco, their model achieved an R^2 of 0.7 for water productivity estimation. This study demonstrated the potential of machine learning techniques for improving water productivity estimates in data-scarce environments, which could be valuable for regions with limited field measurements.

Blatchford et al. (2020) applied the FAO's Water Productivity Open Access Portal (WaPOR) to assess water productivity in the Nile Delta. They used remotely sensed evapotranspiration and biomass production data to estimate water productivity for multiple crops, including wheat. Their study achieved an R^2 of 0.7 when comparing remotely sensed estimates to field measurements, highlighting the potential of open-access remote sensing data for water productivity monitoring in large irrigation schemes.

Chiu et al. (2020) combined optical (Sentinel-2) and thermal (Landsat 8) data to estimate evapotranspiration and biomass production for water productivity assessment. Their approach, applied to wheat fields in northwest China, achieved an R^2 of 0.76 for water productivity estimation. This multi-sensor approach showcased the potential for improving the accuracy and spatial resolution of water productivity estimates.

Ayyad et al. (2021) developed an integrated approach combining the AquaCrop model with remote sensing data for estimating water productivity of wheat in Egypt's Nile Delta. Their method, which incorporated Sentinel-2 derived leaf area index into the crop model, achieved an R^2 of 0.85 for water productivity estimation. This study showcased the potential of combining crop models with remote sensing data for improved water productivity assessment.

The progression from Zwart and Bastiaanssen (2004) review to Ayyad et al. (2021) integrated modeling approach reflects the rapid advancements in the field. Each study builds upon previous work, addressing limitations and exploring new possibilities. For instance, Chiu et al., (2020) focus on temporal dynamics tackled the challenge of capturing seasonal variations in water productivity. These advancements demonstrate the increasing potential for accurate and scalable crop water productivity estimation, which could greatly benefit the management of large irrigation schemes like Gezira.

1.3. Motivation and Research Gaps

The Gezira Irrigation Scheme in Sudan stands as a monumental agricultural endeavor, pivotal to the nation's food security, economic stability, and rural livelihoods. Despite its vast potential and historical significance, the scheme faces substantial challenges in optimizing wheat production, a crop crucial for reducing Sudan's import dependency and ensuring domestic food security. This thesis is driven by several critical factors that underscore its importance and potential impact:

1. Productivity Gap and Food Security Imperatives: Current wheat yields in the Gezira Scheme, ranging from 3.18 to 4.02 t/ha, fall significantly short of the optimal range of 6-9 t/ha (FAO, 2020). This substantial yield gap represents not only unrealized agricultural potential but also missed opportunities for enhancing food security and farmer incomes. Closing this gap could dramatically improve Sudan's self-sufficiency in wheat production, addressing a core national food security challenge.

Research Gap: While studies like Elhag (2014) have applied remote sensing to crop performance assessment in Gezira, there's a lack of comprehensive research using advanced Machine learning techniques for accurate, field-level yield estimation in this complex irrigation scheme.

2. Water Scarcity and Resource Efficiency: In a region increasingly threatened by water scarcity and climate change, the observed water productivity values of 0.32-0.45 kg/m³, compared to a target of 0.58 kg/m³ (Adam et al., 2021), highlight a critical need for improved water management. Enhancing water use efficiency is not just an agricultural imperative but a national priority for sustainable resource management.

Research Gap: Despite the work of Bastiaanssen and Steduto (2017) on water productivity mapping, there's a lack of high-resolution, temporally dynamic water productivity assessments for wheat in large irrigation schemes like Gezira, especially using advanced deep learning techniques.

3. Spatial Variability and Targeted Interventions: The significant variations in productivity across different zones of the scheme, as revealed by our analysis, suggest that localized factors play a crucial role in determining yields. Understanding and addressing these spatial variations could lead to targeted interventions and more efficient resource allocation, unlocking the scheme's full potential.

Research Gap: While Kussul et al. (2017) demonstrated the power of deep learning for crop classification, there's insufficient research on applying these techniques to capture and explain spatial variability in crop area, yield, and water productivity within complex irrigation schemes.

4. Integration of Advanced Technologies: This study's innovative approach, combining advanced remote sensing techniques (Sentinel-2 imagery) with deep learning models, represents a significant step forward in agricultural monitoring and management. The

integration of Support Vector Machine (SVM) and Object-Based Image Analysis (OBIA) for crop classification demonstrates the potential of cutting-edge technology in improving agricultural decision-making and precision farming practices.

Research Gap: Despite the promise shown by Pelletier et al. (2019)in using temporal convolutional neural networks for satellite image time series classification, there's a lack of end-to-end deep learning pipelines that simultaneously address crop area estimation, yield prediction, and water productivity assessment in irrigation schemes.

5. Bridging Technology and Farm Practices: The inclusion of ground-truth data and farmer surveys provides crucial insights into on-the-ground practices associated with higher yields. This bottom-up approach ensures that our recommendations are not only scientifically sound but also practically applicable and aligned with farmers' realities.

Research Gap: There's insufficient research on how to effectively translate complex deep learning model outputs into actionable insights for farmers and irrigation managers, particularly in the context of large schemes like Gezira.

6. Climate Change Adaptation and Resilience: As climate change threatens to disrupt traditional agricultural patterns, enhancing the efficiency and resilience of major irrigation schemes like Gezira is crucial for long-term food security and economic stability in Sudan.

Research Gap: While Ayyad et al. (2021) integrated crop models with remote sensing for water productivity estimation, there's a lack of research on using deep learning to model and predict the impacts of climate change on crop area, yield, and water productivity in irrigation schemes.

7. Economic Development and Livelihoods: Improving the Gezira Scheme's productivity has direct implications for farmers' livelihoods, rural development, and the national economy. By focusing on enhancing agricultural productivity and water use efficiency, this study contributes to broader economic development goals and the improvement of rural livelihoods.

Research Gap: There's limited research on how improvements in crop area estimation, yield prediction, and water productivity assessment through deep learning can translate into economic benefits for farmers and the broader economy, particularly in the context of large irrigation schemes.

In conclusion, this research is driven by the urgent need to optimize the performance of the Gezira Irrigation Scheme, a critical asset for Sudan's food security and economic development. By addressing these research gaps through the innovative application of remote sensing and deep learning techniques, this study has the potential to significantly enhance agricultural productivity, water use efficiency, and overall scheme management. The findings could not only transform the Gezira Scheme but also provide valuable insights for similar irrigation projects globally, contributing to broader efforts in sustainable agriculture and food security.

2. MATERIAL AND METHODS

2.1. Study Area

2.1.1. Introduction

The Gezira Scheme, located between the Blue Nile and the White Nile Rivers to the south of Khartoum, Sudan, is situated in a semi-arid zone (Figure 1) (Ahmed, 2009; Al Zayed et al., 2015a). Its origins date back to 1911, when an experimental farm was established at Tayba village on the west bank of the Blue Nile (Ahmed, 2009). The Gezira scheme is characterized by its large arable area of about 0.9 million hectares (2.2 million feddans) (see Table 1) (Ahmed, 2009). Each farmer owns an average of 8.4 ha, divided into four plots, where they cultivate a range of crops, including cotton, wheat, sorghum, groundnuts, and vegetables (Osman et al., 2011).

Table 1. General Information About Gezira Scheme

Project Name	Total Area (Million Feddans)	Number of Irrigation Divisions	Number of Irrigation Sectors
Gezira and Managil	2.2	34	61

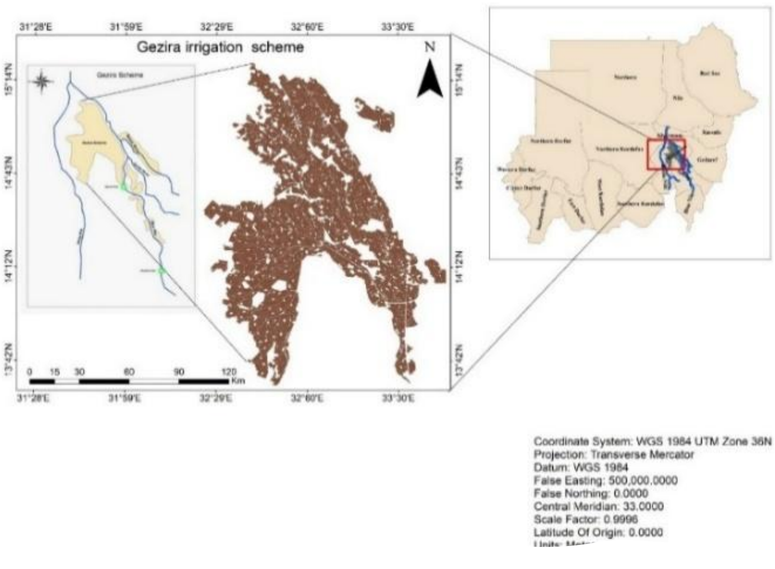

Figure 1. Location of the Gezira Scheme

2.1.2. Irrigation Management

The irrigation system is composed of two main canals that run from Sennar Dam (Figure 2); supplied by over 30,000 major canal networks. (Figure 3) illustrates the canalization system layout in the Gezira and Managil, and table 1 summarizes the details of the canals; the Gezira canal, which has a capacity of 168 m3/s, and the Managil canal, which has a capacity of 186 m3/s. The main canals deliver water to major canals. Then, we convey water to minor canals at determined and fixed levels, ensuring equity in distribution at the field canals (Abu Ishreen). Farmers use the internal canals (Abu Sitta) to irrigate their farms (Figure 3) (Elshaikh and Ahmed, 2018).

Over the years, various combinations of three key institutions have managed the Gezira Scheme: the Sudan Gezira Board (SGB), the Ministry of Irrigation and Water Resources (MOIWR), and the Water Users Associations (WUAs) (Babiker, 2014; World Bank, 2000). Initially, from 1925 to 1994, the MOIWR held primary responsibility for the entire irrigation system, with limited SGB participation (Babiker, 2014).

In 1994, the Sudanese government's policy of economic liberalization led to the establishment of the Irrigation Water Corporation (IWC) as part of the MOIWR, aiming to cover operation and maintenance costs through water fees collected from farmers (Babiker, 2014). In 1999, the SGB assumed responsibility for operating and maintaining Minor canals, while the MOIWR retained control over Main and Major canals (World Bank, 2010).

This arrangement continued until the Gezira Scheme Act of 2005, which mandated a shared management approach between WUAs and MOIWR. The MOIWR managed Main and Major canals, while the WUAs held responsibility for Minor canals (World Bank, 2010).

In 2010, the Gezira irrigation unit was transferred from MOIWR to SGB, and by 2012, the MOIWR was dissolved (Tajelsir, 2013). At this stage, the SGB and WUAs shared responsibilities, with the SGB overseeing Main and Major canals and the WUAs managing Minor canals. Finally, by late 2014, the Act of 2005 was amended, leading to the dissolution of the WUAs, and the sole responsibility for irrigation management at the Gezira Scheme returned to the MOIWR (Ministry of Justice, 2014). Table 2 outlines these organizations and their historical periods.

Table 2. Canalization Characteristics of the Gezira Scheme

Canal	Number	Capacity (m^3/s)	Average width (m)	Length (km)
Main	2	354	50	261
Branch	11	25-120	30	651
Major	107	1.2-15	20	1,650
Minor	1,700	0.5-1.5	6	8,120
Abu Ishreen	29,000	0.116	1	40,000
Abu Sitta	350,000	0.05	0.5	100,000

Table 3. The Main Organizations Responsible for Irrigation Management

Organization (Full Name)	Organization (Short Name)	Period	Duration (Years)
Ministry of Irrigation and Water Resources	MOIWR	1925-1994	69
Irrigation Water Corporation	IWC	1995-1998	3
Sudan Gezira Board & Ministry of Irrigation and Water Resources	SGB & MOIWR	1999-2005	6
Water Users Associations & Ministry of Irrigation and Water Resources	WUAs & MOIWR	2006-2010	4
Water Users Associations & Sudan Gezira Board	WUAs & SGB	2011-2015	4

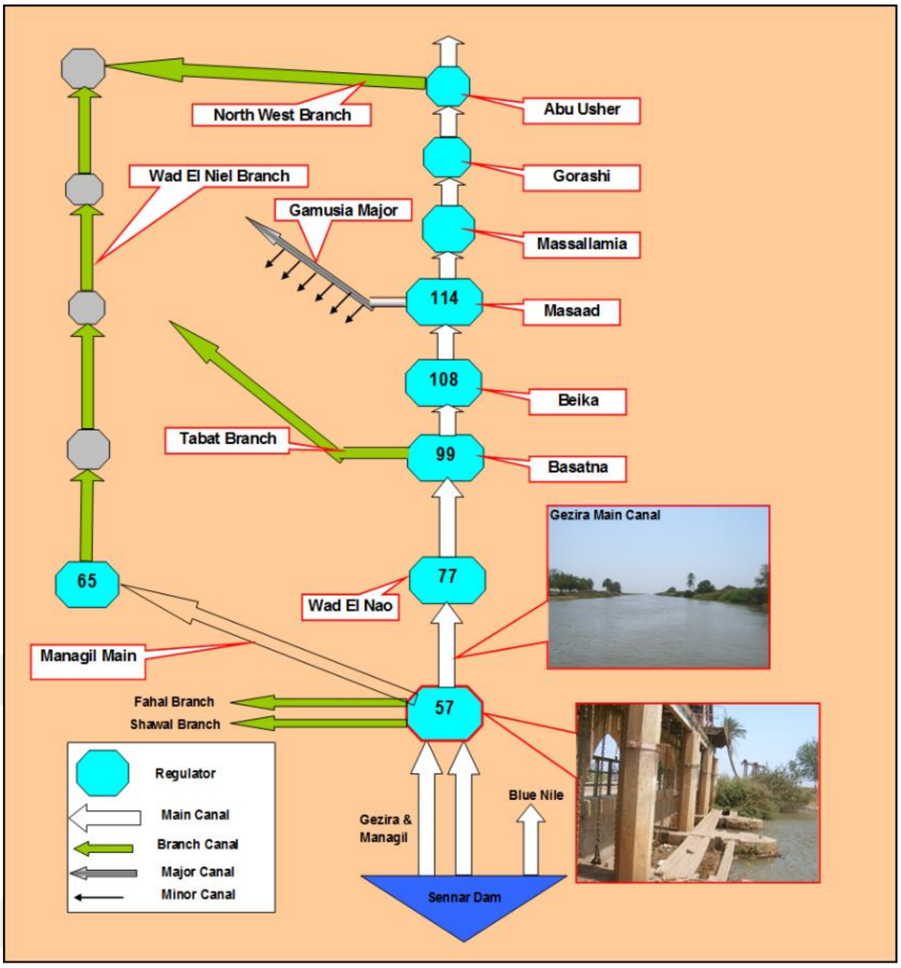

Figure 2. Irrigation System for Gezira Scheme- (MOIWR ,2016)

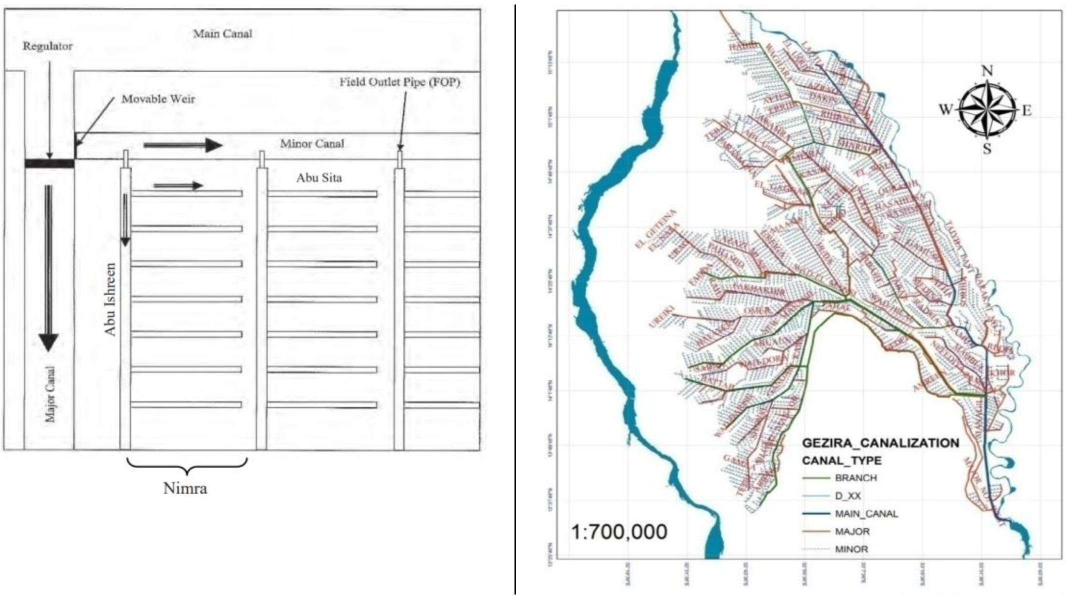

Figure 3. Layout and Irrigation Distribution Network of Gezira Scheme – (Hydraulics Research Center, 2015)

2.1.3. Climate

The Gezira Scheme is situated in a hot, semi-arid region characterized by distinct seasonal variations. Adam et al. (2015) describes three main seasons, winter (November to February), summer (April and May), and autumn (July to September), with March, June, and October serving as transitional periods. Mahmoud et al. (2021) report a north-south gradient in rainfall intensity, with long-term annual averages of approximately 160 mm in Khartoum, 360 mm in Wad Medani, and 480 mm in Sennar. According to Elagib and Mansell (2020), daily mean temperatures in Wad Medani, central to the scheme, typically range from 25°C in winter to 32°C in summer, with autumn temperatures averaging around 30°C. These climatic conditions significantly influence agricultural practices and water management strategies within the Gezira Scheme.

2.1.4 Administrative Division of the Gezira Irrigation Scheme

The Gezira Irrigation Scheme in Sudan is organized into a hierarchical administrative structure, reflecting both its irrigation system and management units (Figure 4). This structure facilitates efficient water distribution and scheme management (Eldaw, 2004).at the smallest level is the 'Hawash', which typically represents an individual farmer's plot or a small group of adjacent plots. Multiple Hawash units are grouped into a 'Nemrah', which forms a basic operational unit for water distribution (Plusquellec, 1990), Several Nemrah units are served by a single Canal, forming the next level of the hierarchy. These canals are crucial for water conveyance across the scheme (Barnett, 2019a), the Office level oversees multiple canals, coordinating water distribution and agricultural activities within its jurisdiction. This level plays a vital role in day-to-day operations and farmer interactions (Plusquellec, 1990), above the Office level is the Sub-Division, which manages several offices. This level is responsible for coordinating larger-scale operations and resource allocation (Eldaw, 2004),at the highest level of the scheme's administrative structure is the Main Division. This level oversees multiple Sub-Divisions and is responsible for overall scheme management, policy implementation, and coordination with national agricultural and water resource agencies (Barnett, 2019b),This hierarchical structure allows for efficient management of the vast Gezira Irrigation Scheme, ensuring water reaches from the main supply down to individual farm plots while facilitating administrative oversight at various levels.

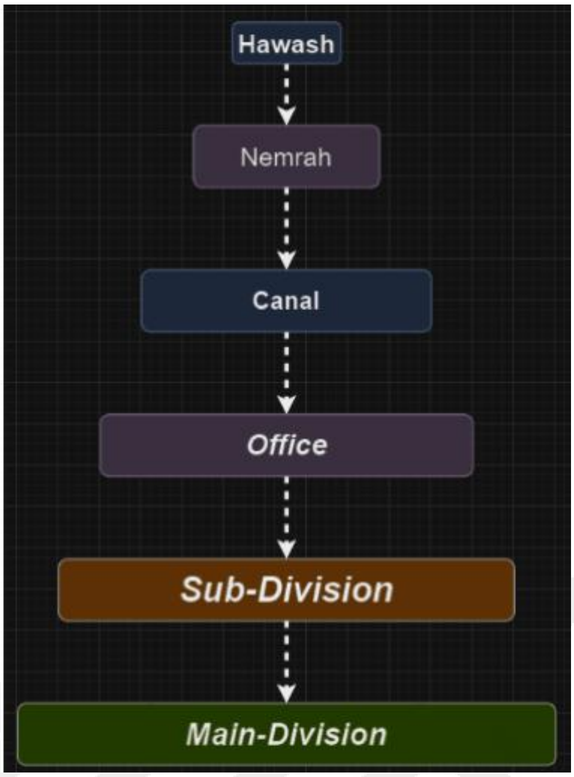

Figure 4. Administrative Division of the Gezira Irrigation Scheme

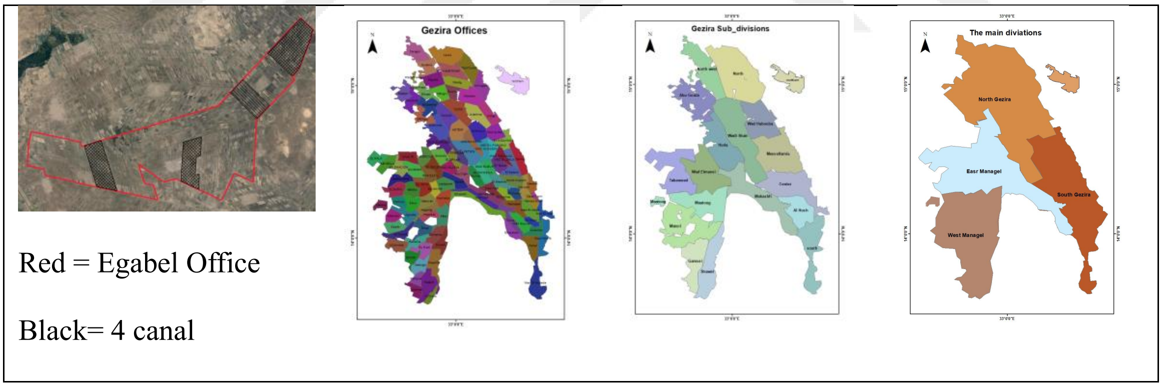

Figure 5. Administrative and Irrigation Structure of the Gezira Scheme

2.1.5. Soil Characteristics of the Gezira Scheme

The Gezira Scheme is predominantly characterized by Vertisols, locally known as "black cotton soil" (Abdelhadi et al., 2000). These soils have the following critical properties:

1. High clay content (50-60%), resulting in significant shrink-swell behavior (Abdalla et al., 2011).

2. Deep soil profile, often exceeding 150 cm (Abdelhadi et al., 2000).

3. Alkaline pH (7.5-8.5) and low organic matter content (<1%) (Adam et al., 2015).

4. High water holding capacity but challenging water management due to cracking when dry (Elias et al., 2001).

5. Relatively fertile despite low organic matter, due to high cation exchange capacity (Elias et al., 2001).

These soil characteristics significantly influence irrigation management, crop selection, and agricultural practices in the Gezira Scheme. While providing good potential for irrigated agriculture, they require careful management to maintain productivity and prevent degradation (Adam et al., 2015).

2.1.6. Comprehensive Analysis of Winter and Summer Cropping Schedules

Tables 4 and 5 illustrate the cultivation schedules for summer and winter crops, respectively, in the Gezira Irrigation Scheme. These tables provide a comprehensive overview of the planting and harvesting timelines for various crops grown within the scheme's agricultural calendar.

Table 4. Winter Crop Cultivation Schedule in the Gezira Irrigation Scheme

Crop Name	Planting Month	Germination Stage (days)	Growth Stage (days)	Maturity Stage (days)	Harvest Month
Wheat	November	5-8	30-40	90-120	March
Barley	November	5-7	30-45	90-110	April
Chickpea	December	7-14	40-60	90-120	March
Cotton	October	7-10	50-70	150-180	March

Table 5. Summer Crop Cultivation Schedule in the Gezira Irrigation Scheme

Crop Name	Planting Month	Germination Stage (days)	Growth Stage (days)	Maturity Stage (days)	Harvest Month
Sorghum	May	3-5	35-50	95-110	September
Maize	May	4-7	45-60	80-100	August
Groundnut	June	10-14	40-60	120-150	October
Cotton	October	7-10	50-70	150-180	March

2.2. Crop Classification Methods

Thesis methodology is built on a statistical foundation, designed to accurately estimate crop areas in the Gezira Irrigation Scheme using satellite imagery and advanced classification techniques. The approach combines field surveys with sophisticated image analysis to provide a comprehensive assessment of agricultural productivity across the scheme.

The study incorporates four primary data sources:

a) Hydraulics Research Center (HRC) Survey: Ground survey data collected by trained personnel from HRC-Sudan, serving as the primary reference for cultivated areas.
b) Agricultural Inspector (OFFICE) Survey: Data collected by agricultural inspectors across three offices, covering ten canals within the Gezira Scheme.
c) Satellite Imagery: Sentinel-2A imagery acquired on February 2, 2020.

2.2.1. Sampling Strategy

This study employed a carefully designed sampling strategy to ensure comprehensive and representative coverage of this vast agricultural area. We selected three administrative offices within the scheme to serve as representative samples,Wad Elbasier Office, Elhoosh Office, and Elgabel Office. This selection ensures a quasi-geographical distribution across the scheme, capturing its spatial variability. Figure 6 illustrates the geographical distribution of these selected offices within the Gezira Scheme, providing a visual representation of our sampling approach.

Within each selected office, we further refined our sampling by choosing a group of canals to represent the agricultural diversity of that office. Figure 7 depicts the layout of the chosen canals within each office. For Wad Elbasier Office, we selected Ganabiah Kafe Canal, Shakaira Canal, and Umtumoun Canal. In Elhoosh Office, our focus was on Elhoosh Canal, Osman Canal, and Wadelmounier Canal. For El Gabel Office, we examined Elwadi Canal (both Right and Left branches), Eltaamier Canal, Elgalaa Canal, and Elkaramah Canal.

This hierarchical sampling approach allows us to extrapolate our findings from the canal level to the office level, and ultimately to the entire Gezira Scheme. By analyzing these carefully selected samples at different administrative levels, we can capture both localized variations and broader patterns across the scheme. The strategy enables us to calculate a statistically rigorous error rate for the entire scheme while maintaining the integrity of our analysis.

Our approach provides a robust foundation for assessing the accuracy of our crop classification and area estimation methods, ensuring that our results are not only precise for the sampled areas but also reliably scalable to the entire Gezira Irrigation Scheme.

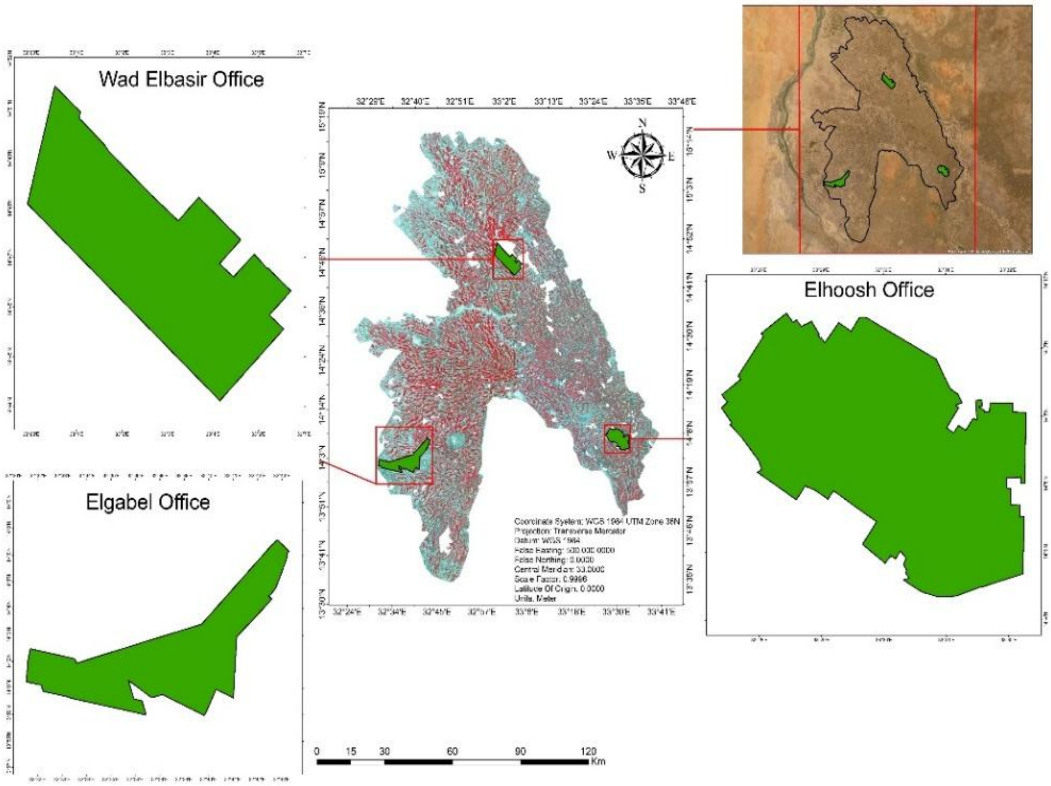

Figure 6. Spatial Distribution of the Three Selected Offices (Wad Elbasir, Elgabel, Elhoosh) within Gezira Scheme

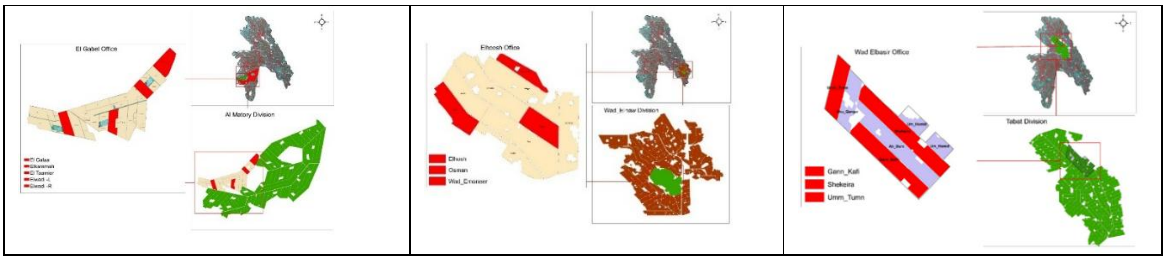

Figure 7. Spatial Distribution of the 10 Selected Canals within Selected Offices

2.2.2. Field Work Methodology

The Hydraulic Research Center assembled and trained a team of technicians and surveyors for field work, emphasizing the importance of this experiment. The fieldwork involves comprehensive area surveys of the selected canals for each office. We collected approximately 807 GPS-tagged crop samples from each office to aid in the classification process.

2.2.3. Advanced Statistical Modeling for Crop Classification

For crop classification, we employed two advanced techniques: Support Vector Machine (SVM) and Object-Based Image Analysis (OBIA). SVM, a powerful machine learning algorithm, was chosen for its ability to handle complex, non-linear classification tasks effectively. OBIA, on the other hand, was selected for its capacity to incorporate spatial and contextual information in the classification process, which is particularly useful in agricultural landscapes with distinct field boundaries.

We applied both methods to the preprocessed Sentinel-2 imagery, comparing their performance in accurately identifying different crop types, with a particular focus on wheat. The results from these two methods were rigorously compared to assess their relative strengths and weaknesses in the context of the Gezira Irrigation Scheme.

Additionally, we documented detailed observations for all canals and offices included in our study area. These observations encompassed not only the quantitative results of our classifications, but also qualitative insights gained during the analysis process. This comprehensive approach allowed us to capture both the broad patterns and nuanced details of crop distribution across the Gezira Irrigation Scheme, providing a rich dataset for further analysis and interpretation, Figure 8 Multi-Source Integration Methodological Framework for Advanced Precision Crop Mapping.

Table 6. Equations and Descriptions for Area Calculations and Comparative Analyses in Crop Classification

Code	**Equation Name**	**Equation**	**Equation NO.**	**Description**
HRC	HRC Area	HRC		Area surveyed by the Hydraulics Research Center
OFFICE	Office Area	OFFICE		Area surveyed by the agricultural inspector
SVM	Satellite Area (Method 1)	SVM		Area obtained from the satellite (Method 1)
OBIA	Satellite Area (Method 2)	OBIA		Area obtained from the satellite (Method 2)
RS	Average Satellite Area	$(\mathrm{SVM} + \mathrm{OBIA})/2$	(1)	Average area obtained from the satellite using both methods
Diff OBIA SVM	Difference OBIA SVM	$\frac{(\mathrm{OBIA} - \mathrm{SVM})}{\mathrm{OBIA}} * 100$	(2)	Percentage difference between OBIA and SVM areas
Avg. SVM OBIA	Average SVM OBIA	$\frac{(\mathrm{SVM} + \mathrm{OBIA})}{2}$	(3)	Average area between SVM and OBIA
Diff HRC Office	Difference HRC Office	$\frac{(\mathrm{HRC} - \mathrm{OFFICE})}{\mathrm{HRC}} * 100$	(4)	Percentage difference between HRC and Office areas
Diff RS HRC	Difference RS HRC	$\frac{(\mathrm{RS} - \mathrm{HRC})}{\mathrm{RS}} * 100$	(5)	Percentage difference between RS and HRC areas
Diff (Gardens/Chickpea /Cotton/Other)	Cotton Difference	$\frac{(\mathrm{HRC} - \mathrm{RS})}{2} * 100$	(6)	Percentage difference for cotton crop
Diff W (Wheat)	Wheat Difference	$\frac{(\mathrm{HRC} - \mathrm{RS})}{2} * 100$	(7)	Percentage difference for wheat crop

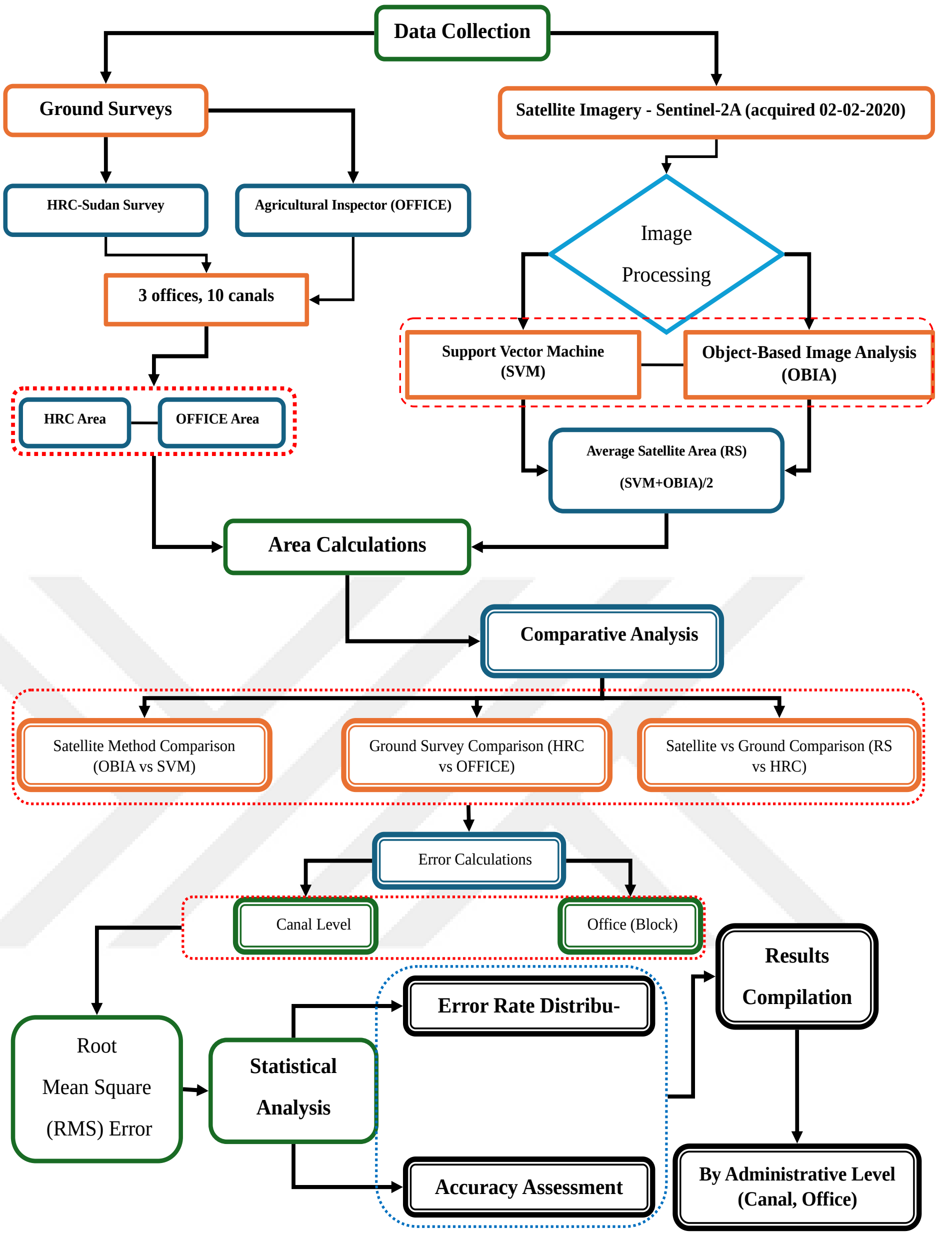

Figure 8. Multi-Source Integration Methodological Framework for Advanced Precision Crop Mapping

2.3.4. Software and Tools for Crop Classification

The crop classification process in our study relied on a suite of specialized software tools, each chosen for its specific capabilities in handling and analyzing remote sensing data. For the initial preprocessing of spatial data, we utilized ArcGIS Pro (version 3.3), leveraging its robust geospatial analysis features to prepare our Sentinel-2 imagery for classification.

This preprocessing stage included tasks such as image mosaicking, atmospheric correction, and feature extraction.

For the Support Vector Machine (SVM) classification, we continued to use ArcGIS Pro, taking advantage of its built-in machine learning algorithms and its ability to handle large volumes of geospatial data efficiently. The Object-Based Image Analysis (OBIA) was performed using eCognition software, which is specifically designed for advanced image segmentation and object-based classification tasks. eCognition's rule-based classification capabilities allowed us to incorporate spatial and contextual information into our analysis, improving the accuracy of our crop identification.

For the calculation of crop areas, error analysis, and other statistical analyses, we employed Microsoft Excel. Excel's versatile spreadsheet functionality and built-in statistical tools provided an efficient platform for organizing our data, performing calculations, and conducting comparative analyses between different classification methods and ground truth data.

The integration of these powerful software tools enabled us to perform a comprehensive and accurate classification of crop types across the Gezira Irrigation Scheme, followed by detailed area calculations and error assessments. By combining the strengths of ArcGIS Pro for preprocessing and SVM classification, eCognition's advanced OBIA capabilities, and Excel's data analysis functions, we were able to achieve high-quality results in our crop mapping efforts and subsequent analyses. This approach demonstrates the importance of selecting and integrating appropriate software tools to effectively handle the complex tasks of crop classification, area estimation, and accuracy assessment using remote sensing data.

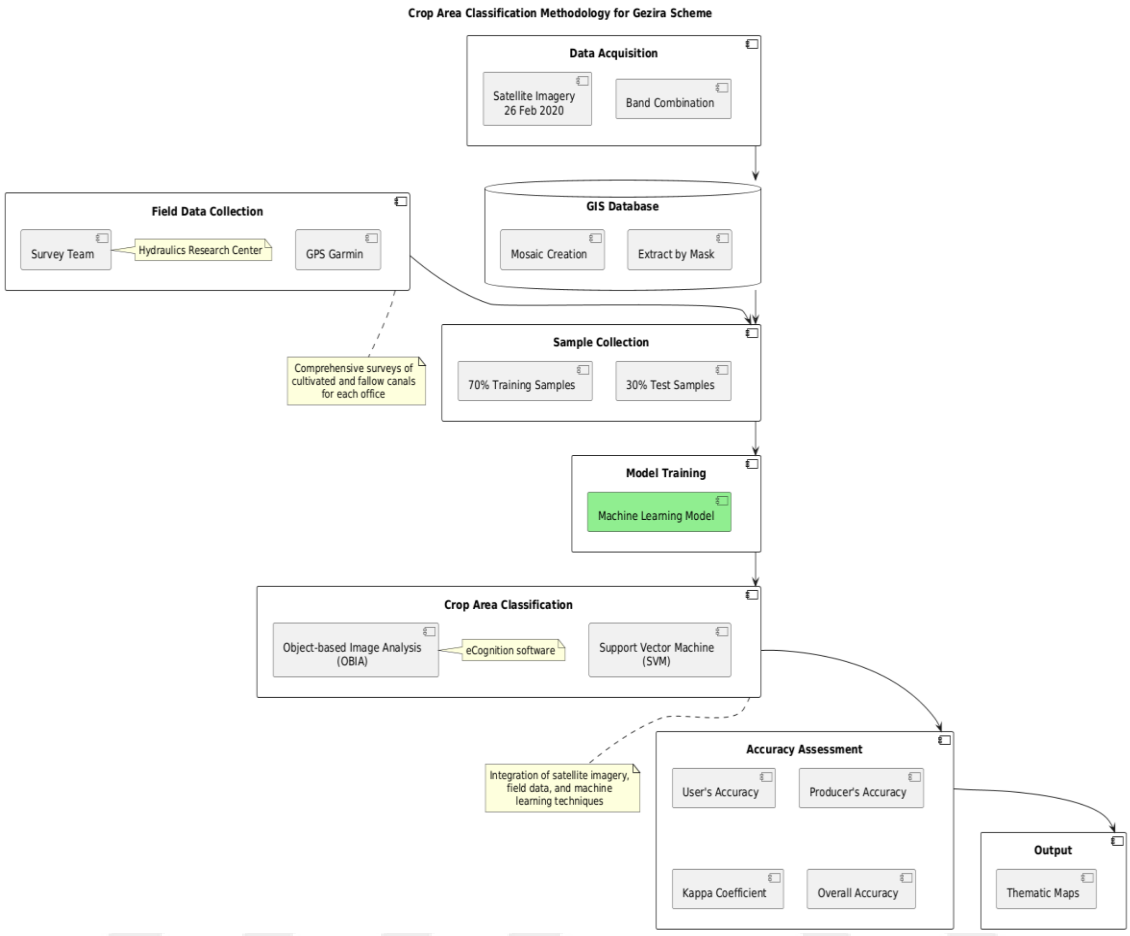

Figure 9. Comprehensive Workflow for Crop Area Classification Using ArcGIS Pro and eCognition

2.3.5. WaPOR Data Sources

• General Information

The Water Productivity Open Access Portal (WaPOR) developed by the Food and Agriculture Organization (FAO), provides a comprehensive set of remotely sensed data crucial for agricultural water management and productivity assessment. This study leverages WaPOR's Level 2 datasets, which offer a resolution of 100 meters for the Gezira Irrigation Scheme in Sudan. The key WaPOR layers utilized include actual evaporation (E), transpiration (T), and net primary production (NPP), all available at a (10-day) timescale. Additionally, the research incorporates precipitation data at 5 km resolution, reference evapotranspiration at 20 km resolution, and annual land cover classification at 100 m resolution. To ensure consistency in spatial analysis, the precipitation and reference evapotranspiration datasets were resampled to 100 m resolution using nearest-neighbor resampling techniques.

The WaPOR database covers Africa and the Near East regions, providing near-real-time data from 2009 to the present. For this study of the Gezira Scheme, data from 2014 onwards were used to ensure consistency, as earlier data were derived from resampled MODIS satellite imagery at 250 m resolution, which could introduce inconsistencies in the analysis. The methodology used for compiling the actual evapotranspiration in WaPOR is based on the ETLook method, further developed by the FRAME consortium. This method has been found suitable for inter-plot comparison of irrigation performance indicators for plots larger than 2 hectares, which is appropriate for the large-scale farming operations in the Gezira Scheme.

WaPOR data undergoes continuous improvements, with the latest version (WaPOR v2.1) incorporating enhancements based on quality assessments by IHE Delft and ITC. These datasets provide a cost-effective means for irrigation performance assessment in the Gezira Scheme, offering spatially distributed data that covers long periods and wide areas. This allows for retrospective analysis, which is particularly valuable in regions like Sudan where ground-based data collection can be challenging or costly. The integration of WaPOR data with field observations and agronomic principles enables a comprehensive assessment of irrigation performance in the Gezira Scheme, including indicators such as uniformity, equity, adequacy, and land and water productivity. This approach demonstrates the potential of remote sensing technologies in revolutionizing agricultural water management and productivity analysis in one of the world's largest irrigation projects, providing valuable insights for improving wheat production and water use efficiency in the semi-arid climate of Sudan.

Table 7. Comprehensive Overview of the Key Parameters Used in the WaPOR System,

Parameter	**Description**	**Type**	**Source**	**Role in WaPOR**
NDVI	Normalized Difference Vegetation Index	Intermediate with external data	Satellite imagery	Key input for multiple components (e.g., Phenology, fAPAR)
Phenology	Crop growth stages	WaPOR layer internal data only	Derived from NDVI	Determines growing seasons
fAPAR	Fraction of Absorbed Photosynthetically Active Radiation	Intermediate internal only	Derived from NDVI	Input for NPP calculation
Weather data	Temperature, humidity, wind speed	Intermediate with external data	Meteorological datasets	Input for Reference ET
Solar Radiation	Incoming solar energy	Intermediate with external data	Satellite/reanalysis data	Input for energy balance calculations
Land Cover	Classification of land use types	WaPOR layer with external data	Satellite imagery + global products	Determines crop types and areas
Reference ET	Potential evapotranspiration	WaPOR layer with external data	Calculated from weather data	Baseline for actual ET estimation
Soil moisture stress	Water availability for plants	Intermediate with external data	Derived from LST and NDVI	Modifies ET and NPP calculations
Precipitation	Rainfall amount	WaPOR layer with external data	Satellite/ground observations	Input for water balance
Surface albedo	Reflectivity of land surface	Intermediate with external data	Derived from satellite data	Input for energy balance
NPP	Net Primary Production	WaPOR layer internal data only	Calculated from multiple inputs (NDVI, fAPAR, weather, soil moisture stress, land cover)	Estimates biomass production
TBP	Total Biomass Production	WaPOR layer internal data only	Derived from NPP	Input for water productivity

Table 8. Structure of WaPOR Database

Level	**Resolution**	**Coverage**	**Monitoring**	**Reference**
Level 1	250 meters	Continental (Africa and Near East)	• Continuous since April 2009 • Every 10 days or daily	Mannaerts et al. (2020)
Level 2	100 meters	• 21 countries • 5 river basins	• Continuous since April 2009 • Every 10 days or daily	WaPOR Database Methodology (2020)
Level 3	30 meters	8 regions in: • Lebanon • Egypt • Ethiopia • Mali • Kenya • Mozambique • Sudan	• Continuous since April 2009 • Every 10 days or daily	Blatchford et al. (2020)

Table 9. The WaPOR Layers Used for Analyses

No.	WaPOR Data	Definition	Spatial resolution	Temporal resolution	Units	Temporal coverage	Reference
1	Evapo-transpira-tion	Total water con-sumed through evaporation, tran-spiration, and in-terception	100 m	10-day	mm/dekad	2009 - pre-sent	WaPOR Database Methodol-ogy (2020)
2	Transpira-tion (T)	Water consumed by plants and re-leased as vapor	100 m	10-day	mm/dekad	2009 - pre-sent	WaPOR Database Methodol-ogy (2020)
3	Net Pri-mary Pro-duction (NPP)	Rate of biomass production by plants	100 m		gC/m²/day	2009 - pre-sent	Running et al. (2004)
4	Land cover classifica-tion (LCC)	Categorization of land surface cover types	100 m	Annual	N/A	2009 - pre-sent	WaPOR Database Methodol-ogy (2020)
5	Precipita-tion (PCP)	Amount of water falling as rain or snow	5 km		mm/dekad	2009 - pre-sent	WaPOR Database Methodol-ogy (2020)
6	Reference Evapo-transpira-tion (RET)	ET from a hypothetical grass reference crop	20 km	Daily	mm/day	2009 - pre-sent	Allen et al. (1998)

Figure 10. WaPOR Layers Used for The Analyses after Download

- **A Framework for Assessing Irrigation Performance Using WaPOR Data:**

Figure 11 shows the flowchart describing the approach to assessing WaPOR-based irrigation performance indicators at Gezira Scheme for Wheat analysis. the approach to assessing WaPOR-based irrigation performance indicators would follow a similar framework, adapted to the specific context of wheat cultivation in Sudan. The process can be described in three main steps:

Firstly, the WaPOR data layers for actual evapotranspiration (ETa), reference evapotranspiration (RET), and net primary production (NPP) were preprocessed. This preprocessing involved matching the spatial resolution of all layers to 100m (the highest resolution available for the Gezira Scheme in WaPOR), removing non-crop pixels using the land cover classification (LCC) layer to focus only on wheat fields, and performing a quality check to ensure data reliability.

Secondly, seasonal calculations were performed for each wheat plot within the Gezira Scheme. The seasonal actual evapotranspiration (ETa,s), seasonal potential evapotranspiration (ETp,s), and seasonal NPP (NPPs) were computed using the respective WaPOR layers. These calculations considered the specific start of season (SOS) and end of season (EOS) dates for wheat in the Gezira Scheme, which typically runs from November to March. The seasonal potential evapotranspiration (ETp,s) was derived by combining the reference evapotranspiration (RET) data with wheat-specific crop coefficients (Kc) appropriate for the local climate and growing conditions.

Finally, the irrigation performance indicators were analyzed. The seasonal NPP data would be converted to above-ground biomass (B) for wheat using crop-specific parameters including the above-ground over total biomass ratio (AOT), a light use efficiency correction factor (fc), and the moisture content of fresh biomass (mc). The wheat yield was to be then estimated by multiplying the biomass by the harvest index (HI) for wheat.

This approach allowed for the calculation of key irrigation performance indicators for the Gezira Scheme, including:

1. Uniformity of water consumption within fields
2. Equity of water distribution across the scheme
3. Adequacy of irrigation (comparing actual to potential evapotranspiration)
4. Land productivity (wheat yield per unit area)
5. Water productivity (wheat yield per unit of water consumed)

These indicators provided a comprehensive assessment of irrigation performance across the Gezira Scheme, offering valuable insights for improving water management and wheat productivity in this crucial Sudanese agricultural region.

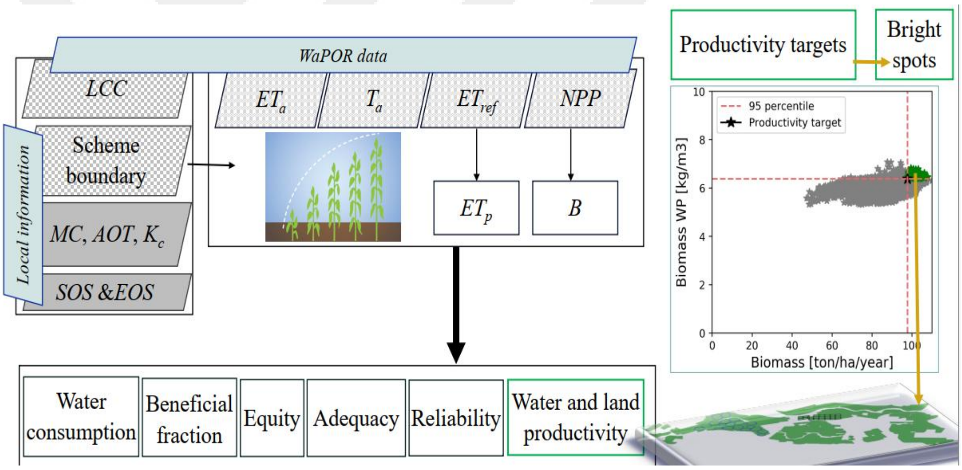

Figure 11. Schematic Representation of WaPOR-Based Irrigation Performance Assessment Framework

Local information: The Gezira Irrigation Scheme analysis was carefully compiled to ensure accurate and context-specific assessment of wheat cultivation performance. The land cover classification for wheat was derived from a combination of Support Vector Machine (SVM) and Object-Based Image Analysis (OBIA) techniques applied to main thematic crop data. This approach allowed for a precise delineation of wheat-cultivated areas within the scheme, essential for focusing the analysis on relevant agricultural zones (Figure 12).

The scheme boundary was obtained from a comprehensive database specifically created for the Gezira Irrigation Scheme. This database provides an accurate representation of the scheme's extent, crucial for defining the spatial scope of the analysis and ensuring all calculations are performed within the relevant agricultural area (Figure 13).

The growing season for wheat in the 2019-2020 agricultural year was defined with specific start and end dates. The Start of Season (SOS) was set as October 7, 2019, and the End of Season (EOS) as April 26, 2020. These dates were carefully selected to reflect the typical wheat cultivation cycle in the Gezira Scheme, accounting for local climatic conditions and agricultural practices.

Parameters used in the biomass and yield analyses for wheat were sourced from comprehensive literature reviews, ensuring they accurately represent the characteristics of wheat cultivation in the region. (Figure 14) shows crop coefficients (Kc) for wheat, while (Tables 10,11) display all crop parameters and parameters used in the biomass and yield analyses of wheat, respectively.

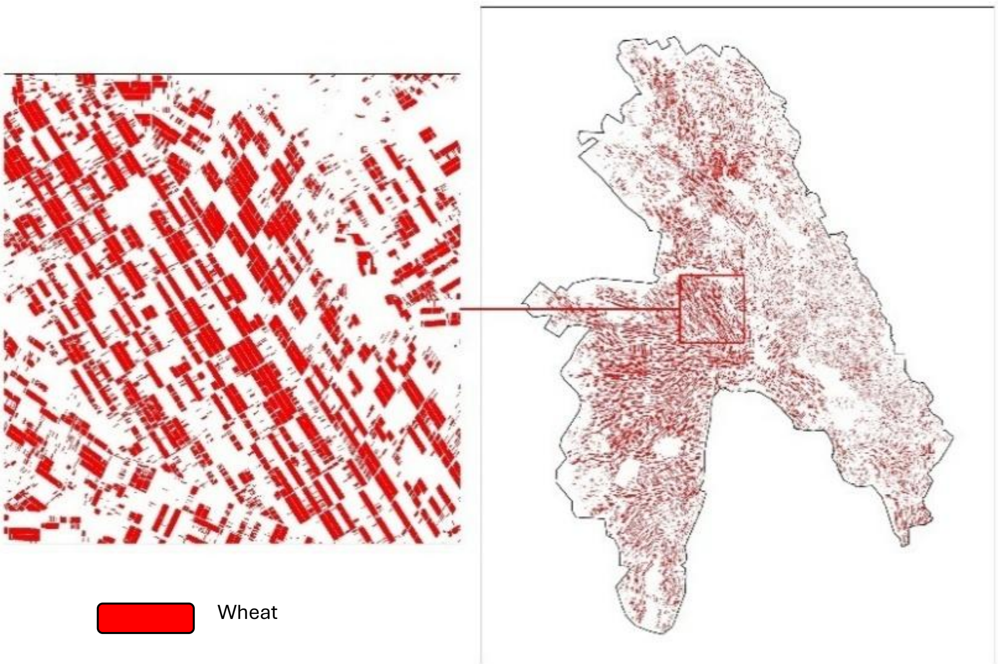

Figure 12.Land Cover Classification of Wheat

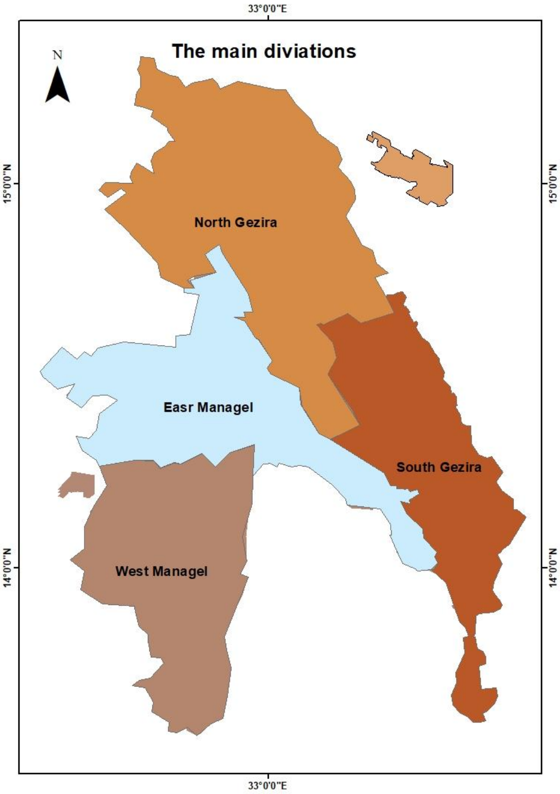

Figure 13. Scheme Boundary

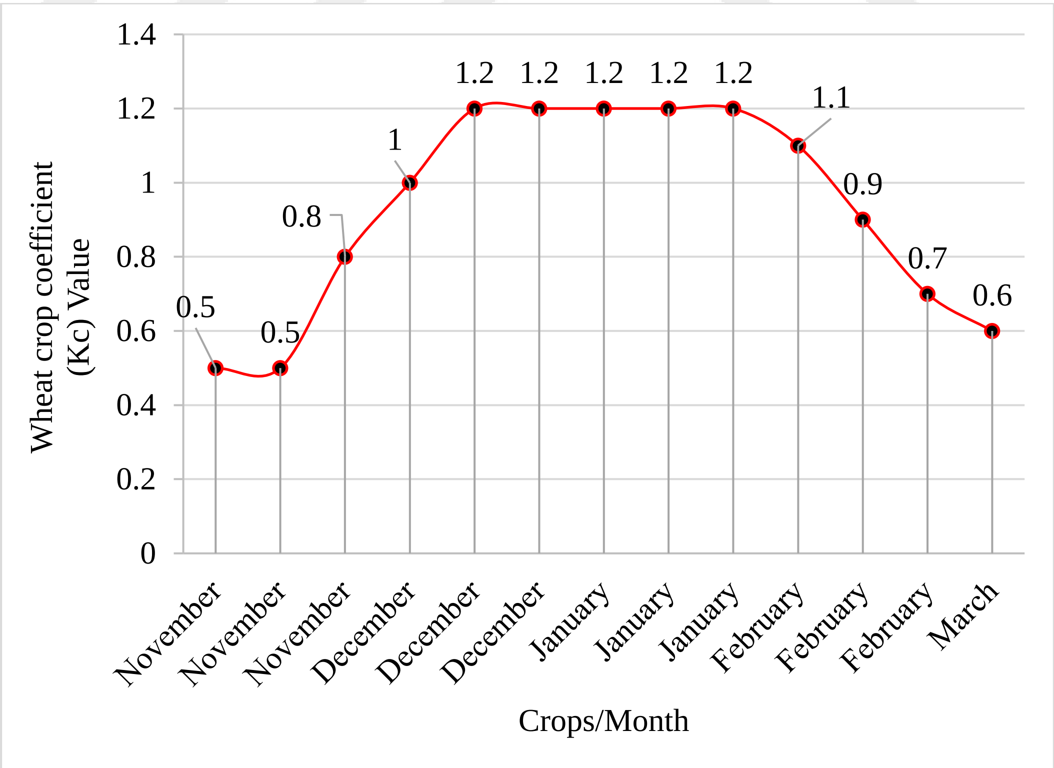

Figure 14. Crop Coefficients (Kc) of Wheat

Table 10. Crops Parameters- (FAO, 2020)

Crop	Harvest Index	Above-ground Over Total Biomass	Moisture Content Ratio
Cotton	0.20	0.80	0.15
Barley	0.30	0.85	0.15
Wheat	0.48	0.85	0.15
Maize (grain)	0.35	0.93	0.26
Sorghum	0.25	0.80	0.20
Rice	0.43	0.75	0.15
Tef	0.24	0.75	0.15
Sugarcane (ratoon)	1.00	1.00	0.70

Table 11. Parameters Used in the Biomass and Yield Analyses of Wheat- (FAO, 2020b)

SOS: Start of season= (07/10/2019)	AOI: above ground over total biomass= (0.85)
EOS: End of season = (26/04/2020)	MC: Moisture content ratio= (0.15)
Average_Kc: crop factor = 0.85	CF: conversion factor = 1
HI: harvest index= (0.36)	

Note:

a) Harvest Index: The ratio of grain yield to total above-ground dry biomass at crop maturity (Unkovich et al., 2010).

b) Above-ground Over Total Biomass: The ratio of above-ground biomass (stems, leaves, and grain) to total plant biomass including roots (Mathew et al., 2017) .

c) Moisture Content Ratio: The proportion of water in the harvested grain, typically expressed as a percentage of total grain weight (Brooker et al., 1992).

d) Conversion Factor (CF): A multiplier used to convert between different units of measurement or to adjust for specific crop characteristics. In the context of wheat yield calculations, it's often used to convert from fresh weight to dry weight or to standardize moisture content (Carr, 2013).

WaPOR Data: The Water Productivity Open Access Portal (WaPOR) provided essential remote sensing data for our analysis of the Gezira Irrigation Scheme, as shown in Figure

10. We downloaded six key datasets: Evapotranspiration (ET), which represents total water consumed by crops and lost to the atmosphere; Transpiration (T), isolating water used specifically by plants; Net Primary Production (NPP), measuring biomass production; Land Cover Classification (LCC), categorizing land use types; Precipitation (PCP), offering information on rainfall patterns; and Reference Evapotranspiration (RET), providing a standardized measure of atmospheric evaporative demand. These high-resolution, spatially explicit datasets formed the foundation of our irrigation performance assessment, enabling a comprehensive analysis of wheat productivity and water use efficiency across the scheme. The integration of these diverse data layers allowed for a nuanced understanding of the agricultural dynamics within the Gezira Irrigation Scheme, supporting evidence-based insights for improving water management and crop productivity.

- **Water Consumption and Irrigation Performance Calculations**

A. Water Consumption and Evapotranspiration

❖ Evapotranspiration (ET): The combined process of water surface evaporation, soil moisture evaporation, and plant transpiration of water into the atmosphere (Allen et al., 1998b).

❖ Reference Evapotranspiration (ETo): The rate of evapotranspiration from a hypothetical reference crop with specific characteristics, assuming no water shortage (FAO, 2006).

❖ Crop Coefficient (Kc): A dimensionless factor, typically ranging from 0.1 to 1.2, used to estimate crop evapotranspiration (ETc) by multiplying it with the reference evapotranspiration (ETo) (Doorenbos & Pruitt, 1977).

❖ Beneficial Fraction (BF): A measure of irrigation efficiency representing the ratio of water beneficially used by the crop to the total amount of water applied through irrigation. A higher BF indicates more efficient water use (Molden et al., 2010)

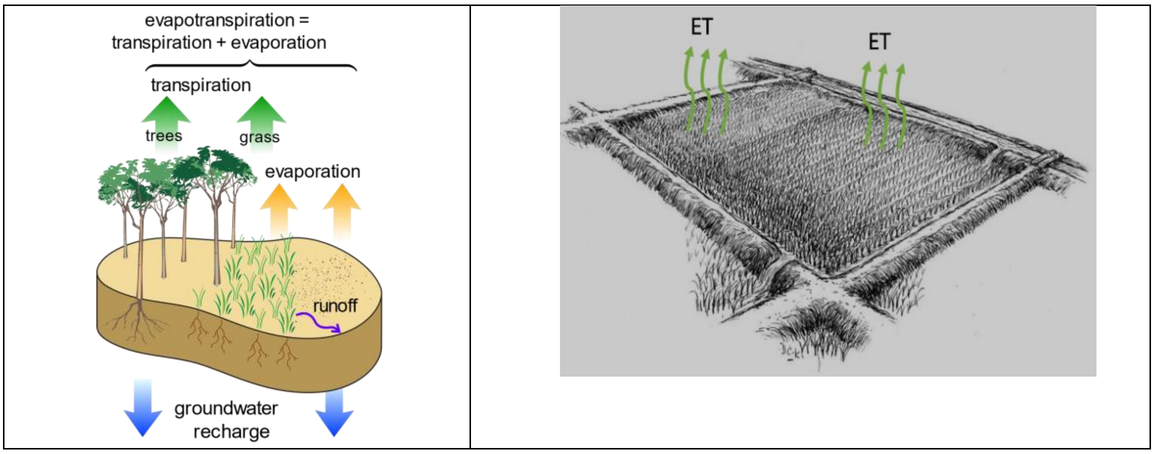

Figure 15. Evapotranspiration and the Water Cycle (Wikipedia)

$$\text{Seasonal Actual Evapotranspiration } ET_{a,s} = \sum_{SOS}^{EOS} ET_a \qquad (8)$$

$$\text{Potential Evapotranspiration } \; ETc = ETo * Kc \qquad (9)$$

Where:

ETa,s = Actual evapotranspiration

SOS = Start of season

EOS = End of season

ETo = Reference evapotranspiration

Kc = Crop coefficient

$$BF = Ta/ETa \qquad (10)$$

Where:

BF = Beneficial Fraction

Ta = Actual Transpiration

ETa = Actual Evapotranspiration

B. Biomass and Yield Estimation

Definitions (Molden et al., 2010):

❖ Biomass: refers to the total mass of living organic matter in plants above the soil surface. For wheat, this includes stems, leaves, and grain. B is typically measured in tons per hectare (t/ha) and is an important indicator of crop growth, health, and potential yield.

❖ Net Primary Production (NPP): is the rate at which all the plants in an ecosystem produce net useful chemical energy. It's a measure of the net amount of carbon dioxide taken in by vegetation and converted to biomass through photosynthesis, minus the amount of carbon dioxide released during plant respiration.

❖ Yield: refers to the quantity of crops produced per unit of land area.

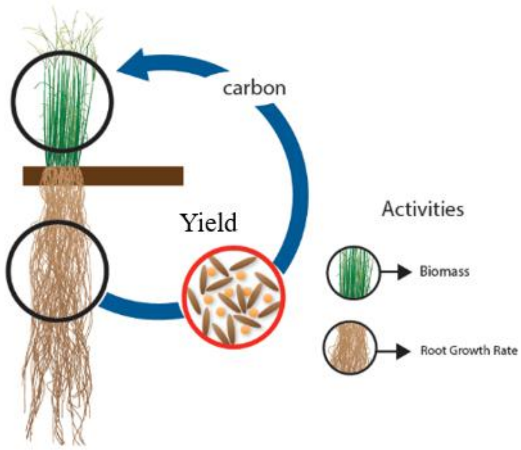

Figure 16. Biomass and Yield (Reference)

$$\text{Biomass } B = \text{AOT} \cdot f_c \cdot \frac{\text{NPP}_S \cdot 22.222}{(1-\text{MC})} \tag{11}$$

$$\text{Yield} = B \cdot \text{HI} \tag{12}$$

Where:

AOT = Above-ground over total biomass ratio

fc = Light use efficiency correction factor

mc = Moisture content of fresh biomass

HI = Harvest Index (Wheat = 0.84)

Units: ton/ha

C. Water Productivity

Definitions (D. Molden et al., 2010):

❖ Crop Water Productivity is a measure of the yield or net income per unit of water used in evapotranspiration. In this context, it represents the efficiency of water use in wheat production, measured in kg/m³ (kilograms of wheat produced per cubic meter of water consumed).

Figure 17. Water Productivity (FAO, 2020)

$$\mathrm{WP} = \frac{Y}{\mathrm{ET_{a,s}}} \tag{13}$$

Where:

B = the total above-ground biomass produced

$ET_{a,s}$ = actual evapotranspiration

Units: kg/m³

D. Irrigation Performance Indicators (Efficiency indicators)

Definitions:

❖ Equity: in irrigation systems refers to the degree to which water deliveries or crop water use are considered fair across all users or areas within the system. It is a crucial indicator of irrigation performance and system management effectiveness (Molden and Gates, 1990).

❖ Adequacy: is a critical efficiency indicator in irrigation systems, quantifying the extent to which crop water requirements are met. It is defined as the ratio of actual evapotranspiration (ETa) to potential evapotranspiration (ETp) over a growing season (Bastiaanssen and Bos, 1999).

❖ Relative Water Deficit (RWD): is a crucial physiological indicator that quantifies the degree of water stress experienced by crops (Steduto et al., 2012).

$$\text{Equity} = \text{CV(ETa)} = (\text{Standard Deviation of ETa} / \text{Mean ETa}) * 100 \qquad (14)$$

Table 12. Performance Indicator Reference Range

Performance Indicator	**Reference Range**
Equity	▪ 0 < E < 10% Good ▪ 10 < E < 25% Fair ▪ E > 25% Poor performance

$$\text{Adequacy (A)} = \text{Seasonal ETa} / \text{Seasonal ETp} \qquad (15)$$

Where:

ETa represents the actual water consumed by crops through evapotranspiration.

ETp represents the theoretical maximum water requirement under ideal conditions.

Performance Indicator Reference Range:

- $0.8 < A \leq 1.0$: Good performance / operational range
- $0.68 < A \leq 0.8$: Acceptable range
- $A \leq 0.68$: Poor performance

$$\text{Relative Water Deficit (RWD)} = 1 - (\text{AETI} / \text{REF}) \qquad (16)$$

Where:

AETI: Actual Evapotranspiration

REF: Reference Evapotranspiration

E. Productivity Gaps

Productivity Gap is the difference between the target productivity and the actual productivity in areas where the actual productivity falls below the target.

❖ Biomass Gap: The difference between the target biomass and the actual biomass in areas where the actual biomass is below the target.

$$Biomass\ gap = \text{Target Biomass} - \text{Actual Biomass}$$
$$\text{(where Actual Biomass < Target Biomass)} \tag{17}$$

❖ Biomass Water Productivity (WPb) Gap: The difference between the target biomass water productivity and the actual biomass water productivity in areas where the actual WPb is below the target.

$$\text{WPb Gap} = \text{Target WPb} - \text{Actual WPb}$$
$$\text{(where Actual WPb < Target WPb)} \tag{18}$$

❖ Crop Yield Gap: The difference between the target crop yield and the actual crop yield in areas where the actual yield is below the target.

$$\text{Yield Gap} = \text{Target Yield} - \text{Actual Yield}$$
$$\text{(where Actual Yield < Target Yield)} \tag{19}$$

❖ Crop Water Productivity (WPy) Gap: The difference between the target crop water productivity and the actual crop water productivity in areas where the actual WPy is below the target.

$$\text{WPy Gap} = \text{Target WPy} - \text{Actual WPy}$$
$$\text{(where Actual WPy < Target WPy)} \tag{20}$$

❖ Target Productivity: The productivity level set as a benchmark, typically the 95th percentile of the productivity distribution in a given area.

$$\text{Target Biomass} = \text{Target WPy 95th percentile of Biomass distribution}$$
$$\text{Target Biomass WP} = \text{95th percentile of Biomass WP distribution}$$
$$\text{Target Yield} = \text{95th percentile of Yield distribution} \tag{21}$$
$$\text{Target Crop WP} = \text{95th percentile of Crop WP distribution}$$

❖ Bright Spots Identification: Areas where both biomass (or yield) and water productivity meet or exceed their respective target values (Nhemachena et al., 2018),Criteria:

$$\begin{gathered}\text{Bright Spot} = (\text{Actual Biomass} \geq \text{Target Biomass})\text{AND }(\text{Actual WPb} \geq \text{Target WPb})\\ \text{Or}\\ \text{Bright Spot} = (\text{Actual Yield} \geq \text{Target Yield})\text{AND }(\text{Actual WPy} \geq \text{Target WPy})\end{gathered} \tag{22}$$

2.3.6. Predicting Wheat Yield and Water Productivity Using Machine Learning

Machine learning is a subset of artificial intelligence that enables systems to learn and improve from experience without being explicitly programmed. These algorithms are designed to identify patterns in data, make decisions, and predict outcomes with minimal human intervention. By leveraging their ability to process and analyze large volumes of complex data, machine learning techniques have revolutionized various fields, including agricultural applications such as crop yield estimation from remote sensing data (LeCun et al., 2015).

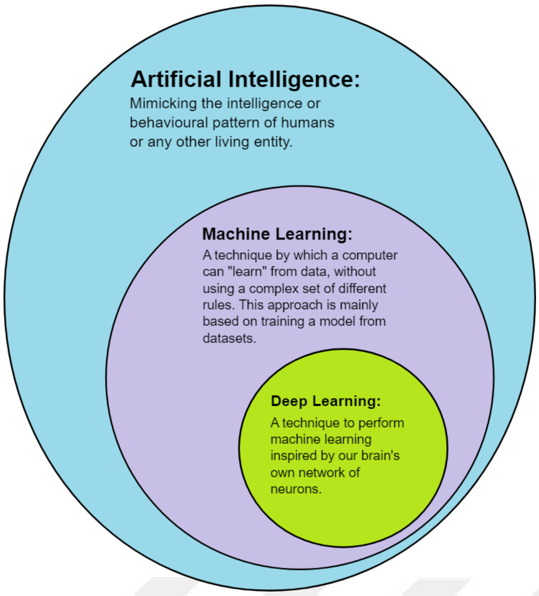

Figure 18. The Nested Relationship of Artificial Intelligence, Machine Learning, and Deep Learning (Bond et al., 2023)

In this study, we employed a diverse array of advanced machine learning techniques to enhance both wheat yield and water productivity (WPy) estimation in the Gezira Irrigation Scheme. Our methodology encompassed seven distinct models, each applied to predict both yield and WPy. Linear Regression served as our baseline, offering a straightforward approach to understand linear relationships within our data. To capture more complex, non-linear patterns, we implemented Random Forest, an ensemble method that excels in handling intricate feature interactions often present in agricultural datasets. Gradient Boosting and its optimized variant, XGBoost, were utilized for their ability to build strong predictive models through sequential learning, potentially uncovering subtle patterns in both yield and water productivity data.

We further expanded our analytical toolkit with K-Nearest Neighbors (KNN), a non-parametric method that bases predictions on the similarity between data points, allowing us to capture localized patterns in yield and WPy across the irrigation scheme. Decision Trees were employed to model hierarchical decision processes, providing interpretable insights into the factors influencing both yield and water productivity. Lastly, we implemented the Bagging Regressor, an ensemble method that reduces variance by combining predictions from multiple models trained on subsets of our data, aiming to create more robust and generalizable predictions for both target variables.

By applying this comprehensive suite of machine learning algorithms to both yield and WPy prediction, our study aimed to not only achieve accurate estimations but also to gain deeper insights into the complex interplay of factors affecting wheat productivity and water use efficiency in the Gezira Irrigation Scheme. This dual-target approach allowed us to explore potential relationships between yield and water productivity, offering a more holistic view of wheat cultivation in the region. Our methodology reflects the multifaceted nature of modern agriculture and the potential of advanced analytics in enhancing our understanding and management of complex agricultural systems.

a) Multisource Data Integration for Advanced Wheat Yield and Water Productivity Prediction in the Gezira Irrigation Scheme

This study focused on a specific section of the Gezira Irrigation Scheme, carefully chosen to represent the diverse agricultural conditions of the region. Figure 19 in our project illustrates this selected area, providing essential spatial context for our analysis and highlighting the geographical scope of this thesis.

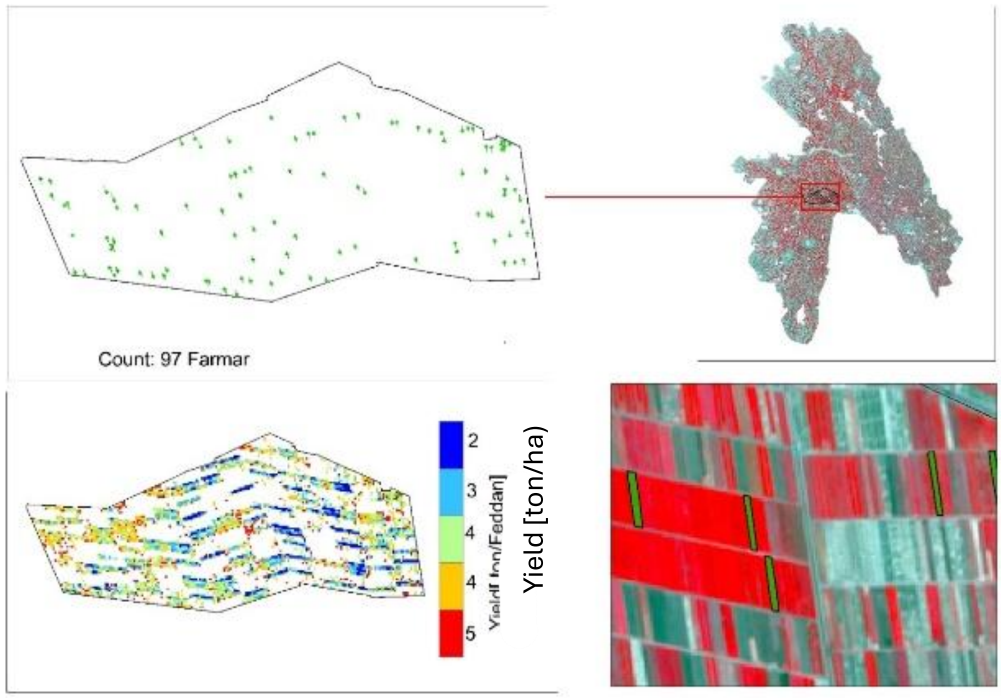

Figure 19. Study Area and Data Distribution in the Gezira Irrigation Scheme for Wheat Yield Prediction Model

This study on wheat yield and water productivity prediction in the Gezira Irrigation Scheme utilized a comprehensive and multi-faceted approach to data collection and integration. The dataset comprised two primary sources, each contributing unique and essential information for robust model development and validation.

The foundation of our analysis was built upon data from the FAO's Water Productivity Open Access Portal (WaPOR). This valuable resource provided crucial agro-meteorological parameters including Actual Evapotranspiration and Interception (AETI, mm), Net Primary Production (NPP, kg/m^2), Transpiration (T, mm), Adequacy (unitless ratio), Biomass Factor (BF, unitless), Above Ground Biomass (AGBM, ton/ha), and biomass Water Productivity (WPb, kg/m^3). Additionally, WaPOR supplied an initial calculated yield estimate in tons per hectare (ton/ha) and Water Productivity (kg/m^3). These parameters offered invaluable insights into water utilization, biomass production, and overall crop health dynamics across our study area. (Table 14) presents a subset of the input parameters from the WaPOR Open Access Portal, illustrating the range and nature of these critical variables, each expressed in their respective units to provide a clear understanding of the scale and comparability of the data used in our analysis.

Table 13. Subset of the Input Parameters From (WaPOR)

RET	AETI	NPP	T	Adequacy	BF	AGBM	WPb	Wpy	NDVI
1855.6	791.2	277.37	615	0.5	0.78	6.16	0.78	0.37	0.35
1855.6	798.5	282.44	616.2	0.5	0.77	6.28	0.79	0.38	0.44
1849.3	815.2	317.2	643.1	0.51	0.79	7.05	0.86	0.42	0.52
1855.6	877.5	322.79	689.2	0.55	0.79	7.17	0.82	0.39	0.58
1855.6	857.6	326.72	681.6	0.54	0.79	7.26	0.85	0.41	0.55

To enhance our understanding of vegetation health and vigor, we utilized Google Earth Engine to derive key vegetation indices: the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Structure Insensitive Pigment Index (SIPI). These unitless indices, ranging from (-1 to 1), provide crucial information about vegetation density, photosynthetic activity, and plant stress levels. Figure 20 illustrates the spatial distribution of these indices across our study area, while Table 15 presents a subset of the derived parameters. Figure 3 displays maps of these input values, offering a visual representation of vegetation health variability across the Gezira Irrigation Scheme. This spatial analysis adds a vital geographic dimension to our study, highlighting areas of high productivity and potential concern, thus enriching our yield and water productivity prediction models.

Table 14. Subset of the Input Parameters Values from Google Earth Engine

NDVI	EVI	SIPI
0.49	3.66	1.49
0.58	3.76	1.32
0.54	3.85	1.2

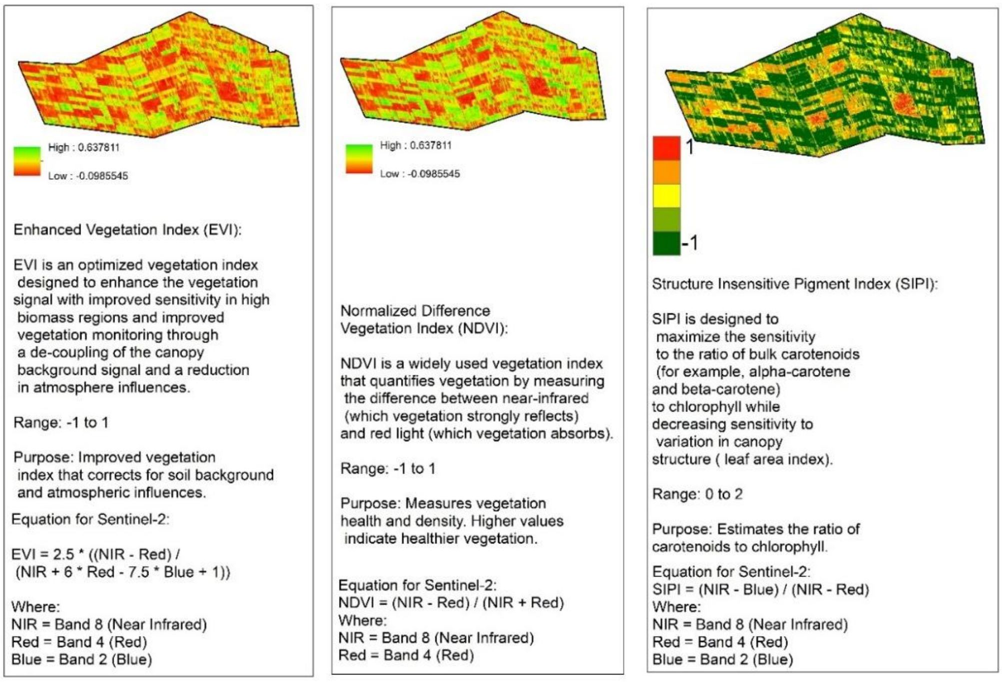

Figure 20. Maps of Input Parameters Values from Google Earth Engine

b)Advanced Machine Learning Models for Wheat Yield and Water Productivity

In preparation for model development and evaluation, we implemented a strategic data partitioning approach. From our collection of 97 farmer data points, we allocated 80 (approximately 83%) for model training. This substantial training set ensured our models were exposed to a wide range of agricultural scenarios and outcomes. The remaining 20 data points (about 17%) were reserved as an independent test set, crucial for unbiased evaluation of model performance on unseen data.

This study predicting wheat yield and water productivity in the Gezira Irrigation Scheme, we utilized seven diverse machine learning models. Each model analyzes our input features-including AETI, NPP, T, Adequacy, BF, AGBM, WPb, WPy, NDVI, EVI, and SIPI-to forecast wheat yield (tons/ha) and water productivity (kg/m^3).

Linear Regression: Linear regression is a statistical method that models the linear relationship between a dependent variable and one or more independent variables(Montgomery et al., 2021). It is used to predict the value of the dependent variable based on the independent variables and to understand the nature of their relationship(Weisberg, 2005).

$$\hat{y} = \beta_0 + \beta_1(\text{AETI}) + \beta_2(\text{NPP}) + \cdots + \beta_{10}(\text{SIPI}) \quad (23)$$

This model assumes a linear relationship between the input features and the target variables. Each coefficient β indicates the change in yield or water productivity for a one-unit change in the corresponding feature, holding other features constant. β_0 is the intercept, representing the predicted yield or water productivity when all features are zero.

Random Forest: is an ensemble learning method that constructs multiple decision trees during training and outputs the average prediction of the individual trees for regression tasks or the mode of the classes for classification tasks (Breiman, 2001). This technique combines the concepts of bagging (bootstrap aggregating) and random feature selection to create a robust and accurate predictive model (Liaw, 2002).

$$\hat{y} = \frac{1}{B}\sum_{i=1}^{B} f_i(x) \quad (24)$$

Where B is the number of trees (set to 100 in our case), and $f_i(x)$ is the prediction from the i-th tree. Each tree is trained on a bootstrap sample of our 80 training points, considering a random subset of features at each split. This approach captures complex, non-linear relationships among the agro-meteorological parameters and the target variables.

Gradient Boosting: is a machine learning technique that produces a prediction model as an ensemble of weak prediction models, typically decision trees. It builds the model in a stage-wise manner, optimizing a differentiable loss function by iteratively adding weak learners that correct the residual errors of the previous stage(Friedman, 2001). This method is known for its high predictive accuracy and ability to handle complex, non-linear relationships in data(Chen and Guestrin, 2016).

$$F(x) = \sum_{i=1}^{M} \gamma_i h_i(x) \quad (25)$$

Here, M is the number of iterations, γ_i is the step length, and $h_i(x)$ are weak learners (usually shallow decision trees). The model sequentially adds weak learners to minimize prediction error, capturing subtle patterns in our agricultural data that simpler models might overlook.

XGBoost (eXtreme Gradient Boosting): is an optimized distributed gradient boosting library designed for high efficiency, flexibility, and portability. It implements machine learning algorithms under the Gradient Boosting framework, providing a scalable, fast, and accurate implementation of gradient boosted decision trees(Chen and Guestrin, 2016b).

$$\hat{y}_i = \sum_{k} f_k(x_i) \text{ where } f_k \in F \tag{26}$$

Here, F represents the space of regression trees. XGBoost optimizes the learning process, efficiently handling sparse data (which may occur in our vegetation indices) and employing regularization techniques to prevent overfitting.

K-Nearest Neighbors (KNN): is a non-parametric method used for classification and regression, where predictions are made based on the k closest training examples in the feature space. In this algorithm, an object is classified by a plurality vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors(Cover and Hart, 1967). For regression tasks, the output is the average of the values of the k nearest neighbors(Altman, 1992). KNN is known for its simplicity and effectiveness in various machine learning applications.

$$\hat{y} = \frac{1}{k}\sum_{i=1}^{k} y_i \tag{26}$$

This model predicts outcomes based on the average of the k nearest neighbors in our 10dimensional feature space. It is particularly effective for capturing localized patterns, where similar agro-meteorological conditions may lead to comparable yields or water productivity.

Decision Trees: are hierarchical models that predict outcomes by making sequential decisions based on feature values(Breiman et al., 1984). They recursively split data using criteria like Information Gain or Gini Impurity, creating a tree-like structure of decision rules(Quinlan, 1986). This approach reveals key feature thresholds influencing the target variable, applicable to both classification and regression tasks. Decision Trees are valued for their interpretability and ability to capture non-linear relationships.

Bagging Regressor: is an ensemble meta-estimator that fits base regressors on random subsets of the original dataset and aggregates their predictions to form a final prediction(Breiman, 1996). It reduces variance and helps to avoid overfitting by creating multiple subsets of the original data through bootstrap sampling, training a separate regressor on each subset, and then averaging the predictions. This technique is particularly effective when the base models are complex and tend to overfit, such as decision trees.

$$\hat{y} = \frac{1}{B}\sum_{i=1}^{B} f_i(x) \tag{27}$$

Similar to Random Forest, this model can utilize various base estimators beyond decision trees. In our implementation, we employed 100 base estimators, each trained on a bootstrap sample of our training data. This approach mitigates the influence of outliers or unusual data points in our agricultural dataset.

By employing these diverse models, we aim to capture a wide range of potential relationships between our agro-meteorological parameters and vegetation indices, ultimately enhancing our understanding of wheat yield and water productivity in the Gezira Irrigation Scheme. This comprehensive approach not only facilitates accurate predictions but also provides valuable insights into the complex dynamics of wheat cultivation in our study area.

c) Methodology for Wheat Yield and WPy Prediction

This study employed a comprehensive machine learning approach to predict wheat yield and water productivity (WPy) in the Gezira Irrigation Scheme. We integrated data from the FAO's Water Productivity Open Access Portal (WaPOR) and Google Earth Engine, encompassing a range of agro-meteorological parameters and vegetation indices. Our dataset comprised 97 farmer data points, which were strategically partitioned into training (80 points) and testing (20 points) sets. We implemented and compared seven diverse machine learning algorithms: Linear Regression, Random Forest, Gradient Boosting, XGBoost, K-Nearest Neighbors (KNN), Decision Tree, and Bagging Regressor. Model performance was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R-squared). This methodological framework aimed to capture the complex relationships between environmental factors and agricultural outcomes, providing insights into the dynamics of wheat cultivation in the study area.

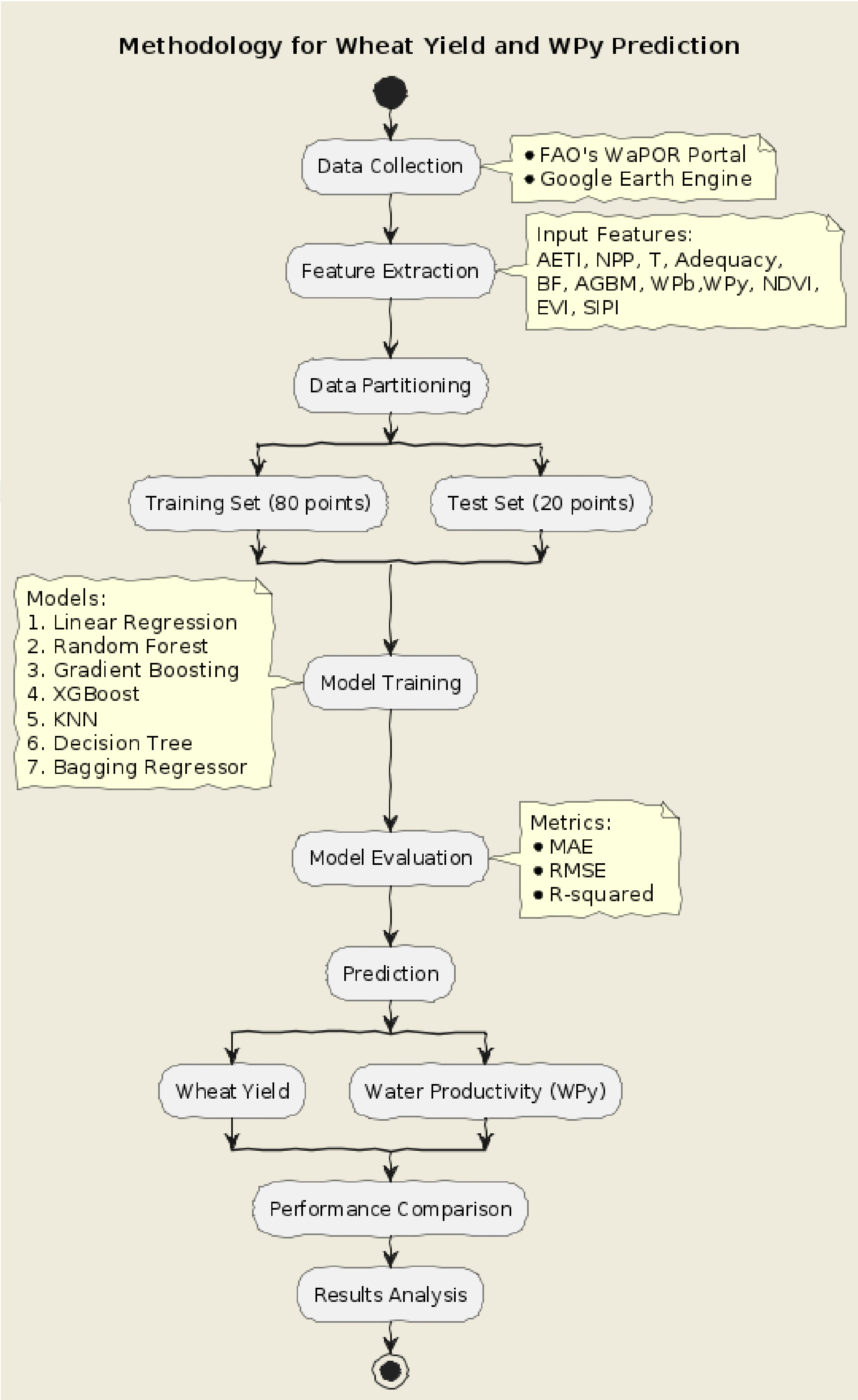

Figure 21. Methodology for Wheat Yield and WPy Prediction Using Machine Learning

3.RESULT AND DISCUSSION

3.1 Crop Classification Results for Elgabel Office

The crop classification results for Elgabel Office are presented through a series of Tables measured in Hectares (feddans = 0.42 ha), Table 16 compares the wheat classification errors between our analysis and the HRC team's findings. Table 17 focus on other crops, including gardens, chickpea, cotton, and miscellaneous cultivations, showing their distribution and classification errors respectively. An overview of all cultivated lands in Elgabel is provided in Table 18 presents the overall errors in cultivated land classification when compared to the HRC team's data. Finally, Figure 22 offers a comprehensive visual representation through maps depicting the spatial distribution of various crops across the Elgabel Office area.

Table 15. Result of Wheat Crops in Elgabel Office

Canal	Cultivated Lands-Wheat (Area / Hectares)		Errors Of Wheat Comparing HRC Team
	HRC (Hectares)	RS (Hectares)	
Elwadi (R, L) Canal	377	372	-0.01
Eltaamier canal	167	173	0.03
Elgalaa Canal	44	46	0.05
Elkaramah canal	75	76	0.02

Table 16. Result of Gardens/Chickpea/Cotton/Crops in Elgabel Office

Canal	Cultivated Lands-Gardens/Chickpea/Cotton/Other (Area / Hectares)		Errors of Gardens/Chickpea/Cotton/Other Comparing HRC Team
	HRC (Hectares)	RS (Hectares)	
Elwadi (R, L) Canal	89	87	0.02
Eltaamier canal	68	59	-0.03
Elgalaa Canal	50	44	0.02
Elkaramah canal	130	123	-0.01

Table 17. Result of Elgabel Cultivated Lands

Canal	Elgabel Cultivated Lands (Area / Hectares)		Elgabel Errors of Cultivated Lands Comparing HRC Team
	HRC (Hectares)	RS (Hectares)	
Elwadi (R, L) Canal	466	459	0
Eltaamier canal	236	232	0.01
Elgalaa Canal	94	89	0.04
Elkaramah canal	205	198	-0.01

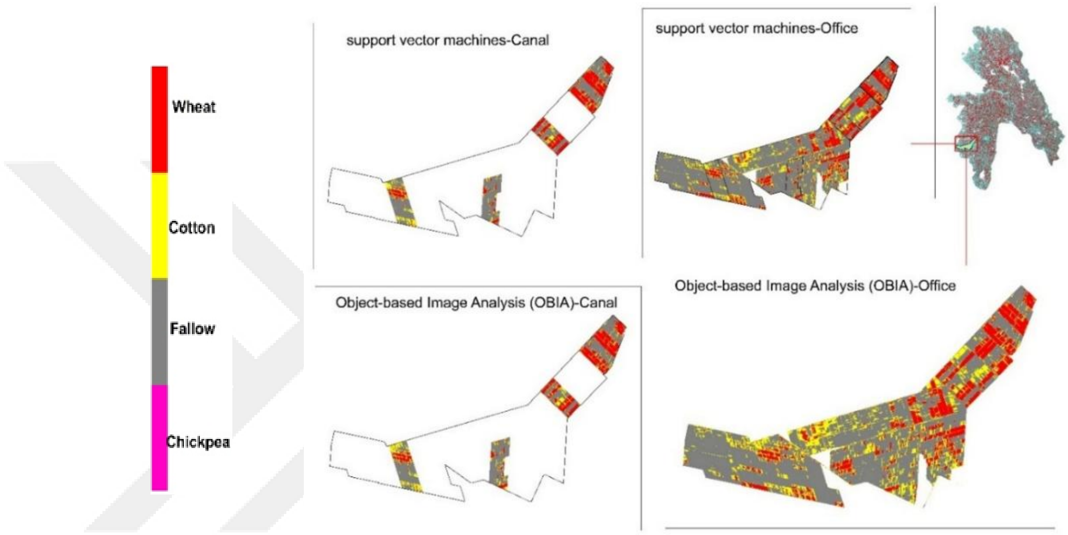

Figure 22. Maps of Spatial Distribution of Crops in Elgabel Office

The accuracy assessment for the Elgabel Office crop classification, based on a (267-point) confusion matrix (Figure 23,24), The accuracy assessment for the Elgabel Office crop classification, comparing the Object-Based Image Analysis (OBIA) method and the Support Vector Machine (SVM) method, reveals high overall accuracy for both approaches, Wheat classification shows strong results for both methods, with OBIA achieving a user's accuracy of 0.98 and a producer's accuracy of 0.96, while SVM attained a perfect user's accuracy of 1.00 and a producer's accuracy of 0.94. For new wheat, both methods performed similarly with a user's accuracy of 0.94, though SVM had a slightly higher producer's accuracy (1.00 vs 0.99).

Fallow land classification demonstrated perfect accuracy (1.00) for both methods, indicating excellent discrimination of these areas. Cotton classification showed some variability, with OBIA achieving a user's accuracy of 0.69 and a producer's accuracy of 0.92, while SVM showed a higher user's accuracy of 0.75 but a lower producer's accuracy of 0.89.

The overall classification accuracy, represented by the Kappa coefficient, is marginally higher for SVM (0.93) compared to OBIA (0.91). This suggests that both methods perform well in crop type mapping for the Elgabel Office area, with SVM having a slight edge in overall accuracy. The choice between methods may depend on specific priorities for minimizing different types of classification errors for particular crop types.

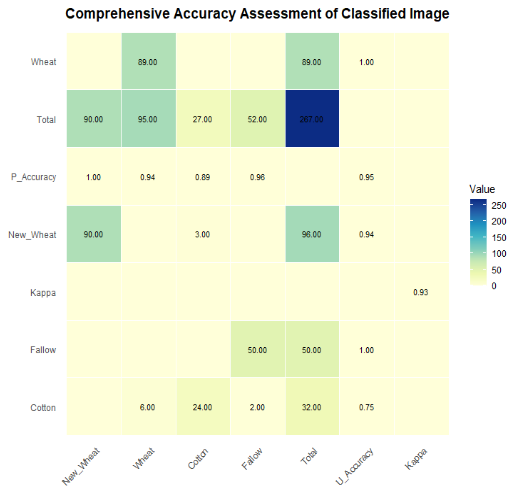

Figure 23. Accuracy Assessment for Legible Office Crop Classification (SVM)

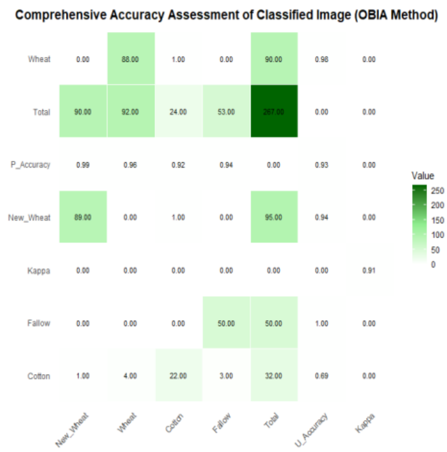

Figure 24.Accuracy Assessment for Elgabel Office Crop Classification (OBIA)

3.2. Crop Classification Results for Elhoosh Office

The crop classification results for Elhoosh Office are presented through a series of Tables. While Table 19 compares the wheat classification errors between our analysis and the HRC team's findings. Table 20 focus on other crops, including gardens, chickpea, cotton, and miscellaneous cultivations, showing their distribution and classification errors respectively when compared to the HRC team's data. An overview of all cultivated lands in Elhoosh is provided in Table 21 presenting the overall errors in cultivated land classification compared to the HRC team's assessment. Finally, Figure 25 offers a comprehensive visual representation through maps depicting the spatial distribution of various crops across the Elhoosh Office area.

Table 18. Result of Wheat Crops in Elhoosh Office

Canal	Cultivated Lands-Wheat (Area / Hectares)		Errors Of Wheat Comparing HRC Team (%)
	HRC (Hectares)	RS (Hectares)	
Elhoosh Canal	130	133	2%
Osman Canal	104	105	3%
Wadelmounier canal	66	68	2%

Table 19.Result of Gardens/Chickpea/Cotton/Crops in Elhoosh Office

Canal	Cultivated Lands-Gardens/Chickpea/Cotton/Other (Area / Hectares)		Errors of Gardens/Chickpea/Cotton/Other Comparing HRC Team (%)
	HRC (Hectares)	RS (Hectares)	
Elhoosh Canal	99	97	2%
Osman Canal	130	135	5%
Wadelmounier canal	76	73	3%

Table 20.Result of Elhoosh Cultivated Lands

Canal	Elhoosh Cultivated Lands (Area / Hectares)		Elhoosh Errors of Cultivated Lands Comparing HRC Team (%)
	HRC (Hectares)	RS (Hectares)	
Elhoosh Canal	229	231	2%
Osman Canal	234	240	4%
Wadelmounier canal	142	141	3%

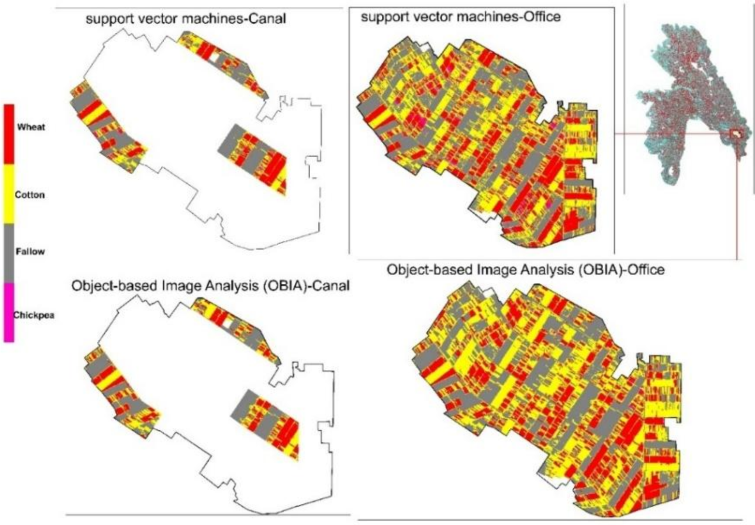

Figure 25.Maps of Spatial Distribution of Crops in Elhoosh Office

Demonstrates exceptional performance based on (297-point) confusion matrix. The accuracy assessment of multi-class crop classification for the Elhoosh Office demonstrates strong performance for both OBIA and SVM methods, with some notable variations across crop types. Wheat classification shows identical results for both methods, while new wheat classification reveals superior user's accuracy for SVM. Both approaches achieve perfect accuracy for fallow land and identical performance for cotton. OBIA outperforms SVM in chickpea classification, particularly in user's accuracy. Overall, SVM slightly edges out OBIA in terms of overall accuracy (0.91 vs 0.87) and Kappa coefficient (0.88 vs 0.82), indicating marginally better general performance.

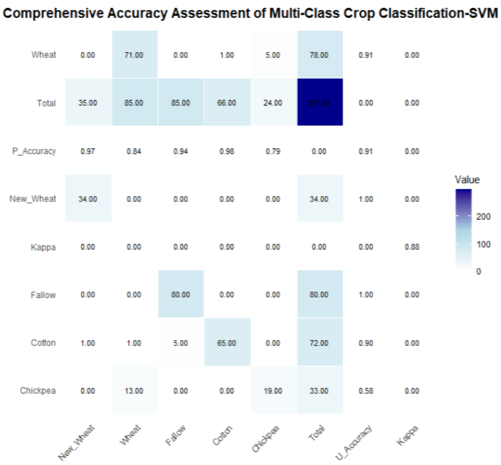

Figure 26. Accuracy Assessment for Elhoosh Office Crop Classification (SVM)

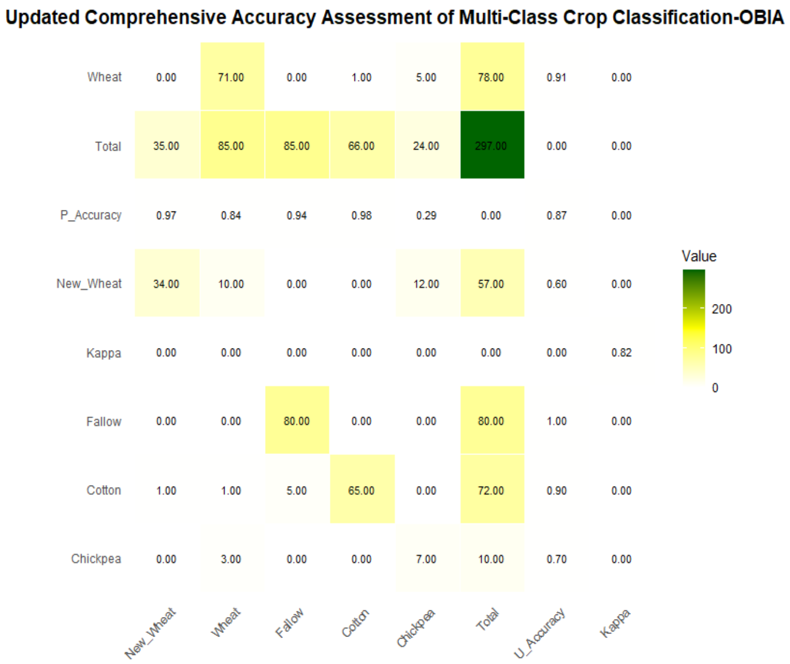

Figure 27.Accuracy Assessment for Elhoosh Office Crop Classification (OBIA)

3.3. Crop Classification Results for Wad Elbasir Office

The crop classification results for Wad Elbashir Office are presented through a series of Tables. Table 22 depicts the distribution of wheat cultivation in Wad Elbashir, while Table 22 compares the wheat classification errors between our analysis and the HRC team's findings. Table 23 focus on other crops, including gardens, chickpea, cotton, and miscellaneous cultivations, showing their distribution and classification errors respectively when compared to the HRC team's data. An overview of all cultivated lands in Wad Elbashir is provided in Table 24 presenting the overall errors in cultivated land classification compared to the HRC team's assessment. Finally, Figure 40 offers a comprehensive visual representation through maps depicting the spatial distribution of various crops across the Wad Elbasir Office area.

Table 21. Result of Wheat Crops in Wad Elbashir Office

Canal	Cultivated Lands-Wheat (Area / Hectares)		Errors Of Wheat Comparing HRC Team (%)
	HRC (Hectares)	RS (Hectares)	
Ganabiah_Kafe Canal	386	385	0%
Shakaira Canal	366	370	0%
Umtumoun Canal	221	231	5%

Table 22. Result of Gardens/Chickpea/Cotton/Crops in Wad Elbashir Office

Canal	Cultivated Lands-Gardens/Chickpea/Cotton/Other (Area / Hectares)		Errors of Gardens/Chickpea/Cotton/Other Comparing HRC Team (%)
	HRC (Hectares)	RS (Hectares)	
Ganabiah_Kafe Canal	439	446	1%
Shakaira Canal	489	444	-3%
Umtumoun Canal	148	153	7%

Table 23.Result of Wad Elbashir Cultivated Lands

Canal	Wad Elbashir Cultivated Lands (Area / Hectares)		Wad Elbashir Errors of Cultivated Lands Comparing HRC Team (%)
	HRC (Hectares)	RS (Hectares)	
Ganabiah_Kafe Canal	825	831	1%
Shakaira Canal	856	814	-2%
Umtumoun Canal	369	384	4%

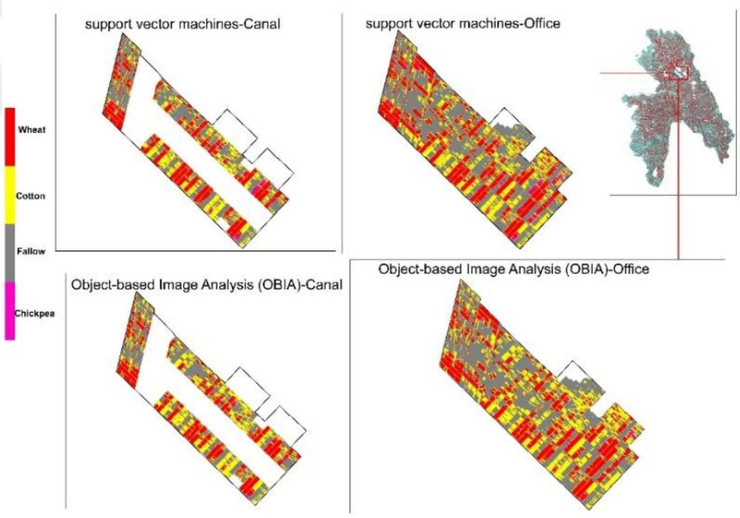

Figure 28. Maps of Spatial Distribution of Crops in Wad Elbasir Office

Demonstrates exceptional performance based on (243-point) confusion matrix, The accuracy assessment for the Wad Elbasir Office crop classification, as depicted in (Figure 29,30) The accuracy assessment of multi-class crop classification for the Elgabel Office demonstrates strong performance for both Support Vector Machine (SVM) and Object-Based Image Analysis (OBIA) methods, with some notable variations across crop types. Wheat classification shows higher user's accuracy for SVM (1.00) compared to OBIA (0.70), while OBIA has a slightly better producer's accuracy (0.81 vs 0.68). Both methods achieve perfect accuracy for new wheat and fallow land classification. Cotton classification yields identical results for both approaches, with a user's accuracy of 0.80 and a producer's accuracy of 0.91. Chickpea classification shows the same user's accuracy (0.72) for both methods, but SVM demonstrates a higher producer's accuracy (1.00 vs 0.46). Overall, SVM slightly outperforms OBIA in terms of overall accuracy (0.91 vs 0.86) and Kappa coefficient (0.88 vs 0.83), indicating marginally better general performance. These results suggest that while both methods are effective for crop type mapping in the Elgabel Office area, SVM may have a slight edge, particularly in wheat and chickpea classification. The choice between methods may depend on specific crop priorities and the desired balance between user's and producer's accuracies for different crop types.

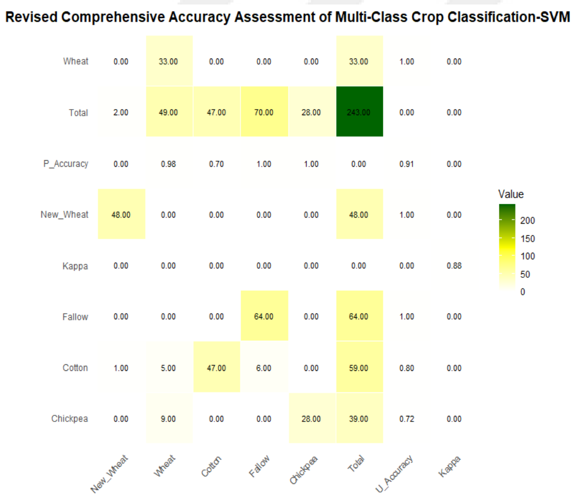

Figure 29. Accuracy Assessment for Wad Elbasir Office Crop Classification (SVM)

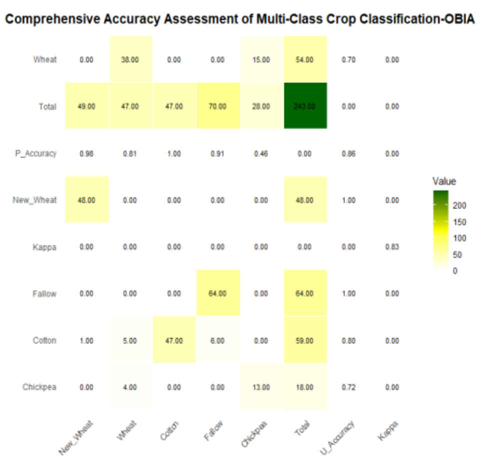

Figure 30.Accuracy Assessment for Wad Elbasir Office Crop Classification (OBIA)

3.4. Crop Classification Results for Gezira Scheme Divisions

Due to the extensive area of the Gezira scheme, the project was divided into four main divisions to facilitate the classification process, The results of the Support Vector Machine (SVM) and Object-Based Image Analysis (OBIA) classifications, along with their averages, are as follows:

Table 24. Crop Classification Results in Four Main Divisions of Scheme

Crops Area for Divisions Parts	**SVM (Hectares)**	**OBIA (Hectares)**
West of Managil		
Wheat	74282.58012	164323.200
Gardens/Chickpea/Cotton/Other	59740.56984	48631.09
East Of Managil		
Wheat	59217.31998	54947.662
Gardens/Chickpea/Cotton/Other	51525.48996	33588.077
South of Gezira		
Wheat	31730.07012	29675.121
Gardens/Chickpea/Cotton/Other	31107.60233	23795.572
North of Gezira		
Wheat	61850.05008	63331.391
Gardens/Chickpea/Cotton/Other	109171.75	91004.149
Total (SVM_Area)		
Wheat	227080.0203	
Gardens/Chickpea/Cotton/Other	251545.4121	

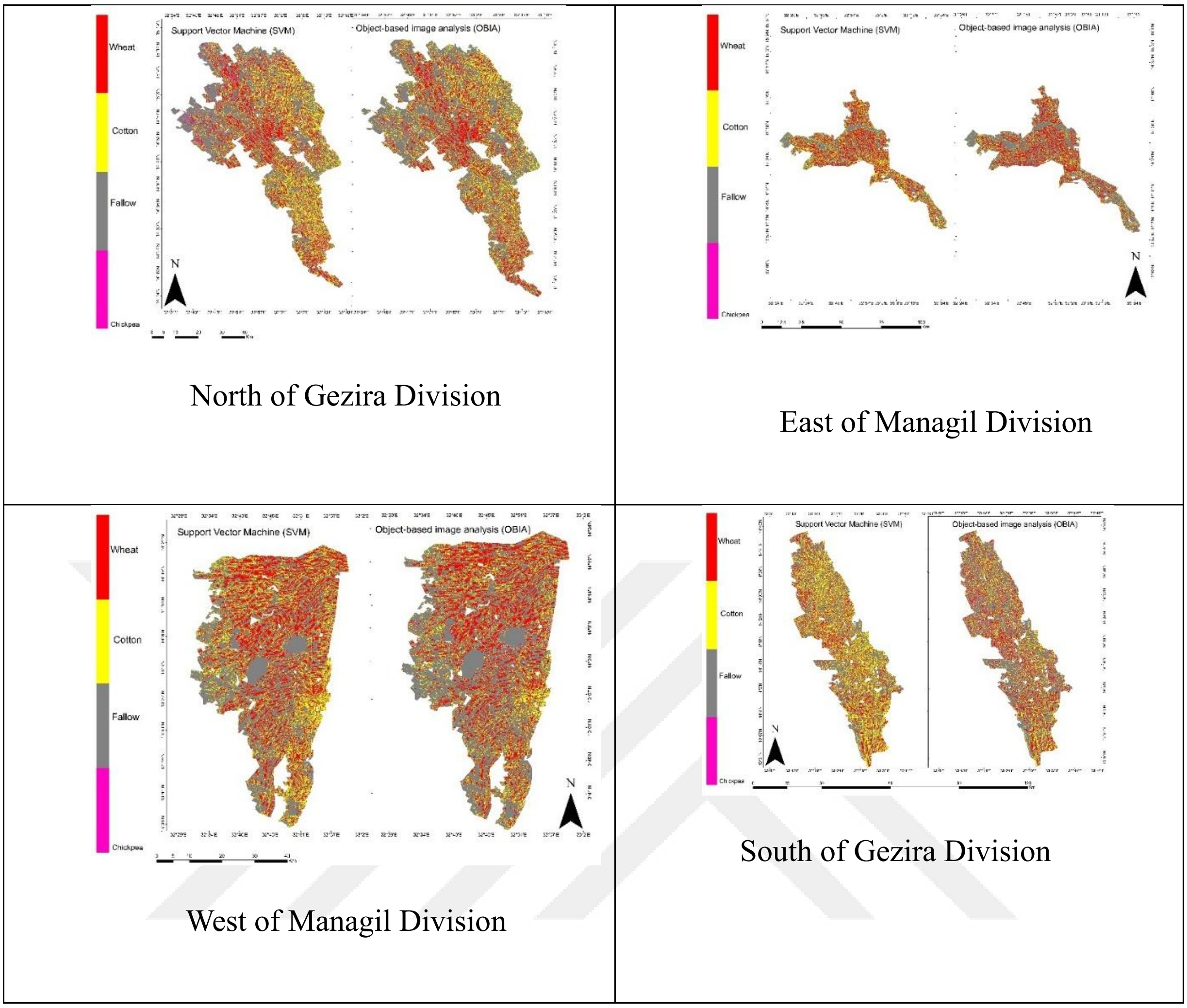

Figure 31. Maps of Spatial Distribution of Crops in Four Main Divisions of Scheme

The accuracy assessment for crop classification across the four main divisions of the Gezira Scheme, as illustrated in (Figures 32,33,34,35,36,37,38,39) demonstrates consistently high performance, West of Managil based on (385 points), East of Managil using (334 points). North of Gezira based on (278 points). South Gezira used (250 points), After analyzing the performance of Object-Based Image Analysis (OBIA) and Support Vector Machine (SVM) methods across four distinct areas of the Gezira scheme - West of Managil, East of Managil, South of Gezira, and North of Gezira - the Support Vector Machine (SVM) method emerges as the superior choice for crop classification. SVM consistently demonstrates higher overall accuracy and Kappa coefficients, indicating better reliability and agreement across all regions. It particularly excels in wheat classification, a likely significant crop in the area, and shows more consistent performance across various crop types. While both methods exhibit strong accuracy in new wheat and fallow land classification, SVM often maintains a slight advantage. For cotton and chickpea, SVM frequently outperforms OBIA in at least one accuracy measure. Although the performance differences between SVM and OBIA are sometimes minimal, SVM's consistent edge across all four areas of the Gezira scheme makes it the preferred method for crop classification in this region. However, it's important to note that both methods demonstrate high accuracy, and the final selection could be influenced by specific priorities for different crop types or areas within the scheme. Overall, SVM's superior performance and consistency make it the recommended method for comprehensive crop classification in the Gezira scheme.

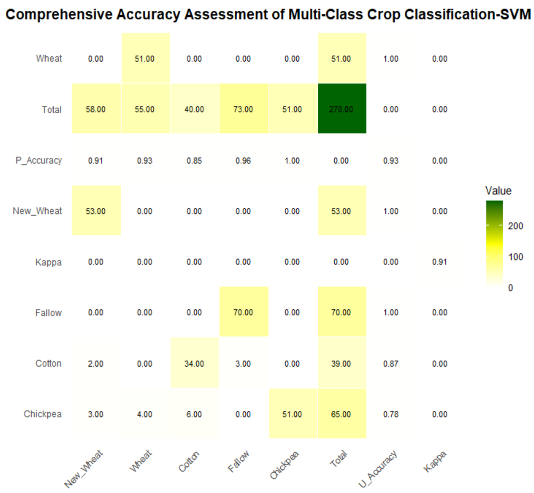

Figure 32.Accuracy Assessment for North of Gezira Division Crop Classification (SVM)

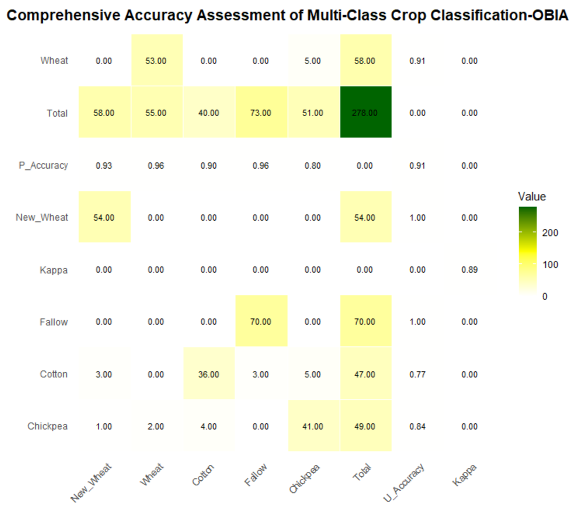

Figure 33.Accuracy Assessment for North of Gezira Division Crop Classification (OBIA)

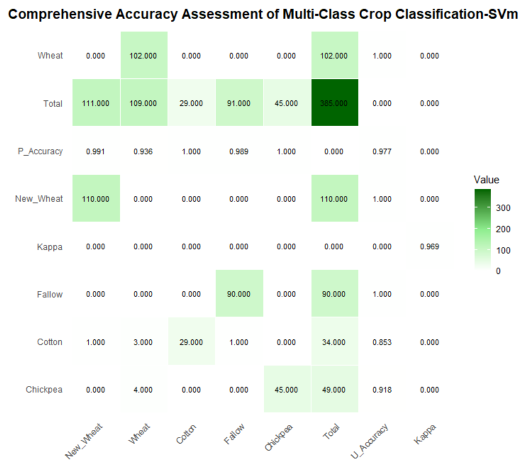

Figure 34.Accuracy Assessment for Weast of Managil Division Crop Classification (SVM)

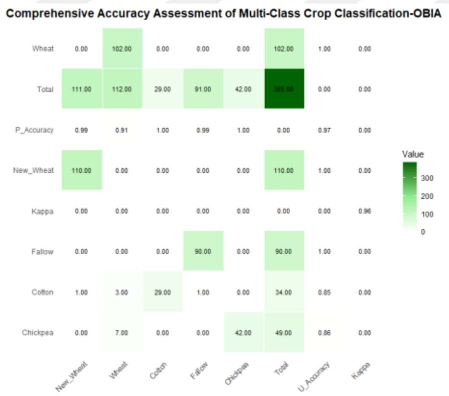

Figure 35.Accuracy Assessment for Weast of Managil Division Crop Classification (OBIA)

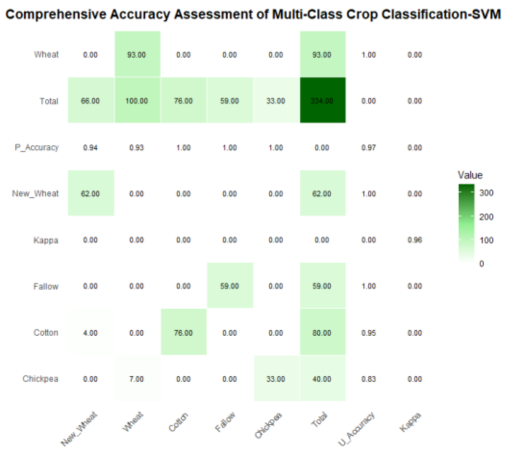

Figure 36.Accuracy Assessment for East of Managil Division Crop Classification (SVM)

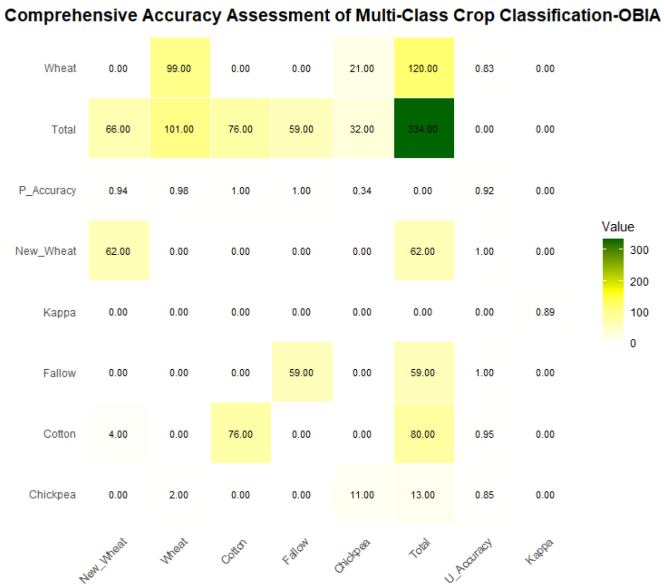

Figure 37.Accuracy Assessment for East of Managil Division Crop Classification (OBIA)

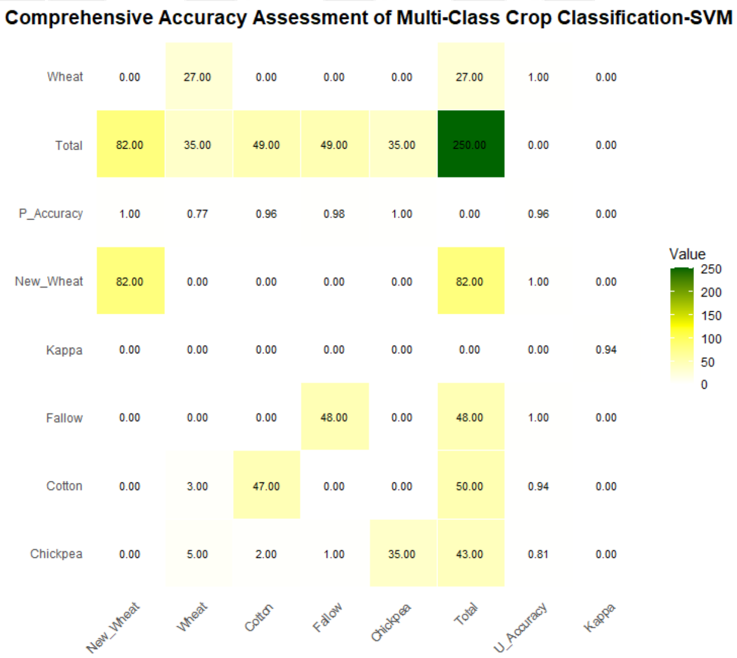

Figure 38.Accuracy Assessment for South of Gezira Division Crop Classification (SVM)

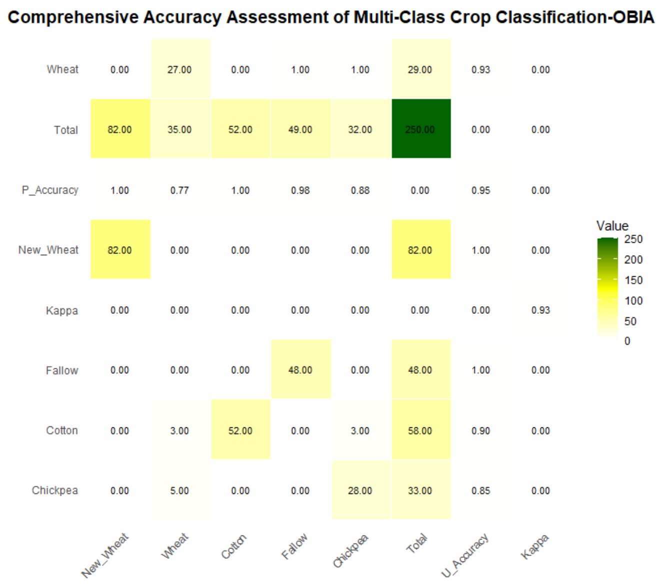

Figure 39.Accuracy Assessment for South of Gezira Division Crop Classification (OBIA)

3.5. Comprehensive Crop Area Estimation for The Gezira Scheme

This table presents a comprehensive crop area estimation for the Gezira Scheme, comparing official records with remote sensing (RS) estimates. It provides area measurements for wheat and other crops (including gardens, chickpea, cotton, and others) in hectares. The data includes error ranges calculated at both canal and block levels, offering insights into the accuracy of the remote sensing methodology compared to official figures.

Table 25. Crop Area Estimation for the Gezira Scheme

Crop Category	Office Gezira (Hectares)	RS Estimate (Hectares)	Error Range (Canal)-(from-to)	Error Range (Block)- (from-to)	Error from Canals	Error From Blocks
Wheat	208,108.8	227,080.0203	215,930.5 - 228,025.8	217,719.6 - 226,525.1	3%	2%
Gardens/Chick-pea/Cotton/Other	250,000.9	251,545.4121	253,618.8 - 270,469.4	253,618.8 - 270,469.4	3%	3%
Total Cultivated Lands	**458,062.5**	**484,304.2**	**472,066.7-496,176.8**	**475,423.2-493,011.1**	**3%**	**2%**

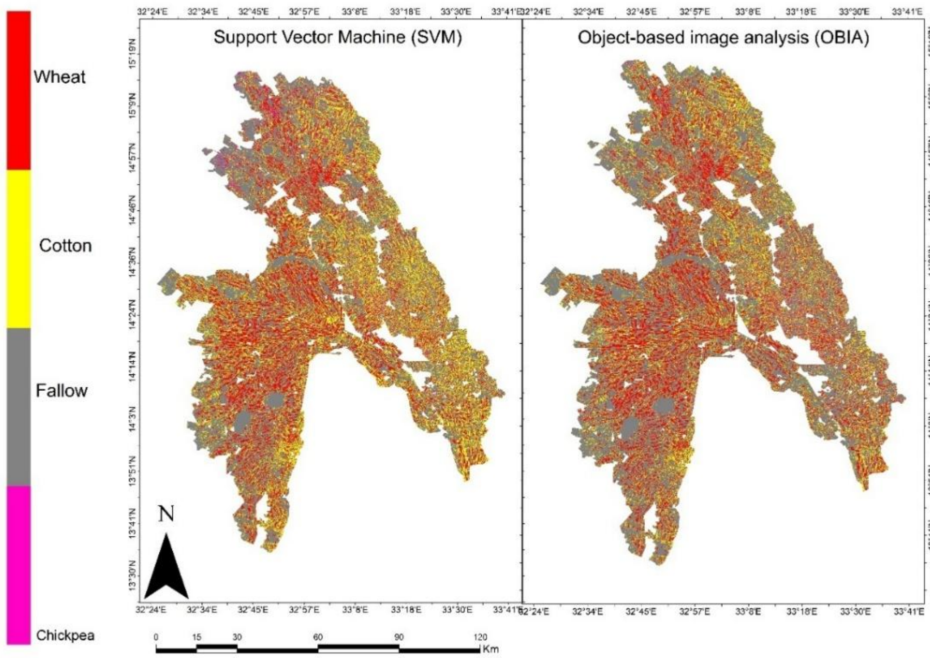

Figure 40.Comparative Thematic Maps of Crop Classification in the Gezira Scheme Using (SVM) and (OBIA) Techniques

3.6. Water Management Indicators

3.6.1. Analysis of Actual Evapotranspiration (AETI) Distribution

The analysis of actual evapotranspiration (AETI) for wheat across the Gezira Scheme divisions during the 2019-2020 growing season revealed significant spatial variability. As depicted in Figure 41, AETI rates exhibited a wide range, from a minimum of 743 mm/season in AbdelMagid Division to a maximum of 1023 mm/season in Alhaj Abdallah. Notably high AETI values were observed in Alhaj Abdallah (1023 mm/season), Albasatna (1011 mm/season), and Northwest Sennar (986 mm/season), indicating areas of potentially higher water consumption or more intensive crop growth. In contrast, divisions such as AbdelMagid (743 mm/season) and Gaboga (787 mm/season) displayed markedly lower AETI rates, suggesting possible differences in irrigation practices, soil characteristics, or local microclimates.

The spatial distribution of AETI, illustrated in Figure 43, further elucidates this variability across the entire Gezira Scheme. The map reveals a pattern of higher evapotranspiration rates concentrated in the central and eastern regions of the scheme, corresponding to the peak values observed in the divisional analysis. This spatial heterogeneity in AETI rates has important implications for water resource management and irrigation scheduling within the scheme.

To provide a more detailed perspective, Figure 42 presents a quantitative analysis of AETI patterns at the small-scale Hawasha level. This granular view allows for the identification of localized variations in evapotranspiration, which may be attributed to factors such as soil type, topography, or specific farm management practices.

The comprehensive analysis of AETI distribution across multiple scales - from individual Hawash to scheme-wide divisions - offers valuable insights for optimizing water use efficiency and crop productivity in the Gezira Scheme. These findings can inform targeted interventions and precision agriculture techniques to address areas of high-water consumption and improve overall scheme management.

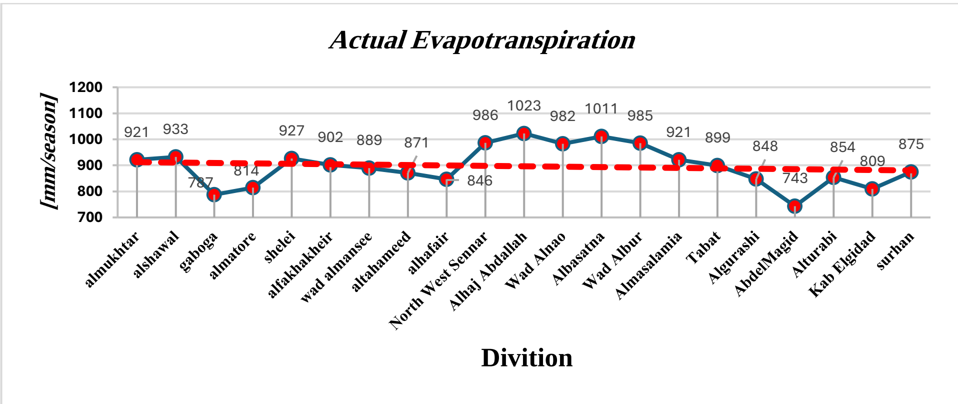

Figure 41.Divisional Variations in Wheat Evapotranspiration Across the Gezira Scheme

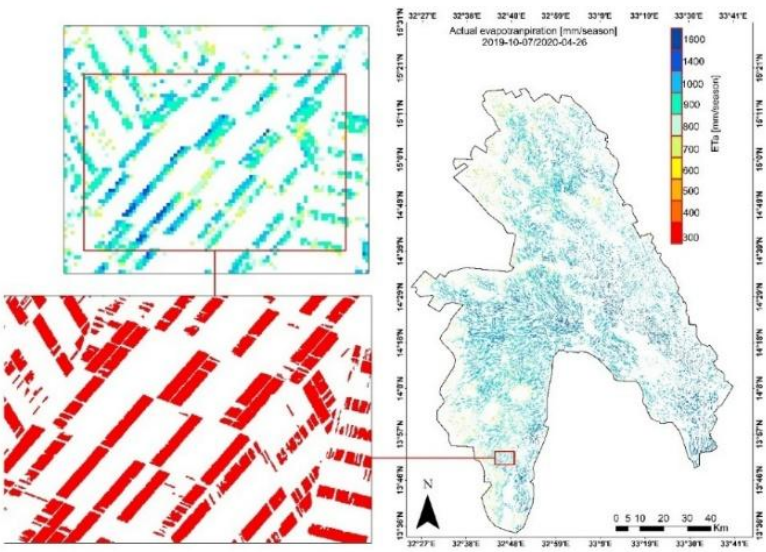

Figure 42.Quantitative Analysis of Wheat Crop Evapotranspiration Patterns Across Small Part (Hawasha)

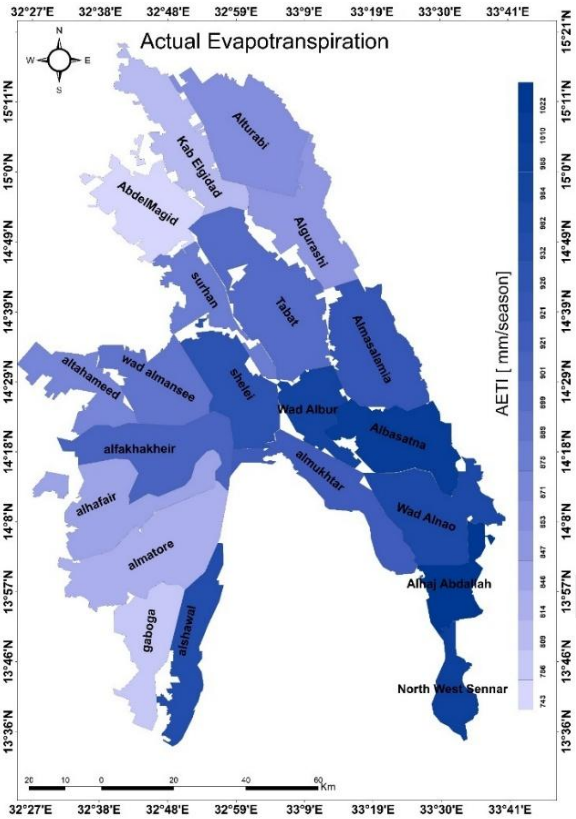

Figure 43. Quantitative Analysis of Wheat Crop Evapotranspiration Patterns Across Gezira Scheme Divisions

3.6.2. Reference - Evapotranspiration (RET)

The analysis of Reference Evapotranspiration (RET) across the Gezira Scheme revealed significant spatial variability and a general increasing trend. As illustrated in Figure 45, the mean RET values fluctuated between approximately 1834 mm/season and 1920 mm/season across the various divisions.

Peak RET values were observed in AbdelMagid Division (approximately 1920 mm/season), followed closely by Altahameed and Kab Elgidad (both exceeding 1905 mm/season). In contrast, the lowest RET values were recorded in divisions such as Almatore with values around 1835 mm/season. Figure 46 provides a comprehensive spatial representation of RET patterns across the entire Gezira Scheme, further elucidating the geographical distribution of evaporative demand. This map highlights zones of high and low RET, offering valuable insights for regional water management strategies. Figure 44 presents a quantitative analysis of RET patterns at the small-scale Hawasha level.

This multi-scale analysis of RET distribution, from individual Hawash as to scheme-wide divisions, provides a comprehensive foundation for optimizing irrigation scheduling and improving water use efficiency across the Gezira Scheme. The findings can inform targeted interventions and adaptation strategies to address the varying evaporative demands across different spatial scales, ultimately contributing to more sustainable and efficient agricultural practices in the region.

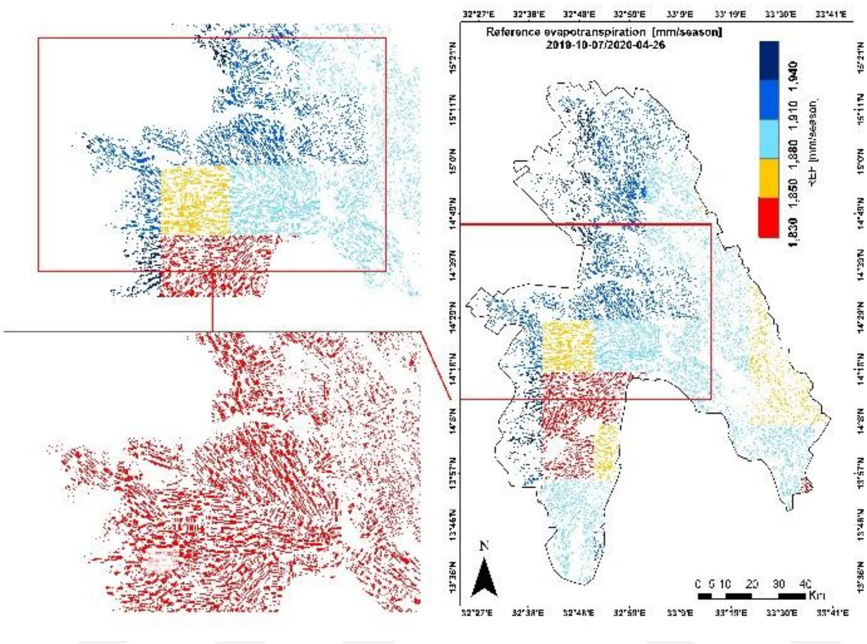

Figure 44. Quantitative Analysis of Wheat Crop RET Patterns Across Small Part (Hawasha).

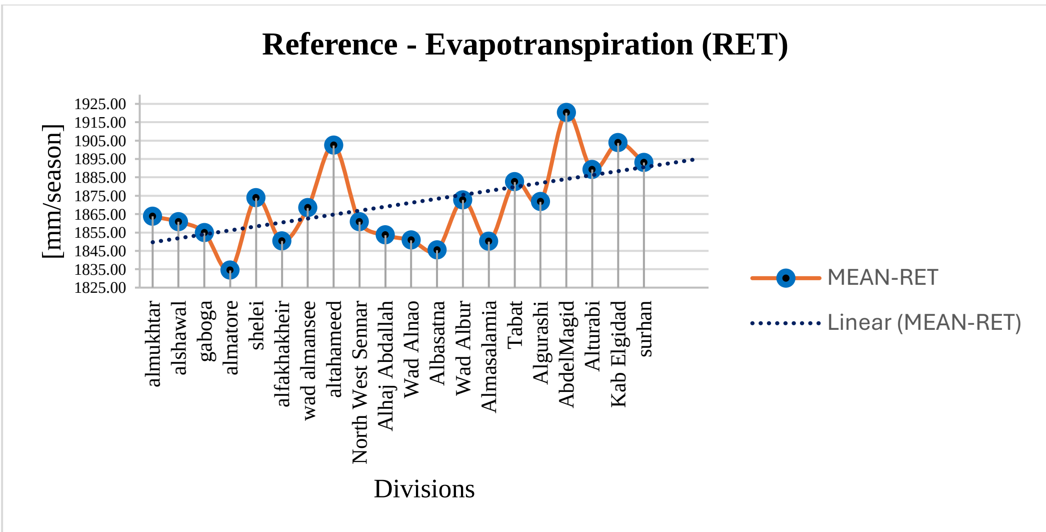

Figure 45. Divisional Variations in Wheat RET Across the Gezira Scheme

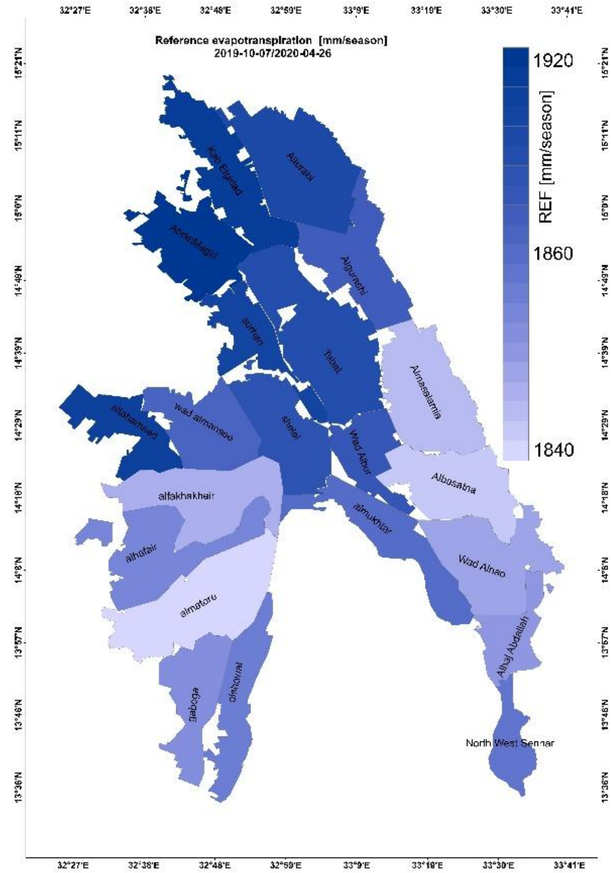

Figure 46. Quantitative Analysis of Wheat Crop RET Patterns Across Gezira Scheme Divisions

3.6.3. Beneficial Fraction

The analysis of the Beneficial Fraction (BF) across the Gezira Scheme divisions revealed subtle variations and a relatively stable trend. As depicted in Figure 47, the mean BF values ranged from approximately 0.80 to 0.83 across the various divisions, the highest BF value was observed in Alshawal Division, reaching nearly 0.83, followed closely by Gaboga and Almatore Divisions, both exceeding 0.81. Conversely, the lowest BF values were recorded in divisions such as Almukhtarand and Almatore Divisions, with values around 0.80.

Figure 49 provides a comprehensive spatial representation of BF patterns across the entire Gezira Scheme, further elucidating the geographical distribution of water use efficiency. This map highlights zones of higher and lower BF, offering valuable insights for targeted irrigation management strategies, to provide a more detailed perspective, Figure 48 presents a quantitative analysis of BF patterns at the Hawasha level.

The observed spatial patterns in BF values, although subtle, have important implications for irrigation management and water resource optimization within the Gezira Scheme. Divisions and areas with lower BF values may benefit from interventions to improve water use efficiency, while those with higher BF values could serve as models for best practices.

This multi-scale analysis of BF distribution, from individual Hawash as to scheme-wide divisions, provides a nuanced understanding of water use efficiency across the Gezira Scheme. The findings can inform targeted interventions and precision agriculture techniques to address areas of lower efficiency and replicate successful practices from high-performing regions. Ultimately, this analysis contributes to the development of more sustainable and water-efficient agricultural practices in the Gezira Scheme, balancing crop productivity with conservation of water resources.

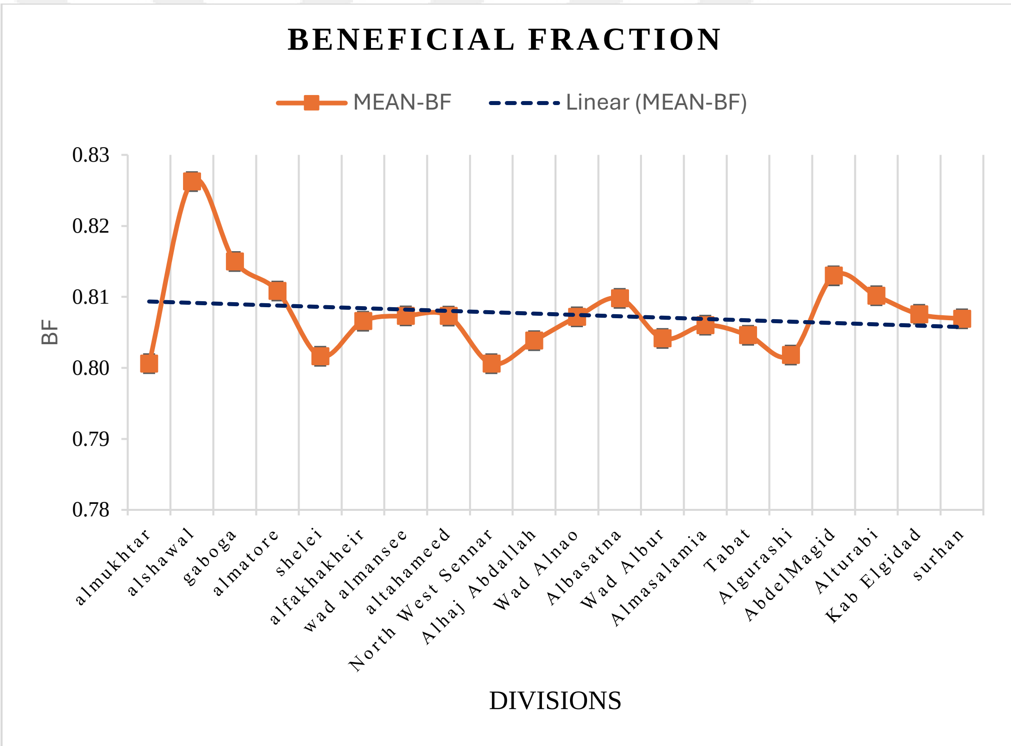

Figure 47. Divisional Variations in Wheat BF Across the Gezira Scheme

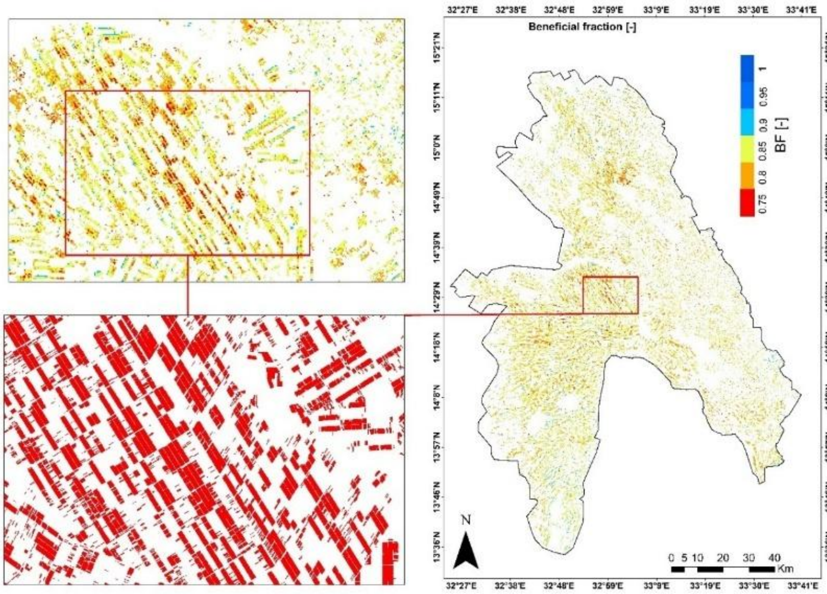

Figure 48. Quantitative Analysis of Wheat Crop BF Patterns Across Small Part (Ha-washa).

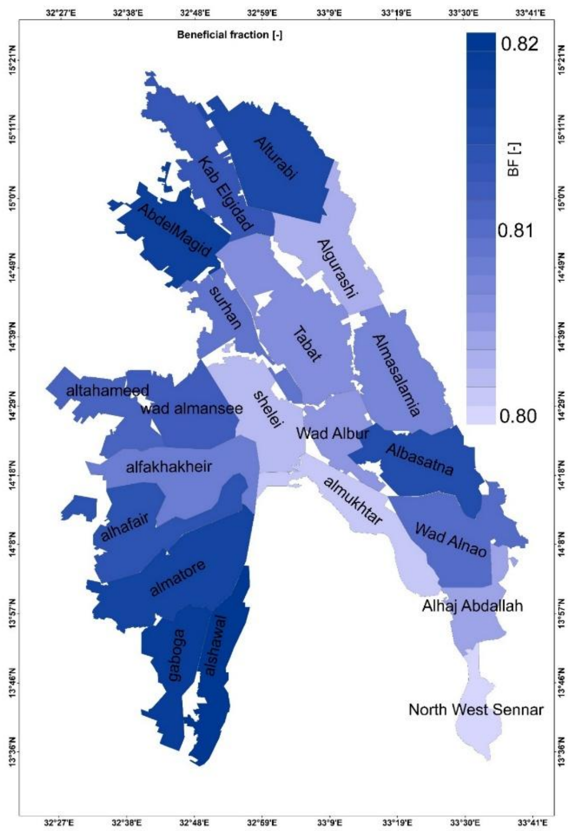

Figure 49. Quantitative Analysis of Wheat Crop BF Patterns Across Gezira Scheme Divisions

3.7 Productivity Indicators

3.7.1.Net Primary Production (NPP)

The analysis of Net Primary Production (NPP) across the Gezira Scheme divisions revealed significant spatial variability, indicating diverse levels of crop productivity. As illustrated in Figure 50, the mean NPP values fluctuated substantially, ranging from approximately 297 gC/m2/season to 377 gC/m2/season across the various divisions.

Peak NPP values were observed in Alfakhakheir and Shelei, both reaching nearly 377 gC/m2/season, indicating areas of high wheat productivity. Conversely, the lowest NPP values were recorded in divisions such as AbdelMagidand Northwest Sennar, with values around 297 gC/m2/season.

Figure 52 provides a comprehensive spatial representation of NPP patterns across the entire Gezira Scheme, further elucidating the geographical distribution of wheat productivity. This map highlights zones of high and low NPP, offering valuable insights for identifying areas of optimal and suboptimal crop performance, to provide a more granular perspective, Figure 51 presents a quantitative analysis of NPP patterns at the Hawasha level.

The observed spatial heterogeneity in NPP values has significant implications for agricultural management and resource allocation within the Gezira Scheme. Divisions and areas with higher NPP values may serve as models for best practices, while those with lower NPP values might benefit from targeted interventions to improve crop productivity.

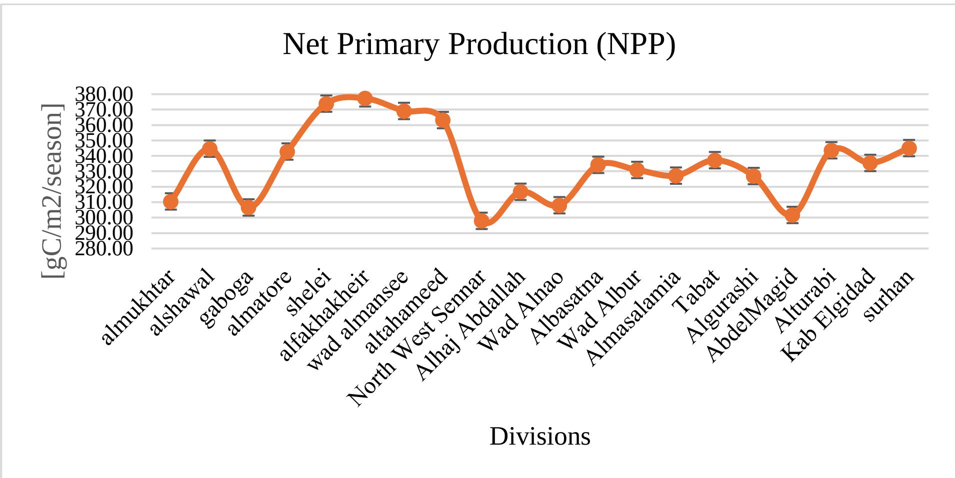

Figure 50. Divisional Variations in Wheat NPP Across the Gezira Scheme

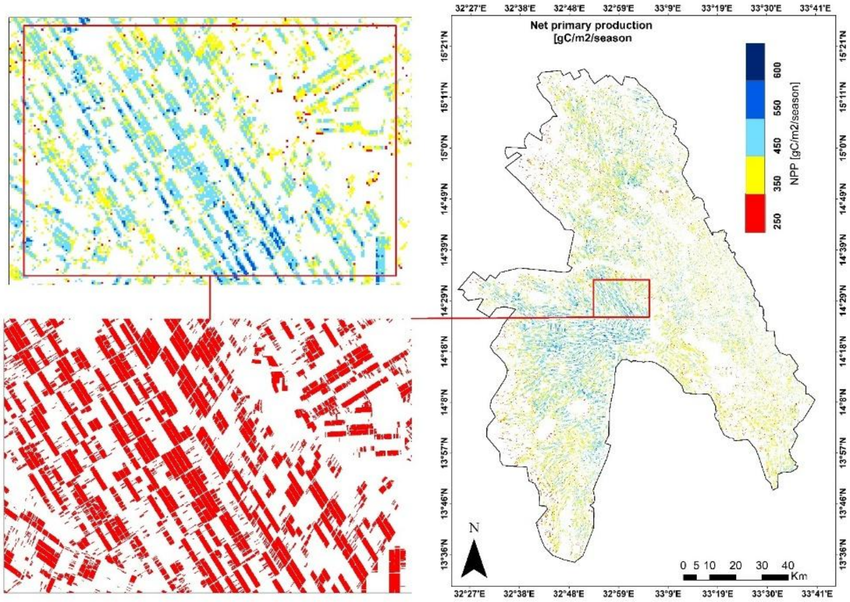

Figure 51. Quantitative Analysis of Wheat Crop NPP Patterns Across Small Part (Hawasha).

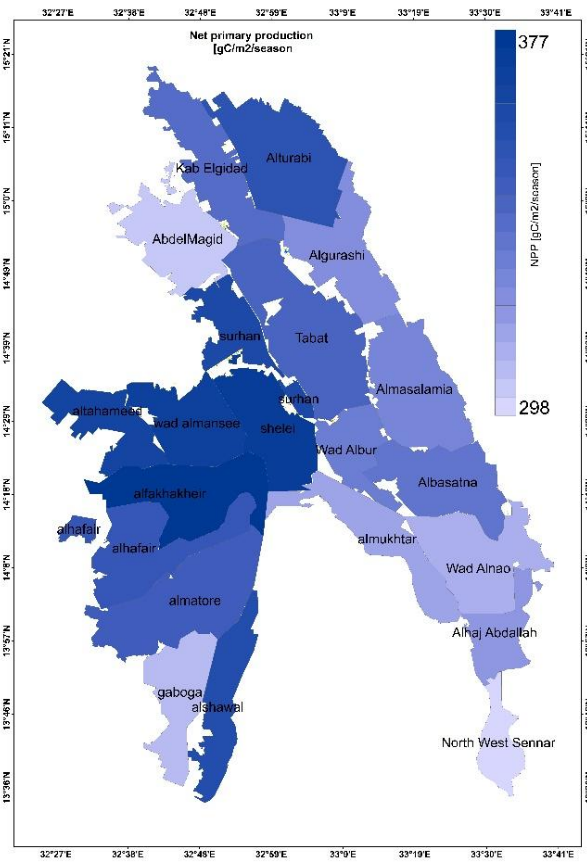

Figure 52. Quantitative Analysis of Wheat Crop NPP Patterns Across Gezira Scheme Divisions

3.7.2. Above Ground Biomass (AGB)

The analysis of Above Ground Biomass (AGB) across the Gezira Scheme divisions revealed notable spatial variability, indicating diverse levels of wheat biomass production. As illustrated in Figure 53, the mean AGB values fluctuated considerably, ranging from approximately 6.5 ton/ha/season to 8.5 ton/ha/season across the various divisions.

Peak AGB values were observed in Alfakhakheirand, Shelei and Wad Almansee Divisions reaching nearly 8.5 ton/ha/season, indicating areas of high wheat biomass accumulation. Conversely, the lowest AGB values were recorded in divisions such as Northwest Sennar and AbdelMagid Divisions, with values around 6.5 ton/ha/season. The graph demonstrates a non-uniform pattern across divisions, suggesting complex interactions of factors influencing biomass production.

Figure 55 provides a comprehensive spatial representation of AGB patterns across the entire Gezira Scheme, further elucidating the geographical distribution of wheat biomass production. This map highlights zones of high and low AGB, offering valuable insights for identifying areas of optimal and suboptimal crop performance in terms of vegetative growth, to provide a more granular perspective, Figure 54 presents a quantitative analysis of AGB patterns at the Hawasha level.

The observed spatial heterogeneity in AGB values has significant implications for agricultural management and resource allocation within the Gezira Scheme. Divisions and areas with higher AGB values may serve as models for best practices in crop management and biomass production, while those with lower AGB values might benefit from targeted interventions to improve overall crop vigor and productivity.

This multi-scale analysis of AGB distribution, from individual Hawash as to scheme-wide divisions, provides a comprehensive foundation for optimizing agricultural practices and improving overall wheat biomass production across the Gezira Scheme. The findings can inform precision agriculture techniques, guide the implementation of site-specific management strategies, and support decision-making processes for resource allocation to enhance vegetative growth.

Furthermore, the variability in AGB across divisions underscores the importance of adaptive management approaches that consider local conditions and constraints. By leveraging these insights, stakeholders can develop tailored strategies to enhance wheat biomass production, which is crucial for improving overall yield potential, ensuring food security, and promoting sustainable agricultural practices throughout the Gezira Scheme.

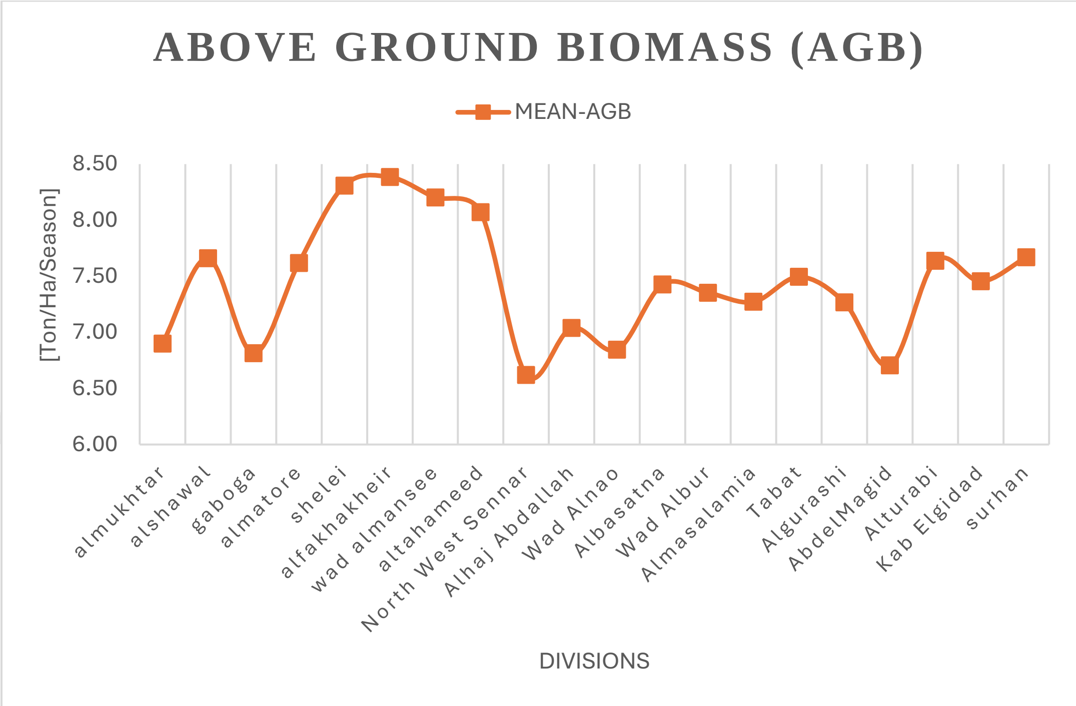

Figure 53. Divisional Variations in Wheat AGB Across the Gezira Scheme

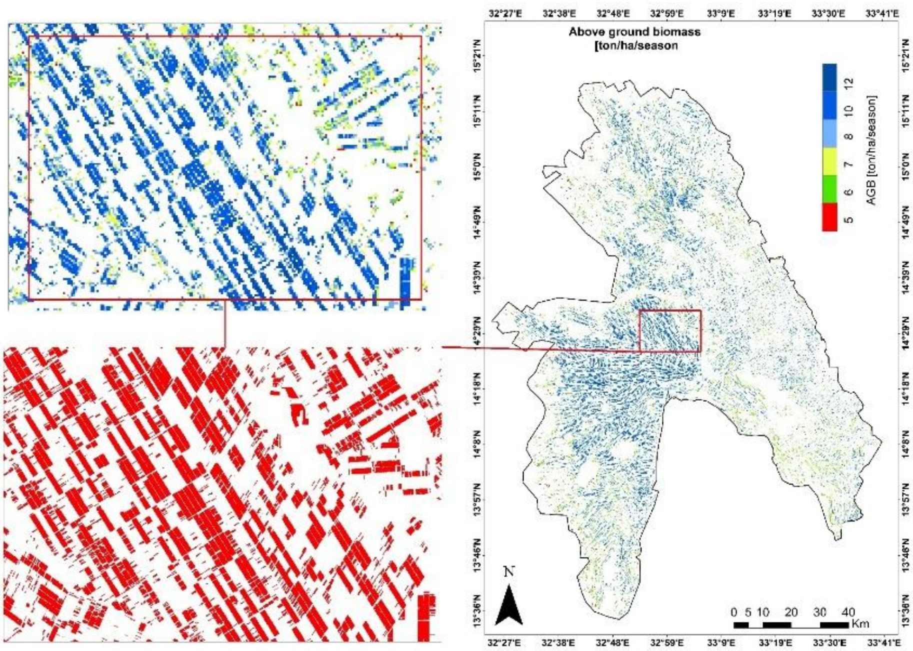

Figure 54. Quantitative Analysis of Wheat Crop AGB Patterns Across Small Part (Hawasha).

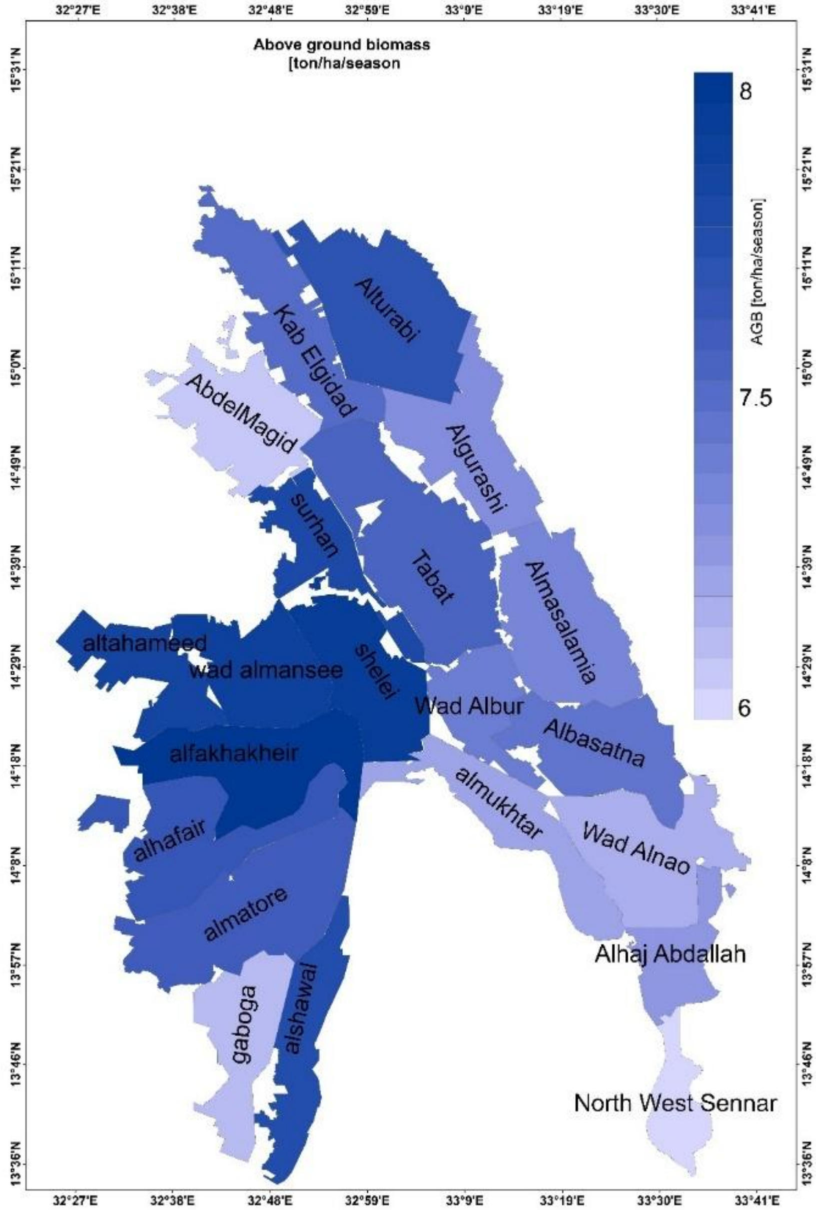

Figure 55. Quantitative Analysis of Wheat Crop AGB Patterns Across Gezira Scheme Divisions

3.7.3. Crop Yield

The analysis of wheat crop yield across the Gezira Scheme divisions revealed significant spatial variability, indicating diverse levels of productivity. As illustrated in Figure 56, the mean crop yield values fluctuated considerably, ranging from approximately 3.18 ton/ha/season to 4.02 ton/ha/season across the various divisions.

Peak crop yield values were observed in Alfakhakheir and Shelei divisions, both reaching nearly 4.02 ton/ha/season, indicating areas of high wheat productivity. Conversely, the lowest crop yield values were recorded in divisions such as Northwest Sennar and Wad Alnao, with values around 3.18 ton/ha/season.

Figure 58 provides a comprehensive spatial representation of crop yield patterns across the entire Gezira Scheme, further elucidating the geographical distribution of wheat productivity. This map highlights zones of high and low crop yield, offering valuable insights for identifying areas of optimal and suboptimal crop performance, to provide a more granular perspective, Figure 57 presents a quantitative analysis of crop yield patterns at the Hawasha level.

The observed spatial heterogeneity in crop yield values has significant implications for agricultural management and resource allocation within the Gezira Scheme. Divisions and areas with higher crop yield values may serve as models for best practices in wheat cultivation, while those with lower crop yield values might benefit from targeted interventions to improve overall productivity.

Furthermore, the variability in crop yield across divisions underscores the importance of adaptive management approaches that consider local conditions and constraints. By leveraging these insights, stakeholders can develop tailored strategies to enhance wheat productivity, which is crucial for improving food security, farmer livelihoods, and promoting sustainable agricultural practices throughout the Gezira Scheme. The identification of high-yielding areas can also provide valuable information for breeding programs and the development of location-specific wheat varieties adapted to the diverse conditions within the scheme.

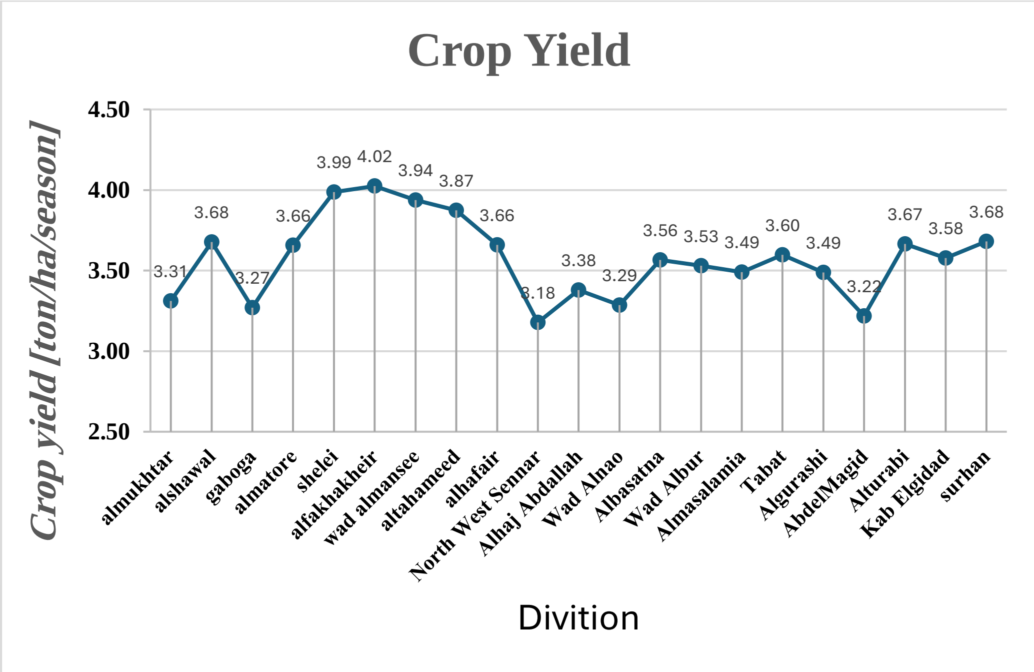

Figure 56. Divisional Variations in Wheat Crop Yield Across the Gezira Scheme

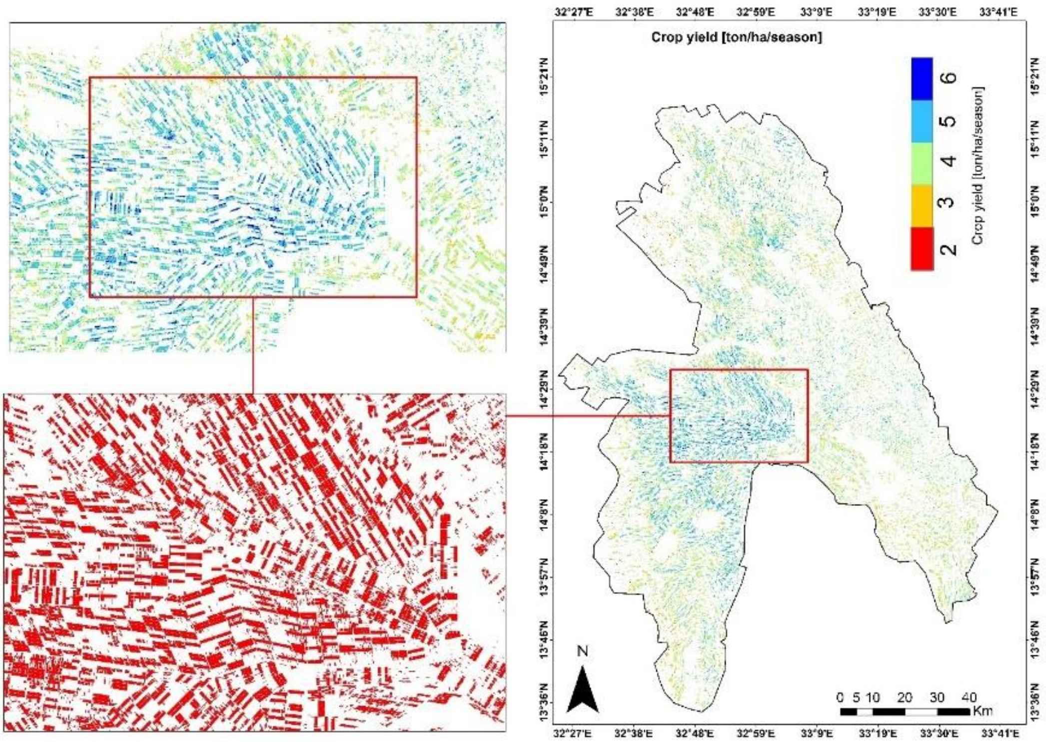

Figure 57. Quantitative Analysis of Wheat Crop Yield Patterns Across Small Part (Hawasha).

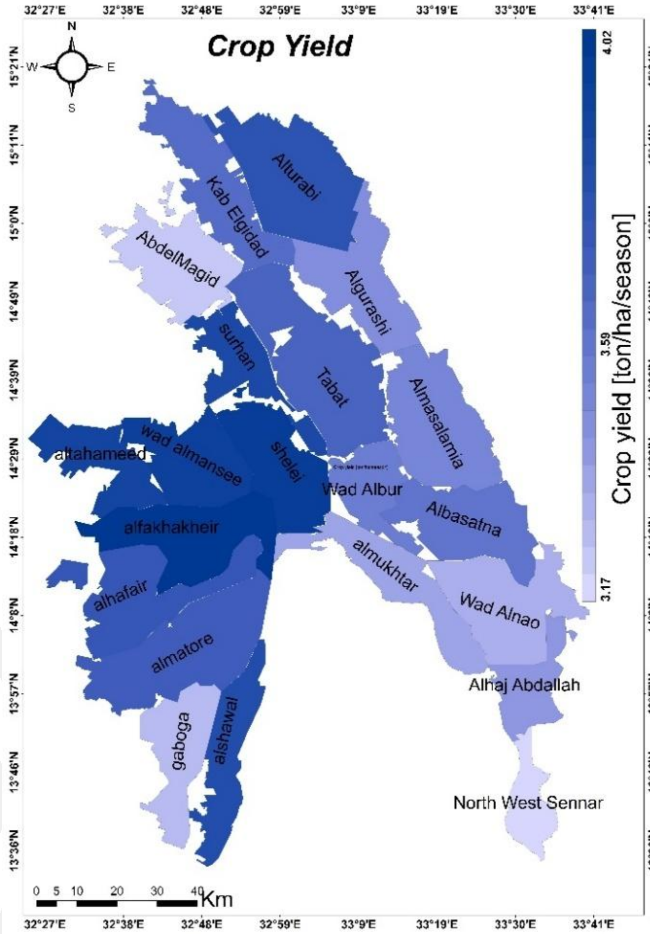

Figure 58. Quantitative Analysis of Wheat Crop Yield Patterns Across Gezira Scheme Divisions

3.7.4. Crop Water Productivity

The analysis of Crop Water Productivity (WPy) for wheat across the Gezira Scheme divisions revealed notable spatial variability, indicating diverse levels of water use efficiency in crop production. As illustrated in Figure 59, the mean WPy values fluctuated significantly, ranging from approximately 0.32 kg/m³ to 0.45 kg/m³ across the various irrigation divisions.

Peak WPy values were observed in Shelei, Alfakhakheir, and wad Almansee reaching nearly 0.45 kg/m³, indicating areas of high water use efficiency in wheat production. Conversely, the lowest WPy values were recorded in divisions such as Northwest Sennar and Alhaj Abdallah, with values around 0.32 kg/m³. The graph demonstrates a non-uniform pattern across divisions, suggesting complex interactions of factors influencing water productivity in wheat cultivation.

Figure 61 provides a comprehensive spatial representation of WPy patterns across the entire Gezira Scheme, further elucidating the geographical distribution of water use efficiency in wheat production. This map highlights zones of high and low WPy, offering valuable insights for identifying areas of optimal and suboptimal water management practices, to provide a more granular perspective, Figure 60 presents a quantitative analysis of WPy patterns at the Hawasha level.

This multi-scale analysis of WPy distribution, from individual Hawash as to scheme-wide divisions, provides a comprehensive foundation for optimizing irrigation practices and improving overall water productivity in wheat cultivation across the Gezira Scheme. The findings can inform precision irrigation techniques, guide the implementation of water-saving strategies, and support decision-making processes for water resource allocation to enhance both yield and water use efficiency.

Furthermore, the variability in WPy across divisions underscores the importance of adaptive water management approaches that consider local conditions and constraints. By leveraging these insights, stakeholders can develop tailored strategies to enhance water productivity in wheat cultivation, which is crucial for improving food security, conserving water resources, and promoting sustainable agricultural practices throughout the Gezira Scheme. The identification of high WPy areas can also provide valuable information for developing and implementing water-efficient cultivation techniques and technologies suited to the diverse conditions within the scheme.

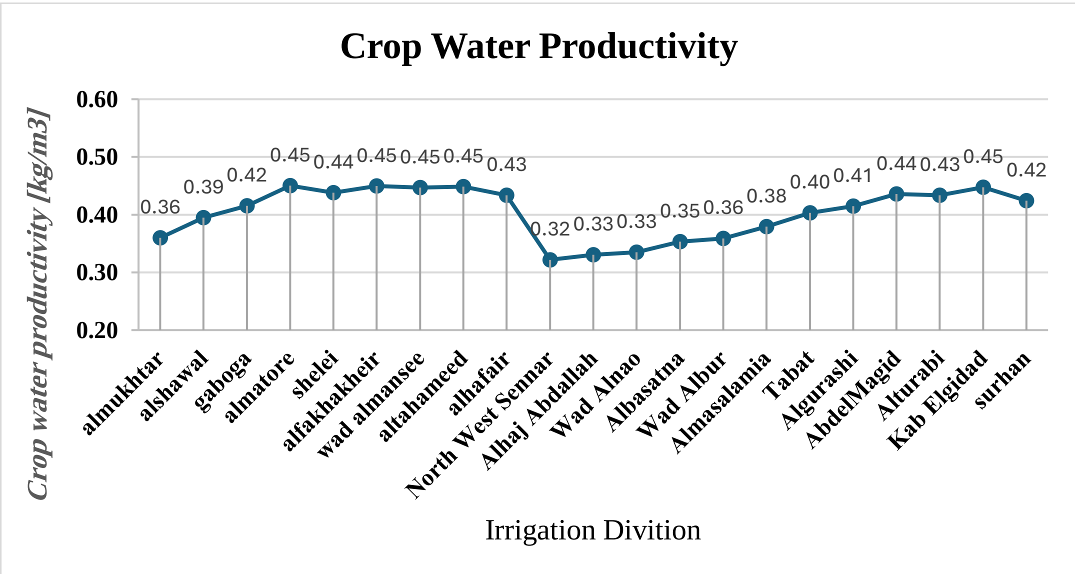

Figure 59. Divisional Variations in Wheat WPy Across the Gezira Scheme

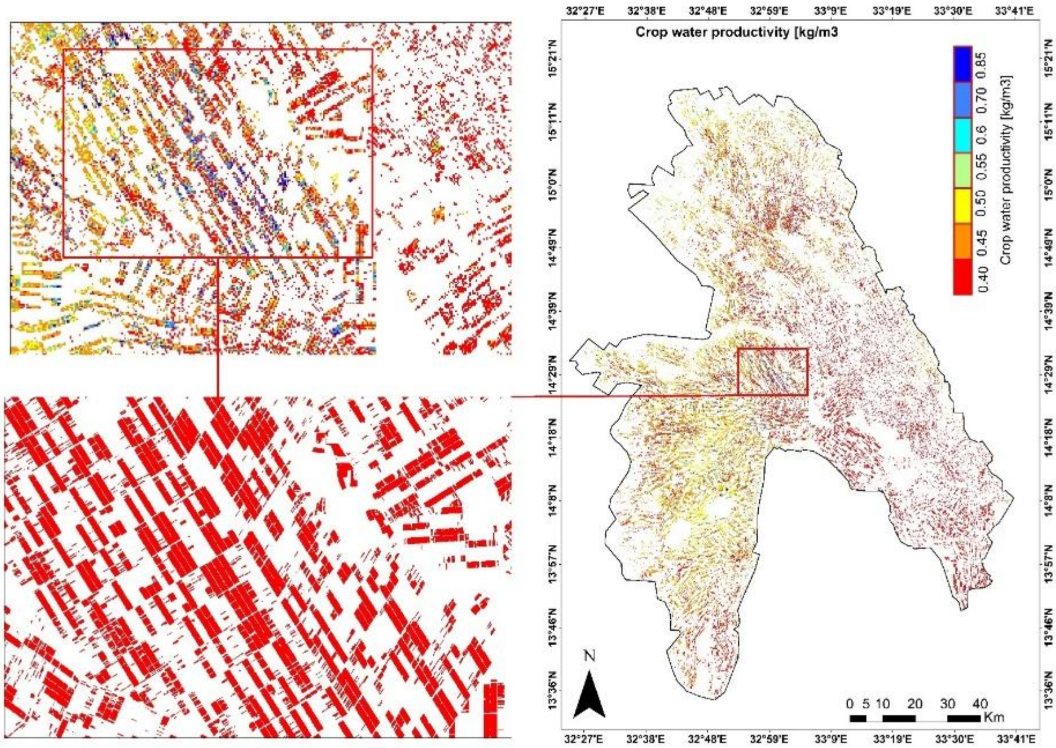

Figure 60. Quantitative Analysis of Wheat WPy Patterns Across Small Part (Ha-washa).

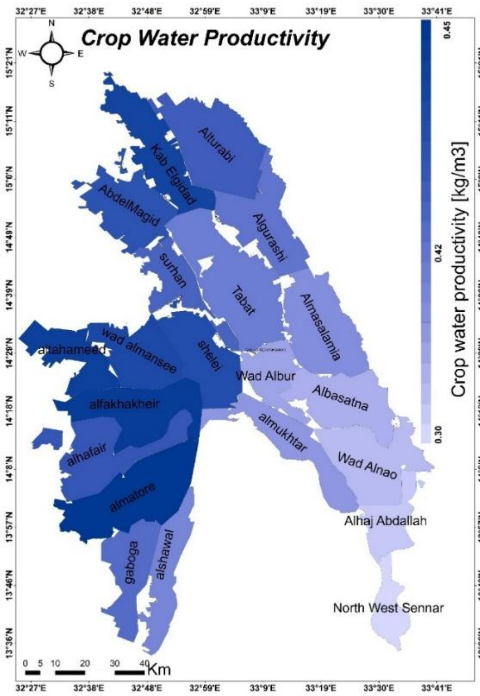

Figure 61. Quantitative Analysis of Wheat WPy Patterns Across Gezira Scheme Di-visions

3.7.5. Crop Yield and WPy Analysis for Wheat in the Gezira Scheme

The integrated analysis of crop yield and water productivity (WPy) for wheat in the Gezira Scheme during the 2019-2020 season reveals a complex interplay between productivity and water use efficiency. This comprehensive assessment provides crucial insights into the scheme's performance and highlights areas for potential improvement.

The study targeted a yield of 4.7 t/ha and a water productivity of 0.58 kg/m³, as outlined in Tables 27. However, actual performance consistently fell short of these targets across all irrigation divisions, indicating systemic challenges within the scheme. The relationship between yield and WPy, visualized in Figure 62, demonstrates a positive correlation, suggesting that improvements in one metric could potentially lead to enhancements in the other.

Spatial variability is a key feature of the scheme's performance. Figure 64 illustrates the range of WPy values across different irrigation divisions, spanning from 0.32 to 0.45 kg/m³. High-performing divisions such as Alfakhakheir, Shelei, and Almatore achieved WPy values around 0.45 kg/m³, while divisions like Northwest Sennar and Alhaj Abdallah lagged behind with values around 0.32-0.33 kg/m³, Figure 63. Similarly, yield variations were observed, with top-performing divisions reaching approximately 4.0 t/ha, still below the target of 4.7 t/ha.

The mean WPy of 0.41 kg/m³ and the average yield of about 3.6 t/ha across all divisions underscore the significant gap between current performance and the set targets. This disparity highlights the need for targeted interventions and strategic improvements throughout the scheme.

Table 26. Target Yield and Target WP

Season	Target Yield [t/ha]	Target WP [Kg/m3]
2019-10-07 to 2020-04-26	4.7	0.58

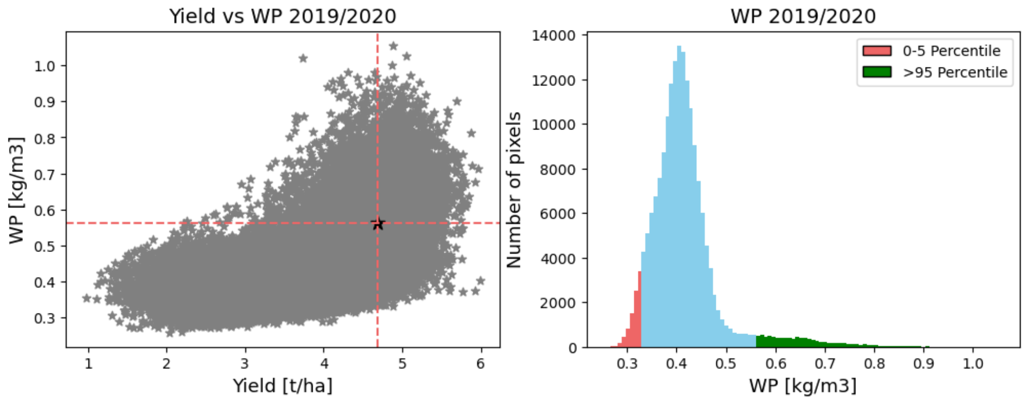

Figure 62. Relationship Between Yield and Water Productivity

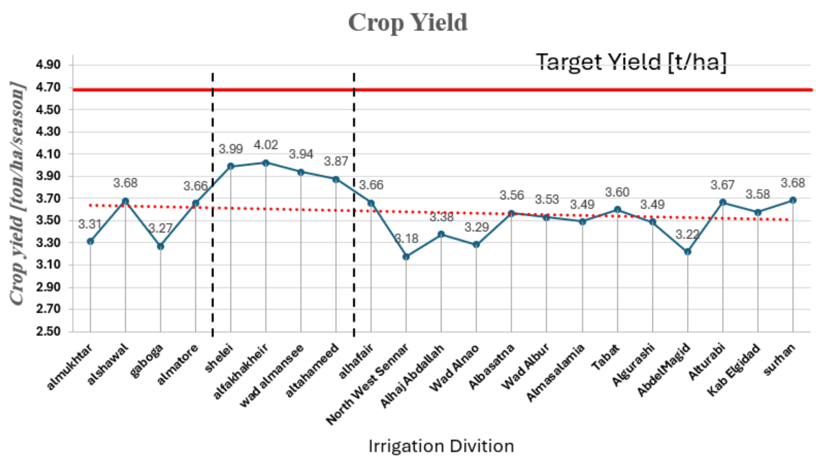

Figure 63. Target Yield Vs. Actual Yield

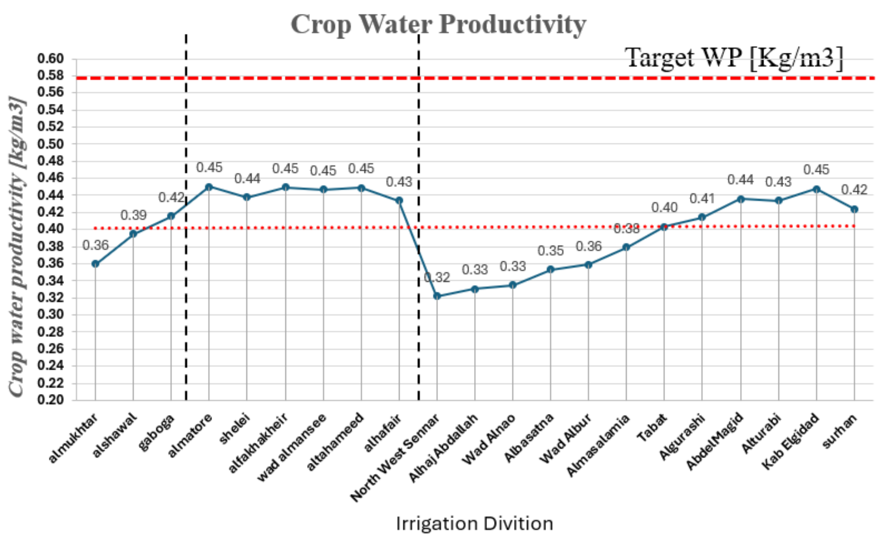

Figure 64.Target WPy vs. Actual WPy

3.8. Efficiency Indicators

3.8.1. Equity Analysis for Wheat Crop in the Gezira Scheme

The equity analysis of water distribution for wheat cultivation in the Gezira Scheme reveals significant insights into irrigation efficiency across different divisions. As illustrated in Figure 65, equity values predominantly fall within the "fair uniformity" range (10% < E < 25%), indicating moderate consistency in water distribution throughout the scheme. However, notable variations exist, with equity values fluctuating between approximately 10% and 20% across divisions. High-performing areas such as AlturabI and Abdelmagid approach the upper limit of fair uniformity, while divisions like Northwest Sennar and Almukhtar demonstrate lower equity values, nearing the threshold of good uniformity (E < 10%), though local variations overshadow this general pattern. Importantly, no division achieves "good uniformity" status, suggesting a systemic opportunity for improvement. The absence of widespread poor performance (E > 25%) indicates that severe water distribution issues are not pervasive but may occur in isolated instances. This comprehensive analysis underscores the need for targeted interventions to enhance water distribution practices, particularly in lower-performing divisions. By addressing these equity disparities through improved infrastructure, advanced irrigation technologies, and enhanced management practices, the Gezira Scheme can potentially optimize water use efficiency, leading to improved crop yields and overall agricultural sustainability in the region.

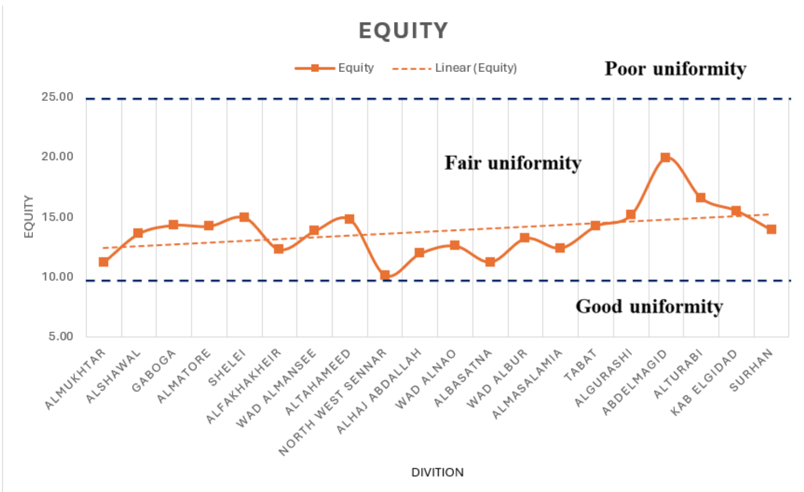

Figure 65. Divisional Variations in Wheat Equity Across the Gezira Scheme

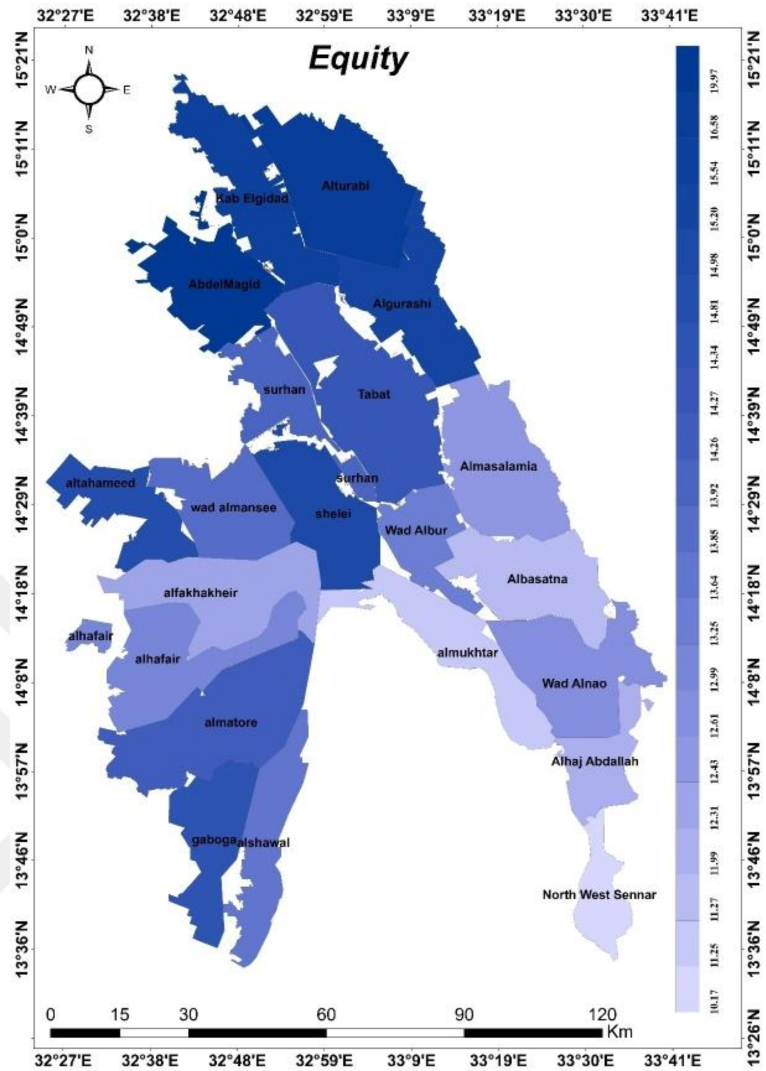

Figure 66. Quantitative Analysis of Wheat WPy Patterns Across Gezira Scheme Divisions

3.8.2. Adequacy Analysis for Wheat Crop in the Gezira Scheme

The adequacy analysis of water supply for wheat cultivation in the Gezira Scheme reveals critical insights into irrigation effectiveness across divisions. As illustrated in Figure 67, adequacy values predominantly fall within the poor performance range ($A \leq 0.68$), indicating a systemic undersupply of water relative to crop requirements. Values fluctuate between 0.47 and 0.64, with no division reaching the acceptable ($0.68 < A \leq 0.8$) or good performance ($0.8 < A \leq 1$) ranges. Alhaj Abdallah and Albasatna demonstrate the highest adequacy at 0.64, while AbdelMagid shows the lowest at 0.47. The majority of divisions cluster between 0.50 and 0.60, consistently within the poor performance category. This pervasive inadequacy in water supply suggests widespread water stress for wheat cultivation, potentially impacting crop yields and overall agricultural productivity across the scheme. The analysis underscores the urgent need for comprehensive water management improvements, including infrastructure enhancements, adoption of water-saving technologies, and implementation of precision irrigation techniques. Addressing these adequacy challenges is crucial for enhancing wheat productivity, optimizing resource utilization, and building resilience to water scarcity in the Gezira Scheme.

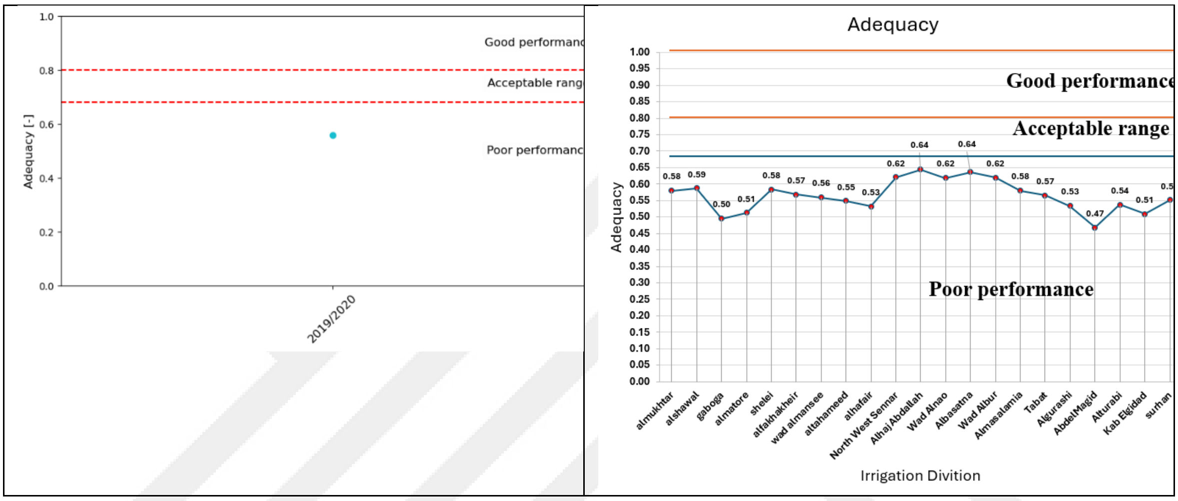

Figure 67. Divisional Variations in Wheat Adequacy Across the Gezira Scheme

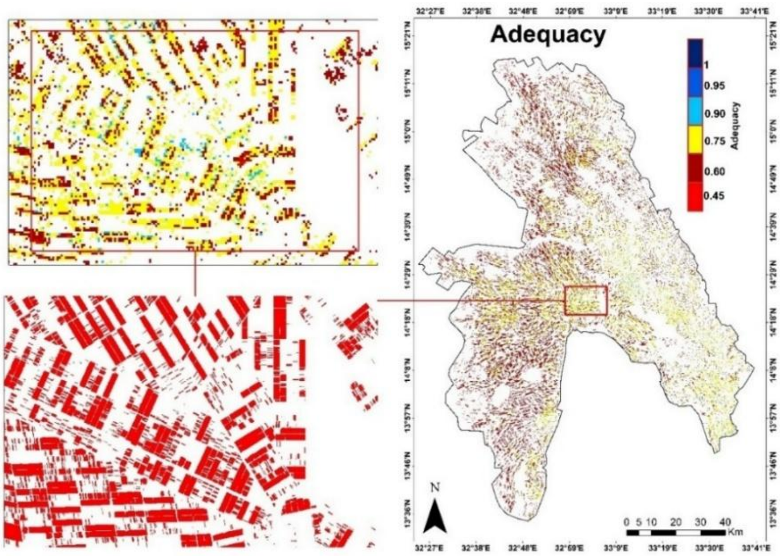

Figure 68. Quantitative Analysis of Wheat Adequacy Patterns Across Small Part (Hawasha).

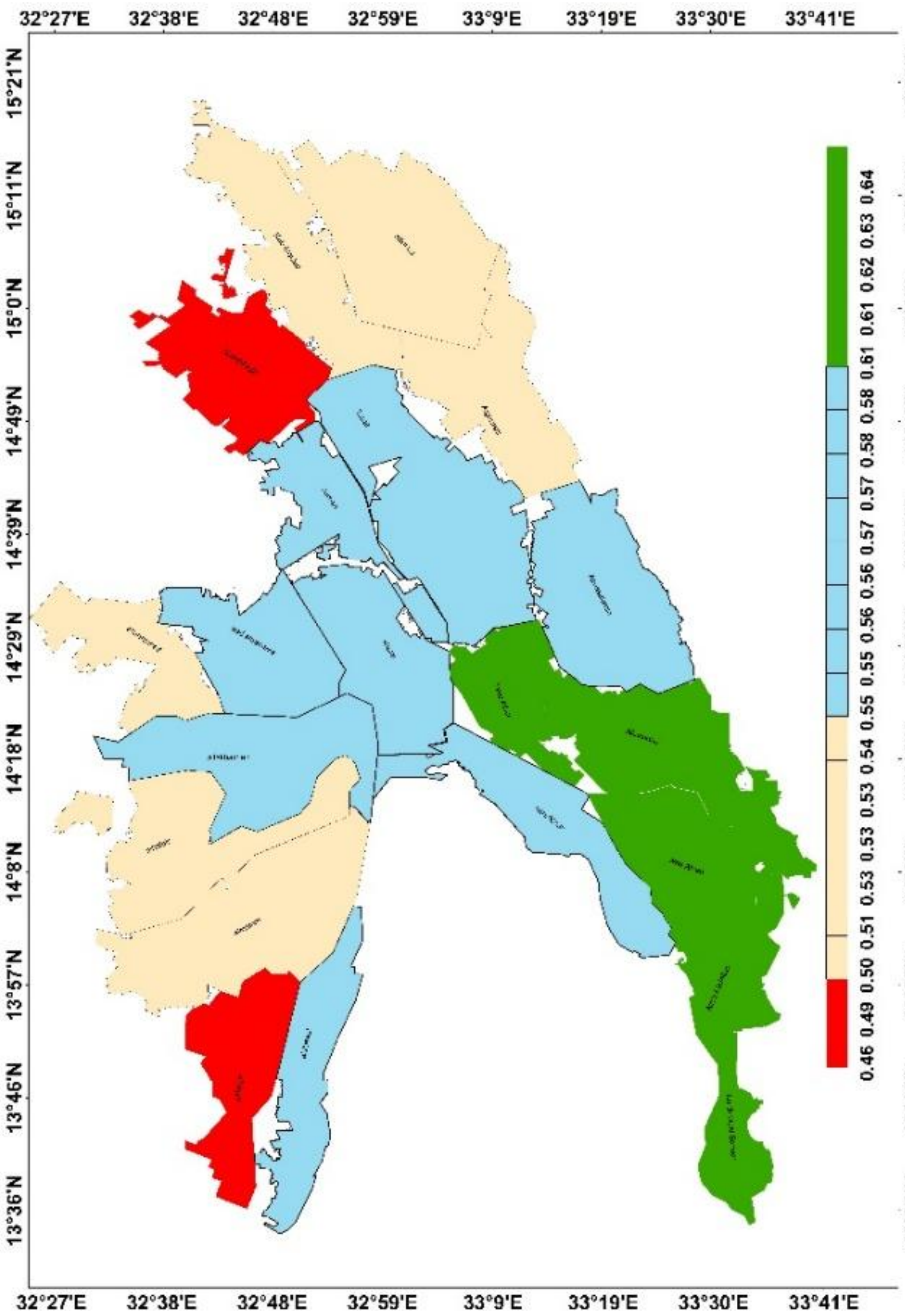

Figure 69. Quantitative Analysis of Wheat Adequacy Patterns Across Gezira Scheme Divisions

3.8.3. Efficiency Indicators: Relative Water Deficit (RWD) Analysis

The Relative Water Deficit (RWD) analysis for wheat cultivation across the Gezira Scheme, as illustrated in Figure 70, reveals significant variations in water stress levels among different irrigation divisions. RWD values range from approximately 0.45 to 0.61, indicating moderate to severe water deficits throughout the scheme. The highest RWD values, observed in divisions such as AbdelMagid and Alshawal (reaching about 0.61), suggest areas experiencing the most severe water stress. Conversely, divisions like Alhaj Abdallah and Alshawal exhibit the lowest RWD values (around 0.45), indicating relatively better water availability, although still deficient. The graph demonstrates a non-uniform pattern across divisions, with notable fluctuations between adjacent areas, highlighting localized differences in water management or environmental conditions.

Critically, the analysis reveals that the Relative Water Deficit for the entire Gezira Scheme in the 2019/2020 season was 27%, meaning that crops in the scheme received only 73% of their optimal water requirements. This scheme-wide deficit underscores the severity of the water stress issue, indicating a substantial shortfall in meeting crop water needs across the entire agricultural system.

This comprehensive analysis, supported by the spatial patterns shown in Figure 71, underscores the widespread challenge of water deficits in the Gezira Scheme. The consistent presence of significant RWD values across all divisions, coupled with the overall 27% deficit, indicates a systemic issue in meeting crop water requirements, likely impacting wheat yields and overall agricultural productivity. These findings emphasize the urgent need for targeted interventions to improve water use efficiency, enhance irrigation infrastructure, and implement drought-resistant cultivation practices across the scheme. Addressing this substantial water deficit is crucial for mitigating the effects of water stress and optimizing wheat production in the face of limited water resources, with potential implications for food security and agricultural sustainability in the region.

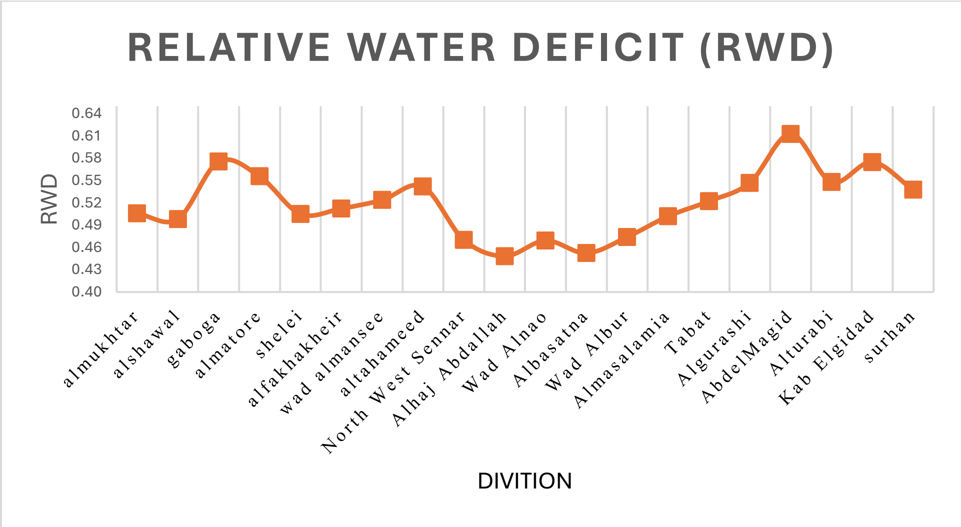

Figure 70. Divisional Variations in Wheat RWD Across the Gezira Scheme

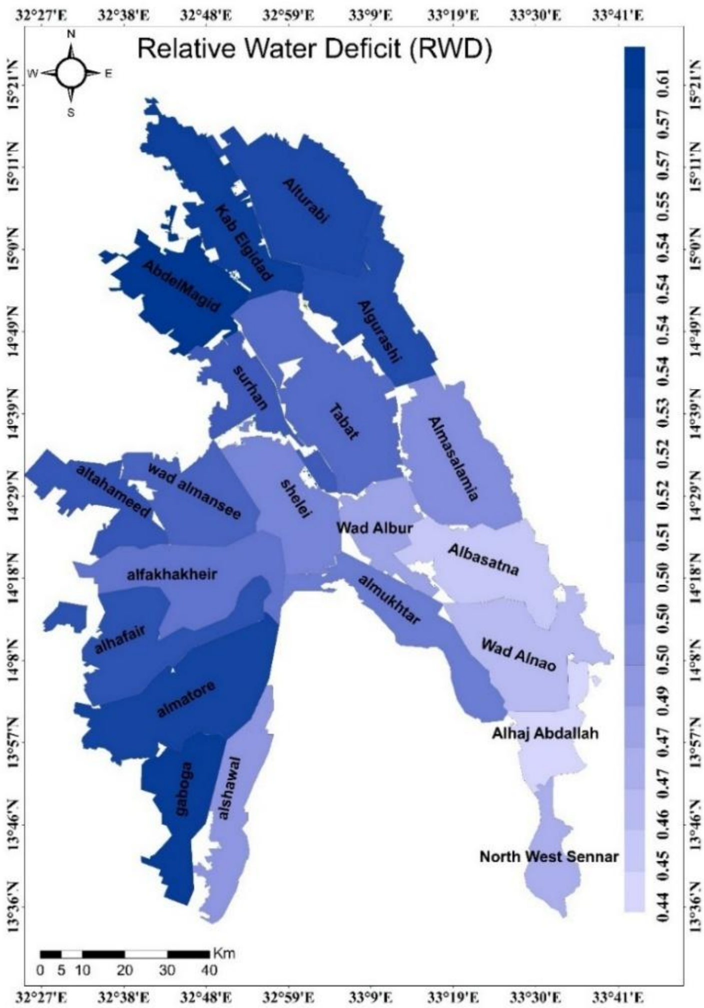

Figure 71. Quantitative Analysis of Wheat RWD Patterns Across Gezira Scheme Divisions

3.9. Gaps Analysis

3.9.1. Analysis of Above Ground Biomass Production and Biomass Gaps

The analysis of Above Ground Biomass (AGB) production and Biomass Gaps for wheat cultivation across the Gezira Scheme's irrigation divisions reveals significant variability in crop performance. AGB production ranged from 6.62 to 8.38 t/ha, with a mean of 7.44 t/ha, while Biomass Gaps varied from 1.69 to 3.18 t/ha, averaging 2.45 t/ha. The highest AGB production was observed in Alfakhakheir (8.38 t/ha), Shelei (8.31 t/ha), and Wad Almansee (8.20 t/ha), corresponding to the smallest Biomass Gaps. Conversely, Northwest Sennar, AbdelMagid, and Gaboga showed the lowest AGB production and largest Biomass Gaps. A strong negative correlation ($r = -0.99$) between AGB and Biomass Gaps indicates that divisions with higher biomass production consistently show smaller biomass gaps. The spatial variability in both metrics suggests the influence of localized factors on wheat biomass production. Performance categorization showed 20% of divisions in high performance (AGB > 8 t/ha), 55% in moderate performance (7-8 t/ha), and 25% in low performance (AGB < 7 t/ha), highlighting areas for potential improvement in the scheme's wheat cultivation practices.

This analysis reveals significant variability in Above Ground Biomass production and Biomass Gaps across the Gezira Scheme's irrigation divisions. The strong negative correlation between AGB and Biomass Gaps underscores the importance of optimizing biomass production to minimize yield shortfalls. Targeted interventions based on the identified performance categories can help improve overall wheat productivity in the scheme. Further research into the specific factors driving high performance in certain divisions will be crucial for developing comprehensive strategies to enhance biomass production and reduce gaps across the entire Gezira Scheme.

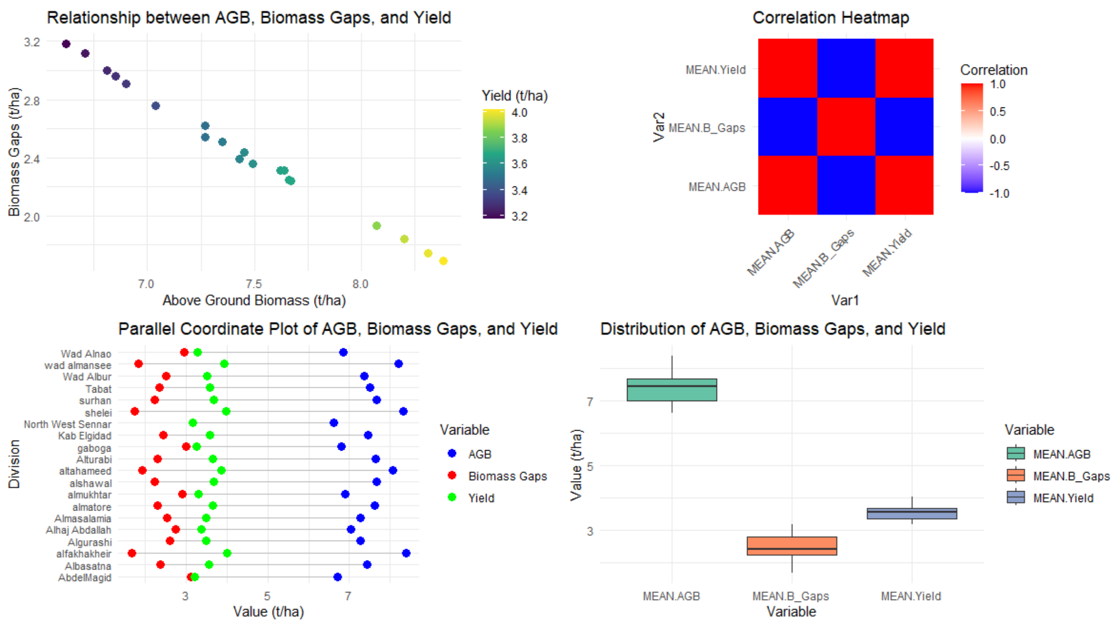

Figure 72. Provides A Comprehensive Visual Analysis of The Relationships Between Above Ground Biomass (AGB), Biomass Gaps, And Yield Across Different Divisions in The Gezira Scheme.

Table 27. Analysis of AGB, Biomass Gaps, and Yield: Key Observations and Implications

Chart Type	Key Observations	Implications
Scatter Plot	Strong negative correlation between AGB and Biomass Gaps. - Higher AGB associated with higher Yield	Increasing AGB likely leads to reduced Biomass Gaps and improved Yield. Focus on strategies to enhance AGB to potentially improve overall productivity.
Correlation Heatmap	-Strong positive correlation: AGB and Yield. - Strong negative correlation: Biomass Gaps with AGB and Yield	Confirms the interrelationships observed in the scatter plot. Reducing Biomass Gaps may be a key driver for increasing both AGB and Yield.
Parallel Coordinate Plot	- Divisions with high AGB tend to have low Biomass Gaps and high Yield. - Signific	
variability across divisions	Identifies high-performing divisions, which can serve as benchmarks. Suggests potential for improvement in other divisions by adopting practices from top performers.	
Boxplots	- AGB: Highest median, widest range. - Yield: Smallest range. - Biomass Gaps: Considerable variation	Indicates consistency in Yield despite variations in AGB and Biomass Gaps. This suggests potential for optimization – achieving high Yield even with moderate AGB.

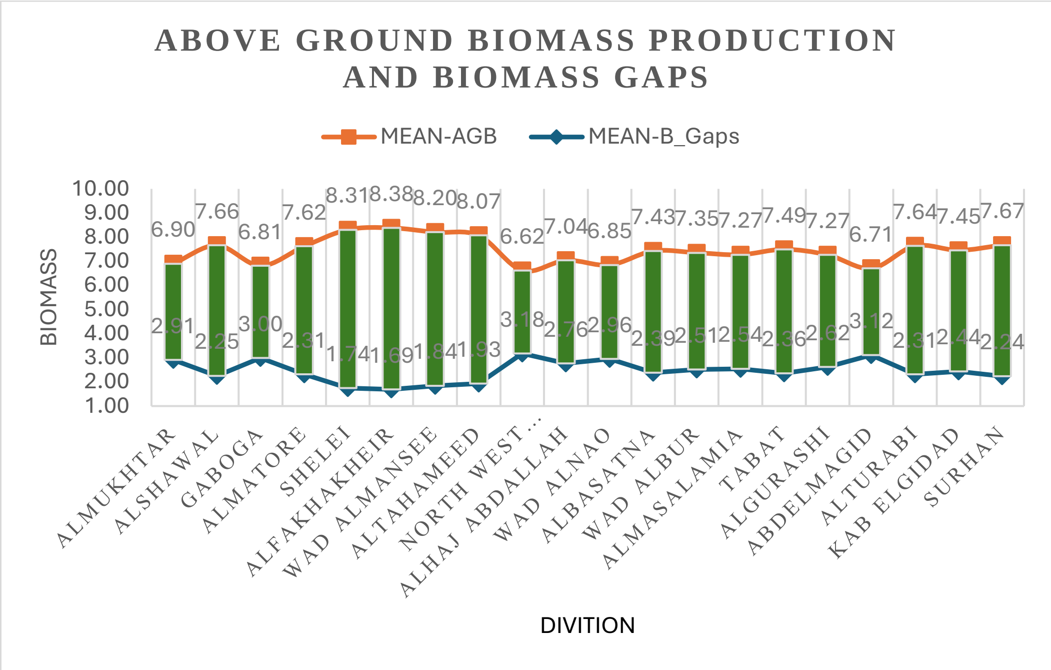

Figure 73. Divisional Variations in Wheat AGB-Gaps Across the Gezira Scheme

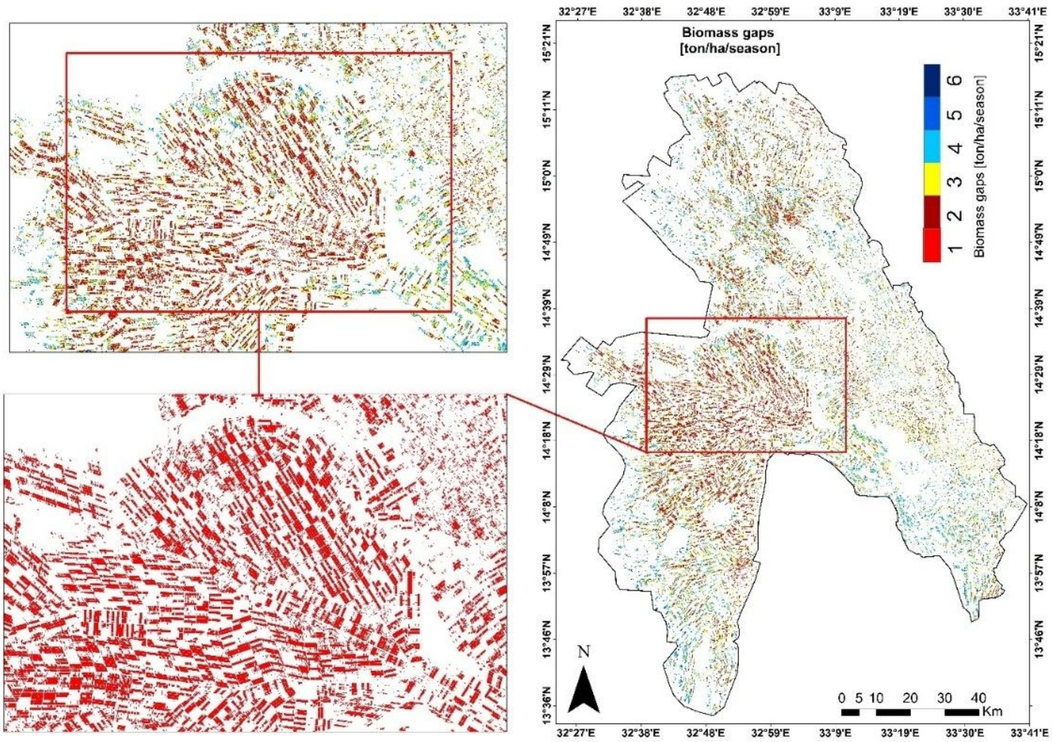

Figure 74. Quantitative Analysis of Wheat AGB-Gaps Patterns Across Small Part (Hawasha).

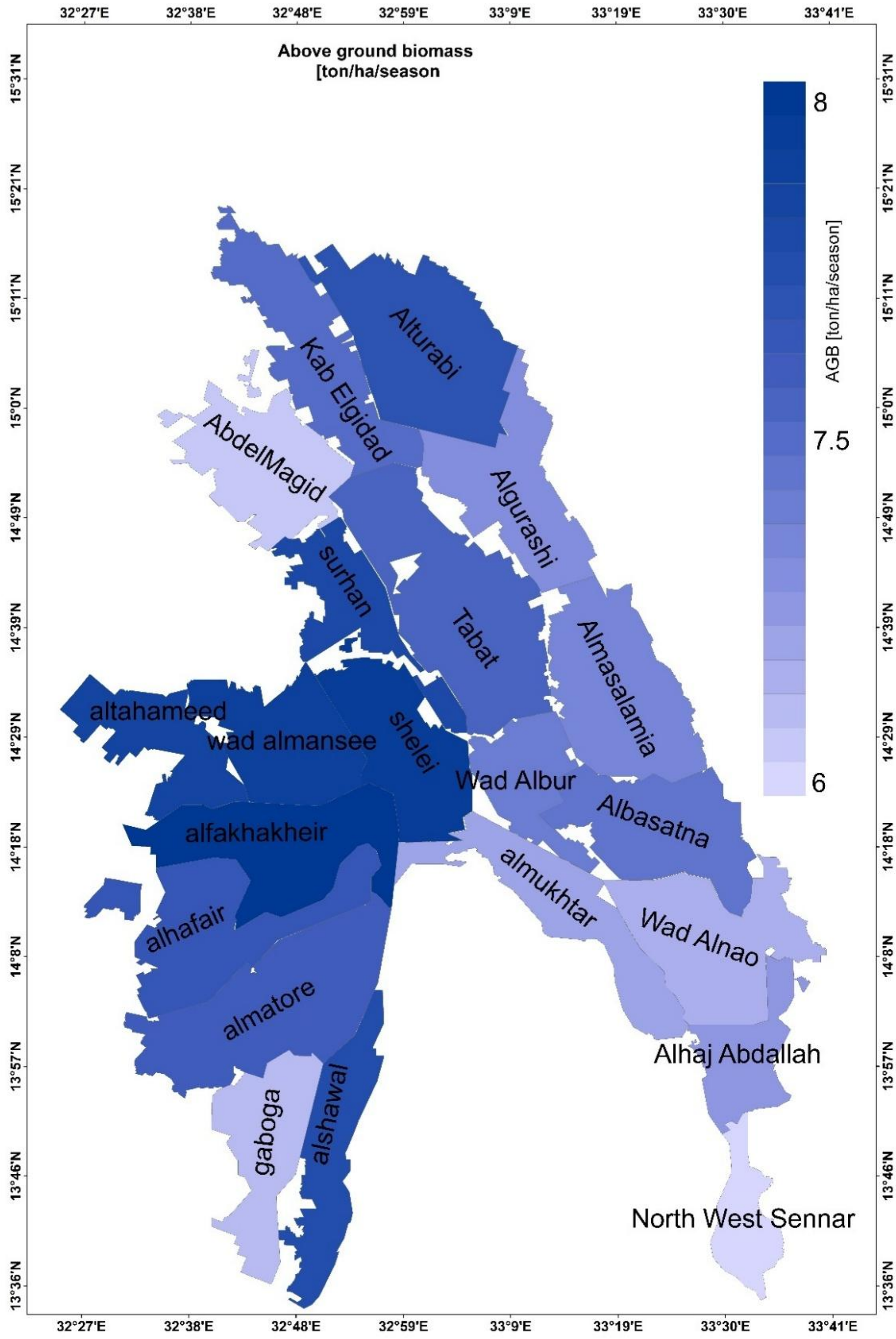

Figure 75. Quantitative Analysis of Wheat AGB-Gaps Patterns Across Gezira Scheme Divisions

3.9.2 Analysis of Wheat Yield Production and Yield Gaps

The analysis of wheat yield production and yield gaps across the Gezira Scheme's irrigation divisions reveals significant insights into agricultural efficiency. As illustrated in Figures 83, 84, and 85, yield production ranged from 3.18 t/ha (Northwest Sennar) to 4.02 t/ha (Alfakhakheir), with a mean of 3.57 t/ha. Correspondingly, yield gaps varied from 0.81 t/ha (Alfakhakheir) to 1.52 t/ha (Northwest Sennar), averaging 1.18 t/ha. Figure 76 clearly demonstrates the inverse relationship between yield production and yield gaps, with high-performing divisions like Alfakhakheir, Shelei, and Wad Almansee showing higher yields and smaller gaps. Figure 77 provides a comprehensive visual analysis of these relationships across divisions, while Figure 78 displays the spatial distribution of yield gaps throughout the scheme. This spatial variability in yield gaps, ranging from 0.68 to 0.83 in efficiency ratio, indicates significant potential for improvement even in the best-performing areas. The consistent presence of yield gaps across all divisions underscores the opportunity for enhancing wheat production efficiency through targeted interventions, particularly in lower-performing areas of the Gezira Scheme.

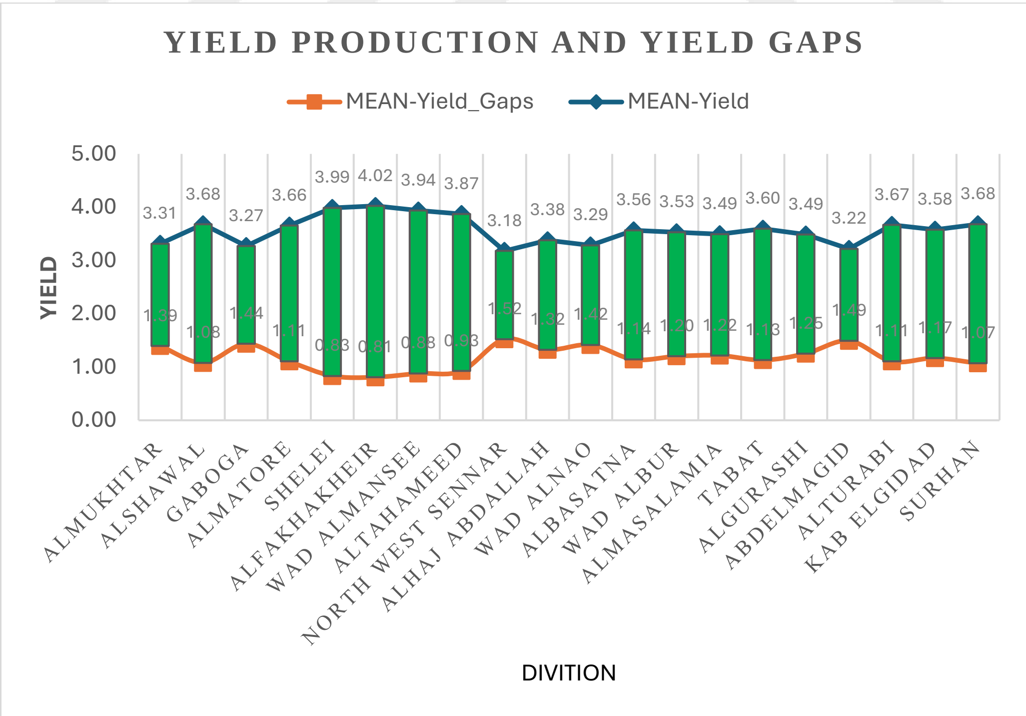

Figure 76. Divisional Variations in Wheat Yield Production and Yield-Gaps Across the Gezira Scheme

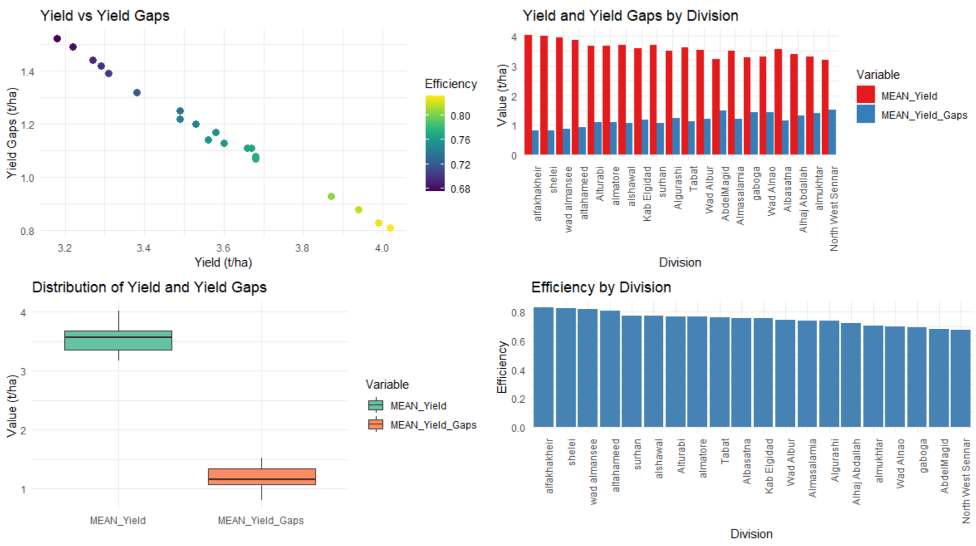

Figure 77. Provides A Comprehensive Visual Analysis of The Relationships Between Yield, Yield Gaps, Across Different Divisions in The Gezira Scheme

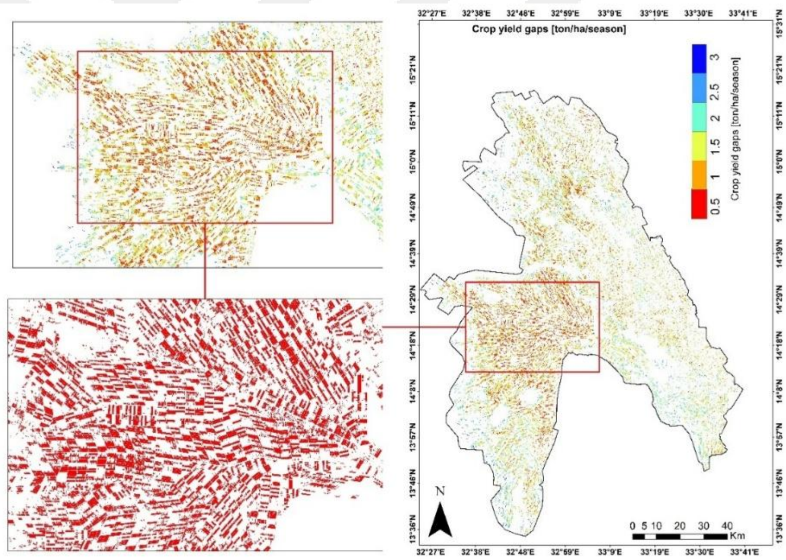

Figure 78. Quantitative Analysis of Wheat Yield-Gaps Patterns Across Small Part (Hawasha).

3.9.3. Analysis of Wheat Water Productivity (Wpy) and Water Productivity Gaps

The analysis of Wheat Water Productivity (WPy) and Water Productivity Gaps (WPy-Gaps) across the Gezira Scheme's irrigation divisions reveals significant insights into water use efficiency. As illustrated in Figures 79, WPy ranged from 0.32 kg/m³ (Northwest Sennar) to 0.45 kg/m³ (Alfakhakheir, Wad Almansee, Altahameed, Kab Elgidad), with a mean of 0.40 kg/m³. Correspondingly, WPy-Gaps varied from 0.26 kg/m³ (Almatore) to 0.50 kg/m³ (Northwest Sennar), averaging 0.35 kg/m³. Figure 79 clearly demonstrates the inverse relationship between WPy and WPy-Gaps, with high-performing divisions showing higher water productivity and smaller gaps. Figure 80 Quantitative Analysis of Wheat WPy-Gaps Patterns Across Small Part (Hawasha), highlighting areas of inefficiency. The efficiency ratio, ranging from 0.39 to 0.63 across divisions, indicates significant potential for improvement even in the best-performing areas. This variability in water productivity and persistent gaps across all divisions underscores the opportunity for enhancing water use efficiency in wheat production through targeted interventions, particularly in lower-performing areas of the Gezira Scheme.

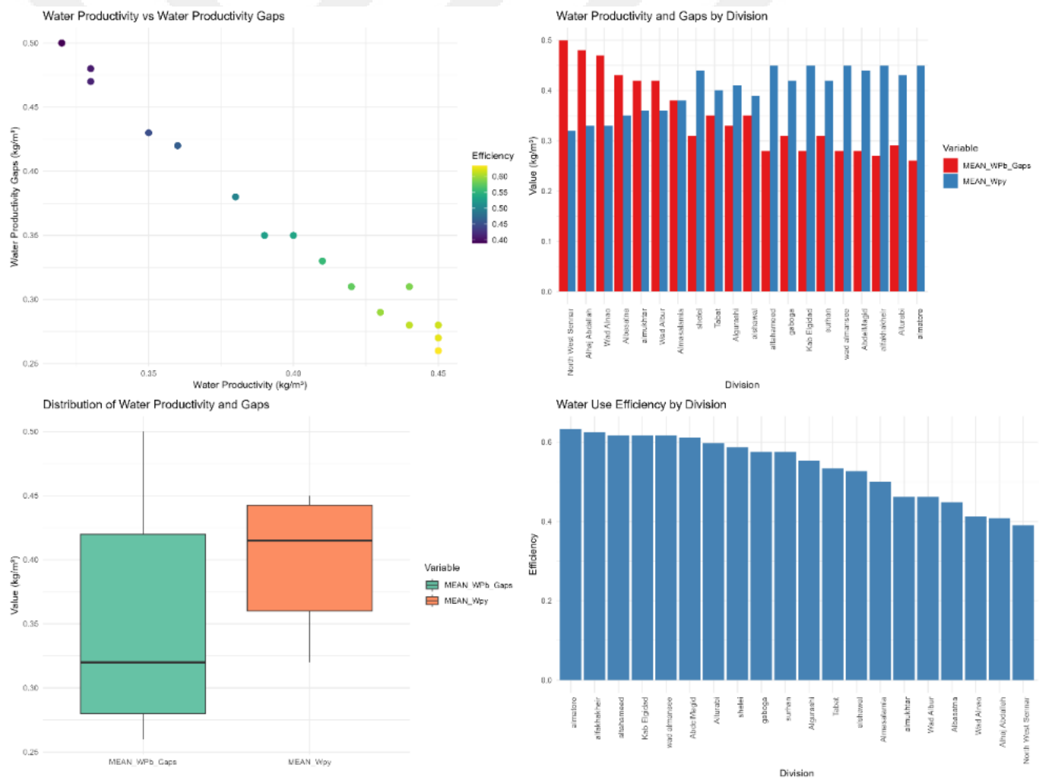

Figure 79. Provides Comprehensive Visual Analysis of The Relationships Between Wpy, Wpy-Gaps, Across Different Divisions in The Gezira Scheme

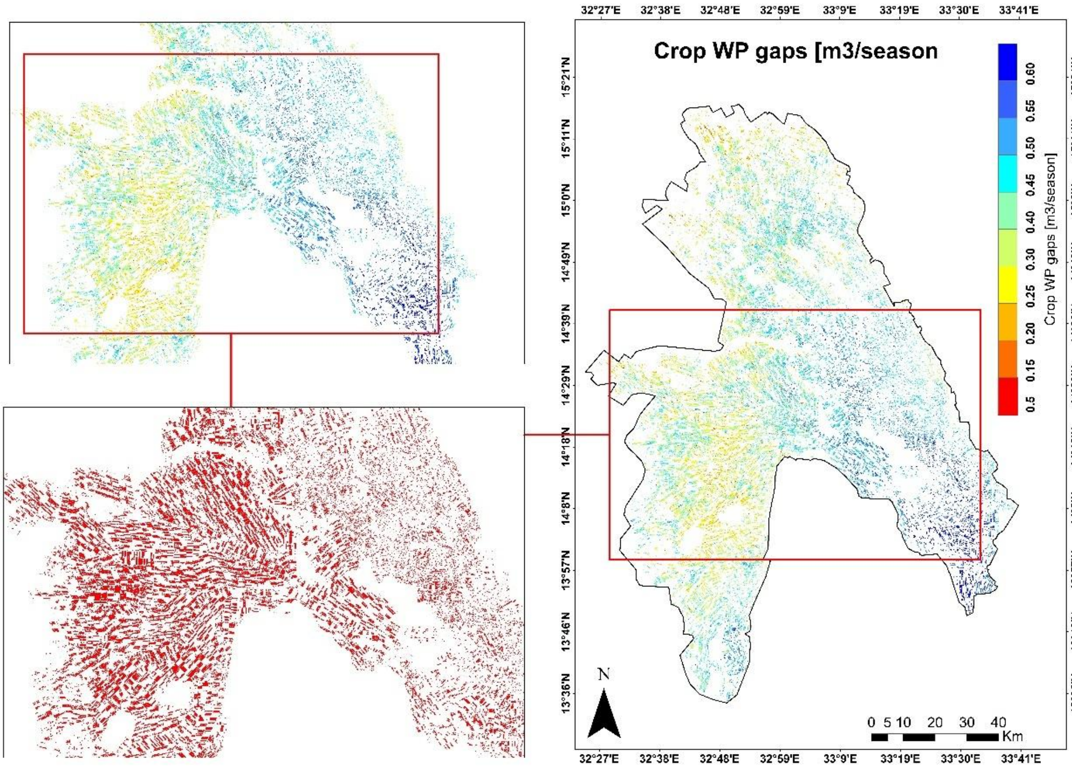

Figure 80. Quantitative Analysis of Wheat WPy-Gaps Patterns Across Small Part (Hawasha).

3.10. Bright Spots Analysis

The Bright Spots analysis for the Gezira Scheme, based on remote sensing data from October 7, 2019, to April 26, 2020, revealed significant insights into high-performing areas of wheat cultivation. The study focused on Above Ground Biomass (AGBM) and Water Productivity (WPy) as key indicators. AGBM values ranged from 2.03 to 12.48 t/ha, with a mean of 7.60 t/ha, while WPy varied from 0.26 to 1.06 kg/m³, averaging 0.42 kg/m³. Using the 95th percentile as a threshold (9.73 t/ha for AGBM and 0.536 kg/m³ for WPy), bright spots were identified as areas exceeding both thresholds simultaneously. Figure 81 illustrates the spatial distribution of these bright spots, highlighting regions of exceptional performance in both biomass production and water use efficiency. These areas represent the scheme's most productive and efficient wheat cultivation zones, offering valuable insights for potential replication of successful practices across the Gezira Scheme.

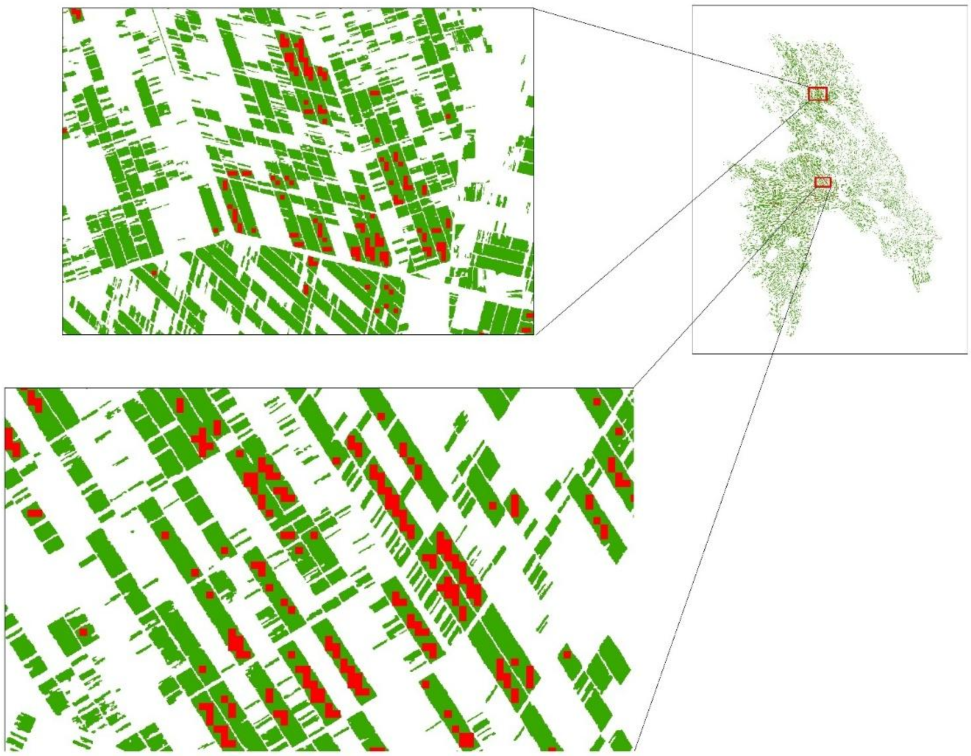

Figure 81. Spatial Distribution of Bright Spot Analysis

3.11. Comparative Analysis of Wheat Yield and Water Productivity

The analysis of wheat production efficiency in the Gezira Scheme reveals significant disparities across different zones, as illustrated in Figure 82. The Managil Zone demonstrates moderate yield performance (4-5 t/ha) but falls short of the optimal range (6-9 t/ha), with water productivity at approximately 0.55 kg/m³, less than 50% of optimal efficiency. In contrast, the South and North Gezira Zones show critical underperformance, with yields mostly below 3.5 t/ha and water productivity under 0.4 kg/m³. These findings highlight substantial yield gaps of 1-5 t/ha and water productivity deficits across all zones, with the South and North Gezira Zones showing particularly acute inefficiencies. The stark differences between zones underscore the need for targeted, zone-specific interventions to improve yield and water use efficiency. This comprehensive analysis emphasizes the urgent requirement for systematic enhancements in wheat cultivation practices, irrigation systems, and water management strategies throughout the Gezira Scheme to approach optimal production levels and resource efficiency.

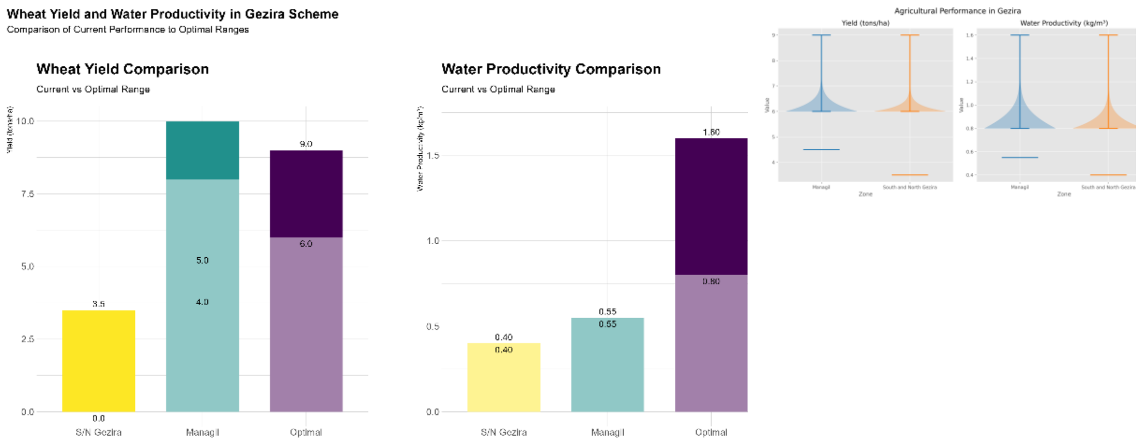

Figure 82. Comparative Analysis of Wheat Yield and Water Productivity in Gezira Scheme

3.12. Comparative Analysis of Real and WaPOR Productivity Yield

The comparative analysis of real productivity yield and WaPOR-calculated productivity for wheat cultivation in the Gezira Scheme reveals significant insights. A moderate positive correlation ($R = 0.52$, $p = 5.5e\text{-}05$) exists between farmer-reported yields and WaPOR estimates, indicating a relationship but also notable discrepancies. Real productivity shows a wider distribution (approximately 5-30 sacks/ha) compared to the narrower, peaked distribution of calculated productivity (centered around 15-17 sacks/ha). The analysis indicates that WaPOR generally underestimates productivity, particularly for high-yielding farms, with real productivity consistently exceeding calculated values for most farmers. WaPOR estimates align better with real productivity in the mid-range (10-20 sacks/ha) but show limitations in accurately capturing very low (<10 sacks/ha) and very high (>25 sacks/ha) productivities. This systematic bias suggests a need for refined calibration of the WaPOR model. The findings highlight both the potential and limitations of using remote sensing for wheat productivity estimation, emphasizing the importance of integrating ground-truth data for more accurate agricultural monitoring and management in the Gezira Scheme.

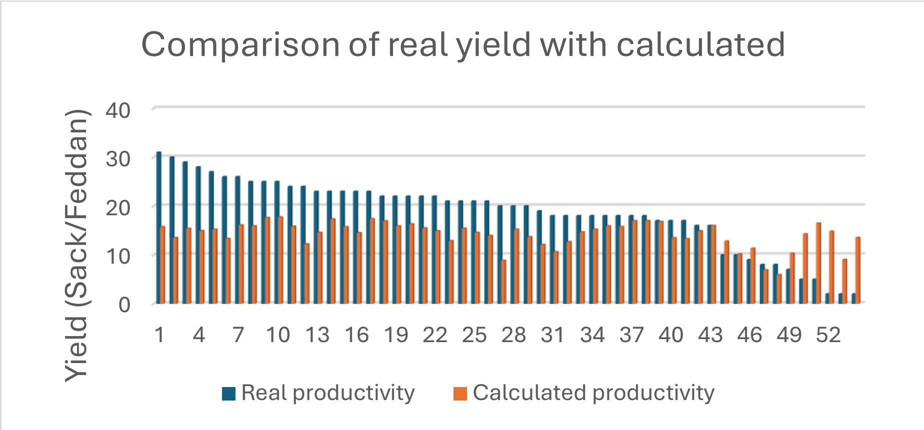

Figure 83. Comparison of Real Yield with Calculated

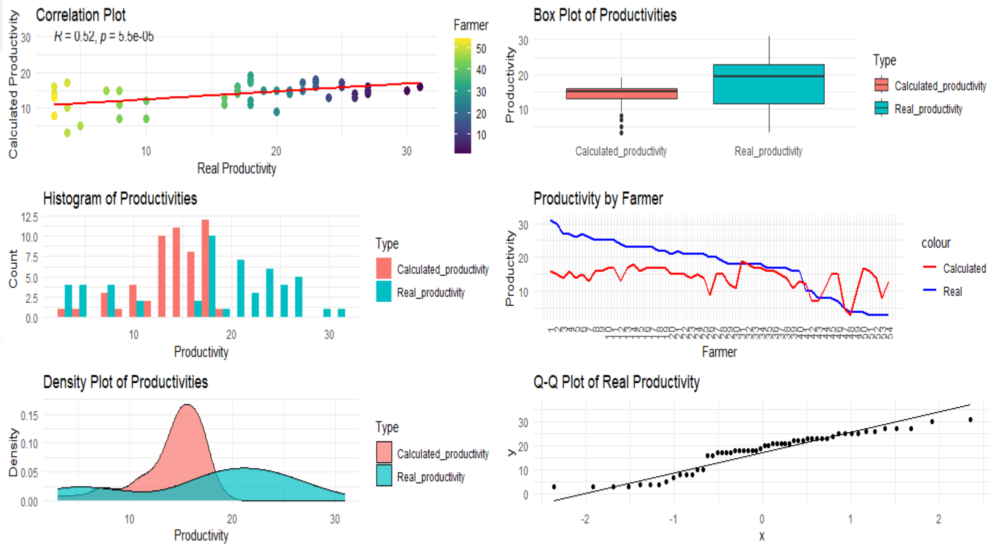

Figure 84. Comparative Analysis of Real Productivity Yield and WaPOR-Calculated Productivity in Wheat Cultivation

3.13 Questionnaire-Based Analysis of Wheat Cultivation Practices

The questionnaire-based analysis of wheat cultivation practices in the Gezira Scheme provides crucial ground-truth data to complement the remote sensing analysis. The survey, conducted with 182 wheat farmers from areas identified as 'bright spots', covered a comprehensive range of farming practices. Yields were classified as high (≥ 16 sacks/feddan) or low (≤ 15 sacks/feddan) to identify practices associated with higher productivity. The survey encompassed various aspects including seed selection, land preparation, fertilizer usage, pest management, and irrigation practices. Table 29 summarizes the suitable practices identified through this analysis. This integrated approach, combining remote sensing data with farmer-reported practices, offers valuable insights for improving water use efficiency and overall wheat production in the Gezira Scheme. The findings from this survey provide a more nuanced understanding of the factors influencing wheat productivity, enabling the development of targeted strategies to enhance agricultural practices across the scheme.

Table 28. suitable practices

No.	Activity	Suitable Practice
1	Seed rate	60 - 70 kg / Feddan
2	Seed preparation	It should be done according to the agricultural inspector or use the ready prepared type
4	Land preparation	Plough 3-4 times according to the rain, leveling 1-2 times
5	Sowing Date	10^{th} – 20^{th} of November
6	First irrigation	10^{th} – 25^{th} of November
7	Second irrigation	Should not be after the end of December
8	Irrigation intervals	12 - 15 days
9	Irrigation time	12 hours
10	Chemical Fertilizers	Dap 60 - 80 kg/feddan – urea 100 - 150kg / feddan
11	Weeds control	Used when its need it
12	Pests control	Used when its need it (Jet spray is enough)
13	Number of Irrigations during the season	7 – 8 times
14	Organic Fertilizers	Not significant

3.14. Results Of Machine Learning Models

This study employed seven machine learning models to predict wheat yield and water productivity (WPy) in the Gezira Irrigation Scheme. We evaluated model performance using

Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R-squared). Table 3 presents a comprehensive overview of these performance metrics for each model.

Table 29. Performance metrics of machine learning models for wheat yield and WPy estimation in the Gezira Irrigation Scheme

Target	**Model**	**MAE**	**RMSE**	**R-squared**
Yield	Linear Regression	0.245	0.322	0.708
Yield	Random Forest	0.167	0.228	0.854
Yield	Gradient Boosting	0.177	0.244	0.832
Yield	XGBoost	0.170	0.245	0.831
Yield	KNN	0.236	0.290	0.763
Yield	Decision Tree	0.170	0.223	0.860
Yield	Bagging Regressor	0.163	0.226	0.857
Wpy	Linear Regression	0.003	0.003	0.999
Wpy	Random Forest	0.006	0.007	0.996
Wpy	Gradient Boosting	0.004	0.008	0.995
Wpy	XGBoost	0.004	0.007	0.996
Wpy	KNN	0.018	0.026	0.945
Wpy	Decision Tree	0.010	0.013	0.986
Wpy	Bagging Regressor	0.005	0.007	0.996

For wheat yield prediction, ensemble methods demonstrated superior performance. The Decision Tree model achieved the highest accuracy with an R-squared value of 0.860 and the lowest RMSE of 0.223. The Bagging Regressor and Random Forest models followed closely, with R-squared values of 0.857 and 0.854, respectively. The Bagging Regressor showed the lowest MAE (0.163), indicating high overall prediction accuracy. Gradient Boosting and XGBoost models performed similarly (R-squared: 0.832 and 0.831), highlighting the effectiveness of boosting techniques. The Linear Regression model (R-squared: 0.708) and K-Nearest Neighbors (KNN) model (R-squared: 0.763) showed moderate performance, suggesting the complex, non-linear nature of factors influencing crop yield.

In contrast, water productivity (WPy) predictions exhibited remarkably high accuracy across all models. Surprisingly, the Linear Regression model outperformed others, achieving an almost perfect R-squared of 0.999 and the lowest MAE and RMSE (both 0.003). This suggests a strong linear relationship between input features and WPy. Ensemble methods (Random Forest, Gradient Boosting, XGBoost, and Bagging Regressor) all performed exceptionally well, with R-squared values of 0.996 or higher. Even the Decision Tree model achieved a high R-squared of 0.986. The KNN model, while still highly accurate, showed the lowest performance for WPy prediction (R-squared: 0.945).

These results underscore the effectiveness of machine learning approaches in predicting both wheat yield and water productivity in our study area. The superior performance of ensemble methods for yield prediction highlights the complex interactions between agricultural variables affecting crop yield. Conversely, the high accuracy of simpler models for WPy prediction suggests a more direct relationship between input features and water productivity. This performance disparity between yield and WPy predictions offers valuable insights into the underlying dynamics of wheat cultivation in the Gezira Irrigation Scheme, warranting further investigation into the factors influencing these two crucial agricultural metrics.

Figure 85 showcases a user interface for an advanced "Wheat Yield and Water Productivity Prediction" tool, designed to assist agricultural professionals and researchers in estimating wheat yields. The tool incorporates a range of critical input parameters, including Reference Evapotranspiration (RET), Actual Evapotranspiration Index (AETI), Net Primary Productivity (NPP), and various vegetation indices such as NDVI, EVI, and SIPI. What makes this tool particularly powerful is its integration of multiple machines learning models, offering users the flexibility to choose from Linear Regression, Random Forest, Gradient Boosting, XGBoost, K-Nearest Neighbors (KNN), Decision Tree, and Bagging Regressor algorithms. This variety allows users to compare different modeling approaches and select the one that best fits their data and prediction needs. The interface also provides additional features like parameter explanations, model saving and loading capabilities, and multiple analysis tabs for performance visualization, correlation heatmaps, and feature importance assessments. By combining diverse input parameters with a suite of advanced predictive models, this tool offers a comprehensive approach to analyzing factors influencing wheat yield, making it an invaluable resource for crop yield forecasting, agricultural planning, and research in crop science and water resource management.

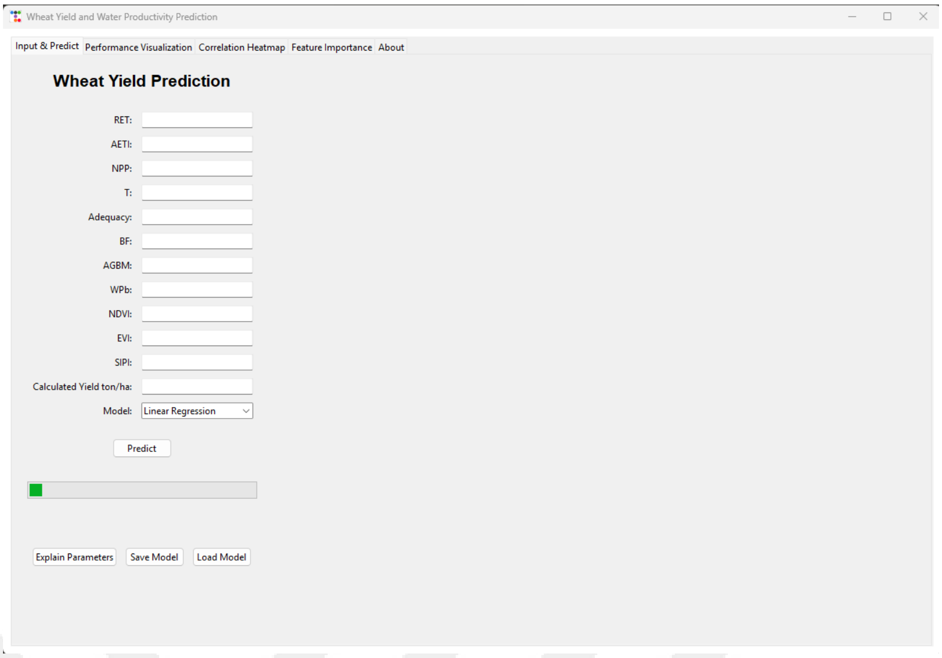

Figure 85.Wheat Yield and Water Productivity Prediction Tool

3.15. Discussion

This study provides a comprehensive analysis of wheat productivity in the Gezira Scheme, integrating remote sensing data with ground-level survey information to offer insights into the complex interplay of factors affecting crop yields and water use efficiency. The findings reveal significant spatial variability in productivity across the scheme and highlight critical areas for improvement in agricultural practices.

3.15.1. Spatial Variability and Performance Gaps

The analysis of Above Ground Biomass (AGB) and Water Productivity (WPy) across different divisions of the Gezira Scheme revealed substantial spatial heterogeneity in wheat production efficiency. The observed range of AGB (6.62 to 8.38 t/ha) and WPy (0.32 to 0.45 kg/m³) indicates that while some areas are performing relatively well, there is significant room for improvement across the scheme. The inverse relationship between yield and yield gaps (ranging from 0.81 to 1.52 t/ha) further underscores the potential for increasing productivity through targeted interventions.

The identification of 'bright spots' - areas exceeding the 95th percentile in both AGB and WPy - provides valuable benchmarks for achievable productivity levels within the local context. These high-performing areas, predominantly found in divisions like alfakhakheir, shelei, and wad almansee, offer opportunities for peer-to-peer learning and the dissemination of best practices across the scheme.

3.15.2. Water Management and Efficiency

The analysis of water-related indicators, including Actual Evapotranspiration (AETI), Reference Evapotranspiration (RET), and Beneficial Fraction (BF), reveals critical insights

into water management efficiency across the scheme. The observed AETI gradient, ranging from 607 to 824 mm/season, suggests significant variations in water consumption that are not always aligned with productivity outcomes. This misalignment is further evidenced by the consistently low adequacy values (ranging from 0.47 to 0.64) across all divisions, indicating widespread water stress in wheat crops.

The Relative Water Deficit (RWD) analysis, showing a scheme-wide average of 27%, further corroborates the challenges in meeting crop water requirements. These findings collectively point to the urgent need for improved irrigation scheduling, enhanced water delivery systems, and the adoption of water-conserving technologies to optimize resource use efficiency.

3.15.3. Yield and Water Productivity Gaps

The comparative analysis between actual yields and WaPOR-calculated productivity ($R = 0.52$, $p = 5.5e-05$) reveals both the potential and limitations of using remote sensing for agricultural monitoring. The systematic underestimation of yields by WaPOR, particularly for high-performing farms, suggests the need for refined calibration of remote sensing models and integration with ground-truth data for more accurate productivity assessments.

The substantial gaps between current and optimal yields (1-5 t/ha in Managil Zone, with other zones showing even larger disparities) and water productivity (current values generally below 0.55 kg/m^3 compared to optimal ranges of 0.8-1.6 kg/m^3) underscore the significant potential for improvement. These gaps represent not just unrealized agricultural potential but also opportunities for enhancing food security and economic returns for farmers in the region.

3.15.4. Factors Influencing Productivity

The survey of 182 wheat farmers in high-performing areas provided crucial insights into management practices associated with higher yields. Key factors identified include optimal seed rates (60-70 kg/feddan), timely sowing (10th-20th November), appropriate fertilizer application (DAP 60-80 kg/feddan, urea 100-150 kg/feddan), and judicious irrigation scheduling (7-8 irrigations per season with 12–15-day intervals). These findings offer valuable guidance for developing best practice recommendations that can be disseminated across the scheme.

The variability in productivity across divisions suggests that localized factors, including soil characteristics, microclimate conditions, and management practices, play significant roles in determining yields. The strong correlation between AGB and yield ($r = 0.99$) emphasizes the importance of focusing on overall plant growth and health to enhance productivity.

3.15.5. Implications for Sustainable Agriculture

The persistent yield and water productivity gaps across the Gezira Scheme highlight the need for a comprehensive approach to agricultural enhancement. This approach should encompass:

1. Targeted interventions in low-performing areas, focusing on improving soil fertility, water management, and crop protection.
2. Knowledge transfer mechanisms to disseminate best practices from high performing 'bright spots' to other areas of the scheme.
3. Investment in irrigation infrastructure to improve water delivery efficiency and reduce water stress on crops.
4. Adoption of precision agriculture techniques to optimize resource use, particularly in water application and fertilizer management.

5. Continued integration of remote sensing technologies with ground-level data collection for more accurate and timely monitoring of crop performance.

3.16. Limitations and Future Research

While this study provides comprehensive insights into wheat productivity in the Gezira Scheme, several limitations should be noted. The reliance on a single season's data limits our ability to account for inter-annual variability in climate and management practices. Future studies should incorporate multi-year analyses to capture temporal trends and the impacts of climate variability on productivity.

Additionally, the discrepancies between WaPOR-calculated productivity and farmer-reported yields highlight the need for further refinement of remote sensing methodologies for agricultural monitoring in this region. Future research should focus on improving the calibration of these models through extensive ground-truthing and the incorporation of high-resolution satellite imagery.

Finally, while our survey provided valuable insights into management practices associated with high yields, a more comprehensive understanding of the socio-economic factors influencing farmer decision-making and technology adoption is needed. Future studies should incorporate in-depth qualitative research to explore these aspects and inform more effective agricultural extension strategies.

4. RECOMMENDATIONS

The comprehensive study of the Gezira Scheme has yielded several critical recommendations to enhance wheat productivity and water use efficiency across its 20 irrigation divisions. These recommendations address the spatial variability in productivity, with a particular focus on improving yields in the underperforming South and North Gezira zones. The Managil Zone, with its superior performance, serves as a benchmark for improvement strategies in other areas.

A key focus area is the optimization of water management practices. The study reveals suboptimal water use across all divisions, with inadequacy values ranging from 0.47 to 0.64 and a scheme-wide average relative water deficit of 27%. Implementing strategies to enhance water distribution equity and reduce deficits is crucial. The farmer survey results suggest an optimal irrigation schedule of 7-8 times per season with 12–15-day intervals, which should be widely promoted.

Agronomic practices play a vital role in yield improvement. The study recommends specific seed rates (60-70 kg/feddan), sowing times (10th-20th November), and fertilizer application rates (DAP 60-80 kg/feddan, urea 100-150 kg/feddan) based on successful farmer practices. These recommendations aim to bridge the significant yield gap between current (3.18-4.02 t/ha) and optimal (6-9 t/ha) production levels.

Improving water productivity is another critical objective. The current range of 0.32-0.45 kg/m³ falls significantly short of the optimal 0.8-1.6 kg/m³. Zone-specific targets and interventions, particularly in divisions with Water Productivity (WPy) values below 0.4 kg/m³, are recommended to address this shortfall.

The integration of remote sensing technology with ground data collection needs refinement. The study suggests improving upon the 2-3% error range in crop area estimation by enhancing the integration of Support Vector Machine (SVM) and Object-Based Image Analysis (OBIA) methods. Regular validation and calibration of remote sensing data with ground-truth information is essential to address discrepancies between calculated and reported yields.

Resource use efficiency can be optimized by targeting improvements in divisions with low Net Primary Production (NPP) values and implementing strategies to reduce high Actual Evapotranspiration (AETI) without compromising yield. Farmer education and training programs should focus on practices identified in the survey that led to high yields, using 'bright spots' as demonstration sites for farmer field schools.

Climate resilience strategies are crucial given the significant evaporative demand indicated by the Reference Evapotranspiration (RET) range of 1830-1920 mm/season. Promoting drought-resistant wheat varieties, especially in divisions with consistently low adequacy values, is recommended.

Further research is needed to understand the factors contributing to high performing 'bright spots' and to investigate the causes of low performance in specific divisions. Policy and governance recommendations include developing incentives for the adoption of best practices and establishing a monitoring and evaluation system based on key indicators used in this study.

Implementation of these recommendations should be prioritized based on the severity of issues in each division and the potential for impact. Regular monitoring and evaluation will be crucial to assess the effectiveness of interventions and make necessary adjustments. By addressing these specific areas, it is possible to significantly enhance wheat productivity, improve water use efficiency, and contribute to the overall sustainability and food security goals of the Gezira Scheme and Sudan as a who

5.CONCLUSION

This comprehensive study of wheat productivity in the Gezira Irrigation Scheme has provided critical insights into the complex interplay of factors affecting agricultural performance in one of the world's largest irrigation projects. By integrating advanced remote sensing techniques with ground-level data and farmer surveys, this This analysis reveals significant variability in Above Ground Biomass production and Biomass Gaps across the Gezira Scheme's irrigation divisions. The strong negative correlation between AGB and Biomass Gaps underscores the importance of optimizing biomass production to minimize yield shortfalls. Targeted interventions based on the identified performance categories can help improve overall wheat productivity in the scheme. Further research into the specific factors driving high performance in certain divisions will be crucial for developing comprehensive strategies to enhance biomass production and reduce gaps across the entire Gezira Scheme.

has illuminated both the challenges and opportunities for enhancing wheat production and water use efficiency in this vital agricultural region, the study revealed significant spatial variability in productivity across the scheme's 20 irrigation divisions. Wheat yields ranged from 3.18 to 4.02 t/ha, falling substantially short of the optimal range of 6-9 t/ha. Similarly, water productivity values (0.32-0.45 kg/m³) were well below the target of 0.58 kg/m³. This performance gap underscores the untapped potential within the Gezira Scheme and highlights the urgent need for targeted interventions.

Our analysis of key indicators including Actual Evapotranspiration (AETI: 607-824 mm/season), Reference Evapotranspiration (RET: 1830-1920 mm/season), Beneficial Fraction (BF: 0.80-0.83), Net Primary Production (NPP: 297.92-377.28 gC/m²/season), and Above Ground Biomass (AGB: 6.62-8.38 t/ha) provided a nuanced understanding of the scheme's performance. The integrated Support Vector Machine (SVM) and Object-Based Image Analysis (OBIA) approach demonstrated high accuracy in crop area estimation, with only a 2-3% error range compared to official records.

Crucially, the study identified suboptimal water management as a key challenge, with equity ranging from 10.17-19.97% (fair performance), adequacy from 0.47-0.64 (poor performance), and a scheme-wide average relative water deficit of 27%. These findings point to significant opportunities for improving irrigation practices and water use efficiency across the scheme.

The farmer survey component of this thesis research yielded valuable insights into on-the-ground practices associated with higher yields. Key factors identified include optimal seed rates (60-70 kg/feddan), timely sowing (10th-20th November), appropriate irrigation scheduling (7-8 times per season, 12–15-day intervals), and judicious fertilizer application (DAP 60-80 kg/feddan, urea 100-150 kg/feddan) These findings provide a practical foundation for developing targeted farmer education and extension programs.

The novel 'bright spots' analysis, identifying high-performing areas that exceeded the 95th percentile in both AGB and Water Productivity, offers valuable benchmarks for achievable productivity levels within the local context. These areas serve as potential models for best practices that could be replicated across the scheme.

While this study has provided a comprehensive assessment of the current state of wheat productivity in the Gezira Scheme, it also highlights areas for further research. The discrepancies observed between remote sensing-based productivity estimates and farmer-reported yields ($R = 0.52$, $p = 5.5e-05$) suggest the need for continued refinement of remote sensing methodologies for agricultural monitoring in this region. Additionally, further investigation into the specific factors contributing to the success of 'bright spots' could yield valuable insights for improving overall scheme performance.

The implications of this thesis extend beyond the immediate context of the Gezira Scheme. The integrated methodology developed here, combining remote sensing analysis with ground-truth data and farmer surveys, provides a robust framework that could be applied to other large-scale irrigation schemes facing similar challenges. Furthermore, the findings contribute to broader discussions on food security, sustainable water management, and climate-resilient agriculture in arid and semi-arid regions.

In conclusion, this study has demonstrated both the challenges and the significant potential for improving wheat productivity and water use efficiency in the Gezira Irrigation Scheme. By addressing the identified yield and water productivity gaps through targeted interventions, improved water management, and the adoption of optimal agronomic practices, there is substantial opportunity to enhance food security, improve farmer livelihoods, and contribute to the sustainable development of Sudan's agricultural sector. The path forward will require concerted efforts from policymakers, scheme managers, researchers, and farmers, guided by the evidence-based insights provided by this thesis.

As we look to the future, the Gezira Scheme stands at a critical juncture. The implementation of the recommendations derived from this study could transform it into a model of efficient, productive, and sustainable irrigated agriculture, with potential ripple effects for food security and agricultural development across the region and beyond. This thesis thus not only contributes to the scientific understanding of irrigated wheat production but also provides a roadmap for tangible improvements in one of Africa's most important agricultural systems.

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RESUME

I, Osman Ibrahim, am a Sudanese surveying and geomatics professional with a strong academic background and extensive practical experience. I obtained my Bachelor of Science (Honours) in Surveying Engineering from Omdurman Islamic University, Sudan, in 2017, graduating with First Class honors. Following this, I embarked on my career in geomatics, serving as a Roads Surveyor at the Ministry of Infrastructure and Transport from 2017 to 2018.

Driven by my passion for water resource management and a commitment to furthering my expertise, I joined the Hydraulics Research Center of the Ministry of Irrigation and Water Resources as a Research Assistant in 2018. My dedication to the field has been demonstrated through my involvement in numerous projects funded by international organizations such as FAO, IFAD, and ZOA, where I applied my skills in GIS, remote sensing, and hydrological modeling to address critical water management challenges.

Since 2018, I have been engaged in various roles, including Surveyor, Water Resources Engineer, and GIS and Remote Sensing Analyst. My commitment to continuous learning is evident through my numerous certifications in areas such as remote sensing, geospatial analysis, and Python programming.

In 2021, I embarked on my master's degree in Geomatics Engineering at Karadeniz Technical University in Turkey.

I am fluent in Arabic, English, and Turkish, which has enabled me to undertake international projects across Sudan, Asia, and globally. My visionary approach focuses on sustainable infrastructure and advancing water resources through strategic expertise, advanced technologies, and collaborative stakeholder engagement.