Water Productivity Analysis: Irrigation Season 2022

APSAN-Vale project

REPORT 239

CLIENT Agência de Desenvolvimento do Vale Zambeze (ADVZ)

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Preface

The APSAN-Vale project aims to increase climate resilient agricultural productivity and food security, with a specific objective to increase the water productivity and profitability of smallholder farmers in Mozambique. The project prioritises small (family sector) farmers to increase food and nutritional security and will demonstrate the best combinations of adoption strategies and technological packages. The impact of the adopted strategies or technological packages is assessed on the farming plot level, sub-basin, as well as basin level. The main role of FutureWater is monitoring water productivity in the target areas (both spatial and seasonal/annual variation) using remote sensing data from Flying Sensors (drones), satellite imagery, and WaPOR data portal in combination with a water productivity simulation model and field observations.

This report shows the water productivity analysis for the 2022 irrigation season (April to September) in three different locations in Mozambique. This analysis is crucial to evaluate the impact of field interventions on water productivity. As this is the last season of the project, an evaluation of the progress of the water productivity for all irrigation seasons in this project is also added.

Summary

Farmers are seeking best practices that can achieve higher crop yields, thus profits and food security. With limited resources such as water, the increase in production needs to be considered per unit of water consumed, which is expressed in the term 'Water Productivity'. Water productivity can be used as a performance indicator to monitor changes in an agricultural area (at plot, farm, or irrigation system level). If interventions are implemented, water productivity can indicate if the intervention had a positive or negative impact on the use of water or if it remained unchanged. This report provides an assessment of the water productivity during the irrigation season of 2022 (April to September) for the APSAN-Vale project areas. The water productivity results as presented in this report provide insight into the impact of the project activities both at the field, sub-basin (community), and basin scale.

Various methods were used to provide a reliable assessment of the water productivity, such as using the data available from the field, flying sensor imagery, and open-access remote sensing datasets from WaPOR and Sentinel 2. The satellite remote sensing data was used supplemental to flying sensor imagery to capture more frequently the crop development and fill in the gaps between the monthly intervals of the flying sensor imagery intervals. The supplemental data provided by Sentinel 2 imagery is useful for a better determination of the crop curve.

At field scale the crop-specific water productivity is calculated using flying sensor (drone) and satellite imagery, and AquaCrop model simulations. The flying sensors used are equipped with a near-infrared camera for detection of the vegetation status. These images are processed and translated to canopy cover values. Ultimately, the images of the flying sensors were combined with the Sentinel 2 imagery, to determine the maximum canopy cover. In AquaCrop the field data and maximum canopy cover from flying sensors and Sentinel 2 are used to simulate the farming practices for each field, to determine yield and water productivity. At sub-basin and basin scale the biomass water productivity is calculated using data from FAO's water productivity data portal WaPOR (http://wapor.apps.fao.org).

During the 2022 irrigation season a total of 143 flying sensor flights were performed, covering a total of 930 ha. In the end, for the water productivity analysis, data from 23 farmers was used: 9 in Báruè, 7 in Moatize, and 7 in Nhamatanda. The results of the flying sensor imagery acquired throughout the season are presented in printed field maps and shared through our online portal. Over the past year, substantial efforts were made to disseminate the maps made by ThirdEye's AgPilots (or flying sensor operators) for a larger public online, through the APSAN-Vale Flying Sensor portal. The portal can be accessed through https://futurewater.eu/apsanvaleportal/.

The field scale water productivity was calculated for the major irrigation season crops cabbage, tomato, and onion, and compared to baseline values. Additionally, water productivity was calculated for beans and maize but these were not compared to baseline values as they are unavailable. For the irrigation season crops improvements in water productivity were found of +55%, +29%, and +63% for Báruè, Moatize, and Nhamatanda respectively, resulting in an average improvement of +49%. This overall average achieves the set target for 2022 of +25% as stated in the project logframe however, is only 1% higher than the previous irrigation season (2021) as a result of an improved methodology and stricter judgment in modelling decisions.

Furthermore, the water productivity was calculated at sub-basin scale, which is representative for the community of farmers adopting practices being demonstrated and promoted by the selected PPCs (Pequenos Produtores Comercial, small commercial farmers). An area of 300 ha around each selected PPC is determined to be representative for the area of the sub-basin (or community). At sub-basin scale the water productivity analysis makes use of the WaPOR data portal and calculates the biomass water productivity. The highest water productivity values were found in Báruè; here the highest values are

observed in Báruè III of 3.11 kg/m3. The biomass water productivity was found to range from 2.84 to 3.11 kg/m3 in Báruè, 2.16 to 2.95 kg/m3 in Moatize, and 2.15 to 2.23 kg/m3 in Nhamatanda. The relative change of water productivity compared to the baseline values is +11%, +4% and +17% for Báruè, Moatize, and Nhamatanda, respectively. The overall increase in water productivity estimated at the sub-basin (community) level is +11%.

At basin scale the catchment delineation from each district was used as the boundary of the basin. The water productivity was determined using the WaPOR data portal providing values on biomass water productivity. These values are compared with the baseline assessment and determined that an increase of water productivity was achieved of +27%, +44%, and +31% for Báruè, Moatize, and Nhamatanda respectively. The average increase in biomass water productivity was +34% for all districts together.

Finally, it is noticed that the field scale water productivity increase was similar to last year's irrigation season (49% vs 48%), while at sub-basin (11% vs 33%) and basin scale (34% vs 62%) the water productivity increase was less compared to last year. As APSAN-Vale farmers had a similar field scale water productivity increase but results including non-APSAN-Vale farmers (i.e. on the sub-basin and basin scale) were lower than last year, this might indicate that APSAN-Vale farmers are more resistant to climatic challenges influencing their harvests than non-APSAN-Vale farmers.

Content

List of Tables

List of Figures

1 Introduction

1.1 APSAN-Vale project description

The APSAN-Vale project started at the end of 2018 and is a 4.5-year project with the objective to: 'Pilot innovations to increase the water productivity (WP) and Food Security for Climate Resilient smallholder agriculture in the Zambezi valley of Mozambique'. Water productivity is used as an indicator to quantify the impact of innovations on smallholder agriculture. These innovations can be technical packages (interventions and training), and the adoption of lessons learned through farmer-to-farmer communication. Information on water productivity needs to incorporate both temporal and spatial aspects. The temporal changes in water productivity indicate if an intervention increased water productivity. The spatial patterns in water productivity indicate if the knowledge is being adopted in the region and increased the overall water productivity of the locality, and district. Project activities take place in three districts namely: Báruè, Moatize, and Nhamatanda. Within each district, various localities are selected for piloting innovations. The location of the districts and current project activities are shown in Figure 1.

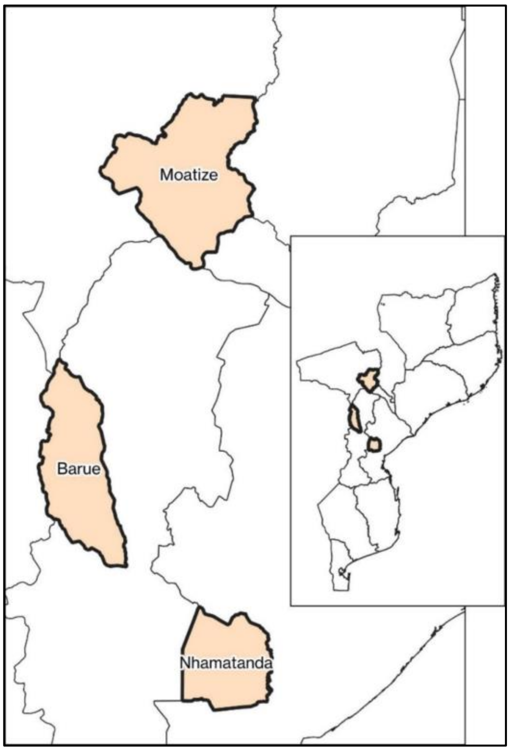


Figure 1. Location districts of APSAN-Vale project activities

1.2 Relevance of analysing water productivity

In order to meet the future needs of food and fibre production, developing and developed countries need to focus more on efficient and sustainable use of land and water (Bastiaanssen and Steduto, 2017)[1]. Farmers have been able to gain profit by increasing agricultural production per unit of land. However, it is key to include the water consumption component in agricultural production. This would allow for improving agricultural production per unit of water consumed.

Water productivity can be used as a performance indicator to monitor changes in an agricultural area (at plot, farm, or irrigation system level). If interventions are implemented, water productivity can indicate if the intervention had a positive or negative impact on the use of water or remained unchanged. In addition, spatial information on water productivity can indicate areas that have higher performance (early adopters) and whether practices are taken over by other farmers.

1.3 Logframe indicators

Within the APSAN-Vale project, several logframe indicators were formulated. The indicators linked with the water productivity assessment are listed in Table 1. Some indicators require the calculation of crop-specific water productivity (1.2 and 1.3), whilst other indicators use biomass water productivity (1.4). The water productivity is calculated at field, sub-basin, and basin scales, thus providing the required maps at different spatial scales. The annual targets for the water productivity outcomes are percentages of

[1] 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.

increase compared to the baseline assessment (Van Opstal and Kaune, 2020)[2] and are indicated in Table 1 as cumulative values, whereas the output maps are the annual total for each year.

Table 1. Logframe indicators related to water productivity

	#	Indicator	Baseline	Target			
				2019	2020	2021	2022
Goal	0.3	Increased water productivity	0%	7.5%	15%	25%	25%
Outcome	1.2	Water footprint for selected crops	0%	7.5%	15%	25%	25%
	1.3	Water productivity for maize	0%	7.5%	15%	25%	25%
	1.4	Biomass water productivity	0%	7.5%	15%	25%	25%
Outputs	1.1.1	# of field-level maps	0	30	60	60	60
	1.1.2	# of sub-basin level maps	0	10	20	20	20
	1.1.3	# of basin level maps	0	6	12	12	12

1.4 Season overview

The irrigation growing season started in April 2022, with the planting of various field crops. The crops planted (and analysed) this season were cabbage (couve and repolho), tomato, maize, beans, onion and potato. For most crops the season ended in September, but in Báruè some crops were harvested until November. Harvest occurs throughout the season at different times depending on the growing length of the crops, local climate conditions, and management strategies. The flying sensor activities occurred with flights taken once every 3-4 weeks with the total number of flights, flight area, and farmers monitored, presented in Table 2. Overview of the number of flights made and farmers monitored during the 2022 irrigation season In the end, for the water productivity analysis, data from 23 farmers was used.

Table 2. Overview of the number of flights made and farmers monitored during the 2022 irrigation season

	Báruè	Moatize	Nhamatanda	Total
Flights taken	60	48	35	143
Farmers monitored	10	8	7	25
Area covered	309 ha	312 ha	228 ha	930 ha
Farmers monitored for WP	9	7	7	23

1.5 Project locations

1.5.1 Fields

For each district, several small commercial farmers (Pequenos Produtores Comercial or PPCs) were selected for the project to implement numerous innovative practices (boas practicas) for boosting water productivity. Most of the selected PPCs were monitored with flying sensor flights. In Báruè, Moatize, and Nhamatanda, nine, seven, and seven PPCs respectively were monitored for the water productivity analysis. The locations of the PPCs monitored during the irrigation season are visualised in Figure 2.

[2] Van Opstal, J.D., A. Kaune. 2020. Water Productivity Technical Report - Baseline assessment for APSAN-Vale project. FutureWater Report 195

Figure 2. Location of selected PPCs monitored with flying sensor flights during the 2022 irrigation season

1.5.2 Sub-basins

The sub-basin scale is the spatial scale between the field scale of the PPCs and the basin scale as described in Section 2.1.3. For the analysis of the sub-basin level water productivity, a representative size is selected of local communities surrounding the PPCs. The objective of the APSAN-Vale project is to increase the water productivity of several communities through knowledge exchange of the interventions being implemented. It is expected that communities surrounding the PPCs will adopt certain best practices. Therefore, the increase in water productivity is best monitored at a scale that captures the change in the communities. The sub-basin or community area is selected using a buffer of approximately 300 ha radius surrounding the selected PPCs. The locations of these communities are presented in Figures 3, 4, and 5 for Báruè, Moatize, and Nhamatanda, respectively. Each has selected 3 to 4 clusters at the location of the PPCs.

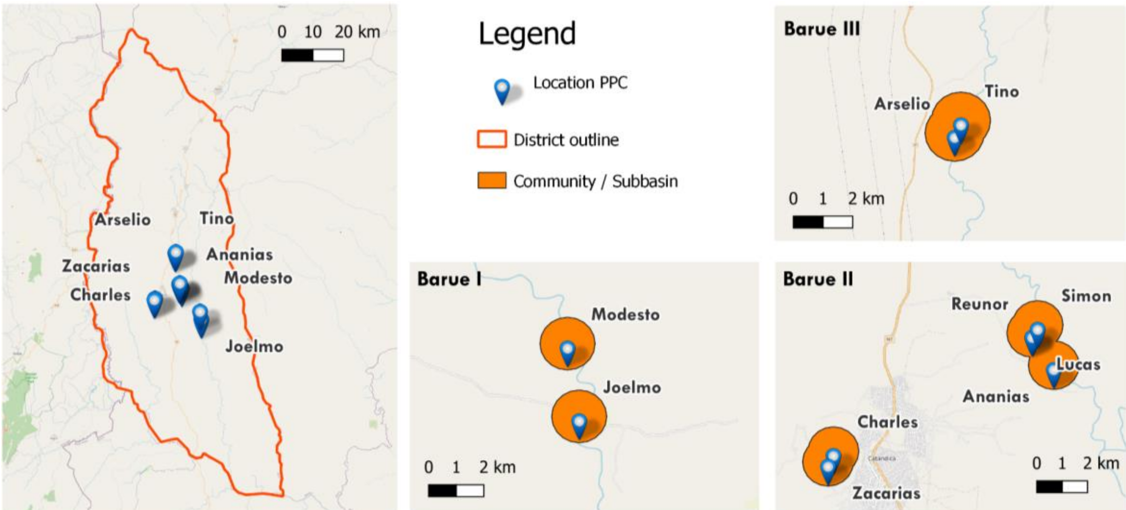


Figure 3. Location and boundaries of sub-basin areas in Báruè

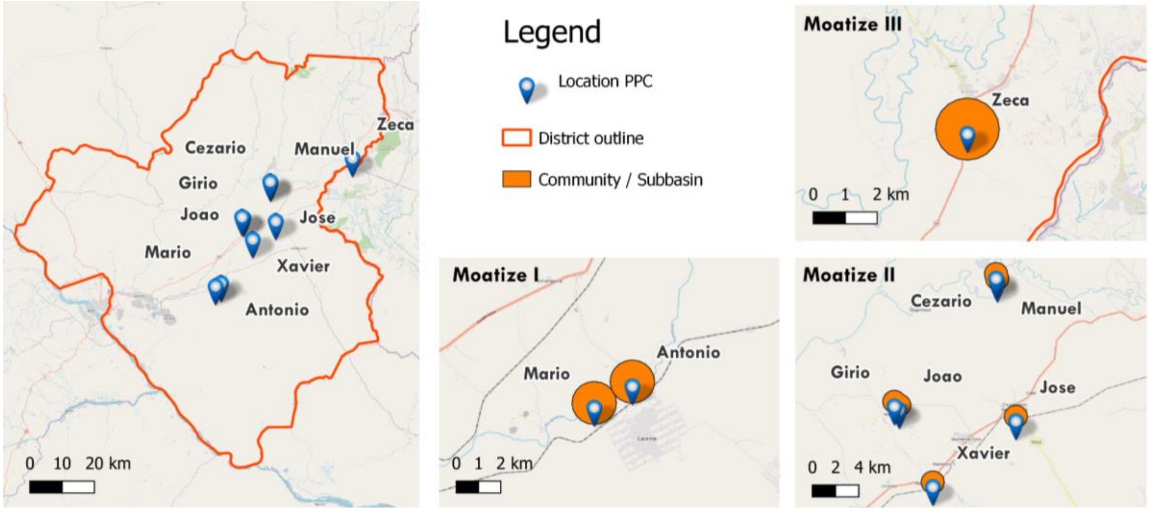


Figure 4. Location and boundaries of sub-basin areas in Moatize

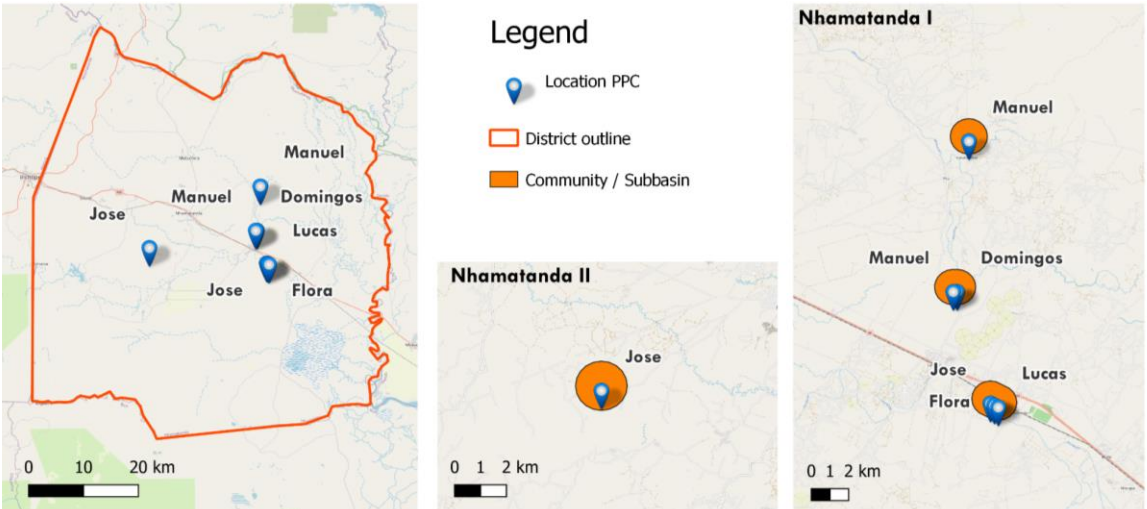


Figure 5. Location and boundaries of sub-basin areas in Nhamatanda

1.5.3 Basins

The basin delineation was performed using a Digital Elevation Model (DEM) at 30m resolution provided by the Shuttle Radar Topography Mission (SRTM) of NASA, and QGIS tools. Details on the steps involved can be reviewed in the manual (Kwast and Menke, 2019)[3]. The outflow points for the basins are determined by evaluating the location of the project activities in the fields, as were determined at the start of the project[4]. The sub-basins are representative of the localities of the project, whereas the basins represent the larger picture of the upstream area. The delineations and locations of project activities are shown in the maps in Figure 6. Measurements of water flow were conducted by project partners at strategic locations in the streams to quantify water abstractions for irrigation.

[3] van der Kwast, H. & Menke, K., QGIS for Hydrological Applications - Recipes for Catchment Hydrology and Water Management, Locate Press, 2019.
[4] Van Opstal, J.D., A. Kaune. 2020. Water Productivity Technical Report - Baseline assessment for APSAN-Vale project. FutureWater Report 195.

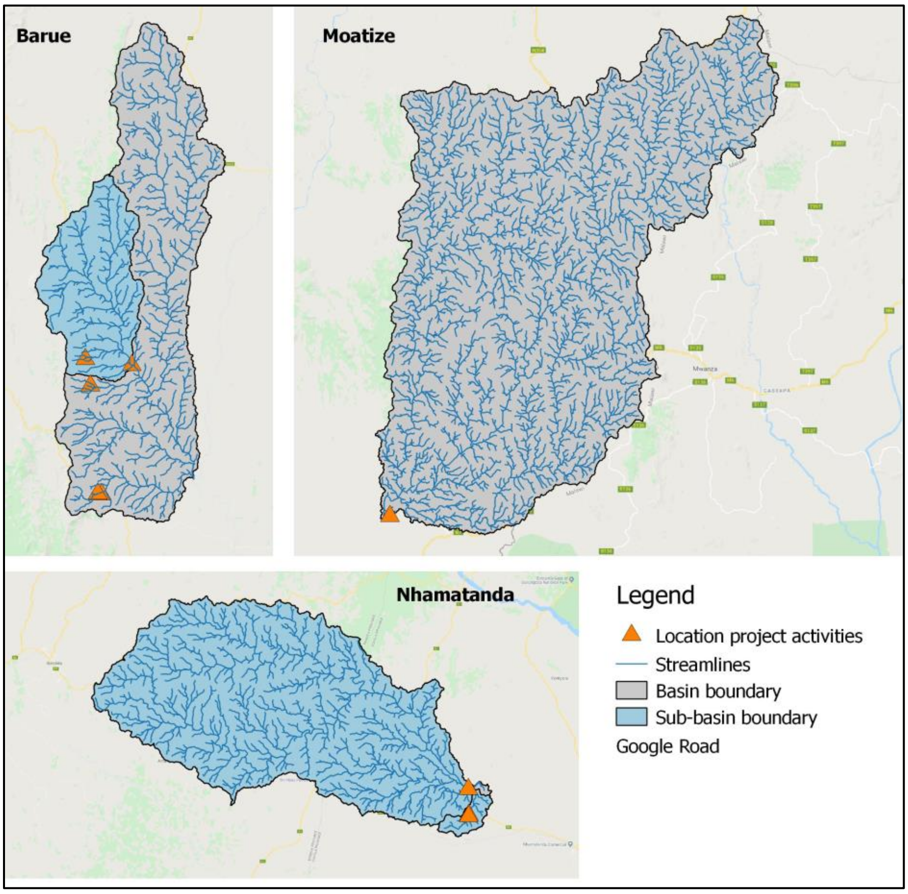


Figure 6. Delineation of basins and streamlines for Báruè, Moatize, and Nhamatanda

1.6 Reading guide

This technical report provides the results of the water productivity analysis at field, sub-basin, and basin scale using Flying Sensor Imagery, crop modelling, and FAO's WaPOR database. The next chapter (chapter 2) elaborates on the methodology used for conducting the water productivity analysis. Chapter 3 provides an analysis of the meteorological conditions during the irrigation season and compares it with past years. Chapters 4, 5, and 6 provide the results of the water productivity analysis at the field, sub-basin, and basin scale respectively. Chapter 7 assesses the water productivity results and compares them with the baseline assessment values. Chapter 8 provides the summarizing and concluding remarks.

2 Methodology

2.1 Approach

2.1.1 Water productivity concept

Water productivity consists of two components: production (either as crop yield or biomass) and water consumed. Water consumption occurs through evapotranspiration 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 (Squire, 2004)[5]. Within this project, the use of evapotranspiration (versus irrigation application) was selected, because it represents the component of the water balance that cannot be reused 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. As such, water productivity can be expressed as:

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

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

This water productivity assessment contains two approaches to measuring water productivity, at different scales:

1. Field scale water productivity: At the field scale, the most detailed information is available regarding crop type, planting and harvesting dates, and management strategies. At this scale, crop-specific water productivity was calculated for the selected crops at the three different districts using crop simulation modelling in combination with flying sensors and satellite imagery (Section 2.1.2).
2. Sub-basin and basin scale water productivity: At sub-basin and basin scales limited information is available on the spatial distribution of the crop types. At this scale biomass water productivity was calculated using data from WaPOR, FAO's Open Access Portal with water productivity data (Section 2.1.3).

2.1.2 Field scale water productivity

The crop-specific water productivity at field scale is determined by crop modelling using field observations and data retrieved from flying sensors and satellite imagery. Figure 7 displays the workflow for performing the crop-specific water productivity analysis. The water productivity is calculated with FAO's AquaCrop model. Field data for setting up the AquaCrop simulations are taken from the weather station and field notebooks. Flying sensors capture images at regular intervals to calculate the canopy cover. This dataset is supplemented with satellite (Sentinel 2) imagery for a higher frequency of data (at lower spatial resolution). This information is integrated with the AquaCrop model to calibrate the model and calculate water productivity. The advantage of combining remote sensing observations from flying sensors, satellite data, and simulation modelling, is that spatial insight is gained in the diversity of farm management practices. Thus, for each field, the most fitting AquaCrop simulation run is selected to be representative of that field. In the next sections, the various steps are elaborated on.

[5] Squire, G. L.: Water Productivity in Agriculture: Limits and Opportunities for Improvement. Edited by J. W. Kijne, R. Barker, D. Molden. Wallingford, UK: CABI Publishing (2003), pp. 352, ISBN 0-85199-669-8, Exp. Agric., 40(3), 395–395, doi:10.1017/S0014479704372054, 2004.

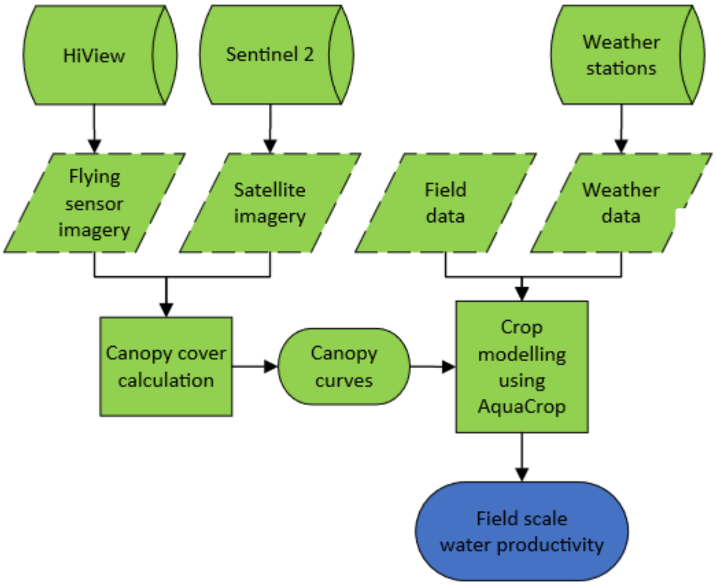


Figure 7. Workflow for calculation of crop-specific water productivity analysis

2.1.3 Sub-basin and basin scale water productivity

WaPOR is FAO's water productivity data portal (https://wapor.apps.fao.org) containing information on evapotranspiration, biomass production, land cover, and many other layers. Information at the basin scale was extracted by deriving a catchment delineation for the selected districts. This was performed using a DEM (digital elevation model). The catchment delineation is shown in Figure 6 for the selected areas.

The land cover layer in WaPOR was used to determine the location of croplands in the basins. The procedure for this analysis follows the guidance provided by the WaterPIP project (Water Productivity in Practice) and the workflow is schematically presented in Figure 8. In Section 2.7 the WaPOR datasets used for this analysis are described in more detail. At the sub-basin scale, similar layers are used for extracting information regarding water productivity.

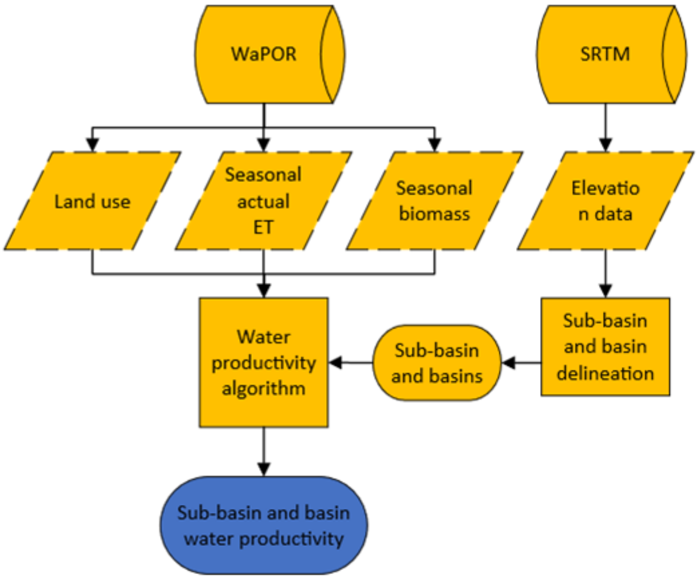


Figure 8. Workflow for biomass water productivity analysis

2.1.4 Overview of methodology

The flowchart provides an overview of the different steps that were taken during this project (Figure 9). The following sub-sections will be dedicated to explaining each step.

1. **Aquiring flying sensor imagery**
   Perform flights with flying sensors to obtain NDVI maps of investigated fields
2. **Enriching data with Sentinel 2 imagery**
   Fill gaps of flying sensor data with additional Sentinel 2 satellite imagery
3. **Processing to canopy cover maps**
   Convert the flying sensor and Sentinel 2 imagery to canopy cover maps
4. **Crop growth modelling**
   Perform crop modelling using the AquaCrop model to determine field scale water productivity
5. **Calibrating crop development to obtain water productivity**
   Use the canopy cover maps to calibrate the AquaCrop model
6. **Calculating sub-basin and basin water productivity**
   Use the WaPOR database to calculate the sub-basin and basin water productivity
7. **Normalizing for annual weather conditions**
   Normalize water productivity results for weather conditions to isolate the impacts of the interventions on water productivity
8. **Seasonal water producitivity assessment**
   Combine the water productivity results from the field scale, sub-basin, and basin analysis and compare to the baseline assessment

Figure 9. Flowchart representing the project methodology

2.2 Step 1: Acquiring flying sensor imagery

2.2.1 Flying sensor equipment

The flying sensor equipment used in APSAN-Vale is a Mavic Pro drone and an additional camera to detect vegetation status. Figure 10 shows a photo of the Flying Sensor used including both cameras. One camera makes RGB (red-green-blue) images, similar to visual images seen with the human eye. The second camera measures the near-infrared (NIR) wavelength, which is not visible to the human eye. The near-infrared wavelength has a good response to the conditions of the vegetation. Figure 11 gives an illustration of the response to stressed conditions of a leaf. 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.

Figure 10. Our flying sensor in action

Another advantage of using the Flying Sensors in this project is the flexibility for imagery capture and the high spatial resolution of the acquired imagery. The flying sensors can make flights when required at the desired intervals. For this project, the frequency of imagery acquisition was aimed at once every 3 weeks, which best captures the crop development stages. This interval was sometimes longer due to weather conditions or logistics. The spatial resolution of the imagery is 4-8 cm, providing sufficient detail to capture the spatial variation of smallholder agriculture.

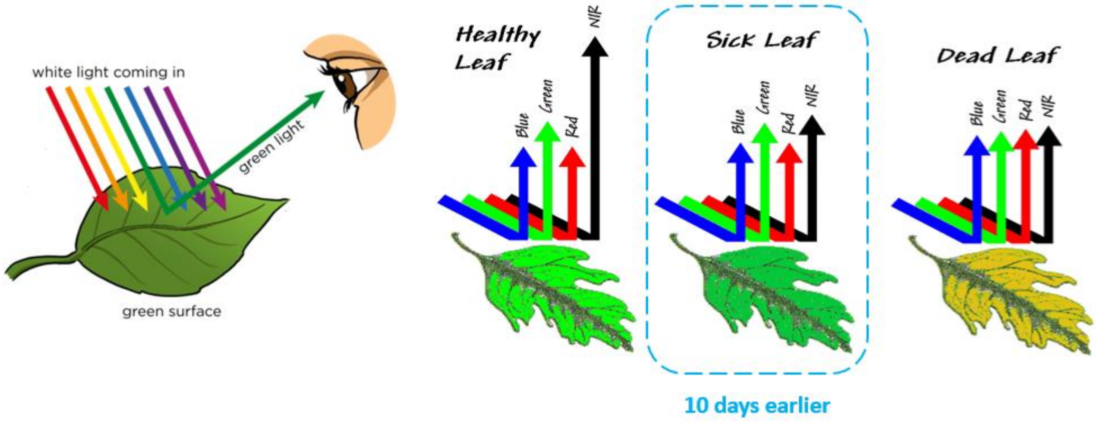


Figure 11. Illustration explaining the response of near-infrared (NIR) wavelength to vegetation status

2.2.2 Flying sensor imagery acquisition

Flying sensor images were acquired at regular intervals throughout the growing season. In Table 3 an overview is provided of the number of flights performed and on which date (sometimes spread over 2 or 3 days). The total number of flights for Báruè, Moatize, and Nhamatanda, were 60, 48, and 35, respectively. The total area monitored with the flying sensors was 309 ha, 312 ha, and 228 ha for Báruè, Moatize, and Nhamatanda, respectively.

Table 3. Overview of flights and area during the irrigation season of 2022

	Báruè	Moatize	Nhamatanda
May		16-05-2022 17-05-2022 18-05-2022 19-05-2022	
June	06-06-2022 10-06-2022 11-06-2022	12-06-2022 13-06-2022 14-06-2022 15-06-2022	
July	04-07-2022 06-07-2022	12-07-2022 13-07-2022 15-07-2022	04-07-2022 05-07-2022 06-07-2022
August	16-08-2022 17-08-2022 18-08-2022	23-08-2022 24-08-2022 27-08-2022	15-08-2022 17-08-2022 18-08-2022
September	05-09-2022 06-09-2022 07-09-2022 27-09-2022 28-09-2022 29-09-2022	13-09-2022 14-09-2022 15-09-2022 16-09-2022	05-09-2022 06-09-2022 07-09-2022

October		28-10-2022 30-10-2022	
November	04-11-2022 05-11-2022		01-11-2022 02-11-2022
Flights taken	60	48	35
Area covered	309 ha	312 ha	228 ha

2.3 Step 2: Enriching data with Sentinel 2 imagery

Sentinel 2 is an open-access satellite platform providing imagery every 3 to 5 days at a spatial resolution of 10x10m. This resolution is sufficient for capturing the crop development of agricultural fields but too coarse for determining detailed within-field spatial variations. These within-field spatial variations can be monitored with flying sensor imagery at a higher resolution. Sentinel 2 data is used supplemental to the flying sensor imagery to capture more frequently the crop development and fill in the gaps between the 3-to-5-week intervals of the flying sensor imagery intervals (as indicated in Table 3).

The Sentinel 2 imagery is first processed to cloud-free imagery through the quality bands provided with the imagery dataset. The NDVI is calculated and used to determine the fraction of vegetational cover by determining the NDVI for bare soil and fully vegetative cover fields. The fraction of vegetational cover is similar to the canopy cover derived from the flying sensor imagery. Processing of the Sentinel 2 imagery was conducted using the cloud computing of Google Earth Engine (https://earthengine.google.com/).

2.4 Step 3: Processing to canopy cover maps

The imagery acquired by the Flying Sensors was post-processed. At first, the single images for each flight were stitched together to form an ortho mosaic. These were then georeferenced so they could be used in further geospatial analysis. These steps were performed using software packages: Agisoft Metashape, and QGIS (geospatial software).

The next processing steps were required to achieve a time series of canopy cover maps. The flying sensor images were processed using R coding, also making the process more efficient. The NIR band of the image was used to determine the vegetation pixels of each image using the 'kmeans' R package for automatic imagery classification. Manually the user determines which class is appointed as vegetation. This information is then used to calculate the canopy cover, which is an indication of the vegetation cover over a surface in percentage and is in the same category as other vegetation indices commonly used in remote sensing e.g., Leaf Area Index (LAI) or Normalized Difference Vegetation Index (NDVI). Canopy cover ranges from 0 to 100%. Full vegetation cover will result in a canopy cover of 100%. A grid of 1x1 meter (=1 m2) is overlaid over a crop field. The number of vegetation pixels (of 0.05x0.05 meter = 0.0025 m2) is counted to determine the percentage of the grid that is covered by vegetation, thus the canopy cover. This information is used in combination with crop modelling to determine the crop yield, and water productivity.

2.5 Step 4: Crop growth modelling

2.5.1 AquaCrop

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

Several crop growth models have been developed to simulate crop yield and water productivity. The model selection depends on the application scale and the ability to constrain model parameter uncertainty. AquaCrop is a widely used crop model developed by FAO, which simulates the yield response to water using physically based parameters. It has been used in climate change impact studies in various parts of the world (Hunink et al., 2014[6]; Hunink and Droogers, 2010[7], 2011[8]). In addition, AquaCrop has been applied to predict water productivity and crop yield based on flying sensor information (den Besten et al., 2017[9], van Opstal, 2019[10]) and to assess irrigation scheduling scenarios (Goosheh et al., 2018[11]). It is especially recommended for small-scale farm-level applications. In addition, it is an open-source model which is freely available for application. Hence, the appropriate model for APSAN-Vale purposes.

FAO has pre-established model parameters to simulate the canopy cover, actual crop transpiration and soil evaporation, biomass, and crop yield for a growth period from sowing to harvest (Figure 12). In this work, selected model parameters were tuned based on observations. Tuned model parameters included plant density, length of the growth period, increase in canopy cover, decrease in canopy cover, harvest index, fertility stress, and cover of weeds.

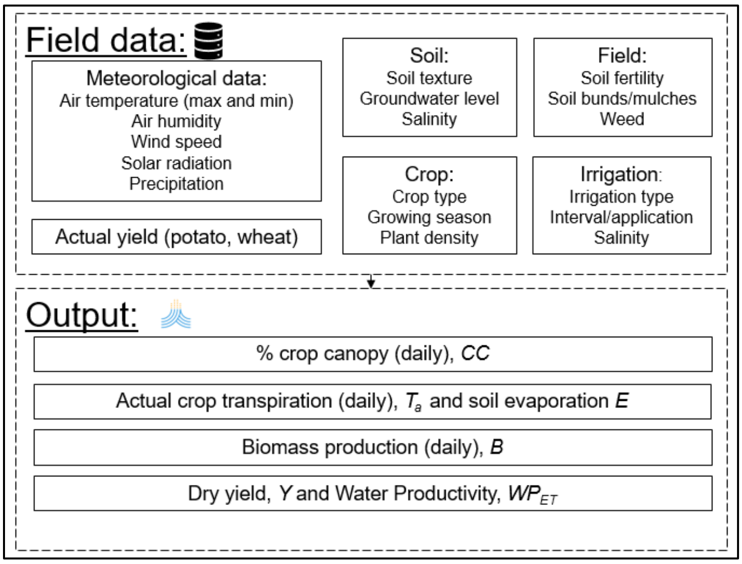


Figure 12. Field data and output simulations of the AquaCrop model

2.5.2 Input data

Weather

Weather data was required as input for the AquaCrop model. This data was derived from a variety of sources. Weather stations from the Trans-African Hydro-Meteorological Observatory (TAHMO) were installed at each district office to represent the weather conditions in the area. These stations were installed in early 2019 and provide meteorological observations until the end of the irrigation season. Occasionally malfunctions occur in the TAHMO equipment. During these periods the weather data was

[6] 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.
[7] 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.
[8] 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
[9] den Besten, N., Simons, G. and Hunink, J.: Water Productivity assessment using Flying Sensors and Crop Modeling. Pilot study for Maize in Mozambique, 2017.
[10] Van Opstal, J.D.. 2019. APSAN-Vale Water Productivity Rainfed season 2018/2019. FutureWater Report.
[11] Goosheh, M., Pazira, E., Gholami, A., Andarzian, B. and Panahpour, E.: Improving Irrigation Scheduling of Wheat to Increase Water Productivity in Shallow Groundwater Conditions Using Aquacrop, Irrig. Drain., 0(0), doi:10.1002/ird.2288, 2018.

supplemented with open-access remote sensing weather data available such as precipitation data from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) database or the WaPOR database for reference evapotranspiration. Additionally, long-term average weather data was acquired from the Global Land Data Assimilation System (GLDAS) data products. This is explained in the baseline assessment report (FutureWater Report 195)[12].

Field data

The next step for the AquaCrop simulations was to collect basic crop information from the selected sites (Báruè, Moatize, and Nhamatanda). Basic information about planting dates, plant density, total growth length (length of the crop cycle), and crop yield is key to obtaining reliable AquaCrop simulations. Several of these parameters are specific to each field. Therefore, the notes taken in the fieldbook of the PPCs were copied and linked to specific fields (indicated with polygons or shape files) to make the simulation tailored to the situation of the PPC. In Annex 1 the input data on management decisions can be found. In the AquaCrop model, several crop parameters must be calibrated to simulate crop-specific canopy cover, transpiration, biomass, and yield during the growing season to finally determine water productivity. Crop-specific parameters were obtained from the original crop files available in the AquaCrop model. For Cabbage and Onion, we obtained the crop parameter information from other studies (Agbemabiese et al., 2017; Pawar et al., 2017; Pérez-Ortolá et al., 2015; Wellens et al., 2013).

Table 4 presents the calibrated crop model parameters per crop. These parameters include the Harvest Index (HI) (%), Increase in Canopy Cover, CGC (-), Decrease in Canopy Cover, CDC (-), and the length of specific growing stages (e.g., sowing to emergence, sowing to maximum rooting depth, etc). HI is a known parameter to convert biomass into crop yield. CGC is a measure of the intrinsic ability of the canopy to expand. After the canopy begins to senesce, the canopy cover is reduced progressively by applying an empirical canopy decline coefficient (CDC). HI, CGS and CDC vary depending on the crop variety and seed quality. The method used to calculate the length of specific growing stages for maize, beans, tomato, and potato was the Growing Degree Days mode (°C days), which accounts for the effects of temperature regimes on crop phenology. For cabbage and onion the calendar days mode was used, which states that the different growth stages of the crops have fixed lengths in days. Eventually, the length of the growing stages was calibrated on the collected field information (Annex 1). This was done by multiplying crop-growth parameters by a common factor until the simulated crop development matched the crop development observed by the flying sensors and satellite imagery.

Table 4. Calibrated crop parameters used in AquaCrop

	Maize	Beans	Tomato	Potato	Cabbage*	Onion*
HI (%)	20	30	60	80	50	40
CGC (-)	0.0050	0.0049	0.0075	0.0162	0.1190	0.1190
CDC (-)	0.0040	0.0044	0.0040	0.0020	0.1000	0.1000
From sowing to emergence (°C days)	132	88	43	310	2	6
From sowing to maximum rooting depth (°C days)	2324	1332	891	1672	40	77
From sowing to start senescence (°C days)	2310	1354	1553	1525	86	45

[12] Van Opstal, J.D., A. Kaune. 2020. Water Productivity Technical Report - Baseline assessment for APSAN-Vale project. FutureWater Report 195.

From sowing to maturity (length of crop cycle) (°C days)	2805	1947	1933	1977	100	85
From sowing to flowering (°C days)	1452	834	525	852	28	67
Length of the flowering stage (°C days)	297	349	750	1	40	18

*Growing stages in calendar days.

Soil and field management information

According to the collected field information the soil texture of each site was determined. The hydraulic properties of the soil are correlated with the soil texture. The AquaCrop model includes pre-established hydraulic properties such as Field Capacity (FC) and Wilting Point (WP) for each soil texture. Field Capacity and Wilting Point values are key to determining the soil water storage capacity and determining the water stress thresholds. In Table 5 the soil textures obtained for each site are shown. The soil type for Báruè was updated in the past season, due to acquired new field data. In Figure 13, an example of FC and WP values (FC=22%, WP=10%) used in the AquaCrop model is shown for sandy loam.

Table 5. Soil texture in each site

Site	Soil texture
Báruè	Sandy Clay Loam
Moatize	Sandy Clay
Nhamatanda	Sandy Clay

```
SandyLoam.SOL
deep uniform 'sandy loam' soil profile
        6.0                 : AquaCrop Version (March 2017)
       46                   : CN (Curve Number)
        7                   : Readily evaporable water from top layer (mm)
        1                   : number of soil horizons
       -9                   : variable no longer applicable
  Thickness  Sat   FC    WP     Ksat   Penetrability  Gravel  CRa       CRb           description
  ---(m)-   ----(vol %)-----  (mm/day)      (%)         (%)    -----------------------------------------
    4.00    41.0  22.0  10.0  1200.0        100          0     -0.323200  0.219363        sandy loam
```

Figure 13. Soil characteristics in Moatize as used in AquaCrop

2.6 Step 5: Calibrating crop development to obtain water productivity

The AquaCrop model was calibrated using the flying sensor and Sentinel 2 data. This was done by determining the maximum canopy cover using a fitted curved trendline. The average canopy cover values were taken and plotted over the course of the growing season. The canopy cover follows a positive curvilinear trend representing the crop development until full cover. The flying sensors monitored the canopy cover throughout the growing season and thus captured parts of the canopy curve at frequent intervals. This data was supplemented with additional data points from Sentinel 2. A similar curvilinear trend of crop development was also simulated in AquaCrop. For the calibration process, the combined maximum canopy cover from the flying sensors and Sentinel 2 data were compared with the AquaCrop simulated canopy cover. The output of AquaCrop was iteratively calibrated until similar results were found between the measured and simulated maximum canopy cover.

The AquaCrop model was set up using the modules and input data as listed in the previous sections. The calibrated parameters were mainly farm management variables that are sensitive in AquaCrop and could not be accurately measured in the field. The parameters selected for calibration were plant density, fertilizer stress, and maximum allowable soil water depletion (for irrigation events). After running the simulations with various parameter combinations, the top simulations were selected displaying limited error with the canopy cover as observed from the flying sensor images. From the selected AquaCrop runs the calculated water productivity, evaporation, transpiration, and dry yield were averaged.

2.7 Step 6: Calculating sub-basin and basin water productivity

The FAO WaPOR database contains several datasets derived from satellite remote sensing and is available through the open-access data portal: https://wapor.apps.fao.org. The layers used from WaPOR are actual evapotranspiration and interception (AETI), net primary production (NPP), and land cover (LCC). This paragraph describes the data layers used from the FAO WaPOR database and explains how they were used to calculate the water productivity values. The data layers were downloaded for the three basins in Mozambique (Figure 6) and aggregated to find seasonal values for the irrigation season of 2022: April 2022 to September 2022. Furthermore, the data layers were also downloaded for the sub-basins (Figures 3, 4, and 5) for the irrigation season of 2022.

2.7.1 Actual evapotranspiration and interception

The actual evapotranspiration from WaPOR is calculated using a surface energy balance algorithm based on the equations of the ETLook model[13]. It uses a satellite platform with both multi-spectral and thermal imagery acquisition. In addition, meteorological data from remote sensing data products were used as input. The energy balance components are calculated with the specified algorithm: net radiation, soil heat flux, and sensible heat flux. The latent heat flux is calculated as residual to the energy balance and represents the evapotranspiration (ET) component of the energy balance.

The WaPOR actual ET dataset used in this report is from Level II (100 meters spatial resolution) and is available monthly. Every image between planting date and harvesting date is summed, which retrieves the seasonal sum for the actual evapotranspiration and interception.

2.7.2 Biomass production

Biomass production was calculated using the monthly net primary production (NPP) data layer from WaPOR. The NPP data was calculated in WaPOR using a light-use efficiency model[14]. This model determines the amount of photosynthetic radiation that arrives at a surface and the amount that is absorbed by vegetation depending on the amount of vegetational cover and (non-)stress conditions. This indicates the result of the photosynthesis process in NPP or dry matter biomass production. The biomass production from WaPOR was summed for the irrigation season. From the seasonal summed biomass and seasonal summed actual evapotranspiration and interception, the water productivity for the 2022 irrigation season was calculated.

2.7.3 Supplemental layers

In addition, reference evapotranspiration (ET) is also provided by the WaPOR data portal at 20 km. resolution and at daily time steps. A time series of this dataset is used as the required weather input data for the crop modelling. Lastly, the land cover map in WaPOR is used to identify the pixels containing croplands. This is used to calculate the biomass water productivity for croplands, thus excluding the pixels of natural vegetation and urban areas.

[13] Bastiaanssen et al. (2012)
[14] Hilker et al. (2008) and several other publications

2.8 Step 7: Normalizing for annual weather conditions

For the baseline assessment[15] meteorological data from a period of 18 years was used for the field scale analysis (2001 – 2018). For the basin scale analysis, this was 10 years of data (2009 – 2018). The period for the basin scale analysis was shorter due to the data availability of WaPOR. Both periods are deemed sufficient for capturing the inter-annual variability in weather conditions with both dry and wet years existing within a time frame of 10 years. The statistical results from this baseline analysis will therefore be representative of the variety of weather conditions.

In further analysis of this project, water productivity values are normalized for weather conditions to determine if changes in water productivity are a result of weather conditions or the impact of the project innovations. The normalization of water productivity values was calculated by using the equation below using 2022 as an example year and using reference evapotranspiration (ET_0) as representative of the annual weather conditions. This equation and methodology were described by Bastiaanssen and Steduto (2016)[16], as a method for comparing water productivity between years and regions with different climatic conditions.

$$WP_{norm}\ [kg/m^3] = \frac{WP_{2022}\ \left[\frac{kg}{m^3}\right] \times ET_{0,average\ 2001-2018}\ [mm]}{ET_{0,2022}\ [mm]}$$

2.9 Step 8: Seasonal water productivity assessment

The final step was the seasonal water productivity assessment. In this step the water productivity results of the field, sub-basin, and basin scale were combined and compared to the baseline assessment and previous seasons. Assessment of the water productivity was performed at three levels. At first, the change in water productivity due to specific interventions in the field of the PPCs was assessed. This level is considered the local scale of changing water productivity. Secondly, the change in water productivity of the surrounding communities was assessed. This will be influenced by neighbouring PPEs and communities adopting the interventions. This level is considered as the increase in the overall water productivity of the region or sub-basin scale. Lastly, the basin level analysis was used to monitor the water productivity on a larger scale as it is expected that the impact of the project is directly measured at the basin scale due to the expanse of the area.

The average results of this season were compared to the 75th percentile[17] values of the baseline as presented in FutureWater Report 195[18]. This provided the average water productivity between 2001 and 2018. This assessment is the baseline of the water productivity for the project locations, without any interventions placed by APSAN-Vale activities. An assumption was made that the PPCs in the baseline had a commercial objective and achieved relatively higher productivity in comparison to the average of all farmers. Therefore, the baseline value used for the comparison is the 75th percentile, indicating that the baseline values were higher than the actual.

[15] Van Opstal, J.D., A. Kaune. 2020. Water Productivity Technical Report - Baseline assessment for APSAN-Vale project. FutureWater Report 195.
[16] Bastiaanssen, W. G. M., & Steduto, P. (2016). The water productivity score (WPS) at global and regional level: Methodology and first results from remote sensing measurements of wheat, rice and maize. Science of The Total Environment, 575, 595–611. https://doi.org/10.1016/j.scitotenv.2016.09.032
[17] This is a measure used in statistics indicating the value below which a given percentage of observations in a group of observations falls. In this case, 25% of the observations are found above the 75th percentile.
[18] Van Opstal, J.D., A. Kaune. 2020. Water Productivity Technical Report - Baseline assessment for APSAN-Vale project. FutureWater Report 195.

3 Seasonal weather conditions

This chapter presents the seasonal weather conditions of the irrigation season of 2022. The chapter includes time series of reference evapotranspiration and precipitation from April to November 2022. Additionally, two bar plots are presented that show the difference in seasonal weather conditions to the baseline report. For these bar plots a different month range was used (April to October), similar to the baseline report.

3.1 Reference evapotranspiration

Meteorological data were collected from weather stations of TAHMO. The observations were used to compute daily reference evapotranspiration (ET) for the different districts throughout the irrigation season of 2022. The time series of daily reference ET shows similar seasonal patterns for the three different districts (Figure 14). The daily reference ET for all districts varied between 2 and 7 mm/day. In the first few months, the fluctuations in daily reference ET are relatively large. The fluctuations decrease steadily throughout the irrigation period up until a rather homogenous reference ET was found at the end of the irrigation season. The calculated reference ET for Báruè was found to be overestimated in the first 15 days. WaPOR data was used to fill the overestimated values. Similarly, gaps were filled with the WaPOR reference ET product for individual days where the TAHMO stations did not record wind speed observations.

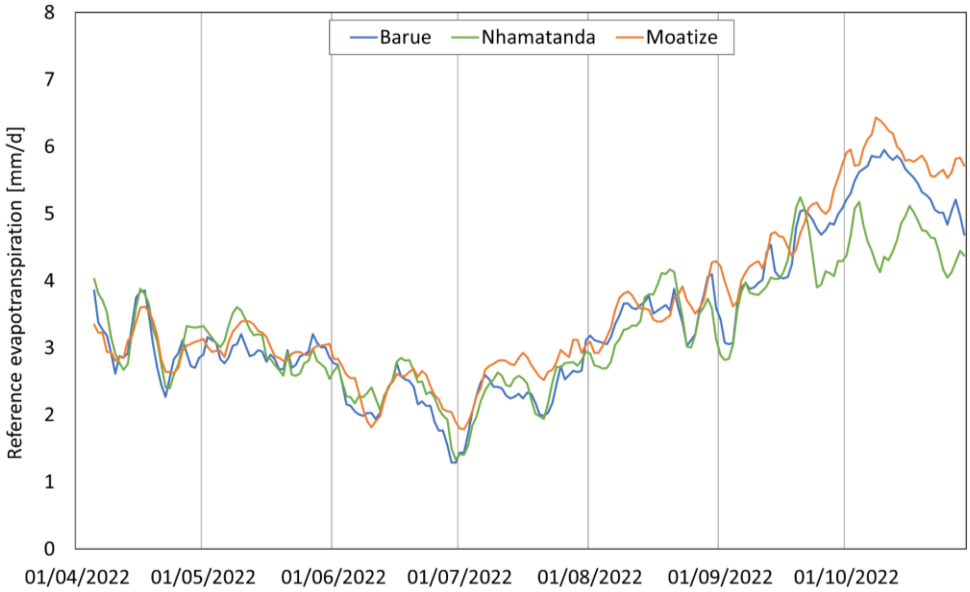


Figure 14. Five-day moving average reference evapotranspiration for Moatize and Nhamatanda during the 2022 irrigation season from TAHMO stations.

The weather conditions of the irrigation season of 2022 were compared to the historical dataset (2001-2018) as used in the baseline assessment (April to September). The historical dataset contains a multitude of dry and wet years and therefore is a good representation of the general weather conditions in the designated districts. The monthly reference ET during the 2022 irrigation season was found to deviate a little from the average conditions (Figure 15). For almost all months, the monthly reference ET in all districts was lower than in the historical dataset. The differences were largest in the Báruè district, where a difference of 44 mm was recorded for the total irrigation season. The total seasonal reference ET is presented in Table 6. It shows the 2022 season and the long-term average for the irrigation season. The presented values are used in the normalization of the water productivity results as described in Section 2.8 of this document.

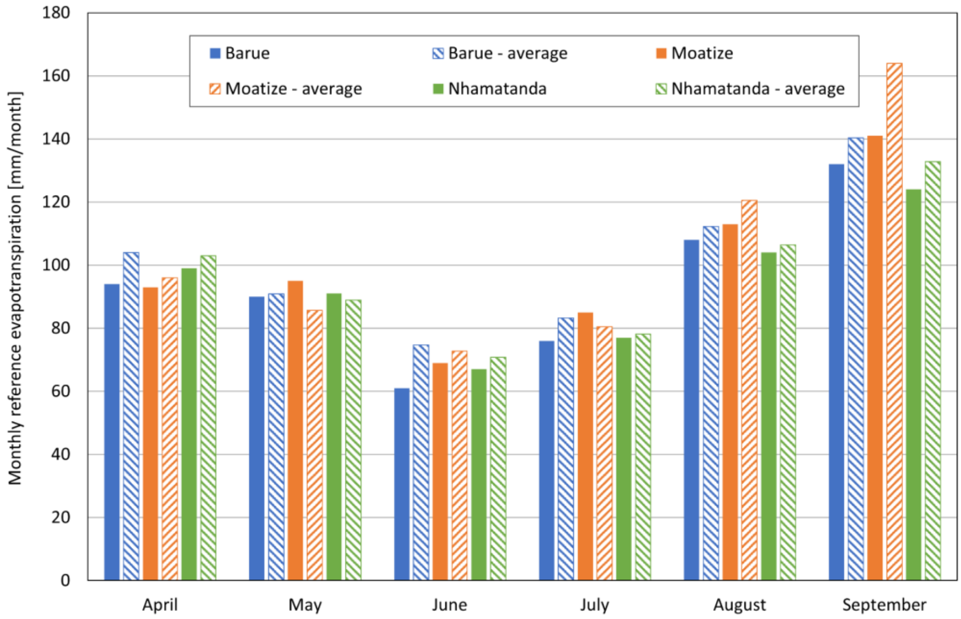


Figure 15. Comparison of 2022 monthly reference evapotranspiration with long-term average (2009-2018) used in the baseline analysis.

Table 6. Seasonal total reference evapotranspiration for Báruè, Moatize, and Nhamatanda during the 2022 irrigation season and long-term irrigation season average (2001-2018).

Reference ET [mm]	Báruè	Moatize	Nhamatanda
2022 irrigation season	561	596	562
2001-2018 long-term average	605	619	580

3.2 Precipitation

During the irrigation season, the rainfall is typically low in this region. The rainfall is recorded at the TAHMO stations. During the season some malfunctions occurred at the stations of Báruè and Moatize, therefore satellite data from CHIRPS (as provided thought the WaPOR portal) is used. The data from the 2022 irrigation season is presented in Figure 16. Daily precipitation for the irrigation season of 2022 from TAHMO. The figure displays heavy rainfall in January for Báruè and Moatize and in May for Nhamatanda. For the rest of the season, precipitation was low.

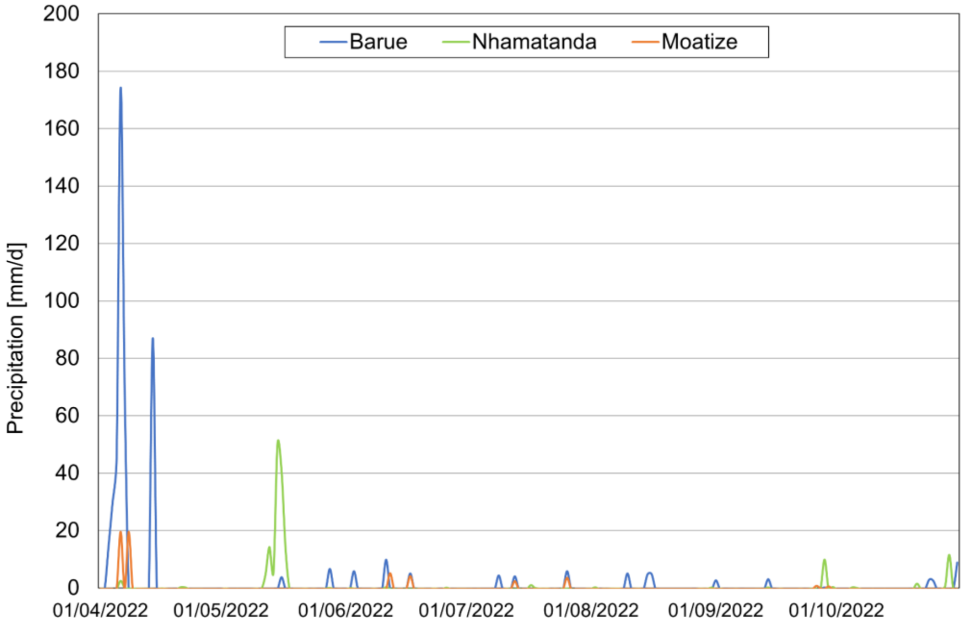


Figure 16. Daily precipitation for the irrigation season of 2022 from TAHMO

The total monthly precipitation shows that April and May were wet months compared to the long-term average (Figure 17). April 2022 was wet for Báruè and Moatize but not for Nhamatanda, where may was the wetter month. The rest of the season was more average for all districts. The seasonal precipitation for the three districts shows that for the whole season Báruè was significantly wetter (494 mm) than the long-term average (Table 7). Moatize and Nhamatanda were 23 and 45 mm wetter respectively.

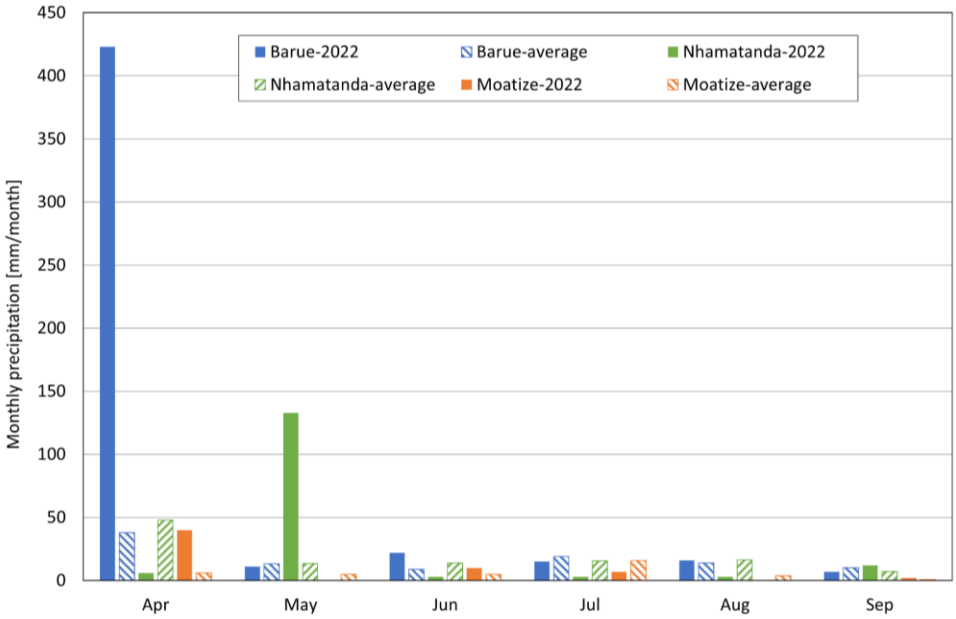


Figure 17. Comparison of the monthly average precipitation during the irrigation season of 2022 with the long-term average (2001-2018) derived from the CHIRPS dataset.

Table 7. Seasonal precipitation for Báruè, Moatize, and Nhamatanda during the 2022 irrigation season and long-term irrigation season average (2001-2018)

Precipitation [mm]	Báruè	Moatize	Nhamatanda
Irrigation season 2022	494	59	160
2001-2018 long-term average	103	36	115

4 Field scale water productivity results

This chapter presents the results of the field scale water productivity assessment. AquaCrop model simulations were performed to present the crop development and farm management of each PPC monitored throughout the irrigation season of 2022. The management decisions and other input data are presented in Annex 1 for each farmer. For Báruè, Moatize, and Nhamatanda the results of the water productivity are presented in Tables 8, 9, and 10, respectively. In the result tables, the water productivity is normalized for the weather conditions using the reference evapotranspiration from Table 6 (Chapter 3), and methodology as described in Section 2.8 of this document.

4.1 Báruè

The canopy curve of PPC Arselio is visualised in Figure 18 and depicts the canopy cover development of a cabbage field. The blue dots indicate field averages of vegetation cover for different moments in the growing season and are measured by flying sensors and satellite imagery. The fitted curvilinear trendline between the blue dots indicates the canopy curve, which represents the growth cycle of the crop. The maximum value of the curve was found to be approximately 44%, reaching this value in the first half of August. The produced maximum canopy cover values were used to calibrate the AquaCrop model to simulate field-scale crop-specific water productivity. The canopy curves from the other PPCs of Báruè are included in Annex 2.

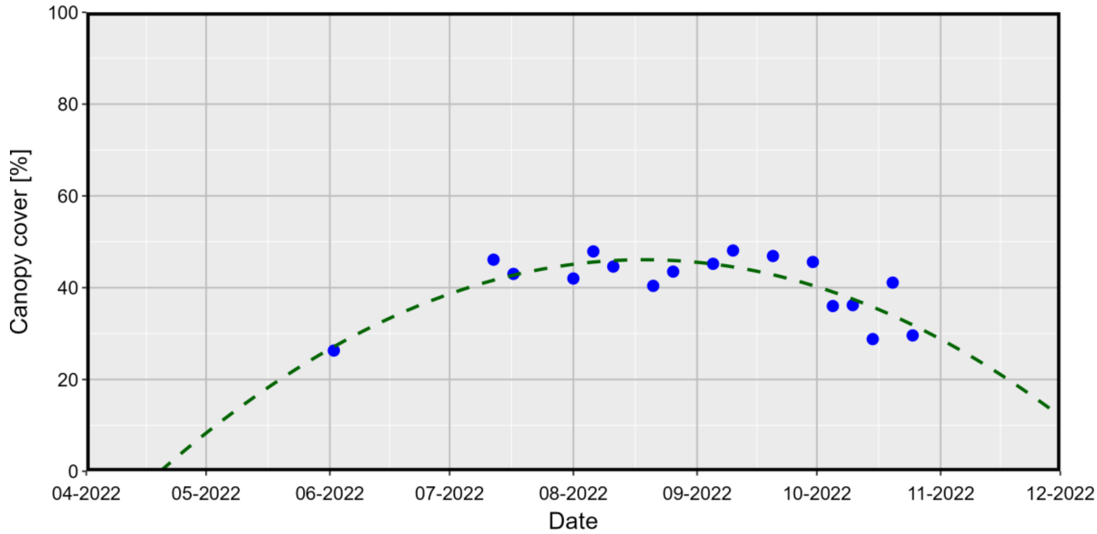


Figure 18. Fitted canopy curve for PPC Arselio with a maximum canopy cover of approximately 44%.

The results of the field scale water productivity analysis for the PPCs in Báruè are presented in Table 8. The water productivity values, normalized for the local climatic conditions (Section 2.8), were found to be improved in all fields for all crops compared to the irrigation season baseline values. The normalised water productivity values vary between 0.71 and 3.03 kg/m^3. The average normalized water productivity is 1.66 kg/m^3. The percentual increase in water productivity compared to the baseline varies between +1% and +189%. On average the improvement for all crops was +38%. The bean and maize fields show an improvement in dry yield, however, the exact change in water productivity cannot be determined due to the absence of a baseline value for this crop. The water productivity of cabbage production was found to be improved the least averaging at +11%. Large improvements were found for the onion and tomato fields with average improvements in water productivity by +123% and +64% respectively. Fields that showed no significant canopy development in the observed canopy curve were excluded from the analysis, as calibrating the model parameters to these often lower maximum canopy cover values resulted in erroneous model output.

Table 8. Results of AquaCrop water productivity, maximum Canopy Covers (CC), dry crop yield, and percent change of water productivity compared to baseline (75th percentile) for Báruè farmers

PPC code	Name	Crop type	Obs. max CC	AQ max CC	Water Productivity [kg/m^3]	Norm. Water Prod [kg/m^3]	% Change with baseline*	Dry crop yield [ton/ha]
BA-CN-01-01	Charles	Beans	75	74	1.43	1.54	N/A	3.2
BA-JR-01-03	Joelmo	Beans	77	77	1.49	1.61	N/A	3.3
BA-SE-01-04	Simon	Beans	52	54	0.66	0.71	N/A	1.6
BA-ZM-01-04	Zacarias	Beans	74	74	1.42	1.53	N/A	3.2
BA-ACI-01-01	Ananias	Cabbage	70	69	1.61	1.74	+34%	4.55
BA-ACI-01-02	Ananias	Cabbage	69	68	1.54	1.66	+28%	4.29
BA-CN-01-04	Charles	Cabbage	68	68	1.30	1.40	+8%	4.01
BA-JR-01-01	Joelmo	Cabbage	66	67	1.27	1.37	+5%	3.94
BA-JR-01-04	Joelmo	Cabbage	62	62	1.21	1.31	+1%	3.57
BA-RF-01-01	Reunor	Cabbage	66	74	1.31	1.41	+9%	2.97
BA-RF-01-03	Reunor	Cabbage	56	60	1.23	1.33	+2%	2.82
BA-SE-01-02	Simon	Cabbage	75	75	1.32	1.42	+10%	3.56
BA-TV-01-01	Tino	Cabbage	65	68	1.52	1.41	+8%	4.35
BA-ZM-01-03	Zacarias	Cabbage	68	70	1.86	1.72	+33%	4.67
BA-CN-01-02	Charles	Maize	69	70	0.66	0.71	N/A	1.56
BA-SE-01-01	Simon	Maize	71	70	0.66	0.71	N/A	1.56
BA-ZM-01-02	Zacarias	Maize	85	87	2.81	3.03	N/A	9.91
BA-AR-01-05	Arselio	Onion	41	40	1.36	1.47	+81%	1.88
BA-LJ-01-04	Lucas	Onion	51	51	1.57	1.69	+99%	1.65
BA-SE-01-03	Simon	Onion	70	70	2.66	2.87	+189%	3.11
BA-ACI-01-04	Ananias	Tomato	82	81	2.35	2.53	+62%	8.57
BA-RF-01-02	Reunor	Tomato	65	69	2.44	2.63	+66%	8.24

* Note: N/A indicates when irrigation season baseline values are not available for these crop types

The water productivity results are presented in field maps in Figure 19. For each PPC the water productivity values are visualised for the different fields. The water productivity values range from medium (yellow) to high (light to dark green).

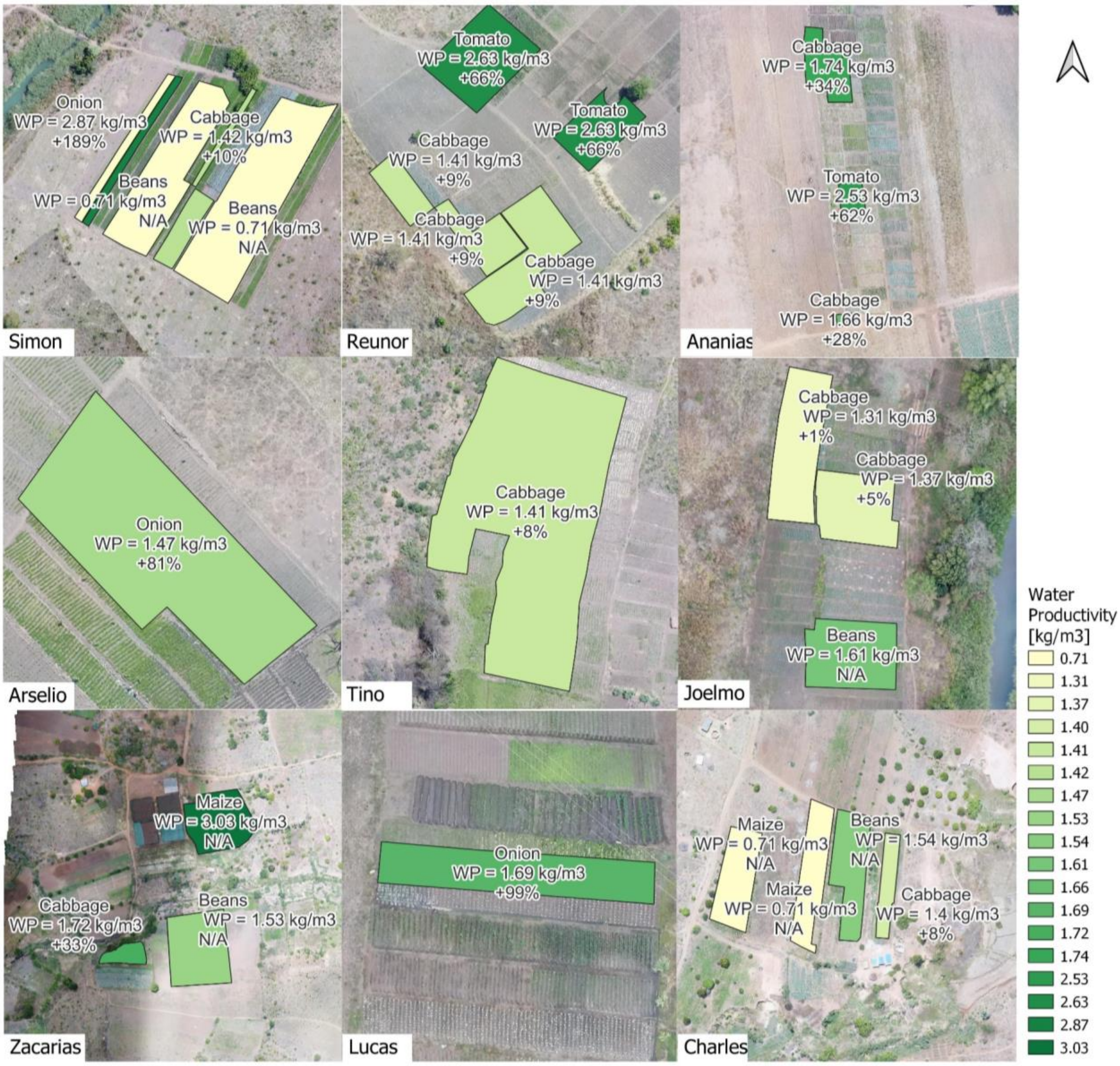


Figure 19. Field water productivity maps of farmers in Báruè for the 2022 irrigation season

4.2 Moatize

The canopy curve of field 4 of PPC Girio is visualised in Figure 20. The maximum value of the curve was found to be approximately 51%. The maximum canopy covers produced were used to calibrate the AquaCrop model and determine the field-specific water productivity. The canopy curves from the other PPCs of Moatize are included in Annex 2.

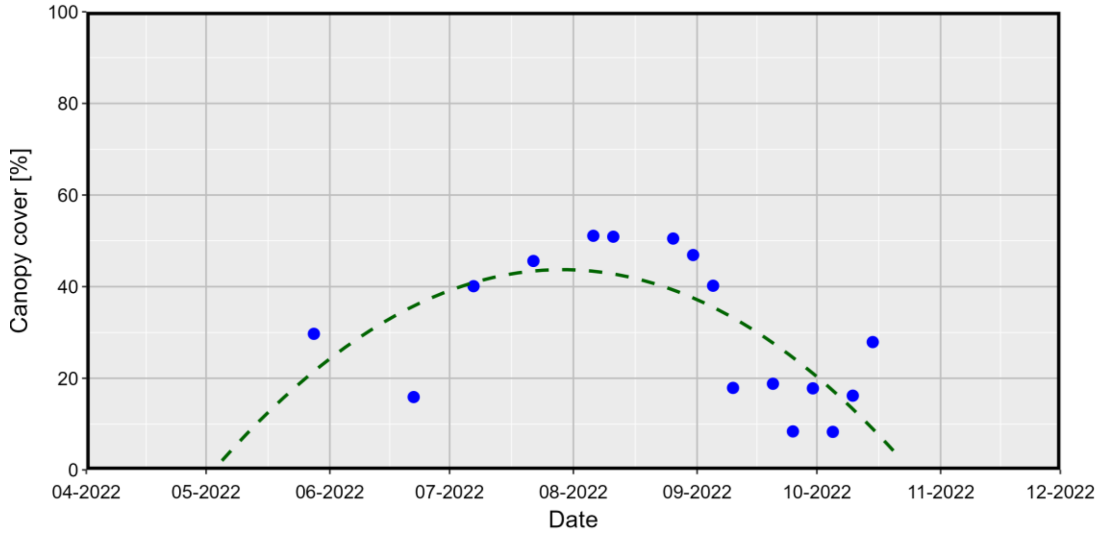


Figure 20. Fitted canopy curve for PPC Girio with a maximum canopy cover of approximately 51%.

The results of the field scale water productivity analysis for the PPCs in Moatize are presented in Table 9. The water productivity values, normalized for the local climatic conditions (Section 2.8), saw improvements but also declined for some fields. The normalised water productivity values vary between 0.64 kg/m^3 for beans and 2.68 kg/m^3 for maize. The average normalized water productivity is 1.39 kg/m^3. The percentual increase in water productivity compared to the baseline varies between -17% for one tomato field and +246% for an onion farmer. On average the improvement for all crops was +19%. The bean fields show an improvement in dry yield, however, the exact change in water productivity cannot be determined due to the absence of a baseline value for this crop. The water productivity of cabbage production was found to be improved the least, averaging at +11%. Large improvements were found for the onion field of PPC Girio at +246%. The tomato fields were deviating the most where some fields showed a decline and others an improvement. Altogether, an average improvement of +11% was found for tomatoes. Fields that showed no significant canopy development in the observed canopy curve were excluded from the analysis, as calibrating the model parameters to these often lower maximum canopy cover values resulted in erroneous model output.

Table 9. Results of AquaCrop water productivity, maximum Canopy Covers (CC), dry crop yield, and percent change of water productivity compared to baseline (75th percentile) for Moatize farmers

PPC code	Name	Crop type	Obs. max CC	AQ max CC	Water Productivity [kg/m^3]	Norm. Water Prod [kg/m^3]	% Change with baseline*	Dry crop yield [ton/ha]
SA-CA-01-01	Cezario	Beans	72	73	0.75	0.78	N/A	1.56
SA-CA-01-02	Cezario	Beans	64	67	0.88	0.91	N/A	2.07
SA-CA-01-03	Cezario	Beans	66	67	0.88	0.91	N/A	2.07
SA-ZM-01-01	Zeca	Beans	72	72	0.73	0.76	N/A	1.49
MA-GM-01-04	Girio	Beans	50	53	0.62	0.64	N/A	1.3
MA-JC-01-02	Joao	Cabbage	50	56	1.36	1.41	+9%	3.92
MA-GM-01-02	Girio	Cabbage	51	56	1.51	1.57	+14%	4.06
MA-GM-01-03	Girio	Onion	40	40	1.32	1.37	+246%	1.88
SA-MC-01-01	Manuel	Tomato	48	44	1.51	1.57	-17%	2.94
MA-JC-01-01	Joao	Tomato	56	58	2.58	2.68	+41%	6.31
MA-GM-01-01	Girio	Tomato	54	51	1.71	1.78	-7%	5.28
CA-AS-01-01	Antonio	Tomato	60	60	2.34	2.43	+28%	5.97

* Note: N/A indicates when irrigation season baseline values are not available for these crop types

The water productivity field maps are presented in Figure 21. For each PPC the water productivity values are visualised for the different fields. The water productivity values range from medium (yellow) to high (light to dark green).

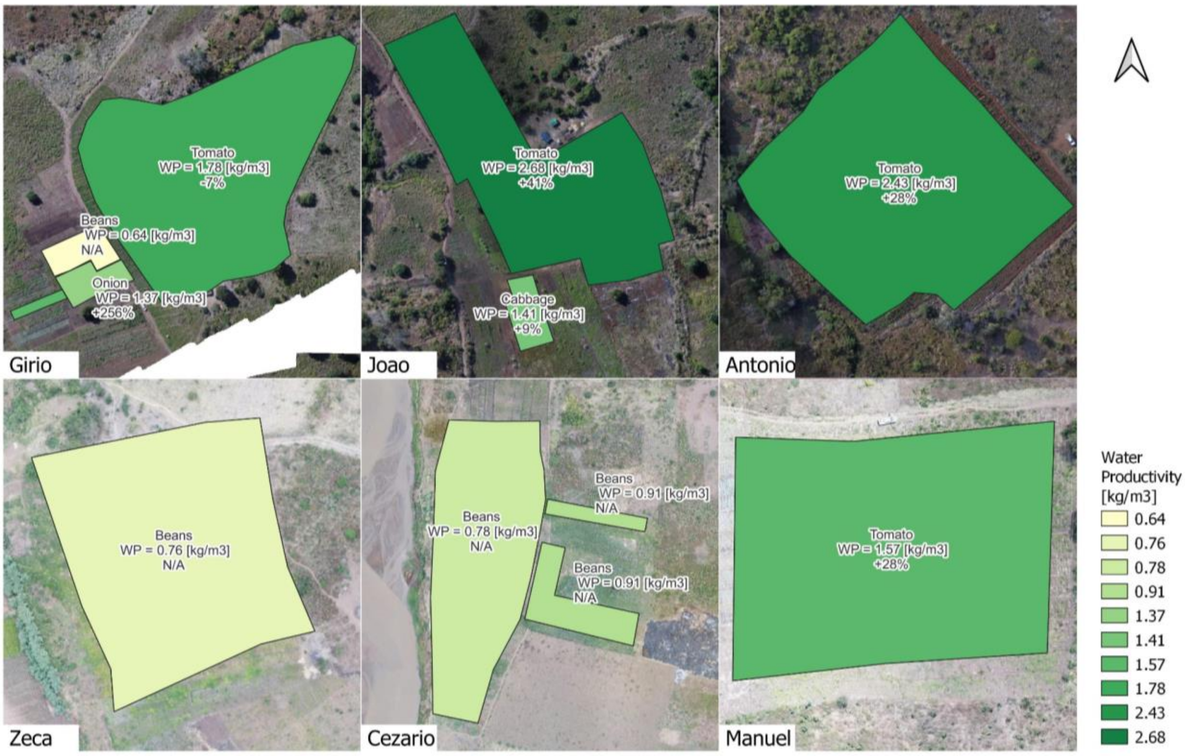


Figure 21. Field water productivity maps of farmers in Moatize for the 2022 irrigation season

4.3 Nhamatanda

The canopy curve of the bean field of PPC Flora is visualised in Figure 22. The maximum value of the curve was found to be 80%. The maximum canopy covers produced were used to calibrate the AquaCrop model and determine the field-specific water productivity. The canopy curves from the other PPCs of Nhamatanda are included in Annex 2.

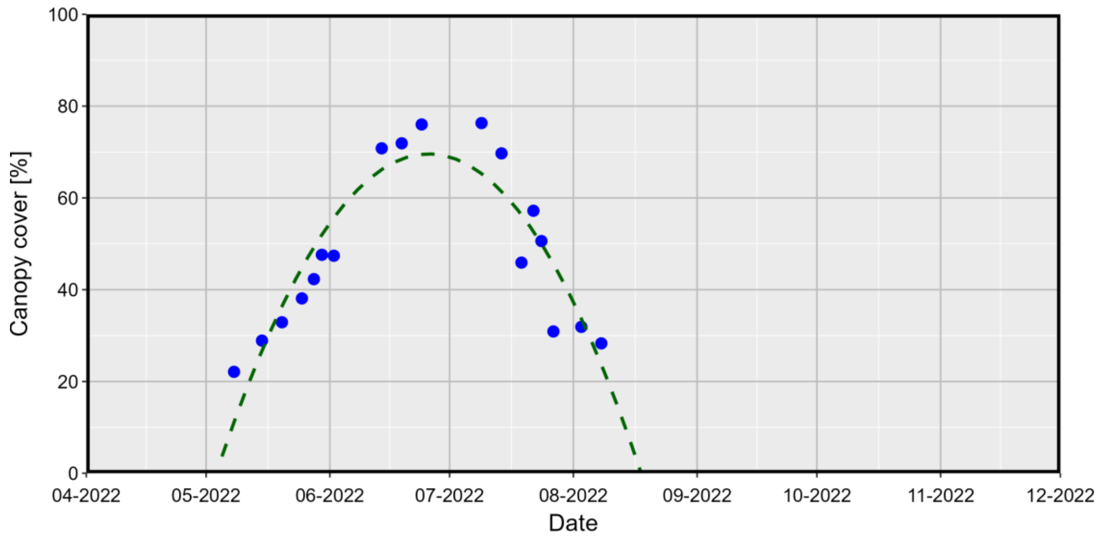


Figure 22. Fitted canopy curve for PPC Flora with a maximum canopy cover of approximately 80%.

The results of the field scale water productivity analysis for the PPCs in Nhamatanda are presented in Table 10. The water productivity values, normalized for the local climatic conditions (Section 2.8), were found to be improved in all fields for all crops compared to the irrigation season baseline values. The normalised water productivity values vary between 0.82 kg/m^3 for a beans field and 2.59 kg/m^3 for a tomato farmer. The average normalized water productivity is 1.39 kg/m^3. The percentual increase in water productivity compared to the baseline varies between +2% and +241%. On average the improvement for all crops was +83%. The bean and maize fields show an improvement in dry yield, however, the exact change in water productivity cannot be determined due to the absence of a baseline value for this crop. The water productivity of cabbage production was found to be improved the least averaging at +19%. Large improvements were found for both the onion field of PPC Manuel 1 and the tomato field of Jose 2, with improvements in water productivity of +241% and +99% respectively. Fields that showed no significant canopy development in the observed canopy curve were excluded from the analysis, as calibrating the model parameters to these often lower maximum canopy cover values resulted in erroneous model output.

Table 10. Results of AquaCrop water productivity, maximum Canopy Covers (CC), dry crop yield, and percent change of water productivity compared to baseline (75th percentile) for Nhamatanda farmers

PPC code	Name	Crop type	Obs. max CC	AQ max CC	Water Productivity [kg/m^3]	Norm. Water Prod [kg/m^3]	% Change with baseline*	Dry crop yield [ton/ha]
NH-DP-01-01	Domingos	Beans	61	61	0.93	0.96	N/A	1.47
NH-MD-01-01	Manuel 2	Beans	49	50	0.79	0.82	N/A	1.41
NH-LB-01-0	Lucas	Cabbage	60	60	1.72	1.78	+30%	3.72
NH-DP-01-02	Domingos	Cabbage	40	58	1.35	1.39	+2%	3.85
NH-MD-01-02	Manuel 2	Cabbage	55	55	1.41	1.46	+6%	3.62
NH-JD-01-02	Jose 1	Cabbage	55	54	1.53	1.58	+15%	3.51
NH-M-01-02	Manuel 1	Cabbage	50	52	1.51	1.56	+14%	2.98
NH-LB-01-01	Lucas	Maize	58	61	1.11	1.15	N/A	3.07
NH-LB-01-02	Lucas	Maize	66	66	1.16	1.20	N/A	3.32
NH-JD-01-05	Jose 1	Maize	58	61	1.13	1.17	N/A	3.21
NH-M-01-01	Manuel 1	Onion	33	32	1.37	1.41	+241%	1.54
NH-JA-01-02	Jose 2	Tomato	62	64	2.51	2.59	+99%	5.81

* Note: N/A indicates when irrigation season baseline values are not available for these crop types

The water productivity field maps are presented in Figure 23. For each PPC the water productivity values are visualised for the different fields. The water productivity values range from medium (yellow) to high (light to dark green).

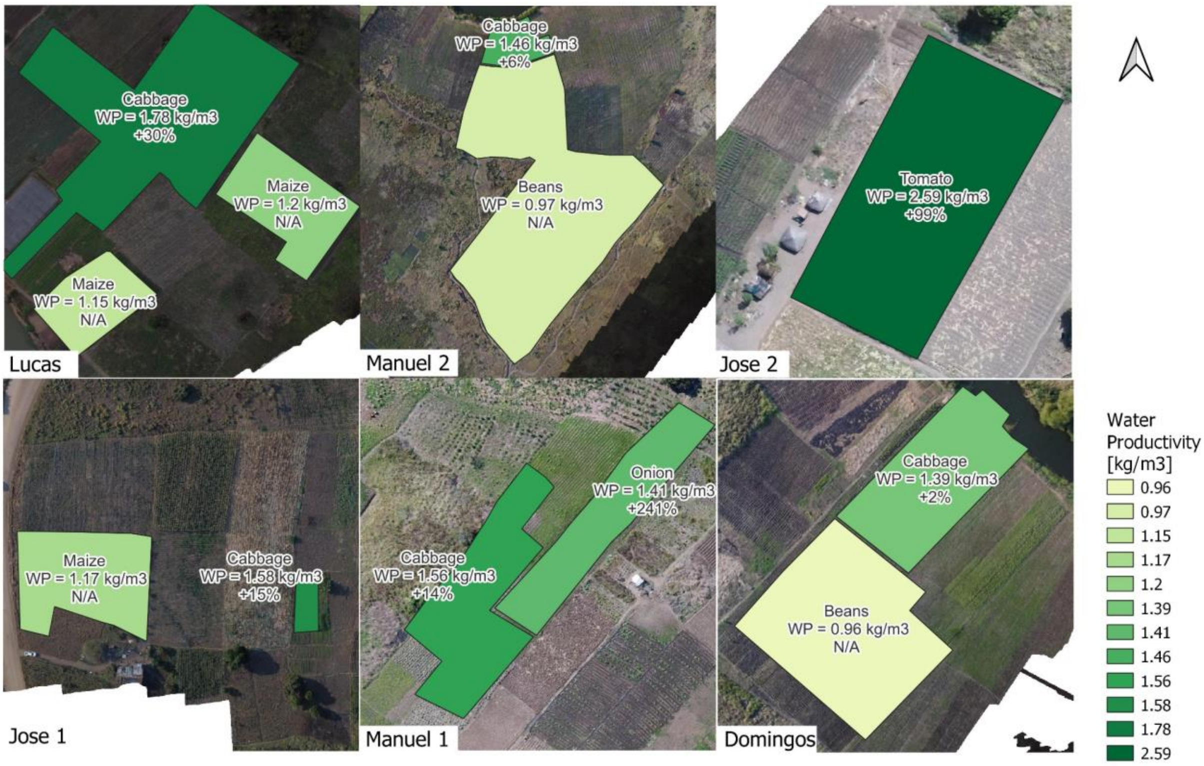


Figure 23. Field water productivity maps of farmers in Nhamatanda for 2022 irrigation season

5 Sub-basin scale water productivity results

The sub-basin scale is described as the level between the field scale of the selected PPCs and the basin scale delineated for each district. The sub-basin scale was determined to be a 300 ha radius around each selected PPC as described in section 2.1.3 of this document and presented in Figures 3, 4, and 5.

Data from the WaPOR portal was retrieved for the irrigation season for the months April to September 2022. The data products downloaded from WaPOR were Actual Evapotranspiration (in mm) and Net Primary Production, which was converted to Above Ground Biomass Production (in ton/ha). These data products were used to calculate the biomass water productivity for each sub-basin location.

Results are presented in Table 11 for each location. The highest water productivity values are consistently found in Báruè, due to the favourable climate in this region. Here the highest values are observed in Báruè III. The lowest values for water productivity are found in Moatize for the communities most downstream. The highest water productivity for Moatize is found in Moatize III, which is located upstream and closer to the mountains. For Nhamatanda the water productivity values are similar for both sub-basins.

Table 11. Water productivity results of sub-basin analysis using WaPOR data portal

District	Sub-basin	Actual Evapo-transpiration [mm]	Biomass Production [ton/ha]	Biomass water productivity [kg/m^3]
Báruè	Báruè I	349	10	2.84
	Báruè II	322	10	3.05
	Báruè III	336	10	3.11
	Average	**336**	**10**	**3.00**
Moatize	Moatize I	254	5	2.16
	Moatize II	287	7	2.41
	Moatize III	377	11	2.95
	Average	**306**	**8**	**2.51**
Nhamatanda	Nhamatanda I	411	9	2.15
	Nhamatanda II	393	9	2.23
	Average	**402**	**9**	**2.19**

The maps of the sub-basin water productivity results are presented in Figures 24, 25, 26 for Báruè, Moatize, and Nhamatanda respectively.

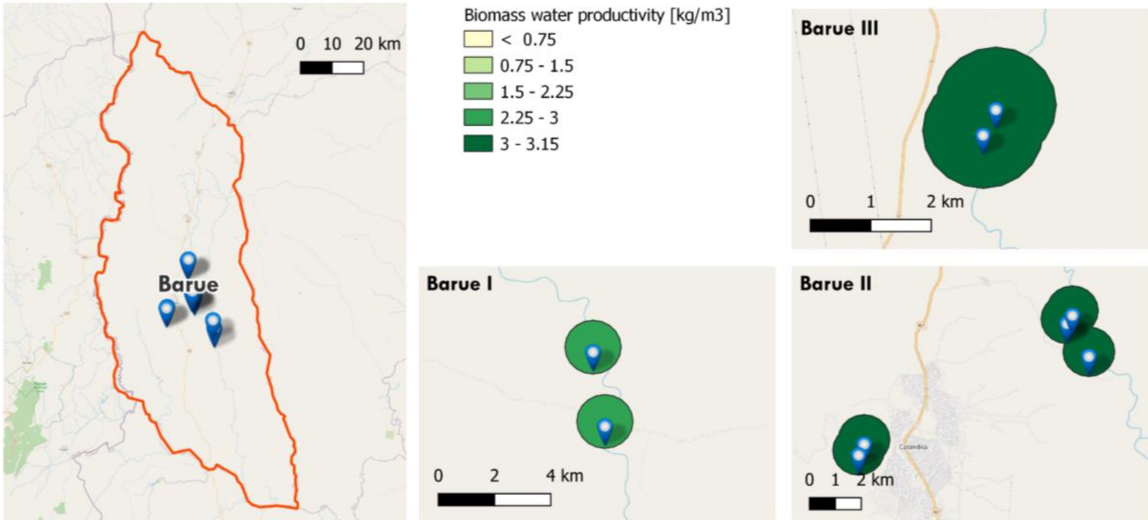


Figure 24. Biomass water productivity (kg/m^3) for sub-basins in Báruè for the 2022 irrigation season

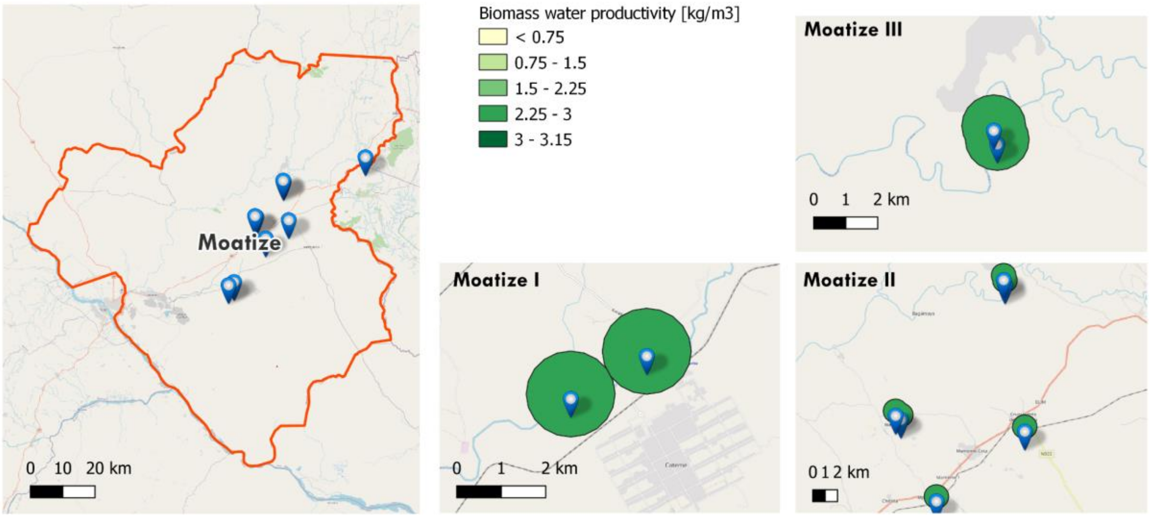


Figure 25. Biomass water productivity (kg/m^3) for sub-basins in Moatize for the 2022 irrigation season

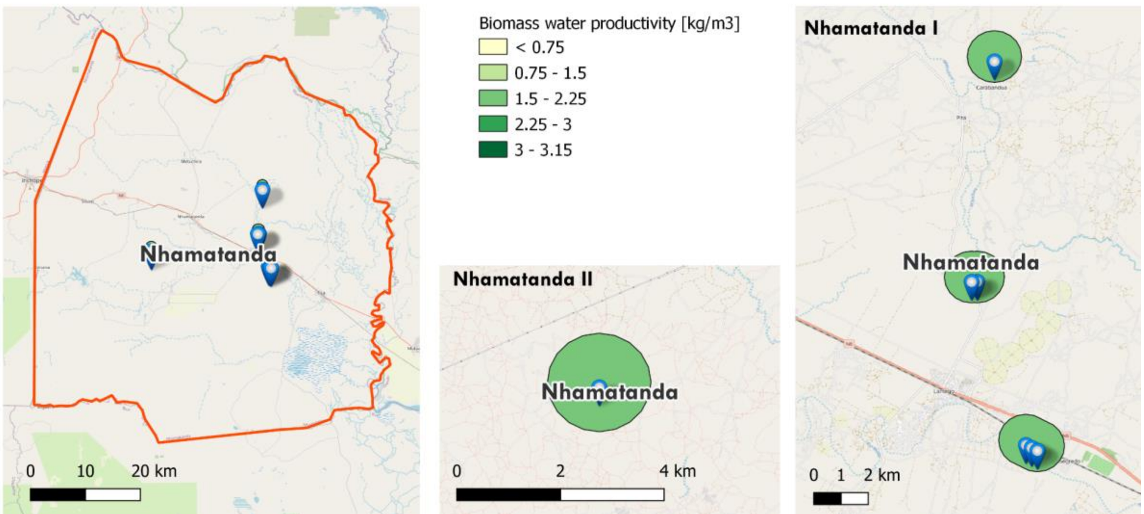


Figure 26. Biomass water productivity (kg/m^3) for sub-basins in Moatize for the 2022 irrigation season

6 Basin scale water productivity results

The basins were delineated for each district as shown in Figure 6 based on hydrological streamlines. These delineations were used with the WaPOR data portal to determine the biomass water productivity for each location. Table 12 provides an overview of the statistics found for actual evapotranspiration, biomass production, and water productivity for each basin, after masking out only the cropland pixels using the landcover layer provided in WaPOR. Báruè displays the highest biomass production of the area, followed by Moatize and Nhamatanda. The water productivity was also highest for Báruè, followed by Moatize, and lastly Nhamatanda.

Table 12. Overview of statistics of actual evapotranspiration, biomass production, and water productivity for the basins of Báruè, Moatize and Nhamatanda

		Báruè	Moatize	Nhamatanda
Actual evapotranspiration [mm]	Average mean	394	379	416
	10th percentile	332	300	364
	90th percentile	455	460	470
Biomass production [ton/ha]	Average mean	7.5	6.9	6.4
	10th percentile	6.0	5.5	5.3
	90th percentile	9.0	8.5	7.7
Water productivity [kg/m^3]	Average mean	1.90	1.83	1.54
	10th percentile	1.75	1.70	1.42
	90th percentile	2.05	1.98	1.66

Figure 27 displays the water productivity maps of each basin. In Báruè, the water productivity downstream shows even distribution, but a higher water productivity is measured close to the mountain range, compared to the rest of Báruè. In Moatize the upstream area (north-east) displays higher water productivity values than downstream. These areas are also closer to the mountain range, which could influence the local weather conditions. The number of cropland pixels in Nhamatanda are limited, therefore less spatial variation can be observed, but is seems to be an even distribution.

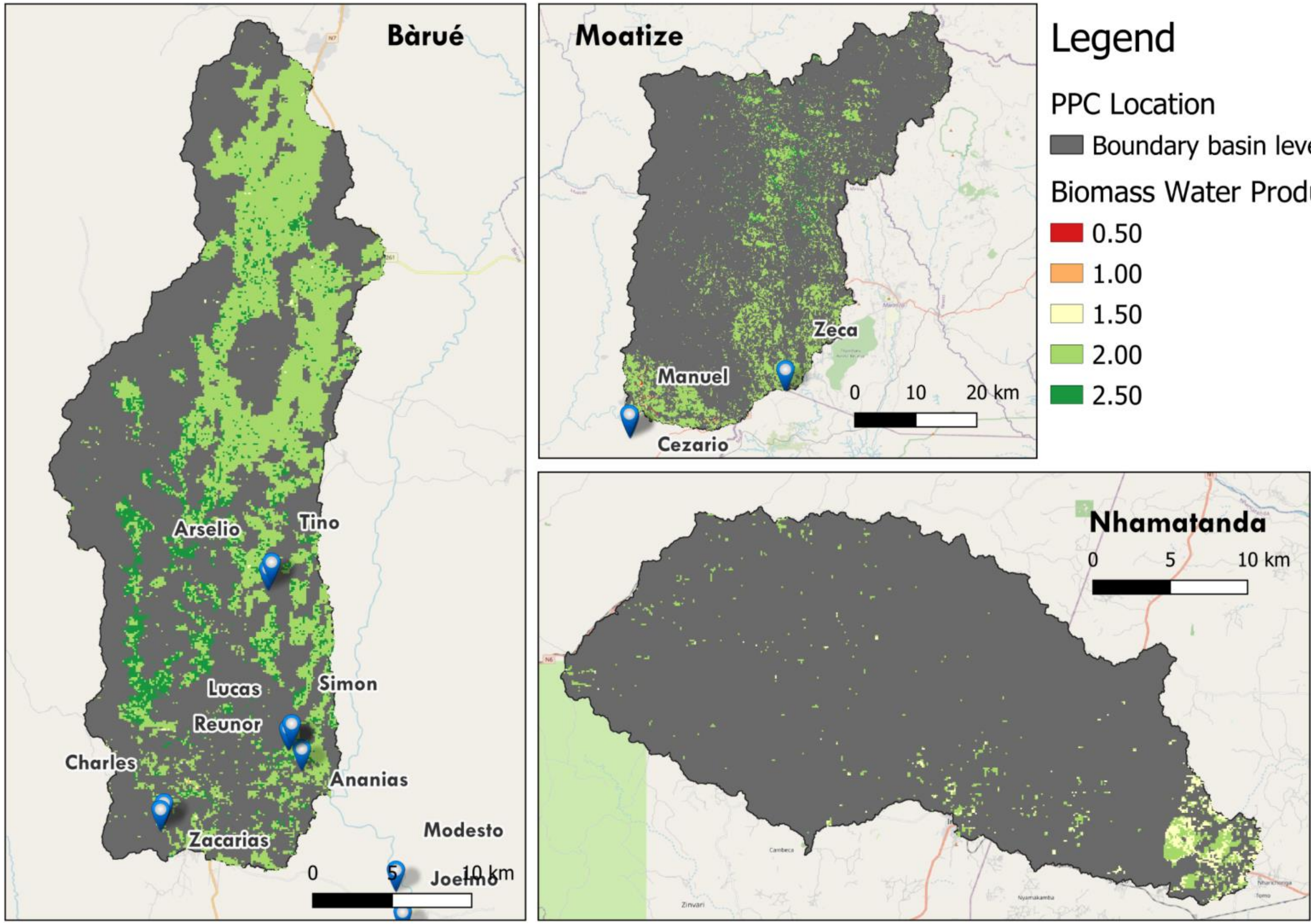


Figure 27. Seasonal biomass water productivity (kg/m^3) at basin scale for cropland pixels in Báruè, Moatize and Nhamatanda for the 2022 irrigation season

7 Seasonal water productivity assessment

The following sections elaborate on the change in water productivity on the different scales in comparison with the baseline; and the change in overall water productivity using the WaPOR database to assess for a larger area. Assessments make use of normalizing the water productivity for the seasonal weather conditions as explained in Section 2.8 of this report. Thus, changes in water productivity linked to seasonal weather are minimised in the assessment. The water productivity assessment at the level of the PPC is presented followed by the overall water productivity assessment at the level of the sub-basins or communities and the basin level.

7.1 Field scale

Chapter 4 of this report presents the results of the field scale water productivity. An overview of this analysis is provided in Table 13 for each district indicating the overall change in water productivity. The values represent the normalized crop water productivity values. The overall increase is calculated by comparing the average (mean) of the normalized water productivity, with the 75th percentile[1] of the baseline. The assumption is that the PPCs are above-average farmers (in the top 25%) compared to the agricultural systems used in the baseline assessment, which is explained in Section 2.9. The overall average improvement in water productivity achieved at the field scale of the PPCs is +49%. The highest increase was observed in Nhamatanda and the lowest in Moatize. The crop-specific water productivity for onion, cabbage, and tomato was on average improved by respectively +142%, +14%, and +122% (Table 13, 14 and 15). On average the combined water productivity of all crops in the irrigation season of 2022 improved by +49% compared to the baseline.

Table 13. Normalized onion water productivity (in kg/m^3) for the irrigation season of 2022 compared to the baseline values

	Báruè	Moatize	Nhamatanda	Overall
Baseline water productivity				
Range				
75th Percentile	0.41	0.80	0.41	
Irrigation season 2022 water productivity				
Range	1.43 – 2.87			
Average (mean)	1.87	1.37	1.41	
Relative change with baseline (%)	+112%	+71%	+245%	**+142%**

Table 14. Normalized cabbage water productivity (in kg/m^3) for the irrigation season of 2022 compared to the baseline values

	Báruè	Moatize	Nhamatanda	Overall
Baseline water productivity				
Range	1.02 - 1.82	0.81 – 1.54	0.78 – 1.55	
75th Percentile	1.68	1.34	1.37	
Irrigation season 2022 water productivity				
Range	1.27 – 1.74	1.41 – 1.57	1.39 – 1.78	
Is Average (mean)	1.47	1.41	1.55	
Relative change with baseline (%)	+14%	+9%	+19%	**+14%**

[1] This is a measure used in statistics indicating the value below which a given percentage of observations in a group of observations falls. In this case, 25% of the observations are found above the 75th percentile.

Table 15. Normalized tomato water productivity (in kg/m^3) for the irrigation season of 2022 compared to the baseline values

	Báruè	Moatize	Nhamatanda	Overall
Baseline water productivity				
Range	0.65 – 1.19	1.50 – 2.25	1.02 – 1.35	
75th Percentile	1.07	1.95	1.27	
Irrigation season 2022 water productivity				
Range	2.53-2.63	1.57 – 2.68		
Average (mean)	2.58	2.11	2.53	
Relative change with baseline (%)	+64%	+45%	+229%	**+122%**

Table 16. The overall change in field scale water productivity for the 2022 irrigation season compared to the baseline for onion, cabbage, and tomato weighted by the number of plots as indicated between brackets

	Báruè	Moatize	Nhamatanda	Overall
Onion	+112% (2)	+71% (1)	+245% (1)	
Cabbage	+14% (10)	+9% (2)	+19% (5)	
Tomato	+65% (2)	+45% (4)	+229 (1)	
Overall change	+55%	+29%	+63%	**+49%**

As this is the final irrigation season included in the APSAN-Vale project, this report contains an overall assessment of the change in water productivity throughout the four years the project lasted. These results are depicted in Figure 28 where values in the table indicate the average water productivity of the production of key irrigation season crops (cabbage, tomato, and onion) within that district. The values located at the top of the bars indicate the percentual change from the baseline.

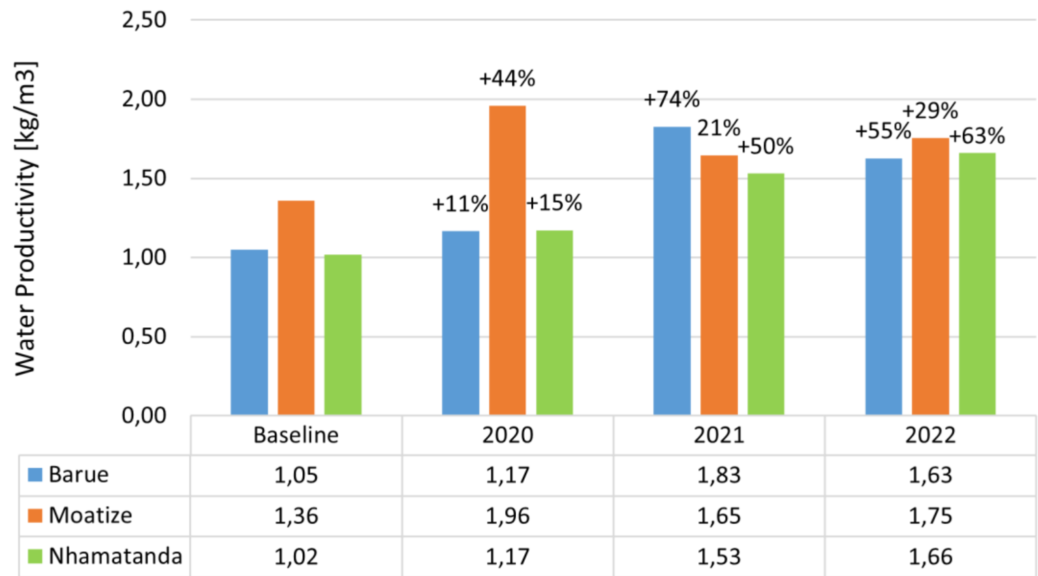


Figure 28. Overview of water productivity results for the irrigation seasons of 2020, 2021, 2022 and the baseline assessment.

Overall, the improvements in water productivity indicate a good achievement of the targets set in the logframe as presented in Section 1.3 of this report. All districts saw a positive change in water productivity throughout the years. The water productivity of Báruè, Moatize, and Nhamatanda increased by +55%, +29%, and +63% respectively., The positive improvements in water productivity were not linear and in some districts, the water productivity values were lower than in the growing season before. This was also the case in the past irrigation season, as the average of the three different districts was only 1% higher compared to the previous irrigation season (2021). This deviation is likely a result of different farm management practices and a change in the water productivity analysis, as the methodology was further improved and the AquaCrop model runs were judged more strictly.

7.2 Sub-basin scale

The sub-basin community-scale water productivity was calculated using the 300 ha areas surrounding PPCs and the water productivity values as provided on the WaPOR data portal. The baseline values were not included for this spatial level in the baseline assessment report. In this case, the basin baseline values were used to calculate normalized water productivity.

Table 17 presents the results of the baseline and comparison with the 2022 irrigation season results. The overall increase in water productivity was observed to be +11% for Báruè, +4% for Moatize, and +17% for Nhamatanda. This indicates positive impact is achieved in the areas surrounding the PPCs and ultimately good practices are adopted to improve water productivity. The overall increase in water productivity is +11%, which is lower than the field scale water productivity due to the spatial scale being larger. It is assumed that the adoption of good agricultural practices is more dispersed at a large spatial scale.

Table 17. Biomass water productivity (kg/m3) for the 2022 irrigation season at the sub-basin scale compared to the baseline of 2015-2020 as derived from the WaPOR data portal.

	Báruè	Moatize	Nhamatanda	Overall
Baseline average 2015 – 2018	1.50	1.48	1.31	
Irrigation season 2022	1.95	1.63	1.42	
Irrigation season 2022 (normalized)	1.67	1.54	1.53	
Relative change with baseline (%)	+11%	+4%	+17%	**+11%**

For the sub-basins, an overall assessment of the change in water productivity through the project years was done as well. As the 2019 irrigation season did not include a sub-basin analysis, only the last three years were included. These results are depicted in Figure 29 where values in the table indicate the water productivity of the corresponding irrigation season in that district. The values located at the top of the bars indicate the percentual change from the baseline.

Báruè and Nhamatanda saw a positive change in water productivity throughout the years. In Moatize, the water productivity was lower than the baseline for most years, but there is an upward trend since 2020. Looking at 2022, the water productivity increase was less than in 2021. Looking at all three years, the positive improvements in water productivity were not linear and in some cases the water productivity increase was lower than the growing season before, compared to the baseline. It requires further investigation to determine the magnitude of the increase compared to the baseline, but the decrease compared to the previous year is related to the field interventions and adoption by the community and/or slightly changing analysis methods.

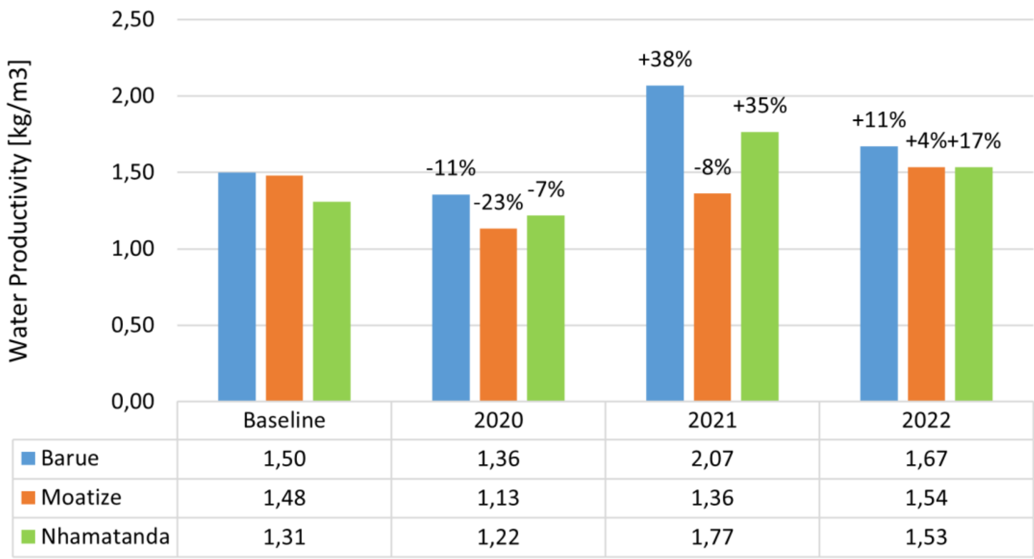


Figure 29. Overview of the water productivity results for the sub-basin scale

7.3 Basin scale

The assessment of water productivity at basin scale was performed using the WaPOR results from chapter 6. These indicate the water productivity values for cropland pixels at the selected basins of the project for the irrigation season. Table 18 presents the values of biomass water productivity after normalizing for the 2022 weather conditions and comparing with the baseline values. An average increase of biomass water productivity of +34% was perceived, ranging from +27% to +44% for the different districts.

Table 18. Biomass water productivity (kg/m^3) for the 2022 irrigation season at basin scale compared to the baseline

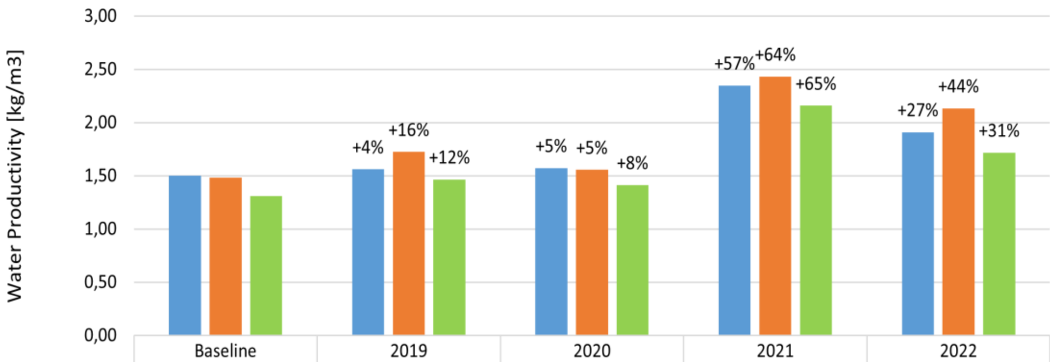
	Bárùè	Moatize	Nhamatanda	Overall
Baseline average 2001-2018	1.50	1.48	1.31	
Irrigation season 2022	1.90	1.83	1.54	
Irrigation season 2022 (normalized)	1.91	2.13	1.72	
Relative change with baseline (%)	+27%	+44%	+31%	**+34%**

Lastly, an overall assessment for the change in water productivity was conducted for the basin analyses. The results are depicted in Figure 30 where values in the table indicate the water productivity of the corresponding irrigation season in that district. The values located at the top of the bars indicate the percentual change compared to the baseline.

All districts saw a positive change in water productivity throughout the years. The water productivity of Bárùè increased by +27%, Moatize improved by +44% and Nhamatanda increased by +31%. The previous irrigation season report (2021)[1] indicated an overall biomass water productivity increase of +62%, indicating that the 2022 irrigation season had a lower increase in water productivity at basin scale compared to the previous year.

[1] Van Opstal, J.D., M. de Klerk, V. Hollander. 2021. Water Productivity Analysis: Irrigation Season 2021. FutureWater Report 236.

The positive improvements in water productivity were not linear and in some cases the water productivity values were lower than the growing season before. This deviation is likely a result of different farm management practices.



	Baseline	2019	2020	2021	2022
Barue	1,50	1,56	1,57	2,35	1,91
Moatize	1,48	1,72	1,56	2,43	2,13
Nhamatanda	1,31	1,47	1,41	2,16	1,72

Figure 30. Overview of the water productivity results for the basin scale

8 Concluding remarks

For the major irrigation season crops improvements in field scale water productivity were found of +55%, +29%, and +63% for Báruè, Moatize, and Nhamatanda respectively, resulting in an average improvement of +49%. This overall average achieves the set target for 2022 of +25% as stated in the project logframe however, is only 1% higher than the previous irrigation season (2021) because of an improved methodology and stricter judgment in modelling decisions. The results of the field water productivity give a good indication of trends in high and low water productivity.

Furthermore, the water productivity was calculated at the sub-basin scale, which is representative of the community of farmers adopting practices being demonstrated and promoted by the selected PPCs. An area of 300 ha around each selected PPC is determined to be representative of the area of the sub-basin (or community). At the sub-basin scale, the water productivity analysis makes use of the WaPOR data portal and calculates biomass water productivity. The highest water productivity values were found in Báruè. Here the highest values are observed in Báruè III at 3.11 kg/m^3. The biomass water productivity was found to range from 2.84 to 3.11 kg/m^3 in Báruè, 2.16 to 2.95 kg/m^3 in Moatize, and 2.15 to 2.23 kg/m^3 in Nhamatanda. The relative change of water productivity compared to the baseline values is +11%, +4% and +17% for Báruè, Moatize, and Nhamatanda, respectively. The overall increase in water productivity estimated at sub-basin (community) level is +11%. The overall increase in the 2021 irrigation season was 33%, indicating a change in the sharing of farm management practices amongst farmers in 2022. The target for the 2022 irrigation season of +25% biomass water productivity increase set at the beginning of the project was not met. Over the course of the whole project an upward increase of water productivity at the basin scale was perceived, but the positive improvements were not linear. It requires further investigation to determine the magnitude of the increase compared to the baseline, but the decrease compared to the previous year is related to the field interventions and adoption by the community and/or slightly changing analysis methods.

At basin scale the catchment delineation from each district was used as the boundary of the basin. The water productivity was determined using the WaPOR data portal providing values on biomass water productivity. These values are compared with the baseline assessment and determined that an increase of water productivity was achieved of +27%, +44%, and +31% for Báruè, Moatize, and Nhamatanda respectively. The average increase in biomass water productivity was +34% for all districts together. This overall average achieves the target set for 2022 of +25% increase in biomass water productivity for the basin scale as stated in the project logframe. However, in the 2021 irrigation season the overall increase in biomass water productivity was +62%. The 2022 irrigation season had a lower increase in water productivity at basin scale compared to the previous year, but when you look at all the irrigation seasons, there is an upward trend in biomass water productivity increase. The positive improvements in water productivity were not linear and in some cases the water productivity values were lower than the growing season before. This deviation is likely a result of different farm management practices.

Finally, it is noticed that the field scale water productivity increase was similar to last year's irrigation season (49% vs 48%), while at sub-basin (11% vs 33%) and basin scale (34% vs 62%) the water productivity increase was less compared to last year. As APSAN-Vale farmers had a similar field scale water productivity increase but results including non-APSAN-Vale farmers (i.e. on the sub-basin and basin scale) were lower than last year, this might indicate that APSAN-Vale farmers are more resistant to climatic challenges influencing their harvests than non-APSAN-Vale farmers.

All results will be combined with the monitoring data from the APSAN-Vale consortium partners, indicating the adoption of practices of these farmers and the training sessions that were attended, in the final 'APSAN-Vale Impact Report'.

Annex 1 – Overview of input data

Table 19. Field input data for Báruè

					Soil		Crop					Field mgt					
Year	Irrigation / rainfed	Region	ID plot	Name farmer	Soil texture (sandyloam, etc)	Stoniness (low, moderate, high)	Crop type (EN)	Crop type (PT)	Planting date	Harvest date (optional) Data de Colheita	Planting density [plnts/m2]	Fertilizer use (low, moderate, optimal)	Mulching yes/no	Weed mgt (low, moderate, high)	Runoff mgt (yes/no)	Irrigation (yes/no)	Irrigation method
2022	Irrigation	Barue	AP_BA_ACI-01-01	Ananias Chicumba	sandy clay	low	cabbage	couve	5-Jun-2022	28-sep	50x65	optimal	no	high	yes	yes	sprinkler
2022	Irrigation	Barue	AP_BA_ACI-01-02	Ananias Chicumba	sandy clay	low	cabbage	repolho	30-May-2022	12-okt	60x70	optimal	no	high	yes	yes	sprinkler
2022	Irrigation	Barue	AP_BA_ACI-01-03	Ananias Chicumba	sandy clay	low	tsunga	tsunga	17-Jul-2022	6-okt	45x50	optimal	no	high	yes	yes	sprinkler
2022	Irrigation	Barue	AP_BA_ACI-01-04	Ananias Chicumba	sandy clay	low	tomato	tomate	22-May-2022	27-sep	60x70	optimal	no	high	yes	yes	sprinkler
2022	Irrigation	Barue	AP_BA_AR-01-01	Arselio Robat	sandy clay	low	tsunga	tsunga	28-May-2022	15-sep	45x50	optimal	yes	high	yes	yes	surface
2022	Irrigation	Barue	AP_BA_AR-01-02	Arselio Robat	sandy clay	low	cabbage	repolho	28-May-2022	12-okt	60x70	optimal	yes	high	yes	yes	surface
2022	Irrigation	Barue	AP_BA_AR-01-03	Arselio Robat	sandy clay	low	maize	milho	20-May-2022	4-okt	80x50	optimal	yes	high	yes	yes	surface
2022	Irrigation	Barue	AP_BA_AR-01-04	Arselio Robat	sandy clay	low	tomato	tomate	19-Jun-2022	14-okt	60x70	optimal	yes	high	yes	yes	surface
2022	Irrigation	Barue	AP_BA_AR-01-05	Arselio Robat	sandy clay	low	onion	cebola	4-Jul-2022	24-okt	20x20	optimal	yes	high	yes	yes	surface
2022	Irrigation	Barue	AP_BA_CN-01-01	Charles Nhamassi	sandy clay	low	beans	feijao	27-Jul-2022	2-nov	50x10	optimal	yes	moderate	yes	tes	surface
2022	Irrigation	Barue	AP_BA_CN-01-02	Charles Nhamassi	sandy clay	low	maize	milho	16-Jul-2022	20-nov	80x50	optimal	yes	moderate	yes	tes	surface
2022	Irrigation	Barue	AP_BA_CN-01-03	Charles Nhamassi	sandy clay	low	lettuce	alface	20-Jun-2022	23-aug	60x20	optimal	yes	moderate	yes	tes	surface
2022	Irrigation	Barue	AP_BA_CN-01-04	Charles Nhamassi	sandy clay	low	cabbage	couve	22-Jun-2022	3-okt	50x65	optimal	yes	moderate	yes	tes	surface
2022	Irrigation	Barue	AP_BA_JR-01-01	Joelmo da Rosa	sandy clay	low	cabbage	couve	17-Jul-2022	28-okt	50x65	moderate	yes	low	yes	yes	surface
2022	Irrigation	Barue	AP_BA_JR-01-02	Joelmo da Rosa	sandy clay	low	tsunga	tsunga	24-Jul-2022	5-okt	45x50	moderate	yes	low	yes	yes	surface
2022	Irrigation	Barue	AP_BA_JR-01-03	Joelmo da Rosa	sandy clay	low	beans	feijao	19-Jul-2022	4-nov	50x10	moderate	yes	low	yes	yes	surface
2022	Irrigation	Barue	AP_BA_JR-01-04	Joelmo da Rosa	sandy clay	low	cabbage	repolho	17-Jul-2022	24-okt	60x70	moderate	yes	low	yes	yes	surface
2022	Irrigation	Barue	AP_BA_LJ-01-01	Lucas Jossefa	sandy clay	low	carrot	cenoura	4-Jul-2022	23-nov	5x5	optimal	yes	moderate	yes	yes	surface
2022	Irrigation	Barue	AP_BA_LJ-01-02	Lucas Jossefa	sandy clay	low	cabbgae	couve	12-Jul-2022	8-okt	50x65	optimal	yes	moderate	yes	yes	surface
2022	Irrigation	Barue	AP_BA_LJ-01-03	Lucas Jossefa	sandy clay	low	lettuce	alface	17-Jul-2022	16-sep	60x20	optimal	yes	moderate	yes	yes	surface
2022	Irrigation	Barue	AP_BA_LJ-01-04	Lucas Jossefa	sandy clay	low	onion	cebola	28-Jul-2022	26-nov	20x20	optimal	yes	moderate	yes	yes	surface
2022	Irrigation	Barue	AP_BA_MD-01-01	Modesto Dique	sandy clay	low	beans	feijao	29-Aug-2022	Not harvest	50x10	optimal	no	high	yes	yes	surface
2022	Irrigation	Barue	AP_BA_RF-01-01	Reunor Finiasse	sandy clay	low	cabbage	repolho	14-Jul-2022	27-okt	60x70	optimal	yes	moderate	yes	yes	surface
2022	Irrigation	Barue	AP_BA_RF-01-02	Reunor Finiasse	sandy clay	low	tomato	tomate	22-Jul-2022	29-okt	60x70	optimal	yes	moderate	yes	yes	surface
2022	Irrigation	Barue	AP_BA_RF-01-03	Reunor Finiasse	sandy clay	low	cabbage	couve	14-Jul-2022	11-okt	50x65	optimal	yes	moderate	yes	yes	surface
2022	Irrigation	Barue	AP_BA_RF-01-04	Reunor Finiasse	sandy clay	low	onion	cebola	29-May-2022	24-okt	20x20	optimal	yes	moderate	yes	yes	surface
2022	Irrigation	Barue	AP_BA_RF-01-05	Reunor Finiasse	sandy clay	low	carrot	cenoura	15-Jun-2022	4-okt	5x5	optimal	yes	moderate	yes	yes	surface
2022	Irrigation	Barue	AP_BA_RF-01-06	Reunor Finiasse	sandy clay	low	tsunga	tsunga	1-Jun-2022	23-sep	45x50	optimal	yes	moderate	yes	yes	surface
2022	Irrigation	Barue	AP_BA_SE-01-01	Simon Eduardo	sandy clay	low	maize	couve	2-Aug-2022	22-okt	50x65	optimal	no	high	yes	yes	surface
2022	Irrigation	Barue	AP_BA_SE-01-02	Simon Eduardo	sandy clay	low	cabbage	repolho	1-Aug-2022	30-okt	60x70	optimal	no	high	yes	yes	surface
2022	Irrigation	Barue	AP_BA_SE-01-03	Simon Eduardo	sandy clay	low	onion	cebola	25-Jul-2022	Not harvest	20x20	optimal	no	high	yes	yes	surface
2022	Irrigation	Barue	AP_BA_SE-01-04	Simon Eduardo	sandy clay	low	beans	feijao	28-Jul-2022	Not harvest	50x10	optimal	no	high	yes	yes	surface
2022	Irrigation	Barue	AP_BA_TV-01-01	Tino Vasco	sandy clay	low	cabbage	repolho	6-Jun-2022	23-okt	60x70	moderate	no	moderate	yes	yes	surface
2022	Irrigation	Barue	AP_BA_ZM-01-01	Zacarias Manuel	sandy clay	low	ginger	gengibre	13-Apr-2022	Not harvest	30x50	optimal	yes	moderate	yes	yes	surface
2022	Irrigation	Barue	AP_BA_ZM-01-02	Zacarias Manuel	sandy clay	low	maize	milho	19-Jul-2022	14-nov	80x50	optimal	yes	moderate	yes	yes	surface
2022	Irrigation	Barue	AP_BA_ZM-01-03	Zacarias Manuel	sandy clay	low	cabbage	repolho	3-May-2022	15-sep	60x70	optimal	yes	moderate	yes	yes	surface
2022	Irrigation	Barue	AP_BA_ZM-01-04	Zacarias Manuel	sandy clay	low	beans	feijao	4-May-2022	21-sep	50x10	optimal	yes	moderate	yes	yes	surface

Table 20. Field input data for Moatize

Year	Irrigation / rainfed	Region	ID plot	Name farmer	Soil texture (sandyloam, etc)	Stoniness (low, moderate, high)	Crop type (EN)	Planting date	Harvest date (optional) Data de Colheita	Planting density [plnts/m2]	Fertilizer use (low, moderate, optimal)	Mulching yes/no	Weed mgt (low, moderate, high)	Runoff mgt (yes/no)	Irrigation (yes/no)	Irrigation method
2022	Irrigation	Moatize	MO-SA-MC-01-02	Manuel Changamica	sandy clay	low	Cabbage	2-jul	14-okt	70X60	Optimal	no	Low	no	Yes	Sprinklers
2022	Irrigation	Moatize	MO-SA-MC-01-01	Manuel Changamica	sandy clay	low	Tomato	20-jun	24-sep	85X60	Optimal	no	Low	no	Yes	Gravity
2022	Irrigation	Moatize	MO-SA-CA-01-01	Cezario Muazanane	sandy clay	low	Beans	5-apr	13-aug	90x40	Optimal	no	Low	no	Yes	Gravity
2022	Irrigation	Moatize	MO-SA-ZM-01-01	Zeca Marcelino	sandy clay	low	Beans	12-mei	17-sep	90x40	Optimal	no	Low	no	Yes	Gravity
2022	Irrigation	Moatize	MO-MA-JC-01-01	Joao Cherene	sandy clay	Moderate	Tomato	25-mei	28-aug	85x60	optimal	no	Low	no	Yes	Gravity
2022	Irrigation	Moatize	MO-MA-JC-01-02	Joao Cherene	sandy clay	Moderate	Cabbage	1-jun	19-sep	70x60	optimal	no	Low	no	Yes	Gravity
2022	Irrigation	Moatize	MO-MA-JC-01-03	Joao Cherene	sandy clay	Moderate	Beans	28-jun	18-okt	90x40	optimal	no	Low	no	Yes	Gravity
2022	Irrigation	Moatize	MO-MA-GM-01-01	Girio Mussanaruca	sandy clay	low	Tomato	16-jun	10-okt	85x60	Optimal	no	Low	no	Yes	Gravity
2022	Irrigation	Moatize	MO-MA-GM-01-02	Girio Mussanaruca	sandy clay	low	Cabbage	28-mei	30-sep	70x60	Optimal	no	Low	no	Yes	Gravity
2022	Irrigation	Moatize	MO-MA-GM-01-03	Girio Mussanaruca	sandy clay	low	Onion	16-mei	3-aug	20x15	Optimal	no	Low	no	Yes	Gravity
2022	Irrigation	Moatize	MO-MA-GM-01-04	Girio Mussanaruca	sandy clay	low	Beans	17-jun	12-okt	90x40	Optimal	no	Low	no	Yes	Gravity
2022	Irrigation	Moatize	MO-MA-JC-01-01	Jose Cinto	sandy clay	Moderate	Tomato	10-mei	19-sep	90x40	Optimal	no	Moderate	no	Yes	Gravity
2022	Rainfed	Moatize	MO-CA-AS-01-01	Antonio Sopinho	sandy clay	Low	Tomato	15-apr	2-aug	85x60	optimal	no	Low	no	Yes	Gravity
2022	Irrigation	Moatize	MO-CA-XT-01-01	Xavier Tomas	sandy clay	Moderate	Beans	13-mei	12-sep	90x50	optimal	no	Low	no	Yes	Sprinklers
2022	Irrigation	Moatize	MO-CA-XT-01-02	Xavier Tomas	sandy clay	Moderate	Cabbage	22-mei	26-sep	70x60	optimal	no	Low	no	Yes	Sprinklers
2022	Irrigation	Moatize	MO-CA-MC-01-01	Mario Chauque	sandy clay	Moderate	Potatoes	24-mei	28-sep	70x60	optimal	no	Low	no	Yes	Sprinklers

Table 21. Input field data for Nhamatanda

Year	Irrigation / rainfed	Region	ID plot	Name farmer	Soil texture (sandyloam, etc)	Stoniness (low, moderate, high)	Crop type (EN)	Planting date	Harvest date (optional)	Planting density [plnts/m2]	Fertilizer use (low, moderate, optimal)	Weed mgt (low, moderate, high)	Runoff mgt (yes/no)	Irrigation (yes/no)	Irrigation method
2022	Irrigated	Nhamatand	AP_NH_JA_01_	Jose Anderson	sandy clay	Low	Tomato	2-jul	5-okt	85x60	Optimal	Low	no	yes	Gravety
2022	Irrigated	Nhamatand	AP_NH_FM_01_	Flora Mustico	sandy clay	Low	Beans	10-mei	18-sep	85x60	Optimal	Low	no	yes	Gravety
2022	Irrigated	Nhamatand	AP_NH_LB_01_	Lucas Bernardo	sandy clay	Low	Cabbage	10-mei	3-okt	50x50	Optimal	Low	no	yes	Gravety
2022	Irrigated	Nhamatand	AP_NH_LB_01_	Lucas Bernardo	sandy clay	Low	Maize	6-jun	11-okt	80x50	Optimal	Low	no	yes	Gravety
2022	Irrigated	Nhamatand	AP_NH_DP_01_	Domingos Pedro	sandy clay	Low	Beans	26-mei	1-okt	85x60	Optimal	Low	no	yes	Gravety
2022	Irrigated	Nhamatand	AP_NH_DP_01_	Domingos Pedro	sandy clay	Low	Cabbage	14-jun	9-okt	50x50	Optimal	Low	no	yes	Gravety
2022	Irrigated	Nhamatand	AP_NH_MD_01	Manuel Dique	sandy clay	Low	Beans	18-apr	9-sep	85x60	Optimal	Low	no	yes	Gravety
2022	Irrigated	Nhamatand	AP_NH_MD_01	Manuel Dique	sandy clay	Low	Cabbage	17-jun	28-sep	50x50	Optimal	Low	no	yes	Gravety
2022	Irrigated	Nhamatand	AP_NH_JD_01_	Jose Domingos	sandy clay	Low	Maize	7-mrt	12-okt	80x50	Optimal	Low	no	yes	Gravety
2022	Irrigated	Nhamatand	AP_NH_JD_01_	Jose Domingos	sandy clay	Low	Cabbage	15-mei	19-aug	50x50	Optimal	Low	no	yes	Gravety
2022	Irrigated	Nhamatand	AP_NH_M_01_(	Manuel	sandy clay	Low	Onion	28-mei	16-sep	20x15	Optimal	Low	no	yes	Gravety
2022	Irrigated	Nhamatand	AP_NH_M_01_(	Manuel	sandy clay	Low	Cabbage	22-mei	27-aug	50x50	Optimal	Low	no	yes	Gravety
2022	Irrigated	Nhamatand	AP_NH_M_01_(	Manuel	sandy clay	Low	Beans	2-jun	5-okt	85x60	Optimal	Low	no	yes	Gravety

Annex 2 – Canopy cover curves

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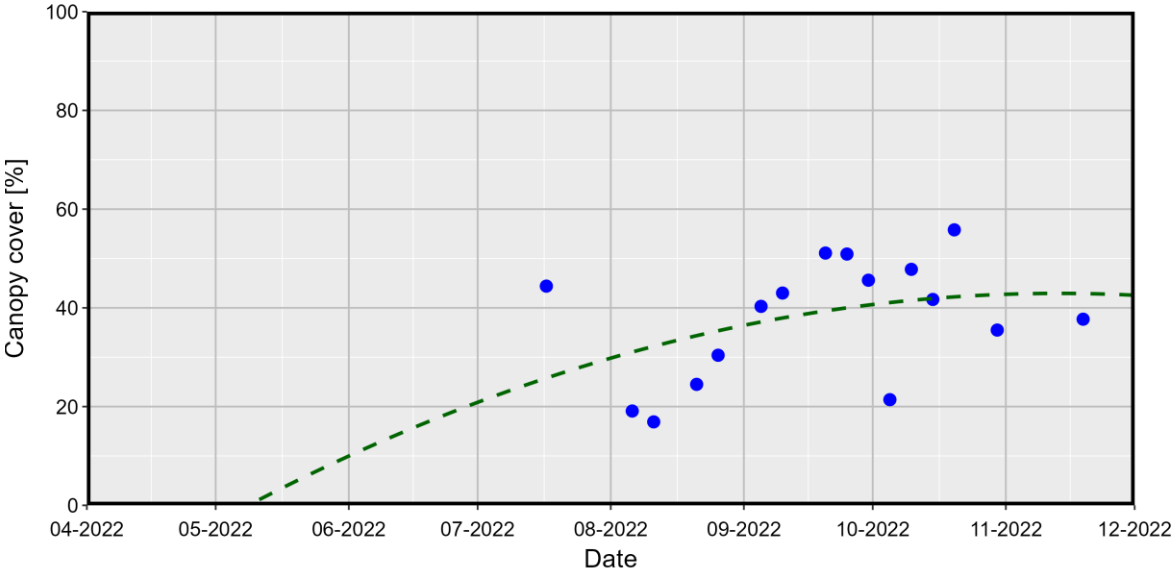

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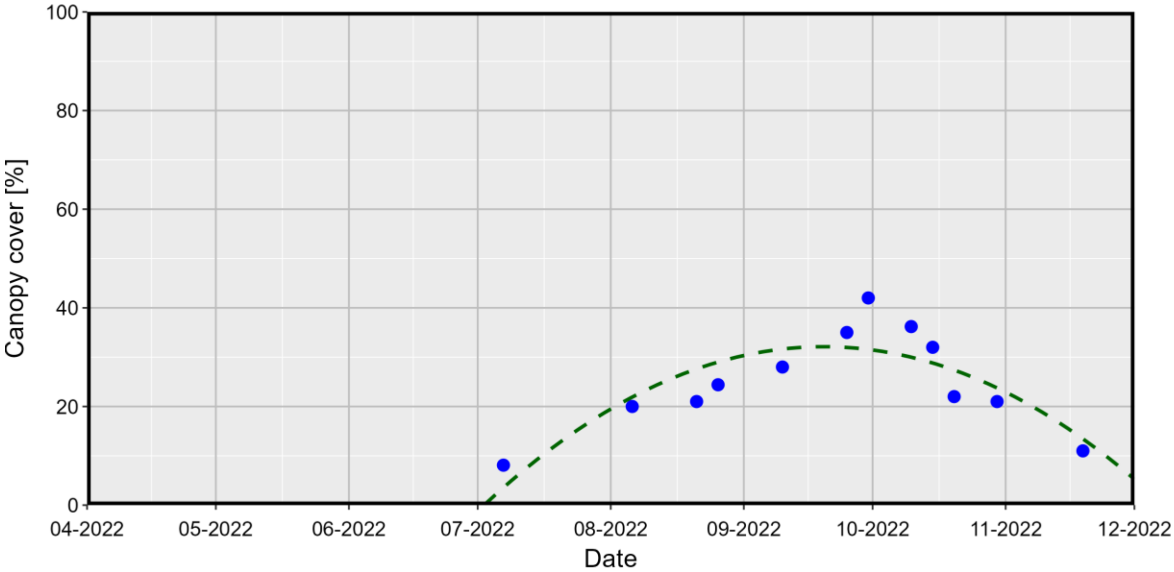

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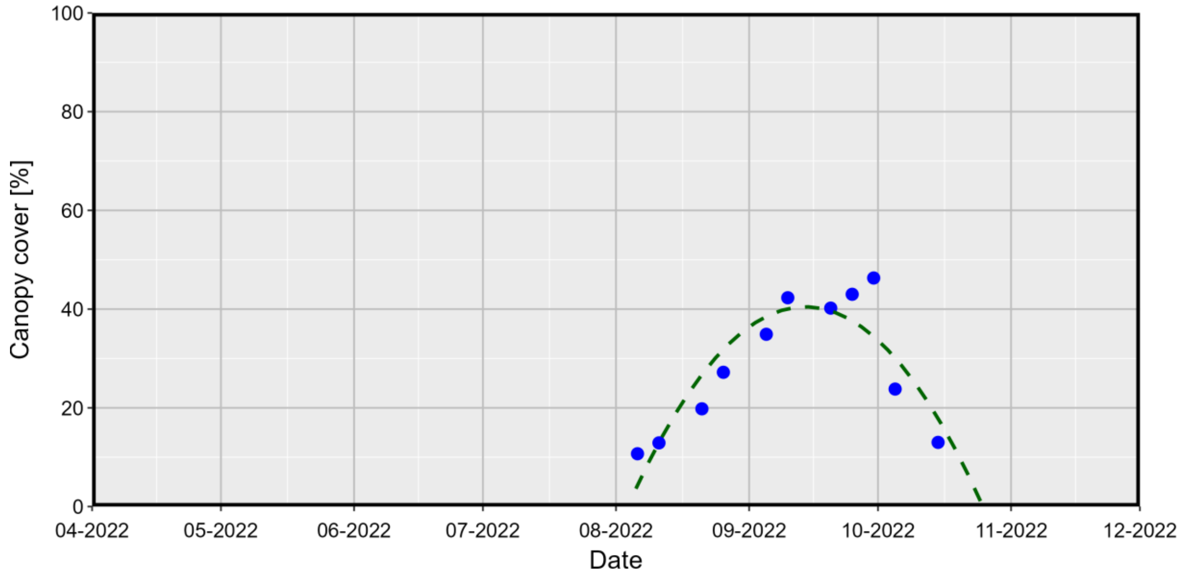

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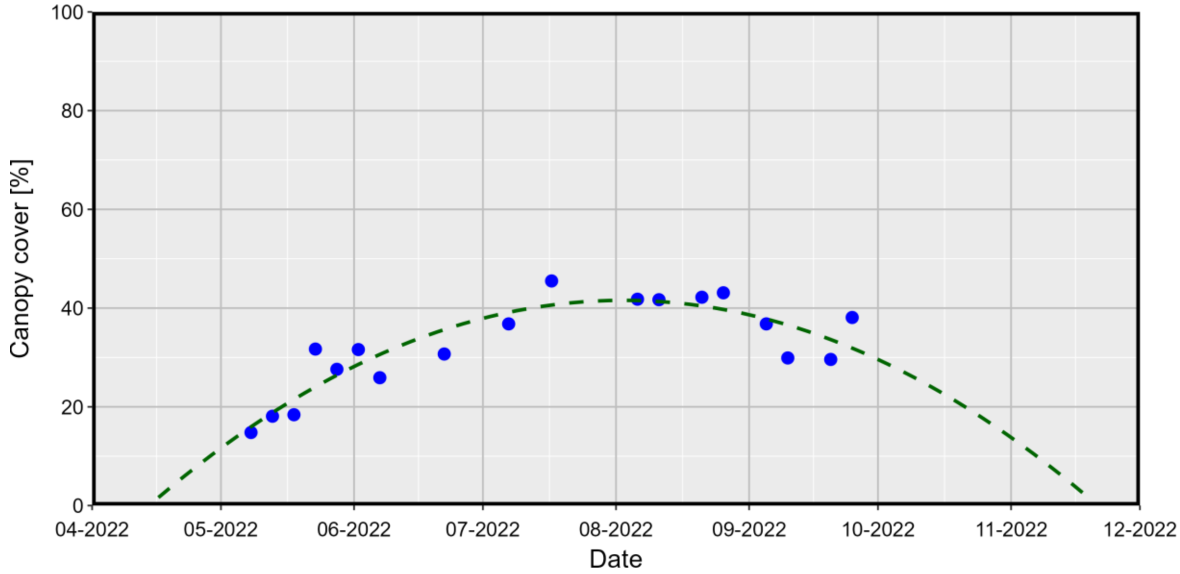

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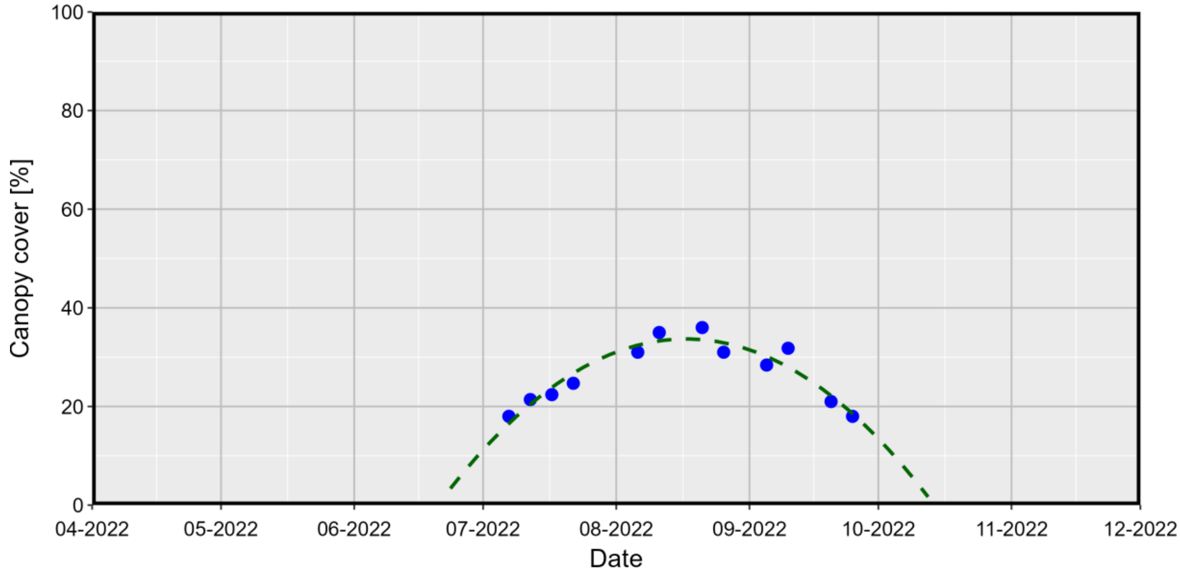

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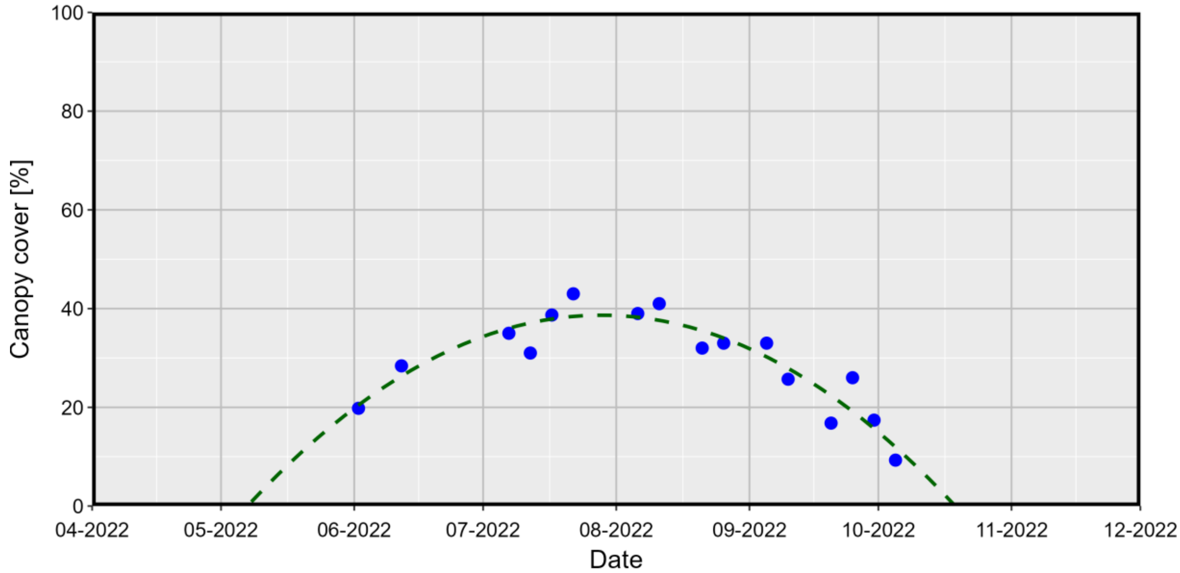

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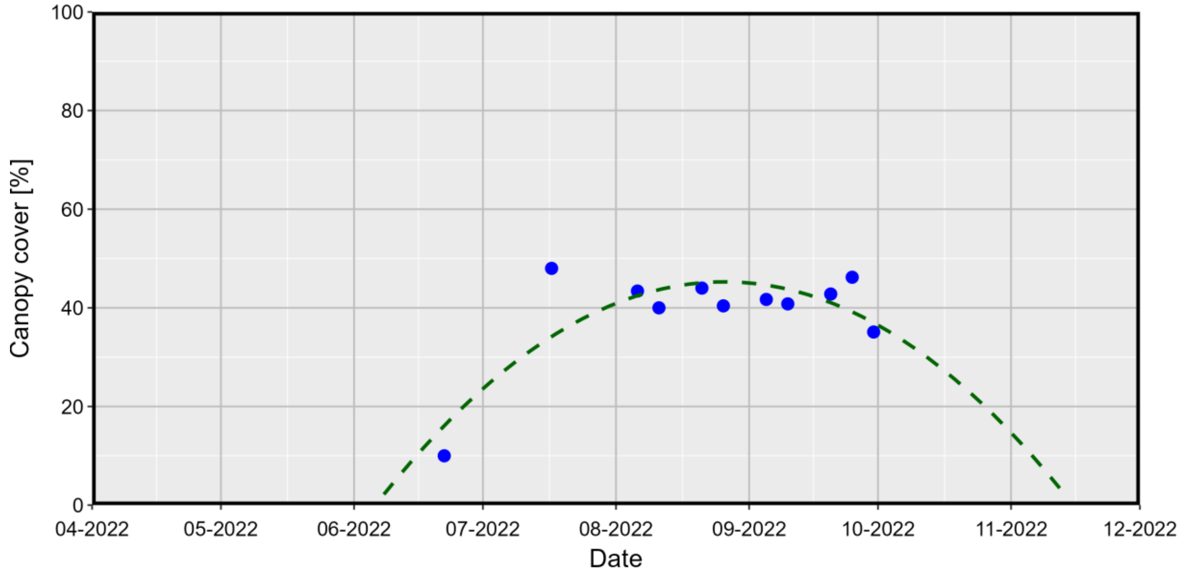

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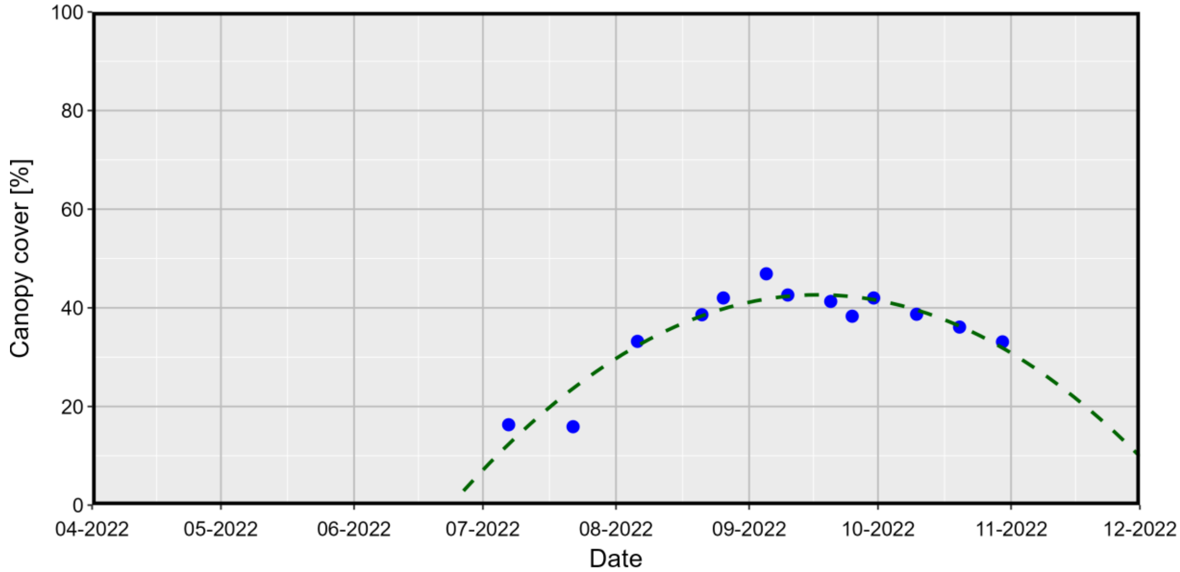

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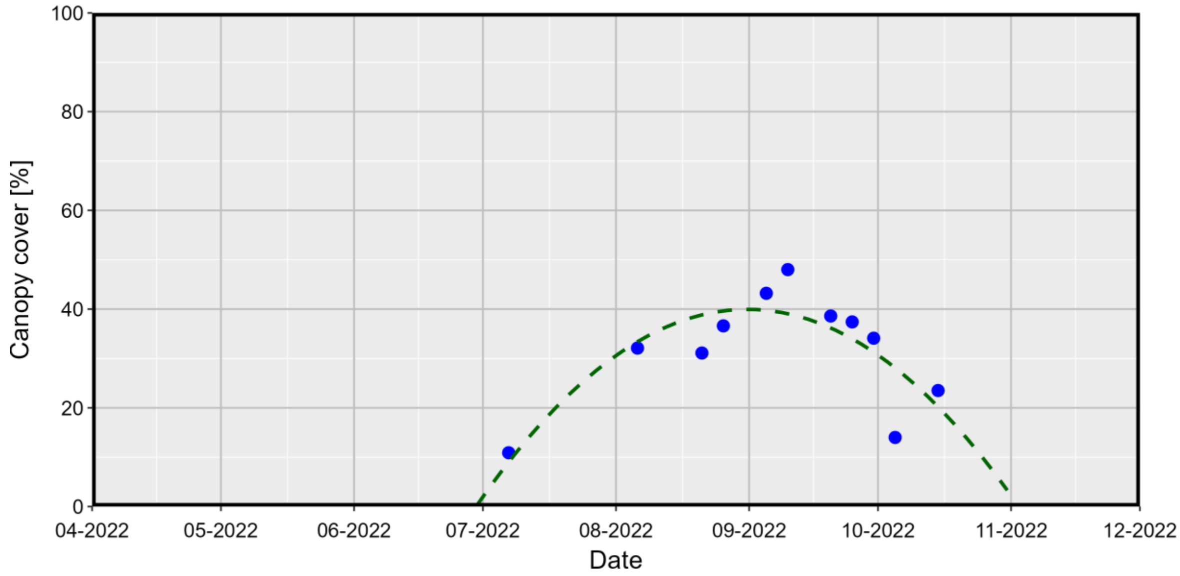

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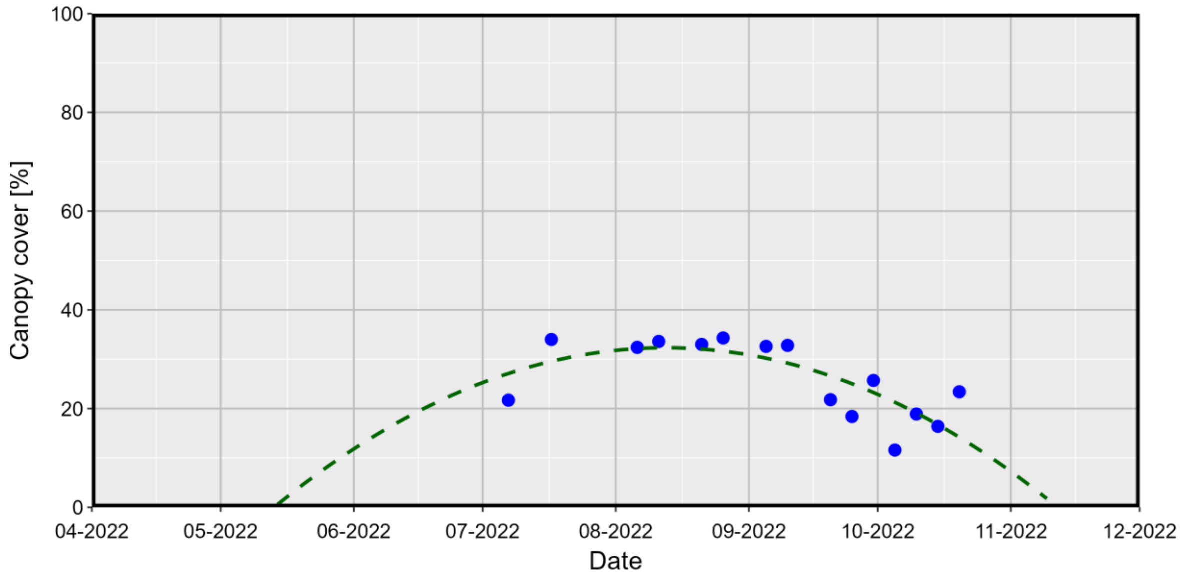

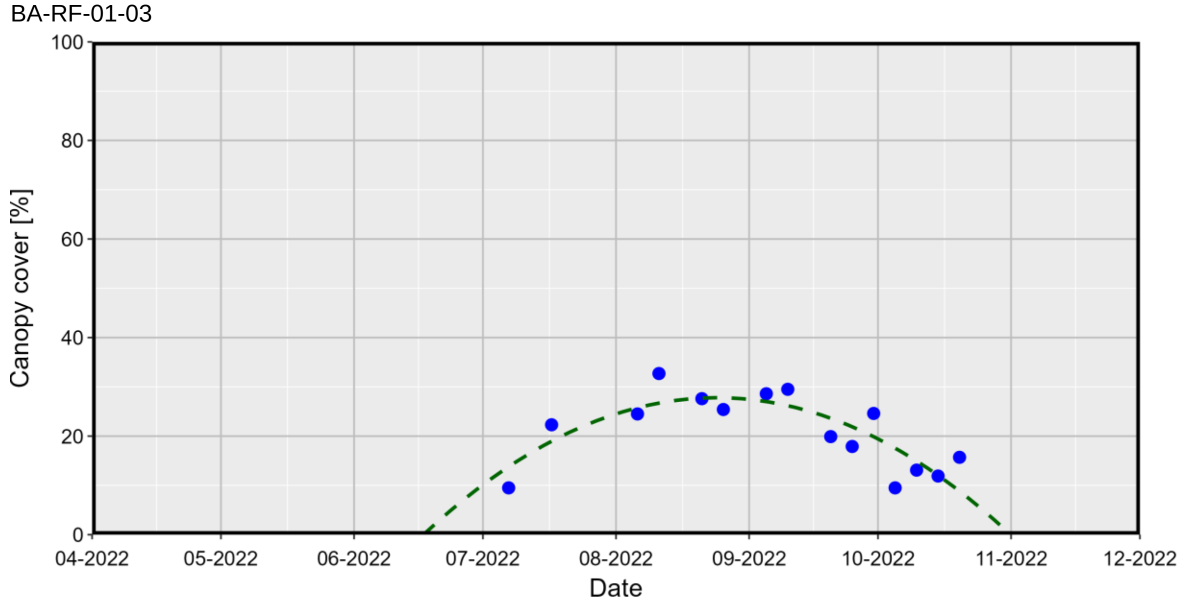
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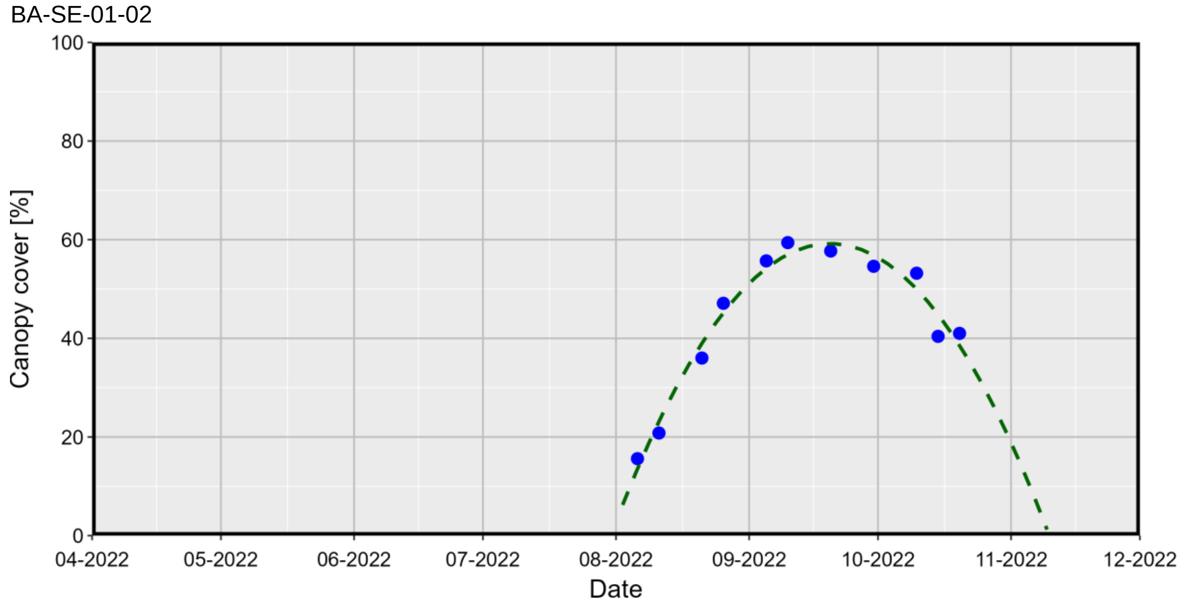
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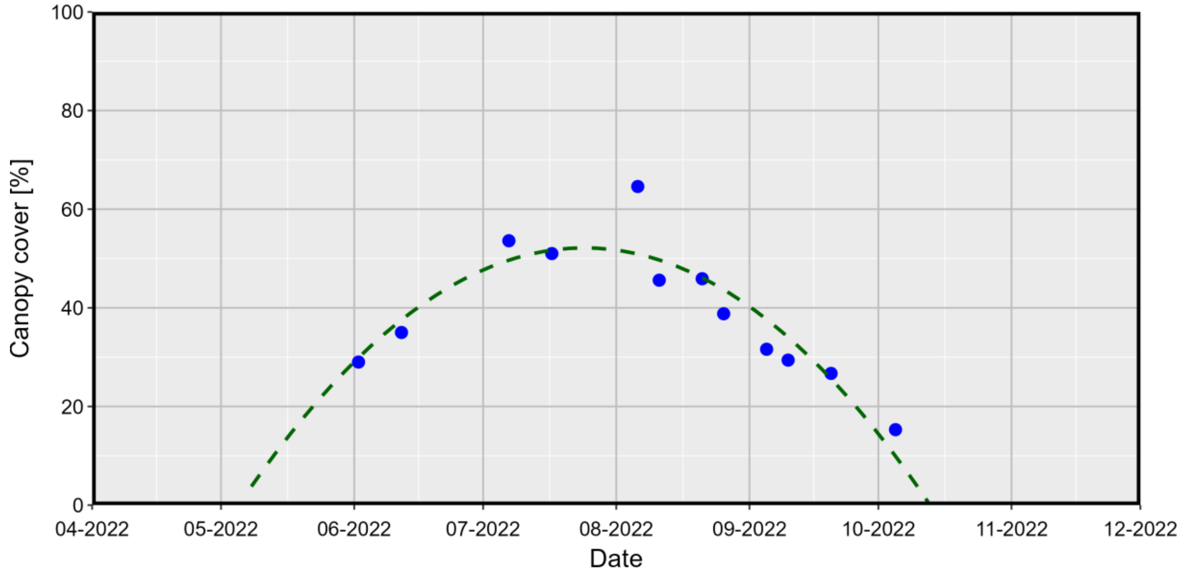

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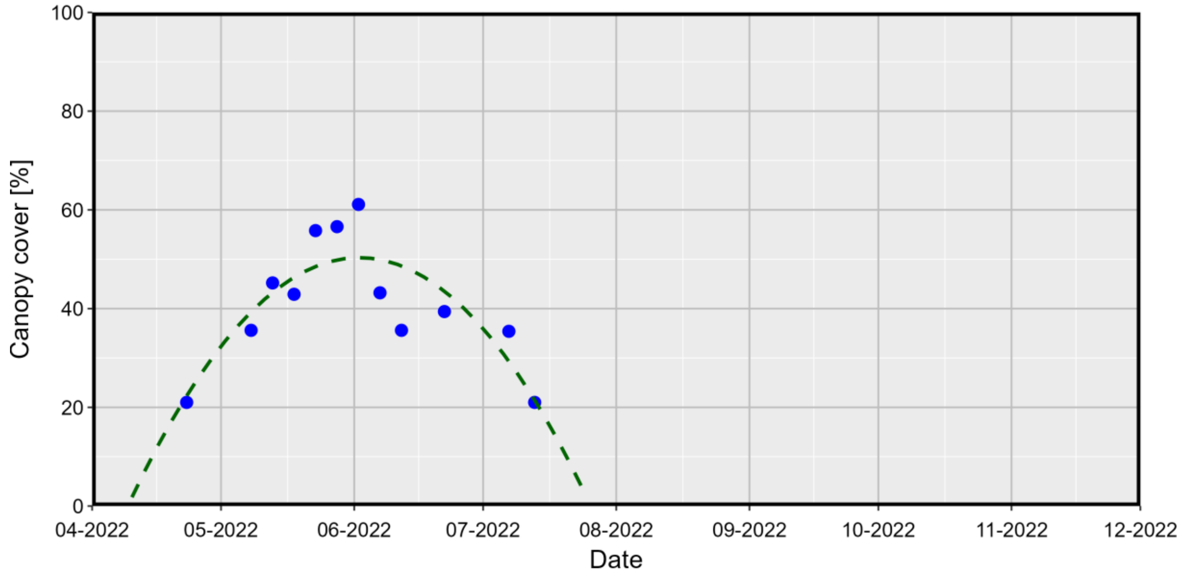

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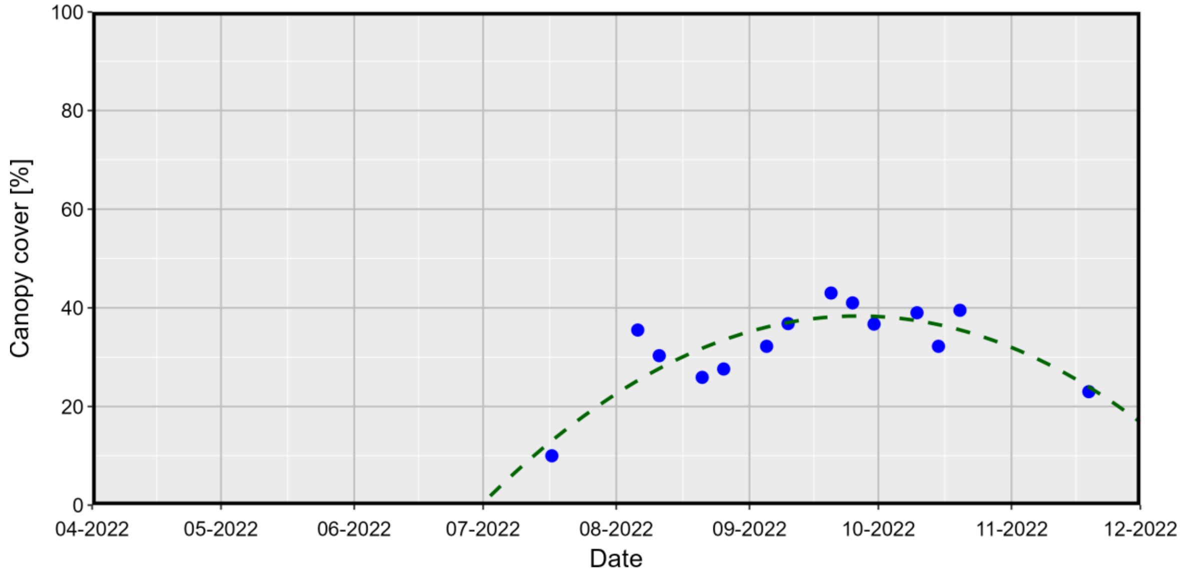

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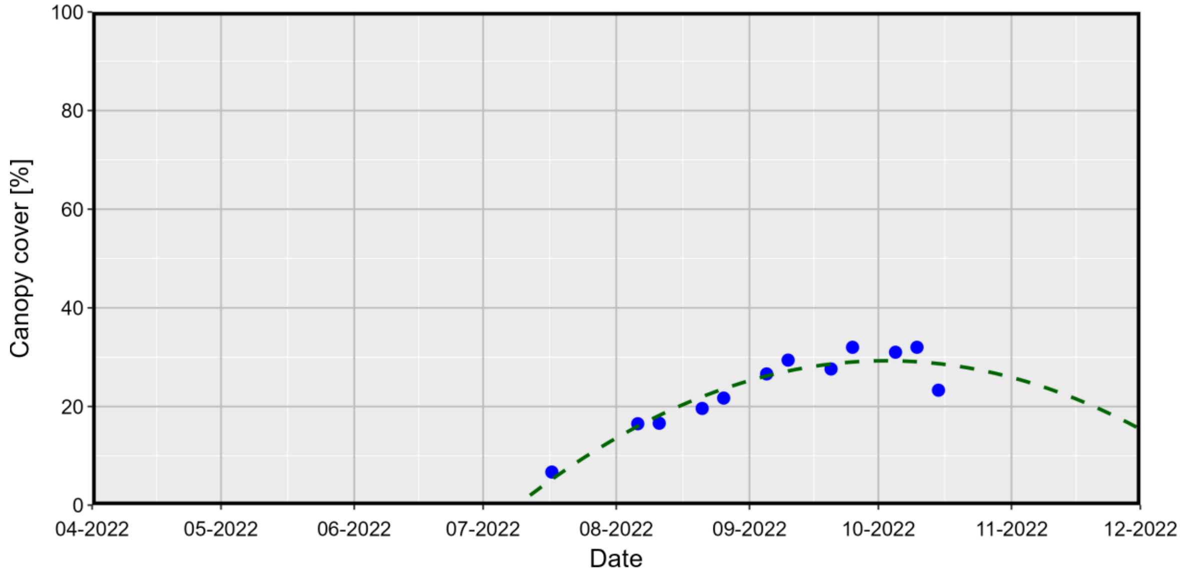

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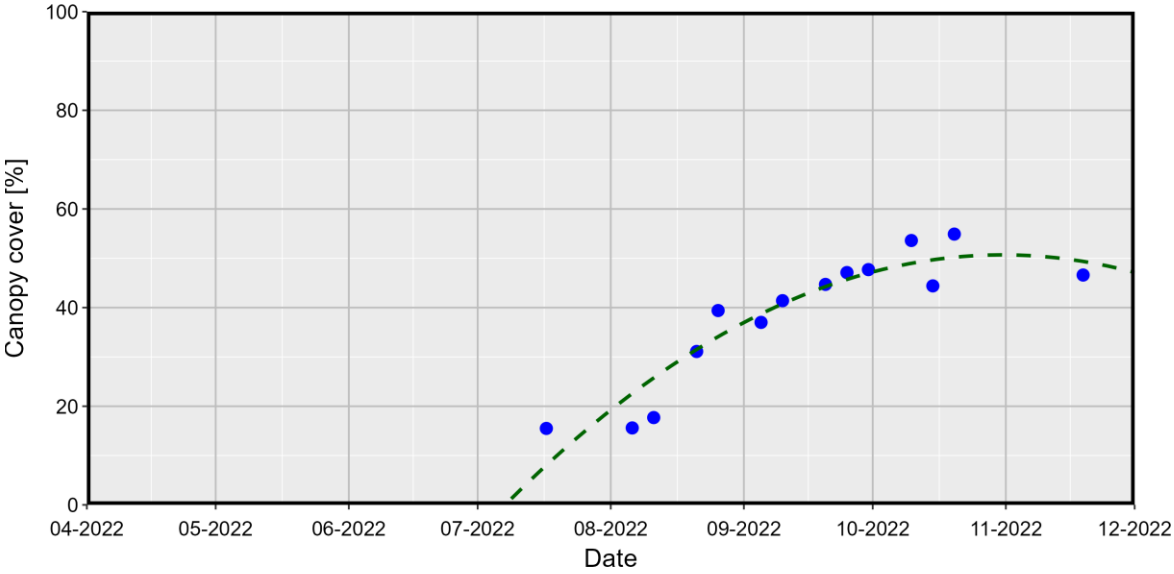

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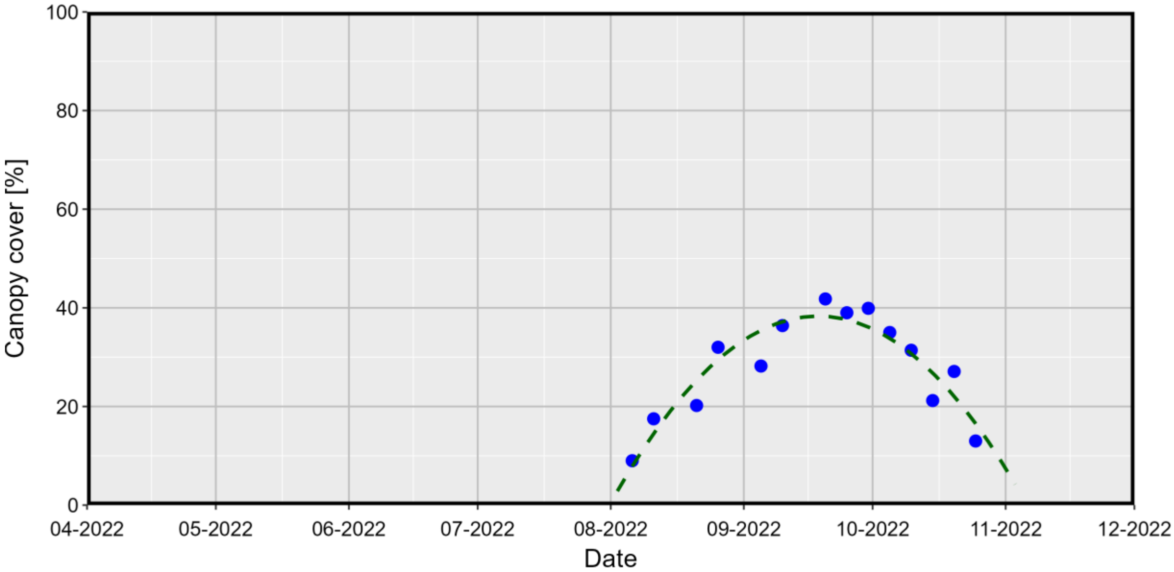

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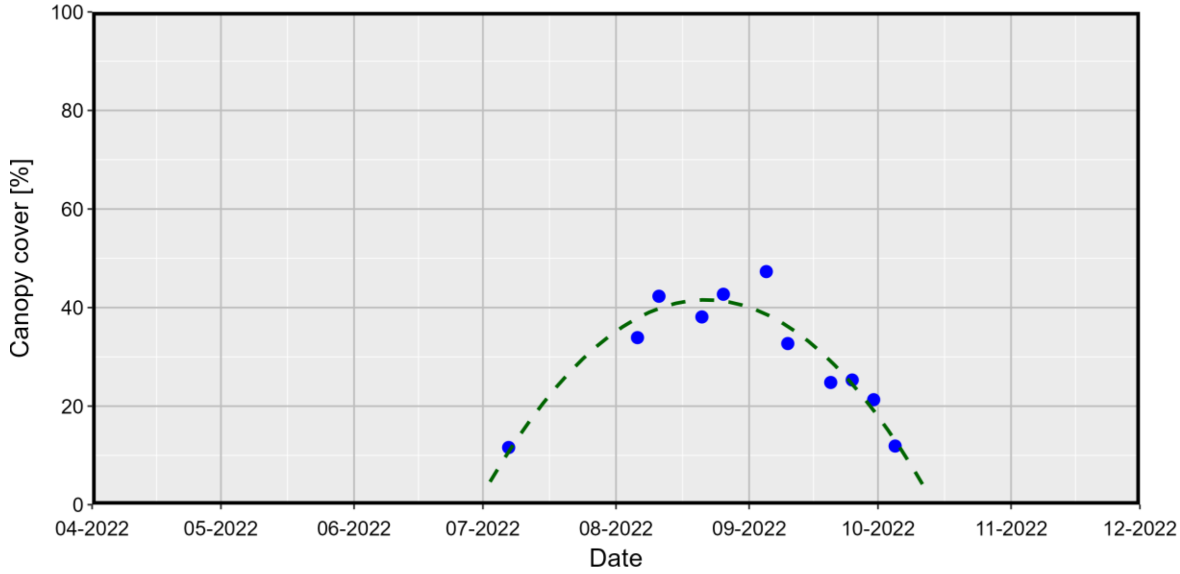

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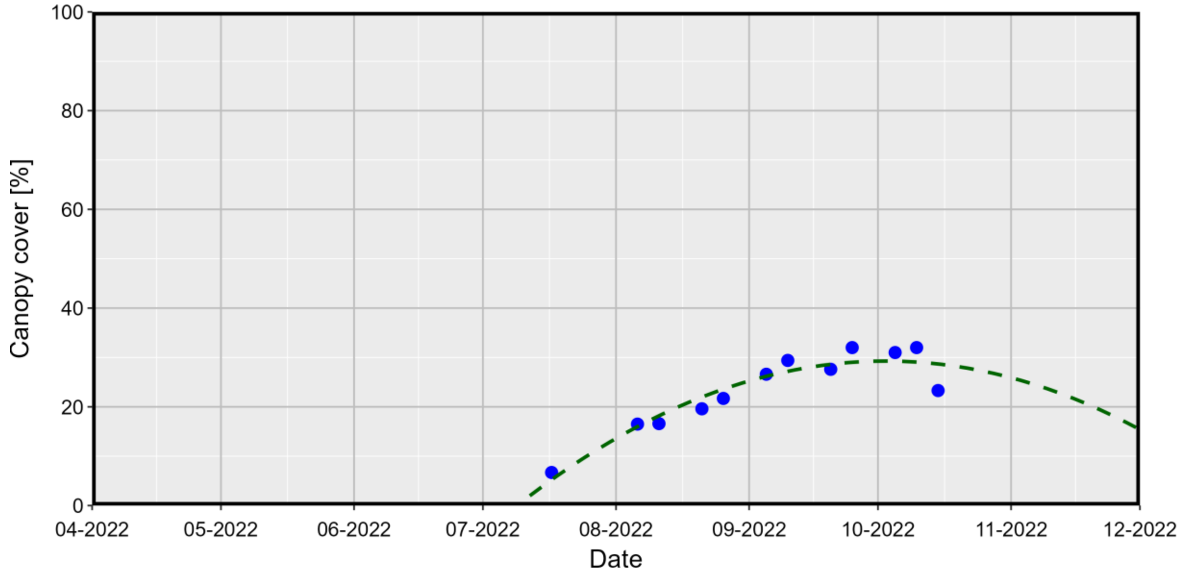

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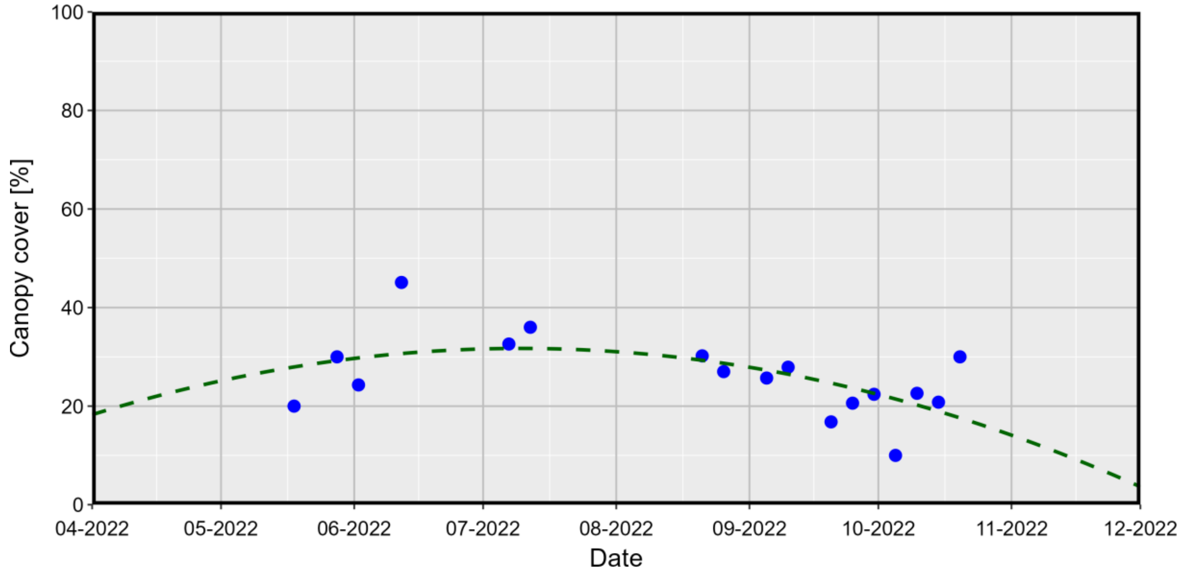

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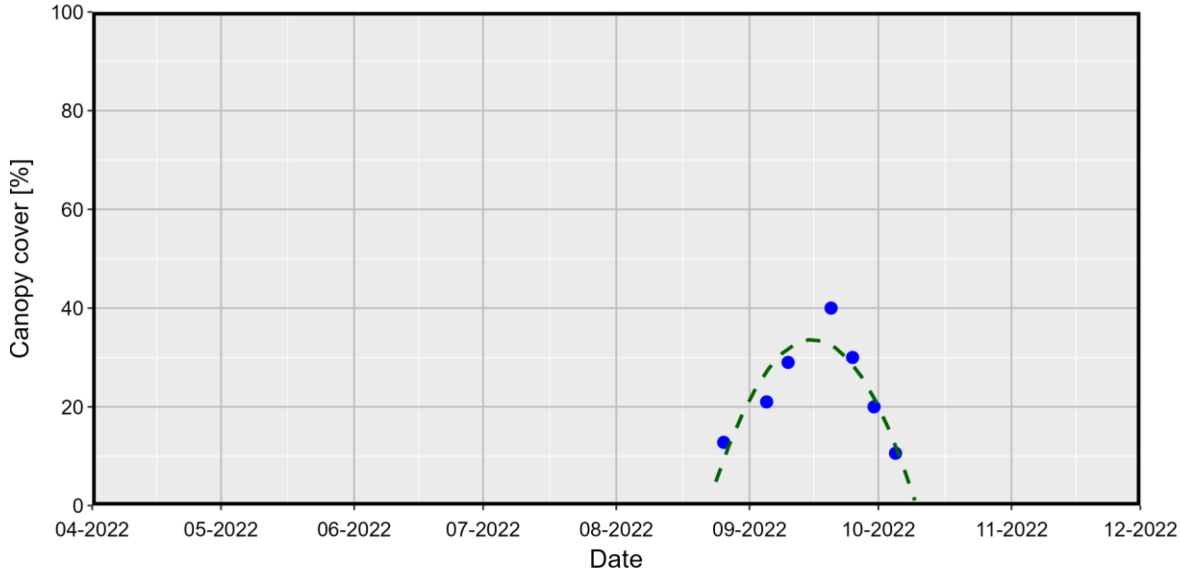

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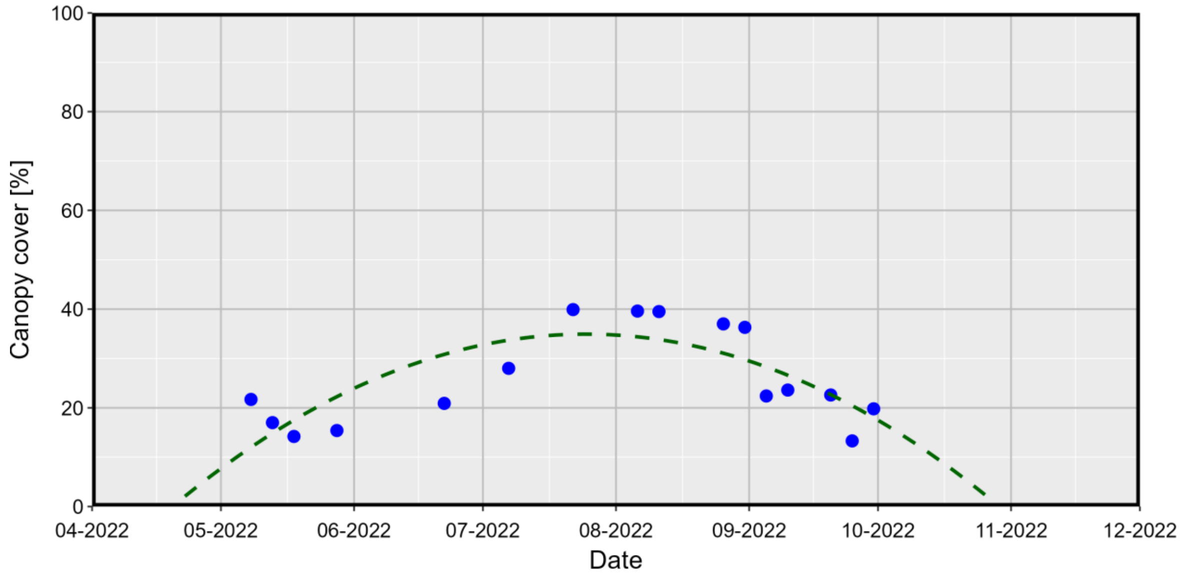

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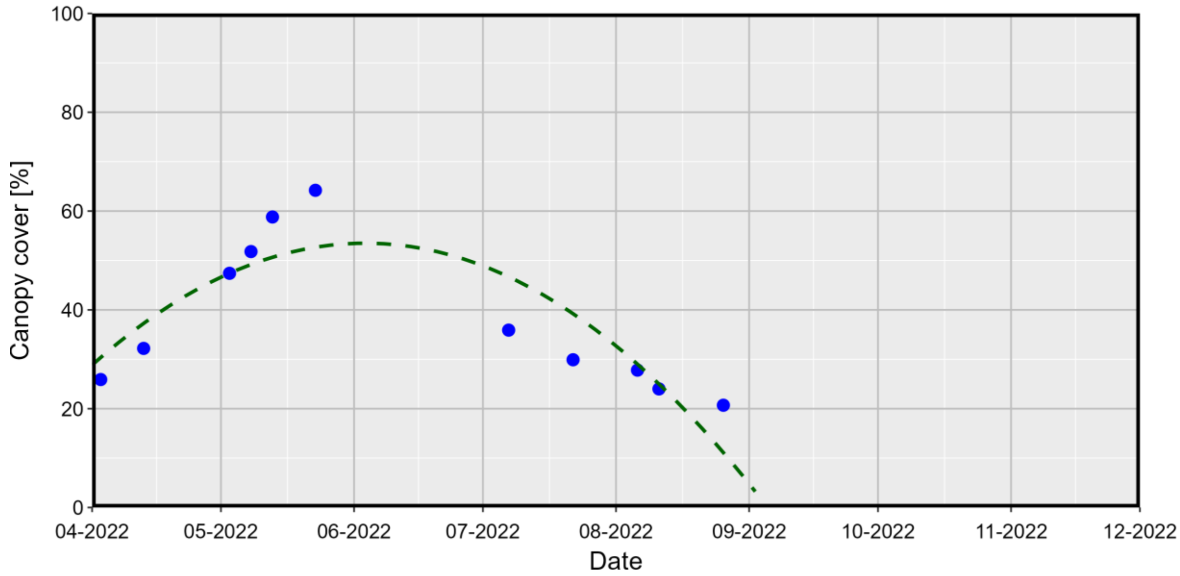

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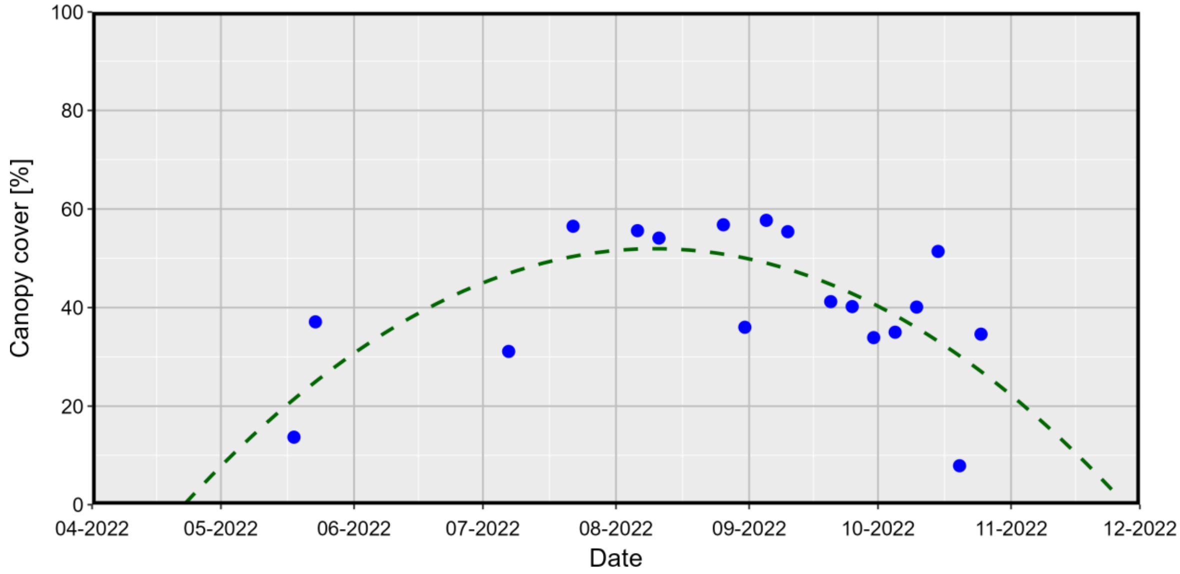

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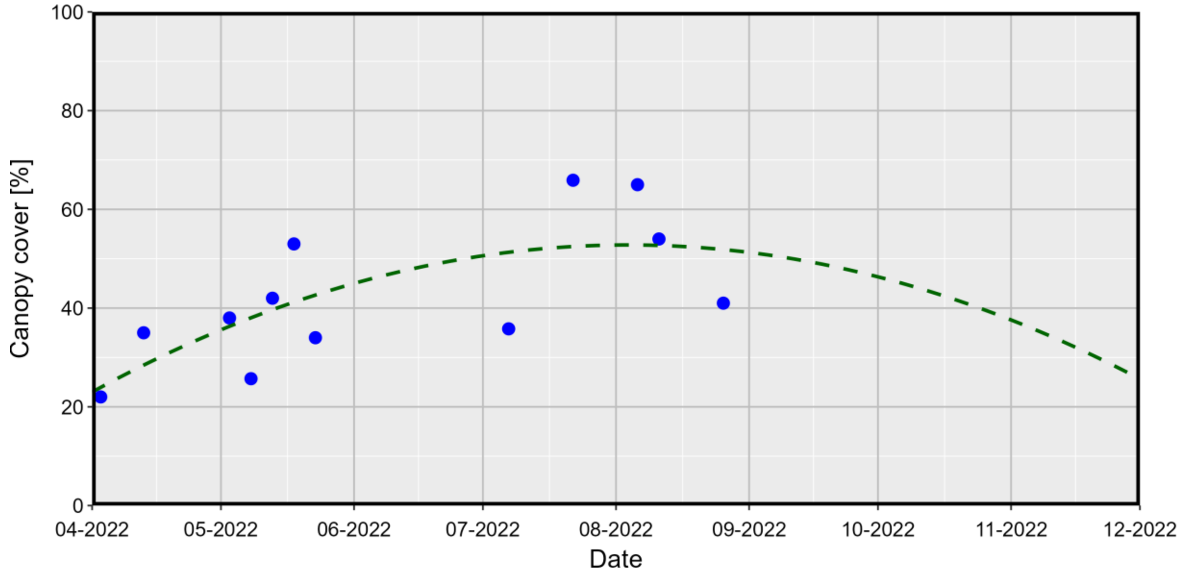

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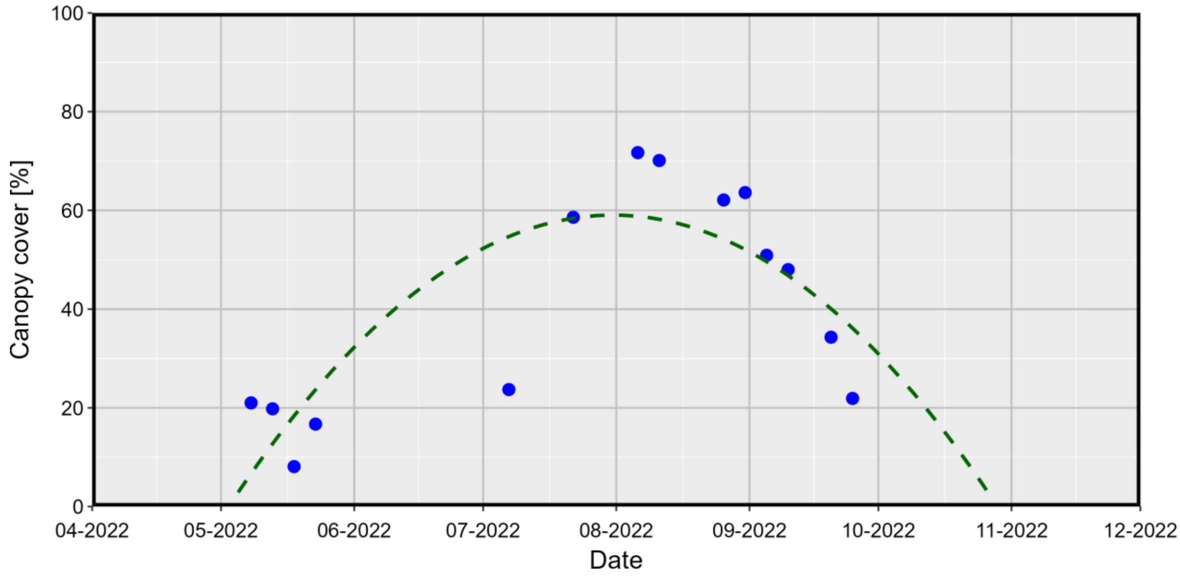

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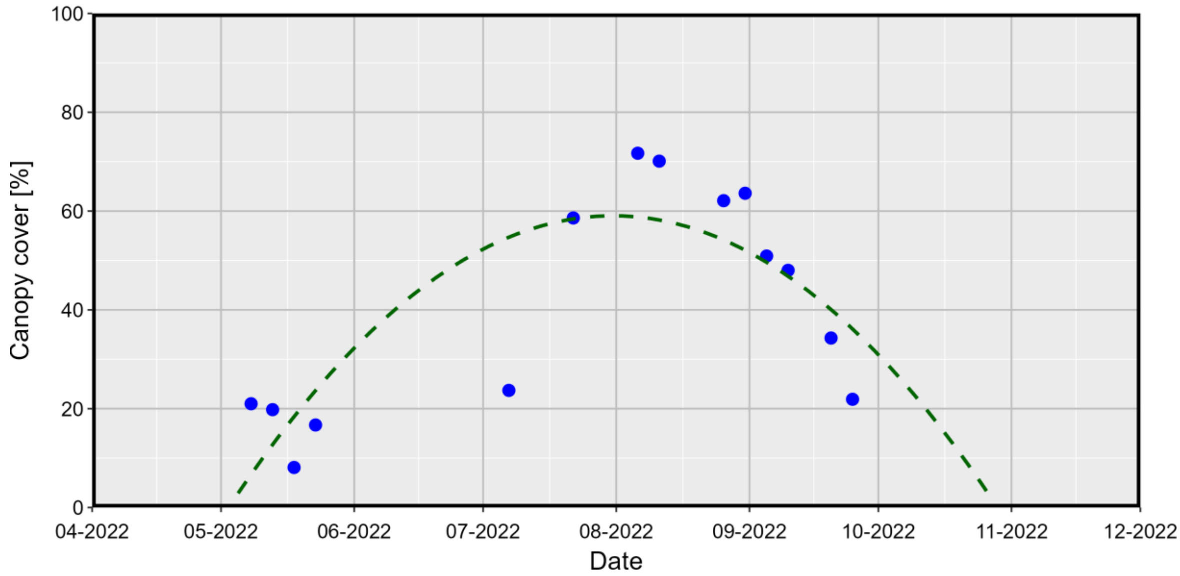

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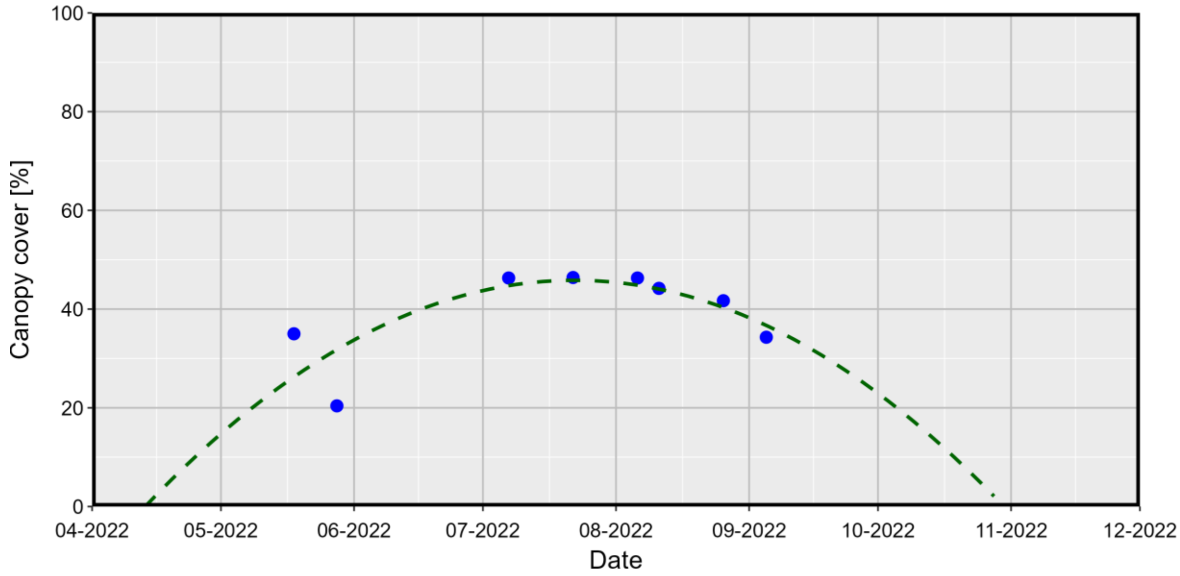

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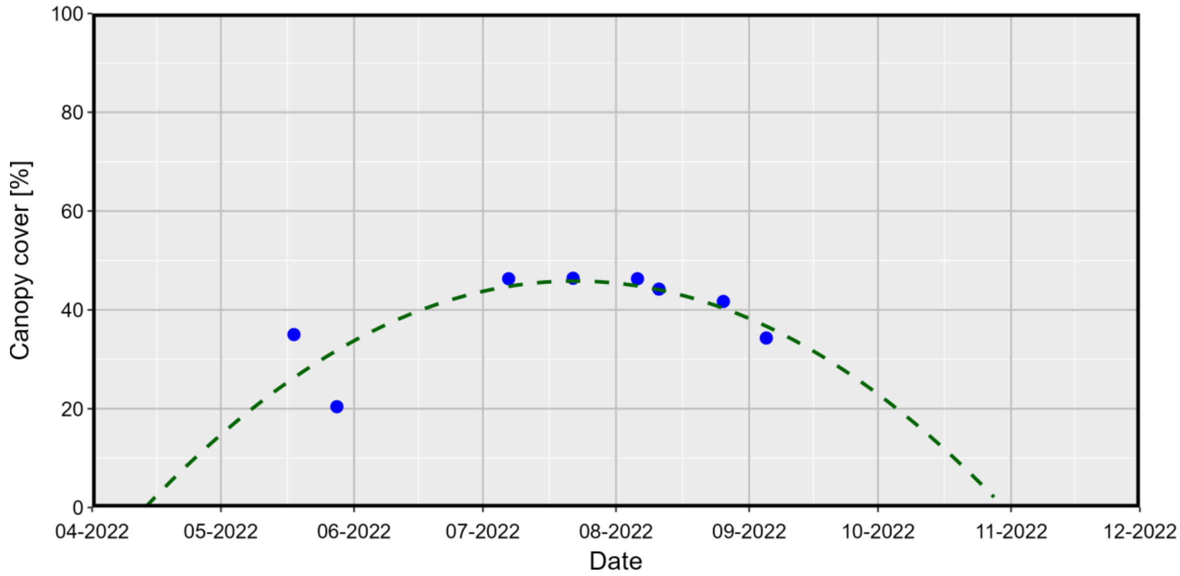

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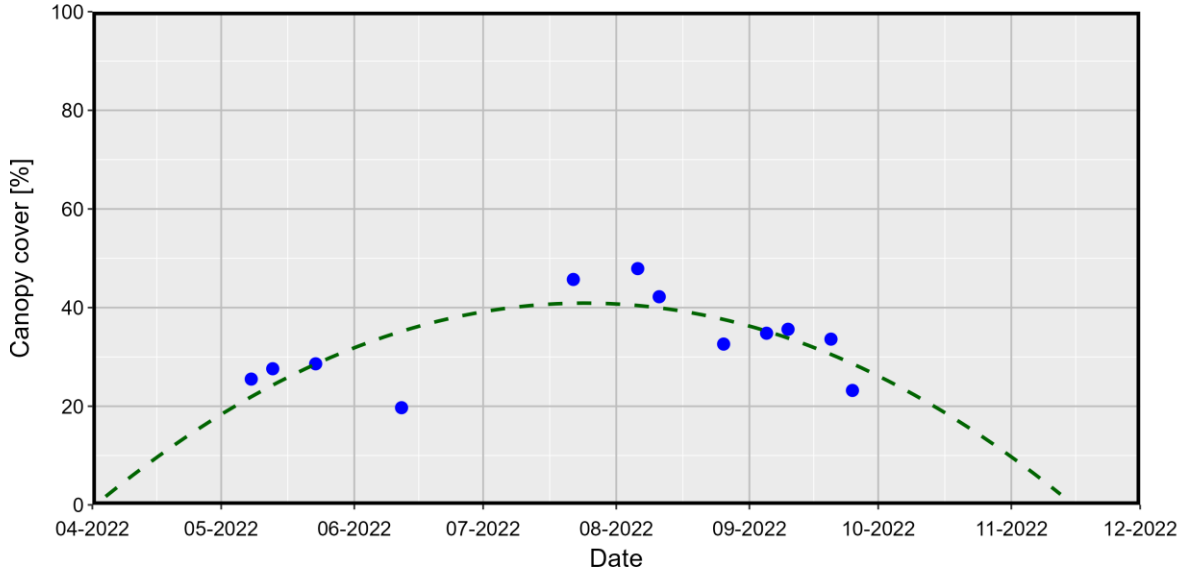

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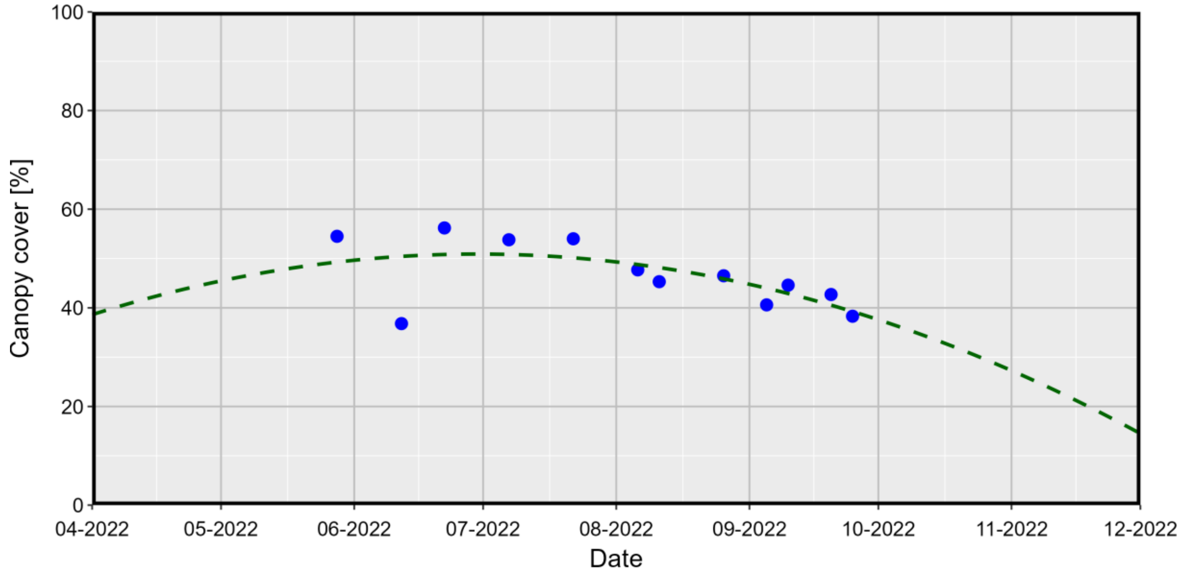

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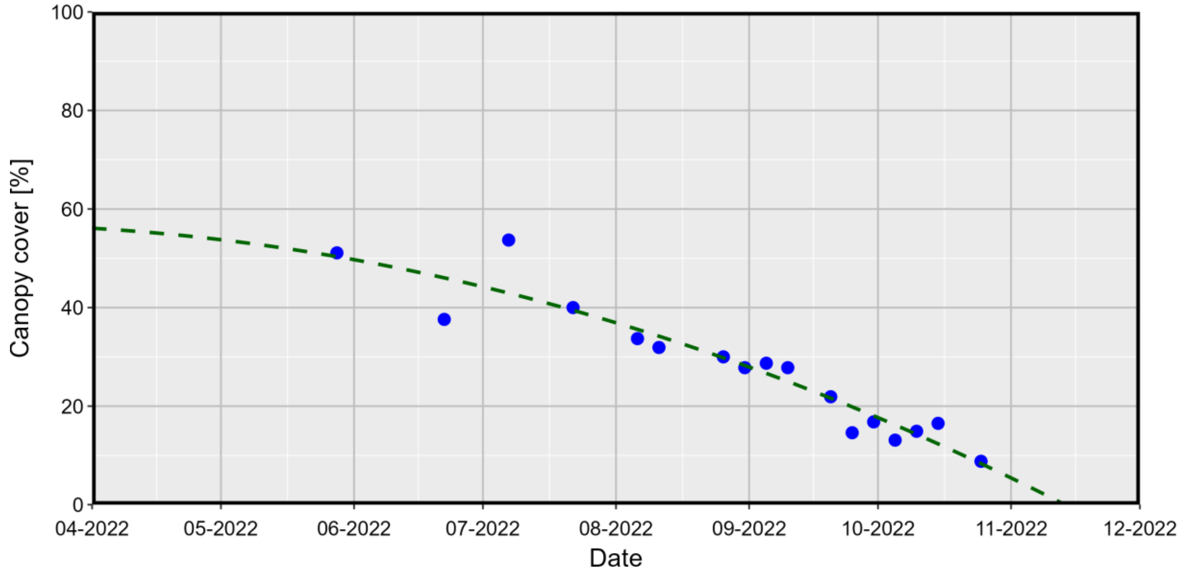

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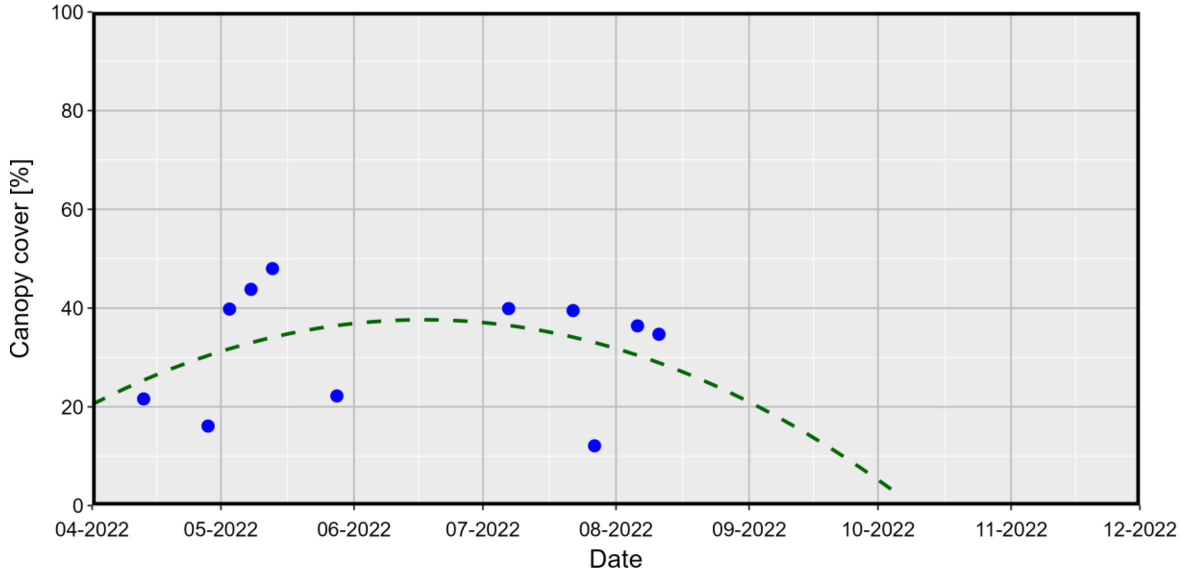

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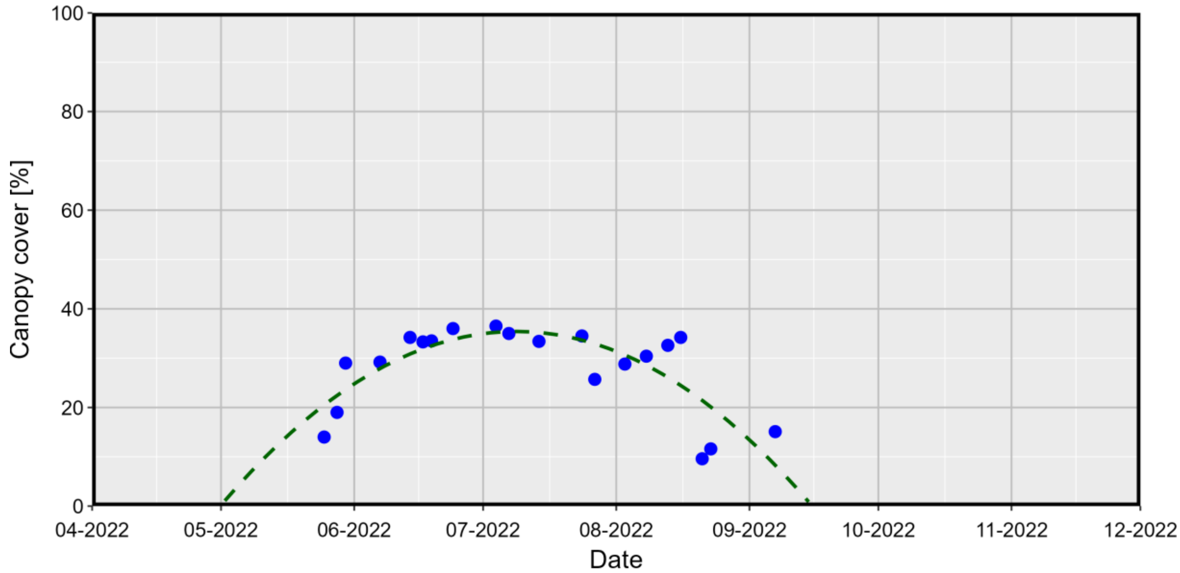

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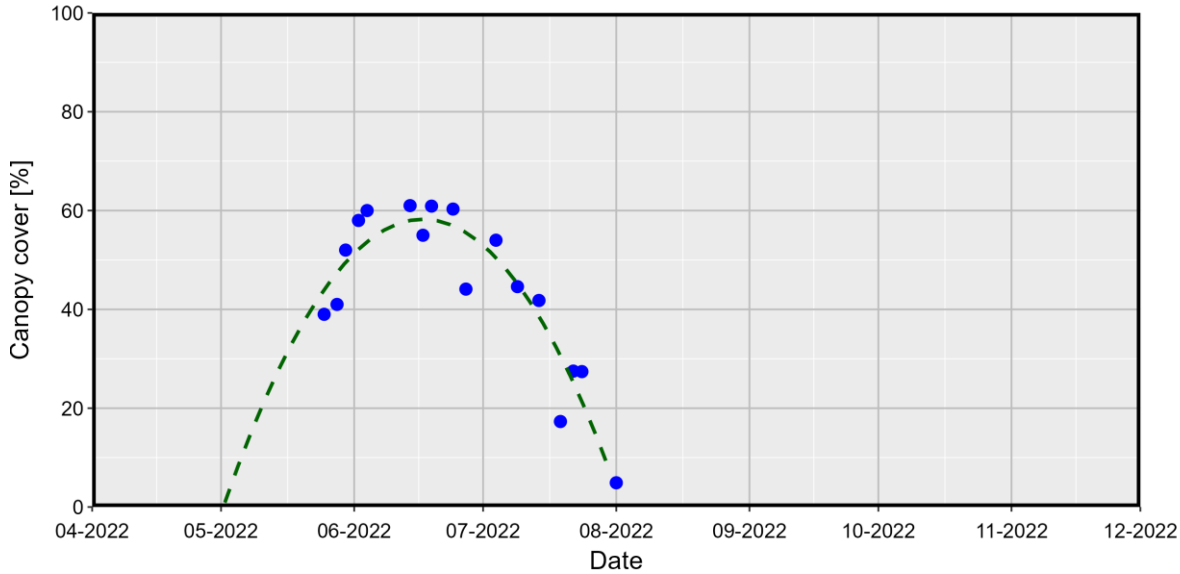

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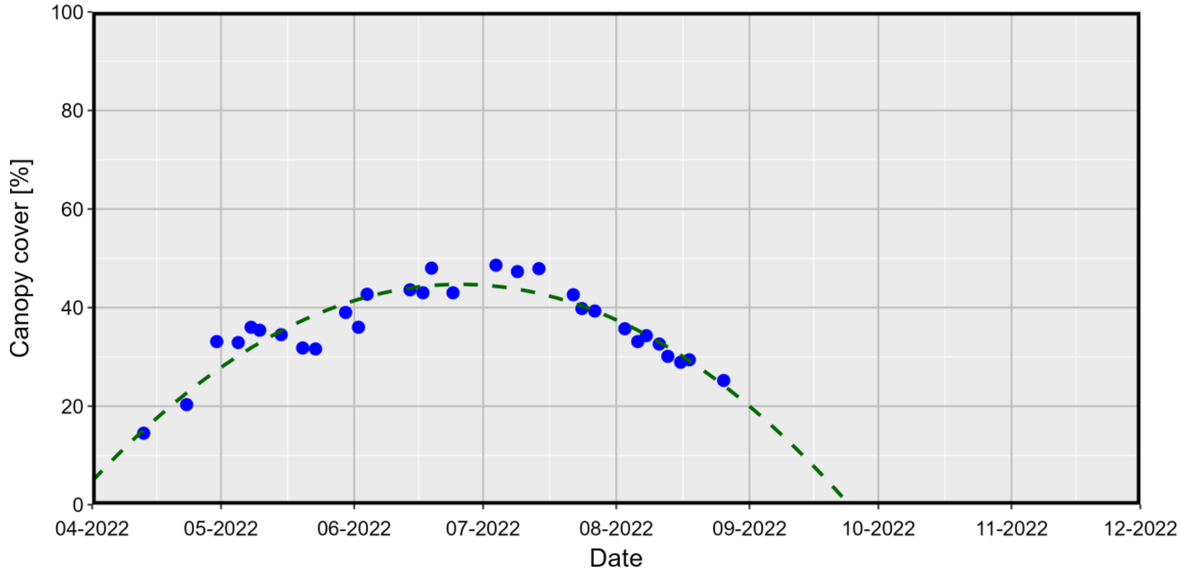

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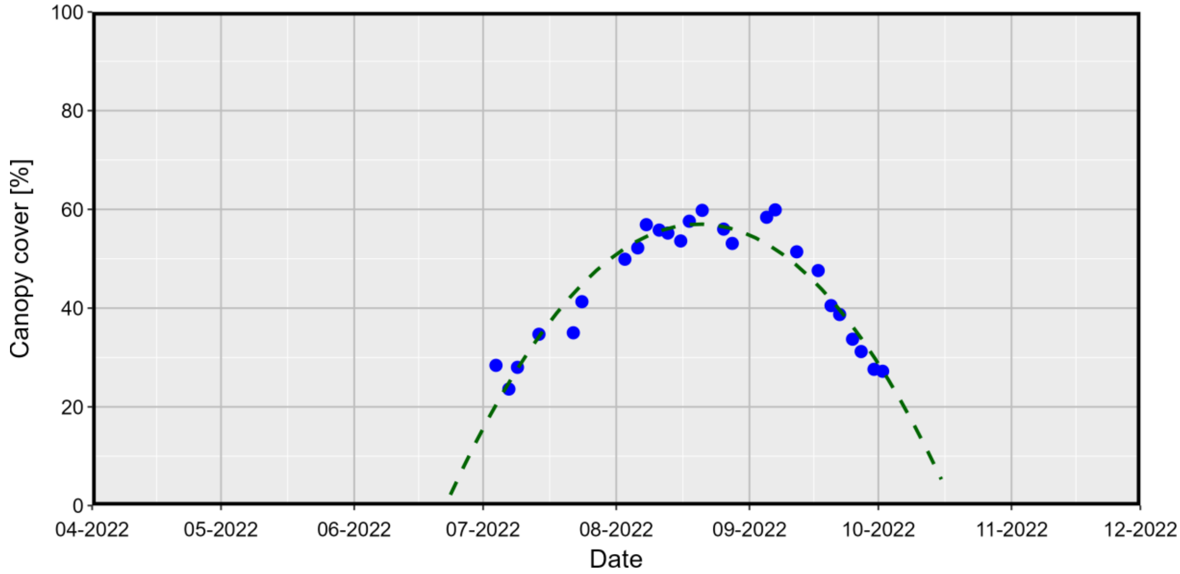

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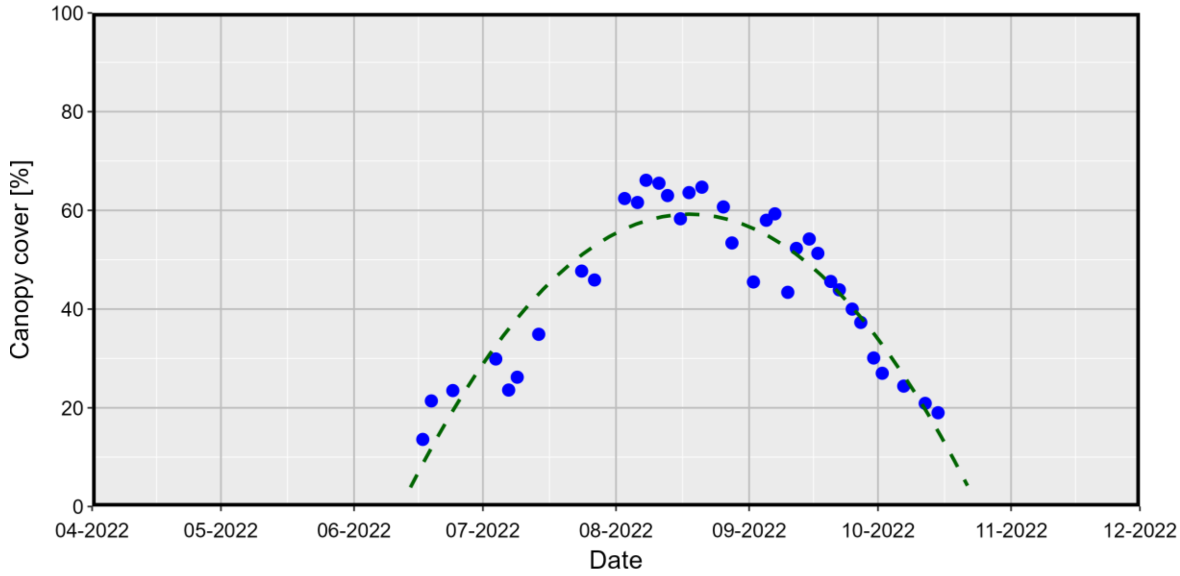

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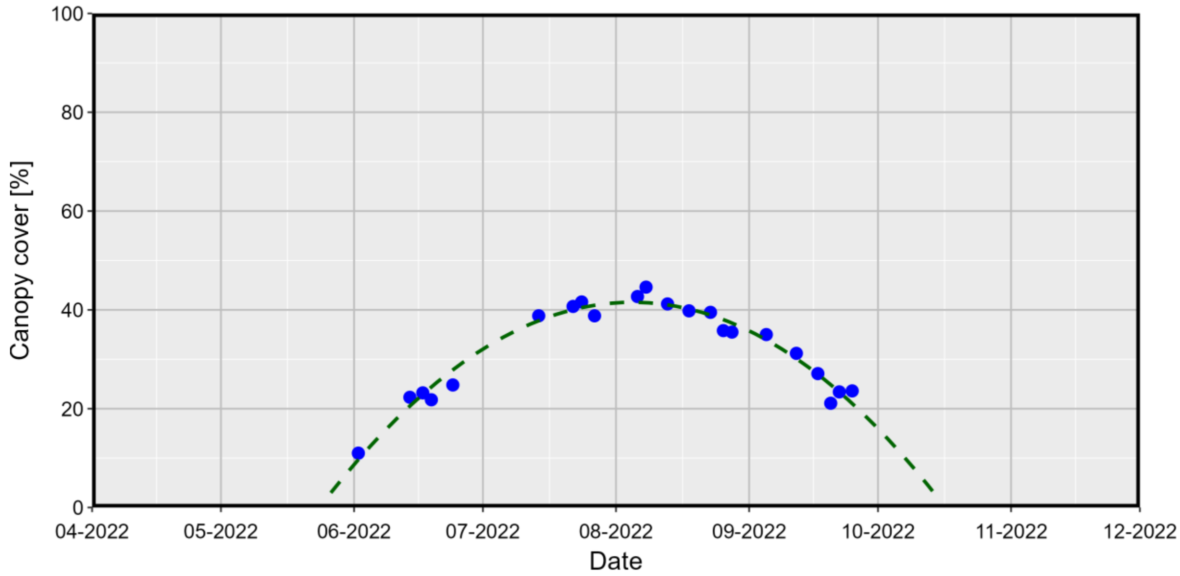

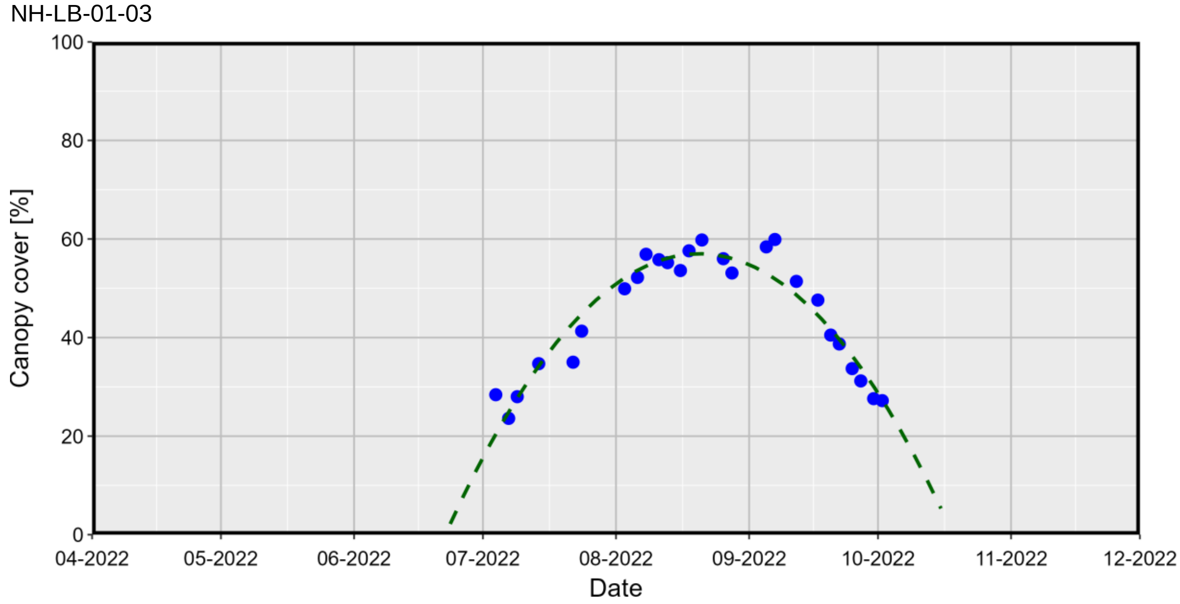
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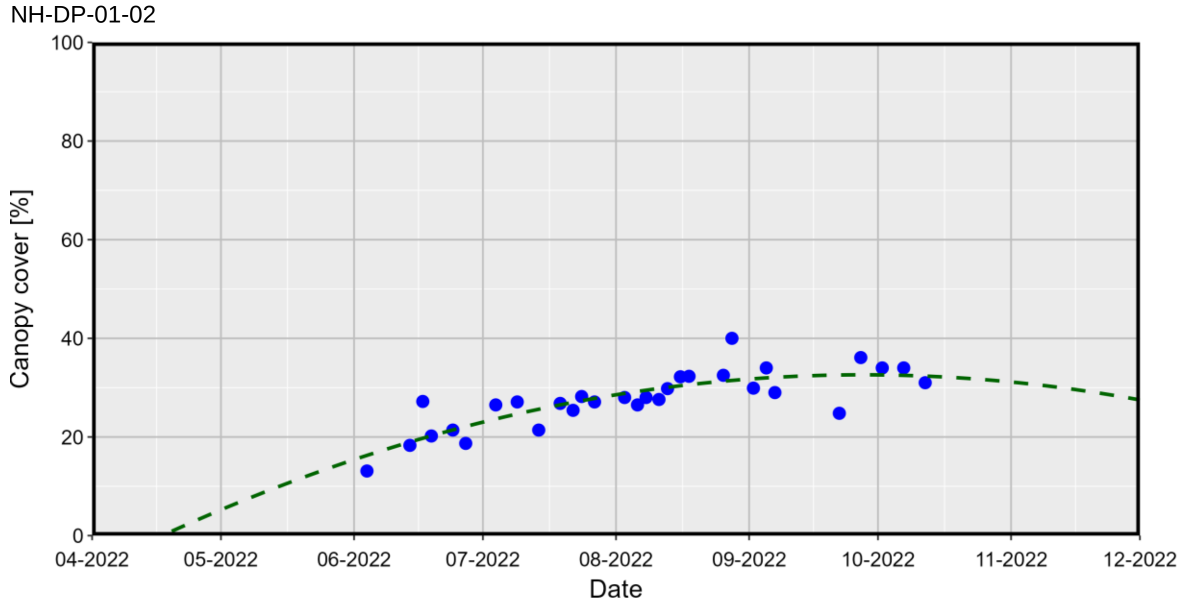
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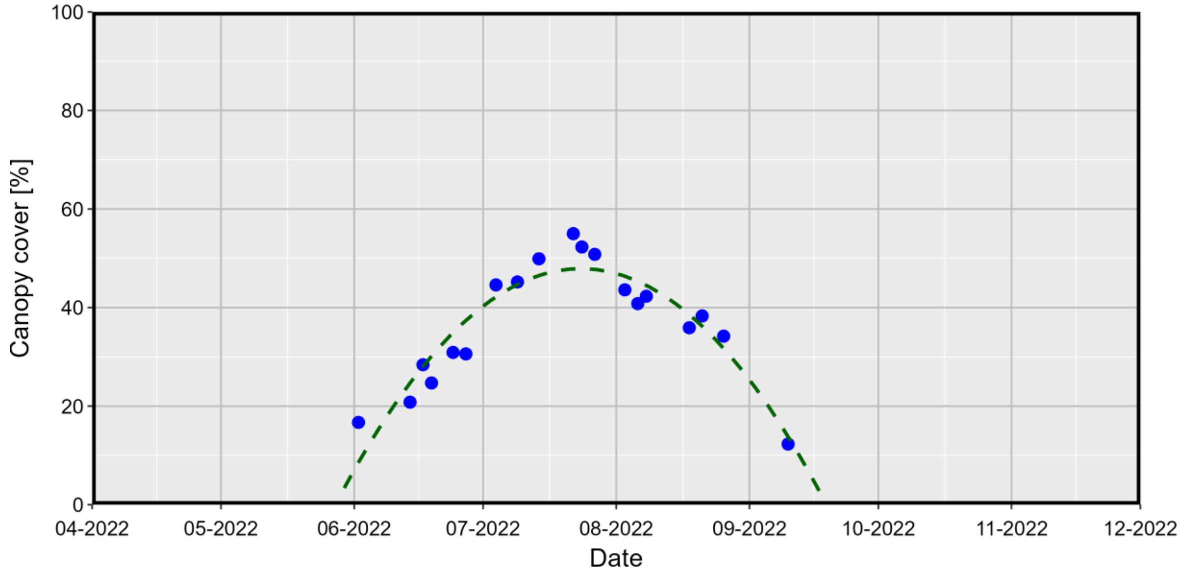

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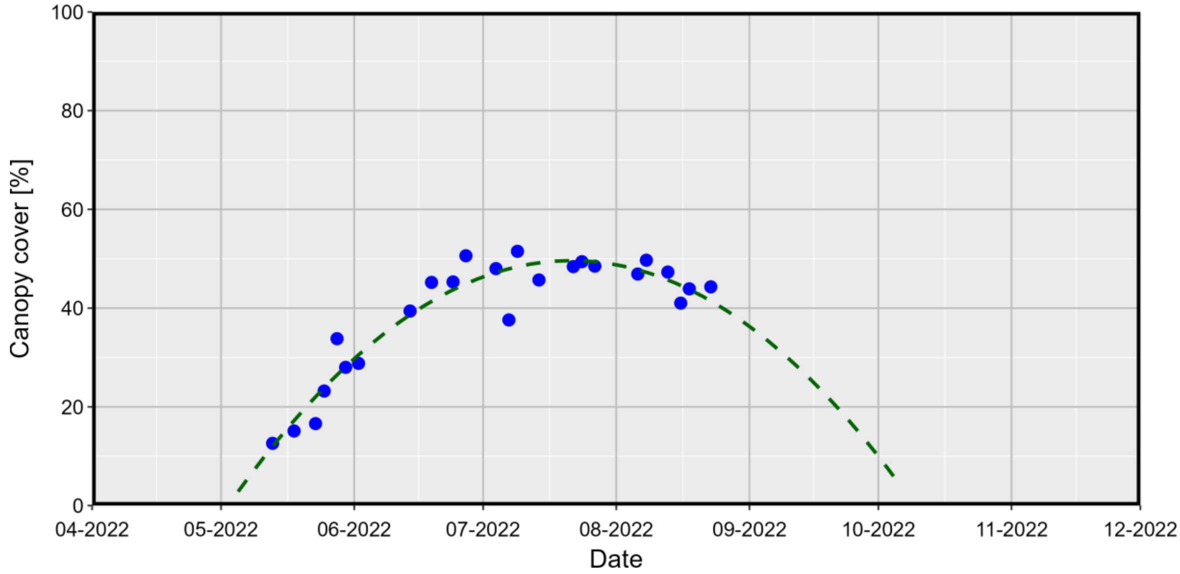

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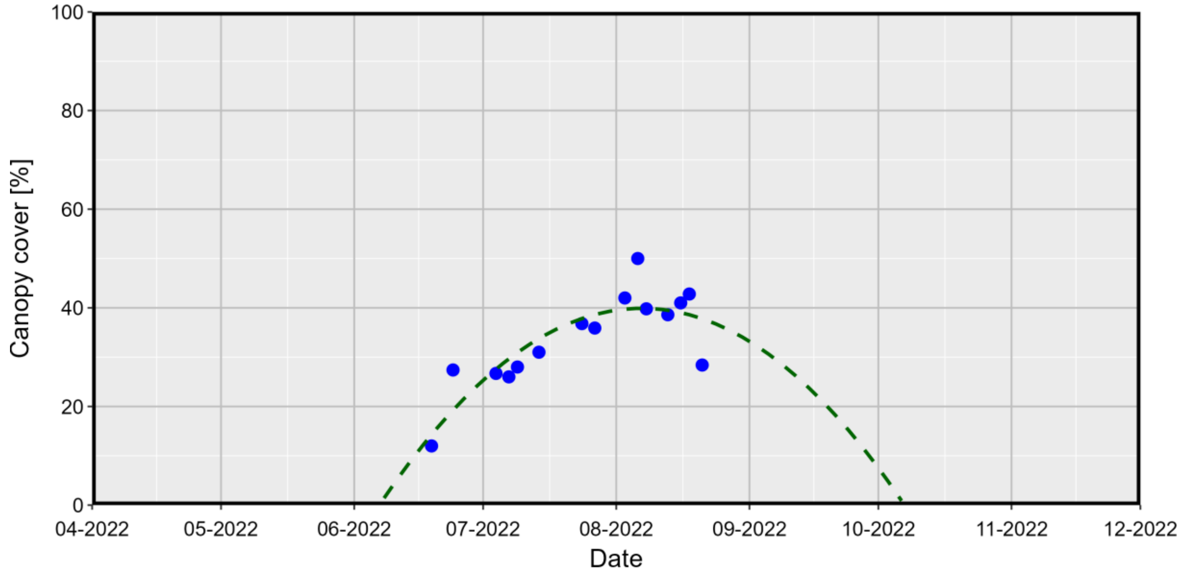

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