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IRRIGATION PERFORMANCE ASSESSMENT USING REMOTE SENSED DATA: THE CASE OF UBOMBO SUGARCANE SCHEME, ESWATINI

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April, 2025

DECLARATION AND RECOMMENDATION

DECLARATION

I declare that this master's thesis is my original work and has not been wholly or in part presented in this university or any other university for the award of a degree.

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RECOMMENDATION

This thesis is the candidate's original work and has been prepared with our guidance and assistance. It is presented for examination with our approval as official University Supervisors.

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DEDICATION

I would especially like to thank my family, whose constant encouragement and support have been my biggest strength.

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ABSTRACT

The rising need to feed the ever-growing population with the limited resources of land and water has put pressure on agriculture to improve on its water use efficiency. This study aimed to assess the performance of Ubombo Sugar Irrigation Scheme using remote sensing data by comparing ET estimates from WaPOR and SEBAL, focusing on their implications for adequacy, equity and water productivity in water distribution. SEBAL recorded an average seasonal ET of 1514 mm with a coefficient of variation (CV) of 0.14, an average relative ET of 0.88 and 26 kg/m^3 average of water productivity and an average Crop Water Deficit (CWD) of 154mm, indicating greater spatial variability due to its sensitivity to surface energy balance components. In contrast, WaPOR data yielded slightly higher values with an average seasonal ET of 1775 mm, a CV of 0.26, a relative ET of 0.82, an average water productivity of 14.5 kg/m3 and a CWD of 242mm, suggesting more stable long-term trends that support large-scale water resource assessments. The results highlight the strengths of SEBAL in capturing localized irrigation disparities and the advantages of WaPOR in providing consistent temporal assessments. Integrating both approaches can enhance irrigation management by improving spatial and temporal water allocation, supporting more efficient and sustainable agricultural practices.

Keywords:

Adequacy, Equity, Evapotranspiration, SEBAL, Sustainable Agriculture, WaPOR, Water Productivity, Water Resource Allocation.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS AND ACRONYMS

Abbreviations and Acronyms	**Meaning**
CV	Coefficient of Variance
CWD	Crop Water Deficit
ET	Evapotranspiration
FAO	Food and Agriculture Organization
GLDAS	Global Land Data Assimilation System
MAPE	Mean Absolute Percentage Error
METRIC	Mapping Evapotranspiration at High Resolution with Internalized Calibration
OLI	Operational Land Image
RET	Relative Evaporation
RS	Remote Sensing
SEB	Surface Energy Balance
SEBAL	Surface Energy Balance Algorithm for Land
USGS	United States Geological Survey
WaPOR	Water Productivity through Open access of Remotely sensed derived data

CHAPTER ONE

INTRODUCTION

1.1 Background Information

Agriculture is the primary water user with 70% of world's water withdrawal and 20% of all agriculture land is attributed to irrigated agriculture which then contributes to 40% of all food produced (FAO, 2020). The success of this industry is highly reliant on water resources because it is the largest contributor to the economy in many nations and agricultural production is heavily dependent on the availability of the water resource. However, in many regions of the world, lack of freshwater poses serious risks to sustainable development and food security due to the prolonged drought caused by climate change, especially in arid and semi-arid regions (Abioye et al., 2020). Therefore, there is a growing need for irrigation systems to adapt to these impacts of climate change and improving irrigation efficiency has a significant positive impact on agricultural product production cost reduction, increasing industry competitiveness and sustainability (Gagandeep et al., 2018). Optimizing agricultural water use is an essential component of sustainable development since better irrigation practices are closely linked to increased employment, income growth, and yield stability. Irrigation has vastly increased the global food security, to meet the future food and fibre demands, there is more increase in agricultural production that needs to happen. According to Hess et al. (2016), agriculture production can be increased either by increasing agriculture land or increasing productivity. Because land and water resources are limited, it is preferable to increase productivity as measured by irrigation performance indicators like land and water productivity. Several technology and practices have shaped agriculture's evolution with developed countries making huge strides in the agricultural sector by using better agricultural practices and cutting-edge technologies to increase agricultural productivity, many developing nations are still unable to reach their full agricultural potential. The absence of appropriate monitoring and control systems for effective farming is thus one of the biggest obstacles (James et al., 2017). The field of irrigation system evaluation has advanced significantly in recent years, shifting from a focus on traditional irrigation efficiency to performance indicators and, more recently, frameworks of water accounting and productivity to determine the water use efficiency at different scales (Ahmad et al., 2009). Scientific developments and satellite data make remote sensing an appealing choice for evaluating irrigation performance at scheme or river basin scale as well as on individual farms (Bastiaanssen & Bos, 1999). Assessment of irrigation performance is therefore a critical step to improving water use efficiency in agriculture, mainly for making decisions on investments and management. Irrigation performance assessment is basically the systematic observation, documentation and interpretation of activities related to irrigated agriculture with the aim to attain resource use efficiency (Bos et al., 2005). In Africa, assessing the performance of irrigation systems haven't been done much compared to other continents like Asia, even though some researchers have evaluated irrigation system performance in Africa over the years (Ahmad et al., 2024). Quite a number of irrigation schemes lack adequate records and water measuring equipment and infrastructure, making it challenging to obtain primary data for research purposes due to the high cost of monitoring, inadequate measuring systems, and poor scheme administration. The combination of ground-based data with remote sensing data presents the opportunity to overcome this shortfall and help improve surface irrigation in Sub-Saharan Africa.

Remote sensing allows for the understanding of agricultural performance at high spatial and temporal resolutions. It makes it easy to estimate agricultural production using remote sensing as they offer more information in more time and space than can be obtained by more conventional techniques, like water balance or ground measurements hence performance indicators are becoming more and more common (Bos et al., 2005). Agricultural production, including the Evapotranspiration (ET_a) and biomass production can be estimated using various remote sensing methods based on surface energy balance (SEB) approaches such as surface energy balance algorithm for land (SEBAL) (Bastiaanssen et al., 1998) and Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC) (McShane et al., 2017). In many regions, particularly in developing countries, obtaining ground-based data for agricultural monitoring can be challenging due to limited resources, high costs, and logistical constraints (Pates et al., 2023). Remote sensing provides a cost-effective and scalable alternative, offering consistent and high-resolution data over large areas without the need for extensive fieldwork. By utilizing satellite imagery and advanced processing techniques, these methods can help bridge data gaps and improve agricultural assessments. Therefore, more research and documentation on irrigation performance are mostly important in Africa especially in developing countries like Eswatini, where ground data may be difficult and quite expensive to obtain (Nizamani et al., 2023).

Ubombo Sugar Estate is located in Lubombo region, Eswatini. The conventional methods currently used in the farm to assess irrigation system performance are point-based measurements that are time consuming in the gathering the necessary data, which can be costly in the long run.

In this study, the irrigation system performance was assessed at Ubombo Sugar Irrigation Scheme using remotely-sensed indicators in order to determine the distribution of the spatial variation in irrigation delivery at the farm.

1.2 Statement of the Problem

Agricultural production and water management are crucial factors in addressing both water scarcity and the growing demand to sustain the ever-growing population. The impact of climate change has led many countries to experience severe water shortages, posing significant threats to agricultural productivity (Kumar et al., 2021). Consequently, approaches for monitoring agriculture water management are essential to enhance productivity. Eswatini heavily relies on agriculture as its primary economic driver, significantly consuming more water than other sectors, emphasizing the necessity for efficient management practices (Teweldebrihan, 2025). Ubombo sugar irrigation scheme is one of the biggest irrigation schemes but still uses the traditional methods of assessing irrigation performance. The major issues facing the scheme are inadequate water distribution, failing irrigation systems and silting canals. The point-based metrics that are currently employed in evaluating irrigation effectiveness need time to gather the required data, making them costly. Therefore, the utilizing remote sensing in assessing irrigation performance offers an opportunity for farm managers to optimize water use effectively, decision making in the farm and improve overall agriculture productivity. Therefore, this study assessed the performance of irrigation systems using selected remote sensing-based indicators such as adequacy, crop water deficit, equity and water productivity (Kharrou et al., 2021).

1.3 Objectives

1.3.1 Main Objective

The main objective of this study was to assess the performance of Ubombo Sugar Irrigation Scheme using remote sensing data.

1.3.2 Specific Objectives

The specific objectives of the study were to:

a) Assess the actual evapotranspiration (ET_a) at Ubombo Sugar Irrigation Scheme using the SEBAL.

b) Assess the irrigation water use performance in terms of adequacy, crop water deficit, equity and water productivity.

c) Compare the actual evapotranspiration (ET_a) and irrigation water use performance in terms of adequacy, crop water deficit, equity and water productivity with WaPOR estimation

1.4 Research Questions

a) How accurately can SEBAL be used for the estimation of actual evapotranspiration (ETa)?
b) How do remote sensing-based indicators contribute to assessing crop water deficit, equity, water productivity and adequacy in water delivery compared to traditional methods?
c) How do the evapotranspiration estimates (ET_a) and irrigation water use performance in terms of crop water deficit, adequacy, water productivity and equity compare with those provided by the WaPOR database?

1.5 Justification of the Study

In areas like Eswatini where rainfall can be erratic, irrigation systems are essential for increasing agricultural productivity. To maintain sustainable water use and optimize crop yields, efficient water distribution is essential. A modern-day, precise, and non-intrusive method for keeping an eye on large agricultural regions is remote sensing technology (Teweldebrihan, 2025). This technology offers comprehensive data on, soil moisture, crop health, and water distribution, all of which are frequently difficult to gauge using conventional ground-based techniques. The economy of Eswatini is heavily dependent on agriculture, and increasing productivity requires effective irrigation techniques (Hellegers et al., 2010). Problems like waterlogging, salinization, and the depletion of water supplies can be avoided with effective water management (Mhlanga-Ndlovu et al., 2017). By assessing water distribution, this study aimed to enhance the efficiency of the Ubombo Sugar irrigation scheme, aligning with the national goal of promoting sustainable agricultural practices. This supports several Sustainable Development Goals (SDGs), including: SDG 2 Zero Hunger - By improving crop yields and food security through better irrigation practices, SDG 8 Decent work and Economic Growth - By preserving the agriculture sector from extinction due to the dwindling water resource that is exacerbated by climate change, hence more jobs will be created and SDG 12 Responsible Consumption and Production - By optimizing resource use and minimizing environmental impacts. Strategies and policies that promote sustainable irrigation methods will be informed by the data-driven insights gathered from this study, supporting both the national agricultural goals of Eswatini and the larger international development agenda. (Asim et al., 2024).

1.6 Scope and Limitations of the Study

The study used satellite data to assess the performance of the Ubombo Sugar Irrigation Scheme. It focused on estimating actual evapotranspiration (ET_a) using Landsat 8 imagery and the SEBAL model and comparing to WaPOR evapotranspiration estimates. By analyzing crop water deficit, equity, water productivity and adequacy metrics, it helped to evaluate how well irrigation water is distributed within the scheme. Remote sensing improves accuracy and helps to drastically cut down on the amount of time spent on particular jobs. This study used free models or software like PySebal and was conducted for the sugarcane growing season from 2017 to 2020. This timeframe allowed for capturing interannual variability and provides a solid dataset for vigorous analysis. The 16 days of the temporal resolution of Landsat 8 presents a limitation in acquiring images, this becomes even a bigger challenge when there is cloud cover for both pictures of that month. Another limitation would be the sensitivity of SEBAL evapotranspiration to meteorological weather parameters like that of wind speed and relative humidity, hence accuracy of the SEBAL outputs used to calculate ET can be compromised by the poor precision of the GLDAS meteorological data for these parameters.

CHAPTER TWO

LITERATURE REVIEW

2.1 Crop Water Requirement (CWR)

Crop water requirement which is sometimes called crop evapotranspiration constitutes of two components, evaporation and transpiration. Crop evapotranspiration measures the quantity of water that crops lose through transpiration from their leaves and evaporation from the soil surface. So basically, crop water requirements refers to the quantity of water needed by a crop to replace the evapotranspiration losses from the cultivated field (Valens et al., 2021). It is affected by a variety of factors, such as temperature, humidity, wind speed, and sun radiation. ET, in a nutshell, is the actual amount of water lost from the soil-plant system, whereas CWR is the quantity of water that must be supplied, either by irrigation or rainfall, to replace the ET loss and ensure optimal plant development and yield. Despite the fact that the values for both terms are the same, crop water requirement and crop evapotranspiration are equal, the two are different in application in agriculture (Fang et al., 2021). The irrigation water requirements essentially represent the difference between the crop water requirement and effective precipitation.

Crop water requirements are an important consideration in agriculture because efficient water management is essential to maximizing crop output and maintaining sustainable agriculture (Ali et al., 2021). Since the advent of huge engineering projects, when it became necessary to predict the water amounts to be supplied to newly irrigated areas, the idea of crop water requirements has gained importance. In general, it is possible to distinguish between the crop water requirements for real-time management, where the climatic data of the ongoing season are applied, and the crop water requirements for long-term planning, where an average climate or a climate with a certain probability of occurrence can be used for CWR estimate (Jaafar et al., 2022). The ET of any crop is calculated as the product crop coefficient, K_c and the reference crop evapotranspiration, ET_0, as shown in Equation 2.1:

$$CWR = ET_C = ET_O * K_C \tag{2.1}$$

Where:

K_c = the crop coefficient

ET_c = is the crop water requirement (mm/day)

ET_o = the reference crop evapotranspiration (mm/day)

2.2 Methods of Determining Crop Water Requirements

Since precise field measurements are hard to come by, prediction techniques are employed to compute the crop water requirements. The climatic and agronomic conditions in which the procedures must frequently be used differ greatly from those in which they were first devised. Numerous methods have been used to compute crop water requirements (Rai et al., 2017). Such methods include: Blaney-Criddle; Penman Monteith; Hargreaves-Samani Equation; SEBAL and METRIC.

2.2.1 Blaney-Criddle Method

The Blaney-Criddle method is an easy, straightforward, practical and widely used approach for estimating potential evapotranspiration or reference crop evapotranspiration based on temperature data. This method only requires temperature as an input data which makes it very difficult to use under extreme climatic conditions, such as very dry or humid environments because it turns to be inaccurate (Zhan & Lin Shelp, 2009). To address this shortfall of the method, scientists have modified the Blaney-Criddle approach to increase the accuracy of ET estimation across a wider variety of climate conditions. One such adjustment is the FAO Blaney-Criddle approach, Equation (2.2), which uses an empirically-derived "b-factor" to modify the original Blaney-Criddle equation:

$$ET_O = a + b(p(0.46T_{mean} + 8.13) \qquad (2.2)$$

Where:

ET_0= the reference evapotranspiration (mm day^{-1})

T_{mean} = the mean daily temperature [°C] given as $T_{mean} = (T_{max} + T_{min})/ 2$

p= the mean daily percentage of annual daytime hours.

a, b = a and b factor which are location-specific coefficients

The consumptive water requirements are then established by applying an empirically derived consumptive use crop coefficient (K). However, temperature and day length alone do not fully capture the effect of climate on agricultural water requirements, factors such as solar radiation, humidity, and wind speed can significantly influence the crop water requirements, beyond just temperature and precipitation crop water requirements hence the crop water requirements differ significantly among climates with comparable values of T and p (Thongkao et al., 2022)

2.2.2 The Penman Monteith Method

The Penman Monteith model for calculating evapotranspiration is one of the widely used methods of ET estimations. Because it integrates the energy balance and aerodynamic methods into a single equation, it takes into account a variety of climatic factors, including wind speed, humidity, air temperature, and solar radiation, as well as surface characteristics like surface conductance and leaf area index. The Penman-Monteith equation offers precise estimates of evapotranspiration under a variety of climatic conditions. It is frequently utilized in a wide range of applications, including climate modeling, irrigation scheduling, and water resource management as shown in Equation 2.3 (Allen et.al., 1998).

$$ET_O = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \tag{2.3}$$

Where:

ET_0 = the reference evapotranspiration (mm/day).

Δ = the slope of the vapor pressure curve (kPa/°C).

R_n =the net radiation at the crop surface ($MJ/m^2/day$).

G = the soil heat flux density ($MJ/m^2/day$).

γ = the psychrometric constant (kPa/°C).

T = the mean daily air temperature at 2 meters height (°C).

u_2 = the wind speed measured at 2 meters height (m/s).

e_s = the saturation vapor pressure (kPa).

e_a = the actual vapor pressure (kPa).

2.2.3 The Hargreaves-Samani Equation

The Hargreaves-Samani equation, which was created based on the Penman-Monteith equation, is a simplified technique for determining reference evapotranspiration with only temperature data as input, and not including meteorological factors like humidity, wind speed, and radiation, Equation (2.4). This method simply requires temperature readings, which are easier to obtain, hence its popularity in areas with a lack of comprehensive meteorological data (Lima et al., 2013).

$$ET_0 = 0.0023(T_{mean} + 17.8) \times (T_{max} - T_{min})^{0.5} \times Ra \qquad (2.4)$$

where:

ET_o = Reference evapotranspiration (mm/day)

T_{mean}= Mean daily temperature (°C)

T_{max} = Maximum daily temperature (°C)

T_{min} = Minimum daily temperature (°C)

Ra = Extra-terrestrial radiation (MJ/m²/day)

2.3 Data Challenges in Determining Crop Water Requirement

Numerous data issues arise throughout the process of estimating agricultural water requirements, which may compromise the precision and dependability of irrigation management. Accurate meteorological data, including temperature, humidity, wind speed, and sun radiation, is important for predicting crop water requirements. Nevertheless, it might be difficult to find accurate and current weather information for a particular area, particularly in areas with a shortage of weather stations or uneven data gathering. Estimates of crop water requirements and evapotranspiration rates can be off due to incomplete or untrustworthy weather data (Shah et al., 2023).

2.3.1 Crop Coefficients

The water requirements of different plant species at various growth stages are represented by crop coefficients (Kc). Accurate crop coefficient calculation, however, might be difficult to do for particular crops and regional circumstances (Paula De Oliveira Mangarotti et al., 2019). Crop coefficient values can change according to a number of variables, including climate in the area, management techniques, soil type, and cultivar. To estimate the amount of water required, it is essential to correctly determine the crop's growth stage and the related crop coefficients (Seidel et al., 2019).

2.3.2 Soil Data

Water holding capacity and drainage characteristics are influenced by several soil features, such as texture, organic matter concentration, and hydraulic characteristics. It can be difficult to obtain precise soil data because of limited soil sampling points and spatial heterogeneity. Examples of such data are soil moisture retention curves and hydraulic conductivity. Estimating soil water availability and irrigation needs can be inaccurate due to inaccurate soil data (Deb et al., 2014).

2.3.3 Crop Water Use Efficiency (WUE)

Crop water use efficiency (WUE) is the amount of biomass produced for each unit of water used. It can be difficult to get precise WUE values for certain crops under various management strategies because cultivars, environments, and irrigation methods can differ. Crop water requirements and irrigation schedule calculation might be impacted by missing or erroneous WUE data (Michelon et al., 2020; Blum, 2009).

2.3.4 Remote Sensing Data

Aerial photos and satellite imagery, for example, can offer important insights about crop water requirements. Nevertheless, there are a number of potential difficulties with gathering and analyzing remote sensing data, such as cloud cover, sensor constraints, image quality, and data accessibility. Accurately interpreting data from remote sensing and combining it with information from other sources is necessary for effective crop water requirement estimation (Jaafar et al., 2022). To tackle these data difficulties, a blend of enhanced data gathering strategies, sophisticated modeling approaches, and incorporation of diverse data sources is necessary. Improving weather monitoring networks, soil data collection, and remote sensing capabilities is necessary to facilitate effective irrigation management and raise the precision of crop water need estimates.

2.4 Use of Remote Sensing Techniques in Irrigation

Remote sensing is the process of gathering information without making physical contact. Hence deriving surface parameters from measurements of electromagnetic radiation coming from the land surface is known as remote sensing. The land radiates and reflects this radiation (Coops et al., 2017). Remote sensing techniques are commonly utilized to improve and monitor water usage in agricultural fields. These methods offer useful data regarding soil moisture content, crop water requirements, and irrigation effectiveness (Shanmugapriya et al., 2019). The following are some remote sensing methods used in management irrigation:

2.4.1 Thermal Infrared Remote Sensing

According to the Globa Climate Observing System, Land Surface Temperature (LST) is amongst the most crucial climate variables (Han et al., 2020). Knowledge of surface temperature is important is determining the surface radiative budge. LST is measured by thermal infrared sensors, and it is affected by crop water stress and soil moisture content. By analyzing the thermal photos, farmers and irrigation managers can identify the areas of a field that require varying quantities of water. Areas that require more or less watering can be identified by hotspots or cool regions in the photos (Dahiru et al., 2020). Numerous studies indicate the success of thermal infrared remote sensing in detecting water stress in agriculture fields (Zhou et al., 2021; Marcq et al., 2023).

2.4.2 Optical Remote Sensing

Optical sensors play a crucial role in remote sensing by capturing data across several portions of the electromagnetic spectrum, including the visible, near-infrared (NIR), and infrared regions. These sensors provide imagery with high-resolution that is important for monitoring crop health, water stress, and overall vegetation conditions (Prasad et al., 2011). One of the most widely used applications of optical sensor data in agriculture is the estimation of vegetation indices, particularly the Normalized Difference Vegetation Index (NDVI). The NDVI works on the principle that healthy vegetation absorbs red light for photosynthesis while strongly reflecting NIR light, which is how the NDVI is calculated from the reflectance values of vegetation in the red and near-infrared spectral bands. This index is an important indicator of vegetation vigor, biomass production, and plant stress levels. Farmers and agricultural specialist can identify early indicators of crop water stress, nutrient deficits, pest infestations, and disease outbreaks by analyzing NDVI measurements. A decline in NDVI over time may indicate insufficient irrigation, requiring adjustments to water management strategies to prevent yield loss (Anderson, 2024).

By continuously tracking NDVI trends over a growing season, farmers can monitor the crop health hence helping in making decisions regarding irrigation scheduling, fertilization, and crop protection measures (Zhang et al., 2014; Panda et al., 2010). This real-time monitoring capability allows for precision agriculture, where resources such as water and fertilizers are applied more efficiently, reducing waste and maximizing productivity. NDVI maps generated from satellite imagery or UAV-based optical sensors help visualize spatial variations in crop health, enabling targeted interventions in areas showing signs of stress. Beyond irrigation management, NDVI-based analysis is also widely used in yield prediction, drought assessment, and land-use monitoring. The improvement of technology in remote sensing affords farmers access to high-resolution, near-real-time NDVI data, which enhances their responsiveness to environmental conditions. The integration of NDVI with other indices, such as the Enhanced Vegetation Index (EVI) and Soil-Adjusted Vegetation Index (SAVI), further improves the accuracy of crop health assessments and water management strategies (Shi et al., 2024).

2.4.3 Microwave Remote Sensing

Microwave remote sensing involves the capability to directly observe large fraction of the land surface directly from space hence sampling soil moisture (Laachrate et al., 2020). Synthetic Aperture Radar (SAR), as a Microwave remote sensing technique has been used in a lot of studies and application in agriculture (Cheng et al., 2021). Estimating the soil moisture content using SAR data aids in figuring out how much irrigation is required. To avoid over- or under-watering, changes in soil moisture, patterns can be tracked and used to improve irrigation schedules (Bhogapurapu et al., 2020).

2.4.4 Ground-based Sensors

Direct measurements of soil moisture can also be obtained using ground-based sensors in addition to satellite or aerial remote sensing. For continuous monitoring of soil moisture, these sensors are positioned in the soil profile at different levels. Water use efficiency can be increased and irrigation scheduling can be adjusted with the help of the sensor data (Jin et al., 2017). Ground-based sensors are extensively used for soil moisture monitoring. Famiglietti et al. (1999) developed a system of ground-based soil moisture sensors to study the moisture dynamics across different soil types and land uses. Ground-based sensors are also used to calibrate and validate remote sensing data, improving the precision of soil moisture estimates and aiding in precise irrigation management (Jackson et al., 2010).

2.4.5 ET Models

Evapotranspiration (ET) models have been extensively used in combination with remote sensing data to calculate agricultural water requirements and improve irrigation water management. These models are essential to modern-day precision agriculture because they offer comprehensive information on crop health, water consumption, and overall irrigation efficiency. Among the widely used ET models, SEBAL and METRIC are particularly notable for their ability to integrate satellite imagery with meteorological data to estimate ET (Bastiaanssen et al., 1998; Allen et al., 2007). Both SEBAL and METRIC rely on remotely sensed land surface temperature, vegetation indices, and energy balance calculations to derive spatially distributed estimates of evapotranspiration rates across agricultural landscapes. These models enable farmers, water managers, and policymakers to assess crop water requirements, monitor plant stress, and optimize irrigation scheduling, ensuring that crops receive the right amount of water at the right time. By providing a scientific basis for water allocation, ET models contribute to improving water use efficiency and reducing unnecessary water losses (Buhshan et al., 2023).

SEBAL and METRIC use a combination of thermal infrared, visible, and near-infrared satellite data to estimate ET. These models calculate actual evapotranspiration (ETa) based on energy balance principles, where incoming solar radiation is partitioned into latent heat flux (ET), sensible heat flux, and ground heat flux (Sun et al., 2011). The ability of these models to derive ET at high spatial and temporal resolutions makes them valuable tools for assessing water productivity, drought conditions, and the impact of climate variability on agricultural production. By incorporating ET models into irrigation planning, decision-makers can determine the best timing and amount of irrigation water required for different crops and soil types (Kang et al., 2009). This helps in reducing water wastage, preventing over-irrigation, and mitigating the risks of water stress in agricultural systems. Additionally, ET models facilitate large-scale agricultural monitoring, allowing for regional and global assessments of water demand and availability.

2.5 Land surface Energy Balance Models (LSEB)

LSEB models are models that are used to calculate the energy flows between the atmosphere and the land surface. The exchange of energy in various forms, including incoming solar radiation, outgoing longwave radiation, sensible heat flow, latent heat flux, and ground heat flux, is simulated by these models, Figure 2.1 (Bretherton, 2019). Quantifying the energy budget of the land surface is the main goal of LSEB models since it is essential to many environmental processes, such as hydrological cycles, weather patterns, and climate dynamics. Scientists and researchers can analyze the effects of vegetation, land surface features, and atmospheric variables on the overall energy exchange by comprehending and accurately portraying the energy balance. For the energy fluxes, LSEB models often combine meteorological data, land surface features (e.g., land cover, soil qualities), and radiative transfer principles. Based on the model's complexity and the available input data, these models can be implemented at different scales, from local to regional to global (Iizuka et al., 2000). The Surface Energy Balance System (SEBS) – SEBAL and METRIC, Penman-Monteith approach, Simplified Surface Energy Balance (SSEB) model, and Two-Source Energy Balance (TSEB) model are a few examples of widely used LSEB models. To effectively depict the intricate interactions between the atmosphere and the ground surface, each model may have its own unique parameterizations, assumptions, and algorithms (McShane et al., 2017). Applications for LSEB models can be found in many domains, such as hydrology, agriculture, climate modeling, weather forecasting, and natural resource management. They aid in the assessment of land surface processes, the comprehension of land-atmosphere interactions, and the enhancement of weather and climate forecasts.

2.5.1 SEBAL

SEBAL model is a well-tested and widely used method that provides an efficient tool for estimating the spatial distribution of evapotranspiration by converting the measured satellite radiances (visible, near infrared, and thermal-infrared) into surface characteristics including surface temperature, surface albedo, and normalized difference vegetation index (NDVI) which are then used to compute the various parts of the energy balance equation (da Silva et al., 2018) (Kharrou et al., 2013)(Wamala et al., 2023). SEBAL outcome have been validated using different instruments in different countries including Bowen ratio and Eddy-correlation towers, scintillometer and lysimeter with a daily ET estimates errors of 16% or lower (M. D. Ahmad et al., 2009).

$$LE = R_n - G - H \tag{2.4}$$

Where:

R_n = net radiation (Wm^{-2}),

G = soil heat flux (Wm^{-2})

H = sensible heat flux (Wm^{-2})

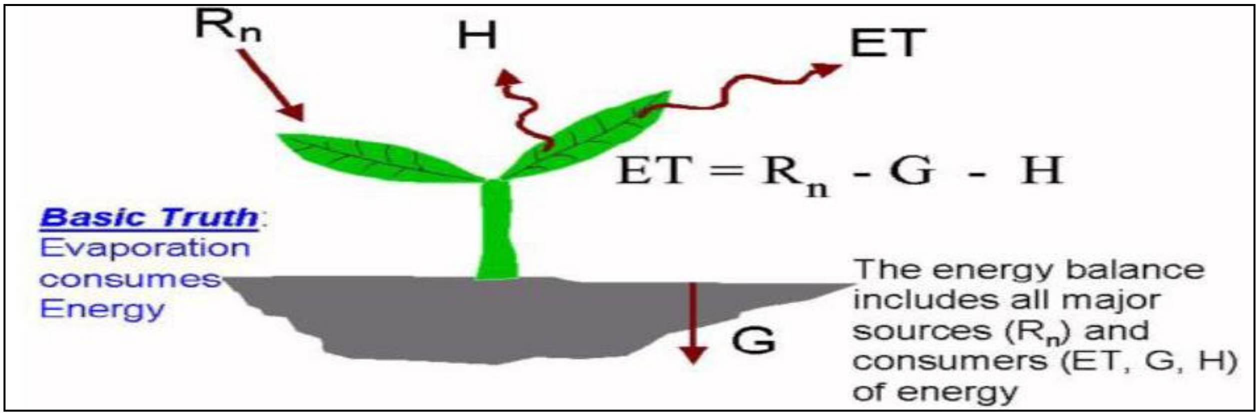

Figure 2.1: Surface Energy balance for ET (Allen et al., 2002)

2.5.2 METRIC

A satellite-based image processing technology called Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC) is used to calculate ET as a residual of the Earth's surface energy balance. METRIC is based on the concepts and methods employed by the significant energy balance model SEBAL (Bastiaanssen et al., 1998). The model has been applied in various studies to estimate ET in different regions and land cover types and uses temperature gradient used in the energy balance modeling of SEBAL hence there is no longer a need for absolute surface temperature calibration, which was a significant obstacle to operational satellite ET. Weather-based reference ET to determine energy balance conditions at a "cold" pixel, METRIC deviates from the SEBAL model. This invention creates a ground reference for the satellite-based actual ET estimate and optimizes the usage of current technology in agricultural areas. METRIC is intended to generate high-resolution, precisely scaled maps of ET for locations of interest that are less than a few hundred kilometers. In contrast, certain models of remote sensing are more broadly based and intended for routine use across wide areas(Allen et al., 2007). METRIC offers notable benefits over conventional satellite-based energy balance applications. Firstly, it is calibrated using reference ET instead of the evaporative percentage. Since ET can exceed daily net radiation in many dry or semi-arid locations, using reference ET for the extrapolation of instantaneous ET from periods of 24 hours and longer accounts for regional advection effects by avoiding coupling the evaporative component to net radiation.

METRIC offers a number of important improvements over traditional techniques for predicting ET from crop coefficient curves, including the fact that it does not require knowledge of the particular crop type or crop growth stages. Furthermore, energy balance can identify decreased ET brought on by a lack of water, as a result, ET is typically calculated from satellite data using an energy balance at the surface, where the residual of the surface energy equation is used to calculate the energy consumed during the ET process (McShane et al., 2017).

2.6 Tradition Performance Evaluation

Field measurements, surveys, and data collecting from farmers, irrigation managers, and relevant stakeholders are frequently used in the traditional performance evaluation of an irrigation scheme. The gathered information is examined and contrasted with accepted norms, standards, or best practices in order to pinpoint areas in need of development and direct choices for the irrigation system's sustainable management. The conventional method of evaluating an irrigation system's performance is evaluating many facets of the system's efficiency and usefulness (Yakubov, 2012). Important elements commonly taken into account in the conventional performance assessment of an irrigation plan consist of:

2.6.1 Water Delivery Efficiency

Assessing irrigation water delivery efficiency involves evaluating how effectively water is transported from the source to the fields while minimizing losses. These losses can be categorized into transportation, distribution, and on-farm losses. Transportation losses occur as water moves through canals or pipelines and are often caused by seepage, evaporation, or infrastructure leaks. Distribution losses happen within the irrigation network due to inefficient gate operations, leaks, or design flaws, leading to uneven water allocation. On-farm losses arise from inefficient application methods, such as over-irrigation, deep percolation, and runoff, which can be influenced by the choice of irrigation techniques like flood or drip irrigation. The efficiency of an irrigation system is calculated by comparing the volume of water extracted from the source with the amount that effectively reaches the crops (Bos et al., 2005). A high efficiency percentage indicates minimal water losses, while a lower percentage suggests significant inefficiencies. Assessing water delivery performance is crucial for identifying weaknesses in the irrigation system, improving water conservation efforts, enhancing agricultural productivity, and ensuring sustainable water resource management, particularly in water-scarce regions. By addressing these losses, irrigation managers can optimize water use, reduce waste, and support long-term agricultural sustainability(Mansour et al., 2014).

2.6.2 Soil Moisture Management

Soil moisture management determines whether irrigation schedules are adequate and whether the ideal soil moisture levels are maintained for crop growth. In order to guarantee that irrigation is applied at the appropriate times and in the appropriate amounts, it involves tracking the soil moisture content using soil moisture sensors or field measurements (Raina et al., 2013). Determining the best time and quantity of irrigation to maintain sufficient soil moisture levels for crop growth is known as soil moisture management. The soil water balance equation, sometimes referred to as the water balance approach, is a frequently used formula for predicting soil moisture, however there are many more approaches and formulas available.

2.7 Use of Performance Metrics

Performance indicators are essential for assessing and enhancing irrigation systems' efficiency. Irrigation managers can evaluate the system's performance, identify areas for development, and make well-informed decisions about water management techniques by measuring and analyzing key performance indicators. The following are typical irrigation system performance metrics:

2.7.1 Water Application Efficiency

This indicator assesses how well the irrigation system distributes and delivers water. It is computed by comparing the volume of water that is genuinely absorbed by the crops and the volume of water that is sprayed on the field. Low water application efficiency might be a sign of problems with leaks, evaporation losses, or inappropriate irrigation techniques. An irrigation system's water delivery and distribution efficiency are measured by a performance parameter called water application efficiency (Howell, 2005). It calculates the percentage of water sprayed to the field that gets to the crops' root zone and is absorbed by the plants. A higher water application efficiency reduces losses from evaporation, runoff, and deep percolation and signifies a more economical use of water resources.

2.7.2 Distribution Uniformity

The uniformity of water application throughout the irrigated area is assessed using distribution uniformity. It is ascertained by contrasting the rates of water application at various fields. When water is distributed uniformly, as shown by a high distribution uniformity, crop water requirements are met consistently throughout the field (Contreras et al., 2021). The variance in water application across the irrigated regions can be ascertained using field measures, such as catch-can tests or distribution uniformity assessments, which are used to evaluate uniformity. Watering One technique to assess if plants are receiving the same quantity of water is to look for uniformity. The measurement unit is percentage (%). The efficiency of the irrigation system increases with distribution consistency.

2.7.3 Water Use Efficiency

Water use efficiency (WUE) is a fundamental measure of agricultural productivity, defined as the crop yield obtained per unit of water applied. It serves as an important indicator of how effectively water is utilized in crop production, directly influencing sustainability and food security. WUE can be assessed by calculating irrigation water use in relation to crop yield, which involves measuring crop water requirements, evapotranspiration rates, and the total amount of water applied. It reflects the ability of a cropping system to convert water into plant biomass or grain, making it a crucial factor in irrigation planning and water resource management (Letseku and Grové, 2022). During the growth season, it encompasses both the utilization of water stored in the soil and rainfall. The efficiency of water use in agriculture depends on multiple factors, including soil properties, climate conditions, irrigation methods, and crop selection. Higher WUE values indicate that crops are effectively converting water into yield, while lower values suggest inefficiencies such as excessive water loss through evaporation, runoff, or deep percolation. Improving WUE requires the implementation of best practices such as precision irrigation, conservation tillage, soil moisture monitoring, and the use of drought-resistant crop varieties. These strategies help maximize water retention in the soil and enhance plant water uptake, leading to increased agricultural productivity while conserving water resources. WUE encompasses both rainfall and soil-stored water usage throughout the growing season, ensuring that all sources of water contributing to crop growth are accounted for (Letseku and Grové, 2022). By optimizing WUE, farmers and policymakers can improve irrigation efficiency, reduce water waste, and enhance resilience to drought conditions. This is particularly important in regions where water scarcity is a growing challenge due to climate change and population growth. Ultimately, improving water use efficiency not only supports higher crop yields but also promotes sustainable water management, ensuring long-term agricultural productivity and food security.

2.7.4 Crop Water Productivity

Crop water productivity (CWP) is a critical measure that quantifies the economic output generated per unit of water consumed in crop production. It serves as an essential indicator of how efficiently water is used to maximize agricultural yields, providing valuable insights into water resource management. CWP is particularly significant in areas facing water scarcity, where optimizing water use is crucial for sustaining agricultural productivity. By integrating crop yield with water use efficiency, CWP helps assess the financial return obtained from water resources, guiding policymakers, researchers, and farmers in making informed decisions on irrigation and water allocation strategies (Zwart and Bastiaanssen, 2004). Optimizing crop water productivity is fundamental for achieving sustainable agriculture, as it ensures that water resources are used effectively without excessive waste. This is especially relevant in irrigation schemes where inefficiencies in water distribution can lead to uneven crop growth and suboptimal yields. Enhancing CWP can be achieved through various strategies, such as improving irrigation efficiency, selecting drought-resistant crop varieties, implementing precision agriculture techniques, and adopting water-saving technologies like drip irrigation (Chetankumar Meshram et al., 2024). By employing these methods, farmers can maximize yield while minimizing water losses, ultimately leading to more resilient and sustainable agricultural systems. Furthermore, assessing CWP provides insights into the effectiveness of different water management strategies and their impact on agricultural output. A high CWP value indicates that crops are producing a significant yield relative to the amount of water used, whereas a low CWP suggests inefficiencies in irrigation or poor crop performance. Studies by Zwart & Bastiaanssen (2004) emphasize the importance of improving crop water productivity as a key step toward addressing global food security challenges while conserving vital water resources. As water availability becomes increasingly uncertain due to climate change and population growth, optimizing CWP plays a crucial role in ensuring long-term agricultural sustainability and resilience (Ponce et al., 2016).

2.7.5 Adequacy

Adequacy in agriculture refers to the quantitative aspect of sufficient amount of water that is delivered to meet the crop water use in an irrigation system (M. D. Ahmad et al., 2009). This concept is important for evaluating the water supplied against the water needed for optimal crop growth. In order to assess the adequacy of irrigation water distribution to a designated command area over time various indicators and metrics are used. The Relative Evaporation (RET) is one indicator that is used, which is the water deficit expressed as the ratio of the actual evapotranspiration over the potential evapotranspiration (Bos et al., 2005). RET is used by irrigation managers and planners to assess the performance of the irrigation system and make decisions to optimize water use ensuring that the irrigation practices are in line with the crop water requirements (Unal et al., 2004; Qureshi et al., 2011).

2.7.6 Equity

Equity in irrigation water distribution is a fundamental aspect of irrigation management, ensuring that water resources are allocated fairly and uniformly across an irrigated area. From the perspective of a system manager, equity plays a crucial role in maintaining efficient, reliable, and just water distribution within large-scale irrigation systems (Alam et al., 2014). A well-managed irrigation system should provide adequate water to all farmers, regardless of their geographical location within the scheme, ensuring fair access to water resources to promote sustainable agricultural productivity and food security. Irrigation equity is generally defined as the even allocation of water to all users within a system. This means that no particular section of the irrigated area should experience excessive water supply while another suffers from deficits (Mollinga, 2008). According to David et al., (1990), a system achieves fair equity when there is uniformity in water distribution across the entire irrigated area. In practice, achieving perfect equity is challenging due to factors such as topography, infrastructure design, variations in soil properties, and differences in crop water requirements. Ensuring equity is critical because water shortages in certain areas can lead to reduced yields and economic losses for farmers, while excessive water supply in other areas may lead to waterlogging, soil degradation, and inefficient water use. Poorly distributed water can create disparities among farmers, leading to conflicts over water access and affecting the overall success of an irrigation scheme. Therefore, system managers and policymakers must implement strategies to monitor and improve equity in irrigation water distribution. Several studies have assessed irrigation equity using quantitative methods, with the coefficient of variation (CV) being a widely used metric (Wamala et al., 2023; Kazbekov et al., 2009). The coefficient of variation measures the degree of water distribution variability within an irrigation system, helping to identify inconsistencies in water allocation. A lower CV value indicates higher uniformity, meaning that water is distributed more equitably, while a higher CV value signifies greater disparities in water delivery. To enhance equity, irrigation management practices must focus on improving conveyance efficiency, upgrading infrastructure, and implementing better scheduling techniques to ensure that water reaches all areas as needed. Technologies such as remote sensing, GIS-based monitoring, and real-time flow measurement systems can help track water distribution and identify regions where supply adjustments are necessary. Additionally, participatory irrigation management, where farmers are actively involved in decision-making, can contribute to fairer and more transparent water allocation(Parra-López et al., 2025).

2.7.7 Yield Response to Water

Yield response to water is a crucial concept in agricultural water management, describing the relationship between crop yield and the amount of water available to plants. Water availability directly influences plant growth, development, and productivity (Greaves & Wang, 2017). Crops have different levels of sensitivity to water stress at various growth stages, with critical periods such as flowering and grain filling requiring optimal moisture. The yield response factor (Ky) is commonly used to quantify the impact of water deficit on yield reduction. Higher Ky values indicate that a crop is highly sensitive to water shortages, leading to significant yield losses. Understanding the yield response to water helps in optimizing irrigation scheduling, ensuring that crops receive adequate water at crucial stages while minimizing wastage (Lovelli et al., 2007). The application of precision irrigation, soil moisture monitoring, and crop modeling tools can enhance water use efficiency and maximize yield potential under varying climatic conditions. While it is widely used to optimize irrigation scheduling, one critique is that the approach assumes a linear relationship between water stress and yield loss, which may not hold true for all crops and conditions. Moreover, the method does not account for soil moisture variability and nutrient interactions, which are critical for accurate yield prediction. The yield response to water is represented by the Equation 2.5 (Doorenbos & Kassam, 1979):

$$K_y = \frac{1-\frac{Y}{Y_m}}{1-\frac{ET_a}{ET_m}} \qquad (2.5)$$

Where:

K_y= Yield response factor

Y= Actual yield (kg/ha)

Y_m= Maximum yield (kg/ha)

ET_a= Actual evapotranspiration (mm)

ET_m= Maximum evapotranspiration (mm)

2.7.8 Crop Water Deficit (CWD)

Crop Water deficit (CWD) is basically the insufficient water supply to a plant to meet its physiological and evapotranspiration demands. It is a key factor influencing crop health, growth, and productivity, particularly in arid and semi-arid regions. CWD can be caused by low rainfall, excessive evapotranspiration, or inefficient irrigation practices. Prolonged periods of water deficit can lead to reduced biomass accumulation, lower photosynthetic activity, and yield losses (Salman et al., 2020). Strategies to mitigate CWD include deficit irrigation, drought-resistant crop varieties, and soil moisture conservation techniques such as mulching and cover cropping. Quantifying water deficit through indices like the crop water stress index (CWSI) allows for better decision-making in irrigation planning, ensuring sustainable water use while maintaining agricultural productivity. An average CWD of 30mm/month is accepted as the critical (Bastiaanssen et al., 2002). CWD is defined as follows, in Equation (2.6).

$$CWD = ET_C - ET_a \tag{2.6}$$

CWD is measured using soil moisture sensors, remote sensing techniques, and water balance models. Despite its usefulness in identifying periods of stress, a limitation of CWD is its dependency on accurate ET estimations, which can be affected by climatic and soil variability. Furthermore, CWD alone does not indicate the impact on yield, requiring additional parameters for a comprehensive assessment of crop response.

2.7.9 Relative Water Supply (RWS)

Relative Water Supply (RWS) is an indicator used to evaluate the adequacy of water availability for agricultural production. It is defined as the ratio of total water supply (irrigation and precipitation) to the total crop water requirement, Equation (2.7). An RWS value greater than 1 indicates a surplus water supply, while an RWS value less than 1 suggests water scarcity, which can lead to crop stress and yield reductions (Ayyad et al., 2019). RWS is a valuable metric for assessing irrigation system performance, helping policymakers and water managers make informed decisions on resource allocation. Effective irrigation management aims to maintain an optimal RWS level, ensuring sufficient water for crop growth without excessive application that leads to waterlogging or nutrient leaching (Kang et al., 2009). Advances in remote sensing and hydrological modeling have improved the estimation and monitoring of RWS, supporting sustainable water resource management in agriculture.

$$RWS = \frac{I+P}{ET_c} \tag{2.7}$$

Where:

I= Irrigation water supply (mm)
P= Precipitation (mm)
ET_c= Crop evapotranspiration (mm)

2.7.10 Water Delivery Index (WDI)

The Water Delivery Index (WDI) is a performance indicator that measures the efficiency and equity of water distribution in irrigation systems. It is calculated as the ratio of actual water delivered to the intended or required water supply (Buhshan et al., 2023). A WDI close to 1 signifies efficient water distribution, whereas values significantly lower indicate deficiencies in the irrigation network, such as conveyance losses, uneven distribution, or operational inefficiencies. Factors affecting WDI include infrastructure quality, scheduling accuracy, and system maintenance. Improving WDI is essential for achieving water use efficiency, reducing losses, and ensuring equitable distribution among farmers (Bastiaanssen et al., 2002). Techniques such as canal lining, automated irrigation scheduling, and the use of modern irrigation technologies (e.g., drip or sprinkler systems) can enhance WDI. Monitoring WDI through field measurements and remote sensing enables better water management practices, leading to improved agricultural productivity and sustainability. Although it’s a good indicator, WDI focuses on the volumetric aspect of water delivery without considering water productivity. An irrigation system may have a high WDI but still suffer from poor water use efficiency if excess water is lost to percolation or runoff (Gray, 1982). Additionally, WDI does not account for crop-specific water requirements, making it less effective for precision agriculture applications. WDI is calculated using the Equation (2.8).

$$WDI = \frac{W_d}{W\ r} \tag{2.8}$$

Where:

W_d= Actual water delivered (m³)

W_r= Required water supply (m³)

2.8 WaPOR Use in Irrigation Assessment

The FAO's WaPOR (Water Productivity through Open access of Remotely sensed derived data) is an open access portal that provides important understanding of irrigation assessment by offering high-resolution real-time data on hydrological and agriculture parameters (Chukalla et al., 2022). It performs its purpose through utilizing remote sensing technology to provide data on spatial distribution of ETa, biomass and water productivity which are crucial for evaluating the sustainability and efficiency. WaPOR is also important in the assessment of irrigation performance indicators of adequacy, equity and efficiency. Equity in its definition is the fair allocation of water assessed through the spatial distribution of Eta (Pates and Pauly, 2023). Adequacy is estimated by comparing the ETa to crop water requirements wherein efficiency is estimated through the water productivity which is basically a ratio of the biomass produced to water consumed. WaPOR also facilitates the monitoring of water productivity at different scales, from farm to basin level, allowing farm managers and policy makers to identify inefficient water use, optimize irrigation schedules and provide policies that are sustainable. WaPOR data also works as a tool for early drought detection by analyzing areas of water stress(Veysi et al., 2024). Ultimately, WaPOR enhances irrigation assessment by providing reliable data for efficient water management, equitable distribution, and sustainable agricultural practices, contributing to food security and water conservation.

2.9 Summary of Literature Review and Research Gap

The literature review highlights the significance of accurate estimation of crop water requirements and evapotranspiration (ET) in irrigation performance assessment. Traditional methods for estimating crop water requirements rely on field-based measurements, which are often time-consuming, expensive, and subject to errors due to spatial variability. Remote sensing techniques, particularly the Surface Energy Balance Algorithm for Land (SEBAL) and Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC), have emerged as effective tools for estimating ET over large agricultural areas. These models integrate satellite imagery with meteorological data to provide spatially distributed ET estimates, which are crucial for assessing irrigation performance.

One of the major challenges in irrigation performance assessment is the availability of accurate and timely data. Many irrigation schemes, particularly in developing countries, lack adequate monitoring infrastructure, leading to difficulties in assessing water distribution efficiency. The research gap identified in this study is the limited application of remote sensing techniques in assessing irrigation performance in Eswatini. While SEBAL and METRIC have been widely used in other regions, their application in Eswatini remains unexplored. This study seeks to bridge this gap by utilizing satellite-derived ET estimates to evaluate irrigation adequacy, crop water deficit, equity and water productivity, comparing them with WaPOR database estimations, and providing recommendations for improved water management practices.

2.10 Conceptual Framework

Figure 2.2 presents the conceptual framework of this research work, showing the relationship between actual evapotranspiration (ET) estimation, irrigation performance, and comparative analysis with remote sensing data with the aim of enhancing irrigation scheduling and water use efficiency.

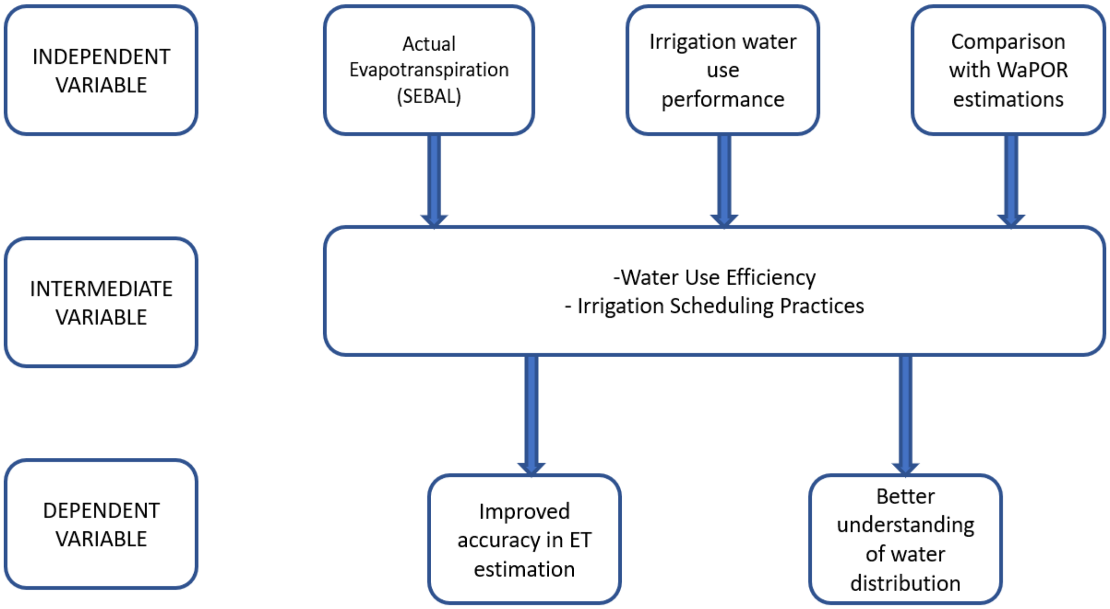

Figure 2.2: Conceptual Framework

CHAPTER THREE

MATERIALS AND METHODS

3.1 Study Area

Eswatini is a landlocked southern African country measuring 17200 Km^2, with a population of 1,252,392 inhabitants (Doyle, 2023). It borders Mozambique from the North and South Africa from almost the entirety of the country. The country has four main climatic zones: the Lubombo Plateau, the Highveld, the middleveld, and the Lowveld. Ubombo Sugar Estate (USE) is the second largest sugarcane farm in Eswatini. This irrigation scheme is located on the eastern part in an area called Big-Bend (Nkilongo) in the Lowveld, on longitude 31° 55' east and latitude 26° 49' south as shown in Figure 3.1. The scheme currently sits on a total area of 234.18 km^2 while 116,48 km^2 of the total scheme area is under sugarcane farming. The remaining part is made up of infrastructure including buildings, roads, dams, canals and the sugar mill that crashes approximately 12000 tons per day of sugarcane. The Lowveld region is the hottest region with an average of 400 to 600 mm annual rainfall between October and March, which is the major rainy season (Davis-Reddy et al., 2017). High temperatures (up to 40°C) and droughts are also common in this region, which raises the demand for irrigation water and occasionally causes unanticipated irrigation reservoir decline. The Great Usuthu River provides the farm with its water, which is subsequently redirected into the farm through 39 km gravity canal that runs across it. The farm uses sprinkler, center pivot, furrow and drip irrigation systems for water distribution at farm level.

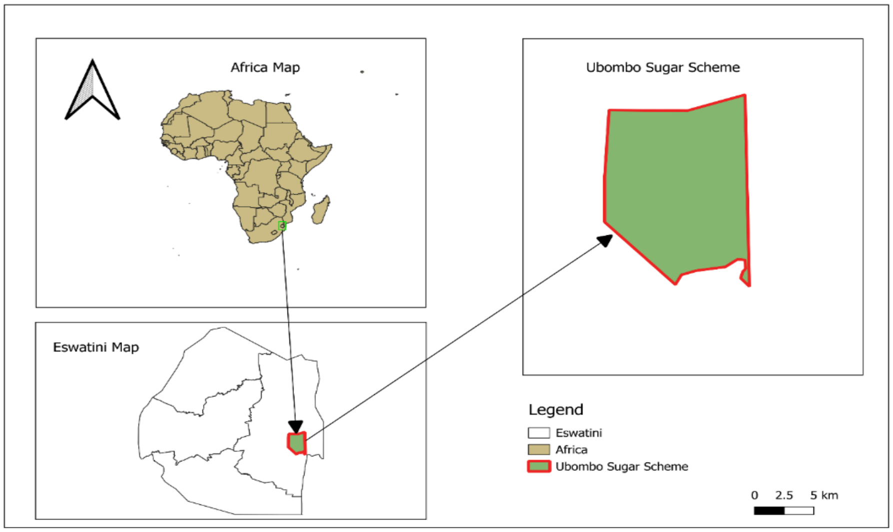

Figure 3.1: Location of Ubombo Sugar Scheme, Eswatini

3.2 Actual Evapotranspiration (ET_a) Assessment Using the SEBAL Model

The SEBAL model, which essentially calculates a complete radiation and energy balance together with the resistances for momentum, heat, and water vapor transport for each pixel, was used to determine evapotranspiration (Bastiaanssen et al., 1998). Evapotranspiration was computed in terms of instantaneous latent energy (LE) (Wm^{-2}) and was defined as the residual of the surface energy balance equation at the time of satellite overpass, pixel by pixel, as presented in Equation (3.1). This method adopted in this study was informed by Awan et al, (2011) who employed SEBAL to estimate actual and potential evapotranspiration in a given time frame.

$$LE = R_n - G - H \tag{3.1}$$

Where:

R_n = net radiation (Wm^{-2}),
G = soil heat flux (Wm^{-2})
H = sensible heat flux (Wm^{-2})

To compute the net radiation, the following equation was used:

$$R_n = (1 - \alpha)R_{sin} + \varepsilon * R_{Lin} - \varepsilon * \sigma * T_s^4 \tag{3.2}$$

Where:

α = the surface albedo,
R_{Sin}= the incoming short wave solar radiation (Wm^{-2}),
R_{Lin}= the incoming longwave radiation (Wm^{-2}),
ε = the surface emissivity ranges from 0 to 1,
σ = the Stefan-Boltzmann constant ($W/K^2 . K^4$),
T_s = the surface temperature (K).

Using an empirical relation function with net radiation and a few additional surface characteristics, including albedo, the normalized difference vegetation index (NDVI), and surface temperature, the soil heat flux G was calculated as shown in Equation (3.3):

$$\frac{G}{R_n} = \frac{T_s}{\alpha}(0.0038\alpha + 0.0074\alpha^2)(1 - 0.98NDVI^4) \tag{3.3}$$

Sensible heat flux H is a function of the temperature gradient, surface roughness and wind speed hence were calculated using Equation (3.4):

$$H = \rho C_P \frac{dT}{r_{ah}} \tag{3.4}$$

Where:

ρ = the air density (kgm^{-3}) which is a function of atmospheric pressure,

C_p = the specific heat capacity of air (≈1004 J kg^{-1}K^{-1}),

dT = the near surface temperature difference (K),

r_{ah} = the aerodynamic resistance to heat transport (sm^{-1}).

LE is a residual factor in the energy budget that determines the instantaneous evaporative fraction, Λ and was calculated using Equation (3.5) given as:

$$\Lambda = \frac{LE}{LE+H} = \frac{LE}{Rn-G} \qquad (3.5)$$

The instantaneous evaporative fraction (Λ) represents the ratio of crop evaporative demand to atmospheric moisture conditions in equilibrium with soil moisture and was used to calculated the daily ET_{24} (mmd^{-1}) using the evaporative fraction from H, G, LE, and Rn (Bastiaanssen et al., 1998) as shown in Equation (3.6):

$$ET_{24} = \frac{86400\Lambda(Rn-G)}{LE} \qquad (3.6)$$

The principal processing of SEBAL model is presented in Figure 3.2 where remote sensed imagery serves as an input.

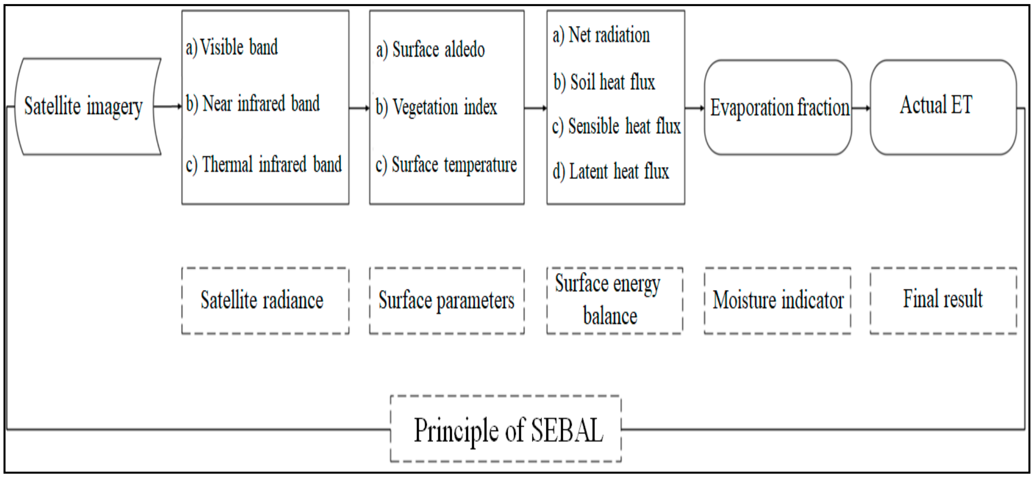

Figure 3.2: Components of SEBAL Model

3.3 Data Collection

3.3.1 Satellite Imagery

Landsat 8 (OLI) satellite images were downloaded from the USGS Earth Explorer. To accommodate 3 sugarcane growing seasons. The images were downloaded for the period between 2017-2020. Landsat 8 was chosen because of its high resolution and freely available datasets as shown in Table 3.1 Landsat sensors have improved from ETM+ to OLI, enabling the use of applications that need narrower, finer bands. The PySEBAL model was also run using a Digital Elevation Model (DEM), which provides data on the elevation of the area of interest.

Table 3.1: Landsat-8 OLI and TIRS Bands

Bands	**Wavelength (µm)**
Band 1- 30m Coastal/ Aerosol	0.435 - 0.451
Band 2- 30m Blue	0.452 - 0.512
Band 3- 30m Green	0.533 - 0.590
Band 4- 30m Red	0.636 - 0.673
Band 5- 30m Near Infrared (NIR)	0.851 - 0.871
Band 6- 30m SWIR-1	1.566 - 1.651
Band 7- 30m SWIR-2	2.107 - 2.294
Band 8- 15m Panchromatic	0.503 - 0.676
Band 9- 30m Cirrus	1.363 - 1.384
Band 10- 100m Thermal Infrared (TIRS) 1	10.60 - 11.19
Band 11- 100m Thermal Infrared (TIRS) 2	11.50-12.51

3.3.2 Meteorological Data

The daily and instantaneous meteorological data for surface temperature, relative humidity, wind speed and incoming solar radiation was downloaded from Global Land Data Assimilation System (GLDAS) for the period between 2017 and 2020. GLDAS data has a spatial resolution of 100 km and 3 hourly and monthly temporal resolutions making it suitable for hydrology, agriculture and climate studies. GLDAS provides wind speed at 10m and for the Penman-Monteith method to calculate evapotranspiration, wind speed must be measured at a height of two meters. As a result, the wind speed obtained from GLDAS needed to be adjusted for the height of measurement. As indicated, the wind speed was adjusted for the measurement height using Equation (3.7) (Allen et al., 1998):

$$U_{2m} = U_z \frac{4.87}{\ln(67.8z \times 5.42)} \tag{3.7}$$

Where:

U_{2m} = Wind speed at 2m (m/s)

U_z= Wind speed measured at z m above ground surface (m/s)

Z = Height measurement above ground surface (m)

3.3.3 Soil Hydraulic Properties

Soil hydraulic properties were obtained from HiHydroSoil v2.0, a database that provides essential soil information for environmental studies and serves as a crucial input for geospatial models. HiHydroSoil offers datasets with a spatial resolution of 250 meters, enabling detailed assessments of soil characteristics relevant to hydrological and agricultural applications. These datasets support various studies, including irrigation management, water resource modeling, and soil moisture estimation, making HiHydroSoil a valuable resource for geospatial analysis and environmental research.

3.3.4 Data Screening

The GLDAS meteorological data parameters were compared against ground data for evaluation of their accuracy and reliability. This comparison aimed to determine how well GLDAS represents actual on-ground weather conditions and identify any discrepancies. The meteorological data such as temperature, humidity, wind speed, and solar radiation were analyzed for correlation with ground station data from two weather stations (Ngogo, Sivunga) situated about 50km from the scheme. Assessing these differences helps validate the use of GLDAS data for applications such as evapotranspiration modeling, irrigation planning, and climate analysis, ensuring its suitability for hydrological and agricultural studies. This was accomplished by creating graphical representations of the data for every parameter and calculating the Mean Absolute Percentage Error (MAPE), for each satellite and ground data parameter. When comparing the ground data from the weather station with the GLDAS data, the MAPE was computed with the following Equation (3.8):

$$M = \frac{100}{n} \sum \frac{At - Ft}{At} * 100 \tag{3.8}$$

Where:

At = actual value (ground data)

Ft= forecast value (GLDAS data >0)

The calculated MAPE values to ground and GLDAS data were described based on the ranges given in Table 3.2.

Table 3.2: Interpretation of MAPE values

MAPE	Interpretation
<10	Very good
10-20	Good
20-50	Fair
>50	Inaccurate

Source: Montaño Moreno et al. (2013)

3.3.5 Tools and Methods

The calculation of evapotranspiration, which was later utilized to evaluate the performance indicators, was performed using pySEBAL version 3.7.3 with Landsat satellite imagery. This version of SEBAL enhances the traditional SEBAL model by integrating Python-based algorithms for improved automation and computational efficiency. One of its primary characteristics is the automatic selection of extreme surface conditions using a population of hot and cold pixels, which helps in the precise estimation of energy fluxes and ET. By combining SEBAL equations with Python, pySEBAL streamlines the processing of large-scale remote sensing data, making it an effective tool for assessing water use efficiency in irrigated agricultural systems. To further enhance data visualization and spatial analysis, QGIS was employed for image processing and map generation, enabling the creation of spatially explicit representations of irrigation performance across the study region. These maps provided valuable insights into variations in evapotranspiration, highlighting areas with potential inefficiencies in water distribution and utilization. The datasets used in this study, along with their respective sources, are summarized in Table 3.2, providing a clear overview of the information utilized for evapotranspiration calculations and irrigation performance assessment.

Table 3.3: Datasets Summary

Datasets	**Function of dataset**	**Source**
Satellite imagery		
Landsat 8	PySEBAL input	USGS (earthexplorer.usgs.gov)
DEM	PySEBAL input	USGS (earthexplorer.usgs.gov)
Meteorological Data		
Relative humidity	PySEBAL input	USGS (earthexplorer.usgs.gov)
Air temperature	PySEBAL input	USGS (earthexplorer.usgs.gov)
Wind speed	PySEBAL input	USGS (earthexplorer.usgs.gov)
Shortwave radiation	PySEBAL input	USGS (earthexplorer.usgs.gov)
Soil Hydraulic Properties		
Saturated water content	PySEBAL input	HiHydroSoil
Residual water content	PySEBAL input	HiHydroSoil
Field capacity	PySEBAL input	HiHydroSoil
Wilting point	PySEBAL input	HiHydroSoil

3.4 Determination of irrigation water use performance.

3.4.1 Determination of Adequacy

The Relative Evaporation (RET) was used for this research which is basically an indicator of water deficit expressed as the ratio of the actual evapotranspiration over the potential evapotranspiration, as shown in Equation (3.9), the ratio is dimensionless (Bos et al., 2005).

$$Adequacy\ (RET) = \frac{ETa}{ETp} \tag{3.9}$$

During the growing season, RET ≥ 0.75 is the accepted value for irrigated agriculture although this value may vary over time. RET varies with the different crop phenological stages and the agriculture yield is linked to the RET (Roerink et al., 1997; Elnmer et al., 2018).

3.4.2 Determination of Equity

Equity was estimated by calculating the coefficient of variation (CV) of ET_a as shown in Equation (3.10) (Rowshon et al., 2014). Similar methodology in assessing the equity of irrigation systems using the CV of ETa was reported by Akhtar et al., (2018) .Good equity is defined as having a CV of 0.0 - 0.10, fair equity as having a CV of 0.10 – 0.25, and poor equity as having a CV > 0.25 (David et al., 1990; Wamala et al., 2023).

$$Equity(CV) = \frac{Standard\ deviation\ of\ ETa\ (\sigma)}{Mean\ of\ ETa\ (\mu)} \tag{3.10}$$

3.4.3 Determination of Water Productivity

Efficiency in agriculture can be assessed using the water productivity (Scheierling et al., 2016). Water productivity basically is defined as the ratio of biomass accumulated (in Kilograms) to water consumed (in cubic meter), see Equation (3.11). The calculation of WP was done on QGIS raster calculator by using the following equation.

$$WP = \frac{B}{ET_a} \tag{3.11}$$

Where:

B= biomass produced (kg)

ETa= Actual evapotranspiration

The source of the biomass produced is solar radiation, specifically the portion used for photosynthesis, also called Absorbed Photosynthetically Active Radiation (APAR). Satellite data is used to calculate the net solar radiation which in turn is used to estimate the NDVI which reflects plant activity (Gitelson et al., 2015). The biomass is then modelled using the Light Use Efficiency (LUE) model, Equation (3.12).

$$\text{Biomass} = \text{APAR} \times \text{LUE} \qquad (3.12)$$

Where:

Biomass= Above-Ground Biomass Production (kg/ha/day)
APAR= Absorbed Photosynthetically Active Radiation (MJ/m^2/day)
LUE= Light Use Efficiency (kg/MJ/ha.m^2)

3.4.4 Determination of Crop Water Deficit

The crop water deficit was determined using Equation (2.6), with an acceptable CWD of 30 mm/ month. The methodology adopted for determining CWD was informed by a study conducted by Asaana and Sadick. (2016). Daily ETa and ETc data were acquired from the pySEBAL output on evapotranspiration.

In summary, the irrigation performance analysis flow chart as shown in Figure 3.3 was used.

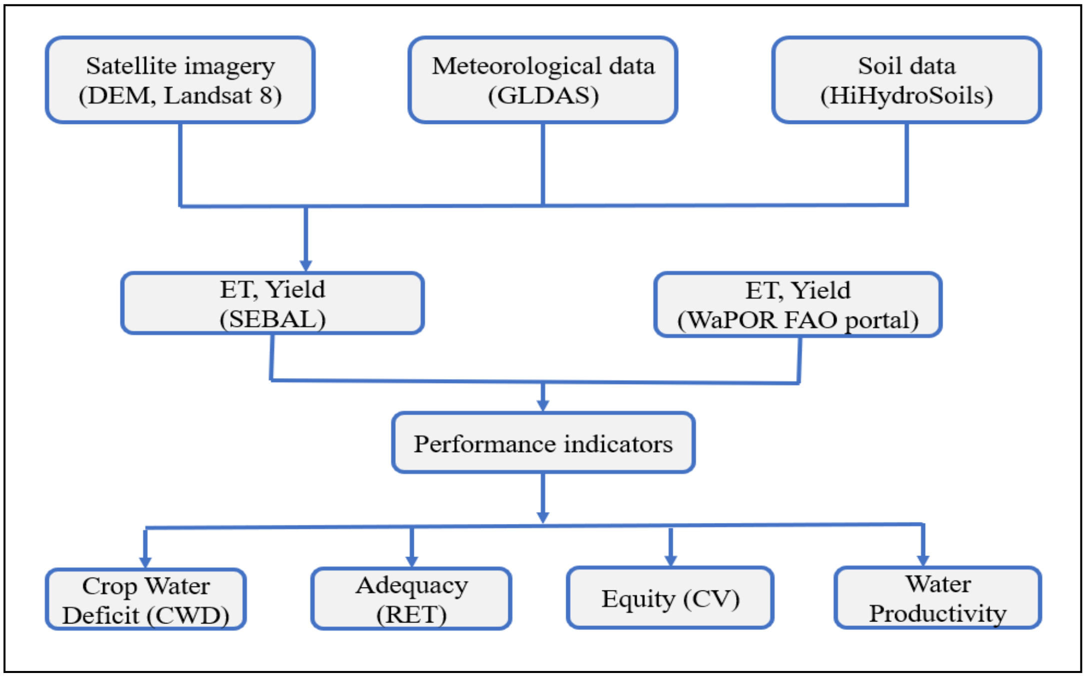

Figure 3.3: Flow Chart for Determining Irrigation Performance Analysis

3.5 Comparison of ETa and irrigation water use performance from SEBAL with WaPOR estimation

3.5.1 WaPOR Data Estimates

This study also utilized the WaPOR (Water Productivity through Open access of Remotely sensed derived data) database, developed by the Food and Agriculture Organization (FAO), which employs satellite-based remote sensing to monitor and assess water productivity in agriculture across Africa and the Near East. The database provides near-real-time datasets at three spatial resolutions: Level 1 (continental scale, 250 m resolution), Level 2 (country scale, 100 m resolution), and Level 3 (project scale, 30 m resolution). For this study, WaPOR Version 2.1 datasets at the country scale (Level 2, 100 m resolution) were used for evapotranspiration (ET) estimation due to its improved data quality and enhanced spatial and temporal consistency. The methodology involved data acquisition from the WaPOR online portal, data extraction for the study area, re-projection and resampling to ensure spatial consistency, and application of cloud and noise filtering techniques. The actual ET was estimated using the AETI (Actual Evapotranspiration and Interception) layer from WaPOR, followed by spatial analysis, temporal aggregation of monthly and seasonal ET values, and validation through comparison with in-situ measurements or other remote sensing datasets. The estimated ET values were analyzed to assess spatial and temporal variations in water use across different agricultural zones and integrated with other hydrological and climatic datasets to evaluate water productivity trends. The results were visualized using QGIS to generate maps and statistical summaries. This methodology ensures a robust estimation of ET using WaPOR Level 2 datasets, contributing to better water resource management and policy development through improved understanding of water use efficiency in agriculture.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Actual Evapotranspiration (ETa) Assessment Using the SEBAL Model

4.1.1 Meteorological Data Screening

4.1.1.1 Temperature

The results of the monthly GLDAS and average ground temperature data is presented in Table 4.1:

Table 4.1: Average Monthly Temperature Data (2002-2022)

Temperature (Celsius)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
GLDAS	22.3	21.5	22.5	21.5	22.1	20.3	19.7	20.0	22.6	21.8	22.5	23.1
Ground	27.5	27.3	26.5	24.0	22.7	21.3	20.1	20.5	22.6	23.9	25.2	26.9

The observed ground data and GLDAS values compared using Mean Absolute Percentage Error (MAPE) value for the average monthly temperature was 9.27%. The temperature data's accuracy was comparatively very good, according to this MAPE rating, Table 3.2. This level of error is consistent with previous studies that have reported varying degrees of accuracy in satellite-derived temperature data. A study by Zhang et al. (2019) indicated that satellite-derived temperature estimates often exhibit a MAPE ranging from 5% to 15%, suggesting that our findings are within the expected range. The accuracy of GLDAS temperature data can be influenced by several factors, including the spatial resolution of the models and the quality of the input data. Given that temperature is a critical variable for numerous applications, including agriculture and climate modeling, the observed error underscores the necessity for continuous refinement of data assimilation techniques (Ji et al., 2015). Future research could benefit from exploring localized calibration methods to enhance the precision of GLDAS temperature estimates. A comparison between the station's monthly temperature data and the values downloaded from GLDAS over the period 2002 to 2022 is shown in Figure 4.1.

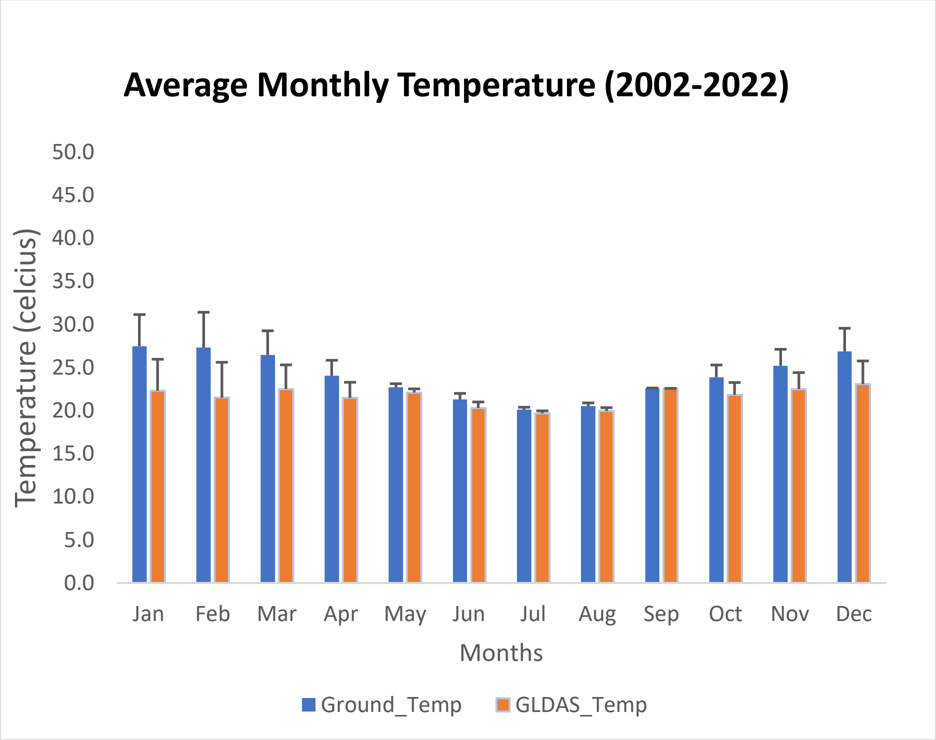

Figure 4.1: Average Monthly Temperature (2002-2022)

4.1.1.2 Radiation

The average monthly solar radiation over the period 2002 to 2022 was computed and is tabulated as shown in Table 4.2:

Table 4.2: Average Monthly Solar Radiation Data (2002-2022)

Radiation (MJ/d)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
GLDAS	22.0	21.6	21.0	18.1	14.8	13.2	15.9	15.5	18.5	20.3	20.8	21.4
Ground	21.3	19.2	18.9	14.2	12.6	10.9	11.5	13.4	15.5	17.5	18.7	20.1

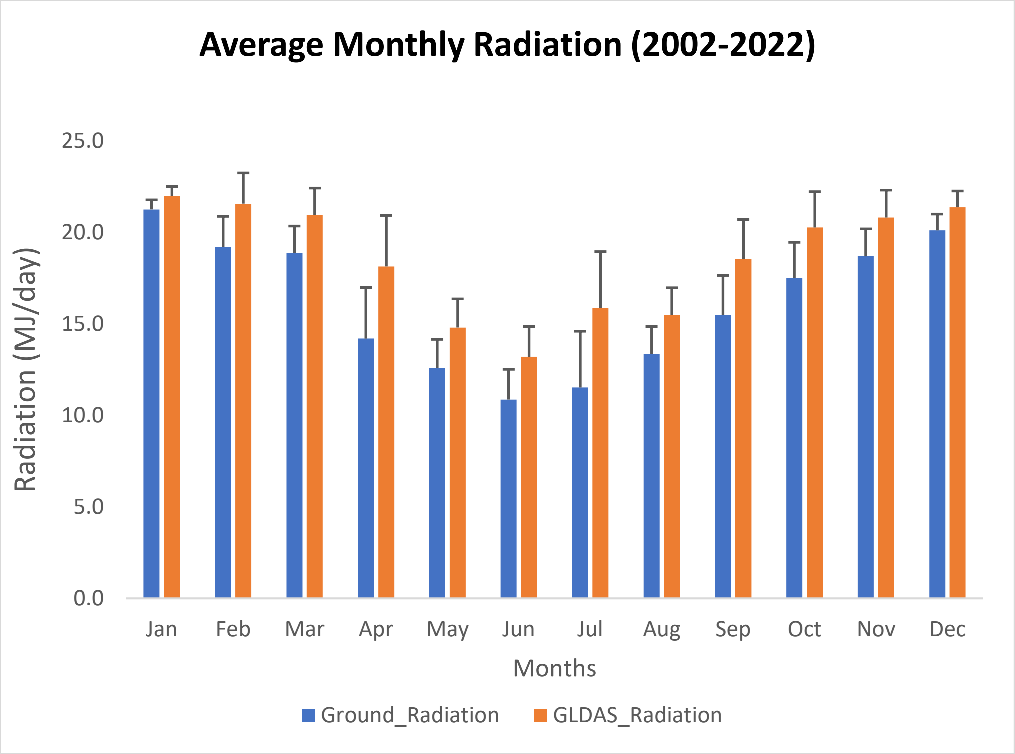

Figure 4.2: Average Monthly Solar Radiation (2002-2022)

The solar radiation measurements, representing how accurately the secondary data is close to ground surface radiation yielded a MAPE value of 16.7%. According to MAPE Classification by Montaño Moreno et al. (2013) this fall within the category considered to be good. This value is notably higher than the error observed for temperature, suggesting a more significant deviation between GLDAS outputs and ground observations in this parameter. This discrepancy may be attributed to the challenges inherent in accurately modeling solar radiation, which is influenced by multiple factors including atmospheric conditions, surface albedo, and geographical features (Müller et al., 2019). Existing literature indicates that satellite-derived radiation estimates often suffer from biases due to cloud cover and atmospheric scattering, which can lead to substantial errors (Li et al., 2021). The implications of these findings are critical for applications reliant on precise radiation data, such as agriculture, where inaccuracies can lead to poor decision-making. Though the extreme values for the GLDAS data were somewhat overextended in comparison to the station data, Figure 4.2 demonstrates that the data sets were following the same pattern.

4.1.1.3 Relative Humidity

Table 4.3 presents the average monthly data for humidity for the period 2002 to 2022:

Table 4.3: Average Monthly Relative Humidity Data (2002-2022)

Month/RH (%)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
GLDAS	70.5	61.6	71.1	60.8	69.5	58.3	68.7	59.9	69.1	61.5	73.0	65.6
Ground	65.5	68.4	67.3	68.9	66.6	65.4	62.5	61.7	61.7	63.5	65.1	66.4

The comparison of average monthly relative humidity between GLDAS and ground data from 2002 to 2022 shows noticeable variations across months, Figure 4.3. The MAPE for relative humidity was the lowest among the variables studied, at 7.6% classified as very good. This value for relative humidity reflects a relatively high level of accuracy in GLDAS data compared to the other parameters assessed. This finding aligns with previous research indicating that humidity estimates from remote sensing tend to exhibit lower biases than temperature or radiation (Soebiyanto et al., 2014). The success of GLDAS in capturing relative humidity can be attributed to its incorporation of various observational datasets, which enhance the reliability of moisture estimates. However, while this level of accuracy is encouraging, it is essential to recognize that relative humidity is often a critical variable in climate modeling and hydrological studies (Qi et al., 2015). Therefore, ongoing validation against ground data is necessary to ensure that these estimates remain robust under varying climatic conditions (Gruber et al., 2020).

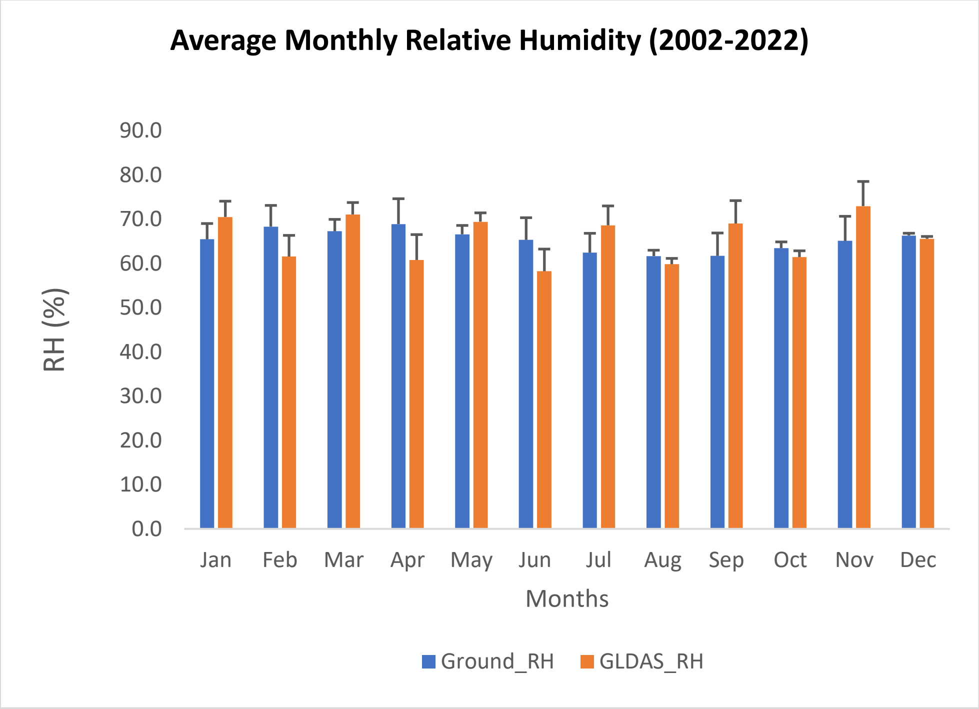

Figure 4.3 Average Monthly Relative Humidity (2002-2022)

4.1.1.4 Wind speed

Table 4.4 presents the average monthly data for wind speed:

Table 4.4: Average Monthly Wind Speed (2002-2022)

Wind speed (km/d)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
GLDAS	136.6	126.4	95.4	81.0	62.2	65.6	75.8	111.5	133.4	133.3	135.4	160.3
Ground	111.0	102.8	77.6	65.8	48.6	50.5	65.9	97.0	116.0	121.2	123.1	112.1

A comparison was made between the ground data and the GLDAS wind speed data. The GLDAS wind speed data shows higher values on the average monthly wind speed graph (Figure 4.4). The MAPE for wind speed was notably high at 21.5% and fall on the category fair in the MAPE classification index, indicating significant discrepancies between GLDAS data and ground measurements. This finding is consistent with previous research that has identified wind speed as a challenging variable to accurately model using remote sensing techniques (Shin et al., 2020). Factors contributing to the high error could include the coarse spatial resolution of GLDAS data and the dynamic nature of wind patterns, which can vary considerably over short distances. The implications of this high error margin are profound, particularly for applications in meteorology and renewable energy, where accurate wind speed data is essential for forecasting and operational planning (Han et al., 2020). Future studies should prioritize the development of high-resolution wind models that can better capture localized wind phenomena, potentially integrating data from ground-based networks to improve the accuracy of GLDAS outputs.

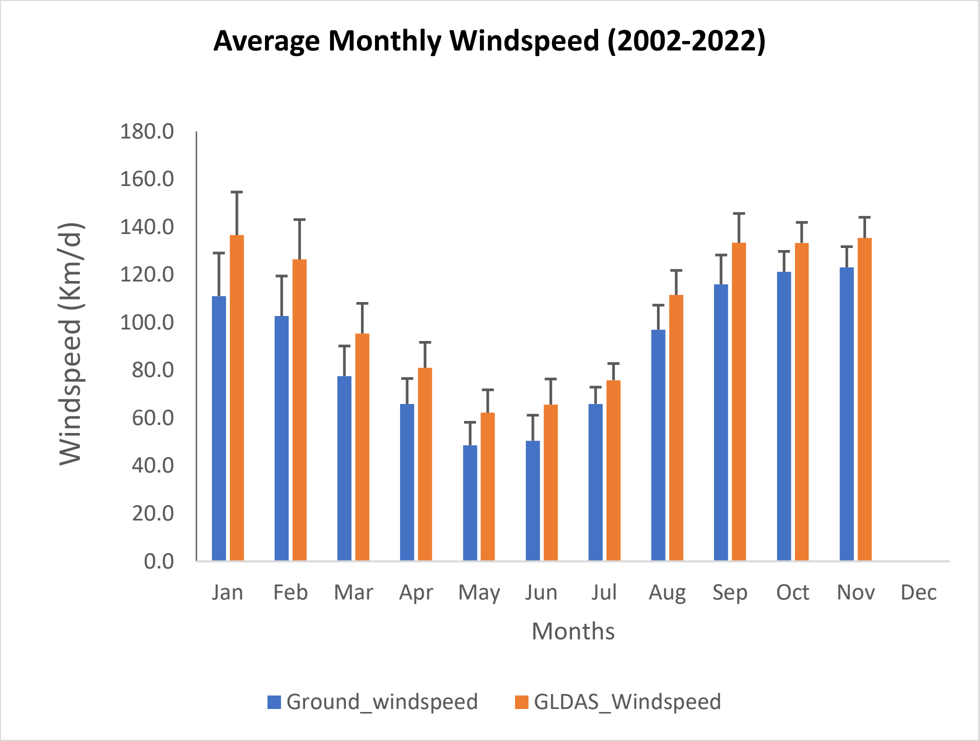

Figure 4.4: Average Monthly Wind Speed (2002-2022)

Weather parameters sensitivity on reference evapotranspiration were tested in a study by (Irmak et al., 2006). According to their research, ET was more susceptible to changes in relative humidity and wind speed. The same study also found that the sensitivity coefficient was comparatively larger in the summer than in the winter. However, in a different study, Sharifi & Dinpashoh (2014) found that reference ET was most sensitive to the daily mean temperature. Porter et al. (2012) also reported high sensitivity of reference ET to weather parameters, particularly wind speed and air temperature. According to Porter et al. (2012), the computed ET showed significant sensitivity to these parameters during the mid-summer period in the semi-arid region of Texas. While no sensitivity analysis has been conducted in Eswatini, it is assumed that the findings would be similar to those recorded in other semi-arid regions, such as the area where the Ubombo Sugar scheme is located. The findings indicate that GLDAS can provide valuable data for temperature and relative humidity, even though the higher error margins for radiation and wind speed call for further investigation and methodological improvements.

4.1.2 Actual Evapotranspiration

Table 4.5: Annual SEBAL Evapotranspiration

Year	Min ETa (mm)	Max ETa (mm)	Mean ETa (mm)	Std.dev (mm)	CV(ET)
2017	752	1504	1128	135	0.12
2018	824	1373	1099	130	0.12
2019	791	1702	1247	181	0.15
2020	591	1478	1035	166	0.16

The seasonal actual and potential evapotranspiration for the Ubombo Sugar Irrigation Scheme was estimated for the four seasons and the results were as presented in Table 4.5. The Figure (4.5) shows the spatial distribution of the ETa values for the years 2017 to 2020 signifying variations in both minimum and maximum values. In 2017, the maximum ETa recorded was 1504 mm, the highest across all four years, while the minimum was 752 mm, suggesting that this year experienced a relatively wide range of evapotranspiration. The mean ETa was 1128 mm, and the standard deviation was 135 mm, indicating moderate variability. In 2018, the maximum ETa was 1373 mm, and the minimum peaked significantly to 824 mm, the highest recorded across the years. The mean ETa decreased to 1098 mm, and the standard deviation increased to 153 mm, suggesting higher variability in ETa across different locations or time periods. For 2019, the maximum ETa was higher at 1702 mm, while the minimum decreased to 535 mm, indicating variation compared to previous years. The mean ETa remained relatively high at 1187 mm, and the standard deviation was the lowest at 1130 mm, showing more uniformity in ETa values. In 2020, the maximum ETa continued to decrease to 1478 mm, and the minimum was 591 mm, similar to 2017. The mean ETa declined further to 1035 mm, while the standard deviation was 166 mm. The variability observed in these findings is consistent with the work of Zhang et al. (2020), who reported similar interannual changes in ETa attributed to variations in meteorological conditions, land cover changes, and water management practices. The ability to accurately estimate ETa can significantly enhance water resource management, agricultural planning, and environmental monitoring (Bastiaanssen et al., 1998). Hellegers et al. (2010) also indicated that sugarcane producers in South Africa's Inkomati Basin have the potential to significantly enhance their water productivity by capping seasonal water use at 1200 mm and minimizing non-productive water losses through improved irrigation management strategies. As a result, the SEBAL-derived ETa indicates that the irrigation system operates within the optimal range for maximizing water use efficiency.

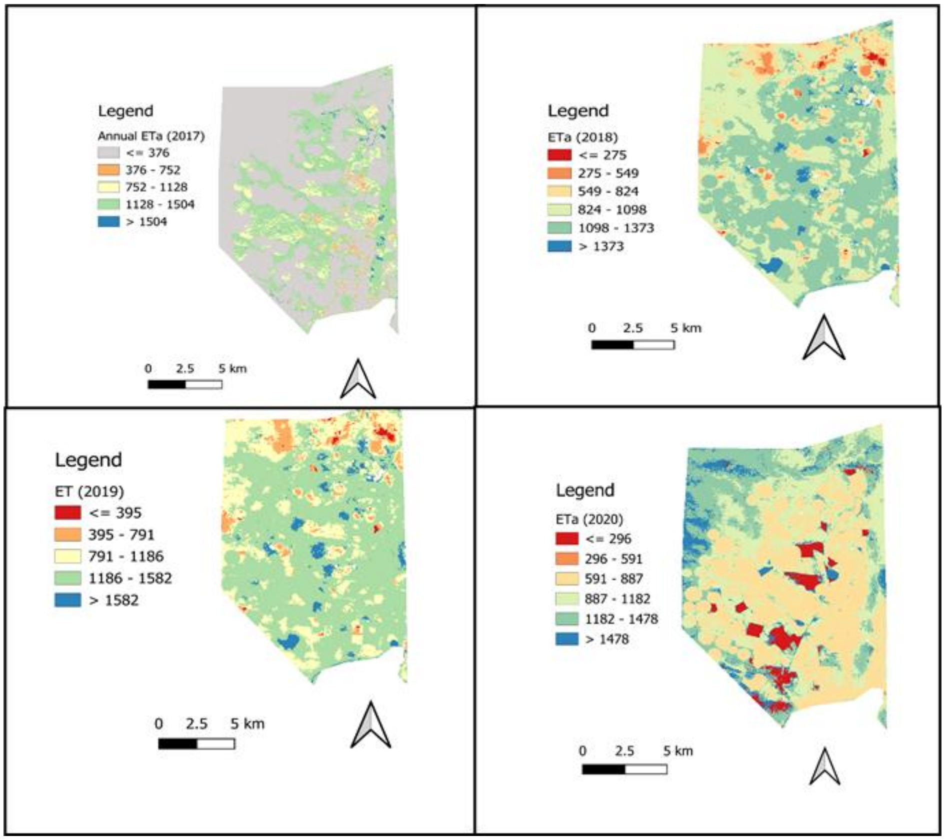

Figure 4.5: Spatial Distribution of Seasonal ETa 2017-2022

4.2 Irrigation Water Use Performance

4.2.1 Equity

This indicator was used to examine the spatial variability of ET, expressed as the coefficient of variation (CV) of seasonal ET. A higher CV indicates greater variability, while a lower CV reflects more consistency in ETa values across the scheme. The results of equity are shown in Table 4.5, presenting 2020 as the year with the highest CV at 0.16, meaning that ETa had the greatest relative variability this year. This variability can be interpreted as a reflection of either uneven water distribution or fluctuating climatic conditions, both of which are critical factors affecting irrigation performance (K.M.P.S.Bandara, 2006). The high standard deviation 166 mm supports this observation. In contrast, 2017 and 2018 had the lowest CV at 0.12, indicating the most stable ETa patterns compared to other years. The standard deviation was also lowest during this period with 135 and 130 respectively further confirming that the variation in ETa was minimal, making this year relatively more uniform in water use and evapotranspiration. The CV value for 2019 (0.15) was moderate, and also recorded the highest maximum ETa of 1702 during, although the minimum was the second largest, this year suggests that there was a huge variation in the ET. The increase in CV from 2017 to 2020 suggests a worrying trend towards greater inequity in water distribution over time, which could have implications for agricultural productivity and sustainability. The observed high CV in 2020 suggests that the spatial distribution of evapotranspiration was significantly uneven, potentially due to factors such as inconsistent water supply or fluctuations in climatic conditions. Studies by Allen et al. (1998) and Tóth et al. (2022) have reported similar variability in ET, , who noted that CV values exceeding 0.15 often indicate challenges in water resource management and distribution equity. This observed trends in equity suggest that stakeholders and policymakers must prioritize the implementation of precision irrigation technologies and practices. These approaches can help to mitigate the effects of variability by providing tailored irrigation solutions that account for the specific needs of different areas within the irrigation scheme (Samreen et al., 2023).

4.2.2 Adequacy

The results for adequacy are summarized and presented in Table 4.6:

Table 4.6: Summary of adequacy results

Year	ETa (mm)	ETc (mm)	CWD (mm)	RET
2017	1128	1282	154	0.88
2018	1098	1292	194	0.85
2019	1187	1364	177	0.87
2020	1035	1125	90	0.92

The RET values derived from SEBAL range from 0.85 to 0.92, as shown in Table 4.6, reflecting variations in climatic and surface conditions over the years. The scheme had an adequate water supply overall, as indicated by the average RET of 0.88, which was higher than the 0.75 criterion

(Wamala et al., 2023) . In 2020, the highest RET value of 0.92 suggests conditions that were more favorable for evapotranspiration. This could be attributed to factors such as higher solar radiation, increased air temperature, lower humidity, or stronger winds, which all contribute to a greater atmospheric demand for water. The lowest RET value of 0.85, observed in 2018, may indicate relatively cooler temperatures, lower solar radiation, or other climatic conditions that resulted in reduced evapotranspiration. Reduced wind speeds and higher relative humidity during this period may have also played a role in lowering atmospheric water demand. The results are similar to those by Akhtar et al. (2018) when measuring adequacy in Kabul River Basin, Afghanistan. Moreover, shifts in land management practices, such as changes in irrigation scheduling or crop cover, might have contributed to variations in RET. Understanding these fluctuations is crucial for improving water resource management and optimizing agricultural productivity under changing climatic conditions.

4.2.3 Crop Water Deficit (CWD)

The CWD values for the period between (2017-2020) show notable variations, Table 4.6. In 2017, the CWD was 154 mm, indicating a moderate level of water deficit. The highest CWD was recorded in 2018 at 194 mm, suggesting significant water stress during that year. In 2019, the CWD slightly decreased to 177 mm, still reflecting a considerable deficit. However, in 2020, the CWD dropped significantly to 90 mm, marking the lowest water stress among the recorded years. The implications of maintaining a low CWD are significant for agricultural sustainability. A CWD of 90 mm, as recorded in 2020, not only reflects reduced water stress but also suggests enhanced irrigation practices that could lead to improved crop yields and resource conservation (Usman et al., 2020). Studies have shown that effective water management can lead to higher agricultural productivity, increased resilience to climate variability, and better soil health (Asaana & Sadick, 2016). By ensuring that CWD values remain well within the accepted limit of 360 mm annually, farmers can optimize water usage, thereby reducing operational costs and minimizing environmental impacts.

4.2.4 Water Productivity (WP)

The water productivity distribution from 2017 to 2020, Figure 4.6, shows significant variations in both magnitude and spatial patterns. In 2017, biomass values were relatively high, with most areas falling within the range of 15-37 kg/m^3. The distribution appeared patchy, suggesting localized variations in productivity. By 2018, biomass values became more evenly spread, with the highest category exceeding 29 kg/m^3. However, in 2019, biomass values peaked significantly, with a maximum category exceeding 164, highlighting a year of high productivity. The spatial distribution was more uniform, with many areas experiencing high biomass accumulation (18-36 kg/m^3). In contrast, 2020 saw a sharp decline, with the highest category dropping to just above 81. The majority of biomass values fell within the 4–17 kg/m^3 range, indicating a reduction in vegetation or productivity. This decrease from 2019 to 2020 suggests the influence of environmental factors such as drought. The benefits of achieving high water productivity values are multifaceted. Enhanced WP not only contributes to increased crop yields but also promotes sustainable water resource management, which is increasingly vital in the face of global climate change and water scarcity (Biswas et al., 2025). A study conducted in the Gharb region of Morocco assessed sugarcane's water requirements and water use efficiency under drip irrigation. The results indicated that applying 5,000 m^3/ha of water, equivalent to 67% of the crop's evapotranspiration, was sufficient to optimize WUE, achieving values between 132 to 157 kg of stems per hectare per millimeter of water (equivalent to 13.2 to 15.7 kg/m^3) (Aabad et al., 2016). This approach not only saved about 50% of the irrigation volume compared to traditional methods but also nearly doubled stem yields and increased sugar yields from 8 to 23 tons per hectare. Likewise, Hellegers et al., (2010) suggested that sugarcane farmers along the Inkomati basin in South Africa can significantly increase water productivity by limiting the seasonal consumption at 1200 mm as well as through reducing the non-beneficial losses by adopting efficient irrigation water management practices.

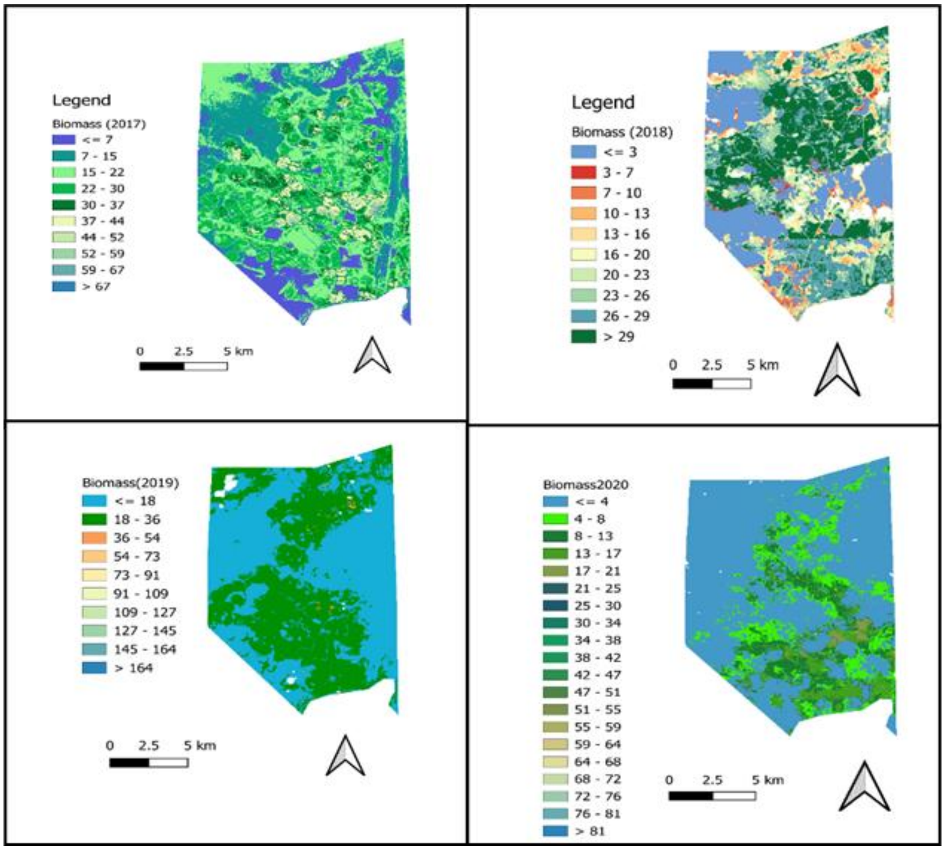

Figure 4.6: Spatial variation of water productivity

4.3 Comparison of the SEBAL output with WaPOR estimations

4.3.1 Actual Evapotranspiration

The results of actual evapotranspiration from the WaPOR data were tabulated as shown in Table 4.7:

Table 4.7: Annual WaPOR evapotranspiration data

Year	Min ETa (mm)	Max ETa (mm)	Mean ETa (mm)	Std.dev (mm)	CV(ET)
2017	345	1737	1041	294	0.28
2018	315	1836	1076	349	0.32
2019	388	1772	1080	276	0.26
2020	552	1755	1154	201	0.17

The ETa for WaPOR data is presented in Table 4.7, which provides annual values of actual evapotranspiration (ETa) from 2017 to 2020, highlighting the minimum, maximum, mean, and standard deviation of ETa values. The spatial representation of ETa (Figure 4.7) offers critical insights into regional water use patterns. Areas showing higher ETa values may indicate regions with vegetation cover requiring substantial water inputs, while lower values may point to either arid zones or effective water management practices. This spatial analysis is consistent with results by Mendicino et al. (2012) who emphasized the importance of localized ET assessments for enhancing irrigation strategies and water resource management. The minimum ETa values fluctuate across the years, with the lowest recorded in 2018 (315 mm) and the highest in 2020 (552 mm). Similarly, the maximum ETa values range between 1,737 mm in 2017 and 1,836 mm in 2018, indicating variations in peak water use across different years. The mean ETa values follow a similar trend, showing a slight increase from 2017 (1,041 mm) to 2020 (1,154 mm), suggesting overall consistency in evapotranspiration patterns. However, variations in the standard deviation reflect the extent of dispersion in ETa values, with the highest standard deviation recorded in 2018 (349 mm), indicating greater variability, while the lowest standard deviation in 2020 (201 mm) suggests a more uniform distribution. These variations in ETa values could be attributed to changes in climatic conditions and irrigation practices. This may reflect broader climatic changes, such as increasing temperatures, which have been documented in numerous studies (IPCC, 2019). The link between rising temperatures and increased evapotranspiration is well established in the literature, as higher temperatures can enhance the rate of evaporation from soil and plant surfaces (Koster et al., 2010). Therefore, this upward trend in mean ETa suggests an urgent need for adaptive water management strategies that account for increasing water demands. Policymakers and agricultural farm managers can utilize these insights to optimize irrigation practices, ensuring that water resources are allocated efficiently and sustainably. The variability in ETa also emphasizes the necessity for tailored irrigation approaches that consider specific climatic conditions and crop requirements, as highlighted by Fereres and Soriano. (2007).

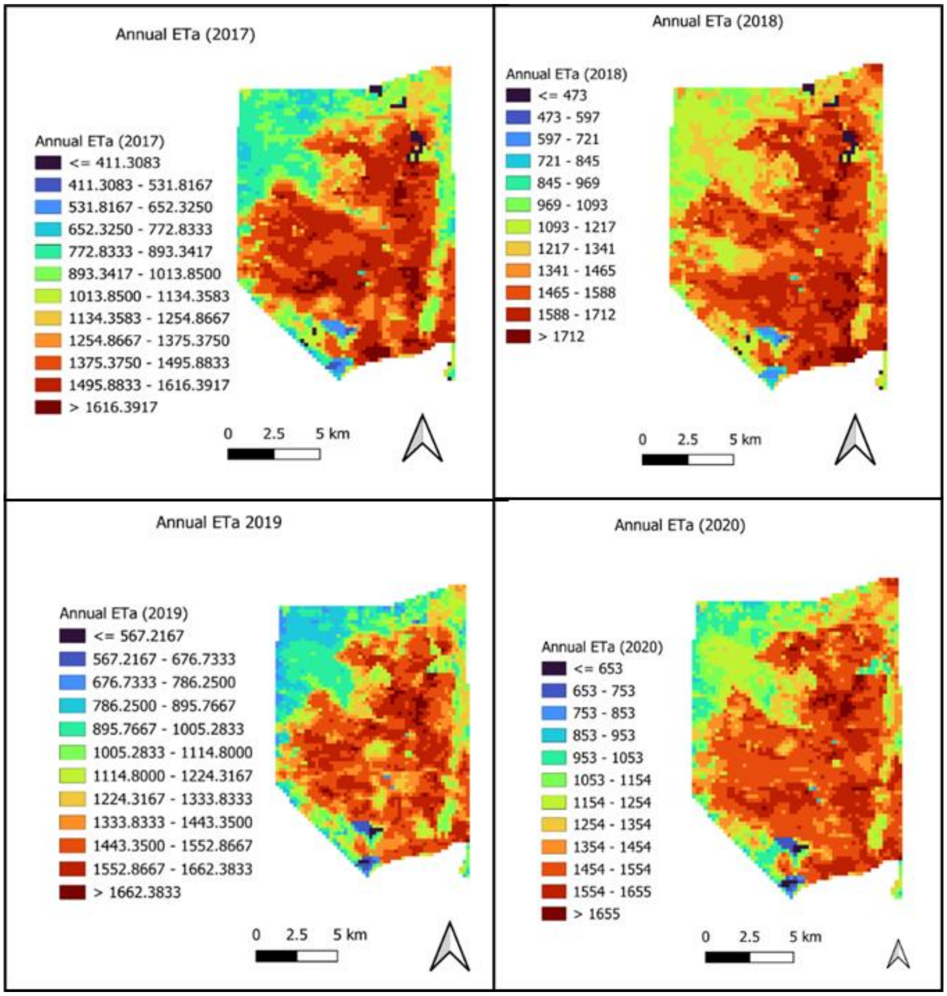

Figure 4.7: Spatial distribution of seasonal ETa 2017-2020

4.3.2 Irrigation Water Use Performance

4.3.2.1 Equity

The CV for WaPOR data was also calculated, as shown in Table 4.7 above. A lower CV for ET indicates minimal variation, suggesting better irrigation water distribution across the field. The CV value ranges from 0 to 1, representing a percentage of variation from 0 to 100%. The CV for WaPOR data was above 0.25 which generally categorized as poor equity, in 2018, for example, the CV is the highest at 0.32, implying significant fluctuations in ETa values for that year. This could be due to varying climatic conditions or inconsistent water availability. Similarly, 2017 also shows relatively high variability with a CV of 0.28, suggesting notable differences in ETa values within that year. In contrast, 2019 and 2020 exhibit lower CV values of 0.26 and 0.17, respectively. The results are similar to a study in Doho Rice Irrigation Scheme, assessing the hydraulic performance evaluation of the water conveyance system by Bwambale et al. (2019). The declining CV over time though does suggests that ETa values became more stable in later years, possibly due to improved water management or more consistent rainfall. The notably low CV in 2020 (0.17) indicates that ETa values were more evenly distributed, reflecting lower variability in water use. The results indicate a significant variation in ETa values, particularly in the years 2017 and 2018, where CV values reached 0.28 and 0.32, respectively. These figures suggest poor equity in irrigation water distribution, which aligns with existing literature that emphasizes the importance of equitable water distribution for sustainable agricultural practices (Sánchez et al., 2015; Zuniga-Teran et al., 2021) .

4.3.2.2 Adequacy

The adequacy, which was calculated using the RET, for the study period was presented in the table below, showing the different adequacy across the irrigation scheme.

Table 4.8: Annual relative evapotranspiration data

Year	ETa	ETc	CWD	RET
2017	1041	1301	260	0.8
2018	1076	1312	236	0.82
2019	1080	1333	253	0.81
2020	1154	1374	220	0.84

As shown in Table 4.8, the RET values derived from the WaPOR dataset range from 0.80 to 0.84, indicating relatively small interannual variations over the study period. The highest RET value (0.84) recorded in 2020 suggests that this year experienced slightly higher atmospheric water demand. This could be attributed to multiple climatic and environmental factors, such as increased temperatures, reduced cloud cover, or seasonal variations in vegetation cover and soil moisture availability. A rise in temperature typically enhances the evaporative demand, while lower cloud cover allows more solar radiation to reach the surface, further driving evapotranspiration (Wang et al., 2023). Additionally, changes in vegetation dynamics, such as variations in crop cycles or forest cover, could have influenced the RET values by altering transpiration rates. Contrary, the lowest RET value (0.80) recorded in 2017 may indicate a year with slightly lower energy availability for evapotranspiration. This could be associated with cooler temperatures, increased cloudiness, or higher soil moisture levels that reduce evaporative demand. Increased precipitation in that year might have also played a role by limiting the need for water uptake from vegetation, thereby affecting overall evapotranspiration rates. Kharrou et al. (2011) stated that under the actual distribution rules, if equity and adequacy of the water delivery are not achieved and the irrigation schedules lead to the variability observed and poorly affect the crop yields. Although the RET values are above the threshold of 0.75, in a counter study Kharrou et al. (2013) argued that crops tend to use available water efficiently despite being under stress. Despite these variations, the relatively narrow range of RET values suggests a stable climatic pattern with minor fluctuations in atmospheric water demand across the analyzed years.

4.3.2.3 Crop Water Deficit

As shown in Table 4.8, the CWD values for the period between (2017-2020) differ for each year. In 2017, the CWD was the highest for the period at 260 mm, indicating a high level of water deficit. The CWD value decreased for the 2018 year to 236mm, suggesting significant less water stress during that year. In 2019, the CWD increased to 253 mm, still reflecting a considerable deficit. However, in 2020, the CWD dropped significantly to 220 mm, marking the lowest water stress among the recorded years. The implications of these results extend to equity considerations within agricultural water management. As water scarcity becomes an increasingly pressing issue, understanding CWD dynamics can inform equitable distribution of water resources, ensuring that vulnerable farming communities are not disproportionately affected by water deficits (Ringler et al., 2016). However, if we are for a deficit of 1mm/day then the CWD is within the accepted limit (Bastiaanssen et al., 2002), but there is still for improvement considering that some values are really close to the allowable deficit value.

4.3.2.4 Water productivity

The water productivity (WP) maps Figure 4.7, show noticeable variations across different years, with productivity values categorized into specific ranges. In 2017, WP values range was mostly concentrated in the 12-24 kg/m^3, suggesting limited efficiency. In 2018, the WP range shifts to ≤12 to >59 kg/m^3, showing a slight decrease in the upper threshold but an overall improvement in distribution, with more regions exhibiting higher productivity (13-19 kg/m^3). By 2019, the WP range further narrows to ≤6 to >33, indicating a significant drop in maximum productivity.

However, productivity appears more evenly distributed across the area, with moderate values (11–17 kg/m^3) dominating. In 2020, the WP range remains ≤6 to >23 kg/m^3, marking the lowest productivity levels observed across the four years. The WP values predominantly ranged between 12-24 kg/m³, suggesting a relatively low efficiency in water use. This aligns with previous studies indicating that water productivity in many regions of Sub-Saharan Africa often falls below optimal levels due to inadequate irrigation practices and inefficient water usage (Molden et al., 2010). The continuous decline in maximum WP values from 2017 to 2020 suggests a reduction in overall water use efficiency, potentially due to climate variability, shifts in irrigation practices. The stark decline in 2020, with a maximum WP of just 23 kg/m^3, raises concerns about agricultural sustainability and highlights the need for enhanced water management strategies to counteract declining productivity trends. The benefits of improving WP for sugarcane cultivation could yield substantial economic returns while simultaneously addressing water scarcity issues. Enhanced WP not only increases crop yields but also reduces the water footprint of sugarcane production, thereby contributing to more sustainable agricultural practices (Olivier and Singels, 2015).

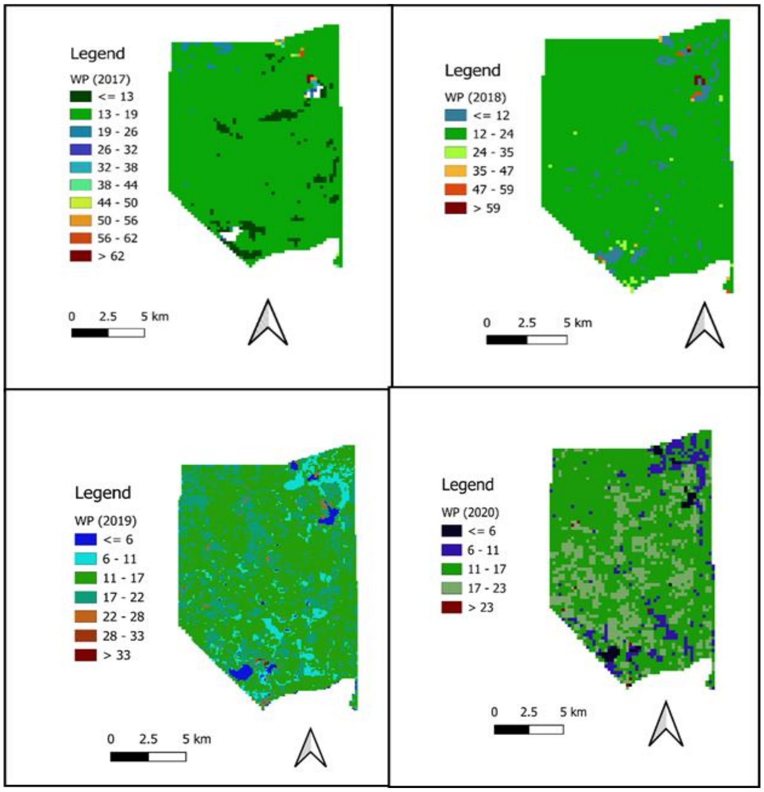

Figure 4.8: Spatial variation of water productivity

4.3.3 Comparison of SEBAL to WaPOR

The data from the two sources was tabulated and compared in Table

Table 4.9: Comparison of SEBAL and WaPOR

	Year	RET	CWD	ETa	CV
SEBAL	2017	0.88	154	1282	0.12
	2018	0.85	194	1292	0.12
	2019	0.87	177	1364	0.15
	2020	0.92	90	1125	0.16
WaPOR	2017	0.8	260	1041	0.28
	2018	0.82	236	1076	0.32
	2019	0.81	253	1080	0.26
	2020	0.84	220	1154	0.17

The data in Table 4.9 presents the data from the two sources, SEBAL and WaPOR. A comparison was done on these sources in terms of RET, CWD, ETa and CV over a period between 2017 to 2020. An analysis reveals differences between the two datasets. SEBAL consistently reports higher RET values, ranging from 0.85 to 0.92, compared to WaPOR's lower range of 0.8 to 0.84. This suggests that SEBAL estimates higher potential evapotranspiration rates, which might indicate more favorable climatic or environmental conditions for water availability. The CWD from SEBAL reports significantly lower values than WaPOR across all years. For instance, in 2017, SEBAL estimates a CWD of 154, while WaPOR reports a much higher value of 260. This trend persists throughout the period, with SEBAL showing a consistent decline in CWD from 154 in 2017 to just 90 in 2020. In contrast, WaPOR's CWD values remain high and vary between 220 and 260 without a clear downward trend. These differences could reflect variations in how the two models assess water stress or crop water needs under similar conditions. The same happens with the ETa, where SEBAL again reports higher values than WaPOR each year, suggesting that it estimates greater actual water use by crops or vegetation. SEBAL's ETa ranges from 1125 to 1364, peaking in 2019 before declining sharply to its lowest value in 2020. WaPOR's ETa values are consistently lower, ranging from 1041 to 1154, with a gradual increase over time. Finally, the CV highlights variability within the datasets. SEBAL shows lower CV values (0.12–0.16), indicating less variability in its estimates compared to WaPOR's higher CV range (0.17–0.32). WaPOR exhibits greater variability overall, with its highest CV value of 0.32 occurring in 2018 before decreasing to 0.17 in 2020. These differences suggest that SEBAL generally provides more optimistic estimates of water availability and lower variability across metrics compared to WaPOR, which reflects greater water deficits and variability over the same period. These discrepancies could be attributed to the spatial resolution of both model and although SEBAL estimates are better than WaPOR improvement should be done on the input datasets. The better performance of SEBAL can be attributed to its integration of various environmental parameters, including land surface temperature and vegetation indices, which are critical in accurately assessing evapotranspiration rates. Previous studies corroborate this observation; for instance, Allen et al. (1998) highlighted the importance of incorporating multiple data sources to enhance the precision of water requirement estimations.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATION

5.1 Conclusions

The following are the conclusions from this study:

1) The study estimated ETa using SEBAL, revealing variations in water consumption across the irrigation scheme. The results highlighted spatial and temporal differences in ETa, which could be influenced by factors such as climatic conditions and irrigation practices. The analysis confirmed that SEBAL is an effective tool for monitoring ETa, providing valuable insights into water use patterns within the study area.

2) The irrigation performance was evaluated by analyzing water distribution within the scheme. The results indicated that some areas received more water than required, while others experienced water deficits, leading to inefficiencies in irrigation water allocation. The variability in ETa suggested inconsistencies in water delivery, emphasizing the need for improved irrigation scheduling and management strategies to ensure fair and sufficient water distribution across the scheme.

3) The comparison between SEBAL-derived ETa and WaPOR estimations showed both similarities and differences in the evapotranspiration values. SEBAL estimate had better CV of the ETa compared to the WaPOR estimates which averaged 0.14 and 0.26 respectively across the period of study. The RET was above 75% for both models, which is the acceptable standard but still SEBAL had better RET compared to the WaPOR data. The water productivity was higher for SEBAL with an average of 26 kg/m3 and WaPOR had an average of 14.5 kg/m3. The CWD average for SEBAL was also lower at 154mm compared to WaPOR at 254mm. The analysis demonstrated that SEBAL can be better in estimating crop water requirements than WaPOR although WaPOR data can still be a useful alternative for large-scale irrigation monitoring, but site-specific calibrations may be required for greater accuracy and reliability.

5.2 Recommendations

The following are the recommendations:

1) Stakeholders in agriculture and water management should establish data validation frameworks to ensure that satellite-based datasets like GLDAS are reliable for local decision-making, particularly in irrigation planning and climate adaptation.
2) Comprehensive study is needed to compare GLDAS and WaPOR estimates with ground data, with a specific focus on different irrigation systems, such as those used in the Ubombo Sugar Scheme, to improve accuracy and applicability in agricultural planning.

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