

Biometeorological and autoregressive indices for predicting olive pollen intensity

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Abstract This paper reports on modelling to predict airborne olive pollen season severity, expressed as a pollen index (PI), in Córdoba province (southern Spain) several weeks prior to the pollen season start. Using a 29-year database (1982–2010), a multivariate regression model based on five indices—the index-based model—was built to enhance the efficacy of prediction models. Four of the indices used were biometeorological indices: thermal index, pre-flowering hydric index, dormancy hydric index and summer index; the fifth was an autoregressive cyclicity index based on pollen data from previous years. The extreme weather events characteristic of the Mediterranean climate were also taken into account by applying different adjustment criteria. The results obtained with this model were compared with those yielded by a traditional meteorological-based model built using multivariate regression analysis of simple meteorological-related variables. The performance of the models (confidence intervals, significance levels and standard errors) was compared, and they were also validated using the bootstrap method. The index-based model built on biometeorological and cyclicity indices was found to perform better for olive pollen forecasting purposes than the traditional meteorological-based model.

Keywords Aerobiology · Pollen · Olive · Modelling · Flowering severity · Biometeorological indices

Introduction

The olive-tree (*Olea europaea* L.) is a characteristic Mediterranean species; olives and olive oil are amongst the oldest agricultural products in this part of the world. The region of Andalusia (southern Spain) boasts the world's largest area of olive-groves (1,511,687 ha in 2009), accounting for one-third of all Andalusian cropland. The region produces over 5 million tonnes of olives per year. Córdoba province is the second largest producer after Jaén, with a surface area of 343,812 ha and an annual output of 1,064,997 tonnes of olives (Andalusia Statistical Yearbook 2010). Most representative olive cultivars in Córdoba are Hojiblanca, Picudo and Picual.

Although the olive-tree was originally an insect-pollinated species, today—due partly to intensive crop practices—wind-pollination also plays a major role (Dominguez et al. 1993a). In anemophilous species, the pollen index (PI), i.e. the detected annual airborne pollen, is regarded as a good indicator for both flowering intensity and plant behaviour during certain phenological stages (Keynan et al. 1989; Aguilera and Ruiz Valenzuela 2009).

In view of the economic and environmental importance of the olive, there has been considerable research into flowering phenology and its aerobiological characteristics (Vázquez et al. 2003; Díaz de la Guardia et al. 2003; García-Mozo et al. 2006; Hernández-Ceballos et al. 2010). Olive pollen grains contain a number of different allergens that give rise to atopy and asthma in a large proportion of the population throughout the Mediterranean area (D'Amato et al. 1998; Barber et al. 2008). Since it covers such a large surface

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area in the Andalusia region, the olive-tree is the leading cause of allergies in this area (Domínguez et al. 1993b). The knowledge in advance of airborne pollen concentrations would be of undoubted value both for allergy specialists, allowing them to plan treatments, and for allergy-sufferers, who could better organize their activities.

Aerobiology and phenology have also aroused considerable interest in the agricultural sciences. In fact, olive PI has proved to be a good indicator for predicting harvests (Galán et al. 2004; García-Mozo et al. 2008; Orlandi et al. 2010a). Armed with detailed knowledge of this index together with factors influencing it, farmers can minimise the environmental impact of crop treatments and have a clear idea of the size of the upcoming crop, thus enabling more efficient resource management for crop distribution and price marketing. Moreover, knowledge regarding the influence of weather-related parameters on pollen production is essential to any decision regarding the introduction of certain olive varieties in new areas.

The bioclimatic requirements for flowering in the olive vary as a function of the tree's phenological status (Fornaciari et al. 1998; Galán et al. 2001a). In late autumn and early winter, olive-trees undergo a dormancy period, when growth and development are temporarily suspended (Melo-Abreu et al. 2004). Afterward, a situation of stress due to low temperatures is required to emerge from dormancy (chilling period). Once the threshold temperature is reached, the plant accumulates heat units until flowering starts, (Galán et al. 2001a). Therefore, knowledge about the influence of previous biometeorological factors influencing pollen production would help researchers to have more accurate predictions regarding the potential effect of climate change on olive flowering development (Galán et al. 2005; García-Mozo et al. 2010a).

Most research into long-term airborne olive-pollen forecasting has focussed on predicting other phenological stages of the olive breeding cycle, especially the onset of flowering (Frenguelli et al. 1989; Alcalá and Barranco 1992; Orlandi et al. 2010b). However, a number of studies have sought to forecast the olive PI in the Mediterranean area by constructing regression models and using simple meteorological-related variables, concurring that the variables that affect pollen production are moderate temperatures and abundant rainfall during March and April, among other less important variables (Galán et al. 2001b; Fornaciari et al. 1997; Ribeiro et al. 2006).

The main objectives of this work were: (1) to propose an accurate model to predict olive PI in Córdoba province. With this purpose in mind, we tested the accuracy of a meteorological-based model constructed using simple meteorological-related variables versus an index-based model based on biometeorological indices and an autoregressive index; (2) to include the influence of Mediterranean extreme climate events on olive pollen production in

the proposed Index-based Model by applying different adjustment criteria; and finally (3) to consider the cyclical component of PI series by the development of a cyclicity index.

This paper reports on the comparison and validation of the two models in order to select the best model to obtain accurate forecasting by taking into account all the potential facts influencing PI variation in Córdoba province.

Materials and methods

Study area and pollen data

The city of Córdoba is situated in the south-west of the Iberian Peninsula (37°50'N, 4°45'O), at a height of 123 m above sea level. It has a Mediterranean climate with some continental features. The annual average temperature is 17.8 °C and the mean annual rainfall is 621 mm. Pollen counts and weather data for the last 29 years (1982–2010) were used for this study. Weather data, provided by the Spanish State Meteorology Agency (AEMET), were based on readings taken at Córdoba Airport, located around 5 km south of the pollen sampler site. Aerobiological data were collected using a Hirst-type volumetric spore trap (Hirst 1952) placed on the roof of the Educational Sciences Faculty, at 15 m above ground level. Pollen counts were obtained using a standard protocol published by the *Spanish Aerobiology Network* (REA) (Galán et al. 2007).

Building of biometeorological indices

The general steps of the study were to build, validate and compare the performance of the created models for forecasting olive PI with both the meteorological-based model and the index-based model.

The bioclimatic indices required for constructing the index-based model were generated during this study. Under a test correlation among the different meteorological-related variables and PI, those exerting most influence on flowering severity in the province of Córdoba were selected. Table 1 shows only those variables that have a higher correlation coefficient, i.e. the variables selected to build the biometeorological indices (Table 1). Two criteria were followed to combine the variables in building the indexes: regarding the first criterion, a discrimination was made between both heat (temperature) and water-related (rainfall) variables, while for the second criterion a discrimination was made between different seasons at which the variables can act in different manners (summer, autumn, winter and early spring). The combination of the variables selected previously to build indices was performed using multiplication or division, to use all the variables selected. Depending on the correlation observed, variables can appear in the formulas of the indices

as a factor (if they show a positive correlation with PI) or splitter (given a negative correlation with PI). Considering the first criterion, in the construction of the indices, we have not used variables of thermal nature and hydric nature at the same time; for the second criterion, we did not employ variables acting on non-consecutive periods of time. For example, the March temperature cannot be combined with the August temperature for failing to meet the second criterion, nor combined with rainfall in March for failing to meet the first criterion; however, March temperatures can be combined with April temperatures if this variable were to be selected in the correlation test. The indices have been constructed specifically for the study area so should not be exported to other areas; however, the method per se can be exported to other areas. The variables that comprise each index are described in the [Discussion](#) and the results are consistent with those obtained in previous studies. The four biometeorological indices were defined as follows: thermal index (TI), pre-flowering hydric index (PFHI), dormancy hydric index (DHI) and summer index (SI).

Thermal index (TI): minimum March temperatures (minTM) and March temperature range (RanTM) were included in the TI as follows:

$$TI_0 = (minTM)/(RanTM)$$

Pre-flowering hydric index (PFHI): the water conditions most affecting reproductive development in early spring; sum of total rainfall in February (RfF) and total rainfall in March (RfM) were included in the PFHI.

$$PFHI = (RfF) + (RfM)$$

Dormancy hydric index (DHI): Cumulative rainfall from September to January (RfS↔J), and mean sunlight hours from September to January (HSunS↔J), as an indicator of water availability at the end of dormancy, were included in the DHI as follows:

$$DHI_0 = (RfS \leftrightarrow J)/(HSunS \leftrightarrow J)$$

Summer index (SI): minimum temperatures from June to September (minTJn↔S) and mean sunlight hours from June to August (HSunJn↔A) were included in SI as the most influential summer conditions over the summer index.

$$SI = (minTJn \leftrightarrow S) \times (HSunJn \leftrightarrow A)$$

Optimisation of biometeorological indices

Moreover we took into account that flowering can also be affected by certain weather conditions occurring prior to and during the pollen season. These conditions are generally the result of extreme climate events, the impact of which needs to be borne in mind. An attempt to include extreme meteorological events in the proposed index-based model was made by applying different adjustment criteria to the defined biometeorological indices. A new method based on extreme weather events has been also developed. This new method aims to optimize the RMSE between typified biometeorological indices and typified PI by adjustment criteria that awards “bonuses” or “penalties” to the biometeorological indices.

Identifying extreme meteorological events and adjustments criteria

Extreme meteorological events affecting flowering intensity were identified by applied the following criteria:

- (1) Since the PI and the biometeorological index present different units of measurement, they were typified to avoid potential errors: $Z = (X_i - \bar{X})/\sigma$
- (2) To identify extreme events not hitherto reflected in earlier correlation analyses, were first searched years having extreme meteorological events with potential influence on olive flowering. Those years were identified as years in which the difference between typical PI and the biometeorological index >1 .
- (3) The search for extreme meteorological events was focussed on finding meteorological outliers in previously identified years. Such meteorological outliers are defined as a meteorological variable with values far away from their normal range as follows:
 - Values over the upper meteorological value limit, considering the upper limit (UL) as:

$$UL = Q_3 + 2 \times (Q_3 - Q_1)$$
 - Values under the lower meteorological values limit, considering the lower limit (LL) as:

$$LL = Q_1 - 2 \times (Q_3 - Q_1)$$
- (4) Previous identified outliers were considered as extreme meteorological events for olive flowering. However, extreme meteorological events are considered only when meteorological outliers are present and in the year identified in point 2 (when the difference between typical PI and the biometeorological index >1).

Once each meteorological variable was identified and its outlier value involved in the extreme event, an

adjustment factor was applied to optimise the biometeorological index concerned. We attempted to minimise the root mean square error (RMSE) between the observed typified PI and the typical biometeorological index using the following rule-based system of “bonuses” and “penalties”:

- 1) Values previously identified as outliers were taken as the extreme values for weather variables.
- 2) A logical approach was adopted to establish whether the value of a variable in any year was higher than a given maximum extreme value or lower than a given minimum extreme value.
- 3) Where the value of a variable was higher than the maximum, a “penalty” (in the case of a negative event) or a “bonus” (for a positive event) was applied to the relevant biometeorological index. The same procedure was applied where the value of the variable was lower than a given minimum.
- 4) The values of “bonuses” and “penalties” were the results of minimising the RMSE between the typified biometeorological indices and the typified PI. Adjustment rules were applied to biometeorological indices prior to typing.
- 5) The “bonus” was applied by adding a value to the relevant biometeorological index in those years in which the extreme weather event took place; conversely, the “penalty” was applied by subtracting a value from the biometeorological index.

Optimization procedure

“Bonuses” and “penalties” obtained to minimise the RMSE were applied to the indices for the following adjustment factors:

- (1) Adjustments to the DHI:

$$DHI_0 = (RfS \leftrightarrow J) / (HSunS \leftrightarrow J)$$

$$DHI_1 = \begin{cases} DHI_0, & \text{if } (DRfS \leftrightarrow J) < 25 \\ DHI_0 + 85, & \text{if } (DRfS \leftrightarrow J) \geq 25 \end{cases}$$

For any year with over 25 days of rainfall between September and January ($DRfS \leftrightarrow J$), a bonus of 85 was applied to the DHI.

- b) Adjustments to the TI:

$$TI_0 = (\min TM) / (\text{Ran} TM)$$

$$TI_1 = \begin{cases} TI_0, & \text{if } (\min TJ) > 0.1 \\ TI_0 - 0.21, & \text{if } (\min TJ) \leq 0.1 \end{cases}$$

For any year in which minimum January temperatures ($\min TJ$) were lower than 0.1°C , a penalty of -0.21 was applied to the TI.

$$TI_2 = \begin{cases} TI_1, & \text{if } (\min TJ) < 7.2 \\ TI_1 - 0.35, & \text{if } (\min TJ) \geq 7.2 \end{cases}$$

For any year in which minimum January temperatures ($\min TJ$) were higher than 7.2°C , a penalty of -0.35 was applied to the TI.

$$TI_3 = \begin{cases} TI_2, & \text{if } (\min TM) < 9.6 \\ TI_2 - 0.59, & \text{if } (\min TM) \geq 9.6 \end{cases}$$

For any year in which the mean minimum temperature in March ($\min MT$) was lower than 10°C , penalty of -0.59 was applied to the TI.

Building of a cyclicity index

The cyclicity index (CI)—an autoregressive index generated using a previous database—enabled us to make an indirect estimation taking into account the influence of cyclical climate behaviour, to be incorporated in the model.

The CI was constructed using pollen data from 1988 to the present, since prior to 1988 the pollen production pattern displayed clear 2-year cycles.

In building the CI, the term “crest” was used to denote the change from a rising to a falling trend in the PI time series, while “valley” referred to the change from a falling to a rising trend.

The first step was to determine the number of years elapsing since the last appreciable crest (AC) and the number of years elapsing since the last appreciable valley (AV). The number of years since the last valley was taken as 0, provided that no rising trend was appreciated in the time series. CI_1 was taken as the sum AC and AV.

$$CI_1 = AC + AV$$

CI_2 included CI_1 and the pollen indices for previous years. The time series for pollen indices shows that a considerable increase in pollen counts with respect to the preceding year marked a change of trend.

$$CI_2 = \begin{cases} CI_1, & \text{if } (PI_{n-1}) < \left(\frac{PI_{n-2}}{1.25}\right) + (PI_{n-2}) \\ \frac{CI_1}{2}, & \text{if } (PI_{n-1}) \geq \left(\frac{PI_{n-2}}{1.25}\right) + (PI_{n-2}) \end{cases}$$

Where pollen counts for the previous year were over 180 % higher than those recorded the year before that, a change of trend was marked, and CI_1 was reduced by half.

$$CI_3 = (CI_2) - (CI_{2,n-1})$$

CI_3 was thus equivalent to CI_2 minus CI_2 for the preceding year, thus providing information on the estimated trend at any given moment in the time series.

$$CI_4 = \begin{cases} 1, & \text{if } CI_3 > 0 \\ 0, & \text{if } CI_3 = 0 \\ -1, & \text{if } CI_3 < 0 \end{cases}$$

To obtain CI_4 , estimated rising trends were taken as 1 and falling trends as -1.

$$CI = \begin{cases} \left(\frac{PI_{n-1}}{4.8}\right) + PI_{n-1}, & \text{if } CI_4 = 1 \\ PI_{n-1}, & \text{if } CI_4 = 0 \\ \left(\frac{PI_{n-1}}{1.8}\right) - PI_{n-1}, & \text{if } CI_4 = -1 \end{cases}$$

The final stage consisted of forecasting pollen counts on the basis of the PI for the previous year and the expected trend, i.e. the mean percentage year-on-year difference over the time series.

Building of Forecasting Models

Once the five indices were defined, two multivariate regression models were constructed to forecast the PI as a dependent variable. The meteorological-based model took simple weather variables as independent variables, whilst the index-based model included the four biometeorological indices and the CI as independent variables.

The performance of the models (confidence intervals, significance levels and standard errors) was compared, and they were also validated using bootstrap method. Bootstrap is a resampling technique used to create confidence intervals for coefficients concerned by performing 1,000 different regressions. The bootstrap can be used to derive accurate standard errors, confidence intervals, and hypothesis tests for most statistics. The sampling distribution of a statistic is constructed empirically by resampling from the sample. The resampling procedure is designed to parallel the process by which sample observations were drawn from the population. The key bootstrap analogy is the following: the population is to the sample as the sample is to the bootstrap samples. Bootstrap regression method has been programmed by R programming language. All variables were typified before bootstrapping to compare the sturdiness of the models to each other. Finally, the performance of the models (bootstrap confidence intervals, significance levels of models and standard errors of models) was compared.

Results

Preliminary correlation analysis

The results of a preliminary correlation analysis between the different meteorological-related variables and the PI indicated

that the meteorological conditions in March, both temperatures and rainfall, were highly correlated with olive PI for the study period (Table 1). Regarding summer conditions, minimum temperature and sunshine hours showed a significant positive influence on PI. Finally, autumn–winter hydric conditions also showed a high correlation in Table 1. In general wet periods (i.e. 2003 and 2010) were associated with higher PI, and dry periods (i.e. 1993 and 2005) with lower PI.

Final indices

The final indices are presented in Fig. 1, which shows the good relationship between PI and the four optimized biometeorological indices.

The CI result is also presented in Fig. 1. The strong correlation between PI and CI is clear, as is the close fit of the two indices.

Table 2 shown the correlation matrix between all indices and the PI.

Models

Meteorological-based model (MM):

$$PI_{MM} = -10916.7 + 3152.31 \times (\text{minTM}) + 96.57 \times (\text{RfF})$$

$$R^2 = 0.47; p = 0.000$$

minTM (minimum March temperatures); RfF (February rainfall)

The variables exerting the strongest effect on the PI were minimum March temperatures and February rainfall. MM standard error was 6818. Minimum temperatures for March and February rainfall are the variables that most affected the model; others that do not contribute much have been eliminated from the model.

Index-based model (IM):

$$PI_{IM} = 1556.78 + 0.696 \times (CI) + 18666.97 \times (TI) \\ + 11.41 \times (PFHI) + 20.58 \times (SI) \\ + 3.43 \times (DHI)$$

$$R^2 = 0.81; p = 0.000$$

IM standard error was 4,288.

The robustness of the two models was tested by means of a bootstrap validation. Confidence intervals at 95 % for the different coefficients obtained by bootstrap resampling can be seen in Table 3.

The medium confidence range of IM coefficients was 0.464 while the medium confidence range of MM coefficients of 0.609, which indicates a highest robustness for the IM.

Table 1 Pearson correlation coefficients between pollen index (PI) and meteorological parameters during the years 1982–2010. *minTM* Average value of daily minimum temperatures in March; *RanTM* average value of temperature range in March; *RfF-M* sum of total rainfall in February and March (mm); *minTJn-S* average value of daily

minimum temperatures in June, July, August and September; *HSunJn-A* average value of daily sunshine in June, July and August (hours); *HSunS-J* Average value of daily sunshine hours in September, October, November, December and January; *RfS-J* sum of total rainfall in September, October, November, December and January (mm)

	minTM (°C)	RanTM (°C)	RfF↔M (mm)	minTJn↔S (°C)	HSunJn↔A (hours)	HSunS↔J (hours)	RfS↔J (mm)
PI	0.483**	-0.316*	0.504**	0.453**	0.508**	-0.363*	0.263*

*Correlation coefficient is significant at the 0.05 level; ** Correlation coefficient is significant at the 0.01 level

The higher determination coefficient and the lower standard error detected for the IM indicated a stronger effectivity of this model. Moreover, the validation test indicated its higher sturdiness. Figure 2 shows the differences, in percentage, between observed and predicted PI using the two models. In 1995, a very high error (%) was detected since this measure is highly dependent on the total amount of pollen and the total concentrations in this year were very low.

Discussion

Knowledge of the main factors influencing the marked year-on-year changes observed in olive flowering intensity is of

considerable scientific, agricultural, environmental and public-health interest. Earlier research in this field found that rainfall and, especially, temperature over the months prior to flowering was one of the most influential meteorological-related factors (Galán et al. 2001b; Ribeiro et al. 2006). It has also been shown that temperature is the most influential factor controlling the most important characteristics of olive reproductive phenology, such as the onset date or the peak date (Galán et al. 2001a; Orlandi et al. 2010b). As it has been indicated by several authors (i.e. Fornaciari et al. 1997), meteorological variables recorded during the pollen season itself also had a considerable influence on PI. However, they have no real predictive value, and should therefore not be included in forecasting models.

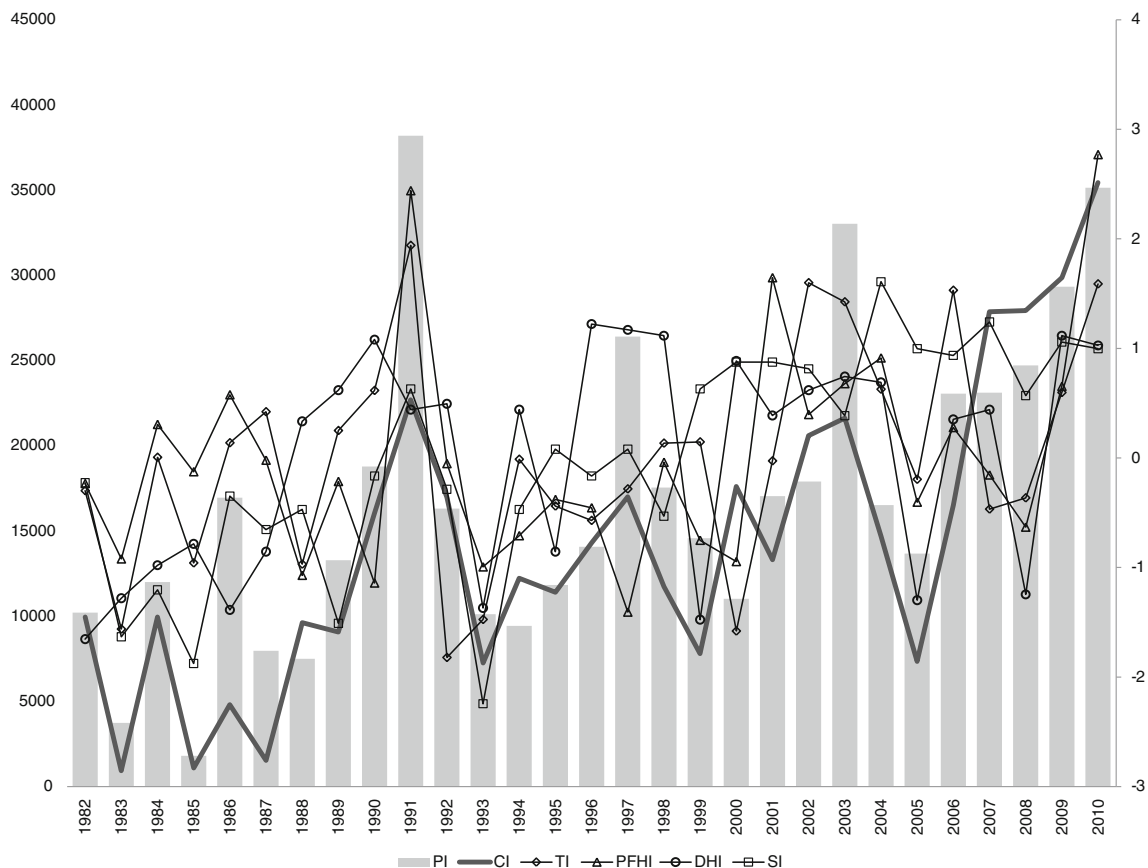


Fig. 1 Pollen index (PI), typical biometeorological indices and cyclicity index (CI)

Table 2 Pearson correlation coefficients matrix applied to PI, biometeorological indices and cyclicity index (CI) during the studied years 1982–2010. *TI* Thermal index, *PFHI* pre-flowering hydric index, *DHI* dormancy hydric index, *SI* Summer index

	TI	PFHI	DHI	SI	CI	PI
TI	1					
PFHI	0.65*	1				
DHI	0.32	0.22	1			
SI	0.47**	0.40*	0.37	1		
CI	0.43*	0.45*	0.56**	0.66**	1	
PI	0.63**	0.50**	0.47**	0.60	0.83**	1

*Correlation coefficient is significant at the 0.05 level, ** Correlation coefficient is significant at the 0.01 level

Although PI is one of the most important phenological and aerobiological characteristics, only a few studies have sought to propose forecasting models to predict PI in different species, for example *Olea* (Galán et al. 2001b; Ribeiro et al. 2006), *Betula* (Dahl and Strandhede 1996), *Quercus* (Corden and Millington 1999) and *Poaceae* (Emberlin et al. 1999; García-Mozo et al. 2010b). This small number of studies could be explained by the difficulty of proposing accurate PI predictions due to the complexity of factors influencing it. Although in general PI-forecasting studies have included simple meteorological variables in the proposed models, some studies have already suggested that bioclimatic indices could provide more information regarding year-on-year changes in the PI, thus affording a sound basis for the creation of forecasting models (e.g. Valencia-Barrera et al. 2002).

The present study sought to propose a biometeorological forecasting model based on biometeorological indices that would reflect the meteorological conditions affecting the physiological status of olive trees before flowering starts. The four proposed biometeorological indices were optimised, taking into account extreme meteorological events characteristics of the Mediterranean climate. An autoregressive CI was also developed. The model is adapted exclusively to the study area. The introduction of all the "bonuses and penalties", the consequent RMSE minimisation process, and the introduction of the CI all combine to make the

model very effective. However, the model can be exported to other areas only with previous accurate knowledge of both meteorological conditions and historical yields.

In constructing the biometeorological indices in this work, a distinction was made between heat-related and water-related variables, since their effects may differ considerably from each other depending on season and phenological stage. This distinction is essential in order to ensure the value of these indices for future research.

March temperatures and rainfall exerted considerable influence on the PI. This result agrees with earlier studies in Córdoba province (Galán et al. 2001b). However, excessively high temperatures—such as those recorded in 2001—can lead to heat stress; accordingly, it was necessary to apply a penalty to the TI. Elsewhere, mean and minimum temperatures from January to March—as well as autumn rainfall—are reported have a major effect on olive flowering (Ribeiro et al. 2006). The strong influence of March temperatures and rainfall on flowering phenology has also been noted for other tree species in temperate climates (García-Mozo et al. 2001).

Regarding extreme abnormal temperature events—although the olive requires a winter chilling period in order to break dormancy, excessively low temperatures will have a negative impact (Bartolozzi and Fontanazza 1999), or at least will not favour the breaking of dormancy (Orlandi et al. 2004). Therefore, for any year in which minimum January temperatures are low, a penalty was applied to the TI.

In Mediterranean climates, spring-flowering tree species require a certain number of days with low temperatures to ensure the heat stress required to break dormancy. The olive needs a minimum number of chilling hours below a threshold temperature of 7.2°C prior to budburst (Aron 1983). For that reason, for any year in which minimum January temperatures were higher than 7.2°C, TI was optimized.

The importance of summer conditions for PI can be explained by the fact that the rate of flowering-bud differentiation after dormancy is influenced heavily by summer weather conditions. Summer temperatures are known to have a major impact on flowering in summer-budding tree species, abnormally high summer temperatures often give rise to abundant pollen in the following spring, (Mandrioli

Table 3 Bootstrap validation summary. Confidence intervals at 95% for the different coefficients obtained by bootstrap re-sampling. *UP* Upper limit, *LL* lower limit, *R* Range

Index-based model				Meteorological-based model			
Coefficient	LL (95%)	UL (95%)	R (95%)	Coefficient	LL (95%)	UL (95%)	R (95%)
Constant	-0.181	0.167	0.348	Constant	-0.279	0.292	0.571
CI	0.437	0.945	0.508	MinTM	0.174	0.752	0.578
TI	0.107	0.610	0.503	RtF	0.078	0.756	0.678
PFHI	-0.225	0.429	0.654				
SI	-0.241	0.171	0.412				
DHI	-0.195	0.166	0.361				

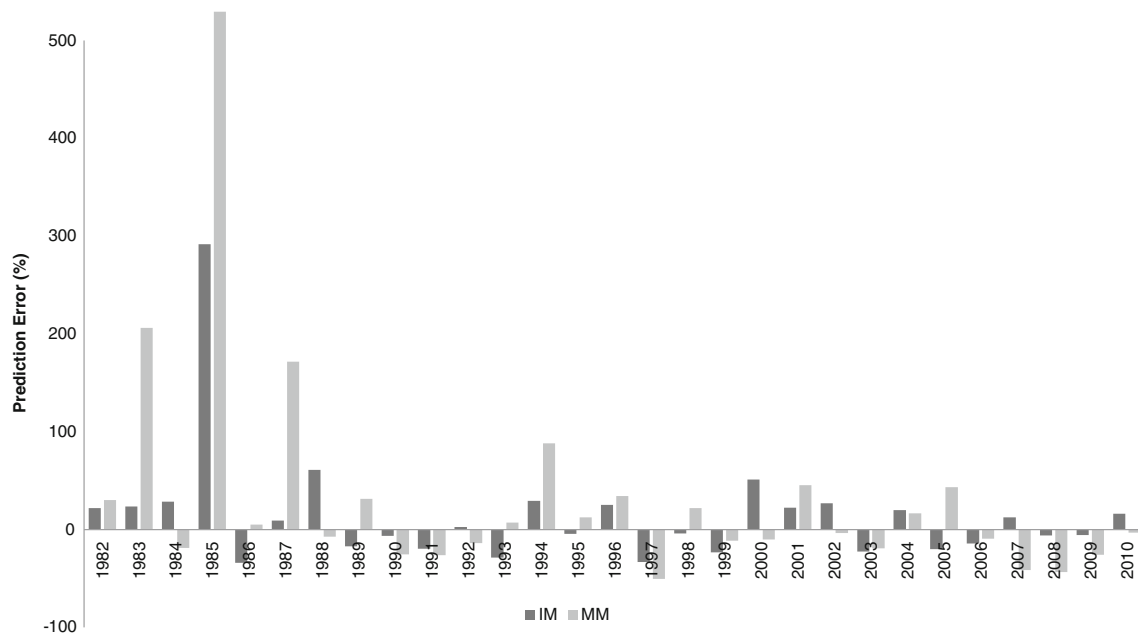


Fig. 2 Differences (in percentage) between observed and predicted PI values. IM Index-based model, MM meteorological-based model

1987). In the case of olive, the rate of flowering-bud differentiation is affected strongly by the prevailing weather conditions over the previous summer (Rallo and Cuevas 2004). A significant correlation was recorded here between the SI and the PI, although other authors report that summer weather conditions tend to correlate more strongly with fruit development than with the PI (Galán et al. 2008; Ribeiro et al. 2008).

It is known that precipitation-induced increase of water availability to the plant and hours of sun are related inversely—a fact corroborated by our results. Water availability is dependent directly on the amount of rainfall; nevertheless, temporal distribution of precipitation is also very important. Moderate rainfall ensures greater water availability for the plant; in contrast, we noted that heavy rainfall concentrations lead to an excessive DHI, and this index is therefore less representative than if rainfall had been lighter and regular. Other authors have also noted that number of days' rainfall is a key factor in plant development (Ribeiro et al. 2006). In this sense it was also observed that in years recording the highest level of 25 days rainfall between September and January, indices were optimised (which prompted us to give a bonus to the DHI).

Since species tend to be well-adapted to their native areas, the relationship between plant development and habitual local weather-related variables appears to be linear. But in fact weather variables do not act on plant development in a linear manner: each species has its own optimum range of values for each variable, outside of which development is less successful. If a variable takes on values that are very high or very low, and cause equally negatives effects on

plant development, it becomes impossible to appreciate global behaviour using a linear relationship. The use of linear models in bioclimatological research thus provides little useful information on non-linear weather phenomena; optimisation seeks to overcome that deficiency. Therefore we considered that it would be important to optimise indices using certain adjustment rules, simply because there is no linear correlation between the variables involved in extreme weather events and the PI. In the revised literature, there are no studies taking into account the effect of extreme weather conditions on PI.

Although time series trends are not usually included in the models, we notice a rising trend on olive pollen concentration at Córdoba province during recent years. This could be due to the fact that, during the study period, the area of olive planting in Córdoba increased by 20.7 % (71,190 ha) and irrigation increased by 92.7 % (16,576 ha) (Agriculture Statistical Yearbook, 1982; 2010). Moreover, the study period also saw a change in weather conditions that may have influenced the trend towards a higher PI.

In order to take this trend into account, an autoregressive CI was also created. A new feature of the present study is the use of this autoregressive method—the CI—for PI forecasting. Other authors have used autoregressive models to forecast daily pollen counts, but not hitherto for long-term PI predictions, perhaps because of the long time-series required to construct models of this kind (Arca et al. 2002; Belmonte and Canela 2002; Rodríguez-Rajo et al. 2006). When grouping years with a view to determining cyclicality, it should be borne in mind that olive-tree also have an alternate bearing cycle that is influenced by a number of factors,

including individual tree age, cultivar and climate. Alternate bearing is an evolutionary strategy through which the tree produces a large amount of seeds in some years, thus enhancing its biological efficiency. Resources are stored over one year and invested in the following year. However, crop practices adopted since the mid-1980s have reduced the effect of the alternate bearing cycle, and have favoured a general increasing trend (Domínguez et al. 1993b). Although the PI time-series used to generate the CI comprised only 29 data points, this were sufficient for the present purpose, i.e. forecasting the trend of the time series. This CI also provides an indication—albeit indirect—of climate conditions in previous years in that it is based on historical pollen indices. Since the plant contains varying levels of reserve substances that are stored from one year to the next, spring flowering intensity is influenced strongly by prior productive status, which is in turn dependent on previous weather conditions (Ramos 2000). The CI also reflects changes in the alternate bearing cycle, although the effect of alternate bearing has been diminished through the adoption of new cropping techniques. Moreover, CI provides information on cyclical variations characteristic of the Mediterranean climate, consisting chiefly in the alternation of wet and dry periods.

The combination of all the methodology proposed in this paper provides a useful tool for prediction in bioclimatology. The use of an autoregressive index and a method for optimizing biometeorological indices in the face of extreme meteorological events have provided very appropriate tools with which to predict the IP. Future studies could use the proposed method to make more accurate predictions. The CI has an obvious advantage over the index-based model, therefore this paper should not be considered as a comparison between the efficacy of using biometeorological indices against simple meteorological variables but rather as a comparison between the effectiveness of a traditional model versus employment of the indices developed here. Finally, the comparison and validation of the models proved that the index-based model is an accurate model that performs better for olive pollen forecasting purposes than traditional meteorological-based model.

Conclusions

The four biometeorological indices provide the basis for future research into the weather-based characterisation of phenological years, for olive and potentially for other species as well.

The proposed method was developed taking into account the effects of extreme events, providing a sound basis for the improvement of phenological forecasting models in the Mediterranean area.

The CI, with its novel use of autoregressive techniques for predicting the PI, considerably improved forecasts. The autoregressive technique has not been employed previously in aerobiological research, and was in fact purpose-built for this study.

The index-based model provided more accurate forecasts than the traditional meteorological-based model, indicating that the use of optimised biometeorological indices together with a CI enhances the performance of prediction models.

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