

UNIVERSITÀ CATTOLICA DEL SACRO CUORE

Sede di Piacenza

Dottorato di ricerca per il Sistema Agro-alimentare

Ph.D. in Agro-Food System

Cycle XXXVIII

S.S.D. AGRI-02/A – IIND-06/B



UNIVERSITÀ
CATTOLICA
del Sacro Cuore

APPROACHES TO PLAN AND DEPLOY SUSTAINABLE AGRIVOLTAIC SYSTEMS

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Matriculation n: 5215841

Academic Year 2024/2025



Finanziato
dall'Unione europea
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ABSTRACT

Agrivoltaics (APV) has emerged as a strategic solution to mitigate land-use conflicts between agricultural production and renewable energy generation. However, its widespread deployment is currently hindered by technical uncertainties regarding compatibility with modern farming practices, complex agronomic-energy trade-offs, and a lack of standardized planning tools. This doctoral thesis aims to define a comprehensive operational framework to support the design, performance assessment, and spatial planning of sustainable APV systems.

The research is structured into three interconnected studies addressing critical barriers to implementation. First, the compatibility between APV infrastructure and agricultural mechanization is analysed. By evaluating design parameters such as row spacing, clearance height, and structural layout, the study demonstrates that without specific co-design strategies, the Field Efficiency (FE) of the agricultural machines can decrease by up to 45% and resulting in significant losses of arable land due to uncultivated buffer zones.

Second, an integrated simulation framework coupling radiation modelling with the GECROS generic crop model is developed to evaluate APV system performances among different typologies. Applied to a case study of processing tomatoes across five Italian locations, the research utilizes Multi-Criteria Decision Analysis (MCDA) to compare various configurations (fixed, vertical, single and dual-axis tracking). The results highlight that while single-axis trackers often provide the highest energy yield, specific elevated or wide-spaced configurations are superior for maintaining flexibility on agricultural operations.

Finally, the study assesses the territorial suitability for APV deployment in Italy using a Fuzzy-MCDM approach (Fuzzy-AHP and Fuzzy-TOPSIS). By integrating regulatory, physical, and agronomic constraints, the spatial analysis reveals that despite excluding significant areas due to environmental restrictions, the availability of "Very High Suitability" land classes is abundant. Meeting the 2030 regional burden-sharing targets would require occupying less than 1% of the suitable agricultural surface, indicating that barriers to diffusion are primarily regulatory rather than physical. Collectively, this research provides policymakers, planners, and farmers with robust methodologies to optimize APV systems, ensuring they are technically feasible, economically viable, and synergetic with agricultural activities.

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List of Abbreviations

Abbreviation	Definition
Ai	Aridity Index
APV	Agrivoltaics (or Agriphotovoltaics)
AV	Agrivoltaics
Aw	Effective working width
AYAPV	Agricultural fresh yield per hectare in APV [Mg ha ⁻¹]
AYFL	Agricultural fresh yield per hectare in full light [Mg ha ⁻¹]
BOS	Balance of system
Bz	Buffer zones
CAPEX	Capital expenditure (Initial)
CC _i	Closeness Coefficient
CLC	CORINE Land Cover
CLCplus	CORINE Land Cover Plus Backbone
CLMS	Copernicus Land Monitoring Service
COD_REG	Regional Code
CR	Crop Ratio [Mg ha ⁻¹ / Mg ha ⁻¹]
Cs	Clearance space
Cu	Coefficient of use
DEM	Digital Elevation Model
EFC	Effective Field Capacity
ER	Energy ratio [MWh ha ⁻¹ / MWh ha ⁻¹]
ET ₀	Reference Evapotranspiration
ETc	Crop evapotranspiration [m ³]
ETc _{,APV}	Crop evapotranspiration in APV condition [m ³ ha ⁻¹]
ETc _{,FL}	Crop evapotranspiration in full light condition [m ³ ha ⁻¹]
ETRS89	European Terrestrial Reference System 1989
EYAPV	Annual energy converted by the APV [MWh ha ⁻¹]
EYPV	Annual energy converted by the reference PV system [MWh ha ⁻¹]
FAHP	Fuzzy Analytic Hierarchy Process
FE	Field Efficiency
FL	Full light
GCR	Ground Coverage Ratio
GHI	Global Horizontal Irradiance
GM-PV	Ground-Mounted Photovoltaic
GNSS	Global Navigation Satellite Systems
GSE	Gestore Servizi Energetici
IMA-APV	Interspace mono-axial sun tracking agriphotovoltaic system
IMU	Inertial Measurement Units
<i>I_w</i>	Implement working width
KPI	Key Performance Indicator
LAEA	Lambert Azimuthal Equal Area
LCLU	Land Cover and Land Use
LCOE	Levelized Cost of Electricity
LER	Land Equivalent Ratio
MCA	Monte Carlo analysis

MCDA	Multi Criteria Decision Analysis
NUTS-2	Nomenclature of Territorial Units for Statistics (Level 2)
OBA-APV	Overhead bi-axial sun tracking agriphotovoltaic system
OL_A	Overlapping Area
OMA-APV	Overhead mono-axial sun tracking agriphotovoltaic system
OPA	Ordinal Priority Approach
O_s	Operating space
PAR	Photosynthetically Active Radiation
P_{max}	Light saturation point
PV	Photovoltaic
r_{min}	Minimum turning radius
RED II	Renewable Energy Directive II (Directive EU 2018/2001)
RES	Renewable Energy Sources
Rp	Row pitch
RR	Radiation ratio [$\text{kWh m}^{-2} \text{ year}^{-1} / \text{kWh m}^{-2} \text{ year}^{-1}$]
RTK	Real-Time Kinematic
Se	Effective speed
SIC	Sites of Community Importance
SLAM	Simultaneous Localization and Mapping
SOC	Soil Organic Carbon
SOM	Soil organic matter
STC	Standard test conditions
TFC	Theoretical Field Capacity
TFN	Triangular Fuzzy Numbers
Tw	Theoretical width covered
Vert-APV	Vertical agriphotovoltaic system
VH, H, M, L, VL	Very High, High, Medium, Low, Very Low (Suitability classes)
wc	Water content coefficient
W_p	Peak power [W]
WSO	Dry weight of storage organs
WSOAPV	Dry weight of storage organs in APV condition [g m^{-2}]
WSOFL	Dry weight of storage organs in full light condition [g m^{-2}]
WUE	Water Use Efficiency
WUEAPV	Crop water use efficiency in APV scenario [Mg m^{-3}]
WUEFL	Crop water use efficiency in full light condition [Mg m^{-3}]
x	Entry/exit-point distance between tracks
ZPE	Extended Protection Zones
ZPS	Special Protection Areas

CHAPTER 01.

INTRODUCTION



1.1. The Agrivoltaics: concepts and scope

The Italian National Integrated Energy and Climate Plan (PNIEC), updated in July 2024, targets a photovoltaic capacity of approximately 80 GW by 2030 [1]. However, assuming the exclusive deployment of ground-mounted PV (GMPV) systems with an average power density of 1 MW ha⁻¹, this capacity would entail the occupation of approximately 80,000 ha of land, an area exceeding the entire territory of the Province of Lodi. Furthermore, the PNIEC projects a total installed renewable capacity of around 131 GW, expected to cover 63.4% of the country's gross final electricity consumption. While such an objective is ambitious given the limited timeframe, reliance on GMPV creates a direct conflict with agricultural land use. This competition arises because agricultural lands hold high solar potential. Notably, Adeh et al. [2] highlighted that agricultural areas provide some of the most suitable environments for PV performance, offering optimal insolation, air temperature, wind speed, and relative humidity. Conversely, rooftop PV installations are generally less economically competitive. This disadvantage stems from higher capital expenditures (CAPEX), reduced efficiency due to suboptimal tilt and orientation [3], and limited economies of scale compared to utility-scale systems (Christ and Wagner, 2025). Consequently, the Levelized Cost of Electricity (LCOE) for rooftop PV remains higher than that of GMPV [4]. Renewable energy projects, particularly when competing for critical resources such as land and water, often face significant challenges regarding social acceptance [5,6]. A proposal to reconcile land use between agriculture and solar energy generation was first formulated in 1982 by Professor Goetzberger, founder of the Fraunhofer Institute for Solar Energy Systems, and Zastrow [7]. They conceptualized Agrivoltaics (APV) as an integrated production system where PV energy generation and agricultural activity coexist on the same land area. Their concept was driven by the anticipation that the widespread deployment of photovoltaic technology would intensify land-use competition, a pressure already exacerbated by urbanization. Recently, this approach has emerged as a key strategy to mitigate the conflict between food and energy production, while significantly enhancing land-use efficiency [8,9]. Consequently, APV is increasingly recognized as a distinct category within renewable energy sources, often benefiting from dedicated policy definitions and subsidies that differentiate it from conventional ground-mounted PV. Italy, for instance, recently codified this distinction in its latest legislative decree (D.L. 175/2025). This decree defines Agrivoltaics as a photovoltaic installation where modules are elevated from the ground, potentially featuring rotation systems, to preserve the continuity of agricultural operations, while also mandating the application of digital and precision agriculture tools.

The recent momentum in international policy support for APV deployment has catalysed a significant increase in scientific research. These studies have predominantly focused on assessing the system's impact on crop yields and evaluating the techno-economic viability of such installations [10–12].

Consequently, a vast literature has formed for APV, encompassing diverse disciplines such as engineering, agronomy, plant physiology, economics, and environmental science. Key areas of investigation include the agronomic performance of crops grown under APV [11,13–17], and integrated model-based simulations for both crop yield prediction [8,18–21] and system optimization [22–25]. Furthermore, significant attention has been devoted to techno-economic analyses [10,12,26,27] and Life Cycle Assessments (LCA) of APV systems [28–30]. The biological rationale for agrivoltaics rests on the discrepancy between the solar energy conversion efficiency of photovoltaic systems (18–22%) [31,32] and plant photosynthesis (4–6%) [33]. Since the photosynthetic rate of many crops saturates below full sunlight intensity as summarized in Figure 1.

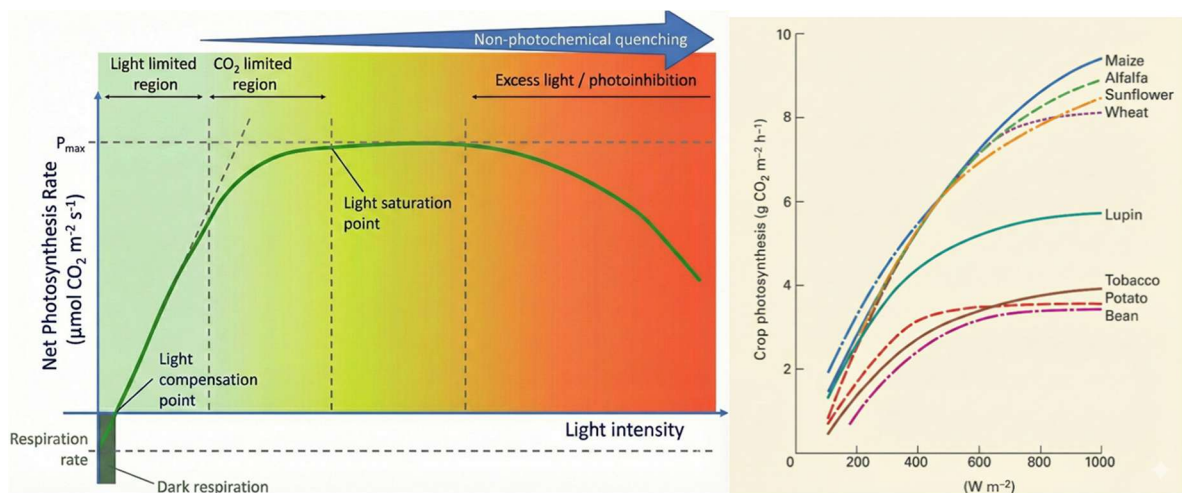


Figure 1. On the left, general leaf Photosynthetic response to light intensity. The light compensation point indicates the radiation intensity required for the net photosynthetic rate to equal zero (balancing respiration). As Photosynthetically Active Radiation (PAR) increases beyond this threshold, net photosynthesis becomes positive. The light saturation point (P_{max}) marks the intensity at which the photosynthetic rate reaches its maximum and stabilizes. Beyond this threshold, excess irradiance may lead to photoinhibition, causing a subsequent decline in the photosynthetic rate [34]. On the right Photosynthetic response curves of various C3 and C4 crops to solar irradiance intensity [W m^{-2}] [35].

APV structures generate significant daily spatial heterogeneity in microclimatic conditions underneath modules by altering the daily distribution of solar radiation reaching the ground growth [36,37]. Moreover, the physical obstruction of the modules modifies precipitation patterns and evapotranspiration dynamics. This creates distinct zones of soil moisture availability, effectively driving spatial variability in the water demand of the underlying crop [38–40]. A general consensus exists regarding the strategic value of APV systems, particularly

in regions prone to drought and characterized by high solar radiation. In these environments, the partial shading provided by photovoltaic panels serves as a critical tool for microclimate regulation [41,42]. From an agronomic perspective, this shading mitigates multiple stressors, including excessive radiation, heat stress, and water deficits, thereby improving crop tolerance to harsh conditions [40,43–48]. By reducing soil water evaporation and plant transpiration demands, APV systems have been shown to significantly increase Water-Use Efficiency (WUE) and reduce overall water consumption [39,49,50]. Furthermore, the physical structure provides protection against adverse weather events, such as hail, heavy rainfall, and strong winds, as well as fruit sunburn, which contributes to higher agricultural product quality and more stable yields over time [13,15,36,51–54]. In terms of land-use efficiency, the combined production of crop yield and electricity contribute to a superior Land Equivalent Ratio (LER) [55,56]. As one of the most widely adopted Key Performance Indicators in APV research, the LER quantifies the increased efficiency of integrated production on a single land unit compared to separate crop cultivation and energy generation on distinct parcels [8,9].

APV induced benefits are not limited to crops. The presence of vegetation beneath photovoltaic modules can reduce panel temperature through crop transpiration, thereby increasing energy conversion efficiency [57,58]. Moreover, vegetation enhances the albedo coefficient, improving solar reflection exploitable by bifacial photovoltaic modules [50,59]. Table 1 summarises the main advantages arising from the synergy between crops and photovoltaic modules in an AV system.

Table 1. Advantages of the interaction between crops and photovoltaic modules in an agrivoltaic system

Environmental & Social	Agronomic	Economic
Climate change mitigation	Increased water-use efficiency	New employment opportunities
Renewable energy generation	Stabilised crop yields	Diversification of farm income
Improved land-use efficiency	Rainwater harvesting for irrigation	Cooling effect on modules and higher conversion efficiency
Greater ecosystem services compared with ground-mounted PV	Reduced crop heat and drought stress	Exploitation of leaf albedo

Potential for off-grid systems to meet rural energy demand	Crop protection from adverse weather	Development of energy communities
Use of peri-urban and marginal land		Rural economic development and food security

Despite these benefits, the implementation of APV on agricultural land presents specific drawbacks. The most immediate is the reduction of effective arable surface due to the footprint of mounting structures and PV modules for some typology; however, this loss is generally marginal compared to the total land exclusion associated with conventional GMPV [60]. A more critical constraint is the potential decrease in crop yield resulting from the reduced photosynthetic active radiation (PAR) reaching the canopy [61,62]. This is most subject to environmental condition and microclimate resulting from the interaction between APV specific configuration and crop [48,63]. Furthermore, the design of an APV system is inherently more complex than that of a conventional GMPV plant. It requires a delicate balance between ensuring adequate light availability for crops and maintaining the spatial feasibility for mechanized farming operations [64]. Moreover, compared to ground-mounted systems, APV installations necessitate elevated modules and wider inter-row spacing (pitch) typically resulting in a lower Ground Coverage Ratio (GCR) compared to GMPV [12,65]. Beyond technical constraints, large-scale deployment may raise social concerns regarding visual impact and landscape integration, particularly when sites are located near residential areas or protected natural environments [66].

1.2. Challenges in APV development

Although APV systems offer a pathway to generate renewable energy while preserving the Water-Energy-Food nexus, their large-scale deployment faces significant technical and operational hurdles. A fundamental prerequisite, ensuring the continuity of agricultural operations, can only be met if system designs effectively accommodate agricultural machineries. The principle of non-disturbance proves effective only if the physical structure does not impose critical constraints on the adoption and manoeuvrability of mechanized equipment. Furthermore, the design topology of APV is highly variable, with numerous parameters defining the final configuration. Given that system performance is heavily dependent on system topology and intrinsically linked to site-specific climatic and environmental conditions, identifying optimal configurations that balance energy and crop yield

is a complex task. Consequently, developing comprehensive simulation frameworks to evaluate the synergistic performance of the integrated PV and crop components is essential. Such decision-support tools are critical for guiding stakeholders, including investors, institutions, and farmers, through the strategic planning phase.

The complexity of APV extends beyond questions of design and performance evaluation, as renewable energy installations are often perceived as intrusive when social acceptance is considered. Across Europe, large areas with naturalistic, historical, or cultural value restrict the installation of renewable energy systems, including APV, even in their vicinity. EU Member States have adopted different policies to define APV and its technical requirements, leading to significant heterogeneity in deployment strategies.

Although most advanced APV systems occupy only a minimal footprint on the agricultural land where they are sited, their development has historically been constrained by regulatory uncertainty. Only recently have countries such as Italy begun to refine their legislative frameworks to establish clear criteria for identifying eligible areas. This regulatory clarity is propaedeutic to achieving the renewable energy generation targets mandated by the EU's decarbonization and carbon neutrality pathways for 2050.

1.2.1. Continuity of agricultural activity

APV is currently experiencing a phase of rapid expansion and technological refinement. In the past three years, numerous experimental and commercial installations have been developed, accompanied by a remarkable increase in scientific publications. Following an initial period of social and market resistance, APV systems have gained significant traction, particularly within EU countries, driven by targeted policy measures and financial incentives. However, several challenges have emerged among stakeholders. One of the most critical issues is the absence of a clear and widely accepted classification of APV systems. Many studies labelled as APV have, in reality, adopted conventional photovoltaic layouts with reduced module density, yet without the necessary design features that enable genuine agricultural integration.

Although experimental trials have been conducted across a wide range of APV configurations and climatic zones, limited attention has been paid to whether the systems were truly designed for agricultural coexistence or merely adapted from traditional PV structures. This limitation becomes especially evident when cultivated areas require mechanized field operations, particularly mechanical harvesting. A primary barrier to APV development in agricultural field is, therefore, the incompatibility between standard agricultural mechanization and the structural constraints imposed by PV arrays that compromise the continuity of agricultural activities [67].

Farmers perceive machinery operations within APV systems as highly restricted, raising concerns about the long-term feasibility of these dual-use systems [68]. Specifically, the introduction of PV structures within a field subdivides the arable land into fixed sectors that enclose portions of arable land [66]. Design of APV systems can vary substantially, therefore the design parameters such as row pitch, height from the ground of the PV module, availability of solar tracking, orientation and array arrangement [69], eventually dictate the available space for machineries to work within these above-mentioned sectors. Agriculture necessitates a variety of operations during the crop growing cycle and between crop cycles, therefore the presence in the field of obstructing pillars of any nature, poses a serious drawback in machinery movement, especially if the goal is to generate high energy per area by setting in place an APV dense configuration that reduces the row pitch to increase the number of modules per hectare, ultimately hindering agricultural operations not only for reduced PAR but for physical impediment in performing soil tillage, harvesting etc.

In Italy, for instance, existing national guidelines primarily address parameters such as module elevation and land coverage, while row spacing remains undefined. As a consequence, the space required for machinery operation is often overlooked, despite national documents emphasizing that APV installations must ensure the continuity of agricultural activity. Ensuring compatibility between APV design and standard mechanized farming operations must therefore be regarded as a fundamental prerequisite for any agrivoltaic system.

Agricultural mechanization is crucial for defining an efficient agricultural system and its widespread adoption discretizes the transition between a market-oriented economy in agriculture and accelerates rural development [67]. Therefore, bridging the gap between agrivoltaics and modern agriculture is critical. To achieve this, it is essential to leverage mechanized equipment and precision agriculture technologies adapting to APV, thereby enhancing the integration, efficiency, and scalability of these systems. Current approaches have seen pre-existing machinery and technology to be adapted to APV. To date, only PV structures have been modified portraying APV, while machinery and digital precision tools are still meant to be used in open field agriculture. Until dedicated technologies and machinery will be developed keeping APV in mind, an adaptation for having suitable matching between machinery is to be done during system design to demonstrate that a system is eligible to be indicated as “non interrupting agricultural operation continuity”. However, despite its operational importance, this key aspect has not been a central focus of research to date. While numerous studies on APV have been conducted, they generally offer only fragmented insights

into agricultural mechanization. Often, the topic is mentioned merely as a logistical constraint to be managed, rather than being the subject of detailed, quantitative analysis.

1.2.2. Models to support APV design

The design of APV systems requires meeting multiple objectives simultaneously, as photovoltaic (PV) parameters influence both electricity generation and crop production, making APV a typical multi-objective optimization problem [70]. The core challenge lies in balancing solar energy output with agricultural productivity. Unlike conventional ground-mounted PV, where optimization focuses exclusively on energy, APV requires a synergistic balance because each design decision affects both outputs, often in conflicting ways [25]. Optimization of the photovoltaic component relies on well-established parameters such as tilt angle, orientation, and inter-row spacing to minimize mutual shading [71]. Crop performance, however, depends on a broader set of interacting factors, including APV configuration (vertical vs. overhead, static vs. tracking), module transparency, and the resulting microclimatic modifications [24,72,73]. Structural variables determine the spatial distribution of Photosynthetically Active Radiation (PAR), precipitation patterns under the modules, and evapotranspiration dynamics [48,63]. For farmers, understanding whether crop production remains acceptable under APV is crucial, even if energy revenues can compensate for moderate yield losses. In many countries, regulatory frameworks constrain reductions in crop yield in APV, making the maintenance of satisfactory crop production a requirement for accessing funding or for eligibility to install APV systems [24,25,63]. While PV output can be reliably predicted using commercial simulation tools such as PVSyst [74], forecasting crop yield under APV remains more uncertain due to environmental and biological variability. APV performance is highly context-dependent: a configuration suitable for lettuce in one climate may underperform for wheat, or even for lettuce under different climatic conditions [62].

Model-based simulations are increasingly used in APV research because they enable extensive *in silico* exploration of design permutations. These tools allow the assessment of optimal ground coverage ratio (GCR), clearance height, and tracking strategies before physical installation [22,25,75], or the comparison of predefined design options to identify the optimal trade-off between agricultural yield and solar energy generation [76]. APV performance is commonly evaluated using Key Performance Indicators (KPI) such as the Land Equivalent Ratio (LER) [23,70]. At the planning stage, APV-adjusted crop models also support large-scale geographic assessments [25,27], helping identify regions with high potential for synergistic benefits, such as hot and arid areas where water savings are particularly valuable [77].

Despite recent progress, a comprehensive comparative framework is still lacking to support decision-makers in identifying which APV configuration (e.g., vertical vs. overhead) is most suitable for a given environment, either to minimize yield reductions (Crop Ratio) or to ensure economic viability under specific climatic conditions. Even when design constraints are respected (e.g., minimum height of 2.10 m; [78,79], several APV configurations remain viable. Assessing which design is most appropriate requires anticipating the outcomes of the interaction among APV configuration, local environment, and crop. This, in turn, demands simulation tools capable of predicting these coupled responses.

1.2.3. Defining spatial potential for APV deployment

Achieving the decarbonization targets mandated by the European Union requires the widespread deployment of renewable energy systems. However, a significant challenge lies in identifying suitable land that balances energy generation with agricultural preservation. While rooftop PV contributes to these targets, its potential is limited by structural constraints and higher Levelized Costs of Electricity (LCOE) compared to ground-mounted systems [80–86]. Consequently, a variety of studies worldwide assessed, adopting different methodologies, the spatial potential for APV on agricultural land also to support policymakers' decision. Victoria and Niazi [87] estimated Europe's APV potential at 51 TW, noting that a capacity density of 30 W m⁻² allows for high generation while preserving over 80% of land for crops. Similarly, Chatzipanagi et al. [88] calculated that meeting the EU Solar Energy Strategy target (730 GWp by 2030) would require less than 1% of the utilized agricultural area. Similarly Jamil et al. [89] found that allocating just 1% of agricultural land of Canada to vertical APV could supply approximately one-quarter of the national energy demand.

Land suitability studies often rely on Geographic Information Systems (GIS) integrated with Multi-Criteria Decision Making (MCDM) frameworks [90]. These frameworks typically adopt weighed criteria such as solar irradiance, slope, and proximity to infrastructure based on stakeholder or expert preferences [91–93]. For example, topographic factors are widely cited as limiting variables; flatter terrain is preferred to minimize erosion risk and simplify construction [94,95]. Furthermore, the Water-Energy-Food nexus is often prioritized by favouring areas where APV can mitigate crop heat and water stress, such as vineyards in South Africa [96] or semi-arid regions anticipated to expand due to climate change [97]. A crucial step in every suitability assessment is the definition of unsuitable areas. These area has zero suitability and APV installation is hindered due to physical-technical constraint or law enforced constraints (such as protected areas) [98]. Consequently, a vast area may become unsuitable due to landscape, environmental, or cultural constraints (Christ & Wagner, 2025; Fattoruso et al., 2024; Khazael et al., 2025).

In the Italian context, the regulatory framework has recently shifted with the introduction of D.L. 15 May 2024, n. 63 and D.M. 21 June 2024. These decrees mandate that regions define "suitable areas" for renewable energy generators installation. However, the implementation so far has been slow; as of September 2024, only a fraction of Italian regions has complied with the mapping requirements. Regional individuation of suitable areas is required to acknowledge what surface is available among each Region to be adopted to meet renewable energy installation target stated in burden sharing within the PNIEC.

1.3. Objectives

To address the challenges described above and to fill the current gaps in the agrivoltaic literature, this thesis provides stakeholders with practical tools for evaluating APV suitability during the design, management, and site-selection phases. It presents a comprehensive review of the mechanization requirements of APV systems and identifies the key design parameters that must be considered to ensure the effective integration of agricultural machinery within APV installations.

Building on this foundation, the thesis pursues three core objectives:

- **O1:** To identify and evaluate the key design parameters necessary to ensure the effective integration of agricultural mechanization within APV systems.
- **O2:** To develop a simulation framework based on integrated APV modelling capable of predicting the outcome of specific APV configuration-crop-environment combinations, thereby supporting decision-making during the design phase.
- **O3:** To provide a comprehensive assessment of spatial potential by applying a fuzzy-MCDM framework that integrates diverse decision-making profiles (Agro, Energy, Planner) and evaluates the sensitivity of land suitability to national (Global) versus regional (Local) classification strategies.

The first study presented in this thesis establishes a practical framework of design criteria suitable for mechanized agriculture. It examines the spatial requirements of agricultural machinery within APV layouts, both in static conditions and during motion, accounting for field overlap and headland manoeuvres. Specifically, the study addresses the following research question:

- Which design parameters must be considered to ensure that APV systems can fully accommodate mechanized agricultural operations?

The subsequent study establishes the foundation for a comprehensive evaluation of the interaction between APV configuration, crop, and environment using simulation software. This study answers the research question:

- How to select the best alternatives between different available APV configurations when comparing different installation sites?

Finally, the third study applies the previously adopted frameworks in conjunction with national policy to identify the optimal locations for APV deployment. Two spatial approaches are utilized at both the national and regional scales to respond to the research questions:

- Where can APV be installed to minimize the impact on the environment and agricultural activities?

- Is the extent of high-suitability land sufficient to meet regional Burden Sharing targets while minimizing conflicts with high-value agricultural activities?

1.4. Thesis outline

This doctoral thesis is organized into five chapters, designed to address the specific barriers to APV deployment identified above: agricultural mechanization compatibility, design performance evaluation, and spatial suitability.

Chapter 2 addresses the often-overlooked challenge of integrating agricultural mechanization within APV systems. While most literature focuses on crop yield or energy output, this chapter investigates the physical and operational constraints imposed by PV structures on farm machinery. Through a systematic review of existing design classifications and operational workflows, it analyses the impact of vertical clearance, horizontal spacing, and mounting structures on field efficiency and machinery manoeuvrability. The chapter aims to establish a baseline for co-design principles that ensure full compatibility between open-field farming operations and energy generation infrastructure.

Chapter 3 focuses on the methodological complexities of evaluating APV system performance. Given the variability in design and geographic context, comparing different APV configurations requires a robust analytical framework. This chapter introduces the integration of radiation and crop growth models to simulate system behaviour, providing a predictive tool to evaluate design parameters before physical installation through a Multi-Criteria Decision Analysis (MCDA) approach based on Key Performance Indicators (KPIs).

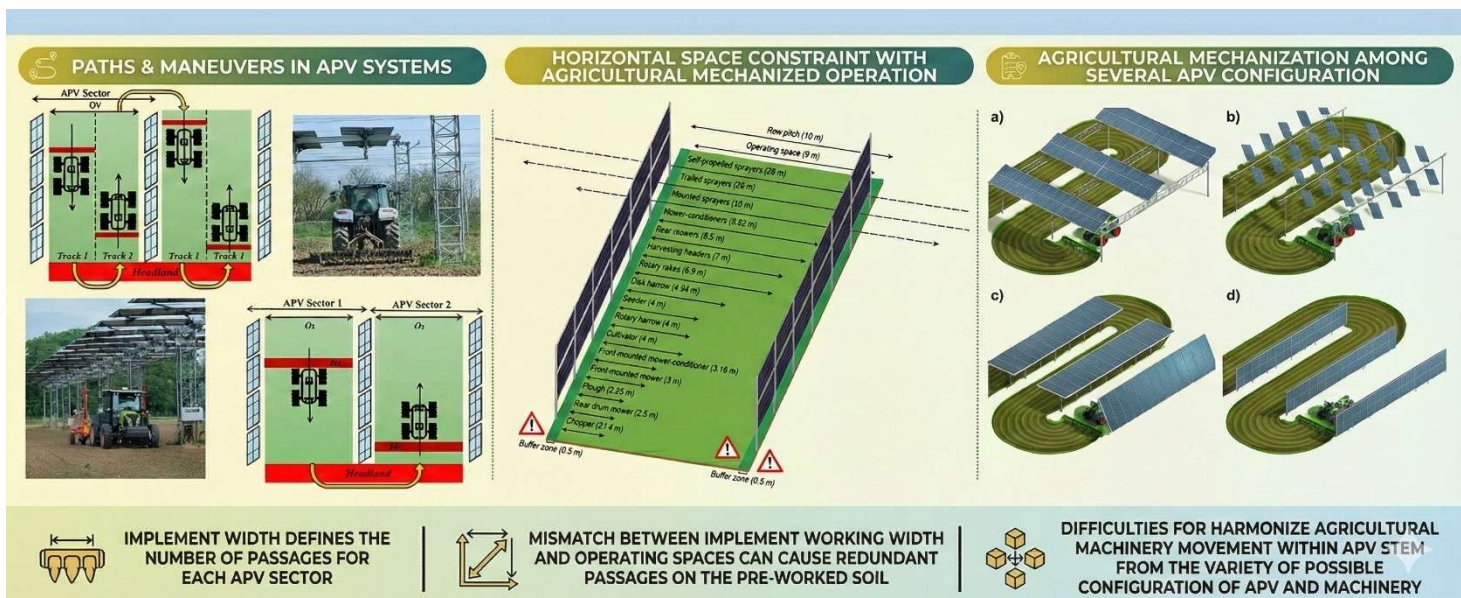
Chapter 4 examines the spatial and regulatory dimensions of APV deployment, with a specific focus on the Italian context. This chapter utilizes a Multi-Criteria Decision Making (MCDM) approach by adopting Fuzzy-AHP to weight evaluation criteria and Fuzzy-TOPSIS to analyse land suitability. By defining exclusion zones and evaluation parameters, this study proposes a framework to identify optimal sites that minimize land-use conflict while maximizing energy generation potential.

Finally, **Chapter 5** presents the general conclusions, synthesizing the findings from the three core chapters. It discusses the implications for policy and industry standards and outlines future research directions necessary to support the large-scale deployment of sustainable APV.

CHAPTER 02.

AGRICULTURAL MECHANIZATION IN AGRIVOLTAIC SYSTEMS: CHALLENGES, ADAPTATION, AND POSSIBLE ADVANCEMENTS

Published in Renewable and Sustainable Energy Reviews. <https://doi.org/10.1016/j.rser.2025.116661>



2.1. Introduction

Global population growth is driving a significant increase in demand for both food [99] and energy [100]. This creates a fundamental challenge, as the production of food and the generation of energy often compete for the same finite resources: land and water [42]. This challenge is intensified by the global shift away from fossil fuels toward renewable energy sources to support sustainable development and decarbonization. Europe, for instance, is at the forefront of this transition, aiming to achieve net-zero emissions by 2050 [101]. The intricate relationship between these sectors has been recognized as the water-energy-food (WEF) Nexus [102]. Growing populations not only increase food and energy needs but also rely on limited water resources for urban, agricultural, and industrial use. Agrivoltaics (APV) has emerged as one of the solutions for developing both energy generation and food production by rationalizing land availability to support increasing population growth. An APV system provide the co-location of photovoltaic (PV) modules and crop production on the same agricultural land. This conceptual idea dates back in the 80's and was conceptualized by Goetzberger and Zastrow [7]. Since then, it has developed into a widely recognized topic within the framework of sustainable development [103]. The concept of co-locating different forms of production from distinct economic sectors on the same land is not new; agroforestry and intercropping systems, in fact, can be seen as a precursor to APV [74]. Agroforestry co-locates forestry and the agricultural activities forcing the farmer to deal with the interaction between two biological systems. As a matter of fact, one of the first employed Key Performance Indicator (KPI) for APV performance evaluation, the Land Equivalent Ratio (LER) has been widely used in agroforestry [8]. Interest in APV has grown rapidly in recent years driven not only by the energy demand increase but also by the sharp decline in PV module prices, approximately 90% between 2010 and 2020 [104], and the recent surge in energy costs, which have made PV systems increasingly attractive as energy source even for investors and private citizen. Since 2016, a growing body of review literature has emerged, covering a wide range of APV-related topics. These include assessments of APV potential application [74], evaluations of associated challenges such as possible yield reduction, soil occupation and the difficulty of machinery operations [105], and analyses of system designs. For instance, Toledo & Scognamiglio [106] reviewed technological and spatial design available options and proposed a methodology to define the main attributes of APV systems, while Trommsdorff et al. [9] focused on the compatibility between their specific APV design and machinery operation during early stages of APV deployment. Additional studies have explored available technical solutions, such as smart farming technologies [64] and wavelength-selective modules [107]. Research interest in APV extends beyond engineering and

solar applications, with considerable attention given to the effect of APV-driven microclimatic growing conditions on crops [45], the positive implications for the water-food-energy nexus [108], and the contribution of APV to various Sustainable Development Goals (SDGs) of the United Nations [109]. Furthermore, several studies have focused on classifying crops according to their suitability to APV conditions, particularly by evaluating the effect of shading on crop yield. For instance, Laub et al., [61] established yield response curves for various crop categories, identifying non-linear correlations between shading intensity and yield loss. These findings highlighted distinct thresholds of shade tolerance across different crop groups. A consecutive study by Dupraz [63] performed a comparable analysis, synthesizing published data on APV systems only and relating yield reduction to the ground coverage ratio (GCR) of the installations. More recently, Magarelli et al. [110] reviewed available APV studies on fruit crops, revealing a threshold of around 30 % shading below which yield reductions become commercially significant. Furthermore, recent research by Tekie et al. [48] has advanced the understanding of crop response in APV by integrating the Standardized Precipitation Evapotranspiration Index (SPEI) into yield prediction models, highlighting that water availability and drought conditions are critical determinants alongside shading intensity for APV crop productivity. Although APV has gained attention for its potential to address food and energy security, its widespread adoption is hindered by a primary challenge: the compatibility of solar structures with mechanized agriculture. This incompatibility introduces significant design complexities, leading farmers to perceive machinery operations within APV systems as highly restricted. In fact, an online survey conducted with 214 German farmers in 2023, pointed out that approximately 75% of farmers expressed concerns about the challenges of using agricultural machinery under APV systems [68].

Mechanization is recognized as a critical factor in developing efficient agricultural systems, playing a key role in the transition from subsistence farming to market-oriented economies [67]. By lowering the operational costs, mechanization enhances the profitability of agricultural systems, making farming activities remunerative, especially in developed contexts [104]. However, despite the importance of mechanization, this aspect within APV has not been a central focus of research to date. A search of the Scopus database using the keywords “agrivoltaics”, “agriphotovoltaic”, and “sunsharing” returned 867 publications, including 86 review articles. To date, only Gorjian et al. [67] have comprehensively addressed the integration of mechanization in APV, reviewing both potential compatibilities and challenges. Several other studies on APV provided only fragmented information on mechanization, often mentioning it briefly without detailed analysis [8,9,12,17,19,28,64,65,70,104,105,111–113]. The main

contributions and specific considerations regarding agricultural mechanization compatibility from these studies are summarized in Table 2. Additionally, limited information can be retrieved from APV producers who provide brief indications, on their websites or in technical sheets, regarding the design features needed to enable proper agricultural mechanization.

Table 2. Consideration on APV mechanization reported in literature

APV type	Specifications	Note
Overhead two axis [19,21,28]	Height [m]: 4.5 - 5 Row pitch [m]: 12 Year of project: 2011 - 2012 Location: Po Valley (Italy)	These APVs feature low module density (13 % GCR both) and have a large distance between rows and between subsequent pillars. As a result, mechanized operations can be conducted with standard machinery. Although the height of these plants may impact the economics of the systems, it guarantees access to all common agricultural machinery, while a lower height would only slightly reduce the cost of the supporting stilts.
Overhead fixed; overhead one axis [8,114,115]	Height [m]: 5 Row pitch [m]: 4 – 6.4 Year of project: 2010 - 2014 Location: Montpellier (France)	Early prototype APV system, the initial version was designed with a 4 m clearance height to facilitate mechanized activities. A dense PV configuration was utilized on a stilt mounted structure, which allowed for pillars to be well-spaced. An update in 2014 involved adding PV rows spaced 6.4 m apart and increasing the clearance height to 5 m. The distance between the supporting pillars was optimized to enable crop mechanization, lower the CAPEX, and maximize mechanical resistance. To avoid hindering cultivation, a module elevation between 4 and 5 m was recommended to ensure access for a variety of tractors.
Overhead fixed [9,12]	Height [m]: 5 Row pitch [m]: 19 Year of project: 2016	Designed to fit full harvesting. Employed a stilt structure with a minimum clearance height of 5 m, ensuring that agricultural machinery, particularly combine harvesters, could operate without obstruction. During the design phase for this system, the dimension of the most used agricultural machinery on the cropland

	<p>Location: Heggelbach (Germany)</p>	<p>was considered. Additionally, since sprayer booms commonly adopted in that area are 6 m wide, the space between supporting pillars was chosen according to these measurements, resulting in 19 m.</p>
<p>Vertical; interspaced one axis [17]</p>	<p>Height [m]: 2.6 Row pitch [m]: 9 Year of project: 2021 Location: Grembergen (Belgium)</p>	<p>A row-to-row distance of 9 m was set to accommodate mechanized farming for both systems, which included an 8 m cultivable area and a 0.5 m buffer on each side. This spacing ensured integration with pre-existing agricultural operations. To optimize the total cultivation area, the APV structures were oriented to follow the main direction of the field. The maximum height of the systems was 2.6 m. It was evaluated that the presence of the APV structure increased farming costs by 30 € per hectare per year, accounting for 5 % of the average farming expenses per hectare.</p>
<p>Overhead fixed [70]</p>	<p>Height [m]: nd Row pitch [m]: nd Year of project: 2021 Location: Bierbeek (Belgium)</p>	<p>An overhead APV with fixed semi-transparent modules was placed over a pear orchard. The south-east orientation and inter-row distance of the PV structures were determined by the existing layout of the orchard rows. The PV modules were raised above the hail netting system (1.8 m above the trees) to accommodate the dimensions of agricultural machinery, such as orchard sprayers. The structure was not elevated further in order to reduce material costs, avoid an increase in foundation costs, and minimize visual pollution. The land loss of this APV orchard system was considered to be zero, because pillars could be installed within the tree lines without interfering with machinery.</p>
<p>Overhead fixed [65]</p>	<p>Height [m]: 5 Row pitch [m]: 13 Year of project: 2021 Location: Belgium (Lovenjoel)</p>	<p>The implant is stilt mounted and distance between supporting pillars was set as the double the width of the machinery (6 m) plus an extra meter as security margin totalling 13 m space from pillar to the subsequent. The plant follows the orientation of the tillage direction. In this case the layout is made of a double inclined</p>

<p>Overhead one axis [111]</p>	<p>Height [m]: 3 Row pitch [m]: 6 – 7.5 Year of project: 2022 Location: Concept</p>	<p>structure (12°) featuring bifacial PV modules in landscape. This system had a 30 % GCR with spacing between PV row of 4.7 m. They adopted a plot combine harvester (<i>Wintersteiger Nurserymaster elite</i>) at a working width of 3 m for harvesting wheat in 2022 and a combine harvester (Deutz-Fahr M660) at 2 m working width in 2023.</p> <p>APV hypothesis for olive trees cultivation in APV. Olive trees cultivar with low vigour are chosen to maintain top height between 2 and 2.25 m to fit the harvesting machinery. The inter row space was assumed to host the olive trees in order to allow the mechanical harvesting. Harvesting machines used in super-intensive olive orchards are the same cross harvester involved in grapefruit cultivation, calibrated for accounting the differences between species. The two possible row distances were calculated to guarantee the minimum safe distance for mechanical harvesting.</p>
<p>Overhead fixed [113]</p>	<p>Height [m]:4 Row pitch [m]: nd Year of project: 2023 Location: Concept</p>	<p>The supporting structure consisted of stilts holding a module frame positioned 4 m above the ground, with modules tilted at a 30° angle in a landscape layout and a GCR of 0.5. The system was designed to accommodate super-intensive olive farming, using suitable cultivars such as Manzanilla and Picual. This APV design aimed to enable harvesting machinery to operate by passing over the olive trees and beneath the PV modules, rather than through the interspaces.</p>
<p>Overhead fixed [64]</p>	<p>Height [m]: 3.4 Row pitch [m]: 3.3 (min) Year of project: 2023 Location: South Korea</p>	<p>To accommodate agricultural machinery in South Korea, an APV system was designed with specific spatial considerations based on safety and operational needs. The column spacing was designed to be a multiple of the crop planting distance. To accommodate the maximum widths of common machinery like tractors (2.5 m), combine harvesters (2.4 m), and rice</p>

transplanters (3.0 m), a minimum column spacing of 3.3 m was adopted, which includes a 10 % extra margin. The vertical clearance was set based on machinery dimensions. For upland fields, a minimum clearance of 3.0 m is sufficient for tractors (max height 2.8 m). For paddy fields, where taller machinery like combine harvesters (max height 3.1 m) is used, a clearance of at least 3.4 m is required to ensure smooth operation and turning.

<p>Overhead fixed [104]</p>	<p>Height [m]: 4 Row pitch [m]: 8 Year of project: 2024 Location: Geisenheim (Germany)</p>	<p>APV design for viticulture can be based on a fixed set of machinery, unlike systems for arable crops which require more adaptability for crop rotations. In the design studied, the APV structure was integrated with the vineyard's trellis system, permitting tractors to traverse the rows. However, there were significant operational constraints such as insufficient clearance height prevented the use of over-the-row mechanical harvesters. Trimming and spraying operations were also restricted by the APV design. As a result, only manual labour was considered feasible for these key tasks, which increased operational costs. An alternative was proposed to enable full mechanization: leaving the areas directly under the PV modules unplanted. The main drawback of this approach is a potential reduction in overall crop yield due to lower vine density.</p>
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Fully mechanized agricultural activity within APV systems requires overcoming both technical and operational constraints and the challenges that arise from this combination. However, addressing these constraints and challenges is fundamental to fully capturing the multiple benefits associated with APV adoption. For instance, as highlighted by Cuppari et al. [109] APV represent a synergistic solution linking food, energy, and sustainability objectives. Their analysis demonstrated that APV can positively influence up to 14 of the 17 Sustainable Development Goals (SDGs), notably by increasing land productivity and farmers' income through the dual production of crops and electricity, improving water-use efficiency via reduced

evapotranspiration, and enabling rural electrification that supports education, health, and local economic growth. At the same time, the study highlights that these benefits depend on design, context, and management, requiring site-specific approaches to balance trade-offs and avoid negative outcomes such as excessive shading or material waste. However, many of the advantages of APV can be compromised if continuous agricultural operations are not maintained, which in turn depends on ensuring full compatibility with mechanized farming. The extensive diversity in farming operations and agricultural practices, combined with the complexities of integrating these with PV systems, makes it challenging to establish a universal framework for APV systems. Consequently, defining standardized operations and requirements remains a complex and context-dependent challenge.

This study offers a synthesis of previous experiences and considerations regarding the challenges and opportunities of mechanization in APV systems. Through a review of the current literature, it aims to identify key factors and formulate recommendations for the effective integration of mechanized open-field farming within these dual-use systems for energy and food production, thereby establishing a baseline for co-design principles toward fully mechanized agriculture in APV installations. This review focuses exclusively on open-field agricultural systems; greenhouse-integrated PV (closed APV systems [116]) are excluded as they entail distinct mechanization dynamics. This overview first examines existing APV classifications, focusing on the design features that directly influence mechanization. It then analyses the primary operational challenges posed by APV structures, including the impact of physical obstructions, the establishment of uncultivated zones and the relative influence on machine field efficiency. Subsequently, secondary issues such as soiling on PV module are discussed. Finally, the study presents an analytical framework used to evaluate and quantify key performance parameters, including machinery manoeuvrability and field operational efficiency as key indicators of overall system compatibility. Broader sustainability aspects of APV, such as its contributions to the Sustainable Development Goals and the food–energy–water nexus, as well as other positive interactions that may occur between APV systems and crop production, have been thoroughly addressed in previous reviews [103,108,109,117–119] and are not discussed in the present manuscript, which focuses specifically on the compatibility of agricultural mechanization with APV layouts.

2.2. Agrivoltaic systems classification

The infrastructure and layout of PV modules in APV systems can be adjusted based on key parameters such as elevation and the spacing between PV arrays, here expressed as “row pitch”,

pillars, and modules. Varying these characteristics affects not only the resulting shade patterns [37,101] but also the system's compatibility with agricultural operations [67]. These variations in design generate several distinct APV typologies. Despite similarities, each country tends to adopt different design parameters [120] and set different requirements such as for land occupancy, relative crop yield, and relative energy conversion, in order to define what can be considered agrivoltaics [25,63]. The classification used in this study (Figure 2) is therefore based on a synthesis of recent scientific reviews, which classified APV [113,121–123] and national guidelines [78,79,116].

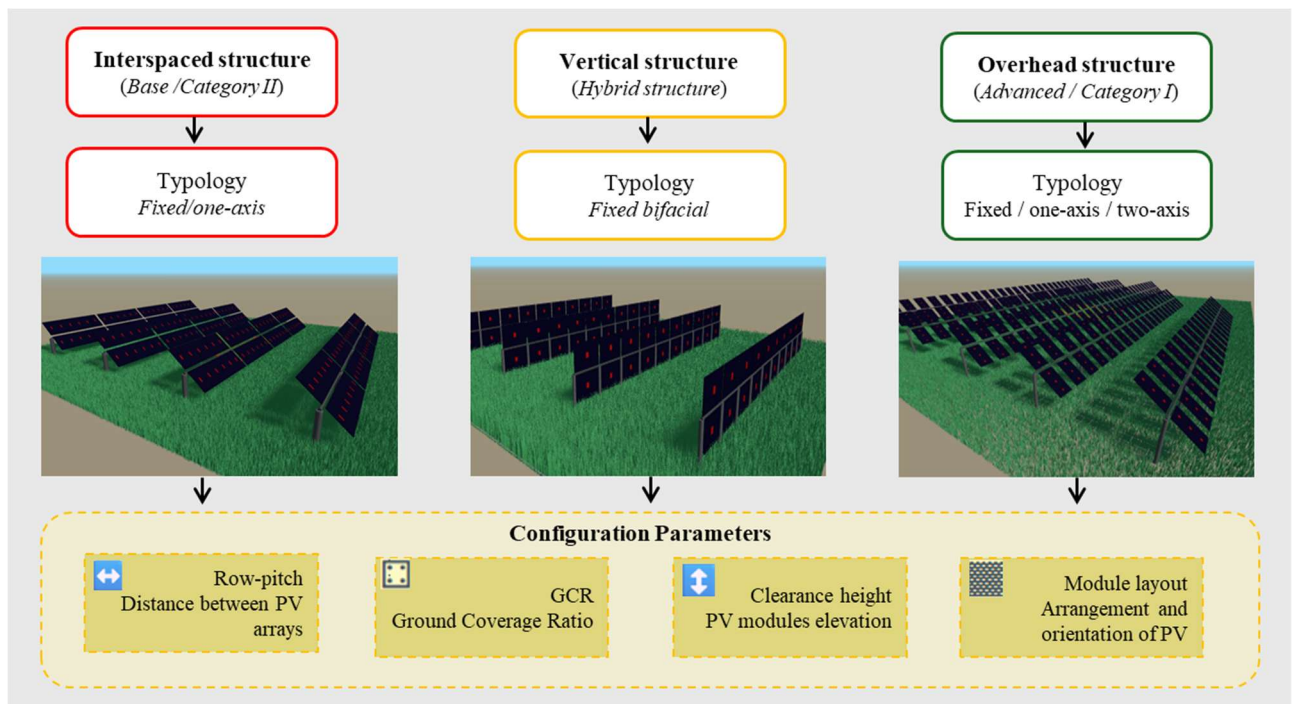


Figure 2. Agrivoltaic systems classification. Vertical systems are considered hybrid due to different policy approach between Countries. In Italy they are considered advanced, such as the overhead, if the minimum height of the module is not lower than 1.30 m, while in Germany they are considered category II, as ground mounted structures.

Overhead APV systems are designed to allow crops to be cultivated underneath PV modules (Figure 3 a, b) [122]. These systems can be elevated high enough above the ground to enable mechanical operations even beneath the module frame [113]. Overhead systems can be equipped with fixed PV modules or sun tracking mechanisms, both one-axis or two-axis. Moreover, when implemented in orchard fields, these types of APVs may also serve as a protective structure against heavy rain, wind, and hail [70]. Overhead structures can achieve higher GCR compared to interspaced ones when mechanization feasibility is considered, as PV panel density can be varied independently of the spacing required for agricultural machinery [65]. The land-use efficiency of overhead PV systems may exceed that of interspace APV

systems [124]. However, due to their greater clearance height and the use of advanced structural components, overhead systems are generally more expensive than interspace configurations [101]. According to the German standard DIN SPEC 91434:2021-05 [78] and the Italian ministerial decree “DM Agrivoltaico 2024” [125], APV systems with a clearance height less than 2.1 m (at maximum tilt angle) are classified as interspaced.

Interspaced APV systems (Figure 3 c) are characterized by having little to no vertical clearance. These installations typically employ either fixed tilted modules or solar tracking technologies. A low clearance height reduces the structure’s exposure to wind, thereby decreasing structural robustness requirements and lowering capital expenditure (CAPEX) compared to more elevated APV systems, which are more susceptible to wind load. Consequently, interspaced systems can sometimes achieve a high module density with a less complex and costly supporting structure than overhead systems. The lower CAPEX requirements for interspaced and vertical APV systems have been highlighted in previous studies. Bellone et al. [101] performed a Monte Carlo Analysis based on averaged data from the literature on APV component installation costs, showing that the main cost differences arise from the supporting structure and installation expenses, which are significantly higher for overhead systems compared with interspaced ones. Trommsdorff et al. [4], in the Fraunhofer guidelines for APV systems, analysed installation costs of various APV configurations in Germany. From these data, Zainali et al. [25] derived a linear relationship indicating an approximate 9 % CAPEX increase for every additional 0.5 m of structure height.

Agricultural machinery operating in interspaced APVs can only work within the spaces between the rows of PV modules [124] because crop cultivation is hindered in the area beneath PV modules. According to NREL [126], interspaced APV installations, especially those using ground-mounted fixed PV modules, are the systems that most hinder mechanized agricultural operations by limiting the space available for cultivation and harvesting, particularly when narrow row pitch is adopted.

Vertical APV systems (Figure 3 d) are a particular type of interspace APV equipped with bifacial PV modules-oriented east–west and tilted 90° relative to the horizontal plane. Such systems generate most of their electricity during the morning and evening hours, when the low solar elevation angle allows for greatest direct sunlight interception by the vertically mounted modules. Conversely, during midday hours, vertically mounted modules rely primarily on diffuse radiation to generate electricity [23,127]. The row pitch in vertically mounted APV systems must be determined based on the top elevation of the array edges to prevent self-shading [121]. In a study by Bellone et al. [101], which compared different vertical APV

configurations, a minimum row pitch of 8 meters was adopted based on specifications provided by the system manufacturer (Next2Sun), from which the APV layout was derived. A distinct advantage of vertical APV systems, when compared to other typologies, is their effectiveness as windbreaks, particularly in windy regions. This configuration provides crop protection from wind damage and can potentially reduce wind-driven soil erosion [124]. Vertical APVs are structurally simpler to install than overhead systems and permit the passage of agricultural machinery regardless of vehicle height. They represent a low-CAPEX solution characterized by potential low reduction in overall solar irradiance available for crop and fair mechanizability. This, however, comes at the expense of lower energy generation than other APV typologies, which in turn can cause these systems to have a higher levelized cost of electricity (LCOE) compared to other configurations [65,101,128,129]. Vertical APV are best suited for low-height crops, to prevent shading of the PV modules during the crop growth cycle. Furthermore, the growing area between the PV arrays is characterized by uneven light distribution throughout the day: the highest shading occurs in the morning and evening on opposite sides of the rows, while direct sunlight reaches the whole canopy around midday [37]. This uneven light distribution may lead to variable crop growth patterns [128,130].

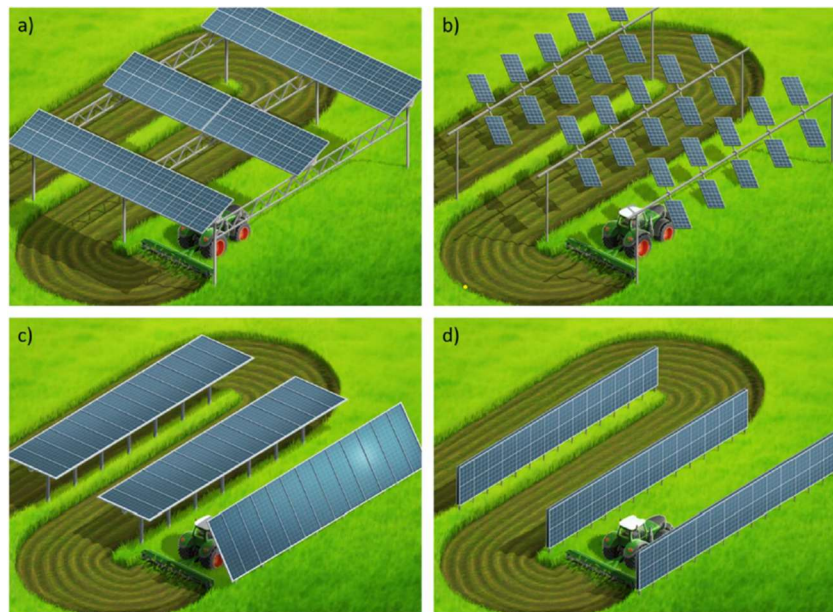


Figure 3. APV system classification based on structure (a) overhead structure with fixed PV modules; b) stilt-mounted structure with two-axis tracking system; c) one-axis tracking structure; and d) vertically mounted structure) [130,131].

2.3. Mechanized Operations in Agriculture

The most important principle of APV is to safeguard the continuity of agricultural activities while providing energy conversion on the same land area, therefore increasing land use efficiency [8,124]. However, since modern agriculture relies heavily on full mechanization, this principle can only be achievable if the APV system is fully accessible to, and compatible with, standard agricultural machinery. Mechanized agriculture involves a wide variety of field operations arranged into specific sequences. These sequences and machine involved are highly dependent on the farming system, whether it involves orchards, industrial field crops, or horticulture [67]. For any given crop, the growth cycle dictates a series of tasks, typically soil preparation, crop management, and finally harvesting, each of which may require specialized machinery and multiple passes to complete [29]. Table 3 highlight the mean, median, minimum and maximum working width of different implement adopted in agriculture. Data are obtained from online database [132] and are related to the following manufacturer speech sheets: Pietro Moro, Kverneland, Vogel & Noot, John Deere, Amazone, Beyne, Horsch, New Holland, Claas, Laverda, Fella, Fendt, Krone, Kuhn, Pegoraro, Rabe, Pöttinger, Bargam, Berthoud.

Table 3. Mean, median, min and max of implement working widths used for arable farming and industrial crops, retrieved from main producers tech sheets [132].

Implements	Mean Working width [m]	Median working width [m]	Min working width [m]	Max working width [m]	Standard deviation [m]	Considered implements [n]
Plough	2.65	2.25	0.29	42.00	2.29	2936
Cultivator	4.61	4.00	0.25	18.30	1.82	2951
Disk harrow	5.00	4.94	1.00	15.20	2.10	2730
Rotary harrow	3.85	4.00	0.50	8.05	1.29	878
Mower-conditioners	9.10	8.92	3.50	13.40	1.00	113
Rear mowers	8.90	8.80	7.24	11.20	0.78	47
Mounted sprayers	17.47	18.00	2.10	36.00	5.36	1122
Trailed sprayers	25.81	24.00	6.00	55.00	7.77	2620
Self-propelled sprayers	27.37	28.00	3.50	57.00	7.58	860
Rotary rakes	7.06	6.90	1.83	19.00	2.95	649
Seeder	4.68	4.00	0.80	27.50	2.64	2252

Front mower- conditioner	3.40	3.16	1.21	12.20	1.24	171
Front mower	2.92	3.00	2.00	4.04	0.41	156
Rear drum mower	2.57	2.20	1.65	8.96	1.30	60
Harvesting headers	7.50	7.00	2.56	15.30	2.63	391
Chopper	2.43	2.14	0.75	9.00	1.22	535

Integrating these diverse, and often large-scale, mechanized operations within the structural and spatial constraints of APV systems requires careful consideration during both design and management phases. An approach for classifying different typology of farming activity in APV was provided by Gorjian et al. [67] who proposed to analyse mechanization in APV systems by distinguishing three hierarchical levels: i) the farm's crop specialization (e.g., arable land, grassland, perennial crops/orchards); ii) the APV typology (e.g., interspaced, overhead); and iii) the specific design characteristics of the APV installation and the actual farming system employed. According to Gorjian et al. [67], the challenges of mechanization in APV systems vary substantially based on the primary crop specialization. Arable farming, for instance, generally involves the most intricate set of machinery for a wide range of operations including tillage, seeding, fertilization, spraying, and harvesting. In contrast, grassland farming is typically less demanding in terms of mechanisation with operations primarily focused on harvesting and post-cutting processes, although cultivation intensity also plays a role. Finally, perennial crops, especially in established intensive systems such as orchards, are likely to pose the fewest additional constraints on the integration with APV systems. In these systems, machinery is often already designed or adapted to operate within spatially defined layouts (e.g., row spacing, trellis) and can be more readily integrated into APV designs [104,133].

It is also recognized that not all mechanized operations hold the same level of flexibility. While some operations, such as primary soil tillage, might be significantly reduced or even eliminated through the adoption of conservation agriculture practices within APV systems [99,134], other operations, particularly those related to ongoing crop management (e.g., precise spraying, weeding) and, critically, harvesting are often non-negotiable and require specific machinery access and performance.

2.4. Key APV Design Parameters Influencing Mechanization

APV system installations inevitably introduce spatial constraints that significantly affect mechanized agricultural management. Key design elements, such as the row pitch, clearance height beneath the PV modules, and the headland width, must therefore be sized according to the operational requirements of the machinery fleet. This includes considering the largest working width, the maximum height of implements [9,12], and the space needed for turning manoeuvres of the machinery involved in the crop rotation plan [67]. The main aspects concerning machine movement within APV systems are discussed in the following sections.

2.4.1. Horizontal Space: Buffer Zones, Row Pitch and Operating space

Structural impediments within APV systems pose considerable difficulties for agricultural operations such as sowing, harvesting, and soil tillage. Consequently, agricultural operations in APV can be treated as separate procedures for each “APV sector”, referring to the space delineated by two consecutive APV arrays. This limitation affects equipment manoeuvrability, particularly for operations that require machines to work in a compound or sequential manner (Figure 4).



Figure 4. Combine harvester in action with concurrent discharge. The combine harvester in the picture is equipped with a header whose width perfectly matches the available operating space (from Next2sun AG, with permission).

There are portions of APV sectors where agricultural operations are unfeasible. These areas consist of the space directly beneath the module axis, plus a variable buffer established to prevent structural damage (Figure 5, Figure 6). The sum of uncultivated areas will be here addressed as “buffer zones” according to [17,23], even though in literature they have been also

indicated as “intermediate strips” [29], “security margin” [101] or “green stripes” [67]. The buffer zone establishment is aimed at guaranteeing the operator safety and the integrity of the structure components (poles, tie-rods, foundations, power lines) and modules by reducing the risk of contact during manoeuvres. In this regard, farmers and agricultural contractors raised several concerns about driving safety distances to the modules, especially during wet and slippery conditions and when working perpendicular to the field’s slope or during harvesting manoeuvres [65]. Moreover, establishing buffer zones, guarantee sustainable use of resources by concentrating operations only in areas that ensure crop productivity, thereby avoiding the unnecessary consumption of inputs (e.g. seeds, fertilizer, pesticides and fuel). However, making an effort to cultivate the areas surrounding the supporting structure may be unprofitable due to low productive potential caused by high shading [36] and the limited accessibility and manoeuvrability for machinery. Dinesh and Pierce [74] were among the first to highlight that in APV cultivation, specific areas may need to be restricted to machinery for preventing damage. Adopted buffer zone within the row pitch found in literature are highlighted in Table 4.

Table 4. Adopted buffer zones and corresponding land loss found in literature.

APV type	Country	Total Buffer width [m]	Row pitch [m]	Land loss	Reference
Vertical APV	Sweden	1	10	10.0%	[130]
Interspaced 1-axis	Belgium	2	9	22.2%	[17]
Vertical APV	Belgium	2	9	22.2%	[17]
Vertical APV	UK (simulated)	0.6	8.4	7.1%	[135]
Overhead fixed tilted	UK (simulated)	0.6	8.4	7.1%	[135]
Overhead fixed tilted	Germany	1.58	19	8.3%	[9]
Overhead 2-axis	Austria (Simulated)	0.5	12	4.2%	[29]
Vertical APV	Austria (Simulated)	0.8	10	8.0%	[29]
Vertical APV	Germany	1	11	9.1%	[136]
Interspaced one-axis	Italy (simulated)	3	10	30.0%	[101]
Interspaced one-axis	Italy (simulated)	3	12	25.0%	[101]

Interspaced one-axis	Italy (simulated)	3	14	21.4%	
Overhead one-axis	Italy (simulated)	1	6	16.7%	
Overhead one-axis	Italy (simulated)	1	8	12.5%	
Overhead one-axis	Italy (simulated)	1	10	10.0%	
Overhead two-axis	Italy (simulated)	1	14	7.1%	
Overhead two-axis	Italy (simulated)	1	16	6.3%	
Overhead two-axis	Italy (simulated)	1	18	5.6%	
Overhead two-axis	Italy	2.4	15	16.0%	Own data
Overhead two-axis	Italy	2.4	18	13.3%	

Note Own data refers to the APV plants installed at the experimental field of Università Cattolica del Sacro Cuore.*

The implementation of buffer zones in APV systems inevitably results in a loss of cultivable land compared to conventional agriculture. While this is generally true for field crops, the situation is different for orchards and, to some extent, horticulture. In orchards, tree rows are already separated by a significant distance. Therefore, if the APV row pitch is designed to match the existing inter-row spacing, the number of trees can remain the same as in a conventional, full-light control plot, preventing any reduction in plant density. This concept is supported by the work of Williams et al. [133]. Campana et al. [23] in Sweden adopted 0.5 m buffer for each side of the structure for a vertically mounted APV system having a row pitch of 10 m (Figure 5); therefore the total buffer resulted in 10% agricultural area. In comparison, a standard ground mounted fixed tilted PV, adopted as APV, would account for about 45% losses [130]. In a study by Willockx et al. [17] conducted in Grembergen (Belgium), a security margin of 0.5 m on each side within the row pitch for both vertical and interspaced mono-axial APV systems was adopted (Figure 6) resulting in a 11% land loss with a row pitch of 9 m. However, the authors noted that during mechanized operations, the farmer could not operate safely with such a margin, and they had to enlarge the buffer zone to 1 m for each side, making it a total buffer of 2 m.



Figure 5. Ley grass harvester in a vertical APV structure facility in Sweden (*Reprinted from [130] with permission of Elsevier*).



Figure 6. Mechanized cultivation in Belgium. The absence of precision farming GPS guided vehicles forced the operator to maintain the machine at 1 m distance from each side of the APV to avoid collisions (*Reprinted from [17] with permission of Elsevier*).

More generally the width of buffer zones should be function of the APV system's typology and configuration [101]. Notably, overhead APV systems generally allow for narrower buffer zones than interspaced systems. For interspaced designs, the PV array's length plays an important role. Specifically, wider arrays might demand increased spacing from system components and machinery, which in turn affects the necessary buffer width. Therefore, for a specific APV setup,

the determination of the buffer zone subsequently fixes the available workable space within the row pitch.

The first important decision in designing an APV is to determine an appropriate row pitch that allows the machinery and the implement used during crop cultivation to operate effectively between the module arrays [12,67,74]. As listed in Table 3, machines and implements have different and variable working width while the workable space in an APV system is fixed for each APV sector and is determined as the row pitch minus the buffer zones. Designing the row pitch based solely on the most demanding machinery operation, such as harvesting, often fails to eliminate inefficiencies arising from the varying working widths of machineries used in the farm [67,136]. Effective APV design must therefore consider a broader range of operations and implements based on the available machines in the farm or the foreseen operation that will be carried out for the whole crop rotation during the lifetime of the APV system [136]. For instance, Lee et al. [64] approached the design of overhead stilt-mounted APV systems in South Korea by determining column spacing based on both the crop's planting distances and the maximum working widths of tractors, combine harvesters, and rice transplanters. Figure 7 depicts an example scenario on the adoption of the machines listed in Table 3 by considering their median working width and assuming a vertical APV system having 10 m row pitch. The figure clearly shows that for some agricultural operations, such as spraying, certain APV configurations are simply unfeasible due to space constraints.

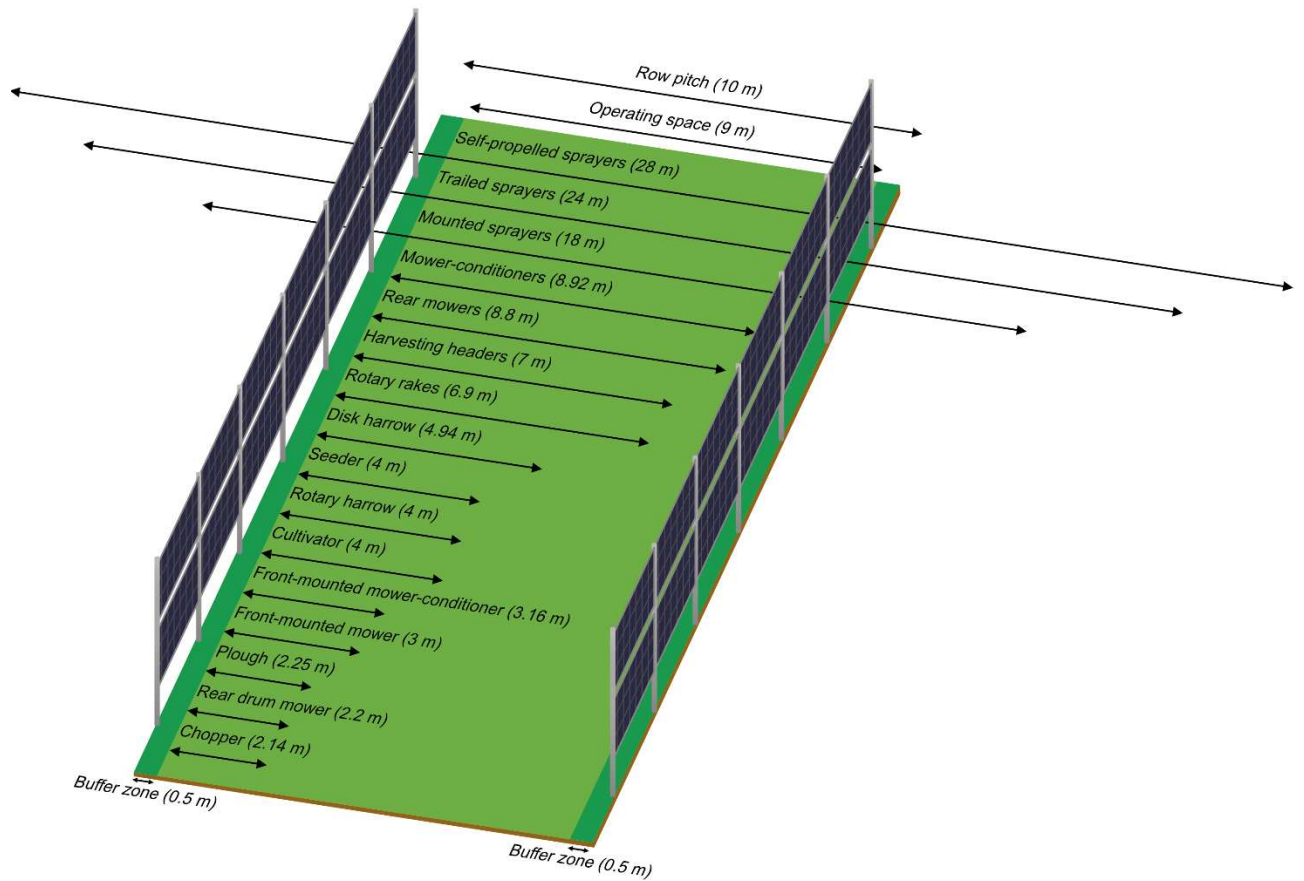


Figure 7. Correlation between the median working width of implements data base listed in Table 3 and the available operating space within a vertical APV sectors. Based on the operating space, defined by the row pitch net of buffer zones, certain machines (e.g., field sprayers) are incompatible with the system. Others may result in redundant passages on worked areas (Overlapping, see section 2.5.2) based on the row pitch (e.g., combine harvesters, disc harrows, ploughs).

The individual tracks enclosed within the supporting structures of an APV, forming parallel tracks (sectors) [66], are depicted in Figure 8, where the operating space (O_s) and the buffer zones (Bz) are highlighted.

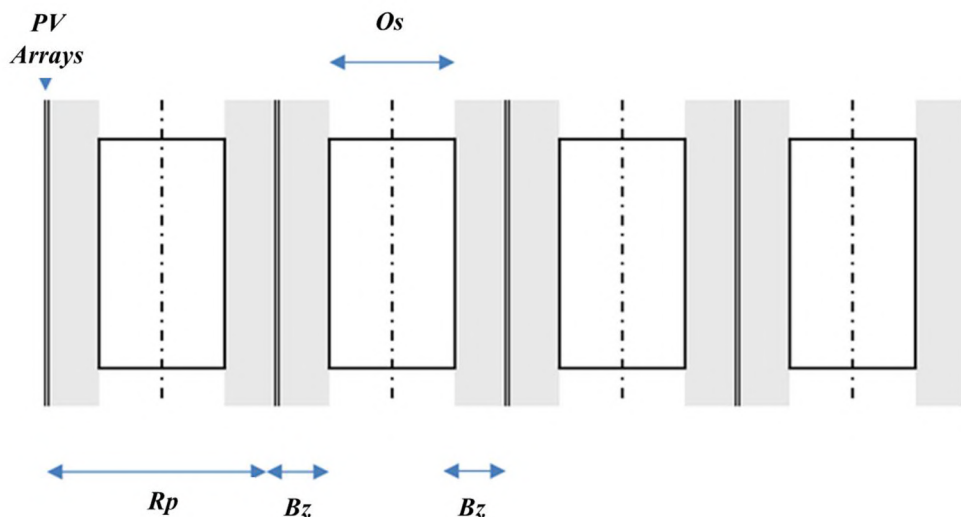


Figure 8. Schematic representation of generic APV sections. Rp = Row pitch; Bz = buffer zone; Os = operating space; PV modules are not showed. The dashed lines stand for the bisector of each individual sector. The sum of Os and Bz equal the row pitch.

The movement of machinery within the APV sectors depends on the relationship between the operating space (Os) and the implement's working width (Iw). In general, four main outcomes can occur depending on this relationship, where the implement width is: equal to the operating space ($Iw = Os$), half of it ($Iw = Os/2$), larger than half ($Iw > Os/2$), or smaller than half ($Iw < Os/2$) (Figure 9).

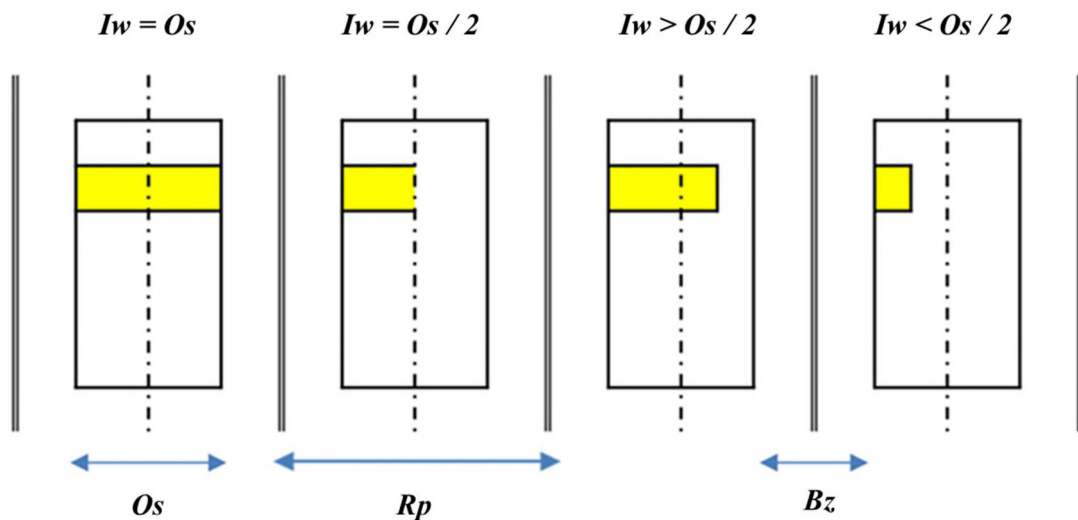


Figure 9. Schematic representation of the possible integration of agricultural machinery in an APV plant. The yellow strips highlight the working width of the machinery. Iw = implement working width; Os = operating space; Rp = row pitch; Bz = buffer zone.

All machinery should ideally be matched to this spacing to ensure operating efficiency. For example, an Os of 8 m can be efficiently managed by adopting an 8-meter-wide combine harvester, and a 4-meter-wide seeder, thereby covering the space in a whole number of passes (one and two, respectively). The same machines would operate inefficiently within an Os of 9 m, resulting in partial-width passes or overlaps and thus increasing operational time. Such mismatches, leading to partial width passes or uncovered areas, can reduce the efficiency of farming operations in terms of time per hectare of worked land and thus increase operating costs. Conversely, using smaller machines to avoid these overlaps would increase the total number of passes required for each APV sector, leading to higher fuel consumption and operational time, therefore higher costs than optimal sized implements.

It is important to note that matching the width of sowing and harvesting machines to the available space limits land loss and overlaps. With a precision seeder, for instance, it is possible to adapt a machine whose working width is wider than the operative space by deactivating one or more seeding units. Using this method, the machine's passes may physically overlap on the

ground, but there will be no overlap in the crop rows, allowing the entire operating space to be seeded and harvested efficiently. This approach was adopted for seeding soybean at the experimental field of Università Cattolica del Sacro Cuore, Italy (Figure 10 a, b).



Figure 10. a) Precision seeder in action within the operating space of the APV at Università Cattolica del Sacro Cuore; b) detailed distance between implement and stilt during sowing (*Original photographs taken by the authors at the APV plant of Università Cattolica del Sacro Cuore, Piacenza, Italy*).

The type of crop sown in APV systems is a critical factor, as crops requiring very large machinery for harvesting or phytosanitary treatments are often unsuitable if the row pitch is not wide enough to accommodate such equipment. However, some sprayers allow the operator to fold part of the spray boom, offering greater flexibility in managing these operations compared to fixed boom systems.

All considered, for a farm that aim to adopt an APV system, a careful evaluation of the existing machinery fleet, or equipment that could be reasonably acquired, in direct relation to the planned APV infrastructure layout is recommended to minimize the inefficiencies during mechanized operations.

In conclusion, what emerged from literatures on APV is that the horizontal space within an APV sector is not fully utilized for cultivation. The row pitch and the width of the buffer zone determine the effective O_s within each APV sector. The width of the buffer depends on the type of APV and the arrangement of the solar arrays, which directly affects land loss (Table 4) and limits manoeuvrability. Since the O_s is fixed once established, while farm implements have varying I_w , setting the row pitch based on a single "most demanding" operation (such as harvesting) often leads to inefficiencies with other implements. A well-designed system aligns

the row pitch and thus the O_s with the entire set of machinery used throughout the planned crop rotations during the lifetime of the APV. This approach aims to achieve O_s values that are integer multiples of the main I_w , minimizing unnecessary machine passes and maximizing operational efficiency. Where possible, orchards and certain horticultural layouts can maintain plant density and reduce loss of arable land [137] by matching the APV row pitch to the existing inter-row spacing of crops, thereby limiting agricultural drawback.

2.4.2. Vertical Clearance

The elevation of an APV system dictates the vertical clearance available for machinery. This concept is linked to the total volume available within the APV array structure, which was previously defined as “porosity” by Scognamiglio et al. [66]. In this study, the cross-section of this available volume inside the APV is referred to as the “clearance space” (C_s). For mechanized operations to be feasible, the clearance space needed by an agricultural machine and its coupled implement must be compatible with the APV configuration. An insufficient module elevation restricts this available C_s , which may, in turn, require wider buffer zones (Section 2.4.1) to prevent collisions between tall machinery and PV modules. Therefore, the C_s is a critical parameter that must be considered during the initial system design phase. Figure 11 depicts examples of the available C_s in different APV configurations. To ease machinery movement through the rows, APV systems equipped with solar trackers can be repositioned during field operations. This strategy increases the available C_s and decreases the risk of collisions, which is especially useful during harvesting when the tallest machineries are typically used. For instance, overhead modules with small array lengths could be tilted to 90° if the tracker design permits. In contrast, interspaced APVs with large arrays that cannot be fully rotated may be tilted to “*alfa* position” [67], i.e., mirrored relative to each other (Figure 11 d), to maximize the available clearance for machines during operations.

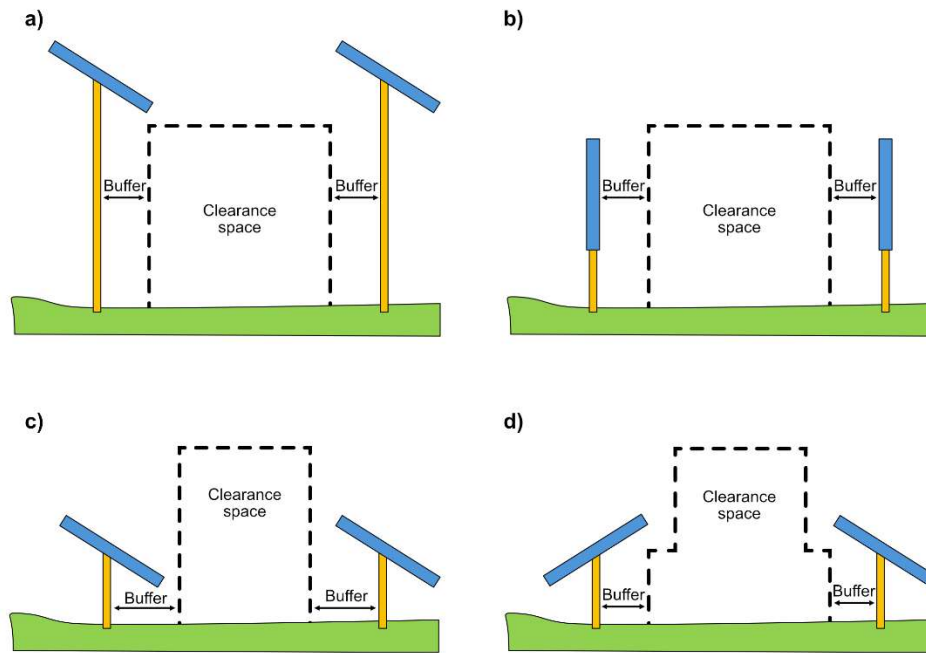


Figure 11. Examples of clearance space between different APV configurations available for machinery: a) overhead mono-axial APV; b) vertical APV; c) interspaced monoaxial APV; d) interspaced mono-axial APV having module in “alpha” position.

Clearance space (C_s) determines whether machines and implements can safely pass under PV modules, or between supporting structures of tall overhead APV without the risk of collision. If the elevation of the modules is insufficient, wider buffer zones are necessary to keep moving machinery at a safe distance from the PV modules. Adequate C_s also helps reduce operator stress when working near the structural edges of APV sectors. Tracker positioning, such as tilting the modules to 90° or adopting a mirrored 'alpha' configuration, can temporarily increase the clearance during critical operations like harvesting, provided that the trackers are designed for such movement and can be controlled remotely. Ultimately, the elevation of the modules should be based on the maximum height of the machinery expected in the cropping system, ensuring there is enough clearance to avoid operational constraints and maintain smooth field logistics.

2.5. Operational Inefficiencies during machinery manoeuvring

Improper sizing of farm machinery relative to the operating space (O_s) available within APV sectors can lead to operational inefficiencies that would result in reduction of field efficiency (FE , see section 2.6) during agricultural operations. A primary consequence may be overlapping (area covered more than once during subsequent machine passes), which, together with the complex headland turning required to navigate the obstructed layout of an APV field, can result in economic losses and soil degradation due to excessive compaction [138]. However, a study

from Chamen et al. [139] demonstrates that Controlled Traffic Farming (CTF), defined as the confinement of all traffic compaction to the least possible area of permanent traffic lanes, significantly mitigates soil compaction, increasing gross margins by up to £117/ha on clay soils and reducing environmental costs. As Agrivoltaic systems require fixed machinery paths between solar arrays, they inherently facilitate the adoption of CTF protocols [140], thereby potentially capturing these agronomic and economic benefits associated with reduced soil compaction.

2.5.1. Manoeuvring Space During Headland Turning

The machine's working pathway consists of a series of tracks. Under APV conditions, the total number of tracks is determined by the number of APV sectors, since each sector may contain multiple tracks depending on the ratio between the O_s and I_w . The minimum number of tracks per sector is one, which occurs when I_w equals O_s . At the headland, machines require sufficient space to turn and move between tracks and APV sectors. The design of the photovoltaic layout and the shape of the field determine the space available at the headlands, while the cardinal orientation of the APV rows determines the angle between headland and the entry point of each track, which in turn can restrict the manoeuvring space. Therefore, sufficient space must be considered during design phase to accommodate machine manoeuvres at the headlands, since headland turns affect the effective working time of the machines [141,142], and insufficient space can further reduce their efficiency. The APV may be positioned within areas of irregular shape, size, and slopes, making the edges of these areas challenging for manoeuvring in and out of the tracks. In APV systems, the orientation of the photovoltaic layout (azimuth) is dictated primarily by energy-efficiency criteria rather than by field geometry. Therefore, if the primary purpose of the APV field is to generate energy, the machinery pathways will be arranged according to the optimal orientation of the PV rows. This misalignment can constrain machinery movement and make manoeuvring during headland turns more difficult compared to open-field conditions. To describe how machines manoeuvre is constrained within APVs, it is here proposed the model adapted from existing approaches in open field conditions used by Hameed et al. [143] and Bochtis and Vougioukas [144], adjusted for the APV spatial constraints. Three main types of machine turning manoeuvres suitable for non-holonomic vehicles such as tractors [144], have been identified from literature as the most common, namely: U-turn (double round corner), T-turn (reverse, or switch-back-turn), and Ω -turn (the loop, or forward-turn) [142,144–146]. In this study, U-turns and Ω -turns were considered the primary manoeuvre types, while T-turns were excluded due to the requirement of two reversing manoeuvres, indicating a non-optimal machine-implement configuration. Each self-propelled machines have a specific

turning radius that corresponds to the distance from the vehicle's instantaneous centre of curvature to the midpoint of the rear axle, measured with the steerable wheels at full lock. The minimum turning radius (r_{min}) [m], that represent the smallest radius achievable by the vehicle under non-slip conditions and maximum steering angle, was used as a critical parameter in determining the feasibility of each manoeuvre. It stands for the tightest circle in which the machinery can turn without reversing or adjusting the steering. U-turns were assumed feasible when the available space from the exit-point of the current track (x) to the entry-point of the next track satisfied the conditions:

$$x \geq \frac{2r_{min}}{Iw}, \quad \text{for U turn} \quad (2.1)$$

$$x < \frac{2r_{min}}{Iw}, \quad \text{for } \Omega \text{ turn} \quad (2.2)$$

Where Iw is the working width of the implement.

Values of the component $\frac{2r_{min}}{Iw}$ are presented in the supplemental material (Table S1).

The minimum lengths required to perform a manoeuvre of degree " d ", either a U-turn or an Ω -turn at the headland, can be estimated using kinematic equations for non-holonomic vehicles (Eq. 2.3 – 2.4) [143,144]:

$$U_d = d_{ij} \cdot Iw + (\pi - 2)r_{min} \quad (2.3)$$

$$\Omega_d = r_{min} \left(3\pi - 4\sin^{-1} \left(\frac{2r_{min} + d \cdot Iw}{4r_{min}} \right) \right) \quad (2.4)$$

Where $d_{ij} = |i - j|$, i is the track, or APV sector, considering Iw and Os , through which the machine exits at the beginning of the manoeuvre and j is the track the machine enters at the manoeuvre's end. For exemplification purposes, we considered two adjacent tracks ($d_{ij} = 1$). If the machine exits from track 1 and immediately enters the adjacent track, then $d = 1$ (as assumed in this exemplification for simplicity). Consequently, if the machine proceeds from track 1 to track 4, then $d = 3$; Iw is the working width of the implement [m]. Figure 12 depicts the application of the two-turning solution at the headlands of APV related to the Iw to Os .

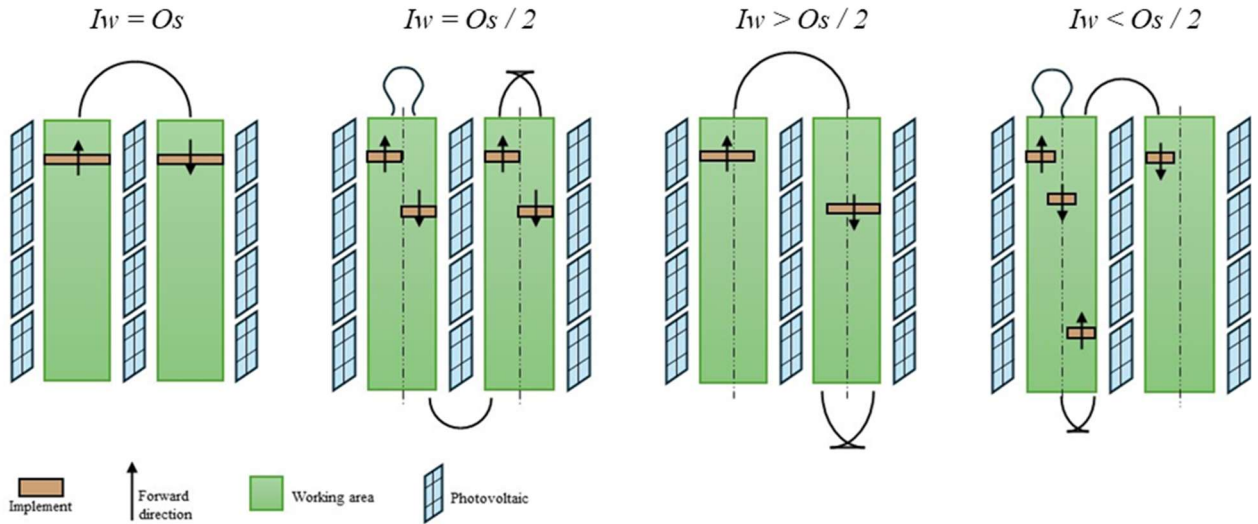


Figure 12. Examples of integration among APV system and type of headland turning in presence of different width of the implement.

During headland turning, the key objective is to minimize the time the implement remains active but not performing productive work, in order to reduce inefficiencies. Table 5 presents the space required for headland turning for both U-turn and Ω -turn manoeuvres. These values are calculated using Eq. 3 and 4, assuming seven different Iw . These widths were chosen to represent the most frequent occurrences based on the data presented in Table 3.

Table 5. Space required [m] for U-turn or Ω -turn by considering implement working width (Iw) and turning radius.

	Turning radius [m]	Implement working width (Iw) [m]						
		2	3	4	5	6	7	8
U-turn	1	3.14	4.14	5.14	6.14	7.14	8.14	9.14
	2	4.28	5.28	6.28	7.28	8.28	9.28	10.28
	3	5.42	6.42	7.42	8.42	9.42	10.42	11.42
	4	6.56	7.56	8.56	9.56	10.56	11.56	12.56
Ω-turn	1	9.35	9.33	9.32	9.30	9.28	9.26	9.25
	2	18.42	18.35	18.28	18.21	18.14	18.07	18.00
	3	27.00	26.84	26.68	26.53	26.37	26.21	26.05
	4	34.87	34.59	34.30	34.02	33.73	33.44	33.15

Performing a U-turn requires less space than an Ω -turn, assuming the machinery fits the O_s of the APV. U-turn is more time-efficient and thus would be beneficial to utilize whenever feasible.

In the practical application of an APV system, however, the choice of manoeuvre and the required space must also account for the distance of the entry/exit point (x) between two consecutive APV sector. In presence of short entry /exit point distance ($x = 2 - 4$ m), the Ω -turn can be performed with different turning radius and often occurs with small Iw (1 - 3 m, see supplemental material, Table S2). In general, U-turns, where the machine leaves a track and enters an adjacent track or, skipping a track, enters the adjacent track, are fast and require less space for manoeuvring than other turning possibilities [145]. For large entry /exit point distances the feasible turning shifts progressively from Ω - to U-turns (supplemental materials, Table S2). Otherwise, it could be useful to elaborate track planning within the APV layout optimizing the adoption of the U-turn, but this requires case specific planning. These observed differences in turning efficiency and space requirements are intrinsically linked to the design characteristics of the machinery and the Iw . The manoeuvrability of a tractor-implement system is a complex characteristic shaped by trade-offs among design parameters. Path tracking and stability, for instance, are generally enhanced by a longer wheelbase and wider APV sectors, thus in turn wide Os . In contrast, turning time at headlands is optimized by a short wheelbase, a narrow track width, and a large maximum steering angle. To provide context, 4WD tractors feature wheelbases range between 3.50 and 5 m and steering angles exceeding 50° , creating an inherent conflict between stability during field passage and agility during turns [132]. When adapting a machinery fleet for APV systems the ideal solution involves selecting highly manoeuvrable machines to navigate the constrained layout and reduce operational time and costs. Particularly relevant are narrow-track tractors and models with enhanced steering capabilities (turning of the entire axle) [147] which achieve sharper turns. While these technologies improve turning, any associated increase in wheelbase (e.g., by 10-15 cm) must be evaluated, as it can partially offset the advantage by slightly increasing the turning radius. Ultimately, achieving fully mechanized crop production in APV requires not only a well-designed APV system and appropriately selected machineries but also the expertise of skilled operators to navigate its complexities effectively [148].

2.5.2. *Overlapping*

In APV systems, the formation of overlapping areas (OLA), which occurs when the Iw does not match, or is not an even submultiple of, the operating space (Os) [136] (Figure 13), may negatively impact the soil within the Os . This inefficiency leads to a cascade of negative consequences that can impact both the farm's cost-effectiveness and the environment,

including: increased soil compaction, unnecessary loss of inputs like seeds and agrochemicals, and higher fuel, labour, and operating costs [149].

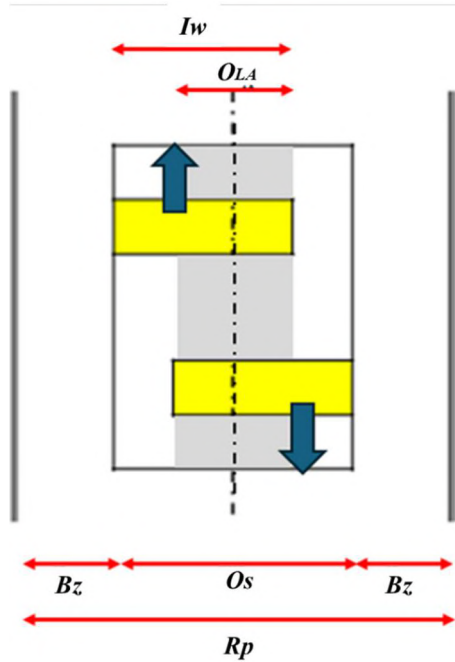


Figure 13. Overlapping within a track of APV. Iw = Implement working width; Os = operating space; Rp = row pitch; Bz = Buffer zone; OLA = Overlapping area.

It is possible to calculate the linear overlapping within an APV sector (OLA) by applying the following methodology that consider an implement working width (Iw) ranging from 1 to 9 m and an operative space (Os) ranging from 6 to 9 m:

1. First, the minimum number of passes (n) required for an implement to fully cover the Os have to be determined as the ratio between Os and Iw . If the ratio is not an integer, it means there will be overlapping.
2. The theoretical width covered (Tw) by the implement after n passes can be then calculated as:

$$Tw = Iw \cdot n \quad (2.5)$$

3. The linear overlapping (OLA) within the APV sector can be quantified as the difference between the theoretical width covered and the Os per linear meter:

$$OLA = Tw - Os \quad (2.6)$$

4. Finally, to evaluate the geometric efficiency of the operation, a coefficient of use (Cu) can be calculated. This coefficient, ranging from 0 to 1, represents the ratio of the Os to

the total theoretical width covered by the machine. A value of 1 indicates perfect geometric harmony (no overlap) during mechanized operation.

$$Cu = \frac{Os}{Tw} \quad (2.7)$$

Calculation results are provided in the supplemental materials (Table S3), showing that unless the Os is an exact multiple of the Iw , the machine will have to make at least one partial pass, meaning that only a portion of its width covers unworked ground. This geometric mismatch between Iw and Os results in a lower Cu and an increase in the OLA . Figure 14 illustrates this relationship for various APV Os configurations. When the operating space is an exact multiple of the Iw , the Cu reaches 1, and the OLA drops to zero, indicating that the implement effectively utilizes its full width without needing redundant passes. Similarly, when Iw is an exact divisor of the Os , the Cu again reaches unity, meaning no redundant passes are necessary. However, any deviations from these conditions leads to a rapid rise in OLA , suggesting that mismatch between Os and Iw can result in geometric inefficiencies. These inefficiencies are likely to manifest as higher fuel consumption, extended operational times, and increased soil compaction [149]. In open field conditions, the number of tracks a machine will cover is calculated by dividing the field width by Iw [144]. In contrast, under APV conditions, similar to vineyard cultivation, the number of tracks is determined by the specific combination of APV Os and Iw .

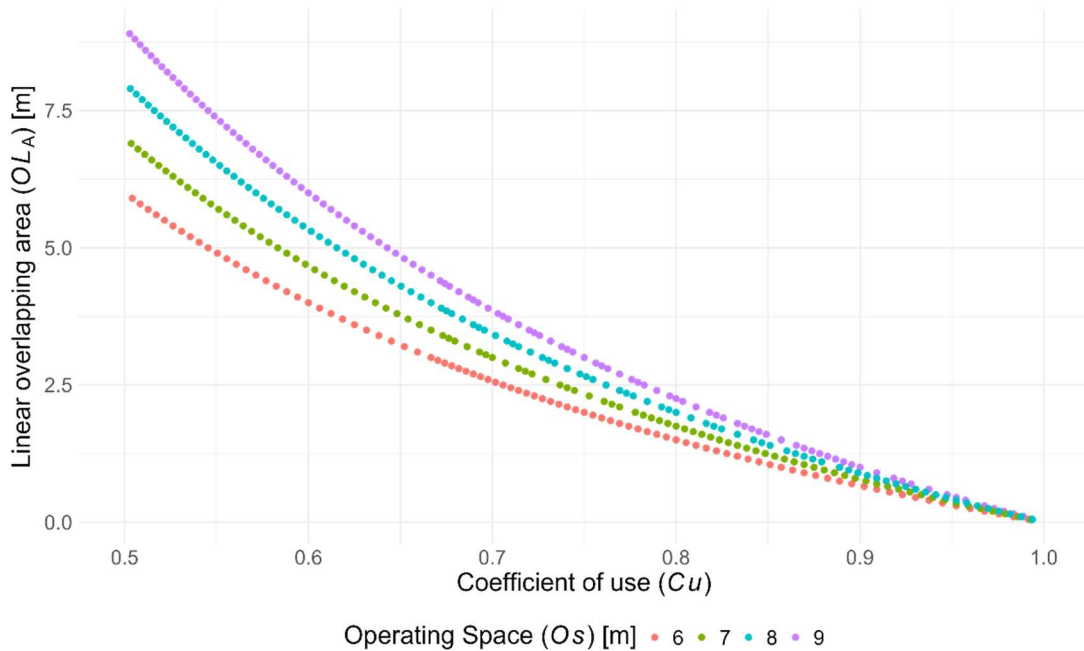


Figure 14. Relationship between the Coefficient of use (Cu) and the extent of Overlapping area (OLA). Different colours represent different distinct Operating spaces (Os).

Operational inefficiencies during mechanized operations occur both in open fields and within APV systems. These inefficiencies include time lost during headland turns and overlap of previously worked soil. However, the APV environment tends to worsen these inefficiencies and introduce new challenges, such as speed adjustments due to constrained operating space (O_s), obstructed headland areas, and mismatches between the implement working width (I_w) and O_s . For instance, while a complex turn in open-field conditions may result in overlapping worked soil [143], in an APV layout, it can lead to collisions with the supporting structures of the modules. When performing headland turns to change APV sectors, the entry/exit distance between consecutive sectors (x) and the I_w determine whether fast U-turns are feasible or if wider, slower Ω -turns are necessary. According to the adopted models [143,144], U-turns are feasible when x is greater than or equal to 2 times the minimum turning radius (r_{min}) divided by I_w ; otherwise Ω -turns are required, which increases unproductive time. If O_s is not an exact multiple of I_w , at least one partial pass through pre-worked soil is unavoidable, resulting in overlapping areas and reducing the implement's coefficient of use (C_u). This geometric mismatch between I_w and O_s leads to higher fuel consumption, longer working times per hectare, wasted inputs, and localized soil compaction [150]. Since turning is the primary source of time losses in constrained layouts [151], providing adequate headland width is an effective strategy to reduce these inefficiencies when x cannot be increased. In addition, using a narrower I_w in combination with specialized high-steering machines (which have a smaller r_{min} and improved steering geometry) can mitigate headland inefficiencies. This adaptation enhances the feasibility of U-turns in the limited O_s present in APV systems. Furthermore, it is theoretically possible to modify x when transitioning to another APV sector by optimizing the machine pathway at the headlands. This optimization approach has already been demonstrated in open-field conditions by Hameed et al. [143], who employed a genetic algorithm to minimize non-productive travel. Future studies can apply this optimization process to APV layouts to develop a decision-support tool capable of optimizing machine trajectories based on specific values of I_w and O_s .

2.6. Field Efficiency

Field efficiency (FE) is a key performance metric that accounts for the reduction in a machine's theoretical productivity due to factors such as partial utilization of its working width (e.g. when overlapping occurs), time lost during manoeuvres or idle periods, and specific field characteristics [152,153]. While FE is influenced by numerous operational factors, established

literature provides typical values for various implements operating in open-field conditions, which serve as a benchmark for comparison (Table 6) [152].

Table 6. Range and typical field efficiency (*FE*) of many implements measured in open fields [152]. Sp = self-propelled.

Implement / machine	Field efficiency (<i>FE</i>)		Implement / machine	Field efficiency (<i>FE</i>)	
	Range (%)	Typical (%)		Range (%)	Typical (%)
Tillage & planting			Harvesting		
Mouldboard plough	70-90	85	Corn header	60-75	65
Disk harrow	70-90	85	Combine	60-75	65
Tandem disk harrow	70-90	80	Combine (Sp)	65-80	70
(Coulter) chisel plough	70-90	85	Mower	75-85	80
Field cultivator	70-90	85	Mower (rotary)	75-90	80
Spring tooth harrow	70-90	85	Mower-conditioner	75-85	80
Roller-packer	70-90	85	Mower-conditioner (rotary)	75-90	80
Mulcher-packer	70-90	80	Windrower (Sp)	70-85	80
Rotary hoe	70-85	80	Side delivery rake	70-90	80
Row crop cultivator	70-90	80	Rectangular baler	60-85	75
Rotary tiller	70-90	85	Large rectangular baler	70-90	80
Row crop planter	50-75	65	Large round baler	55-75	65
Grain drill	55-80	70	Forage harvester	60-85	70
			Sugar beet harvester	50-70	60
Others			Potato harvester	55-70	60
			Cotton picker (Sp)	60-75	70
Fertilizer spreader	60-80	70			
Boom-type sprayer	50-80	65			
Air-carrier sprayer	55-70	60			

The typical *FE* values reported in Table 6 confirm that real-world performance is not constant, fluctuating with factors like field shape, operational patterns, and crop conditions [144]. To quantify these variations, real-world performances in APV are assumed and compared against a theoretical benchmark by calculating the theoretical field capacity (*TFC*). The *TFC* represents the maximum performance rate (ha h^{-1}) achievable if a machine operates continuously at its full implement working width (*Iw*), with no overlapping and at its rated forward speed (*S*). It can be calculated as follow [152,153] :

$$TFC = \frac{S \cdot Iw}{10} \quad (2.8)$$

Where TFC is the theoretical field capacity (ha h^{-1}), S is the forward speed of the machine (km h^{-1}).

TFC cannot be sustained over extended periods due to various loss-inducing factors. These factors encompass, but are not limited to, the partial utilization of the implement width when overlapping occurs, time expenditure during headland turns, and other operational delays stemming from variables such as operator proficiency and field geometry [136,152]. Consequently, the actual rate of performance is more accurately expressed as the Effective Field Capacity (EFC) [153]. Given the limited current knowledge regarding APV-specific impacts on individual agricultural operations, and the broad range of conditions that can reduce machine field capacity, this study provides general insights. This is achieved by considering default operating speed reductions, the number of passes for each APV sector, and overlap incidence. The EFC can be calculated in APV conditions by considering the effective working width of the implement (Aw), defined as the average productive width of land covered per pass ($Os \text{ m}^{-1}$), which is lower than the implement's width (Iw) in case of overlaps during operations (see Table S3 in supplemental materials). The second is the effective speed (Se), for which a reduction from the theoretical speed must be assumed to account for manoeuvring constraints within the APV structure [136]. EFC can be calculated as follows:

$$EFC = \frac{Aw \cdot Se}{10} \quad (2.9)$$

Where Aw is the effective working width (m) and Se is the effective speed of the machine (km h^{-1}). The ratio of the EFC to the TFC defines the machine's FE [153] and expressed as percentage:

$$FE = \frac{EFC}{TFC} \cdot 100 \quad (2.10)$$

Where EFC is the effective field capacity and TFC is the theoretical field capacity.

To investigate how APV-specific constraints impact FE , a calculation model was applied. FE can be estimated based on Iw and Os , which were here set to range from 1 to 9 m and 6 to 10

m, respectively, for simplicity. To date, no studies have specifically quantified the extent to which operating speed is decreased due to APV constraints. However, it is recognized that operating at machine full speed in APV condition can be dangerous, especially when operating close to structures, inverters or modules. Therefore, to account for limitations highlighted in the literature [136] and test how FE varies with operating speed, three distinct operational scenarios were assumed in this study. These included an Optimistic scenario with a 5% speed reduction, representing ideal conditions with advanced guidance systems; a Moderate scenario with a 15% reduction (considered the baseline); and a Pessimistic scenario with a 25% reduction, reflecting more challenging field conditions or less advanced machinery. The FE resulting from the utilization of different implement's working width at different operating spaces, considering three case scenarios of speed reduction is highlighted Figure 15.

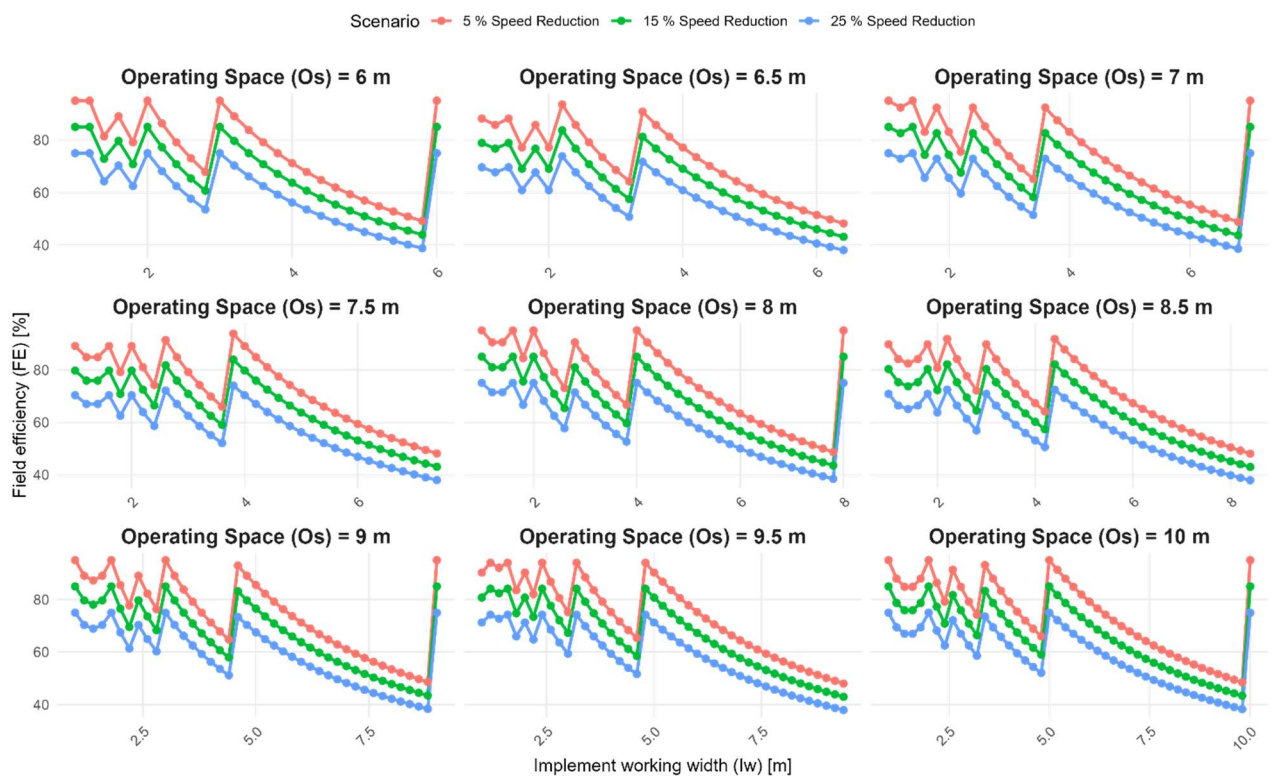


Figure 15. Sensitivity of Field efficiency (FE) to Implement working width (Iw) under varying operating spaces (Os) and speed reduction scenarios. The graph illustrates the calculated FE [%] for implement working widths ranging from 1.0 m up to each specified operating space. Three distinct speed reduction scenarios are presented: optimistic (5% reduction), moderate (15% reduction, serving as a baseline), and pessimistic (25% reduction), reflecting different operational challenges. Each facet represents a unique operating space, showing the interplay between implement width, operational area, and assumed speed limitations on field efficiency.

Figure 15 highlights that, FE in APV is fundamentally dictated by the geometric harmony between the Iw and the Os . FE reaches its maximum value for each scenario only when the Os is perfectly covered by the machine and when Iw is an exact submultiple of Os , corresponding

to a Cu of 1 (supplemental material Table S3). Conversely, FE drops significantly when this geometric harmony is poor, indicated by a low Cu . The data also highlight two additional trends: for any given Os , FE tends to decrease as implements become wider, whereas for a fixed Iw , a larger Os improves the FE by mitigating the negative effects of overlap. For example, when $Os = 6$ m, the best-performing machines are those with working width 3 and 6 m and for Os 9 m the best performing machines are that with Iw of 4.5 and 9 m. While these results indicate optimal Iw to Os combinations, it is important to acknowledge that the calculated FE values represent a theoretical potential. Achieving this maximum in practice is unlikely, partly due to unavoidable driving imperfections, even with skilled operators and due to other time losses such as machine adjustments, turning, and refuelling [154,155]. It is also important to keep in mind that machine performance is not only linked to the field geometry but also to the type of machine and function of the machines themselves [156] and to the crop setting in which they operate [157].

Field efficiency (FE) is determined by the effective working width (A_w) and the effective operating speed (S_e) of the machine. FE reaches its peak when the coefficient of use (Cu) is equal to 1, meaning there is no overlap, and when the machine can maintain a consistent S_e . However, FE decreases significantly when implements are not well harmonized with Os . For a specific Os , the most effective implements are those whose Iw exactly divide Os . For example, an Iw of 3 or 6 meters is ideal for an Os of 6 meters, while an Iw of 4.5 or 9 meters works best for an Os of 9 meters. Using implements with an Iw that matches the Os can save time by reducing the number of passes needed to cover an area. However, Iw that are divisors of the Os may achieve maximum FE due to no overlap, but they can result in longer operation times and increased fuel consumption. It's important to note that actual performance will typically be lower than the predicted results due to unavoidable driving errors, combinations that lead to inefficient turns, and other delays.

2.7. Handling of uncultivated areas

The management of uncultivated buffer zones presents a distinct challenge in APV systems. As these areas are not part of the main cultivation and are often difficult to access with standard agricultural machinery, weed control is particularly problematic. In vertical APV systems, for instance, uncontrolled weed growth can lead to significant energy losses by shading the lower parts of the bifacial PV cells (Figure 16, Figure 17). This issue was also mentioned in Bellone et al. [101] and the impact on energy generation was assessed by Campana et al., [23]. To

mitigate this specific issue, Willockx et al. [17] suggested controlling weed growth in these areas every six months. Similarly, Krexner et al. [29], in their study on the environmental impacts of two APV configurations, modelled the annual mowing of buffer areas using a motor mower. For the overhead APV system, they assumed that mowing could be performed in a single pass along each row thanks to the use of a swivelling mowing tool, whereas for the vertical APV configuration, two separate passes were required, one on each side of every PV row.



Figure 16. Grass not removed by the forage harvester close to the PV modules support structure (Reprinted from [23] with permission of Elsevier).



Figure 17. Weeds development in the non-cultivated areas of Vertical APV system (left) and interspaced monoaxial APV system (right) (Reprinted from [17] with permission of Elsevier).

For other configurations, such as interspaced systems with low ground clearance, the options may be more constrained, potentially making manual intervention with hand-held equipment the only feasible, albeit labour-intensive, solution compared to fully mechanized solutions. Moreover, for particular supporting structures, as the overhead biaxial APV system at Università Cattolica del Sacro Cuore, Piacenza, Italy, even manual weed control may be challenging (Figure 18) resulting in chemical weed control as the most appropriate.



Figure 18. Uncultivated buffer zone in the APV system of Università Cattolica del Sacro Cuore, Piacenza, Italy. The supporting pillars prevent the machines to execute weeding (*Original photograph taken by the authors at the APV plant of Università Cattolica del Sacro Cuore, Piacenza, Italy*).

Aside from the specific approach chosen, the need to manage buffer zones itself poses a clear drawback as, regardless the chosen buffers management, it will cause additional operational costs that are excluded in conventional open field agriculture. Using a walking mower (finger bar) for mechanized weeding may be feasible for small experimental APV fields but highly time demanding for utility scale plants. In overhead systems, managing uncultivated areas may be generally easier than in interspaced or vertical systems, as a wider range of machinery can be suitable due to higher vertical clearance compared to interspaced APVs. The most suitable options may be tractor-mounted implements adapted from specialized viticulture, such as side-mounted mowers, inter-row shredders, and under-vine weeders, which often include sensing

devices to automatically navigate around obstacles like structural pillars [158,159]. Chemical weed control may also be considered, particularly before sowing or just before sowing, to minimize the risk of spray drift that could harm the cultivation. Unfortunately, common tractor-mounted sprayers may face access limitations within buffer zones due the arrangement of modules supports; therefore, the application of chemicals in these areas might need to be carried out using manual equipment. The wide variety of possible APV designs currently prevents the establishment of a general management strategy suitable for utility-scale adoption. Consequently, each farm, depending on its specific configuration, will likely need to design a case-specific solution for this issue. Finally, occasional manual interventions may still occur under specific conditions but should be limited to module cleaning, inspection, repairs, or precise buffer management when required. If the goal is to maintain agricultural operational costs comparable to open-field conditions, the design target should be to minimize manual work through full mechanization.

2.8. Soiling effect on PV modules

The efficiency and economic viability of any PV systems are directly impacted by environmental factors, with module surface contamination, a phenomenon known as soiling, being a primary operational challenge. The term soiling losses describes the decrease in photovoltaic energy output that occurs when airborne materials settle on the surface of solar modules [160]. These deposits can include mineral dust (such as sand, clay, or limestone particles), organic residues, pollen, textile fibres, and pollutants generated by vehicles or industrial activity. As reported by Ilse et al. [161] the nature of soiling is not uniform; rather, its composition varies significantly depending on the system's location. In arid regions, The predominant contaminants can range from airborne mineral dust (Figure 19 A) to biological sources such as bird droppings (Figure 19 B) and microbial biofilms (Figure 19 C). In other environments, soiling may be characterized by organic matter like plant debris and pollen (Figure 19 D), or by anthropogenic pollutants from engine exhausts, industrial emissions (Figure 19 E), and agricultural activities (Figure 19 F).



Figure 19. Different sources of particle deposition in utility scale PV system (*Reprinted by [161] With permission of Elsevier*).

The economic consequences from soiling losses have been estimated in a recent study by Fernandez Solas et al. [162] that found that soiling can increase the LCOE of PV systems by up to 4% in regions with evenly distributed seasonal rain, and up to 15% in arid locations where natural cleaning is absent. Other authors reported soiling losses up to 30 % in the worst case scenario [160]. Consistent with the previous assessments, Ilse et al. [161] estimated potential global energy conversion reduction due to dusting on PV modules by at least 3 – 4 % even by implementing optimized cleaning scenarios. In APV installations, PV modules are exposed to additional particle deposition from agricultural activities, including machinery movement and crop harvesting [74,160,163]. Ghosh [103] noted that the higher humidity and microclimatic stability created by shading under APV structures and crop canopies may help reduce soil erosion, thereby limiting particle deposition on PV modules when the soil surface is covered by plant canopy during the crop growth cycle. However, the same author also acknowledged that tillage operations can increase dust generation and module soiling. Direct studies on APV that address dusting are very limited and lack long-term assessment [103]. However during a six months monitoring in a pilot APV plant in Chile, Jung et al [160] reported that the field beneath the PV panels was tilled with a plough and disk ripper, as scheduled for common practice. They found average daily soiling losses of $0.35\% \text{ day}^{-1}$ in summer, reducing to $0.17\% \text{ day}^{-1}$ in winter. Notably, dust generated by this land preparation reached the panels despite a 3.5 m ground clearance, highlighting the increased severity of soiling from agricultural operations. Soil moisture content is another critical variable that significantly determines the quantity of dust produced. This factor is itself dynamic, varying with the season, the timing of tillage, and the presence or absence of vegetation cover [164,165]. The generation of dust during agricultural

operations, including phytosanitary treatments, is a complex issue in APV environments being influenced by the interplay of multiple factors. These include the type of crop cultivated and its specific development stage, the required machinery employed, prevailing climatic conditions such as wind speed, and even the presence of local fauna like birds [161,166]. The likelihood of dust particle deposition on panel surfaces is influenced by factors such as the distance from the machinery, the height and tilt of the APV structure, and the panels' intrinsic surface properties. Regarding the type of implement used during agricultural operations, rotary harrows or forage choppers may disperse a greater number of debris compared to ripper ploughs or seeding machines. The significance of dust generation from agricultural operations has been quantified in several studies. For example, Telloli et al. [167] found that threshing and ploughing operations produced a ten-fold higher particle mass concentration than sowing, while Marzen et al. [164] measured dust emissions ranging from 7 to 35 g m⁻² min⁻¹ during tillage in vineyards. Given these significant particle emission rates, managing dust deposition should be considered through both cleaning programmes and mitigation strategies. For example by adopting specific agronomic practices, with conservation agriculture and no-tillage farming being optimal for reducing dust generation [163]; by using particular PV panel surface treatment, such as anti-soiling coatings film [160,168] and through direct intervention, such as periodic panel cleaning, for which the frequency and method must be adapted to the specific agricultural context [166]. On this regard there are many possible cleaning strategies to be applied for PV from manual cleaning performed using handled tools by operators to semi-automatic strategies by using machinery and by adopting a fully automatic cleaning system for each PV array row (Figure 20) [161].

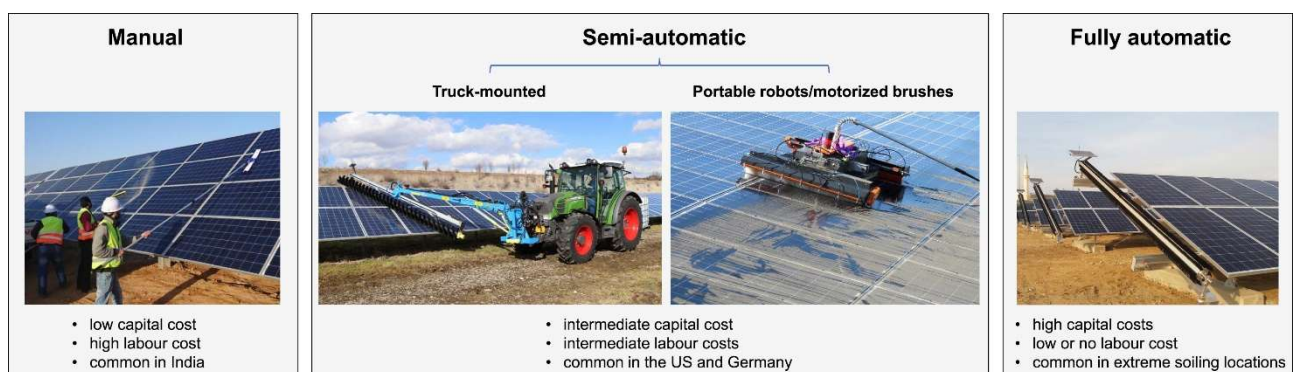


Figure 20. Example of cleaning strategies applied in utility scale ground mounted PV system (*Reprinted by [161] With permission of Elsevier*).

In APV systems, soiling represents a maintenance concern rather than an investment cost factor. Agricultural operations such as tillage, harvesting, and soil traffic may increase dust deposition on PV modules, increasing cleaning frequency and thus OPEX. However,

quantitative data on the economic impact of this effect are still lacking and require long-term dedicated field studies.

2.9. Perspective for precision agriculture application in APV

The adoption of precision agriculture technologies, particularly GPS-guided vehicles and crop growing monitoring systems, hold significant potential for mechanization in APV systems. Advanced guidance systems, such as those using Real-Time Kinematic (RTK) positioning, enable more precise driving paths. This precision can, in turn: reduce the risk of collision with PV structures (a key concern in vertical APV configurations), allow for narrower buffer zones, and minimize operational overlapping [65,154]. However, the adoption of Global Navigation Satellite Systems (GNSS) presents a significant challenge, particularly for overhead APV systems. These satellite-based systems are fundamental to many precision farming applications, including field mapping, automated machinery guidance, and yield monitoring, all of which depend on clear signal reception that can be obstructed by solar panels. Such interference can impair the performance and accuracy of these technologies and similarly affect self-guided autonomous harvesting machines or comparable robotic systems [148]. For instance, operational experiences in Lovenjoel (Germany) by Reher et al. [65] highlighted issues where GPS self-driving machinery repeatedly lost satellite signals under PV modules, leading to practical problems like uneven seed density at plot borders. To mitigate GNSS signal degradation, there are possible strategies that can be implemented. These include modifying solar panel layouts to reduce obstruction, adopting advanced positioning correction systems like RTK positioning, or utilizing hybrid systems that combine GNSS with Inertial Measurement Units (IMUs) or local reference stations to enhance reliability [148]. In scenarios with persistent signal issues, alternative navigation methods such as manual driving or Light Detection and Ranging (LiDAR) assisted guidance may be necessary, particularly in large-scale APV installations [169]. Furthermore, Simultaneous Localization and Mapping (SLAM) technologies offer a promising avenue for navigation independent of GNSS signals [148]. Overall, precision agriculture technologies have the potential to enhance the operational efficiency and safety of agricultural machinery utilization in APV context. Since precise driving is essential to minimize inefficiencies and ensure safe manoeuvring, future research should focus on developing assisted-driving solutions capable of mitigating GPS signal interference caused by PV modules.

2.10. Agricultural machinery adaptation to APV

The integration of agricultural mechanization with APV systems presents farmers with critical strategic decisions concerning the machinery fleet to adopt. Farmers must choose between adapting their existing equipment, either entirely or partially, to the APV system's design, or investing in new machinery whose working widths are specifically chosen to optimize operations within the APV design.

A fundamental issue, particularly during the initial phases of APV adoption, is determining the optimal approach: whether to acquire new, purpose-built machinery or modify existing on-farm equipment. The ideal strategy and its implications for operating costs remain largely unquantified, primarily due to the recent stage of commercial APV adoption outside of research contexts, which limits the availability of comprehensive operational data. Initially, farmers may seek to leverage their existing machinery within the APV system. However, this may lead to reduced field efficiency compared to conventional open-field conditions due to the mismatch between O_s in APV and available I_w . This necessitates potential future investments in machinery upgrades or reliance on specialized third-party contractors. Furthermore, the adoption of advanced farming technologies, such as autonomous tractors and robots, may present a dual advantage: beyond improving farming efficiency and minimizing soil compaction, their generally more compact size compared to traditional tractors makes them particularly suitable for highly specialized APV plants, allowing for more efficient utilization of the available space within the APV structure [140]. As discussed in Section 4.1, implements of smaller dimensions generally offer superior compatibility with the constrained row spacing inherent to many APV panel structures. Consequently, as illustrated in Figure 21, for implement that are likely to be available in small width version such as stem chopper, cultivators, disk harrows, seeders, ploughs and front mounted mowers, the probability of adapting in APV the pre-existent implements is higher than the one of adapting implements more likely available in large width version such as rear mowers, sprayers and harvesting headers to be coupled with combine harvesters.

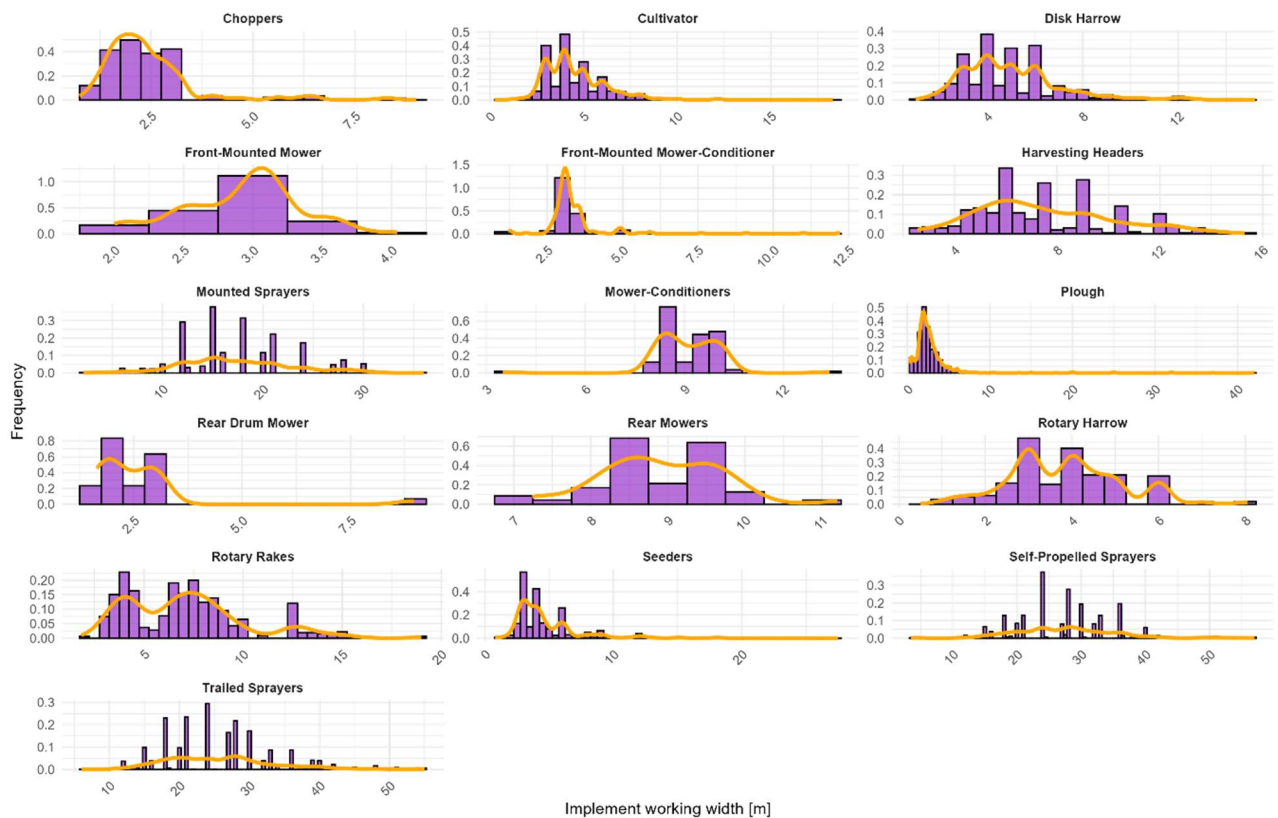


Figure 21. Distribution of implement working widths (I_w) for 16 categories of agricultural machinery relevant to field operations in APV systems. Each subplot displays the relative frequency of working widths (in meters) as purple histograms, overlaid with a kernel density estimation (orange line) to highlight underlying trends. Data were sourced from commercial machinery databases and reflect the range of equipment currently available on the market (Table 2) [132].

Consequently, if such suitable implements are not already part of the farm's existing inventory, their acquisition could negatively impact the company's economics, necessitating additional budget allocation after initial planning.

For many current APV systems, particularly those covering only a few hectares, the acquisition of smaller, specialized equipment solely for APV operations may not be economically viable due to the machinery's limited annual utilization [136]. In contrast, for large-scale APV, particularly those that might benefit from government incentives, optimizing mechanized activities for technical and economic efficiency may likely drive farmers or energy company to invest in co-designing APV and machinery fleet to optimize the mechanized operations. A pertinent example is the German APV policy, which mandates that crops cultivated under APV must achieve at least 66% of the yield compared to full-sun conditions. Such performance-based funding criteria incentivize farmers to select the most suitable implements and machinery, thereby maximizing agricultural yield within the available space. This is because, when funding is contingent upon meeting specific yield thresholds, farmers and multi-utility companies are

more inclined to invest in appropriate machinery and equipment to ensure continued eligibility for subsidies [25]. This ensures a higher degree of compatibility and can lead to improved long-term operational performance.

2.11. Conclusion

The co-location of PV energy generation and crop production in APV systems presents a promising avenue for sustainable land use offering the concurrent generation of energy while providing food production, yet its widespread adoption conflicts with fully mechanized open-field agricultural operations due to unguaranteed compatibility of machines with every APV structures. This study identified these challenges by providing an analysis of the constraints of open-field agriculture mechanization within APV systems to guide the co-design process to harmonize APV design and agricultural machineries. The primary outcome of this review is that key APV design parameters, particularly horizontal space (including buffer zones and operating space) and clearance space, have a critical influence on machinery accessibility and operational efficiency. The literature indicates that buffer zones alone may account for up to 30% of land loss when large, interspaced PV arrays are adopted. Field efficiency in mechanized operations is generally lower under APV conditions, potentially dropping to around 45%, primarily due to reduced operating speeds and suboptimal geometric alignment between implement's working width and available operating space. Additionally, machinery manoeuvrability during headland turns and the management of uncultivated inter-row areas represent further operational constraints. APV systems introduce several complexities for agricultural mechanization. From a mechanization standpoint, the presence of APV structural elements in the field primarily creates spatial and operational constraints and, in addition, dictates machinery pathways according to the APV orientation rather than the natural field orientation. When properly designed, APV layouts aim mainly to minimize efficiency losses in mechanized operations compared with open-field conditions. Within this perspective, "best-design" conditions imply a neutral effect, no additional penalties over a conventional agricultural system. However, effective integration can be achieved through meticulous planning and a co-design approach that accounts for all the agricultural operations required across a crop rotation management that should consider the entire lifespan of the APV system. There is no universal solution that fits all possible APV configurations and the optimal strategy for mechanizing agriculture in APV depends on a nuanced interplay of APV, farm scale, crop selection, available machinery, third party contractors' availability for mechanized operations and company investment capacity. However, to contextualize these findings, certain limitations

of this study should be acknowledged. A primary limitation stems from the vast heterogeneity in agricultural machinery, farm characteristics, and APV designs, which makes universally applicable recommendations challenging. The analyses of operational parameters were also based on defined assumptions (e.g., general speed reductions, ideal operator skill and squared field geometry) and do not encompass all possible real-world variations such as soil conditions or terrain uneven shape. Finally, this study highlighted economic implications but did not provide a comprehensive economic analysis, which would require dedicated modelling beyond its primary scope. In fact, techno economic analyses carried out for APV available in literature never assessed the impact on operational cost that stem from the challenges related with agricultural mechanization due to the obstruction of the PV structures. Moreover, the energy demand associated with mechanization, and how it varies according to APV system configuration and machinery dimensions, was not addressed in this study. The APV design influences not only the time required to complete agricultural operations but also the fuel consumption of the machinery involved. In fact, increased energy use compared to open-field conditions primarily results from overlapping passes when machinery is not properly dimensioned for the available operating space. Conversely, to minimize overlapping, an operator may opt for equipment with smaller working widths, which, although reducing redundant passes, requires more total passages than in conventional fields, thereby increasing both fuel consumption and operational time and costs. Fuel consumption of agricultural machinery operating within APV layouts remains a relevant yet underexplored topic. While Krexner et al. [29], assumed that total fuel use per hectare may decrease compared to open-field operations due to the presence of uncultivated buffer areas, this metric provides an incomplete evaluation of operational efficiency. A more accurate assessment should evaluate fuel consumption to the effectively cultivated area. When considering the actual productive surface, specific fuel consumption is likely to increase due to the inefficiencies arising from possible overlapping and the higher frequency of turning manoeuvres associated with narrower implements that may be favoured in an APV context compared to open-field conditions. These aspects illustrate how the mechanical and spatial constraints imposed by APV structures affect fuel consumption and operational time, potentially leading to higher operational expenses compared to open-field conditions, and therefore require quantification through field measurements. A systematic evaluation of these factors would allow for more accurate life-cycle assessments of APV systems relative to open-field cultivation and help quantify the extent to which APVs can offset emissions from agricultural mechanization. However, such an analysis is complicated by the large variability in available machinery, with differences in size,

technical specifications, and efficiency, and by the diversity of APV configurations. Each combination of machinery and plant geometry, including row pitch, buffer zones, and headland layout, would require dedicated assessment to determine their influence on operational fuel consumption. These aspects represent a relevant economic and environmental factors that should be explored in future research focusing on the optimization of the operational efficiency and energy consumptions of agricultural machineries within APV systems. All the considered limitations reported can provide a pathway to guide future research, which should focus on a wider variety of real-world APV installations and cropping systems. There is a clear need for continued innovation in specialized agricultural machinery designed for APV environments and for long-term economic analyses of the different mechanization strategies discussed. Advancements in precision agriculture technologies, including GPS-guided machinery and optimized route planning software, hold considerable promise for mitigating the discussed operational constraints. Ultimately, a concerted effort involving researchers, industry stakeholders, and policymakers would be essential to foster the widespread adoption of efficiently mechanized and agriculturally productive APV systems.

CHAPTER 03. SIMULATION-BASED DECISION SUPPORT FOR AGRIVOLTAIC SYSTEMS

Article published in Applied Energy 369 (2024) 123490 - 10.1016/j.apenergy.2024.123490



3.1. 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 [170]. Despite the various environmental regulations issued up to that point, CO₂ concentration in the atmosphere continues to rise [171]. 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 [172]. Solar energy, in particular, witnessed significant growth, reaching a total installed capacity of 849 GW [171]. Notably, the implementation of renewable energy plants in Europe is expected to steadily increase by 2050 [173]. Photovoltaics (PV) are capable of reducing CO₂ net emission compared to most of the traditional energy sources [28]. 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 [32,174], large scale PV in Spain, still occupy a mean area of 2 ha per MW_p [175]. 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 km² of land per year for PV, potentially exacerbating competition for land use [175,176] and unsettling the Land-Water-Energy nexus [177,178]. To address the land-use concerns associated with large-scale ground-mounted PV systems, the agrivoltaics (AV), first conceptualized by Goetzberger and Zastrow [7], 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, [50,54]. In recent years, various APV prototypes and commercial systems have emerged, featuring diverse PV module layouts, designs, heights, dimensions, and sun-tracking capabilities [63]. 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 [179,180];
- Crop yield [63];
- Water Use Efficiency (WUE) [39,50];
- Land Equivalent Ratio (LER) [8,9];
- Levelized Cost of Electricity (LCOE) [12,28].

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 [181]. Numerous methods and variants of MCDA have already been adopted among sustainable energy systems [182,183]. 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 [184]. 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 [185]. These integrated models offer a versatile tool to simulate crop responses under APV, including yield [8,74], water availability and conservation [39,186], irradiance interception [9,187], net revenues and crop production revenues [74,112]. 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 [19,21], EPIC [23], APSIM [10,18], STICS [8,74], and DSSAT [20].

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:

- 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 agrivoltaics (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.

3.2. Materials and methods

3.2.1. 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° (Figure 22; Table 7). 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 [188]. 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 x 25 km, were considered. Daily data from Agri4cast were converted in hourly data [189] and simulations were run adopting a 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 [190], this choice provides a pertinent benchmark for highlighting yield variations among these locations.

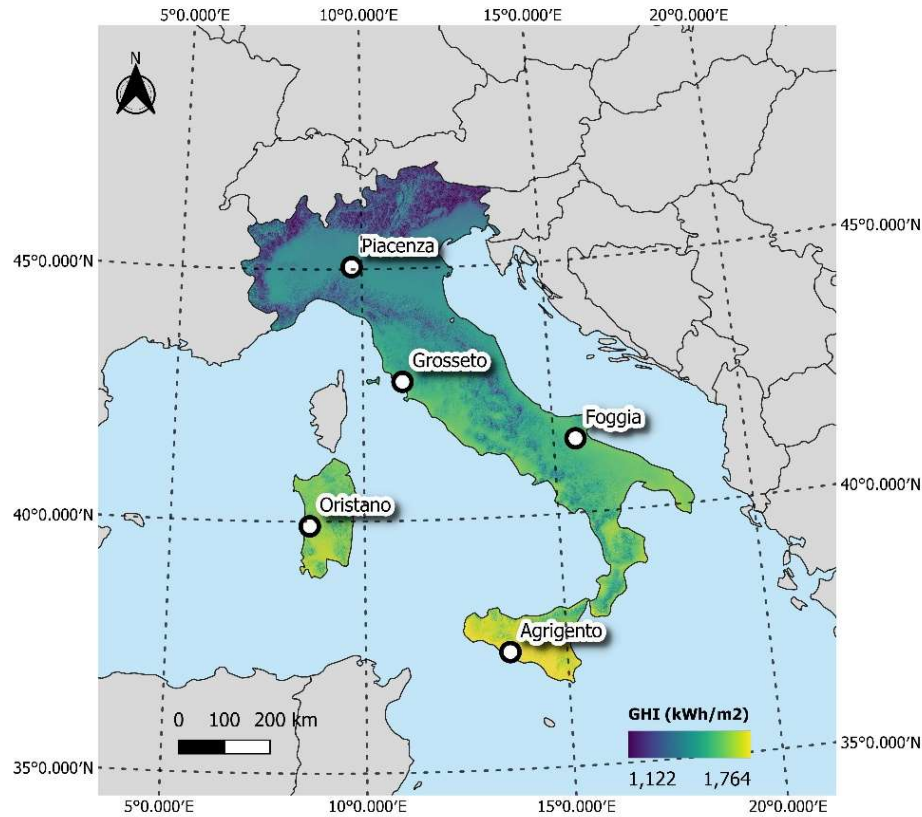


Figure 22. Site locations and Photovoltaic power potential in Italy [191].

Table 7. 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)

To limit the agricultural yield variability to weather conditions only, 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 8) according to the USDA soil texture classification [192].

Table 8. 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

3.2.2. 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 [79]. 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 [74,105]. 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 [193]; 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 [63] and, excluding the IMA-APV, they are categorized as advanced

according to the Italian's guidelines [79]. This classification is based on their layouts (vertical) or minimal height from the ground. These four APVs (illustrated in Figure 23).

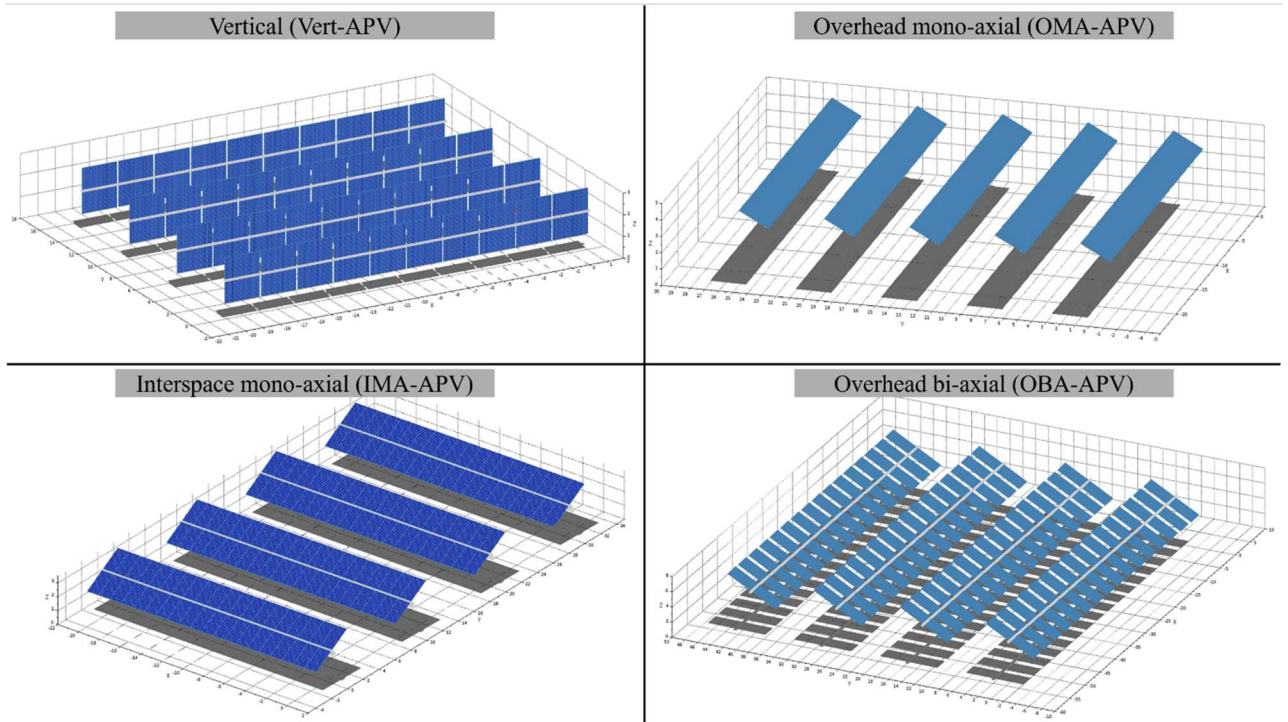


Figure 23. Scilab 3D render representation of the APV configurations adopted in the simulations.

Table 9. APV and reference systems settings. P = portrait; L = landscape.

APV	Bifaciality factor [%]	Main axis Height [cm]	PV layout	Single PV size [m]	Pitches [m]	GCR [%]
OMA-APV	80	343	1P	2.01 x 0.99	6, 8, 10, 12, 14	33, 25, 20, 17, 14
Vert-APV	80	170*	2L	0.99 x 2.01	8, 10, 12, 14, 16	25, 20, 17, 14, 12
IMA-APV	80	230	2P	2.01 x 0.99	10, 12, 14, 16, 18	40, 33, 28, 25, 22
OBA-APV	80	500	6L	1.30 x 2.38	14, 16, 18, 20, 22	38, 33, 29, 26, 24

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 10.

Table 10. PV modules specifications.

Type	Bifacial Half-cell
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

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 how elements in the atmosphere (like water vapor 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 [194].

3.2.3. 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 [19] and [21]. 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 (pitch² [m]). This area is further divided into pixels with an individual area of 0.5² [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.

3.2.3.1. 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 [195], 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).

3.2.3.2. 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 [196]. 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.

3.2.4. Model inputs

3.2.4.1. 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) [197] 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).

3.2.4.2. 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 11. 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 [198]. 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 determined according to the crop management disciplinary of the Italian Regions involved in this study. The nitrogen distribution schedule is presented in Table 12.

Table 11. 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 % ET _c	150
Grosseto	20 April					
Piacenza	30 April					

Table 12. 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	

3.2.5. 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 [8,9], WUE [39,50], energy conversion per hectare [199], specific energy yield [193] and agricultural yield [11]. 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 [9]. A LER value greater than 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 [8]. 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. [10]. The KPIs adopted in this study are discussed in depth in the subsequent paragraph.

3.2.5.1. 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. 3.1:

$$AY_{FL} = WSO_{FL} \cdot \left(\frac{1}{1 - WC} \right) \cdot 10^{-2} \quad (3.1)$$

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 [74]. In this study a security margin of 0.5 m for each side of APV supporting structures [17] 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 13.

Table 13. 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

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. 3.2 as follow:

$$AY_{APV} = \overline{WSO}_{APV} \cdot \left(\frac{1}{1 - WC} \right) \cdot 10^{-2} \quad (3.2)$$

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)* [10] 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. 3.3:

$$CR = \frac{AY_{APV}}{AY_{FL}} \quad (3.3)$$

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.

3.2.5.2. 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 [200]. 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 [193] and improves overall system efficiency. Additionally, considering the same PV 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 14.

Table 14. The primary assumptions for simulating the power output of APV.

Parameters	Value/type
Yearly Albedo	0.25 [201]
Cable losses [%]	2 [202,203]
Soiling losses [%]	2 [202,203]
Mismatching losses [%]	2 [202,203]
Losses due to deviation from standard spectrum [%]	1 [202,203]
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

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) [10]. The reference PV was assumed as a sun tracking ground mounted PV system with a North-South oriented rotation axis [204], a bifacial module array with 8 m pitch and 50% GCR [85]. The features of the reference PV system are listed in Table 15.

Table 15. 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 x 0,998	8	50

Electrical characteristics of the reference system modules are the same adopted for APVs (Table 10).

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. 3.4:

$$ER = \frac{EY_{APV}}{EY_{PV}} \quad (3.4)$$

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.

3.2.5.3. 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 [39]. 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. 3.5:

$$WUE_{APV} = \frac{AY_{APV}}{\sum ET_{c,APV}} \quad (3.5)$$

where AY_{APV} [Mg ha⁻¹] is the yield of fresh fruit produced for the specific APV scenario and $\sum ET_{c,APV}$ [m³ 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:

$$WUE_{FL} = \frac{AY_{FL}}{\sum ET_{c,FL}} \quad (3.6)$$

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

3.2.5.4. 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 [205,206]. 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 [206]. 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 [207].

The cost items considered for Capex and their mean value are displayed in Table 16. The mean values of each item has been determined from previously published data [12,17,28,126,208–

210], and thanks to communication with some of the major Italian companies involved in the APV sector.

Table 16. 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*

Since Capex 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 MW_p⁻¹] are detailed in Table 17.

Table 17. 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

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 impacts the overall final investment.

3.2.6. Multi Criteria Decision Analysis framework (MCDA)

As reported by Wang et al. [182] and Kumar et al. [183], 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” [211] 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 [211]. 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 [212], the TOPSIS method can be summarized in 6 steps:

1. Normalization of the decision matrix, rendering it dimensionless;
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 [182,212]. TOPSIS calculations were carried out using the Python module Scikit-Criteria [213]. 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.

3.2.6.1. Ordinal Priority Approach-based weighting

The TOPSIS method involves assigning weights to each criterion (KPI). In this study, the Ordinal Priority Approach (OPA) [214], 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 [215], 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 [91]; (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 were further subdivided into researchers and commercial operators on both sides. 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.

3.3. Results And Discussion

The comparison among APVs was carried out first for each single KPI (sections 3.2.1 to 3.2.4) and then combining all KPIs in a Multi Criteria Decision Analysis (MCDA) (section 3.2.5).

3.3.1. 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 Figure 24. 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 Figure 25. The negative effect of shading on processing tomato yield is also indicated by the trend of decreasing CR that was found for all

APV when the pitch decreases and the GCR increases [216,217]. 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 [218] 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.

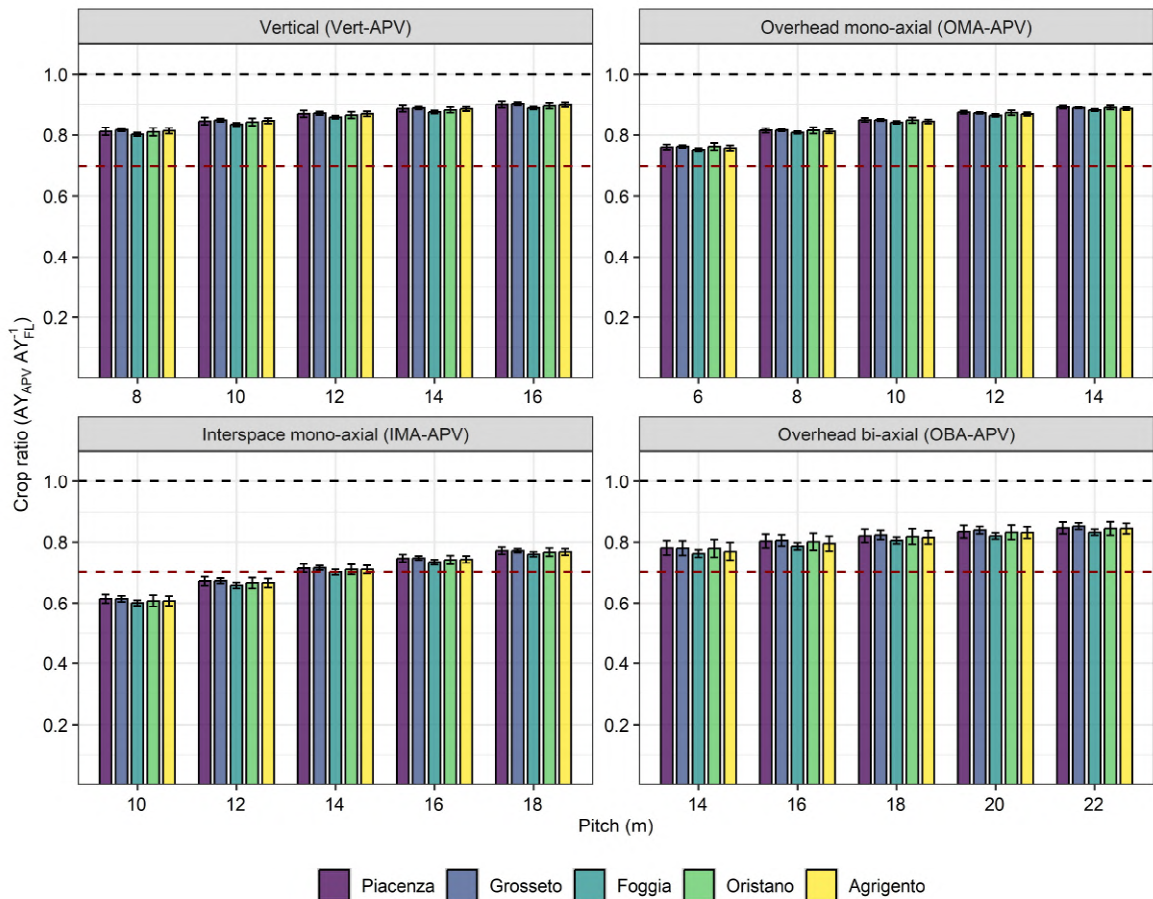


Figure 24. Ten-year mean and standard deviation of crop ratio (CR) for each site and APV with showcase of different pitches adopted. Black dashed line stands for CR = 1 (FL yield), red dashed line stands for CR = 0.7. The closer the CR is to 1, the less crop yield has been lost. CR of 0.7 (red dashed line) represent the limit of production depletion according to the UNI/PdR 148:2023 [218].

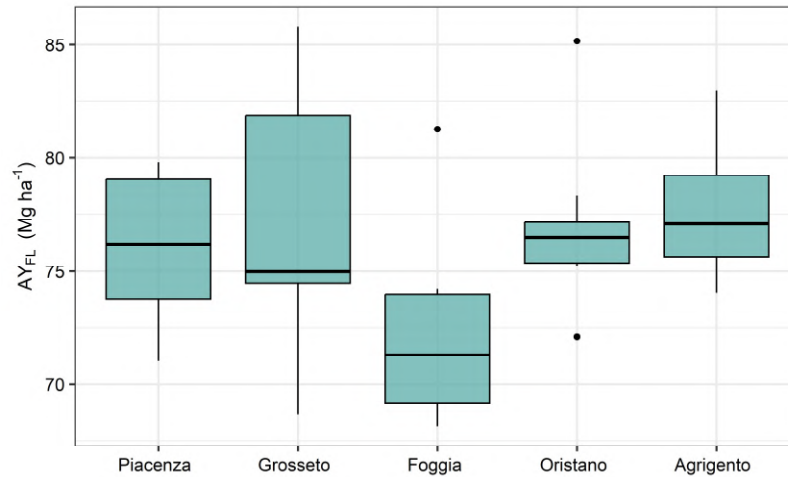


Figure 25. Box plot of the fresh fruit yield of processing tomato under Full Light (AY_{FL}) conditions. Data are simulated on a ten-year period.

Figure 26 and Figure 27 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 normalised. 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 [21,37,179] the pattern of CR follows closely the one depicted in Figure 27 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 during most of the day.

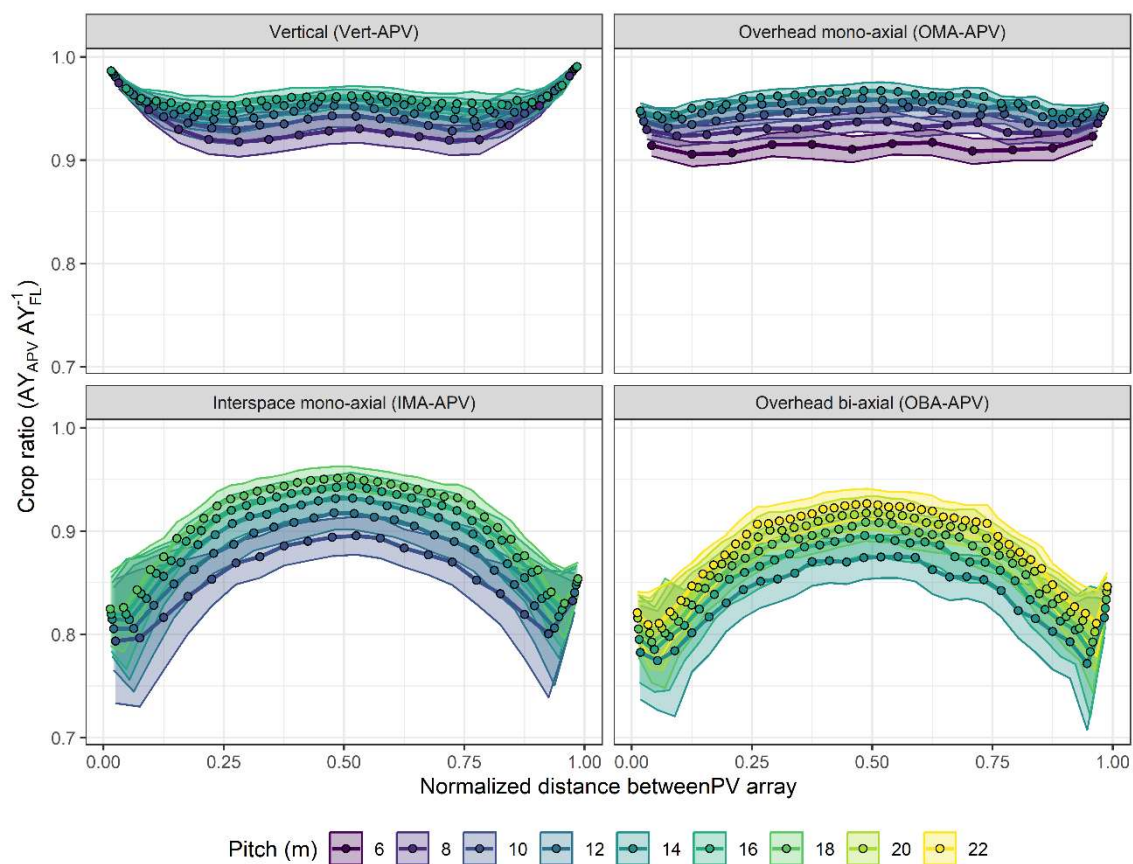


Figure 26. Mean of ten-year Crop Ratio (CR) distribution within the area included in the pitch of APV. Pitch widths are normalized. Shaded area represents standard deviation.

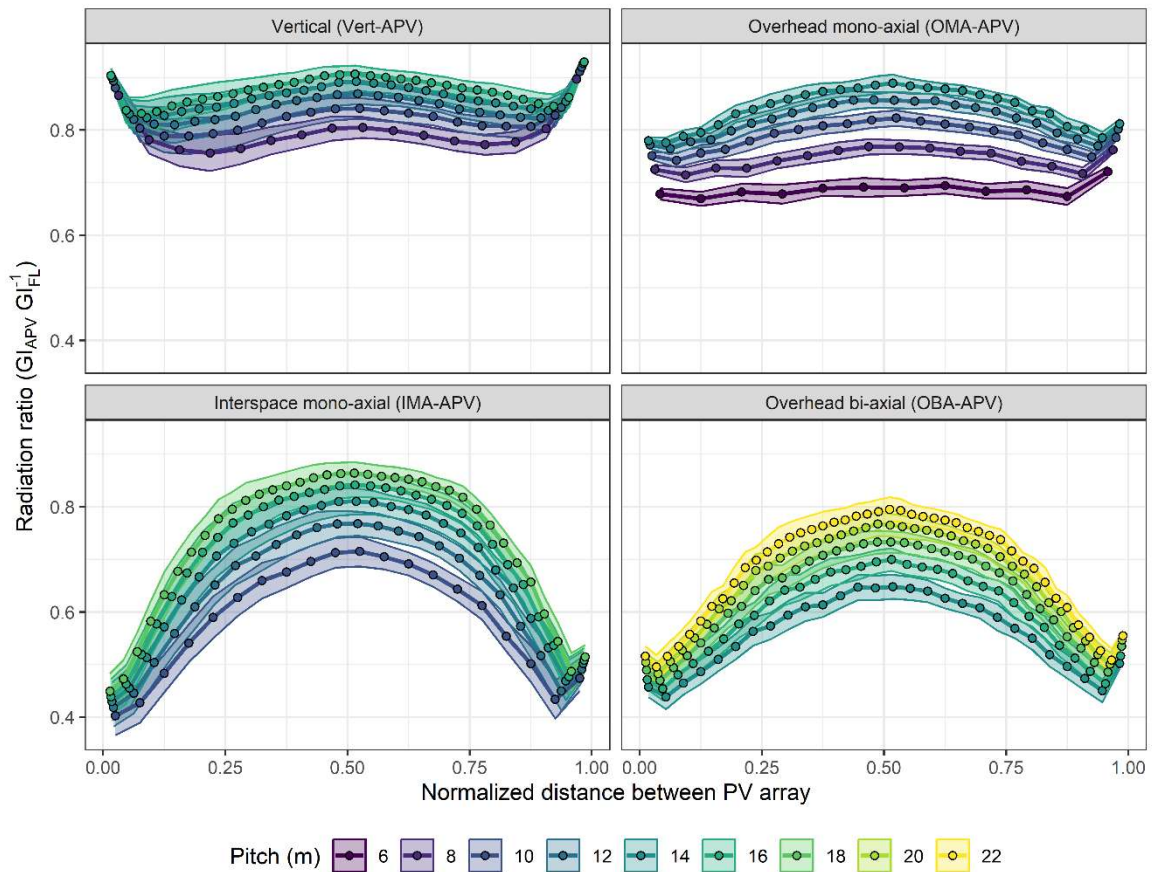


Figure 27. Radiation ratio (RR) distribution for normalized pitch. The normalized distance at 0.5 represent the mid-point between two AV arrays. The 0 and 1 points indicate the position beneath the modules array. The lines represent the mean values obtained from a ten-year simulation across all sites. Shaded areas depict the standard deviation.

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 [216,219–224]. Under very dry conditions it has been estimated that tomato yield under APV condition may also increase [50]. 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.

3.3.2. 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 [39,49,50,216,225] 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 [50,83,226]. 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 (Figure 28). 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 (Figure 28), 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.

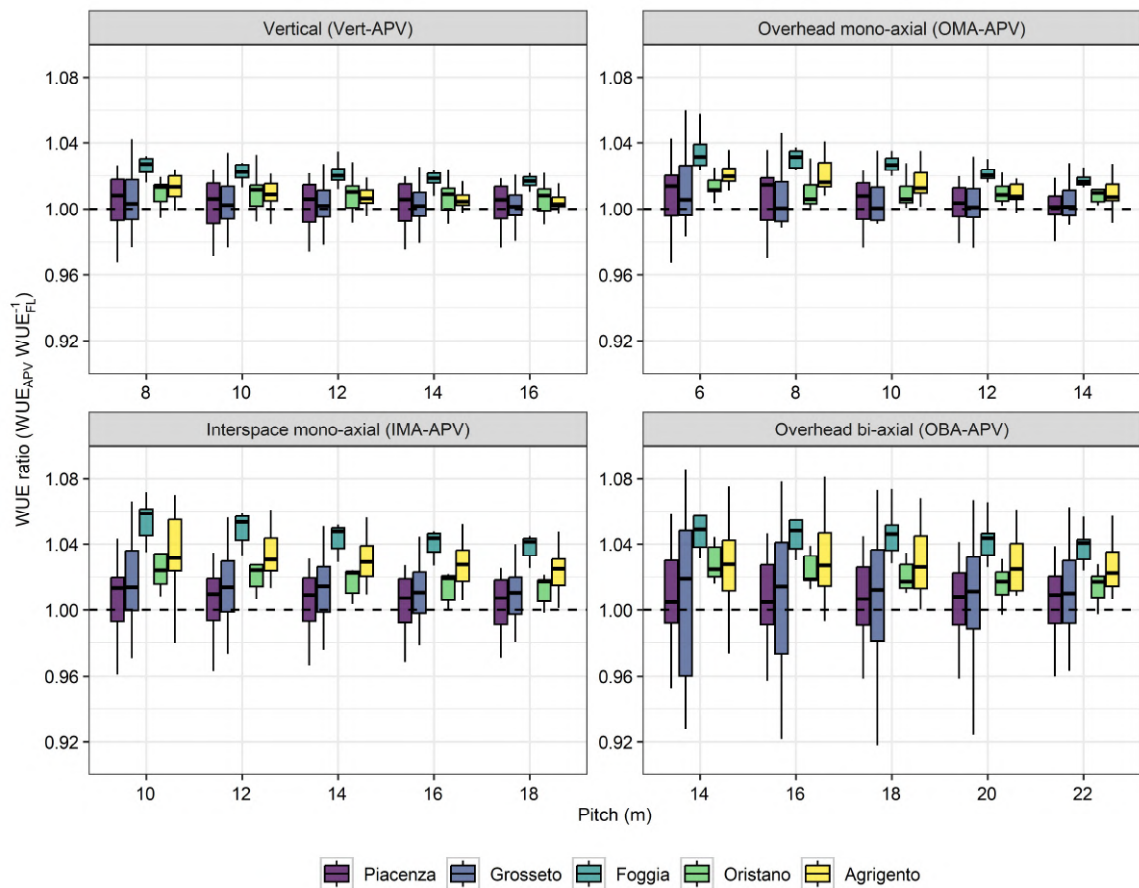


Figure 28. Water Use Efficiency (WUE) ratio simulated over ten-year period (2010-2019) for the selected Italian sites, APV and pitches.

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 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 [17,54] and, as highlighted by various authors, for APV may play a role in mitigating the adverse effects of climate change and extreme weather phenomena [54,227].

3.3.3. 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 Figure 29 and Figure 30, respectively, for each site. The highest mean energy conversion per hectare and per year (Figure 29), 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 (Figure 30), 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.

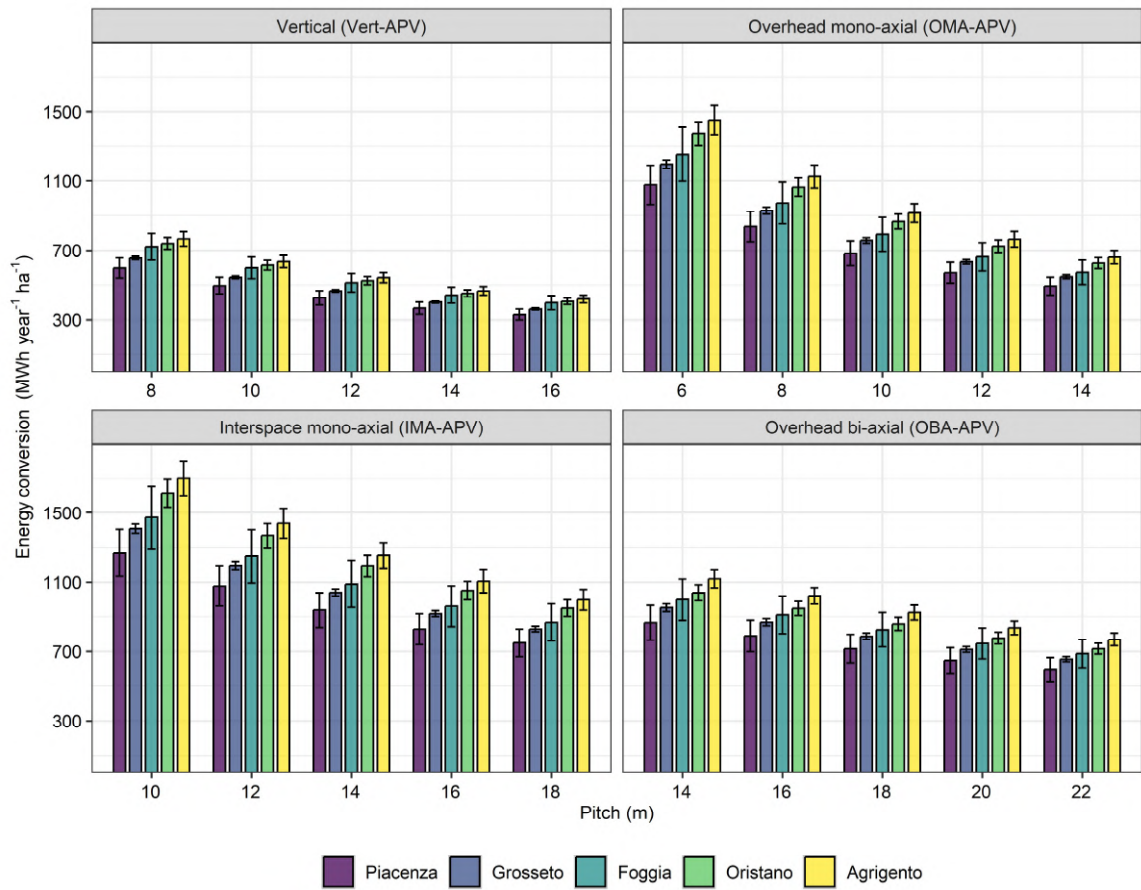


Figure 29. Mean annual AC energy output per hectare over ten years [MWh ha⁻¹ year⁻¹]

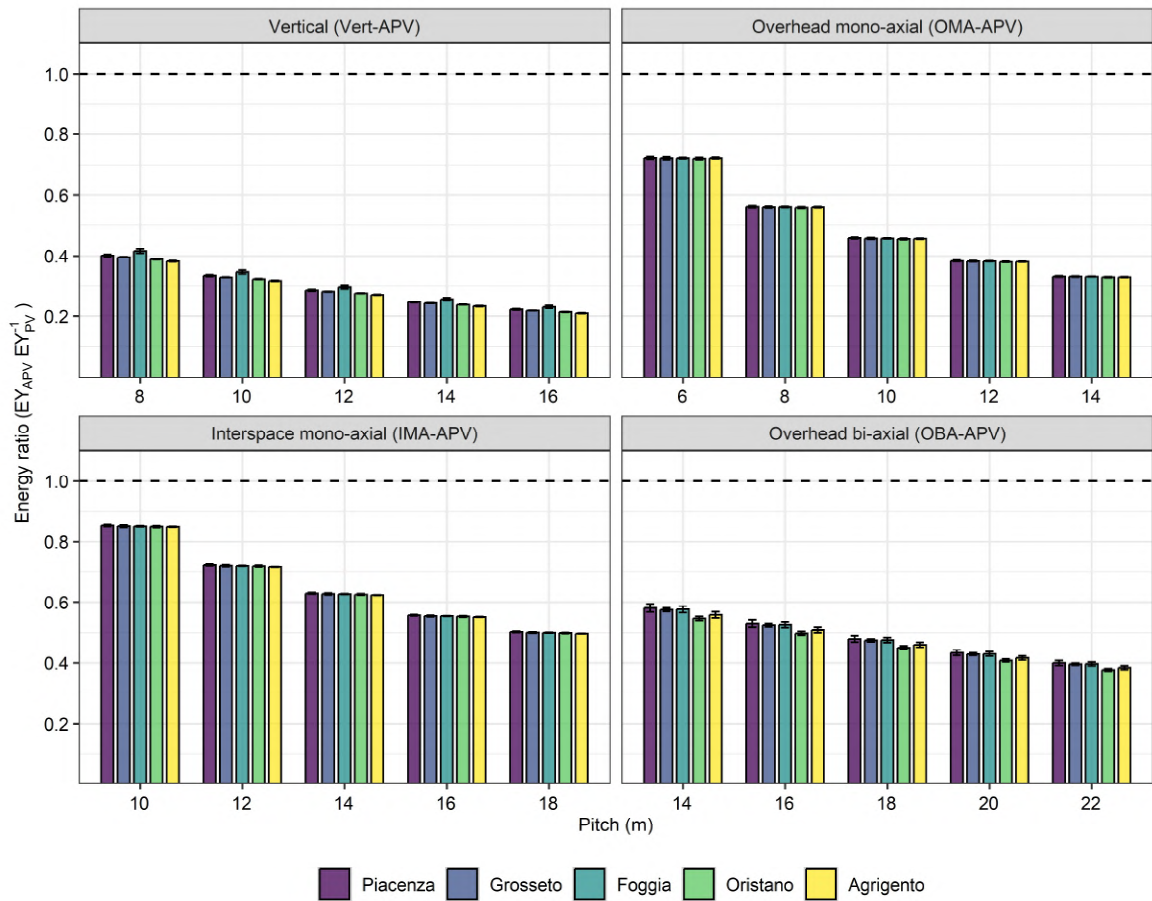


Figure 30. Mean energy ratio over ten years.

As highlighted in Figure 31, 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) (Figure 29), 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 (Figure 32). The highest efficiency in energy conversion was observed in the OBA-APV with a 22 m pitch, which achieved the highest energy conversion $2048 \text{ kWh kWp}^{-1}$ in Agrigento. IMA-APV and OMA-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 $1600 \text{ kWh kWp}^{-1}$ for pitch 16 m in Agrigento, the best result, and around $1163 \text{ kWh kWp}^{-1}$ with pitch 8 m in Piacenza, lowest result. This outcome was expected, especially due to the fixed design of the modules.

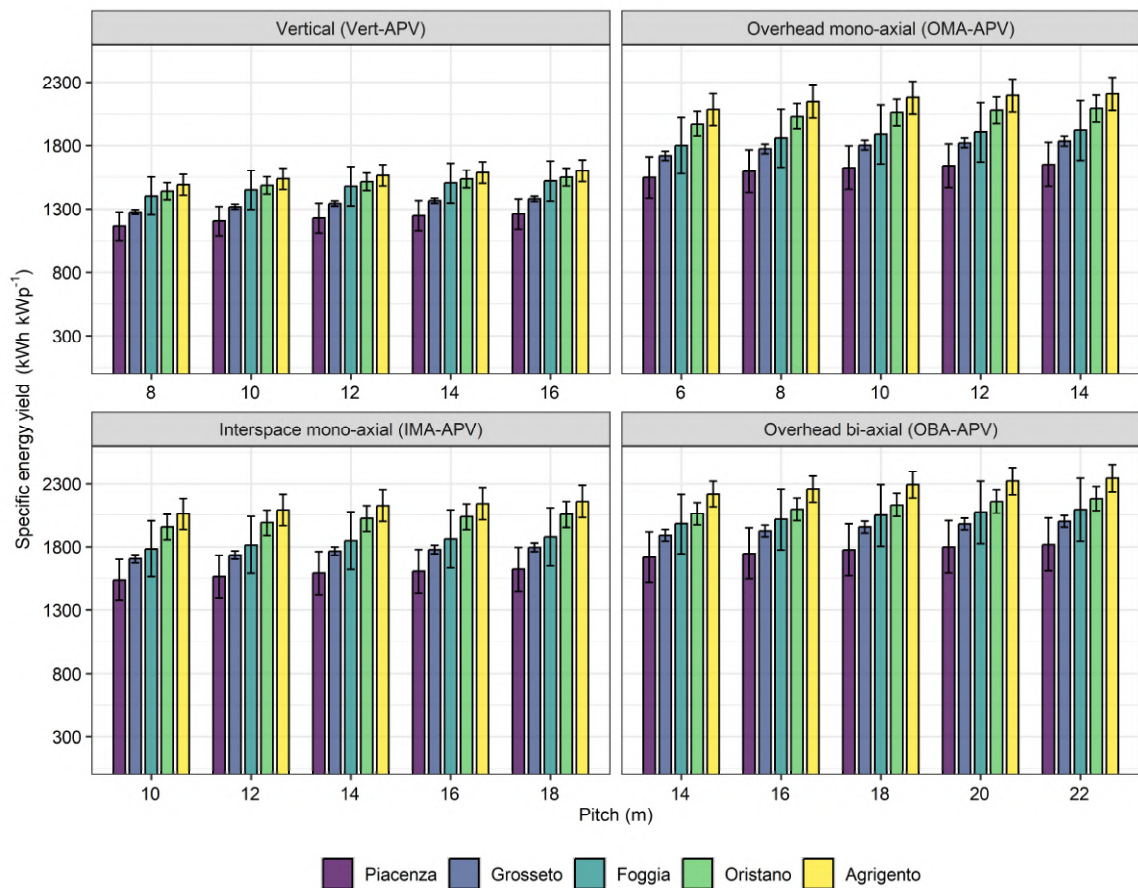


Figure 31. Specific energy yield [kWh kWp^{-1}] for each APV having different pitch and each Italian site.

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 [184], however it must be considered that, as indicated in the study by Campana et al. [23], 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.

3.3.4. APV initial capital expenditure (Capex)

The results of the Monte Carlo Analysis are illustrated in Figure 32, 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.

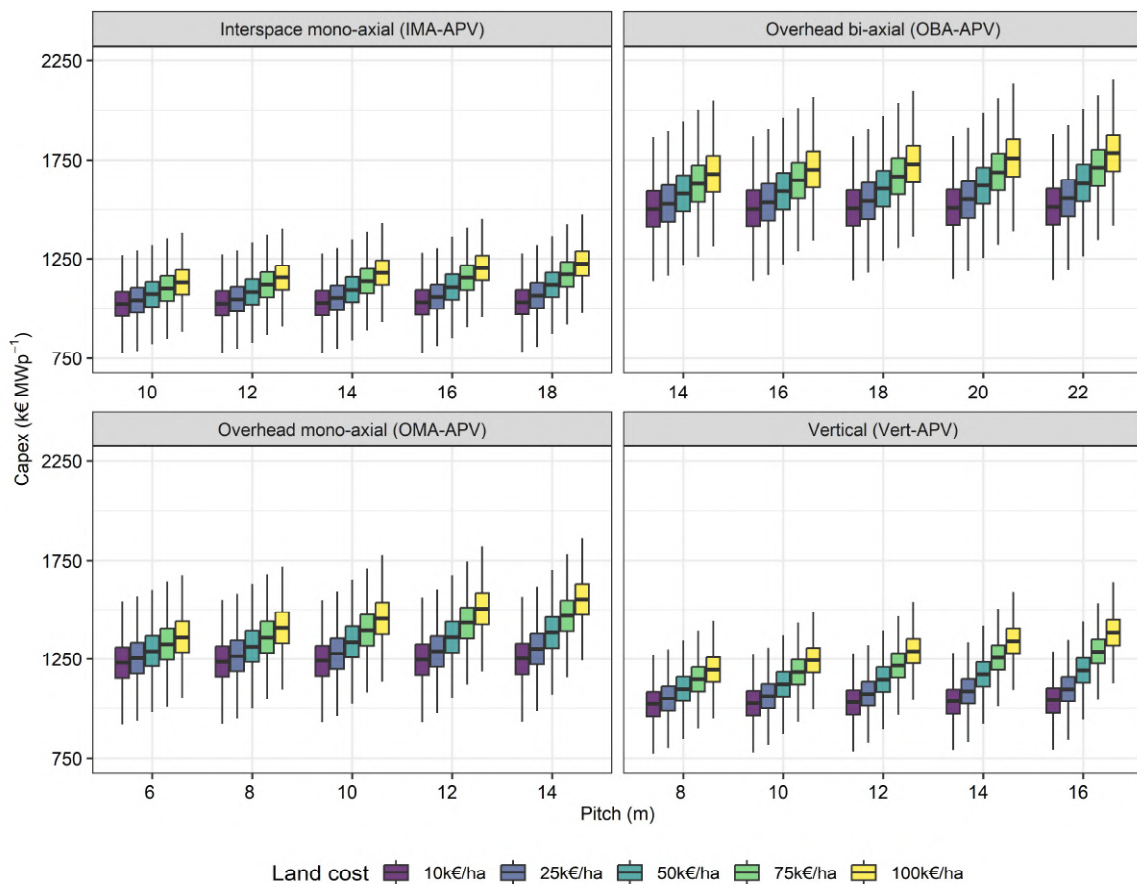


Figure 32. Monte Carlo Analysis (MCA) outcome for initial capex requirement. The initial Capex is intended for placing a 1 MW_p APV. Different land costs are assumed to represent cost variability throughout different Italian Regions.

3.3.5. MCDA output

3.3.5.1. OPA weighting for MCDA

Starting from the OPA method described in section 3.2.6.1, the optimal weightage of each KPI, adopted to carry out the MCDA process, is highlighted in Table 18. All the ranking outcomes, given by the experts and used as a proxy for weight computing, are also showed.

Table 18. Criteria and expert ranking for optimal weights calculation by means OPA model.

Experts list	Ra1	Ra2	RPV1	RPV2	Farm1	Farm2	Park dev. 1	Park dev. 2	Optimal weights
Criterion name									
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.

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.

3.3.5.2. MCDA based optimal APV

The outcome of MCDA is presented in Figure 33. 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).

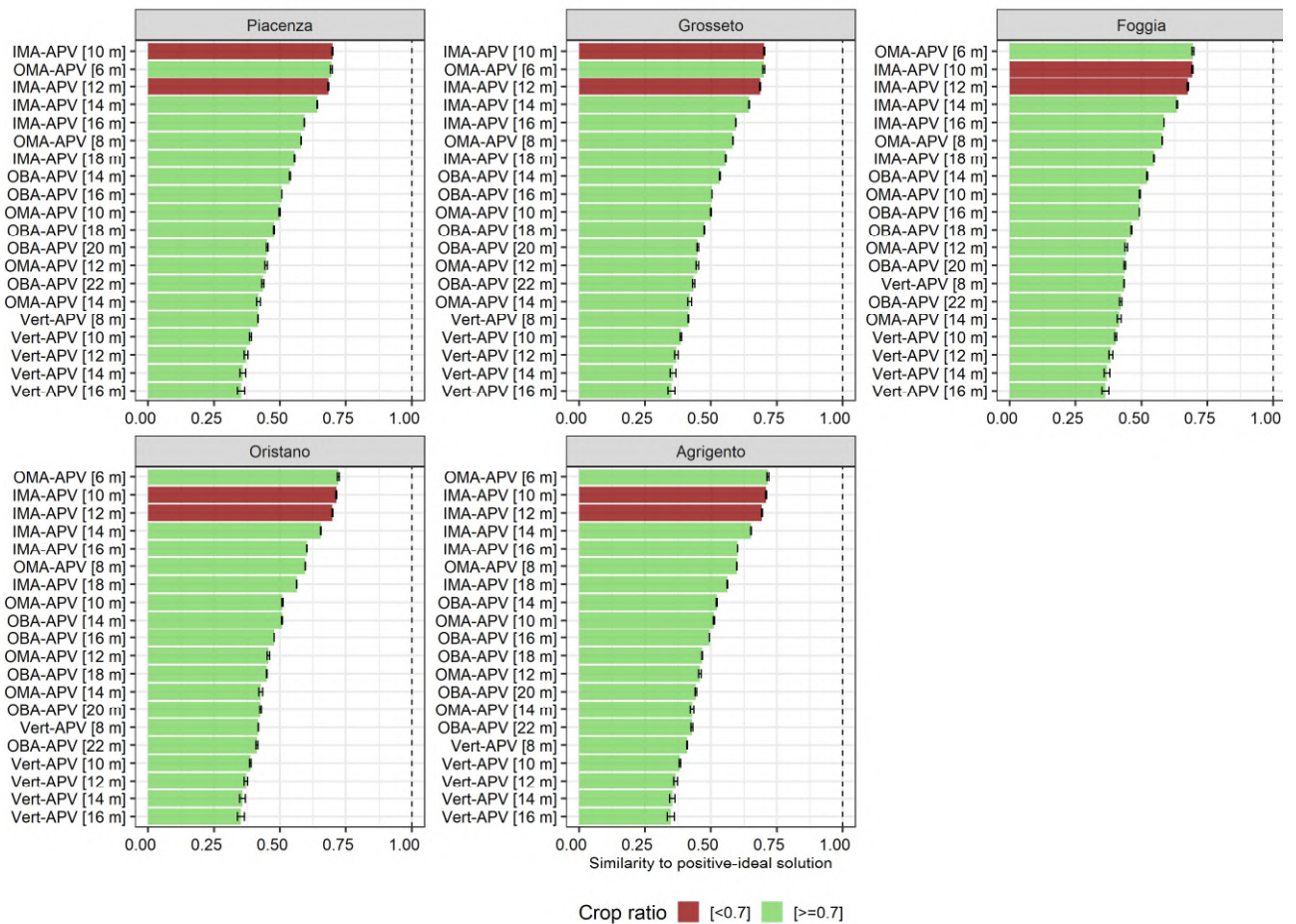


Figure 33. TOPSIS Similarity indexes for each APV alternatives. APVs alternatives are listed according to sites. The similarity indexes are calculated as mean value that consider all the possible land costs added to the median value of the Capex obtained through Monte Carlo Analysis. The higher the standard 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 Figure 33, 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. 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 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 17. 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 [88] 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.

3.4. 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 [61] 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. [228]. 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.

3.5. 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:

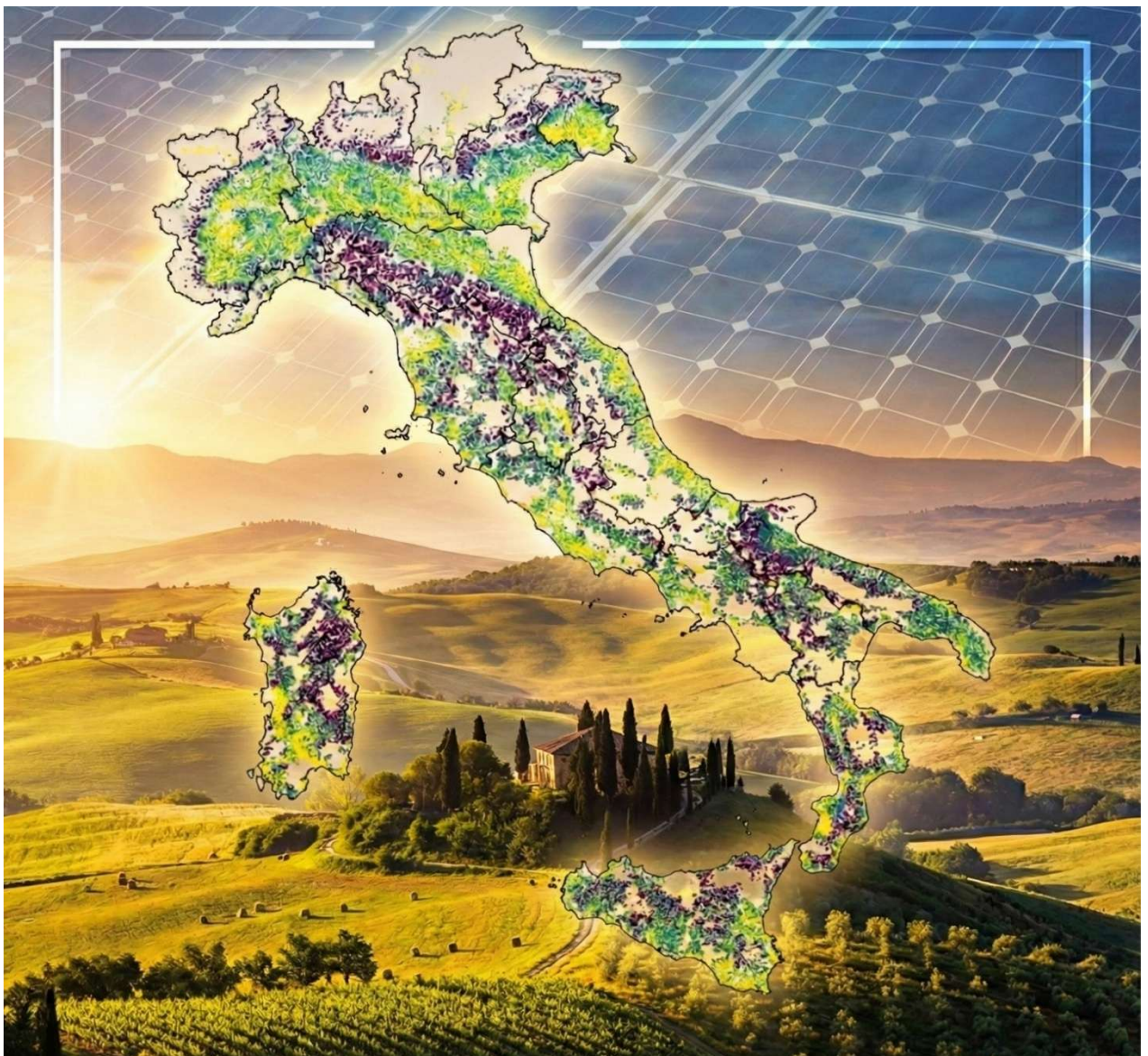
- Mono-axial systems, with narrow pitches, had the best ranking in all environments;
- The overhead mono-axial and the vertical systems create more uniform radiation condition for the crops compared to the interspace mono-axial and the overhead bi-axial systems;
- In agriphotovoltaic systems with narrow 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 [28].

CHAPTER 04.

ASSESSING AGRIVOLTAIC POTENTIAL AGAINST REGIONAL ENERGY TARGETS: A SPATIAL FUZZY-MCDM ANALYSIS IN ITALY



4.1. Introduction

Renewable energy sources offer an opportunity to generate large amounts of energy without pollutant emissions, providing a pathway to decarbonize the energy sector. In pursuit of carbon neutrality by 2050, the European Union is encouraging member states to develop large-scale renewable energy systems across their territories [229]. However, renewable energies, particularly wind power and photovoltaics (PV), require extensive land surfaces, which may be diverted from other uses, including agriculture [2]. Indeed, ground-mounted PV plants are often perceived as competing with crop production for land use. In this context, marginal or low-fertility lands have been considered preferable for conversion from agriculture to energy generation [230] to avoid unnecessary depletion of food production. An alternative to reduce land use competition among renewable energies is the deployment of rooftop PV, which has been increasingly promoted and subsidized across EU Countries [231]. However, as highlighted by Bòdis et al. [81] through a high-resolution geospatial assessment, rooftop PV across the EU Countries could only supply up to 24.4% of total energy demand. While the study accounted for obstructions, unsuitable orientation, and shading, it did not consider that many rooftops, particularly in historic urban areas, may not be structurally capable of supporting PV installations. Therefore, the study's estimates may be somewhat optimistic. Nonetheless, the results emphasize the continued need for ground-mounted PV in EU countries. The challenge, however, lies in land availability, which is limited and competes with other essential activities, primarily agriculture. Agricultural land, in fact, provides some of the most favourable conditions for PV performance, as highlighted by Adeh et al. [2]. Their global assessment identified croplands as having the highest potential for PV installations and estimated that if only 1% of croplands were equipped with PV systems, the world's total energy demand could be met. In comparison rooftop PV installations are generally less economically attractive than ground-mounted PV systems. This is due to their higher capital investment (Capex), reduced efficiency caused by suboptimal tilt and orientation [3], and limited economies of scale compared to utility-scale ground-mounted systems, resulting in a higher levelized cost of electricity (LCOE) for rooftop PV [4]. Moreover, studies comparing the LCOE of both systems consistently reported higher values for rooftop PV than for ground-mounted PV [80,82–86]. All things considered, APV represent a promising solution to overcome the trade-off between land occupation by GM-PV systems and the loss of agricultural land, by integrating energy generation with crop production. Moreover, APV systems provide multiple co-benefits, fostering self-sufficiency in both food and energy production and enabling landowners to generate dual income streams from agricultural and energy outputs. These advantages are

particularly relevant in remote or arid areas, while also contributing to environmental sustainability by reducing reliance on fossil-fuel-based generators [28,232]. Numerous studies evaluating the Land Equivalent Ratio (LER) of agrivoltaic systems have reported values exceeding one [55] suggesting that APV can enhance land-use efficiency relative to monoculture agriculture or stand-alone ground-mounted photovoltaic systems [8,19,23]. Land allocation for renewable energy has generated intense debate in Italy. The most recent decree defining suitable areas was annulled following objections raised by regional authorities [233]. The Agriculture Decree (Decree-Law 15 May 2024, no. 63, converted into Law 12 July 2024, no. 101) introduced restrictions on new ground-mounted photovoltaic plants in agricultural areas, amending the regulatory framework for renewable energy suitable areas established under Legislative Decree 199/2021. In parallel, a Ministerial Decree on suitable areas was adopted to provide uniform national criteria for the siting of renewable energy installations. Specifically, the Ministerial Decree of 21 June 2024, which entered into force on 3 July 2024, established a 180-day deadline for regional authorities to adopt legislation identifying “suitable areas”. This deadline expired in early January 2025. However, as of September 2024, only five out of 22 regions (Calabria, Lombardy, Piedmont, Apulia, and Sardinia) had enacted the required legislation [233]. As a result, the national mapping of suitable areas remains incomplete, constituting a persistent barrier to APV deployment [28]. In this context, geospatial planning, also referred to as site suitability assessment, has been increasingly adopted by both researchers and public institutions to support the identification of suitable areas for APV systems. In fact, inappropriate land allocation of APV may compromise the balance between agricultural productivity and solar energy generation, undermining crop performance and reducing social acceptance. Although the benefits of APV systems are increasingly acknowledged, the identification of suitable installation areas remains contested at the global scale. Consequently, a growing body of literature has focused on estimating APV deployment potential, ranging from large-scale continental assessments to high-resolution national analyses. Several studies have focused on estimating the macro-scale potential of APV to meet energy demands. At the European level, Victoria and Niazi [87] estimated the continent's technical APV potential at 51 TW, roughly 25 times the current electricity demand, by utilizing just 16.2% of eligible areas. Their analysis highlighted that while single-axis tracking systems maximize total electricity yield, vertical bifacial configurations often offer better price-weighted yields in specific regions. Chatzipanagi et al. [88] further corroborated this potential using Eurostat data, estimating that the EU Solar Energy Strategy target of 730 GWp by 2030 could be met by utilizing merely 0.77% of the EU’s utilized agricultural area. Similar potential

has been identified in North America. In an early study on the Phoenix Metropolitan Area (USA), Majumdar and Pasqualetti [234] demonstrated that agricultural lands, which are predominantly privately owned and flat ($<10^\circ$ slope), could generate several times the region's energy demand. Jamil et al. [89] provided a rougher estimate for Canada, suggesting that vertical APV on just 1% of agricultural land could supply approximately one-quarter of the national energy demand. Recent research for renewable energy land suitability assessment has increasingly adopted Geographic Information Systems (GIS) combined with Multi-Criteria Decision-Making (MCDM) methods to identify suitable sites with great precision. Yamada and Ogata [93] utilized a multi-criteria method in Kyoto, Japan, integrating risks, costs, associated with power plant deployment. Their framework integrated farmland data and assigned weights to evaluation criteria based on stakeholder preferences, enabling the identification of farmland suitable for power generation. Similarly, Elkadeem et al. [91] applied an Ordinal Priority Approach (OPA) in Sweden based on expert interviews to weight techno-agro-socio-economic criteria. They classified 8.6% of Sweden's land as suitable, with potential capacity far exceeding national consumption. Dere et al. [235] employed a Fuzzy Analytical Hierarchy Process (FAHP), to overcome the subjective judgement of expert to weight criteria, combined with TOPSIS to assess land suitability of APV among three Turkish provinces. Their robust framework accounted for detailed exclusion and evaluation criteria, including proximity to infrastructure (roads, energy grid) and risk factors (fault lines, flood risks), to rank candidate sites effectively. In Jordan, Ayadi et al. [236] linked APV suitability to the water–energy–food nexus, estimating that installing APV on 1% of suitable land (at 50% GCR) could meet significant energy targets while saving up to 4% of the national water budget. Similarly, Brent et al. [96] in South Africa highlighted orchards and vineyards in water-stressed regions as priority sites due to APV's potential to enhance water retention and mitigate water and heat stress. Focusing specifically on Italy, Fattoruso et al. [92] developed a comprehensive GIS-MCDM framework incorporating photovoltaic, agrivoltaic, agricultural, and technical criteria. Their 30 m-resolution maps identified 10.7 million hectares as eligible, suggesting that the 2030 national target of 80 GW would require only 1.24% of this area (or 5% of arable land and permanent cropland), reinforcing the argument that APV deployment has a marginal land-use impact compared to its benefits. Finally, land suitability is dynamic over time due to changing climate. Neesham-McTiernan and Barron-Gafford [97] highlighted that as climate change expands the regions subjected to drought and high temperatures, the areas classified as “highly suitable” for APV will increase accordingly. Their projections for the southwestern USA indicate that by 2080, highly suitable land could expand by over 50% as the microclimatic

benefits provided by APV becomes increasingly valuable for sustaining crop production. Conversely, unsuitable areas are delineated by strict policy and technical constraints. Specifically, renewable energy deployment is often restricted within and around protected zones to safeguard natural and historical landscapes. These exclusions encompass nature reserves, parks, cultural heritage sites, and sometimes they also consist of additional buffer zones to safeguard the landscape view [237]. Consequently, a significant portion of land classified as unsuitable stems from these restrictions on protected landscapes and environmental assets [90,92,137]. The selection of suitable areas may also be time-sensitive, particularly in light of climate change. Neesham-McTiernan and Barron-Gafford [97] demonstrated that climate change projections foresee an increase in suitability as rising temperatures, drought, and other climate-related stresses intensify. This is expected, since many assumptions underlying area suitability assessments suggest that regions exposed to extreme temperatures, water deficits, and droughts benefit the most from APV installations, as they help reduce crop stress under adverse climatic conditions [43,45,47]. However, while climate and climate change can influence whether an area is more or less suitable for APV, they do not solely determine whether an area is excluded. This outcome largely depends on policy factors among the others, which often play the most decisive role in APV deployment.

Identifying suitable areas for implementing APV systems requires the evaluation of multiple parameters [91]. Among these, solar radiation and other climatic variables are fundamental [92,95]. Long-term meteorological records on solar radiation, temperature, precipitation, humidity, and wind provide insights into both crop performance and PV efficiency, supporting more accurate suitability assessments [91,238]. Among the criteria used to assess the land suitability for APV installation, many are related to topographic characteristics such as slope, aspect, and elevation [91,92,97,137,230,239]. Flatter terrain reduces erosion risks, facilitates construction, and improves solar panel orientation [94,95]. Land use or land cover is often included among both the exclusion [91,92,97,238] and evaluation criteria [85,92,240]. The CORINE Land Cover (CLC) database [241] enables the identification of impermeable surfaces such as settlements, roads, railways, and airports, as well as nature-based areas such as forests, water bodies, and agricultural lands, further subdivided into categories like arable land, irrigated lands, pastures, and orchards [241]. In recent studies solar installations have been often prioritized on land with lower agricultural capacity, such as grasslands, marginal soils with low fertility or poor structure, and areas characterized by low productivity [239,242,243]. Although defining suitability between different classes of agricultural land cover is a meaningful criterion for conventional ground-mounted PV installations, it is somewhat counterintuitive in the

context of agrivoltaics where the goal is to preserve productive agriculture. The siting of APV systems should primarily be guided by environmental conditions and climatic constraints that determine agricultural viability. These same limiting factors often marginalize specific areas, making them naturally less suitable for intensive cultivation.

To integrate these diverse parameters, spatially explicit multi-criteria analyses approaches offer powerful tools for developing site suitability models [90]. This study aims to assess the geographical suitability for APV system installation at the national scale, with a specific focus on Italy. The analysis considers multiple constraints, including regulatory limitations, physical feasibility, and current land use patterns. Suitability is evaluated through a fuzzy spatially explicit multi-criteria (fuzzy-MCDM) framework based on a fuzzy Analytic Hierarchy Process (F-AHP) for attributing weight to criteria and a fuzzy-TOPSIS for classifying the territory into five suitability levels ranging from very low suitability to very high Suitability. The assessment is further refined at the regional scale by evaluating each Italian region's capacity to meet its share of renewable energy targets (burden sharing), assuming APV systems as the sole renewable energy source. Unlike previous spatial decision-making studies conducted for Italy, this research mitigates biases in criteria weighting and classification by implementing a comprehensive fuzzy Multi-Criteria Decision Making (MCDM) approach, integrating both Fuzzy AHP and Fuzzy TOPSIS. Furthermore, it proposes two distinct criteria classification strategies: a Global method, based on the classification of criteria by the distribution of criteria values across the entire country, and a Local method, which scales classification thresholds relative to each region. Specifically, this study addresses three main research objectives: (1) to identify national-scale APV suitability in compliance with the latest national and regional regulations; (2) to evaluate how these two classification strategies influence the spatial distribution of suitable areas across the country; and (3) to estimate the strategic contribution of these suitable lands toward meeting regional burden-sharing targets.

4.2. Materials and methods

Identifying suitable sites for renewable energy deployment is a complex process that requires the integration of multiple factors, including regulatory, economic, climatic, physical, and social considerations. In the case of agrivoltaics, the selected criteria influence both energy generation and agricultural productivity; therefore, they must be carefully weighted to ensure a balanced and reliable assessment of site suitability.

The initial stage in defining suitable areas for agrivoltaics involves applying exclusion criteria. This approach allows for the efficient elimination of substantial amounts of data without the

need for extensive processing. APV systems can only be established on land designated for agricultural use. Therefore, any areas not classified as agricultural can be excluded from consideration a priori. Within the remaining agricultural land, further restrictions based on environmental concerns limit the areas suitable for agrivoltaics. These exclusions encompass protected areas such as nature reserves, areas near waterways and lakes, settlements, archaeological sites, and similar locations. All such restrictions must be considered prior to defining the specific evaluation criteria for APV suitability. A simplified framework of this study is depicted in Figure 34.

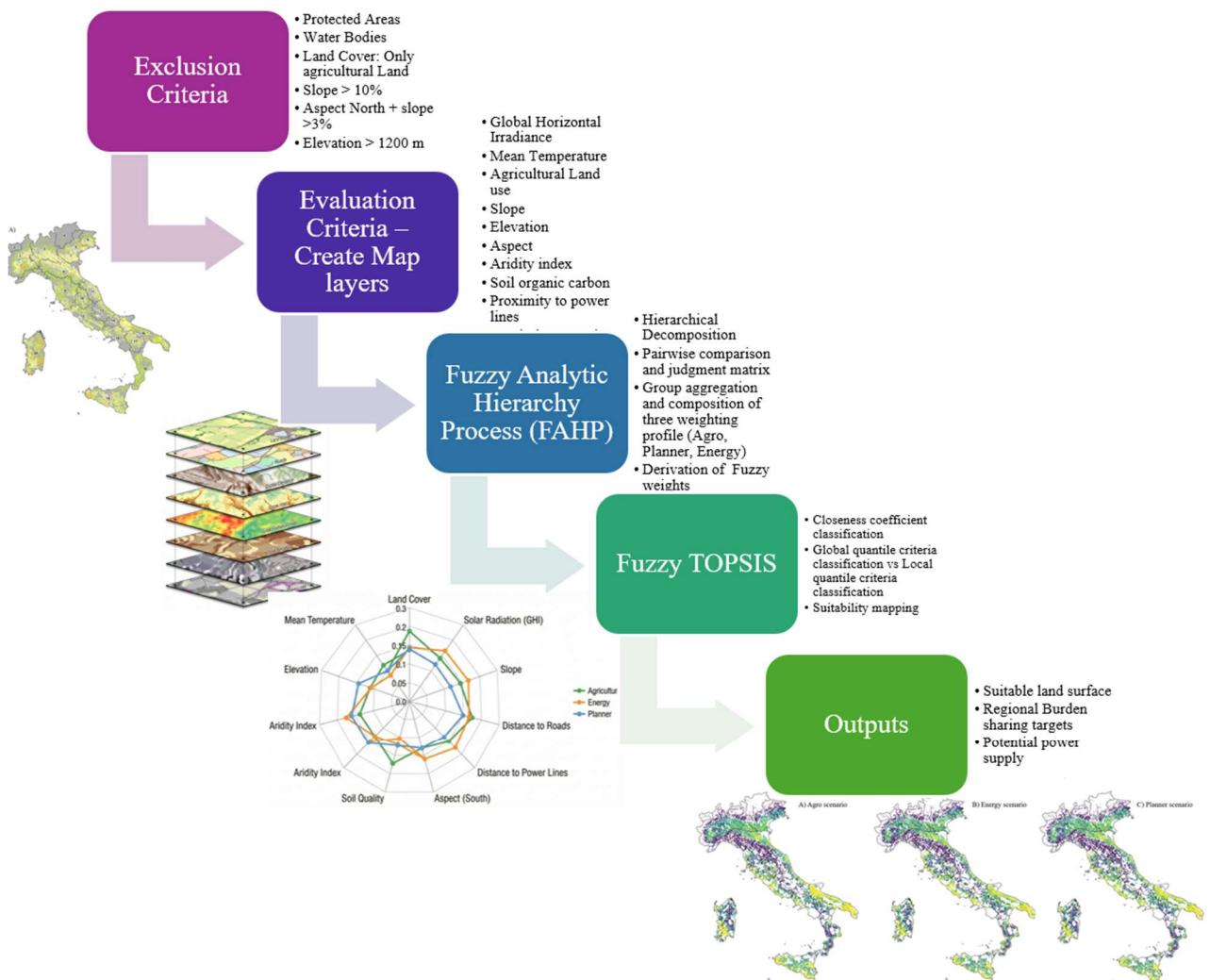


Figure 34. Spatially Explicit Multi-Criteria analyses simplified workflow

4.2.1. Study Area and reference system

The analysis covers the entire Italian territory, including the mainland and the two major islands, Sicily and Sardinia. Italy extends from 36.6° N to 47.1° N and from 6.6° E to 18.5° E, encompassing approximately 302,073 km², of which about 41.6% consists of hills, 35% mountains, and 23.2% plains [92] The country spans three major bioclimatic zones, Alpine,

temperate, and Mediterranean [244], which generate substantial variability in both topography and climatic conditions. Elevation ranges from sea level along extensive coastal plains to the Monte Bianco peak at 4,807 m, resulting in wide variability in topography and climatic conditions. Mean annual global horizontal irradiance (GHI) varies from about 1000 kWh m⁻² yr⁻¹ in the Alps to nearly 1900 kWh m⁻² yr⁻¹ in southern and insular regions [191], following a marked latitudinal gradient [191] (Figure 35). Mean annual air temperature spans from 8 °C in Alpine areas to 19 °C in southern coastal zones (ISPRA, 2024), while average annual precipitation ranges from roughly 450 mm in southern Sicily and Apulia to more than 1500 mm in the Alpine arc, with a national mean close to 900 mm yr⁻¹. The administrative framework used in this study is based on the official municipal boundaries released by the Italian National Institute of Statistics (ISTAT, 2025). These boundaries were employed to define the national analysis extent and to aggregate results at the regional scale (NUTS-2) using the regional code (COD_REG). All spatial datasets were harmonized in the ETRS89 / LAEA Europe coordinate reference system (EPSG:3035), consistent with the Copernicus Land Monitoring Service (CLMS) products. AI. The Italian Land Cover and Land Use (LCLU) map at 10 m resolution, developed by ISPRA by integrating CLCplus Backbone [241] and national soil consumption datasets, was adopted as the common analysis grid. Each raster cell therefore covers 10 m × 10 m (0.01 ha). All spatial datasets were resampled to a 10 m grid, defined by the national CLCplus land cover map.



Figure 35. GHI gradient through Italy [191]

4.2.2. Land cover: reference raster

The land cover and land use information used in this study is based on two complementary Copernicus products. The primary spatial reference layer is the CLCplus Backbone 2018 [241], a 10-m resolution pan-European land-cover dataset derived from Sentinel-2 time series and organized into 11 high-level classes (Copernicus Land Monitoring Service). The CLCplus raster, cropped and masked to Italian municipal boundaries, was adopted as the template grid for all geospatial operations and as the basis for calculating the pixel area ($10\text{ m} \times 10\text{ m} = 0.01\text{ ha}$). Its classification codes were used to identify agricultural land for the preliminary suitability filtering. In addition, the CORINE Land Cover 2018 (CLC2018) dataset (100-m resolution, version 2020_20u1) [245] was reprojected and resampled onto the 10-m CLCplus grid. This layer was used to compute a synthetic land-use suitability score (0–1) reflecting the relative compatibility of different agricultural and semi-natural classes, such as arable land, pastures, permanent crops, and agro-forestry mosaics, with APV deployment.

4.2.3. Exclusion Criteria

The analysis begins by establishing restriction criteria to filter out the non-agricultural land and the agricultural land that isn't usable. The exclusion criteria identify all factors that

automatically render an area unsuitable for APV installation, corresponding to zones where suitability equals zero. These include both regulatory constraints, such as legally protected areas, and physical limitations that prevent construction or operation.

As the first stage of the suitability analysis, exclusion criteria delineate the spatial framework for subsequent evaluations. Exclusion criteria prevent the inclusion of areas where environmental, technical, or socio-economic trade-offs are unacceptable due to physical, climatic, or policy restrictions. Incorporating these constraints early in the geospatial workflow safeguards ecologically sensitive areas, including reserves, nature parks, forests, and wildlife habitats, and simultaneously improves computational efficiency by narrowing the analysis to potentially viable zones.

As summarized in Table 20, additional land-cover-related constraints such as proximity to settlements, airports, and archaeological, historical, or military sites are also considered. Although the assessment focuses exclusively on agricultural land as the eligible class for APV deployment, buffer zones surrounding specific protected categories are analysed separately to ensure accurate spatial delineation. The adopted exclusion framework aligns with established methodologies used in previous renewable-energy suitability assessments.

4.2.3.1. Policy Exclusion criteria

Policy and legal constraints refer to land-use restrictions that prohibit or limit the installation of APVs. As described by Hauger et al. [98,240], legally restricted areas can be categorized into two main types:

- Hard restrictions, which apply to areas where APV installation is entirely incompatible with land use (e.g., urban zones) or where protection is mandated by law, such as national parks, biodiversity conservation areas, or hydrologically important sites.
- Soft restrictions, which refer to areas that are not directly prohibited but fall within buffer zones surrounding legally protected areas.

These constraints typically include distance from protected areas, rivers, lakes, and other water bodies. In the Italian and European context, protected areas are defined by several legal instruments, including Italian Law 394/1991 on protected natural areas, the EU Habitats Directive and Birds Directive under the Natura 2000 framework, and national regulations governing hydrological protection zones. The Italian regulatory framework, which combines national laws with the implementation of EU directives on protected areas, is extremely articulated and complex. Moreover, the central government has delegated to the regional authorities the responsibility for defining the final phase of suitability assessment for the deployment of renewable energy plants. As a result, differences may exist among regions, and

the legal framework may evolve over time, potentially changing by the time this article is published. In 2010, the Italian government issued the Guidelines for the Authorization of Renewable Energy Plants (DM 10 September 2010), followed by the Ministerial Decree of 6 July 2012, which defined support mechanisms for renewable energy sources (RES). These measures established the fundamental principles for site selection, promoting projects that minimize land consumption, encourage the reuse of degraded or anthropized areas, exploit existing infrastructures, and employ environmentally responsible technologies.

The 2010 Guidelines also defined as non-suitable for RES installation territories subjected to landscape or cultural protection constraints, which are automatically excluded from site suitability assessments. Subsequently, the Ministerial Decree of 15 March 2012 introduced the Burden Sharing mechanism, allocating renewable energy targets among Italian regions according to the Regional Potentials outlined in the National Action Plan (PAN) 2010. At the European level, Directive (EU) 2018/2001 (RED II) urged Member States to strengthen renewable energy deployment while ensuring environmental and landscape protection. In Italy, the Directive was transposed through Legislative Decree No. 199/2021, further supported by Law No. 53/2021, which specifies that the identification of suitable areas must respect cultural heritage, landscape, agricultural and forested lands, air and water quality, and should prioritize the use of built surfaces such as industrial roofs, parking lots, and non-productive or degraded lands. For protected areas falling under the above-mentioned legal frameworks, a 500 m buffer zone is applied. Within this buffer, renewable energy systems (RES) cannot be installed (D.Lgs. 42/2004; D.Lgs. 199/2021). The shape files containing all the protected areas were available from institutional website of the Italian Ministry of culture [246] and by web tool by GSE (Gestore Servizio Energetico) [247]. Lakes, major rivers, and primary watercourses were identified using the EU Hydro River Network 2006–2012 dataset [248], while additional mapping of smaller rivers, streams, and minor lakes was performed using OpenStreetMap data [249]. The identification of these water bodies enabled the application of the buffer zones defined by Italian environmental legislation (Codice dell’ambiente, D.Lgs. 152/2006), which establishes a 300 m buffer around lakes and reservoirs and a 150 m buffer around rivers and watercourses. In this assessment, no buffer was applied around small water bodies with a surface area below 1 ha, in order to avoid including artificial agricultural reservoirs in the exclusion process. Regulatory framework used to map protected areas and relative buffer around Italian Country are listed in Table 19.

Table 19. Regulatory framework applied to assessing the protected areas around Italy

Regulation	Definition
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<i>DM 10 September 2010</i>	National Guidelines for Renewable Energy Plants.
<i>DM 6 July 2012</i>	Support mechanisms for renewable energy sources.
<i>DM 15 March 2012</i>	Definition of Regional Burden Sharing
<i>Legislative Decree 199/2021</i>	Transposition of EU Directive 2018/2001 (RED II).
<i>Law 53/2021</i>	Regulation on the identification of suitable areas.
<i>Legislative Decree 42/2004</i>	Cultural Heritage and Landscape Code.
<i>Law 394/1991</i>	Framework Law on Protected Areas.
<i>Legislative Decree 152/2006</i>	Environmental Code.
<i>EU Directives 92/43/EEC and 2009/147/EC</i>	Natura 2000 Network.
<i>Suitable Areas Decree 2024</i>	Only APV allowed on agricultural land

For lakes, rivers, canals, and reservoirs, the GIS layer was created by combining datasets from EU-Hydro and OpenStreetMap (OSM). The layer of main rivers and lakes was derived from the EU-Hydro dataset [248], while waterways and minor water bodies were extracted from OpenStreetMap [249].

4.2.3.2. Physical Exclusion criteria

Physical exclusion criteria refer to factors that prevent the installation of APV systems due to physical constraints or significant economic unsuitability, or because land is already impermeabilized by infrastructural construction. These areas are excluded because their terrain, accessibility, or structural characteristics would make APV deployment technically difficult or economically unfeasible. Among the commonly adopted criteria, Global Horizontal Irradiance (GHI), the total annual sum of diffuse and direct solar radiation received on a horizontal plane, has often been used as an exclusion criterion in previous suitability assessments [90]. However, in Italy, solar irradiance is generally high across most regions [191], and even the areas with the lowest GHI values remain above the exclusion thresholds reported by Elkadeem et al. [91] for Sweden and comparable with high GHI sites for Germany [137]. Therefore, GHI is not considered a limiting factor in this study and is consequently not applied as an exclusion criterion. The physical exclusion considered in this study refer to land cover and topographic criteria.

Regarding land cover (CLC) [241], only agricultural land is considered in this analysis. This follows current regulations, which define advanced APV as the only renewable energy system permitted on agricultural land. Topographic exclusion criteria were evaluated Using the Copernicus Digital Elevation Model (DEM) GLO 30 [250] that allowed to consider additional land properties such as elevation above sea level [m.], slope [%] and aspect [0 – 360 °]. Elevation above sea level has been adopted as exclusion criteria in similar study by Fattoruso et al. [92] and a recent report from Ricerca sul Sistema Energetico (RSE) [237]. In this study, areas located over 1,200 m above sea level were excluded due to their limited agricultural suitability and reduced GHI [191]. Moreover, according to the landscape protection constraint established by Art. 142, Legislative Decree 42/2004, the Apennine territories above 1,200 m are subject to landscape protection; therefore, this threshold was adopted as a uniform elevation exclusion criterion for the entire country. Land having slope > 10 % were excluded as done by Elkadeem et al. [91] due to constraints to installation of APV and mechanization of agriculture [97]. In the Northern Hemisphere slope orientation (aspect) toward the North receive substantially less GHI than south-facing slopes. Because of reduced direct irradiance affect both PV conversion and crop production, such areas are generally less suitable for APV or conventional PV installations, compared to other land aspects. Consistent with the study by Fattoruso et al. [92], and similarly to the study by Elkadeem et al. [91], this study excluded North facing lands, indicated as lands having at least 3 % slope North oriented. All exclusion criteria adopted are listed in Table 20 together with exclusion threshold and reference of previous study that adopted these criteria.

Table 20. Exclusion criteria considered in the spatial analysis

Exclusion Criterion	Law / threshold value	References
Protected Areas	National Law 394/91. Recognition of EUAP areas	[92,233,251]
	Natura 2000 network: SIC – Sites of Community Importance (Habitats Directive 92/43/EEC); ZPS – Special Protection Areas (Birds Directive 2009/147/EC); ZPE – Extended Protection Zones, consisting of buffer areas surrounding protected sites.	[92,137,233,240,251]
	D.Lgs. 42/2004 (MIBAC (SITAP) bound and UNESCO Italy bound) by considering also DM 10/09/2010 and DM 21/06/2024	[233,251]
	D.Lgs 199/2021(EU Directive 2018/2001 (RED II)), 2024 Suitable Areas Decree and law 101/2024	[233,251]
Protected areas Buffer	For protected areas included in the previous law, regulation a supplemental 500 m buffer of exclusion is added.	[233,251]

Water Bodies. D.Lgs. 152/2006 Codice dell’Ambiente	Included areas + 150 m buffer from main water course and + 300 m buffer from lakes and reservoirs.	[91,238,240,251]
Land Cover and Buffer	Settlements, Airports, Roads, Railways, industrial complex, power plants, forest.	[91,92,97,238,245]
Slope [%]	10 %	[91,92,97,137,238,239]
Elevation	1200 m above sea level	[92,237]
Aspects North	North facing (slope > 3%)	[91,92]

4.2.4. Evaluation Criteria Definition

Suitability criteria encompass all factors considered when assessing the suitability of a defined land area for APV installation. These criteria generally reflect the interconnected relationship between the environment crop production and energy conversion. They express criteria among three main categories, photovoltaic potential, water availability, and land quality.

4.2.4.1. Environmental Criteria

Climatic conditions play a key role in determining the technical performance of APV systems, influencing both PV output and crop productivity.

Global Horizontal Irradiance (GHI)

Global annual horizontal irradiance (GHI), measured in kWh m⁻² yr⁻¹, is a primary determinant of photovoltaic output potential. GHI is the most widely used parameter in APV suitability analysis literature, as it quantifies the total solar resource available for a site for both PV and crop production [90]. While a higher GHI correlates with greater photovoltaic output, it concurrently increases the risk of photoinhibition in plants [107]. The GHI raster dataset for this study was retrieved from the Global Solar Atlas [191]. In this analysis It is defined as a benefit criterion, meaning higher irradiation values increase suitability.

Temperature

Temperature is a critical evaluation criterion for APV installation. An area that is frequently exposed to high temperatures may see enhanced APV suitability due to the shading-induced cooling to the crops below the modules; yet elevated temperatures reduce the conversion efficiency of photovoltaic modules. When crops are subjected to extreme temperatures, they experience significant physiological stress and potentially cease photosynthesis, particularly when high temperatures are coupled with drought events [97]. The raster datasets used for this analysis were obtained from ERA5-Land [252]. The specific data employed were the long-term annual means (2000–2024) of minimum, maximum, and average air temperature.

Water availability

Water availability refers to the capacity of a specific environment to provide enough water to support agriculture. This criterion encompasses factors such as seasonal precipitation, seasonal evapotranspiration, and. In this study, the Aridity Index (A_i) was used as a criterion that combine environmental water availability (average seasonal precipitation) and atmospheric water pull (reference evapotranspiration) [253]. The Aridity Index is defined as the ratio of mean annual precipitation to mean annual reference evapotranspiration (ET_0). The ET_0 is calculated using the FAO-56 Penman-Monteith equation, which represents the atmospheric demand for water. Aridity index is expressed as follow:

$$A_i = \frac{m_a_rain}{m_a_ET_0} \quad (4.1)$$

Where, A_i is the aridity index, m_a_rain is the average annual rainfall [mm] and $m_a_ET_0$ is the average annual reference evapotranspiration [mm].

The A_i data raster and methodology were drawn directly from the "Global Aridity Index and Potential Evapotranspiration Database - Version 3" (Global-AI_PET_v3) by Zomer et al. [254]. The aridity index quantifies moisture availability for potential crop growth; lower A_i values signify more arid conditions (where atmospheric water demand exceeds precipitation), while higher values indicate more humid conditions. From literature it has been assessed that arid and semi-arid regions derive greater benefits from APV deployment. This is attributed to the mitigating effects of PV modules on drought stress, thanks to reduced evapotranspiration and enhanced soil moisture retention [45,47]. These advantages are typically more pronounced in water-scarce regions compared to humid climates [255] probably due to non-limiting growth condition for the full light control. Therefore, this study will indicate areas with low aridity index as more suitable for APV installations than area with high aridity index. This trend in interpreting spatial water availability is consistent with the previous study of Neesham-McTiernan and Barron-Gafford [97]. Furthermore, related analyses have favoured areas where water use efficiency is higher [236], or where crop water stress is most pronounced [91].

4.2.4.2. Topographic Criteria

Topographic criteria play a dual role in the geospatial planning of APV systems, acting as both exclusion and evaluation factors. As discussed in Section [4.2.3.2], topographic variables not only constrain technical feasibility but also significantly influence installation and subsequent management by complicating on-site operations [92,240,256]. Consequently, elevation, slope, and aspect are frequently analysed in suitability studies [90]. Elevation dictates solar radiation

intensity and ambient temperature, thereby directly affecting both PV energy output and crop productivity [91,92].

Regarding the land slope, steeper terrain exacerbates construction challenges and increases project costs. Consequently, flat or gently sloping terrains are considered optimal for the coexistence of PV infrastructure and mechanized agricultural activities [97,240,256]. Aspect determines site insolation; in the Northern Hemisphere, south-facing slopes are optimal, as higher solar exposure enhances both PV generation and crop growth rates. Suitability declines progressively from south-facing (optimal) to north-facing (unsuitable) orientations, with intermediate aspects (e.g., southeast, southwest) receiving varying degrees of suitability [91,95,235]. All topographic criteria were derived from a Digital Elevation Model (DEM) [250]. These parameters were treated as evaluation criteria, specifically regarding their capacity to simplify operations during the installation and management of the APV system.

For the aspect criterion, a geometric transformation was applied to create a continuous “South-facing index” by converting azimuth degrees into a normalized score ranging from 0 to 1. The absolute angular distance from South (180°) was first calculated. Subsequently, the distance was normalized so that 180° (South facing) equals 1 and 0° or 360° (North facing) equals 0. A flat terrain correction was applied to consider aspect irrelevant (i.e., optimal) when the terrain is flat (slope $< 3\%$). The Aspect score (S_{aspect}) was thus calculated as follows:

$$S_{aspect} = 1 - \frac{|x - 180|}{180}$$

If slope (4.2)

< 3%, then Aspect_{score} = 1

Where x represents aspect in degrees.

4.2.4.3. Soil Quality

Soil properties directly influence agricultural productivity. Among them, soil organic carbon (SOC) is a fundamental indicator of soil fertility that contributes to crop yield capacity [257]. High SOC content enhances moisture retention, nutrient supply, and crop yield potential. Reflecting these attributes, a spatially explicit MCDM assessment for rainfed agriculture in Iran incorporated SOC as a key positive indicator, acknowledging its critical role in sustaining land productivity where water supply acts as the limiting factor [258]. However, for APV suitability, this relationship is inverted. In high-SOC soils, which naturally maintain favourable moisture and nutrient conditions, the microclimatic benefits introduced by APV, such as reduced evapotranspiration (ET), are less critical. Instead, solar radiation becomes the primary driver of

yield. Consequently, the shading caused by PV structures acts as a limiting factor, reducing the expression of the soil's high natural productive capacity and resulting in a proportional yield reduction. This criterion is based upon Liebig's Law of the Minimum, which states that biological growth is limited not by the total resources available, but by the scarcest essential resource [259]. In the context of APV on fertile land, light becomes the scarce resource, restricting crop growth despite the availability of abundant nutrients and optimal soil conditions. Conversely, low-SOC soils have intrinsically lower fertility and poorer moisture retention. In these cases, the microclimatic benefits of APV, such as reduced ET and higher soil humidity, may partially compensate for the soil's limitations, reducing the relative impact of shading [140]. For this reason, soils with higher SOC are considered less suitable for APV installation, because the negative effects of shading outweigh the limited additional benefits APV can provide in already fertile conditions. For this reason, soils with higher SOC are considered less suitable for APV installation in this study, as the yield penalty from shading outweighs the marginal additional benefits APV provides in already fertile conditions.

4.2.4.4. Land Cover

Land-use classification has been widely adopted both as an exclusion criterion and as an evaluation criterion in land suitability assessments [90]. Using the Corine Land Cover (CLC) dataset [245] several land cover classes can be identified as more suitable than others for APV. In this study, non-irrigated arable lands were favoured over irrigated arable and horticultural lands, under the assumption that rain-fed systems derive greater benefit from the microclimatic stabilization provided by APV. Land cover classes used as evaluation criteria in suitability assessment is consistent with other previous study [91,92,98,240]. A reclassification step was conducted to convert categorical Corine Land Cover (CLC) classes into a dimensionless suitability score ranging from 0 (worst) to 1 (best). This was achieved by applying discrete expert scoring to the categorical input: specific land use classes were assigned a fixed agronomic suitability score (e.g., arable land = 1.0, forests = 0.0) prior to the statistical classification analysis. CLC classes and scores are listed in Table 21.

Table 21. CLC classes and corresponding score assigned. A score of 1 means highest suitability of the CLC class for APV.

CLC class	Class description	Score assigned
211	Non-irrigated arable land	1.00
212	Permanently irrigated land	0.80
213	Rice field	0.70
231	Pastures	1.00
241	Annual crop associated with permanent crops	0.50

222	Fruit trees and berry plantations	0.40
223	Olive groves	0.40
221	Vineyards	0.70
242	Complex cultivation patterns	0.30
243	Land occupied by agriculture	0.20
311	Broad-leaved forest	0.00
411	Inland marshes	0.00
511	Water courses	0.00

4.2.4.5. Proximity to power infrastructures

Proximity to Grid connection plays a role in APV site suitability; specifically, short connection distances limit transmission losses [137] and cabling costs [92], and logistical constraints [90]. Ideally, connection points should be identified using data on medium Voltage lines and substations [98]. However, due to the limited public availability of distribution grid data [92,137], this study utilized a shape file from OSM [249] to assess the power grid network and to subsequently calculate the distances from agricultural fields. Proximity to road is used in this study as a proxy to define the accessibility of a field or an area. Easily accessible field benefit from lower installation costs and lower maintenance costs due to simplification of the logistic. This can be true for both PV installation and maintenance (such as cleaning procedure), and crop productivity (easy access to the field for agricultural machineries and product transport). Similarly to the power line shape file, also road network was obtained as a shape file from OSM [249]. The Euclidean distance from the centroid of each pixel falling into agricultural land (by CLC classification) to the nearest potential connection point of the power line network and nearest road network was calculated. The resulting distances were reclassified into suitability classes ranging from 1 (least suitable) to 5 (most suitable). The classification thresholds were defined based on quantile method based on the distribution of proximity between each pixel and the closest infrastructure connection.

4.2.5. Criteria Classification

All criteria were classified into a qualitative scale ranging from “very low” (VL) to “very high” (VH). For continuous raw data (GHI, proximity to power lines, proximity to roads, elevation, slope, temperature, SOC, aridity index), a statistical quantile classification was applied. Since these criteria lack absolute agronomic thresholds, a distribution-based approach was adopted. Quantile classification was carried out by sampling 1×10^6 pixels (30 x 30 m) from the entire national rasterization. The break points were calculated at the 20th, 40th, 60th and 80th percentiles, corresponding to probabilities of 0.2, 0.4, 0.6, 0.8, respectively. The continuous values were mapped into 5 ordinal classes based on the intervals as follows for benefit criteria:

- Very Low: the bottom 20% of the criterion value;

- Low: values between the 20th and the 40th percentile of the criterion;
- Medium: values between the 40th and 60th percentile of the criterion;
- High: values between the 60th and 80th percentile of the criterion;
- Very high: the top 20% of the criterion values.

The opposite applies to Cost criteria. This classification was performed under two scenarios: Country scale and regional scale. In the Country scale, quantiles are calculated on the national dataset, ensuring consistency across regions. In the Regional scale, quantiles are recalculated based on the data distribution within the specific region being analysed. For the Land Use (CLC) criterion, discrete expert scores (e.g., 0.2, 0.7, 1.0) were assigned to the Corine Land Cover classes as described in Section 4.2.4.4. In this instance, the quantile method acted as a frequency-based filter, grouping the discrete land use scores into suitability classes according to their prevalence in the study area. This ensures that the most common high-value land uses in a specific region are correctly identified as “Very High Suitability” (relative to that region), even if the region lacks the theoretical maximum score (1.0). Table 22 lists all the evaluation criteria used in this study.

Table 22. List of evaluation Criteria adopted in the study. Criterion typology can be benefit or malus. Benefit criteria are better when maximized corresponding to higher APV suitability; conversely cost criteria are better when minimized corresponding to higher suitability for APV.

Criterion	Study Source	Layer source	Typology	Raw Classification
Global Horizontal Irradiance,GHI [kWh/m ² /y]	[91,92,95,240,260]	[191]	Benefit	Statistical quantiles approach
Mean Temperature [C°]	[91,92,97]	[252]	Benefit	Statistical quantiles approach
Land use [Classes]	[85,91,92,97,240,261]	[241,245]	Benefit	Expert-Based Approach
Slope [%]	[91,92,137,239,261]	[250]	Cost	Statistical quantiles approach
Elevation [m]	[90–92]	[250]	Cost	Statistical quantiles approach
Aspect [°]	[90–92,95,260,261]	[250]	Benefit	Geometric. Normalized to South-facing
Aridity index	[91,92,238,261,262]	[254]	Benefit	Statistical quantiles approach
SOC	[257,258]		Cost	Statistical quantiles approach
Proximity to power lines [km]	[92,137,240,261]	[249]	Cost	Statistical quantiles approach
Proximity to road network [km]	[236,238,260]	[249]	Cost	Statistical quantiles approach

4.2.6. Spatially Explicit Multi-Criteria analyses

Multi-Criteria Decision-Making (MCDM) is a robust methodological framework designed to address complex problems characterized by multiple, often conflicting, criteria [119]. Renewable energy site selection, and APV planning in particular, requires balancing a broad spectrum of criteria, including geophysical, technical, environmental, and agricultural factors [90,237]. These techniques systematically structure the decision-making process, enabling the rigorous examination and weighting of diverse criteria [263]. Consistent with various studies on site suitability for APV, criteria are typically weighted by expert judgment through the Analytic Hierarchy Process (AHP) [92,235,240,261]. However, to address the uncertainty and imprecision inherent in quantifying subjective expert judgments, similarly to previous study [263,264], this study integrates a Fuzzy Analytic Hierarchy Process (FAHP) with a Fuzzy-TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) approach. Unlike conventional methods that use rigid numerical scales, this fuzzy framework allows experts to define a range of importance [235] using linguistic variables operationalized as Triangular Fuzzy Numbers (TFNs). A TFN is defined by a triplet (l, m, u) , where l is the lower bound, m is the modal value, and u is the upper bound, effectively encompassing judgement uncertainty [263,264]. Its primary objective is to derive the relative fuzzy weights of the decision criteria. The methodological workflow implemented in this study comprises the following stages:

1. **Hierarchical Decomposition:** The decision problem is structured into a hierarchy featuring the overarching goal at the apex ("Optimal APV Suitability"), evaluation criteria at the intermediate level (e.g., Solar Irradiation, Slope, Land Use), and the spatial alternatives (pixels) at the base.
2. **Pairwise Comparison and Judgment Matrix:** A panel of experts assesses the relative importance of each criterion against others using linguistic variables (e.g., "Equal importance", "Moderate importance"). These qualitative judgments are converted into Triangular Fuzzy Numbers (TFNs).
3. **Group Aggregation:** To overcome the bias of a single decision-maker, judgments from multiple experts are aggregated. This ensures the final weighting scheme reflects a comprehensive range of stakeholder perspectives (Energetic, Agronomic, Social, etc.).
4. **Derivation of Fuzzy Weights:** Applying fuzzy arithmetic operations, the fuzzy geometric mean is computed for each criterion to establish the final weights. Crucially, these weights are maintained as TFNs rather than being defuzzified into single crisp values. This preserves the uncertainty information throughout the subsequent ranking process.

4.2.6.1. Fuzzy TOPSIS workflow

In this study a hybrid spatially explicit multi criteria analysis has been adopted. The evaluation relied on 10 criteria discussed in section 4.2.4. A cost-benefit vector was defined to assign a typology to each criterion: benefit criteria (to be maximized, e.g., GHI) and cost criteria (to be minimized, e.g., Slope).

Step 1: FAHP weighting. Criteria weights were derived through FAHP involving five simulated expert profiles: Energy, Agri-environmental, Social, Planner, and Engineer. Each expert provided a 10×10 pairwise comparison matrix using a 9-grade linguistic scale converted into TFNs. For example, equally important criteria E is represented by (1, 1, 1); moderate importance criteria are represented by L (2, 3, 4) and so on. Judgments were aggregated into three distinct planning scenarios (Energetic, Agro-oriented, Planner-oriented), where each scenario assigns different importance to the experts (e.g., Agro scenarios assigned 40% weight to the agro-environmental expert). Aggregation was done by using the Fuzzy Geometric Weighted Mean:

$$\tilde{r}_{ij} = \prod_{k=1}^K (\tilde{a}_{ijk})^{wk} \quad (4.3)$$

Where: \tilde{a}_{ij} represent the judgement of expert k and wk is the expert's weight in the considered scenario.

Fuzzy weights (\tilde{w}_j) for each criterion were calculated using Buckley's geometric mean method [265]. these weights were maintained as TFNs throughout the analysis to preserve judgment uncertainty. The fuzzy geometric mean was calculated for each row of the matrix (criterion), and all criteria were then normalized by dividing each of them by the sum of the geometric averages of all criteria. This way, for each scenario, a vector of fuzzy weight $\tilde{W} = (w_l, w_m, w_u)$ is obtained for each of the 10 criteria. These weights were maintained as TFNs throughout the analysis to preserve judgment uncertainty.

Step 2: Fuzzification (normalization). Before applying TOPSIS, continuous raster data required normalization. In this analysis, each pixel represents a decision alternative. Unlike standard linear normalization, this study employed a Quantile-based Fuzzification approach to transform raw data into a comparable scale. Continuous raster values were classified into five ordinal suitability classes (Very Low to Very High) based on the statistical distribution of the data (20th, 40th, 60th, 80th percentiles). Each class was directly mapped to a standardized TFN on a 0–1 scale, effectively normalizing the data without requiring additional linear transformation equations. Since the analysis was performed throughout the whole Italian

Country, to attribute comparable classes to the spatial data among different Regions, this method was applied separately to Country scale (Global) and Regional scale (Local). Regional Quantile were therefore calculated separately for each Region.

Step 3: Fuzzy TOPSIS ranking. The Fuzzy TOPSIS has been applied for classifying the suitable pixels [264]. The ranking was performed on a 30×30 m resolution grid. Same resolution has been applied for Regional (Local), scale subsequently. The raster stack was processed in R using vectorized matrix operations. The weighted decision matrix (\tilde{V}) was constructed by multiplying the normalized fuzzy rating of each pixel (\tilde{x}_{ij}) by the criterion's fuzzy weight (\tilde{w}_j):

$$\tilde{v}_{ij} = \tilde{x}_{ij} \times \tilde{w}_j \quad (4.4)$$

Where \tilde{v}_{ij} represent the weighted fuzzy value of one specific pixel (pixel i) for one specific criterion (j) inside the matrix.

Distance calculations, calculated respectively for each pixel, utilized the Euclidean distance for Fuzzy number, Vertex Method [266] The Fuzzy Positive ideal solution, (A^{**}) was defined as the maximum possible weighted value, which corresponds to the criterion's fuzzy weight (\tilde{w}_j) (since the maximum normalized rating is $\tilde{1}$). The Fuzzy Negative Ideal Solution (A^*) was defined as $\tilde{0}$.

For Benefit and cost criteria, the distances (d) were calculated respectively as:

$$d(\tilde{v}_{ij}, A^*) = \sqrt{\frac{1}{3}[(v_l - w_l)^2 + (v_m - w_m)^2 + (v_u - w_u)^2]} \quad (4.5)$$

$$d(\tilde{v}_{ij}, A^-) = \sqrt{\frac{1}{3}[(v_l - 0)^2 + (v_m - 0)^2 + (v_u - 0)^2]} \quad (4.6)$$

The total distance for each alternative is the cumulative distance of all criteria.

Finally, for each pixel, the closeness coefficient (CC_i) was calculated to determine the final suitability score (0–1). CC_i represents the relative closeness for each pixel to the ideal solution [235,264,267]. It allows to determine the final ranking and was calculated as follows [266]:

$$CC_i = \frac{d_i^-}{d_i^* + d_i^-} \quad (4.7)$$

The CC_i value vary from 0 (minimum suitability) and 1 (highest suitability). Finally, the resulting CC maps were subsequently reclassified into 5 suitability classes (Very Low to Very High).

4.2.7. Annual potential power

The annual potential electricity supply of APV within the suitable areas was calculated to highlight the potential energy generation obtainable from the most suitable areas resulting from the analysis. The method used for this calculation was already adopted in the study from Campana et al., [140] and Elkadeem et al. [91] through the adoption of ERA5 meteorological dataset [252] for the specific pixel involved. The spatial distribution of suitable land was coupled with long-term photovoltaic (PV) performance indicators and assumed AV installation densities. This approach provides an estimate of the theoretical annual electricity generation potential of a theoretical APV systems and does not account for grid capacity constraints, temporal demand–supply matching, or site-specific design limitations, which remain outside the scope of this assessment. All assumption made for calculating the power potential and to reach the Burden sharing targets for each region are listed in Table 23.

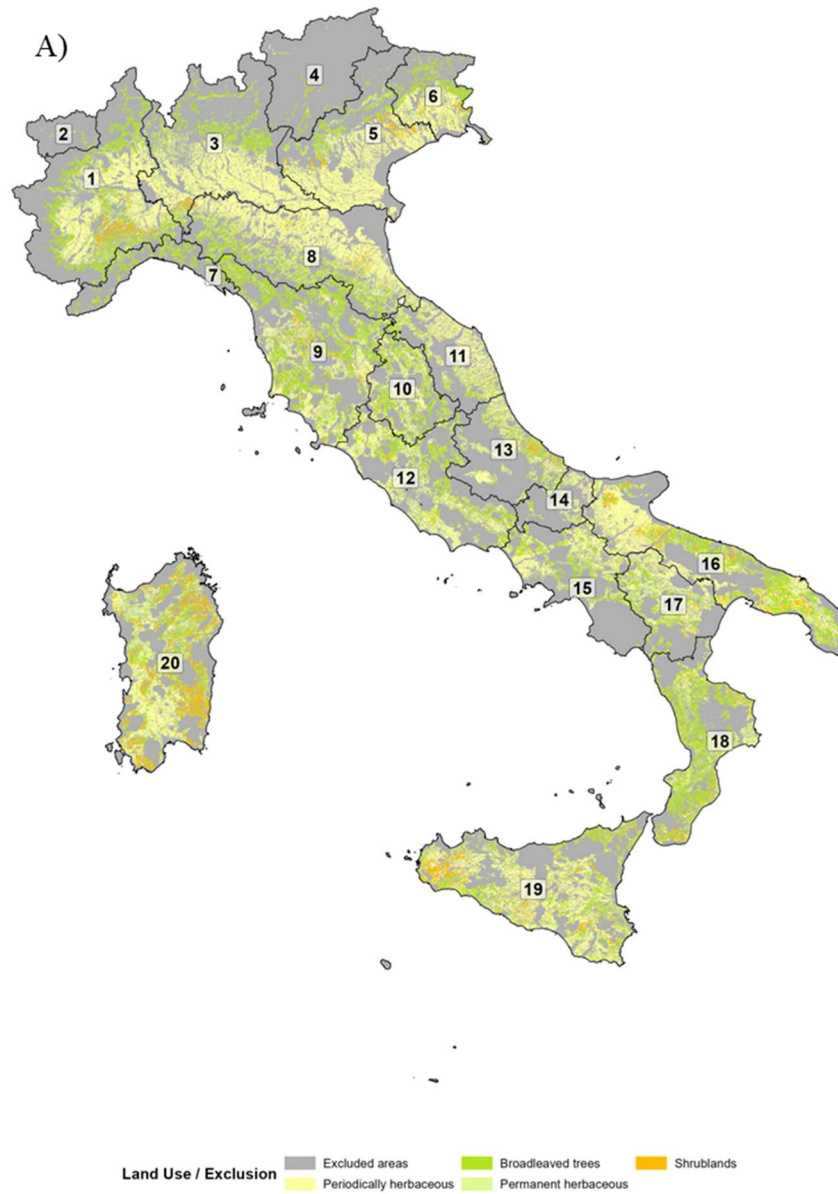
Table 23. Assumption made to calculate the annual power potential. Optimal power density is assumed for regular shaped field assuming infinite APV system.

Parameter	Value	Description
Tracker configuration	Overhead one axis tracker 1P	APV configuration
Row pitch	8 m	Horizontal distance between APV structure
PV module width	1.3 m	Physical width of the PV module
PV nominal power	600 W	Nominal power per PV module
Structure Footprint	0.10 m	Width of the pile/post on the ground
Buffer zone (Bz)	0.5 m	Buffer between structure and cropped area
GCR	26 %	Ground covered by PV modules
Power density	0.58 MW ha ⁻¹	Optimal power density per hectare

4.3. Results

4.3.1. Spatial distribution and impact of exclusion criteria

Figure 36 (A) shows the final mask derived from the CLC map, with excluded areas highlighted in grey, revealing a heterogeneous distribution of agricultural land eligible for APV installation, primarily concentrated in major plains and coastal regions.



reduction of approximately 3.6%, reflecting the consistent application of buffer zones around rivers and lakes. Protected areas (Step 4) emerged as the most restrictive factor in the analysis. The application of regulatory constraints (National Parks, Natura 2000, UNESCO sites) caused a median loss per region of approximately 35% of the initial area. However, this step exhibits high variability; regions with extensive mountainous natural landscapes, such as Trentino-South Tyrol (Region 4), experienced extreme reductions, losing over 80% of its potential area at this stage. The final topographic filter (Step 5), which excludes slopes >10% and elevations >1200 m, resulted in a further median loss of roughly 12–15%. This step acted as a disproportionate constraint on mountainous regions, such as Valle d'Aosta (Region 2), which lost an additional 46.8% of its remaining land due to steep slopes and high elevations. The final composition of suitable land (Figure 2C) indicates that three key regions account for nearly 30% of the total suitable area available for APV deployment. Sicily (Region 19) holds the largest eligible area surface with 1.17 Mha (10.0% of the national total), followed closely by Sardinia (Region 20) with 1.11 Mha (9.4%). Emilia-Romagna (Region 8) represents the primary contribution from Northern Italy with 1.07 Mha (9.1%), driven by the flat topography of the Po Valley. Other significant contributions come from Apulia (Region 16) and Piedmont (Region 1), while predominantly mountainous regions contribute marginally to the national potential.

4.3.2. Fuzzy weight from FAHP

Results from the process of criteria weighting during F-AHP for each of the three expert profiles are reported in Figure 37.

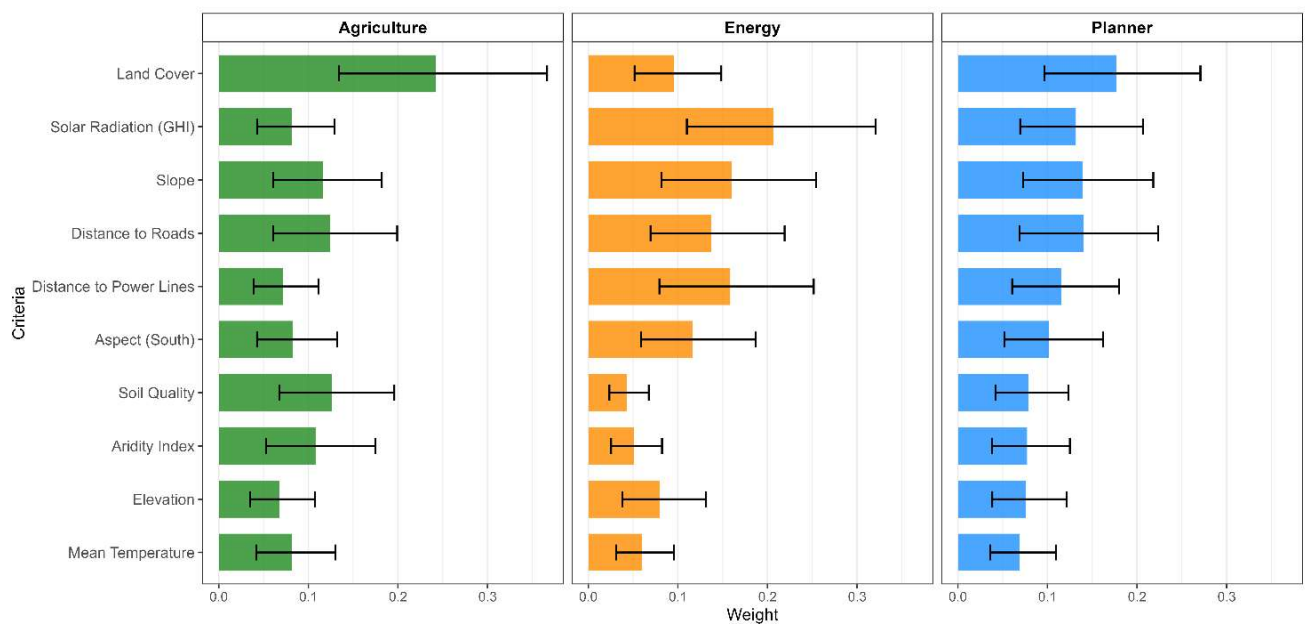


Figure 37. Ranking of suitability criteria across the three defined scenarios (Energy, Agriculture, and Planner). Weights were calculated using a Fuzzy Analytical Hierarchy Process (F-AHP). The main bars

display the final crisp weight for each criterion, representing its relative importance, while the black whiskers denote the fuzzy interval (minimum and maximum values), highlighting the variability in expert judgments.

The Agriculture (Agro) profile favours criteria associated with agricultural activity. A high weight is assigned to land cover, based on the CLC classification of agricultural land, with the aim of prioritising marginal land, non-irrigated arable land, and agricultural areas characterised by lower economic productivity. This behaviour of the Agro profile is intended to avoid land-use conflicts on high-value land, particularly in areas where water availability and climate already favour the thriving of agricultural crops. In contrast, the Energy profile assigns greater importance to criteria that facilitate APV infrastructure deployment, including global horizontal irradiation (GHI), slope, distance to power lines, and aspect. More favourable conditions for these variables reduce installation complexity and costs, ultimately leading to lower Levelized Cost of Electricity (LCOE). The Planner profile exhibits a more balanced weighting scheme, positioning itself between the Agriculture and Energy profiles and reflecting a compromise-oriented decision perspective. Across all profiles, criteria weights display variability due to the use of fuzzy numbers, with greater dispersion observed where expert judgments diverge more strongly. The application of fuzzy methods within both F-AHP and TOPSIS allows this uncertainty to be explicitly accounted for, ensuring a robust handling of judgmental uncertainty.

4.3.3. Country suitability map

The application of the Fuzzy TOPSIS method using Global Quantiles for criteria classification yielded three distinct suitability maps corresponding to the defined decision-making profiles: Agro (Panel A), Energy (Panel B), and Planner (Panel C), as illustrated in Figure 38. The resulting Closeness coefficient (CC_i) was classified into five categories ranging from Very Low (VL) to Very High (VH) based on the quantiles of the national distribution.

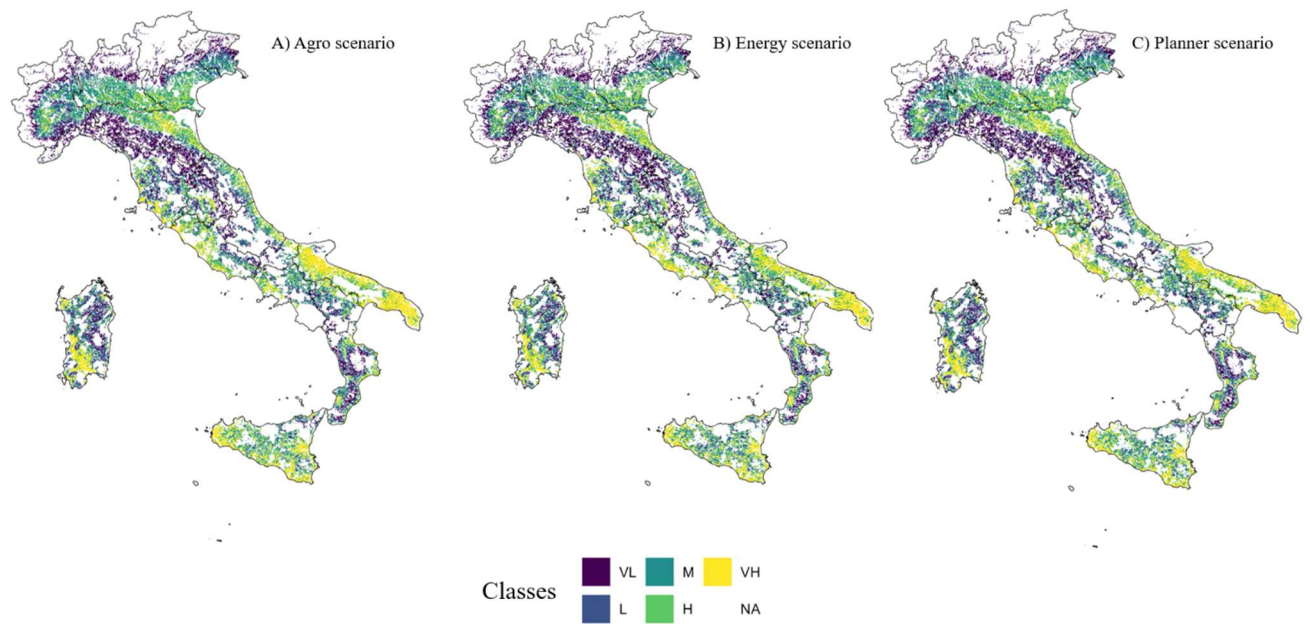


Figure 38. National suitability maps derived from the Fuzzy TOPSIS analysis using Global Quantiles. The maps illustrate the spatial distribution of the Closeness Coefficient (CC_i) classified by means quantile among the entire Country for the three decision-making profiles: (A) Agro profile, (B) Energy profile, and (C) Planner profile. Classes range from Very Low (VL, dark purple) to Very High (VH, yellow).

Across all profiles, the spatial pattern reveals a pronounced concentration of High (H) and Very High (VH) suitability classes in southern Italy and in the coastal areas of the centre Italy. In particular, the Apulia region exhibits the highest density of VH and H pixels, most prominently under the agro profile (Figure 36, A). The Energy profile further enhances suitability in Latium region, where an increase in the concentration of high and very high classes is observed compared to the other profiles.

Southern regions consistently benefit from favourable climatic and radiative conditions, including higher GHI, higher mean temperatures, and elevated aridity index values, which jointly contribute to increased suitability and generate a north–south gradient for very high classes across all profiles (agro, energy, planner). Nevertheless, areas within the Po Valley maintain a remarkable concentration of high suitability in all profiles. This result is primarily driven by the extensive availability of flat terrain and dense infrastructure networks, which facilitate the installation and the operational management of APV systems, partially compensating for less favourable environmental conditions relative to southern Italy.

Despite differences in criteria weighting among profiles, all profiles exhibit a broadly distributed suitability pattern, with persistent clusters of H and VH classes. In the agro scenario (Figure 36,A), where maximum weight is assigned to Land Use value (CLC score) and Soil

Organic Carbon (SOC), indicated as soil quality, areas characterized by complex cultivation patterns, orchards, and irrigated agriculture are penalized to preserve high-value agricultural soils. Consequently, this profile preferentially identifies marginal lands and areas with lower pedological value as more suitable, effectively diverting highest potential APV installations away from the most productive croplands. In contrast, the Apennine ridge and the Alpine arc consistently exhibit Very Low (VL) and Low (L) suitability across all scenarios. This pattern remains invariant to weighting strategies, as these areas are constrained by geomorphological (slope and aspect), as well as by lower infrastructure availability, which act as limiting variables within the fuzzy-TOPSIS framework. The shares of suitability classes composing the total eligible agricultural land and excluded areas are further highlighted in Figure 39. The regional distribution of suitability classes for each decision-making profile, expressed as the percentage of total regional surface is displayed in the figure together with classes attribution within the global criteria weighting assessment.

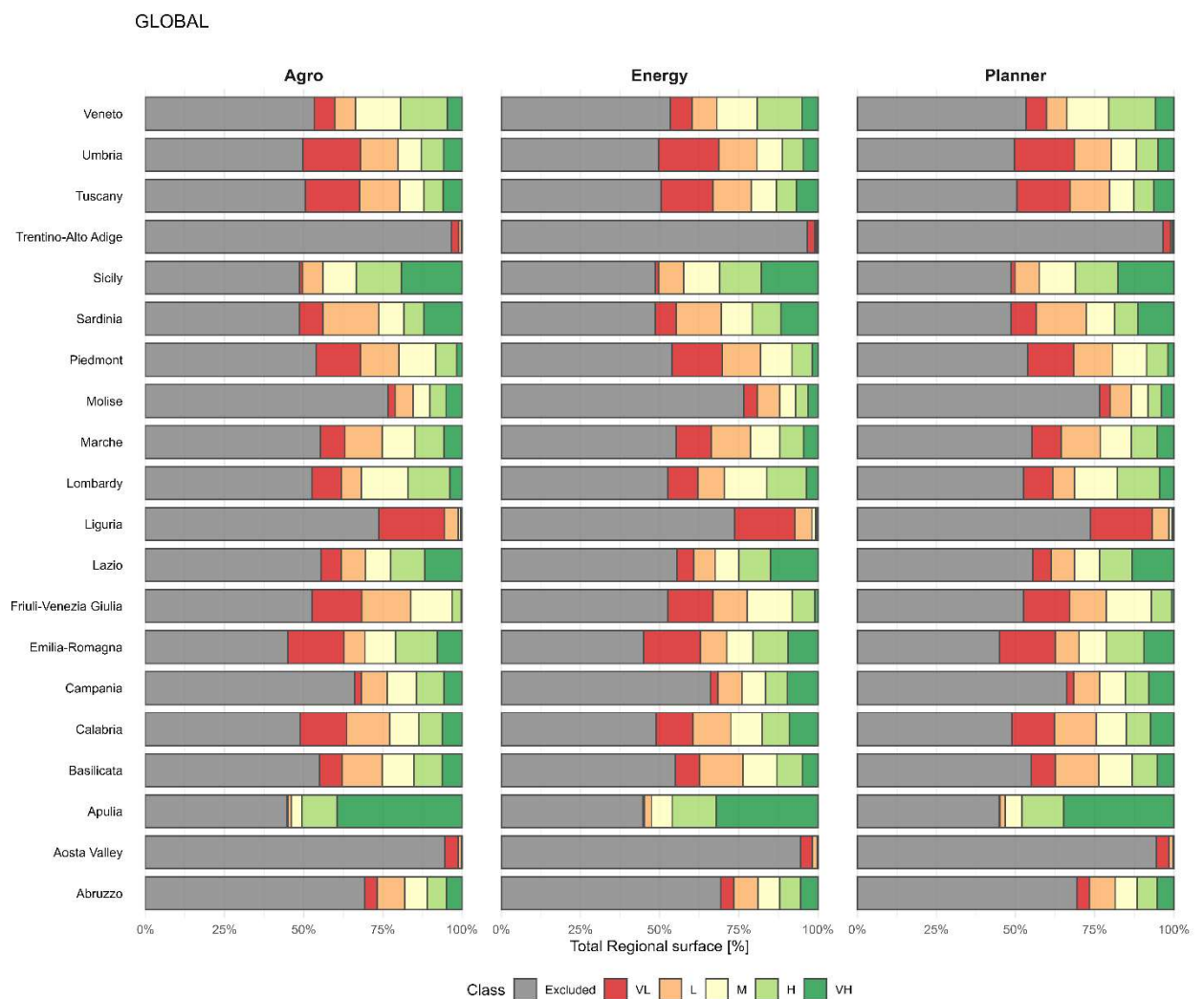


Figure 39. Regional distribution of suitability classes (Global Quantiles). The stacked bar charts illustrate the percentage composition of the total regional surface area across five suitability classes

(Very Low to Very High) and the Excluded portion (grey), for the Agro (left), Energy (centre), and Planner (right) scenarios. Regions are listed on the y-axis. The grey bars represent the portion of regional territory filtered out by exclusion criteria (e.g., urban areas, protected zones, steep slopes). The coloured segments represent the suitability gradient of the remaining eligible land, calculated using global quantiles to allow for inter-regional comparison.

For all regions among each scenario, a substantial share of land is excluded, with Apulia region showing the least excluded surface and Trentino-Alto Adige and Aosta Valley having the highest share of excluded areas.

Marked regional contrasts emerge when considering the relative contribution of High (H) and Very High (VH) suitability classes. The highest concentration of very high suitability classes is observed in Apulia, followed by Sicily and southern Sardinia, with Apulia emerging as the region being the most suitable land surface for APV having the highest share of very high suitability among each scenario and the highest allocable agricultural surface together with Emilia-Romagna. In particular, under the Agro scenario for Apulia, the selected criteria express the highest potential for APV installation compared to all region of the Country, where VH pixels cover a substantial proportion of the regional surface. Sicily and Sardinia also show consistently high shares of H and VH classes among Italian regions, confirming their strong suitability for APV deployment irrespective of the weighting strategy. Central regions such as Latium, Marche, and Abruzzo display a more balanced distribution across M, H, and VH classes, with a noticeable increase in H and VH surfaces under the Energy scenario, consistent with the higher weight assigned to radiative and infrastructural criteria. In contrast, several northern regions, including Lombardy, Veneto, Piedmont, and Emilia-Romagna, exhibit a limited presence of VH suitability classes among the suitable land. Nevertheless, a negligible share of H and M suitable lands remain, reflecting favourable topographic and infrastructural conditions despite less advantageous climatic factors for APV deployment. Together with Aosta Valley and Trentino–Alto Adige, other regions characterised by steep terrain and irregular slopes, such as Liguria, Tuscany, and Umbria, exhibit a high share of VL suitability classes of suitable lands across all profiles, with Liguria showing the highest proportion of VL areas. This analysis shows that adopting different criteria-weighting profiles results in only minor changes in the regional distribution of suitability classes when criteria are classified using national quantiles. In addition, the fuzzy approach, applied both during the AHP weighting process and in the pixel-level classification of the national map, contributes to reducing variability and moderating the influence of individual criteria weights.

4.3.4. Regional suitability map

While the national suitability map (Section 3.3) highlights marked disparities between Northern and Southern Italy due to absolute differences in solar irradiation, mean temperature, and aridity index, the regional suitability map, Figure 40 presents results obtained when criteria are classified using region-specific quantiles prior to applying the fuzzy-TOPSIS algorithm. Unlike the national analysis, which ranks pixels against the entire country-wide dataset, this approach normalises criteria thresholds within each administrative region. This shift from an absolute to a relative evaluation perspective substantially alters the resulting suitability patterns.

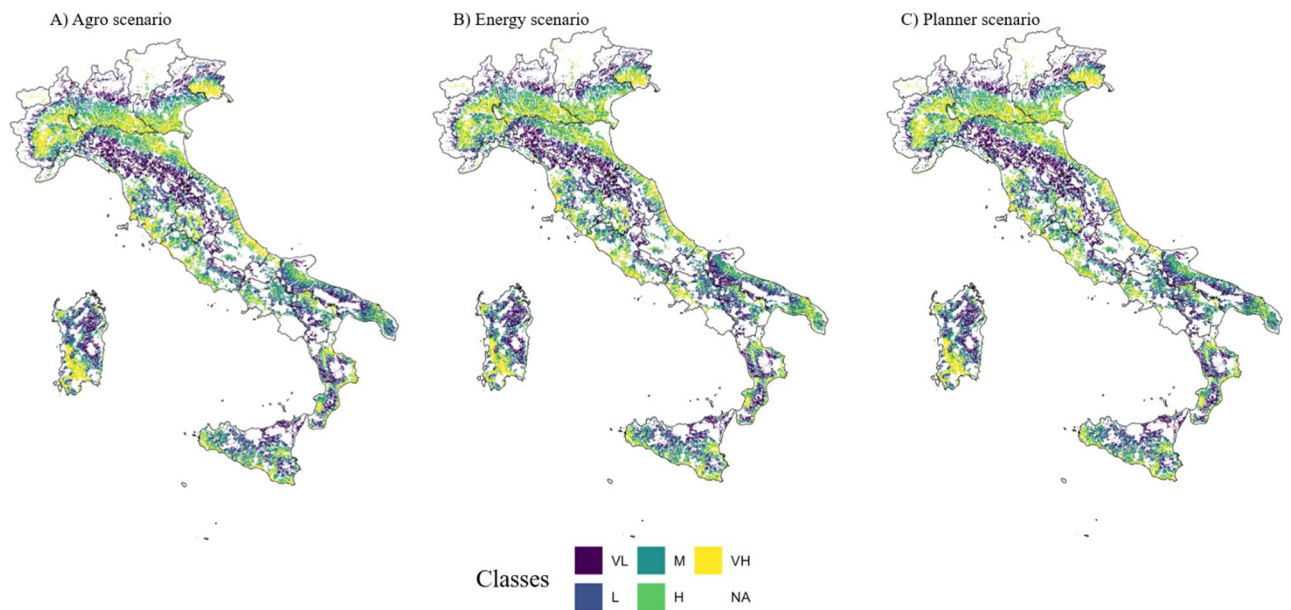


Figure 40. Agrivoltaic suitability maps derived from region-specific (local) quantile classification for the (A) Agriculture, (B) Energy, and (C) Planner profiles, highlighting relative suitability patterns within each administrative region.

This methodological shift substantially alters the regional distribution of suitability classes. In contrast to the global analysis, where northern regions were largely dominated by higher share of lower suitability classes compared to southern part of the Country this approach reveals that each region contains a locally optimal tier of land, corresponding to the top 20% of its internal CCi distribution. The comparison between the agro (panel A), energy (panel B) and planner (panel C) profiles highlights how suitability priorities change at the local scale. In the Po Valley a continuous belt of VH land suitability reflect the best local combination of grid accessibility and flat terrain, irrespective of GHI and other climatological variables. Across the different criteria-weighting profiles, the spatial pattern of Very High (VH) land suitability clusters appears more uniform than in the global (national-scale) classification. Sardinia, in particular, shows results that are highly consistent with the global assessment. In contrast, regions composing the Po Valley experience an overall increase in both Very High (VH) and High (H) suitability classes

of suitable land. Apulia, on the other hand, exhibits a marked reduction in the share of Very High suitability areas under the regional (local) assessment, a trend that is consistent across all scenarios. From a governance perspective, this map functions as a strategic planning tool, enabling regional authorities to identify priority zones within their jurisdiction rather than competing for suitability on a national scale. Despite the normalization effect, land classified as Very Low (VL) suitable persists in areas characterized by complex morphology, particularly along the Alpine arc and Apennine ridge. This confirms that even under regional quantile classification, physical constraints such as slope and terrain ruggedness remain the dominant limiting factors. The share of suitability classification and excluded areas for each region and for the three different criteria considered is highlighted in Figure 41 for the Local criteria classification.

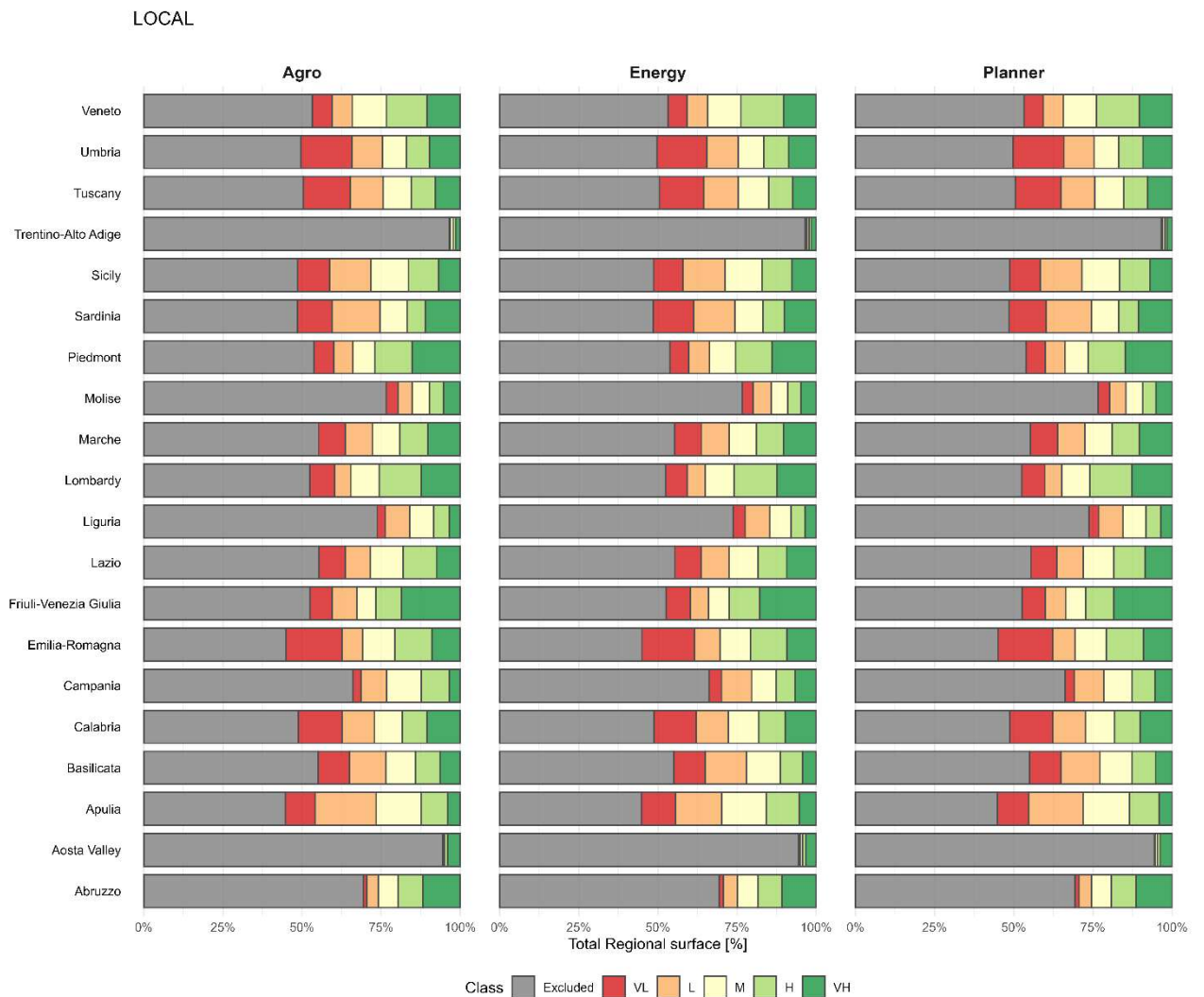


Figure 41. Regional distribution of suitability classes based on Local Quantiles classification. The stacked bar charts illustrate the percentage composition of the total regional surface area across five suitability classes (Very Low to Very High) and the Excluded portion (grey), calculated using regional-wise quantiles for classifying criteria. Unlike the global classification, this method normalizes suitability thresholds within each region, identifying the relative best areas locally. The charts display the results

for the agro (left), energy (centre), and planner (right) profiles. This approach highlights that high-suitability clusters (High and Very High classes) are identifiable in every administrative region, regardless of their absolute resource ranking on the national scale.

The figure quantitatively supports the spatial patterns observed in the regional suitability maps by reporting the percentage distribution of suitability classes within each region under the local quantile approach. As expected, in this case H) and VH classes are present in every administrative region across all scenarios with a notable share, confirming that regional heterogeneity is sufficient to identify locally optimal sites regardless of absolute national ranking. Compared to the global classification, the relative contribution of H and VH classes becomes more evenly distributed across regions, particularly in northern and central Italy. Interestingly in the local criteria classification, the polarization of very high suitability areas is Northern-wise compared to the global assessment criteria method. Mountainous regions such as Aosta Valley, Trentino-Alto Adige, and Liguria despite having most of their territories excluded, express the highest share of VH suitable land among the remaining suitable areas. The most striking feature of Figure 41 is the distributional balance of the suitability classes across the peninsula. By standardizing the scoring thresholds at the regional level, the analysis ensures that the top tier (approximately top 20%) of the eligible land in every region is classified as Very High (VH), confirming that every administrative unit possesses a distinct stock of "prime" land relative to its specific environmental context. The regional, local criteria classification strategies identify the most favourable sites in the country within the Po Valley, where the most intensive and technologically developed agriculture is practiced despite their lower energy conversion potential due to lower GHI. Overall, the APV suitability on regional base shows that the local quantile approach redefines suitability patterns by highlighting the most suitable areas within each region. This reinforces the complementary role of the regional analysis with respect to the national-scale assessment. Again, the difference between suitability shares among regions is negligible between weighting profile (agro, energy, planner), confirming that fuzzy approach in the spatially explicit multi-criteria analyses overcome the need of relying in different weighting strategies by minimizing the impact of them on the *CCi* distribution on the studied territories.

4.3.4.1. Burden sharing target

The burden-sharing target for each region was calculated based on the assumed APV configuration reported in Table 23. Figure 42 contextualizes the regional renewable energy

targets for 2030 against the land availability results obtained in this study, providing a quantitative assessment of the potential land-use implications.



Figure 42. Assumed land requirement (%) to meet the 2030 Burden Sharing targets [1]. The heatmap illustrates the agricultural surface that would need to be allocated to APV systems to meet the renewable energy deployment targets for 2030, assuming a representative APV power density of 0.577 MW ha^{-1} . Results are presented using two complementary reference bases: (a) percentage relative to suitable land only, and (b) percentage relative to total regional surface.

The land area required to meet the 2030 targets assuming medium-density APV installations is extremely limited across all regions. In most cases, the required surface ranges between 0.65% and 1.66% of the suitable land and corresponds to less than 0.5–1% of the total regional territory. Two outliers are observed in Aosta Valley and Trentino–Alto Adige, where the higher percentages are driven by the limited extent of suitable land. Regions characterized by extensive suitable areas, such as Sicily, Sardinia, and Apulia, despite having the highest absolute power targets (in GW), exhibit a relatively low percentage impact on their suitable land (typically < 2%). This reflects the large availability of suitable surfaces identified in these regions (as shown in previous sections), which can accommodate ambitious deployment targets without generating significant land-use pressure. Overall, the results indicate that the identified suitable areas are more than sufficient to absorb the planned APV capacity, without inducing competition for land or forcing installations into suboptimal locations. Furthermore, unlike ground-mounted photovoltaic systems, land occupied by APV installations remains largely available for agricultural use. Only marginal portions of land are effectively removed from cultivation, such as areas occupied by inverters, electrical equipment and buffer zones due to proximity to supporting structures or modules for low elevated APV [101]. Finally, the substantial margin between required and available suitable land suggests that policymakers and developers retain considerable flexibility in project siting. This allows the prioritization of areas with Very High suitability, thereby maximizing agronomic synergies and minimizing local conflicts, even in more constrained regions such as Aosta Valley, Trentino–Alto Adige, and Liguria, where deployment may rely partly on lower suitability classes.

Instead, the potential energy generation from APV systems installed on lands classified as High and Very High suitability is illustrated in Figure 43. This analysis focuses exclusively on the Planner profile, as it represents the most balanced perspective among the three, providing an intermediate estimation of potential annual energy generation. The assessment assumes that the entire surface area classified as H and VH within each region is utilized for APV systems, based on the technical configuration detailed in Table 23.

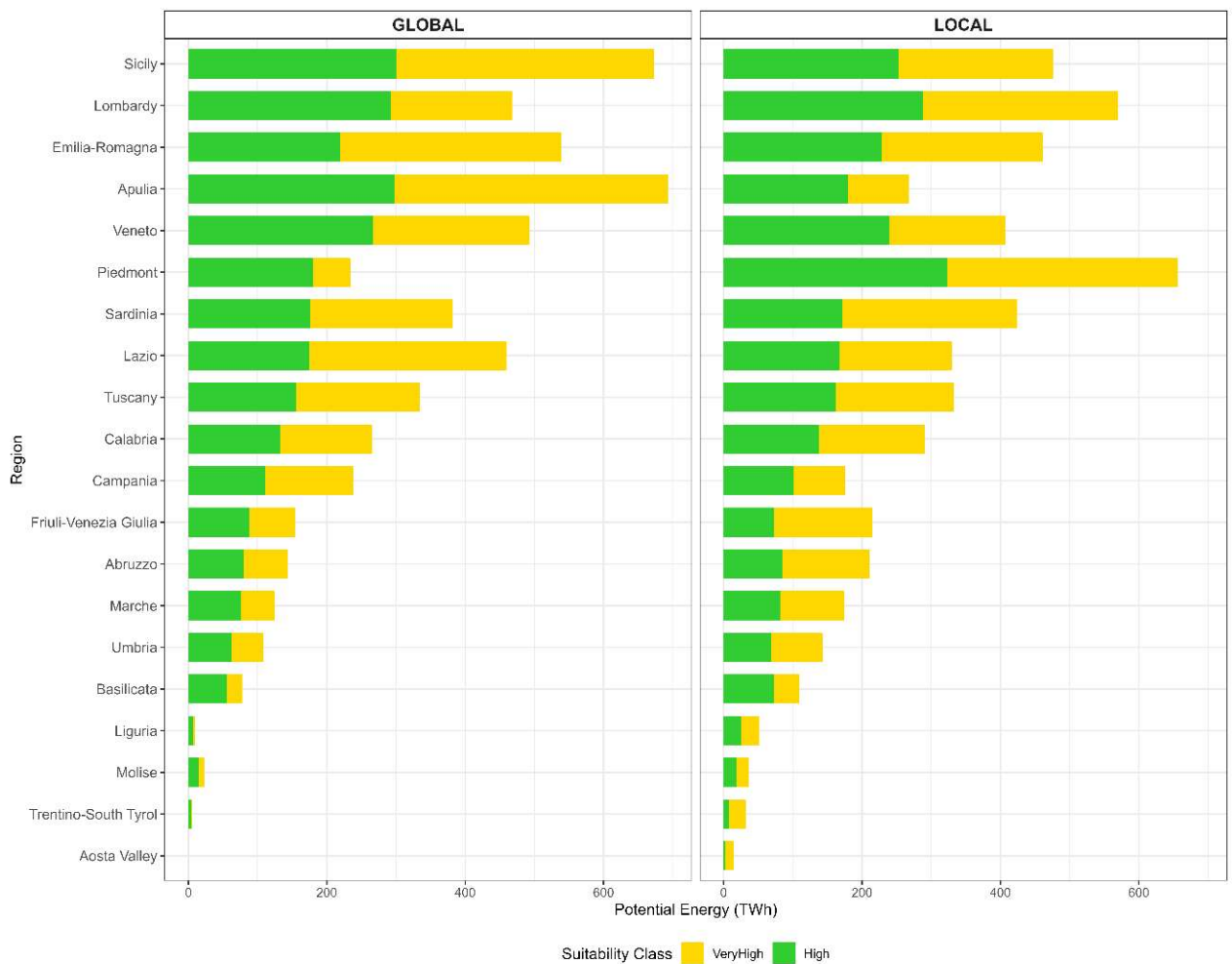


Figure 43. Regional potential APV energy supply (TWh) considering the High and Very High suitability classes. The chart compares the results obtained using the Global and Local criteria classification methods. The criteria weighting profile used is the Planner, since is intermediate between Agro and Energy. Regions are ranked by total energy potential, highlighting the variation in the extent of the most suitable areas between the two methodological approaches.

The extent and distribution of these suitable lands vary significantly depending on the classification method used. As shown in the comparison between the Global and Local approaches, the Local method tends to increase the identified potential in Northern Italy while reducing it in Southern regions relative to the Global baseline. This shift suggests that the Global method penalizes Northern regions due to lower absolute solar radiation and complex topography, whereas the Local method highlights the best available areas relative to the specific regional context. For instance, under the Local classification, Piedmont exhibits a 180% increase in potential energy generation from suitable lands, whereas Apulia experiences a decrease of approximately 61%. The complete regional percentage variations in potential energy supply when shifting from Global to Local classification are detailed in Table 24.

Table 24. Comparison of the potential agrivoltaic energy supply (TWh) estimated for each region under the Planner scenario using the Global and Local classification methods. The percentage change ($\Delta\%$) highlights the variation in total potential when shifting from a national (Global) to a regional (Local) standardization approach.

Region	Global Method (TWh)	Local Method (TWh)	Variation (%)
Abruzzo	143.29	210.63	46.99%
Aosta Valley	0.54	15.02	2696.63%
Apulia	693.01	267.58	-61.39%
Basilicata	77.87	109.82	41.03%
Calabria	265.34	291.1	9.71%
Campania	238.88	175.24	-26.64%
Emilia-Romagna	539.23	461.63	-14.39%
Friuli-Venezia Giulia	154.49	214.86	39.07%
Lazio	459.63	329.86	-28.23%
Liguria	9.79	51.55	426.79%
Lombardy	467.99	570.23	21.85%
Marche	124.97	174.42	39.57%
Molise	23.2	36.69	58.14%
Piedmont	234.21	656.4	180.27%
Sardinia	381.84	424.24	11.10%
Sicily	672.99	476.74	-29.16%
Trentino-South Tyrol	5.15	32.51	531.28%
Tuscany	334.59	332.63	-0.59%
Umbria	108.87	143.68	31.97%
Veneto	492.61	407.42	-17.29%

4.4. Discussions

4.4.1. Excluded areas

The exclusion-driven spatial pattern identified in this study is broadly consistent with previous APV suitability assessments conducted at national and regional scales. The dominant role of protected areas as the primary exclusion factor aligns closely with findings reported for Italy by [92], who similarly identified environmental and landscape protection constraints as the main limitation on APV expansion in Italy. In both studies, the strongest reductions occurred in Alpine and Apennine regions, confirming that the extent of protected areas, rather than agricultural land scarcity, are the principal determinant of spatial eligibility. However, the magnitude of exclusion observed in this study is notably higher for several regions, particularly Trentino–South Tyrol and Valle d’Aosta compared to the previous study. This discrepancy is largely attributable to the stricter treatment of elevated and north oriented areas, which applied a conservative exclusion logic. As a result, this study likely represents a lower-bound estimate of realistically deployable APV land under current Italian regulation. When compared with

national-scale APV assessments conducted in Germany, such as those by Rösch and Fakharzadehshirazi [239] and Hauger et al. [98], a clear divergence emerges in the relative importance of topographic constraints. While German studies report slope and elevation as secondary filters due to the predominance of low-elevated agricultural landscapes, the Italian context shows topography acting as a decisive secondary exclusion layer. The additional median loss of 12–15% (Figure 36, B) after applying slope and elevation exclusion criteria is substantially higher than values reported for Germany and reflects Italy’s more complex geomorphology.

At the European scale, comparisons with studies such as Elkadeem et al. [91] for Sweden and Neesham-McTiernan et al. [242] for Great Britain further highlight the specificity of the Italian case. In northern European contexts, climatic and solar resource constraints play a more prominent role in shaping eligible lands, whereas regulated protected areas are comparatively less restrictive. In contrast, the present results show that even in regions with high solar potential and extensive agricultural land, eligibility is sharply reduced by land protection policies. Thus, in Italy, APV potential is primarily policy-limited rather than resource-limited. The relatively minor impact of infrastructure and hydrographic exclusions observed in this study is also consistent with earlier PV and APV suitability analyses, both for Italy and internationally. Similar marginal effects have been reported by Nugroho et al. [238] and Dere et al. [235], suggesting that buffers around roads, rivers, and settlements rarely constitute binding constraints at the strategic scale. Table 25 highlight that while the qualitative hierarchy of exclusion drivers identified in this study is consistent with the literature, the quantitative impact of exclusions is systematically higher for Italy, particularly in mountainous regions. Compared with other national-scale assessments, the Italian case stands out for the combined effect of dense protected-area coverage and complex geomorphology, which jointly amplify land exclusion beyond levels reported for Central and Northern Europe. Differences across studies are largely attributable to normative methodological choices, especially the treatment of protected areas as hard exclusions versus weighted constraints, and the adoption of explicit elevation thresholds.

Table 25. Comparison of exclusion drivers and spatial constraints between the present study and recent relevant literature on APV suitability.

Study	Spatial scale	Main exclusion drivers	Reported impact of protected areas	Reported impact of topography	Notes on methodological differences
Fattoruso et al. [92]	National (Italy)	Protected areas, slope, land use	~20–30%	<10% in most regions	Mixed suitability weighting
Rösch & Fakharizadehshirazi [239]	National (Germany)	Legal restrictions, soil quality	~15–25%	<5%	Flat geomorphology; focus on permanent crops; lower elevation variability
Hauger et al. [240]	National (Germany)	Regulatory + economic constraints	~20–30%	nd	No elevation cut-off
Elkadeem et al. [91]	National (Sweden)	Climate, land use, slope	<20%	<10%	Radiative and climatic factors more limiting than regulation
Neesham-McTiernan et al. [242]	National (Great Britain)	Land use, environmental designations	~25–35%	nd	nd
Nugroho et al. [238]	Regional (Indonesia)	Slope, land cover, water	nd	nd	Mountainous areas excluded mainly by slope
Dere et al. [235]	National (Türkiye)	Slope, land cover, infrastructure	<25%	nd	Less restrictive conservation framework compared to Italy

In summary, while the general spatial logic of excluded areas is consistent with the literature, this study highlights that the stringency of exclusion criteria substantially alters national APV potential estimates.

4.4.2. Country-scale APV potential and implications for regional burden sharing

Across all decision-making profiles adopted in this study, suitability remains strongly driven by climatic and radiative gradients, with southern regions systematically demonstrating more suitable than northern ones. This North–South gradient found with global criteria classification method is in contrast with the findings of Fattoruso et al. [92], who reported higher eligibility and capacity potential for both southern Italy, particularly in Apulia, Sicily, and Sardinia and for the whole Po Valley. Other national-scale studies conducted in flatter countries such as

Germany or Great Britain, found a more even suitable lands distribution after exclusions. In those contexts, spatial patterns are relatively homogeneous, reflecting limited topographic variability and a lower density of strictly protected areas [239,240,242]. Findings of this study, instead, appears structurally polarized, with regional disparities amplified by the combined effect of complex geomorphology of Italy and extensive protected-area coverage. While several previous studies restricted suitability assessment to regional or sub-national domains, producing rankings that are meaningful locally but difficult to compare broadly [235,238], these approaches rarely contrast absolute, national-scale suitability with regionally normalised classifications. Consequently, the distinction between nationally competitive areas and locally optimal areas has remained less investigated [91,92,240].

By applying a local quantile classification, the present analysis demonstrated that all administrative regions retain a locally optimal tier of land capable of supporting APV deployment, even where absolute suitability is low in the national context. From a planning perspective, this dual-scale approach clarifies a key ambiguity in the literature: national maps are effective tools for strategic prioritisation, whereas regionally normalised maps are more appropriate for local governance. Treating these outputs as complementary enables a more coherent transition from national energy strategies to region-specific implementation.

The burden-sharing analysis carried out in this study provides a conservative test of these implications on the land suitability for APV by assuming that APV alone contributes to meeting Italy's 2030 renewable energy targets. Although this represents an extreme scenario, results indicate no tangible risk of agricultural land depletion. In most regions, less than 2% of suitable land, and typically well below 1% of the total regional surface, is sufficient to meet these targets. This is consistent with previous estimates for Italy [92] and Germany [98,240]. The only notable exceptions are mountainous regions like Aosta Valley and Trentino–Alto Adige, where deployable potential is naturally constrained by slope and elevation of the landscape [92,239]. Finally, compared with studies focusing on GM-PV, the implications of agrivoltaics are fundamentally different. While conventional GM-PV entails a direct conversion to energy-only use, often intensifying land-use conflicts [81], APV preserves agricultural functionality across most of the installation area, substantially reducing the effective land-use trade-off. Table 26 lists and 2a compare the main findings from literatures on land suitability classes attribution.

Table 26. Comparison with other studies main findings on land suitability classification

Study	Country / scale	Total suitable area (% of territory or agri land)	Notes
Fattoruso et al. [92]	Italy (national)	~10.7 Mha	(~35% of Italian territory)

Study	Country / scale	Total suitable area (% of territory or agri land)	Notes
Elkadeem et al. [91]	Sweden (national)	~8.6% of national territory	“Excellent” ≈ 0.2%; “Very good” ≈ 15%
Hauger et al. [240]	Germany (national)	~8–13%	Regulatory potential
Neesham-McTiernan et al. [261]	Great Britain (national)	~55% of agricultural land	Not discretised into VH/H
Dere et al. [260]	Türkiye (national)	~20–30%	region-dependent
Nugroho et al. [238]	Indonesia (regional)	~25–40%	Determined on study area

4.5. Conclusion

This study presented a spatially explicit Fuzzy Multi-Criteria Decision-Making (MCDM) framework to assess the land suitability to host agrivoltaic systems across Italy, integrating legislative constraints, physical limitations, and agronomic priorities. The analysis reveals that while protected areas and complex territorial geomorphology exclude a significant portion of the Italian territory, approximately 35% due to environmental protection and an additional 12–15% due to topographic constraints, the remaining eligible land is more than sufficient to support the energy transition that for this study was assumed entirely based on agrivoltaic systems deployment. The application of two distinct criteria classification strategies, Global and Local, highlighted that the Global (national-quantile based) assessment confirmed a noticeable North-South gradient for land suitability, where higher solar irradiation and favourable climatic conditions drive the highest suitability concentrations in Southern regions and major islands. Conversely, the Local (regional quantile based) assessment demonstrated that every administrative region possesses a "top tier" of suitable land (approximately the top 20% of eligible areas) capable of hosting APV systems effectively. This finding is significant for governance, suggesting that suitability maps should be used as complementary tools: national maps for strategic prioritization and resource allocation, and regionally normalized maps for operational planning and local authorization. Furthermore, the burden-sharing analysis indicates that meeting the 2030 renewable energy targets requires a negligible fraction of agricultural land to be co-used within APV systems. In most regions, installing APV systems to meet these goals would occupy less than 1% of the total regional surface and typically under 2% of the identified suitable land. This wide margin offers policymakers and developers substantial flexibility to prioritize High and Very High suitability areas, thereby minimizing land-use conflicts and maximizing agronomic synergies. Finally, the comparison of decision-making profiles (agro, energy, planner) did not substantially alter the distribution of suitable areas for either the global or local assessments. The fuzzy approach effectively buffered the

analysis against subjectivity, absorbing and distributing the variability introduced by the different profiles. By prioritizing marginal lands and areas with lower Soil Organic Carbon (SOC) under the agro scenario, the framework ensures that APV deployment can coexist with high-quality food production without displacing intensive agriculture. Ultimately, this study confirms that the primary barriers to APV expansion in Italy are regulatory rather than physical, and that a harmonized, multi-scalar planning approach can effectively balance energy generation with landscape preservation and agricultural sustainability. The deployment of agrivoltaics aimed at meeting national decarbonization goals does not pose a threat of agricultural land consumption or landscape saturation in any of the considered profiles and scenarios; therefore, objections based on these grounds appear to be ideological rather than factual.

5. GENERAL CONCLUSION

5.1. Main results

The comprehensive objective of this doctoral thesis was to develop a coherent and operational framework to support the planning, design, and spatial deployment of agrivoltaic (APV) systems, ensuring the continuity of agricultural activity while contributing to national and European decarbonisation targets. To achieve this goal, the thesis addressed three interlinked research objectives concerning (O1) agricultural mechanization compatibility with APV systems, (O2) APV design evaluation through integrated modelling, and (O3) spatial suitability for APV deployment at national and regional scales. In this chapter, each objective is addressed, reporting the main results presented in the previous chapters.

The widespread adoption of APV may be hindered by the challenge of fully integrating agricultural mechanization with APV structures. Chapter 2 addressed the identification and evaluation of the key design parameters necessary to ensure the effective integration of agricultural mechanization within APV systems (O1). The study analysed the compatibility between APV systems and mechanized open-field farming, outlining the main spatial, structural, and operational constraints that influence machinery performance. This analysis aimed to answer the research question: Which design parameters must be considered to ensure that APV systems can fully accommodate mechanized agricultural operations?

The study examines how key APV design parameters, such as horizontal space (specifically row pitch and buffer zones) and vertical clearance, affect field efficiency, machinery manoeuvrability, and operational overlap, and proposes analytical tools for assessing these interactions. The analysis reveals that field efficiency (FE) in APV can be substantially reduced, dropping to as low as 45% due to reduced operating speeds and geometric mismatches between implement working widths and the available operating space. Additional factors, such as uncultivated buffer zones and dust accumulation on PV modules due to mechanized operations, further contribute to operational inefficiencies and potential increases in operating costs.

The literature indicates that buffer zones alone can cause up to 30% land loss when large, interspaced PV arrays are adopted. Based on these findings, effective mechanization in APV systems, despite being challenging, is feasible through a holistic, farm-specific co-design process. Achieving optimal integration requires a careful alignment of the APV layout with machinery selection and operational needs, underscoring the necessity for innovation in specialized equipment and advanced navigation systems to unlock the full potential of these

dual-use systems. Ultimately, effective integration requires a co-design approach where APV layout and machinery fleets are harmonized to minimize tillage overlapping and maximize the coefficient of use (Cu) of the implements.

A simulation framework to compare the performances of different APV systems in a range of environments was developed, tested (O2), and presented in Chapter 3. The study was based upon an integrated APV model coupling radiation and crop growth models (GECROS). Model outputs were processed by mean Multi-Criteria Decision Analysis (MCDA) approach. This model predicted the outcome of specific APV configuration-crop-environment combinations, capturing the complex interactions involved to answer the research question: how to select the best alternatives between different available APV configurations when comparing different installation sites?

The main Key Performance Indicators (KPIs) adopted for evaluation were crop ratio (relative crop yield), energy conversion per hectare, specific energy yield, Water Use Efficiency (WUE), and initial capital expenditure. Four APV systems typology, namely vertical, interspace mono-axial, overhead mono-axial, and overhead bi-axial, were modelled with five pitch widths for each typology. These were simulated with a processing tomato crop across five sites (from North to South Italy) over a ten-year period. The results demonstrated that the overhead mono-axial APV with a 6 m pitch ranked best at each site when a 0.7 crop ratio threshold was considered. In fact, mono-axial systems with narrow pitches were often part of the top ranking in the MCDA outcome due to high energy conversion per hectare, despite causing higher shading disturbance to the crop. Global irradiation distribution beneath modules, and thus crop yield, were more homogeneous in vertical and overhead mono-axial systems than in the other APVs. However, the study confirmed that APV systems can improve Water Use Efficiency (WUE), particularly in Southern regions with drier climates, where shading mitigates evapotranspiration demand. While overhead bi-axial systems offered the greatest flexibility for agriculture and the highest specific energy yield, they were the most capital-intensive. The framework highlighted that optimal APV configurations vary depending on climatic conditions and stakeholder priorities; configurations maximising energy production do not necessarily correspond to those minimizing crop yield losses. The framework proved effective in identifying optimal trade-offs, fulfilling the 70% yield threshold proposed in the Italian APV best practices from 2023. This framework could serve as a valuable tool for assessing the performance of different APV solutions and their compliance with national regulations, as well as economic and technical targets.

A spatially explicit fuzzy multi-criteria approach was developed to provide a comprehensive assessment of Italy's spatial potential for APV. This assessment, which adopts key criteria for site suitability to ensure compliance with regulatory, physical, and agronomic constraints (O3), was presented in Chapter 4. The study was carried out to answer the following research questions:

- Where can APV be installed to minimize the impact on the environment and agricultural activities?
- Is the extent of high-suitability land sufficient to meet regional Burden Sharing targets while minimizing conflicts with high-value agricultural activities?

A spatially explicit Fuzzy Multi-Criteria Decision-Making (MCDM) framework was developed, integrating a Fuzzy Analytic Hierarchy Process (F-AHP) for criteria weighting and Fuzzy TOPSIS for suitability ranking across three expert profiles: agro, energy, and planner. A comparison between "Global" (national) and "Local" (regional) criteria classification strategies was adopted considering quantile of different criteria distribution among the Country and Regions.

The analysis applied strict exclusion criteria, including regulatory protections and topographic limitations, which render approximately 35% and 12–15% of the territory unsuitable for APV, respectively. The remaining eligible agricultural land is abundant to support the energy transition. Two criteria classification strategies were implemented: a "Global" method, which reveals a North-South suitability gradient driven by solar irradiance, and a "Local" method, which normalizes thresholds to identify optimal sites within each administrative region.

The results demonstrate that meeting the 2030 regional burden-sharing targets would require co-occupation of less than 1% of the total regional surface and typically under 2% of the suitable land identified. Furthermore, the comparison between classification methods highlights that while a North-South gradient exists due to solar irradiance (Global assessment), every administrative region possesses a significant "top tier" of suitable land (Local assessment). Ultimately, the framework confirms that every region possesses sufficient high-suitability land for APV deployment. Overall, the analysis shows that the availability of suitable agricultural land is not a limiting factor for APV deployment at the national scale. Consequently, the primary barriers to further expansion appear to be regulatory rather than physical.

5.2. Implications and outlook

The research conducted during this PhD has contributed to expanding the body of knowledge on agrivoltaics (APV) during a period of rapid global growth for the sector, particularly within

Europe. The studies presented here provide the research community with essential tools, serving as a foundation for both sophisticated integrated modelling software and user-friendly interfaces. These tools are designed to assist private APV designers in navigating bureaucratic approval pathways and fostering social acceptance. In particular, at the time of writing, contributions in literatures reporting comprehensive classifications of agricultural mechanization in APV were limited, scarce, and fragmented. Frequently, reports for approval of new APV fail to address mechanization adequately, struggling to report realistic dimensions for implements or identifying only limited aspects of the foreseen mechanization during crop rotations. This deficiency stems from a widespread lack of technical information regarding this aspect. From a national perspective, the identification of suitable areas has become a critical issue, exacerbated by the continued postponement of the decree intended to regulate APV installation. While current regulations do not explicitly prevent APV installation on agricultural land, several regions have opposed deployment to safeguard landscape aesthetics. This study, incorporating the latest policy updates, aims to bring clarity to this context. It reveals that suitable land is abundantly available throughout the country, with a significant quantity of "Very High" suitability land existing within every administrative region. The analysis demonstrates that meeting renewable energy capacity targets through APV deployment would require the co-occupation of approximately 1% of the agricultural land identified as suitable at the national scale (assuming a mean APV power density). This indicates that APV deployment does not entail a significant loss of agricultural land availability.

5.3. Future research

Future research is expected to develop APV-specific integrated models for the design phase that synthesize all issues related to agricultural operativity within APV, particularly regarding machinery, with design selection for specific environments and site suitability analysis. Furthermore, research should address the design of next-generation machinery capable of coping with the heterogeneity of APV systems worldwide. This equipment should be dimensioned specifically to perform all required agricultural operations without being constrained by APV structures. Moreover, optimization approaches must incorporate mechanization feasibility as a core variable in the optimization problem to account for the needs of the real system users. Finally, a new concept of "shape factor" should be integrated into the selection of the most suitable areas. This metric would prioritize specific field plots capable of hosting APV structures that facilitate machinery operation and manoeuvrability, thereby reducing the operational costs associated with APV implementation.

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Acknowledgements

I would like to thank my supervisors, Stefano Amaducci and Pietro Elia Campana, for the guidance and the opportunity provided during this PhD. I also wish to thank Stefano Maran for his professional supervision and support on behalf of Ricerca sul Sistema Energetico (RSE) S.p.A.

I am especially grateful to Dr. Giorgio Impollonia and Dr. Michele Croci for their essential support and significant technical contributions throughout the development of this thesis.

This PhD research was primarily funded by Ricerca sul Sistema Energetico - RSE S.p.A. Additional support was provided by the Portus Project, funded by the Romeo and Enrica Invernizzi Foundation. I also gratefully acknowledge the funding received from Mälardalen University (MDU) in Västerås, Sweden. Finally, I would like to thank the Rotary Club Fiorenzuola d'Arda for their recognition and support of the studies conducted in this thesis.

List of publications

- Bellone, Y., Croci, M., Impollonia, G., Zad, A. N., Colauzzi, M., Campana, P. E., & Amaducci, S. (2024). Simulation-based decision support for Agrivoltaic systems. *Applied Energy*, 369, 123490. <https://doi.org/10.1016/j.apenergy.2024.123490>
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- Zainali, S., Lu, S. M., Bellone, Y., & Campana, P. E. (2025). Optimisation of Agrivoltaic Systems within the Water-Energy-Food Nexus. <https://doi.org/10.1016/j.jclepro.2025.147275>
- Bellone, Y., Santangelo, E., Assirelli, A., Zainali, S., Impollonia, G., Croci, M., ... & Amaducci, S. (2026). Agricultural mechanization in agrivoltaic systems: Challenges, adaptation, and possible advancements. *Renewable and Sustainable Energy Reviews*, 229, 116661. <https://doi.org/10.1016/j.rser.2025.116661>

Publications in revision

- Silvia Ma Lu, Arash Khosravi, Xiaolin Wang, Matthew Haworth, Amirhossein Nik Zad, Yuri Bellone, Pietro Elia Campana (2026). Increasing land productivity with semi-

transparent colored CdTe thin-film photovoltaics and broccoli cultivation in agrivoltaic systems. *npj Nanophoton.*

- Michele Colauzzi, Gabriele Sortino, Eleonora Potenza, Yuri Bellone, Giorgio Impollonia, Amirhossein Nik Zad, Michele Croci, Giancarlo Ghidesi, Iliana Le Bossenec, Stefano Amaducci (2026). Potato cultivation in agrivoltaic systems in Northern Italy: a four-year case study on array setup, shading patterns, and yield response. *Smart Agricultural Technology.*

Projects

Value4Farm: The Value4Farm project is a collaborative initiative funded by the EU Horizon Europe program, dedicated to integrating renewable energy into farming. The goal of the project is to increase on-farm renewable energy production while preserving food production, soil health, biodiversity, and reducing water and fertilizer usage. The VALUE4FARM project develops cropping systems for sheltering and vertical agrivoltaics integrated with biomethane and green biorefineries. It advances power-to-methane technologies and small-scale microturbines while providing decision support tools and agricultural protocols to optimize food and energy production. By offering renewable energy and storage solutions for farm residues, heat, and mobility, the project validates three circular value chains through demonstration to ensure their replicability and broad adoption. <https://value4farm.eu/>

AGRIVOLT-ER: Is a project funded by PR FESR Emilia Romagna programme 2021-2027. Azione 1.1.2 “*Supporto a progetti di ricerca collaborativa dei laboratori di ricerca e delle università con le imprese*”. Agrivolt-ER was established with the primary objective of advancing the research necessary to develop sustainable agrivoltaic (AV) systems, where agricultural activity remains the primary focus and electricity production is complementary. The implementation of experimental cultivation trials in advanced AV systems and the use of IoT monitoring systems will enable the validation of a decision support system. This system will be used to coordinate agronomic choices and PV infrastructure management synergistically to maximize land use, minimize agricultural production losses due to shading, preserve soil quality, and increase water use efficiency. Agrivolt-ER will contribute to the decarbonization of the agricultural sector by promoting electricity use through the development of energy communities and supporting self-consumption for agri-food industries and land reclamation consortia. <https://www.agrivolter.it/>