Water and Soil Management and Modeling

Online ISSN: 2783 - 2546

University of Mohaghegh Ardabili

Estimating water productivity of center-pivot irrigation systems using the WaPOR (Case study: Moghan plain)

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Abstract

Water productivity is essential for sustainable agriculture, especially in semi-arid regions with limited water resources. In the Moghan Plain during 2020–2024, this study evaluates Net Biomass Water Productivity (NBWP) and Gross Biomass Water Productivity (GBWP) in three agricultural fields (P, Q, and R) cultivating silage maize under center pivot irrigation from 2020 to 2024. Ground measurements of irrigation depth, crop yield, and evapotranspiration, combined with temperature and precipitation data, were analyzed to understand temporal variations and the impact of environmental and management factors. Results showed that NBWP increased from 2.42 to 3.03 kg/m³ in Field P, 2.40 to 3.33 kg/m³ in Field Q, and 2.12 to 3.56 kg/m³ in Field R, with Field Q achieving the highest gain (39%). GBWP fluctuated more significantly, ranging from 1.5 to 2.63 kg/m³, with the lowest values in 2021 corresponding to drought conditions and high temperatures. Comparison between field data and WaPOR satellite-based estimates revealed systematic underestimation by the portal, with GBWP and NBWP values underestimated by 40–50%, mainly due to differences in spatial resolution, input data quality, and algorithmic assumptions for evapotranspiration estimation, as well as its inability to capture localized agronomic practices such as crop rotation and irrigation scheduling. The study also identified uniform irrigation rates applied throughout the crop cycle, ignoring the dynamic water demands during different growth stages. This led to over-irrigation during maturity and under-irrigation during critical reproductive phases, exacerbating water stress under high temperatures. The findings emphasize the necessity of integrating precise field measurements with remote sensing data for accurate water productivity assessment. Implementing stage-specific irrigation management can optimize water use efficiency and maintain crop biomass production under varying climatic conditions. This research provides valuable insights for improving irrigation strategies and water resource management, contributing to agricultural resilience in water-scarce semi-arid environments facing climate variability.

Keywords: Water Efficiency, Remote Sensing, GBWP, NBWP, Evapotranspiration

Article Type: Research Article

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Citation: Azizi Mobaser, J., HeydariAlikamar, M., Amirzadeh, A., Kohan, M.R., Rasoulzadeh, A., Raoof, M., & Ramezani Moghadam, J. (2025). Estimating water productivity of center-pivot irrigation systems using the WaPOR (Case study: Moghan plain), Water and Soil Management and Modeling, 5(4), 174-190.
doi: 10.22098/mmws.2025.17934.1635
Received: 29 July 2025, Received in revised form: 11 September 2025, Accepted: 19 October 2025, Published online: 07 November 2025
Water and Soil Management and Modeling, Year 2025, Vol. 5, No. 4, pp. 174-190.
Publisher: University of Mohaghegh Ardabili

1. Introduction

Water scarcity is recognized as one of the fundamental challenges of the 21st century. According to the Food and Agriculture Organization of the United Nations (FAO), agriculture is both a major cause and a victim of water scarcity, accounting for approximately 70% of global water withdrawals (Hoekstra and Mekonnen, 2012; FAO, 2020). Climate change, population growth, and rising water demands across various sectors have intensified competition for limited water resources while also driving an increase in food demand by more than 40% (Feng et al., 2015). Consequently, adopting more efficient irrigation practices has become essential (Hanjra and Qureshi, 2010; Jägermeyr et al., 2016). Water scarcity impacts are especially severe in arid and semi-arid regions, where limited precipitation and high evapotranspiration rates exacerbate water stress (UNEP, 2021). These regions face intensified challenges in balancing water availability with agricultural and ecological demands, making efficient water management critical (World Bank, 2022).The concept of Water Productivity (WP) serves as a metric for evaluating the performance of both irrigated and rainfed agriculture. It is defined as the amount of biomass produced per unit of water consumed, which includes soil water available in the root zone between planting and harvest, in-season rainfall, and applied irrigation (Angus and Van, 2001). WP is recognized as a crucial indicator for evaluating irrigation performance and informing water resource management decisions (Molden et al., 2010; van Halsema and Vincent, 2012). Investigating water productivity provides essential insights into the efficiency of water utilization in agricultural production. This analysis facilitates the identification of opportunities for enhancing performance and optimizing resource management (Zwart and Bastiaanssen, 2004; Steduto et al., 2012). The accurate assessment of WP necessitates the availability of reliable data concerning both crop yield and water consumption; however, obtaining such data at a large scale often presents significant challenges (Karimi et al., 2013; Blatchford et al., 2020). To improve water productivity in agriculture, two primary strategies are typically employed: the initiation of new irrigation projects; and the optimization of existing irrigation systems through comprehensive performance evaluation (Torres-Cobo, 2024). Center pivot irrigation systems are widely used due to their uniform water distribution, automation, and higher efficiency compared to surface irrigation methods (O'Brien et al., 2010). Since their introduction in the 1950s, they have advanced through innovations such as variable-rate irrigation, precision water application, and integration with decision-support tools (McCarthy et al., 2014; Yari et al., 2017). However, actual field performance often falls short of its theoretical potential. This gap is attributed to factors such as suboptimal system design, operational inefficiencies, environmental variability, and poor management (Lamm et al., 2012; Trout and DeJonge, 2017). Traditional methods for assessing irrigation performance—based on field measurements—are time-consuming, expensive, and spatially limited (Burt et al., 1997; Perry, 2011). As a result, there has been growing interest in remote sensing technologies for evaluating irrigation performance over large areas and extended periods (Bastiaanssen et al., 2007; Irmak et al., 2011).

Recent advancements in remote sensing—particularly through models like SEBAL and METRIC—have greatly enhanced agricultural water management by enabling large-scale evaluation of water productivity using earth observation data. These methods offer high spatial and temporal resolution, allowing for detailed analysis across extensive agricultural landscapes (Al-Bakri et al., 2022). To support improved monitoring, the Food and Agriculture Organization (FAO) launched the Water Productivity Open-access Portal (WaPOR), which provides satellite-based data on key water balance components such as actual evapotranspiration and biomass production (FAO, 2018). By minimizing the need for field measurements, WaPOR facilitates cost-effective calculation of water productivity indicators (Chukalla et al., 2020; Blatchford et al., 2020). The portal offers data at three spatial resolutions—250 m, 100 m, and 30 m—to meet varying analytical needs (FAO, 2020). In a study conducted by Platonov et al. (2008), remote sensing technologies were utilized to assess water productivity in the Syr Darya Basin located in Central Asia. The results revealed that water productivity in this region ranged from 0 to 0.9 kg/m^3, with 55% of the area demonstrating water productivity levels below 0.30 kg/m^3. The authors underscored the importance of enhanced water resource management as a means to improve both water productivity and agricultural yields. Patil et al. (2014) conducted a comprehensive investigation into agricultural water productivity within desert farming systems in Saudi Arabia, utilizing remote sensing products. Their research employed the SEBAL model to estimate evapotranspiration and the NDVI index to assess crop yield. The findings indicated that water productivity for various crops ranged from 0.38 to 2.01 kg/m^3, showing moderate agreement between satellite-based estimates and field measurements. Franco et al. (2016) conducted an estimation of water productivity (WP) within watershed areas utilizing remote sensing data, the Monteith and SAFER models, as well as Landsat 8 imagery. Their study underscored that water productivity is influenced by varying spatial and temporal conditions and illustrated the effectiveness of remote sensing in accurately capturing these variations. The research conducted by Choudhury and Bhattacharya (2018) employed Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data to assess agricultural water productivity in India. This study utilized Gross Primary Production (GPP) and actual evapotranspiration (ETa) data to produce comprehensive maps illustrating water productivity and crop evapotranspiration levels across India from 2007 to 2012. The findings revealed that Agricultural Water Productivity (AWP) and Rainfall Water Productivity (RWP) exhibited values ranging from 1.10 to 1.30 kg/m³ and 0.94 to 1.00 kg/m³, respectively. More recently, Chiraz et al. (2022) demonstrated that water productivity in olive orchards varied significantly based on the cultivation system employed. Furthermore, remote sensing emerged as an effective methodology for assessing soil moisture and managing water productivity, thereby offering substantial potential for enhanced decision-making in agricultural water management. A recent study by Fakhar and Kaviani (2024) evaluated the WaPOR model across 16 provinces in Iran's four main climatic zones by comparing 10-day evapotranspiration estimates from WaPOR and the FAO-56 method. The highest agreement was observed in semi-arid regions ($R^2 = 0.95$, RMSE = 0.43). The analysis showed notable ET variations in the Caspian Sea and Zagros foothill areas between 2015 and 2022. Additionally, net blue water productivity in rainfed lands was strongly linked to precipitation. The results support WaPOR's reliability in estimating evapotranspiration and managing agricultural water use across diverse Iranian climates. Similarly, Safi et al. (2024) assessed SDG 6.4.1 in Lebanon, showing that WaPOR-based remote sensing data can effectively estimate agricultural water productivity by using actual evapotranspiration instead of water withdrawals. Despite differences in absolute values—mainly due to inconsistencies between WaPOR and AQUASTAT irrigated area data—the trends were consistent. WaPOR's focus on actually irrigated areas makes it a valuable tool for reliable SDG monitoring in agriculture. In another study, Veysi et al. (2024) utilized data from the FAO WaPOR portal to assess crop water productivity in a semi-arid basin in Iran. The findings revealed that conventional indicators such as GWP and NWP may not accurately reflect water productivity, highlighting the necessity of developing a dimensionless index for more precise identification of low-productivity areas and improved water resource management. Singh et al. (2024) employed the SETMI model in conjunction with remote sensing data to assess regional-scale water productivity for wheat crops in a semi-arid region of India. The results indicated considerable spatial and temporal variation in water productivity for wheat, with actual evapotranspiration estimates ranging from 101 mm to 325 mm. This methodology highlights the effectiveness of remote sensing in delivering reliable assessments of water productivity dynamics. Most recently, Mukandiwa et al. (2025) assessed crop water productivity (CWP) in the Chisumbanje sugarcane and Ratelshoek wheat farms of Zimbabwe was assessed using data from the WaPOR portal and the SEBS model. The results showed that actual evapotranspiration (ETa) reached 9 mm/day in the summer and 3.98 mm/day in the winter. Additionally, crop water productivity for wheat ranged from 2.4–3.0 kg/m³, while for sugarcane it ranged from 1.2–1.6 kg/m³.

The Moghan Plain is one of the most important agricultural areas of Iran since the northwest of Iran is characterized by strategic crops of silage maize, wheat, and sugar beet. The region has good soils and a fairly level topography, making mechanized agriculture possible and modern methods of irrigation, especially center pivot irrigation. Nonetheless, notwithstanding these benefits, the region is severely affected by changes in semi-arid weather, which is characterized by both its low amounts of rainfall of unequal distribution, high evapotranspiration levels, and a rising rate of drought occurrences. With these climatic factors and unsustainable water resource management policies--including excessive extraction of groundwater and standard irrigation timings that fail to factor in the varying needs of different crops-scarce water resource management issues come to the fore, jeopardizing the sustainability of long-term agricultural practices. These challenges make the Moghan Plain an ideal case study for evaluating and improving irrigation water productivity (Nazari et al., 2018; Choopan and Emami, 2020; Akhavan et al., 2021; Abdiaghdam Laromi et al., 2024).

In this context, the current research endeavors to estimate the water productivity of center pivot irrigation systems utilizing data sourced from the WaPOR portal within the Moghan Plain region. Furthermore, the study aims to evaluate the existing water productivity gap in the designated study area.

2. Materials and Methods

2.1. Study Area

The study area is geographically located within the Moghan Irrigation Scheme in Parsabad County, Ardabil Province, where forage maize is the primary cultivated crop (Figure 1). Due to its geographical position and access to surface water resources, this region is organized as one of Iran's most important agricultural and livestock production zones, playing a significant role in national crop production, particularly maize. It is among the largest surface-water-based irrigation projects in the country. The total area covered by the Moghan Irrigation Scheme is approximately 40,000 hectares. This scheme is situated between the Aras and Balharoud rivers, and its water resources are utilized to irrigate agricultural lands. Based on the De Martonne aridity index (Equation 1), calculated using long-term average annual precipitation (269.13 mm) and mean annual temperature (15.92 °C), the climate of the region is classified as semi-arid, consistent with previous studies (Dinpashoh and Allahverdipour, 2025). Climatic conditions in the region are characterized by notable variability in temperature and precipitation, with annual averages illustrated in Figure 2 for the period 2020–2024. Detailed soil and crop characteristics, including soil texture, cultivated area, field capacity, and wilting point moisture content for forage maize fields, are provided in Table 1.

$$I = \frac{P}{(T + 10)} \tag{1}$$

Where:
I = Aridity Index (De Martonne);
P = Mean annual precipitation (mm);
T = Mean annual temperature (°C).

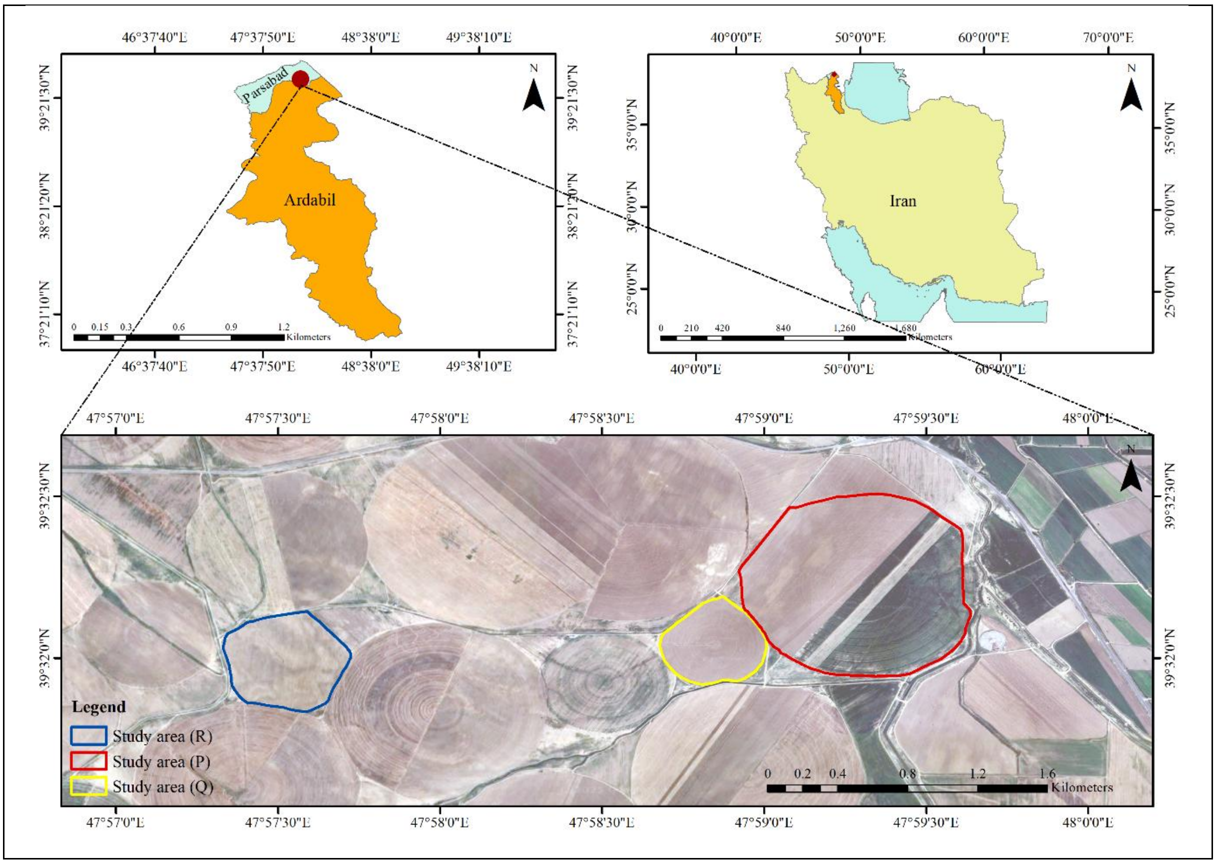

Figure 1- Geographical location of the study area

Table 1. Detailed soil and crop specifications for the forage maize fields.

Farm Name	Crop Type	Area Under Cultivation (hectares)	Soil Texture	Planting Date	Harvest Date	Field Capacity (%)	Wilting Point Moisture (%)
P	Forage Maize	82.96	Silty Clay	First Decade of July	First Decade of October	32.9	21
Q	Forage Maize	14.25	Silty Clay	First Decade of July	First Decade of October	31.5	22
R	Forage Maize	21.22	Silty Clay	First Decade of July	First Decade of October	32	20

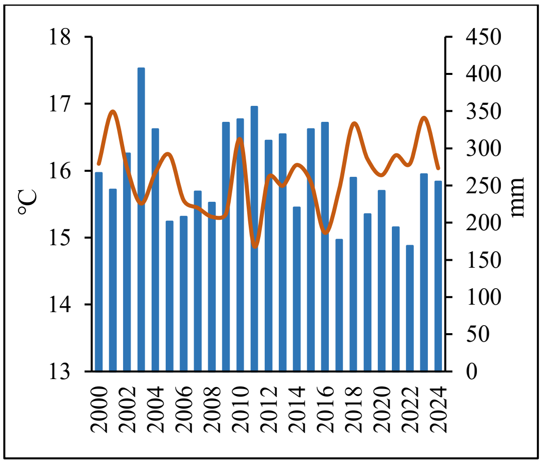

Figure 2- Average annual temperature and precipitation levels in the study area (2020-2024)

2.2. WaPOR Portal

WaPOR v3 represents the third iteration of the Food and Agriculture Organization's Water Productivity Open-access Portal, delivering comprehensive remotely sensed data on water productivity and evapotranspiration across agricultural landscapes in Africa and the Near East (FAO, 2020a). This significantly enhanced version offers improved methodological frameworks, expanded geographical coverage, and multi-scale spatial resolutions: continental (250m), national (100m), and subnational (30m), with temporal resolutions ranging from dekadal to annual assessments (FAO, 2020b; Chukalla et al., 2022). The computational infrastructure of WaPOR v3 leverages Google Earth Engine's cloud computing capabilities to process extensive multi-sensor satellite imagery from platforms including MODIS (MOD09GQ, MOD09GA), Landsat-7/8 (ETM+, OLI), and Sentinel-2 (MSI), applying the physically-based ETLook algorithm for actual evapotranspiration estimation and a Monteith light use efficiency framework for biomass production calculations (Blatchford et al., 2020; FAO, 2020c; Mul et al., 2021). The platform employs a rigorous validation protocol against flux tower measurements and field observations, achieving improved accuracy metrics compared to previous versions with RMSE values below 0.8 mm/day for daily ET estimations and R^2 values exceeding 0.85 for seasonal assessments (FAO, 2022). This comprehensive database spans from 2009 to the present, facilitating sophisticated analyses of key biophysical indicators across various agroecological zones and hydrological basins, providing an essential scientific foundation for evidence-based agricultural water management, irrigation system efficiency evaluation, and climate adaptation policy formulation (Mul and Bastiaanssen, 2019; Chukalla et al., 2023).

In the present study, the WaPOR v3 portal was used at the national (100m) resolution to quantify Gross Biomass Water Productivity (GBWP) and Net Biomass Water Productivity (NBWP), as well as to estimate water productivity gaps.

2.3. Gross Biomass Water Productivity (GBWP)

Gross Biomass Water Productivity (GBWP) quantifies the relationship between biomass production output and total water consumption over a specified period (FAO, 2016a). This indicator, calculated as the ratio of Total Biomass Production (TBP) to the sum of soil evaporation, canopy transpiration, and interception, offers critical insights into how vegetation development affects consumptive water use and overall water balance within agricultural systems (Allen et al., 1998; Steduto et al., 2007; Seijger et al., 2023). The Food and Agriculture Organization makes GBWP data available through the Water Productivity Open Access Portal (WaPOR) on a seasonal basis at different spatial resolution levels, while also enabling user-defined temporal aggregations through dekadal Net Primary Productivity data (FAO, 2020). GBWP is calculated using equation (2):

$$\mathrm{GBWP} = \frac{\mathrm{TBP}}{(\mathrm{E} + \mathrm{T} + \mathrm{I})} \tag{2}$$

where, TBP represents Total Biomass Production in kgDM/ha, and E, T, and I represent soil evaporation, canopy transpiration, and interception in mm, respectively. This approach enables assessment of water use efficiency in agricultural systems by relating biomass accumulation to water consumption, supporting evidence-based decision making for sustainable water resource management (Molden et al., 2010; Mul and Bastiaanssen, 2019).

2.4. Net Biomass Water Productivity (NBWP)

Net Biomass Water Productivity (NBWP) quantifies the relationship between total biomass production and the volume of water beneficially consumed through canopy transpiration, excluding soil evaporation (FAO, 2016a). Unlike Gross Biomass Water Productivity, NBWP specifically focuses on monitoring how effectively vegetation (particularly crops) utilizes water for biomass development and yield production, making it a valuable indicator for agricultural water management assessment (Steduto et al., 2007; Kijne et al., 2003). The Food and Agriculture Organization provides NBWP data through the Water Productivity Open Access Portal (WaPOR) on a seasonal basis at spatial resolution levels 2 and 3, with options for user-defined temporal aggregations using dekadal input data (FAO, 2020). NBWP is calculated using equation (3):

$$\mathrm{NBWP} = \frac{\mathrm{TBP}}{\mathrm{T}} \quad (3)$$

where, TBP represents Total Biomass Production in kgDM/ha and T represents transpiration in mm. This calculation requires input data on total biomass production, transpiration, and phenology (when calculated on a seasonal time-step), without necessitating external data sources (Bastiaanssen et al., 2012; Mul and Bastiaanssen, 2019). By isolating transpiration from other water consumption components, NBWP provides a more precise measure of plant water use efficiency, supporting targeted interventions in agricultural water management systems.

2.5. Actual Evapotranspiration and Interception (ETIa)

The ETIa-WPR model is based on a modified version of the ETLook model, known as ETLook-WaPOR (Bastiaanssen et al., 2012; Pelgrum et al., 2012). This model employs a remote sensing-based Penman-Monteith approach to estimate actual evapotranspiration (ETa), which is also the method adopted by FAO and detailed in the FAO-56 Irrigation and Drainage guidelines (Allen et al., 1998). In ETIa-WPR, soil evaporation and plant transpiration are estimated separately using specific equations, while the interception component is calculated as a function of vegetation cover, leaf area index (LAI), and precipitation (PCP). Ultimately, ETIa-WPR is computed as the sum of evaporation, transpiration, and rainfall interception.

$$\lambda E = \frac{\Delta\left(R_{n,soil} - G\right) + \dfrac{\rho_{air} C_p (e_{sat} - e_a)}{r_{a,soil}}}{\Delta + \gamma\left(1 + \dfrac{r_{s,soil}}{r_{a,soil}}\right)} \quad (4)$$

$$\lambda T = \frac{\Delta\left(R_{n,canopy}\right) + \dfrac{\rho_{air} C_p (e_{sat} - e_a)}{r_{a,canopy}}}{\Delta + \gamma\left(1 + \dfrac{r_{s,canopy}}{r_{a,canopy}}\right)} \quad (5)$$

A summary of all variables, their definitions, and units used in Equations 4–7 of the ETIa-WPR model is provided in Table 2. Evaporation (E) and transpiration (T) are expressed in units of $kg.m^{-2}.s^{-1}$, while λ denotes the latent heat of vaporization ($J.kg^{-1}$). Net radiation (Rn) is partitioned into soil (Rn, soil) and canopy (Rn, canopy) components, each measured in $MJ.m^{-2}.day^{-1}$. Ground heat flux is represented by G ($MJ.m^{-2}.day^{-1}$). The air density (ρ_{air}) is given in $kg.m^{-3}$, and the specific heat capacity of air (C_P) is expressed in $MJ.kg^{-1}.°C^{-1}$. The vapor pressure deficit (VPD), calculated as the difference between saturated and actual vapor pressures ($e_{sat} - e_a$), is measured in kPa. Aerodynamic resistance (r_a) and surface resistance (r_s) are expressed in $s.m^{-1}$, where r_s corresponds to either soil or canopy resistance, depending on whether evaporation or transpiration is being estimated using the Penman-Monteith (PM) model. The slope of the saturation vapor pressure curve with respect to air temperature is denoted by Equation 5 ($kPa \cdot °C^{-1}$), and γ is the psychrometric constant ($kPa \cdot °C^{-1}$).

$$\Delta = \frac{d(esat)}{dT} \quad (6)$$

This approach decomposes the ETIa-WPR into its constituent components—evaporation and transpiration—using modified formulations of the PM equation. These formulations distinguish net available radiation and resistance terms based on vegetation cover, in alignment with the ETLook model framework (Bastiaanssen et al., 2012). A key distinction between the ETLook-WaPOR model and the original ETLook model lies in the source of remote sensing data used for soil moisture estimation. Whereas the original ETLook utilized passive microwave data, the WaPOR approach derives soil moisture from a model combining land surface temperature (LST) and vegetation indices (Wang, 2012). Additionally, the Normalized Difference Vegetation Index (NDVI) is employed to partition Rn into Rn, soil, and Rn, canopy, and to support the estimation of rainfall interception, ground heat flux, and minimum stomatal resistance. Interception (I) refers to the fraction of rainfall that is captured by the plant canopy and subsequently evaporates directly from the leaf surface, thereby reducing the energy available for transpiration. It is expressed in mm/day and modeled as a function of vegetation cover, leaf area index (LAI), and precipitation (PCP). This process is critical in energy balance assessments, as it represents a distinct component of evapotranspiration that does not contribute to plant water use.

$$\mathrm{I} = 0.2 I_{LIA}\left(1 - \frac{1}{1 + \dfrac{C_{veg} PCP}{0.2 I_{LIA}}}\right) \quad (7)$$

Table 2. Definitions and units of variables used in the ETIa-WaPOR model (Equations 3–6).

Variable	Description	Unit
E	Evaporation	$kg.m^{-2}.s^{-1}$
T	transpiration	$kg.m^{-2}.s^{-1}$
λ	the latent heat of vaporization	$J.kg^{-1}$
Rn, soil	Net radiation partitioned into soil components	$MJ.m^{-2}.day^{-1}$
Rn, canopy	Net radiation partitioned into canopy components	$MJ.m^{-2}.day^{-1}$
G	Ground heat flux	$MJ.m^{-2}.day^{-1}$
ρ_{air}	air density	$kg.m^{-3}$
C_P	Specific heat capacity of air	$MJ.kg^{-1}.°C^{-1}$
e_{sat}	saturated vapor pressures	kPa
e_a	actual vapor pressures	kPa
Ra, soil	Aerodynamic resistance of soil	$s.m^{-1}$
Ra, canopy	Aerodynamic resistance of the canopy	$s.m^{-1}$
Rs, soil	Surface resistance of soil	$s.m^{-1}$
Rs, canopy	Surface resistance of the canopy	$s.m^{-1}$
Δ	slope of the saturation vapor pressure curve with respect to air temperature	$kPa.°C^{-1}$
γ	psychrometric constant	$kPa.°C^{-1}$
I	Rainfall interception by the canopy	$mm.day^{-1}$
LAI	Leaf Area Index	-
C_{veg}	Fractional vegetation cover	-
PCP	Daily precipitation	$mm.day^{-1}$

2.6. Water Productivity Gap

The water productivity gap defines the difference between the potential or the optimum productivity of water that can be obtained in the field under ideal agronomic and environmental conditions and the realized water productivity under the existing field conditions. Production of water. (WP) is computed as an output divided by the amount of water used, normally expressed as actual evapotranspiration, also known as (ETa). In this study, the water productivity gap (WP_{gap}) was calculated in a systematic solicitation of actual water productivity values (WP_{actual}) and ideal water improvement standards ($WP_{optimal}$) in the form of Equation (8) (Zheng et al., 2018):

$$WP_{gap} = WP_{optimal} - WP_{actual} \tag{8}$$

where, WP_{gap} is the water productivity gap, representing the shortfall from the potential, expressed in $kg{\cdot}m^3$; WP_{actual} is the actual water productivity measured under existing field, management, and climatic conditions; and $WP_{potential}$ is the optimal or potential water productivity attainable under best management practices and favorable environmental conditions.

Within the frame of this study, WP_{actual} was obtained by measurements of field-observed crop yields and remotely sensed ETa and was a representation of the current on-farm practice and specific site environment limitations. On the other hand, $WP_{optimal}$ was derived in terms of literature-reported benchmarks and in terms of simulation product under high-yielding cultivar, high-quality agronomical management, non-limiting soil fertility, and limited water supply. The discrepancy between these two values gives an evidence-based estimate of the unrealized water use efficiency, hence, lines up opportunities to intervene in a specific area like efficient irrigation scheduling, deficit irrigation technique, or precision water management.

3. Results and Discussion

3.1. Evaluation of NBWP and GBWP Based on WAPOR Portal Data

This analysis is based on a comparative evaluation of Net Biomass Water Productivity (NBWP) and Gross Biomass Water Productivity (GBWP) across agricultural lands P, Q, and R from 2020 to 2024 (Table 3), utilizing tabulated productivity values along with associated temperature and precipitation data (Figure 3). The results reveal significant trends influenced by environmental conditions and water management practices. During this period, NBWP increased steadily in all three fields, while GBWP exhibited more fluctuations, likely due to variations in rainfall, temperature, and irrigation practices (Figure 4-5).

Table 3. Yearly values of GBWP and NBWP (kg/m^3) for agricultural fields P, Q, and R during 2020–2024.

Year	P		Q		R	
	GBWP (Kg/m^3)	NBWP (Kg/m^3)	GBWP (Kg/m^3)	NBWP (Kg/m^3)	GBWP (Kg/m^3)	NBWP (Kg/m^3)
2020	1.97	2.42	1.84	2.40	2.47	3.15
2021	1.50	2.25	1.54	2.30	1.46	2.12
2022	2.29	3.07	2.42	3.35	1.28	2.89
2023	2.33	3.09	2.63	3.61	2.50	3.56
2024	2.07	3.03	2.45	3.33	2.71	3.55

In Field P, NBWP rose from 2.42 to 3.03 kg/m³, indicating a 25% increase. This improvement may be attributed to enhanced irrigation efficiency or reduced water losses. However, a notable drop in GBWP in 2021 (down to 1.5 kg/m³), coinciding with the lowest recorded rainfall (10 mm), suggests a direct impact of drought or elevated temperatures. By 2023, with rainfall reaching 60 mm, NBWP improved to 3.09 kg/m³, confirming the role of

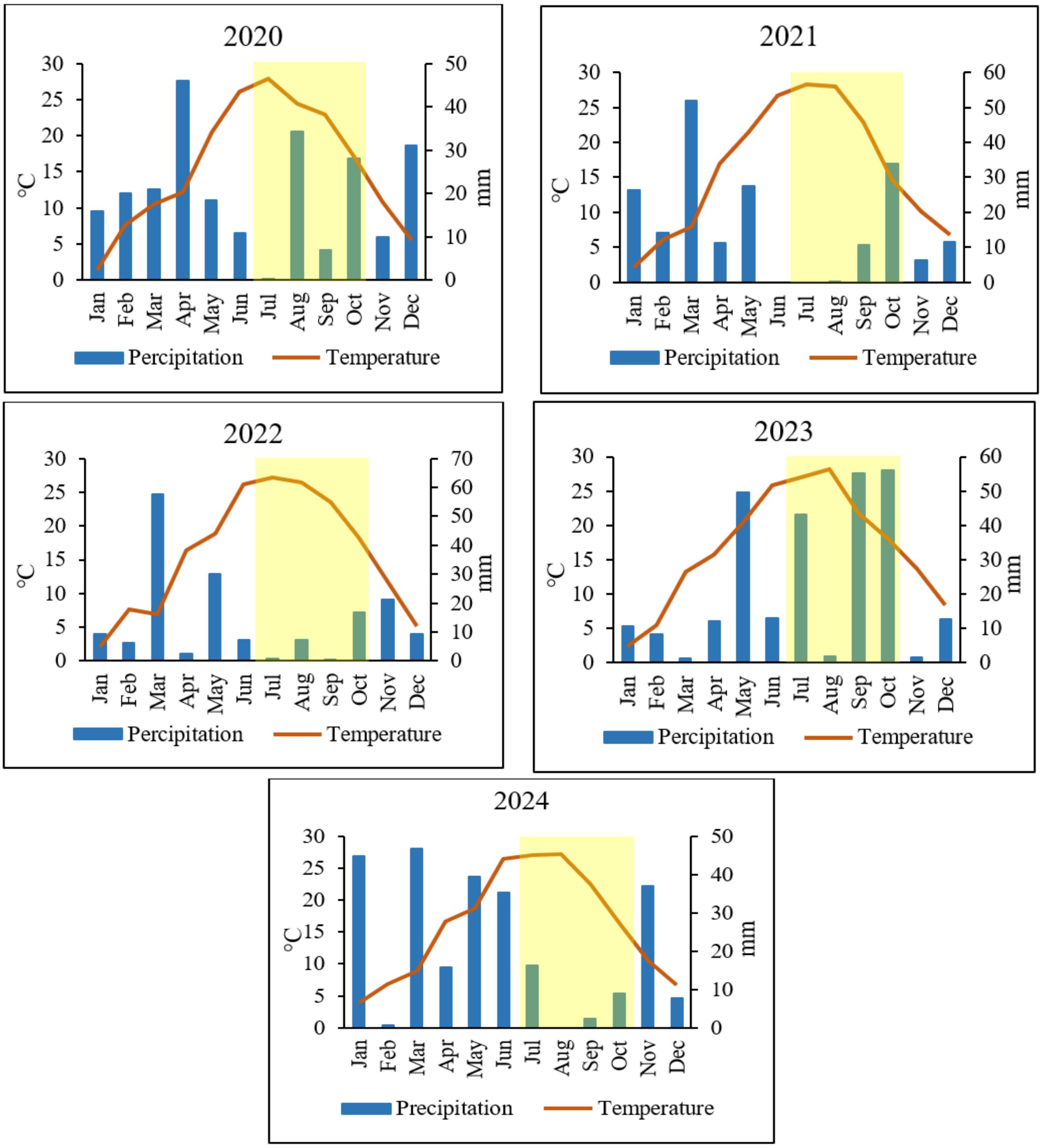

Figure 3 – Temperature and precipitation trends: a five-year analysis (2020–2024), with yellow highlights indicating the crop growth period

favorable environmental conditions in enhancing water productivity.

Field Q experienced the highest increase in NBWP, rising from 2.40 kg/m³ in 2020 to 3.33 kg/m³ in 2024 (a 39% increase). This upward trend likely reflects a better adaptation to environmental conditions and the adoption of advanced irrigation technologies. In 2023, under the highest recorded temperature (25°C) and substantial rainfall (60 mm), NBWP peaked at 3.61 kg/m³, highlighting how optimal temperature and moisture balance can maximize water use efficiency. Nonetheless, the GBWP drop in 2021 (to 1.54 kg/m³) underscores this field’s sensitivity to sudden climatic variations.

Field R demonstrated the greatest responsiveness to rainfall variability. In 2021, with rainfall dropping to 10 mm, NBWP declined to 2.12 kg/m³—the lowest value among all fields during the study period—

highlighting the need for targeted drought management. However, by 2023, with rainfall improving to 60 mm, NBWP recovered sharply to 3.56 kg/m³, revealing the field's high recovery potential under adequate water availability. Interestingly, NBWP declined in 2022 (2.89 kg/m³) despite moderate rainfall and temperature, possibly due to secondary stress factors like pest outbreaks or reduced soil quality.

Satellite imagery showing the spatial and temporal variations of NBWP and GBWP across fields P, Q, and R supports the conducted analyses (Figures 6-7). Figure 6 illustrates the spatial and temporal dynamics of GBWP, ranging from 0.7 to 3.1 kg/m³, while Figure 7 depicts NBWP variations ranging from 1.5 to 6.7 kg/m³. These figures highlight field-specific and inter-annual differences in biomass water productivity, complementing the meteorological data shown in Figure 3.

Temperature and precipitation data presented in Figure 3 were obtained from the Parsabad-Moghan Meteorological Station, with temperature in °C and precipitation in mm, providing the climatic context for analyzing the trends in GBWP and NBWP.

The gap between NBWP and GBWP also reveals insights into hidden water losses. For instance, in Field Q during 2023, the notable difference between GBWP (2.63) and NBWP (3.61) may indicate reduced evaporation losses or improved water retention due to efficient drainage systems. In contrast, Field P in 2024 shows a narrower gap (GBWP = 2.07, NBWP = 3.03), possibly reflecting new limiting factors such as soil salinity or thermal stress.

The year 2021 emerges as a critical turning point across all fields, where decreased rainfall and possibly higher temperatures led to simultaneous drops in both NBWP and GBWP. Field R was most affected, with NBWP falling to its lowest level (2.12 kg/m³), emphasizing the need for robust drought mitigation strategies. Conversely, 2023—characterized by high rainfall and optimal temperatures—marked a peak in water productivity for Fields Q and R, suggesting that environmental balance is key to maximizing efficiency.

Consistent with the findings reported by Parchami-Araghi et al. (2022), who analyzed physical water productivity (WPI) for soybean in the downstream sectors of the Moghan irrigation network and reported average values around 0.42 kg/m³. Their results confirm that improved irrigation scheduling and reduced water losses significantly enhance water use efficiency under semi-arid conditions similar to the current study area. In a recent assessment by Akhavan Giglou et al. (2023), the physical and economic water productivity of major crops such as silage maize, cotton, and tomato was evaluated across the Moghan plain. They concluded that biomass water productivity was highly sensitive to inter-annual climatic variability and management decisions, which aligns with the GBWP fluctuations observed in our Fields P, Q, and R. Moreover, Farahza et al. (2020) demonstrated that the adoption of modern irrigation systems (e.g., sprinkler and drip) in the Moghan region led to simultaneous improvements in both physical and economic water productivity. These findings support the upward NBWP trend observed in Field Q, likely due to the implementation of advanced water management technologies during the study period.

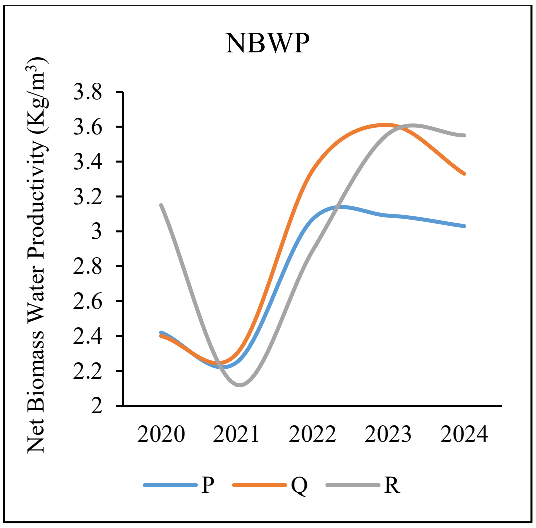

Figure 4- NBWP (Kg/m³) for Agricultural fields P, Q, and R between (2020-2024)

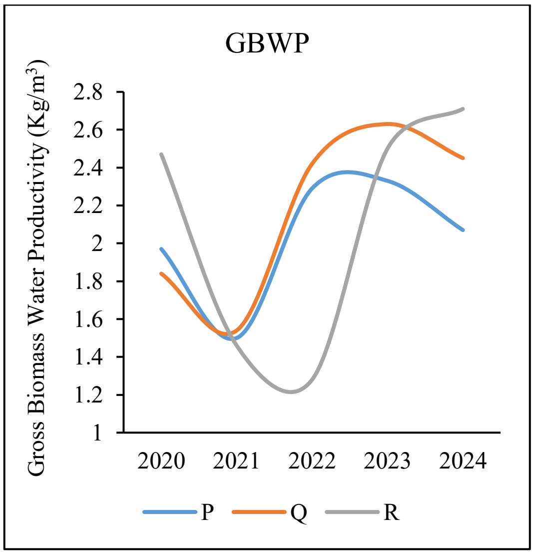

Figure 5- GBWP (Kg/m³) for agricultural fields P, Q, and R (2020-2024)

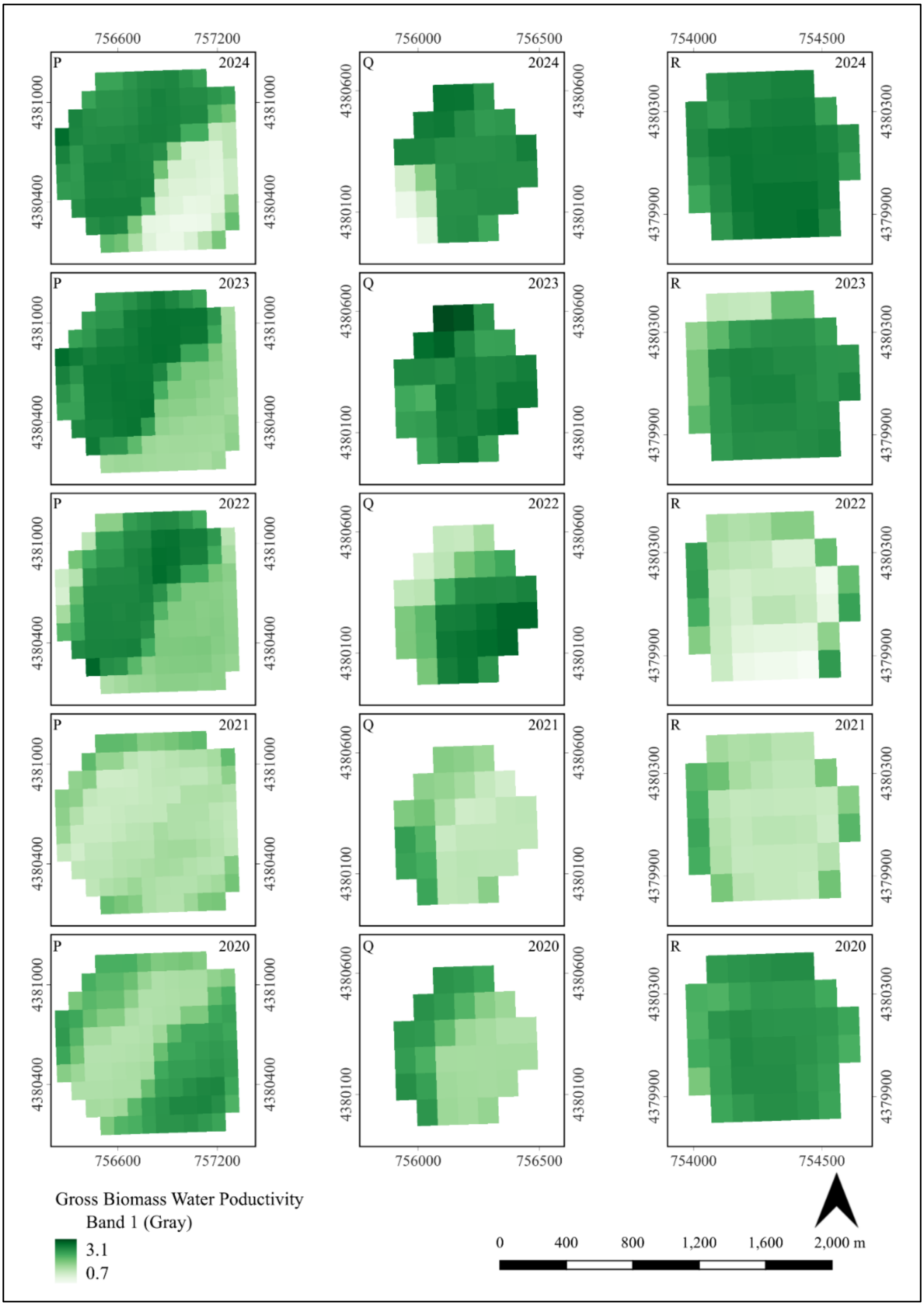

Figure 6- Spatial and temporal dynamics of GBWP in agricultural fields P, Q, and R (2020–2024)

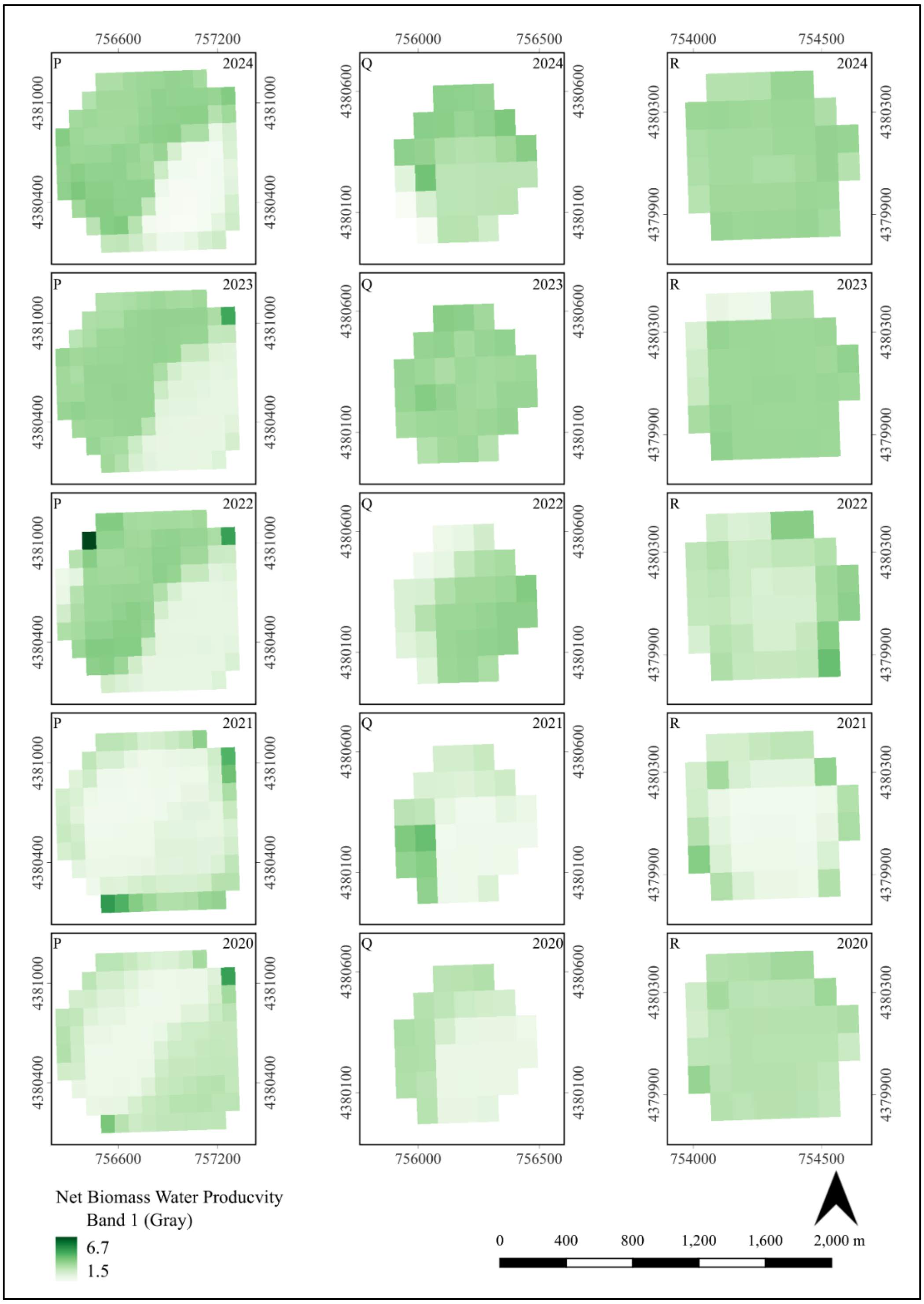

Figure 7- Spatial and temporal dynamics of NBWP in agricultural fields P, Q, and R (2020–2024)

3.2. Water Productivity Gap

A comparative analysis of Gross and Net Biomass Water Productivity (GBWP and NBWP) across the three agricultural centers (P, Q, and R), based on both ground-based measurements and WaPOR estimations, reveals consistent and significant discrepancies (Tables 4, 5, and 6). In all years from 2020 to 2024, GBWP values calculated from field data were consistently higher than those estimated by WaPOR. For instance, in 2024, the measured GBWP in field Q was 5.49 kg/m³, while the WaPOR estimate for the same field and year was only 2.45 kg/m³ (Table 5). A similar pattern was observed in NBWP, where field-based values ranged between 4.17 and 5.71 kg/m³, while WaPOR estimations remained between 2.12 and 3.61 kg/m³ (Table 6).

Table 4. Field-based irrigation and yield parameters for maize cultivation in selected agricultural centers

Farm Name	Irrigation Water Depth (mm)	Covered Area (ha)	Maize Yield (Kg)	Previous Crop Before Maize
P	552.41	82.95	2488726.32	Wheat
Q	234.69	14.24	480797.978	Canola
R	268.32	22.89	384638.382	Wheat

Table 5. Comparison of measured and WaPOR portal GBWP values for fields P, Q, and R (kg/m³) from 2020 to 2024

YEAR	P (Kg/m^3)		Q (Kg/m^3)		R (Kg/m^3)	
	Measured	WaPOR Portal	Measured	WaPOR Portal	Measured	WaPOR Portal
2020	4.86	1.97	5.47	1.84	4.38	2.47
2021	4.62	1.50	5.20	1.54	4.16	1.46
2022	4.57	2.29	5.14	2.42	4.11	1.28
2023	4.35	2.33	4.89	2.63	3.91	2.50
2024	4.88	2.07	5.49	2.45	4.39	2.71

Table 6. Comparison of measured and WaPOR portal NBWP and WP Gap values for fields P, Q, and R (kg/m³) from 2020 to 2024

YEAR	P (Kg/m^3)				Q (Kg/m^3)				R (Kg/m^3)			
	NBWP		WP Gap		NBWP		WP Gap		NBWP		WP Gap	
	Measured	WaPOR	Measured	WaPOR	Measured	WaPOR	Measured	WaPOR	Measured	WaPOR	Measured	WaPOR
2020	5.02	2.42	4.98	7.58	5.65	2.4	4.35	7.60	4.52	3.15	5.48	6.85
2021	4.63	2.25	5.37	7.75	5.21	2.3	4.79	7.70	4.17	2.12	5.83	7.88
2022	4.62	3.07	5.38	6.93	5.19	3.35	4.81	6.65	4.15	2.89	5.85	7.11
2023	4.81	3.09	5.19	6.91	5.41	3.61	4.59	6.39	4.33	3.56	5.67	6.44
2024	5.13	3.03	4.87	6.97	5.71	3.33	4.29	6.67	4.62	3.55	5.38	6.45
Mean	**4.84**	**2.77**	**5.16**	**7.23**	**5.43**	**3.00**	**4.57**	**7.00**	**4.36**	**3.05**	**5.64**	**6.95**

To calculate the water productivity gap (Equation 7), first, the potential water productivity was calculated. According to the field data, the highest yield of 70 ton/ha was recorded with the T-type irrigation system, with an efficiency of 90% and a water consumption of 7000 m^3/ha. Therefore, in the potential case, the water productivity value was obtained as 10 kg/m^3. Considering the potential productivity, the productivity gap was calculated. The results showed that the water productivity gap for the measured data in the P, Q and R farms was 5.16, 4.57 and 5.64 kg/m^3, respectively, and for the data extracted from the WaPOR Portal for the P, Q and R farms, the values were 7.23, 7 and 6.95 kg/m^3, respectively (Table 6) .These discrepancies stem from fundamental differences in data sources and methodological approaches. Field-based measurements rely on direct records of irrigation water depth, cultivated area, and actual harvested yield (Table 4), thereby reflecting localized agronomic management such as crop rotation, irrigation frequency, and fertilization practices. For example, field Q, which consistently showed the highest water productivity, followed a canola–maize rotation—a practice widely recognized to improve soil health and enhance nutrient and water uptake. Such agronomic details are rarely captured in remote sensing–based models like WaPOR. Conversely, WaPOR relies on medium-resolution satellite imagery and bio-physical modeling, which inherently apply spatial and temporal averaging. While this ensures regional consistency and enables large-scale assessments, it often overlooks farm-level management heterogeneity, leading to an underestimation of actual water productivity. The discrepancy may also be exacerbated by differences in evapotranspiration estimation techniques, the use of generalized crop coefficients, and the static nature of some WaPOR input layers. Notably, temporal trends of field-based GBWP and NBWP values remained relatively stable across the five years, while WaPOR-derived values exhibited a more variable and increasing trend. This divergence could result from annual updates in WaPOR algorithms or climatic changes influencing satellite-based evapotranspiration estimates. However, considering that local agronomic practices remained largely consistent during the study period, field-based data likely provide a more reliable representation of true productivity performance.

The observed productivity gap is not unique to this study. Recent investigations support similar findings. For example, Blatchford et al. (2020) emphasized the limitations of coarse-resolution remote sensing in accurately capturing water productivity at the plot scale. Additionally, Patil et al. (2015) highlighted the importance of integrating field observations with Earth observation data to reduce uncertainty in productivity assessments across diverse agroecosystems.

3.3. Assessment of Portal-Based Estimates versus Observed Field Data

In plot P, a uniform irrigation depth of 55.24 mm per 10-day period appears adequate and well-aligned with crop water requirements during early development (vegetative and rapid leaf expansion stages, mid-June to early July). This is supported by high ETIa (41.97 mm) and Water Stress Coefficients (WSC) values (>1.5), which resulted in a favorable GBWP of 1.97 kg/m³ in 2020. However, as the season progressed into July–August (tasseling and ear formation), crop water demand gradually declined, yet the irrigation rate remained unchanged. With evapotranspiration (ETc) slightly dropping and day temperatures rising (above 24.5 °C), this resulted in marginal over-irrigation during late reproductive stages, possibly increasing non-beneficial losses and contributing to a GBWP drop in 2021 to 1.50 kg/m³ despite consistent irrigation.

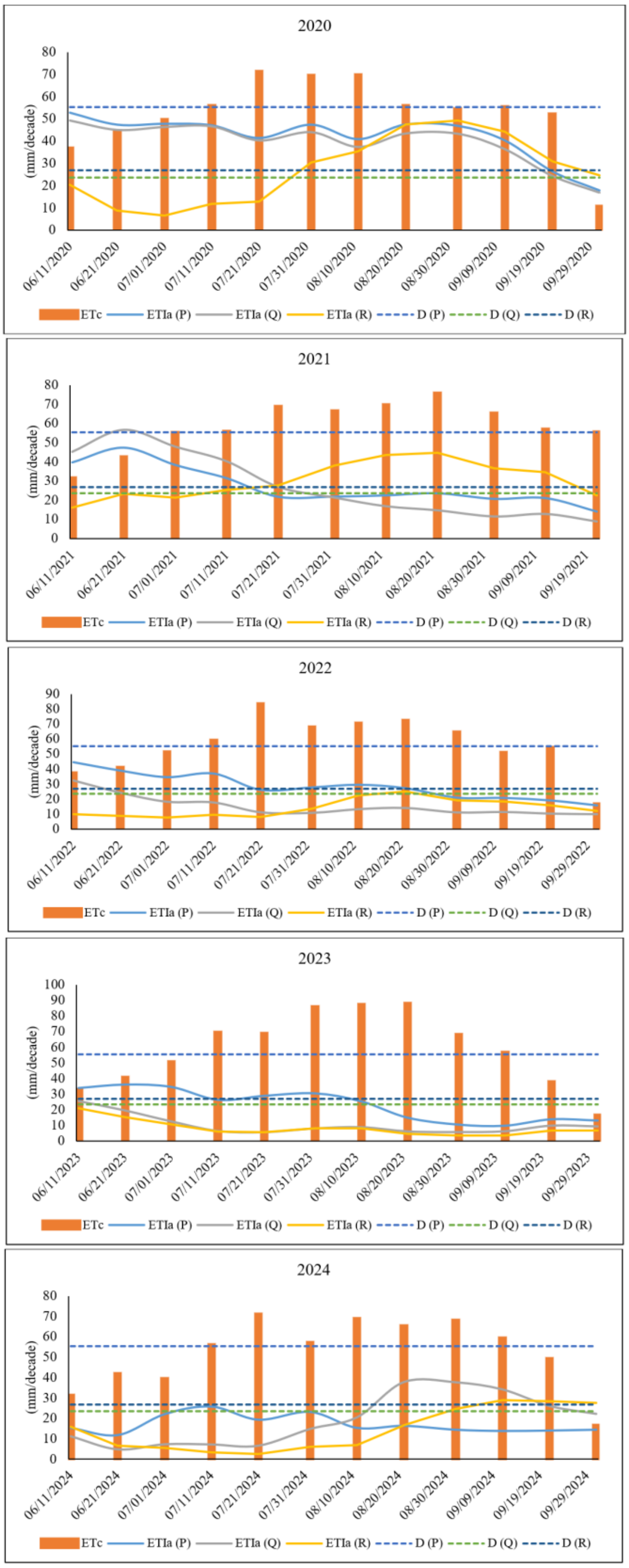

Figure 8 – Annual comparison of measured ETc, portal-based ETIa, and decadal irrigation water depth across fields P, Q, and R (2020–2025)

In contrast, plot Q received only 23.47 mm of irrigation per 10 days—sufficient for early growth but inadequate during mid-to-late season, especially during the reproductive phase when ETc surpassed 50 mm. This under-irrigation, combined with elevated temperatures (~25 °C in July 2021), likely limited photosynthetic efficiency and biomass accumulation. As a result, ETIa dropped below 20 mm in several decades, and GBWP declined to 1.54 kg/m³ in 2021, while NBWP followed a slower recovery trend despite improved weather conditions in subsequent years. Plot R, irrigated with 26.83 mm per 10-day period, exhibited similar constraints. While this amount may have met early-season requirements, it failed to match peak ETc demands during tasseling and grain-filling stages (July–August), which coincided with hot and dry weather. Consequently, actual crop water uptake (ETIa) remained suboptimal, particularly in 2021, where NBWP dropped to its minimum (2.12 kg/m³), indicating acute water stress. Recovery in GBWP and NBWP was observed in 2023, likely due to enhanced rainfall (60 mm) and moderate temperatures (~23 °C), which helped mitigate irrigation shortfalls.

A key observation is that none of the plots implemented stage-specific irrigation. Fixed irrigation rates across all decades ignored the bell-shaped curve of crop water demand, leading to inefficiencies—over-irrigation during physiological maturity (e.g., September) and under-irrigation during peak demand periods (mid-season). The absence of flexible scheduling likely suppressed yield potential and water productivity, especially under heat stress conditions where crops require tightly controlled moisture regimes to maintain stomatal function and assimilate production.

Conclusion

This study conducted a comprehensive comparative analysis of Net and Gross Biomass Water Productivity (NBWP and GBWP) across three agricultural fields (P, Q, and R) over five growing seasons (2020–2024), incorporating both ground-based measurements and WaPOR remote sensing estimates. The findings reveal clear inter-annual and spatial variability in water productivity, closely influenced by irrigation scheduling, rainfall patterns, temperature fluctuations, and crop management practices such as rotation. While NBWP showed a consistent upward trend in all fields—especially in Field Q, where advanced irrigation techniques and a canola–maize rotation contributed to sustained gains—GBWP was more sensitive to climatic extremes and non-optimized water use. The year 2021 emerged as a critical turning point marked by simultaneous declines in both GBWP and NBWP due to limited rainfall and elevated temperatures. Conversely, 2023 presented optimal climatic conditions, leading to productivity recovery, particularly in Fields Q and R. The comparison between WaPOR estimates and field-derived data highlighted a significant water productivity gap, with satellite-derived GBWP and NBWP values consistently underestimating actual productivity by up to 50% or more. This discrepancy is primarily attributed to the coarse spatial resolution, static model assumptions, and inability of WaPOR to capture localized agronomic nuances, such as stage-specific irrigation or soil fertility variations. Nonetheless, WaPOR's consistent structure offers valuable insights for regional-scale assessments and long-term monitoring. Moreover, the analysis of decade-wise irrigation depth emphasized the limitations of uniform irrigation scheduling. Fixed irrigation rates failed to meet dynamic crop water requirements, leading to either over-irrigation in late-season stages or water stress during peak demand phases (tasseling and grain filling), especially under high-temperature conditions. These mismatches likely suppressed both biomass production and water use efficiency. In conclusion, this study underlines the critical need for integrated irrigation scheduling, climate-adaptive management, and field-calibrated remote sensing approaches to bridge the productivity gap and enhance sustainable water use. These should be implemented in a practical manner based on smart irrigation (e.g., based on soil moisture sensors, variable rate irrigation, automated delivery systems), precision agriculture tools (e.g., various UAV-based capabilities to monitor crops and implement site-specific nutrient applications), and stage-based plans of allocating water. Adoption of these measures can improve the accuracy of water productivity assessments, increase resource-use efficiency, and strengthen the resilience of agroecosystems in semi-arid regions such as Moghan.

Authors' contribution

Javanshir AziziMobaser: Writing - original draft preparation
Mahsa Heydari-Alikamar: Resources, Software, Manuscript editing
Arash Amirzadeh: Formal analysis and investigation
Mohammad Reza Kohan: Formal analysis and investigation
Ali Rasoulzadeh: Conceptualization, methodology
Majid Raoof: Final Rewriting
Javad Ramezani Moghadam: Visualization, Supervision

Conflicts of interest

The authors of this article declared no conflict of interest regarding the authorship or publication of this article.

Data Availability Statement

The datasets are available upon a reasonable request to the corresponding author.

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