Monitoring Water Productivity: Demonstration Case for ThirdEye Mozambique

August 2017

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Executive summary

Monitoring Water Productivity is set as a target for Sustainable Development Goal 6 (“ensure availability and sustainable management of water and sanitation for all”). This report summaries a demonstration case for the ThirdEye area in southern Mozambique on methods to monitor Water Productivity.

This demonstration case is financially supported by:

- Securing Water for Food (USAID)
- Brigaid (EU-H2020)
- Mkb-innovatiestimulering Regio en Topsectoren (MIT)
- Core funds FutureWater

Interactions, inspiration, and/or information obtained from various people have been highly appreciated:

- Mr. Job Kleijn (Ministry of Foreign Affairs, The Netherlands)
- Mrs. Antje van Driel (NL Embassy, Maputo)
- Mr. Jan Vlaar (NL Embassy, Kigali)
- Mr. Ku McMahan (USAID)
- Mr. Wim Bastiaanssen (UNESCO-IHE)
- Mr. Jippe Hoogeveen (FAO)
- Mr. Ebel Smidt (W4GR)
- Mr. Rob Nieuwenhuis (W4GR)
- Mr. Maurits Voogt (eLEAF)
- Mr. Chris Perry (IWMI)

1 Introduction

1.1 Background

In the context of the Sustainable Development Goal 6 (“ensure availability and sustainable management of water and sanitation for all”) the Government of the Netherlands has adopted the monitoring of target 6.4 (“change in water use efficiency over time”). To explore how this can be put in practice, a demonstration case has been setup focusing on measuring Water Productivity (WP) for a project area in southern Mozambique.

The demonstration area is part of FutureWater’s ThirdEye project in Mozambique that aims at supporting farmers’ decision making using Flying Sensors (drones). Two scale levels are used for this demonstration:

- project area of 700 ha
- individual fields of on average 0.15 ha

Water Productivity information was obtained from:

- Level_01: based on WaPOR (FAO’s Water Productivity database)
- Level_02: based on satellite MODIS
- Level_03: based on satellite Landsat
- Level_04: based on Flying Sensors (drones)

The overall objective of this demonstration case can be summarized as: “to demonstrate strengths and weaknesses of various Water Productivity information products”.

2 Methodology and Data

2.1 Project Area

The ThirdEye project supports farmers in Mozambique with their decision making in water and crop management by setting up a network of Flying Sensors (drones) operators. These operators are equipped with Flying Sensors and tools to analyze the obtained imagery. This project is unique as it is a first demonstration in a developing country to supply information on a regular base using Flying Sensors. At the moment, more than ten Flying Sensors and operators are supporting around 8000 farmers in southern Mozambique.

Details on the ThirdEye project can be obtained from *http://www.thirdeyewater.com/* and *http://www.futurewater.eu/.*

The ThirdEye project is undertaken in various regions in southern Mozambique. For this particular Water Productivity (WP) monitoring demonstration focus will be on the Xai-Xai area (Figure 1). Two levels of WP monitoring are considered: (i) sub-project level and (ii) field level. At the sub-project level, an area receiving ThirdEye services of 700 ha is compared to a control area not receiving ThirdEye advice. At the second level, individual maize fields of on average area of 0.15 ha are monitored (Figure 2).

Cropping pattern varies substantially within the Xai-Xai area and is also influenced by prevailing weather conditions and availability of water for irrigation. For this ThirdEye demonstration area maize is the main crop with growing season of planting date around 20-May and harvesting at 1-September. A second growing season runs from around 20-September to 31-December.

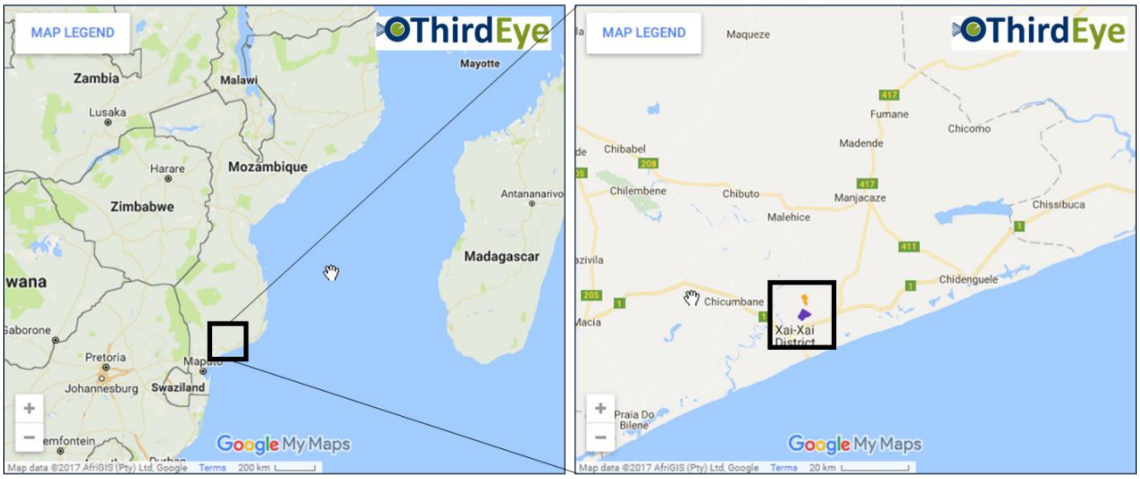

Figure 1. ThirdEye study area in the Xai-Xai region in southern Mozambique.

Figure 2. The two levels of Water Productivity analysis: sub-project level (left) and field level (right).

2.2 Water Productivity Data

Water Productivity information was obtained from four different sources:

- Level_01: based on WaPOR (FAO's Water Productivity database)
- Level_02: based on MODIS sensor on board of Aqua and Terra satellites (NASA)
- Level_02: based on Landsat satellites (NASA)
- Level_04: based on Flying Sensors (drones)

Summary of these data are shown in Table 1. Details on the listed data sources are described in the Appendix.

Table 1. Summary of the four Water Productivity monitoring date sets used.

Name	Source	Spatial Resolution	Spatial Extent	Temporal Resolution	Temporal Extent
WaPOR*	FAO	250 m	Africa, Near East	Annual**	2010 – 2016
MODIS	NASA	250 m	Global	Daily	1999 – present
LANDSAT	NASA	30 m	Global	14-days	1972 - present
Flying Sensors	HiView	0.1 m	Project specific	Project specific	Project specific

* *Level 1 product; level 2 and 3 are under development*
** *Lower level data (e.g. biomass, evapotranspiration) available at 10-days interval*

3 Results

3.1 Water Productivity monitoring based on FAO-WaPOR

The WaPOR Water Productivity data can be obtained directly from the WaPOR website and is available for Africa and Near East. Typical output at country level is shown in Figure 3. WP values vary substantially over the country, with high values in the northern part of the country. Differences between years can also be substantially mainly as function of precipitation rates (Figure 4).

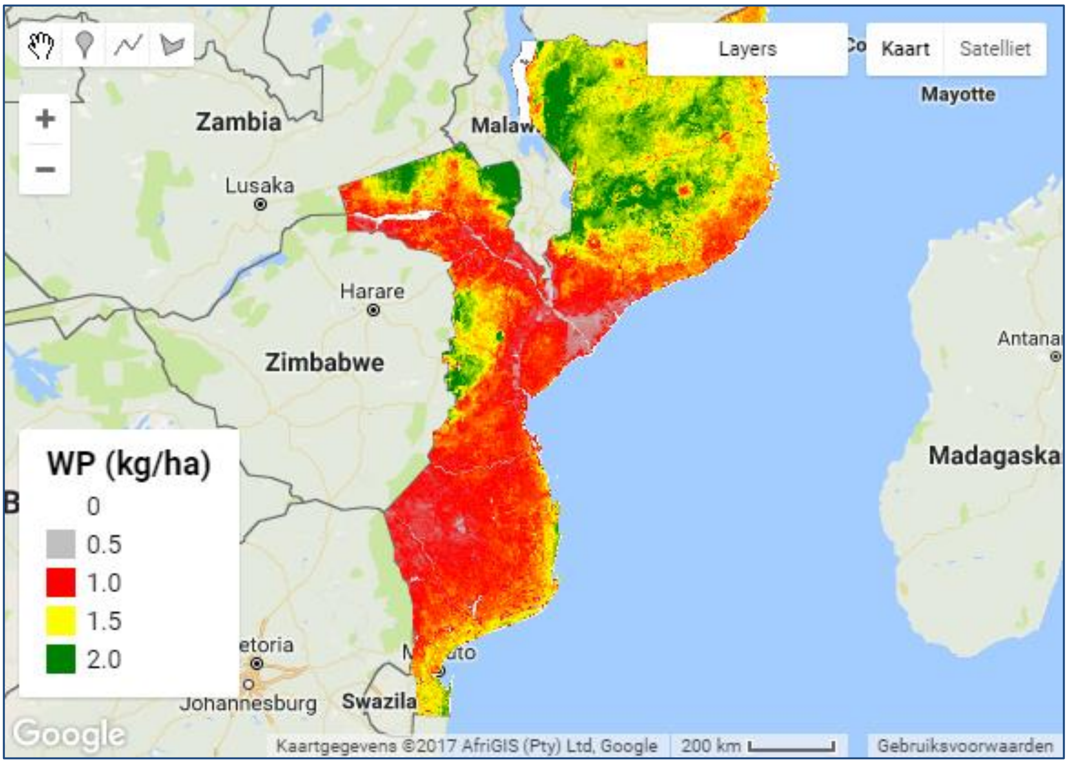

Figure 3. Average annual water productivity (kg/m^3) for the years 2010-2016 based on the FAO-WaPOR database for the entire Mozambique.

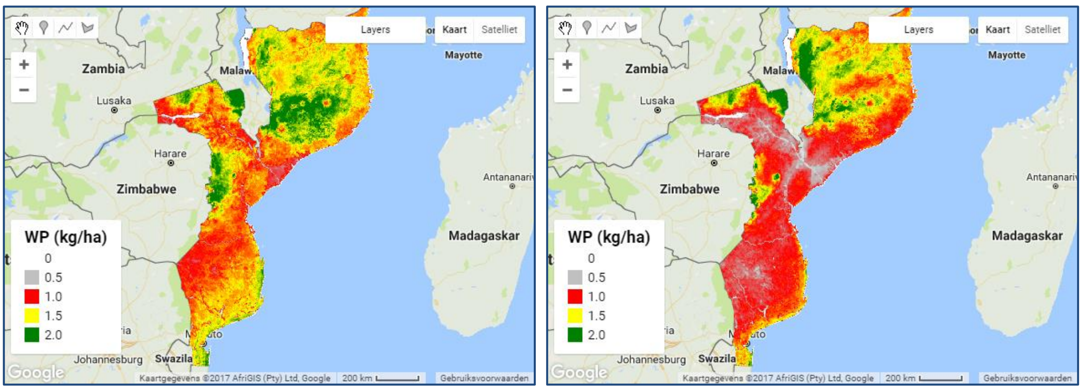

Figure 4. Annual water productivity (kg/m^3) for the years 2012 (left) and 2016 (right) based on the FAO-WaPOR database.

For the ThirdEye demonstration case 2016 WP maps based on WaPOR are plotted in Figure 5 and Figure 6. At project level the spatial resolution provides a reasonable level of detail (Figure 5), but at field scale level insufficient (Figure 6). The WaPOR data include biomass and not actual harvestable yield. WaPOR WP information is only readily available over an entire year, and multiple cropping seasons, non-agricultural vegetation or bare periods are all lumped together. Post-processing is required to derive WP for a specific period of interest. The big advantage of the WaPOR database is that it is freely available and based on the most advanced algorithms to calculate WP.

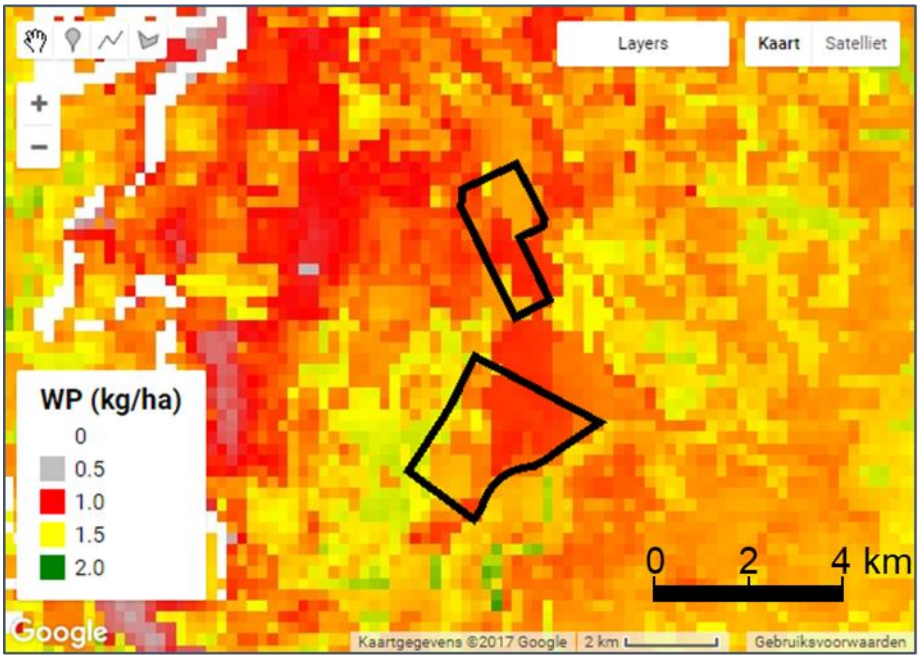

Figure 5. Annual water productivity (kg/m^3) for the year 2016 based on the FAO-WaPOR database for the ThirdEye and Control site.

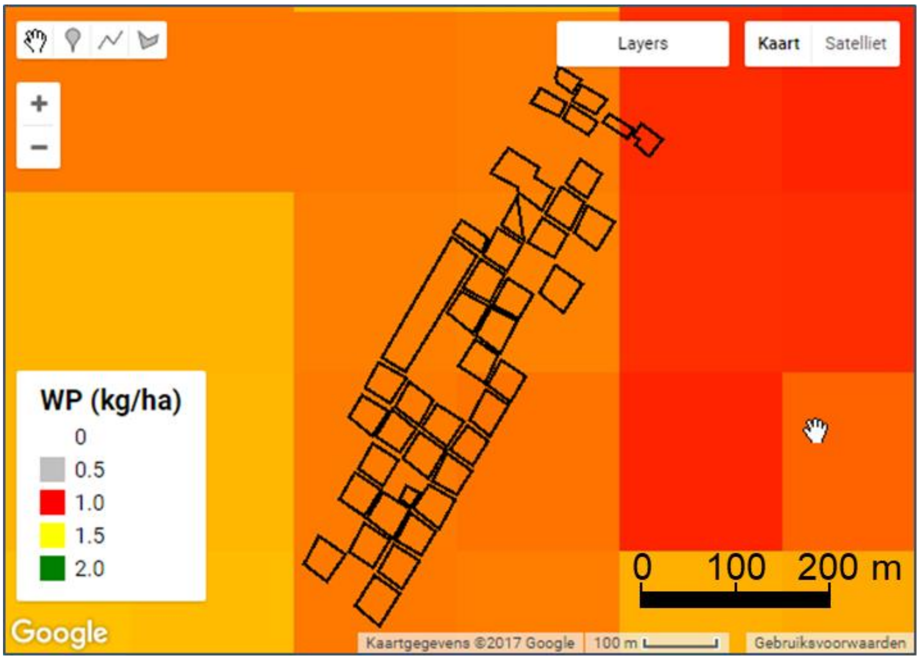

Figure 6. Annual water productivity (kg/m^3) for the year 2016 based on the FAO-WaPOR database for the demonstration fields.

The summarized WP results based on WaPOR are plotted in Figure 7. Since the start of the ThirdEye project in 2015, WP values of the ThirdEye area are higher compared to the Control site. At the same time a decline compared to previous years can be seen, mainly attributed to the poor rainfall conditions in the last years. Figure 8 shows the underlying information for the WP calculations (biomass and actual evapotranspiration), indicating that less water has been consumed by the ThirdEye area compared to the Control.

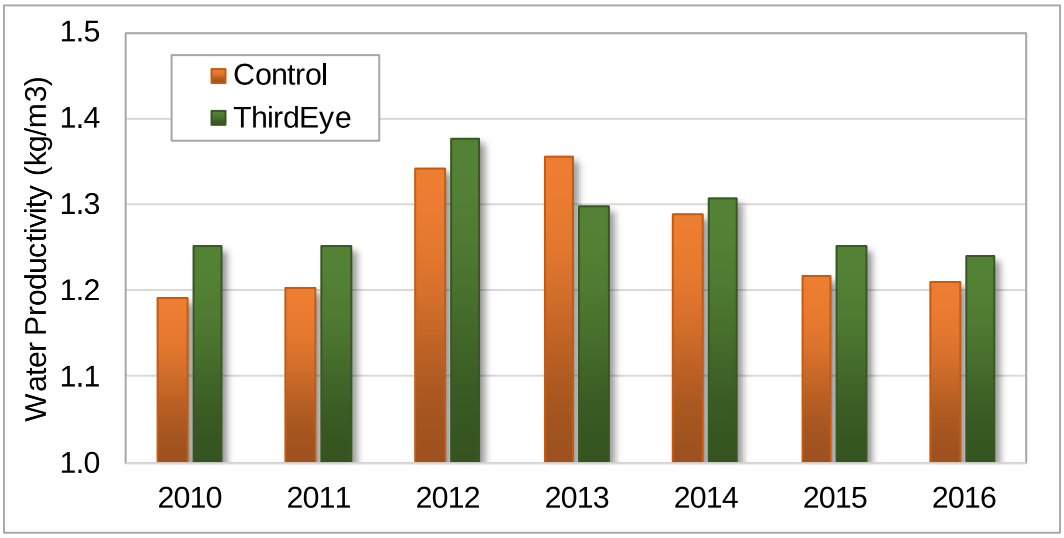

Figure 7. Average annual water productivity (kg/m^3) for the years 2010-2016 based on the FAO-WaPOR database.

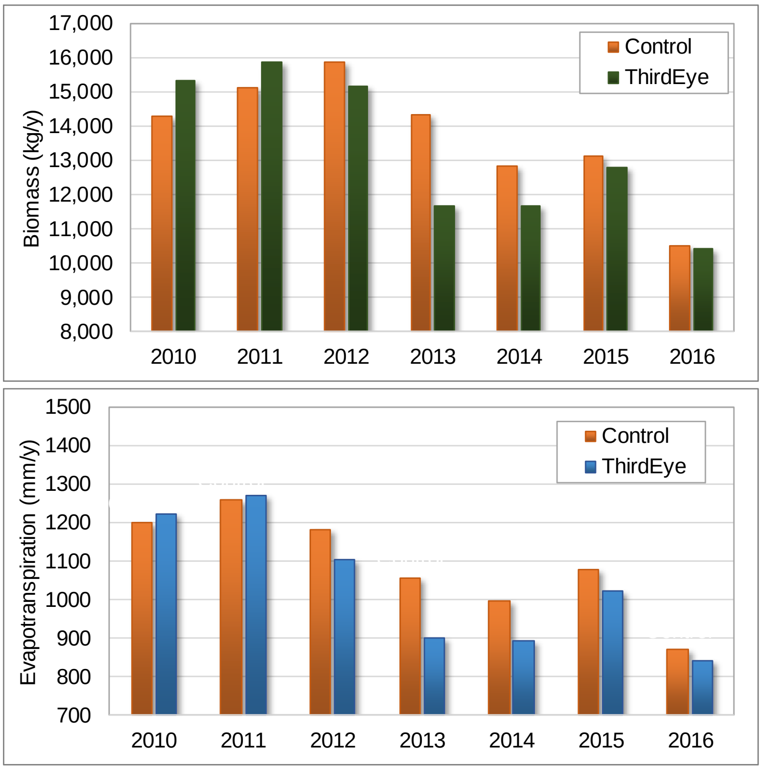

Figure 8. Components of the Water Productivity: biomass (top) and actual evapo-transpiration (bottom). Data based on the FAO-WaPOR database.

3.2 Water Productivity Based on MODIS

To overcome the restrictions in the WaPOR database (entire year, only biomass), Google Earth Engine has been used to calculate WP using the MODIS satellite information. Results can be seen in Figure 9 and Figure 10. Main differences with the WaPOR data are that now actual crop yields are calculated, and only the corresponding growing season is considered. Results show that the ThirdEye service has a positive impact in terms of Water Productivity.

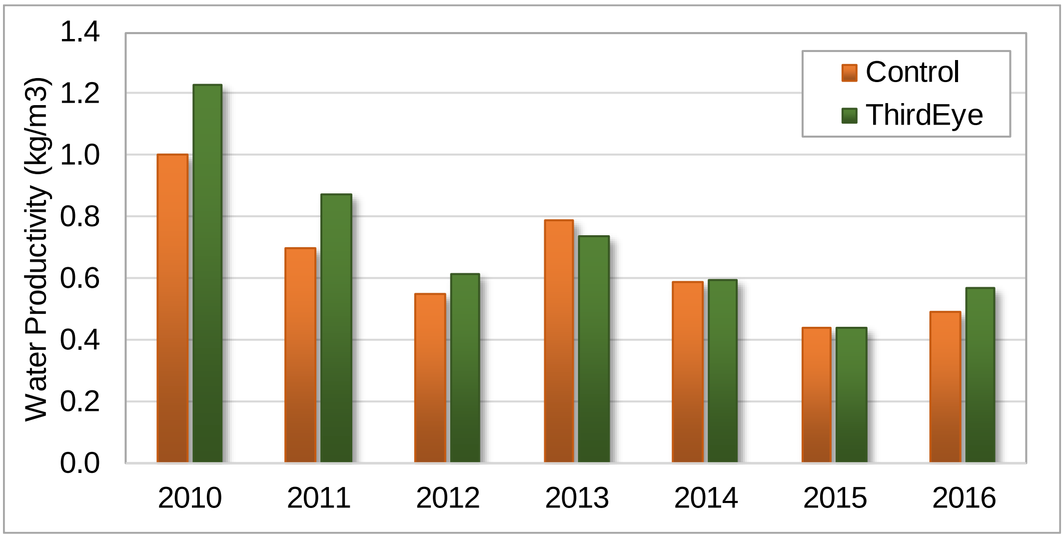

Figure 9. Growing season water productivity (kg/m^3) for the years 2010-2016 based on the MODIS satellite data.

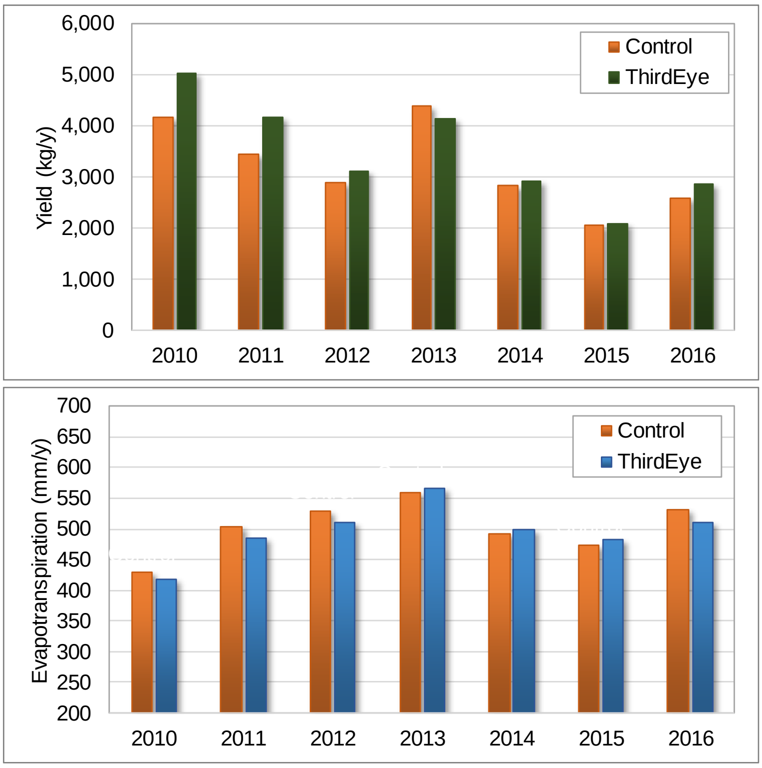

Figure 10. Components of the Water Productivity: yield (top) and actual evapo-transpiration (bottom) during the growing season. Data based on MODIS satellite data.

3.3 Water Productivity Based on LANDSAT satellite

To overcome spatial resolution problems of WaPOR and MODIS (both 250 x 250 m, i.e. 6.25 ha per pixel) the LANDSAT satellite has been used to calculate WP. Figure 11 and Figure 12 demonstrate the high spatial resolution, making it almost applicable for the small fields (average 0.15 ha) in the ThirdEye area.

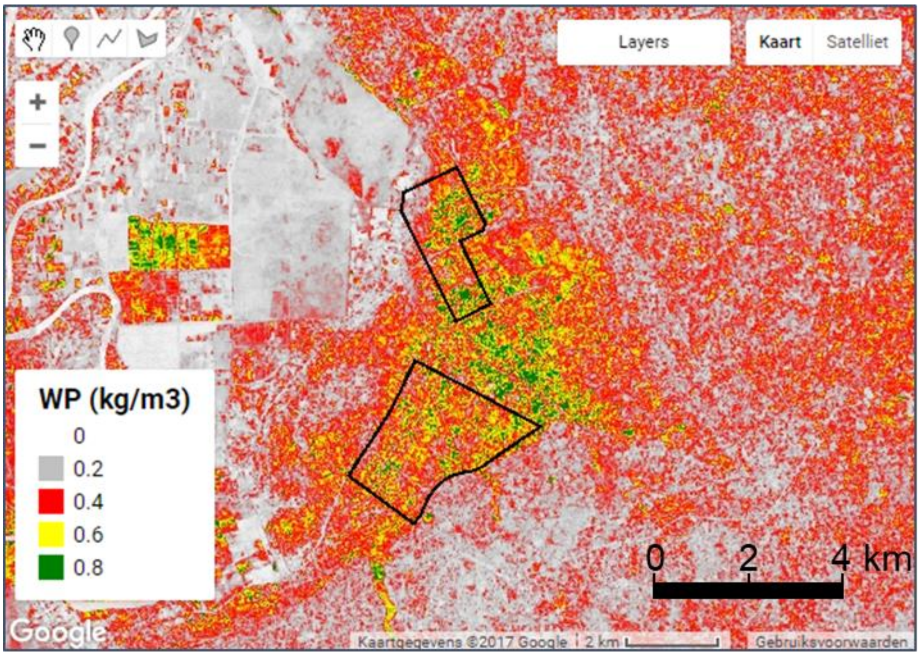

Figure 11. Growing season Water Productivity (kg/m^3) for the year 2016 based on the LANDSAT satellite for the ThirdEye and Control site.

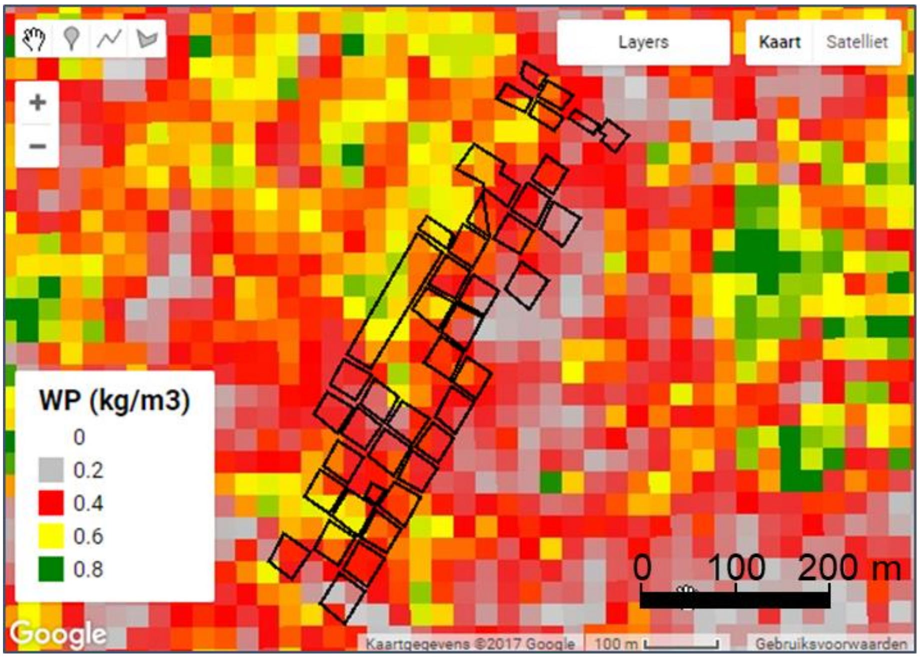

Figure 12. Growing season Water Productivity (kg/m^3) for the year 2016 based on the LANDSAT satellite for the maize fields.

The summarized WP results based on LANDSAT are plotted in Figure 13. Note that data are based on LANDSAT 8 which was launched in 2013. Other LANDSAT satellites can be used to go further back in time. Results show that only in 2016, when ThirdEye was fully operational, WP was higher compared to Control. Differences with the WaPOR and MODIS results are most likely due to 'mixed pixels' (=more crops/vegetation types) effect of WaPOR and MODIS.

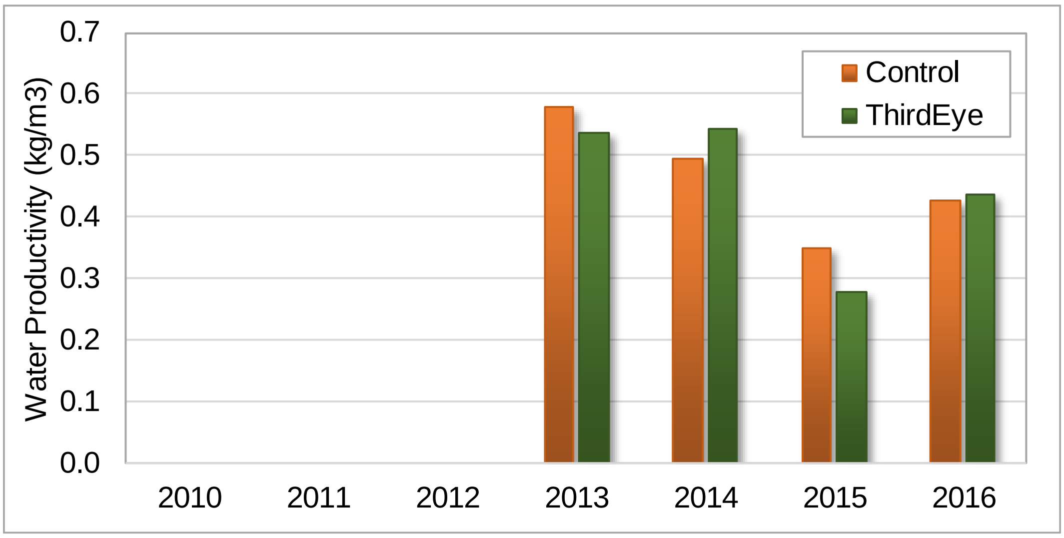

Figure 13. Growing season water productivity (kg/m^3) for the years 2010-2016 based on the LANDSAT satellite data.

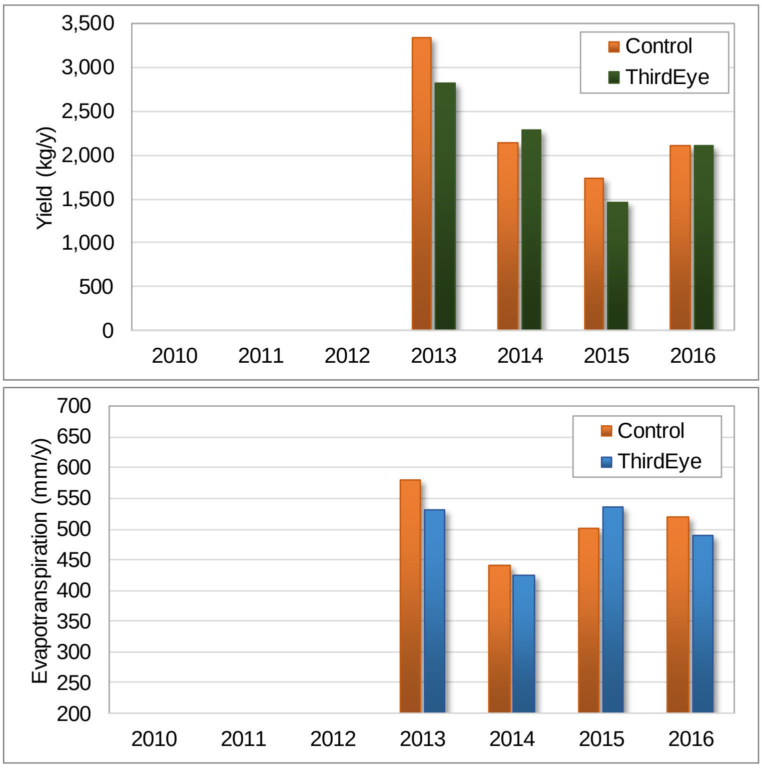

Figure 14. Components of the Water Productivity: yield (top) and actual evapo-transpiration (bottom). Data based on LANDSAT satellite data.

3.4 Water Productivity Based on Flying Sensors

Given spatial and temporal restrictions of the previous WP monitoring methods, data of the Flying Sensors (drones) were used to evaluate WP at local scales. Figure 15 and Figure 16 demonstrate the high level of detail that can be obtained. Moreover, results of Flying Sensors are directly available after growing season, or even during the growing season. Although Flying Sensor data were mainly used to support farmers in their decision making, data are also useful to monitor WP. Results show that there exis a huge variation in WP between and within fields.

Figure 15. Growing season Water Productivity (kg/m^3) for the year 2017 based on the Flying Sensor information for the maize fields. White fields are bare.

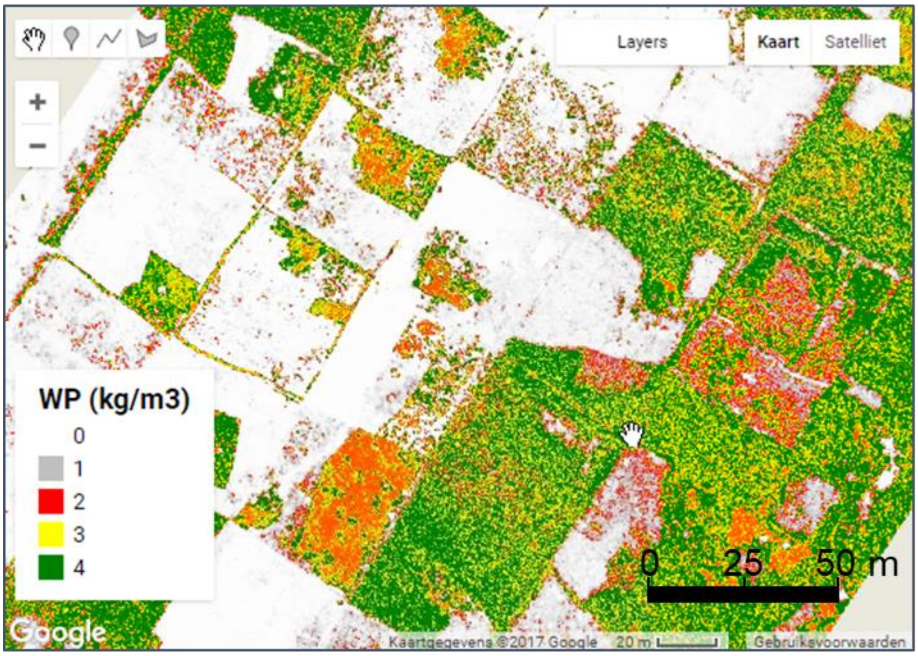

Figure 16. Detail ofFigure 15.

4 Conclusions and Recommendations

The ThirdEye services based on Flying Sensors (drones) have a positive impact on Water Productivity. Based on previous analyses, farmers indicated that the information was mainly used for: early crop stress detection by the near-infrared information; better insight of within-field variation; comparing farmers' practices in the same area; and supporting decisions on irrigation, fertilizer, and harvest timing.

The four types of information for monitoring Water Productivity were demonstrated by looking at sub-project level (700 ha) and field level (0.15 ha). The four WP monitoring tools show consistent results, although distinct variation in the type of monitoring and its applicability became evident. Not one of the methods outperforms the others, but each has its own merits. Table 2 summarizes the main strengths and weaknesses. This table can be used to make a sound decision on which Water Productivity monitoring method fits the requirement for a specific application.

Table 2. Strengths and weaknesses of the four Water Productivity monitoring date sets used in this demonstration case.

Method	Strengths	Weaknesses
FAO-WaPOR*	• Most advanced and rigorous calculation algorithms • Easy accessible • Low level of expertise needed • Entire Africa and Near East	• Based on biomass (not yield) • Available for entire year only • Spatial resolution (250 m)
MODIS satellite	• Based on yield • Growing season specific • Simplified calculation algorithms • Locally adjustable calculation algorithms • Applicable world-wide	• Moderate level of expertise level needed • Spatial resolution (250 m)
LANDSAT satellite	• Based on yield • Growing season specific • Simplified calculation algorithms • Locally adjustable calculation algorithms • Applicable world-wide • Spatial resolution (30 m)	• Moderate level of expertise level needed • Cloud sensitive
Flying Sensors (drones)	• Based on yield • Growing season specific • Simplified calculation algorithms • Locally adjustable calculation algorithms • Applicable world-wide • Spatial resolution (0.1 m)	• High level of expertise level needed • For smaller areas • Costs

* *Level 1 product; level 2 and 3 are under development*

In order to achieve true WP improvement and work towards SDG 6.4, monitoring of WP is an important first step. In addition to monitoring, it is crucial to understand and anticipate on the long-term impacts of different water and farm management options on local and regional WP. This would support an understanding of why certain interventions are effective within a specific agricultural, environmental and climatological context. Coupling of remotely sensed information, such as demonstrated in this report, to agro-hydrological simulation models is an effective method to quantify WP under different scenarios.

WaPOR

FAO (in collaboration with eLeaf and UNESCO-IHE and support from the Netherlands Government) is developing a publicly accessible near real time database using satellite data that allows monitoring of agricultural water productivity.

The annual Gross Biomass Water Productivity expresses the quantity of output (above ground biomass production) in relation to the total volume of water consumed in the year (actual evapotranspiration). By relating biomass production to total evapotranspiration (sum of soil evaporation and canopy transpiration), this indicator provides insights on the impact of vegetation development on consumptive water use and thus on water balance in a given domain. When the focus is on monitoring performance of irrigated agriculture in relation to water consumption, it is more appropriate to use transpiration alone as a denominator, as a measure of water beneficially consumed by the plant. This latter indicator, for which we use the term ‘net water productivity’, provides useful information on how effectively vegetation (and particularly crops) uses water to develop its biomass (and thus yield).

Unit
    kgDM/m^3/year is the ratio of kg of dry matter per cubic meter of water consumed.
Spatial resolution
    250m (0.00223 degree)
Spatial extent
    Africa and Near East
Temporal resolution
    Annual
Temporal extent
    from 2010 to date
Methodology
    The calculation of gross biomass water productivity is as follows: WPb_g=AGBP/ETa
    Where AGBP is annual Above Ground Biomass Production in kgDM/ha and ETa is annual Actual EvapoTranspiration in m^3/ha. The following data is used for calculating WPb_g - Annual AGBP - Annual ETa

MODIS Combined 16-Day NDVI

The Normalized Difference Vegetation Index is generated from the Near-IR and Red bands of each scene as (NIR - Red) / (NIR + Red), and ranges in value from -1.0 to 1.0. This product is generated from the MCD43A4 MODIS surface reflectance composites.

Data availability (time)
    Feb 18, 2000 - Mar 14, 2017
Provider
    Google
ImageCollection ID
    MODIS/MCD43A4_NDVI

Landsat 8 8-Day NDVI Composite

These Landsat 8 composites are made from Level L1T orthorectified scenes, using the computed top-of-atmosphere (TOA) reflectance. See Chander et al. (2009) for details on the TOA computation. The Normalized Difference Vegetation Index is generated from the Near-IR and Red bands of each scene as (NIR - Red) / (NIR + Red), and ranges in value from -1.0 to 1.0.

These composites are created from all the scenes in each 8-day period beginning from the first day of the year and continuing to the 360th day of the year. The last composite of the year, beginning on day 361, will overlap the first composite of the following year by 3 days. All the images from each 8-day period are included in the composite, with the most recent pixel as the composite value.

Data availability (time)
    Apr 7, 2013 - May 1, 2017
Provider
    Google
ImageCollection ID
    LANDSAT/LC8_L1T_8DAY_NDVI

Flying Sensors

A Flying Sensor consists of two major components, a flying platform and one or more sensors. Flying platforms can be either multi-copter or fixed wing. The flight of Flying Sensors may operate with various degrees of autonomy: either under remote control by a human operator, or fully or intermittently autonomously, by onboard computers.

Two types of platforms are being employed: multi-copters and fixed wing airplanes (Figure 17). Both aerial platforms have several advantages and limitations. Multi-copters were first designed as universal aerial platforms mainly dedicated to aerial film/photography with great stability and maneuverability and no take-off or landing runway requirements. Usually, multi-copters are built out of light, resistant materials (such as carbon fiber, aluminum, glass fiber and kevlar) developed with couples of brushless motors running clock- wise and counter-clockwise, respectively (4, 6 or 8 engines depending on the payload requirement). The fixed-wing aircrafts offer simpler flight systems and longer durations, increasing their capacity to cover wider areas. However, they are also not able to hover and require more space for launching and landing.

 

Figure 17: Typical example of a multi-copter (left) and fixed-wing (right) platform.

<u>Sensors</u> are available in a wide range of types, accuracies, prices, configuration etc. The most important differentiation is passive versus active sensing. Passive sensing is based on the sun as a source of energy or radiation. The sun's energy is either reflected, as it is for visible wavelengths, or absorbed and then re-emitted, as it is for thermal infrared wavelengths. Sensor systems which measure energy that is naturally available are called passive sensors. Passive sensors can only be used to detect energy when the naturally occurring energy is available. For all reflected energy, this can only take place during the time when the sun is illuminating the Earth. There is no reflected energy available from the sun at night. Energy that is naturally emitted (such as thermal infrared) can be detected day or night, as long as the amount of energy is large enough to be recorded.

Active sensors, on the other hand, provide their own energy source for illumination. The sensor emits radiation which is directed toward the target to be investigated. The radiation reflected from that target is detected and measured by the sensor. Advantages of active sensors include the ability to obtain measurements anytime, regardless of the time of day or season. Active sensors can be used for examining wavelengths that are not sufficiently provided by the sun, such as microwaves, or to better control the way a target is illuminated. However, active systems require the generation of a fairly large amount of energy to adequately illuminate targets. Some examples of active sensors are a laser fluorosensor and a synthetic aperture radar (SAR).

Flying Sensors are normally equipped only with passive sensors as the energy need and the weight of active sensors make it impossible to attach them to a platform.

The physics behind sensing is based on the electromagnetic (EM) spectrum which can be considered as radiation (energy) at various wavelengths (Figure 18). Only part of the EM is visible by the human eye from about 390 to 700 nm.

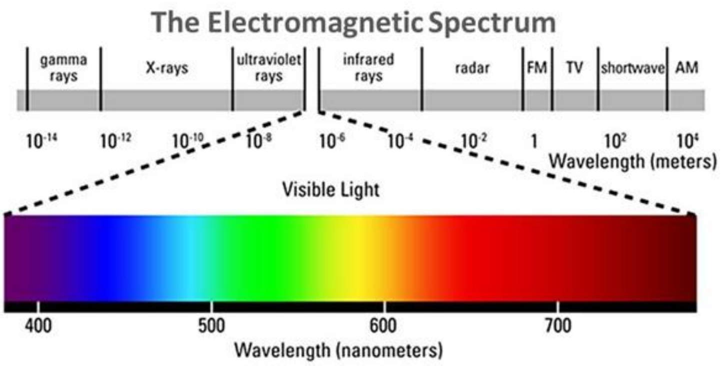

Figure 18: The electromagnetic spectrum with its names and wavelengths.

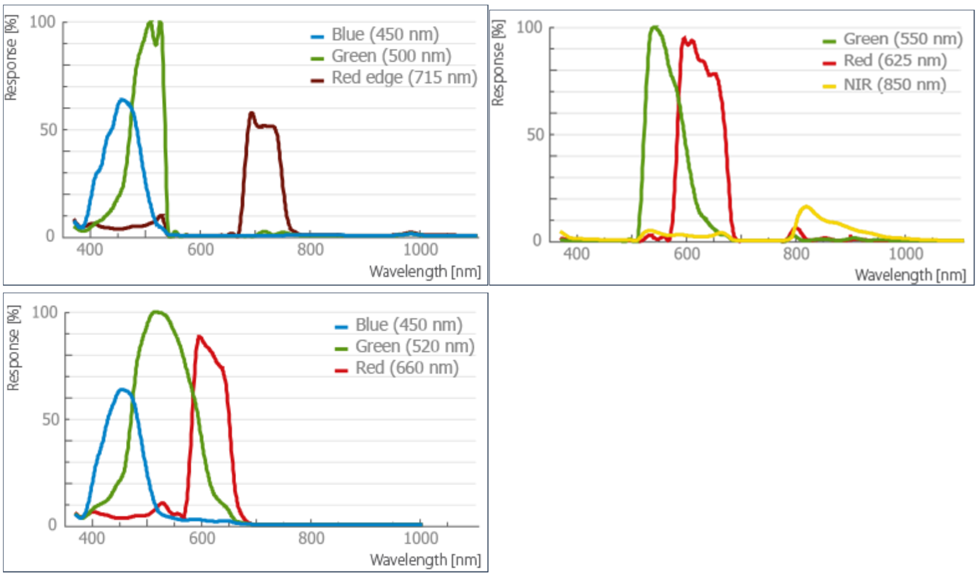

Figure 19: Some typical examples of sensors with responses in different wavelength: RGB (top), NIR (middle) and Red Edge (bottom). Source: SenseFly

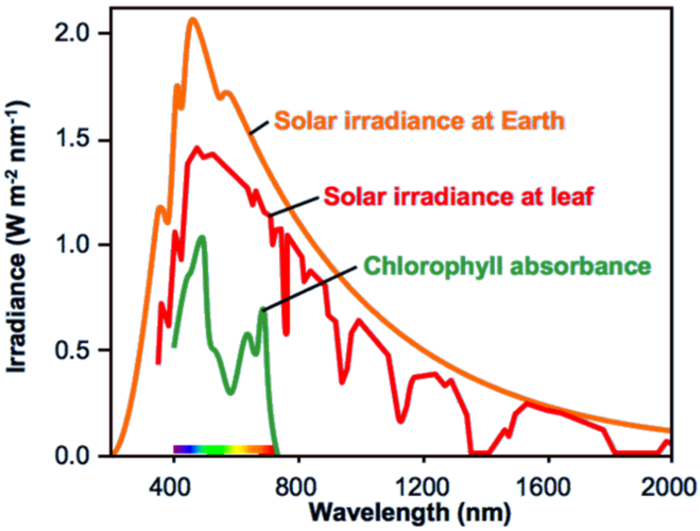

Figure 20: Solar irradiance and absorbance of leaves in various wavelengths. Source: Siegmund, Menz 2005.

Appendix: Calculation Algorithms

A large number of algorithms to calculate biomass, yield and evapotranspiration based on satellite data are described in the literature. Each of these methods has its own merits, strengths, weaknesses and application area. For this project two generically applicable approaches were used to calculate yield and actual evapotranspiration based on NDVI.

Definition Water Productivity

Water Productivity (WP) in general is defined as the quantity of output per quantity of water consumed. This can relate to any production process that uses water (e.g. cars, trees, nature). More specifically in agriculture WP is defined as output of crop per unit of water consumed and is calculated by:

$$WP = \frac{Y}{ET_{act}}$$

where

WP = water productivity ($kg \cdot m^{-3}$)
Y = crop yield ($kg \cdot ha^{-1}$)
ET_{act} = actual evapotranspiration ($m^3 \cdot ha^{-1}$)

In order to compare different crops, the numerator can be replaced by a monetary unit resulting in WP with unit (e.g. US$$\cdot m^{-3}$).

Higher WP can be obtained in two ways: the same production from less water resources, or a higher production from the same water resources.

Therefore, in order to calculate WP, two quantities should be obtained: crop yield and actual water consumed.

Obtaining yield

Yield can be obtained directly based on measuring at time of harvesting. Although straight forward and very accurate, this type of data provides yield aggregated over a field (or a smaller sampling area). In order to obtain WP at smaller scales information from satellites or Flying Sensors (drones) can be used. There are several methods known to estimate yield based on remote sensing, all based on the concept of obtaining the biomass production and the so-called harvest index. Biomass can be estimated using complex algorithms or more straightforward relations with vegetation indices:

$$Y = B \cdot HI$$

$$B = a \cdot e^{b \cdot NDVI}$$

where

Y = crop yield ($kg \cdot ha^{-1}$)
B = biomass ($kg \cdot ha^{-1}$)
HI = harvest index (-)

a = regression coefficient (-); 463
b = regression coefficient (-); 4.48

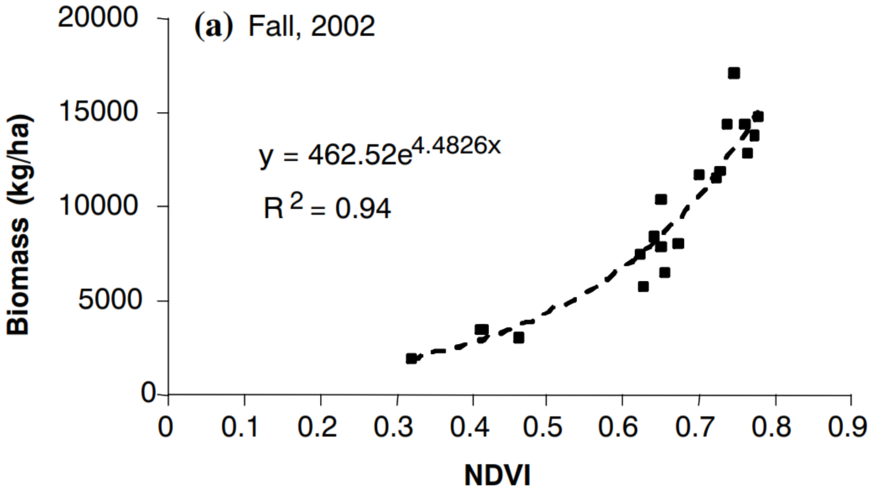

Figure 21. Relation between NDVI and biomass. Source: Jones et al., 2007

Obtaining ETact

Measurements of actual evapotranspiration can be done by a wide range of methods such: as soil water balance, eddy-correlation, sap-flow, lysimeters, etc. For a brief overview see e.g. http://swhydro.arizona.edu/archive/V7_N1/feature3.pdf.

The use of remote sensing to estimate ET_{act} is presently being developed along two approaches: (i) land surface energy balance (EB) methods, which include applications of the Penman–Monteith (P–M) equation, using visible and near infrared spectral bands and ancillary meteorological data; (ii) a reflectance-based vegetation index (VI) approach that relies on the ability of vegetation indices (VIs), derived from surface reflectance data to trace the crop growth and estimate the basal crop coefficient (K_{cb}). This second method determines spatially distributed values of K_{cb} that capture field-specific crop development and are used to adjust daily reference ET (ET_0) estimated from local weather station data or climate data sets derived ones. The main advantage of the VI-based methods is that satellite images in the reflective bands of the spectrum are more readily available than the thermal band data, and generally at higher spatial resolution. (Source: Minacapilli, 2016).

There is a strong correlation between NDVI and ETact (Glenn et al., 2008). Different correlation equations were found, depending on crop and physical setting. In general, the best estimate can be found by developing site-specific correlation factors. A robust and generally applicable approach can be followed by using the concept of relative evapotranspiration (ET_{act} / ET_{ref}) and by using the adjusted $NDVI^*$ (Groeneveld et al., 2007):

$$ET_{act} = K_{act} \cdot ET_{ref}$$

$$K_{act} = a \cdot NDVI^* + b$$

$$NDVI^* = \frac{NDVI - NDVI_0}{NDVI_S - NDVI_0}$$

where

ET_{act} = actual evapotranspiration (mm)

K_{act} = actual crop coefficient that considers effects of moisture stress reduction coefficient, 0 to 1 (-)

ET_{ref} = reference evapotranspiration (mm)

a = regression coefficient (-); 0.925

b = regression coefficient (-); 0.058

NDVI = Normalized Difference Vegetation Index (-)

$NDVI^*$ = Adjusted NDVI (-)

$NDVI_0$ = NDVI with lowest value in imagery (-)

$NDVI_S$ = NDVI with highest value in imagery (-)

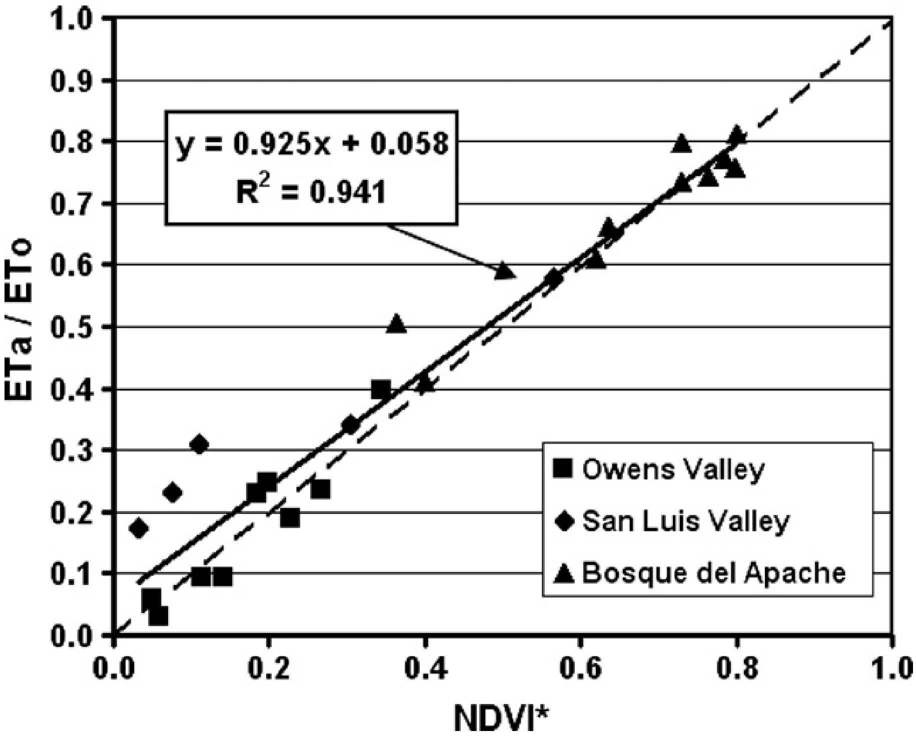

Figure 22. Relation between K_{act} (ET_{act} / ET_{ref}) and $NDVI^*$. Source: Groeneveld et al., 2007