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Experimental results, integrated model validation, and economic aspects of agrivoltaic systems at northern latitudes

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Abstract

Agrivoltaic systems, which allow the coexistence of crop and electricity production on the same land, are considered an integrated water-energy-food nexus solution to allow the simultaneous attainment of conflicting Sustainable Development Goals. This study aims to analyse experimental results on ley grass yield and quality response to shadings in the first agrivoltaic system in Sweden and validate an integrated modelling platform for assessing agrivoltaic systems' performances before installation. An economic analysis is carried out to compare the profitability of agrivoltaic with conventional ground-mounted photovoltaic systems and to identify the most sensitive parameters affecting the profitability through a Monte Carlo analysis.

Despite an average reduction of about 25% for photosynthetically active radiation produced by the agrivoltaic systems supporting structures and PV modules, no significant statistical yield was observed between the samples under the agrivoltaic system compared to the samples in the reference area. The agrivoltaic system attained a land equivalent ratio of 1.27 and 1.39 in 2021 and 2022, respectively. The validation results of the integrated modelling platform show that the sub-model concerning the crop yield response to shading conditions tends to underestimate the actual average crop yield under the agrivoltaic system of about 15% when no crop adaption measures to shadings are provided as input. If measured leaf area index information concerning the ley grass adaptation under shading conditions is provided as input to the sub-model, a more satisfactory model prediction is attained. The results of the economic analysis show that from a net present value perspective, agrivoltaic systems can produce about 30 times more than a conventional crop rotation in Sweden.

Keywords: agrivoltaic, soil moisture, leaf area index, integrated modelling, shading, validation, profitability.

1 Introduction

One of the main criticisms of PV systems, especially large-scale conventional ground-mounted photovoltaic (CGMPV) systems built on agricultural land is the competition with food production (Jones et al., 2015; Roddis et al., 2020). The rivalry between land for energy and land for food is seen as a threat to food security, and it creates deep conflicts among the Sustainable Development Goals (SDGs) (i.e., Zero Hunger, Affordable and Clean Energy, and Climate Action) (Nonhebel (2005); Dinesh and Pearce, 2016; Brunet et al., 2020). Applying the concept of agrivoltaic (APV) systems, see Figure 1, can solve this conflict because agricultural crop production and green electricity production from PV systems can be synergistically combined.

The land use efficiency of the APV system is higher as compared to the sole use of land for agricultural or electricity production, and this is typically measured with the Land Equivalent Ratio (LER), a reference key performance indicator used to evaluate intercropping or agroforestry projects (Dupraz et al., 2011). A LER value lower than one indicates that the combined production, i.e., crops plus PV, is less productive than the mono production. On the other hand, a LER bigger than one indicates higher productivity in the combined production system compared to a mono-production system. Assuming to use one reference hectare of land for installing an optimised CGMPV farm, the output of the reference hectare will be mostly electricity, i.e., 100% electricity (this does not consider other co-benefits produced by the solar farm, such as biodiversity or soil restoration, or the possibility to integrate livestock grazing). If the same hectare is used only for agriculture, the output will be 100% crop production. Suppose it is forbidden to use the reference hectare of land for installing a conventional solar farm, for instance, by authorities releasing the building permit due to laws and regulations that protect food security. For instance, according to the Swedish Environmental Code, agricultural land that is suitable for cultivation is of "national importance", and it cannot be exploited for other purposes unless it is to satisfy a significant national interest and there is no other possible land to use (Chapter 3, Section 4) (The Swedish Government, 2000). In that case, a conflict arises between SDG 2 Zero Hunger, SDG 7 Affordable and Clean Energy, and SDG 13 Climate Action. This situation does not allow the attainment of multiple SDGs. In the APV scenario, land can be used simultaneously for agricultural and PV production. The APV electricity supply is lower than an optimised CGMPV farm due many factors. CGMPV aims at producing maximum energy with the lowest possible cost which lead to high PV modules density per hectare. In contrast, an optimised APV use relatively higher distance between the adjacent rows to avoid excessive shading on the crops and this leads to lower density of PV modules per hectare, i.e., X electricity production in Figure 1 is lower than 100%. The crop output depends on the APV configuration, such as the PV modules density per hectare and related shading levels, geographical location of the system, specific weather conditions, and crop type. The yield Y that can be lower or higher than the crop yield in the reference agricultural land, i.e., Y crop production can be lower or higher than 100% (Laub et al., 2021). For example, a typical case of higher crop production under an APV system is connected to the installation in arid or semi-arid regions (Barron-Gafford et al., 2019). Higher crop yields under APV systems can be obtained during the occurrence of extreme weather phenomena such as heat waves, drought, or compound heat-drought extremes (Trommsdorff et al., 2021; Stott et al., 2004; Barriopedro et al., 2011; Zscheischler et al., 2018 Manning et al., 2019; Zscheischler and Fisher, 2020; Bastos et al., 2021). Valle et al. (2017) reported a LER greater than 1.5 for combined solar-tracked PV systems with lettuce. In Germany, researchers found an LER of 1.87 on celeriac in the harvest of 2018 on an integrated bifacial PV system with a height clearance of 5.5 m (Trommsdorff et al., 2021). A study from Oregon in the USA reported values of LER for herbage dry mass of 1.68 in combination with fixed tilt CGMPV farm (Andrew et al., 2021). Although the LER has been a well-used indicator for the performance of APV systems, Toledo and Scognamiglio (2021) mentioned that caution needs to be taken when using the LER as a key performance indicator since it does not differentiate between electricity production and crop yield and high LER values can be obtained even if the crop yield is a minor output of the combined system. Campana et al. (2021) also pointed out that the trade-offs to be considered in an APV system are multiple, so a comprehensive system optimisation cannot be carried out by only relying on the maximisation of the LER. Maximising LER might induce APV system configurations that are neither optimal from the PV or agricultural perspectives.

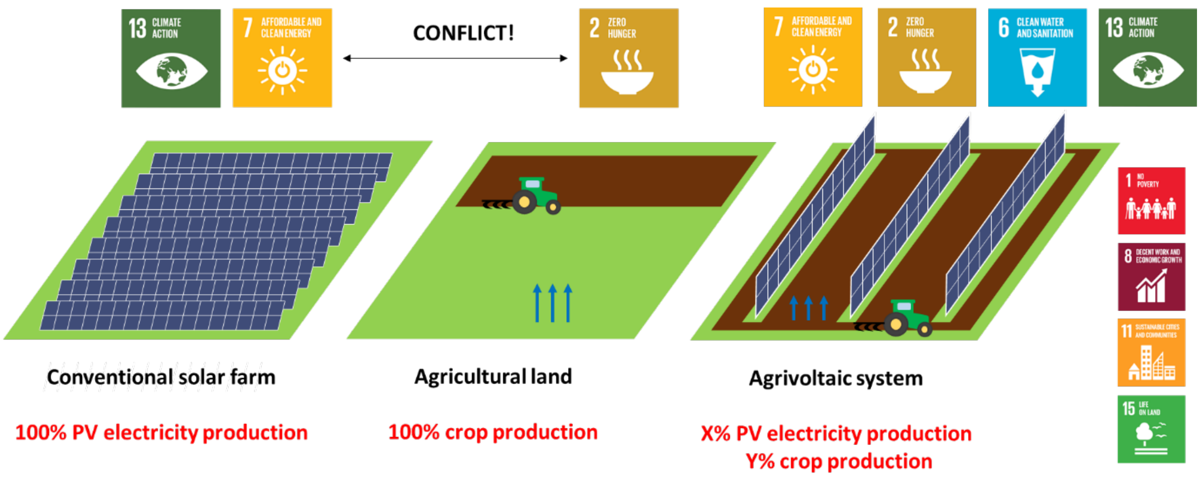

Figure 1: Land use conflicts between solar farms and agriculture and how this conflict can be relieved by implementing APV systems in the context of Sustainable Development Goals. Adapted from Fraunhofer ISE (2022).

Despite crop production and electricity production, APV systems present other benefits. Agostini et al. (2021) have qualitatively assessed the impacts of Agrovoltaico® system, a patented APV configuration, on the SDGs and identified that the APV system could positively impact 14 out of 17 SDGs. For instance, as compared to solo agriculture, the presence of PV modules creating shadings affects the energy balance at the ground and crops level reducing evapotranspiration and thus water loss from soils and crops (Elamri, 2018) (i.e., SDG6, Clean Water and Sanitation). Reduced evapotranspiration can significantly benefit areas with high water stress indexes. The APV system has shown an excellent synergy between electricity production, crop production, grazing land, and animals. The animals can use the shading as shelter during warm days, and the land is used for grazing simultaneously. The dual synergy of using a pasture-based APV system can significantly reduce greenhouse gas emissions and fossil energy demand compared to conventional meat and electricity production (Pascaris et al., 2021). Gomez-Casanovas et al. (2021) highlighted that APV systems could have, as emerging technology, positive potential effects on grassland productivity, biodiversity, carbon sequestration, non-CO2 GHG mitigation, and water use efficiency. At the same time, APV systems offer an opportunity for farmers in terms of revenues since the same reference area can produce two streams of revenues, i.e., revenues from electricity production and crop production. The higher value of electricity income compared to crop income, especially for conventional crop rotations and without subsidies, can lead to higher specific income (i.e., €/m^2) for the farmers. Increasing the specific profit per area can also be attained by leasing the land to a third-party company, which directly invests in the APV system and pays for the annual rent of the land. Moreover, combining PV and crop production can also lead to more stable revenues, especially from the crop production stream, since shading reduces the shocks produced by extreme weather phenomena such as droughts on crop yield (Dietz et al., 2021). The positive economic aspects connected to the implementation of APV systems are pivotal for small-holder farms, typically marked out by poorer economies compared to large-scale industrial farms, and generally for the economic development in rural areas (i.e., SDG 8, Decent Work and Economic Growth).

On the other hand, APV systems present several challenges, such as uneven distribution of precipitation, soil erosion (Verheijen and Bastos, 2023) and the general risk of decreasing agricultural production. Crop yield reduction under APV systems can occur due to the reduction of light reaching the crops caused by the shading from the PV modules. A fundamental step is thus the designing process of the APV system for maximizing both crop yield and electricity production, despite those objectives are conflicting (Campana et al., 2021). Typical parameters to be considered are the shade level, the shade tolerance, the water stress coefficients, the need for irrigation, the crop rotation during the lifetime of the APV system, and the increased cost of farming the land between the PV system. The crop yield reduction under the APV system is typically considered a crucial key performance indicator for meeting policy requirements. Indeed, the development of the APV technology has led to the development of policies to promote and support the APV market, providing first clear definitions of what an APV system is compared to CGMPV systems. A clear definition of what an APV is has been given by the European Commission Joint Research Centre (Chatzipanagi et al., 2022; Chatzipanagi et al., 2023) as systems with the primary function of supporting agriculture while converting solar energy into electrical energy. APV systems support agriculture by providing services such as climate change adaptation, animal or human welfare, reduced crop stresses, and better income without significantly degrading crop production, quantitatively and qualitatively. In countries where APV systems have been implemented for several years or at least research activities have been active for a long time, the legislators have provided their definitions of APV systems and have identified clear policy targets. For instance, those policy targets focus on the maximum crop yield reduction under APV systems or the maximum area coverage from PV modules to classify the PV system as APV systems. To cite some, in Germany, the law set the maximum crop yield reduction under the APV system as 34% (European Standards, 2023). In Italy, an APV system is marked out by a PV module area coverage lower than 40%. At the same time, the continuity of agricultural activities should be guaranteed (Italian Ministry of the Environment and Energy Security, 2023). The Japanese legislation defines crop yield under an APV system as at least 80% compared to the yield in open-field conditions (US Department of Energy, 2022; Gonocruz et al., 2022).

It is fundamental to have integrated tools that estimate crop yield reduction under APV systems before installations to meet policy targets. Integrated tools typically combine algorithms for PV system electricity production, microclimate produced by the shadings, and crop growth. Dupraz et al. (2011) and Dinesh and Pearce (2016) predicted the crop yield under the APV systems using computer software such as the STICS (Simulateur mulTIdiciplinaire les Cutures Standard) developed in France (Brisson et al., 2003; STICS, 2023). Amaducci et al. (2018) used GECROS v3.0 to obtain the leaf temperature, photosynthesis, transpiration, and crop yield under APV systems. Elamri et al. (2018) used the software AVirrig to assess the impact of fluctuating shadings on crop growth (by assuming stomatal conductance as a relevant variable) to help with irrigation scheduling. Campana et al. (2021) integrated the crop model EPIC (environmental policy impact climate) in the open-source package OptiCE (Campana et al., 2017; OptiCE, 2023) for PV systems electricity modelling to study the effects of shadings produced by APV systems on oats and potatoes.

In 2022, according to Mamun et al. (2022), Sweden's first APV system was the world's northmost APV research system. The decision to conduct research activities on the APV system was driven by research on minimising irrigation water requirements during drought conditions in Sweden (Campana et al., 2018; Campana et al., 2022). Further critical motivations of the project were to avoid the conflicts between food production and solar parks and provide better incomes for farmers. Some of the critical aspects of Sweden's current food, agriculture, and energy sectors are summarized in Figures 2-4. Currently, according to the Federation of Swedish Farmers (Lantbrukarnas riksförbund, 2018) the country's food self-sufficiency is about 50%, with significant differences between food products as seen in Figure 2. For instance, bovine meat self-sufficiency is about 55%, while wheat self-sufficiency is above 100% (Food and Agriculture Organization [FAO], 2023). Food self-sufficiency was about 80% during the seventies, and it has been significantly decreased because of several factors, including dietary changes as well a reduction of Swedish production because of reduced agricultural area and number of farms (Swedish Board of Agriculture, 2023a; FAO, 2023), as depicted in Figure 3. The agricultural area in Sweden has been drastically decreased from about 4.2 Mha in 1961 to 3 Mha in 2019 while the number of farms has passed from a total of about 232 thousand in 1961 down to about 72 thousand- with several differences among farms sizes. For instances farms with area comprised between 2.1 ha and 10 ha to have undergone a significant decline passing from about 142 thousand to 23 thousand, while farms marked out by areas greater than 50.1 hectares have passed from about 7.6 to 18 thousand (Swedish Board of Agriculture, 2023a). At the same time, Sweden has set highly ambitious targets for renewable electricity, aiming at 100% renewable electricity production by 2040 and electrification targets aiming at no net greenhouse emissions by 2045 (International Energy Agency, 2023). According to the electricity transmission system operator in Sweden, Swedish Grid (2022), the forecasted electricity consumption in 2050 can be 30% to 110% higher as compared to the electricity consumption in 2020 (Swedish Energy Agency, 2021) depending on different electrification scenarios as depicted in Figure 4.

In 2020, at the beginning of the first APV project in Sweden, the utility-scale CGMPV systems represented a relatively new market segment, with a share of about 7% of the total PV market (Lindahl et al., 2022). Nevertheless, although unsubsidised in the last two years, the market for CGMPV systems has grown significantly due to several factors, including utility-scale PV systems reaching grid parity (i.e., the cost of electricity from PV has reached the same level of conventional power sources) and increasing spot market electricity prices. Despite being a new market segment and the land availability in Sweden, the rapid interest in utility-scale CGMPV systems has encountered resistance from some Country Administrative Boards, the entities releasing the building permits due to the competition between food production and energy conversion (Nordiskaprojekt, 2023). In this context, the APV system can represent an intelligent solution to preserve food production while simultaneously allowing the attainment of renewable energy and electrification targets. Currently, no definition and guidelines for the APV system exist in Sweden.

As compared to the study by Campana et al. (2021), which was focused on the development of the integrated modelling platform for simulations and optimization of APV systems, this study aims to analyse the crop performance under the APV system and validate the integrated modelling platform with special consideration to the crop model calibration and validation. The validation is carried out using the first two years' data of research activities conducted at the first APV system at Kärrbo Prästgård in Sweden using ley grass as a crop. This study also summarises the performance of the APV systems in terms of crop adaption and soil moisture, LER, and provides insights into the economic performances of APV systems compared to CGMPV systems and agriculture.

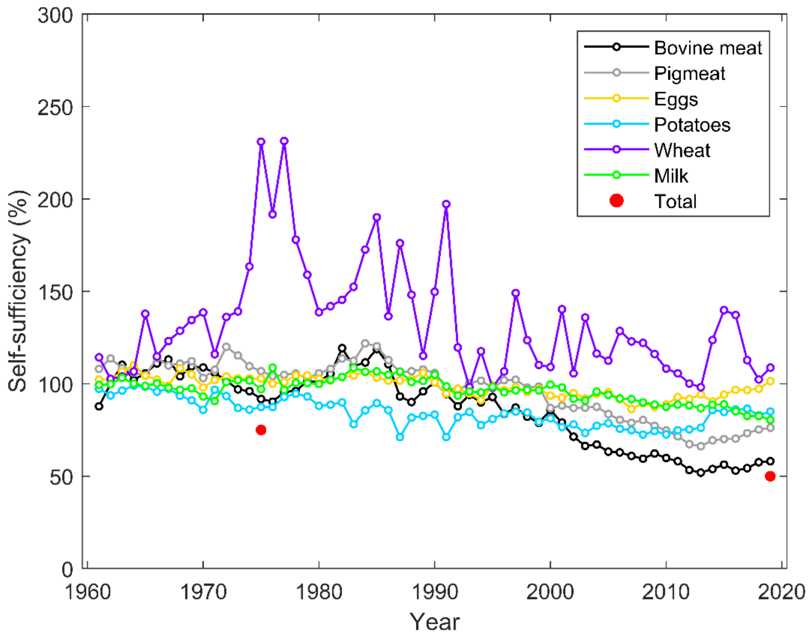

Figure 2: Food self-sufficiency in Sweden. Total values are from Lantbrukarnas riksförbund (2018), while specific food values are from FAO (2023).

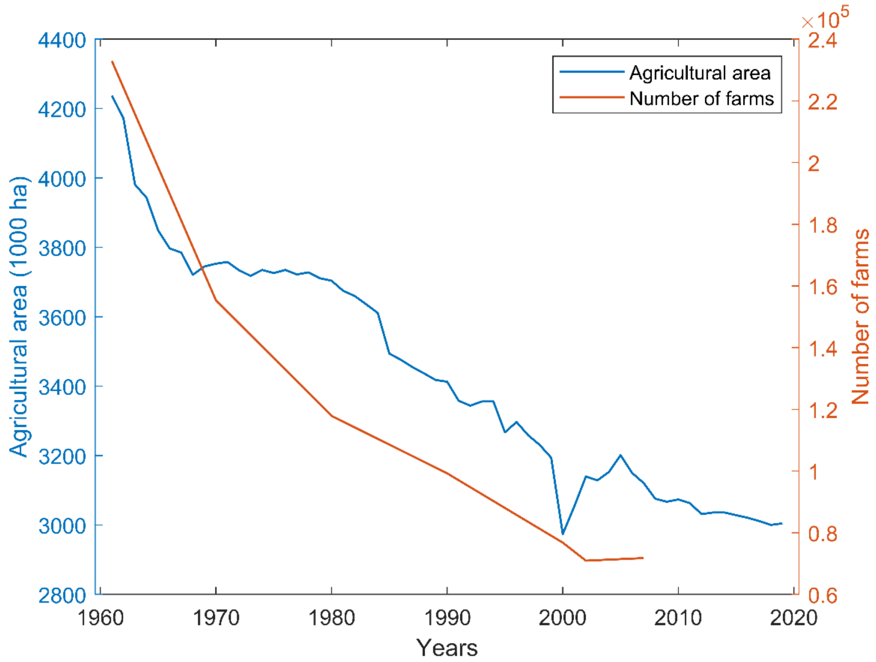

Figure 3: Agricultural area (FAO, 2023) and number of farms trend from 1960 until 2020 (Swedish Board of Agriculture, 2023a).

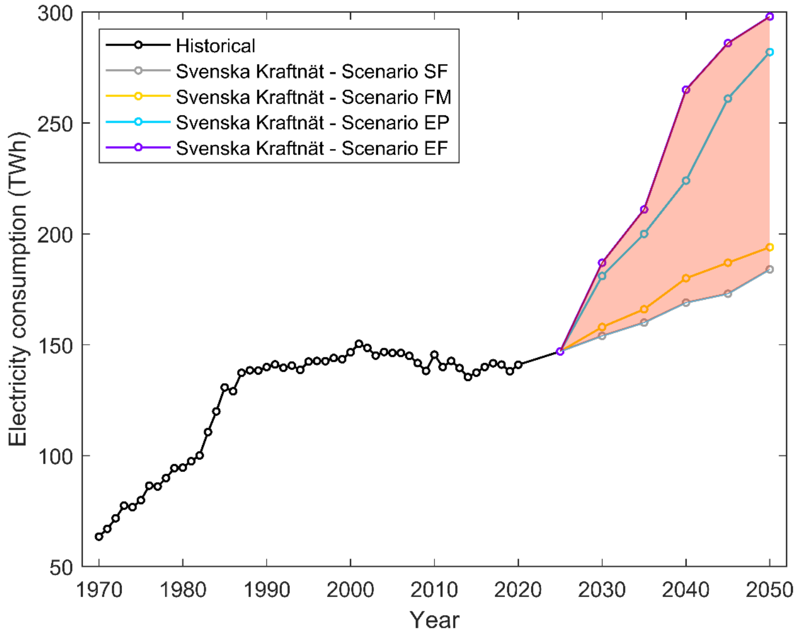

Figure 4: Historical (Statistics Sweden, 2021; Swedish Energy Agency, 2023) and forecasted (Swedish Grid, 2022) electricity consumption in Sweden.

The remainder of the paper is organized as follows: Section 2 describes the siting and the principal characteristics of the APV experimental facility, the crop experiments, the integrated modelling platform development, and the economic model for APV systems; Section 3 presents the main results of the study in terms of integrated APV modelling platform with particular focus on crop model validation, and the results of the techno-economic analyses. Section 4 summarizes the conclusions of the study.

2 Methods

2.1 Siting and experimental facility description

The siting for the APV system experimental facility was performed in early 2021 by analysing differences in crop yield and chemical composition for a selected field within a farm located nearby Västerås, Sweden: Kärrbo Prästgård (59.5544N, 16.7534E). The siting aimed to identify a plot with even vegetation. This task has been performed using CropSAT (2021), a tool that visualises crop variation within fields using satellite images post-processed to produce a vegetation index. The vegetation depicts the relationship between infrared and red light reflected from the foliage and correlates to the crop biomass content (CropSAT, 2021; Söderström et al., 2016; Lundström and Lindblom; 2018; Alshihabi et al., 2020). CropSAT is based on satellite images retrieved from the satellites Sentinel-2 and Landsat 8, and it was evaluated and proved to give satisfactory results by Söderström et al. (2015). The site selection based on the vegetation index retrieved for five dates during the crop growing season in 2020 is presented in Figure 5.

The APV system is designed with vertically mounted bifacial modules installed in a north-south direction, with a row distance of 10 meters, to facilitate the harvest of the ley grass. The APV system capacity is 22.8 kW_p. The PV system comprises 60 bifacial PV modules arranged in three rows of 18 m in length and a pitch of 10 meters. The APV system is compared to a reference system built as a CGMPV system of 11.8 kW_p. It comprises 32 bifacial PV modules arranged in two rows 8.5 m long with a tilt 30°. Figure 6 shows the APV system while performing the first cut in 2021 with the CGMPV system in the background. The system configuration takes inspiration from the experimental setup presented by Barron-Gafford et al. (2019). A summary of the characteristic parameters of the APV and reference CGMPV system is provided in Table 1. At the end of 2022, the experimental facility was monitored with more than 20 sensors for weather, microclimate, power, and agricultural parameters. A schematic diagram of the monitoring system is presented in Figure 7.

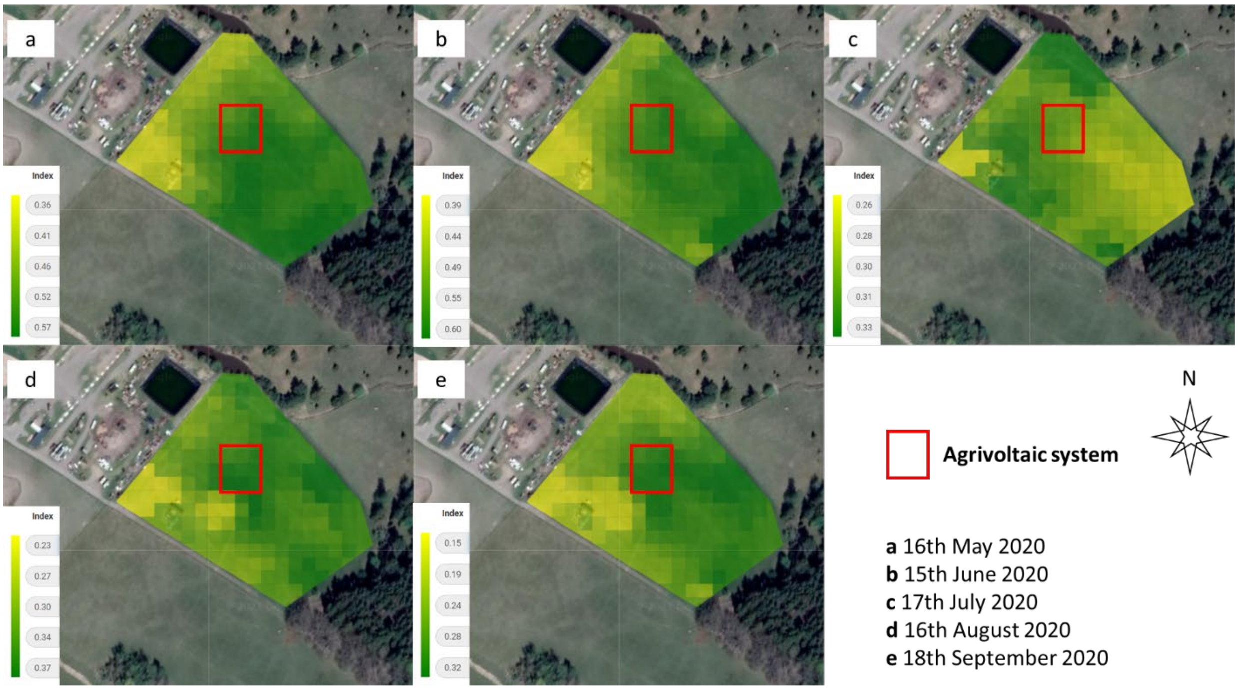

Figure 5: Site selection based on satellite images processed in CropSAT (2023). The colour scheme shows that yellow grids correspond to in-field sites with the lowest biomass level, while dark green grids correspond to in-field areas with the highest biomass level.

Figure 6: Vertically mounted APV system during the first cut in 2021 and reference CGMPV system in the background.

Table 1: Summary of the characteristic parameters of the APV and reference CGMPV systems.

	APV	**Reference CGMPV**
Azimuth (°)	-84	187
Tilt (°)	90	30
Power (kW_p)	22.8	11.8
Number of strings	2	2
Row-to-row distance	10	9.1
	PV modules	
Manufacturer	Jolywood	Longi
Model	JW-D72N-380	LR4-60HBD-370 M
Type	Bifacial, mono	Bifacial, mono
P_{mp} (W_p)	380	370
I_{mp} (A)	9.44	10.79
V_{mp} (V)	40.2	34.3
I_{sc} (A)	9.93	11.50
V_{oc} (V)	49.5	40.9
Length (m)	1.974	1.755
Width (m)	0.992	1.038
Module efficiency (%)	19.4	20.3
Front side efficiency (%)	19.4	-
Back side efficiency (%)	16.5	-
Temperature coefficient of max power (%/°C)	-0.38	-0.35
	Inverter	
Manufacturer	SunGrow	SunGrow
Model	SG20RT	SG15KTL-M
AC Power (kW)	20	15
Max efficiency (%)	98.4	98.6
Euro efficiency (%)	97.4	98.3
MPP inputs	2	2

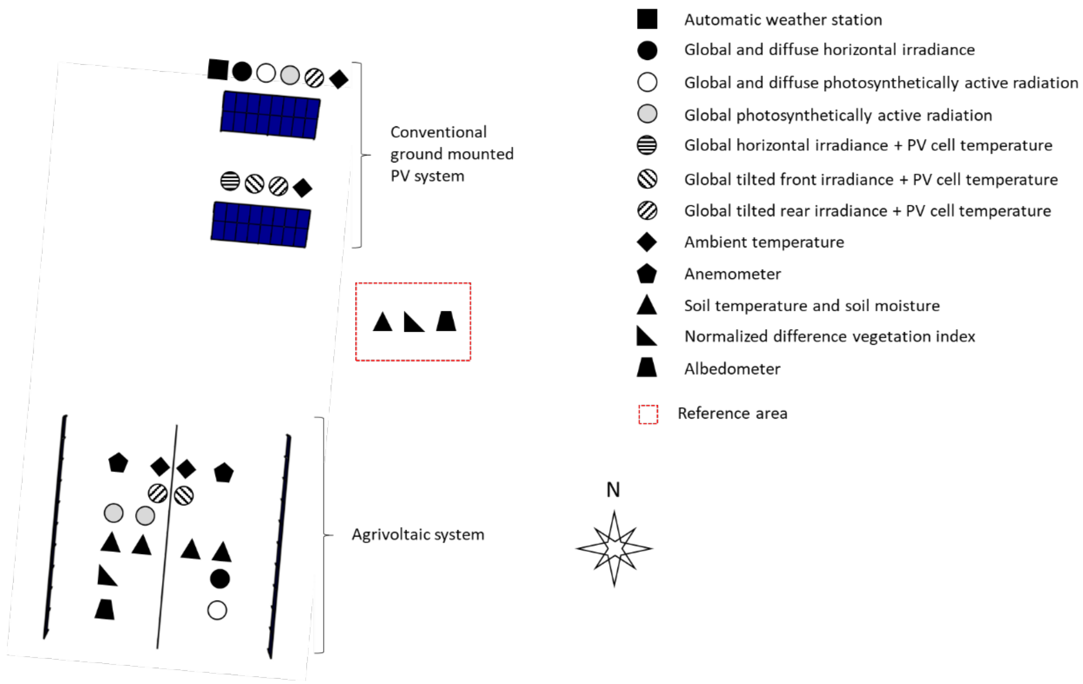

Figure 7: Schematic diagram of the experimental facility and sensors integrated at the end of 2022.

2.2 Crop experiments

2.2.1 Crop biomass yield and nutrient content

The APV experimental facility is built on a field that has been in grass production for several years. Most crop species are grasses, but there are also a wide variety of legumes and herbs, most of which are perennial plants. Hereafter, we will refer to the crop as “ley grass”. The farm owner maintains the ley grass field with an organic farming approach.

To study the influence of shading from the PV modules, both for the APV system and CGMPV system, in 2021, thirty squares (each 0.25 m^2) were distributed in six groups of five plots, as depicted in Figure 8. In 2022, fifty squares (each 0,25 m^2) were distributed in six groups of five plots, as shown in Figure 9. Thirty squares had the same position as in 2021. The other twenty squares were distributed in four groups of five plots to study more in-depth the plots in the same position as A, B, C and R. Thus, in 2022, there were four groups with ten plots (A, B, C and R) and two groups with five plots (D and E).

The maps in Figures 8 and 9 also include the samples' reference numbers. The ground control for monitoring the differences in crop yield under the APV system and the reference CGMPV system is located on the east side of the installation.

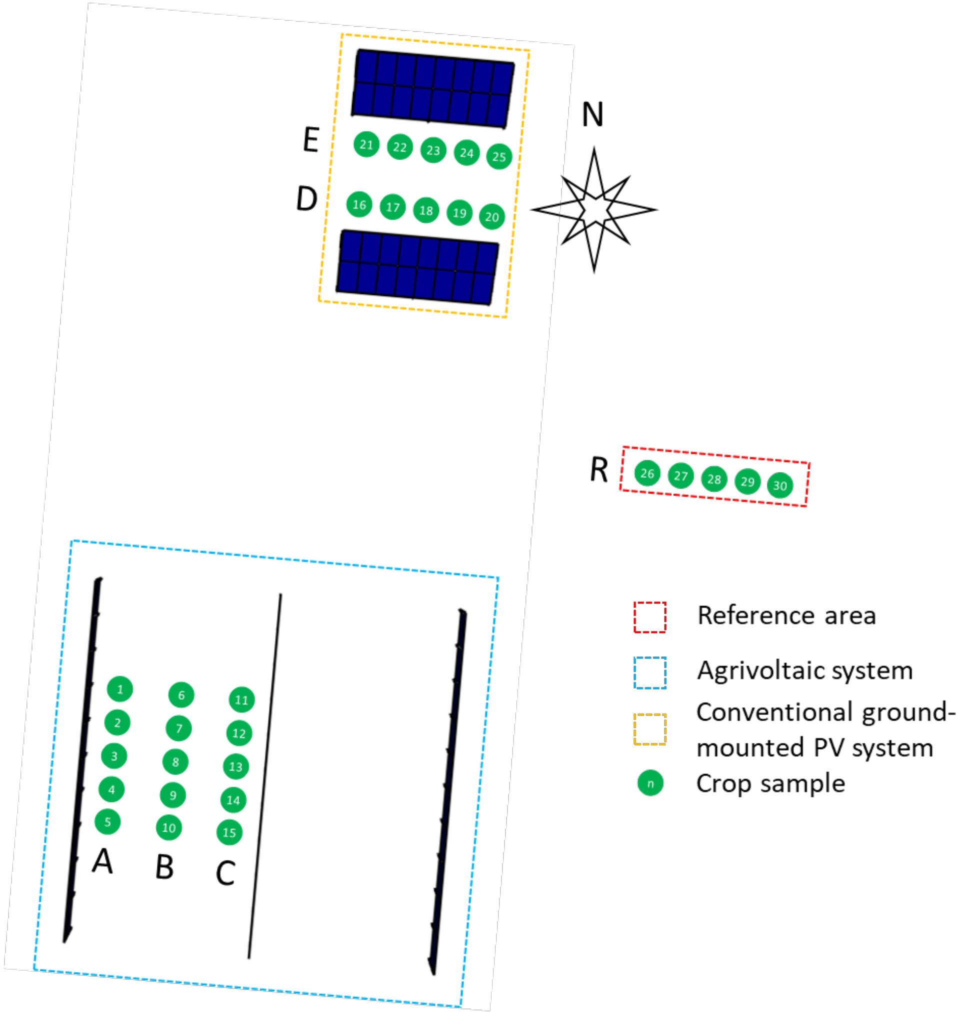

Figure 8: Crop yield experiment layout in 2021. "Group A" corresponds to samples 1-5, "Group B" corresponds to samples 6-10, "Group C" corresponds to samples 11-15, "Group D" corresponds to samples 31-35, "Group E" corresponds to samples 36-40, and "Group R" corresponds to samples 41-45.

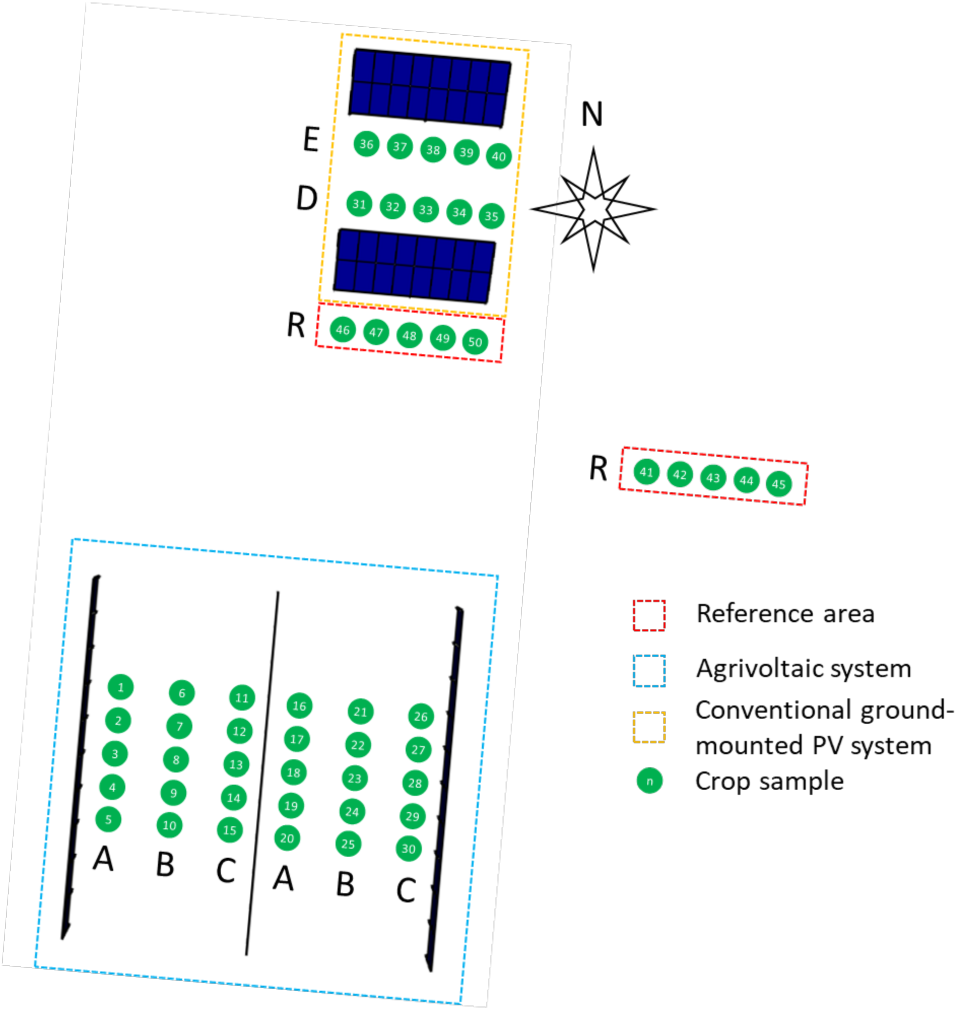

Figure 9: Crop yield experiment layout in 2022. "Group A" corresponds to samples 1-5 and 16-20, "Group B" corresponds to samples 6-10 and 21-25, "Group C" corresponds to samples 11-15 and 26-30, "Group D" corresponds to samples 31-35, "Group E" corresponds to samples 36-40, and "Group R" corresponds to samples 41-50.

In 2021, in correspondence with the samples in groups A (1-5), B (6-10), C (11-15), and R (26-30) of Figure 8, soil samples were taken to analyse the type of soil. The chemical characteristics of the soil show typical values for soil with a high clay content that has been in ley grass for several years. The only notable point is that assimilable phosphorous in sample group C is much lower than in the other groups. For more detailed information, see Table 1A in the Appendix.

In 2022, a botanical analysis was performed by analysing the percentage content of the following components: "grass", "legumes", and "other". In Figure 10, the average distribution is presented. Behind the average is a wide variation for most Groups except D. About 50% of the botanical composition is grass, but for A and C is only 40%, while D has about 66%. The content of legumes is, on average, 34%. The analysis for group R showed the lowest content at 24%, while groups C and E showed the highest content at 41-43%. The different species of plants in the groups are not determined, so therefore, it is impossible to know the effect of this difference.

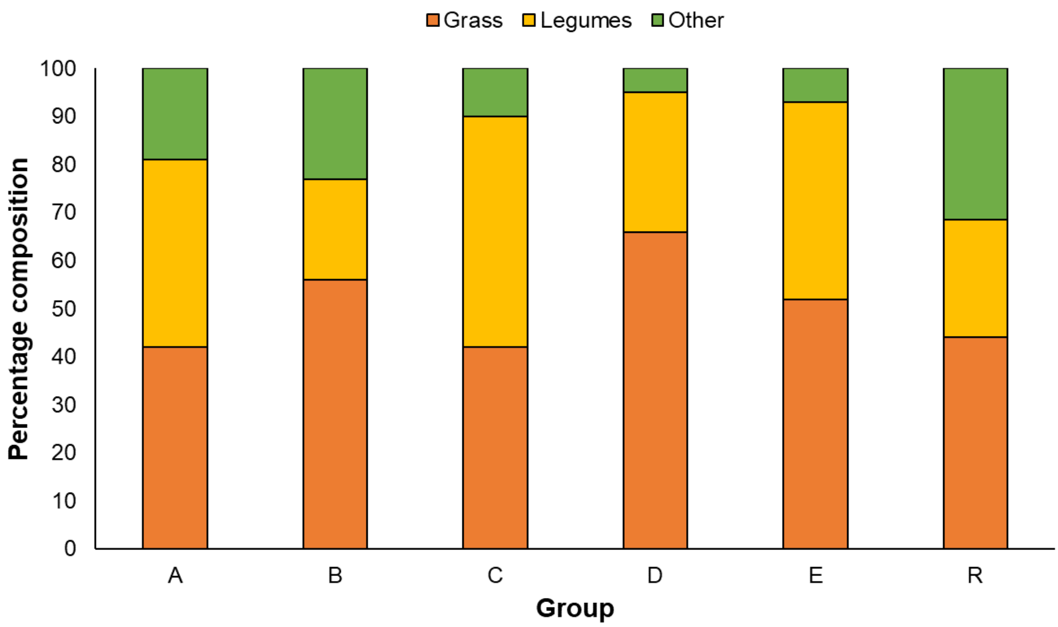

Figure 10: Botanical analysis carried out the 14th of July 2022 (second cut).

In 2021, no additional nutrients were supplied to the ley grass. The crop depended on mineralisation from the soil and air assimilation. The farm owner spread solid manure from cattle in 2020. To minimise the effect of nutrient deficiency, in 2022, a necessary amount of N, P, and K were distributed to the plots, as summarised in Table 2.

Table 2: Amount of fertilizer, presented as pure N, P and K, that was given to the plots in 2022.

	N (g/m^2)	P (g/m^2)	K (g/m^2)
First cut	5,8	1,4	2,9
Second cut	4	1,0	2,0
Third cut	2	0,5	1,0

In the statistical analysis, the yield, energy, and protein content, for the three harvests, during the year were used as a response. Given the layout of the experiments, the statistical analyses were performed as a balanced one-way ANOVA with five replicates during 2021 and an unbalanced one-way ANOVA with five and ten replicates during 2022.

The plots were hand-harvested to determine the biomass yield and nutrient content, such as crude protein and energy content. The grass samples were dried for 24 h at 60°C and weighed to determine the dry matter (DM) (%) and total crop yield (kg of DM/ha) (Åkerlind et al., 2011). The chemical analysis was performed by further drying and milling the grass samples to estimate the ash content, the Nitrogen content with the Kjeldahl method, and the metabolizable energy (ME) through 96 h in vitro digestibility using standard methods (Volden & Nielsen. 2011).

2.2.2 Soil moisture

In 2021, data concerning soil moisture at the reference plot and under the agrivoltaic system were available only for part of the season due to sensors' failure during a thunderstorm that occurred at the end of July. Soil moisture sensors Campbell Scientific CS655 were installed at 10 cm depth in groups A, B, C, and R. In 2022, the soil moisture campaign was strengthened by installing four soil moisture sensors Truebner SMT50 at group R (3 moisture sensors were installed at 10 cm depth, while one soil moisture sensor was installed at 20 cm depth). Four soil moisture sensors Truebner SMT50 with a layout like group R were installed in groups B and C.

2.2.3 Leaf area index

The leaf area index (LAI) is one of the crops' morphological traits mainly influenced by shading conditions (Potenza et al., 2022). LAI measurements were carried out in 2022 with a SunScan Canopy Analysis System - SS1, to study the crop adaption mechanisms under shading conditions. Five measurements for groups A-C were performed, with five replicates of each measurement.

2.3 Integrated modelling and optimization

The model developed by Campana et al. (2021, 2022) has been employed in this study to simulate the effects of shadings on crop yield. The model has at its core the shading model that calculates both shadings on the ground and PV modules. The shadings on the ground are used as a starting point to calculate the total photosynthetically active radiation (PAR) and diffuse PAR reaching the crop. The computation of shading is also a starting point for calculating other microclimatic variables, such as ground temperature, evapotranspiration, and soil moisture distribution. A conceptual diagram of the integrated model is presented in Figure 11.

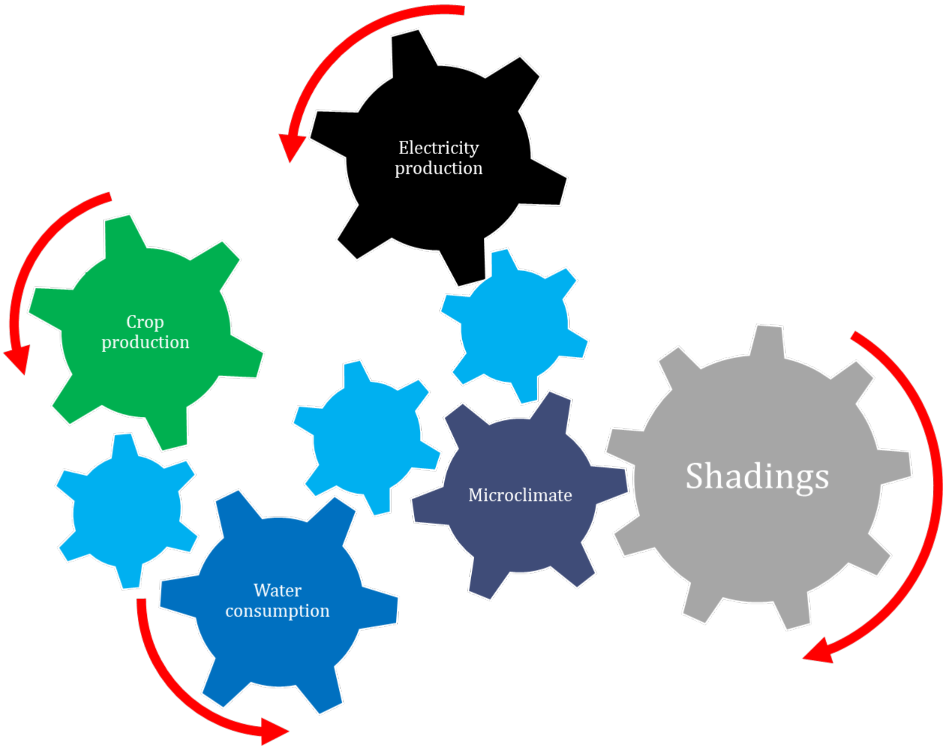

Figure 11: Concept of the integrated model for APV simulations.

Since the sub-model for energy performances has been cross-validated in Campana et al. (2021) with commercial software and given that other parallel studies are investigating the energy aspects of the agrivoltaic system and validation of the energy sub-model with actual measurements (Ma Lu et al., 2023; Zainali et al., 2023), this study will only focus on the crop response to shading. The methodology applied is the following: 1) the crop model parameters for ley grass have been retrieved from crop databases such as those available in EPIC (Williams, 1989) and literature. Some of the key crop parameters are summarized in Table 3; 2) the crop model has calibrated with crop yield measurements from the reference area; 3) the calibrated model has been then fed with the microclimatic conditions of the agrivoltaic system with a similar approach as in Campana et al. (2022) to simulate the effect of the shading and microclimate produced by shadings on the crop yield; 4) crop adaption measurements such as the leaf area index development under shading conditions have been fed into the model to simulate the effects of shadings and microclimate on the crop yield as well as the effects of shadings on the crop morphogenesis. The model calibration has been performed by minimizing the Root Mean Square Error (RMSE) between measured (y_m [t/ha]) and simulated (y_s [t/ha]) crop yield in open-field conditions at each cut with an approach like Campana et al. (2022). The optimization function is the following:

$$\min_x f(x), \qquad f(x) = RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{s,i} - y_{m,i})^2}, \tag{1}$$

where, n is the number of cuts, $y_{s,i}$ is the simulated yield for the i-th cut, and $y_{m,i}$ is the measured yield for the i-th cut. The optimization model uses as algorithm a variant of Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Deb et al., 2000) available in the Matlab® Global Optimization Toolbox. The decisional variables x of the optimization model are the key parameters defining the biomass production and LAI curve development. Those parameters and their corresponding lower and upper boundaries are summarized in Table .

Table 3: Ley grass crop parameters for model initialization.

Parameter	Value	Comment/Reference
Harvest index	0.7	Schils et al. (2013)
Biomass–energy ratio ((kg/ha)/(MJ/m^2))	24	Derived from Schils et al. (2013)
Base temperature (°C)	3	Derived from Kiniry et al. (1995)
Optimal temperature (°C)	20	Derived from Kiniry et al. (1995)
Maximum LAI (m^2/m^2)	5	Derived from Schils et al. (2013)
Water stress-yield factor	0.01	Derived from Williams et al. (1989)
LAI declining factor	1.5	Derived from Kiniry et al. (1995)
Fraction of growing season when leaf area declines	0.85	Derived from Kiniry et al. (1995)
First point on optimal leaf area development curve	40	Derived from Kiniry et al. (1995)
First point on optimal leaf area development curve	70	Derived from Kiniry et al. (1995)
Fraction of root weight at maturity	0.2	Derived from Williams et al. (1989)

Table 4: Lower and upper boundaries for the crop model calibration

Parameter	Value	Comment/Reference
Harvest index	0.7±25%	Assumption derived from Schils et al. (2013)
Biomass–energy ratio ((kg/ha)/(MJ/m^2))	10-40	Derived from Schils et al. (2013)
Base temperature (°C)	0-4	Derived from Kiniry et al. (1995) and Williams et al. (1989)
Optimal temperature (°C)	15-25	Derived from Kiniry et al. (1995) and Williams et al. (1989)
Maximum LAI (m^2/m^2)	4-6	Schils et al. (2013)
LAI declining factor	1-2	Derived from Kiniry et al. (1995)
First point on optimal leaf area development curve	35-50	Derived from Kiniry et al. (1995)
Second point on optimal leaf area development curve	60-90	Derived from Kiniry et al. (1995)

As pointed out by Schils et al. (2013), the biomass–energy ratio ((kg/ha)/(MJ/m^2)) is relatively stable during the crop growing season but might decrease in the last stage of the growth. Thus, a more advanced optimization is run, adding a dedicated biomass–energy ratio for the last cut of the ley grass as a further decisional variable.

2.4 Economic analysis

In APV systems, several business models can exist since several actors can provide different functions, such as the provision of the land for the installation of the system, agricultural management, agrivoltaic system installation, and PV system operation (Gorjian & Campana, 2022; Trommsdorff et al., 2022). To tackle this multitude of business models and the related economic aspects, we have created a flexible MS-Excel tool that can be adapted to different actors to analyse the profitability of APV systems. It can be found in the Supplementary Material.

In the economic analysis, we have analysed a case where the landowner owns a commercial-scale APV system built on 0.2 ha. For the APV system, we have also anlysed the case the landowner leases the land to a third-party company. We have assumed a permanent crop and a cropping system for the agricultural part of the APV system. In the first, the APV system is combined with permanent ley grass, while in the second, it is combined with a conventional crop rotation as follows: barley, ley grass, ley grass, winter rape seed, winter wheat, winter wheat (Tidåker et al., 2016). The annual profit given by the selected crops for a medium to high-yield configuration has been retrieved from Rosenqvist (2019). EU direct support for farmers accounts for about 150 €/ha/year plus 15.4 €/ha/year for the first 150 ha that receive support (Swedish Board of Agriculture, 2023b). We have investigated and compared three scenarios, i.e., APV, CGMPV, and only agriculture. A case is added in which the landowner is not the actual owner of the APV system but leases the land to a third-party company. It must be noted that for the APV scenario, although agriculture can coexist with electricity production, farmers currently cannot receive EU direct support (Scania County Administrative Board, 2023). The tool calculates the net present value (NPV) and the Discounted Payback Period (DPBP) of the project defined as follows:

$$\mathrm{NPV} = -\mathrm{ICC} + \sum_{\mathrm{y}=1}^{\mathrm{n}} \frac{\mathrm{CF_y}}{(1+\mathrm{d})^{\mathrm{y}}}, \tag{2}$$

$$DPBP = Y_{DCCF>0} - 1 + \frac{\left|DCCF_{t=(Y_{DCCF>0}-1)}\right|}{DCF_{t=(YD_{CCF>0})}} \tag{3}$$

where, ICC is the initial capital cost (Euro [€]), $\mathrm{CF_y}$ is the cash flow in the y-th year (€), and d is the real discount rate (%), $Y_{DCCF>0}$ is the first year at which the discounted cumulative cash flow (DCCF [€]) is greater than 0, and DCF is the discounted cash flow (€). The ICC is calculated as a product of the installed capacity times the specific cost (i.e., €/kW$_p$). The revenues generated by the system are given by the profit of the agricultural production (i.e., annual profit [€/ha] and influence of PV modules on crop yield/annual profit [%]) and electricity sale or self-consumption. The costs of the system are associated with operation and maintenance, replacements, and decommissioning. The operation and maintenance costs are assumed to equal 1% of the ICC occurring each year (value derived from Lindahl et al. [2022]). We have assumed inverter replacements in the 17th year, costing 55 €/kW$_p$ (Lindahl et al., 2022). Decommissioning costs, depreciation, and salvage values were omitted in this study, as in Lindahl et al. (2021). The main technical and economic input data for the reference CGMPV system and APV system can be found in Table 5. For converting between Swedish Krona (SEK) and Euro (EUR [€]), we have assumed the average exchange rate in 2022 was 0.0941 EUR/SEK (Exchange Rates UK, 2023).

Table 5. Summary of the technical and economic input data.

	Reference CGMPV	APV	Comment/Reference
Total ground area (m²)	2,000	2,000	Assumed.
PV system capacity (kW_p)	150	85	For the reference CGMPV system, we have assumed that 11.8 kW_p cover a net area of 8.6m*18.2m. For the APV system, we have assumed that 22.8 kW_p cover a net area of 30m*17.9m. Those geometries refer to the net area of the systems described in Table 1.
Area loss due to supporting structure (%)	35	10	For the reference CGMPV system, we have assumed that 11.8 kW_p cover a net area of 8.6m*18.2 m. The PV modules of one row covers an area of 8.6m*3.1m. An extra 1 m can be added as a clearance distance for agricultural machineries. For the APV system, a 10% loss due to the structure was assumed as in in Campana et al. (2021).
Electricity production ($kWh/kW_p/1^{st}$ year)	1,116	1,067	Based on simulations of the PV system with bifacial modules with OptiCE.
System degradation rate (%/year)	0.2	0.2	Lindahl et al. (2022)
PV system specific cost (€/kW_p)	880	940	For the reference CGMPV, 880 €/kW_p refers to 9,380 SEK/kW_p that was the average price for commercial projects in the order of 100-255 kW_p in Lindahl et al. (2022). For the APV system, 940 €/kW_p refer to 10,000 SEK/kW_p. Those values were used based on quotations for vertically mounted APV systems projects.
Operation and maintenance (% system cost/year)	1	1	Derived from Lindahl et al. (2022)
Invert replacement costs (€/kW_p)	55	55	55 €/kW_p refers to 582 SEK/kW_p occurring at the 17^{th} year as assumed in Lindahl et al. (2022).
Other replacement costs (€/kW_p)	0	0	This value can be changed depending on other planned equipment replacement.
Rent (€ha/year)	0	0	This value can be changed depending on the actor and

			business model adopted. For instance, a PV investor should consider land rental cost.
Other costs (€/kWh, or €/year, or €/ha/year)	0	0	This value can be changed depending on the actor and business model adopted. For instance, a PV investor should consider the crop management costs.
Decommissioning costs (% system cost)	0	0	Lindahl et al. (2021)
Electricity selling price (€/kWh)	0.07	0.07	0.07 €/kWh refers to 0.76 SEK/kWh that was the average electricity price during the period 2020-2022 in area SE3 (Nord Pool, 2023).
Electricity buying price (€/kWh)	0	0	We assumed 0% self-consumption while comparing the APV system with the CGMPV system. In Table 6 and section 3.5, we have investigated the effect of the self-consumption on the APV system built on 0.2 ha land.
Self-consumption (%/year)	0	0	This value can be changed depending on the actor and business model adopted, and simulations or measured data.
Other revenues (€/kWh, or €/year, or €/ha/year)	0	0	This value can be changed depending on the actor and business model adopted.
Salvage value (% system cost)	0	0	Lindahl et al. (2022)
Real discount rate (%)	1.4	1.4	Lindahl et al. (2022)
Annual profit ley grass (€/ha)	-	−151	−151 €/ha refers to −1,608 SEK/ha from Rosenqvist (2019). It refers to values classified as “Medium to high yield”.
Annual profit barley (€/ha)	-	95	95 €/ha refers to 1,012 SEK/ha from Rosenqvist (2019). It refers to values classified as “Medium to high yield”.
Annual profit winter rape seed (€/ha)	-	262	262 €/ha refers to 2,791 SEK/ha from Rosenqvist (2019). It refers to values classified as “Medium to high yield”.
Annual profit winter wheat (€/ha)	-	371	371 €/ha refers to 3,948 SEK/ha from Rosenqvist (2019). It refers to values classified as “Medium to high yield”.

EU direct support for farmers accounts for about (€/ha/year)	-	150 + 15.4	Swedish Board of Agriculture (2023b).
Land lease (€/ha/year)		850	Dagens Industry (2021).

Concerning the crop yield reduction under shading conditions, we have assumed no reduction for the permanent ley grass, given the results in Section 3.1.1. Nevertheless, the actual crop yield under the APV system should be reduced by 10% due to the non-harvestable area close to the PV modules supporting structures. For the crop rotation, we have assumed a reduction of about 25%, given the simulation results in Campana et al. (2021), Campana et al. (2022), and Zainali et al. (2023) concerning PAR reduction under the APV system.

Given the uncertainty of several parameters, a Monte Carlo Analysis is carried out for the APV system built on a 0.2 ha land and owned by the landowner by varying the sensitive parameters listed in Table 6, assuming a Normal (Gaussian) Distribution. To further analyse the impact of the sensitive parameter on the NPV, the Pearson Correlation Coefficient (PCC) is calculated. While calculating the PCC, to understand the effect of the agronomic part on the NPV of the project, we have assumed the 30-year average crop profit for the crop rotation.

Table 6: Sensitive parameters of the Monte Carlo Analysis.

Sensitive parameter	Mean value	Standard Deviation	Comment
Electricity production (kWh/kW$_p$/1st year)	1,067	105	The standard deviation is assumed to be 10% of the mean value
PV system specific cost (€/kW$_p$)	940	188	The standard deviation is assumed to be 20% of the mean value
Operation and maintenance (% system cost/year)	1	0.2	The standard deviation is assumed to be 20% of the mean value
Inverter replacement (€/kW$_p$)	55	11	The standard deviation is assumed to be 20% of the mean value
Electricity selling price (€/kWh)	0.071	0.014	The standard deviation is assumed to be 20% of the mean value
Electricity buying price (€/kWh)	0.14	0.028	The standard deviation is assumed to be 20% of the mean value
Self-consumption (%/year)	20	10	The mean value is assumed. The standard deviation is assumed to be 50% of the mean value
Discount rate (%)	1.4	0.28	The mean value is from Lindahl et al. (2022). The standard deviation is assumed to be 20% of the mean value
Crop profit (€/ha/year)	133	26.6	The standard deviation is assumed to be 20% of the mean value
Crop yield reduction factor due to shadings (%)	25	5	The standard deviation is assumed to be 20% of the mean value

3 Results and discussions

3.1 Crop experiments

3.1.1 Crop yield

In the 2021 season, the harvesting dates were the 1st June 2021 (first cut), 20th July 2021 (second cut), and 17th September 2021 (third cut). In May, before the first cut, the precipitation was 119 mm. Between the first and second cuts, the precipitation was 71 mm (48 days), while between the second and third cuts, it was 201 mm (59 days) (SMHI, 2023). According to SMHI data for Västerås, as presented in Table 7, May and August 2021 had more than 50% more precipitation than normal, June was dryer, and July was normal (SMHI, 2023). In the 2022 season, the harvesting dates were 3rd June 2022 (first cut), 14th July 2022 (second cut), and 26th August 2022 (third cut). In May, before the first cut, the precipitation was 69 mm. Between the first and second cuts, the precipitation was 87 mm (34 days), while between the second and third cuts, 81 mm were measured (20 days) (SMHI, 2023). In 2022, May and August had more rain than the reference period (1990-2010), while June and July had lower precipitation than the reference period, about a 45% and 49% decrease, respectively.

Table 7: Precipitation for the period May-August 2021 and 2022 compared to the reference period 1990-2010 (SMHI, 2023).

Month	2021	2022	Reference period 1990-2020
May	119	60	44
June	43	38	69
July	89	39	77
August	109	99	71

For the crop yield analysis, the focus is on the total dry matter (DM) yield per hectare. The yield for the individual cuts varies depending on the yearly variation in temperature, precipitation, and other local climatic factors. Therefore, the total yearly crop yield is a better parameter to analyse since there is less variation between years. The crop yield results per cut are provided in the Appendix. Given the crop samples in Figures 8 and 9, it must be noted that it is only possible to directly compare values for 2021 with 2022 for groups D and E, given the increased number of sampling plots in 2022 for groups A, B, C, and R. The total crop yield results from the samples for 2021 and 2022 are presented in Table 8. It must be noted that the actual crop yield of the field in kg DM/ha should consider the losses due to the unused land. Those losses for the APV system are about 10%, as described by Campana et al. (2021), if no specific agricultural management practices are applied (i.e., adopting special agricultural machinery to harvest the grass underneath the PV modules supporting structure or animal grazing). The losses due to unused land in the CGMPV system are about 35% as calculated in Table 5.

The crop yield in 2021 was higher but showed a wider variation between the groups. In 2022, the crop yield was lower, but the variation was also lower. The statistical analyses showed a significant difference in total crop yield between Group R and Group D in 2021. For 2022, statistical analyses showed no significant differences between the groups. Similar results were achieved in Kannenberg et al. (2023) who showed that although light availability in a managed semiarid grassland in Colorado, USA, was reduced by 38%, the aboveground net primary productivity was reduced by only 6–7%.

The weather conditions might explain the higher yield in 2021, with abundant rain in May, which gives good conditions even for an average or dry June and July. The farm manager also indicates that the overall weather conditions in 2021 were excellent by stating, "*This is my best year so far*" (Andersson, 2021). Another factor is that the third cut in 2021 was performed ten days later than in 2022, giving less growth time. A further factor affecting the variation across the groups could have been the lack of nutrients in 2021 since adding fertiliser in 2022 reduces this variation.

One of the limitations of this study is connected to the wide variety of species across groups, as shown in the botanical analyses presented in Figure 10. The differences in botanical composition among the groups make analysing the single effect of shading on crop production more challenging. Nevertheless, installing an APV system on an established ley grass field represents a likely actual situation in the APV sector in Sweden and, thus, a case worth investigating. After two years of experiments on an established ley grass field, in spring 2023, our research group started investigating a typical Swedish crop rotation.

From a LER perspective, assuming the simulated electricity production, the net area provided in Table 5, and the average crop yield in Table 8, the APV system showed a LER of 1.27 in 2021 and 1.39 in 2023. The LER values justify implementing the APV system from a land-use efficiency perspective. A summary of the LER calculation is provided in Table 9.

Table 8: Total DM yield in 2021 and 2022 and Statistical analyses for the crop yield using the Tukey Pairwise Comparisons (see Figures 8 and 9 for the position of the groups). The crop yield refers to the samples. The actual crop yield in kg DM/ha should be reduced by 10% for the APV and by 35% for the CGMPV due to the non-harvestable area close to the PV modules supporting structures.

	2021			2022		
Area	Number of samples	Mean kg DM/ha	Grouping*	Number of samples	Mean kg DM/ha	Grouping*
Group A	5	6,348	ab	10	5,044	a
Group B	5	6,660	ab	10	5,454	a
Group C	5	6,265	ab	10	4,634	a
Group D	5	4,746	b	5	5,444	a
Group E	5	6,119	ab	5	5,668	a
Group R	5	7,894	a	10	5,326	a

*Grouping Information Using the Tukey Method and 95% Confidence. Means that do not share a letter are significantly different.

Table 9: LER calculations

Contribution of PV electricity production to LER				
	Electricity production (kWh/kW$_p$/1st year)	**Installed capacity (kW$_p$)**	**Net area (m^2)**	**Specific production per net area (kWh/m^2/1st year)**
CGMPV	1,116	11.8	157	84
APV	1,067	22.8	537	45
Contribution of PV to LER		0.54		
Contribution of crop production to LER				
	Average yield in 2021 (kg DM/ha)		**Average yield in 2022 (kg DM/ha)**	
APV	5,782*		4,540*	
Reference area	7,894		5,326	
Contribution of crop production to LER	0.73		0.85	
LER				
Year	2021		2022	
LER	1.27		1.39	

*Value reduced by 10% due to land loss for the supporting structure of the PV modules.

3.1.2 Crop metabolized energy content

The metabolized energy content analyses show typical values for this kind of crop (Spörndly, 2003) as summarized in Table 10, and there is a slight variation within the groups of about ±1-2%. A higher value indicates a crop with more carbohydrates produced in photosynthesis.

As in the study of total yield, Group R is used as a reference for energy content. Few samples are significantly different using the Tukey post hoc method. Studying the six cuts, Groups A, C, and D are statistically different from Group R in one comparison, and Group E differs from Group R in two comparisons. When just studying the values in Table 10, it is notable that 21 out of 30 samples´ mean values for Groups A-E show higher metabolized energy contents than Group R for the same cut each year.

Table 10: Statistical analyses for the metabolized energy (MJ/kg DM) for first, second, and third cut in 2021 and 2022 including the statistical analyses for the crop yield using the Tukey Pairwise Comparisons (see Figures 8 and 9 for the position of the groups). Values in bold refer to mean values for the groups A-E higher than Group R.

Area	Number of samples	Metabolized energy 2021		Number of samples	Metabolized energy 2022	
		Mean MJ/kg DN	Grouping*		Mean MJ/kg DM	Grouping*
			First cut			
Group A	5	**10.79**	a	10	**10.47**	c
Group B	5	**10.78**	a	10	**10.53**	bc
Group C	5	**10.69**	ab	10	**10.72**	ab
Group D	5	**10.52**	ab	5	**10.95**	a
Group E	5	**10.53**	ab	5	**10.62**	bc
Group R	5	10.38	b	10	10.44	c
			Second cut			
Group A	5	8.97	bc	10	**10.22**	ab
Group B	5	**9.73**	a	10	**10.58**	a
Group C	5	9.24	abc	10	**10.30**	ab
Group D	5	9.00	bc	5	9.98	b
Group E	5	8.68	c	5	9.87	b
Group R	5	9.48	ab	10	10.17	b
			Third cut			
Group A	5	**10.70**	ab	10	**10.25**	ab
Group B	5	**10.66**	ab	10	10.15	b
Group C	5	**10.79**	a	10	**10.42**	ab
Group D	5	**10.73**	ab	5	**10.68**	a
Group E	5	10.38	b	5	10.16	ab
Group R	5	10.48	ab	10	10.22	ab

*Grouping Information Using the Tukey Method and 95% Confidence. Means that do not share a letter are significantly different.

3.1.3 Crop crude protein

The analyses of the crude protein show average, typical values for this kind of crop (Spörndly, 2003), but there is a significant variation between the plots, especially in the third cut, as provided in Table 11. A high value is an indicator that plants have enough nutrients.

As for energy, the influence of the PV modules is studied using Group R as a reference. Using the Tukey post hoc method, more differences are found for the crude protein. Studying the six cuts, Group A, C and D are different from Group R in four cuts, and Group B is different from Group R in one cut. When just studying the values in Table 11 it is notable that 25 out of 30 samples show higher samples´ mean values for crude protein than Group R for the same cut each year. The available Nitrogen is a significant factor in the high crude protein content. If there is high legume content, it also adds more protein to the plant. Another factor is the total yield, where a high yield can reduce protein content.

Group E shows a lower content in most of the samples. Looking at the botanic composition in Figure 10, it is not evident that this can be the explanation. Nevertheless, since the crop was not divided into species, it is not easy to draw detailed conclusions. Another explanation can be the availability of nutrients. Nevertheless, the soil in these plots was not analysed.

Table 11: Statistical analyses for the crude protein (g/kg DM) for the first, second, and third cut in 2021 and 2022 including statistical analyses for the crop yield using the Tukey Pairwise Comparisons (see Figures 8 and 9 for the position of the groups). Values in bold refer to mean values for the groups A-E higher than Group R.

Area	Number of samples	Crude protein 2021 Mean g/kg DM	Crude protein 2021 Grouping	Number of samples	Crude protein 2022 Mean g/kg DM	Crude protein 2022 Grouping
			First cut			
Group A	5	**129.1**	ab	10	**122.0**	a
Group B	5	**125.6**	ab	10	**101.5**	b
Group C	5	**142.8**	a	10	**124.9**	a
Group D	5	**131.6**	ab	5	**137.9**	a
Group E	5	94.8	c	5	75.6	c
Group R	5	118.3	b	10	82.6	c
			Second cut			
Group A	5	**107.0**	bc	10	**107.1**	ab
Group B	5	**115.5**	abc	10	**94.9**	bc
Group C	5	**118.6**	ab	10	**114.4**	a
Group D	5	**134.0**	a	5	**115.9**	a
Group E	5	93.4	c	5	88.6	c
Group R	5	105.6	bc	10	94.4	bc
			Third cut			
Group A	5	**178.1**	a	/	**130.1**	a
Group B	5	**150.2**	bc	10	**120.9**	ab
Group C	5	**167.7**	ab	10	**131.3**	a
Group D	5	**171.5**	ab	5	**135.4**	a
Group E	5	132.0	c	5	**110.0**	b
Group R	5	139.4	c	10	109.7	b

*Grouping Information Using the Tukey Method and 95% Confidence. Means that do not share a letter are significantly different.

3.2 Soil moisture

The soil moisture data measured in 2022 are depicted in Figure 12. The measurements are plotted as a scatter plot due to the lack of a complete time series during the agricultural season. The soil moisture sensors at 10 cm depth installed in the centre of the APV system rows showed higher soil moisture values than the reference ground control plot. Higher soil moisture values were measured from the soil moisture sensors in Group C close to the PV modules and subjected to higher shading than those in Group B. Interestingly, for the measurements performed at 20 cm depth, lower soil moisture data were recorded in Groups B and C as compared to Group R at the beginning of the measurement campaign in May 2022. Nevertheless, higher soil moisture values were measured in Groups B and C compared to

Group R towards the end of August 2022. This seasonal trend might be explained, but it still needs to be verified, that the APV system acts as a barrier for snow, leading to lower snow depth values within the APV rows than the reference open-field area and, thus, lower snow water equivalent. As shown in previous studies, such as by Hassanpour Adeh et al. (2018), Amaducci et al. (2018), and Wu et al. (2022), the shading produced by APV systems leads to higher soil moisture values and thus to preferable conditions for biomass growth. Due to the lack of an extensive soil moisture measurements campaign across different points and depths of the APV system and reference ground, we cannot accurately explain if the higher soil moisture under the APV system has affected crop yield and quality.

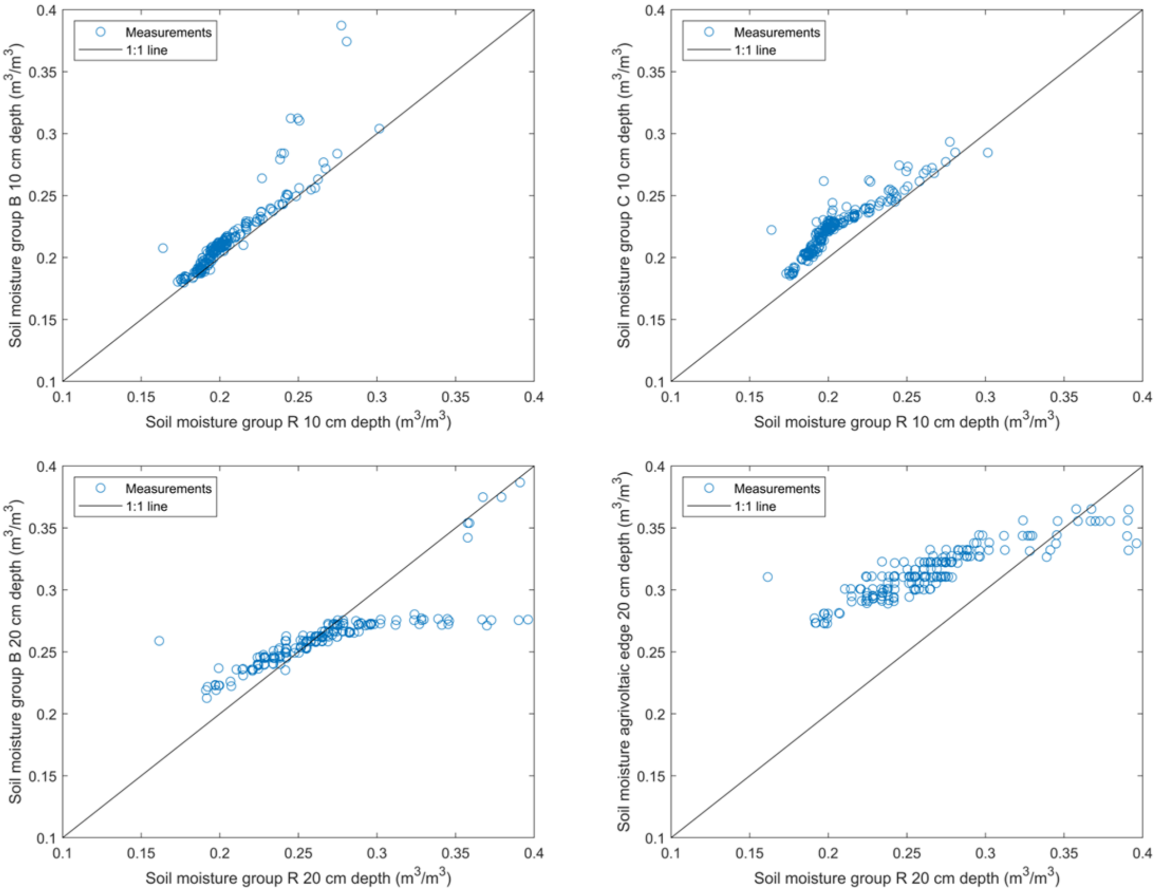

Figure 12: Soil moisture data comparison between group R and groups B and C at different depths in 2022.

3.3 Leaf area index

The results concerning the leaf area index are presented in Figures 13 and 14. The LAI measurements for groups A-C were carried out on the 23rd of June 2022, the 5th and the 28th of July, and the 12th and 25th of August 2022, with five replicates of each measurement.

Figure 13 shows the average trend of the LAI measurements in group R compared to the average LAI measurements under the APV system (i.e., groups A-C). In Figure 14, the measurements under the agrivoltaic system are split between Group B results in the middle of the agrivoltaic field and Groups A and C on the edges of the agrivoltaic field. On average, the LAI under the agrivoltaic field is 12% higher than Group R, with a peak of 24.2%. On average, the LAI shows higher values than Group R in Groups A and C, especially in Group B. The mechanism of increasing LAI under shading conditions is a common adaption measure investigated in several studies, such as in Marrou et al. (2013) for lettuce, in Weselek et al. (2021) for winter wheat, potatoes and grass-clover, and in Potenza et al. (2022) for soybean with similar conclusions.

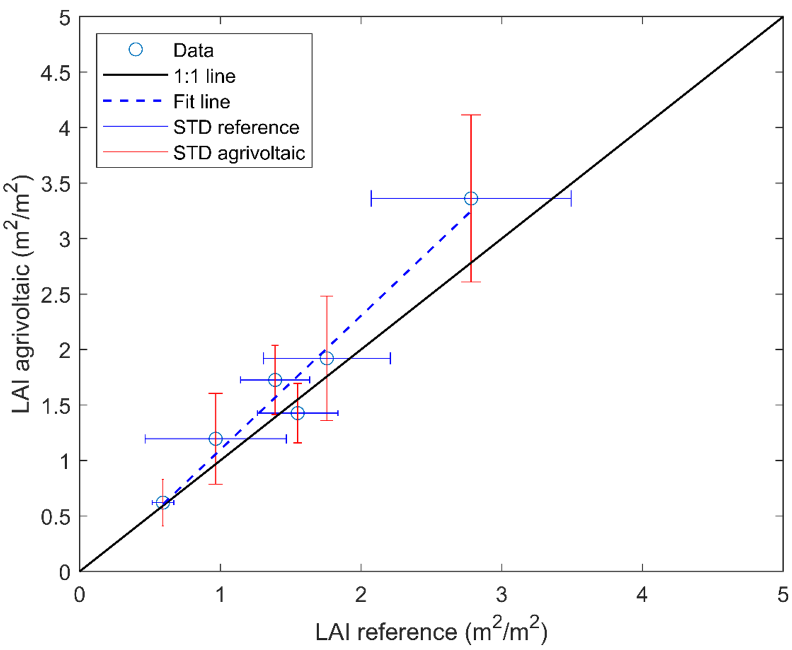

Figure 13: Leaf area index (LAI) measurements comparison between reference ground control (i.e., group R) and APV system (i.e., groups A-C) in 2022.

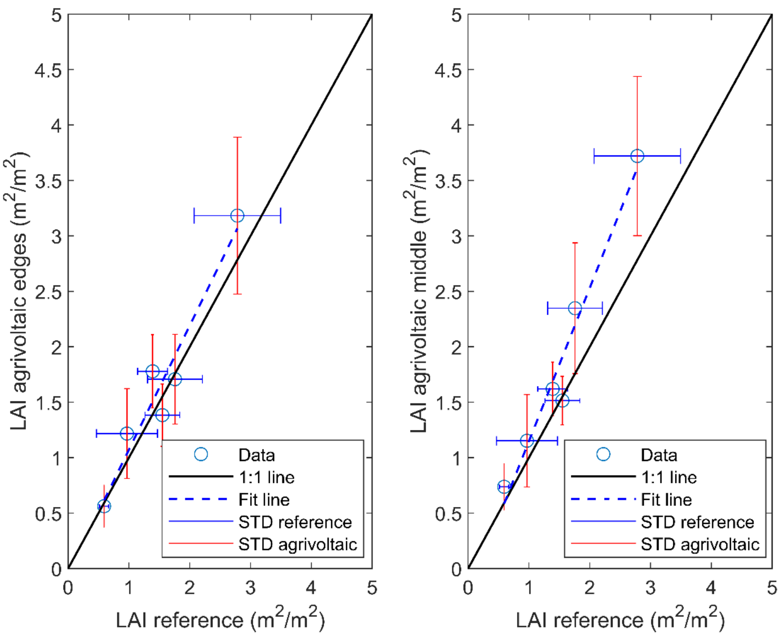

Figure 14: Leaf area index (LAI) measurements comparison between reference ground (i.e., group R) control and APV system (i.e., groups A and C [edges] and group B [middle]) in 2022.

3.4 Crop modelling validation

The crop model calibration and validation results are presented in Figure 15 for the reference area. In particular, the crop yield at different cuts and the total crop yield are reported for the crop yield measured, the crop yield simulated with literature values provided in Table 3, and crop yields after calibrating the model with the procedure described in Section 2.4. From Figure 15, using literature data for crop modelling leads to accurate seasonal crop yield assessment. However, the crop yield estimation across the different cuts shows significant differences from the actual measurements. The model calibration shows that there is a deviation of about 5% from the actual measurements on a seasonal basis, with the model tending to overestimate the seasonal crop yield. After model calibration, the modelling results show that the model can produce crop yield results that follow the actual trend of the measured crop yield across the three cuts. The most performing results are achieved using two different biomass–energy ratios, as highlighted in Schils et al. (2013), with high accuracy both on a single cut and the seasonal crop yield.

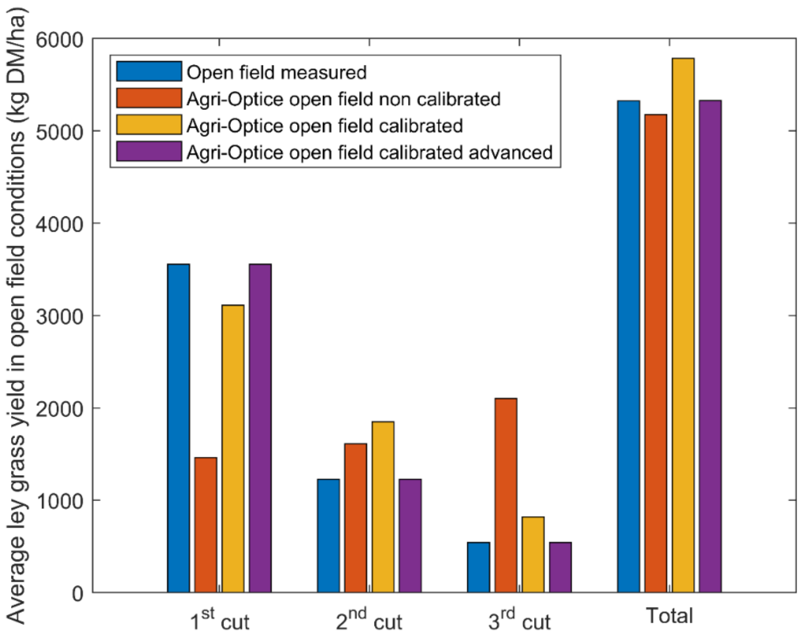

Figure 15: Average ley grass yield in 2022 in open-field conditions (i.e., group R) versus simulated yield using the integrated modelling platform Agri-OptiCE with literature data concerning crop parameters (i.e., Agri-OptiCE open field no calibrated), after calibration (i.e., Agri-OptiCE open field calibrated), and after an advanced calibration using two biomass–energy ratios for the first two and last cuts separately (i.e., Agri-OptiCE open field calibrated advanced).

The crop modelling results under the APV system for 2022 are summarised in Figure 16. The results show the comparison between the average yield under the APV system with the average yield simulated by Agri-OptiCE. The calibrated model in Figure 16 refers to the model calibrated with two biomass–energy ratios, as performed in Figure 15, while Agri-OptiCE calibrated + adaptation refers to the model calibrated in Figure 15 with a maximum LAI increase of 12% as measured in Section 3.3. From Figure 16, two main conclusions can be drawn. The first conclusion is that the calibrated model shows a difference of 15% compared to the actual measurements of the average crop yield under the APV system. Given the complexities of the modelling, it can still be considered a good result. Potenza et al. (2022) applied the model developed by Amdaucci et al. (20218) to simulate the effects of shading on the grain yield of soybean. They reported different normalised root mean square errors between predicted and observed yields ranging between 12.9% to 2.82% depending on different shading levels. They observed that the integrated modelling platform tended to underestimate the crop yield while the shading level increased.

As highlighted in Campana et al. (2021), the developed modelling platform can simulate the worst-case scenario for the impact of shadings on crop yield if no crop adaption measures are measured or available. Such modelling and results can be of extreme importance while predicting the crop yield under the APV systems for assessing the performance of future installations, for instance, at the design and permit stage. The second conclusion is that, as highlighted in Campana et al. (2021), supplying the model with adjusted input parameters that can further depict the adaption measures of crops under shading conditions can enhance the model's accuracy. Compared to the measured results, the model developed in this study underestimates the crop yield under shading conditions by about 5% compared to the actual average measured values. This result shows how important the availability of crop adaption measures is for accurately estimating crop yield under shading conditions. As pointed out in the literature review, the crop yield under APV systems and its percentage reduction compared to open-field conditions is one of the most crucial key performance indicators for APV systems. It is a target or design parameter in laws regulating APV systems. High accuracy in an integrated APV platform can significantly impact the APV system's design to meet policies and, thus, the cost-benefit analysis of the system.

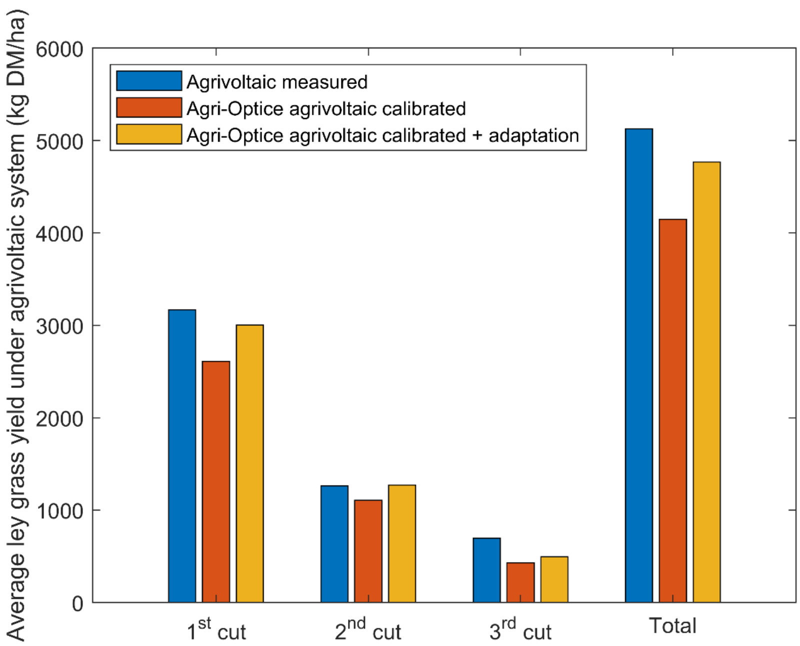

Figure 16: Average ley grass yield in 2022 under the APV system versus simulated yield using the integrated modelling platform Agri-OptiCE. Agri-OptiCE calibrated refers to the model calibrated using two biomass–energy ratios as in Figure 15, while Agri-OptiCE calibrated + adaptation refers to the model calibrated in Figure 15 where the LAI curve input parameters are updated with the percentage increase as measured in Section 3.3.

3.5 Economic perspective

The results of the economic analysis are summarized in Figure 17 in terms of discounted cumulative cash flow for the reference CGMPV system, for the APV system on permanent ley grass and combined with a traditional crop rotation, and for the APV system owned and managed by a third-party company for which the land is leased by the farmer. The cumulative cash flows of the permanent ley grass and for the crop rotation are also provided. The NPVs and DPBPs are summarized in Table 12.

The APV system shows a significantly lower NPV (i.e., the last value of the cumulative cash flow diagram) than the reference CGMPV system, i.e., 46.7 k€ for the system combined with permanent ley grass compared to 107 k€, respectively. This result is mainly due to lower electricity production and higher investment costs (see Table 5). The DPBP for the CGMPV system is 14.3 years versus 17.4 years for the APV system. Although the crop rotation shows better profit than permanent ley grass, the effect on the cumulative cash flows and NPV of the APV system is minimal (it must be noted that the cumulative cash flows of the permanent ley grass and crop rotation are multiplied by 10 in Figure 17 to allow an easier comparison with the CGMPV and APV cash flows). It can be noted that from a farmer's perspective, the area used for the installation of an APV system can lead to a 30-year profit of about 30 times (for the crop rotation) to more than 600 times (for the permanent ley grass) higher as compared to the agricultural production with EU farmer support, based on the input data in Table 5. Leasing the land leads to a NPV of 3.5 k€ that is 40 times higher compared to only permanent grass.

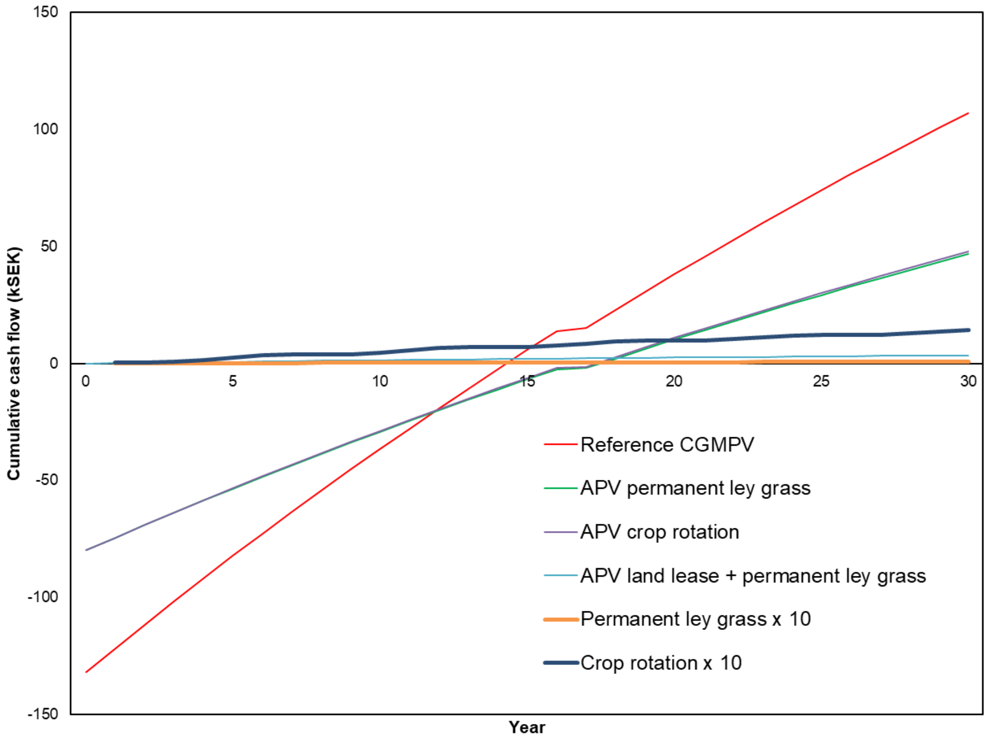

Figure 17: Cumulative cash flows for the reference CGMPV system, for the APV system with permanent ley grass and crop rotation, for the APV system owned and managed by a third-party company for which the land is leased by the farmer, and for the permanent ley grass and crop rotation. The cumulative cash flows of the permanent grass and crop rotation are multiplied by 10 for an easier visualization.

Table 12: NPVs and DPBPs of the investigated cases and scenarios.

Scenario/case	NPV (k€)*	DPBP (years)**
CGMPV system owned by the farmer	107	14.3
APV system owned by the farmer with permanent ley grass	46.7	17.4
APV system owned by the farmer with crop rotation	47.8	17.4
APV system owned by a third-party company with permanent ley grass	3.5	-
Permanent ley grass	0.1	-
Crop rotation	1.4	-

*The NPV considers both revenues from PV electricity and crop production.

**The DPBP refers only to the CGMPV or APV investment.

The results of the Monte Carlo Analysis for an APV system built on a 0.2 ha land owned by the farmer in terms of distribution of the NPV are depicted in Figure 18. At the same time, Table 13 summarizes the Pearson Correlation Coefficients for the sensitive parameters listed in Table 6.

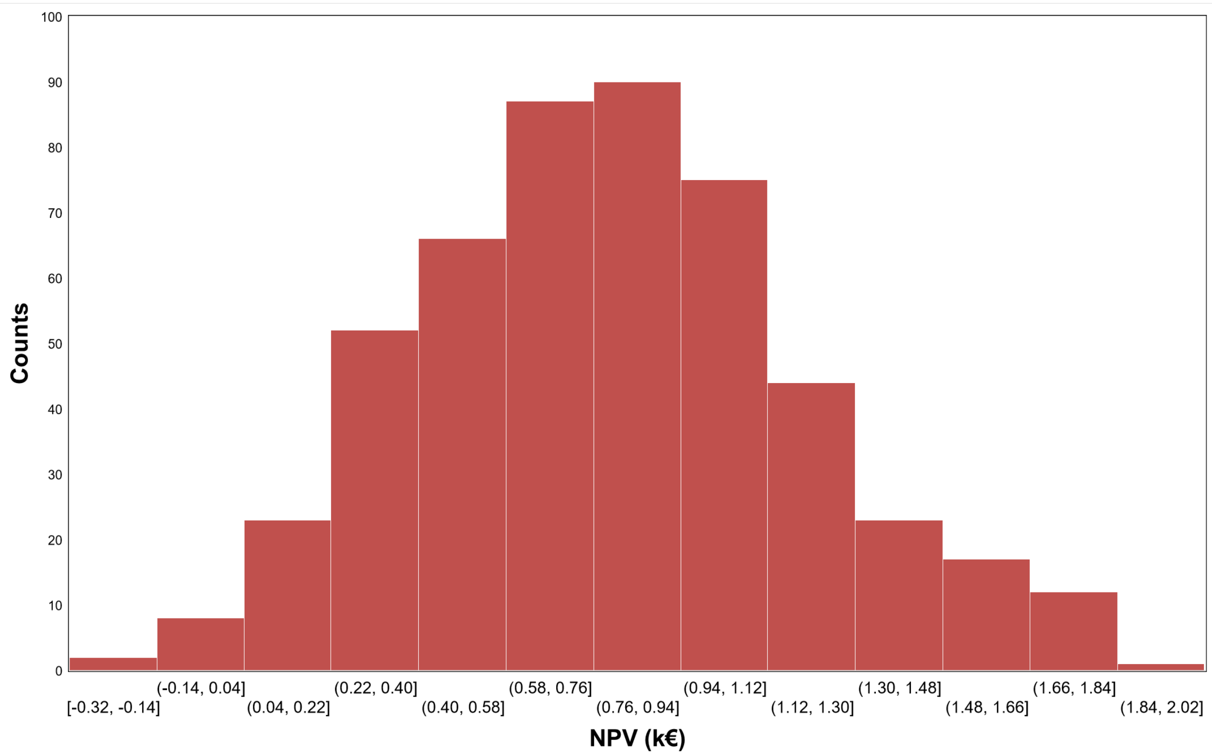

Figure 18: Net Present Value distribution.

Table 13: Pearson Correlation Coefficient for the investigated sensitive parameters.

Sensitive parameter	Pearson Correlation Coefficient
Electricity production ($kWh/kW_p/1^{st}$ year)	0.47
PV system specific cost (€/kW_p)	-0.58
Operation and maintenance (% system cost/year)	-0.18
Inverter replacement (€/kW_p)	-0.01
Electricity selling price (€/kWh)	0.63
Electricity buying price (€/kWh)	0.32
Self-consumption (%/year)	0.12
Discount rate (%)	0.01
Average crop profit (€/ha/year)	-0.05
Average crop/profit reduction due to shading (%)	-0.02

In the 500 runs of the Monte Carlo Analysis, 98% of the runs provided a positive NPV showing a significant tendency for the project to be profitable. The most sensitive parameters affecting the NPV of the project are the selling electricity price with a PCC of 0.63, followed by the PV system-specific costs (PCC=–0.58), the specific electricity production (PCC=0.47), and the electricity buying price (PCC=0.32). The average annual crop profit and the average crop/profit reduction due to shading for the crop rotation showed a nonsignificant influence on the NPV with the lowest PCCs.

Although APV systems represent an intelligent solution to avoid the conflict between land use for food production versus energy conversion and increase land use efficiency, specific laws should protect crop production. Indeed, despite APV systems allowing the coexistence of food and electricity production, by analysing the results of Figure 17 and Table 12, the high revenues for PV electricity might discourage the farmer from conducting agricultural activities, leading to situations like a CGMPV system where land is used only for PV production.

4 Conclusions

This study summarises some of the most important results of establishing Sweden's first agrivoltaic system. It summarises the results concerning the crop yield and properties observed under the APV system compared to open field conditions. The crop yield results are used to calibrate and validate an integrated modelling platform for APV system simulation and optimisation. The economic aspects of implementing APV systems in Sweden are also addressed by analysing the benefits produced compared to CGMPV systems and sole agriculture. The following conclusions can be drawn:

- The statistical analyses of the samples showed a significant difference in total crop yield only between Group R (i.e., reference area) and Group D (i.e., between the rows of the CGMPV system) in 2021. For 2022, statistical analyses of the samples showed no significant differences between the groups. The actual crop yield of the field in kg DM/ha should consider the losses due to the unused land. Those losses for the vertically mounted APV system are about 10%, as Campana et al. (2021) described. 21 out of 30 samples´ mean values show metabolised energy content values higher than Group R. 25 out of 30 samples´ mean values show crude protein values higher than Group R.
- The measurements of the LAI showed a tendency to increase under shading conditions. On average, the LAI under the agrivoltaic field is 12% higher than Group R, with a peak of 24.2%. On average, the LAI shows higher values than Group R in Groups A and C, especially in Group B.
- Higher soil moisture values were reported at different soil depths under the APV system compared to the reference area in the open-field. Nevertheless, due to the need for an extensive soil moisture measurements campaign across different points and depths of the APV system and reference area (Group R), we cannot accurately explain if the higher soil moisture under the APV system has affected crop yield and quality.
- The calibrated crop sub-model of the integrated modelling platform for APV systems showed a difference of 15% compared to the actual measurements of the average crop yield under the APV system. Supplying the model with adjusted input parameters that can further depict the adaption measures of crops under shading conditions can enhance the model's accuracy. Compared to the measured results, the model developed in this study underestimates the crop yield under shading conditions by about 5% compared to the actual average measured values.
- From a farmer's perspective, the area used for installing an APV system can lead to a 30-year profit of about 30 times (for the crop rotation) to more than 600 times (for the permanent grass) higher than the agricultural production, including EU farmer support.

- The Monte Carlo Analysis for a 0.2 ha APV system serving a farm showed that 98% of the runs provided a positive NPV showing a significant tendency for the project to be profitable. The most sensitive parameter affecting the NPV of the project is the selling electricity price, followed by the PV system specific investment costs, the specific electricity production, and the electricity buying price.

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Appendix

The chemical characteristics of the soil measured in 2021 and summarized in Table A1 shows normal values for soil with high clay content which has been in pasture for a long time. The only notable point is that assimilable phosphor in Sample group C is much lower than the other groups.

Table 1A: Soil characteristics measured in 2021.

Samples ID/Group	1-5/ A	6-10/ B	11-15/ C	26-30/ R
pH	5.8	6.0	6.0	5.9
Assimilable P (mg/100g)	6.3	12.2	3.7	8.1
Assimilable K (mg/100g)	24.2	32.4	21.0	27.3
Assimilable Mg (mg/100g)	45.1	49.6	40.4	46.1
K/Mg-AL	0.5	0.7	0.5	0.6
Assimilable Ca (mg/100g)	274	359	237	258
Assimilable Al (mg/100g)	27	26	28	25
Assimilable Fe (mg/100g)	45	45	47	37
K-HCl (mg/100g)	-	-	-	-
P-HCl (mg/100g)	-	-	-	-
Cu-HCl (mg/100g)	-	-	-	-
B (mg/kg)	-	-	-	-
Organic matter (%)	6.0	7.1	5.9	6.6
Clay (%)	31	31	31	30
Limo (%)	49	48	48	48
Sand (%)	14	14	15	15
Classification	loamy soil intermediate clay	loamy soil intermediate clay	moderately humus-rich intermediate clay	loamy soil intermediate clay
C-tot (g/kg)	35	40	34	38
N-tot (g/kg)	3.2	3.6	3.1	3.4
Ca-tot (g/kg)	5.4	6.6	5.5	5.7

The crop yield results per cuts and year are depicted in Figures A1-A6.

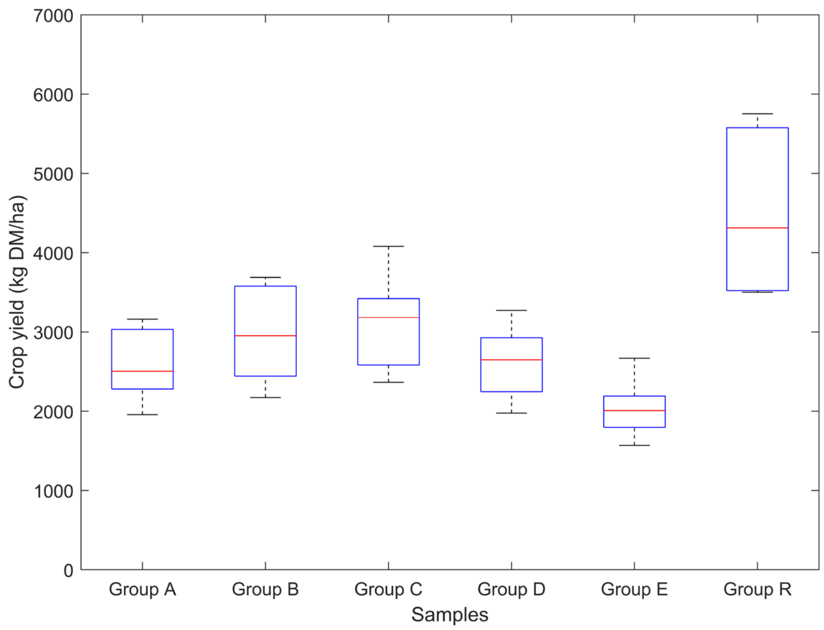

Figure A1: Crop yield results for the first cut in 2021.

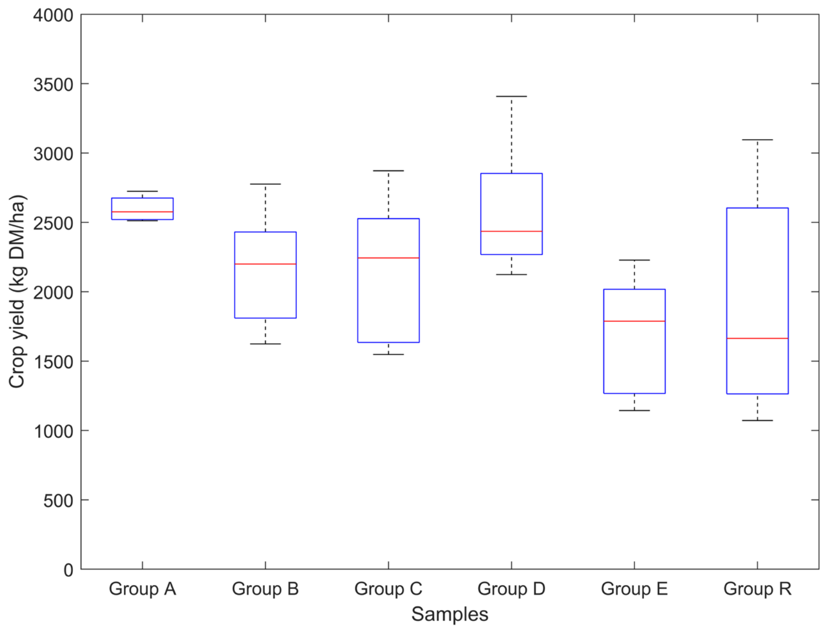

Figure A2: Crop yield results for the second cut in 2021.

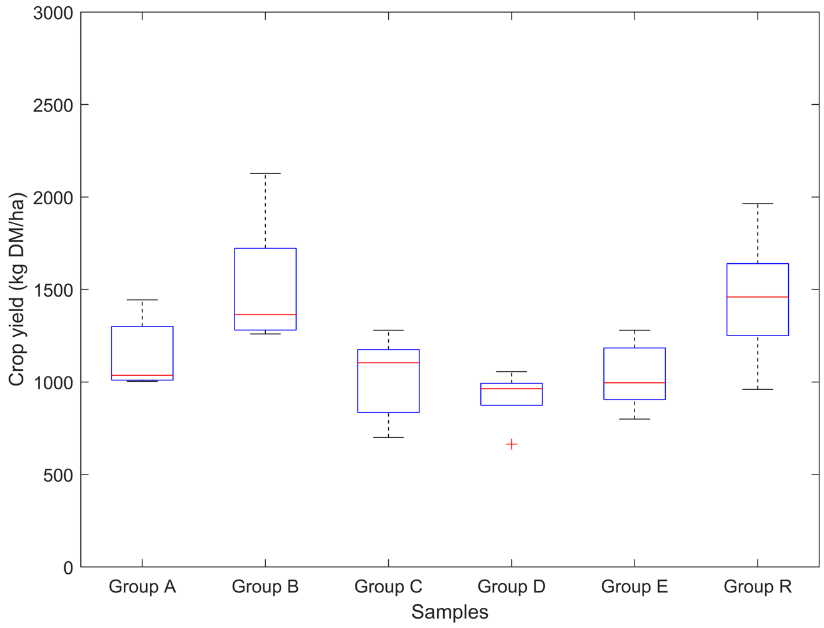

Figure A3: Crop yield results for the third cut in 2021.

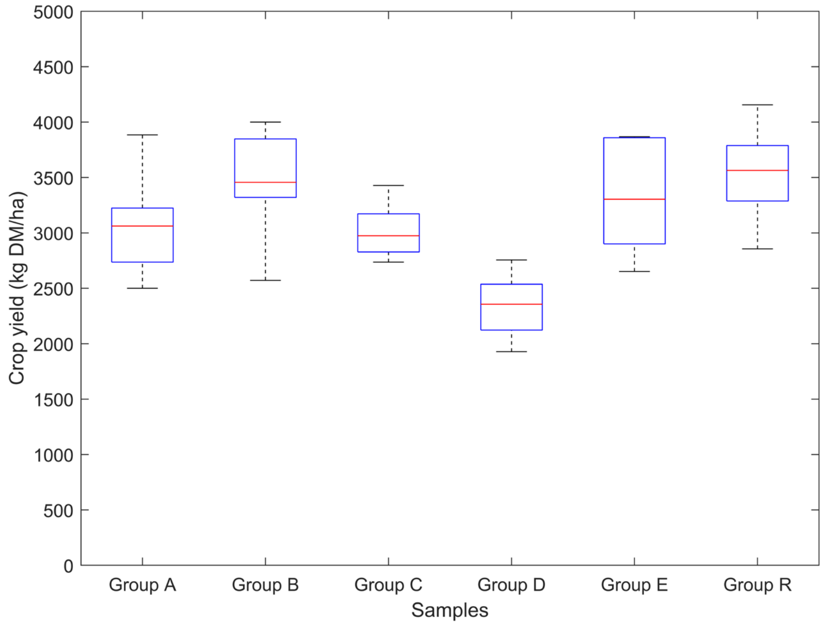

Figure A4: Crop yield results for the first cut in 2022.

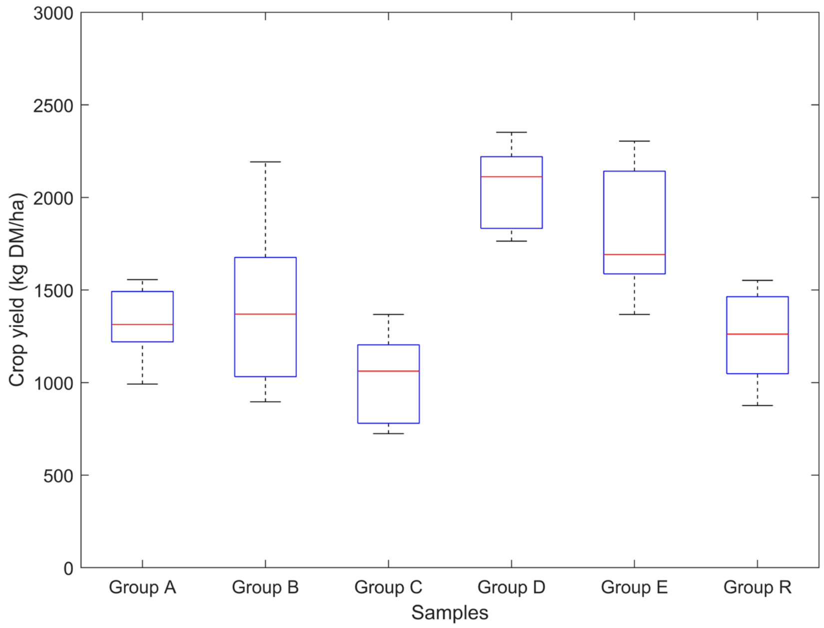

Figure A5: Crop yield results for the second cut in 2022.

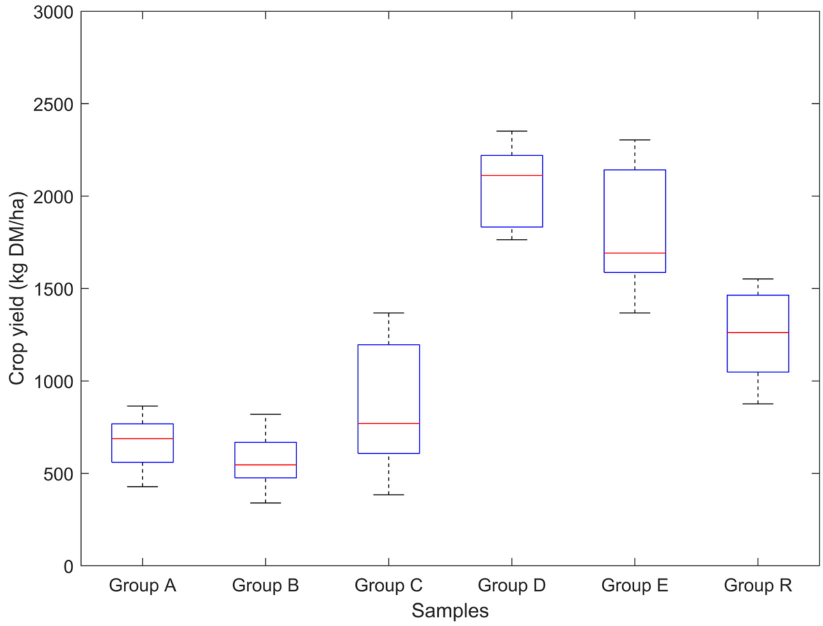

Figure A6: Crop yield results for the third cut in 2022.

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