This manuscript's first original version was submitted on July 2nd, 2024, for consideration in the peer-reviewed Environmental Research Letters journal. Please note that the manuscript has not undergone peer review yet and has not been formally accepted for publication. Subsequent versions of this manuscript may have different contents. Please feel free to contact the corresponding authors. We welcome feedback.

Unraveling the crop yield response under shading conditions through the deployment of a drought index

Sultan Tekie[1,*], Sebastian Zainali[1], Tekai Eddine Khalil Zidane[1], Silvia Ma Lu[1], Mohammed Guezgouz[1], Jie Zhang[2], Stefano Amaducci[3], Pietro Elia Campana[1,*]

[1]Mälardalen University, Department of Sustainable Energy Systems, Västerås, Sweden

[2]Department of Earth Sciences, Uppsala University, Uppsala, Sweden

[3]Department of Sustainable Crop Production, Università Cattolica del Sacro Cuore, Piacenza, Italy

*Corresponding author: sultan.tekie@mdu.se, pietro.campana@mdu.se

Abstract

Extensive research has explored the impact of shading on vegetation growth and crop yield under agrivoltaic (APV) systems. These studies have revealed a notable connection between shading and crop yields, 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 crop yield, 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 crop yield across various crops. The SPEI implicitly includes information concerning temperature, potential evapotranspiration, and precipitation, and it is easily retrievable globally and at a reasonable temporal resolution. Multiple linear regression (MLR) techniques are used to analyse different crop categories. The MLRresults with and without incorporating SPEI are compared to assess the shading influence on determining crop yield amidst varying environmental conditions. Including SPEI resulted in improved performance metrics across all crop categories. For example, the least improvement was observed in Fruit with a 17.1% increase in R^2, while the most significant improvement was seen in Maize with a 62.8% increase in R^2. Moreover, the analysis revealed that in over half of the crop categories, the SPEI statistics exhibited greater significance compared to the shading level parameter.

Consequently, this study concludes that considering environmental factors implicitly included in SPEI alongside the shading level offers a more comprehensive understanding of crop yield dynamics under APV systems.

Keywords: agrivoltaic, 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 reaching grid parity in several countries and regions around the world (Shah, 2020; Liza & Islam, 2020; Thomas et al., 2023). However, the extensive deployment of this technology creates rivalry between the use of land for energy and food. (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 crop yield. This line of research is timely since the ongoing development of APV systems regulatory frameworks shows a trend to set the maximum crop yield reduction under APV systems compared to open-field conditions (Dupraz, 2023).

For instance, Germany has taken an initial step toward standardising APV system specifications with the technical specification DIN SPEC 91434:2001-05 (DIN-Media, 2021). This specification mandates that crop reduction should not exceed one-third of the reference yield without PV (Chatzipanagi et al., 2023). 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 area occupied by the APV system and PV modules coverage of agricultural fields should remain below 40% (Chatzipanagi et al., 2023). No reference to crop yield reduction was made by the Italian Ministry, but the Italian Standards Body UNI, in its specification “Agri-voltaic systems - Integration of agricultural activities and photovoltaic implants” (UNI/PdR 148:2023), indicated that crop yield under APV should not be reduced by more than 70% 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 crop yield should not be reduced by more than 10%, and PV installations on the field cannot cover more than 40% of the crop field (Gwénaëlle Deboutte, 2024; Legifrance, 2024). 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 crop yield must be maintained above 60% (Pilar Sanchez Molina, 2024). These regulations force farmers operating APV systems to achieve a minimum crop yield.

The primary challenge associated with APV 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 (Wagner et al., 2023). 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 (Uldrijan et al., 2022; Widmer et al., 2024; Semeraro et al., 2024). One primary market and research challenge is to simulate or assess the impact of shading on crop yields to meet policy targets on crop yield reduction under APV systems.

Laub et al. (2022) conducted a meta-analysis investigating the impact of shading on crop yield. By compiling diverse research findings, the study categorises the effects of shading on various crop types, including Berries, Fruits, Fruiting Vegetables, Leafy Vegetables, C_3 Cereals, Maize, Tubers/Root Crops, Grain Legumes, and Forages. Through this comprehensive analysis, the research aims to elucidate the nuanced effects of shading across different crop categories, offering valuable insights for agricultural practices and management strategies correlating the shading rate to crop yield reduction. The research addresses 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, Dupraz (2023) correlated the relative crop yield under APV systems with the ground coverage ratio (GCR), which was used as a proxy for the shading rate on the crops. The author mentioned but, in the analysis, did not differentiate between the data of the meta-analysis in the type of APV systems and type of data (i.e., experimental data from a commercial greenhouse and open field, irrigated and non-irrigated or modelling results), and APV systems' PV modules type (i.e., with fixed PV modules, with solar tracking system or with agricultural tracking system). An exponential regression was applied to the meta-analysis data.

A common objective of the studies conducted by Laub et al. (2022) and Dupraz (2023) is to provide simple correlations between shading rate and relative crop yield, 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 crop yield 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 crop yield, while meteorological conditions, wetness of the soil, or other factors critical to crop yield are neglected. For example, it is extremely difficult to compare the results from two identical APV system designs with the same shading rate on the ground and installed in the exact 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 crop yield by curtaining the irradiance level, while during a dry year, the shading rate can positively affect the crop yield. This shortcoming could produce misleading results.

To support policymakers with more accurate information, additional environmental factors should be included as independent variables of the correlation between crop yield and shading level. This study seeks to incorporate a drought indicator into existing research of shading effects on crop yield to evaluate the significance of environmental conditions in determining the resulting crop yield.

Many indicators have been developed for drought monitoring, the most well-known of which are the Standardised Precipitation Index (SPI), the Palmer Drought Severity Index (PDSI), and the SPEI. SPI is a multi-scalar index that only relies on precipitation but can be calculated at different time scales (McKee et al., 1993). PDSI uses precipitation and temperature information but has a fixed time scale (Palmer,1965). SPEI, considering both precipitation and temperature, combined the strengths of SPI and PDSI, and having a multi-scalar characteristic (Vicente-Serrano et al., 2010), 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 Vicente-Serrano et al. (2010). 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 crop yield response (Qin et al., 2023; Sjulgård et al., 2023; Bashir et al, 2022: Santini et al., 2022). In the APV sector, the SPEI, as an index of drought, easily retrievable from services like the SPEI database (Global SPEI database, 2024), could enhance the understanding of the relationship between shading rate and crop yield, by providing crucial information concerning temperatures, evapotranspiration, and water availability.

2. Data and Methods

This study builds on the meta-analysis conducted by Laub et al. (2022) and Dupraz (2023). The study by Laub et al. (2022) correlated the shading level for various types of shading materials (PV, shading cloth, and intercropping shading) with crop yield data. Similarly, Dupraz (2023) 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 Laub et al. (2022) and Dupraz (2023). Laub et al. (2022) initially included 58 studies with shading treatments and corresponding crop yields. An additional 26 research studies were collected in this study using the keyword "shading level and crop yield", totalling 84 studies. The proposed meta-analysis enriched previous databases with further key variables to enhance the understanding of shading rate and crop yield under APV systems. These variables include the crop growing season and the corresponding monthly values during the crop growing season. Thus, this work excluded previously published studies that needed more explicit information on crop harvest dates. This information is necessary to retrieve the temporal trend of the SPEI during the crop growing season. If specified, the crop growing season has been retrieved from the published studies or derived from the specified planting or harvest dates as reported by Allen et al. (1998).

For this reason, only 59 articles were viable for conducting the proposed meta-analysis in this study, as 25 studies were excluded due to insufficient information on the experimental period. Moreover, we considered only 41 non-irrigated research studies in the main body of this study since irrigation can offset the environmental impact or drought effect on crops as well as the benefit of shading.

The monthly SPEI values during the crop growing season were retrieved from the SPEI database (Global SPEI database, 2024) 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.

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.

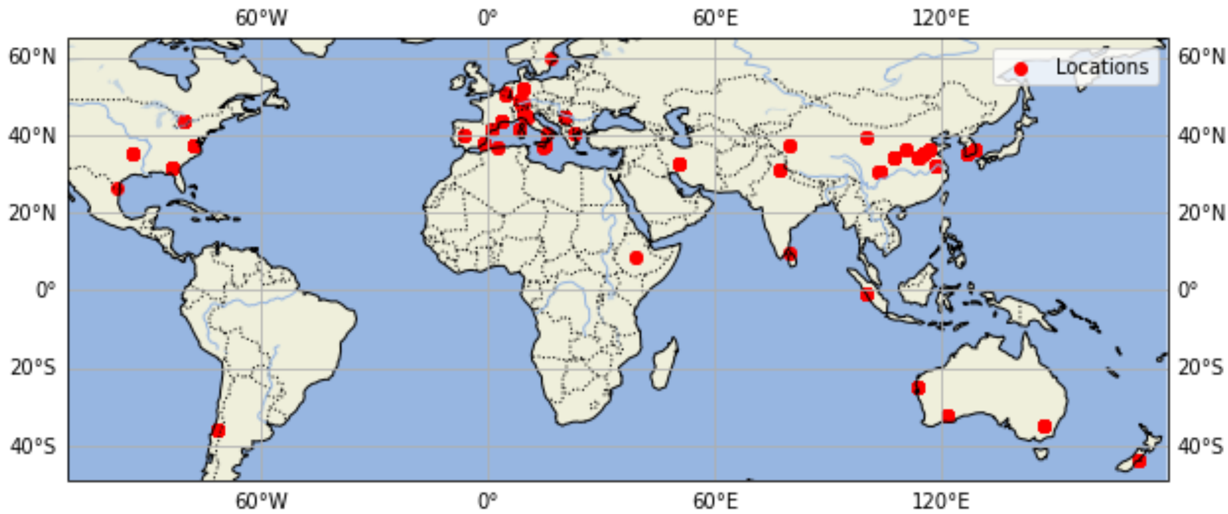

Figure 1 Map of the locations reported in the studies being part of the meta-analysis conducted in this work.

In the study conducted by Laub et al. (2022), 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.

2.1 Regression models

In this study, we compare the results of a linear regression (LR) model that uses shading level as the sole independent variable (as done in previous studies by Laub et al. (2022) and Dupraz (2023)) with those of a MLR model that includes both shading level and SPEI as independent variables. Correlation analysis was conducted among the four SPEI statistical values to mitigate redundancy. The shading level variable ranges from 0 to 100, while the SPEI values range from below -2 for extremely dry to above 2 for extremely wet conditions. Therefore, it was crucial to normalise the data to ensure that the values were scaled within a similar range. Following normalisation, the dataset underwent smoothing to eliminate outliers and redundant data points as follows:

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

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 LR is as follows:

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

where, Y is the dependent (response) variable, i.e., the crop yield, 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:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n, \quad (3)$$

where, Y is the dependent (response) $\beta_1, \beta_2, \ldots \beta_n$ 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.

Both LR and MLR models were examined to observe their impact on performance metrics. 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 Uncertainty quantification

The prediction interval evaluates the differences in uncertainty levels between the MLR model (without SPEI statistics) and the MLR model (with SPEI statistics) at a 95% confidence level. The model that better generalizes the measured crop yield percentage is deemed more certain. Prediction Interval Coverage Probability (PICP) is used to quantify uncertainty, 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, the line of equality 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 0.64 to 0.88, MAE decreased from 4.02 to 2.43, and MSE decreased from 26.01 to 9.02.

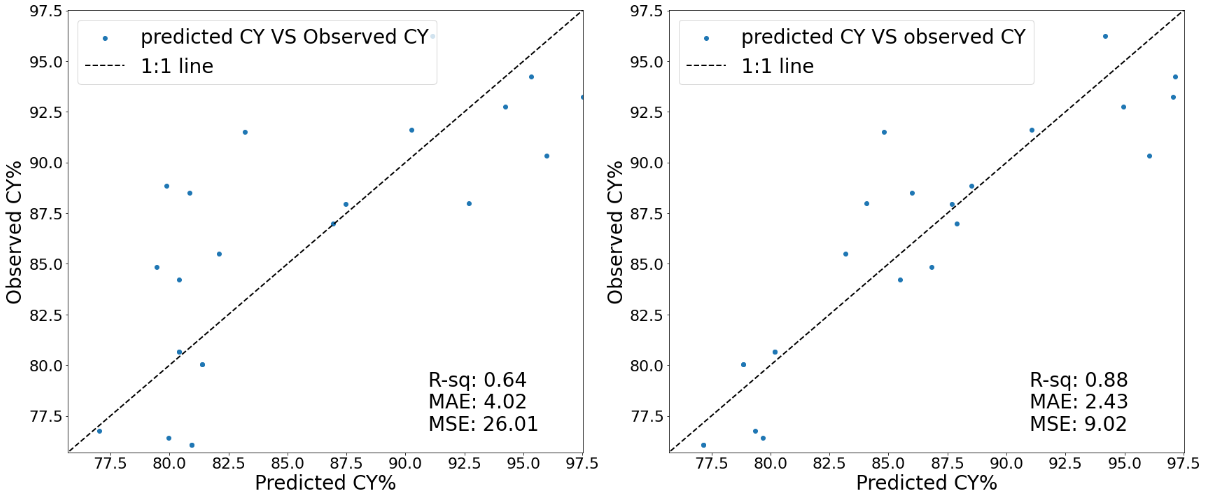

Figure 2: Predicted crop yield percentage vs Observed crop yield percentage not considering (i.e., in LR model) (left) or considering (i.e., in MLR model) (right) the SPEI statistics for C_3 Cereal non-irrigated.

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 crop yield reduction under shading conditions and thus the performance metrics. However, for Forage, the improvement was relatively low, with an R^2 value of around 31%, significantly lower than other crop categories, which achieved R^2 values above 65%. In general, Forage displayed poor performance for both models, with R^2 values of only 25% without SPEI and 31% with SPEI.

Table 1: Performance metrics of the linear model without/with SPEI statistical values for non-irrigated crop categories. The left values represent the metrics without SPEI (i.e., LR model), while the right values indicate those with SPEI (MLR model).

Crop category	R^2	MSE	MAE
C3 Cereals	0.64/0.88	26/9	4/2.4
Berries	0.42/0.79	282/99	13.96/8
Maize	0.19/0.79	47.5/7.9	5.7/2.22
Grain Legumes	0.52/0.91	73.8/13.8	6.7/3.1
Fruits	0.75/0.92	8.2/2.6	2.2/1.25
Leafy Vegetables	0.44/0.99	743/2.1	22.5/1
Root Crop	0.56/0.93	324/177	13.8/10.52
Forage	0.25/0.31	250/166	13/10.6

Table 2 presents the linear equation correlating the input variables and the crop yields. Y represents predicted crop yield, X1 represents the shading level, X2 represents mean SPEI, X3 represents min SPEI, X4 represents max SPEI, and X5 represents standard SPEI. Those handy correlations can be used to derive potential crop yield 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 linear and MLR models for non-irrigated crop categories.

Crop type	Equation
C3 Cereals	Y=106.34-0.44X1 Y=84.79-0.42X1+0.07X2+0.1X3-0.13X4+0.42X5
Berries	Y=-13.36+2.22X1 Y=20.68+1.2X1-0.76X2+0.98X3+0.47X5
Maize	Y=61.82+0.25X1 Y=99.38+0.084X1+0.48X2+0.32X3-0.81X4+0.92X5
Grain Legumes	Y=104.54-0.52X1 Y=48.57+0.12X1-0.85X2+1.12X3-0.9X4+1.03X5
Fruits	Y=101.74-0.21X1 Y=130.82-0.34X1+0.11X2-0.15X3+0.05X4-0.35X5
Leafy Vegetables	Y=58.49+1.31X1 Y=134,53-1.17X1+1.1X2+0.26X3-0.20X4
Root Crop	Y=111.12-0.91X1 Y=136.38-0.60X1+0.38X2-0.90X3-0.08X4
Forage	Y=144.14-1.22X1 Y=139.31-1.34X1+0.38X3-0.73X4+0.68X5

3.2 Statistical test

A p-value derived from a statistical hypothesis test was used for further analysis. A significance level of 5% ($\alpha \leq 0.05$) was selected to reject the null hypothesis. A p-value of a feature above the stated significance level means failure to reject the null hypothesis, indicating weak evidence against it. Conversely, a p-value below the stated significance level leads to rejecting the null hypothesis, indicating strong evidence against it. Table 3 presents the p-values for each independent variable considered in the MLR model and for all the crop categories to determine if any feature fails to reject the null hypothesis. The p-values for the crop categories C3 Cereals, Maize, Grain Legumes, and Fruits reveal that the shading level variable holds more predictive power than all the SPEI variables in determining crop yield. However, for crop categories Berries and Root crops, one or more SPEI variables demonstrate greater significance than the shading level. For all non-irrigated crop categories except for Leafy Vegetables, the shading factor resulted in a p-value ≤ 0.05. However, the p-value of shading level fail to reject the null hypothesis for Leafy Vegetables. The low significance of the shading level for Leafy

Vegetables could be attributed to the minimal number of available data points for non-irrigated conditions. Conversely, either of the SPEI statistics maintain significance for all crop categories except for Forages scoring a p-value ≥ 0.05. The low significance of the SPEI statistics and the high significance of shading level for Forage crop yield might be attributed to their high drought tolerance or the remarkable advantages that Forage crops experience under shading compared to open field reference conditions. Some source data indicated negligible yield reduction with increased shading levels on Forage crops (Pang et al., 2019; Campana et al., 2024), while other sources reported an increase in yield with increased shading (Edouard et al., 2023; Gray et al. 2022). These results underscore the practical importance of shading levels and SPEI statistics in predicting crop yield, advocating for their inclusion in APV systems research and management.

Table 3: p-value for each independent variable considered in the MLR model for non-irrigated crop categories. N indicates the number of data samples for every crop category.

Crop category	**Shading level (%)**	**Mean SPEI**	**Min SPEI**	**Max SPEI**	**Std SPEI**	**N**
C3 Cereals	1.89e-07	0.16	0.07	0.073	7.8e-05	29
Berries	1.94e-05	0.136	5.12e-08	-	6.7e-04	36
Maize	0.042	0.20	0.07	0.25	0.0099	21
Grain Legumes	6.3e-04	0.043	0.18	0.17	0.31	18
Fruits	6.22e-05	0.045	0.0044	8.9e-03	4.2e-04	14
Leafy Vegetables	0.216	0.008	0.026	0.029	-	5
Root Crop	7.8e-03	0.636	5.5e-03	-	0.529	11
Forage	4.78e-05	-	0.23	0.44	0.55	58

3.3 Uncertainty

Linear regression 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 results that better fit the measured CY% are considered more certain. PICP was used to quantify the uncertainty level for both models, providing a numerical comparison of the visual differences between the models. Figure 3 visually inspects the coverage of the measured CY% by both models with and without SPEI for C3 Cereals, while Table 4 provides PICP quantification to compare the models.

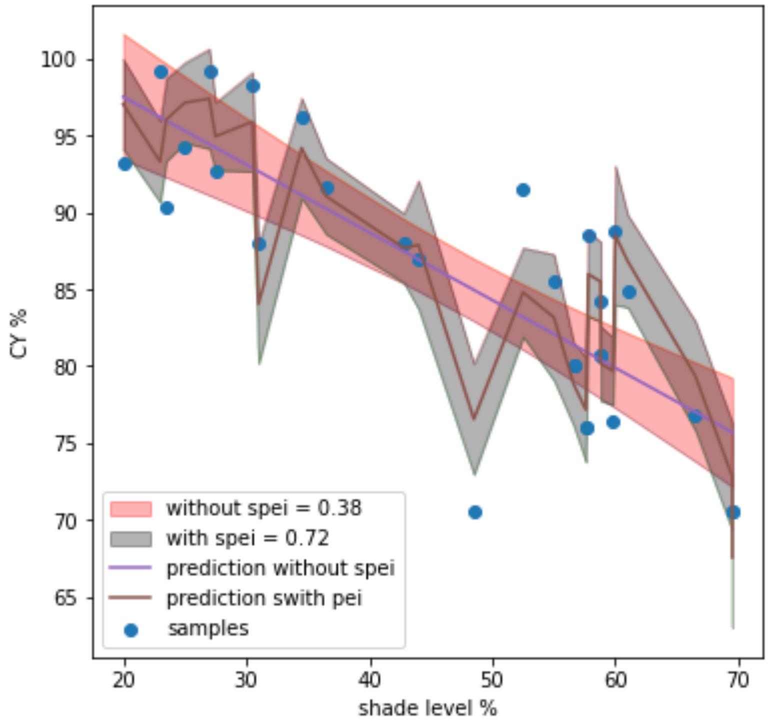

Figure 3: Uncertainty analysis with and without SPEI for C3 Cereals at 95% confidence interval.

Table 4: Uncertainty by the PICP for non-irrigated crops (confidence interval: 95%)

Crop category	Simple linear model without SPEI	MLR model with SPEI
C3 Cereals	0.38	0.72
Berries	0.31	0.53
Maize	0.52	0.71
Grain Legumes	0.50	0.83
Fruits	0.64	0.93
Leafy Vegetables	1	1
Root Crop	0.55	1
Forage	0.20	0.43

As shown in Figure 3 and Table 4, the model with SPEI is more certain than the model without SPEI. The minimum difference in uncertainty was observed with Berries, where the model with SPEI showed 22% higher certainty than the model without SPEI. The most remarkable difference was seen with C3 Cereals, with the model including SPEI showing up to 34% 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 is to underscore the combined impact of the environmental factors implicitly included in the SPEI and shading level on crop yield response. Previous studies have focused only on decrypting the crop yield reduction from shading by only correlating it with the shading level as ground coverage ratio (Laub et al., 2022; Dupraz, 2023). Providing accurate information about how the shading level produced by an APV system affects crop yield 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 (Amaducci et al., 2018, Campana et al., 2021).

The analysis conducted in this study focused only on non-irrigated crops because irrigation can offset the benefits produced by the APV systems' shadings and thus led to misleading relationships between the shading levels produced by the APV system and the resulting crop yield. 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 (Birthal *et al.*, 2021). The analysis conducted for all the crop categories without eliminating the studies where irrigation under shading conditions was applied can be found in the Appendix for further comparison.

While comparing the results of LR models (crop yield response is only a function of the shading level) versus MLR models (crop yield response is a function of shading level and SPEI statistics), the performance metrics (i.e., R^2, MSE, and MAE) showed a substantial improvement for most of the crop categories when SPEI variables are included. For instance, the crop yield reduction prediction of C3 Cereals improves by 24% (i.e., the R^2 improves from 0.64 to 0.88, see Figure 2). From a policy perspective, the MLR models developed in this study could support policymakers to make more accurate assessments of the effects of APV systems deployment on crop yield at regional or national level, and thus set less stringent crop yield targets. The support to policymakers can also be translated to a support for PV and APV companies since less stringent crop yield targets translate into higher installed specific PV capacity (i.e., kW_p/ha) and thus higher energy supply to meet decarbonisation and energy transition targets.

5. Conclusions

This study aimed to investigate the impact of environmental factors on crop yield alongside shading level, a component often neglected in most meta-analysis of shading and crop yield. A drought index, SPEI, representing environmental conditions during crop growing season, was added 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. The least improvement was observed in the Fruit category, with an R^2 increase of 17.1%, while the Maize category experienced the most improvement, with an R^2 increase of 62.8%.
- Similarly, the model with SPEI demonstrated greater certainty across all crop categories, with a minimum increase of 22% in Berries and a maximum increase of 45% in Root crops.
- SPEI showed more significant impact on crop yield than the shading level in crop categories Berries and Root Crop
- Forage proved to be both shading and drought tolerant.

Including SPEI was a critical determinant for most crop categories tested, as evidenced by performance metrics, hypothesis testing, 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 crop yield to enhance the predictability of crop yield 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

Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). FAO Irrigation and drainage paper No. 56. Rome: Food and Agriculture Organization of the United Nations, 56(97), e156.

Ault, T. R. (2020). On the essentials of drought in a changing climate. Science, 368(6488), 256-260.

Amaducci, S., Yin, X. and Colauzzi, M. (2018) ‘Agrivoltaic systems to optimise land use for electric energy production’, Applied Energy, 220, pp. 545–561. Available at: https://doi.org/10.1016/j.apenergy.2018.03.081.

Bashir, B., Elbeltagi, A., Széles, A., ... & Harsanyi, E. (2022). Assessing the impacts of agricultural drought (SPI/SPEI) on maize and wheat yields across Hungary. Scientific Reports, 12(1), 8838.

Bingham, N.H. & Fry, J.M. (2010). Regression Linear Models in Statistics. Springer. ISSN: 1615-2085. DOI 10.1007/978-1-84882-969-5

Birthal, P. S., Hazrana, J., Negi, D. S., & Pandey, G. (2021). Benefits of irrigation against heat stress in agriculture: Evidence from wheat crop in India. Agricultural Water Management, 255, 106950. https://doi.org/10.1016/j.agwat.2021.106950

Campana, P.E. et al. (2021) ‘Optimisation of vertically mounted agrivoltaic systems’, Journal of Cleaner Production, 325, p. 129091. https://doi.org/10.1016/j.jclepro.2021.129091.

Campana, P. E., Stridh, B., Hörndahl, T., Svensson, S. E., Zainali, S., Lu, S. M., ... & Colauzzi, M. (2024). Experimental results, integrated model validation, and economic aspects of agrivoltaic systems at northern latitudes. Journal of Cleaner Production, 437, 140235.

Chatzipanagi, A., Taylor, N., Jaeger-Waldau, A. (2023). Overview of the potential and challenges for agri-photovoltaics in the European Union. JRC SCIENCE FOR POLICY REPORT. ISSN: 1831-9424. doi:10.2760/208702

Deboutte, G. (9 April 2024). France Issues new rules for agrivoltaics. PV magazine. https://www.pv-magazine.com/2024/04/09/france-issues-new-rules-for-agrivoltaics/#:~:text=Agrivoltaic%20installations%2C%20except%20for%20livestock,of%20an%20agricultural%20plot%20surface.

DIN Media. (May 2021). Agri-photovoltaic systems - Requirements for primary agricultural use. https://dx.doi.org/10.31030/3257526

Dupraz, C. (2023) Assessment of the ground coverage ratio of agrivoltaic systems as a proxy for potential crop productivity. Agroforestry Systems . https://doi.org/10.1007/s10457-023-00906-3

Birthal, P.S. et al. (2021) ‘Benefits of irrigation against heat stress in agriculture: Evidence from wheat crop in India’, Agricultural Water Management, 255, p. 106950. Available at: https://doi.org/10.1016/j.agwat.2021.106950.

Farid, K., & Guleed, A. (2023). SHADING ANALYSIS OF AGRIVOLTAIC SYSTEMS : The shading’s effect on lettuce and potato from elevated agrivoltaic system in Sweden (Dissertation). Retrieved from https://urn.kb.se/resolve?urn=urn:nbn:se:mdh:diva-63829

Global SPEI database (2024). https://spei.csic.es/spei_database/#map_name=spei01#map_position=1463

Gray S, Mahama A, Suza W. 2022. Alfalfa ‘Sholty’ – Hardiness, Drought Tolerance, Conservation. In: Volk GM, Chen K, Byrne P (Eds.) Plant Genetic Resources: Success Stories. Fort Collins, Colorado: Colorado State University. https://colostate.pressbooks.pub/pgrsuccessstories/chapter/alfalfa-sholty-hardiness-drought-tolerance-conservation/

Laub, M., Pataczek, L., Feuerbacher, A. et al. Contrasting yield responses at varying levels of shade suggest different suitability of crops for dual land-use systems: a meta-analysis. Agron. Sustain. Dev. 42, 51 (2022). https://doi.org/10.1007/s13593-022-00783-7

Legifrance. (8 April 2024). 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. https://www.legifrance.gouv.fr/jorf/id/JORFTEXT000049386027

Liza, Z. A. & Islam, M.R. (2020). Solar Park: The Next Generation Energy Source in Bangladesh. Journal of Energy Research and Reviews. 4(2): 9-19, 2020; Article no.JENRR.54460 ISSN: 2581-8368. DOI: 10.9734/JENRR/2020/v4i230121

McKee, T. B., Doesken, N. J., & Kleist, J. (1993, January). The relationship of drought frequency and duration to time scales. In Proceedings of the 8th Conference on Applied Climatology Vol. 17, No. 22, pp. 179-183.
AMS_Relationship_of_Drought_Frequency_and_Duration_1993.pdf (droughtmanagement.info)

Molina, P.S. (30 April 2024). Catalonia sets guidelines for agrivoltaics. Pv magazine. https://www.pv-magazine.com/2024/04/30/catalonia-sets-guidelines-for-agrivoltaics/

Naumann, G., Alfieri, L., Wyser, K., Mentaschi, L., Betts, R. A., Carrao, H., ... & Feyen, L. (2018). Global changes in drought conditions under different levels of warming. Geophysical Research Letters, 45(7), 3285-3296. https://doi.org/ 10.1002/2017GL076521

Palmer, W. C. (1965). Meteorological drought. US. Weather Bureau Res. Paper, 45, 1-58. Meteorological Drought. Research Paper No. 45, 1965, 58 p. (droughtmanagement.info)

Pang, K., Van Sambeek, J. W., Navarrete-Tindall, N. E., Lin, C.-H., Jose, S., & Garrett, H. E. (2019). Responses of legumes and grasses to non-, moderate, and dense shade in Missouri, USA. I. Forage yield and its species-level plasticity. Agroforestry Systems, 93(1), 11–24. https://doi.org/10.1007/s10457-017-0067-8

Qin, N., Lu, Q., Fu, G., Wang, J., Fei, K., & Gao, L. (2023). Assessing the drought impact on sugarcane yield based on crop water requirements and standardized precipitation evapotranspiration index. Agricultural Water Management, 275, 108037Mohammed, S., Alsafadi, K., Enaruvbe, G. O., Sjulgård, H., Keller, T., Garland, G., & Colombi, T. (2023). Relationships between weather and yield anomalies vary with crop type and latitude in Sweden. Agricultural Systems, 211, 103757. DOI: 10.1016/j.agwat.2022.108037.

Santini, M., Noce, S., Antonelli, M., & Caporaso, L. (2022). Complex drought patterns robustly explain global yield loss for major crops. Scientific reports, 12(1), 5792. DOI: 10.1038/s41598-022-09611-0

Semeraro, T., Scarano, A., Curci, L.M., Leggieri, A., Lenucci, M., Basset, A., Santino, A., Piro, G. & De Caroli, M. (2024). Shading effects in agrivoltaic systems can make the difference in boosting food security in climate change. Applied Energy. 358. 122565. ISSN: 0306-2619. https://doi.org/10.1016/j.apenergy.2023.122565

Shah, k. (2020). India’s Utility-Scale Solar Parks a Global Success Story. Institute for Energy Economics and Financial Analysis (IEEF). Indias-Utility-Scale-Solar-Parks-Success-Story_May-2020.pdf (ieefa.org)

Smola, A.J. & Schölkopf, B. (2003). A tutorial on support vector regression. Statistics and computing 14. 199-222. SmoSch04.pdf (smola.org)

Spinoni, J., Vogt, J. V., Naumann, G., Barbosa, P., & Dosio, A. (2018). Will drought events become more frequent and severe in Europe?. International Journal of Climatology, 38(4), 1718-1736. DOI: 10.1002/joc.5291

Thomas, S.J., Thomas, S., Sahoo, S.S., Kumar Gd, A., & Awade, M.M. (2023). Solar parks: A review on impacts, mitigation mechanism through agrivoltaics and techno-economic analysis. Energy Nexus. 11. 100220. ISSN: 2772-4271. https://doi.org/10.1016/j.nexus.2023.100220

Uldrijan, D., Černý, M., & Winkler, J. (2022). Solar Park: Opportunity or Threat for Vegetation and Ecosystem. Journal of Ecological Engineering (JEE). 23(11), 1–10 https://doi.org/10.12911/22998993/153456

UNI. (3 August 2023). Agri-voltaic systems - Integration of agricultural activities and photovoltaic implants. https://store.uni.com/en/uni-pdr-148-2023

Vicente-Serrano, S. M., Beguería, S., & López-Moreno, J. I. (2010). A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. Journal of climate, 23(7), 1696-1718. DOI:10.1175/2009JCLI2909.1

Wagner, M., Lask, J., Kiesel, A., Lewandowski, I., Weselek, A., Högy, P., Trommsdorff, M., Schnaiker, M. & Bauerle, A. (2023). Agrivoltaics: The Environmental Impacts of Combining Food Crop Cultivation and Solar Energy Generation. Agronomy. 13. 299. Doi.10.3390/agronomy13020299

Wimer, J., Christ, B., Grenz, J. & Norgrove, L. (2024). Agrivoltaics, a promising new tool for electricity and food production: A systematic review. Renewable and Sustainable Energy Reviews. 192. 114277. ISNN:1364-0321. https://doi.org/10.1016/j.rser.2023.114277

Appendix

Table A1 presents the performance metrics for the linear model without/with SPEI statistical values for all crop categories and including in the dataset both irrigated and non-irrigated data. Table A1 can be directly compared to Table 1, which shows the results including only non-irrigated data. This comparison illustrates the impact of irrigation on the performance metrics. For instance, C3 Cereals linear model with SPEI statistical values showed an R^2 of 0.88 when irrigated data are not included but 0.34 when they are included.

Table A2 displays the p-values from the hypothetical tests for all crops, encompassing both irrigated and non-irrigated conditions, allowing for a comparison with Table 3, which focuses solely on non-irrigated crops.

Table A3 provides the uncertainty quantification metrics for all crops, including both irrigated and non-irrigated conditions, and can be contrasted with the results in Table 4 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 crop yield.

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	R^2	MSE	MAE
C3 Cereals	**0.17/0.34**	**110.9/88.78**	**8.4/7.9**
Berries	**0.001/0.78**	**439/95**	**16.9/7.7**
Maize	**0.13/0.51**	**324.49/181.93**	**13.72/10**
Grain Legumes	**0.75/0.76**	**116/108**	**9/8.4**
Fruits	**0.001/0.32**	**25.3/19.8**	**4/3.6**
Leafy Vegetables	**0.07/0.51**	**743/2.1**	**22.5/1**
Root Crop	**--/--**	**--/--**	**--/--**
Forage	**0.42/0.49**	**802.28/703.84**	**22.48/21.8**

Table A2: p-value for each independent variable considered in the MLR model for irrigated and non-irrigated crop categories. N indicates the number of data samples for every crop category.

Crop category	Shading level (%)	Mean SPEI	Min SPEI	Max SPEI	Std SPEI	N
C3 Cereals	0.001	0.048	0.0015	0.64	0.0025	53
Berries	0.87	0.048	9.7e-07	-	8.8e-04	41
Maize	0.036	0.38	0.0063	0.015	0.0044	32
Grain Legumes	3.11e-11	0.5	0.25	0.011	0.060	34
Fruits	0.84	0.0022	0.31	0.10	0.98	46
Leafy Vegetables	0.70	8.13e-06	0.80	1.47e-05	-	43
Root Crop	--/--	--/--	--/--	--/--	--/--	--/--
Forage	8.66e-10	0.10	0.66	0.45	0.25	70

Table A3: Uncertainty by the PICP for irrigated and non-irrigated crops (confidence interval: 95%).

Crop category	Linear model without SPEI	MLR model with SPEI
C3 Cereals	0.40	0.45
Berries	0.34	0.54
Maize	0.47	0.78
Grain Legumes	0.26	0.59
Fruits	0.67	0.73
Leafy Vegetables	0.51	0.72
Root Crop	--	--
Forage	0.24	0.34