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Unraveling the crop yield response under shading conditions through the deployment of a drought index: A meta-analysis

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ABSTRACT

Extensive meta-analyses have examined the effects of shading on vegetation growth and Crop Yields (CY) in Agrivoltaic (AV) systems. These studies have demonstrated a strong relationship between shading and crop performance. Certain varieties, such as Berries and Leafy Vegetables, thrive under shaded conditions, while Forage Crops remain largely unaffected. Conversely, other crops, including C3 Cereals, Grain Legumes, Fruits, and Root Crops, experience reduced yields when exposed to shade. Previous meta-analyses often neglected environmental factors such as temperature, evapotranspiration, and precipitation when evaluating the effects of shading on CY, making it difficult to fully understand how shading influences crop performance. This study seeks to address this research gap by integrating a drought index, the Standardized Precipitation Evapotranspiration Index (SPEI), for an improved meta-analysis on shading and CY across various crops. SPEI, encompassing information on potential evapotranspiration and precipitation is an effective indicator of moisture availability and accessible worldwide at a reasonable temporal and spatial resolution. Multiple Linear Regression (MLR) techniques are used to analyze various crop categories. From a policy perspective, the MLR models developed in this study can help policymakers make more accurate assessments of the impact of AV systems deployment on CY at both national and regional levels.

The results of the MLR models, both with and without the inclusion of the SPEI, were compared to evaluate the impact of shading on determining CY under different environmental conditions. Incorporating SPEI into the MLR models improved performance metrics across all crop categories with adequate sample sizes. The least improvement was observed for Fruits, with a marginal 0.01 gain in coeffiecient of determination (R^2), while the most substantial improvement was seen in Berries, with a 0.32 increase. The analysis was reinforced by uncertainty quantification, which demonstrated that the predictability of CY improves when SPEI was included, as supported by a 95 % confidence level. In all crop categories, the MLR model exhibited increased certainty when SPEI was considered, compared to using shading alone as a determinant for CY in the uncertainty analysis. A minor improvement of 13 % was observed in Forage Crops, while a significant increase of 47 % was noted in Root Crops.

1. Introduction

Large-scale ground-mounted photovoltaic (PV) systems are among the most economically competitive renewable energy technologies, providing green electricity at a low levelized cost and achieving grid parity in various countries and regions worldwide [1–3]. However, the widespread use of PV technology can create competition between land needed for energy conversion and land needed for food production. Agrivoltaic (AV) systems have been proposed as an integrated solution to address this conflict by combining PV energy conversion with

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agricultural activities. Studies have demonstrated that AV can increase the land equivalent ratio by allowing for simultaneous food production and energy conversion, optimizing land use efficiency, promoting sustainability, and maximizing resource utilization [4–6]. Multiple studies have evaluated the effects of AV shading on Crop Yield (CY). This area of research is particularly relevant as current developments in AV systems regulations increasingly emphasize establishing limits on the maximum permissible reduction of CY compared to open-field conditions [7].

For instance, Germany has made a significant step toward standardizing AV system specifications through the *Deutsches Institut für Normung* (DIN) Specification, a technical standard known as DIN SPEC 91434:2021-–05 [8]. This specification mandates that CY reduction under AV systems should not exceed one-third of the open-field CY [9]. In Italy, the Ministry of the Environment and Energy Security issued guidelines indicating that agricultural activity should continue on >70 % of the areas occupied by AV systems, PV modules coverage of agricultural fields should remain below 40 % and electricity production should at least be >60 % of conventional PV system [9]. The Ministry of the Environment and Energy Security made no reference to CY reduction. However, the Italian Standards Body *Ente Nazionale Italiano di Unificazione* (UNI), in its specification “Agri-voltaic systems - Integration of agricultural activities and photovoltaic implants” [10], indicated that CY under AV systems should be maintained >70 % of the open-field reference. In France, the government issued a Decree No 2024–318 [11], defining conditions for installing AV systems. According to this decree, agricultural CY should not be reduced by >10 % under AV systems compared to the reference, and PV modules should not cover >40 % of the crop field for large arrays with an installed capacity above 10 MW_p [11,12]. In Spain, the Department of Climate Action, Food, and Rural Agenda of the autonomous region of Catalonia issued a provision regulating the deployment of AVs on farmland. The regulation stipulates that AV systems can cover no >15 % to 20 % of the farmland, depending on the structure’s height, and that CY must be maintained >60 % [13,14]. These regulations require farmers operating AV systems to achieve a minimum CY that is supposed to warrant the continuity of agricultural activities under the AV system.

The primary challenge associated with AV systems is the microclimate created by the shading, which can have either beneficial or detrimental effects on crop development and yield [15,16]. Certain crops may benefit from shading, as it could mitigate evapotranspiration within the crop field or alleviate excessive irradiance and temperature, but could otherwise prove detrimental to specific crops that are sensitive to shading [15,17,18]. One primary market and research challenge is to simulate or assess the impact of shading and microclimate on CYs to meet policy targets on CY reduction under AV systems before installation.

A meta-analysis conducted by Laub et al. [19] investigated the effects of shading on CY. The study aimed to clarify how shading impacts various types of crops (i.e., Berries, Fruits, Fruity Vegetables, Leafy Vegetables, C3 Cereals, Maize, Tubers/Root Crops, Grain Legumes, and Forages), providing valuable insights for agricultural practices and management strategies. The findings revealed significant differences in yield responses among crop types as shading levels increased, supporting the idea that different crop varieties react differently to reduced sunlight. Similarly, Dupraz [7] used experimental data from various sources to explore the relationship between the relative CY under AV systems with the Ground Coverage Ratio (GCR), which was used as a proxy for the shading rate on the crops. The author categorized various types of AV systems, differentiating between greenhouses and open fields, as well as fixed and mobile PV modules. Additionally, a regression analysis was performed to examine the relationship between GCR and relative CY, aiming to predict agricultural productivity under AV systems and agroforestry conditions. However, the study did not conduct a detailed analysis of the significant differences between rainfed and irrigated systems despite their critical role in shaping crop productivity. Understanding these distinctions is also essential, as irrigation can mitigate water stress, influence soil conditions, and enhance yield stability, whereas rainfed systems are more susceptible to climatic variability. A deeper exploration of these factors would provide valuable insights into the environmental influences on agricultural output. Unfortunately, the available site-crop data points were too limited to develop separate regression models for each type of AV system and various climatic zones. Hermelink et al. [20] conducted a meta-analysis on Berry shade tolerance in AV systems and applied a mixed-effects model to assess the impact of shading on CY. However, this study did not incorporate environmental factors alongside shading levels, limiting its ability to account for broader influences on agricultural productivity.

A common goal of Laub et al. [19], Dupraz [7] and Hermelink et al. [20] was to establish simple correlations between shading rate and relative CY. These correlations can serve as valuable tools for developing AV policies. In particular, they can help develop regulations that manage the maximum allowable reduction in CY on a large scale. However, a significant limitation of these studies is that they only consider the impact of shading rate, or GCR, on CY, while neglecting other important factors such as meteorological conditions and soil moisture, which are also critical to CY. Comparing the CY results of two identical AV systems can be challenging, even when they share the same shading rate, are installed in the same location, and cultivate the same crop. Difficulties arise when data is collected from different years with significantly varying weather conditions, such as wet and dry seasons. In a wet year, increased shading may negatively impact CY by reducing irradiance levels, which limits photosynthesis. In contrast, during a dry year, the same shading rate can be beneficial, as it helps to reduce heat stress and decrease evapotranspiration, ultimately promoting crop growth. While shading provides a partial glimpse into CY, the true picture remains elusive without consideration of cultivation-period weather dynamics. Therefore, additional environmental factors should be included as independent variables in the analysis of the correlation between CY and shading levels. This addition will provide policymakers with more accurate information.

Drought is widely recognized as a crucial determinant of CY and is consistently highlighted in numerous studies that examine the environmental impacts on CY [21,22]. Warming conditions accelerate the water cycle, and observational evidence demonstrates intensifying drought conditions across the globe [23]. Future climate scenarios project rising temperature, shifting precipitation patterns, and increasing evapotranspiration [24]. More frequent, severe and long-lasting drought events are more likely to occur in the warming future [25,26], resulting in significant impacts across sectors (e.g., agriculture). Drought is becoming an increasingly critical issue, even in European countries where it was previously of little concern. The rising frequency and severity of drought conditions are creating alarming situations, threatening water resources, agriculture, and ecosystems, and prompting urgent attention to climate resilience and sustainable resource management [27–29]. This highlights the increasing importance to develop CY prediction models that go beyond shading effects and explicitly account for water availability and drought stress, thereby capturing the multifactorial nature of climate impacts on agricultural productivity. Thus this study aims to incorporate a drought indicator into existing studies on the effects of shading on CY, allowing for a better evaluation of how environmental conditions affect CY.

Several indicators have been developed for monitoring drought conditions, with the most recognized being the Standardized Precipitation Index (SPI), the Palmer Drought Severity Index (PDSI), and the Standardized Precipitation Evapotranspiration Index (SPEI) [30]. SPI is a multi-scalar index that relies solely on precipitation and can be calculated over different time scales [31]. PDSI incorporates data on precipitation and temperature, but it operates on a fixed time scale [32]. SPEI incorporates both precipitation and temperature, offering multi-scalar characteristics [33]. It was chosen to represent the drought conditions in this study. The SPEI is calculated using a straightforward climatic water balance factor, which is derived by subtracting evapotranspiration from precipitation. This calculation is performed over various time scales ranging from 1 month to 48 months. The resulting data is then normalized to fit a log-logistic distribution. For more detailed information on the SPEI calculation, refer to Vicente-Serrano et al. [33]. The advantages of SPEI enable consistent and more accurate drought analysis across time and space and at different time scales [30–33]. In recent years, SPEI has been increasingly used in agriculture to explore CY response. The SPEI, as an index of drought, is easily retrievable from services like the SPEI database [34], could enhance the understanding of the relationship between shading rate and CY, by providing crucial information concerning temperatures, evapotranspiration, and water availability.

Therefore, this study investigated the impact of the SPEI on CY, alongside the traditional analysis of shading effects, using Multiple Linear Regression (MLR), whereas previous meta-analyses have focused solely on shading levels and relied on Simple Linear Regression (SLR). To assess improvements in CY prediction, several performance metrics were utilized, including the coefficient of determination (R^2), Mean Squared Error (MSE), Mean Absolute Error (MAE), and uncertainty quantification. Models were compared based on two approaches: those considering only shading levels, and those integrating shading with four SPEI-derived variables (mean, minimum, maximum, and standard deviation). This highlights the increasing importance to develop CY prediction models that go beyond shading effects and explicitly account for water availability and drought stress, thereby capturing the multifactorial nature of climate impacts on agricultural productivity.

The remainder of this paper is organized as follows. Section 2 describes the data sources and regression models as methods applied in this study. Section 3 presents the results derived from the methods. In Section 4 these findings are discussed in relation to existing literature and practical considerations including the policy implications. Section 5 concludes by highlighting the key points of the study.

2. Data and methods

Laub et al. [19] and Dupraz [7] conducted studies on various crops, which significantly influenced the crop categories adopted in this study. Although Hermelink et al. [20] also performed a meta-analysis, their focus was limited to Berries. Overall, all the three studies provided valuable foundations for this study. However, in developing the data structure and defining crop categories, the framework used by Laub et al. [19] was particularly influential and served as the primary inspiration for our data organization. The critical addition in this study is the incorporation of the SPEI, an effective indicator of water availability crucial for crops [35–38] but absent in earlier meta-analyses. This integration allows for a more comprehensive analysis that considers not only shading levels but also the influence of water availability on crop performance, and introduces a new perspective for interpreting CY predictions under shading from different objects such as PV panels or shading nets.

2.1. Data

Laub et al. [19] included 58 studies, Hermelink et al. [20] included 22 studies and Dupraz [7] included 21 studies that examined shading treatments and their corresponding CY. However, 9 duplicates of the three meta-analyses were removed to total the collection to 92. An additional 15 studies were identified in this study using keywords such as "shading level and crop yield," "agrivoltaics," and "shading net" which brought the total number of studies to 107. However, not all these studies could be included in the meta-analysis because they lacked essential parameters necessary for a thorough evaluation, such as precise location details, planting and harvesting periods. Moreover, the greenhouse studies did not provide direct comparisons with open-field conditions and failed to consider complex microclimate interactions, making them unsuitable for this analysis. The systematic filtering of available sources is based on the following criteria:

- Articles without a specific date for planting and/or harvesting and crop growth period were excluded since they did not allow retrieval of the correct values of monthly SPEI data corresponding to the crop growth period.
- Articles that reported average CY over multiple years or seasons were excluded, as it is challenging to align these averaged yields with the corresponding SPEI values, which are specific to particular time periods.
- Articles without specific coordinates of the experimental site were excluded since they did not allow retrieval of the correct values of SPEI data.
- Greenhouse experiments were excluded because the microclimate cannot be accurately represented by shading alone.

A total of 40 articles were excluded from consideration due to a lack of sufficient details regarding the timing of the growing season, the study location, and greenhouse studies. For the studies that included known harvest dates, the crop growing season was either directly extracted from the published data, when specified, or inferred based on the provided planting or harvest dates, using the reported crop growth cycles as a guide [39]. Consequently, only 67 articles were identified as suitable for this study.

The selected studies were divided into two groups: non-irrigated and irrigated. A total of 40 studies were categorized as non-irrigated and included in the primary analysis, as irrigation can alleviate the effects of drought and diminish the benefits of shading. Within the main analysis, 13 studies were conducted over a single season or year, 17 studies lasted for two years, and 10 studies extended for up to three years (note that those studies that lasted for more than two years presented CY for every year or season). The 27 irrigated studies were included in the Appendix to analyze the differences in the meta-analysis results between irrigated and non-irrigated crops, considered either separately or together. A summary of the studies included in this meta-analysis is presented in Fig. 1, beginning with the data from Laub et al. [19], Dupraz [7], and Hermelink et al. [20] and applying additional filters. In the study conducted by Laub et al. [19] crops were categorized into distinct categories, including C3 Cereals, Berries, Maize, Grain Legumes, Fruits, Leafy Vegetables, Root Crops, and Forage. In this study, consistency is maintained by adhering to the same crop categories except for the Fruity Vegetables because all the studies on those crops were conducted under irrigation.

Although the geometrical dimensions and characteristics of shading objects, such as their height, are crucial in determining the shading rate, only a few studies have reported this information [6,40–48]. The lack of adequate information regarding the geometrical information of the shading material has made it difficult to consider it in this study. Consequently, this study decided to exclude this aspect from our analysis and instead focus on the shading rate provided by the studies.

Monthly values of the SPEI for each month of the crop growing season were obtained from the SPEI database [34] using the geographic coordinates from all the research studies included in this meta-analysis. Since SPEI can vary significantly throughout the growing season due to alternating periods of extreme wet and dry periods, this study used statistical measures such as the mean, minimum, maximum, and standard deviation as independent variables of SPEI along with shading level. Fig. 2 illustrates the importance of these SPEI statistics by depicting the variance from extremely wet to extremely dry conditions for C3 Cereal crops used in this study. It is important to note that if the SPEI remained stable throughout the crop growing season, its mean, minimum, maximum, and standard deviation would likely be highly correlated, making it redundant to include all four variables independently. However, since the SPEI fluctuates between dry and wet conditions throughout the crop growth period in our dataset, this variability must be accounted for by incorporating all four SPEI variables.

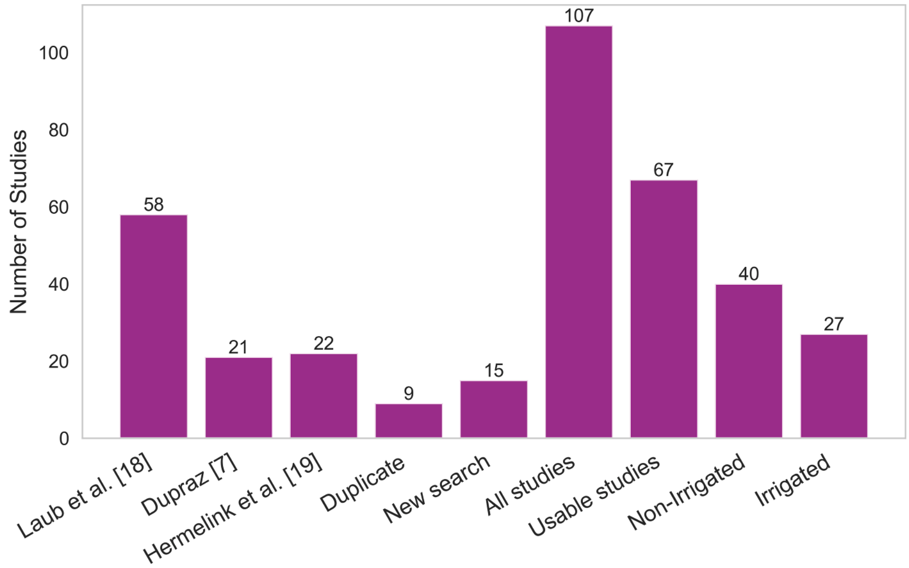

Fig. 1. Number of studies considered in previous meta-analyses versus number of studies considered in this study after filtering and classification into non-irrigated (main focus) and irrigated (further investigated in the Appendix).

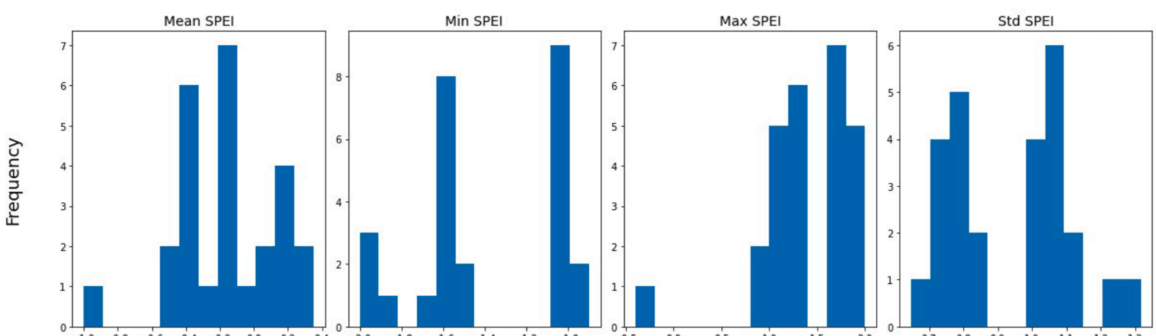

Fig. 2. Histogram illustrating the distribution of SPEI variables for C3 Cereals. Negative value in the distribution indicate dryness while positive values indicate wetness.

The research studies included in the proposed meta-analysis were gathered from diverse global locations, as illustrated in Fig. 3, which also lists the number of studies per country. The wide range of shading levels across various climatic conditions and cropping patterns enhances the study's ability to generate broadly applicable conclusions, ensuring the findings can be effectively generalized across different AV environments and agricultural settings.

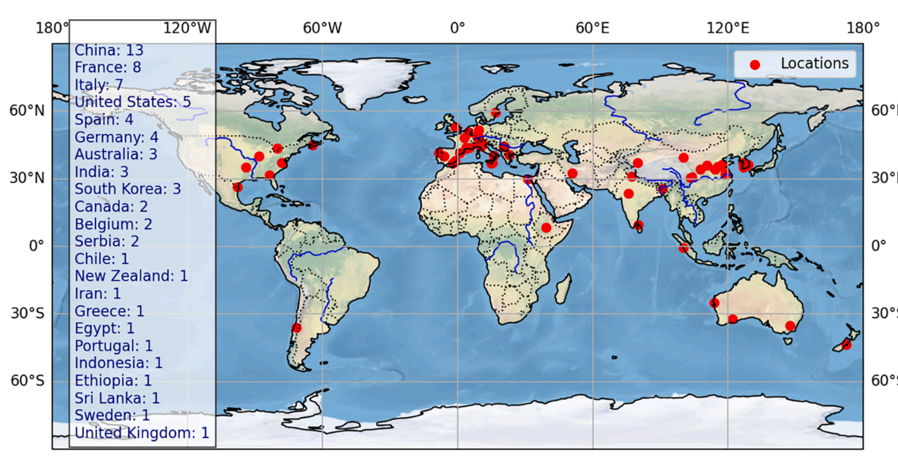

Fig. 3. Map of the locations reported in the studies being part of the meta-analysis.

2.2. Methods

In agricultural research, statistical hypothesis tests are often used to assess the significance of each independent variable on CY. This helps to determine how much influence a particular variable has on CY. However, in the present study, statistical hypothesis testing was not applied. The main reason for this decision is that all the SPEI statistics mean, minimum, maximum, and standard deviation are considered as determinants. These statistics can be highly correlated, for example during years or seasons with stable meteorological conditions, making it difficult to formulate a coherent statistical hypothesis. When variables are highly correlated, it becomes challenging to isolate their individual effects and accurately assess their significance through traditional hypothesis testing. Therefore, the analysis focuses on the overall impact of these SPEI statistics on CY without relying on hypothesis tests. This approach helps us avoid potential issues arising from multicollinearity and provides a clearer understanding of their combined influence. This approach enhances the ability to capture the complex interactions between these climatic variables and CY. Therefore, this study employs regression modeling and uncertainty quantification to evaluate and compare the improvements achieved relative to previous studies.

2.2.1. Regression model

In this study, a SLR (shading level as the sole determinant as done previously by Laub et al. [19], Hermelink et al. [20] and Dupraz [7]) and a MLR (shading level and the SPEI statistical values together as determinants) were compared to investigate how the inclusion of SPEI affects the predictability of CY.

The shading level variable in the collected data ranges from 0 to 100, where a value of 100 represents complete blockage of solar irradiation. In contrast, the SPEI values obtained for the study locations and periods span from −2.6, indicating extreme dryness, to 2.5, signifying extreme wetness. To ensure consistency when analyzing the impact of each independent variable on the CY, it is needed to normalize these variables to bring them onto a comparable scale. This normalization is crucial for accurately assessing the impact of each independent variable, shading level and SPEI statistical values on CY. It is important to note that the normalization of the data does not influence the performance metrics across different crop categories or the linear relationship between the independent variables (shading level and SPEI) and the dependent variable (CY). Eq. (1) was used to normalize each variable:

$$x' = 100 * \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where x is the original value, x_{min} is the minimum of the dataset, x_{max} is the maximum of the dataset, and x' the normalized value. The equation normalizes the SPEI values in the range of 0 to 100.

The model used for SLR is given in Eq. (2):

$$Y = \beta_0 + \beta_1 X_1, \tag{2}$$

where, Y is the dependent (response) variable CY, β_0 is the intercept, β_1 is the slope coefficient, and X_1 is the independent variable shading level.

With shading level and SPEI statistics as independent variables, the model used for MLR is given in the following Eq. (3):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n, \tag{3}$$

where, Y is the dependent (response) variable CY, $\beta_1, \beta_2, \ldots \beta_n$ are the slope coefficients, and $X_1, X_2 \ldots X_n$ were the independent variables, i.e., shading level, average SPEI, minimum SPEI, maximum SPEI, and SPEI standard deviation.

The R^2, MSE, and MAE were used as performance metrics to compare the SLR model against the MLR model, which adds the SPEI statistics as independent variables.

2.2.2. Uncertainty quantification

In addition to standard performance metrics, this study assessed the uncertainty of the SLR and MLR models to provide a more robust evaluation of their predictive reliability. For each model, the study constructs 95 % Prediction Intervals (PI), SLR excluding SPEI statistics, and MLR including them, and then quantifies two complementary properties of those intervals:

1. **Prediction Interval Coverage Probability (PICP):** the empirical proportion of observed CY values that fall within the bounds of the PI, ideally matching the nominal 95 % level. A higher PICP (closer to 1) indicates better calibration of the intervals against the true variability of the data [49,50].
2. **Mean Prediction Interval Width (MPIW):** the average width of the PI, reflecting their sharpness (informativeness). Narrower bands (lower MPIW) are preferable, provided they still cover the truth, as they give more precise guidance [50].

Reporting PICP and MPIW together allows us to see not only whether the intervals are well-calibrated, but also how tight they are, thus giving a detailed assessment of each model's uncertainty. This dual-metric approach enhances the robustness of our comparative analysis by balancing the reliability and precision of the SLR vs. MLR models.

3. Results

3.1. Regression models' performance

In Fig. 4, a parity plot for C_3 Cereals under non-irrigated conditions is displayed with and without SPEI. The performance metrics show significant improvements with the inclusion of SPEI statistical values: R^2 increased from 0.35 to 0.53, MAE decreased from 8.96 % to 6.81 %, and MSE decreased from 173.29 % to 123.58 %.

The performance metrics for all the crop categories investigated are summarized in Table 1. Across all crop categories, the inclusion of SPEI statistics improved the prediction of the CY reduction under shading conditions and thus, the performance metrics. However, the crop category Fruits showed only a marginal improvement, with R^2 increasing by just 0.01 when SPEI was included. For Forage, the improvement was also relatively low, with R^2 value of about 0.07, significantly lower than other crop categories, which achieved R^2 improvements above 0.18. Overall, Forage displayed poor performance for both models, with R^2 values of only 0.11 without SPEI and 0.18 with SPEI. The results for Leafy Vegetables can also be explained also by the small dataset, which included only five data points. This limited sample size led to a drastic change in R^2, jumping from 0.02 to 1 when SPEI was introduced, indicating potential overfitting or a lack of robust statistical support.

A linear equation for both SLR and MLR is derived using the original scale (i.e., without normalization) to facilitate a direct interpretation of the relationships between the independent variables (shading level and SPEI statistical values) and CY. Table 2 summarizes the linear equation correlating the input variables and the CY. X_1 represents the shading level, X_2 represents mean SPEI, X_3 represents minimum SPEI, X_4 represents maximum SPEI, and X_5 represents SPEI standard deviation. Those handy correlations can be used to derive potential CY reductions based on shading level, i.e., the design parameter of AV systems and historical values of SPEI statistics.

Fig. 5 illustrates the influence of each independent variable on the dependent variable across different crop categories based on the coefficients of all independent variables when normalized. Each crop category is represented in every row with its independent scale on the right side, which allows comparison of the variables for each crop category within the row. The five independent variables are shown as colored horizontal bars to highlight their impact on CY. A histogram is also included to show the distribution of each variable across crop categories. Overall, Fig. 5 allows for a comparison of each variable's

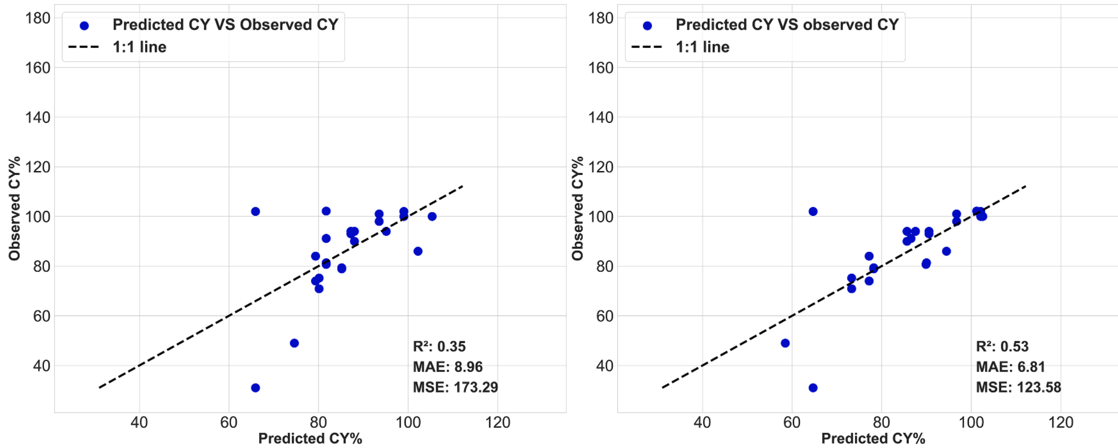

Fig. 4. Predicted CY (%) versus Observed CY (%) without considering SPEI (left) and with considering SPEI (right) for C3 Cereal non-irrigated.

Table 1
Performance metrics of the linear model without/with SPEI statistical values for non-irrigated crop categories.

Crop category	R^2		MSE		MAE		Sample
	Without SPEI	With SPEI	Without SPEI	With SPEI	Without SPEI	With SPEI	
C3 Cereals	0.35	0.53	173.29	123.58	8.96	6.81	26
Berries	0.01	0.33	1718.51	1157.91	32.42	27.55	67
Maize	0.07	0.31	413.93	308.17	16.71	14.21	31
Grain Legumes	0.28	0.64	300.75	149.73	12.75	10.38	22
Fruits	0.40	0.41	79.59	77.96	7.16	7.11	18
Leafy Vegetables	0.02	1.00	2331	6.4	38.91	1.6	5
Root Crop	0.37	0.63	493.22	290.77	17.56	13.6	15
Forage	0.11	0.18	1580.39	1460.19	33.17	31.81	62

Table 2
Summary of the equations retrieved for SLR and MLR models for non-irrigated crop categories. X_1 is shading level, X_2 is SPEI mean, X_3 is SPEI minimum, X_4 is SPEI maximum, and X_5 is SPEI standard deviation.

Crop Type	Equation	R^2
C3 Cereals	$105.35 - 0.78X_1$	0.35
	$71.34 - 0.76X_1 + 5.84X_2 + 12.47X_3 - 8.01X_4 + 67.09X_5$	0.53
Berries	$99.39 + 0.25X_1$	0.01
	$111.584 + 0.02X_1 - 16.78X_2 - 7.84X_3 - 50.16X_4 + 70.31X_5$	0.33
Maize	$82.32 - 0.391X_1$	0.07
	$86.84 - 0.47X_1 + 53.21X_2 - 9.54X_3 - 46.75X_4 + 49.29X_5$	0.31
Grain Legumes	$94.70 - 1.05X_1$	0.28
	$126.25 - 0.87X_1 - 37.61X_2 + 48.93X_3 - 5.39X_4 + 38.47X_5$	0.64
Fruits	$105.44 - 0.43X_1$	0.40
	$107.06 - 0.42X_1 + 6.52X_2 - 5.42X_3 - 2.22X_4 - 5.94X_5$	0.41
Leafy Vegetables	$106.92 + 0.28X_1$	0.02
	$460.35 - 2.6X_1 + 16.23X_2 + 190.62X_3 + 16.15X_4 - 75.47X_5$	1.0
Root Crop	$111.55 - 1.06X_1$	0.37
	$20.59 - 0.81X_1 - 26.50X_2 - 17.96X_3 - 22.61X_4 + 84.89X_5$	0.63
Forage	$127.48 - 0.75X_1$	0.11
	$78.68 - 0.93X_1 + 86.36X_2 - 31.22X_3 - 64.20X_4 + 123.21X_5$	0.18

influence while illustrating shading levels and environmental dryness or wetness across all samples.

Berries and Forage crops exhibit a relatively high level of shade tolerance, with an average shading level exceeding 40 %, which is higher than most other crop categories. Additionally, the impact of shading on these crops is less significant than at least one of the SPEI statistical values, suggesting that climatic conditions have a more substantial influence on their productivity. For Fruit and Leafy Vegetables, shading levels significantly affect CY more than all SPEI statistical values. This result indicates that light availability is a critical factor in the productivity of these crop categories, particularly for Fruit-Bearing plants and Leafy Greens. However, as mentioned earlier, the results for Leafy Vegetables should be interpreted with caution, as the dataset for this category is extremely limited, raising concerns about the accuracy of the findings. One or more SPEI statistical values show a stronger influence on CY than shading levels for the remaining crop categories. This result suggests that climatic factors such as drought or excess moisture, have a more pronounced impact on yield than shading. These findings highlight the varying sensitivities of different crop types to environmental stressors, emphasizing the need for tailored AV systems and climate adaptation strategies.

3.2. Uncertainty analysis

The inclusion of the SPEI in the predictive model significantly improves the PICP across most crop categories, demonstrating a clear enhancement in the model's ability to capture climatic variability and its impact on yield. For example, the PICP increases from 0.46 to 0.92 for C3 Cereals, from 0.40 to 0.76 for Maize, and from 0.61 to 0.89 for Fruits. This improvement, however, comes with a corresponding increase in the MPIW, reflecting a broader uncertainty band around the predictions. For instance, MPIW rises from 14.97 to 24.45 for C3 Cereals and from 21.26 to 34.82 for Maize. The results for the rest of the crop categories are summarized in Table 3. This trade-off is expected, as a wider interval is often required to achieve higher coverage in the presence of greater variability, particularly under drought conditions. Importantly, the general principle in probabilistic modeling is to first aim for high coverage, ideally a PICP of at least 0.95 [51], before seeking to reduce the width of the PI. From this perspective, the SPEI-enhanced model

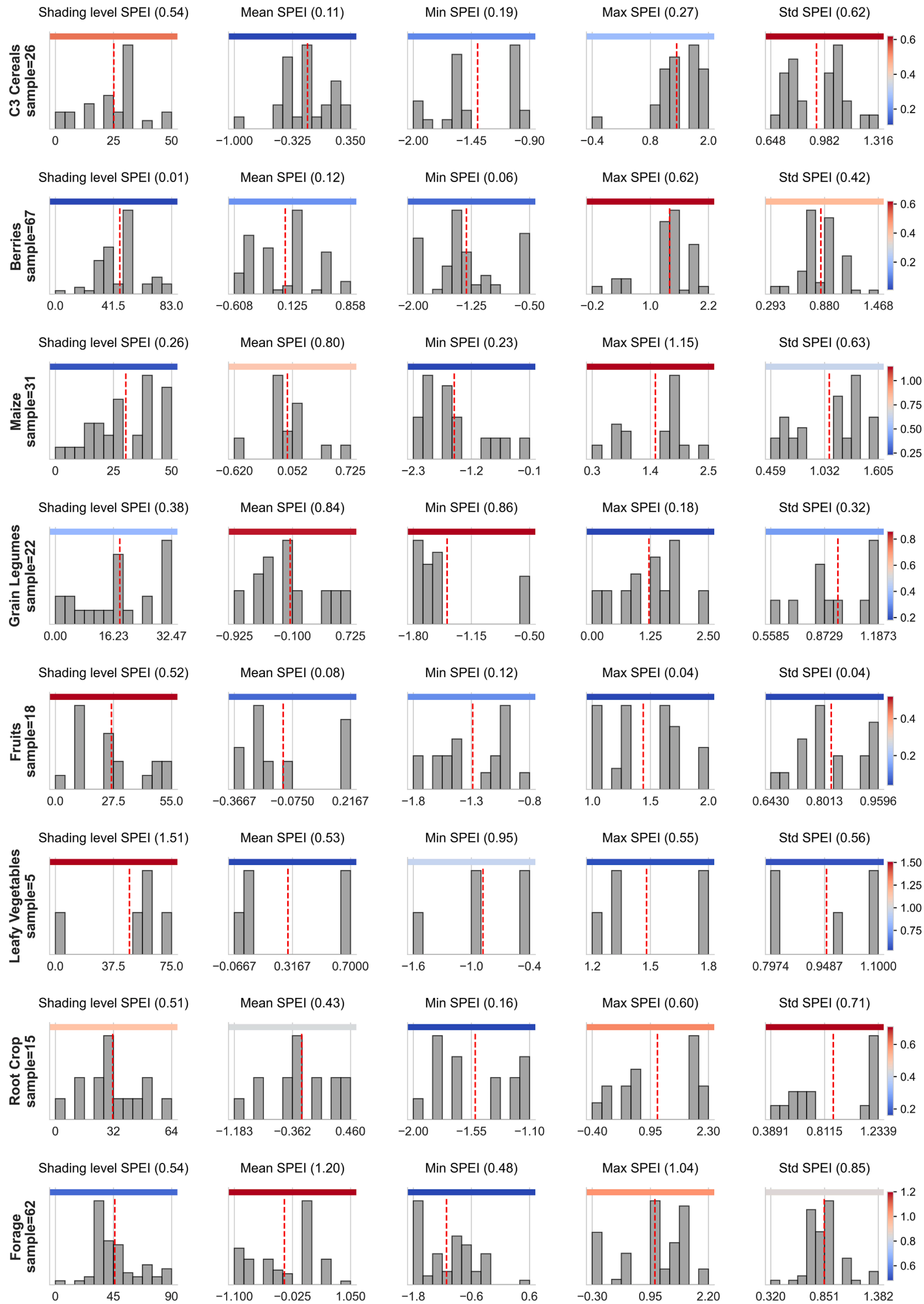

Fig. 5. Impact distribution comparison of independent variables for every crop category with heat map and histogram where the vertical dash line indicates the mean distribution in every variable.

represents a substantial advancement, offering more reliable and informative uncertainty estimates. Nonetheless, the increased interval width also highlights the potential for further improvement, either through the integration of additional explanatory variables, the use of larger or more diverse datasets, or the development of more advanced modeling approaches that can achieve both high coverage and narrower intervals. The current results underscore the value of incorporating climate stress indicators such as SPEI into yield prediction frameworks,

Table 3
PICP and MPIW results for non-irrigated crops (confidence interval: 95 %).

Crop category	PICP	PICP SPEI	MPIW	MPIW SPEI	Sample
C3 Cereals	0.46	0.92	14.97	24.45	26
Berries	0.35	0.55	27.55	40.99	67
Maize	0.40	0.76	21.26	34.82	31
Grain Legumes	0.55	0.77	22.25	31.12	22
Fruits	0.61	0.89	13.01	26.82	18
Leafy Vegetables	1	1	239.13	126.91	5
Root Crop	0.53	1	35.92	62.43	15
Forage	0.24	0.37	27.71	48.66	62

while also pointing to future directions for improving model precision.

Fig. 6 provides a visual complement to our PICP/MPIW analysis. The blue markers are the measured CY % at each shading level; the translucent red "floor" is the SLR model's 95 % PI (low coverage, narrow width), and the translucent gray "floor" is the MLR model's 95 % PI (high coverage, wider width). The MLR intervals cover almost every blue point (PICP 0.92) but at the cost of greater sharpness (MPIW 24.45 vs. 14.97). This makes explicit the calibration–sharpness trade-off quantified in Table 3. Fig. 6 shows that at shading levels between 0–30 %, the MLR model with SPEI consistently covers most of the observations, whereas the simple SLR model fails to capture many of the lower yield points. The inclusion of SPEI improves the MLR model's ability to generate wider, well-calibrated intervals that successfully encompass these lower-yield outliers. Additionally, the MLR model is more effective at capturing extreme shading levels, such as the one at 38 %, which the SLR model misses entirely. This capability to address extreme conditions explains the generally higher MPIW observed with the MLR model. One potential future direction for improvement would be to investigate the model's performance when shading rates above a certain threshold (e.g., 30 %) are excluded, as these higher levels are often agronomically extreme and typically avoided in practice. This could potentially enhance the robustness of the models, making them more reflective of real-world conditions where extreme shading is less common.

4. Discussion

4.1. Comparison with previous studies

The primary objective of this meta-analysis was to highlight the combined impact of environmental factors implicitly included in the SPEI and shading levels on CY. Previous studies have mostly concentrated on assessing the reduction in CY due to shading by correlating it with the shading level for shaded crops or the GCR for AV systems [7,19,20]. It is essential to provide accurate information about how the shading level produced by an AV system affects CY, as this is crucial for the large-scale deployment of this technology. Additionally, evaluating the performance of AV systems before installation is vital, and this should be done without relying solely on integrated mechanistic models, especially for large-scale assessment [52,53].

The analysis conducted in this study focused solely on non-irrigated crops. This decision was made because irrigation can mitigate the benefits provided by the shading of the AV systems, potentially leading to misleading correlations between the shading levels produced by the AV systems and the resulting CY. In drought conditions, crops with controlled irrigation may experience little to no impact, which can mask the effects of environmental stress [54–58]. The analysis of all crop categories, including both irrigated and non-irrigated crops, as well as a specific review of only irrigated crops, is detailed in the Appendix, along with the related discussions and conclusions.

This meta-analysis also revealed several statistical limitations that warrant attention. When assessing heteroscedasticity and normality of residuals (via heteroscedasticity tests and QQ-plots), it was found that most CY data were better fitted with a linear regression model. Applying a quadratic model, as proposed by Laub et al. [19], did not improve model fit or error distribution; QQ-plots remained non-normal in both cases. These findings suggest that conventional model assumptions (e.g., homoscedasticity, normality) are not fully met in our dataset, raising concerns about the reliability of associated p-values and hypothesis tests. Therefore, caution is warranted when interpreting classical statistical results, and there is a clear need for more robust, high-quality data before drawing definitive conclusions based on parametric inference. Importantly, the primary goal of this study was not to establish statistical significance per se, but to evaluate how well linear models, particularly MLR incorporating SPEI, capture the effects of drought and seasonal variability on CY. Therefore, this study evaluated the effect of shading on CY in isolation and in conjunction with drought conditions, treating both stressors on equal footing. This approach provides valuable insights into how predictive models can be improved by incorporating additional environmental factors alongside shading, thereby offering a more nuanced understanding of crop responses under AV systems. Nonetheless, these limitations underscore the complexity of modeling crop responses and emphasize the need for further methodological refinement in future work.

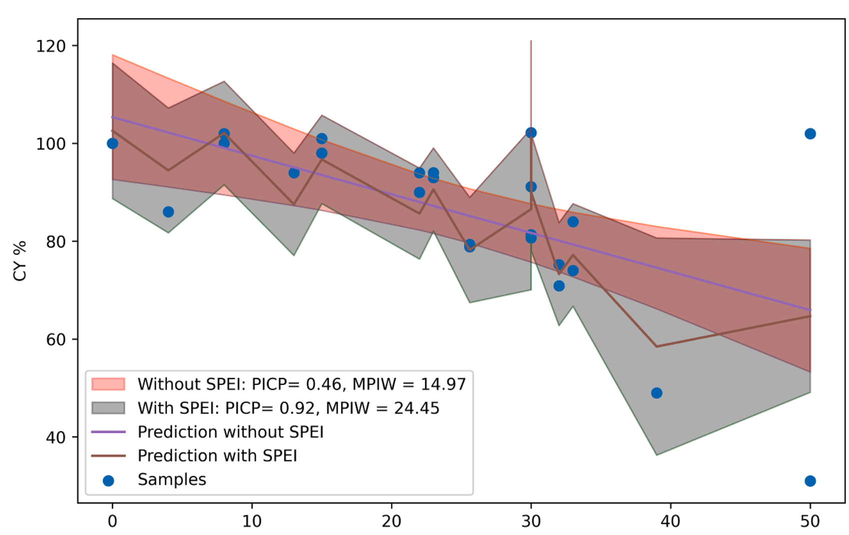

Fig. 6. Uncertainty analysis with and without SPEI for C3 Cereals at 95 % confidence interval.

In terms of model performance, the Fruit crop category showed no noticeable improvement in model performance with the inclusion of SPEI variables, even though a large portion of the data came from Mollerussa, Spain, a region that experienced consecutive years of low rainfall and high temperatures during the study period [59]. Apple trees, in particular, demonstrated low tolerance to shading, as supported by previous studies [60,61], suggesting that the shading level had a greater impact on yield than climatic stress indicators like SPEI. In contrast, the crop category Maize displayed minimal sensitivity to shading when analyzed using linear regression without incorporating SPEI. However, when SPEI was included alongside shading levels, the performance metrics improved significantly. While Maize is generally expected to respond negatively to shading due to its shade intolerance [62,63], some Maize varieties used in this study exhibited greater shade tolerance than anticipated, which may account for the observed variation [64,65]. Some sources indicated negligible yield reduction in Forage CY with increased shading levels [66,67], while others reported an increase in yield under the same conditions [5,68]. These contrasting results highlight the practical importance of both shading levels and SPEI statistics in predicting CYs, advocating for their inclusion in research and management of agricultural systems.

The usable studies as indicated in Fig. 1 do not provide as many data points as ideally required, which remains a key challenge in meta-analyses of this nature. This limitation has also been highlighted in the meta-analysis by Laub et al. [19], Dupraz [7] and Hermelink et al. [20] for certain crop categories. For instance, the Leafy Vegetables crop category comprises only five data points, while C3 Cereals, Grain Legumes, Fruits, and Root Crops each have fewer than 30 data points. This highlights the limited data availability in this field, underscoring the need for further research and more comprehensive studies. However, despite data scarcity in Leafy Vegetables this study retains the crop category because it provides initial indications of trends that warrant further investigation, particularly in relation to the factors examined in our study, such as SPEI and shading levels. Additionally, including Leafy Vegetables allows us to benchmark our findings against previous studies and maintain consistency in the meta-analysis framework.

4.2. Crop adaptation mechanism

Several studies have highlighted the critical role of microclimate [69–72] and crop adaptation mechanisms in accurately predicting CYs under AV systems as well as under other shading structures [17,44,73,74]. Microclimate effects under AV systems, such as changes in temperature, humidity, soil moisture, and wind patterns, can be evaluated using precise energy balance models and detailed simulations of heat and mass transfer [40,75,76].

However, understanding crop adaptation mechanisms under shaded conditions remains more complex. These mechanisms include physiological and morphological changes such as variations in Leaf Area Index , Radiation Use Efficiency, stomatal conductance, and light acclimation responses [17,44,52,77]. Even advanced mechanistic crop models often struggle to fully capture these dynamic plant responses, especially under variable and intermittent shading typical of AV systems [40,76].

Similar to the approach adopted in this study, investigating these crop adaptation processes could become a key focus for future meta-analyses [7,19,20]. The meta-analyses developed here, combined with previous works, provide a valuable foundation for exploring these mechanisms further. For instance, the relationships outlined in Table 2 of this study can serve as tools for evaluating crop adaptation. Specifically, in the context of the SLR model applied to C3 Cereals, this involves comparing predictions from the equation CY = 105.35 - 0.78 X_1 (X_1 is shading level) with outcomes from a basic linear model that assumes proportional yield reductions under shading. Any discrepancies between these results can then be interpreted as evidence of crop adaptation mechanisms, reflecting the plant's capacity to partially compensate for reduced light availability.

Integrating meta-analysis results, such as derived crop adaptation mechanism (i.e., % increase/decrease at specific shading rate), can significantly improve the performance of more mechanistic crop models, as shown in Campana et al. [67]. Such modeling advancements can improve the accuracy of AV systems' mechanistic tools for enhanced optimal design of AV systems.

4.3. Policy implications

While comparing the results of SLR models (i.e., CY response is only a function of the shading level) versus MLR models (i.e., CY response is a function of shading level and SPEI statistics), the performance metrics (i.e., R^2, MSE, and MAE) showed substantial improvement for most crop categories when SPEI variables are included. For instance, the CY reduction prediction of C3 Cereals improves by about 0.18 (i.e., the R^2 improves from 0.35 to 0.53, see Fig. 4).

From a policy perspective, the MLR models developed in this study can help policymakers make more accurate assessments of the impact of AV systems deployment on CY at both national and regional levels. This can lead to the establishment of more flexible CY targets that do not hinder the deployment of PV systems while still maintaining high levels of crop production. Additionally, the MLR models can be used for larger-scale assessments, such as at the European level, to predict where CY targets may or may not be met. This information can help develop general directives based on factors like climate, drought occurrences, and crop categories. Policymakers often establish CY targets to ensure that farmers maintain agricultural production under AV systems. However, reducing the uncertainty associated with yield reductions at the national or regional level could allow for less stringent CY targets while still ensuring food security. Using simplified crop models like the relationships proposed in this study or by Laub et al. [19] as performed in Zidane et al. [78] or in decision support systems [79] might result in over- or underestimated CY. In the case of real commercial projects, this might lead to:

1) non-compliance with regulatory frameworks and thus not attain the required performance before installation (in case of CY underestimation), or
2) non-compliance with regulatory framework concerning the report of agricultural performances during operation (in case of CY overestimation).

Thus, the modeling approach used in this study is recommended primarily for large-scale assessments rather than for specific projects, where more complex and mechanistic crop models are preferable. If applied to specific projects, it is essential to conduct an uncertainty analysis to evaluate the reliability of the results. Furthermore, as new data from the literature becomes available, recalibration of the proposed model is advised to enhance its accuracy and predictive performance.

By analyzing the effects of drought frequency and severity, as well as the shading levels produced by AV systems, this study can define less stringent CY targets for specific countries or regions, particularly for different crop categories. In areas with infrequent and non-severe droughts, CY targets could be less strict, as crops would be less affected by shading conditions and food security issues would likely be less impacted by drought. Stricter targets in those areas might make it impossible to attain the required CY, effectively prohibiting AV systems. On the other hand, in regions where droughts are frequent and/or severe, more rigorous CY targets may be necessary since crops benefit more from shading in these conditions.

The insights gained from this study not only support policymakers but also benefit PV and AV companies. Improved accuracy in MLR models allows for more flexible CY targets, enabling the design of systems with higher specific PV capacities (expressed in kW_p/ha). This increase in energy conversion efficiency per unit of land can significantly boost renewable energy output while maintaining agricultural productivity [52,76]. Ultimately, such advancements contribute to achieving decarbonization goals and accelerating the broader transition toward sustainable energy systems.

5. Conclusions

This study aimed to investigate the impact of the environmental factor SPEI on CY in conjunction with shading level. SPEI serves as a drought index that reflects soil moisture and temperature conditions during the crop growing season, a factor that is often overlooked in previous meta-analyses on the impacts of shading on CY. The following conclusions can be drawn from this study:

- The performance metrics for all crop categories investigated improved significantly, except for Forage and Fruits. The least improvement was observed in the Fruit category, which saw only a 0.01 increase in R^2, whereas the Grain Legumes category experienced the most significant improvement, with a 0.36 increase. It is important to note that the improvement observed in Leafy Vegetables may be unreliable due to limited data, as there were only five data points available for this category.
- Models incorporating SPEI data exhibited greater certainty across all crop categories, with performance improvements ranging from a minimum increase of 13 % in Forage to a maximum increase of 47 % in Root Crops.
- For the Berries category, environmental conditions represented by SPEI had a more substantial effect on CY than shading levels. Additionally, Forage demonstrated drought tolerance, while the Maize variant studied proved to be shade resistant as well [64,80].
- The MLR models developed in this study can assist policymakers in multiple ways. They provide more accurate assessments of the impact of AV system deployment on various crop categories at both national and regional levels. Additionally, these models can evaluate current AV policies or inform the creation of new policies based on factors such as shading rate, climate conditions, drought occurrences, and specific crop categories.
- The results of this meta-analysis, as those conducted previously, can be used to derive fundamental information about crop adaption mechanisms under shading conditions. This information can be passed to more mechanistic crop models to further enhance modelling accuracy of AV integrated platforms and accordingly improve prediction of performance before installation.

SPEI emerged as a critical determinant in most crop categories tested, as evidenced by performance metrics and uncertainty quantification. Therefore, integrating SPEI with the established shading level factor significantly improved all performance metrics. One limitation of this research is the lack of sufficient data across all crop categories, particularly for Leafy Vegetables, which had minimal data. Future studies should consider additional factors that influence CY to further enhance the predictability of CY responses in agricultural varieties.

CRediT authorship contribution statement

Sultan Tekie: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sebastian Zainali:** Writing – review & editing, Validation, Formal analysis. **Tekai Eddine Khalil Zidane:** Writing – review & editing, Validation, Supervision. **Silvia Ma Lu:** Writing – review & editing, Validation. **Mohammed Guezgouz:** Writing – review & editing, Validation, Supervision. **Jie Zhang:** Writing – review & editing, Writing – original draft, Validation, Formal analysis, Data curation. **Stefano Amaducci:** Writing – review & editing, Validation. **Christian Dupraz:** Writing – review & editing, Validation. **Pietro Elia Campana:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: The company European Energy AB is financing half of Sebastian Zainali's Ph.D. salary.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.nexus.2025.100523.

Appendix

Analysis concerning the combined non-irrigated and irrigated data

Table A1 presents the performance metrics for the linear model both with and without SPEI statistical values across all crop categories, including both irrigated and non-irrigated data. This table can be directly compared to Table 1 of the manuscript, which focuses solely on non-irrigated data. This comparison illustrates the impact of irrigation on the performance metrics. Table A2 offers uncertainty quantification metrics for all crops, encompassing both irrigated and non-irrigated conditions. It can be compared with the results in Table 3, which pertains only to non-irrigated conditions. These supplementary tables emphasize the rationale for concentrating on non-irrigated studies while also demonstrating how irrigation can alleviate the effects of environmental factors, such as drought, thereby influencing the reliability and significance of the CY results related to shading. It is important to note that the Root Crop category is not included, as the data available for that category pertains solely to non-irrigated conditions.

Table A1
Performance metrics of the linear models without/with SPEI statistical values for combined irrigated and non-irrigated crop categories.

Crop category	R^2		MSE		MAE		Sample
	Without SPEI	With SPEI	Without SPEI	With SPEI	Without SPEI	With SPEI	
C3 Cereals	0.28	0.34	294.08	270.09	12.43	11.93	51
Berries	0.001	0.32	1594.93	1078.52	30.76	25.10	76
Maize	0.23	0.41	388.58	297.80	16.42	13.91	35
Grain Legumes	0.3	0.48	318.94	237.71	13.27	12.5	31
Fruits	0.00	0.23	1911.05	1478.27	22.40	26.06	42
Leafy Vegetables	0.01	0.38	562.29	349.82	14.41	12.64	46
Root Crop	–	–	–	–	–	–	
Forage	0.26	0.30	1421.22	1346.02	30.53/	28.41	73

Table A2
Uncertainty by the PICP for combined irrigated and non-irrigated crops (confidence interval: 95 %).

Crop category	SLR without SPEI	MLR model with SPEI	Sample
C3 Cereals	0.37	0.57	51
Berries	0.22	0.05	76
Maize	0.31	0.57	35
Grain Legumes	0.48	0.68	31
Fruits	0.69	0.76	42
Leafy Vegetables	0.48	0.48	46
Root Crop	–	–	–
Forage	0.22	0.49	73

For the investigated non-irrigated data, introducing the SPEI improves the model accuracy because, as it is discussed in the main part of this study, as it integrates information related to water avaliability, thus validating the main hypothesis. As can be seen in Table A1, for the combined non-irrigated and irrigated data, the model loses accuracy due to the wider data spread.

Analysis concerning only irrigated data

Tables A3 and A4 present the results using only irrigated crop data. Table A3 can be compared directly to Table 1 for non-irrigated crops and to Table A1 for combined non-irrigated and irrigated crops.

Table A3
Performance metrics of the linear model without/with SPEI statistical values for irrigated crop categories.

Crop category	R^2		MSE		MAE		Sample
	Without SPEI	With SPEI	Without SPEI	With SPEI	Without SPEI	With SPEI	
C3 Cereals	0.40	0.73	331.22	150.74	14.74	8.85	25
Berries	0.02	0.97	126	3.4	7.11	1	10
Maize	0.97	0.97	21.58	21.58	3.63	3.50	6
Grain Legumes	0.85	0.90	82.61	54.47	5.92	6.67	11
Fruits	0.01	0.84	4029.6	654.99	45.45	22.17	17
Leafy Vegetables	0.01	0.43	155.61	90.38	9.55	7.41	41
Root Crop	–	–	–	–	–	–	–
Forage	0.71	0.94	274.45	55.28	13.45	5.90	13

Table A4
Uncertainty by the PICP for irrigated crops (confidence interval: 95 %).

Crop category	Linear model without SPEI	MLR model with SPEI	Sample
C3 Cereals	0.44	0.80	25
Berries	0.90	0.90	10
Maize	0.83	1.0	6
Grain Legumes	0.82	0.91	11
Fruits	0.71	0.94	17
Leafy Vegetables	0.37	0.51	41
Root Crop	–	–	–
Forage	0.77	0.92	13

In the analysis of only irrigated data, lower error metric values can be achieved compared to non-irrigated data, regardless of whether the SPEI is included. These results can be explained as follows:

- When analyzing the data without considering SPEI, a clearer relationship between CY and the shading level becomes apparent. Irrigation can offset the benefits of shading, indicating that CY is primarily influenced by shading rate, as water is not a limiting factor. While the crops are reported as irrigated, many studies do not provide detailed information regarding the extent or quantity of irrigation applied. This lack of specific irrigation data limits the ability to fully assess its impact on crop performance across different environmental and water management conditions in the analysis.
- The analysis using the SPEI shows a stronger correlation, despite shading is the main limiting factor. Irrigated crops are typically those that are more susceptible to drought or are situated in regions that experience drought more frequently, which is linked to lower SPEI values. This trend is supported by SPEI data from the study locations for cereals, where the average SPEI for irrigated crops is lower than that for non-irrigated crops, indicating more severe drought conditions. Interestingly, the standard deviation for the irrigated dataset is also lower than that for the non-irrigated dataset. This observation reinforces the notion that irrigation was applied during more intense drought periods. Such information suggests a higher R^2 value, as the shading rate remains the primary influencing factor. Furthermore, the lower and more consistent SPEI values in the irrigated dataset resemble the effects of smoothed data, which tend to increase the R^2 value, indicating that the irrigated dataset is smoother and has a lower standard deviation.
- For irrigated crops, drought or water availability is not usually the primary limiting factor affecting yield. Instead, other factors like shading play a more significant role in this study. Therefore, even without considering the SPEI, the original R^2 value for irrigated crops is already higher when compared to non-irrigated, which is expected. While including SPEI does increase the R^2 value further, as indicated in Table A3, this relative increase in percentage terms is minimal. In contrast, for non-irrigated crops, water and shading do act as limiting factors. Consequently, the original R^2 value without SPEI is typically lower for non-irrigated crops than for irrigated crops. However, after including SPEI, a more substantial relative increase in the R^2 value for non-irrigated crops is observed.

It is important to recognize that the data for irrigated and non-irrigated crops within each category are not evenly matched in terms of quantity and crop type. For example, Fig. A1 shows significant differences in the variety and number of irrigated versus non-irrigated crops across all analyzed categories. This discrepancy makes it difficult to draw more in-depth comparisons, as each category lacks consistency between the irrigated and non-irrigated datasets. Additionally, some crop categories contain little or even no data for one of the groups, either irrigated or non-irrigated, which further complicates any comprehensive comparison. These differences are crucial to consider as they affect the reliability and scope of the conclusions drawn from the data regarding the effects of irrigation across various crop types.

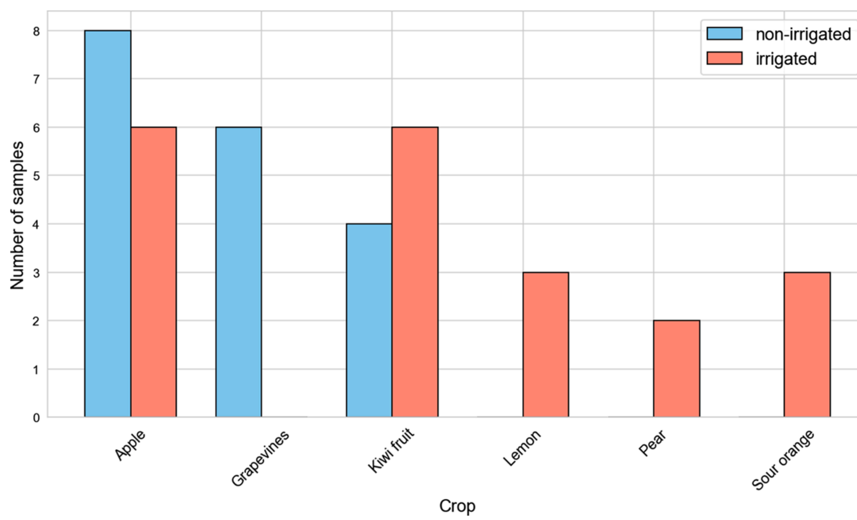

Fig. A1. Types of Fruits and data points included in the dataset for irrigated and non-irrigated crop categories.

Data availability

Data will be made available on request.

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