An assessment of the spatial variability of basal area in a terrain covered by Mediterranean woodlands

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Abstract

Spatial patterns of Mediterranean woodlands are largely unknown. An exploratory analysis of the spatial structure of basal area was carried out in this type of community. Specifically, an area of non-disturbed woodlands located in the north-east of the Iberian peninsula was analysed. Direct and indirect evidences for the hypothesis stating that environmental factors lead to the establishment of spatial patterns on the basal area of non-disturbed Mediterranean woodlands were investigated. The results showed that the variability of this parameter occurs within really short spatial intervals (of less than 100 m) and neither radiation nor the slope seemed to have an important effect on it. In consequence, results did not support the previously mentioned hypothesis. Among others, long term effects of forest management, an uneven presence of relief conditions and a complex dynamics of basal area within plots were suggested as explanations for the results found. Finally, some recommendations and practical advises were set for future inventories and studies of spatial patterns in Mediterranean woodlands. © 2000 Elsevier Science B.V. All rights reserved.

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1. Introduction

Although Mediterranean woodlands are affected by diverse biotic and abiotic factors, human activities may have significant effects modifying their dynamics and the ruling power of such factors on their final structure. In addition, the frequent wildfires occurring in Mediterranean areas, sometimes due to natural causes, have important consequences over woodlands. They break the growing process of individuals, attenuate the ruling capacity of biotic and abiotic agents in the late stages of woodland dynamics and often increase the heterogeneity of landscapes.

Yet, some specific areas with special interest have been preserved for many years avoiding human intervention and the occurrence of wildfires. In these cases it might be expected for the biotic and abiotic factors to affect significantly the structure of Mediterranean woodlands. For instance, since abiotic factors such as radiation and the slope are directly related to water availability in plants and to soil properties, they will probably have a noticeable effect (Hellmers et al., 1955; Oechel et al., 1981; Spetch, 1988; Mayor and
Rodà, 1994), but the less known biotic agents, such as the dispersion processes, may be also significant (Herrera et al., 1994).

Clearly, these factors will not act in an independent way in the different sites of a forest but will create spatial patterns in its structure. In order to deal with the analysis of the spatial distribution of variables a number of statistical tools have been developed (see Legendre and Fortin (1989) for an applied review). These tools usually quantify the spatial autocorrelation, which is the degree of similarity (or dissimilarity) between points due to their relative spatial location (Cliff and Ord, 1981). Several autocorrelation coefficients have been defined to estimate the degree of resemblance of point values located at a specific distance apart from each other. In addition to the study of the original data, there is also the chance to check for the presence of spatial autocorrelation in residual values (after considering the effect of other variables through a linear model) or to build a more complex model containing an autoregressive structure (Cliff and Ord, 1981; Ripley, 1981).

The development of geographical information systems (GIS) in recent years allows an easier management of geolocated data (Burrough and McDonnell, 1998). Specifically, data coming from various layers of information may be derived and combined with point data sampled in the field to carry out further analyses. For instance, some of the previously mentioned variables, such as radiation and slope, may be obtained from digital elevation models (DEMs) and analysed together with woodland structural parameters derived from forest surveys. Due to its direct relation to biomass and to its easy collection, basal area (BA) is one of the most suitable parameters to describe the structure of woodlands. Although BA is species and succession stage dependent it can be hypothesised that, within uneven stands of mixed species left growing freely for a large period of time, environmental variables will shape its spatial patterns.

The primary objective of this study was the exploratory analysis of the spatial structure of BA in a terrain covered by Mediterranean woodlands, which have not been affected by timbering or wildfires for a long period of time. Direct and indirect evidences for the hypothesis stating that environmental factors lead to the establishment of spatial patterns on the BA of non-disturbed Mediterranean woodlands were investigated.

2. Methodology

2.1. The study area and the field information available

This study was carried out with different data derived from the Parc de Collserola, a protected woodland area beside the city of Barcelona, on the northeastern coast of Spain. It has an extension of 8465 ha with a rather mountainous relief (Fig. 1). Altitudes range from 100 to 512 m with a typical Mediterranean climate (annual mean precipitation of 504 mm and monthly mean temperatures ranging from 8.8°C in January to 23.7°C in July) with high levels of water deficit during summer. The main large woody species belong to the genus *Quercus* and *Pinus*, but other Mediterranean shrubs are also abundant. This vegetation grows above lithological strata predominantly of shales and granite but limestone is also present in a few places.

Last intensive extraction of timber in the study area occurred just after the Spanish civil war (1936–1939), and a demographic study (Canadell and Irizar, 1988) points to a period of, at least, 50 years with no intervention until the present day (with the exception of timber extraction in few local areas). Thus, woodlands have grown freely achieving a clearly uneven-aged structure. This process has been supported by an effective fire suppression program avoiding significant wildfires in all the study area except the south-facing slope next to the city of Barcelona.

Data from previous forest field surveys was available at different densities, and a square mesh of one plot every 100 m was sampled in several parts of the area. In total, 1520 plots located in woodlands were used in the study (Fig. 1). Each plot had a square shape with 20 m of side, and the BA of all woody individuals was inferred from measurements of the diameter at breast height (DBH) (the minimum DBH considered was 7.5 cm). Frequently, plots analysed had a heterogeneous species composition. Data for the different species found in each plot was originally kept separate and their BA was given in m²·ha⁻¹.
Fig. 1. Digital elevation model, limits of the study area and location of the 1520 field plots used.

The joint BA values for each plot were used to analyse the global effect of factors and levels of variability described in Section 2.2 below. Separate BA values were also used for the five woody species most frequently found in the study area: *Quercus ilex* L. (present in 1440 plots), *Pinus halepensis* Mill. (in 1382 plots), *Quercus cerrioides* Wk. (in 1146 plots), *Arbutus unedo* L. (in 603 plots) and *Pinus pinea* L. (in 207 plots). Although, the BA of any one species in a mixture was dependent on the BA of other species present, the analysis of each species separately determined the net effect (on individual species) of the factors and levels of spatial variability studied.

2.2. Three levels of spatial variability

As suggested in the introduction, various biotic and abiotic factors were probably affecting the spatial distribution of the BA in the study area. However, a separate examination of each of them was beyond the scope of this work and more general procedures were applied to study the BA spatial structure. Specifically, two criteria were used to select the analyses to be carried out: (1) the information of the study area available in a direct or indirect way, and (2) the expected ability of the analyses to explain the spatial patterns of BA. Following both criteria, the study of the spatial patterns of BA was summarised in three different analyses directly related to three distinct levels of spatial variability. These are described in the following sections.

2.2.1. The regional level variability

This level is concerned with medium and large scale variations such as environmental gradients. Many of them are caused by gradual modifications in the mean meteorological conditions (e.g. the latitudinal gradients or the gradients due to distance from the sea). Obviously, since big areas are more likely to be affected by this type of variability, it was not expected that such gradients would explain the greater part of the variance observed in the BA in the study area (although coastal regions may be more prone to strong environmental variations).

The existence of variability at a regional level can be easily accounted for by a trend surface analysis (Burrough and McDonnell, 1998). Such analysis is based on a polynomial regression in which the values of the coordinates are used as independent variables, and the variable of interest (BA) is considered as the dependent variable. In this study the original Universal Transverse Mercator projection coordinates (UTM) for $x$ and $y$ (in km), their squared values
Table 1

Matrix of correlation coefficients found between the independent variables to be used in the trend surface analysis, before and after their re-scaling\(^a\)^\(^b\);

<table>
<thead>
<tr>
<th></th>
<th>x</th>
<th>y</th>
<th>x(^2)</th>
<th>y(^2)</th>
<th>xy</th>
</tr>
</thead>
<tbody>
<tr>
<td>x</td>
<td>1.0 (1.0)</td>
<td>0.581 (0.581)</td>
<td>0.998 (−361)</td>
<td>0.586 (0.113)</td>
<td>0.992 (0.072)</td>
</tr>
<tr>
<td>y</td>
<td>1.0 (1.0)</td>
<td>0.599 (0.052)</td>
<td>0.999 (−0.129)</td>
<td>0.682 (0.181)</td>
<td></td>
</tr>
<tr>
<td>x(^2)</td>
<td>1.0 (1.0)</td>
<td>0.602 (−0.201)</td>
<td>0.993 (0.328)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>y(^2)</td>
<td>1.0 (1.0)</td>
<td>1.0 (1.0)</td>
<td>0.684 (0.453)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>xy</td>
<td>1.0 (1.0)</td>
<td>1.0 (1.0)</td>
<td>1.0 (1.0)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\(^a\) UTM coordinates of all field plots (n=1520) were used.

\(^b\) Values re-scaled are given in parenthesis.

\((x^2, y^2)\) and their cross-products \((xy)\) were tried as independent variables for all species except \(P.\ pinea\). In this species, only the original \(x, y\) coordinates were used in order to avoid the possibility of fitting spurious models as a consequence of a much lower number of available plots.

The inclusion of original and squared values of the same variable in a model frequently leads to matrix collinearity problems (Rawlings et al., 1998). Since full UTM coordinates were initially used (i.e. large and positive numbers) very high correlations were found between some of the derived independent variables (see Table 1). Following Peña (1989) the original UTM coordinates were re-scaled by subtraction of their mean value, obtaining much lower correlations (Table 1). This same process linked the minimum absolute values for \(x^2\, y^2\) and \(xy\) to the new origin of coordinates located close to the central part of the study area, allowing an easier interpretation of significant coefficients as differences between the central region and the boundaries of the study area.

2.2.2. The set of physical variables related to relief

A digital elevation model (DEM) of the study area was available with a high grid resolution of 5 m. From all the variables possibly derived from a DEM, two of them were chosen as they would probably affect the structure of woodlands in a significant way: the slope and the mean value of the daily potential solar radiation for the whole year over each plot. This last parameter was regarded as potential since it does not consider the presence of clouds. However, being a small area, large spatial differences in mean cloudiness were not expected and potential values were considered as nearly proportional to the real ones.

The retrieval of slopes was directly carried out by choosing the maximum weighted differences in height values of neighbour grid points (Burrough and McDonnell, 1998). Data were given in degrees (range 0–90). The calculation of the mean value of the daily potential solar radiation for the whole year took into account the sun elevation angle, the slope, the aspect and the indirect shadowing produced by the surrounding mountains (Pons, 1996). Radiation data were given in units of \(10^6\) J m\(^{-2}\) m\(^{-1}\). In order to obtain reliable values of both variables and to minimise sample noise, mean values from 5×5 pixel windows centred in the plot coordinates were given for each one of the field plots.

The two variables selected were probably related, in an indirect way, with other variables that may also have a significant influence over the structure of woodlands, but which required complicated and irksome measurements (such as the soil depth, the soil water content or the real radiation). Therefore, if there were a consistent effect of these variables over the BA, some statistical significance in the variables analysed would be expected.

Linear regression was again selected to model the effect of radiation and slope on the BA values. Indeed, to integrate factors in a single model, both variables were considered in the fitting of the trend surface analysis of the previous subsection. This was carried out by a stepwise variable selection method (Rawlings et al., 1998). Starting with models including all possible independent variables \((x, y, x^2, y^2, xy,\ radiation\ and\ slope)\) less informing variables were sequentially dropped as these led to the lowest value of the \(C_p\) statistic (until the elimination of any variable could not lower the \(C_p\) of the previous model). See Salvador and Pons (1998a) and Mont-
2.2.3. The autocorrelation at the local level

There are many statistics available to quantify the autocorrelation within a sample. One of the most commonly used is the Moran autocorrelation coefficient, which is defined by Cliff and Ord (1981) as:

\[ I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} z_i z_j}{s_1 \sum_{i=1}^{n} z_i^2} \]  (1)

where \( n \) is the total number of plots, \( w_{ij} \) the geographical connection between plot \( i \) and plot \( j \) (usually given as the reciprocal of a simple function of the distance), and \( z_i \) is the value of the studied variable (BA) in plot \( i \), after re-scaling through the subtraction of the sample mean. The \( s_1 \) parameter is the addition of all \( w_{ij} \) values, and although usually (but not necessarily) \( w_{ij} = w_{ji} \), each \( w_{ij} \) with a different subscript (so, \( ij \neq ji \)) is considered as a single value to be included in the addition. Furthermore, one plot cannot be connected to itself (\( w_{ij} = 0 \)).

An intuitive idea of the information given by \( I \) can be easily gained by considering separately the lower and upper sums as

\[ S_1 = \frac{\sum_{i=1}^{n} z_i^2}{n}, \quad S_2 = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} z_i z_j}{s_1} \]  (2)

where \( S_1 \) can be clearly identified as a sample variance (i.e. the mean value of the squared differences to the sample mean). Hence, it provides information about the average variability of the sample. The parameter \( S_2 \) is similar to a sample covariance that only considers the pairs of points with some connection (\( w_{ij} > 0 \)). So, it gives the average co-variability of values of plots connected. Consequently, \( I = S_2 / S_1 \) is a standardised covariance, which means a correlation. Indeed, there is a clear similitude between the formula of the Pearson’s correlation coefficient and \( I \).

In an ideal scenario, with almost full autocorrelation, near plots would be expected to have very similar values (\( z_i \approx z_j \)), which leads to \( z_i z_j \approx z_i^2 \), to \( S_2 \approx S_1 \) and to \( I \approx 1 \). However, although values between \(-1\) (very high negative autocorrelation) and \(+1\) may be expected, analytically set limits of \( I \) do not always agree with these values (Cliff and Ord, 1981). In a similar manner, although values of \( I \) close to zero are expected when there is no spatial autocorrelation, the expectation of \( I \) without correlation will usually differ slightly from zero (see formulas given in the Appendix A).

An alternative to a single value of \( I \) for the whole sample is given by the spatial correlogram (Cliff and Ord, 1981). This is based on the division of all distances found between pairs of plots in several distance classes, and on the retrieval of a different value of \( I \) for each one of these classes. The division is usually made by assigning a connection of 1 to all pairs of plots with a distance value included in the class being analysed and a connection of 0 to all other pairs. Hence, the similitude of values of pairs of plots located within some range of distances apart are quantified. It should be noted that values of \( w_{ij} \) and \( s_1 \) will vary between distance classes. Information on spatial correlograms is usually given in a visual way by means of graphics. Distance classes used in this study are shown in Table 2.

Additionally, as pointed out in the Section 1, if the effect of other factors on the variable analysed has been previously studied by fitting a linear model (and the model fitted is statistically significant) it may be more appropriate to calculate \( I \) using the residuals of the fitted model (also using Eq. (1)).

There are several approaches to test the significance of \( I \) against the null hypothesis that there is no auto-

<table>
<thead>
<tr>
<th>Distance class</th>
<th>Lower limit (km)</th>
<th>Upper limit (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>&gt;0</td>
<td>0.10</td>
</tr>
<tr>
<td>2</td>
<td>&gt;0.10</td>
<td>0.15</td>
</tr>
<tr>
<td>3</td>
<td>&gt;0.15</td>
<td>0.30</td>
</tr>
<tr>
<td>4</td>
<td>&gt;0.30</td>
<td>0.50</td>
</tr>
<tr>
<td>5</td>
<td>&gt;0.50</td>
<td>0.75</td>
</tr>
<tr>
<td>6</td>
<td>&gt;0.75</td>
<td>1.00</td>
</tr>
<tr>
<td>7</td>
<td>&gt;1.00</td>
<td>1.25</td>
</tr>
<tr>
<td>8</td>
<td>&gt;1.25</td>
<td>1.50</td>
</tr>
<tr>
<td>9</td>
<td>&gt;1.50</td>
<td>1.75</td>
</tr>
<tr>
<td>10</td>
<td>&gt;1.75</td>
<td>2.00</td>
</tr>
<tr>
<td>11</td>
<td>&gt;2.00</td>
<td>2.25</td>
</tr>
<tr>
<td>12</td>
<td>&gt;2.25</td>
<td>2.50</td>
</tr>
<tr>
<td>13</td>
<td>&gt;2.50</td>
<td>2.75</td>
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<tr>
<td>14</td>
<td>&gt;2.75</td>
<td>3.00</td>
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<tr>
<td>15</td>
<td>&gt;3.00</td>
<td>3.25</td>
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<tr>
<td>16</td>
<td>&gt;3.25</td>
<td>3.50</td>
</tr>
<tr>
<td>17</td>
<td>&gt;3.50</td>
<td>3.75</td>
</tr>
<tr>
<td>18</td>
<td>&gt;3.75</td>
<td>4.00</td>
</tr>
</tbody>
</table>
correlation. The most commonly used approach supposes approximate normality of \( z_i \) (where \( z_i \) may be the original or the residual centred values). Formulas for the expectations \( E[I] \) and variances \( \text{Var}[I] \) under the null hypothesis and normality of \( z_i \) are given in the Appendix A (note that these change when regression residuals are used instead of the original data). Finally, as shown in Cliff and Ord (1981), the values of \( I \) under the null hypothesis can be expected to be normally distributed for samples bigger than 50, which allowed testing their significance through the comparison of the standardised deviates \( (I - E[I])/\sqrt{\text{Var}[I]} \) against those of the standard normal distribution.

3. Results

3.1. Regional variability and physical variables

Information from the regression models of the different species selected by the stepwise procedure is shown in Table 3 and Fig. 2. In all models the BA was modified (by a logarithmic or square root transformation) to improve the distribution of the residuals. Furthermore, these transformations usually led to better fittings. In some cases a small number of points were rejected as outliers.

Table 3 and Fig. 2 clearly show that, in general, the fittings achieved in all models were low. No model could explain more than 10% of the variability observed in the BA (given by the determination coefficient). From the point of view of the regional variability, these results were not completely unexpected since the study area was relatively small. Conversely, a much more clear effect could be foreseen for the slope and the relief. On the other hand, in spite of the low \( R^2 \) values achieved and as a consequence of the large sample sizes, the effect of many of the independent variables was supported by a clear statistical significance. Hence, these variables had (with high probability) an effect on the BA, although such effects were obviously low in magnitude.

The model that considered the total BA values in plots had the lowest fitting. In this model, \( xy \) is by far the most significant variable (displaying a negative sign). Hence, the model pointed to a slightly higher BA in the NW and SE parts of the study area (where \( xy \) always attained negative values). Concerning the slope and the radiation, there seems to be no general effects (the same total BA is expected regardless of their values).

The \( Q. ilex \) model achieved a comparatively much higher fitting. However, the regional pattern of the BA was complex and difficult to understand. Notwithstanding, slope and radiation effects were clear: there seemed to be higher BA values of \( Q. ilex \) in areas with lower radiation and lower slope (both variables have negative significant coefficients in the \( Q. ilex \) model of Table 3). These areas were the valley bottoms, with deeper soils and less water deficit in summer.

\( P. halepensis \) BA had a relatively poor fitting, with also a rather complex regional pattern. Interestingly, the distribution of this species regarding the radiation and slope was contrary to that for \( Q. ilex \), having a higher BA in steep slopes and highly radiated areas. These results seem to fit well with some ecological studies carried out with both species (Espelta et al., 1992).

Table 3
Models built by the stepwise procedure applied to join data (ABtot) and to each one of the species separately

<table>
<thead>
<tr>
<th>Model</th>
<th>( n )</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \ln(\text{ABtot})=3.33^{(<em><strong>)}-0.010x^2+0.009y^2-0.014xy^{(</strong></em>)} )</td>
<td>1520</td>
<td>0.014 (***</td>
</tr>
<tr>
<td>( \ln(\text{AB}Q_{ilex})=2.22^{(<em><strong>)}-0.038x+0.042y-0.020x^{2^{(</strong></em>)}+0.038y^2+0.014xy^{(<em><strong>)}-0.027rad^{(</strong></em>)}-0.016slp^{(***)} )</td>
<td>1435</td>
<td>0.084 (***</td>
</tr>
<tr>
<td>( \sqrt{\text{AB}_P.halepensis)=3.38^{(<em><strong>)}-0.045x^2+0.074y^2+0.012xy^{(</strong></em>)}-0.022xy^{(<em><strong>)}+0.037rad^{(</strong></em>)}+0.012slp^{(***)} )</td>
<td>1365</td>
<td>0.037 (***</td>
</tr>
<tr>
<td>( \sqrt{\text{AB}_D.cerisoides)=1.96^{(<em><strong>)}+0.033x^{(</strong>)}-0.025xy^{(<strong>)}-0.019rad^{(</strong>)}-0.009slp^{(</em>)} )</td>
<td>1102</td>
<td>0.054 (***</td>
</tr>
<tr>
<td>( \sqrt{\text{AB}_A.unedo)=1.69^{(<strong>)}-0.099y^{(</strong>)}-0.024x^{(**)}-0.041y^2+0.032xy^{(*)}-0.010rad )</td>
<td>588</td>
<td>0.097 (***</td>
</tr>
<tr>
<td>( \ln(\text{AB}P.pinea)=1.59^{(<em><strong>)}+0.079x^{(</strong>)}-0.12y^{(</em>)} )</td>
<td>208</td>
<td>0.068 (***</td>
</tr>
</tbody>
</table>

*Independent variables selected are multiplied by their respective partial regression coefficients. The statistical significance of the coefficients, the general statistical significance and the degree of fitting are also given. rad: mean value of the daily potential solar radiation for all year on the plot, slp: slope of the plot, \( n \): number of plots used in the fitting, \( R^2 \): determination coefficient (%), In: natural logarithm, \( \sqrt{ } \): square root, *: \( p<0.05 \), **: \( p<0.01 \) and ***: \( p<0.001 \).
The regional variables pointed to highest BA values of *Q. cerrioides* in the SE part of the park (which agrees with a more spread distribution of this species in that area). On the other hand, similar results to those of *Q. ilex* were found with reference to the effect of slope and radiation. This may be ascribed to ecological aspects coming from their phylogenetic closeness, but could be also caused by a previous similar management.

The highest fitting was achieved with the BA of *A. unedo*. However, it was not significantly affected by slope and radiation, and its spatial distribution in the study area was quite complex. From the high significance of \((-\) y and \((-\) \(x^2\) the largest values of BA were expected in the southern central area.

Finally, there was no significant effect of slope and radiation on the BA of *P. pinea*. The highest values for this species were found in the eastern part of the study area. Notice that more complex regional patterns could not be analysed since \(x\) and \(y\) were the only regional variables examined for this species.
3.2. Autocorrelation analysis

Since models fitted in the previous section were statistically significant, \( I \) was obtained from the residuals of the regressions built. This allowed the minimisation of the effect of regional trends, of the slope and of the radiation over the analyses of autocorrelation. The expected moments of values of \( I \) calculated from residuals were used to test for the presence of autocorrelation (see the Appendix A).

Correlograms from the residuals considering the 18 distance classes given in Table 2 were derived. Since each of the \( I \) obtained in every distance class was tested against the null hypothesis of no autocorrelation, a Bonferroni approximation was applied to deal with such simultaneous tests (Rawlings et al., 1998). Thus, to keep a joint significance level (\( \alpha \)) of 0.05 for all 18 classes of a correlogram, a more restrictive \( \alpha' \) of 0.0028 (\( \alpha' = 0.05/18 \)) was applied to each single test.

Correlograms derived are shown in Fig. 3. When values of \( I \) are approximately compared to the range of values to be expected from a Pearson correlation coefficient, it becomes clear that autocorrelations found were low. In general, maximum values achieved were lower than 0.2. However, and in spite of the highly conservative Bonferroni thresholds, many \( I \) values were statistically significant. As in the regression models of the Section 3.1, this was caused by the large samples available for the species studied.

As might be expected, positive autocorrelations were found when considering the classes that include the smallest distances. Such results can be reason-

![Fig. 3](image-url)
ably explained by processes occurring at a local scale. However, the negative autocorrelations found at further distance classes are much more difficult to explain in a functional sense and are probably caused by limitations of the rather simple linear models previously fitted. Even so, although significant in some cases, these negative autocorrelations had usually extremely low $I$ values.

Limitations of the linear models were probably more evident in the correlogram of $P$. pinea. This species achieved the highest positive and negative autocorrelations, the later being unusually high. It should be remembered that, due to a lower sample size, only $x$ and $y$ values were used as independent variables in the trend surface analysis of $P$. pinea. In consequence, it was likely that these higher $I$ values observed were due to a lower fitting capability of the simpler model derived for this species.

4. Discussion

Overall, the woodlands of the study area did not display strong regional gradients, and they were not affected in a clear way by slope or the mean amount of radiation received. Generally, they feature the greatest part of their variability in short distance ranges (significantly shorter than the minimum distance of 100 m considered in this study). Nevertheless, and because of the large sample sizes available, many subtle effects and tendencies were proven statistically. In consequence, the hypothesis stating that environmental factors will lead to the establishment of prominent spatial patterns on the BA in non-disturbed Mediterranean woodlands was not supported by the results of the study.

The most striking outcome of the study probably concerns the low effects of radiation. Since radiation is directly linked to water deficit in summer, it would be expected for a Mediterranean woodland to be largely affected by this variable. However, although the majority of the area had not been timbered for at least 50 years, it possibly still retained some effects of previous management. Indeed, due to the usual low productivity of Mediterranean forests (Ibáñez et al., 1999), consequences of activities carried out in the past may last for long periods of time. Another probable explanation comes from the fact that woodlands in the study area are more frequently located on slopes facing east or west. Actually, there is a big contrast between the main south facing part of the study area, adjacent to the city of Barcelona, and the other parts. Due to a high recurrence of fires, this south facing portion has hardly any forest and, in consequence, few survey plots were located in this area. Thus, although important, this big contrast between south and north facing slopes was omitted in the models fitted in this study.

It might be also suggested that the effect of other non-controlled factors, such as the availability of a limiting nutrient (Mayor and Rodà, 1994), has overridden the effects of the radiation. However, unless the spatial distribution of these non-controlled factors were highly variable in short spatial distances, their significant effects would have been reflected through strong autocorrelation values (which were not observed). In fact, the poor fittings of models and low values of autocorrelations found suggested that the inner dynamics of BA evolution, during the development of each site, was complex leading to high variability that masked the effect of all environmental factors studied.

Concerning methodological aspects, stepwise methods have been widely (and fairly) criticised as not being reliable under many situations (Sen and Srivastava, 1990; Christensen, 1996). Nevertheless, independent variables selected by the stepwise method used in this study agree almost completely with more significant variables found in models preliminarily fitted with all variables at the same time (results not shown). This agreement probably comes from the large sample sizes available (compared to the number of independent variables tried) and ensures the reliability of the models selected.

On the other hand, the detection of spatial autocorrelation is only evidence for the presence of links between values of spatially related points. These links may, however, be due to many direct or indirect causes. In this study, several biotic (e.g. demographic dynamics and dispersion processes), abiotic (other non-controlled factors besides slope and radiation, with high spatial variability) and human driven factors (similar past forest management in near sites) may have been responsible for the, rather humble, levels of autocorrelation observed.

Indeed, as the results of $P$. pinea illustrate, even some deficiencies in the regression models previously fitted may be quantified as autocorrelation. The divi-
sion of the spatial variability in three levels carried out in this study was, in some degree, theoretical. Specifically, the limit between the regional variability and the autocorrelation processes was, somehow, arbitrary. Both items may be caused by a variety of factors which will not be always exclusive. However, it may be expected for the regional variability to display a gradual trend, while autocorrelation processes are expected to occur locally and, more often, with positive values. Again, it may be expected that the large samples available in this study have led to a fairly good discrimination of both variability levels.

When a significant degree of autocorrelation is detected for the residuals, the least square estimates of the regression coefficients, although unbiased, loose their efficiency. Under such circumstances, Cliff and Ord (1981) propose the use of more complex procedures that include a spatial autoregressive component in the linear models. Thus, instead of the simple covariance matrix presumed in the ordinary least squares (\( \sigma^2 I \), where \( I \) is the identity matrix) a more sophisticated approach may be considered by means of generalised least squares. In this case, the autoregressive structure of residuals is given to the model through a matrix \( V \) of order \( n \times n \) (and the covariance matrix is presumed to be \( \sigma^2 V \)). However, although being more adequate under theoretical grounds, these models are based on often unstable iterative fittings that frequently lead to parameter estimates that are less reliable than those given by ordinary least squares (Rawlings et al., 1998). Therefore, and considering the low autocorrelations achieved, original models fitted were accepted as valid in this study.

The results of this study also have practical consequences. The low autocorrelations observed pointed to poor interpolation capabilities for BA values in the study area. This work showed how plots located 100 m apart have BA values nearly as different as those located much further away. This has some important implications on the design of future forest surveys in the study area. Thus, if mapping of a continuous variable (such as BA) has to be carried out by interpolation, a much denser grid will be necessary, although this may be economically unaffordable. In consequence, remote sensing may be proposed as an alternative to sampling in the field. However, further results supporting this option in this type of woodlands are still required (Salvador and Pons, 1998b).

5. Conclusions

Spatial variability of BA of woodlands studied occurs within really short spatial ranges (of clearly less than 100 m), and neither the radiation nor the slope seem to have an important effect upon this parameter. In consequence, such results do not support the hypothesis giving a prominent role to environmental variables as factors leading to the establishment of significant spatial patterns of the BA on non-disturbed Mediterranean woodlands. Various factors such as a long term effect of forest management, an uneven presence of relief conditions and a complex dynamics of the BA within plots are suggested as possible explanations for the results found. On the other hand, the low autocorrelations observed will impose severe restrictions when interpolating BA values in the study area. This will have practical consequences in the design of forest inventories.

Finally, the following recommendations are suggested for future studies concerning spatial patterns in the structure of Mediterranean woodlands: (1) measurements at interval distances less than 100 m may be better suited for autocorrelation analyses, (2) the assessment of the effect of different plot sizes may also help understanding the spatial patterns observed. Specifically, block kriging can be applied (Goovaerts, 1997), (3) the usage of a similar methodology in other areas with a more even distribution of geographical conditions (such as a higher proportion of forested south facing slopes) and a wider extension may improve the conclusions derived from the present study, (4) new studies should explore the complex effect of interactions between species found in the same plot, and (5) further attempts with high resolution digital imagery may help in the description and understanding of spatial patterns in the structure of Mediterranean woodlands.

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Appendix A

Formulas for the $E(I)$ and Var($I$) under the null hypothesis of no autocorrelation, supposing normality of the data. Eqs. (A.1) and (A.2) give the moments to apply when we are working with the original values, and Eqs. (A.3) and (A.4) are the moments to use with residuals of regressions (all of them come from Cliff and Ord (1981) with some slight modifications). As given, Eqs. (A.3) and (A.4) can only be applied when symmetrical connections are used (i.e. $w_{ij} = w_{ji}$ for all $i$ and $j$).

\[
E(I) = -\frac{1}{n-1} \quad \text{(A.1)}
\]

\[
\text{Var}(I) = \frac{1}{(n^2 - 1)s^2_t} \left( n^2 \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} (w_{ij} + w_{ji})^2 
- n \sum_{i=1}^{n} (w_{i} + w_{j})^2 + 3s^2_t \right) - \left( \frac{1}{n - 1} \right)^2 \quad \text{(A.2)}
\]

\[
E(I) = -\frac{n \text{Tr}((X^T X)^{-1}X^T W X)}{(n-k)s_t} \quad \text{(A.3)}
\]

\[
\text{Var}(I) = \frac{n^2}{s^2_t(n-k)(n-k-2)} \left\{ 2 \sum_{i=1}^{n} w_{ii}^2 
+ 2 \text{Tr} \left( ((X^T X)^{-1}X^T W X)^2 \right) 
- \text{Tr}(W X)^T (W X) \right\} - \left[ 2 \text{Tr}(W X)^T (W X) \right] / n-k \quad \text{(A.4)}
\]

where $n$ is the number of plots, $s_t$ the sum of all connections, $w_{ij}$ the connection between plots $i$ and $j$, $w_i$ the sum of all connections involving plot $i$ as the first plot (if connections are symmetrical $w_i = w_{-i}$), $k$ the number of independent variables included in the model $-1$, $X$ the $n \times k$ matrix with the values of all independent variables given in columns plus an extra column of ones as the first column. $W$ the $n \times n$ matrix with all $w_{ij}$ values (in Eqs. (A.3) and (A.4) this is expected to be symmetrical). Tr() the trace of the matrix, superscript $-1$ the inverse of the matrix and superscript $T$ is the transpose of the matrix.

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