Potential productivity of forested areas based on a biophysical model. A case study of a mountainous region in northern Spain

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Original article

Potential productivity of forested areas based on a biophysical model. A case study of a mountainous region in northern Spain

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Abstract
• Today's forest managers face a number of important challenges involving an increasing need for precise estimates of forest structure and biomass, potential productivity or forest growth. The objective is to develop a model for potential productivity in a mountainous region of Spain. The model combines climatic, topographic and lithological data using a variant of a traditional biophysical model: the Paterson index.
• In a first approach, the climatic productivity is assessed by modelling the required parameters using different geostatistical techniques and software supported by GIS. A second approach includes the correction of the former productivity classes considering the different lithological *facies*. The potential forest productivity model involves the integration of both models.
• Finally, data from the National Forest Inventory (NFI) are used to compare the real and potential yield data within different regions of the studied area.
• The results of these analyses demonstrate the usefulness of the model, particularly in mountainous regions, where no significant differences are found between the data from the NFI and the model, but they also show the discrepancies between the estimates and real data when the latter are considered for different tree species, diameter classes or management.

Mots-clés :
techniques géostatistiques / SIG / gestion de l'usage des sols / modélisation / rendements

Résumé – Productivité potentielle des forêts à partir d'un modèle biophysique. Étude du cas d'une région montagneuse dans le nord de l'Espagne.
• Les gestionnaires forestiers doivent actuellement faire face à de nombreux défis qui impliquent un besoin croissant d'estimateurs précis de la structure et de la biomasse, de la productivité potentielle et de la croissance des forêts.
• L'objectif de ce travail est la modélisation de la productivité potentielle dans une région montagneuse de l'Espagne. Le modèle combine des données climatiques, topographiques et lithologiques et se base sur une variante d'un modèle biophysique classique : l'indice de Paterson.
• Dans une première approche, la productivité climatique est estimée en modélisant les paramètres requis grâce à différentes techniques géostatistiques et de logiciels relevant des systèmes d'information géographique (SIG). Une deuxième approche consiste corriger les anciennes classes de productivité en prenant en compte les facies lithologiques. Le modèle de productivité forestière potentielle a été obtenu en combinant ces deux modèles. Finalement, les données de l'Inventaire Forestier National (IFN) sont utilisées pour comparer les rendements réels et potentiels dans les différentes régions de la zone étudiée.
• Les résultats de ces analyses ont montré l'utilité du modèle, en particulier dans les régions montagneuses, où aucune différence significative n'a été décelée entre les données IFN et le modèle. Ces résultats ont cependant mis aussi en évidence des divergences entre la productivité potentielle et données réelles lorsque l'on compare différentes espèces, classes de diamètre ou modes de gestion.

1. INTRODUCTION

Today's forest managers face a number of important challenges. One of the most critical is the need to provide forest

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products for an increasing world population despite a shrinking natural-resource base challenged by climate change, desertification, environmental pollution, loss of biodiversity and other stresses. Forests have acquired a renewal and special significance due to their key role in environment conservation, recreation and sustainable production as one of the bases of rural development. In current forest science research, the requirement to encompass this new paradigm involves an increasing need for precise estimates of forest structure and biomass, potential productivity or forest growth (Tickle et al., 2001), and modelling on different scales, from stand to landscape level. In this regard, a deep knowledge of forest productivity of the states is essential to develop forestry and land use plans and policies (Lansberg, 2003).

Different criteria and methods have been used to evaluate forest site productivity (Vanclay, 1994). A traditional classification divides the variety of approaches into phytocentric, considering the phytomass production as the ultimate measure of a site's productivity, or geocentric methods, asserting the dependence of site productivity upon soil and climatic variables. Among phytocentric approaches, the use of a site index is broadly accepted as a surrogate for the potential productivity for pure even-aged stands (Wang et al., 2005). However, there are some cases in which the site index seems to be an inappropriate tool since it is linked to a specific species and forest structure (Bravo and Montero, 2003; Bravo-Oviedo and Montero, 2005; Monserud and Sterba,1996). Hence, it is impossible to obtain this index where there are no trees, where the species concerned is not present (Ung et al., 2001) or with some specific species, e.g. *Quercus* spp. (Adame et al., 2006), due to their traditional management techniques (coppice or pruning) or their slow growth rate. Furthermore, a site index should not be used for young stands, since a slight error in estimation at this age could lead to a much larger error, as the curves tend to join at age zero (Goelz and Burk, 1992). Thus, alternative methods to phytocentric ones for site productivity assessment are important.

The prediction of the site index from site attributes (geocentric) has been researched thoroughly, although it is difficult to test them against the true site productivity (Daniel et al., 1979). Main approaches have developed models based on climatic, topographic, soil and biotic factors (Vanclay, 1994). The best known climatic index of forest growth is Paterson's CVP index (Paterson, 1956) which was designed to predict the maximum growth potential in terms of volume production (Hägglund, 1981; Johnston et al., 1967). Traditionally, this index has been used for large areas, even on a global scale (Lemieux, 1961; Sánchez Palomares and Sánchez Serrano, 2000). Nevertheless, with the aid of new technologies and the existence of more and better data sets, this index can be applied on regional scales. In spite of its limitations, it can be very useful for comparing zones located within the same region, regardless of the presence or absence of trees, the age of the stand or the species (Vanclay, 1994).

Simulation modelling has been proven as a practical and effective approach for forest dynamics and yield research throughout time and space. In fact, it is an economically efficient way – maybe the only one – to investigate the implications of different management strategies (Bravo and Díaz-Balteiro, 2004; Rodríguez Soalleiro et al., 2004), or the upscaling of productivity estimates from individual sites to larger areas (Bernier et al., 1999; García López and Allué Camacho, 2006; Landsberg and Waring, 1997). Besides, some other "Digital Forestry" techniques such as geographic information systems (GIS) have become some of the most useful and widespread tools in forestry and information management (Shao and Reynolds, 2006).

The aim of this study is to review a model of potential productivity initially developed by Serrada (1976), and later revised by Sánchez Palomares and Sánchez Serrano (2000) for mainland Spain. This model is based on a modified bioclimatic index: the Paterson Index, weighted according to lithology. It has been widely used by forest managers in Spain with acceptable results on regional scales. In this study we propose new approaches for the required inputs, using GIS and other statistical tools such as geostatistical techniques to improve base climatic models. In addition, the results of this geocentric approach are tested for the first time using actual yield data, applying this methodology to a complex and mountainous region in the North of Spain, Asturias.

2. MATERIALS AND METHODS

2.1. The study area

The study area comprises the region of Asturias in North Spain, covering an area of 10 604 km^2. Its northern boundary is the Cantabrian Sea (with a coastline of 354 km), and the Cantabrian Mountains form a natural border to the South (Fig. 1a). This region is characterised by steep topography, with altitudes ranging from sea level to 2 648 m in just 40 km. Thus, 80% of the territory has slopes greater than 20% and 34.5% exceeds 50%.

2.2. Data

The initial data were the mean monthly temperatures and rainfall obtained from the meteorological stations of the National Meteorology Institute located in Asturias and nearby provinces (Fig. 1b). According to the World Meteorological Organisation, a 30-year period is required to establish the climatic baseline. Therefore, the 1970–2000 data set was used for the modelling, previously completing the missing data through regression analyses. A Digital Elevation Model (DEM) was taken as ancillary data, with a spatial resolution of 50 m.

Data obtained from the plots of III National Forest Inventory of Spain (NFI) (Ministry of Environment of Spain, 2003) were compared with the model. The forestry database in Asturias comprises a total number of 1 877 plots, which means one plot every 240 ha. For this study a total of 836 plots was selected, being those which were most significant in terms of forestry and productive species (Fig. 1). These species were *Pinus sylvestris* L., *Pinus radiata* D. Don, *Pinus pinaster* Aiton., *Eucalyptus globulus* Labill., *Betula* spp., *Fagus sylvatica* L., *Castanea sativa* Mill., *Quercus robur* L. and *Quercus petraea* (Mattuschka) Liebl., and a minimum basal area of 15% of any of these species was required for the selection. Production data

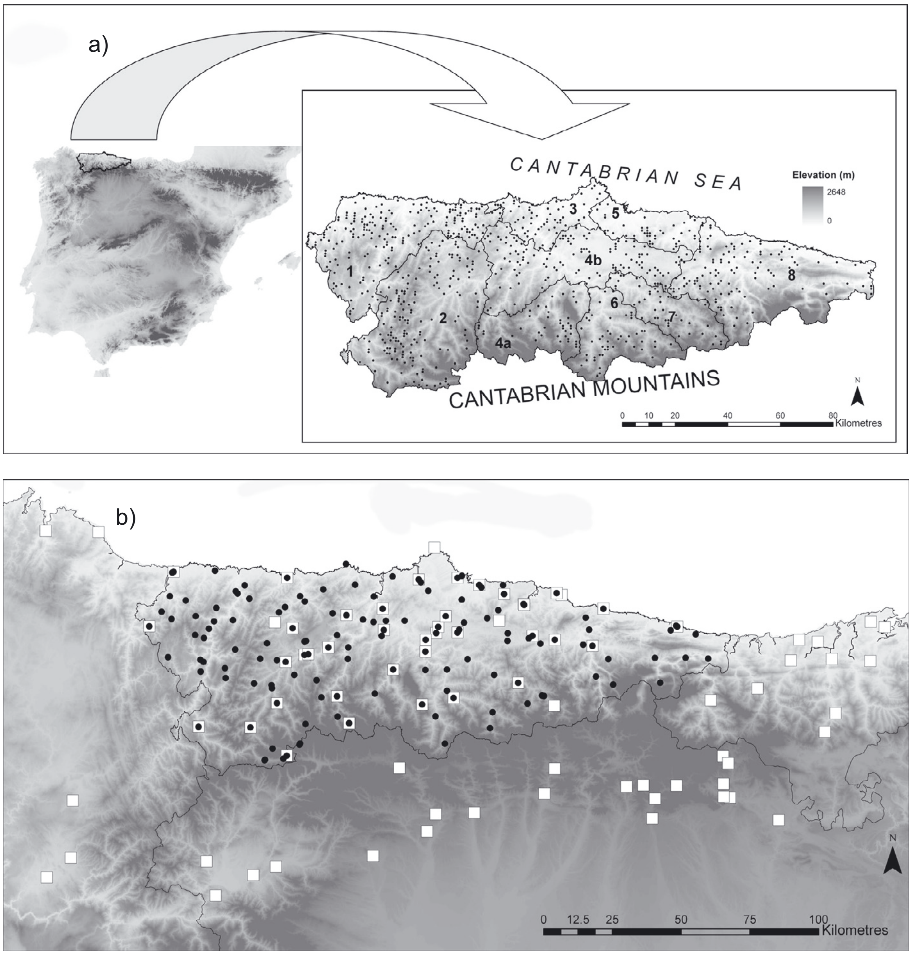

Figure 1. (a) Location of the study area, with its regions and the locations of the selected plots from the III National Forest Inventory (the number of plots per region -R- is: 191 for R1; 163 for R2, 59 for R3; 42 for 4Ra; 125 for R4b; 45 for R5; 50 for R6; 43 for R7; and 118 for R8). (b) Location of the selected meteorological stations to model the climatic variables (white squares are the stations with temperature data, and black circles are stations used to model rainfall data).

(annual increment in volume of wood per ha, henceforth AIVW, defined as $m^3\,ha^{-1}\,yr^{-1}$) and the UTM coordinates of every plot were obtained using the BASIFOR software (Del Río et al., 2002), version 2.0. (Bravo et al., 2005) developed by the University of Valladolid (Spain). Productive data for the different tree species and diameter classes (sorted every 10 cm) were recorded in each plot. The BASIFOR 2.0. software uses data from the II and III NFI, comparing the volume of every marked tree to assess the increment in volume, according to tree volume tables, and applying some factors to extend the results per hectare.

2.3. Climatic Productivity

The Paterson Index (PI) used in this work is a variant developed by Serrada (1976).

$$PI = \frac{V.P.G.f}{A.12} \tag{1}$$

where V is the mean monthly temperature of the warmest month (°C); A is the difference between the mean maximum temperature of the warmest month and the mean minimum temperature of the coolest month (both in °C); P is the mean annual rainfall (in mm), calculated as the sum of the 12 mean monthly rainfall; G is the length (number of months) of the growing period according to the Gaussen criteria (Gaussen, 1954); that is, the total number of months in which rainfall (mm) was more than double the mean temperature (in °C), as long as this temperature was equal to or exceeded a minimum threshold of 6 °C. Finally, f is the insolation factor proposed by Gandullo (1994):

$$f = \frac{2500}{(n + 1000)} \tag{2}$$

where n is the number of sun hours in one year.

To assess and lay out the spatial modelling of these ecological variables, all the techniques used and exposed below were implemented using the software ArcGis 9.0 (ESRI, Inc., Reedlands, 2004).

The insolation factor f decreases when the number of sun hours increases. It is considered that the growth of forest covers in the Iberian Peninsula, with frequent summer droughts and with a high number of annual sun hours, is favoured by low insolation, which reduces evapotranspiration and increases height growth. The number of sun hours was estimated through an approach based on the model developed by Kumar et al. (1997). The original model consisted of a program

Table I. Description of the productive classes and sub-classes, with their lithologic correction coefficient (C) and productivity ranges ($m^3\ ha^{-1}\ y^{-1}$) (Serrada, 1976).

Class	C	Subclass	Production	Description
		Ia	> 9.0	
I	1.66	Ib	8.25–9.0	No limitation for productive forest growth
		Ic	7.5–8.25	
		IIa	6.75–7.50	
II	1.44	IIb	6.0–6.75	Slight limitations for productive forest growth
		IIIa	5.25–6.0	
III	1.22	IIIb	4.50–5.25	Moderate limitations for productive forest growth
		IVa	3.75–4.5	
IV	1	IVb	3.0–3.75	Moderately severe limitations for productive forest growth
		Va	2.25–3.0	
V	0.77	Vb	1.5–2.25	Severe limitations for productive forest growth
		VIa	1.0–1.5	
VI	0.55	VIb	0.5–1.0	Very severe limitations for productive forest growth
VII	0.33	VII	< 0.5	Enough limitations to hinder the growth of any productive forest
VIII	0	VIII	0	Unproductive lands

that was capable of estimating the ground radiation, even in mountainous regions, because it took into account both slope and aspect, and was supported by formulas which incorporated latitude, the day of the year, the time of the day and the azimuth. In any case, this model only considered radiance in cloudless conditions. In the variant used in this study, the hours per day when radiation measurements exceeded 120 $W\,m^{-2}$ (minimum threshold detected by heliographs) were computed. Estimates were assessed every 20 min.

To obtain the parameters V, A, P and G, it was necessary to model the monthly rainfall and mean temperatures, and the mean maximum and minimum temperatures of the warmest and the coolest months, respectively. First, data from meteorological stations for a 30-year period were selected (1970–2000), refined, filtered and completed with regression analysis, and then the modelling was carried out using geostatistical techniques, attempting to identify the approach which gave the least estimation errors. Full details of the techniques applied can be found in Benavides et al. (2007), in which 5 geostatistical methods were compared for estimating the mean January and August temperatures in Asturias. In the present study, the five geostatistical techniques were compared for the monthly rainfall and temperature estimates. The methods included ordinary kriging (OK), developed in the XY plane and in the X, Y and Z axes (OKxyz), with zonal anisotropy in the Z axis, along with three techniques that included elevation from the DEM as an explanatory variable: ordinary kriging with external drift (OKED) and universal kriging, using the Ordinary Least Squares residuals to estimate the variogram (UK1) or the Generalised Least Squares residuals (UK2). The spatial resolution of the resulting models was a pixel size of 0.25 km^2. Once the models were mapped, the mean error or bias (ME) and the mean absolute error (MAE) at the observed points were computed to determine the accuracy of the different approaches.

2.4. Potential versus real forest productivity

Apart from climate, soil is another important factor related to plant growth and as such, should be taken into account (Bravo-Oviedo and Montero, 2005; Milner et al., 1996; Wang et al., 2005). Hence, a correction of the climatic productivity was carried out based on the lithology map of Asturias on a 1:25 000 scale (Environmental and Territorial Cartography Centre of Asturias), previously rasterised with a spatial resolution of 10 m. The different types of *facies* were sorted into eight productive classes, according to the productive characteristics of the soils normally derived from them. Next, each productive class was given a correction coefficient (C) according to the values given in Table I (Sánchez Palomares and Sánchez Serrano, 2000). These coefficients resulted from a study of the yield tables of native species under similar management regimes, inferring that yield variations were attributable to differences in soils.

The relationship between the PI and the real productivity was assessed through Equation (3), an algorithm developed by Paterson and validated for mainland Spain by Serrada (1976). Hence, the map of potential forest productivity (PP) for Asturias was obtained through Equation (4), with the previously modelled input variables. The climatic variable models were resized to reach the same pixel size as the lithological input; thus, the spatial resolution of the output was likewise 10 m. Then the land was classified into different productive classes (Tab. I) according to the resulting figures.

$$PP = 5.3 \cdot \log PI - 7.4 \tag{3}$$

$$PP = C \cdot 5.3 \cdot \log\left(\frac{V f PG}{A12}\right) - 7.4. \tag{4}$$

Once the potential productivity model was mapped, their values in every plot previously selected from the NFI were compared with the real figures. In the present study, Asturias was divided into 8 regions (Fig. 1). Each region is similar in terms of the environment, population, main economic sectors, and the quality and quantity of infrastructure, equipment and communications. Region 4 was subdivided since the area was very large and had two very distinct regions: a mountainous part (4a) and an inner part (4b).

Correlations and univariate analyses of variances were carried out in each of the 9 regions, using the SPSS software (SPSS, Inc., Chicago, 2004). The analysis of variance made it possible to identify in every region where the real data (AIVW) from the NFI, with all the main species pooled together, and the potential productivity data (obtained from the model) were similar, and where they were not. Then, correlation analyses were carried out to identify the factors which contributed to the dissimilarities between the two data sets;

Table II. Mean Error (ME) and Mean Absolute Error (MAE) obtained estimating mean monthly temperatures (T) and rainfall (R), and the mean minimum temperature of January (MinJ) and mean maximum temperature of August (MaxAg), with different techniques: Ordinary Kriging (OK) in the XY plane, and with anisotropy in the Z axis (OKxyz), Ordinary Kriging with External Drift (OKED) and two variants of Universal Kriging (UK1 and UK2).

			January	February	March	April	May	June	July	August	September	October	November	December	MinJ	MaxAg
T (°C)	ME	OK	0.05	0.03	0.05	0.04	0.04	0.02	0.06	0.03	0.03	0.04	0.05	0.05	0.10	0.03
		OKxyz	0.02	0.02	0.00	0.03	0.02	0.01	0.05	0.01	0.04	0.03	0.04	0.03	0.02	–0.01
		OKED	0.02	0.01	0.02	0.02	0.02	0.03	0.04	0.03	0.03	0.03	0.02	0.04	0.02	–
		UK1	0.02	0.01	0.02	0.02	0.02	0.03	0.04	0.03	0.04	0.03	0.02	0.03	0.02	–
		UK2	0.02	0.01	0.03	0.03	0.02	0.09	0.05	0.03	0.03	0.03	0.03	0.03	0.03	–
	MAE	OK	0.73	0.74	0.76	0.83	0.82	0.80	0.80	0.79	0.76	0.71	0.69	0.69	0.87	1.05
		OKxyz	0.67	0.57	0.55	0.52	0.49	0.51	0.49	0.57	0.51	0.54	0.57	0.77	0.67	0.80
		OKED	0.77	0.62	0.55	0.53	0.55	0.61	0.67	0.62	0.48	0.51	0.65	0.58	1.09	–
		UK1	0.79	0.60	0.55	0.54	0.53	0.61	0.65	0.62	0.51	0.52	0.65	0.79	1.09	–
		UK2	0.78	0.62	0.56	0.57	0.53	0.63	0.57	0.61	0.53	0.57	0.66	0.61	1.00	–
R (mm)	ME	OK	0.13	0.10	0.17	0.19	0.08	0.09	0.25	0.18	0.06	0.37	–0.07	–0.18	–	–
		OKxyz	–0.42	–0.28	–0.22	–0.13	–0.11	–0.06	0.13	0.21	–0.05	0.15	–0.10	–0.33	–	–
		OKED	–0.04	–0.12	–0.02	0.06	–0.05	–0.01	0.17	–	–0.06	0.17	–0.20	0.16	–	–
		UK1	–0.06	–0.14	–0.02	0.12	0.06	–0.02	0.16	–	–0.08	0.15	–0.25	–0.33	–	–
		UK2	0.02	0.04	–0.06	–0.03	–0.08	–0.02	–0.02	–	0.06	0.19	–0.24	–0.32	–	–
	MAE	OK	13.42	13.44	13.73	14.59	11.89	7.33	6.84	7.73	9.03	11.85	15.32	18.29	–	–
		OKxyz	13.31	12.92	13.96	16.44	11.03	7.02	6.83	8.36	8.83	11.66	15.76	17.21	–	–
		OKED	12.76	12.62	13.48	14.12	10.65	6.76	6.56	–	9.21	10.59	14.67	17.81	–	–
		UK1	12.82	12.76	13.48	14.68	11.97	6.80	6.60	–	8.66	10.67	14.81	17.21	–	–
		UK2	12.80	12.71	13.12	13.89	10.47	6.67	6.22	–	8.59	10.67	14.81	16.89	–	–

thus, the AIVW data were correlated with variables resulting from the management such as the type of tree species (slow- and fast-growing species), the diameter classes and the stems per ha.

3. RESULTS

3.1. Modelling the ecological variables

The monthly rainfall, mean temperatures, and mean maximum and minimum temperatures of the extreme months were spatially modelled using the five geostatistical techniques, generating regional maps from point data (Fig. 1b) previously analysed (filtered, and completed by estimating missing data with regression analysis) for each month. The errors associated with the different methods can be seen in Table II. The estimates were more precise when elevation data were taken into account. Hence, OKxyz was proven to be the best and selected to model the temperatures and UK2 for rainfall modelling. The mean rainfall of August was an exception because no correlation was found between the variable and the elevation, therefore OK was run with the lowest error.

It should be noted that temperature errors were inferior to ± 1°C and were fairly unbiased since the mean errors were very close to zero. In general, the errors in summer predictions were smaller than those for winter. With regard to rainfall, the absolute residuals were lower in summer, coinciding with the drier season. However, errors in spring and autumn were proportionally inferior as the rainfall was more regular during these months. On average, the value of MAE was 10% of the predicted rainfall.

Once the kriging techniques had been selected and the monthly climate models developed, the parameters A, V, P and G (required for the Paterson Index) were mapped (Figs. 2a–2d). Fig. 2e shows the insolation factor (Gandullo, 1994) assessed after calculating the number of annual sun hours. It can be noticed that the flat regions and South-facing hillsides presented the lowest f value since they received the highest number of sun hours. Finally, by implementing Equation (1), we obtained the potential climatic productivity map (Fig. 3a).

3.2. Potential Forest Productivity

The correction factor derived from the lithology was mapped (Fig. 3b) according to Table I. The final step was to represent the potential productivity estimates (Fig. 4a) generated by using Equation (4) with the modelled inputs. The productivity figures ranged from 2.91 to 13.11 m^3 ha^{-1} y^{-1}.

3.3. Data from the III National Forest Inventory

The Analysis of Variance showed that the production data (m^3 ha^{-1} y^{-1}) did not differ significantly ($p < 0.05$) when comparing the actual values with those of our model for regions 2,

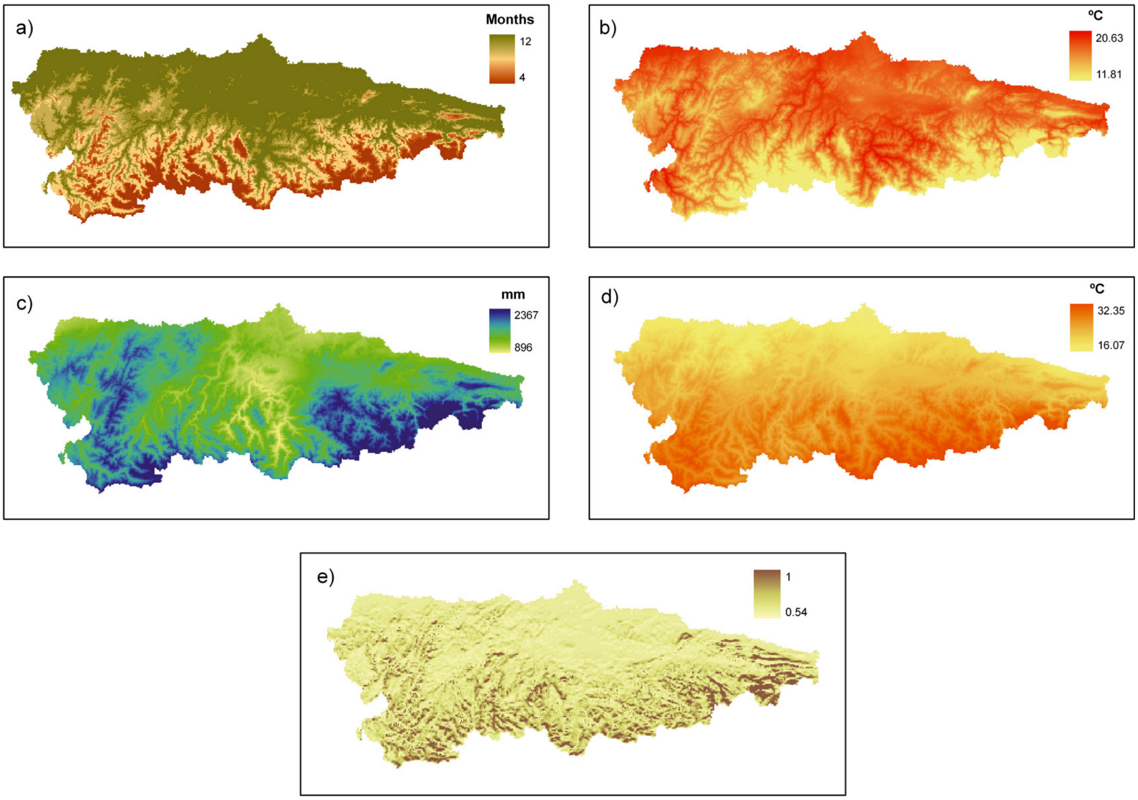

Figure 2. Modelled inputs to assess the Paterson Index: (a) number of vegetation active months; (b) mean temperature of August, in °C; (c) annual rainfall, in mm; (d) thermic fluctuation, in °C; (e) insolation coefficient.

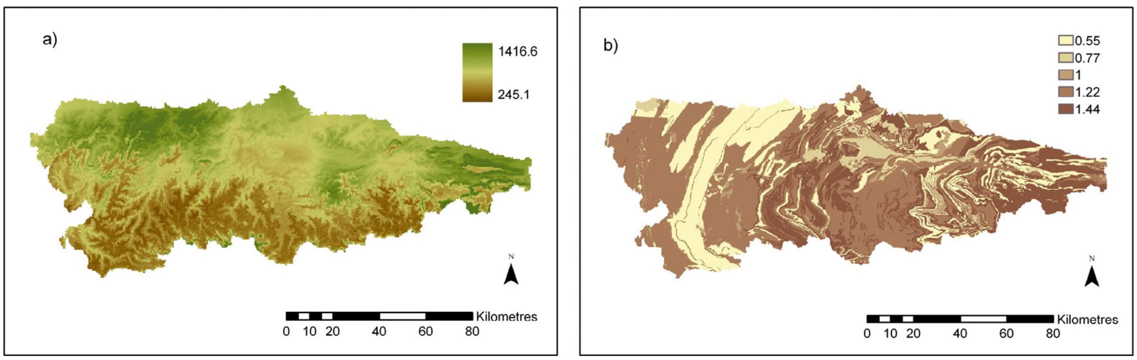

Figure 3. (a) Map of the Paterson Index model obtained in Asturias using the previously modelled inputs (Fig. 2); (b) map of the correction coefficients due to lithology, obtained after classifying the types of *facies* and using Serrada's correction factor (Serrada, 1976).

4a, 6 and 8 (Tab. III). These four regions comprised all the mountainous regions with high altitudes and steep slopes. Region 7 was the only mountainous region missing from this list.

A detailed study of the remaining regions showed that the differences between paired data (real versus potential productivity) may be the result of management factors. It was found that the type of species, the age and the stocking rate were factors which significantly influenced the real production (Tab. IV). The main factor affecting the AIVW was the tree density, with a positive correlation coefficient of $\rho = 0.800^{**}$ when data for the whole of Asturias were pooled together. The type of tree species (fast-versus slow-growing) and the diameter classes also showed significant correlation with IAVW, but negative ($\rho = -0.609^{**}$ and $\rho = -0.530^{**}$, respectively).

It was found that regions 1, 3 and 4.b (less mountainous and closer to the coast) have a real productivity higher than the potential one, with negative values resulting from the subtraction between real and potential averages (Tab. V). Higher

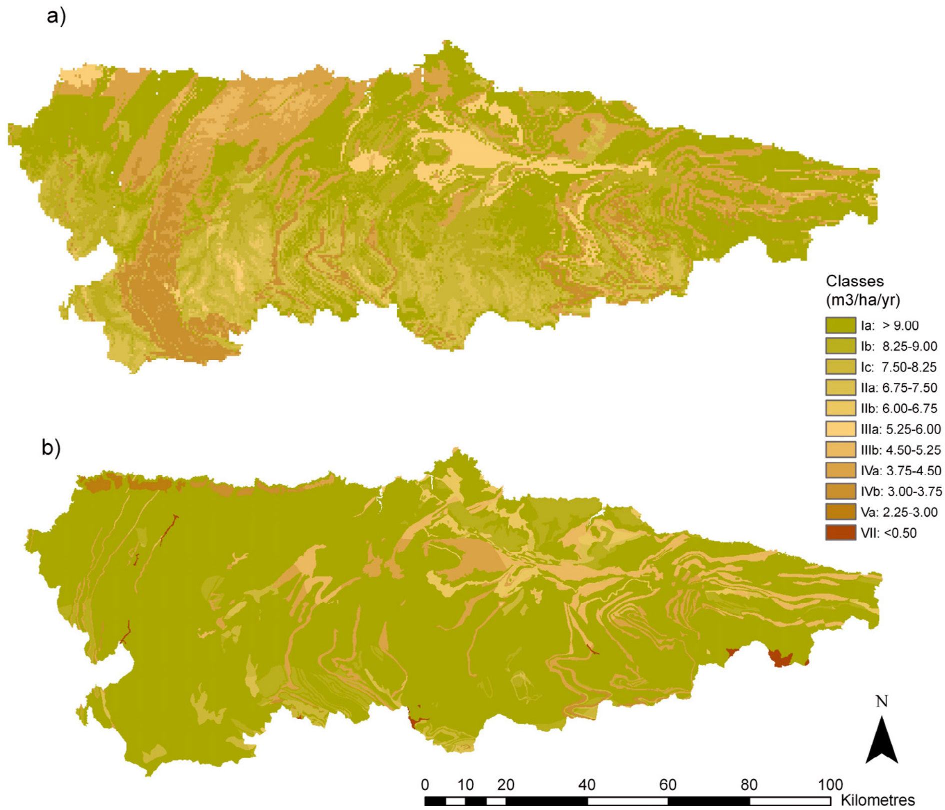

Figure 4. (a) Potential forest productivity map modelled using the new techniques (geostatistics, GIS), (b) potential forest productivity model assessed by Sánchez-Palomares and Sánchez Serrano (2000).

Table III. Effect of the origin of data (National Forestry Inventory versus Model) on the productivity ($m^3\ ha^{-1}\ y^{-1}$), in the different regions of Asturias.

Region	*N*	Mean		S.E.M.	Sig. (*p*-value)
		NFI	Model		
1	191	11.066	7.108	0.733	0.000
2	163	6.647	5.546	0.627	0.215
3	59	17.366	8.103	1.325	0.000
4a	42	5.856	6.452	0.646	0.516
4b	125	11.714	7.373	0.914	0.001
5	45	14.260	7.997	1.544	0.005
6	50	6.215	7.888	0.588	0.051
7	43	3.912	7.967	0.485	0.000
8	118	9.213	7.739	0.753	0.168

S.E.M.: standard error of the mean; N: number of data pair.

Table IV. Correlation coefficients between the data of AIVW and main management factors: type of species (*S*) – fast or low-growing –, number of trees per plot (*N*) and diameter classes (*DC*).

	Region	*S*	*N*	*DC*
	1 (*n* = 942)	–0.516**	0.740**	–0.263**
	2 (*n* = 1028)	–0.500**	0.833**	–0.570**
	3 (*n* = 448)	–0.531**	0.768**	–0.415**
	4a (*n* = 394)	–0.178**	0.871**	–0.644**
	4b (*n* = 854)	–0.550**	0.800**	–0.514**
AIVW	5 (*n* = 361)	–0.579**	0.739**	–0.352**
($m^3 ha^{-1} y^{-1}$)	6 (*n* = 276)	–0.234**	0.860**	–0.590**
	7 (*n* = 231)	–	0.881**	–0.685**
	8 (*n* = 905)	–0.538**	0.830**	–0.601**
	total area (*n* = 5439)	–0.609**	0.800**	–0.530**

AIVW was correlated with the existence of high-yielding trees (mainly eucalyptus), with high stocking rates and low diameter classes.

As regards region 7, the real values also differed significantly from the potential values (Tab. III), although in this case the former were lower (Tab. V). This appears to be due to the complex orography of the region and the influence this has on the species found in the plots (only slow-growing species).

When real yield figures are considered separately for different species and at different ages, the analysis of variance showed no similarities with the values of the model. That is because we cannot extract from the model information for different age classes or tree species as it shows potential productivity yields.

Table V. Descriptive statistics of the variables SUBTRACTION (between the potential productivity, PP, and the AIVW) and the RATIO (division between the AIVW and PP).

Region	Subtraction		Ratio	
	Mean	SD	Mean	SD
1	–1.63	7.08	1.43	1.22
2	0.89	4.54	0.88	0.91
3	–4.37	8.79	1.69	1.29
4a	1.72	5.81	0.78	0.71
4b	0.54	6.77	0.98	0.93
5	–2.24	7.88	1.32	1.03
6	1.87	5.95	0.78	0.76
7	3.88	3.18	0.53	0.41
8	1.87	5.65	0.82	0.81

SD: Standard deviation.

4. DISCUSSION

4.1. Productivity modelling

Most climatic models previously developed have used a pixel size of at least 1 km^2 (Goodale et al. 1998; Hudson and Wackernagel, 1994). However, as elevation and temperature can vary dramatically in mountainous regions, a smaller grid, 0.25 km^2 pixel size, was chosen in this study.

The errors made with the geostatistics techniques were acceptable, especially considering the complex topography. It is remarkable that errors made in summer temperature predictions were smaller than those made in winter. This is due to the higher variability in the cold season data and agrees with a similar trend found by Rolland (2002) in Alpine regions, and by Benavides et al. (2007) in Asturias. A visual appreciation of the variables related to air temperature figures (Fig. 2) reveals the well-known correlation between the temperature estimates and the altitude (Stoutjesdijk and Barkman, 1992). The estimates became progressively cooler when moving inland from the coast towards the mountains in the South, and the growing season was found to be longer and the thermic ranges smaller in coastal areas than in the Cantabrian Mountain range. However, the warmest regions in summer corresponded to the inner basin of the main rivers due to the "buffering effect" of the sea (Benavides et al., 2007).

The fact that rainfall is greatest in mountainous areas suggests that elevation again plays an important role. Other authors have already detected and quantified this phenomenon (Goovaerts, 2000; Havesi et al., 1992). It can also be observed that the western part of the area registered higher values than the eastern part. This is due to the predominance of weather fronts from the NW (Marquínez et al., 2003).

Bearing all this in mind, the figures for the climatic productivity index ranged from 245 to 1417, exceeding the value of 25 which is considered the threshold value for natural regeneration of a forest (Gandullo, 1994). The model developed indicated higher potential productivity in low, flat areas, closer to the sea, because these registered warmer temperatures, a smaller thermic range and a longer growing season. There were also some differences between the East and West which may be due to the weather fronts predominantly entering.

The influence of lithology on the productivity map can be clearly seen. The climatic productivity appeared as a continuous variable, similar to the behaviour of the climatic and topographic variables (adjacent points registered similar values for the variables). However, the lithology presented abrupt transitions on our scale. A strip of land can be identified in the western half of the region, crossing Asturias from North to South, where correction factor values were low. This was due to the characteristics of the lithology: quartzites that give rise to acid soils with many outcrop rocks.

Comparing these results with those of the previous model represented in Figure 4b. and developed by Sánchez Palomares and Sánchez Serrano (2000), a more detailed performance of the newer model can be appreciated. On one hand, a more accurate scale of the lithology map was used (from 1:50 000 to 1:25 000). On the other hand, the use of geostatistical interpolations and the advantages offered by the GIS allow us to obtain more precise information on the ecological variables throughout the region, especially in mountainous regions where modelling is always difficult and challenging (Carrega, 1995). Hence, an altitudinal gradient can be distinguished in the present model, but not in the earlier study. In the old model, 77.4% of the Asturian surface was considered a region with maximum climatic productivity (Ia > 9 m^3 ha^{-1} y^{-1}) compared with 27.3% in our case, and the lithology was the only clearly stated factor that resulted in lower productivity. However, this picture does not appear to reflect the real situation as it does not take into account the fall in temperature associated with altitude, an important variable affecting vegetation growth (Landsberg and Waring, 1997; Ni, 2004).

4.2. Usefulness for land use planning

This approach has been widely used for decades and its practical implementation has proved its worth for silvicultural planning in Spain, together with other more specific studies, focused on assessing the site potentiality for certain tree species (Bravo-Oviedo and Montero, 2005; García López and Allué Camacho, 2006). Its incorporation into the forest managers' decision-making process is an important milestone which many productivity models do not attain (Battaglia and Sands, 1998). In spite of the usefulness of the model, its validation can be somewhat complex due to the lack of adequate data for directly testing the potential productivity estimates. It is difficult to separate the site, stocking, age, structure and species effects when analysing plot growth data, especially with mixed or uneven-aged stands (Milner et al., 1996). In a mountainous region the ecological variables may also differ significantly from the estimates because the samples are usually scarcer. The climatic variables in Asturias were tested with an acceptable level of errors by Benavides et al. (2007), particularly bearing in mind that the greatest errors were detected at the highest altitudes, above the altitudinal limit of the forest. The lithology was simply proposed as an approximate description of soil characteristics, but the lack of correlation between the real productivity and the lithological coefficient (data not shown) suggests that other factors contribute greatly to the development of the soil, especially in mountainous regions. These factors include slope, altitude (Odeh et al., 1994), rainfall, and historic and current land management practices, e.g. the existence or absence of vegetation cover, soil preparation or fertilisation particularly for fast-growing species plantations, or the use of fire as a management tool (Fernández et al., 2005).

A significant correlation between the two databases (real and potential) can be observed, thus partially validating our model. However, the value of the coefficient is small (ρ = 0.203^{**}), highlighting the aforementioned difficulties involved in assessing potential productivity and the differences between the two data sets. The statistical analysis showed that our model was capable of generating values similar to the real values in mountainous regions, when all the species and ages are pooled. This is especially relevant given the difficulty in modelling areas with complex topography. Conversely, in flat areas close to the sea, the real figures exceeded the potential ones due to the management practices and the existence of eucalyptus (*Eucalyptus globulus* Labill.) stands, which is exotic high-yielding forest species, managed at high densities using short rotations.

Moreover, the evaluation of the coefficients of the potential productivity formula (Eqs. (3) and (4)) may be biased when it is used in small areas, because Paterson (1956) included in the statistical analysis data from large areas with a great diversity of annual growth rates, and Serrada (1976) validated Paterson's approach using data from plots located all over the Iberian Peninsula, including the Mediterranean area, which in general terms has lower productivity rates than Asturias (less favourable climatic conditions) but covers a larger surface area. In addition, the advances made in terms of genetics (new clones with better yield rates) and the new technical knowledge (silvicultural performances) might also affect the results, which were not contemplated when the original model was developed.

To sum up, it should be stated that this model has a number of limitations which should be borne in mind. The spatial interpolations are smoothing techniques, and therefore, introduce errors which can be propagated to the model output. Moreover, the accuracy of the prediction may improve when using an accurate model for soil. However, where precise edaphic information is not available, it would be more costly to obtain this data in situ rather than using the lithology map.

Further research is required in order to refine and improve the assessment of potential productivity and its implementation as a management tool. In the meantime, the present model can be used, bearing in mind its limitations, to define the areas on a regional scale where productivity is potentially the highest, regardless of the existing management practices (density, ages, silvicultural actions) or tree species. It also allows us to evaluate the current state of the forest stands, defining areas, species and management methods which produce yields above or below the potential productivity figures. This possibility is very useful both for land use planning and for aiding forest managers to make appropriate decisions.

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