1 A Framework for Irrigation Performance Assessment Using
2 WaPOR data: The case of a Sugarcane Estate in Mozambique

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15 Abstract

16 The growing competition for the finite land and water resources and the need to feed an ever-growing
17 population requires new techniques to monitor the performance of irrigation schemes and improve land
18 and water productivity. Datasets from FAO's portal to monitor Water Productivity through Open access
19 Remotely sensed derived data (WaPOR) is increasingly applied as a cost-effective means to support
20 irrigation performance assessment and identifying possible pathways for improvement. This study
21 presents a framework that applies WaPOR data to assess irrigation performance indicators including
22 uniformity, equity, adequacy and land and water productivity differentiated by irrigation method (furrow,
23 sprinkler and centre pivot) at the Xinavane sugarcane estate, Mozambique. The WaPOR data on water,
24 land and climate is near-real-time and spatially distributed, with the finest spatial resolution in the area
25 of 100m. The WaPOR data were first validated agronomically by examining the biomass response to
26 water, then the data was used to systematically analyse seasonal indicators for the period 2015 to 2018
27 on ~8,000 ha. The WaPOR based yield estimates were found to be comparable to the estate-measured
28 yields with ± 20% difference, root mean square error of 19±2.5 ton/ha and mean absolute error of 15±1.6
29 ton/ha. A climate normalization factor that enables the spatial and temporal comparison of performance
30 indicators are applied. The assessment highlights that in Xinavane no single irrigation method performs
31 the best across all performance indicators. Centre pivot compared to sprinkler and furrow irrigation
32 shows higher adequacy, equity, and land productivity, but lower water productivity. The three irrigation
33 methods have excellent uniformity (~ 94%) in the four seasons and acceptable adequacy for most
34 periods of the season except in 2016, when a drought was observed. While this study is done for
35 sugarcane in one irrigation scheme, the approach can be broadened to compare other crops across
36 fields or irrigation schemes across Africa with diverse management units in the different agro-climatic
37 zone within FaO WaPOR coverage. We conclude that the framework is useful for assessing irrigation
38 performance using the WaPOR dataset.

39 **Keywords:** irrigation performance indicators; water productivity; remote sensing; Africa; sugarcane

40

1.   Introduction

Increasing agricultural production to feed the growing global population can be achieved through either expanding agricultural land or by increasing productivity of the existing agricultural areas. With growing competition and scarcity of the finite water and land resources, and the environmental and social costs of expanding agricultural land (Hess et al., 2016), improving irrigation performance indicators including land and water productivity has a clear preference.

The increasing global demand for sugar is also reflected in the steady increase in sugarcane production in Mozambique at an average annual rate of 10 percent (FAO, 2019). The majority of this increase comes from expanding agricultural land (Hess et al., 2016). Whilst Moraes et al. (2018) estimate there is a vast potential for expanding sugarcane production in Mozambique (~ 15% of the land area is suitable for sugarcane production), the water and land resources in the country are under increasing strain due to land degradation (Sutton et al., 2016), sectoral competition and climate effects (e.g. drought and flood) (Van der Zaag and Carmo Vaz, 2003; Arndt et al., 2011). With the land productivity well below the global average (Binswanger-Mkhize and Savastano, 2017; Nkamleu, 2013), and amongst the lowest in the Southern African region (Johnson et al., 2014), there is an opportunity to meet the demand without expanding the agricultural land. Thus, raising sugarcane productivity per unit of land and water on existing croplands needs to be explored by conducting irrigation performance assessment.

Monitoring irrigation performance indicators is key to check the general health, compare the spatial and temporal performances of the scheme, and to look for causes and provide corrective action that aims at improving overall service provision and productivity (Molden et al., 1998; Bos et al., 2005). The traditional irrigation performance assessment considers indicators that can be categorised as (i) water balance, water service and maintenance, (ii) environment, and (iii) economic indicators. The water balance, water service and maintenance indicators are water fluxes and production based indicators. The water delivery and production based indicators include uniformity (evenness of water distribution within fields), equity (uniformity of water distribution between fields), adequacy (sufficiency of irrigation delivery compared to the requirement), land productivity (production per unit area), water productivity (production per unit water use) and efficiency (the fraction of productive water use) (Molden and Gates, 1990; Bos, 1997; Molden et al., 1998). These irrigation performance indicators were assessed using field data such as flow (discharge), crop yield, and plot level water consumption estimate using lysimeter or crop model (Araya et al., 2011; Dejen, 2015; Edreira et al., 2018).

Recent developments and improvements of remote sensing (RS) products offer a viable alternative (Bastiaanssen et al., 1996; Karimi et al., 2011). RS-derived data have been increasingly applied as a cost-effective means for irrigation performance assessment. The RS derived irrigation performance assessment are based on production and actual water consumption, which the latter is fairly considered as the net outcome and result of effective rainfall and irrigation, allowing a hydrological assessment and quantification of the net water abstracted by irrigated crops. In addition, it provides spatially distributed data, covers long periods and wide areas and can be done retrospectively (Bastiaanssen et al., 1996; Karimi et al., 2011). Field data, in contrast, does not represent well the spatial variation across an irrigation system and is costly to obtain (Bastiaanssen et al., 2000). The traditional and RS-based performance assessments are complementary as the former has strength in observing the horizontal water fluxes such as discharges while the latter has strength in observing high resolution vertical water fluxes and biomass production.

Earlier studies provide insight into the application of RS-derived data to assess irrigation performance indicators. In this research, the earlier RS-based irrigation performance assessment studies are

86 strengthened by considering a simple consistency check to validate the RS-derived data for established
87 biomass response to water consumption (Steduto and Albrizio, 2005) and by introducing a
88 comprehensive framework that guide the step by step translation of RS-derived datasets into irrigated
89 agricultural performance indicators. In addition, the current study introduces a climate normalization
90 factor that enables the spatial and seasonal comparison of irrigation performance indicators. The
91 climate normalization is applied to distinguish climatic factors from agricultural management factors in
92 their effect on irrigation performance.

93 This study first evaluates the WaPOR data for consistency based on the established agronomic
94 principle (biomass response to water consumption). It is then used to develop a framework to assess
95 irrigation performance indicators, including adequacy, uniformity, equity and land and water
96 productivity. This framework is then used to assess the irrigation performance at Xinavane sugarcane
97 estate differentiated by irrigation method.

98

2. Materials and Methods

2.1. Study area

101 The study focusses on one of the largest sugarcane estates in Maputo province in Mozambique, the
102 Xinavane estate. The estate is located on the banks of the Incomati River, approximately 136 km
103 northwest of Maputo. This region is characterized by optimal conditions for sugarcane production in
104 terms of climate, soils and water availability. With a seasonal long-term average precipitation of 721
105 mm/year (den Besten et al., 2020), the sugarcane production requires irrigation water especially during
106 the dry season, supplied by the Incomati river.

107 The most important water infrastructure in the Incomati Basin in Mozambique is the Corumana Dam,
108 which was built for improving flood control, regulating downstream irrigation abstractions (including
109 Xinavane) and hydropower production (de Boer and Droogers, 2016). Xinavane sugarcane estate,
110 despite receiving allocations from the dam, remains largely vulnerable to climate variability. During a
111 recent drought in 2016, reservoir levels in the Corumana Dam dropped drastically and little water was
112 available for irrigation in the Xinavane sugarcane estate. This resulted in a significant reduction in
113 sugarcane production in 2016 compared to previous years (Tongaat Hullet, 2018). Such events are
114 expected to continue to occur. To partially address this, Mozambique put drought mitigation measures
115 in place for the Xinavane area, including the construction of the new Moamba Major Dam (760 Mm^3)
116 and the heightening of the Corumana Dam wall, which will result in a capacity increase from 879 Mm^3
117 to 1,260 Mm^3 (Tongaat Hullet, 2018).

118 The widely used irrigation methods at the Xinavane sugarcane estate are furrow, overhead sprinkler
119 (hereinafter referred to as sprinkler) and centre pivot irrigation (Figure 1). A total of 8,027 ha categorized
120 into 387 georeferenced fields and three irrigation application methods are considered in our analysis.
121 Furrow, sprinkler and centre pivot irrigation cover 3,343 ha, 3,629 ha and 1,055 ha, respectively. The
122 average field size under furrow, sprinkler and centre pivot irrigation methods is 17 ha, 18.3 ha and 55.8
123 ha, respectively. All fields in the sample are operated and managed by the estate; fields operated by
124 out-growers were excluded from the analyses.

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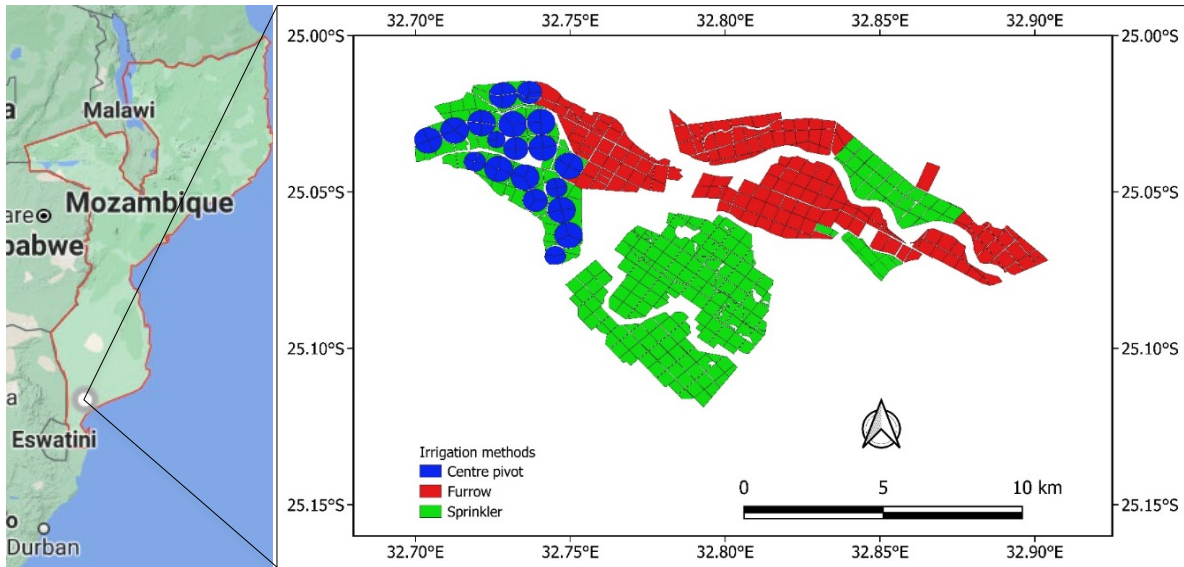

126 *Figure 1. Irrigated areas (estate operated) with different application methods at Xinavane sugarcane estate,*
127 *Mozambique showed in the map of Mozambique (Map data ©2021 Google, AfriGIS(Pty) Ltd)*
128

2.2.   WaPOR datasets

130 Datasets from FAO's portal to monitor Water Productivity through Open access Remotely sensed
131 derived data (WaPOR; URL: https://wapor.apps.fao.org/home/WAPOR_2/1) are used for the analyses
132 as it provides the required layers to estimate both land and water productivity. The database covers
133 Africa and the Near East regions in near real-time for the period between 2009 to date (2021) (FAO,
134 2020c). WaPOR datasets are available at the continental scale (Level 1 at 250 m), country (Level 2 at
135 100 m) and project level (Level 3 at 30 m). The latest WaPOR version (WaPOR v2.1) is an improvement
136 from WaPOR v1.0 following the quality assessments by IHE Delft and ITC (Mul and Bastiaanssen,
137 2019; FAO, 2020a). The methodology used for compiling the actual evapotranspiration of WaPOR is
138 based on the ETLook method (Bastiaanssen et al., 2012) and further developed by the FRAME
139 consortium (the full description of the methodology is provided in FAO (2020b)). WaPOR v2.1 was
140 found suitable for inter-plot comparison of irrigation performance indicators for plots larger than 2 ha
141 (Blatchford et al., 2020).

142 At Xinavane, the finest resolution of the WaPOR data is 100 m (Level 2). The WaPOR Level 2 datasets
143 used in this study include layers for actual evaporation (E), transpiration (T), and net primary production
144 (NPP) at a dekadal (10-day) timescale. In addition, daily precipitation at 5 km resolution, daily reference
145 evapotranspiration at 20 km resolution, and annual land cover classification (LCC) at 100 m resolution
146 were used. The precipitation (P) and reference evapotranspiration (RET) datasets were resampled to
147 100 m resolution using the nearest neighbour resampling techniques (GDAL, 2021). An overview of the
148 WaPOR data used in the analyses is presented in Table 1.

149 Although there is a continuous WaPOR L2 dataset (100 m) available from 2009 to date (2021), only the
150 data from 2014 is derived that stems from the PROBA-V satellite. The data prior to 2014 is derived from
151 resampled L1 (250m) data which is obtained from the MODIS satellite. Since this creates a discontinuity
152 in the data as observed by Chukalla et al. (2020b), the pre 2014 data has been discarded in this analysis
153 and only data starting from the 2014-2015 growing season onwards has been selected.

154 *Table 1: The WaPOR layers used for the analyses*

WaPOR layer	Spatial resolution	Temporal resolution (coverage)
Evaporation (E)	100 m	
Transpiration (T)	100 m	
Net primary production (NPP)	100 m	Dekadal (2014-2018)
Precipitation (P)	5 km	
Reference evapotranspiration (RET)	20 km	
Land cover map (LCC)	100	

155

2.3. A framework for assessing irrigation performance using WaPOR data

Figure 2 shows the flowchart describing the approach to assess WaPOR based irrigation performance indicators at the Xinavane sugarcane estate. Irrigation performance indicators are derived from WaPOR and field data in three main steps. First, actual evapotranspiration (ET_a = E+T), reference evapotranspiration (RET) and net primary production (NPP) layers of FAO WaPOR are pre-processed to match the spatial resolution, remove non-crop pixels using crop map or land cover classification (LCC) and undergo a quality check. Second, the seasonal ET_a ($ET_{a,s}$), seasonal potential evapotranspiration ($ET_{p,s}$) and seasonal NPP (NPP_s) are calculated from their respective WaPOR layers between the start of the season (SOS) and end of the season (EOS) for each plot. $ET_{p,s}$ is derived from RET and crop coefficient (K_c). Finally, the irrigation performance indicators are analysed. At this stage, NPP_s is translated to above-ground biomass (hereafter referred to as biomass (B)) using crop specific information (above over total biomass (AOT) for non-root corps or below over total for root and tuber crops, light use efficiency correction factor (f_c) and moisture content of fresh biomass (m_c)). The biomass is multiplied by harvest index (HI) to derive the crop yield. The remainder of this section describes in more detail the input data and equations used in each step.

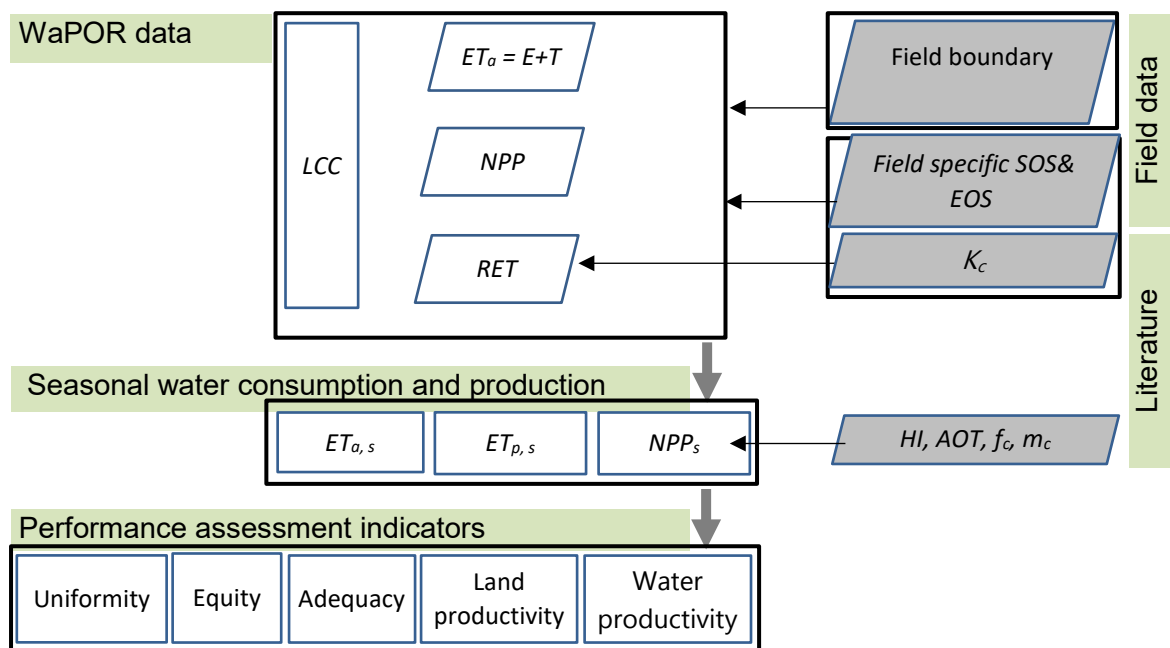
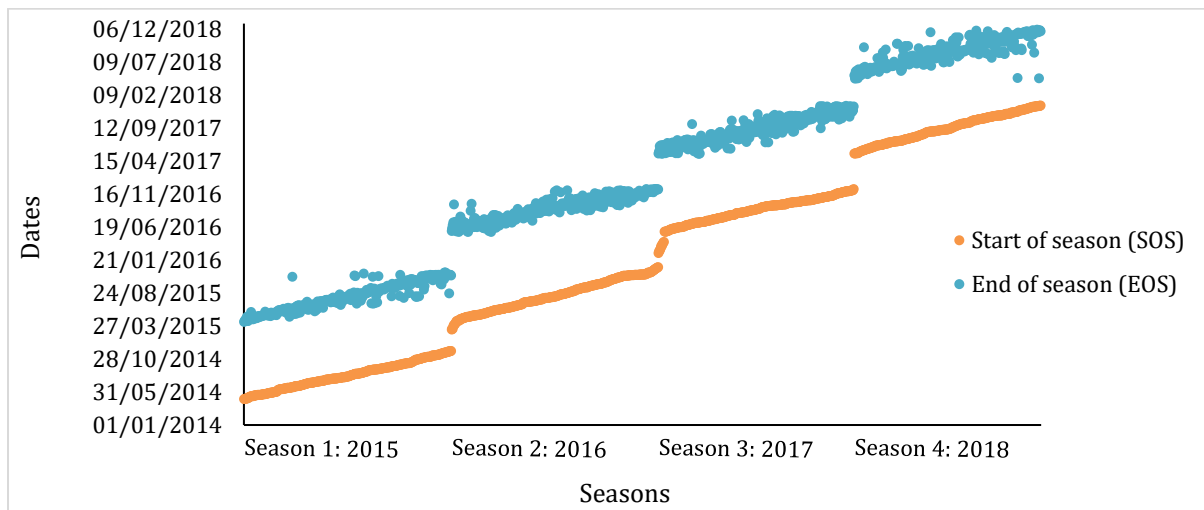



Figure 2. Schematic representation of WaPOR based Irrigation performance assessment framework

174

2.3.1. Seasonal water consumption and crop yield

Growing season

177 The sugarcane estate operates on a ratooning system. Thus, the start of the growing season (one day
178 after harvesting) and end of season (next year's harvesting date) varies per field. The actual growing
179 period of each field was used to calculate the production per unit of land and per unit of water consumed.
180 The average length of the growing season is 347±32 days. This study covers four growing seasons:
181 season 1 (2014/2015), season 2 (2015/2016), season 3 (2016/2017) and season 4 (2017/2018)
182 reported as 2015, 2016, 2017 and 2018, respectively, i.e. the year the fields are harvested (Figure 3).

183

184 *Figure 3. The start and end of season for individual fields for the four growing seasons at Xinavane estate*

Seasonal water consumption

186 Actual water consumption refers to the amount of water that is depleted from the root zone through the
187 process of transpiration by a crop and direct evaporation from the soil represented by WaPOR $E + T$
188 (ET_a). The seasonal ET_a is the total actual water consumption during the cropping season.

189

Crop yield

191 The season NPP layer from WaPOR, accumulated over the crop growing period (Figure 3), is converted
192 to above-ground biomass (B) in kg/ha and crop yield (Y) in kg/ha using Equation 1 and 2 (Mul and
193 Bastiaanssen, 2019):

$$B = AOT * f_c * \frac{NPP*22.222}{(1-m_c)} \qquad \text{Equation 1}$$

195 where m_c[-] is the moisture content of the fresh biomass, f_c [-] is the light use efficiency (LUE) correction
196 factor calculated by dividing the LUE of the crop (in this case sugarcane) by the LUE of a generic crop
197 type that WaPOR NPP layer uses (2.7 MJ/g biomass; FAO (2018) and FAO (2020b)), and AOT[-] is the
198 ratio of above ground over total biomass. The B and Y can be expressed in in ton/ha, by dividing the in
199 kg/ha by a 1,000. Crop yield is calculated by multiplying the biomass by the harvest index (HI[-]):

201     $Y = B*HI$ Equation 2

203   In absence of field data, literature was consulted to estimate these crop parameters. Table 2 presents
204   the values and the source of the parameters.

206   *Table 2: Parameters used in the biomass and yield analyses of sugarcane*

Parameter	Description	Value	Source
m_c	Moisture content of fresh crop biomass	59%	Yilma, 2017; Mul and Bastiaanssen, 2019
f_c	Light use efficiency correction factor	1.6	Villalobos and Fereres, 2016
AOT	The ratio of above ground over total biomass (AOT)	1	FAO, 2020c
HI	Harvest index	1	FAO, 2020c

208   The WaPOR based sugar cane yield was validated with sugarcane yields as measured by the Xinavane
209   estate for four seasons on 387 fields. In addition, the WaPOR based biomass and water consumption
210   were checked for consistency with agronomic principles. An increasingly strong linear relationship is
211   expected between biomass and evapotranspiration (Steduto and Albrizio, 2005), between biomass and
212   transpiration (De Wit, 1958), and between biomass and normalized transpiration (Steduto and Albrizio,
213   2005), whereby the normalized transpiration is the sum of the daily ratio of transpiration over reference
214   evapotranspiration over the crop season (Steduto et al., 2007).

216   2.3.2.   Performance assessment indicators

217   The irrigation performance indicators selected for this study are uniformity, equity, adequacy and
218   productivity, these were selected as these could be assessed (sometimes with a slight modification)
219   using the WaPOR data. These performance indicators are further explained below, and the set of
220   equations for water consumption based performance indicators are presented in Table A1 (in the
221   Appendix).

222   Uniformity measures the evenness of water consumption within an irrigated field. It is calculated by
223   assessing the coefficients of variation (CV) of seasonal ET_a within a field. Thus, uniformity is one minus
224   the CV (Ascough and Kiker, 2002). It serves as a measure for the heterogeneity of soil water storage
225   capacity and thus water storage efficiency in a field. It can serve as a proxy for irrigation distribution
226   uniformity (Burt et al., 1997) in farms where the management is central and consistently the same level
227   of inputs are applied (e.g. variable rate input application in not practices). Other factors like soil type,
228   fertility, pest, crop variety can also affect actual water consumption and thus uniformity. Thus, CV of
229   seasonal ET_a indicates the combined effect of all factors (water, fertility, pests, diseases, salinity).

230 According to Pitts et al. (1996), the acceptable standard uniformity of irrigation application distribution
231 for centre pivot, sprinkler, drip and furrow irrigation methods are 75%, 75%, 85% and 65%, respectively.
232 The distribution uniformity exceeding the standard threshold is considered excellent.

233 Equity measures the evenness of water consumption between fields within an irrigation scheme with a
234 homogenous crop, which could be a proxy for an even distribution of water to the different irrigated fields.
235 It is calculated as the CV of the average ET of each field, which is an indication of equity in the scheme.
236 A CV of 0 to 10% is defined as good equity, CV of 10 to 25% as fair equity and CV > 25% as poor equity
237 (Bastiaanssen et al., 1996; Karimi et al., 2019).

238 Adequacy (A) is the measure of the degree of agreement between the actual water use and crop water
239 requirement (Bastiaanssen and Bos, 1999; Clemmens and Molden, 2007). Adequacy is estimated as
240 the ratio of seasonal actual evapotranspiration ($ET_{a,s}$) over seasonal potential evapotranspiration ($ET_{p,s}$)
241 (Kharrou et al., 2013; Karimi et al., 2019). Potential evapotranspiration is the maximum crop
242 evapotranspiration from disease-free and well-fertilized cropped fields under optimum soil water
243 conditions; it is calculated by multiplying reference evapotranspiration by crop coefficient (Allen et al.,
244 1998). The seasonal $ET_{p,s}$ of sugarcane is aggregated from the monthly value of crop coefficient times
245 the reference evapotranspiration (Table A2 in the Appendix). Good adequacy performance is defined
246 for the range of 0.8<A<=1, acceptable range 0.68<A<=0.8 and poor performance A <=0.68 (Karimi et
247 al. 2019).

248 Productivity is a measure of benefit generated per unit of resource used. The benefit could be
249 biophysical, economic and/or social; the resource base could be consumed or supplied water or land
250 covered by the crop (Zwart and Bastiaanssen, 2004; Hellegers et al., 2009; Karimi et al., 2011). This
251 study focussed on biophysical production per unit of land or evapotranspiration, also known as land and
252 water productivity.

253 Land productivity is defined as biomass production or crop yield per unit of land. For water, we similarly
254 distinguish biomass water productivity (WP_b) and crop yield water productivity (WP). WP_b is defined as
255 the ratio of biomass over seasonal $ET_{a,s}$, whereas WP is defined as the yield over $ET_{a,s}$. Since for
256 sugarcane we use a harvest index of 1, WP_b is here equal to WP.

257 Spatial-temporal variations can be caused by both management practices and climate. Figure B1 in the
258 Appendix shows a correlation between water productivity and reference evapotranspiration (r^2 of 0.5,
259 0.7 and 0.8 for furrow, sprinkler and centre pivot irrigated fields, respectively). The correlation between
260 actual evapotranspiration and reference evapotranspiration (Figure B2 in the Appendix) is even stronger
261 ($r^2 > 0.8$). Thus, to exclude the climate related factor, we normalized the water productivity and
262 evapotranspiration using a climate normalisation factor. This is defined as the ratio of the weighted
263 average reference evapotranspiration (weighted based on the field size and growing length of the fields)
264 to the reference evapotranspiration at the field (Equation 3).

265
$$f_{norm} = \left(\frac{\overline{RET}}{RET_i} \right)$$
Equation 3

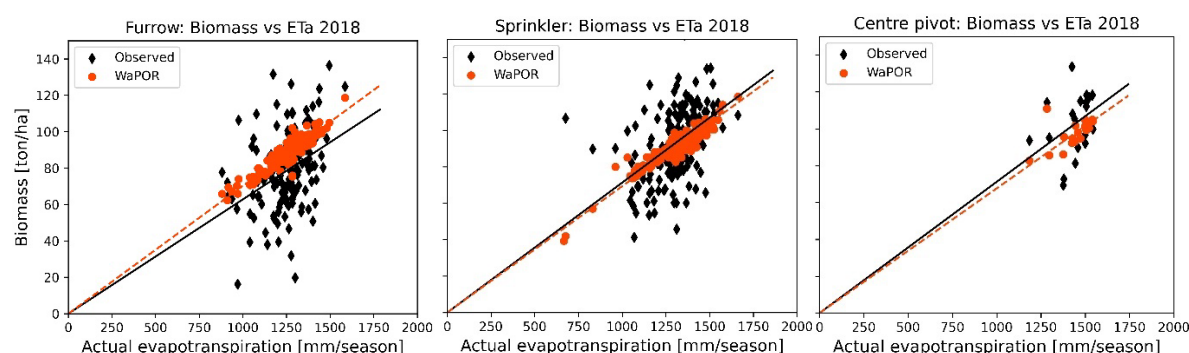
266 where f_{norm}[-] is the normalizing factor for the selected indicator, $\overline{RET}$ is weighted average reference
267 evapotranspiration, and RET_i is reference evapotranspiration at a field in mm per season.

268 2.4 Consistency check of WaPOR data

269 Figure 4 shows the relationship between biomass (B; WaPOR derived and observed) and water
270 consumption of irrigated fields categorized by irrigation methods for the year 2018 (with the
271 supplementary materials, Figure S1, showing the other 3 year from 2015 to 2017). In furrow and sprinkler
272 irrigated fields, the WaPOR derived biomass and actual evapotranspiration show a high correlation (a

273 minimum r² of ~0.83 (n≈150) in 2015, 2017 and 2018 and r² ≈ 0.63 in the relatively dry year of 2016),
274 indicating consistency between the two independently generated datasets. For the centre pivot irrigated
275 fields r² is much lower with a value of ≈ 0.6 in 2015, 2016 and 2017 and lowest r² of 0.2 (n≈19) in 2018.
276 The low number of fields irrigated by centre pivots may have contributed to the low correlation. Moreover,
277 the estate-observed yield at Xinavane sugar estate versus ET_a shows a high spread and thus a low
278 correlation (r² ≈ 0.13).

279 The supplementary materials, Table S1, provide the analyses of the relationship between biomass and
280 transpiration and biomass and normalised transpiration for the entire period of analyses (2015-2018). In
281 contrast to expectations based on agronomic principles, the correlation is decreases when considering
282 biomass and transpiration (~0.80) and biomass and normalized transpiration ($\sum T_a/RET$) (~0.71) (see
283 further Supplementary materials). The accuracy of the evaporation and transpiration split in WaPOR is
284 therefore questioned, this was also observed by Mul and Bastiaanssen (2019). Further analyses will
285 therefore only focus on indicators that use evapotranspiration, not evaporation and transpiration, as
286 input. For instance, the beneficial fraction (i.e., the ratio of transpiration over evapotranspiration) is not
287 included in the analysis. Yet, two tests based on WaPOR derived biomass and total actual
288 evapotranspiration (ET_a) have confirmed the agronomic expectations (Table S2 in the supplementary
289 material). The first is that the correlation coefficient of the linear regression line passing through the
290 origin for the biomass vs. normalized actual water consumption is higher than that of the correlation
291 coefficient for the biomass vs. actual water consumption. Second, the crop water productivity normalized
292 by reference evapotranspiration (WP*), is confirmed to be conservative and within the range of values
293 for C4 crops (30-35 g/m²) including sugarcane (Steduto et al., 2007; Steduto et al., 2009).

294

295 *Figure 4. The relationship between biomass (as measured by the estate and derived from WaPOR) and actual*
296 *evapotranspiration (derived from WaPOR) of furrow (left), sprinkler (centre) and centre pivot (right) irrigated fields*
297 *at Xinavane sugar estate harvested in 2018*

298

299 3. Results

300 3.1. Seasonal water consumption

301 Figure 5 shows the seasonal actual and potential evapotranspiration, and seasonal precipitation at
302 Xinavane sugarcane estate, distinguished by the three irrigation application methods. The four-season
303 (2015 to 2018) average precipitation is 640 mm/season and ranges from the minimum of 500
304 mm/season in 2016 to the maximum precipitation of 875 mm/season in 2017. The four-season average
305 ET_a at Xinavane is 1,350 mm/season and its average seasonal values range between 1,255 mm/season
306 in 2018 at furrow irrigated fields to 1,533 mm/season in 2016 at fields irrigated by centre pivot. In the
307 four seasons the ET_a is significantly the highest (*P-value < 0.05*) at fields irrigated by centre pivot
308 followed by sprinkler and furrow (Table A4 in the Appendix).

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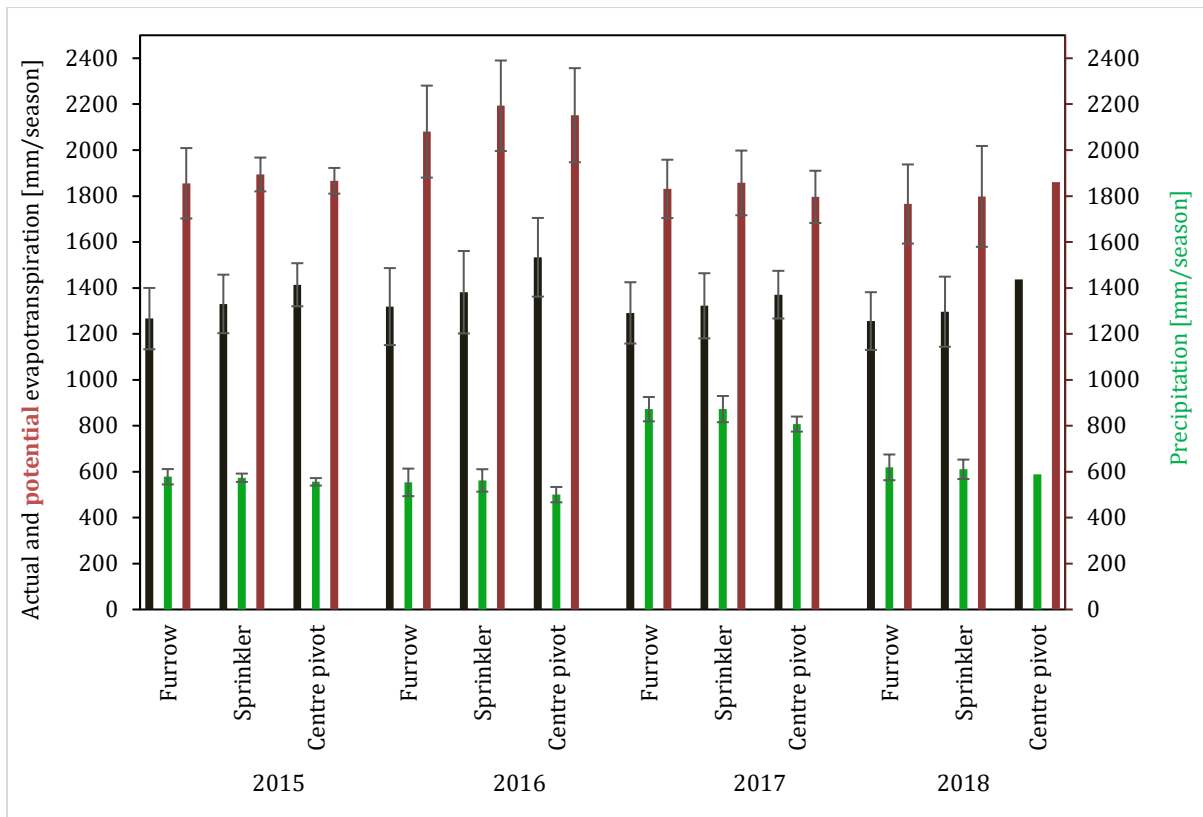
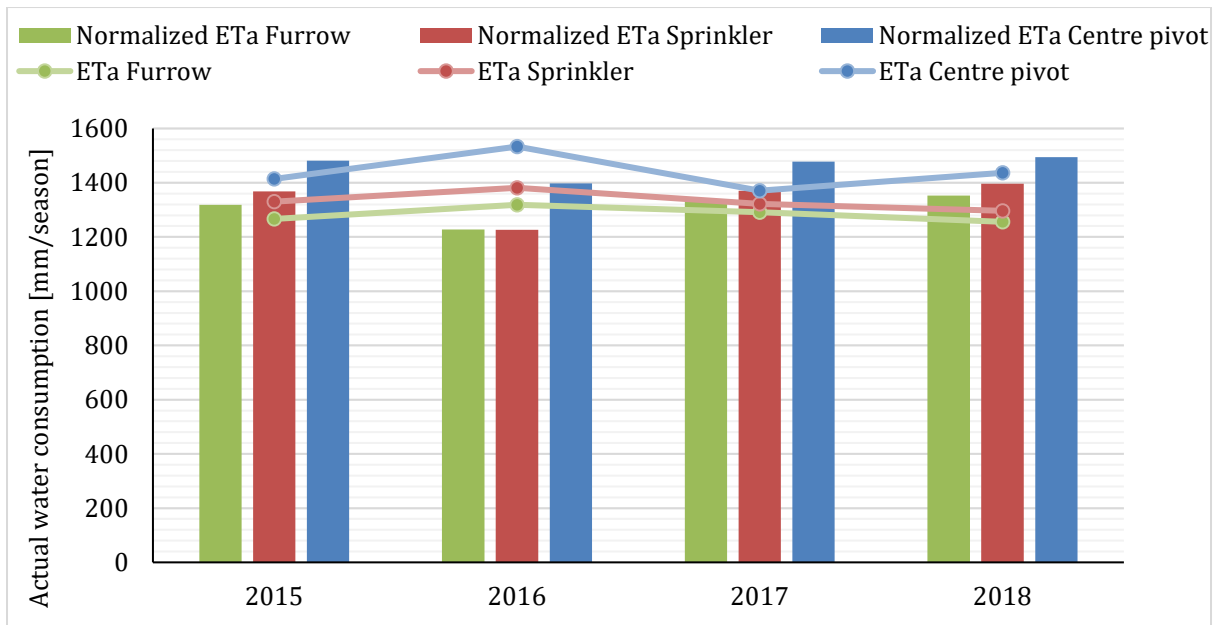

310 *Figure 5. Seasonal actual and potential evapotranspiration and precipitation at Xinavane sugar estate from 2015*
311 *to 2018. The error bar indicates the variation across the fields irrigated by an irrigation method.*

312 The high *average ET$_a$* over Xinavane irrigation scheme in 2016 coincides with the reported drought
313 year. This mainly manifested itself with high *ET$_{pot}$* as the annual precipitation that fall within the
314 command area was not much lower than in 2015 and 2018. After normalizing for climate variation, the
315 normalised *ET$_a$* is actually lowest for 2016, indicating higher water deficit (lowest actual per unit of
316 potential evapotranspiration), with the drought having more impact on sprinkler and furrow irrigation
317 than on centre pivot. Despite the *ET$_a$* being the highest in 2016, when normalised by climate the results
318 show that 2016 experiences the highest water deficit. The four-season average actual water
319 consumption of centre pivot remains the highest followed by sprinkler and furrow, except for 2016, when
320 the sprinkler normalised *ET$_a$* is at the same level as furrow *ET$_a$* (Figure 6). This indicates that the
321 sprinkler system was more affected by the drought conditions in 2016 compared to the other systems.

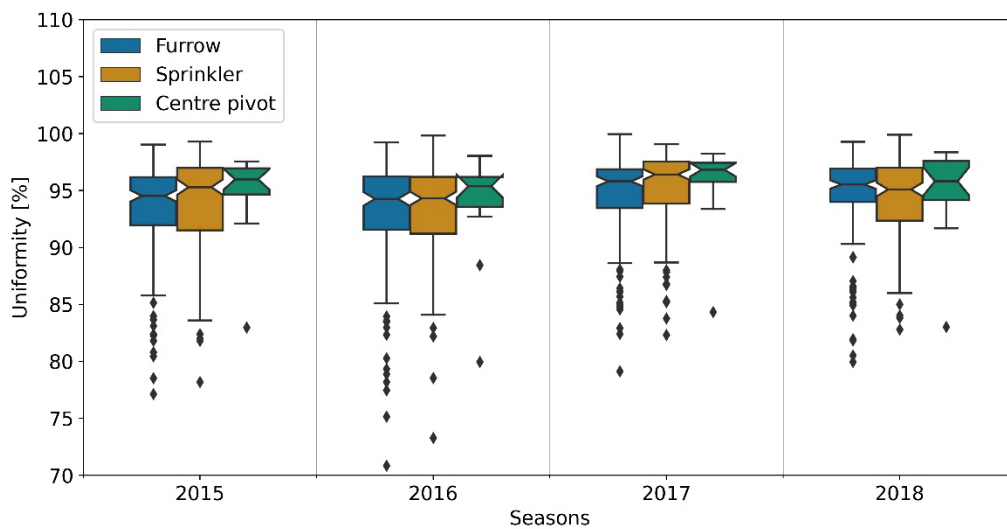
322

323 *Figure 6. Normalized actual evapotranspiration at Xinavane sugar estate categorized by irrigation methods from*
324 *2015 to 2018.*

325

3.2. Performance of irrigation delivery

3.2.1. Uniformity

328 The uniformity of water consumption within the fields is ~ 94% for all three irrigation methods (Figure 7).
329 The calculated uniformity is above the standard values per irrigation method and are therefore
330 considered as excellent. Centre pivots show an even higher uniformity than the other irrigation methods.

331

332 *Figure 7. Coefficient of variation of actual water consumption per pixel inside a field at Xinavane sugar estate*
333 *categorized by irrigation methods from 2015 to 2018. The lower and upper whisker in the box plot show the minimum*
334 *and maximum values. The lower, middle and upper bar of the box show the 25, 50 and 75 percentiles of the values.*

335

3.2.2. Equity

The average seasonal coefficient of variation (CV) of $ET_{a,s}$ among fields irrigated by the same irrigation method is 15% (Figure 8). Fields irrigated using furrows, with a CV of 18%, have the highest heterogeneity in water consumption compared to areas irrigated using sprinkler (CV=14%) and centre pivot irrigation method (CV=13%). The coefficient of variation of water consumption between fields irrigated by a particular irrigation method and thus equity of water use among the fields is considered fair.

343

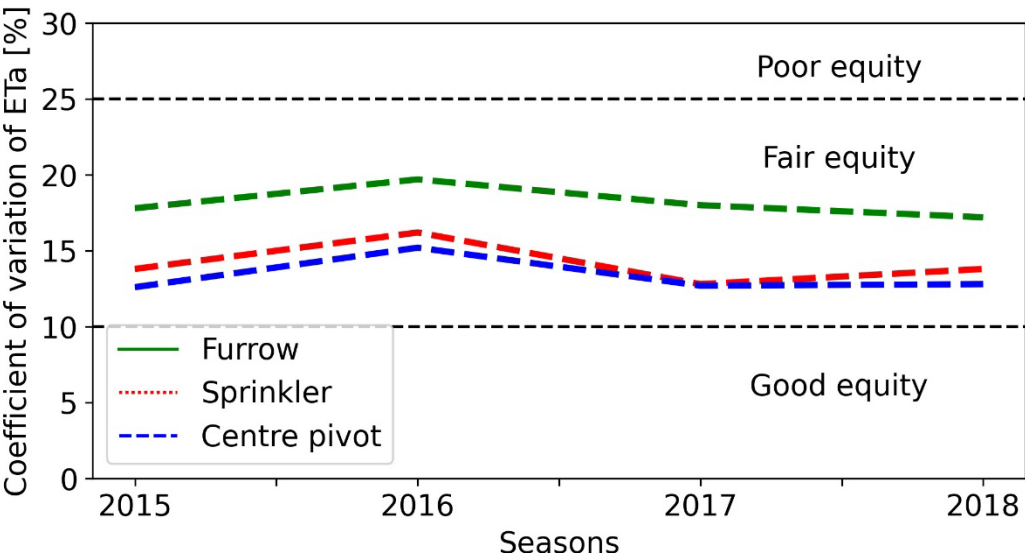



Figure 8. Coefficient of variation of actual water consumption between fields irrigated by an irrigation method at Xinavane sugar estate from 2015 to 2018.

346

3.2.3. Adequacy

The four-season average adequacy varies spatially across the Xinavane irrigation scheme with visible differences between fields irrigated using centre pivot compared to fields irrigated using furrow and sprinkler for the period analysed. Figure 9 shows the highest adequacy for fields irrigated using centre pivot (0.75) followed by fields irrigated using sprinkler and furrow (~0.69). In the study period, the adequacy performance at fields under centre pivot fall in the acceptable range (from 0.68 and 0.8) for sugarcane (Karimi et al., 2019). The adequacy in fields under sprinkler and furrow also is acceptable except in the year 2016, which is recognized as a drought year, when adequacy was poor.

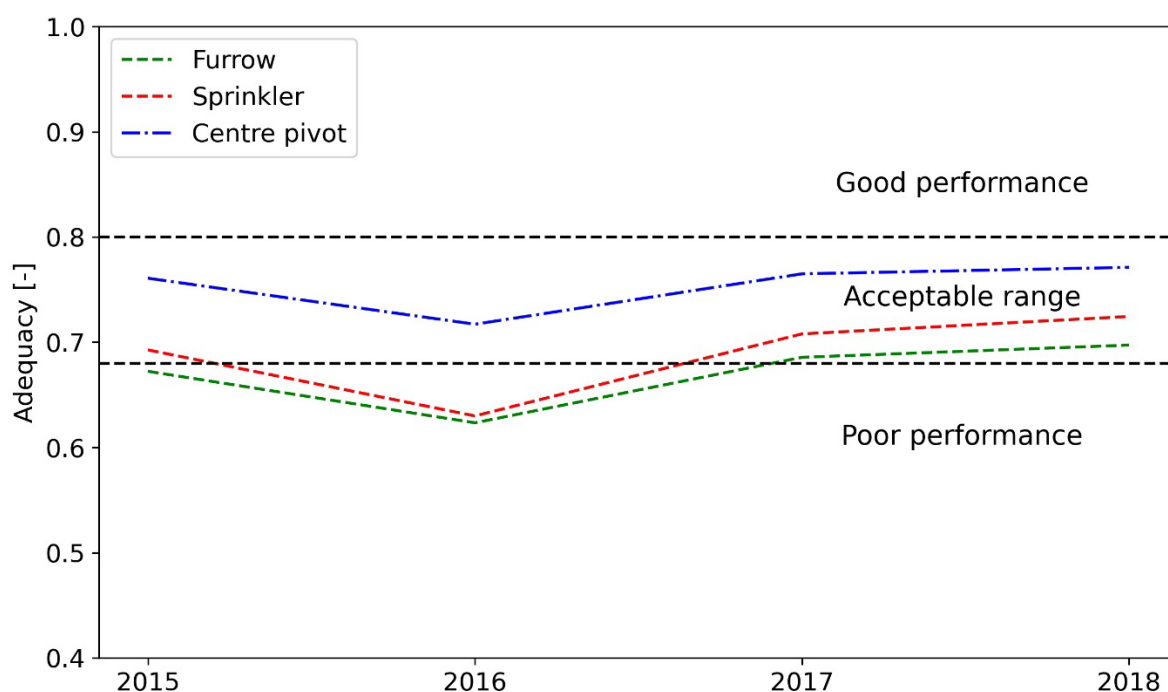



Figure 9. Adequacy [-] at Xinavane sugar estate categorized by irrigation methods.

3.2.4. Land productivity

The four-year seasonal average WaPOR based yield is 89 ton/ha (86 ton/ha for fields irrigated using furrow, 88 ton/ha for areas irrigated using sprinkler and 93 ton/ha for fields irrigated using entre pivot). For all years (except 2017) the highest sugarcane yield (land productivity) at Xinavane is found in fields irrigated by centre pivot followed by fields irrigated by sprinkler and furrow irrigation methods (Figure 10).

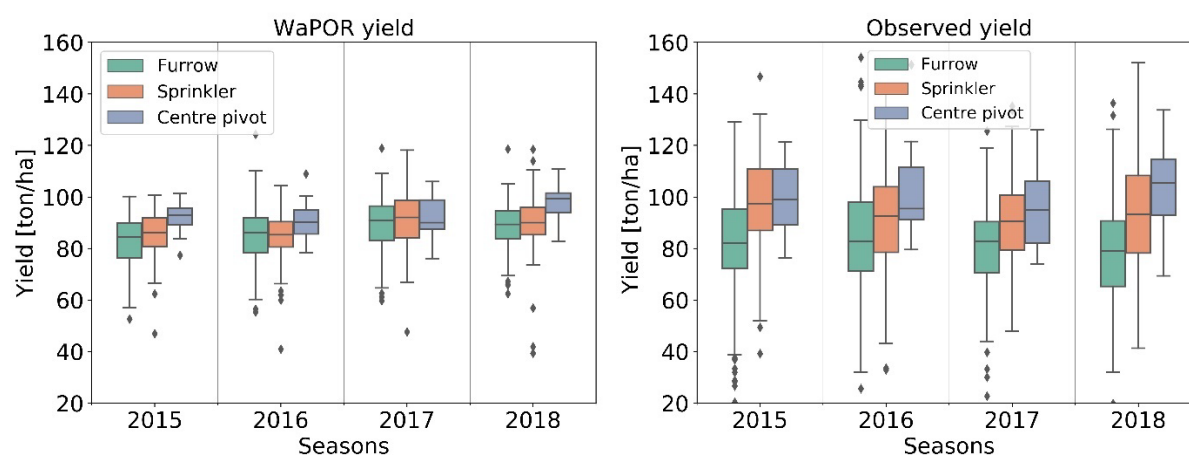
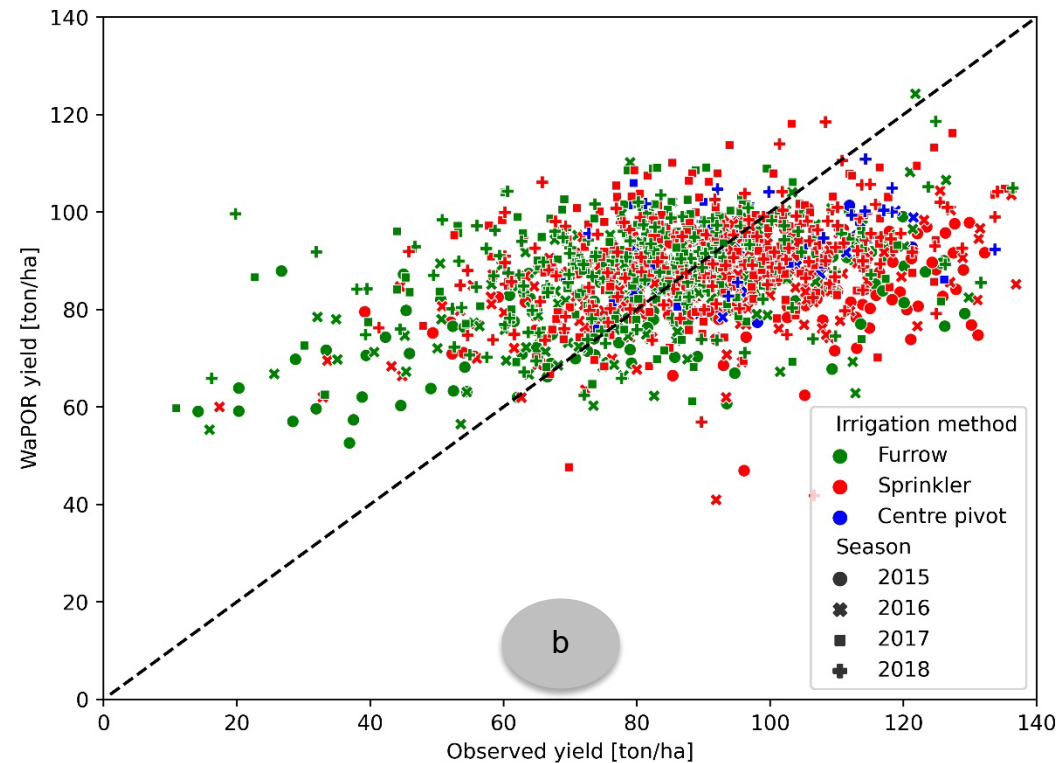
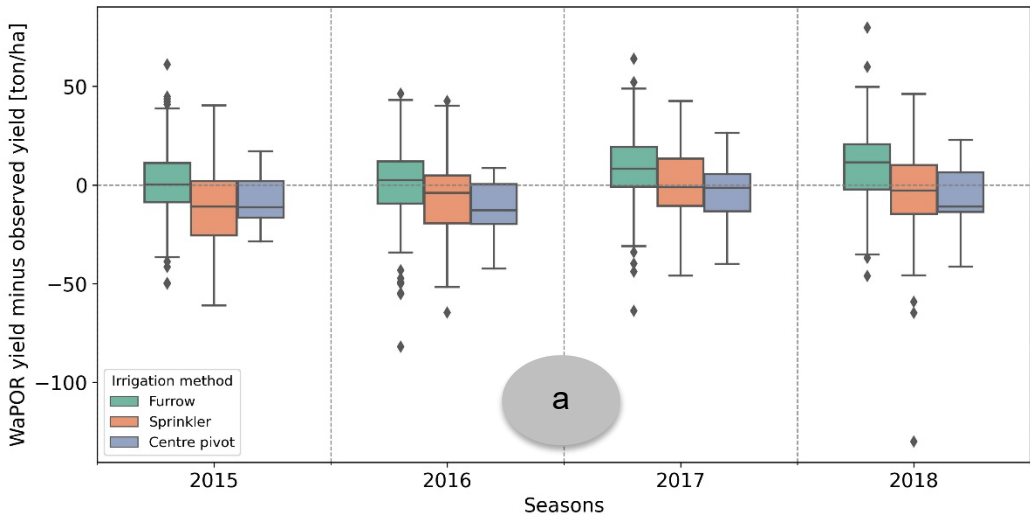



Figure 10. Boxplot of yield at Xinavane sugar estate categorized by irrigation methods from 2015 to 2018: WaPOR yield (a) and estate-measured (observed) yield (b). The lower and upper whisker in the box plot show the minimum and maximum values across the fields irrigated by an irrigation method. The lower, middle and upper bar of the box show the 25, 50 and 75 percentiles of the values across the fields irrigated by an irrigation method.

369 The four-year seasonal WaPOR yield is in the same order of magnitude compared to the estate-
370 measured sugarcane yield: 86 ton/ha vs. 81.4 ton/ha, 88 ton/ha vs. 93 ton/ha and 93 ton/ha vs. 99
371 ton/ha for fields irrigated using the furrow, sprinkler and centre pivot irrigation methods, respectively.
372 Part of the minor discrepancy between the WaPOR and estate-measured yield could be due to the
373 selection of crop parameters such as harvest index and moisture content. Yet, the comparison between
374 both yields shows acceptable statistics (Table A3 in the Appendix), with a Root mean square error of
375 19±2.5 ton/ha and Mean absolute error of 15±1.6 ton/ha.

376 Whilst the average values for WaPOR based yields are of the same magnitude as the estate-observed
377 data (65% of yield differences at the fields are within ± 20%), WaPOR overestimates relatively low yields
378 (marks on scatter plot above 1:1 line) and underestimates relatively high yields (marks on scatter plot
379 below 1:1 line) (Figure 11). WaPOR yields thus show a marked less variation in yields than reported by
380 the estate.

381

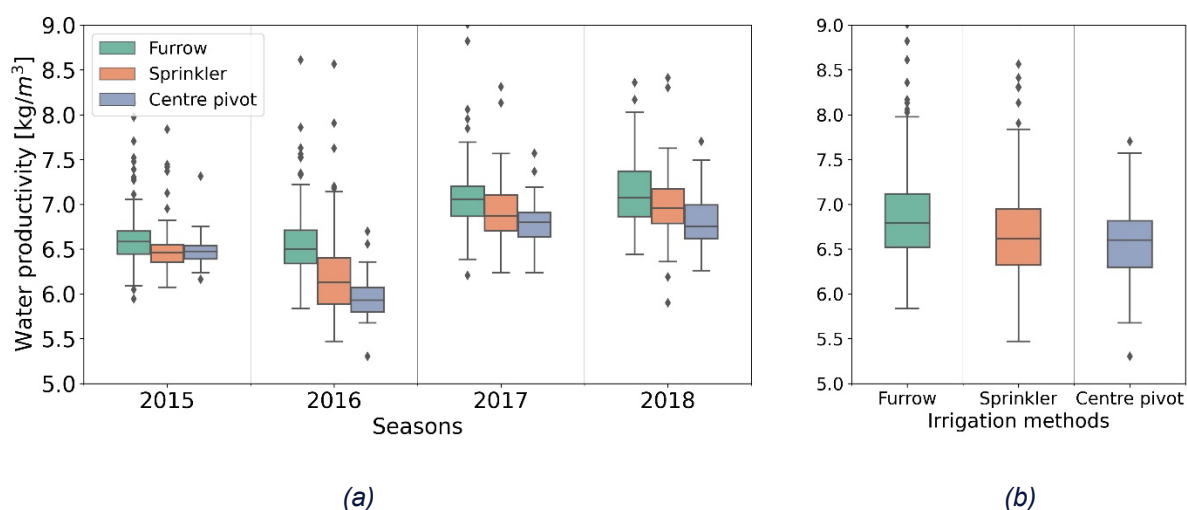
382

385

3.2.5.   Water productivity

387 The seasonal and four-season average water productivity at Xinavane is shown in Figure 12. The four-
388 season average water productivity is the highest for furrow irrigated fields (6.9 kg/m³), compared to the
389 values for fields irrigated with sprinkler (6.7 kg/m³) and centre pivot (6.6 kg/m³). One of the reasons for
390 such differences is the fraction of ET_a being utilised for productive purposes (transpiration) compared
391 to non-productive evaporation. Raes et al. (2013) reports that centre pivot and sprinkler irrigation wets
392 100% of the field compared to furrow that wets ~ 80% of the field and thus results in higher evaporation
393 rates, which is in line with our observations.

394

395   (a)   (b)

396 Figure 12. Boxplot of water productivity in kg/m³ at Xinavane sugarcane estate categorized by (a) irrigation methods
397 in 2015 to 2018 and (b) four-season average. The lower and upper whisker in the box plot show the minimum and
398 maximum values across the fields irrigated by an irrigation method. The lower, middle and upper bar of the box
399 show the 25, 50 and 75 percentiles of the values across the fields irrigated by an irrigation method.

400 The large variation of WP over the years (Figure 12) is also apparent after normalizing for climate
401 variation (Figure 13). The normalised WP is highest in a relatively dry year (2016) compared to the other
402 three years, this is opposite to WP, where 2016 has the lowest WP. It indicates that climate-related
403 parameters expressed through potential evapotranspiration has a large impact on the WP. The
404 normalised WP shows the variations which are related to management practices, during the drought of
405 2016, the Xinavane estate practiced deficit irrigation, which is reflected in the high normalised WP
406 values.

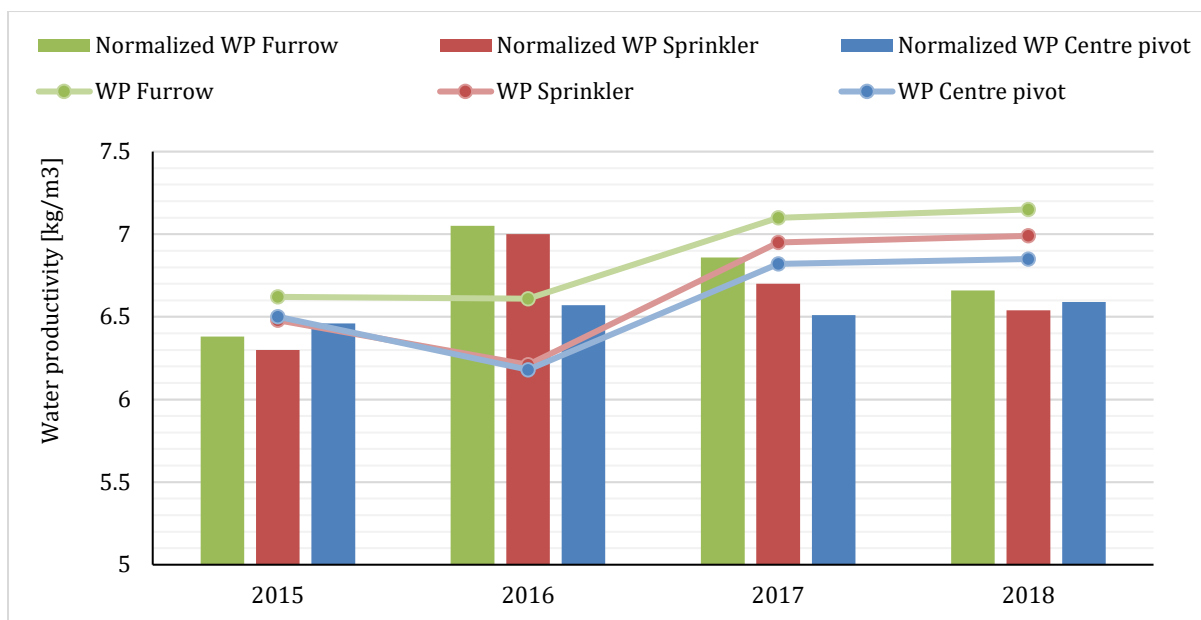



Figure 13. Normalized water productivity at Xinavane sugarcane estate categorized by irrigation methods in 2015 to 2018.

4.   Discussion

4.1.   The framework

The presented framework was used to conduct an irrigation performance assessment using WaPOR data. Our analysis shows that fields irrigated using centre pivots have the highest equity, adequacy and land productivity followed by fields irrigated using sprinkler and furrow. This outcome agrees with the conclusion by Karimi et al. (2019) who assessed performance of irrigated sugarcane in Eswatini (Swaziland) by differentiating areas according to management regimes including irrigation methods. The adequacy performance under the three irrigation methods was generally acceptable except in 2016 when performance of all three irrigation methods was poor. Fields under centre pivots do, however, have the lowest water productivity followed by sprinkler and furrow irrigation, which is contrary to the finding by Karimi et al. (2019) who reported the WP of centre pivot to exceed that of furrow irrigation. In fact, it is claimed that pressurized irrigation (sprinkler and centre pivot) improve uniform distribution, application efficiency of irrigation water and increase crop yield (Magwenzi and Nkambule, 2003; Playán and Mateos, 2006). Yet, these irrigation methods increase seasonal evaporation (Playán and Mateos, 2006), which could be due to differences in percentage of land wetted. Our findings show that the uniformity of water consumption on the fields under the three irrigation methods are reasonably comparable and high (~ 94%), which can be regarded as excellent according to the standard set by Pitts et al. (1996). The high uniformity of water consumption in furrow irrigated fields is in the same range as that of centre pivot and sprinkler, which is unlike what was found in South Arica (Griffiths and Lecler, 2001).

The results of normalisation for climate differences of the water consumption and water productivity allows for comparing the results under different climate conditions (different years). While the ranking for the different irrigation technologies according to the indicators remains the same, it clearly shows the impact of the climate. In particular during the drought year of 2016 when the potential evapotranspiration was relatively high, the normalised water consumption was low, indicating higher water deficit compared to the other years. The impact on sprinkler irrigated field was the highest. On

437 the other hand, the normalised *WP* during 2016 was the highest of all the years, even though the *WP*
438 was lowest for the same biomass in 2016, indicating the climate having a large impact on non-beneficial
439 evaporation.

440 This finding seems to suggest that production constraints can be addressed by taking certain measures,
441 including improved farm practices. However, one factor that influences crop yield but that is difficult to
442 influence, and that has not been assessed by this study, is the age of the crop. It is known that the early
443 ratoons (harvests after first planting the cane) achieve significantly higher yields than subsequent
444 ratoons (Mehareb and Galal, 2017). So, achieving the 90th percentile targets may not be easy for fields
445 with older crops, even though the Xinavane Estate uses a higher target yield than the 90th percentile
446 crop yield.

447 This study shows that the presented framework offers a systematic approach to assess irrigation
448 performance indicators using WaPOR and field data. Five WaPOR-derived irrigation performance
449 indicators, namely uniformity, equity, adequacy, and land and water productivity, are used to monitor
450 the quality of the irrigation and agronomic services. Our framework builds on earlier studies that assess
451 irrigation performance indicators based on RS (Karimi et al., 2019; Blatchford et al., 2020) and provides
452 a comprehensive and simple step-by-step framework to conduct an agronomic evaluation using
453 WaPOR data. The approaches in the framework are scripted with Python in Jupyter Notebooks that can
454 be run on local machine and Google Colaboratory (Colab) is published together with observed yield
455 data in GitHub (Chukalla et al., 2020a). It shows that with limited field information (crop type and
456 cropping season) and some parameters obtained from the literature the analyses can be implemented.

457

4.1.1. Limitations of the WaPOR database

459 The linear relationship between the independently derived WaPOR biomass and water consumptions
460 agrees with the expected agronomic principles (De Wit, 1958; Steduto and Albrizio, 2005). However,
461 the correlation coefficient of the biomass versus actual evapotranspiration is higher than the correlation
462 coefficient of the biomass versus transpiration and biomass versus normalized transpiration. This
463 implies an inaccurate estimation of transpiration (T) and evaporation (E) in WaPOR. WaPOR separates
464 the available energy into T and E using a factor $\alpha*LAI$, where α is the light extinction factor (FAO, 2018;
465 Mul and Bastiaanssen, 2019). A review on values for α shows large differences between different land
466 use classes and within land use classes (Zhang et al., 2016). Thus, WaPOR applying only one fixed
467 value for α could have serious implications for the use of the T and E layers of WaPOR such as in
468 quantifying beneficial fraction (the ratio of transpiration over evapotranspiration).

469 Even though the analyses seem to be consistent with the understanding of how the different irrigation
470 technologies perform, there are some known limitations of RS and WaPOR data in particular, which
471 need to be mentioned here. These may stem from: (i) the Land Surface Temperature (LST) used by
472 WaPOR (which is taken from MODIS and has a resolution of 1 km; this layer is used to derive moisture
473 stress and thus to calculate the actual evapotranspiration and net primary production; this could be the
474 cause for the reduced variation of WaPOR biomass data, and may affect the spatial variation of
475 evapotranspiration as well)); (ii) land cover noise of non-sugarcane land use such as farm roads, and
476 irrigation and drainage infrastructures within a pixel; (iii) the number of cloud free RS images on which
477 the analysis and numerical interpolation are based (the fewer the cloud free images the poorer the data
478 quality, the higher the uncertainty in the indicators one can expect); (iv) the time of day when the images
479 are taken (determinant for which part of the daily ET curve is monitored and the time of day the water
480 stress is more or less severe); and (v) the angle of image capture and its correction function.

The methods used in WaPOR for data production and statistical methods for the reconstruction of missing values are, however, at par with those used in other RS based products for monitoring agro-hydrological parameters developed by the scientific community. As such some of these limitations are inherent to the use of remote sensing in general. Yet, our analysis shows consistency between the different datasets.

4.1.2. Limitation of the crop related information

Crop specific parameters such as harvest index, the moisture content of the fresh yield and the ratio between above ground over total biomass ratio were fixed values and determined using literature and fieldwork in Ethiopia. However, it is known that these crop parameters can vary significantly based on climatic or field management conditions. Other variations may stem from differential exposure to pests and diseases, and soil and rooting conditions caused by waterlogging (den Besten et al., 2021) and soil salinity, which are not catered for. We were unable to determine how much these assumptions affect the results. All these factors are potential sources of (slight) deviations in the numerical output of WaPOR that may lead to over- and under-estimations of crop yield and *WP*.

Having noted this, we did perform a validation of the WaPOR biomass data using observed harvested cane data of more than 300 fields over four seasons. WaPOR biomass data for ~65% of the field level comparison differed within a ± 20% range. The comparison between the estate-measured yield and WaPOR biomass showed acceptable statistics (Table A3 in the Appendix).

4.2. The way forward

Investments in high quality public domain global and regional remote sensing data product for water and lands, us e.g. WaPOR datasets, has made it possible to conduct spatiotemporal analysis of irrigation performance at multiple scales from an irrigation scheme to district, basin and the whole country. This provides a great advantage especially in areas where both water and land resources are scarce and in-situ data are scant. This study presents a RS based assessment framework and showcases the power of using the WaPOR dataset in providing spatial and temporal irrigation performance indicators. Such information cannot be generated with the data collected traditionally (point data) or would come at a significant cost.

Yet, accurate interpretation of the results, diagnosing the causes of the performance variation and formulation of practical solutions cannot be made unless the WaPOR analyses and results are complemented with observed data of field conditions (e.g., the level of water and nutrient inputs, waterlogging, and salinity levels) that can help explore the constraints. Though this limitation puts a disclaimer on our findings, the procedures in this study can provide a useful reference for similar future studies.

Subsequent studies could additionally consider socio-economic performance indicators, such as social water productivity (e.g., employment per unit water or land use) and economic water productivity (economic return per unit water or land use), which could help to implement comprehensive performance assessment of irrigation schemes.

5. Conclusions

Remote sensing datasets are increasingly applied as innovative tool for monitoring the performance of irrigation schemes in order to improve land and water productivity amid the growing competition for finite and even dwindling resources (land and water). In this study, first, the remotely-sensed FAO WaPOR dataset were successfully validated by comparing WaPOR derived sugarcane yield with the field observation as well as gnomically. The yield response to water confirms agronomic expectations: (i) the correlation between biomass and actual water consumption normalized for climate is stronger than the correlation between biomass and actual water consumption, and (ii) the water productivity of sugarcane normalized by reference evapotranspiration falls within the conservative values reported for C4 crops. Second, the WaPOR derived datasets were applied to assess irrigation performance indicators including uniformity, equity, adequacy, and land and water productivity at Xinavane sugarcane estate, segmented by irrigation method. We conclude that the systematic approach demonstrated in the current study can serve as a framework to operationalize the use of WaPOR-derived data and other increasingly available RS-derived products for irrigation performance monitoring and assessment.

The comprehensive WaPOR based irrigation performance assessment in this sugarcane state, finds that fields irrigated by centre pivots have the highest adequacy, land productivity and equity followed by sprinkler and furrow irrigated fields, but the lowest water productivity.

We identified that part of the spatial and seasonal variation of indicators, water productivity and seasonal water consumption in particular, are explained by non-climatic factors that can be influenced by management interventions. Investigating the root causes of the land productivity variation and whether proper management of inputs, and controlling of salinity and drainage could improve productivity and the overall performance require further study, including field-based observations.

Appendices

Appendix A. Tables

Table A1. Water consumption-based irrigation performance assessment criteria and indicators

Criteria	Indicator	Equation*	Reference
Uniformity	CV of ET	CV of seasonal average ET_a per pixels in a field	Karimi, 2019
Equity	CV of ET	CV of seasonal average ET_a per field inside the scheme/block	Karimi, 2019
Adequacy	The ratio of $ET_{a,s}$ over $ET_{a,p}$ or relative evapotranspiration (RET)	$RET = \frac{ET_{a,s}}{ET_{p,s}}$ $ET_{a,s} = \sum_{SOS}^{EOS} ET_a$ $ET_{p,s} = \sum_{SOS}^{EOS} ET_{p,m}$ $ET_{p,m} = \sum_{SOS}^{EOS} k_{c,m} * RET_m$	Karimi, 2019

Land productivity	Biomass production (B)	$B = AOT * f_c * \dfrac{NPP_s*22.222}{(1-MC)}$ AOT is above over total biomass, fc is light use efficiency correction factor and MC is moisture content in fresh biomass.	Mul and Bastiaanssen, 2019
	Yield	Yield = B*HI HI is harvest index.	FAO 66
Water productivity	Biomass WP (WP$_b$)	$WP_b = \dfrac{B}{ET_{a,s}}$	
	Crop yield WP (WP)	$WP = \dfrac{Y}{ET_{a,s}}$	

548 *where *SOS* and *EOS* is start of season and end of season, $ET_{a,s}$ is seasonal actual evapotranspiration, $ET_{p,s}$ and
549 $ET_{p,m}$ are seasonal and monthly potential evapotranspiration, RET_m is monthly reference evapotranspiration, $k_{c,m}$ is
550 crop coefficient, and NPP_s is seasonal net primary production.

551

552 *Table A2. Crop coefficients of sugarcane*

Crop stages	Duration of crop development stages		Kc values [-]
	Default in CROPWAT 8.0 (Smith, 1992) [Days]	%	
Initial	30	8	0.4
Development	60	16	[0.4 - 1.25]
Mid-season	180	49	1.25
Late-season	95	26	[1.25 - 0.75]
	365		

553

554 *Table A3. Statistical comparison of WaPOR yield and estate-measured yield*

Season	Irrigation method	Number of fields compared (n)	Root mean square error [ton/ha]	Mean absolute error [ton/ha]
2015 (n=352)	Furrow	175	18.5	14
	centre pivot	16	14.7	13
	sprinkler	160	22.5	18
2016 (n=351)	Furrow	153	20.3	15
	centre pivot	17	16.7	13
	sprinkler	180	19.6	15
2017 (n=332)	Furrow	152	21	16.5
	centre pivot	19	16	13
	sprinkler	161	17	14
2018 (n=317)	Furrow	149	21.7	17
	centre pivot	19	16.7	14.5
	sprinkler	149	22	16
Average			18.9	14.9
SD			2.5	1.6

555

556 *Table A4. Summary of the statistical test whether the average seasonal actual water consumption (ET_a) at*
557 *Xinavane estate are different*

SUMMARY: Anova: Single Factor for ET_a[mm/season] in 2015

Groups	Count [-]	Sum* [mm/season]	Average [mm/season]	Variance [mm/season]^2
Furrow	175	221,623	1,266	17,823
Sprinkler	160	212,857	1,330	16,236
Centre pivot	16	22,621	1,414	8,795

ANOVA

Source of Variation	SS	df	MS	F	P-value	F critical
Between Groups	550,210	2	27,5105	16.46	**1.47E-07**	3.022
Within Groups	5,814,685	348	16,709			
Total	6,364,895	350				

558

SUMMARY: Anova: Single Factor for ETa[mm/season] in 2016

Groups	Count [-]	Sum [mm/season]	Average [mm/season]	Variance [mm/season]²
Furrow	153	20,1762	1,319	28,102
Sprinkler	180	248,632	1,381	32,201
Centre pivot	17	26,067	1,533	29,346

ANOVA

Source of Variation	SS	df	MS	F	P-value	F critical
Between Groups	852,752	2	426,376	14.084	**1.315E-06**	3.022
Within Groups	10,505,019	347	30,274			
Total	11,357,771	349				

559

SUMMARY: Anova: Single Factor for ETa[mm/season] in 2017

Groups	Count [-]	Sum [mm/season]	Average [mm/season]	Variance [mm/season]²
Furrow	152	196,271	1,291	17,828
Sprinkler	161	212,875	1,322	20,093
Centre pivot	19	26,044	1,371	10,756

ANOVA

Source of Variation	SS	df	MS	F	P-value	F critical
Between Groups	147,266	2	73,633	3.97	**0.020**	3.02
Within Groups	6,100,424	329	18,542			
Total	6,247,690	331				

560

SUMMARY: Anova: Single Factor for ETa[mm/season] in 2018

Groups	Count [-]	Sum [mm/season]	Average [mm/season]	Variance [mm/season]²
Furrow	149	187,113	1,256	15,781
Sprinkler	149	193,172	1,296	23,265
Centre pivot	19	27,304	1,437	9,258

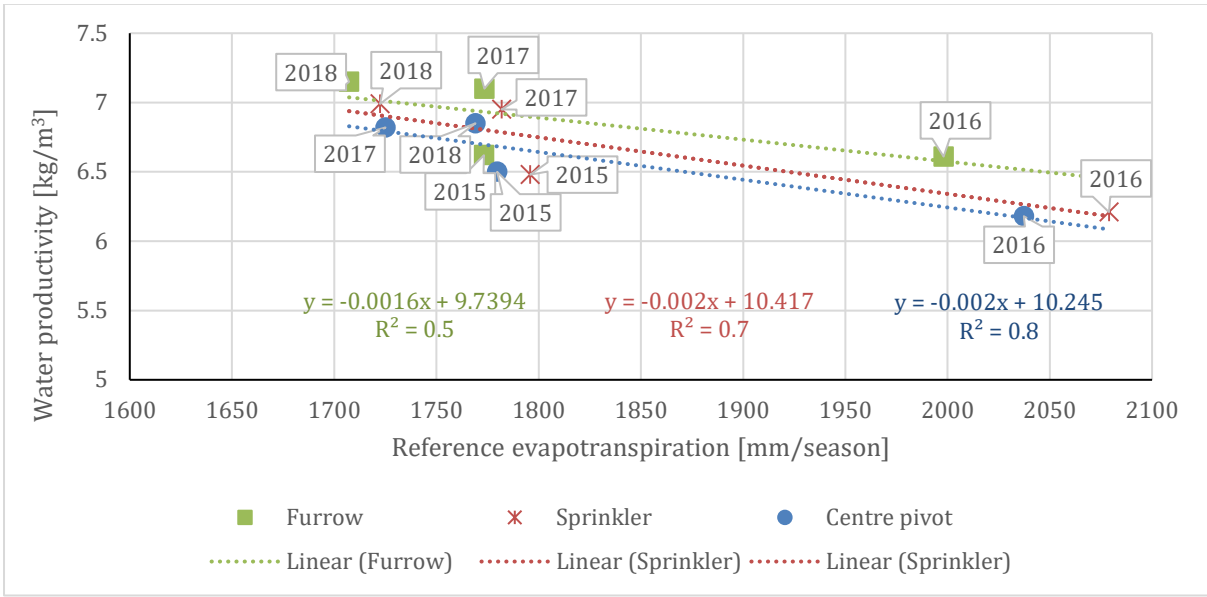
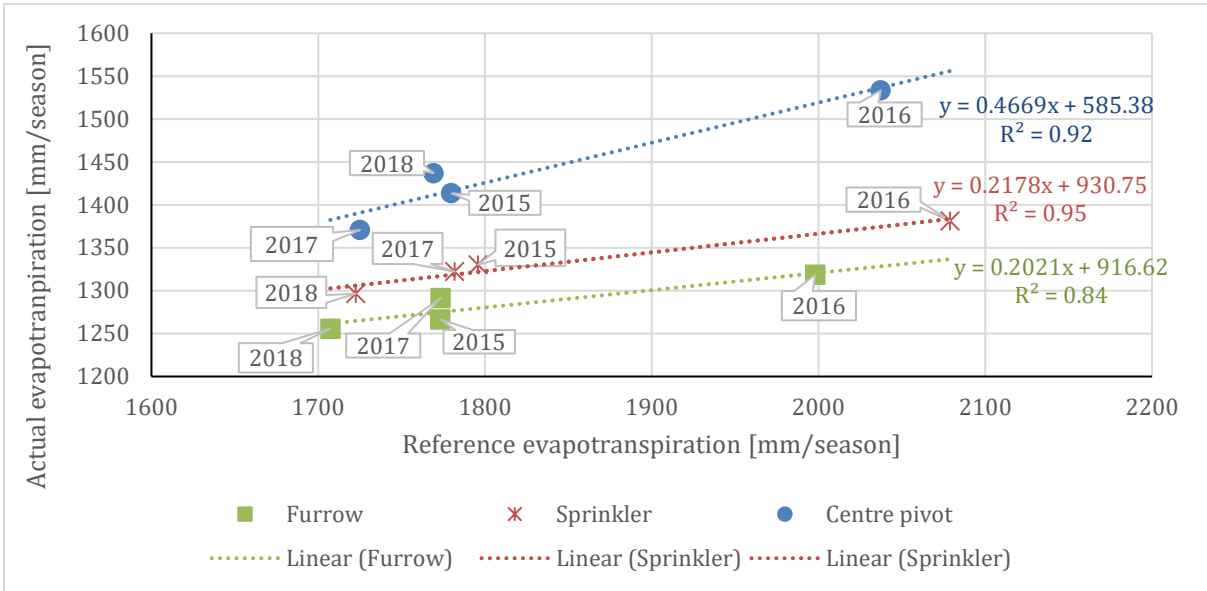
ANOVA

Source of Variation	SS	df	MS	F	P-value	F critical
Between Groups	585,782	2	292,891	15.47	**3.91E-07**	3.02
Within Groups	5,945,377	314	18,934			
Total	6,531,158	316				

561 * Sum is the product of Count [-] and Average [mm/season]

562

564 *Figure B1. Relationship between water productivity and seasonal reference evapotranspiration at*
565 *Xinavane sugarcane estate categorized by irrigation methods in 2015 to 2018.*

567

568 *Figure B2. Relationship between seasonal actual evapotranspiration and reference evapotranspiration*
569 *at Xinavane sugarcane estate categorized by irrigation methods in 2015 to 2018.*

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