Instituto Nacional de Investigación y Tecnología Agraria y Alimentaria (INIA)
Available online at www.inia.es/forestsystems

Forest Systems 2011 20(1), 50-64
ISSN: 1131-7965
eISSN: 2171-9845

Environmental variability and its relationship to site index in Mediterranean maritime pine

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Abstract

Environmental variability and site productivity relationships, estimated by means of soil-site equations, are considered a milestone in decision making of forest management. The adequacy of silvicultural systems is related to tree response to environmental conditions. The objectives of this paper are to study climatic and edaphic variability in Mediterranean Maritime pine (*Pinus pinaster*) forests in Spain, and the practical use of such variability in determining forest productivity by means of site index estimation. Principal component analysis was used to describe environmental conditions and patterns. Site index predictive models were fitted using partial least squares and parsimoniously by ordinary least square. Climatic variables along with parent material defined an ecological regionalization from warm and humid to cold and dry sites. Results showed that temperature and precipitation in autumn and winter, along with longitudinal gradient define extreme site qualities. The best qualities are located in warm and humid sites whereas the poorest ones are found in cold and dry regions. Site index values are poorly explained by soil properties. However, clay content in the first mineral horizon improved the soil-site model considerably. Climate is the main driver of productivity of Mediterranean Maritime pine in a broad scale. Site index differences within a homogenous climatic region are associated to soil properties.

Key words: Mediterranean region; *Pinus pinaster;* site index; soil-site.

Resumen

Variabilidad ambiental de las masas de pino negral y su relación con el índice de sitio

La relación entre variabilidad ambiental y la productividad de estación, estimada mediante el índice de sitio, es clave en la toma de decisiones en la gestión forestal sostenible, ya que su conocimiento permite adecuar la práctica selvícola a la respuesta de la masa a dicha variabilidad ambiental. Los objetivos de este trabajo son estudiar la variabilidad climática y edáfica de *Pinus pinaster* en su distribución mediterránea en España y el uso práctico de dicha variabilidad en la determinación de la productividad de la estación mediante la estimación del índice de sitio. Para la descripción de la variabilidad ambiental se realizó un análisis de componentes principales y para la predicción del índice de sitio se optó por una regresión por mínimos cuadrados parciales, y de forma más parsimoniosa, mediante mínimos cuadrados ordinarios. Las variables climáticas, junto al material parental definieron regiones que comprendían estaciones que van de cálidas y húmedas hasta frías y secas. Los resultados mostraron cómo la temperatura media anual, la precipitación en otoño e invierno, junto con un gradiente longitudinal define calidades de estación extremas. Las mejores calidades se encuentran en estaciones cálidas y húmedas mientras que las peores están en estaciones frías y secas. Las variables edáficas explican poca variación del índice de sitio, aunque la inclusión del contenido en arcilla mejora notablemente el modelo. El clima es el precursor de la calidad de estación mientras que diferencias en el índice de sitio en zonas climáticamente homogéneas se asocian a variables edáficas.

Palabras clave: índice de sitio; material parental; *Pinus pinaster;* región mediterránea.

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Received: 15-04-10; Accepted: 07-01-11.

Introduction

Mediterranean environmental conditions, such as water stress, limit forest growth. However, there is a high environmental variability in the Mediterranean region and mesic forest ecosystems such as those found in Central Europe can also exist (Scarascia-Mugnozza *et al*., 2000). The great variability in climate, soil and physiographic conditions leads to a great variability of tree species, growth response and productivity, as it is the case of Maritime pine (*Pinus pinaster* Ait.). In this species the environmental variability has derived into two groups in the Iberian Peninsula with great differences in growth performance; the Atlantic Maritime pine (AMP), which is more productive and found mainly in areas with an Atlantic climate, and the Mediterranean Maritime pine (MMP), which grows under pure and mesic Mediterranean climate conditions with an irregular precipitation regime and diverse soil origin which, along with stand isolation, has lead to geographic differentiation of tree attributes such as tree height, stem straightness or productivity (Alía *et al*., 1997; Río *et al*., 2004; Bravo-Oviedo *et al*., 2007).

Stand forest dynamics is related to site properties and the application of silvicultural systems must be based on the knowledge of current environmental conditions. These properties are often considered to be the foundations of silviculture (Toumey and Korstain, 1947). Autoecology, or the study of environmental factors and their effects on plants (SAF, 2008), has a long tradition in forestry studies in Spain. The first study on applied autoecology in Spain was conducted for *Pinus pinaster* within an important research program started in the early sixties. These studies first aimed to establish the autoecology of species of genus *Pinus*, as they were systematically used in restoration programs. Regarding Mediterranean *Pinus pinaster* (MMP) this study was carried out according to six natural regions (Nicolás and Gandullo, 1967) and the authors finally presented 5 ecotypes according to physical-soil properties. Recently, several works have increased the knowledge on tree-environment relation on forestry application for other species (Díaz-Maroto *et al*., 2007; Sánchez-Palomares *et al*., 2007, 2008; Alonso *et al.,* 2010).

Sustainable Forest Management must consider the environmental variability as an important factor in forest stand dynamics. The study of cause-effect relationships is essential in furthering scientific knowledge and understanding of biological processes. However, standard management requires simple tools to aid decision-making. One example of these are models which include indirect measures, like those used for evaluating forest quality and yield through site index (Curt *et al*., 2001).

Forest site quality studies have the aim of describing, classifying and predicting the potential of a site to sustain biomass productivity. Forest site evaluation in even-aged forests is usually expressed as a function of intrinsic stand properties, such as tree height and age (Hägglund, 1981), *i.e.* site index. Forest site index, described as the dominant height attained at a reference age, is an indirect and partial measure of site quality. It is devoted to the tree bole production of aboveground biomass and it is related to mean annual volume increment, which is a basic unit of forest management. Consequently, a careful selection of appropriate dominant trees must be made. In some cases such trees are rare or even absent, *e.g.* marginal agricultural lands subjected to forestation, high graded or very sparse stands, etc. Where this situation exists, forest productivity can be assessed in one of two ways (Curt *et al*., 2001): the first is known as the synoptic approach and correlates site index to site attribute classes, such as regional classification according to a composite of ecological features (Wang and Klinka, 1996; Curt *et al*., 2001; Romanyà and Vallejo, 2004). The second method is analytical and consists of measuring site variables and relating site index to them (Chen *et al*., 2002; Klinka and Chen, 2003). The latter method is known as a soil-site study and has been widely used in forest productivity studies (Carmean, 1975; Monserud *et al*., 1990; Hollingsworth *et al*., 1996; Dunbar *et al*., 2002; Fontes *et al*., 2003; Nigh, 2006).

In the course of a study on dominant height growth for MMP (Bravo-Oviedo *et al*., 2007), some regional and local differences in growth performance were detected using base-age invariant (BAI) equations, along with ecological regions defined by Costa *et al*. (2005). BAI is considered to be superior to base age specific equations, like previous existing curves for the species (Pita, 1968), in terms of site index model applicability and statistical validity (Krumland and Eng, 2004). The use of BAI species-specific equations may indicate relationships among site conditions, *i.e.* climate and soil, and forest growth. Thus, a revision of soil-site relationships is needed for the species in order to estimate forest productivity.

The main objective of this paper is to analyze the statistical variability in climate, soil and physiography and its relationship to site index in the distribution area of Mediterranean maritime pine in Spain. The specific objectives were to a) analyze the environmental variability and define homogeneous environmental regions, b) analyze the relationship between environmental variability and productivity values, estimated by means of site index, c) to develop a model for site index prediction from environmental variables. We hypothesized that climatic and edaphic variability explains differences in site productivity.

Material and methods

Stand selection and Site Index

This study deals with most of the distribution of Mediterranean Maritime pine in Spain, which accounts for around 724,000 ha in Spain (DGCN, 1998). Within the institutional framework of the Sustainable Forest Management Research Institute (SFMRI; www.research4forestry.org), 191 plots were selected in the study area (Fig. 1). Ninety three of them belong to the CIFOR-INIA network of experimental plots installed in 1964 to study the growth and yield of *Pinus pinaster*, in which measurements have been taken periodically until 2004. In addition, 20 complementary plots were established in 2004 for stem analysis in order to complete the data from the first source. Finally, 78 plots belonging to the network installed by the University of Valladolid to study *Pinus pinaster* growth dynamics in the Iberian Mountain Range were incorporated into our database. In each plot, dominant height was calculated according to the mean value of the 100 thickest stems per hectare and the age was determined from cores of a sample (4 to 15) of dominant trees. Site index values were calculated according to the dominant height model developed by Bravo-Oviedo *et al.* (2007) using dominant height at the age of 70 years. We used a general model which is common to all regions, because we intend to find environmental variables that drive forest productive irrespective to regions. Average site index is 14.8 m (standard deviation 4.3 m), maximum site index is 26.1 m and the minimum is 4.7 m.

Environmental attributes

Climatic and physiographic data

Climatic data for every plot were retrieved from the GENPT and COMPLET programs (Fernández-Cancio and Manrique, 2001; Manrique and Fernández-Cancio, 2005). Monthly climatic values for each plot were calculated according to regression models or mean values

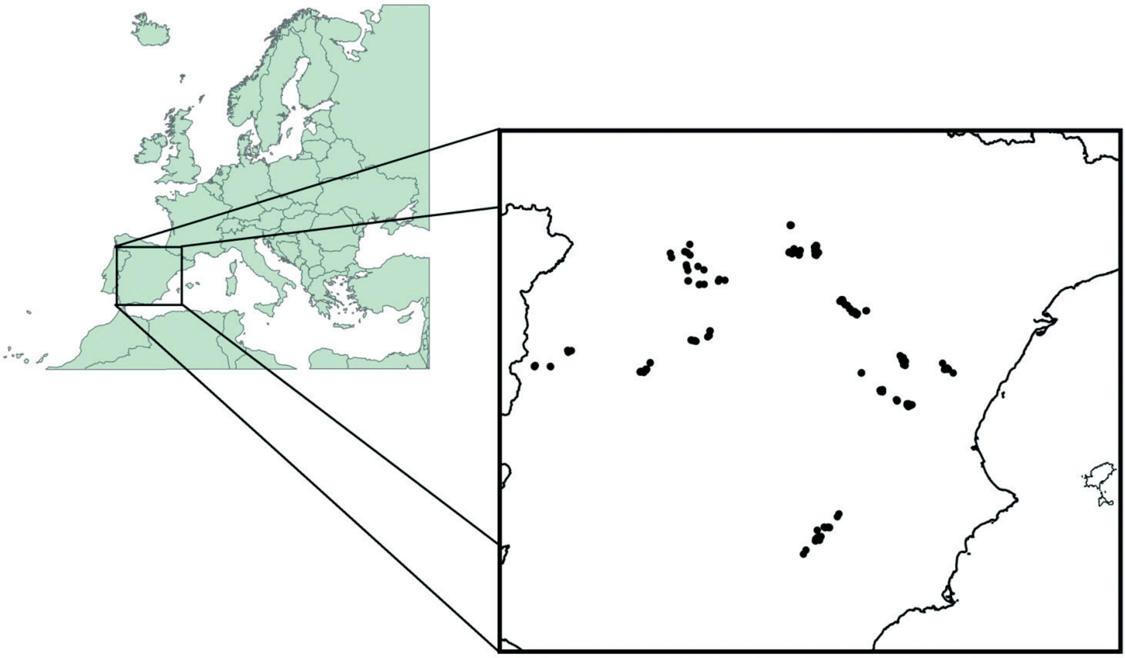

Figure 1. Plot location in *Pinus pinaster* Ait. stands in Spain.

from the ancillary nearest climatic stations. The program requirements are: longitude, latitude and altitude. The reference period 1961-1990 was used to calculate average climatic conditions for each plot. Physiographic data were obtained from a digital terrain model with a pixel size of 25 × 25 m. Climate-related variables such as drought length, intensity of drought, evapotranspiration, physiological drought, surplus, deficit, annual hydric index and surface drainage were also calculated (Table 1).

Soil data

Soil data were obtained in a subsample of 65 plots in the SFMRI database, according to elevation and soil parental material. A sample of every soil horizon was extracted for analysis in the laboratory. The soil attributes measured were: water-pH, conductivity, organic matter (oxidizable organic carbon via Walkley-Black's method), total organic matter according to loss-on-ignition method, carbonates and active calcium (using

Table 1. Description of physiographic, climatic and climate-realted variables

Variables type[a]	Units	Mean	Std. Dev.	Min.	Max.
Physiographic					
Longitude (XUTM)	m (zone 30)	503,317	126,534	187,386.0	702,502.0
Latitude (YUTM)	m (zone 30)	4,479,273	106,935	4,226,960.0	4,631,322.0
Elevation (ELV)	m	1,021	224.8	377.0	1437.0
Slope (SLP)	%	16.7	12.4	0	63.7
Aspect (ASP)	º	70.9	111.9	0.0	356.8
Insolation[1] (INS)		1	0.2	0.4	1.3
Climatic					
Annual rainfall (P)	mm	576	81	420.0	792.0
Spring rainfall (SGP)	mm	164.9	18.2	118.6	204.5
Summer rainfall (SMP)	mm	79.7	17.7	50.8	121.1
Autumn rainfall (AUP)	mm	175.5	36.3	121.0	297.5
Winter rainfall (WP)	mm	156.5	47.6	82.7	307.1
Mean annual Temperature (T)	°C	11.4	1.6	8.9	15.9
Lowest Monthly mean temperature (TMF)	°C	3.3	1.4	0.6	7.2
Highest Monthly mean temperature (TMC)	°C	21.4	1.8	18.0	26.1
Mean value of minima temperature in the coldest month (TMMF)	°C	–1.3	1.5	–4.6	2.2
Mean value of maxima temperature in the warmest month (TMMC)	°C	29.7	1.8	26.5	35.4
Climate-related					
Drought lenght[2] (DSQ)	Months	2.6	0.7	1.6	4.5
Intensity of drought[3] (ISQ)		0.1	0.1	0.0	0.3
Annual Evapotanspiration (ET)	mm	678.6	53.5	597.9	851.3
Winter ET	mm	30.7	6.9	17.2	46.8
Spring ET	mm	137.3	11.3	112.4	169.4
Summer ET	mm	358.4	26.7	315.3	449.7
Autumn ET	mm	153.2	12.8	135.3	187.2
Potential Evapotranspiration (PET)	mm	444.7	33.3	358.7	538.0
Annual physiological drought[4] (APD)	mm	234.0	72.1	78.3	426.3
Surplus[5] (SUP)	mm	224.9	81.7	70.6	413.0
Deficit[6] (DEF)	mm	326.9	62	225.7	500.6
Annual Hydric Index[7] (AHI)		4.3	11.2	–17.6	34.7
Drainage[8] (D)	mm	131.9	93.1	0.0	380.1

[a] In parenthesis acronym used in the analysis. [1] According to Gandullo (1974). [2] Number of months where precipitation curve is under temperature curve in the Walter-Lieth climodiagram. [3] Quotient between dry area (temperature curve is above precipitation curve) and humid area (temperature curve is under precipitation curve) in the Walter-Lieth climodiagram. [4] Sum of monthly values where evapotranspiration is higher than potential evapotranspiration. [5] Sum of monthly values where precipitation is higher than evapotranspiration. [6] Sum of monthly values where precipitation is lower than evapotranspiration. [7] AHI = (100xS-60xD)/ET. [8] Estimated soil drainage according to Thornthwaite (1957) and Gandullo (1985).

Bernard's calcimeter), phosphorus (according to Olsen's Method), exchangeable calcium, magnesium, potasium and sodium (according to the ammonium acetate method), Cation-Exchange Capacity (determined according to Bascomb's procedure), and nitrogen (according to Kjeldahl's method). Physical properties and variables for nutrient availability were averaged for the whole pit. The topmost organic horizon A_{00} was discarded in the sampling because of little differentiation of needles that would not have any influence in past growth of the stand, the rest of A horizons (A_0, A_1 and A_2), if presented, were bulked together to form the first horizon sample. Nutrient variables, bulk density calculated according to the method proposed by Honeysett and Ratkowsky (1989) and the depth and percentage of roots were also recorded. Table 2 presents a description of soil attributes.

Statistical analysis

Multivariate analysis was performed in three ways: descriptive, explanatory and predictive. The first one was used to describe the environmental variability and to identify the most influential variables and homogeneous regions; the explanatory analysis was carried out to identify and select the environmental variables that better explain the site index variation. Finally, the predictive approach was done to develop a site index model depending on environmental variables.

Descriptive multivariate techniques identify the tendencies and latent variables influencing the relationship of the explanatory variables under analysis and they serve to identify observations that share the same region in a multivariate space. Factor analysis, according to the principal component extraction method (PCA), was used to identify likely environmental gradients. The analysis was performed firstly using climatic and physiographic variables (191 plots) and secondly adding soil data (65 plots). Those variables which were found to have a measure of sampling adequacy (Kaiser's MSA) below 0.5 were rejected (Hair *et al.*, 1999) and the analysis repeated until variables had an adequate Kaiser's MSA (above 0.7). Principal components analysis will serve as a tool to delineate environmental classes or groups in order to define homogenous climatic regions that will be coded and treated as synoptic variables. Synoptic variables were introduced into a one-way analysis of variance to test differences in site index through climatic classes. Normality and independence of residuals within each group were also tested. Tukey-Kramer's test for unequal sample size was applied to compare group means (SAS, 2004).

As a second method, we used partial least squares regression, PLS (Abdi, 2003) to find a model capable of explaining site index from a large set of potential variables. The PLS regression is a powerful analysis tool and one of the least restrictive options in multivariate analysis. This technique is appropriate when the number of predictors is equal or higher than the number of observations or when there exists high correlation among predictors (Carrascal *et al.,* 2009), which is the most common case in ecological based studies. It can be used as an exploratory analysis tool to select suitable predictor variables and to identify outliers before applying classical linear regression. It can be also used as a predictive analysis when predictors are many and collinear (Tobias, 1995). We applied the former case to analyse the relationship between site index and the matrix of environmental variables that loaded most heavily in the factor analysis for the sub-sampling containing soil and climate information.

Multiple regression analysis was used to obtain parsimonious predictive models. This technique applies on large databases and it is usually performed with stepwise regression as selection method. Stepwise selection method often depends on the pool of variables that are included in the first stage, to the extent that by dropping one variable in the first stage the result could be different. Besides, the use of a sequential variable selection method may not be biologically sound (Fontes *et al.*, 2003a) and there might exist a big uncertainty that the truly best model is not produced (Myers, 1990). Consequently, a direct selection of candidate variables was performed on the basis of the results found in the PLS analysis.

Visual inspection of Q-Q plots and formal statistical tests were performed for normality assumption. Multicollinearity was assessed using the condition number index (Myers, 1990). Homogeneity of variance was evaluated according to visual inspection of ordinary and studentized residuals over predicted values.

Model validation requires an independent data set that it is not used in the fitting phase. This requirement is often omitted as data gathering is expensive. In addition, splitting the sample may lead to differences in the results depending on the method chosen to split the sample. We select the one leave-one out approximation where one observation is deleted at a time and the model

Table 2. Average soil attributes description

Variables type	Units	Mean	Std. Dev.	Min.	Max.
Physical properties for the whole pit					
Fine fraction (%F)	%	60.3	26.7	16.9	100
Coarse fraction (%C)	%	39.7	26.7	0	83.1
Sand	%	65	21.2	20.5	93.3
Clay	%	11.5	10.8	2	49.7
Silt	%	23.5	14.2	1.6	61.9
CCC		0.2	0.4	0	2.5
CIL		0.1	0.1	0	0.5
Permeability		4	1.3	1	5
Chemical properties for the whole pit					
Water Holding Capacity (WHC)	mm	104.3	74.7	12.8	367.8
Equivalent humidity (EH)	mm	16.7	7.6	7	35.4
pH		6.6	0.9	5.1	8.7
Organic matter (OM)	%	1.3	1.3	0.1	8.5
Total organic matter (TOM)	%	1.8	1.7	0.2	11.3
Calcium (Ca^{++})	ppm	1,071.7	1,231.3	100.1	5,496
Sodium (Na^{+})	ppm	22.5	16.3	2.4	64.2
Potasium (K^{+})	ppm	84.7	99.1	15.9	498.9
Phosporus (P)	ppm	0.8	2.7	0	14.6
Magnesium (Mg^{++})	ppm	253.3	561.7	14.1	3,201.4
Nitrogen (N)	%	0.1	0	0	0.3
Carbonates (CB)	%	4.1	8.8	0	38.5
Active carbonates (ACB)	%	0.4	1.1	0	6.3
Conductivity (CVY)	mmhos cm^{-1}	0.1	0.1	0	0.4
Cationic Exchange Capacity (CEC)	meq 10 g^{-1}	10.8	5.8	3.9	32
Base sum (S)	meq 100 g^{-1}	7.8	9.8	1	43.6
Saturation Rate (TSAT)	%	57.6	38.8	6.9	186.3
Chemical and physical properties for the first horizon					
Water Holding Capacity (WHC1h)	mm	97.2	66.9	11.4	383
Organic matter (OM1h)	% oxidable	1.9	2	0.1	10.5
Calcium (Ca1h)	meq 100 g^{-1}	5.6	7.1	0.5	27.6
Sodium (Na1h)	meq 100 g^{-1}	0.1	0.1	0	0.6
Potassium (K1h)	meq 100 g^{-1}	0.3	0.4	0	2
Magnesium (Mg1h)	meq 100 g^{-1}	2.3	5.1	0.1	26.4
Nitrogen (N1h)	%	0.1	0.1	0	0.4
Carbonates (CB1h)	meq 100 g^{-1}	3.7	9.2	0	46.4
Cationic Exchange Capacity (CEC1h)	meq 100 g^{-1}	11.6	6.8	4.1	30.6
Saturation Rate (TSAT1h)	%	56.9	42.3	6.8	198.4
Carbon-Nitrogen rate (CN1h)	%	30.6	16	3.3	73.5
Bulk density (BD1h)	g cm^{-3}	1.4	0.4	0.6	2.3
Depth (D1h)	cm	25.2	10.7	10	70
Roots (R1h)	%	84.7	15.8	10	100

In parenthesis, the abbreviation used in the text. CCC: compactness capacity coefficient. CIL: silt impermeability coefficient.

is fitting to the remaining *n-1* data (Vanclay, 1994). Finally, model performance was evaluated according to biological sense and statistical properties (Soares *et al.*, 1995). The statistical validity of the model was evaluated computing bias and precision values (Huang *et al.*, 2003). The selected prediction statistics for bias was the mean residual without current observation [$\bar{e}_{-1}$, eq. 1] and its percentage error [$\bar{e}_{\%}$, eq. 2]. The mean squared error of prediction without current observation [*RMSEP*, eq. 3] ant the relative error in prediction [$RE_{\%}$, eq. 4] was computed to evaluate the precision of the multiple linear model.

$$\bar{e}_{-1} = \sum_{i=1}^{k} \frac{(y_i - \hat{y}_{i,-i})}{k} \qquad [1]$$

$$\bar{e}_{\%} = 100 \times \frac{\bar{e}_{-1}}{\bar{y}} \qquad [2]$$

$$RMSE = \sqrt{\sum_{i=1}^{k} \frac{(y_i - \hat{y}_{i,-i})}{k-1-p}} \qquad [3]$$

$$RE_{\%} = 100 \times RMSEP / \bar{y} \qquad [4]$$

where y_i is the i^{th} site index observation, $\hat{y}_{i,-i}$ prediction without current i^{th} observation, k is the number of observations and p is the number of parameters.

Results

Descriptive analysis

Principal components analysis

The variance explained by the two first climatic factors in PCA is 82% (Table 3). Climatic factor analysis showed that the temperature regime, drought length, elevation and evapotranspiration accounted for the maximum amount of variance in the first factor (58%). The second factor can be labelled as precipitation regime, as long as annual precipitation, seasonal rainfall in autumn and winter, water surplus and annual hydric index loaded most in this factor.

Table 3. PCA's factor loadings for climate attributes

Variable	Factor 1	Factor 2	Factor 3	Factor 4
YUTM	–0.28	–0.20	**0.87**	0.27
ELV	**–0.87**	–0.03	–0.40	–0.11
DSQ	**0.86**	0.19	0.07	–0.20
P	0.13	**0.98**	–0.13	–0.01
T	**0.95**	0.17	–0.22	–0.11
TMF	**0.94**	0.21	–0.19	–0.10
TMC	**0.85**	0.18	–0.41	–0.20
TMMF	**0.90**	0.23	–0.18	–0.12
TMMC	**0.87**	0.15	–0.29	–0.16
WP	0.47	**0.85**	–0.02	–0.08
AUP	0.35	**0.87**	–0.12	–0.09
Winter ET	**0.91**	0.21	–0.05	–0.07
Spring ET	**0.97**	0.04	0.09	–0.01
Summer ET	**0.86**	0.19	–0.38	–0.15
Autumn ET	**0.89**	0.30	–0.24	–0.08
ET	**0.95**	0.18	–0.20	–0.10
PET	–0.19	–0.10	0.21	**0.95**
APD	**0.79**	0.18	–0.25	–0.51
SUP	0.22	**0.96**	–0.09	–0.10
AHI	–0.29	**0.95**	–0.01	0.00
ISQ	**0.84**	–0.15	0.02	–0.26
Eigenvalue	11.72	4.78	1.69	1.52
% Variance	0.58	0.24	0.08	0.08
Cumulative % variance explained	0.58	0.82	0.90	0.98

Bold indicate loadings greater than 0.7.

The inclusion of site index in the analysis as supplementary variable did not show any discernable pattern in the PCA. However, the incorporation of rock type and elevation in the climatic PCA, showed a pattern of aggregation. Figure 2 depicts regions with common rock type origin when axis 1 and 2 of climatic PCA are displayed, while Table 4 shows the main physiographic, climatic variables and parental material type, as well as site index values of each group. Those groups were incorporated into a one-way analysis of variance to detect statistical differences in mean site index. Groups were only entered into the analysis if at least 5 observations were available.

The first region (A in Fig. 2) holds acidic conglomerate rock under humid and cold conditions. The plots belonging to this region are included in Soria-Burgos Mountains and are located in the northern part of the study area.

Dolomite origin stands are located in two latitude bands and differ in temperature values. The warmest band (mean annual temperature of 13.1°C, Table 4) is located in Segura-Alcaraz area (Factorial region B). The second group is formed by three sampled stands located in the colder Iberian Mountains. This last group is underrepresented in our study and it was not used in the following analysis.

The acidic warm sites, which include slate and schist origin, are located next to each other in the western part of the study area (D and E group, respectively). Granite origin is separated into two open subgroups according to temperature and elevation. The stands below 900 m of altitude (group C) grow within the Tiétar river basin (the same area where stands on schist origin grow, group E) with mean annual temperature above 12°C and annual rainfall above 640 mm. The stands growing on granite over 900 m of altitude (group F) are located within the Tagus river basin and the mean temperature is under 12°C.

Soils developed on gravels (G group) and sand drifts origin (H group) are located in the same Castilian Plateau. However, gravels are found in the eastern part of the region, whereas sand drifts are spread within the whole region following an elevation gradient.

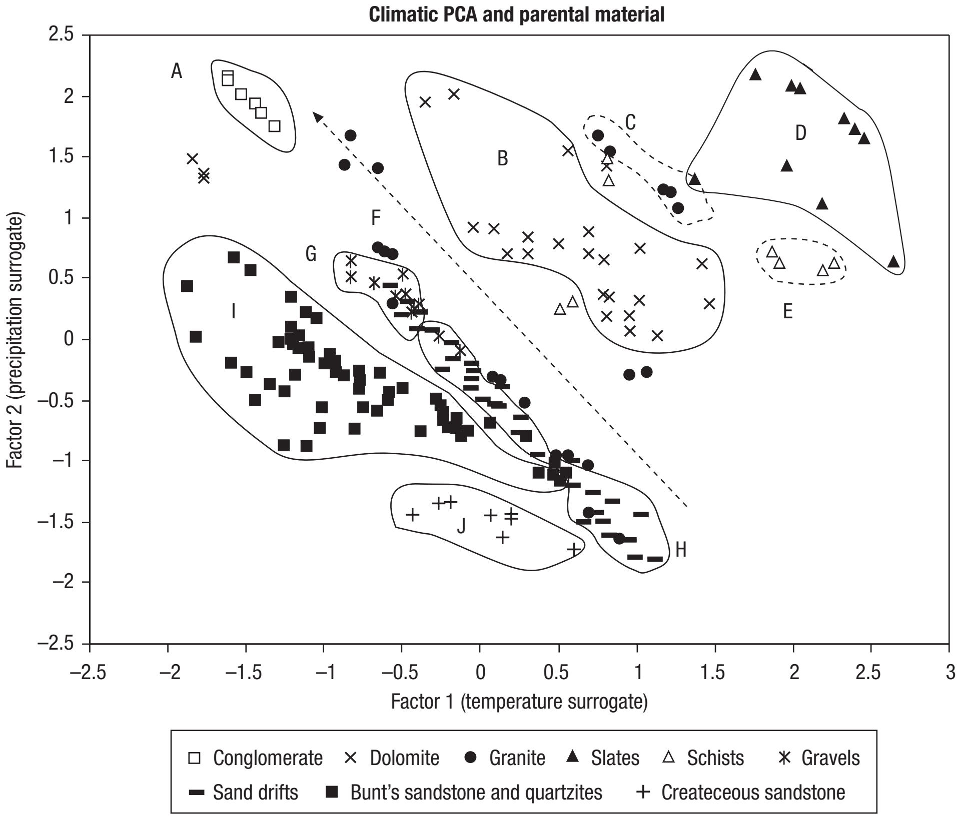

Figure 2. Principal component analysis and groups defined using parental material information.

Stands located on Buntsandstein's sandstone and quartizite bedrock are embedded in a broad factorial domain (Group I). Finally, the stands located in cretaceous' sandstone (J region) in the eastern part of the study area are characterized by cold temperature and low precipitation.

When climatic and edaphic variables are analysed together in the PCA, 91% of variance is explained by four axes (Table 5). The first factor is related to the temperature regime and elevation, the second to soil reaction, the third to nutrient status and the fourth to soil texture type, whereas precipitation is relegated to

Table 4. Main climatic and physiographic features and site index values found in the regions defined in PCA

Factorial domain	Parenteral material	N	Longitude		Latitude (N)		Elevation		Annual temperature		Annual precipitation		Site index	
			Mean	Min/Max	Mean	Min/Max	Mean	Min/Max	Mean	Min/Max	Mean	Min/Max	Mean	Min/Max
A	Conglomerate	11	−2° 57.7'	−2° 57'/−2° 58'	41° 49.2'	41° 49'/41° 50'	1,204	1,181/1,226	9.0	8.9/9.2	704	690/714	15.9	13.9/18.5
B	Dolomite	25	−2° 31.9'	−2° 17'/−2° 47'	38° 24.3'	38° 11'/38° 38'	1,099	844/1,286	13.1	9.9/14.2	651	603/739	14.8	7.3/19.8
C	Granite < 900 m	11	−4.9° 13.7'	−6° 0'/−4° 40'	40° 14.4'	40° 10'/41° 32'	735	605/895	13.2	11.9/15.9	610	439/699	19.4	13.4/23.6
D	Slate	8	−6° 23.6'	−6° 8'/−6° 40'	40° 16.6'	40° 12'/40° 24'	483	377/607	15.0	14.6/15.4	756	688.9/792	19.8	16.6/21.8
E	Schists	8	−5° 6.8'	−5° 5'/−5° 8'	40° 11'	40° 11'/40° 11'	652	465/927	13.8	12.3/15.1	648	594/692	22.9	19.7/26.1
F	Granite > 900 m	14	−4.1° 15.9'	−5° 0'/−4° 25'	40° 32.9'	40° 17'/40° 39'	1,138	914/1,339	11.2	10.4/12.9	594	500/690	15.2	12/19.1
G	Gravel	12	−2° 41.6'	−2° 33'/−2° 56'	41° 32.8'	41° 29'/41° 36'	1,010	949/1,100	10.2	9.8/10.6	585	556/607	15.6	11.5/19.7
H	Miocene's sand drifts	38	−2.9° 39.4'	−4° 1'/−2° 59'	41° 26.4'	41° 10'/41° 36'	873	697/1,024	11.1	10.1/12.1	501	420/589	16.4	8.2/22.4
I	Bunt's sandstone and quartzite	58	−1.3° 19.7'	−2° 0'/−1° 59'	39.6° 41.9'	39° 00'/41° 59'	1,193	945/1,437	10.4	9/12.2	545	501/606	11.5	4.7/19.1
J	Createceous sandstone	8	0° 42.3'	0° 37'/0° 46'	40° 12.8'	40° 10'/40° 16'	1,066	976/1,127	11.4	10.9/12	489	471/496	9.1	6.5/10.6

Table 5. PCA's factor loadings for climate and soil attributes

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Elevation	–0.74	0.26	0.33	0.10	0.16
Annual rainfall	0.19	0.24	0.36	0.15	0.85
Summer rainfall	–0.72	–0.31	0.13	–0.09	–0.32
Autumn rainfall	0.47	0.24	0.28	0.14	0.77
Winter rainfall	0.49	0.28	0.19	0.13	0.78
Mean annual temperature	0.96	0.14	0.10	0.10	0.12
Lowest monthly mean temperature	0.94	0.21	0.06	0.07	0.10
Highest monthly mean temperature	0.85	0.17	0.27	0.17	0.17
Mean value of minima temperature in the coldest month	0.86	0.35	0.04	0.04	0.16
Mean value of maxima temperatrue in the warmest month	0.90	0.08	0.16	0.16	0.18
Drought length	0.88	0.23	–0.12	0.07	0.20
Intensiy of drought	0.85	0.18	–0.22	0.03	–0.12
Annual evapotranspiration	0.96	0.10	0.10	0.10	0.14
Spring evapotranspiration	0.95	–0.02	–0.15	–0.01	–0.01
Summer evapotranspiration	0.86	0.09	0.24	0.15	0.22
Autumn evapotranspiration	0.88	0.22	0.09	0.18	0.22
Winter evapotranspiration	0.85	0.28	–0.02	0.00	0.01
Annual physiological drought	0.78	0.19	0.31	–0.14	0.18
Surplus	0.30	0.29	0.27	0.15	0.85
Fine fraction	0.17	–0.01	–0.61	–0.23	0.00
Sand	–0.11	–0.13	–0.36	–0.85	–0.14
Clay	0.09	0.40	0.02	0.87	0.05
CCC	0.06	0.38	0.09	0.77	0.13
Permeability	–0.07	–0.22	–0.09	–0.93	–0.05
Equivalent humidity	0.12	0.24	0.37	0.85	0.13
Organic matter	0.06	0.26	0.91	0.08	0.12
Total organic matter	0.04	0.32	0.90	0.09	0.11
pH	0.25	0.81	–0.04	0.01	0.10
Calcium	0.12	0.79	0.29	0.42	0.04
Potasium	0.21	0.74	0.25	0.34	0.20
Conductivity	0.21	0.80	0.25	0.23	0.20
Carbonates	0.22	0.70	0.01	0.34	0.21
Active carbonates	0.16	0.63	0.01	0.40	0.22
Nitrogen	0.16	0.41	0.76	0.27	0.13
Magnesium	0.21	0.78	0.11	0.04	0.09
Cationic exchange capacity	0.23	0.73	0.35	0.29	0.01
Saturation rate	0.11	0.79	0.24	0.34	0.01
Base sum 1st horizon	0.13	0.83	0.41	0.25	0.15
Saturation rate 1st horizon	–0.02	0.67	0.39	0.36	0.15
Bulk density 1st horizon	0.05	–0.14	–0.85	–0.08	–0.25
Organic matter 1st horizon	0.03	0.16	0.91	–0.03	0.13
Calcium 1st horizon	0.04	0.66	0.47	0.36	0.13
Magnesium 1st horizon	0.20	0.78	0.21	0.03	0.11
Cationic exchange capacity 1st horizon	0.25	0.67	0.53	0.14	0.10
Nitrogen 1st horizon	0.13	0.30	0.82	0.04	0.15
Clay horizon B	0.07	0.33	–0.08	0.88	0.01
Eigenvalue	12.45	9.68	7.18	6.01	3.55
% Variance explained	0.32	0.25	0.18	0.15	0.09
Cumulative % variance explained	0.32	0.57	0.75	0.91	1.00

the fifth axis. Again, when plotting factorial axis using site index as a supplementary variable no clear distinction is detected in the pattern of dispersion. Dolomite stands are clearly grouped together according to the second axis. Little information is gained with this analysis comparing when only climatic variables are consi-

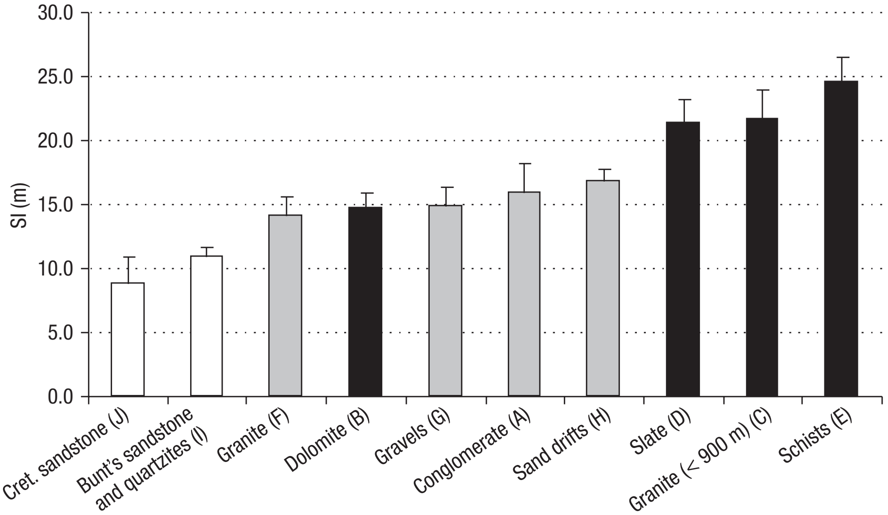

Figure 3. One-way analysis of variance of climatic groups according to parental material information, where black bars indicate warm and humid sites, grey bars are climate intermediate sites and white bars are cold and dry sites. The letter in brackets indicates the same code used in Figure 2.

dered. Thus, we put aside soil profile information in the formation of environmental groups to evaluate differences among mean site index, but taking into account that this information will be useful for predicting purposes.

One-way analysis of variance

The overall analysis of variance of climatic regions led to the rejection of the null hypothesis of equal site index values among regions. Figure 3 shows the multiple mean comparison results of the analysis of variance using defined groups.

The higher site indices are found in humid and warm sites (C, D, E, located in the western area) with the exception of stands growing on dolomites (B), which show statistically significant lower site indices (Fig. 3). Another group is formed by a broad set of stands that follows an altitudinal gradient (dashed line in Fig. 2). These can be considered of medium productivity on average. They include several parental materials such as conglomerate (A), dolomite (B), granite over 900 m of altitude (F), gravels (G) and sand drifts (H).

Finally, stands with the lowest productivity are located at the coldest sites in the Iberian Mountain Range on Bunt sandstone and quartzite (I) and cretaceous sandstone (J), in the east of the study area. According to these results, stands may be ordered from those with the highest productivity in the western part of the study area to the lowest productivity in the eastern part.

Explanatory analysis: Partial Least Squares Regression

One of the aims of PLS is to identify the number of components that account as much Y variation as X variation. Figure 4 shows the variance explained (y-axis) against the number of components (x-axis) for the response variables and for predictors. The point where both curves crosses indicate the number of components beyond which there is little information gained by increasing the number of selected components. The site index variation explained by the model is 56.2% using 41.5% of the original information from the predictors' matrix. The first component is associated to elevation,

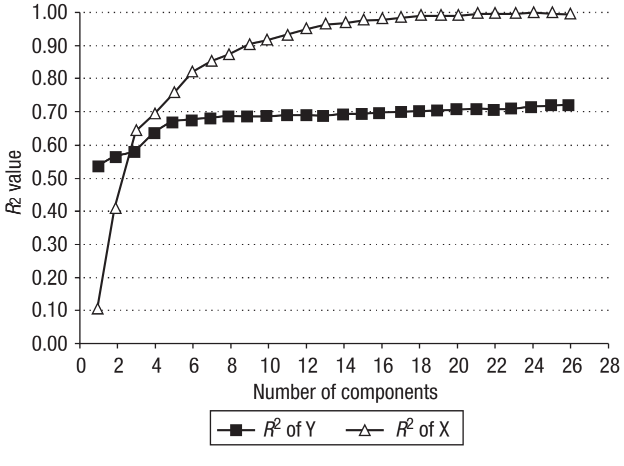

Figure 4. Variance explained of Y and X's by PLS components.

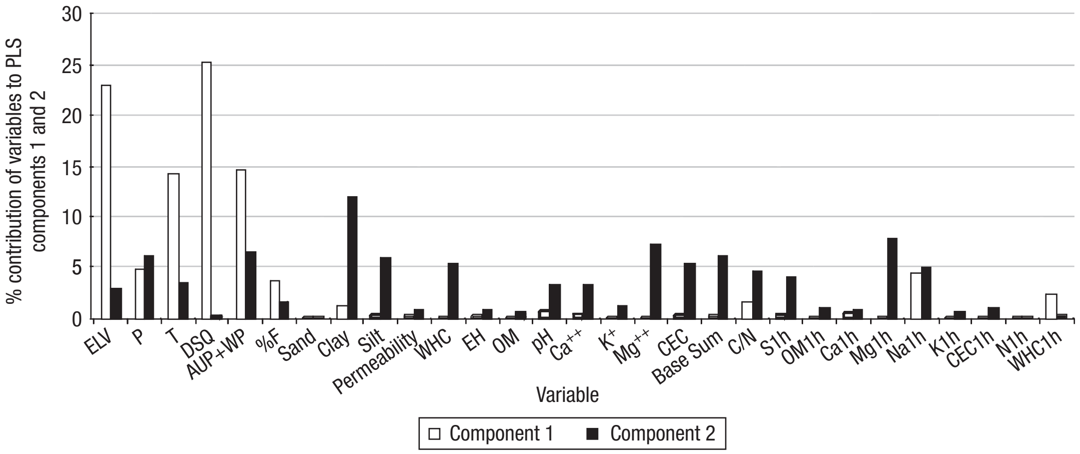

Figure 5. Percentage of variation explained by each variable in two PLS components.

mean annual temperature, drought length and the sum of rainfall in winter and autumn (Fig. 5). Component 1 only uses 10.5% of information from predictors but it is able to predict 53.1% of site index variability. The second component can be associated to annual water availability (annual rainfall), soil water storage (sand and fine percentage, water holding capacity), and clay content. Nutrient status represented by carbon nitrogen ration and magnesium content in the first horizon have some influence in site index variation The gain of explanation of site index variability is very poor (3%) comparing the large percentage of predictor variability gained (31%).

Predictive analysis: multiple linear regression

A multiple linear regression was fitted to data in order to achieve a parsimonious model that helps in making decisions to classify stands according to site index classes, in the case of absence of dominant trees. In the course of the preceding PCA analysis, we have seen how site index values follow a positive longitudinal gradient from east to west. Longitude is highly correlated with elevation (correlation coefficient 0.76). Temperature and seasonal precipitation are another important factor in site index variation as indicated by PLS analysis. Soil properties account little for site index variation but, comparatively, they increased the predictor variability in the analysis. The variables that loaded most in the second component are related to soil water storage or impediment for root depth such as fine percentage, water holding capacity or clay content. Consequently, we tested to fit linear models that include some of the following variables: elevation, temperature, precipitation, fine percentage, clay content in the B horizon and carbon nitrogen ratio.

The best fit was achieved using two equations. The first equation explained 55.2% of site index variation. Predictors were seasonal precipitation in winter and autumn, squared elevation and squared temperature. When soil clay content was included as predictor, temperature was not significant and this lead to its exclusion in a second equation that explained 56.6% of site index variation (Table 6). This exchange between clay and temperature as predictors deserved a deeper insight according to regions defined in PCA analysis. Results indicated that site index of stands growing in warm and wet conditions is better predicted using the linear model that includes clay content whereas predictions in the rest of regions are better achieved by the temperature-based model. The superiority of the temperature linear model is higher in the intermediate climate where the site index value is also intermediate (Table 6).

Discussion

This work confirms the great variability of soil and climatic conditions in the southwest Europe distribution area of MMP and the relationship between this environmental variability and site index. This is an expected result as our data lay within the auto-ecological parameters defined by Gandullo and Sánchez-Palomares (1994). These authors also built a soil-site predictive model based on observations and discrete site quality classes according to a base age specific site index mo-

Table 6. Multivariate linear regression analysis and evaluation by PCA regions

Fitting phase

Model	Adj-R^2	RMSE	Bias
$SI_T = 17.6\text{-}0.0000079ELV^2 + 0.0353PR\text{-}0.0435T^2$	0.552	2.88	$-0.0016^{\text{n.s.}}$
$SI_{Clay} = 12.5\text{-}0.0000057ELV^2 + 0.0285PR\text{-}0.0945Clay$	0.567	2.83	$-0.0081^{\text{n.s.}}$

Evaluation phase

Regions	Model	Bias		Accuracy	
		MPRESS	%MPRESS	RMSEp	RMSEp%
V1	SI_T	0.87 n.s.	4.55	3.26	17.12
	SI_{Clay}	0.20 n.s.	1.05	3.10	16.24
V2	*SIT*	0.03 n.s.	0.20	3.25	19.89
	SI_{Clay}	0.84 n.s.	5.15	3.18	19.46
V3	*SIT*	–0.37 n.s.	–2.48	3.80	25.52
	SI_{Clay}	–0.54 n.s.	–3.60	3.29	22.13
V4	*SIT*	–0.13 n.s.	–1.23	3.33	30.32
	SI_{Clay}	–0.33 n.s.	–2.97	3.46	31.51

V1: warm and wet cliamte. *V2:* intermediate cliamte. *V3:* dolomite. *V4:* cold and dry climate (see caption on Fig. 3).

del using mean height instead of dominant height. Unfortunately, the stand variables that they used in their study are not available and we cannot calculate the site index value according to Bravo-Oviedo *et al*. (2007) base age invariant model in order to contrast both results.

Climatic PCA defines homogenous regions in terms of temperature and precipitation. Within each of these climatic regions there exists variability in site index values leading to a not so clear relationship between site index value and climatic regions. However, there is a patent longitudinal gradient from the poorest site indices, which are located in the east on cold and dry sites, to the best site indices on warm and wetter climate in the west. The intermediate stands are located in the central part of Spain and northwards, mean site index is around 15-16 m and although there are also cold sites, like those located on conglomerate rock type, the precipitation is higher than in the eastern stands. Other exception to the longitudinal gradient is the dolomite stands. They have a warm and humid climate like the group with the best site index values; however they have a lower site index than expected according to climate.

Precipitation and temperature seem to be the most important environmental factors explaining extreme site index qualities. However, the variability in some of them indicates that site index variability is therefore partly due to other environmental characteristics. Dolomite rock increases magnesium content that can block the adsorption of other cations leading to nutrient deficiencies. In addition, precipitation is relegated to the fifth axis when climatic and edaphic variables are analyzed jointly in PCA, explaining only 4% of variation (results not shown). The second component is then devoted to chemical properties, such as pH, that differentiates dolomite stands.

The components of principal component analysis do not show any discernable relationship with site index values. This is due to the fact that PCA searches for latent variables or factors which explain the variability of independent variables (X) and, as a result, the use of these factors in an ordinary regression analysis (*i.e.* $Y = f(F_1, F_2 \ldots)$, where F_i is a linear combination of X variables) often leads to poor results. As a generalization of PCA, the partial least square regression is capable of finding factors to explain X variables that are also important for Y variables (Abdi, 2003). As a drawback, the PLS model still needs many independent variables.

Studies undertaken in temperate and boreal areas indicate that high temperature is related to high site index values (Fries *et al*., 2000). However, in warmer areas, such as the Mediterranean basin, this effect is positive if precipitation is also high. If this is not the case, the temperature would increase water deficit and site index values may be lower than expected. Seynave *et al*. (2005) described a parabolic relationship between site index and elevation. This relationship is positive up to a maximum elevation after which it decreases. Our predictive model shows the decreasing part of this relationship whereas the positive, increasing part is reflected by other variables such as precipitation, since a positive relationship exists between elevation and rainfall. However, the stands located at low elevation sites are the most productive in the entire study area. This may be explained by the orientation of the mountains. Rain clouds come from the southwest and west component. They reach the western part of the central mountain range orthogonally and leave precipitation in this region firstly (Nicolás and Gandullo, 1967). This means that precipitation decreases from west to east, so does site index.

Chen *et al*. (2002) found that climatic variables and local soil conditions are good predictors for large geographic areas, whereas soil and foliar nutrient concentrations lead to excellent predictive site index models in smaller areas (Sánchez-Rodríguez *et al*., 2002). We can only corroborate this fact if we divide the study area in four groups, for example, in the western part of the study area (*V1*, see Table 6) where the temperature model showed higher bias than the clay content model. Contrary, in *V3* region temperature plays a major role in site index estimation even if clay content is higher in these stands than in the *V1* region. In cold and dry regions (*V2* and *V4*) temperature is a main driver of site index estimation because of the lack of precipitation which indicates that a rising in temperature lead to a decreasing trend in productivity being more intense in sandy soils. This may be explained by a high soil temperature when air temperature is also high in this area.

We are aware that soil-site studies are designed to evaluate potential productivity in terms of site index when proper trees are not available. The predictive models presented here are unbiased and their precision is high enough to be considered for management purposes until proper trees are available and site index assessment using base age invariant site index curves can be performed. If a forest manager needs to use one of the models proposed here we suggest that the temperature-based model is the best option. However, when predicting site index in stands located in the western part of the species distribution a larger error is expected. Consequently, the forest manager should consider if the cost associated to soil profile analysis outperforms the cost of committing a larger error when applying the temperature-based model.

The wide use of multiple linear regressions to estimate forest productivity, in spite of its lack of accuracy, is due to its simplicity and utility when no other information exists. Conceptually, the linear relationship between dendrometric values and environmental features might be untenable because many of the relationships in nature are non-linear because of interactions, compensations or facilitation processes. Some empirical efforts have been done (Romanyà and Vallejo, 2004) to model nonlinear soil-site relationships, and other promising approach to overcome the linear limitation is the use of neural networks (Lek *et al.*, 1996), although the need of large databases to train the net and the «black-box» assumption, which lay underneath, makes its use less general than expected.

The attempts to have multiple linear models to predict site index values in broad areas are always poor comparing to another approaches, such those that use synoptic variables. The reasons for such low predicted availability according to Monserud *et al.* (1990) are the number of factors that can exceed the sample size, and the failure to measure the true causes of site productivity. Another likely cause is the nonlinearity of soil-site index relationship and the interactions that we were unable to detect by using a linear approximation. In a parallel study published earlier (Bravo-Oviedo *et al*. 2008) a nonlinear model parameterized according to the generalized algebraic approach (GADA) showed how the inclusion of precipitation in winter and autumn, mean annual temperature, drought length and rock type (dolomite versus non dolomite) increase the predictive ability of this type of models. The model was plot-based and consequently the site index estimation was considered local. Here, we present a region-based linear approximation to be used in case of lack of appropriate dominant trees where Bravo-Oviedo *et al*. (2008) model cannot be applied.

Conclusions

Three main broad site index groups according to climatic characteristics may be defined in the distribution area of Mediterranean maritime pine in Spain according to the mean annual temperature, precipitation during autumn and winter, and elevation. These climatic attributes, along with soil features such as clay content, satisfactorily explained site index for the intended purpose. Partial least squares regression provides a useful tool for selecting environmental predictor variables in soil-site models, avoiding the necessity to apply any variable selection method in stepwise multiple linear regressions.

Acknowledgement

The authors want to thank C. Ordóñez, A. I. Lucas, I. Lizarralde, R. Ruiz-Peinado, E. Garriga and R. Calama who helped in soil sampling. We are in debt to Dr. Fernández-Cancio for providing climatic data and two referees for their comments on a early manuscript. Otilio Sánchez-Palomares helped in soil analysis. A. Bravo-Oviedo is deeply grateful to Dr. Curt and Michel Vennetier (from CEMAGREF-Aix-en-Provence; France) for their assistance in using multivariate techniques during a first attempt to analyze part of the data used in this study. This study was financially supported by projects OT-03-002, AGL 2004-007094-C02-02 and AGL-2007-65795-C02-01.

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