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Towards enhanced agronomic diagnostics based on remote sensing-derived crop water productivity for center pivot irrigated agriculture system

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I N F O

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A B S T R A C T

Efforts to expand irrigated agriculture faces challenge of managing scarce water resources amid rising food demand and impacts of climate change especially in ASAL districts. The objectives of this study were; to monitor spatial-temporal changes in performance of irrigation production system and to relate agronomic causes of variation in productivity. The open access remotely sensed WaPOR database was applied to assess chronology of land and water productivity of maize crop. Decadal data was bulk downloaded from FAO WaPOR portal delimited to the boundary of Galana Kulalu irrigation scheme in Kilifi, Kenya for four cropping seasons, 2018 to 2022. Soil chemical properties were analyzed for bright/hot spots in the scheme. The 2018-2019 season recorded highest net primary productivity (NPP) and actual evapotranspiration (AETI) and was high in center pivots located southern side of the scheme. Irrigation equity was rated fair but deteriorated to poor rating in the 2021-2022 season. Crop water productivity ranged between 0.43 and 1.07 Kg/m^3. Poorly performing center pivots were characterized by significantly high soil moisture content ($p< 0.05$), highly alkaline soil pH 8.6 – 8.9 and high exchangeable sodium (ES) levels. Strong negative correlation existed between water productivity and exchangeable sodium levels. Critical remedial measures are needed to restore soil health, improve efficiency of water consumption and crop yield performance.

1. Introduction

A key production strategy of modern agriculture is to optimize resource utilization and enhance productivity (Farooq et al., 2019). While challenges of agriculture and food production seem to burgeon, especially in Africa, they are not insurmountable if the relevant solutions based on well-defined pathways are applied (FAO, 2018). Thus, looking into the future, progress of modern agriculture will heavily depend on successfully integrating emerging agro-technological and agro-ecological methodologies, to ensure agricultural sustainability is attained while cognizant of the socio-cultural interests that define the 21st century societies (Breinbauer et al., 2020).

In this context, irrigated agriculture is touted as a key investment strategy by governments and institutions, especially in tropical Africa to guarantee a stable and consistent food supply, eradicate poverty and improve livelihood (Africa Union, 2020). As global population grows, fresh water demand is expected to outstrip supply by about 40% by the year 2030 pushing significant segment of populations to living under conditions of severe water scarcity especially in Africa (Antonio et al., 2009; Boretti and Rosa, 2019). The escalating demand for water is being aggravated the high rate of urbanization especially in African cities, expansion in irrigation projects by governments, investment in water intensive crops and industrial development, leading to decline in per capita supply of water (Güneralp et al., 2017; Khor, 2022; Tuyishimire et al., 2022). Considering the climatic historical trends in rainfall

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patterns and the projected future trend for decline in rainfall, there is heightened concern to re-strategize on the nexus between water and food in anticipation of the negative impacts expected from effects of climate change (Trisos et al., 2023).

To sustain the growing demand of food against the scarce resources, agricultural water productivity and application of modern technologies and adoptable on-farm practices is important for any production investment to offer socio-economic benefits (FAO, 2021a; Howell, 2001; Pareeth et al., 2019; Waweru et al., 2024). Climate and crop performance information to guide monitoring of agricultural water projects and promote efficient use of the scarce natural resources is important. In Kenya and most sub-Saharan Africa, irrigation projects, of different typologies, are expanding but are highly constrained by the issue of efficiency and economical use of water and land against the extreme weather conditions characterized by high temperatures and water loss (Kanda and Lutta, 2022; Mati, 2023). Thus, in the Kenya Vision 2030 development agenda on food and nutrition security, the government strategized to establish flagship projects on food security through mega-irrigation projects targeting the vast arid and semi-arid lands (GoK, 2023, 2007). One of the policy objectives for irrigated agriculture in Kenya is to increase available water for irrigation through innovative technologies (Ministry of Water and Irrigation, Kenya, 2017). Quantifying water balance components and land productivity for irrigated agriculture finds important application in assessing water and land productivities, (Blatchford et al., 2018) and improving irrigation management and systems (Kharrou et al., 2013). For us to sustainably intensify production and efficiency, we need to enhance resiliency of farmers and assist them adopt smart agricultural practices aiming for improved crop water productivity which forms the basis for achieving the United Nations Sustainable Development Goals (SDGs), SGD1.5, SGD2.3 and SGD6.4 (Atapattu et al., 2024; United Nations, 2024)

As the impacts of climate change increase, water scarcity effects exacerbated by high temperatures, heat extremes and evapotranspiration rates will create more stressful environments for crop production (LIU et al., 2024). High evapotranspiration and soil infiltration rates especially, in dry climates of arid and semi-arid regions reduce soil moisture and consequently increase irrigation requirements, which in face of scarce water, call for increased observational studies for better agricultural water management (Aguilar et al., 2015; Süle et al., 2024; Wanniarachchi and Sarukkalige, 2022). The WaPOR project of FAO is a portal with data sets for monitoring Water Productivity through Open access of Remotely sensed derived data (WaPOR) over Africa and the Near East countries (FAO, 2020). Under this project, technological developments of the new generation of remote sensors with improved spatial and/or temporal resolution are providing the opportunity for new observational and modeling perspectives especially focusing on management of water resources for agriculture. To determine where water productivity can be improved and what the causes are for not reaching its potential, the current levels must be understood at spatial and temporal scales (Chukalla et al., 2021; Kilemo, 2022; Zwart et al., 2010) and related to site diagnostic information with goal of improving performance. The objectives of this study were; (i) to characterize the status of water use and water productivity in the Galana Kulalu irrigation scheme through use of the WaPOR database, (ii) to diagnose the in-situ soil properties and relationship with crop performance, and (iii) to identify opportunities in the use of remote sensing tools and modern diagnostics to provide information for assessing performance of irrigated agriculture.

2. Methodology

2.1 Study site description

The Galana Kulalu irrigation and Food security project is located in Kilifi County, Kenya (Figure 1) on expansive land in the Coastal region of Kenya. The land is owned by the Agricultural Development Co-corporation (ADC), a government parastatal within the Ministry of Agriculture, Fisheries and Livestock. Agro-climatic condition of the area falls under zone V, classified as semi-arid. This zone is characterized by low annual rainfall of 450 -900 mm, vegetation cover is dominated by low trees of *Acacia spp* and scattered shrubs (Jaetzold and Schmidt, 1982). The irrigation scheme is managed and

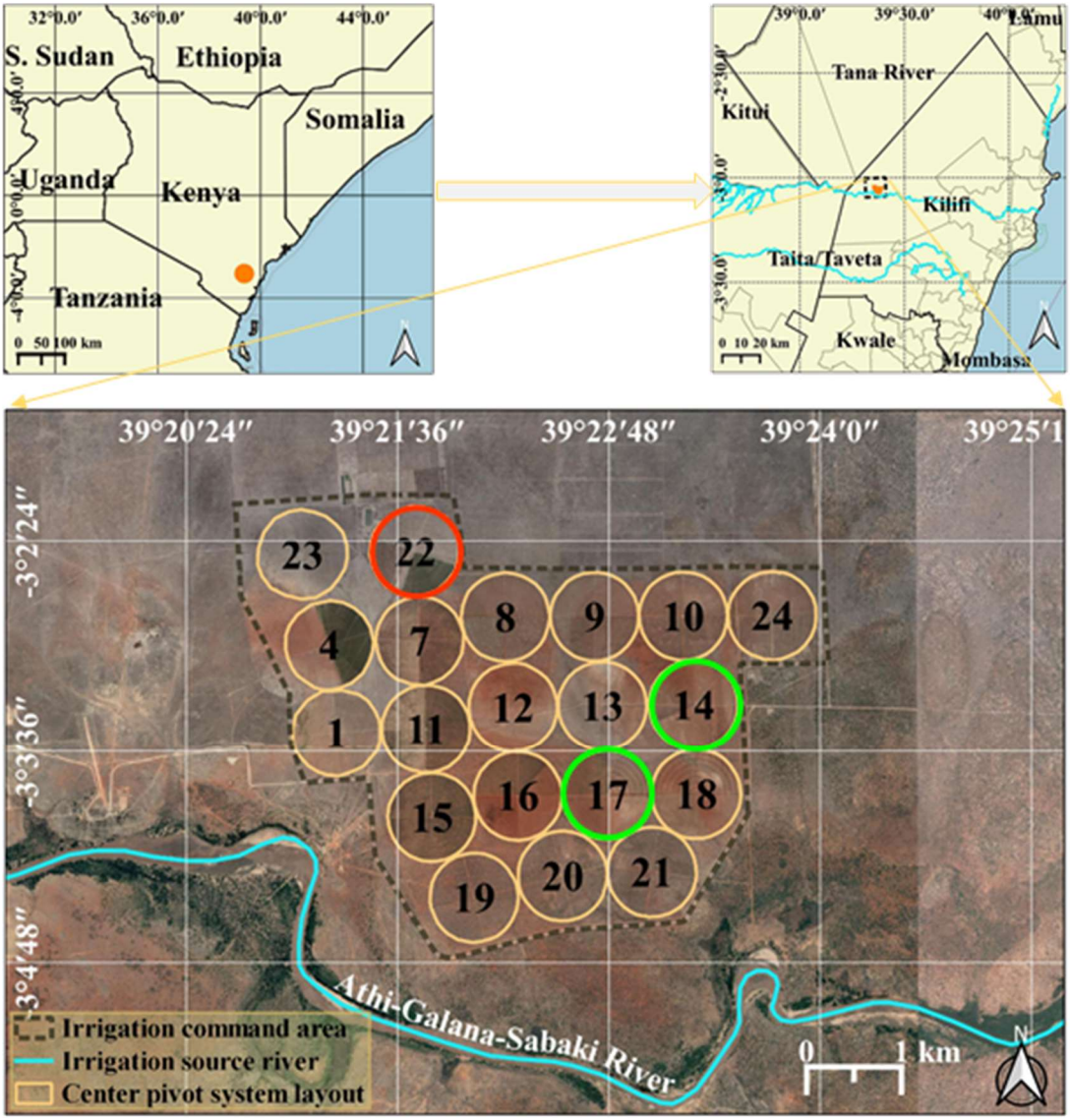


Figure 1: Location of the Galana Kulalu food security irrigation project and layout of the center pivot irrigation system. The red and green circled pivots, were sampled for soil diagnostic analysis

operated by the National Irrigation Authority (NIA), initially called the National Irrigation Board (NIB), which is a parastatal within the Ministry of Water, Sanitation and Irrigation. The Galana-Kulalu irrigation project and food security scheme was unveiled in 2014 as a one-million-acre model farm and is a key focus project for the government (NIA, 2019). The scheme is supplied with water from the Athi-Galana Sabaki River through inlets currently serving an irrigated command area of 5,000 acres of land, regularly put under maize production. The water is distributed through a system of 150 m long, 20 center pivots each covering about 160 acres of land. It is estimated that during its lowest flow volumes, the Athi-Galana Sabaki River can irrigate about 10, 000 acres of land for a whole crop season, (Scheme manager). In the year of 2023, the government renewed efforts to enhance operations of the scheme targeting finally to bring about 350,000 acres of land under irrigated cultivation (Kilimo News, 2023).

The main cultivated crop is maize (common varieties; DK90-89, DK80-33, Panar7M-81 and Tsavo-4141).

2.2 Data acquisition

The data for calculating water consumption and water productivity was obtained from the WaPOR portal, a publicly accessible near real time remote sensing database. The WaPOR (Water Productivity through Open access of remotely sensed derived data) database is published by FAO and focuses on the various parameters relevant for crop monitoring and agricultural water management. The data is hosted in the FAO based WaPOR database (https://wapor.apps.fao.org), (FAO, 2020). The WaPOR data sets initially covered Africa and the Near East countries but has expanded since 2023 to cover the whole globe at different scales. Data for analysis was accessed at the github repository for WaPORWP data outputs of the seasonal water consumption and net primary productivity variables. The shapefile delineating the irrigation scheme, was prepared from high resolution Google satellite image through online digitization. Distinction between irrigated and non-irrigated areas was based on the on the Copernicus Global Land cover map (250 m resolution) which is availed at WAPOR database (https://wapor.apps.fao.org/catalog/WAPOR_2/1). Based on available farm records, the cropping season for maize crop was set to twelve months beginning April to March of the following year, for four cropping seasons; (1/4/2018-31/3/2019, 1/4/2019-31/3/2020, 1/4/2020-31/3/2021 and 1/4/2021-31/3/2022). Another key input data for the analysis was the crop co-efficient, Kc value for maize. The Kc value represents the integrated effects of changes in leaf area, plant height, crop characteristics, irrigation method, rate of crop development, crop planting date, degree of canopy cover, canopy resistance, soil and climate conditions, and management practices. Each crop has a set of specific crop coefficient and will predict different water use for different growth stages (Pereira et al., 2015; Shao et al., 2023). The downloaded data for this analysis was from WaPOR version 2.0 (100 m spatial resolution), 10 days interval (dekadal data) of Actual Evapotranspiration and Interception (AETI), Transpiration (Ta), Net Primary Production (NPP), Precipitation (P, 5 km resolution, resampled to 100m resolution) and Reference Evapo-transpiration (ETRef, 20 km resolution, resampled to 100m resolution). The processing of the spatial data and bulk download of dekadal data images was computed using the WaPORWP python scripts. Thirty six decadal data images were downloaded for every cropping season and for each of the five remote sensing data sets. The QGIS open source software was used to bulk process the downloaded dekadal image data of seasonal water variables of AETI (ETa), Ta, P, ETRef and NPP for the geographical extent of the irrigated area of Galana Kulalu irrigation scheme. The procedure followed for the computation is shown in Figure 2.

2.2.1

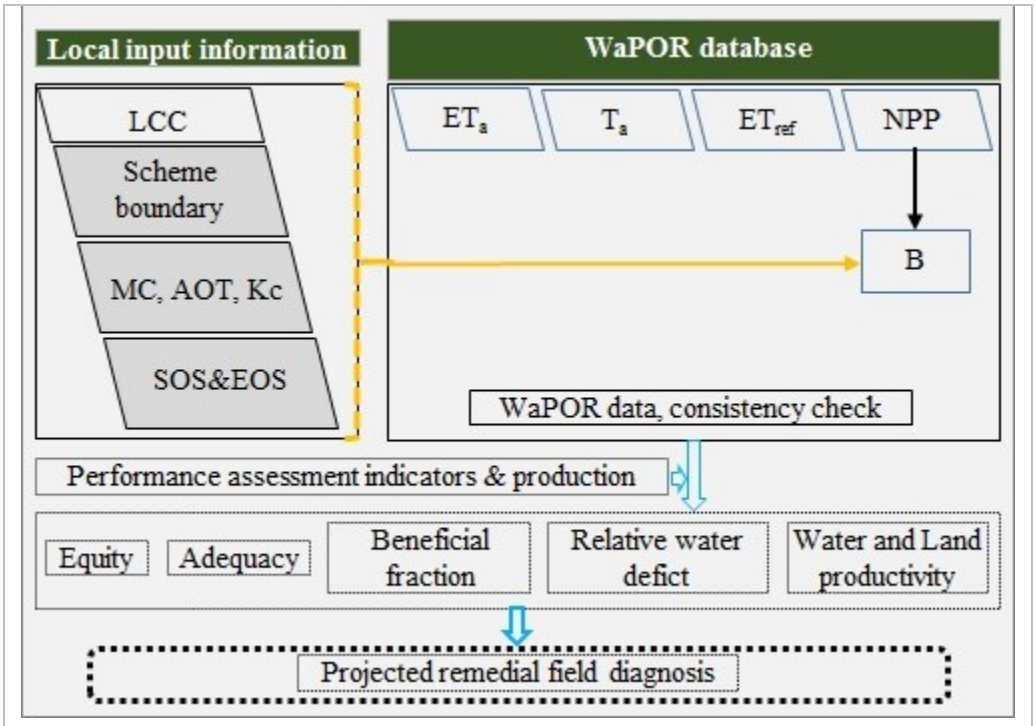


Figure 2. Flow chart for calculating indicators and productivity for irrigated maize at Galana Kulalu. ETa, is actual evapotranspiration (AETI); Ta, actual transpiration; ETref, reference evapotranspiration; NPP, net primary production; LCC, land cover classification; MC, moisture content in fresh biomass; AOT, above ground over total biomass; Kc, crop coefficient; SOS, start of season; EOS, end of season and B for above ground biomass

Irrigation performance indicators

The following irrigation performance indicators were computed;

(a) Equity; Defined as the coefficient of variation (CV) of seasonal actual evapotranspiration and interception (AETI). A CV of 0 to 10% is good, 10 to 25% is fair and CV > 25% is poor uniformity (Karimi et al., 2019).

(b) Beneficial Fraction (BF); It is estimated as the ratio of the water that is consumed as transpiration to overall field water consumption;

$$\mathrm{BF} = \frac{\mathrm{Ta}}{\mathrm{AETI}} \quad (1)$$

(c) Adequacy; estimated as the ratio of seasonal actual evapotranspiration (AETI) to seasonal potential evapotranspiration (ETp). It is a measure of the degree of agreement between the actual water use and crop water requirement;

$$\mathrm{Adequacy} = \frac{\mathrm{AETI}}{\mathrm{ETp}}. \quad (2)$$

Seasonal ETp = Average Kc * Seasonal RET. The average Kc for maize is 1.8. Where; AETI = actual evapotranspiration and interception, ETp = potential evapotranspiration, Kc = crop coefficient, RET = Reference evapotranspiration.

(d) Relative Water Deficit (RWD). It is expressed as;

$$\mathrm{RWD} = 1 - \frac{\mathrm{AETI}}{\mathrm{ETx}}. \quad (3)$$

ETx = ETp or 99 percentile of the actual evapotranspiration.

2.2.2 Water productivity

Land productivity is defined as the above-ground biomass production or yield in ton/ha/season, which is estimated from the seasonal net primary production. Biomass and crop water productivity is estimated as the ratio of above-ground biomass or yield over actual evapotranspiration. Above ground biomass (Kg/ha) was computed based on the formula;

$$Biomass = AOT * fc * \left(\frac{NPP * 22.222}{1 - mc}\right) \quad (4)$$

Where, AOT = above ground over total biomass production ratio, fc is light use efficiency correction factor (a coefficient for the efficiency by which vegetation converts energy into biomass), NPP; seasonal net primary production in gC/m^2/season, mc; moisture content in the fresh biomass. For maize crop, the values were; mc =0.26, f_c = 1.8 and AOT = 0.93, (Carr, 2013; Theodore. C Hsiao and Elias, Fereres, 2012).
Crop yield was then derived using the formula;

$$\text{Crop yield} = HI * \mathrm{B} \quad (5)$$

Where, HI = harvest index which indicates how much of the biomass production contributes to the harvestable fraction of a crop (yield). It is expressed as the ratio of weight of dry grains over the above-ground dry matter. For maize, HI was set to 0.35, B = above ground biomass.
Crop water productivity in Kg/m^3 was finally derived using the formula;

$$\mathrm{WPy} = \frac{\mathrm{Yield}}{\mathrm{AETI} * 10} \quad (6)$$

Where, WP_y= Crop water productivity; AETI= Actual evapotranspiration and interception.
Output images for each of the variables were styled in QGIS to optimize display of the spatial distribution of the parameter. Further analysis was conducted using the layer raster statistics processing tool to derive values of the respective variable for the different cropping seasons. Tables and figures were prepared in Microsoft excel software.

2.3 Diagnostic test of in-situ soil properties

Based on observations from WaPOR analysis output supported by agronomist experience and crop performance records, three center pivots (representing high yielding, moderate yielding and low yielding) were selected for diagnostic field soil sampling studies (Figure 1). From spatial analysis context, these center pivots were distinguishable by high concentration of the favourable or the unfavourable water consumption phenomena of AETI, BF, RWD or WP_y, representing the potential bright (favourable) and hot (unfavourable) spots for this analysis. Out of the four lots in each center pivot, two lots (sites), opposite facing, were selected for soil sampling and soil diagnosis. A hole, 1.5 m deep was dug with the help of a hydraulic backhoe mini-excavator to break through compacted soil layers and expose the soil profile. Undisturbed soil samples were then scooped from three depths of 0-5 cm, 20-25 cm and 70-75 cm in each soil profile using soil sampling rings. Three soil samples were drawn from each depth level (total nine samples per site) and repeated for the six sites for three center pivot locations (CPs 14, 17 and 22, Figure 1). The samples were bagged and secured to avoid disturbance and dispatched to the JKUAT, Horticulture laboratory for analysis. The following soil physico-chemical tests were conducted in the lab; soil moisture content, soil pH, soil electrical conductivity (EC) and exchangeable sodium (Exch. Na).

3. Results

3.1 Seasonal water consumption and net primary productivity

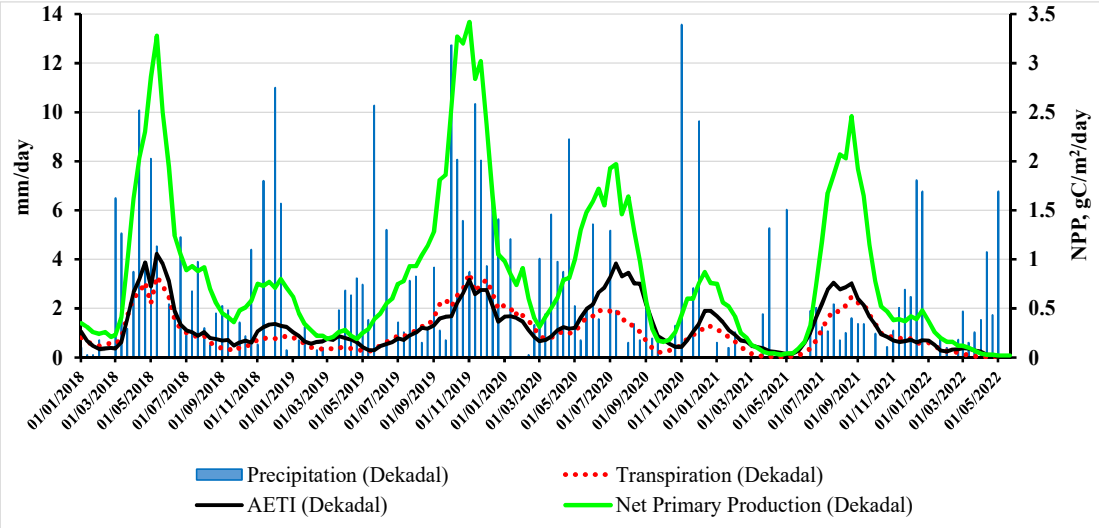


Figure 3. Time series of dekadal precipitation, transpiration, actual evapotranspiration and net primary production of center pivot maize fields for period of 1/1/2018 to 31/05/2022 in Galana Kulalu Irrigation scheme, Kilifi county, Kenya

The pattern of precipitation (P), transpiration (T), actual evapotranspiration and interception (AETI) and net primary productivity (NPP) between January 2018 and May 2022 is shown in Figure 3. Peak periods for P, T, AETI and NPP seem to coincide. From the graph the cropping season could be estimated to fall between the months of April and March, between which the peaks of water consumption and NPP occur. The contribution to AETI from irrigation is particularly evident in the September, 2021 date where precipitation was low. The mean value results of seasonal water consumption (AETI) and net primary productivity (NPP) over the four cropping seasons are shown in Figure 4. Net primary

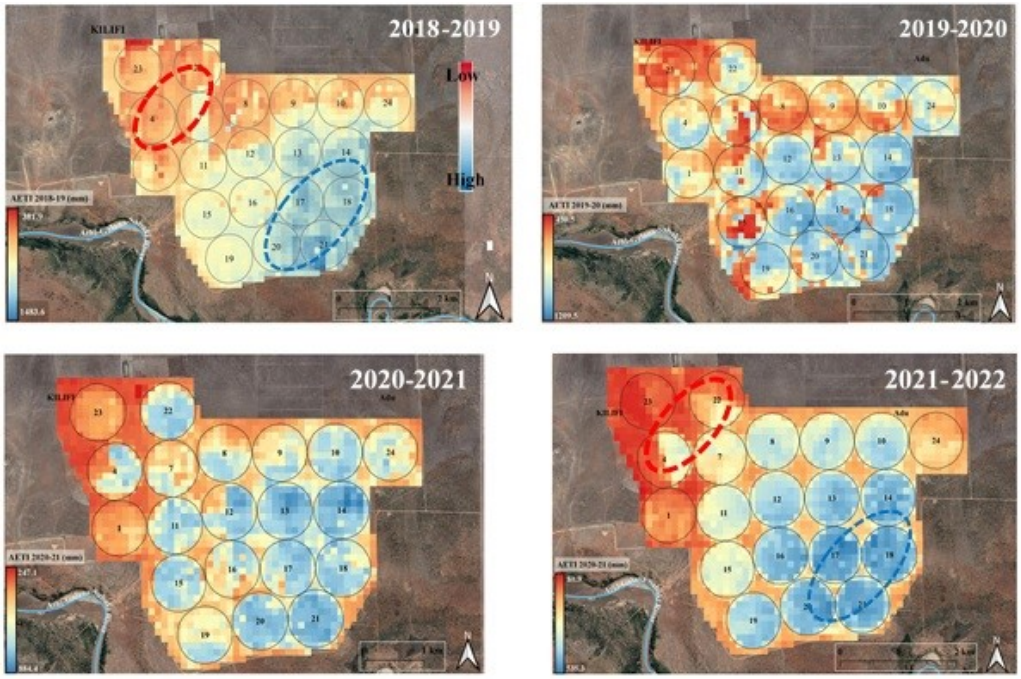


Figure 5. Spatial-temporal variation of seasonal water consumption (AETI). Clusters circled in red mark out pivot areas of low water consumption, the blue circled cluster mark pivots of high water consumption.

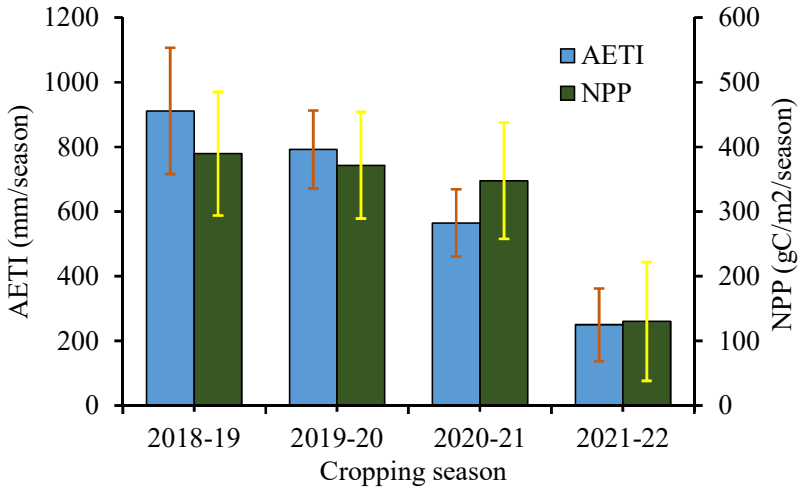


Figure 4. Seasonal variation of water consumption (AETI) and net primary productivity for maize crop at the Galana Kulalu Irrigation scheme

productivity and AETI followed similar trend between the cropping seasons; the 2018-2019 season having the highest values and the 2021-2022 season, the lowest (Figure 4). The low values calculated for 2021-22 season draw attention as to the crop performance within the scheme. High water consumption was observed in pivots to the southern side of the scheme (center pivots 14, 17, 18, 20, 21) while low water consumption was clearly distinguishable in pivots towards the northern parts of the scheme (center pivots 4, 22 and 23), (Figure 5). The results indicate that high water volumes were consumed in the 2018-19, 2019-20 and 2020-21 cropping seasons matching the high biomass production (NPP) recorded in the same seasons as compared to the 2021-22 cropping season. It is notable, that variability in AETI between the low AETI center pivots (orange colour) in 2018-19 is not as

Table 1. Computed seasonal irrigation performance indicators of coefficient of variability (equity), beneficial fraction, adequacy and relative water deficit (RWD)

Cropping season	CV (Equity)	Beneficial Fraction	Adequacy	RWD
2018-19	21.40	0.74±0.08	0.23±0.05	0.30±0.15
2019-20	15.23	0.7±0.08	0.22±0.03	0.25±0.11
2020-21	18.41	0.67±0.08	0.16±0.03	0.28±0.13
2021-22	45.04	0.51±0.24	0.07±0.03	0.47±0.23

distinguishable as in the 2021-22 season (blue colour). Such variation across a given irrigation scheme could be attributed to several factors including water variability, soil physical properties, soil fertility, topography, and crop management practices (Bastiaanssen and Steduto, 2017; Foley et al., 2020).

3.2. Irrigation performance indicators

The mean values for the different irrigation performance variables are shown in Table 1. Equity, a measure of the evenness of water supply within the irrigated area varied between the cropping seasons. Based on (Bastiaanssen and Bos, 1999) rating of equity, the uniformity recorded here was poor in the 2021-2022 season (CV > 25%), and fair in the other three previous seasons. The big difference could be attributed to the actual irrigation practices being non-uniform between the center pivots and could also

point to inefficiencies in water volume application. Another cause could arise from the different scheduling in cropping dates (start of season and end of season) between the center pivots which means variation in crop growth stage and thus water delivery between center pivots was different and more pronounced in 2021-2022 cropping season. Beneficial fraction tells about variation in efficiency of on farm water and agronomic practices. This efficiency was lowest in the 2021-2022 season and highest in 2018-2019 season. Adequacy, indicator for degree of agreement between the actual water use and crop water requirement varied in similar pattern as BF. The spatial distribution of relative water deficit (RWD) is shown in Figure 6. Center pivots to the north-west were high water deficit areas while the south-eastern center pivots had low water deficit. Thus water was more optimally utilized by the crops, in the lower than in the northern parts of the scheme (CPs 4, 7, 22, and 23).

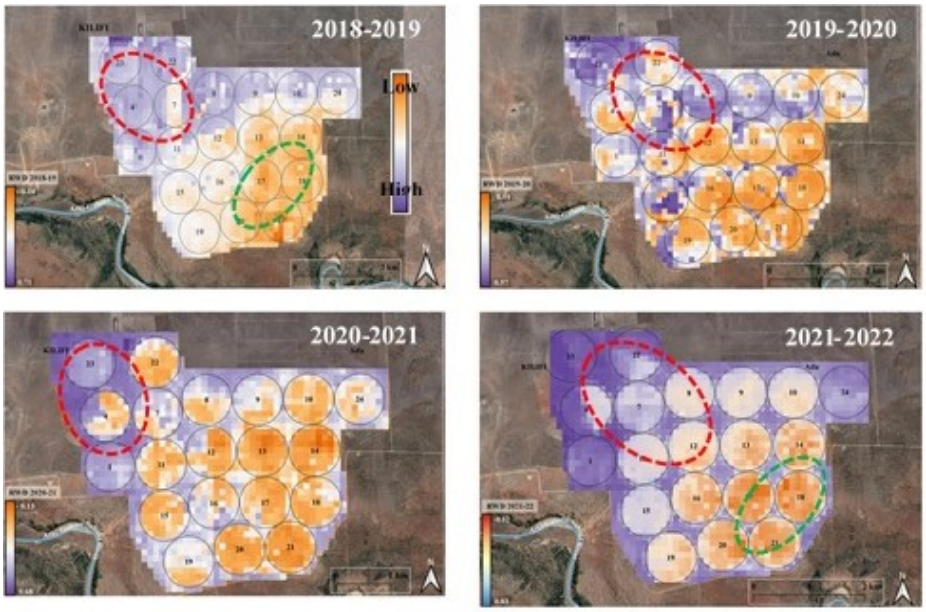


Figure 6. Spatial-temporal variation of relative water deficit (RWD). Clusters circled in red mark out pivots of high RWD, the green circled clusters mark pivots of low RWD.

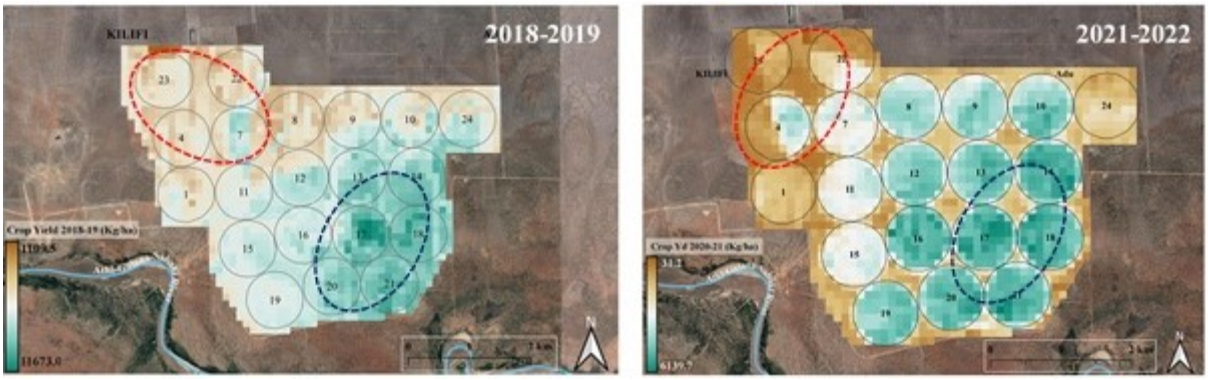
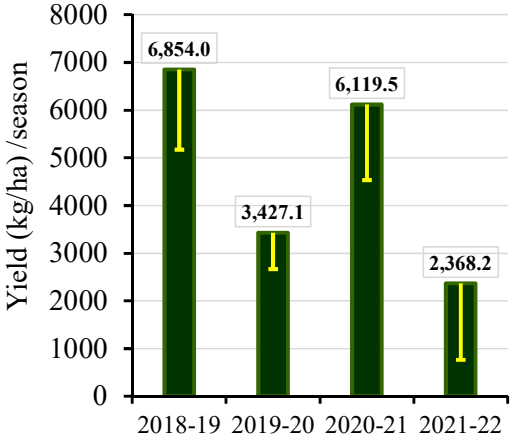


Figure 7. Spatial variation of crop yield for 2018-2019 and 2021-2022 cropping seasons. Clusters circled in red mark-out pivots of low yield, the blue circled mark pivots of high yield.

3.3. Spatial distribution of crop yield estimates

Yield estimate for 2018-2019 cropping season was markedly high in center pivots (CP) 15,16,17,18 and 14 but low in CPs 1,11,12,4,7,23,22,24 (Figure 7). Estimated mean yield was highest in the 2018-2019 cropping season, followed by 2020-2021 season and lowest in the 2021-2022 cropping season (Figure 8A). Even in the lowest season of 2021-22, yield estimate was high for CPs 14, 16,17,18,19,21 and low in CPs 1, 4, 22, 23, 24, same pattern as for the highest season of 2018-2019 season (Figure 8). Figure 8B shows maize yield as recorded at the scheme office compared to WaPOR derived estimate. Except for 2020-2021 season, the computed values were lower compared to the farm records.



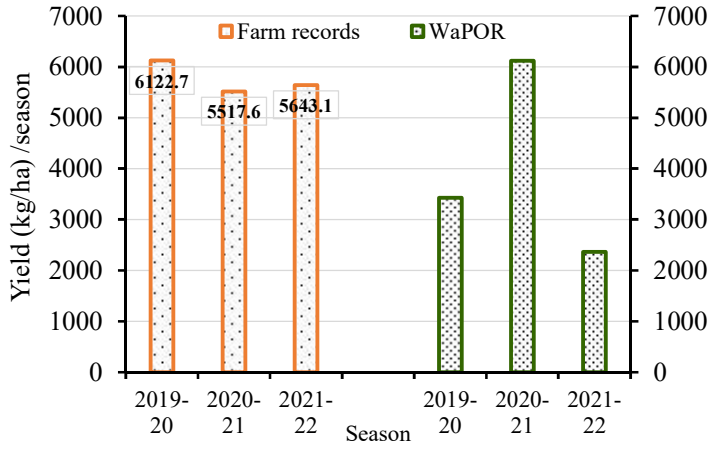


Figure 8. Con ıputed yield; **B**, the actual R estimates

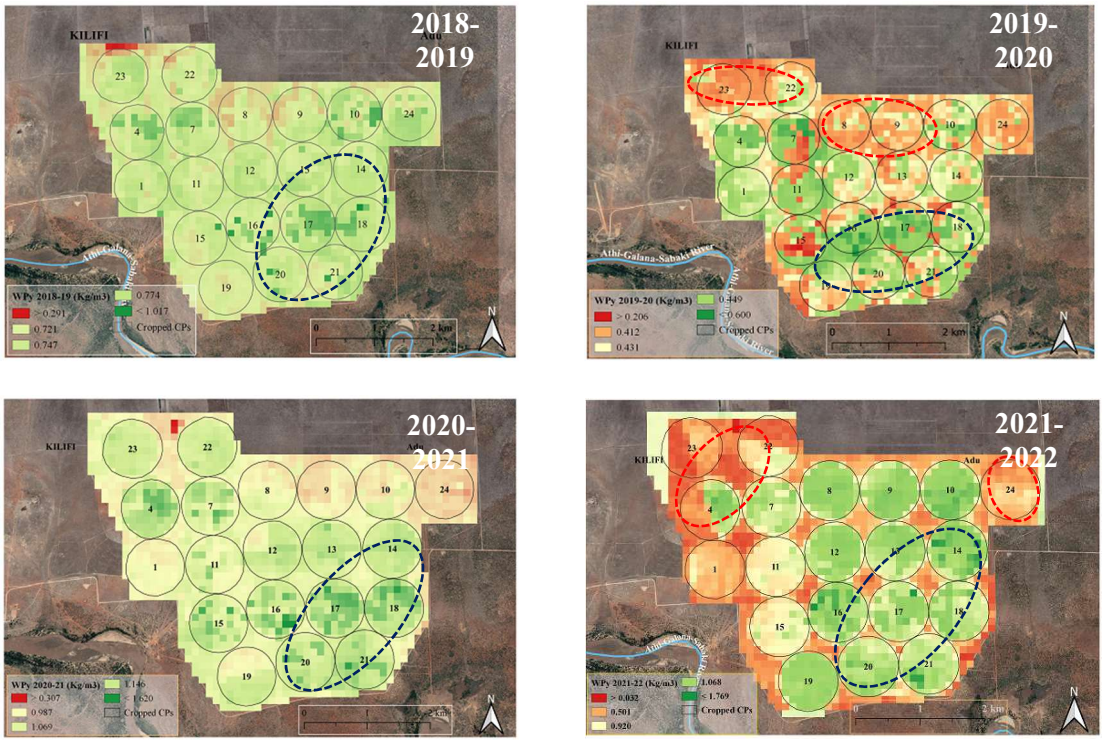


Figure 9. Spatial temporal distribution of crop yield water productivity (WPy). Clusters circled in red mark out pivots of low water productivity, the blue circled mark high water productivity pivots.

3.4. Spatial variation of crop water productivity estimates

The results of the WaPOR based computation of crop yield water productivity are shown in figure 9. Compared to the other water use parameters, water productivity metric, returned a slightly different verdict on efficiency of conversion of absorbed water fraction to actual harvestable yield across the center pivots and between crop seasons. Spatially, spots in the northern part of the scheme CPs (1, 4, 22, 23, and 24) recorded low water productivity values while spots in the southern part of the scheme

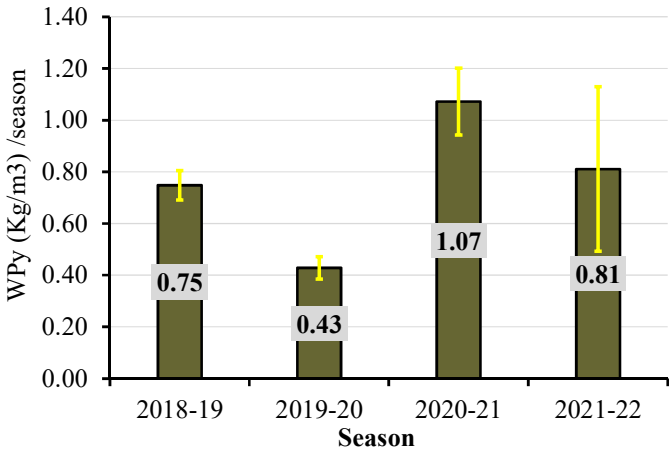


Figure 10. Seasonal trend of the estimated crop water productivity (WPy) for the four cropping seasons at the Galana Kulalu irrigation scheme

CPs 9, 10, 14, 16, 17 and 18 recorded high water productivity values. Figure 10 shows the estimated mean of seasonal crop yield water productivity. The 2020-2021 cropping season returned the highest water productivity, (mean, 1.07 Kg/m^3) followed by 2021-2022 cropping season and lowest in the 2019-2020 cropping season, (0.43 Kg/m^3), (Figure 10). Although the 2018-2019 cropping season recorded highest yield values than other seasons, this was accompanied by high AETI which translates to lower water productivity as compared to the 2021-22 season. The lowest WPy for the scheme was in 2019-2020 season but improved in the following season of 2020-2021. It is likely that timing of watering and regulating water delivery volumes according to crop growth stage were factors that influenced the spatial and seasonal differences in WPy between the seasons. Climatic and agronomic factors influence irrigation water productivity to different extents depending on geographical context of a region (Li et al., 2016). So, key to improving crop water productivity, is applying water-saving technologies and optimizing agronomic practices. In this study the results of soil diagnostic tests were investigated.

3.5. Soil physicochemical properties

3.5.1. Soil moisture

The pattern of soil moisture status for the three sample center pivots (CPs) is shown in Table 2. Notable is that soils of CP17 and CP14 had higher moisture content at 0-5cm depth than CP22. At the deep levels of 20-25cm and 70-75cm, soils in CP22 had the highest moisture content. At the deep profile depths, the soil of CP14 had gravelly texture while those of CP 22 had a clayey texture. Even in dry weather conditions, clay soils retain moisture at the deep layers and this was evident of soils at CP 22.

3.5.2. Soil pH and electrical conductivity

Soil pH gives a measure of soil acidity or alkalinity and significantly influences myriads of soil biological, chemical, and physical properties and processes that affect plant growth and biomass yield

Table 2. Soil physico-chemical properties of soil moisture content, soil pH, electrical conductivity and exchangeable sodium for the three sample center pivots at 0-5cm, 20-25cm, 70-75cm depth and for the overall soil profile

Center pivot station	Soil profile depth (cm)			Mean all depths
	0-5	20-25	70-75	
	% Soil moisture (v/v)			
CP14	1.89	1.41		1.18±1.40^a
CP17	2.02	4.39	6.44	4.29±2.17^b
CP22	0.73	7.09	9.82	6.91±3.76^b
	Soil pH			
CP14	8.58	8.49	9.11	8.72±0.47
CP17	8.34	9.07	9.61	9.00±0.65
CP22	8.89	9.45	8.74	9.03±0.40
	Electrical conductivity (dS/m)			
CP14	0.274	0.523	0.267	0.35±0.21
CP17	0.513	0.366	0.702	0.56±0.23
CP22	0.614	1.441	0.254	0.77±64
	Exch. Na (meq/100g)			
CP14	1.517	3.295	4.577	3.13±1.77^a
CP17	4.487	7.167	12.513	8.06±4.51^{ab}
CP22	8.039	19.987	24.359	17.46±7.67^b

(Minasny et al., 2016). The pH level was lowest in soils at depths of 0-5 cm for all CPs and ranged from 8.3 to 8.9 which is classified as alkaline (Table 2). At the lower soil depths of 20-25 and 70-75 cm, the pH levels were largely above 9, classified as highly alkaline (Esilaba A.O. et al., 2023; Okalebo, JR et al., 2002). In all depth levels, there was no significant difference in pH between the sampled CPs, ($p > 0.05$), based on Mann-Whitney U test. The optimal pH range for maize growth in Kenya is between 5.5 and 7.0, (NAAIAP, 2017; Weil, RR and Brady, NC, 2017). The pH for the sampled soils appeared to be highly alkaline for maize growth. Highly alkaline soils could have toxic amounts of bi-carbonate and aluminum and bring about nutrient deficiencies, such as Phosphorus and Boron, (Miller, JO, 2016). Because of the high pH recorded, remedial measures are needed to keep the pH within optimal range for maize and most crops' growth. Experimental field tests could be the starting point to establish appropriate practices for lowering soil pH before adopting for application to the larger scheme. Electrical conductivity estimates the concentration of soluble salts in soil water solution by how well an electrical current passes through the medium giving a surrogate measure of salinity (FAO, 2021b). High EC means many negatively charged sites (clay and organic particles) are in the soil and thus cations (such as Ca, Mg, K, Na, Cu, Fe) are being held in the soil. Low EC levels mean low available nutrients and too high EC levels would mean an excess of soluble salts thus causing salinity. The highest EC of 1.86 dSm^{-1} was recorded for CP22, considered as upper limit for optimal crop growth.

3.5.3 Soil exchangeable sodium (ES) levels

The levels of exchangeable sodium in the soils of the sample center pivots are shown in Table 2. High levels were recorded in the deep soil layer of 70-75 cm, followed by 20-25 cm and lowest in the top layer 0-5cm in similar pattern for the three center pivots. At CP 22 the exchangeable sodium values was significantly higher than in CP17 and CP14. The impact of soil salinity on the productivity of several vital crops, such as *Zea mays*, has been shown to result in significant reductions in yield and in addition reduces the amount of water available for plant growth (Ahmed et al., 2024; Läuchli, A and Grattan, SR, 2011). Although not conclusive, it is noted that sodium was predominantly high especially in soils of CP 22 and especially in the deep soil layers. The chief characteristic of sodic soils from the

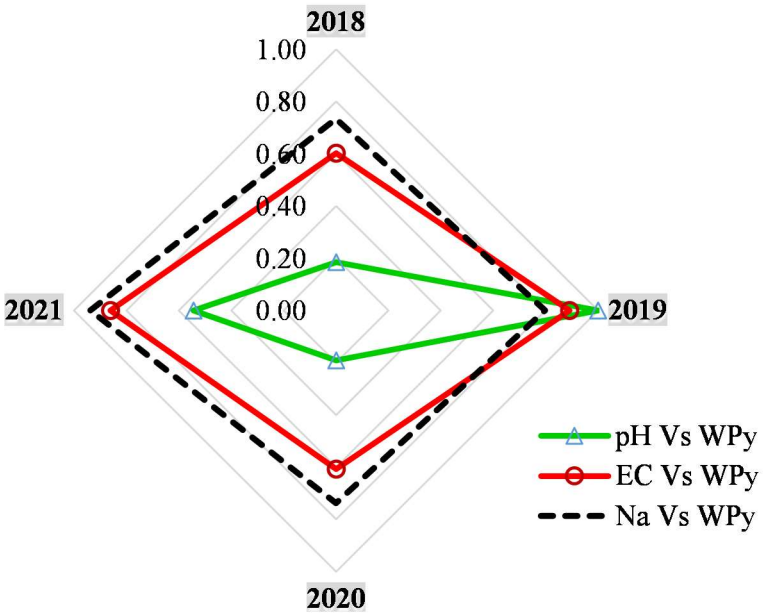


Figure 11. Plot of outputs of Pearson correlation coefficient (r) between soil properties of pH, EC and Na with crop water productivity (WPy) for the three CPs (14, 17 & 22) repeated for the four crop seasons. NB: (the actual tabulated r values are negative (Table 3) but for visualization purpose drawn here as positive)

Table 3: Output of Pearson correlation coefficient (r) between soil properties of pH, EC and Na with crop water productivity (WPy) for the three CPs (14, 17 & 22) for the four crop seasons.

Soil property Vs Wpy	Season			
	2018	2019	2020	2021
pH Vs WPy	-0.184	-1.000	-0.191	-0.544
EC, WPy	-0.602	-0.891	-0.607	-0.861
Na, WPy	-0.734	-0.797	-0.738	-0.937

agricultural stand point is that they contain sufficient exchangeable sodium to adversely affect the growth of most crop plants. Sodic soils are characterized by high level in exchangeable sodium, EC is less than 2 dSm^{-1} and soil pH usually greater than 8.5, (Zamora-Re, MI et al., 2022). For this study sites around CP22 had mean EC of 0.77 dsm^{-1}. The soil could thus be classified as sodic soil which makes them alkaline as observed by the high pH (Table 2). Excess sodium in the soil causes clay and organic matter to disperse, which in turn blocks the soil pores, resulting in poor water infiltration making cultivation of crops difficult (Abrol, IP et al., 1988). Indeed soils at CP22 appeared clayey and saturated at the 70-75 cm depth while at the same time the surface soils were dry and equally reported lower yields than CP14 and CP 17, corroborating other reports such as (Abrol, IP et al., 1988; Hailu, B and Mehari, H, 2021).

The Pearson correlation coefficient (PCC) values between the measured soil properties of pH, EC and Na with maize water productivity, from the three test CPs, for the four seasons showed strong and weak negative correlations that ranged between -0.18 and -0.99 (Figure 11, Table 3). Sodium concentration led in all the seasons in having the highest negative correlation with crop water productivity followed by EC. One of the effects of excess exchangeable sodium on plant growth is through its effect on soil pH that results in lowering the availability of some essential plant nutrients such as calcium and magnesium in the soil solution as pH increases, lowering crop growth performance and yields, (Abrol, IP et al., 1988; Vaughan, R, 2024).

4. Conclusions and Implications

Application of the remote sensing derived WaPOR database contributed to broad-scale analysis and evaluation of maize crop water usage at the Galana Kulalu irrigation scheme providing a strong basis for wide application in agricultural water management (Karimi, 2014). Irrigation performance variables of CV, beneficial fraction, adequacy and RWD showed that the center pivots to the northern parts of the scheme (CPs 4, 7, 22, and 23) performed lowly compared to the southern center pivots. The final water productivity estimates delineated, spatially, between favourable and less favourable areas of the scheme which mirrored the results of the performance indicators. The average WPy for the cropping seasons, however, showed marked difference in the trend with the 2020-2021season rating highest than the other seasons that also reflected high CV values of AETI.

Diagnostic studies on soil properties at the farm level have shown that the sample pivot 22 located to the north of the scheme haboured high soil moisture content at lower soil layers despite the extended dry weather at the time of sampling, which indicate poor drainage conditions and potential for water logging. The observed soil pH and EC were high in all sample plots with CP22 recording the highest values, beyond the requirements for optimal maize growth. High levels of exchangeable sodium, indicated existence high sodicity conditions especially in CP22 located in the northern part of the scheme. This result corroborated the findings of the WaPOR data analysis that depicted the northern areas of the scheme as low performing in terms of irrigation performance indicators and the computed WPy. Within the scope of the study, the WPy estimate flagged out areas of the scheme that need more

investigation to determine constraining factors. Several authors such as (Chukalla et al., 2022; Zwart and Bastiaanssen, 2004), note that irrigation management practices, soil fertility management and weather factors as some of the key variables that can influence spatial and seasonal variations in WPy estimates. Diagnostic tests improved our interpretation of WPy results, however it would be important to increase resolution of sampling to capture deeper understanding of underlying causes of low crop performance (hot spots) in sections of the scheme. The input variables for the WaPORWP algorithm such as cropping season dates and land cover maps could affect estimated WPy values and need continual refinement (Cheng et al., 2022).

The Galana Kulalu irrigation scheme was initiated as food security project by the government to meet increasing demand for food especially maize. Geographically, the scheme is in semi-arid location and water loss through evapotranspiration is high among other environmental vulnerabilities. At the farm level, water saving practices such as water harvesting, use of mulches, cover crops, soil organic amendments, limited tillage, provision of wind breaks and choice of crop variety will potentially enhance efficiency of water use and lower AETI component of water productivity (Khalifa et al., 2022; McMillen et al., 2022; Wani and Karuku, 2022). Practices such as ridge furrow mulching has been found to improve soil water availability and maize productivity and could potentially perform in irrigated maize production (Mo et al., 2016; Zhang et al., 2024). In addition to addressing the risks associated with water scarcity and insufficient water supply, below-par irrigation system performance is often a consequence of water oversupply due to mis-match between water delivery schedules and crop water requirements (Ingrao et al., 2023; Toma et al., 2022), often, caused by lack of usable technical information or low human capacity. If water use is not well monitored by accounting for water volumes utilized by the crop and hence the yield, it becomes difficult visualize the existing gaps and the overall effect on returns on the investment. To surmount these challenges, innovative, cost effective agro-meteorological tools and sensors for measuring the various water and climate variables to inform irrigation scheduling and optimize water management are critical especially in the Africa region (Bjornlund et al., 2020; Kanda and Lutta, 2022; Wang and Cai, 2009).

As the government, irrigation scheme managers and other stakeholders seek to increase efficiency of production, aspects of water accounting in irrigation, adapting agronomic practices to specific site needs and use of real time data should be evaluated to offer accurate and timely interpretation of derived WPy estimates. In our study area of Galana, critical remedial measures are needed to restore soil health through soil amendment measures, for production per unit land and water to increase, (Du et al., 2015; FAO, 2022) and provide positive net returns on the investment. The available online climate and phenology database, offer customizable opportunity to monitor performance of irrigated and rain-fed agriculture systems for both large and small scale enterprises beneficial to producers and resource use optimization. However, as evidenced in this study and other studies (Bjornlund et al., 2020), such online data must be complimented by investment into equipment and tools that provide localized data necessary for monitoring and validating observed trends.

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