Modeling the Potential Distribution of Forests with a GIS

A.M. Felicísimo, E. Francés, J.M. Fernández, A. González-Díez, and J. Varas

Abstract
One of the objectives of forestry planning is to set out criteria for a territory's reforestation oriented towards the reduction of fragmentation and the conservation of biodiversity. This objective may be attained by establishing for each forest type appropriate suitability models, which express the suitability of each point of the territory for the growth of each forest formation. The suitability models may be constructed by utilizing spatial analysis methods, which relate the current presence/absence of forest type to a set of environmental variables. On the basis of maps of diverse environmental variables, we elaborated suitability models for the forests present in the study area using logistic regression and weights-of-evidence techniques integrated into a geographic information system. Combining the suitability models for each forest type using simple comparison operators allowed us to construct a potential vegetation map to use as an objective orientation to the forestry potential of the territory.

Introduction
Forestry planning in a territory is an attempt to resolve a set of problems, including forest conservation and restoration. In a zone such as the Iberian Peninsula, where forests have been steadily eliminated over centuries, two of the major aims of any forestry zoning plan are to reduce fragmentation of the forest and to conserve its biodiversity.

To achieve these goals requires basic territorial information of good quality (Lund and Iremonger, 2000). This information includes the present distribution of vegetation, and a set of climatic, lithological, etc., data which together constitute a spatial information system. The information stored in this system will allow one to develop a variety of models, including those which permit decisions to be taken on an objective and methodologically robust basis.

The information that is put into the information system has to allow one to determine the suitability of each point of the territory for the growth of each type of vegetation. This suitability is expressed on a scale between the values zero and unity (incompatible/ideal). The value of the suitability depends on a set of physical and biological factors that favor or limit the implantation of each forest type. With a knowledge of the suitability of the territory, it is then possible to make decisions on which reforestation actions to take on an objective basis and with rational criteria.

A.M. Felicísimo is with the Área de Ingeniería Cartográfica, Geodesia y Fotogrametría, Departamento de Expresión Gráfica, Universidad de Extremadura, 10071 Cáceres, Spain (amfeli@unex.es).

E. Francés, J.M. Fernández, and A. González-Díez are with the Departamento de Ciencias de la Tierra, Universidad de Cantabria, Santander, Spain.

J. Varas is with the Dirección General de Medio Ambiente, Gobierno de Cantabria, Santander, Spain.

The set of values of a territory's suitability constitutes a spatial distribution model. The model is constructed by analyzing the presence/absence of a forest type in its current area of distribution, and the values of the potentially influential environmental variables excluding anthropogenic factors.

With one such model for each type of forest, a potential area of distribution can be delimited, where the environmental factors present suitable values for the implantation and growth of the forest. The present area of distribution is usually significantly less than the potential area, because the forest has been artificially cleared from zones where it was present in the past: the distribution models allow these areas to be delimited in order to appropriately orient future reforestation plans.

Once the potential distribution models have been defined, each place in the territory will be represented by a set of suitability values, one for each type of forest. From this set of values, one determines which type of forest presents the greatest suitability value at each point and constructs a potential vegetation model.

The above process is carried out under the hypothesis that the present forest distribution is a sufficient sample of the potential distribution. If there is only a remnant of some forest type, it will be impossible to construct a sufficient sample or to generate an adequate model.

In the following, we will describe the methods used in elaborating potential vegetation models for the Liébana basin in the Cantabria Autonomous Community (northern Spain).

Materials and Methods

Study Area
The Cantabria Autonomous Community is located in the north of Spain, and is 5330 km^2 in area (Figure 1). The territory presents sharp topographical and phytogeographical contrasts. To elaborate the models, it was divided into homogeneous zones which coincide with the main river catchment areas. The zone presented here is the catchment area known as Liébana, situated in the west of Cantabria. It is 629 km^2 in area, 11.8 percent of the total area of Cantabria. Henceforth, all data mentioned will refer to this catchment area.

Database Collection
The models were elaborated from the following maps:

- Vegetation map, from the Earth Sciences Department of the Universidad de Cantabria, which covers 180 classes of vegetation, of which 18 are forest;

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Figure 1. Geographical location of the study zone (Cantabria, northern Spain)

- Lithological map, from the Instituto Tecnológico y Geominero of Spain, with 78 lithological classes; and
- Topographical map, from the Army Geographic Service of Spain, with a contour interval of 20 meters.

The Dependent Variables: The Forest Maps

The vegetation map was digitized and integrated into a geographic information system. From that, six maps were constructed representing the presence/absence of each of the forests existing in the zone:

(1) **Bf**: oligotrophic beech wood (*Fagus sylvatica, Blechno spicanti-Fageto S.*, 89.6 km^2);
(2) **Cf**: eutrophic beech wood (*Fagus sylvatica, Carici sylvaticae-Fageto S.*, 11.9 km^2);
(3) **Cq**: holm oak wood (*Quercus rotundifolia, Cephalanthero longifoliae-Querceto rotundifoliae S.*, 53.2 km^2);
(4) **Liqpe**: arid durmast oak wood (*Quercus petraea, Linario triornithophorae-Querceto petraeae S.*, 44.6 km^2);
(5) **Liqpy**: moist durmast oak wood (*Quercus petraea, Luzulo henriquesii-Querceto petraeae S.*, 59.5 km^2); and
(6) **Mf**: eutrophic durmast oak wood (*Quercus petraea, Mercurialidi perennis-Fraxineto excelsioris S.*, 12.6 km^2).

The forests were defined according to the criteria given in Díaz-Gonzalez and Fernández-Prieto (1994). The maps with the present distribution of each forest type are shown in Figure 2.

The Independent Variables: Construction of the Digital Terrain Models (DTM)

The digital terrain models that represent the independent variables were constructed from the topographical map:

- altitude: the digital elevation model (DEM) was constructed using Delaunay's triangulation algorithm (Peucker *et al.*, 1978), followed by a transform to a regular grid structure with a 50 m cell size.
- slope: the digital slope model (DSM) was constructed from the DEM by applying Sobel's operator (Horn, 1981).
- potential insolation: the models were constructed by simulation from the DEM, analyzing topographical shading (Fernández-Cepedal and Felicísimo, 1987) as a function of the sun's trajectory for standard date periods (Heywood, 1964). The result is an estimate of the amount of time that each point of the terrain receives direct solar radiation, with a 20-minute temporal resolution and 50-m spatial resolution
- distance from the sea: a model elaborated as an estimator of the oceanic-continental gradient in the territory, given that other climatic data were not available (see below).

The above variables were chosen because they are potential predictors of the vegetation distribution in a mountainous zone, and because they had already been completely mapped or could be estimated by diverse means. On the other hand, other factors (such as rainfall and temperature) could not be used due to the lack of complete and reliable data, even though their potential influence is important.

All the digital terrain models were generated with a 50-m cell size.

Data Analysis

The data were analyzed following a mixed procedure consisting of two quite distinct methods: logistic regression and weights of evidence. Logistic regression was used to create a preliminary model using the quantitative environmental factors as independent variables. A weights-of-evidence method was then used to adjust the results of the preliminary model to the associations observed with the lithological classes, the only nominal (non-quantitative) factor included in the analysis.

The process therefore was sequential: initially a logistic model was established and then the estimated probabilities were modified by means of the weights-of-evidence model. A flow diagram of the process is presented in Figure 3, and the methodological basis of the two methods will be explained in the following two sections.

Logistic Multiple Regression (LMR)

Logistic multiple regression has been used as a forecasting method to generate probability models in a variety of fields. Examples are epidemiology (Thomson *et al.*, 1999), geological prospecting (Agterberg, 1992), silviculture (Wilson *et al.*, 1996), and wildlife conservation (Mladenoff *et al.*, 1999).

The method fits our purposes well because the dependent variable is dichotomous (presence/absence) and the model admits non-Gaussian independent variables. Also, the values of the logistic function vary smoothly from 0 to 1, so that it is well-suited to generating a probability model (Jongman *et al.*, 1995).

The introduction of a spatial component into the LMR to generate cartographic models is recent, and is usually integrated into geographic information systems as a development tool. Guisan *et al.* (1998) use LMR in the ArcInfo GIS (ESRI Inc.) to generate a model of the distribution of a plant species, *Carex curvula*, in the Swiss Alps. A similar study, applied to aquatic vegetation, was performed by van de Rijt *et al.* (1996) using the GRASS GIS (U.S. Army Construction Engineering Research Laboratory).

The logistic model for the dependence of the probability of presence, $P(i)$, on the value of n explanatory variables is

$$P(i) = 1/[1 + \exp -(b(0) + b(1) \cdot x(1) + b(2) \cdot x(2) + \ldots + b(n) \cdot x(n))] \quad (1)$$

where $P(i)$ is the probability of presence of the forest type; $x(1)$,..., $x(n)$ represent the values of the environmental variables; and $b(1)$, ..., $b(n)$ represent the corresponding coefficients. The statistical forecast of the spatial distribution of a species is based on the hypothesis that its present area of distribution is representative of its response to the environmental factors.

The results for each point of the terrain vary between the extreme values zero (incompatible) and unity (ideal).

The values of the logistic regression coefficients were calculated from stratified random samples over the areas of presence and absence of each type of forest. To avoid biases, the samples were balanced to have the same number of positive and negative cases (Narumalani *et al.*, 1997).

The logistic equation was applied to the whole territory to generate the preliminary probability models.

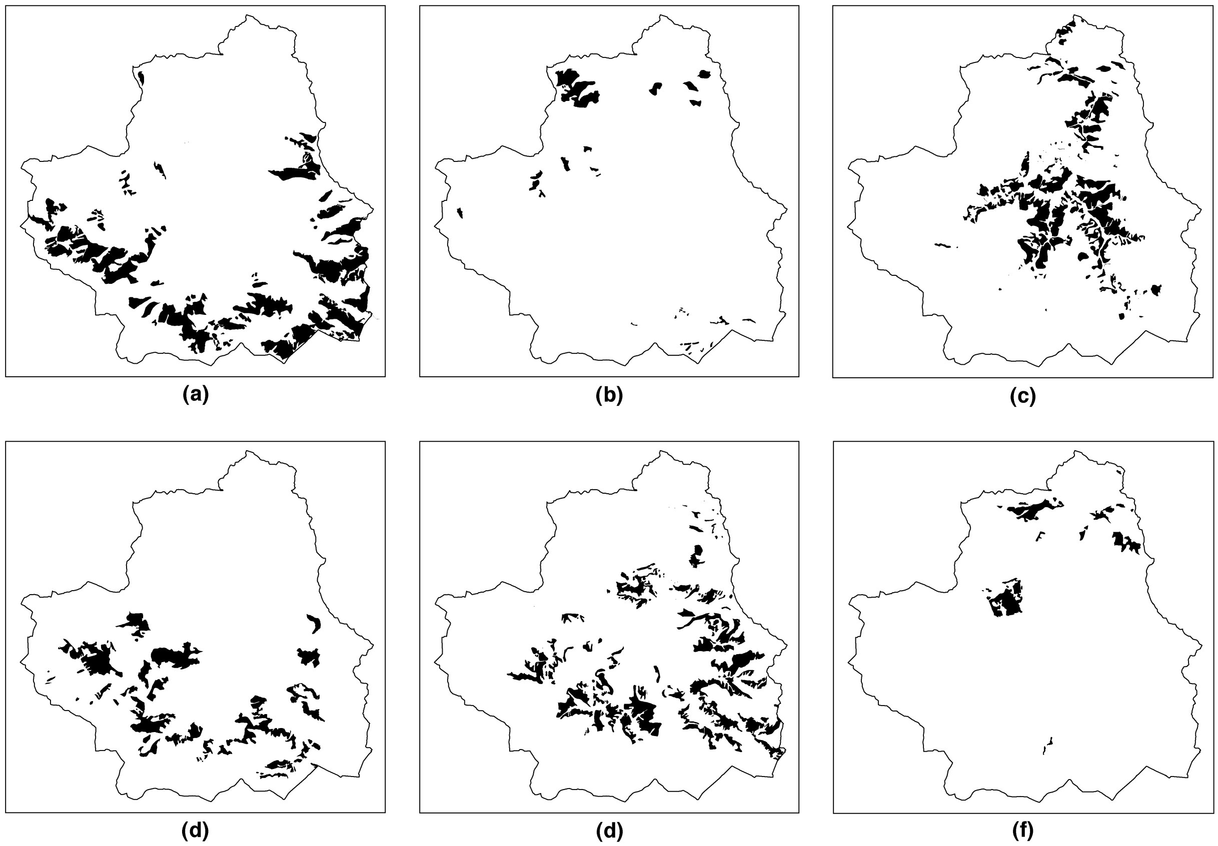

Figure 2. Present distribution of the six forest types in the study zone according to the vegetation map elaborated by the Universidad de Cantabria. (a) Bf, oligotrofic beech wood (*Fagus sylvatica*). (b) Cf, eutrophic beech wood (*Fagus sylvatica*). (c) Cq, holm oak wood (*Quercus rotundifolia*). (d) Liqpe, arid durmast oak wood (*Q. petraea*). (e) Liqpy, moist durmast oak wood (*Q. petraea*). (f) Mf, eutrophic durmast oak wood (*Q. petraea*).

The Weights-of-Evidence Method (WE)

Methods based on weights of evidence have a relatively long history. "Les profils écologiques" were defined in the 1960s (Godron, 1965) as a quantitative method to analyze the association between the presence of certain types of vegetation and the values of environmental variables. An ecological profile is defined as "a frequency distribution of a species as a function of the states of a variable" (Gauthier *et al.*, 1977).

Tests for the statistical significance of ecological profiles were developed at that time with the limitation of the small sample size that was usually available, because they were constructed from hand-collected vegetation inventories (Daget *et al.*, 1972).

The main development in these methods has been the adoption of a more explicit spatial point of view, in integrating them into geographic information systems, and in certain changes in the statistics associated with the construction of the profiles. Although the most recent work has been on geological topics (Agterberg, 1992; Bonham-Carter, 1994; Agterberg and Bonham-Carter, 1999), the basic methods are similar.

In the context of the present work, the weights-of-evidence (WE) method represents a simple procedure to assign a weight W^+ to each forest/lithology combination, where W^+ may be used as a non-parametric measure of association (positive or negative). The process of assigning the weights begins with the construction of a table of presence/absence frequencies for each forest type versus each lithological class, as is shown in Table 1.

Marginal totals $f1\cdot$ and $f2\cdot$ represent the totals of presence and absence, respectively, in the zone, using the 50- by 50-m cell as sampling unit. The totals $f\cdot i$ represent the area of each lithological class in the total area.

Next, the odds are calculated for each lithological class. The odds are defined as the ratio between the probability of presence and the probability of absence of the forest type in each lithological class. For the lithological class *i*,

$$O(i) = \frac{f1i/f\cdot i}{f2i/f\cdot i} = \frac{f1i}{f2i}. \quad (2)$$

Finally, the weight W^+ (positive weight of evidence) is calculated for each class from the expression

$$W^+(i) = \ln\frac{O(i)}{O(\cdot)} = \ln\frac{f1i/f2i}{f1\cdot/f2\cdot}, \quad (3)$$

i.e., each weight is calculated from the *a posteriori* to *a priori* odds ratio for each lithological class (Agterberg and Bonham-Carter, 1999). A high presence of the forest type in a specific lithological class increases the *a posteriori* odds relative to the *a priori* odds, which is general for the whole of the working zone, thereby increasing the value of W^+. If there is no association between the vegetation and the lithological class, the value of W^+ will be null ($\ln 1 = 0$). Positive associations will show values of $W^+ > 0$, and negative associations $W^+ < 0$.

The set of values of W^+ for a forest type is called the weighted profile, and may be used as a measure of the positive

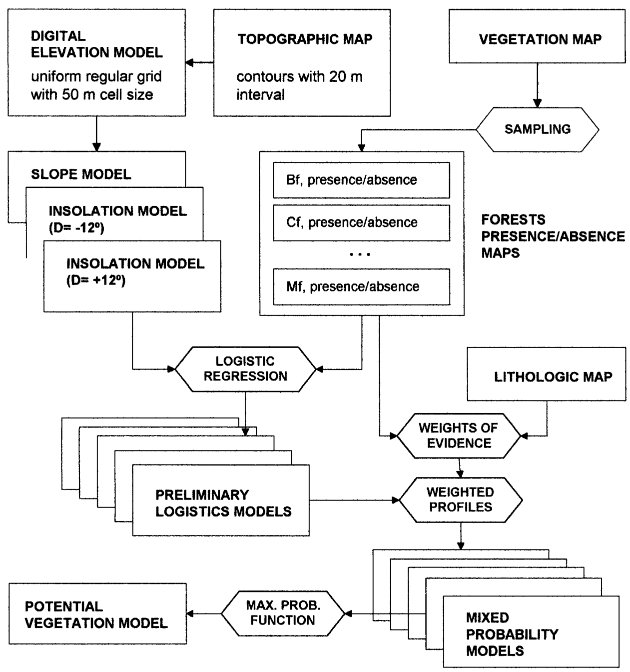

Figure 3. Flow chart of the process of generating the probability models and the potential vegetation model.

Table 1. Scheme of the Frequency Table Used to Construct the Weighted Profiles

	Lithology				
Forest	Class 1	Class 2	…	Class n	Total
Presence	f11	f12	…	f1n	f1·
Absence	f21	f22	…	f2n	f2·
Total	f·1	f·2	…	f·n	f··

or negative association of the forest type to each lithological class. As will be seen below, the weights of evidence were used to raise or lower the probability obtained from the logistic model, adapting it to the new predictor (the lithological class).

Results

The Logistic Model

We generated a logistic model for each of the six forest types present in the study zone. The coefficients and the values of the area under the ROC (Receiver Operating Characteristic) curve are listed in Table 2.

The above results allow suitability models to be constructed for each forest type. These models give values between 0 (incompatible) and 1 (ideal). The value of the area under the ROC curve is an estimator of the goodness of fit of the model to the test data. A value of unity for AUC indicates an exact model which describes the data with no error. A value of 0.5 indicates a random model. One sees that there are values that define excellent models (Cq, Mf), while the model for Liqpe is only mediocre.

It must be emphasized that the fit estimated by means of the area under the ROC curve refers exclusively to the results of the logistic model, before correcting the probabilities for the lithology. This latter process notably improves the fit of the model, even though our assessment of the improvement was only subjective.

The Weights-of-Evidence Model

The weighted profiles were used to quantify the association between the forest types and the lithological substrate. The lithology was the only nominal variable considered (the rest were quantitative), and for some of its values it has to be considered as a blocking (or exclusion) variable, i.e., those values are directly incompatible with some of the forest types. Although logistic regression allows nominal factors to be introduced as independent variables, the results showed that the method is incapable of reproducing the exclusion phenomenon. The final model was therefore a mixed one, and the weighted profiles were used to adjust the LMR suitability estimates to the influence of the lithology.

The lithological classes were the following (simplified): A: boulders; B: slide deposits; C: slope detritus; D: gravels; E: coluvial deposits; F: quartzites; G: sandstones; H: shales; I: siliceous conglomerates; J: sandstones with conglomerates; K: limestones; L: stratified sandstones; M: silt; and N: microcrystalline limestones.

Figure 4 shows the results in detail for the Liqpe forest.

From the values shown in Figure 4, one has the following Liqpe/lithology relationships:

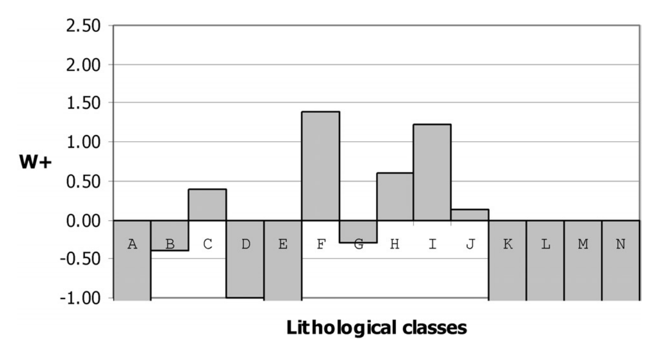

Figure 4. Weighted profile for the *Liqpe* forest. The lithological classes are shown along the horizontal axis, and the values of the "positive weight of evidence" W^{+} along the vertical axis.

Table 2. Values of the Logistic Model Coefficients for each Forest Type. The Value of the Area Under the ROC Curve is an Indicator of the Goodness of Fit of the Model (See Text)

forest	altitude	slope	insol − 12	insol + 12	distance	constant	ROC area
Bf	0.0530	−0.0035	−0.0633	0.0383	−0.1588	11.3901	0.78
Cf	0.0403	−0.0019	−0.0648	0.0932	0.1804	−16.3152	0.85
Cq	−1.2305	0.0625	0.1480	0.0622	−0.0632	9.5052	0.96
Liqpe	−0.1952	−0.0040	0.0816	0.0007	−0.1327	11.0672	0.68
Liqpy	−0.4954	0.0141	0.1598	0.0383	−0.1183	10.3771	0.84
Mf	−0.3732	−0.0527	0.1330	−0.1936	0.2960	−17.4117	0.93

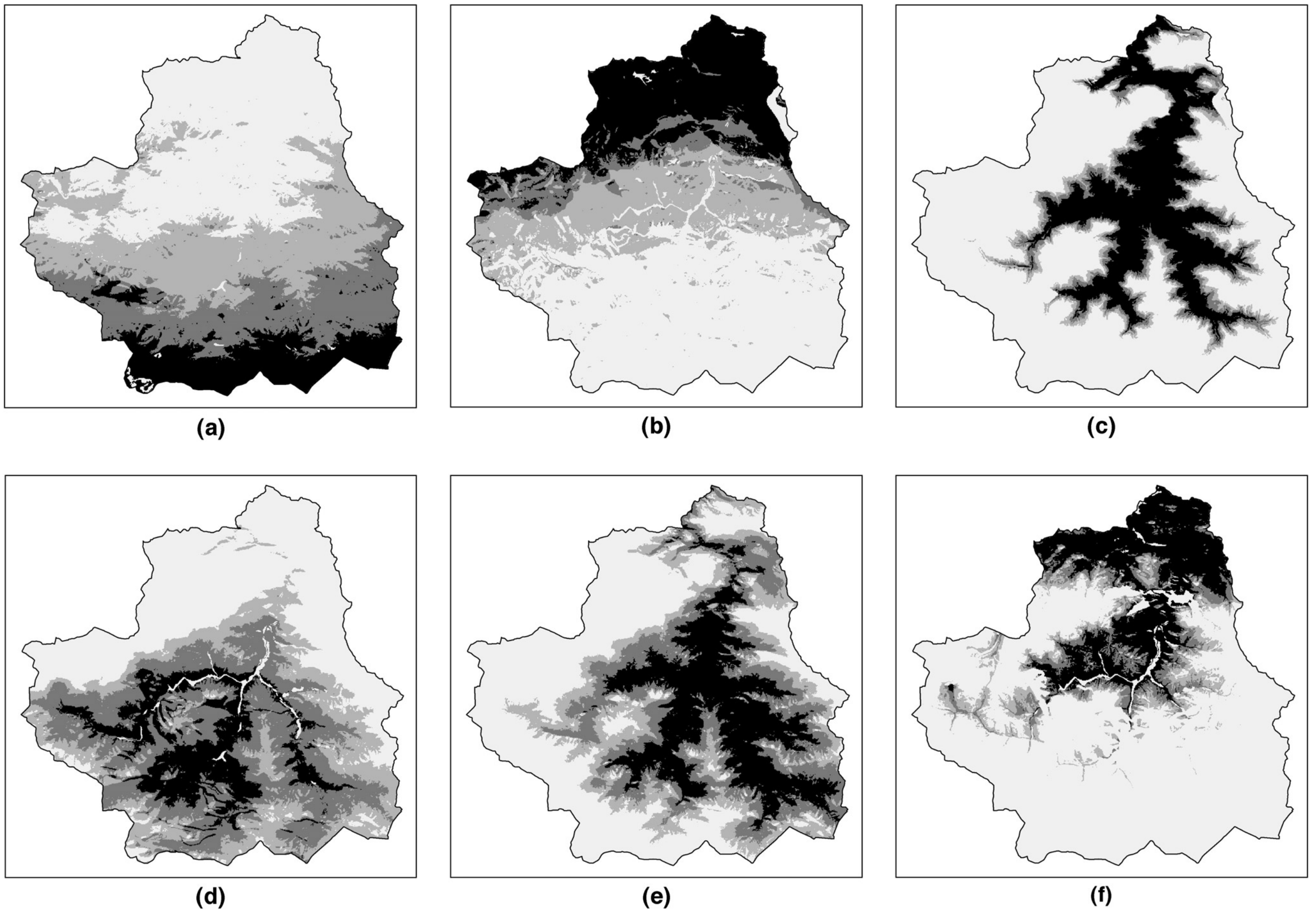

Figure 5. Probability (suitability) maps for the six forest types present in the study zone, as determined from their corresponding logistic models: 0.0 to 0.25 (light gray), 0.26 to 0.50 (gray), 0.51 to 0.75 (dark gray), and 0.76 to 1.00 (black). (a) Bf, oligotrofic beech wood (*Fagus sylvatica*). (b) Cf, euktrophic beedh wood (*Fagus sylvatica*). (c) Cq, holm oak wood (*Quercus rotundifolia*). (d) Liqpe, arid durmast oak wood (*Q. petraea*). (e) Liqpy, moist durmast oak wood (*Q. petraea*). (f) Mf, euktrophic durmast oak wood (*Q. petraea*).

- Absent in the lithological classes A, D, E, K, L, M, and N.
- A strong positive association with the classes F and I.
- The less significant associations are with the classes H, C, and J (positive) and B and G (negative).

The numerical values of the complete set of profiles are listed in Table 3.

The Mixed Probability Model

The probability maps given by the logistic model were then modified using the values of W^+ corresponding to each lithological class as weights. Correction of a preliminary model by weighting with other criteria is a frequently used procedure in constructing mixed decision systems (Bonham-Carter, 1994). The probability values are raised for positive associations and lowered for negative associations. They are set to zero for the cases of incompatible lithological classes. This procedure guarantees that the lithology will be treated as a blocking variable when the case arises, an aspect that is hard to achieve with the logistic model.

The logistic model probabilities $P(i)$ were modified according to the expression $P'(i) = P(i) \cdot k$, where k depends on the value of W^+ (see Table 4). The values of k are subjective with the goal of calibrating the probabilities according the weights of evidence.

Table 3. Values of W^+ According to Lithological Class and Forest Type. The Symbol (—) Represents Incompatible Classes, Where the Forest Type Was Absent

Lithology	Bf	Cf	Cq	Liqpe	Liqpy	Mf
A	—	+0.41	+2.78	−1.62	—	—
B	+0.88	—	−0.65	−0.40	+0.08	−0.65
C	−0.71	−1.24	+0.46	+0.39	+0.46	−1.55
D	−0.39	+2.42	—	−1.01	−1.64	−0.25
E	−0.99	—	+1.54	—	+0.53	—
F	−0.49	+0.35	−0.71	+1.38	−0.16	—
G	+0.39	−1.44	−0.08	−0.29	+0.18	−0.26
H	−0.20	−2.14	+0.08	+0.60	+0.27	—
I	−0.22	−2.49	−0.09	+1.23	−0.44	−1.79
J	+1.61	—	—	+0.14	−0.67	—
K	−1.81	+1.84	+0.42	−2.48	−2.31	+1.21
L	−1.23	+1.87	−0.80	—	−0.53	+2.78
M	+0.90	+2.21	−1.89	—	—	+1.29
N	—	—	—	—	+0.69	+3.71

The resulting models are shown in Figure 5, which clearly shows the different patterns of distribution of the forest formations.

Table 4. Values of the Weights k as a Function of the Values of W^+

W^+	k	Lithology
$-\infty$	0.00	incompatible
<-2.5	0.70	very unfavorable
-2.5 to -1.5	0.80	unfavorable
-1.5 to -0.5	0.90	moderately unfavorable
-0.5 to $+0.5$	1.00	indifferent
$+0.5$ to $+1.5$	1.10	moderately favorable
$+1.5$ to $+2.5$	1.20	favorable
$>+2.5$	1.30	very favorable

The Potential Vegetation Model

In the previous process, we generated six probability (suitability) models, one for each type of forest present in the zone. With these models we constructed a map in which each cell or place of the terrain is assigned the forest that presents the greatest probability. This was done by comparing the values cell by cell and selecting the forest with the maximum likelihood.

The result of applying the process of evaluation is a model which shows the type of forest with the greatest probability at each place in the study area. It may be interpreted as a potential vegetation model (Figure 6).

Discussion

Maps of potential vegetation are theoretical constructions deriving from a hypothetical-deductive process. They may be interpreted as biologically reasonable hypotheses, based on sets of evidence and underpinned by some of the prevailing theoretical frameworks in ecology. Understood as hypotheses, however, they can not be readily subjected to experimental tests, and in this sense lack one of the properties that is usually required in the scientific method: that of being refutable or, vice versa, verifiable.

Despite the above considerations, potential vegetation maps represent a useful tool for environmental management because they synthesize different types of knowledge about the reality of the territory which are difficult to integrate in any other way. Until now, potential vegetation maps have been elaborated mostly by subjective methods, by means of the experience that an expert connoisseur of the terrain has of its characteristics. The problems with this way of working are obvious: the maps will vary in quality according to the "quality" of the expert, and above all they will not be repeatable because there is no explicit method of elaborating them (an algorithm).

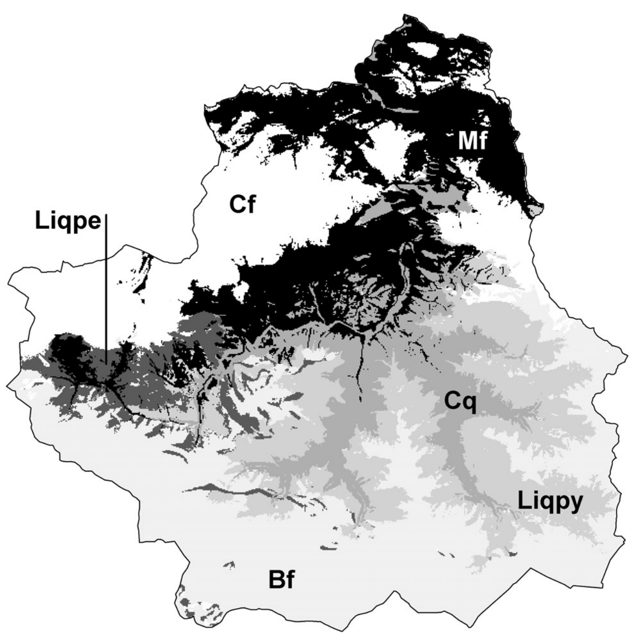

Figure 6. Map of potential vegetation constructed from the probability models of the six forests present in the study zone.

In contrast with this way of working, we have proposed a method based on robust statistical operations and objective cartographical territorial information. There exists an explicit procedure to get to the final result, so that the entire flow of information is "visible." As it is based on statistical methods, the quality of the model may be evaluated by standard measures of goodness of fit.

As in any model, the quality may be improved in two ways: by reducing the error in the independent variables or by introducing new variables that may contribute to explaining the spatial distribution of the forests. In this sense, the role of climate variables is *a priori* important. We did not use the classical variables (rainfall, temperature, etc.) in the present work because there are very few meteorological observatories in the study zone, so that it would not have been possible to define the spatial climatic variation with a resolution compatible with the other variables. To reduce the impact of this problem, we generated potential insolation models, which are able to describe reasonably some microclimatic contrasts by evaluating the influence of hill shading in a terrain of such sharp relief.

A difficult problem to solve is that caused by an insufficient presence of forests at the present time. For instance, if a forest has been totally eliminated from zones that are lower in altitude, the model will set those zones as being incompatible, when they are not so in reality. For this reason, this type of model should only be developed in zones where there still exists a sufficient sample of the original forests.

To put the potential vegetation model to use in territorial management, one will have to take into account other variables that are more specific to management: land ownership, current regime of use, etc. In light of these variables, it will be possible to define initiatives and zones of intervention rationally. For instance, the reduction in fragmentation of the forest will be directed at zones with a high potential and where there already exist scattered fragments of the original forest. The priority conservation zones will be those where the potential zone is mostly occupied by forest today. Increase in diversity can be actively encouraged in zones where there exists a high potential for more than one forest type, allowing complex spatial distribution patterns.

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