Master's Thesis - Water Sciences and Management
Department of Geosciences

Spatial and temporal analysis in land and water productivity using WaPOR data

A case study of the sugarcane plantations of Metahara, Ethiopia

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Abstract

The Ethiopian government faces a challenge in which they aim to increase the yields of the sugarcane fields of Metahara, while decreasing the water consumption. Hence, this research analyzed the spatial and temporal distribution of land and biomass water productivity in Metahara. WaPOR data covering 2009-2021 was used to analyze five irrigation scheme performance indicators: *i)* land and water productivity, *ii)* productivity gaps, *iii)* water consumption, *iv)* uniformity, and *v)* adequacy. The WaPOR data was compared to ground-level data for validation. Stakeholders were consulted to understand the results and the results of the WaPOR data were compared to two other variables: soil texture and the influence of the saltwater of Lake Basaka.

The temporal results from this research revealed that water productivity decreased over time, and that droughts explained partly for temporal variations. Furthermore, biomass did not increase, and water consumption increased instead of decreased over time. Due to soil compaction and the related decreased infiltration capacity, more water is applied while not more water reaches the crops. Spatial variation in land and water productivity was related to the influence of Lake Basaka. Fields closer to Lake Basaka had lower productivity. More compacted and finer soil textures had a higher water consumption, better uniformity, and higher adequacy. Soil texture did not explain for spatial land and water productivity variation but did explain for temporal variations. Also, fields with a higher water consumption had an overall higher biomass production. Concluding, spatial and temporal distribution in water productivity related to the influence of Lake Basaka, soil texture, and droughts.

This research contributes to the wider scope of knowledge in remote sensing-based data because it has proven that on-the-ground knowledge is needed to explain for varieties in time and space shown by remote sensing data. Some findings in spatial land and water productivity could only be declared with stakeholder knowledge. Nevertheless, the remote sensing-based research is valuable, and the future potential is high.

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Acronyms

ABWAP	Awash Basin Water Allocation Strategic Plan
CV	Coefficient of variation
EOS	End of season
FAO	Food and Agriculture Organization
GTP	Growth and Transformation Plan
IHE	The International Institute for Hydraulic and Environmental Engineering
IPCC	Intergovernmental Panel on Climate Change
SD	Standard deviation
SOS	Start of season
UNEP	United Nations Environment Program
WaPOR	Water Productivity through Open access of Remotely sensed derived data

List of symbols

AOT	Above ground over total biomass
ET_{act}	Actual evapotranspiration
B	Biomass production
WP_b	Biomass water productivity
ET_c	Crop evapotranspiration
K_c	Crop factor
HI	Harvest index
f_c	Light use efficiency correction factor
Mc	Moisture content
NPP	Net primary production
$\sum T/ET_{ref}$	Normalized transpiration
PCP	Precipitation
ET_{ref}	Reference evapotranspiration
T	Transpiration

1.0 Introduction

1.1 Background and problem description: Water shortage in Ethiopia

In March 2022 the United Nations Environment Program (UNEP) reported that the Horn of Africa was experiencing an extremely severe drought, causing food and water shortages for over 13 million people. This number was likely to increase up to 25 million (UNEP, 2022). Scientists blamed the drought on climate change and the Intergovernmental Panel on Climate Change (IPCC) reported that sectors will be struck hard in the future due to rising climate change (IPCC, 2022). East Africa, particularly parts of Somalia, Djibouti, Kenia, and Ethiopia, have been struck by this drought. Although organizations such as the UNEP have implemented urgent humanitarian help, long-term investments are crucial to save lives and cope with future droughts (UNEP, 2022).

Ethiopia is recognized as the 'water tower' of Africa because 14 major rivers' headwaters flow through the country. Yet water scarcity issues are common (Ingebretsen, 2015). Ethiopia has a high hydrological variability with twelve major river basins, high surface water resource potentials, and several drought-experiencing areas (Food and Agriculture Organization of the United Nations (FAO), 2016). Two out of twelve basins are dry, two contain a water surplus, and eight experience water shortages (Adeba et al., 2015). The basin of interest in this study, the Awash River Basin, falls under the latter category. In this basin, several factors lie at the source of water shortages. To start, strong subsidies for water and the resulting low water price result in high amounts of water used in all sectors (Adeba et al., 2015). Secondly, urbanization and population growth increase water requirements in large cities. On top of that, large cities, agricultural wastewater, and industrialization cause water pollution, which further aggravates water shortages. Thus, industry and the agricultural sector are two large water-consuming sectors. In fact, the agricultural sector is the largest water-consuming sector in Ethiopia, consuming 85% of all freshwater withdrawals (Karimi et al., 2019). This is remarkably high compared to the global average percentage of all freshwaters used in the agricultural sector of 70% (FAO, 2016).

The Awash River is experiencing water shortages because large-scale withdrawals from the Awash River are used for irrigation purposes in commercial and non-commercial farming. More than 70% of all Ethiopian agricultural practices are taking place along the whole stretch of the river (Gedefaw et al., 2019). The sugarcane industry, for example, requires lots of water, namely 164 m^3 per ton of production (Ministry of Foreign Affairs of the Netherlands, 2016). Simultaneously, it lies at the source of pollution, because large wastewater amounts that contain agricultural chemicals and fertilizers are discharged into the Awash River (Taddese et al., 2010). This amplifies water shortages in the basin and causes negative impacts on agricultural activities. Problems arise for the Ethiopian government since the economy relies for a large part on agricultural activities (FAO, 2016). Future climate change will likely further reduce water availability through increasing temperatures and less precipitation. Especially when considering this, the urge to improve water management arises (Gedefaw et al. 2019; FAO, 2016).

To deal with the water scarcity issues in the Awash Basin, the Ethiopian government developed the Awash Basin Water Allocation Strategic Plan (ABWAP) in 2017 which aims for a better distribution of water in the basin. The ABWAP is an 8-year program in which domestic water use, livestock, irrigated agriculture, and industry all get certain amounts of water allocated (Awash Basin Authority, 2017). Each sector needs to make changes to survive with the restricted amount of water it gets allocated. According to Adeba et al. (2015), irrigation efficiency is low in the Awash Basin, which could be increased by changing the management strategy e.g. irrigation types or irrigation schedules. Whenever better management is enacted and water is used in an optimized way, the total irrigation

scheme performance could be improved. Irrigation scheme performance indicates how well water is used and distributed in an area. Dejen et al. (2015) stated that irrigation scheme performance in African countries, including Ethiopia, is lower than expected. Water must be used efficiently in the agricultural industry, to cope with water shortages and to keep the yields from the sector high. The agricultural industry contributes not only to the Ethiopian economy by creating jobs and exporting products but is also consumed in domestic areas. Hence, the socioeconomic value of the agricultural sector in Ethiopia is high and investments to improve the irrigation scheme performance via plans such as the ABWAP are essential.

1.2 Sugarcane in Ethiopia

In Ethiopia, sugarcane is one of the main cultivated crops and multiple commercial sugarcane farms are located within the Awash River Basin (FAO, 2016). Sugarcane grows best under warm conditions with a mean temperature between 22 and 30°C and high radiation. Since the 16th century, sugarcane has been cultivated in different parts of Ethiopia (Tena Gashaw et al., 2018). Mostly smallholders cultivated sugarcane and it was used for confectionary production, consumption by households, selling on a small scale, and feeding livestock. Approximately four centuries later, in 1951, commercial sugarcane cultivation started when the Dutch Handel Vereniging Amsterdam founded the Wonji sugarcane plantation in the Awash River Basin. In 1970, the sugarcane estate at Metahara was established followed by the Fincha sugarcane estate in 1998 (Tena et al., 2016). Since the fall of the emperor's regime in 1974, the sugar estates were owned by the government. Currently, there are various smallholder sugarcane farms in Ethiopia and six state-owned sugar factories, namely Wonji-Shoa, Fincha, Tendaho, Arjo-dedessa, Kessem, and Metahara (Tena Gashaw et al., 2018). The sugarcane industry has grown tremendously and has a significant role in the society and economy of Ethiopia. It creates job opportunities, is used as an export product, and is produced for domestic consumption (Tena Gashaw et al., 2018).

Decreasing yields over time have stimulated the Ethiopian government to implement strategic plans that aim for higher production. The total area for sugarcane production has doubled since 1993 from 16000 ha to 32069 ha in 2019, while contrastingly the yield has decreased from 117 tons/ha in 1993 to 50 tons/ha in 2020 (FAO, 2022). According to Paul & Gĩthĩnji (2017), this happened mainly because large farm holders expand their area instead of smallholders, while smallholders use their land more intensively. The decreasing yield is alarming for the Ethiopian government. Resultingly, the Ethiopian government has launched the Growth and Transformation Plan (GTP) in 2010 to increase production. The plan included large investments to increase the yields by expanding irrigation developments, scaling up the best practices in the sector, educating farmers, and increasing capacity (Ministry of Finance and Economic Development, 2010). These investments aimed to boost the Ethiopian sugarcane industry to a production of 3.9-4.17 million tons per year. Thereby, Ethiopia would upswing to the top 10 sugar producers in the world (Sequeira, 2021).

The goals from the GTP have however not been reached yet. This is due to, among other reasons, management issues, delayed funding, and cost overruns (Sequeira, 2021). Another challenge arose because the actions that follow from the GTP should be in line with the ABWASP (Awash Basin Authority, 2017). These plans are however vulnerable to changes caused by e.g. droughts and a growing water demand downstream. Bastiaanssen (2019) highlighted that the Metahara Sugar Estate abstracts slightly more water than allowed according to the ABWASP. Thus, challenges emerged in which no more water should be abstracted from the Awash River while reaching for higher yields. To increase

the yield without depleting water sources, it is important to obtain a good understanding of the factors influencing biomass production and water use.

1.3 Land and water productivity in remote sensing analysis

A widely used indicator to compare biomass production with water use is biomass water productivity (WP_b) (Ali & Talukder, 2008; Sharma et al., 2015; Alemayehu et al., 2020). WP_b is defined as '*the ratio of the net benefits to the amount of water used to produce those benefits*' (Sharma et al., 2015). In this study, WP_b is referred to as the ratio of above-ground dry biomass production (B) over actual evapotranspiration (ET_{act}). The ratio of WP_b alone however carries little interest when B and ET_{act} are not considered (Ali & Talukder, 2008; Zoebl, 2006). A high WP_b does not necessarily coincide with a high B. For instance, WP_b can be high while B is low and ET_{act} is extremely low. Therefore, B and ET_{act} should be included to draw valuable conclusions for farmers and irrigation managers. According to Zoebl (2006) not only B and ET_{act} should be included, but also other factors such as crop water requirement need to be considered to find and understand spatial or temporal variations in WP_b. When including all these factors, the irrigation scheme performance can be analyzed thoroughly. To improve WP_b and water use in an area, a good understanding of the agronomic practices as well as irrigation scheme performance in the area is needed. Analyzing the performance can contribute to resolving the challenge of water limitations for farmers in the Awash River Basin.

To understand irrigation scheme performance, the following indicators can be analyzed: *i)* water consumption patterns, *ii)* spatial-temporal land and water productivity patterns, *iii)* target productivities, and *iv)* potential causes for low land and water productivities. These variables have previously been analyzed using remote sensing (Hellegers et al., 2008; Campos et al., 2018). Zwart et al. (2010) created a tool in 2010 to model the WP_b from remotely sensed data on the surface albedo, vegetation index, NDVI, radiation, and air temperature. Ever since research into such models and methods has been developed and currently remote sensing methods to analyze the WP_b can support decision-making for social and environmental purposes (Hellegers et al. 2008). Remote sensing offers a feasible, cost-effective method for measuring irrigation scheme performance compared to traditional field methods (Bastiaanssen et al., 1996). Although remote sensing methods to study land and water productivity and irrigation scheme performance are still under development, they have been accepted as viable methods and have been used in scientific research.

In 2018, the FAO launched the open source and freely accessible portal to monitor Water Productivity through Open access of Remotely sensed derived data (WaPOR), which can be used to analyze land and water productivity (FAO, 2018). The International Institute for Hydraulic and Environmental Engineering (IHE) Delft has created a standardized protocol for analyzing land and water productivity and irrigation scheme performance when using WaPOR data. This protocol illustrates the irrigation scheme performance by addressing five indicators: land and water productivity, productivity gaps, water consumption, uniformity, and adequacy. Land and water productivity are especially important because it relates biomass to water use directly. Thus, land and water productivity can be used as main indicators to describe irrigation scheme performance. The FAO WaPOR data and the IHE protocol kept on developing and WaPOR 2 was launched in 2020, which is the most recent version (FAO, 2020a). The WaPOR data has already been used in several studies (Blatchford et al., 2020; Chukalla et al., 2022; Alemayehu et al., 2020). Ergo, this research assumes it is viable to use the WaPOR data.

1.4 Research gap

This research contributes to understanding the land and water productivity in the research area, which can eventually support irrigation scheme managers and farmers in decision-making to improve land and water productivity of sugarcane in Ethiopia. To reach the high ambitions of the GTP, a good understanding of the irrigation scheme performance in the research area should be obtained. Therefore, this study analyzes and relates causes to the spatial and temporal distribution of land and water productivity by applying open-source and ground-level data. Metahara will be used as a case study area, which surrounds Metahara Sugar Estate and lies within the Awash Basin. Research has already been done into the spatial and temporal variation in land and water productivity, the influencing factors, and how to improve the productivity, this however has not been done for Metahara. The variation in land and water productivity in Metahara is not well understood and for that reason, this research focuses on analyzing the land and water productivity in Metahara.

Although WaPOR data have been used in lots of research to study land and water productivity in different areas (Alemayehu et al., 2020; Bastiaanssen, 2019; Khanal et al., 2020), it does often not include ground-level data. This is crucial because it is assumed that solely using remote sensing data can result in wrong conclusions. Not all temporal and spatial differences can be explained properly when solely using remote sensing data. Various studies use the WaPOR data without validating the data themselves because they assume the WaPOR data is validated by other studies (Barideh & Nasimi, 2022; Chukalla et al., 2022; Gemechu et al., 2020). Servia et al. (2022) validated the WaPOR data by comparing it to other models; other research by Blatchford et al. (2020) or Weerasinghe et al. (2020) validated the data, but only on ET_{act}. The WaPOR quality assessment report is the only report that has validated the WaPOR B data with ground-level data for several areas. Thus, little research has been done into the validation of the WaPOR B data. This research contributes to the scientific knowledge for remote sensing analysis by evaluating and comparing the use of WaPOR data only, and the use of WaPOR data in combination with ground-level data via a case study. An analysis will be performed with only remote sensing data from the WaPOR portal; another analysis complemented the pre-analysis by also consulting stakeholders from the research area and using ground-level data to better understand the spatial and temporal differences in land and water productivity.

1.5 Objective and research questions

The objective of this research is to understand how land productivity, WP_b, and irrigation scheme performance in Metahara is distributed over time and space and what factors can help to explain the variations. The irrigation scheme performance indicators used are land and water productivity, productivity gaps, water consumption, uniformity, and adequacy which are calculated with WaPOR data and the IHE protocol. The research is split into two sections: *i)* The first section will describe the spatial-temporal differentiation of irrigation scheme performance by using the five different indicators. *ii)* The second section is used to explain the results of section one by comparing the results to soil texture and to the influence of the saltwater of Lake Basaka. Furthermore, stakeholders from Metahara were consulted.

The stakeholders consulted are the irrigation manager from Metahara and a member of the plantation team in Metahara. The primary research question is:

What are the spatial and temporal variability in land and water productivity in Metahara and how can these be explained?

The following sub-questions are answered to help find an answer to the main research question.

1. How is the seasonal land productivity (B) spatially and temporally distributed in the irrigation season?
2. How is the seasonal water productivity (WP_b) spatially and temporally distributed in the irrigation season?
3. What are the productivity targets and gaps?
4. What are the water consumption, uniformity, and adequacy, and what do these factors in combination with the water productivity imply for the irrigation scheme performance?
5. To what extent can the water productivity and irrigation scheme performance over the area be explained by soil texture and by the influence of Lake Basaka?

The sub-questions can be assigned to two different sections. Sub-questions 1-4 are assigned to the first section on operating the WaPOR protocol to define the irrigation scheme performance indicators. Sub-question 5 is linked to the second section on understanding the differentiation in productivity.

After finishing the analyses, the potential of remote sensing, in general, will also be discussed. Because this is a valuable question to the wider scope of remote sensing research, this will be addressed in the discussion. The focus of this research is however on land and water productivity, so the potential of remote sensing analysis, in general, will neither be addressed in the method, nor the results sections.

1.6 Theoretical framework

Irrigation scheme performance

Irrigation scheme performance assessments are often performed in research in various ways and for different purposes. Bos et al. (2005) stated '*Performance assessment of irrigation and drainage is the systematic observation, documentation, and interpretation of the management of an irrigation and drainage system.'* Hence, management is included in the total framework of irrigation scheme performance. The purpose of evaluating irrigation scheme performances can be *i)* optimizing the use of resources, *ii)* assessing trends, or *iii)* comparing different schemes in their irrigation performance (Santos et al., 2010). In this research, the goal for the irrigation scheme performance is a combination of all three purposes. Two irrigation schemes will be compared, and spatial and temporal trends will be analyzed to optimize the irrigation performance of the schemes.

There is no consensus on the indicators used to describe the irrigation scheme performance within the field of research (Santos et al., 2010). The research by Bos et al. (2005) uses 23 indicators to describe the irrigation scheme performance, while other research by Malano & Burton (2001) has defined 11 indicators. Often the indicators describing the irrigation scheme performance are related to the traditionally used variables adequacy, equity, and reliability of the water service (Bastiaanssen & Bos, 1999). This research uses the five indicators for irrigation scheme performance from the IHE protocol, which will be described in section 2.4.1 (Chukalla et al., 2020).

Land and water productivity

Land and water productivity are two widely used variables in the scientific literature and are used in this research as the main variables describing irrigation scheme performance (Molden et al., 2010; Nouri et al., 2018; Desiere & Joliffe, 2018). It is defined as the production of the aspect of interest per unit of land for land productivity and per unit of water consumed for water productivity. The focus of this research lies on biophysical land and water productivity, meaning that it will exclude factors such as

social or economic water productivity. Other dimensions such as economical water productivity are outside the scope of this research. In this research, WP_b refers to the relation between B and the amount of water consumed in a given period (Nouri et al., 2018). WP_b differs from an index such as water use efficiency or irrigation scheme performance in the sense that it includes B as well. Water use efficiency only reflects how effectively water is delivered to crops (Molden et al., 2010). Thus, WP_b is a highly important variable for farmers.

Land productivity is described in the literature as self-reported production divided by plot size (Desiere & Jolliffe, 2018). Often biomass production or yield is used to describe land productivity. In this research, the same definition for land productivity is used as in Alemayetu et al. (2020) which covers the total B in ton/ha/season.

2.0 Methodology

This section explains the methodological approach executed to explore the research questions. First, the study area is described, followed by a section on the research set-up and a further in-depth description of the methodology.

2.1 Research area

The research focused on the agricultural fields of Metahara which are established in the East Shoa Zone, approximately 200 km east of Addis Ababa (***Figure 1***). Metahara produces sugarcane for the Metahara Sugar Company and is divided into two irrigation schemes, Merti and Abadir. It has a semi-arid climate according to the Köppen climate characterization with an average annual precipitation of 551 mm and a temperature of 24 ˚C, which is suitable for sugarcane production (Fanjana, 2020; Fito et al., 2017). Because the temperature is quite constant throughout the year, the area is suitable for constant sugarcane production (FAO, n.d.). Most precipitation falls in July and August, so in these months the fields are prepared for the rest of the growing season. In the irrigation season (September – June) irrigation is applied, which is mostly done via furrow irrigation through a large network of canals that are manually operated.

The water from the Awash River, which runs through the center of the research area, is used for irrigation. The river originates in the highlands 150 km west of Addis Ababa whereafter it transports its water from the upper Awash Basin to the northern lower lying areas in Djibouti and Somalia, where the river ends in endorheic lakes that only lose water by evaporation (Edossa et al., 2009). Lake Basaka is such a lake that is located nearby the study area. Yet, the water from this lake cannot be used for irrigational purposes because the water is too saline (Dinka, 2012). Lake Basaka lies in the Rift Valley of Ethiopia which is known for its salt accumulation due to the influence of volcanic activities and high evaporation rates (Chernet et al., 2001; Dinka et al., 2015). Currently, the lake is expanding to the northeast and south, which poses a threat to the villages Methara Merti and Metahara (Dinka, 2012; Tenagashaw & Tamirat, 2022).

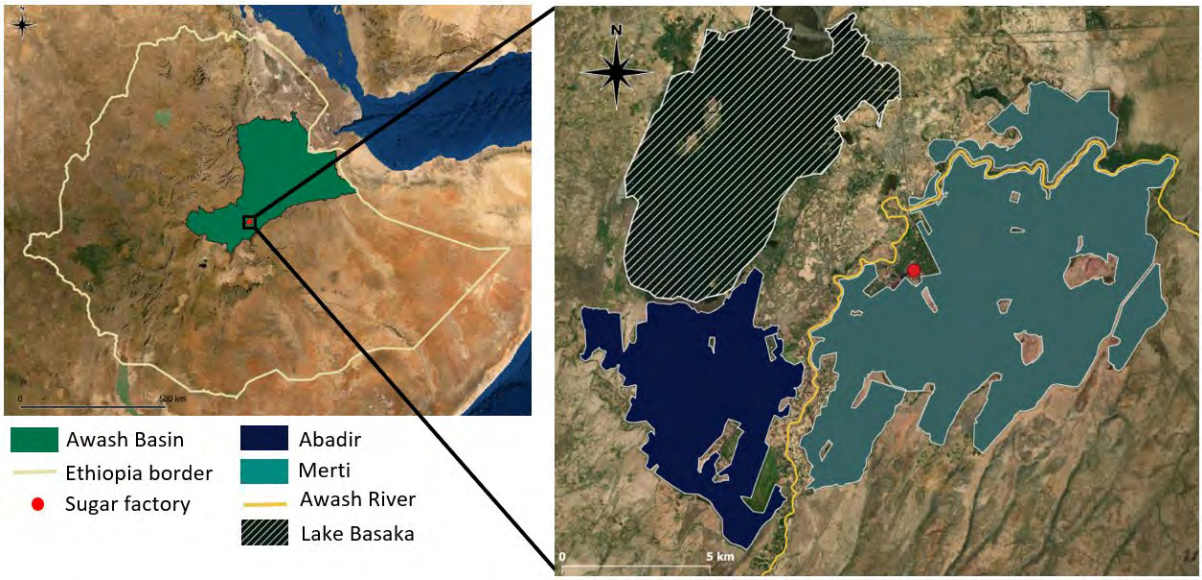


Figure 1. *The research area. The border of Ethiopia with the Awash Basin in green (left). The research area Metahara Merti and Abadir (right).*

2.2 Research set-up

This research consists of two parts of which the first part focused on analyzing the irrigation scheme performance with remote sensing data; the second part concentrated on using ground-level data to declare the results from the first part. WaPOR provided spatiotemporal data for Africa and the Near East to monitor land and water productivity and was used to perform the first part of this analysis. The methodology used to analyze this data was based on the WaPOR protocol developed by IHE Delft (Chukalla et al., 2020). The schematic overview of the WaPOR protocol in ***Figure 2*** illustrates that the protocol is organized into several modules in which the data is preprocessed and checked for consistency before it was used to calculate the performance assessment indicators. Within this research, the Merti and Abadir irrigation schemes were compared, and a separation was made between the irrigation and precipitation season.

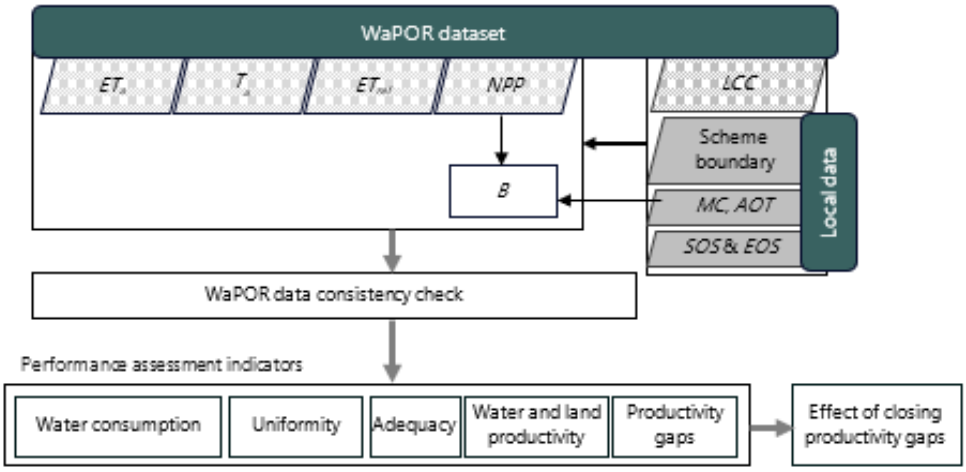


Figure 2. *A schematic overview of the WaPOR protocol created by IHE Delft that was used to analyze the WaPOR data (Chukalla et al., 2020).*

For the second part of this research, stakeholders from Metahara were consulted for a better understanding of the results from the first part. The stakeholders gave two indicators that were used to analyze the productivity: soil texture and the location with respect to Lake Basaka. The following sections will elucidate the data and methodology for each part.

2.3 Datasets

The data used for this study originates from the FAO WaPOR portal. At all locations in Africa and the Near East, the data was available on a continental scale (L1 at a grid size of 250 m) and country scale (L2 at a grid size of 100 m). Some areas, including the Merti and Abadir irrigation schemes, were also available on project level (L3 at a grid size of 30 m) (***Table 1***). For this research decadal L3 data on reference evapotranspiration (ET_{ref}), precipitation (PCP), actual evapotranspiration and interception (ET_{act}), transpiration (T), and net primary production (NPP) for the period *01/01/2009 – 31/12/2021* was retrieved. All datasets were available at L3, except for ET_{ref} and PCP, which were only available at L1. The datasets combined remote sensing data on water use, NPP, land cover classification, phenology, and climate variables such as temperature and soil moisture content (***Table 1***). The data was gathered by the FAO from multiple satellites and was preprocessed before the data was made available

for download. The WaPOR database provides extensive information on the compiling of the WaPOR datasets (FAO, 2019).

***Table 1**: Data variables retrieved from WaPOR, the components used to calculate the WaPOR variables, the satellites used to retrieve the information, and the spatial/temporal resolution (FAO, 2020a; FAO, 2020b).*

Level	Variable	Input components	Satellite	Spatial and temporal resolution	Notes
L3	NPP	Solar radiation	MSG, MERRA/GEOS-5	1.67 km | 15 min 25 km | daily	
		Soil moisture stress	Landsat, MERRA/GEOS-5	30 – 60 m | 5-16 days, 25 km | daily	Low quality in cloudy/rainy conditions
		Land cover	Landsat	30 – 60 m | 5-16 days	
		Weather data	MERRA/GEOS-5	25 km | daily	
		PCP	TRMM, GPM		
		fAPAR	Landsat	30 – 60 m | 5-16 days	
	ET_{act}	-	-	-	The ET_{act} is a summation of the evaporation, transpiration (T), and interception. The Penman monteith is used to calculate the E with soil variable inputs, the T with canopy variable inputs, and the I with vegetation cover, leaf area index, and precipitation
	T and evaporation	Solar radiation	MSG, MERRA/GEOS-5	1.67 km | 15 min 25 km | daily	Based on the Penman monteith with canopy values
		Land cover	Landsat	30 – 60 m | 5-16 days	
		Weather data	MERRA/GEOS-5	25 km | daily	
		PCP	TRMM, GPM		
		Albedo	Landsat	30 – 60 m | 5-16 days	
		NDVI	Landsat	30 – 60 m | 5-16 days	Low quality in cloudy conditions
		Soil moisture stress (only for evaporation)	Landsat, MERRA/GEOS-5	30 – 60 m | 5-16 days 25 km | daily	Low quality in cloudy/rainy conditions
	interception	NDVI	Landsat	30 – 60 m | 5-16 days	Low quality in cloudy conditions
		PCP	TRMM, GPM		
L1	ET_{ref}	Solar radiation	MSG, MERRA/GEOS-5	1.67 km | 15 min 25 km | daily	Penman monteith is used to calculate the ET_{ref}
		Weather data	MERRA/GEOS-5	25 km | daily	
	PCP		TRMM, GPM	5 km | daily	

In addition to the WaPOR data, a dataset with ground-level measured data on planting and harvesting dates, and sugarcane production per field was provided by the stakeholders. The dataset was used to verify the WaPOR data. They also provided a detailed soil texture map of Metahara which was used for sub-question five. Five types of soil textures are present in the area: gravel, sand, loam, clay, and heavy clay. Each soil texture has a different water holding capacity and infiltration capacity, which influences the efficiency of irrigational water use. Ergo, this variable was used to analyze spatial differentiations in productivity.

2.3.1 Preprocessing the WaPOR data

Preprocessing the data included selecting the research area from the bulk data, downscaling the data to the desired spatial resolution, summing for seasonality, and calculating the above-ground dry biomass production (B). First, the bulk data was downloaded, data outside the study area was removed, and ET_{ref} and PCP were processed to L3 resolution. Afterward, the data per season was summed based on the start (SOS) and end (EOS) of a cropping season following ***Equation 1***.

$$NPP_s = \sum_{SOS}^{EOS} NPP \qquad \textbf{\textit{Eq. 1}}$$

The SOS and EOS vary per farmer because the farmers plant and harvest their sugarcane at different periods within a year to always provide sugarcane for the Metahara Sugarcane factory. Because of the lack of time to run the protocol separately for each field, this research assumed that all farmers had the same SOS and EOS based on the start and end of the irrigation season (September – June) and precipitation season (July – August) (Bastiaanssen, 2019). By using differentiation in seasonality, the intra- and interseasonal utilization of water resources could be compared.

After harmonizing the data to the desired spatial resolution and seasonality, B was calculated in ton/ha/season with ***Equation 2*** (Mul & Bastiaanssen, 2019; Ajour, 2021).

$$B = AOT * f_c * \frac{NPP}{(1-MC)} * \frac{22.222}{1000} \qquad \textbf{\textit{Eq. 2}}$$

For this equation, NPP, as well as some specific crop parameters were needed which were retrieved from literature. First, the ratio of the above ground over total biomass (AOT) [-] was used which had a value of 0.8 (Alemayehu et al. 2020). The WaPOR NPP was estimated based on the NDVI, which is a measure for the total above as well as below ground biomass growth. So, to exclude root growth from NPP the AOT is used. Second, the light use efficiency correction factor (f_c) [-] was needed which had a value of 1.8 (Villalobos & Fereres, 2016). Notwithstanding that NPP was based on C3 crops, sugarcane is a C4 crop that has a different light use efficiency. Therefore, NPP was multiplied by f_c. Lastly, to calculate the dry matter production NPP was divided by one minus the moisture content of the crop (MC), which had a value of 0.59 (Yilma et al., 2017). NPP in gC/m^2 was adjusted to B in ton/ha multiplying with the factor 22.222/1000 (FAO, 2020a; Ajour, 2021). In this factor, the fraction of carbon in organic matter was assumed to be 0.45.

2.3.2 Review of the WaPOR data

Before analyzing the data, the data needed to be checked for consistency by plotting B against T (***Figure 3***). Because the fluxes in B and T are known for their linear relation in sugarcane, the linear regression

lines were forced through the origin (Ben-Gal et al., 2003). B was plotted against T, ET_{act}, and the normalized transpiration ($\sum T/ET_{ref}$). The normalized transpiration measures the sum of the product of the decadal T over the decadal ET_{ref} according to the method of Steduto et al. (2007). The consistency check was performed for Merti and Abadir over the annual average data of 2009 – 2021. The results for all three comparisons to B showed clear, consistent relations. The overlap in data in the variables T, ET_{act}, and $\sum T/ET_{ref}$ explained this homogeneous relation. ET_{act} only differed from T in the sense that E and I were included in ET_{act}, whereby E and T were both calculated with a different variation of the Penman-Monteith. $\sum T/ET_{ref}$ only differed from T because it was divided by ET_{ref}, which were both calculated in an equivalent way but with different input values. Resultingly, it was not surprising that the plots were alike. Outstanding were the outliers that were present in the annual average plots for Merti. These were also present in the individual plots for each year (Appendix A). Although it seemed like there was a trend in the outliers, for each year the outliers were situated at distinct locations in the research area. Resultingly, they could not be removed from the plot. In addition, the distribution of the outliers in the research area was scattered, making it hard to detect specific locations with different or no vegetation.

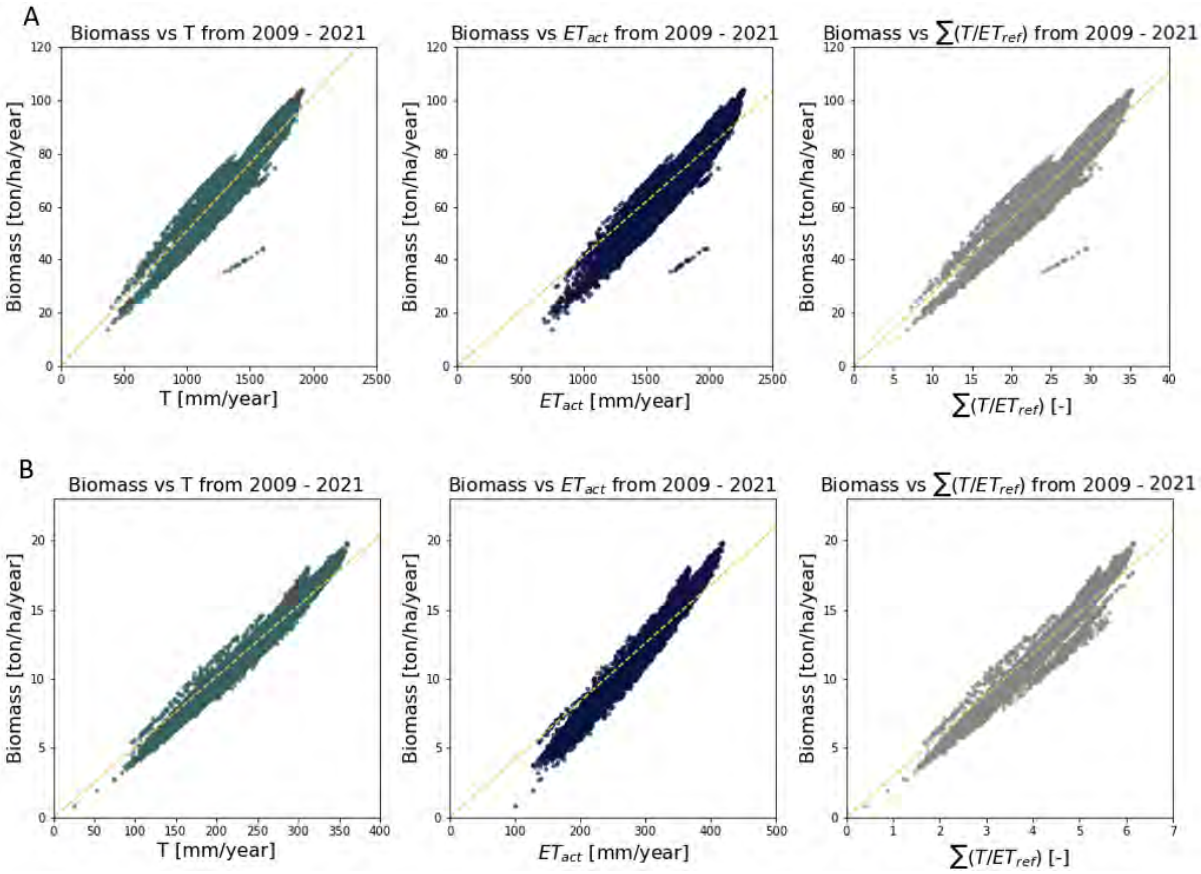


Figure 3. *Scatterplots of the annual average biomass against T (left), ET_{act} (center), or $\sum T/ET_{ref}$(right) of Merti (A) and Abadir (B). The data used for the scatterplot runs from 01/01/2009 – 31/12/2021.*

Table 2 reveals the regression parameters corresponding to the linear relationships in ***Figure 3***. The linear correlation of B with T, and B with $\sum T/ET_{ref}$ was strong. The relation between B and ET_{act} was steeper, which was attributed to the inclusion of unintended E within ET_{act}. E has no linear relationship with B which resulted in a less strong linear relation between B and ET_{act}. Furthermore, the slopes for Merti and Abadir were equivalent to each other, and the relations between B and T, and

B and $\sum T/ET_{ref}$ were stable. The R^2 values were higher for the datasets of Abadir than of Merti, although this difference was not significant.

Table 2. *Regression parameters belonging to the linear regression lines of the WaPOR consistency check for the annual average data of Merti and Abadir.*

	Regression parameters	Merti	Abadir
$B\ vs\ T$	Slope	0.060	0.061
	R^2	0.962	0.976
$B\ vs\ ET_{act}$	Slope	0.049	0.050
	R^2	0.908	0.931
$B\ vs \sum \frac{T}{ET_{ref}}$	Slope	3.513	3.601
	R^2	0.961	0.975

To check for reliability the WaPOR data has also been compared to the ground-level dataset given by the stakeholders. Due to time limits, a selection of 10 fields that represented the research area was analyzed (Appendix B). All fields had different growing seasons, so the WaPOR data for these fields was retrieved and summed according to the planting and harvesting cycles of each field as described in the ground-level dataset. The WaPOR B [ton/ha] was calculated and plotted in a scatterplot against the ground-level B [ton/ha] with the trendline (***Figure 4a***).

The correlation between the WaPOR and ground-level B was only 0.368 (R^2-value=0.14), indicating that the WaPOR data was far off from the ground-level data. Overall, the ground-level measured B was higher than the WaPOR data, so the WaPOR data was underestimated. This could be explained by the fact that the WaPOR data only contained dry sugarcane, while the ground-level data covered the sugarcane plus the moisture it contained. Sugarcane variety has been included in ***Figure 4b*** to see if this could better explain for differences in B between WaPOR and ground-level data. However, some data points had to be excluded, because the ground-level dataset did not properly state what the sugarcane variety was for each field since some fields had a mixed variety. Consequently, only 55 data points were included in ***Figure 4b***. Sugarcane variety NC0334 had the best correlation with 0.81. It should be noted that not all sugarcane varieties contained the same amount of data, so it still could not be said whether the sugarcane variety explained the variation in WaPOR and ground-level estimated B.

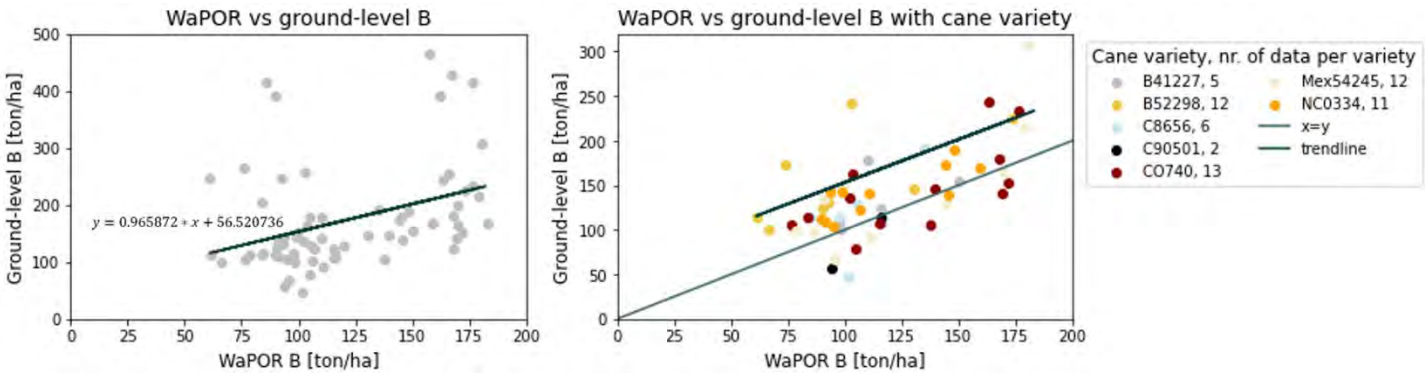


Figure 4. *a) Scatterplot of the WaPOR data vs the ground-level data. 70 data points were taken into account. Each point represents the data for one crop cycle in one of the ten fields that have been selected. The trendline indicates the general relation between WaPOR and ground-level data. b) Scatterplot of the selected WaPOR data vs ground-level data considering sugarcane variety. 55 data points were taken into account. The same trendline as in Figure 4a is also plotted. The legend gives the sugarcane variety and the number of data points used per variety.*

The plotted WaPOR and ground-level data over time in ***Figure 5*** did not always match equally well for all fields. Yet, for some fields like O17, the trends were similar for WaPOR and ground-level data. The WaPOR data showed to be consistent in ***Figure 3***, hence the WaPOR dataset was used in this research because comparisons could still be made.

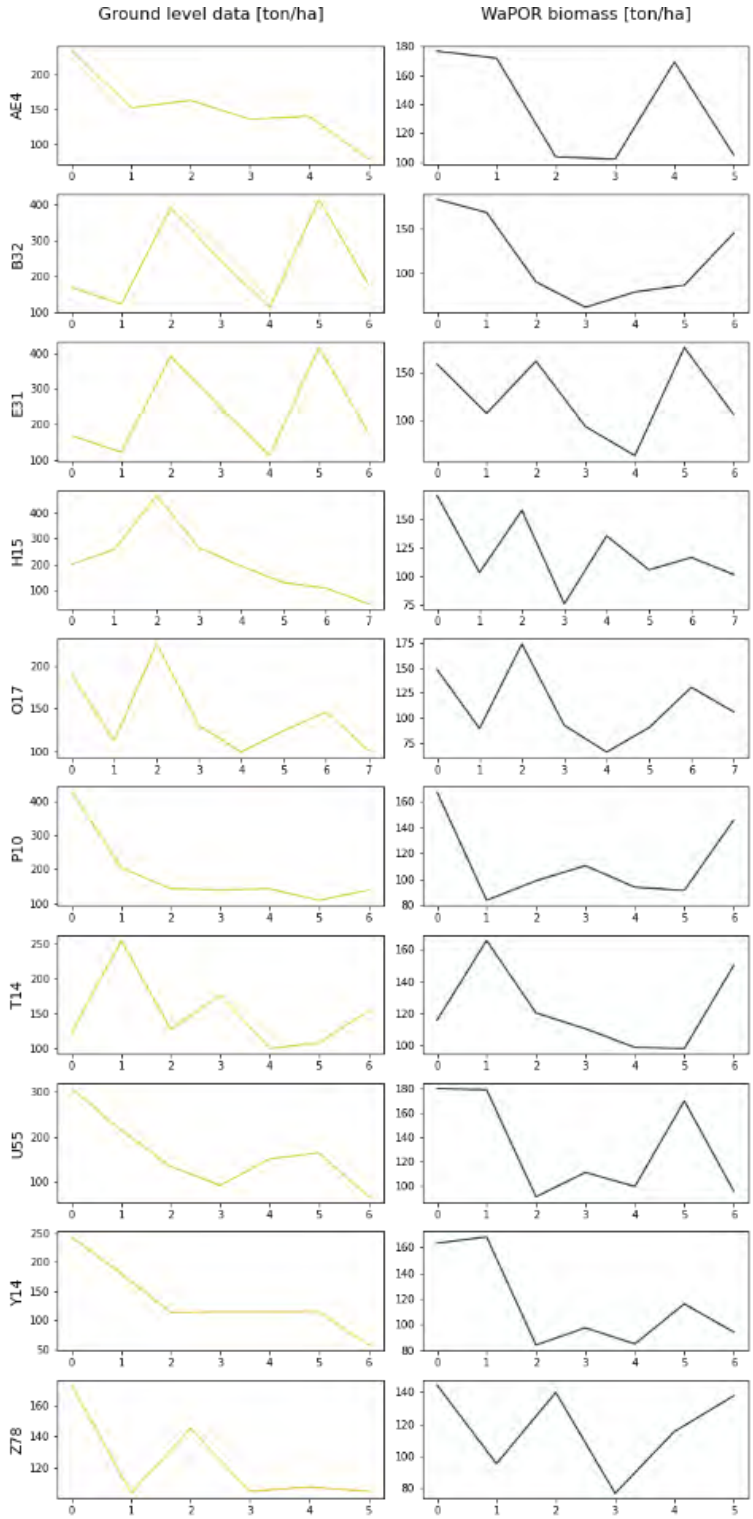


Figure 5. *Trendlines that demonstrate the sugarcane biomass in ton/ha/season on the y-axis and the number of the growing season on the x-axis. Because all growing seasons differ, the x-axis is represented as the number of the growing season instead of the dates of that season. The data from the ground-level data is represented by the gold lines and the WaPOR data is represented by the teal-colored lines.*

2.4 Analysis

2.4.1 Calculation of the performance assessment indicators

The performance of the irrigation schemes is measured by five indicators. How each indicator is calculated is described below.

Water consumption

The total water consumption was estimated as ET_{act} [mm/season]. It included all water depleted from the root zone through transpiration and all water that had not been used by the crop. In addition to ET_{act}, the irrigational water consumption was calculated by subtracting PCP [mm/season] from ET_{act} (Snyder et al., 2012). Because the precipitation season was much shorter than the irrigation season, the inter-seasonal variation in ET_{act} was tested with the decadal data via a Wilcoxon Signed rank test. It was expected that the decadal PCP in the precipitation season was higher than the irrigation season. Because the irrigation season knows higher temperatures and more sunlight which directly influences the ET_{act}, it was expected that the decadal ET_{act} for the irrigation season was much stronger than the precipitation season. A Mann-Kendall trend test determined whether there was a significant trend in ET_{act} over time.

Uniformity

Uniformity [%] is a measure of evenness of water supply in the irrigation scheme and is quantified as the coefficient of variation (CV) of the seasonal ET_{act} (Chakulla et al., 2021; Bastiaanssen et al., 1996), which equals the SD divided by the mean. The uniformity was categorized as good, fair, or poor. When the CV had a value between 0 and 10%, the uniformity was considered good; a CV between 10 and 25% was considered fair uniform; a CV > 25% was defined as poor uniform. Testing for a trend in uniformity over time was done with a Mann-Kendall test.

Adequacy

Adequacy [-] describes the sufficiency of the crop water use compared to the water requirements (Chukalla et al., 2020). It was calculated as the ratio of ET_{act} [mm/season] over the crop water requirement (ET_c) [mm/season] (***Equation 4***).

$$Adequacy = \frac{ET_{act}}{ET_c} \qquad \textbf{\textit{Eq. 4}}$$

The crop water requirement was calculated by multiplying the ET_{ref} [mm/season] with the crop coefficient (K_c) [-] (***Equation 5***).

$$ET_c = ET_{ref} * K_c \qquad \textbf{\textit{Eq. 5}}$$

The K_c represents the crop characteristics over the growing season and incorporates averaged effects of evaporation from the soil (FAO, 1998). Research from Yadeta et al. (2020) revealed that the K_c values of sugarcane in Ethiopia slightly differ from the values initiated by the FAO (***Table 3***). Since the growing and harvesting periods differ per farmer field in Metahara, uniform use of the growing stages and their corresponding K_c over the whole research area would result in incorrect estimations of the ET_c. Therefore, an average K_c value was used in this research. The length of each growing stage was considered in calculating the mean.

Table 3. *Kc values throughout the various stages in a growing season as provided by the FAO and by literature, and the length of the growing stage in days.*

	FAO K_c	Yadeta et al. (2020) K_c	Length of stage [days]
Initial season	0.4	0.42	35
Developing season	0.83	0.93	60
Mid-season	1.25	1.26	190
Late-season	0.75	1.05	120
Mean	**0,966**	**1,076**	

Land and water productivity

Land productivity is the total production per unit area which was described by B. The spatial variation in land productivity was analyzed by plotting the mean B over 2009 – 2021; the temporal variation was analyzed by plotting the seasonal mean B values over time. Because the precipitation season was only two months, the precipitation season was not considered in analyzing land productivity. Mann-Kendall test determined if there were trends over time.

WP_b was calculated with ***Equation 6*** in kg/m^3/season. The ratio $\frac{B}{ET_{act}}$ was multiplied by the factor 10^{-2} to obtain the desired units from B [ton/ha/season] and ET_{act} [mm/season]. Both irrigation and precipitation water were incorporated in ET_{act}.

$$WP_b = \frac{B}{ET_{act}} * 10^{-2} \qquad \textbf{\textit{Eq. 6}}$$

The spatial mean WP_b in the irrigation and precipitation season for the period of 2009 – 2021 were mapped to visualize the spatial differences in WP_b. Again, only the irrigation season was considered. The seasonal mean values were plotted in a line plot over time to reflect the differences in WP_b over time. A Mann-Kendall test showed whether there was a significant trend over time and a Wilcoxon Signed rank test indicated if there were significant differences between the irrigation and precipitation season.

Productivity targets and gaps

The target productivity is the upper productivity of a particular crop that is attainable within a similar agro-climatic zone. Fields that realize the target productivity are classified as strikingly active spots, which is attributable to management or beneficial soil conditions. This research estimated the target productivity by selecting the upper 5% in the spatial distribution of productivity which was determined by the 95th percentile. The 95th percentile has been used in similar studies and was used to exclude outliers that could skew the productivity target (Licker et al., 2010; Zwart & Bastiaanssen, 2004; Filippi et al., 2022). Using observed data was chosen over global averages to determine target productivities because the observed data considered current and local climatic conditions, management techniques, and current technologies. The productivity was projected in a scatterplot with B on the x-axis and WP_b on the y-axis in which the target values were highlighted as dashed lines (***Figure 6***).

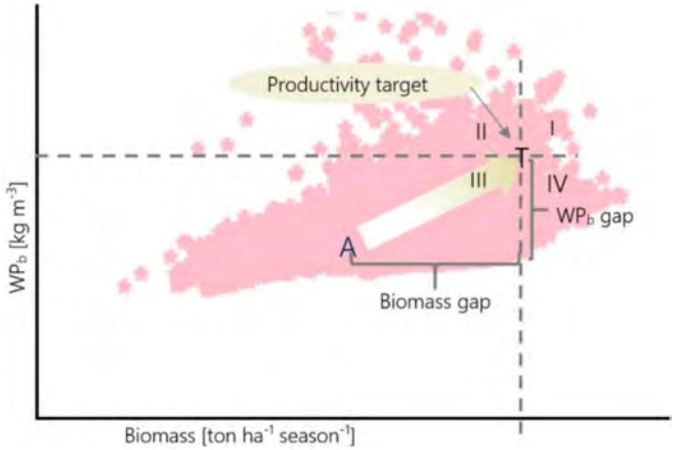


Figure 6. *A schematic overview of a scatterplot that illustrates the biomass against the water productivity. The dashed grey lines are the biomass and water productivity targets (Chukalla et al., 2020).*

The productivity gaps were defined as the difference between the actual and target productivity of a certain field. The gaps were calculated for B and WP_b separately. The productivity was split into four different quadrants (***Figure 6***). Quadrant I covered the pixels that achieved the target B and WP_b; the pixels in quadrant II belonged to the pixels with the desired WP_b, but do have a B gap; quadrant IV demonstrated the pixels that had a gap in WP_b but not in B; quadrant III demonstrated the pixels that had both a B and WP_b gap. The total B and WP_b gaps were calculated with ***Equations 7*** and ***8***, in which i indicated a certain pixel and t indicated the target productivity. Only the values of the pixels with lower productivity than the target were included.

$$total\ AGBM\ gap = \sum(AGBM_i - AGBM_t) \qquad AGBM_i < AGBM_t \qquad \textbf{Eq. 7}$$

$$total\ WP_b\ gap = \sum(WP_{b,i} - WP_t) \qquad WP_{b,i} < WP_t \qquad \textbf{Eq. 8}$$

2.4.2 Explain land and water productivity patterns

An analysis was performed to find an explanation for the spatial differentiation in land and water productivity. First, the stakeholders were consulted to get a better understanding of potential causes for the variation in land and water productivity. Several possible explanations came from the meeting and two factors were chosen to further analyze: soil texture and the location with respect to Lake Basaka, which are described in this section. The other explaining elements are shortly discussed in the results section.

Soil texture analysis

The first variable that could explain the spatial variability in B and WP_b was soil texture. It was expected that soils with a coarser texture have a higher B and WP_b. Since water infiltrates easier in these soils, less effort is needed to water the roots and manage the soils. Additionally, less water remains on the soil, which is favorable for lower evaporation. This would result in a higher WP_b for coarser soil textures. According to Sarimong (2016), sugarcane can grow equally well in all soil textures if there are no other constraints. The soil map of ***Figure 7*** was used to create shapefiles for each soil texture whereafter the WaPOR protocol was run per soil texture. All the mean irrigation scheme performance indicators were calculated per soil texture and were plotted in bar charts to visualize the differences per soil texture. Kruskal-Wallis tests followed by Wilcoxon-Signed rank tests and t-tests were used to define the differences between the soils.

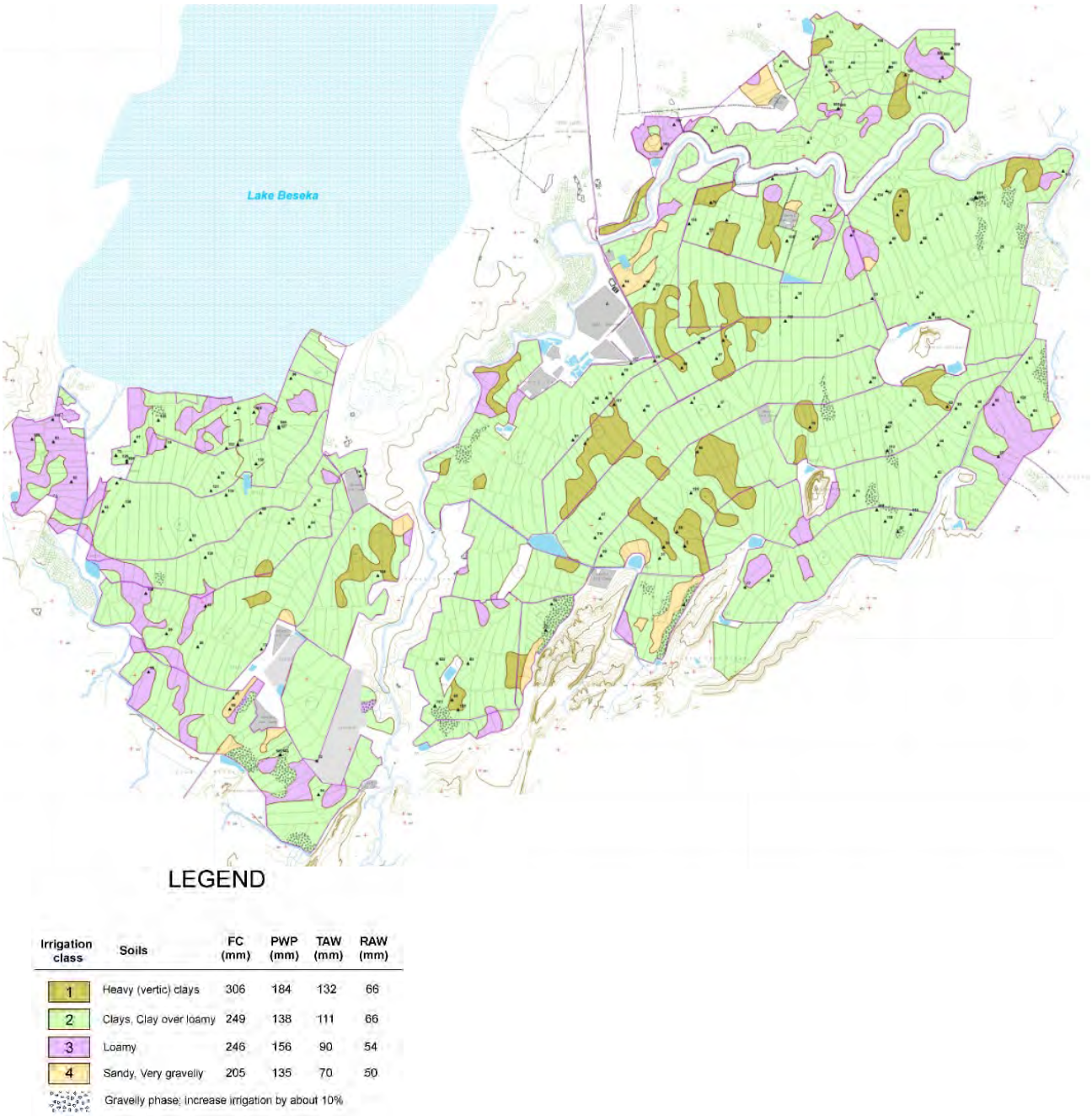


***Figure 7**. Soil texture map of Metahara created by Booker Tate and Generation Integrated Rural Dev't Consultant.*

Lake Basaka

The second influencing factor that was researched was the influence of the salt water of Lake Basaka that threatens the production in the northern parts of Abadir and Merti. Sugarcane cannot grow well under salty conditions; hence, salinization can strongly decrease its production. Research has revealed that Lake Basaka is expanding towards the northeast, thus the northern section of Merti which is found north of the Awash River was compared with the rest of Merti. In both the northern section as well as in the rest of Merti 30 random fields were selected (Appendix C). Only clay fields were selected to exclude the influence of soil texture. All mean productivity values of each field for the irrigation season were selected and Mann-Whitney U tests were run to define if there was a difference in productivity between the northern fields and the rest of Merti.

Over the years Lake Basaka slowly increased in size and it has already taken up several fields (Dinka, 2012). To analyze the influence of the expansion of Lake Basaka on sugarcane production in 2009 – 2021, the normalized productivity for each irrigation season was calculated. This is described as B over the mean seasonal B. Again, only the irrigation season was used because the precipitation season was relatively short. By using the normalized productivity all different seasons could be compared because all values were positive and roughly 1. The percentage of the total area that was below 1 was calculated for each year to see if there was a decreasing trend in B in the north of Merti.

3.0 Results

This section describes the results of the spatiotemporal variability in productivity and the other irrigation scheme performance indicators. The spatial and temporal results from the WaPOR protocol are described per indicator for both Merti and Abadir. The maps exhibit the mean values between 2009 and 2021, and the temporal variation is presented by the mean seasonal data.

3.1 Performance assessment indicators

Land productivity

Land productivity has been defined as the total B and is exhibited in ***Figure 8***. The B in Abadir and Merti were comparable and did not differ significantly from each other with mean values of 74.67±10 and 65.36±9 ton/ha/season. Although B was quite evenly distributed over the research area, there were some locations with a lower mean B (***Figure 8***): the northern section in Abadir (A), the southern section of Abadir (B), the northern section in Merti close to the Awash River (C), the southeast section in Merti (D), the most southwestern fields in Merti (E) and the southern part of Merti (F). The areas with the highest land productivity were in the center of Abadir and Merti.

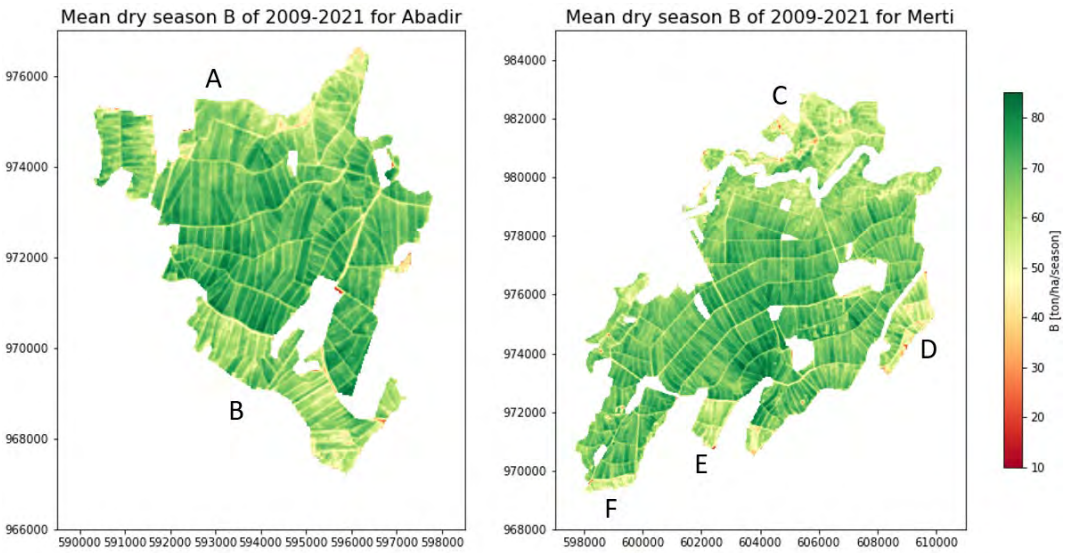


Figure 8. *Spatial variation in irrigation seasonal biomass production in Abadir and Merti. The lower producing fields are lettered.*

Figure 9 illustrates the temporal variation in the mean irrigation season B over the period of 2009 – 2021. For Merti and Abadir the trends and range in B were similar, so no significant differences between the two schemes were detected. Additionally, no significant trends over time were identified with a Mann-Kendall test. The lowest mean B was observed in the irrigation season of 2015-2016 with values of 52 and 51 ton/ha/season for Abadir and Merti.

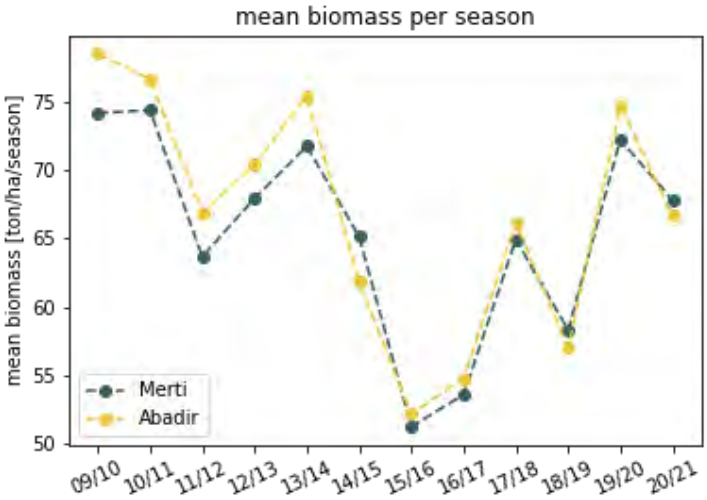


Figure 9. *Line plot of the average seasonal above-ground biomass over time for Abadir and Merti. The average is based on the irrigation seasonal values for the period of 2009 – 2021.*

Water productivity

Figure 10 demonstrates the mean irrigation seasonal spatial variation in WP_b in Merti (4.1±0.2) and Abadir (4.3±0.2) in kg/m^3. Equivalent to B the sections A, C, and D were lower in WP_b and the center of Abadir and Merti were higher in WP_b. This exhibits that not only B was lower in these areas but also that ET_{act} was relatively high, so increased water use was needed to produce the same amount of biomass. In contrast to B, WP_b was not much lower in sections B and F.

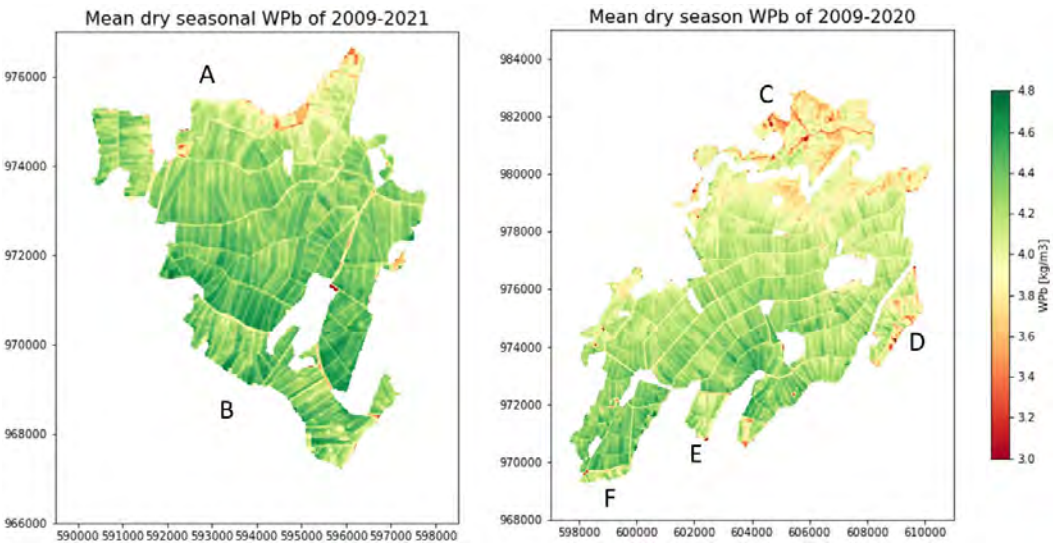


Figure 10. *Spatial variation in irrigation seasonal biomass water productivity in Abadir and Merti.*

The temporal variation in seasonal mean WP_b over 2009 – 2021 is exhibited in ***Figure 11***. Abadir and Merti were not significantly different in WP_b, nor was there a trend visible over time in the mean seasonal data of ***Figure 11***. However, when considering the decadal $WP_{b,}$ a Mann-Kendall test revealed that there was a significant decreasing trend of -0.002 kg/ m^3/decade for Abadir (p=0.001). The temporal decrease was only significant in Abadir and was equally distributed over the area. The lowest WP_b values were observed in 2016-2017 with a value of 3.3±0.3 kg/m^3 for both irrigation schemes. In both the highest and the lowest years, the spatial variation in WP_b was similar and was quite equal over the whole research area with few outliers. Remarkable dips were present in the mean

WP_b of both schemes in 2011, and from 2015-2019. After 2018-2019 WP_b started to rise again, but it has not yet reached similar levels as before 2014-2015.

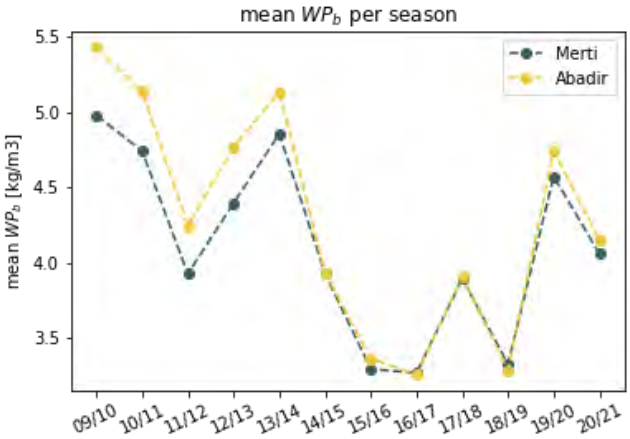


Figure 11. *Line plot of the average seasonal above-ground biomass water productivity over time for Abadir and Merti. The average is based on the irrigation seasonal values for the period of 2009 – 2021.*

Productivity targets and gaps

Figure 12a illustrates a scatterplot of the land and water productivity in which each grid cell is plotted together with the target productivities and ***Figure 12b*** exhibits the normal distribution of the WP_b. ***Figure 12*** is based on the mean irrigation season values of 2009 – 2021. The green highlighted cells were the locations that meet or exceed the target WP_b and B, which were perceived as the bright spots. ***Figure 12a*** displayed that most cells in the research area should eighter increase B or increase both B and WP_b to reach target levels. For both irrigation schemes, the target WP_b was 4.4 kg/m^3. The target B was 77.0 ton/ha/season for Merti and 78.0 ton/ha/season for Abadir. As can be seen in ***Figure 12b,*** the WP_b was normally distributed and most pixels were close to the mean, which makes the SD small.

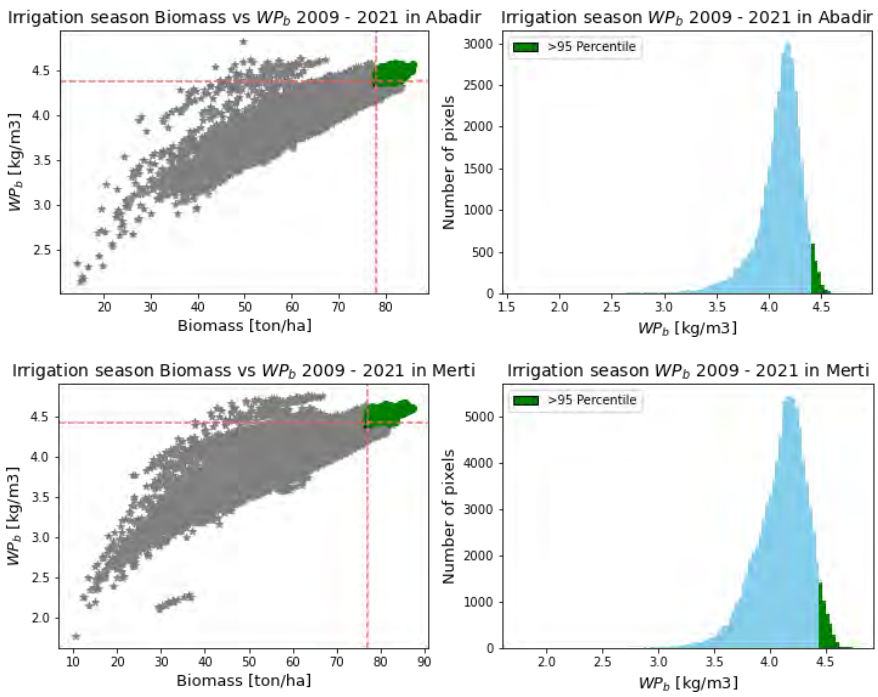


Figure 12*. Scatterplot of the annual biomass against the annual biomass water productivity (a). The dashed lines present the land and water productivity targets. The right figure presents the annual biomass water productivity (b), the top 5%, and the bottom 5% in a normally distributed histogram.*

Figure 13 demonstrates the locations that reach the target levels in B (green), WP_b (red), and the bright spots (blue). The fields that reached the target B in Merti were mainly located in the center while the fields that meet or exceeded the target WP_b were also in the south. In Abadir, most of the fields that reached the target levels were located just below the center. The fields that meet the B target, but fail to meet the WP_b target, used a lot of water to reach B. Reversely, the fields that did not meet the target B but did meet the target WP_b, did not produce enough biomass and use little water. These fields could increase their water use if it increases coextensively with B.

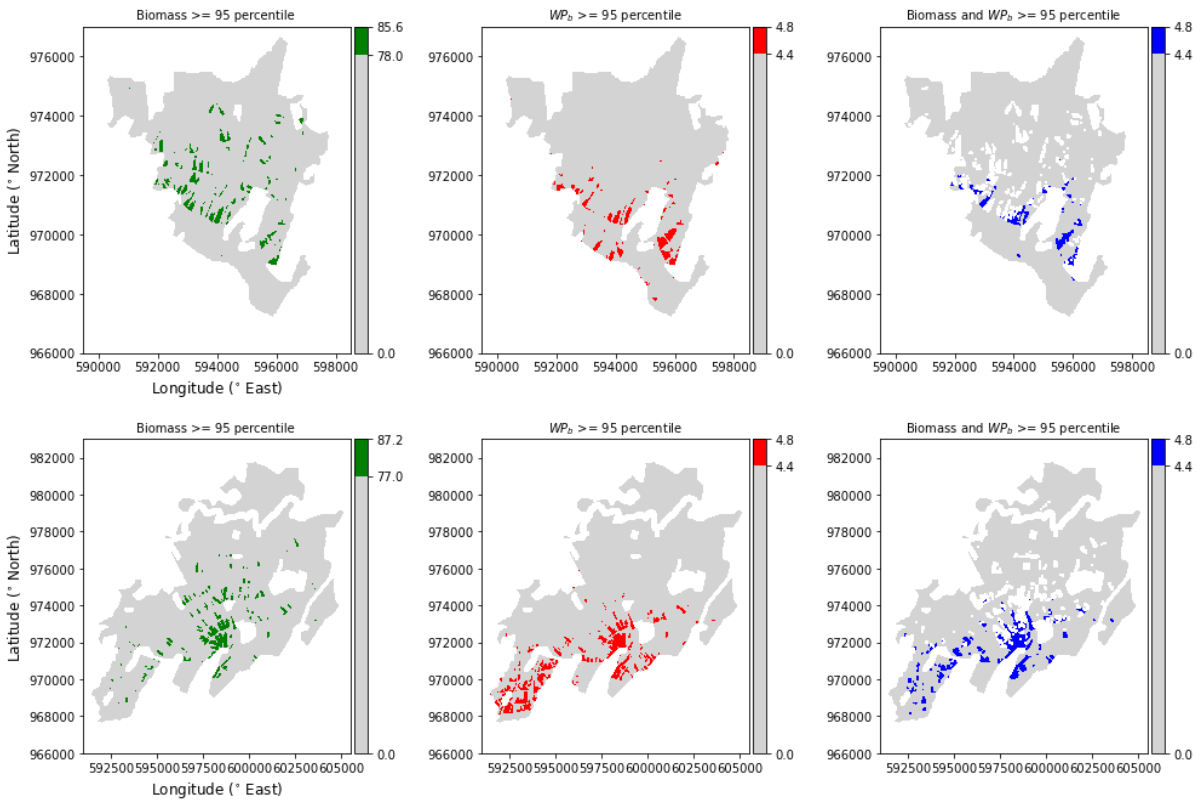


Figure 13*. Spatial distribution of the bright spots, which are the cells that meet or exceed the top 5% in land productivity (left), water productivity (center), or both (right).*

For each grid cell, the gap between the actual value and the target value in B and WP_b was calculated and plotted (***Figure 14***). The spatial variation was similar to that of B and WP_b. The mean production gaps of the average B were 12.3±8.7 ton/ha/season for Merti and 12.0±8.4 ton/ha/season for Abadir. This corresponded to a gap in WP_b of 0.3±0.2 kg/m^3 for both Merti and Abadir. In calculating the productivity gaps, the grid cells that already meet or exceeded the productivity targets were excluded. In the hypothetical situation where all the gaps are closed and all pixels produce target productivity values, 34.1 Mm^3 extra water should be applied per year.

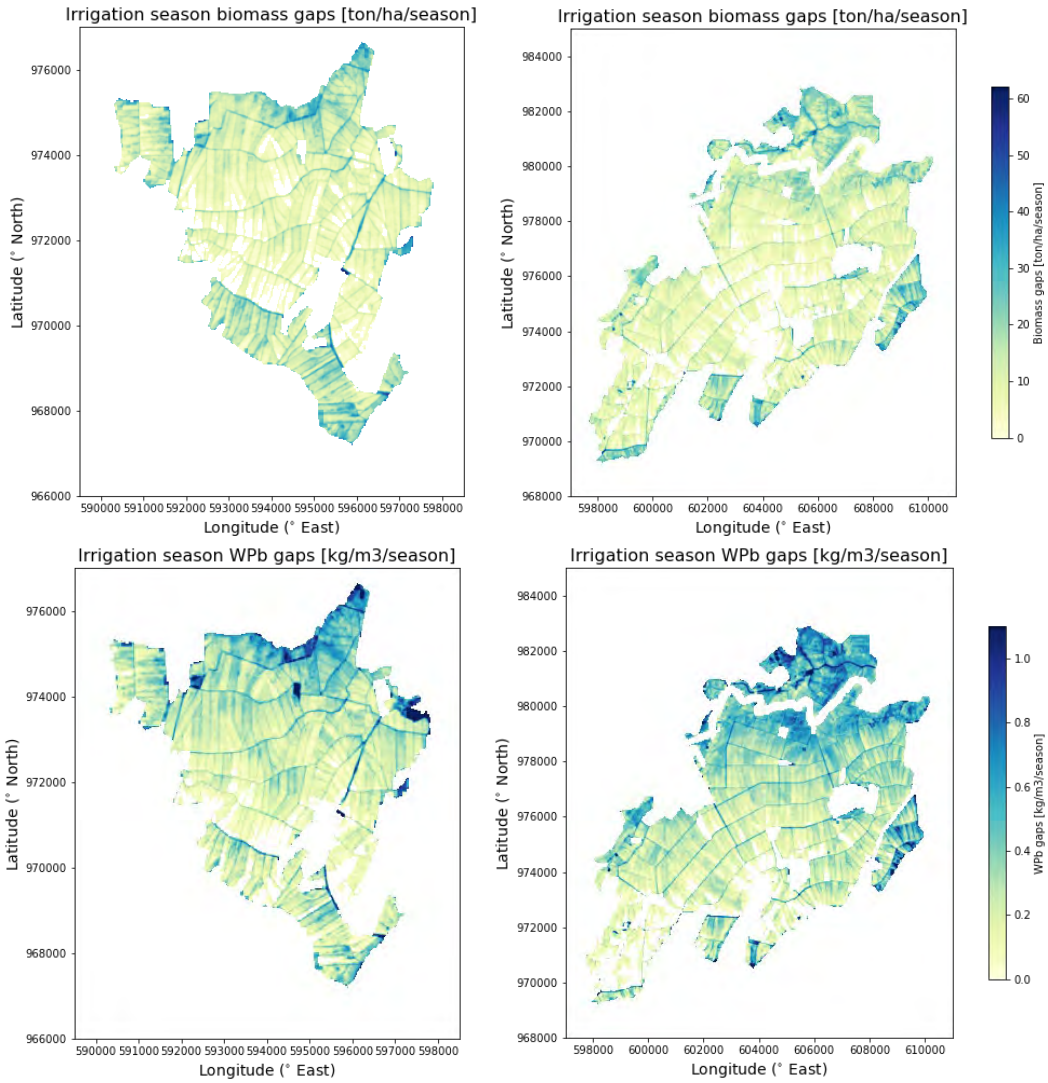


Figure 14. *Difference between each plot with the target biomass production (upper figures) and target biomass water productivity (lower figures).*

Water consumption

The mean decadal ET_{act}, T, and PCP revealed that the 11-year average irrigation and precipitation seasonal values for Merti and Abadir were comparable (***Figure 15***). Apart from the significant increasing trend in decadal ET_{act} for both Merti (slope=0.014 and p=6.2e-6) and Abadir (s=0.021 and p=2.6e-11), there were no significant changes over time.

When analyzing ET_{act}, a differentiation between the precipitation and irrigation season was incorporated. As expected, decadal PCP was higher in the precipitation season than in the irrigation season. It was expected that the decadal ET_{act} for the irrigation season was higher than the precipitation season. Contrastingly, ***Figure 15*** demonstrates that this assumption was rejected since ET_{act} in the irrigation season was overall lower than in the precipitation season. Hence, more water was used in the precipitation season which could partly be explained by higher PCP values. In the precipitation season (July – August) all fields rely on PCP only, ergo no water from the Awash River was abstracted for irrigation as was stated by the stakeholders. However, between 2014-2016 the precipitation seasonal PCP decreased enormously, while simultaneously ET_{act} increased, indicating that other sources of water were used apart from PCP. The last remarkable detail was the wider fluctuation of the

precipitation season ET_{act} compared to the irrigation season, which could be explained by the fact that the precipitation season relied much more on PCP as a source of water.

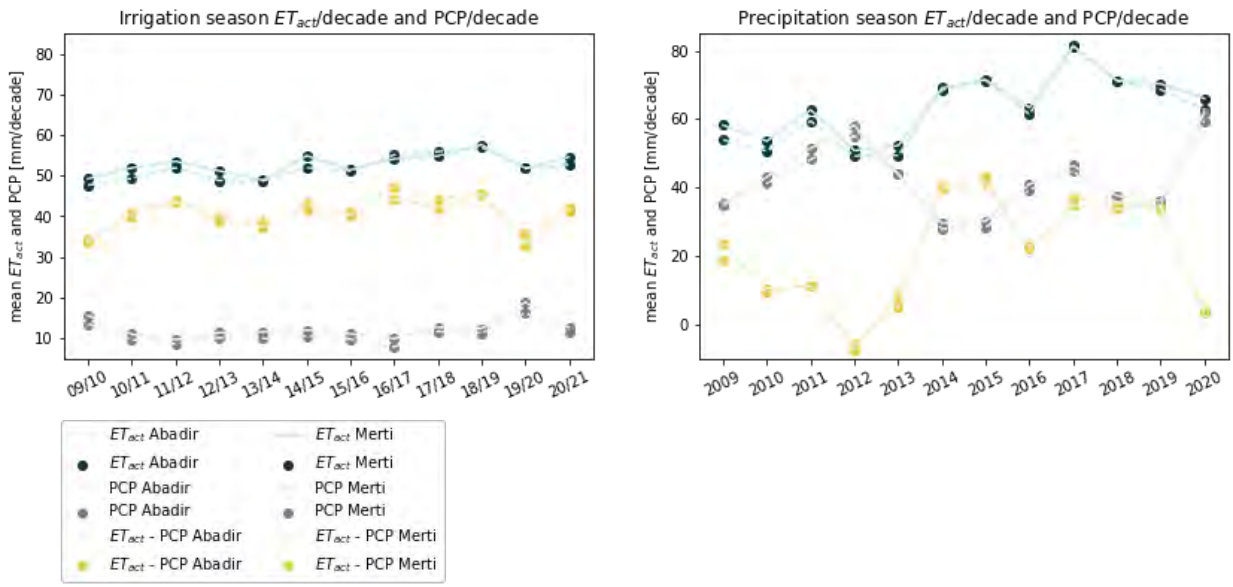


Figure 15. *Line plot of the average decadal actual evapotranspiration, and precipitation over time for the irrigation schemes Abadir and Merti. The average is based on the spatial average seasonal values for the period of 2009 – 2021. The precipitation season is from July to August and the irrigation season runs from September to June.*

Uniformity

The uniformity for Merti and Abadir lay within the same range and knew a fair uniformity in all individual years. In 2020 – 2021 the uniformity was highest for both Merti and Abadir. The CV of the ET_{act} in Merti increased over time with a slope of 0.43 (p=0.01), which exhibits that the fair distribution of water worsened over time. Especially the fields that also had a lower B received less water compared to the other fields, these included all sections A-F.

Table 4. *Coefficient of variation of the ETact for each irrigation season from 2009 – 2021 in Abadir and Merti.*

Season	Abadir	Merti
2009 – 2010	16.9	15.1
2010 – 2011	18.0	15.7
2011 – 2012	18.0	15.7
2012 – 2013	15.2	13.3
2013 – 2014	19.0	16.1
2014 – 2015	16.1	14.3
2015 – 2016	14.2	13.2
2016 – 2017	19.1	15.7
2017 – 2018	13.7	16.1
2018 – 2019	18.7	18.2
2019 – 2020	18.4	19.2
2020 – 2021	19.4	21.2

Adequacy

An overview of the calculated adequacy for Merti and Abadir in the irrigation and precipitation season is given in ***Table 5***. The mean, irrigation season adequacy over a period of 2009 – 2021 was 0.57±0.06 for Merti and 0.56±0.05 for Abadir. In the precipitation season, these values were 0.71±0.05 and

0.69±0.05. It was noticeable that the adequacy exceeded 1 once in 2017 with a value of 1.06 in the most southern fields of Abadir, which indicated that ET_{act} was larger than ET_c. This could be explained by ET_c in this area which was calculated with a different ET_{ref} value than the rest of Abadir. Consequently, ET_{ref} and thus ET_c was lower in this part.

Table 5. *Mean seasonal adequacy values and the standard deviation per season for Merti and Abadir.*

	Merti		Abadir	
Season	***Precipitation***	***Irrigation***	***Precipitation***	***Irrigation***
2009 (/2010)	0.68 ± 0.10	0.61 ± 0.09	0.63 ± 0.11	0.59 ± 0.10
2010 (/2011)	0.72 ± 0.11	0.59 ± 0.09	0.68 ± 0.11	0.56 ± 0.10
2011 (/2012)	0.72 ± 0.09	0.56 ± 0.09	0.68 ± 0.09	0.54 ± 0.10
2012 (/2013)	0.69 ± 0.08	0.58 ± 0.08	0.67 ± 0.08	0.55 ± 0.08
2013 (/2014)	0.70 ± 0.12	0.56 ± 0.09	0.67 ± 0.11	0.55 ± 0.11
2014 (/2015)	0.69 ± 0.12	0.57 ± 0.08	0.69 ± 0.14	0.54 ± 0.09
2015 (/2016)	0.68 ± 0.10	0.57 ± 0.07	0.68 ± 0.09	0.56 ± 0.08
2016 (/2017)	0.69 ± 0.13	0.55 ± 0.08	0.67 ± 0.15	0.56 ± 0.11
2017 (/2018)	0.75 ± 0.11	0.59 ± 0.10	0.75 ± 0.10	0.60 ± 0.08
2018 (/2019)	0.72 ± 0.09	0.59 ± 0.11	0.82 ± 0.10	0.59 ± 0.11
2019 (/2020)	0.74 ± 0.12	0.59 ± 0.11	0.73 ± 0.11	0.59 ± 0.11
2020 (/2021)	0.74 ± 0.11	0.55 ± 0.12	0.71 ± 0.12	0.53 ± 0.10
Mean	**0.71 ± 0.05**	**0.57 ± 0.06**	**0.69 ± 0.05**	**0.56 ± 0.05**

3.2 Explaining factors for the spatial distribution of productivity

The stakeholders were consulted to find a better explanation for the spatial and temporal variation in productivity. Several findings came from this meeting. The temporal variation could mainly be explained by weather conditions according to the irrigation manager. He also stated that in the past some fields received a different fertilizer, but currently all fields retrieve the nitrogen fertilizer UREA. However, it was not known when the fields shifted from fertilizer. When looking at the data it could have been that this happened since 2012, explaining the variance in ET_{act} after 2012.

Spatial variation was also discussed in the meetings. First, sections B and F, which both had a lower B, received less water because the main channel that provides water for irrigation lies north of these areas. The southern parts have a higher elevation, so the water needs to be pumped upwards to water the crops in sections B and F. Since it was difficult to always provide the pumps with fuel, it was harder to water these areas and resultingly these areas had a lower B. Secondly, sections D and E have been prone to social conflicts with local people who claim these lands and let their cattle graze in these areas, making it harder to grow sugarcane in these fields. Resultingly, the B was lower in these areas. Thirdly, sections A and C were low in production because they were heavily under influence of Lake Basaka. Lastly, the more productive fields had better production due to different soil textures. These last two factors are further discussed in sections 3.2.1 and 3.2.2.

3.2.1 Soil texture comparison

This section analyzed the relation between the performance indicators of the Metahara study area and soil texture. The graph for each indicator is presented in ***Figure 16***.

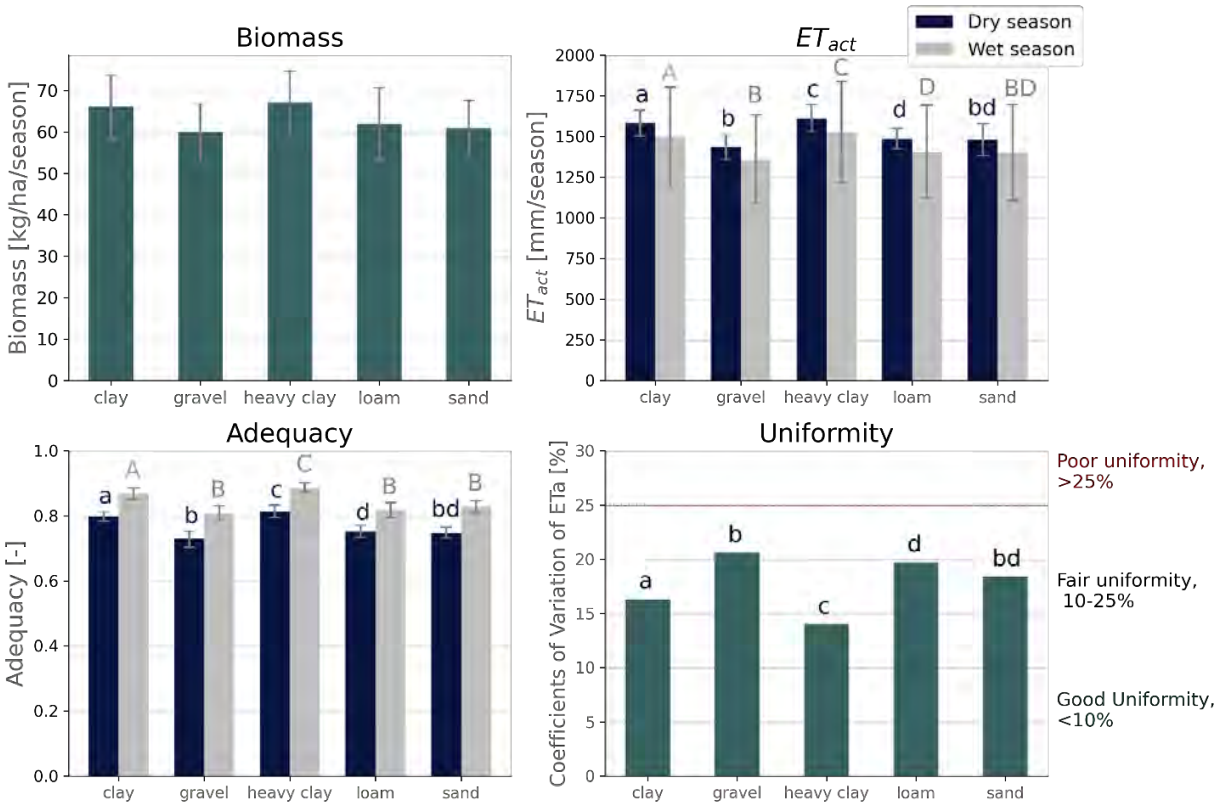


Figure 16. *Performance assessment indicators per soil texture. 16a: B per soil texture in the irrigation season in ton/ha; 16b: water consumption per soil texture in the irrigation and precipitation season as ETact in mm/season; 16c: adequacy for the irrigation and precipitation season per soil texture; 16d: uniformity per soil texture.*

Land and water productivity

B is plotted in ***Figure 16a*** and was highest for heavy clay with a mean value of 67.1±7.6 ton/ha/season. The mean B for clay and heavy clay was higher compared to the other three soil textures. The mean B for gravel was lowest with a value of 60.0±6.9 ton/ha/season. Although it seemed like there was a trend present in which the finest soil texture produced the highest B, a Kruskal-Wallis test demonstrated that there was no significant difference between the soil textures in B. Neither for WP_b a significant difference was detectable. Rather, the mean WP_b differences were exceedingly small and ranged between 4.088 kg/m^3 for sand and 4.153 for clay kg/m^3.

Water consumption

Figure 16b illustrates the mean ET_{act} for the different soil textures in the irrigation and precipitation season. ET_{act} between the different soil textures was statistically different (p=9e-05) following the results of the Kruskal Wallis test. Apart from the comparison between loamy and sandy soils, all tests on revealed that finer soils have a higher ET_{act}. Thus, heavy clay soils consumed most water, followed by clayey soils. Sandy soils were in third place among water consumers, although expected that loamy soils would consume more. Fourth, loamy soils consumed most water, and lastly gravel soils.

As expected, ET_{act} in the irrigation season was larger than in the precipitation season, because the irrigation season was longer. Furthermore, the precipitation season had an overall larger SD, which could be declared by the fact that the distribution of water in the precipitation season variated more than in the irrigation season since there was less irrigation taking place. However, like the results from the previous section, the decadal ET_{act} in the precipitation season was higher than in the irrigation season.

Uniformity

Heavy clay soils were the most uniform and gravel soils were the least uniform which was in line with the expectations. All performed tests were significant, except for the comparison between sandy and loamy soils. In all individual irrigation seasons, the soils were fair uniform with three exceptions: In the season of 2019-2020 both loam and gravel soils were poorly uniform with a CV value of 25.3% for both soils; in 2020-2021 only gravel soils performed poorly with a CV of 28.6%. In 2019-2020 the gravel soils in sections B and E experienced a lower ET_{act} than the other gravel soils. The loamy soils in the northwest of Abadir and section C also had a lower ET_{act} than the other loamy soils, with some extremely low values ranging between 500 – 1000 mm/season.

Adequacy

As follows from ***Figure 16c*** the adequacy statistically differed slightly per season and soil texture. The precipitation season had overall a higher adequacy than the irrigation season but the variation between soil textures per season was similar. In both seasons firstly heavy clay had the largest adequacy, followed by clay. Furthermore, the adequacy of loam did not differ significantly from sand, but the adequacy for gravel was significantly lower than for sand. In the precipitation season, the adequacy of loam also did not significantly differ from gravel.

3.2.2 Influence of Lake Basaka

It was expected that ET_{act} and B in Metahara were influenced by the saltwater from Lake Basaka. Some fields in the northern fields of Merti and Abadir are already abandoned because sugarcane crops cannot grow under strong saline conditions (***Figure 17***). Although previous research exhibited that Lake Basaka grew in the past, there was no trend visible in the data over time (Appendix D). The percentage of the normalized productivity that was below 1 fluctuated throughout the years. Where Lake Basaka has been expanding over the years according to e.g. research by Dinka (2012), satellite images of Google Earth Timelapse showed that the boundaries of the lake are quite stable over the 2009 – 2021 period.

Figure 17*. A) Salt on the soil from salinization in the northern part of Abadir. B) Abandoned fields where sugarcane cannot grow due to salinization in the north area of Abadir. In the back, at the end of the field, Lake Basaka starts.*

An analysis was performed to distinguish differences between the northern section, that is to a great extent under influence of Lake Basaka, and the rest of the study area. The comparison between the field plots reveals that the fields in the northern section had significantly lower B values in all individual years. Only during the irrigation season of 2015-2016, the northern section did not have a statistically significant different B value.

4.0 Discussion

This chapter first discusses the potential and limitations of remote sensing-based research in general, followed by a critical review of the methodology and results of this research. This includes a review of the WaPOR data and methodology, the main findings from this research, how these findings relate to the GTP and ABWAP, and some exceptional results. Finally, this section expands on the research limitations and indicates directions for future research.

4.1 Potential of remote sensing-based research

Since 2000, remote sensing-based research expanded and has proven to be applicable on small-scale levels where it can be used for decision-making support (Khanal et al., 2020). For example, in precision agriculture where grid levels are <5m, the use of remote sensing in decision-making has increased over the years because the influence of management practices such as fertilizers application or water use can be easily analyzed (Sishodia et al., 2020). The WaPOR data can be used for thorough as well as detailed, small-level comparisons due to the availability of different grid sizes. Despite this potential, large differences between the two schemes Abadir and Merti were not found within this research, because of homogeneity in management between both schemes. Besides the ability to analyze management implications in very fine grids, remote sensing can be used as a simple method to variate over time and space, making it easy to detect trends that are of potential use for decision-making support (Sishodia et al., 2020). The remote sensing-based analysis in this research was performed quickly for a large area and over a broad timespan compared to traditional measuring methods. This benefit of remote sensing research has also been stressed in another research by Bastiaanssen et al. (1996). Moreover, the WaPOR data was easily gathered compared to traditional biomass weight measurements executed by farmers. Furthermore, it could simply be compared and related to various elements like soil texture, and saltwater intrusion of Lake Basaka. Hence, it can be said that remote sensing-based research is valuable and has a high potential in scientific research.

Remote sensing and ground-level data

Although remote sensing has great scientific potential, a complete understanding of the results of good quality is difficult without ground-level data. The lower performing sections E and D in this research are a perfect example of this since these areas cope with social complications that could not have been detected with remote sensing only. Also, when the protocol was run for the first time, it seemed like the land and water productivity had a relation to the distance to the main water inlet. This assumption turned out to be false when the stakeholders said that there are usually no water shortages. Findings of other research as Conrad et al. (2020) align with the statement that ground-level data is crucial in remote sensing-based research because using remote sensing data as the only source leads to misinterpretations of the results. Not only is ground-level data needed for understanding the results, but it is also key to verifying trends and absolute values in remote sensing data. According to Blatchford et al. (2019) trends are often visible to a trustworthy degree, whereas absolute data can variate strongly. Therefore, real-time data must be compared to remote sensing data to draw the right conclusions.

The comparison of the WaPOR data to ground-level data in this research revealed that the WaPOR data can be off. Consequently, it is questionable how reliable the outcomes of research with WaPOR data are. According to the WaPOR quality assessment report, the WaPOR calculated *B* is continuously underestimated by 58% (FAO, 2020b). Still, the report of the FAO found a much better correlation between ground-level and WaPOR *B* of 0.71 (R^2=0.5). The low correlation found in this research is attributable to several factors. First, the reliability of the retrieved ground-level dataset is

questionable since some uncertainties or errors were found (e.g. double measurements). Moreover, the fact that a minor selection of the research area was used due to lack of time makes that out of more than 10,000 available data points only 70 were used. According to the method of Israel (1992), the sample size should be at least 385 when considering a confidence interval of 95% and a margin of error of 5%. The minor selection in this research does not represent the area well enough so more data points should be used to get a more reliable correlation between WaPOR and ground-level data. However, due to lack of time, it was not possible to include more data points. It was time-consuming to compare both datasets because the ground-level data was inconsistent in growing seasons over time and per field. Blatchford et al. (2019) also state that the comparison of remote sensing data to ground-level data has been proven to be difficult due to several circumstances: The ground-level data is often measured on local and point scales, while remote sensing data is spatially and temporally continuous (Blatchford et al., 2019); systematic errors are often found in remote sensing data, due to spatial and temporal differences in energy balance components (Foken, 2008); lastly, remote sensing assumes vegetation heterogeneity in a pixel which is not always the case and can lead to wrong conclusions as a result (Blatchford et al., 2019; Conrad et al., 2020). Concluding, even though it remains crucial to verify the remote sensing data with ground-level data, this cannot always be done properly in research.

4.2 Review of the method and findings

This section discusses the main findings followed by a critical review of the WaPOR data and method used. Finally, some remarkable results will be discussed.

4.2.1 Main findings

The main aim of this research was to understand the spatial and temporal differences in land and water productivity in Metahara. The first four sub-questions focused on describing the spatial and temporal differences in land productivity (B) and water productivity (WP_b), productivity gaps, water consumption (ET_{act}), uniformity, and adequacy.

The temporal findings of sub-questions 1 & 2 revealed that the average WP_b decreased over time, meaning that over time more water was needed to produce the same amount of biomass. The Ethiopian government aimed at the opposite. They aimed for increasing production according to the GTP, while decreasing water use according to the ABWAP. Hence, the goals of the GTP are not met yet, since no significant trend was observed in B.

From sub-question 3 followed that the goals of the ABWAP are neither met because ET_{act} increased, and the uniformity worsened over time. Thus, contradictory to the goals of the ABWAP more instead of less water was used. To obtain optimal crop growth, even more water is required as followed from the adequacy. The adequacy was mainly above 0.7, so the crops received much but not all the water they require for optimal growth.

The spatial variation analysis exhibited that the fields in the center of the irrigation schemes had the highest ET_{act} and the highest B. Soil texture did not explain for the spatial variability in WP_b and B. However, a clear relation between soil texture and ET_{act} was revealed, being that finer soil textures had a higher ET_{act}. Compacted soils with finer soil textures have a lower infiltration capacity, and thus more water is used to water the roots. However, B does not increase with the extra water applied because lots of this extra water evaporates instead of infiltrates, so it is not used by the crops. Research by Wakgari (2021) also found that long term cultivation of sugarcane and use of tractors in the fields causes soil compaction. Consequently Wakgari (2021) found higher water consumptions over

time, but no higher biomass productions. This explains for the decreasing water productivity over time. Hence, it can be said that temporal trends in land and water productivity are influenced by soil compaction and thus relate to soil texture, whereas spatial trends in land and water productivity are not related to soil texture.

It was found that there was a strong relation between B and the location of the fields with respect to Lake Basaka. A closer location to Lake Basaka correlated to a lower B. This is in line with the research by Zhao et al. (2020) that stated that high salinity levels are devastating for sugarcane growth because salinity disturbs stomatal conductance and causes lower leaf photosynthetic rates. Salinization also reduces leaf area or the number of leaves, depending on the type of sugarcane (Plaut et al., 2000). It is challenging to detect salinity influences with remote sensing, because *i)* salinization is hugely dynamic in the soil, *ii)* it occurs below the soil surface, and *iii)* crop cover blurs the accuracy of soil salinity flux analysis (Conrad et al., 2020). Nevertheless, from the results followed that B in the northern areas was significantly lower in all individual seasons. Hence it can be said that the saltwater infiltration of Lake Basaka is among others one of the factors influencing the spatial variability in land and water productivity.

From the results of sub-questions 1-4 follows that the goals of the GTP and ABWAP are far from achieved. It is debatable whether the Ethiopian government should implement other management strategies, and whether they should implement a new GTP with other attainable goals. When making these decisions it is of utter importance that not only this research is being considered, but that other research that specifically reviews the GTP and ABWAP should be included as well. Especially since this research is only partly validated by ground-level data.

4.2.2 WaPOR data and protocol

The WaPOR data and protocol that were used in this research have been broadly used in agricultural research (Chukalla et al., 2020; Alemayehu et al., 2020; Blatchford et al., 2020). Yet the data and protocol should be handled with care since numerous limitations and assumptions made could have manipulated the results. First, in this research, ET_{ref}, NPP, and ET_{act} all relied on solar radiation and weather data that originated from the same satellite images. Ergo, the variables were not completely independent of each other, and it was therefore not surprising that the spatial trends in NPP and ET_{act} overlapped. In addition, ET_{ref}, E and T were all calculated with a variation of the Penman-Monteith equation (FAO, 2020a). Contemplating this remark is critical because it cannot be assumed that there is a direct relation between variables when the data originates from the same source or when the variables are based on similar calculations.

A second limiting factor in the WaPOR data concerned the quality of the data which was limited from time to time due to low-quality measurements. Low-quality or missing remote sensing images emerge due to e.g. cloud cover. This resulted in data gaps that were corrected with interpolated data that consequently brought noise to the data (Chukalla et al., 2020). Although the WaPOR variables were validated by Blatchford et al. (2020) and by the WaPOR quality assessment report (FAO, 2020b), Blatchford et al. (2020) reported that ET_{act} was often overestimated in eastern Africa when dry, hot conditions occurred due to a low-quality soil moisture content or a high vapor pressure deficit. Although the error was only a few mm/day, this could add up when accounting for the seasonal values. Low-quality data in ET_{act} could occur because remote sensing images were taken at varying times of the day and different angles. Considering ET_{act} varied over the day due to differences in water stress over time, correction factors were needed to account for these varieties (Chukalla et al., 2020). However, small errors could result from these correction factors that influence ET_{act}.

Thirdly, assumptions were made within the protocol to convert raw data to the requested variables. For example, within the protocol, it was assumed that all fields had the same SOS and EOS, while in reality crop cycle duration and crop growth stage differed per field. Because sugarcane is ratooned up to seven times and growing seasons go up to 18 months, inaccuracies emanated from these simplified assumptions in SOS and EOS (Sugar Corporation Research and Development Center, 2016). Important as well were the correction factors K_c, AOT, f_c, and MC used to convert ET_{ref} to ET_c and NPP in B. Such factors are regularly used in research, but these are often retrieved from other research, which is not in line with the specific situation. Moreover, the calculation for B was simplified which caused a reoccurring error, and the K_c in this research was considered constant which resulted in miscalculations of the ET_c (Alemayehu et al., 2020; Blatchford et al., 2019).

Fourth, some of the WaPOR data variables were based on data that needed to be downscaled in grid size (e.g. E or T) or that was downscaled to the required grid size within the protocol (L1 data of PCP and ET_{ref}). Because the original data did not account for differences on a small level as 30 m, the data might be varied from reality for a certain pixel. This was for example highlighted in section 3.1-Adequacy, where the very southern area of Abadir had a different ET_c because it was calculated with a different ET_{ref} (***Figure 18***). As proposed by Huang et al. (2018), small grid size remote sensing calculation should not only rely on large-scale data but should be combined with local data (e.g. weather information) as well to decline uncertainties. Blatchford et al. (2020) complement this argument since their research stated that changes in decadal data for L3 are not always captured as well as for L1 or L2 data.

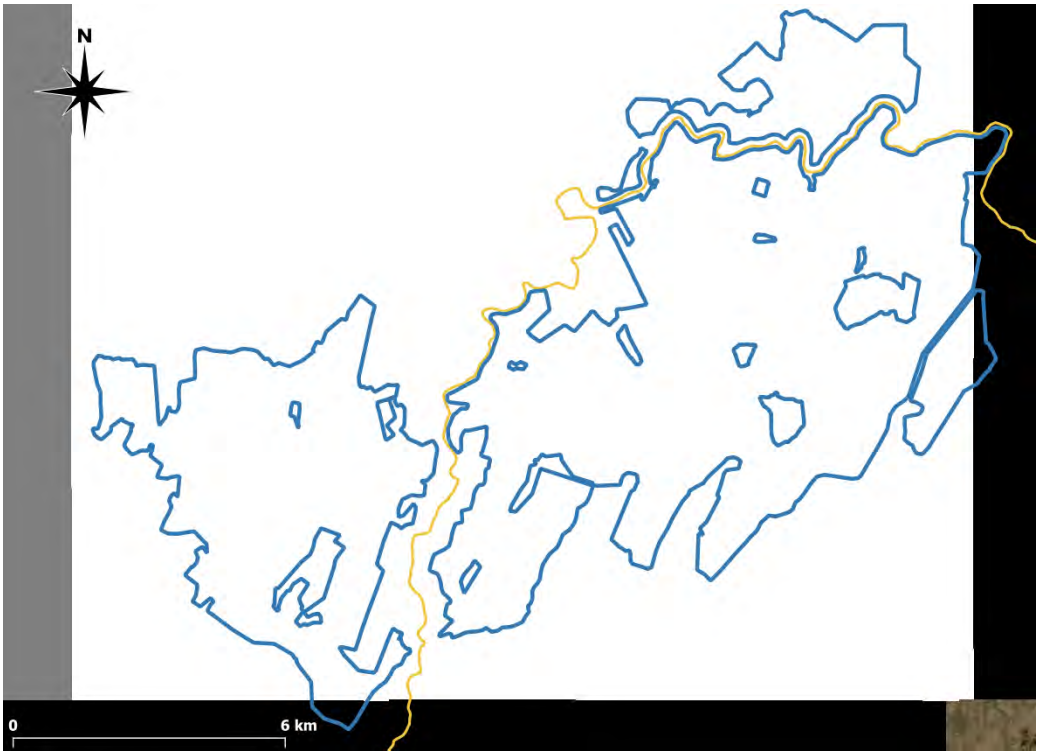


Figure 18. *Deviation of the grids of L1 ET_{ref} in Abadir in Methara. Different values for ET_{ref} are indicated with a different white, grey, or black tint.*

At last, the WaPOR protocol provided the possibility to select only the land cover classified areas of interest. This WaPOR data layer for L3 was however very low in quality and could therefore not be used in this research. Consequently, the shapefile that was used to perform this research included some areas that were not of interest like farmer roads where no agriculture took place. Although this

only accounted for a small area within the total research area, the incorporation of these non-agricultural grid cells slightly influenced the data.

4.2.3 Remarkable anomalies in the results

When the results from this research were analyzed, a few interesting aspects were found that could be related to several factors. First, as described in the previous section B in Metahara was not completely in line with the field observed B. It was hard to compare in situ sugarcane B with remote sensing observed data, because the farmers were not interested in the total B but were only interested in the cane. Farmers burned the sugarcane fields to remove all leaves before harvesting the sugarcane. Afterward, farmers measured the weighted sugarcane as biomass and measured the sugar that is retrieved from the sugarcane as yield (Sugar Corporation Research and Development Center, 2016). However, in their biomass weighting, the moisture content of the sugarcane was included while this was removed in the WaPOR calculation (Shitahun et al., 2018). Furthermore, WaPOR included the total growth of the plant which also included the sugarcane leaves. The ratio of leaves/cane and cane/sugar can vary per sugarcane type (Singh & Rao, 1987). Consequently, the absolute B values from the WaPOR data were not exactly similar to the ground-level measured data. Besides, it was difficult to define the amount of sugar from B with WaPOR data.

Secondly, the adequacy once exceeded 1 in the precipitation season, meaning that ET_{act} was larger than ET_c. There were several explanations for this: there was overirrigation in the area; this research assumed that the Kc factor was always similar for all locations, which might give over or underestimations of ET_c; or ET_{act} responded badly to soil moisture fluctuations and soil moisture limitations, causing ET_{act} to be overestimated (Blatchford et al., 2020). Moreover, in the precipitation season, ET_{act} was less reliable because the NDVI and land surface temperature which were needed to calculate ET_{act} were of low quality in cloudy conditions. This might also explain the high ET_{act} found in the precipitation season.

Thirdly, in the irrigation season of 2011-2012 a strong drop in B and WP_b occurred which was attributed to drought, reflected by the drop in PCP in the irrigation season. The ET_{act} however did not respond to this drought, which might be explained by the soil moisture content that responds badly to fluctuations in PCP. Though, it is more likely that other sources of water have been used in this season to account for water shortages.

Fourthly, in 2015 WP_b, as well as B, decreased which can be explained by the strong El Niño that occurred in 2015 (Mera, 2018). The El Niño resulted in severe droughts throughout Ethiopia with low PCP values which devastated the crops in that period and the years after. While crops needed multiple seasons to recover from the strong El Niño, the production only started to rise after 2018/2019.

Lastly, after 2013 the precipitation season $ET_{act} - PCP$ increased, indicating that the utilization of freshwater sources other than PCP enlarged. Likely the El Niño caused that other sources of water were needed. A trend starting in 2013 was also reflected in the WP_b, that is lower after 2013. This might be explained by the fact that the fertilizer use of several fields shifted in the past years from diammonium phosphate to the nitrogen fertilizer UREA. When this shift exactly took place was unknown by the stakeholders.

4.3 Limitations and recommendations

This research exhibited the spatiotemporal variation in land and water productivity in Metahara and related it to explanatory variables. Additionally, this research revealed that the GTP and ABWAP are far from achieving and that more investments should be made to increase biomass while decreasing water consumption. Although the influencing factors of soil texture and salinization of Lake Basaka

have been acknowledged, this research failed to describe the exact importance of the variables to water consumption and productivity. Future research can combine all variables to define the importance of each variable and how they impact each other. Also, future research can be done into measures that can be taken to cope with the expansion of Lake Basaka. It might be wise for Metahara to expand the fields towards the south since Lake Basaka will likely flood more of the fields in the future because of its expansion. Furthermore, the farmers in Metahara could consider growing other salt resistant crops. Moreover, to support the Ethiopian government in their decisions on the GTP, the GTP should be further reviewed in other areas as well to define if and how well the plans have worked. Lastly, to be able to use water productivity for decision-making reports, other water productivity dimensions such as the economic water productivity should be considered, which entails the economic profit over the amount of water consumed. Thus, future research should include other water productivity dimensions.

This research contributes to the wider scientific knowledge of remote sensing research because it showed the possibilities of remote sensing research while it also reflected the importance of ground-level data. More research needs to be done into further developing remote sensing-based analysis. Research into remote sensing and its possibilities have expanded since 1980 (Xiao et al., 2019). Since the 1990s vegetation indices used to define biomass growth and crop yield were implemented in remote sensing research and research into WP_b with remote sensing started (Blatchford et al., 2020). Ever since remote sensing-based research has increased tremendously and has been acknowledged to be of great potential in decision-making (Huang et al., 2018). However, because there are still errors in remote sensing data, the data should always be used with ground-level data. By developing remote sensing-based methods, future remote sensing analysis will improve and contribute to understanding and solving problems within agricultural systems. Additionally, acceptance of remote sensing among farmers and other agricultural stakeholders will increase which enlarges the potential (Conrad et al., 2020).

5.0 Conclusion

This research analyzed the spatial and temporal variation in land and water productivity in Metahara with WaPOR and ground-level data to find explanations for the spatiotemporal differences. The first sub-question focused on the spatial and temporal distribution of land productivity in the irrigation season, described by total dry biomass production (B). Some lower-performing areas within the spatial distribution of B were attributable to salinization due to Lake Basaka (sections A and C), social issues (sections D and E), and difficulties regarding pumping irrigation water to areas located upstream (sections B and F). The temporal findings revealed that B did not decrease nor increase over time. However, there was a drop in B in the irrigation season of 2015-2016. The strong El Niño that occurred in 2015-2016 reduced water availability and crop growth. To achieve the plans of the GTP, the B should increase, whereas it rather seems to decrease or remain constant. So, the plans of the GTP are still far being from achieved.

The second sub-question focused on the spatial and temporal distribution of biomass water productivity (WP_b) in the irrigation season. The spatial distribution of WP_b and B were similar. For Abadir the decadal WP_b significantly decreased over time, indicating that more water was used to produce the same B. This is attributable to the combination of *i)* increased water consumption over time consequently to soil compaction, and *ii)* the fact that B does not increase with the extra water applied, because the excess of water mainly evaporates instead of infiltrates. Also, low productivity values were found in the 2015-2016 season because of the El Niño.

The third sub-question was used to define the productivity targets and gaps. The mean targets and gaps for Abadir and Merti were comparable. The best producing fields were the fields with a higher ET_{act} which were in the center of the irrigation schemes. In the hypothetical situation where all fields would produce up to target levels, 34.1 Mm^3 extra water should be applied per year.

The fourth sub-question focused on the uniformity, adequacy, and water consumption. The results revealed that ET_{act} significantly increased over time in Abadir and Merti and that other sources of water than PCP were used in both the irrigation and precipitation seasons. Ergo, the plans of the ABWAP that aim at reducing water use are far from achieved. The uniformity was mostly fair; thus, the water is fairly distributed over the area. The crop water requirements were also quite well met, while the adequacy was mostly above 0.7. The values for the ET_{act}, uniformity, adequacy, and WP_b for Abadir and Merti were close to each other. Hence, the irrigation schemes Abadir and Merti performed equally well.

The fifth sub-question was attributed to relating the water productivity and irrigation scheme performance to soil texture and the influence of Lake Basaka. This research found that there were no significant relations between the spatial variation in WP_b or B and soil texture, but there were significant relations between soil texture and ET_{act}, adequacy, and uniformity. Finer soils had a larger ET_{act} because the water infiltrated slowly. Hence, more water was evaporated, but not more water was used by the crops. Finer soil textures also had a higher adequacy and better uniformity. Furthermore, it was shown that the saltwater infiltration of Lake Basaka was of influence on B. The fields in the northern section significantly had a lower B than the other fields in Merti. However, when analyzing the data over time, it could not be shown that the influence of Lake Basaka is increasing over time. This is likely because Lake Basaka has not expanded much between 2009-2021 as was shown by Google Earth Timelapse images.

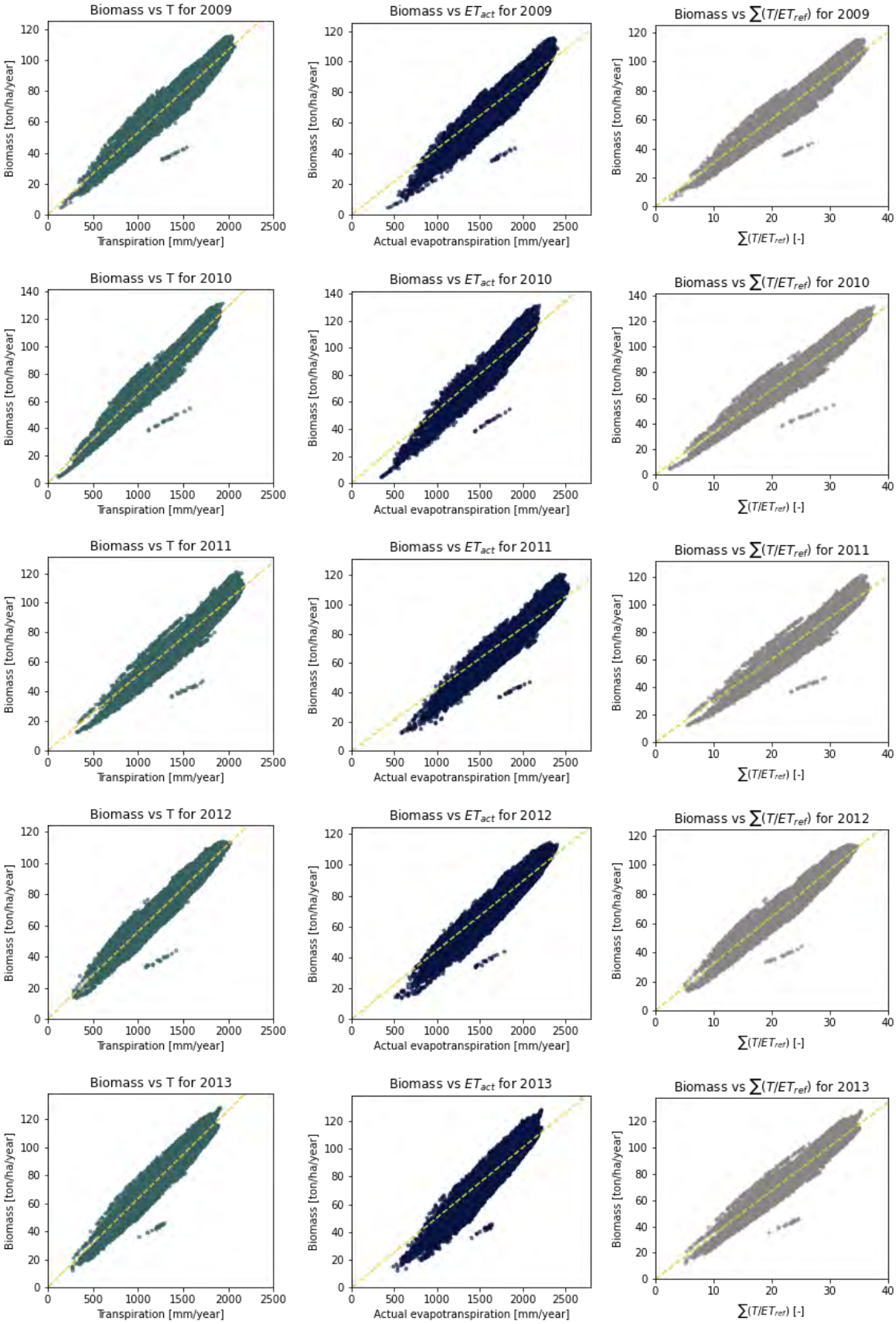
The five sub-questions were answered to answer the main research question:

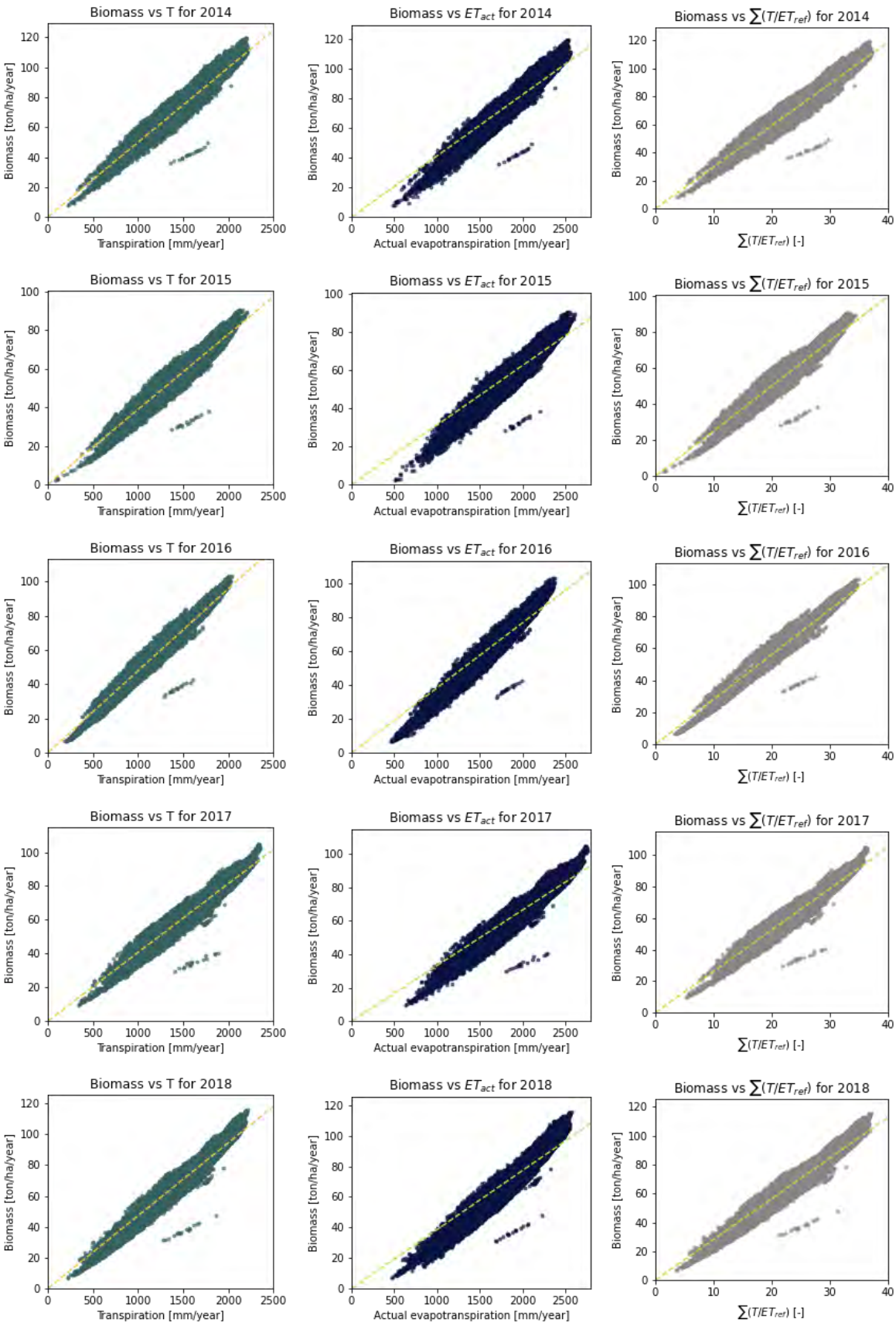
What are the spatial and temporal variability in land and water productivity in Metahara and how can these be explained?

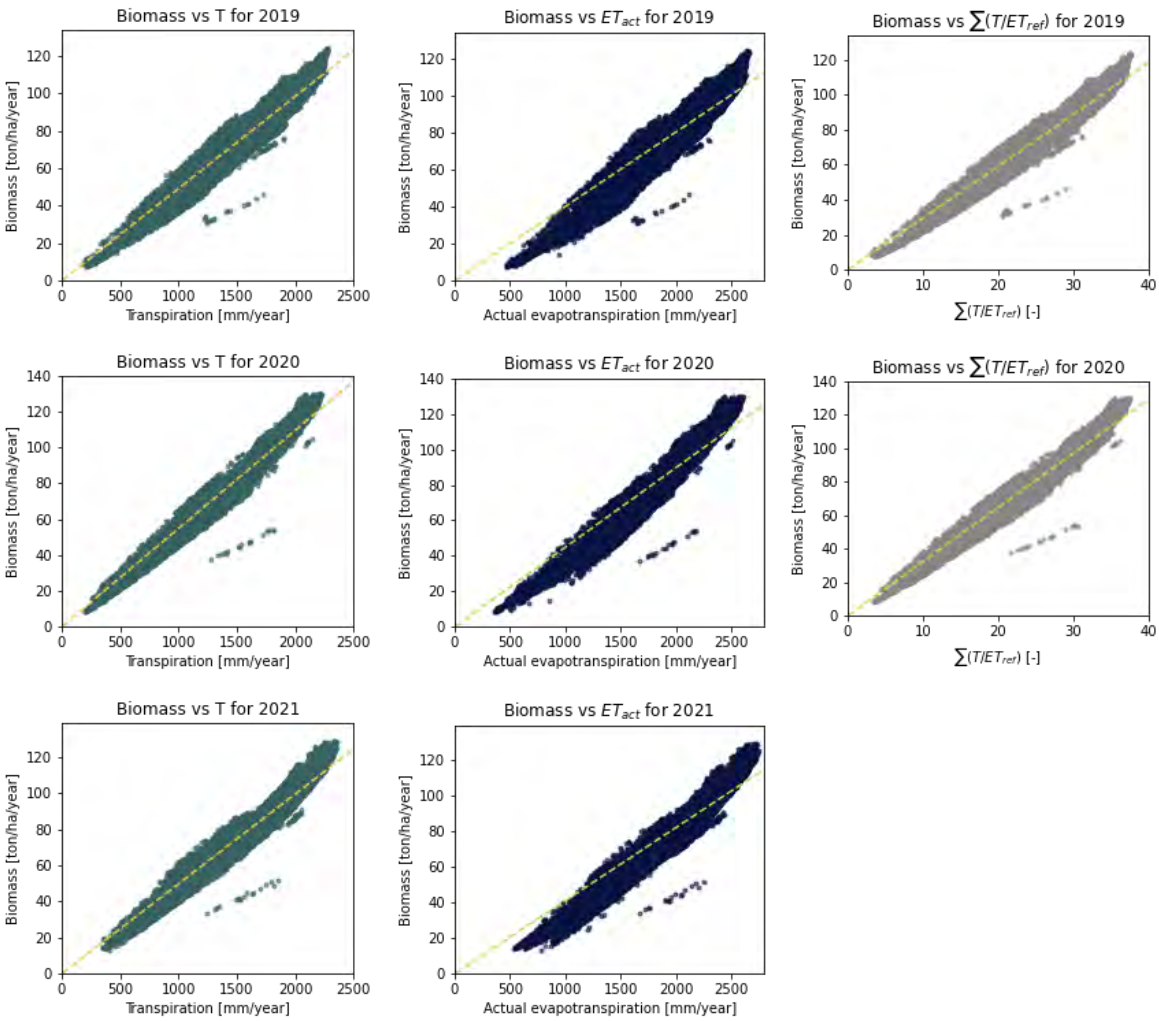
The spatial and temporal variability in land and water productivity was described in sub-questions 1 and 2. The temporal variability showed that WP_b is decreasing over time and that there was no significant trend in B, which was attributable to soil compaction and the resulting excess of water used. Thus, soil texture explained for the temporal trends in land and water productivity. Furthermore, both WP and B showed a drop in 2015-2016 due to the influence of El Niño. The spatial variability could partly be explained by water consumption and salinization by Lake Basaka. Fields with a finer soil texture had a higher water consumption but soil texture did not explain for spatial variability in land or water productivity. Then again, the fields with the highest biomass productivity also had a relatively large water consumption. Furthermore, fields that were closer to Lake Basaka performed less well, but the influence of Lake Basaka over time did not seem to increase in this research. Lastly, the exact contributing value of each factor should be further analyzed in future research.

Appenix

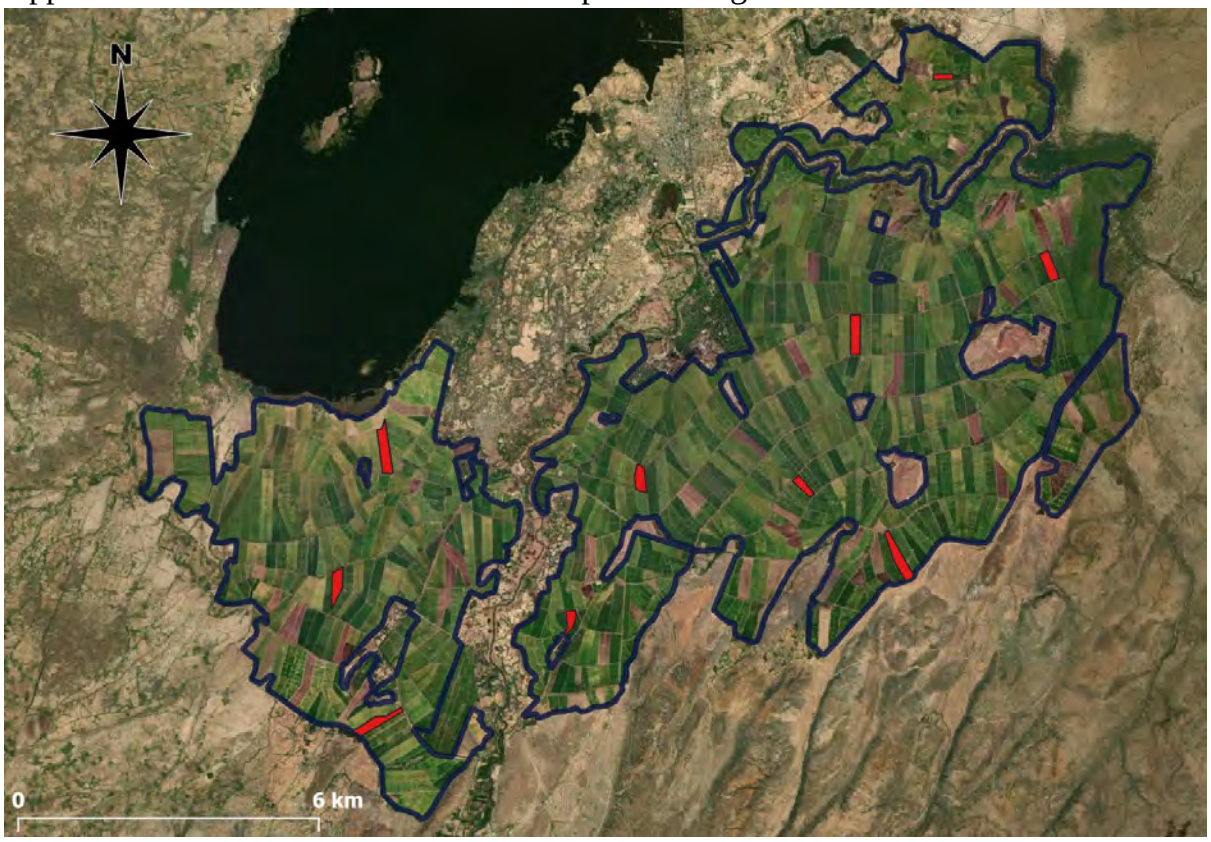
Appendix A - The consistency check with outliers for each year for Merti.



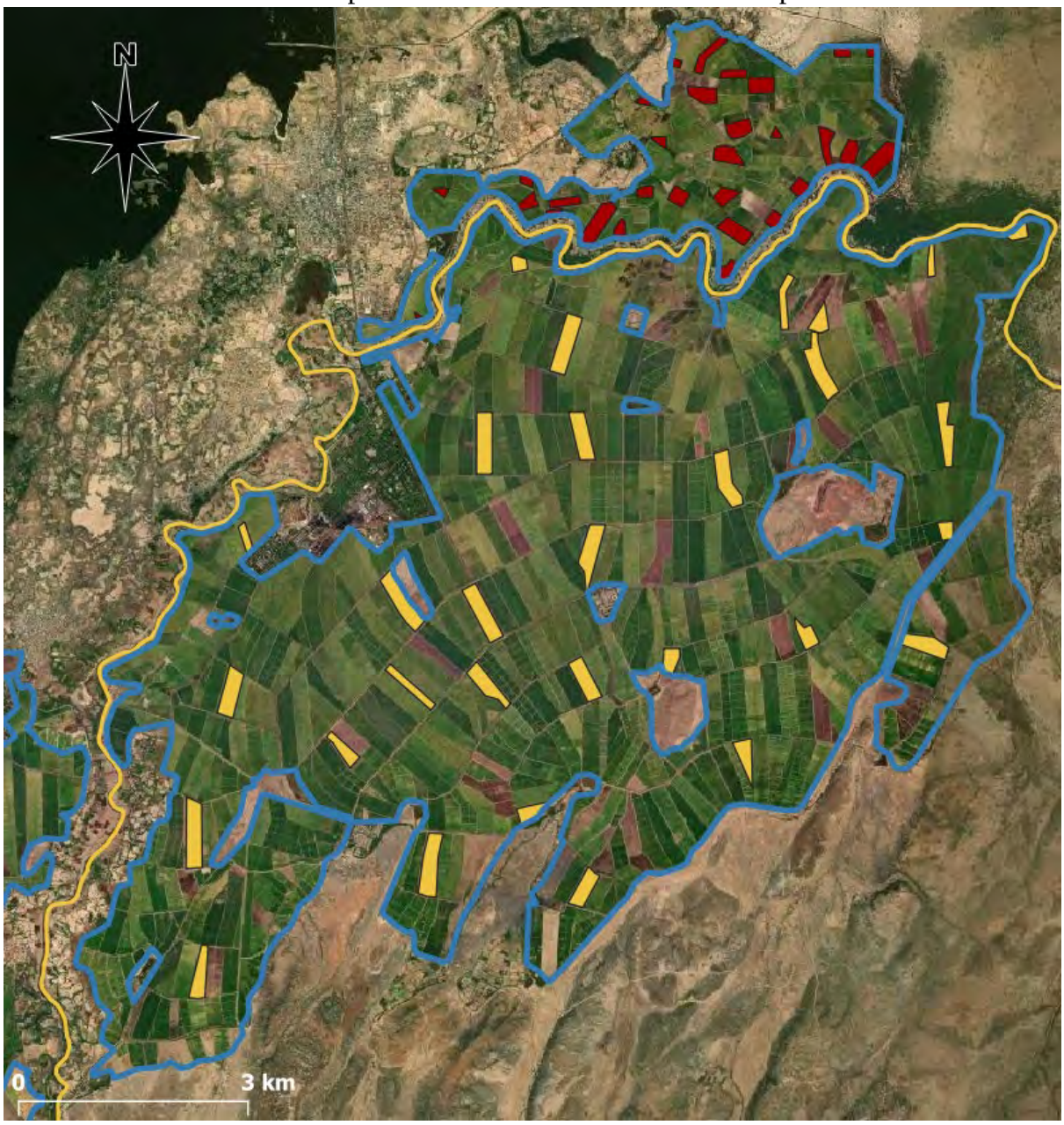

Biomass vs T for 2014
Biomass vs ET_{act} for 2014
Biomass vs $\sum(T/ET_{ref})$ for 2014
Biomass vs T for 2015
Biomass vs ET_{act} for 2015
Biomass vs $\sum(T/ET_{ref})$ for 2015
Biomass vs T for 2016
Biomass vs ET_{act} for 2016
Biomass vs $\sum(T/ET_{ref})$ for 2016
Biomass vs T for 2017
Biomass vs ET_{act} for 2017
Biomass vs $\sum(T/ET_{ref})$ for 2017
Biomass vs T for 2018
Biomass vs ET_{act} for 2018
Biomass vs $\sum(T/ET_{ref})$ for 2018
Biomass [ton/ha/year]
Transpiration [mm/year]
Actual evapotranspiration [mm/year]
$\sum(T/ET_{ref})$ [-]


Biomass vs T for 2019
Biomass vs ET_{act} for 2019
Biomass vs $\sum(T/ET_{ref})$ for 2019
Biomass vs T for 2020
Biomass vs ET_{act} for 2020
Biomass vs $\sum(T/ET_{ref})$ for 2020
Biomass vs T for 2021
Biomass vs ET_{act} for 2021
Biomass [ton/ha/year]
Transpiration [mm/year]
Actual evapotranspiration [mm/year]
$\sum(T/ET_{ref})$ [-]

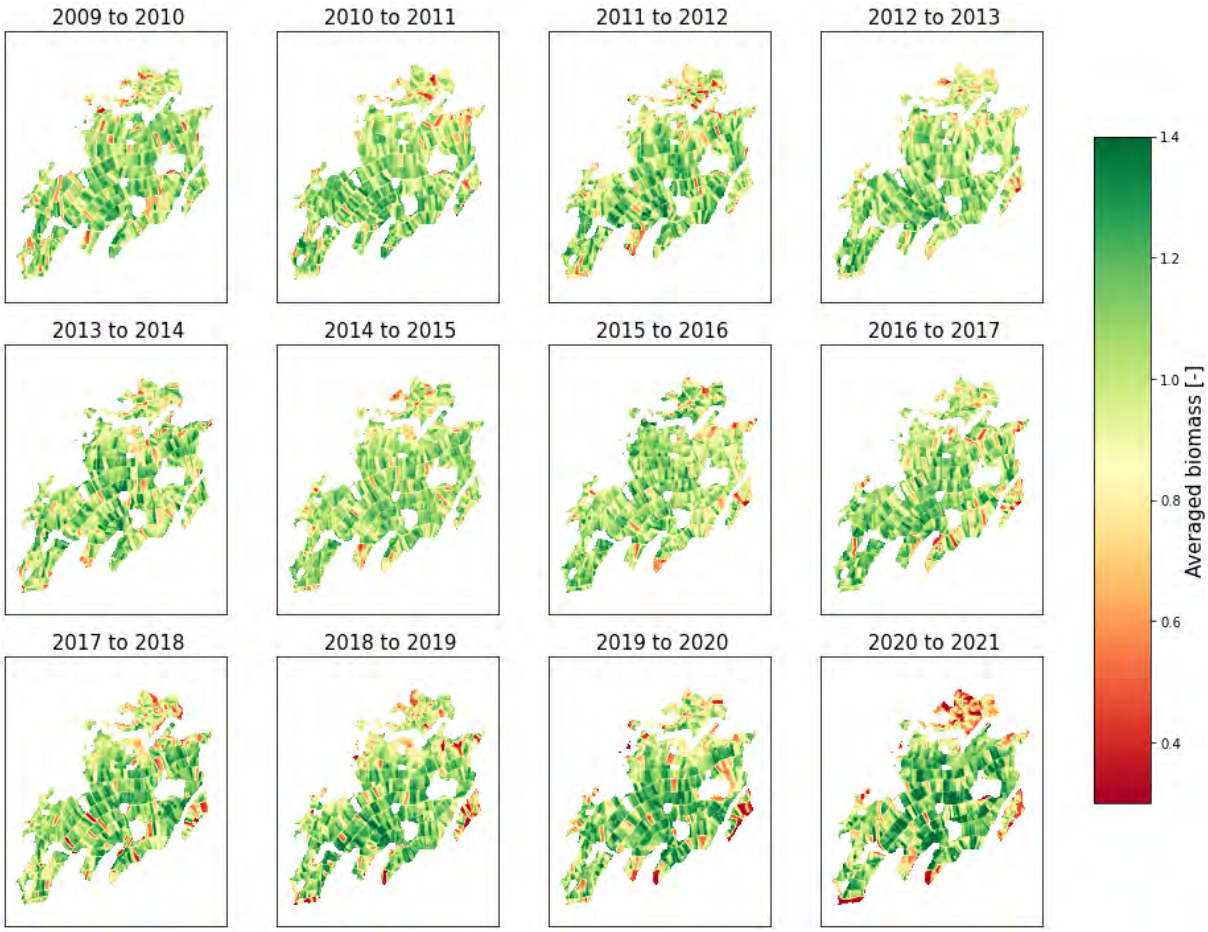
Appendix B - The fields used for the comparison of ground-level data to WaPOR data



Appendix C - The fields in the north and in the rest of Merti used to analyze if the location of the field with respect to Lake Basaka influences the production



Appendix D - The averaged biomass per irrigation season to visualize the influence of the expansion of Lake Basaka.



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