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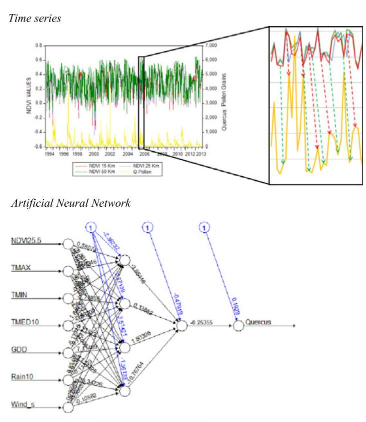
HIGHLIGHTS

- Relationship between NDVI associated to oak trees within three training data polygons
- Analysis of oak (*Quercus*) pollen concentration measured for a 20-year period
- 9 years had significant results with Granger causality and 12 years with Spearman test
- Production of oaks tree inventory maps at 15, 25 and 50 km-distance
- A predictive model by using Artificial Neural Network was applied (r = 0.77).

GRAPHICAL ABSTRACT



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ABSTRACT

Techniques of remote sensing are being used to develop phenological studies. Our goal is to study the correlation among the Normalized Difference Vegetation Index (NDVI) related with oak trees included in three set data polygons (15, 25 and 50 km to aerobiological sampling point as NDVI-15, 25 and 50), and oak (*Quercus*) daily average pollen counts from 1994 to 2013. The study was developed in the SW Mediterranean region with continuous pollen recording within the mean pollen season of each studied year. These pollen concentrations were compared with NDVI values in the locations containing the vegetation under a study based on two cartographic sources: the Extremadura Forest Map (MFEx) of Spain and the Fifth National Forest Inventory (IFN5) from Portugal. The importance of this work is to propose the relationship among data related in space and time by Spearman and Granger causality tests. 9 out of 20 studied years have shown significant results with the Granger causality test between NDVI and pollen concentration, and in 12 years, significant values were obtained by Spearman test. The distances of influence on the contribution of *Quercus* pollen to the sampler showed statistically significant results depending on the year. Moreover, a predictive model by using Artificial Neural Network (ANN) was

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Granger causality test
Akaike information criterion (AIC)
Artificial Neural Network (ANN)

applied with better results in NDVI25 than for NDVI15 or NDVI50. The addition of NDVI25 with the lag of 5 days and some weather parameters in the model was applied with a RMSE of 4.26 (Spearman coefficient r = 0.77) between observed and predicted values. Based on these results, NDVI seems to be a useful parameter to predict airborne pollen.

1. Introduction

Techniques of remote sensing (such as MODerate resolution Imaging Spectroradiometer (MODIS) and Advanced Very High Resolution Radiometer (AVHRR), among others) are being used to develop phenological studies (Liu et al., 2017; Walker et al., 2015; Zhang, 2015). The satellite sensors capture the annual variability and the phenological dynamics of vegetation by land surface phenology (LSP) (de Beurs and Henebry, 2004). The phenology of the vegetation and the pollen grain emissions to the air have been widely studied, showing a close relationship (Romero-Morte et al., 2018; Tormo-Molina et al., 2015; Velasco-Jiménez et al., 2015). Satellite-derived sources, such as the Normalized Difference Vegetation Index (NDVI), have been used to capture the phenology of different types of vegetation (oak and grass) in the Mediterranean environment (Liu et al., 2017). The NDVI is measured as follows: NDVI = (Ch2 − Ch1) / (Ch2 + Ch1), where Ch1 and Ch2 are reflectance measured in the near infrared and red channels, respectively (Lillesand and Kiefer, 1994).

Furthermore, this index has been already applied for oak trees in some recent studies related with modelling the spectral reflectance of open cork oak woodland (Häusler et al., 2016). The regression tree model was applied to high-resolution remote sensing data for predicting the percentage of tree cover in a Mediterranean ecosystem (Donmez et al., 2015), analyzing aerial CIR images in forestry (Lehmann et al., 2015) and conducting dynamic analyses of ecological environments combined with land cover (Li et al., 2017). Land use modifications and phenological cycle of vegetation were explained due to anthropic effect (García-Mozo et al., 2016). Remote sensing applications by one parameter as NDVI and Aerobiology have interest with dispersal processes and ecological scaling (Gage et al., 1999). Also in phenological phenomena of *Betula* trees to establish the onset of flowering season (Hogda et al., 2002), predicting the onset of *Betula pendula* with thermal data (Bogawski et al., 2019), for forecasting land use phenology by short term data at real time sampling (White and Nemani, 2006) and to predict long time series of NDVI (Barbosa et al., 2006). Meteorological studies based on trends in vegetation dynamics and their relationship to rainfall (Barbosa et al., 2015) and air temperature (Lakshmi Kumar et al., 2013) were also studied. Among other applications of NDVI related with pollen have been produced a satellite map of start pollen season of *Betula pollen* grains (Karlsen et al., 2009) and for the identification of urban sources as the potential origin of *Poaceae* airborne pollen by geographic information system (Skjøth et al., 2013). Additionally, different landscapes can be analyzed considering the response of native and non-native bee species, such as *Eucalyptus* pollen foraging (Hilgert-Moreira et al., 2014) or the potential of detecting the maize pollen release stage, by using vegetation indices (Lu et al., 2015).

Climate change has been evaluated through plant phenology as an indicator of the response of ecosystems to the increase in temperature (García-Mozo et al., 2008; Ma et al., 2013; Parmesan and Yohe, 2003). Changes in the timing of flowering and the release of pollen grains from oak trees (Fernández-Rodríguez et al., 2016a; Grundström et al., 2019), cypresses (Silva-Palacios et al., 2016) and olives (Fernández-Rodríguez et al., 2016b) have been recorded in SW Europe. The relationships among the airborne pollen spectrum, pollination phenology, plant distribution and land cover modifications provoke alterations in the aerobiological content (Maya-Manzano et al., 2017). The relation between land cover influence and aerobiological data was analyzed (García-Mozo et al., 2016; Rojo and Pérez-Badia, 2015) with the identification of factors related to the emission sources (Maya-Manzano et al., 2016). Nevertheless, our understanding of the relationship between the distribution of pollen types and their sources of origin, which can often be difficult to identify, should be improved (Maya-Manzano et al., 2017).

In view of the effect of climate change (IPCC, 2017), forecasting is increasingly important, and it is necessary to use statistics (García-Mozo et al., 2016; García de León et al., 2015; Oteros et al., 2013). Several statistics are needed to correlate data, such as the pollen grains by the Granger causality test (Makra et al., 2016; Olchev et al., 2017) or the Spearman correlation test (Fernández-Rodríguez et al., 2016a; Maya-Manzano et al., 2016; Ríos et al., 2016; Uguz et al., 2017). NDVI has been correlated with Granger causality through several relationships, including vegetation and temperature (He et al., 2017), rainfall (He and Lee, 2016), local surface climate (Jiang et al., 2015), CO_2 with global surface temperature (Leggett and Ball, 2014; Leggett and Ball, 2015), rainfall and land surface (Philippon et al., 2005), or phenology in grassland ecosystems (Zhu and Meng, 2014). The Granger causality consists in a statistical supposition test to decide if one time series is useful for forecasting another (Granger, 1969). To apply the test, it is necessary to select the number of delays or lags between the data of two time series.

Machine learning is a term used to define complex algorithms trying to replicate complex systems where the interactions between variables can be difficult to explain. They have increasingly been used in atmospheric science studies (Scheifinger et al., 2012). Due to its complexity sometimes can be difficult to understand (Astray et al., 2016). However, these state-of-the-art statistical techniques are capable of obtaining very high performances relevant to pollen modelling (Voukantsis et al., 2010). Among these techniques, the most commonly used has been the Artificial Neural Networks (thereafter ANN), particularly the Multi-Layer Perceptron approach because they are particularly tolerant with discontinuous sampling (missing data) in data collection periods (Puc, 2012). The input layer composes the first datasets to be introduced in ANN, and after that the processing is carried out by some hidden layers needed to generate the results (output layer) (Sánchez-Mesa et al., 2002). Some authors have reported performances using ANN, such as Puc (2012) with *Betula*, Astray et al. (2016) with *Castanea* or Csépe et al. (2014) trying to predict ragweed pollen concentrations.

Mediterranean forest-derived ecosystems in the SW Mediterranean region are mainly formed by tree species of oak (*Quercus*) (Maya-Manzano et al., 2016). These kind of trees occurs as in the studied area as "dehesas" forming rural landscape. Only in Extremadura oak trees occupy 1/3 of the total area (Morillo and Espejo, 2008). To analyze the size and frequency distribution of polygons of land cover and trees maps is used the methodology of Potential Natural Vegetation (PNV) (Ibáñez and Gómez, 2016). Polygons are widely used to delimit space units for riparian vegetation (Wang et al., 2018) to assess the effects of different feature sets on land cover classification (Chen et al., 2018) and to correlate among the land uses and aerobiological airborne particles with dispersion patterns of air masses (Maya-Manzano et al., 2017). Other papers have studied the landscape pattern and its relationship with vegetation naturalness (Szilassi et al., 2017) and the response of land surface phenology to variation in tree cover during green-up and senescence periods (Cho et al., 2017). Furthermore, vegetation surveys using drone images and image analysis software (Han et al., 2017) and to address islands of biogeodiversity (Ibáñez et al., 2016) have recently been carried out.

The advanced features in this aerobiological study are based in the innovation of remote sensing and the application of machine learning. Remote sensing data are important predictors in habitat types related to forests, rock outcrops and pastures. Ecological modelling by remote sensing have multiple advantages over traditional field surveys and image interpretation of habitat maps in time scale (Álvarez-Martínez et al., 2018). In order to forecast aerobiological data, ANN is being an important tool of different machine learning algorithms to work modelling complex data inputs of data as pollen concentration (Astray et al., 2016; Iglesias-Otero et al., 2015), for vegetation dynamic change simulations (Cai and Wang, 2010) and NDVI times series (Fernandes et al., 2017).

Our goal is to study the correlation among the NDVI related with oak trees included in three set data polygons (15, 25 and 50 km to aerobiological sampling point as NDVI-15, 25 and 50), and oak (*Quercus*) daily average pollen counts from 1994 to 2013 in the SW Mediterranean region. Spearman correlation and Granger causality tests have been used to accomplish these goals. Moreover, a predictive model using ANN and testing the use of the different values of NDVI for each distance to the sampler was created as a first attempt to test the validity of this parameter (NDVI) as a forecasting tool.

2. Materials and methods

2.1. Sampling site

The studied city is placed in Badajoz (SW Mediterranean region). The analyzed area encompassed a diameter of 15, 25 and 50 km to aerobiological sampling point (Hirst, 1952) (Fig. 1). The areas were established by considering previous studies of *Quercus* pollen, such as Jato et al. (2002), which suggested adequate distances of 15 to 30 km based on the pollen in the air and the phenological stage of *Q. robur* and *Q. pyrenaica*. Other authors such as Hernández-Ceballos et al. (2015) suggested pollen transport distances of 40 km, and most recently, Maya-Manzano et al. (2016) estimated transport values of up to 65 km as suitable.

The sampling point was located (38°53′45″N, 6°58′07″W) at 6 m above ground level in the School of Agricultural Engineering belonging to the University of Extremadura, studying oak (*Quercus*) daily average pollen counts from 1994 to 2013. The adhesive petrolatum white (CAS number 8009-03-8) was used to capture airborne *Quercus* pollen, as in previous studies by Tormo-Molina et al. (2013) and Maya-Manzano et al. (2018). Standardized data procedures were followed as indicated by the Spanish Aerobiology Network (REA) (Galán et al., 2007).

Meteorological information (maximum and minimum temperature, mean temperature and rainfall for the previous ten days, and growing degree days, GDD, over 0 °C) were supplied by the AEMET placed in the airport (38°53′N, 6°49′W) during the period 1993–2000 and from the university campus (38°53′N, 7°00′W) for the period 2001–2013.

2.2. Satellite images of NDVI from NOAA/AVHRR

Daily NDVI data (image files) were downloaded by the United States Geological Survey (USGS) from 1981 to 2013, on the website https://earthexplorer.usgs.gov/. These images have 1 km of nominal spatial resolution (depending on the angle of view of the satellite) that have been resampled at 1 km^2. Additionally, maximum search algorithms have been applied for the elimination of cloud cover. NDVI values from the corrected data are stored in a separate channel (Eidenshink and Faundeen, 1994), as well as Projection Goode Homolosine (Goode, 1925), radiometric and geometric corrections and the width of the image (approximately 2700 km). The pixel info of the images is scaled to 10,000. Therefore, to obtain the real NDVI values, it is necessary to multiply them by a scale factor of 0.0001.

In order to analyze the NDVI images, they were compared with the days of the Oak (*Quercus*) Main Pollen Season (MPS) from 1994 to 2013, estimated by Fernández-Rodríguez et al. (2016a). Based on the MPS of each year, a dataset of 1279 NDVI images was studied by extracting the values of the vegetation index in the three training areas.

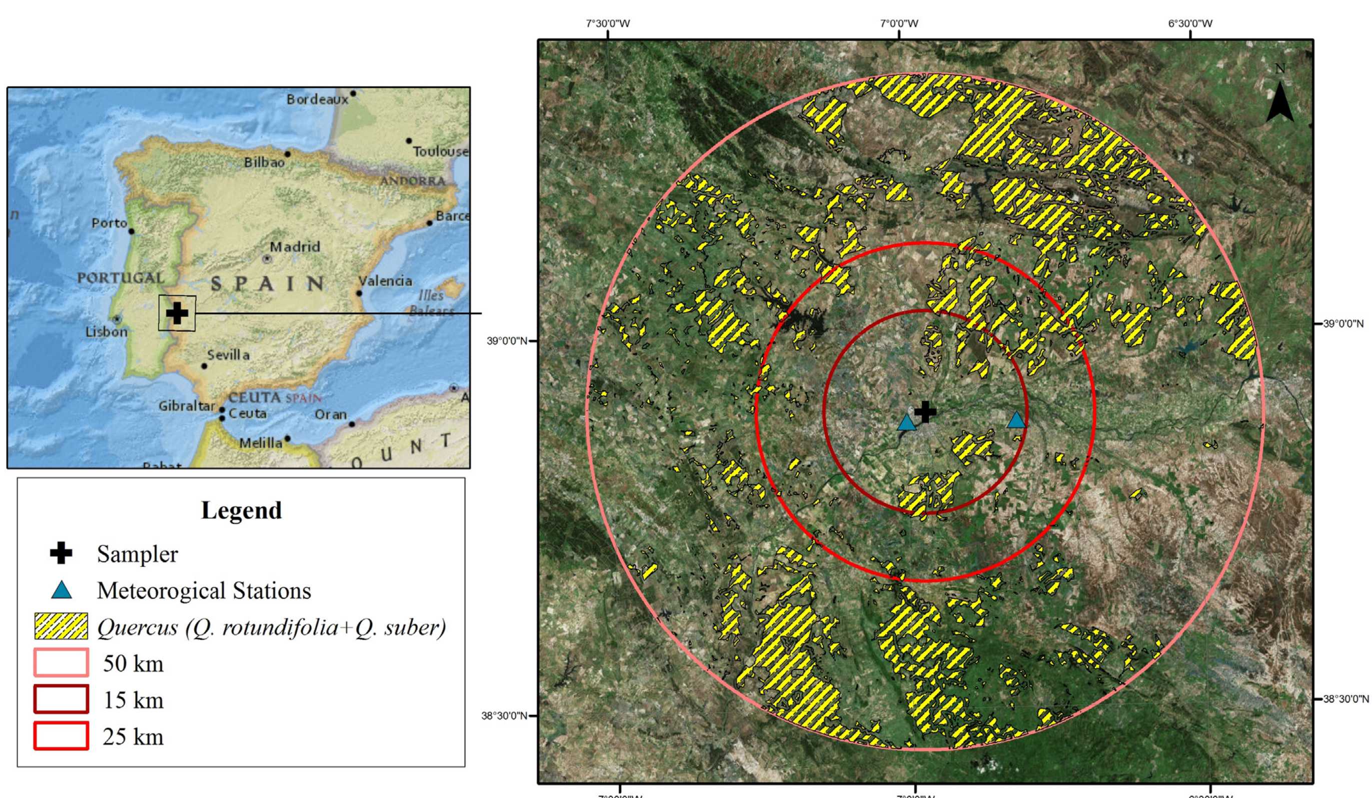


Fig. 1. Study area.

2.3. Cartography

The analyzed area includes two regions, Extremadura in Spain and Alentejo in Portugal, of the SW Mediterranean region. For this reason, the Extremadura Forest Map (MFEx) and data from the Fifth National Forest Inventory of Portugal (IFN5), related with oak trees, were used. Autoridade Forestal Nacional (AFN) (2010) supplied IFN5 information from National Forest Inventory 2005-06, Continental Portugal-IFN5 2005-06. The polygons containing the vegetation (oak trees) under study were extracted from the MFEx and the IFN5, and to avoid the possible georeferencing misalignments of the different data sources, inner buffers of 200 m were achieved. To establish the distribution of *Quercus* within each one of the study areas, one intersection of those polygons and three circumferences of 15, 25 and 50 km-distance around the volumetric sampler were performed, and the NDVI values for each MPS day were extracted (Fig. 1).

The training area located 15 km around the sampler contained 25 polygons with oak trees with a total area of 227.01 km^2. For the area approximately 25 km from the sampler, 69 polygons in an area of 433.58 km^2 were studied. Finally, covering the total training area of 50 km, 268 polygons that entail an area of 2598.60 km^2 were evaluated. Lastly, a graphic representation of both time series (NDVI values and pollen concentration) was created to establish the correspondence between them (Fig. 2).

2.4. Statistical analysis

The relationship between oak (*Quercus*) pollen concentration and NDVI was evaluated by the Spearman and the Granger causality test. The objective of the latter test was to determine if one variable X causes another variable Y. Once the variables X and Y are defined, the regression of the endogenous variable Y_t on its own past, that is, Y_{t-1}, Y_{t-2}, Y_{t-3}; on the variable X_t a series of delayed values of the same, that is, X_{t-1}, X_{t-2}, X_{t-3}, etc. Once this regression is done, it is determined if it is easier to predict the future of the variable Y with this instrument or if it would be easier to estimate Y_t exclusively using the function of its past without knowing its relation with X. In other words, it is analyzed if the current X variable and past provides valuable information to explain the future of Y (it is said, in that case, that X is the Granger cause of Y).

In this study, this Granger causality test aimed to test if there is causality between NDVI and the oak (*Quercus*) airborne pollen concentration within the studied areas. If NDVI behaves as a predictor of pollen concentration, then NDVI becomes the causal Granger for oak (*Quercus*) pollen concentrations. A crucial aspect for the causality test is to determine the number of delays or lags between the two time series with which the prediction can be ensured. The lag is important for a suitable forecasting, and its determination can be tested by different decision criteria such as FPE: final prediction error; AIC: Akaike information criterion; SC: Schwarz information criterion; or HQ: Hannan-Quinn information criterion. AIC is the most commonly used estimator for this determination. On basis to the set of the model data, AIC calculates the quality of each model in relation to the rest of the other models (Akaike, 1978; Akaike, 1979; Akaike, 1987). Initially, the study of several lags must be attained between the time series of each year, and via the AIC, the best one must be selected. The AIC statistic has been used to analyze the fit among forecast models. AIC model with lower value has a suitable fit to the observed data and a better model performance (Taghipour Javi et al., 2014). Some studies as Huang et al. (2010) and Jing et al. (2014), have utilized the AIC to estimate the correlation of NDVI data for modelling and prediction of crop canopy coverage (Ottosen et al., 2019).

The relationship between oak (*Quercus*) pollen concentrations and different meteorological parameters (maximum and minimum temperature, mean temperature and rainfall for the previous ten days, wind speed and growing degree days, GDD, over 0 °C) and NDVI values (NDVI50, NDVI25, NDVI15) was evaluated and modelled by ANN analysis (Zhang Guoqiang et al., 1998), to predict *Quercus* pollen. To do it, the package "neuralnet" in R software (Team, 2014) has been used. Data normalization (in our case from 0 to 1) was performed before the training process in order to avoid computational problems (Lapedes and Farber, 1988), according to the specifications in the mentioned package. The 70% of data were used to train the model, and the remaining 30% for validation. After the validation, the results were rescaled. The ANN model with the lowest RMSE (root mean square error) was chosen after optimization for the different NDVI combinations under evaluation. Later, according to the AIC index, we chose those lags days with better results (3, 4 and 5 days) belonging to this training area (NDVI25), and all of them were compared depending again on the RMSE. Spearman rho's rank is also shown for the chosen one. Thus, for NDVI25 the optimal lag day was 5 days.

3. Results

3.1. Time series

The average of NDVI values within the three training areas for each day of the MPS were calculated and represented. This time series, NDVI 15 km, NDVI 25 km and NDVI 50 km (Fig. 2), was correlated

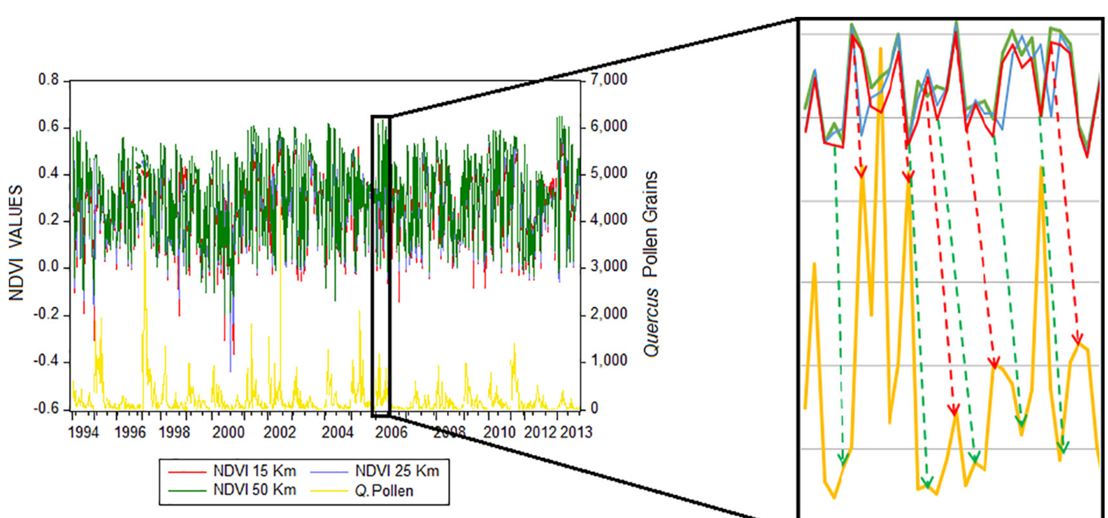


Fig. 2. NDVI and airborne pollen concentration time series. Negative values of NDVI come from wet soil caused by rain before the date of acquisition of the satellite imagery.

with airborne pollen concentration during the MPS from 1994 to 2013. From the visual analysis of the matching between time series, peaks of NDVI that predicted peaks of *Quercus* can be detected. Fig. 2 shows in 2006, the maximum and minimum peaks of NDVI precede the maximum and minimum peaks of pollen concentration.

3.2. Determination of lags

Based on the AIC, the optimum lags between time series were determined. As shown in Table 1, the value is not constant but ranges from only 1 day (years 1996, 1997, 1999, 2002 and 2011) up to 13 days in 2007 and 2012.

3.3. Statistical analysis

The correlation was statistically studied using the Spearman test and the Granger causality test. The results forthcoming from the Spearman correlation test (Table 1) show that 1996, 1999 and 2012 had non-significant correlations with pollen concentration within the three training areas. Additionally, years 1994, 2000 and 2006 had few significant correlations in only one training area, with substantial dispersions in the other training areas. Fig. 3a–d, the percentage of modification between consecutive data of pollen time series versus the percentage of change of the mean NDVI within the three training areas is represented. The graphs underwrite the Spearman correlation results for those years. More dispersion in the graphs generally means low values in the Spearman correlation, as in 1996, 1999 and 2000. On the other hand, 1995, 1997 and 2001, with correlations, present slightly scattered graphs.

45% of the years (1994, 1996, 1999, 2003, 2006, 2008, 2010, 2011 and 2012) had significant results in the Granger causality test in all training areas (Table 1), and 2000 and 2013 had significant results in two of the training areas. As can be appreciated, only 2003, 2008 and 2011 had significant values of positive correlation and causality in the three study areas, but there is no year with no correlation and causality significance.

Focusing on the yearly results, there are two years with significant values of positive correlation in some of the study areas where there are no significant results of causality. In particular, in 2000, there were significant correlation values in the 25 km zone around the collector and significant causality results in the 50 and 15 km zones, and in 2006, there was significant correlation at 50 km and significant causality at 25 km. Similarly, on four occasions, there was a significant positive correlation in all areas of study and significant causality in only some of them. For example, in the years 2004 and 2007, there was significant causality only in the 50 km area, but there was correlation in all training areas. In the same way, for the year 2005, significant causality occurred only within the 15 km zone, and in 2009, there was significant causality at 50 and 25 km around the measuring station. Finally, two years (2010 and 2013) had significant values of causality within the three areas of study and significant correlation in only some of them.

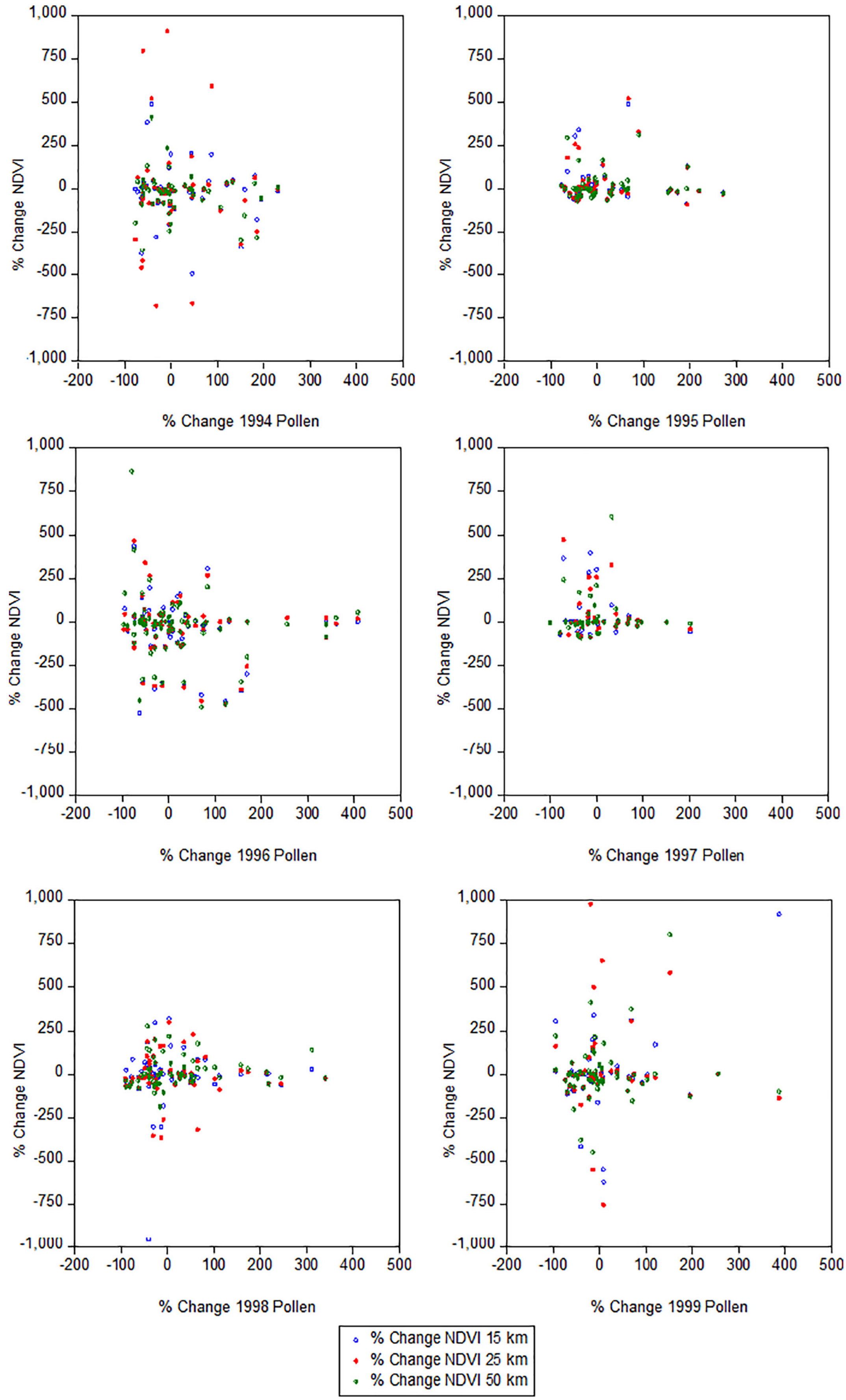
According to the RMSE values (Table 2), the ANN model containing all the NDVI values showed slightly better results than the one without values of NDVI. The fact that all together did not show comparatively as good results as by separate, it can be due to the addition of some correlated variables can cause multicollinearity and can mask the interactions (Yu et al., 2015). NDVI25 obtained better results than those considering NDVI25 and NDVI50, not only by separate but also by groups. The better result was the model by using only NDVI25 values. Due to the results obtained were quite similar between the model with NDVI25 and the model with NDVI_lag5, obtaining the second slightly higher error, it was finally selected. It is because, to introduce the NDVI_lag5 allows to predict for 5 days in advance, due to we can obtain 5 different values from the lag day to the present day, plus the forecasted weather, instead of only one (if we used NDVI25). Only seven different parameters were needed to performance the model, and all the weather parameters are easy to obtain. The final structure for our ANN model showed a layer's structure of 6:8:4:1, which is shown in Fig. 4. Fig. 5 shows the difference between observed and predicted values for the validation subset.

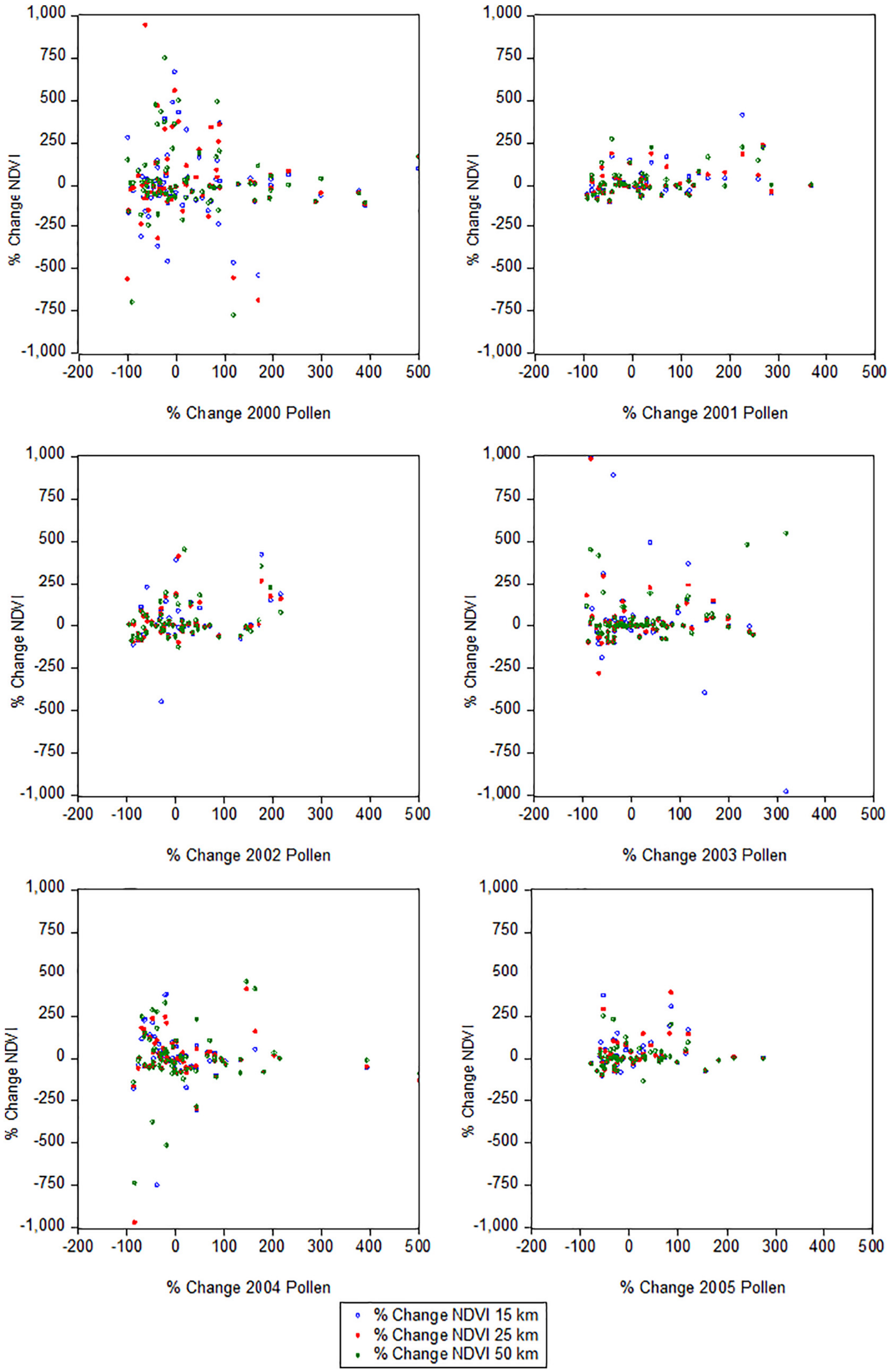
4. Discussion

NDVI has been used to correlate pollen grain release (such as *Poaceae* pollen) of one cultivation as maize, indicating that the time most suitable for this relationship is the flowering stage (Lu et al., 2015). This work studied whether variations in the NDVI can precede variations in the accumulation of pollen in the atmosphere. Until this work, there were no studies demonstrating this premise. However, the opposite assertion has been established in the mentioned study. In this way, it has been demonstrated that after the release of pollen grains, the value of NDVI decreased. This could be caused by the reflectance in the visible and near-infrared wavelengths decreasing once the pollen release begins. The NDVI decreases from the day when the maximum concentration of pollen is reached (Lu et al., 2015). Moreover, this

Table 1
Statistical test results within the three training areas (significant correlations in bold).

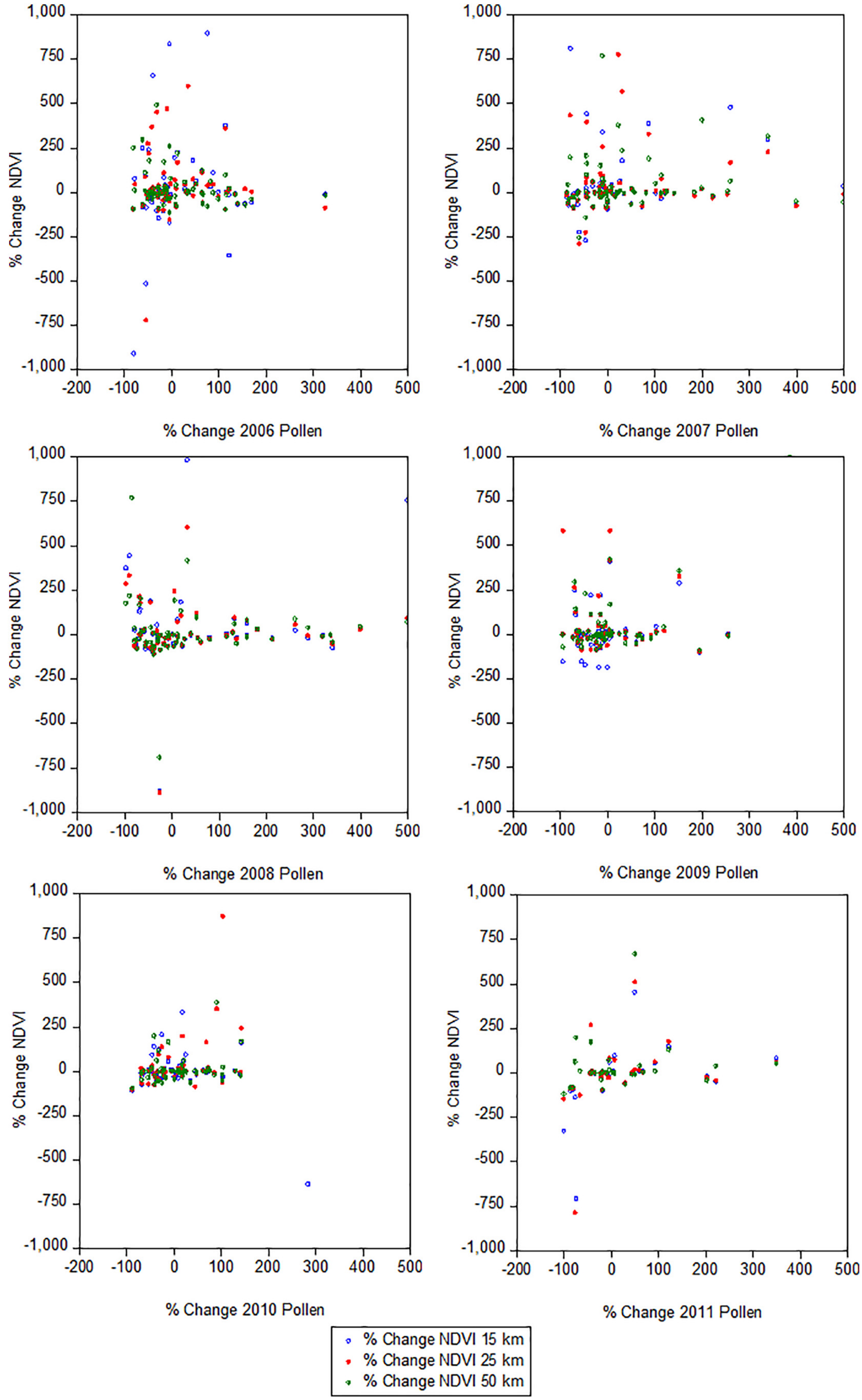
Year	LAGS	50 km			25 km			15 km		
		Spearman correlation	Spearman p-value	Granger p-value	Spearman correlation	Spearman p-value	Granger p-value	Spearman correlation	Spearman p-value	Granger p-value
1994	9	**0.3510**	**0.0080**	**0.0092**	0.3220	0.0160	**0.0038**	0.3120	0.0190	**0.0460**
1995	8	**0.5320**	**<0,0001**	0.6798	**0.3490**	**0.0100**	0.9318	**0.2870**	**0.0360**	0.7063
1996	1	0.2070	0.1380	**0.0350**	0.1920	0.1690	**0.0462**	0.1450	0.3000	**0.0448**
1997	1	**0.5930**	**<0,0001**	0.1400	**0.6340**	**<0,0001**	0.1300	**0.5760**	**<0,0001**	0.1500
1998	10	**0.3910**	**0.0010**	0.5200	**0.3810**	**0.0020**	0.6000	0.0970	0.4390	**0.0300**
1999	1	0.0900	0.5200	**0.0290**	0.1480	0.2890	**0.0242**	0.0830	0.5550	**0.0086**
2000	12	0.2170	0.1040	**0.0009**	**0.2200**	**0.0460**	0.2013	0.1480	0.2710	**0.0464**
2001	4	**0.5210**	**<0,0001**	0.0509	**0.5060**	**<0,0001**	0.1110	**0.5000**	**<0,0001**	0.0900
2002	1	**0.4280**	**0.0010**	0.0800	**0.5330**	**<0,0001**	0.1100	**0.3940**	**0.0020**	0.1100
2003	11	**0.3060**	**0.0060**	**0.0428**	**0.3000**	**0.0070**	**0.0321**	**0.2550**	**0.0220**	**0.0363**
2004	4	**0.2820**	**0.0410**	**0.0445**	**0.4060**	**0.0030**	0.2096	**0.3570**	**0.0090**	0.1793
2005	12	**0.4820**	**0.0000**	0.2796	**0.5210**	**<0,0001**	0.2038	**0.3510**	**0.0060**	**0.0495**
2006	15	**0.2290**	**0.0470**	0.3960	0.1080	0.3510	**0.0290**	0.1030	0.3770	0.2510
2007	13	**0.3190**	**0.0060**	**0.0400**	**0.3370**	**0.0040**	0.0600	**0.3220**	**0.0060**	0.1400
2008	7	**0.4370**	**0.0010**	**0.0149**	**0.4400**	**0.0010**	**0.0077**	**0.4160**	**0.0020**	**0.0094**
2009	6	**0.2570**	**0.0460**	**0.0150**	**0.2580**	**0.0450**	**0.0310**	**0.2800**	**0.0290**	0.0900
2010	9	0.2520	0.0620	**0.0400**	**0.3260**	**0.0150**	**0.0300**	**0.3500**	**0.0080**	**0.0400**
2011	1	**0.6080**	**0.0000**	**0.0209**	**0.6060**	**0.0000**	**0.0176**	**0.5950**	**0.0000**	**0.0038**
2012	13	0.0350	0.7580	**0.0045**	−0.0480	0.6740	**0.0153**	−0.2030	0.0720	**0.0189**
2013	9	**0.4690**	**0.0000**	0.2400	**0.4790**	**0.0000**	**0.0360**	**0.4490**	**0.0010**	**0.0217**


% Change NDVI
% Change 1994 Pollen
% Change 1995 Pollen
% Change 1996 Pollen
% Change 1997 Pollen
% Change 1998 Pollen
% Change 1999 Pollen
% Change NDVI 15 km
% Change NDVI 25 km
% Change NDVI 50 km



index was applied for determining the start dates of birch pollen seasons over 18 years (Hogda et al., 2002). In this way, we have studied 1279 days over 20 years, which is a longer period than in other studies. Furthermore, NDVI has been used for phenological studies on species such as oak trees (Liu et al., 2017) or birches, by the onset flowering for 8 years (Karlsen et al., 2009), the length of the growing season for 7 years (Karlsen et al., 2008) and the onset of phenological phases (Karlsen et al., 2006) for 20 years.

Focusing on our results, the maximum correlation between NDVI and airborne *Quercus* pollen MPS for the studied period and three training area zones varied between 0.63 and 0.59. Lu et al. (2015) obtained a correlation (R^2 = 0,26 for NDVI) among the vegetation index at the red


% Change NDVI
% Change 2006 Pollen
% Change 2007 Pollen
% Change 2008 Pollen
% Change 2009 Pollen
% Change 2010 Pollen
% Change 2011 Pollen
% Change NDVI 15 km
% Change NDVI 25 km
% Change NDVI 50 km

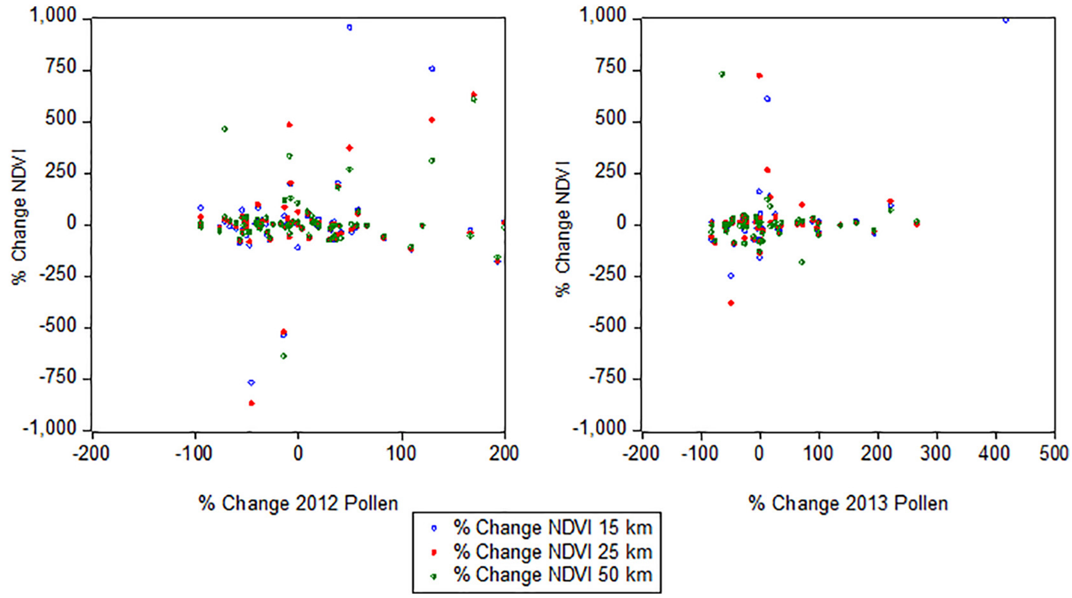


Fig. 3. a: Percentage of change between consecutive data of pollen time series versus the percentage of change in the mean NDVI within the three training areas (years 1994–1999). b: Percentage of change between consecutive data of pollen time series versus the percentage of change in the mean NDVI within the three training areas (years 2000–2015). c: Percentage of change between consecutive data of pollen time series versus the percentage of change in the mean NDVI within the three training areas (years 2006–2011). d: Percentage of change between consecutive data of pollen time series versus the percentage of change in the mean NDVI within the three training areas (years 2012–2013).

edge and 2-day average maize pollen. He et al. (2017) correlated linear trends of growing season NDVI and temperature, obtaining values of R^2 between 0.44 and 0.01. In this study, the distances of influence on the contribution of oak (*Quercus*) pollen to the sampler have shown statistically significant results depending on the year studied. In the same way, the number of days of NDVI that can predict values that will be recorded in the sampler varies depending on the year (from 13 days in 2007 and 2012 to 1 day in 1996, 1999 and 2000). Several works indicated results in this line. White and Nemani (2006) showed that a hypothetical land surface phenology event could be predicted with a lead-time of 7 days for an allowable prediction uncertainty of 2 days. For Karlsen et al. (2006), the onset of the growing season in the NDVI-based measurements is tuned to occur, on average, <2 days before the onset of leafing. The standard deviation (SD) between field data and NDVI data is <10 days for all stations.

The relationship between distant sources of oak trees and the sampler point has been explained by the long distance transport (LDT) for *Quercus* pollen in the UK (Skjøth et al., 2015) and Spain, such as in Andalucía (Hernández-Ceballos et al., 2011) or Extremadura (Maya-Manzano et al., 2016). The last authors estimated the closest sources of airborne *Quercus* pollen in 40 km (Plasencia-North Ex), 66 km (Don Benito- Middle Ex), and 62 km (Zafra-South Ex). In the same region, Maya-Manzano et al. (2017) reported also a medium-long transport behaviour for this pollen type. These results agreed with the maximum predictive power observed for the current study at medium and long distance transport (being better for NDVI25). Among all the combinations that were studied, the combination between NDVI50 and NDVI25 was also the one with the most predictive capability. In this work, we have studied the regional scale (50, 25 and 15 km) up to a 100 km limit to consider a wide range of potential sources (Seinfeld and Pandis, 2006). The importance of the relation between the distribution of the oak trees and the distance to the trap was studied in Spanish urban areas, such as Badajoz and Córdoba (Fernández-Rodríguez et al., 2014b; Velasco-Jiménez et al., 2013). The idea of the present study is to analyze, with detail, the influence of short and medium-distance sources (local urban, surrounding urban and far away urban) on the regional scale and the relationship with NDVI to improve future forecasting of *Quercus* pollen concentrations (Fernández-Rodríguez et al., 2016a). Also the wind speed has been proposed as having great importance by Maya-Manzano et al. (2016), who reported an increase in the *Quercus* concentrations in wind speed range from 6 to 10 m s^{-1}, in the same region of study. In the same way, the wind direction is important, because the sources are playing an important role in the airborne content and the oak forests are heterogeneously dispersed along the territory. Moreover, wind direction pattern can overestimate concentration if sources are in the line of the predominant wind direction pattern. However, the lack of records for this parameter during a part of the studied period made impossible to include it in the model.

The use of polygons for delimiting soil and vegetation was created by several methodologies. Nevertheless, considering the number and size of the polygons for mapping, both fit well to power laws across several orders of magnitude, showing that both exhibit a scale invariance pattern (Ibáñez et al., 2016). In the Ibáñez study, totals of 5864

Table 2
Comparative values for all the Artificial Neural Networks models are shown, including and removing NDVI values. The goodness of fit was expressed by RMSE values (lower values meaning better results). The optimized structure for hidden layers in each model is shown. Sheets in bold are shown the best performance for the models. The more robust (NDVI25) was compared with other by adding the Lag 5 days.

	All NDVI included 4:1	None NDVI included 5:1	NDVI50 5:3	NDVI25 10:4	NDVI15 5:3	NDVI25 and NDVI15 4:1	NDVI25 and NDVI50 4:1	NDVI15 and NDVI50 4:1
RMSE	4.365	4.375	4.366	**4.254**	4.339	4.367	4.321	4.367

	NDVI25 10:4	**NDVI25_Lag 5 8:4**
rho Spearman	0.774	0.771
RMSE	4.254	4.261

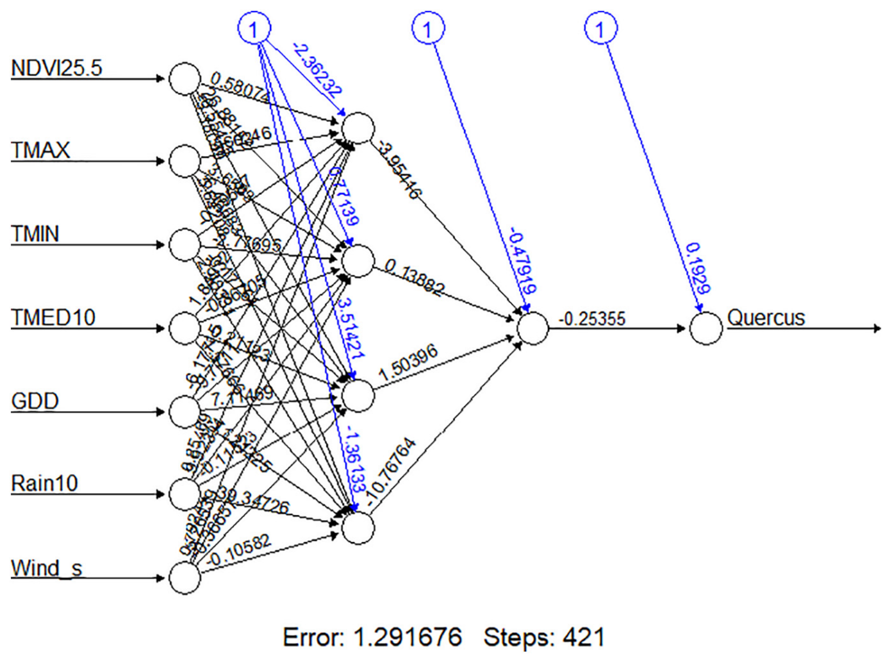


Fig. 4. Artificial Neural Network for the model proposed (Including NDVI25_lag5).

(1:10,000) and 2448 (1:100,000) polygons were created for potential vegetation analysis and soil associations, respectively, in the Almería province (8775 km^2). The proportion of our study is similar with a maximum total training area of 50 km (7853 km^2) located in Badajoz and Alentejo provinces. Inside this area, we have studied 268 polygons of *Quercus* spp. covering an area of 2598 km^2. Cho et al. (2017) produced 100 polygons to determine the influence of varying tree cover, and Wang et al. (2018) created 106,300 vegetation polygons in a reach of the Sacramento River, USA, for five major vegetation types (cottonwood, mixed forest, riparian shrub, invasive species and grass) simulated in 20 vegetation species. (Szilassi et al., 2017) studied 40,000 CLC polygon categories for class-level analyses of the landscape pattern (artificial surfaces, agricultural areas, forest and semi natural areas, wetlands and water bodies).

According to the range of years, in all years of this study (except 1996 and 1999, in which significant results were not obtained for the Spearman test), there is a statistically significant positive correlation. However, 2012 showed a negative correlation. He et al. (2017) found negative correlations between NDVI and vegetation growth for several

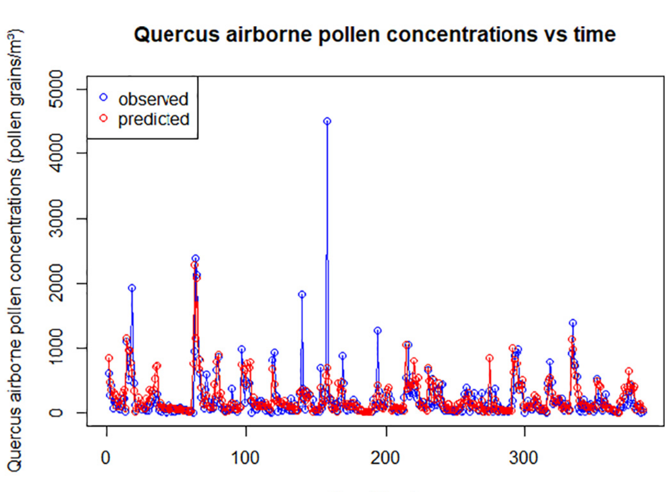


Fig. 5. Observed vs. predicted values obtained by the ANN model (r = 0.77).

years (1998–2011) of their study. They explained this fact by the sensitivity of vegetation growth to temperature change. We found 14 years with statistically significant results using the Granger causality test (1994, 1996, 1999, 2000 and 2003–2013). Among those years with significant results using the Granger test, there is no significant correlation between NDVI and vegetation growth in 1996, 1999 and 2012. Therefore, for these years, it cannot be said that the NDVI that was measured in the different study areas behaves as a predictor of the pollen concentration recorded in the sampler.

If we consider the distance, approximately 50 km, to the sampler, in 2004 and 2007, there was significant causality. For these years, it can be affirmed with a 95% probability of success that the NDVI measured in the study area located 50 km around the collector is a predictor of the amount of pollen recorded in it. In 2004, a rise in the value of the NDVI predicted increases for pollen that were recorded 4 days later in the collector, while in 2007, the prediction was made 13 days in advance.

In 2005, a significant causality occurred in the 15 km zone, and NDVI predicted increases for pollen 12 days later in the sampler. Likewise, in 2009, there was significant causality at 50 and 25 km around the sampler with increases in the NDVI, having predicted increases in oak (*Quercus*) pollen concentration 6 days later in the sampler. In 2010 and 2013, there was only a significant positive correlation in the areas of 25 and 15 km. In these zones, the NDVI is the Granger cause of the concentration of pollen registered in the sampler. The main contribution to the pollen collected in the sampler comes from the production sources located at short and medium distances (15 and 25 km). For both years, rises in the NDVI have predicted increases in pollen recorded in the collector 9 days later. On four occasions (1994, 2003, 2008 and 2011), there were significant values of positive correlation and causality in the three study areas with increases in the NDVI predicted (9, 11, 7 and 1 days later, respectively) over sources located at short, medium and long distance (15, 25 and 50 km). Finally, in five years (1995, 1997, 1998, 2001 and 2002), significant values of causality were not found, but a positive correlation in the three study areas was. Therefore, in these years, the NDVI and pollen variables were positively related to each other, but it cannot be affirmed that the NDVI can be a predictor of the concentration of pollen registered in the sampler.

Consequently, we assume that temporal correlations between years and spatial correlations of several distances between the NDVI values of oak trees (Fernández-Martínez et al., 2012; Pinto et al., 2011) and the concentration of airborne oak (*Quercus*) pollen are influenced by meteorology (García-Mozo et al., 2012; García-Mozo et al., 2007). Moreover, it should be noted that Spearman correlation and Granger causality tests require checking whether the results of one variable serve to predict another one and whether this relationship is unidirectional or bidirectional. Therefore, we have studied two variables, NDVI and pollen concentration; however, new related reports should contemplate additional statistical analyses, including those of meteorological data (considering parameters such as temperature and accumulative temperature, rainfall and wind or even sunlight hours, which influence phenology). Moreover, it would be interesting to study other pollen types such as *Olea* or *Poaceae* pollen, which are, together with *Quercus* pollen, the most represented and abundant of Extremadura and Alentejo in the SW Iberian Peninsula (Fernández-Rodríguez et al., 2015; Fernández-Rodríguez et al., 2016a; Fernández-Rodríguez et al., 2014a). The novelty of this study includes the positive role of big data analysis in ecological environmental change and natural management, specifically related to land cover and NDVI change trend analysis. In this way, future studies could be designed as local responses to activities and ecological changes at several scales, being in line with Li et al. (2017). The use of available satellite data, such as NDVI, together with pollen grain sampling, meteorological and phenological data (Bogawski et al., 2019), has been proposed as a powerful tool to be used with aerobiological purposes (Scheifinger et al., 2012). It should allow a quick information at real-time monitoring, predicting short-term data of oak (*Quercus*) pollen concentration to be implemented (Fernández-Rodríguez et al., 2016a).

5. Conclusions

The innovation in this article is the relationship among the NDVI value of oak trees (*Q. rotundifolia* and *Q. suber*) over several distances; local urban (15 km), surrounding urban (25 km) and far away urban (50 km), with oak pollen count daily average from 1994 to 2013 in the SW Mediterranean region, by Spearman and Granger causality tests. Also the creation of one predictive analysis by using ANN models, with a $r = 0.77$ and a forecast horizon of 5 days, applying the 5 days-lag for NDVI25. Of the 20 studied years, 9 showed a significant relationship between NDVI and pollen concentration with the Granger causality test, while there were showed significant values in 12 years by Spearman test.

The distances of influence on the contribution of oak (*Quercus*) pollen to the sampler showed statistically significant results depending on the year studied. In the same way, the number of days that NDVI values can predict recorded values of pollen concentration in the sampler ranged depending on the year (from 13 days in 2007 and 2012 to 1 day in 1996, 1999 and 2000). The number of years with significant correlations obtained within 50 km and 25 km was similar, but within 15 km, the number decreased slightly, and it may be in relation to a lower abundance of trees closer to the urban area. It agreed with the findings regarding the forecast capacity for the different NDVI indexes in the ANN model. It could be explained the variability among years due to the influence of local meteorology, including the effect of far away air masses with aerobiological particles from potential sources. For this assumption, new studies should be considered phenological data, additional statistical analysis, more pollen types in order to get quick information at real-time monitoring, predicting short-term data aerobiological information.

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