Modelling light-sharing in agrivoltaics: the open-source Python Agrivoltaic Simulation Environment (PASE 1.0)

Article *in* Agroforestry Systems · October 2024

DOI: 10.1007/s10457-024-01090-8

Highlights

Modelling light-sharing in agrivoltaics: the open-source Python Agrivoltaic Simulation Environment (PASE 1.0)

Roxane Bruhwyler, Nicolas De Cock, Pascal Brunet, Jonathan Leloux, Pierre Souquet, Etienne Perez, Etienne Drahi, Sebastian Dittmann, Frédéric Lebeau

- PASE assesses agrivoltaics at various space and time scales with process-based models
- The proposed VTK 3D computer graphics agrivoltaics light-sharing model is validated
- PASE paves the way to optimise agrivoltaics real-time operations as a virtual entity
- PASE demonstrates partnership open-source business model to improve knowledge sharing

Modelling light-sharing in agrivoltaics: the open-source Python Agrivoltaic Simulation Environment (PASE 1.0)

Roxane Bruhwyler[a], Nicolas De Cock[b], Pascal Brunet[c], Jonathan Leloux[d], Pierre Souquet[e], Etienne Perez[f], Etienne Drahi[g], Sebastian Dittmann[i,h], Frédéric Lebeau[a]

[a] *DEAL, BioDynE, Liege University, Gembloux, 5030, Belgium*
[b] *DC-Core, Les Bons Villers, 6210, Belgium*
[c] *Naldeo Technologies Industries, Tarnos, 40220, France*
[d] *LuciSun, Villers-la-Ville, 1495, Belgium*
[e] *TotalEnergies OneTech, PERL, Lacq, 64170, France*
[f] *Ombrea, Aix-en-Provence, 13290, France*
[g] *TotalEnergies OneTech, Courbevoie, 92400, France*
[h] *Fraunhofer-Center for Silicon Photovoltaics CSP, Halle, 06120, Germany*
[i] *Hochschule Anhalt University of Applied Sciences, Köthen, 06366, Germany*

Abstract

Driven by the urge to expand renewable energy generation and mitigate the intensifying extreme climatic events effects on crops, development of agrivoltaics is currently accelerating. However, harmonious deployment requires to assess both photovoltaic and crop yields to ensure simultaneous compliance with energetic and agricultural objectives of stakeholders within evolving local legal contexts. Based on the community's priority modelling needs, this paper presents the Python Agrivoltaic Simulation Environment (PASE), an MIT-licensed framework developed in partnership to assess the land productivity of agrivoltaic systems. The various expected benefits of this development are outlined, along with the open-source business model established with partners and the subsequent developments stemming from it. Examples illustrate how PASE effectively fulfils two primary requirements encountered by agrivoltaics stakeholders: predict irradiation on relevant surfaces and estimate agricultural and energy yields. In a dedicated experiment, PASE light model assumptions resulted in 1% error in the daily irradiation received by a sensor under two contrasted types of sky conditions. PASE's ability to predict photovoltaic and crop yields and land equivalent ratio over several years is demonstrated for wheat on the BIODIV-SOLAR pilot. Ultimately, a sen-

Email address: `f.lebeau@ulg.ac.be` (Frédéric Lebeau)

sitivity analysis of inter-row spacing demonstrates its usefulness to optimise systems according to different criteria.

Keywords: agrivoltaics, modelling, efficiency, crop model, ray tracing

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

University of Liege research is supported by a FRNS FRIA grant 40015573. The research for the Anhalt University of Applied Sciences is supported by the German Federal Ministry of Education and Research under the project "Biodiversity in solar parks - Innovative concepts and construction of demonstrators for a better compatibility of photovoltaic systems, nature conservation and agriculture (BIODIV-SOLAR)", 13FH133KX0. Work of Jonathan Leloux was partially funded by the European Commission through the Horizon 2020 project SERENDI-PV, 953016, which belongs to the Research and Innovation Programme. The authors would also like to thank Hugo Sanchez and Carlos Meza for acquiring meteorological data at the Wallhausen agrivoltaic demonstrator site, as well as Bernd Günther for managing the demonstrator's crops and Maxence Delannoy for the agronomic surveys carried out.

Acronyms

AV Agrivoltaics.

BHI Beam Horizontal Irradiance.

CAD Computer-Aided Design.

DEAL Digital Energy and Agriculture Lab.

DHI Diffuse Horizontal Irradiance.

FRIA Fund for Research Training in Industry and Agriculture.

GCR Ground Coverage Ratio.

GHI Global Horizontal Irradiance.

HDKR Hay Davies Klucher and Reindl.

LER Land Equivalent Ratio.

PASE Python Agrivoltaic Simulation Environment.

POA Plane Of Array.

PV Photovoltaic.

1. Introduction

1.1. Context

Agrivoltaics (AV) is one of the potential solutions to increase the pace of renewable electricity generation development. Indeed, Chatzipanagi et al. (2023) pointed out that 50% of Photovoltaic (PV) power is expected by SolarPower Europe to be installed on agricultural land, to target the 2050 European carbon-neutrality goal. In regions where surface availability for ground-mounted PV plants is scarce, AV can preserve local agriculture while boosting the PV power capacity. In regions were cultivation is climate constrained, AV can protect crops from damages and yield losses. Initially described as a dual land use system combining crop and PV productions by Goetzberger and Zastrow (1982), it was then characterised by the Land Equivalent Ratio (LER), index of the system's productivity compared with disjointed productions on the same area (Dupraz et al., 2011). Several researches have highlighted that AV often achieves higher land-use efficiency than the decoupled production, with LER greater than 1 (Dupraz et al., 2011; Valle et al., 2017; Amaducci et al., 2018). However, this metric may hide excessive crop yield reduction to maintain profitable agriculture as the comparatively high value of generated electricity favor projects prioritizing energy. Therefore, the preservation of agricultural function requires to fix additional regulatory requirements. Leader countries in AV adoption, such as France, Germany, Italy, Japan or South Korea have therefore refined the initial AV definition in their labels and policies to preserve their agricultural land productivity. The common objective is to maintain the agricultural activity of the plot through some of the following requirements: maximum relative loss in crop yield, maximum Ground Coverage Ratio (GCR), limitation in cultivated area loss, minimum vertical clearance (Dupraz, 2023) and mounting structures reversibility. Additionally, AV may have to be designed to benefit the crops directly by improving the microclimate, i.e., reducing detrimental extreme climatic events such as sunburns, hail, and spring frost or improving resource use efficiency, i.e., by reducing the seasonal hydric deficit.

To comply with these requirements, simulation tools are needed to assess the impact of PV geometry and trackers control strategy on crops both in development and operation stages. Bankable energy projects also require to assess precisely PV energy production (Björn et al., 2016). There is therefore a need for modelling tools to assess both crop and PV productivity of AV systems. These models need to be generic considering the existing and projected diversity of AV facilities in terms of soil and climate conditions, agricultural activities, PV technologies and PV plant geometries. Finally, these should be easily available for the different stakeholders, from researchers, farmer representatives, energy project developers, engineering consultancy companies up to the public administrations.

1.2. Review of past agrivoltaics land productivity modelling and identification of gaps

From the outset of AV research, *in silico* analyses have been undertaken to evaluate the ability of AV to obtain increased LER, using models to assess PV, agronomical productions and resources use efficiency (Dupraz et al., 2011; Dinesh and Pearce, 2016). Several modelling tools have been developed but only a few are well-balanced between the three key components that should be modelled: light sharing, crop development and PV productivity. In fact, in existing agrivoltaics framework, at least one of these components is often modelled empirically (Riaz et al., 2021; Trommsdorff et al., 2021; Kim et al., 2023) which fails to reach the genericity of process-based models. Many process-based crop models exist, differing in their aim and the way processes are conceptualised and extended work is done to validate and compare them (Franke et al., 2020; Rötter et al., 2012). At least, the following have already been used in agrivoltaic modelling tools: STICS (Dupraz et al., 2011;

Dinesh and Pearce, 2016), Optirrig (Elamri et al., 2018), GECROS (Amaducci et al., 2018), WOFOST (Willockx et al., 2020), EPIC (Campana et al., 2021), APSIM-Oryza (Ahmed et al., 2022), SIMPLE (Mengi et al., 2023) and APEX-Paddy (Kim et al., 2023). These crop models have different levels of integration and complexity just like the light models used to compute irradiance reaching the crop. The first levels encountered are geometrical projection algorithms (Amaducci et al., 2018; Campana et al., 2021; Grubbs et al., 2024) and geometrical algorithm based on angular sectors (Riaz et al., 2021; Ahmed et al., 2022). Other frameworks use ray casting, a single interception algorithm (Dupraz et al., 2011; Elamri et al., 2018), or ray tracing, a multi interceptions algorithm explicitly accounting for optical properties (Trommsdorff et al., 2021; Katsikogiannis et al., 2022; Mengi et al., 2023). In modelling tools developed, many open source components are mobilised like pvlib (Grubbs et al., 2024), Radiance (Trommsdorff et al., 2021; Katsikogiannis et al., 2022), GECROS (Amaducci et al., 2018) and WOFOST (Willockx et al., 2020). However, to the best of our knowledge, complete permissive open-source simulation tools are not available yet.

1.3. Outline of the present approach

Based on scientific literature regarding AV community's simulation needs, it turns out that much work is devoted to developing AV simulation tools worldwide. Various research questions drive the model development priorities. However, it appears that much of the development addresses similar needs and that the light-sharing issue is always central. We postulated that the sector could benefit from a well-balanced permissive open-source simulation tool to boost efficient and innovative development. We also recognize the need to reflect the diversity of research questions at both spatial and temporal scales with different levels of integration and complexity. It was stated that a framework approach could meet this challenge and ease future developments, especially regarding the diversity of crop models. This paper therefore presents the first stabilized version of the Python Agrivoltaic Simulation Environment (PASE) resulting from these statements. PASE 1.0 is available on ORBi under an MIT licence (Bruhwyler and Lebeau, 2023) and on the Liege University public GitLab (`https://gitlab.uliege.be/pase/pase_1.0`). This paper aims to present:

- PASE development methodology with the open-source business model and the collaborative work initiated

- PASE 1.0 modular architecture and modules description
- Material and methods of the case studies presenting PASE 1.0 functionalities
- Results of these case studies
- Planned future developments

2. PASE development methodology

2.1. Open-source development model

Buitenhuis and Pearce (2012) have described how open-source design can accelerate innovation in PV industry and achieve the energetic transition faster. They highlighted the advantages of open-source software development: increased speed and lower costs of development of reliable and innovative computer code, faster adoption by the community and contributions from users who become developers. Open-source software are successful because of the gift culture creating reciprocity in the contributions, the hacker community debugging and sharing ideas, and the code's modularity (Buitenhuis and Pearce, 2012). The later enables to divide the complex system into small and easily manageable parts, to support reuse, to parallelise work which can be carried out by different teams, and to integer new modules or switch from one module to another without difficulty (Turner, 2018). The four components constituting a free and open-source software solution are the license, the development process, the software itself and its community, which reflects why people get involved (AlMarzouq et al., 2005). Its main characteristics are the free redistribution, including source code and the authorization of modifications and derivative works (Perens and Sroka, 2007). We therefore postulate that the tool's transparency through access to the source code is an advantage, mainly because it makes it auditable. It allows also replication of the studies and multiple validations of the different sub-modules on the scale of the user community. It appears an efficient way to increase general knowledge about modelling the land productivity of AV systems. Along the open-source licenses used for software distribution, some of them, such as the BSB and MIT, allow to reuse all or parts of the software without restriction, whether it is integrated into free or proprietary software, which secures unconstrained valorisation for the contributing parties.

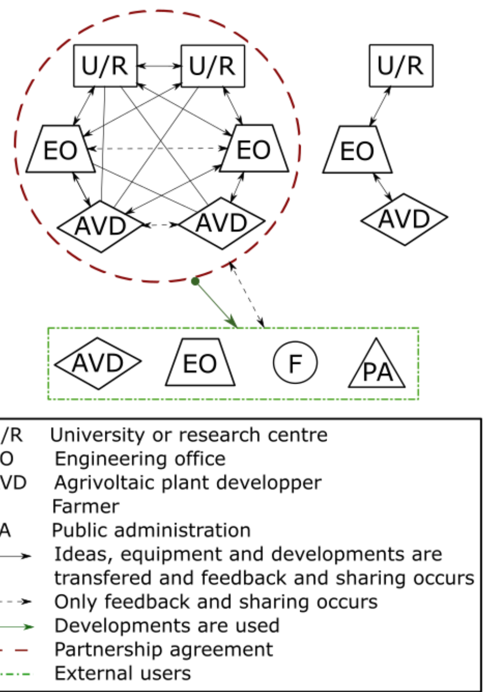

Fig. 1 Partnership model for the development of an open-source modelling tool to evaluate agrivoltaics land productivity

2.2. Open-source business model

Of the open-source business models described in (Buitenhuis and Pearce, 2012), the PASE's development method closely adopts the partnership model, and will strengthen this approach in future developments. Early developments of PASE were mainly driven and supported by the Fund for Research Training in Industry and Agriculture (FRIA) through a PhD funding at the Digital Energy and Agriculture Lab (DEAL) from the University of Liege, Belgium. This applied research program encourages social and economic relevance to the public and private sector. Therefore, exchanges of experience and collaborations were quickly established with companies, third-party developers and other research centres and universities to share work and knowledge around the modelling of AV systems. The partnership initially described and illustrated for PV industry has been slightly adapted for AV simulation purposes and is presented in Figure 1.

The main idea is creating a partnership agreement represented by the red dashed circle, where members share knowledge acquired, test equipment and facilities and work together on challenges like the development and validation of a modelling tool to evaluate AV facilities land productivity. For a partnership model to work and be virtuous for everyone, companies need to retain competitive advantages. The partnership agreement must therefore be drawn up specifically, targeting the needs of each partner (Buitenhuis and Pearce, 2012). In this business model, external users, such as other research institutes, AV developers, engineering offices, farmers representatives or public administrations benefit from the versions of the framework that are publicly released after validation by the partnership.

2.3. Collaborative road-map to PASE 1.0

The FRIA funding launched the project to develop an open-source tool for assessing the PV and agricultural yields of AV systems. On that basis, the choices and sequence of developments were prioritized according to respective needs of the industrial and scientific partners. Figure 2 details the evolution of PASE. There was a clear objective to create a modular framework where building blocks can be easily add depending on individual needs.

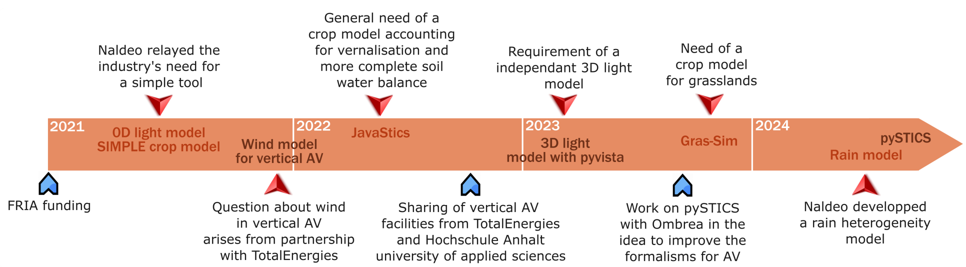

Fig. 2 Processus of evolution of PASE

The first objective targeted in collaboration with Naldeo company was to conceptualize and validate the framework architecture while reusing available modelling blocks. In a lean approach, a basic yet complete framework was designed to deliver initial estimates of yields based on simplifying assumptions. A zero-order model based on an irradiance reduction rate linked to GCR was established. This was coupled to SIMPLE (Zhao et al., 2019), a straightforward crop model. For temperate regions, this model has the weakness of lacking the vernalisation process. The very simplistic formalism for the soil water balance is another limitation to describe expected AV benefits on water use efficiency. However, the modular architecture and data transfer methods were already established.

Through the work undertaken by the various partners, the general urge for a more complete crop model, that would allow the simulation of winter crops while taking account the vernalisation process, as well as photoperiod sensitive crops, became apparent. As the ability of AV to improve the water status of the crop was also a central research question, there was a need for a crop model that would more explicitly represent root development and processes controlling the soil water balance. STICS (Beaudoin et al., 2023) was therefore integrated into the modelling environment for research via co-simulation using the Javastics executable.

The background presented above, and the choices made by our partners highlight that the trend is to develop one's own light model or to use the Radiance software, which has the disadvantage of presenting high barriers to entry. Bifacial_radiance, a python wrapper of Radiance for bifacial PV simulation is also an option, but it does not straightly allow the user to calculate light on any surface, interception of light by the PV modules being its focus. Inspired by LuSim, the high-resolution light simulation engine for solar energy applications of LuciSun (Robledo et al., 2019), the choice was made to integrate an open-source solution in Python that would allow both scene creation using 3D computer graphics and ray casting: PyVista (PyVista, n.d.). This package is a python wrapper of Visualization Toolkit, VTK (Schroeder et al., 2006), which uses the Embree library (Embree, n.d.) to perform an efficient ray casting.

Inspired by the PCSE development carried out by Wageningen University (de Wit, 2024), a collaborative work was launched in with Ombrea. The objective is to code the STICS modules that are relevant to AV in Python to make it easier to interface with other models and tools, and to have control over the formalisms so that some of them can be adapted to AV modelling. A first version of PySTICS with the main formalisms needed to simulate an annual crop was developed (Perez, n.d.) and will be integrated into PASE architecture in a later release, as soon as a thorough validation of Pystics has confirmed the almost total equivalence of the outputs compared with JavaStics for the same inputs. Given the popularity of permanent grasslands for the installation of AV projects, the Gras-Sim grassland model has similarly been coded in Python and is now available into PASE. It allows the growth dynamics of multi-specific grasslands to be simulated (Kokah et al., 2023).

2.4. PASE 1.0: modular architecture and description of modules

Figure 3 represents the modular organization of PASE 1.0 (first released version) with the main modules and how they interact with each other. Inputs required and models available for each module are presented. Elements in red show future developments, which are described in section 5.

To make simulations with PASE, users have to fill in several configuration files about:

- The geometry and technical data of the PV plant
- The geometry and technical data of the PV modules
- The source for the weather data (PVGIS or user's own)
- The resolution for sun positions in the ray casting algorithm of the light model
- The spatial resolution and position of the mesh for light and crop modelling
- The crop model they want to use and the corresponding inputs

All the input files of PASE are provided in the data serialisation language YAML, chosen for its data-oriented feature and readability. This file type for configuration makes the modelling environment consistent and easier for the users to interact with. These files are designed to help users encode their parameters by providing definitions, information on the typical expected value and range of allowed values. PASE 1.0 is natively connected to the PVGIS weather databases, so users can choose to have weather data automatically retrieved based on the chosen location. Alternatively, users can select their own weather data provided that the recommended .csv file format is adopted. In both cases, data are imported as a dictionary, in which each element is a meteorological year in the form of a Pandas DataFrame. Appendix A shows a class diagram that provides a detailed view of the code architecture and the modules implemented. PASE is not yet available as a graphical interface, so the user has to run the main Python file after completing all the input YAML files. As illustrated in Figure 3, PASE 1.0 already offers several options for modelling some components. The next sub-sections detail the models available.

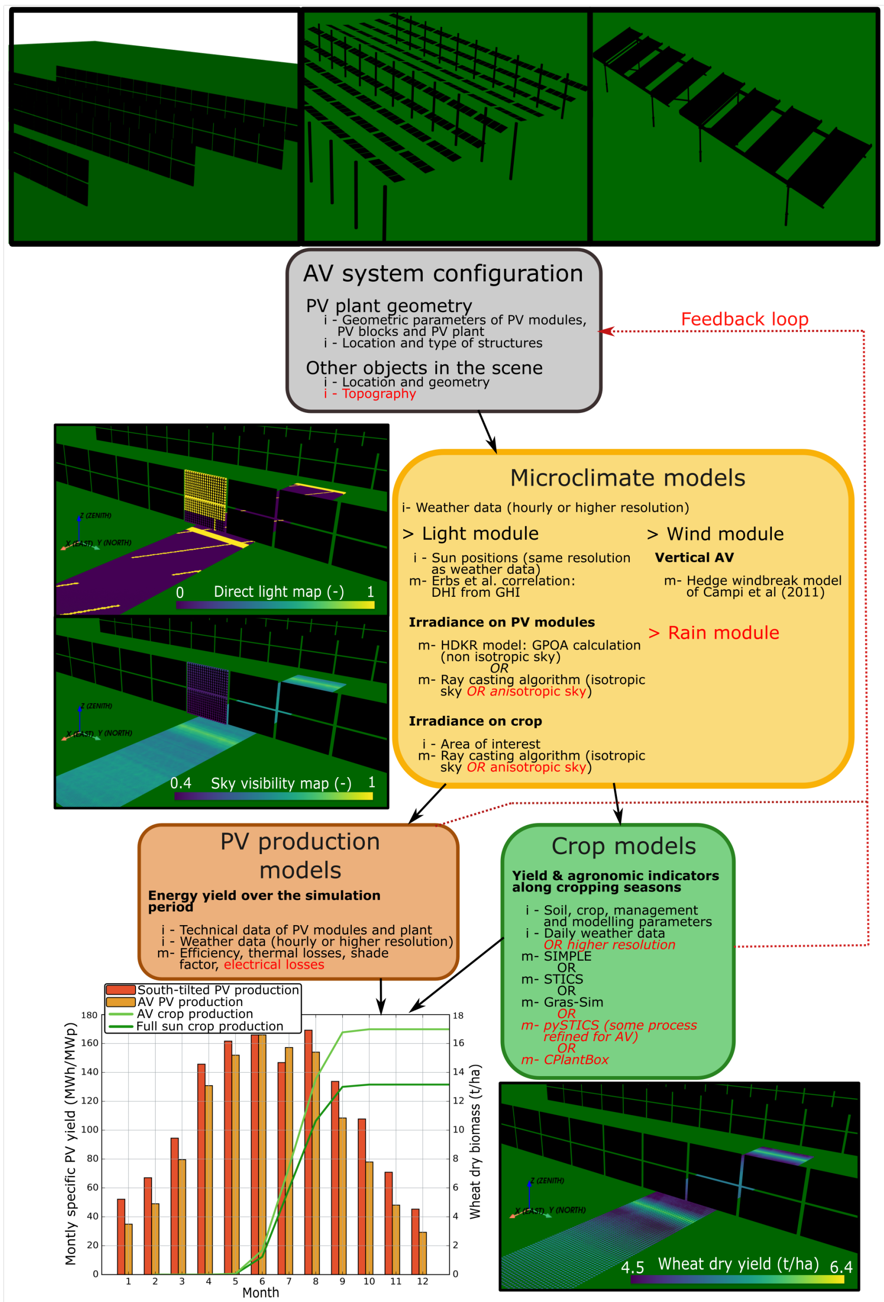

Fig. 3 Organigram of PASE 1.0: main modules, links between modules, (i -) inputs, (m-) models available and future developments in red

2.4.1. Agrivoltaic system configuration module

The PyVista library, VTK's pythonic wrapper, is used to create the 3D scenes, which at this stage mainly comprise the PV installation and the ground. PyVista is used to create 3D geometries using its PolyData paradigm. Creation is based on the definition of vertex coordinates and their assembly to form faces. The PolyData representing a PV module is regularly replicated to form the PV modules blocks and the PV power plant. These PolyData are also rotated to obtain the right tilt and azimuth. PyVista also allows to import 3D geometry in .obj, .ply, .stl and other formats, created elsewhere using Computer-Aided Design (CAD) software. PASE 1.0 allows PV plants to be created with a rotation axis operating with a sun-tracking and a back-tracking algorithm, implemented according to the algorithm proposed by the NREL (Anderson and Mikofski, 2020).

2.4.2. Micro-climate module

The micro-climate module of PASE 1.0 (Figure 3) includes a module for light and a module for wind.

For light, the decomposition model used to break down the Global Horizontal Irradiance (GHI) data into the Beam Horizontal Irradiance (BHI) and the Diffuse Horizontal Irradiance (DHI) is the Erbs correlation (Equation 2.10.1 in Duffie and Beckman (1982)). For light reaching the PV modules, the Plane Of Array (POA) irradiance can be calculated using either the geometric transposition model or the ray casting algorithm implemented. The Hay Davies Klucher and Reindl (HDKR) transposition model (Equation 2.16.7 in Duffie and Beckman (1982)) was chosen among others for its simplicity despite its ability to take into account the 3 components of the diffuse and its conservative and strictly analytical aspects. The second method to compute the POA or crop irradiance performs separate backward ray casting algorithms for direct and diffuse light, which is considered to be isotropic. The first consists of casting rays from all the points of interest in the mesh towards the position of the sun and extracting direct light maps as shown in Figure 3, where 0 means that the ray has been intercepted and vice versa for 1. Ray casting for the diffuse consists of launching rays from all the points of interest towards a set of isotropic light source points distributed homogeneously in the sky hemisphere according to a Fibonacci spiral (Alexa, 2020). This is used to extract a sky visibility map (Figure 3) whose factors correspond to the proportion of non-intercepted rays out of the total number of rays launched from each point of interest. These direct and sky visibility maps are then respectively multiplied by the BHI and DHI to get the irradiance amount on the crop. As the crop models currently available in PASE 1.0 operate on a daily time step, these irradiance data are integrated on a daily basis, but in the future they should be used in crop models with a higher temporal resolution. The use of BHI and DHI has not yet been adapted to non-horizontal surfaces. The ray casting from the PV modules is therefore limited to the information of shadows cast and sky visibility. The light models operate at the time resolution imposed by the weather data and can be used at < 1 min time resolution if a balance is found with the size of the area of interest and the complexity of the scene. There is also an option to reduce the number of sun positions considered for the ray casting algorithm.

For wind, in the case of a vertical AV installation, an empirical model based on a type of windbreak is available in PASE 1.0 and has been detailed in Bruhwyler et al. (2023).

2.4.3. Photovoltaic production module

The losses considered for the transformation of irradiance into PV power are mutual shading losses (Appendix B) and thermal losses. It is the PVsyst cell temperature model (SNL, 2024) that is implemented in PASE 1.0 (with constant heat transfer component = 25 $W/m^2.k$ and convective heat transfer component = 1.2 $W.s/m^3.k$). The power generated by a PV module, P_{pv} (W), is then calculated using Equation 1:

$$P_{pv} = \eta A_{pv}(POAI_{front} + POAI_{rear}\beta)(1 + \frac{\alpha}{100}(T_{pv} - T_{stc})) \quad (1)$$

where β is the bifaciality factor of the PV module, η, its conversion efficiency in STC, A_{pv}, its surface area, α, its temperature coefficient relative to maximum power (negative value) and T_{pv}, its temperature.

2.4.4. Crop module

The users need to opt for one of the crop models available: SIMPLE and Gras-Sim (both implemented in Python) or STICS (co-simulation with JavaStics) whose formalisms and equations are fully described respectively in Zhao et al. (2019); Kokah et al. (2023); Beaudoin et al. (2023). This choice has to be based on the level of precision required and the ability to accurately parameterise the soil, the crop and the technical itinerary. The model SIMPLE will offer more generic results on the effect of light reduction on yield for relatively simple parameterisation, while STICS incorporates more formalisms and complex processes requiring more parameters. Users can also select one model rather than another depending on the crop and variety. As the availability of validated crop models parameters is strongly linked to local habits, the addition of more crop models is planned.

3. Material and methods: case studies presenting PASE 1.0 functionalities

3.1. Case study about light modelling

A field test was carried out on a ground-mounted AV system (Figure 4a) provided by SigueSol, a manufacturer and installer of PV structures, to evaluate the embedded light model in Werbomont, Belgium (latitude: 50.376 and longitude: 5.677). Irradiance data were measured from 10^{th} to 27^{th} August 2023 with one Davis 6450 pyranometer in full sun conditions (purple frame in the Figure 4a), and another one in AV conditions (red frame).

Fig. 4 (a) SigueSol agrivoltaic prototype and experimental set up with full sun condition pyranometer in purple and agrivoltaic pyranometer in red and (b) experimental set up reproduced in PASE

A Campbell CR1000 data logger recorded sensor irradiance measurements at 1 Hz frequency. The PV modules blocks had an azimuth of 25° (south-south-west orientation), a tilt of 20° and four 238 x 130 cm^2 PV modules, spaced 56 cm apart. The AV pyranometer was located under the center of the easternmost PV modules block. The middle of PV modules was 166 cm high and the space between PV modules blocks was 62 cm. Those geometric parameters measured on site were used for the simulations performed with PASE. The 3D model of the PV block with the structure was supplied as a STL file by SigueSol and imported into PASE to reproduce the setup as closely as possible (Figure 4). The virtual sensor was a specific point of interest in the simulation to reproduce the AV pyranometer. PASE 1.0 used the irradiance field data in full sun conditions at a quarter hour time step as an input for light decomposition. The exact solar positions of the day were used for the simulation. Irradiance levels computed were then compared with field data from the AV pyranometer over the entire data availability period.

3.2. Case study about multi-year land productivity modelling

This case study was based on the 60.2 kWp vertical AgriPVplus demonstrator of the Hochschule Anhalt University of Applied Sciences, located at Heide Hof in Wallhausen (Germany, latitude: 51.458, longitude: 11.174). This facility (Figure 5), was developed as part of the BIODIV-SOLAR project.

Fig. 5 Vertical AgriPVplus demonstrator in Wallhausen, Germany: (a) strip cultivated with spring wheat in the AV facility and (b) spring wheat in the reference zone

This multi-year land productivity analysis used the geometric and technical parameters of this AV installation as input parameters in PASE 1.0. They are listed in Tables C.1 and C.2. The crop model chosen for this generic analysis was SIMPLE with the spring wheat variety yecora rojo whose parameters are presented in Zhao et al. (2019). Sowing was set on 30^{th} April and soil parameters used are described in Table C.3. The multi-year analysis was performed with PASE 1.0 using the hourly weather data PVGIS-SARAH from PVGIS (JRC, 2022), available on 12 years, and the rain and vapor pressure daily data from Agri4Cast for that location (JRC, n.d.). The windbreak model was not activated in this study and the HDKR model was used to compute the POA irradiance with a constant ground albedo of 0.25. The land productivity was compared with the respective reference systems: a south-tilted PV system as defined in Trommsdorff et al. (2021) (technical features in Tables C.1 and C.2) and the same crop growing in full-sun conditions.

The LER, introduced in section 1.1, was calculated as follows:

$$LER = \alpha \frac{CROPyield_{AV}}{CROPyield_{Ref}} + \frac{PVyield_{AV}}{PVyield_{Ref}} \quad (2)$$

where CROPyield$_{Ref}$ and PVyield$_{Ref}$ stand for the surface production of the respective reference systems: the full-sun crop and the typical ground-mounted and south-tilted PV system. The α coefficient is used to take account of the cultivable area loss due to the presence of PV structures and the safety margin for the use of machinery. Here, a 50 cm of uncultivated strip was considered on each sides of PV modules rows. Also, this analysis did not take into account edge effects, as if these agrivoltaic and photovoltaic plants were of infinite size.

4. Results and discussion: functionalities of PASE 1.0 through case studies

Priority modelling needs have been identified for the AV community, which PASE 1.0 can help to satisfy. The first is to estimate the sharing of light components reaching PV modules and crop with sufficient accuracy. To create virtuous AV power plants, it is also essential to be able to estimate their efficiency by modelling PV and crop productivity. Last but not least, the observations made often require supporting modelling to help understand observations. The following sections aim to illustrate these applications.

4.1. PASE 1.0 to model irradiance in agrivoltaics

The capacity to compute irradiation reduction at crop level is essential for AV systems sizing, as it determines the expected yield losses under non-stressful conditions. It is also a major asset to conceptualize experimental trials and identify locations of contrasting light levels. This section aims to illustrate PASE capability to accurately model the light on interest points, i.e., the crop and PV modules. As shown in Figure 3, PASE light module offers the flexibility to compute light on any surface. It can be a PV module, a horizontal plane representing the crop canopy layer, the organ of a 3D plant structural model or a virtual sensor, such as in the next case study.

Figure 6 presents the results of light modelling in the Siguesol AV installation. It shows the irradiance reaching the full sun and AV in situ pyranometers, as well as the virtual sensor on the 10th August, a day of clear-sky conditions and on the 19^{th} August, a cloudy day. The figure highlights comparable results with RMSE of respectively 90.1 and 33.1 W/m$^{\mathbf{2}}$ on the 10^{th} and 19^{th} August. Considering daily irradiation, which is the main input of crop models and therefore an important metric, the light model of PASE 1.0 presents relative errors of 2.4% on the 10^{th} of August and 0.5% on the 19^{th} of August. As far as the entire period of measurements is concerned, the model made a relative error of 1.0% on the cumulative irradiation received by the sensor.

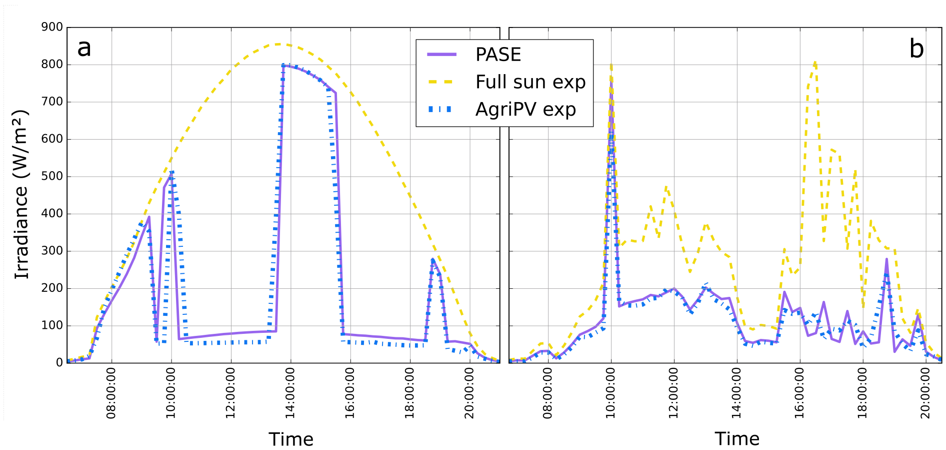

Fig. 6 Comparison between experimental irradiance data in agrivoltaic conditions and the same irradiance data simulated with PASE by reproducing the experimental setup: (a) 10^{th} August 2023, clear sky day and (b) 19^{th} August 2023, cloudy day

The main limitation on accuracy, especially regarding the small irradiance peak shifts, probably arise from a lack of precision in the in-situ geometric parameters measurement: especially the azimuth of the AV system and the relative position of the pyranometer. In further comparisons with trials, the scene's geometric features should be measured very precisely. The current PASE light model slightly overestimated diffuse irradiance when PV modules were casting a shadow on the sensor on the 10^{th} August. One plausible explanation lies in the fact that the current model hypothises diffuse light to be isotropic, whereas it has been shown that it is anisotropic, with a greater amount of diffuse light coming from the horizon and circumsolar areas. In principle, these slight errors are not very important when feeding crop model with formalisms based on daily irradiation, but this improvement would be relevant if a photosynthesis model with higher temporal resolution was to be used. These first results provide confidence in the proposed light model as an input for the spatialized crop models currently implemented in PASE. However, as this validation was carried out over a short period and on a single experimental site, further validations should be performed on datasets from different AV geometries, locations and periods of the year.

4.2. PASE 1.0 to predict and optimize multi-year land productivity of agrivoltaic systems

A key challenge in AV modelling is the capacity to predict the system's land productivity. The effect of PV modules on crop yields needs to be assessed over several years to account for local climate variability and possibly the planned crop rotation. Usually, photovoltaic energy production potential is assessed on typical meteorological years (TMY), but to analyse the impact of cultivation on this production, a multiyear simulation may also be of interest. The section presents PASE capability to predict the productivity of a vertical AV facility and to optimise the design depending on criteria that must be achieved.

The results of the vertical AV multi-year land-productivity analysis are presented in Figure 7. They highlighted an inter-annual variability in agricultural yields that was uncorrelated with electricity production. Unlike PV modules, crop yields depend on the inter-annual variability of rainfall and are also positively affected by high temperatures until 34 °C for this wheat cultivar. In addition, atmospheric water demand increases positively with higher daily irradiation, temperature, and wind speed, which can have a negative impact on the water balance. Stress in terms of temperature and water content has an even greater impact on yield if it occurs during the crop's growth peak. Best crop yields were achieved in 2013 and 2014, which were also the years with the least water stress for the crop. At this location, agricultural yield in AV conditions presented an average reduction of 19.7% ±0.5% over the 12-year period compared with the open-field yield. This reduction in yield is explained by the average 21.3% reduction in irradiation received over the agricultural season and a slight improvement in the water balance. The average water stress factor for wheat was reduced by 1.2% on average over the 12 years. However, given the basic formalism for water balance, called ARID, used in SIMPLE, this model is not the best suited to highlight the reduction in evapotranspiration and, consequently, the improved water status of the crop. SIMPLE is clearly too simple to make precise predictions of the yields to be expected under specific soil, climatic and crop management

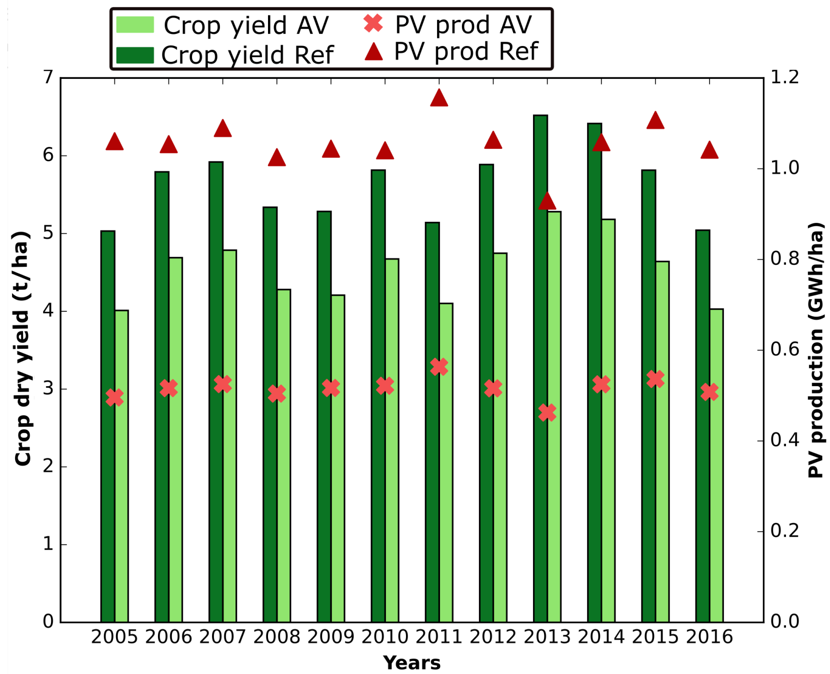

Fig. 7 Multi-year comparison between the PV production and the spring wheat yield of the Wallhausen vertical agrivoltaic demonstrator and the respective reference systems: a south-oriented PV plant (tilt = 20°, GCR = 50%) and spring wheat in open-field

conditions. It does, however, allow to determine the potential yield loss associated with the reduction in irradiation corresponding to the yield loss to be expected in non-limiting conditions.

In terms of PV output per hectare, this AV configuration produced 53.6% ±0.8% less on average over the 12 years than the reference system. The vertical AV installation at Wallhausen had a GCR of 18.9%, i.e. 62% lower than the reference PV system, although the PV modules were bifacial. PV energy production could be explained almost exclusively by the level of irradiation, with the best (2011) and worst years (2013) showing total annual GHI of 1.19 and 0.99 MWh/m^2, respectively.

Similarly to what has been done by Campana et al. (2021), a sensitivity analysis of the PV rows distance on productivity was carried out using average yields from 2005 to 2016. The other parameters of the Wallhausen vertical AV system remain unchanged from the previous analysis and the same reference systems were considered to calculate LER. Figure 8a presents

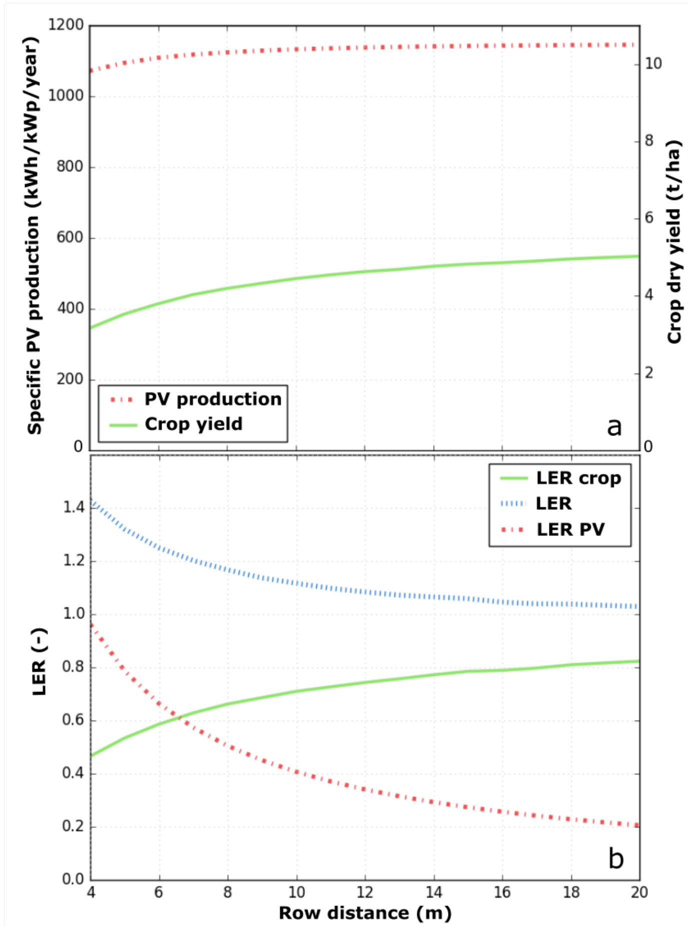

Fig. 8 Relationship of the row distance of the Wallhausen vertical AgriPVplus demonstrator with (a) specific PV energy production and spring wheat dry yield, and (b) LER and its PV and crop components

the improvement in spring wheat yield and the change in specific PV yield with increasing row spacing. By increasing the distance between rows of PV arrays from 4 m to 20 m, the dry yield of wheat increased from 3.2 to 5.0 t/ha. The specific electricity yield increased with the inter-row distance until there was no longer significant mutual shading between the PV arrays. Figure 8b illustrates the impact of inter-row distance on the LER and its two components. The graph shows that the LER of the AV system decreased with the inter-row distance because the PV yield per hectare decreased more than the agricultural yield increased. By moving from 4 to 20 m, the agricultural component of the LER increased by 43.4%, while the PV component decreased by 78.6%. The LER therefore felt from 1.42 to 1.03 when the spacing increased from 4 to 20 m. Taking into account the loss of arable land, an inter-row spacing of 17 m was required to achieve an agricultural yield loss of no more than 20%. A spacing of 6.3 m gave equivalent contributions from the two components of the LER. This sensitivity analysis therefore demonstrated the possibility to choose an optimum inter-row distance based on criteria needed to be achieved regarding local regulations.

This study highlights PASE ability to predict the agricultural and PV yield of an AV installation for a series of years of meteorological data. The sensitivity analysis shows that PASE could be used with optimisation algorithms to parameterize AV plants. PASE could also be used for permit applications computing criteria to be achieved. The generic and user-friendly aspects of PASE make it easy to reproduce studies carried out by other research groups, making the results more robust. However, for the analysis of realistic scenarios, this multi-year analysis should take into account the crop rotation carried out by the farmer. It would therefore be appropriate to carry out this analysis for the different crops in a rotation. In addition, a possible improvement would be to take into account the simulated post-harvest soil condition for the following year. This kind of analysis is classical using advanced crop models like STICS.

5. Future developments

This article presents PASE 1.0, but the DEAL laboratory aims to continue the development undertaken with its partners, while opening the door to new collaborators. The modular design of PASE facilitates collaborative work on various components of the modelling environment simultaneously, while also enabling effortless integration of new models or modules. It is evident that the actual models available lack the capacity to encompass all the phenomena altered by AV. That is why a list of prioritized developments was drawn up. These various improvements appear in red in the Figure 3. As mentioned in section 2.3, the development of a Python version of STICS was initiated by Ombrea. pySTICS (Perez, n.d.) will be integrated into PASE, making it possible to access the STICS formalisms and modify them for the AV context. For instance, it will be interesting to adapt the STICS RUE formalism to take account of the dynamic shading that occurs in AV conditions and the transient phases through which photosynthesis passes. Integrating a dynamic photosynthesis formalism would mean using microclimatic data at a higher temporal resolution than what is currently done in crop models. With the same idea of refining crop modelling, PASE was designed to be easily coupled with the CPlantBox (Giraud et al., 2023) functional and structural plant model (FSPM), which is also an open-source modelling framework using the VTK library. Regarding the microclimatic module, a rainfall spatialisation model is currently being developed for the needs of our industrial partner Naldeo, but this development are expected to be released after an embargo period. In this same module, a future development will be the integration of anisotropic sky models in the ray casting mode of the light model to be able to calculate more precisely, in a complex scene, irradiation reaching PV modules and the crop. The PV production module also needs to be improved by integrating existing open-source tools for calculating losses linked to the electrical configuration. Another need identified by Naldeo is to integrate slopes and complex topographies. Furthermore, as a virtual entity, PASE paves the way for the development of real-time operational strategies with PV trackers using a feedback loop and the digital twin paradigm. Last but not least, long term developments need to integrate automated LCA analysis and ecological evaluation.

6. Conclusion

As identified by the background on the modelling of AV systems land productivity, PASE was conceptualized to meet modelling needs of the AV community. After proper parameterisation, it can be used to model the PV energy production and the development of the underlying crops, including their yield. Its light model efficiently estimates the quantity of light on any surface of the system. These three components, i.e., light, agricultural yield and PV energy production, had already been grouped together within modelling frameworks previously, but PASE 1.0 is, to the best of our knowledge, the first to offer a permissive open-source stabilised version to the AV community. The chosen open-source business model proved its effectiveness through the released of this first stabilised version of PASE. Further developments are planned with current partners and open to new ones to address the needs of the sector. PASE 1.0 major strengths are its pythonic and object-oriented nature, its modularity and its integration of powerful libraries for 3D computer gaphics and ray tracing, allowing high spatial and temporal resolutions. The modularity of PASE is a real asset when it comes to add new functionalities and it will enable it to keep in step with user needs. It offers a great deal of freedom over the source and duration of their weather data. Users can also select the models and formalisms to meet their needs, with different levels of complexity. This paper illustrates that PASE can be used as a tool for sizing and optimizing AV systems by its ability to predict accurately available irradiation on PV modules and crops. It also provides an initial indication of the PV and agricultural yields to be expected. PASE aims to foster the deployment of PV worldwide on agricultural land by developing synergies to make agriculture more resilient in the wake of increasingly severe climatic events. Engineers and researchers are invited to use and contribute to this tool to create virtuous systems combining low-cost energy production and services directly to the crop or the farm. Public administrations are also invited to adopt such tool for AV projects permitting and favor those in line with the local food-water-energy nexus challenges.

Credit authorship contribution statement

Roxane Bruhwyler: Conceptualization, Methodology, Software, Validation, Writing - Original Draft, Funding acquisition. **Nicolas De Cock:** Methodology, Software, Writing - Review and Editing. **Pascal Brunet:** Conceptualization, Methodology, Writing - Review and Editing. **Jonathan Leloux:** Conceptualization, Writing - Review and Editing. **Pierre Souquet:** Conceptualization, Project administration. **Etienne Perez:** Methodology, Software, Writing - Review and Editing. **Etienne Drahi:** Conceptualization, Writing - Review and Editing. **Sebastian Dittmann:** Resources, Writing - Review and Editing, Project administration. **Frédéric Lebeau:** Conceptualization, Project administration, Funding acquisition, Writing - Review and Editing.

Appendix A. PASE 1.0 architecture: class diagram

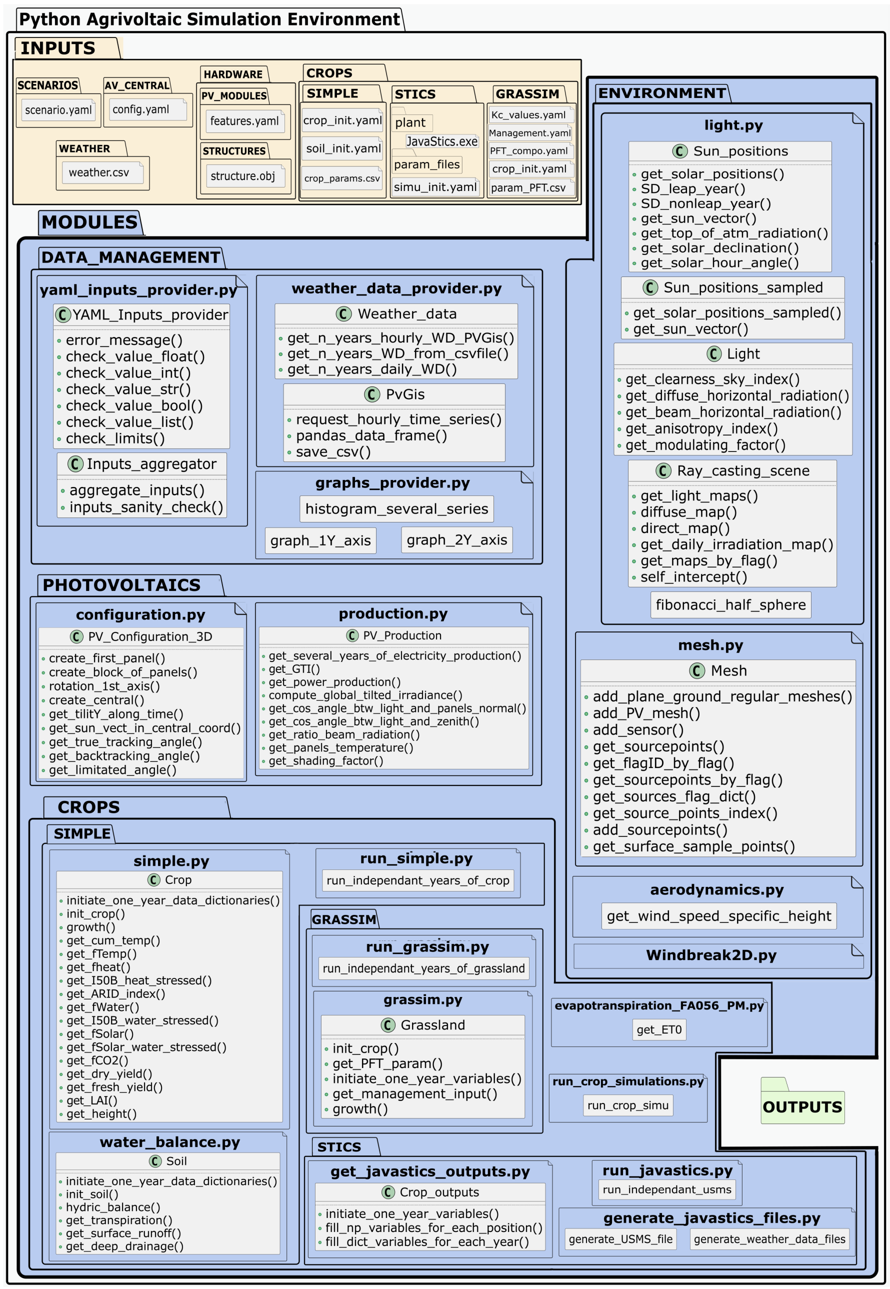

Fig. A.9 Class diagram of PASE 1.0

Appendix B. Geometrical mutual shading losses

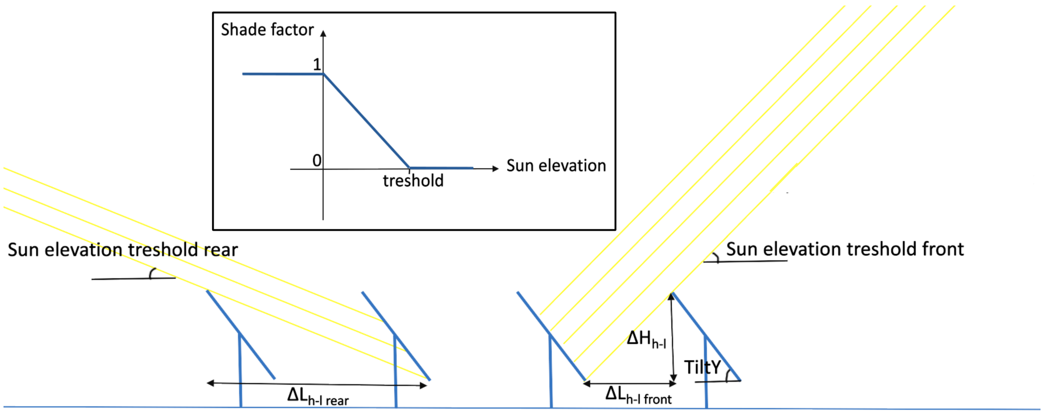

Fig. B.10 Diagram explaining the geometric calculation of the mutual shading factor

Appendix C. Setting up PASE for the multi-year and the sensitivity analysis

Table C.1 PV modules parameters of the Wallhausen vertical AV (a) and the reference system (b)

	Length	Width	Peak power	Bifaciality factor
a	1.98 m	1.04 m	430 Wp	0.7
b	1.98 m	1.04 m	430 Wp	0

Table C.2 PV system parameters of the Wallhausen vertical AV (a) and the reference system (b)

	Peak power	Rows number	Rows distance	Tilt	Azimuth
a	60.2 kWp	5	11 m	90°	-90°
b	139.7 kWp	11.6	4.17 m	20°	0°

Table C.3 SIMPLE soil parameters

Water holding capacity	Initial amount of available water	Drainage coefficient	Root zone depth	Runoff curve number	Albedo
0.18	180 mm	0.41	1000 mm	72	0.2

References

Ahmed, M.S., Khan, M.R., Haque, A., Khan, M.R., 2022. Agrivoltaics analysis in a techno-economic framework: Understanding why agrivoltaics on rice will always be profitable. Applied Energy 323. doi:10.1016/j.apenergy.2022.119560.

Alexa, M., 2020. Super-fibonacci spirals: Fast, low-discrepancy sampling of so(3). CVF Conference on Computer Vision and Pattern Recognition , 8281–8290.

AlMarzouq, M., Zheng, L., Rong, G., Grover, V., 2005. Open source: Concepts, benefits, and challenges. Communications of the Association for Information Systems 16. doi:10.17705/1cais.01637.

Amaducci, S., Yin, X., Colauzzi, M., 2018. Agrivoltaic systems to optimise land use for electric energy production. Applied Energy 220. doi:10.1016/j.apenergy.2018.03.081.

Anderson, K., Mikofski, M., 2020. Slope-Aware Backtracking for Single-Axis Trackers. National Renewable Energy Laboratory URL: https://www.nrel.gov/docs/fy20osti/76626.pdf.

Beaudoin, N., Lecharpentier, P., Ripoche-Wachter, D., Strullu, L., Mary, B., Léonard, J., Launay, M., Justes, E., 2023. Stics soil-crop model. conceptual framework, equations and uses.

Björn, M., Laura, H., Alfons, A., Klaus, K., Christian, R., 2016. Yield predictions for photovoltaic power plants: Empirical validation, recent advances and remaining uncertainties. Progress in Photovoltaics Research and Applications 24. doi:10.1002/pip.2616.

Bruhwyler, R., Lebeau, F., 2023. Pase: Python agrivoltaic simulation environment. URL: https://orbi.uliege.be/handle/2268/310262. accessed: 2024-04-04.

Bruhwyler, R., Sánchez, H., Meza, C., Lebeau, F., Brunet, P., Dabadie, G., Dittmann, S., Gottschalg, R., Negroni, J.J., 2023. Vertical agrivoltaics and its potential for electricity production and agricultural water demand: A case study in the area of chanco, chile. Sustainable Energy Technologies and Assessments 60. doi:10.1016/j.seta.2023.103425.

Buitenhuis, A.J., Pearce, J.M., 2012. Open-source development of solar photovoltaic technology. Energy for Sustainable Development 16. doi:10.1016/j.esd.2012.06.006.

Campana, P.E., Stridh, B., Amaducci, S., Colauzzi, M., 2021. Optimisation of vertically mounted agrivoltaic systems. Journal of Cleaner Production 325. doi:10.1016/j.jclepro.2021.129091.

Chatzipanagi, A., Taylor, N., Jaeger-Waldau, A., 2023. Overview of the potential and challenges for Agri-Photovoltaics in the European Union. Scientific analysis or review, Policy assessment KJ-NA-31-482-EN-N (online). Luxembourg (Luxembourg). doi:10.2760/208702.

Dinesh, H., Pearce, J.M., 2016. The potential of agrivoltaic systems. doi:10.1016/j.rser.2015.10.024.

Duffie, J.A., Beckman, W.A., 1982. Available Solar Radiation. John Wiley and Sons, Ltd. chapter 2. pp. 43 – 137. doi:10.1002/9781118671603.

Dupraz, C., 2023. Assessment of the ground coverage ratio of agrivoltaic systems as a proxy for potential crop productivity. doi:10.1007/s10457-023-00906-3.

Dupraz, C., Marrou, H., Talbot, G., Dufour, L., Nogier, A., Ferard, Y., 2011. Combining solar photovoltaic panels and food crops for optimising land use: Towards new agrivoltaic schemes. Renewable Energy 36. doi:10.1016/j.renene.2011.03.005.

Elamri, Y., Cheviron, B., Lopez, J.M., Dejean, C., Belaud, G., 2018. Water budget and crop modelling for agrivoltaic systems: Application to irrigated lettuces. Agricultural Water Management 208, 440–453. doi:10.1016/j.agwat.2018.07.001.

Embree, I., n.d. High performance ray tracing. URL: https://www.embree.org/. accessed: 2024-04-15.

Franke, J.A., Müller, C., Elliott, J., Ruane, A.C., Jägermeyr, J., Balkovic, J., Ciais, P., Dury, M., Falloon, P.D., Folberth, C., François, L., Hank, T., Hoffmann, M., Izaurralde, R.C., Jacquemin, I., Jones, C., Khabarov, N., Koch, M., Li, M., Liu, W., Olin, S., Phillips, M., Pugh, T.A., Reddy, A., Wang, X., Williams, K., Zabel, F., Moyer, E.J., 2020. The ggcmi phase 2 experiment: Global gridded crop model simulations under uniform changes in co2, temperature, water, and nitrogen levels (protocol version 1.0). Geoscientific Model Development 13. doi:10.5194/gmd-13-2315-2020.

Giraud, M., Samuel, L., Harings, M., Javaux, M., Leitner, D., Meunier, F., Rothfuss, Y., Dusschoten, D., Vanderborght, J., Vereecken, H., Lobet, G., Schnepf, A., 2023. Cplantbox: a fully coupled modeling platform for the water and carbon fluxes in the soil-plant-atmosphere-continuum. in silico Plants 5. doi:10.1093/insilicoplants/diad009.

Goetzberger, A., Zastrow, A., 1982. On the coexistence of solar-energy conversion and plant cultivation. International Journal of Solar Energy 1. doi:10.1080/01425918208909875.

Grubbs, E., Gruss, S., Schull, V., Gosney, M., Mickelbart, M., Brouder, S., Gitau, M., Bermel, P., Tuinstra, M., Agrawal, R., 2024. Optimized agrivoltaic tracking for nearly-full commodity crop and energy production. Renewable and Sustainable Energy Reviews 191, 114018. doi:https://doi.org/10.1016/j.rser.2023.114018.

JRC, 2022. Photovoltaic geographical information system (pvgis). URL: https://joint-research-centre.ec.europa.eu/photovoltaic-geographical-information-system-pvgis. accessed: 2024-04-02.

JRC, n.d. Agri4cast resources portal. URL: https://agri4cast.jrc.ec.europa.eu/DataPortal/Index.aspx. accessed: 2024-04-02.

Katsikogiannis, O.A., Ziar, H., Isabella, O., 2022. Integration of bifacial photovoltaics in agrivoltaic systems: A synergistic design approach. Applied

Energy 309, 118475. doi:https://doi.org/10.1016/j.apenergy.2021.118475.

Kim, S., Kim, S., An, K., 2023. An integrated multi-modeling framework to estimate potential rice and energy production under an agrivoltaic system. Computers and Electronics in Agriculture 213, 108157. doi:https://doi.org/10.1016/j.compag.2023.108157.

Kokah, E.U., Knoden, D., Lambert, R., Himdi, H., Dumont, B., Bindelle, J., 2023. Modeling the daily dynamics of grass growth of several species according to their functional type, based on soil water and nitrogen dynamics: Gras-sim model definition, parametrization and evaluation. Journal of Agriculture and Food Research 14. doi:10.1016/j.jafr.2023.100875.

Mengi, E., Samara, O.A., Zohdi, T.I., 2023. Crop-driven optimization of agrivoltaics using a digital-replica framework. Smart Agricultural Technology 4. doi:10.1016/j.atech.2022.100168.

Perens, B., Sroka, M., 2007. The open source definition. URL: http://perens.com/OSD.html.

Perez, E., n.d. pystics v1.0. URL: https://github.com/OmbreaPV/pySTICS/tree/main. accessed: 2024-06-18.

PyVista, n.d. 3d plotting and mesh analysis through a streamlined interface for the visualization toolkit (vtk). URL: https://docs.pyvista.org/version/stable/. accessed: 2024-04-10.

Riaz, M.H., Imran, H., Younas, R., Butt, N.Z., 2021. The optimization of vertical bifacial photovoltaic farms for efficient agrivoltaic systems. Solar Energy 230. doi:https://doi.org/10.1016/j.solener.2021.10.051.

Robledo, J., Leloux, J., Lorenzo, E., Gueymard, C.A., 2019. From video games to solar energy: 3d shading simulation for pv using gpu. Solar Energy 193. doi:https://doi.org/10.1016/j.solener.2019.09.041.

Rötter, R.P., Palosuo, T., Kersebaum, K.C., Angulo, C., Bindi, M., Ewert, F., Ferrise, R., Hlavinka, P., Moriondo, M., Nendel, C., Olesen, J.E., Patil, R.H., Ruget, F., Takáč, J., Trnka, M., 2012. Simulation of spring barley yield in different climatic zones of northern and central europe:

A comparison of nine crop models. Field Crops Research 133, 23–36. doi:10.1016/j.fcr.2012.03.016.

Schroeder, W., Martin, K., Lorensen, B., 2006. The Visualization Toolkit (4th ed.). Kitware.

SNL, 2024. PV Performance Modeling Collaborative (PVPMC): Modeling Guide. Accessed: 2024-07-24.

Trommsdorff, M., Kang, J., Reise, C., Schindele, S., Bopp, G., Ehmann, A., Weselek, A., Högy, P., Obergfell, T., 2021. Combining food and energy production: Design of an agrivoltaic system applied in arable and vegetable farming in germany. Renewable and Sustainable Energy Reviews 140. doi:10.1016/j.rser.2020.110694.

Turner, R., 2018. Modularity. Springer Berlin Heidelberg, Berlin, Heidelberg. doi:10.1007/978-3-662-55565-1{_}17.

Valle, B., Simonneau, T., Sourd, F., Pechier, P., Hamard, P., Frisson, T., Ryckewaert, M., Christophe, A., 2017. Increasing the total productivity of a land by combining mobile photovoltaic panels and food crops. Applied Energy 206. doi:10.1016/j.apenergy.2017.09.113.

Willockx, B., Herteleer, B., Cappelle, J., 2020. Theoretical potential of agrovoltaic systems in europe: A preliminary study with winter wheat. Conference Record of the IEEE Photovoltaic Specialists Conference 2020-June, 0996–1001. doi:10.1109/PVSC45281.2020.9300652.

de Wit, A., 2024. Pcse: The python crop simulation environment. URL: https://pcse.readthedocs.io/en/stable/index.html. accessed: 2024-04-17.

Zhao, C., Liu, B., Xiao, L., Hoogenboom, G., Boote, K.J., Kassie, B.T., Pavan, W., Shelia, V., Kim, K.S., Hernandez-Ochoa, I.M., Wallach, D., Porter, C.H., Stockle, C.O., Zhu, Y., Asseng, S., 2019. A simple crop model. European Journal of Agronomy 104. doi:10.1016/j.eja.2019.01.009.

Total number of word (including references): 9214
Total number of word (excluding references): 6241
Abstract number of words: 198
Number of words in Supplementary Information: /