TECHNICAL ANALYSIS

# ThirdEye Kenya – Water Productivity Report

REPORT 190

CLIENT SNV

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DATE December 2019

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**FutureWater Report 190**

**Client**
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**Date**
December 2019

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Summary

In November 2017 HiView and FutureWater (The Netherlands) set up the ThirdEye flying sensor (drone) service as part of the Smart Water for Agriculture (SWA) project, implemented by SNV, funded by the Embassy of the Netherlands in Kenya. This report presents the results of a technical analysis done on the change in water productivity for farmers who received the service. The approach for this water productivity analysis was using satellite data in combination with an algorithm for estimating water productivity. Three areas where ThirdEye activities were conducted were analysed and each ThirdEye area was paired with a control field with similar weather conditions and cropping pattern.

The results for water productivity from the 17 Landsat images were analysed and used to determine an average water productivity for each crop growing season. The results of this technical study display an increase of water productivity for the Kibirichia and Marimba locations, indicating a positive impact of ThirdEye activities in this region. The overall average increase achieved for Kibirichia is 33% and for Marimba it is 7%. These results are based on a comparison using satellite derived water productivity results. Even though inaccuracies were encountered in the outputs of the satellite derived results (mainly due to cloud cover issues), the outputs were sufficient to make an insightful comparison of the impact of ThirdEye during this project period.

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# 1 Introduction

A key factor in enabling more efficient and increased food production is providing farmers with relevant information. Such information is needed as farmers have limited resources, such as seeds, water, fertilizer, pesticides and labour, and are hindered in their access to information sources. Spatial information from ThirdEye's flying sensors (drones) can be used for this. Our low-cost flying sensors have cameras which can measure the reflection of near-infrared light, as well as visible red light. These two parameters are combined with a formula, giving the Normalized Difference Vegetation Index (NDVI). This information is delivered at a resolution of 2x2 cm in the infra-red spectrum. Infra-red is not visible to the human eye but provides information on the status of the crop about 10-days earlier than what can be seen by the red-green-blue spectrum that is visible to the human eye.

Our innovation is a major transformation in farmers' decision making regarding the application of limited resources such as water, seeds, fertilizer and labour. Instead of relying on common-sense management, farmers are now able to take decisions based on facts, resulting in an increase in water productivity. The flying sensor information helps farmers to see when and where they should apply their limited resources. We are convinced that this innovation is game-changing, comparable with the introduction of mobile phones that empowered farmers with instantaneous information regarding markets and market prices. With information from flying sensors they can also manage their inputs to maximize yields, and simultaneously reduce unnecessary waste of resources. In summary, the missing information on markets has been solved by the mobile phone introduction, the flying sensors close the missing link to agronomic information on where to do what and when.

The ThirdEye service was set up by HiView and FutureWater (The Netherlands) in Meru in November 2017 as part of the Smart Water for Agriculture (SWA) project, implemented by SNV, funded by the Embassy of the Netherlands in Kenya. Ever since, ThirdEye was officially registered as company in Kenya, a company office was opened at Kaguru ATC, the team has grown to eight professionally trained flying sensor operators, thousands of paying farmers have adopted the service and many field campaigns have taken place. ThirdEye's operators are equipped with flying sensors, tools to analyse the obtained imagery and knowledge to give valuable advice to improve farming practices. Apart from this, ThirdEye is offering other services such as training, soil testing and input supply, far beyond the border of Meru County alone.

This report presents the results of a technical analysis done on the change in water productivity for farmers who received the ThirdEye service. 'Water Productivity' is a concept used frequently in agricultural water management. It represents the amount of production that is achieved with a certain volume of water. In this study water productivity is defined as biomass production per volume of consumed water, which is evapotranspiration. The approach for this water productivity analysis is using satellite data in combination with an algorithm for estimating water productivity. Three areas, where ThirdEye activities were conducted, are selected for an analysis of the water productivity. Each ThirdEye study field is paired with a control field with similar weather conditions and cropping pattern. Another water productivity study by student Simon Oseko Mogere (from Jomo Kenyatta University of Agriculture and Technology and guided by SNV) should have been finished in December 2019 as well, but his study titled 'Assessment of Plot-level Water Productivity Using 'ThirdEye' in Some Irrigation Fed Areas in Meru County' has yet to be finished.

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# 2 Methodology

## 2.1 Study area

Three areas, where ThirdEye activities were conducted, are selected for an analysis of the water productivity. The three locations are in the vicinity of Kibirichia, Miathene, and Marimba in Meru county, as indicated in Figure 1. Both Kibirichia and Marimba are fields with an area of <1 ha., whilst Miathene encompasses an area of approximately 43 ha. ThirdEye activities in Miathene took place with a tenfold of farmers (of the few thousand farmers), therefore the actual area of ThirdEye activities in Miathene is a fragment of the total area indicated in Figure 1. Even though the ThirdEye activites were dominant in Miathene, the water productivity results for the Miathene area had to be excluded because the indicated field boundary in Figure 1 could not be representative for the various ThirdEye farmers scattered within this area.

Each ThirdEye study field is paired with a control field with similar weather conditions and cropping pattern. These fields are also indicated in Figure 1 and have a similar area of 1-2 ha. in Kibirichia and Marimba.

There are two crop growing seasons in this region. The first season is from February to May and the second season is from August to November. The ThirdEye activities were mainly implemented in 2018 and 2019, therefore these seasons are selected for the analysis. Two seasons for 2018 (S1 and S2) are analysed and one season for 2019 (S1).

The main crops grown in Kibirichia are cabbage and Irish potato. For Marimba the main crops are cabbage, French beans, and snow peas. For Miathene the main crops are French beans and onions. The control fields contained the same cropping pattern as the ThirdEye fields, enabling easier comparison in water productivity results.

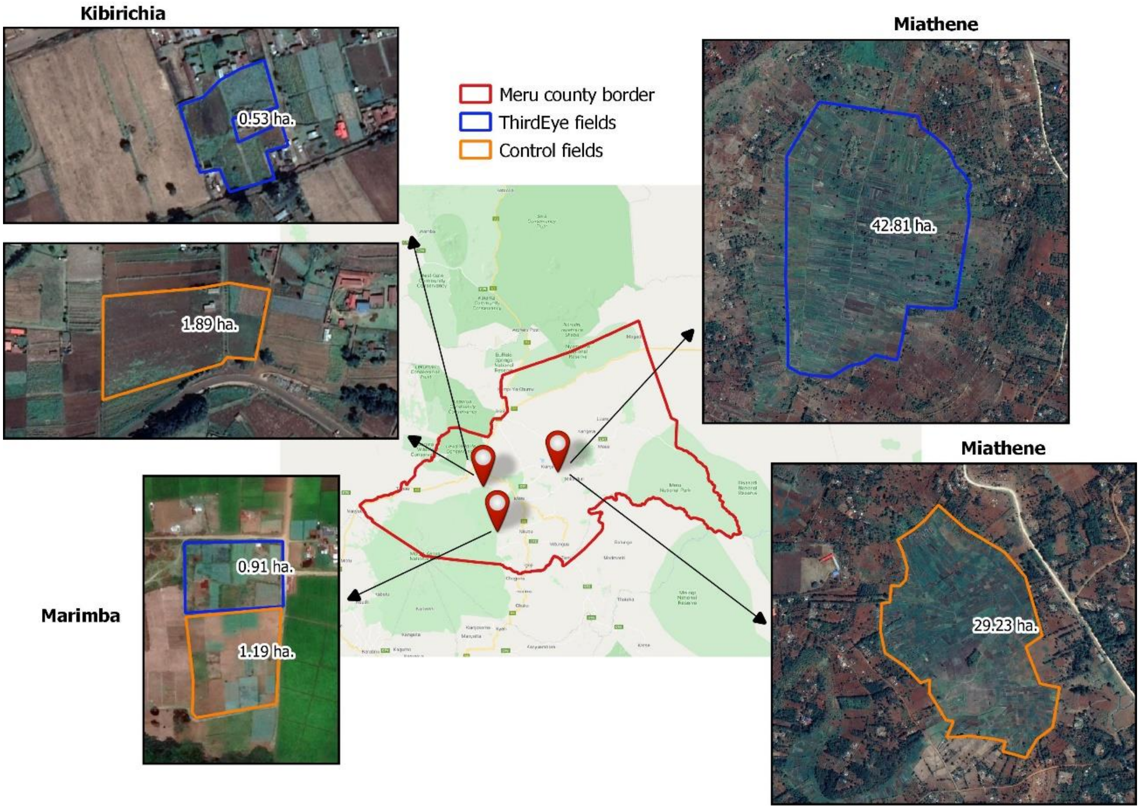


**Figure 1 Location of ThirdEye and control fields including area size in hectares.**

## 2.2 Satellite data

### 2.2.1 Weather data

The local weather was recorded intermittently at a TAHMO station in this region. Due to the inconsistency of the dataset in both recording periods and active sensors, this dataset was found insufficient for an analysis of water productivity for a crop growing season. For this reason, two satellite derived data products were used to provide consistent data during the growing season for the selected area. The GLDAS data product (https://ldas.gsfc.nasa.gov/gldas) was used for air temperature, wind speed, and relative humidity. The CFSR v2 data product (https://cfs.ncep.noaa.gov/) was used for the incoming solar radiation. These data products combined were used to calculate daily reference evapotranspiration using FAO's Paper 56 Penman-Monteith equation (http://www.fao.org/3/X0490E/X0490E00.htm).
Results for the weather data are found in Annex 1 of this report.

### 2.2.2 Landsat data

The analysis for water productivity requires satellite data with multispectral and thermal data. The satellite platform that fulfils these requirements, and has the best pixel resolution, is the Landsat platform. For this study both Landsat 7 and 8 data were used as downloaded from the USGS site (https://earthexplorer.usgs.gov). In Figure 2 the outline of a Landsat 8 tile is indicated showing that the three study locations are within one Landsat tile. An area of interest is masked from the Landsat tile for the analysis with SEBAL (see next section) to speed up computing time. A total of 17 Landsat images were selected for processing and further analysis for all three seasons (2018-S1, 2018-S2, and 2019-S1). Several images were excluded due to the cloud cover in the image (see chapter 3).


**Figure 2 Location of area of interest for SEBAL runs in comparison with Landsat tile.**

## 2.3 Remote sensing algorithm (pySEBAL)

Ideally, the Flying Sensor data achieved through the ThirdEye activities could be used to improve the pixel resolution of the output and avoid issues due to cloud cover. However, flights were made intermittently therefore providing snapshots throughout the project and not regularly monitoring the crop development during the growing season. Due to the limited data available, the approach for this water productivity analysis was using satellite data in combination with an algorithm for estimating water productivity.

An energy balance remote sensing algorithm (pySEBAL) was selected for the analysis of water productivity. This algorithm gives results for evapotranspiration and biomass production. It is based on the well-established SEBAL algorithm, which has been applied and validated in several agricultural areas worldwide (Bastiaanssen et al., 1998)[1]. pySEBAL is the python version, which automates the selection of hot and cold pixels, thereby enabling batch processing of multiple satellite images. Evapotranspiration is calculated using a one-source energy balance model. The energy fluxes for net radiation ($R_n$), soil heat flux (G), and sensible heat flux (H) are calculated. The latent heat flux (LE), which is the energy for evapotranspiration, is calculated as a residual of the energy equation. Biomass production is calculated using a light use efficiency model based on the absorbed photosynthetic active radiation (PAR) and the light use efficiency of the crop (Hilker et al, 2008)[2].

The required input data for pySEBAL is:

- multispectral and thermal satellite data (from Landsat)
- a DEM (digital elevation model) indicating the area of interest (see figure 2)
- daily and hourly weather data (air temperature, relative humidity, wind speed, and incoming solar radiation)

## 2.4 Water productivity calculation

'Water Productivity' is a concept used frequently in agricultural water management. It represents the amount of production that is achieved with a certain volume of water. In this study water productivity is defined as biomass production per volume of consumed water, which is evapotranspiration. It was selected to use evapotranspiration because it represents the component of the water balance that cannot be re-used by downstream users in a river basin context. Return flows from agricultural areas (through runoff or subsurface flow) are available for re-use in the downstream areas if the quality of the water is sufficient.

The definition of water productivity as calculated in this study is calculated with (dry weight) biomass production (see equation below). The ThirdEye and control fields have similar cropping patterns therefore a comparison using biomass water productivity is possible, and does not require calculating a crop-specific water productivity which incorporates crop (and location) specific parameters.

$$Biomass\ water\ productivity\ [kg/m^3] = \frac{Biomass\ production\ [kg]}{Evapotranspiration\ [m^3]}$$

[1] Bastiaanssen, W. G. M., Menenti, M., Feddes, R. A., & Holtslag, A. A. M. (1998). A remote sensing surface energy balance algorithm for land (SEBAL). 1. Formulation. Journal of Hydrology, 212–213, 198–212. https://doi.org/10.1016/S0022-1694(98)00253-4

[2] Hilker, T., Coops, N. C., Wulder, M. A., Black, T. A., & Guy, R. D. (2008). The use of remote sensing in light use efficiency-based models of gross primary production: A review of current status and future requirements. Science of the Total Environment, 404(2–3), 411–423. https://doi.org/10.1016/j.scitotenv.2007.11.007

# 3 Results from satellite remote sensing

## 3.1 Cloud cover

One major disadvantage of using satellite data (for multispectral and thermal sensors) is the issue of cloud cover. Clouds are not penetrable for these sensors; therefore information cannot be provided. This is an advantage of flying sensors, which is not influenced by cloud cover. The Landsat images used for this water productivity analysis are 17 in total as displayed in Figure 3. In grey the cloud masks are indicated showing that there were limited number of days of clear sky during the selected crop growing season. For the selected fields these images still provided sufficient results. Note that the cloud gaps can cause some inaccuracies in the results of the analysis. However, the focus of this analysis is the comparison between fields, therefore it is assumed that the inaccuracies in one pixel will be similar to the inaccuracies found in the neighbouring pixel. This assumes that inaccuracies will have limited influence on the comparative analysis.

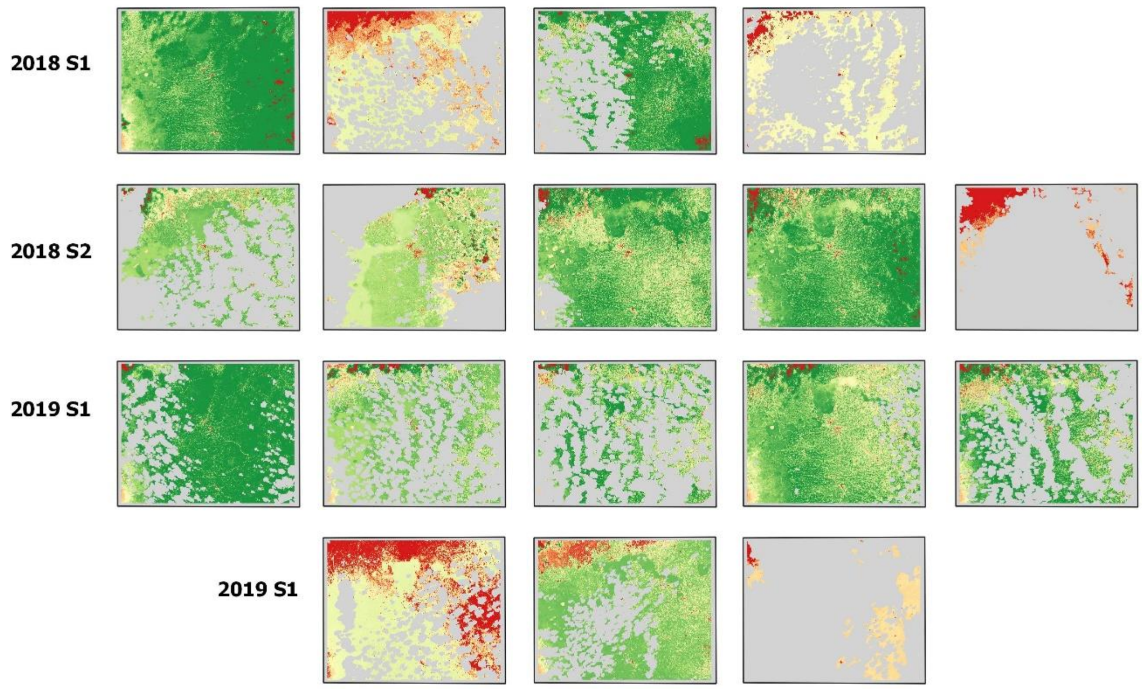


**Figure 3 Cloud masks (in grey) for satellite results during each growing season.**

## 3.2 pySEBAL results for Landsat

Several outputs are provided with the pySEBAL algorithm. The results of one of the Landsat images (12$^{th}$ October 2018) are displayed in the figures below (4-6) for the key outputs relevant for the water productivity analysis and quality control of the images. Figure 4 indicates the False colour (using Near-Infrared, Red, and Green bands) and True colour (using Red, Green, and Blue bands) images for the Landsat image. Clouds are present in the area of Mount Kenya (southwest corner), and the red colours in the False colour images indicates the presence of vegetation both natural and agricultural.

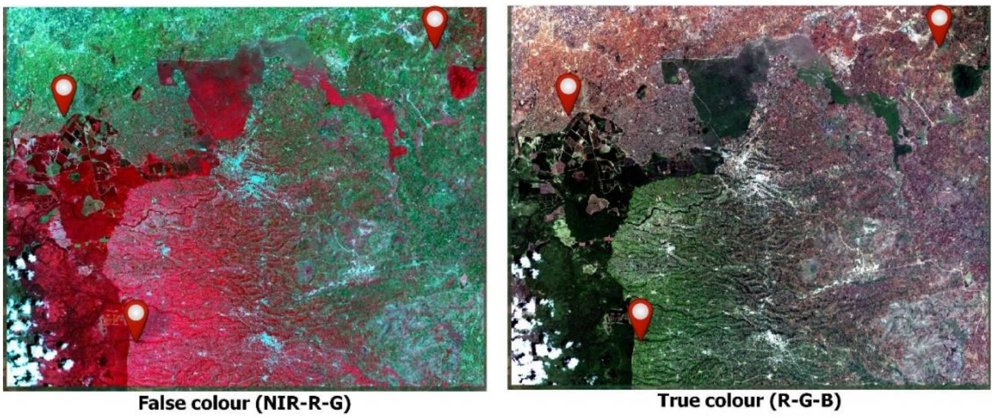


**Figure 4 Landsat 8 reflectance for 2018/10/12.**

Figure 5 displays the NDVI (normalized difference vegetation index) with green colours being areas with more vegetation. The thermal band indicates the surface temperature after atmospheric correction. The pixel resolution is coarser for the thermal band in comparison with the shortwave bands (used for the NDVI). Spatial patterns seem similar for both and the range of values are within the expected range for these outputs.

Figure 6 displays the end result of pySEBAL for actual evapotranspiration (extrapolation to a daily value) and the water productivity. These are results relevant for the day the satellite image was captured, namely 12th October 2018. Similarly, the values range within expected values for evapotranspiration and biomass water productivity for this region.

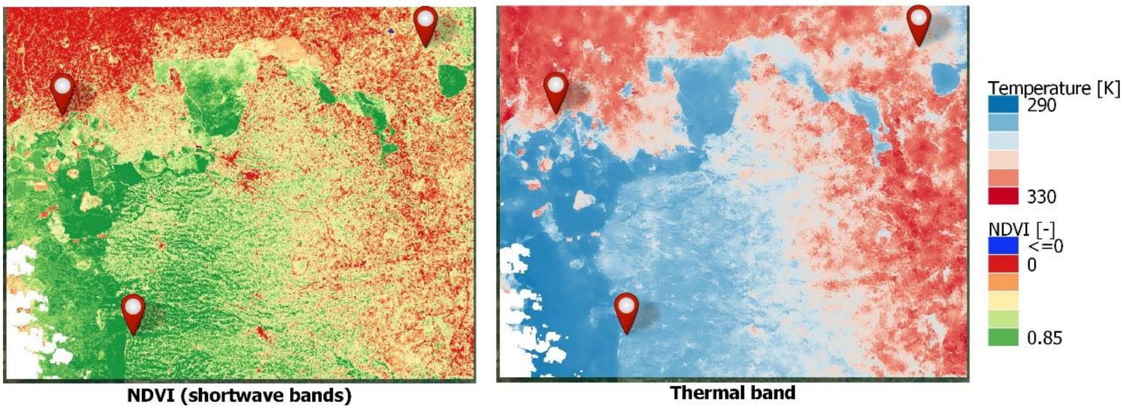


**Figure 5 NDVI and thermal band from Landsat 8 for 2018/10/12**

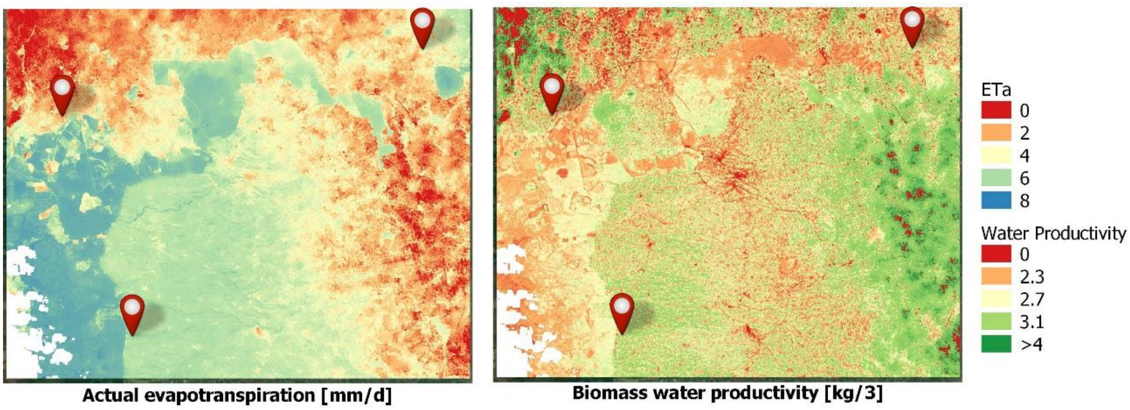


**Figure 6 Results from pySEBAL runs for 2018/10/12 Landsat data.**

# 4 Water Productivity results

The pySEBAL results for water productivity from the 17 Landsat images are analysed and used to determine an average water productivity for each crop growing season. It is assumed that the water productivity is reasonably constant during the crop growing season for a given location. This assumption is based on the linear relationship between biomass production and transpiration (mentioned in Perry et al, 2009)[1]. In practice some variability may exist in water productivity during the crop growing season due to different management practices and other factors. Averaging the water productivity during the crop growing season will level out the outliers and give insight on the water productivity of each field for the crop season.

Results of this comparison is displayed in figure 7 for the three seasons of analysis. The ThirdEye fields are indicated in blue colour and the control fields in orange colour. For the Kibirichia location the water productivity of the ThirdEye fields were higher for each season. The difference between the ThirdEye and control fields was largest in the second 2018 season. For the Marimba location the water productivity was higher for both 2018 seasons and was similar in the 2019 season.

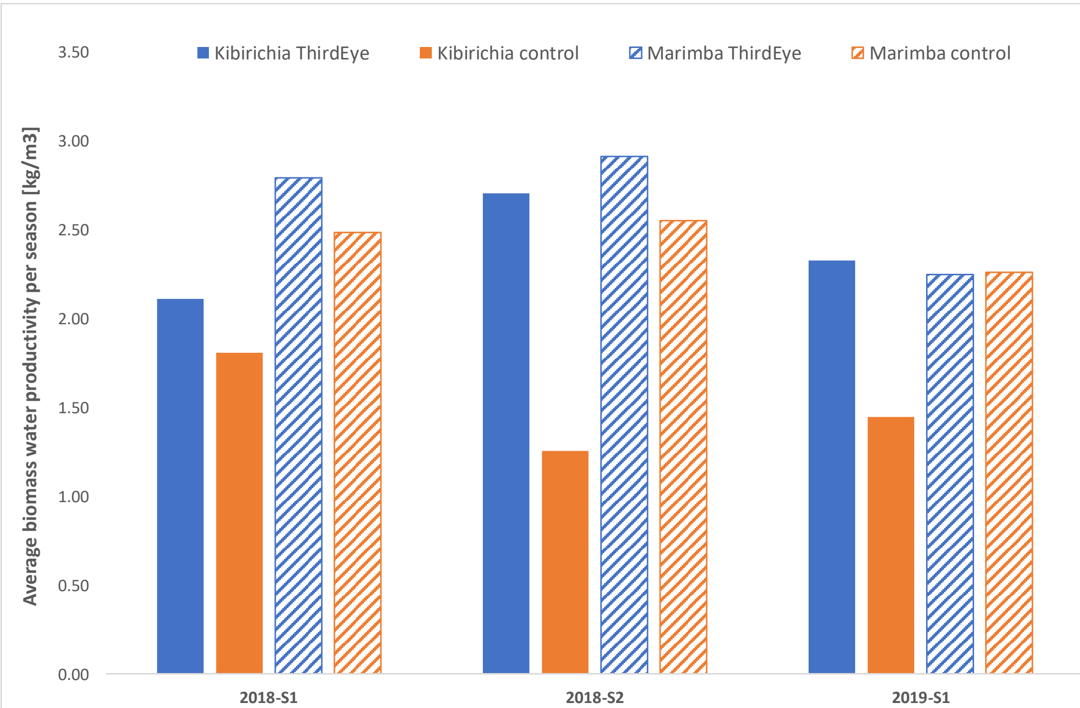


**Figure 7 Average biomass water productivity for each growing season.**

[1] Perry, C., Steduto, P., Allen, R. G., & Burt, C. M. (2009). Increasing productivity in irrigated agriculture: Agronomic constraints and hydrological realities. Agricultural Water Management, 96(11), 1517–1524. https://doi.org/10.1016/j.agwat.2009.05.005

An evaluation of the impact of ThirdEye activities can be analysed by comparing the water productivity values between the ThirdEye and control fields. For the 17 Landsat images and the corresponding water productivity results the difference between both fields are calculated. These differences are averaged for each growing season with the results as presented in Table 1. The largest impact on water productivity was achieved in the Kibirichia location. The water productivity had an overall average increase of 33% and ranged between 12% to 54% per season. For the Marimba location the overall water productivity increase was 7%, with the largest increase of 12% in the second season of 2018. The second season of 2018 displayed the highest difference for both fields indicating that the ThirdEye activities implemented in this season were successful and had the most impact.

**Table 1 Average percentage difference between ThirdEye and control fields per growing season.**

| Year | Season | Location | |
|---|---|---|---|
| | | Kibirichia | Marimba |
| 2018 | S1 | 12% | 3% |
| | S2 | 54% | 12% |
| 2019 | S1 | 33% | 6% |
| Overall average | | 33% | 7% |

In conclusion, the results of this technical study display an increase of water productivity for the Kibirichia and Marimba locations, indicating a positive impact of ThirdEye activities in this region. The overall average increase achieved for Kibirichia is 33% and for Marimba it is 7%. These results are based on a comparison using satellite derived water productivity results. Even though inaccuracies were encountered in the outputs of the satellite derived results (mainly due to cloud cover issues), the outputs were sufficient to make an insightful comparison of the impact of ThirdEye during this project period.

# Annex 1 – Time series of weather data


**Figure 8 Ten day moving average for daily temperature from GLDAS data.**

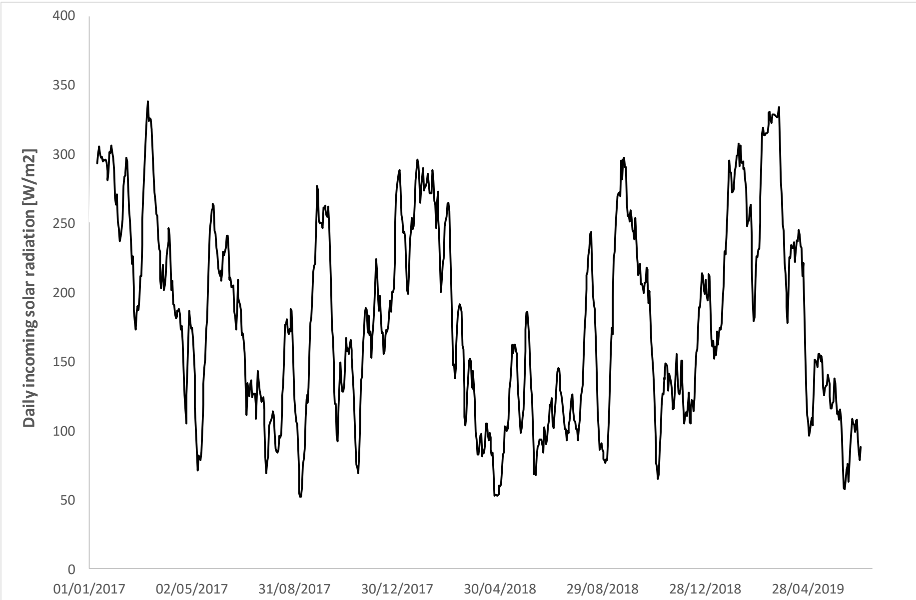


**Figure 9 Ten day moving average for incoming solar radiation from CFSR data.**

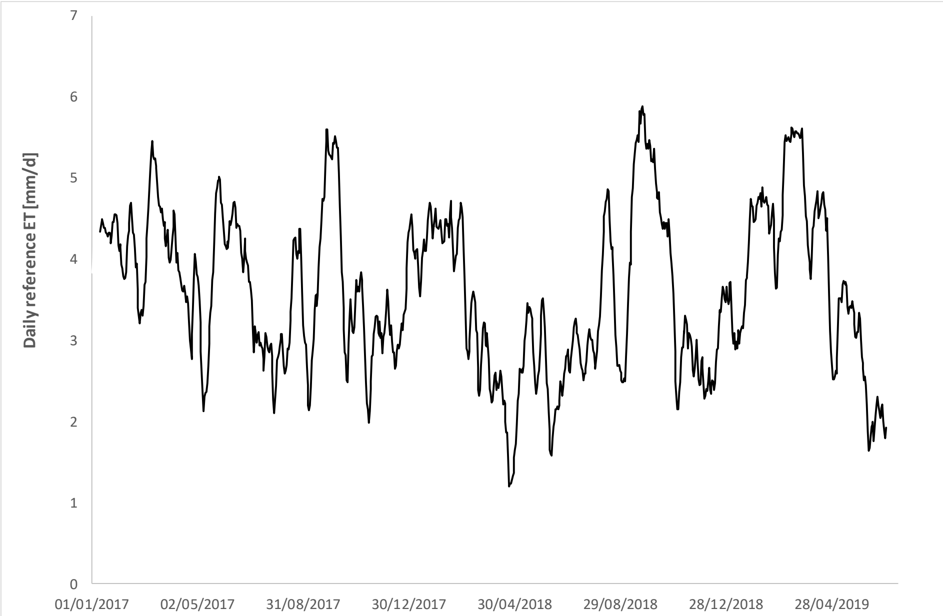

**Figure 10 Ten day moving average for reference evapotranspiration.**