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Simulation-Based Decision Support for Agrivoltaic Systems

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HIGHLIGHTS

- A simulation-based comparative assessment of APVs was proposed.
- A MCDA was used to rank APV alternatives and site-specific settings.
- Processing tomato demonstrated high adaptability to APV conditions.
- The overhead mono-axial APV with 6 m pitch ranked best across 5 Italian sites.
- The overhead bi-axial APV is the most flexible technology to suit agricultural activities.

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ABSTRACT

In this study, a framework to compare the performances of different agrivoltaic systems, or agriphotovoltaic systems, in a range of environments was developed and tested. A set of key performance indicators derived from simulations was combined in a multi criteria decision analysis approach. The agriphotovoltaic systems were then ranked based on their similarity to the optimal solution for a specific environment. Main key performance indicators were crop ratio, energy conversion per hectare, specific energy yield, water use efficiency, and initial capital expenditure. Four agriphotovoltaics, namely vertical, interspace mono-axial, overhead mono-axial, and an overhead bi-axial, with five pitch width for each agriphotovoltaic and cultivated with processing tomato, were modelled across five sites (from the North to the South of Italy) during a ten-year period. The different scenarios were simulated in Scilab, in which a radiation model and GECROS crop model were coded. Global irradiation distribution beneath modules, and thus crop yield, were more homogeneous in vertical and overhead mono-axial than in the other agriphotovoltaic. Processing tomato demonstrated high adaptability to shading and yield was marginally affected in most of the agriphotovoltaic system alternatives. Vertical and overhead mono-axial accounted for the least yield reduction when the same pitch is compared. Overall, overhead mono-axial APV with 6 m pitch ranked first in each site when a 0.7 crop ratio threshold was considered. This framework could serve as a valuable tool for assessing the performance of different solution of agriphotovoltaics systems and their compliance with national regulation, and economic and technical targets.

1. Introduction

The Paris Climate Agreement (Paris climate conference, COP21), formally ratified in 2016, set ambitious climate targets, aiming to limit the rise in global temperature to below 2 °C and pursuing efforts to limit it to 1.5 °C [1]. Despite the various environmental regulations issued up to that point, CO_2 concentration in the atmosphere continues to rise [2]. Therefore, the European Climate Law (Regulation (EU) 2021/1119) formally established the objective outlined in the European Green Deal, which aims for Europe to achieve climate neutrality by 2050 and reduce net greenhouse gas emissions by a minimum of 55% by 2030, compared to the levels recorded in 1990, becoming the first carbon-neutral continent. Achieving climate neutrality requires reducing greenhouse gas emissions and investing in environmentally friendly technologies. Consequently, global renewable energy installed capacity reached approximately 3.1 TW by 2021 [3]. Solar energy, in particular, witnessed significant growth, reaching a total installed capacity of 849 GW

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Nomenclature

APV	Agriphotovoltaics
AV	Agrivoltaics
AY_{APV}	Agricultural fresh yield per hectare in APV [MG ha^{-1}]
AY_{FL}	Agricultural fresh yield per hectare in full light [MG ha^{-1}]
BOS	Balance of system
Capex	Initial capital expenditure
CR	Crop Ratio [Mg ha^{-1} / Mg ha^{-1}]
ER	Energy ratio [MWh ha^{-1} / MWh ha^{-1}]
ETc	Crop evapotranspiration [m^3]
$ET_{c,APV}$	Crop evapotranspiration in APV condition [m^{-3} ha]
$ET_{c,FL}$	Crop evapotranspiration in full light condition [m^{-3} ha]
EY_{APV}	Annual energy converted by the APV [MWh ha^{-1}]
EY_{PV}	Annual energy converted by the reference PV system [MWh ha^{-1}]
FL	Full light
GCR	Ground Coverage Ratio
IMA-APV	Interspace mono-axial sun tracking agriphotovoltaic system
KPI	Key performance indicator
LCOE	Levelized Cost of Electricity
LER	Land Equivalent Ratio
MCA	Monte Carlo analysis
MCDA	Multi Criteria Decision Analysis
OBA-APV	Overhead bi-axial sun tracking agriphotovoltaic system
OMA-APV	Overhead mono-axial sun tracking agriphotovoltaic system
OPA	Ordinal Priority Approach
PAR	Photosynthetically Active Radiation
PV	Photovoltaic
RR	Radiation ratio [kWh m^{-2} year^{-1} / kWh m^{-2} year^{-1}]
SOM	Soil organic matter
STC	Standard test conditions
Vert-APV	Vertical agriphotovoltaic system
wc	Water content coefficient
W_p	Peak power [W]
WSO	Dry weight of storage organs
WSO_{APV}	Dry weight of storage organs in APV condition [g m^{-2}]
WSO_{FL}	Dry weight of storage organs in full light condition [g m^{-2}]
WUE	Water Use Efficiency
WUE_{APV}	Crop water use efficiency in APV scenario [Mg m^{-3}]
WUE_{FL}	Crop water use efficiency in full light condition [Mg m^{-3}]

[2]. Notably, the implementation of renewable energy plants in Europe is expected to steadily increase by 2050 [4]. Photovoltaics (PV) are capable of reducing CO_2 net emission compared to most of the traditional energy sources [5]. Additionally, PV plants can enable energy independence for small-scale owners. However, utility scale ground-mounted PV plants raise concerns about the potential loss of arable land for food production. Despite advancements in PV technology reduced land use per installed MW_p [6,7], large scale PV in Spain, still occupy a mean area of 2 ha per MW_p [8]. This inefficiency becomes especially apparent when considering EU targets. Achieving the Integrated National Energy and Climate Plan's (NECPs) ((EU) 2018/1999) goal would require up to 60 km^2 of land per year for PV, potentially exacerbating competition for land use [8,9] and unsettling the Land-Water-Energy nexus [10,11]. To address the land-use concerns associated with large-scale ground-mounted PV systems, the agrivoltaics (AV), first conceptualized by Goetzberger and Zastrow [12], has gained increasing attention. Agrivoltaics, or sun sharing, or agriphotovoltaics (APV) represents an integrated system that couples renewable energy production and crop cultivation on the same arable land with mutual interaction. Beside reducing carbon emissions, APV can potentially mitigate the impact of adverse climatic events on crops, including high temperature, excessive radiation, and drought, [13,14]. In recent years, various APV prototypes and commercial systems have emerged, featuring diverse PV module layouts, designs, heights, dimensions, and sun-tracking capabilities [15]. A key aspect that is highly influenced by the design of APV is the dynamic distribution of shading cast to the ground by PV modules. This affects microclimate beneath and between the modules, impacting factor as evapotranspiration, soil temperature, available radiation, crop growth, yield, and crop quality. Many studies have investigated the influence of APV on several key parameters such as:

- Photosynthetically active Radiation (PAR) distribution [16,17];
- Crop yield [15];
- Water Use Efficiency (WUE) [13,18];
- Land Equivalent Ratio (LER) [19,20];
- Levelized Cost of Electricity (LCOE) [5,21].

Although many APVs have already been tested, there is a lack of comparative evaluations to determine which system performs better under specific conditions. A particular APV may express different performances according to its design and geographic location. Therefore, a more comprehensive assessment that involves agricultural crop yield, energy conversion, and economic aspects is required. To address the complexities in evaluating different APVs, a set of Key Performance Indicators (KPIs) could serve as a valuable basis to carry out a Multi Criteria Decision Analysis (MCDA). MCDA is a valuable tool to support a decision making process on complex systems as it provides a way to evaluate multiple criteria that may not always be directly comparable [22]. Numerous methods and variants of MCDA have already been adopted among sustainable energy systems [23,24]. Performing an MCDA based on KPIs for APV evaluation in a specific environment requires a significant amount of data that must be available before the APV system is installed. To overcome this challenge, system-based models can be used to simulate utility scale APVs, thus avoiding the need of having the actual APV installed. Simulations provide valuable data on both crop performance and energy output, making them a useful tool for optimizing APV designs and management in response to specific environmental conditions [25]. Simulating APVs involves the integration of radiation models and crop models which consists of a set of mathematical equations depicting the way crops develop and interact with the surrounding environment. The outcome of a crop model, generally entails the prediction of agricultural crop yield spanning from the potential yield in an ideal scenario to a scenario with one or more constraints [26].

These integrated models offer a versatile tool to simulate crop responses under APV, including yield [19,27], water availability and conservation [18,28], irradiance interception [20,29], net revenues and crop production revenues [27,30]. Existing research demonstrates the ability of crop models to adjust phenological development in response to APVs shading patterns with numerous studies utilizing models such GECROS [31,32], EPIC [33], APSIM [34,35], STICS [19,27], and DSSAT [36].

The main objective of this study was to develop a framework for identifying the most suitable APV configuration among different APV technologies for a set of locations with diverse climatic conditions in Italy.

To pursue the main objective, the following additional objectives were prior tracked:

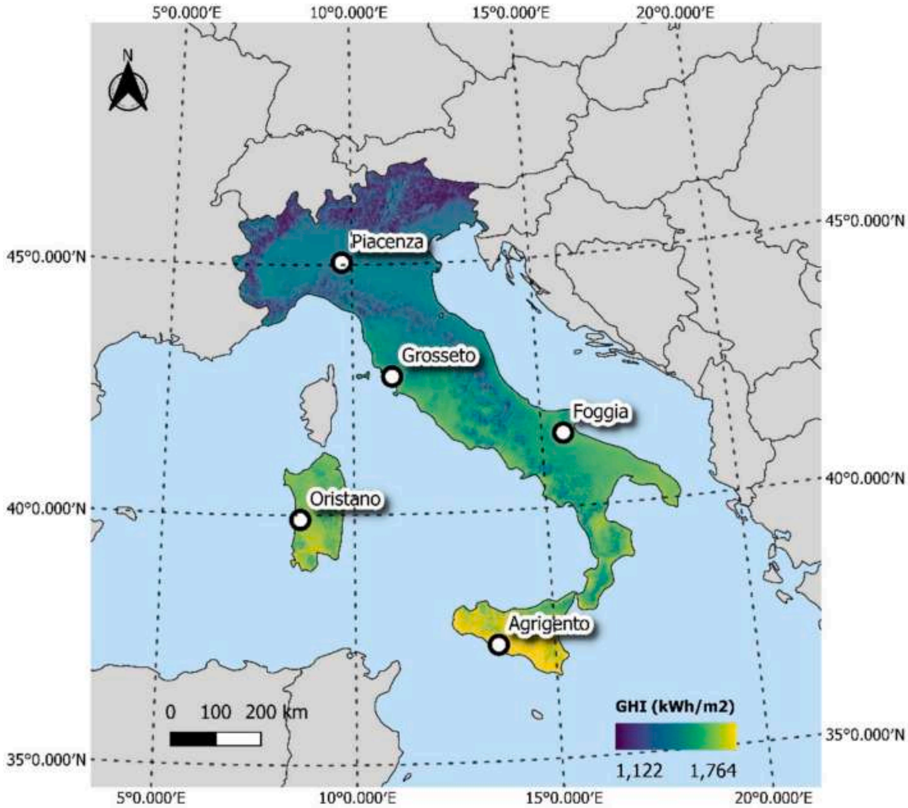

Fig. 1. Site locations and Photovoltaic power potential in Italy [40].

Table 1
Coordinates of the investigated Italian locations.

Latitude	Longitude	Site name	Province
44.97441	09.89243	Piacenza	(PC)
42.71292	11.11353	Grosseto	(GR)
41.43448	15.56456	Foggia	(FG)
39.99426	08.44488	Oristano	(OR)
37.20920	13.81800	Agrigento	(AG)

a) to determine which APV configuration matched the threshold of 70% crop production compared to full light condition as proposed in the Italian best practices for agriphotovoltaics (UNI/PdR 148:2023). The UNI institution is the National standardization body for Italy. This “*PdR*” represents technical guidelines. The Uni/PdR standards are issued when there are no existing national, European, or international standards in place to address an emerging topic. Since the original Italian government guidelines from 2022 did not address many aspects of agrivoltaics, as allowed yield reduction, these guidelines were employed in this workflow to provide a specific benchmark;
b) to examine the dynamic interaction between various APV layouts and pitches (row to row space within PV array) with specific environments, thus assessing the impact of the APV array on PAR availability for crops during the growth cycle, PV energy conversion and WUE;
c) to attribute to each APV configuration the initial capital expenditure (Capex) by considering 1 MW_p plant as reference;
d) to carry out a MCDA that combine a set of KPIs to determine the optimal APV configuration for a specific latitude when processing tomato crop is considered.

Table 2
Soil input data.

Soil feature	Value
Sand [%]	47
Clay [%]	18
Silt [%]	35
SOM [%]	2.2
Bulk density [g cm^{-3}]	1.5
Total N [g kg^{-1}]	1.5
C/N	10.5

2. Materials and methods

2.1. Scenarios description

The simulation study was carried out on five distinct geographic sites across Italy, spanning from the Southern to the Northern Regions, covering a latitude range of 37° to 45° (Fig. 1; Table 1). Site distribution considered the diverse climatic conditions and solar irradiation in Italy. The simulations were conducted over a ten-year period (from 2010 to 2019), using weather data obtained from the nearest virtual weather stations for each site provided by the EU Joint Research Centre, MARS-AGRI4CAST project [37]. Specifically, total global irradiation, daily mean temperature, daily maximum temperature, daily minimum temperature, daily precipitation, and vapour pressure over the entire growing season time span, having a resolution of 25 × 25 km, were considered. Daily data from Agri4cast were converted in hourly data [38] and simulations were run adopting an hourly time-steps for each APV configuration at each site, with a processing tomato crop as reference. Since tomato is a major crop in all selected sites, as reported by ISTAT [39], this choice provides a pertinent benchmark for highlighting yield variations among these locations.

To limit the agricultural yield variability to weather conditions only,

Table 3
APV and reference systems settings. P = portrait; L = landscape.

APV	Sun-track	Bifaciality factor [%]	Main axis Height [cm]	Array layout	Single PV size [m]	Pitches [m]	GCR [%]
OMA-APV	yes	80	343	1P	2.01 × 0.99	6, 8, 10, 12, 14	33, 25, 20, 17, 14
Vert-APV	no	80	170*	2 L	0.99 × 2.01	8, 10, 12, 14, 16	25, 20, 17, 14, 12
IMA-APV	yes	80	230	2P	2.01 × 0.99	10, 12, 14, 16, 18	40, 33, 28, 25, 22
OBA-APV	yes	80	500	6 L	1.30 × 2.38	14, 16, 18, 20, 22	38, 33, 29, 26, 24

* *Vertical system height is composed as following: free structure 0–70 cm; 1st module 70–170 cm; 2nd module 170–270 cm.*

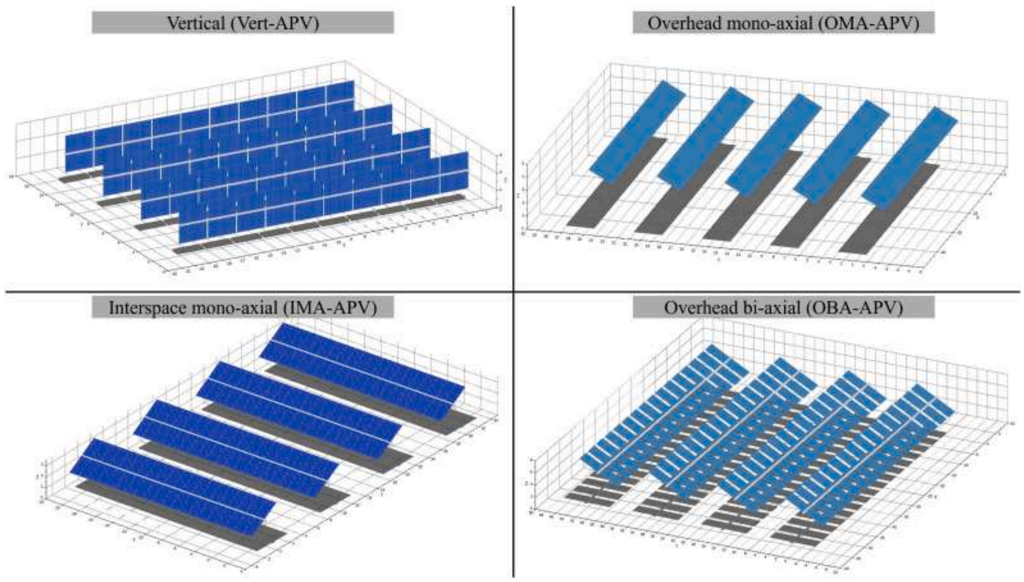

Fig. 2. Scilab 3D render representation of the APV configurations adopted in the simulations.

the same soil type input was assumed for each of the five sites under investigation. Soil input was made of an average loamy soil with mean values of soil organic matter (SOM), total nitrogen, and C/N ratio (Table 2) according to the USDA soil texture classification [41].

2.1.1. Agrivoltaic systems configuration

In this study five potential pitch widths for each APV configurations are considered, starting from the narrowest acceptable and incrementing by 2 m. This approach aimed to cover a wide range of pitches while reducing the number of simulations and approaching to the 40% ground coverage ratio (GCR, i.e. the ratio of total module area to land area) threshold. In fact, The pitch adopted for APV must be sufficiently wide to maintain a GCR below 40%, in accordance with the guidelines for APV plants issued by the Italian Ministry [42]. The selected pitches for each APV and the adopted design solutions are detailed in Table 3. Moreover, the pitch adopted in APV should be adjusted to facilitate the mechanization of agricultural operations and to reduce PV modules' self-shading. In particular, there should be sufficient space for tractors to manoeuvre under the system [27,43]. APVs with smaller array surface can adopt narrower pitches as long as it meets the minimum distance to allow machinery movement. The larger the PV array, the larger the minimum viable pitch is. These considerations resulted in different sets of pitches for each APV. The vertical APV layout is the most affected by self-shading and adequate distance must be provided during the design process. According to the Next2sun website (www.next2sun.com), the pitch for vertical APV installation start from 8 m width in consideration of this issue. Pitch width and module size are linked to the GCR [44]; therefore, every pitch resulted in different GCR and module density (Table 3). The design and configuration of each APV systems were implemented in Scilab 2023.1.0 environment (Dassault Systèmes, France). This included the implementation of a vertical APV (Vert-APV), an overhead mono-axial sun tracking APV (OMA-APV), an interspace mono-axial sun tracking APV (IMA-APV), and an overhead bi-axial APV (OBA-APV) (provided with a stilt mounted bi-axial sun tracking system) configurations. The APVs in this study are among the most widely adopted and studied so far [15] and, excluding the IMA-APV, they are categorized as advanced according to the Italian's guidelines [42]. This classification is based on their layouts (vertical) or minimal height from the ground. These four APVs (illustrated in Fig. 2).

Table 4
Modules specifications.

Type	Bifacial Half-cell module
Peak power (P_{max}) [W_p]	420
Maximum power point current (I_{mpp}) [A]	9.84
Maximum power point voltage (V_{mpp}) [V]	42.7
Short circuit current (I_{sc}) [A]	10.34
Open circuit voltage (V_{oc}) [V]	51
Nominal operation module temperature [°C]	42 ± 2
Temperature coefficient for P_{max} [%/°C]	−0.32
Temperature coefficient for V_{oc} [%/°C]	−0.26
Temperature coefficient for I_{sc} [%/°C]	0.05
Bifaciality [%]	80
Number of cells	144
Efficiency [%]	20.7
Power Tolerance (W)	0–5

The same PV module technology was adopted for every APV to set up a fair comparison for energy conversion. PV modules have a power output of 420 W_p and about 21% efficiency. Electrical characteristics are summarized in Table 4.

Solar panels have standard performance ratings based on Standard test conditions (STC) according to IEC 60904, namely: irradiance (1 kW m^{-2}), cell temperature (25 °C), air mass (1.5). Air mass represents how the sun's rays are filtered through the Earth's atmosphere, it describes

Table 5
Crop management input data. Wheat crop is assumed as the preceding crop.

Field sites	Transplant date [dd-mm]	Crop residues N [g m^{-2}]	Crop residues C [g m^{-2}]	Plant density [plant m^{-2}]	Irrigation	Total N fertilization [kg ha^{-1}]
Agrigento	10 April					
Oristano	10 April					
Foggia	20 April	3.5 NO_3 3.5 NH_4	530	3.3	100% ETc	150
Grosseto	20 April					
Piacenza	30 April					

how elements in the atmosphere (like water vapour and dust) can change the sunlight hitting the solar modules. This change in sunlight affects the energy transfer in the panel, which in turn, impacts its efficiency. The Air Mass of 1.5 is a standard for comparison across different solar panels [45].

2.2. Models description

Simulations were carried out using a modified version of the models, coded and developed in SciLab 2023.1.0 (Dassault Systèmes, France), described in [31,32]. In particular, a system-model which simulates the hourly irradiation distribution at ground level under a given APV, and a crop model which simulates growth and development of a crop cultivated under the same APV, were coded in SciLab modelling platform.

To account for the variations in daily PAR within the APV caused by modules shading, the model calculates data for a delimited area equal to the square of the pitch spacing (pitch^2 [m]). This area is further divided into pixels with an individual area of 0.5^2 [m]. For each pixel, the crop model independently computes an output based on the micrometeorological conditions in that specific location within the APV. The number of pixels involved in each simulation is therefore determined by the spacing of the simulated APV.

2.2.1. Radiation model

Solar irradiance distribution under each APV were simulated for both Direct irradiance and Diffuse irradiance, considered separately as component of the Global irradiance [46], from which is possible to calculate the PAR. According to a ten-year weather file obtained through Agri4Cast tool for each of the five sites, both shading and irradiation at ground level were computed for each of the studied APV, at hourly time-step. The radiation model and its validation are described in depth in the supplementary materials (section B).

2.2.2. GECROS crop model description

GECROS crop model was used to simulate crop development, yield, photosynthesis, and other morphological and physiological related traits in response to the dynamic APV shading effect. GECROS is a generic photosynthesis-based crop growth model specifically designed to simulate genotype-by-environment interactions; therefore, it can predict how irradiation, temperature, wind speed and partial vapour pressure, given as hourly inputs, affect crop biomass and yield. A comprehensive description of the model is given by Yin & Laar [47]. Since GECROS dynamically adjusts the root-shoot partitioning in response to external conditions (solar radiation, water, nitrogen input) with hourly time steps it is suitable to simulate crop growth dynamics under the rapid changes occurring in APV systems. It is also well structured for responding to stressful limiting events such as shading (intended as PAR reduction). The actual hourly irradiation calculated for each pixel beneath the APV through the radiation model is used as input for the crop model at hourly time-step.

2.3. Model inputs

2.3.1. Tomato crop Inputs

Although some crops are not included in the GECROS crop model, it is possible to manually add missing crops. Processing tomato crop is not included by default in GECROS, thus, to carry out this study, parametrization data for tomato were collected from literature and field trials. Moreover, some data were estimated by using optimization functions included in the Scilab environment. Field data had been collected from previously established experimental tomato field (*Lycopersicon esculentum*, L., H3460 hybrid) [48] from which parameters from laboratory analyses were also obtained. The parameters used to calibrate tomato in GECROS are summarized in the supplementary materials (Section E; Table s2).

2.3.2. Crop management inputs

Processing tomato is an industrial crop with a protracted planting interval and, consequently, a lengthy harvest calendar. Tomatoes thrive with high temperatures, due to climatic differences between Southern and Northern Italy, the transplanting is progressively delayed moving from South to North. In this study, a ten-day delay between major islands, coastal central regions, and the Po Valley was hypothesized accounting for the earlier onset of favourable conditions in Southern areas. Therefore, three mid-term planting dates, corresponding to three distinct management files, were inputted. Transplanting dates along with information on previous crop residues (representing the initial soil nitrogen and carbon content), and other crop management parameters, are summarized in Table 5. For each of the five sites, ten processing tomato growing cycles (2010–2019) were simulated to account for potential yield variability due to unusual weather patterns. Additionally, processing tomato cultivation was simulated under each of the five pitches for the four APV systems at each site. GECROS crop model was configured to trigger automated irrigations every three days (check period). Irrigation input was set at 100% of crop evapotranspiration (ET_c) in all scenarios to avoid water stress. This allowed to focus the study solely on the impact of PAR reduction and environmental temperatures on crop growth. Additionally, irrigation check was stopped three weeks before harvest, in line with common practice [49]. Nitrogen supply was provided to the crop according to the phenological phase, to respect the high nitrogen demand during the development cycle, in four interventions each growing cycle. The total provided nitrogen was

Table 6
Nitrogen supply distribution: dates of nitrogen supply are in accordance with the different transplanting dates.

Field sites	1st Application		2nd Application		3rd Application		4th Application	
	[dd-mm]	[kg ha^{-1}]	[dd-mm]	[kg ha^{-1}]	[dd-mm]	[kg ha^{-1}]	[dd-mm]	[kg ha^{-1}]
Agrigento	09 April		01 May		10 May		10 June	
Oristano	09 April		01 May		10 May		10 June	
Foggia	19 April	45	10 May	40	30 May	40	20 June	25
Grosseto	19 April		10 May		30 May		20 June	
Piacenza	29 April		20 May		10 June		30 June	

Table 7
Security margin assumed for each APV.

APV	Security margin [m]	Row to row loss [m]	Pixel stripes removed from data raster
IMA-APV	1.5	3	6
Vert-APV	0.5	1	2
OMA-APV	0.5	1	2
OBA-APV	0.5	1	2

Table 8
The primary assumptions for simulating the power output of APV.

Parameters	Value/type
Yearly Albedo	0.25 [54]
Cable losses [%]	2 [55,56]
Soiling losses [%]	2 [55,56]
Mismatching losses [%]	2 [55,56]
Losses due to deviation from standard spectrum [%]	1 [55,56]
Annual PV module degradation [%]	0.43
Resolution of the data	One hour
Diffuse Irradiation onto horizontal plane model	Hofmann
Irradiance onto tilted surface model	Hay & Davies

determined according to the crop management disciplinary of the Italian Regions involved in this study. The nitrogen distribution schedule is presented in Table 6.

2.4. Key performance indicators (KPI)

Simulation output data were analysed to assess the performance of APVs according to the main KPIs adopted in literature. Performance indicators that have previously been used to evaluate APV system include LER [19,20], WUE [13,18], energy conversion per hectare [50], specific energy yield [44] and agricultural yield [51]. LER had been widely adopted in literature so far to estimate land use efficiency gain obtained by using APV in agricultural land and it is well described in [20]. A LER value >1 indicates increased efficiency per unit of land, while a LER value below 1 signifies a reduction in land use efficiency due to the adoption of APV. Initially designed to gauge the efficiency gains in intercropping systems, LER proved effective in the early stages of APV research, showcasing how land efficiency could be significantly enhanced with APV adoption [19]. However, it does not strike a proper balance between agriculture productions and energy conversion. Optimizing an APV based solely on LER tends to prioritize energy conversion at the expense of agricultural output. In light of these considerations, LER is not adopted as KPI in this study. Instead it was adopted the approach of splitting LER into crop ratio (CR) and energy ratio (ER), as proposed by Ahmed et al. [34]. The KPIs adopted in this study are discussed in depth in the subsequent paragraph.

2.4.1. Agricultural yield and crop ratio

GECROS simulates the agricultural yield by estimating the crop dry matter of storage organs "WSO" [g m^{-2}] at harvest for each of the pixel included in the raster, as discussed in section 2.2. In this study the processing tomato WSO was assumed as 7% of the fruit fresh weight. The Processing tomato fresh yield per hectare was calculated, for both the FL and the APV conditions. Agricultural fresh yield in FL "AY_{FL}" [Mg ha^{-1}] was calculated according to Eq. 1:

$$AY_{FL} = WSO_{FL} \bullet \left(\frac{1}{1 - wc}\right) \bullet 10^{-2} \tag{1}$$

where WSO_{FL} is the dry weight of storage organs obtained in full light condition [g m^{-2}] and "wc" is the water content coefficient of tomato fresh fruits at harvest. It was considered fixed for all simulated conditions, $wc = 0.93$.

To calculate the agricultural fresh yield in APV "AY_{APV}" [Mg ha^{-1}], land losses were considered for each system's design. Land losses were introduced to reproduce the realistic situations related to the need of a security margin for agricultural mechanization and APV infrastructures [27]. In this study a security margin of 0.5 m for each side of APV supporting structures [52] was considered to avoid modules and structures damage assuming mechanized operations. However, for the IMA-APV, a 1.5 m security margin for each side was hypothesized due to its large array and low module's height. In fact, in such APV when modules reach the maximum tilt (55° to the horizontal plane) they are likely to collide with the crop. The employed security margins for each APV configurations are reported in Table 7.

Security margin has implication for yield losses among APV in comparison to FL treatments. The percentage of non-cropped surface is highest for narrow-pitch APV plants. To account for the assumed land losses, raster pixel stripes within the security margin of the APVs were excluded. From the remaining pixels of each APV data raster, the mean WSO was calculated and the agricultural fresh yield per hectare "AY_{APV}" [Mg ha^{-1}] was determined according to Eq. 2 as follow:

$$AY_{APV} = \overline{WSO}_{APV} \bullet \left(\frac{1}{1 - wc}\right) \bullet 10^{-2} \tag{2}$$

where $\overline{WSO}_{APV}$ [g m^{-2}] is the mean of the WSO obtained for each pixel not excluded from the simulation output data raster.

The term *Crop Ratio (CR)* [34] is adopted to indicate the ratio between agricultural yield obtained in APV condition to the agricultural yield obtained in full light condition It was computed according to Eq. 3:

$$CR = \frac{AY_{APV}}{AY_{FL}} \tag{3}$$

where AY_{APV} [Mg ha^{-1}] is the agricultural fresh yield per hectare produced in APV and AY_{FL} [Mg ha^{-1}] is the agricultural fresh yield per hectare produced in full light condition.

A CR of 1 indicates that the agricultural yield obtained in the investigated APV scenario matches the yield of its respective FL control. Importantly, the CR is influenced by the available PAR at each pixel, highlighting the significance of irradiation distribution within the pitch. Likewise, the term Radiation Ratio (RR) is used in this study to indicate the ratio between the mean yearly global irradiation that reach the ground in APVs to the yearly mean global irradiation referred to FL condition in the same site. A value next to 1 stands for less shading and less difference in PAR availability for crop compared to FL.

2.4.2. Energy conversion and energy ratio

Energy conversion was assessed by designing each of the studied APV in PVsyst® software, (version 7.4 26/06/2023 www.pvsyst.com). This tool is commonly employed by solar energy professionals to maximize PV efficiency and evaluate the performance of solar parks before installation. It allows users to design PV plants and conduct dynamic simulations and analysis [53]. Two energy related KPIs were employed: energy conversion per hectare [MWh ha^{-1}] and Specific energy yield [kWh kWp^{-1}]. While both relate to energy conversion, they serve distinct purposes:

- Energy conversion per hectare indicates the power density of an APV system, measuring the annual energy produced per hectare of land. This KPI increases when pitch width is reduced, as more panels can fit in a given area;
- Specific energy yield measures the efficiency with which a given solar energy conversion technology can convert solar radiation into electricity. For a given technology, this KPI increases by enlarging the pitch, as this reduces modules self-shading [44] and improves overall system efficiency. Additionally, considering the same PV

Table 9
Settings data sheet for the reference PV system.

APV	Sun-track	Bifaciality factor [%]	Main axis Height [cm]	Array layout	Single PV size [m]	Pitch [m]	GCR [%]
Reference PV	yes	80	217	2P	2,01 × 0,998	8	50

module power, efficiency increases progressively from fixed tilted PV to mono-axial sun tracking PV and then to bi-axial sun tracking PV.

The power output was considered net of losses. Additional assumptions made to set PVsyst® simulations are presented in Table 8.

Annual degradation coefficient of the PV modules was retrieved from the module's datasheet. Additionally, a conventional solar park was simulated as a reference to compare the APV's energy conversion performance. The ratio between the energy converted by the APV to the reference PV system, considering the same land surface, is known as energy ratio (ER) [34]. The reference PV was assumed as a sun tracking ground mounted PV system with a North-South oriented rotation axis [57], a bifacial module array with 8 m pitch and 50% GCR [58]. The features of the reference PV system are listed in Table 9.

Electrical characteristics of the reference system modules are the same adopted for APVs (Table 4).

The *ER* has been calculated according to the results provided by the simulations in PVsyst® for each year. It can be calculated according to Eq. 4:

$$ER = \frac{EY_{APV}}{EY_{PV}} \quad (4)$$

where EY_{APV} [MWh ha^{-1}] is the annual energy converted by the APV and EY_{PV} [MWh ha^{-1}] is the annual energy converted by the reference PV system.

This ratio expresses how close is the considered APV to the reference PV system and if the ratio is lower than 1 it means a reduction in energy conversion capacity for the APV compared the reference solar park.

2.4.3. Water use efficiency (WUE) and WUE ratio

WUE, expressed as mass of agricultural product per volume of consumed water, relates the crop yield obtained in both APV and Full Light (FL) to the total cumulative ET_c to produce that yield [18]. It represents a KPI that gauges the APV's capacity to mitigate climate-related challenges like drought. In this study, solely the seasonal crop evapotranspiration was considered.

WUE was calculated for each APV scenario "WUE_{APV}" [Mg m^{-3}] according to Eq. 5:

$$WUE_{APV} = \frac{AY_{APV}}{\sum ET_{c,APV}} \quad (5)$$

where AY_{APV} [Mg ha^{-1}] is the yield of fresh fruit produced for the specific APV scenario and $\sum ET_{c,APV}$ [m^3 ha^{-1}] is the corresponding cumulative daily crop evapotranspiration for APV condition.

WUE was calculated for the control FL conditions "WUE_{FL}" [Mg m^{-3}] according to Eq. 6:

$$WUE_{FL} = \frac{AY_{FL}}{\sum ET_{c,FL}} \quad (6)$$

where AY_{FL} [Mg ha^{-1}] is the yield of fresh fruit produced at FL condition for a given site and $\sum ET_{c,FL}$ [m^3 ha^{-1}] is the corresponding cumulative daily crop evapotranspiration for FL condition.

To emphasize the difference in crop WUE between APV scenarios and FL conditions, WUE ratio was introduced. It stands for the ratio of WUE_{APV} to WUE_{FL}.

A WUE ratio higher than 1 stands for gain in WUE that represent water savings compared to FL condition.

2.4.4. Capital expenditures (Capex)

To compare power generating plants, the levelized cost of electricity (LCOE) is commonly employed for assessing the economic sustainability of one investment in comparison to another. Calculating the LCOE necessitates knowledge of various parameters, including the initial required capital, the annual operational maintenance cost, annual energy conversion, and other financial factors. Particularly for renewable energy sources, these components in the LCOE calculation are characterized by higher degree of uncertainty respect to non-renewable power plants [59,60]. Moreover, other KPIs related to energy conversion are already adopted; therefore, in this study it was decided not to consider the LCOE. Instead, this study focuses solely on the initial capital expenditure (Capex) required for place 1MW$_p$ of each APV configuration, excluding future expenses such as maintenance and operation, depreciation, and the Weighted Average Cost of Capital (WACC). The Capex of renewable energy power plants is known to vary significantly based on technology, size, and location [60]. Given the structural and technological variations among the APVs considered in this study, substantially different installation costs are likely. To address the uncertainty associated with Capex, a Monte Carlo analysis (MCA) was performed. The MCA was adopted to interpret statistical distributions of input variables, generate random values based on these distributions, calculate Capex, and aggregate the results. It enabled the exploration of numerous input combinations, revealing likely outcomes for the cost items of the studied APVs, which were assumed normal distributed. The analysis was carried out in R using the "propagate" package [61].

The cost items considered for Capex and their mean value are displayed in Table 10. The mean values of each item has been determined from previously published data [5,21,52,62–65], and thanks to communication with some of the major Italian companies involved in the APV sector.

Since Capex was calculations were based on 1 MW$_p$ APVs, wider pitch scenarios have greater costs to meet the land requirement for achieving an of 1 MW$_p$ installed capacity. The land area required for 1 MW$_p$ was assessed for each APV, accounting for all pitches. The specific land requirements [ha MWp^{-1}] are detailed in Table 11.

Finally, given the diverse and heterogeneous nature of the agricultural land market in Italy, obtaining a widely applicable agricultural land cost for all considered locations proved unfeasible. Hence, was chosen to assign a range of land cost values, ranging from 10,000 € ha^{-1} to 100,000 € ha^{-1}, while evaluating the extent to which land cost

Table 10
Mean value of cost items of the Capex used as input for the Monte Carlo Analysis (MCA). All cost items are expressed as € kWp^{-1}.

APV	PV module	inverters	Electric BOS*	Supporting structure	Installation and work	Professionals and fees
IMA-APV	316	65	162	175	227	64
OBA-APV	349	77	282	340	373	61
Vert-APV	291	58	153	160	267	72
OMA-APV	305	65	100	316	354	77

* BOS = *balance of system.*

Table 11
Land requirement for installing 1 MW_p of each APV by considering different pitches.

IMA-APV			OMA-APV			Vert-APV			OBA-APV		
Pitch [m]	MWp ha^{-1}	ha MWp^{-1}	Pitch [m]	MWp ha^{-1}	ha MWp^{-1}	Pitch [m]	MWp ha^{-1}	ha MWp^{-1}	Pitch [m]	MWp ha^{-1}	ha MWp^{-1}
10	0.83	1.21	6	0.70	1.44	8	0.51	1.95	14	0.50	1.98
12	0.69	1.45	8	0.52	1.91	10	0.41	2.42	16	0.45	2.21
14	0.59	1.70	10	0.42	2.38	12	0.35	2.88	18	0.40	2.48
16	0.52	1.94	12	0.35	2.87	14	0.29	3.40	20	0.36	2.78
18	0.46	2.16	14	0.30	3.34	16	0.26	3.82	22	0.33	3.05

impacts the overall final investment.

2.5. Multi criteria decision analysis framework (MCDA)

As reported by Wang et al. [23] and Kumar et al. [24], there are numerous methods and variants of MCDA used in the field of renewable energies. In this study, the chosen MCDA method is the Technique of Order Preference Similarity to the Ideal Solution (TOPSIS). The TOPSIS operates based on the principle that the optimal alternative should exhibit the shortest Euclidean distance from the “positive ideal solution” and the maximum Euclidean distance from the “negative ideal solution” [66] in a multidimensional space. The “positive ideal solution” represents a hypothetical alternative that achieves the best possible score on all KPIs (criteria). In other words, it represents a combination of the best possible values attainable for each individual KPI [66]. The index derived from the TOPSIS method, “similarity to positive-ideal solution” is called Similarity index. This index is used to rank the competing alternatives and helps in the interpretation of the ranking. According to [67], the TOPSIS method can be summarized in 6 steps:

1. Normalization of the decision matrix, rendering it dimensionless;

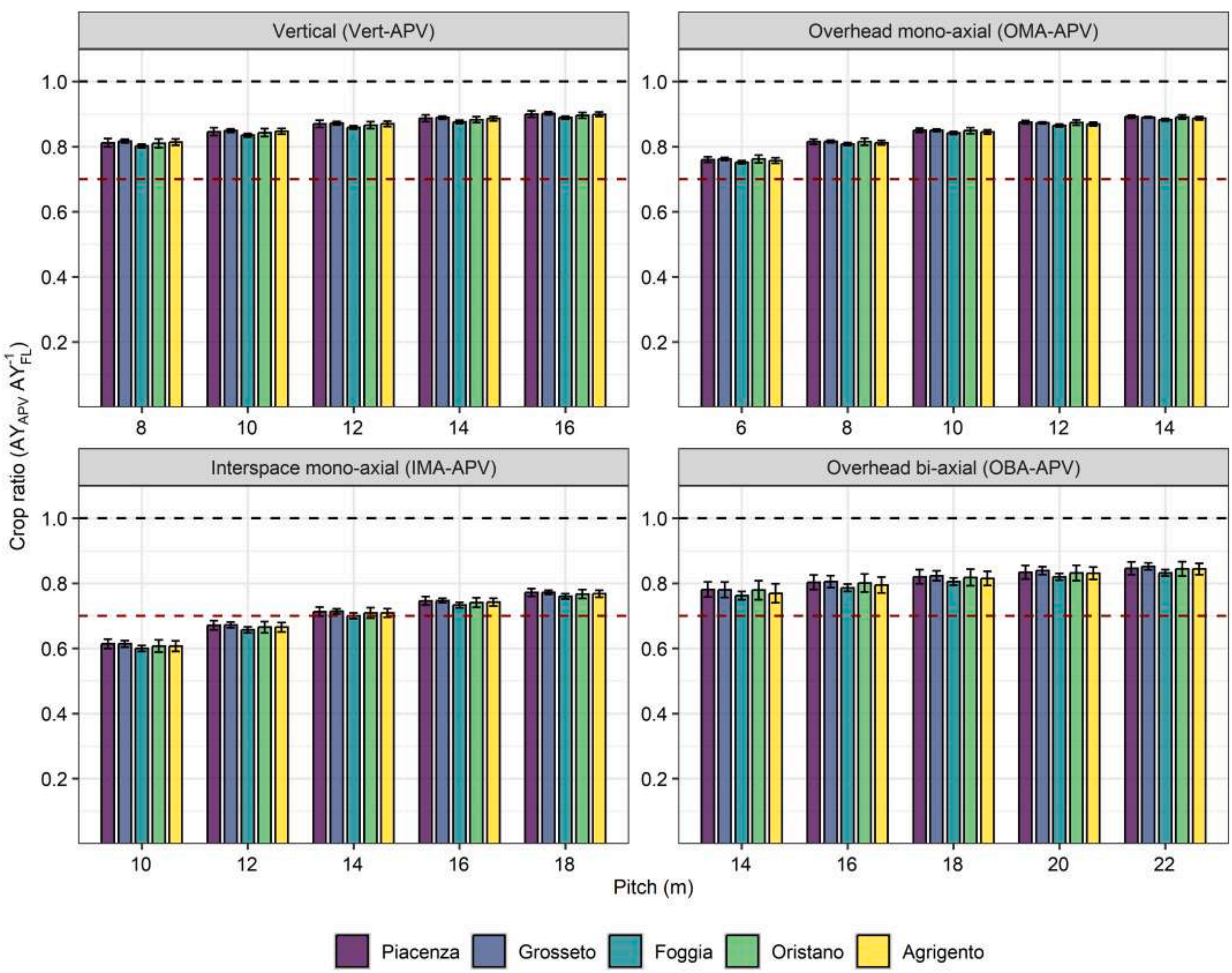

Fig. 3. Ten-year mean and standard deviation of crop ratio (CR) for each site and APV with showcase of different pitches adopted. Black dashed line stands for CR = 1 (FL yield), red dashed line stands for CR = 0.7. The closer the CR is to 1, the less crop yield has been lost. CR of 0.7 (red dashed line) represent the limit of production depletion according to the UNI/PdR 148:2023 [74]. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

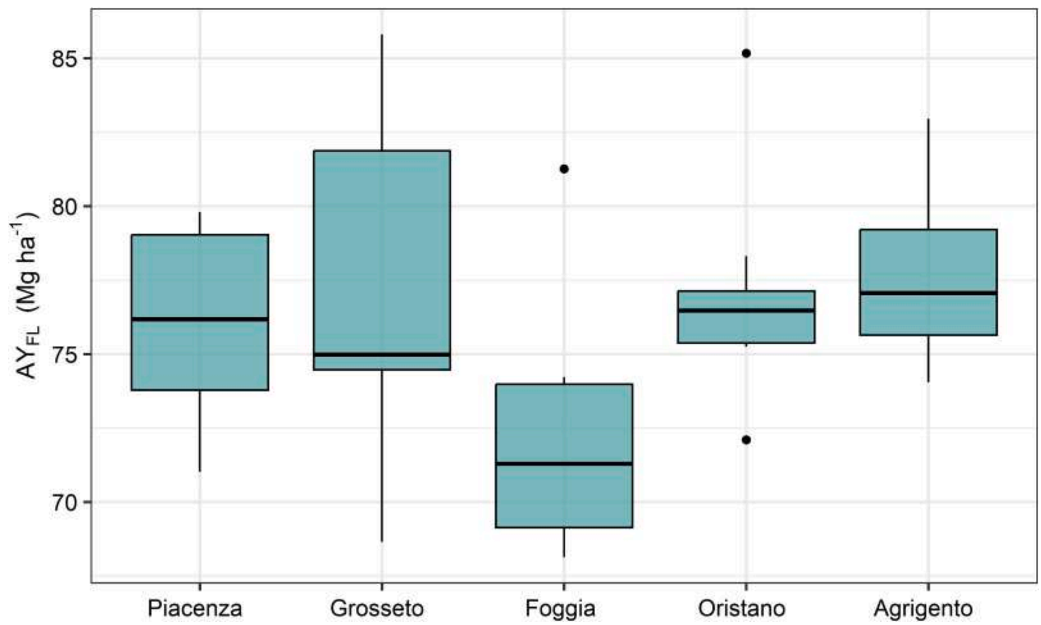

Fig. 4. Box plot of the fresh fruit yield of processing tomato under Full Light (AY_{FL}) conditions. Data are simulated on a ten-year period.

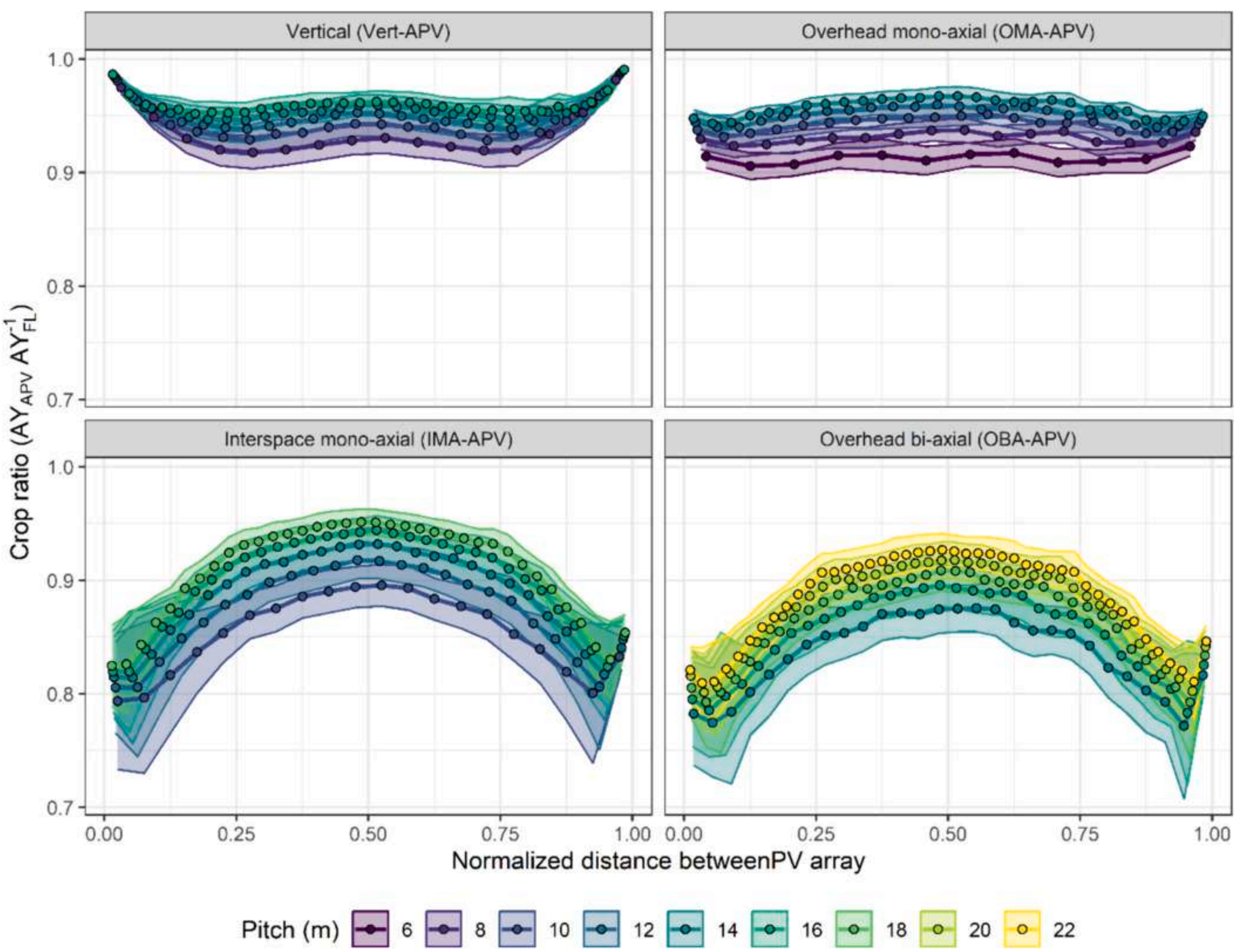

Fig. 5. Mean of ten-year Crop Ratio (CR) distribution within the area included in the pitch of APV. Pitch widths are normalized. Shaded area represents standard deviation.

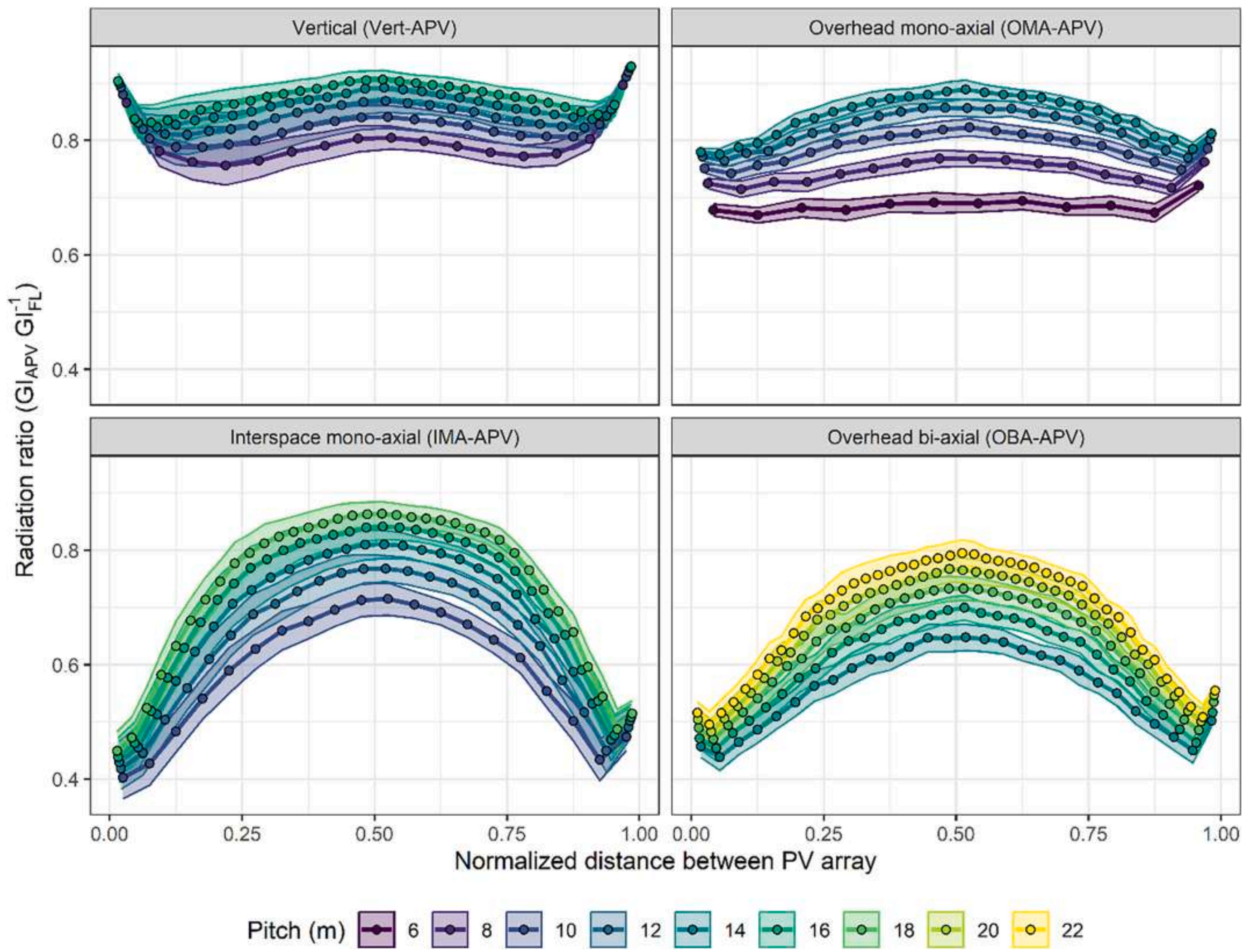

Fig. 6. Radiation ratio (RR) distribution for normalized pitch. The normalized distance at 0.5 represent the mid-point between two AV arrays. The 0 and 1 points indicate the position beneath the modules array. The lines represent the mean values obtained from a ten-year simulation across all sites. Shaded areas depict the standard deviation.

2. Computation of the weighted normalized decision matrix, where the weights represent the only subjective parameter within the method. This step involves multiplying the normalized decision matrix by the weight assigned to each criterion;
3. Determination of ideal solutions, in which the optimal performance for each KPI (criterion) is identified;
4. Calculation of separation measures, where the geometric distance of each alternative from the ideal solution is assessed;
5. Computation of the relative closeness to the positive and negative ideal solutions yielding a score between 0 and 1, where a score closer to 1 indicates higher similarity to the ideal solution;
6. Ranking of the alternatives, where the alternatives are arranged based on their proximity to the positive ideal solution.

A detailed mathematical description of the TOPSIS MCDA problem structure is given in [23,67]. TOPSIS calculations were carried out using the Python module Scikit-Criteria [68]. The scores for the alternatives were ranked independently for each site and the results were used to evaluate the best performing pitch-system combination for each location. Five KPIs were adopted as criteria to represent each APV: CR, WUE ratio, energy conversion per hectare, specific energy yield, and Capex as mentioned in section 2.4. While energy conversion per hectare and specific energy yield are not completely independent, including specific energy yield in the MCDA serves a specific purpose. OBA-APV designs utilize empty spaces within PV arrays, resulting in a lower GCR compared to traditional layouts for the same occupied land area. Specific energy yield is a valuable KPI in this context because it focuses on energy production efficiency and is independent of land use requirements. In contrast, energy conversion per hectare is heavily influenced by the number of modules installed per hectare, which directly relates to land use.

2.5.1. *Ordinal priority approach-based weighting*

The TOPSIS method involves assigning weights to each criterion (KPI). In this study, the Ordinal Priority Approach (OPA) [69], was used to determine these weights. This method offers advantages such as ease of use and enables the consideration of preference rankings. The OPA workflow as reported in [70], includes (i) defining the list of criteria; (ii) performing a questionnaire analysis by specifying the group of experts, assigning a rank to each expert, and collecting feedback from the experts regarding their prioritisation of the criteria according to their views; (iii) solving the linear mathematical model of the OPA [71]; (iv) calculating the weights of each criterion. A brief survey was conducted by involving eight experts representing the two APV categories, agriculture and energy. To achieve a balanced perspective, experts where further subdivided into researchers and commercial operators on both sides.

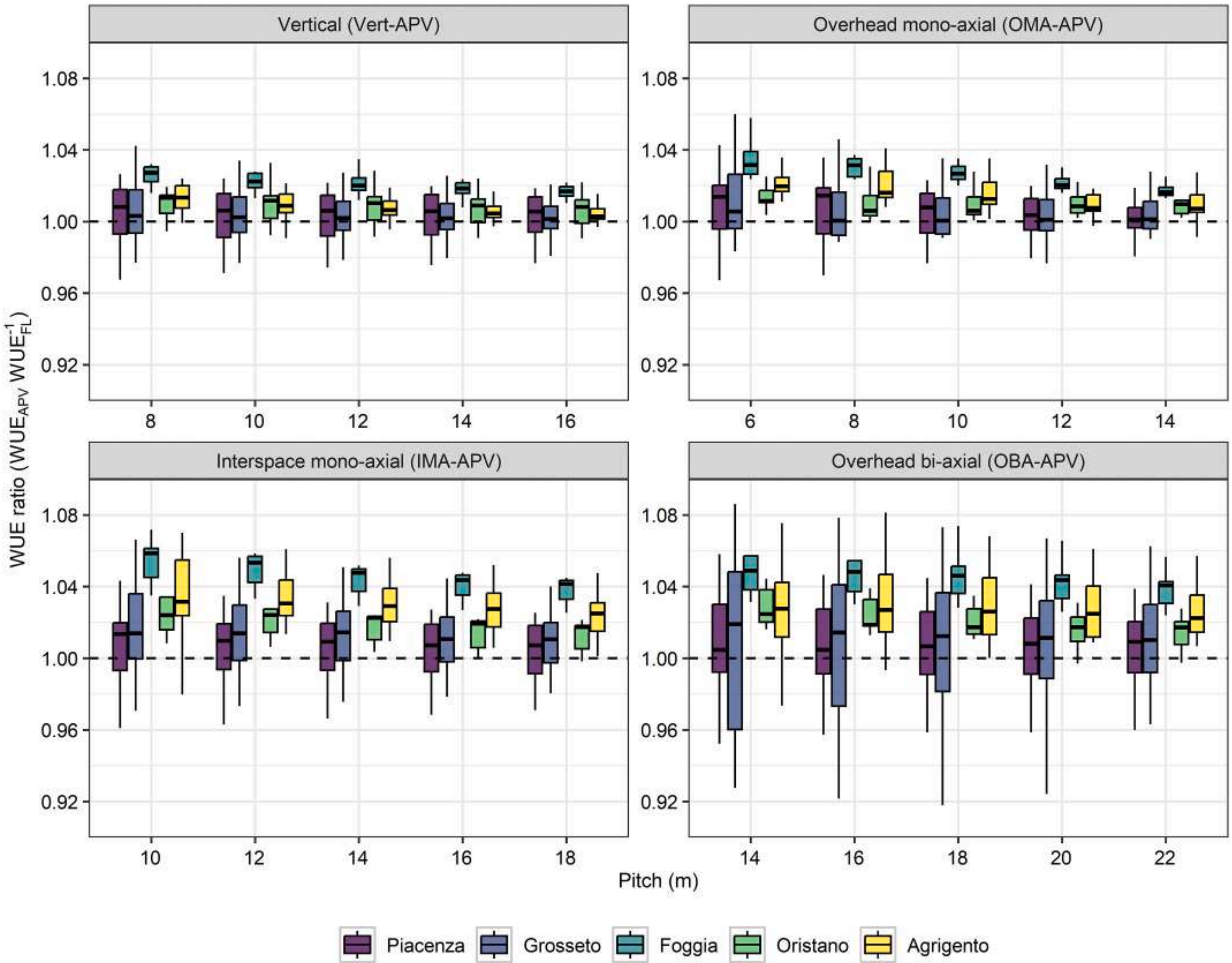

Fig. 7. Water Use Efficiency (WUE) ratio simulated over ten-year period (2010–2019) for the selected Italian sites, APV and pitches.

Specifically, the survey was provided to two researchers in agricultural field, two researchers in PV field, two farmers, and two responsible of solar park development. They were asked to give a rank from 1 to 5 for each of the five KPIs involved. Each expert ranking has the same impact on the final weight assessment.

3. Results and discussion

The comparison among APVs was carried out first for each single KPI (sections 3.1 to 3.4) and then combining all KPIs in a Multi Criteria Decision Analysis (MCDA) (section 3.5).

3.1. Crop ratio and radiation ratio

The results of Crop Ratio (CR), the proportion of the agricultural yield calculated under the APV compared to the agricultural yield calculated under full light (FL), are presented in Fig. 3. Under all conditions, CR was lower than 1 (black dashed line), which indicates that tomatoes yield was higher under full light condition than under any of the simulated APV conditions. The FL yield per hectare, is depicted in Fig. 4. The negative effect of shading on processing tomato yield is also indicated by the trend of deceasing CR that was found for all APV when the pitch decreases and the GCR increases [72,73]. It is interesting to evaluate APV, and their different configurations, because of the possibility to achieve at least 0.7 of CR (red dashed line), which is the threshold value proposed in the recent reference standard UNI/PdR 148:2013 [74] for APVs in Italy. Among studied APVs, the IMA-APV meets this requirement (CR $>$ 0.7) only for pitches larger than 14 m. Advanced APVs showed improvements in CR compared to the IMA-APV. Therefore, even with narrow pitch they achieved a CR above the 0.7 threshold.

Fig. 5 and Fig. 6 illustrate, respectively, how the CR and the radiation ratio (RR) vary according to the position across the pitch, from the axis of one PV array to the axis of the next one. To compare the pattern of the CR and RR variation across the pitch length for all the simulated APV, the distance between the PV arrays was normalized. As expected, both the CR and RR value increased when the distance between PV arrays increases. For all the simulated APV, the value of RR is highest at the centre of the pitch area, where the distance from PV arrays is highest, and it is lowest near the PV arrays, where shade is highest conversely. As crop production under APV is highly influenced by the available irradiation [16,32,75] the pattern of CR follows closely the one depicted in Fig. 6 for the RR. The Vert-APV and the OMA-APV have the highest and most homogenous CR and RR values, while the IMA-APV and the OBA-APV have a sharp CR and RR decrease in proximity to the PV arrays. The peculiar pattern that the RR of the vertical APV has near the PV arrays is a consequence of the gap of 0.7 m from the soil to the PV panels, which permit to sun's rays to reach the ground in proximity of the PV arrays

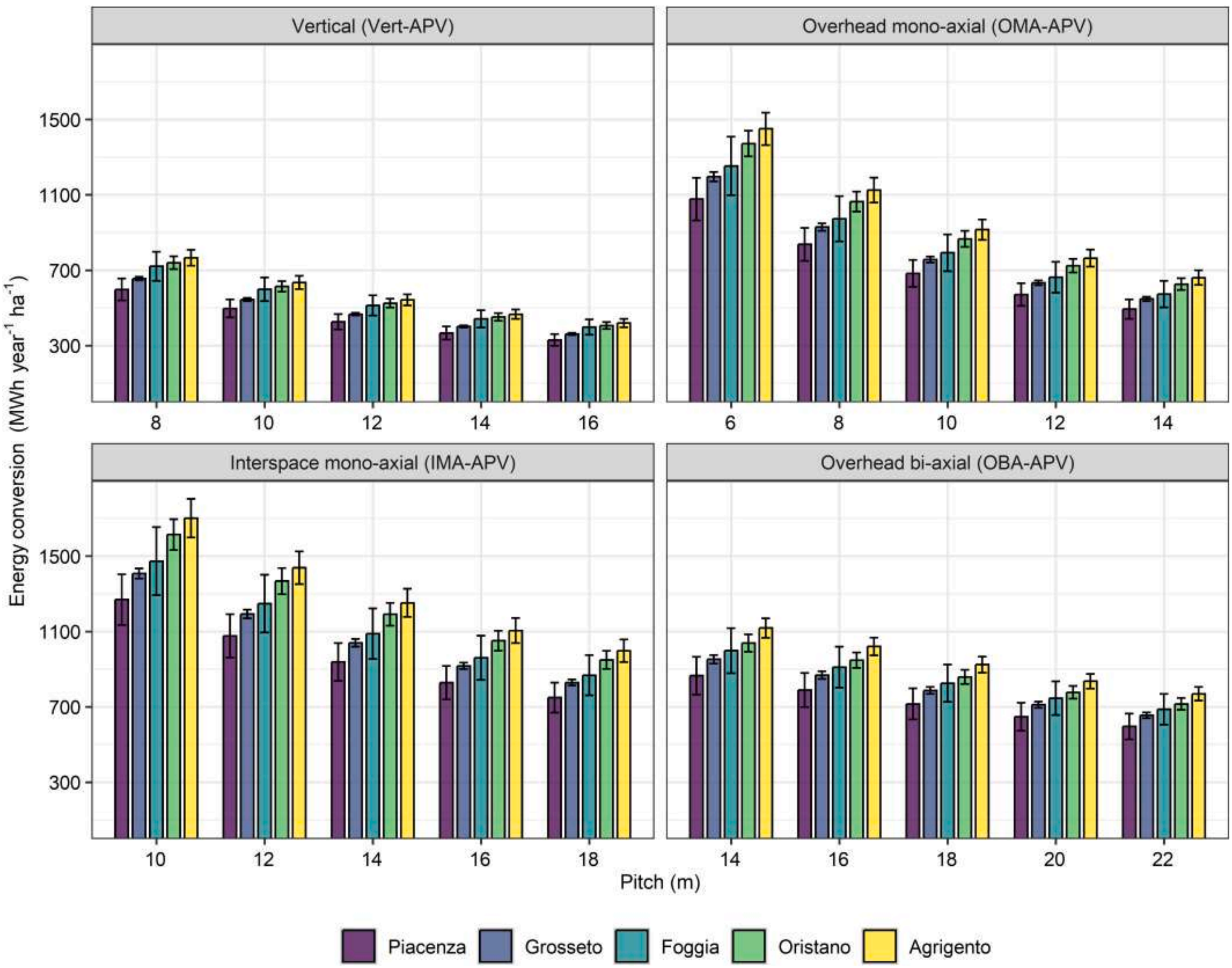

Fig. 8. Mean annual AC energy output per hectare over ten years [MWh ha^{-1} $year^{-1}$].

during most of the day.

It should be noted that the yield reduction consequent to the application of the security margin affects more severely the APV configurations with narrow pitches, which having more PV arrays have higher uncultivated area than APVs with wider pitches. The simulation results regarding the crop yield obtained under the contrasting AV conditions of this study, confirm that tomato is potentially an interesting crop to be cultivated in APV. Yield reduction under the shade of the APV found in this study is in line with results from previous studies [72,76–81]. Under very dry conditions it has been estimated that tomato yield under APV condition may also increase [13]. The inputs used for the simulations assumed the provision of 100% of ET_c, thereby eliminating water stress during the crop growth cycle. Under conditions of both water scarcity and warm climate, crops grown under APV could exhibit comparatively lower yield reduction than that of the full light treatment.

3.2. Water use efficiency (WUE) ratio

WUE ratio, the WUE of the tomato crop cultivated under the APV vs the WUE of the same crop cultivated at the same site in FL condition, on average was above 1, which indicates that under APV conditions WUE is higher than in FL. This is consistent with results found in literature [13,18,72,82,83] and it is a consequence of a reduction in transpiration under shade that is more than proportional than the reduction of photosynthesis, especially for warm climates [13,84,85]. The positive effect of shading on WUE is in fact largest in the Southern sites, which have a much drier climates than the Northern ones (Fig. 7). In particular, the highest gain in WUE was measured in Foggia, where the WUE was 5% higher under AV than under FL conditions. The effect of the pitch is also noticeable with the highest WUE values found at the lowest pitches (where shade is highest), while the effect of the APV is limited but predictable, with the lowest WUE values found for the Vert-APV (which has the lowest shading) and the highest for the IMA-APV (which has the highest shading).

The variability of the WUE ratio, whose magnitude is represented by the length of the whiskers in the box plot (Fig. 7), is a consequence of year-to-year weather variation in the target simulation period (2010–2019). It is noticeable that under any conditions, the WUE ratio data are almost always above 1 in the Southern sites. While the median WUE ratio is always above 1 also in the Northern sites, where in some years WUE ratio was lower than 1. Data of WUE ratio under 1 indicate that a lower yield under APV than under FL was obtained with the same amount of water.

The limited variation in WUE between FL and APV across sites is probably a consequence of the lack of stress in the simulations, which were performed restoring 100% of ET_c, and for the fact that simulation was run considering a short cycle early-sown variety to reduce the impact of high temperatures during the growth cycle. Northern sites

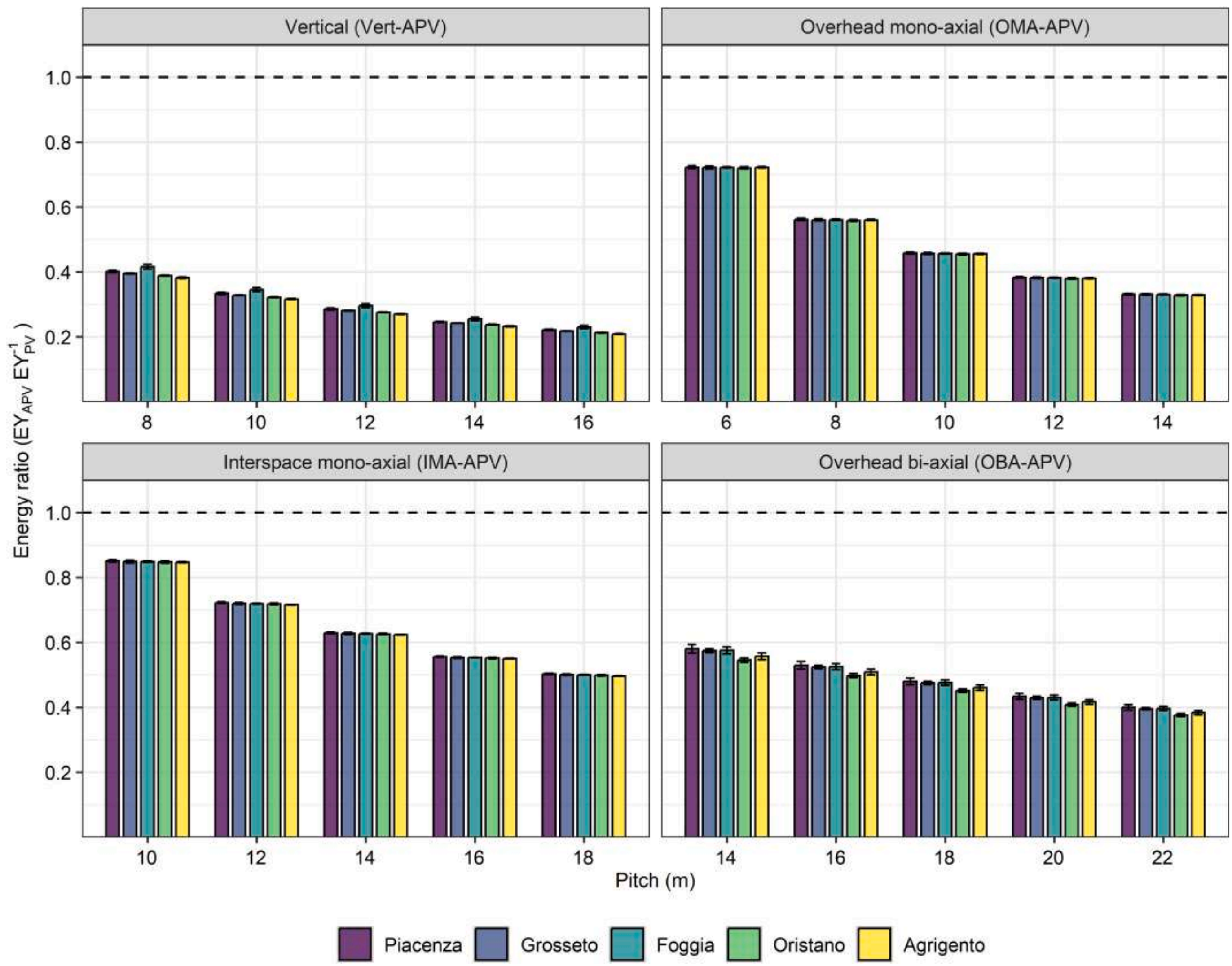

Fig. 9. Mean energy ratio over ten years.

provided more suitable conditions for crop growth in FL. The higher WUE in southern and dryer regions, where water scarcity and drought occur frequently, has already been reported [14,52] and, as highlighted by various authors, for APV may play a role in mitigating the adverse effects of climate change and extreme weather phenomena [14,86].

3.3. Energy conversion

The annual mean energy conversion per hectare [MWh ha^{-1} $year^{-1}$] by APV and the yearly mean energy ratio for each pitch are illustrated in Fig. 8 and Fig. 9, respectively, for each site.

The highest mean energy conversion per hectare and per year (Fig. 8), among all APVs, was observed in Agrigento, whereas the lowest mean energy conversion was consistently recorded in Piacenza, for each APV.

Among various pitches and APV configurations, the IMA-APV with a 10 m pitch had the highest energy conversion per hectare. In Agrigento, this configuration resulted in an average electrical output of approximately 1700 MWh ha^{-1} $year^{-1}$. Conversely, in Piacenza, the same configuration resulted in comparatively less energy, with an annual mean of 1268 MWh ha^{-1} $year^{-1}$. The highest energy ratio (ER), among the tested APV, was obtained by the IMA-APV with a 10 m pitch configuration, which achieved 0.85 ER (Fig. 9), across all sites. In contrast, the largest 18 m pitch configuration achieved only a 0.5 ER. OMA-APV performed well particularly when narrow pitches are adopted. The mean energy conversion for the OMA-APV in the Southern location (Agrigento) was approximately 1450 MWh ha^{-1} $year^{-1}$ with a 6 m pitch configuration. In contrast, in Piacenza, this configuration achieved 1077 MWh ha^{-1} $year^{-1}$. The ER for this APV was 0.72 for the 6 m pitch and 0.33 for its largest configuration (14 m pitch) at each site. OBA-APV, on average, generated 1091 MWh ha^{-1} $year^{-1}$ with the densest PV modules configuration (14 m pitch) in Agrigento, while only 840 MWh ha^{-1} $year^{-1}$ in Piacenza. It achieved a mean yearly ER of 0.54 for 14 m pitch and 0.37 for 22 m pitch. The Vert-APV had the lowest energy conversion. In Agrigento, with 8 m pitch, the Vert-APV obtained a mean output of about 766 MWh ha^{-1} $year^{-1}$ and 597 MWh ha^{-1} $year^{-1}$ in Piacenza. For this system, the lowest overall ER mean was obtained: 0.38 was achieved for 8 m pitch and only 0.20 for 16 m pitch in each site.

As highlighted in Fig. 10, the highest specific energy yield [kWh kWp^{-1}] is achieved in all scenarios when pitches are largest. In fact, although the energy conversion per unit surface (kWh ha^{-1}) increases with increasing GCR (or a reduction in pitch width) (Fig. 8), also self-shading of PV panel increases, and this reduces specific energy yield. Moreover, the higher is the GCR the more initial capital expenditure is required (Fig. 11). The highest efficiency in energy conversion was observed in the OBA-APV with a 22 m pitch, which achieved the highest energy conversion 2048 kWh kWp^{-1} in Agrigento. IMA-APV and OMA-

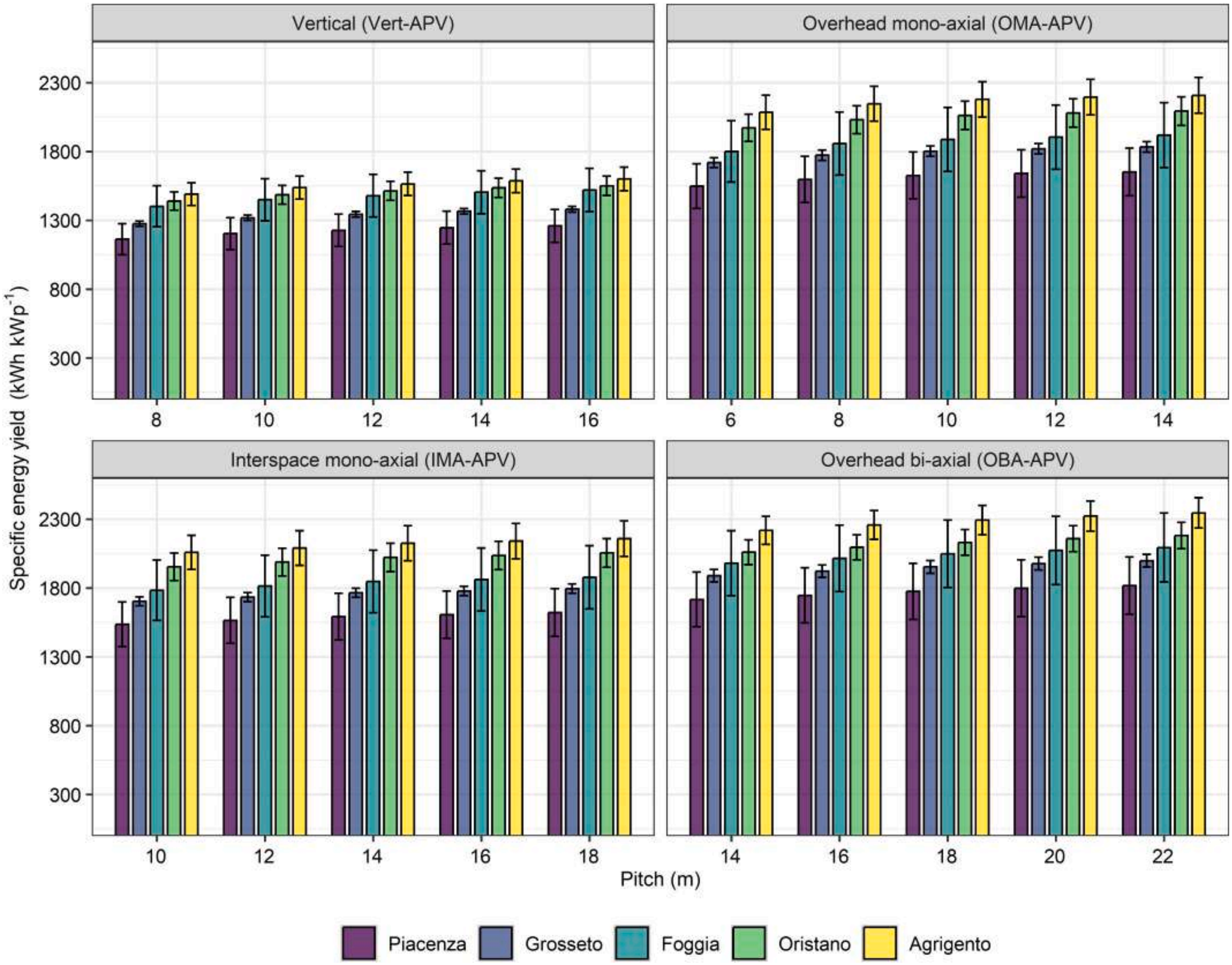

Fig. 10. Specific energy yield [kWh kWp^{-1}] for each APV having different pitch and each Italian site.

APV performed similarly, but in comparison, when the same pitch is adopted (e.g. 14 m) the OMA-APV performs best. The OBA-APV performs better among each of the other system. Conversely, the Vert-APV performs worst in any combination of pitch and site. It resulted in a specific energy yield of 1600 kWh kWp^{-1} for pitch 16 m in Agrigento, the best result, and around 1163 kWh kWp^{-1} with pitch 8 m in Piacenza, lowest result. This outcome was expected, especially due to the fixed design of the modules.

As expected, all energy related KPIs were highly influenced by site and climatic conditions, with Southern locations having the highest photovoltaic potential. In each scenario, APV characterized by high module density (narrow pitch and therefore more modules per surface unit of land) converted the highest energy. Interestingly, the energy ratio for OBA-APV was slightly higher in Northern sites. Despite employing the widest pitch among the studied systems, which is favourable for agricultural activities, the OBA-APV achieved the highest efficiency in energy conversion thanks to the double axis sun tracking system. Vert-APV generated the lowest amount of electricity in all the considered scenarios, which was expected [25], however it must be considered that, as indicated in the study by Campana et al. [33], electrical energy conversion of a vertically mounted bifacial module peaks at sunrise and sunset, thereby compensating for an energy deficit that occurs during those hours in common PV systems.

3.4. APV initial capital expenditure (Capex)

The results of the Monte Carlo Analysis are illustrated in Fig. 11, displaying the distribution of all potential outcomes for the Capex of each APV, considering different pitches and varying land cost assumptions. It is important to note that, in this study, geographical sites are assumed to have no influence on the Capex. Instead, technological and technical solutions adopted for each systems have a strong influence on the initial investment. The OBA-APV has the highest initial capital expense due to its dual axis sun tracking system and for the highest stilted supporting structure. On the other hand, OBA-APV has the highest specific energy yield and the lowest impact on agricultural activities due to the good accessibility to the field. In this work, the cost of additional wiring related to the pitch enlargement was considered negligible, therefore the increase in Capex with increasing pitches, which was on average 0.41% for each m of pitch enlargement, is only related to land costs.

3.5. MCDA output

3.5.1. OPA weighting for MCDA

Starting from the OPA method described in section 2.5.1, the optimal weightage of each KPI, adopted to carry out the MCDA process, is highlighted in Table 12. All the ranking outcomes, given by the experts

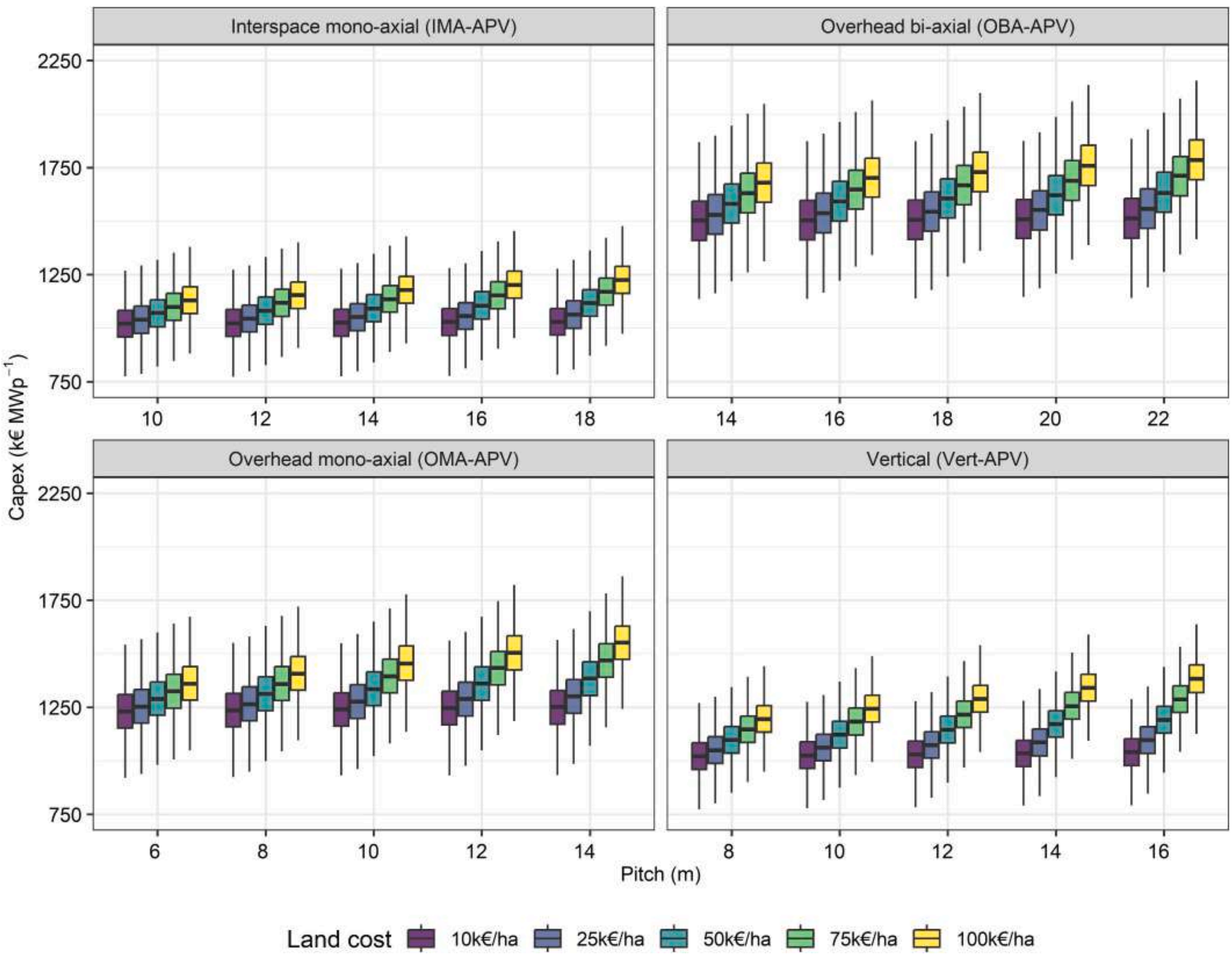

Fig. 11. Monte Carlo Analysis (MCA) outcome for initial capex requirement. The initial Capex is intended for placing a 1 MW_p APV. Different land costs are assumed to represent cost variability throughout different Italian Regions.

Table 12
Criteria and expert ranking for optimal weights calculation by means OPA model.

Experts list / Criterion name	Ra1	Ra2	RPV1	RPV2	Farm1	Farm2	Park dev. 1	Park dev. 2	Optimal weights
CR	1	1	4	4	1	1	4	4	0.255
WUE	2	2	5	5	3	4	5	5	0.118
Specific energy yield	5	4	1	1	5	5	2	1	0.235
Energy conversion per hectare	3	5	2	3	4	2	3	3	0.163
Capex	4	3	3	2	2	3	1	2	0.229

Notes: Ra1: Researcher Agricultural 1, Ra2: Researcher Agricultural 2, RPV3: Researcher PV 1, RPV4: Researcher PV 2; Farm1: Farmer 1, Farm 2: Farmer 2, Park dev. 1: park developer 1, Park dev. 2: park developer 2.

and used as a proxy for weight computing, are also showed.

The CR, constrained by yield reduction policy, was the KPI with the highest significance in the MCDA process. Specific energy yield was identified as the second priority KPI by the experts, underscoring its critical role in assessing PV performance when comparing different plants. The Capex was of particular interest to all experts, particularly since the analysis did not account for any economic contributions from policy makers in any of the considered scenarios. Lastly, WUE and Energy conversion per hectare interested only the expert related to agriculture, thus they represent the least important KPI in our MCDA study.

3.5.2. MCDA based optimal APV

The outcome of MCDA is presented in Fig. 12. Ranks of each APV discretized by the pitch are listed from the worst, in the bottom part of each graph, to the best, at the top of each graph. Each graph represents one of the given Italian sites. In the Northern sites, Piacenza and Grosseto, the IMA-APV (with 10 m pitch), having the highest similarity index was the best option. The OMA-APV with 6 m pitch, scored the highest for each of the remaining sites. Vert-APV ranked the lowest for each of the sites, with the largest pitch (16 m).

APV with narrow pitches are ranked at the top of the lists (excluding the Vert-APV), most likely for the energy conversion per unit of land that

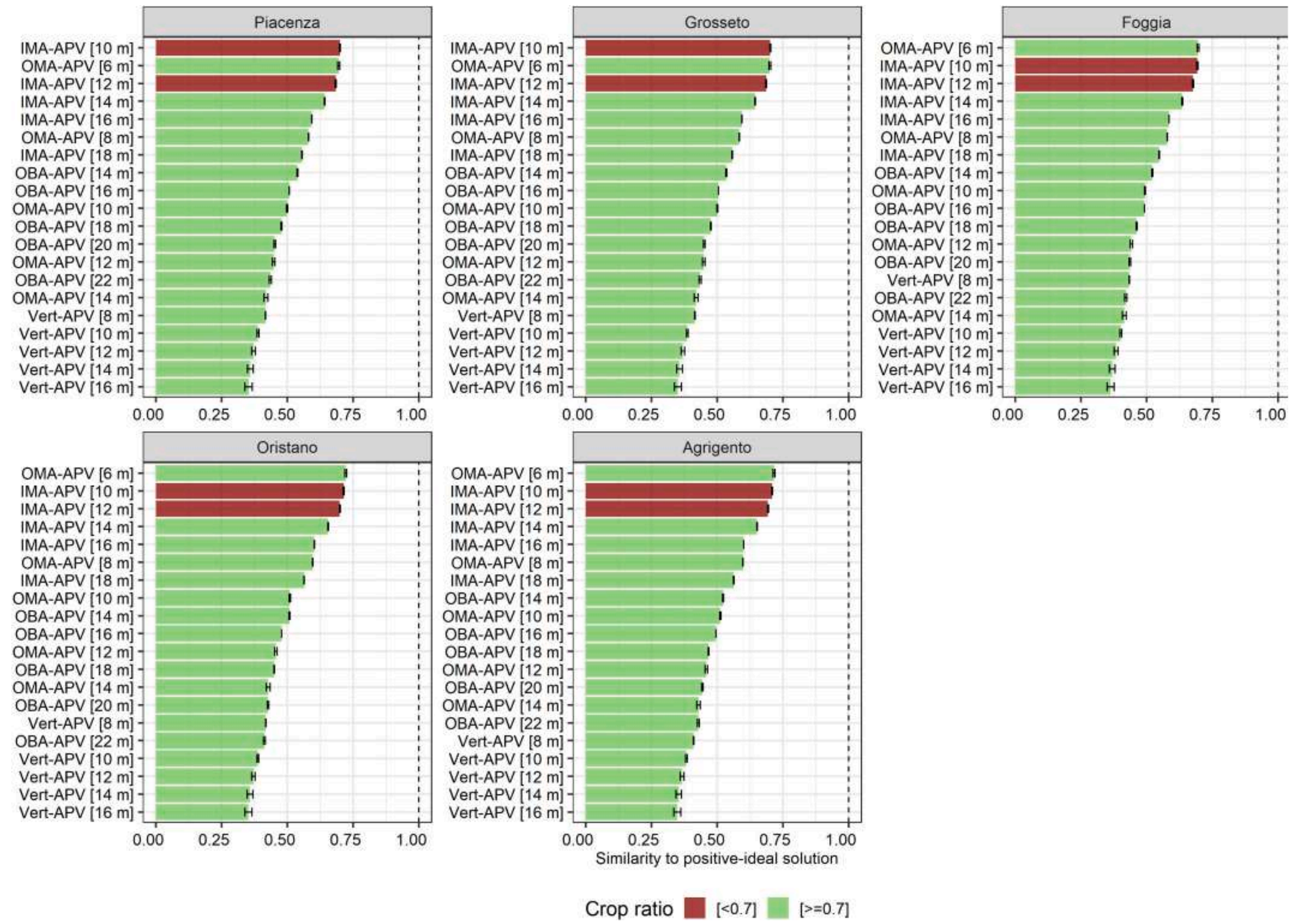

Fig. 12. TOPSIS Similarity indexes for each APV alternatives. APVs alternatives are listed according to sites. The similarity indexes are calculated as mean value that consider all the possible land costs added to the median value of the Capex obtained through Monte Carlo Analysis. The higher the standard deviation the more incident is the land cost on the overall similarity index. The Alternatives are ranked from the worst (bottom of each graph) to the best (top of each graph). Rankings in Piacenza and Grosseto were very similar, while some variations were observed in the other sites, which highlighted the influence of climate on APV ranking and the possibility to select specific APV solution for a given site. In Fig. 12, APV solutions marked in red do not satisfy the CR threshold indicated by the UNI /PdR 148:2023. Therefore, the OMA-APV, with 6 m pitch, ranked highest in each of the studied locations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

increases with decreasing pitches (high GCR). Furthermore, since the initial Capex was calculated for the installation of 1 MW_p APV, with decreasing pitch less land surface is required, as indicated in Table 11. It must be noted that, in this assessment, APV suitability to agricultural mechanization is not considered. Rankings are therefore useful to highlight the best performing APV according to the mentioned KPIs only, but the final choice should be limited to those APV alternatives compatible with a wide range of operating machines. OBA-APV and all other APVs having large pitches offer more flexibility to agricultural choices, which is a desirable feature for APV as indicated by the JRC [87] but have higher cost than others alternatives. IMA-APV resulted top ranked due to a low initial Capex and a high electricity conversion per hectare.

3.6. Limitations of the study

The simulations in this study do not consider year-to-year soil dynamics. For each new simulation, the crop model resets its initial input and starts a new cycle with the next weather file. This approach precludes assumptions about long-term soil organic matter storage and the implications for crop rotation. Moreover, although processing tomato seems to maintain a fair production under APVs, other crops may be more significantly affected by the altered micro-environmental conditions. This differential crop adaptability to shading [88] could significantly alter the rankings derived from the MCDA, and further investigation in this area would be required. Due to the study's complexity, the attentions were focused on comparing pitches as the primary design parameter among APV types. Future research should investigate the impact of varying APV heights on crop production and energy conversion. In this study, simulations were carried out using historic weather data. Given the impacts of climate change on agriculture, future research could use projected climate data to evaluate the potential of APVs to mitigate the detrimental effects on processing tomato, as outlined by Cammarano et al. [89]. The findings are specific to the context of Italy's agricultural practices and agrivoltaics policies. The methodology's reliance on GCR and crop yield policy constraints may limit its direct applicability to other European Countries with differing regulatory frameworks. The methodology developed in this study requires specialized computational resources and expertise. This could pose a barrier to widespread adoption and limit the accessibility of results for non-technical stakeholders in the APV sector. The MCDA framework offers a structured approach, but it may oversimplify the real complexities of APVs, such as interactions with local ecosystems, long-term environmental impacts, and socio-economic considerations. This simplification could potentially lead to suboptimal decision-making in certain contexts. Future research could refine the methodology to enhance its applicability and reduce computational requirements. Additionally, integrating new KPIs into the MCDA could address further aspect of APVs such as environmental impacts and suitability for mechanization.

4. Conclusions

Agriphotovoltaics are complex systems, whose design and management must be optimised using a broad set of KPIs and considering environmental conditions. In this study, a modelling approach, coupled to a Multi Criteria Decision Analysis, was used first to calculate the value of a selection of Key Performance Indicators (Crop Ratio, Water Use Efficiency, Energy conversion [MWh ha^{-1}], Specific energy yield [kWh kWp^{-1}] and initial Capital expenditure) and then to rank and select the optimal agriphotovoltaic solutions for a given environment. Simulations performed by coding the models in SciLab generated reasonable outputs, with levels of crop yield and energy conversions in line with results from other studies. In particular, it was found that:

- Mono-axial systems, with narrow pitches, had the best ranking in all environments;
- The overhead mono-axial and the vertical systems create more uniform radiation condition for the crops compared to the interspace mono-axial and the overhead bi-axial systems;
- In agriphotovoltaic systems with narrow pitch, the agricultural yield is reduced due to both high shading and unproductive areas bearing. These areas are necessary for safe machinery operation and to prevent crops damaging from PV modules solar tracking. This yield reduction is more pronounced in narrow-pitch and interspaced systems compared to overhead and larger pitch systems;
- Interspace mono-axial APV have the lowest initial Capex and the highest energy conversion per hectare, but the worst agronomic performances;
- Overhead bi-axial APV has the highest specific energy yield [kWh kWp^{-1}] and the greatest flexibility for agricultural exploitation but is the most capital intensive;
- Effect on water use efficiency, although limited in this study due to the absence of water stress (ET_c restitution 100%), are present for all configurations. Specifically, narrow pitches, due to increased shading, had on average the highest water use efficiency. The greatest water savings were observed in sites characterized by hotter and drier climate in comparison, indicating a pronounced environmental influence on the magnitude of this Key Performance Indicator.

In the coming years, a significant increase in the development of agriphotovoltaic is expected worldwide and in Italy. The development of sustainable agriphotovoltaic, which support decarbonisation while maintaining acceptable agricultural productivity, will benefit from the availability of optimisation procedures like the one proposed in this study. The optimisation of agriphotovoltaics will have to be further improved, particularly considering environmental impact. In future studies Multi Criteria Decision Analysis will have to be extended to environmental Key performance indicators, for example including Life cycle assessment impact categories as climate change, resource use, and critical materials [5].

CRediT authorship contribution statement

Yuri Bellone: Writing – original draft, Investigation, Formal analysis, Data curation, Conceptualization. **Giorgio Impollonia:** Writing – review & editing, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Amirhossein Nik Zad:** Writing – review & editing, Formal analysis, Data curation. **Michele Colauzzi:** Writing – review & editing, Methodology, Formal analysis, Data curation, Conceptualization. **Pietro Elia Campana:** Writing – review & editing, Methodology, Conceptualization. **Stefano Amaducci:** Writing – review & editing, Funding acquisition, Conceptualization.

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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2024.123490.

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