



Modeling olive pollen intensity in the Mediterranean region through analysis of emission sources



J. Rojo ^{a,b,*}, F. Orlandi ^b, R. Pérez-Badía ^a, F. Aguilera ^c, A. Ben Dhiab ^d, H. Bouziane ^e, C. Díaz de la Guardia ^f, C. Galán ^g, A.M. Gutiérrez-Bustillo ^h, S. Moreno-Grau ⁱ, M. Msallem ^d, M.M. Trigo ^j, M. Fornaciari ^b

^a University of Castilla-La Mancha, Institute of Environmental Sciences, 45071 Toledo, Spain

^b Department of Civil and Environmental Engineering, University of Perugia, 06121 Perugia, Italy

^c Department of Animal Biology, Plant Biology and Ecology, University of Jaen, 23071 Jaen, Spain

^d Institut de l'Olivier, BP 208, 1082 Tunis, Tunisia

^e Laboratory of Ecology, Biodiversity and Environment, Faculty of Sciences, University Abdelmalek Essaâdi, 2121 Tetouan, Morocco

^f Department of Botany, University of Granada, 18074 Granada, Spain

^g Department of Botany, Ecology and Plant Physiology, University of Cordoba, 14071 Cordoba, Spain

^h Department of Plant Biology II, Complutense University of Madrid, 28040, Madrid, Spain

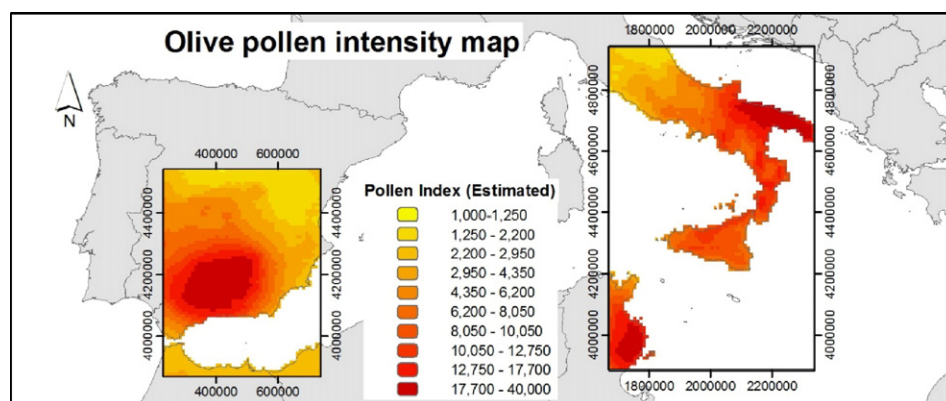
ⁱ Department of Chemical and Environmental Engineering, Polytechnic University of Cartagena, 30202 Cartagena, Spain

^j Department of Plant Biology, University of Malaga, 29080 Malaga, Spain

HIGHLIGHTS

- The Pollen Index for olive tree was modeled in the main olive cultivation areas.
- The emission surface was related with pollen intensity using Concentric Ring Method.
- Different emission patterns of pollen were influenced by the altitude of the groves.
- The mean influence of the pollen emission ends at the 175 km radius from the sites.
- The results of the models were shown in airborne olive pollen maps.

GRAPHICAL ABSTRACT



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ABSTRACT

Aerobiological monitoring of *Olea europaea* L. is of great interest in the Mediterranean basin because olive pollen is one of the most represented pollen types of the airborne spectrum for the Mediterranean region, and olive pollen is considered one of the major cause of pollinosis in this region. The main aim of this study was to develop an airborne-pollen map based on the Pollen Index across a 4-year period (2008–2011), to provide a continuous geographic map for pollen intensity that will have practical applications from the agronomical and allergological points of view. For this purpose, the main predictor variable was an index based on the distribution and abundance of potential sources of pollen emission, including intrinsic information about the general atmospheric patterns of pollen dispersal. In addition, meteorological variables were included in the modeling, together with

* Corresponding author.

E-mail address: jesus.rojo.ubeda@gmail.com (J. Rojo).

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spatial interpolation, to allow the definition of a spatial model of the Pollen Index from the main olive cultivation areas in the Mediterranean region. The results show marked differences with respect to the dispersal patterns associated to the altitudinal gradient. The findings indicate that areas located at an altitude above 300 m a.s.l. receive greater amounts of olive pollen from shorter-distance pollen sources (maximum influence, 27 km) with respect to areas lower than 300 m a.s.l. (maximum influence, 59 km).

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1. Introduction

The olive tree (*Olea europaea* L.) is an entomophilous species that has evolved toward the anemophily with high flower and pollen production (Rojo et al., 2015b). Due to the large areas of its land cover in the Mediterranean region, olive pollen is considered one of the most represented pollen types of the airborne pollen spectrum for the entire region (Caiola et al., 2002; Pérez-Badia et al., 2010; Martínez-Bracero et al., 2015). On this basis, olive pollen monitoring is important from the agricultural (Galán et al., 2008; Ribeiro et al., 2008), ecological (Orlandi et al., 2014) and medical (Bonofiglio et al., 2013) points of view, which has resulted in numerous studies into several aerobiological parameters related to olive flowering (e.g., Oteros et al., 2013a; Zhang et al., 2014).

The Pollen Index (PI) is derived from the sum of the daily airborne pollen grains during the pollen season. It is an aerobiological variable that is directly related to flower production (Rojo et al., 2015b), and it can be considered an important indicator of flowering intensity for the olive tree (Orlandi et al., 2014), and then olive pollen intensity. The PI can show marked year-on-year variations, as it is governed by different factors related to pollen emission and dispersal. The olive is a spring-flowering tree and its reproductive cycle is regulated by bioclimatic requirements that must be satisfied during the period from summer of the previous year to the flowering time (Rojo and Pérez-Badia, 2015a). During this period, the processes involved in floral organ development take place (Rallo and Martin, 1991; Connor and Fereres, 2005) for olive flower production, and thereby pollen emission (Oteros et al., 2013a). Furthermore, the olive tree is characterized by alternate pollen production cycles, because its reproductive cycle is completed over 2 years. This is produced through a balance in the endogenous hormone levels that can promote or inhibit flowering (Al-Shdiefat and Grunfleh, 2008), which is a behavior that is reflected in the variability of the PI (Galán et al., 2001; Ribeiro et al., 2005).

Once pollen grains have been released into the air, spatiotemporal variations in meteorological conditions influence the extent of pollen dispersal and airborne pollen transport (Jones and Harrison, 2004; Damialis et al., 2005; Makra et al., 2010). Furthermore, the distances from and the distributions of potential pollen sources largely determine the amounts of pollen that will be recorded for any given geographic location (Fernández-Rodríguez et al., 2014). Oteros et al. (2015) estimated that for specific sampling stations selected in their study, the maximum influence on pollen emissions is provided by olive groves that are located some 37 km from a trap. However, the small size of the olive pollen favors its long-range transport (Hernández-Ceballos et al., 2014; Rojo and Pérez-Badia, 2015b). Therefore, from the standpoint of the spatial variability, the olive-growing areas must be considered for any PI modeling. Moreover, temporal variations in the emission surface of the olive groves are of great relevance in the analysis of long-term trends in the PI, as documented by García-Mozo et al. (2014).

Olive pollen concentrations have previously been studied from a spatial point of view (Hidalgo et al., 2002; Fernández-Rodríguez et al., 2014), taking into account both the distribution of the potential pollen sources and the dispersal conditions in the atmosphere. Techniques based on spatial interpolation for aerobiological studies, such as kriging, can be used because of the spatial correlation shown for airborne pollen concentrations (Alba et al., 2006; García-Mozo et al., 2006). Thus, the combination of these modeling techniques is of great interest in the analysis of airborne pollen levels (Rojo and Pérez-Badia, 2015b).

Spatial interpolation allows a given variable to be modeled over a continuous area in the region, using data measured in a specific number of sampling points, an aspect that is one of the most important advantages of these techniques (Oliver and Webster, 2014). In this sense, the number of studies now based on geostatistical techniques is increasing in terms of investigations into the parameters related to the plant reproductive cycle, such as the flowering time and the airborne pollen intensity (e.g., Schröder et al., 2014; Aguilera et al., 2015a). In addition, this methodology allows the sampling stations to be optimized by minimizing the number of sites or searching for the most appropriate locations (García-Mozo et al., 2006; Hengl, 2007). This will thus reduce the time and economic resources associated with aerobiological monitoring.

The main goal of the present study was to model the olive atmospheric pollen intensity (i.e., PI) using regression-kriging technique, and an index based on the distribution and abundance of the potential sources of pollen emission and meteorological variables as predictors. This regression model operated in conjunction with spatial interpolation that provided a continuous geographic model of the PI from the main olive cultivation areas in the Mediterranean region, which can be used for prediction of pollen intensities in unsampled areas.

Table 1
Characteristics of sampling sites.

Country	Number	Site	Altitude (m a.s.l.)	UTM coordinates (latitude/longitude)	Pollen Index 2008–2011 (pollen grains)
Spain	1	Madrid	719	4,482,461/425,573	2733
	2	Guadalajara	710	4,497,691/485,565	1878
	3	Talavera	369	4,424,105/342,516	5353
	4	Toledo	450	4,413,311/410,899	6470
	5	Aranjuez	498	4,430,894/447,574	4243
	6	Cuenca	987	4,436,641/574,118	2235
	7	Ciudad Real	629	4,316,380/420,118	7558
	8	Albacete	693	4,315,112/599,144	4293
	9	Cordoba	130	4,197,709/348,758	30,126
	10	Jaen	440	4,182,612/431,618	44,925
	11	Cartagena	21	4,163,797/678,332	2668
	12	Granada	668	4,115,102/445,993	22,331
	13	Malaga	66	4,064,513/368,406	10,358
	14	Almeria	46	4,079,076/551,909	7209
Morocco	15	Tetouan	24	3,937,865/285,892	2694
Italy	16	Perugia	427	4,888,604/1,753,706	1931
	17	Benevento	278	4,712,535/1,976,486	7669
	18	Avellino	555	4,716,434/2,021,914	8354
	19	Bari	127	4,740,783/2,156,098	22,859
	20	Salerno	424	4,662,939/2,033,046	18,416
	21	Taranto	64	4,678,329/2,264,417	16,716
	22	Lecce	36	4,694,285/2,292,081	23,135
	23	Cosenza	238	4,574,327/2,161,109	18,475
	24	Catanzaro	335	4,476,949/2,203,726	13,818
	25	Reg. Calabria	351	4,417,872/2,154,583	16,716
	26	Messina	353	4,371,497/2,068,203	16,379
Tunisia	27	Palermo	18	4,337,092/1,969,812	13,585
	28	Trapani	191	4,290,660/1,895,760	11,174
	29	Agrigento	306	4,278,087/1,943,296	5274
	30	Mornag	48	4,140,968/1,691,620	6358
	31	Jemmel	36	4,031,991/1,743,384	14,010
	32	Chaal	78	3,907,729/1,726,101	16,914

Projected Coordinate System: WGS 1984.

2. Methods

2.1. Pollen records

Airborne olive pollen concentrations were recorded at 32 sampling sites in the Mediterranean region that belong to four of the most important countries in terms of the world olive oil production: Spain, Italy, Tunisia, and Morocco (Table 1; Fig. 1).

Daily pollen samples were obtained according to the standardized method proposed by the Spanish Aerobiology Network (REA) (Galán et al., 2007) and following the minimum requirements from the European Aeroallergen Network (EAN) (Galán et al., 2014). The PI was calculated as the sum of the daily pollen concentrations recorded during the main pollen season according to Andersen (1991). This study was performed over 4 years (2008–2011), taking into account the continuous availability of aerobiological data in each study area, and considering together the selection of as great as possible a number of sampling sites, and to have greater availability of real data to develop the model. The average annual PI recorded during this period was used as the dependent variable for the modeling.

2.2. Olive grove emission surface

The influence of the data for the olive grove emission surface was calculated using the Concentric Ring Method proposed by Oteros et al. (2015), and their nomenclature is also followed here with respect to the required indices: the Influence Index (II), and the Specific Influence Index (SII). This methodology analyzes the relationships between the PI and the theoretical influence of the emission surfaces of the olive-growing areas that are divided into concentric rings from the pollen

station. The olive grove emission surfaces were obtained from the CORINE Land Cover database (CLC, 2006).

The II was calculated for all of the concentric rings, which were considered consecutively for the entire total influence area from the sampling points. The II shows the theoretical influence of the pollen emission from the olive groves in relation to their location from the sampling point (i.e., distance), and it was calculated as a function of the correlation between the PI and the concentric ring distances (Oteros et al., 2015). In this case, the function with the best fit of the data in terms of the goodness-of-fit was selected.

To calculate the II, rings of 10 km (i.e., increasing radius by 10 km each time) were considered as the most suitable taking into account the magnitude of the calculations in this study, in terms of the large geographical areas covered. Indeed, the calculations showed that the accuracy of the II calculation is appropriate with respect to using smaller rings. However, the mathematical integration of the curve for the II was performed using rings of 1 km (i.e., increasing radius by 1 km each time) for the determination of the maximum influence on the PI as well as where the influence ended. The II calculations were also carried out independently for the stations, which depended on the different altitudinal ranges to determine the different dispersion patterns of the pollen according to topographical characteristics related to the elevation.

Then, the SII was determined as the sum of the olive grove emission surface included within each ring, and weighted by the corresponding II according to the distance from the sampling point. In a practical sense, the SII reflects the characteristics of a given geographic area for its receiving of the pollen grains in relation to the distribution of potential pollen sources and to the dispersion dynamics of the particles considered; i.e., the *Olea* pollen.

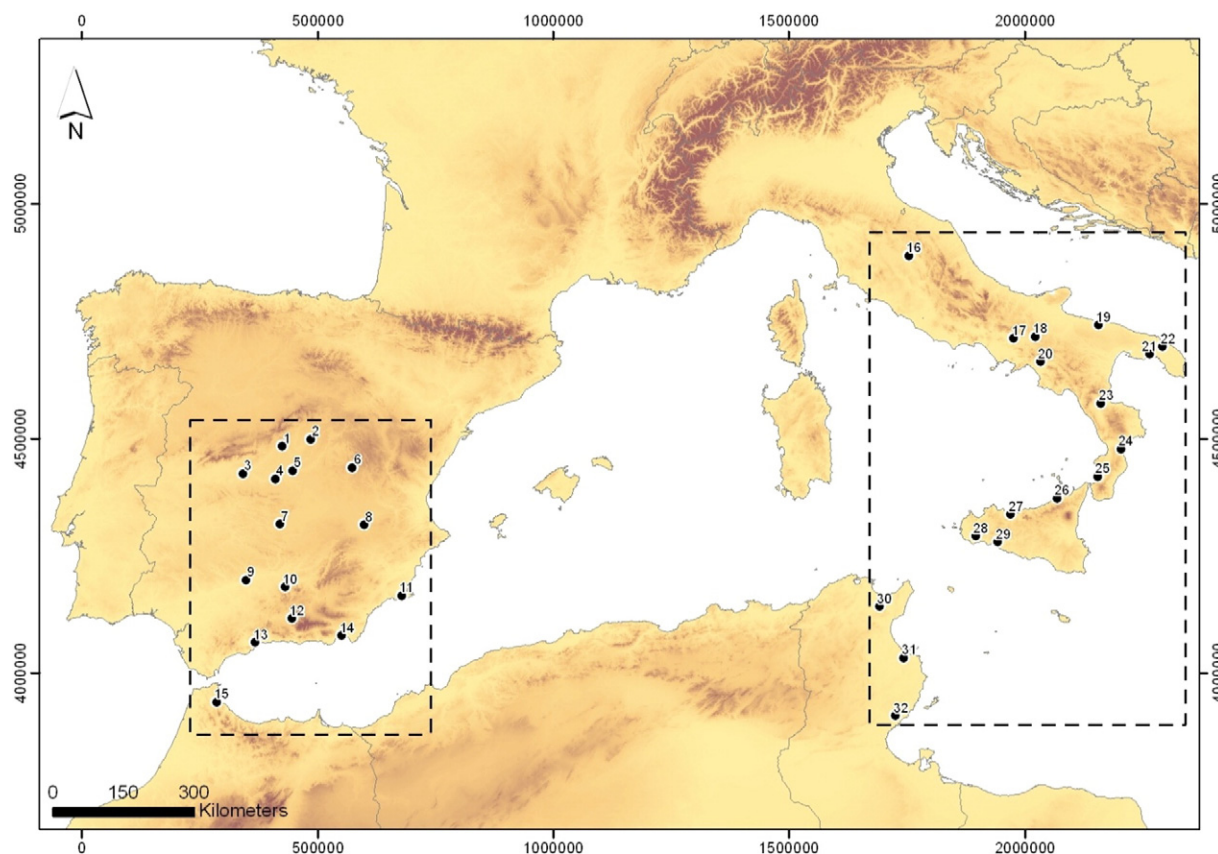


Fig. 1. Study areas (dashed line) and sampling sites (points). Spain: 1, Madrid; 2, Guadalajara; 3, Talavera; 4, Toledo; 5, Aranjuez; 6, Cuenca; 7, Ciudad Real; 8, Albacete; 9, Cordoba; 10, Jaen; 11, Cartagena; 12, Granada; 13, Malaga; 14, Almeria. Morocco: 15, Tetouan. Italy: 16, Perugia; 17, Benevento; 18, Avellino; 19, Bari; 20, Salerno; 21, Taranto; 22, Lecce; 23, Cosenza; 24, Catanzaro; 25, Reg. Calabria; 26, Messina; 27, Palermo; 28, Trapani; 29, Agrigento. Tunisia: 30, Mornag; 31, Jemmel; 32, Chaal. Digital elevation model provided by the WorldClim (Hijmans et al., 2004).

In the present study, a continuous layer with the SII was performed for the entire area of study according to the II calculated for each ring from the sampling station analysis. The SII layer was developed as a continuous grid of 10 km × 10 km, where the SII was calculated at the centroid of the pixel as described above. Finally, this SII variable was included as an independent variable for modeling the PI.

2.3. Meteorological data

Meteorological data were obtained from the weather stations nearest to the sampling sites. The weather stations belonged to the National Council of Agricultural Research in Italy, the Physics Department of the Faculty of Science in Morocco, the Spanish Meteorological Agency in Spain, and the National Meteorological Institute in Tunisia. The meteorological variables that were analyzed were maximum temperature, minimum temperature, and cumulated rainfall, from both monthly and seasonal periods.

Furthermore, continuous layers in the study area were performed for the meteorological variables included in the regression model. To develop these layers, the daily meteorological gridded datasets were obtained from the European Climate Assessment and Dataset (<http://www.ecad.eu>; Haylock et al., 2008), with these data transformed to a grid of 10 km × 10 km.

2.4. Pollen Index maps

A general regression model was generated to model the PI using the independent variables measured from the sampling points. The SII is an important variable to predict the PI, as these variables are strongly correlated, according to Oteros et al. (2015). Furthermore, the meteorological variables such as maximum temperature, minimum temperature and rainfall were included in the model through step-wise selection and collinearity analysis. In addition, an internal validation (R^2) and five-fold cross validation were performed to check the reliability of the model. The regression equation obtained was used thereafter for spatial modeling of the PI using geostatistical techniques. For this purpose, regression-kriging was used, with the independent variables selected (i.e., SII, meteorological variables) as continuous layers in space, the design of which was as described above.

Regression-kriging is a technique that is included in spatial prediction models, and it combines both correlation with independent predictors and spatial autocorrelation (Hengl, 2007). Spatial modeling of the PI was carried out considering the entire study area (Fig. 1). However, to improve the visualization of the results, airborne-pollen maps are independently shown for the Spain–Morocco area (341 700 km²) and the Italy–Tunisia area (703 500 km²). In both cases, the boundaries were selected according to rectangular areas that contained sufficiently close sampling points, without considering larger areas where no sampling points were present, and consequently for which statistical validation cannot be performed.

The analysis of the spatial behavior of the data was required for spatial modeling purposes. Given the asymmetrical distribution of the PI and the SII, a logarithmic transformation was required for the geostatistical analysis (Li and Heap, 2014). In addition, these transformations improved the distribution of the PI and SII data and avoided excessive weight on certain sampling points (e.g., Spanish sites such as Jaen and Cordoba). Then the variograms for the model were constructed to analyze the spatial behavior of the data. The best fitting function in the experimental variogram was selected to model the response variable (Oliver and Webster, 2014).

Finally, the goodness of fit of the spatial model obtained was also tested by internal validation (R^2) and by five-fold cross-validation (Q^2), which enabled estimated values to be compared to observed values. Moreover, the mean error (ME), the root mean square error (RMSE), and the mean absolute error (MAE) were obtained for both validation methods.

The models were constructed using the R software (R Development Core Team, 2015), and the 'gstat' package was used for the regression-kriging analysis (Pebesma, 2004).

3. Results

The influence area of the pollen emission from the olive groves surrounding the sampling sites is shown in Fig. 2, where a third-degree polynomial function fitted well to the data from the relationship between both olive grove emission surface for each ring and the correlation with the PI. According to the calculation of the II from all of the sampling sites, the influence of the pollen emission ends at the 175 km radius around the sampling sites (Fig. 2a). This indicates that pollen emission from olive groves located at distances greater than 175 km away do not influence the PI of a given site.

On the other hand, the distance of the maximum influence on the PI was 42 km (Fig. 2a). However, considerable differences were observed for the maximum influence when using different altitudinal ranges. In

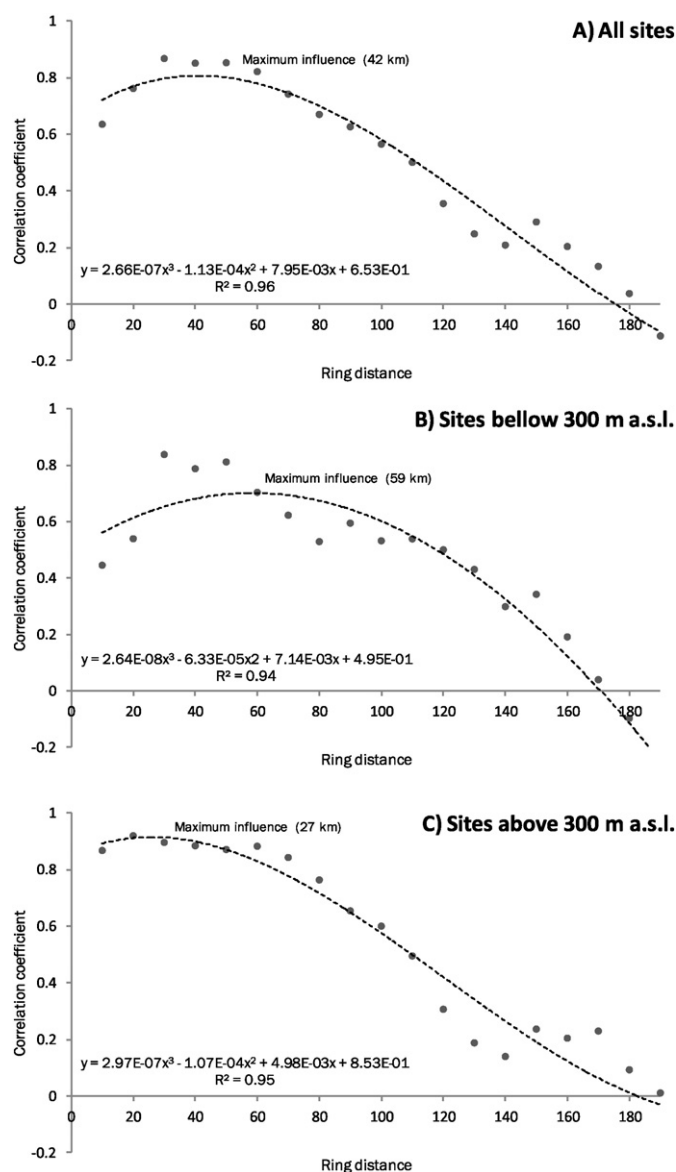


Fig. 2. Relationships between the ring distance and the correlation coefficients which have been calculated between Pollen Index and emission surface, for all sites (A), for sites below 300 m a.s.l. (B) and for sites above 300 m a.s.l. (C). The maximum influence on the Pollen Index was calculated using the integration of the polynomial function from the rings for 1 km radius increments.

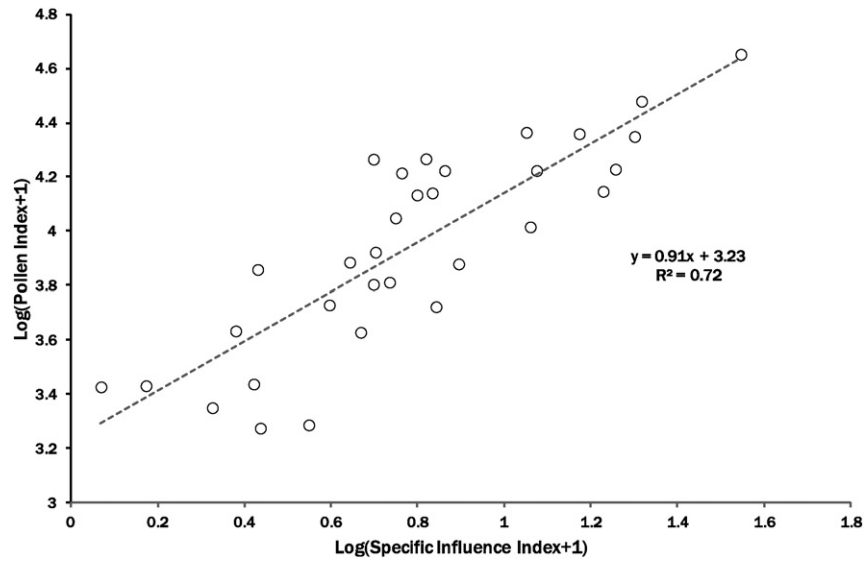


Fig. 3. Relationship between the Pollen Index and the Specific Influence Index, following logarithmic transformation.

this sense, at sites lower than 300 m a.s.l., the maximum influence was at 59 km from the sampling points (Fig. 2b), while at sites above 300 m a.s.l., the maximum influence was at 27 km (Fig. 2c), as a difference of 32 km with respect to the lower altitude sites.

The SII was calculated using both the influence area under the curve of the polynomial function (Fig. 2) and the olive grove emission surfaces located within each ring. In the first instance, the SII was calculated from the sampling points, and a positive relationship was observed between the SII and the PI ($R^2 = 0.72$) (Fig. 3), which allowed the use of the SII as the most important independent variable for the spatial modeling of the PI. Then, the SII was calculated for the entire study area, which provided the SII map, where dark green (values near 40) represents the geographic areas that were more influenced by the pollen emission and dispersion (Fig. 4).

The general regression model from the 32 sampling sites generated in this study is shown in Table 2. The PI (a transformed variable) is explained by the SII (a transformed variable) and the cumulative rainfall during May, with all of the variables calculated as 4-year means (i.e., over the period 2008–2011). As indicated above, the SII had a strong positive correlation with the PI, while the cumulative rainfall during May had a negative influence on the PI (Table 2). This model was adequately fitted ($R^2 = 0.77$), and the cross-validation of the model showed a coefficient of determination $Q^2 = 0.74$.

The analysis of the spatial behavior of the regression model was carried out using the experimental variogram (Fig. 5). According to the spatial autocorrelation of the residuals from the regression analysis, the variance of the residuals was fitted to a linear model that is defined by the following parameters: Nugget = 0.02; Sill = 0.04; and

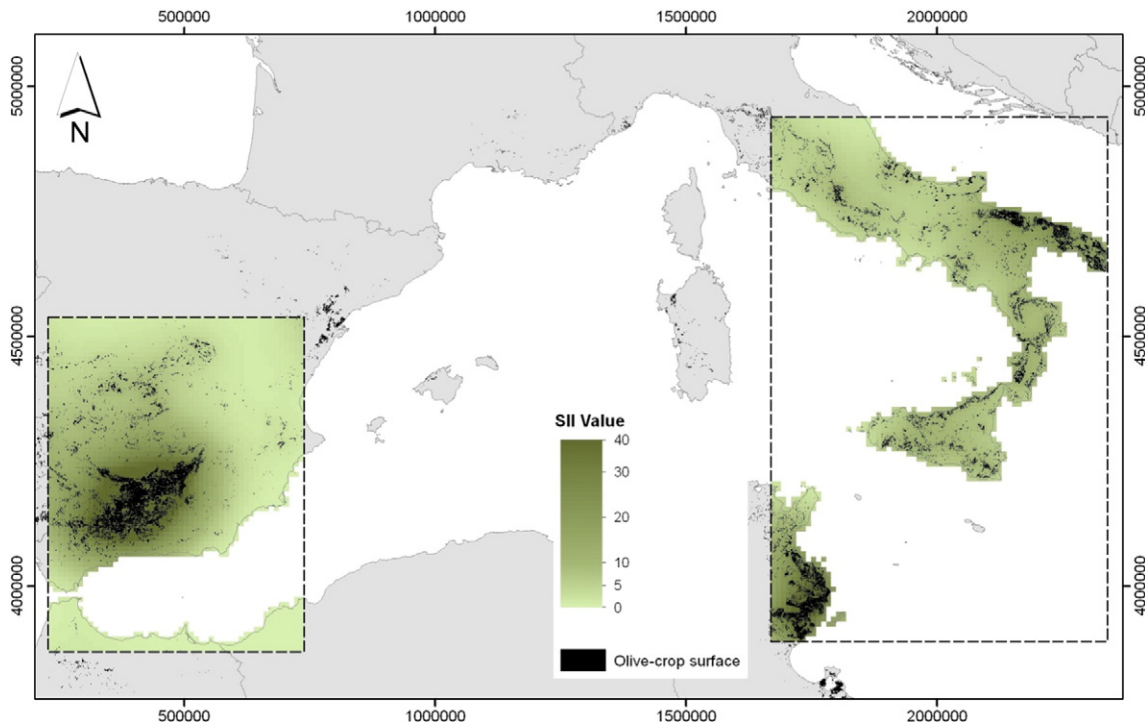


Fig. 4. Spatial distribution of the Specific Influence Index for the study area. Olive-crop map provided by Corine Land Cover 2006.

Table 2

Regression model of the Pollen Index using emission surface data and meteorological data from the sampling stations.

Model fit			
Dependent variable: Log(PI + 1)	Coefficients	SE	t value
Intercept	3.473	0.120	28.99**
Log(SII + 1)	0.817	0.105	7.77**
RMay	−0.006	0.002	−2.93*
Model validation			
	Coefficient	RMSE	MAE
Coefficient of determination (R^2)	0.765	0.178	0.143
Cross-validation coefficient (Q^2)	0.743	0.186	0.150

SE, standard error; RMSE, root mean square error; MAE, mean absolute error.

* 99% significance level.

** 99.9% significance level.

Range = $6E+5$. This function was adequately fitted with a coefficient of determination (R^2) of 0.70 and a sum square error of $7E-13$.

The spatial modeling for the PI is shown in Figs. 6 and 7. These airborne-pollen maps are constructed through the combination of the regression model for the PI (Table 2) and the spatial autocorrelation analysis for the semivariance of the residuals from the regression model (Fig. 5).

According to the model of the spatial distribution for the mean PI in the study area, the highest concentration was observed in the south-central Spanish area, in the southeastern Italian area, and in the Tunisia study area (Figs. 6 and 7). These areas included the sampling sites where the greatest mean annual PI (for the period 2008–2011) was recorded, which included: Jaen (44 925 pollen grains), Cordoba (30 126 pollen grains) and Granada (22 331 pollen grains) in Spain; Lecce (23 135 pollen grains) and Bari (22 859 pollen grains) in Italy; and Chaal (16 914 pollen grains) in Tunisia (Table 1).

The areas where the highest PI values were reached (as highlighted above) were distributed around the most important olive grove emission surfaces in these regions (Figs. 6 and 7). In the Spanish area, the PI calculated in the territories near to those that showed the maximum

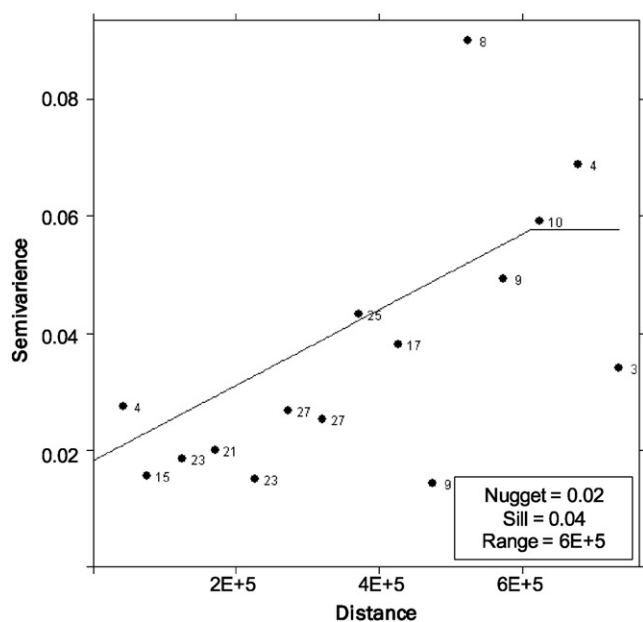


Fig. 5. Variogram showing the relationship between semivariance and distance from pairs of sampling points. Values represent numbers of point pairs next to each plotted semivariance symbol.

PI was seen to be influenced by the most important olive growing areas. Therefore, the areas of the concentric band are shown where the PI intensity decreased as the distance from the most important potential pollen sources increased (Fig. 6). However, this relationship did not show a linear behavior; i.e., the maximum influence on the PI was observed at 42 km from the emission source, as calculated in Fig. 2. On the other hand, some of the sampling sites located within the influence area from the most important olive grove emission surfaces (Fig. 2, 175 km) showed a high relative PI; e.g., Almeria (7209 pollen grains) and Albacete (4293 pollen grains) (Table 1). This was despite these sites having sparse olive grove emission surface in their proximity.

In the case of the Italy–Tunisia area, a concentric pattern in the variation of the PI was again observed; i.e., the PI decreased as the distance from the olive groves increased (Fig. 7). In Italy, certain sampling sites, such as Cosenza (18 475 pollen grains) and Salerno (18 416 pollen grains) (Table 1), should be highlighted because they had a low olive grove emission surface in their proximity with a high PI.

The internal validation ($R^2 = 0.88$; RMSE = 3521) and the cross-validation ($Q^2 = 0.74$; RMSE = 4871) from the spatial modeling for the PI reflect the goodness and the accuracy of the model (Fig. 8). Therefore, the estimated PI values from the airborne-pollen maps are particularly reliable with respect to the observed values from the sampling sites considered.

4. Discussion

The PI model presented here was generated by taking into account the spatial autocorrelation of the pollen concentrations and the strong relationships between both the PI and the SII in the main olive cultivation areas along the Mediterranean basin, which represent approximately 75% of the total Mediterranean olive growing areas, according to the CORINE land cover data. The SII might be a complex term because this index includes different kinds of information. In this sense, the SII reflects the general characteristics of the pollen dispersal in a given geographic area, depending on the distance to the potential pollen sources, the atmospheric dynamics, and the aerodynamic features of olive pollen (Oteros et al., 2015). The SII calculation was based on the Concentric Ring Method, and these results fit well with those reported by Oteros et al. (2015).

Therefore, the PI model provides a general way to study the dispersal features of olive pollen and the potential distance at which pollen grains can be transported in the Mediterranean region. For this purpose, the modeling was performed from the annual means of the PI, to reduce temporal variability. Then, as the flower production in olive trees is related to the alternate bearing behavior, which is generally fitted to a biennial pattern (Gonzalez-Minero et al., 1998; Al-Shdiefat and Qrunfleh, 2008; Rojo et al., 2015b), selecting a 4-year period allowed consideration of the same number of bearing years ('on' years of production) and non-bearing years ('off' years of production) from a productivity point of view. In this way, the alternate bearing effects that are characteristic of the physiological behavior of olive trees (Baktir et al., 2004; Lavee, 2007) were smoothed out for the modeling.

The annual mean for the 4-year period also allowed the integration and homogenization of the dynamics of the atmospheric circulation patterns that directly influence the pollen transport (Makra et al., 2010; Hernández-Ceballos et al., 2015), which shows information included in the SII. Therefore, this methodology is shown to be useful to analyze pollen dispersal that depends on the general features that affect pollen transport in the study areas. This has practical applications because this technique allows the mapping and monitoring of the olive atmospheric pollen intensity in the Mediterranean region.

However, other techniques should also be considered to study pollen transport according to particular atmospheric processes or during a given period of time, such as the study of local-scale winds (Damialis et al., 2005; Silva et al., 2000; Rojo et al., 2015a), long-range transport of pollen (Hernández-Ceballos et al., 2014; Rojo and

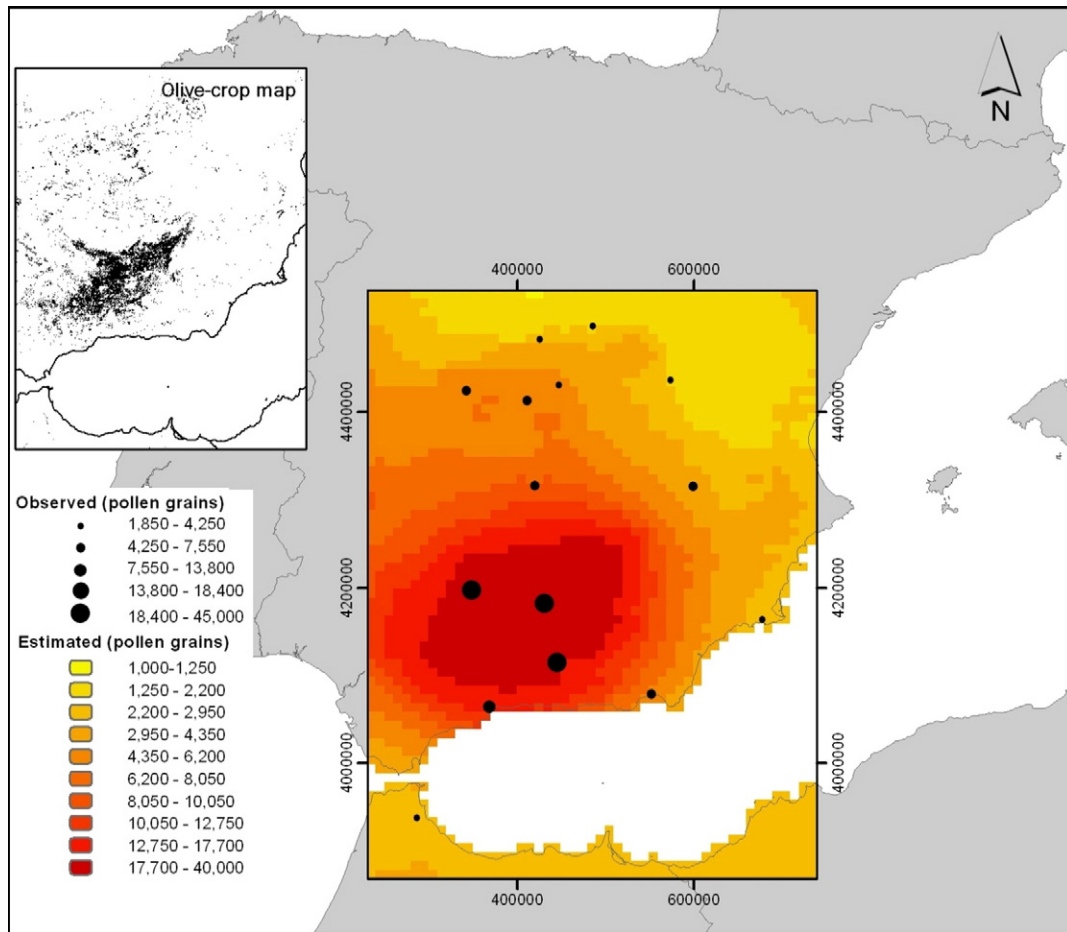


Fig. 6. Airborne-pollen maps showing the mean of the annual Pollen Index (for 2008–2011) for the area of Spain–Morocco. The classes for the Pollen Index shown in the legend were obtained by quantile analysis of the data distribution (frequency of occurrence). Olive-crop map provided by Corine Land Cover 2006.

Pérez-Badia, 2015b), and in combination with other environmental features like the distribution of the emission sources or the topography (Hidalgo et al., 2002; Fernández-Rodríguez et al., 2014).

The olive tree reproductive cycle is strongly influenced by meteorological variables prior to the flowering period (Oteros et al., 2013b), as mainly the temperature (Aguilera et al., 2015b; Orlandi et al., 2010, 2014), and it has been shown that temperature and water availability influence flowering intensity, and then the PI (Galán et al., 2001; Sicard et al., 2012). In this sense, the SII includes information about the meteorological variables that influence flower-bud development. On the other hand, the results of this PI model show that the rainfall during May (a portion of the pollen season) negatively influences the PI, as documented by Sicard et al. (2012). This reflects the washing effects of this rainfall, which thus restricts pollen dispersal in the atmosphere and favors pollen precipitation instead (Bonofiglio et al., 2008; Rojo et al., 2015a).

Using the Concentric Ring Method implies uniformity of the study area conditions with respect to pollen emission and pollen dispersal (Oteros et al., 2015). However, from the spatial variability point of view, other environmental factors, such as topography, might vary these homogeneous conditions, and thus terrain topography is an important issue to be considered in relation to pollen dispersal (García-Mozo et al., 2004). The distribution of the olive grove emission surfaces in combination with the relief of the land might influence pollen dispersal due to topographic effects, thus limiting pollen transport (Kasprzyk, 2008). Our model was generated according to different altitudinal ranges (below and above 300 m a.s.l.), and took into account part of this spatial variability related to the topography. The patterns

associated with pollen dispersal were studied for each altitudinal range, with considerable differences relating to the maximum influence obtained; i.e., the distance of the most influential olive grove emission surfaces on the PI.

According to our results, areas higher than 300 m a.s.l. in elevation receive greater amounts of pollen from shorter-distance pollen sources (maximum influence, 27 km) with respect to areas lower than 300 m a.s.l. (maximum influence, 59 km). This difference might be related to the topographic characteristics of the regions (Hidalgo et al., 2002), because in general, higher altitudinal areas are associated with more irregular reliefs, which can sometimes limit pollen transport by providing an effective orographic barrier. Otherwise, lower altitudinal areas in general are related to more homogeneous regions from a topographical point of view, thus favoring pollen dispersal mainly in areas close to the coastline and in the broad fluvial valleys (García-Mozo et al., 2004; Hernández-Ceballos et al., 2011).

The model presented in this study showed high reliability for modeling the PI in the Mediterranean region, as highlighted by the validation process. According to this finding, the spatial model explained 88% of the variance of the PI. Therefore, the spatial interpolation method used for geostatistical modeling (i.e., regression-kriging) is shown to be useful for analysis of the spatial variability of airborne pollen concentrations, as has also been documented for other geostatistical techniques (Alba et al., 2006; García-Mozo et al., 2006; DellaValle et al., 2012; Aguilera et al., 2015a). It is important to emphasize that the areas that show lower olive grove emission surface in their proximity might anyway record relatively high pollen concentrations that will mainly be due to pollen from external sources (Fernández-Rodríguez et al.,

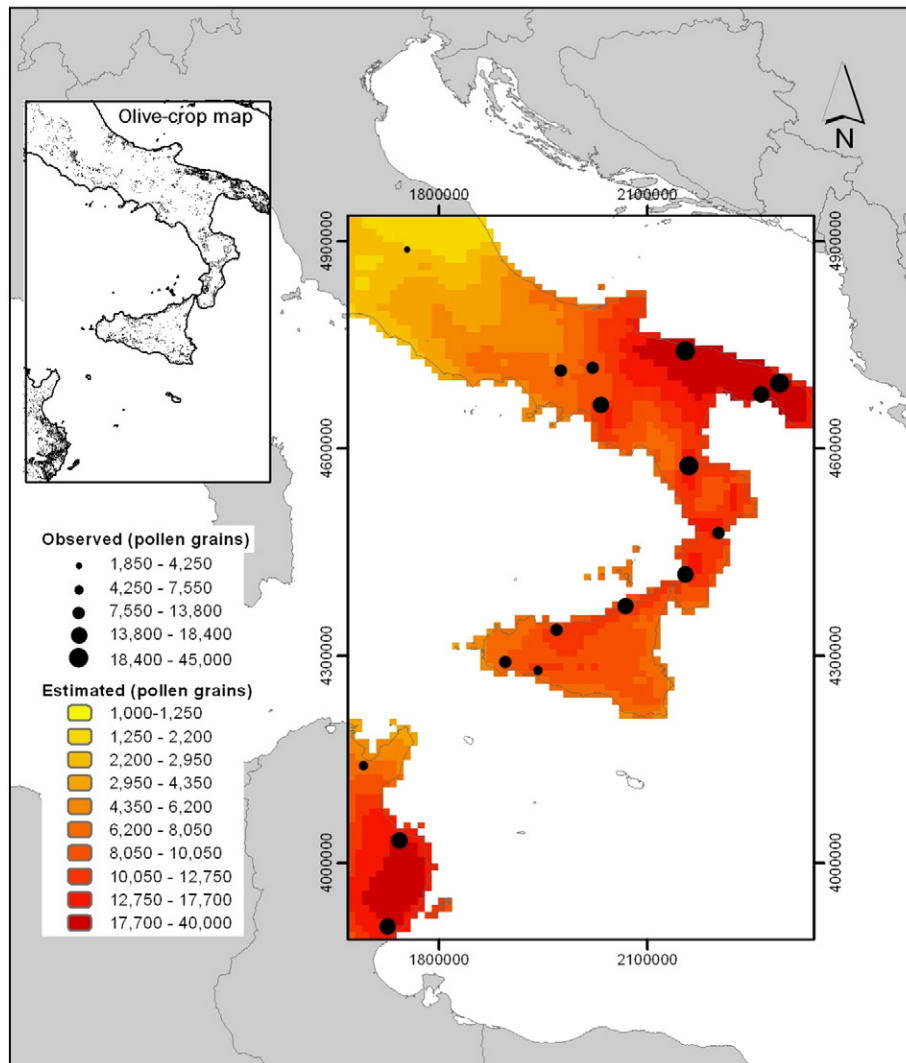


Fig. 7. Airborne-pollen maps showing the mean of the annual Pollen Index (for 2008–2011) for the area of Italy–Tunisia. The classes for the Pollen Index on the legend were obtained by quantile analysis of the data distribution (frequency of occurrence). Olive-crop map provided by Corine Land Cover 2006.

2014). In general, these areas are less sampled from the standpoint of aerobiological research based on olive pollen, and thus spatial modeling might be a useful tool for predicting pollen intensity in unsampled areas.

In general, mixed geostatistical models, such as co-kriging or regression-kriging, might result in more accurate predictions than using simple kriging methods (Yao et al., 2013), as these techniques combine both spatial interpolation and inference of the response variable from one (co-kriging) or several (regression-kriging) predictors (Knotters et al., 1995). According to our findings, using the SII and the rainfall during May as predictors increased the cross-validation significantly when compared with ordinary kriging ($Q^2 = 0.65$; RMSE = 5591; MAE = 3884) or co-kriging with only the SII used ($Q^2 = 0.73$; RMSE = 4979; MAE = 3427). However, regression-kriging is not always the most appropriate technique for spatial modeling from an environmental variable (Hosseini et al., 2014), and otherwise the selection of the optimal geostatistical technique depends on both response variable characteristics and spatial autocorrelation (Hengl, 2007; Li and Heap, 2014).

One case where the PI estimated by the model was particularly different from the PI observed (i.e., with one of the greatest errors of prediction; residual: – 6525 pollen grains) was the Salerno station (Italy). The mean annual PI observed in Salerno was 18 416 pollen grains, which was relatively high considering the olive grove emission surfaces

surrounding the pollen trap. Furthermore, Salerno is located in a topographically isolated region that is surrounded by mountains, which suggests that probably the pollen recirculation phenomenon within this area is particularly important. In this sense, the maximum influence according to pollen emission must be reached at a shorter distance from the pollen trap, when compared with the rest of sampling points.

In addition, a marked inter-annual variability with respect to the PI (mean = 20 045; standard deviation = 21 752; coefficient of variation = 109%), was observed for the Salerno station when taking into account a greater number of years (period 1999–2011). This alternating behavior might be influenced by less developed agricultural techniques that favor the alternate bearing (Fernández-Escobar et al., 2004; Bustan et al., 2011; Fernández et al., 2015) when compared with other Italian regions where olive growing is more relevant. This might also reflect that the pollen recorded in Salerno is originated in a reduced geographical area with homogeneous environmental conditions, thus favoring the year-to-year synchrony of the olive groves (Monselise and Goldschmidt, 1982). This might support the hypothesis of pollen recirculation, although other studies must be performed for an analysis at a local or regional scale for studying the wind direction patterns and the pollen dispersion in more detail.

On the other hand, the cases of Jaen and Cordoba stations are located in areas with particularly widespread olive groves (Díaz de la Guardia

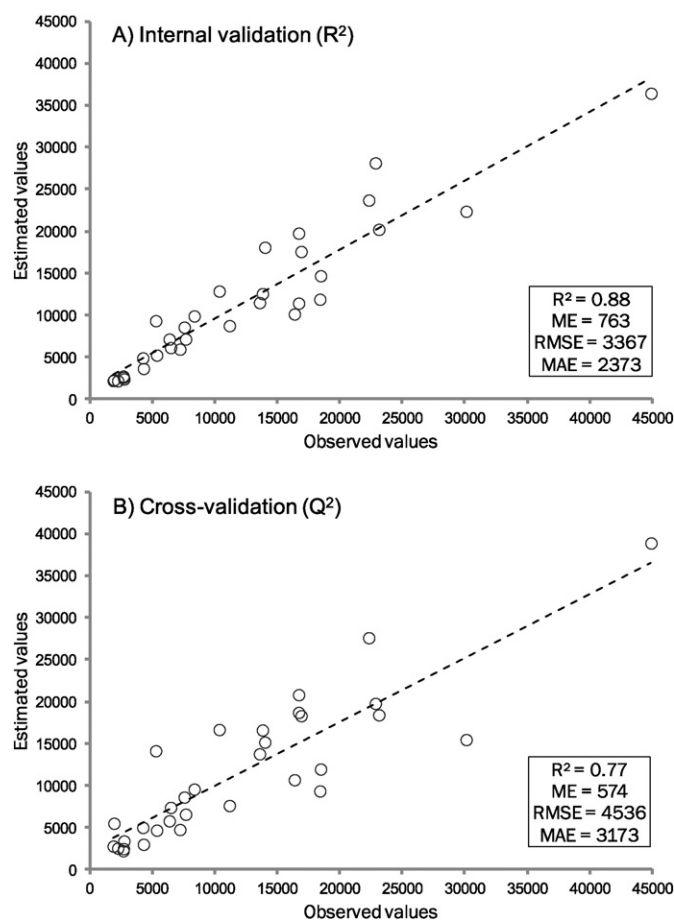


Fig. 8. Internal validation (A) and cross-validation (B) analyses from airborne-pollen maps. ME, mean error; RMSE, root mean square error; MAE, mean absolute error.

et al., 2003; Martínez-Bracero et al., 2015), and specifically the largest olive grove emission surface in the Mediterranean region (Barranco et al., 2008). Therefore, both of these stations showed large differences in the PI when compared with the rest of the sampling sites, and thus the PI for these sites has been underestimated.

5. Conclusions

The spatial model generated in this study provides a very powerful tool, with the construction of a reliable PI map for the most important Mediterranean areas in terms of olive production. Furthermore, the model also includes information about general patterns of pollen dispersal from the potential sources, as the SII and rainfall during the pollen season (May) were included as predictors, and these airborne-pollen maps may have important agricultural implications due to interest in the PI for forecasting of accurate crop yields. In this sense, the geographical variability of the olive production can be studied according to the spatial distribution of the PI. On the other hand, airborne-pollen maps allow the definition of higher risk areas for pollen allergy sufferers showing the interaction between the olive agroecosystem and the environment.

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