Water Productivity assessment using Flying Sensors and Crop Modelling. Pilot study for Maize in Mozambique

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Preface

Achieving Food Security in the future while using water resources in a sustainable and productive manner is a major challenge nowadays and will be even more for the next generations due to population growth and climate change. Agriculture is in most basins in the world the largest water user, thus accurate monitoring of water productivity is necessary. But besides monitoring, even more important is to explore opportunities to increase water productivity. For this type of assessments, a combination of observations and simulations are necessary.

Based on the many years of experience in water productivity studies using remote sensing and simulation models, FutureWater has developed an innovative methodology that relies on Flying Sensor imagery and state-of-the-art crop models to assess current and future water productivity of crops. This report describes a pilot study that was carried out in 2017 on multiple plots managed by several smallholders, cultivating maize, in Mozambique

The pilot study was financially supported by the MIT feasibility fund of the Dutch Enterprise Agency RVO, and the European Horizon 2020 project BRIGAID (www.brigaid.eu).

Summary

The objective of this pilot study was to achieve plot-level maps of water productivity and yield, to and test a methodology to assess the performance of different farmers in order to provide them with recommendations to improve water productivity. More specifically, this pilot study combined high-resolution imagery from Flying Sensors with a crop water productivity model to assess yield and water productivity for several plots with maize in Mozambique. Canopy cover was derived from the imagery and linked with the crop model simulations to obtain water productivity maps covering the entire growth cycle. The methodology also monitoring of crop performance during the growth season and can be used to forecast yield by the end of the season.

Nowadays, projects that invest in sustainable water management and agriculture require evidence that the targeted measures to boost water productivity are effective. Water productivity monitoring therefore becomes increasingly important. Water productivity requires data on yields and water consumption (evapotranspiration). Yield data are often difficult to obtain from farmers, especially in areas with many smallholders. Evapotranspiration is even more difficult to assess in the field. Remote sensing-based and model-based monitoring of water productivity has a large potential, also to identify yield gaps and assess the local feasible effectiveness of measures.

This feasibility study demonstrated that there is an opportunity to further develop a service that monitors water productivity based on FS-imagery and crop modelling. Service costs outweigh the additional revenues obtained by farmers. The experimental development has demonstrated that the service is technically feasible and can provide the tangible outputs needed. To bring the proposed service to a higher level of maturity, it is recommended to focus future development activities on (i) Testing for different locations and crops, (ii) Further enhancing link between FS-based imagery and crop modelling, and (iii) Involving end-users and testing within a project where WP-measures are implemented.

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1 Introduction

Agricultural losses are abundant and pose a threat to food security. Water stress, pests, and weeds hamper the growth of crops worldwide. To exemplify, estimated global crop loss potential due to pests varies from 50 to 80 percent. Weeds also constitute a major source of crop losses (32%). Animal pests, pathogens, and viruses contribute less to the potential losses seen in agriculture (Oerke and Dehne, 2004). Additionally, water stress troubles the productivity of a lot of farmers worldwide. Timely identifying pests, water stress, and weeds, can therefore significantly reduce the potential loss for an individual farmer. As a growing global population demands increased productivity to continue feeding people across the world, yield gaps should be assessed and closed.

Since most of the farmers worldwide are not meeting their potential yields, agricultural management should be focussed on closing the yield gap, by predominantly pest management control and timely irrigation where possible. To do that, farmers need to allocate their (natural) resources in an optimal way, to avoid wasting expensive fertilizers and scarce water resources, and boosting their yield at the same time.

To assess how efficiently farmers are using or could be using the available water, a useful performance indicator is “Water Productivity” (WP). WP assess the amount of biomass, yield or economic return produced per cubic meter of water consumed. By assessing WP, farmers and decision-makers can for example:

- find regions where water productivity is too low
- propose solutions to use water more efficiently
- reduce water stress
- contribute to a sustainable increase of agricultural production

WP can be monitored using field measurements, and remote sensing data, as for example is pursued by the Food and Agricultural Organisation of the United Nations (FAO) in the WaPOR project: an operational and open access database, to monitor agricultural water productivity in near real time. Satellite-based imagery is however limited in spatial precision and may not be enough to monitor WP at field level (see Figure 1).

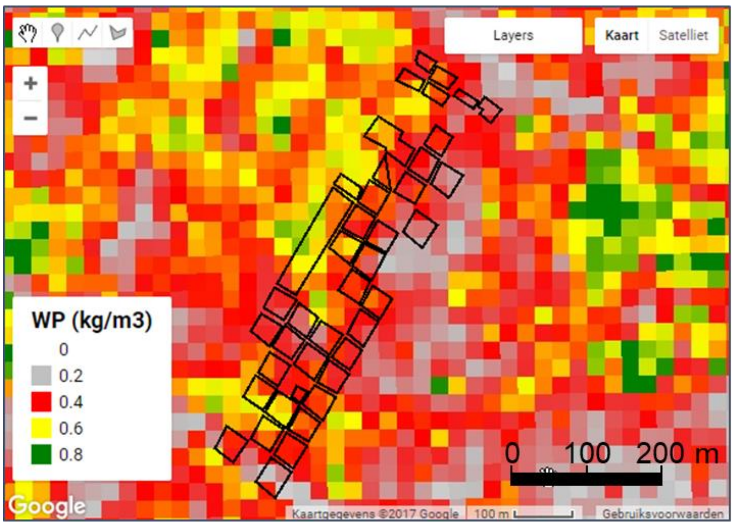

Figure 1. Growing season Water Productivity (kg/m^3) for the year 2016 based on the LANDSAT satellite for the maize fields. Source: Droogers et al., 2017

But monitoring of WP becomes actually useful when options can be explored to improve WP. To assess solutions to improve WP, simulation models are required that evaluate how changes in the farmer´s practices and biophysical conditions influence the WP. These simulations models rely on past observations from the field or remote sensing but allow future scenarios to be studied to assess the potential for improvement.

Previous work by FutureWater, based on satellite-based remote sensing imagery and crop water productivity modelling showed the potential of combining observations with modelling to assess WP improvement potential and yield gaps. In Central Asia, climate change impacts and several climate adaptation options were explored to boost water productivity (Hunink and Droogers, 2010, 2011) In the Lower Mekong basin, food balance sheets were assessed for future scenarios, including climate change and population growth scenarios, as well as improvements in agricultural practices (Hunink et al., 2014).

Another promising new field applicable to the monitoring of performance in agricultural fields is the use of Flying Sensors (also called UAVs or drones). They are increasingly cost-efficient and provide high-resolution imagery on the crop cover, and water stress patterns. For example, the Thirdeye technology (http://thirdeyewater.com/) rolled out in Mozambique and Kenya demonstrates the cost-effectiveness and the adoption of this new technology to improve on-field water management. A recent report that assessed the various options to monitor field-level WP using satellite and Flying Sensor-based remote sensing imagery was published based on work in Mozambique (Droogers et al., 2017).

Data received from Flying Sensors (FS) can lead to precise estimates of WP, but on itself do not provide useful guidance to improve WP. The combination of this information with crop water productivity modelling allows assessing the yield gap and options to close this gap. The purpose of this pilot study was to test this innovative methodology.

In this report, we evaluate the technical feasibility of linking data from FS with crop models, and assess the potential for this technology. In the analysis, we focus on the African continent. We start with an analysis of the economic potential of using FS data for crop yield forecasting and water productivity assessment. In this analysis, we consider suitable areas on the African continent in terms of environmental conditions, and identify existing services. Hereafter, in Section 3, the technical feasibility of the idea is further assessed based on previous studies. Furthermore, we analyse different Vegetation Indices (VIs) that can be assessed using Flying Sensors, and the agro-hydrological crop model that can be linked to these indices.

The principal outcome of this pilot study is reported in Section 4, where we detail the methodology and show results and recommendations of the pilot study.

2 Economical potential

2.1 Feasibility study

FutureWater has been active in Africa with a Flying Sensor (FS) service since the start of 2014. Under the name ThirdEye, FutureWater set up an extension service based on crop stress monitoring with the help of Flying Sensors (FS, also called UAVs or drones) and a Near Infra-Red camera that was specifically produced for this purpose. The images resulting from the flights are converted to crop stress maps. Since September 2017, ThirdEye is also active in Kenya. Based on these previous experiences a few components have been identified of importance to a successful implementation of a Flying Sensor based service.

As water productivity (WP) monitoring is becoming increasingly important to assess the effectiveness of interventions and projects aiming to enhance food security in Africa, this feasibility study assesses whether the FS service can be extended with crop water productivity monitoring. To assess potential service locations, we focus on the following points:

a) Agricultural areas
Setting up a Flying Sensor-based monitoring system can only be cost-effective in locations where agricultural areas are dominant

b) Areas with high level of cloudiness
Satellite products are also available to deliver relevant information to farmers, however FS outperform satellite products in terms of spatial resolution, and there flexibility. A major advantage though is that cloudiness does not obstruct the data delivery. It is thus expected that the FS provide the greatest added value in frequently clouded areas.

c) Agriculture under irrigation
The Flying Sensor service aims to increase WP. Irrigated areas have generally a higher potential to increase WP compared to rainfed areas, although also in rainfed areas a wide range of interventions can boost WP.

To evaluate the best locations for the potential service in Africa, we visualize the different components in an opportunity map. This map combines different layers of spatial information on the different components identified of importance in choosing a new service location (see Figure 2). The following information was used to create this opportunity map:

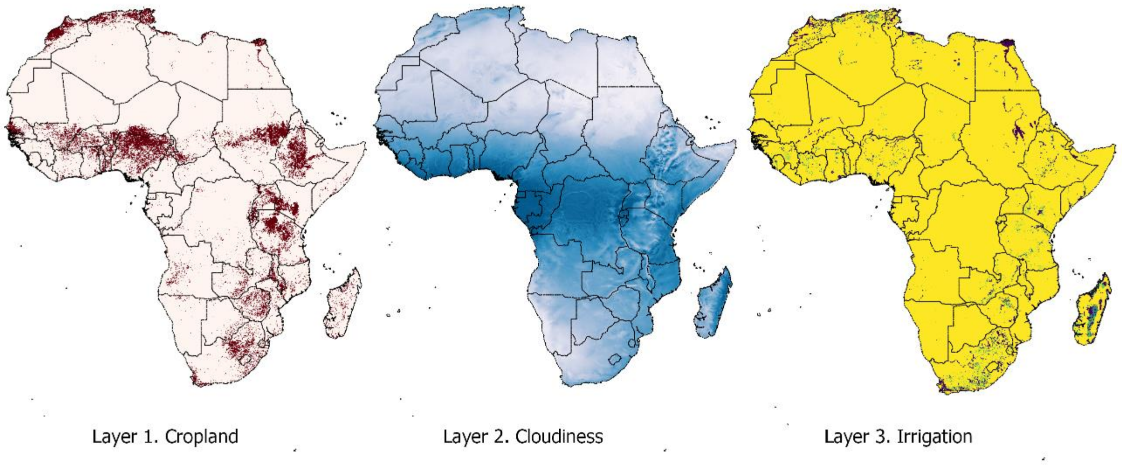

Figure 2.These three raster layers were used to analyse the best location for services based on Flying Sensors. We consider the abundance of cropland, degree of cloudiness, and the abundance of irrigated areas.

Layer 1: The Copernicus Global Land Cover Service contains a database with different spatial information. For the Cropland layer we used the newly available land cover map of Africa with a spatial resolution of 100m x100m (Copernicus Information Service, 2015). *Accessible through:* http://land.copernicus.eu/global/products/lc

Layer 2: Mean annual cloud frequency in percentages over a time series from 2000 until 2014 was used to evaluate the degree of cloud formation, thus the need of FS for remotely sensed data. The spatial resolution of the product is 1km (Wilson and Jetz, 2016).
Accessible through: http://www.earthenv.org/cloud

Layer 3: For the Irrigation layer we used a map containing the amount of area equipped for irrigation around the year 2005 as a percentage of the total area. The spatial resolution of these maps are 10km grids. (Siebert et al., 2013)
Accessible through: http://www.fao.org/NR/WATER/aquastat/irrigationmap/index10.stm

The previous layers were combined in one map to display potential new location sites to implement a FS-based service, see Figure 3. Several key hotspot regions can be identified:

- East Africa, principally:
  - Tanzania
  - Kenya
  - Uganda
  - Rwanda
  - Burundi
  - Mozambique
- West Africa, principally:
  - Ghana
  - Togo
  - Benin
  - Nigeria
  - Gambia

This list of countries excludes those countries with a relatively low share of agriculture to GDP (<10%) (FAOSTAT, 2013).

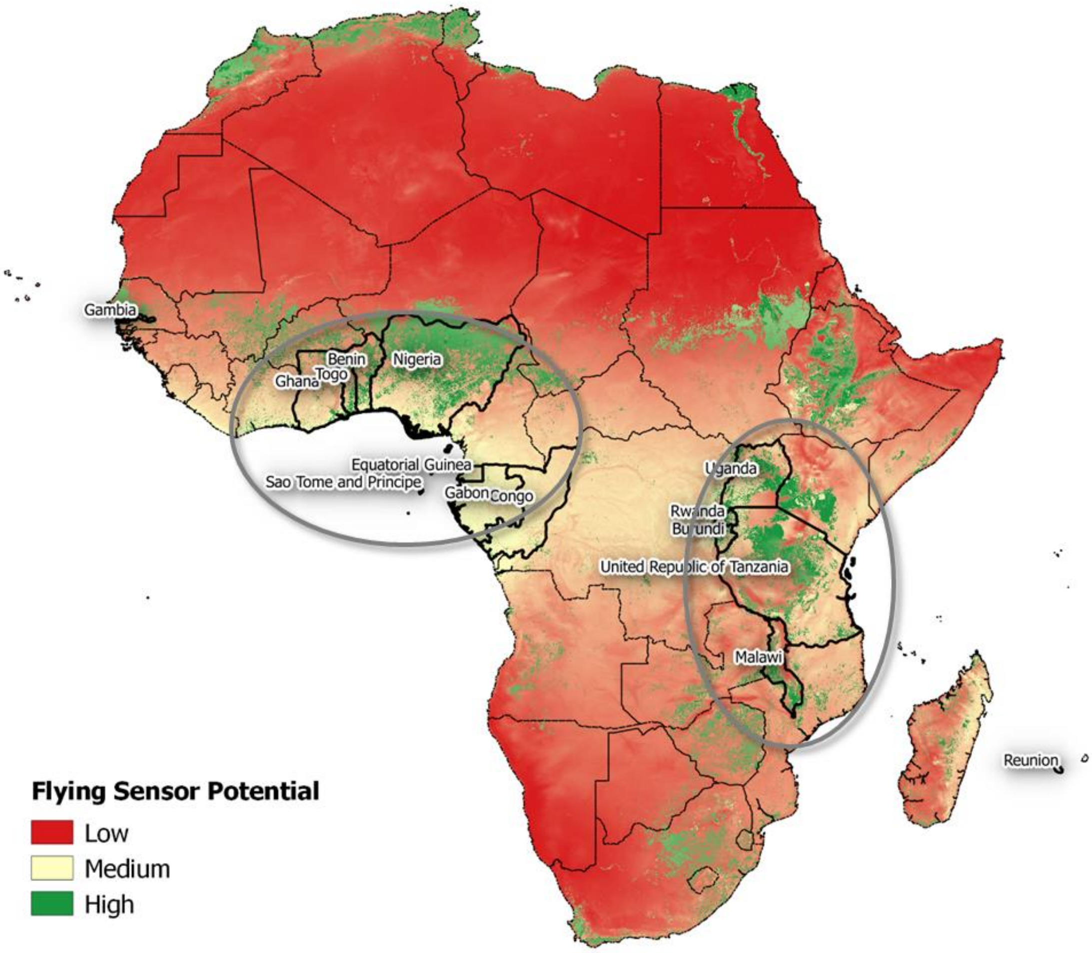

Figure 3: **This map visualizes the potential areas where Flying sensors can be of use, by looking at the abundance of cropland, the cloudiness and irrigation present in an area.**

2.2 Market opportunities and competition

There are various companies active in Africa aiming at the provision of FS-based services for farmers. Most of the companies are start-ups and projects. Moreover, a lot of new services are tested in Africa, because of the relative flexible legislation on drone use.[1] Examples are drone use for health service, e.g. delivering blood or vaccines, or the use of UAVs to combat poaching or illegal deforestation. Given the fact that a lot of countries in Africa are struggling with proper infrastructure, UAVs might be an opportunity to unlock people's needs in remote areas.

To analyse the UAV competing companies present in Africa, focussing on agriculture, a short summation is given in Table 1. Overall South African companies seem to be the lead suppliers in UAV services throughout Africa:

[1] https://qz.com/1003810/the-worlds-first-commercial-drone-delivery-operates-from-a-hill-in-rwanda/

Table 1. An overview of companies specializing in UAV-based crop monitoring techniques active in Africa.

	HiView: Active in Mozambique and Kenya and delivering an operational service to farmers with a team of local operators, providing information by means of bulletins on a regular basis, on crop water stress. Several WP monitoring activities have already been demonstrated to farmers, in collaboration with FutureWater. More information: http://www.thirdeyewater.com/ and http://hiview.nl/
	Agri-sense: Agri-sense specializes on UAV techniques useful for agriculture: land use planning irrigation and drainage design, crop assessments, and more, based in South-Africa. Agri-sense is involved in a lot of different irrigation projects, but does not have the expertise at the moment to perform WP predictions **Website:** https://www.agrisenseinternational.com/
	Airinov: French based company delivering a UAV based service throughout their network of operators. They are mostly active in Europe, but also in northern Africa. Their main focus lies on deploying drones as a monitoring tool for agriculture. **Website:** https://www.airinov.fr/en/
	Agridrone: Agridrone is a drone system deliverer based in South Africa, specialized in building their own drone systems with the relevant software. **Website:** http://agridrone.co/
	SMOPS: Specialized in aspects of land and drone surveying. Their services and product offers are derived from up to date high precision photography, which they collect on site with the use of their own, state of art aerial surveying equipment. **Website:** https://www.facebook.com/smopslda/
	HAEVIC: HAEVIC promotes itself as the farmer's right hand, where UAVs are being used to outlay problems in the field with the help of Infra-red cameras. They also offer the possibility to fly with thermal cameras to detect criminals **Website:** http://www.haevic.co.za/index.php/home/about-us

2.3 Cost-benefit analysis

By optimizing water productivity farmers can improve their businesses. However, despite the potential practical and theoretical benefits for the farmer, UAV based services have been proven hard to survive economically. In a survey conducted by Erickson & Widmar (2015), it was shown that a great number of companies that use FS-based services struggle to survive economically (see Figure 4). From all the 261 respondents, 16 percent were selling UAV as precision technology. Of those companies offering FS-based services, 46 percent are not breaking even. Whereas, a mere 14 percent is making profit. The previous study is conducted in the USA, in areas with more developed agricultural businesses than Africa. It can be deducted that FS-based services in Africa are therefore an economically challenging endeavor as a company.

However, the survey also shows that the services that include advisory services in addition to precision agriculture (as for example WP monitoring and advice on WP-enhancing interventions) are more profitable. Also, for the African context, the strength and key of success of the ThirdEye approach is to use low-cost equipment and local staff to perform the flights.

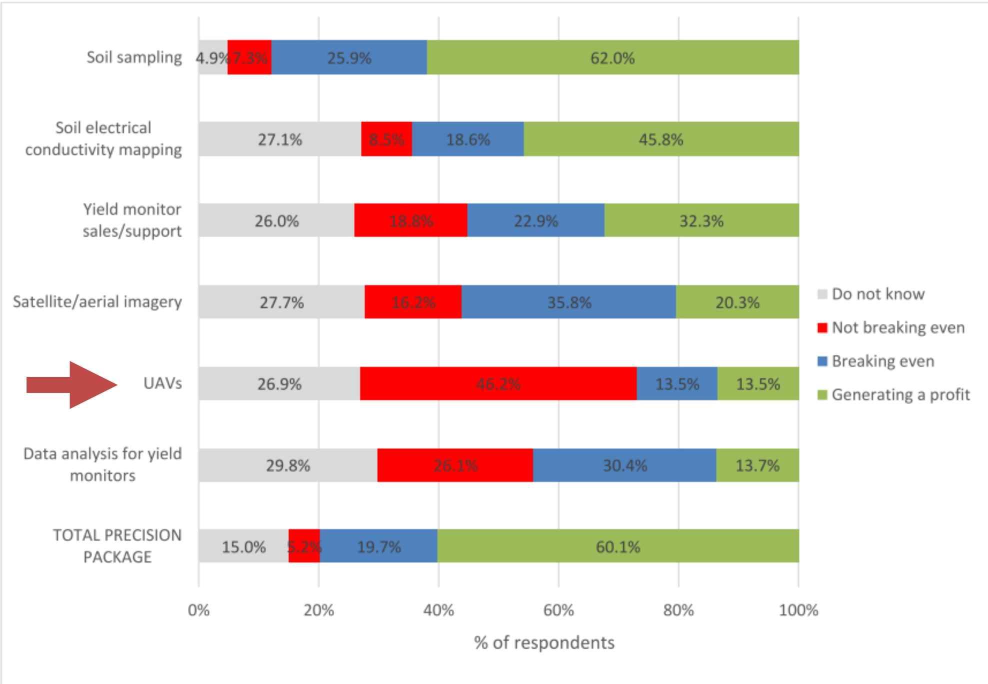

Figure 4. An overview on the profitability of precision service offerings. The results are based on a questionnaire with that was filled in by 261 respondents across the US. Only 13.5 percent of the companies that offer UAV-based services generate profit (Erickson and Widmar, 2015).

If we look at the yield gap figures of Ghana and Tanzania, two priority countries for a FS service in Africa, we can see that are a lot of possibilities. For example, in Ghana on average, only 18 percent of the potential yield is met. The percentage of potential crop water productivity that is met is around the same, 19 percent. In Tanzania, the situation for crop water productivity is better, 25 percent of the potential is reached. However, just like Ghana, only 18 percent of the potential yield is reached. (http://www.yieldgap.org/, 2016)

Closing the yield gap requires specialized advisory services (or extension services and aid-funded projects) that monitor water productivity and give advice to farmers on enhanced farmers practices. Such a service should not only provide WP maps, but also tailored advice on how to boost WP and yields.

The benefits to the farmer are related to a more efficient use of (natural) resources, but also time management, as labour costs will decrease in case of optimal farm management. Additionally, the crop yield increases, which will lead to more revenue at the end of the season. To exemplify this, we calculated in **Table 2** the net benefits for a sugarcane farmer of a yield increase of five percent. An increase in yield of five percent gives approximately a gross benefit of 153,600 USD. If a roughly estimated cost of the WP-monitoring and advisory service is subtracted, a net benefit of 133,600 USD is obtained.

Table 2. Cost-benefits of the Flying Sensor-based WP-monitoring service – example for sugarcane

Yield increase in Flying Sensor area				
Yield increase	*5%*			

	Current		**Potential with Flying Sensor (FS)**	
Average yield	64	tonnes/ha	67	tonnes/ha
Area	600	ha	600	ha
Total yield	38,400	tonnes	40,320	tonnes
Raw sugar production	3,840	tonnes	4,032	tonnes
Raw sugar price	800	US$/tonne	800	US$/tonne
Revenue	3,072,000	US$	3,225,600	US$

Gross revenue increase	**153,600**	**US$**
Costs Flying Sensor imagery and processing	5,000	US$
Costs modelling and WP-monitoring	15,000	US$
Total costs of service	**20,000**	**US$**
Net revenue increase	**133,600**	**US$**

3 Technical feasibility

In the previous chapter we have identified hotspot regions in Africa for a Flying Sensor-based WP improvement service. An analysis of the available competition shows that there are numerous companies active in Africa, but they do not focus on yield prediction or water productivity in their services. In this chapter, the latest technological possibilities to combine FS imagery with agro-hydrological modelling to predict yield and water productivity are analysed. The main questions of interest are: What has already been done so far with FS imagery and WP prediction? And what is possible by connecting FS data and agro-hydrological models?

We will start with an introduction on water productivity and yield forecasting. Hereafter we will revise existing literature on using FS imagery to predict yield and water productivity. We end with a comparison of different indices that can be computed from FS images and link these indices to agro-hydrological models to find the most suitable model for our endeavour.

3.1 Introduction

Our global water demand is rising, due to increased food demand induced by an expanding population. In order to meet the future need of food production, developing and developed countries need to focus more on efficient and sustainable use of natural resources and land, amongst other strategies. (Bastiaanssen and Steduto, 2017) To continue, the production per unit land should increase (yield, kg ha^{-1}), but also the production of per unit water (water productivity, kg m^{-3}) (Bastiaanssen and Steduto, 2017).

Water Productivity consists of two components: crop yield and water consumed. Water consumption occurs through evapotranspiration (ET_{act}) which is the sum of plant transpiration through the stomata in the leaves, and evaporation that occurs from the soil surface and intercepted water by the leaves. As such, water productivity can be expressed as:

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

where WP = water productivity (kg/m^3), Y = crop yield (kg/ha) and ET_{act} = actual evapotranspiration (m^3/ha)

Higher water productivity can be obtained in two ways: maintaining the same production while consuming less water resources, and/or achieving a higher production while consuming an equal amount of water. Thus, to assess WP and evaluate the impact of interventions in the field, yield should be documented, but also ET_{act}.

Yield can be recorded and measured in several ways. Online databases exist on predominantly national or provincial level but these are not site-specific. Field surveys can be conducted to inquire farmers on their yield of last year or last years. However, this is generally costly and time-consuming. Therefore, yield is often predicted using crop water simulation models, or agro-hydrological models (see section 3.5). An additional advantage to use these models is that they actually allow assessing the potential for improvements and performing scenario analysis. The models also require field data (soil, planting density, etc) but generally easier to obtain by either field visits or remote sensing.

ET_{act} is hard to measure in the field, and therefore commonly studies use potential evaporation resulting from a reference crop and crop coefficients. These crop coefficients need to be adjusted to the actual soil moisture and soil salinity situation, to calculate the correct actual evaporation. Remote sensing can also be used to measure the actual evaporation, as with thermal infra-red observations and surface energy models it is possible to quantify water consumption (Bastiaanssen and Steduto, 2017). However, these methodologies have certain limitations in terms of applicability in agriculture. Often the satellite data is of low temporal and spatial resolution, or data is unavailable due to cloud formation (Xiang and Tian, 2011). Therefore, we argue that, on field scale, highest quality results can be obtained by using an agro-hydrological model, combined with FS remotely sensed data, and meteorological data. This way, WP can be assessed at the farm-level and options to improve WP can be compared.

3.2 Literature review

The high-resolution data from Flying Sensors can play a crucial role in closing the gap between satellite-based imagery and ground observations (Xiang and Tian, 2011). Although most academic research focusses on FS applications for agricultural management (Caruso et al., 2017 and Katsigiannis et al., 2016**,** amongst others), there has been some academic attention for crop yield prediction methodologies using FS-derived data. Most of these crop prediction methodologies compute DEMs or height of the plants as an input for regression models.

Especially vineries have experimented with FS use in their agricultural practices (Caruso et al., 2017; Fiorillo et al., 2012; Rey-Caramés et al., 2015) Flying sensor data has been used to estimate grape quality parameters and wine productivity. For example, by creating a digital Crop Surface Model (CSM) and NDVIs of the vinery it is possible to get biophysical and geometrical characteristics of grapevines, such as pruning weight, canopy volume and Leaf Area Index (LAI). These variables are important indicators for the farmer to manage their farm; e.g. where to irrigate, and apply fertilizers.

Furthermore, biomass estimation has been proven useful in yield prediction. Biomass can be estimated from Vegetation Indices (VIs) incorporating NIR reflectance (Bendig et al., 2015). Additionally, it is also possible to estimate biomass through crop surface models, or in combination with vegetation indices (Possoch et al., 2016). CSMs are DEMs that require a baseline to measure the relative crop height, consequently calculating the volume of the crop. Based on CSMs constructed with low cost FS, Bendig et al. (2015) proposed an FS-based methodology with VIs and Plant Height (PH). They applied several regression models to estimate the biomass with a combination of VI and/or PH as the variables. The results show a normalised ratio index, named GnyLi, and PH show the highest correlation with dry biomass.

The GnyLi index put forward by Gnyp et al., 2014 was computed in a study on winter barley. The basis of this index lies in the NRI, Normalized Ratio Index, calculated from NIR and SWIR bands. Like NRI, GnyLi focusses on two absorption and reflection features that range between 800 and 1300 nm. The high reflection in these bandwidths is due to the intercellular structure of plants. The absorption signature in this bandwidth is dependent on presence of water in the plant, for example. To capture these signatures and relate them to biomass, an optimization approach is followed to identify the four spectra visible in reflectance and absorbance of the crop. This methodology can only be applied with a multi-spectral camera (Anon, 2004)

$$\frac{R_{900} \times R_{1050} - R_{955} \times R_{1220}}{R_{900} \times R_{1050} + R_{955} \times R_{1220}}$$ (Gnyp et al., 2014).

Another example of combining VIs with CSMs is provided by Geipel, Link, & Claupein, 2014. In their research they assessed the potential to use CSM to calculate potential yield with the help of linear regression models. The researchers focussed on corn grain yield at early- to mid-season growth stages. In their methodology they computed a CSM, and with the help of ExG (Excess Green Index) the area covered with crop was extracted from the uncovered area. The latter was done to produce an average crop height, with different ExG thresholds. The mean crop height was then used as an input for three standard linear regression models to predict corn yield. Results showed that the resolution of the CSM is of importance at the beginning of the growing stage, later the regression models show fairly equal outcomes in terms of correlation. Yield prediction can benefit from including CSMs and VI in the methodology. (Geipel et al., 2014)

More research on the application of CSMs in agriculture has been performed, already formulating and testing opportunities of the FS-retrieved data (Bendig et al., 2013), with Eisenbeiss (2004) one of the first to showcase the potential added value of CSMs to crop monitoring (Aasen and Gnyp, 2014). Bendig et al. (2014) deployed a simple low-cost drone with an RGB camera to research applicability for crop yield prediction. In their approach they abstracted a mean Plant Height as an input for five linear models estimating biomass (fresh and dry) and tested through cross-validation.

As one can conclude from this overview of academic work on usage of FS- retrieved data in the domain of precision agriculture, no literature links FS-derived VIs directly to crop growth models. Neither there is literature on the effect of the farmer's yield after incorporating FS-based information.

There are, however, existing yield forecasting methodologies based on satellite remote sensing and crop growth models (Johnson, 2014). An example is the study by Bolton & Friedl (2013), who deployed MODIS imagery to predict maize and soybean yields with linear models. Various studies have shown the correlation between VIs and yield varies in different stages. Bolton & Friedl (2013) found yield prediction after 65-75 days after green-up of maize most successful. In their research they also point out that the spatial resolution of the product used (500m) will hamper the applicability to regions with less intensive agriculture. Other approaches focus on estimating photosynthetically active radiation (PAR), or link imagery to crop simulation models for calibration (Sibley et al., 2014).

The development of FS-based yield forecasting can be inspired by existing methodologies within the field of satellite remote sensing. That said, it is important that databases with small-scale resolution imagery are created to improve research and refine methodologies. Because there is little to no literature on existing methodologies linking FS imagery to agro-hydrological models, the next sections will be dedicated to outlay the possible information that can be retrieved with simple, low-cost UAVs (NIR-G-B or RGB cameras). Additionally, we explore the different parameters that can be linked to existing crop models, to evaluate the possibilities to link FS information directly to modelling outcomes.

3.3 Sensor techniques

When light falls on a leaf, reflection occurs. The amount of reflection of green light (540 nm) is very high, therefore the plant is observed green by humans. Healthy vegetation does not reflect much red light (700 nm), since it is absorbed by chlorophyll abundant in leaves. In the near-infrared spectrum (800 nm) the amount of reflection increases rapidly to 80% of the incoming light (see Figure 5). This increase is caused by the transition of air between cell kernels. This is characteristic for healthy vegetation.

Damaged plant material does not show this increase in reflected near-infrared light. Moreover, the reflection of red light is much higher than in healthy plant material. By measuring the reflection in these spectra, damaged plant material can be distinguished from healthy plant material (van der Schans et al., 2012).

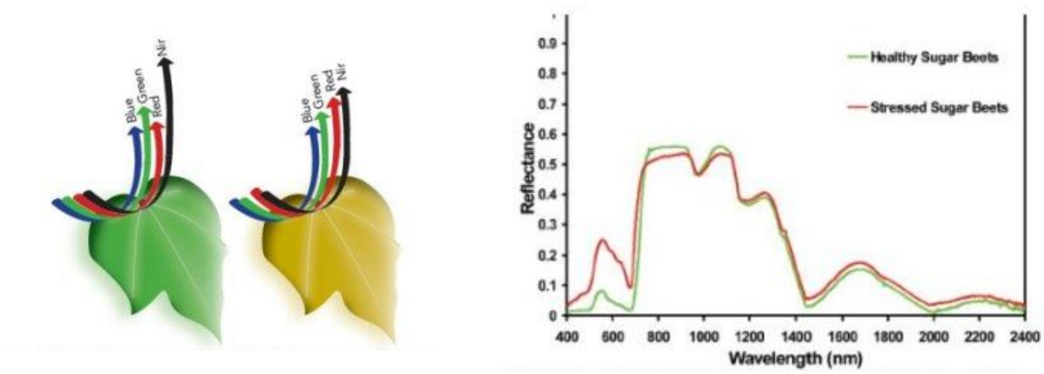

Figure 5 An illustration of the spectral reflectance of a healthy sugar beet plant and a sugar beet plant that faces stress. **Source: http://www.aces.edu/pubs/docs/A/ANR-1398/index2.tmpl**

3.4 Possible vegetation indices

In this section we present the possible vegetation indices that can be computed with low-cost FS and in what way the data coming from the FS can be used to obtain relevant crop information. Low-cost FS (e.g. Mavic, Phantom) contain, or can be customized to facilitate, two types of sensor technologies. The first type is a sensor with RGB bands, capturing the reflectance of the red, green and blue wavelengths/bandwidths. The other possibility is a camera capturing NIR-G-B spectra. Table 4 lists the possible Vegetation Indices (relevant to yield forecasting) available for the type of spectra available (NIR, R, G, B).

Table 3. A list of possible Vegetation Indices that can be sensed with the available low-cost UAVs, an explanation and relevant crop information is also given.

Vegetation indices ↓	**Explanation**	**Relevant crop information**
NDVI[1]	$\frac{R_{NIR} - R_{Red}}{R_{NIR} + R_{Red}}$ The Normalized Vegetation Index quantifies the difference between near infra-red and red light. NIR is reflected by vegetation, while red light is absorbed. This pattern changes as the plant faces stress.	Canopy cover, LAI, Biomass, Crop stress
NDVI-B	$\frac{R_{NIR} - R_{Blue}}{R_{NIR} + R_{Blue}}$ When the NDVI is replaced by blue light the index becomes less sensitive to crop stress. Compared to red NDVI, the blue NDVI shows less contrast between stressed and unstressed crops. When a plant is facing	Canopy cover, LAI, Biomass, Crop stress

[1] Only possible if two flights will be performed with the available drones

Vegetation indices ↓	**Explanation**	**Relevant crop information**
	stress the changes in reflectance in the blue spectrum is not directly linked to crop stress, but leaf pigment.[1]	
GNDVI	$\frac{R_{NIR} - R_{Green}}{R_{NIR} + R_{Green}}$ In the green NDVI the red band is replaced by the green band. GNDVI is more sensitive to chlorophyll content, which indicates the nitrogen and water uptake. (Hunt et al., 2011)	Canopy cover, LAI, Biomass, Crop stress
SAVI	$\frac{R_{NIR} - R_{Red}}{R_{NIR} + R_{Red} + L}(1 + L)$ NDVI has been found unstable, varying with soil type amongst other factors. Soil Adjusted Vegetation Index attempts to correct for soil brightness with an adjustment factor, L. Areas with little vegetation will give low values.	Canopy cover, LAI, Biomass, Crop stress
GRVI	$\frac{R_{Green} - R_{Red}}{R_{Green} + R_{Red}}$ Green-Red Vegetation Index can be used to distinguish between green vegetation and other types of ground cover. In comparison to NDVI, GRVI can detect the phenology better during saturation, thus can detect subtle disturbances in the growing period better. (Motohka et al., 2010)	Canopy cover, detecting subtle disturbances
RVI	$\frac{R_{NIR}}{R_{Red}}$ Th Ratio Vegetation Index is the predecessor of the NDVI. Dense green vegetation will produce a high ratio, while soil reflectance will turn out low. This creates a contrast between the different land cover types.	Canopy cover, LAI, Biomass, Crop stress
ExG	$2 \times R_{Green} - R_{Red} - R_{Blue}$ Excess Green Index is an index used for greenness identification.[2] With this index it is possible to detect (healthy) crops from bare ground.	Canopy cover, LAI, Biomass,
CSM	$\text{Plant Height} = DEM_{crops} - DEM_{base}$ Crop Surface models can be constructed with the help of Digital Elevation Models (DEM). With CSMs it is possible to derive plant height distribution and determine biomass.	Biomass, yield

3.5 Model overview

Table 3 gives a general overview of the most important VIs that are possible to be derived from imagery of low-cost Flying Sensors. To evaluate the most suitable crop growth model that can be

[1] http://www.senteksystems.com/2015/11/23/ndvi-definitions-red-blue-enhanced/

[2]https://ac.els-cdn.com/S2214317315000347/1-s2.0-S2214317315000347-main.pdf?_tid=84fcfb32-bbd8-11e7-a658-00000aab0f01&acdnat=1509192607_d0b0e57757fc92033313dd996189955b good for discussion

used in combination with FS data, this section discusses several widely accepted models and their potential linkage to the crop information retrieved from FS data. We identified five available crop growth models that could be used in combination with crop growth models, these are: WoFost, SWAP, Aquacrop, SWAT and APSIM. A selection of the most suitable crop growth model to use in combination with vegetation indices from FS should focus on (i) the applicability on field scale, (ii) the ease to (in)directly link to vegetation indices, (iii) the input data intensity, and (iv) the potential to assess water productivity. Hydrological models that are based on FAO-56 crop coefficient approach, as for example the SPHY model (Terink et al., 2015) have not been included in this evaluation.

The objective of this assessment is to select a suitable crop growth model applicable at field level (see Figure 6), where it is possible to assess water productivity and link the outcomes to VIs, considering data scarcity as a limiting factor. The following sections describe each of the models shortly.

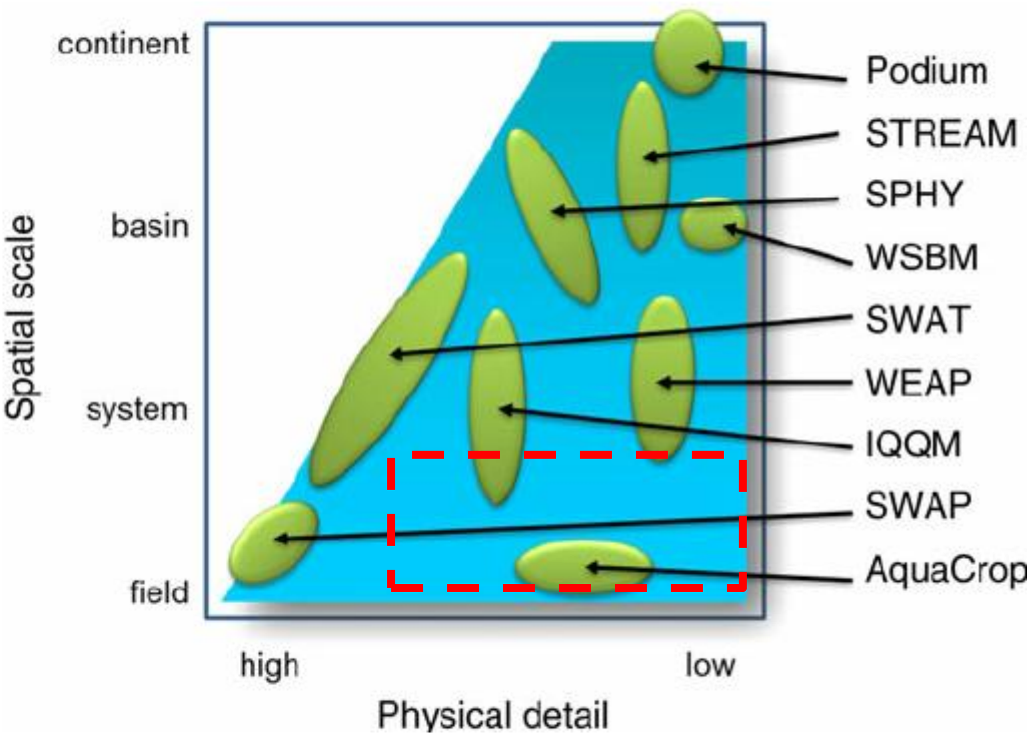

Figure 6 The objective of this assessment is to find an agro-hydrological crop model that is functional on field scale and does not require extensive datasets of the location under study. The perfect model would therefore end up in the lower right corner of the graph pictured; a model containing sufficient physical detail and available at field scale (Droogers and Bouma, 2014)**.**

3.5.1 WoFost

A generic crop model that was developed by Alterra, Wageningen (the Netherlands) is the World Food Studies (WOFOST) model, the development of WOFOST started in 1988. This model can also be linked to SWAP.

WOFOST has three sub-models that can be distinguished. The first one is the most simple one and assumes a continuously moist soil. The crop water requirements are quantified as the sum of crop transpiration and evaporation from the shaded soil under the canopy. The second water balance in the water-limited production situation applies to a freely draining soil, where groundwater is so deep that it cannot have influence on the soil moisture content in the rooting zone. The soil profile is divided in two compartments, the rooted zone and the lower zone between actual rooting depth and maximum rooting depth. The subsoil below rooting depth rooting depth is not defined. The second zone merges gradually with the first zone as the roots grow deeper. The third water balance is for water-limited production on soils influenced by shallow groundwater in the rooting zone. The principles are similar to the freely draining situation. Different is that the soil moisture retention capacity is determined by the depth of the groundwater, as is the percolation rate. There is capillary rise if the rooted soil dries out. The groundwater level can be controlled by artificial drainage and the moisture content within the root zone does not vary with depth.

WOFOST needs a significant amount of input data that can be added to several tabs: general, crop, weather, timer, soil, nutrients, and reruns. In the general tab one can choose to focus on potential crop growth, water-limited crop growth, and nutrient-limited crop growth. If you select the potential crop growth and water-limited crop growth, there is no need to fill in data on nutrients. (Centre and Centre, n.d.)

WOFOST includes the following components to calculate water fluxes: rainfall (R), surface storage (SS), surface run-off (SR), soil surface evaporation (E), crop transpiration (T), percolation from the root zone to deeper layers (PC) and higher capillary rise into the root zone (CR), see Figure 7). This means that interception is not considered, only when WOFOST is linked to SWAP, or MetaSWAP, in a methodology described by Walsum & Supit (2012). Consequently, to calculate water productivity, the interception should be added to the soil evaporation and transpiration during the growing period.

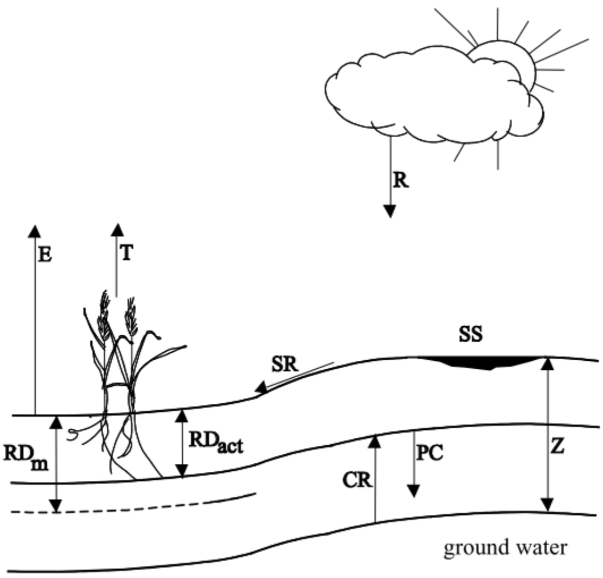

Figure 7. Visualization of the hydrological phenomena considered by the WOFOST model. (Centre and Centre, n.d.)

3.5.2 SWAP

SWAP (Soil-Water-Atmosphere-Plant) is an integrated physically based simulation model for water, solute and heat transport in the saturated-unsaturated zone in relation to crop growth. The first version of the SWAP dates back to 1978. Since then the model went through various phases. The SWAP model has been applied and tested for many different conditions and locations and has been proven to produce reliable and accurate results (SWAP, 2003). Several studies have been done so far in which SWAP is applied within a distributed context and several data assimilation techniques have been tested using SWAP, sometimes coupled with WOFOST.

SWAP requires a significant amount of data on meteorology, irrigation, crop, soil, drainage, bottom boundary condition, solute transport and heat transport. (SWAP manual, 2000) Research has been done by linking satellite-based indices to SWAP. A good example is Vazidefoust et al. (2009) who demonstrated how internal variables within a distributed SWAP model can be continuously updated. This updating method is fed by ET_{act} and LAI sensed by MODIS. The LAI is computed by a logarithmic function including the Soil Adjusted Vegetation Index (SAVI) (Vazifedoust et al., 2009).

With crop and soil factors the reference evapotranspiration (ET_{ref}) is converted to the actual evapotranspiration. Interception is calculated by a precipitation interception coefficient. When precipitation increases the interception asymptotically increases until the interception coefficient times LAI. When irrigation is applied, SWAP also considers and documents interception. The output of soil evaporation, interception and transpiration can be found in the water & solute balance component, see Figure 8 (SWAP manual, 2000).

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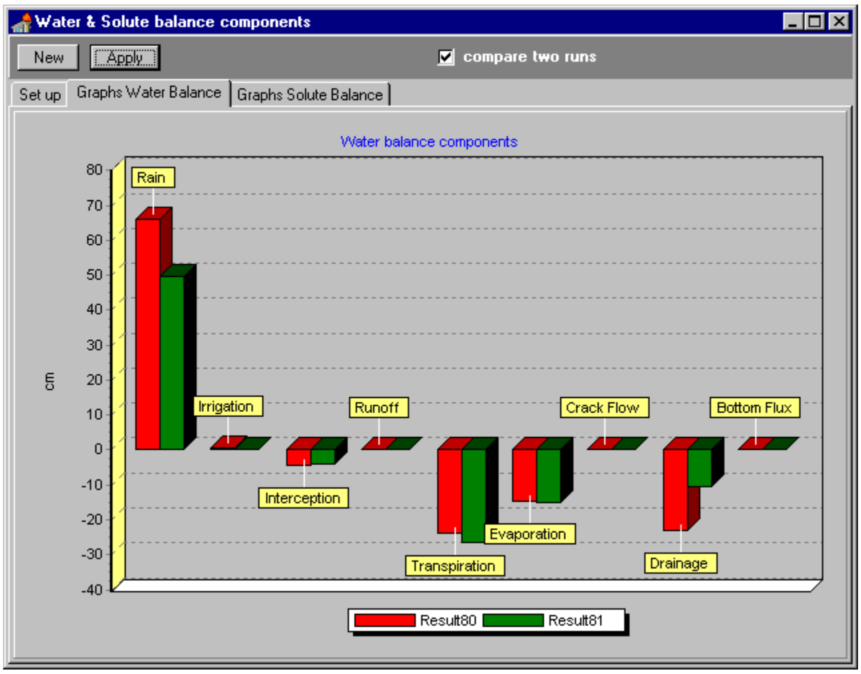


Figure 8. Example of output of SWAP for soil evaporation, interception and transpiration.

3.5.3 AquaCrop

AquaCrop is the FAO crop-model to simulate yield response to water. It is designed to balance simplicity, accuracy and robustness. AquaCrop is a companion tool for a wide range of users and applications including yield prediction under climate change scenarios. AquaCrop is a completely revised version of the successful CropWat model previously designed by FAO. The main difference between CropWat and AquaCrop is that the latter includes more advanced crop growth routines. Aquacrop is water driven, unlike, for example WoFOST.

AquaCrop includes the following sub-model components: the soil, with its water balance; the crop, with its development, growth and yield; the atmosphere, with its thermal regime, rainfall, evaporative demand and CO2 concentration; and the management, with its major agronomic practice such as irrigation and fertilization. AquaCrop flowchart is shown in Figure 10.

The particular features that distinguish AquaCrop from other crop models is its focus on water, the use of ground canopy cover instead of leaf area index, and the use of water productivity values normalized for atmospheric evaporative demand and of carbon dioxide concentration. This enables the model with the extrapolation capacity to diverse locations and seasons, including future climate scenarios.

The input files needed for Aquacrop are relatively few. To simulate Aquacrop effectively a climate file is needed – containing temperature, ET_{ref}, rain, perhaps CO_2 – other environmental information is also required: crop type, management specification, soil profile, groundwater file. Furthermore, the start of the growing season is needed, some information about the initial condition, and the simulation period. (Raes et al., 2012) However, Aquacrop has still around 100 parameters relating to crop, soil, management and input factors (Silvestro et al., 2017).

Vegetation indices can be linked to Aquacrop by calibrating canopy cover to obtain better results. The dimensionless crop growth indicator, canopy cover, can be retrieved from high-resolution satellite data, FS imagery or field-based images. Satellite imagery has the issue of clouds, and are often too expensive for high-resolution images. Field-based cameras are only useful for small plots and are not feasible for the monitoring of several plots at the same time.

Crop water productivity can be assessed easily with Aquacrop, where crop water productivity [kg m^{-3}] is defined as the ratio of the mass marketable yield to the volume of water used by the crop (Geerts and Raes, 2009). AquaCrop has been applied also in climate change impact studies previously in various parts of the world (Hunink et al., 2014; Hunink and Droogers, 2010, 2011).

3.5.4 APSIM

The Agricultural Production Systems sIMulator (APSIM) software is especially created for on-farm decision making. It was developed to simulate biophysical processes in farming systems, to assess the effects of climate change on the economy or explore management options. APSIM consists out of two main modules: a soil water dynamics module and a crop growth module.

In APSIM there are soil water dynamics modules for the two major modelling approaches that are commonly used for the soil water balance, namely bucket or cascading layer approach and a solution of the Richard's equation methods. The implementation in the APSIM model is based on the 'standalone' SWIMv2.1 (Soil Water Infiltration and Movement). Parameterisation of the soil water properties for APSWIM requires specification of the moisture characteristic and hydraulic conductivity relationships in each soil layer. Runoff is dealt with by considering surface roughness.

As APSIM contains different modules that simulate key physiological processes in response to daily weather data, soil characteristics and crop management actions. Typical site parameters are considered for the soil modules, soil surface characteristics and surface residue definition. Additionally, management practices are considered within simple modelling statements. (Keating et al., 2003)

Crop growth modules are available for crops, pasture and forests, including their interaction with soil. The plant modules simulate the key physiological processes and operate on a daily time step in response to input daily weather data, soil characteristics and crop management actions. The crop modules have evolved from early versions for focus crops such as maize.

The basic APSIM module calculates soil evaporation and transpiration, but only with the inclusion of the module MICROMET, interception is taken into account. The latter will be of importance when aiming to calculate water productivity. Figure 9 visualizes the flow chart of the MICROMET calculations. (Snow and Huth, 2004)

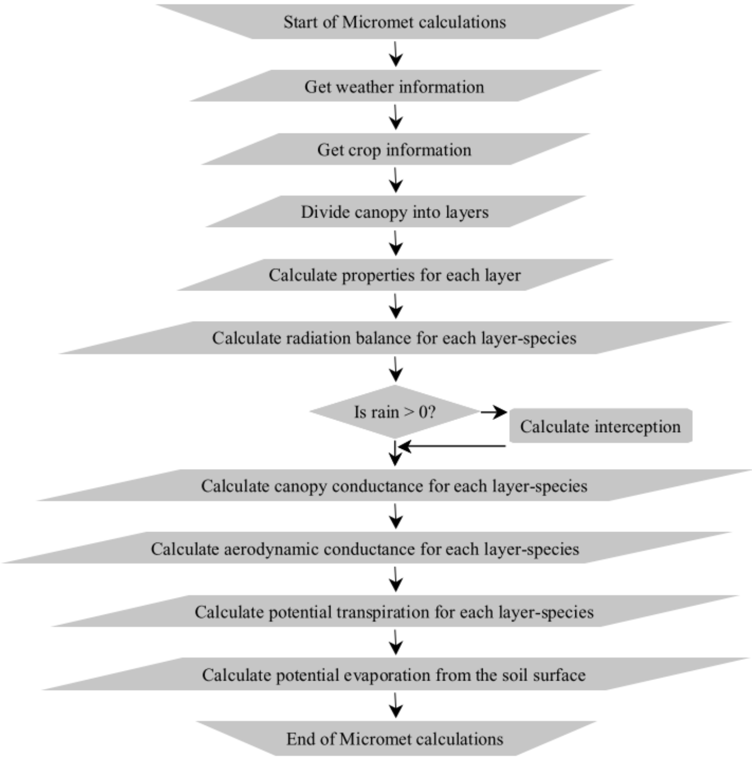


Figure 9. A visualization of the calculation procedure in MICROMET, a module of APSIM (Snow and Huth, 2004).

3.5.5 SWAT

SWAT was developed primarily by the United States Department of Agriculture (USDA) to predict the impact of land management practices on water, sediment and agricultural chemical yields in large complex watersheds with varying soils, land use and management conditions over long periods of time.

SWAT uses a cascading approach to simulate the dynamics of soil water content. It computes infiltration using either the Curve Number (CN) method at daily intervals or the Green-Ampt method when hourly precipitation data are available. A routing module is used to simulate flow of soil water through each soil layer in the root zone. Downward movement or percolation occurs when field capacity of a soil layer is exceeded and the underlying layer is not saturated. SWAT simulates the movement of saturated flow between soil layers and assumes the uniform distribution of soil moisture within a given layer. Unsaturated flow between soil layers is indirectly estimated by the distributions of plant water uptake and soil water evaporation through two parameters: the soil evaporation compensation coefficient, ESCO and the plant uptake compensation factor, EPCO, respectively. Although these two parameters relate directly to crop water stress, determination of their values is not documented in SWAT.

Crop growth simulation in SWAT is based on the EPIC model, using daily accumulated heat units, harvest yield, biomass from solar radiation and water and temperature stress adjustments. It provides a general description of the growth of a vegetative canopy using deterministic relationships based on physiological or physical processes.

To apply SWAT on a single field the plot would need to be considered a hydrological response unit (HRU). Input requirements for SWAT are daily precipitation, temperature, solar radiation, wind speed, relative humidity, potential evapotranspiration, land cover, a tillage database file, pesticide and fertilizer file, soil characteristics (also chemical), groundwater level, amongst other optional files. SWAT has been applied in many contexts across the world, among others for land-use impact assessments (Hunink et al., 2013; Vogl et al., 2017).

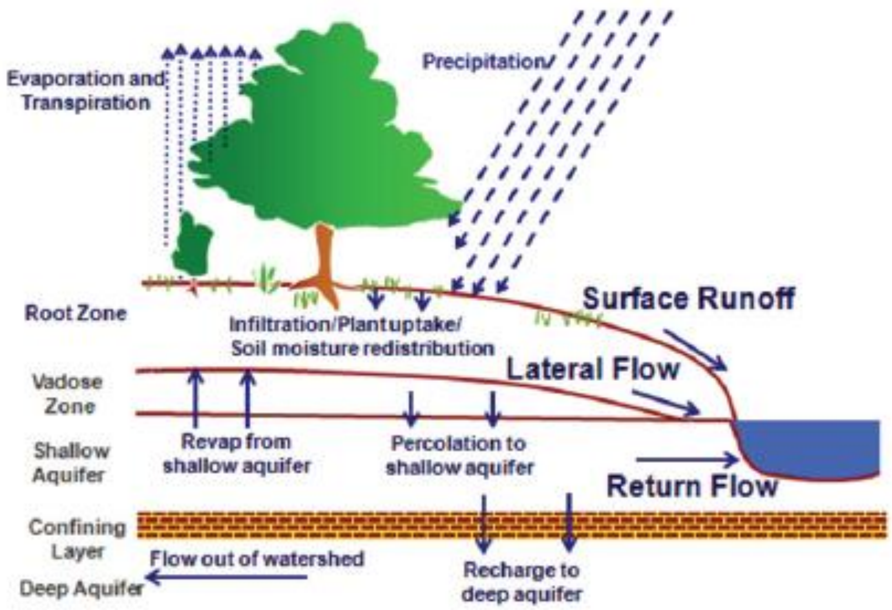


Figure 10. Visualization of the hydrological components considered in the SWAT model (Skaggs, 2013).

3.6 Model evaluation & VIs

The different agro-hydrological models presented previously were evaluated based on several criteria:

- Their ability to provide outputs on the plot- or farm-level
- Data requirements
- Possibility to link with VIs assessed by Flying Sensors
- Their readiness for assessing Water Productivity

Table 4 shows the outcomes of this evaluation. Considering the capability of the models to simulate on individual farm level, the data requirements, the (in)direct linkages to VIs and the capability of the model to assess water productivity three models scored best: SWAP, APSIM and AquaCrop.

Table 4. An overview of the assessed crop growth models assessed by four factors: suitability to simulate at farm level, the data intensity of the model, direct linkages to Vegetation Indices, and the possibility to assess water productivity

	WoFost	SWAP	Aquacrop	APSIM	SWAT
Farm level	Good (3)	Good (3)	Good (3)	Good (3)	Low (1)
Data intensity	High (1)	Average (2)	Average (2)	Average (2)	High (1)
Link to VI	LAI (2)	LAI (2)	Canopy cover (3)	LAI (2)	LAI (2)
Assess water productivity	Average (2)	Good (3)	Good (3)	Average (2)	Average (2)
Total score	**8**	**10**	**11**	**9**	**6**

The Leaf Area Index (LAI) can be retrieved from Vegetation Indices, such as NDVI. However, this is not so trivial. Remotely sensed imagery can be used to estimate LAI. Relationships have been researched between VIs and LAI, by using non-linear and linear models. However, these relationships differ for UAV retrieved VIs, where the resolution is much higher. As a result, of non-random distribution of leaves within the canopy or blockage of light within the canopy, methodologies can over-estimate LAI values. The finer resolution of UAV retrieved data can bias the LAI estimation, due to shadows. To overcome this bias a geometric optical model could for example be used (Zheng and Moskal, 2009).

On the contrary, the dimensionless index Canopy Cover is more easily abstracted from remotely sensed imagery. Since the definition of the canopy cover is an index for the area of plant coverage within a defined area, the definition itself enables an easier link to remotely sensed data. Canopy cover does not require a linear or non-linear regression model, solely a definition on the area covered by a crop in a defined area. The challenge with UAV imagery would be filtering out weed and finding the most suitable VIs to abstract canopy cover (Wellens et al., 2015).

Since Canopy Cover is more easily computed from remotely sensed imagery, Aquacrop is preferred above APSIM and SWAP. Also, the relatively low data requirements make Aquacrop a suitable candidate to link to UAV imagery to assess the integration of crop growth modelling with UAV remote sensing. Vegetation Indices as ExG, NDVI, NDVI-B or GNDVI could be used to abstract canopy cover. In the next section the potential of linking one of these VIs to Aquacrop is further explored.

4 Experimental development

4.1 Concept

To assess and monitor water productivity on the plot-level, a technology is being developed that combines low-cost Flying Sensor imagery providing high-resolution information on the crop growth status, and a crop growth model that uses these data and other easily available ground data to estimate a number of output variables, including crop water consumption, yield, water productivity. Also yield gaps (difference between the actual yield and the feasible yield given the local biophysical constraints of a location) can be assessed and mapped for the different plots analysed. With a calibrated model, also future scenarios can be studied to improve water productivity, but this was out of scope of this pilot study.

Figure 11 summarizes the overall concept of the technology. From the previous evaluation, the Flying Sensor-based NDVI-B, GNDVI and ExG in combination with the simulation model Aquacrop (FAO) was identified as the most suitable for monitoring water productivity at the field level.

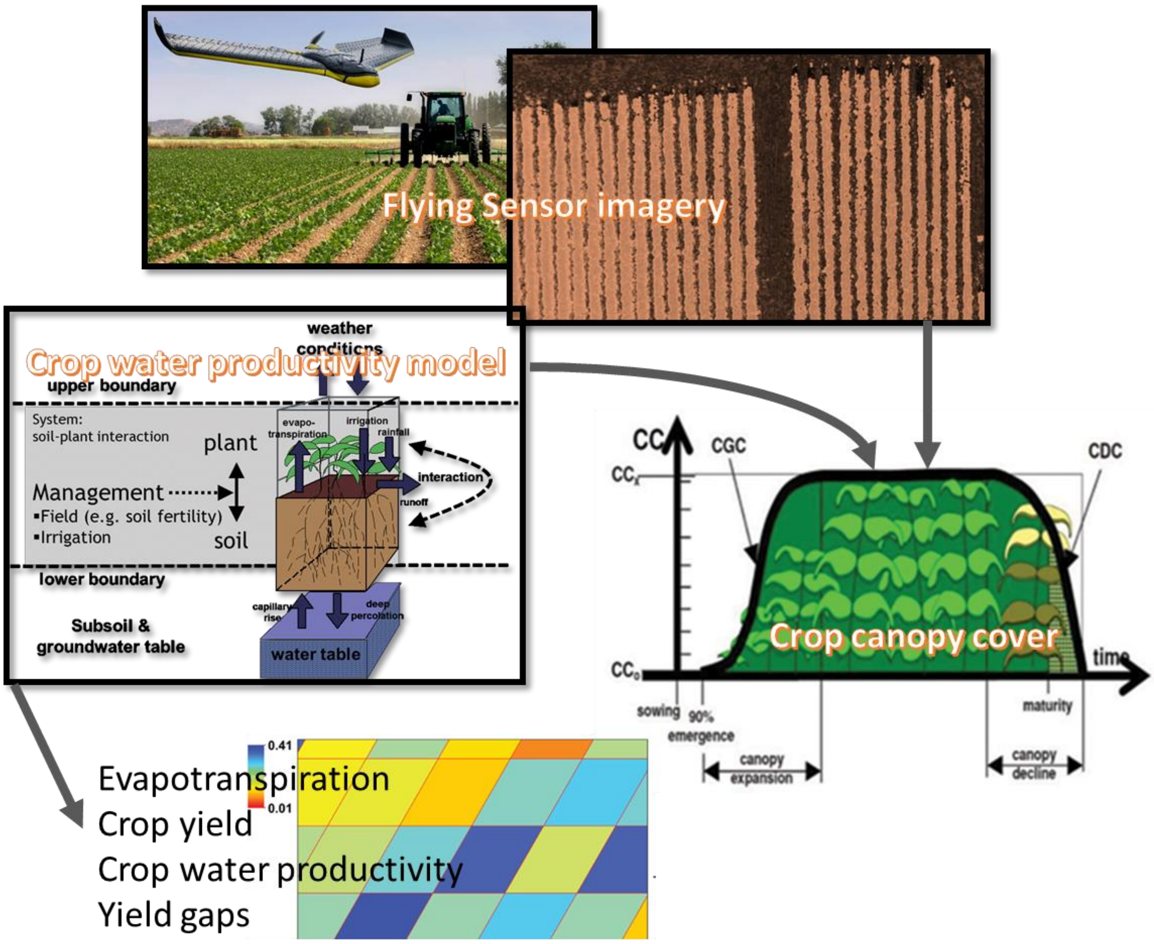


Figure 11. The overall concept of the technology to assess and monitor water productivity for agricultural fields

The main steps in the analysis procedure are:

- Flying Sensors (FS) imagery collection to capture the growth curve
- Canopy Cover (CC) extraction in GIS, resulting in maps and timeseries per plot
- Crop model setup simulating the existing variability in the agricultural district
- Based on the FS-based CC curves, identify the best fit with the model simulations
- Produce water productivity and yield gap maps for the agricultural district

In the next sections, the experimental development is set out, leading to first outputs of the tool, and several recommendations for further improvement.

4.2 Pilot area

Currently FutureWater runs a project in Gaza province, Mozambique, named ThirdEye. ThirdEye is a project where low-cost UAVs are deployed to assist farmers in managing their farms by timely detecting crop stress with NDVI-B maps. There are two project areas in Gaza province, in Chókwè and in Xai-Xai. For this trial we identified an area in Xai-Xai where the proposed methodology was tested. The pilot area is situated in a district of the local irrigation and drainage authority (Regadio do Baixo Limpopo, RBL), the pilot area is inside a zone called Nhampondzoene (see Figure 12).

Nhampondzoene is part of the drainage system of RBL, where exfiltrating water from nearby dunes is directed to the river Limpopo. Between the exfiltration points and the river Limpopo, a drainage system supplies water to thousands of smallholders. The drainage system contains a main channel, secondary and tertiary channels, that supply farmers with water throughout the year. Only in years with deficit rainfall (e.g. 2016), the exfiltration is insufficient to supply the drainage schemes throughout the year. It should be mentioned that 2017 did not suffer from extreme drought. On the contrary, RBL faced problem draining the channels beginning of 2017, due to excess rainfall, therefore groundwater levels were relatively high at the beginning of the second cropping season. As a consequence, the second cropping season started later than usual.[1]

In Nhampondzoene we identified an area of 31 hectares suitable to fly weekly and monitor the maize production. At the beginning of May we identified several fields where smallholders started producing maize. From the start of May until the end of October we monitored 44 maize fields (see Figure 12). The 44 maize fields have an average size of 0.25 hectares. The crops produced on the fields in Nhampondzoene are primarily for domestic use. During the spatial analysis we focussed on plots producing maize, other crops were left out. Field visits showed weed management was low in the maize plots monitored.

[1] Mozambique has two seasons: the rainy season and the dry season. Depending on the intensity of the rainy season, farmers in Nhampondzoene grow maize throughout the year, combined with vegetables such as tomatoes or cabbage. Other crops are sweet potatoes and cassava. However, maize is predominantly produced for their staple food: xima (maize porridge).

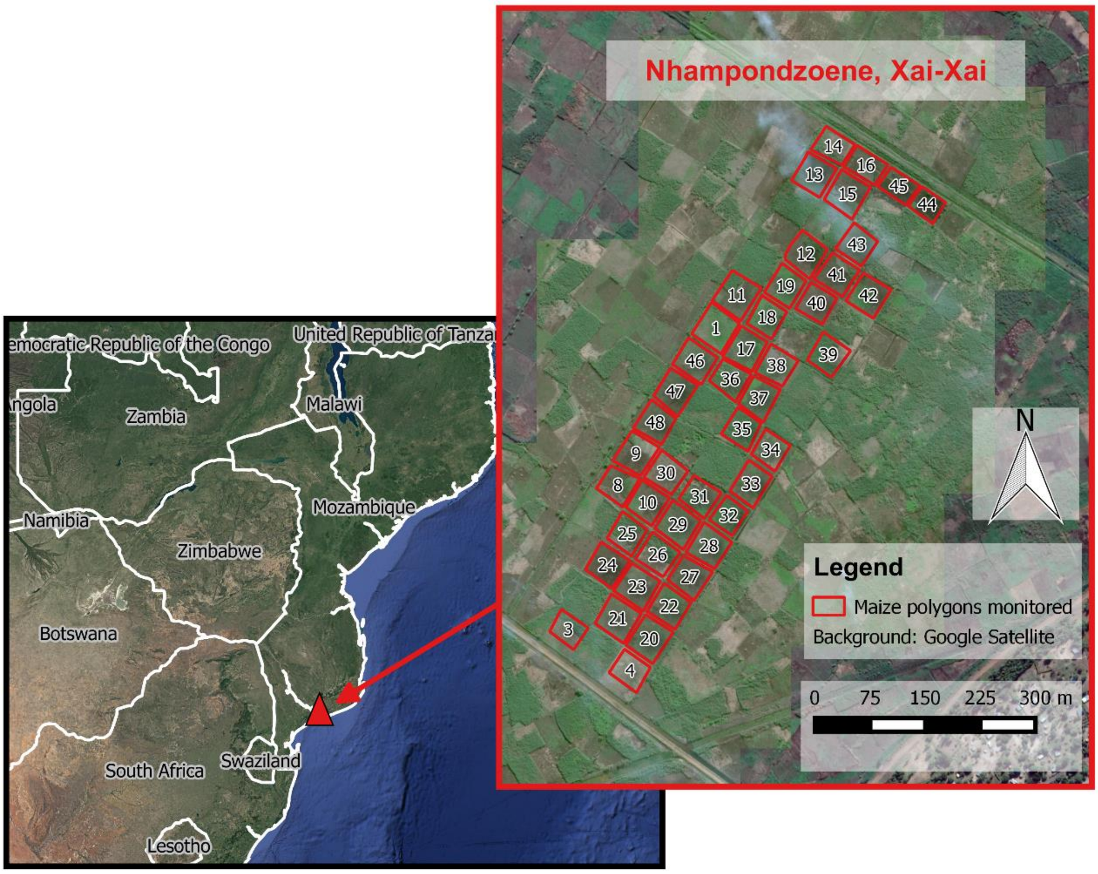


Figure 12. Location of the pilot area. The area is part of the ThirdEye project, consisting of 31 ha. The area is located in Xai-Xai, Gaza province. In local nomenclature the area is referred to as Nhampondzoene. 44 maize areas in Nhampondzoene were monitored weekly in the period from May-October 2017.

4.3 Ground data collection

4.3.1 Meteorological data

For the pilot area, data from a close meteorological station was available and was downloaded from the was retrieved from the Global Summary of the Day (GSOD) database archived by the National Climatic Data Center (NCDC). This database offers a substantial number of stations with long-term daily time-series across the world. The GSOD database submits all series (regardless of origin) to extensive automated quality control. Therefore, it can be considered as a uniform and validated database of relative high quality.

Data was downloaded for the Xai-Xai weather station. Figure 13 and Figure 14 show the precipitation, reference evapotranspiration and minimum and maximum temperature for January to October 2017. The cropping period is from May – October.

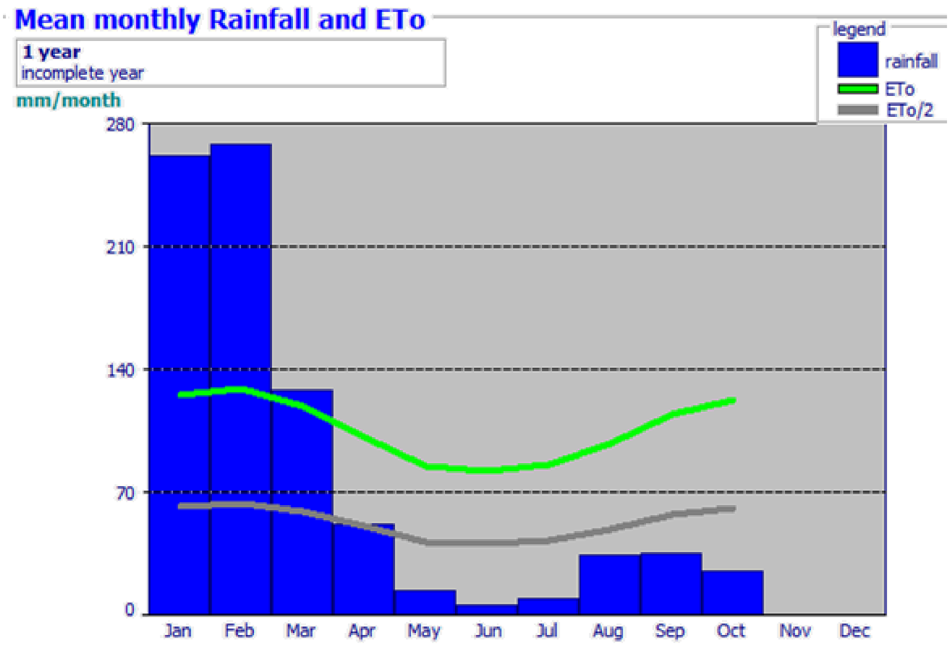


Figure 13. Mean monthly rainfall and reference evapotranspiration (ETo) for Jan-Oct 2017

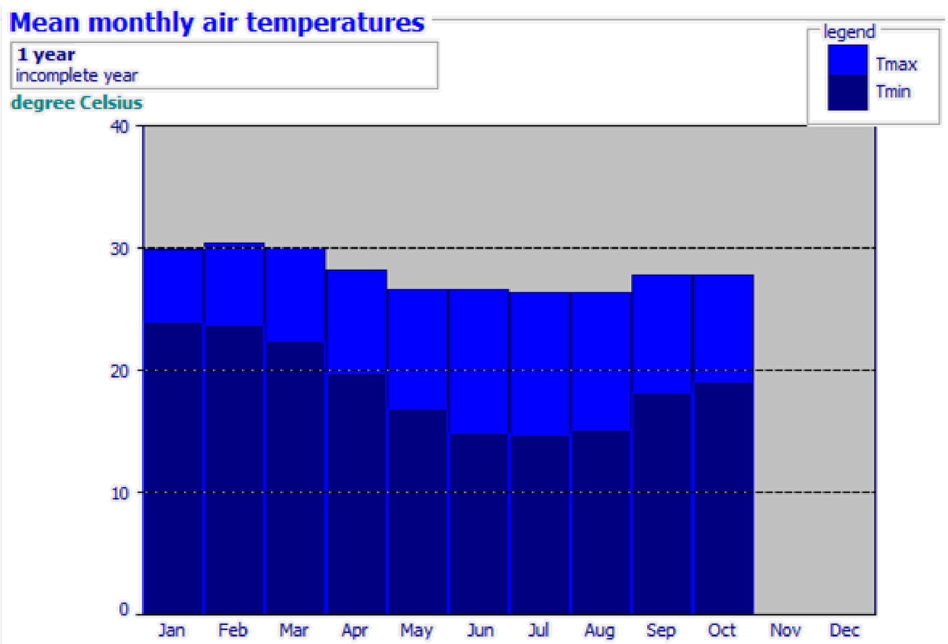


Figure 14. Mean monthly minimum and maximum temperature for Jan-Oct 2017

4.3.2 Soil characteristics and groundwater

Soil type in the area was determined by taking samples and using a simple technique based on the settling velocity of the different fractions. The soil type in the area is Loamy Clay for the root zone.

The area has relatively low groundwater levels. Groundwater level was measured during several moments by digging a hole reaching the phreatic level (Figure 15). Groundwater level was between -70 cm and -110 cm below ground surface.

Figure 15. Root zone and phreatic level in study area

4.3.3 Crop yields

The FS operators requested each farmer to report on the yields for the different plots. Figure 16 shows the histogram of the 44 surveyed plots. The mean fresh yield for all plots is 2,300 kg/ha = 2.3 ton/ha. Most farmers harvested between the end of September and the end of October.

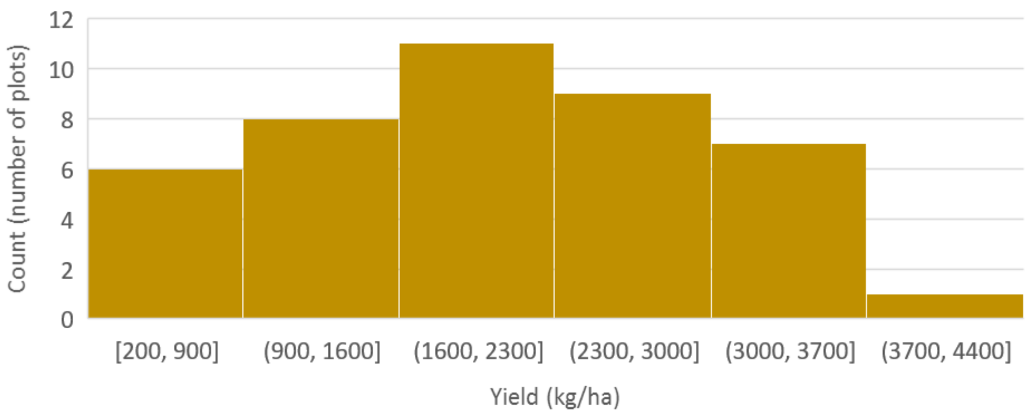


Figure 16. Histogram of fresh crop yields (kg/ha) that were surveyed

4.4 Flying Sensor data collection

The weekly flights in Nhampondzoene were performed by a local operator in Xai-Xai, under the supervision of a FutureWater employee. A low-cost UAV was used: a Phantom 3 Advanced, with a 12 megapixel camera. The standard RGB camera was converted to a NIR-G-B lens. Due to the camera modification, the flights could be used to compute an NDVI-B map. After the flights, the photographs were computed to an orthomosaic with the help of Agisoft Photoscan Professional, see the workflow in Figure 17.

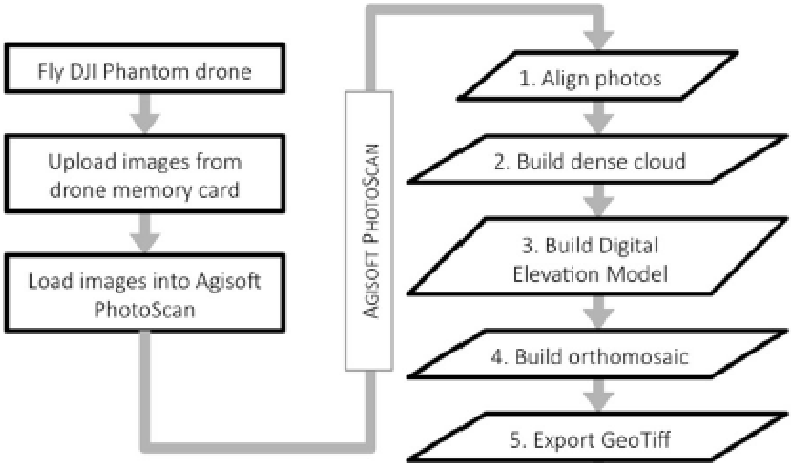


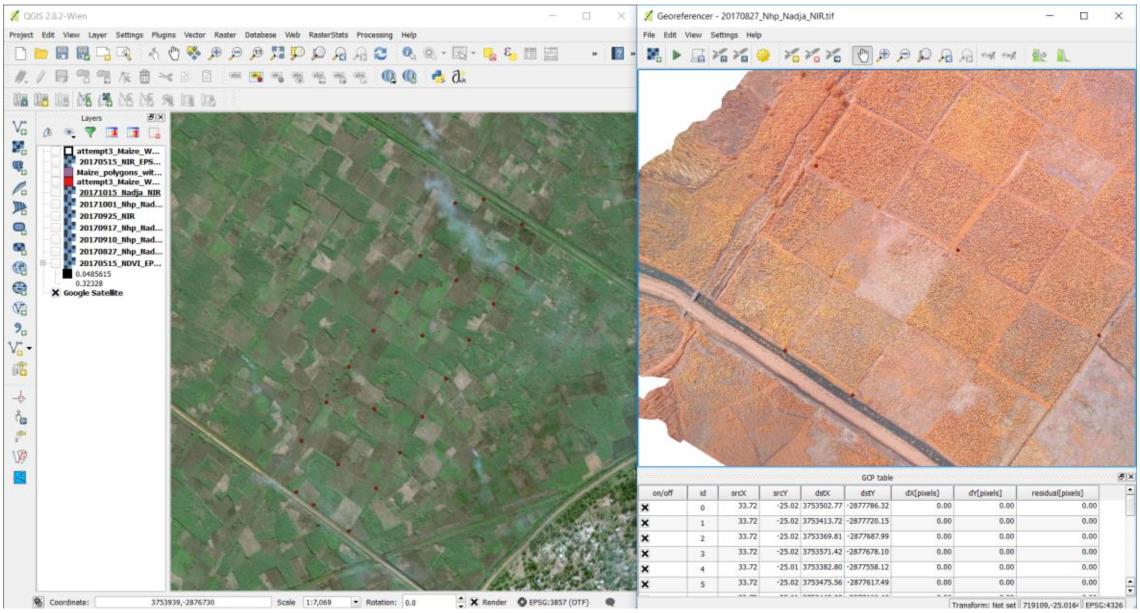
Figure 17 Workflow of the first part of the image processing. (Hardy et al., 2017)

4.5 Canopy cover extraction

The following procedure was carried out to extract vegetative cover (VC) from the imagery of each of the flights (21 in total) (see Figure 18):

1. Georeferencing the orthomosaics with 22 Ground Control Points (GCPs) and google Satellite
2. Python script to extract the NDVI-B and resample to 0.1m
3. Create a shapefile containing the polygons of the maize plots
4. Use zonal statistics to calculate amount of pixels of each field with vegetation (combination of crop and weed). For this first testing, we assumed a threshold value of NDVI-B > 0.2 in a python script.
5. Calculate the percentage of canopy cover (in this case threshold >2) in each plot by comparing to the total amount of pixels in each plot

This methodology creates a timeseries with a weekly interval of the canopy cover in the 44 areas assessed.



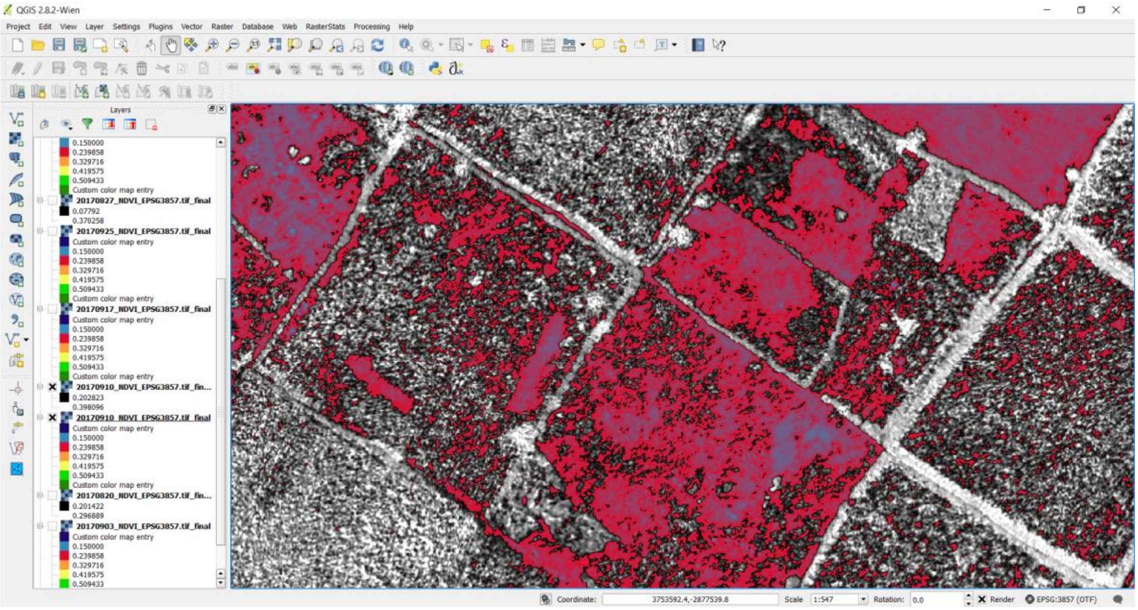


Figure 18. Screen shots of the analysis in python on qGIS. The first screenshots visualizes the process of georeferencing with a build-in qGIS tool named Georeferencer. The second screenshot visualizes the extraction of NDVI-B values below 0.2.

The vegetative cover at the start of the season, or the weeks just before planting, was used to correct for weed cover during the cropping period. The assumption is that the weed in each plot at the start or just before the season is a good indication of the weed cover during the cropping season – depending on the local conditions (soil moisture, availability of seeds, etc) but also farmers´ practices: some farmers take more effort in weeding than others.

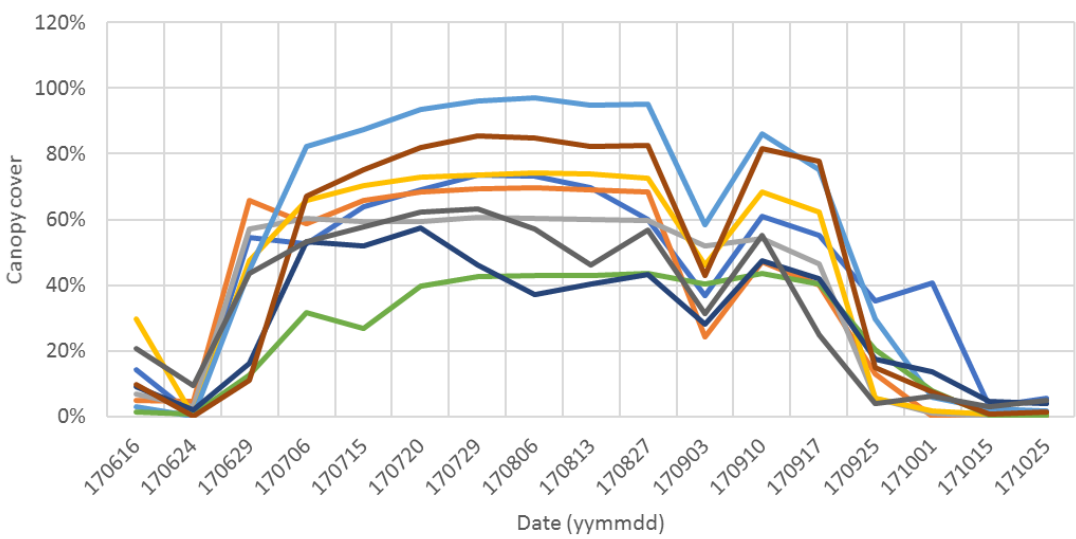


Figure 19. Canopy cover during the cropping season of several plots, corrected for weeds

For this particular area, the CC curve was calculated as follows:

- The average Weed Cover (WC) was calculated from the first 5 images when all plots were recently planted or not yet planted
- The VC values extracted from the FS-imagery were then corrected for WC to obtain CC, as follows:

- CC = VC*(1-WC)
- For this development phase of the tool, the maximum canopy cover was used to map the observations with the simulations. The maximum CC was obtained from the period between 15-Jul and 17-Sep when all plots were at its peak in terms of CC

The above procedure leads to a CC curve for all plots in the area, as shown in Figure 19 for several plots. From this image it can be seen that there is some variability in the CC measured most likely due to the variability in weed cover, but also atmospheric issues and other errors in the FS images. From this curve, it can be concluded that:

- During the crop development phase, weekly images are necessary to capture the steep gradient
- When the crop reaches its maximum, bi-weekly images are sufficient
- Around the senescence period, it is not necessary to obtain imagery as this period is not influential on the crop production

The maximum canopy cover extracted following this procedure explains approximately half (R^2 = 0.49) of the variability in crop yields as they were reported by the farmers, as shown in Figure 20. This is fairly high, given the large uncertainties in collecting yield data and the very unregular planting densities and presence of weed complicating the canopy cover extraction from FS imagery.

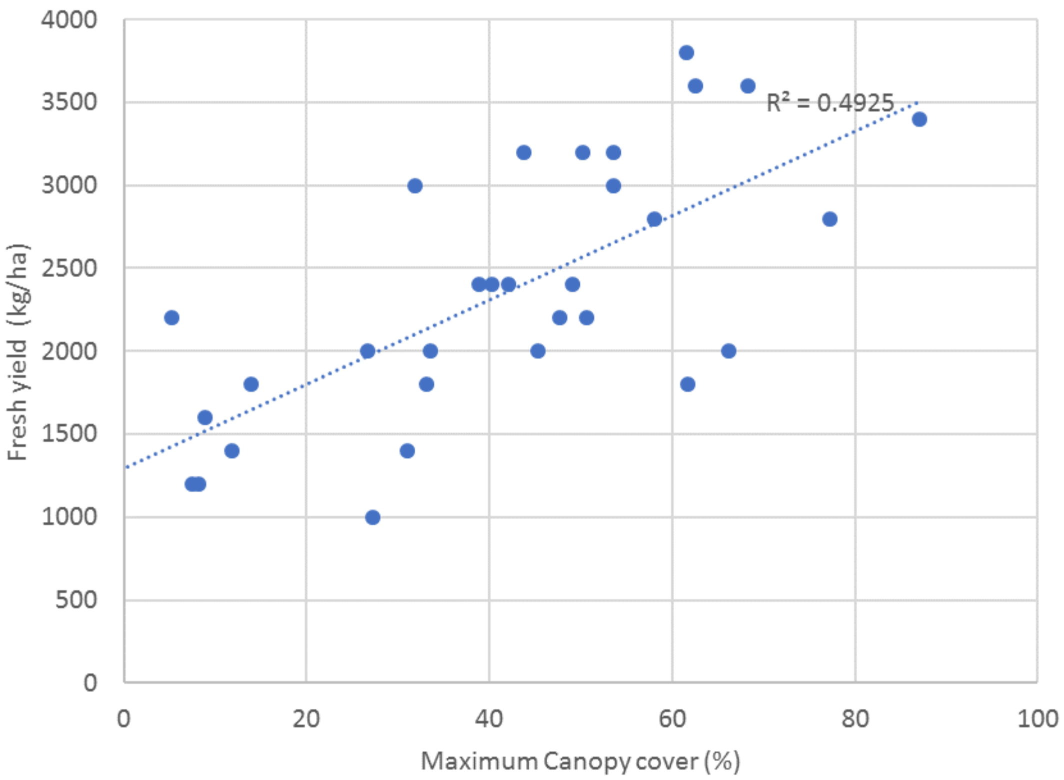


Figure 20. Maximum canopy cover versus yields reported by the farmers

4.6 Crop model specifications

A general description of the Aquacrop model is provided in Paragraph 3.5.3. This section further specifies the model properties relevant to this application.

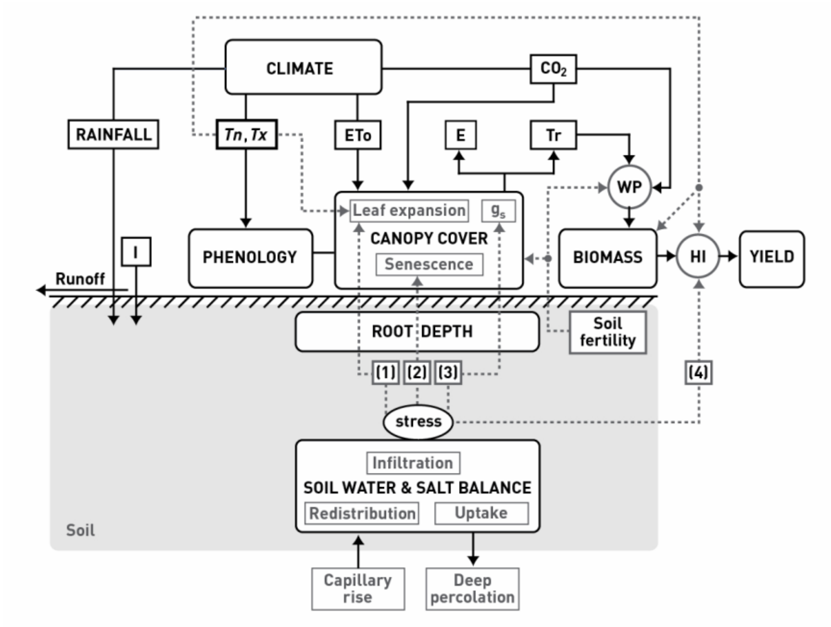


Figure 21. Main processes included in AquaCrop.

4.6.1 Theoretical assumptions

The complexity of crop responses to water deficits led to the use of empirical production functions as the most practical option to assess crop yield response to water. Among the empirical function approaches, FAO Irrigation & Drainage Paper 33 (Doorenbos and Kassam, 1979) represented an important source to determine the yield response to water of field, vegetable and tree crops, through the following equation:

$$\left(\frac{Y_x - Y_a}{Y_x}\right) = k_y \left(\frac{ET_x - ET_a}{ET_x}\right) \qquad \text{Eq. 1}$$

where Y_x and Ya are the maximum and actual yield, ET_x and ETa are the maximum and actual evapotranspiration, and k_y is the proportionality factor between relative yield loss and relative reduction in evapotranspiration.

AquaCrop evolves from the previous Doorenbos and Kassam (1979) approach by separating (i) the ET into soil evaporation (E) and crop transpiration (Tr) and (ii) the final yield (Y) into biomass (B) and harvest index (HI). The separation of ET into E and Tr avoids the confounding effect of the non-productive consumptive use of water (E). This is important especially during incomplete ground cover. The separation of Y into B and HI allows the distinction of the basic functional relations between environment and B from those between environment and HI. These relations are in fact fundamentally different and their use avoids the confounding effects of water stress on B and on HI. The changes described led to the following equation at the core of the AquaCrop growth engine:

$$B = WP \cdot \Sigma Tr \qquad \text{Eq. 2}$$

where Tr is the crop transpiration (in mm) and WP is the water productivity parameter (kg of biomass per m^2 and per mm of cumulated water transpired over the time period in which the biomass is produced). This step from Eq. 1.1 to Eq. 1.2 has a fundamental implication for the robustness of the model due to the conservative behavior of WP (Steduto et al., 2007). It is worth noticing, though, that both equations are different expressions of a water-driven growth-engine in terms of crop modeling design (Steduto, 2003). The other main change from Eq. 1 to AquaCrop is in the time scale used for each one. In the case of Eq. 1.1, the relationship is used seasonally or for long periods (of the order of months), while in the case of Eq. 2 the relationship is used for daily time steps, a period that is closer to the time scale of crop responses to water deficits.

4.6.2 Software and scripts

For this analysis, the AquaCrop version 6.0 was used with the accompanying plugin. The main components included in AquaCrop to calculate crop growth are Figure 22:

- Atmosphere
- Crop
- Soil
- Field management
- Irrigation management

More details on each of these components can be found in the AquaCrop documentation (Raes et al., 2009)

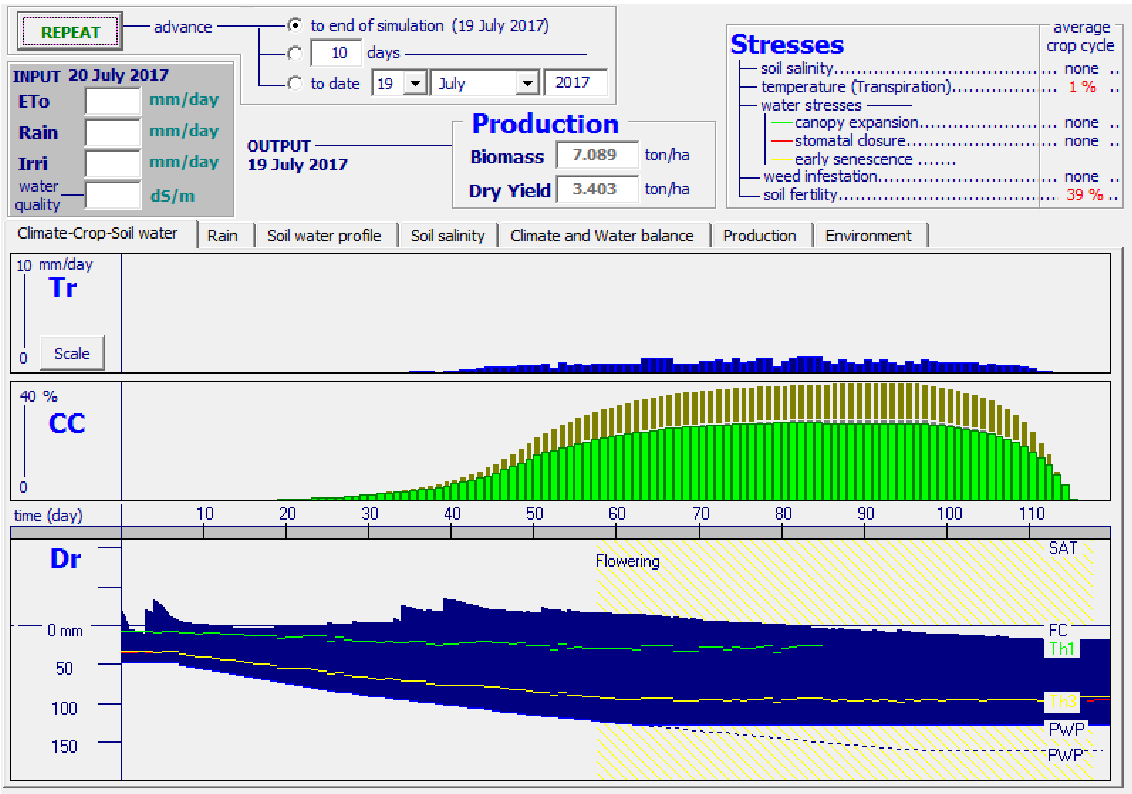


Figure 22. Example of a simulation in AquaCrop of a plot in the study area (Tr = transpiration, CC = canopy cover, Dr = soil moisture)

The plugin was used to automate the simulations, reading a large number of parameter combinations from an Excel file. The automation procedure scripted in Python was further enhanced compared to an earlier version, including two additional parameters that are extracted from the daily output file, instead of the seasonal output file:

- Maximum canopy cover
- The day after planting that the maximum cover was reached.

This shell around Aquacrop developed by FutureWater allows a large number of crop simulations to be carried out in a small amount of time, easily adjustable and analysable. Sensitivity analysis can be carried out, calibration and validation, and the existing variability within an area can be simulated by running all combinations at once.

4.7 Crop model simulations

Crop model simulations were carried out, covering the existing variability in the plots in terms of rooting depth, maximum canopy cover, fertility stress and planting density. The below table shows the ranges and the steps used for these model iterations.

Table 5. Parameter combination simulated covering the possible variability in the area

Parameter	*Minimum*	*Maximum*	*Step*
Rooting depth	0.3	0.8	1
Planting density	20000	50000	10000
Fertility	20	60	20

These simulations resulted in timeseries and outputs for canopy cover, evapotranspiration, water productivity and other relevant output variables. Figure 23 shows the relation with water productivity (kg per m^3 of consumed water).

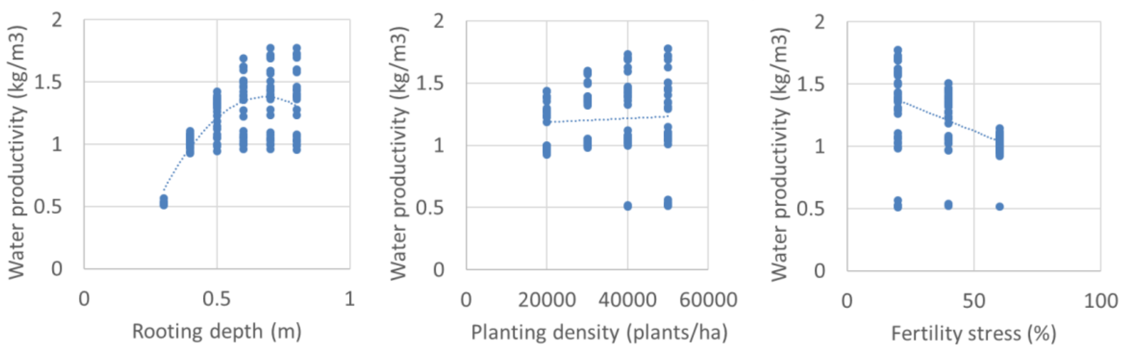


Figure 23. Simulated water productivity for all combinations in Table 5

To link the model simulations with the conditions in each field different methods can be used depending on the data available, the variability in the field in terms of planting density, planting and harvesting date, etc. Given the large variability for this pilot area in terms of planting density even within a single plot, the method that was chosen was to use the simulated relationship between maximum canopy cover and the different variables of interest as for example yield and water productivity.

So as visually explained in Figure 24, for example for a plot of which the Flying Sensor imagery indicated a maximum canopy cover of 40%, a Water Productivity of 1.2 kg/m3 is computed. The same method is applied for yields and yield gap.

As can be seen in the same figure, there is quite some variability around the grey fitted line (i.e. uncertainty), which means that there is the potential to improve this mapping procedure (i.e. linking of observations with simulations). Further testing and development in a more homogeneous environment (small within-plot variability) can likely lead to further improvements.

Figure 25 shows the variability in simulated crop yields. The simulated yield (dry) variability spans approximately the same range as the surveyed yields (fresh) (see Figure 16). When comparing both histograms, one has to take into account the conversion from fresh yield to dry yield (in the case of maize a factor between 0.85 and 0.9).

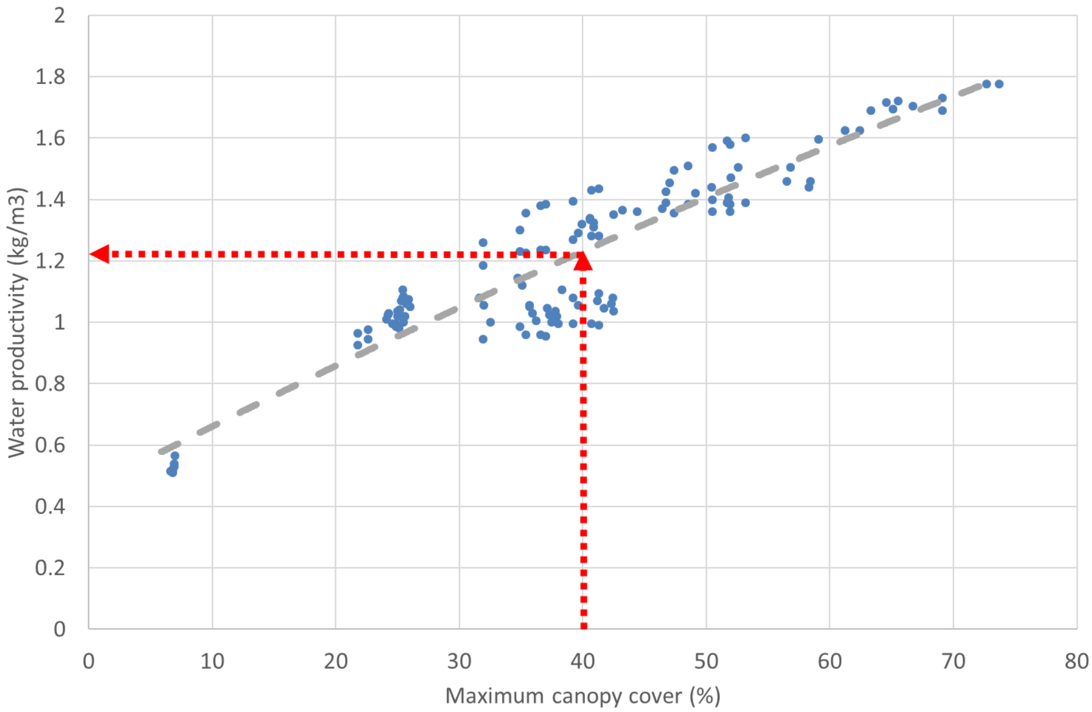


Figure 24. Simulated relationship between maximum canopy cover and water productivity

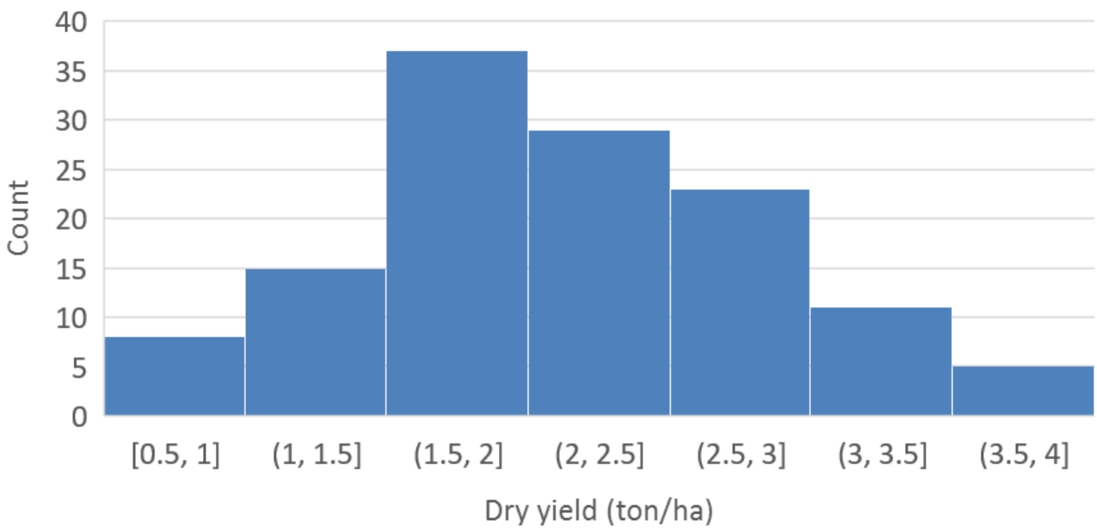


Figure 25. Histogram of simulated dry yields (ton/ha)

4.8 Mapping water productivity and yield gap

By combining the Flying Sensor imagery, the canopy cover values and the simulations carried out, maps can be made for the entire area with the different output variables of the water productivity tool. Figure 26 shows maize yields for all plots.

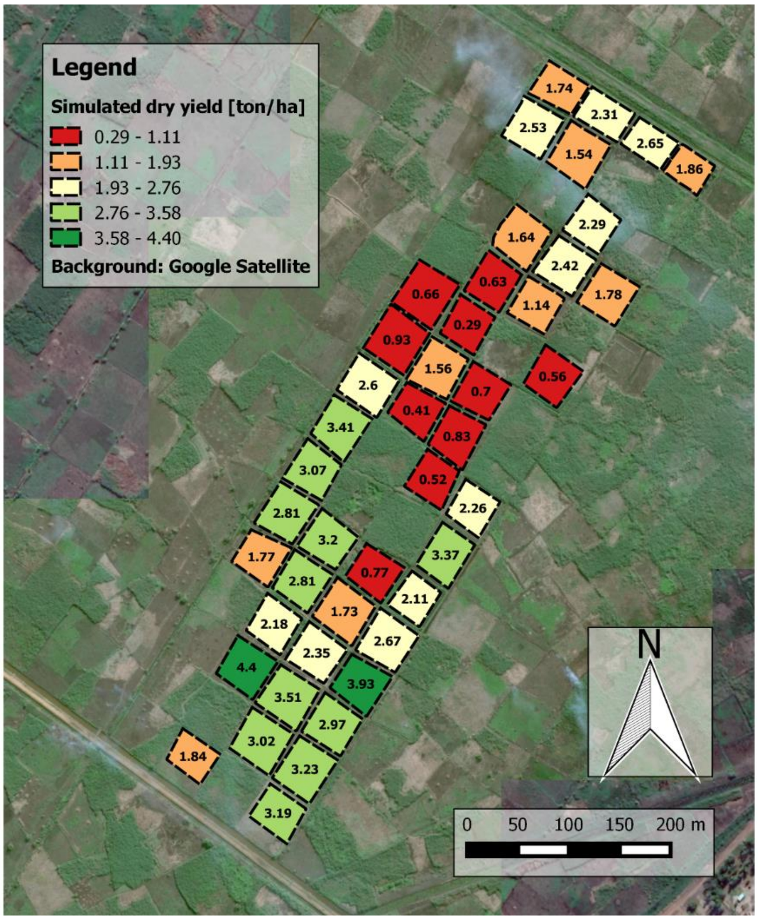


Figure 26. Map of maize yields (ton/ha) for all plots

To map crop water productivity for complex and heterogeneous areas as the one presented in this study, the developed tool can provide water productivity maps for each plot and smallholder. Figure 27 shows the map of crop water productivity for the pilot area.

If this tool would be applied again during forthcoming growing seasons, differences in crop water productivity can be assessed and linked with changes in farmers practices or other interventions.

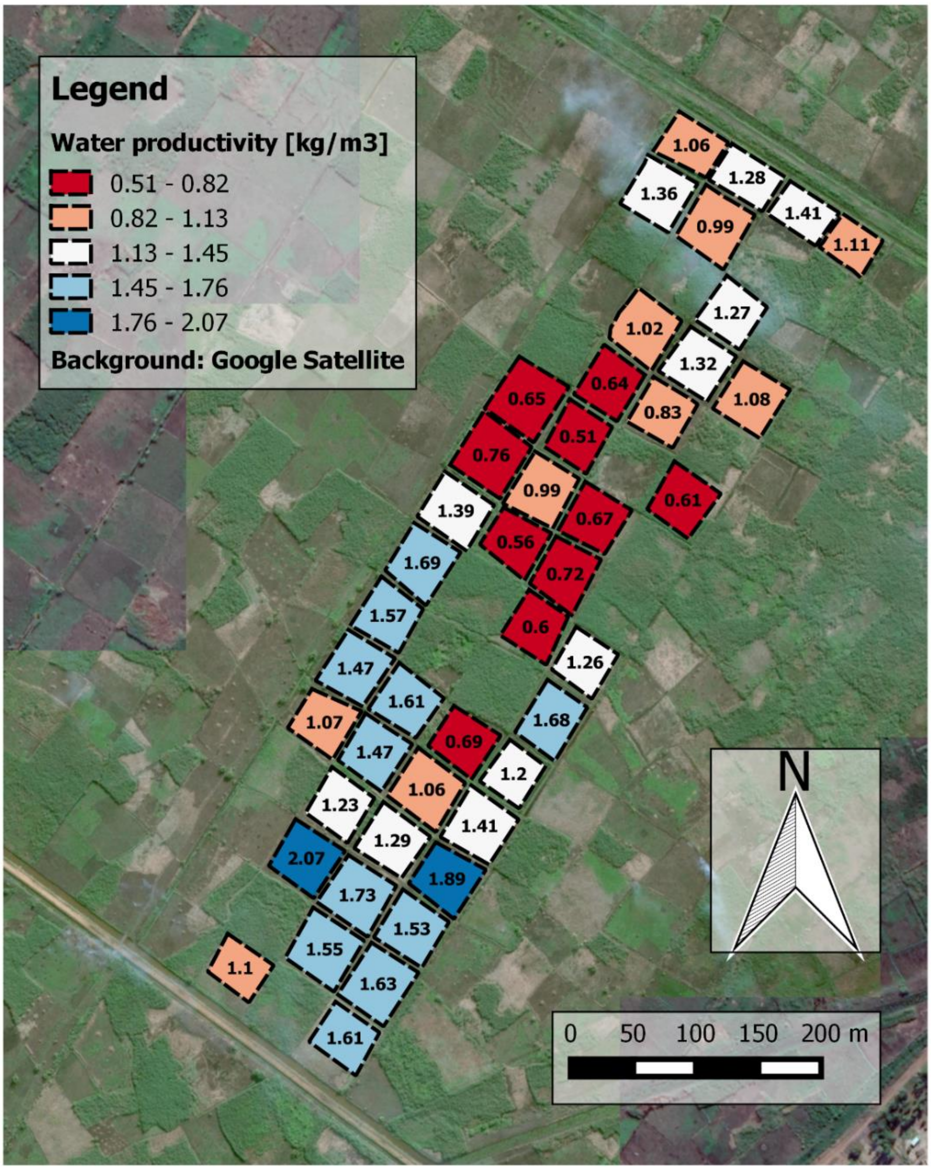


Figure 27. Map of water productivity (kg/m^3) for all plots

To analyze the potential for enhancing crop water productivity and yields, a yield gap map can be made by comparing the performance of each plot with a targeted performance (yield or water productivity) value. Figure 28 shows the yield gap for all plots, by calculating the difference with the best performing plot in the area. This is a straightforward way to assess which plots and smallholders can improve their practices in terms of weed management, planting density and other factors, to increase yield and increase water productivity.

The model can be used to assess the scope to further improve yield and water productivity by reducing fertilizer stress, improving soil conditions, supplemental irrigation practices, soil evaporation reduction measures and other agricultural practices. This was out of the scope of this pilot study.

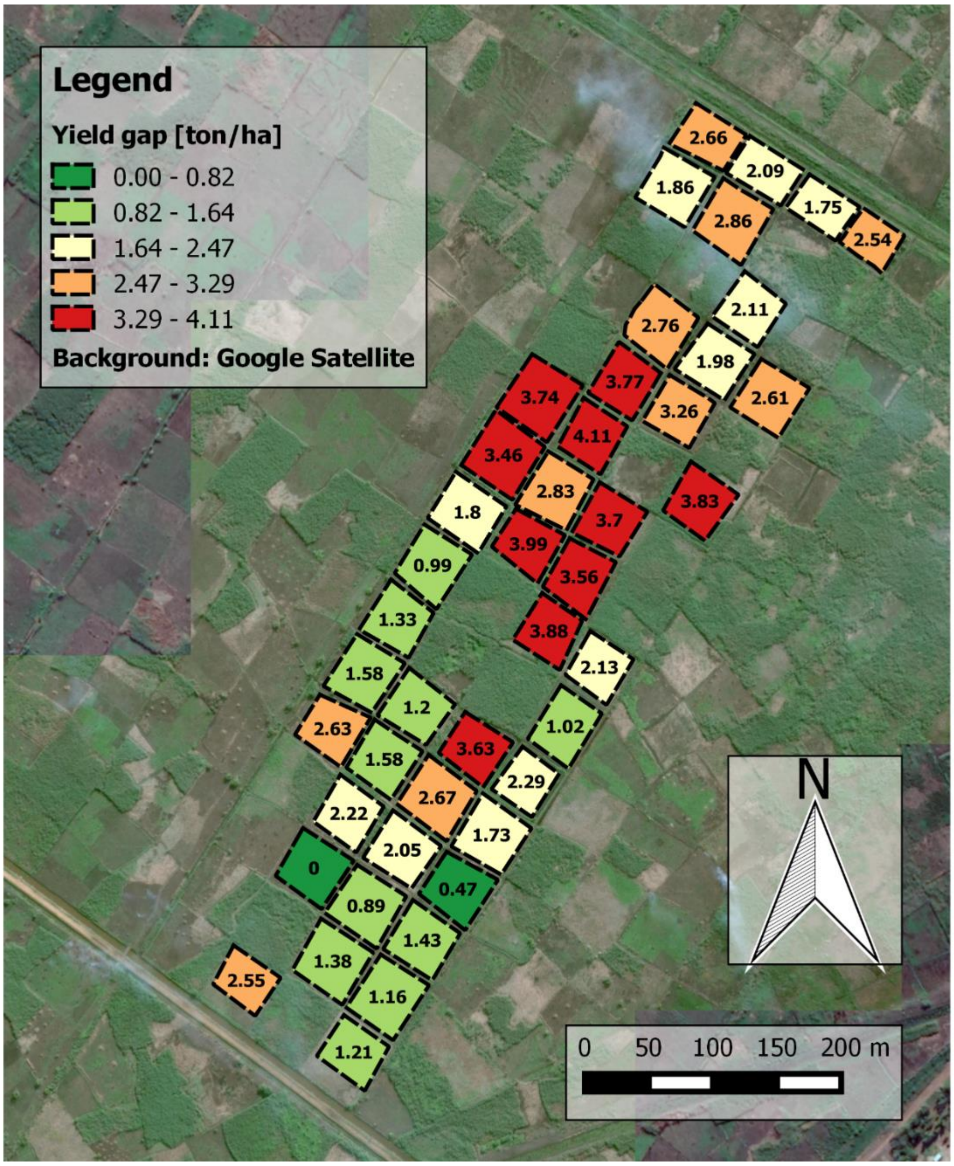


Figure 28. Map of yield gap based on difference with best performing plot

4.9 Future improvements

This experimental development phase of the water productivity tool revealed several issues that can be further improved, principally:

- The post-processing of the FS imagery, taking into account weeds. Other vegetation indices could be more appropriate and other threshold values could be studies to obtain more accurate estimates of canopy cover. Especially in this extremely heterogeneous pilot area improvements on this subject can lead to more accurate WP estimates.
- More information of the canopy cover curve can be used or combined with the crop growth model: calibrating the curve using the observations, but at the same time taking into account the within-plot variability. Or other parameters, as for example the day after planting that the maximum CC was reached can be used to link the simulations with the observations to create the water productivity maps, possibly leading to more accurate estimates.

- An uncertainty assessment could study the influence of local variability, errors in FS-data collection and modelling uncertainties (inputs, processing and outputs) on the output accuracy.

5 Conclusion

This pilot study combined high-resolution imagery from Flying Sensors with a crop water productivity model to assess yield and water productivity for several plots with maize in Mozambique. Canopy cover was derived from the imagery and linked with the crop model simulations to obtain water productivity maps covering the entire growth cycle. The methodology also monitoring of crop performance while growing and can be used to forecast yield.

So far, few applications exist that link FS imagery to crop models for this purpose. Literature focusses mainly on the computation of Crop Surface Models with the help of Flying sensors, to assess biomass and forecast yield, thus using elevations models rather than spectral reflectance properties indicative of vegetation cover and crop health. There are opportunities in linking different Vegetation Indices to agro-hydrological crop growth models.

Taking into account scale, data intensity, linkage to Vegetation Indices, and suitability to assess water productivity, we selected Aquacrop as the most suitable model for connecting to FS imagery, due to its relative simplicity and easy linkage to remote sensing through the Canopy Cover parameter.

Nowadays, projects that invest in sustainable water management and agriculture require evidence that the targeted measures to boost water productivity are effective. Water productivity monitoring therefore becomes increasingly important. Water productivity requires data on yields and water consumption (evapotranspiration). Yield data are often difficult to obtain from farmers, especially in areas with many smallholders. Evapotranspiration is even more difficult to assess in the field. Remote sensing-based and model-based monitoring of water productivity has a large potential, also to identify yield gaps and assess the local feasible effectiveness of measures.

This feasibility study demonstrated that there is an opportunity to further develop a service that monitors water productivity based on FS-imagery and crop modelling. Service costs outweigh the additional revenues obtained by farmers. The experimental development has demonstrated that the service is technically feasible and can provide the tangible outputs needed.

To bring the proposed service to a higher level of maturity, it is recommended to focus future development activities on:

- Testing for different locations and crops
- Further enhancing link between FS-based imagery and crop modelling
- Involving end-users and testing within a project where WP-measures are implemented

Aasen, H. and Gnyp, M. L.: Spectral comparison of low-weight and UAV- based hyperspectral frame cameras with portable spectroradiometers measurements, Proc. Work. UAV-basaed Remote Sens. Methods Monit. Veg., (JANUARY), 1–6, doi:10.5880/TR32DB.KGA94.2, 2014.

Anon: Imagery from multispectral sensors vs . imagery from cameras, 2004.

Bastiaanssen, W. G. M. and Steduto, P.: The water productivity score (WPS) at global and regional level: Methodology and first results from remote sensing measurements of wheat, rice and maize, Sci. Total Environ., 575, 595–611, doi:10.1016/j.scitotenv.2016.09.032, 2017.

Bendig, J., Willkomm, M., Tilly, N., Gnyp, M. L., Bennertz, S., Qiang, C., Miao, Y. and Bareth, G.: Very high resolution crop surface models (CSMs) from UAV-based stereo images for rice growth monitoring In Northeast China, Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci., XL(September), 4–6, doi:10.5194/isprsarchives-XL-1-W2-45-2013, 2013.

Bendig, J., Bolten, A., Bennertz, S., Broscheit, J., Eichfuss, S. and Bareth, G.: Estimating biomass of barley using crop surface models (CSMs) derived from UAV-based RGB imaging, Remote Sens., 6(11), 10395–10412, doi:10.3390/rs61110395, 2014.

Bendig, J., Yu, K., Aasen, H., Bolten, A., Bennertz, S., Broscheit, J., Gnyp, M. L. and Bareth, G.: Combining UAV-based plant height from crop surface models, visible, and near infrared vegetation indices for biomass monitoring in barley, Int. J. Appl. Earth Obs. Geoinf., 39, 79–87, doi:10.1016/j.jag.2015.02.012, 2015.

Bolton, D. K. and Friedl, M. A.: Forecasting crop yield using remotely sensed vegetation indices and crop phenology metrics, Agric. For. Meteorol., 173, 74–84, doi:10.1016/j.agrformet.2013.01.007, 2013.

Caruso, G., Tozzini, L., Rallo, G., Primicerio, J., Moriondo, M., Palai, G. and Gucci, R.: Estimating biophysical and geometrical parameters of grapevine canopies (’Sangiovese’) by an unmanned aerial vehicle (UAV) and VIS-NIR cameras, Vitis - J. Grapevine Res., 56(2), 63–70, doi:10.5073/vitis.2017.56.63-70, 2017.

Centre, W. C. and Centre, W. C.: User manual for WOFOST and the WOFOST Control Centre, n.d.

Copernicus Information Service: Copernicus Global Land Service - Land Cover, 2015.

Droogers, P. and Bouma, J.: Simulation modelling for water governance in basins, Int. J. Water Resour. Dev., 30(3), 475–494, doi:10.1080/07900627.2014.903771, 2014.

Droogers, P., Simons, G. W. H., Besten, N. I. den, Til, J. van and de Klerk, M.: Monitoring Water Productivity : Demonstration Case for ThirdEye Mozambique, FutureWater Report 169., 2017.

Eisenbeiss, H.: the Autonomous Mini Helicopter : a Powerful Platform for Mobile Mapping, Archives, 37, 3–11, 2004.

Erickson, B. and Widmar, D. A.: PRECISION AGRICULTURAL SERVICES DEALERSHIP SURVEY RESULTS SPONSORED BY CROPLIFE MAGAZINE AND THE by, 2015.

Fiorillo, E., Crisci, A., De Filippis, T., Di Gennaro, S. F., Di Blasi, S., Matese, A., Primicerio, J., Vaccari, F. P. and Genesio, L.: Airborne high-resolution images for grape classification: Changes in correlation between technological and late maturity in a Sangiovese vineyard in Central Italy, Aust. J. Grape Wine Res., 18(1), 80–90, doi:10.1111/j.1755-0238.2011.00174.x, 2012.

Geerts, S. and Raes, D.: Deficit irrigation as an on-farm strategy to maximize crop water productivity in dry areas, Agric. Water Manag., 96(9), 1275–1284, doi:10.1016/j.agwat.2009.04.009, 2009.

Geipel, J., Link, J. and Claupein, W.: Combined spectral and spatial modeling of corn yield based on aerial images and crop surface models acquired with an unmanned aircraft system, Remote Sens., 6(11), 10335–10355, doi:10.3390/rs61110335, 2014.

Gnyp, M. L., Bareth, G., Li, F., Lenz-Wiedemann, V. I. S., Koppe, W., Miao, Y., Hennig, S. D., Jia, L., Laudien, R., Chen, X. and Zhang, F.: Development and implementation of a multiscale biomass model using hyperspectral vegetation indices for winter wheat in the North China Plain, Int. J. Appl. Earth Obs. Geoinf., 33(1), 232–242, doi:10.1016/j.jag.2014.05.006, 2014.

Hardy, A., Makame, M., Cross, D., Majambere, S. and Msellem, M.: Using low-cost drones to map malaria vector habitats, Parasit. Vectors, 10(1), 29, doi:10.1186/s13071-017-1973-3,

2017.
Hunink, J. E. and Droogers, P.: Climate Change Impact Assessment on Crop Production in Albania. World Bank Study on Reducing Vulnerability to Climate Change in Europe and Central Asia (ECA) Agricultural Systems, FutureWater Report 105., 2010.
Hunink, J. E. and Droogers, P.: Climate Change Impact Assessment on Crop Production in Uzbekistan. World Bank Study on Reducing Vulnerability to Climate Change in Europe and Central Asia (ECA) Agricultural Systems, FutureWater Report 106., 2011.
Hunink, J. E., Niadas, I. A., Antonaropoulos, P., Droogers, P. and Vente, J. De: Targeting of intervention areas to reduce reservoir sedimentation in the Tana catchment (Kenya) using SWAT, , 0(0), 1–15, 2013.
Hunink, J. E., Droogers, P. and Tran-mai, K.: Past and Future Trends in Crop Production and Food Demand and Supply in the Lower Mekong Basin., 2014.
Hunt, E. R., Hively, W. D., McCarty, G. W., Daughtry, C. S. T., Forrestal, P. J., Kratochvil, R. J., Carr, J. L., Allen, N. F., Fox-Rabinovitz, J. R. and Miller, C. D.: NIR-Green-Blue High-Resolution Digital Images for Assessment of Winter Cover Crop Biomass, GIScience Remote Sens., 48(1), 86–98, doi:10.2747/1548-1603.48.1.86, 2011.
Johnson, D. M.: An assessment of pre- and within-season remotely sensed variables for forecasting corn and soybean yields in the United States, Remote Sens. Environ., 141, 116–128, doi:10.1016/j.rse.2013.10.027, 2014.
Katsigiannis, P., Galanis, G., Dimitrakos, A., Tsakiridis, N., Kalopesas, C., Alexandridis, T., Chouzouri, A., Patakas, A. and Zalidis, G.: Fusion of spatio-temporal UAV and proximal sensing data for an agricultural decision support system, , (August), 96881R, doi:10.1117/12.2244856, 2016.
Keating, B. A., Carberry, P. S., Hammer, G. L., Probert, M. E., Robertson, M. J., Holzworth, D., Huth, N. I. and Hargrea, J. N. G.: An o v er v iew of APSIM , a model designed for farming systems simulation, , 18, 2003.
Motohka, T., Nasahara, K. N., Oguma, H. and Tsuchida, S.: Applicability of Green-Red Vegetation Index for remote sensing of vegetation phenology, Remote Sens., 2(10), 2369–2387, doi:10.3390/rs2102369, 2010.
Oerke, E. and Dehne, H.: Safeguarding production — losses in major crops and the role of crop protection, , 23, 275–285, doi:10.1016/j.cropro.2003.10.001, 2004.
Possoch, M., Bieker, S., Hoffmeister, D., Bolten, A. A., Schellberg, J. and Bareth, G.: Multi-Temporal crop surface models combined with the rgb vegetation index from UAV-based images for forage monitoring in grassland, Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. - ISPRS Arch., 2016–Janua(July), 991–998, doi:10.5194/isprsarchives-XLI-B1-991-2016, 2016.
Raes, D., Steduto, P., Hsiao, T. C. and Fereres, E.: Calculation Procedures, Aquacrop Ref. Man. verion 4.0, (June), 125, 2012.
Rey-Caramés, C., Diago, M. P., Pilar Martín, M., Lobo, A. and Tardaguila, J.: Using RPAS multi-spectral imagery to characterise vigour, leaf development, yield components and berry composition variability within a vineyard, Remote Sens., 7(11), 14458–14481, doi:10.3390/rs71114458, 2015.
van der Schans, D., van Evert, F., Malda, J. and Dorka-Vona, V.: Sensorgestuurde advisering van Stikstof bijbemesting in aardappel., 2012.
Sibley, A. M., Grassini, P., Thomas, N. E., Cassman, K. G. and Lobell, D. B.: Testing remote sensing approaches for assessing yield variability among maize fields, Agron. J., 106(1), 24–32, doi:10.2134/agronj2013.0314, 2014.
Siebert, S., Henrich, V., Frenken, K. and Burke, J.: Global Map of Irrigation Areas, 2013.
Silvestro, P. C., Pignatti, S., Pascucci, S., Yang, H., Li, Z., Yang, G., Huang, W. and Casa, R.: Estimating wheat yield in China at the field and district scale from the assimilation of satellite data into the Aquacrop and simple algorithm for yield (SAFY) models, Remote Sens., 9(5), 1–24, doi:10.3390/rs9050509, 2017.
Skaggs, R. W.: Review of nitrogen fate models applicable to forest landscapes in the southern U.S, , (November), doi:10.13031/trans.56.10096, 2013.
Snow, V. and Huth, N.: The APSIM – M ICROMET module, 2004.
Terink, W., Lutz, A. F., Simons, G. W. H., Immerzeel, W. W. and Droogers, P.: SPHY v2.0: Spatial Processes in HYdrology, Geosci. Model Dev., 8(7), 2009–2034, doi:10.5194/gmd-8-2009-2015, 2015.
Vazifedoust, M., van Dam, J. C., Bastiaanssen, W. G. M. and Feddes, R. A.: Assimilation of satellite data into agrohydrological models to improve crop yield forecasts, Int. J. Remote

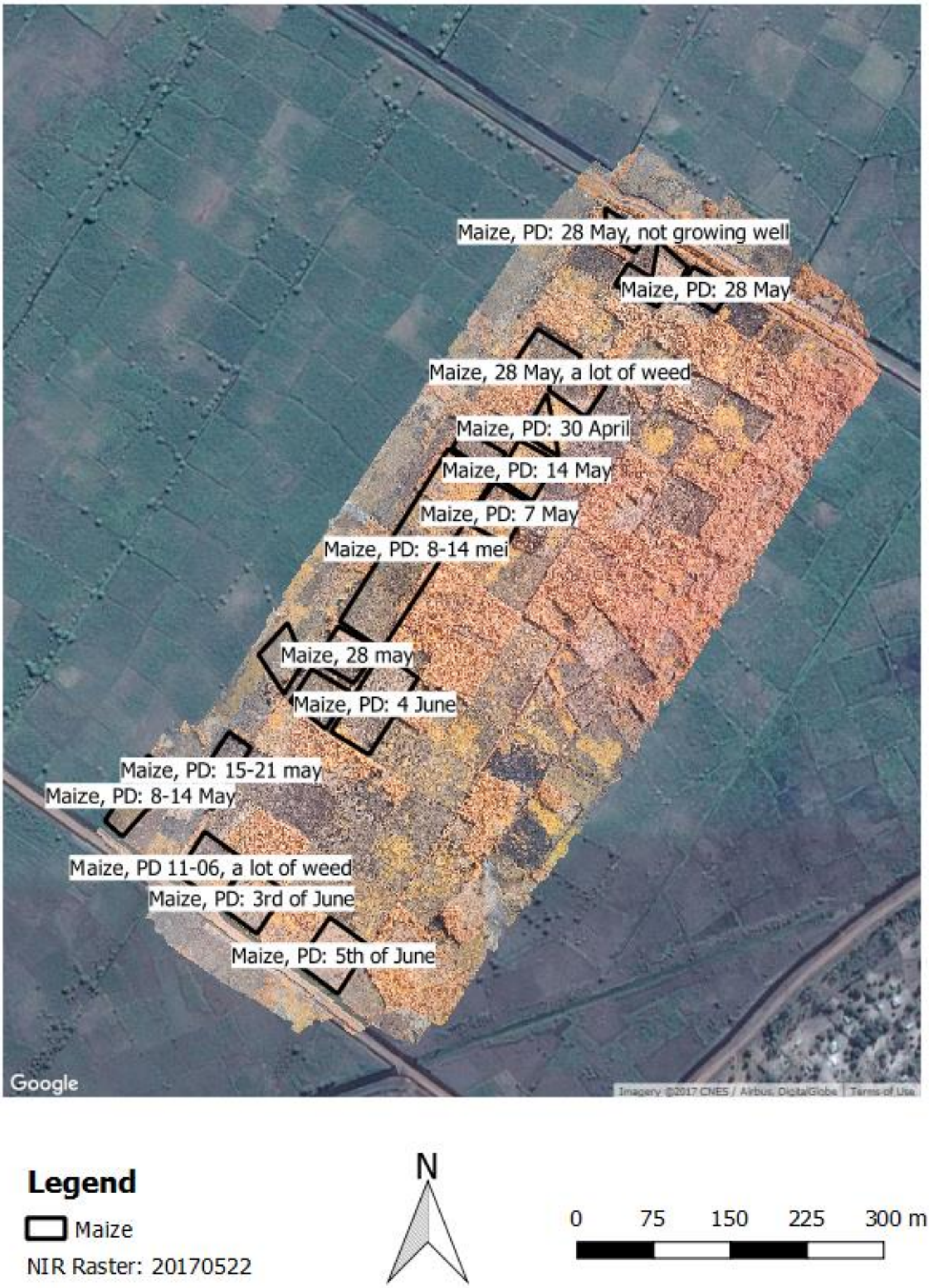
Sens., 30(10), 2523–2545, doi:10.1080/01431160802552769, 2009.
Vogl, A. L., Bryant, B. P., Hunink, J. E., Wolny, S., Apse, C. and Droogers, P.: Valuing investments in sustainable land management in the Upper Tana River basin, Kenya, J. Environ. Manage., 195, doi:10.1016/j.jenvman.2016.10.013, 2017.
Walsum, P. E. V. Van and Supit, I.: Influence of ecohydrologic feedbacks from simulated crop growth on integrated regional hydrologic simulations under climate scenarios, , 1577–1593, doi:10.5194/hess-16-1577-2012, 2012.
Wellens, J., Sallah, A. H., Tychon, B., Planchon, V. and Goffart, J. P.: Assessment of AquaCrop for maize and winter wheat using satellite derived fCover data, 2015.
Wilson, A. M. and Jetz, W.: Remotely Sensed High-Resolution Global Cloud Dynamics for Predicting Ecosystem and Biodiversity Distributions, , doi:10.1371/journal. pbio.1002415, 2016.
Xiang, H. and Tian, L.: Development of a low-cost agricultural remote sensing system based on an autonomous unmanned aerial vehicle (UAV), Biosyst. Eng., 108(2), 174–190, doi:10.1016/j.biosystemseng.2010.11.010, 2011.
Zheng, G. and Moskal, L. M.: Retrieving Leaf Area Index (LAI) Using Remote Sensing: Theories, Methods and Sensors, Sensors, 9(4), 2719–2745, doi:10.3390/s90402719, 2009.

Appendix 1: Flight dates

Flight date	**Days between flights**	**Mean visibility [.1 miles]**	**Operator**	**Georeferenced?**
15-05-2017		15.5	Operator Dercio	Yes
22-05-2017	7	18.6	Operator Dercio	Yes
29-05-2017	7	16.3	Operator Dercio	Yes
09-06-2017	11	18.6	Operator Dercio	Yes
16-06-2017	5	18.2	Operator Dercio	Yes
24-06-2017	8	17.9	Operator Dercio	Yes
29-06-2017	5	18.6	Operator Dercio	Yes
06-07-2017	7	18.6	Operator Dercio	Yes
15-07-2017	9	18.6	Operator Dercio	Yes
20-07-2017	5	18.6	Operator Dercio	Yes
29-07-2017	9	18.6	Operator Dercio	Yes
06-08-2017	9	18.6	Operator Dercio	Yes
13-08-2017	7	15.6	Operator Dercio	Yes
20-08-2017	7	Flew too late	Operator Dercio	No
27-08-2017	7	16.4	Operator Dercio	Yes
03-09-2017	7	18.6	Operator Dercio	Yes
10-09-2017	7	18.6	Operator Dercio	Yes
17-09-2017	7	14.8	Operator Dercio	Yes
25-09-2017	7	18.6	Operator Dercio	Yes
01-10-2017	6	18.6	Operator Dercio	Yes
09-10-2017	8		Operator Dercio	Yes
15-10-2017	6		Operator Dercio	Yes

Field visit	**Comments**	**Who?**
		Charlotte, Nadja & Dercio
		Nadja & Dercio
		Nadja & Dercio
		Nadja & Dercio

Appendix 2: Field inspection 11-06-2017



Observations during a field visit on the 11th of June 2016. PD: Planting Date.