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RESEARCH PAPER

A simple method for estimating suitable territory for bioenergy species in Chile

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Abstract

L. Morales-Salinas, E. Acevedo, G. Castellaro, L. Román-Osorio, J. Morales-Inostroza, and M.F. Alonso. 2015. A simple method for estimating suitable territory for bioenergy species in Chile. Cien. Inv. Agr. 42(2): 227-242. In the past 20 years, different areas of research concerning native and exotic species, herbaceous crops and forest plantations have been oriented toward satisfying domestic, industrial and transportation energy requirements. Because bioenergy species constitute an important resource, it would be strategic for a country to have a method for identifying areas suitable for their cultivation to properly incorporate the establishment of energy crops into land use planning. In this study, we sought to define the suitable territories for 16 bioenergy species and their energy potential based on their soil and climate requirements in Central and Southern Chile. We used an adapted version of the FAO EcoCrop database implemented through DIVA-GIS software to predict the crop suitability of different geographical areas, and our results indicate that this method is a simple way to identify land suitable for the establishment of bioenergy species, which is information that can be used in land use planning. Furthermore, spatially explicit regression and ordinary kriging proved to be satisfactory tools for interpolating data from weather station networks through the generation of continuous climatic information grids. Land suitability is presented at a scale of 1:1,000,000 in a continuous digital format expressed in probabilistic terms.

Key words: Bioenergy species, EcoCrop, ecological niche model, land suitability.

Introduction

Biomass is a renewable source of energy, and its use is of particular interest because it can reduce greenhouse gas emissions, waste volume in landfills and dependence on non-renewable energy sources (Rudnick *et al.*, 2011).

Biomass has high energy potential in Chile, and the primary sources are the residues from the management and utilization of native and commercial forests (ProChile, 2009). According to a study of the biomass market in Chile (UACH,

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2013), there are 2 million hectares available for the establishment of energy crops nationwide, which would reduce the country's dependence on imported energy and improve the condition of soils degraded as a result of human action (FAO, 2008).

Territorial suitability has a direct impact on crop productivity (Parthasarthy *et al*., 2007), and climatic variables are the most important factors determining the geographic distribution of a species, although soil variables are important as well. Currently, there is a wide variety of available ecological niche models (Grinnell 1917, 1924; Leibold, 1995; Chase and Leibold, 2003), such as GARP (Stockwell and Peters, 1999), Maxent (Phillips, 2006), BIOCLIM (Busby, 1991), and EcoCrop (FAO, 2000) among others. All can be used to identify areas with optimal climatic conditions for growing crops (Parthasarthy *et al*., 2007; Pliscoff and Fuentes, 2011), but due its simplicity, EcoCrop has comparative advantages for modeling the potential geographic distribution of a species (Ramirez-Villegas *et al*., 2013).

EcoCrop calculates a suitability index for the growth of a species based on climatic parameters (i.e., absolute and optimal temperatures and precipitation), and the predictive model is implemented in DIVA-GIS software (Hijmans *et al*., 2002). However, although it is frequently used, the EcoCrop model does not account for soil properties when predicting land suitability, and this could be restrictive when modeling crop potential (Ramirez-Villegas *et al*., 2013).

This study proposes a simple method for the determination of land suitability for 16 energy species in the Central and Southern zones of Chile. The method is an adaptation of the EcoCrop model that predicts land suitability based on both soil and climate species requirements.

Materials and methods

Study area and selected species

From north to south, the study area covered eight regions within the current administrative divisions in Chile: Valparaíso (Valparaíso), Metropolitana (Santiago), O'Higgins (Rancagua), Maule (Talca), Bío-Bío (Concepción), Araucanía (Temuco), Los Ríos (Valdivia) and Los Lagos (Puerto Montt) (Figure 1).

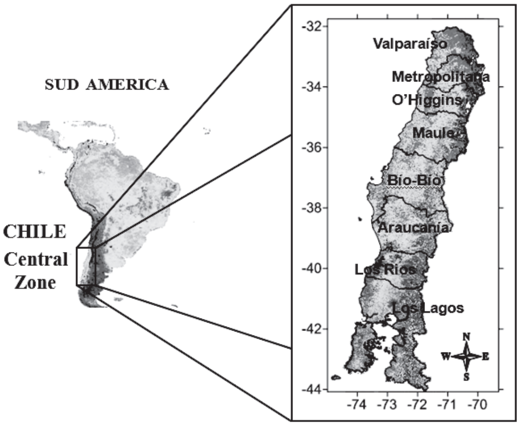

Figure 1. The study area in Central and South-Central Chile.

The following bioenergy species were assessed: *Acacia melanoxylon*, *Acacia mearnsii*, *Acacia dealbata*, *Acacia saligna*, *Eucalyptus camaldulensis*, *Eucalyptus globulus*, *Eucalyptus nitens*, *Opuntia ficus-indica*, *Paulownia* spp., *Populus deltoides*, *Populus* spp, *Robinia pseudoacacia*, *Salix viminalis*, *Arundo donax*, *Panicum virgatum* and *Miscanthus x giganteus.* These species were selected because of their high performance in different countries, the quality of their biomass for energy production purposes and their high yield potential in Central and Southern Chile (Alonso *et al*., 2010).

Climatic information

The climatic data came from four sources: Climatología de Chile (PNUD-Gobierno de Chile, 1964), Atlas Agroclimático de Chile (Novoa *et al.*, 1989), Dirección General de Aguas (DGA) and Dirección Meteorológica de Chile (DMC). Temperature and precipitation data were collected from 1,239 weather stations located in the above-mentioned regions, but only stations with a minimum of 10 years of continuous data were considered. Thus, data from a total of 625 weather stations with a minimum of 11 years and a maximum of 140 years of monthly averaged information were used and compared to similar studies (Novoa *et al.,* 1989; Santibáñez and Uribe, 1990, 1993a and 1993b). Because data from different sources were indexed under different cartographic projections and time zones, they were standardized under the same index system (WGS84 spherical datum).

Digital elevation model

A digital elevation model (DEM) corresponds to a data matrix with a spatial distribution of altitudes (Felicísimo, 1994). In this study, the free distribution DEM model from the Shuttle Radar Topography Mission (SRTM) was used in the construction of the topoclimatic model, and the data corresponded to SRTM-4 with a 90-m pixel, which is a scale of approximately 1:100,000 (Farr *et al.*, 2007). The slope and aspect variables were calculated from the DEM, and the distance to the coast was estimated by calculating the linear distance from the coast to one of the pixels in the DEM matrix.

Topoclimatic modeling

Minimum, average and maximum temperatures for January and July and average annual precipitation were used in a geographically weighted multiple regression model (Novoa *et al.,* 1989; Santibáñez and Uribe, 1990, 1993a and 1993b) with latitude (LAT), longitude (LON) and altitude (ALT) as the predictor variables (Fotheringham *et al.,* 2002).

The climatic variation over the study area was represented by physiographic and land use factors and determined by a topoclimatic analysis (Morales *et al.*, 2006), which quantitatively modeled the climate using a combination of land surface parameters (Okolowicz, 1969; Kaminski and Radosz, 2002).

To estimate the spatial variability of the climatic data, global regressions were run with one spatial variable. The coefficients of the resulting equation could have had significant spatial variation (Morales *et al.*, 2007, 2010). Thus, spatially explicit equations describing the changes in climatic variables were calculated using weighted least squares; the weight was dependent on the distance between each point and the rest of the observations (Berry and Feldman, 1985; Fotheringham *et al.*, 2002). The geographically weighted regression (GWR; Brunsdon *et al.,* 1996) was used to find the spatial variability in the estimated parameters through a multiple linear regression that incorporates the geographical coordinates of the observations into its equation.

In summary, the goal was to adjust the same number of regressions as the number of observations in the space considered in the analysis based on the hypothesis that closer observations have greater weights in the regression, which is simulated by a function that decays with distance. The climatic variables were modeled by Equation [1]:

$$y_i = a_0(u_i, v_i) + \sum_k a_k(u_i, v_i)x_{ik} + \varepsilon_i \quad \text{[Eq.1]}$$

where (u_i, v_i) indicates the coordinates of the i^{th} point in the space; y_i is the value of the dependent variable; x_{ik} is an independent descriptive variable at point i; $a_k (u_i, v_i)$ is a regression parameter for the independent variable, and ε_i is the error at point i. The coefficients, $a_k (u_i, v_i)$, were determined as follows:

$$a_k(u_i, v_i) = \left[X^T \cdot W(u_i, v_i) \cdot X\right]^{-1} \cdot X^T \cdot W(u_i, v_i) \cdot Y \quad \text{[Eq.2]}$$

where the independent observations or descriptive variables are in the X matrix, and the dependent variables are in the Y matrix. W_i is a diagonal matrix of (*N, N*) order in which the elements of the diagonal are the weights, w_{ij}, which are a function of the focal observation and the rest of the observations (Fotheringham *et al.*, 1997, 2000 and 2002). They are calculated by the following equation:

$$W(u_i, v_i) = e^{-\alpha \cdot d_{ij}^2} \quad \text{[Eq.3]}$$

where α is a parameter expressing the decreasing distance between two points in space, and dij is the distance between points i and j. From a practical point of view, a point that is more distant from i will have less statistical influence on the final numeric relationship (Morales *et al.*, 2007). It is noteworthy that the descriptive variables, x_{ik}, can be derived from interactions among or powers of the fundamental variables (Morales *et al.*, 2006).

The statistical model of the spatial distribution of the climatic variables with GWR [Equation 1] was formulated using a computer code developed with the statistical software R (R Development Core Team, 2009). The digital mapping method based on the topoclimatic model was carried out using Idrisi 32® software tools (Clark University, Worcester, MA, USA); digital charts of latitude, longitude and altitude were used as independent variables in the multiple regressions defined in Equation [1]. Under this procedure, a value for the climatic variables was obtained for each pixel, which generated a digital map composed of seven image files (maximum, minimum and average temperature for January and July; annual average precipitation). The resulting climatic variable matrices have the same dimensions as the matrices for the independent variables, i.e., the same number of rows and columns as for latitude, longitude and altitude.

Soil information

To create digital charts of the soil variables, we collected and digitized soil data from basic sources of soil information (CIREN, 1996, 1997, 1999a, 1999b, 2001). The soil variables (properties) associated with each soil series were both (1) qualitative, which included the soil order and taxonomic classification of the soil series (USDA-NRCS, 1999), and (2) quantitative, which included the depth of each soil layer (SD) as well as its textural class, particle distribution, field capacity, wilting point, bulk density, pH, organic carbon and organic matter contents. Using the depth of each soil layer as the weighting factor, weighted averages of each of the soil variables representing the soil series profile were calculated.

Some of the soil series in the study area were obtained from previous reports and studies (CIREN, 1996, 1997, 1999a, 1999b, 2001), so the quantitative information for the modal profile was incomplete for these variables. The GWR algorithm was used to estimate depth and soil pH according to descriptive variables or covariables, which were the altitude and normalized difference vegetation index (NDVI) value at each point in the territory from MODIS images (Saini, 1966; Rawls *et al.*, 1982; Saxton *et al.*, 1986; Heuscher *et al.*, 2005). The model used to estimate the missing data is proposed in Equations 1 to 3. As for the climatic variables, the regression coefficients in Equation 1 were calculated using the multiple linear GWR method, in which the independent variables were altitude and the NDVI-MODIS value (Fotheringham *et al.*, 1997, 2000, 2002). Due its widespread use and good results, ordinary kriging was used to estimate the spatial variability of the coefficients of the equation used to estimate soil depth and pH (Ojeda *et al.*, 2011; Martinez-Cob, 1996; Miranda-Salas and Condal, 2003; Vicente-Serrano *et al.*, 2003). The equation was applied using interpolated coefficients determined by SIG Idrisi 32® software on each polygon from the soil vectorial files to estimate the variables in those series for which there were no values. The polygon vectorial files were rasterized, and the resulting matrices had the same dimensions as the matrices of the independent variables and thus the same number of rows and columns as altitude and NDVI.

Land suitability and plant species adaptability

According to the ecological characteristics of the different species, *A. melanoxylon* is found between regions VII and X in the Central Valley below an altitude of 500 m in red and yellow podzolic or alluvial soils (Hebert and Baurele, 1995). *A. mearnsii* is found between regions V and X in low coastal zones and foothills from sea level to 900 m (INFOR, 2000a). *A. dealbata* is located in warm to cold sub-humid zones; it is found from high steppes to deep valleys along streams and rivers (INFOR, 2000a). *A. saligna* is distributed between regions III and VII where it tolerates superficial saline and alkaline soils and grows in zones of irregular and limited precipitation between 100 to 250 mm year^{-1} (INFOR, 2001). *E. camaldulensis* grows in zones with an annual precipitation of 250 mm year^{-1} from sea level to 600 m in altitude, and it tolerates poor and degraded soils of low to moderate fertility (INFOR, 2000b). In Chile, there are numerous *Eucalyptus* species including *E. globulus, E. nitens* and *E. camaldulensis*. *E. globulus* grows in a precipitation range from 200 to 1,250 mm year^{-1}; *E. nitens* grows in a range of 750 to 1,350 mm year^{-1} and *E. camaldulensis* between 600 to 1,100 mm year^{-1}. All of these species grow in thin, moderate and deep and silty to clay loamy soils with light to heavy textures (INFOR, 2005). *O. ficus-indica* is located at altitudes between 800 to 1,800 m in clay loamy soils with a pH value between 6.5 to 8.5 and precipitation of 150 to 1,800 mm year^{-1}. It tolerates drought and requires a mean annual temperature between 16 to 28 ºC (Gerencia Regional Agraria de La Libertad, 2009). *Populus* sp. are found between 300 to 3,000 m and require temperatures ranging between 14 and 30 ºC, precipitation between 1,200 to 2,500 mm year^{-1} and light to moderate soil textures (Cazanga *et al*., 2010). *R. pseudoacacia* naturally grows in regions with a Mediterranean climate including annual precipitation between 500 to 1,500 mm and a mean annual temperature between 10 and 18 ºC. It tolerates all types of soils with the exception of those that are extremely dry or compacted (INFOR, 1999). *A. donax*, *Panicum virgatum* and *Miscanthus x giganteus* are perennial rhizomatous grasses, and they all grow on almost any soil type from light to moist and compact with a pH from 5 to 8.7. *A. donax* tolerates salinity and requires a minimum temperature of 9 ºC; *P. virgatum* requires a minimum temperature of 13 ºC, and *Miscanthus x giganteus* requires deep soils and a minimum temperature of 6 ºC (El Bassam, 2010).

The adaptability of a species was expressed as a relative score (0-1), where 0 indicates null adaptability and 1 indicates an optimum fit. This score was calculated using five meteorological variables (annual rainfall, maximum and minimum temperature in the warmest (January) and coldest (July) months) and two soil variables (depth and pH). To generate the scores, a response or performance function to each of these variables was calculated for all of the species based on their soil and climate requirements. These values were obtained from the EcoCrop database (FAO, 1997, 2000), and the adaptability score for annual rainfall, temperature and soil pH was defined by the function shown in Figure 2. The performance function for a species can be described by a parameterized function with four coefficients specific to each species (Table 1): minimum critical value (V_{min}), minimum optimal value (Vop_{min}), maximum optimal value (Vop_{max}) and maximum critical value (V_{max}). The species performance function (F) was calculated with the following equation:

$$F = \begin{cases} 0 & V \leq V_{min} \quad o \quad V \geq V_{max} \\ 1 & Vop_{min} \leq V \leq Vop_{max} \\ \dfrac{V - V_{min}}{Vop_{min} - V_{min}} & V_{min} \leq V \leq Vop_{min} \\ 1 - \dfrac{V - Vop_{max}}{V_{max} - Vop_{max}} & Vop_{max} \leq V \leq V_{max} \end{cases} \qquad \text{[Eq.4]}$$

The performance function (F) for soil depth (SD) is described by two coefficients: V_{min} and Vop_{min}, which are specific to each species (Table 1). The performance function was calculated according to the following equation:

$$F = \begin{cases} 0 & V \leq V_{min} \\ 1 & V \geq Vop_{min} \\ \dfrac{V - V_{min}}{Vop_{min} - V_{min}} & V_{min} \leq V \leq Vop_{min} \end{cases} \quad \text{[Eq.5]}$$

After calculating the performance function for precipitation (F_{pp}) and temperature (F_t) and the soil variables pH (F_{pH}) and depth (F_{depth}), an index of overall adaptability (IA) was obtained from the weighted linear sum of all of the adaptability functions (Equations 6 and 7):

$$IA = \sum_{i=1}^{N} W_i \cdot F_i \quad \text{[Eq.6]}$$

$$\sum_{i=1}^{N} W_i = 1 \quad \text{[Eq.7]}$$

where W_i represents the specific weight assigned to each variable F_i. The weights for annual rainfall, temperature, pH and soil depth were defined as 0.35, 0.35, 0.10 and 0.20, respectively (Equation 8) based on expert judgment and previous studies (Cazanga *et al*., 2010).

$$IA = 0.35 \cdot F_{pp} + 0.35 \cdot F_t + 0.1 \cdot F_{pH} + 0.2 \cdot F_{depth} \quad \text{[Eq.8]}$$

The variables included in the index (IA) were processed with Idrisi® 32 software to produce digital charts of the adaptability of each species at a scale of 1:250,000 in the WGS84 and latitude and longitude projection in degrees. The species adaptability results should be interpreted based on the maximum productivity without climatic restrictions (FAO, 1997). From the literature and the IA values, it is possible to classify suitability into the following categories: very suitable (> 80%), suitable (60-80%), moderately suitable (40-60%), marginally suitable (20–40%) and unsuitable (< 20) and to assign each category the ranks of 5, 4, 3, 2, or 1, respectively (Sridhar *et al*., 2014; Fand *et al*., 2014; Mendas and Delali, 2012; Parra-Quijano *et al*., 2012; Sonder *et al*., 2010; Geerts *et al*., 2006; Utpala *et al*., 2006).

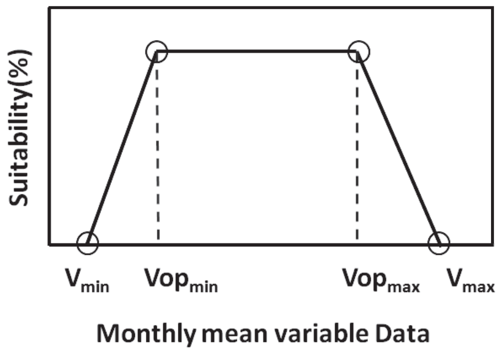

Figure 2. Species performance functions based on the independent soil and climate variables.

Statistical analysis

The statistical analysis compared the simulated and observed results. For the agroclimatic variables, the comparisons were made at a monthly average level, but a single value was compared at a territorial level for the soil variables. The BIAS, MBE (mean bias error), MABE (mean absolute bias error), RMSE (root mean square error) statistics were calculated. A simple regression analysis was performed to determine the coefficient of determination (r^2), which is widely used to evaluate the goodness of fit between calculated and observed values, and the index of agreement, or Nash-Sutcliffe model efficiency (E), was also determined (Yorukoglu and Celik, 2006; Almorox *et al*., 2005; Legates and McCabe, 1999). Due to its utility in comparisons of two or more statistical models that use the same dependent variable, the Akaike Information Criteria (AIC) was applied to evaluate the GWR topoclimatic model (Akaike, 1973; Burnham and Anderson, 2002).

Results

Topoclimatic modeling

The values of the spatially modeled annual mean rainfall (AMR), mean temperature in January and July (TM01, TM07), maximum temperature in January and July (TX01, TX07) and minimum

Table 1. Description of the species-specific coefficients: minimum critical value (V_{min}), minimum optimal value (Vop_{min}), maximum optimal value (VOP_{max}) and maximum critical value (V_{max}).

Species	Annual Rainfall				Temperature				Soil depth				pH			
	V_{min}	V_{max}	Vop_{min}	Vop_{max}	V_{min}	V_{max}	Vop_{min}	Vop_{max}	V_{min}	V_{max}	Vop_{min}	Vop_{max}	V_{min}	V_{max}	Vop_{min}	Vop_{max}
Acacia melanoxylon	600	2700	800	2200	4	30	18	22	100	-	150	∞	5.0	7.5	6.0	6.5
Acacia mearnsii	300	3000	700	1600	5	35	18	30	100	-	150	∞	4.5	7.5	5.0	6.5
Acacia dealbata	300	1500	600	1000	6	32	15	26	100	-	150	∞	5.0	7.0	5.5	6.5
Acacia saligna	300	1000	400	700	5	36	20	32	35	-	100	∞	4.5	8.0	5.5	7.0
Eucalyptus camaldulensis	250	2500	600	1000	7	40	12	28	35	-	150	∞	4.5	8.0	5.0	7.0
Eucalyptus globulus	550	1800	700	1400	6	30	18	23	35	-	150	∞	5.0	7.5	5.5	6.5
Eucalyptus nitens	750	2000	900	1750	4	30	14	26	100	-	150	∞	5.5	7.5	6.0	6.5
Opuntia ficus-indica	100	800	125	500	10	30	18	26	35	-	100	∞	6.5	8.2	7.0	7.5
Paulownia tomentosa	200	1500	500	1000	6	35	8	29	35	-	150	∞	5.0	8.9	5.5	8.0
Populus spp	150	3000	1200	2500	8	34	14	30	50	-	150	∞	4.5	8.0	4.9	7.6
Populus deltoides	600	3000	1200	2500	8	34	14	30	100	-	150	∞	4.5	8.0	5.5	6.5
Robinia pseudoacacia	300	1600	450	700	6	40	15	32	100	-	150	∞	4.5	8.2	5.5	6.5
Salix viminalis	250	700	300	600	5	40	15	25	35	-	100	∞	6.5	8.5	7.0	8.0
Arundo donax	400	1800	600	1200	10	47	18	33	35	-	100	∞	4.5	8.5	5.0	7.0
Panicum virgatum	550	2500	950	1400	6	36	17	32	35	-	100	∞	4.9	8.2	6.0	7.0
Miscanthus x giganteus	700	3200	1050	1600	8	42	17	32	35	-	100	∞	4.7	8.4	5.5	7.0

temperature in January and July (TN01, TN07) are presented in Table 2. The root mean square error (RMSE), the efficiency ratio (E), the statistical variance parameters, the regression parameters (adjusted r^2 and the significance value, P) and the Akaike information criteria (AIC) are also presented in Table 2. The efficiency ratio of the model ranged from 48 to 92% for the average and maximum temperatures in July, and the adjusted coefficient of determination (r^2) indicates that the model explains between 67 and 89% of the variability in each of the climatic variables depending on the altitude. The P value indicates that the relationships are statistically significant at a 99% confidence level for each model, and the results show that it is possible to estimate the spatial distribution of each climate variable by altitude. The annual average values were calculated from the average monthly matrices of each of the variables. The spatial distributions of some of the variables modeled by the regression equations are shown in Figure 3(a, b).

Based on the statistical criteria, the results presented in Table 1 are satisfactory and more accurate compared with those from previous studies (Novoa *et al.*, 1989; Santibañez and Uribe, 1992). In Chile, the previously used methods have been based on the interpolation of isolines, which are usually drawn freehand by an expert climatologist, but this method fails when attempting linear interpolations between isolines (Declercq, 1986). Indeed, the results obtained by interpolating between isolines are highly method-dependent and only constitute a trend. Instead, with the methodology used in this work, the maps of the climatic variables are generated by a continuous spatial model in a digital format with the advantage that they can be integrated into a geographic information system (GIS) for easy analysis and incorporation with other databases.

Soil variables

Soil depth and pH are shown in Table 3. The calculated ratios illustrate the variability in their spatial distribution, so it was not feasible to use only one equation coefficient for the entire study area. The analyses yielded an E of 71% in the estimation of soil depth with an RMSE of 14.85, which is equivalent to 5.21%, and an r^2 of 0.876 (P = 0.01). Soil pH had a higher agreement rate of 80%, an RMSE of 0.41, which is equivalent to 6.44%, and an r^2 of 0.81 (P = 0.01). Figure 3(c, d) shows the results of the estimation of soil depth and pH in throughout the study area.

Species zoning

The suitability maps of the studied species are shown in Figure 4; the suitability of the land for each species is indicated by the color bar.

To interpret the results, we used the homogeneous environmental area zones developed by ODEPA, Ministerio de Agricultura (Chile), which correspond to a synthetic description of the Chilean agricultural sector. ODEPA also delivered a complete database with the information collected in the 7th National Agricultural Census (2007). It is not advisable for bioenergy crops to compete for the land used for food crops, so bioenergy species

Table 3. Linear regression coefficients for the estimation of the spatial variation in soil depth (SD) and pH as a function of altitude and the NDVI coefficient using a GWR model. RMSE: mean quadratic error; E: efficiency index; r^2: determination coefficient and AIC: Akaike criterion.

Variable	Intercept		Altitude Coefficient		NDVI Coefficient		RMSE	E	r^2	P[1]	AIC[2]
SD	92.81659	±7.585	-0.00155	± 0.024097	0.5005	± 6.93701	14.85	0.71	0.876	**	8977.572
pH	5.79069	± 469.42	0.09378	± 1.12473	-5.70803	± 618.2	0.413	0.80	0.810	**	2372.196

[1]** P≤0.01
[2]AIC: Akaike criterion

Table 2. Linear regression coefficients for the estimation of the spatial variation in the climatic variables under study as a function of altitude using a GWR model. RMSE: mean quadratic error; E: efficiency index; r^2: determination coefficient and AIC: Akaike criterion.

Variable	Intercept		Slope		RMSE	E	r^2	p[1]	AIC[2]
AMR	1053.504	± 30.75	-0.26043	± 0.025716	317	0.88	0.87	**	18165.23
TM01	18.265	± 0.247	-0.00167	± 0.000168	1.53	0.87	0.83	**	1361.25
TM07	9.493	± 0.379	-0.001633	± 0.000258	4.3	0.48	0.76	**	1931.76
TX01	25.138	± 0.315	-0.0014	± 0.000228	1.9	0.86	0.82	**	1648.08
TX07	13.518	±0.316	0.000096	±0.000228	1.4	0.92	0.89	**	1472.10
TN01	11.769	±0.205	-0.001851	±0.000147	2.0	0.71	0.70	**	1506.10
TN07	5.4035	±0.214	-0.00237	±0.000153	2.4	0.82	0.67	**	1628.17

[1]**P≤0.01.
[2]AIC: Akaike Criterion.

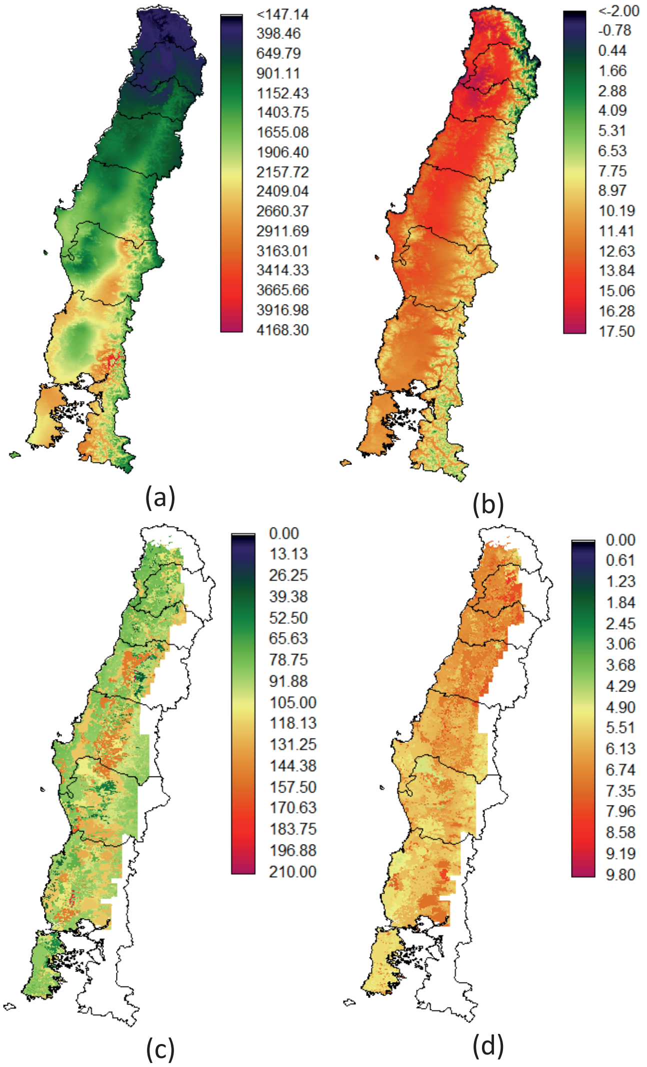

Figure 3. Spatial distributions of (a) annual mean rainfall (mm year^{-1}), (b) temperature (°C), (c) soil depth (cm) and (d) pH as estimated by the GWR model.

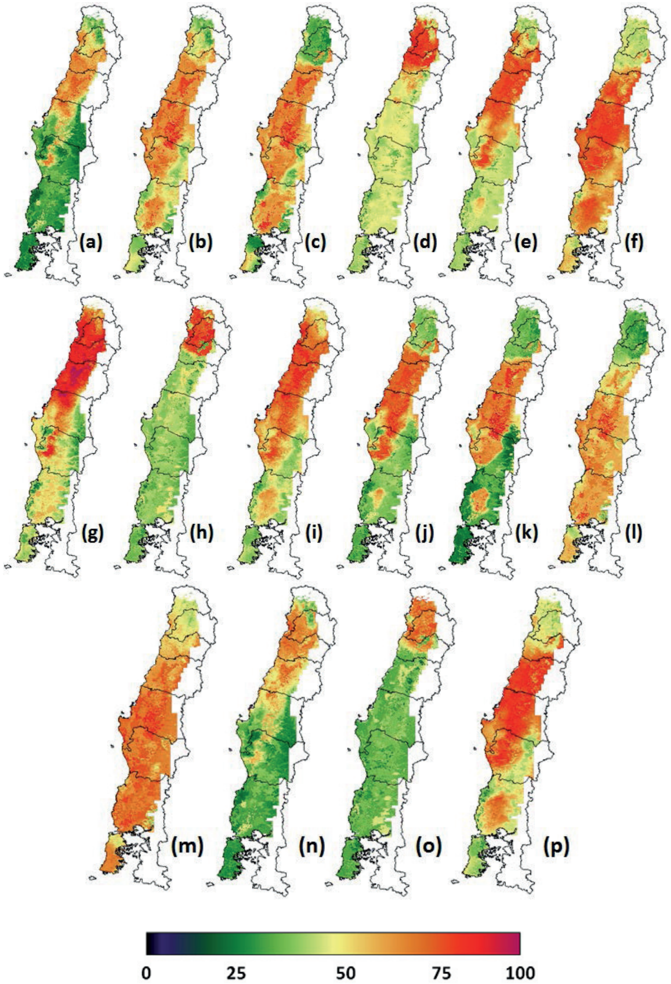

Figure 4. Land suitability maps for *Acacia dealbata* (a), *A. mearnsii* (b), *A. melanoxylon* (c), *A. saligna* (d), *Arundo donax* (e), *Miscanthus x giganteus* (f), *Paulownia spp.* (g), *Salix viminalis* (h), *Eucalyptus camaldulensis* (i), *E. globulus* (j), *E. nitens* (k), *Populus deltoides* (l), *Populus* spp. (m), *Robinia pseudoacacia* (n), *Opuntia ficus-indica* (o) and *Panicum virgatum* (p).

could potentially be established in rainfed areas. The ODEPA environmental homogeneous areas in each administrative region were used to estimate the suitability of the rainfed land for each species. Rainfed land accounts for approximately 47.435% of the area in Valparaíso, 24.17% in Metropolitana, 30.482% in O'Higgins, 31.335% in Maule, 38.215% in Biobío, 25.303% in Araucanía, 10.477% in Los Lagos and 26.857% in Los Rios. Table 4 summarizes the mean agroclimatic suitability classes for the species by the administrative regions in the study area (Mendas and Delali, 2012; Parra-Quijano *et al.*, 2012).

Discussion

This study demonstrated that the habitat distribution patterns of bioenergy species in Central and Southern Chile can be effectively modeled using a small amount of occurrence data, environmental variables and the edapho-climatic requirements of species, which are available in databases such as EcoCrop. This study presents the spatial distributions of 16 bioenergy species based on their performance functions (Figure 1) and independent explanatory variables. Similar studies have used EcoCrop and DIVA-GIS to map the fundamental

Table 4. Mean agroclimatic classes of the studied species in the coastal and interior rainfed areas of Valparaíso (V), Libertador Bernardo O'Higgins (VI), Maule (VII), Bío-Bío (VIII), Araucanía (IX), Los Lagos (X), Metropolitana (XIII) and Los Ríos (XIV). Regions are numbered as in Figure 1.

Species	V	VI	VII	VIII	IX	X	XIII	XIV
Acacia dealbata	3	4	4	3	2	2	3	2
Acacia mearnsii	3	4	4	4	4	4	3	3
Acacia melanoxylon	2	3	4	4	4	4	2	3
Arundo donax	4	4	5	4	4	3	3	3
Acacia saligna	5	4	3	3	3	3	5	3
Eucalyptus camaldulensis	4	4	5	4	4	4	4	3
Eucalyptus globulus	3	4	4	4	3	2	3	2
Eucalyptus nitens	2	3	4	4	4	2	2	2
Miscanthus x giganteus	3	3	4	5	4	4	3	4
Opuntia ficus-indica	4	3	2	2	2	2	4	2
Panicum virgatum	3	4	5	5	4	3	3	3
Paulownia tomentosa	5	5	5	4	3	3	5	3
Populus deltoides	2	3	3	4	4	4	2	4
Populus spp	3	3	4	4	4	4	3	4
Robinia pseudoacacia	4	4	4	3	3	2	4	2
Salix viminalis	4	3	3	3	3	3	5	3

ecological niches of species based on bioclimatic variables, but the applications have been limited due to the use of only two independent variables (Peterson, 2001; 2003; Pearson, 2007).

Based on the land suitability predicted by the EcoCrop method (Hijmans *et al*., 2005), the most suitable areas for *A. dealbata* were found to be the O´Higgins and Maule regions, principally on Alfisol, Mollisol, Vertisol, Inceptisol and Andisol soils (CIREN, 2010). When using EcoCrop (Hijmans *et al*., 2005), we found that the areas with higher spatial suitability for *A. mearnsii* were the Maule, Bío-Bío and Araucanía regions on Alfisols, Mollisols, Vertisols, Inceptisols, Andisols, Histosols and Ultisols. These results agree with those from the INFOR (2014) database, which suggests that the south-central part of the country has the highest growth potential for this species. For *A. melanoxylon,* the regions with higher land suitability are Maule, Bío-Bío and Araucanía, but INFOR (2014) only identifies Bío-Bío as a potential region for this species. Similar to INFOR (2014), our results indicate that the most suitable regions for *A. saligna* are Valparaiso and Metropolitana on Alfisol, Entisol, Mollisol, Vertisol and other miscellaneous soils.

For both *E. globulus* and *E. camaldulensis,* EcoCrop (Hijmans *et al*., 2005) and INFOR (2014) predict suitable territory between the Valparaiso and Los Rios regions. As for *E. nitens,* its territorial suitability extends from the Maule to Los Rios regions.

Our results, as well as those from the INFOR (2014) database, predict that the most suitable territory for *Populus* spp .is the Bío-Bío region on Ultisol, Andisol and Histosol soils. However, *P. deltoides* grows in a wide range of edapho-climatic conditions, so the suitable area for its cultivation extends from O´Higgins to Los Lagos.

The most suitable territory for *R. pseudoacacia* is located between Valparaíso and Maule but in patches with probabilities of occurrence between 50 and 62%. In contrast, the most suitable territory for *O. ficus-indica* is found in the Valparaíso, Metropolitana and O'Higgins regions.

A novel finding of this work is the high potential for rhizomatous perennial grasses, such as *A. donax, Miscanthus x giganteus* and *Panicum virgatum*, which are suited to the wide edapho-climatic conditions of Central and Southern Chile. The most suitable area for these species is between the O'Higgins and Bio-Bio regions.

Differences in the predicted territorial suitability of the studied species between EcoCrop (Hijmans *et al.*, 2005) and INFOR (2014) can be attributed to the variables used in both studies. In this work, we used precipitation, temperature, soil depth and pH as the explanatory variables, but in the INFOR (2014) studies, not all of the species were evaluated using the same variables. However, the results from both studies are not very different, and the predictions are quite similar in some cases.

The methodology presented here could be used to quantify the habitat distribution patterns of other plant species of ecological or economic interest. In particular, it has great potential for use in the study of threatened or endangered species as well as conservation and restoration efforts.

The results of this study are promising, especially considering the enormous energy potential of biomass in Chile (ProChile, 2009). Currently, there are 2 million hectares in the country available for reforestation (INFOR, 2011), and bioenergy crops will steadily accumulate biomass over time, positively affecting soils and preserving the country's natural resources (Rudnick *et al.*, 2011).

Biomass is an abundant resource in Chile, but the country strongly depends on imported energy sources and is threatened by the permanent rise in international energy prices. For this reason and because of its commitment to reduce greenhouse gas emissions (Figueres, 2007), Chile must aim to increase its use of biomass as an energy source.

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Resumen

L. Morales-Salinas, E. Acevedo, G. Castellaro, L.R. Osorio, J. Morales-Inostroza y M.F. Alonso. 2015. Un método simple para la estimación de la idoneidad territorial de especies bioenergéticas en Chile. Cien. Inv. Agr. 42(2): 227-242. En estos últimos 20 años diversas líneas de investigación en especies nativas y exóticas, cultivos herbáceos y plantaciones forestales se han orientado al desarrollo de aplicaciones energéticas domésticas, industriales y para el transporte. Como son un recurso importante, es estratégico contar con un método que permita identificar en el territorio nacional las áreas con aptitud para el cultivo de estas especies, con el objetivo de realizar una planificación territorial adecuada para el establecimiento de las plantaciones bioenergéticas. En este estudio se presenta un método simple para definir la idoneidad territorial de 16 especies con potencial energético (El Bassam, 2010) en el Centro y Sur de Chile, en base a sus requerimientos de suelo y clima. Se utilizó una adaptación del método EcoCrop implementado en el software DIVA-GIS para predecir la idoneidad de los cultivos en dicha zona geográfica. Los resultados muestran que el método propuesto representa una forma sencilla de estimar las zonas del territorio con idoneidad adecuada para establecer plantaciones bioenergéticas específicas, información que puede ser utilizada para la toma de decisiones en la planificación del territorio. La regresión espacialmente explicita y el kriging ordinario mostraron ser una herramienta satisfactoria de interpolación de los datos obtenidos de redes de estaciones climáticas para la generación de rejillas continuas de datos climáticos. La idoneidad territorial se presenta en un formato digital continuo expresado en términos probabilísticos a una escala 1:1,000,000.

Palabras clave: EcoCrop, especies bioenergéticas, idoneidad territorial, modelo de nicho ecológico.

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