DISSERTATION

SPATIAL MODELING OF SITE PRODUCTIVTY AND PLANT SPECIES DIVERSITY USING REMOTE SENSING AND GEOGRAPHICAL INFORMATION SYSTEM

Submitted by

Adel Ahmed Hassan Mohamed

Department of Forest and Rangeland Stewardship

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Doctoral Committee:

Advisor: Robin M. Reich
Co-Advisor: Rajiv Khosla

Allan Andales
Yu Wei

ABSTRACT

SPATIAL MODELING OF SITE PRODUCTIVITY AND PLANT SPECIES DIVERSITY USING REMOTE SENSING AND GEOGRAPHICAL INFORMATION SYSTEM

The primary objective of this study was to describe the variability in site productivity of the diverse forests found in the state of Jalisco, Mexico. This information is fundamental for the management and sustainability of the species-rich forests in the state. The study also contributes to developing conservation-management program for the plant species diversity in Elba protected area in Egypt.

The objective of chapter 1 was to develop site productivity index (SPI) curves for eight major forest types in the state of Jalisco, Mexico, using the height-diameter relationship of the dominant trees. Using permanent plot data, selected height-diameter functions were evaluated for their predictive performance within each of the major forest types. An important finding of this study was that a simple linear model could be used to describe the height-diameter relationship of the dominant trees in all of the major forest types considered in this study. SPI varied significantly among forest types, which are largely determined by the trends in temperature and precipitation. SPI decreased with increasing temperature and increased with increasing precipitation. The height-diameter

relationship of the dominant trees was independent of stand density, and the more productive sites are able to sustain higher levels of basal area and volume, than the less productive sites. Trees on more productive sites had less taper than trees on less productive sites; and stand density did not influence the form or taper of the dominant trees.

Chapter 2 evaluates methods to model the spatial distribution of site productivity in eight major forest types found in the state of Jalisco, Mexico. A site productivity index (SPI) based on the height-diameter relationship of dominant trees was used to estimate the site productivity of 818 forests plots located throughout the state. A combination of regression analysis and a tree-based stratified design was used to describe the relationship between SPI and environmental variables which included soil attributes (pH, sand, and silt), topography (elevation, aspect, and slope), and climate (temperature and precipitation). The final model explained 59% of the observed variability in SPI. GIS layers representing SPI for each forest type, along with associated estimates of the prediction variance are developed.

Chapter 3 characterizes plant species richness on four major transects in Elba protected area in Egypt. Species data recorded on 63 sample plots were used to characterize the plant species richness by species group (trees, shrubs and subshrubs). Poisson regression was used to identify explanatory variables for estimating species richness of each species group. Important variables included the location of the line transect (A, B, C, and D), soil texture (gravel, sand, silt and clay), pH, and elevation. The final models explained 65%, 49%, 33%, and 21% of the variability in species richness on transects A, B, C, and D, respectively and explained 23%, 58%, and 52% of the

variability in species richness for shrubs, subshrubs, and trees, respectively. The results of the study will contribute to the development of an inventory and monitoring program aimed at the conservation and management of species diversity in Elba protected area of Egypt.

DEDICATION

I would like to dedicate my dissertation to the memory of my father who gave me a lifetime of love and support without condition. To my beloved mother who waited all these years to fulfill my dream of receiving my Ph.D. To my sister, and my brothers. To my wife and my son.

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Lastly, I would like to thank my wife, who provided me with the encouragement and loving support I needed to complete this project, and my beloved mother, sister and brothers for wishing me the best in my life.

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CHAPTER 1 SITE PRODUCTIVITY CURVES FOR THE DIVERSE FOREST TYPES OF JALISCO, MEXICO

1.1 INTRODUCTION

The forests of Jalisco, Mexico, have a very diverse and unique community of endemic and specialized species of plants, animals, reptiles, and amphibians. Tropical dry forests in the region are among the richest tropical dry forests in the world, and have more endemic tree species than elsewhere in the Neotropics (Challenger, 1998), while forests found in the temperate climate region are recognized as a center of diversity for the *Quercus* genus (Nixon, 1993). Climatic conditions play an important role in the diversity and distribution of forest types in the state (Reich *et al*., 2010).

The trees in these forests are important to local inhabitants as a source of products for their daily needs, and the close proximity of forests to the towns and cities has accelerated the exploitation of these forests through grazing, fuel wood extraction, selective logging and other economic activities (Pande, 2005). These disturbances impact both the diversity and the productivity of the forests (Reich *et al*., 2010). Soil characteristics, climatic factors and management may also affect site quality and thus the inherent site potential. Understanding the patterns in site productivity in relation to these factors, as well as other important ecological drivers, is critical for land resource management purposes.

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Productivity can be defined in many ways, depending on the objectives of resource managers. For example, productivity could be defined as the ability of a site to maintain its diversity while providing goods and services to the local inhabitants. From a forest management perspective, productivity is generally defined as the ability of a site to produce wood volume (Van Laar, 2007), since this type of information is readily available from inventory records.

In 2006, a network of 1,442 permanent plots was established to characterize the natural resources (e.g., forest, grassland, agriculture, wildlife, soils, etc.) in the state of Jalisco (Reich *et al.*, 2008b). Unfortunately, it will take decades to obtain long-term records needed to develop reasonable and realistic measures of site productivity based on volume production for all the forests in the state. In the meantime, resource managers require a simple measure of productivity that can be estimated from survey data. For a measure to be useful in quantifying site productivity, Vanclay (1992) lists four criteria that should be met: 1) reproducible and consistent over time; 2) indicative of the site and not influenced by stand conditions or past management history; 3) correlated with the site's productivity potential; and 4) determined easily from field records.

A simple and quick approach to quantifying the productivity of a site is based on the height-diameter relationship of dominant trees (Huang and Titus, 1992; Vanclay and Henry, 1988). Known as the site productivity index (SPI), this approach uses the expected height of a dominant tree at a defined reference diameter as a measure of site productivity. It is assumed that 1) decreasing tree taper is associated with increasing site productivity, and 2) stand density does not affect the height-diameter relationship of the dominant trees in the stand. The advantage of this approach is that it does not rely on tree

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age, which is difficult if not impossible to obtain for the majority of tree species found in the state.

A review of the literature indicates a lack of consensus regarding the feasibility of using the height-diameter relationship of dominant trees to assess the productivity of both uneven-aged and mixed species stands. Some studies indicate the height-diameter relationship is useful in quantifying the productivity of a site (Stout and Shumway, 1982; Huang and Titus, 1992; Herrera-Fernández *et al*., 2004), while Wang (1998) points out the opposite. These results suggest the need for further testing, especially since the use of the height-diameter relationship of dominant trees is being considered for use in the species-rich forests of Jalisco.

The biggest challenge in this study was to select a tree species to represent the productivity of a site. Most studies select one species, or a group of species of commercial value, and develop SPI curves for each species. There are 538 tree species known to occur in Jalisco (FIPRODEFO, 2006) and there is no one species, or group of species, with high enough frequency of occurrence to represent the conditions in all forest types (Reich *et al*., 2008a). Also, most of the tree species that occur in the tropical and semi-arid regions have limited commercial value. Thus it was decided to ignore tree species and use the tallest trees to represent the productivity of a site, which raised a concern of using a single model to describe the height-diameter relationship of multiple tree species. Fang and Bailey (1998), however, show that it is possible to model the height-diameter relationship of multiple tree species using a single model while providing acceptable levels of precision and bias.

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The objectives of this study were: 1) to develop a set of productivity measures (SPI) based on the height-diameter relationship of dominant trees representing the species composition of the major forest types; 2) to test the validity of SPI as a measure of site productivity by relating SPI to measures of stand density and average tree size; and 3) to quantify the influence of climate on the productivity of the forest types in the state.

1.2 MATERIALS AND METHODS

1.2.1 Study Area

The state of Jalisco is located in the west central part of Mexico (20° 34′ 0″ N, 103° 40′ 35″ W), covers an area of approximately 7.9 million ha and it is characterized by three broad climatic regions which correspond to three major ecological regions: 1) the tropical zone located along the Pacific coast and characterized by high temperatures, rain during the summer months (730-1200mm), and an annual dry period that lasts for 5 to 9 months; tropical dry forests dominate this zone with elevation ranging from sea level to 2000 m.a.s.l.: 2) the temperate zone occurs at the higher elevations (1000-2500 m), with an average annual rainfall of 900-1500 mm; pine, oak and mixed deciduous hardwood forests dominate this region; this zone gradually changes to: 3) the semi-arid region located in the eastern part of the state which is characterized by low annual precipitation with a dry period lasting 6-8 months; the vegetation in this region is dominated by mesquite-acacia and xerophitic shrubs (Reich *et al*., 2008b).

1.2.2 Data

To gather baseline information on the natural resources (e.g., forest, grasslands, agriculture, etc.) within the state, 1,442 permanent plots were established in 2005 (Reich

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et al., 2008b). Sample plots were allocated using a stratified design that took into consideration the climatic variability within the state and the spectral variability of the vegetation cover (Figure A.1). Sample plots classified as non-forested (359), or that did not contain any merchantable trees (249), were removed from the data set. An additional 16 plots were removed from the data set because they occurred in forest types with less than ten plots. These forest types were not considered in this study. Of the remaining 818 sample plots, 380 plots were located in the tropical region, 353 plots in the temperate region, and 85 in the semi-arid region, representing eight major forest types: pine (PN), oak (OK), pine-oak (PO), oak-pine (OP), tropical semi-evergreen forest (SM), tropical dry forest (SB), subtropical scrub (MS), and *mezquital–huizachal* (MH).

The sample plots measured 30 m x 30 m and were subdivided into nine 10 m x 10 m subplots. On each sample plot, five subplots were systematically selected to obtain measurements on merchantable trees (≥ 12.5 cm DBH) which included both commercial and non-commercial tree species using a circular plot with a 5 m radius. A partial list of the tree data collected on the sample plots included: diameter at breast height (DBH, cm), total tree height (H, m), tree species, percent canopy closure, tree health and forest type (Reich *et al*., 2008b). The dimensions of the dominant tree were defined as the average total height and average DBH of the five tallest trees, irrespective of species, and with one tree being selected from each of the five subplots. Not all subplots contained merchantable trees and, therefore, a fewer number of trees were used to define the dominant tree. Individual tree taper (HD) was calculated as total tree height divided by DBH and then averaged over all trees on a sample plot to obtain an estimate of the

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average tree taper. Total basal area (m^2 ha^{-1}), average tree diameter (cm) and average total tree height (m) were also calculated for each sample plot.

Reich *et al*. (2010) classified each sample plot into one of three temperature zones: cool, warm and hot, and one of four precipitation–(minus) evaporation zones: dry, moist, damp and wet. The temperature and precipitation-evaporation zones were based on climate models of average monthly temperature, precipitation and evaporation developed for Jalisco (Reich *et al*., 2008a). Temperature, precipitation and evaporation are forest production drivers and have been used to study the impacts of climate change on forest productivity (Vanclay, 1992; Boisvenue and Running, 2006).

1.2.3 Height-Diameter Functions

Fang and Bailey (1998) evaluated 33 height-diameter models to predict total tree height as a function of DBH for individual trees in the tropical forests of China. Six of these equations (see footnote in Table 1.3) were selected as candidate functions to model the height-diameter relationship of the dominant trees on the sample plots. Models selected included a linear function (M1), three exponential functions (M3, M5, M6), one power function (M2), and one hyperbolic function (M4). Models were selected based on ease of fitting, low bias and relatively good precision in estimates.

1.2.4 Parameter Estimation and Model Evaluation

The fitting of the height-diameter functions was accomplished using the linear and non-linear least squares procedures in the R statistical package (R Development Core Team, 2010). Preliminary analysis indicated that the eight forest types had similar height-diameter relationships for the dominant trees, suggesting the possibility of using a single model to quantify the site productivity of the forests in Jalisco. Models were ranked

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based on the mean squared error (MSE) and FIT statistic, which is defined as the square of the linear correlation between the observed and predicted observations. FIT provides a better representation of the model fit for non-linear models as well as models with spatially or temporally correlated errors. The estimated coefficients were evaluated for signs and values, especially the asymptotes, to ensure models conformed to the biological growth patterns of the various forest types. Based on these considerations the top three models were selected for further evaluations.

In the second step, the top three models were fit to the data from the eight forest types. In addition to the criteria used in the first step, a ten-fold cross validation was performed to evaluate the predictive performance of the models (Stone, 1974). Additional criteria used to evaluate the models included estimates of the mean prediction error, mean absolute prediction error and the root mean squared prediction error. The top ranked model for each forest type was selected to represent the average height-diameter relationship of the dominant trees on the sample plots.

1.2.5 Site Productivity Index Curves

The top ranked model for each forest type was used as a guide curve to construct a set of anamorphic site productivity index (SPI) curves. In constructing the curves, it was assumed that the dominant tree height, H_{SPI}, for a given SPI was proportional to the ratio of the predicted average height of a dominant tree H(D) with diameter D, to the predicted height of a dominant tree H(D*) with reference diameter D^*:

$$H_{SPI} = SPI\left[\frac{H(D)}{H(D^*)}\right] \tag{1.1}$$

where H (.) is a specified height-diameter function.

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A reference diameter of 50 cm was used for all forest types except the MS, and MH forest types, in which a 30 cm reference diameter was used. The 50 cm size was selected to ensure better discrimination among sites of different productivity. Vanclay (1992) noted that in some pure and mixed stands of larch (*Larix* sp.), the discrimination was not apparent between good and poor sites until the trees exceeded a 50 cm diameter. All forest types had diameters exceeding 50 cm in our study. In the MS and MH forest types there were not enough sample plots with this size to ensure reliable estimates, so a smaller reference diameter was used. The SPI curves produced from these equations passed through the appropriate height and reference diameters and are reference diameter invariant (Bailey and Clutter, 1974).

Values of H and D from each sample were substituted into Eq. (1.2) to obtain an estimate of SPI:

$$SPI = H\left[\frac{H\left(D^{*}\right)}{H\left(D\right)}\right] \tag{1.2}$$

Correlations were used to test the assumptions that 1) the HD ratio increased with increasing SPI, and 2) SPI is independent of stand density. Analysis of variance was used to test if SPI and HD varied significantly among the temperature and precipitation-evaporation zones as well as forest types.

1.3 RESULTS AND DISCUSSION

1.3.1 Sample Data

Summary characteristics of the sample plots in each of the eight forest types are provided in Table 1.1. In all forest types, total basal area, average tree diameter and average height had distributions skewed to the right. In some forest types, the

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distributions had more of a reverse-J shaped distribution. In the PN forest type, diameters were skewed to the left, while tree heights had a U-shaped distribution; there were more sample plots with small or large average tree heights than sample plots with intermediate heights. The distribution of average tree height in the MH forest type also followed this U-shaped distribution. Because of the small sample sizes (n<20), the sample plots may not be representative of these two forest types with respect to species richness, stand density, heights and site conditions.

The distribution of sample plots by temperature and precipitation-evaporation zones reflect the influence of climate on the distribution and species richness of forest in Jalisco (Reich *et al.*, 2010) (Table 1.2). The occurrence and distribution of the various forest types can be explained in part by geophysical characteristics and seasonal patterns in precipitation and temperatures (Swaine and Hall, 1983).

1.3.2 Model Evaluations

All six models had similar performance when applied to the entire data set, although linear model M1 and the two exponential models (M5 and M6) showed the best performance. The MSE was 3.89 for models M5 and M6, and 3.90 for M1. Models not considered were: 1) M2 because it had the largest MSE (3.94) and it increased in almost a linear fashion with no apparent asymptote; 2) M4 because of an estimated asymptote of 46.8 m; and M3 because it was ranked fifth due to its MSE of 3.92 (Table A.1, Figure A.2).

The models, M1, M5 and M6 had similar rankings when applied to the individual forest types. Model M1 had the smallest MSE and largest FIT statistics for all forest types except for the MH forest type. Model M5 had the best fit for this forest type, while model

Table 1.1. Summary statistics of selected sample plot attributes by forest type, in Jalisco. Mexico.

Plot characteristic		Forest type							
		Pine	Pine-Oak	Oak	Oak-Pine	Tropical Semi Evergreen	Tropical Dry	Subtropical Scrub	*Mezquital-Huizachal*
No. sample plots		13	89	197	54	102	278	66	19
Average tree height (m)	Min	7.0	3.9	3.4	4.0	4.0	3.3	3.0	3.0
	Mean	14.3	13.6	8.5	9.5	10.4	7.9	6.0	5.8
	Max	26.0	24.7	15.5	17.0	24.0	16.2	18.5	9.7
	SD†	5.4	4.6	2.9	2.7	3.6	2.0	2.4	1.7
Average tree diameter (cm)	Min	17.2	17.2	13.0	13.0	14.0	13.0	13.0	13.0
	Mean	34.8	28.0	22.5	24.5	25.3	19.6	18.1	20.3
	Max	50.0	59.1	52.0	49.9	102.0	38.0	55.0	47.0
	SD	10.2	8.7	6.3	7.6	11.8	4.6	5.9	8.2
Dominant tree height (m)	Min	7.0	4.4	4.0	4.0	4.0	2.0	3.0	3.0
	Mean	17.0	17.7	9.9	11.1	12.7	9.3	6.4	6.4
	Max	30.5	35.5	24.0	21.3	25.8	28.0	29.0	10.0
	SD	7.5	6.8	4.0	3.9	4.9	3.0	3.6	2.2
Dominant tree diameter (cm)	Min	21.0	14.0	13.0	13.0	13.0	13.0	13.0	13.0
	Mean	40.2	36.3	27.1	28.3	31.3	23.7	19.2	23.4
	Max	56.0	112.0	76.0	59.0	102.0	95.0	55.0	47.0
	SD	12.3	14.6	9.7	9.8	16.6	10.4	6.8	9.5
Basal area (m^2 ha^{-1})	Min	2.2	2.4	0.3	0.3	0.4	0.3	0.3	0.3
	Mean	14.2	16.3	11.1	13.7	17.3	9.4	3.2	4.2
	Max	47.2	106. 7	38.8	55.1	141.9	58.0	10.9	14.1
	SD	4.0	2.7	8.5	19.2	10.3	7.1	12.8	12.2
Average height- diameter ratio (m cm^{-2})	Min	0.2	0.2	0.1	0.2	0.2	0.2	0.2	0.1
	Mean	0.4	0.5	0.4	0.4	0.5	0.4	0.3	0.3
	Max	0.6	1.0	0.8	0.6	0.9	0.7	1.1	0.5
	SD	0.1	0.2	0.1	0.1	0.1	0.1	0.1	0.1
Tree species richness (Trees ha^{-1})		13(150.83)	50(253.50)	110(256.59)	37(269.74)	152(264.88)	202(255.66)	33(111.55)	8(107.22)

†SD = standard deviation.

Table 1.2. Average site productivity index (SPI) and height-diameter ratio by temperature and precipitation-evaporation zones and forest type. Means with the same letters are not significantly different at the 0.05 level of significance.

Description	Site Productivity Index (m)	Height-Diameter Ratio (m cm^{-1})
	Temperature zone	
Cool	16.72 a	0.459 a
Warm	15.04 b	0.438 a
Hot	13.44 c	0.399 b
	Precipitation-Evaporation zones	
Dry	11.36 a	0.394 a
Moist	13.91 b	0.433 ab
Damp	14.85 bc	0.438 b
Wet	15.70 c	0.429 ab
	Forest type[1]	
PN	20.34 a	0.436 abcd
PO	21.85 a	0.526 a
OK	15.19 c	0.405 c
OP	16.49 abc	0.422 bc
SM	17.33 ab	0.465 b
SB	13.18 d	0.432 bc
MS	7.23 e	0.345 d
MH	7.84 e	0.316 d

[1] Forest types: PN-Pine, PO-Pine-Oak, OK-Oak, OP-Oak-Pine, SM-Tropical Semi Evergreen, SB-Tropical Dry, MS-Subtropical Scrub, and MH-*Mezquital–Huizachal*.

Table 1.3. Parameter estimates and fit statistics of models† M1, M5 and M6 for the major forest types in Jalisco, Mexico.

Forest type	No. sample plots	Model M1				Model M5					Model M6			
		A	*B*	MSE‡	FIT§	a	*b*	*c*	MSE	FIT	*a*	*b*	MSE	FIT
Pine	13	-27.91	12.34	6.50	0.33	-18.17	41.84	0.05	6.79	0.33	37.16	0.02	6.52	0.32
Pine-Oak	89	-19.43	10.54	5.54	0.35	0.39	31.03	0.02	5.58	0.34	31.06	0.02	5.55	0.34
Oak	197	-15.50	7.85	3.05	0.43	-4.86	22.60	0.04	3.06	0.43	23.83	0.02	3.07	0.42
Oak-Pine	54	-17.08	8.58	2.84	0.49	3.43	-141.60	0.003	2.86	0.49	29.68	0.02	2.85	0.49
Tropical Semi Evergreen	102	-14.22	8.07	3.46	0.51	-1.89	24.28	0.03	3.47	0.51	23.49	0.03	3.46	0.51
Tropical Dry	278	-5.48	4.78	2.56	0.30	3.49	21.72	0.01	2.57	0.30	14.63	0.05	2.57	0.29
Subtropical Scrub	66	2.94	3.22	3.50	0.06	3.49	21.72	0.01	3.52	0.06	9.98	0.06	3.50	0.06
Mezquital – Huizachal	19	-7.52	4.53	1.46	0.61	-10.49	19.75	0.10	1.38	0.67	11.42	0.04	1.46	0.61

†Models: M1: $H = a+b\ \ln(D)$; M2: $H = aD^{b}$; M3:– $H = a\ e^{b/D}$; M4:– $H = aD/(b+D)$; M5: $H = a+b(1-e^{-cD})$; M6:– $H = a(1-e^{-bD})$, where H is the dominant tree height (m), D = diameter of the dominant tree (cm), a, b and c are regression parameters to be estimated, ln is the natural logarithm and e is the base of the natural logarithms.

‡MSE = mean squared error.

§FIT = correlation between the observed and predicted values squared.

M6 consistently outranked model M5 except for MH, and tied with model M1 for forest types SM and MS. The additional parameter associated with model M5 did not significantly improve the fit of the model (Table 1.3).

The cross-validation of the three models by forest type confirmed these rankings, indicating that all three models were unbiased in estimating tree heights (< 0.05 m). It is also interesting to note that model M1 outperformed both M5 and M6 for the MH forest type. Based on these results, the simple, two-parameter, linear model (M1) was selected to describe the height-diameter relationship of the dominant trees in each forest type (Figure A.3). Fang and Bailey (1998) also ranked this model high for describing the height-diameter relationship of the individual trees in tropical forests of China.

1.3.3 Estimating the Site Productivity Index for the Forest Types

Model M1 was used to develop SPI curves for each forest type (Figure 1.1) as well as to assign a SPI value to each sample plot (Table A.2). The PO (SPI = 21.8 m) and PN (SPI = 20.3 m) forest types were the most productive on average, while the MS (SPI = 7.2 m) and MH (SPI = 7.8 m) were the least productive forest types. The other forest types had intermediate levels of productivity, ranging from 13.2 m for the SB forest type to 17.3 m for the SM forest type (Figure A.4).

1.3.4 Relationship of SPI and HD Ratio to Climate Conditions

SPI increased significantly with decreasing temperature and increasing precipitation-evaporation; besides, it also differed significantly among forest types (Table 1.2). The distribution of forest types in the state is largely determined by the trends in temperature, precipitation and evaporation (Reich *et al.*, 2010). The average SPI within the temperature and precipitation-evaporation zones is influenced by the distribution or area associated with the individual forest types. The cooler regions of Jalisco are dominated by the temperate forest types (PN, OK, PO and OP), resulting in a higher than average SPI.

With increasing temperature, the proportion of temperate forest types decreased while the tropical forest types (SM, SB and MS) increased in frequency, thus lowering the average SPI. In the driest part of Jalisco forest types (SB, MS and MH) with some of the smallest dominant tree heights dominate the region resulting in low values for SPI. As precipitation increased, the frequency of tropical (SM) and temperate (OK and PO) forest types increased, thus increasing the average SPI. In the wettest regions, the three most dominant forest types (OK, PO and SM) have some of the tallest dominant trees. Given that temperature, precipitation and evaporation are major ecological drivers that influence both the distribution and abundance of forest types throughout Jalisco (Reich *et al*., 2010), this explains nicely the relationship observed between SPI and climatic conditions.

Trees in the hot temperature zone had significantly more taper (smaller HD ratio) than trees in the other two temperature zones. The HD ratio increased significantly with increasing precipitation, reaching a maximum in the damp regions, and then decreased slightly in the wet region. Climatic regions with the highest SPI have trees with less taper than climatic regions dominated by forest types with a lower SPI.

1.3.5 Relationship of SPI and HD Ratio with Stand Characteristics

Strong positive correlations ($0.79 < r < 0.95$; $p \leq 0.01$) were observed between SPI and the HD ratio in all forest types. For a given diameter, trees are taller (less taper) on good sites compared to those on poor sites (more taper), which supports the assumption that tree taper should decrease with increasing SPI.

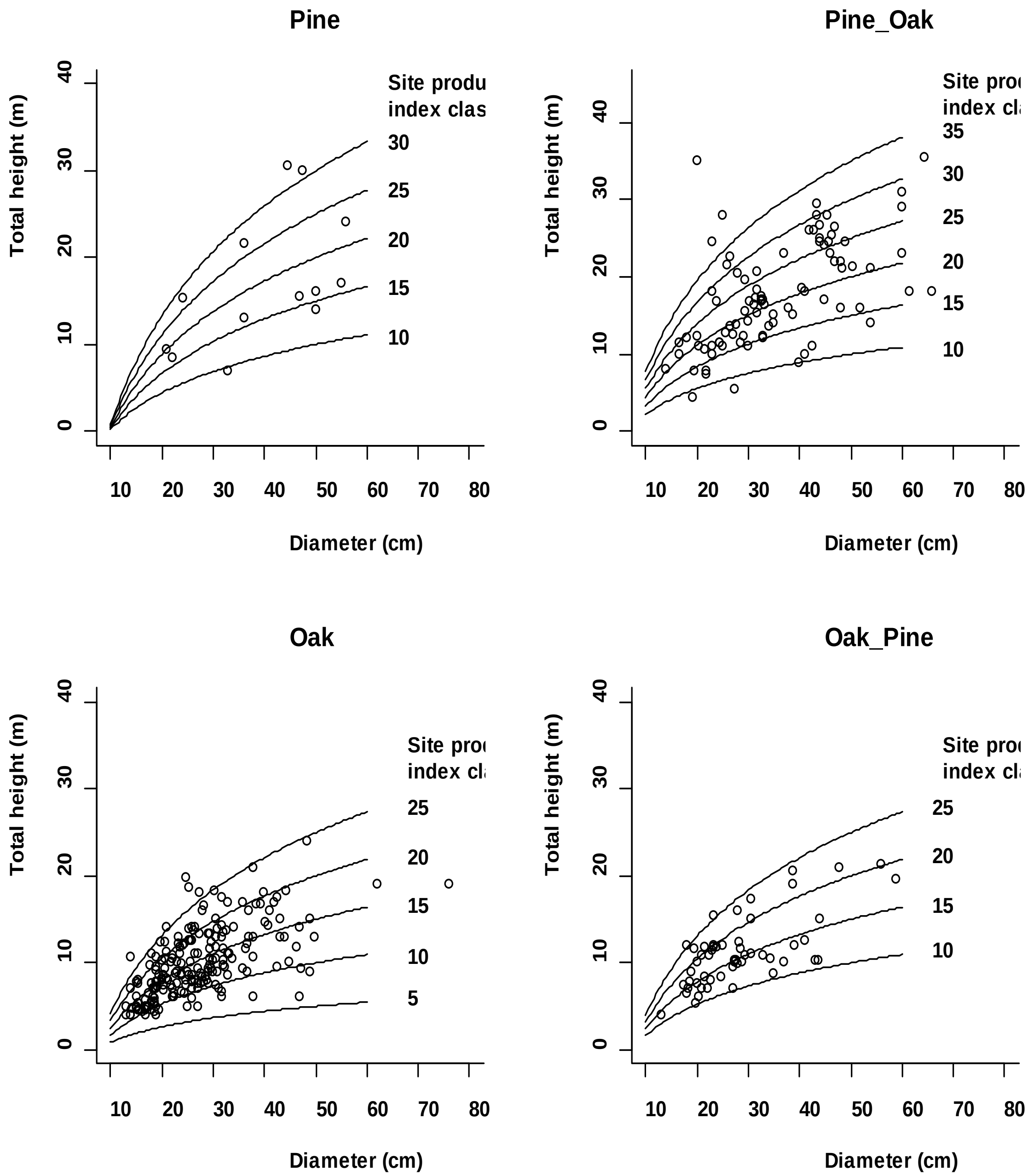

Figure 1.1. Site productivity index curves for the major forest types in Jalisco, Mexico.

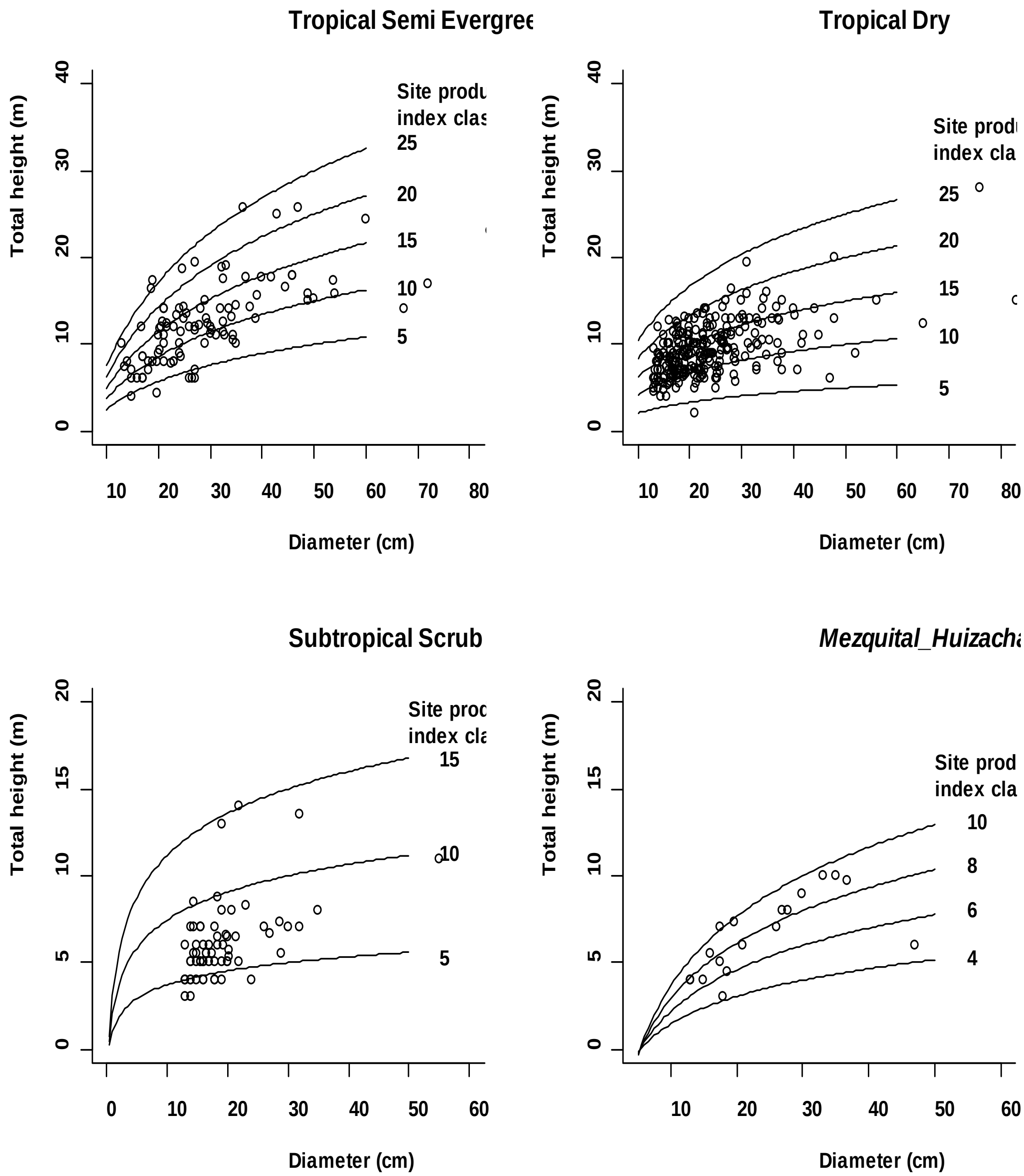

Figure 1.1. Continued.

SPI also showed significant correlations ($0.68 < r < 0.99$; $p \leq 0.01$) with the height of the dominant trees, while being independent of the diameter of the dominant trees. The exception to this was in the PN forest type, where there was a strong positive correlation ($r = 0.77$; $p \leq 0.01$) between SPI and the diameter of dominant trees. This strong correlation is attributed to the large number of sample plots that had an average diameter close to the 50 cm reference diameter used in computing SPI (Table 1.4). Except for this one situation, estimates of SPI are diameter invariant (Bailey and Clutter, 1974); the height-diameter relationship of the dominant trees is independent of stand density.

SPI showed a weak, but significant correlation ($0.24 < r < 0.29$; $p \leq 0.01$) with basal area in the OK, OP, and SB forest types. Moderate non-significant correlations between SPI and total basal area were observed in the PN ($r = 0.50$; p > 0.05) and MH ($r = 0.41$; $p > 0.05$) forest types, possibly due in part to the small sample sizes available (Table 1.4). These results indicate that sites with a higher SPI are able to sustain higher levels of basal area (i.e., volume) than sites with a lower SPI (Vanclay, 1992).

The HD ratio showed moderate to strong correlations ($0.43 < r < 0.86$; $p \leq 0.05$) with the height of the dominant trees while being independent of the diameter of the dominant trees, although an exception was observed in the PN ($r = 0.62$; $p \leq 0.01$) and SB ($r = -0.16$; $p \leq 0.01$) forest types. The HD ratio was independent of total basal area in all forest types except for the OK ($r = 0.34$; $p \leq 0.01$) forest type (Table A.3). These results indicate that trees on sites with a higher SPI have less taper than trees on productive sites with a lower SPI, and that stand density does not influence the form, or taper of the dominant trees.

1.4 CONCLUSION

The site productivity index (SPI), defined as the expected height of a dominant tree with a 50 cm or 30 cm DBH, is shown to be a useful indicator of site potential in the forests of Jalisco. An important finding is that a single model can be used to describe the height-diameter relationship of the dominant trees in the eight forest types considered in this study. The small bias (< 0.05 m) associated with some forest types provides an indication that additional research is still required, particularly in the under-represented forest types. The SPI models developed in this study provide a starting point in understanding the complex relationship between forest productivity and environmental and ecological conditions. However, any increase in the complexity of the models needs to be carefully balanced against the cost-effective change in precision. When implemented in a GIS environment, models can be used to predict forest site productivity throughout Jalisco, information which is critical for the management and sustainability of species-rich forests in this state.

Table 1.4. Correlation of site productivity index (SPI) with selected sample plot attributes by forest type.

Forest type[1]	DH[2]	DD[3]	BA[4]	HD[5]
PN	0.82*	0.766*	0.50	0.95*
PO	0.79*	-0.005	0.13	0.75*
OK	0.74*	0.004	0.30*	0.79*
OP	0.69*	0.002	0.29*	0.79*
SM	0.68*	-0.004	0.17	0.80*
SB	0.82*	-0.002	0.24*	0.81*
MS	0.99**	0.109	0.22	0.91*
MH	0.67*	0.008	0.41	0.88*

*Significantly different from zero at the 0.01 level.

[1]PN-pine, PO-pine-oak, OK-oak, OP-oak-pine, SM-tropical semi-evergreen, SB-tropical dry, MS- subtropical scrub, and MH-*Mezquital- Huizachal*.

[2]DH-dominant height, [3]DD-dominant tree diameter, [4]BA-tree basal area, and [5]HD-height-diameter ratio.

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CHAPTER 2 SPATIAL ESTIMATION OF SITE PRODUCTIVITY INDEX FOR THE SPECIES RICH FORESTS OF JALISCO, MEXICO USING ECOLOGICAL VARIABLES

2.1 INTRODUCTION

The forests of Jalisco, Mexico, have a very diverse and unique community of endemic and specialized species of plants, animals, reptiles, and amphibians. Tropical dry forests in the region are among the richest tropical dry forests in the world, and have more endemic tree species than elsewhere in the Neotropics (Challenger, 1998), while forests found in the temperate climate region are recognized as a center of diversity for the Quercus genus (Nixon, 1993). Climatic conditions play an important role in the diversity and distribution of forest types in the state (Reich *et al*., 2010).

The trees in these forests are important to local inhabitants as a source of products for their daily needs, and the close proximity of forests to the towns and cities has accelerated the exploitation of these forests through grazing, fuel wood extraction, selective logging and other economic activities (Pande, 2005). These disturbances impact both the diversity and the productivity of the forests (Reich *et al*., 2010). Soil characteristics, climatic factors and management may also affect site quality and thus the inherent site potential. Understanding the patterns in site productivity in relation to these factors, as well as other important ecological drivers, is critical for land resource management purposes.

Many decisions in forestry rely on estimates of the land's inherent ability to grow trees and yield timber (Stearns, 2001). Estimates of site productivity help improve the understanding of forest production, and aid in the management of forest ecosystems over large geographical regions (Ma, 2006).

Site productivity can be estimated using either direct or indirect methods. Direct methods use the average yield of fully stocked stands as a measure of site productivity. Fully stocked stands are defined as stands that fully utilize the growth potential of a site. Because of the difficulty in identifying such stands and the lack of long term inventory data in many countries, makes this method of estimating site productivity difficult to implement over large geographical regions (Avery and Burkhart, 2002).

Indirect methods try and relate the productivity of a site to stand characteristics, environmental variables, plant indicator species or vegetative characteristics (Vanclay, 1992). Methods based on stand characteristics generally use the height of a dominant tree as an indicator of site productivity. Such measures are independent of stand density and past management activities, and are easily obtained from inventory records (Carmean, 1975; Avery and Burkhart, 2002). Site productivity can also be assessed by characterizing the composition of the ground vegetation, the presence-abundance of selected indicator species, or size of understory plants (MacLean and Bolsinger, 1973a; Wiant *et al.*, 1975; and Webb *et al.*, 1971). Because of the sensitivity of the understory vegetation to disturbances such things as fire and grazing, this method of characterizing the productivity of a forested site has applications to undisturbed sites (Avery and Burkhart, 2002).

Four approaches have been used to model the relationship between site productivity and environmental variables. These include linear and nonlinear regression analysis, classification and regression tree, general additive models and artificial neural network (Wang, 2005). In all of these approaches, site productivity is modeled as a function of biotic and abiotic site characteristic, such as climate, topography, soil and vegetation characteristics. Most studies have shown that climatic variables (evapotranspiration, annual temperature, mean annual precipitation and mean monthly temperature) are useful predictors of site productivity (Lemieux, 1961; Leith and Box, 1972). Carmean (1967) estimated site productivity of upland oaks in southeastern Ohio using topographic data such as aspect, slope shape and position on slope.

Numerous studies have included soil information to refine estimation of site productivity (Carmean, 1973; Fralish and Loucks, 1975; Schmidt and Carmean, 1988). This approach has been also used to predict and map the spatial variation in site index of even-aged, fully stocked forests stand of Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco) throughout the Pacific Northwest. The model based on median values of enhanced vegetation index derived from a 3km x 3km smoothed raster image, soil depth, soil texture and stone content, explained 53% of the spatial variability in site productivity (Waring, 2006). Watt (2009) developed a nonlinear regression to describe the spatial variability of *Cupressus lusitanica* site index as a function of mean air temperature, potential root depth, forest establishment date, and degree of ground frost in the summer in New Zeland (Watt, 2009) and accounted for 76% of the variability in site index.

Binary regression tree has also been used to model the spatial distribution of site index for lodgepole pine (*Pinus contorta var. latifolia*) in the mixed forests of Alberta, Canada (Wang, 2005). The regression tree was used to relate site index to climate, topography and soil conditions. Soil variables included depth of mineral soil, depth of organic soil, available water capacity, soil texture; topographic data only included aspect, slope and slope position. The climatic variables included monthly minimum-maximum temperature, mean annual temperature and mean annual precipitation. The model explained 70% of the observed variability in lodgepole pine site productivity.

Wang (2005) used general additive models to predict the spatial variation in site index for lodgepole pine (*Pinus contorta var. latifolia*) in the Wapiti region of Alberta, Canada. Independent variables included latitude, longitude, elevation, mean air temperature, precipitation, soil sand fraction as well as other variables. Artificial neural network has also been used to model spatial variation of site index for lodgepole pine in the Wapiti region of Alberta, Canada. Using the same set of independent variables, the general additive model was able to explain 75% of the variability observed in site productivity (Wang, 2005).

The objective of this study was to develop models describing the spatial variability in site productivity of the major forest types in the state of Jalisco, Mexico as a function of environmental variables available as GIS layers.

2.2 MATERIALS AND METHODS

2.2.1 Study Area

The state of Jalisco is located in the west central Mexico (20° 34′ 0″ N, 103° 40′ 35″ W) and covers an area of approximately 7.9 million hectares (Fig.2.1). The state is characterized by three broad climatic regions which correspond to three major ecological regions: 1) tropical zone is located in the west part of the state along the Pacific coast and is characterized by high temperature, rain during the summer month (730-1200mm), and annual dry period that lasts for 5 to 9 months. Tropical dry forests dominate this zone with elevation ranging from sea level to 2000 m; 2) Temperate zone occurs at the higher elevations 1000-2500 m and covers a large part of the state with average annual rainfall of 900-1500 mm. Pine, oak and mixed deciduous hardwood forest dominate this region. This zone gradually changes to 3) Semi-arid region located in the eastern part of the state which is characterized by low annual precipitation with a dry period lasting 6-8 month. The vegetation in this region is dominated by mesquite-acacia and zerophitic shrubs (Reich *et al*., 2008).

Sandy loam and sandy clay loam are the dominant soil textural classes in the state (Sergio, 1997). These two soil classes occur primarily in the central portion of the state dominated by grasslands and agricultural lands. Sandy clay loam soils also occur in the coastal region dominated by tropical dry forests and in the semi-arid region in the eastern part of the state. Soils are acidic with pH ranging from 5.8 to 7.0. Soils are derived primarily from volcanic rock and slightly acidic at the lower elevations and in the central and western part of the state. As the elevation increases the soil pH becomes more acidic.

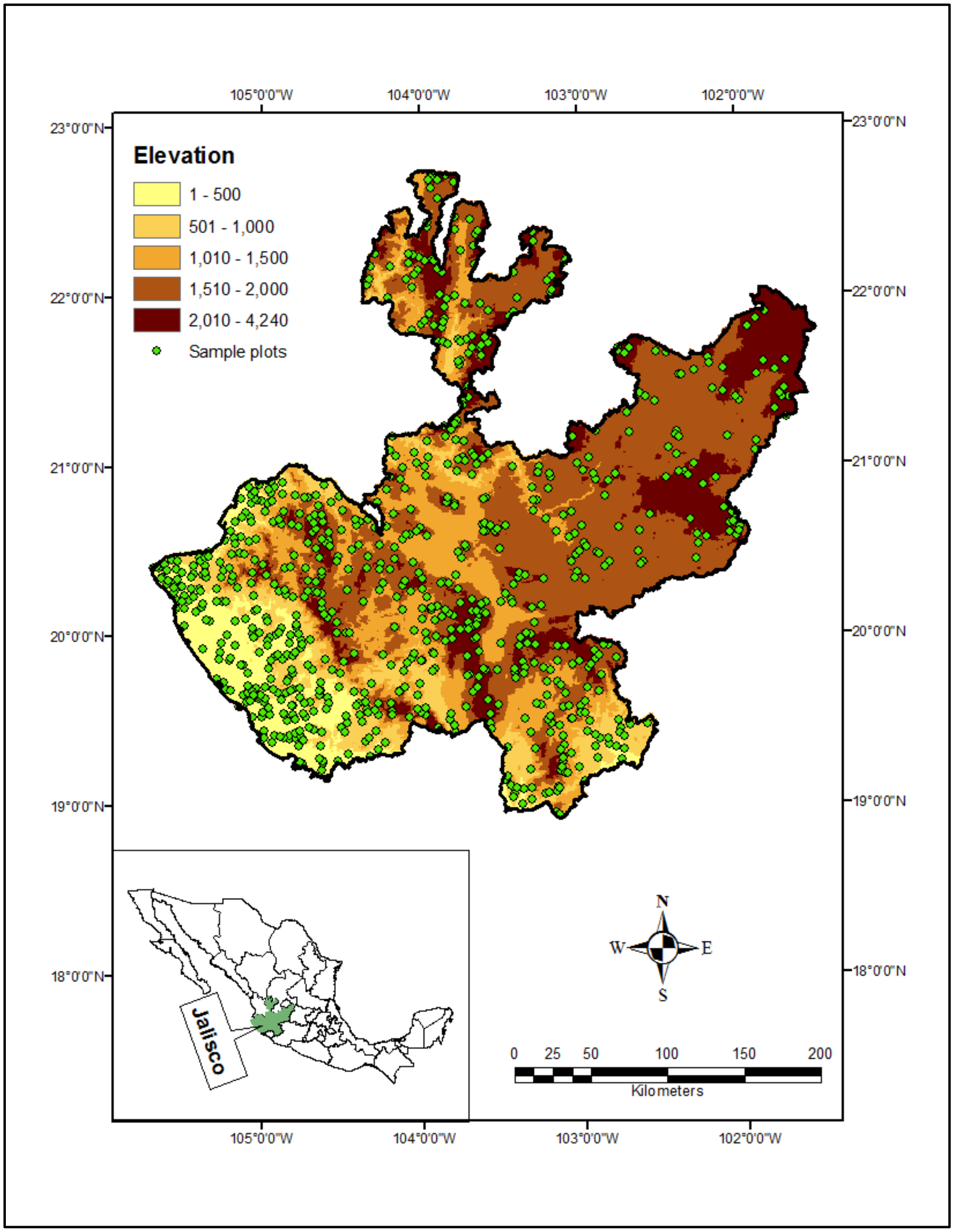

Figure 2. 1. Locations of 1,442 sample plots in the state of Jalisco, Mexico.

2.2.2 Site Productivity Index Data

In 2004, 1442 permanent sample plots were located throughout the state, of which 818 plots were classified as forested plots. The site productivity index (SPI) was estimated for each of the forested sample plot using the models developed in Chapter1. Eight major forest types: pine (PN), oak (OK), pine-oak (PO), oak-pine (OP), tropical semi-evergreen forest (SM), tropical dry forest (SB), subtropical scrub (MS), and *mezquital–huizachal* (MH) are represented in the study area. Estimates of SPI were based on the assumption that the productivity of a site was proportional to the total tree height of a dominant tree with a 30 cm or 50 cm reference diameter, depending on the forest type.

2.2.3 GIS Data

GIS raster layers included a digital elevation model (elevation, slope and aspect), climatic data (temperature and precipitation - evaporation zones) (Reich *et al*., 2008) and soil attributes (sand, silt, clay and pH) (Pongpattananurak, 2008). All raster layers had a 30m spatial resolution. Each sample plot was assigned to one of three temperature zones: cool, warm or hot, and one of four precipitation zones: dry, moist, damp or wet (Reich *et al*., 2010), and when combined created 12 unique climate zones. The values of elevation, slope, aspect, soil attributes and climate zones were extracted from the grid layers and assigned to the individual sample plots.

2.2.4 Modeling Site Productivity Index

Site productivity was modeled using procedures developed by Reich *et al.* (2011). First, regression analysis was used to describe the large scale variability in site productivity. Independent variables used in the model included soil texture (sand, silt, and clay), soil pH, elevation, aspect, slope, temperature zone, precipitation - evaporation zone and forest type. Forest type, temperature and precipitation - evaporation zones were treated as categorical variables in the analysis. Interactions between the categorical variables (forest types, temperature and precipitation - evaporation zones) and the continuous variables (pH, aspect, elevation, slope and soil texture) were included in the model. A stepwise AIC (Venables and Ripley, 2002) was used to identify the set predictors the minimized the AIC.

Residual analysis was performed to evaluate the underlying assumptions of the regression model describing the large scale variability of site productivity. Preliminary analysis indicated that the variability in estimating SPI increased with increasing SPI. To account for the unequal variances, weighted least squares was used to estimate the coefficients of the regression model. To estimate the error variance, the absolute values of the residuals (estimates of the standard deviation) were regressed on the predicted estimates of SPI, using polynomial regression, starting with a linear model, then a quadratic model and so on until no improvement was observed in the AIC (Akaike, 1969). The weights used in the regression analysis were defined as $W_i = \frac{1}{\widehat{s_i^2}}$, where $\widehat{s_i^2}$ is the estimated variance associated with the *i*th estimate of SPI.

The small-scale variability (i,e, estimated errors from the regression model) in SPI was modeled using a tree-based stratified design (Reich *et al*., 2011). Independent variables considered in the stratification included forest type and topographic variables. To evaluate the effectiveness of modeling the small-scale variability in SPI using a tree-based stratified design, different binary regression trees were fit to the residuals from the GLM model. This was accomplished by varying two parameters that controlled the recursive partitioning algorithm used to construct the tree. The first parameter *minsize* controls the minimum size of the strata in which the last split was performed. The parameter *minsize* was initially set to take values 5, 15, 25, and then increased in increments of 10 if no optimal tree structure was identified. The second parameter *best* is an integer that controls the number of strata, or the number of terminal nodes in the tree. The number of strata was varied from a minimum of 10 to the maximum possible number in increments of 5 strata. All the analysis was done in R software (R Development Core Team, 2010).

2.2.5 Cross-Validation

A 10-fold cross validation was used to evaluate the prediction performance of the model (regression + tree) (Reich *et al*., 2004). The data was split into 10 parts consisting of approximately 81 sample plots. The first subset of data was removed from the data, and the models were fitted to the remaining nine parts of the data and then the fitted model was used to predict the part of the data removed from the modeling process. This procedure was repeated 10 times. The prediction errors were then inferred from the predicted minus the actual values. This information was used to generate a set of statistics to evaluate the performance of the models.

The goodness-of prediction statistic (G-statistic).

$$G = 1 - \frac{\sum_{i=1}^{n}[Z_i - \hat{Z}_i]^2}{\sum_{i=1}^{n}[Z_i - \overline{Z}_i]^2} \tag{2.1}$$

was used to evaluate the predictive performance of the model, where Z_i is the observed value of i^{th} observation, $\hat{Z}_i$ is the predicted value of the i^{th} observation and $\overline{Z}_i$ is the sample mean.The G-statistic evaluates the effectiveness of the model relative to the sample mean. A G-statistic equal to one indicates perfect prediction and a positive value indicates the model provides more reliable estimates than the sample mean, while a negative value indicates the model provides estimates worse than if the sample mean had been used.

During the cross-validation, 95% prediction intervals were calculated for the prediction datasets under the assumption of normality. Confidence intervals for mean response were also computed. Coverage rates were calculated as the proportion of intervals that covered the true value (Reich *et al*., 2006).

In addition, the standardized mean square error (SMSE) was used to test the null hypothesis that the variance estimates were unbiased (Reich *et al.*, 2004):

$$\text{SMSE} = \frac{1}{n} \sum_{i=1}^{n} \frac{\left(e_i^*\right)^2}{\hat{\sigma}_i^{2*}} \tag{2.2}$$

where $\hat{\sigma}_i^{2*}$ is the estimation error variance and $(e_i^*)^2$ is the observed estimation error. The estimated variances were assumed to be consistent with the true errors if SMSE fell within the interval $[1 \pm 1.96\,(2/n)^{0.5}]$ (Hevesi *et al.*, 1992).

A decision rule developed by Reich *et al.* (2011) was adopted to identify a tree size that minimized the error in estimating the variance of the mean response and the prediction variance:

$$CC = \sqrt{\left(\left(\text{SMSE}_\text{M} - 1\right)^2 + \left(\text{SMSE}_\text{P} - 1\right)^2\right)} + \text{MSEP} / (\text{df} + \text{n}) \tag{2.3}$$

where SMSE_M is standardized mean square error of the variance of the mean response, SMSE_P is the standardized mean square error for the prediction variance, MSEP is the mean squared error of prediction obtained from the 10-fold cross-validation, df is degree of freedom and n is the number of terminal nodes in the tree.

2.2.6 GIS Maps of SPI

Raster layers representing the large scale variability in site productivity were developed for each forest type by passing the appropriate raster layers through the regression equations using the raster calculator in ArcGIS 9.3 (ESRI, 2008). Raster layers representing the residuals of the regression models were developed in ArcGIS using conditional if statements in the raster calculator of ArcGIS. The two raster surfaces were combined to develop the final surface for each forest type. Furthermore, variance surfaces associated with the predicted forest site productivity was developed as raster layers.

A surface representing the average site productivity was developed by multiplying the individual layers of SPI for the various forest types by the probability of observing a forest type in a given climate zone. The joint probabilities were calculated as the proportion of sample plots in a given forest type and climate zone. This surface represents the most likely SPI for a given location given the variability in forest types and site conditions in the state.

2.3 RESULTS

2.3.1 Data

Summary statistics of the explanatory variables evaluated in the model are summarized in Table 2.1. Sandy loam was the dominant soil texture on the sample plots with an average soil pH of 6.2. Elevation on the sample plots ranged from 16 m to a maximum of 3173 m with an average slope of 14% (Table 2.1).

Table 2.1. Summary statistics of the variables evaluated to describe the forest productivity in the state of Jalisco, Mexico.

Variable	Minimum	Mean	Maximum	Std. Dev.
Elevation (m)	16.0	1322.1	3173.0	717.7
Sand (%)	12.1	61.0	97.2	9.6
Clay (%)	1.4	15.8	46.1	6.2
Silt (%)	7.3	23.2	41.9	4.7
pH	3.2	6.2	8.7	0.5
Aspect (degree)	-1*	180.4	359.4	100.4
Slope (%)	0.0	14.0	40.5	8.0
Forest type[1]	Observed SPI (m)			
PN	9.4	20.4	32.8	7.1
PO	7.7	21.4	42.1	6.3
Ok	6.2	15.2	31.2	4.6
OP	10.3	16.5	25.6	4.1
SM	7.6	17.3	31.5	4.8
SB	2.9	13.2	24.3	3.4
MS	3.6	6.8	15.1	2.2
MH	4.3	7.8	10.1	1.6

*aspect assigned to locations with no slope.

[1] PN-Pine, PO-Pine-Oak, OK-Oak, OP-Oak-Pine, SM-Tropical Semi-Evergreen, SB-Tropical Dry, MS-Subtropical Scrub, and MH-*Mezquital–Huizachal*.

Estimates of SPI based on the height-diameter relationship of dominant trees indicated that the maximum average SPI was recorded for pine-oak (PO) forest type (21.4 m) while the minimum average SPI was 6.8 m for subtropical scrub (MS) forest type (Table 2.1).

2.3.2 Site Productivity Index Model

Weighted least squares was used to model the relationship between SPI and a set of environmental variables. A second degree polynomial was used to describe the variability in the estimates of SPI as a function of predicted SPI. Important variables included in the regression model to describe the large scale variability in SPI include topographic data (elevation, aspect and slope), soil attributes (pH, sand and silt), climatevariables (temperature and precipitation zones) and forest type (Table 2.2). Although some main effects were not significant, they were included in the final model because of their significant interaction with other variables. The final model explained 53 % of the observed variability in the forest site productivity. The most important variable in the model was forest type, which accounted for 35% of the observed variability in SPI. Temperature and precipitation accounted for only 8% to 9% of the variability in SPI while the soil attributes accounted for less than 4% of the variability observed in SPI.

The relationship between site productivity, forest type, climate and soil characteristics exhibited complex patterns across the state. In general, the temperate forest types (PN, PO, OP, OK) were more productive than the tropical (SM, SB) or semi-arid (MS, MH) forest types. Site productivity decreased with increasing temperature and decreasing amounts of precipitation. The temperate forest types occur at higher elevations

Table 2.2. Estimated regression coefficient and associated statistics for the regression model used to describe the large scale variability in site productivity for the major forest types in the state of Jalisco, Mexico.

Variable	Coefficient	SE[1]	P-value	
Intercept	4.818	6.547	0.462	
Pine-Oak (PO)	2.764	6.074	0.649	
Oak (OK)	2.215	5.657	0.696	
Oak-Pine (OP)	1.194	5.986	0.842	
Tropical Semi Evergreen (SM)	2.578	5.830	0.658	
Tropical Dry (SB)	0.398	5.491	0.942	
Subtropical Scrub (MS)	-4.213	5.479	0.442	
Mezquital – Huizachal (MH)	-7.478	7.160	0.297	
Sand (%)	0.038	0.023	0.092	+
Silt (%)	0.124	0.072	0.086	+
pH	0.008	0.295	0.977	
Elevation (m)	0.005	0.003	0.088	+
Aspect	0.005	0.002	0.024	*
Moist Zone	-7.642	3.116	0.014	*
Damp Zone	-3.809	3.314	0.251	
Wet Zone	2.692	0.981	0.006	**
Warm Zone	10.708	3.361	0.002	**
Hot Zone	-1.924	4.982	0.699	
Slope (%)	0.045	0.017	0.010	*
PO:elevation	-0.003	0.003	0.360	
OK:elevation	-0.005	0.003	0.045	*
OP:elevation	-0.003	0.003	0.261	
SM:elevation	-0.007	0.003	0.014	*
SB:elevation	-0.006	0.003	0.023	*
MS:elevation	-0.006	0.003	0.043	*

Table 2.2. Continued.

Variable	Coefficient	SE[1]	P-value	
OK:Moist	9.430	3.452	0.006	**
OP:Moist	5.824	3.297	0.078	+
SM:Moist	11.459	3.710	0.002	**
SB:Moist	9.358	3.138	0.003	**
MS:Moist	9.416	3.035	0.002	**
PO:Damp	7.472	3.518	0.034	*
OK:Damp	5.640	3.610	0.119	
OP:Damp	3.987	3.411	0.243	
SM:Damp	7.423	3.767	0.049	*
SB:Damp	6.100	3.351	0.069	+
MS:Damp	4.769	3.260	0.144	
MH:Damp	5.450	3.661	0.137	
OK:Wet	0.219	1.727	0.899	
SM:Wet	1.791	2.096	0.393	
SB:Wet	0.209	1.160	0.857	
Silt:Warm	-0.202	0.084	0.017	*
Silt:Hot	-0.088	0.072	0.224	
pH:Warm	-0.756	0.384	0.050	*
pH:Hot	0.872	0.704	0.216	
Aspect:Moist	-0.009	0.003	0.007	**
Aspect:Damp	-0.005	0.003	0.090	+
Aspect:Wet	-0.006	0.003	0.050	+

Significant levels: *** 0.001, ** 0.01, * 0.05, + 0.1.

AIC: 4438.1

Sample size: 817

R^2: 0.53

[1] SE is the standard error.

near the west coast, where temperatures are cooler and receive substantial amounts of precipitation. The rate of change in SPI varied depending on the forest type, with some forest types more sensitive to change in temperature and precipitation than other forest types. Site productivity increased with elevation for the temperate forest types, while site productivity decreased with increasing elevation for all other forest types. Site productivity increased with increasing sand and silt content in the soil. The tropical forest types were more productive on soils with a high pH, while the temperate and semi-arid forest types were more productive on less acidic soils.

The final tree size used to describe the small-scale variability had a *minsize* of 5, with 8 strata (Table 2.3).The binary regression tree accounted for an additional 5% of the variability observed in SPI. Important variables used to describe the small-scale variability in SPI included the predicted values of SPI, slope, aspect and elevation (Figure 2.2). The final regression tree indicated that on the more productive sites (SPI > 21.6 m) the regression model underestimated SPI by 13.3 m on northerly aspects. For all other conditions only slight adjustments were made to estimated SPI (-1.9 m to 4.6 m).

The model overestimated the prediction variance by as much as 25%, in that the standardized mean squared error of prediction ($SMSE_P = 0.75$) differed significantly from one (Table 2.3). In contrast, variance estimates of the mean response were unbiased ($SMSE_M = 0.95$). Coverage rates for the prediction of SPI at new locations and for the mean response was 0.96 which is close to the nominate rate of 0.95. The analysis of the residuals from the cross-validation showed normal distribution (Figure 2.3).

Table 2.4 compares the predicted values of site productivity index with the observed values. A paired t-test indicated no significant difference between the observed and predicted estimates of site productivity index at the 0.05 level of significance.

2.3.3 Maps of Forest Site Productivity

The final surfaces of SPI for each forest type are displayed in Figure 2.4. The most productive pine forests were located at the higher elevations in the western part of the state with SPI values greater than 20 m (Figure 2.4.A). The pine-oak forests were most productive in the west-central part of the state with SPI values greater than 20 m, while oak SPI values were greater than 15 m in the western part of the state (Figure 2.4.B and Figure 2.4.C).

Oak-pine and tropical dry forest site productivity had similar distribution with estimates of SPI ranging from 10 m to 20 m throughout the western and central parts of the state. The most productive forests were located in patches in the central and south parts of the state (Figure 2.4.D and Figure 2.4.E). The most productive tropical semi-evergreen forests occurred as patches in the western and northern of the state (Figure 2.4.F). The least productive forest types were the *mezquital–huizachal* (MH) and subtropical scrub (MS) with SPI less than 10 m in the western and central parts of the state (Figure 2.4.G and Figure 2.4.H).

The estimated prediction variances for pine is shown in Figure 2.5. The surface reflects the uncertainty in estimating SPI at a given location. The mean prediction variance was 12.4 m^2, with the largest errors associated with the tropical region along the coast. Figure 2.6 shows the estimated prediction variance for tropical semi-evergreen forest, with an average prediction variance 1.8 m^2. Similar surfaces were generated for the other forest types but are not displayed.

The weighted SPI values are displayed in Figure 2.7. The most productive forest region is located in the mountains in the western part of the state. The productivity decreases slightly in the central part of the state. The lowest productivity is found in the eastern part of the state in the semi-arid region and along the coast at lower elevations.

2.4 DISCUSSION

The objective of this study was to identify the ecological factors influencing forest site productivity. The results of the study indicated that forest types, soil attributes (pH, sand, and silt), and topographic variables (elevation, aspect, and slope) and climate conditions (temperature and precipitation) were the most important ecological variables related to the forest site productivity. Forest type was the most important variable used to describe the variability in site productivity. These results are similar to the results found by Reich *et al.* (2010) for defining the pattern of species richness in the state of Jalisco, Mexico.

Ercanli *et al*. (2008) showed that topographic variables (landform, slope and aspect) are highly correlated with site productivity index for oriental spruce (*Picea orientalis*). Similar results obtained by Louw and Scholes (2006) in describing the site productivity index of patula pine (*Pinus patula*) using topographic and climatic variables.

Table 2.3. Summary statistics of the final model (regression + tree) used to estimate the site productivity in the state of Jalisco, Mexico.

Minimum tree size*	No. tree nodes	GLM (R^2)	G Statistic	MSEP[1]	SMSE$_M$[2]	CRM[3]	SMSE$_P$[4]	CRP[5]	CC[6]
5	8	0.529	0.588	13.043	0.950	0.958	0.751	0.960	0.271

[1] MSEP: mean squared error of prediction.
[2] SMSE$_M$: standardized mean square error of model.
[3] CRM: confidence rate of the model.
[4] SMSE$_P$: standardized mean square error of prediction.
[5] CRP: confidence rate of prediction.
[6] CC: the cost complexity rate.
*Minimum size is the parameter *minsize* which defines the number of classes (observations) at which the last split is performed.

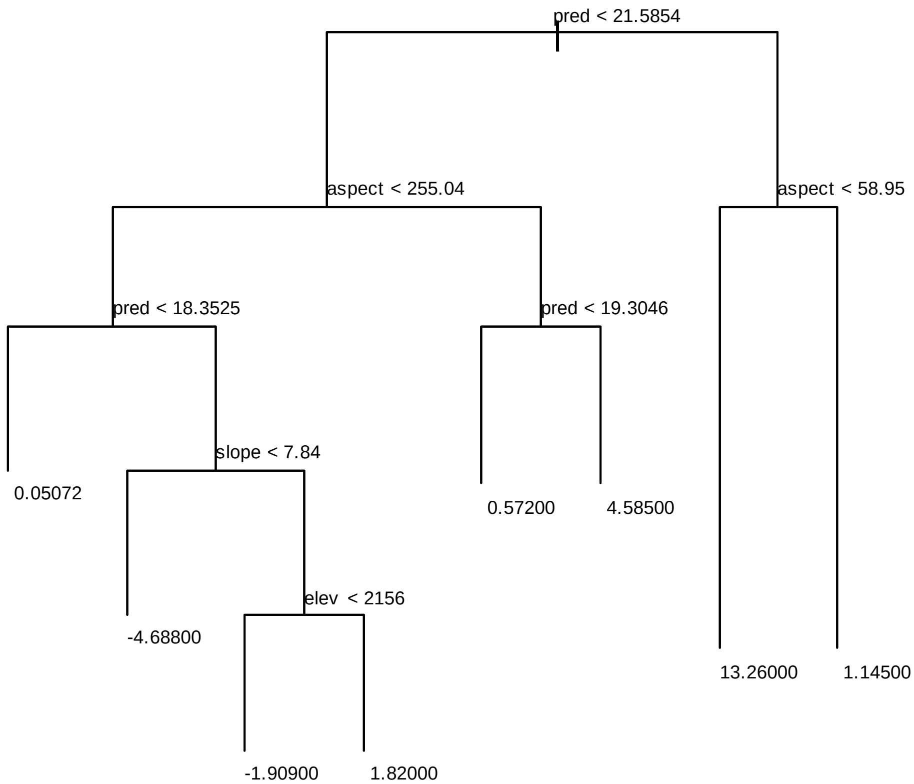

Figure 2.2. Regression tree of the residuals for the major forest types in the state of Jalisco, Mexico. (pred= predicted values of site productivity, and elev=elevation)

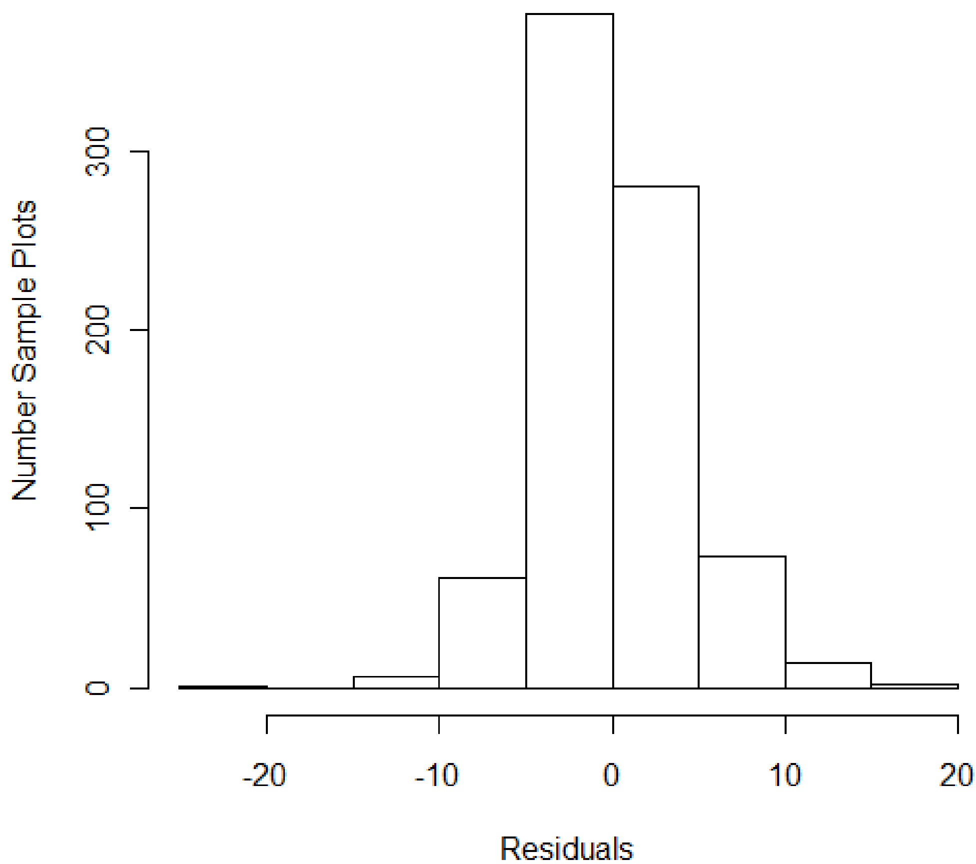

Figure 2.3. Histogram of residuals from the 10-fold cross-validation of the final model of site productivity index for the major forest types in the state of Jalisco, Mexico.

Table 2.4. Comparison between the observed values of site productivity index and the estimated site productivity index using the environmental variables for the major forest types in the state of Jalisco, Mexico.

Forest[1] type	Sample size	Observed SPI (m)				Predicted SPI (m)				Paired t-test	P-value	Mean difference (m)
		Min	Average	Max	SD	Min	Average	Max	SD			
PN	13	9.4	20.4	32.8	7.1	12.0	18.6	25.4	4.4	0.82	0.43	1.77
PO	88	7.7	21.4	42.1	6.3	12.0	21.4	41.1	4.6	-0.05	0.96	-0.04
Ok	197	6.2	15.2	31.2	4.6	5.7	15.1	19.4	1.8	0.40	0.69	0.13
OP	54	10.3	16.5	25.6	4.1	11.7	16.3	19.9	2.0	0.39	0.70	0.19
SM	102	7.6	17.3	31.5	4.8	8.2	17.1	20.6	1.9	0.48	0.63	0.24
SB	277	2.9	13.2	24.3	3.4	7.9	13.3	16.5	1.7	-0.55	0.58	-0.11
MS	65	3.6	6.8	15.1	2.2	4.2	6.9	9.9	1.2	-0.23	0.82	-0.06
MH	19	4.3	7.8	10.1	1.5	6.5	8.2	12.2	1.4	-0.76	0.45	-0.39

[1] PN-Pine, PO-Pine-Oak, OK-Oak, OP-Oak-Pine, SM-Tropical Semi-Evergreen, SB-Tropical Dry, MS-Subtropical Scrub , and MH-*Mezquital–Huizachal*.

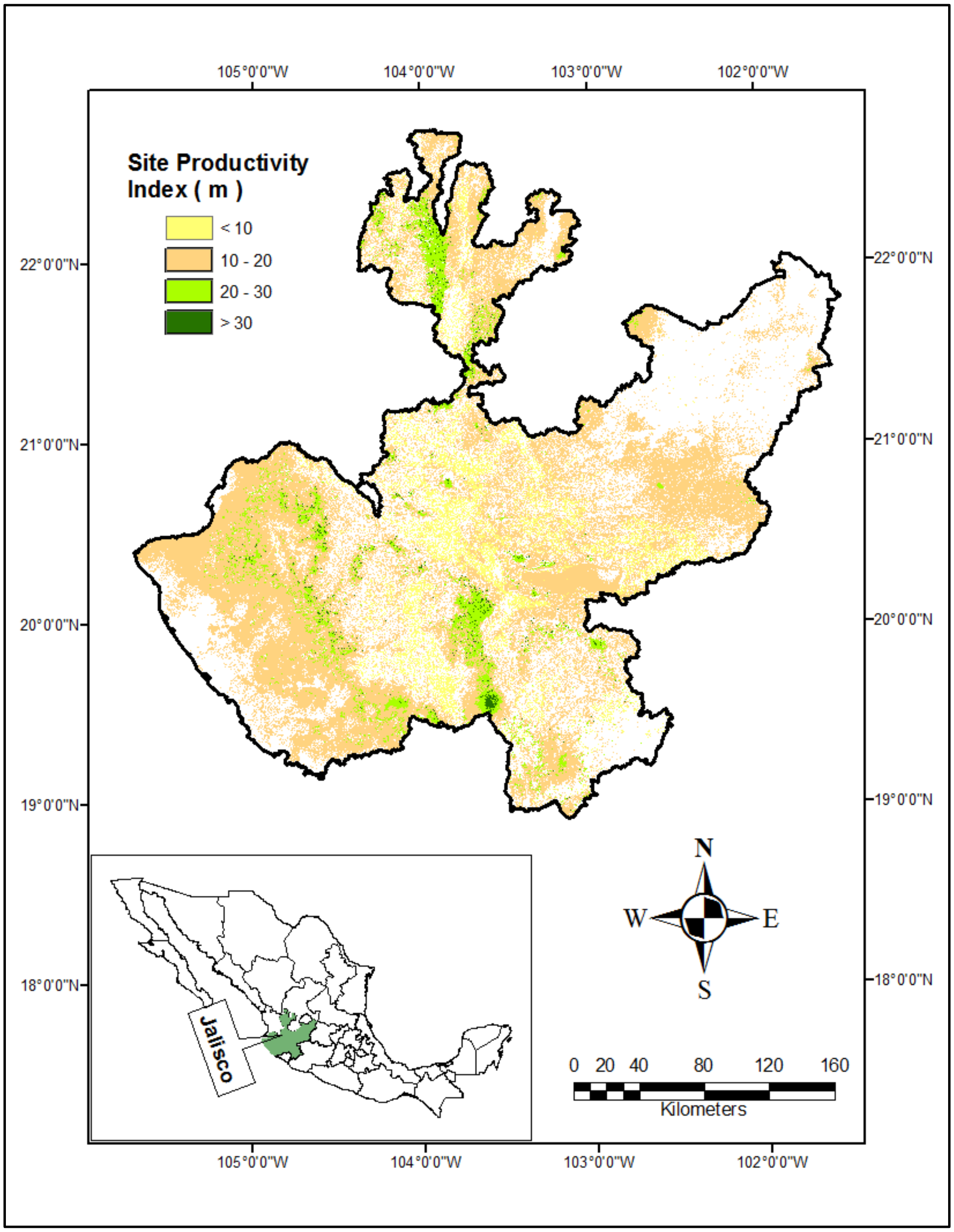

Figure 2.4. Spatial distribution of site productivity by forest type in the state of Jalisco, Mexico. A) Pine, B) Pine-Oak, C) Oak, D) Oak-Pine, E) Tropical Semi-Evergreen, F) Tropical Dry, G) Subtropical Scrub , and H) *Mezquital–Huizachal*.

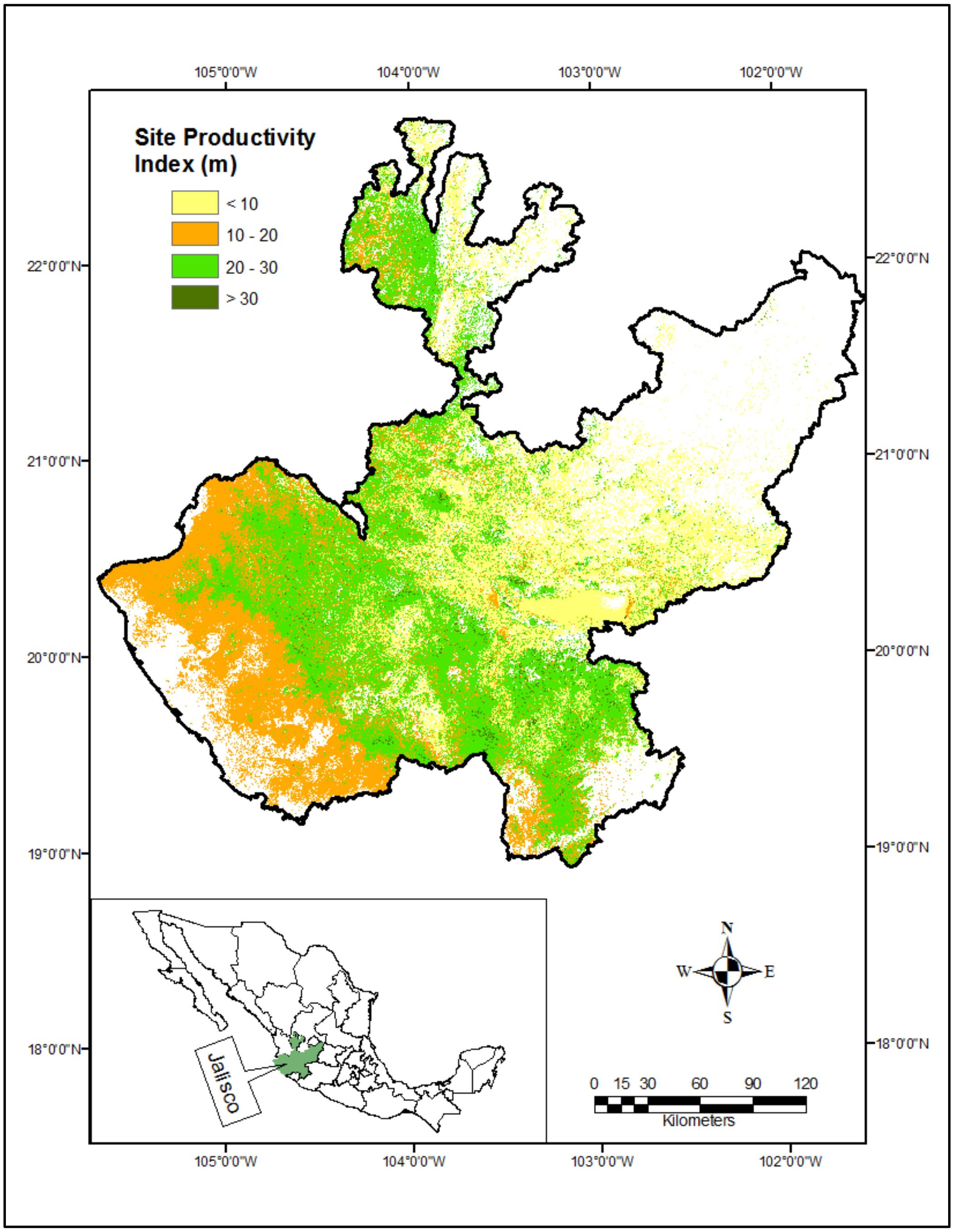

Figure 2.4.B. Continued.

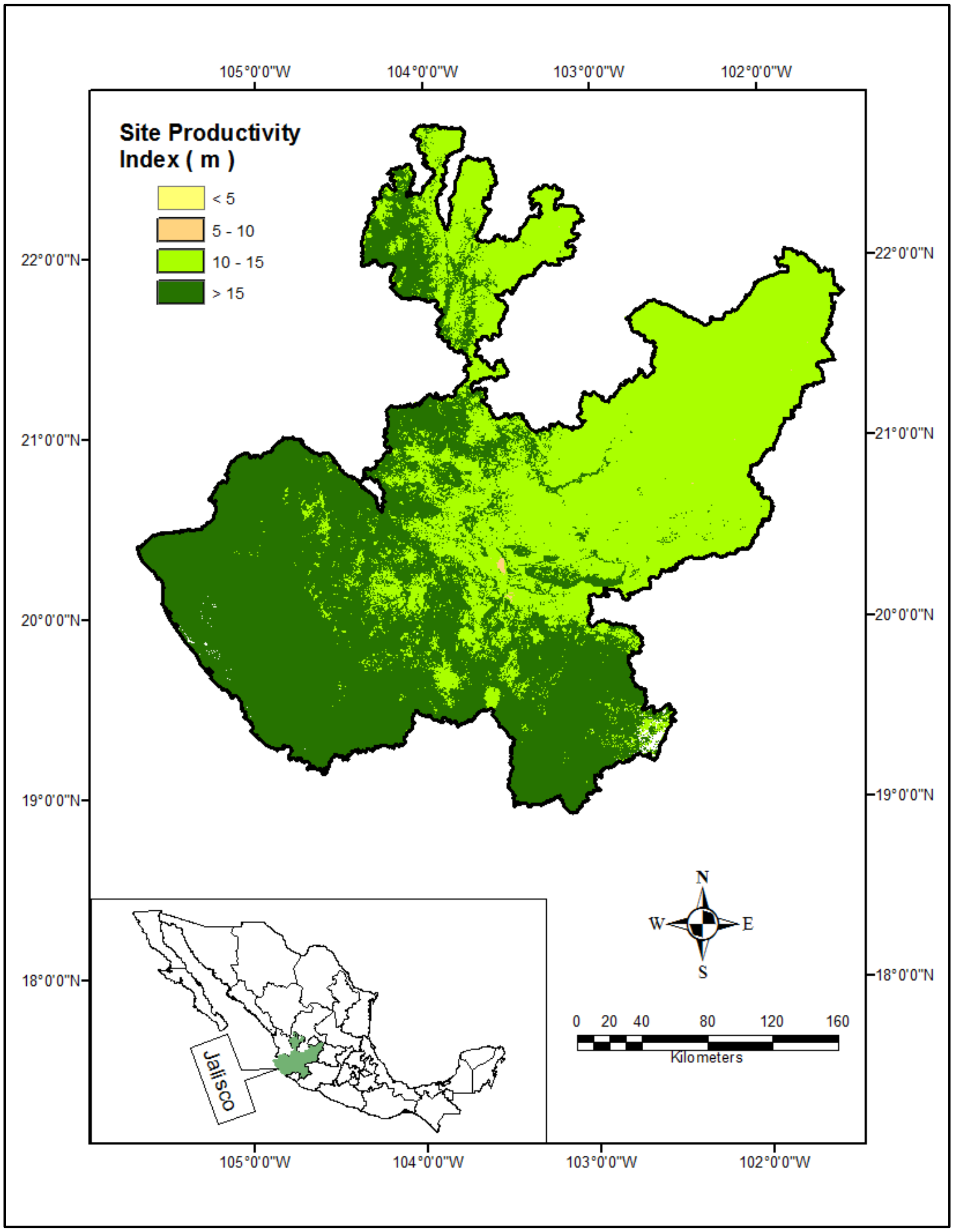

Figure 2.4.C. Continued.

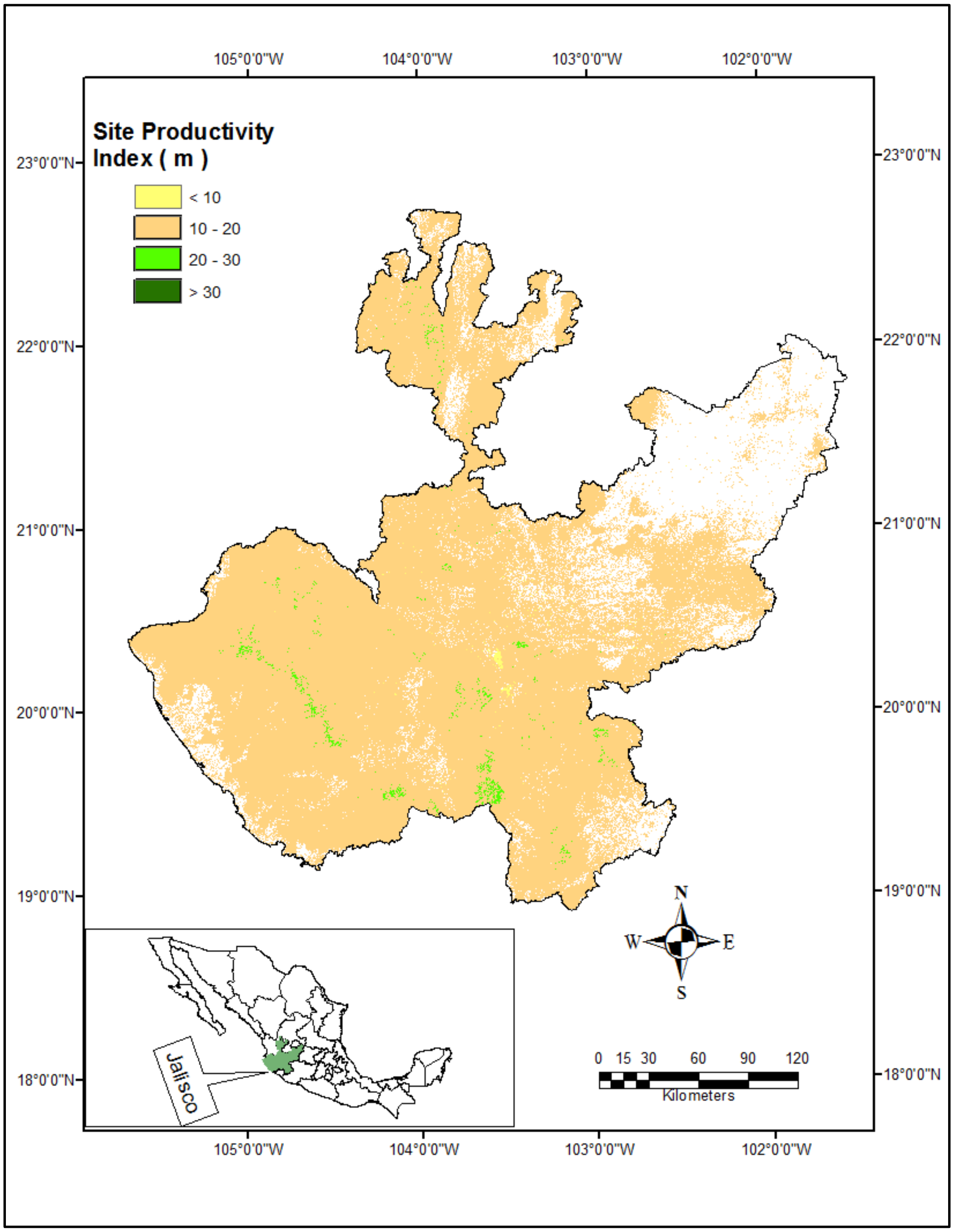

Figure 2.4.D. Continued.

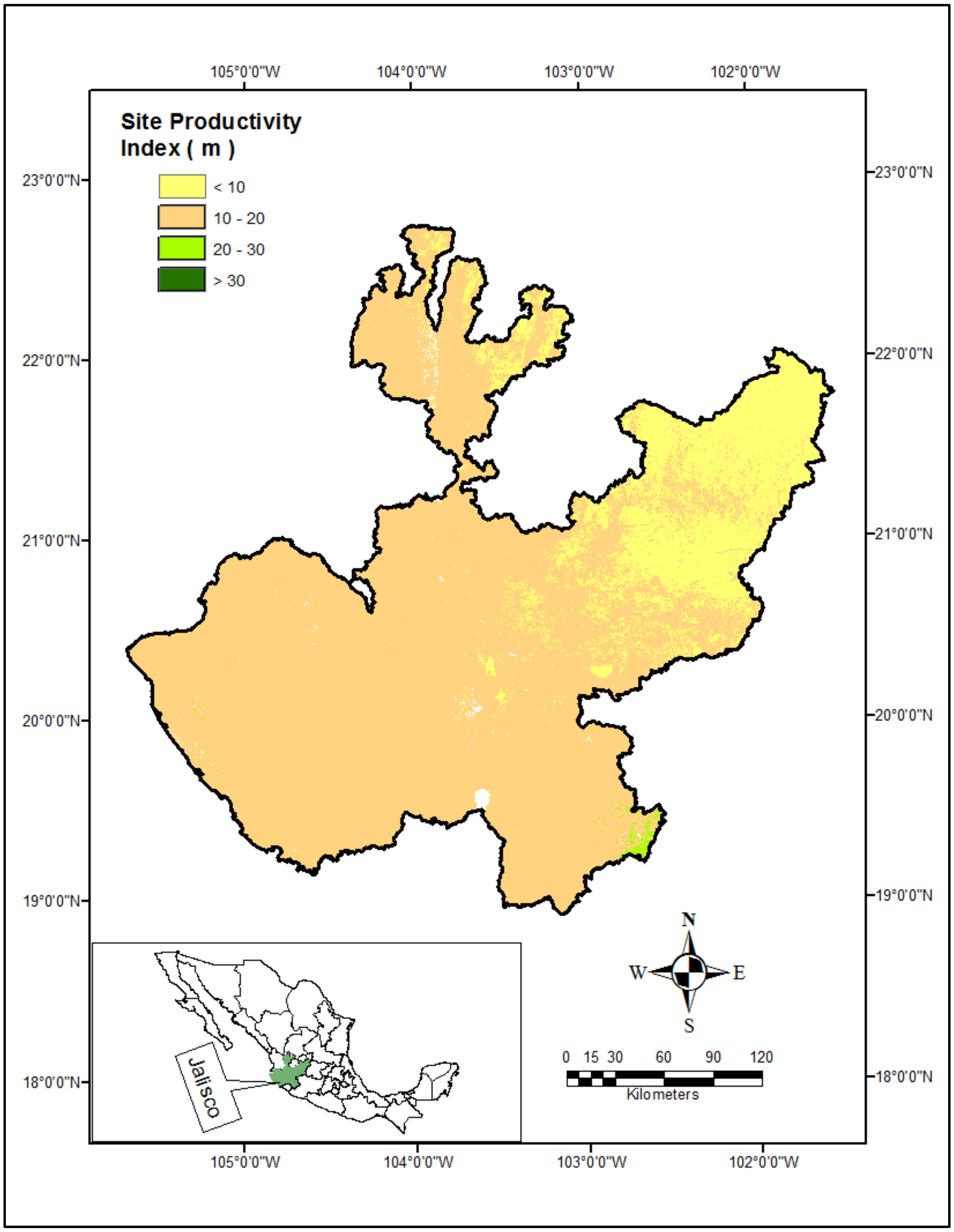

Figure 2.4.E. Continued.

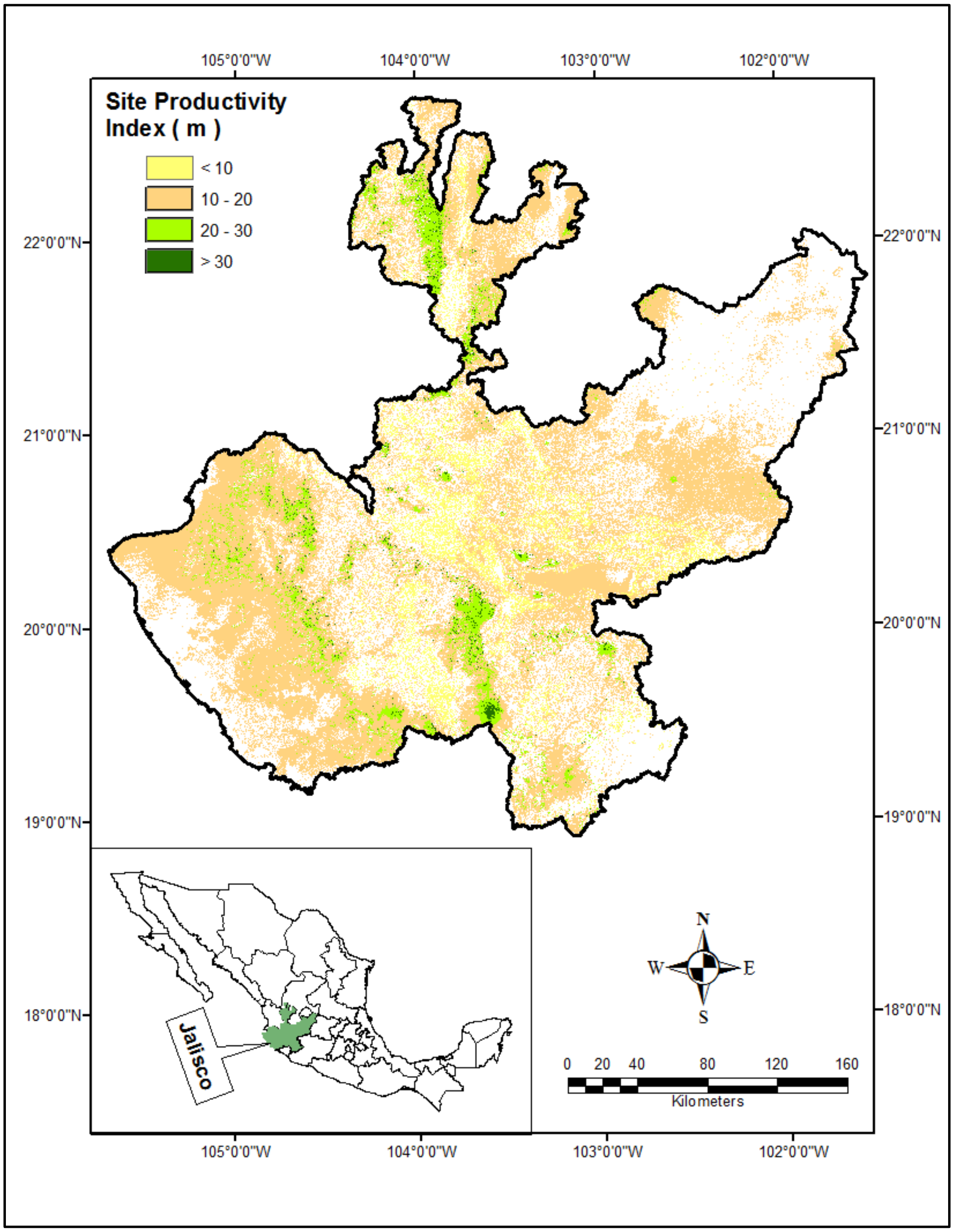

Figure 2.4.F. Continued.

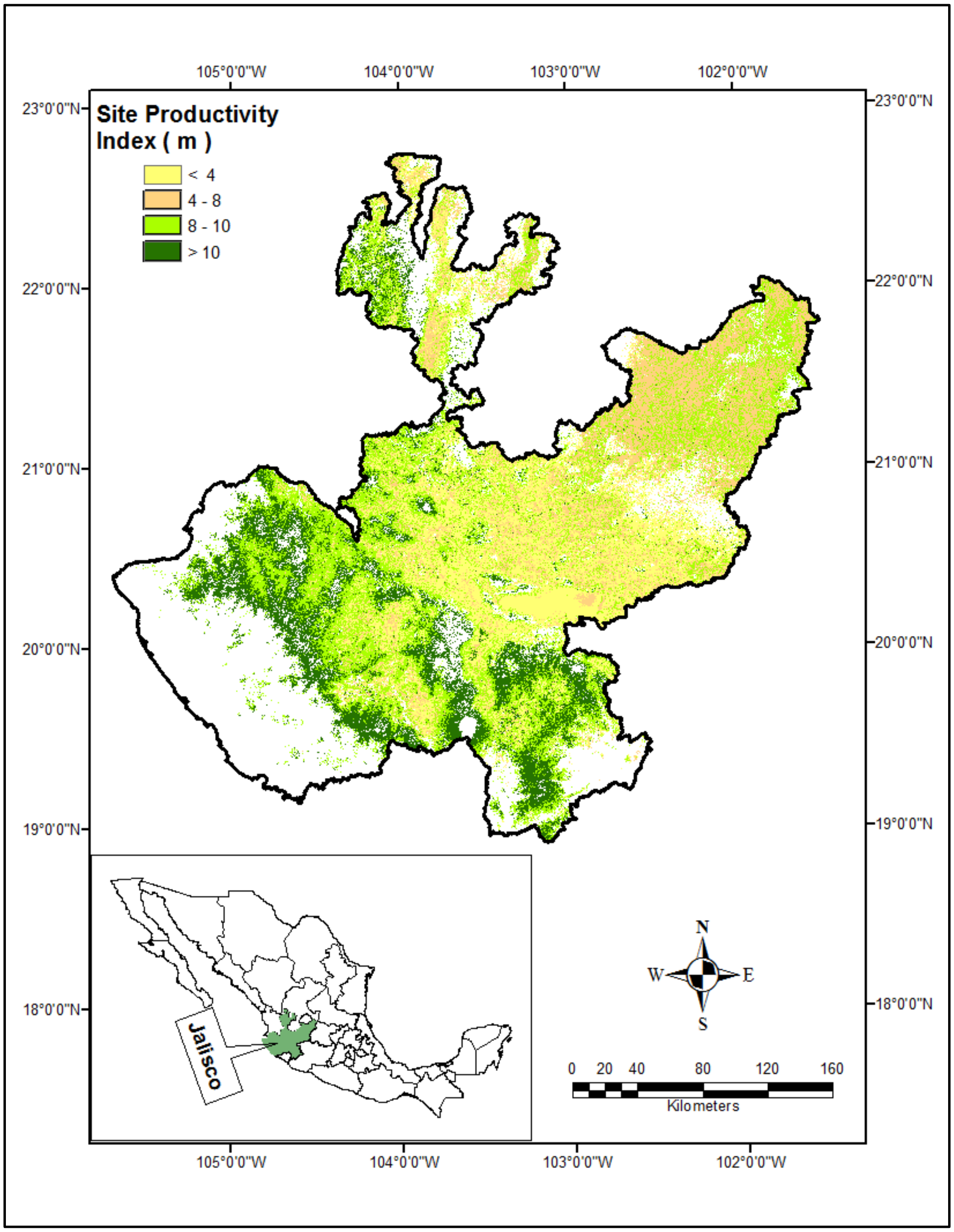

Figure 2.4.G. Continued.

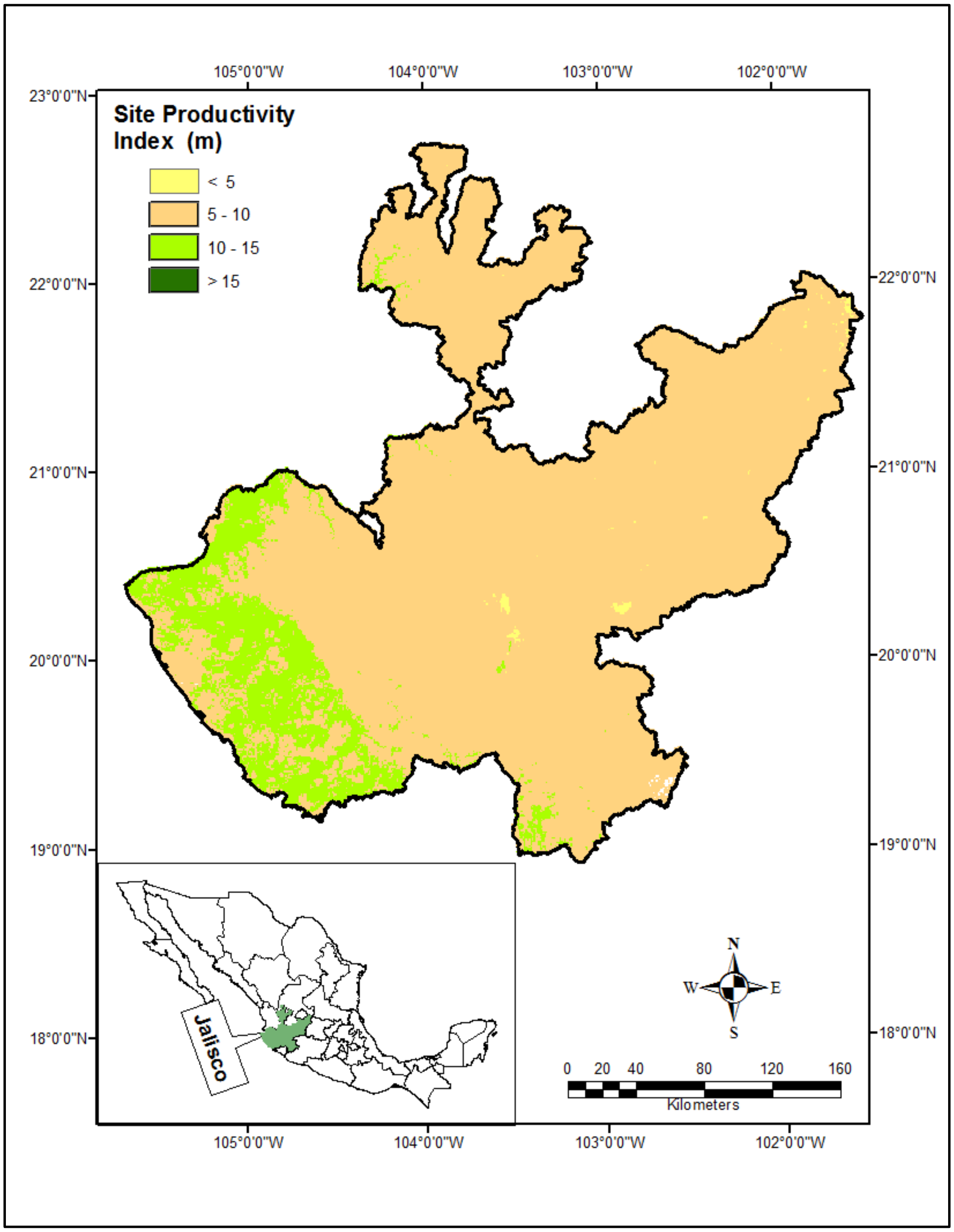

Figure 2.4.H. Continued.

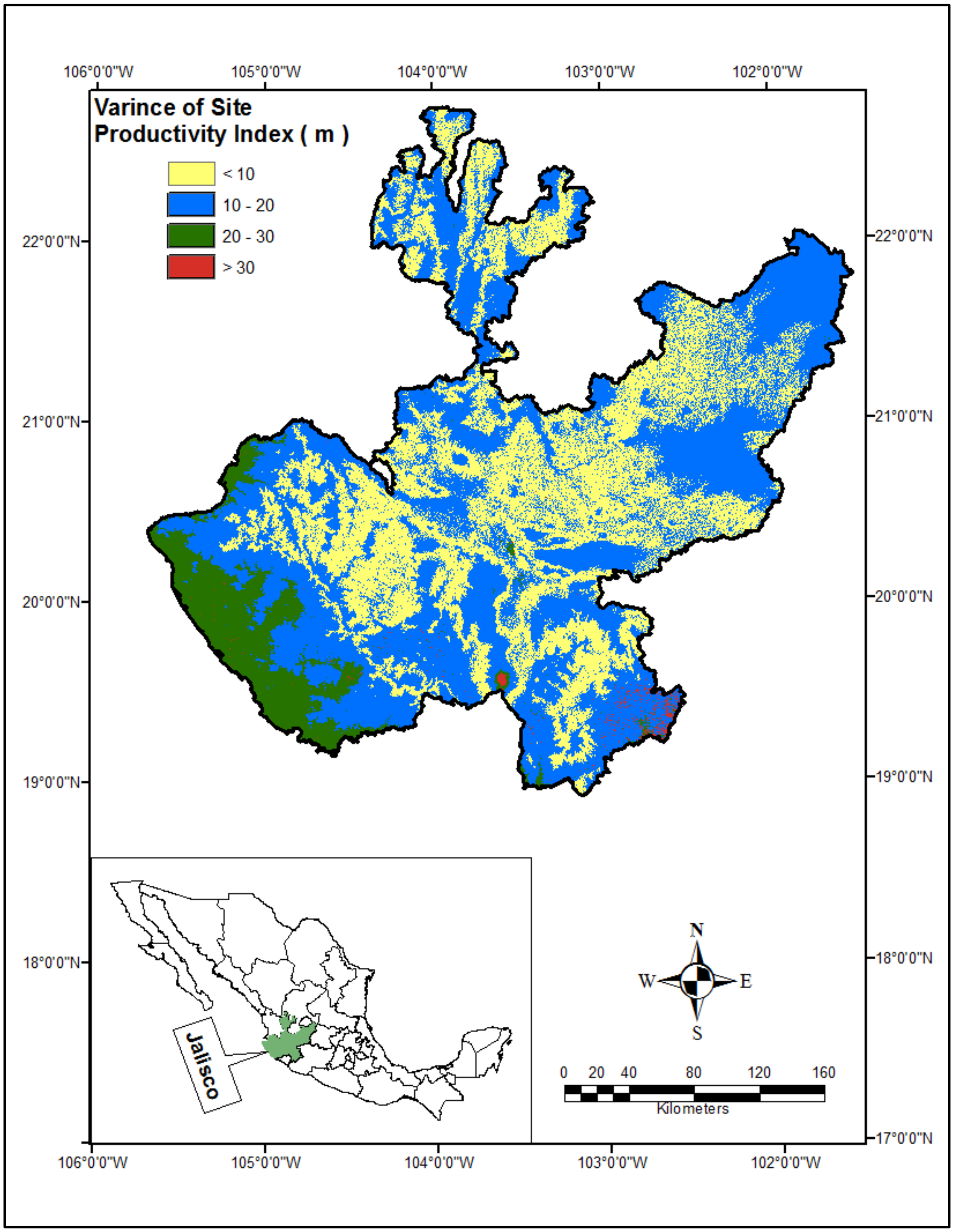

Figure 2.5. Estimated variance of site productivity of pine forest type in the state of Jalisco, Mexico.

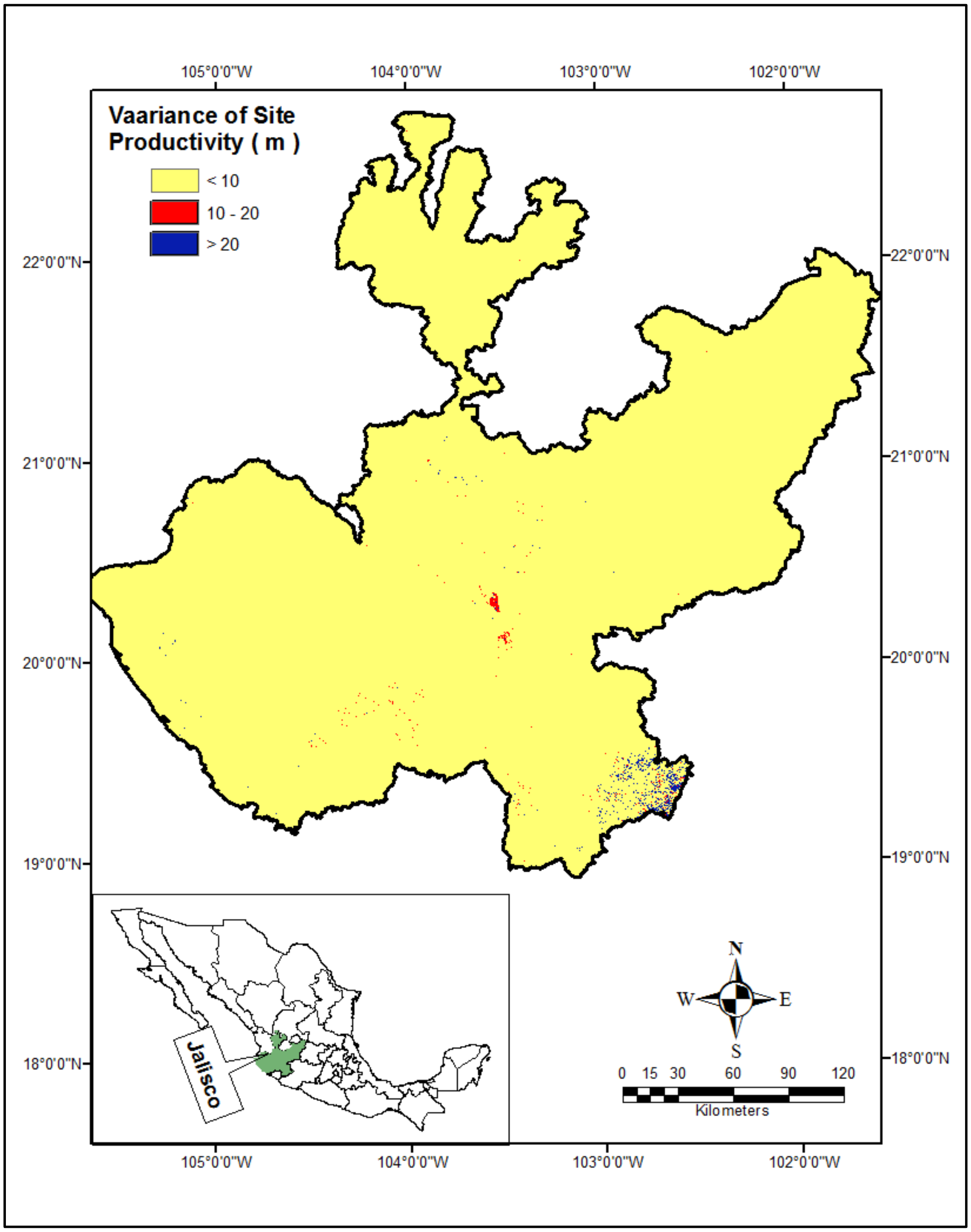

Figure 2.6. Estimated variance of site productivity of tropical semi-evergreen forest type in the state of Jalisco, Mexico.

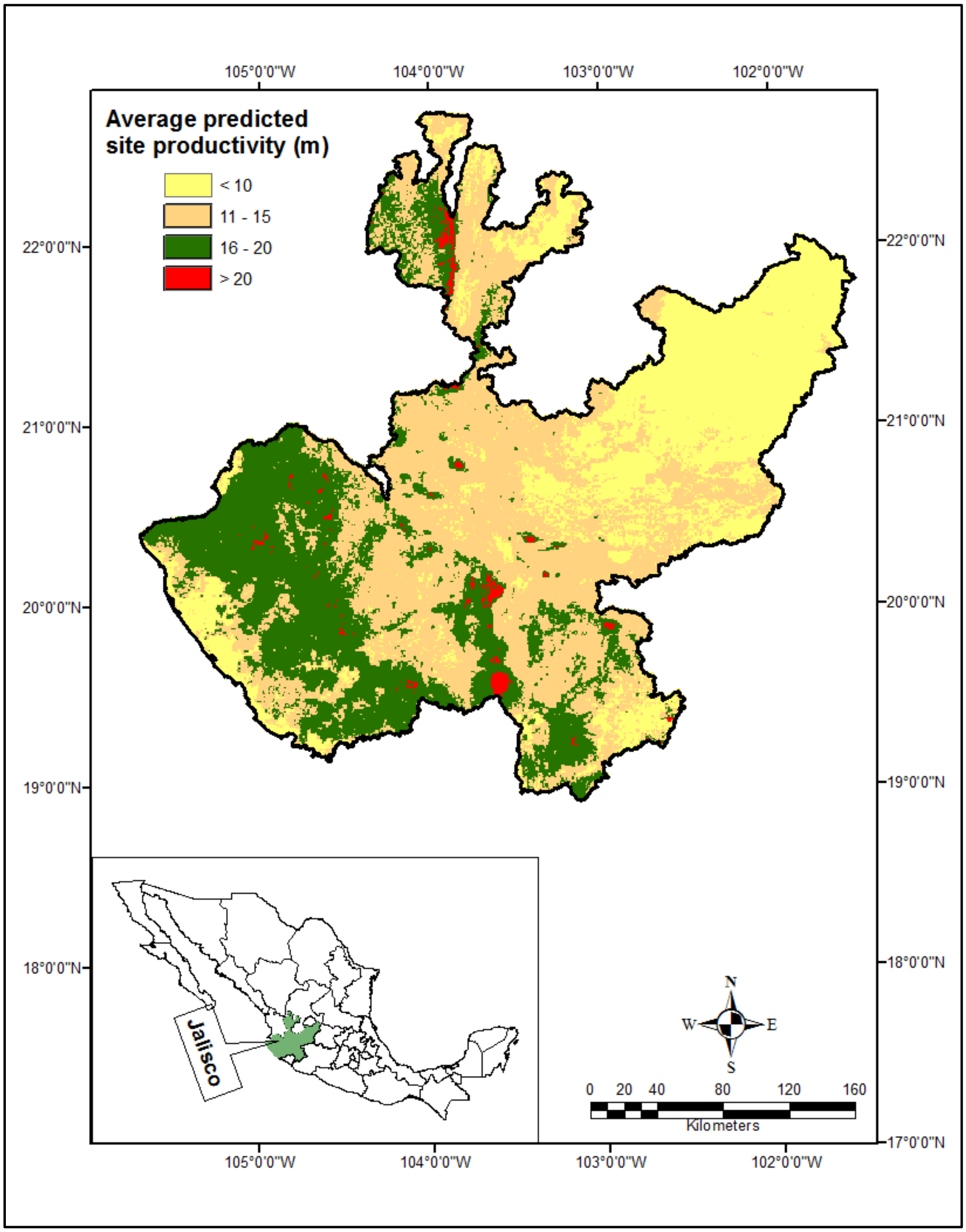

Figure 2.7. Average of predicted site productivity weight proportional to the probability of observing a given forest type in the state of Jalisco, Mexico.

Wang (2005) observed that the site productivity of lodgepole pine (*Pinus contorta var. latifolia*) in the Wapiti region, Alberta, Canada, was negatively correlated with elevation, climate moisture index and annual precipitation and positively correlated with summer temperature. Watt (2009) used mean minimum air temperature and establishment date to model site productivity of *Cupressus lusitanica* in New Zealand. McKenny (2001) developed a model for site productivity of jack pine in Ontario, Canada indicating that depth of mineral soil, mean annual temperature, and amount of precipitation were important factors for determining site productivity.

In this study, the precipitation and temperature zones accounted for only 9% of the variability in SPI. However, it is clear that forest site productivity followed the trends in temperature and precipitation in the state, as site productivity increased from the east to the west. This corresponds the distribution of forest types in the state which are strongly correlated to the climatic conditions in the state (Reich *et al.*, 2010).

The predictive performance of the final model (R^2 = 0.59) was considered satisfactory. Similar studies have reported R^2 values ranging from 0.4 to 0.8 (Green *et al*., 1989; and Mckenney *et al*., 2003). The moderate R^2 value may be related to 1) estimates of site productivity may not reflect the true productivity of a site, 2) environmental variables are not responsive to changes in site productivity and 3) important explanatory variables were excluded from the model. Other studies have recorded R^2 values ranging from 82% to 90% for estimating site productivity as a function of environmental variables. The high R^2 values are generally associated with modeling an individual tree species in even aged stands (Watt 2009; Waring *et al*., 2006). There are no comparable studies that have modeled site productivity of mixed species stands, making it difficult to compare the results of our study. Wang (2005) evaluated both parametric and nonparametric methods for evaluating the spatial predictions of site index for lodgepole pine (*Pinus contorta var. latifolia*) productivity. The parametric models based on non-linear regression had R^2 values ranging from 0.61 to 0.69, while the nonparametric methods based on neural networks and generalized additive models had R^2 values ranging from 0.73 to 0.75.

The spatial model of SPI developed in this study provided unbiased estimates of SPI for all forest types, while estimates of the prediction variance were biased, the coverage rates were close to the nominal rate of 0.95. This suggests that it is possible to use estimates of the variance to evaluate the uncertainty of the estimates.

This study also developed a map showing the expected SPI of the forests in the state of Jalisco, taking into consideration the probability of observing the various forest types at a given location, while no information was available on the distribution of forest types in the state, the map does provide the expected site productivity given the probability of observing a particular forest type.

2.5 CONCLUSION

The spatial site productivity index identified using the ecological variables showed to be a useful indicator of site productivity in the tropical and temperate forests of Jalisco, Mexico. An important finding of this analysis is that the forest type is the most significant variable for estimation of forest site productivity index. The spatial models of SPI developed in this study provide a starting point in understanding the complex relationship that exists between forest productivity and environmental and ecological conditions in the state. It is clear that the spatial site productivity models are reliable and accurate within the ecological ranges of the data. This study documents an important approach for determining the relationship between forest productivity and environmental variables and how site productivity can be estimated from this relation. The results highlight the utility of GIS tools in developing maps displaying the spatial variability in site productivity. The results emphasize the importance of the environmental variables as determinants of forest site productivity in the state. To increase the precision of the estimates, more samples can be taken in locations with large prediction variance.

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CHAPTER 3 MODELING PLANT SPECIES RICHNESS IN ELBA PROTECTED AREA, EGYPT

3.1 INTRODUCTION

The Red Sea has very rich and varied environment, compared with many other tropical and subtropical seas. The coastal mountain ranges of the Red Sea consist essentially of a backbone of high and rugged mountains running parallel to the coast. These mountains do not form a continuous range, but a series of mountain groups with some detached masses and peaks (Said, 1962 and 1990).

Both sides of the Red Sea encompass spectacular flora and interesting plant communities. The region is valued for its unique environment, high diversity, and great scientific and ecological importance. The coast and the mountain ranges of the Red Sea comprise three principal habitat types that include coastal marshes, coastal desert plains and mountain escarpment. Coastal marshes comprise areas of land bordering the sea, more or less covered with vegetation and is characterized by diverse coral edges, mangrove wetlands, sandy beaches and salt marshes. These habitats are influenced by their proximity to the sea (Tansley, 1939). Two halophytic types of vegetation have been recorded along the Red Sea coast; 1) mangrove vegetation, comprising the shallow water along the shore including a single layer of *Avicennia marina* that may be mixed with

Rhizophora muccronata in the most southern part of Egypt and 2) salt marsh vegetation, in zones following the shoreline, is characterized by *Arthrocnemum glaucum(=A. macrostachyum), Halopeplis perfoliata, Halocnemum strobilaceum, Limonium pruinosum, Limonium axillare, Sporobolus spicatus, Zygophyllum album, Nitraria retusa, Suaeda monoica and Tamarix nilotica* (Kassas and Zahran, 1967).

The coastal desert plains lies between the littoral zone and the mountain escarpment so it is usually non-saline. It is essentially a gravel plain traversed by the downstream extremities of the main wadis and is dissected by smaller drainage runnels. The vegetation of the coastal desert plain supports a greater number of plant species and the floristic composition of the communities is usually more diverse than that of the salt marshes.

Mountain escarpment comprise an almost continuous range of mountains and hills of varying heights (Hegazy and Amer, 2002). The presence of this coastal mountain range has influenced the climate and the water resources of the Eastern Desert (Murray, 1951). The Red Sea coastal mountains of Egypt are categorized into; 1) mountains facing the Gulf of Suez from the western side, 2) mountains facing The Red Sea proper, which include four groups of mountains; Gebel Shayeb, Gebel Nugrus, Gebel Samiuki and Gebel Elba (Kassas and Zahran, 1971).

Gebel Elba is principally a range of granite mountains located on the Sudano-Egyptian border (Lat 20° N). It has the richest vegetation especially on its north and east sides (Zaharan, 2008). The flora of Gebal Elba group includes more than 450 species (Täckhalm, 1974; Boulos, 1995; Ahmed, 1999) where *Acacia* is the most widespread genus as it is represented by 7 tree and shrub species: *Acacia tortilis subsp. tortilis,* *Acacia tortilis subsp raddiana, Acacia oerfota and Acacia ehrenbergiana* (lower water requirements) and *Acacia etbaica, Acacia asak, Acacia mellifera and Acacia laeta* (higher water requirements). The other trees and shrubs of ecological interest include *Leptadenia pyrotechnica, Ochradenus baccatus, Ziziphus spina-christi, Commiphora opobalsamum, Salvadora persica, Lycium arabicum, Ephedra alata, Grewia tenax, Indigofera oblongifolia, Balanites aegyptiaca, Maerua crassifolia, Maerua oblongifolia, Cadaba farinosa, Cadaba glandulosa, Cadaba rotundifolia, Capparis decidua* and *Moringa peregrina.*

The different mountain groups are interconnected by wadis that are deeply incised into the coastal plains and their floodwater, seldom reaches the sea, as it is gradually absorbed by the sandy substratum.

Few studies have been conducted to explore the plant ecology of Elba protected area in Egypt. Montasir (1938) provided an ecological description of the salt marshes, the mangrove and the maritime vegetation. Hassib (1951) described the life form spectrum of the flora on Mersa Halaib in Elba protected area. Kassas (1952, 1953, 1957 and 1960) presented ecological information on the Red Sea coastal land of Sudan and provided detailed analysis of the plant community types and their vegetation and ecological relationships. Abd El-Ghani (2006) documented 179 species along six wadis in Elba protected area and found the family *Compositae* was the most diverse species family. Al-Gohary (2008) recorded 114 species confined to Elba protected area through studying the floristic composition of 11 major wadis in the area.

Previous studies by Kassas and Zahran (1962), Zahran and Mashaly (1991) and Zahran and Willis (1992) distinguished the vegetation of the Egyptian Red Sea coastal desert plain into two main types; 1) Ephemeral vegetation consisting of grasslands and herbaceous vegetation covering extensive areas of the coastal plain and the mountains and is dependent on the distribution of patterns in precipitation. 2) Perennial vegetation; this is classified into two main types: suffrutescent vegetation and frutescent perennial vegetation. Suffrutescent vegetation is widespread throughout the Egyptian Red Sea coastal desert. This vegetation type consists of an upper layer (30-120 cm) which includes dominant suffrutescent species (e.g. , *Zygophyllum coccineum, Salsola baryosma* and *Zilla spinosa*) and a ground layer (< 30 cm) with associated annuals and cushion-forming perennials (e.g., *Cleome droserifolia, Fagonia mollis* and *Panicum turgidum*). The frutescent perennial forms include the scrubland types of the desert vegetation and dominated by *Acacia raddiana, A. tortills, Leptadenia pyrotechnica, Balanites aegyptiaca and Tamarix aphylla*.

Vegetation dynamics of arid ecosystems are controlled by highly fluctuating external factors (Noy-Meir, 1973; Westboy, 1979; Evenari *et al*., 1986) which complicate the distinction between short-term fluctuations and long-term directed changes in the vegetation (Rabotnov, 1974). The vegetation in arid areas near open water bodies may be influenced by wind-borne sea moisture, as in the Namib Desert (Walter, 1936) and the Peruvian Desert (Ellenberg, 1959). Coastal moist wind may form a marked vertical vegetation zones on the arid mountains (Ellenberg, 1959). When air-moisture is successively lost with increasing distance from the sea, a horizontal zonation of vegetation is created (Kassas, 1956; Kassas and Zahran, 1971).

Quantitative investigations of desert vegetation indicate that biotic interaction plays an important role in determining the structure of desert plant communities (Went, 1942; Waisel, 1971; Yeaton and Goody, 1976; Yeaton *et al.*, 1977). Ecologists and conservationists are interested in the variation in pattern of plant diversity (Stevens, 1989). The measurement of species diversity can be divided into three major levels, alpha, beta, and gamma (Whittaker, 1972). The within-habitat (alpha) diversity or species richness is the total number of species in a uniform habitat or community. Between-habitat (beta) diversity or gradient diversity is the amount of species turnover from one habitat to another on an environmental gradient. Regional (gamma) diversity is defined simply as the total number of species present in all habitats of a region (Whittaker, 1960).

From the view point of scientific knowledge, there is some degree of uncertainty about the way in which species diversity is related to the function of an ecosystem (Ehrlich, 1993). However, from the view point of conservation, indicators of both parameters can be used to assess the ecological health in restoration project monitoring (U.S. Environmental Protection Agency, 1990).

Lack of appropriate historical data has seriously impeded research into the extent and influences of deforestation in arid lands such Elba Protected Park in Egypt. The objective of this study was to evaluate the influence of topography and soils on species richness in Elba Protected Park in Egypt.

3.2 MATERIALS AND METHODS

3.2.1 Study Area

Elba protected park is a mountainous block located in the most southeastern corner of the Red Sea coastal desert in Egypt in the Sudano-Egyptian border (from 22º 50′ N to 22º N and from 36°E to 36° 55′ E) (Figure 3.1), covering approximately 36,500 km^2 (Abd El-

Ghani, 2006). Gebel Elba (1428 m) is favored by its position near the Red Sea (20 - 25 km west of the Sea) which has a significant effect on the amount of orographic rain received by this mountain. Orographic rain is considered the main source of water for Gebel (Ayyad *et al*., 1993). The total annual rainfall may reach 50 mm/year (Ayyad and Ghabour, 1986).The area lies in the arid climatic region with hot summers (28-33° C) and mild winters (18-22° C).

3.2.2 Data

The study area was stratified in a north-south direction based on visual classification of vegetation. Four transects were established running in a north-east-south-west direction perpendicular to the coast. Along each transect, stands and sites were selected to represent the variation in vegetation, climatic and edaphic characteristics associated with each stratum.

The first transect (A) was 25 km in length and extended through Kansisrob, Yahameib, Akaw wadis into Elba mountain from the sea level. Twenty-two plots were located along the transect. The second transect (B) was 15 km in length and extended through Kansisrob, Aideib wadis and Elba mountain from sea level to the west side of Elba mountain. Ten sample plots were located along the transect. Eighteen plots were located on the third transect (C) which extended through Serimatai, Oser Erab wadis and Karm Elba mountain for 16 km. The last transect (D) was 26 km in length and extended through Shelal wadi, Shelal mountain and Shendodi mountain. Thirteen sample plots were located along the transect (Figure 3.1). All sample plots were 10 m X 10 m in size.

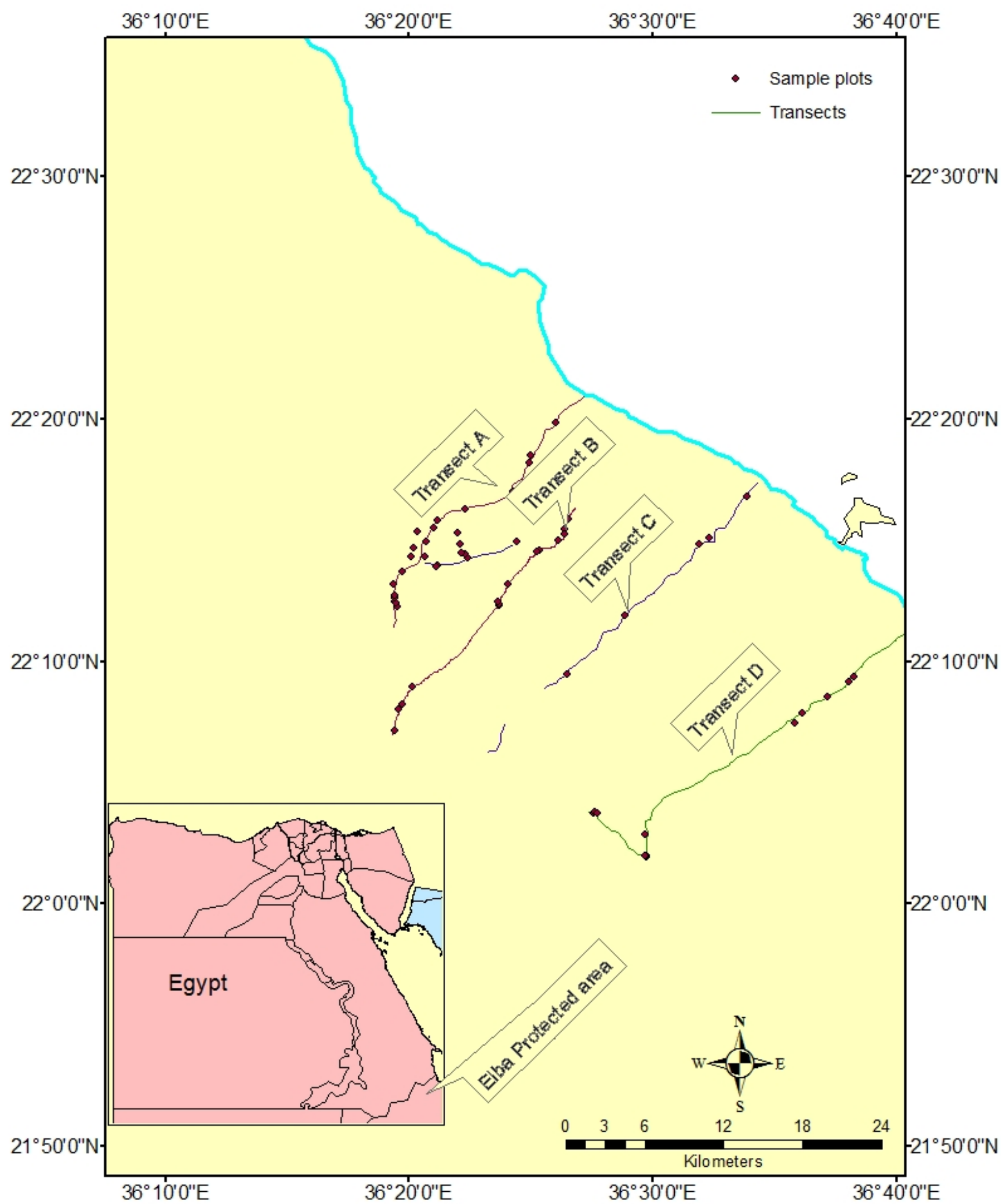

Figure 3.1. Location of vegetation transects in Elba protected area, Egypt.

The data collected on the sample plots included the number of grasses, shrubs, subshrubs and trees by species. Three soil samples were collected from each plot at a depth of 0 to 30 cm. Samples were pooled to form one composite sample. Each sample was air dried, passed through a 2 mm. sieve to remove and debris any packed in plastic bags for physical and chemical analysis.

Soil texture was determined using the sieve method. A known weight of air dried soil samples were passed through a series of sieves of 2 mm, 0.5 mm, 0.25 mm, 0.125 mm. and 0.05 mm diameters to separate gravels (>2.057 mm), coarse and medium sand (2- 0.25 mm), fine sand (0.25 – 0.05 mm) and silt and clay (<0.05 mm) (Allen *et al*., 1974). The hydrogen ion concentration (pH) of the soil extract was measured by using an electric pH meter with a glass electrode (Richards, 1954). The electrical conductivity (EC) of the soil samples was determined by using an electrical conductivity meter.

3.2.3 Species Diversity

Species richness was defined as the total number of plant species in each sample plot and was determined for the three major species groups (subshrubs, shrubs, and trees) identified in the survey. The Shannon–Weaver (1949) index (H′) and the Evenness index (J) (Pielou, 1966) were used to assess the uniformity of abundance in plant species by species group and environmental characteristics (e.g., soil texture (gravel, sand, silt and clay), pH, electrical conductivity (EC) and elevation). The Shannon–Weaver Index (H′) and the Evenness index were calculated as follows:

The Shannon – Weaver Index, $H' = -\sum_{i}^{s} p_i \ln(p_i)$ (3.1)

where: s is the number of species, pi = proportion of species i in the community .

Evenness index, $J = H' / \ln(s)$ (3.2)

3.2.4 Model Development and Evaluation

Different techniques have been used to investigate relations between response variables and sets of predictors (Guisan *et al*., 2002).The most widely used are the regression methods, but the assumptions required by these techniques are hardly respected by real data (Legendre and Legendre, 1998; Guisan *et al*., 2002). Count data such as the number of species generally follows a Poisson distribution and are generally not normally distributed (Oksanen and Minchin, 2002; Ohlemüller *et al*., 2004). General linear models (GLM) are considered the most flexible of the regression methods (McCullagh and Nelder, 1989) in that they can accommodate a large variety of data type and response variable distributions including Gaussian, Poisson and Negative Binomial (Dalthorp, 2004 ; Engler *et al*., 2004).

A Poisson regression which is a form of a generalized linear model (GLM) was used to identify a set of explanatory variables to describe responses in plant species richness on the sample plots. A list of explanatory variables tested and their observed sample statistics are summarized in Table 3.1.

The Pearson Chi-Square statistic and deviance divided by the degrees of freedom were used to test the goodness-of-fit of the Poisson regression models. Values greater than 1 indicates over-dispersion which indicates the true variance is larger than the mean while values less than 1 indicate under-dispersion, the true variance is smaller than the mean. Evidence of under-dispersion or over-dispersion indicates inadequate fit of the Poisson model.

Three regression models were used to characterize plant species richness in the study area. The first model (M1) described species richness on each transect (A, B, C, and D) as a function of the environmental variables (e.g., soil texture, pH, EC, topography) and species group (subshrubs, shrubs, and trees). Species group was treated as a categorical variable. The second model (M2) was a subset of the first model, with species group removed and used to characterize species richness on each transect. The third model (M3) was fit the data of each species group (subshrubs, shrubs, and trees) to identify the environmental variables that characterize the species richness of each species group as a function of transect location, topography, soil texture, pH and EC. A stepwise AIC was used to identify the best combination of variables to characterize the species richness in each of the three models.

3.3 RESULTS

3.3.1 Stand Data

The variability in elevations along the line transects increased in a southerly direction, with transect A having the least variability and transect D, the most. The soil analyzed from these transects are considered alkaline with average pH of 7.14 to 7.23. The electrical conductivity of soils (EC) varied depending on soil moisture; EC correlates strongly to soil particle size and texture. The line transects A and C have lower EC values compared to transects B and D. Soil texture on transects A and C consisted of gravel while transects B and D consisted mostly of clay and silt particles (Table 3.1).

3.3.2 Plant Species Richness

The variability in the number of plant species richness by transect and species group are provided in Table 3.2 and Table 3.3, respectively. A total of 2,356 individual plants representing 44 species were counted on the sample plots (Appendix B).

Table 3.1. Summary statistics of explanatory variables evaluated in a GLM to describe the variability in plant species richness in Elba protected area, Egypt.

Variable	Transect	Min	Mean	Max	SD
Elevation (m)	A	180	277	460	77
	B	34	226	380	124
	C	40	205	511	144
	D	1	298	464	156
pH	A	7.0	7.1	7.4	0.1
	B	7.0	7.2	7.7	0.2
	C	7.0	7.3	7.7	0.2
	D	7.0	7.2	7.6	0.2
EC (µS/cm)	A	0.8	1.9	3.7	0.7
	B	1.0	2.3	4.0	1.0
	C	0.4	1.4	2.7	0.6
	D	1.5	2.9	4.3	0.8
Gravel %	A	14.9	37.0	60.3	11.3
	B	4.8	28.4	54.2	16.6
	C	13.5	45.6	68.9	14.6
	D	13.2	37.6	53.4	13.6
Sand %	A	24.8	37.3	54.4	7.8
	B	25.9	39.9	50.7	6.0
	C	17.4	35.0	62.9	12.5
	D	13.9	29.1	45.1	7.6
Clay and Silt %	A	10.8	25.7	49.2	10.2
	B	1.0	31.6	59.8	19.3
	C	0.6	19.4	37.1	10.0
	D	14.9	33.3	73.0	17.4

Table 3.2. Plant species richness and diversity in 63 plots by transect in Elba protected area, Egypt.

Transect	Number of sample plots	Distribution of species number on sample plots				Shannon-Weaver Index (H′)	Evenness Index (J)
		Total number of species recorded	min	mean	max		
A	22	21	3	4.9	7	2.67	0.88
B	10	26	3	6.6	12	3.10	0.97
C	18	23	2	4.3	8	2.90	0.91
D	13	20	1	4.2	9	2.85	0.92

Table 3.3. Plant species richness and diversity in 63 plots by species nature in Elba protected area, Egypt.

Species Group	Number of sample plots	Distribution of species number on sample plots/Transect				Total number of plant species	Shannon-Weaver Index / Transect					Evenness Index / Transect				
		A	B	C	D		A	B	C	D	Total	A	B	C	D	Total
Subshrubs	38	5	13	12	8	21	1.4	2.4	2.4	2.0	2.7	0.5	0.7	0.8	0.6	0.7
Shrubs	60	11	11	10	11	16	2.2	2.3	2.1	2.4	2.4	0.7	0.7	0.7	0.8	0.6
Trees	27	5	2	1	2	6	1.4	0.7	0.0	0.4	1.3	0.5	0.2	0.0	0.1	0.4

The subshrubs group represented 47.7 % of the total species richness while the tree species group had the lowest species richness representing 13.6 % of the total number of species. Transect B was the most diverse with 26 species, while transects A, C and D had 21, 23, and 22 species, respectively. The distribution of the number of plant species on the sample plots had a reverse J-shaped distribution with most sample plots having one to three species with an overall average of 2.1 species.

The plant species diversity (H′) increased from north to south. The species diversity on transect B (H′ = 3.10) was the most diverse given that it was the shortest transect compared to the other transects. Transect A was the least diverse (H′ = 2.67). Similar trends were observed with the evenness index, with the highest values for transect B (J = 0.97) and the lowest values for transect A (J = 0.88) (Table 3.2). Transects C and D had an evenness index intermediate to those observed on transects A and B.

Shrubs were found on 95% of the sample plots with 16 species, while trees occurred on 43% of the plots with six species. Twenty one subshrubs were identified on 60% of the sample plots. Plant species diversity, estimated by the Shannon-Weaver Index (H′) varied within the different species groups. Species diversity of the subshrubs species was highest on the transect B and C. The diversity of the trees species was the highest on transect A. Shrub species had the highest diversity on transects B and D. Similar trends were observed in the evenness index (Table 3.3). In general, species diversity of the subshrubs and shrubs groups increased from north to south, while the reverse trend was observed for the tree group.

3.3.3 Poisson Regression Model for the Transects

A stepwise AIC (Venables and Ripley, 2002) of the first model (M1) indicated that the presence-absence of species group (shrubs, subshrubs and trees) was important in estimating total species richness on transect A (Table 3.4). Removing the effect of species group from the model (M2) indicated that gravel soil texture, pH, and EC were important environmental variables. The fitted Poisson regression models (M1 and M2) for transect B are provided in Table 3.5. Trees and shrubs were important variables in the first model (M1), while sand and silt soil texture were the important variables in describing species richness on transect B after removing the influence of species group (Model 2). Species group (trees and shrubs) and electrical conductivity (EC) were significant variables in estimating species richness of transect C (Model 1) (Table 3.6). Elevation was the most important variable in estimating species richness on transect C when species group was ignored (Model 2). Trees and shrubs were the important species group in estimating species richness along transect D based on the first model (M1). No environmental variables were significant in estimating species richness species along this transect using the second model (M2) (Table 3.7).

All models did not deviate significantly from the assumption of a Poisson distribution based on both the Pearson chi-square and deviance statistic. Poisson regression explained 65%, 49%, 33% and 21% of the observed variability in species richness on the four transects (Model 1). The second model (Model 2) explained 33%, 23%, 14% and 16% of the observed variability in species richness on the four transects.

Table 3.4. Poisson regression model for estimating plant species richness in transect A, Elba protected area, Egypt.

Poisson regression with species group (M1)					Poisson regression without species group (M2)				
	Coefficient	SE[3]	P-value			Coefficient	SE	P-value	
Intercept	1.363	0.108	<0.001	***	Intercept	-12.122	7.120	0.089	.
SGsu[1]	-1.209	0.288	<0.001	***	Gravel %	0.0196	0.009	0.022	*
SGtr[2]	-0.757	0.324	0.018	*	pH	1.8034	0.072		.
					EC (μS/cm)	-0.234	0.121	0.053	.
AIC	126.93					143.59			
Residual deviance/df	0.281		0.99			0.696		0.913	
Pearson deviance/ df	0.271		0.99			0.630		0.965	

Significant levels: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

[1] Presence-absence of subshrubs species group

[2] Presence-absence of trees species group

[3] Standard error

Table 3.5. Poisson regression model for estimating plant species richness in transect B, Elba protected area, Egypt.

Poisson regression with species group (M1)					Poisson regression without species group (M2)				
	Coefficient	SE[3]	P-value			Coefficient	SE	P- value	
Intercept	1.131	0.180	<0.001	***	Intercept	3.374	1.375	0.014	*
SGsu[1]	0.290	0.258	0.262		Sand %	-0.043	0.028	0.131	
SGtr[2]	-0.949	0.446	0.033	*	Silt %	-0.019	0.009	0.056	.
AIC	76.737					82.681			
Residual deviance/df	0.410		0.988			0.723		0.798	
Pearson deviance/ df	0.339		0.997			0.653		0.881	

Significant levels: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

[1] Presence-absence of subshrubs species group

[2] Presence-absence of trees species group

[3] Standard error

Table 3.6. Poisson regression model for estimating plant species richness in transect C, Elba protected area, Egypt.

Poisson regression with species Group (M1)					Poisson regression without species group (M2)				
	Coefficient	SE[3]	P-value			Coefficient	SE	P-value	
Intercept	1.543	0.294	<0.001	***	Intercept	0.531	0.205	0.010	**
SGsu[1]	-0.289	0.247	0.242		Elevation (m)	0.0015	0.001	0.035	*
SGtr[2]	-0.996	0.470	0.034	*					
EC (µS/cm)	-0.395	0.222	0.076	.					
AIC	113.34					115.52			
Residual deviance/df	0.518		0.986			0.678		0.914	
Pearson deviance/ df	0.516		0.99			0.792		0.795	

Significant levels: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

[1] Presence-absence of subshrubs species group

[2] Presence-absence of trees species group

[3] Standard error

Table 3.7. Poisson regression model for estimating plant species richness in transect D, Elba protected area, Egypt.

Poisson regression with species group (M1)					Poisson regression without species group (M2)				
	Coefficient	SE[3]	P-value			Coefficient	SE	P-value	
(Intercept)	0.917	0.2	<0.001	***	(Intercept)	0.624	0.134	<0.001	***
SGsu[1]	-0.280	0.314	0.373						
SGtr[2]	-0.675	0.334	0.043	*					
AIC	91.85					91.57			
Residual deviance/df	0.449		0.993			0.565		0.970	
Pearson deviance/ df	0.494		0.989			0.692		0.890	

Significant levels: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

[1] Presence-absence of subshrubs species group

[2] Presence-absence of trees species group

[3] Standard error

3.3.4 Poisson Regression Model for Species Groups

A stepwise AIC was used to identify the best linear combination of the environmental variables to include in the Poisson regression model (Model 3) for estimating species richness for each plant species group. Parameter estimates of the final model for the shrubs species is provided in Table 3.8.

The location of the line transect (A, C and D) was the only variable important in estimating species richness of shrubs species. The model showed that the species richness of shrubs decreased in a north to south direction. The model for subshrubs species indicated that the transect location, pH, and gravel soil texture were the important variables in describing species richness (Table 3.9).

The best combination of environmental variables for estimating tree species richness included transect location, elevation, and soil texture (gravel, sand and silt) (Table 3.10). The results showed a negative correlation between species richness of the trees and soil texture. The Poisson regression models explained 23%, 58%, and 52% of species richness variability for shrubs, subshrubs, and trees species group, respectively.

3.4 DISCUSSION

The number of species counted on the sample plots included only 44 species, or 11.6 % of the total number of species recorded by Al-Gohary (2008) on eleven wadis in the study area. While this number of species richness is 25% of the number recorded by Abd El-Ghani (2006) through six major wadis, the small number of recorded species may be attributed to collecting the data during the dry season and the few number of sample plots located in the study area.

Table 3.8. Poisson regression model for estimating plant species richness for shrubs species, Elba protected area, Egypt.

	Coefficient	SE[1]	P-value	
(Intercept)	1.363	0.108	<0.001	***
Transect B	-0.232	0.210	0.268	
Transect C	-0.302	0.176	0.085	.
Transect D	-0.709	0.227	0.002	**
df	59			
AIC	228.980			
Residual deviance/df	0.714		0.950	
Pearson Chi/df	0.681		0.974	
log likelihood	-110.490			

Significant levels: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

[1] Standard error

Table 3.9. Poisson regression model for estimating plant species richness for subshrubs species, Elba protected area, Egypt.

	Coefficient	SE[1]	P-value	
(Intercept)	15.148	7.299	0.038	*
Transect B	-0.969	1.219	0.427	
Transect C	1.228	1.141	0.282	
Transect D	-1.559	1.379	0.258	
Gravel %	-0.021	0.025	0.398	
pH	-2.083	1.017	0.041	*
Transect B:gravel	0.083	0.034	0.016	*
Transect C:gravel	-0.001	0.030	0.961	
Transect D:gravel	0.067	0.035	0.058	.
df	54			
AIC	171.030			
Residual deviance/df	1.010		0.453	
Pearson Chi/df	0.731		0.944	
log likelihood	-76.515			

Significant levels: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

[1] Standard error

Table 3.10. Poisson regression model for estimating plant species richness for trees species, Elba protected area, Egypt.

	Coefficient	SE[1]	P-value	
(Intercept)	126500.00	52940.00	0.02	*
Transect B	-24.43	12.96	0.06	.
Transect C	-1.13	3.17	0.72	
Transect D	-1.40	2.98	0.64	
Elevation (m)	< 0.00	< 0.00	0.81	
Gravel %	-1265.00	529.40	0.02	*
Sand %	-1265.00	529.40	0.02	*
Silt %	-1265.00	529.40	0.02	*
Transect B:elevation	-0.02	0.02	0.11	
Transect C: elevation	-0.01	0.01	0.14	
Transect D: elevation	0.00	0.00	0.88	
Transect B:sand	0.66	0.34	0.04	*
Transect C:sand	0.07	0.07	0.30	
Transect D:sand	0.09	0.07	0.21	
df	49			
AIC	120.470			
Residual deviance/df	0.680		0.96	
Pearson Chi/df	0.598		0.99	
log likelihood	-46.237			

Significant levels: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

[1] Standard error

Transect B the most diverse in terms of species richness with a maximum of 26 species reflects sampling through most parts of Elba mountain and two wide wadis Aideb and kansisrob wadi. These results were consistent with results found by Abd El-Ghani (2006) through studying the floristic composition of six major wadis in Elba protected park in Egypt.

This study observed that species diversity, by species group increased in a north to south direction for the shrubs and subshrubs groups which can be associated to their proximity of the line transects B, C and D to the Red Sea coast, and the orographic rain on Elba peak. Similar results were reported by Abd El-Ghani (2006) and Al-Gohary (2008).

The final models explained 65%, 49%, 33% and 21% of the observed variability in species richness variability on transects A, B, C, and D, respectively and explained 23%, 58%, and 52% of the observed variability in species richness for shrubs, subshrubs, and trees species group, respectively. The Poisson regression models were considered adequate for estimating species richness by species group, and agreed with the results of Reich *et al.* (2010) for modeling tree species richness in Jalisco, Mexico.

3.5 CONCLUSION

The results of this study indicate that the relationships between plant species richness, environmental variables, topography and climate can be a very important step in understanding plant diversity in the protected area and can significantly contribute to the conservation and management of the area. An important finding of this study is the importance of selecting an appropriate sampling design, plot size and sample size in designing a regional inventory. It was evident that the sample design used in this study did not reflect the species diversity and environmental relationships in the area. The inclusion of satellite imagery in the sample design should also be considered in designing any future studies in this area.

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APPENDIX A

Table A.1. Parameter estimates for six height-diameter models fitted with data from 818 forested plots from Jalisco, Mexico.

Model	Function[1]	df[2]	Parameter Estimate			MSE[3]	FIT[4]
			a	b	c		
M1	$H=a+b\log D$	816	-17.67	8.84		3.90	0.44
M2	$H=aD^{b}$	816	1.07	0.71		3.94	0.43
M3	$H=ae^{b/D}$	816	26.46	-22.28		3.92	0.43
M4	$H=aD/(b+D)$	816	46.78	86.50		3.91	0.43
M5	$H=a+b(1-e^{-cD})$	815	-1.50	27.37	0.02	3.89	0.44
M6	$H=a(1-e^{-bD})$	816	29.01	0.018		3.89	0.44

[1] H = dominant tree height (m), D = dominant tree diameter (cm), a, b and c are regression parameters to be estimated, log is the natural logarithm, and e is the base of the natural logarithim.

[2] df = degree of freedom.

[3] MSE = mean squared error.

[4] FIT = correlation between the observed and predicted values squared.

Table A.2. Variability in estimated site productivity index (m) for the major forest types in Jalisco, Mexico.

Forest type	Number of sample plots	Site Productivity Index (m)			
		Min	Average	Max	SE[1]
Pine	13	9.4	20.35	32.8	1.90
Pine-Oak	89	7.7	21.83	62.8	0.81
Oak	197	6.2	15.19	31.2	0.33
Oak-Pine	54	10.3	16.49	25.6	0.56
Tropical Semi-evergreen	102	7.6	17.34	31.5	0.48
Tropical Dry	278	2.9	13.20	24.3	0.21
Subtropical Scrub	66	3.6	7.23	34.6	0.50
Mezquital–Huizachal	19	4.2	7.84	10.1	0.36

[1]SE = standard error of the mean.

Table A. 3. Correlation of the average height: diameter ratio (HD) with selected attributes of the samples by forest type.

Forest Type[1]	DH[2]	DD[3]	BA[4]
PN	0.65*	0.62*	0.35
PO	0.54**	-0.16	0.15
OK	0.67**	0.12	0.34**
OP	0.43**	-0.18	0.18
SM	0.55**	-0.05	0.08
SB	0.57**	-0.16**	0.07
MS	0.86**	-0.17	0.06
MH	0.45	-0.21	0.16

*Significantly different from zero at the 0.05 level.

**Significantly different from zero at the 0.01 level.

[1]PN-pine, PO-pine-oak, OK-oak, OP-oak-pine, SM-tropical semi-evergreen, SB-tropical dry, MS- subtropical scrub, and MH-*Mezquital- Huizachal*.

[2]DH-dominant height, [3]DD-dominant tree diameter, [4]BA-tree basal area.

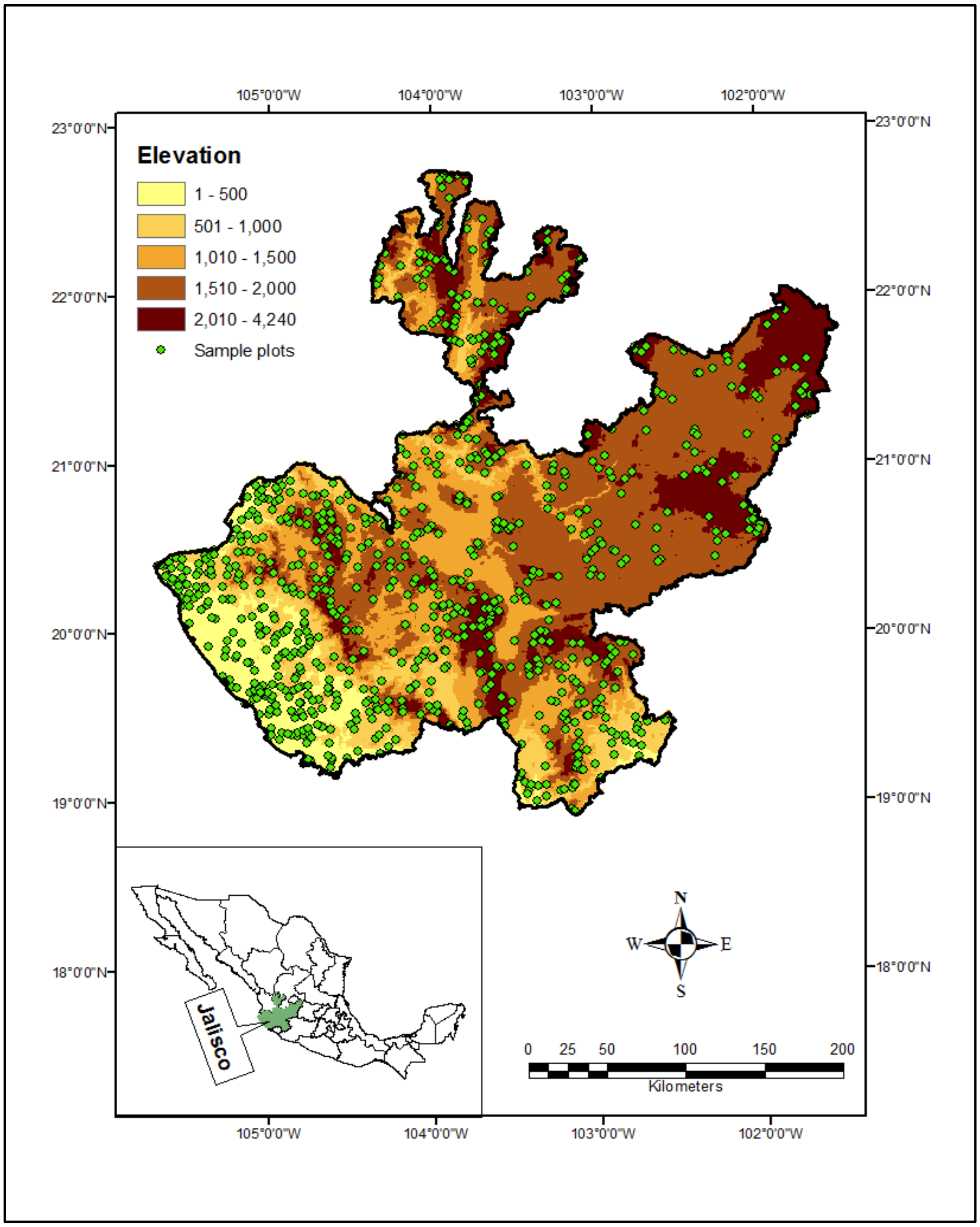

Figure A.1. Locations of 1,442 sample plots in the State of Jalisco, Mexico.

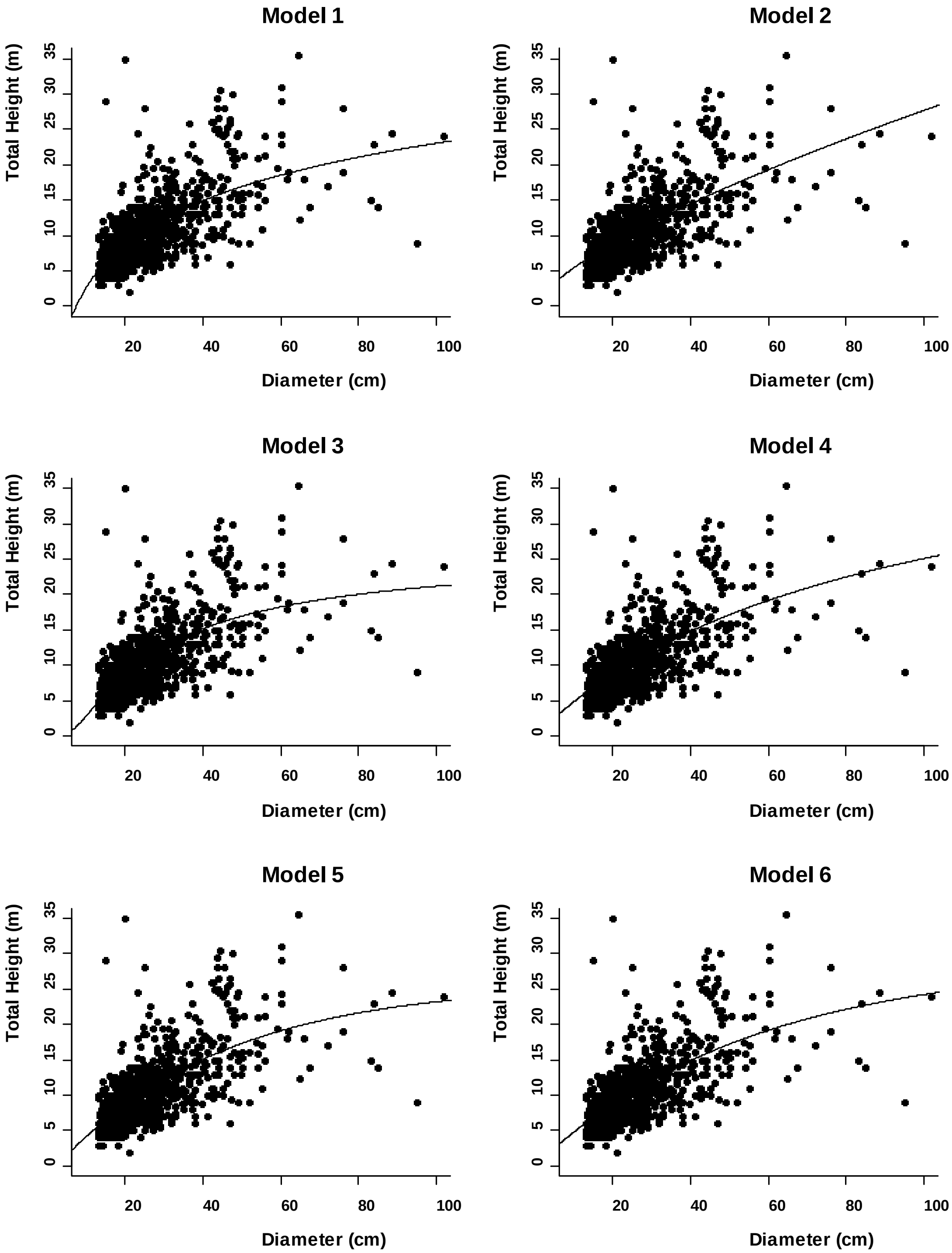

Figure A.2. Comparison of the six fitted models describing the average dominant height-diameter relationship on forested plots in Jalisco, Mexico.

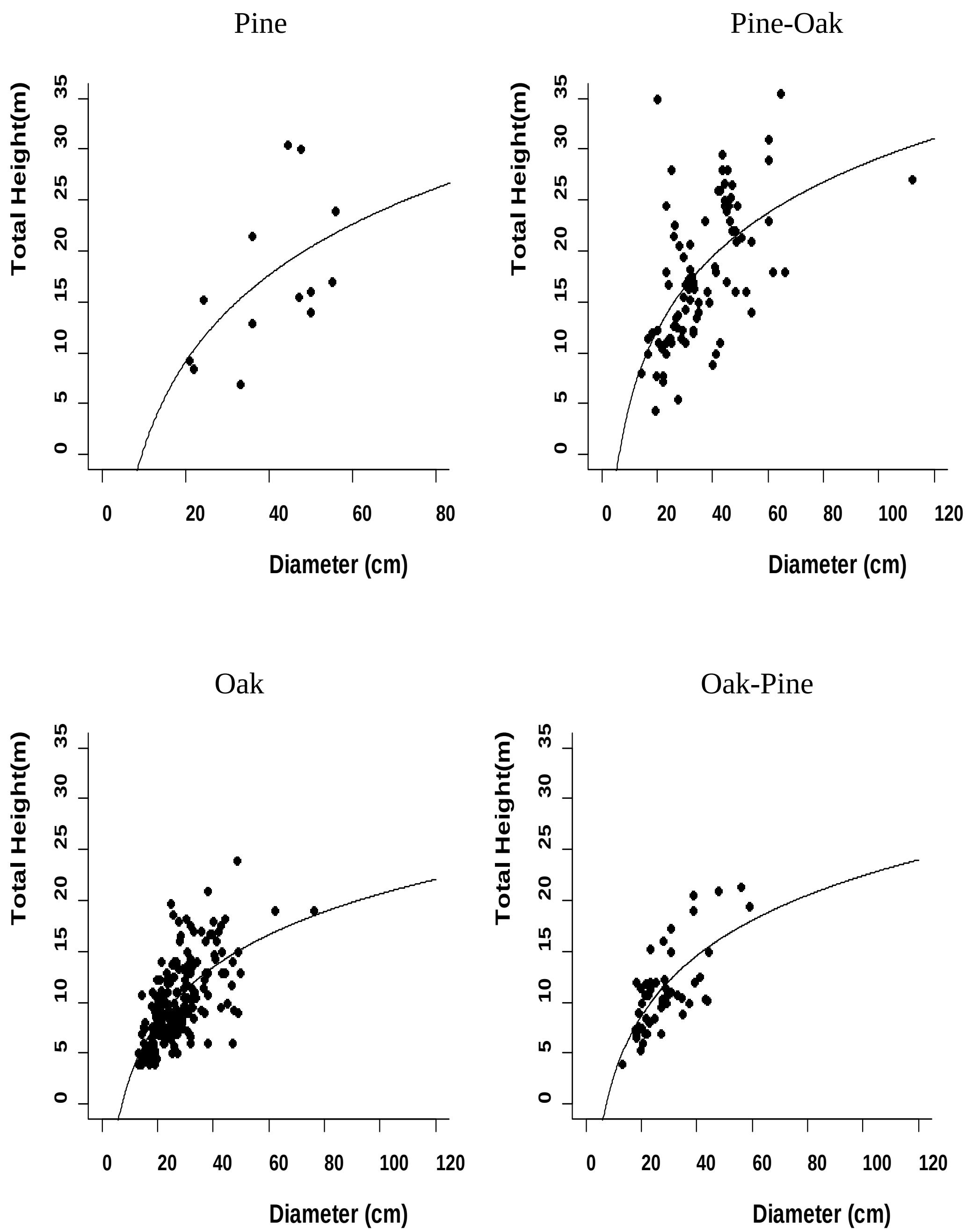

Figure A.3. Comparison of the average dominant height-diameter relationship of the major forest types using model 1.

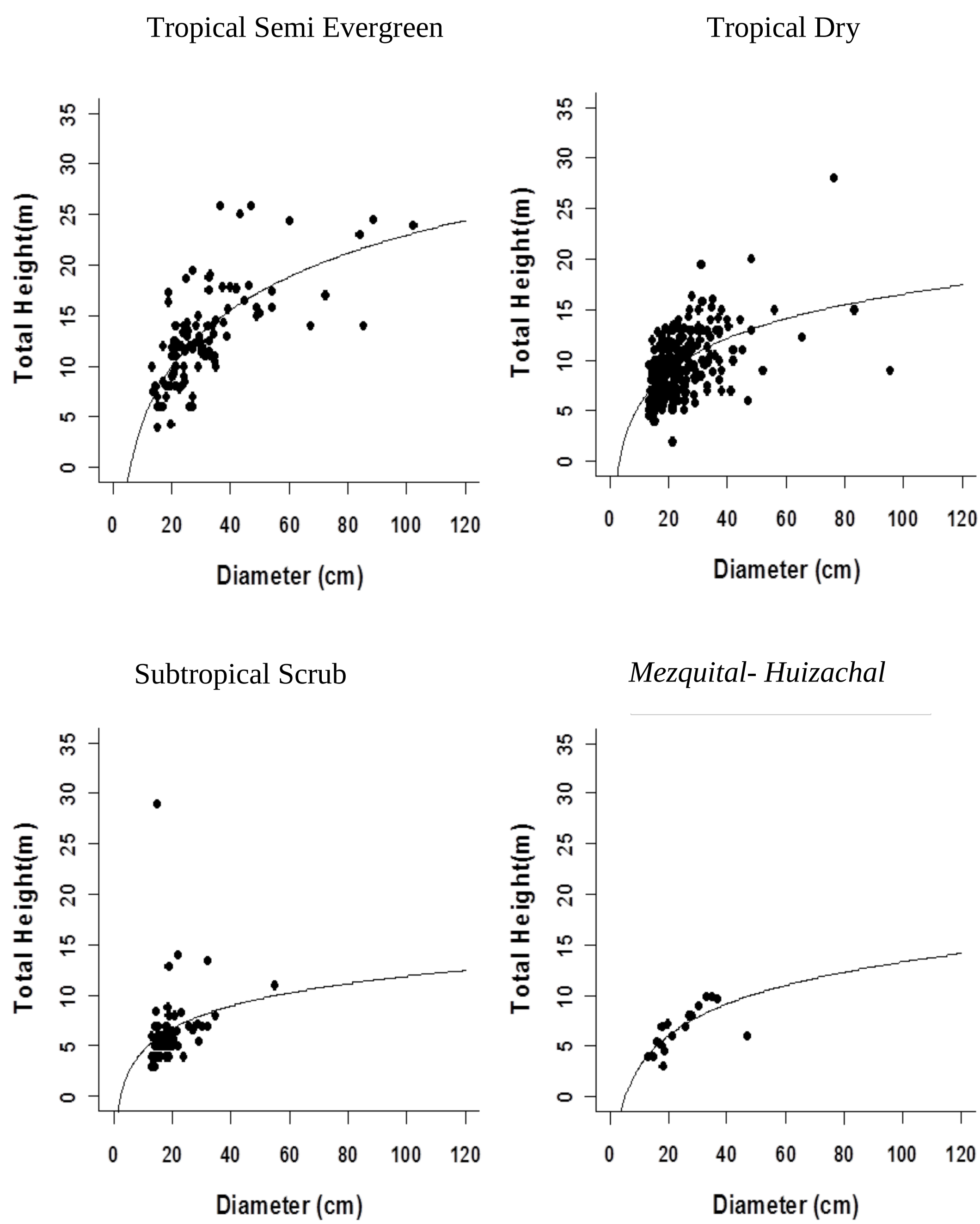

Figure A.3. Continued.

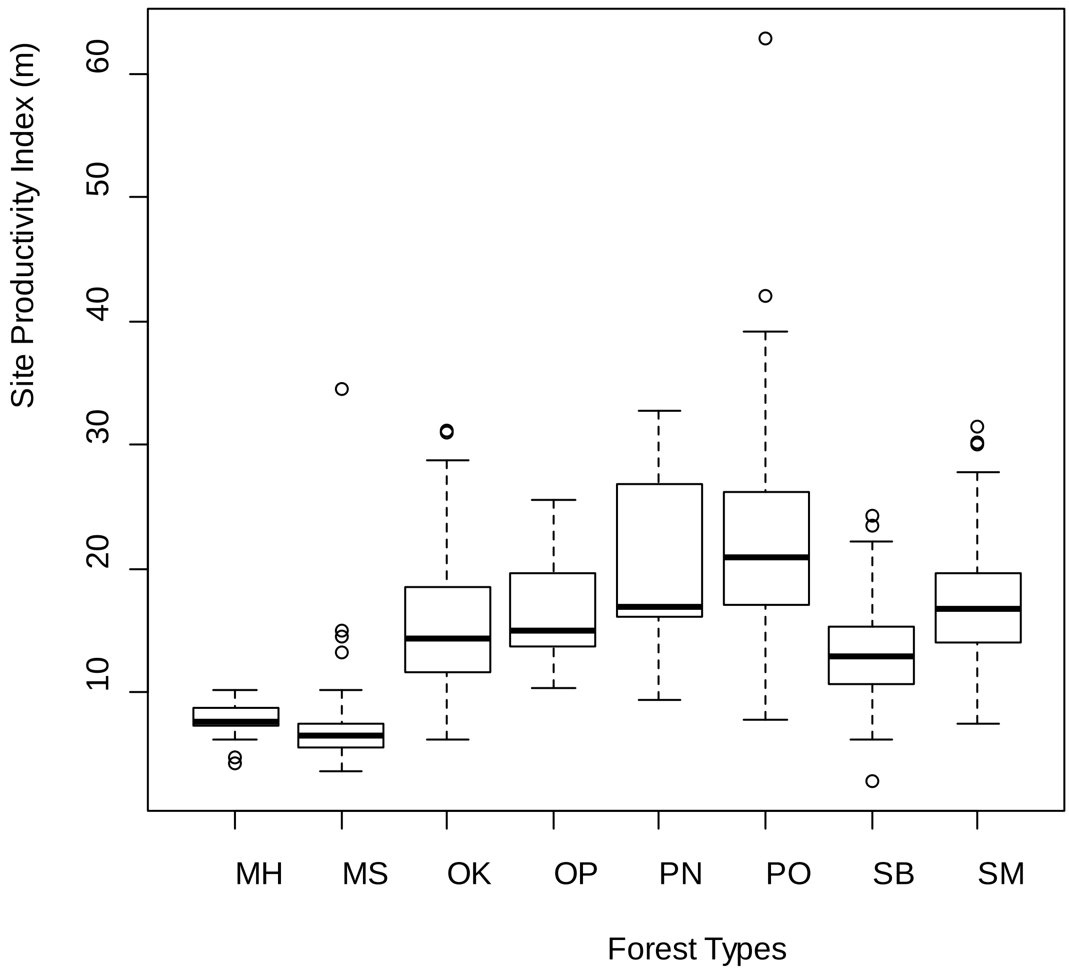

Figure A.4. Box plot of the predicted site productivity index illustrating the variations among the eight major forest types: PN-pine, PO-pine-oak, OK-oak, OP-oak-pine, SM-tropical semi-evergreen, SB-tropical dry, MS- subtropical scrub, and MH-Mezquital-Huizachal. The central line and out edges of each box represent the median and range of the inner quantiles of the data, respectively. The vertical lines represented values falling within 1.5 time the inter quantile range; circles represent observations values outside this range.

APPENDIX B

List of plant species recorded in Elba Protected area, Egypt.

Species	SG[1]	LF[2]	Transect A	Transect B	Transect C	Transect D
Abutilon pannosum	sh	P	+	+	+	+
Acacia asak *	sh	P	+	+	+	
Acacia mellifera	sh	P	+	+	+	
Acacia ehrenbergiana	sh	P				+
Acacia raddiana	tr	P	+	+		+
Acacia tortilis	tr	P	+		+	+
Aerva lanata *	su	P			+	
Aizoon canariense	su	A		+		
Asphodelus viscidulus	su	A		+		
Balanites aegyptiaca	sh	P	+	+	+	+
Calitropis procera	sh	P	+			+
Capparis deciduas	sh	P	+			+
Chrozophora oblongifolia (Delile) Spreng.	su	P		+		
Citrullus colocynthis	su	P	+	+	+	+
Cocculus pendulus	sh	P		+	+	+
Convolvulus hystrix	su	A			+	+
Delonix elata *	tr	P	+			
Dracaena ombet *	tr	P	+			
Echinops hussonii	su	P		+		+
Euphorbia granulata	su	P	+	+	+	
Euphorbia scordifolia	su	A	+	+	+	
Fagonia indica	su	P			+	
Ficus cordata subsp. *salicifolia*	tr	P	+			
Forsskaolea viridis *	su	P		+		+
Heliotropium arbainense *	su	P			+	
Helitropium bacciferum	su	P			+	
Indigofera articulate	su	P		+	+	
Iphiona scabra	sh	P		+	+	
Lavandula coronopifolia	su	P		+		+

Appendix B Continued.

Leptadenia pyrotechnica	sh	P	+	+	+	+
Lycium shawii	sh	P	+	+	+	+
Maerua oblongifolia	sh	P	+	+	+	+
Matthiola elliptica R. Br. ex DC.	sh	P				+
Moringa peregrina	tr	P		+		
Ochradenus baccatus	sh	P		+	+	+
Paronychia argentea	su	A		+	+	
Rumex vesicarius	su	A		+		
Salsola imbricata	sh	A	+	+		
salvadora persica	sh	P	+			
Senna italica	su	P	+		+	+
Tephrosia uniflora	su	P	+	+		+
Zygophyllum coccinium	su	A				+
Zygophyllum simples	su	B			+	

[*] Species is confined to Elba protected area

[1] SG is the species group (sh=shrubs, su=subshrubs, and tr=trees)

[2] LF is the life form (P=Perennial, and A=Annual).