

Validation of modelling tools for the PV crops tandem yield



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1 Introduction

1.1 Description of the Deliverable Content

The integration of photovoltaic (PV) systems with agricultural production, known as agrivoltaics, introduces new challenges and opportunities in the assessment of light distribution, crop growth, and energy yield. In particular, the quantification of photosynthetically active radiation (PAR) under agrivoltaic structures is essential for understanding crop productivity and optimizing system design. Unlike conventional PV installations, where the solar resource is evaluated primarily in terms of broadband irradiance and energy yield, agrivoltaic systems require a dual assessment: the solar energy available for electricity generation and the fraction of radiation transmitted or reflected in spectral regions relevant to photosynthesis. This duality adds complexity to resource characterization, especially when semi-transparent modules, spectrally selective coatings, or greenhouse glazing are employed.

This deliverable builds upon the objectives of Task 2.3, which focuses on the assessment and modelling of PAR, spectral selectivity, and long-term climate impacts on both PV and crops. The task integrates contributions from several partners: LuciSun and KUL provide advanced simulation and climate analysis methodologies, while ABOVE and UPC contribute innovative monitoring approaches through albedo assessment and multi-spectral imaging. Together, these efforts support the broader aim of SYMBIOSYST to develop and validate a comprehensive framework for agrivoltaic design, combining physical models, experimental data, and demonstrator monitoring.

The first part of the work addresses the empirical and physics-based methods for converting broadband irradiance into PAR estimates. Empirical factors provide a practical baseline, while spectrally resolved modelling captures the selective transmittance and reflection introduced by agrivoltaic components. These methods have been implemented into 3D simulation engines, allowing the generation of spatially and temporally resolved maps of PAR and daily integral (DLI) under different structural and climatic conditions.

The second part considers the long-term variability and evolution of the solar resource and climate. Historical records and climate projections are analysed to quantify interannual variability and to assess the potential impacts of climate change on PV performance and crop suitability. The analysis covers the three SYMBIOSYST demonstrators: an open-field system in Belgium, an orchard system in Italy, and a greenhouse system in the Netherlands. Each of these represents a distinct combination of climatic context, agricultural practices, and agrivoltaic configuration, providing a robust basis for comparative assessment.

In parallel, ABOVE and UPC have initiated the development of novel monitoring technologies to support model validation and enhance understanding of agri-PV interactions. These include advanced albedo assessment methods, combining aerial imaging and pyranometer data, and multi-spectral imaging for crop health monitoring. These tools will provide complementary datasets to refine models and to connect energy and agronomic performance metrics.

2 Light evaluation model

2.1 Incorporate 3D information on reflectance, PV modules, plants and crops (LUCISUN, IMEC)

Agrivoltaic systems contain different components such as the PV modules, crops, support structures and the ground which need to be properly accounted for (modelled) to accurately assess the light sharing between the PV modules and the crops. The optical properties of the different materials within the scene impact the light reaching the PV modules and crops. As bifacial PV modules are commonly used (or desired) in agri-PV systems, the rear PV irradiation and PV bifacial energy gain is highly dependent on the albedo of the ground and the reflectance of the crop leaves. As different farming practices contain crops with different leaf colors, the reflectance profile of green and brown crop leaves was measured and used as valuable input. Figure 2.1 shows the reflectance profile of green and brown plant leaves.

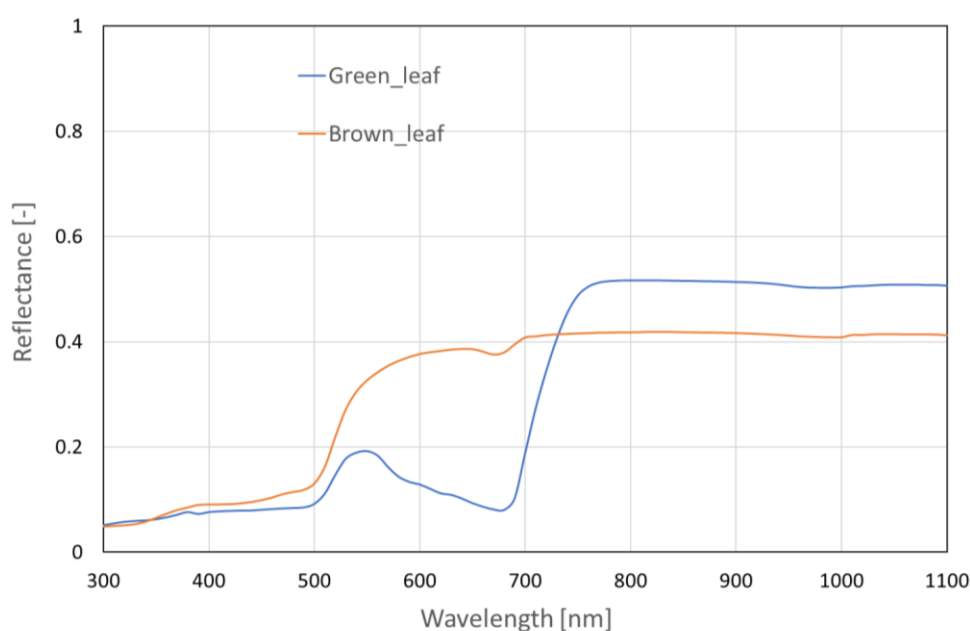


Figure 2.1: Reflectance of green and brown leaves. Measured data for green leaves is used as input for the reflectance of the tree leaves in the optical modelling.

To accurately model the different components and assess the irradiance distribution in agrivoltaic systems, in this work, the agrivoltaic pear orchard in Bierbeek, Belgium (50°49'05.6"N 4°46'34.5"E) was used as a case study. Details of the agrivoltaic system have been provided in Section 5. To faithfully assess the PV and crop irradiance and yields (crop and energy) of the proposed agrivoltaic system, detailed geometric modelling of the system components was carried out using SketchUp Pro 2023. The modelled pear orchard which includes the PV array, pear trees and support structures is shown in Figure 2.2 (A-C).

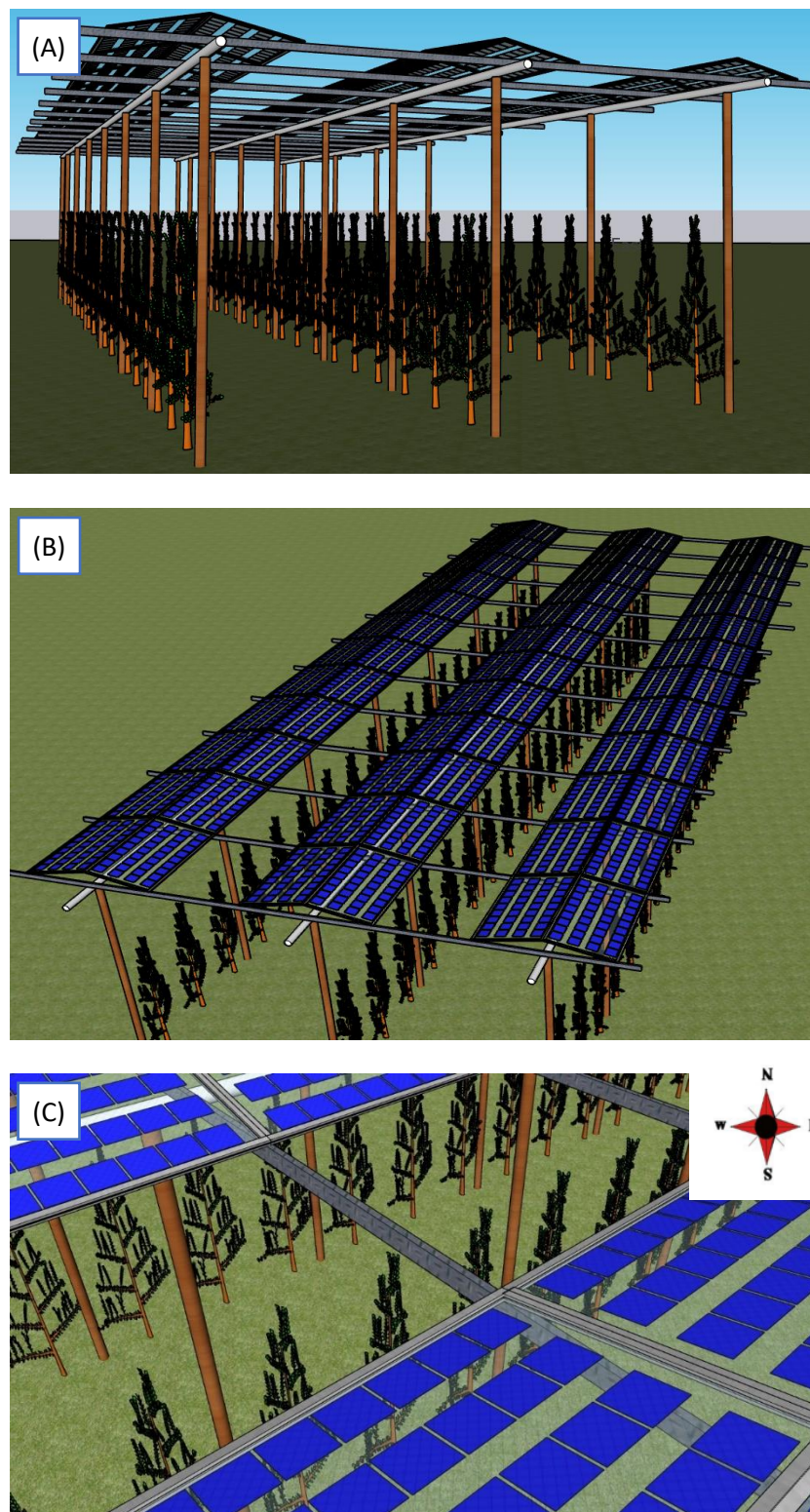


Figure 2.2: (A) 3D model of the Bierbeek agrivoltaic pear orchard showing the semitransparent PV modules, pear trees and support structures. (B) Top view showing trees along the SW-NE axis. (C) Zoomed-in view showing the semitransparent PV modules and trees. The 3D model (scene) is a key input used in the simulation framework.

The generation of the 3D scenario in LuSim is created directly in the tool, using different objects and PV modules agreed between the partners and uploaded into LuSim's database, locating and orienting them according to the existing demonstrator in Bierbeek (more details provided in section 5). Each object is assigned a material from the library of materials available, that includes different properties as directional albedo (although for this analysis it has been assumed that all the materials have Lambertian properties).

The objects can be included as individual elements or as patterns (repetition) of individual elements and possible variations of a baseline distribution can be analysed using the batch capability of the tool (for example to analyse the influence of tilt angles, distance to ground, separation between elements, tracking laws if applicable, etc).

When evaluating the irradiance received on an object, different zones can be defined, to provide later a result of the analysis in a specific point, the overall object or one of those zones.

A generic layout of the subscale element of the installation, containing 3 rows of 21 trees can be seen in the following figure. The separation between the rows is 3.3 m and the distance between the trees is 1 m. A detailed description of the setup is included in section 5.

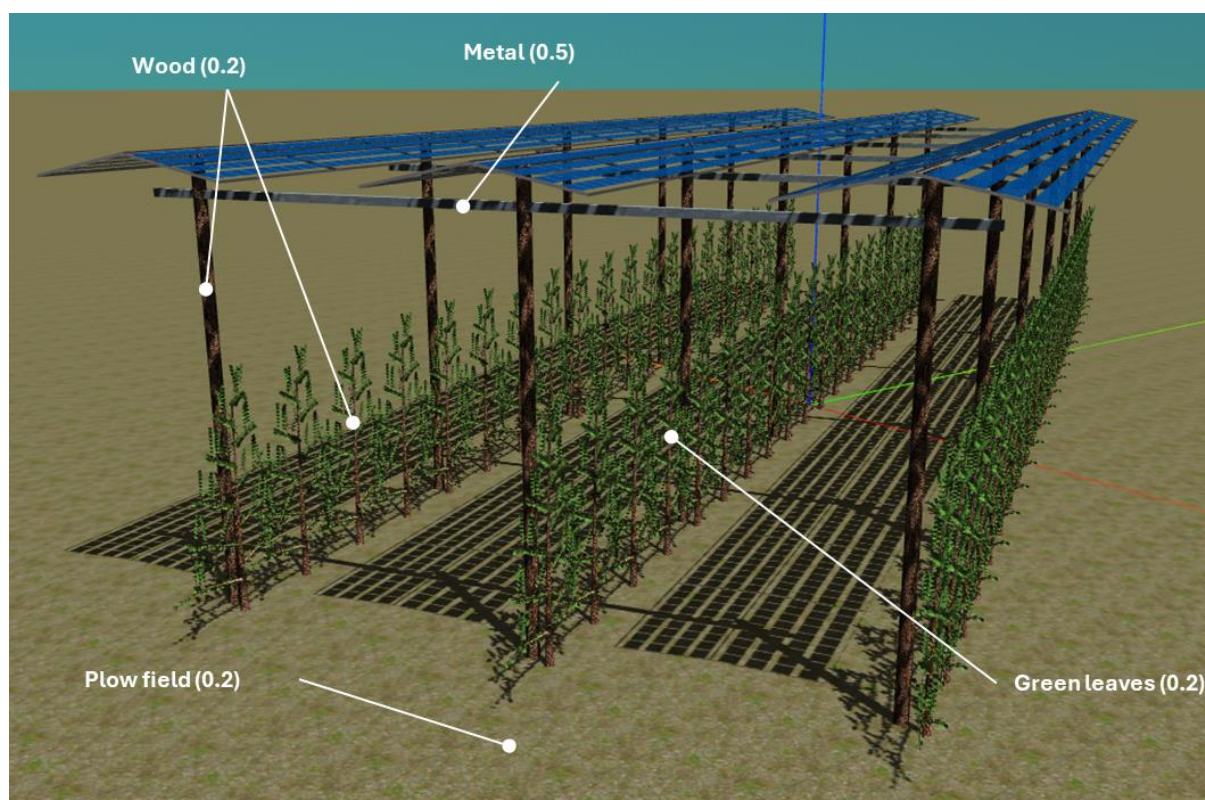


Figure 2.3: Different elements considered in the 3D scenario created in Lusim for the irradiance analysis.

The 3D elements considered included:

- **Ground terrain** – A generic plow field material is considered with an albedo of 0.2
- **Installation structure** – Composed of vertical poles in wood (albedo 0.2) and metal structure (albedo 0.5). Geometrical characteristics and distribution based on site description in section 5.
- **Pear trees** – Divided in two objects: trunk and leaves for irradiance analysis later. The trunk has a wood material assigned with an albedo of 0.2 and the leaves have a generic green material assigned with an albedo of 0.2.
- **PV modules** – With a 4x9 cells configuration and overall, 40% of free glass surface with a transmissivity of 90%. Details of the modules are included in section 5.

In terms of the definition of the zones for the evaluation of the irradiance over the leaves, 5 zones were considered as described in section 5 of the document and explained in the following figure, where a different colour is assigned in the 3D model of a single tree to visualize the zones considered in the analysis.

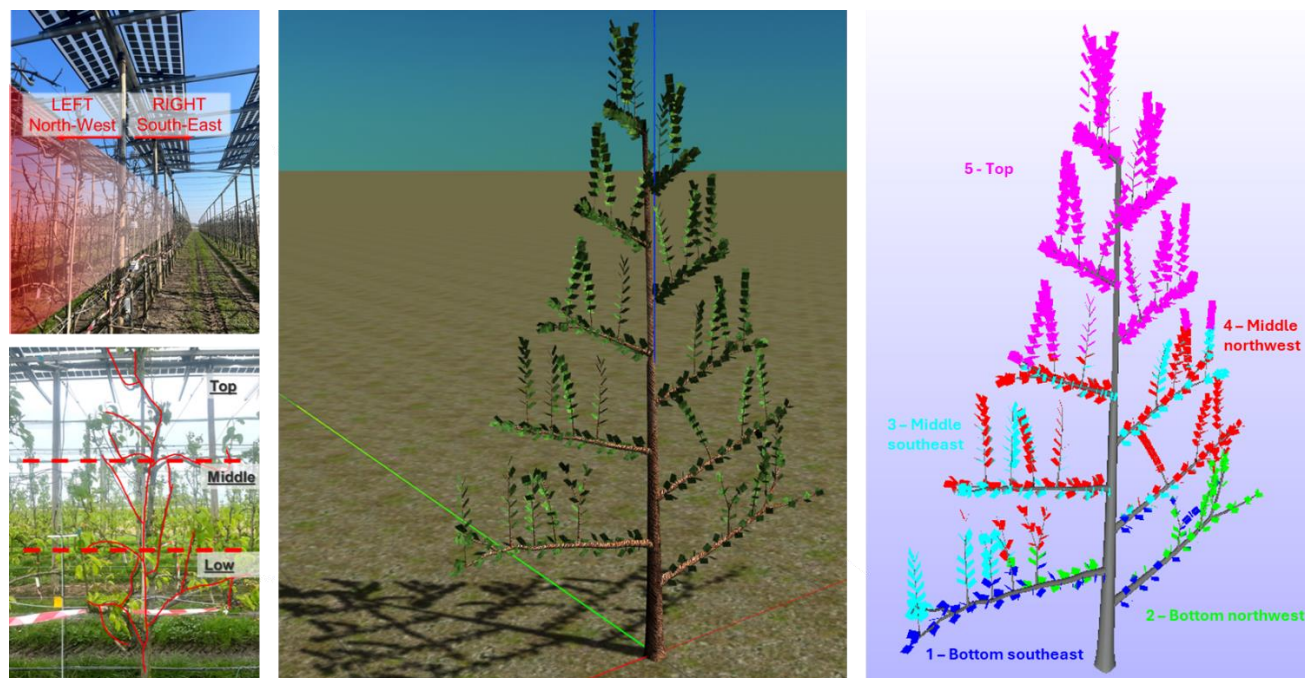


Figure 2.4: Zone subdivision of the leaves in the tree for the irradiance simulation.

2.2 Measurement systems for albedo and crop health assessment (ABOVE, UPC)

2.2.1 Aerial thermography and in-situ pyranometry for albedo modelling

Traditional albedo measurements are sparse in spatial and time domain. Above have developed a methodology to do the dense albedo measurements at scale using aerial platforms. An image-based albedo estimation methodology is also developed and results tested against the pyranometer obtained albedo values.

Equipment Setup

1. A Ground station setup with an upward facing class-A pyranometer for measuring global Irradiance and an accompanying custom data logger device with the capability to tag each pyranometer measurement with accurate GPS timestamp and location. The setup is shown below in Figure 2.5.
2. Drone mounted custom setup consisting of onboard computer with a downward facing pyranometer for measuring reflected irradiation. The onboard computer communicates with drone over ROS interface and tags each pyranometer measurement with IMU information from the drone (Relative altitude, GPS position, drone yaw & drone roll, GPS timestamp etc).
3. RGB drone payload camera (Zenmuse-P1) with mechanical shutter capable of capturing both raw and jpeg images and each image taken is tagged with GPS timestamp at exposure time. The full aerial setup is shown in Figure 2.6.
4. 10mm thick 10cm*10cm Teflon marker plates used as reference (reflectivity of close to 1).



Figure 2.5: Ground Station setup used for global irradiance measurements



Figure 2.6: Drone setup used for Reflected Irradiance measurements and Image Collection.

Data Collection

1. The ground station was setup at a stationary position and drone measurements are made within 20-30 meters circle of the station location. A 0.5 second interval was used for collecting ground station measurements.
2. The reference Teflon markers are placed at different location around the ground station with slightly changing conditions (like changing background like dirt road, green grass and varying distances to table structures).
3. The drone measurements are collected at each marker location by hovering the drone for 3-4 minutes at different altitudes (~3-4M, ~8-9, ~16-18M). The interval of the pyranometer measurements in the drone depended on the ROS message frequency and resulted in average of a measurement per sec. A funnel shaped mount was placed around the drone pyranometer to make the pyro measurement footprint area match the footprint of the digital image roughly. The data was collected close to solar noon of the day as the Teflon markers reflect maximum amount of irradiation when angle of incidence is closer to 90 degrees.
4. The digital images (both raw and jpeg) are collected at an interval of 10 seconds at a spot with following settings, constant ISO, constant aperture and exposure time, and constant white balancing.

Processing

1. The GPS time stamps are used to match the ground station measurements, drone mounted pyro measurements and digital images to one another.
2. The raw images are converted into RGB domain using a linear demosaicing algorithm with no gamma correction and corrected for vignetting effect and lens distortions. The comparison between histograms is shown in Figure 2.7.
3. Polygon annotations are drawn manually for images to mark off the area in the image containing Teflon marker.
4. Average value of the area containing marker and full image average is calculated as compared to the global irradiance measured by the pyranometer values. Figure 2.8 shows the relationship between pixel values and global irradiance measured by class-A pyranometers.
5. At all altitudes the data showing linear digital numbers showed linear relationship with raw digital values and processed values but at lower altitudes the data showed a bit of randomness. Using the higher altitudes data a line functions is fit for converting the global illumination into digital numbers of the image.
6. The data showed strong correlation with a positive Pearson correlation coefficient of 0.92 and the fitted line function showed R^2 value of 0.86 (Figure 2.9).
7. The coefficients of the fitted line function are used to illuminate correct the images. Without the need of Teflon markers on each image.

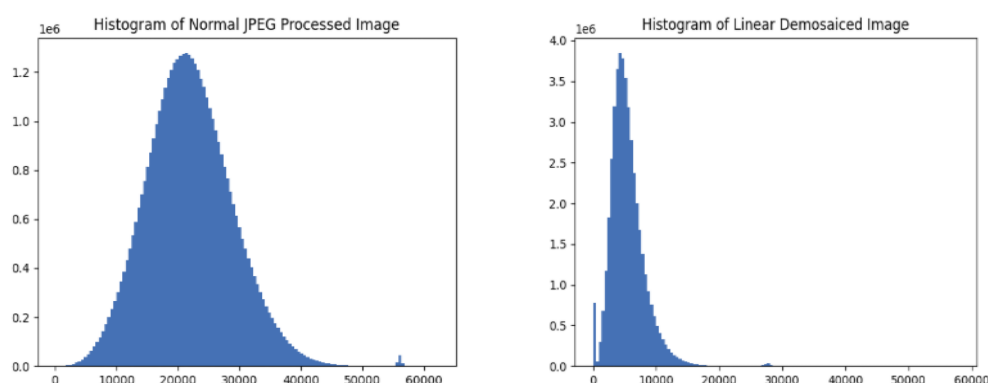


Figure 2.7: Histograms of the normal processed instance to custom processed instance.

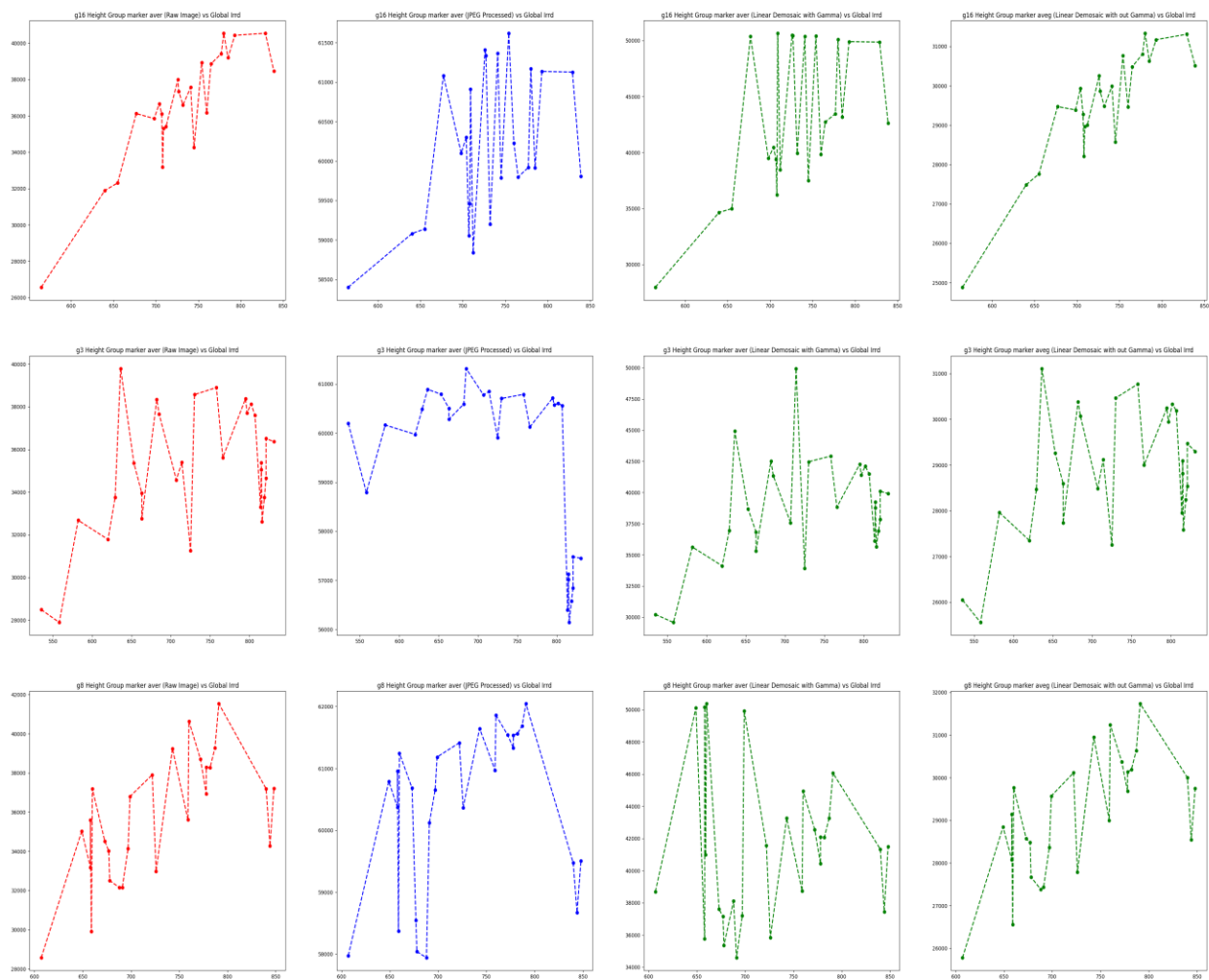


Figure 2.8: Average Marker Area digital values plotted against the global Irradiance measured during that time.

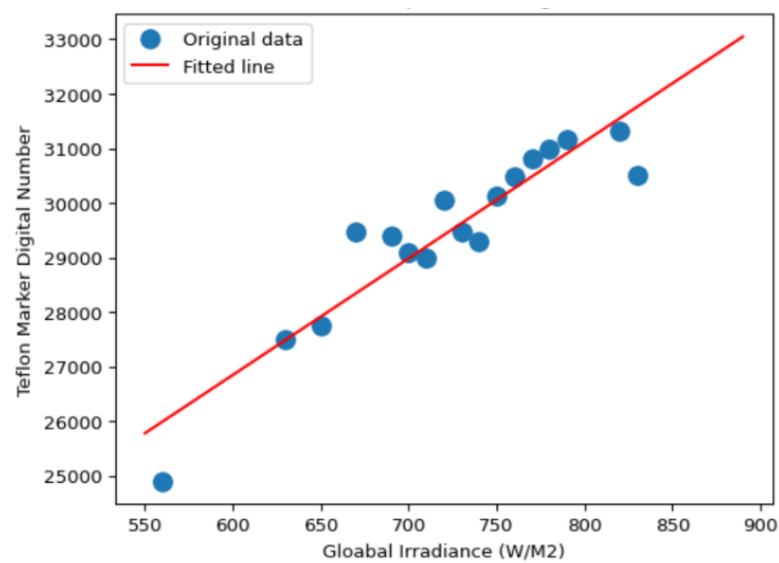


Figure 2.9: Graph showing fitted line function against the real data used.

Albedo Estimation on a sample Area

A sample dataset was collected using a mapping mission (images collected along the drone travel path, drone doesn't stop at each point) on the area closer to ground station. Both ground station pyro and drone pyro measurements were collected for the duration of the mission. The images are corrected using the process described above. The albedo is estimated for each image using the digital numbers of the illuminated corrected image and compared to the albedo calculated based on the pyranometer measurements.

In the Figure 2.10 the green circle represents the albedo value at that point measured by the pyranometers and the red circle represents the value of the albedo at that point estimated using digital images. The size of the circle is directly proportional to the albedo values at the point. The pyranometers are reporting less albedo on top of the solar panels and more on grass patches whereas the digital image-based albedo was showing the exact opposite. This is a direct result of the albedo values from pyranometer measurements are based on the broad spectrum of 285 to 3000 nm whereas the image-based albedo was taking red, green and blue bands of the visible spectrum.



Figure 2.10: Pyranometer measured Albedo vs the digital image estimated albedo.

A dense albedo map was created using the illumination corrected images in photogrammetry software and the albedo values are estimated per pixel level. The values are averaged out for areas of 10cm² area. The dense map can be seen in Figure 2.11. The resulted albedo values are clipped to range between 0.0 and 1.0 to account for glare effects caused by module glass and metal surfaces. In addition, area's shaded by the structural elements exhibited lower albedo values compared to adjacent regions exposed to direct illumination.

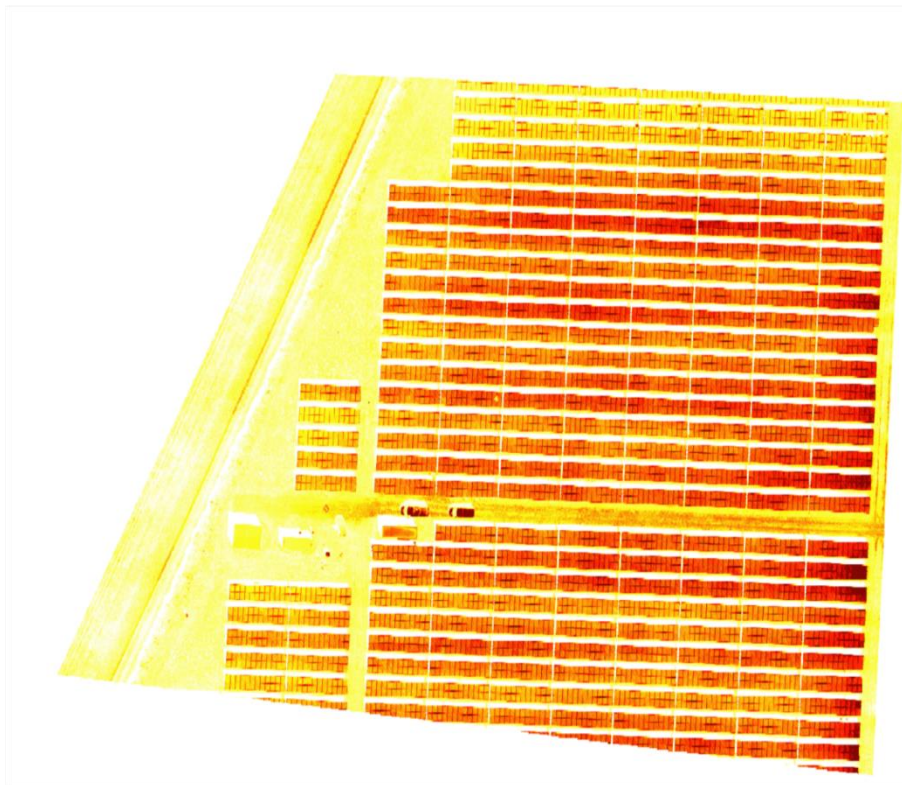


Figure 2.11: Albedo Map of the sample area. Pixel resolution 10 cm² (Albedo measurement area).

Albedo Estimation using Multispectral data

To address the limitation of lacking info on the reflected NIR band radiation in albedo estimation, digital multispectral images were collected using a drone platform called DJI M3M. This data set includes images from Red, Green, Red Edge and NIR bands of the electromagnetic spectrum. The same methodology described above was applied for downward global irradiance measurements and Teflon marker images at different altitudes. The collected images are illumination corrected, and the average reflected radiation from markers in digital images was compared against the global irradiance at each point (Figure 2.12).

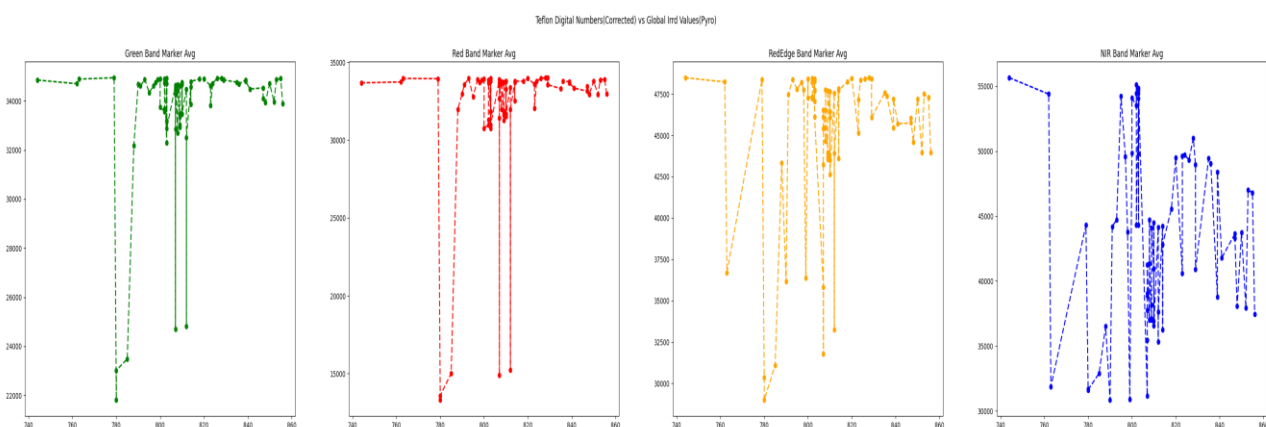


Figure 2.12: The relationship between reflected radiation from digital images in each band to the global irradiance recorded by pyranometer.

When a comparison was made with global illumination values measured by the light sensor present in drone and the ground station pyranometer. The average value of the marker area got saturated to the max possible

value in red, green and red-edge bands and the value in NIR bands showed no linear relationship like in the previous payload. The saturation in three bands is a result of the images being already in their processed state instead of their raw state. The processed images are scaled to highlight the features and there was no easy way to undo this scaling. Note: the drop in values 780 w/m² is an artifact of the marker not being in direct illumination but got covered in shade of the table structure.

To further advance the albedo estimation, we are considering investigating scientific imaging sensors capable of capturing digital images across various electromagnetic bands in the rawest format possible. Alternatively, the development of a reference dataset containing albedo values for various materials under different weather conditions could be considered. Digital images could then be used for classifying the surface into one of the predefined categories within this dataset, enabling the corresponding albedo value assignment.

2.2.2 Multi-spectral imaging for crop health assessment

In the original project proposal, ABOVE intended to develop a system for assessing crop health using aerial imagery, with the aim of providing automated analysis for solar farm developers, operators and environmental consultants. This was to be applied to both agri-PV and conventional PV sites—assessing hedgerows and wildflower meadows in the latter, and evaluating crop health in the former, specifically in areas adjacent to and between module rows.

Initial efforts focused on evaluating suitable drone and camera technologies, as detailed below. In 2023 (a few months after the start of the SUPERNOVA project), DJI released the 'DJI Multispectral' platform, accompanied by a dedicated application for crop health monitoring. Given the availability of this mature and commercially supported solution, it was determined that the task no longer represented a significant innovation. ABOVE therefore decided not to pursue in-house development and communicated this in regular project updates.

Subsequently, for the purposes of fulfilling this subtask and in agreement with the task leader and UPC, a revised approach was adopted: ABOVE would acquire aerial data using a hired DJI Multispectral drone, and UPC would develop a methodology for processing and analysing the imagery to assess crop health.

Above used a multispectral drone platform (DJI Mavic 3 multispectral) to obtain data in the following bands of the spectrum described in Table 2.1.

Table 2.1 Multispectral bands collected for the plant health analysis.

Band Name	Central Wavelength	Bandwidth
Green	560 nm	± 16 nm
Red	650 nm	± 16 nm
Red Edge	730 nm	± 16 nm
NIR	860 nm	± 26 nm

Data Collection

The data is collected using a mapping mission with the target multispectral GSD (Ground Sampling distance) of 3cm per pixel. The images are collected in tiff format, and the downward radiation (Global irradiance) is measured using a light sensor built into the top of the drone platform. The radiation is measured in each band separately as well along with the total radiation and the measured values are baked into the image XMP (Extensible metadata platform) metadata. Along with the multispectral images normal RGB images are also collected during the same flight.

Data Processing & Outputs

The images are illumination corrected using the global illumination values measured by the light sensor and the sensor sensitivity parameters for different bands provided. Using the corrected images. The corrected images are then used to generate different vegetation indexes used in crop health analysis like

NDVI: (Normalized difference Vegetation index)

It provides info on the amount of green vegetation over a given area. It uses the difference between near infrared and red band reflectance divided by their sum. The values range between -1 to 1 with low values corresponding to exposed soil or rock and higher values corresponding to greener vegetation.

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \quad (2.1)$$

GNDVI: (Green Normalized Difference Vegetation Index)

The GNDVI provides info on the photosynthetic activity of the plants over a given area. The index is calculated using the near infrared and green bands of the electromagnetic spectrum. The index values vary between -1 to 1 and lower values like $(-1$ to $0)$ correspond to bare soil or water and values between $(0$ to $1)$ correspond to the greenness of the plant.

$$GNDVI = \frac{(NIR - Green)}{(NIR + Green)} \quad (2.2)$$

NDRE: (Normalized Difference Red-Edge Index)

The NDRE index provides info on the chlorophyll content in the plants. The index is calculated using the near infrared and red edge band of the electromagnetic spectrum. The value in the index varies between -1 to 1 with values between -1 to 0.2 corresponds to bare soil or developing crop, values between 0.2 to 0.6 corresponds to unhealthy or not mature crop and values above 0.6 to 1 shows healthy and mature crops.

$$NDRE = \frac{(NIR - RedEdge)}{(NIR + RedEdge)} \quad (2.3)$$

Figure 2.13 shows the vegetation indexes calculated on a solar farm in UK.

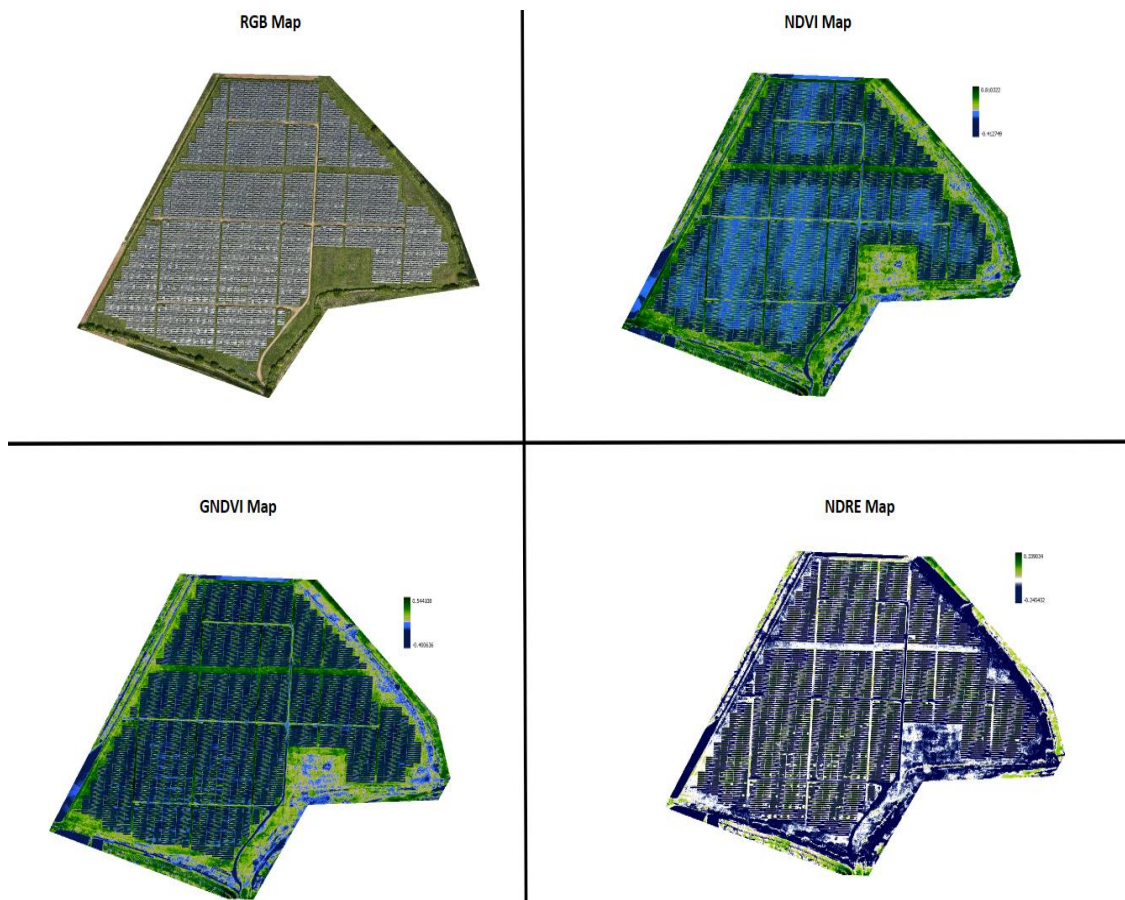


Figure 2.13: RGB map & Vegetation index Maps of a solar farm

The data was collected at a solar farm with only grass and hedgerows present. This data was provided to UPC for the purposes of understanding the format of the information contained within the images, and to understand how to interpret the data collected at an agri-pv site with crops/plants present.

A suitable agri-PV site was required—one that featured active crop growth and for which flight permissions could be obtained. UPC's Agropolis installation in Barcelona, where lettuce cultivation was planned for July 2025, was identified as a potential site. ABOVE submitted a drone flight application to ENAIRE on 16 June 2025. Although initial approval was granted, it was withdrawn on 11 July 2025, with ENAIRE stating that the approval had erroneously been granted under an old regulatory framework (RD 517/2024), necessitating a new application under the updated framework.

Given the timing of the next lettuce crop cycle and the time required for data analysis, and the considerable amount of time it takes to apply for flight permission from ENAIRE, it was collectively agreed that data collection would not be feasible in time to be incorporated into this deliverable.

Due to limitations in drone access under the agrivoltaic panels in the Agropolis pilot site, as well to be capable simulate low-altitude UAV flights, the planned multispectral imaging was replaced with a terrestrial robot-based approach. A ground platform developed by the UPC was deployed to collect crop health indicators directly from within the lettuce plots. The robot was equipped with: one crop circle sensor ACS-211 (Holland Scientific, Lincoln, NE, USA) for NDVI measurements (proxy for vegetative vigor); one RGB camera Intel RealSense Depth D457 (Intel Corporation, Santa Clara, CA, USA) for structure-from-motion (SfM) and color-based analysis; and one thermal camera Optris XI 400 (Optris GmbH, Berlin, Germany) to evaluate canopy temperature.

The robot traversed the central portion of each agronomic block under the three shading configurations (Control area without PV panels, Translucent PV modules, opaque PV modules). Multisensor data was collected for each lettuce row to evaluate plant development and physiological status under the different radiation regimes created by the solar structures. The RGB imagery was also used for semantic segmentation of plant rows and canopy area estimation, while thermal and NDVI signals were used to detect zones of differential transpiration or stress. All sensor acquisitions were georeferenced and timestamped, and the robot's path was manually aligned with the planting geometry to avoid disturbing the crop.



Figure 2.14: Left: Detail of the sensor suite mounted on the ground robot (RGB camera, thermal camera and Crop Circle sensor). Right: The robot performing agronomic monitoring

The robot featured a compact four-wheel chassis, with independent electric drive motors and low-pressure tires suitable for operating on bare soil between rows of lettuce. Its dimensions fitted between ridges (90 cm

width) and under the fixed PV structures (Figure 2.14). It was manually guided along the planting rows. A reinforced aluminium frame supported the sensor suite on a vertical mast at the front of the platform. The frame was modular allowing quick repositioning of sensing units as needed. RGB camera mounted at approximately 85 cm above the canopy, oriented downward with a 45° angle to capture both top-view and side canopy structure. The thermal camera was co-mounted with the RGB sensor on the same mast. The crop circle sensor was located at a lower position (45 cm above vegetation), aligned perpendicular to the plant rows. All the sensors were regulated by an onboard control unit. There were also a data logging and power management placed in a central box on the chassis.

Sensor calibration was performed before each mission, and shading artefacts from the PV panels were considered in the interpretation of NDVI and thermal readings. The robot was powered via onboard battery packs, and operated in short bursts to minimize soil compaction.

Currently, the data are under analysis. It is intended to the acquired data were used to quantify vegetative vigour, correlating light regimes under PV structures with physiological crop response. The initial statistical analysis of NDVI values across the three sections (Open Air, Translucent PV modules, opaque PV modules) showed no statistically significant differences. Although conventional modules display a slightly lower mean NDVI, the overlapping confidence intervals indicate that the observed differences are not significant at the 95% confidence level (Figure 2.15). Values of NDVI typically ranged between 0.85 and 0.88 among the varieties and blocks.

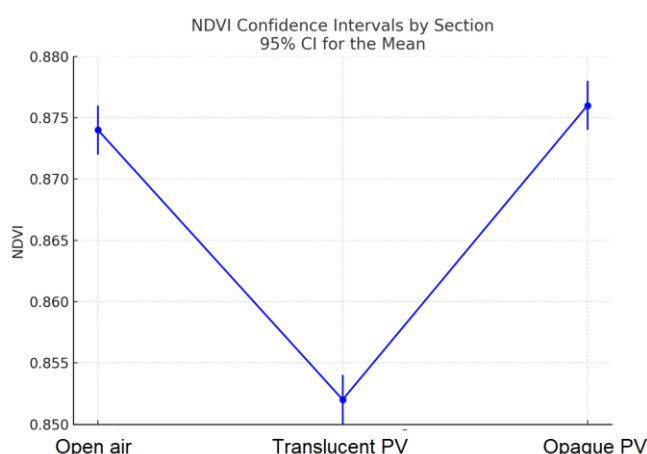


Figure 2.15: Comparison of Mean NDVI Values ($\pm 95\%$ CI) across the experimental sections in lettuce crops.

From an agronomic point of view, this could indicate that the reduced light transmission under OPV structures has not negatively affected the vegetative development of the lettuces (at least as measured by NDVI at this point in the crop cycle corresponding to the previous week to harvesting). It could be possible that the shading effect was partially offset by improved microclimatic conditions (e.g., reduced evapotranspiration or thermal buffering), although further physiological and yield-based measurements would be required to confirm this. However, further analysis will be needed to confirm this preliminary hypothesis (especially considering other factors such as variety, microclimate variability, and temporal evolution).

2.3 Modelling and simulation procedures (LUCISUN, IMEC)

2.3.1 Imec: Bifacial Raytracing

Imec's simulation framework is a rigorous, patented, bottom-up physics-based approach that applies advanced ray-tracing techniques to model the path of light through the PV modules, crop canopies, and other components of agrivoltaic systems. This framework provides a detailed understanding of light interactions by incorporating physical models for light scattering, reflection, transmission, and ground-reflected irradiance

(albedo). It supports the simulation of various PV configurations, including mono- and bifacial modules, fixed-tilt and tracked systems, and integrated designs such as BIPV and floating PV systems. The framework's raytracing capabilities enable accurate resolution of the effects of partial shading caused by surrounding objects and allow for the calculation of incident irradiance on both the front and rear sides of bifacial modules. Hence, the shading impacts of PV modules and support structures on the crops in agrivoltaic systems can be accurately accounted for.

Components within the agrivoltaic scene, such as PV module interlayers (glass, encapsulants, cells and backsheet), the ground, and vegetation, are defined in Radiance by assigning material properties, including reflectivity, transmissivity, and emissivity. This granular approach enables the analysis of different PV module materials and configurations, including semi-transparent modules, by capturing their impact on energy yield and light availability for crops. The framework can also account for the complex optical properties of plant surfaces, making it highly adaptable to diverse agrivoltaics scenarios. The features of the framework have been previously described [1], and the framework has been used to simulate the irradiance distribution and energy yield for different agrivoltaic topologies with arable crops for the Belgian climate [2] and for apple orchards in Italy [3]. Figure 2.16 summarizes Imec's modelling framework as applied to agrivoltaic systems.

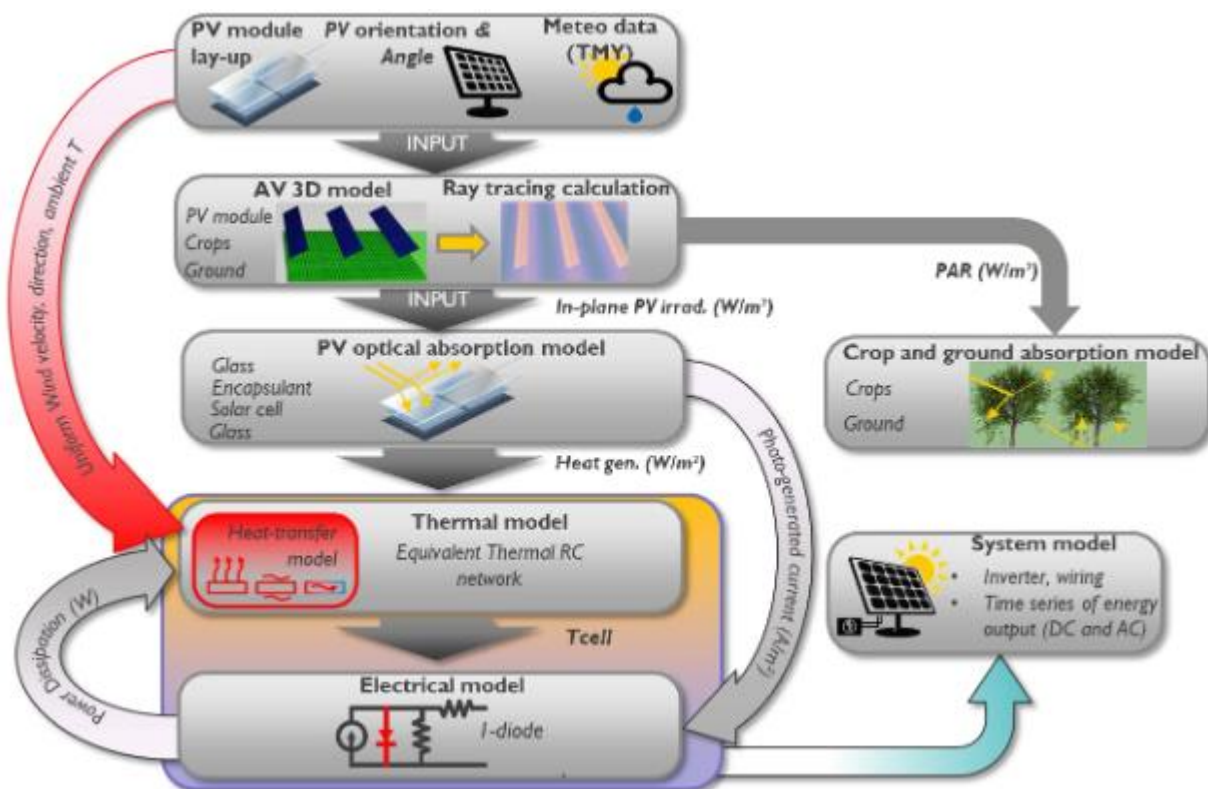


Figure 2.16: Imec's raytracing-based simulation framework as applied to agrivoltaic systems.

To accurately identify the different agrivoltaic system components and their material types in Radiance, the materials were given pre-defined Radiance material properties such as plastic (RadPlastic), glass (RadGlass) and metal (RadMetal), which determine how light interacts with the geometric surfaces [4]. Radiance deals with a single band of red, green and blue (RGB) colors, and these are used in the definition of the optical properties. The reflectance properties of the crops were defined based on the reflectance profiles of green leaves as earlier defined in Figure 2.1. The solar cells are defined in Radiance using the RadPlastic category which takes five parameters defined by RGB reflectance, specularity and roughness values [5]. The specularity describes the specular reflectance and refers to the gloss of the material, while roughness defines the surface

roughness. The RadPlastic material category was also assigned to the soil and trees (stem and leaves). The specular and the surface roughness of the RadPlastic were neglected to represent the optical properties of the materials defined. The front PV module glass was defined as RadGlass which represents a material that refracts and transmits light. The RadGlass type is defined by a refractive index and transmission in the RGB at normal incidence. The RadMetal property is further used to define the PV module frame (usually made of aluminum) and the steel support structures. The metal material takes similar parameters as the plastic, except the fact that its highlights are altered by the material color. More details on the Radiance properties of the different components in the agrivoltaic system are shown in Table 2.2.

In the energy yield modelling, a maximum power point tracking (MPPT) algorithm can be added at the module and PV string level. This makes it possible to assess the DC power output in real life conditions while accounting for temporal fluctuations and non-uniformities such as mismatch due to partial shading. The main output from the PV energy simulation is the instantaneous DC output power at the maximum power point.

Table 2.2 Radiance parameters of the different components in the agrivoltaic system.

Geometric components	Material type	Radiance material properties						
		Color						
		R	G	B	Spec.	Rough.	trans	tspec
Solar cells	RadPlastic	0.05	0.05	0.05	-	-	-	-
Glass	RadGlass	0.90	0.90	0.90	-	-	-	-
Backsheet	RadGlass	0.90	0.90	0.90	-	-	-	-
PV module frame	RadMetal	0.5176	0.5294	0.5373	0.8	0.1	-	-
Leaves	RadPlastic	0.11	0.16	0.08				
Stem	RadPlastic	0.20	0.20	0.20				
Ground	RadPlastic	0.20	0.20	0.20	-	-	-	-
Steel supports	RadMetal	0.5176	0.5294	0.5373	0.8	0.1	-	-

2.3.2 Lusim: an irradiance analysis tool

LuSim, the 3D irradiance analysis tool developed by LuciSun, is built on a proprietary simulation engine that exploits the computer's GPU to compute geometrical view factors for the different irradiance components. The overall simulation process requires that the different elements in the 3D scene are meshed using triangular elements as shown in Figure 2.17 and different reception points are assigned on those triangular meshes. As a reference, for the example considered in this analysis each tree had over 12,000 triangles, each pole around 600, each bar around 300 and the terrain around 3,000.

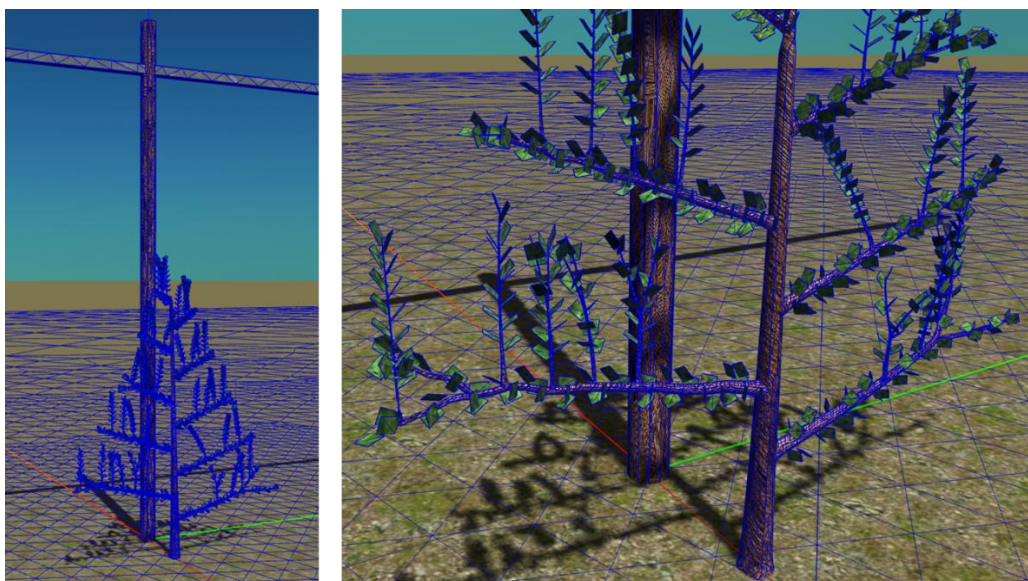


Figure 2.17: Example of meshes used by Lusim for the analysis over different elements.

The irradiance components are separated into three possible contributors:

- **Direct irradiance** – Parallel rays that comes from the sun direction. The impact of this contribution and particularly to identify if one of the reception points are in a shade area or not, is done performing a depth analysis over an orthographic projection of the field of view from the sun. This constitutes the direct shading factor for this component.
- **Diffuse irradiance from the sky** – Irradiance that comes from each direction of the sky dome. The impact of this contribution is done generating a spherical view factor over a 180° fish eye view projection from each reception points and evaluating the non-obscured areas from the sky of the picture. This constitutes the diffuse shading factor for this component.
- **Reflected irradiance** – Irradiance that comes from each direction of the surrounding objects. As done before, the impact of this contribution is done through a 180° fish eye view, but considering now the albedo properties of the materials, and the already shading impact of the elements viewed, both from a diffuse albedo component (photons reflected that come from the sky) as well as direct albedo component (photons reflected that come from the sun) and diffuse transmissivity of glass material. This constitutes the diffuse albedo and direct albedo view factors (see Figure 2.18).

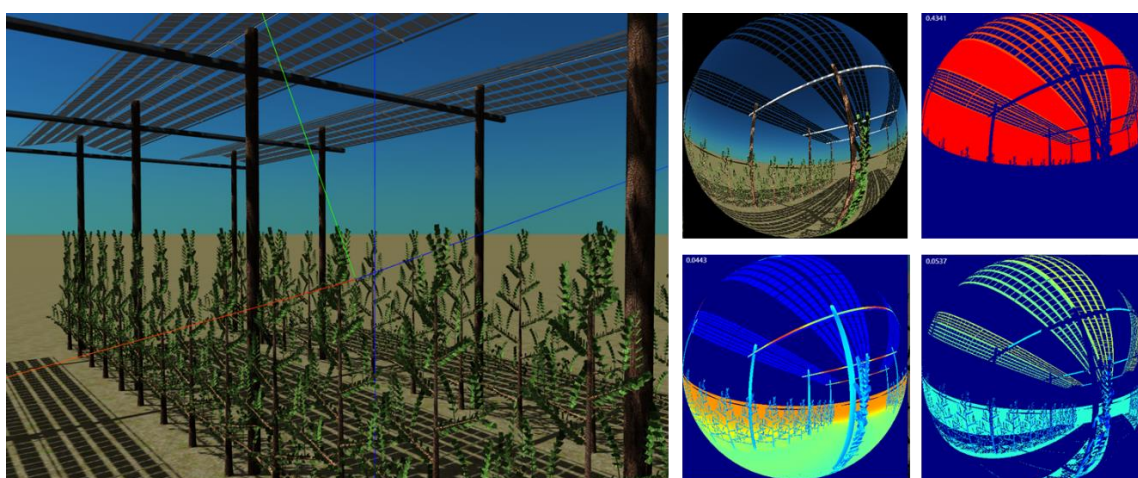


Figure 2.18: Example of view factors from a leaf (axis on left figure) for each different component (top left – real view, top right – sky view factor, bottom left – diffuse albedo view factor and bottom right – direct albedo view factor).

2.4 Light distribution on orchard crops (LUCISUN, IMEC)

2.4.1 Impact of crops on PV performance

The presence of crops in agrivoltaic systems interferes with the rear PV irradiance and hence the current and power output. The Bierbeek AV orchard was modelled as a bifacial system to assess the impact of the trees on the PV module parameters such as irradiance, temperature and current. Given the orientation of the PV array, the SE modules generally received more irradiance and higher output power Figure 2.19 A,B.

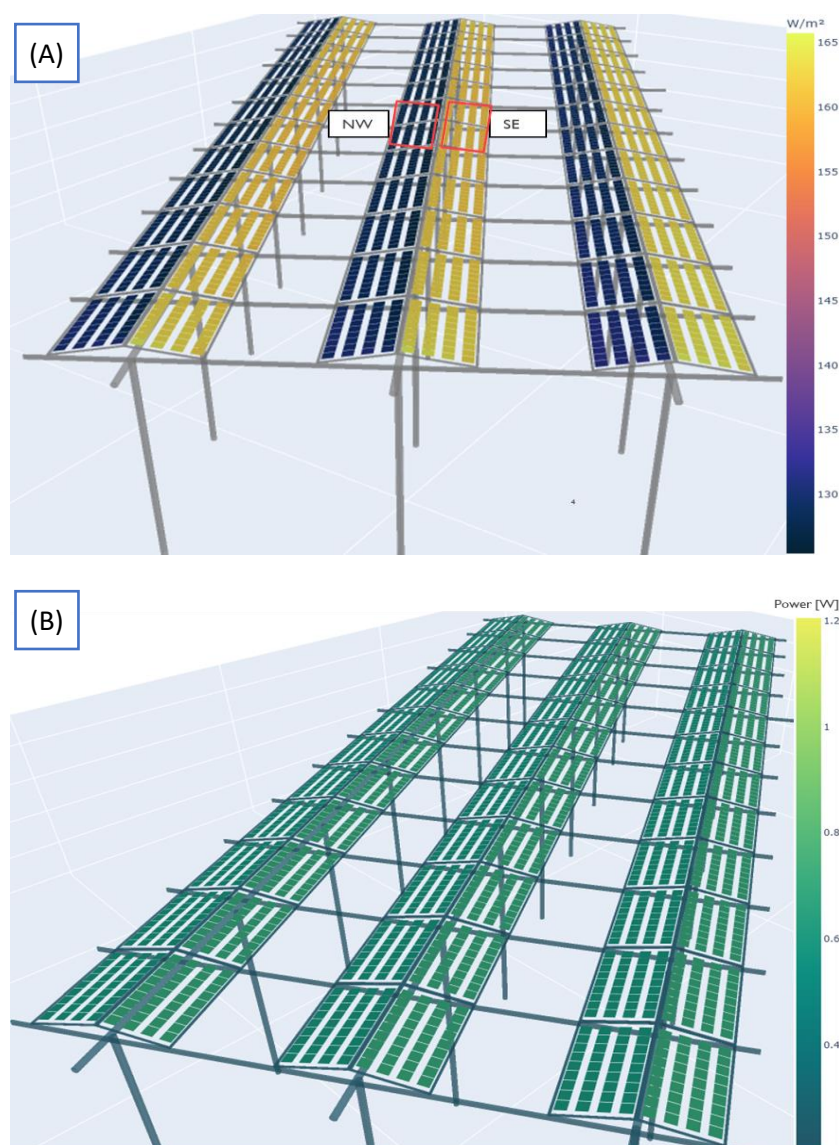


Figure 2.19: (A) Yearly average irradiance on south-east (SE) and north-west (NW) facing PV modules. Highlighted PV modules are used for analyses in the following sections. (B) Yearly average output power for AV systems (without crops).

To assess the impact of the trees on the PV performance, two scenarios were assessed: with and without trees using the south-east (SE) and north-west (NW) PV modules located in the central of the AV farm as shown in Figure 2.19 (A). It was observed that for both SE and NW facing PV modules, the rear PV irradiance was lower with the trees (Figure 2.20 (A, B)). This behaviour is expected as the trees intercept diffuse and ground reflected light thereby reducing the irradiance reaching the rear of the PV modules. Also, the reflectance of the crop

leaves is lower than that of the ground (Table 2.2). hence, the reflected irradiance from the leaves reaching the rear PV modules is reduced with the trees compared to the case without trees.

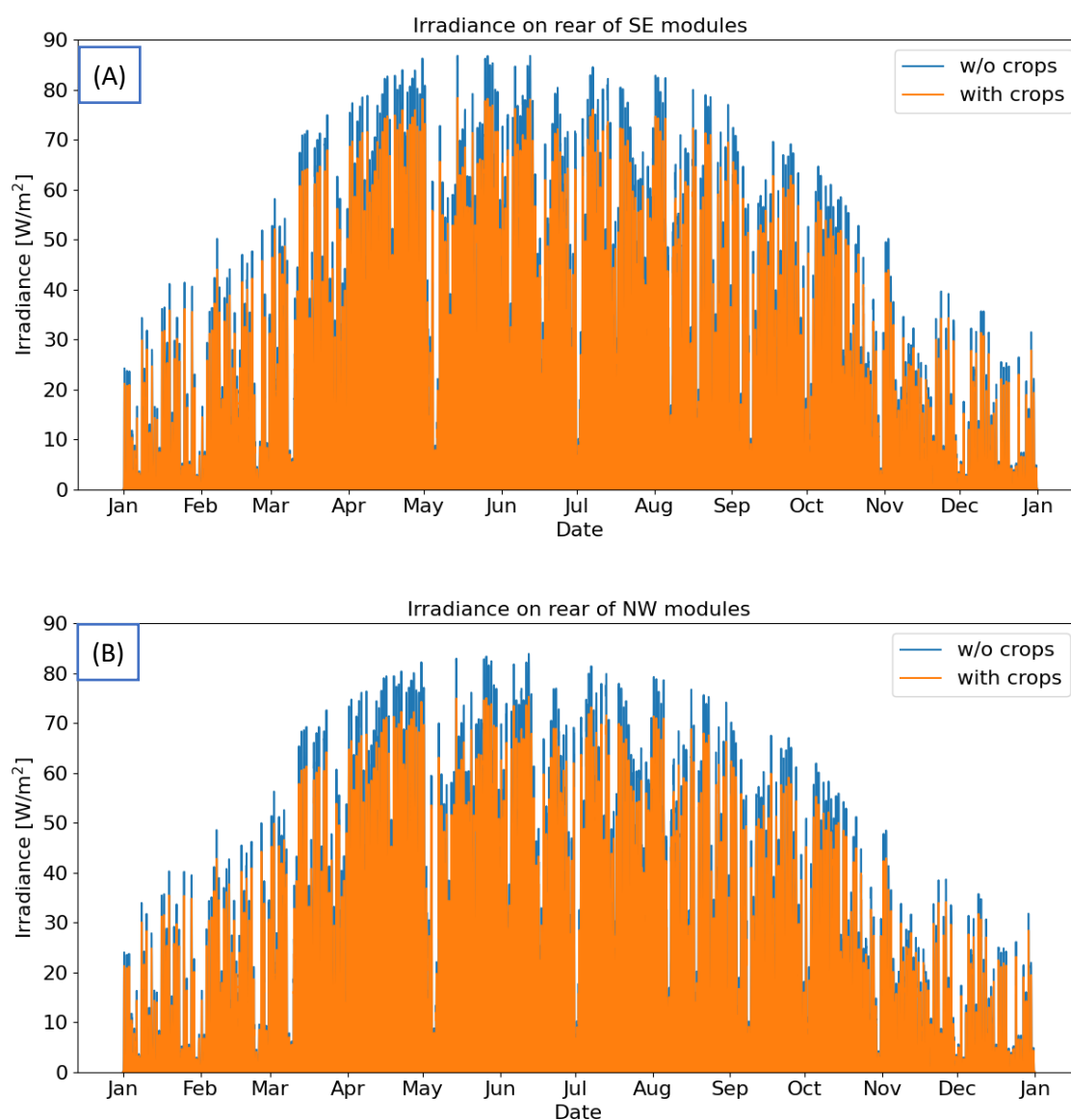


Figure 2.20: Irradiance on the rear of the selected central PV modules with and without the trees for the (A) SE and (B) NW facing PV modules

In Figure 2.21, the yearly average rear PV irradiation distribution is shown for the scenarios with and without the pear trees. In this birds-eye view, the regions with noticeable discrepancies in irradiance are highlighted with the red boxes. In general, there are more cells with lower irradiance for the case with the trees. This effect is more pronounced in the NW facing array (where the irradiance is generally lower than the SE facing array).

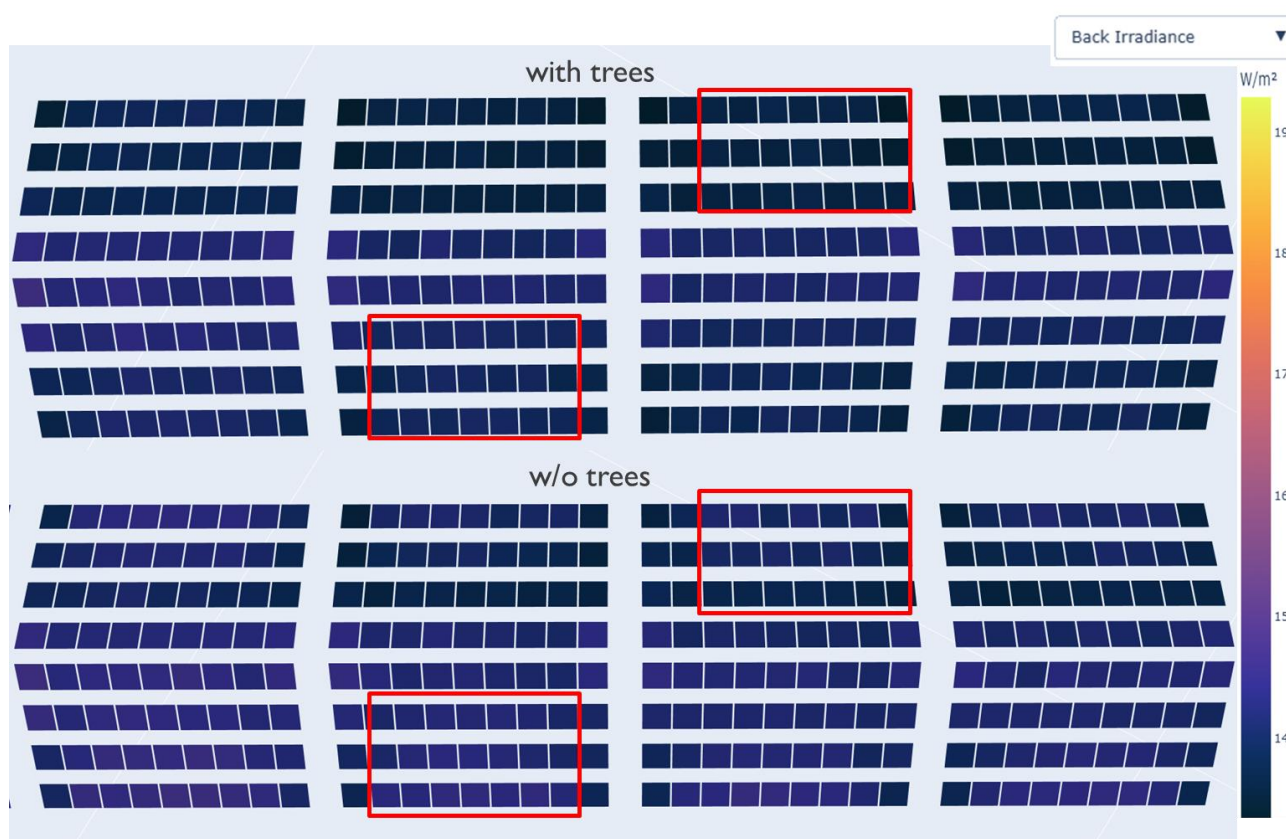


Figure 2.21: Sky-view illustration of the yearly average irradiance on the rear of the PV modules with and without the trees.

In general, the temperature of PV modules in AV systems is expected to be lower than for ground-mounted PV installations due to better convective cooling (owing to higher elevations) and cooling from crop transpiration. The impact of the trees on PV temperature based on the optical and electrical simulations was assessed. The coupled electrical-thermal framework of imec considers the net power absorbed by the solar cells, part of which is converted to electrical energy and the other part to heat. The latter, in addition to the ambient temperature influence the cell temperature. Based on these two factors, the PV module temperature was also assessed for the scenarios with and without the trees as shown in Figure 2.22. In general, the PV module temperature was slightly higher ($\sim 0.5\text{K}$) without the trees compared to the case with the trees. The temperature difference is also higher around the summer months. The difference in temperature can be attributed to the enhanced rear PV irradiance and heat generated in the PV modules as accounted for in the electrical-thermal framework.

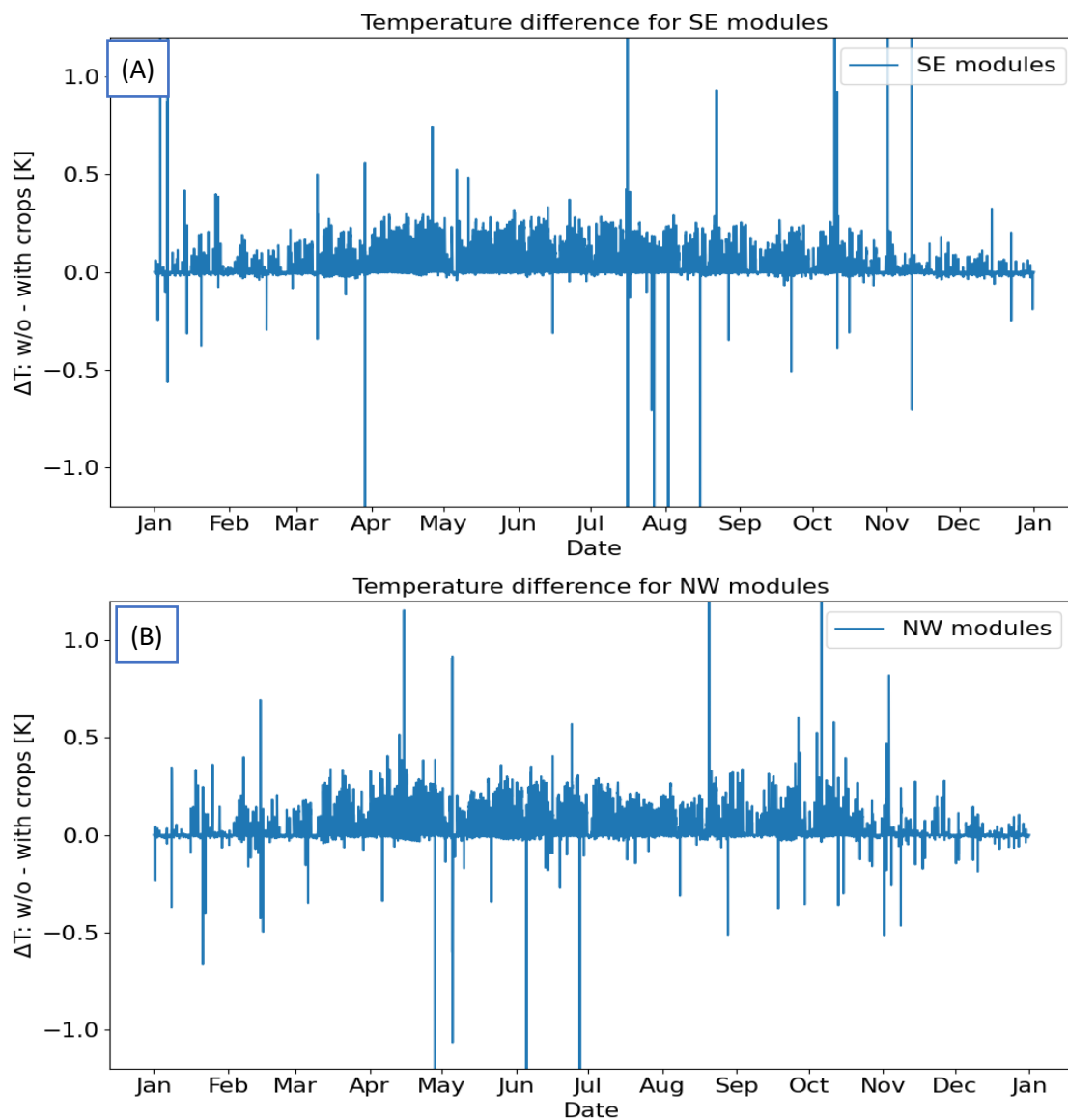


Figure 2.22: Temperature difference for scenarios with and without the trees for (A) SE and (B) NW PV modules.

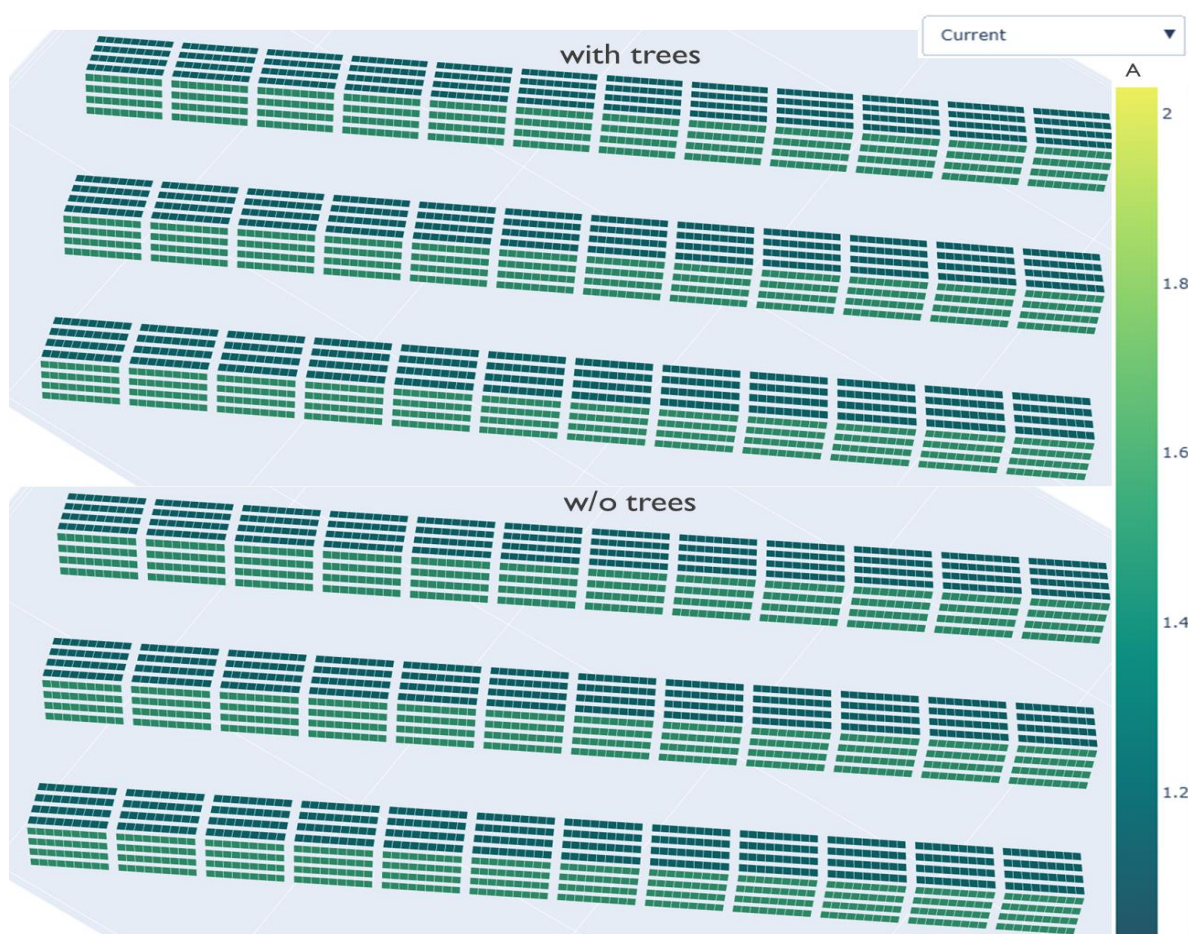


Figure 2.23: (A) illustration of the yearly average power of the PV cells with and without the trees

2.4.2 Irradiance distribution on orchard

The geometric model on the pear trees for the agrivoltaic Bierbeek site is shown in Figure 2.24 (A). The leaf density and distribution was randomly assigned with 1024 leaves per tree. The irradiance distribution on the orchard was simulated for a typical growing season for fruit orchards, which runs from April- August. The trees were divided into six microclimatic zones: top, middle, and bottom of the NW and SE facing leaves as shown in Figure 2.24 (B) and described in section 5.1.2. For each zone, five leaves were randomly selected and the , average irradiance on calculated and compared.

The irradiance on the different zones for a clear sky day in spring and summer is presented in Figure 2.25. Given the low solar elevation in spring, the lower parts of the trees receive higher irradiance compared to the top zone, with the bottom zone receiving the highest irradiance. In the early mornings (sunrise) and late afternoons (sunset), the bottom and middle zones clearly receive higher irradiance compared to the top zone. In the summer period, given the high solar elevation, the main shading of the crops comes from the PV modules. Hence, the irradiance on the different zones is slightly lower in summer compared to the spring for the selected clear sky day. Also, since the top zone is closer to the PV panels and given the high solar elevation, there is higher shading of the top zone compared to the lower sections.

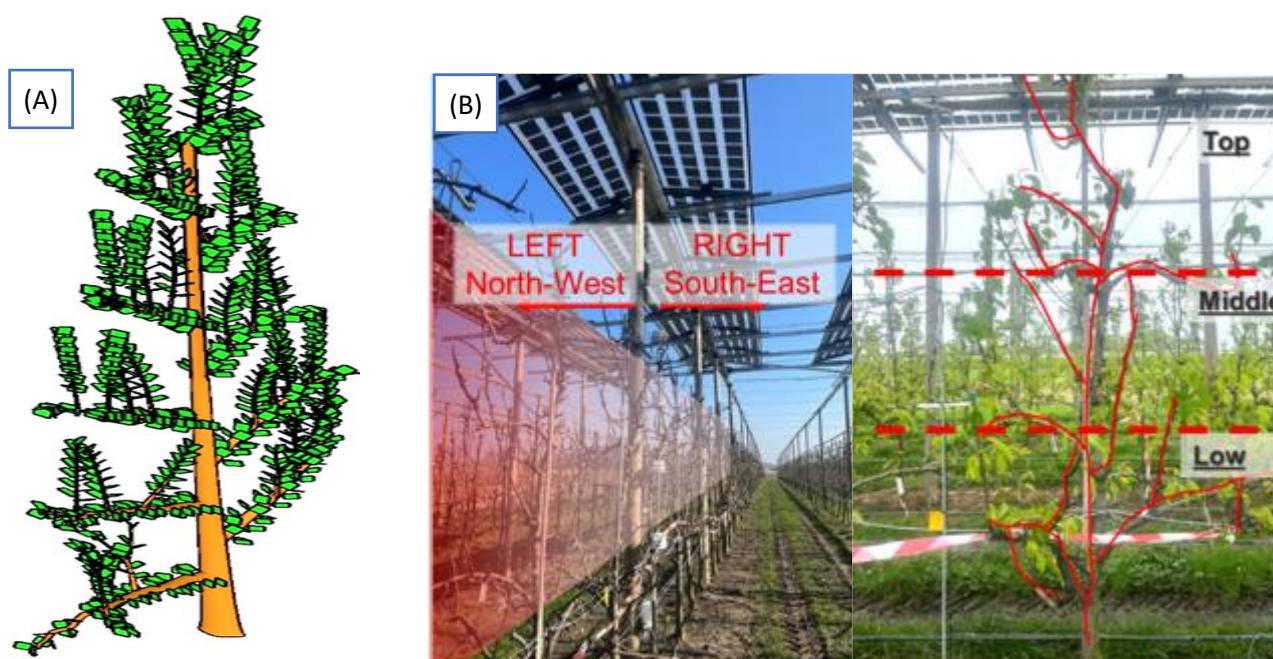


Figure 2.24: (A) Geometric model of pear tree used in the AV system modelling. (B) Illustration of the tree zones used for the irradiance analysis.

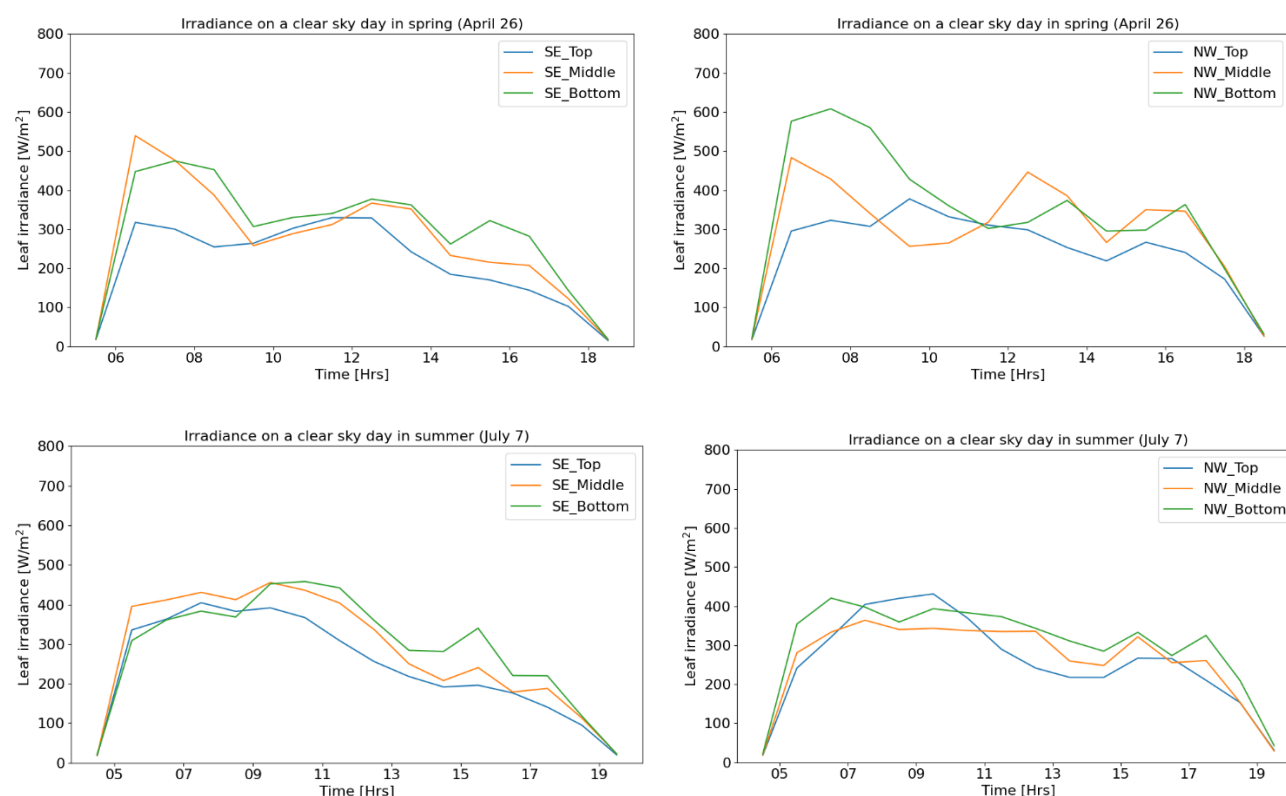


Figure 2.25: Irradiance on different zones of tree leaves for clear sky day in spring and summer.

Across the growing season (April – August), the middle zone of the SE region of the trees received the highest irradiance followed by the bottom zone. The difference in irradiance was much higher in spring, when the solar elevation was low while in summer, the middle and bottom zones have comparable irradiances. The top

zone received the lower irradiance and can be explained by higher PV shading especially during summer with the high solar elevation. For the NW sections, the bottom received the highest irradiance and was more noticeable in spring. Given the lower shading of the panels during the sun's trajectory, the top zones benefit from higher irradiance in summer with the higher solar elevation and low PV shading in the NW facing section of the canopy. Visualizations of the irradiance distribution on the canopy and PV modules around noon on a clear sky day is shown in Figure 2.27.

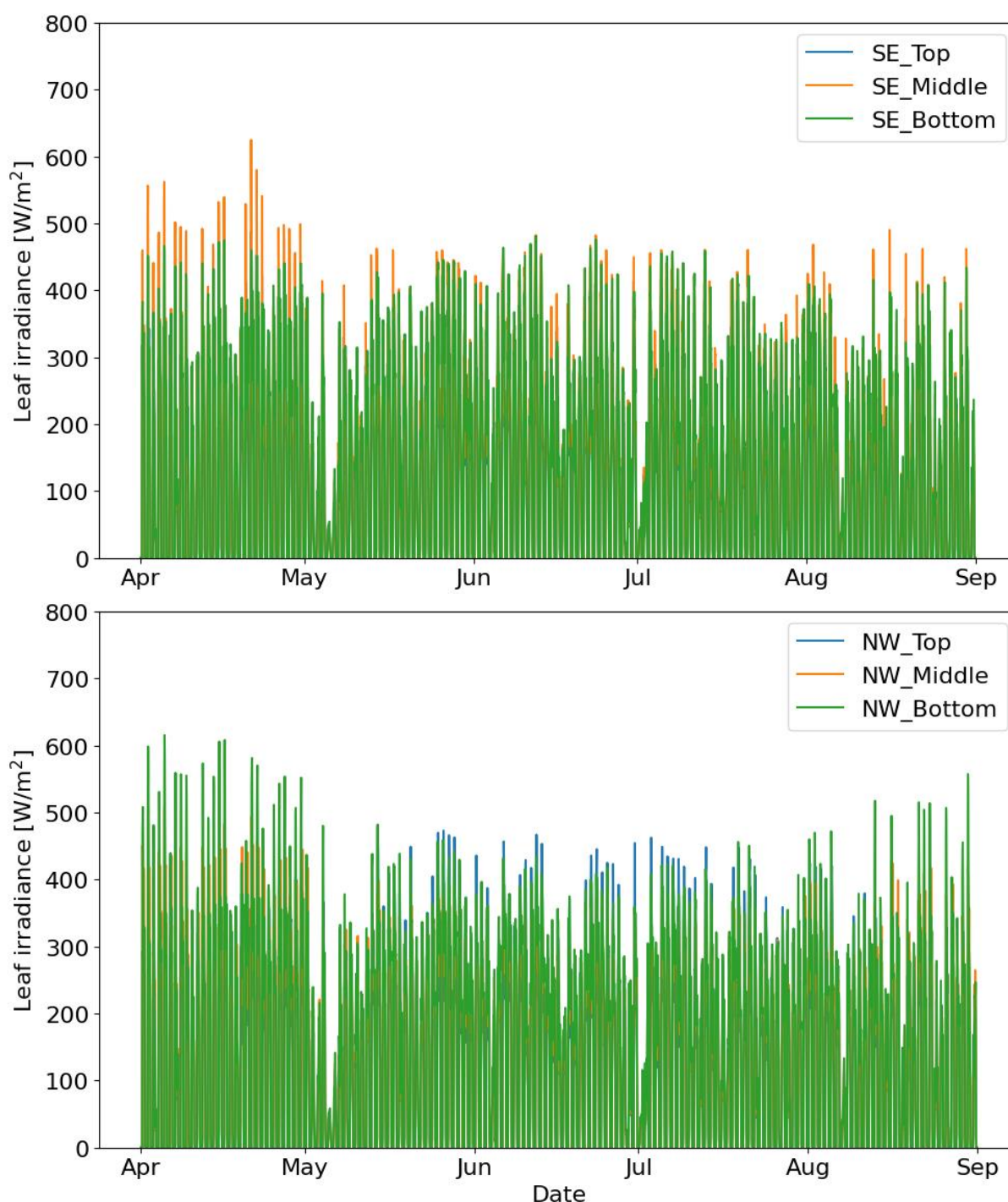


Figure 2.26: Irradiances on the pear tree leaves for the six different zones for a growing season.

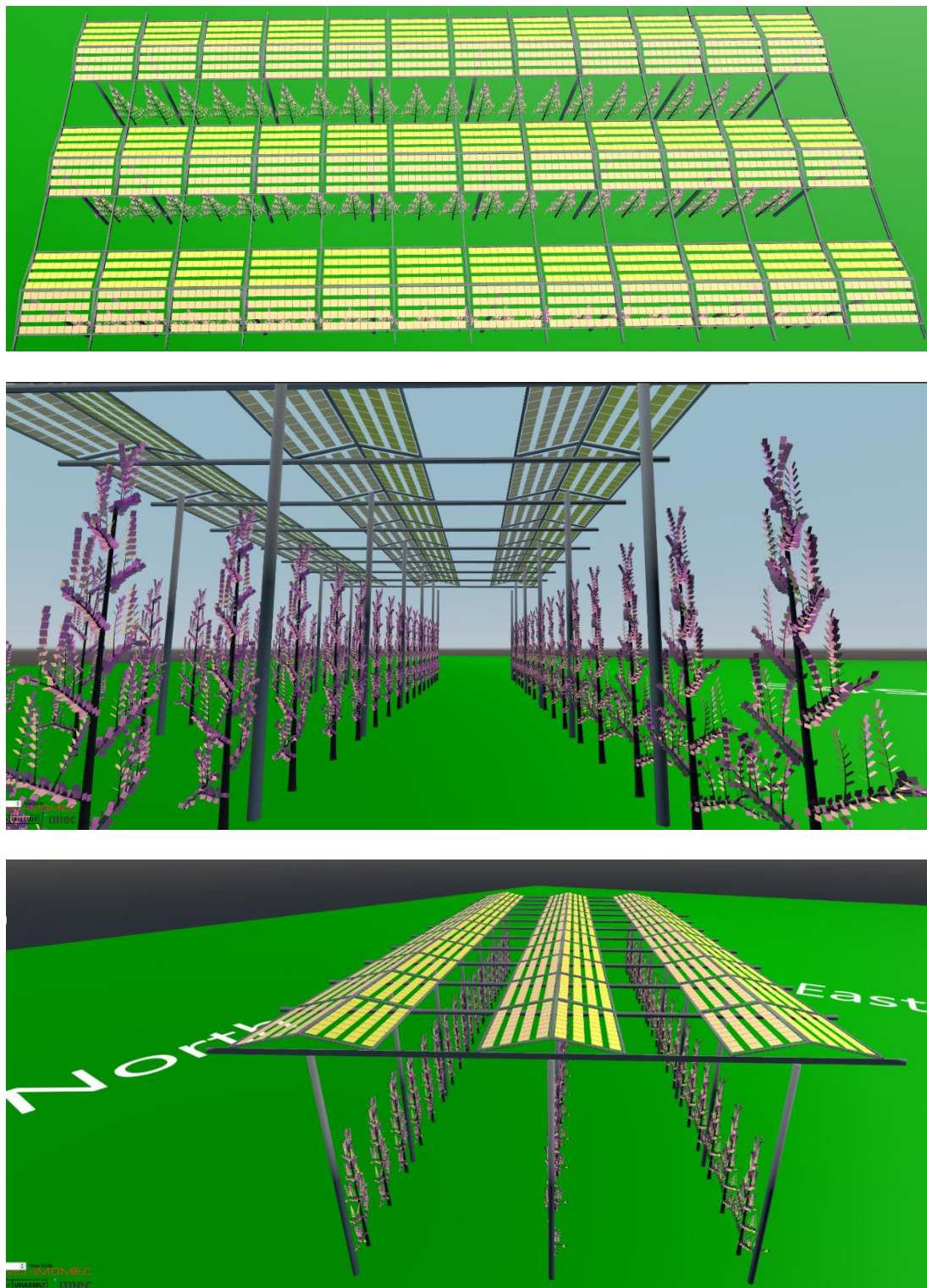


Figure 2.27: Irradiance distribution on apple orchard around noon on a clear sky day.

2.4.3 Irradiance analyses

The analysis performed with Lusim can be divided into two objectives:

- Irradiance received at cell level on each side of the PV modules
- Irradiance received at each zone of the leaves of the tree as described in section 2.1.2

For each of the analysis, two kinds of outputs are generated:

- Heatmaps of the distribution of irradiance for a specific time step (overall irradiance information is presented, but separation for components in a further analysis is possible)
- Time series of irradiance over a complete zone or PV generator side. This information is presented as a time series for specific period.

Irradiance over the PV modules

Front side

Due to the low tilt angle (12°) of the installation and the 60° orientation, there is not so much difference between each of the slopes ("south side" and "north side") of the generator. A comparison of the irradiance received during the morning, noon and the evening of a summer (June 19th) and winter day (December 30th) with clear-sky conditions is presented in Figure 2.28 to highlight these differences. On each scale, the colour scale is adapted for better visualisation.

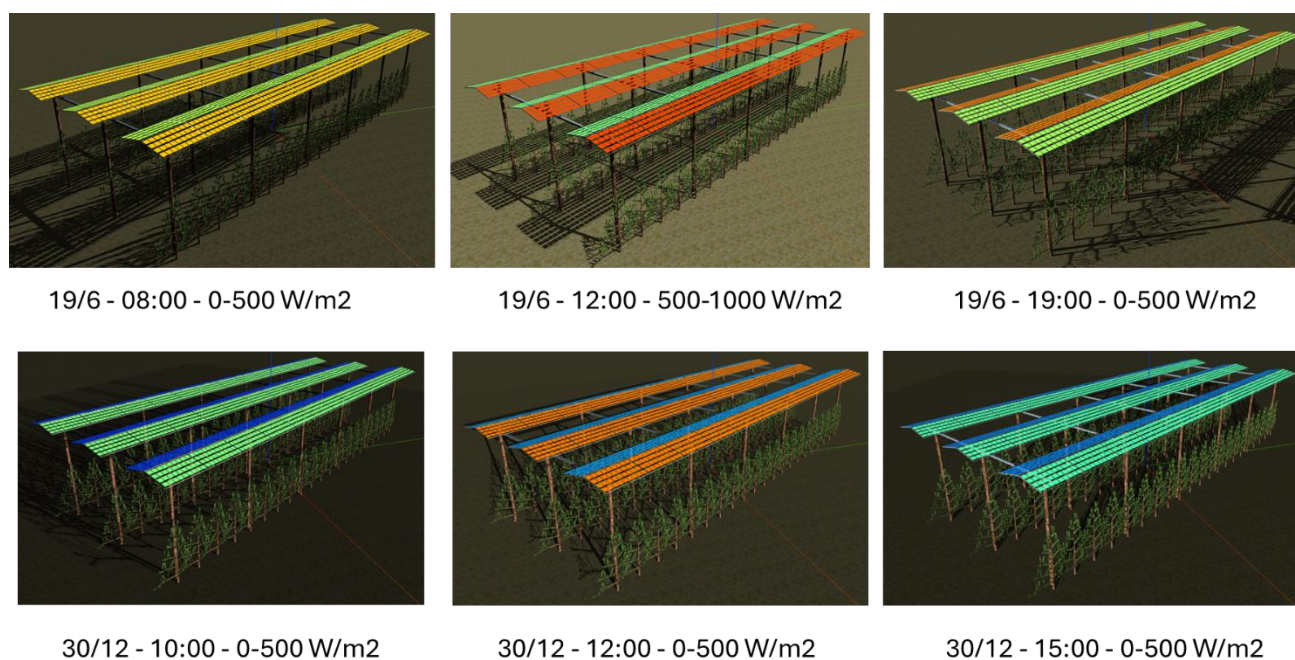


Figure 2.28: Instantaneous irradiance heatmap over the front side of the modules for June 19th and December 30th

In terms of irradiance over time, the front side presents a 22 % difference of overall production along the year between the "south" side (1495.6 kWh/m²) with respect to the "north" side (1163 kWh/m²). A comparison of the irradiation at the two days shown in the previous figures (June 19th and December 30th) and monthly level can be seen in Figure 2.29.

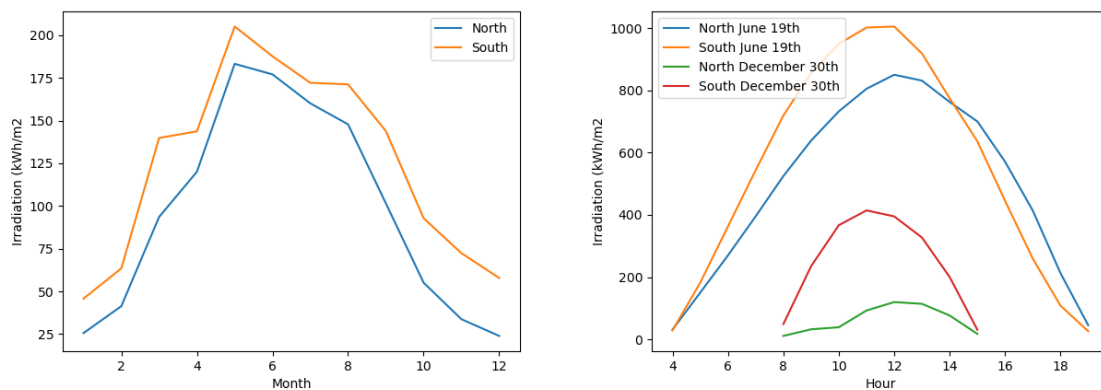


Figure 2.29: Irradiation comparison for the front side between the north and south side at monthly level and for two representative days

Rear side

The rear side presents a much bigger non homogenous irradiance, due to the presence of structural elements with different albedos and border effects that are dependent on the sun position. The heatmap distribution for the same days and times considered on the front side can be seen in the figure below. The colour scales are customised for each period to highlight those differences.

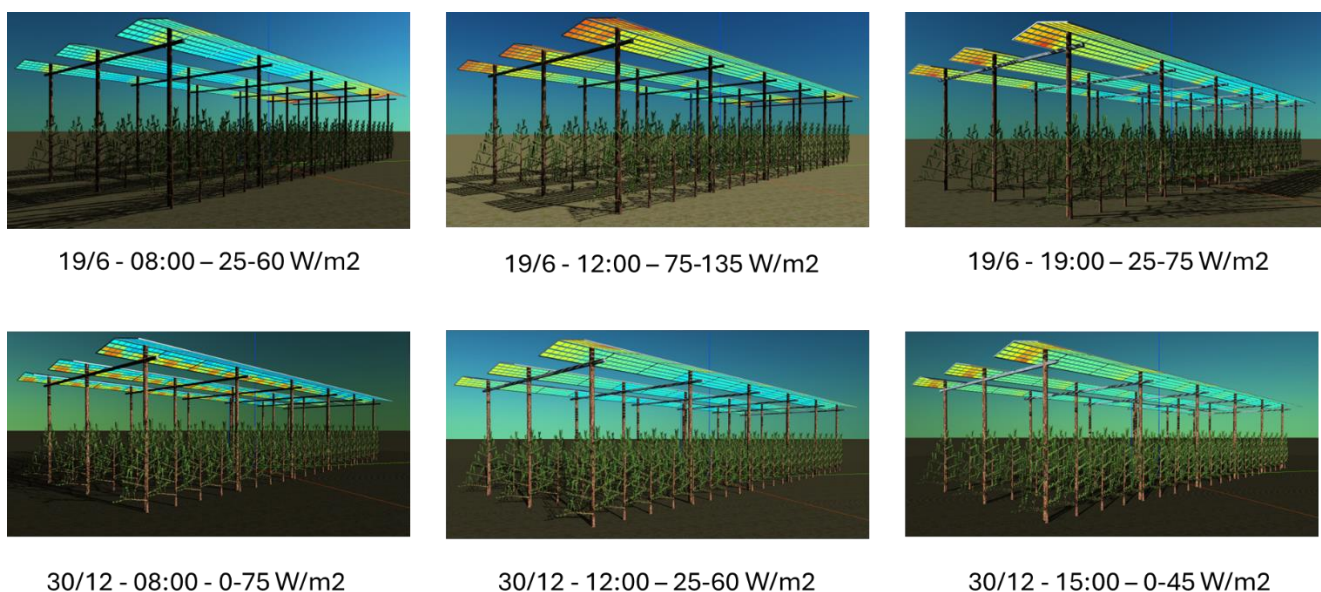


Figure 2.30: Instantaneous irradiance heatmap over the rear side of the modules for June 19th and December 30th.

The details effect needs to be discussed case by case, but when performing the breakdown of the contribution by the different irradiance components, the main contributor is the albedo for the direct part of the irradiance, which is significantly affected by the sun position and the elements seen. To provide an example of this effect, Figure 2.31 shows the view factor for this contribution at different locations of the rear side of the modules on the evening of June 19th, showing that the non-homogeneity comes from the different albedo of the metallic part of the structure and the shadow of the overall installation on the ground.

This analysis allows us to obtain complete irradiance level for each cell that is used for a IV modelling curve of the electrical generation. However, even if the level of non-homogeneity on the rear side is significant locally (for example in the figure below oscillates between 25 and 75 W/m² depending on the cell), the overall

irradiance received by the cell is mainly dominated by the irradiance received on the front side (in the range of 500 W/m^2 in this case) and consequently the overall mismatch is small.

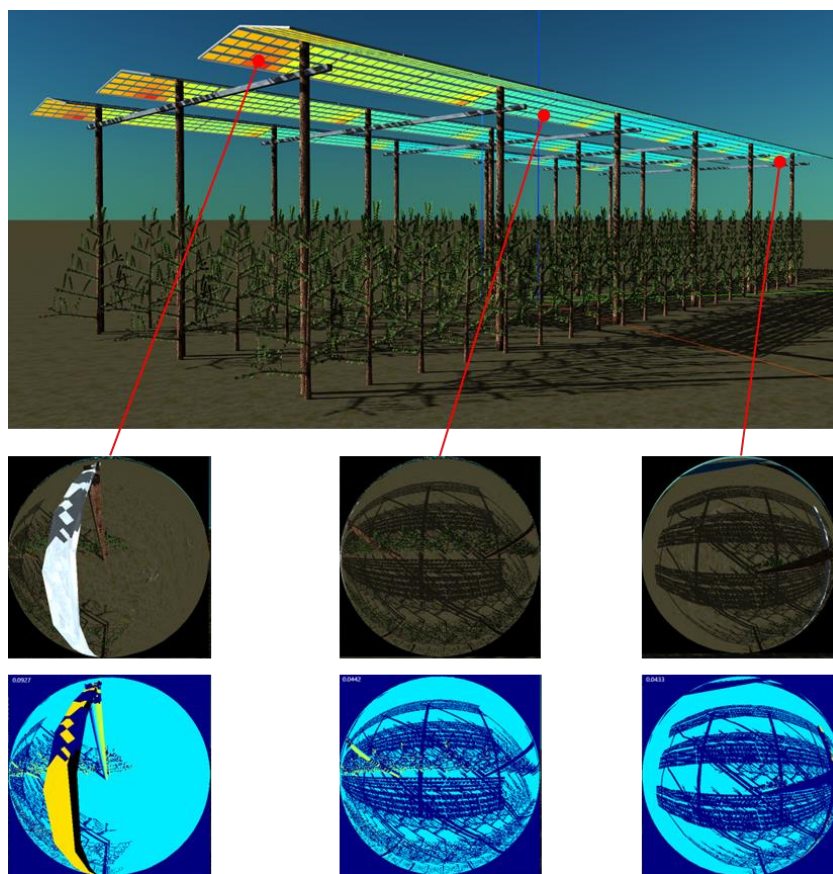


Figure 2.31: Details on the non-homogeneous irradiance distribution on the rear side of the modules for June 19th at 19:00

As presented before, it is also possible to perform a time series analysis of the irradiance received on the overall rear side of the modules at different time intervals, as shown in the figure below.

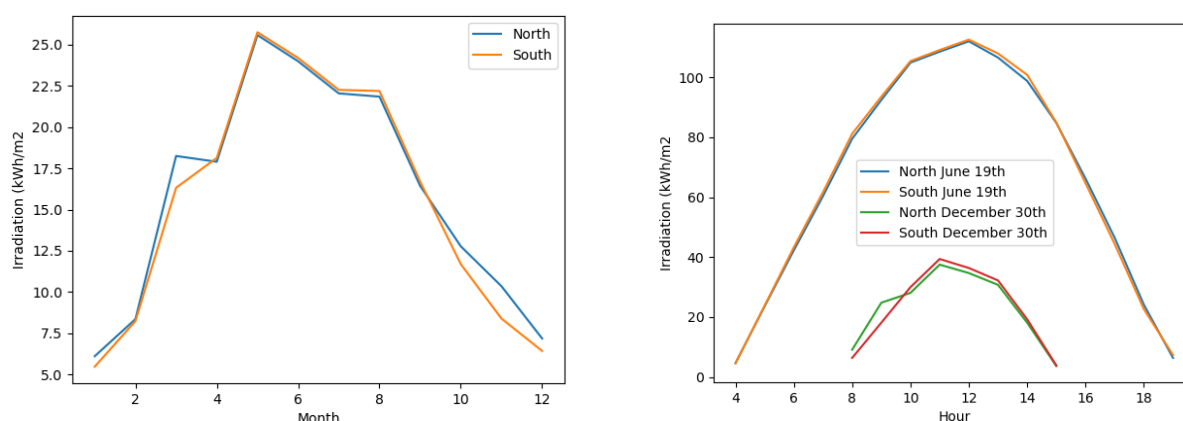


Figure 2.32: Irradiation comparison on the rear side between the north and south side at monthly level and for two representative days

Irradiance on crops

Similarly, as done for the PV modules, it is possible to generate the instantaneous irradiance values over the different objects of the installation and provide the overall values for different zones on the leaves.

Figure 2.33 presents an overall picture of the complete installation at two different time stamps (noon of the two clear sky days evaluated before, June 19th and December 30th), where the difference in the impact of the modules and the other trees in the shading can be observed (on summer the main shading at that time comes from the modules on top, due to the high sun elevation, while in winter it comes from the tree in front of the leaves, due to the lower sun elevation). In this case and for better clarity, the same irradiance colour scale, between 0 and 1000 w/m² is considered.

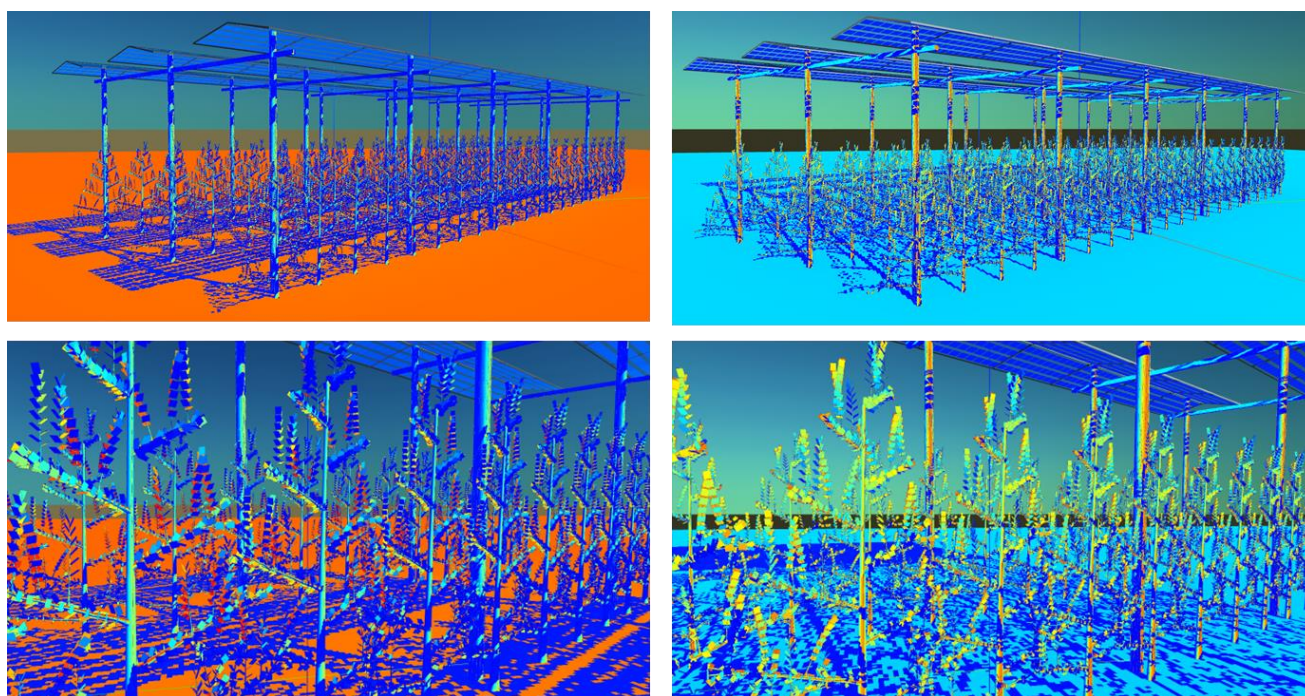


Figure 2.33: Heatmap of the irradiance over each element of the scene at noon summer (left, June 19th) and noon winter (right, December 30th)

The irradiance time series for each leaves zone as described before, is presented in the following graph, at different time resolutions. It is important to mention that a complete year is considered, but the same 3D model of the plant is used. It is possible to vary the 3D model of the plant over the time and generate details time graphs. This activity is ongoing in coordination with the evolution modelling of the crops.

From a times series perspective and per zone, the distribution of irradiance in summer and winter are quite different. In summer, due to the high elevation, there are two moments during the day when the PV modules' shade covers the trees completely, reducing the irradiance (particularly for a clear sky day as the one considered). This can be seen in Figure 2.34, where the irradiance per zone and per time for June 19th is correlated with the irradiance heatmap at the two "shading" points identified, particularly at 10:00 and 16:00. Different generator setup would create similar effects at different times of the day.

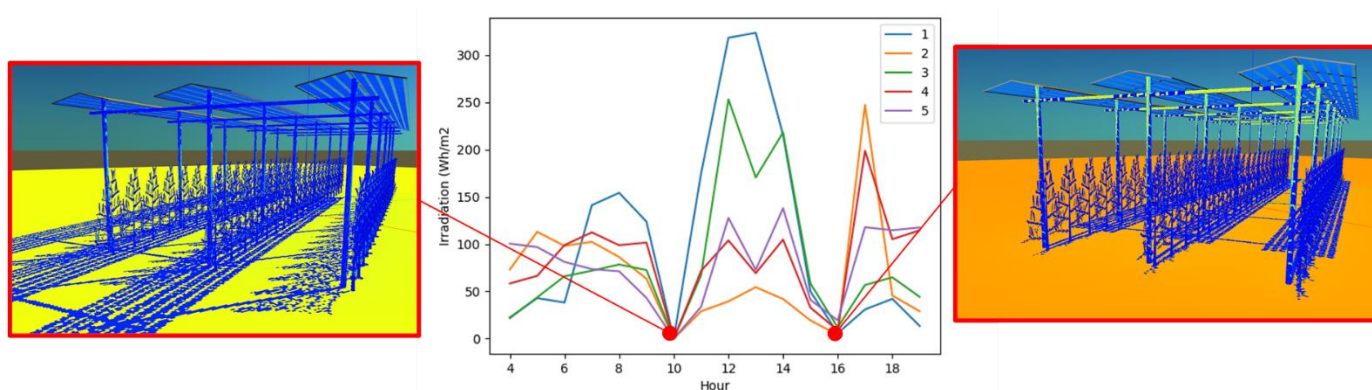


Figure 2.34: Time series of irradiance per zone and full shading identified at two-day moments in summer (June 19th)

This situation does not happen in winter, when the low sun elevation does not create a full shading, because the setup simulated only includes 3 rows of modules and trees. It is probable that configurations with more rows would present a different behaviour and could be something to evaluate in future works.

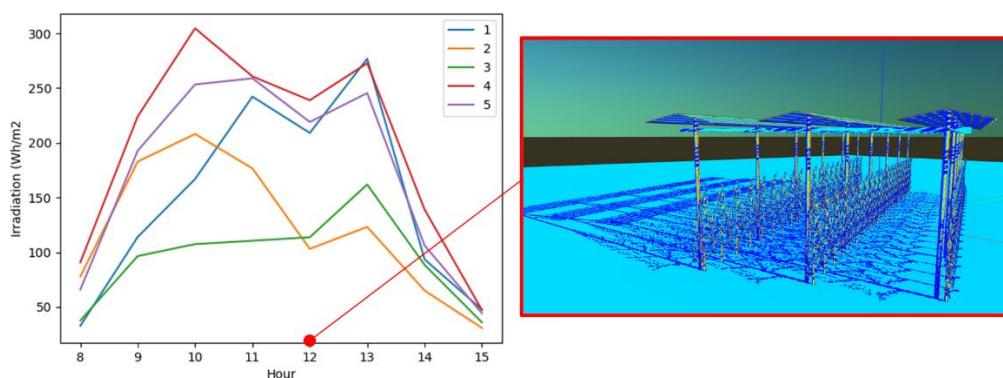


Figure 2.35: Low sun elevation in winter moves the PV modules shade again, but probably more rows should be included in the simulation to reproduce a more accurate scenario

Figure 2.36 illustrates the seasonal evolution of irradiance distribution per zone. Since the tree canopy is represented as a nearly bidimensional 3D model with leaves fixed in a single orientation, as defined by the agronomists, and in line with the current practices in crops modelling, the absence of random leaf orientations limits the possibility of Monte Carlo analysis. The results should therefore be interpreted in light of these modelling assumptions.

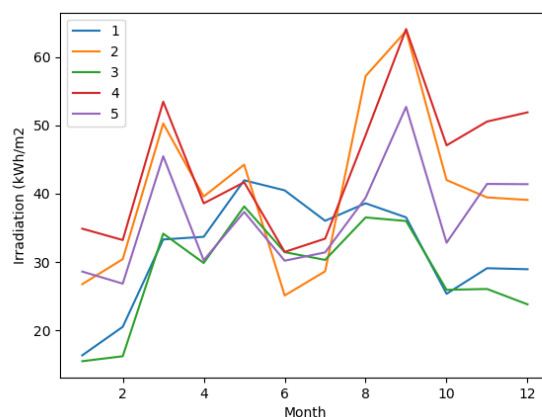


Figure 2.36: Irradiance per zone along the year (1: Low southeast, 2: Low northwest, 3: Middle southeast, 4: Middle northwest, 5: Top)

2.5 The impact of the placement of a mesh netting (UPC, LUCISUN)

2.5.1 Introduction

Protective netting is widely used in agriculture to safeguard crops against multiple risks. Wildlife attacks on agricultural fields are common in semi-natural and peri-urban environments, often causing severe yield losses and substantial economic damage. In some farming areas—particularly within designated bird protection zones, such as delta regions where vegetable crops are cultivated—overhead netting is essential to prevent bird damage. Similarly, perimeter fencing is required where populations of wild boars, rabbits, or other mammals pose a threat to production.

Beyond wildlife protection, nets are also deployed to shield crops from hail and excessive solar exposure. However, their installation inevitably modifies the crop's light environment by creating shading effects. Smaller netting spans typically lead to a greater reduction in light transmission, while larger spans allow more radiation to penetrate. These changes have agronomic consequences, as reduced availability of photosynthetically active radiation (PAR) may limit photosynthesis and affect yield. In the context of SYMBIOSYST open agri-PV demonstrators, such modifications have a dual relevance: they alter the PAR available to the canopy and, at the same time, influence photovoltaic performance by shifting the balance between direct and diffuse irradiance. Since both crop productivity and PV yield depend on the quality and stability of transmitted radiation, it is essential to accurately characterize the optical and shading properties of the netting. Accordingly, the objective of this study is to quantify the extent of light reduction induced by a commercial netting system and to evaluate its potential impact on crop productivity and PV performance.

Measurements of irradiance under the nets were conducted by UPC, using dedicated instrumentation to separate the contributions of solar irradiance. These measurements provided a direct characterisation of the transmission behaviour of the protective nets under different sky conditions. The results confirmed that the nets attenuate direct beam irradiance more strongly than diffuse radiation. Under cloudy or diffuse-dominated conditions, a substantial fraction of incoming light is transmitted, leading to relatively uniform canopy illumination, whereas under clear-sky conditions with high direct irradiance, the attenuation is more pronounced and the transmitted irradiance beneath the nets is reduced.

To integrate these effects into agrivoltaic modelling, LuciSun parameterised the nets in the LuSim simulation environment. LuSim is a GPU-based 3D irradiance simulation engine developed by LuciSun that computes geometrical view factors for all relevant irradiance components. This allowed the nets to be represented not simply as neutral shading elements, but as semi-transparent structures with specific optical properties that influence both spectral quality and angular distribution of transmitted light.

The resulting simulations generated irradiance maps, PAR distributions, and daily light integrals (DLI) at canopy level under the nets at the Barcelona demonstrator. This methodology provides a realistic description of the role of nets as active modifiers of the radiative environment, linking field measurements to 3D simulation outputs. It ensures that the protective structures are consistently accounted for in the analysis of crop growth conditions, microclimatic modification, and energy balance within the agrivoltaic system.

2.5.2 Methodology

To evaluate the impact of installing bird netting on crop microclimate and light conditions, a field trial was set up using a standard-size mesh by UPC. The net was mounted on a rectangular frame of poles, forming a grid of 3.5×5.0 m, with an overall structure measuring 15.5 m in length, 7.5 m in width, and 2.5 m in height. This arrangement reproduced typical conditions of protective netting commonly used in open-field horticultural systems (see Figure 2.37).



Figure 2.37: Mesh netting setup experiment.

Environmental variables were monitored both inside and outside the netted area using Guardian sensors (Apogee Instruments, USA), which continuously recorded air temperature, relative humidity, and incident radiation (ePAR) (see Table 2.3). The sensors were placed at 1m above ground level. Data collection was carried out from April through July, covering the main spring–summer growth period. Measurements were logged at 10-minute intervals, resulting in a high-resolution dataset that captured both diurnal cycles and seasonal variability.

Table 2.3 Radiance parameters of the different components in the agrivoltaic system.

Sensor	Magnitude	Range	Error
Guardian (apogee)	Temperature (°C)	-60 to 80°C	±0.2°C
	Relative humidity (%)	0 to 95%	±3% (from 20% to 80%)
	ePAR (μmols/m ² s)	0 to 4000 (μmols/m ² s)	±5%

The analysis focused on quantifying the effect of the netting on incoming radiation and crop microclimate. Specifically, paired inside–outside ePAR values were compared to determine the shading effect of the mesh. Linear regression was used to estimate the proportional reduction in light transmission. In addition, observed ePAR values were benchmarked against crop-specific light saturation thresholds (lettuce, beans, onions, cabbage) to assess whether the netting increased the share of conditions falling below the optimal light range for photosynthesis. Parallel analyses were performed for air temperature, relative humidity, and vapor pressure deficit (VPD) to evaluate possible microclimatic modifications induced by the netting.

2.5.3 Modelling

To represent the nets as realistically as possible, LuciSun modelled them in LuSim with a cosh catenary shape rather than as perfectly flat surfaces. This approach reflects the way nets behave in real installations, where they sag between supporting poles due to their own weight and tension. Introducing a catenary geometry allows the model to capture the 3D effects of the mesh on incoming radiation. First, the finite width of the net fibres creates partial shading that depends on the incidence angle of the sun. Second, the curved shape modifies the effective path of light rays through the net, making the transmittance slightly lower than what would be predicted under the simplified assumption of orthogonal light on a flat mesh. Third, solar elevation varies throughout the day and across seasons, further enhancing the angular dependence of shading. By including these effects, the simulations reproduce more faithfully the real behaviour of protective nets in the

field, ensuring that both the attenuation of direct irradiance and the redistribution of diffuse irradiance are quantified in a physically consistent way.

The modelling workflow is illustrated by a series of visual outputs generated with LuSim. These visualisations show how the nets are represented structurally, how they modify the sky view from canopy level, and how they affect the resulting irradiance maps and angular transmission functions.

In the simulations, three irradiance components were distinguished: direct normal irradiance (DNI), circumsolar diffuse irradiance (DIFcirc), and isotropic diffuse irradiance (DHIiso). The presence of the net reduced the DNI component significantly, with stronger attenuation at higher solar elevations. At the same time, a larger fraction of the diffuse components (DIFcirc and DHIiso) was transmitted, meaning that under cloudy or mixed sky conditions the nets allowed sufficient radiation to reach the canopy.

Figure 2.38 shows a 3D structural representation of the demonstrator with protective nets. The 3D structural model of the demonstrator defines the geometry of both shading elements and vegetation, ensuring that LuSim can compute the angularly dependent transmission and shading patterns of the nets.

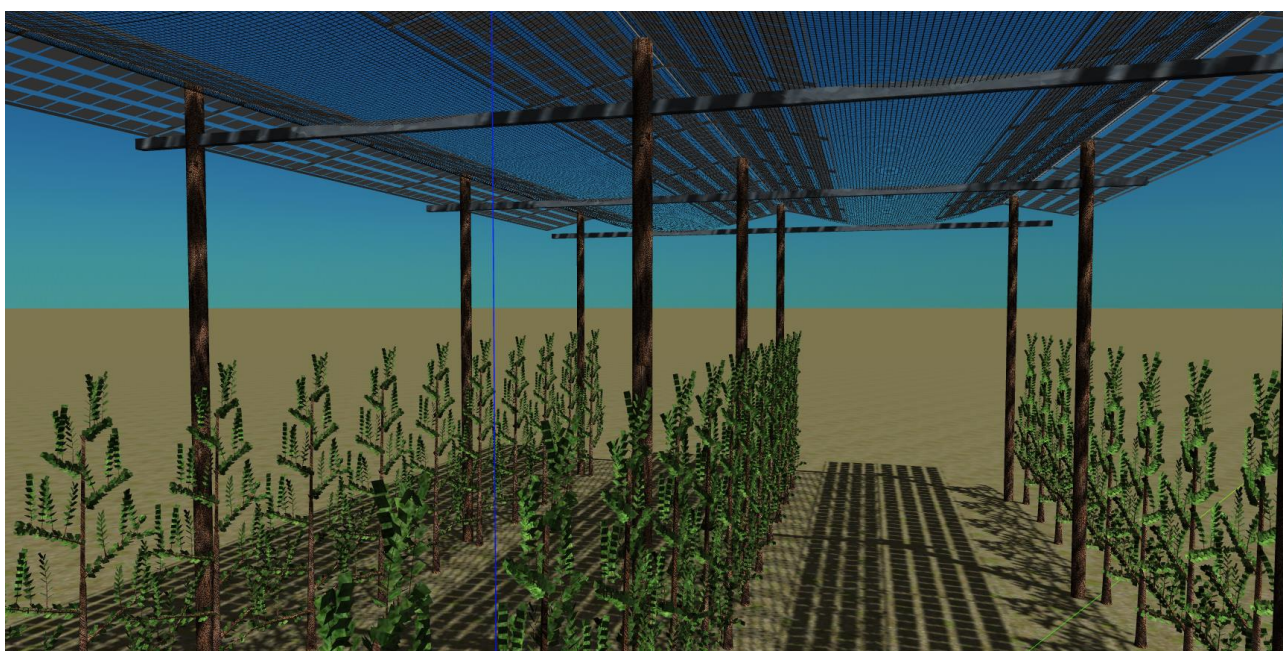


Figure 2.38: 3D structural model of the demonstrator with protective nets.

Figure 2.39 shows a hemispherical view of the nets from canopy perspective. A hemispherical projection from canopy level shows the sky view filtered through the nets. The reduction in visible sky fraction demonstrates the selective attenuation of DNI while diffuse components (DIFcirc and DHIiso) continue to penetrate.

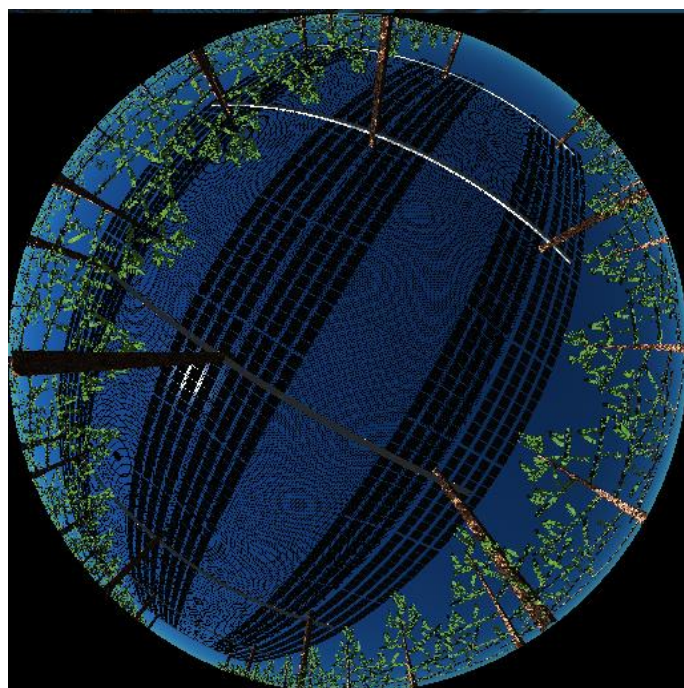


Figure 2.39. Hemispherical canopy-level view of the nets.

Figure 2.40 shows Irradiance maps with and without nets. Without nets, irradiance is dominated by DNI, producing strong contrasts between shaded and sunlit zones. With nets, attenuation of DNI is evident, but diffuse transmission yields a more uniform PAR distribution across the canopy. The results can be seen in the comparative plots produced with LuSim. For a low solar elevation case with high diffuse contribution (DNI around 100 W m^{-2} , DHLiso about 300 W m^{-2}), the attenuation by the net was moderate and the transmitted radiation was dominated by the diffuse components. This led to a relatively uniform canopy illumination despite the presence of the net. In contrast, for a high solar elevation clear-sky case (DNI above 800 W m^{-2} , DHLiso around 60 W m^{-2}), the attenuation of the direct component was more pronounced, resulting in a larger reduction of total transmitted irradiance beneath the net.

The modelling confirmed that the nets act as spectrally and angularly selective filters rather than neutral shading devices. By reducing direct irradiance more than diffuse irradiance, they change the light quality at canopy level. This has two important implications for the Barcelona demonstrator. For crops, the higher relative share of diffuse radiation under the nets can enhance the uniformity of PAR within the canopy. For PV modules, the reduced direct irradiance has only a minor impact on total system yield since diffuse light is still effectively captured.

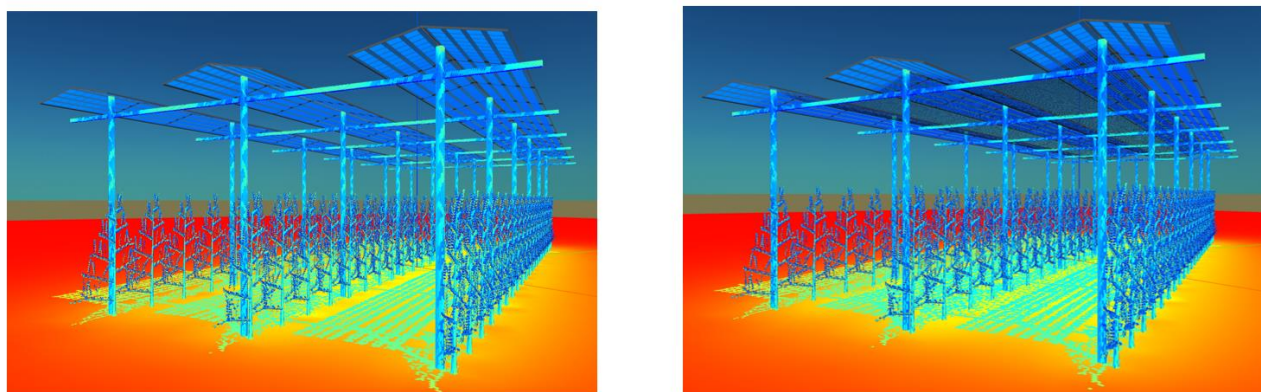


Figure 2.40. Irradiance maps of the demonstrator without nets (Left) and with nets (Right). Scale range: $0 - 436 \text{ W/m}^2$. DNI: 100 W/m^2 , DIFcirc: 50 W/m^2 , DHLiso: 300 W/m^2 .

The irradiance transmission and integration into LuSim is illustrated in Figure 2.41. Angularly dependent transmission functions of the nets are illustrated by circular insets, while 3D renderings show their integration into LuSim. This guarantees that the net's effect is represented consistently across the entire sky dome.

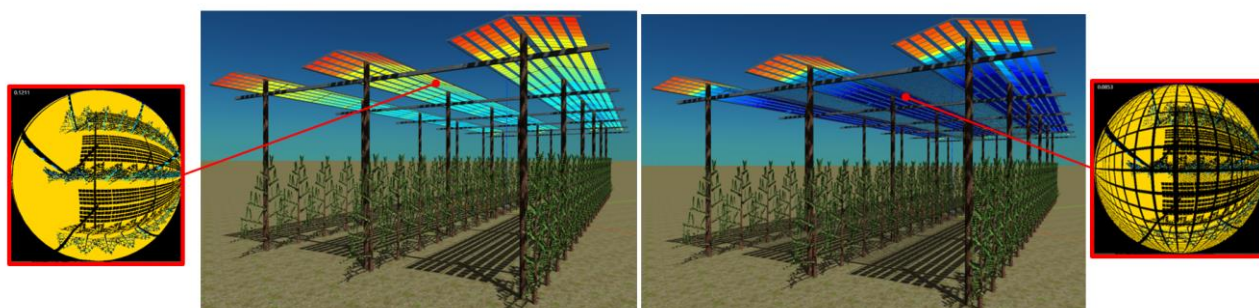


Figure 2.41. Integration of irradiance transmission of nets into LuSim simulations. Scale range: 80 – 150 W/m², DNI: 850 W/m², DHlcirc: 110 W/m², DHliso: 60 W/m².

The annual impact of the net on total irradiation, shown in Table 2.4 ranges between 3.5% and 7% depending on the canopy zone. Zone 1 (bottom south-east) shows a reduction of –7.05%, Zone 2 (bottom north-west) – 3.39%, Zone 3 (middle south-east) –6.57%, Zone 4 (middle north-west) –4.59%, and Zone 5 (the top of the canopy) –6.37%. The overall transparency of the net is approximately 90%. In the present configuration, the simulation considered nets covering only the top of the crops and not the lateral sides. Combined with the fact that the tree models are nearly bidimensional, most of the incident light originates from lateral directions and is therefore less affected by the net. As a result, the effective reduction is lower than the 10 per cent that might have been expected with a net whose orthogonal transmittance is close to 90%).

The variability observed across canopy zones reflects the assumptions used in the current modelling approach, in which a single 3D tree model was applied. The results provide a clear first estimate of irradiation reductions due to nets and demonstrate the value of integrating these structures into the simulation framework. A natural extension of this work would be to introduce statistical variation in leaf orientation, for example through a Monte Carlo approach, in order to capture a wider range of canopy geometries and provide even more representative estimates.

Table 2.4. Definition of model parameters and values used in degradation rate simulation.

	Zone 1		Zone 2		Zone 3		Zone 4		Zone 5	
Month	Net	No net	Net	No net	Net	No net	Net	No net	Net	No net
January	15.1	15.4	24.5	24.7	14.0	14.3	31.8	32.1	27.8	28.0
February	18.1	18.5	27.6	28.0	14.1	14.5	31.0	31.4	25.5	26.2
March	28.9	30.0	43.6	45.2	28.2	29.9	48.7	51.1	41.8	44.1
April	26.3	29.2	33.9	35.3	24.9	27.6	34.2	36.7	26.8	29.6
May	30.8	34.5	38.3	41.1	29.3	33.2	35.5	39.0	30.1	34.8
June	31.7	36.7	20.8	23.9	26.0	29.2	25.6	30.1	24.7	29.0
July	27.3	32.0	24.8	26.7	24.3	27.4	27.8	31.1	26.3	29.7
August	32.3	35.0	53.5	55.3	31.8	34.5	43.8	46.5	33.8	37.4
September	30.1	31.9	53.7	54.6	30.7	32.5	56.3	58.2	47.9	50.4
October	23.1	23.6	36.1	36.5	22.6	23.1	42.1	42.9	29.2	30.6
November	25.5	25.9	33.3	33.5	24.3	24.5	46.5	46.8	38.7	39.0
December	25.5	25.7	34.5	34.7	21.7	21.9	45.6	45.8	38.9	39.1
Annual	314.5	338.4	424.5	439.4	291.9	312.5	468.9	491.5	391.4	418.0
	-7.05%		-3.39%		-6.57%		-4.59%		-6.37%	

2.5.4 Field measurements

The relationship between outside and inside incident EPAR is shown in Figure 2.42. The regression line indicates a slope of 0.875, which corresponds to an average 12.5% reduction in light under this net compared with outside conditions. The very high coefficient of determination ($R^2 = 0.994$) confirms the consistency of this shading effect.

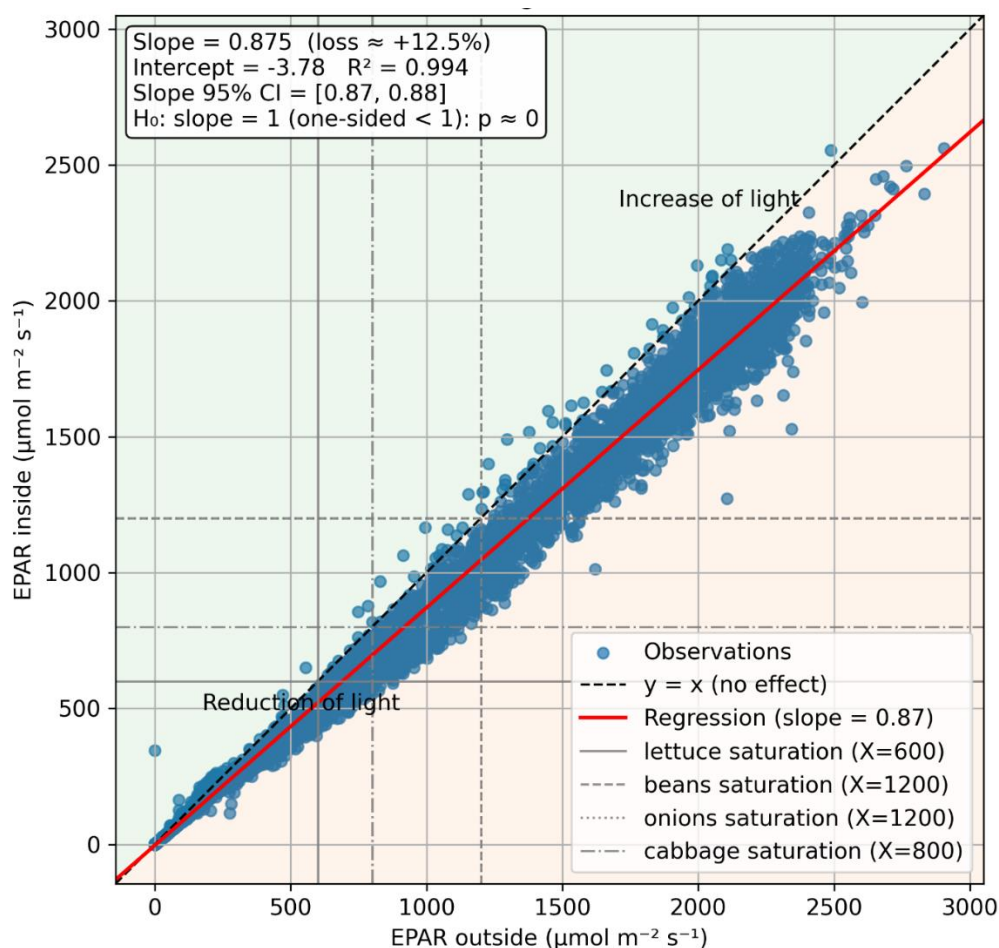


Figure 2.42. Inside versus Outside EPAR showing regression and saturation thresholds for the various crops.

When the reduction is compared with crop-specific light saturation thresholds (lettuce: $600 \mu\text{mol m}^{-2} \text{s}^{-1}$; beans and onions: $1,200 \mu\text{mol m}^{-2} \text{s}^{-1}$; cabbage: $800 \mu\text{mol m}^{-2} \text{s}^{-1}$), the share of observations below saturation increases slightly, as shown in Figure 2.43. The changes are modest:

- Lettuce: from 58.0% outside to 60.4% inside (+2.4%)
- Beans: from 69.6% to 73.5% (+3.9%)
- Onions: from 69.6% to 73.5% (+3.9%)
- Cabbage: from 61.9% to 65.0% (+3.1%)

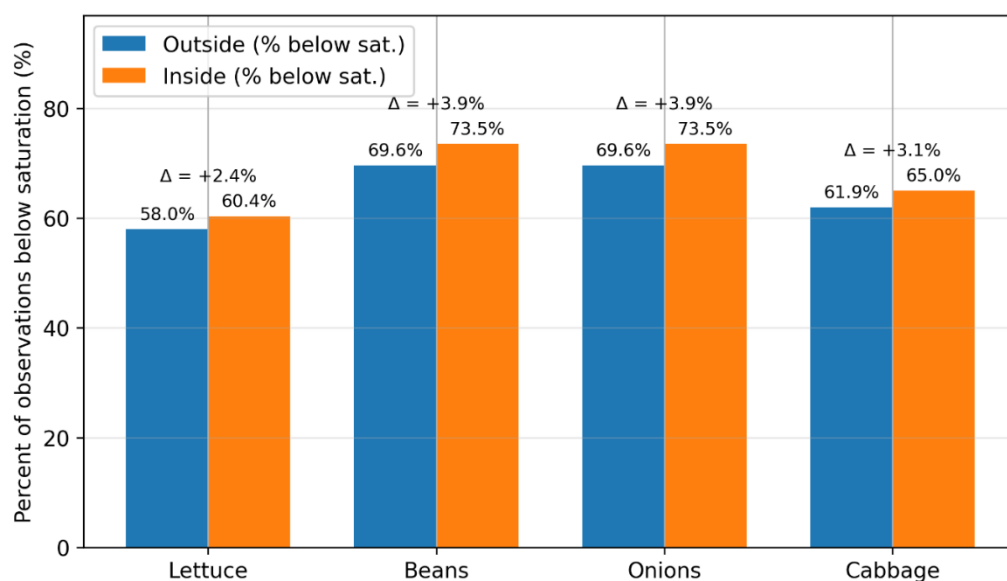


Figure 2.43. Below-saturation share by crop, Inside versus Outside.

It should be highlighted that the dataset includes nighttime observations, when EPAR is zero. This explains the relatively high proportion of below-saturation values, especially for beans and onions, which have higher light requirements. During daytime—particularly in summer—incident radiation often exceeds the saturation thresholds, so the effective impact of the net on photosynthetic activity is smaller than the percentages alone may suggest.

Microclimate effects of the bird netting

Besides reducing incident radiation, the bird netting also modifies the microclimate around the crops. Differences between inside and outside measurements were evaluated for temperature (ΔTemp), relative humidity (ΔHum), and vapor pressure deficit (ΔVPD).

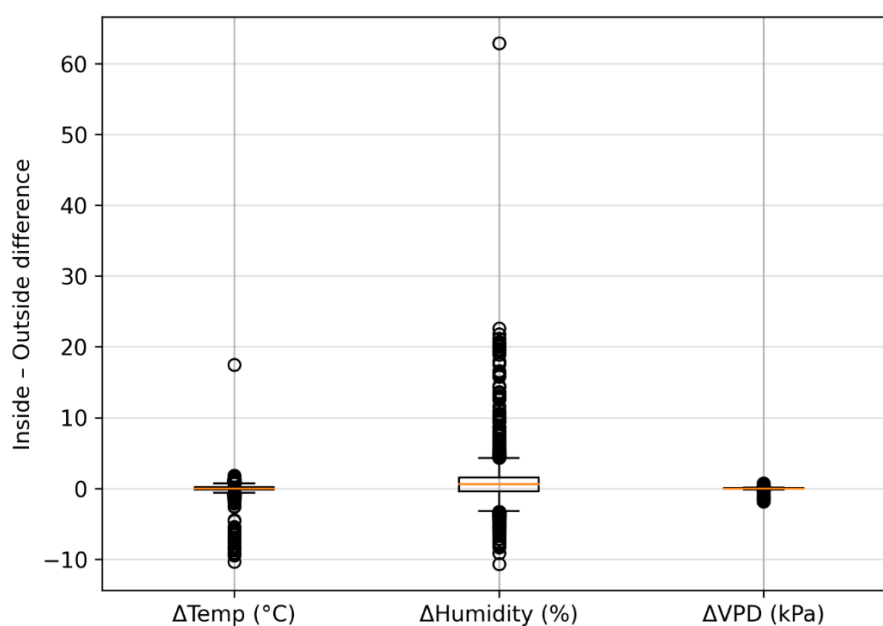


Figure 2.44. Distribution of microclimate differences between Inside and Outside the nets in terms of temperature, relative humidity and water vapor pressure deficit (VPD).

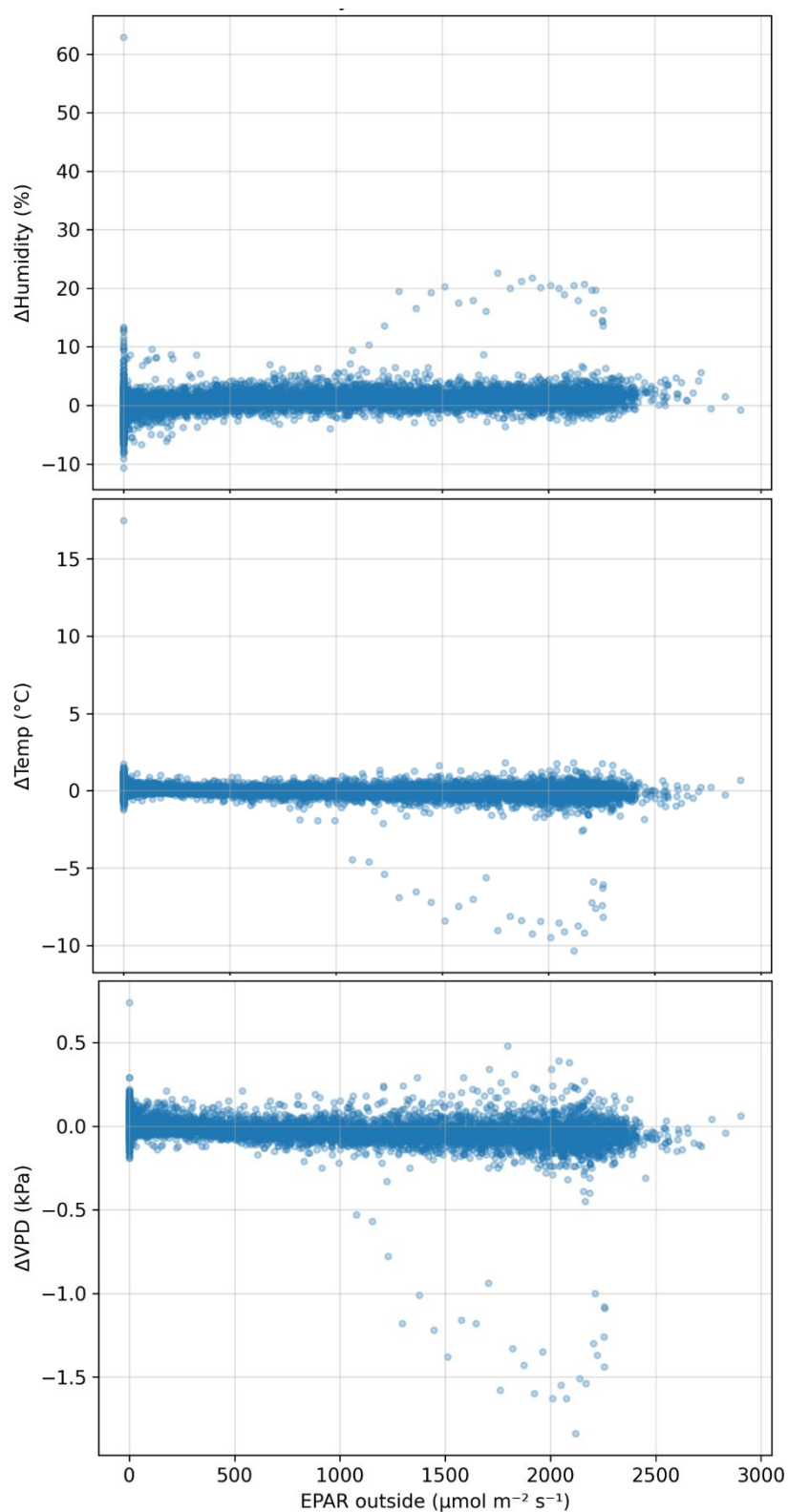


Figure 2.45. Microclimate differences between Inside and Outside the nets as a function of outside radiation.

The results (Figure 2.44) show that the temperature under-net and open field remains practically identical, with an average difference close to 0 $^{\circ}\text{C}$ and interquartile values within ± 0.2 $^{\circ}\text{C}$. This confirms that the netting does not significantly modify air temperature in crops in open field.

By contrast, relative humidity under-net is slightly higher, with a median increase of about +0.6%, and most values within a +1.5% margin. This modest rise in humidity directly translates into a slight reduction in VPD, with a median difference of approximately -0.01 kPa (Figure 2.45). Lower VPD inside the net indicates that crops experience a marginally less demanding evaporative environment, potentially reducing water stress and transpiration rates, but it could create conditions that made crops more susceptible to fungal diseases.

Overall, the microclimatic impact of the netting is light but consistent: no meaningful temperature shift, a small increase in humidity, and a corresponding decrease in VPD. These effects suggest that, beyond limiting light, the netting may help stabilize crop water relations by creating a slightly more humid and less stressful microenvironment.

2.6 Modelling the impact of orchard crops and PV shading on PV degradation (IMEC)

Studies have shown that PV modules in open agri-PV systems provide a cooling effect [6–8] through two main processes: evapotranspiration from crop and soil, which lowers ambient temperature, and shading from PV panels, which reduces microclimate temperature behind the modules. Also, PV temperature is expected to be lower due to better (wind) convective cooling due to the high elevations. While research has demonstrated these effects on module temperature and energy yield (Figure 2.46), models that quantify the impact of crops on ambient temperature or PV shading on microclimate temperature are still missing in the literature. Within SYMBIOSYST project, a model to quantify crop-induced and PV shading cooling effects has been introduced. These cooling effects affect the energy outputs and degradation of the PV modules since both are highly influenced by operating temperature of the PV module. In this section we provide the modeling approach of the developed cooling model and how it can be applied to energy yield and degradation modelling.

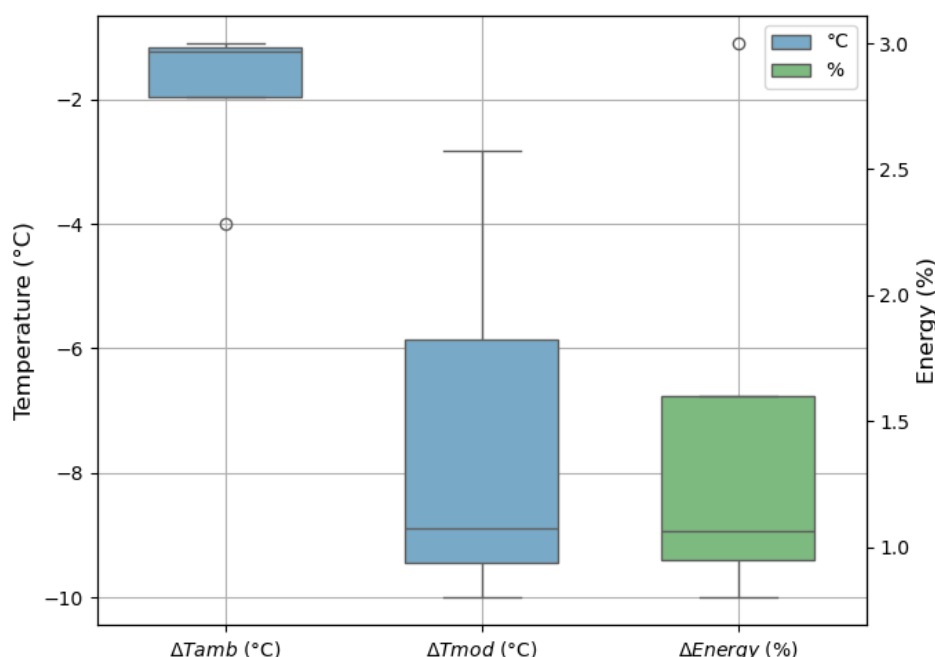


Figure 2.46. Comparison of Agri-PV and standard PV in air temperature, module temperature, and energy yield from literature data

Methodology

The methodology to quantify the cooling impact of AgriPV systems is developed based on two main assumptions: (a) cooling through evapotranspiration from crops, and (b) cooling induced by shading from PV modules. Therefore, the general methodology has two sub-models (a) Vegetation cooling sub model referred to here as orchard sub model and (b) PV shading cooling sub model as described below:

A. Orchard Cooling Submodel

We define the orchard microclimate temperature T_{orch} as:

$$T_{orch} = T_{air} + \Delta T \quad (2.4)$$

where the temperature offset ΔT arises from the difference in sensible heat flux between orchard canopy and bare soil:

$$\Delta T = \frac{(H_{bare} - H_{orch})}{h} \quad (2.5)$$

$$h = h_o + C * WS \quad (2.6)$$

with:

- H_{orch} : sensible heat flux over the orchard canopy
- H_{bare} : sensible heat flux over bare soil reference
- h : convective heat transfer coefficient-
- h_o : Base convective heat transfer coefficient
- C : Wind scaling for convection
- WS : wind speed

The sensible flux H is obtained from the surface energy balance:

$$Rn = H + LE + G + R_{LW} \quad (2.7)$$

$$H = Rn - LE - G - R_{LW} \quad (2.8)$$

$$Rn = G_{soil} + G_{canopy} \quad (2.9)$$

where:

- Rn : net radiation after accounting for albedo and leaf-area effects
- $LE = \lambda ET$: latent heat flux via evapotranspiration (modeled using Penman–Monteith formulation)
- G : soil heat flux (fraction of Rn or prescribed nighttime cooling)
- $R_{LW} = \epsilon \sigma (T_s^4 - T_{sky}^4)$: longwave radiation loss, T_s : surface temperature

Radiation partitioning between canopy and soil follows Beer–Lambert's law:

$$RG_{soil} = (1 - \alpha) \cdot G_{in} \cdot e^{-k_{ext} \cdot LAI} \quad (2.10)$$

$$G_{canopy} = (1 - \alpha) \cdot G_{in} - G_{soil} \quad (2.11)$$

where:

- k_{ext} : Extinction coefficient
- LAI : Leaf area index
- α : canopy albedo
- G_{in} : incident radiation

Evapotranspiration is estimated via a Penman–Monteith-like formulation[9]:

$$ET = \frac{\Delta(Rn - G) + \rho_a c_p (es - ea)/r_a}{\lambda(\Delta + \gamma(1 + r_s/r_a))} \quad (2.12)$$

$$es = 0.6108 * \exp\left(\frac{17.27 * T}{T + 237.3}\right)$$

$$ea = es * \left(\frac{RH}{100} \right)$$

$$\Delta = 4098 * \frac{es}{(T + 237.3)^2}$$

$$\gamma = 0.054$$

$$r_a = \frac{\ln \left[\left(\frac{z-d}{z_0} \right)^2 \right]}{k^2 * WS}$$

$$r_s = \frac{50}{LAI}$$

with:

- es : saturation vapour pressure at air temperature
- $es-ea$: vapor pressure deficit --VPD (depends on RH, T)
- r_a : aerodynamic resistance (wind speed, canopy height)
- r_s : surface resistance (depends on LAI, stomatal conductance)
- λ : Latent heat of vaporization (J/kg)
- c_p : Air specific heat capacity
- ρ_a : mean air density at constant pressure
- Δ : slope of the saturation vapour pressure temperature relationship
- γ : psychrometric constant, 0.054 [kPa/°C.]
- z : height of wind measurements (m)
- d : zero plane displacement height (m) = 0.667 * canopy height
- k : von Karman's constant, 0.41 [-],
- WS : Wind speed
- z_0 : Roughness length governing momentum transfer = 0.123 * canopy height

B. PV Shading Cooling Submodel

To capture the cooling from PV shading, an additional sensible flux change ΔH is introduced:

$$\Delta H = f_H (\Delta SW_{abs} + \Delta LW) \quad (2.13)$$

Where the two main components are,

- a) Reduction in shortwave absorption due to shading given as:

$$\Delta SW_{abs} = \alpha_{under} \cdot (G_{PV} - G_{noPV}) \quad (2.14)$$

- b) Longwave exchange replacing sky view expressed as:

$$\Delta LW = F_{PV} \cdot \varepsilon_{under} \cdot \sigma \cdot (T_{PV}^4 - T_{sky}^4) \quad (2.15)$$

- f_H : is the sensible heat partitioning fraction (dimensionless, 0–1). It represents the fraction of net radiative change that is converted into sensible heat flux.
- G_{PV} : is the irradiance on crops under PV
- G_{noPV} : is the irradiance on crops not covered by PV

This flux converts to temperature change as:

$$\Delta T_{PV} = \frac{\Delta H}{h_{air}} \quad (2.16)$$

with:

$$h_{air} = \frac{\rho c_p}{r_{a,canopy} + r_{gap}} \quad (2.17)$$

where:

$$r_{gap} = h_{gap} / (C_{vent} WS) \quad (2.18)$$

with:

- ρ : is the air density
- h_{air} : is the effective convective heat transfer coefficient linking canopy/PV exchange to the air above
- c_p : specific heat capacity of air at constant pressure
- $r_{a,canopy}$: is the aerodynamic resistance of the canopy (s/m)
- r_{gap} : ventilation resistance of PV–canopy gap (s/m)
- h_{gap} : gap height; vertical clearance between PV module underside and canopy top (m)
- C_{vent} : is the ventilation coefficient; dimensionless factor representing efficiency of air exchange in the PV-canopy gap
- WS : is the wind speed (m/s)

C. Integrated cooling effect for agriPV

The final cooling effect for agriPV systems is derived from the orchard cooling and PV shading cooling submodels as:

$$T_{AgriPV} = T_{orch} + \Delta T_{PV} \quad (2.19)$$

D. Simulating the impact of agriPV cooling on PV module degradation rate

To evaluate the impact of AgriPV induced cooling on the degradation rate of the PV modules, we applied a physic-based empirical model [10]. The model estimates the total degradation rate of power (DR_T [%/year]) as a function of specific degradation mechanisms/processes based on the applied climatic stresses as[11]:

$$DR_T = A_N \cdot (1 + DR_H)(1 + DR_P)(1 + DR_{Tm}) - 1 \quad (2.20)$$

Where DR_H , DR_P and DR_{Tm} are the degradation rates for hydrolysis, photodegradation, and thermomechanical degradation, respectively. These rates are evaluated as[11,12]:

$$DR_H(T, RH) = A_H \cdot \exp\left(\frac{-E_{aH}}{k_B \cdot T}\right) \cdot RH^n \quad (2.21)$$

$$DR_P(UV, T, RH) = A_P \cdot UV^y \cdot (1 + RH^{n_1}) \cdot \exp\left(\frac{-E_{aP}}{k_B \cdot T}\right) \quad (2.22)$$

$$DR_{Tm}(\Delta T, T_{max}) = A_T \cdot (\Delta T + 273)^x \cdot C_r \cdot \exp\left(\frac{-E_{aT}}{k_B \cdot T_{max}}\right) \quad (2.23)$$

Here, k_B (8.62×10^{-5} eV/K) is the Boltzmann constant, T [Kelvin] annual average module temperature, T_{max} [Kelvin] is the annual average maximum temperature of the module, ΔT is the annual average cyclic temperature of the module, UV [kWh/m²] is the total annual UV dose, RH [%] annual average relative humidity, C_r [cycles/year] annual temperature cycling frequency (assumed as 1 cycle per year). Definitions of other model parameters and values used are presented in Table 2.5 below.

Table 2.5. Definition of model parameters and values used in degradation rate simulation.

Parameter	Quantity
A_N normalization constant of the physical quantities	1 year^{-2}
A_H exponential coefficient for hydrolysis	$4.91e7 \text{ year}^{-1}$
A_P exponential coefficient for photodegradation	$7.3e7 \text{ (kWh/m}^2\text{)}^{-1}$
A_T - exponential coefficient for thermomechanical degradation	2.04 cycle^{-1}
E_{aH} , E_{aP} and E_{aT} [eV] activation energies, for hydrolysis, photodegradation and thermomechanical degradation respectively	Simulated as a distribution
n , n_1 , y and x are model parameters that describe the effect of RH	$n = 1.9$, $n_1 = 0.1$, $y = 0.63$ and $x = 2.04$

The details description of model parameters and usages are explained in previous publications[11–14].

E. Simulating the cooling effect using the proposed model and impact on the degradation rate

To simulate the cooling effect, the same Bierbeek agri-PV system used in the light simulation in the previous sections was used as a case study. The only difference here is that instead of using the tree model geometry, simplifications were made by using rectangular geometry with sensors on the sky-facing part to read the irradiance on the crops as shown in Figure 2.47. Also, the AV system is modelled to have trees under and between PV array to assess the impact of shaded and unshaded regions of the plant as required to assess the cooling impact of PV modules.

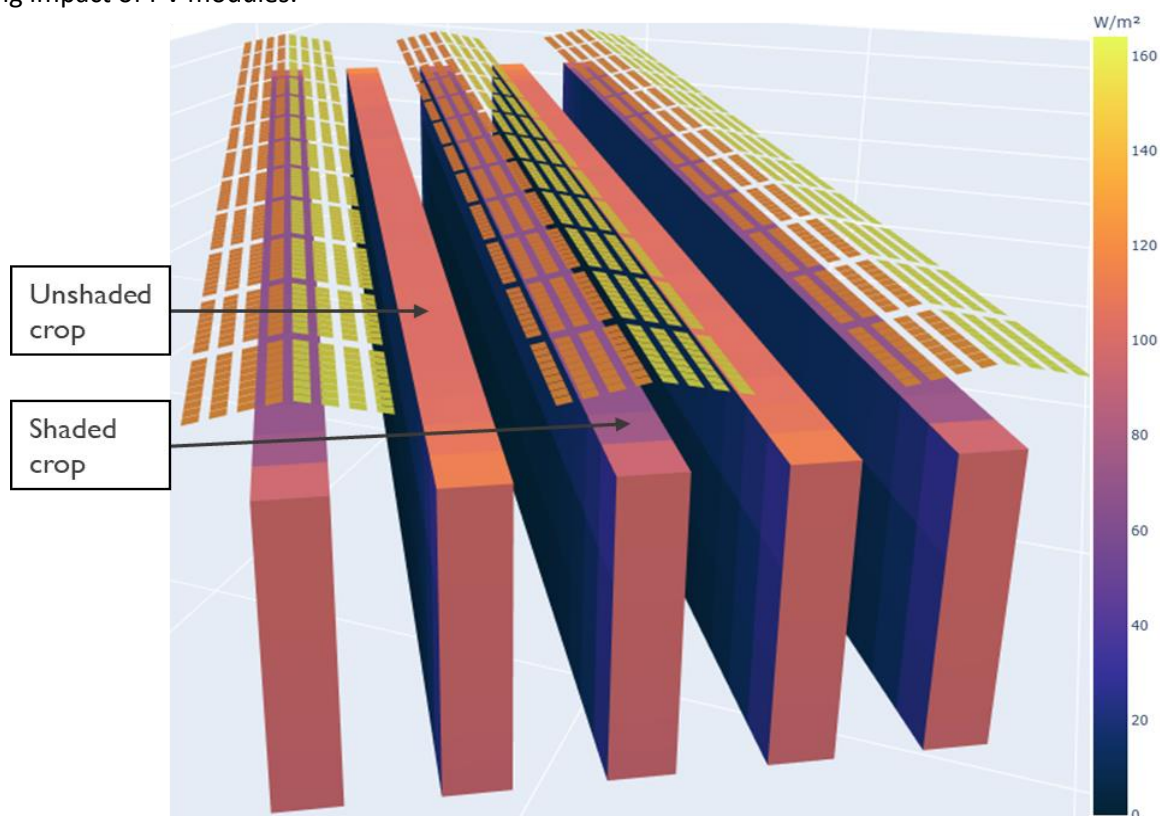


Figure 2.47. Bierbeek AV system simulated with box geometry to represent crops. Here we show an example of the average yearly irradiance distribution on PV modules, shaded and unshaded crops

We applied the orchard cooling sub model to evaluate the cooling impact of the orchards as shown in Figure 2.48(A). Figure 2.48(B) shows the differences in air temperature due to the presence of crops. To have more accurate representation of the growing seasons, the parameters of the models influenced by the growing stages of the orchard (such as the LAI and albedo) were adjusted to capture these variations as shown also in Figure 2.48(B). It can be shown that the presence of crops could lead up to 2.5°C temperature difference. The magnitude of cooling of course will depend on many other factors such as the locations and the properties of the crops, the coverage ratio of the crops. In literature[15] large green spaces with trees (>1 ha) had average cooling of ~ 4.5 °C (max ~6 °C), with cooling effects observed up to ~90 m (less strongly up to 180 m) into the surrounding areas. Smaller or grass-only areas had much smaller effects – often < 2 °C, which could be consistent with our simulated scenario.

Figure 2.49(A) shows the estimated difference in air temperature comparing an agri-PV with a reference system as well as an agri-PV system with a control system. From the figure we can see that the cooling impact due to PV system shading can range from 0.5°C to 1.5°C depending on the season of the year. The corresponding cooling impact on the module temperature is of the same magnitude to the cooling effect of air temperature as shown in Figure 2.49 (B). Not that the module temperature is derived from the energy yield simulation framework described in section 2.3.

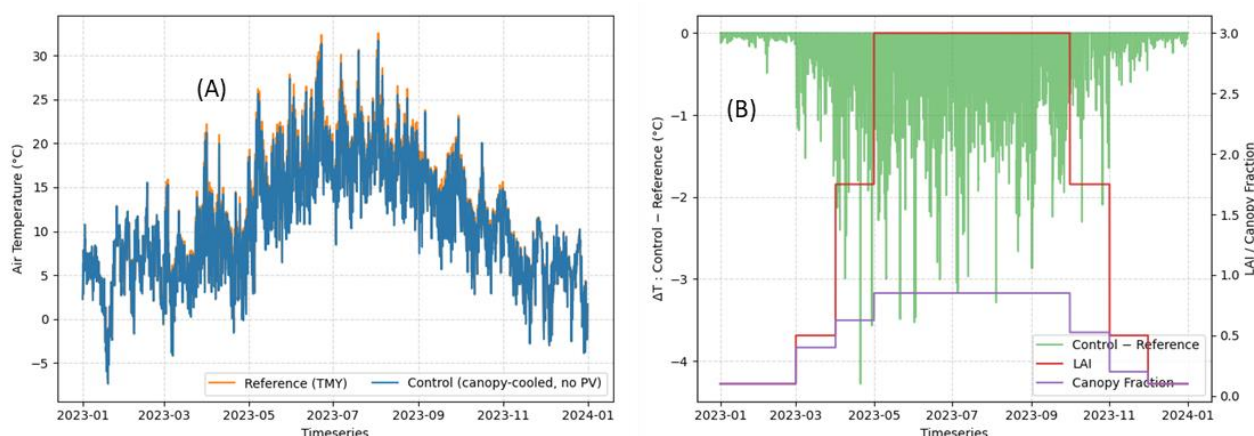


Figure 2.48. (A) Reference temperature and simulated air temperature with vegetation and (B) evaluated temperature deltas. The red and purple steps show the variations in leaf area index (LAI) and canopy fraction with the seasons.

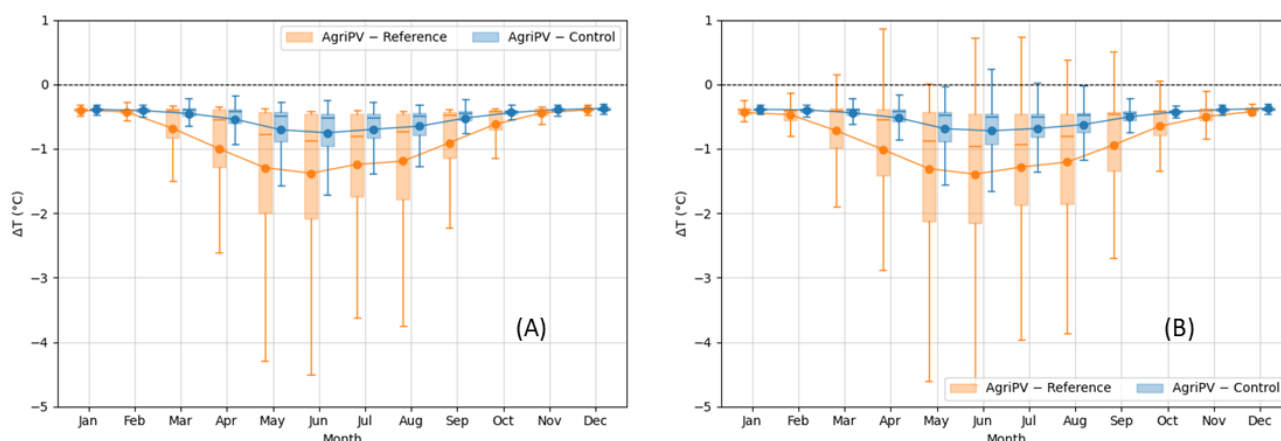


Figure 2.49. (A) Monthly boxplots of air temperature deltas for an agri-PV system compared with the reference and control systems. (B) the corresponding differences of module /backsheet temperature respectively.

In this section the main goal was to evaluate the impact of the cooling impact on the degradation rate of the PV module. We kept all other environmental variables such as relative humidity and UV dose constant to 77.1% and 61.9 kWh/m² respectively. These values correspond to the annual mean for relative humidity and the cumulative annual UV dose evaluated as 5% portion of the PV plane of array irradiation for the entire year. Figure 2.50(A) shows the differences in minimum, maximum and mean annual temperature for a control and agri-PV systems compared to the reference system. Using the degradation models, we evaluated the degradation rate for the three system scenarios, i.e. using module temperature considering reference, control and agri-PV cooling impacts. The differences in degradation rate due to crops only and combined crops and PV shading induced cooling are visible in Figure 2.50(B). The evaluated degradation rate for a reference scenario is 0.51%/year, compared to 0.45%/year and 0.42%/year for a control and agri-PV scenarios. In relative values the cooling could lead to -11.7% lower degradation rate when crop cooling is considered and -17.6% when both crop and PV shading cooling impacts are considered. This also implies that PV shading cooling only could result to about -7.1% lower degradation rate. It should be noted that these values will change depending on the sensitivity of a module to temperature, for more resilient module, the impact of these temperature differences on the degradation rate will be lower compared to less resilient modules in terms of reliability. In deliverable D2.6 of task 2.6, we shall investigate the impact of these temperature deltas on different modules with different bill of PV materials based on indoor testing.

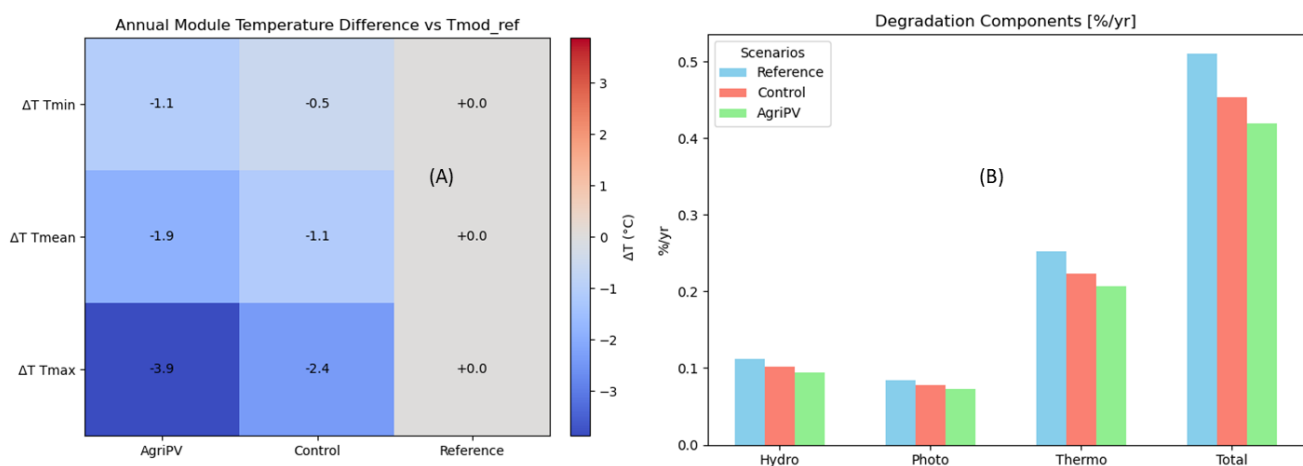


Figure 2.50. (A) simulated annual module temperature differences for a control and AgriPV systems compared to the reference system. (B) simulated power degradation rates for the three scenarios resulting from the differenced in operating module temperatures.

2.7 Photosynthetically active radiation (PAR) under agrivoltaic structures (LUCISUN)

Modelling of PAR under spectrally selective transmittance and reflection conditions was a key aspect of this work, since plant growth is primarily driven by the number of photons in the 400–700 nm range rather than the total radiant energy received. Conventional broadband irradiance measurements provided by pyranometers or simulation tools cannot be used for agronomic assessment without an appropriate conversion to photosynthetically active radiation. A simple and widely applied approach is to assume a constant conversion factor α that translates global broadband irradiance G in W m⁻² into photosynthetic photon flux density PPFD in $\mu\text{mol m}^{-2} \text{s}^{-1}$ as:

$$PPFD [\mu\text{mol m}^{-2} \text{s}^{-1}] = \alpha [\mu\text{mol J}^{-1}] \times G [\text{W m}^{-2}] \quad (2.24)$$

A commonly used value is:

$$\alpha \approx 4.6 \sim \mu\text{mol J}^{-1} \approx 4.6 \mu\text{mol J}^{-1} \quad (2.25)$$

which corresponds to the average number of photons in the PAR region per joule of solar energy under mid-latitude conditions. Analysis of mid-latitude datasets shows that the ratio of PAR to broadband radiation varies

between approximately 0.44 and 0.50 depending on sky conditions and season. Clear sky at high solar elevation tends to yield lower ratios near 0.44 to 0.46, while cloudy or overcast conditions increase the relative share of PAR to around 0.48 to 0.50. For this reason we also apply piecewise empirical relationships conditioned on clearness index to reduce bias. This improves performance under the variable sky conditions typical of Belgium and Northern Europe.

While the empirical approach is sufficient for open field conditions when the interest is in average trends, it cannot capture the spectral selectivity introduced by agrivoltaic devices. Semi-transparent or bifacial modules, spectrally selective coatings, mesh netting, and greenhouse glazing transmit and reflect different fractions of incident light as a function of wavelength. To account for this we implement a physics based approach. The incoming spectral irradiance $G(\lambda)$ is either measured or modelled from reference spectra such as ASTM G173 and site specific conditions. The transmitted $PPFD_{trans}$ at canopy level is then calculated as:

$$PPFD_{trans} = \int_{400\text{ nm}}^{700\text{ nm}} \frac{G(\lambda) T(\lambda, \theta)}{E_{ph}(\lambda)} d\lambda \quad (2.26)$$

with:

$$xE_{ph}(\lambda) = \frac{hc}{\lambda} \quad (2.27)$$

where $T(\lambda, \theta)$ is the wavelength and incidence angle dependent transmittance of the module or glazing, h is Planck's constant and c is the speed of light. Reflection spectra $R(\lambda)$ are also considered, particularly where reflected light can re-enter the canopy from structural elements or the ground surface. This method enables the explicit calculation of both total PAR transmission and the spectral quality of light within the demonstrators.

The modelling is coupled to 3D GPU based irradiance simulations developed by LuciSun and to ray tracing approaches implemented by IMEC. The integration of spectrally resolved transmittance into the 3D light engines allows spatial maps of PPFD below agrivoltaic structures to be computed in both open field and greenhouse conditions. For crop growth simulations these maps are aggregated to derive daily light integrals and crop relevant spectral indices. At canopy scale we also compute absorbed PAR when needed as:

$$PAR_{abs} = \sum_j k_j PAR_j \quad (2.28)$$

where k_j is an organ level absorption coefficient that accounts for leaf optical properties and orientation. We use the standard definition of the daily light integral:

$$DLI [mol\ m^{-2}\ day^{-1}] = 10^{-6} \int_{day} PPFD(t) dt \quad (2.29)$$

and, when needed for communication with PV engineers, we provide radiometric equivalents with the understanding that they are spectrum dependent. A practical relation for the daily average PAR irradiance is:

$$\langle E_{PAR} \rangle [W\ m^{-2}] \approx \frac{DLI \times 10^6}{86400} \times 0.218 \approx 2.52 \times DLI \quad (2.30)$$

This approximation is acceptable for open field conditions when spectra are close to standard, and it becomes less accurate when glazing or PV layers are spectrally selective.

Three demonstrators are considered, namely an open field agri-PV site in Belgium, an open field orchard agri-PV site in Italy, and a greenhouse in the Netherlands. For the open field sites the constant α model provides a practical baseline and the clearness aware model reduces bias when clouds increase the diffuse fraction. For the Netherlands greenhouse the spectral approach is necessary because glazing with integrated PV modifies both the amount and the spectral composition of transmitted light. Preliminary optical characterisation and simulations indicate that while about fifty five percent of total shortwave radiation is transmitted through the

glazing, the effective PAR transmission is lower, near forty eight percent, and the red to far-red ratio inside the greenhouse is reduced by about ten to fifteen percent relative to outdoors. The blue to red ratio is also altered because absorption in the blue region is more pronounced. These spectral shifts can influence crop morphology and therefore need to be included in the agronomic assessment.

To illustrate the basic conversion behaviour at hourly resolution the Belgian open field demonstrator is first used Figure 2.51. A scatter of PPFD versus GHI is shown with points coloured by sky condition, and with straight guide lines for the constant α model and the clearness aware model that assigns representative α values to clear, partly cloudy and overcast conditions. The figure shows that the constant factor performs reasonably well on average, while the clearness aware model better represents PPFD under overcast conditions where the diffuse fraction enhances the relative share of PAR.

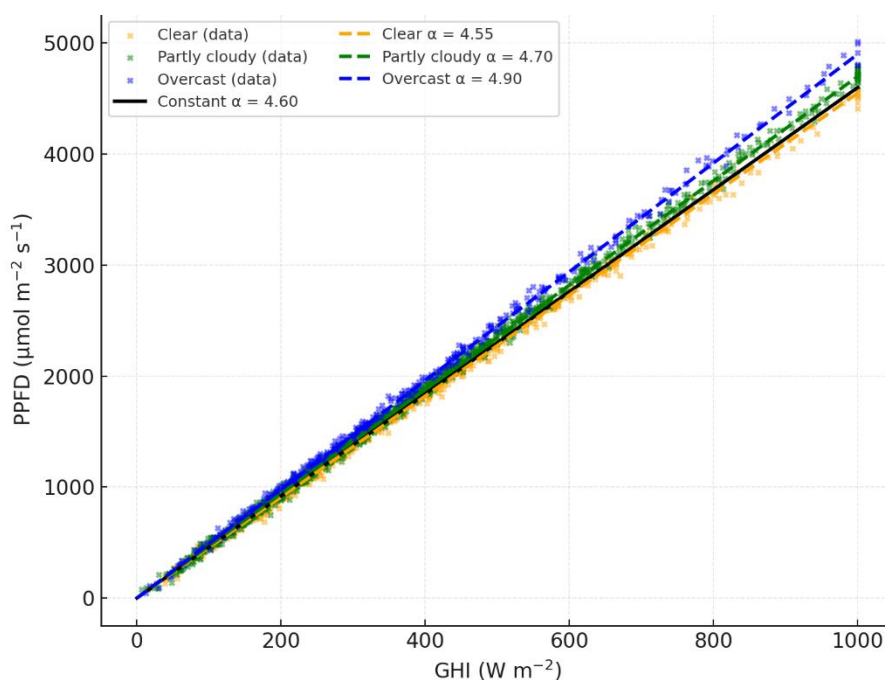


Figure 2.51. Belgium open field agri-PV. Hourly PPFD versus GHI coloured by sky condition. Black line shows constant $\alpha=4.6$. Coloured dashed lines show clearness aware α for clear, partly cloudy and overcast skies.

A complementary temporal view is provided by diurnal profiles for representative days. For the same Belgian site a clear summer day (Figure 2.52) and an overcast day (Figure 2.53) are shown. The synthetic measured PPFD is compared to the constant α model and to the clearness aware model. In clear conditions all models track the bell shaped irradiance pattern, although the constant factor tends to slightly underestimate morning and evening PPFD due to spectral shifts at high solar zenith. In overcast conditions the constant factor systematically underestimates PPFD, whereas the clearness aware approach reproduces the higher relative PAR fraction of diffuse light. These two figures make the daily bias patterns explicit.

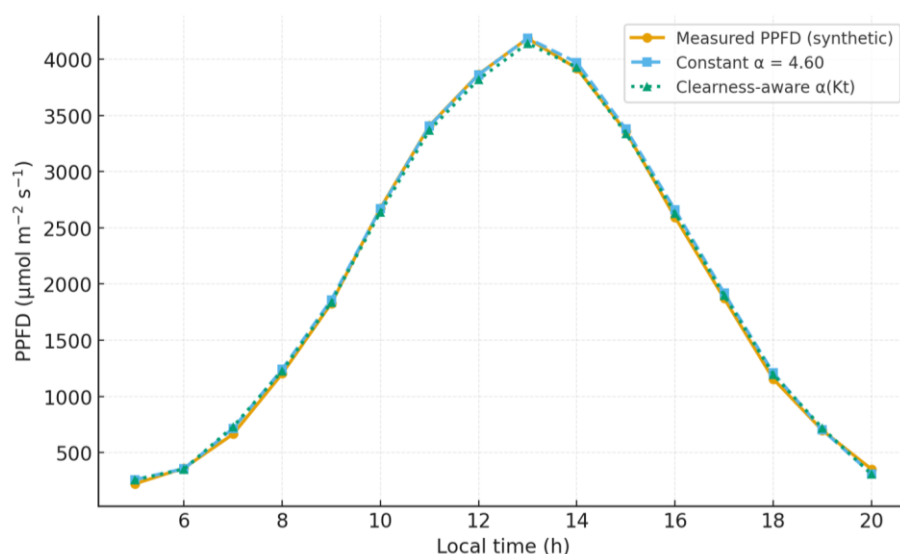


Figure 2.52. Belgium open field agri-PV. Diurnal profile of PPFD for a clear summer day. Constant α and clearness aware models compared to synthetic measured PPFD.

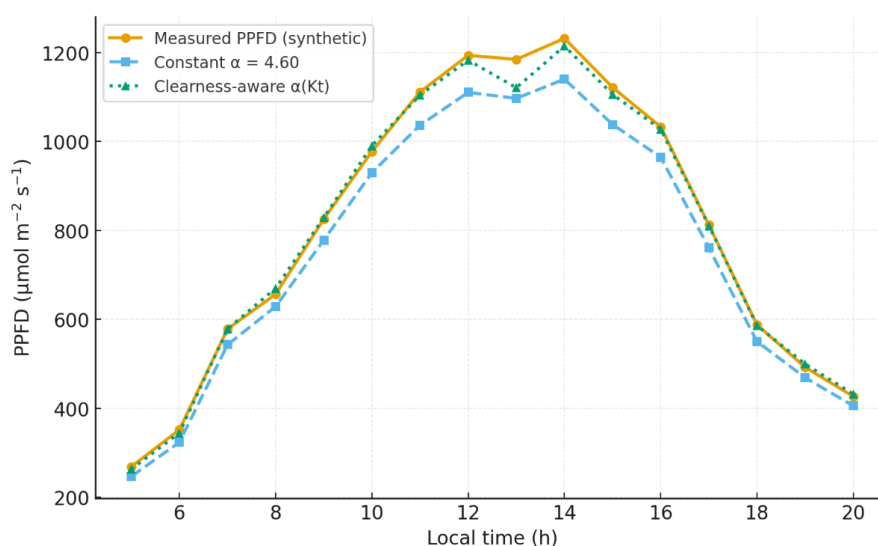


Figure 2.53. Belgium open field agri-PV. Diurnal profile of PPFD for an overcast day. The clearness aware model captures the diffuse enhancement of PAR.

The same scatter analysis is then applied to the Italian orchard demonstrator (Figure 2.54). The clear sky α is slightly lower on average than in Belgium, which is consistent with clearer Alpine skies that carry relatively more near infrared energy. Overcast conditions again show higher α . This confirms that site specific conditions shift effective α values and that the clearness aware approach improves consistency across sky states.

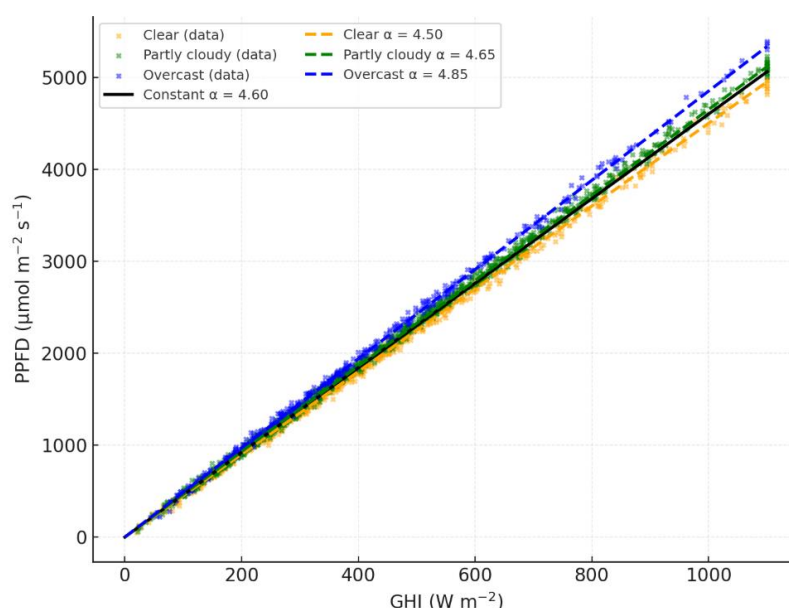


Figure 2.54. Italy open field orchard agri-PV. Hourly PPFD versus GHI coloured by sky condition. Comparison of constant α and clearness aware α .

Spatial heterogeneity is central in the orchard case. A transect across the alley between tree rows at midday shows PPFD as a function of lateral position for clear sky and overcast conditions. Under clear sky shading by the PV row and by trees generates strong local minima, while open alley regions approach unshaded levels. Under overcast conditions the distribution is much smoother and more uniform due to scattering.

To summarise the variability of α across the three sites over a typical year we present distributions of hourly PAR fractions relative to the constant $\alpha=4.6$ (Figure 2.55). Belgium and Italy cluster near unity, with spread driven by sky variability. The Netherlands greenhouse shows a systematic downward shift due to the spectrally selective glazing, which reduces PAR relative to broadband irradiance further emphasized by the box plots from Figure 2.56. These distributions represent the expected range of hourly values over one year.

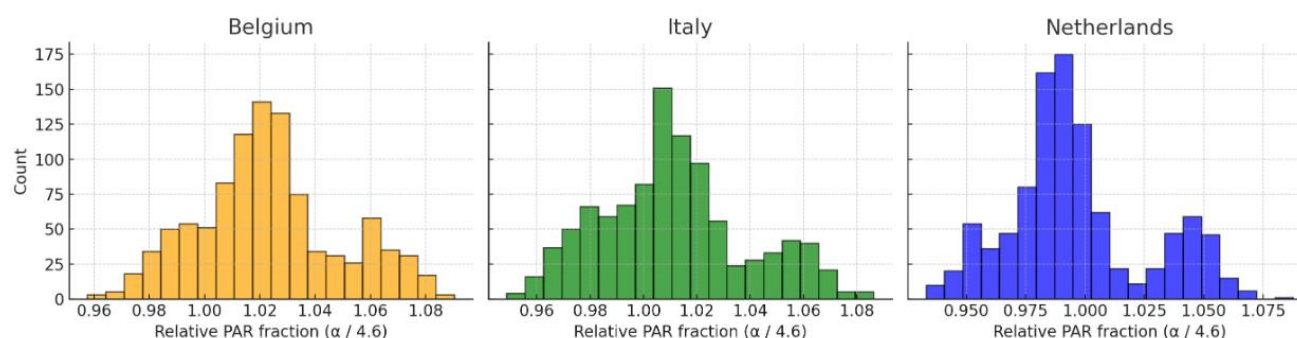


Figure 2.55. Belgium, Italy, Netherlands. Distributions of hourly $\alpha/4.6$ as histograms. The greenhouse shows lower relative PAR fractions due to spectral selectivity.

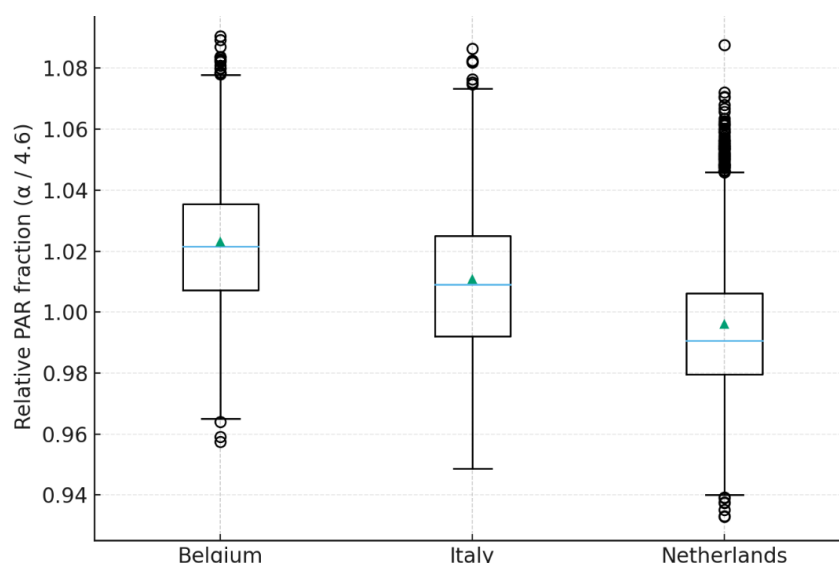


Figure 2.56. Belgium, Italy, Netherlands. Distributions of hourly $\alpha/4.6$ as boxplots. The greenhouse shows lower relative PAR fractions due to spectral selectivity.

Seasonal patterns are assessed through daily light integral mapping under structures. For Belgium we show a map obtained with the constant α model, a map obtained with the clearness or spectral aware model, and the corresponding difference map. The difference map (Figure 2.57) shows local increases of DLI in shaded zones in the spectral aware case, which is consistent with diffuse light enhancement and with additional scattering contributions from vegetation that are not captured by a broadband constant conversion. For the Netherlands greenhouse the broadband constant model overestimates plant available light, while the spectral and diffuse aware model yields a lower absolute DLI but also a narrower distribution that indicates improved uniformity across the greenhouse floor. The difference map reveals the magnitude and spatial structure of the error incurred when spectral selectivity is neglected.

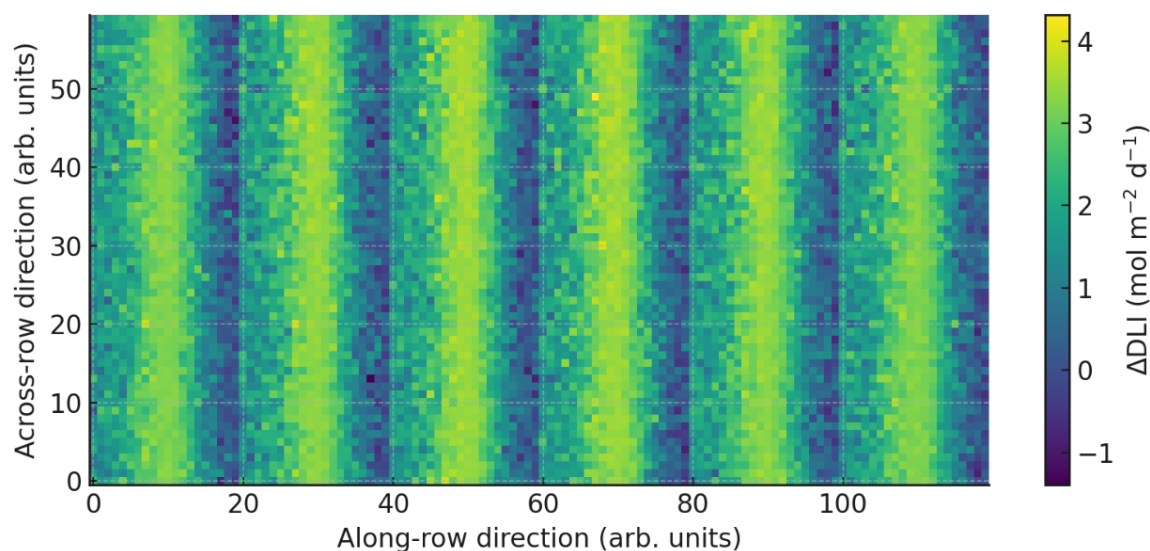


Figure 2.57. Belgium open field agri-PV. Seasonal DLI map with clearness or spectral aware conversion.

Preliminary comparisons between simulated PAR distributions and measurements from quantum sensors installed at canopy level confirm the added value of accounting for spectral selectivity. In the Belgian site the use of a constant conversion factor leads to a mean absolute error near eighteen percent with respect to

measured PPFD, while the spectral treatment reduces the error to about nine percent. Similar improvements are observed in the Italian orchard case. These results show that spectrally resolved approaches provide a more physically consistent basis for PAR modelling and lead to significant accuracy gains when validated against measurements. They also demonstrate that the combination of empirical sky aware conversion for operations and data gaps, and spectral modelling when materials or optical designs are selective, is a robust and pragmatic strategy across demonstrators.

This integrated workflow connects broadband data streams, empirical sky aware conversion, spectral optical characterisation, and 3D spatial modelling. It produces temporally and spatially resolved PPFD and DLI fields and the spectral quality indicators that crop models require. The Belgian and Italian demonstrators show that simple models already deliver useful estimates with some bias that can be mitigated by conditioning on sky state, while the Netherlands greenhouse illustrates the necessity of full spectral treatment. The results obtained here provide the basis for coupling light modelling with crop models in the next stages of the project and for design optimisation that considers both PV performance and plant light requirements.

3 Crop model (KUL)

3.1 Model development

3.1.1 Modelling concept

The crop model was developed to evaluate the effects of agri-photovoltaic (APV) systems on pear tree fruit yield and quality. Simulations are driven by simulated or measured light interception, measured temperature and measured relative humidity data, corresponding to the relevant APV configuration. The model quantifies how modified light regimes and associated microclimate conditions influence photosynthesis, water relations, carbon allocation, and ultimately fruit growth.

To balance robustness and computational feasibility, the model is formulated at the individual plant level. This modular design allows simulations to be upscaled from tree to orchard level according to planting configuration and microclimate variation. Model outputs are used to assess agronomic performance and quality under different APV designs, supporting scenario analysis and system optimization.

The following sections describe the model structure (3.1.2), compartment definitions (3.1.3), integrated workflow (3.1.4), structural rules for the model (3.1.5), inputs and outputs (3.1.6), and sub models for leaf function module, water and sugar transport module, and fruit growth module (3.1.7).

3.1.2 Model Structure

The model combines the flexibility of an object-oriented framework (OOM) with the computational efficiency and advanced optimization capabilities of AMIGO2[16].

- The OOM framework provides a modular, hierarchical representation of the tree structure, allowing explicit definition of parent-child relationship among Tree, Branch, Leaf, and Fruit compartments. Climate zones can be directly assigned to individual leaves, while local physiological properties (organ size, transport distance, etc.) and processes (photosynthesis, transpiration, sugar and water transport) are formulated symbolically.
- AMIGO2 provides a robust simulation and optimization environment for solving large systems of ODEs, parameter calibration and sensitivity analysis. A generic modelling procedure allows symbolic equations and compartment definitions from the OOM framework to be automatically converted into AMIGO2-compatible formats and expanded according to the specific tree structure. The CVODES solver is then used to integrate the complete set of ODE states efficiently.

This hybrid approach captures organ-level physiological detail while enabling computationally efficient whole-tree simulations, as well as reproducibility and standardization for collaborative projects.

3.1.3 Compartment definitions and functions

The model consists of four primary compartments types, representing functional units of the tree system. Each compartment contains specific properties embedded in a hierarchical architecture that mirrors real plant physiology.

- Tree: Top level compartment that aggregates information from branches and coordinates whole-system interactions.
- Branch: Structural axis that connects leaves and fruits. Branches serve as conduits for water and carbohydrate flows and host axial transport processes.
- Leaf: Source organ that assimilates carbon through photosynthesis and loses water through transpiration. Each leaf is assigned to a microclimate zone, enabling spatial differentiation in light and climate responses.

- Fruit: Sink organ where growth results from sugar and water import as well as internal osmotic and mechanical properties. Fruits feed back to the system through sink demand and turgor-driven constraints.

This organization enables explicit definition of source-sink relationships and supports feedback among compartments, for example, fruit demand influencing branch transport, or leaf stomatal conductance responding to water status. Climate as external boundary conditions provides environmental drivers (PAR, temperature, humidity) at specific intervals (see section 5).

3.1.4 Integrated Workflow

The workflow for combining OOM and AMIGO2 follows six phases (Table 3.1).

Table 3.1 Workflow phases for integrated OOM-AMIGO2 modelling.

Phase	Activities	Tools used
1. Model Structure Design	- Define system hierarchy (Tree, Branch, Leaf, Fruit). - Generate test plant structures for exploratory simulations. - Formulate physiological processes symbolically.	OOM (MATLAB classes) MATLAB script
2. Equation Management	- Store generic equations - Use clean indexing logic	Excel/CSV
3. Automatic Code Generation	- Generate AMIGO2 input files. - Expand and index all variables automatically.	MATLAB script
4. Simulation & Parameter Estimation	- Perform parameter estimation and sensitivity analysis. - Validate model predictions.	AMIGO2 toolbox
5. Model Refinement	- Iterate model improvements based on AMIGO2 results. - Update structure and equations in OOM.	OOM + AMIGO2
6. Final Deployment & Reporting	- Generate final models for publication. - Document model assumptions and performance.	AMIGO2 Reports + OOM documentation

Generic equations are stored in EquationInput.csv and automatically indexed according to the tree structure in AMIGO2. Detailed formulations of the sub-models are provided in Section 3.7.

3.1.5 Structural Rules

There are a few assumptions applied to the tree model:

- The tree structure over a growing season is static.
- No orchard management is involved (e.g. pruning).
- Each branch has at least one leaf and one fruit.

For each simulation, a tree structure was automatically generated with random properties: leaf and fruit number for each branch, branch length, branch volume, leaf area, leaf thickness, distances between nodes, etc. The total number of leaves and fruits are pre-defined when generating the tree, while other traits are randomly assigned within a reasonable range. Additionally, each leaf was assigned with a microclimate zone to receive local climate input in Section 5.1.2.

Several rules govern the organization of compartments and flows (Figure 3.1 Figure 3.2):

- Compartment hierarchy: Branches operate at a higher hierarchical level than fruits and leaves, while tree is at higher level than branches.
- Node representation: Fruits and leaves are represented as nodes connected to a branch.
- Axial flow zones: Adjacent nodes within a branch define axial transport pathways for xylem and phloem.
- Water potential assumption: Phloem and xylem within the same compartment at the same position are assumed to share the same water potential.

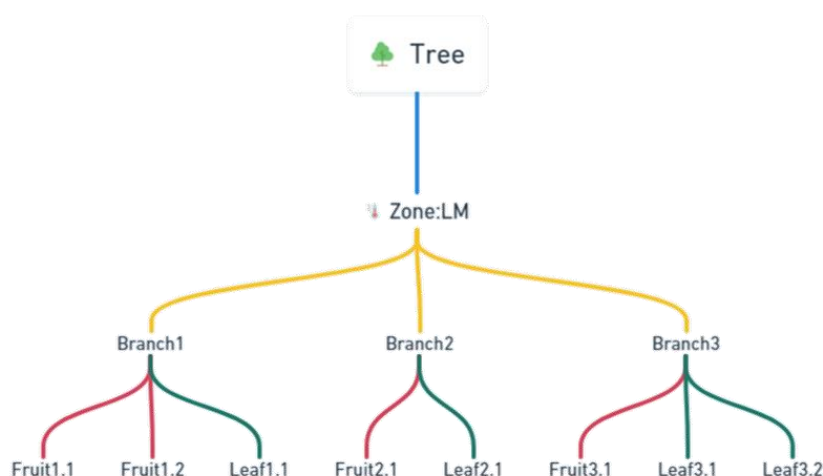


Figure 3.1 Hierarchical information flow scheme of object-oriented modelled tree

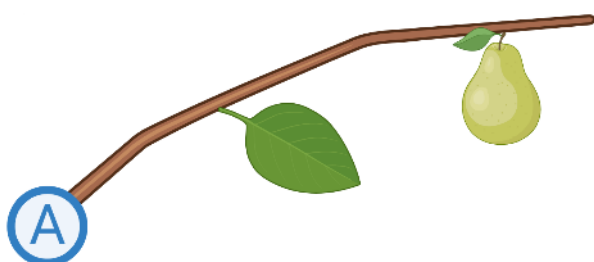


Figure 3.2 [Leaf] and [Fruit] presented as node on a [Branch].

3.1.6 Model Inputs and Outputs

The model integrates structural and environmental drivers to simulate tree-scale processes:

- Inputs:
 - Climate conditions (light, temperature, humidity, optionally soil water potential)
 - Plant architectural parameters (e.g. number of branches, leaf area)
 - Physiological parameters (e.g. dark respiration rate, photosynthetic capacity, phloem conductance)
- Outputs:
 - Leaf-level transpiration and photosynthesis rate
 - Sugar and water flows across organs
 - Branch- and organ-level sugar concentrations and water potentials
 - Fruit growth (fresh weight, dry matter, sugar concentration)
 - Whole-tree productivity and quality indicators

The relationships are summarized in Figure 3.3, where climate drivers (yellow) feed into process modules (green), update organ states (blue), and ultimately determine model outputs (purple).

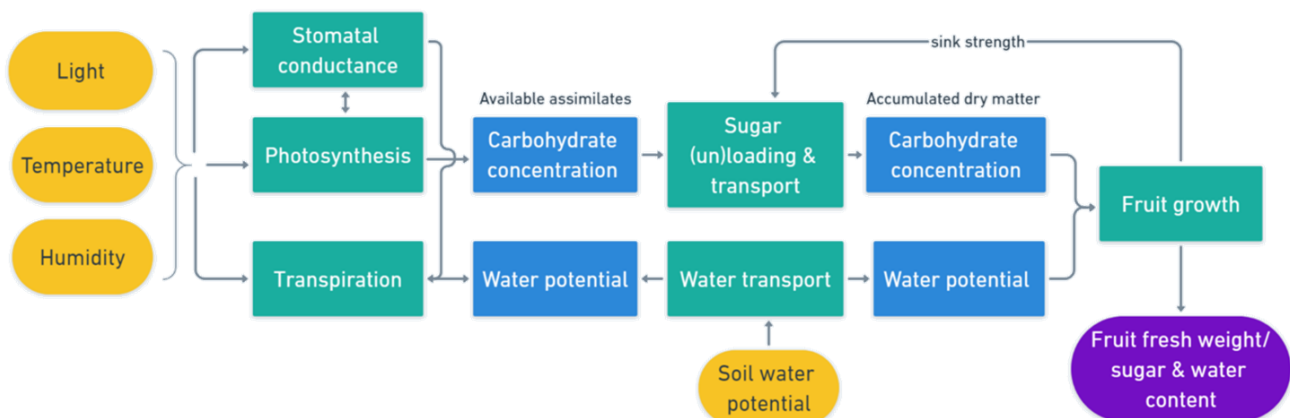


Figure 3.3 Conceptual fruit-tree model. Yellow boxes represent input from actual climate conditions. Green boxes represent functional modules that conduct simulation. Blue boxes represent updated states for each compartment type that will be transferred to the next module. Purple box represent the final output of the model.

3.1.7 Sub-models

The overall model integrates light interception, photosynthesis, water and sugar transport, and fruit growth module within a hierarchical tree structure. Leaves act as the primary sources of assimilates, branches as conduits for water and sugar transport, and fruits as dynamic sinks where growth is determined by sugar accumulation and turgor-driven water uptake. Environmental inputs (light, temperature, humidity) and structural parameters (tree topology, leaf/fruit distribution) drive the sub-models, while feedbacks between sugar concentration, osmotic potential, water potential and transport processes ensure consistent coupling between sugar and water fluxes. These modules can provide a mechanistic simulation framework to evaluate the impacts of agrivoltaic system on tree growth, yield, and fruit quality.

3.1.8 Leaf model

In APV systems, the impacts of light and microclimate factors (temperature, humidity) are primarily perceived by leaves. Leaves are functional compartments that assimilate carbon through photosynthesis and transpire water. Each leaf, independent of its parent branch, is assigned to a microclimate zone. The zone-specific climate inputs are used directly in the photosynthesis, transpiration and stomatal conductance model.

Leaf photosynthesis

Hourly leaf photosynthesis was computed based on the Farquhar, von Caemmerer and Berry (FvCB) model developed by Farquhar et al. [17], which uses the inputs of absorbed PAR (photosynthetic active radiation). The photosynthesis module was calibrated separately for APV and control conditions with the light response curve and CO₂ response curve measured in section 2, to account for potential acclimation of leaves under APV.

In the FvCB model, the net photosynthesis rate, A_n , was regulated by two parallel biochemical limitations: Rubisco carboxylation and electron transport (optionally triose phosphate utilization - TPU)[17–19]. This approach is mechanistic and widely used in carbon-based plant models. It accurately reflects the interplay among primary biochemical processes regulating C₃ photosynthesis. In the implemented model, net assimilation is calculated as[18,20]:

$$A_n = \min(A_c, A_j, A_p) - R_d \quad (3.1)$$

Where:

- A_c = Rubisco-limited carboxylation rate [$\mu\text{mol m}^{-2} \text{s}^{-1}$],

- A_j = light-driven electron transport-limited rate [$\mu\text{mol m}^{-2} \text{s}^{-1}$],
- A_p = triose phosphate utilization (TPU)-limited rate [$\mu\text{mol m}^{-2} \text{s}^{-1}$],
- R_d = dark respiration rate [$\mu\text{mol m}^{-2} \text{s}^{-1}$].

TPU-limited assimilation A_p was not included, as TPU might not be the most important limitation under field conditions[19,21] relevant to pear orchards and the parameter cannot be robustly estimated from the available datasets. Therefore, only Rubisco and electron transport limitations were considered.

The limiting rates are defined as:

Rubisco-limited (carboxylation-limited):

$$A_c = \frac{V_{c,\max}(C_i - \Gamma^*)}{C_i + K_c(1 + \frac{O}{K_o})} \quad (3.2)$$

Electron transport-limited:

$$A_j = \frac{J(C_i - \Gamma^*)}{4(C_i + 2\Gamma^*)} \quad (3.3)$$

Electron transport rate J depends on absorbed PAR through a non-rectangular hyperbola equation[17]:

$$J = \frac{I_2 + J_{\max} - \sqrt{(I_2 + J_{\max})^2 - 4\theta I_2 J_{\max}}}{2\theta} \quad (3.4)$$

R_d is commonly parameterized with:

$$R_d = 0.015V_{c,\max} \quad (3.5)$$

where

- C_i = intercellular CO_2 concentration [$\mu\text{mol mol}^{-1}$],
- Γ^* = CO_2 compensation point in the absence of respiration [$\mu\text{mol mol}^{-1}$],
- K_c, K_o = Michaelis-Menten constants for CO_2 and O_2 [$\mu\text{mol mol}^{-1}$],
- O = oxygen concentration [mmol mol^{-1}],
- $V_{c,\max}$ = maximum Rubisco carboxylation rate [$\mu\text{mol m}^{-2} \text{s}^{-1}$],
- J = electron transport rate [$\mu\text{mol m}^{-2} \text{s}^{-1}$],
- I_2 = absorbed PAR by photosystem II [$\mu\text{mol m}^{-2} \text{s}^{-1}$],
- $J_{\max}$ = maximum electron transport rate [$\mu\text{mol m}^{-2} \text{s}^{-1}$],
- θ = curvature factor [-].

Key parameters ($V_{c,\max}$, $J_{\max}$, R_d) were calibrated from measured light-response and CO_2 -response curves (Section 5 and 6). By implementing FvCB model, the biochemically grounded representation of photosynthetic limitations that supports modular integration with other sub-models. This module feeds assimilated carbon into the sugar transport network component of the overall crop model, contributing to the simulation of sugar flows, fruit growth and final fruit production and quality.

Sugar Flow in Leaf

Following photosynthesis, leaf sugar concentration is updated through a mass balance of carbon input, respiration and export to branch phloem. Net photosynthesis (A_n) from the FvCB model provides the input

flux, part of this carbon is consumed by respiration and the remainder is available for export. The change in leaf sugar concentration ($c_{s,leaf}$) is then given by:

$$\frac{dc_{s,leaf}}{dt} = \frac{A_n \cdot LA - R_{leaf} \cdot LA - J_{s,out}}{V_{leaf}} \quad (3.6)$$

where:

- $c_{s,leaf}$ = leaf sugar concentration [g m⁻³],
- LA = leaf area [m²],
- R_{leaf} = leaf respiration rate [g s⁻¹],
- V_{leaf} = leaf volume [m³],
- $J_{s,out}$ = sugar outflow to phloem [g s⁻¹].

The export flux $J_{s,out}$ couples the leaf source strength to the transport system (whole-tree carbon allocation). This flux enters the branch phloem, implying the loading mechanism which will be further introduced in Section 3.7.3. The leaf sugar balance is illustrated in Figure 3.4.

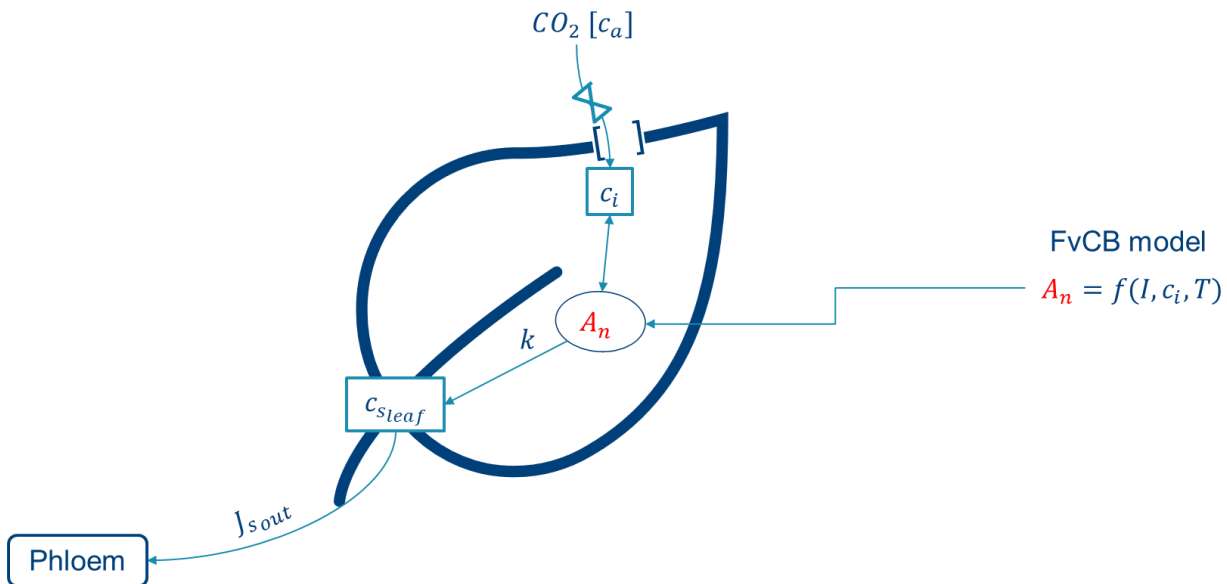


Figure 3.4 Scheme of sugar flow in leaf.

Leaf transpiration

Transpiration was calculated based on Penman-Monteith equation[22] that integrates net radiation, vapor pressure deficit (VPD) and stomatal conductance. Net radiation and VPD were converted from the climate inputs of light, temperature and relative humidity.

$$E = \frac{(\Delta(R_n) + \rho c_p VPD g_v)}{\left(\Delta + \left(1 + \frac{g_v}{g_{s,H_2O}} \right) \gamma \right)} \cdot \frac{1}{\lambda} \quad (3.7)$$

where:

- E = transpiration rate [g m⁻² s⁻¹],
- λ = latent heat of evaporation of water [MJ kg⁻¹],
- R_n = net radiation at the leaf surface [W m⁻²],
- ρ = density of air [kg m⁻³],

- c_p = specific heat of air [J kg⁻¹ K⁻¹],
- VPD = vapor pressure deficit [Pa],
- g_v = leaf boundary layer conductance for water vapor [m s⁻¹],
- Δ = slope of the saturation vapor pressure curve at air temperature [kPa K⁻¹],

Stomatal conductance for water vapor g_{s,H_2O} was calculated using the Ball-Woodrow-Berry model[22,23] (3.8)

$$g_{s,H_2O} = \frac{mA_n \cdot RH}{C_a} + g_0 \quad (3.8)$$

where:

- g_{s,H_2O} = stomatal conductance for water vapor [mol m⁻² s⁻¹],
- m = dimensionless coefficient, set at 8 for C3 plants [-],
- RH = relative humidity [-],
- C_a = CO₂ concentration at the leaf surface [μmol mol⁻¹],
- g_0 = minimum conductance at night [mol m⁻² s⁻¹].

Since the Penman-Monteith equation needs the stomatal conductance in m s⁻¹, a conversion was made based on ideal gas law.

$$g_s^{(m/s)} = g_s^{(mol)} \frac{RT}{P_{air}} \quad (3.9)$$

Where:

- $g_s^{(mol)}$ = stomatal conductance [mol m⁻² s⁻¹],
- R = universal gas constant [8.314 J K⁻¹ mol⁻¹],
- T = temperature [K],
- P_{air} = air pressure [Pa].

Leaf water flow

Water inflow is driven by water loss in leaf via transpiration (Figure 3.5). The water balance can be described as:

$$\frac{d\psi_l}{dt} = \frac{J_{w,in} - J_{w,out} - \frac{E_l}{\rho_w}}{L_{C,l}} \quad (3.10)$$

where:

- $J_{w,in}$ = water inflow to leaf [m³ s⁻¹]
- $J_{w,out}$ = water outflow from leaf [m³ s⁻¹]
- E_l = leaf transpiration account for leaf area [g s⁻¹]
- ρ_w = water density [g m⁻³]
- $L_{C,l}$ = leaf water capacitance [m³ Pa⁻¹]

Leaf water capacitance was set to constant value based on measurements of leaf water potential and water content from sample trees. In the current version, leaf area growth was also fixed to focus model sensitivity on the fruit module. This simplification reduces system dimensionality and isolates fruit-level processes in the current model version.

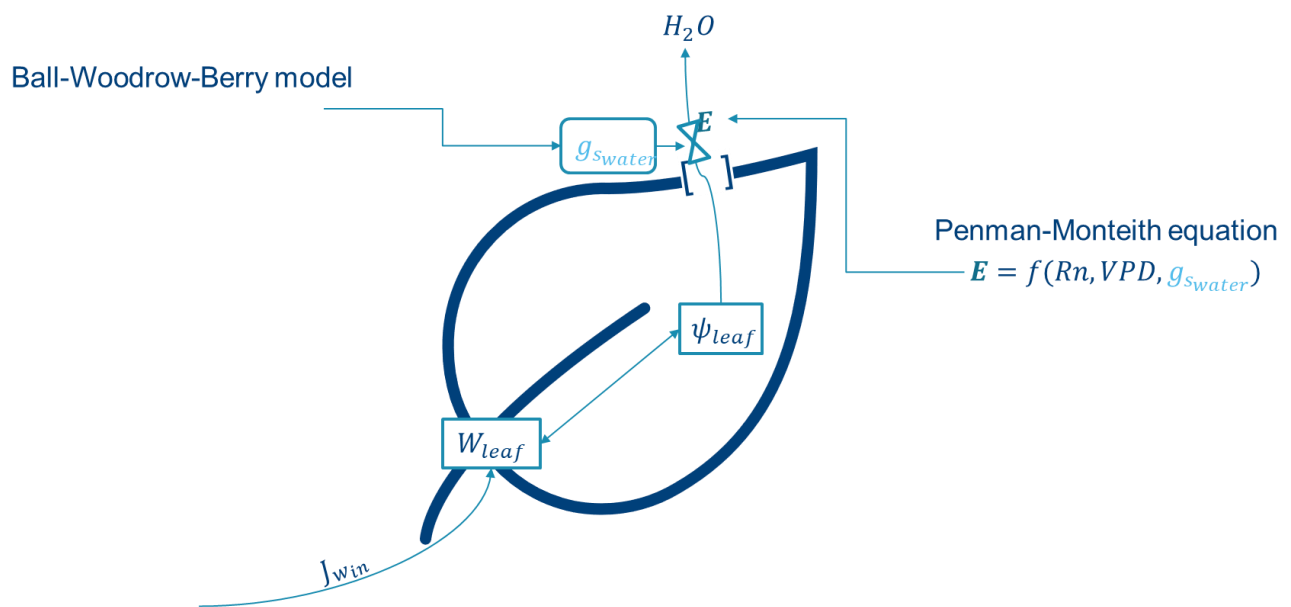


Figure 3.5 Scheme of water flow in leaf.

3.1.9 Water transport

Water transport was simulated following the hierarchical tree structure, with flows driven by gradients of water potential. Water enters the tree from the soil and is transported upwards through the xylem to the branches, and subsequently to leaves and fruits.

At the branch level, transport was represented at three scales (Figure 3.6):

- Inter-branch transport via xylem connections,
- Axial transport within a branch through xylem and phloem between the branch base and organ nodes,
- Cross-membrane exchange between organ nodes and leaf/fruit.

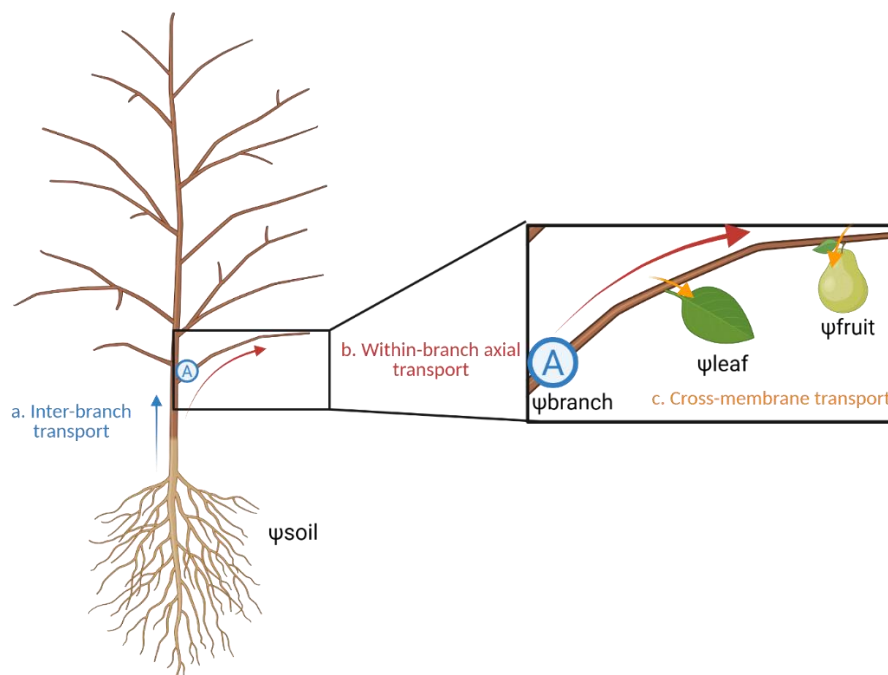


Figure 3.6 Water flow scheme in the tree structure

All flows were modelled as passive transport processes according to gradients in water potential[24]. Leaf transpiration provided the main driving force for water movement. The representation of water flows thus establishes the hydraulic framework of the model in Figure 3.6. The following section describes how sugars are loaded from leaves and unloaded in fruit, and how carbon transport was simulated in parallel with water transport.

Between branch transport:

$$J_{x,b(i) \rightarrow b(i+1)} = \frac{K_{x,b}}{l_b} (\psi_{b,i} - \psi_{b,i+1}) \quad (3.11)$$

Within branch transport:

To represent the pathway within one branch, organ interfaces were defined as intermediate nodes (Figure 3.7):

- “lb” node = branch node attached to a leaf,
- “bf” node = branch node attached to a fruit,
- Branch base node = representing the flow at branch level before transporting to fruits and leaves, connection to higher branch level.

Transport occurs through:

1. Axial transport between lb/bf nodes and the branch base,
2. Cross-membrane transport between lb/bf nodes and their attached leaves or fruits.

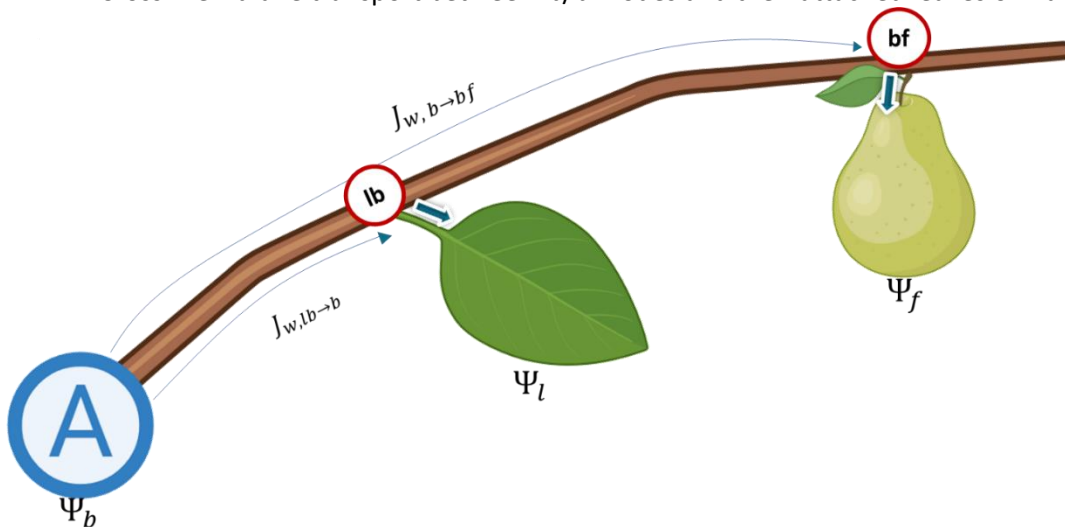


Figure 3.7 Within branch water transport, including axial and cross-membrane transport.

Axial transport in branch to node attached with leaf/fruit. It worth mentioning that the direction of axial transport between leaf node (lb) and branch base (b) are different in xylem and phloem.

$$J_{x,b \rightarrow lb} = \frac{K_{x,b}}{l_{b \rightarrow lb}} (\psi_b - \psi_{lb}) \quad (3.12)$$

$$J_{x,b \rightarrow bf} = \frac{K_{x,b}}{l_{b \rightarrow bf}} (\psi_b - \psi_{bf}) \quad (3.13)$$

$$J_{p,lb \rightarrow b} = \frac{K_{p,b}}{l_{b \rightarrow b}} (P_{p,lb} - P_{p,b} + \delta(\pi_{lb} - \pi_b)) \quad (3.14)$$

$$J_{p,b \rightarrow bf} = \frac{K_{p,b}}{l_{b \rightarrow bf}} (P_{p,b} - P_{p,bf} + \delta(\pi_b - \pi_{bf})) \quad (3.15)$$

where:

- J_x, J_p = xylem/phloem water flow [m³ s⁻¹],
- $K_{x,b}, K_{p,b}$ = xylem/phloem conductivity for branch axial transport [m⁴ s⁻¹ Pa⁻¹],
- $l_{b \rightarrow bf}, l_{lb \rightarrow b}$ = distance between two nodes for transport [m],
- ψ_i = water potential for node i [Pa],
- $P_{p,i}$ = phloem hydrostatic pressure for node i [Pa],
- π_i = osmotic potential for node i [Pa],
- δ = effective reflection coefficient of phloem [-].

Cross-membrane transport:

From the node attached with organ into organ

$$J_{x,lb \rightarrow l} = A_{x,l} \cdot L_{x,lb} \cdot (\psi_{lb} - \psi_l) \quad (3.16)$$

$$J_{x,bf \rightarrow f} = A_{x,f} \cdot L_{x,bf} \cdot (\psi_{bf} - \psi_f) \quad (3.17)$$

$$J_{p,l \rightarrow lb} = A_{p,l} \cdot L_{p,lb} \cdot (P_{p,l} - P_{p,lb} + \delta(\pi_l - \pi_{lb})) \quad (3.18)$$

$$J_{p,bf \rightarrow f} = A_{p,f} \cdot L_{p,bf} \cdot (P_{p,bf} - P_{p,f} + \delta(\pi_{bf} - \pi_f)) \quad (3.19)$$

Passive diffusion into fruit:

$$J_{d,f} = A_{p,f} k_{s,f} (C_{s,bf} - C_{s,f}) \quad (3.20)$$

where:

- A_x, A_p = xylem/phloem membrane area [m²],
- L_x, L_p = hydraulic conductivity of xylem/phloem membrane [m³ m⁻² Pa⁻¹ s⁻¹],
- $k_{s,f}$ = effective mass transfer coefficient for sugar across the composite membrane [m³ m⁻² s⁻¹].

A_x, A_p are proportional to fruit surface area:

$$A_x = a_x A \quad (3.21)$$

$$A_p = a_p A \quad (3.22)$$

Where:

a_x, a_p = constant proportionality of xylem/phloem membrane area to the area A of fruit surface (for fruit compartment), or leaf petiole cross-section (for leaf compartment).

Leaf petiole cross-sectional area is estimated by the diameter of petiole stem and assumed to be constant. Therefore, the related xylem and phloem membrane area are also constant. Since this diameter deviates within a very small range, it is initialized randomly together with the random tree structure and stored in the leaf class in the OOM structure as properties.

Fruit surface area A_f is converted from the fruit volume which will be updated in the feedback loop. The conversion between fruit surface area and fruit volume is fitted based on the measurements.

$$A_f = a_{V \Rightarrow A} V_f \quad (3.23)$$

Where the shape of the fruit is assumed to be “a cone attached to a ball” shape with fruit dimensions of length and diameter measured in section 5.

$$V_f = \frac{4}{3} \pi \left(\frac{D_f}{2} \right)^3 + \frac{1}{3} \pi \left(\frac{D_f}{2} \right)^2 \left(\frac{L_f}{2} \right) \quad (3.24)$$

$$A_f = 2\pi \left(\frac{D_f}{2} \right)^2 + \pi \left(\frac{D_f}{2} \right) \sqrt{\left(\frac{D_f}{2} \right)^2 + \left(L_f - \left(\frac{D_f}{2} \right) \right)^2} \quad (3.25)$$

Osmotic potential is determined by Van't Hoff relation:

$$\pi = \pi_0 - RT \frac{C}{(1-C)M_s} \quad (3.26)$$

where:

- π_0 = base osmotic potential of solutes other than carbohydrates [Pa],
- R = gas constant [8.314 J K⁻¹ mol⁻¹],
- T = temperature [K],
- C = sugar concentration [g m³],
- M_s = molecular mass of sucrose [342 g mol⁻¹].

Hydrostatic pressure P_p is given by the difference between water potential and osmotic potential within the compartment:

$$P_p = \psi - \pi \quad (3.27)$$

Because water redistribution occurs at short time scales, a quasi-steady state (QSS) assumption (no water storage) was initially tested. However, this approach required algebraic matrix solving, which became complex when coupled with sugar transport. For consistency across modules and to allow direct updating of fruit water status, water potentials were therefore formulated as ODE states in the final implementation. This provides stable numerical integration and better connects the water balance with the sugar transport and fruit growth modules.

$$\frac{d\psi_b}{dt} = \frac{1}{L_{C,b}} \left(J_{x,b_in} - \sum (J_{x,b \rightarrow bf}) - \sum (J_{p,b \rightarrow bf}) - \sum (J_{x,b \rightarrow lb}) + \sum (J_{p,lb \rightarrow b}) \right) \quad (3.28)$$

$$\frac{d\psi_l}{dt} = \frac{1}{L_{C,l}} \left(J_{x,lb \rightarrow l} - J_{p,l \rightarrow lb} - E_l \right) \quad (3.29)$$

$$\frac{d\psi_f}{dt} = \frac{1}{L_{C,f}} \left(J_{x,bf \rightarrow f} + J_{p,bf \rightarrow f} - T_f \right) \quad (3.30)$$

The intermediate nodes of lb and bf act as conduit tubes that do not store water, so all the water flow in should flow out immediately. Then Eqn.(3.12) should equal to Eqn. (3.16); Eqn. (3.13) equals to Eqn.(3.17); Eqn.(3.14) equals to Eqn.(3.18); Eqn.(3.15) equals to Eqn.(3.19). And the water potentials at the lb, bf nodes can be solved as:

$$\psi_{x,lb} = \frac{\frac{K_{x,b}}{l_b} \psi_b + A_{x,l} L_{x,lb} \psi_{x,l}}{\frac{K_{x,b}}{l_b} + A_{x,l} L_{x,lb}} \quad (3.31)$$

$$\psi_{x,bf} = \frac{\frac{K_{x,b}}{l_b} \psi_b + A_{x,f} L_{x,bf} \psi_{x,f}}{\frac{K_{x,b}}{l_b} + A_{x,f} L_{x,bf}} \quad (3.32)$$

$$P_{p,lb} = \frac{\frac{K_{p,b}}{l_{lb \rightarrow b}} (P_{p,b} + \delta\pi_b) + A_{p,l} L_{p,lb} (P_{p,l} + \delta\pi_l)}{\frac{K_{p,b}}{l_{lb \rightarrow b}} + A_{p,l} L_{p,lb}} - \delta\pi_{lb} \quad (3.33)$$

$$P_{p,bf} = \frac{\frac{K_{p,b}}{l_{b \rightarrow bf}} (P_{p,b} + \delta\pi_b) + A_{p,f} L_{p,bf} (P_{p,f} + \delta\pi_f)}{\frac{K_{p,b}}{l_{b \rightarrow bf}} + A_{p,f} L_{p,bf}} - \delta\pi_{bf} \quad (3.34)$$

3.1.10 Sugar transport

At this stage, sugar transport was assumed to occur locally within each branch, under the condition that each branch carries at least one leaf and one fruit. Assimilates produced in leaves are thus reserved within the same branch, resulting in locally elevated sugar concentrations. This assumption facilitates validation of the model structure by avoiding long-distance interactions between branches. In future extensions, inter-branch transport will be implemented, and branches may be subdivided into unit-length nodes to represent axial transport in more detail.

To represent this pathway, organ interfaces were defined as intermediate nodes:

- “lb” node = branch node attached to a leaf,
- “bf” node = branch node attached to a fruit,
- Branch base node = reserve for the sugar pool on the branch before transporting to fruits, connection to higher branch level.

Transport occurs through:

3. Axial transport between lb/bf nodes and the branch base,
4. Cross-membrane transport between lb/bf nodes and their attached leaves or fruits,
5. Active unloading from bf nodes into fruits.

This structure provides a clear coupling between organ level sugar dynamics and branch-level axial transport.

When leaves assimilate sugar through photosynthesis, the assimilates are exported to the branch phloem (Figure 3.8). many herbaceous plants employ thermodynamically active mechanisms of phloem loading, in most trees – including pear – loading is considered passive, characterized by low phloem conductivity and high osmolarity[25]. In the current model, leaf sugar export (loading) is represented together with cross-membrane transport between the leaf and its attached lb node. Both processes are assumed to follow a linear relationship with the sugar concentration gradient, consistent with passive diffusion. Thus, loading is implicitly included in the cross-membrane transport formulation in Equation (3.18).

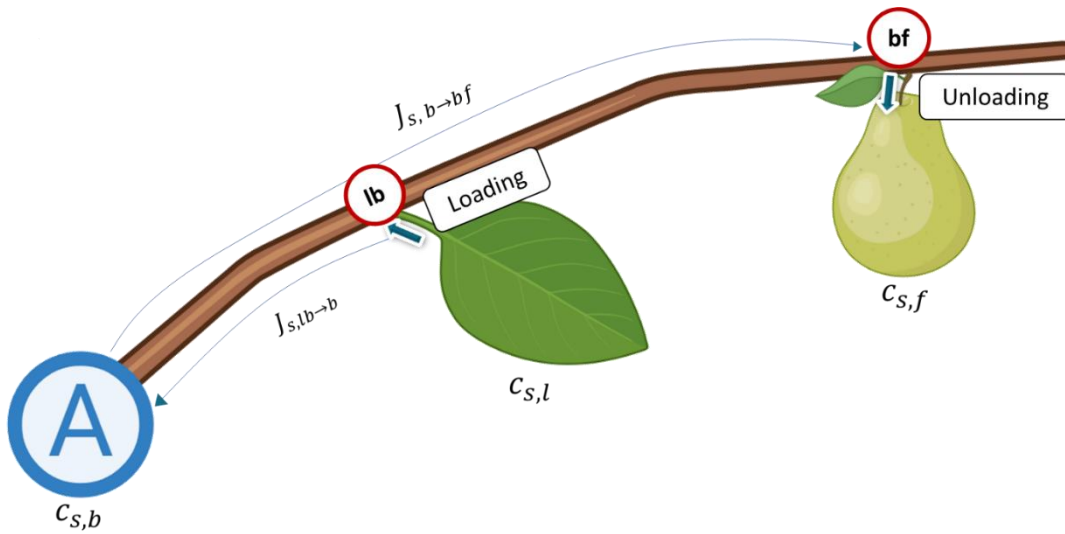


Figure 3.8 Local sugar flow in branch, from source to sink.

Assimilate utilization in sink organs was modelled as an active unloading process. The rate of import into fruits is typically described by a curvilinear relationship following Michaelis-Menten kinetics[26,27]:

$$J_{s,unload} = \frac{C_{s,bf}(t) \cdot V_{\max,f}}{K_{m,f} + C_{s,bf}(t)} \quad (3.35)$$

where:

- $J_{s,unload}$ = unloading rate [g s⁻¹],
- $C_{s,bf}(t)$ = sugar concentration of bf node at time t [g m⁻³],
- $V_{\max,f}$ = potential maximum growth rate [g s⁻¹]
- $K_{m,f}$ = Michaelis-Menten affinity coefficient. [g m⁻³],.

Sugar and water transport are dynamically coupled in the model. Updated sugar concentration influence osmotic potential, which changes local water potentials and drivers water flow. Conversely, water flow affects sugar concentrations via dilution and bulk transport. This feedback loop ensures consistent interaction between carbon and water fluxes and provides the driving mechanism for fruit growth.

As mentioned before, initially the water transport was solved by algebraic matrix for faster computation. A corresponding linearized sugar transport module - following research by Seleznyova and Hanna[28] - was tested together, for purely axial branch transport. But then the active unloading mechanism introduced complexity into the system, so the current approach focuses on solving coupled ODE states for sugar concentration:

$$\frac{dC_{s,b}}{dt} = \frac{\sum(J_{p,lb \rightarrow b} C_{s,lb}) - C_{s,b} \sum(J_{p,b \rightarrow bf})}{V_b} \quad (3.36)$$

$$\frac{dC_{s,l}}{dt} = \frac{A_n \cdot LA - C_{s,l} J_{p,l \rightarrow lb} - R_l \cdot LA}{V_l} \quad (3.37)$$

$$\frac{dC_{s,f}}{dt} = \frac{(1-\delta)C_{s,bf}J_{p,bf \rightarrow f} + J_{s,unload} + J_{d,f} - R_f}{V_f} \quad (3.38)$$

$$C_{s,lb} = \frac{C_{s,l} \cdot J_{p,l \rightarrow lb}}{J_{p,lb \rightarrow b}} \quad (3.39)$$

$$C_{s,bf} = \frac{C_{s,b} \cdot J_{p,b \rightarrow bf} - J_{s,unload} - J_{d,f}}{J_{p,bf \rightarrow f}} \quad (3.40)$$

3.1.11 Fruit growth model

The fruit growth module was developed based on the published model by Dequeker et al. in 2024 [29] as shown in Figure 3.9. The model focuses on individual fruit development throughout the growing season. The model input are the hydrostatic pressure in xylem and phloem and sugar concentration in phloem before entering the fruit, which was defined as the “bf” node in Section 3.7.

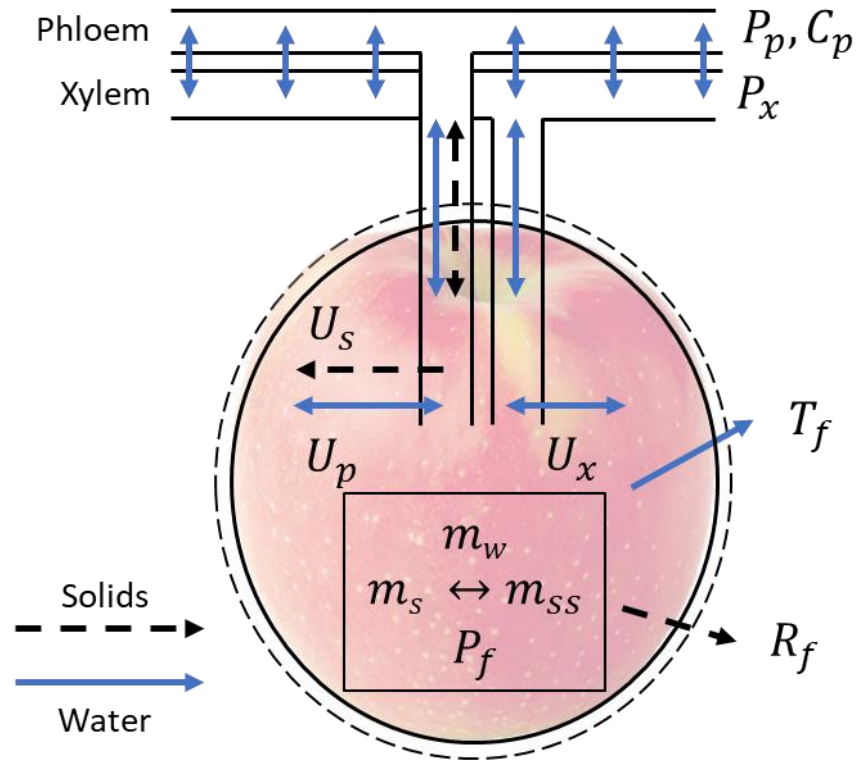


Figure 3.9 Schematic representation of the fruit growth module by Dequeker et al. [29]. Dashed arrows represent sugar flux. Solid arrows represent water flux.

The main parts introduced from Dequeker’s model include:

- fruit transpiration,
- fruit respiration,
- active unloading of sugar from phloem,
- fruit volume growth driven by fruit turgor pressure.

Fruit transpiration

Water is lost from fruit surface through transpiration, which is driven by the difference between air filled space in fruit and the ambient atmosphere.

$$T_f = A_f \frac{M_w P^*}{RT} (RH_f - RH_a) \quad (3.41)$$

where:

- A_f = fruit surface area [m²]
- M_w = molecular mass of water [g mol⁻¹]
- P^* = saturation pressure [MPa]
- RH_f, RH_a = fruit internal and ambient relative humidity, respectively.

Fruit respiration

Carbon losses from fruit are represented as the sum of growth and maintenance respiration:

$$R_f = q_{gr} \frac{dm_s}{dt} + q_{ma,293} Q_{10,r}^{\frac{T-293}{10}} \quad (3.42)$$

where:

- q_{gr} = coefficients for growth respiration (at 293 K) [-],
- $q_{ma,293}$ = coefficients for growth respiration (at 293 K) [h⁻¹],
- m_s = fruit dry mass [g],
- $Q_{10,r}$ = temperature ratio of maintenance respiration [-]
- T = Temperature [K]

Active unloading

In the original formulation (3.35), unloading followed a Michaelis-Menten relationship. In this implementation, the maximum uptake rate $V_{\max,f}$ was extended to scale with fruit dry weight, maximum active transport capacity, and temperature (Q_{10} concept). This approach has been previously applied and validated in fruit-tree models [29–31]:

$$J_{s,unload} = \frac{m_s Q_{10}^{\frac{T-293}{10}} k_{s,max} C_{s,bf}}{\left(1 + e^{\frac{t-\tau_2}{\tau_1}}\right) K_{m,f} + C_{s,bf}} \quad (3.43)$$

where:

- m_s = fruit dry mass [g],
- Q_{10} = Temperature ratio of active transport [-],
- T = Temperature [K]
- t = time [s],
- τ_1, τ_2 = kinetic parameters accounting for “inhibitory” effect [-],
- $k_{s,max}$ = maximum rate of active transport per unit of dry mass [g g⁻¹ h⁻¹].

Fruit turgor pressure and volume growth

Turgor pressure P_f was updated from the balance of osmotic potential and hydrostatic pressure in the fruit. Water inflow, osmotic gradients and transpiration jointly regulate the dynamics of P_f . This formulation ensures fruit turgor pressure responds to both water and sugar import.

$$\frac{dm_{w,f}}{dt} = A_{x,f} \cdot L_{x,bf} \cdot (\psi_{bf} - \psi_f) + A_{p,f} \cdot L_{p,bf} \cdot (P_{p,bf} - P_{p,f} + \delta(\pi_{bf} - \pi_f)) - T_f \quad (3.44)$$

$$\frac{dP_f}{dt} = \varepsilon \left(\left(\frac{1}{\rho_w V_f} \frac{dm_{w,f}}{dt} + \frac{1}{\rho_s} \frac{dC_{s,f}}{dt} \right) - \varphi (P_f - Y) \right) \Big|_{P_f > Y} \quad (3.45)$$

Fruit volume growth was linked to fruit turgor pressure. The change of fruit volume can be expressed as the result of volume variations due to irreversible (plastic) and reversible (elastic modulus in Eqn. (3.48)) deformations[32] as Eqn.(3.46). Plastic modulus followed the Lockhart equation on irreversible plant growth in Eqn. (3.47) [33]. Elastic modulus was further developed by Ortega regarding the cell wall expansion[32].

$$\frac{dV_f}{dt} = plas. + elas. \quad (3.46)$$

$$\frac{dV_{plas.}}{dt} = \begin{cases} V_f \varphi (P_f - Y) & P_f > Y \\ 0 & 0 < P_f < Y \end{cases} \quad (3.47)$$

$$\frac{dV_{elas.}}{dt} = \frac{1}{\varepsilon} V_f \frac{dP_f}{dt} \quad (3.48)$$

where:

- V_f = fruit volume [m^3]
- $V_{plas.}, V_{elas.}$ = plastic and elastic growth of fruit volume [m^3]
- φ = cell wall extensibility [$MPa^{-1} h^{-1}$]
- Y = threshold pressure for growth [MPa]
- ε = cell wall elastic modulus [MPa]

In some fruit growth models, the elastic deformation to volume changes are neglected[30]. For simplicity, the elastic term was primarily muted in the model development, focusing on the irreversible growth component. The values of parameters are given in separate files.

3.2 Experimental results

In the following sections, sub-models are illustrated using simplified tree structures (often at branch level or with a single branch), which allow clear demonstration of individual processes and computational testing. More complex and realistic canopy structures are introduced selectively (e.g. water transport model) to highlight the impact of structural complexity on physiological outputs. This approach ensures that mechanisms are first evaluated against published values at modular scale before being integrated into whole-tree simulations.

3.2.1 Photosynthesis evaluation

Photosynthesis measurements provided the parameterization of the FvCB photosynthesis sub-model used. Light response curves were measured for both treatments and fitted to the FvCB model to simulate net assimilation rates (Figure 3.10). Parameters fitting was carried out separately for APV and controlled conditions (FS) to account for potential long-term acclimation to shading. Among the estimated parameters, the maximum net photosynthesis rate A_{max} derived from the light response curves indicated the existence of leaf adaptation to shading in APV (Figure 3.11). Lower A_{max} under APV linked to reduced net assimilation rate at saturated light intensities, which suggests acclimation to reduced light availability under shaded condition. The simulated net assimilation rate, light compensation point and the relative comparison between APV and FS were comparable to the reported ranges of apple trees by Juillion et al. across multiple years[34]. The calibrated parameters were then implemented in the leaf photosynthesis sub-model to drive canopy assimilation in simulations.

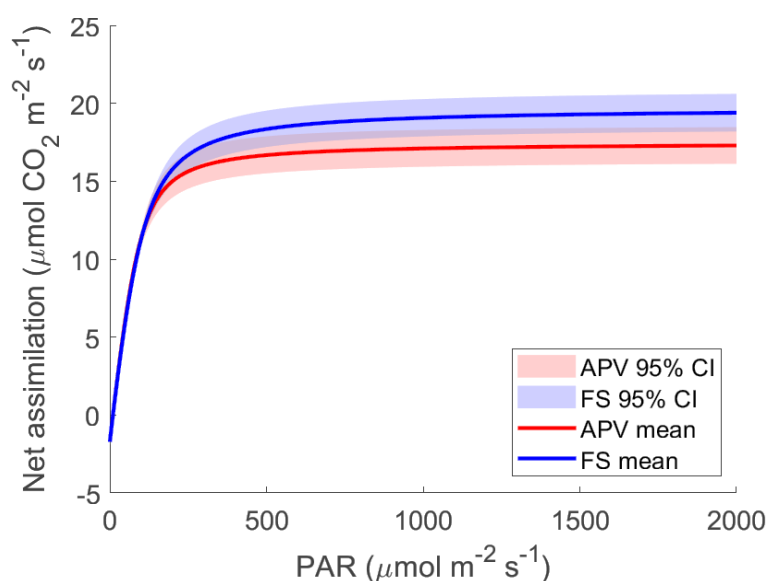


Figure 3.10 Simulated light response curve with fitted parameter in FvCB model. Solid lines indicate the mean value, the transparent regions indicates the 95% confidence interval.

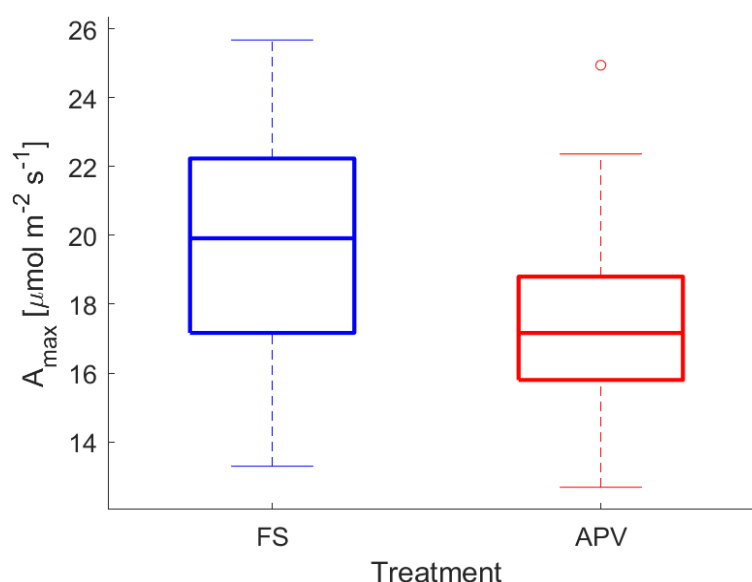


Figure 3.11 Estimated maximum net photosynthesis rate (A_{max}) for APV and FS ($P < 0.01$).

The accumulated potential carbon supply was calculated for 2024 by applying the fitted FvCB parameters to actual measured inputs of light intensities (Figure 3.12). To reveal the instant impact of light variation across microclimate zones, parameters were kept constant across treatments. Overall, potential carbon supply was slightly lower under APV compared to FS, reflecting reduced light availability in shaded condition even without accounting for acclimation. Moreover, APV induced heterogenous vertical light environment, while FS retained the homogeneity of light across canopy heights. This strengthen the importance of considering vertical light distribution in canopy models. APV likely reduced maximum assimilation while promoting less balanced source strength inside the canopy.

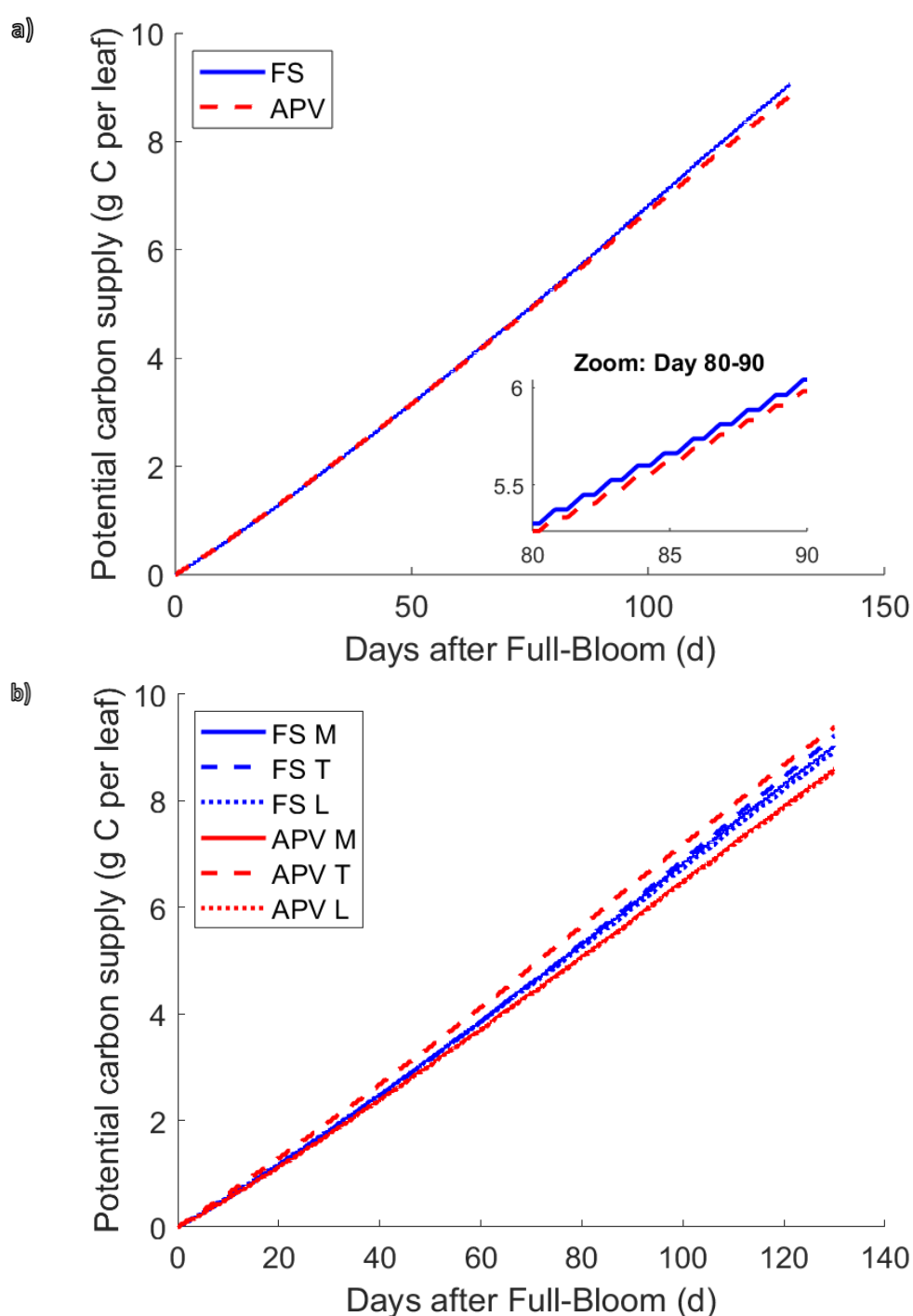


Figure 3.12 Instant impact on leaf assimilation in APV and FS. (a) Tree-level simulation; (b) Zonal simulation for different height levels in the tree canopy (L-Low, M-Middle, T-Top).

Based on the fitted parameters of the FvCB model, leaf-level dry matter production was simulated and compared with fruit dry matter measured at harvest in 2024 (Figure 3.13). Given the reduced light availability and shade acclimation of leaves under APV, simulated potential dry matter of fruits was expected lower in APV than FS. However, the observed fruit dry weight showed a larger variation than the simulated potential carbon gain. This discrepancy likely reflects additional influences beyond photosynthetic capacity, such as water balance and sink-source ratio of the entire fruit tree.

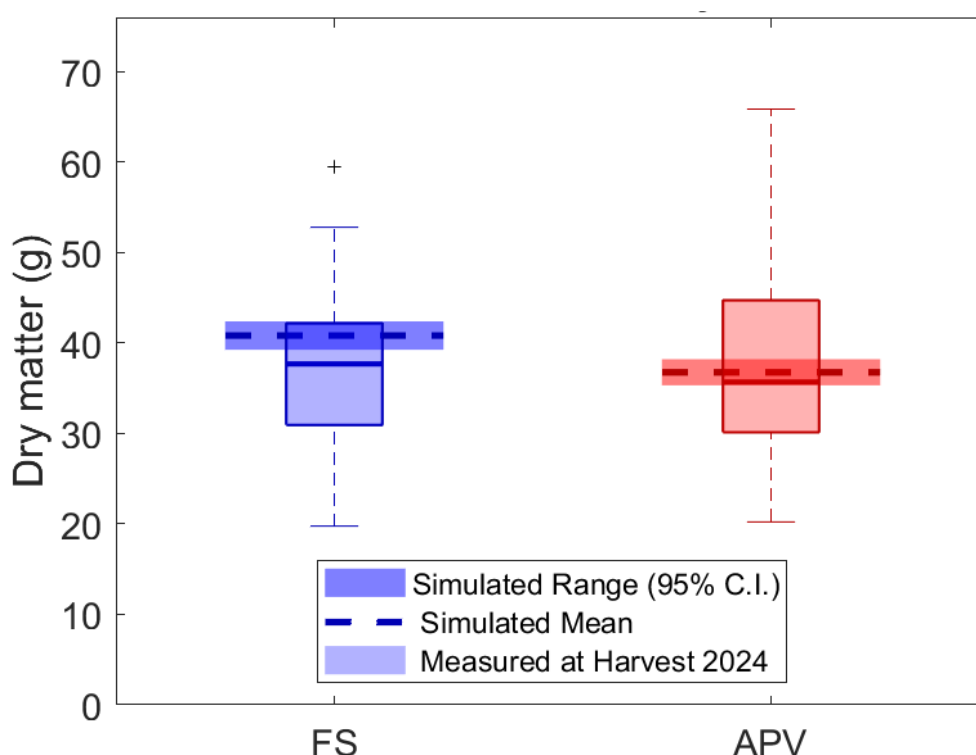


Figure 3.13 The simulated and actual dry matter production for APV and FS conditions.

3.2.2 Water transport evaluation (with transpiration)

Following the water transport model described in Section 3.1.9, branch water potentials were primarily simulated under quasi-steady state conditions using measured temperature and humidity inputs over a 10-day period. The climate inputs were used to compute leaf transpiration, which provided the driving force for water flows into branches. The cumulative transpiration demand of leaves generates differences in branch water potential, consequently determining water availability for fruits.

In Figure 3.14, average fruit water potential was simulated by only activating the hydraulic pathway of the tree model for a randomly generated sample tree consisting of 5 branches, 50 leaves and 10 fruits. A larger, more realistic tree structure with 20 branches, 490 leaves and 50 fruits was also simulated (Figure 3.15). While the temporal dynamics of fruit water potential were similar in both cases, the larger tree produced consistently lower fruit water potentials due to the higher leaf density and greater cumulative transpiration demand per branch. This illustrates that tree structural complexity strongly influences simulated outputs, especially in an open system where transpiration represents a continuous water loss pathway.

Furthermore, the simulated fruit water potentials of the larger tree fell within a range closer to that reported by Dequeker et al. [29] of pome fruits, suggesting that more realistic canopy structures are necessary to obtain physiologically consistent predictions.

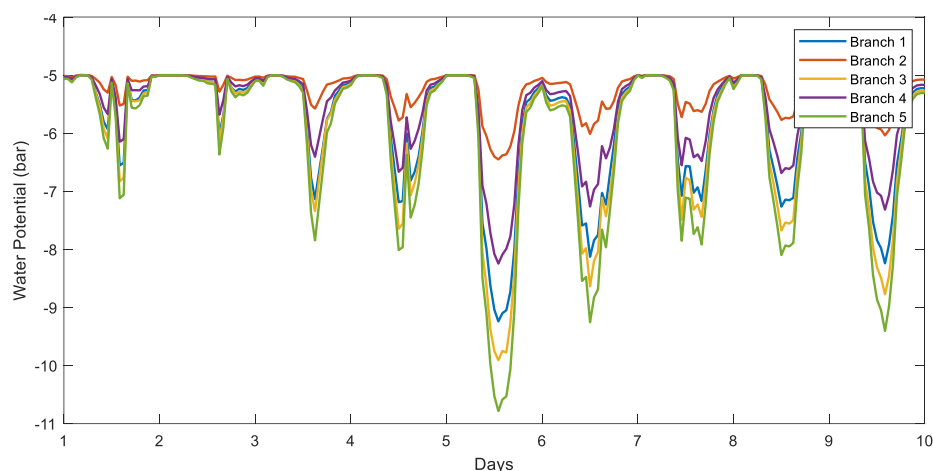


Figure 3.14 Simulated water potential within ten days with a tree structured with 5 branches, 50 leaves and 10 fruits.

Figure 3.15 Simulated water potential within ten days with a tree structured with 20 branches, 490 leaves and 50 fruits

3.2.3 Model simulation for the sample tree

The model simulation started with a simplified tree structure with one branch, two fruits and three leaves to drive the whole system. The model output revealed the time-variant state variables for each compartment (branch, leaf, fruit) based on the real inputs of light, temperature and humidity. The preliminary simulation after completion of building the complete model system was displayed in Figure 3.16. The model successfully ran through the entire growing season without numerical instability, demonstrating the feasibility of coupling the sub-models within a unified framework.

The simulated outputs showed physiologically consistent patterns. Water potential followed daily fluctuations driven by leaf transpiration, with amplitudes reflecting the climate input dynamics. Fruit and branch water potentials exhibited smooth variations without unrealistic spikes. Sugar concentrations in leaves and fruits showed gradual seasonal increases, with relatively stable short-term dynamics compared to water potential. These trends are consistent with expectations: water potentials illustrated daily fluctuations in response to leaf transpiration, whereas sugar concentrations vary more smoothly, combining short-term diurnal patterns with long-term cumulative increase.

Nevertheless the simulated amplitudes of water potential variations were smaller than expected, and the magnitude of sugar concentrations remains uncertain. These discrepancies are mainly due to parameter uncertainty, as many hydraulic and transport coefficients were initially estimated from literatures rather than

site-specific measurements. While the overall behavior of the model is plausible, further calibration is needed to obtain realistic absolute values.

The current parameterization status has been summarized (Table 3.2). Parameters related to photosynthetic rates have been calibrated with field measurements, while many hydraulic and transport parameters (e.g. xylem conductivity, membrane permeability, fruit unloading kinetics) remain uncertain. These parameters were temporarily constrained by assumptions.

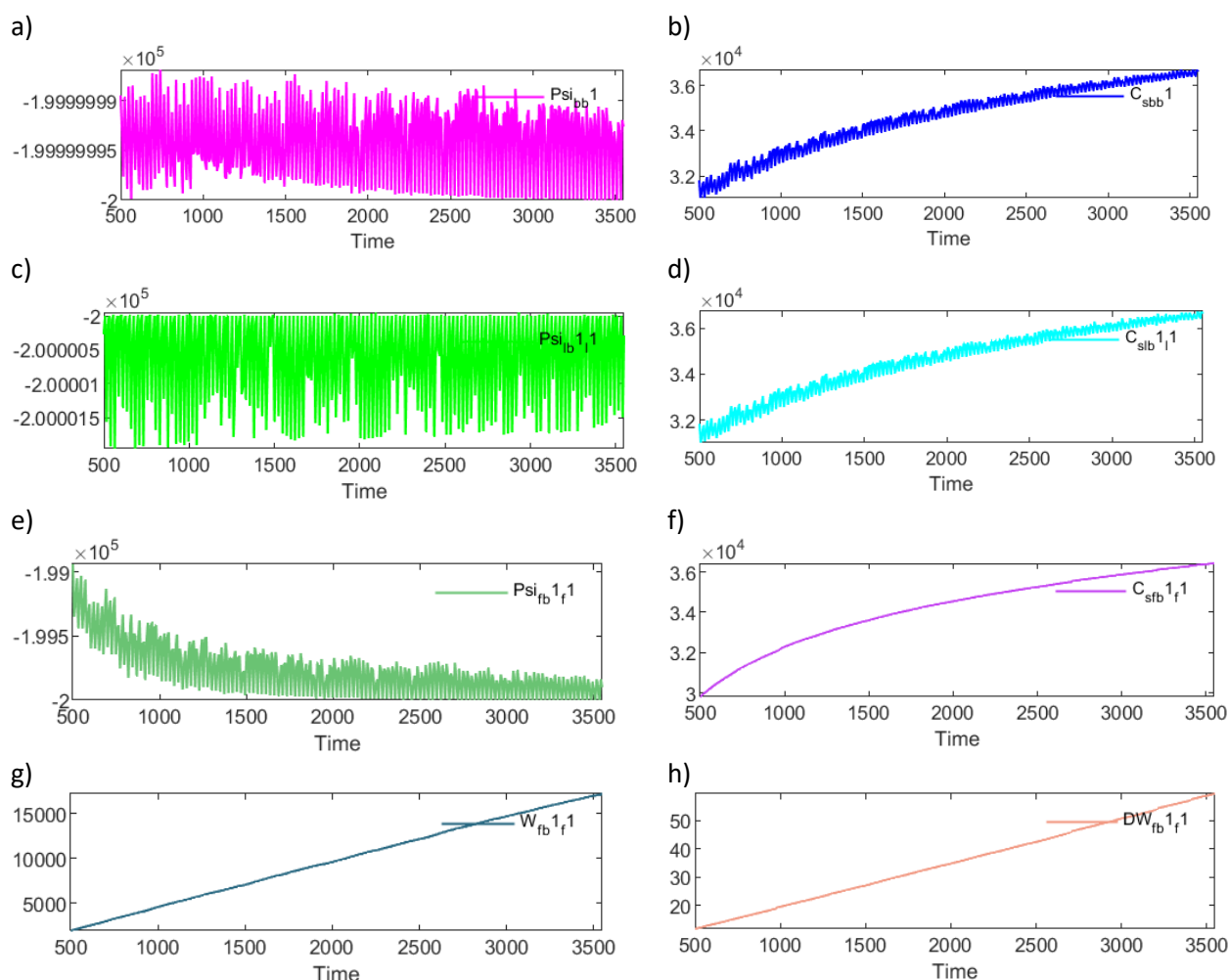


Figure 3.16 Simulation result of complete model system with assumed parameters and tree structure of 1 branch, 3 leaves and 2 fruits. a) branch water potential (Pa); b) branch sugar concentration (g m^{-3}); c) leaf water potential (Pa); d) leaf sugar concentration (g m^{-3}); e) fruit water potential (Pa); f) fruit sugar concentration (g m^{-3}); g) fruit water content (g); h) fruit dry matter (g).

Future work will focus on targeted experimental campaigns such as stem cross-section microscopy to obtain site-specific parameter ranges. In addition, systematic parameter estimation and sensitivity analysis will be performed using AMIGO2 to refine parameter values and identify the most influential traits. This iterative process will allow the model to move from capturing general physiological trends to providing quantitatively accurate predictions.

Table 3.2 Overview of parameters and planned improvements

SUB-MODEL RELATED	PARAMETERS		SOURCE OF PARAMETERS		
LEAF PHOTOSYNTHESIS	Boundary layer conductance		Estimated from field measurements		
	maximum carboxylation rate				
	maximum electron-transport rate				
	dark respiration rate				
	Michaelis-Menten coefficient for CO ₂				
	Michaelis-Menten coefficient for O ₂				
	CO2 compensation point				
	curvature parameter of electron transport				
LEAF STOMATAL CONDUCTANCE	Ball-Berry intercept		Retrieved from literature		
	Ball-Berry slope				
LEAF WATER RELATION	leaf water capacitance	m ³ /Pa	Estimated from measurements		
FRUIT MODEL	fruit elasticity	Pa	Retrieved from literature		
	conversion from fruit surface area to fruit xylem surface area	-			
	conversion from fruit surface area to fruit phloem surface area	-			
	Turgor pressure threshold for volume growth	Pa			
	relative humidity of fruit intercellular space	-			
	coefficient fruit unloading	g/m ³			
	Growth respiration coefficient	-			
	Maintenance respiration coefficient	1/h			
	water capacitance	m ³ /Pa			
	maximum solid mass fruit	g			
	permeability of the composite membrane to sugar transport	g/m ² /h			
	TRANSPORT MODEL (XYLEM/PHLOEM)	Fruit membrane transfer coefficients		m ³ /m ² /Pa/s	To be estimated from further measurement
		Leaf membrane transfer coefficients		m ³ /m ² /Pa/s	
Branch hydraulic conductivity		m ⁴ /s/Pa			

3.2.4 Nodal Sugar transport (prospective)

The following demo illustrates a potential nodal strategy for sugar transport. This approach is not yet implemented in the complete model, which currently assumes direct transfer from leaves to the branch base and then to fruits.

This sugar transport module was demonstrated on a simplified branch structure divided into five zones (Figure 3.17), with explicitly defined distances between nodes, numbers of leaves and fruits. This setup enabled clear illustration of the transport mechanism along the axial phloem pathway. Inputs were defined as artificial but mechanistically consistent boundary conditions: sugar loading rates at leaf nodes and unloading rates at fruit nodes, which should be determined by other modules in the complete system. The loading rates were modelled to reflect the influence of light intensity with daily pattern varying between minimum (no photosynthesis) and maximum (saturated photosynthesis). Such daily pattern followed a sinusoidal function with highest loading rate at solar noon and lowest loading rate between sunset and sunrise. The magnitude of the loading at each node was scaled by the number of leaves attached. Unloading rates were defined based on the fruit growth data, fitted to the empirical growth curves, and scaled by the number of fruits per node.

The simulation outputs were the sugar concentration at each node along the branch, illustrated at different time scales of 3, 50, and 150 days (Figure 3.18). Short-term dynamics (3 days) reflected daily fluctuations in loading, while longer terms (50-150 days) captured the cumulative effects of sustained loading and unloading on branch-level concentration gradients. Comparisons of different unloading rates further demonstrated how sink strength regulates the dynamics and distribution of sugars within the branch.

The current demo provided a mechanistic basis for representing axial sugar transport and its modulation by source-sink interactions. The simplified framework ensures that the functioning of sugar transport sub-model is transparent and consistent with the overall crop model structure, while further extensions will be embedded in the open system of tree model with climate inputs.

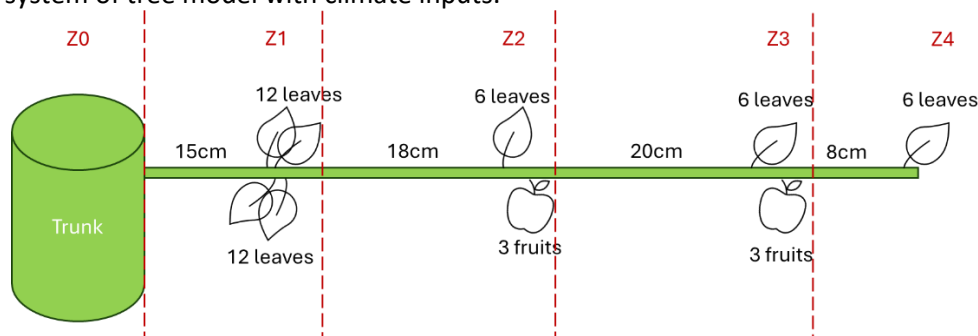


Figure 3.17 Scheme of branch structure used in the sugar transport demo with specific information on each node. Zones were divided based on the existence of organ compartments (leaf, fruit).

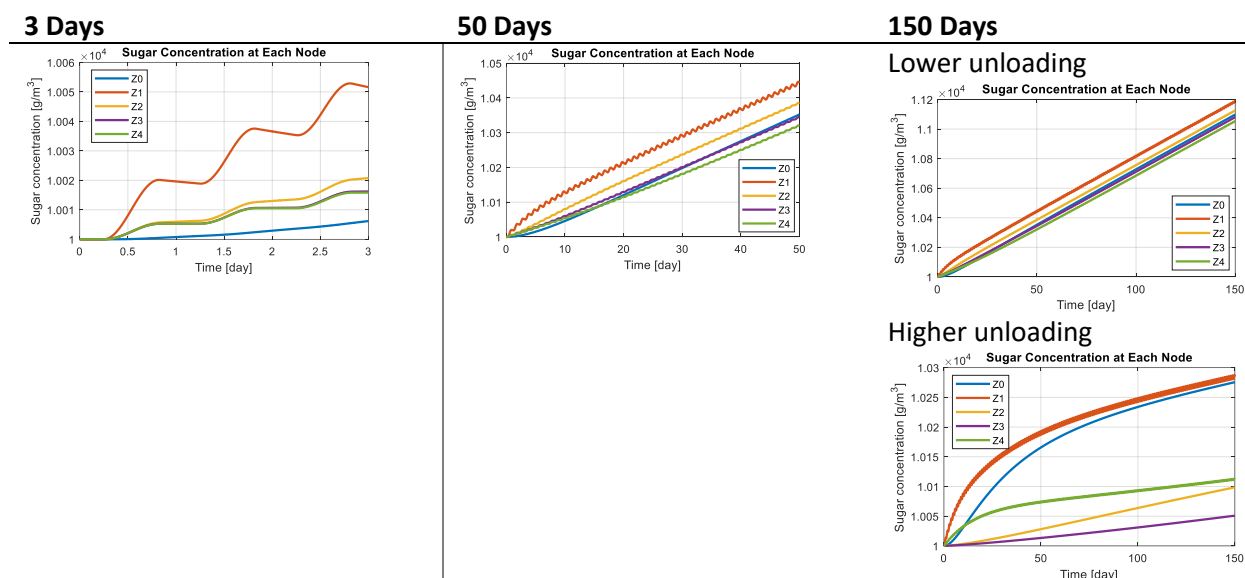


Figure 3.18 Simulation outputs regarding different time scales (3 days, 50 days, 150 days). Inputs included loading rate (g mol^{-1}) and unloading rate (g mol^{-1}) which were synthetic data. Outputs were sugar concentrations of each node (g m^{-3}), with comparison of low and high input unloading rates for 150-day simulation.

3.2.5 Crop parameters

Manual measurements and plant attached sensors were used to estimate physiological parameters for model calibration.

Tree topological information

At the start of the 2024 and 2025 seasons, four sample trees (two per treatment) were selected in the central row. Tree height, internode length, stem diameter, branch length, leaf number per branch, fruit number per branch were recorded. Identical trees and labelled branches were used in both years to ensure consistency.

- In 2024, weekly measurements were performed on mature leaf area, fruit diameter, and fruit length (9 replicates per treatment). Fruit dimensions were used to estimate volume growth through a geometric pear-shape equation (3.24).
- In 2025, leaf counts per branch were repeated in June to determine maximum canopy leaf density.

Phenotypic traits of the sample trees are summarized in Table 3.3. Comparisons of leaf and fruit numbers between treatments are shown in Figure 3.19.

Table 3.3 Phenotypic traits in APV and FS treatments (2024 and 2025).

Year	2024				2025			
Treatment	APV		FS		APV		FS	
Tree	T1	T2	T1	T2	T1	T2	T1	T2
Leaf nr. in April	468	398	637	460	484	294	453	283
Leaf nr. in June	/	/	/	/	2254	1640	3485	2336
Fruit nr. at full bloom	306	337	235	202	600	543	385	369
Fruit nr. at harvest	35	33	58	47	126	75	134	102

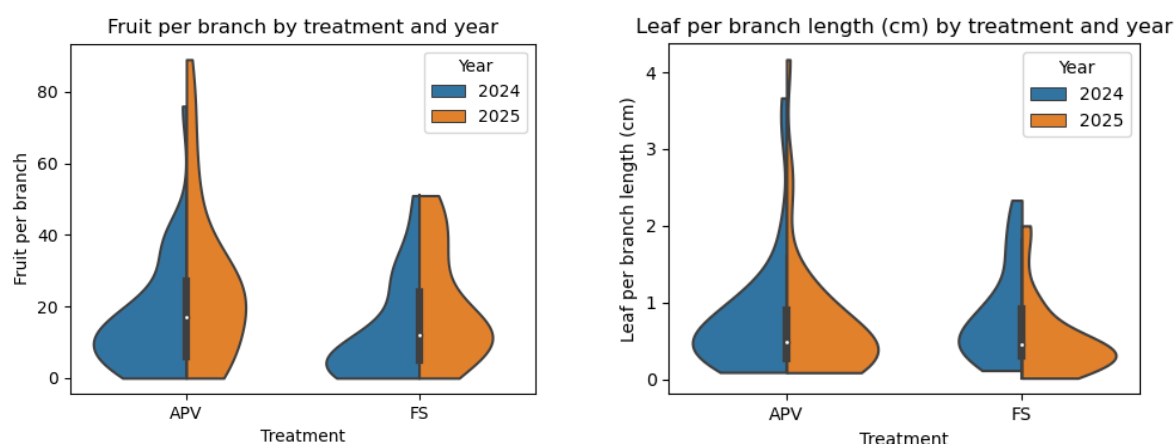


Figure 3.19 Leaf and Fruit counts in spring in 2024 and 2025

Tree topological information was used as reference structure for evaluating the light interception model and served as input for the transport sub-models as the network framework.

Water flow measurements

Sap flow sensors (Ecometik SF-HP, DE) were installed in June 2024 and 2025 on two trees with three sensors per treatment. In 2024, three sensors were placed: two at the base of the canopy below the first branch, and one higher level in the canopy. In 2025, three sensors were placed at the base of the canopy on three different trees. Microtensiometers (FluoraPulse, US) were installed from June 2025 at the canopy base on two trees per treatment to continuously monitor water potential and assess dynamic water flows (Figure 3.20 and Figure 3.21). Water flow measurements provided the parameterization and validation of the water transport sub-model.

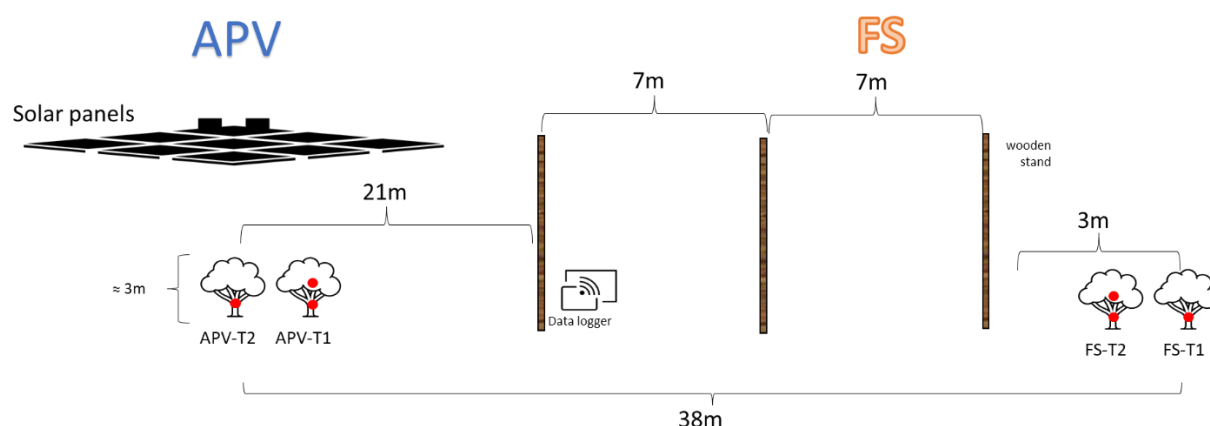


Figure 3.20 Sap flow sensor placement in 2024. Red circles on the tree indicate the position of the sap flow sensors.

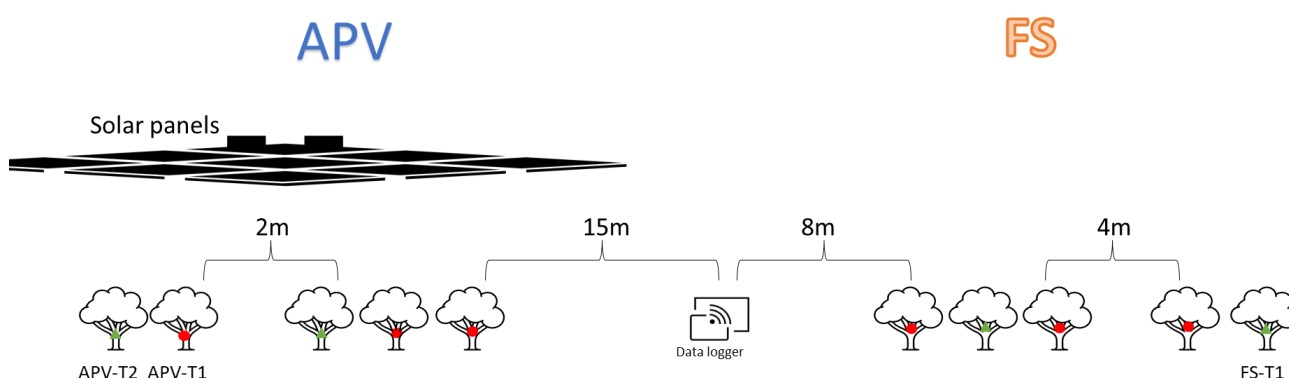


Figure 3.21 Sap flow sensor and micro-tensiometer placement in 2025. Red circles indicate sap flow sensors, green triangles indicate micro-tensiometers.

Fruit harvest

The harvest dates were suggested by the Flanders Centre of Postharvest Technology (Heverlee, Belgium) based on the time evolution of common maturity indices: 26 August 2024, 18 August 2025. Harvest measurements were conducted over 2-3 days in each year. Fruits were collected per plot, per tree, and per canopy zone. All fruits on the sample trees were harvested, with the corresponding number in microclimate zones.

For each individual fruit, fresh weight, volume, soluble solids content ($^{\circ}\text{Brix}$), and firmness were determined:

- *Volume* was measured by the water displacement method.
- *Firmness* was measured immediately after harvest using a benchtop penetrometer with a 0.5 cm² plunger.
- *Total dissolved solids* ($^{\circ}\text{Brix}$) were determined from expressed juice with a digital refractometer (Mettler Toledo, US).

Additional analyses were conducted on subsamples, three fruits per zone and tree ($n = 30$ per plot):

- In 2024, 30 subsamples per plot were selected for dry weight and osmolarity.
- In 2025, the same subsample design was used, with addition of water potential measurements.
- *Dry weight* was measured by drying pear tissue samples in aluminum cups at 70 $^{\circ}\text{C}$ for ≥ 4 days until weight stabilized ($<1\%$ change).

- *Osmolarity* was measured with Osmomat 3000 (Gonotec) after centrifugation of pear juice, with three technical replicates per sample.
- *Water potential* was measured immediately after harvest using a pressure chamber (PMS instrument Model 670) to minimize post-harvest water loss.

Fruit harvest measurements provided the estimates of fruit growth sub-model and validation data for the tree model.

Photosynthesis

In May 2024, photosynthesis-related measurements were conducted on sample trees in both plots over a two-week period. The measured leaves were fully expanded and healthy.

- **Light response curves** were measured using an LCpro T advanced photosynthesis system (ADC BioScientific Ltd.) with an external white light module at ambient $[\text{CO}_2]$. Measurements were taken on three leaves per canopy zone, per tree, per plot ($n = 30$ per plot). Curves were generated by recording CO_2 uptake at stepwise decreasing light intensities from $2050 \mu\text{mol m}^{-2} \text{s}^{-1}$, with equilibrium reached at each step.
- **CO_2 response curves** were measured at a fixed PAR of $1500 \mu\text{mol m}^{-2} \text{s}^{-1}$ on five leaves per tree per plot ($n = 10$ per plot).
- Both light and CO_2 response curves were fitted to the FvCB model[17,35], using the optimization tool OptiPa[36]. From these fits, the dark respiration rate, light compensation point, carbon assimilation at saturating light, and maximum carboxylation rate were estimated.
- **Instantaneous photosynthesis rates** under ambient field conditions were measured with the LCpro T (three replicates per condition).

3.2.6 Plant growth measurements

Sap flow velocity

Sap flow velocity was measured in cm h^{-1} at the sensor positions shown in Figure 3.20 and Figure 3.21. Sap flow reflects the driving force of canopy transpiration, as higher transpiration rates induce water transport from trunk and soil into branches. On average, sap flow velocity was slightly higher under APV than FS, but the peak spikes were less frequent. Such slight differences in sap flow between APV and FS were not reflected in stem water potential (Figure 3.22), which remained similar across treatments. This suggests that the short-term variations in transpiration dynamics as midday were buffered at the canopy level. When related to concurrent temperature and humidity data, the lower sap flow velocities corresponded to periods of high humidity with mild temperature ($\sim 20^\circ\text{C}$), likely associated with rainfall events. This coherence further explains the effect of climate on water transport in trees. These measurements directly supported the water transport simulation for the canopy level.

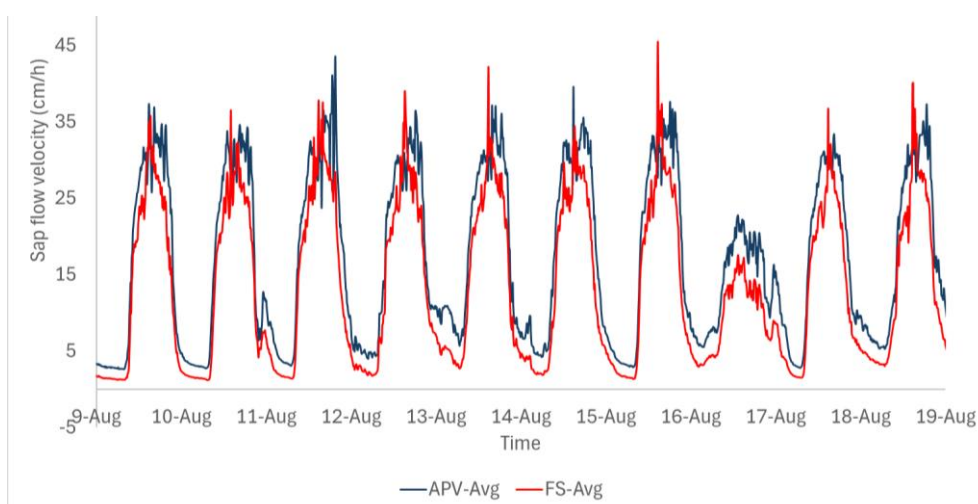


Figure 3.22 Sap flow velocity (cm/h) measurement from 9 August to 19 August 2025. Each line represents the average value of three sensors in each field.

Stem water potential

The average values of water potential followed the same pattern with slightly higher values at night under APV. The daily lowest water potential at midday were close between APV and FS. With the installation of micro-tensiometers at the bottom of tree canopy, the measured stem water potential gave information about the overall canopy water status. Stem water potential integrates both water loss via transpiration and water supply from the soil. A decrease in stem water potential can thus result either from high transpiration demand or from soil water deficit. Stable and high water potential waters reflect a well-watered tree or low transpiration (e.g. at night). With low water potential corresponds to high transpiration (no water stress assumed), subsequently higher sap flow velocity. For instance, the high water potential without spike midday drop on 17 August (Figure 2.34) indicated that the trees were well irrigated, likely due to rainfall with the information given in Figure 5.8. In this case, the datasets can be cross-validated. Furthermore, stem water potential, together with sap flow velocity, can be used to parameterize the water transport sub-model regarding hydraulic conductivity.

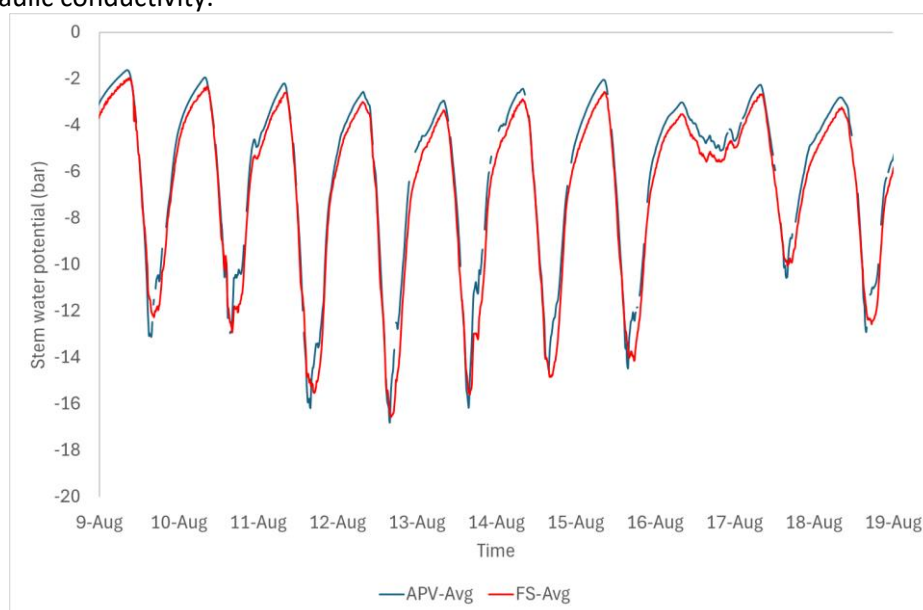


Figure 3.23 Stem water potential (bar) measurement from 9 August to 19 August 2025. Each line represents the average value of two sensors in each field.

4 Model integration

4.1 Impact of the potential long-term evolution of solar resource and climate on PV and crops yield (LUCISUN, KUL)

4.1.1 Scope and rationale

This subsection explains why we evaluate the long term evolution of the solar resource and climate for the SYMBIOSYST demonstrators, and how the results are used in the project. Our objective is twofold.

1. First, we quantify year to year variability that affects operational planning and risk.
2. Second, we characterise multi decadal changes that inform design choices, investment decisions, and adaptation strategies for both PV systems and crops.

The assessment covers the three SYMBIOSYST demonstrators in Belgium, Italy, and the Netherlands. The Belgian site represents an open field agri PV context with vegetable crops in Gembloux. The Italian site is an apple orchard in Bolzano with elevated agri PV structures. The Dutch site is a greenhouse with semi transparent PV glazing. Analysing these three cases together allows a comparison of open field and controlled environments and provides a North–South perspective on European climate drivers that influence both PV performance and crop productivity.

The analysis focuses on variables that matter for energy yield and crop growth. For the solar resource we evaluate global, direct, and diffuse components and their partitioning, and we derive photosynthetically active radiation and daily light integral for crop models. For climate we consider air temperature, humidity and vapour pressure deficit, wind speed, and precipitation, and we compute derived agronomic indicators such as growing degree days, chill accumulation, and frost occurrence around sensitive phenological stages. These variables are assessed historically to understand variability and tested in climate projections to explore plausible futures.

The outputs are used in two ways. They feed the PV modelling chain to estimate plane of array irradiance, module temperature, performance ratio, and specific yield under historical and projected conditions. They also drive the crop light and climate response models to estimate absorbed PAR, daily light integral, and stress factors for temperature, vapour pressure deficit, and water availability. In the greenhouse case we translate outdoor forcing to indoor conditions through glazing transmission and simple control rules, so that both spectral and thermal effects are represented.

4.1.2 Datasets and methodology

Climate data sources

The evaluation of long term impacts on PV and crops requires climate datasets that are consistent, spatially resolved, and sufficiently long to capture both variability and trends. In this task we rely on two main categories of data. The first are historical reanalyses and satellite derived solar datasets that reconstruct past weather and radiation conditions. The second are climate model projections that extend into the future and provide scenarios of possible evolution under different greenhouse gas pathways.

For the historical period 1991 to 2020 we use ERA5 Land, a reanalysis produced by the European Centre for Medium Range Weather Forecasts. It provides hourly values of surface variables at about nine kilometre resolution, including global, direct, and diffuse irradiance, temperature, humidity, wind and precipitation. This dataset was complemented by satellite based solar resource products in order to better resolve GHI and its components. Together these sources provide robust inputs for PV and crop modelling across the three SYMBIOSYST demonstrators in Belgium, Italy and the Netherlands.

For the future period we rely on climate projections from the CMIP6 ensemble under scenarios SSP1 2.6, SSP2 4.5, and SSP5 8.5. These scenarios represent different greenhouse gas concentration pathways and provide a range of plausible futures. The global simulations were dynamically downscaled in the EURO CORDEX

framework to a resolution of about twelve kilometres. The same variables as in ERA5 Land were extracted from the ensemble so that historical and projected conditions can be analysed consistently. To correct systematic biases in model outputs and to adapt temporal resolution to the needs of PV and crop models, bias correction and downscaling techniques such as quantile mapping were applied. This resulted in coherent hourly datasets that cover both the past and the future.

The variables included in the analysis cover the main drivers for energy yield and crop performance. For the solar resource we consider GHI, DNI, and DHI, together with derived indices such as the clearness index, the diffuse fraction, the PAR fraction and the daily light integral. For meteorology we use air temperature, relative humidity, wind speed, precipitation and surface albedo. For crop related climate drivers we compute growing degree days, chill accumulation, frost occurrence, tropical days, vapour pressure deficit, and drought indices such as the Standardised Precipitation Evapotranspiration Index. For the greenhouse demonstrator we additionally include glazing transmittance spectra, ventilation control rules, and indoor to outdoor differences in temperature and humidity.

Analytical methods

The evaluation of climate impacts on PV and crop yield required a combination of statistical trend analysis, bias correction of climate projections, and integration of the corrected datasets into PV and crop modelling chains. Each of these methodological steps is described below.

Trend and variability analysis

To characterise the historical evolution of the solar resource and climate drivers we analysed annual time series of global horizontal irradiance (GHI), diffuse horizontal irradiance (DHI), and the fraction of photosynthetically active radiation (PAR) over the period 1991 to 2020. The datasets used were ERA5 Land and satellite derived solar products, which provided consistent inputs across the three demonstrator sites. Long term tendencies were estimated using the Theil–Sen robust regression method, which is less sensitive to outliers than ordinary least squares. Statistical confidence intervals at the 95 per cent level were computed using bootstrap resampling. This approach allows us to separate systematic long term signals from interannual variability, which is often large in mid latitude climates. Results are illustrated in Figure 4.1, which shows the evolution of GHI, DHI, and PAR fraction with corresponding trend lines and confidence bands.

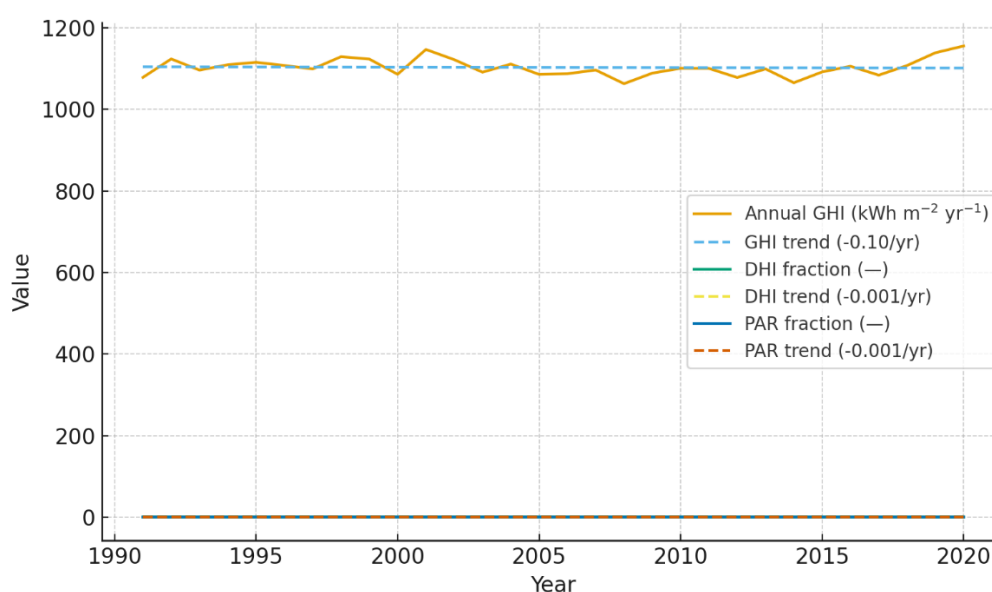


Figure 4.1 Time series of annual GHI, DHI, and PAR fraction (1991–2020), with Theil–Sen trend lines and 95% confidence bands.

Bias correction and downscaling

Climate model outputs often exhibit systematic deviations from reanalysis or observational datasets. To ensure consistency, we applied a bias correction procedure based on quantile mapping. This method aligns the cumulative distribution of modelled variables with that of the reference dataset, in this case ERA5 Land for the historical period. The correction was performed separately for each variable of interest, with special care taken to maintain physical consistency across correlated variables such as GHI, DNI, and DHI.

Daily distributions were adjusted using quantile mapping, and diurnal cycles were reconstructed so that solar geometry was respected and the partitioning between diffuse and direct components was preserved. To avoid inconsistencies between variables, a copula based adjustment was applied, which ensures that the statistical dependencies among variables such as irradiance, temperature, and humidity remain realistic. An example of the effect of quantile mapping is shown in Figure 4.2, which illustrates the alignment of modelled and observed distributions of daily GHI and near surface air temperature for the Belgian site.

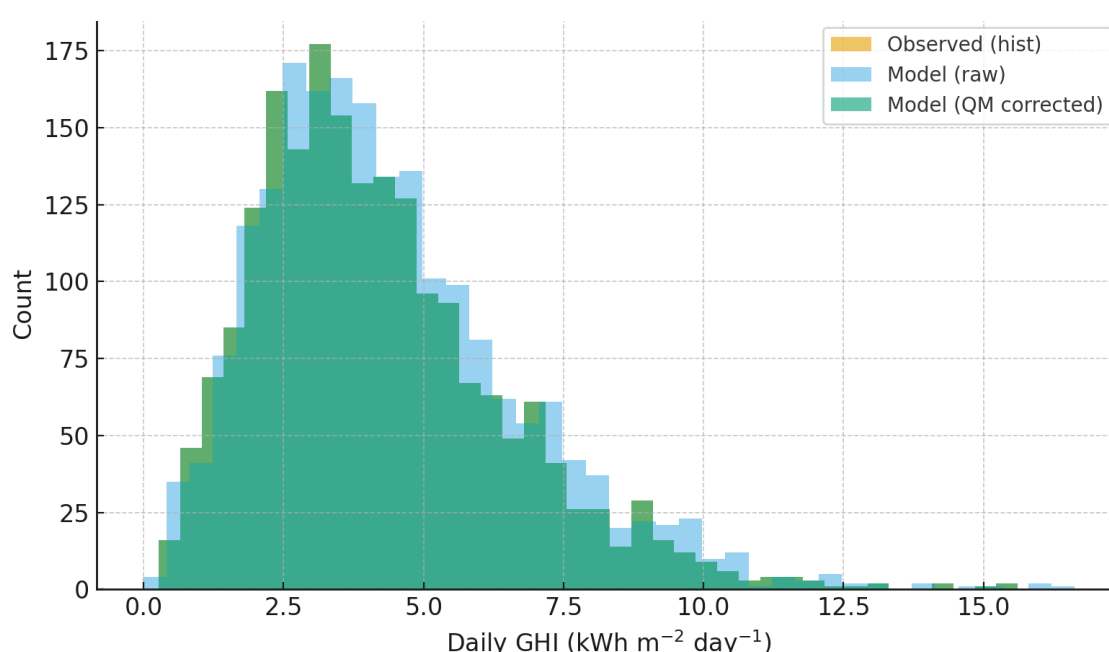


Figure 4.2 Example of quantile-mapping bias correction for daily GHI and T_a , Belgium site.

Integration into PV and crop models

The corrected and downscaled datasets were used as inputs to PV and crop simulation models. For PV, the variables include irradiance components, air temperature, wind speed, and surface albedo, which together allow estimation of plane of array irradiance, module temperature, performance ratio, and specific yield. For crops, the variables include photosynthetically active radiation, daily light integral, growing degree days, chill accumulation, frost occurrence, vapour pressure deficit, and drought indices, which drive crop growth models and stress indicators. For the greenhouse demonstrator, indoor climate variables were derived from outdoor forcing conditions by applying glazing transmittance spectra and simplified ventilation control rules.

Through this integrated approach we are able to quantify the impacts of both interannual variability and long term climate evolution on PV and crops, and to provide results that are directly relevant to the design and evaluation of agrivoltaic systems.

PV modelling

- Plane-of-array irradiance G_{POA} computed with shading and bifacial view factors.
- Module temperature T_m :

$$T_m = T_a + \frac{G_{POA}}{U_0 + U_1 WS} \Delta T_{ref} \quad (4.1)$$

- PV DC efficiency vs temperature:

$$\eta_{DC}(T_m) = \eta_{STC} [1 + \gamma (T_m - 25^\circ\text{C})] \quad (4.2)$$

- KPIs:

$$Y = \frac{E_{AC}}{P_{STC}} \quad (4.3)$$

$$PR = \frac{E_{AC}}{G_{POA,ref} P_{STC}} \quad (4.4)$$

$$CF = \frac{E_{AC}}{P_{STC} \times 8760} \quad (4.5)$$

Crop response

Light-use efficiency (LUE) approach:

$$APAR(t) = f_{PAR}(t) PAR(t) \quad (4.6)$$

$$GPP(t) = \varepsilon_{max} f_T(t) f_{VPD}(t) f_W(t) APAR(t) \quad (4.7)$$

- For orchards (Italy): chill portions, forcing, frost risk after budbreak.
- For greenhouse (Netherlands): PAR and spectrum adjusted by glazing transmission; indoor T/RH from control rules.

4.1.3 Results

Historical variability (1991–2020)

The period 1991 to 2020 provides a useful baseline for assessing interannual variability in both solar resource and climate drivers at the three SYMBIOSYST demonstrator sites. Variability was quantified using coefficients of variation for irradiance and derived metrics, together with analysis of agronomic indicators relevant to each site. Figure 4.3 illustrates the main results obtained for the three locations.

In Belgium, where the demonstrator consists of an open field agri PV system, interannual variability of global horizontal irradiance is relatively modest with coefficients of variation on the order of three to five per cent. The diffuse fraction exhibits a larger spread because of the strong dependence on cloudiness and atmospheric conditions. For PV systems this translates into year to year yield fluctuations of approximately plus or minus three to four per cent. For crops the higher diffuse fraction observed during cloudy years can be beneficial because it increases the proportion of radiation within the photosynthetically active range and improves light penetration within the canopy.

In Northern Italy, where the demonstrator is located in an apple orchard, the baseline level of GHI is higher than in Belgium or the Netherlands, reflecting the more favourable solar resource of the Alpine foothill region. The conversion efficiency of solar energy into photosynthetically active radiation is slightly lower under the clearer skies of this region because the proportion of diffuse light is reduced. Historical records indicate that chill accumulation has so far been sufficient for apple production, although the frequency of late frost events is already a recurrent risk. Within the orchard, daily light integral in shaded alleys has proven more stable than expected, which is explained by the contribution of diffuse light that compensates for direct shading effects.

In the Netherlands, the demonstrator is a greenhouse with semi-transparent PV glazing. In this case the outdoor variability of the solar resource is filtered by the transmission properties of the glazing. As a result, the mean daily light integral measured inside the greenhouse is lower than the outdoor value but its spatial distribution is more uniform. Interannual variability of indoor DLI is also reduced compared to the variability observed in outdoor GHI, which demonstrates the buffering effect of greenhouse structures.

Taken together, these results highlight the importance of considering both absolute levels and variability of irradiance when assessing the implications for PV yield and crop productivity. While PV yield variability is moderate and largely driven by fluctuations in GHI, crop responses are more sensitive to the balance between direct and diffuse light and to the stability of daily light integral, especially in orchard and greenhouse systems.

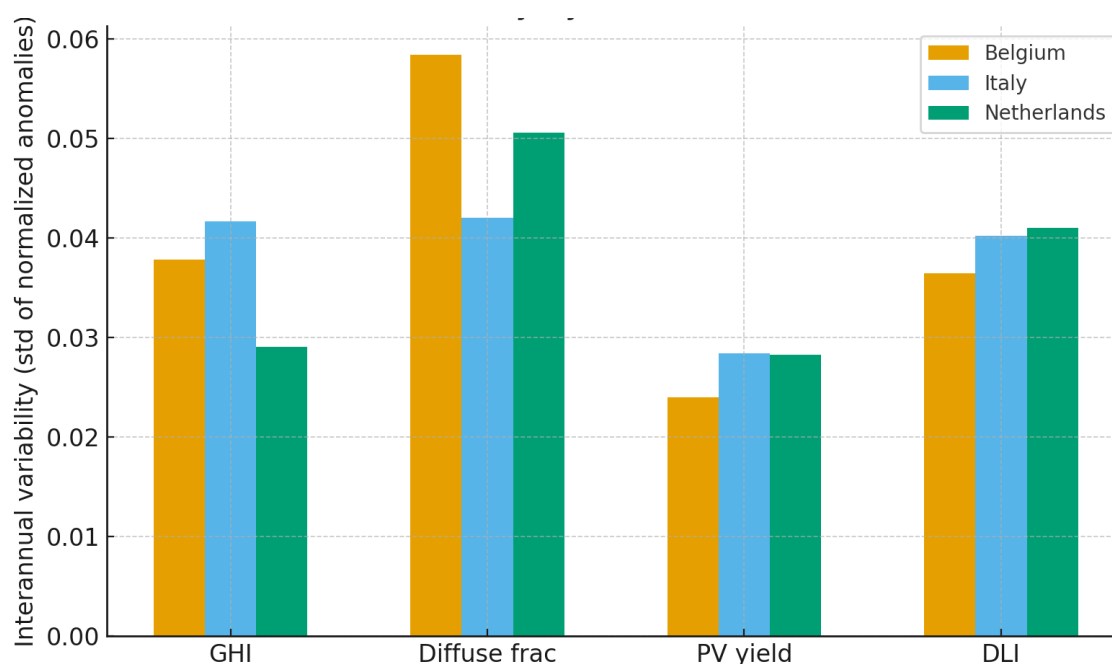


Figure 4.3 Interannual bars (1991–2020): GHI, diffuse fraction, PV specific yield, DLI (open field vs greenhouse).

Mid-century projections (2031–2060)

The period 2031 to 2060 corresponds to the mid-century horizon that is particularly relevant for the expected lifetime of agrivoltaic demonstrators. Climate model projections under scenarios SSP1 2.6, SSP2 4.5 and SSP5 8.5 were analysed for the three SYMBIOSYST sites in Belgium, Italy and the Netherlands. The focus was on changes in solar irradiance, diffuse fraction, air temperature and derived agronomic indicators.

In Belgium, global horizontal irradiance is projected to remain broadly stable with changes in the range of minus one to plus two per cent depending on the scenario. The diffuse fraction shows a slight increase which leads to a more uniform distribution of photosynthetically active radiation under agrivoltaic structures. Temperature is projected to rise by about 1.5 to 2.0 °C compared to the 1991 to 2020 baseline. For PV systems this increase reduces the performance ratio by approximately 0.5 per cent due to higher module operating temperatures. For crops the main impacts are the growing frequency of tropical days and the intensification of vapour pressure deficit stress. These factors can accelerate water loss and reduce crop resilience, although shading provided by the agrivoltaic structures partly mitigates the stress.

In Northern Italy, warming is projected in the range of 1.5 to 2.5 °C by mid-century. This rise reduces the number of winter chill portions, which are critical for apple orchards. As a result, budbreak is expected to occur earlier in the season, thereby increasing the probability of frost events after budbreak. Such frost events can cause significant damage to developing flowers and fruits and therefore represent a major risk to orchard productivity. For PV systems in this region, higher temperatures slightly reduce yield through thermal effects on module efficiency, although the overall resource remains favourable. The increase in diffuse radiation can help improve light distribution within the orchard canopy and therefore partly counteract the shading effects of the structures.

In the Netherlands, outdoor global horizontal irradiance is projected to remain nearly stable. The diffuse fraction shows an upward trend, but its positive effect is moderated by the presence of greenhouse glazing, which reduces total transmission. The increase in outdoor temperature directly affects indoor conditions, as the baseline temperature inside the greenhouse rises unless cooling and ventilation systems are adapted. Crops grown in this environment are less sensitive to interannual variability of irradiance but are more

vulnerable to indoor thermal drift. The combination of higher outdoor temperatures and limited ventilation capacity could create challenging conditions for greenhouse management.

Overall, mid-century projections suggest that PV yields will remain relatively stable with only modest losses due to temperature effects, while crops are likely to face increasing risks. These include greater heat and water stress in Belgium, loss of winter chill and frost risk in Italy, and thermal management challenges in Dutch greenhouses. The findings underline the potential of agrivoltaic structures to mitigate crop stress by providing shading and improving light distribution, while maintaining stable PV energy generation.

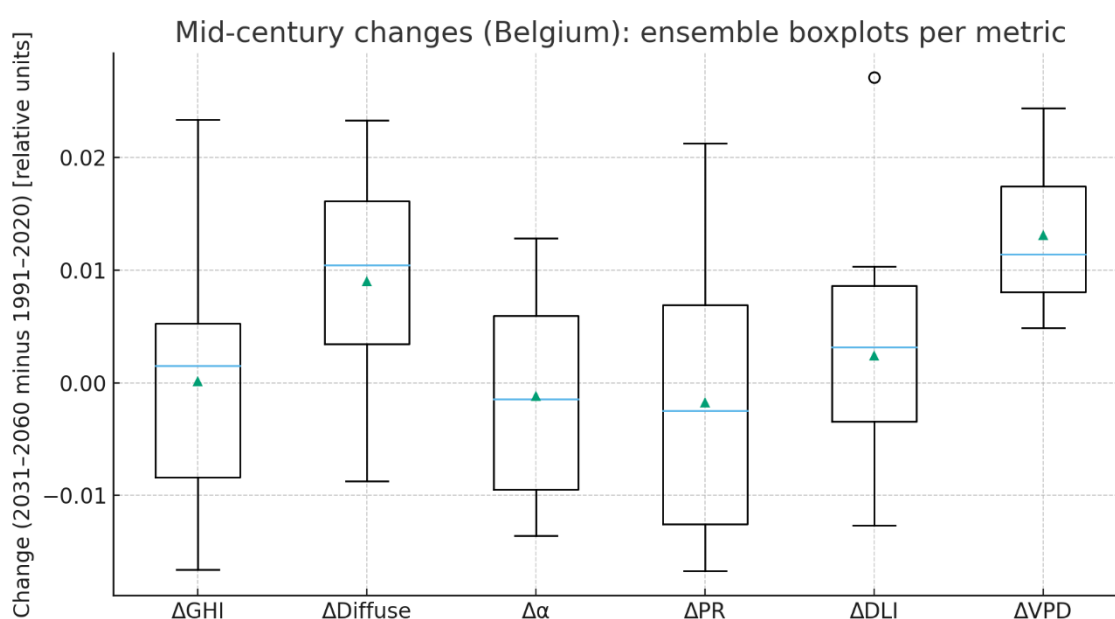


Figure 4.4 Delta maps and boxplots (2031–2060 vs 1991–2020): GHI, diffuse fraction, α , PV PR, DLI, and VPD metrics.

Late-century projections (2061–2090)

The period 2071 to 2100 represents the late-century horizon, which corresponds to the expected lifetime of second- and third-generation agrivoltaic deployments. Projections from the CMIP6 ensemble under scenarios SSP1 2.6, SSP2 4.5 and SSP5 8.5 were analysed for the three demonstrator sites to evaluate potential long-term risks and opportunities.

In Belgium, global horizontal irradiance remains essentially stable with projected changes generally within a range of minus two to plus three per cent. The diffuse fraction continues to increase, leading to more uniform spatial distribution of photosynthetically active radiation under agrivoltaic structures. Air temperature is projected to rise by 2.5 to 4.5 °C depending on the emission scenario. For PV systems, this additional warming reduces the performance ratio by about one per cent compared to the historical baseline, which remains a modest effect on yield. For crops, however, the increase in tropical days and higher vapour pressure deficit greatly intensify water stress and heat stress. The agrivoltaic shading effect is expected to play a critical role in buffering these stresses, highlighting the potential adaptation value of such systems in Belgian open-field agriculture.

In Northern Italy, warming is more pronounced with projections indicating increases of 3.0 to 5.0 °C by late century. This substantially reduces the number of winter chill portions, which are essential for apple orchards. The decrease may render traditional cultivars increasingly unsuitable unless adaptation strategies such as cultivar change or artificial rest-breaking techniques are adopted. Earlier budbreak will occur more frequently, coinciding with persistent frost risk in spring, which amplifies the vulnerability of fruit production. For PV systems, yield reductions due to higher module temperatures remain limited, while the increase in diffuse

radiation enhances light penetration within the orchard canopy. The net balance for agriculture, however, is expected to be negative unless adaptation measures are implemented.

In the Netherlands, late-century projections indicate that outdoor global horizontal irradiance remains stable but that outdoor air temperature increases by 3.0 to 4.5 °C depending on the scenario. In greenhouse systems, this translates into higher indoor temperatures unless major changes in ventilation or cooling strategies are adopted. The result is a risk of persistent overheating that could compromise crop productivity and require additional energy input for climate control. Variability of indoor daily light integral remains buffered by glazing, but the main challenge shifts towards thermal regulation rather than light availability. For PV integrated into greenhouses, the increase in diffuse fraction partly offsets transmission losses, but the dominant concern for crop performance is maintaining indoor thermal balance under warming conditions.

Across the three demonstrators, the late-century horizon reveals a strong contrast between the relative stability of PV energy yield and the growing risks faced by agriculture. PV remains a resilient energy source, with only small reductions due to higher operating temperatures, while agricultural systems face multiple stressors including loss of winter chill, increased frost exposure, and higher frequency of heat and water stress. Agrivoltaics therefore gain strategic importance not only as a dual land-use technology but also as an adaptation measure to sustain agricultural productivity under severe climate change scenarios.

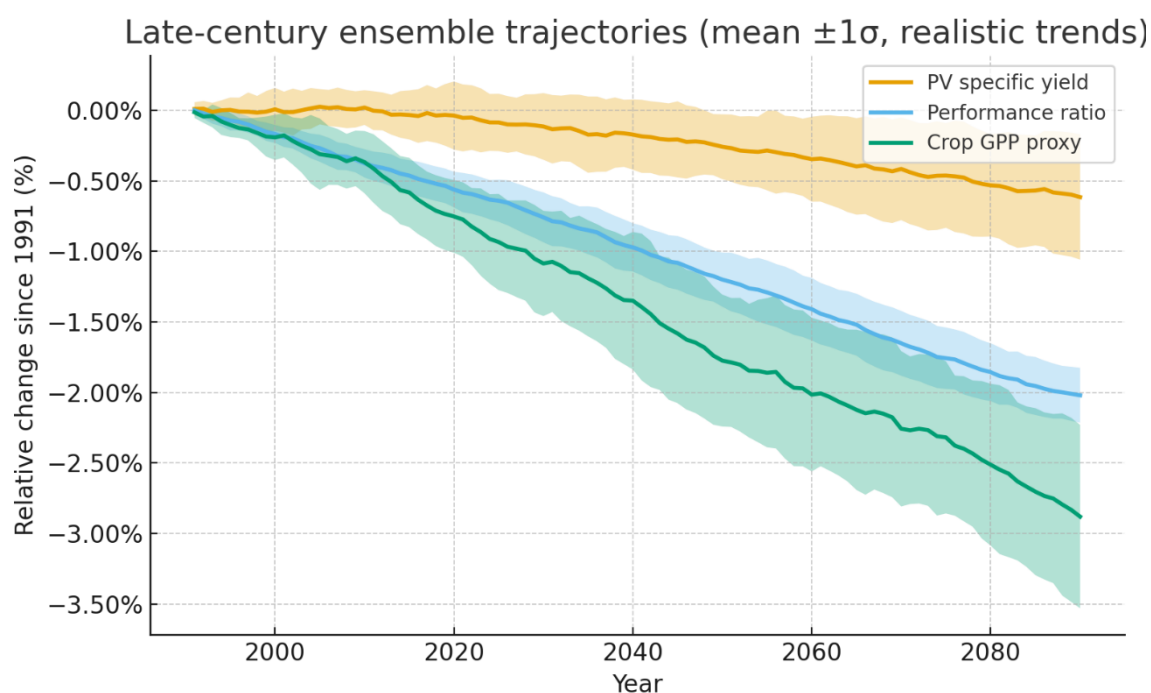


Figure 4.5 Ensemble “spaghetti” for site KPIs to 2090: PV specific yield, PR; crop seasonal GPP proxy; chill portions and frost risk.

4.1.4 Conclusion and outlook

The joint assessment of long-term solar resource and climate evolution shows that PV systems in the three SYMBIOSYST demonstrators will remain a robust energy source, with only marginal impacts from projected climate change. While interannual variability in solar irradiance persists, long-term trends in GHI are close to neutral, and the associated yield reductions due to temperature-induced efficiency losses remain modest. From the PV perspective, the risks are therefore relatively low and manageable through continued improvements in system design and thermal management.

For agriculture, the consequences are more pronounced. In Belgium, warming increases the frequency of heat and water stress events, which may affect crop yields unless irrigation and crop management practices are adapted. In Northern Italy, fruit production faces a double challenge: the progressive reduction of winter chill

threatens cultivar suitability, while earlier budbreak combined with persistent frost risk increases vulnerability. In the Netherlands, greenhouse systems are more insulated from outdoor variability, but rising outdoor temperatures will put pressure on ventilation and cooling, with higher energy demands for climate control. Across all sites, the increase in diffuse light fraction is likely to improve light distribution under canopies, which can partially compensate for heat and water stresses by enhancing photosynthetic efficiency. This is where agri-PV systems provide a tangible advantage. The combination of shading and light redistribution can reduce canopy stress, while bifacial and semi-transparent technologies ensure that PV yield is not compromised. The resilience of PV generation complements the adaptive potential of agriculture, positioning agri-PV as a climate adaptation strategy as well as a clean energy source.

The comparative analysis of Belgium, Italy, and the Netherlands highlights the site-specific role of agri-PV: in Belgium, as a buffer against heat and water stress; in Italy, as part of a broader adaptation to changing phenological requirements; and in the Netherlands, as a way to balance greenhouse climate control and energy self-sufficiency. These findings reinforce the interest of integrating agri-PV into long-term agricultural and energy planning, both for sustaining crop productivity and for achieving renewable energy targets under climate uncertainty.

4.2 Bifacial modelling – digital twin (3E)

SynaptiQ is 3E's digital platform for planning, operating, and optimizing renewable energy projects. Using physics based digital twin and domain expertise, it streamlines asset deployment, provides accurate simulations, enables targeted operational management, and delivers advanced solar analytics.

In the SYMBIOSYST Agri-PV project, SynaptiQ supports both crop production and clean energy generation by addressing challenges such as crop shading, albedo-driven bifacial yield changes, degradation detection, soiling loss quantification, and optimizing tracker and cleaning schedules in line with agricultural activities—aiming to harmonize crop growth and energy output.

Configurator: Employs a uniform object model to define business plans and plant setups—modules, inverters, layout, shading—mapped to the digital twin for KPI integration, smart alarms, and data enrichment, ensuring consistent, repeatable configurations.

Simulation Model: Merges real-time data with satellite and meteorological inputs to forecast yield and spot deviations early. Like PVsyst, it considers key design and equipment parameters but improves accuracy through live data, enabling faster loss recovery.

Asset Operations: Generates near real-time KPIs shown in custom dashboards to quickly detect underperformance, with a smart alarm system and task management for rapid corrective or preventive action, boosting efficiency and uptime.

Advanced Loss Analysis: A solar plant generates thousands of time series data, making root cause analysis labor-intensive. Solar Analytics automates this, delivering granular, accurate loss breakdowns (Figure 4.6).

Key capabilities include:

- Production loss breakdown into 21 root cause categories (e.g., bifacial, shading, soiling, equipment faults).
- Recommendation engine suggesting corrective actions with cost–benefit analysis.
- Configuration check to ensure digital twin accuracy and flag data quality issues.
- Sensor checks comparing on-site sensors to high-quality satellite data to identify calibration errors or faults.

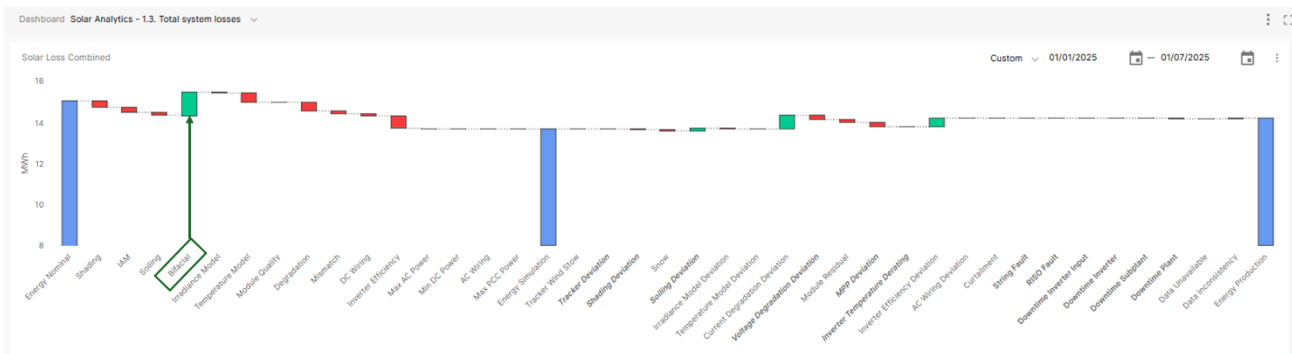


Figure 4.6 Loss waterfall with expected and unexpected losses for an example plant with Bifacial gain (highlighted)

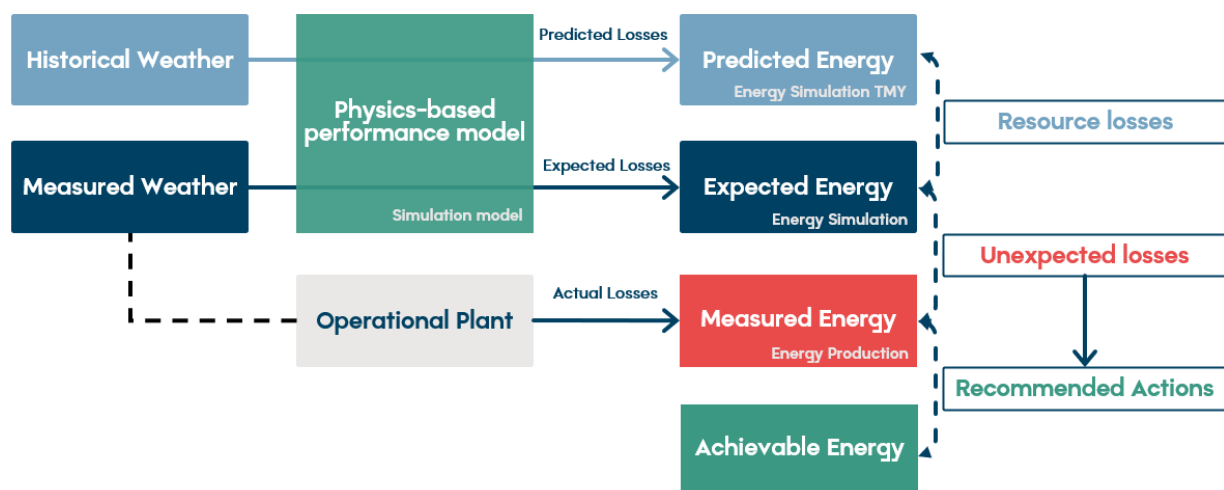


Figure 4.7: Performance analysis flow in SynaptiQ Solar Analytics

The performance analysis flow in SynaptiQ is modelled as seen in Figure 4.7.

- Calculate expected system losses, which are losses from the simulation model (also see left side of loss waterfall in Figure 4.6).
- Calculate unexpected system losses, namely, Simulation Loss Deviations: deviations between actual and simulated losses and Additional Losses: loss components that come on top of the expected losses, like due to downtime or snow (also see right side of loss waterfall in Figure 4.6).
- Recommend actions to avoid future losses. These recommendations are issued whenever a recoverable loss exceeds a preset threshold. A recoverable loss is a potentially avoidable loss.

Developments in Bifacial PV Calculation within SynaptiQ

A significant recent advancement in SynaptiQ is the enhanced capability to model bifacial PV systems, which utilize both the front and rear surfaces of PV modules to capture solar irradiance, thus increasing energy yield compared to conventional mono-facial modules. The accurate calculation of bifacial gain is central to realizing the true benefits of bifacial PV technology, and SynaptiQ's development in this domain reflects state-of-the-art modelling techniques incorporating multiple critical parameters. This bifacial gain model is based on the "infinite sheds" irradiance model, like the implementation in the open source pvlib library.

Infinite Sheds Model:

The "infinite sheds" model is a simplified 2D model for simulating bifacial PV systems, particularly useful for large, regularly arranged, row-based installations. This model assumes infinitely long sheds, neglecting edge

effects, and allows for a simplified calculation of mutual shading between rows - a valid assumption for large-scale PV plants and Agri-PV fields.

What are "Infinite Sheds"?

- **Simplified 2D Calculation:** The "infinite sheds" model uses a 2D calculation to determine shading factors, making it computationally efficient for large systems.
- **No Edge Effects:** It assumes that the sheds are long enough that edge effects (like those at the beginning and end of a row) can be ignored.
- **Regular Row Arrangement:** It's designed for systems where PV modules are arranged in regularly spaced rows.

Key physical effects modelled (Figure 4.8):

- **Direct sunlight and diffuse irradiance** from both the sky and the ground.
- **View factors:** The model calculates the fraction of visible sky and ground from the ground and module surface, which controls how much diffuse and reflected light is captured.
- **Shading:** It accounts for shading effects between rows, structural shading (from mounting hardware), and the transmission of light through and around the modules.
- **Albedo:** Rear-side gain depends strongly on ground reflectivity (albedo), which can vary with soil, vegetation, or crop cover.

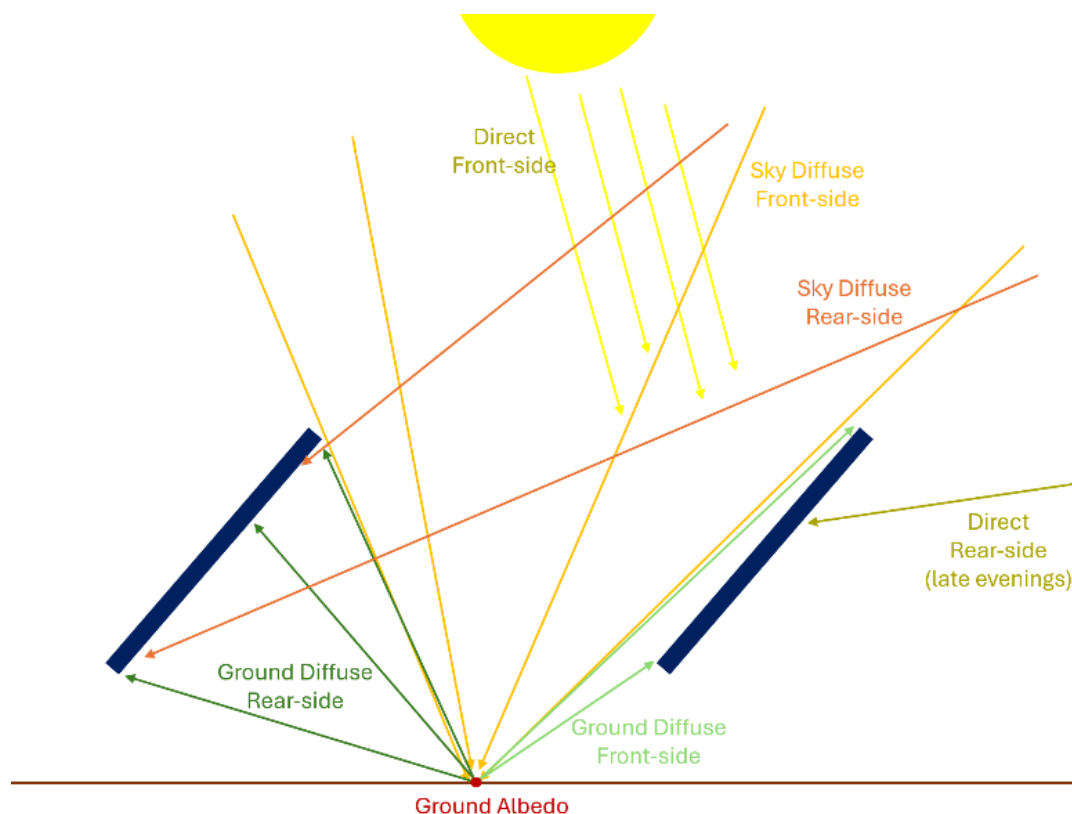


Figure 4.8: Direct and diffuse components on front and rear surface of modules

Why use it (or not)?

- **Computational Efficiency:** For large bifacial systems, the 2D calculation is much faster than a full 3D simulation.
- **Simplified Approach:** It provides good approximation for many large-scale bifacial PV projects.

However, the "infinite sheds" model is not suitable for systems with complex row arrangements or where edge effects are significant. The current bifacial model is based on this simplified 2D approach and may not capture all the nuances of a complex 3D scene.

To further improve the accuracy of bifacial modelling for Agri-PV systems, an adaptive calculation process is included that uses both real-time performance data and field measurements. Instead of solely relying on fixed site parameters, the simulation adapts its input parameters when sensors detect changes in key factors such as ground albedo or plant growth. For example, seasonal vegetation cycles or soiling events can alter ground reflectivity and shading conditions, prompting updates to the estimated bifacial gain. These changes are clearly captured by the on-site albedo measurements.

Since direct albedo measurements are rare in commercial Agri-PV plants, seasonal albedo trends from well-instrumented reference sites are used as valuable baseline data. By correlating these trends with the types of crops grown beneath the PV arrays, it becomes possible to estimate typical albedo variations for other installations with similar crop and climate conditions. This approach fills data gaps where on-site albedo sensing is unavailable, supporting more realistic modelling of bifacial gain across diverse Agri-PV systems. Incorporating such crop-specific, seasonal albedo proxies into self-learning framework enhances the adaptive capability of the digital twin and improves accuracy of yield predictions across diverse Agri-PV installations. The goal is to enhance the robustness of bifacial yield estimates under varying conditions by continuously evaluating historic and current operational data. Although fully automated data-driven algorithms are still in development, the platform is designed to integrate these capabilities in the future by accepting albedo as a timeseries input, enabling ongoing refinement of simulation performance as more operational data becomes available.

Integration within SynaptiQ

Bifacial gain—the increase in energy output from the additional rear-side irradiance—is calculated in SynaptiQ based on several defining factors (see below). In SynaptiQ's Configurator module, users can input these parameters under the "Bifacial Only" section for the module group, enabling customization tailored to specific system designs and local conditions. The platform uses these inputs to perform detailed view factor calculations and irradiance modelling, combining physical optics and environmental data to yield high-precision forecasts of bifacial energy contributions.

- **Bifaciality Factor:** This parameter represents the relative efficiency of the rear side of the PV module compared to the front side and is derived from the module's datasheet. It quantifies how effectively the rear side converts irradiance into useful electrical energy.
- **Ground Albedo:** The fraction of solar irradiance reflected by the ground surface significantly influences the rear side illumination. Surfaces with higher albedo, such as light-colored soils or reflective ground covers, increase the irradiance reaching the module rear, enhancing bifacial gain.
- **Rear Shading Factor:** Shading on the rear side caused by supporting structures or mounting components reduces the effective irradiance contributing to energy generation. Accurate modelling of this shading is crucial to realistic gain estimates.
- **Rear Mismatch Loss:** Variability in irradiance distribution across the rear face of the module leads to electrical mismatch losses among cells, adversely affecting the overall output. SynaptiQ factors these losses into its bifacial gain calculations to reflect practical operating conditions.
- **Module Transparency:** This denotes the fraction of solar irradiance that penetrates through or between modules to the ground, affecting the amount of light available for reflection and subsequent irradiance on the module rear.
- **Height Above Ground:** The vertical installation height of PV modules determines the view factor to the ground and influences the amount of reflected irradiance captured by the rear surface. A higher elevation generally improves the rear irradiance component.

SynaptiQ's bifacial modelling framework captures both the theoretical maximum bifacial gain—assuming ideal conditions—and the diminished gain after accounting for real-world losses, including rear shading and mismatch effects (see Figure 4.9 and Figure 4.10). This holistic approach aligns with other industry-leading tools but is enhanced through the integration of real-time monitoring data and advanced digital twin capabilities. Notably, the platform's physics-based digital twin allows continuous refinement of bifacial gain estimates based on actual operational performance and environmental interactions.

The bifacial calculation enhancements are particularly salient for Agri-PV applications, where the spatial and temporal interplay between crop growth and PV module performance is complex. For instance, the crop canopy can introduce dynamic shading on the module rear, and soil reflectance can vary seasonally or with ground cover type. SynaptiQ's advanced bifacial models facilitate maximized combined agricultural and energy yields by analyzing variables such as module tilt, height, row spacing, varying albedo and tracking algorithms. This enables stakeholders to balance energy production with crop health and productivity.

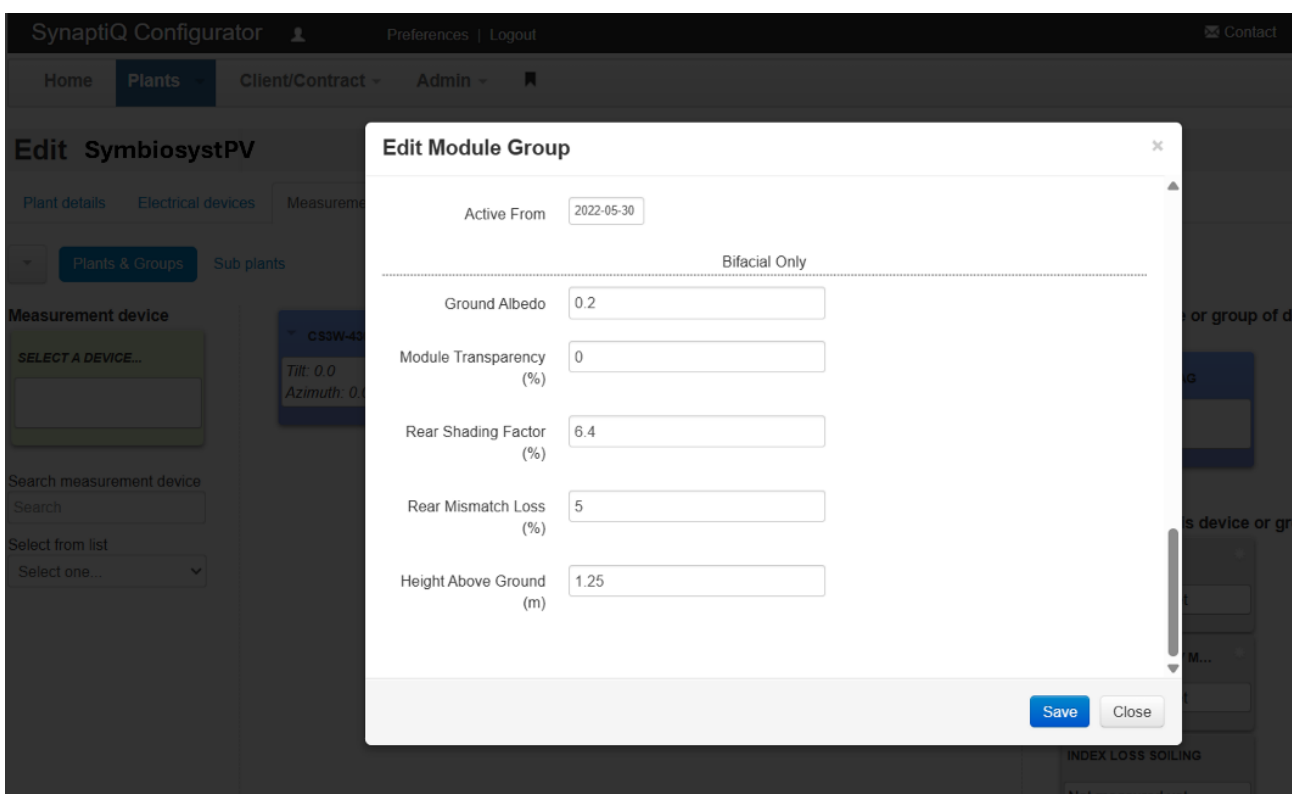


Figure 4.9: Bifacial parameters in SynaptiQ Configurator

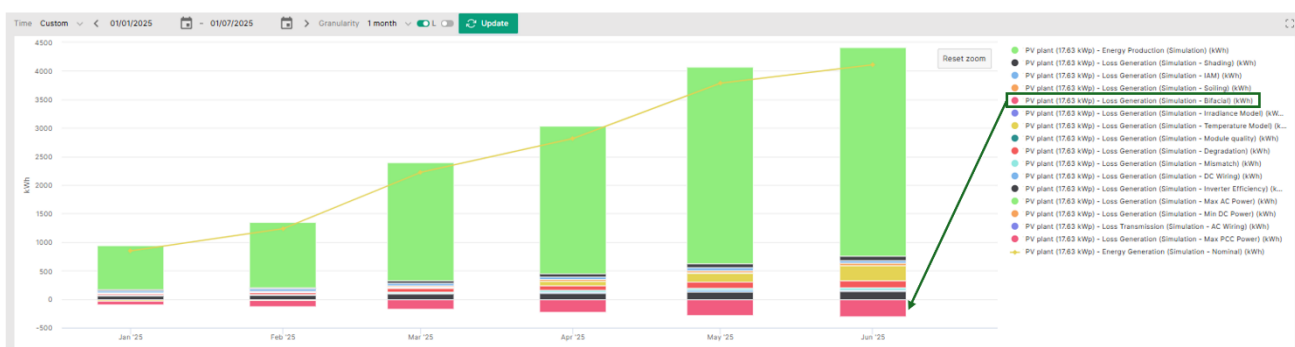


Figure 4.10: Monthly expected losses for an example plant with Bifacial gain (highlighted)

In practice, the bifacial gain calculation in SynaptiQ supports:

- True-to-life yield nowcasting: Reflects actual site conditions (crop cover, soil type, seasonal changes).
- Assessment of environmental impacts: Including seasonal changes in vegetation and soil conditions influencing albedo and shading.
- Predictive maintenance and performance diagnostics: Early detection of deviations in bifacial gain indicative of soiling, damage, or module degradation, guiding maintenance decisions

Together, these capabilities make SynaptiQ an essential tool for the evolving Agri-PV sector, bridging the gap between renewable energy technology and sustainable agriculture. By integrating detailed bifacial simulation into a unified digital platform, SynaptiQ enables stakeholders to precisely predict, monitor, and improve the performance of bifacial solar assets in diverse agricultural settings, ultimately supporting sustainable food and energy production goals.

5 Configuration of demonstration site (KUL)

5.1 Validation site

5.1.1 Orchard

The validation site in Bierbeek, Belgium, is located 50°49'05.6"N 4°46'34.5"E. The site is a demonstration orchard where an agri-photovoltaic (APV) system was installed on existing 'Conference' pear trees. The rows are placed along the field slope direction, shifted with a deviation of 60° to the West from the N–S axis (Figure 5.1). The APV structure consisted of a 12° roof angle supported by wooden posts and steel-wire ground anchors[37]. Trees were 2.4m tall on average, planted at 1m within-row and 3.3m inter-row spacing. Rows were oriented along a SW-NE axis, shifted 60 ° west from the N-S direction (Figure 5.1).

The PV modules had a diffuse back sheet and standard c-Si wafers (15.6 × 15.6 cm). Three double rows of 21m length were placed above the pear tree rows. Control plots (full sun, FS) were covered with a translucent HDPE hail net ("crystal") from bud break to post-harvest, resulting in ~9% PAR reduction (April-September)[38]. In the APV plot, the hail net was removed. The APV system produced a ground coverage ratio of 25.45% and an average annual PAR reduction of 24%[38].

Meteorological reference data from the local weather station (50°49'07.0"N 4°46'41.3"E) was used to calibrate the light interception model.



Figure 5.1 APV demo site at Bierbeek, Belgium (left); Orientation of the site (right)

5.1.2 Microclimate Zones

Vertical light interception within the canopy was expected to affect both temperature and relative humidity. To capture the gradients, microclimate zones were defined based on tree height and row orientation. The canopy was divided into three height levels (low, middle, top) and two sides (north-west and south-east), resulting in five zones: LW, LE, MW, ME, and T (Figure 5.2). Trees were trained in the shape of "slender spindle". The numbers of zones may be further adjusted depending on the variance in light distribution within leaf clusters in the simulation if necessary.

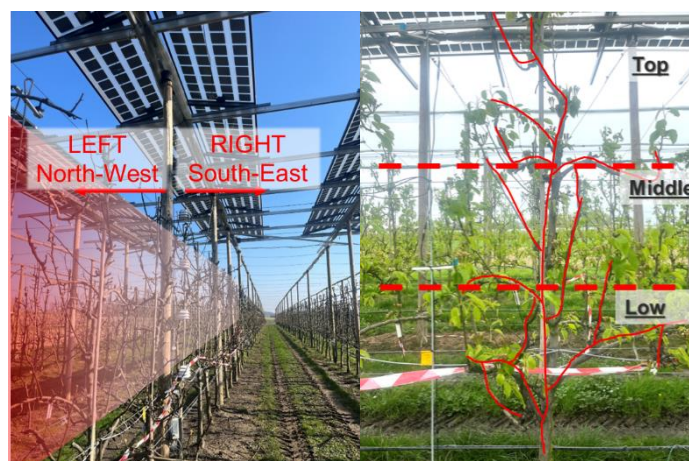


Figure 5.2 Division of microclimate zone on the tree level. a) NW side of row (left), SE side (right); b) vertical division into low, middle, and top.

5.2 Measurements

To minimize edge effects, two sample trees were selected from the centre of the APV plot for phenotypic trait assessment and fruit harvest (red dot in Figure 5.1 , right). In the FS plot, two sample trees were selected in the same row as the APV samples to ensure parallel comparison and consistent sensor placement. All climate and plant-attached sensors were installed along this central row. All sensors were factory-calibrated and periodically checked during the season. Data were screened for inconsistencies and missing values prior to model use.

5.2.1 Environmental conditions

Measurements of photosynthetically active radiation (PAR), air temperature, and relative humidity were carried out during the growing seasons of 2024 and 2025.

- PAR
 - 2024: Apogee SQ500 sensors placed between two trees per row to capture light at canopy boundaries (Figure 5.3). Sensors were installed at 60, 150, and 250 cm heights in both APV and FS plots. Data was logged at 10-min intervals (instant values).
 - 2025: Apogee SQ110 sensors placed inside the canopy along the trunk to capture vertical penetration of light (Figure 5.4). Data were recorded as 10-min averages, min and max.



Figure 5.3 PAR sensor placement in 2024 [38]. Yellow dots indicate sensor heights ($h = 60, 150$ and 250 cm).

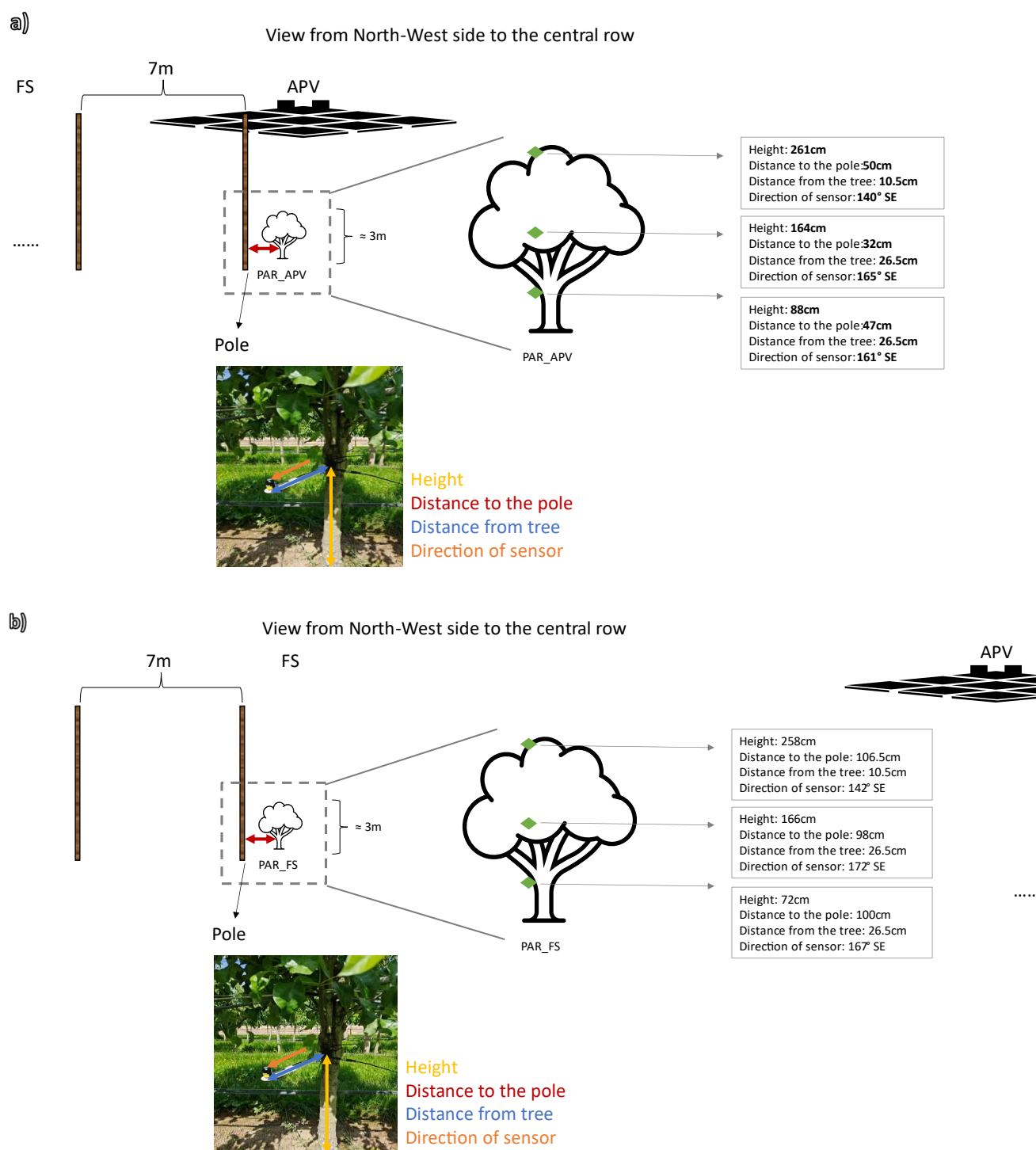


Figure 5.4 PAR sensor placement and orientation in 2025. a) APV plot. b) FS plot.

- Temperature and Humidity
 - 2024: Testo 174H dataloggers placed in custom 3D-printed radiation shields at ~150 and 250 cm heights (Figure 5.5).
 - 2025: SENSIORION SHT4x loggers installed on one tree per plot at ~65, 135, and 250 cm (APV) and ~80, 150, and 250 cm (FS) (Figure 5.6).



Figure 5.5 Temperature and humidity sensor placement in 2024. a) APV plot. b) FS plot. Height for the sensors: 1- approx. 250cm. 2&3 - approx. 150cm.



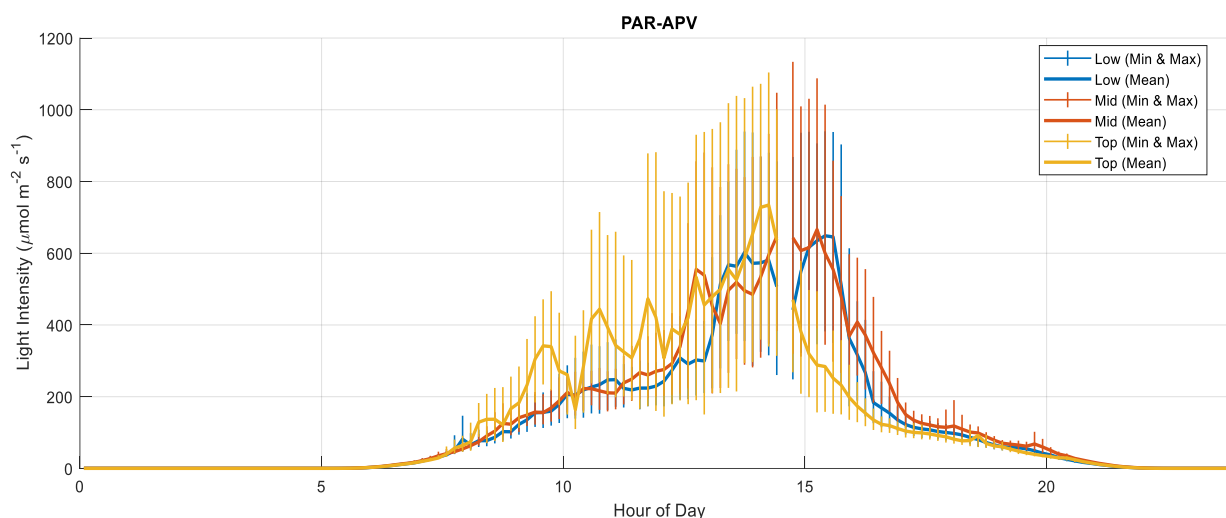
Figure 5.6 Temperature and humidity sensor placement in 2025. a) APV plot. Sensor height: 1 - approx. 265cm; 2 - approx. 155cm; 3 - approx. 100cm. b) FS plot. Sensor height: 1 - approx. 265cm; 2 - approx. 175cm; 3 - approx. 110cm.

5.2.2 Environmental measurements

PAR

The photosynthetically active radiation (PAR) for both treatments (APV and FS) was summarized over a 24-hour cycle between 16 May and 10 September 2025 (Figure 5.7). The figure presents the daily minimum, maximum and mean values. The difference in light intensity across the height in the canopy was greater in controlled condition (FS) compared to APV, indicating a more heterogeneous light environment without the solar panels. An elevated baseline was recorded by the low-position sensor in FS during nighttime, caused by a weak ground connection. This issue was subsequently corrected, but the affected data were retained for reference and will be treated during post-processing.

a)



b)

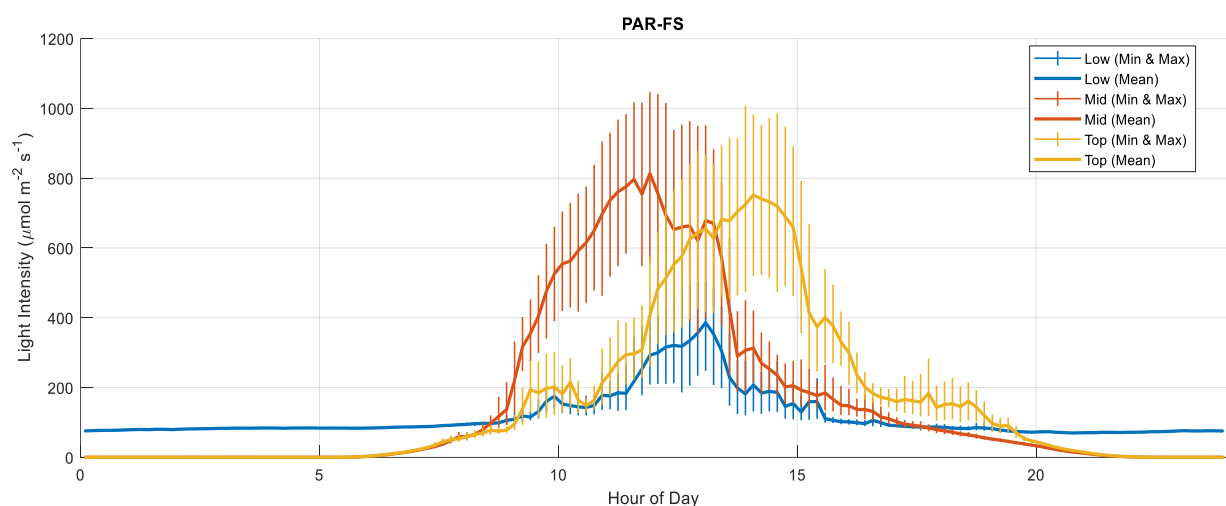


Figure 5.7 PAR radiation mean, minimum, maximum value of a day from 16 May to 10 September, 2025. a) APV; b) FS.

Temperature and Relative humidity

Temperature and relative humidity followed consistent daily patterns over the measuring period, while more difference across height levels in the tree canopy was observed under APV (Figure 5.8). The top-position sensor in APV field recorded a milder midday conditions, with lower peak temperatures and less drops in humidity. Meanwhile, the top sensor in FS measured more extreme condition at noon, with higher temperature and lower humidities than sensors at middle and low-canopy levels. These opposite vertical trends between treatments supports the importance of using canopy-level microclimate inputs to drive leaf functions in the model.

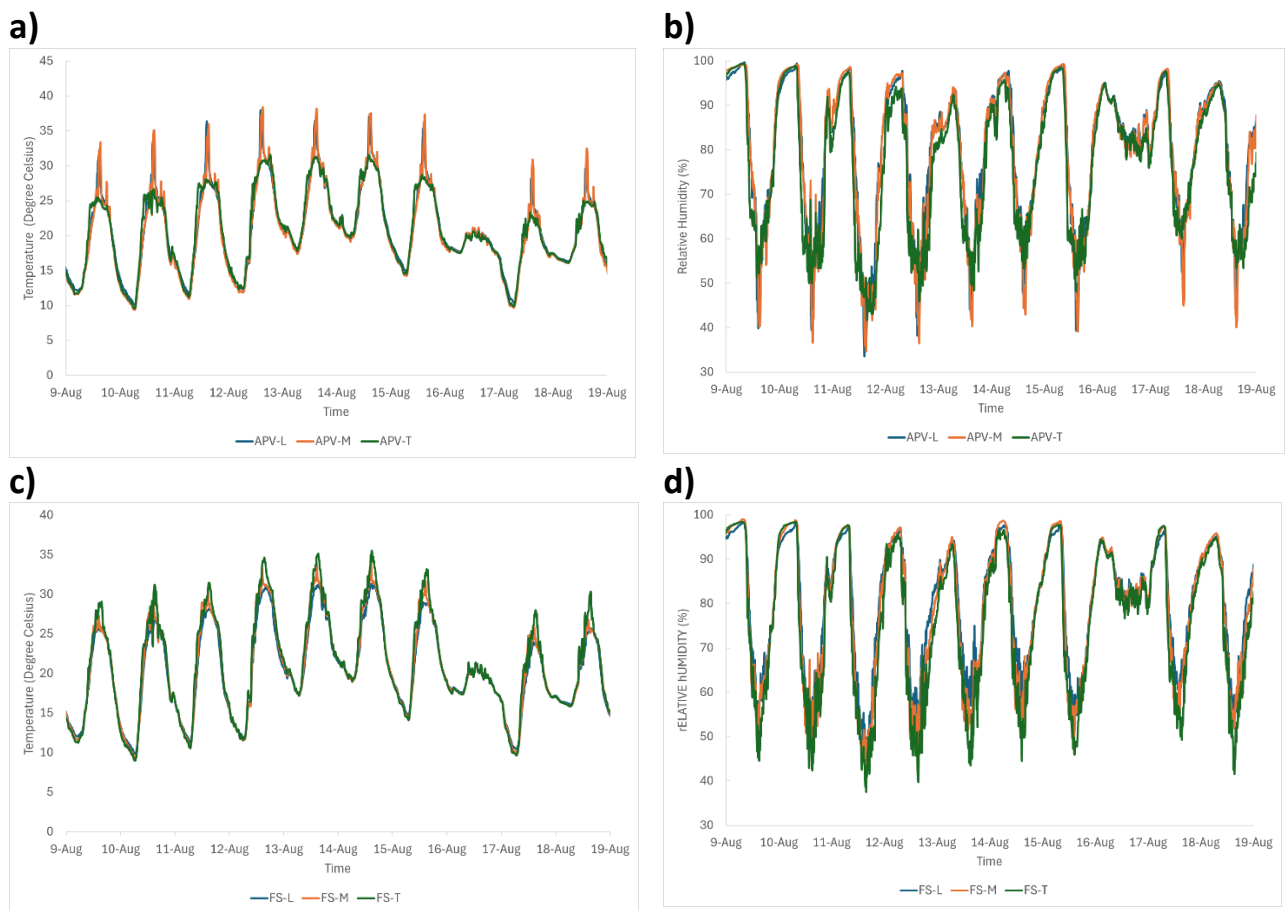


Figure 5.8 Measured temperature and relative humidity from 9 August to 19 August 2025. a) APV Temperature (°C); b) APV Relative humidity (%); c) FS Temperature (°C); d) FS Relative humidity (%).

6 Conclusions and perspectives

This deliverable has presented the methodologies and first results obtained for the assessment of the light environment in agrivoltaic demonstrators, with particular emphasis on photosynthetically active radiation (PAR), the long-term evolution of solar resource and climate, and the development of novel monitoring approaches. The work carried out has demonstrated that both empirical and physics-based approaches can be combined to estimate PAR under open-field and greenhouse agrivoltaic conditions. Empirical conversion factors between broadband irradiance and PAR provide a practical baseline for large-scale assessments, while spectrally resolved methods are required to account for the selective transmittance and reflection of semi-transparent modules, greenhouse glazing, and bifacial devices. The integration of these approaches into 3D light engines enables the spatial mapping of PAR and daily light integral (DLI) at canopy level, providing a solid foundation for crop growth simulations.

The long-term analysis of climate projections has indicated that global horizontal irradiance in Belgium, Italy, and the Netherlands is expected to remain relatively stable over the coming decades, with interannual variability being more critical than systematic trends. Temperature increases will slightly reduce PV performance ratios, but overall PV yield impacts remain modest. For agriculture, however, projected changes in temperature, precipitation, and vapor pressure deficit are more significant. Reduced winter chill in Northern Italy threatens the suitability of certain fruit cultivars, while increased frequency of heat and water stress events in Belgium and higher cooling requirements in Dutch greenhouses will require adaptive management. Complementary contributions have been initiated to develop new monitoring and validation capabilities. ABOVE has begun investigating advanced albedo assessment techniques combining aerial thermography and pyranometer measurements, as well as the use of multi-spectral imaging for crop health assessment in collaboration with UPC. These activities will provide valuable datasets for model validation and will support the integration of biophysical crop indicators with energy system simulations.

Overall, the findings reinforce the dual perspective of agrivoltaics: PV generation remains robust under climate change, while agricultural systems face increasing risks. The combination of shading, spectral selectivity, and improved monitoring offers a pathway to enhance crop resilience while maintaining energy production. The methods developed here will serve as a basis for the next phases of SYMBIOSYST, where model validation, demonstrator monitoring, and the integration of agronomic and energy results will be further advanced.

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