FLYING SENSORS FOR SMALLHOLDER FARMING:AN INNOVATIVE TECHNOLOGY FOR WATER PRODUCTIVITY ASSESSMENT

Jonna D. van Opstal[1], Alexander Kaune[2], Corjan Nolet[2], Jan van Til[3], and Johannes E. Hunnink[4]

ABSTRACT

Agricultural water productivity is frequently used as an indicator to determine the performance of an agricultural area. It relates both efficient water consumption and profitable crop production in one indicator, thereby aiming at achieving increased food production whilst ensuring sustainable water management in agriculture. Remote sensing technologies have been used in the past to monitor water productivity through time and space. These technologies are mainly dependent on satellite remote sensing, which have a fixed spatial and temporal resolution. Multispectral remote sensing satellite platforms can be used for providing information on the crop conditions through vegetation indices. However, the highest spatial resolution found for satellite platforms is 10 or 30 meters with a limited re-visit time at the same location. An upcoming innovative solution for acquiring information is the use of flying sensors. These are adapted drones with an additional sensor to calculate vegetation cover and evaluate stress conditions. This innovative technology has been found to be suitable especially for smallholder farming and is rapidly being adopted in several countries. With this high-resolution imagery, it is possible to distinguish cropping patterns within small fields and determine crop cover. This information is coupled with a crop simulation model (AquaCrop) to calculate crop water productivity for each field and estimate the yield gap compared to optimal (non-stress) growing conditions. This information gives smallholder farmers the spatial location of yield losses due to crop stress (water, nutrients, diseases, etc.). Crop model simulations indicated that the introduction of mulching to reduce soil evaporation resulted in an increase of water productivity by 18%. The resulting spatial maps of water productivity indicated the fields with lower water productivity. The high-resolution imagery of the flying sensors was able to detect the fields displaying uneven planting densities. Planting density can be made more homogeneous throughout the field to achieve an overall higher water productivity. The integration of flying sensor technology and crop modelling is proven to be applicable for assisting smallholder farmers in their decision-making, which is demonstrated by the example of a case study of smallholder agriculture in Mozambique.

Keywords: Water productivity, Flying Sensors, Remote sensing, Crop modelling, AquaCrop, Smallholder agriculture

1. INTRODUCTION

Water productivity expresses the production achieved with a certain volume of water consumed and is frequently known in the common language as ‘more crop per drop’. With limited water availability existing in several regions worldwide, the agricultural sector is urged to reduce their water demands, whilst increasing the production of food. Smallholder farmers have a significant part in the agricultural sector, managing

[1] Water Productivity Specialist, FutureWater B.V., Wageningen, the Netherlands E-mail: j.vanopstal@futurewater.nl

[2] FutureWater B.V., Wageningen, the Netherlands

[3] HiView B.V., Arnhem, the Netherlands

[4] FutureWater B.V., Cartagena, Spain

up to 80% of the agricultural lands in sub-Saharan Africa and Asia (FAO, 2012). They have a major contribution to the food security of these regions. In addition, the livelihoods of many communities depend on the production of smallholder farm fields.

Information on water productivity can be obtained through remote sensing with satellite data. The application of satellite remote sensing for monitoring water productivity is gaining importance amongst researchers, policy-makers, and gradually also practitioners. However, satellite remote sensing is limited in the spatial resolution (pixel size 10m-250m are common) and temporal resolution (frequency of overpass). The available satellite platforms currently available are not suitable for capturing the heterogeneity, which is typical for smallholder farming. Flying sensors are expected to be more suitable which is an innovative technology increasing fast in popularity and becoming more cost-effective. In the agricultural sector it is often applied for precision farming, mainly by pioneering farmers. However, this technology can become more applicable for a larger target group. For smallholder farming having remote sensing data from flying sensors, can assist in the management of their limited resources and make most effective use of for instance fertilizer application or irrigation scheduling.

Flying sensors have the capability to indicate the spatial distribution at high resolution of the vegetation status. The approach introduced in this study is to combine the flying sensor with a crop simulation model, thereby unlocking a broader scope of information. Results provide insight on the water balance and crop production which can be used for assisting decision-making. The results are not merely for monitoring water productivity but have practical impact by gaining insight on the potential to increase water productivity by simulating interventions and determining locations with lower water productivity values.

This paper provides a description of the methodology and presents results from the flying sensor imagery, crop modelling, and integration into the water productivity assessment. The objective is to demonstrate the applicability of this integrated approach for increasing water productivity in smallholder agriculture.

2. METHODS

2.1 Overview

In Figure 1 a schematic overview is provided showing the approach of this study and indicating the different input datasets and methods used. Flying sensor imagery is integrated with a crop simulation model (AquaCrop). The integration of spatial data (of the flying sensors) with the crop simulation model provides additional information that cannot be achieved solely with the flying sensor imagery. Insight is gained on water productivity, water consumption, and crop yields. This is enabled by establishing a relation between the AquaCrop canopy cover variable, and the flying sensor estimated canopy cover values. The following sections provide an elaborate description of the different steps within this approach.

2.2 Flying sensor imagery and processing

Flying sensors were deployed to acquire imagery once every month thereby monitoring the crop development throughout the growing season. The flying sensor equipment used is a Mavic Pro drone with an additional camera to detect vegetation status. The default camera of the Mavic drone captures RGB (red-green-blue) images, similar to visual images as seen with the human eye. The second camera measures the Near Infrared wavelength, which is not visible to the human eye. The near infrared (NIR) wavelength has a good response to the conditions of the vegetation. If the leaf is in optimal health the NIR wavelength has a high response. If the leaf is under stressed or sick conditions the NIR wavelength has a lower response. This is already measured by the NIR wavelength before it is visible to the human eye. The resulting spatial resolution of the flying sensor imagery is 4-8 cm., thereby providing sufficient detail to capture the heterogeneity of small holder agriculture.

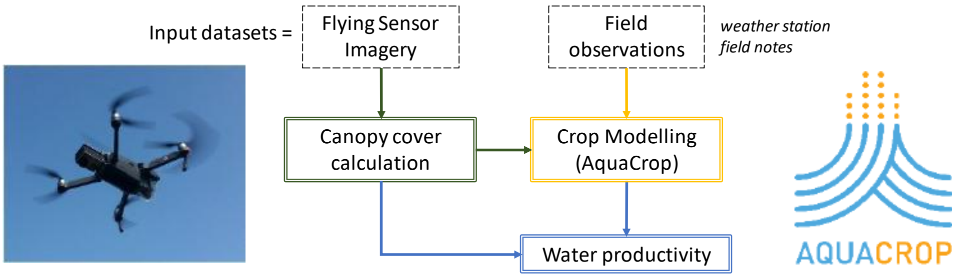

Figure 1. Schematic overview of workflow combining flying sensor imagery (photo)and crop modelling to make a water productivity assessment.

The imagery acquired by the flying sensors undergoes further processing. Firstly, the single images for each flight (approximately 20 hectares) are stitched together to form an ortho-mosaic. These are then geo-referenced, so it can be used in further geospatial analysis. These steps are performed using software packages: Agisoft Metashape, ICE (Image Composite Editor), and QGIS (geospatial software).

The next processing steps are required to achieve a time series of canopy cover maps throughout the growing season. Canopy cover is an indication of the vegetation cover over a surface expressed as a percentage. The NIR band of the image is used to determine the vegetation pixels of each image. Pixels above a certain threshold are classified as vegetation pixels, and below they are considered as bare soil (or other surface). With this information canopy cover is calculated with full vegetation cover resulting in 100% and bare soil in 0%. Figure 2 shows the different steps for calculating canopy cover for an example field. A grid of 1x1 meter (=1 m2) is laid over a crop field, in this example maize crop. The number of vegetation pixels (of 0.08x0.08 meter = 0.016 m2) is counted to determine the percentage of the grid that is covered by vegetation, thus the canopy cover. The canopy cover (Figure 2 bottom left) clearly indicates the variation of vegetation within the field with areas showing mostly bare soil, whilst over parts of the field have (full) vegetation up to 90%.

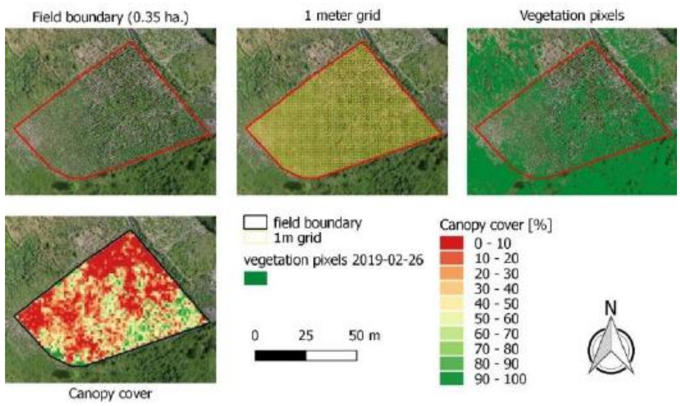

Figure 2. Canopy cover calculation using flying sensor imagery and a 1x1m. grid

2.3 AquaCrop model simulations

The AquaCrop model was selected for simulating the crop growth and water consumption, which is based on FAO principles as are reported in FAO Irrigation and Drainage Papers #56(Allen et al., 1998) and #66(Steduto et al., 2012). It simulates both crop development and the water balance, resulting in crop water productivity results.

The required input data for meteorological parameters were achieved from a local weather station. Remote sensing derived data products such as GLDAS (Global Land Data Assimilation System) and WaPOR (FAO Water Productivity Portal)[5] were supplemented to fill any data gaps in the weather station time series.

The model was set-up choosing default files guided by field observations of the locations. The selected parameters and data files used for the AquaCrop simulation runs are listed in Table 1. Three parameters were selected as a range instead of a fixed value, namely: plant density, fertility stress, and weed stress. These parameters are assumed to be different for each field depending on management decisionsand have impact on the canopy cover and ultimately the crop productivity. This compares to the field observations made during the growing season.

Two parameters were changed to calibrate the model to local conditions, namely maximum canopy cover and canopy growth coefficient. These parameters are assumed to be fixed for the crop type, thus are not influenced by management conditions. However, they are specific for the local maize crop variety selected and need adjustment to represent the local crop variety. For calibration the canopy cover and yield statistics were used.

The maximum canopy cover values for each simulation run (102 runs total) are compared with the water productivity and crop yield for the run. It is assumed that the runs represent the various scenarios possible in farm management and biophysical conditions. A linear relationship is developed to connect maximum canopy cover with crop yield and water productivity. This linear equation is thereafter used with the flying sensor derived maximum canopy cover to achieve maps of water productivity.

Table 1. AquaCrop model set-up and selected parameters

Model and parameters	Value	Comments
Planting date	11 November 2018	
Harvest date	20 March 2019	
Soil type	Sandy Loam	Default parameters (AquaCrop file)
Irrigation	None	Rainfed season
Initial soil water conditions	Wilting point	End of dry season will have mostly depleted the soil water storage
Groundwater table	None	
Crop type	Maize	Default parameters (AquaCrop file)
Maximum canopy cover	0.85	Fraction to soil cover (under optimal conditions)
Canopy growth coefficient	0.12	Increase in canopy cover
Planting density [plants/ha]	8,000 – 40,000	Range with steps of 2,000 plants/ha
Management		
Fertility stress	30 – 50 %	Range with steps of 10 %
Weed stress	10 and 20 %	

[5] https://wapor.apps.fao.org

2.4 Water productivity assessment

The definition of water productivity used in this study is as follows:

$$Crop\ specific\ water\ productivity\ [kg/m^3] = \frac{Crop\ harvestable\ yield\ [kg]}{Seasonal\ evapotranspiration\ [m^3]}$$

This analysis makes the calculation of crop specific water productivity for maize crop during rainfed season. The overview in figure 1 shows that water productivity maps are produced by combining the outputs from crop modelling, and canopy cover from the flying sensor imagery. The water productivity is calculated as average of each field, and for each 1x1m grid block, indicating the spatial variation within fields.

2.5 Case study description

This methodology of integrating flying sensor imagery with crop modelling is demonstrated for a case study in Moatize district of Mozambique (34.11E, 15.77S). An agricultural area of approximately 190 hectares was monitored throughout the rainfed season starting November 2018 until March 2019 as part of an on-going project with the focus on water productivity and climate resilient agriculture for smallholder farming. The type of agriculture in this area is generally smallholder agriculture with farm plots having a size of less than a hectare. The livelihood of the farmers largely depends on the harvest from their fields. For this study the most dominant rainfed crop for this area is selected, namely maize. A total of 73 fields were identified and used in this analysis.

Field observations are noted to simulate the current situation accurately in AquaCrop. In addition, a few scenarios for improving water productivity are considered. Mulching as an intervention to reduce soil evaporation is considered in this study to indicate the potential for improving water productivity.

3. RESULTS AND DISCUSSION

3.1 Flying sensor imagery

Figure 3 shows the result for the flying sensor imagery as an ortho-mosaic of eight flights with both the RGB and NIR cameras. The red coloured areas in the NIR image are generally water pixels or shaded areas. The contrast between bareland, sparsely vegetated, and fully vegetated areas is more evident in the NIR image than in the RGB image. The bare land areas are indicated by the more yellowish hues, whilst full vegetated areas are green. The fully vegetated areas are a mix of either natural vegetation (trees and shrubs) or cultivated areas.

The result of canopy is presented for the delineated maize fields as shown in Figure 3 (right image). These results indicate that some fields are under full vegetated cover during the growing season, with high canopy cover indicated as green. In contrast, other fields are more heterogeneous displaying parts of the field with low canopy cover (red colour) corresponding to mostly bare soil, and other sections of the field with high canopy cover (green colour). This is similar the observations made in the field where some maize crops were sown in rows to achieve a homogenous and full cover field, whilst other farmers spread the crop seed randomly over the field resulting in uneven spacing of the crop.

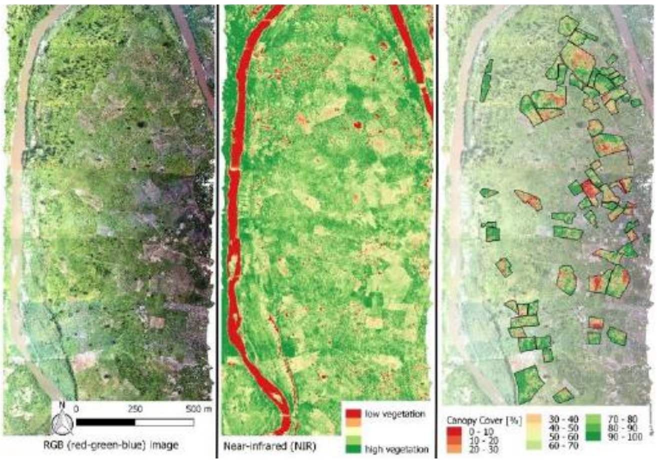

Figure 3. Flying sensor image of 8 flights made 26/02/2019-27/02/2019 showing the RGB (visual) and NIR image, and the result for canopy cover.

3.2 AquaCrop

AquaCrop model simulations gave insight in the water balance and crop productivity of the simulated scenarios. Figure 4 presents the results on water productivity from the batch runs simulating the different management scenarios of the current situation. These different management scenarios varied in planting density, fertility stress, and weed cover. The crop (dry) yield values correspond to the expected values with an average of 2.58 ton/ha. According to the FAO paper #66, crop yields are reported to be in the range of 1-2 ton/ha for less industrialized areas and 3-4 in industrious countries. The country statistical reports (published on FAOSTAT) indicates an average in Mozambique of 0.98 ton/ha for maize yield.

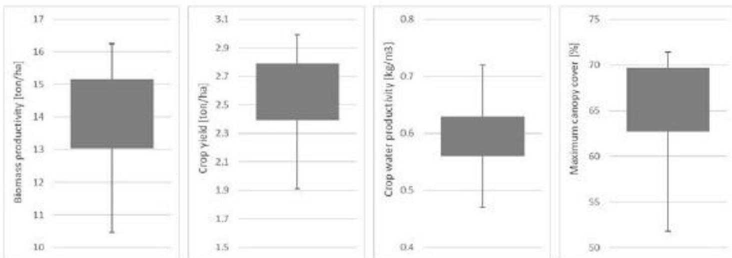

Figure 4. Boxplots displaying the results for productivity, yield, and maximum canopy cover, from all AquaCrop runs for maize crop in Samoa, Mozambique

The result on water consumption can also be derived from the AquaCrop simulations and gives insight in the current water management for this farming system. Figure 5 displays the time series of evapotranspiration (ET), soil evaporation (E), and transpiration (T) during the maize growing season for anAquaCrop run with optimal management conditions (full vegetation cover and low fertility stress). Logically, the major part of ET at the start of crop development is evaporation. At the peak of crop development, the major component of ET is transpiration, with some soil evaporation due to the spacing between plants. There is a period of low soil evaporation around day 60 after planting, which coincides with a period of no rainfall. Transpiration then occurs as result of the available water remaining in the root zone.

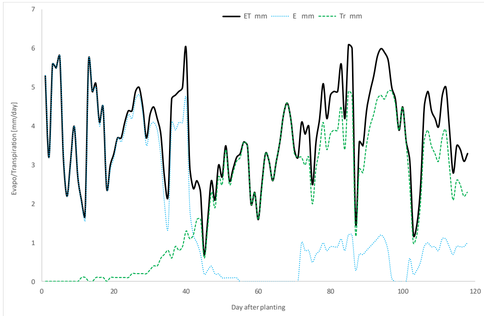

Figure 5. Evapotranspiration (ET), soil evaporation (E), and transpiration (T) displayed as time series during maize growing season for AquaCrop run with high plant density and low fertility stress

The strength of using a crop simulation model is the capability of simulating other scenarios that might be introduced in the future. Mulching is an intervention that is being demonstrated in this project as potential intervention for improving farming practices. The impact of mulching on water consumption and productivity is simulated with AquaCrop, with the results summarized in Table 2. Mulching reduces the amount of water lost through soil evaporation, which is a non-beneficial component of water consumption, as it does not result in crop production. By introducing mulching, there is the potential of decreasing soil evaporation by 34%. The maize yield is increased slightly, due to an increase in transpiration. The combination of reduced water consumption due to lower soil evaporation and increase of crop yield gives an overall increase in water productivity by 18%. This result indicates the potential for making improvements in water productivity by introducing a cost-effective intervention such as mulching. It is beneficial in the perspective of increasing yields and reducing water consumption which is especially of importance in the limited water availability.

The simulations focussed on the rainfed season, therefore timing of water is not controllable. However, another scenario that can be simulated is the impact of supplemental irrigation during the rainfed season, which could be applicable during a dry period of several weeks, as occurred during this season. There are several more water management and agronomy related interventions that can be simulated with the model to determine the potential of introducing certain management changes.

Table 2. Comparison between current (normal) management conditions and the potential of introducing mulching practices, indicating the impact on seasonal water consumption and productivity.

	Evapotrans-piration [mm]	Evaporation [mm]	Transpiration [mm]	Maize yield [ton/ha]	Water Productivity [kg/m3]
Normal	449	196	253	2.99	0.67
Mulching	399	129	270	3.16	0.79
Change	-11%	-34%	7%	6%	18%

3.4 Water productivity assessment

Spatial information on water productivity was achieved by comparing the canopy cover calculation from flying sensors with the results of AquaCrop. With the batch run of AquaCrop a linear relationship was achieved between canopy cover and water productivity. It is expected that a higher canopy cover will achieve higher crop yields and evapotranspiration will mostly be beneficially used towards transpiration. The result of the integration with the flying sensor imagery is presented in Figure 6.

The left image shows the result as represented by each 1x1 meter grid cell. It indicates low water productivity for areas with mostly bare soil (low canopy cover) and high values for fully vegetated areas indicating low stress conditions. A review article (Zwart and Bastiaanssen, 2004)indicates a range of water productivity for irrigated maize of 1.1 to 2.7 kg/m3. Rainfed conditions are expected to have a different water productivity value than irrigated, but this does indicate the potential for increase in water productivity compared to the maximum values for water productivity currently calculated of 0.7-0.8 kg/m3. Figure 6 also indicates the average per polygon showing that most polygons with lower water productivity values are also association with the polygons with high variation in water productivity, with the variation within fields being visible on the left image. This spatial variation within fields can be due to the variation in plant density with areas having sparse vegetation during the crop season. In general, higher water productivity values are found closer to the river, where distance to a water source is smaller. This can indicate that water is retained longer in the root zone, or a different management regime is applied at these locations.

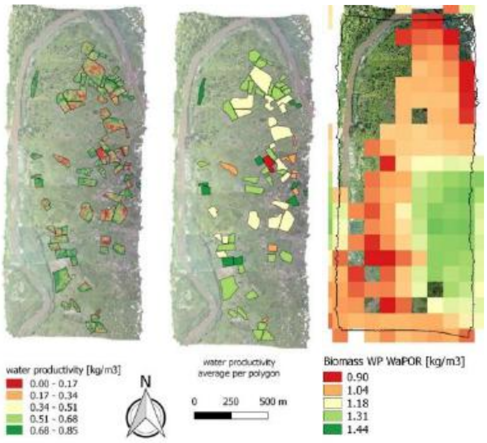

Figure 6. Result of water productivity presented for the maize fields in Samoa in the left and middle images from the Flying Sensor results, and the same location from FAO WaPOR portal (Level II-100m) as biomass water productivity

The high resolution also shows that there is potential to improve water productivity if the fields are cultivated more homogeneously and achieving full vegetation cover. If the variability within fields is decreased the overall average water productivity per field can potentially increase. Identifying those fields is possible by having the resulting spatial map in water productivity, whilst solely crop modelling cannot identify these locations. This indicates the added value achieved by combining crop modelling with flying sensor data. It gives the capability to assist decision-makers with introducing interventions that can be effective considering the current situation. However, it should be mentioned that the next step for improving water productivity and changing practices requires close interaction with the local farmers to determine their motivation for changing current management. This will differ per farmer with those interested in achieving higher production, and those who want to keep business as usual.

Lastly, the right image in Figure 6 shows the results found from satellite imagery. As example the Level II 100m resolution dataset from WaPOR (FAO Water Productivity Portal) is used. This comparison between satellite imagery and flying sensor imagery shows the necessity for having flying sensor imagery for making assessments over smallholder farming. It has the capability to capture the spatial variation and derive information to assist in introducing interventions. Satellite derived data can be useful for the monitoring of the overall area to determine if there is a positive trend, after interventions have been introduced.

4. CONCLUSIONS

This paper demonstrated an integrated approach of combining crop modelling with the innovative capabilities of flying sensor imagery. This approach is concluded to be applicable for smallholder farming to capture the typical aspects of smallholder agriculture being small and heterogenous fields with a variety of management strategies. Flying sensor technology can capture the heterogeneity and size of the smallholder fields. The combination with crop modelling translates the imagery into meaningful information on crop productivity and water consumption. This resulted in a spatial map of water productivity indicating the variation within and between fields.

Crop simulations can also calculate the potential of making changes in the management system. A scenario with mulching introduced to the field is simulated indicating that water productivity has the potential to increase by 18%. The water consumption is decreased by reducing the soil evaporation; whereas crop yield increases. Multiple other management strategies can be simulated, unlocking the potential for giving guidance to decision-makers.

The map on water productivity resulting from the flying sensor imagery displays the variation of water productivity within fields resulting from inconsistent planting schemes. This shows the potential for increasing water productivity, by stimulating more evenly covered fields.

In conclusion, this study shows the potential of using flying sensor imagery to make improvements in water productivity by indicating problematic areas and giving advice on interventions that can be implemented. This will give the farmers the capability to improve their production and ultimately increase their livelihood. In addition, insight on water consumption leads to more sustainable water management and enables the farmer to be more resilient to future climate scenarios with reduced or unreliable water availability.

5. ACKNOWLEDGEMENTS

The authors of this paper want to acknowledge the on-going project ‘APSAN-Vale’ funded by the Dutch Embassy in Maputo, Mozambique, for providing the casestudy and input data for this paper. The project partners are acknowledged: Resilience B.V., HUB, and Agência de desenvolvimento do Vale do Zambeze (ADVZ). The team of Flying Sensor operators located in Chimoio, Mozambique are acknowledged for performing the flying sensor flights for this study.

6. REFERENCES

Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. FAO Irrigation and Drainage Paper No. 56 Crop Evapotranspiration. Rome.

FAO, 2012. Factsheet Smallholders and Family Farmers.

Steduto, P., Hsiao, T.C., Fereres, E., Raes, D., 2012. Crop yield response to water FAO66.

Zwart, S.J., Bastiaanssen, W.G.M., 2004. Review of measured crop water productivity values for irrigated wheat, rice, cotton and maize. Agric. Water Manag. 69, 115–133. https://doi.org/10.1016/j.agwat.2004.04.007