The published version of the paper " J. Rojo, F. Orlandi, R. Pérez-Badia, F. Aguilera, A. Ben Dhiab, H. Bouziane, C. Díaz de la Guardia, C. Galán, A.M. (2016). Modeling olive pollen intensity in the Mediterranean region through analysis of emission sources. Science of The Total Environment, (551–552), 73-82" is available at: http://dx.doi.org/10.1016/j.scitotenv.2016.01.193

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

Rojo J, Orlandi F, Pérez-Badia R, Almeria, Cordoba, Granada, Jaen, Madrid, Malaga, Marruecos, Murcia, Tunisia, Fornaciari M

Abstract

The aerobiological monitoring of *Olea europaea* L. is of great importance in the Mediterranean basin due to olive pollen is one of the most represented pollen types of the airborne pollen spectrum for the entire territory. The main aim of this study was to elaborate an airborne-pollen map based on the Pollen Index considering a 4-year period (2008-2011) in order to obtain a geographic continuous map for the pollen intensity with practical applications from an agronomical and allergological point of view. For this purpose, the main predictor variable was an index based on the distribution and abundance of the potential sources of pollen emission, including intrinsic information about the general atmospheric patterns of pollen dispersal and the aerodynamical features of the olive pollen. Other meteorological variables were included in the modeling in conjunction with spatial interpolation, allowing obtaining a spatial model of the Pollen Index from the main olive cultivation areas along the Mediterranean region. The results showed marked differences with respect to the dispersal patterns associated to the altitudinal gradient. The findings pointed that areas located at an altitude above than 300 m a.s.l. receive a greater amount 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).

Keywords: *Olea europaea*, mapping, geostatistics, pollen index, aerobiology, olive groves

1. Introduction

Olive tree is primarily an anemophilous species with high flower and pollen production (Rojo et al., 2015b). Due to its great land cover extensions in the Mediterranean region, olive pollen is considered one of the more represented pollen types of the airborne pollen spectrum for the entire territory (Caiola et al., 2002; Perez-Badia et al., 2010; Martínez-Bracero et al., 2015). In this sense, olive pollen monitoring has become an important aspect from an agricultural (Ribeiro et al., 2008), ecological (Orlandi et al., 2014) or medical (Bonofiglio et al., 2013) point of view, promoting the study of several aerobiological parameters related to olive flowering (e.g. Díaz de la Guardia 2003; Zhang et al., 2014).

The Pollen Index ('PI'), i.e. the yearly sum of daily pollen grains per m^3 of air, is an aerobiological variable directly related to flower production (Rojo et al., 2015b), and considered an important indicator of the flowering intensity for the olive tree (Orlandi et al., 2014). The 'PI' is associated to marked year-on-year variations, being governed by different factors related to pollen emission and pollen dispersal. 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 (year x-1) to the flowering time (year x) (Rojo and Pérez-Badia, 2015a). During this period, processes involved in floral organ development take place (Rallo and Martin, 1991; Connor and Fereres, 2005), determining olive flower production and thereby pollen emission (Oteros et al., 2013a). Furthermore, olive tree is characterized by displaying alternate pollen production cycles because olive reproductive cycle is completed over two years, producing a balance in endogenous hormones levels which promote or inhibit flowering (Al-Shdiefat and Qrunfleh, 2008); this behavior is reflected in the variability of the pollen production (Galán et al., 2001; Ribeiro et al., 2005).

Once pollen grains have been released into the air, spatiotemporal variations on the 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, distance and distribution of the potential pollen sources, largely determine pollen amounts recorded in a given geographic location (Fernández-Rodríguez et al., 2014). Oteros et al. (2015) estimate that in a given sampling station the maximum influence on pollen emission is observed in olive groves located to 37 km of distance from the trap. However, the small size of the olive pollen favours long range transport of pollen (Hernández-Ceballos et al., 2014; Rojo and Pérez-Badia, 2015b). Therefore from the standpoint of the spatial variability, olive-growing areas must be considered for 'PI' modeling. Furthermore, temporal variations of the olive grove surface is of great relevance for analyzing long-term trend in the 'PI', as documented by García-Mozo et al. (2014).

The olive pollen concentration has previously been studied from a spatial point of view (Hidalgo et al., 2002; Fernández-Rodríguez et al., 2014), taking into account both distribution of the potential pollen sources and dispersal conditions in the atmosphere. Otherwise, techniques based on spatial interpolation for aerobiological studies i.e. kriging, may be carried out due to the spatial correlation showed in airborne pollen concentration (Alba et al., 2000). Thus, the combination of these modeling techniques results of great interest in order to analyze airborne pollen levels (Rojo and Perez-Badia, 2015b).

Spatial interpolation allows modeling a given variable along a continuous area in the territory from data measured in a specific number of sampling points, being this aspect one of the most important advantages of these techniques (Oliver and Webster, 2014). In this sense, nowadays the number of papers based on geostatistical techniques is increasing according to the study of the parameters in relation to the plant reproductive cycle such as time flowering or pollen intensity (e.g. Schröder et al., 2014; Aguilera et al., 2015). In addition, this methodology allows optimizing the sampling stations by minimizing the number of sites or searching the most appropriate locations (Garcia-Mozo et al., 2006; Hengl, 2007), thereby reducing time and economical resources associated to the aerobiological monitoring.

The main goal of the study was to model the Pollen Index ('PI') using as main predictor variable an index based on the distribution and abundance of the potential sources of pollen emission which contemporary consider intrinsic information about the general atmospheric patterns of pollen dispersal and the aerodynamical features of the olive pollen. Other meteorological variables were included in the modeling in conjunction with spatial interpolation allowing obtaining a geographic continuous model of the 'PI' from the main olive cultivation areas in the Mediterranean region in order to predict the pollen intensity in unsampled areas.

2. Methods

2.1 Pollen records

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

Daily pollen samples were obtained according to the standardized Spanish method (Galán et al. 2007). The Pollen Index (PI) was calculated as the sum of the daily pollen concentrations recorded during the Main Pollen Season (MPS). The MPS includes 95% of the seasonal total pollen count, starting on the day when the sum of daily pollen concentrations reaches 2.5% of the total annual sum and ending on the day when the sum reaches 97.5% (Andersen, 1991), as the best criterion to estimate MPS in the area considered. This study was performed over four years (2008-2011) taking into account the continuous availability of aerobiological data in each study area and considering contemporary the selection of a number of sampling sites as great as possible to have the major availability of real data to elaborate the model. The average amount of annual 'PI' recorded during this period was used as the dependent variable for modeling.

2.2 Emission surface data

The influence of the emission surface data was calculated by using the Concentric Ring Method (CRM) proposed by Oteros et al. (2015) and also the same nomenclature has been followed with respect to the required indexes, i.e. the Influence Index 'II' and the Specific Influence Index 'SII'. This methodology analyzes the relationship between pollen index and theoretical influence of the emission surface from the olive-growing areas which are divided into concentric rings from the pollen station. Olive grove surface was obtained from the CORINE Land Cover database (CLC, 2006).

The Influence Index 'II' was calculated for all concentric rings which were considered consecutively for the entire total influence area from the sampling points. This index 'II' shows the theoretical influence for the pollen emission of the olive groves in relation to their location from the sampling point (distance) and was calculated as a function of the correlation between pollen index and ring distance (Oteros et al. 2015).

In order to calculate the Influence Index, rings with a width of 10 km were considered as the most suitable width taking into account the magnitude of the calculations in this work, considering so large geographical areas. Nevertheless, it was proved that the accuracy of the Influence Index calculation is appropriate with respect to a smaller width considered. However, the mathematical integration of the curve for the Influence Index was performed to rings 1 km wide in order to determine the maximum influence on the Pollen Index as well as the end of the influence. The 'II' calculation also was carried out independently for stations depending on different altitudinal ranges in order to determine different dispersion patterns of pollen according to topographical characteristics related to the elevation.

Then, the Specific Influence Index ('SII') was determined as the sum of olive grove surface included in each ring and weighted by the corresponding Influence Index according to the distance from the sampling point. In a practical sense, 'SII' reflects the characteristics of a given geographic area to receive pollen grains in relation to the distribution of potential pollen sources and to the dispersion dynamics of the particle considered, i.e. *Olea* pollen.

In the present study, a continuous layer with the 'SII' was performed for the entire studied area according to the Influence Index calculated at each ring from the sampling stations analysis. The 'SII' layer was elaborated as a continuous grid of 10 x 10 km where 'SII' was calculated at the centroid of the pixel such as described above. Finally, this variable 'SII' was included as independent variable for modeling the 'PI'.

2.3 Meteorological data

Meteorological data were obtained from the weather stations nearest to sampling sites. The weather stations belong to: the National Council of Agricultural Research (CRA-Cma) in Italy, the Physics Departament of the Faculty of Science in Morocco, the Spanish Meteorological Agency (AEMET) in Spain, and the National Meteorological Centre (NIM) in Tunisia. The meteorological variables analyzed have been maximum temperature, minimum temperature and cumulated rainfall from monthly and seasonally periods.

Furthermore, the continuous layers in the study area were performed for the meteorological variables included in the regression model. In order to elaborate these layers, daily meteorological gridded dataset were obtained from the European Climate Assessment & Dataset (ECA&D, http://www.ecad.eu, Haylock et al., 2008) whose data were transformed to a grid of 10 x 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' since these variables are strongly correlated according to the results shown in Oteros et al. (2015). Furthermore, meteorological variables were included in the model by means of stepwise selection and collinearity analysis. In addition to internal validation (R^2) 5-fold cross validation was performed in order to check the reliability of the model. The regression equation obtained was used thereafter for spatial modeling of 'PI' using geostatistical techniques. For this purpose, regression-kriging was used taking the independent variables selected ('SII' and meteorological variables) as continuous layers in space whose design has been described above.

Regression-kriging is a technique included in spatial prediction models that 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 in order to improve the visualization of the results, airborne-pollen maps are independently shown for the Spain-Morocco area (341,700 km^2) and Italy-Tunisia area (703,500 km^2). In both cases, the boundaries were selected according to rectangular areas containing sufficiently close sampling points, not considering larger areas where no sampling points are present and consequently the statistical validation cannot performed.

The analysis of the spatial behavior of the data was required for spatial modeling purposes. Given the asymmetrical distribution of the Pollen Index and Specific Influence Index, a logarithmic transformation was required for the geostatistical analysis (Oliver and Webster, 2014). Furthermore, these transformations improved the distribution of 'PI' and 'SII' data and avoided excessive weights of certain sampling points (Spanish sites such as Jaen and Cordoba). After, the variograms for the model were performed in order 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, also the goodness of fit of the spatial model obtained was tested by internal validation (R^2) and by 5-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 from both validation ways.

Models were constructed using 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 sampling sites is shown in Fig. 2 where a third-degree polynomial function is well fitted to the data resulting from the relationship between both olive-grove surface in each ring and correlation with 'PI'. According to the calculation of the Influence Index ('II') from all sampling sites, the influence of the pollen emission ends at the 175 km surrounding the sampling sites (Fig. 2a). This fact indicates that the pollen emission from olive groves located at greater distances do not influence Pollen Index recorded for a given site.

On the other hand, the distance of the maximum influence on the 'PI' is observed at 42 km (Fig. 2a), however considerable differences are observed taking into account the maximum influence, using different altitudinal ranges. In this sense, at sites lower than 300 m a.s.l. the maximum influence is observed at 59 km from the sampling points (Fig. 2b); while at sites above 300 m a.s.l. the maximum influence is found at 27 km (Fig. 2c), showing a difference of 32 km with respect to lower sites.

The 'SII' is calculated using both the influence area under the curve of the polynomial function as shown in the Fig. 2 and olive-grove surfaces located in each ring. In the first place, this index ('SII') has been calculated from the sampling points where a positive relationship is observed between 'SII' and 'PI' ($R^2 = 0.72$) (Fig. 3), allowing the use of 'SII' as the most important independent variable for the spatial modeling of 'PI'. Then, 'SII' was calculated for the entire study area obtaining the 'SII' map where the dark green (values near 40) represents the geographic areas more influenced by pollen emission and dispersion (Fig. 4).

The general regression model from the 32 sampling sites generated in this work is shown in Table 1. The 'PI' (transformed variable) is explained by the 'SII' (transformed variable) and the cumulative rainfall during May, all variables being calculated as four years average (period 2008-2011). As commented above, the 'SII' presents a strong positive correlation with the 'PI', while cumulative rainfall during May shows a negative influence on 'PI' (Table 1). This model is adequately fitted ($R^2 = 0.77$) and the cross-validation of the model shows a coefficient of determination $Q^2 = 0.74$.

The analysis of the spatial behavior of the regression model is carried out using experimental variogram (Fig. 5). According to the spatial autocorrelation of residuals from the regression analysis, the variance of the residuals is fitted to a linear model which is defined by the following parameters: Nugget = 0.02 ; Sill = 0.04 ; Range = 6E+5. This function is adequately fitted with a coefficient of determination (R^2) of 0.70 and a Sum Square Error (SSE) of 7E-13.

The spatial modeling for 'PI' is shown in both Figs. 6 and 7. These airborne-pollen maps are the result by combining the regression model for 'PI' (Table 1) 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 is observed in the South-central Spanish area, in the Southeast Italian area and in the Tunisia studied area (Figs. 6 and 7). These areas include the sampling sites where the greatest mean annual 'PI' (period 2008-2011) were recorded such as: Jaen (44,925 grains m^{-3} air), Cordoba (30,126 grains m^{-3} air) and Granada (22,331 grains m^{-3} air) in Spain; Lecce (23,135 grains m^{-3} air) and Bari (22,859 grains m^{-3} air) in Italy; Chaal (16,914 grains m^{-3} air) in Tunisia.

The areas where the highest 'PI' values are reached as highlighted above, are distributed surrounding the most important olive-grove surfaces in the territory (Figs. 6 and 7). In Spanish area, the 'PI' calculated in the territories near to those that show the maximum 'PI' values is observed to be influenced by the most important olive-growing areas. Therefore, concentric band areas are showed where the 'PI' intensity decreases as the distance from the most important potential pollen sources is increased (Fig. 6). However, this relationship do not present linear behavior, i.e. the maximum influence on the 'PI' is observed at 42 km from the emission source as calculated in the Fig. 2. On the other hand, some sampling sites located within the influence area from the most important olive-grove surfaces (175 km, Fig. 2) display a high relative 'PI' ,e.g. Almeria (7,209 grains m^{-3} air) and Albacete (4,293 grains m^{-3} air), despite that these sites account with a sparse olive-grove surface in their proximities.

In the case of Italy-Tunisia area, the concentric pattern in the variation of the 'PI' is again observed, i.e. 'PI' decreases as the distance from the olive groves increases (Fig. 7). In Italy, certain sampling sites such as Cosenza (18,475 grains m^{-3} air) and Salerno (18,416 grains m^{-3} air) should be highlighted because they have a low olive-grove surface in their proximities displaying a high 'PI' value.

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, estimated 'PI' values from the airborne-pollen maps are quite reliable with respect to the observed values from the sampling sites considered.

4. Discussion

The 'PI' model presented in this paper was generated taking into account the spatial autocorrelation of the pollen concentration and the strong relationship between both 'PI' and 'SII' in the most important

Mediterranean areas in terms of olive production. ‘SII’ may be a complex term because this index includes information of different kinds. In this sense, ‘SII’ reflects the general characteristic 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 the olive pollen (Oteros et al., 2015). The ‘SII’ calculation was based on the Concentric Ring Method and our results was found to be fitted well with those documented by Oteros et al. (2015).

Therefore, the ‘PI’ model allows to study in a general way the dispersal features of the olive pollen and the potential distance at which the pollen grains can be transported in the Mediterranean region. For this purpose, modeling was performed from the annual average of the ‘PI’, dealing to reduce temporal variability. Then, since the flower production in olive trees is related to 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 allows considering 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, alternate bearing effects being characteristic of the physiological behavior of the olive trees (Baktir et al., 2004; Lavee, 2007), were smoothed out for the modeling task.

The annual average for the 4-year period also allowed determining the general dynamics of the atmospheric circulation patterns directly influencing pollen transport (Makra et al., 2010; Hernández-Ceballos et al., 2015), information included in the ‘SII’. Therefore, this methodology is shown to be useful in order to analyze pollen dispersal depending on the general features affecting pollen transport in the study areas, with practical applications because this technique allows mapping and monitoring the olive pollen intensity in the Mediterranean region.

However, other techniques should be considered to study pollen transport according to particular atmospheric processes or during a given period of time, such as the study of the 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 Pérez-Badia, 2015b), or the combination with other environmental features such as 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), mainly temperature (Aguilera et. al., 2014; Orlandi et al.2010; 2014), and it has been documented that temperature and water availability influence pollen production (Galán et al., 2001; Siscard et al., 2012), in this sense, ‘SII’ includes information about meteorological variables influencing flower bud development. On the other hand, the results of this ‘PI’ model showed that the rainfall during May (portion of the pollen season) negatively influences ‘PI’ as documented by Sicard et al. (2012). This fact reflects the washing effect of rainfall, thus restricting pollen dispersal in atmosphere and favouring pollen precipitation (Bonofiglio et al., 2008; Rojo et al., 2015a).

Using Concentric Ring Method implies to consider uniformity in the study area conditions with respect to pollen emission and pollen dispersal (Oteros et al., 2015). However from a point of view of the spatial variability, other environmental factors such as topography may vary these homogeneous conditions, thus terrain topography is an important issue to be considered in relation to the pollen dispersal (García-Mozo et al., 2004). The distribution of the olive grove surfaces in combination with the relief of the land may influence on pollen dispersal due to the topographic effect, thus limiting pollen transport (Kasprzyk, 2008). Our model was generated according to different altitudinal ranges (below and above 300 m a.s.l.), taking into account part of this spatial variability related to the topography. The patterns associated to pollen dispersal were studied for each altitudinal range, obtaining considerable differences about maximum influence, i.e. the distance of the most influential olive grove surfaces on the 'PI'.

According to our results, areas higher than 300 m a.s.l. in elevation receive a greater amount 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 may be related to the topographic characteristics of the territories (Hidalgo et al., 2002), because in general, higher altitudinal areas are associated with more irregular reliefs sometimes limiting pollen transport by an effective orographic barrier. Otherwise, lower altitudinal areas in general are related to more homogeneous territories from a topographical point of view, thus favouring 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 work showed high reliability for modeling the 'PI' in the Mediterranean region, as highlighted by 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, showed to be useful for analyzing the spatial variability in airborne pollen concentrations, as documented also from other geostatistical techniques (Alba et al., 2006; DellaValle et al., 2012; Aguilera et al., 2015). It is important to emphasize that areas showing a lower olive grove surface in their proximities, may record relative high pollen counts mainly coming from external pollen sources (Fernández-Rodríguez et al., 2014). In general, these areas are less sampled from the standpoint of the aerobiological researches based on olive pollen, thus spatial modeling may be a useful tool for predicting pollen intensity in unsampled areas.

In general, mixed geostastical models such as cokriging or regression-kriging may result in more accurately predictions than simple kriging methods (Yao et al., 2013) since these techniques combine both spatial interpolation and inference of the response variable from one (cokriging) or several (regression-kriging) predictors (Knotters et al., 1995). According to our findings, using 'SII' and rainfall during May as predictors increased cross-validation in a significative way when compared with ordinary kriging (Q^2 = 0.65; RMSE = 5591; MAE = 3884) or cokriging only ‘SII’ being 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), otherwise the selecting 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’ value estimated by the model was more different with respect ‘PI’ observed value i.e. with one of the most greater error of prediction (residual: -6,525 grains m^{-3} air), is the Salerno station (Italy). The average annual ‘PI’ observed in Salerno was 18,416 grains m^{-3} air, a relative high value considering the olive grove surfaces surrounding to the pollen trap. Furthermore, Salerno is located in a topographically isolated territory surrounded by mountains, suggesting that probably pollen recirculation phenomenon within this area may be particularly important. In this sense, the maximum influence according to pollen emission must be reached to shorter distance from the pollen trap when compared with the rest of sampling points.

On the other hand, a marked interannual variability with respect to the pollen production, i.e. ‘PI’ value (mean = 20,045; standard deviation = 21,752; coefficient of variation = 109 %) was observed in the Salerno station taking into account a greater number of years (period 1999-2011). This alternating behavior may be influenced by a less developed agricultural techniques favouring 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. But also this fact may reflect that the pollen recorded in Salerno is originated in a reduced geographical area with homogeneous environmental conditions, thus favouring the year-to-year synchrony of the olive groves (Monselise and Goldschmidt, 1982). This fact may support the hypothesis of pollen recirculation, although other studies must be performed taking into account a local or regional scale for studying wind direction pattern and more detailed pollen dispersion.

The ‘PI’ values estimated by the model in the Jaen and Cordoba stations also show a certain error with respect to observed values (residuals: -8,498 grains m^{-3} air y -7,762 grains m^{-3} air, respectively). In this case, the prediction error may be due to both sites are located in areas with important extensions of olive groves (Díaz de la Guardia et al., 2003), specifically the largest olive groves surface in the Mediterranean region (Barranco et al., 2008). Therefore, both stations displayed a large difference in ‘PI’ values when compared with the rest of the sampling sites. For this reason, logarithmic transformation was required in order to improve skewness of the distribution of data, being an important premise for the geostatistical techniques (Li and Heap, 2014).

5. Conclusions

The spatial model generated in this study results to be a very powerful tool, obtaining a reliable Pollen Index map in the Mediterranean region. Furthermore, the model also includes information about general patterns of pollen dispersal from the potential sources, since Specific Influence Index and rainfall during the pollen season (May) was included as predictors. The airborne-pollen maps may have important agricultural implications due to the interest of the Pollen Index for forecasting accurately crop yields. In this sense, geographical variability of the olive production may be studied by the spatial distribution of the Pollen Index. On the other hand, airborne-pollen maps allow defining higher risk areas for pollen allergy sufferers.

Mapping was carried out from the main olive cultivation areas along the Mediterranean basin, representing approximately 75 % of the total Mediterranean olive-growing areas, according to CORINE land-use data. Modeling was not extended to the entire Mediterranean region because the lack of sampling sites in the certain areas, thus limiting the statistical validation of the results. In the future, the model may be extended to the entire Mediterranean region as long as the presence of aerobiological sampling sites are also increased.

References

Aguilera, F., Ben Dhiab, A., Msallem, M., Orlandi, F., Bonofiglio, T., Ruiz-Valenzuela, L., Galán, C., Díaz-de la Guardia, C., Giannelli, A., Trigo, M.M., García-Mozo, H., Pérez-Badia, R., Fornaciari, M., 2015. Airborne-pollen maps for olive-growing areas throughout the Mediterranean region: spatio-temporal interpretation. Aerobiologia, doi: 10.1007/s10453-015-9375-5.

Aguilera, F., Fornaciari, M., Ruiz-Valenzuela, L., Galán, C., Msallem, M., Ben Dhiab, A., Díaz de la Guardia, C., Trigo, M.M., Bonofiglio, T., Orlandi, F., 2014. Phenological models to predict the main flowering phases of olive (*Olea europaea* L.) along a latitudinal and longitudinal gradient across the Mediterranean region. International Journal of Biometeorology 59, 629-641.

Alba, F., Nieto-Lugilde, D., Comtois, P., Díaz de la Guardia, C., De Linares, C., Ruiz, L., 2006. Airborne-pollen map for *Olea europaea* L. In eastern Andalusia (Spain) using GIS: Estimation models. Aerobiologia 22, 109-118.

Al-Shdiefat, S.M., Qrunfleh, M.M., 2008. Alternate bearing of the olive (*Olea europaea* L.) as related to endogenous hormonal content. Jordan J Agric Sci 4(1), 12-25.

Andersen, T., 1991. A model to predict the beginning of the pollen season. Grana 30, 269 275.

Baktir, I., Ulger, S., Kaynak, L., Himelrick, D.G., 2004. Relationship of seasonal changes in endogenous plat hormones and alternate bearing of olive trees. HortScience 39(5), 987-990.

Barranco, D., Fernáandez-Escobar, R., Rallo, L., 2008. El cultivo del olivo, 8ª ed. Junta de Andalucía y Ediciones Mundi-Prensa, Madrid, Spain.

Bonofiglio, T., Orlandi, F., Ruga, L., Romano, B., Fornaciari, M., 2013. Climate change impact on the olive pollen season in Mediterranean areas of Italy: air quality in late spring from an allergenic point of view. Environ Monit Assess 185, 877-890.

Bonofiglio, T., Orlandi, F., Sgromo, C., Romano, B., Fornaciari, M., 2008. Influence of temperature and rainfall on timing of olive (*Olea europaea*) flowering in sourthern Italy. New Zealand Journal of Crop and Horticultural Science 36: 59-69.

Bustan, A., Avni, A., Lavee, S., Zipori, I., Yeselson, Y., Schaffer, A.A., Riov, J., Dag, A., 2011. Role of carbohydrate reserves in yield production of intensively cultivated oil olive (*Olea europaea* L.) trees. Tree Physiology 31, 519-530.

Caiola, M.G., Mazzitelli, A., Capucci, E., Travaglini, A., 2002. Monitoring pollinosis and airborne pollen in a Rome university. Aerobiologia 18, 267-275.

CLC, 2006. CORINE Land Cover, Internet, http://www.eea.europa.eu/publications/COR0-landcover (accessed 10.06.15).

Connor, D.J., Fereres, E., 2005. The physiology of adaptation and yield expression in olive. Horticultural Reviews 31, 155, 229.

Damialis, A., Gioulekas, D., Lazopoulou, C., Balafoutis, C., Vokou, D., 2005. Transport of airborne pollen into the city of Thessaloniki: the effects of wind direction, speed and persistence. International Journal of Biometeorology 49(3): 139-145.

DellaValle, C.T., Triche, E.W., Bell, M.L., 2012. Spatial and temporal modeling of daily pollen concentrations. International Journal of Biometeorology 56, 183-194.

Díaz de la Guardia, C., Alba, F., Trigo, M.M., Galán, C., Ruíz, L., Sabariego, S., 2003. Aerobiological analysis of *Olea europaea* L. Pollen in different localities of southern Spain. Grana 42, 234-243.

FAOSTAT, 2013. Food and Agriculture Organization of the United Nations, Statistics Division, Internet, http://www. http://faostat3.fao.org/ (accessed 24.08.15).

Fernández, F.J., Ladux, J.L., Searles, P.S., 2015. Dynamics of shoot and fruit growth following fruit thinning in olive trees: Same season and subsequent season responses. Scientia Horticulturae 192, 320-330.

Fernández-Escobar, R., Moreno, R., Sánchez-Zamora, M.A., 2004. Nitrogen Dynamics in the olive bearing shoot. HortScience 39(4), 1406-1411.

Fernández-Rodríguez, S., Skjøth, C.A., Tormo-Molina, R., Brandao, R., Caeiro, E., Silva-Palacios, I., Gonzalo-Garijo, A., Smith, M., 2014. Identification of potential sources of airborne *Olea* pollen in the Southwest Iberian Peninsula. International Journal of Biometeorology 58(3), 337-348.

Galán, C., Cariñanos, P., Alcázar, P., Domínguez-Vilches, E., 2007. Spanish Aoerobiology Network (REA): Management and Quality Manual. Servicio de Publicaciones Universidad de Córdoba, Córdoba.

Galán, C., Cariñanos, P., García-Mozo, H., Alcázar, P., Domínguez-Vilches, E., 2001. Model for forecasting *Olea europaea* L. Airborne pollen in South-West Andalusia, Spain. International Journal of Biometeorology 45, 59-63.

García-Mozo, H., Comtois, P., Kuehne, E., 2004. Aerobiological clines: The role of topography as a barrier for establishing dispersal corridors. Aerobiologia 20, 161-172.

García-Mozo, H., Galán, C., Vázquez, L., 2006. The reliability of geostatistic interpolation in olive field floral phenology. Aerobiologia 22, 97-108.

García-Mozo, H., Yaezel, L, Oteros, J., Galán, C., 2014. Statistical approach to the analysis of olive long-term pollen season trends in southern Spain. Science of the Total Environment 473-474, 103-109.

Gonzalez-Minero, F.J., Candau, P., Morales, J., Tomas, C., 1998. Forecasting olive crop production based on ten consecutive years of monitoring airborne pollen in Andalusia (southern Spain). Agriculture, Ecosystems and Environment 69, 201-215.

Haylock, M.R., Hofstra, N., Klein Tank, A.M.G., Klok, E.J., Jones, P.D., New, M., 2008. A European daily high-resolution gridded dataset of surface temperatura and precipitation. J. Geophys. Res. 113, doi:10.1029/2008JD10201.

Hengl, T., 2007. A Practical Guide to Geostatistical Mapping of Environmental Variables, EUR 22904 EN Scientific and Technical Research series. Office for Official Publications of the European Communities, Luxemburg.

Hernández-Ceballos, M.A., García-Mozo, H., Adame, J.A., Domínguez-Vilches, E., Bolívar, J.P., De la Morena, B.A., Pérez-Badia, R., Galán, C., 2011. Determination of potential sources of Quercus airborne pollen in Córdoba city (southern Spain) using back-trajectory analysis. Aerobiologia 27, 261-276.

Hernández-Ceballos, M.A., García-Mozo, H., Galán, C., 2015. Cluster analysis of intradiurnal holm oak pollen cycles at peri-urban and rural sampling sites in southwestern Spain. International Journal of Biometeorology 59(8), 971-982.

Hernández-Ceballos, M.A., Skjøth, C.A., García-Mozo, H., Bolívar, J.P., Galán, C., 2014. Improvement in the accuracy of back trajectories using WRF to identify pollen sources in southern Iberian Peninsula. International Journal of Biometeorology 58(10), 2031-2043.

Hidalgo, P.J., Mangin, A., Galán, C., Hembise, O., Vázquez, L.M., Sanchez, O., 2002. An automated system for surveying and forecasting *Olea* pollen dispersion. Aerobiologia 18: 23-31.

Hijmans, R., Cameron, S., Parra, J., Jones, P., Jarvis, A., 2004. The WorldClim Interpolated Global Terrestrial Climate Surfaces, Version 1.3. http://www.worldclim.org/ (accessed 10.06.15).

Hosseini, S.Z., Kappas, M., Bodaghabadi, M.B., Chahouki, M.A.Z., Khojasteh, E.R., 2014. Comparison of different geostatistical methods for soil mapping using remote sensing and environmental variables in Poshtkouh rangelands, Iran. Pol J Environ Stud 23(3), 737-751.

Jones, A.L., Harrison, R.M., 2004. The effects of meteorological factors on atmospheric bioaerosol concentrations–a review. Science of the Total Environment 326, 151-180.

Kasprzyk, I., 2008. Non-native Ambrosia pollen in the atmosphere of Rzeszów (SE Poland); evaluation of the effect of weather conditions on daily concentratrions and starting dates of the pollen season. International Journal of Biometeorology 52, 341-351.

Knotters, M., Brus, D.J., Oude Voshaar, J.H., 1995. A comparison of kriging, co-kriging and kriging combined with regression for spatial interpolation of horizon depth with censored observations. Geoderma 67, 227-246.

Lavee, S., 2007. Biennial bearing in olive (*Olea europaea*). Ann Ser hist nat 17, 101-102.

Li, J., Heap, A.D., 2014. Spatial interpolation methods applied in the environmental sciences: A review. Environmental Modelling & Software 53, 173-189.

Makra, L., Sánta, T., Matyasovszky, I., Damialis, A., Karatzas, K., Bergmann, K.C., Vokou, D., 2010. Airborne pollen in three European cities: Detection of atmospheric circulation pathways by applying three-dimensional clustering of backward trajectories. Journal of Geophysical Research 115: D24220, doi: 10.1029/2010JD014743.

Martínez-Bracero, M., Alcázar, P., Díaz de la Guardia, C., González-Minero, F.J., Ruiz, L., Trigo, M.M., Galán, C., 2015. Pollen calendars: a guide to common airborne pollen in Andalusia. Aerobiologia, doi: 10.1007/s10453-015-9385-3.

Monselise, P.S., Goldschmidt, E.E., 1982. Alternate bearing in fruit trees. Hort Rev 4, 128-173.

Oliver, M.A., Webster, R., 2014. A tutorial guide to geostatistics: computing and modeling variograms and kriging. Catena 113, 56-69.

Oteros, J., García-Mozo, H., Alcázar, P., Belmonte, J., Bermejo, D., Boi, M., Cariñanos, P., Díaz de la Guardia, C., Fernández-González, D., González-Minero, F., Gutiérrez-Bustillo, A.M., Moreno-Grau, S., Pérez-Badia, R., Rodríguez-Rajo, F.J., Ruíz-Valenzuela, L., Suárez-Pérez, J., Trigo, M.M., Domínguez-Vilches, E., Galán, C., 2015. A new method for determining the sources of airborne particles. J. Enviro. Manage. 155, 212 218.

Oteros, J., García-Mozo, H., Hervás-Martínez, C., Galán, C., 2013a. Year clustering analysis for modelling olive flowering phenology. International Journal of Biometeorology 57, 545-555.

Oteros, J., García-Mozo, H., Vázquez, L., Mestre, A., Domínguez-Vilches, E., Galán, C., 2013b. Modelling olive phenological response to weather and topography. Agriculture, Ecosystems and Environment 179, 62-68.

Orlandi, F., García-Mozo, H., Ben Dhiab, A., Galán, C., Msallem, M., Fornaciari, M., 2014. Olive tree phenology and climate variations in the Mediterranean area over the last two decades. Theor Appl Climatol 115, 207-218.

Orlandi, F., Sgromo, C., Bonofiglio, T., Ruga, L., Romano, B., Fornaciari, M., 2010. Spring influences on olive flowering and threshold temperatures related to reproductive structure formation. HortScience 45(7), 1052-1057.

Pebesma, E.J., 2004. Multivariable geostatistics in S: the gstat package. Comput. Geosci. 30, 683 691.

Pérez-Badia, R., Rapp, A., Morales, C., Sardinero, S., Galán, C., García-Mozo, H., 2010. Pollen spectrum and risk of pollen allergy in central Spain. Ann Agric Environ Med 17, 139-151.

R Core Team, 2015. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. http://www.R-project.org/ (accessed 10.06.15).

Rallo, L., Martin, G.C., 1991. The role of chilling in re leasing olive floral buds from dormancy. J Amer Soc Hort Sci 116(6), 1058-1062.

Ribeiro, H., Cunha, M., Abreu, I., 2005. Airborne pollen of *Olea* in five regions of Portugal. Ann Agric Environ Med 12, 317-320.

Ribeiro, H., Cunha, M., Abreu, I., 2008. Quantitative forecasting of olive yield in Northern Portugal using a bioclimatic model. Aerobiologia 24, 141-150.

Rojo, J., Pérez-Badia, R., 2015a. Models for forecasting the flowering of Cornicabra olive groves. International Journal of Biometeorology, doi: 10.1007/s00484-015-0961-6.

Rojo, J., Pérez-Badia, R., 2015b. Spatiotemporal analysis of olive flowering using geostatistical techniques. Science of the Total Environment 505, 860-869.

Rojo, J., Rapp, A., Lara, B., Fernández-González, F., Pérez-Badia, R., 2015a. Effect of land uses and wind direction on the contribution of local sources to airborne pollen. Science of the Total Environment 538, 672-682.

Rojo, J., Salido, P., Pérez-Badia, R., 2015b. Flower and pollen production in the 'Cornicabra' olive (*Olea europaea* L.) cultivar and the influence of environmental factors. Trees 29, 1235-1245.

Schröder, W., Schmidt, G., Schönrock, S., 2014. Modelling and mapping of plant phenological stages as bio-meteorological indicators for climate change. Environmental Sciences Europe 26(5), doi: 10.1186/2190-4715-26-5.

Sicard, P., Thibaudon, M., Besancenot, J.P., Mangin, A., 2012. Forecast models and trends for the main characteristics of the Olea pollen season in Nice (south-eastern France) over the 1990-2009 period. Grana 51: 52-62.

Silva, I., Tormo, R., Muñoz, A.F., 2000. Influence of wind direction on pollen concentration in the atmosphere. International Journal of Biometeorology 44: 128-133.

Yao, X., Fu, B., Lü, Y., Sun, F., Wang, S., 2013. Comparison of Four Spatial Interpolation Methods for Estimating Soil Moisture in a Complex Terrain Catchment. PLoS ONE 8(1): e54660, doi: 10.1371/journal.pone.0054660.

Zhang, R., Duhl, T., Salam, T., House, J.M., Flagan, R.C., Avol, E.L., Gilliland, F.D., Guenther, A., Chung, S.H., Lamb, B.K., VanReken T.M., 2014. Development of a regional-scale pollen emission and transport modeling framework for investigating the impact of climate change on allergic airway disease. Biogeosciences 11, 1461-1478.