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Agronomic analysis of WaPOR applications: Confirming conservative biomass water productivity in inherent and climatological variance of WaPOR data outputs

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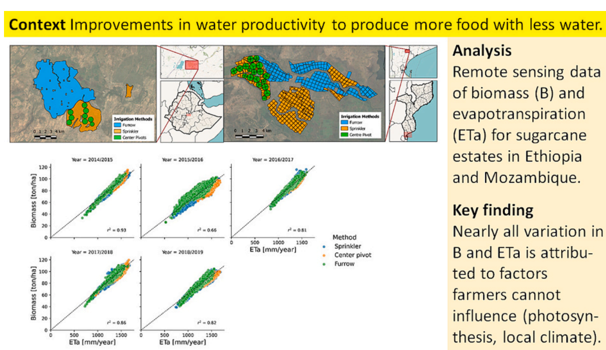
HIGHLIGHTS

- WaPOR remote sensing database monitors biomass (B) and evapotranspiration (ET).
- Variation in WaPOR data for B and ET was assessed through agronomic analyses.
- Nearly all variation was attributed to crop, local climate and irrigation method.
- Remaining (unexplained) variation falls within an accuracy range of +/− 9%.
- Scope to improve biomass water productivity through WaPOR monitoring is very small.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Improvements in agricultural water productivity with constrained water resources are often regarded a prerequisite to meet food demands of a growing world population. The WaPOR data portal was launched to monitor biomass, evapotranspiration and biomass water productivity in Africa and the Near East using remote sensing technologies. The WaPOR database shows spatial pixel variation in biomass, suggesting scope to improve water productivity at field level.
OBJECTIVE: The aim of this paper is to assess with regression analyses for different spatial and temporal scales whether spatial variability in biomass and evapotranspiration as revealed by WaPOR can be attributed to human influenceable factors, variations in local climate, or methodologically inherent inacuracies of the WaPOR data.
METHODS: Variation in biomass and evapotranspiration data was assessed through agronomic linear regression analyses, for two large-scale irrigated sugarcane estates in Ethiopia (Wonji) and Mozambique (Xinavane).
RESULTS AND CONCLUSIONS: In these cases 82–94% of the variation in biomass and evapotranspiration is attributed to crop photosynthetic efficiency (very large influence), local climate (large influence) and irrigation technology (small influence). The remaining unexplained spatial variability is small (6–18%) and falls within an

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error range of +/− 9%. In conclusion, WaPOR performed very well by neatly reproducing the conservative relationship between biomass and evapotranspiration, which also means there is very limited scope to improve biomass water productivity through WaPOR monitoring. Further research is recommended on the magnitude of WaPOR accuracy and other sources that explain variations in biomass and evapotranspiration.
SIGNIFCANCE: Applicability of the WaPOR database to monitor biomass water productivity was assessed. Spatial variability in biomass and evapotranspiration data largely stemmed from photosynthesis and local climate, factors farmers and water managers can hardly influence.

1. Introduction

Given the worldwide growing pressure on water resources and increasing demand for food, improvements are desirable in agricultural water productivity. Improvements could potentially lead to higher levels of agricultural production, with reduced additional amounts of water (Bouman, 2007; Molden, 2007; Moore et al., 2011). There are many interpretations and definitions of agricultural water productivity (see for an overview Giordano et al., 2017). In this paper we focus on biomass water productivity, defined as the ratio between biomass produced and water consumed through evapotranspiration (Steduto et al., 2007; Giordano et al., 2017). Biomass water productivity indicates how efficient a crop is in transforming water into biomass; values for biomass water productivity differ per crop and crop variety due to different photosynthesis efficiencies of C3 and C4 crops with a general decrease from cereals, to legumes to oil crops (Sinclair et al., 1984; Steduto et al., 2007).

Whereas many organizations promote policy goals of increasing agricultural water productivity, the actual reporting remains vague with definitions mostly akin to 'more-crop-per-drop' interpretations without critically assessing changes in water availability for downstream uses, and with little attention for monitoring improvements in water productivity (Scheierling et al., 2014; Scheierling and Treguer, 2016). In the analysis of agricultural systems, remote sensing is increasingly used to assess biomass formation (Fritz et al., 2019; Nave et al., 2022) and crop evapotranspiration (Al Zayed et al., 2015; Bonfante et al., 2019). This paper focuses on WaPOR data to monitor biomass water productivity. In 2017, the FAO Water Productivity Open-access Portal[1] (WaPOR) was launched to monitor agricultural water productivity through open access of remotely sensed data in Africa and the Near East. Biomass water productivity is calculated as the sum of biomass produced divided by actual (seasonal) evapotranspiration (ETa). Different factors influence biomass production and actual evapotranspiration, key ones are photosynthesis pathways, climate, nutrients, irrigation and soils (Sinclair et al., 1984; Allen et al., 1998; Ali and Talukder, 2008).

Recent WaPOR applications show a keenness to improve biomass water productivity; not only in WaPOR reports (FAO, 2020a; FAO and IWMI, 2021), but also in scientific publications (Blatchford et al., 2018; Safi et al., 2022), and communication by the Dutch Government (Ministry of Foreign Affairs of the Netherlands, 2015). Often, satellite studies in water productivity assess variability across an area and then formulate recommendations towards achieving a targeted biomass productivity value that was monitored (e.g. Zwart and Bastiaanssen, 2007; Ahmad et al., 2008; Bastiaanssen and Steduto, 2017; Safi et al., 2022). Instead of assuming (high) pixel values as absolute targets for biomass water productivity, this paper analyses spatial variability in biomass water productivity from an agronomic point of view with agronomically-informed regression analyses. Biomass and crop evapotranspiration are linearly related (De Wit, 1958; Steduto et al., 2007), hence any real variation in biomass water productivity within an area should be manifested in a different linear regression of biomass and evapotranspiration data for different spatial and temporal scales. The WaPOR data is thus spatially and temporally disaggregated into smaller parts by linear regression and agronomic theory.

It is relevant to take different linear regressions as criterion for spatial variation in biomass water productivity because variability in WaPOR data has different sources of origin that are not always agronomiccaly warranted. First, climate variability in temperature, rainfall, and relative humididity are factors that one cannot control and directly affect climatic evaporative demand. Second, agronomic variability in crop choice, seeds, irrigation and other crop inputs (e.g. nutrients) are factors on which farmers have influence. Third, there is (seeming) variation in WaPOR data which is related to the method of remote sensing, within this paper we label this type of variation methodological variability. Methodological variability is variation in WaPOR data on biomass and evapotranspiration that is caused by inaccuracies in sensor readings, different resolutions of sensors, spatial and temporal gapfilling due to cloud cover, and conversions of a heterogenous earth surface into squared spatial pixels with one value.

Given the ambitions to improve water productivity and the different sources of variability in WaPOR data on biomass water productivity, the aim of this paper is to assess with regression analyses for different spatial and temporal scales whether spatial variability in biomass and evapotranspiration as revealed by WaPOR can be attributed to human influenceable factors, variations in local climate, or methodologically inherent inacuracies of the WaPOR data. In this paper we kept methodological variability as small as possible by conducting the analyses on two agricultural systems of irrigated sugarcane estates in Ethiopia and Mozambique. Sugarcane estates represent a favourable setting to analyse variability in WaPOR data as the uniform crop and fields can cope best with WaPOR limitations, these limitations are: a coarse resolution due to data inputs ranging from 30 m to 100 m, 1 km and 20 km; an inability to detect different crops as WaPOR provides biomass for C3 crops; no information on yield formation due to the absence of (dynamic) harvest indexes.

2. Material and methods

The methodology is explained in three sections, starting with the WaPOR calculation procedures (Section 2.1), followed by the case studies (Section 2.2) and conducted analyses (Section 2.3).

2.1. WaPOR calculation procedures

The WaPOR portal provides data on 21 parameters including above ground biomass and actual evapotranspiration, at spatial resolutions of 30, 100 and 250 m at a 10 day interval. Based on numerous quality assessments, improvements in the portal and data layers were made, including a beta version, version 1.0, 1.1, 2.0, 2.1 (FAO and IHE Delft, 2019; FAO, 2020a). This study was conducted with WaPOR version 2.1.

WaPOR data are made available in different data layers, spatial resolutions and for different areas. Level 1 data is available at a resolution of 250 m for Africa and the Near East, level 2 data has a resolution of 100 m for a set of countries and river basins, and level 3 data has a resolution of 30 m for selected agricultural areas in Africa and the Near East. WaPOR data are available at daily, dekadal, monthly and annual temporal resolutions (FAO, 2020a). The time between data acquisition and availability is relative short; intermediate WaPOR data is available within 10 days, and this data is updated with the final product within 6

[1] https://wapor.apps.fao.org/

weeks. Fig. 1 shows which components are used in WaPOR to derive biomass water productivity (net water productivity in WaPOR terminology). The grey boxes are intermediate data components from external data, the blue boxes are data variables that are generated by WaPOR.

The WaPOR data layers used in this paper are Net Primary Production (NPP), transpiration (T), evaporation (E) and reference evapotranspiration (ETref). The data were processed to convert them into biomass, actual evapotranspiration (ETa) and ETref. Here we summarise the processing. More detailed information on the WaPOR data layers, processing and input data can be found in the WaPOR methodology manual (FAO, 2020b).

Biomass is calculated using the WaPOR Net Primary Production (NPP, in gC/m2) layer. NPP expresses how carbon dioxide is converted into biomass through photosynthesis. The value of NPP is derived from weather data, soil moisture stress, solar radiation, the green active photosynthetic fraction (fAPAR) and land cover. Above ground biomass (B, in ton/ha) is calculated using the formula below.

$$B = AOT^{*} f_{c}{}^{*} \frac{NPP^{*}22.222}{(1 - MC)}$$

MC (−) is the moisture content of the fresh biomass, f_c (−) is the light use efficiency (LUE) correction factor calculated by dividing the LUE of the crop (in this case sugarcane) by the LUE of a generic crop type that WaPOR NPP layer uses, and AOT (−) is the ratio of above ground over total biomass. Values were selected from literature, with an an MC of 0.59 (FAO and IHE Delft, 2019), fc of 1.6 (Villalobos and Fereres, 2016), and AOT of 1 (FAO, 2020a).

Actual evapotranspiration (*ETa,* in mm) is calculated by adapting the Penman-Monteith equation to remotely sensed input data and corrected for water stress through the Land Surface Temperature (LST) data component. ETa was derived from the separately calculated Evaporation (E, in mm) and Transpiration (T, in mm).

Reference evapotranspiration (ETref, in mm*)*, defined as the climate driven evapotranspiration from a well-watered virtual uniform grass crop, is in WaPOR estimated using data from GEOS-5 and MSG satellite sensors at a resolution of 20 km (Blatchford et al., 2020a; FAO, 2020a)

2.2. *Case studies: sugarcane in Wonji (Ethiopia) and Xinavane (Mozambique)*

We selected two large sugarcane estates for our analyses, Wonji Estate in Ethiopia and Xinavane estate in Mozambique (see Fig. 2a/b). The estates are comparable in crop, estate size and irrigation methods, they thus represent an interesting comparison to assess different sources of spatial variability in the WaPOR database across similar contexts. WaPOR highest resolution data is available in level 2 (100 m) for Xinavane and level 3 (30 m) for Wonji. WaPOR biomass data was already validated against biomass data for Xinavane, Chukalla et al. (2022) found that in 65% of the comparisons the data was within a +/− 20% range (Chukalla et al., 2022). Also the WaPOR biomass data for Wonji are in line with values reported in literature (Gemechu et al., 2020; Wakgari, 2021).

In Ethiopia, the Wonji sugar estate is in the downstream part of the Awash river basin, in the Oromia region 80–100 km southeast of Addis Ababa (see Fig. 2a). The estate is located between 8.33 and 8.62°N and 39.21–39.40°E, and has a tropical savanna climate. The predominant soil types in the area of Wonji sugarcane estate are described as Fluvisols, Andosols and Leptosols (FAO et al., 1998). Wonji Main is the oldest part of the scheme, which was expanded from 2009 onwards with subschemes of Wake Tiyo, Welencheti, North Dodota and Ulaga. The total cropping area is about 15,000 ha (Alemayehu et al., 2020). The main irrigation methods are furrow, sprinkler and center pivot. The cropping schedule within the scheme is determined by the soil type that is being cropped. The areas with heavier soils have a shorter total cycle of planting crop and ratooning compared to the areas with lighter soils. The duration of the sugarcane growing season is on average 12 months, early and late harvest occurs to ensure year-round operation of the sugar

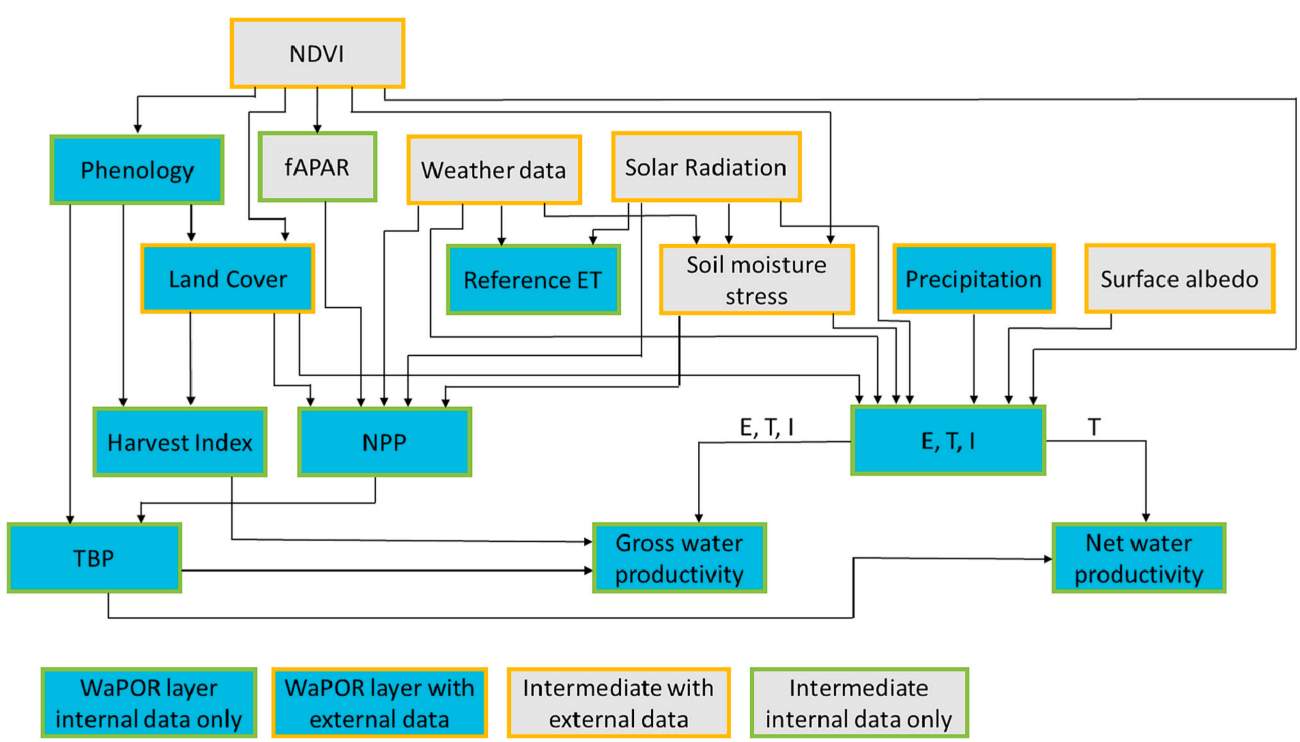
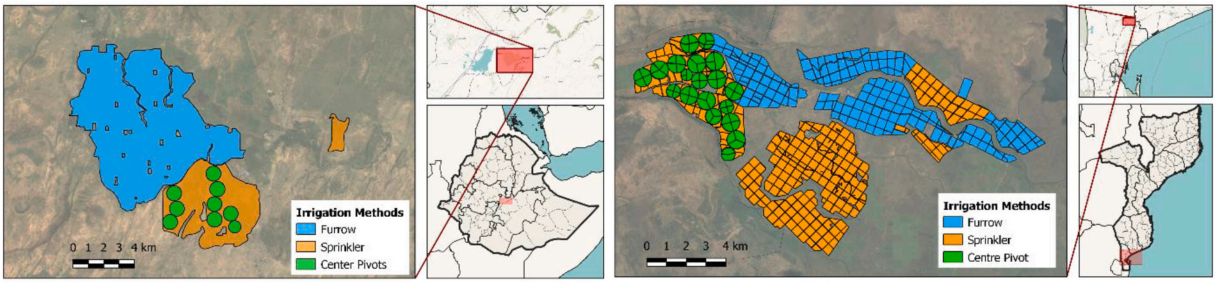


Fig. 1. Input data components and output datasets of WaPOR database. Green outlines represent data compenents from internal data, orange outlines are solely based on external data. NDVI is Normalised Difference Vegetation Index, fAPAR is green active photosynthetic fraction, E is evaporation, T is transpiration, I is Interception, NPP is net primary production, TBP is Total Biomass production. Source: FAO, 2020b. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



(a) (b)

Fig. 2. Locations of sugarcane estates in Africa and identified spatial clusters for irrigation methods in a) Wonji, Ethiopia and b) Xinavane, Mozambique.

mills. Within the estate different varieties of sugercane are cropped. The fertiliser application rates in the estate are the same, regardless of variety or soiltype. However, a differentiation is made between planting cane (200 kg/ha Urea) and ratooning cane (500 kg/ha Urea) (Alemayehu et al., 2020). The sugarcane yield in Wonji for the season 2017/2018 was on average ~ 110 t per hectare (Alemayehu, 2020).

The Xinavane sugar estate lies in Maputo province, southern Mozambique (see Fig. 2b) in the semi-arid Incomati Valley, between 25.00 and 25.12°S and 32.70–32.90°E (Jelsma et al., 2010). The cropping area expanded from 12,000 ha in 2005 to 18,000 ha in 2016 (De Boer and Droogers, 2016). Also here, the main irrigation types are furrow, center pivot and sprinkler (Chukalla et al., 2020). Soil in the Xinavane sugarcane estate is dominated by sand content (Sonneveld, 2012). The estate uses different crop management practices, such as mechanised and manual land preparation, planting, harvesting, weeding and irrigation (Sonneveld, 2012). The sugarcane crop is on average harvested after 12 months, yet earlier and later harvest takes place to ensure throughout the year a stable supply of sugarcane to the sugar mills. Based on an overview between 2008 and 2019, the sugarcane yield at Xinavane sugarcane estate ranged from 40 to 150 t per hectare, with an average of ~90 t per hectare depending on the variety, age, irrigation and fertilisation (Chukalla et al., 2022; Den Besten et al., 2020, 2021).

Table 1 summarises the WaPOR data analysed for both case studies. For Wonji and its sub-schemes, data was analysed from 2014/2015 to 2018/2019. Two areas were excluded, the Welencheti as there was no data available at a 30 m resolution, and Wake Tio as the area was not continuously cropped for all seasons. For Xinavane, the data was analysed on 8000 ha of the estate, from 2014/2015 to 2018/2019. Pre 2014 data at Xinavane was discarded as it was obtained from another sensor (MODIS at 250 m resolution and then resampled) and showed a much larger scatter for biomass and ETa than the 2015–2019 data which was obtained from PROBA-V (Chukalla et al., 2020). This gives an indication of the sensitivity of WaPOR output to sensor accuracy.

WaPOR data was extracted and prepared for analysis. The cropping areas of the sugar estates were demarcated in such a way that they fall within a few of the 20 × 20 km ETref cells with similar values for reference evapotranspiration and thus a similar local climate. Appendix A Figs. A and B show how the ETref cells overlay the sugarcane estates at Xinavane and Wonji. The WaPOR data were analysed at a spatial resolution of 100 m (Xinavane) and 30 m (Wonji). The precipitation and reference evapotranspiration datasets were resampled to 100 m (at Xinavane) and 30 m (at Wonji) using the nearest-neighbour method (GDAL, 2021). Next, different irrigation methods in the estates were digitized based on Google Earth maps and ground observations (Den Besten et al., 2020). Fig. 2 shows for both estates the areas for furrow, sprinkler and center pivot irrigation as analysed in this paper.

The time unit of analysis, or growing season, had to be defined so that it resembles the growing season of sugarcane in each case. This is important as the biomass-ET relation is governed by the phenological crop cycle. It commences when the crop starts to grow and gradually builds up as the crop goes through different phenological stages and ends when the crop is being harvested (Allen et al., 1998). A too-early (before emergence) or too-late (after harvest) time frame will result in a higher accumulation of evapotranspiration that does not contribute to photosynthesis and biomass formation and thus results in a lower biomass water productivity. On-the-ground deviations from assumed growing seasons will add inaccuracy and seeming variation in data output. For both Xinavane and Wonji the hydrological year resembles the growing season for sugarcane most closely. The first month of the rainy season marks the start of the hydrological year. For Wonji the hydrological year runs from July untill June. For Xinavane the hydrological year runs from October to September (Chukalla et al., 2020). The two estates are thus analysed over different time horizons but in an identical unit of analysis of 365 days each. Biomass and evapotranspiration were thus annualized, by summing up dekal (E, T, NPP) or daily (ETref) values within the hydrological year.

2.3. Agronomic regression analyses on WaPOR data

The analyses presented in this paper on WaPOR data focus on a specific sub-field of agronomy that investigates how crop physiological processes govern water consumption and biomass production (De Wit, 1958; Steduto et al., 2007). Two major insights in this field are i) the

Table 1
WaPOR layers used in Wonji and Xinavane analyses. Adapted from Alemayehu et al. (2020) and Chukalla et al. (2022).

	Wonji estate, Ethiopia		Xinavane estate, Mozambique	
Remote sensing products	Spatial resolution[a]	Temporal resolution, coverage	Spatial resolution[a]	Temporal resolution, coverage
Evaporation	30 m	10 days,	100 m	10 days, 2014/2015–2018/2019
Transpiration	30 m	2014/2015–2018/2019	100 m	
Net Primary Production	30 m		100 m	
Reference Evapotranspiration	20 km		20 km	
Land surface Temperature (LST)	100 m		1 km	
Land Cover Classification			100 m	annual, 2015–2019

[a] Spatial resolution of both level 2 data (Xinavane) and level 3 (Wonji) make use of data components with different resolutions ranging for level 2 from 100 m to 20 km, and for level 3 from 30 m to 20 km. For instance the Land Surface Temperature (LST) has in level 2 a resolution of 1 km and is one of the data components to calculate E, T, and NPP.

linear relationship between biomass and transpiration due to stomata being open or closed for photosynthesis and transpiration (De Wit, 1958) and ii) the relative constant nature of this relationship, meaning biomass water productivity is approximately constant, once accounted for differences in evaporative demand and carbon dioxide concentrations (Steduto et al., 2007). Water productivity of biomass is thus taken to be fairly stable. Nutrient deficiencies do have a major constraining impact on biomass formation and evapotranspiration, in a range of 26–32% (Steduto et al., 2007; Qi et al., 2020).

Agronomic regression analyses were conducted to explore sources of spatial variability in WaPOR biomass – ETa data plots. The data plots can be analysed for spatial variability as each point in the plot represents a spatial pixel with a particular value for the end of the growing season. The spatial resolution of the pixels for the Wonji estate was 30 by 30 m, and Xinavane 100 by 100 m. Due to the linear relationship between biomass and transpiration, a simplified statistical approach of linear regression models was applied to examine spatial variability in biomass and ETa. It should be noted that in WaPOR biomass and ETa are calculated from a different set of remote sensing inputs (see also Fig. 1) and that the observed linear relationship between biomass and ET is not an artefact how WaPOR computes biomass and ETa (FAO, 2020b).

In the agronomic regression analyses, the slope of the trendline indicates the biomass water productivity value, and the amount of scatter around the linear line forms an indication of the spatial variability of the dataset. The r^2 is then a measure how well the linear model fits the data, and how much of the spatial variability is in line with what one would expect based on agronomic theory. For instance, an r^2 of 0.85 implies that 85% of the data fit the linear model, and that 85% of the WaPOR-reported spatial variability is explained by the linear regression model. Linear regression models were fitted with an intercept of 0 in the biomass-ETa data plots because sugarcane is a perennial crop which is cut down above the ground. Hence there will be no fields and pixels with evaporation without biomass accumulation. The intercept for a linear trendline for biomass-ET is thus at 0 biomass and 0 ET. Where other studies of rainfed crops may report a typical evaporation of 150–250 mm before aboveground biomass is formed (Kang et al., 2002; Mueller et al., 2005), this relates to the start of season being applied before the crop germinates and emerges.

Agronomic regression analyses were conducted on multiple spatial and temporal scales for both sugarcane estates (see Table 2) on four aspects. First, biomass was plotted against ETa for the entire sugarcane estate, in an aggregated manner in which all growing seasons and irrigation methods were combined to examine whether WaPOR would, in line with crop physiological processes (De Wit, 1958; Steduto et al., 2007), largely reproduce the linear relation between biomass and transpiration. Second, biomass was plotted against ETa for all irrigation methods for the whole sugarcane estate (see Fig. 2a/b) per growing season, to examine how much of the variation could be attributed to differences in local growing seasons and to explore whether water productivity values are season-dependent due to interseasonal climate variability (e.g. Ilbeyi et al., 2006; Ray et al., 2015).

Third, the area of the sugarcane estates was disagregated in 3 zones according to different irrigation methods to explore what part of the variation in biomass-ETa data could be linked to the irrigation types of sprinkler, furrow and center pivot in the sugarcane estates (zones shown in Fig. 2a/b); and whether furrow has a higher water productivity than sprinkler and pivot due to a lower soil wetting fraction and irrigation frequency (Allen et al., 1998). Fourth, evapotranspiration data per growing season for the sugarcane estates were normalised with ETref data from WaPOR to examine how much variation in biomass and evapotranspiration is attributed to variations in ETref, to examine whether ETref accounts for nearly all variation in climatic evaporative demand caused by weather and climate (Allen et al., 1998; Steduto et al., 2007; Allen and Pereira, 2009). It should be noticed that no analysis on nutrient variations was conducted, it was assumed that both commercially managed sugarcane estates would apply sufficient nutrients because for Wonji uniform nitrogen application was reported depending on the cutting (first, second, third and more ratoons) of the sugarcane (Wakgari, 2021). In addition, our datasets did not indicate variations for biomass-ETa in the range of 20–30% which is typical for nutrient deficiencies. Nutrient variations were thus small, and they could not be observed and desegregated separately (a point which we elaborate in Discussion Section 4).

Agronomical theory states a linear biomass-T relationship (De Wit, 1958; Steduto et al., 2007), hence data was initially extracted to examine Biomass-T relationships. Yet in contradiction to theory the Xinavane plots of Biomass-T had more scatter than Biomass-ETa (Appendix A Fig. C), due to incorrect separation of evaporation and transpiration in WaPOR. This suggests WaPOR has a problem in separating E from T, as a lower regression for Biomass-T than Biomass-ET cannot be explained by agronomic theory. Separation of E and T in WaPOR is guided by a factor αLAI (where α is a light extinction factor, LAI is leaf area index). WaPOR applies one fixed value for α (FAO and IHE Delft, 2019; Chukalla et al., 2022), whereas in reality α differs substantially between and within land use classes (Zhang et al., 2014). Biomass-T data was therefore discarded, and the analysis focused on biomass-ETa data. Using ETa, and thus including E, will add some variation in the linear relationship of biomass-T, as E does not contribute to biomass and may be variable due to crop patterns, irrigation practices, climate and soil. This is acceptable as over a crop growing season the portion of E is relatively small and mostly limited to the initial crop stage when bare soil evaporates as it is not yet entirely covered by plant leaves (Allen et al., 1998). Thus it is expected that biomass-ETa still resembles a linear relationship, but with a slightly lower correlation factor as compared to an accurate biomass-T relation (Steduto et al., 2007).

3. Results

3.1. Overall biomass water productivity

WaPOR data plots of five growing seasons of biomass versus ETa are shown for the sugarcane estates of Xinavane, Mozambique (Fig. 3) and Wonji, Ethiopia (Fig. 4). The data plots indicate that absolute numbers of ETa and biomass vary; Xinavane ETa in the range of 522–1688 mm and biomass 25–120 ton/ha, Wonji ETa in the range of 217–2382 mm and biomass 5–189 ton/ha. The range in ETa and biomass within a scheme is explained by harvest of the sugarcane crop; early harvest results in a lower ETa and biomass whereas late harvest allows the crop to prolong its transpiration and biomass formation. On the estates there is early and late harvest to have year-round operation of the sugar mills. The biomass is in range of the biomass targets adopted by the estate managers, for Xinavane the targeted biomass yield is about 80 ton/ha, whereas in Wonji the targeted biomass ranges from 110 ton/ha (Wonji main subscheme) to 150 ton/ha (Dodota and Wake Tio) and 200 ton/ha (Walencheti subshceme). The WaPOR biomass data is thus in line with local practices, and also in line with previous research conducted in the sugarcane estates of Xinavane (Gemechu et al., 2020; Chukalla et al., 2022) and Wonji (Wakgari, 2021).

Although absolute numbers of ETa and biomass vary spatially and

Table 2
Overview of agronomic regression analyses.

WaPOR data	Spatial scale	Temporal scale	Agricultural system
Biomass – ETa	Sugarcane estate	5 growing seasons	Xinavane, Wonji
Biomass – ETa	Sugarcane estate	1 growing season	Xinavane, Wonji
Biomass – ETa	Estate sub-areas for furrow, sprinkler, center pivot	1 growing season	Xinavane, Wonji
Biomass – ETa/ETref	Estate sub-areas for furrow, sprinkler, center pivot	1 growing season	Xinavane, Wonji

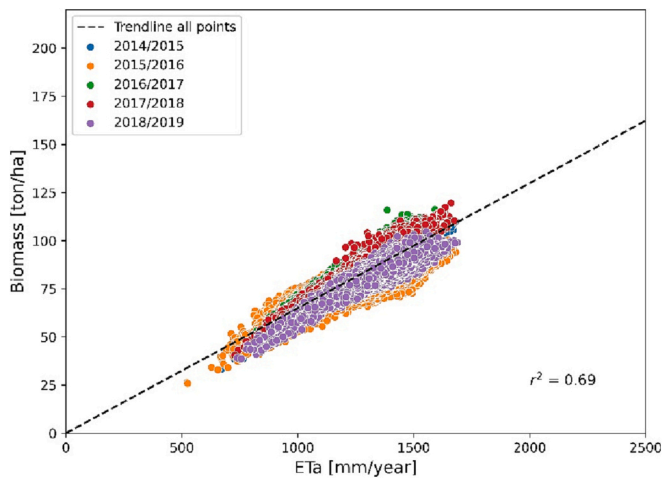


Fig. 3. Biomass versus ETa in different growing seasons in Xinavane (2014/2015–2018/2019). Each point represents seasonal biomass and evapotranspiration for a spatial pixel of 100 × 100 meter, the plot has 32,297 points.

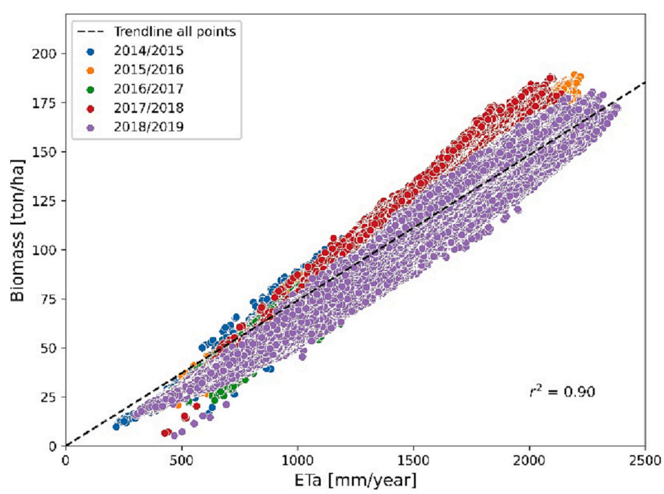


Fig. 4. Biomass versus ETa in different growing seasons in Wonji (2014/2015–2018/2019). Each point represents seasonal biomass and evapotranspiration for a spatial pixel of 30 × 30 meter, the plot has 526,300 points.

temporally, their ratio of productivity remains largely the same as a crop has a stable photosynthetic efficiency which governs the accumulation of carbon and release of water through stomata in the leaves. Both plots show a linear trend that represents a single biomass water productivity value. For Xinavane, the plot has an r^2 of 0.69, indicating 69% of the variation in biomass is explained by variation in ETa. For Wonji the linear trend is even stronger, as the plot has an r^2 of 0.90, indicating 90% of the variation in biomass is explained by variation in ETa. The regression analysis thus reveals that despite major variations in ETa and biomass values, the linear trend is clear and robust (within one season, across multiple seasons, and across case studies). This is conform agronomical theory: crop physiological processes govern photosynthesis and stomata control and link transpiration to carbon assimilation. Maximum biomass and ETa in Wonji are considerable higher than in Xinavane as Wonji is closer to the equator (Wonji 8.33°N, Xinavane 25.00°S), so there is more energy available to be converted into biomass and water vapour. In addition, the reference evapotranspiration is also higher at Wonji (see Appendix A table I), so a higher atmospheric demand for water in Wonji contributes to higher ETa values.

3.2. Disaggregation of seasons and irrigation types

Fig. 5 displays for Xinavane plots for each growing season of biomass versus ETa. Table 2 presents the agronomic regression analyses and biomass water productivity values. All growing seasons, except for season 2015/2016 which has an r^2 of 0.66, have an r^2 of 0.81 to 0.93 which is much higher than the r^2 of 0.69 of Fig. 3. The seasonal influence of ETa on biomass is indeed present, as reflected in an improved fit of the ETa and biomass data per season when compared to all seasons. There is a clear interseasonal (climate) influence of ETa on biomass as water productivity values fluctuate with 11% from 6.1 kg·m^{-3} in 2015–2016 to 6.9 kg·m^{-3} in 2016–2017. The data plot of the 2015/2016 season shows much more variation in biomass compared to the other seasons. This may be explained by 2016 being a very dry year (Chukalla et al., 2022) with the occurance of (severe) water stress affecting both ETa and biomass production. As water stress is accounted for through the LST sensor (in the case of Xinavane with a resolution of 1 km, for Wonji 100 m), higher levels of data variations may be expected through coarseness of the value (resulting in over- and undercorrections for biomass and ETa), resulting in a broader data plot when compared to the other growing seasons in Fig. 5.

So far the irrigation methods were aggregated in one combined dataset, yet ideally some of the variation in biomass and ETa should be attributed to differences in irrigation methods. Table 3 therefore presents regression analyses and water productivity values for the identified spatial clusters of furrow, sprinkler and center pivot irrigation. The water productivity values are slightly higher or lower when compared to the combined irrigation dataset; with ranges in water productivity for furrow 6.3–7.0 kg·m^{-3}, sprinkler 6.0–6.9 kg·m^{-3} and center pivot 5.8–6.8 kg·m^{-3}. Furrow irrigation has in all seasons a higher water productivity than sprinkler and center pivot. When the seasonal r^2 values of the specific irrigation methods (rows 3–5 in Table 3) are compared to the aggregated irrigation data (row 2, Table 3), similar or even higher r^2 values are obtained for sprinkler and furrow. For center pivots the r^2 values were lower for most seasons than the plot wherein all irrigation methods were combined.The high variation within the center pivot data plot is probably caused by the coarse LST sensor at a 1 km resolution. The pivot sprays irrigation water on the canopy, resulting in evaporation of intercepted irrigation water. This results in a cooler canopy temperature affecting LST and soil moisture correction calculations of WaPOR. Pivot-irrigated areas which are not yet irrigated will return higher canopty temperatures. At a coarse resolution of LST, these values are averaged, potentially adding variation in output. Whereas furrows wet the soil and not the canopy, thus resulting in much smaller differences in canopy temperature between just irrigated pixels and not irrigated pixels and thus less noise in LST values. As a result, in a coarse LST sensor of 1 km pivot LST values are more blurred than furrow. Getting grip on the influence of LST on WaPOR level 1, 2 and level 3 data for biomass and ETa needs further research and is addressed in the Discussion.

For Wonji, Fig. 6 and Table 4 present data plots, agronomic regression analysis and water productivity values per growing season and irrigation method.

Also for Wonji, the separation of the multi-season data plot (Fig. 4) into separate growing seasons (Fig. 6) results in r^2 values of 0.90 to 0.95 which are higher than the r^2 of 0.90 of Fig. 4. The water productivity of the aggregated irrigation dataset fluctuates (Table 4, row 2), ranges from 7.0 kg·m^{-3} in 2016–2017 to 7.8 kg·m^{-3} in 2017–2018. So also in Wonji the seasonal influence of ETa on biomass is present, resulting in water productivity values fluctuating with 11%. By further delineating the different irrigation methods in the dataset (Table 4, rows 3–5), the r^2 increases slightly from 0.93 to 0.94 for furrow, 0.95 for sprinkler and 0.94 for center pivot. The water productivity values of the specific irrigation methods cover a wider range than the irrigation combined dataset, with sprinkler generally being higher (7.4–8.3 kg·m^{-3}) followed by center pivot (7.3–8.1 kg·m^{-3}) and furrow irrigation (6.9–7.6

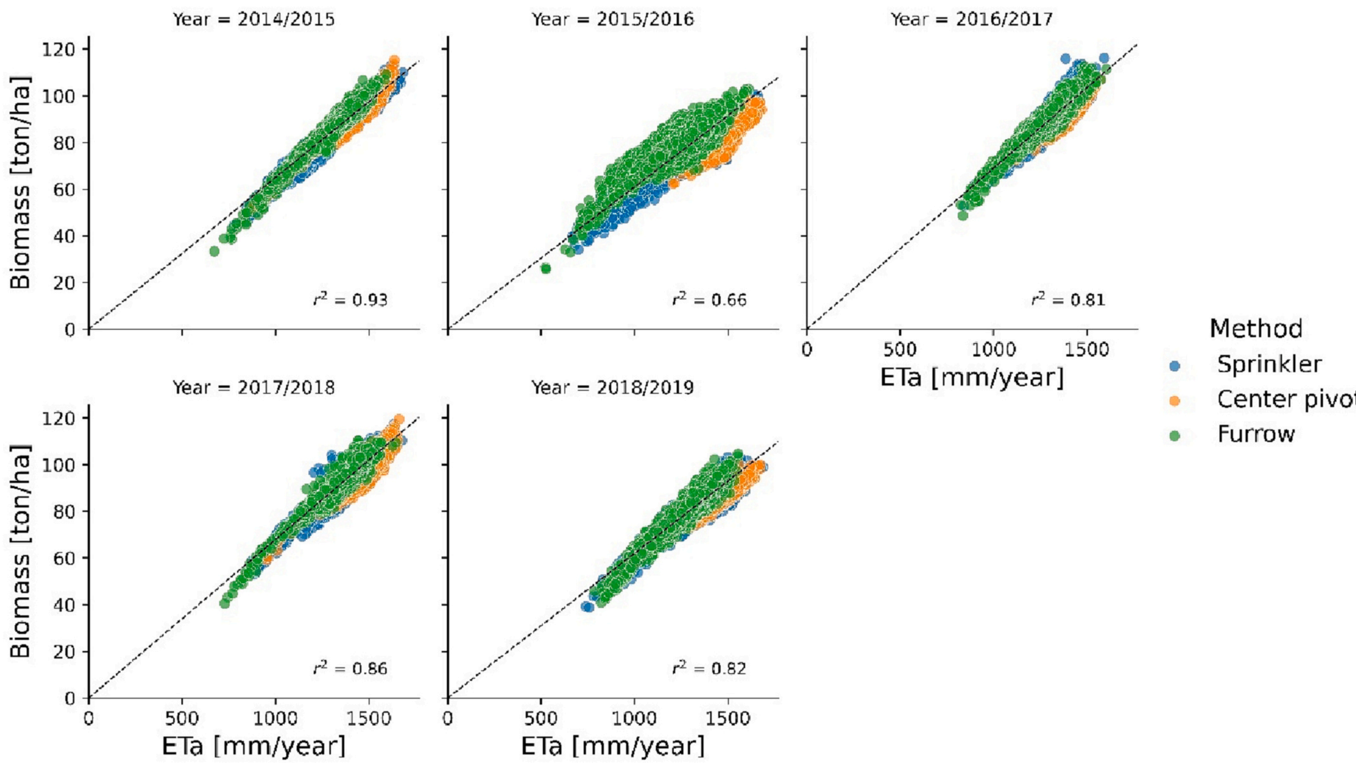


Fig. 5. Biomass versus ETa at Xinavane sugar estate categorized by irrigation methods from 2014/2015 to 2018/2019. The r^2 shown in the graph relates to the entire data plot when all irrigation methods are combined. Each point represents seasonal biomass and evapotranspiration for a spatial pixel of 100 × 100 meter; the plot of year 2014/2015 has 6459 points, 2015/2016 has 6458 points, 2016/2017 has 6440 points, 2017/2018 has 6440 points, and 2018/2019 has 6440 points.

Table 3
Linear regression parameters and water productivity of biomass and ETa for sugarcane at Xinavane for different growing seasons and irrigation methods. a and r^2 are the slope and regression coefficient of the regression line, WP_bm is biomass water productivity.

	2014–2015			2015–2016			2016–2017			2017–2018			2018–2019			Average r^2
	Regression parameters		WP_bm (kg/m^3)	Regression parameters		WP_bm (kg/m^3)	Regression parameters		WP_bm (kg/m^3)	Regression parameters		WP_bm (kg/m^3)	Regression parameters		WP_bm (kg/m^3)	
B vs ETa, irrigation combined	a	0.065		a	0.061		a	0.069		a	0.068		a	0.062		
	r^2	0.93	6.5	r^2	0.66	6.1	r^2	0.81	6.9	r^2	0.86	6.8	r^2	0.82	6.2	0.82
B vs ETa, furrow	a	0.066		a	0.064		a	0.070		a	0.069		a	0.063		
	r^2	0.93	6.6	r^2	0.76	6.4	r^2	0.89	7.0	r^2	0.89	6.9	r^2	0.88	6.3	0.87
B vs ETa, sprinkler	a	0.064		a	0.060		a	0.069		a	0.068		a	0.061		
	r^2	0.93	6.4	r^2	0.696	6.0	r^2	0.78	6.9	r^2	0.87	6.8	r^2	0.82	6.1	0.82
B vs ETa, center pivot	a	0.065		a	0.058		a	0.068		a	0.066		a	0.059		
	r^2	0.93	6.5	r^2	0.65	5.8	r^2	0.72	6.8	r^2	0.77	6.6	r^2	0.72	5.9	0.76

$kg{\cdot}m^{-3}$). The order of water productivity values in Wonji is the reverse of Xinavane (where furrow was highest) probably due to incorrectly assigning soil moisture stress to furrow fields in Wonji. This point is further elaborated in the Discussion Section 4.

3.3. Normalisation for local climate variability

Efforts to normalise seasonal ETa data for seasonal climate variability through ETref are provided in Appendix A Figs. D and E. The results were excluded from the analysis as the normalisation outcomes were inconsistent. Accumulation of daily or decadal ETa/ETref values as recommended by Steduto et al. (2007) was not feasible. In WaPOR ETa values are not generated on a daily basis, nor on a neat fixed interval. Instead WaPOR images are made available on an irregular interval as it can be 10 days, but also 8, 9, or 11 days, which are converted into decadal values with gap filling and interpolation processes. In Xinavane nearly all data lie in one ETref cell (see Appendix A Table 1) so the influence of normalisation for ETref is expected to be small, yet the r^2 increased from 0.82 (disaggregated seasons and irrigation methods) to 0.90 for normalised ETa/ETref data. Whereas in Wonji, the study area occupies four ETref cells and normalisation for ETref is expected to result in a better fit of biomass and normalised evapotranspiration data the opposite happened, as r^2 reduced from 0.94 to 0.92.

3.4. Comparison of agronomic regression analyses and cases

Table 5 shows a comparison of the average r^2 of the different datasets presented in this paper for Xinavane and Wonji. Table 5 shows that the agronomic regression analyses further improved the r^2 to different degrees. For Xinavane, at first 69% of the biomass and ETa data fitted the linear regression model indicating that 69% of the spatial variability in data fits the linear regression trend which exists between biomass and

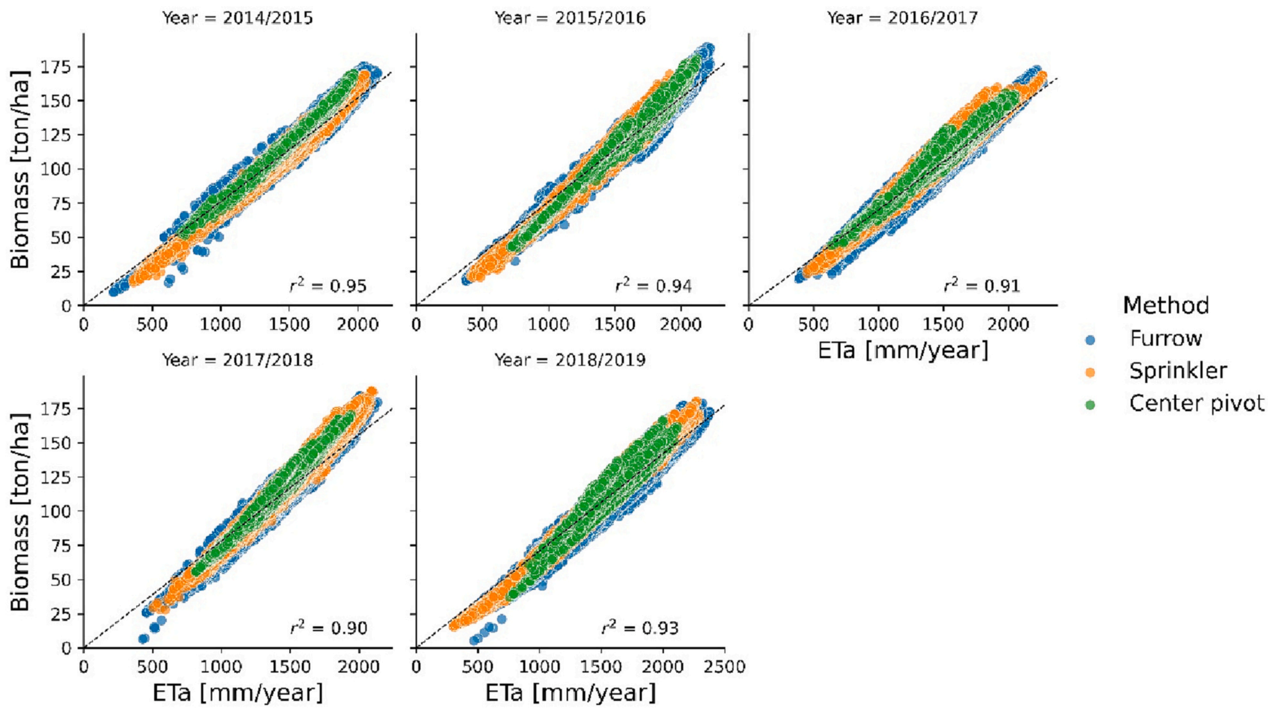


Fig. 6. Biomass versus ETa at Wonji sugar estate categorized by irrigation methods from 2014/2015 to 2018/2019. Each point represents seasonal biomass and evapotranspiration for a spatial pixel of 30 × 30 meter; the plot of year 2014/2015 has 105,263 points, 2015/2016 has 105,255 points, 2016/2017 has 105,256 points, 2017/2018 has 105,263 points, and 2018/2019 has 105,263 points.

Table 4
Linear regression parameters and water productivity of biomass and ETa for sugarcane at Wonji for different growing seasons and irrigation methods. a and r^2 are the slope and regression coefficient of the regression line, WP_bm is biomass water productivity.

Dataset	2014–2015		2015–2016		2016–2017		2017–2018		2018–2019		Average r^2
	Regression parameters	WP_bm (kg/m^3)	Regression parameters	WP_bm (kg/m^3)	Regression parameters	WP_bm (kg/m^3)	Regression parameters	WP_bm (kg/m^3)	Regression parameters	WP_bm (kg/m^3)	
B vs ETa, irrigation combined	a 0.076 r^2 0.95	7.6	a 0.076 r^2 0.94	7.6	a 0.070 r^2 0.91	7.0	a 0.078 r^2 0.90	7.8	a 0.071 r^2 0.93	7.1	0.93
B vs ETa, furrow	a 0.076 r^2 0.96	7.6	a 0.075 r^2 0.95	7.5	a 0.069 r^2 0.93	6.9	a 0.076 r^2 0.92	7.6	a 0.069 r^2 0.94	6.9	0.94
B vs ETa, sprinkler	a 0.077 r^2 0.95	7.7	a 0.078 r^2 0.95	7.8	a 0.074 r^2 0.94	7.4	a 0.083 r^2 0.94	8.3	a 0.074 r^2 0.96	7.4	0.95
B vs ETa, center pivot	a 0.080 r^2 0.97	8.0	a 0.079 r^2 0.96	7.9	a 0.073 r^2 0.97	7.3	a 0.081 r^2 0.94	8.1	a 0.074 r^2 0.87	7.4	0.94

Table 5
Summary of r^2 for different agronomic analyses at Xinavane and Wonji.

Dataset	Xinavane	Wonji	Source
B vs ETa all seasons irrigation combined	0.69	0.90	Fig. 3 and 4
B vs ETa by season irrigation combined	0.82	0.93	Tables 3 and 4, row 2
B vs ETa by season by irrigation method	0.82	0.94	Tables 3 and 4, row 3–5

ETa. The r^2 increased to 0.82 when different growing seasons were identified. Separation of the dataset into different irrigation methods had no influence. In Wonji smaller increases were achieved. Here, already 90% of the biomass and ETa data across all growing seasons fitted the linear regression model, indicating that 90% of the spatial variability fits the linear regression trend. The explanation of spatial variability only slightly increased from 90% to 93% and 94% when the dataset was subdivided by growing season and irrigation method. When the two cases are compared, the explained spatial variation in WaPOR data was greatly increased up to 82% in Xinavane and 94% in Wonji. The remaining unexplained spatial variability in both cases is similarly small, namely 18% for Xinavane and 6% for Wonji.

4. Discussion

The aim of this paper was to assess with agronomic regression analyses for diferent spatial and temporal scales wether spatial variability in biomass and evapotranspiration data as revealed by WaPOR can be attributed to human influenceable factors variations in local climate, or methodologically inherent accuracies of WaPOR data. Generally, WaPOR performed very well under these monocropping circumstances of large sugarcane estates as WaPOR reproduced the linear relation between biomass and crop evapotranspiration. The spatial variability of

WaPOR biomass-ETa data in our case study is largely related to factors which are difficult to influence, namely crop-determined photosynthetic efficiency of sugarcane and local inter-seasonal climate variability. The variation that was explained by differences in irrigation technology, a factor that humans can influence, was small. In both cases, the remaining share of unexplained spatial variability was small, with 6% in Wonji and 18% in Xinavane. When we assume WaPOR data outputs have an error range of +/− 9%, which is in range with the acuracy assessed in similar models, for instance the SEBAL model has an error range of +/− 5 to 15% (Bastiaanssen et al., 2005), all observed unexplained variation of our study falls well within the accuracy range of WaPOR output. WaPOR thus confirms the stable relation of biomass water productivity. Although variations in biomass and ETa were found in the two agricultural systems, their ratio of productivity did not change which means that increasing biomass production of a crop (e.g. vary in sowing density, planting and harvesting date) is largely a matter of producing more biomass with more water consumption without real opportunities for physical water savings.

Our insight on the limited applicability of WaPOR to detect spatial variations in biomass water productivity is consistent with previous research. Agronomists have claimed for decades that biomass water productivity of a crop is a conservative relationship, meaning that there is limited scope to make gains in biomass water productivity (Sinclair et al., 1984; Bouman, 2007; Molden and Oweis, 2007; Steduto et al., 2007). Furthermore, other WaPOR studies did also not present reliable results on spatial variations in biomass water productivity at a field scale. Instead, they presented reliable results on the aggregated (coarse) spatial-temporal scale of river basin-wide long term annual evapotranspiration (Weerasinghe et al., 2020) or, they report for one cropping season large discrepancies up to +/− 50% of ETa between WaPOR data and field studies for alfalfa in Iran (Javadian et al., 2019) and maize, sugar beet, and orchard fields in the Nile Delta (Swelam et al., 2019). Due to coarse input parameters like reference evapotranspiration at a resolution of 20 by 20 km and soil moisture stress with an LST sensor at a resolution of 1 km for level 1 and 2, we concur with Nhamo et al. (2020) and Blatchford et al. (2020b) that the WaPOR resolution is too coarse to analyse smallholder croplands.

The reported water productivity values, ranging from 5.8 to 7.0 kg·m^{-3} in Xinavane and 6.9–8.3 kg·m^{-3} in Wonji are in line with those reported by Da Silva et al. (2013) for a Brazilian sugarcane estate whose values ranged from 5.6 to 8.3 kg·m^{-3}.The hypothesised differences in water productivity among different irrigation methods, with furrow having a higher water productivity due to infrequent and partial wetting of the soil, were present in Xinavane but not present in Wonji. This discrepancy may be explained by the influence of the soil moisture stress correction factor applied by WaPOR on the biomass and ET data output. In the case of Wonji, this is based on the Land Surface Temperature (LST) sensor with a pixel resolution of 30 m and the application of the improved trapezoid method of Yang et al. (Yang et al., 2015; FAO, 2020b). The soil moisture correction factor then depends on the determination of the cold and warm edge of surface temperature to determine the interpolation range for water stress correction between non-stressed (cold edge full canopy) and stressed (warm edge full canopy) pixels (FAO, 2020b). An interpolation and trapezoid that needs to be determined for each obtained satellite image (covering typically 180 by 180 km for Landsat images).

In the case of Wonji, the cold edge full canopy (point C of the trapezoid, Fig. 20 in FAO, 2020b) representing the coldest surface temperature at full canopy, will by definition be a pixel under pivot and/or sprinkler irrigation that has just been, or is, irrigated and returns the lowest surface temperature due to intercepted irrigation water on the canopy. Furrow irrigation, in contrast, even when just irrigated will have a dry canopy of higher temperature whilst evaporation of furrows under a full canopy will be minimal. This introduces a methodological bias in WaPOR, whereby furrow irrigation will be slightly corrected for water stress, even when just irrigated, as the cold edge of the trapezoid is determined by the wet canopy of sprinkler/pivot. A correction that affects both biomass and ETa, and may also influence the high biomass values obtained in Wonji. This methodological limitation for irrigation types especially at high resolution, as imposed by the improved trapezoid method, merrits further assessment and quantification. In Xinavane this is less of an issue, as the LST sensor has a pixel resolution of 1 km, and by definition will not be “clean” in its value, but return averaged values for 1 km^2 areas. How these may affect the overall WaPOR values for biomass and ET will need to be assessed in the future as areas become available that are covered by both level 2 and level 3 data for the same time periods.

Having found that WaPOR performed very well in those uniform cropped areas, and as three factors were successfully identified that influence biomass water productivity (crop photosynthetic efficiency, inter-seasonal climate variability, irrigation method), further research is recommended to identify with agronomic regression analysis other sources of variation in WaPOR biomass – ETa data for case studies on a similar scale of 10,000–20,000 ha. The influence of nutrients could be compared within one watershed or irrigation division, with spatial clusters of sub-optimal and optimal nutrient conditions, to examine whether optimal nutrients increase crop water productivity in similar ranges as the 26–32% reported in literature (Steduto et al., 2007; Qi et al., 2020). Differences between head- and tail-end farmers could be explored (e.g. FAO and IWMI, 2021), where it is expected that head-end fields generally return a higher biomass water productivity than tail-end fields as head-end farmers frequently have better access to nutrients and water resources. Alternatively, the influence of soils could be investigated when local climate and crops are comparable, because heavy soils (clays, clay-loam) have a higher capacity to hold water, organic material and nutrients, which results generally in higher water productivity values than medium (loam) and light soils (sand) (Ali and Talukder, 2008; Ahmadi et al., 2010; Safi et al., 2022). Focusing on uniform-cropped regions is important as heterogenous crops and smaller field sizes will only introduce noise in WaPOR data which does not reflect field level variations in biomass and evapotranspiration. Furthermore, the variation caused by WaPOR methodology has different origins ranging from inaccuracies in satellite observation, input data processing, different spatial resolutions and parameterisation (e.g. coarse separation of E and T), and therefore justifies further study how large its influence is on WaPOR data for biomass and evapotranspiration. Having found that WaPOR neatly reproduces the conservative relationship of biomass water productivity it would be interesting to systematically explore how other regional-global agricultural monitoring systems perform such as MODIS and USDA-FAS (Fritz et al., 2019).

In conclusion, although the WaPOR database contains data which suggest variation in local biomass and evapotranspiration, and although these variations inform ambitions to improve (agricultural) water productivity (Ministry of Foreign Affairs of the Netherlands, 2015; FAO, 2020a), we have demonstrated in this paper that from an agronomical point of view little additional insight is obtained from WaPOR as almost all variation can be attributed to the photosynthetic efficiency of sugarcane (very large influence), local climate variability (large influence), and irrigation technology (small influence). The remaining unexplained spatial variability falls within an error range of +/− 9%. We thus show that the origin of variability in biomass and evapotranspiration largely lies in factors farmers and water managers cannot control, and that there is thus very limited scope to improve biomass water productivity based on WaPOR data and agronomic theory. The limited scope also means that increases in food production are achieved through (nearly) linear increases in water consumed. Variabiliy in yield, as opposed to biomass, may be considerable. This is, however, governed by the crop variety specific responses to stresses (water, temperature) that result in a high variation of harvest indexes (Steduto et al., 2012). WaPOR, however, cannot deal with these and adopts for yield cacluations a fixed harvest index that is agronomically not warranted and requires expertise to transform it into a better variable harvest index tailored to local climate-crop development dynamics (e.g. heat and cold stress, rainfall supply between crop flowering and harvest). This study thus forms a key step towards enhancing our understanding how WaPOR variations in biomass and evapotranspiration should be analysed with agronomic theory.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2023.103712.

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