VALIDATION OF FAO-FRAME REMOTE SENSING BASED AGRICULTURAL WATER PRODUCTIVITY ESTIMATES IN THE UPPER AWASH RIVER BASIN, ETHIOPIA

TEMESGEN BEDANE TESHITE

February, 2018

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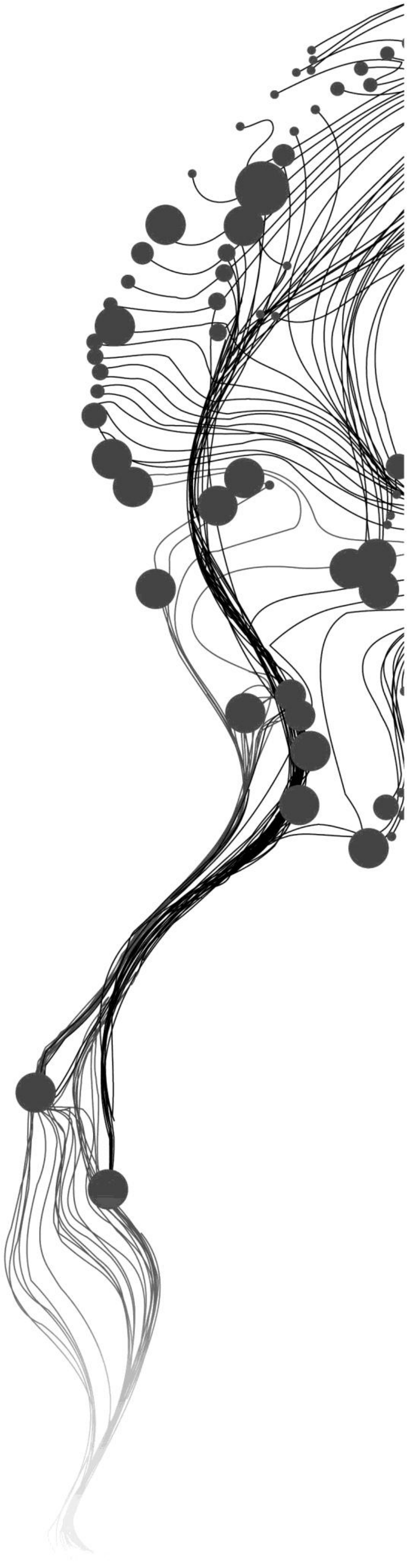

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Enschede, The Netherlands, February, 2018

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
Specialization: Water Resource and Environmental Management

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ABSTRACT

Increased demand for food due to the rapid growth of population coupled with fierce competition from other sectors and uncertainty in climate change, has put tremendous pressure on agricultural water. To meet food demands for the coming generations, the agricultural sector needs to use its water resource more efficiently. To meet this challenge, the production per unit water consumed, the crop water productivity needs to be improved. To improve agricultural water use efficiency, FAO is developing a remote sensing tool (FRAME) at three different spatial levels; level -I (250m), level – II (100m) and level – III (30m) to monitor agricultural water productivity for sustainable improvement of agricultural production.

This study evaluated level –III (30m) water productivity data components of FRAME by comparing it with AquaCrop model output and in-situ data based on case study of Wonji sugarcane plantation. AquaCrop model was applied using 30 plots selected from the study area. The plot by plot comparison of FRAME with in-situ data for sugarcane yield (AGB) gave RMSE (ton/ha) ranging from 2.97 to 24.12. While in terms of R^2 it ranges from 0.03 to 0.99. Further comparison of FRAME with model revealed RMSE (ton/ha) ranging from 3.55 to 22.87 and R^2 from 0 to 0.99. The analysis revealed that AGB estimated by FRAME has consistently under estimated in reference to in-situ data and model output. The overall average of seasonal AET over 30 plots estimated by FRAME and model is 1686 mm and 915 mm respectively with RMSE (mm/season) of 842. Analysis of dekadal time step between FRAME and model did not give significant correlation for both AET and AGB. The water productivity in terms of AGB computed from FRAME is 1.43 – 3.46 kg/m3 while the model estimate gave 2.49 – 5.39 kg/m3. As expected, the WP estimated from FRAME is lower than the model estimate.

It is discussed that lack of sufficient data for reliable calibration of the model was a limitation in this study and therefore recommendations are proposed including the need for more measured data, evaluation of FRAME in short growing cycle crop (rain-fed agriculture), and the need for further integration of remote sensing with AquaCrop for model calibration.

Key words: water productivity, FAO, FRAME, remote sensing, AGB, AET, AquaCrop

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

AET	*Actual Evapotranspiration*
AGB	*Above Ground Biomass*
DMP	*Dry Matter Production*
ET	*Evapotranspiration*
FAO	*Food and Agriculture Organization of the United Nations*
FRAME	*Consortium consisting of eLEAF, VITO, ITC and the Waterwatch Foundation*
HI	*Harvest Index*
NDVI	*Normalised Difference Vegetation Index*
NPP	*Net Primary Productivity*
PAR	*Photosynthetically Active Radiation*
Pbias	*Percent bias*
RMSE	*Root Mean Squared Error*
RS	*Remote Sensing*
Tr	*Transpiration*
WaPOR	*FAO portal to monitor Water Productivity through Open access of Remotely sensed*
WP	*water productivity*

1. INTRODUCTION

1.1. Background and problem definition

The population of the world is expected to reach 7.9 billion, more than 80% of whom will live in developing countries (UN, 2015). This growth in population coupled with the expected rise in living standards will put a significant degree of stress on available water resources (Rijsberman, 2006). A major challenge for the coming years is to provide a secure food supply for future generations given that majority of populations in developing countries are already undernourished (Zwart et al., 2010). Agricultural sector, the single highest consumer of planet's accessible fresh water (Clay, 2004), is facing enormous pressures from increasing demand for food, fierce competitions from other sectors and uncertainties due to climate change resulting in situations where the agriculture sector is unlikely to be allocated more water in the coming years (Zwart et al., 2010). Thus in such conditions increasing agricultural water productivity, a key indicator for evaluating agricultural water management (Wesseling & Feddes, 2006), is required to produce more food per drop to meet food demands for the coming generations.

Agricultural water productivity is defined as the ratio of crop yield per unit of water consumption by evapotranspiration (Molden et al., 2010). In order to improve the performance of agricultural water use we need to understand the quantity, distributions and patterns of water productivity over a given area. In most cases, water productivity is assessed at plot or field level or determined from secondary crop yield and water use data, however actual evapotranspiration may be unknown and measurements may not well represent spatial variation (Bastiaanssen et al., 2000). This calls for development of new technologies for better water productivity to guarantee food security in the future. Recent advancements in earth observation techniques offer estimations of crop patterns, evapotranspiration, biomass, and yield accumulation both at greater spatial coverage and spatial detail at a regular time interval (Cai et al., 2009). Remote sensing based assessment of water productivity helps us to pinpoint areas of higher and lower water productivity and analyze the reasons for variability and assess the potentials for improvement through scientific research.

To this end, FAO-FRAME is recently developing a publicly accessible database of biomass, actual evapotranspiration, water productivity and other datasets mainly derived from remote sensing covering Africa and the Middle East at spatial resolutions of 250 m (level - I), 100 m (level - II) and 30 m (level - III) starting from the year 2009. The aim is to help monitoring of water productivity, identifying water productivity gaps, proposing solutions to reduce these gaps and contributing to sustainable improvement of agricultural production (FAO, 2017). If the reliability and accuracy of these datasets is considered acceptable, it will greatly help water managers, agronomists, farmers and all other concerned bodies in making decisions on the best management practices according to practical situations and further improve sustainability in agricultural production. However, despite advancements in remote sensing there exist uncertainties and errors in those derived data sets mainly resulting from algorithms used for deriving biomass and actual evapotranspiration (AET), key variables used for water productivity (WP) estimation. As a result assessment of the level of the accuracy of those data sets is important.

Given the above background, the main goal of this study is to evaluate level -3 (30 m resolution) FRAME data components that are used for estimating water productivity using AquaCrop model (model based validation) together with data gathered from the field. The study focused on Wonji sugar cane plantation located in Upper Awash basin of Ethiopia, one of the validation sites of FRAME (level -3).

1.2. Objective

The overall objective of this study is to validate the FAO-FRAME remote sensing based WP data components using AquaCrop model simulation and in-situ data. To achieve this, the following specific objectives were executed;

- To calibrate and validate AquaCrop model based on in-situ data
- To compare FRAME estimate of AGB with actual field data
- To compare FRAME estimate of AGB, AET and WP with AquaCrop model estimate

1.3. Research question

The main research question of this study is:

- How well FRAME remote sensing based WP data components are correlated with in-situ data and AquaCrop model estimate?

2. LITERATURE REVIEW

2.1. Agricultural water productibity (WP)

The concept of water productivity in agricultural production system is based on "more crop per drop", a key term in evaluation of agricultural water use and in its broader sense defined as the value or benefit obtained from the use of water (Kijne et al., 2003; Oweis et al., 2010). It is a useful tool when comparing the productivity of water in different parts of the basin and also when comparing the productivity of water in agriculture with other competing sectors (Zwart & Bastiaanssen, 2004). In the context of this study it is defined as kilograms of yield (or dry biomass) produced per unit of m^3 water lost by evapotranspiration (equation2-1).

$$WP = \frac{Y}{AET} \; (kg/m3) \text{ ----------------------------- } (2\text{-}1)$$

Where Y is the actual crop yield (kg/ha) and AET is the sum of water lost by soil evaporation and crop transpiration during the crop cycle (m3/ha). One can consider that crop water production is derived by transpiration only (i.e. only transpired water is used in a productive way). As the partitioning of evapotranspiration into crop transpiration and soil evaporation (which does not directly contribute to crop production) is difficult, defining crop WP in terms of evapotranspiration makes practical sense (Zwart & Bastiaanssen, 2004). WP can be affected by several factors, such as crop cultivar type, water availability and climate, soil characteristics and management practices (Ali & Talukder, 2008).

Indicative WP values of various crops around the world was first compiled by (Doorenbos & Kassam, 1979) and published on FAO drainage paper 33. More recently Steduto et al. (2012) have published WP values of various crops on FAO drainage paper 66 based on their review of the result of field experimental measurements reported in international literature. It has been reported that the recent WP values of most crops are higher than those of 1970's, this was attributed to the development of improved crop varieties that are able to produce higher yields, drought and pest/disease resistant crops, improved soil fertility and land water management practices.

2.2. Remote sensig of water productivity

Over the past decades advancements in remote sensing and development of quantitative algorithms for converting raw data from sensor into useful information has greatly contributed to water resources research and applications especially in the agricultural sector (Schultz & Engman, 2000). The potential use of satellite data is of great importance for obtaining reliable and accurate, real time information on physical land surface processes especially over vast agricultural lands (Bastiaanssen et al., 2000). The derivation of remotely sensed WP on the first hand requires conversion of remotely sensed spectral radiances into energy fluxes and estimation of crop parameters (biomass and yield). And once those two parameters are derived, WP can then be easily estimated by using equation (2-1). Energy balance algorithms such as SEBAL(Bastiaanssen et al., 2000), SEBS (Su, 2002), METRIC (Allen et al., 2007) and ETLook (Bastiaanssen et al., 2012) can be used to derive AET from satellite images. ETLOOK is an algorithm used by FRAME project for calculation of AET. The details of the algorithm are not presented here as it is beyond the scope of this study and the reader is advised to consult the authors of the algorithm.

The idea of estimating crop production from RS was derived from Monteith(1972) who related that the plant biomass production is directly proportional to the photosynthetically active radiation (PAR) over the course of the growing cycle of the crop. PAR (0.4 - 0.7μm) which is a part of shortwave solar radiation (0.3 - 3.0μm) is the primary source responsible for production of crop biomass. PAR is absorbed by chlorophyll for plant photosynthesis and it regulates the net primary production (Bastiaanssen & Ali, 2003). The algorithm used for derivation of biomass production from satellite imagery is given in detail in Veroustraete et al. (2002) and it has been implemented by FRAME project. By applying harvest index, i.e. the harvestable portion of above ground biomass, the yield can be estimated from biomass production.

Increasing crop WP is one important way toward more efficient water use in agricultural production as it helps in achieving real water saving and thereby meeting food demands (Seckler, 1996). In order to define an action towards increasing WP one has to achieve two important steps. First, reliable and accurate mapping of current levels of WP at farm level, this requires knowledge of current levels of real farm conditions. Second, understanding of why such spatial variations of WP occur.

Bastiaanssen et al. (2000), Cai et al. (2009), Ahmad et al. (2009), Blatchford (2016), Van Dam et al. (2006) and several other studies have used satellite data (high and low resolution) for mapping spatial variations of WP. In all those studies it has been stressed that RS has the strength of showing an overview of spatial variation of WP both at farm and regional scale thereby helping water managers to pinpoint where water resources are wasted and where WP can be improved. These achievements in RS has recently motivated FAO undertaking development of an operational and open access remotely sensed database covering Africa and Middle East (FRAME) to assess and monitor WP in real time. However, one of the biggest problems of RS products is that they suffer from uncertainties. Therefore, it is important to validate and check the level of accuracy of RS products. Without validation, any RS products derived from any methods, models or algorithms cannot be used plausibly for agricultural, water resources or other intended purposes.

2.3. Validation of remote sensing of water productivity

Validation is defined as the process of determining whether the simulation model is an accurate representation of the real world for a particular purpose of the study (Law, 2006). Validation is necessary for ensuring the quality of RS products before they can be further used for decision making. For validation of RS estimated WP, ground data (measured) of each component of water productivity:

evapotranspiration and yield are required. Evapotranspiration is the key component of WP that has to be accurately measured or validated. The most common approach for validation of RS estimated AET primarily involves comparison of direct evapotranspiration measurements from lysimeters, Large Aperture Scintillometer (LAS), tower based energy flux measurement system using Bowen ratio methods and eddy correlation (Xiong et al., 2008). Data from these measurements can make a valuable contribution to boost confidences in RS estimates. Allen et al. (2011), Sun et al. (2012), Teixeira et al. (2009), Tasumi et al.(2005) have used ground measured data of ET using the above mentioned techniques to evaluate RS based ET estimates at various resolutions.

In those studies it has been stressed that the level of accuracy of the RS estimates (the degree of correlation with observed data) mainly depends on the quality and spatial resolution of satellite images used, the quality of model (algorithm) employed, measurement precision, time of measurement (wet or dry season) and the land surface characteristics where measurements are taken. However, the above methods of routine direct field measurements of evapotranspiration are often difficult to conduct due to cost and time constraints as in the case of this study. Thus alternative methods based on crop simulation model which use weather data; for calculation of Penman-Monteith reference evapotranspiration (ETo) and crop coefficient (Kc) as described in Allen et al. (1998) can be used to indirectly validate remote sensing estimates.

2.4. Crop models

The need for crop growth and yield modelling has received tremendous attention in recent times due to global climate change and food security problem emerging from high population growth (Castro Teixeira, 2008). One of the main purposes of crop growth models is to simulate yield production as a function of weather parameters, soil conditions and land and water management practices. In the past few decades, a number of crop yield models such as WOFOST (Diepen et al., 1989), Daisy (Abrahamsen & Hansen, 2000), DSSAT (Jones et al., 2003), APSIM (Mccown et al.., 1996), CERES (Wang et al., 2009) have been developed and applied at different scale in the simulation of crop development and production. However, these models are relatively sophisticated (a large number of parameters) and require a detailed and extensive input data that are often not easily available for a diverse range of crops (Kim & Kaluarachchi, 2015). Another widely used relatively simple model is AquaCrop (Steduto et al., 2009) model developed by Food and Agricultural Organization (FAO) of the United Nations. This model provides a balance between detailed simulation models mentioned above and the simplicity of empirical functions described in Doorenbos & Kassam (1979) with low input requirement, applicability for a wide range of crops, reasonable accuracy, robustness and ease of use (Hsiao et al., 2009). As a result, AquaCrop model was selected for this study.

2.5. AquaCrop model

AquaCrop is a water driven model designed for simulating green canopy and root growth under governing environmental conditions (Steduto et al., 2009). It simulates daily water balances in the root zones and crop development with limited number of input requirement (air temperature, rainfall, ETo and CO2 concentration). AquaCrop separates ET into soil evaporation and crop transpiration to calculate the daily crop biomass and yield production whereas the first empirical model known as crop yield function (Doorenbos & Kassam, 1979) does not consider the separation between soil evaporation and crop transpiration. The separation makes it possible to avoid the confounding effect of non productive (soil evaporation) water consumption. The model has been successfully applied for a wide range of climate conditions, different soils and different crops throughout the world.

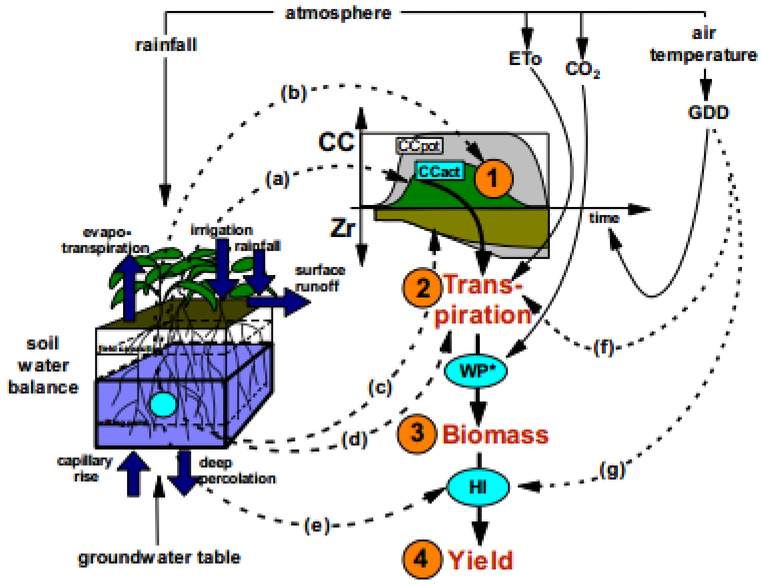

Figure 2-1: simulation steps of AquaCrop model. Dotted arrows indicate the processes affected by water stress (a to e) and temperature stress (f to g). CC is the simulated canopy cover, CCpot is the potential canopy cover, Zr is the root deepening, ETo is the reference evapotranspiration, GDD is the growing degree days, WP is the normalized crop water productivity, and HI is the harvest index (Raes et al., 2017)*

The general simulation procedure of the model is described in figure 2-1. AquaCrop simulates the daily soil water balance by considering climate, soil, crop and management practices (field and irrigation). The amount of water stored in root zone is calculated by accounting of incoming (rainfall, irrigation and capillary rise) and outgoing (runoff, ET, deep percolation) water fluxes at its boundaries. The amount of water stored in the root zone determines the magnitude of water stress affecting: (a) green canopy (CC) expansion, (b) canopy senescence and decline, (c) root system deepening, (d) stomatal conductance and transpiration, and (e) harvest index. Apart from water stress, temperature stress reduces crop transpiration (f) and reduces harvest index (g) (figure 2-1).

AquaCrop uses green canopy cover (CC) to express the foliage development. The CC and reference evapotranspiration (ETo) are then used with crop coefficient to calculate transpiration from plant and with the soil evaporation coefficient to calculate soil evaporation. The model simulates the separation of yield into biomass and harvest index (HI). Crop yield is simulated as a product of biomass and HI (equation 2-3). Cumulative above ground biomass production is function of daily ratio of crop transpiration (Tr) and ETo and the normalized biomass water productivity (WP^*) (equation 2-2). Biomass water productivity is the slope of linear relationship between biomass and cumulative transpiration over growth cycle of crop. When normalizing it by evaporation demand of the atmosphere and carbon dioxide concentration of a certain place, WP* acts approximately constant (becomes conservative parameter) for a given species of crop (Raes et al., 2017).

$$B = WP^* \sum Tr/ETo \quad \text{(2-2)}$$

$$Y = HI * B \quad \text{(2-3)}$$

Where, B = cumulative aboveground biomass production (g/m2)

WP^* = normalized biomass water productivity (g/m2)

Tr = daily crop transpiration (mm/day)

ETo = reference evapotranspiration (mm/day)

Y = yield production (g/m2)

HI = harvest index (-)

Raes et al. (2017) gives complete details of simulation procedure of AquaCrop model and the reader is advised to consult it. AquaCrop is available in different versions; standard window, plug-in, GIS and OS versions. The choice of version for a particular study depends on the number of simulations required. The standard window version is available with user interface and it supports a single simulation at a time. The other three versions can help to make high number of simulations at a time and thereby providing a significant computational time savings as compared to original standard window version. For this AquaCrop plug-in (version 6) was selected.

3. METHODOLOGY

3.1. Study area description

The study focused on Wonji Shoa large scale sugarcane irrigation scheme located in Upper Awash basin, one of validation sites of level -3 FAO-FRAME project. Wonji Shoa scheme was the first commercial large scale irrigation scheme in Ethiopia. The Wonji sugar esate is situated downstream of Koka dam in central rift valley of Ethiopia, 110 km South East of Addis Ababa. The source of irrigation for the scheme is the Awash River, a perennial river. The scheme is situated at $8^{0}21'$- $8^{0}29'$ N and $39^{0}12'$- $39^{0}18'$ E (figure 3-1) at average altitude of 1550m asl with area under cane of over 7000 ha (excluding currently expanded project areas). Wonji plain is characterized by very gentle and regular topography making it most suitable for irrigation. Sugarcane is grown in the area mostly as monoculture. Legume crops such as crotalaria and haricot bean are grown on heavy clay soils during the fallow period in case of cane after fallow system. These legume crops are usually used for increasing the fertility of fallow soils.

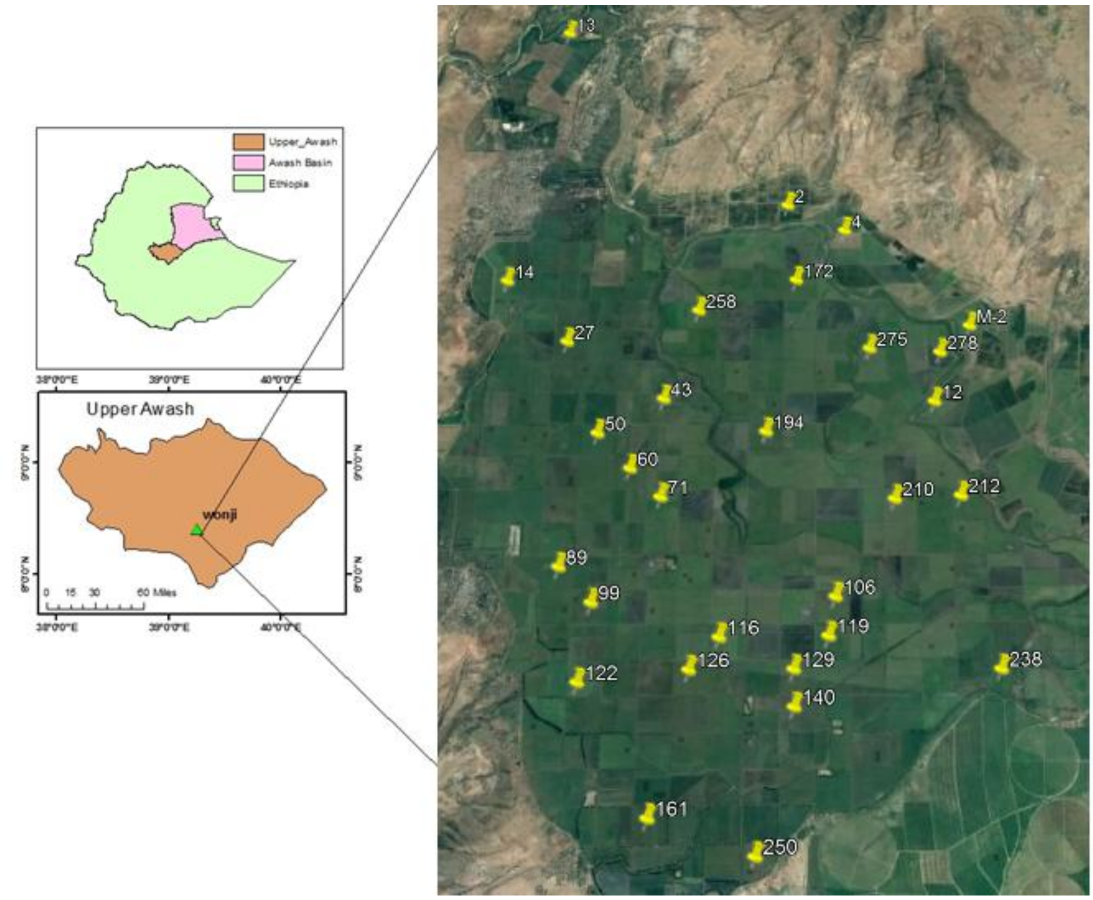

Figure 3-1: location of study site. The right picture indicates plots selected for AquaCrop model application and subsequent evaluation of FRAME

The climate of the area is characterised as semi arid. The main rainy season take place between month of June to September (figure 3-2). The rainfall of the area is erratic both in quantity and distribution. The area receives mean annual rainfall of 831 mm with mean annual maximum and minimum temperature of 27^{o}C and 15 ^{o}C respectively while the peak daily evapotranspiration is 4.8 mm. In general, the climate of the area is suitable for production of sugarcane.

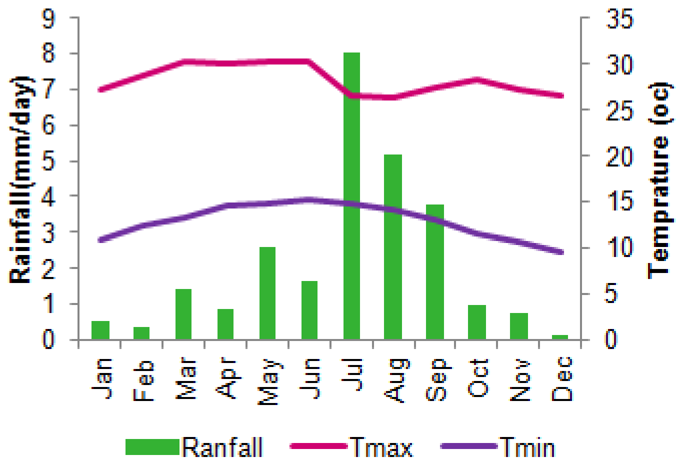

Figure 3-2: Average daily rainfall and temperature in month. (Source: observed climatic data for Wonji during period 2007-2016)

3.2. Methodological framework

The methodology followed to achieve the stated objective is summarized in figure 3-3. AquaCrop plug-in (version-6) was selected because of two main reasons. Firstly, the model has to be applied for multiple plots (multiple simulations); 30 plots were selected for this study (figure 3-1). The selection was based on availability of crop production data that cover the period of 2009-2016 as purpose of evaluating FRAME. Secondly, the crop calendar of each plot is varying from cycle to cycle (this can be easily noticed from a sample of crop production data given in appendix A). Thus a separate project files and input files were created for each crop calendar (the model is run for each crop calendar separately). The model output was then compared with FRAME extract as basis of evaluating the accuracy of FRAME. A brief description of methods used in this study is given in the following sections.

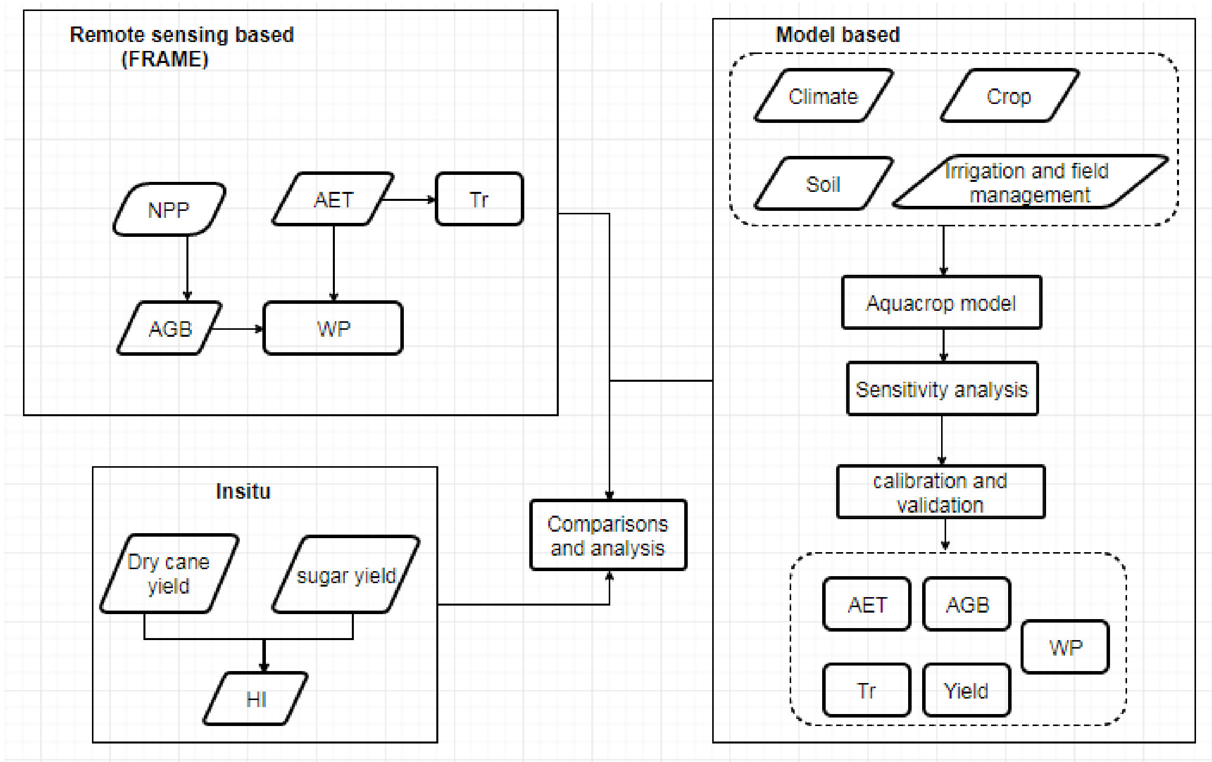

Figure 3-3: Methodological framework adapted in this study

3.2.1. Data collection

During a three weeks visit to field, data relevant to application of AquaCrop model and subsequent evaluation of FRAME was collected. These include weather, crop, soil, irrigation and field management. Thirty (30) plots were selected for analysis. The location of each selected plots were recorded using handheld GPS. Consequently, the shape files of each plot were created from Google earth. A brief description is presented below.

Weather data

The atmospheric environment of the crop is described in the climate module of the AquaCrop and deals with key input meteorological variables. The daily climatic data required for running AquaCrop model was collected from estate research centre. Rainfall (mm), maximum and minimum temperature (°C), relative humidity(%), sunshine hours(hr) and wind speed(m/s) at daily time step for the period of 2007- 2016 were collected. The wind speed measured at day and night was averaged to get mean daily values and the original unit of km/hr were converted into m/s. Similarly the relative humidity measured at 6hr, 12hr, 15hr and 18hr are averaged to get for the mean daily relative humidity. The reference evapotranspiration was then calculated by ETo calculator program built within AquaCrop model based on FAO Penman-Montheith equation described by (Allen et al.,1998) (equation 3-1). The program also offers a method for estimating missing climatic parameters. In case of missing rainfall and temperature a data from nearby weather station was used. The model also requires annual atmospheric CO2 concentration. Default CO2 concentration of Mauna Loa in Hawaii given by AquaCrop model was used in this study.

$$ET_0 = \frac{0.408\,\Delta\,(R_n - G) + \gamma\,\frac{900}{T + 273}\,u_2(e_s - e_a)}{\Delta + \gamma\,(1 + 0.34\,u_2)} \qquad \text{------------------------------- (3-1)}$$

where *ET0* = reference evapotranspiration rate [$mm.day^{-1}$], *Rn* = net radiation at the crop surface [$MJ.m^{-2}.day^{-1}$], *G* = soil heat flux density [$MJ.m^{-2}.day^{-1}$], *T* = mean daily air temperature [°C], *u2* = average wind speed at 2 m height [$m.s^{-1}$], *es* = saturation vapour pressure [kPa], *ea* = actual vapour pressure [kPa], Δ = slope of the vapour pressure curve [$kPa.°C^{-1}$], and γ = psychrometric constant [$kPa.°C^{-1}$].

Crop data

The crop module of AquaCrop has five major components: phenology, canopy development, root deepening, production of biomass and harvestable yield. All these parameters can be measured from the field at regular time interval throughout the growing season of the crop. However, for this study due to lack of time for regular measurement coupled with long growth cycle of crop under study, historical data of fresh cane yield and field sugar yield together with planting/harvesting date for a period of 2007- 2016 was used as a basis for model calibration. A factor of 0.3 as a dry matter content of sugar cane (Steduto et al., 2012) is applied to fresh cane yield to obtain dry above ground biomass. Average harvest index was then calculated as the ratio of the dry biomass to field sugar yield from time series data of the selected plots. For estimation of initial canopy cover, the plant and row spacing were measured. Apart from this, information on general crop management practices like, initial field conditions, crop cultivars, fertilizer and pesticide applications, weeding and harvesting mechanisms were gathered.

Soil

The soil type distribution over sugarcane field is shown in figure 3.4. The soil texture of the study area is generally classified as heavy textured (clay) with high soil moisture holding capacity and medium/coarse textured soils with low water holding capacity (loam and sand). AquaCrop model requires the number of soil horizons present and the physical characteristics of each horizon such as the soil water content at field capacity, permanent wilting point and saturation and the saturated hydraulic conductivity. This can be obtained by field soil sampling (profile pit excavation) and soil laboratory analysis at the expense of time and resource. For this study no field sampling was run and measurements are not available. Thus, the physical characteristics of the soil was estimated using pedo-transfer function described in Saxton et al. (1986) and a single soil horizon was assumed for AquaCrop model application.

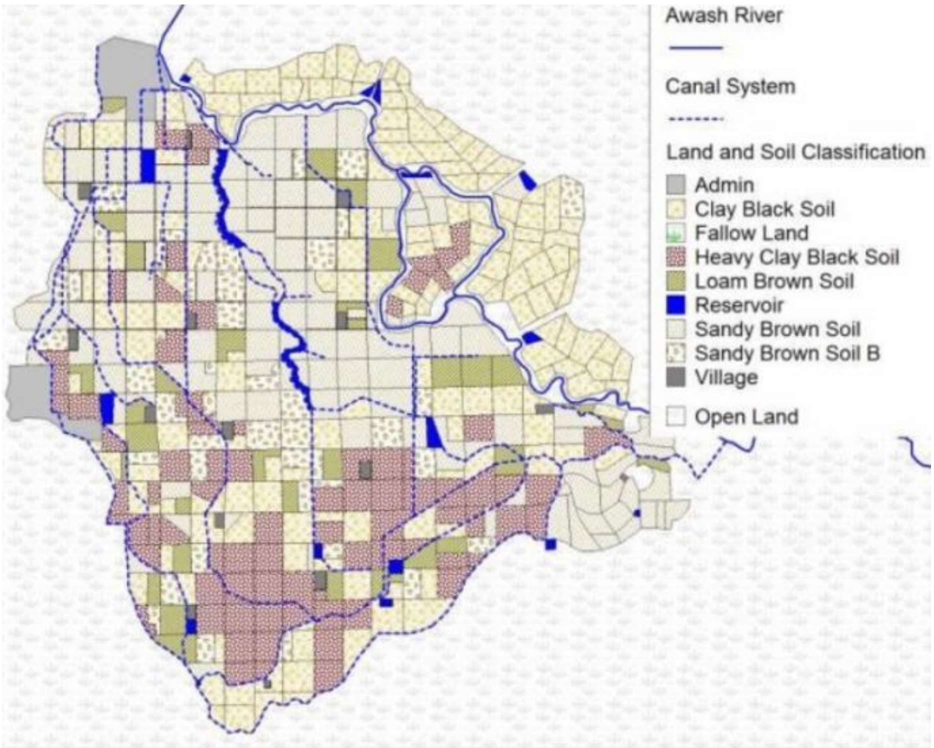

Figure 3-4: soil type distribution of Wonji plantation (Ruffeis et al., 2006)

Ground water

The groundwater table of the area is characterised as shallow and spatially and temporally varying (Dinka & Ndambuki, 2014). Thus for application of AquaCrop model the presence of groundwater table is taken into account. However, there is no clear-cut information about the depth of groundwater table below the soil surface. Dinka & Ndambuki (2014) stated that about 90% of the plantation is affected by water logging problem due to shallow ground water table and they revealed that the depth of groundwater table in the plantation is approximately 1.5m on average based on ground water monitoring conducted over the period of 2007-2009. Their study also revealed that there is no significant difference of groundwater table depth between summer (rainy season) and winter (dry season). The shallow groundwater depth in plantation and Wonji area in general is as result of seepage losses from storage reservoirs, channels, Lake Koka reservoir and frequent over irrigation. Though, the current groundwater table depth may differ from the finding of Dinka & Ndambuki (2014) due to lack information on current status of groundwater approximate depth of 1.5m was assumed in this study.

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Irrigation

Blocked end furrow type of irrigation is used to irrigate sugarcane fields of both estate and out growers expect for newly expanded areas which use centre pivot sprinkler irrigation system. Irrigation is diverted to field canals from Awash River using centrifugal pumps. Irrigation is run from beginning of October to end of June. Irrigation application volume and intervals vary depending on the type of soil and the growth stage of crop. Generally the gross application rate is 30 lit/sec for low plant canes and 75 lit/sec for high plant canes and ratoons. Duration of irrigation lasts for 9 hr (the output is 1.5 ha). The interval of irrigation application varies from 15 days for sand soil, 25 days for loam soil and 30 days for clay soil. Depending on the condition of rainfall irrigation is usually delayed for one day for every 5 mm depth of rainfall (if rainfall occurs during irrigation season). This was due to the fact that the long term average evaporative demand of study area is 4.8 mm/day. Irrigation is shut off roughly about two months prior to harvest (pre harvest drying off) to facilitate for movement of vehicles and man powers for easy harvesting. Irrigation water quality is generally very good (< 2 ds/m). This locally collected information was put into irrigation module of AquaCrop model. Since AquaCrop model does not take into account irrigation losses, an application efficiency of 60% was assumed based on FAO irrigation guidelines.

Field management

Irrigation is applied immediately after planting in order to ensure proper germination of cane and reduce delay in germination. So when running AquaCrop model the initial condition is assumed as soil water content at FC. Practices like mulching and soil bunds are not present in the study area. Weed management practices, soil fertility level, pest and disease control are assumed optimal for application of AquaCrop model.

3.2.2. AquaCrop model Sensitivity analysis

Sensitivity analysis helps us to investigate how the variation in model output can be attributed to changes in input parameters, guiding us to where calibration has to be focused (Pianosi et al., 2016). If changes in values of input parameters have minor effects on model output, that input data have insignificant effect on the result and it is termed as less or non sensitive. Thus to study the behaviour of AquaCrop model to changes in model parameters (inputs) sensitivity analysis was carried out. This was done by altering non conservative crop parameters and the soil conditions by ±10 and ± 20 %. First AquaCrop model was run with default parameter values and the result was considered as the basic output. Then for each next run one parameter at time is changed and the others kept constant. The relative changes in simulated biomass for each change in model parameters were used for assessment by graphical approach. Sensitivity analysis was then followed by model calibration.

3.2.3. AquaCrop model calibration and validation

Calibration is the process of adjusting model parameters to reach a best agreement between measured and simulated variables (Pianosi et al., 2016). The four important parameters required for calibration of AquaCrop model are; canopy cover, soil moisture content, above ground biomass and yield. These parameters are typically available through ground measurements conducted at different stages of growth cycle of crop. The effort to conduct ground measurements of these parameters can be costly, labor intensive, and time consuming as the data needs to be collected over a complete cropping cycle.

The AquaCrop model has been parameterized and crop database has been constructed for many crops including sugarcane (Steduto et al., 2012). The parameterization and testing of model for variety of crops under different local conditions has led to establishment of conservative parameters (parameters which do not change significantly with locations). For better simulation result conservative parameters still needs to be calibrated however, that requires extensive measurement on experimental fields. As result, for this study conservative parameters are retained and calibration focused on non conservative/cultivar specific parameters.

To calibrate AquaCrop model in-situ cane production data for the year 2007-2016 were used. During calibration process crop parameters like time to reach different phenological stages, maximum canopy cover, and the rooting depth were fine tuned iteratively until the observed and simulated dry biomass and yield are in close agreement. Soil water stresses coefficients for leaf expansion, stomatal closure, and early canopy senescence were also fine tuned by simply changing different stress classes. Phenological stages were calibrated in calendar day mode, as the growing degree day (GDD) mode is more precise only when crop development is limited by unfavourable temperature (heat or cold stress). The result of calibration was then validated on the rest of plots based on their respective soil type. This method of validating on multiple plots gives us some confidences on calibration result.

Goodness of fit of simulation results of calibration and validation were assessed against field data using root mean squared error (RMSE) and percent bias (Pbias) and coefficient of determination (R^2). RMSE is an overall a mean deviation between observed (obs) and simulated (sim) values and Pbias measures the average tendency of simulated result to be under estimating (positive values) or over estimating (negative values) the observed data (Moriasi et al., 2007).

$$R^2 = \frac{\sum(obs-\overline{obs})(sim-\overline{sim})}{sqrt(obs-\overline{obs})*\sum(sim-\overline{sim})} \quad \text{(3-2)}$$

$$Pbias = \frac{\sum(obs-sim)*100}{\sum obs} \quad \text{(3-3)}$$

$$RMSE = sqrt\left(\frac{\sum(obs-sim)2}{N}\right) \quad \text{(3-4)}$$

3.2.4. FRAME data components: extraction, analysis and evaluation

Level -3 FRAME data components net primary production (NPP), actual evapotranspiration (AET) and transpiration fraction (Tfrac) of Awash basin was made available by ITC Faculty of University of Twente. Overview of the data used for this study is presented in table 3-1. Temporal resolution of data components are in dekadal resolutions. In one month there are 3 dekads with the first two dekads containing 10 days while the last dekad ranges between 8 to 11 days. The method (algorithms) used for derivation of each data components is given in detail in WaPOR database methodology document (FAO, 2017).

Table 3-1: Overview of FRAME data components used for this study

level	Data component	Temporal resolution	Temporal extent	Spatial resolution	Coordinate system	Conversion factor	The unit
L3	NPP	dekad	2009-2016	30 m	WGS 84	multiplied by 0.001	$gC/m^2/day$
L3	AET	dekad	2009-2016	30 m	WGS 84	multiplied by 0.1	mm/day
L3	Tfrac	dekad	2009-2016	30 m	WGS 84	none	%

NPP indicates the conversion of CO2 into biomass driven by photosynthesis. It is used to calculate above ground biomass production (AGBP). Dry matter production (DMP) which represents dry biomass increase of vegetation is directly related to NPP by following relationship (FAO, 2017). The relationship indicates that NPP and DMP only differ by constant (the efficiency of conversion between carbon and dry matter is 0.45).

1 kgDM/ha/day = 1000 gDM/ha/day = 0.1 gDM/m2 /day ----------------------------------- (3-4)

NPP [gC/m2 /day] = DMP [kgDM/ha/day] * 0.45 * 0.1 --------------------------------------- (3-5)

AGBP indicates the sum of above ground dry matter produced during the course of growing season. Thus, AGBP increases steadily between start towards the end of growing season. AGBP by dekad is the average daily value in dekad multiplied by the number of days in each dekad. To account for the division between the above and below ground components of dry matter, i.e the shoot/root ratio, a constant value of 0.65 was applied. Generally,

AGBP [kg/ha/dekad] = DMP [kgDM/ha/day] * 0.65 * number of days of that dekad ---------- (3-6)

Once AGBP is calculated for each dekad, its accumulation can be calculated as sum (cumulative) over growth period of crop. It can also be expressed in units of ton/ha (1 ton = 1000 kg).

The harvestable yield of AGBP can be calculated by using harvest index (HI). Since HI data of FRAME is not available yet to calculate yield, HI estimated from in-situ data was used. WP was estimated by using equation 2-1. With the help of transpiration fraction (Tfrac), AET was separated into crop transpiration and soil evaporation.

Time series of FRAME data components of Awash basin was masked to Wonji plantation using model builder function of ArcGis tool. A conversion factor was applied as given in table 3-1. The shape file of selected plots of Wonji plantation was created from Google earth. The area of selected plots varies from 7 ha to 24 ha which is greater in spatial extent as compared to FRAME resolution (30 m resolution). As result FRAME has to be aggregated to the same spatial extent of plots. This was done by using zonal statistics as table function of ArcGis each plot representing zone. The method of statistics used was mean that calculates the average of all pixel values belonging to zone. Since the spatial distribution of growth of plants in a certain selected plot may vary as result of non uniformity in irrigation application or part of plants may suffer from kind of stresses/disease, averaging method of aggregation which takes into account all pixels found in selected plot was selected. The calculated zonal statistics table was then exported to excel to further compare extracted values with AquaCrop output and in-situ data

AquaCrop model offers simulations at daily, 10-daily and monthly time step. In this study the model was run at 10-daily time step to match temporal resolution of FRAME. Care should be taken that the simulated output for transpiration (T), evaporation (E), actual evapotranspiration (AET) and biomass are 10-daily total. In FRAME data components are given as the daily average of that dekad. Therefore the 10-daily totals of T, E and AET simulated by model are converted to average by dividing the totals by number of days of that dekad. Biomass of FRAME converted to dekad can be directly compared to model output. The seasonal biomass can be calculated by cumulative of dekadal simulated biomass over growth period of the crop. The extracted values of FRAME was analysed and compared with AquaCrop model output and in-situ data using statistical analysis and graphical approaches. Details of analysis and evaluation are presented in next chapter.

4. RESULT AND DISCUSSIONS

4.1. Assessment of data collected

Weather data

The weather condition of the environment has a crucial influence on crop production. It generally defines the amount of energy available for evaporation and therefore, when it comes to applying models for simulation of crop production assessment of quality of weather data is important. The key meteorological parameters used for calculating ETo was collected from Wonji estate research centre. The data record has a lot of missing and suspicious data points were detected based on visual graphical analysis. To deal with this problem other nearby principal stations; Melkasa, Nazreth and Metehara located at approximate distance of 10 km, 15 km and 100 km respectively from Wonji are used. Figure 4-1 presents analysis of rainfall and mean daily temperature of stations for the period where the data record is available. The analysis clearly shows that stations Melkasa and Nazreth have close similarity with Wonji station as a result of close proximity in distance. Therefore, for gap filling and cleaning up of suspicious records stations Melkasa and Nazreth are used by means of direct transfer. However, for wind speed 30% of data points are still missing as there is no record for surrounding stations too. AquaCrop model can still estimate ETo when solar radiation, wind speed and/or air humidity data are missing based on calculation procedures as outlined in FAO Irrigation and Drainage paper Nr. 56. The average daily wind speed based on available record is about 1.27 m/s. For estimating missing wind speed a general class of light to moderate winds in the area was selected. Wind speed has significant impact on estimated ETo as it plays main role in transport of heat and water vapour.

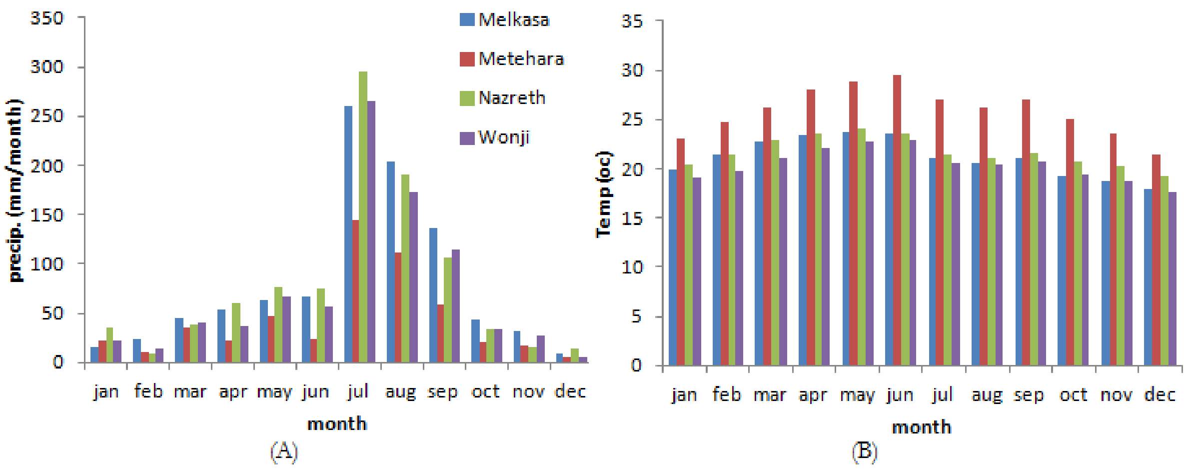

Figure 4-1: (A) average monthly precipitation, (B) average daily temperature in a month of stations

Even though, the large percentage of missing in wind speed data puts uncertainty in estimated evapotranspiration, the daily average of ETo as computed by model (after filling the gap) based on data record of 2007- 2016 is 4.55 mm/day which is quite the same as the long term average evaporative demand of study area (Wonji) reported in literatures. Figure 4-2 presents average monthly precipitation and computed ETo based on data record 2007- 2016. The main rainy season runs from end of June to end of September. During main rainy season the evapotranspiration rate has decreased probably due to less incoming solar radiation as result of high cloud coverage and then starts to rise after rainy season. The mean monthly ETo ranged from 123 to 164 mm while the mean monthly precipitation ranged from 5 to 236 mm.

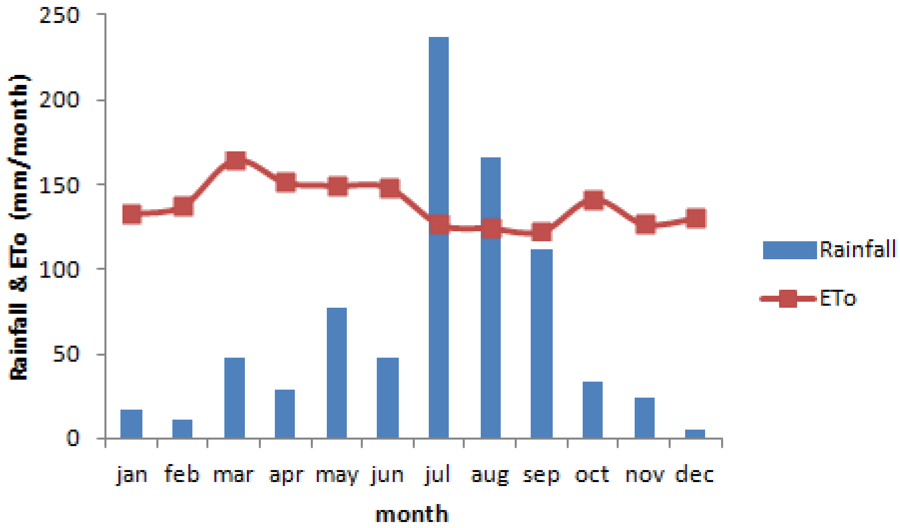

Figure 4-2: average monthy precipitation and ETo of wonji. . (Source: observed climatic data for Wonji during period 2007-2016)

Management practices

A short description of the management practices used by sugar estate as discussed with agricultural operation manager and irrigation foreman during field visit is presented here. The general management practices which have direct link with outcome of crop production are field management, irrigation application, fertilizer application, pest/disease control and weed management were discussed.

For the purpose of obtaining good production fallow fields are usually properly managed by planting legume crops such as crotalaria and soya beans. These legume crops help to improve the soil nitrogen content, the soil physical, chemical as well as biological properties. Deep ploughing of land is practiced as sugarcane stands in field for long time usually more than a year.

Extensive network of irrigation canals and drains are used for application of water to field. The furrow width of 145cm and three different lengths of 32 m, 48m and 64 m are being used depending on gradient of farm. Irrigation scheduling varies as per type of soil and growth stage of plant as described in section 3.2.1. Irrigation foreman is responsible for deciding the need for irrigation. Usually the hand feel or finger test method is practiced in the scheme. The test is conducted at soil depth of 30 cm and 60 cm few days before expected date of irrigation and the time for next irrigation application is fixed when the test result indicates dry soil. The limitation of this method is that the decision for scheduling irrigation is rather subjective and depends on the experience of irrigation foreman in charge. Nitrogen fertilizer (urea) at rate of 2 qt/ha for plant cane and 4.5 qt/ha for ratoon crop is applied for providing nutrient for plant finally providing higher yield per unit area.

Insecticides are sprayed on top of soil before first irrigation for controlling beetle attack based on recommended dosage. It has been reported that the sugarcane plantation of the study area suffers from diseases that affect the crop production. Smut, ratoon stunting disease and bacterial disease prevail in Wonji. Proper treatments are applied for prevention. The effect of weed in sugarcane yield is understandable. The sugar estate applies proper weed control mechanism to ensure that sugarcane is not suffering from weed infestations. Herbicides are generally applied three times over growth season of sugarcane.

Keeping this on mind for application of model field management practices assumed as optimal. Even though the management practices being used in the estate is described as good/best, it is difficult to believe if those practices are being efficiently and uniformly being applied throughout the plantation field. The average seasonal production of sugarcane from field to field is varying with coefficient of variation of 20% based on crop production data of 30 plots. Irrigation scheduling was the main challenge in this study when constructing model input. The field collected information on irrigation in particular management practices in general are standard and it is not well known how efficiently the estate is managing the plantation. Therefore, irrigation scheduling was constructed based on the following criteria:

- At the time of sowing initial soil moisture is at field capacity
- Apply irrigation at the time of germination to avoid possible delay
- Irrigation application depth pre establishment stage < post establishment
- No irrigation when there is rain
- Delay irrigation by 1 day for every 5 mm depth of rain
- Soil type
- Pre harvest drying off (2 months before harvest)

Productivity of sugarcane

Table 4-1 presents commercial average, commercial maximum and experimental maximum of sugarcane yield as reviewed by Irvine (1983). Commercial average yield is the average of reported yield of all kinds of varieties under all environmental conditions and under all management practices (ranging from poor to best management practices). Commercial maximum yields are for best management practices (use of good plant nutrition, irrigation and pest/disease control). Experimental maximum yield is obtained when sugarcane is grown in environment where water and nutrients are none limiting and free of pest, disease and weeds. As depicted in table 4-1the yield in all aspect is varying from country to country as a result of differences in climate. Waclawovsky et al. (2010) has reported that recently in Brazil due to advancements in breeding technology a commercial maximum yield of 260 ton/ha and experimental maximum of 299 ton/ha in irrigated sugarcane which exceeds the values reported in table 4-1. Under favourable climatic condition and adequate water supply experimental yield of 200 ton/ha can be achieved (Steduto et al., 2012). Based on crop production data of 30 plots of Wonji sugar plantation, the fresh cane yield per plot varied from 85 to 186 ton/ha with average fresh cane yield of 117 ton/ha. Despite high variability this average production is comparable with worldwide fresh cane yield of 120 ton/ha considered by FAO as a good yield under full irrigation (Steduto et al., 2012) . Even though, the achievable yield of sugarcane depends on climate, soil condition, management practice and cultivars, the average cane yield of study area is close to the values reported in literatures. The high variation in observed production data may be a result of not proper management of plots of low yield.

Table 4-1: commercial average, commercial maximum and experimental maximum sugarcane yield (Irvine, 1983)

location	Cane yield (ton/ha/year)		
	Average	Commercial max	Experimental max
Australia	81	100	250
Colombia	78	202	219
Iran	100	167	221
Louisiana	53	129	242
South Africa	94	141	166
Zimbabwe	115	180	200

4.2. Model sensitivity analyis, calibration and validation

4.2.1. Sensitivity analysis

Sensitivity analysis was conducted in order to analyze the influence of parameters on model output. In the current version of AquaCrop used for this study (version -6), there are over 40 parameters. It is not important to analyse the sensitivity of all these parameters as most of them are conservative. Only few key parameters are used as basis for understanding the behaviour of AquaCrop model to changes in input parameters. The result of sensitivity analysis of some key parameters conducted on field number 106 is shown in figure 4-3. The most influential non conservative crop parameters were found to be the maximum rooting depth and time to senescence. The maximum canopy cover (CCx) and time to maximum canopy cover were found to be moderately sensitive, while plant density and normalized water productivity (WP*) seems less sensitive. On the other hand, initial soil water content was the most influential soil parameter. Although a different type of crop, the result of high sensitivity of biomass and thus yield to rooting depth, time to senescence and initial soil water content found in this study is in agreement with result reported in Geerts et al. (2009) and Salemi et al. (2011). The maximum rooting depth is difficult parameter to measure in field and reliable estimate are important for model calibration.

In FAO Irrigation and Drainage paper Nr. 56 the maximum effective rooting depth for sugarcane is about 1.2 – 2 m. Ohashi et al., (2015) reported effective rooting depth of 0.4 m based on field experiment conducted on three sugar cane cultivars in Brazil. In this study calibration gave a maximum effective rooting depth of 0.9 m.

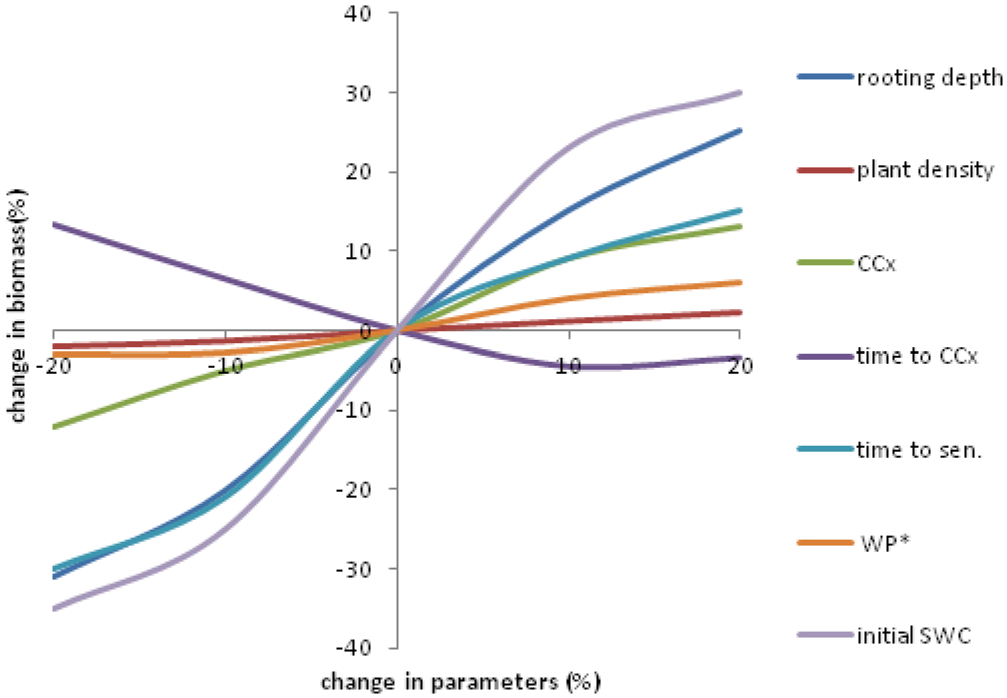

Figure 4-3: Sensitivity analysis of selected parameters

As shown in figure 4-3 there is positive relationship between rooting depth and biomass production. This is due to the fact that biomass production is directly dependent on crop transpiration which is more limited by availability of water in root zone. The rooting depth parameter needs to be calibrated with care as increased root depth triggers more water extraction resulting in high transpiration and biomass accumulation (Steduto et al., 2009). Time to maximum canopy cover and senescence are the two crop phonological parameters controlling the canopy growth and decline rate respectively. The influence of time to senescence on biomass output was found to be stronger than time to reach maximum canopy cover. As expected, a shorter time to senescence, triggers crops to decline and die off prematurely resulting in lower biomass and yield than longer and increased time to senescence while time to reach maximum canopy cover influences in opposite manner as reflected in figure 4-3.

The initial soil water content is the crucial soil parameter controlling model output and found to be one of sensitive parameters as compared to others. Geerts et al. (2009) stated that the high sensitivity of model to initial soil water content can be circumvented by running a model starting from a known very dry (PWP) or very wet (FC) period. The planting density directly influences the canopy cover and the model showed no significant change in biomass. The normalized water productivity (WP*) parameter has slightly impacted the model output in this study while, Geerts et al. (2009) and Salemi et al. (2011) reported moderate sensitivity. As WP* is a proportional factor for deriving biomass from accumulated transpiration, the low sensitivity of WP* found on this study reflect the biomass production simulated by the model is mostly affected by transpiration. And the transpiration is directly influenced by the soil moisture. This is a clear indication of how crucial is the soil moisture data for reliable calibration of AquaCrop model. The lack of soil moisture data in this study remains one of the biggest concern and uncertainty in simulated/calibrated model result.

4.2.2. Calibration and validation

Calibration and validation of the model was accomplished by comparing simulated and observed dry cane yield. To select plots for calibration the observed cane yield of each plot was analysed. The average observed cane yield on dry basis varied from 25.71 ton/ha in field number 43 to 56 ton/ ha in field number 13 which indicates the large difference in production of cane yield. The overall cane yield is about 35.2 ton/ ha. Therefore to balance between high and low yield, some of plots with average cane yield around 30 - 40 ton/ha are selected as representative for calibration. Based on this 12 plots (7 from heavy soil and 5 from light soil) are selected which makes 40% of samples. During calibration process non conservative crop parameters were fine tuned until a good agreement between observed and simulated is obtained. Much attention was given to sensitive parameters reported in section 4.2.1. List of parameters calibrated/used in this study is presented in appendix B. Table 4-2 and 4-3 presents statistical summary of model calibration and validation respectively. The number of years considered are 5 for plot 14, 3 for plot 50, 71, 126, 161, 210 and 2 while for the rest of plots 4 years are considered.

Calibration performance of model gave respectively, RMSE (ton/ha) ranging from 3.75 to 13.46 and R^2 ranging from 0.14 to 0.98. Based on statistical metrics calculated in table 4-2, there is a good agreement between model and observed data for all soil classes. To check reliability of calibrated model, it was validated on remaining fields (table 4-3).

Table 4-2: Statistical result of AquaCrop model calibration for dry cane yield

		In-situ			model			In-situ vs model		
Field #	Soil	Min (ton/ha)	Max (ton/ha)	Mean (ton/ha)	Min (ton/ha)	Max (ton/ha)	Mean (ton/ha)	RMSE (ton/ha)	Pbias (%)	R^2
12	clay	22.24	50.86	34.32	29.75	46.63	37.84	6.76	-10.23	0.98
14	sand	32.78	49.18	42.87	31.48	43.54	37.62	6.24	12.25	0.69
27	sand	22.67	45.33	32.27	33.87	41.51	38.11	12.02	-18.08	0.62
71	clay	28.2	60.37	40.49	30.67	55.74	42.38	5.46	-4.69	0.93
89	loam	20.64	59.21	36.99	30.06	37.25	34.35	13.46	7.14	0.14
129	clay	17.95	47.13	33.93	34.39	40.01	37.32	12.91	-9.97	0.77
161	clay	25.95	45.47	36.72	29.74	41.95	34.14	5.5	7.02	0.66
172	sand	25.61	38.4	33.34	36.33	47.59	41.57	12.52	-24.7	0.81
212	loam	25.59	48.17	37.17	34.69	38.76	37.43	9.32	-0.7	0.5
250	clay	23.95	50.46	34.39	28.62	39.79	33.81	7.85	1.69	0.41
275	clay	29.59	50.9	36.37	28.46	49.14	36.37	3.75	0.02	0.8
278	clay	34.11	41.09	36.94	23.67	39.55	33.87	5.5	8.29	0.54

The validation result gave RMSE (ton/ha) ranging from 5.67 to 20.07 while the R^2 ranges from 0 to 0.95 for the entire validation plots. Despite a good agreement in calibration good performance of model in validation could not be obtained in all plots but for most of plots its performance is fairly well. The validation result shows that the model tends to overestimate the cane yield in majority of plots. Table 4-4 summarizes the performance of model per soil class and overall. The overall result suggests that RMSE and PBias are fairly acceptable but good correlation could not be obtained.

The model overestimation observed in most of plots can be attributed to the following reasons. Firstly, in field during harvest cane is taken as the stalk cut at the base (near the ground) up to below the apex, since top portion of stalk is unproductive and is removed. Also on farm cane losses such as high cut and missed cutting and transport losses are inevitable as the cane is transported from field to mill where it is weighted before crushing. These combinations may lead to model overestimation. Secondly, the discrepancy may arise due differences in irrigation scheduling input in model and actual irrigation application in field. In AquaCrop model the irrigation schedule was constructed considering the rainfall conditions and soil type, however this may be significantly different from actual date of irrigation application in field. Thirdly, the observed data are subject to non negligible errors. Furthermore, a plot is cultivated with different cultivars from season to season and this variation in cultivars could have led to discrepancies between model simulations and in-situ data. Management practices were assumed optimal (non/limiting) when running the model but in actual case the plants may not be always growing under good management as this was reflected in low observed cane yield (lower than the commercial maximum values presented in table 4-1) allowing the model to overestimate..

For plots in which the model simulation showed reasonable performance, its reliability is still under question as the model is calibrated based on cane yield data observed at the time of harvest (i.e. the manner in which the plants were developing from start of planting till harvest as simulated by model might be much different from the manner of actual growth of plants in field). This remains biggest uncertainty and limitation of AquaCrop model in this study. This uncertainty could have been reduced by calibrating the model using observations (soil moisture, canopy cover and biomass/yield) made at different growth stages of plant. Therefore, data scarcity for model calibration is the major limitation in this study.

Furthermore, despite the presence of sugarcane crop in AquaCrop model crop database, its effectiveness of simulating physiological processes of sugarcane growth leading to final yield is under question. Most of internationally published literatures involving validation and evaluation of reliability of AquaCrop model are focused on crops other than sugarcane and have witnessed that the model is reliable. But that does not guarantee for sugarcane as the physiological processes are indeed different from plant to plant.

Table 4-3: *Statistical result of AquaCrop model validation for dry cane yield*

		In-situ			model			In-situ vs model		
Field #	Soil	Min (ton/ha)	Max (ton/ha)	Mean (ton/ha)	Min (ton/ha)	Max (ton/ha)	Mean (ton/ha)	RMSE (ton/ha)	Pbias (%)	R^2
2	clay	35.88	57.47	44.76	36.64	47.7	41.92	5.67	6.35	0.95
4	clay	33.56	51.24	39.66	34.47	49.52	41.04	11.81	-3.47	0.27
13	clay	39.34	73.06	56.04	33.23	55.09	47.12	14.16	15.93	0.71
43	sand	17.93	41.17	25.71	32.94	48.35	41.25	20.07	-60.42	0.06
50	clay	15.18	42.66	28.08	27.92	53.08	41.01	17.07	-46.05	0.22
60	sand	28.12	51.06	40.27	35.44	51.21	42.63	12.59	-5.88	0.05
99	clay	23.85	43.36	35.44	26.5	41.55	34.37	10.32	3.02	0
106	clay	19.29	50.49	29.97	30.74	37.77	35.41	12.28	-18.15	0.31
116	loam	17.03	37.2	26.42	31.8	34.75	33	11.20	-24.90	0.71
119	clay	20.31	41.98	28.61	26.98	34.27	32.08	12.11	-12.15	0.87
122	clay	20.6	28.55	25.98	31.17	42.41	36.76	11.72	-41.46	0.03
126	clay	22.38	51.49	34.91	34.66	43.21	39.77	16.32	-13.92	0.78
140	clay	18.47	42.16	29.06	29.6	51.46	39.35	13.38	-35.40	0.26
194	sand	18.59	42.25	32.73	30.21	47.9	36.23	9.10	-10.70	0.29
210	loam	29.28	42.68	35.46	33.1	36.89	34.42	6.03	2.95	0.01
238	clay	21.97	34.62	28.41	33.46	41.16	35.53	11.06	-25.08	0.34
258	sand	18.7	49.37	32.01	28.64	47.3	36.75	10.44	-14.78	0.35
M-2	clay	31.72	64.8	47.7	29.18	54.55	40.97	11.46	14.12	0.84

Table 4-4: overall and per soil class statistics of AquaCrop model simulation

	In-situ			model			In-situ vs model		
Soil	Min (ton/ha)	Max (ton/ha)	Mean (ton/ha)	Min (ton/ha)	Max (ton/ha)	Mean (ton/ha)	RMSE (ton/ha)	Pbias (%)	R^2
Heavy	15.18	73.06	35.81	23.67	55.74	37.82	10.68	-5.62	0.29
Light	17.03	59.21	34.28	28.64	51.21	37.65	11.77	-9.82	0.01
overall	15.18	73.06	35.22	23.67	55.74	37.75	11.11	-7.18	0.18

4.3. FRAME, model and in-situ: intercomparisons and assessement

To assess the accuracy of FRAME data products, the AquaCrop model output and sugarcane yield data collected from field were used. For biomass inter comparisons were made between FRAME, model and in-situ, while for actual evapotranspiration FRAME estimate was compared with model output as there is no in-situ evapotranspiration. Finally, the water productivity computed from FRAME data components was compared to model estimate. The result of statistical metrics and discussions are presented in following sections.

4.3.1. Biomass

It is well known that plant transpiration and photosynthesis are strongly related because stomata are the pathway for absorbing the CO_2 and releasing the water vapour by transpiration. Therefore it is important to check the linearity between NPP and AET of FRAME before making comparison with in-situ or model. To do this, a scatter plot between NPP and AET is done for each 30 plots. The result of regression analysis per plot revealed R^2 value ranging from 0.48 in plot number 275 and 0.75 in plot number 50. On average the coefficient of determination (R^2) is 0.64 which indicates significant linear relationship between NPP and AET. An example of time series plot for field number 50 and 275 is presented in figure 4-4.

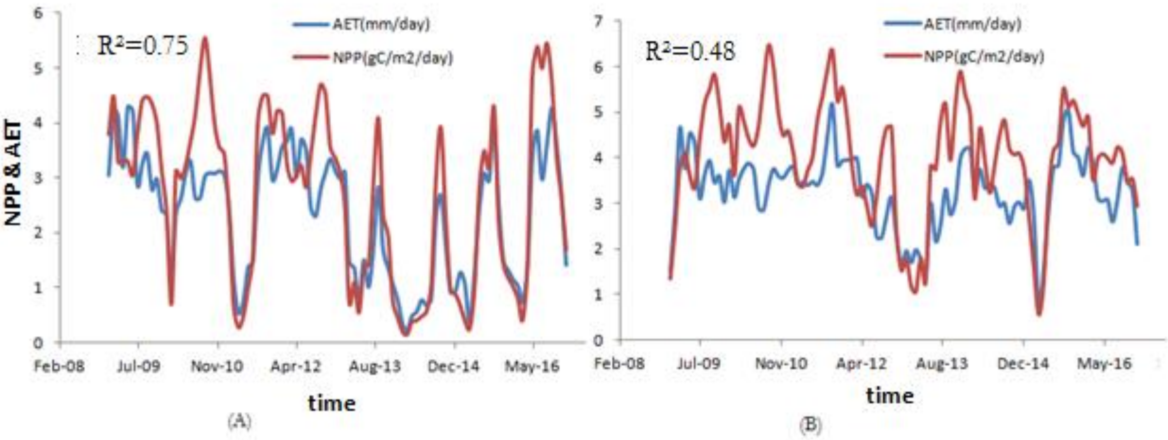

Figure 4-4: Time series plot between NPP and AET for (A) field # 50 and (B) field # 275 for 2009-2016

As depicted in figure 4-4 there is strong relationship between AET and NPP; high AET corresponds with high NPP and vice versa in field number 50 as compared to field number 275. The low correlation in field number 275 is as result of low transpiration associated with high NPP. This may be attributed to presences of stresses affecting the growth/transpiration of plant. Since NDVI is a major input for computation of AET and it is influenced by availability of water, temperature and nutrient. NPP is significantly controlled by fPAR which is a function of solar radiation and land cover (plant density). This is to mean even if plants have high ground cover and there is abundant solar radiation leading to high fPAR (and thus NPP), presence of stresses and pest/disease which affect the greenness of plant (NDVI) will result in lower AET. Further checking for seasonality of NPP is important which can be easily detected in rain-fed agriculture. In this study because the study area is irrigated agriculture and the planting/harvesting dates are not confined to specific season, it is difficult to check for seasonality.

In order to assess how well the model estimates and FRAME captures the spatial behaviour of observed data, the seasonal averages (from 2009 – 2016) of biomass was computed for 30 plots as shown in figure 4-.5. As can be seen from figure 4-5 the FRAME biomass was consistently underestimated when compared to both in-situ data and model output. The FRAME biomass under estimation can be further shown by figure 4-6. It is clearly depicted in figure 4-6 that the transpiration simulated by model is much lower than that of FRAME yet, conversely the biomass appears to be higher as compared to FRAME. Biomass is a direct function of transpiration and it is undeniable that if the model simulates the transpiration to the same level as FRAME, the expected biomass would be much higher. This suggests FRAME has underestimated the biomass.

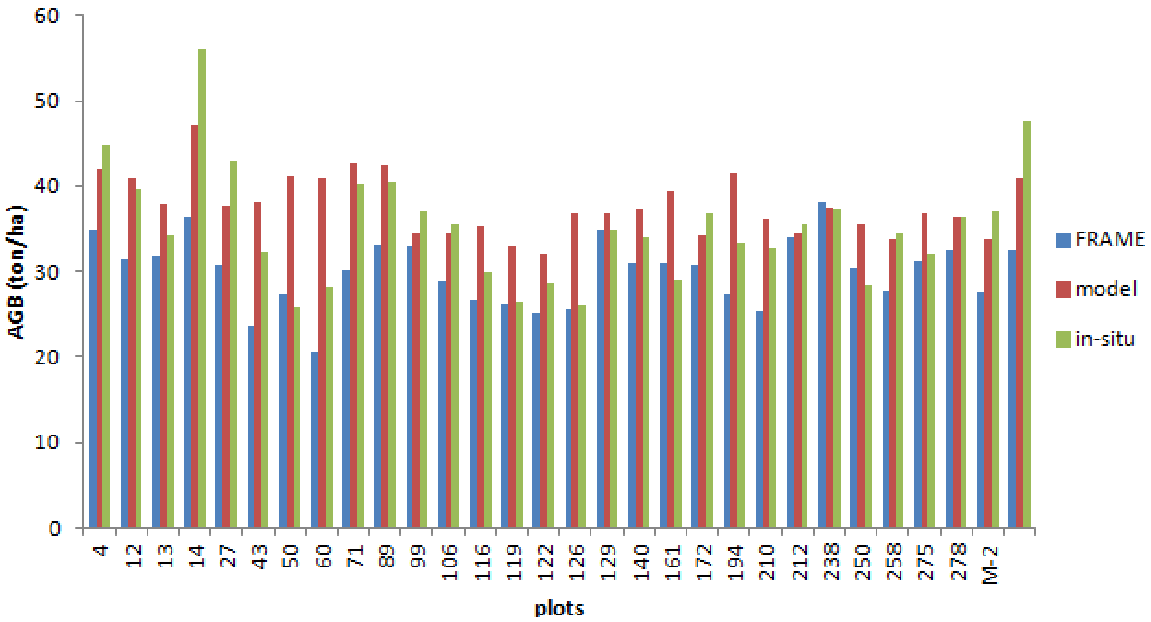

Figure 4-5: plot of seasonal averages of 30 plots of AGB between in-situ, model and FRAME

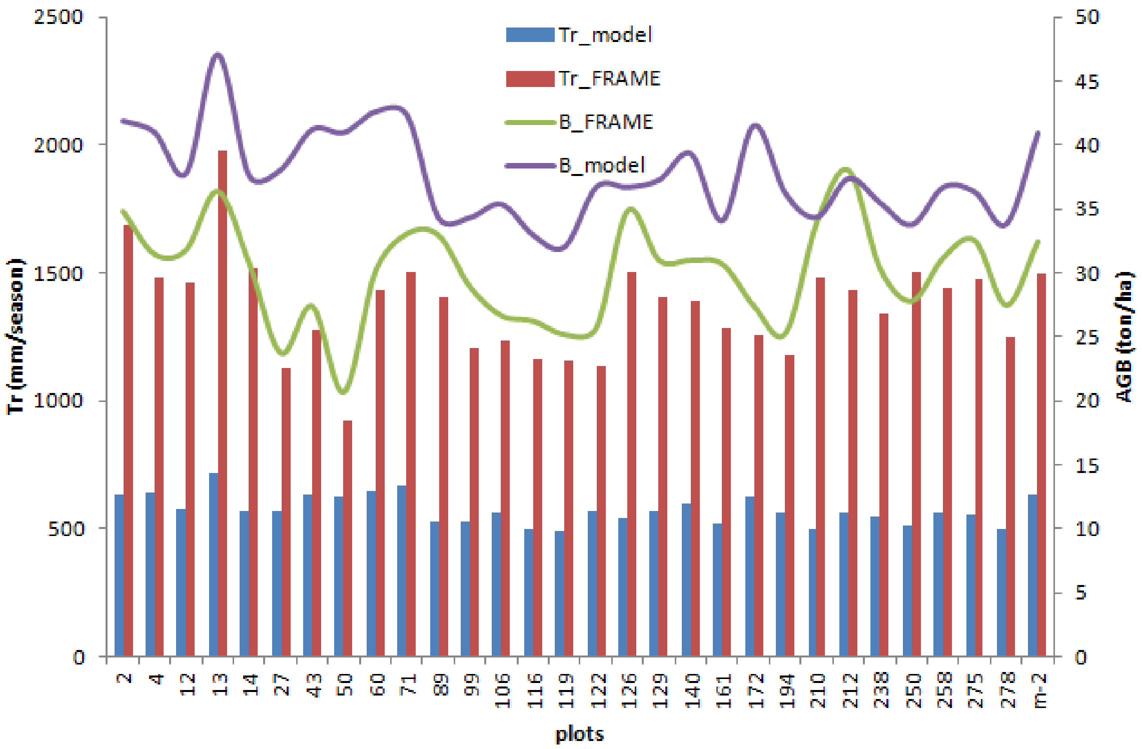

Figure 4-6: plot of seasonal averages of transpiration and biomass of FRAME and model over 30 plots

Statistical metrics between in-situ and FRAME as well as FRAME and model for biomass computed per plot is shown in table 4-5, while the metrics between model and in-situ is presented in section 4.2.2. The plot by plot comparison of FRAME with in-situ gave RMSE (ton/ha) ranging from 2.97 to 24.12 where the RMSE in majority of plots is below 10. While in terms of R^2 it ranges from 0.03 to 0.99 with $R^2 > 0.5$ in 18 plots out of 30 plots. Further comparison of FRAME with model revealed RMSE (ton/ha) ranging from 3.55 to 22.87 and R^2 from 0 to 0.99. The overall agreement of FRAME and model in reference to in-situ is shown in figure 4-7. The regression plots revealed that the correlations are poor; however, as compared to model FRAME has better agreement with in-situ. For model the relation has too much wide scattering because of model bias and this has led to poor correlation between model and FRAME. This suggests that a good correlation or low errors could not be found in all 30 plots. In terms of R^2 a good correlation between the three components (in-situ, model and FRAME) is found in 10 plots (plot # 126, 161, 12, 275, 2, 172, M-2, 71, 129 and 13). Figure 4-8 shows this correlation. However, despite good correlation between model and FRAME on seasonal time step further analysis on dekadal time step did not give good correlation suggesting that the manner in which the model simulates and the FRAME estimated the biomass is different. As an example the dekadal biomass time series as simulated by model and estimated by FRAME for some selected plots is shown in figure 4-9. The correlation on seasonal basis was higher while on dekadal basis no significant correlation could be found. Uncertainty in model is one factor for such poor correlation.

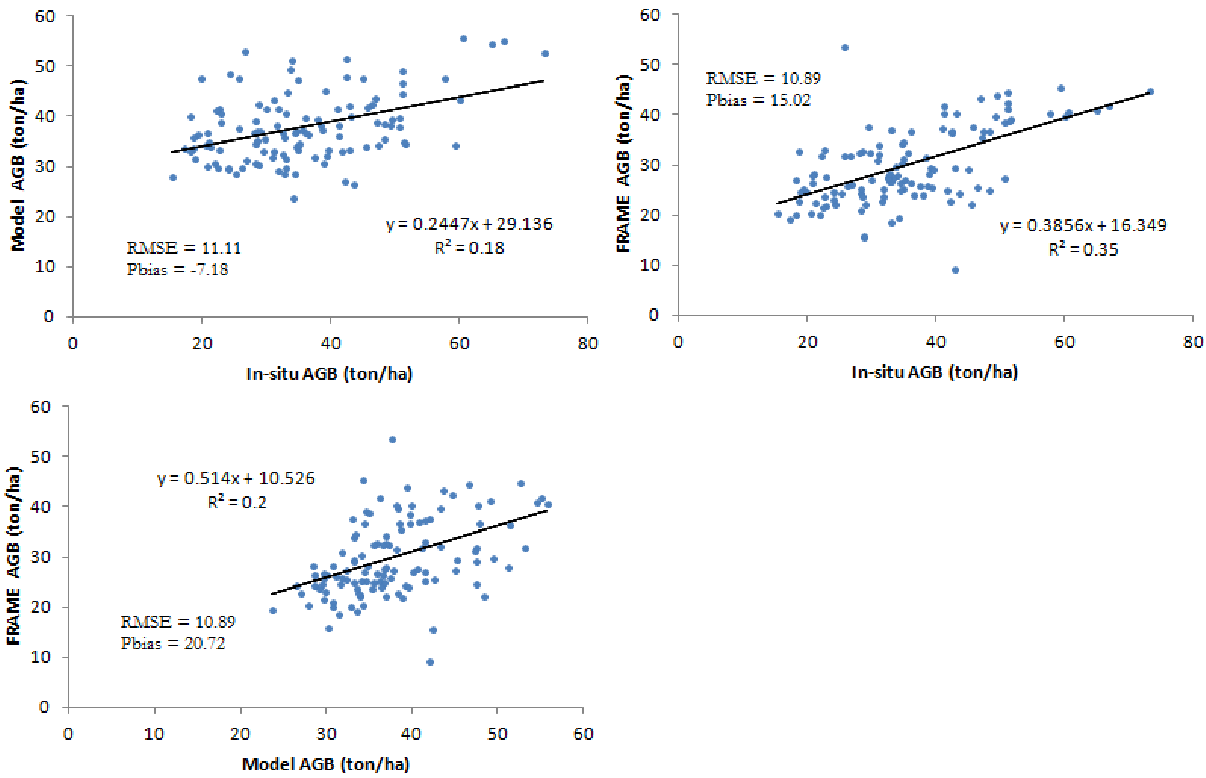

Figure 4-7: scatter plots of seasonal AGB between in-situ, model and FRAME by combining all 30 plots

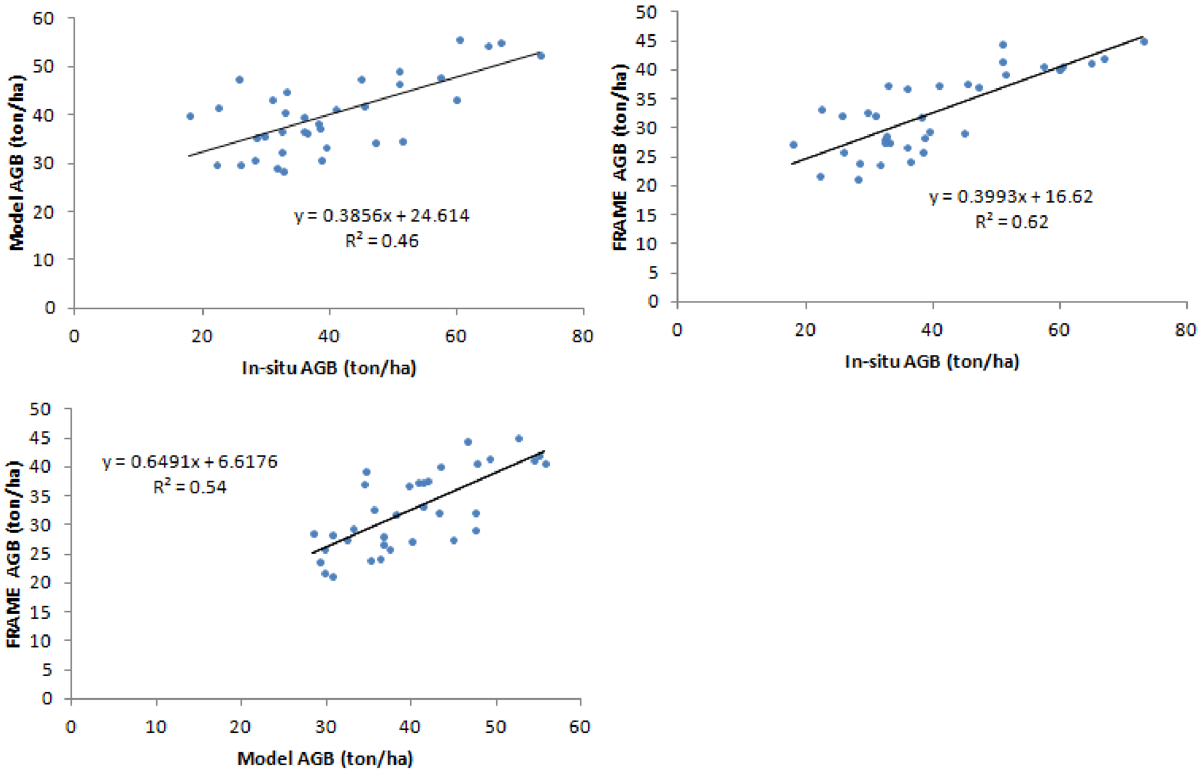

Figure 4-8: plots of seasonal AGB between in-situ, model and FRAME for the selected plots

The potential sources of error that led to discrepancies could be attributed to a number of reasons. In FRAME biomass is computed as a sum of dekadal AGB throughout the growing season of crop. To do this, start and end of growth period of crop should be accurately specified. The field reported planting/harvesting date could have error leading to significant differences between FRAME and in-situ biomass. Though, this is not the case for all plots as for instance as shown in figure 4-9 both model and FRAME shows similar seasonal trend. The significant under estimation of FRAME biomass compared to in-situ and model can be attributed to potential misclassification of information related to crop type from land cover classified as agriculture. Sugarcane is classified as C4 crop and as compared to C3 crops; C4 crops are more efficient in water use and photosynthetic processes(Sinclair & Horie, 1989). In computation algorithm for biomass a parameter called light use efficiency (ability of crop to convert absorbed radiation in to dry biomass) is one of input and it varies with crop type. Therefore, lower value of light use efficiency parameter used for C4 crops while C4 crops actually demonstrate much higher values of light use efficiency parameter than C3 might have led to underestimation of FRAME biomass. This is further shown in figure 4-10 that the slope between AET and biomass known as water use efficiency is higher in model than FRAME. Moreover, the weather data specially temperature used as input in algorithm to derive NPP are available at coarser resolution and they may not well represent and may over estimate the actual weather condition of the area under study. Over estimation in temperature would mostly result in higher plant respiration consequently yielding lower NPP.

Table 4-5: statistical summary of in-situ vs FRAME as well as FRAME vs model

	FRAME			In-situ vs FRAME			Model vs FRAME		
Field #	Min (ton/ha)	Max (ton/ha)	Mean (ton/ha)	RMSE (ton/ha)	Pbias (%)	R^2	RMSE (ton/ha)	Pbias (%)	R^2
2	26.59	40.55	34.85	11.33	22.15	0.67	7.49	16.87	0.86
4	27.19	39.01	31.48	8.77	20.63	0.88	13.12	23.29	0.1
12	21.74	44.63	31.82	3.84	7.29	0.90	7.12	15.9	0.93
13	29.2	45.04	36.42	24.12	35.02	0.97	12.02	22.71	0.59
14	18.77	43.52	30.75	12.13	28.28	0.66	9.89	18.27	0.44
27	22.12	27.25	23.69	12.30	26.59	0.03	14.53	37.83	0.54
43	20.18	42.17	27.38	2.97	-6.49	0.93	18.62	33.62	0.08
50	9.27	32.07	20.63	19.80	26.53	0.34	22.87	49.7	0.2
60	24.59	42.7	30.11	12.73	25.21	0.38	14.66	29.36	0.13
71	21.31	40.68	33.09	12.31	18.27	0.54	10.43	21.93	0.79
89	26.47	45.79	32.96	7.98	10.89	0.90	7.84	4.05	0.04
99	24.58	40.66	28.9	9.94	18.44	0.26	8.41	15.91	0.29
106	20.37	33	26.63	12.08	11.14	0.11	9.22	24.79	0.65
116	19.51	31	26.22	6.89	0.78	0.26	8.29	20.56	0.08
119	20.61	34.19	25.15	9.65	12.09	0.07	9.04	21.62	0.01
122	15.75	32.71	25.67	7.77	1.22	0.09	14.39	30.17	0.37
126	32.27	39.2	34.9	9.50	0.03	0.83	8.32	12.24	0.99
129	27.15	36.98	30.98	7.88	8.71	0.88	8.5	16.98	0.61
140	26.84	36.61	31	8.67	-6.67	0.16	10.03	21.22	0.59
161	25.95	37.75	30.69	7.47	16.44	0.76	3.55	10.13	0.99
172	24.11	32.07	27.39	9.70	17.85	0.86	14.41	34.12	0.82
194	16.16	36.94	25.27	10.85	22.79	0.38	11.16	30.25	0.92
210	29.77	37.84	34.03	8.94	4.04	0.99	3.67	1.13	0
212	25.55	53.82	38.06	16.19	-2.40	0.06	9.42	-1.16	0.26
238	23.79	34.83	30.32	5.38	-6.74	0.34	6.92	14.66	0.06
250	22.46	38.6	27.78	7.73	19.21	0.94	8.02	17.82	0.34
258	24.38	44.16	31.2	4.41	2.55	0.93	9.23	15.1	0.28
275	27.39	41.48	32.55	5.93	10.52	0.76	4.76	10.51	0.93
278	19.81	40.41	27.46	10.93	25.64	0.78	9.12	18.92	0.35
M-2	23.76	41.11	32.46	16.66	31.94	0.99	9.49	20.76	0.82

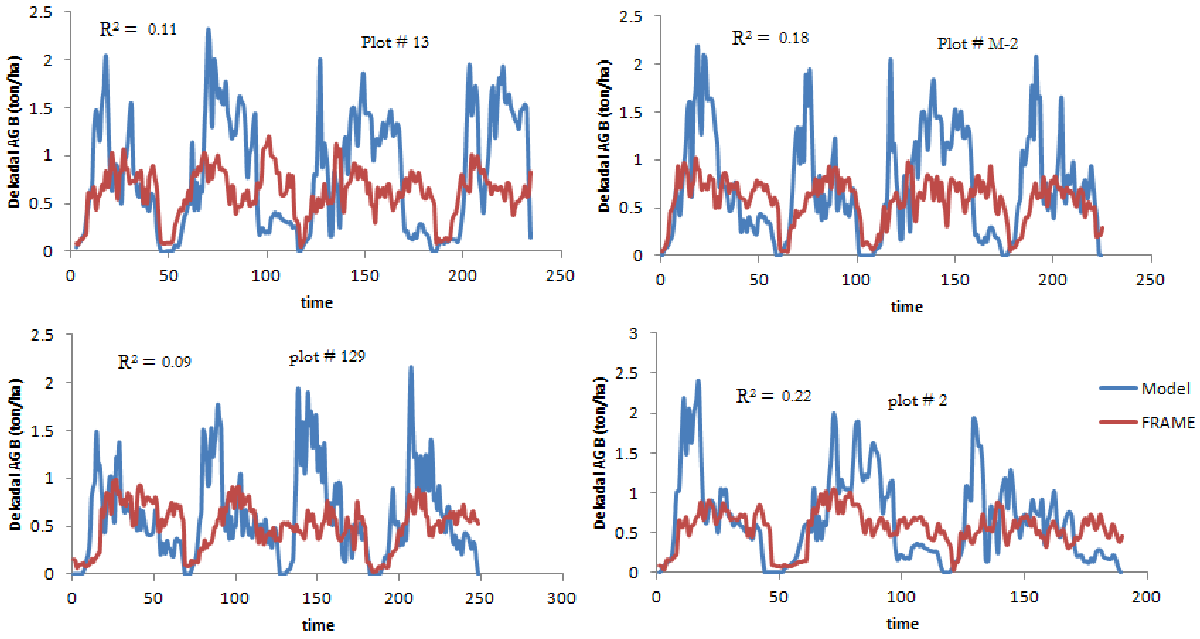

Figure 4-9: dekadal AGB time series of some selected plots

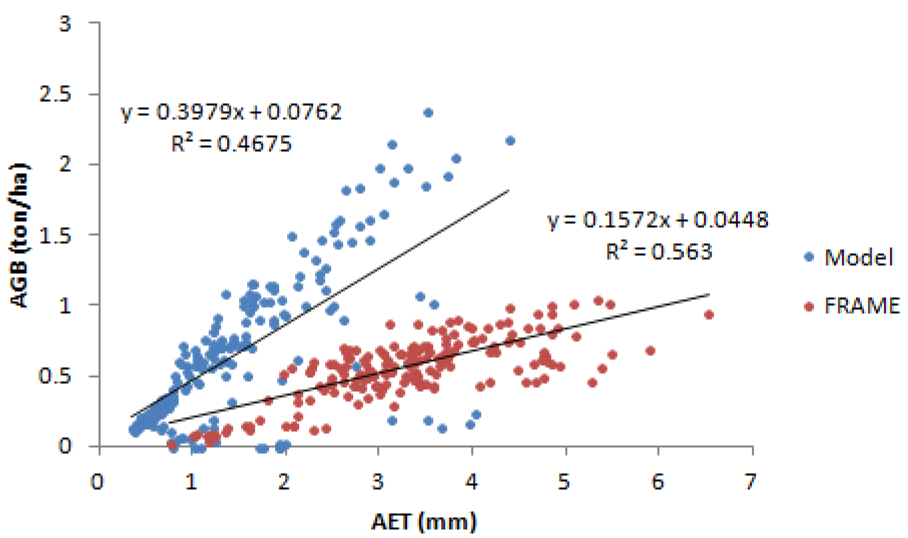

Figure 4-10: AET and AGB relationship for field # 2

4.3.2. Actual evapotranspiration

In this section comparison of AET is made between FRAME and model output as there is no measured information about AET. The average daily AET as estimated by FRAME over 30 plots varied from 2.26 to 3.98 mm/day and the overall average is about 3.06 mm/day while as estimated by model it varied from 1.48 to 1.94 mm/day and the overall average is about 1.71 mm/day. The average daily ETo calculated based on meteorological data collected for the year 2007- 2016 is 4.55 mm/day which confirms the AET estimated by FRAME and simulated by AquaCrop model is lower than potential. The average seasonal AET as estimated by FRAME over 30 plots varied from 1199 to 2327 mm with overall average of 1686 mm and corresponding overall average dry cane yield of 30 ton/ha (fresh cane yield of 100 ton/ha) while for model it varies from 771 to 1067 mm with overall average of 915 mm and corresponding overall average dry cane yield of 37.7 ton/ha (126 ton/ha of fresh cane) suggesting a big difference between FRAME and model. Table 4-6 presents the actual evapotranspiration of sugarcane conducted by different researchers at different sites. Even though, the AET depends on climate, availability of water, growth cycle of crop (crop age), crop cultivar, the type of crop (plant/ratoon) and other factors, assessment of the result of AET and cane yield found in this study with the result of other studies is helpful. As shown in table 4-6 the AET are different from place to place and even under the same climatic condition degree of precision of measurements/estimations of AET depends on algorithm/method employed.

Table 4-6: studies involving sugarcane evapotranspiration

sources	AET (mm/season)	condition	country	Method
Cabral et al., (2012)	685 -829	Rain fed	Brazil	Eddy covariance
De et al., (2016)	1180	Irrigated	Brazil	Remote sensing
Omary & Izuno, (1995)	1060	Irrigated	USA	Water balance
Osorio et al., (2014)	1081 - 1544	Irrigated	USA	SWAT model
Bezuidenhout et al., (2006)	440 - 705	Rain fed	South Africa	Thompson's model of yield-ET relationship
Bryant et al., (2009)	970 – 1281	Irrigated	Australia	Eddy covariance
Bongani Jameson, (2015)	582 - 1259	Irrigated	Swaziland	Remote sensing
Esteves et al., (2005)	1088.19	Irrigated	Brazil	Bowen ratio
Hiyane et al., (2004)	1043.9	Irrigated	Japan	Bowen ratio

The result of AET estimated by model is comparable with those values presented in table 4-6 involving in-situ measurements. When assessing AET estimated by FRAME it looks like over estimating the values reported in literatures. The high AET estimated by FRAME could have produced higher cane yield as a net water supply of 1800 mm would produce a yield of 200 ton/ha as described in Steduto et al., (2012).

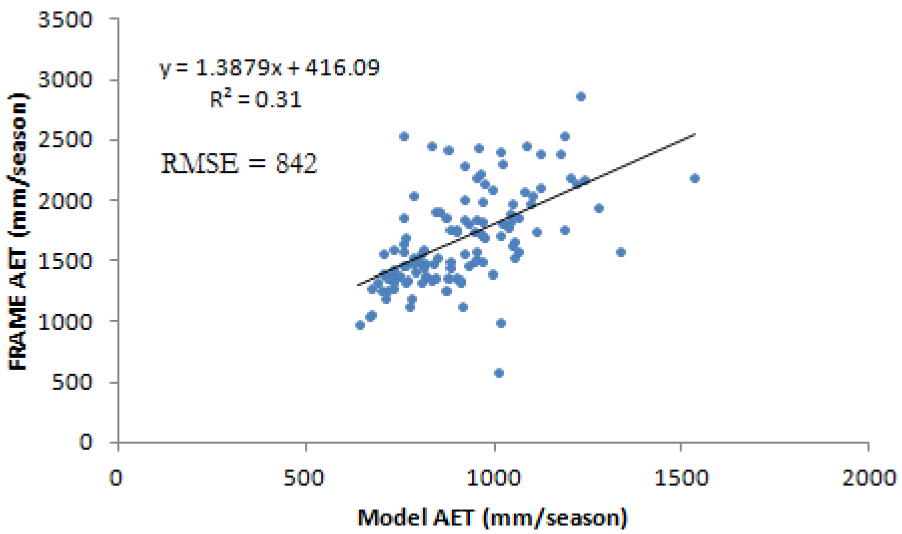

Figure 4-11: scatter plot between FRAME and model seasonal AET over 30 plots

Figure 4-11 shows scatter plot between model and FRAME seasonal AET by combining all 30 plots. The RMSE (mm/season) is about 842 suggesting large difference. As for biomass further analysis on dekadal time step did not give significant correlation between model and FRAME AET.

The discrepancies and low correlations observed between model and FRAME could be attributed to a number of reasons. The first and foremost reason may be explained by soil moisture stress. Water stress affects the crop during all the growth season leading to low transpiration and yield reduction. AquaCrop model considers different types of soil moisture stress namely; canopy expansion, stomata closure, early canopy senescence and aeration stress. In FRAME the algorithm used for AET computation, ETLook model also considers soil moisture stress. However, AquaCrop model seems to be more efficient than remote sensing in taking into account the soil moisture stress to reasonably simulate the soil evaporation and plant transpiration. In remote sensing the soil moisture stress is often derived from top soil layer and the plant transpiration mostly depends on root zone soil moisture. The other important reason may be as result of aeration stress. Excessive water in the root zone as result of heavy rainfall, shallow ground water and frequent irrigation may cause aeration stress forcing lower plant transpiration. This case has been mostly simulated in AquaCrop in this study, while aeration stress is unlikely to be detected from remote sensing. Moreover, the date of satellite image acquisition and the date when plants were experiencing stress may not coincide resulting in exaggerated estimation of transpiration.

In AquaCrop model the simulated transpiration during the crop establishment stage and near harvesting is lower which is naturally true contrary to FRAME which appears to be higher at the beginning and end of growth season of crop. This case has been observed often resulting in big accumulated difference between model and FRAME. An example of time series of transpiration for plot number 99 for a single growth season (May 2014 to September 2015) is shown in figure 4-12. It is clearly depicted how different the FRAME and model are at the beginning and end of growth season of crop leading to low correlation and high error. This mismatch may arise due to incorrect planting/harvesting date reported from field data.

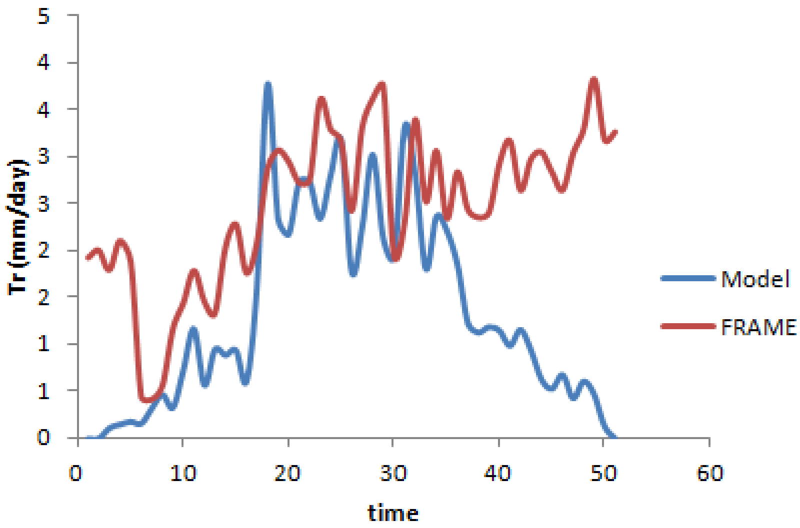

Figure 4-12: Time series (dekadal time step) plot of transpiration simulated by model and FRAME estimate for single crop season

The uncertainty of AquaCrop model is a critical factor that has to be considered as well. The data used in this study was not sufficient for reliable calibration of model. Even though, it can be derived from rainfall irrigation scheduling input to model has significant effect on simulated AET. The field collected information about irrigation does not tell us the exactly date and amount (depth) of application. This uncertainty is even more exaggerated in sugarcane as it has a very long growth cycle. Errors and uncertainties resulting from such cases could be reduced by applying AquaCrop model in rain-fed agriculture and cereal crops which has short growth cycle. Therefore, further testing of FRAME in rain-fed agriculture is important. Considering such uncertainty embedded in model the FRAME estimates of AET could be reliable. The reliability of ETLook model has already been tested for different climatological conditions and locations (Bastiaanssen et al., 2012).

4.3.3. Water productivity

In this section the water productivity based on model simulation and FRAME estimate was compared. As discussed in section 2.1. water productivity is a function of AGB/yield and AET. Therefore, the accuracy of estimated water productivity depends on accuracy of AGB/yield and AET. For model the water productivity estimated in terms of above ground biomass ranges from 2.49 - 5.39 kg/m3 while for FRAME it ranges from 1.43 - 3.46 kg/m3. As a result of high AET and low AGB estimated by FRAME the water productivity is lower than that of model. The result estimated by model is comparable with value 3.5 - 5.5 kg/m3 mentioned by Steduto et al., (2012). Leal et al., (2017) found water productivity in terms of stem fresh biomass ranging from 11.45 to 18.45 kg/m3 conducted for 23 sugarcane varieties in Brazil under two level of drip irrigation. Assuming moisture content of 70% for sugarcane the water productivity value estimated by model is comparable with result of Leal et al., (2017). Teklay & Ayana (2014) estimated water productivity in terms of yield for major crops (cotton, sugarcane and onion) grown in upper and middle Awash basin based on survey conducted on 29 irrigation water users (including the Wonji irrigation scheme) for 2005/06 – 2009/10 production year using CROPWAT model. Their study revealed crop water productivity for sugarcane varied from 9.8 – 18.8 kg/ m3 with average value of 15.2 kg/m3. Considering harvest index of 0.4 (estimated based on crop production data of 30 plots) the model estimate of water productivity is in agreement with that of Teklay & Ayana (2014).

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5. CONCLUSIONS AND RECCOMENDATIONS

The goal of present study was to evaluate FAO-FRAME remote sensing derived water productivity data components by using the AquaCrop model together with observed in-situ data. Three data components; NPP, AET and Tfrac of FRAME for the year 2009 - 2016 were extracted for each plots and used for the analysis. The AquaCrop model was applied to 30 selected plots of the study area. A sensitivity analysis of Aquacrop model variables revealed that the rooting depth has to be calibrated with great care as increased root depth triggers more water extraction resulting in high transpiration and biomass accumulation while high sensitivity of model to initial soil water content can be circumvented by running a model starting from a known very dry (PWP) or very wet (FC) period. Since the AquaCrop model is being proposed as a bench mark for evaluation of the FRAME water productivity data, it is important to have reasonable model simulations. This study has demonstrated that use of only biomass/ crop yield for AquaCrop model calibration is not good enough for a reliable simulation of the model as the model originally demands observations made at different growth stages of the crop and not only just at the time of harvest. Therefore, it is recommended to have more continuous measurements of canopy cover, soil moisture and biomass. Remote sensing data can be also used to derive such local information at different stages of crop. The study also demonstrated that irrigation scheduling has a significant impact on simulated AET and thus the final AGB and crop yield suggesting that accurate local information on irrigation is needed at the plot (field) level. To overcome this problem it is recommended to also apply the AquaCrop model in rain-fed agriculture involving cereal crops. The study revealed that the FRAME data generally underestimate the AGB as compared in-situ observed and simulated model output. This has been further motivated by low transpiration and high AGB simulated by model while FRAME estimate went in opposite manner. As expected the water productivity computed from FRAME appears lower compared to the simulated AquaCrop model output. Given the limitations and low confidences in model output, it is generally difficult to judge or conclude about the final accuracy of FRAME data. Therefore, further research needs to be undertaken for more detailed and accurate in-situ evaluation of FRAME. This can be achieved by undertaking in-situ AET measurements using likes of flux towers, derivations of WP data components using algorithms and satellite images which were not employed by FRAME and making comparisons and further evaluation of FRAME in rain-fed agriculture.

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APPENDICES

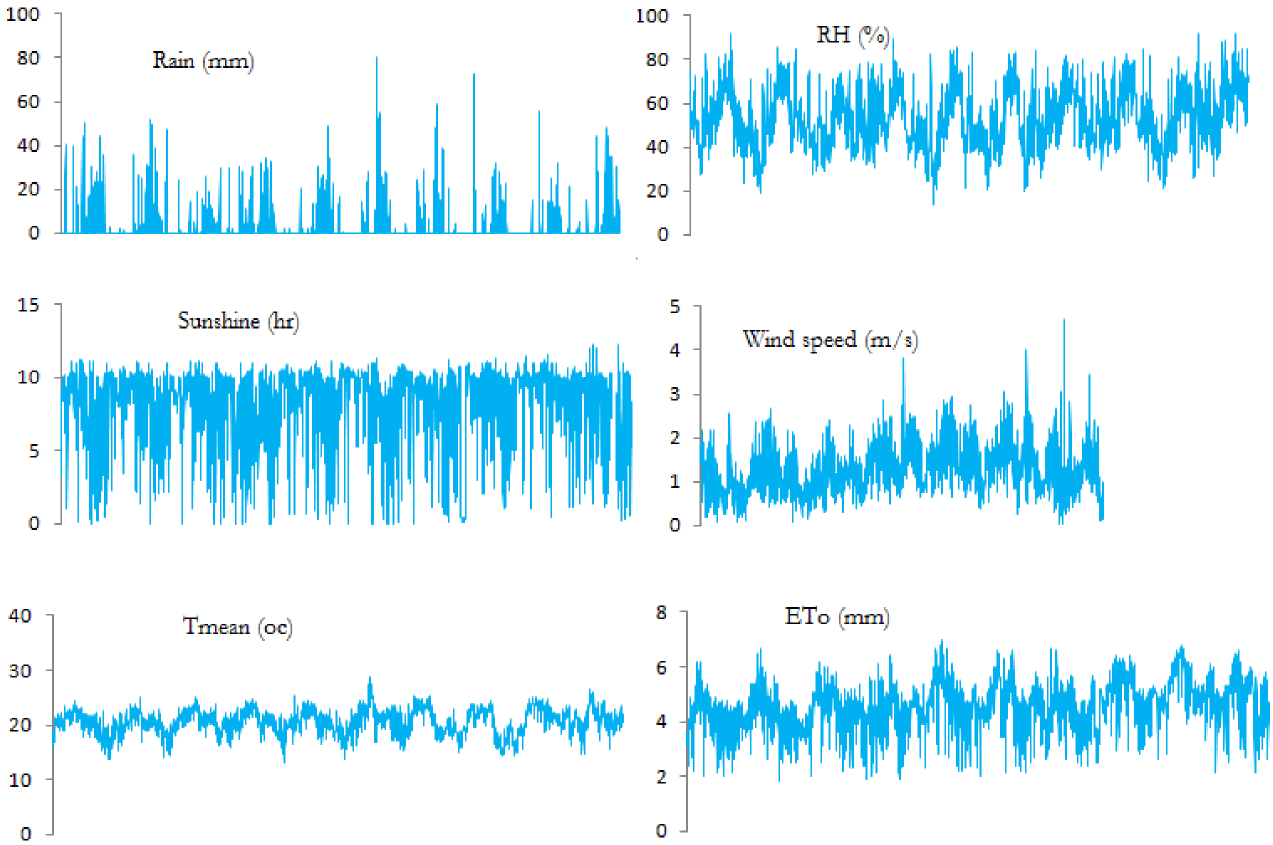
A. Samples of crop data collected

Field number	Soil type	Planting date	Harvesting date	Cane type	Area (ha)	Cane yield (ton/ha) (fresh)	Field sugar (ton/ha)
4	Clay	*Dec-08*	Mar-10	*3rd ratoon*		116.33	12.48
		Mar-11	Dec-12	*Plant crop*		170.80	21.49
		Jan-13	Jul-14	*1st ratoon*		111.86	14.45
		Aug-14	Dec-15	*2nd ratoon*	11	129.81	16.17
14	Sand	*Feb-09*	Mar-10	*1st ratoon*		154.51	16.85
		Apr-10	May-11	*2nd ratoon*		130.80	15.31
		Jun-11	Jan-13	*3rd ratoon*		163.93	20.90
		Feb-13	Jan-15	*4th ratoon*		156.04	19.97
		Feb-15	Dec-15	*5th ratoon*	24	109.28	12.43
43	Sand	*Dec-08*	Mar-10	*1st ratoon*		80.50	7.88
		Apr-10	May-11	*2nd ratoon*		59.77	6.71
		Dec-11	May-14	*Plant crop*		137.22	17.59
		Jun-14	Nov-15	*1st ratoon*	23	65.36	8.26
50	Clay	*Apr-08*	Dec-09	*Plant crop*		78.13	10.26
		Jan-10	Jan-11	*1st ratoon*		50.61	5.82
		May-11	Feb-13	*Plant crop*		87.99	11.59
		Mar-13	Aug-14	*1st ratoon*	18	142.20	17.01
60	Sand	*Dec-08*	Mar-10	*3rd ratoon*		93.74	10.01
		Dec-10	Jan-12	*Plant crop*		160.72	18.09
		Feb-12	May-14	*1st ratoon*		170.19	23.20
		Jun-14	Dec-15	*2nd ratoon*	23	112.24	14.55
71	Clay	*Dec-09*	Nov-11	*Plant crop*		201.24	25.51
		Dec-11	Feb-14	*1st ratoon*		109.59	14.71
		Mar-14	Jun-15	*2nd ratoon*	22	94.01	11.02
89	loam	*Dec-08*	Mar-10	*2nd ratoon*		108.85	11.13
		Apr-10	May-11	*3rd ratoon*		68.79	7.43
		Dec-11	Apr-14	*Plant crop*		197.38	26.65
		May-14	Dec-15	*1st ratoon*	24	118.14	15.94
116	loam	*Feb-09*	May-10	*Plant crop*		67.71	7.64
		Jun-10	Oct-11	*1st ratoon*		139.94	15.92
		Feb-12	Dec-13	*Plant crop*		103.20	12.97
		Jan-14	Mar-15	*1st ratoon*	9	70.60	8.08

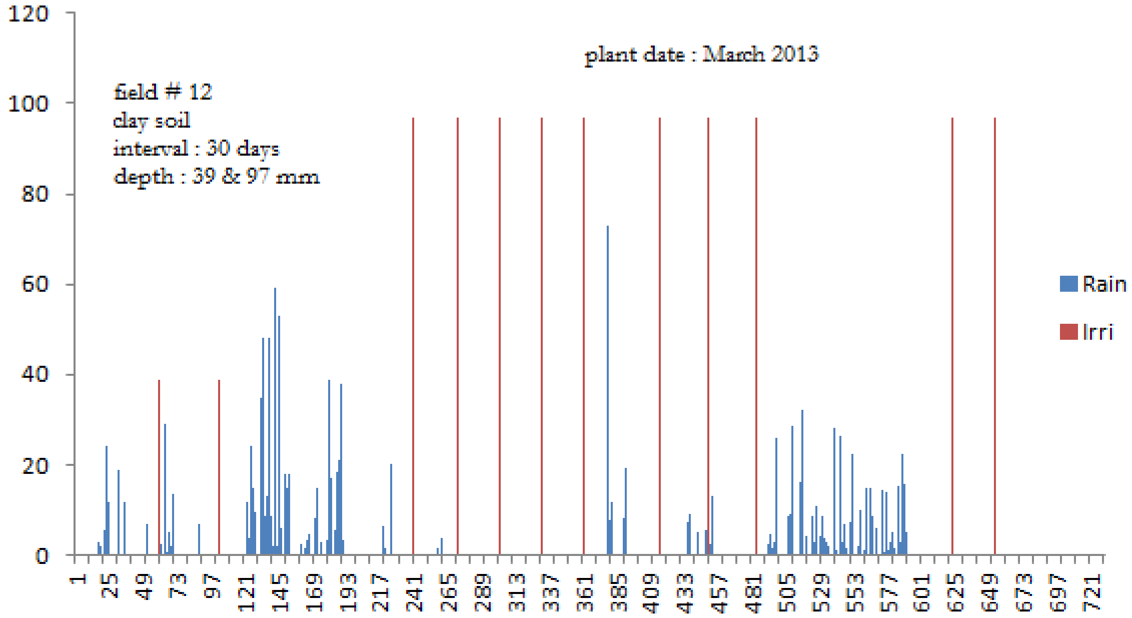
B. List of AquaCrop model parameters used

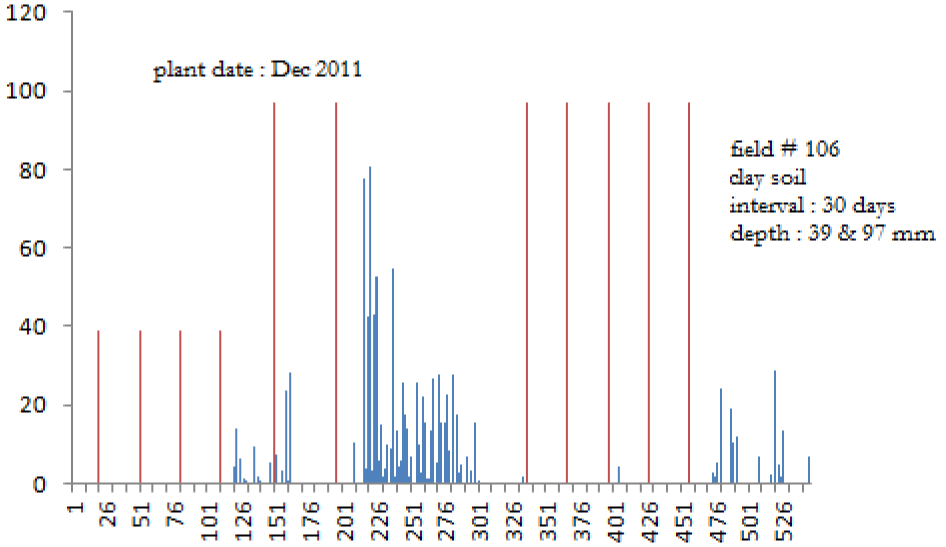
description	Value	unit
Base temperature	9	^{o}C
Upper temperature	32	^{o}C
Upper threshold for canopy expansion (P_{upper})	0.1 - 0.2	% TAW
Lower threshold for canopy expansion (P_{lower})	0.45 - 0.55	%TAW
Shape factor for water stress coefficient for canopy expansion	3	-
Upper threshold for stomatal closure	0.45 - 0.55	%TAW
Shape factor for water stress coefficient for stomatal control	3	-
Canopy senescence stress coefficient (P_{upper})	0.45 - 0.55	%TAW
Shape factor for senescence stress coefficient	3	-
Aeration stress sensitivity to water logging	10	%
Crop coefficient when canopy is complete but prior to senescence	1.02	-
Decline of crop coefficient as a result of ageing, nitrogen deficiency	0.16	%/day
Minimum effective rooting depth	0.5	m
Maximum effective rooting depth	0.9	m
Shape factor describing root zone expansion	9	-
Soil surface covered by an individual seedling at 90 % emergence	6	cm2
Number of plants per hectare	137,931	-
Canopy growth coefficient (CGC)	0.06012	%/day
Canopy decline coefficient (CDC)	0.13048	%/day
Maximum canopy cover (CCx)	90	%
Calendar Days: from sowing to emergence	20 (for ratoon) and 60 (for plant crop)	days
Calendar Days: from sowing to maximum canopy cover	Emergence + 120 days	days
Calendar Days: from sowing to start senescence	30 days before maturity	days
Calendar Days: from sowing to maturity	Harvest date!	days
Water Productivity normalized for ETo and CO2 (WP*)	30	(gram/m2)
Reference Harvest Index (HIo)	40	(%)

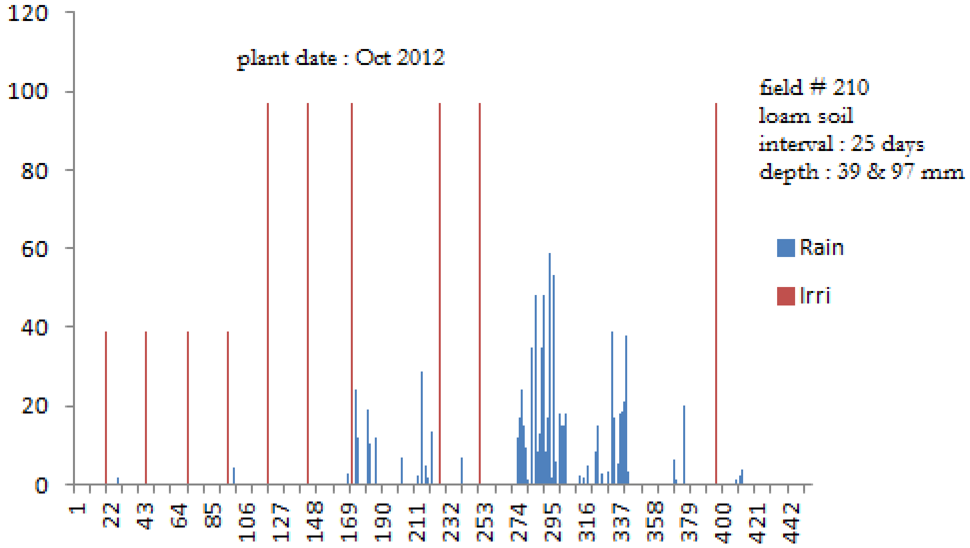
C. Wonji climate (2007-2016)

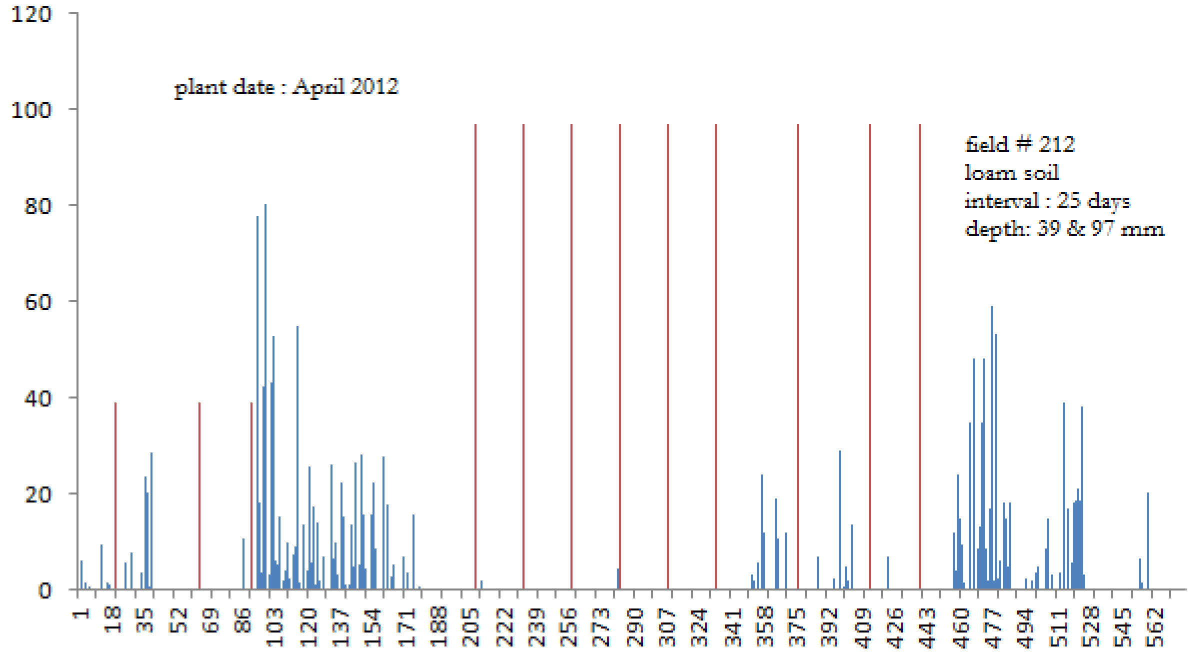


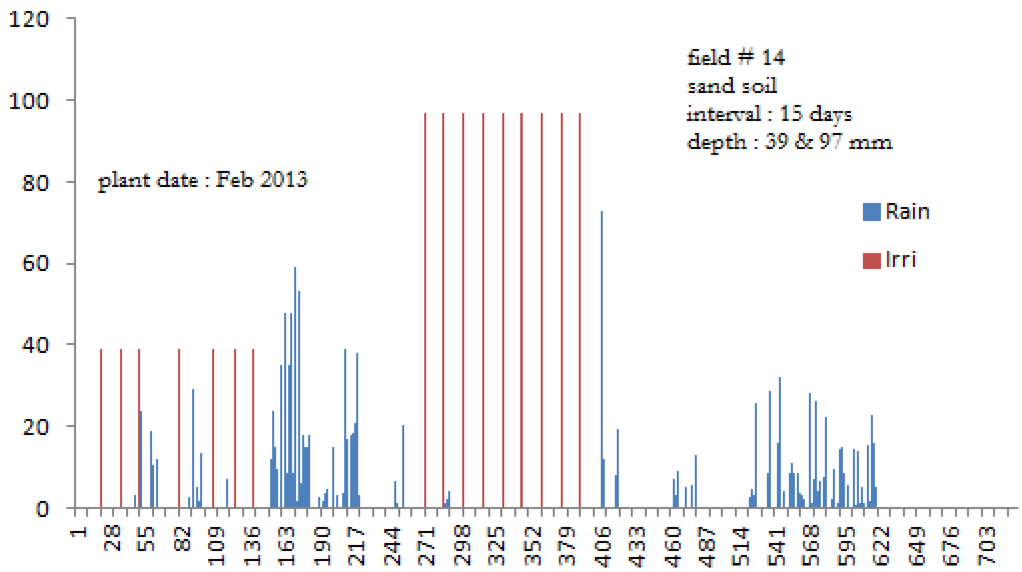
D. AquaCrop irrigation input example

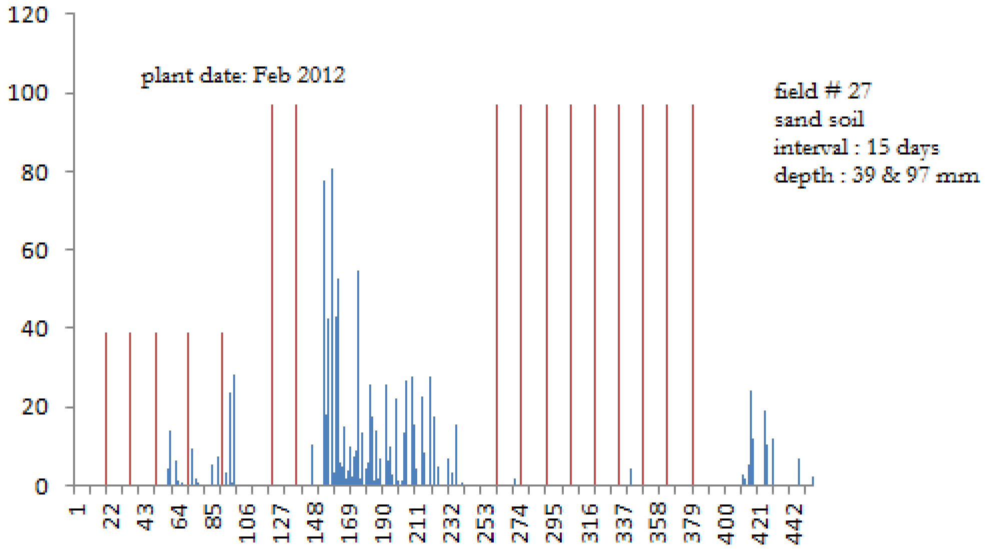





plant date : Oct 2012
field # 210
loam soil
interval : 25 days
depth : 39 & 97 mm
Rain
Irri


plant date : April 2012
field # 212
loam soil
interval : 25 days
depth: 39 & 97 mm


120
100
80
60
40
20
0
plant date : Feb 2013
field # 14
sand soil
interval : 15 days
depth : 39 & 97 mm
Rain
Irri
1
28
55
82
109
136
163
190
217
244
271
298
325
352
379
406
433
460
487
514
541
568
595
622
649
676
703


120
100
80
60
40
20
0
plant date: Feb 2012
field # 27
sand soil
interval : 15 days
depth : 39 & 97 mm
1
22
43
64
85
106
127
148
169
190
211
232
253
274
295
316
337
358
379
400
421
442