The initial version of this manuscript was submitted to the peer-reviewed journal *Energy Nexus* on November 21, 2024. Please note that it has not yet undergone peer review or been formally accepted for publication. An earlier version was previously submitted to *Environmental Research Letters* on July 2, 2024. Subsequent versions of the manuscript may differ in content. We welcome feedback and encourage you to contact the corresponding authors with any questions or comments.

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

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Abstract

Extensive research has explored the impact of shading on vegetation growth and crop yield (CY) under agrivoltaic (APV) systems. These studies have revealed a notable connection between shading and CYs, with certain crop varieties showing benefits from shadings e.g., Berries and Leafy Vegetables, Forage remaining largely unaffected, and some crops e.g., Cereals, Grain Legumes, Fruits, and Root crops experiencing reduced yields when subjected to shaded conditions. Previous studies often overlooked environmental factors such as temperature, evapotranspiration, and precipitation when assessing shading effects on CY, making it difficult to fully understand their impact on crop performance. This study seeks to address this research gap by integrating a drought index, known as the Standardized Precipitation Evapotranspiration Index (SPEI), into existing improved meta-analysis on shade and CY across various crops. SPEI, encompassing information on potential evapotranspiration, and precipitation is highly relevant to soil moisture, and accessible worldwide with a reasonable temporal resolution. Multiple linear regression (MLR) techniques are applied to analyse different crop categories. The MLR models' results with and without incorporating SPEI are compared to assess the influence of shading on determining CY amidst varying environmental conditions. The inclusion of SPEI in MLR models resulted in improved performance metrics across all crop categories with good sample sizes, with the least and most significant improvements observed for Fruit (1% increase in model precision) and Berries (40% increase in model precision) respectively.

The analysis is strengthened by uncertainty quantification, demonstrating how the predictability of CY improves with the inclusion of SPEI, supported by a 95% confidence level. The MLR model in all crop categories showed improved certainty when SPEI was factored in, compared to using shading alone as a determinant for CY in the uncertainty analysis. Similarly, incorporating SPEI into the uncertainty analysis of the MLR models enhanced the certainty levels across all crop categories, with the smallest improvement observed in Forage at 13% and the largest in Root Crops at a 50% increase.

Keywords: Agrivoltaics, Standardized Precipitation Evapotranspiration Index, Shading, Multiple linear regression, Crop Yield, Meta-analysis.

1 Introduction

Large-scale ground-mounted Photovoltaic (PV) systems are one of the most economically competitive renewable energy conversion technologies to supply green electricity at low levelized cost of electricity and reach grid parity in several countries and regions around the world [1, 2, 3]. However, the extensive deployment of this technology creates rivalry between land use for energy and food. Agrivoltaic (APV) systems have been proposed as an integrated solution to solve this dispute by synergically integrating solar energy conversion and food production. Several research studies have assessed the impact of APV shading on CY. This line of research is timely since the ongoing development of APV systems regulatory frameworks shows a trend to set the maximum allowed CY reduction under APV systems compared to open-field conditions [4].

For instance, Germany has taken an initial step toward standardising APV system specifications with the technical specification DIN SPEC 91434:2001-05 [5]. This specification mandates that crop reduction should not exceed one-third of the reference yield without PV [6]. In Italy, the Italian Ministry of the Environment and Energy Security issued guidelines indicating that agricultural activity should continue on at least 70% of the areas occupied by APV systems and PV modules coverage of agricultural fields should remain below 40% [6]. The Italian Ministry made no reference to CY reduction, but the Italian Standards Body UNI, in its specification “Agri-voltaic systems - Integration of agricultural activities and photovoltaic implants" [7], indicated that CY under APV should not be reduced to less than 70% as compared to full light conditions. Additionally, the French government issued Decree No. 2024-318, defining conditions for installing APV systems. According to this decree, agricultural CY should not be reduced by more than 10%, and PV installations on the field cannot cover more than 40% of the crop field for large arrays with an installed capacity above 10MWp [8, 9]. The Department of Climate Action, Food, and Rural Agenda of the autonomous region of Catalonia in Spain issued a provision regulating the deployment of APVs on farmland. The regulation stipulates that APVs can cover no more than 15% to 20% of the farmland, depending on the structure's height, and that CY must be maintained above 60% [10]. These regulations force farmers operating APV systems to achieve a minimum CY that is supposed to warrant the continuity of the agriculture activity in the APV system.

The primary challenge associated with APV systems lies in its ability to establish a micro-climate within the agricultural field, which may exert beneficial or detrimental effects on crop development and yield [11]. 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 shading sensitive [12, 13, 14]. One primary market and research challenge is to simulate or assess the impact of shading on CYs to meet policy targets on CY reduction under APV systems.

[15] conducted a meta-analysis investigating the impact of shading on CY. Through this comprehensive analysis, the research aimed to elucidate the nuanced effects of shading across different crop categories (Berries, Fruits, Fruity Vegetables, Leafy Vegetables, C3 Cereals, Maize, Tubers/Root Crops, Grain Legumes, and Forages), offering valuable insights for agricultural practices and management strategies. The research demonstrated notable discrepancies among crop types in their yield responses to escalating levels of shading, supporting the notion that distinct crop varieties demonstrate diverse responses to decreasing solar irradiation. Similarly, using literature data, [4] used experimental data to correlate the relative CY under APV systems with the ground coverage ratio (GCR), which was used as a proxy for the shading rate on the crops. The author differentiated the type of APV systems (greenhouse vs open field; fixed panels vs mobile panels) but not between rainfed and irrigated systems. A regression between GCR and relative CY was applied in the metanalysis to predict the yield of crops in agrivoltaics and agroforestry. The number of site-crop data was too low to establish a regression for each type of APV system or for different climatic zones. A common

objective of [15] and [4] is to provide simple correlations between shading rate and relative CY, which can be used, for instance, to support APV policies. Indeed, those correlations can be used as an easy tool to develop policies that regulate the sector especially when it concerns the maximum allowed CY reduction on a large-scale. Nevertheless, a major limitation of the abovementioned studies is that they only consider the effect of shading rate, or GCR, on CY, while meteorological conditions, wetness of the soil, or other factors critical to CY are neglected. For example, it is extremely difficult to compare the results from two identical APV system designed with the same shading rate on the ground and installed in the same location and with the same crop grown underneath if the results are retrieved from different years marked out by significantly different weather conditions (i.e., wet season versus dry season). During the wet year, the shading rate might cause detrimental effects on the CY by curtaining the irradiance level, while during a dry year, the shading rate can positively affect the CY by alleviating heat stress and evapotranspiration.

To support policymakers with more accurate information, additional environmental factors should be included as independent variables of the correlation between CY and shading level. The drought factor is widely recognized as a critical determinant of crop yield, consistently highlighted in numerous studies examining the environmental impacts on agricultural productivity [16, 17]. Its significance underscores the need for comprehensive analysis when assessing factors influencing crop performance under varying climatic and environmental conditions. This study seeks to incorporate a drought indicator into existing research on shading effects on CY to evaluate the significance of environmental conditions in determining the resulting CY.

Many indicators have been developed for drought monitoring, and the most well-known ones include the Standardised Precipitation Index (SPI), the Palmer Drought Severity Index (PDSI), and the Standardised Precipitation Evapotranspiration Index (SPEI). SPI is a multi-scalar index that only relies on precipitation but can be calculated at different time scales [18]. PDSI uses precipitation and temperature information but has a fixed time scale [19]. SPEI, which considers both precipitation and temperature has multi-scalar characteristic [20], was selected to describe the drought conditions in this study. To calculate the SPEI, a simple climatic water balance factor (precipitation minus evapotranspiration) over different time scales (1 month up to 48 months) is used as the input and normalised into a log-logistic distribution. For details of SPEI calculation, please refer to [20]. The advantages of SPEI enable consistent and more accurate drought analysis across time and space and at different time scales. In recent years, SPEI has been increasingly used in agriculture to explore CY response [21, 22, 23, 24]. In the APV sector, the SPEI, as an index of drought, easily retrievable from services like the SPEI database [25], could enhance the understanding of the relationship between shading rate and CY, by providing crucial information concerning temperatures, evapotranspiration, and water availability.

2 Data and Methods

This study builds on the meta-analysis conducted by [15] and [4]. The study by [15] correlated the shading level for various types of shading materials (PV, shading cloth, and intercropping shading) with CY data. Similarly, [4] used the GCR of APV systems to represent shading levels. In contrast, this study adds an indirect environmental factor, the SPEI, to the methods previously applied by [15] and [4]. SPEI is a critical microclimate parameter highly correlated to soil moisture [26, 27, 28] but missing in previous meta-analyses, which can significantly affect the effect of shading on crop yield.

2.1 Data

[15] initially included 58 studies with shading treatments and corresponding CYs. An additional 26 research studies were collected in this study using the keyword "shading level and CY", totalling 84 studies. The proposed meta-analysis enriched previous databases with further key variables to enhance the understanding of shading rate and CY under APV systems. These variables include the definition of the crop growing season (i.e., sowing and harvest dates). Thus, this work excluded previously published studies that lack more explicit information on at least the crop plantation and harvest dates. This information is necessary to retrieve the temporal trend of the SPEI during the crop growing season. For this reason, only 59 articles were viable for the proposed meta-analysis in this study, with 25 studies excluded due to insufficient information regarding the timing of the growing season. The crop growing season has been retrieved from the published studies, if specified, or derived from the specified planting or harvest dates relying on the specific crop growing season as reported by [29].

The remaining studies were divided into irrigated and non-irrigated groups. Of these, 41 studies were non-irrigated and are included in the main analysis, as irrigation can reduce drought impact on crops and diminish the shading benefits. The 18 irrigated studies are presented in the appendix to underscore the differences between irrigated and non-irrigated crops. To further highlight these differences, a detailed comparison of relevant data appears in the appendix. The tables in the appendix mirror those in the main study and offer a more in-depth look at irrigation's impact on various variables. While the main body focuses on key findings, the appendix provides supplementary data for readers seeking a comprehensive analysis. Including these tables strengthens the study's depth and clarifies variations between irrigated and non-irrigated outcomes. In the study conducted by [15], crops were categorised into distinct groups, including C_3 Cereals, Berries, Maize, Grain Legumes, Fruits, Leafy Vegetables, Root Crops, Forage, and Fruity Vegetables. 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 the effect of irrigation.

The monthly SPEI values during the crop growing season were retrieved from the SPEI database [25] using the geographic coordinates extracted from all the research studies included in this meta-analysis. Since SPEI can vary significantly during the crop growing season, for instance, due to the alternance of extremely wet and dry periods, statistics such as mean, minimum, maximum, and standard deviation of the SPEI are utilised as independent variables. It must be noted that if the SPEI is stable during the crop growing season, the mean, minimum, maximum, and standard deviation of the SPEI might be highly correlated and thus redundant.

The research studies for the proposed meta-analysis were sourced from various locations worldwide, as depicted in Figure 1. To provide a wide relevance to our research a broad range of shading levels across diverse climatic conditions and cropping patterns were considered.

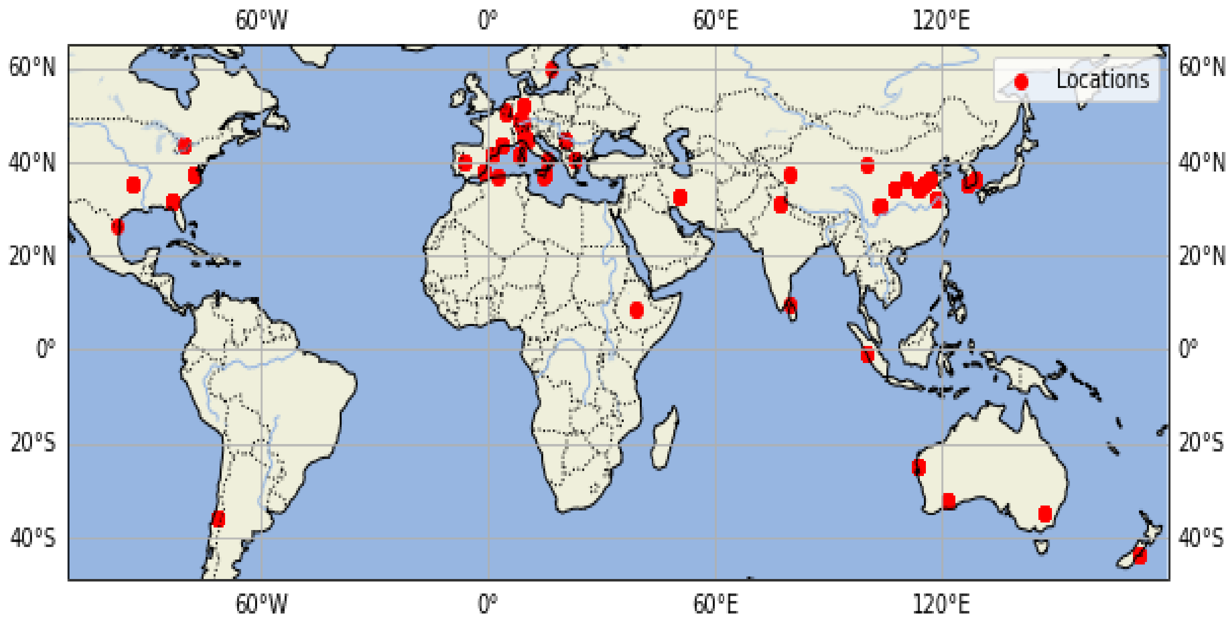

Figure 1: Map of the locations reported in the studies being part of the meta-analysis conducted in this work.

2.2 Method

2.2.1 Regression Model

In this study, a simple linear regression- SLR (shading level as the sole determinant as done previously by [15] and [4]) and a multiple linear regression- MLR (shading level and SPEI as determinants) compared to investigate the impact of the inclusion of the SPEI on CY predictability. The shading level variable spans from 0 to 100, with 100 representing complete absence of light. In contrast, SPEI values range from below -2, indicating extreme dryness, to above 2, indicating extreme wetness. To ensure consistency, it was essential to normalize these variables, bringing them onto a comparable scale for accurate analysis.

$$x' = 100 * \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

where x is the original value, x_{min} is the minimum of the data set, x_{max} is the maximum of the data set, and x' the normalised value. The equation normalises the SPEI values in the range of 0 to 100.

The model used for SLR is as follows:

$$Y = \beta_0 + \beta_1 X1, \quad (2)$$

where, Y is the dependent (response) variable, i.e., the CY, β_0 is the intercept, and β_1 is the slope coefficient, and X1 is the independent variable, i.e., the shading level.

With shading level and SPEI statistics as independent variables, the model used for MLR is as follows:

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

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

The mean squared error (MSE), mean absolute error (MAE), and coefficient of determination (R^2) are used as performance metrics to compare the LR model against the MLR model, which adds the SPEI statistics as independent variables.

2.2.2 Uncertainty quantification

The prediction intervals are used to evaluates the differences in uncertainty levels between the SLR model (without SPEI statistics) and the MLR model (with SPEI statistics) at a 95% confidence level. The model that better fits the measured CY percentage with the prediction interval is deemed more certain and can be observed visually. Prediction Interval Coverage Probability (PICP) is used to quantify certainty, complementing the visual presentation. PICP values range from 0 to 1, with higher values indicating greater certainty.

3 Results and discussion

3.1 Performance comparison

In Figure 2, 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 35% to 53%, MAE decreased from 8.96% to 6.81%, and MSE decreased from 173.29%^{2} to 123.58%^{2}.

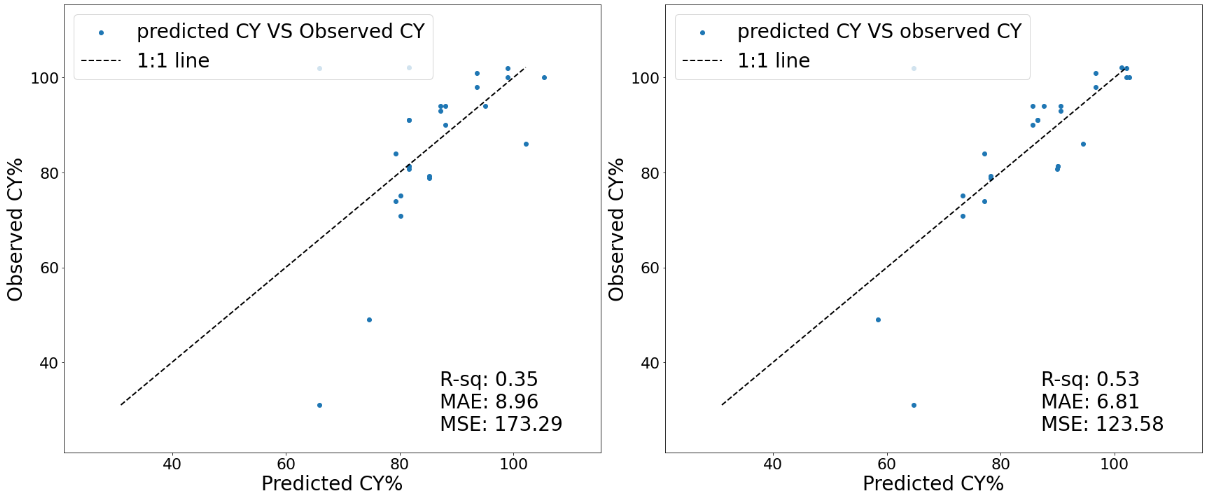

Figure 2: Predicted CY percentage vs Observed CY percentage not considering (i.e., in LR model) (left) or considering (i.e., in MLR model) (right) the SPEI statistics for C_3 Cereal non-irrigated.

The performance metrics for all the investigated crop categories are summarised in Table 1. Across all 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 1% when SPEI was included. For Forage, the improvement was also relatively low, with an R^2 value of around absolute 7%, significantly lower than other crop categories, which achieved R^2 improvements above absolute 18%. In general, Forage displayed poor performance for both models, with R^2 values of only 11% without SPEI and 18% with SPEI. The result for Leafy Vegetables may be unreliable, as the test was based on a very small data set, causing the R^2 to spike from 2% to 100% with the addition of SPEI.

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

Crop category	**R^2**		**MSE**		**MAE**		**N$\underline{^0}$**
	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	0.03	0.43	853.67	498.37	23.07	18.05	40
Maize	0.01	0.35	243.9	161.39	13.26	9.52	25
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	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 presents the linear equation correlating the input variables and the CYs. Y represents predicted CY, X1 represents the shading level, X2 represents mean SPEI, X3 represents minimum SPEI, X4 represents maximum SPEI, and X5 represents standard deviation SPEI. Those handy correlations can be used to derive potential CY reductions based on shading level (i.e., design parameter of APV systems) and historical values of SPEI statistics.

Table 2: Summary of the equation retrieved for SLR and MLR models for non-irrigated crop categories with X1 is shading level, X2 is SPEI mean, X3 is SPEI minimum, X4 is SPEI maximum and X5 is SPEI standard deviation.

Crop Type	Equation
C3 Cereals	$105.35 - 0.78X1$
	$71.34 - 0.76X1 + 5.84X2 + 12.47X3 - 8.01X4 + 67.09X5$
Berries	$93.98 + 0.45X1$
	$185.30 + 0.14X1 - 51.14X2 + 100.52X3 - 5.83X4 + 95.71X5$
Maize	$79.72 - 0.11X1$
	$89.30 - 0.38X1 + 75.45X2 - 31.46X3 - 45.5X4 + 15.28X5$
Grain Legumes	$94.70 - 1.05X1$
	$126.25 - 0.87X1 - 37.61X2 + 48.93X3 - 5.39X4 + 38.47X5$
Fruits	$105.44 - 0.43X1$
	$107.06 - 0.42X1 + 6.52X2 - 5.42X3 - 2.22X4 - 5.94X5$
Leafy Vegetables	$106.92 + 0.28X1$
	$460.35 - 2.6X1 + 16.23X2 + 190.62X3 + 16.15X4 - 75.47X5$
Root Crop	$111.55 - 1.06X1$
	$20.59 - 0.81X1 - 26.50X2 - 17.96X3 - 22.61X4 + 84.89X5$
Forage	$127.48 - 0.75X1$
	$78.68 - 0.93X1 + 86.36X2 - 31.22X3 - 64.20X4 + 123.21X5$

3.2 Uncertainty

LR models with uncertainty quantification were utilised to estimate both upper and lower prediction intervals, considering the inclusion and exclusion of SPEI statistics as independent variables. A comparative uncertainty analysis was conducted by observing the fill plot with and without SPEI at a 95% confidence level. The model with a result of predicted CY% intervals that better fit the measured CY% within the intervals are considered more certain. PICP is used to quantify the uncertainty level for both models, providing a numerical comparison of the visual differences between the models. Figure 3 visually examines how the measured CY% falls within the prediction intervals of both models—with and without SPEI—for C3 Cereals, while Table 3 quantifies this comparison through the PICP metric.

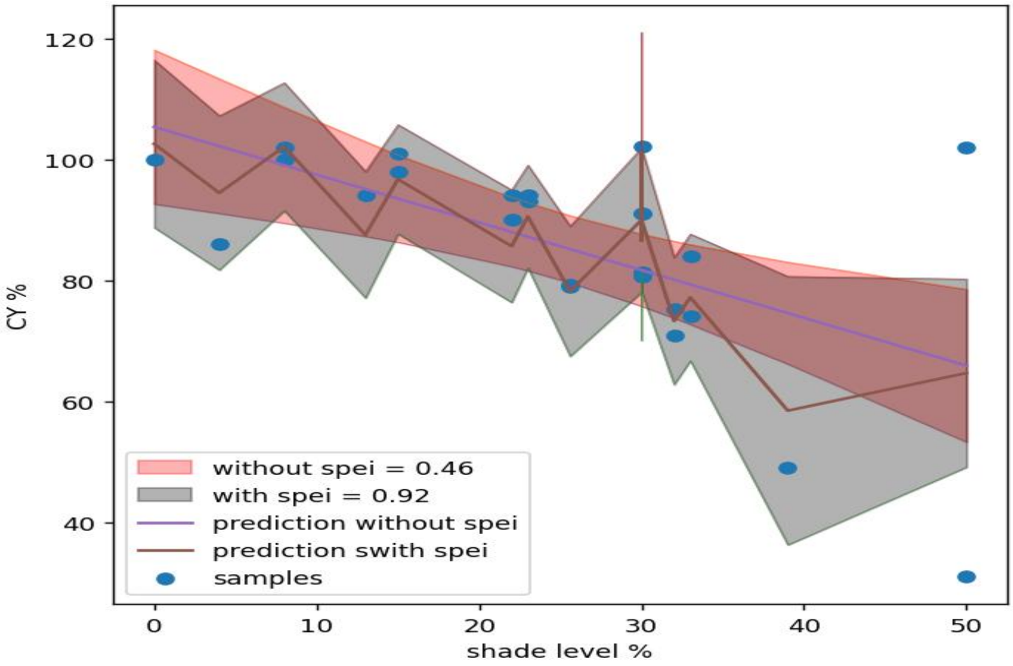

Figure 3: Uncertainty analysis with and without SPEI for C3 Cereals at 95% confidence interval.

Table 3: Uncertainty by the PICP for non-irrigated crops (confidence interval: 95%)

Crop category	**SLR without SPEI**	**MLR model with SPEI**	**N⁰**
C3 Cereals	0.46	0.92	26
Berries	0.35	0.55	40
Maize	0.40	0.76	25
Grain Legumes	0.55	0.77	22
Fruits	0.61	0.89	18
Leafy Vegetables	1	1	5
Root Crop	0.53	1	15
Forage	0.24	0.37	62

As shown in Figure 3 and Table 3, the model with SPEI shows higher certainty than that without SPEI. The minimum difference in uncertainty was observed with Forages, where the model with SPEI showed an absolute 13% higher certainty than the model without SPEI. The most remarkable difference was seen with Root Crop, with the model including SPEI showing up to 47% higher certainty. The test for Leafy Vegetables indicated 100% certainty for both models with and without SPEI, which could be misleading due to the limited dataset, consisting of only 5 data points.

4 Policy implications

The primary objective of this meta-analysis was to underscore the combined impact of the environmental factors implicitly included in the SPEI and shading level on CY . Previous studies have focused only on investigating the CY reduction from shading by only correlating it with the shading level for shaded crops or the ground coverage ratio for APV systems [4,15]. Providing accurate information about how the shading level produced by an APV system affects CY is fundamentally important for the large-scale deployment of these systems. It is also crucial to assess APV system performance before installation without relying on integrated mechanistic models [30, 31].

The analysis conducted in this study focused only on non-irrigated crops because irrigation can offset the benefits produced by the APV systems' shadings, which leads to misleading relationships between the shading levels produced by the APV system and the resulting CY. It should be noted that drought conditions can have little to no impact on crops with controlled irrigation, which neutralises the effect of environmental stress [32]. The analysis performed for all crop categories, encompassing both irrigated and non-irrigated data, as well as the subset focusing solely on irrigated crops, is presented in the appendix.

While comparing the results of SLR models (CY response is only a function of the shading level) versus MLR models (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 an absolute 18% (i.e., the R^2 improves from 35% to 53%, see Figure 2). From a policy perspective, the MLR models developed in this study could support policymakers to make more accurate assessments on the effects of APV systems deployment on CY at national or regional level, and thus set less stringent CY targets.

While policymakers often establish CY targets to ensure that farmers maintain agricultural production under APV systems, reducing the uncertainty associated with CY reductions at national or regional level could lead to a reduction of CY targets while guaranteeing food security. Defining less stringent CY targets for a specific country or region could also be achieved by analysing the effects of frequency and severity of drought conditions and shading levels produced by the APV systems on the CY. The effects of those can be verified with the model developed in this study. More specifically, in countries or regions with low infrequent and non-severity of drought conditions, the CY targets could be less strict given that crops would benefit less from shading conditions. Contrarily, if the frequency and/or severity of drought occurrences is high, more restrictive CY target could be demanded as in these conditions the crops benefit more from the shade. This support for policymakers also extends to PV and APV companies, as relaxed crop yield targets allow for higher specific PV capacity installations (i.e, kWp/ha). This, in turn, enhances energy production per unit of land, contributing to decarbonisation goals and advancing energy transition efforts.

The crop category "Fruits" shows no improvement with the inclusion of SPEI, as much of the data comes from Mollerussa, Spain, which experienced low rainfall and higher temperatures during consecutive years of the experiment period [33]. The SPEI data collected from this site also reflects the area's low rainfall, and the result in Table 1 of this paper aligns with these conditions showing no significance to the yield in the Fruits crop category. The crop category "Maize" displayed minimal sensitivity to shading when analysed using linear regression without incorporating SPEI. However, performance metrics significantly improved when SPEI was included alongside shading levels. While maize is typically expected to react to shading because it is shade intolerant, some of the maize varieties used in this study demonstrated higher shade tolerance than expected, which may explain the observed variation [34].

Some source data indicated negligible yield reduction with increased shading levels on Forage crops [35, 36], while other sources reported an increase in yield with increased shading [37, 38]. These results underscore the practical importance of shading levels and SPEI statistics in predicting CY, advocating for their inclusion in APV systems research and management.

In agricultural research, statistical hypothesis tests are commonly employed to evaluate the significance of each independent variable on CY which can help determine how influential a proposed determinant is on the CY. However, in this study, we opted not to use statistical hypothesis tests. The primary reason is that all the SPEI statistics—mean, minimum, maximum, and standard deviation—are considered as determinants. These statistics can be highly correlated with each other, which complicates the process of forming 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, we decided to focus on the overall impact of these SPEI statistics on CY without relying on hypothesis tests, to avoid potential issues arising from multicollinearity and to provide a clearer understanding of their combined influence. This approach allows us to better capture the complex interactions between these climatic variables and CY.

5 Conclusions

This study aimed to explore the impact of the environmental factor SPEI on crop yield (CY) in conjunction with shading level, a factor often overlooked in most meta-analyses of shading and crop yield. A drought index, representing environmental conditions during crop growing season, SPEI was added in addition to the commonly studied shading level factor. The following conclusions can be drawn:

- The performance metrics for all the investigated crop categories improved significantly, except for Forage and Fruits. The least improvement was observed in the Fruit category, with an R^2 increase of 1%, while the Berries category experienced the most improvement, with an R^2 increase of 40%. The improvement observed in Leafy Vegetables may be unreliable due to the limited data, as only five data points were available.
- Similarly, models with SPEI information demonstrated greater certainty across all crop categories, with a minimum increase of 17% in Forage and a maximum increase of 50% in Root crops.
- For the crop category Berries, environmental conditions represented by SPEI had a greater impact on CY than shading levels. Forage proved to be drought tolerant while the Maize variant used in some studies proved to be shade resistant in this study as well [34, 39]

SPEI was a critical determinant in most crop categories tested, as evidenced by performance metrics and uncertainty quantification. Therefore, incorporating SPEI with the established shading level factor significantly improved all performance metrics. A limitation of this research was the need for more data for some crop categories (e.g., Leafy Vegetables). Future studies should consider additional factors that influence CY to enhance the predictability of CY responses under shading.

Acknowledgements

The authors acknowledge the financial support received from the Swedish Energy Agency through the projects “Evaluation of the first APV system facility in Sweden to compare commercially available APVtechnologies (MATRIX)" (grant number P2022-00809) and “The Solar Electricity Research Centre (SOLVE)” (grant number 52693-1). Pietro Elia Campana acknowledges FORMAS, the Swedish Research Council for Sustainable Development, for the funding received through the early career project “Avoiding conflicts between the sustainable development goals through APVsystems”, grant number FR-2021/0005. The authors also acknowledge the Swedish Board of Agriculture for their financial support through the project “Samarbete för ökad kunskap om samexistens mellan jordbruk och solbruk i Sverige” 2023-4323-1.

References

[1] K. shah, ‘India’s Utility-Scale Solar Parks a Global Success Story’, *Institute for Energy Economics and Financial Analysis (IEEF).*, 2020. [Online]. Available: https://ieefa.org/wp-content/uploads/2020/05/Indias-Utility-Scale-Solar-Parks-Success-Story_May-2020.pdf

[2] Z. A. Liza and M. R. Islam, ‘Solar Park: The Next Generation Energy Source in Bangladesh’, *JENRR*, pp. 9–19, Feb. 2020, doi: 10.9734/jenrr/2020/v4i230121.

[3] S. J. Thomas, S. Thomas, S. S. Sahoo, A. K. G, and M. M. Awad, ‘Solar parks: A review on impacts, mitigation mechanism through agrivoltaics and techno-economic analysis’, *Energy Nexus*, vol. 11, p. 100220, Sep. 2023, doi: 10.1016/j.nexus.2023.100220.

[4] C. Dupraz, ‘Assessment of the ground coverage ratio of agrivoltaic systems as a proxy for potential crop productivity’, *Agroforestry Systems*, Sep. 2023, doi: 10.1007/s10457-023-00906-3.

[5] ‘DIN SPEC 91434:2021-05: Agri-photovoltaic systems - Requirements for primary agricultural use’, May 2021. [Online]. Available: https://dx.doi.org/10.31030/3257526

[6] A. Chatzipanagi, N. Taylor, and A. Jaeger-Waldau, ‘Overview of the Potential and Challenges for Agri-Photovoltaics in the European Union’, *JRC SCIENCE FOR POLICY REPORT*, 2023, doi: doi:10.2760/208702.

[7] *UNI/PdR 148:2023. Agri-voltaic systems - Integration of agricultural activities and photovoltaic implants*, 2023. [Online]. Available: https://store.uni.com/en/uni-pdr-148-2023

[8] GWÉNAËLLE DEBOUTTE, 'France issues new rules for agrivoltaics', Apr. 09, 2024. [Online]. Available: https://www.pv-magazine.com/2024/04/09/france-issues-new-rules-for-agrivoltaics/

[9] 'Decree No. 2024-318 of 8 April 2024 on the development of agrivoltaism and the conditions for the establishment of photovoltaic installations on agricultural, natural or forestry land.', *Legifrance*, Apr. 08, 2024. [Online]. Available: https://www.legifrance.gouv.fr/jorf/id/JORFTEXT000049386027

[10] S. Molina, 'Catalonia sets guidelines for agrivoltaics', *pv magazine*, Apr. 30, 2024. [Online]. Available: https://www.pv-magazine.com/2024/04/30/catalonia-sets-guidelines-for-agrivoltaics/

[11] M. Wagner *et al.*, 'Agrivoltaics: The Environmental Impacts of Combining Food Crop Cultivation and Solar Energy Generation', *Agronomy*, vol. 13, no. 2, p. 299, Jan. 2023, doi: 10.3390/agronomy13020299.

[12] D. Uldrijan, M. Černý, and J. Winkler, 'Solar Park – Opportunity or Threat for Vegetation and Ecosystem', *J. Ecol. Eng.*, vol. 23, no. 11, pp. 1–10, Nov. 2022, doi: 10.12911/22998993/153456.

[13] J. Widmer, B. Christ, J. Grenz, and L. Norgrove, 'Agrivoltaics, a promising new tool for electricity and food production: A systematic review', *Renewable and Sustainable Energy Reviews*, vol. 192, p. 114277, Mar. 2024, doi: 10.1016/j.rser.2023.114277.

[14] T. Semeraro *et al.*, 'Shading effects in agrivoltaic systems can make the difference in boosting food security in climate change', *Applied Energy*, vol. 358, p. 122565, Mar. 2024, doi: 10.1016/j.apenergy.2023.122565.

[15] M. Laub, L. Pataczek, A. Feuerbacher, S. Zikeli, and P. Högy, 'Contrasting yield responses at varying levels of shade suggest different suitability of crops for dual land-use systems: a meta-analysis', *Agron. Sustain. Dev.*, vol. 42, no. 3, p. 51, Jun. 2022, doi: 10.1007/s13593-022-00783-7.

[16] k. J. Dietz, J. Zörb, and C. M. Geilfus, 'Drought and crop yield', *Plant biology*, vol. 23(6), pp. 881–893, 2021, doi: https://doi.org/10.1111/plb.13304.

[17] B. T. Nguyen and H.-X. T. Ho, 'Design, Implementation and Performance Analysis of a Dual Axis Solar Tracking System', *Adv. sci. technol. eng. syst. j.*, vol. 5, no. 3, pp. 41–45, 2020, doi: 10.25046/aj050306.

[18] T. B. Mckee, N. J. Doesken, and J. R. Kleist, 'THE RELATIONSHIP OF DROUGHT FREQUENCY AND DURATION TO TIME SCALES', 1993. [Online]. Available: https://api.semanticscholar.org/CorpusID:129950974

[19] W. C. Palmer, 'Meteorological drought', US. Weather Bureau Res. paper, 1965. [Online]. Available: https://www.researchgate.net/publication/285600502_Meteorological_Drought_Research_Pa

per_No_45_1965_58_p/citation/download?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InB1YmxpY2F0aW9uIiwicGFnZSI6InB1YmxpY2F0aW9uIn19

[20] S. M. Vicente-Serrano, S. Beguería, and J. I. López-Moreno, 'A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index', *Journal of Climate*, vol. 23, no. 7, pp. 1696–1718, Apr. 2010, doi: 10.1175/2009JCLI2909.1.

[21] N. Qin, Q. Lu, G. Fu, J. Wang, K. Fei, and L. Gao, 'Assessing the drought impact on sugarcane yield based on crop water requirements and standardized precipitation evapotranspiration index', *Agricultural Water Management*, vol. 275, p. 108037, Jan. 2023, doi: 10.1016/j.agwat.2022.108037.

[22] H. Sjulgård, T. Keller, G. Garland, and T. Colombi, 'Relationships between weather and yield anomalies vary with crop type and latitude in Sweden', *Agricultural Systems*, vol. 211, p. 103757, Oct. 2023, doi: 10.1016/j.agsy.2023.103757.

[23] S. Mohammed *et al.*, 'Assessing the impacts of agricultural drought (SPI/SPEI) on maize and wheat yields across Hungary', *Sci Rep*, vol. 12, no. 1, p. 8838, May 2022, doi: 10.1038/s41598-022-12799-w.

[24] M. Santini, S. Noce, M. Antonelli, and L. Caporaso, 'Complex drought patterns robustly explain global yield loss for major crops', *Sci Rep*, vol. 12, no. 1, p. 5792, Apr. 2022, doi: 10.1038/s41598-022-09611-0.

[25] 'Global SPEI database'. 2024. [Online]. Available: https://spei.csic.es/spei_database/#map_name=spei01#map_position=1463

[26] Z. Pei, S. Fang, L. Wang, and W. Yang, 'Comparative Analysis of Drought Indicated by the SPI and SPEI at Various Timescales in Inner Mongolia, China', *Water*, 2020, [Online]. Available: https://api.semanticscholar.org/CorpusID:225578086

[27] S. Yuan, S. M. Quiring, and C. Zhao, 'Evaluating the Utility of Drought Indices as Soil Moisture Proxies for Drought Monitoring and Land–Atmosphere Interactions', *Journal of Hydrometeorology*, vol. 21, pp. 2157–2175, 2020, doi: 10.1175/jhm-d-20-0022.1.

[28] Z. H. Hoylman, Z. Holden, R. K. Bocinsky, D. Ketchum, A. Swanson, and K. Jencso, 'Optimizing Drought Assessment for Soil Moisture Deficits', *Water Resources Research*, vol. 60, no. 6, Jun. 2024, doi: 10.1029/2023wr036087.

[29] A. Richard G., P. L.S., R. Dirk, and S. M., 'FAO Irrigation and drainage paper No. 56', *Food and Agriculture Organization of the United Nations*, 1998, [Online]. Available: https://www.unirc.it/documentazione/materiale_didattico/1462_2016_412_24101.pdf

[30] S. Amaducci, X. Yin, and M. Colauzzi, 'Agrivoltaic systems to optimise land use for electric energy production', *Applied Energy*, vol. 220, pp. 545–561, Jun. 2018, doi: 10.1016/j.apenergy.2018.03.081.

[31] P. E. Campana, B. Stridh, S. Amaducci, and M. Colauzzi, 'Optimisation of vertically mounted agrivoltaic systems', *Journal of Cleaner Production*, vol. 325, p. 129091, 2021, doi: https://doi.org/10.1016/j.jclepro.2021.129091.

[32] P. S. Birthal, J. Hazrana, D. S. Negi, and G. Pandey, ‘Benefits of irrigation against heat stress in agriculture: Evidence from wheat crop in India’, *Agricultural Water Management*, vol. 255, p. 106950, 2021, doi: https://doi.org/10.1016/j.agwat.2021.106950.

[33] I. Ignasi and A. Sima, ‘The effect of anti-hail nets on fruit protection, radiation, temperature, quality and profitability of “Mondial Gala” apples’, *Journal of Applied Horticulture*, 2006, [Online]. Available: https://doi.org/10.37855/jah.2006.v08i02.22

[34] R. K. Dewi, I. Suliansyah, A. Anwar, A. Syarif, and M. Rahmah, ‘Effect of shading on plant growth of 4 varieties of hybrid corn’, *IOP Conference Series: Earth and Environmental Science*, vol. 1097, no. 1, p. 012011, Oct. 2022, doi: 10.1088/1755-1315/1097/1/012011.

[35] K. Pang, J. W. Van Sambeek, N. E. Navarrete-Tindall, C.-H. Lin, S. Jose, and H. E. Garrett, ‘Responses of legumes and grasses to non-, moderate, and dense shade in Missouri, USA. I. Forage yield and its species-level plasticity’, *Agroforestry Systems*, vol. 93, no. 1, pp. 11–24, Feb. 2019, doi: 10.1007/s10457-017-0067-8.

[36] P. E. Campana *et al.*, ‘Experimental results, integrated model validation, and economic aspects of agrivoltaic systems at northern latitudes’, *Journal of Cleaner Production*, vol. 437, p. 140235, 2024, doi: https://doi.org/10.1016/j.jclepro.2023.140235.

[37] S. Edouard, D. Combes, M. V. Iseghem, M. N. W. Tin, and A. J. Escobar-Gutiérrez, ‘Increasing land productivity with agriphotovoltaics: Application to an alfalfa field’, *Applied Energy*, vol. 329, p. 120207, 2023, doi: https://doi.org/10.1016/j.apenergy.2022.120207.

[38] S. Gray, A. Mahama, and W. Suza, ‘Alfalfa “Sholty” – Hardiness, Drought Tolerance, Conservation; DEVELOPMENT OF “SHOLTY” YELLOW FLOWERED ALFALFA (MEDICAGO FALCATA) VARIETY FOR SEMI-ARID GREAT PLAINS’, Colorado State University. [Online]. Available: https://colostate.pressbooks.pub/pgrsuccessstories/chapter/alfalfa-sholty-hardiness-drought-tolerance-conservation/

[39] D. Parsons, M. Lindberg, J. Oliveira, V. Picasso, and M. Halling, ‘Resilience of forages to drought in Nordic countries’, Jun. 2024.

Appendix

Table A1 presents the performance metrics for the linear model without/with SPEI statistical values for all crop categories and includes irrigated and non-irrigated data in the dataset. Table A1 can be directly compared to Table 1 in the main body, which shows the results including only non-irrigated data. This comparison illustrates the impact of irrigation on the performance metrics.

Table A2 provides the uncertainty quantification metrics for all crops, including both irrigated and non-irrigated conditions, and can be contrasted with the results in Table 3 that pertain only to non-irrigated conditions.

These supplementary tables underscore the rationale behind the primary focus on non-irrigated studies in the main body of the research. They highlight how irrigation can mitigate the effects of environmental factors, such as drought, thus influencing the reliability and significance of the results related to shading and CY.

In this section, the Root Crop category is not included as the used data in that category is only non-irrigated.

Table A1: Performance metrics of linear model with SPEI statistical values for all crops including in the dataset both non-irrigated and irrigated crop categories. The direct contrast of this result in the main body is Table 1.

Crop category	**R2**		**MSE**		**MAE**		**Nº**
	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**	**0.39**	**836.1**	**509.32**	**23.05**	**18.18**	**44**
Maize	**0.27**	**0.55**	**289.86**	**181.27**	**14.8**	**10.52**	**29**
Grain Legumes	**0.3**	**0.48**	**318.94**	**237.71**	**13.27**	**12.5**	**31**
Fruits	**0.00**	**0.29**	**2358.35**	**1668.86**	**26.53**	**29.4**	**33**
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 irrigated and non-irrigated crops (confidence interval: 95%).

Crop category	Linear model without SPEI	MLR model with SPEI	N$\underline{^0}$
C3 Cereals	0.37	0.57	**51**
Berries	0.27	0.45	**44**
Maize	0.34	0.76	**29**
Grain Legumes	0.48	0.68	**31**
Fruits	0.70	0.73	**33**
Leafy Vegetables	0.48	0.48	**46**
Root Crop	--	--	
Forage	0.22	0.49	**73**

The next section of the appendix presents a result showing only from irrigated crop fields.

Table B1: Performance metrics of linear model with SPEI statistical values for all crops including in the dataset both irrigated crop categories. The direct contrast of this result in the main body is Table 1 and Table A1.

Crop category	**R2**		**MSE**		**MAE**		**N<u>o</u>**
	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	**0.61**	**0.61**	**5.67**	**5.67**	**1.67**	**1.67**	**6**
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 B2: Uncertainty by the PICP for irrigated crops (confidence interval: 95%). The direct contrast of this result in the main body is Table 3 and Table A2.

Crop category	**Linear model without SPEI**	**MLR model with SPEI**	**N<u>o</u>**
C3 Cereals	0.44	0.80	**25**
Berries	0.83	0.83	**6**
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**

The following conclusions can be drawn from the appendix part:

1. For the investigated non-irrigated data, introducing the SPEI improves the model accuracy because, as it is discussed in the main body of this paper it introduces information directly related to soil moisture and it validates the hypothesis in the objective of this paper

2. For the investigated combined data of non-irrigated and irrigated cases, as seen in Appendix A1, the model suffers due to the wider data spread between the irrigated and non-irrigated parts.

3. For the investigated irrigated data as seen in Appendix B1, the better results compared to non-irrigated data, for both with and without including the SPEI, can be explained by the fact that:

   a. For analysing the data without SPEI, a more accurate relationship emerges between CY and shading rate. Irrigation appears to offset the benefits of shading rate, suggesting that CY might be better determined solely by shading rate, as water is not a limiting factor. Even if it is known that the crops are irrigated though without certainty about full irrigation or exact amounts this information is included in the paper without delving deeper into those specific details.

   b. For the analysis with SPEI, similar results show a better correlation due to shading being the main limiting factor. Logically, irrigated crops tend to be those more susceptible to drought or located in areas prone to drought, generally associated with lower SPEI values. This trend is confirmed by SPEI data from the study locations for cereals, where the average SPEI is lower compared to the non-irrigated dataset (indicating more severe drought conditions). Interestingly, the standard deviation for the irrigated data is also lower than for the non-irrigated dataset, supporting the idea that more severe droughts occur when irrigation is applied. This information suggests a higher R^2 value, as the shading rate remains the primary driver, while the lower and more consistent SPEI in the irrigated data resembles the effect of smoothed data on increasing R^2, with the irrigation dataset being smoother and having a lower standard deviation.

c. For irrigated crops, drought or water availability is not a limiting factor (or at least not the primary limiting factor), so yield is mainly influenced by other factors, such as shading in this study. Consequently, even without SPEI, the original R^2 is already high for irrigated crops, which is logical. Including SPEI further increases R^2, but as shown in Table B1, the relative increase is minimal in percentage terms. For non-irrigated crops, however, both water and shading serve as limiting factors, so the original R^2 without SPEI is expectedly lower than that of irrigated crops. Notably, a larger relative increase in R^2 is observed for non-irrigated crops after including SPEI.

4. It is important to note that the data for irrigated and non-irrigated crops within each category are not evenly matched, both in quantity and in crop type. For instance, Figure B1 highlights distinct differences in the variety and number of irrigated versus non-irrigated crops across all categories analysed. This discrepancy makes it challenging to draw direct comparisons, as each category lacks consistency between irrigated and non-irrigated data sets. Additionally, some crop categories have minimal or even no data for one of the groups either irrigated or non-irrigated further complicating any full comparison. These differences are essential to consider, as they impact the reliability and scope of conclusions drawn from the data regarding irrigation effects across different crop types.

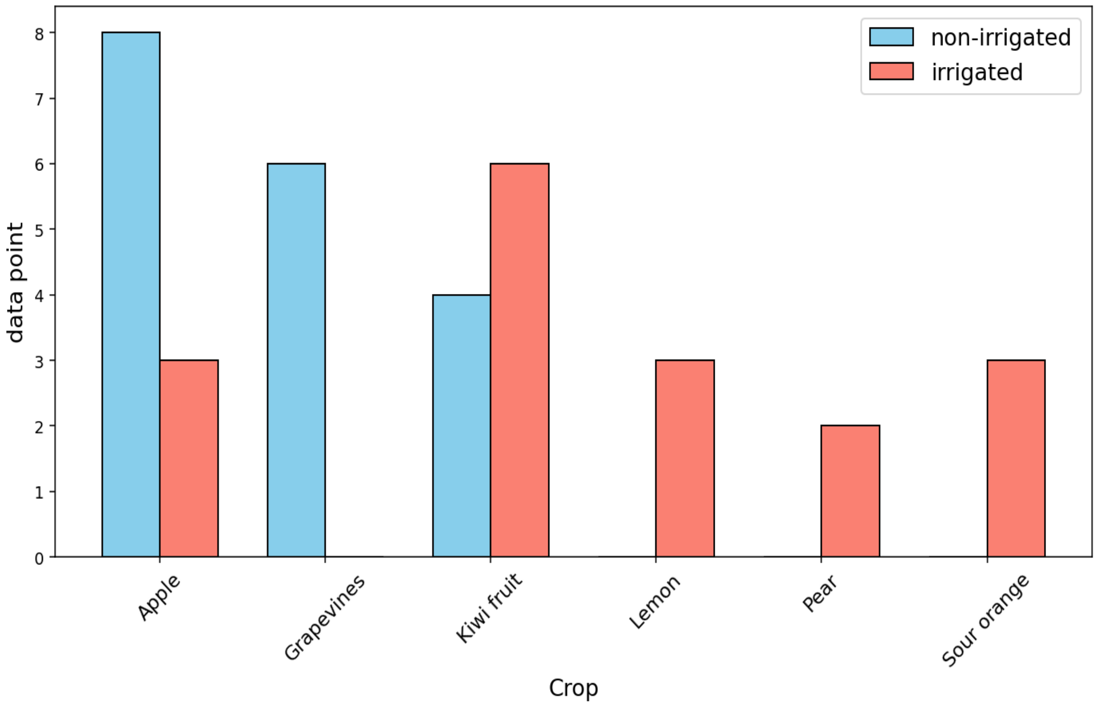

Figure B1: types of fruits included in the data set for irrigated and non-irrigated