

Article

Integrating Thermo-Ombroclimatic Indicators into Sustainable Olive Management: A Pathway for Innovation and Education

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Abstract: The study explores the integration of thermo and ombroclimatic bioindicators into sustainable agricultural practices, focusing on olive production in the Mediterranean. Given the increasing challenges posed by climate change, the study highlights the critical role of bioindicators in optimizing crop resilience and yield. Using data from the CHELSA model and long-term olive production records, the research identifies the impact of key climatic factors, such as temperature and precipitation, on olive yield variability. Principal component analysis (PCA) revealed that geographical location, precipitation, and thermal extremes significantly influence productivity. Furthermore, a multiple linear regression model confirmed the ombroclimatic index (Io) as a strong predictor of yield, emphasizing the necessity of balanced climatic conditions. The findings advocate for the integration of bioclimatic principles into agricultural training programs, promoting a holistic approach to crop management. Ultimately, the study underscores the need for informed decision-making and adaptive practices to ensure sustainable agricultural production under varying climatic conditions. This research provides a framework for future studies aiming to enhance crop resilience and address climate challenges, suggesting a pathway towards an innovative, sustainable agricultural model.

Keywords: sustainable agriculture; olive production; climate change; crop resilience; adaptive management; education for sustainable development



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1. Introduction

The rapid growth of agricultural production has been a necessary response to the global food demand driven by the increasing world population [1,2], as highlighted by [3]. However, this enhancement in production has come at a significant cost to natural ecosystems and environmental stability. Intensive use of natural resources and reliance on unsustainable agricultural practices have led to soil degradation, deforestation, and biodiversity loss; all of which undermine the capacity of ecosystems to support both human and other wildlife species life [4–8]. Despite technological advancements, many agricultural systems have failed to adapt to sustainability principles, prompting an environmental crisis that demands urgent intervention [9–12].

Olive crops in the Mediterranean region are facing increasing challenges due to climate change, which has led numerous studies to investigate how climate variability affects their productivity. However, there are important gaps in the current literature regarding the application of specific and recent bioclimatic models for olives. In particular, the Rivas-Martínez Bioclimatic Model [13]—widely recognized for its accuracy in characterizing climates and bioclimates at the local scale—has been underutilized in applied olive research [14]. While some studies have focused on how general climatic factors, such as temperature and precipitation, affect olive productivity, few have incorporated detailed models that allow an accurate characterization of local bioclimates and their direct relationship with crop resilience [15,16]. This limitation in the literature has hindered the

development of specific adaptation and crop management strategies that consider both climatic variability and the effects of extreme conditions, such as prolonged droughts and heat waves. Some recent applications of bioclimatic models have been used in the Iberian Peninsula in other crops such as vineyards [17].

Shifting towards more sustainable agriculture is not solely about adopting innovative technologies and techniques [9,18,19]. The implementation of integrated policies, as discussed in the work of Guo et al. (2023) [20], highlights how a multi-objective approach can improve agricultural sustainability by balancing production objectives with environmental conservation. These lessons are applicable to olive grove management in mountainous areas, where it is crucial to address socioeconomic and environmental pressures simultaneously [21].

Sustainable olive management in the context of climate change requires innovative approaches that integrate bioclimatic indicators into agricultural practices. This study focuses on applying thermo-ombroclimatic indicators to optimize olive production while addressing sustainability challenges. Furthermore, it highlights the importance of educating future generations about these tools to enhance their adoption and effectiveness. By bridging bioclimatic models and sustainable practices, this research provides a framework for resilient olive cultivation.

It also requires a global educational transformation. In this context, education for sustainable development (ESD) plays a crucial role in training agricultural professionals and environmental experts to apply bioclimatic principles in crop planning and management [22–24]. ESD equips future farmers and experts with the necessary skills to address environmental, social, and economic challenges and promotes a holistic approach that balances agricultural productivity with the conservation of natural resources [25–28].

Integrating climatic bioindicators into agricultural training programs is essential for empowering farmers and experts to make informed decisions about crop selection, water management, and soil conservation [15,16,29–31]. In addition to bioindicators, initiatives such as the PICSA program (Participatory Integrated Climate Services for Agriculture), led by the University of Reading and other institutions, emphasize the practical value of incorporating climate services into agricultural training. These tools enhance farmers' capacity to adapt to climate fluctuations and better manage risks [32–34]. By educating future professionals in the interpretation and application of these bioindicators, agriculture can become more resilient to climatic variability, while promoting the sustainable use of resources and the conservation of ecosystems. Such adaptive capacity is crucial for ensuring long-term agricultural productivity and minimizing environmental degradation [35–37].

Nevertheless, there is a significant gap in awareness and education regarding sustainable development [38,39]. Globally, education on sustainable agricultural practices remains insufficient, both at the professional level and within farming communities. As highlighted by UNESCO, education for sustainable development (ESD) has the potential to transform society by moving towards a more balanced and environmentally conscious model [39–41]. ESD goes beyond teaching efficient resource use; it empowers individuals to make responsible decisions that consider long-term environmental and societal impacts [39,41]. By closing this educational gap, ESD can drive a shift towards sustainable agriculture and more resilient ecosystems.

By promoting sustainability as a core element of educational programs, education for sustainable development (ESD) fosters a deeper awareness of the impact of human activities on the planet [19,22,23,31,42–44]. In the agricultural context, this education enables future farmers to adopt technologies and techniques that not only boost productivity but also minimize environmental harm and restore degraded ecosystems [45–47]. Ultimately, the goal is to develop a resilient agricultural system that is capable of withstanding the impacts of climate change and effectively responding to fluctuations in essential resources such as water and soil fertility [7,9,16,39].

In this context, thermo and ombroclimatic bioindicators emerge as essential scientific tools for advancing sustainable agricultural models [16,17,40]. These indicators help iden-

tify optimal climatic conditions for agricultural production, enabling data-driven decisions about which crops are best suited for specific geographic areas. This reduces the need for intensive agricultural practices that deplete soil and water resources) [48–51]. However, for these tools to be effectively utilized, it is crucial that agricultural and environmental training programs incorporate the teaching of bioindicators into their curricula. Only by training experts in the application of these indicators can we implement agricultural production models that are both productive and sustainable.

The Mediterranean region is highly vulnerable to global warming, with significant decreases in precipitation, leading to a reduction in available water resources across the circum-Mediterranean area [52]. Specifically, due to its location and complex orography, the Iberian Peninsula experiences high climatic variability, making it particularly susceptible to climate change [53–55]. Precipitation distribution is uneven across different areas and is influenced by several geographic factors [18,56,57].

Advances in bioclimatic research have led to a better understanding of how plant species and communities function, establishing significant relationships between climatic data and plant distribution [58]. These authors applied bioclimatic indices to correlate climatic data with the distribution of plant communities, which has been fundamental for the characterization of agricultural regions.

In the specific case of the olive tree (*Olea europaea* L.), research has shown that its distribution is closely linked to Mediterranean macrobioclimates. Bioclimatic studies on olive cultivation in the Iberian Peninsula have identified that most plantations are located in areas with Mediterranean pluvisseasonal and xeric bioclimates. These regions are characterized by thermal and precipitation conditions that directly influence olive productivity. For instance, the ombroclimatic index (Io) is crucial, as in areas with Io values below 2.0, plantations typically require supplementary irrigation due to water stress, as observed in certain regions of Andalusia and Castilla-La Mancha [19].

The main olive varieties in southern Spain—such as *Picual*, *Cornicabra*, and *Hojiblanca*—thrive in thermomediterranean and mesomediterranean bioclimates, where temperatures and precipitation levels are optimal for olive growth. However, when plantations are located outside their optimal bioclimatic range, as seen during the severe frosts of 2005, yields decrease significantly; and, in extreme cases, prolonged low temperatures can lead to tree mortality [18].

Climate variability in the Mediterranean region, exacerbated by climate change, is creating additional challenges. Future projections indicate increased aridity in traditionally olive-producing areas, highlighting the need to use bioclimatic indices as tools for planning more resilient and sustainable crops [52,54,55]. When applied precisely at a local level, bioclimatology provides a pathway to an agricultural model that not only maximizes productivity, but also reduces environmental impact and safeguards at-risk water resources.

In this study, we hypothesize that thermo and ombroclimatic bioindicators can effectively identify the optimal bioclimatic conditions to enhance the sustainability and productivity of olive crops in the Mediterranean region. By integrating these bioindicators into agricultural planning, it becomes possible to improve crops' resilience to climate change and optimize resource use. The main objectives of this study are:

- (1) To highlight the importance of integrating education for sustainable development (ESD) into agricultural training programs, providing future professionals with the skills to apply bioclimatic principles in crop management.
- (2) To evaluate how thermo-ombroclimatic indicators can improve agricultural planning and enhance the resilience of olive crops to climate variability.
- (3) To explore the policy implications of using bioclimatic models, offering actionable recommendations for farmers, policymakers, and other stakeholders to adopt sustainable practices.

This study provides an innovative perspective by integrating the Rivas-Martínez Bioclimatic Model in the analysis of olive crop resilience in the Mediterranean, highlighting its relationship with the specific bioclimatic conditions of the region. Unlike previous research,

which tends to focus on general climatic factors such as temperature and precipitation, this work applies a detailed bioclimatic approach to identify the optimal conditions that favor olive resilience and productivity in the face of extreme conditions such as prolonged drought and heat waves. This allows an accurate characterization of local bioclimates and provides practical tools to improve crop adaptation to climate variability.

2. Materials and Methods

2.1. Study Area

The study area is located in the southern Iberian Peninsula, primarily covering the Jaén province, a region almost exclusively dedicated to olive cultivation (Figure 1). This territory features a continentalized Mediterranean climate, which is characterized by extremely dry and hot summers due to its distance from the coast, as well as cold winters influenced by the continental nature of the plateau. The study area is classified within a Mediterranean macrobioclimate, specifically the Mediterranean Pluvial Oceanic bioclimate, characterized by hot summers and cold winters, along with frequent thermal inversion phenomena.

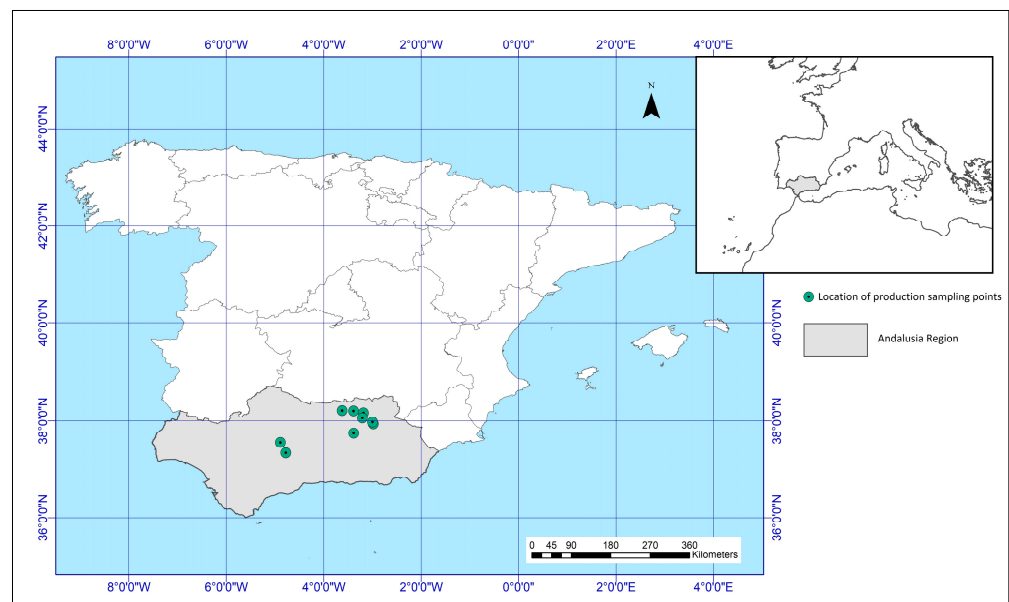


Figure 1. Location of the study area and olive production sites.

The minimal maritime influence, combined with its inland location, contributes to particularly high temperatures during the dry summer season. Within the Mediterranean macroclimate, seven bioclimates have been identified; with this study focusing on the Mediterranean Pluvial Oceanic bioclimate (Mpo) [13]. The study area's thermotype ranges from upper thermomediterranean to supramediterranean, while the dominant ombrotype varies between dry and subhumid. From the edaphic point of view, the 13 farms cover an important geological and edaphic variability, with a predominance of calcareous materials, marls, sandstones, conglomerates, siltstones, and limestones. The predominant soils are calcareous cambisols, regosols, and luvisols. Likewise, the climatic characterization of each of the farms can be seen in Table 1.

The production data collection period covers from 2009 to 2023, but not for all farms; the longest series being those of Sierra de Cazorla, with 14 years of productions. The criteria for choosing the farms were based in the first place on the predisposition of the farmers known to us to provide the data, as well as trying to represent the greatest possible variability in the two main crop varieties, Picual and Arbequino, in the rainfed mode.

Table 1. Geological, edaphic, and climatic characterization of the farms studied (P = Mean annual precipitation, T = Mean annual temperature).

ID	Period	Mean Production (Kg/Ha)	Coordinates	Altitude	P	T	Geology	Soil
Sierra de Cazorla01	2010–2023	4614	37.9353; −2.9783	750	437	14.4	Limestone and marl	Vertic Cambisols
Sierra de Cazorla02	2010–2023	4272	37.9743; −2.9963	620	421	14.8	Sandy limestone, sandstone, sand, and marl	Calcic Cambisols and Regosols
Finca Los Robledos	2012–2017	5160	38.1627; −3.1816	500	380	16.5	Dolostone, limestone, and oolitic and nodular limestone	Calcic Cambisols and Regosols
La Loma	2012–2017	5919	37.7444; −3.3826	891	518	13.6	Dolostone, limestone and nodular limestones	Calcic Cambisols with Calcic Luvisols
Pichilín	2012–2016	3621	38.06; −3.2035	626	410	16.0	Conglomerate, calcarenite, reef limestone, sandstone, and marl with turbiditic beds	Vertic Cambisols and Chromic Vertisols
El Guijarrillo01	2009–2014	3215	37.5551; −4.8866	141	579	17.7	Conglomerate, sandstone, and marl	Calcareous Fluvisols
El Guijarrillo02	2009–2014	3750	37.5551; −4.8866	141	579	17.7	Conglomerate, sandstone, and marl	Calcareous Fluvisols
Salido Bajo01	2010–2014	3288	38.2019; −3.3848	438	403	16.5	Variegated mudstone and gypsum	Calcic Luvisols
Salido Bajo02	2010–2014	2813	38.2019; −3.3848	438	403	16.5	Variegated mudstone and gypsum	Calcic Luvisols
La Mina01	2019–2023	2300	37.3411; −4.7755	275	599	17.3	Gravel, sand, clay, and silt.	Calcic Luvisols
La Mina02	2019–2023	2645	37.3411; −4.7755	275	599	17.3	Gravel, sand, clay, and silt.	Calcic Luvisols
La Mina03	2019–2023	1725	37.3411; −4.7755	275	599	17.3	Alluvial deposits, beach, point bars	Chromic Luvisols with Calcareous Regosols
Carboneros	2012–2017	4667	38.21; −3.62	476	417	16.8	Conglomerate, sand, reef, yellow siltstone	Eutric Cambisols, Chromic Luvisols, and Orthic Luvisols

All the average productions had a cultivation modality with plant cover, at least in the years studied for each farm; therefore, it was necessary to discard some years in which the farmer assured us that he or she had changed from a management based on plant covers to a management based on tillage or the use of herbicides. We consider that 5 years of minimum yields are representative to eliminate the effect of alternate production (i.e., alternation in production intrinsic to the physiology of each tree) and that it is the climatic component that has the greatest influence on yields.

The spontaneous vegetation covers that appear on the farms are generally dominated by nitrophilous species belonging to the phytosociological order *Sysimbretalia officinalis*. In the “Sierra de Cazorla01” farms, during the period 2018–2024, some phytosociological inventories of the vegetation covers were carried out, which can illustrate and serve as an example of the floristic composition of the high areas of the Guadalquivir valley. The rest of the farms have a similar floristic composition in their vegetation covers (Appendix A).

2.2. Bioclimatic Characterization

For the bioclimatic analysis of this region, data from the CHELSA model (Climatologies at High Resolution for the Earth’s Land Surface Areas) were used, which provides high-resolution climate data at 30 arc seconds ($\sim 1 \text{ km}^2$) [59].

The starting data for CHELSA are monthly mean maximum temperature, monthly mean minimum temperature, and monthly mean accumulated precipitation; all these variables cover the period 1970–2019. The choice of variables corresponds to the variables needed to apply the Rivas-Martínez bioclimatic model, which requires monthly averages of precipitation and temperature. The calculation of the different bioclimatic variables was carried out using the map algebra implemented in the ArcGIS 10.8 package. These data were corrected and validated using approximately 800 meteorological stations distributed throughout Andalusia from the Spanish state meteorological agency (AEMET), as well as from other databases of the regional government of Andalusia, improving the accuracy of the climate estimates for the bioclimatic study of the region. Key climate variables such as the Compensated Termicity Index (Itc), Ombroclima, extreme temperatures, and edaphic data are fundamental to understanding the plant dynamics of this region. The bioclimatic interpretation of the territory follows the criteria established by Rivas-Martínez [13], adapted to the data obtained from CHELSA.

2.3. Production Data

The production data were collected from various olive farms located mainly in the provinces of Jaén and Córdoba (Figure 1). The data represent olive yields expressed in kilograms per hectare (kg/ha) (Table 1) and were collected based on the *Picual* variety of olive tree, planting density, and cultivation practices. The study focused on two main olive varieties: *Picual* and *Arbequina*.

Planting densities were categorized according to the type of cultivation system. Traditional rainfed systems (Figure 2), with densities ranging from 62 to 100 trees per hectare, were contrasted with more intensive and super-intensive irrigated systems, which have densities ranging from 200 to 2500 trees per hectare (non-studied in this work). This division allowed for the evaluation of how different cultivation systems affect yield potential.

To capture the impact of different soil management practices, data were collected from farms that used various methods, including tillage, no-tillage, and ground cover management. This methodological design provided insights into how soil practices influence olive production, particularly under rainfed conditions. For example, some farms employing ground cover management in rainfed *Picual* groves were included to evaluate its effect on productivity, compared with tillage and no-tillage practices in *Arbequina* groves.



Figure 2. Satellite image and ground view of an olive grove located in Cazorla, Jaén. The left image shows a detailed aerial view, highlighting the structured plantation pattern typical of traditional olive farming in the region. The right image captures the ground perspective, illustrating the spacing between the trees and the dry soil, characteristic of rainfed (dryland) olive cultivation. This combination of perspectives emphasizes the importance of geographical and climatic factors in the productivity of olive groves in this area.

For intensive and super-intensive irrigated systems, data collection focused on understanding the relationship between higher planting densities and yields. Farms with super-intensive systems (over 2000 trees/ha) were selected to study the impact of higher tree density on varieties such as *Arbequina* and *Picual*, and how these systems optimize production in irrigated environments.

To account for the alternation (*vecería*) typical of olive trees, long-term production data spanning 13 years were collected (2010–2023). This strategy ensured that the cyclical nature of olive production was addressed, allowing for more accurate and stable assessments of production averages. The primary data analyzed in this study were five-year averages, which were then combined with long-term series to adjust for annual yield variability and ensure robust correlations with bioclimatic variables.

Finally, the collected production data will be correlated with climatic variables such as the ombroclimatic index, and maximum and minimum temperatures. This approach ensures that the influence of climatic factors on olive yields can be accurately assessed, allowing for more reliable insights into the relationship between bioclimatic conditions and agricultural performance.

2.4. Statistical Analyses

The statistical analysis was carried out using R Studio version 2023.12.1, while cartographic outputs and mapping processes were handled in ArcGIS 10.8. The analytical procedure began with an exploratory data analysis, designed to reveal underlying patterns and distributions within the dataset. This step involved calculating basic descriptive statistics such as means, standard deviations, and ranges for both the production variables (kg/ha) and key climatic indicators, including minimum and maximum temperatures and precipitation. This exploratory phase helped establish a baseline understanding of the data and informed subsequent analytical choices.

Following this, a Principal Component Analysis (PCA) was conducted to reduce the dimensionality of the climatic dataset. By identifying principal components, this technique allowed the study to focus on the most influential climatic variables impacting olive yield. The PCA isolated the key factors contributing to variability, facilitating a more streamlined analysis that emphasized variables with the greatest explanatory power. This step was particularly important in clarifying the relative importance of different climatic conditions across the study area.

To assess the feasibility of applying Principal Component Analysis (PCA), tests were performed on the assumptions of correlation and sample adequacy. Initially, Bartlett's test of sphericity could not be calculated due to the presence of multicollinearity among some of the selected variables, indicating a high correlation between them and suggesting redundancy in the data. To address this problem, collinear variables were identified and eliminated, which reduced redundancy and improved the structure of the data.

After the elimination of these collinear variables, the adequacy of the sample was reassessed using the Kaiser–Meyer–Olkin index (KMO). The average KMO value obtained was 0.734, indicating a satisfactory sample adequacy to perform the PCA, since values above 0.6 are acceptable and values above 0.7 are considered good. This refinement process ensures that the remaining variables provide a more solid basis for the PCA analysis, allowing the identification of the principal components that explain the variability in the dataset without the interference of highly correlated relationships between the variables.

Next, a multiple linear regression model was developed, incorporating key climatic variables as predictors of olive yield. The multiple linear regression (MLR) model was used to evaluate the relationship between various climatic variables and bioclimatic indices and yield represented in the variable “Kg/Ha”. This approach allows identification of how specific climatic factors contribute to yield variability, providing a quantitative analysis that supports decision making to improve production under climate change conditions. The regression coefficients obtained allow interpretation of the magnitude and direction of the influence of each independent variable on olive production, providing a clear perspective on how each factor affects yield.

As for the assumptions of the MLR model, the main ones were verified: linearity, independence of the errors, homoscedasticity, and normality of the residuals. The Durbin–Watson statistic was 2.757, close to 2, which confirms the independence of the errors and the absence of significant autocorrelation. The normality of the residuals and of the independent variables was evaluated by several tests (Shapiro–Wilk, Anderson–Darling, Lilliefors, and Jarque–Bera), and although some tests indicated deviations from normality in certain variables such as the continentality index (Ic) and some other monthly precipitation variables, other tests did not show such deviations. This variability in the results suggests that, although certain variables may present slight deviations, in general, no serious normality problem is observed that could affect the interpretation of the model; therefore, techniques such as data transformation were not necessary.

Overall, the multiple linear regression model proves to be adequate, explaining 88.1% of the variability in production with an adjusted R^2 of 0.881. This high level of fit supports the model's ability to capture the relationship between climatic factors and olive yield. Interpretation of the results can be made with confidence, and the model provides a solid basis for understanding and predicting the impact of climatic factors on agricultural production in similar contexts.

Variables such as maximum and minimum temperatures, ombroclimatic indices, and monthly precipitation were included in the model, with olive production per hectare as the dependent variable. The model's fit was evaluated using the R^2 and adjusted R^2 , which provided a measure of how much variance in the production data was explained by the climatic variables. Residual diagnostics were performed, including tests for autocorrelation and heteroscedasticity. Ljung–Box and Box–Pierce tests were applied to detect any autocorrelation in the residuals, while the McLeod–Li test was used to check for heteroscedasticity, ensuring that the model's assumptions were met.

In the final phase of the analysis, normality and white noise tests were conducted to ensure that the residuals followed a normal distribution and behaved as random noise. The Jarque–Bera test was applied to confirm normality, and no significant deviations were found. The model was further validated through a split of the data into training and testing subsets, allowing for an evaluation of the model's predictive accuracy using metrics such as the RMSE and MAPE.

3. Results

3.1. Principal Component Analysis (PCA)

The principal component analysis (PCA) conducted on olive yield data and the associated geographical and climatic variables effectively reduced the dimensionality of the dataset, highlighting the most influential factors in explaining the variability in production, measured as Production/Ha. Through PCA, two principal components (F1 and F2) were identified, which together account for 94.05% of the total variability in the dataset (Table 2). These two components are sufficient to capture most of the variation in olive yields and environmental conditions.

Table 2. Results from Principal Component Analysis (PCA), showing eigenvalues, explained variance, and cumulative variance for components F1, F2, and F3. F1 accounts for 68.88% of the total variance, F2 adds 25.18%, leading to a cumulative variance of 94.05%. Together, these components capture the majority of variability in the dataset, summarizing key climatic and geographical influences on olive production.

	F1	F2	F3
Eigenvalue	18.597	6.797	0.881
Variance (%)	68.877	25.175	3.264
Cumulative %	68.877	94.053	97.316

3.1.1. Geography and Precipitation

The first component (F1), which explains 68.88% of the total variability, is dominated by geographical variables and precipitation. The factor loadings for longitude (0.991) and latitude (0.904) are the highest, suggesting that the geographical location of the olive farms is a key determinant in the variability of olive yields (Table 3). Differences in latitude and longitude indicate that yields are strongly correlated with the geographical position of the farms. This may be related to local factors such as microclimates or soil characteristics favorable for olive cultivation, which have not been well studied or addressed in the present work.

Table 3. Correlation coefficients and loadings from Principal Component Analysis (PCA) for various climatic and geographical variables related to olive production (Kg/Ha). The table highlights how variables such as latitude (Lat) and longitude (Long) are positively correlated with Axes F1, indicating a strong geographical influence on production. Variables such as maximum temperature (Tmax) and several precipitation indices (e.g., P01, P02) show varied loadings across F1 and F2, reflecting their different impacts on olive yield, with darker loadings suggesting stronger associations with each axis. In bold, statistically significant values at 95% confidence.

Variables	Production (Kg)/Ha Correlation	Axis F1	Axis F2	Variables	Production (Kg)/Ha Correlation	Axes F1	Axes F2
Lat	0.516	0.904	0.385	P01	−0.588	−0.975	−0.217
Long	0.639	0.991	−0.059	P02	−0.502	−0.937	−0.348
Tp	−0.689	−0.706	0.703	P03	−0.323	−0.796	−0.6
Itc	−0.715	−0.778	0.624	P04	−0.336	−0.806	−0.579
Io	−0.161	−0.654	−0.755	P05	0.224	−0.051	−0.969
Pp	−0.503	−0.941	−0.338	P06	0.8	0.879	−0.425
P	−0.503	−0.941	−0.338	P07	0.723	0.969	−0.222
m	−0.763	−0.866	0.495	P08	0.749	0.904	−0.358
M	−0.701	−0.847	0.521	P09	−0.178	−0.755	−0.609
Ic	0.637	0.989	0.074	P10	−0.568	−0.981	−0.171
Tmin	−0.73	−0.858	0.511	P11	−0.591	−0.986	−0.156
Tmax	−0.307	−0.008	0.976	P12	−0.602	−0.989	−0.148
T	−0.689	−0.706	0.703				

The Continentality index (I_c) also shows a high loading (0.989) on F1 (Table 3), indicating that the overall climatic conditions of the study area are significant drivers of farm yield variability. The climatic index includes factors such as the distribution of temperature and precipitation throughout the year, which appear to positively correlate with olive production.

Conversely, the monthly precipitation variables (P01 to P12) exhibit negative loadings on F1, with P01 (−0.975) and P02 (−0.937) being the most pronounced (Table 3). This suggests that high precipitation, particularly in the early months of the year, is negatively correlated with olive production. This pattern indicates that excessive rainfall may hinder olive yields, possibly due to poor drainage or increased soil moisture, which could promote disease development or reduce the efficiency of photosynthesis.

Regarding the primary variable of interest, Production/Ha—representing the yield per hectare—has a moderate loading of 0.678 on F1. This confirms that a significant portion of the yield variability is associated with the geographical and climatic variables captured by this component. Farms situated in more favorable geographical locations, with an optimal climatic index, tend to show higher yields, while excessive rainfall in certain months appears to limit productivity.

3.1.2. Temperature and Production

The second component (F2), which explains 25.18% of the variability, is primarily associated with maximum temperatures. Maximum temperature (T_{max}) has an extremely high loading on F2 (0.976), indicating that thermal extremes are a key factor in explaining the variability in olive yields. In areas where maximum temperatures are higher, yields may be negatively impacted by heat stress, suggesting that olive farms exposed to extreme heat conditions tend to experience reduced productivity if temperatures exceed certain thresholds (Table 3). Additionally, average temperature (T) and average precipitation temperature (T_p) also show moderate positive loadings (0.703 in both cases), indicating that general thermal conditions contribute to yield variability; though to a lesser extent compared to maximum temperatures. These thermal conditions may positively affect olive growth if they remain within an optimal range, but their impact may turn negative when combined with extreme temperatures or prolonged water deficits.

In this second component, Production/Ha has a moderate negative loading of −0.357, indicating that elevated temperatures have an inverse effect on olive yields. In regions with particularly high maximum temperatures, yields tend to decrease, supporting the hypothesis that farms exposed to thermal extremes experience difficulties in maintaining high productivity.

The PCA (Figure 3) results reveal that geographical location and precipitation are major determinants of olive yield, while temperature extremes also play a critical role, particularly in determining a farm's ability to maintain high yields under heat stress. The analysis shows that farms located in regions with a favorable climatic index and controlled precipitation tend to be more productive, while high rainfall and extreme temperatures can negatively affect yield.

In general, Component 1 captures the large-scale geographical and climatic variations, while Component 2 reflects the impact of extreme thermal conditions. Together, these two components explain most of the observed variation in olive yields, emphasizing the need for agricultural practices to be adapted to local conditions to optimize productivity.

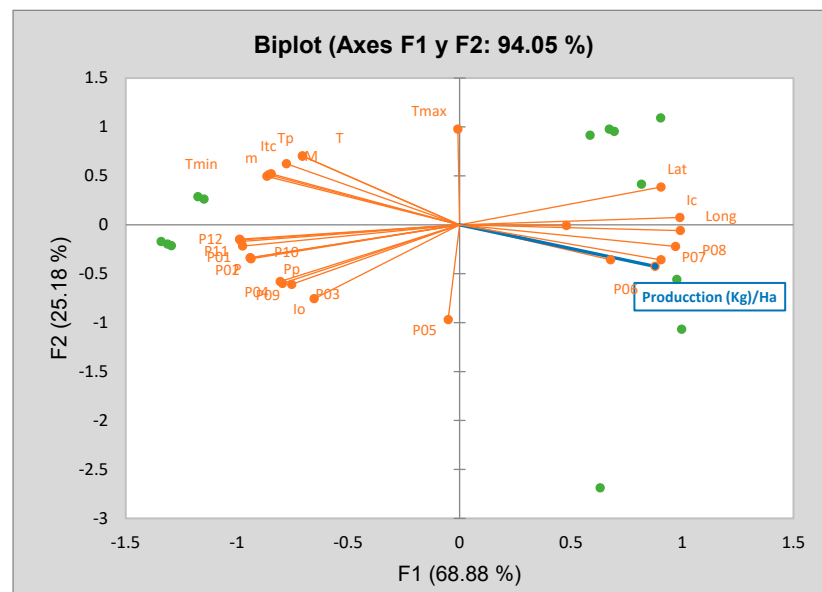


Figure 3. Biplot of the first two principal components (F1 and F2) from the PCA, explaining 94.05% of the total variance. The axes F1 (68.88%) and F2 (25.18%) illustrate the relationships between climatic variables and olive production (Kg/Ha). Geographical factors such as latitude (Lat) and longitude (Long) are strongly associated with F1, indicating a significant influence on production, while climatic factors such as maximum temperature (Tmax) and precipitation indices (P01–P12) exhibit varied loadings. Variables closer to “Production (Kg/Ha)” suggest stronger correlations, with the analysis highlighting the impact of location, temperature, and precipitation on olive yields. Green dots = production sites.

3.2. Multiple Linear Regression Analysis

A multiple linear regression analysis was conducted to quantify the impact of various climatic and geographical variables on olive yield, specifically measured as Production/Ha. The regression model included independent variables such as the thermal index (Itc), the ombroclimatic index (Io), and the continentality index (Ic), as well as maximum temperature (Tmax) and monthly precipitation (P01, P02, P10, P11, P12), all of which were identified as potentially significant predictors through previous exploratory analyses in PCA. The objective of this analysis was to develop a predictive model that explains the variability in olive yield based on these environmental factors.

3.2.1. Correlation Matrix

The initial correlation matrix showed significant relationships between various climatic variables and the production of olives (Production/Ha). The ombroclimatic index (Io) exhibited a positive correlation with yield ($r = 0.637$), suggesting that more favorable ombroclimatic conditions are associated with higher production levels. However, other variables, such as maximum temperature (Tmax) and the compensated thermicity index (Itc), displayed negative correlations with yield ($r = -0.307$ and $r = -0.715$, respectively). This indicates that increases in temperature, particularly during the hotter months, may have a detrimental effect on olive yield. The correlation matrix further revealed that precipitation in the first month (P01) had a moderate negative correlation with yield ($r = -0.588$), suggesting that excessive rainfall during the early stages of the growing season may adversely impact production.

3.2.2. Goodness-of-Fit Statistics

The goodness-of-fit statistics for the multiple linear regression model showed strong predictive capability. The model’s R^2 value of 0.960 indicates that 96% of the variance in olive yield can be explained by the included independent variables. The adjusted R^2 of

0.881 reflects the model's capacity to account for the variability in yield after adjusting for the number of predictors (Figure 4). The RMSE (Root Mean Square Error) of 414.711 and the MAPE (Mean Absolute Percentage Error) of 6.1% suggest that the model has a good fit with a relatively low error in its predictions. Additionally, the Durbin–Watson (DW) statistic of 2.757 confirms that there is no significant autocorrelation in the residuals, validating the independence of the error terms.

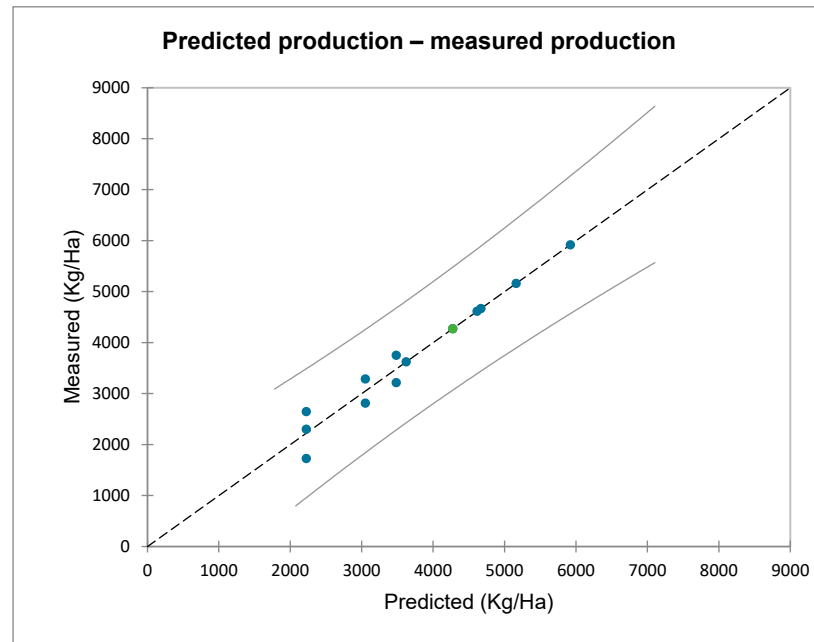


Figure 4. Analysis of variance (ANOVA) and multiple linear regression model fit between observed and model-predicted yields ($R^2 = 0.96$).

3.2.3. Analysis of Variance (ANOVA)

The ANOVA for the regression model confirmed its overall significance, with an F-statistic of 12.094 and a p -value of 0.015 ($p < 0.05$). This suggests that the model significantly explains the variation in olive yield and that at least one of the predictors has a meaningful impact on the outcome variable. The different parameters of the model are shown in Table 4. The analysis indicates that climatic variables such as the ombroclimatic index (Io) and precipitation play a significant role in determining yield variability, whereas other factors such as maximum temperature (Tmax) have more marginal effects in this context.

Table 4. Analysis of variance (ANOVA) model parameters.

	GL	F	Pr > F	Significance
Model	8.000	12.094	0.015	*
Error	4.000			
Total corregido	12.000			

Signification codes: 0.01 < * < 0.05.

The regression coefficients reveal important insights into the individual contributions of each predictor variable. The ombroclimatic index (Io) is the most influential variable in the model, with a coefficient of 46,682 and a p -value of 0.010, indicating that it significantly influences yield. Specifically, for each unit increase in Io, olive yield is expected to increase by 46.682 units (Production/Ha), holding all other variables constant. This finding underscores the importance of favorable ombroclimatic conditions—defined by an optimal balance of precipitation and temperature—on the productivity of olive groves.

Precipitation in the first month (P01) has a negative impact on yield, with a coefficient of -1196.929 and a marginal p -value of 0.133 . This suggests that excessive rainfall early in the growing season may reduce olive yield, possibly due to waterlogging, poor soil drainage, or increased susceptibility to diseases under wet conditions. Although not statistically significant at the 5% level, the negative sign and size of the coefficient highlight the potential adverse effects of high precipitation.

The maximum temperature (Tmax) also shows a negative relationship with yield, with a coefficient of $-44,076$; although its p -value of 0.308 suggests that the effect is not statistically significant in this model. This result implies that while high temperatures may be detrimental to olive production, their impact might be overshadowed by other climatic factors, such as precipitation and overall climatic conditions (Ic and Io). All the details and parameters of the multiple linear regression model can be found in Table 5.

The resulting regression equation for predicting olive yield (Production/Ha) is as follows:

$$\begin{aligned} \text{Production/Ha} = & 117,623.03 + 1690.61 \cdot \text{Itc} + 46,682.20 \cdot \text{Io} + 27,300.32 \cdot \text{Ic} \\ & - 44,076.87 \cdot \text{Tmax} - 1196.93 \cdot \text{P01} - 863.39 \cdot \text{P02} - 228.24 \cdot \text{P11} \\ & + 192.39 \cdot \text{P12} \end{aligned}$$

Table 5. Statistical parameters of the multiple linear regression model with standardized coefficients for the production variable (Kg/Ha).

Variable	Value	Standard Error	t	Pr > t	Lower Limit (95%)	Upper Limit (95%)	Signification
Itc	58.628	41.919	1.399	0.234	−57.757	175.012	°
Io	16.450	3.528	4.662	0.010	6.653	26.246	**
Ic	31.342	32.611	0.961	0.391	−59.200	121.884	°
Tmin	0.000	0.000					
Tmax	−34.553	29.599	−1.167	0.308	−116.733	47.627	°
T	0.000	0.000					
P01	−17.994	9.569	−1.880	0.133	−44.561	8.574	°
P02	−8.249	6.314	−1.306	0.261	−25.781	9.283	°
P10	0.000	0.000					
P11	−3.570	4.154	−0.859	0.439	−15.102	7.962	°
P12	3.040	9.406	0.323	0.763	−23.076	29.155	°

Signification codes: $0.001 < ** < 0.01$; $0.1 < ° < 1$.

This equation allows for the prediction of olive yield based on the included climatic variables, with Io and P01 being the most influential in determining variability in production. The multiple linear regression analysis indicates that the ombroclimatic index (Io) is the most critical factor influencing olive yield, followed by precipitation. While maximum temperatures (Tmax) have a negative effect, their statistical significance is limited in this model. These results highlight the need to carefully manage water availability and monitor climate conditions to optimize olive production. Overall, the model provides a reliable framework for predicting olive yields based on key climatic variables, and can be used as a tool for improving agricultural practices in olive cultivation.

The projected model of potential olive production, specifically for rainfed (dryland) cultivation, highlights areas in Andalucía where climatic conditions are most favorable for high yields (Figure 5). The darker tones on the map indicate zones with higher production potential, suggesting optimal bioclimatic conditions that align with factors such as temperature, precipitation, and other environmental indices. This distribution reflects the integration of the ombroclimatic index (Io), temperature extremes, and geographical factors as determined by the multiple regression model.

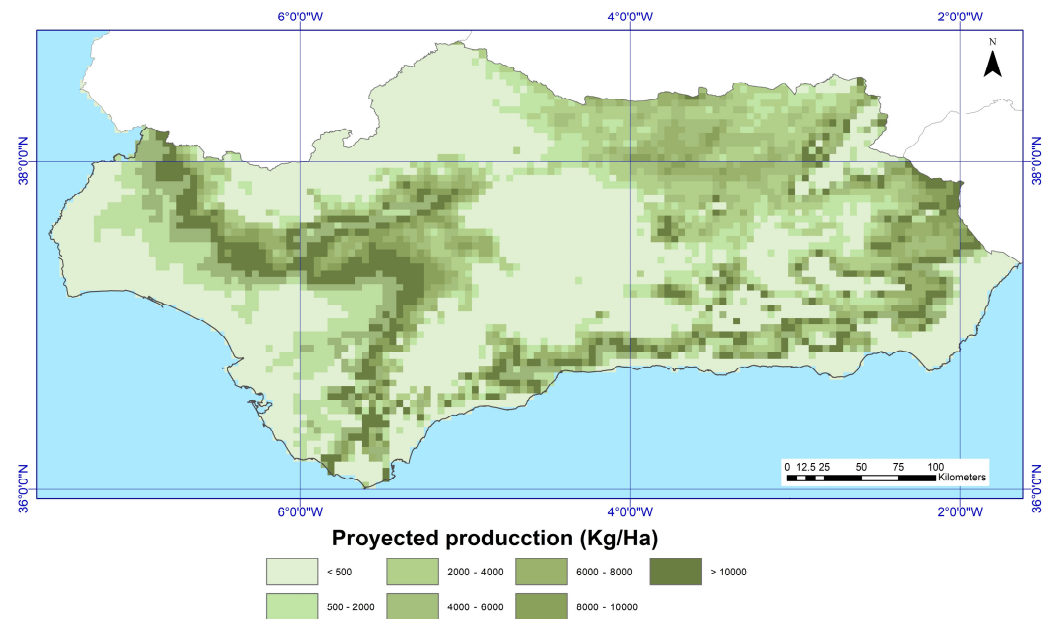


Figure 5. Projected potential olive production in rainfed cultivation areas across Andalucía, based on a multiple linear regression model that integrates key climatic variables such as the ombroclimatic index (Io), maximum temperature (Tmax), and monthly precipitation indices (P01–P12). Darker tones indicate areas with higher production potential, reflecting more favorable bioclimatic conditions for olive cultivation.

These findings can be further supported and understood by examining bioclimatic maps from Piñar-Fuentes (2023) [54], which provide additional context on regional climate patterns. For example, the Positive Temperature (Tp) Map in [54] shows regions with moderate temperatures throughout the year, which overlap with the darker-toned, high-yield areas on the production map. This suggests that consistent positive temperatures support olive growth, avoiding the detrimental effects of extreme heat or cold that can reduce productivity.

Additionally, the Evapotranspiration Map in [54] and the Aridity Index highlight areas where water availability—particularly during the summer months—remains balanced, preventing water stress. Areas with lower evapotranspiration rates align with higher production potentials, indicating that moderate water loss due to evaporation supports better olive yields. This is critical in a dryland farming context, where excessive evapotranspiration can lead to water deficits and decreased production.

The Ombro-Evaporation Index (IOE) and Humidity Index further emphasize regions where precipitation and humidity levels are favorable for olive growth. Areas with higher humidity levels and balanced IOE values tend to show better production potential, as these conditions help in maintaining soil moisture without the risk of waterlogging. Lastly, the Bioclimatic Floor Map provides insight into the broader climatic classification of these regions, with zones categorized as “mesomediterranean” or “thermomediterranean” showing particularly high suitability for olive cultivation due to their mild winters and warm, dry summers; conditions well matched to the physiological needs of olive trees.

The integration of these climatic maps helps explain why certain regions have been projected to have higher olive yields. Understanding these bioclimatic factors allows for better agricultural planning and management, guiding the selection of optimal sites for expanding or maintaining olive cultivation in a sustainable manner.

The exploratory analysis of the olive yield time series from farms O1 and O2, both located in the Sierra de Cazorla (Province of Jaén), was conducted using various tests for normality and white noise. Farm O1, situated at latitude 37.934°, longitude −2.979°, altitude 730; and farm o2, located at latitude 37.974°, longitude −2.996°, altitude 620, have annual production data available from 2010 to 2023, enabling long-term yield analysis. The

tests applied, including Box–Pierce, Ljung–Box, and McLeod–Li, were critical in identifying autocorrelation and heteroscedasticity in the residuals of the time series (Table 6).

Table 6. Summary of statistical tests comparing two olive production datasets (O1 and O2). Significant autocorrelation was detected in O1 (Ljung–Box test, $p < 0.0001$), along with non-linearity (McLeod–Li test, $p = 0.005$). In contrast, O2 showed no significant autocorrelation or non-linearity, indicating a more stable time series. Both datasets passed the normality test (Jarque–Bera, $p > 0.05$).

Statistic	O1—Value	O1— p -Value	O2—Value	O2— p -Value
Box–Pierce (6 DF)	3.028	0.805	3.07	0.8
Ljung–Box (6 DF)	4.973	0.547	4.829	0.566
McLeod–Li (6 DF)	14.071	0.029	7.924	0.244
Box–Pierce (12 DF)	11.037	0.526	3.838	0.986
Ljung–Box (12 DF)	62.71	<0.0001	7.771	0.803
McLeod–Li (12 DF)	28.357	0.005	11.395	0.495
Jarque–Bera (2 DF)	1.561	0.458	0.623	0.732

For the Kg/Ha (O1) time series, the results from the Box–Pierce and Ljung–Box tests, at both 6 and 12 degrees of freedom (DF), indicated no significant autocorrelation in the residuals (p -values > 0.05), suggesting that the residuals do not exhibit repetitive temporal patterns. However, the McLeod–Li test at 6 DF yielded a p -value of 0.029, indicating the presence of significant heteroscedasticity, or varying residual variance over time. This finding aligns with the expected variability in olive yields from one season to another, potentially driven by climatic conditions and farm management practices. Furthermore, at 12 DF, both Ljung–Box and McLeod–Li confirmed the presence of heteroscedasticity, indicating non-constant residual variance over time for farm O1.

In contrast, the time series for Kg/Ha (O2) showed more stable behavior. Both the Box–Pierce and Ljung–Box tests at 6 and 12 DF did not reveal significant autocorrelation in the residuals, and the McLeod–Li test also showed no significant heteroscedasticity. This suggests that the residuals in O2 are more homogeneous in terms of variance. These results imply that olive production in O2, situated at a slightly lower altitude than O1, experiences fewer fluctuations, possibly due to microclimatic differences or divergent management practices between the two farms.

Additionally, the Jarque–Bera test, applied to both O1 and O2, found no significant deviations from normality in the residuals, indicating that the residuals follow a normal distribution. This further supports the robustness of the models applied to these time series analyses.

In summary, while O1 shows evidence of heteroscedasticity and yield variability, likely driven by climatic factors at higher altitudes and more pronounced interannual fluctuations, O2 displays a more stable production pattern, with no significant issues of heteroscedasticity or autocorrelation in the residuals. These results provide valuable insights for refining predictive models and addressing the production differences between the two farms.

4. Discussion

Olive cultivation is highly sensitive to climatic factors such as temperature and precipitation, with these variables playing a crucial role in determining yield variability [19,51,60]. Numerous studies, including those focused on Mediterranean regions, confirm that temperature extremes (both high and low) and precipitation patterns are the main drivers of olive productivity. According to [61], fluctuations in precipitation—particularly during key growth stages—can significantly influence olive yield, particularly in rainfed systems. This aligns with our PCA results, which show that geographical factors such as latitude

and longitude (linked to local climatic conditions) and precipitation are among the most influential variables impacting olive yield.

The role of precipitation in olive cultivation has been further emphasized by studies such as those by [19,61–63], which demonstrated that regions experiencing excess rainfall during certain months (e.g., early spring) face higher risks of reduced olive yields due to waterlogging or the development of diseases. This corresponds with the negative loadings found for precipitation variables (P01, P02) in our PCA analysis, indicating that excessive rainfall in these months negatively impacts olive productivity. Furthermore, this highlights the need for careful water management strategies to optimize olive production under varying climatic conditions.

The second principal component (F2) in our analysis, which is primarily associated with maximum temperatures, underscores the importance of thermal extremes in olive production. This finding is consistent with studies such as those by [64–68], which observed that high temperatures, especially during the growing season, can cause significant heat stress in olive trees, leading to reduced fruit set and lower yields. Such conditions are becoming more frequent with climate change, as documented in recent reports from the World Meteorological Organization (WMO). The increased frequency of extreme weather events, including heat waves and droughts, is already affecting the productivity of olives, especially in regions such as southern Spain and Portugal, where temperatures regularly exceed the optimal thresholds for olive growth [19,61,62,69].

Studies conducted by [65] also show that extreme heat exacerbates the stress experienced by olive trees, particularly in regions where water is scarce, further limiting yields. Our results, indicating that maximum temperatures significantly influence yield (as shown by the high loading of Tmax on F2), confirm these observations and suggest that without adequate mitigation measures, such as improved irrigation or adaptive farming practices, yields in warmer regions may continue to decline.

The multiple linear regression analysis conducted on olive yield data reveals significant insights into how climatic variables impact production. This aligns with previous studies that have examined the influence of temperature and precipitation on crop yields. For example, research has demonstrated that temperature extremes can negatively affect yields across different agricultural systems. In Mediterranean environments, where olives are predominantly grown, heat stress and excessive temperatures, especially during the growing season, can lead to reduced productivity. This effect is confirmed by findings from studies in southern Europe and similar climates, where high maximum temperatures (Tmax) during the flowering and fruit-setting phases often correlate with lower yields, as observed by [68,70–72].

The regression results underscore that maximum temperatures (Tmax) exert a negative influence on olive yield, although this variable did not show statistical significance within this model. Similar findings have been reported in broader agricultural contexts. A number of studies [70–72] have found that rising Tmax values during critical growth phases often result in reduced fruit development, due to increased evapotranspiration rates and heat stress. This highlights the importance of managing thermal conditions, particularly in regions already experiencing high temperatures. Additionally, other research has indicated that elevated Tmax can disrupt physiological processes in olives, such as photosynthesis and water uptake, further contributing to lower yields [68].

However, while Tmax appears to affect olive yields, it is not always the most critical variable. Studies have shown that mean temperatures and minimum temperatures can sometimes play a more significant role, particularly when these factors lead to prolonged warm conditions that extend the growing season or protect crops from early frost [73,74]. These nuances suggest that future models might benefit from incorporating a wider range of temperature variables, including diurnal temperature ranges and season-long temperature averages.

The regression analysis identified precipitation during the early months of the year (P01) as having a moderately negative effect on production. This finding is consistent

with reports from studies such as [61], which suggest that excessive rainfall during the early growth stages can lead to issues such as waterlogging and increased soil moisture, conditions that may hinder root aeration and increase susceptibility to fungal diseases. Furthermore, it has been observed that periods of high precipitation early in the year can disrupt the delicate balance needed for olive flowering and fruit setting, potentially reducing yield outputs [75,76].

This relationship emphasizes the importance of water management strategies in rainfed olive systems. Studies such as [76,77] also highlighted that, in Mediterranean climates, an imbalance in early-season precipitation can cause significant variability in yield, demonstrating the delicate nature of precipitation's role in crop health. Therefore, regions where waterlogging is a risk may need to adopt improved drainage techniques or controlled irrigation to mitigate these effects.

One of the most significant findings from this analysis is the positive correlation between the ombroclimatic index (Io) and olive yield. The regression coefficient for Io was the highest among the variables, indicating that favorable climatic conditions—characterized by a balanced relationship between temperature and precipitation—can greatly enhance productivity. Previous research has similarly concluded that regions with an optimal Io tend to maintain higher yields due to better synchronization between climatic conditions and crop phenology [16,18,47,65]. This suggests that farms located in regions with favorable ombroclimatic conditions, or those that can simulate these conditions through controlled irrigation, are more likely to achieve stable and high yields.

Educational and Policy Implications of the Findings

The findings of this study provide valuable insights into the relationship between climatic factors and olive productivity, highlighting the critical role of thermo-ombroclimatic indicators. However, the implications of these results extend beyond scientific observations, offering actionable insights for agricultural policy and management [19]. Moreover, and related to the above, the integration of education for sustainable agricultural development (ESD) can play a pivotal role in achieving this. Training programs should focus on fostering a deeper understanding of how climatic factors, such as temperature and precipitation, directly impact crop productivity. For example, recent educational initiatives, such as those led by the International Olive Council and local agricultural institutions, have developed training modules on climate adaptation, which include modules on water management and the use of bioclimatic indices to predict crop yields more accurately [6,78,79].

The strong correlation between olive yield and bioclimatic variables such as precipitation and extreme temperatures underscores the necessity of integrating these indicators into regional agricultural policies. Policymakers can leverage this knowledge to design adaptive strategies that promote sustainable olive farming in regions highly vulnerable to climate variability. For instance:

- (a) **Water Resource Management:** The results suggest that excessive or insufficient precipitation impacts yields. Policies could prioritize investment in efficient irrigation systems, particularly in areas where the ombroclimatic index indicates high water stress. Implementing efficient irrigation systems and water conservation practices can mitigate the impact of irregular precipitation patterns on olive yields. This approach is crucial in areas experiencing increased drought frequency due to climate change.
- (b) **Climate-resilient varieties:** The findings support the development of programs to encourage the adoption of drought- and heat-resistant olive cultivars. These programs could be supported by subsidies or incentives targeting farmers in regions prone to extreme weather conditions. Encouraging the adoption of drought- and heat-resistant olive varieties can enhance resilience to extreme weather conditions. Breeding programs focused on developing such cultivars are essential for maintaining productivity under changing climatic scenarios.
- (c) **Local planning and zoning:** The geographical variability observed in this study highlights the importance of zoning agricultural activities based on bioclimatic suitability.

Decision-makers could use these data to guide land-use planning, optimizing crop placement for maximum productivity and sustainability.

- (d) Agroecological practices: Promoting soil conservation techniques, such as cover cropping and mulching, can improve soil moisture retention and fertility, supporting olive tree health during periods of climatic stress. These practices contribute to the overall sustainability of olive farming systems.
- (e) Educational initiatives: Integrating education for sustainable development (ESD) into agricultural training programs equips farmers with the knowledge and skills to apply bioclimatic principles in crop management. This education fosters adaptive capacity and informed decision-making among agricultural communities.

Further reinforcing this, studies by the Food and Agriculture Organization (FAO) highlight the importance of climate-smart agriculture (CSA) as an educational tool. CSA techniques not only increase adaptive capacity but also emphasize the need for sustainable water usage and soil management, which align directly with the findings from the PCA and regression models of this study. These techniques involve practical, hands-on training that enables farmers to implement new strategies effectively [80]. For instance, the use of drip irrigation systems, as seen in many CSA practices, can help manage water resources more efficiently in olive farming, mitigating the negative impacts of excessive or insufficient precipitation observed in the regression analysis [41,78,79].

One successful example of integrating these educational elements is the Feed the Future Innovation Lab for Crop Improvement (ILCI), which has launched online courses that blend technical skills with cutting-edge research in agriculture. These courses provide lessons on building resilience in crop systems, particularly by teaching methods to manage environmental stressors such as temperature extremes and variable rainfall. The emphasis is not only on the technical aspects of farming, but also on understanding the socioeconomic implications, making it easier for farmers to adopt these practices [80,81].

Moreover, the role of indigenous and traditional knowledge in developing sustainable farming practices has been increasingly recognized. A study highlights how integrating traditional farming knowledge with modern agronomic training can offer innovative solutions to climate resilience [82]. In regions with a strong tradition of olive cultivation, such as the Mediterranean basin, blending traditional water-conservation practices with modern irrigation technology can lead to more sustainable farming models. This concept of blending modern science with traditional practices can be particularly effective in regions such as Andalusia, where the local climate poses unique challenges to olive production [22,23,82,83].

The olive sector requires adaptive measures to maintain sustainability, while minimizing risks associated with climate variability. Current strategies mainly focus on individualized farm practices, yet fail to address broader socioenvironmental challenges. Territorial Management Contracts (TMC) have proven to be an effective solution to address sustainability issues in mountain olive groves [21]. These contracts foster cooperation between farmers and public administrations, integrating collective commitments that improve production conditions and ecological and socioeconomic aspects. In addition, they make it possible to overcome problems such as land abandonment by offering financial incentives to groups of farmers who meet the objectives set out in the contract. This collective approach contributes significantly to territorial development, favoring spatial connectivity and improving both economic efficiency and environmental performance [21,84,85].

Incorporating these educational strategies within the framework of agricultural policy could significantly improve the resilience of olive production systems. Governments and agricultural bodies need to promote continued education and training programs that teach both young and established farmers how to utilize climate data effectively, implement sustainable water management practices, and adopt new technologies that can reduce the impact of climate change on yields [80,86,87]. Programs focusing on digital tools for climate prediction and adaptive farming, as developed by the FAO and other organizations, can

enable farmers to better anticipate and prepare for climatic variability, further enhancing the sustainability of their farming operations.

Although this study has provided valuable information on the use of thermo-ombroclimatic indicators in sustainable olive orchard management, there are several areas that deserve further research. First, it would be relevant to conduct long-term studies that evaluate the effectiveness of these indicators under future climate change scenarios, integrating detailed climate projections. This would allow assessing how climate trends will affect the productivity and sustainability of olive orchards in various Mediterranean regions.

In addition, it is suggested to investigate how the implementation of integrated policies, such as territorial management contracts, can be scaled up to regional or national levels to maximize their impact. It would be particularly useful to explore mechanisms to foster cooperation between farmers and other stakeholders, as well as economic incentives that can ensure the widespread adoption of sustainable practices.

Finally, future research could focus on modeling the specific impacts of extreme weather conditions, such as heat waves and prolonged droughts, on olive yields. This would include identifying more resilient olive varieties and designing adaptive strategies that optimize productivity without compromising environmental sustainability. While this study emphasizes the role of bioclimatic models, further research is needed to evaluate their application across other Mediterranean regions and crop types. Additionally, integrating socioeconomic factors into future analyses could provide a more holistic understanding of the challenges faced by farmers and policymakers.

5. Conclusions

This study demonstrates that biophysical indicators, particularly thermo-ombroclimatic indices, are essential tools for optimizing olive grove management in the face of climate change challenges. By applying the Rivas-Martínez Bioclimatic Model to Mediterranean olive crops, this research highlights the critical role of local climatic conditions in achieving agricultural sustainability and productivity. The findings suggest that adopting bioclimatic principles not only enhances crop resilience but also enables more efficient management of natural resources, such as water and soil. The obtained results demonstrate that informed and adaptive agricultural management is fundamental not only for maximizing yield but also for mitigating the environmental degradation associated with unsustainable practices.

The objectives set forth at the beginning of this work have been significantly achieved:

- From a policy perspective, these results provide a foundation for developing adaptive agricultural strategies, integrating bioclimatic models into public policies and training programs. Such approaches contribute not only to mitigating the impacts of climate change but also to advancing the transition toward a more sustainable agricultural model.
- For decision-makers, the implementation of these methods offers practical solutions to address the challenges of climatic variability, enabling more precise and region-specific planning. Furthermore, incorporating these insights into educational programs fosters the training of professionals equipped to tackle future challenges, promoting a balance between agricultural productivity and environmental conservation.

However, the study has also identified areas for improvement that could enrich future research. In particular, it is imperative to adopt a multidisciplinary educational approach that encompasses not only bioclimatology and ecology, but also emerging technologies applied to agriculture. This will enable students and professionals not only to learn about bioindicators but also to understand their interrelation within a broader agricultural context. Additionally, promoting applied research in collaboration with local farmers could facilitate effective knowledge transfer, ensuring that sustainable strategies are practically and effectively implemented in the field.

In summary, this work underscores the importance of agricultural management based on bioclimatic principles, establishing a framework for future research and paving the way for resilient and sustainable agricultural systems. The potential impact of this approach

extends beyond improving agricultural yields to preserving natural resources and fostering innovative farming practices that benefit both local communities and society at large.

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Appendix A

Table A1. Floristic composition of the vegetation covers present in the “Sierra de Cazorla01” farm at different points of the farm, during the period 2018–2024. 5 = 85% vegetation cover, 4 = 65%, 3 = 45%, 2 = 25%, 1 = 12.5%, “+” = 5% or few individuals, “r” = < 2% or a single individual.

Date	20 April 2018	21 April 2018	15 May 2022	20 May 2018	20 May 2018	5 April 2024	11 May 2024
Latitude	37.9361	37.9340	37.9340	37.9361	37.9378	37.9355	37.9355
Longitude	−2.9922	−2.9816	−2.9816	−2.9800	−2.9818	−2.9774	−2.9809
Altitude	547	742		715	735	775	
Slope (°)	15.7	18		24	36		
Orientation	N	N	W	NE	NE	W	W
Sampling area (m ²)	4	9	9	9	4	4	9
Vegetation layer cover E1 (%)	100	80	100	95	100	100	100
Height of vegetation layer E1 (cm)	90	60	90	35	75	25	75
Vegetation layer cover E2 (%)			80			70	90
Height of vegetation layer E2 (cm)	55		30			8	30
Vegetation layer cover E3 (%)						60	
Height of vegetation layer E3 (cm)						1 (<i>Bryophyta</i> sp.)	
Number of species	5	11	18	17	21	11	14
<i>Aegilops geniculata</i> Roth				4			
<i>Allium roseum</i> L.				+			
<i>Anacyclus clavatus</i> (Desf.) Pers.					(+)		
<i>Lysimachia arvensis</i>			+	+	1		r
(L.) U.Manns & Anderb.							
<i>Anchusa azurea</i> Schur			+				
<i>Anchusa puechii</i> Valdés		r	r		+	+	
<i>Andryala integrifolia</i> L.					+		
<i>Anthyllis vulneraria</i> subsp. <i>gandogeri</i>				1		+	
(Sagorski) W. Becker							
<i>Atractylis cancellata</i> L.					2		
<i>Avena barbata</i> Pott ex Link				1			
<i>Avena sterilis</i> L.					3		1
<i>Bituminaria bituminosa</i> (L.) C.H.Stirt.				+	+	+	
<i>Bromus matritensis</i> L. ex Roem. & Schult.	3	2	2	+		1	+
<i>Bromus sterilis</i> Láng ex Kumm. & Sendtn.				1			3
<i>Bromus tectorum</i> L.			2				
<i>Bupleurum rotundifolium</i> L.					1		
<i>Calendula arvensis</i> L.		1	2		1		+
<i>Campanula erinus</i> L.		+					
<i>Catapodium rigidum</i> (L.) C.E.Hubb.				+	1		+
<i>Centaurea melitensis</i> L.					+		
<i>Centaurea pullata</i> subsp. <i>pullata</i> L.				(+)	+		
<i>Centranthus calcitrapae</i> (L.) Dufr.				+			
<i>Cerastium brachypetalum</i> Desp. ex Pers.						r	
<i>Convolvulus althaeoides</i> L.				+	2		
<i>Convolvulus meonanthus</i> Hoffmanns. & Link				(+)	1		

Table A1. Cont.

Date	20 April 2018	21 April 2018	15 May 2022	20 May 2018	20 May 2018	5 April 2024	11 May 2024
<i>Coronilla scorpioides</i> (L.) W.D.J.Koch				2	+	1	+
<i>Crepis taraxacifolia</i> Willd.							2
<i>Crepis vesicaria</i> subsp. <i>congenita</i> Babcock				+			
<i>Crupina vulgaris</i> Pers. ex Cass.					1		
<i>Daucus carota</i> L.						+	
<i>Echinaria capitata</i> (L.) Desf.				1		2	
<i>Erodium aethiopicum</i> subsp. <i>pilosum</i> (Thuill.) Guitt.					1		
<i>Erodium malacoides</i> (L.) L'Hér.		+	1				
<i>Euphorbia exigua</i> L.			1	r		+	
<i>Euphorbia helioscopia</i> L.		+	1		+		
<i>Euphorbia minima</i> (Haw.) Mart.			+				
<i>Euphorbia segetalis</i> L.				+	1		
<i>Fedia cornucopiae</i> (L.) Gaertn.		1	2				
<i>Filago pyramidata</i> L.						+	r
<i>Fumaria capreolata</i> L.		+	2				
<i>Fumaria officinalis</i> L.		1	2				
<i>Galium aparine</i> L.	1						
<i>Galium minutulum</i> Jord.	+					1	r
<i>Galium parisiense</i> Pall.							r
<i>Geranium robertianum</i> L.				1			
<i>Geranium dissectum</i> L.				+			
<i>Geranium purpureum</i> Gilib.			+				
<i>Geranium rotundifolium</i> L.							2
<i>Geropogon hybridus</i> (L.) Sch.Bip.				+	1		
<i>Hordeum murinum</i> subsp. <i>leporinum</i> (Link) Arcang.							4
<i>Lactuca serriola</i> L.		+					+
<i>Lagoecia cuminoides</i> L.					r		
<i>Lathyrus cicera</i> L.	+						
<i>Linaria micrantha</i> (Cav.) Hoffmanns. & Link					+		
<i>Lolium rigidum</i> Gaudin				3			2
<i>Malva hispanica</i> L.					+		
<i>Matricaria chamomilla</i> L.							r
<i>Medicago doliata</i> Carmign.		1	1				
<i>Medicago minima</i> (L.) Bartal.				1		1	
<i>Medicago orbicularis</i> (L.) Bartal.				1			1
<i>Medicago polymorpha</i> L.				1			1
<i>Medicago rigidula</i> (L.) All.	2	1	3	2		5	4
<i>Medicago truncatula</i> Gaertn.				+			
<i>Minuartia hybrida</i> (Vill.) Schischk.							+
<i>Muscari neglectum</i> Guss. ex Ten.				+			
<i>Muscari olivetorum</i> Blanca, Ruíz Rejón & Suár.-Sant.		+	+	+	+		
<i>Minuartia hybrida</i> (Vill.) Schischk.						r	+
<i>Orlaya daucoides</i> (L.) Greuter				+	1		
<i>Pallenis spinosa</i> (L.) Cass.					1		
<i>Picnemon acarna</i> (L.) Cass.	r		+				r
<i>Ranunculus arvensis</i> L.		+	+	+		r	+
<i>Reichardia intermedia</i> (Jan ex DC.) Dinsm.		(+)			3		
<i>Rhagadiolus stellatus</i> (L.) Gaertn.				1	2		
<i>Roemeria hybrida</i> (L.) DC.							+
<i>Sagina apetala</i> Ard.							+
<i>Sanguisorba minor</i> Scop.				(+)			
<i>Scandix pecten-veneris</i> L.	+	1	1	1	(+)	2	1
<i>Scorpiurus muricatus</i> L.			1	2	2	3	
<i>Senecio vulgaris</i> L.		+	+				
<i>Sherardia arvensis</i> L.		+	2	2		+	
<i>Silene colorata</i> Fenzl		1	(+)				
<i>Sinapis alba</i> subsp. <i>mairei</i> (H. Lindb. fil.) Maire	4	4	4	+	4	r	
<i>Sonchus asper</i> (L.) Hill			1				
<i>Sonchus oleraceus</i> L.							r
<i>Sonchus tenerrimus</i> Schur		1		+	2		
<i>Stellaria media</i> (L.) Vill.		+	1				

Table A1. Cont.

Date	20 April 2018	21 April 2018	15 May 2022	20 May 2018	20 May 2018	5 April 2024	11 May 2024
<i>Thlaspi perfoliatum</i> L.		+					
<i>Thrinicia hispida</i> (L.) Roth							1
<i>Torilis arvensis</i> (Huds.) Link							1
<i>Trachynia distachya</i> (L.) Link					1	1	
<i>Tragopogon hybridus</i> L.						+	
<i>Urospermum picroides</i> (L.) Scop. ex F.W.Schmidt							1
<i>Valerianella coronata</i> (L.) DC.					+		
<i>Valerianella discoidea</i> (L.) Loisel.						1	
<i>Veronica polita</i> Fr.		1	+				
<i>Vicia cordata</i> Wulfen ex Hoppe						1	1
<i>Vicia lutea</i> L.		+					
<i>Vicia narbonensis</i> L.	1	r	1	1	1		

References

- Daszkiewicz, T. Food Production in the Context of Global Developmental Challenges. *Agriculture* **2022**, *12*, 832. [\[CrossRef\]](#)
- Miladinov, G. Impacts of Population Growth and Economic Development on Food Security in Low-Income and Middle-Income Countries. *Front. Hum. Dyn.* **2023**, *5*, 1121662. [\[CrossRef\]](#)
- Becker, S.; Fanzo, J. Population and Food Systems: What Does the Future Hold? *Popul. Environ.* **2023**, *45*, 20. [\[CrossRef\]](#)
- Bodirsky, B.L.; Rolinski, S.; Biewald, A.; Weindl, I.; Popp, A.; Lotze-Campen, H. Global Food Demand Scenarios for the 21st Century. *PLoS ONE* **2015**, *10*, e0139201. [\[CrossRef\]](#)
- Cano-Ortiz, A.; Fuentes, J.C.P.; Cano, E. Analysis of Toxic Contaminants in Agriculture: Educational Strategies to Avoid Their Influence on Food. *Res. J. Ecol. Environ. Sci.* **2024**, *4*. [\[CrossRef\]](#)
- Cano-Ortiz, A.; Musarella, C.M.; Piñar Fuentes, J.C.; Quinto-Canas, R.; Igbareyeh, J.; Astrid Laface, V.L.; Cano, E. The Teaching of Environmental Sciences in Secondary Education, High School and University to Fight Against Climate Change. In *International Symposium: New Metropolitan Perspectives*; Springer International Publishing: Cham, Switzerland, 2022; Volume 482.
- Ali, M.A.; Kamraju, M. Land Use and Agriculture. In *Natural Resources and Society: Understanding the Complex Relationship Between Humans and the Environment. Earth and Environmental Sciences Library*; Springer: Cham, Switzerland, 2023; pp. 115–127. [\[CrossRef\]](#)
- Devi, S.; Goswami, S.; Bisaria, J.; Sinha, B. Approaches for Land Restoration: An Alternative Strategy for Climate Change Mitigation. In *Forests and Climate Change: Biological Perspectives on Impact, Adaptation, and Mitigation Strategies*; Springer Nature: Singapore, 2024; pp. 535–551. [\[CrossRef\]](#)
- Akkaya, D.; Bimpikis, K.; Lee, H. Government Interventions to Promote Agricultural Innovation. *Manuf. Serv. Oper. Manag.* **2021**, *23*, 437–452. [\[CrossRef\]](#)
- Puertas, R.; Marti, L.; Calafat, C. Agricultural and Innovation Policies Aimed at Mitigating Climate Change. *Environ. Sci. Pollut. Res.* **2023**, *30*, 47299–47310. [\[CrossRef\]](#)
- Liu, H.; Wen, S.; Wang, Z. Agricultural Production Agglomeration and Total Factor Carbon Productivity: Based on NDDF–MML Index Analysis. *China Agric. Econ. Rev.* **2022**, *14*, 709–740. Available online: <https://www.emerald.com/insight/content/doi/10.1108/caer-02-2022-0035/full/html> (accessed on 18 November 2024). [\[CrossRef\]](#)
- Shi, R.; Yao, L.; Zhao, M.; Yan, Z. The Role of Climate-Adaptive Technological Innovation in Promoting Agriculture Carbon Efficiency: Impact and Heterogeneity in Economic Development. *Environ. Sci. Pollut. Res. Int.* **2023**, *30*, 126029–126044. [\[CrossRef\]](#)
- Rivas-Martínez, S.; Rivas-Sáenz, S.; Penas-Merino, A. Worldwide Bioclimatic Classification System. *Glob. Geobot.* **2011**, *1*.
- Adaptaciones Del Olivar al Cambio Climático—Blog Agromillora.Com. Available online: <https://www.agromillora.com/olint/adaptaciones-del-olivar-al-cambio-climatico/> (accessed on 14 November 2024).
- Igbareyeh, J.M.H.; Cano-Ortiz, A.; Cano, E. Case Study: Analysis of the Physical Factors of Palestinian Bioclimate. *Am. J. Clim. Chang.* **2014**, *3*, 223–231. [\[CrossRef\]](#)
- Igbareyeh, J.M.H.; Cano-Ortiz, A.; Cano, E. Biological and Bioclimatic Basis to Optimize Plant Production: Increased Economic Areas of Palestine. *Agric. Sci. Res. J.* **2014**, *4*, 10–20.
- del Río, S.; Álvarez-Esteban, R.; Alonso-Redondo, R.; Álvarez, R.; Rodríguez-Fernández, M.P.; González-Pérez, A.; Penas, A. Applications of Bioclimatology to Assess Effects of Climate Change on Viticultural Suitability in the DO León (Spain). *Theor. Appl. Clim.* **2024**, *155*, 3387–3404. [\[CrossRef\]](#)
- Cano, E.; Cano-Ortiz, A.; Musarella, C.M.; Piñar Fuentes, J.C.; Igbareyeh, J.M.H.; Leyva Gea, F.; del Río, S. Mitigating Climate Change Through Bioclimatic Applications and Cultivation Techniques in Agriculture (Andalusia, Spain). In *Sustainable Agriculture, Forest and Environmental Management*; Springer: Singapore, 2019; pp. 31–69. [\[CrossRef\]](#)
- Cano-Ortiz, A.; Fuentes, J.C.P.; Gea, F.L.; Igbareyeh, J.M.H.; Quinto Canas, R.J.; Meireles, C.I.R.; Raposo, M.; Gomes, C.J.P.; Spampinato, G.; del Río González, S.; et al. Climatology, Bioclimatology and Vegetation Cover: Tools to Mitigate Climate Change in Olive Groves. *Agronomy* **2022**, *12*, 2707. [\[CrossRef\]](#)

20. Guo, B.; Chen, K.; Jin, G. Does Multi-Goal Policy Affect Agricultural Land Efficiency? A Quasi-Natural Experiment Based on the Natural Resource Conservation and Intensification Pilot Scheme. *Appl. Geogr.* **2023**, *161*, 103141. [CrossRef]
21. Rocamora-Montiel, B.; Glenk, K.; Colombo, S. Territorial Management Contracts as a Tool to Enhance the Sustainability of Sloping and Mountainous Olive Orchards: Evidence from a Case Study in Southern Spain. *Land Use Policy* **2014**, *41*, 313–324. [CrossRef]
22. Arjen, E.; Wals, J.; Kieft, G. *Education for Sustainable Development Research Overview*. Edita 2010 Art. no. Sida61266en. 2010. ISBN: 978-91-586-4131-0. Available online: <https://www.sida.se/en/about-sida/publications-archive/education-for-sustainable-developmentresearch-overview> (accessed on 18 November 2024).
23. UNESCO Education for Sustainable Development 2023. Available online: <https://www.unesco.org/en/sustainable-development/education/esd-net?hub=72522> (accessed on 18 November 2024).
24. de Pauw, J.B.; Gericke, N.; Olsson, D.; Berglund, T. The Effectiveness of Education for Sustainable Development. *Sustainability* **2015**, *7*, 15693–15717. [CrossRef]
25. Jordan, C.F. A Systems (Holistic) Approach to Sustainable Agriculture. In *An Ecosystem Approach to Sustainable Agriculture. Environmental Challenges and Solutions*; Springer: Dordrecht, the Netherlands, 2013; pp. 1–38. [CrossRef]
26. Caron, P.; Ferrero y de Loma-Orsio, G.; Nabarro, D.; Hainzelin, E.; Guillou, M.; Andersen, I.; Arnold, T.; Astralaga, M.; Beukeboom, M.; Bickersteth, S.; et al. Food Systems for Sustainable Development: Proposals for a Profound Four-Part Transformation. *Agron. Sustain. Dev.* **2018**, *38*, 41. [CrossRef]
27. Bisht, I.S.; Rana, J.C.; Jones, S.; Estrada-Carmona, N.; Yadav, R.; Bisht, I.S.; Rana, J.C.; Jones, S.; Estrada-Carmona, N.; Yadav, R. Agroecological Approach to Farming for Sustainable Development: The Indian Scenario. In *Biodiversity of Ecosystems*; IntechOpen: Rijeka, Croatia, 2021. [CrossRef]
28. Gliessman, S. Defining Agroecology. *Agroecol. Sustain. Food Syst.* **2018**, *42*, 599–600. [CrossRef]
29. Nimmo, E.R.; Nelson, E.; Gómez-Tovar, L.; García, M.M.; Spring, A.; Lacerda, A.E.B.; de Carvalho, A.I.; Blay-Palmer, A. Building an Agroecology Knowledge Network for Agrobiodiversity Conservation. *Conservation* **2023**, *3*, 491–508. [CrossRef]
30. Cano, E.; García Fuentes, A.; Torres, J.A.; Salazar, C.; Melendo, M.; Pinto Gomes, C.; Valle, F. Phytosociologie Appliquée a La Planification Agricole. *Colloq. Phytosociol.* **1997**, *27*, 1007–1022.
31. Cano Ortiz, A. Teaching about Biodiversity from Phytosociology: Evaluation and Conservation. *Plant Sociol.* **2023**, *60*, 25–37. [CrossRef]
32. Dayamba, D.S.; Ky-Dembele, C.; Bayala, J.; Dorward, P.; Clarkson, G.; Sanogo, D.; Diop Mamadou, L.; Traoré, I.; Diakité, A.; Nenkam, A.; et al. Assessment of the Use of Participatory Integrated Climate Services for Agriculture (PICSA) Approach by Farmers to Manage Climate Risk in Mali and Senegal. *Clim. Serv.* **2018**, *12*, 27–35. [CrossRef]
33. Clarkson, G.; Dorward, P.; Osbahr, H.; Torgbor, F.; Kankam-Boadu, I. An Investigation of the Effects of PICSA on Smallholder Farmers’ Decision-Making and Livelihoods When Implemented at Large Scale—The Case of Northern Ghana. *Clim. Serv.* **2019**, *14*, 1–14. [CrossRef]
34. Clarkson, G.; Dorward, P.; Poskitt, S.; Stern, R.D.; Nyirongo, D.; Fara, K.; Gathenya, J.M.; Staub, C.G.; Trotman, A.; Nsengiyumva, G.; et al. Stimulating Small-Scale Farmer Innovation and Adaptation with Participatory Integrated Climate Services for Agriculture (PICSA): Lessons from Successful Implementation in Africa, Latin America, the Caribbean and South Asia. *Clim. Serv.* **2022**, *26*, 100298. [CrossRef]
35. Cleves, A.; Youkhana, E.; Toro, J. A Method to Assess Agroecosystem Resilience to Climate Variability. *Sustainability* **2022**, *14*, 8588. [CrossRef]
36. Chen, Y. Biodiversity and Pest Management in Agroecosystems. *J. Environ. Qual.* **2005**, *34*, 729–730. [CrossRef]
37. Holt-Giménez, E. Measuring Farmers’ Agroecological Resistance after Hurricane Mitch in Nicaragua: A Case Study in Participatory, Sustainable Land Management Impact Monitoring. *Agric. Ecosyst. Environ.* **2002**, *93*, 87–105. [CrossRef]
38. Aich, A.; Dey, D.; Id, A.R. Climate Change Resilient Agricultural Practices: A Learning Experience from Indigenous Communities over India. *PLoS Sustain. Transform.* **2022**, *1*, e0000022. [CrossRef]
39. Shehzad, M.; Zahid, N.; Maqbool, M.; Singh, A.; Liu, H.; Wu, C.; Khan, A.; Wahid, F.; Saud, S. Climate Resilience in Agriculture. In *Building Climate Resilience in Agriculture*; Springer: Cham, Switzerland, 2022; pp. 67–82. [CrossRef]
40. Bhaduri, D.; Sihi, D.; Bhowmik, A.; Verma, B.C.; Munda, S.; Dari, B. A Review on Effective Soil Health Bio-Indicators for Ecosystem Restoration and Sustainability. *Front. Microbiol.* **2022**, *13*, 938481. [CrossRef]
41. El Chami, D.; Daccache, A.; El Moujabber, M. How Can Sustainable Agriculture Increase Climate Resilience? A Systematic Review. *Sustainability* **2020**, *12*, 3119. [CrossRef]
42. Lee, H.; Calvin, K.; Dasgupta, D.; Krinner, G.; Mukherji, A.; Thorne, P.; Trisos, C.; Romero, J.; Aldunce, P.; Barret, K. *IPCC, 2023: Climate Change 2023: Synthesis Report, Summary for Policymakers. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*; Core Writing Team, Lee, H., Romero, J., Eds.; IPCC: Geneva, Switzerland, 2023.
43. Núñez-Michuy, C.M.; Veloz-Segura, V.T.; Agualongo-Chela, L.M.; Bayas-Romero, E.L. Integración de La Inteligencia Artificial En La Educación Para El Desarrollo Sostenible: Oportunidades y Desafíos. *Mag. Las Cienc. Rev. Investig. Innovación* **2023**, *8*, 96–108. [CrossRef]
44. Cano-Ortiz, A.; Piñar Fuentes, J.C.; Cano, E. Didactics of Natural Sciences in Higher Secondary Education. *IJHSSE* **2021**, *8*, 6–10.

45. Mendoza-Fernández, A.J.; Martínez-Hernández, F.; Salmerón-Sánchez, E.; Pérez-García, F.J.; Teruel, B.; Merlo, M.E.; Mota, J.F. The Relict Ecosystem of Maytenus Senegalensis Subsp. Europaea in an Agricultural Landscape: Past, Present and Future Scenarios. *Land* **2020**, *10*, 1. [CrossRef]
46. Pereira, A.J.; Porto, M.; Correia, O.; Beja, P. Traditional Ploughing Is Critical to the Conservation of Threatened Plants in Mediterranean Olive Groves. *Agric. Ecosyst. Environ.* **2024**, *359*, 108775. [CrossRef]
47. Cano-Ortiz, A.; Piñar Fuentes, J.C.; Quinto Canas, R.J.; Pinto Gomes, C.J.; Cano, E. Analysis of the Relationship between Bioclimatology and Sustainable Development. In *Smart Innovation, Systems and Technologies*; Springer: Cham, Switzerland, 2021; Volume 178.
48. Lipper, L.; Thornton, P.; Campbell, B.M.; Baedeker, T.; Braimoh, A.; Bwalya, M.; Caron, P.; Cattaneo, A.; Garrity, D.; Henry, K.; et al. Climate-Smart Agriculture for Food Security. *Nat. Clim. Chang.* **2014**, *4*, 1068–1072. [CrossRef]
49. Ma, W.; Rahut, D.B. Climate-Smart Agriculture: Adoption, Impacts, and Implications for Sustainable Development. *Mitig Adapt Strat. Glob. Chang.* **2024**, *29*, 44. [CrossRef]
50. Mishra, A.K.; Sinha, D.D.; Grover, D.; Roohi Mishra, S.; Tyagi, R.; Sheoran, H.S.; Sharma, S. Regenerative Agriculture as Climate Smart Solution to Improve Soil Health and Crop Productivity Thereby Catalysing Farmers' Livelihood and Sustainability. In *Towards Sustainable Natural Resources: Monitoring and Managing Ecosystem Biodiversity*; Rani, M., Chaudhary, B.S., Jamal, S., Kumar, P., Eds.; Springer International Publishing: Cham, Switzerland, 2022; pp. 295–309. ISBN 978-3-031-06443-2.
51. Piñar Fuentes, J.C.; Leiva, F.; Cano-Ortiz, A.; Musarella, C.M.; Quinto-Canas, R.; Pinto-Gomes, C.J.; Cano, E. Impact of Grass Cover Management with Herbicides on Biodiversity, Soil Cover and Humidity in Olive Groves in the Southern Iberian. *Agronomy* **2021**, *11*, 412. [CrossRef]
52. Giorgi, F.; Lionello, P. Climate Change Projections for the Mediterranean Region. *Glob. Planet. Chang.* **2008**, *63*, 90–104. [CrossRef]
53. Font Tullot, I. *Climatología de España y Portugal*, 2nd ed.; Ediciones Universidad de Salamanca: Salamanca, España, 2000; ISBN 978-84-7800-944-2.
54. Piñar Fuentes, J.C. Influencia Del Cambio Climático En La Vegetación Andalucía: Especial Referencia a Los Hábitats de Interés Comunitario, Universidad de Jaén, 2023. Available online: <https://hdl.handle.net/10953/2496> (accessed on 18 November 2024).
55. Navarro-Serrano, F.; López-Moreno, J.I.; Azorin-Molina, C.; Alonso-González, E.; Aznarez-Balta, M.; Buisán, S.T.; Revuelto, J. Elevation Effects on Air Temperature in a Topographically Complex Mountain Valley in the Spanish Pyrenees. *Atmosphere* **2020**, *11*, 656. [CrossRef]
56. Rivas-Martínez, S.; Penas, Á.; del Río, S.; Díaz González, T.E.; Rivas-Sáenz, S. Bioclimatology of the Iberian Peninsula and the Balearic Islands. In *The Vegetation of the Iberian Peninsula. Plant and Vegetation*; Springer: Cham, Switzerland, 2017; pp. 29–80.
57. del Río, S.; Herrero, L.; Fraile, R.; Penas, A. Spatial Distribution of Recent Rainfall Trends in Spain (1961–2006). *Int. J. Climatol.* **2011**, *31*, 656–667. [CrossRef]
58. Rivas-Martínez, S.; Loidi Arregui, J. Bioclimatology of the Iberian Peninsula. *ItineraGeobotánica* **1999**, *13*, 41–47.
59. Karger, D.N.; Nobis, M.P.; Normand, S.; Graham, C.H.; Zimmermann, N.E. CHELSA-TraCE21k-High-Resolution (1 Km) Downscaled Transient Temperature and Precipitation Data since the Last Glacial Maximum. *Clim. Past* **2023**, *19*, 439–456. [CrossRef]
60. Galán, C.; Vázquez, L.; García-Mozo, H.; Domínguez, E. Forecasting Olive (*Olea europaea*) Crop Yield Based on Pollen Emission. *Field Crops Res.* **2004**, *86*, 43–51. [CrossRef]
61. Rodrigo-Comino, J.; Salvia, R.; Quaranta, G.; Cudlín, P.; Salvati, L.; Gimenez-Morera, A. Climate Aridity and the Geographical Shift of Olive Trees in a Mediterranean Northern Region. *Climate* **2021**, *9*, 64. [CrossRef]
62. Orlandi, F.; Rojo, J.; Picornell, A.; Oteros, J.; Pérez-Badia, R.; Fornaciari, M. Impact of Climate Change on Olive Crop Production in Italy. *Atmosphere* **2020**, *11*, 595. [CrossRef]
63. Arenas-Castro, S.; Gonçalves, J.F.; Moreno, M.; Villar, R. Projected Climate Changes Are Expected to Decrease the Suitability and Production of Olive Varieties in Southern Spain. *Sci. Total Environ.* **2020**, *709*, 136161. [CrossRef]
64. Guerfel, M.; Baccouri, O.; Boujnah, D.; Chaïbi, W.; Zarrouk, M. Impacts of Water Stress on Gas Exchange, Water Relations, Chlorophyll Content and Leaf Structure in the Two Main Tunisian Olive (*Olea europaea* L.) Cultivars. *Sci. Hortic.* **2009**, *119*, 257–263. [CrossRef]
65. Moriana, A.; Villalobos, F.J.; Fereres, E. Stomatal and Photosynthetic Responses of Olive (*Olea europaea* L.) Leaves to Water Deficits. *Plant Cell Environ.* **2002**, *25*, 395–405. [CrossRef]
66. Iniesta, F.; Testi, L.; Orgaz, F.; Villalobos, F.J. The Effects of Regulated and Continuous Deficit Irrigation on the Water Use, Growth and Yield of Olive Trees. *Eur. J. Agron.* **2009**, *30*, 258–265. [CrossRef]
67. Tuzet, A.; Perrier, A.; Leuning, R. A Coupled Model of Stomatal Conductance, Photosynthesis and Transpiration. *Plant Cell Environ.* **2003**, *26*, 1097–1116. [CrossRef]
68. Giorio, P.; Sorrentino, G.; D'Andria, R. Stomatal Behaviour, Leaf Water Status and Photosynthetic Response in Field-Grown Olive Trees under Water Deficit. *Environ. Exp. Bot.* **1999**, *42*, 95–104. [CrossRef]
69. De Graaff, J.; Eppink, L.A.A.J. Olive Oil Production and Soil Conservation in Southern Spain, in Relation to EU Subsidy Policies. *Land Use Policy* **1999**, *16*, 259–267. [CrossRef]
70. Ben-Ari, G.; Biton, I.; Many, Y.; Namdar, D.; Samach, A. Elevated Temperatures Negatively Affect Olive Productive Cycle and Oil Quality. *Agronomy* **2021**, *11*, 1492. [CrossRef]

71. Bitá, C.E.; Gerats, T. Plant Tolerance to High Temperature in a Changing Environment: Scientific Fundamentals and Production of Heat Stress-Tolerant Crops. *Front. Plant Sci.* **2013**, *4*, 273. [CrossRef]
72. Fraga, H.; Moriondo, M.; Leolini, L.; Santos, J.A. Mediterranean Olive Orchards under Climate Change: A Review of Future Impacts and Adaptation Strategies. *Agronomy* **2021**, *11*, 56. [CrossRef]
73. Lobell, D.B.; Field, C.B. Global Scale Climate-Crop Yield Relationships and the Impacts of Recent Warming. *Environ. Res. Lett.* **2007**, *2*, 014002. [CrossRef]
74. Lobell, D.B.; Gourdj, S.M. The Influence of Climate Change on Global Crop Productivity. *Plant Physiol.* **2012**, *160*, 1686–1697. [CrossRef]
75. Rodrigo-Comino, J.; Senciales-González, J.M.; Yu, Y.; Salvati, L.; Giménez-Morera, A.; Cerdà, A. Long-Term Changes in Rainfed Olive Production, Rainfall and Farmer's Income in Bailén (Jaén, Spain). *EuroMediterr. J. Environ. Integr* **2021**, *6*, 58. [CrossRef]
76. Bardi, L.; Martins, S.; Pereira, S.; Dinis, L.-T.; Brito, C. Enhancing Olive Cultivation Resilience: Sustainable Long-Term and Short-Term Adaptation Strategies to Alleviate Climate Change Impacts. *Horticulturae* **2024**, *10*, 1066. [CrossRef]
77. Mairech, H.; López-Bernal, Á.; Moriondo, M.; Dibari, C.; Regni, L.; Proietti, P.; Villalobos, F.J.; Testi, L. Sustainability of Olive Growing in the Mediterranean Area under Future Climate Scenarios: Exploring the Effects of Intensification and Deficit Irrigation. *Eur. J. Agron.* **2021**, *129*, 126319. [CrossRef]
78. Course: Introduction to Climate-Smart Agriculture | FAO Elearning Academy. Available online: <https://elearning.fao.org/course/view.php?id=439> (accessed on 22 October 2024).
79. Climate Resilient Farmer Field Schools Handbook. Available online: <https://ccafts.cgiar.org/resources/publications/climate-resilient-farmer-field-schools-handbook> (accessed on 22 October 2024).
80. Alvar-Beltrán, J.; Elbaroudi, I.; Gialletti, A.; Heures, A.; Neretin, L.; Soldan, R. *Climate Resilient Practices: Typology and Guiding Material for Climate Risk Screening*; FAO: Rome, Italy, 2021; Volume 36.
81. Free Online Course Teaches Agricultural Resilience | CALS. Available online: <https://cals.cornell.edu/news/2021/10/free-online-course-teaches-agricultural-resilience> (accessed on 22 October 2024).
82. Albizua, A.; Bennett, E.M.; Larocque, G.; Krause, R.W.; Pascual, U. Social Networks Influence Farming Practices and Agrarian Sustainability. *PLoS ONE* **2021**, *16*, e0244619. [CrossRef] [PubMed]
83. Ramankutty, N. Both Technological Innovations and Cultural Change Are Key to a Sustainability Transition. *PLoS Biol.* **2023**, *21*, e3002298. [CrossRef] [PubMed]
84. Broch, S.W.; Vedel, S.E. Using Choice Experiments to Investigate the Policy Relevance of Heterogeneity in Farmer Agri-Environmental Contract Preferences. *Environ. Resour. Econ.* **2012**, *51*, 561–581. [CrossRef]
85. Dessart, F.J.; Barreiro-Hurlé, J.; Van Bavel, R. Behavioural Factors Affecting the Adoption of Sustainable Farming Practices: A Policy-Oriented Review. *Eur. Rev. Agric. Econ.* **2019**, *46*, 417–471. [CrossRef]
86. Climate-Smart Agriculture | Food and Agriculture Organization of the United Nations. Available online: <https://www.fao.org/climate-smart-agriculture/en/> (accessed on 22 October 2024).
87. FAO. *FAO Strategy on Climate Change 2022–2031*; FAO: Rome, Italy, 2022.

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