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Research

Mapping and characterizing social-ecological land systems of South America

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ABSTRACT. Humans place strong pressure on land and have modified around 75% of Earth's terrestrial surface. In this context, ecoregions and biomes, merely defined on the basis of their biophysical features, are incomplete characterizations of the territory. Land system science requires classification schemes that incorporate both social and biophysical dimensions. In this study, we generated spatially explicit social-ecological land system (SELS) typologies for South America with a hybrid methodology that combined data-driven spatial analysis with a knowledge-based evaluation by an interdisciplinary group of regional specialists. Our approach embraced a holistic consideration of the social-ecological land systems, gathering a dataset of 26 variables spanning across 7 dimensions: physical, biological, land cover, economic, demographic, political, and cultural. We identified 13 SELS nested in 5 larger social-ecological regions (SER). Each SELS was discussed and described by specific groups of specialists. Although 4 environmental and 1 socioeconomic variable explained most of the distribution of the coarse SER classification, a diversity of 15 other variables were shown to be essential for defining several SELS, highlighting specific features that differentiate them. The SELS spatial classification presented is a systematic and operative characterization of South American social-ecological land systems. We propose its use can contribute as a reference framework for a wide range of applications such as analyzing observations within larger contexts, designing system-specific solutions for sustainable development, and structuring hypothesis testing and comparisons across space. Similar efforts could be done elsewhere in the world.

Key Words: *automatization; hierarchical clustering; multidisciplinary data; participatory mapping; social-ecological mapping*

INTRODUCTION

Because natural systems (i.e., not affected by human enterprise) are becoming rare across the world (Allan et al. 2017, Riggio et al. 2020), there is an increasing need for analyzing and understanding land through the lens of coupled human-nature systems. Humans are not mere inhabitants of ecosystems but strongly influence ecological processes (Ellis and Ramankutty 2008, Maxwell et al. 2016). Ecoregions and biomes are useful geographic units to represent coherent patterns of biophysical features. However, to characterize the current configuration of land systems, which necessarily involves human activity (Verburg et al. 2009), we need a land classification scheme that integrates both the social and the biophysical dimensions.

With increasing data availability, new opportunities for large-scale and synthesis research arise. Nevertheless, comparing findings from different locations and linking them to global or distant processes is still a challenge (Rocha et al. 2020), partly due to the lack of appropriate spatial frameworks at large scales to place them in context (Kuemmerle et al. 2013). Land system science, as a research field, is growing fast, and new methodological approaches to address this gap are diversifying and consolidating (GLP 2016). An example is the syndrome and archetype analysis (Meyfroidt et al. 2018, Oberlack et al. 2019, Sietz et al. 2019), which analyzes social-ecological systems (SES) by means of identifying recurrent patterns of land use characteristics and processes, and have been used to detect the

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occurrence of target social-ecological systems across the territory as well as to generate land system classifications.

Several endeavors applied the archetype logic to generate large-scale land classifications of social-ecological systems. Early global initiatives by Ellis and Ramankutty (2008) combined land cover with irrigation and population data to generate the Anthropogenic Biomes of the world. Subsequent efforts included more detailed data on production activities. Letourneau et al. (2012) generated a global land use systems map; van Asselen and Verburg (2012) produced the global scale land systems, and Václavík et al. (2013) developed global land system archetypes. At a continental scale, Levers et al. (2018) analyzed archetypical patterns and trajectories of land systems in Europe.

These studies combined data of different aspects of nature (e.g., land cover, land use intensity, biophysical factors) using computerized classification methods (e.g., multi-stage empirical process, hierarchical clustering, self-organizing maps) to produce maps with medium spatial resolution (~10 km to 20 km). However, they tended to center their classifications on land use, particularly identifying different types of agropastoral production. In most cases, information on the characteristics of the social communities was represented only through population density or accessibility, as indicators of land use intensity. Political, environmental, and socioeconomic factors were used in some cases ex-post to describe the classes, but not to generate them. Culture and governance are important to reflect the complex behavior of agents influencing the landscape (Lambin et al. 2001, Verburg et al. 2009, Rounsevell et al. 2012) and are very difficult to include in global models (Václavík et al. 2013). The most comprehensive was the global land systems archetypes (Václavík et al. 2013). They produced an exhaustive classification that considered several physical variables, photosynthetic activity (NDVI), gross domestic production (GDP), and political stability.

Classifications at the global scale are ideal to present general patterns across the world, but they fall short in understanding land systems at regional or local scales. For example, Václavík et al. (2013) classified roughly half of the South American continent (~12,000 km²) as the same class: "forest systems in the tropics." Working at finer spatial scales would allow for more detail in the classes' descriptions, the inclusion of variables of regional relevance with particular values range, and higher likelihood of finding complete and coherent sets of specific variables; such as cultural and political variables.

South America has particular characteristics that justify having a specific continental classification scheme that enhances the understanding within and across the local social-ecological systems. These include, for example, low overall human population density with more than 80% of the population concentrated in urban areas; a history of land use strongly influenced by social groups in high altitude regions, followed by a highly transformative European colonization period, including a massive replacement of wild herbivores by livestock; numerous Indigenous communities with diverse cultural heritage legacies; economy and agriculture production oriented toward exports and linked with some of the highest deforestation rates in the world.

In a first attempt to integrate social-ecological knowledge into the characterization of land systems for Latin America, Boillat et al. (2017) proposed a "simplified biome-level typology of social-ecological land systems (SELS)." They described seven SELS based on biophysical, economic, settlements, institutions, technology, historical legacies, and potential future trends. Nevertheless, this typology was exclusively based on expert knowledge and lacks a map connecting to a specific spatial representation, thus limiting its use and application.

In this study, we made the concept of SELS operational with a precise and systematic spatial classification for South America. Our overarching goal was to contribute to the development of a geographical reference framework to facilitate contextualizing the discussion of social-ecological findings and studies in land system science and territorial planning. More specifically, we (1) created a map of SELS typologies for South America, (2) analyzed the key variables that differentiated the typologies, and (3) described and discussed the resulting SELS map regarding the representation of our territorial knowledge and adequacy to the conceptual SELS descriptions from Boillat et al. (2017). Additionally, we highlight key data gaps that would allow further delving into characterizations of this kind.

METHODS

We generated a classification of South America into general typologies of social-ecological land systems by analyzing spatial patterns of characteristics along a multidimensional continuum and depicting areas with similar profiles (Meyfroidt et al. 2018, Sietz et al. 2019). Our research objective may not have a single one correct solution, thus we prioritized further applicability value by heeding the collective experience of researchers working on the region.

We designed a hybrid methodology combining machine learning techniques for analyzing a set of social and environmental spatial data, with a knowledge-based evaluation by an interdisciplinary group of regional specialists (authors). The computational spatial analysis allowed for replicability and spatial explicitness, whereas the expert-knowledge approach contributed with enhanced collective criteria for making decisions on the analysis design as well as on the interpretation of the outputs. We decided not to rely exclusively on automated data analysis, acknowledging data constraints (i.e., usage of proxies due to data gaps), which were also unbalanced across the variable's domains impacting more heavily on the social than the biophysical aspects. Under this scenario, mathematical optimal solutions might not always be the thematically most meaningful ones. Therefore, expert knowledge was applied to favor coherent territorial clusters, making subjective decisions on top of the evidence provided by the results. The potential bias of these subjective decisions was minimized through diversifying the profiles of the group of regional specialists.

The regional specialists were involved for the 22-month duration of this study. We had three stages of personal surveys on input variables and partial results, one in person workshop session at the GLP Open Science Meeting in April 2019, a subgroups' work instance to thoroughly discuss individual SELS, and overall reviews of the final manuscript. The group of specialists consisted of 21 researchers of different backgrounds, affiliations, disciplines, skill profiles, gender, and nationalities, with extensive local and regional experience covering the geographical and territorial diversity of South America (many co-authors of the publication Boillat et al. 2017). The disciplinary profiles represented in our group included ecology, ethnobiology, geography, agronomy, ecological economics, anthropology, and forestry.

We followed an iterative process of: (1) defining the relevant variables and scale of analysis, (2) generating the maps and identifying key explanatory variables, and (3) discussing the outputs and describing the resulting SELS (Appendix 1, Fig. A1.1). Details on every methodological step (e.g., rationales behind the methods, explanation of statistical analysis, parameters, evaluation metrics) are thoroughly documented in Appendix 1 along its four sections.

Conceptual framework and variable selection

Looking at the definition by Boillat et al. (2017), we understand SELS as nested complex and dynamic systems that developed with humans as the major agent of change but dependent on the underpinning ecological characteristics and opportunities. Each SELS is defined by its particular configuration of social and environmental conditions, settlement patterns, land-use dynamics, and contextual factors. To guide the variable selection process, we used the biome-level SELS typologies described in Table 1 of Boillat et al. (2017; hereafter conceptual SELS) as a reference. In the process of operationalizing the theoretical definitions we: (1) deviated the primary focus on patterns of land-use change toward static conditions that may reflect them, (2) structured the descriptions by organizing them within a classification of research components for social-ecological systems studies (Winkler et al. 2018), and (3) discarded and added variables based on availability of appropriate datasets and balance across different aspects of the social-ecological systems (Appendix 1, Table A1.1).

To be included in our analysis, all spatial datasets were required to cover the full extent of the continent (dismissing islands) with a consistent methodology and a spatial resolution not greater than our grid size (exceptions are the national "governance indicators," and "plant diversity" with pixel size of 110 km), with preference for datasets representative of the year 2010 (or the closest available). The final set of input data for our analyses (Table 1) consisted of 26 variables organized within 7 dimensions (variables per dimension: 3 physical, 2 biological, 6 landscape, 7 economic, 2 demographic, 4 political, and 2 cultural), 11 of which corresponded to the environmental domain and 15 to the socioeconomic domain. Our input data included both quantitative and qualitative data because two of our variables were represented by categorical data, i.e, urbanization type and anthropization century.

Spatial clustering analysis

Our analysis design was largely shaped by two characteristics of our input data: we mixed quantitative and categorical data, and most of our variables do not present a normal distribution (Appendix 1, Fig. A1.3). We used a hierarchical clustering approach to map SELS, which is widely used for spatial identification of social-ecological typologies (FAO 2011, Letourneau et al. 2012, van Asselen and Verburg 2012, Václavík et al. 2013, Sietz et al. 2019, Rocha et al. 2020). For this, we (1) divided South America into a continuous grid of hexagonal units of 40 km side to side (area ~1400 km², n = 13,287), (2) aggregated variables to the hexagon level, which we then used as input to (3) calculate the distances between every 2 pairs of hexagons along the multidimensional space, and finally (4) computed a divisive hierarchical clustering (DIANA; Kaufman and Rousseeuw 1990) to group hexagons into clusters sharing similar characteristics.

Distances or (dis)similarities were computed with the Gower distance method (Gower 1971) because it is the preferred algorithm for clustering mixed data (Gower 1971, Kaufman and Rousseeuw 1990, Kassambara 2017, Boehmke and Greenwell 2019) and it is less sensitive to outliers and non-normal distributions than other popular methods such as Euclidean (Kassambara 2017, Boehmke and Greenwell 2019). Nevertheless, we applied logarithmic transformations to those variables that presented highly exponential distributions (see Table 1) and range-based standardization to all variables (forcing them to range between 0 and 1) to mitigate potential effects of data artifacts.

Divisive hierarchical clustering (DIANA) is an unsupervised method that constructs a hierarchy of clusters starting by the root (all observations in one cluster) and iteratively divides them until all observations constitute their own cluster (Maechler et al. 2019). At each iteration, the most heterogeneous of the clusters (which contains the largest dissimilarity between any two of its observations) is divided into two new clusters, where the "splinter group" is initiated by its most disparate observation (largest average dissimilarity).

Most methods build their clusters starting from their terminal nodes (leaves), randomly selecting the initial point and considering local patterns or proximate neighbors to make decisions. Instead, DIANA starts from the root of the tree, taking into consideration the overall distribution of the data points for the initial splits, gaining in accuracy and favoring the capture of the main structure of the data prioritizing larger groups coherence rather than smaller groups purity (Kaufman and Rousseeuw 1990, Kassambara 2017, Boehmke and Greenwell 2019).

We considered the results at two nested spatial levels of detail (1st level corresponds to social-ecological regions or SER and 2nd level to social-ecological land systems or SELS) because findings at different levels can complement each other and improve analysis robustness (Sietz et al. 2017, 2019, Vallejos et al. 2020). The authors analyzed the clustering outputs (spatial layout, cluster's statistics, and method's performance metrics) at successive dendrogram cuts in relation to their territorial knowledge to agree on the optimal number of clusters. Further details are in Appendix 1.

To analyze which are the most informative variables for the classification, we ran boosted regression trees (BRT; Elith et al. 2008) on the cluster classification outputs. Boosted regression trees is a regression-classification technique from machine learning in which a model is trained to relate a response to their predictors by iterative binary splits, where variables' relative contributions can be measured as the mean number of times it is selected for splitting the tree. To examine case-dependent fluctuations in the relevance of variables, this analysis was repeated several times with different classification targets: two multi-nominal analysis targeting differentiation of all clusters simultaneously in SER and in SELS classifications, and n specific binary analyses for each of the SELS targeting to differentiate

Table 1. Compilation of input data. Note: WBI = World Bank Indicator.

Variable	Hexagon measurement	Resolution	Year
Physical:			
flat relief†	percent non-mountain cover	250 m	-
temperature†	median of mean annual temperature‡	1 km	1981-2010
precipitation†	median of mean annual rainfall‡	1 km	1981-2010
Biological:			
plants diversity	vascular plant species richness‡	110 km	-
protected areas (PA)	percent of PA	polygons	2019
Land cover:			
forest cover	percent cover	250 m	2001-2014
shrublands cover	percent cover	250 m	2001-2014
grasslands cover	percent cover	250 m	2001-2014
crop cover	percent cover	250 m	2001-2014
plantations cover	percent cover	250 m	2001-2014
cover diversity	diversity index of 9 land cover classes‡	250 m	2001-2014
Economic:			
centrality	national centrality inde ‡§	1 km	2012
cattle density	density of cattle production‡	1 km	2010
mine sites density	number of mining sites‡§	point data	2011
crop diversity	diversity index of 175 crops areas‡	10 km	2000
irrigation†	percent area equipped for irrigation‡	polygons	2005
cities travel time†	mean travel time to the nearest city‡	250 m	2000
ports travel time†	mean travel time to the nearest port‡	250 m	2018
Demographic:			
population density	mean environmental population‡§	2.5 arc-minutes	2012
urbanization type	category of biggest city in 100 km buffer	point data	2000
Political:			
WBI gov. effectiveness†	government effectiveness‡|	country	2015
WBI political stability†	political stability and absence of violence‡|	country	2015
WBI rule of law†	rule of law‡|	country	2015
WBI regulatory quality†	regulatory quality‡|	country	2015
Cultural:			
languages density	number of languages spoken 100 km buffer‡	polygons	2007
anthropization century	century reaching 30% anthropic land cover	1 km	1700-2000

Variables with an † were incorporated by this study in comparison with Boillat et al. (2017).
Data transformations: ‡ = min-max standardization, § = log transformation, and | = downweighted (0.25).

that particular cluster from the rest as a whole (n = number of clusters in SELS). Further specifications on model parameters in Appendix 1, Box A1.1.

Far from being homogeneous units, clusters involve some internal heterogeneity. To unravel variations in the clusters' representativity across their territorial extents, we evaluated the clusters' internal heterogeneity (as means of average dissimilarity) and generated a map that depicts core and marginal zones of clusters' representativity. We propose this metric as an indicator of spatial variations in classification uncertainty. The level of uncertainty for each hexagon was calculated by averaging the dissimilarity values between that hexagon and all the others within the same SELS cluster. Greater dissimilarity meant greater deviation of that hexagon to the average characteristics of the SELS cluster it belonged to. All analyses were performed in R version 3.6.1 (R Core Team 2019). For clustering, we used the "daisy" (distance calculation) and DIANA (clustering analysis) functions from the "cluster" package (Maechler et al. 2019). For the boosted regression trees analyses, we used the "gbm" (multinomial models) function from the "gbm" package (Greenwell et al. 2019) and "gbm.step" (binary models) function from the "dismo" package (Hijmans et al. 2017).

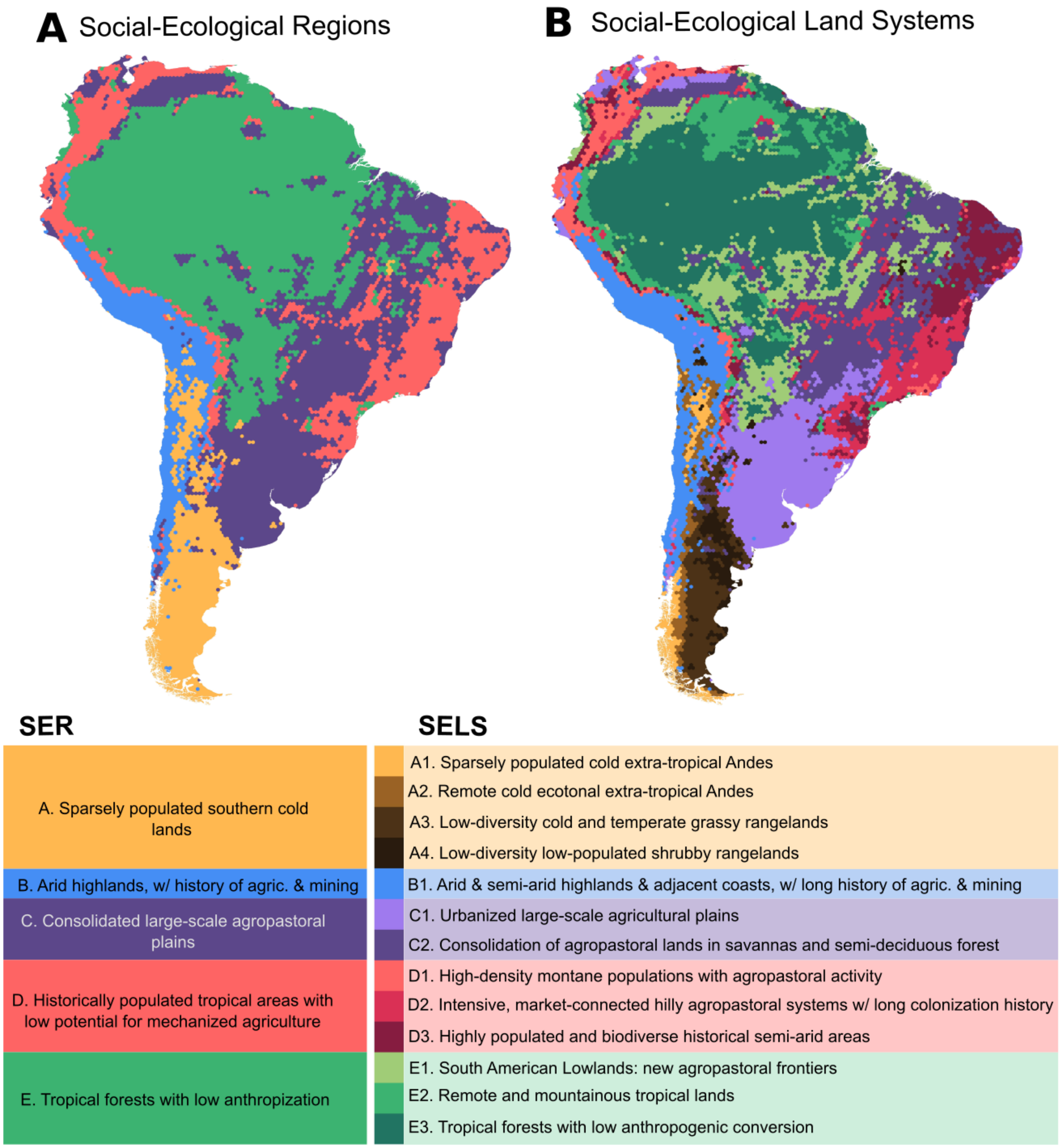
Social-ecological land systems (SELS) interpretation

To generate a sound interpretation of the resulting SELS, the authors of this publication were arranged into panels of four to seven regional specialists specific for each SELS. The panels thoroughly discussed the consistency between the SELS and their territorial knowledge, described the characteristics of that SELS, named it, and evaluated its alignment with the conceptual SELS from Boillat et al. (2017).

RESULTS

Our classification divided the continent into five larger-sized typologies of social-ecological regions (SER), which reflected main biomes and dominant land uses (Fig. 1A). Nested within these, 13 smaller-sized typologies of social-ecological land systems (SELS), each with distinctive characteristics representing more specific features of their territories (Fig. 1B). The SELS classification uncertainty was lower on the flat inner portion of the continent than on the coastal areas and nearby regions (including the Andes cordillera; Appendix 2). Some regions with greater uncertainty included: the eastern cordillera of the northern Andes, the eastern coast of Venezuela, the central portion of the Guayanas, and the northernmost and southernmost regions of the Brazilian coast.

Fig. 1. (A) Maps of social-ecological regions (SER) and (B) social-ecological land systems (SELS) of South America. The map depicts the spatial distribution of the typologies of social-ecological land systems in South America. High resolution map is available in Appendix 6.

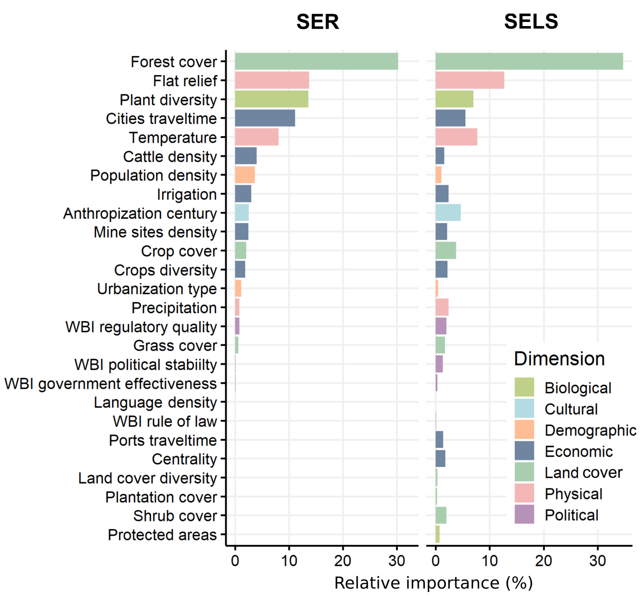


Influence of variables on the social-ecological land systems (SELS) classification

The most relevant variables for characterizing the classes varied depending on the scale of analysis. The variables relevant for separating the 5 SER were a subset of those relevant for sorting the 13 SELS (Fig. 2), which indicated that the diversity of variables facilitated the specificity of the SELS classification. This was even more evident when looking at the most relevant variables for differentiating each of the individual SELS from the rest (Appendix 3, Table A3.1). Several variables that showed very little influence over the general SER classification resulted among the most informative variables to define some of the individual SELS.

The five most relevant variables in defining the classification were shared by both SER and SELS levels: forest cover, percent of flat land, plant diversity, travel time to cities, and temperature, adding up to 70.60% (SER) and 65.58% (SELS) of the explained variance of the cluster's distribution (Fig. 2). Forest cover was dominant, representing approximately one-third of the explained variance, more than double than the second-ranked variable in both classification levels. Differences arose between the sixth and tenth positions in the contribution of relative information: the SER model relied more on population and cattle density, whereas the SELS model on cropland and the century of anthropization (Fig. 2). Except for the political dimension, all other 6 dimensions were represented within the 10 most relevant variables in both cases (i.e., SER and SELS models). However, there was a domain shift in dominance with more environmental variables occupying the highest positions and more socioeconomic variables toward the middle range.

Fig. 2. Relative importance plots for the social-ecological regions (SER; left) and social-ecological land systems (SELS; right). The values indicate the percent variable's contribution to each of the two classification models generated through independent boosted regression trees. The colors of the bars indicate to which dimension the variables belong. Note: WBI = World Bank indicator.



On the other extreme of the relative importance ranking, 5 variables ranked 6th or lower in all 15 models examined (Appendix 3, Table A3.1): plantation cover, land cover diversity, World Bank indicator rule of law, urbanization type, and language density.

Typologies of social-ecological land systems in South America

We describe the five typologies at the SER level. Due to length concerns, the 13 SELS' descriptions and associated diagnostic plots are in Appendix 4 and 5, respectively.

SER A. Sparsely populated, southern cold lands

Includes both forested and non-forested ecosystems, which despite this key ecological difference (driven mainly by differences in moisture) share important social-ecological characteristics: (1) cold climate and associated slow biogeochemical cycles (reflected for example in the existence of peatlands (mallines and bofedales), (2) relatively low levels of biological diversity, but high levels of endemism associated with historical biogeography, (3) little potential for cultivation outside localized irrigated valleys, (4) low human population and very extensive unpopulated areas, (5) extensive minor livestock (i.e., sheep and goats) and cattle, often in decline, (6) widespread (although often underdeveloped) mining activities, most commonly associated with the energy industry (e.g., gas, oil, coal, lithium), (7) growing importance of tourism, (8) extensive protected areas, and ongoing processes of spontaneous rewilding of native fauna (e.g., guanacos in Patagonia, vicuñas in Puna and their associated predators). The temperate forests sectors are characterized by a very distinctive biota derived from Gondwanic lineages with high levels of endemism, partly threatened by the expansion of exotic invasive species (e.g., beaver, deer, pines, many ornamental plant species). This SER comprises four SELS, detailed in Appendix 4.

SER B. Arid and semi-arid highlands and adjacent coast, with a long history of agriculture and mining

Corresponds to the Central Andes of Peru, Bolivia, Chile, and Argentina, the Ecuadorian dry inter-Andean valleys, the dry Pacific coast of Peru and Chile, as well as the Mediterranean Andes. It is characterized by a rough geomorphology, wide altitudinal ranges, high-climatic diversity (overall cool and dry), ancient settlement history, and relatively high population density (including some major cities). As a coastal area it is largely influenced by the economics of overseas trade. Due to climatic conditions, agriculture is limited to irrigated areas in valleys and coasts or seasonally rainfed subsistence cultivation in the highlands. With high biological and cultural diversity, this SER ranks highest in crop diversity, but also in mining density. This SER comprises one SELS, detailed in Appendix 4.

SER C. Consolidated large-scale agropastoral plains

Corresponds to plains and low rolling terrains with mostly fertile soils dominated by productive landscapes mostly in Argentina, Uruguay, Brazil, Paraguay, and a separate block in Venezuela and Colombia, but it also includes smaller patches within the Amazon. This SER includes the largest and most productive areas of grain and meat production and exports of the continent, as well as some of the largest cities and the most developed infrastructure for transportation and export of commodities. Biodiversity fluctuates but it is medium in most of the region and there are few protected areas. The area includes natural ecoregions of open vegetation such as the Pampas and Campos grasslands, but also sectors of tropical and subtropical forests such as the Amazon, Chaco, and Espinal. Those forest-embedded sectors are represented by consolidated agricultural clusters commonly developed around middle-sized urban centers or major roads that facilitate their connection to the main cities and to the exporting outlets. A large fraction of the agricultural commodities exported by the continent originated in the area covered by this SER. This SER comprises two SELS, detailed in Appendix 4.

SER D. Historically populated tropical areas with low potential for mechanized agriculture

Includes the south-eastern region of Brazil, mountain regions of Colombia and Ecuador, and a narrow strip along the eastern slopes of the tropical Andes (both humid and dry). In general, the areas have been the basis of pre-Hispanic and early colonial settlements. Human population density continues to be high, however, these areas have become comparatively marginal agricultural lands because they have low capacity for expansion of modern mechanized agriculture due to steep slopes, limited accessibility, comparatively poor or degraded soils, sometimes suboptimal climatic conditions, and land tenure characterized by high fragmentation and small farm size. The region has high biological diversity and endemism. Mainly in association with steep topography, many areas are experiencing forest recovery. The SELS within this SER include a gradient of accessibility to ports, with SELS D2 (South-East Brazil) being the most connected, and in consequence the most developed with largest cities. This SER comprises three SELS, detailed in Appendix 4.

SER E. Tropical forests with low anthropization
Includes the whole Amazon biome, extended to the south over Bolivia, western Paraguay and the north of Argentina. It corresponds to plains and hilly terrains dominated by natural forests with high biodiversity and a huge stock of biomass. It extends over warm and moist climates, with mostly poor and acidic soils, including a gradient of human transformations that encompasses relatively unmodified forests (SELS E3), transition zones with active deforestation frontiers (SELS E1), and areas with a high fraction of protected areas (SELS E2). A dynamic history of agricultural expansion over the plains and low rolling terrains of the continent suggests that in the future the contact between this SER and SER C will experience displacements and zones with characteristics of SER C may expand over areas currently classified as SER E. This SER comprises three SELS, detailed in Appendix 4.

DISCUSSION

Novel ways to use data and synthesis methods that improve our understanding of land systems are among the featured innovations needed to advance key thematic research areas in land system science (GLP 2016); specially by combining social and natural sciences, as well as quantitative and qualitative data (Rounsevell et al. 2012). Our SELS approach improves the understanding of characteristics, extent, and location of human-nature interactions operating at regional scales in South America, carved through centuries of human intervention on the environment. As such, our approach provides new insights into the Anthropocene as well as a transferable geographical framework that facilitates contextualizing and articulating research on land science.

Relevance of variables in defining the social-ecological land systems (SELS)

Both levels of classification (SER and SELS) relied on the same five key variables according to their explanatory power of SELS' patterns. A handful of variables concentrated most of the relative information for our classification, especially for the coarse SER typologies. However, it is at smaller/detailed scales that we see the real contribution of incorporating larger and more diversified sets of variables that highlight the individual characteristics that differentiate the SELS typologies. For example, the "century of anthropization" was key to differentiate the SELS within the SER D sorting the areas with longer history of use (SELS D1 and D3) from the most recently settled (SELS D2); "density of mine sites" was the second most relevant variable for SER B; "shrub cover" was the most relevant variable for SELS D3 and A4 (Appendix 3, Table A3.1; Appendix 5).

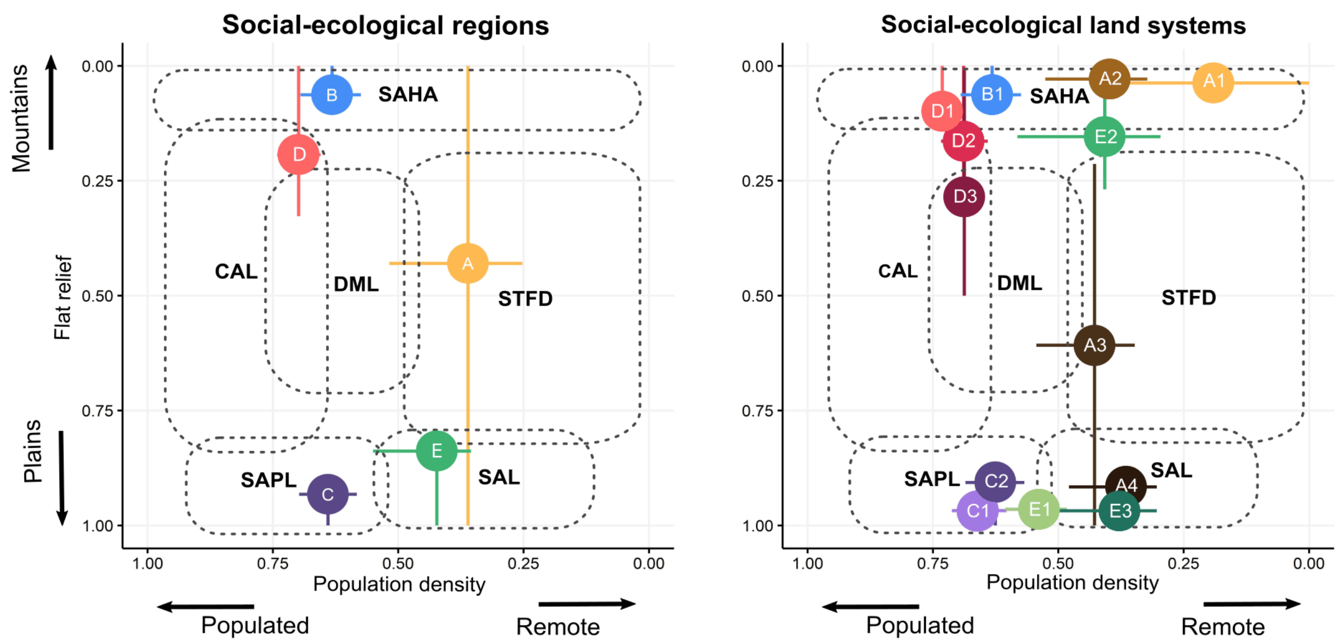
Several of the most relevant variables for the classification (e.g., forest cover, relief, plant diversity, temperature) corresponded to the environmental realm. Hence, our results suggest that biological and physical characteristics, similar to a biome/ecoregion classification scheme, continue to prevail regardless of human impact at that scale. This suggested they have a power to determine or place limits on the development possibilities of certain socioeconomic activities.

The single most relevant variable in defining the SELS distribution was "forest cover," which accounted for one-third of the explained variance. Such a relevance is reasonable considering that forests occupy a large area of the continent with an uneven distribution (FAO and UNEP 2020), and that "forest cover" is a complex and synthetic variable. It summarizes the combination of physical variables such as altitude, precipitation, and temperature, but it also informs indirectly about anthropic historic and present land use. For example, in cases in which physical conditions are suitable for forests, its absence in certain areas sorts a physically homogeneous region into deforested vs. not converted forest.

The second most relevant variable was topographic relief, represented here as the "percentage of flat terrain," not only for the general multinomial models SER and SELS, but also ranked within the top 5 for 9 out of the 13 SELS (Appendix 3, Table A3.1). Topography is a main conceptual differentiation for the current and potential of land use in South America because it largely dictates the suitability for mechanized agriculture. In our analysis, the differentiation between mountains vs. rolling and flat plains was critical and probably underpins multiple biophysical and socioeconomic properties. The third explanatory variable was "plant diversity," and the same as with forest cover, it summarizes major aspects of climatic conditions and resource availability (Kreft and Jetz 2007), which is often assumed as the main organizing variable of biophysical diversity in the continent. The fourth was "travel time to cities," the only socioeconomic variable within the top five in the relevance ranking. The presence of large cities encompasses two interlinked geographical properties. On one hand, they represent access to infrastructure utilities and economic opportunities, generating a sort of gravitational power over human activities (Lambin et al. 2001, Grimm et al. 2008). On the other hand, most of the cities were strategically settled centuries ago to best serve colonial South America (i.e., warfare against Indigenous people and transporting goods to Europe) and the persistence of their location may have influenced the distribution of human land uses in the present. The fifth was "temperature," which is not a surprise considering the wide range of temperatures on the continent (mean air temperature from 6° to 24° C; Collins et al. 2009), varying mostly with latitude and altitude.

"Precipitation," which is often assumed as the main organizing variable of biophysical diversity in the continent, showed up in the 14^{th} place instead of standing out among the main physical determinants such as relief and temperature. However, it was in the top five for those SELS particularly related to dry climate (A1, A2, A3, and B).

Fig. 3. Overlap diagram of conceptual social-ecological land systems (SELS; Boillat et al. 2017) and spatial social-ecological regions (SER; left) and spatial SELS (right) along two gradients of population and terrain roughness. Circles represent the mean values and bars represent the first to third quantile range of the spatial SELS percent of flat land (y axis) and population density (x axis). Dashed lines depict the hypothetical distribution of the conceptual SELS along those axes. Acronyms refer to the conceptual SELS from Boillat et al. (2017): SAHA = South American highlands and altiplano; CAL = coastal agricultural lands with long colonization history; DML = dry and mediterranean lands; SAL = South American Lowlands: new agropastoral areas; SAPL = South American plateau lowlands: agropastoral historical areas; STFD = southern temperate forests and drylands.



“Cattle density” was an important human-related variable, even more than crop cover. Cattle are the main herbivores in the world, and their significance is disproportionally high in South America (Bar-On et al. 2018). Three of the five countries in the world with large ratios between cattle and people occur in the region (Argentina, Brazil, and Uruguay; FAO 2022). Cattle density serves to characterize both intensive production (e.g., intensive systems that compete with croplands in the Pampas or Cerrado) but also to discriminate between non-agricultural regions because extensive cattle production characterizes mesic ecosystems that are not too dry (where sheep and goats dominate herbivory) and not too humid as the Amazon rainforest, where cattle do not occur outside deforested areas (Seo et al. 2010).

The political dimension had in general an intermediate to low influence in characterizing SELS, possibly due to their broad spatial resolution (i.e., country level) of the data. However, some political aspects were shown to be relevant for particular locations (e.g., regulatory quality was the 2nd variable to sort SELS A1). The low impact of “language density” on the SELS classification was however notable, and contrary to expert expectations and literature findings (Maffi 2005, Gorenflo et al. 2012). It is possible that our measurement unit (i.e., number of languages spoken within a 100 km buffer zone) may have been inadequate, although difficult to contrast given the lack of guiding references from other publications. We encourage future work to further examine this concern and to look for alternative variables to reflect cultural diversity.

In the last decade, there was a clear evolution in land systems classifications to incorporate the complexity of the human-nature interactions. Compared to previous classifications, we delved into a holistic consideration of the social-ecological land systems. We further diversified the input variables achieving the representation of seven complementary dimensions of social-ecological systems: physical, biological, land cover, demographic, economic, political, and cultural. In addition, we prioritized the inclusion of attributes more pertinent to the continent such as mining and distance to ports. Our effort to explicitly incorporate deeper social aspects of human societies represents a clear step toward a qualitative leap in the field from mapping land use systems to mapping social-ecological systems. However, a series of limitations need to be addressed to fully achieve that goal, especially regarding data gaps and quality.

Alignment with the conceptual social-ecological land systems (SELS)

The SELS definitions produced by this study allowed for the refinement of the expert knowledge-based conceptual SELS described in Boillat et al. (2017). Some social-ecological regions had a high correspondence with the conceptual SELS (Fig. 3). These included: (1) the consolidated large-scale agropastoral plains (SER C), which corresponded with the conceptual SELS “South American plateau lowlands/agropastoral historical areas,” and (2) the tropical forests with low anthropization (SER

E), which corresponded with the conceptual SELS "South American lowlands/new agropastoral areas." In this last category, our study added more remote tropical lands, which were not addressed by Boillat et al. (2017) because of their primary focus on land-use change. Such high correspondence showed the importance of the historical occupation in shaping social-ecological characteristics of the South American lowlands.

We found only medium correspondence between spatial and conceptual SELS in the Andean and Patagonian regions. The arid and semi-arid highlands and adjacent coast, with a long history of agriculture and mining (SER B) covered the dry Central Andes and roughly fell within the conceptual SELS "South American highlands and altiplano." It however differed with the inclusion of Mediterranean Chile and the exclusion of the Northern Andes. Instead, the Northern Andes were included in the "historically populated tropical areas with low potential for mechanized agriculture" (SER D), which corresponded with the conceptual SELS "coastal agricultural lands with long colonization history" covering the Brazilian Atlantic forest and Caribbean and Pacific coastlines. Finally, the highest and coldest areas of the Central Andes fell within the "sparsely populated southern cold lands" (SER A), showing more affinity to the Patagonian Andes due to sparse population and cold climate. Apart from this inclusion, SER A highly corresponded to the "southern temperate forests and drylands" conceptual SELS.

Drylands were the most challenging areas in terms of correspondence in our analyses. The conceptual SELS "dry and mediterranean lands" appeared to be split into three different SER, namely (1) the Mediterranean Andes, which had more affinity with the Central Andes within SER B, (2) the Brazilian Caatinga, which corresponded to SER D representing historically used tropical areas, and (3) Western Argentina, which was assigned to the SER A also covering Patagonia. This showed the ambiguity of the category of drylands that had very different social-ecological configurations depending on the geographic location and settlement histories. This suggests that humans may interact very differently with drylands depending on both biophysical and socioeconomic factors at play.

Nevertheless, given the differences in the methodological approach, the similarity of the two classifications is remarkable. This is underlined by considering the disparity in our input variables. Although we made advancements in quantitative rigor, reproducibility, operability, and spatial explicitness, it is worth noting that the attributes mentioned by Boillat et al. (2017) were included in our analysis through approximate renders and proxies, mainly because of limitations in data availability. The characterization of conceptual SELS by Boillat et al. (2017) were unobstructed by such data constraints and thus were more consistent with the authors' understanding of the systems. Furthermore, the role of trends in land-use change was central for the conceptual SELS, whereas in this study, we considered the current state only, leaving to future work the mapping of land changes and transitions.

Methodological considerations

Models are inherently simplifications of reality, and as such our maps do not reproduce precisely all the features of the territory to its full extent. Compromises of mapping complex systems are many and we discuss some of them in the following paragraphs. We highlight the hybrid methodology as a strength of this study. Interdisciplinary researchers' opinions contributed enormously by assessing the performance of the automated process, screening plausible data sources, and discussing the results in light of sound territorial knowledge.

Data constraints

The largest downside of data-driven approaches is that they are limited by the availability of adequate datasets. Often data availability and quality restrict the characterization of important aspects of the systems. In this section, we highlight and discuss a brief summary of the main data gaps we faced in this study that potentially could have enriched it, hoping they can be addressed in the future.

- (1) Socio-environmental conflicts: the only dataset we found was by Scheidel et al. (2020), who are developing a comprehensive spatial database, although currently based on self-reporting cases instead of a systematic registry. A potential source worth exploring is data mining through Google searches.
- (2) Natural ecosystems degradation: it modifies environmental processes and ecosystem services with varying impacts on sustainability (Sasaki and Putz 2009, Garrett et al. 2019). Ecosystem degradation is a complex concept, partly value-driven and with extremely variable situations, moving in a continuum from pristine to fully transformed. The lack of consensus on its definition (Schoene et al. 2007) makes its assessment difficult.
- (3) Governance: it influences land systems in a multi-level, partly hierarchical scheme. National level variables are often accessible, but they underestimate the importance of local formal and informal governance rules, which sometimes can be highly influential on land use (Tucker 2020, Rajão et al. 2020).
- (4) Exports: much of South America's land use is aimed at net food exports (UN 2003). Having export data at a subnational resolution would represent a great improvement. Initiatives such as TRASE (SEI and Global Canopy 2022) can help fill this gap but they do not yet provide wall-to-wall datasets for all of South America.
- (5) Cultural variables: This is probably the least represented dimension within SELS inputs. Some countries such as Bolivia, Brazil, and Colombia have good spatial records of Indigenous and/or traditional communities, but no unified dataset was found at the continental level. Other aspects of cultural diversity, reflecting community cohesion or preferred land use practices would be valuable too. This would be a priority to better synthesize societies' land-related, decision-making processes into land system science in connection with local governance.
- (6) Land tenure (or farm size): it informs about the most likely farm management types, as well as the degree in which smallholders have access to land. The datasets we could find to represent this variable were either partial (not covering the whole continent; Graesser and Ramankutty 2017), had

a country-level resolution, or were heterogeneous in their methodology (compendium of national statistics).

Fuzzy borders, spatial detail, and isolated pixels

We emphasize the importance of considering the classification uncertainty map (Appendix 2) to assist in the interpretation and application of the SELS map.

In our SELS map, observations are hexagons of 1385 km², which include a fair amount of heterogeneity summarized to a single value. A map may appear fuzzy due to classification artifacts or properties of the landscape that may blur the general appearance, but at the same time may present important information. Some spatially succinct events, such as the presence of a city or a humid valley, may differentiate the classification of one hexagon from its surroundings, generating scattered patterns. Mountain regions or heterogeneous landscapes may also show a fuzzy classification. We decided to display our classification output without filtering out the isolated pixels due to the relevant information they can often contain. On the other extreme, some regions appearing homogeneous in the map (e.g., Chile, Western Amazon) do not necessarily have uniform landscapes. Apparent homogeneity should rather be interpreted as having unique characteristics that make those hexagons more similar to each other than to the rest of the hexagons in the continent.

Temporal dynamics and social ecological land systems (SELS)

For this study we only considered static variables, prioritizing consistency of the model structure, however trends and directions of change are very important characteristics of social-ecological land systems and can also be used to differentiate them. We encourage future studies to generate a SELS classification that incorporates land change regimes. In addition, changes could potentially modify the characteristics of regions enough to merit future revision of the typologies assigned in this study, as described for the SELS within the SER A and the SELS within the SER E (Appendix 4).

CONCLUSION

This study presents three major contributions: (1) it provides a comprehensive and reasonable characterization of the social-ecological land systems of South America (SELS), (2) it offers a spatial representation of the SELS in an easily operable and freely available format, and (3) its methodological approach bridges hurdles of social-ecological land classifications such as the combination of qualitative and quantitative data, and the blending of data-driven and expert knowledge-based perspectives.

The hybrid methodology represents a major strength of this study. The inclusion of a group of interdisciplinary experts was crucial to guide the data search and contrast the automated classifications with the territorial knowledge. In addition, it improved the utility of the resulting maps because of the increased coherence and relevance for the researchers' community and territorial planners.

The SELS classification is a reproducible, sound, and operative characterization of social-ecological land systems of South America that facilitates the incorporation of regional contexts for analyzing local realities in the Anthropocene. We envision the SELS map will provide an orientative geographical framework for analyzing observed patterns within a larger context and for designing system-specific solutions for sustainability.

Responses to this article can be read online at:
https://www.ecologyandsociety.org/issues/responses.php/13066

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Data Availability:

The data/code that support the findings of this study are openly available in GitHub at https://github.com/luciazarba/SELS-SA

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Appendix 1. Methodological Details and Rationales.

This appendix is dedicated to expand on the details, rationales and performance evaluation of the methodology followed through this study. The sections are organized following the methodological steps listed in Fig. A1.1, however the actual work implied numerous feedback loops and reiterations of previous steps which are omitted for simplicity.

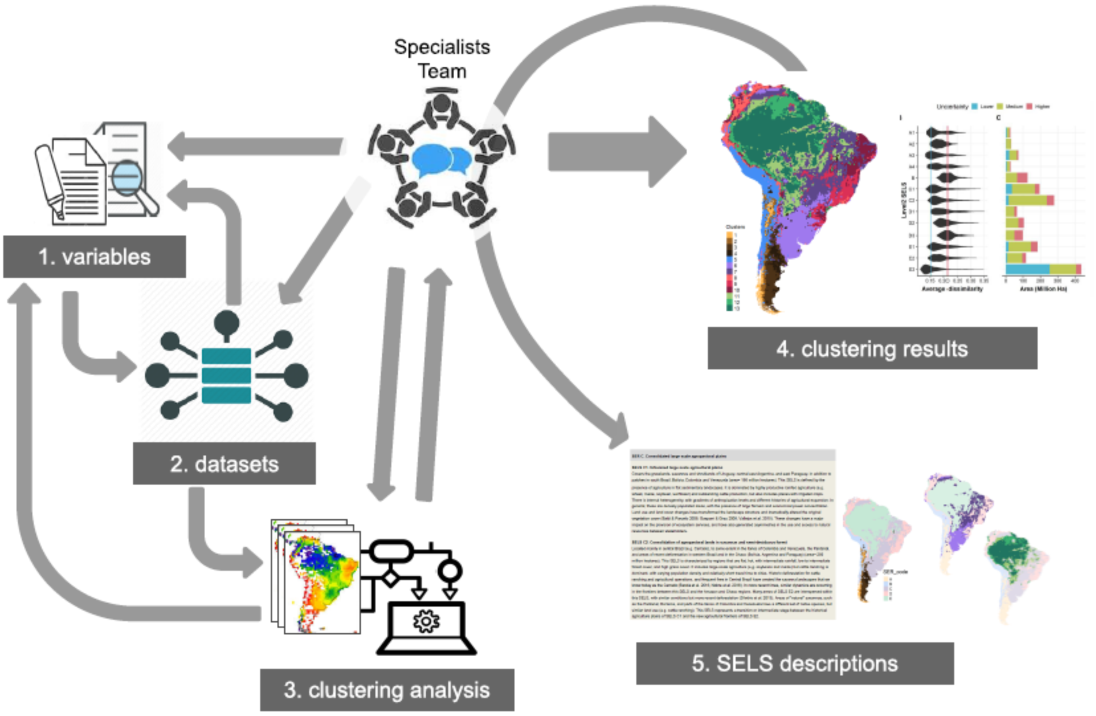

Figure A1.1. Diagram of the methodological steps followed by this study. (1) Variables: analyze and systematize the conceptual SELS descriptions in Table 1 of Boillat et al. (2017) defining a list of variables to use as inputs for the clustering. (2) Datasets: search and retrieve the spatial data to best represent the selected variables. (3) Clustering analysis: generate automated classifications through hierarchical cluster analysis. (4) Clustering results: analyze the clustering outputs and agree on the SELS representation according to the specialists group's territorial knowledge. (5) SELS descriptions: arrange in subgroups of regional specialists to discuss and describe each particular SELS. Arrows pointing backwards in relation to the numerical steps represent the feedback loops and local iterations of our process.

1. Variables

We used as a reference the biome-level SELS typologies described in Table 1 of Boillat et al. (2017; hereafter conceptual SELS) to guide the variable selection process. Such descriptions were in a narrative form with no shared standard structure. We first exhaustively analyzed the conceptual SELS descriptions and listed all attributes mentioned for each of them. We then synthesized the list of attributes into general variables that represented the data we needed to acquire in order to capture those properties. The product of this process was our ideal input data list including 25 general variables (Table A1.1), from which we discarded and added variables through a heavily iterative process connected with step (2) Datasets.

On one hand we had to discard all general variables lacking a dataset that was adequate (representative proxy) and spatially continuous (covering the whole continental extent) with a coherent methodology. On the other hand, we discarded all variables that referred to trends, since combining measures of state and trajectories raised concerns among the authors about methodological philosophical inconsistencies.

Finally, to visualize whether our data was balanced across different aspects of the social-ecological systems we arranged the general variables within broader dimensions following the framework of Winkler et al. (2018). Compared to other popular frameworks, such as Ostrom's framework for analyzing sustainability of social-ecological systems (Ostrom 2009) ideal for addressing specific issues, the Winkler's framework has a more general scope, which fits better the continental-scale broad multifaceted typologies of our study. We considered all Level III Winkler categories except *Health*, due lack of data. We recognized underrepresented dimensions in our original list of 25 general variables (Table A1.1), such as the *Physical* dimension, mentioned in the conceptual SELS names yet not in their descriptions; the *Political* dimension, which was indirectly suggested but not explicitly addressed; or infrastructural aspects of the *Economic* dimension. To complement and balance the representation of all different dimensions we incorporated the following variables: *Flat relief*, *Temperature, Precipitation, Irrigation, Cities traveltime, Ports traveltime,* and *Governance indicators*.

Table A1.1. Systematization process of the conceptual SELS's descriptions: synthesis of all mentioned attributes into general variables.

General Variable	Description in Boillat et al., 2017	Included in this study
Natural land cover	SAL: forested areas; DML: semi-arid shrublands	Yes
Rate of land use change	SAL: relatively rapid rate of land use change; high rate of deforestation	No (trends)
Change in cropland cover	SAL: expansion of agricultural frontiers; STFD: decreasing agriculture	No (trends)
Change in livestock	SAL: expansion of cattle ranching; STFD: decreasing livestock; DML:extensive livestock grazing	No (trends)
Main livestock Species	DML: particularly goats	No (concerns on representation of informal livestock on datasets)
Crop exports	SAL: commodity markets driving LUC; CAL: some areas have shifted to export-oriented agriculture	No (national level statistics)
Ecosystem Degradation	SAL: forest degradation due logging; DML: extensive degradation due capital-intensive land use and extensive cattle ranching; CAL: highly degraded and threatened natural ecosystems ('lomas costeras', dry tropical forests, wetlands) and Important biomes such as Brazil's Atlantic forest have become highly fragmented	No (unclear definition/lack of data)
Biodiversity loss	SAL: biodiversity loss	No (IUCN data not spatial)
Carbon emissions	SAL: high carbon emissions	No (unclear impact)
Protected areas	SAL: expansion of protected areas; STFD: extensive formal conservation	Yes

Cultural diversity	SAL: expansion of indigenous areas; SAHA: high cultural diversity	Yes
Endemisms	SAHA: high endemisms; DEM: high species endemisms	No (lack of spatial data)
Size of production units	SAL: shifting to larger management/production units in some areas; SAPL: expansion of sizes of agricultural and livestock farms, large scale land acquisitions in recent years; SAHA: small subsistence-oriented management units; CAL: large scale land acquisitions for tourism and other developments	No (lack of data covering the full continent)
Land use diversity	SAL: other areas with diversity of land systems; SAHA: high diversity of landscapes, limited mechanized agriculture and relatively high levels of biodiversity within anthropogenic landscapes; CAL: with mixed land and forest usages; SAPL: agribusiness surrounding indigenous and conservation areas in the Cerrado; DML: dominated by irrigated agriculture within matrix of semi-arid shrublands	Yes
Crop diversity	SAHA: livelihood diversification; high agro-ecological diverstity	Yes
Environmetal conflicts	SAL: new land uses in conflict with local and indigenous communities	No (lack of data)
Type of urbanization	SAL: chaotic urbanization and peri urban expansion; DML: various degrees of urbanization; CAL: home to high population densities	Yes
Historical land use	SAPL: long history of cropland and ranching settlements; SAHA: most landscapes with long history of human settlement; CAL: long history of human occupation	Yes
Migration rates	SAHA: eleveated rates of rural out-migration	No (lack of spatial data)

Political/economical relevance	SAL: enhanced contributions to national economic growth and food security; SAHA: may become peripheral as political power and people move to the lowlands; CAL: concentration of political and economic power	Yes
Change in agriculture yields	SAL: dramatic increases in ag productivity	No (trends)
Main crop types	SAPL: high tech agribusiness (soybeans, maize and other grains and fiber); DML: high capital crops (vineyards, olives, fruit orchards); CAL: traditional tropical crops (sugar cane and coffee) & expanding crops (oil palm and eucalyptus)	No (difficulties in creating the metric)
Plantations	STFD: growing forestry plantations (exotic conifers), low agriculture value; DML: high capital crops (vineyards, olives, fruit orchards); CAL: traditional tropical crops (sugar cane and coffee) & expanding crops (oil palm and eucalyptus);	Yes
Mining	SAHA: opened up to new wave of mining	Yes
Tourism	STFD: growing tourism; SAHA: opened up to new wave of tourism activities	No (lack of data)

The first column indicates the general variable we associated with the descriptions of column 2. The second column contains direct transcripts of all the descriptions on Table 1 of Boillat et al. (2017) sorted by the general variable we associated it with. The third column indicates whether the general variable was included in this study and the reason in case of not. Acronyms refer to the SELS typologies by Boillat et al. (2017): SAHA - South American Highlands and Altiplano; CAL - Coastal Agricultural Lands with long colonization history; DML - Dry and Mediterranean Lands; SAL - South American Lowlands: new agropastoral areas; SAPL - South American Plateau Lowlands: agropastoral historical areas; STFD - Southern Temperate Forests and Drylands.

2. Datasets

To be used in this study, all spatial datasets were required to cover the full extent of the South American continent (dismissing islands) with a consistent methodology, in addition we preferred those closer to the year 2010 and a spatial resolution not greater than our grid size (exceptions are the *governance indicators* which are at the national scale, and *plant diversity* at 110km pixels). Country level data, as well as biomes and ecoregions, were allegedly discarded since they imply an artificial homogenization of the territory within arbitrary boundaries which may impact on the spatial representation of the SELS by misleading them to resemble those boundaries. It was a decision taken by the group of authors to avoid using country resolution data for all our variables except those representing political aspects.

We tested for correlations, considering correlation coefficient of |0.75| (absolute value) as the maximum accepted correlation for two variables in the model (Fig. A1.2). We selected Spearman's rank correlation coefficient due it is non-parametric, assesses monotonic relationships, and poses less strict data requirements than Pearson's method (e.g. normal distribution or linear relationships).

The final list of input variables for our analyses consisted in 3 physical, 2 biological, 6 landscape, 7 economic (includes infrastructure), 2 demographic, 4 political, and 2 cultural variables; 11 of which corresponds to the biophysical domain and 15 to the socio-economic domain (Table 1). Most of the variables are non-normally distributed (Fig A1.3), the implications of this on the results are addressed in the next section. Below we expand on the details of calculation of hexagon values for all input variables.

Flat relief: Proportion of the hexagon covered by non-mountain classes in Karagulle et al. (2017) landforms classification. In this classification the mountain classes are four: high mountains, scattered high mountains, low mountains, and scattered low mountains. We chose this variable due it performs better than others in recognizing mountainous terrains embedded in other terrain types (Sayre et al. 2018).

Temperature: Hexagon median of mean annual temperature based on the climate maps generated by ClimateSA. ClimateSA data averages the climatic conditions between 1981 and 2010.

Precipitation: Hexagon median of mean annual rainfall based on the climate maps generated by ClimateSA. ClimateSA data averages the climatic conditions between 1981 and 2010.

Plant diversity: Vascular plant species richness based on the Kreft and Jetz (2007) global patterns of vascular plant species richness calculated with the ordinary co-kriging method. We consider Plant biodiversity as a proxy of overall biodiversity since diversity of different taxa such as mammals, birds, plants, reptiles and amphibia were found to be correlated regardless of environmental conditions (Qian and Ricklefs 2008) and vegetation heterogeneity has shown to be a strong predictor of species richness (Qian and Ricklefs 2008, Stein et al. 2014).

Protected areas: Percent of the hexagon covered by protected areas, considering all categories of protection in the World Database on Protected Areas by UNEP-WCMC and IUCN. The data was downloaded in May 2019 and there is no information to sort protected areas created after our year of reference 2010. Although not the ideal situation, we consider the potential error is acceptable for the purpose of this study.

Land cover: Percent of the hexagon covered by each of the considered classes (i.e. forest, shrublands, grasslands, crops and plantations) based on Graesser et al. (2015) annual land cover classification for South America. To represent our reference year we used the average land cover between 2009 and 2011.

Cover diversity: The land cover diversity of each hexagon was calculated as the shannon diversity index of the area covered by each of the nine land cover classes included in Graesser et al. (2015). To represent our reference year we used the average land cover between 2009 and 2011.

Centrality: This variable is a proxy of the hexagon share of the country's economy, indicating the economic relevance of a particular region to the country. It was calculated by distributing the national gross domestic product (GDP) over the country's territory following the relative distribution of nighttime lights (NTL). The value for each hexagon was calculated as the national GDP * hexagon sum NTL/national sum NTL. For hexagons that overlays with more than one country we consider it part of the one with major area. National 2012 GDP data was obtained from the World Bank database, and 2012 nighttime lights map from the NASA Earth Observatory.

Cattle density: Total cattle production by hexagon according to the gridded Livestock of the World 2.0 by Livestock Geowiki (Robinson et al. 2014) available to download from https://livestock.geo-wiki.org/home-2/.

Mine sites density: Number of mine sites by hexagon considering all categories of mines in the Mineral Resources Data System (MRDS) for the year 2011 available to download from https://mrdata.usgs.gov/mrds/.

Crop diversity: Shannon diversity of the area covered by all different crops in the hexagon based on the 175 crop types by Monfreda et al. 2008.

Irrigation: Percent of the hexagon equipped for irrigation based on the layer "gmia_v5_aei_pct_cellarea" of the Global Map of Irrigation Areas (GMIA) by FAO AQUASTAT (Siebert et al. 2005).

Cities travel time: Mean of travel time in hours to the nearest city of 50,000 or more people (Nelson et al. 2008).

Ports travel time: Mean of travel time in hours to the nearest port. The map was produced for this study following the methodology of Weiss et al. (2018). The road network data was downloaded from the Global Accessibility Map project repository (https://forobs.jrc.ec.europa.eu/products/gam/). We considered all sea ports and inland ports on rivers included in the Río de la plata and Amazonas basins. Ports locations were obtained from Natural Earth (https://www.naturalearthdata.com/) and Ports.com accessed in February of 2018. The distance to ports map together with a detailed explanation of its development (including input data and the reproducible script), are available to download through this link. https://github.com/luciazarba/SELS-SA.

Population density: Mean environmental population by hexagon, based on the Landscan environmental population for the year 2012 (Bright et al. 2012).

Urbanization type: Category of biggest city in a 100 km buffer zone. Cities categories were: rural (no cities within the buffer zone), small city (less than 100,000 inhabitants), medium city (less than 1,000,000 inhabitants), big city (less than 10,000,000 inhabitants), and metropolis (more than $1x10^7$ inhabitants). Cities' data was downloaded from the Global Accessibility Map project repository (https://forobs.jrc.ec.europa.eu/products/gam/).

WBI governance indicators: Country values of the Worldwide Governance Indicators by the World Bank: Voice and Accountability, Political Stability and Absence of Violence, Government Effectiveness, Regulatory Quality, Rule of Law, Control of Corruption. Data was downloaded for the year 2010 from the World Bank website (https://databank.worldbank.org/source/worldwide-governance-indicators). Political Stability and Absence of Violence and Control of Corruption were eventually discarded due high correlation with other variables. In the model, the four political variables included as inputs were weighted down to 0.25 to minimize enforcing national boundaries. In this way the four political variables all together weigh as much as one of the variables in the other domains.

Languages density: Number of different languages spoken within a 100 km buffer zone around each hexagon. The map of language distributions for South America was kindly provided by Mutur Zikin (Zikin 2007), and it was georeferenced and vectorized by the authors of this publication.

Anthropization century: The earliest century in which a 30% of the hexagon was covered by anthropic land cover classes based on Ellis et al. (2010) classification. It consists of anthrome classification maps for each century from 1700 to 2000. We considered as anthropic all classes except for water, remote croplands, remote rangelands, remote woodlands, wild woodlands, and wild treeless and barren lands.

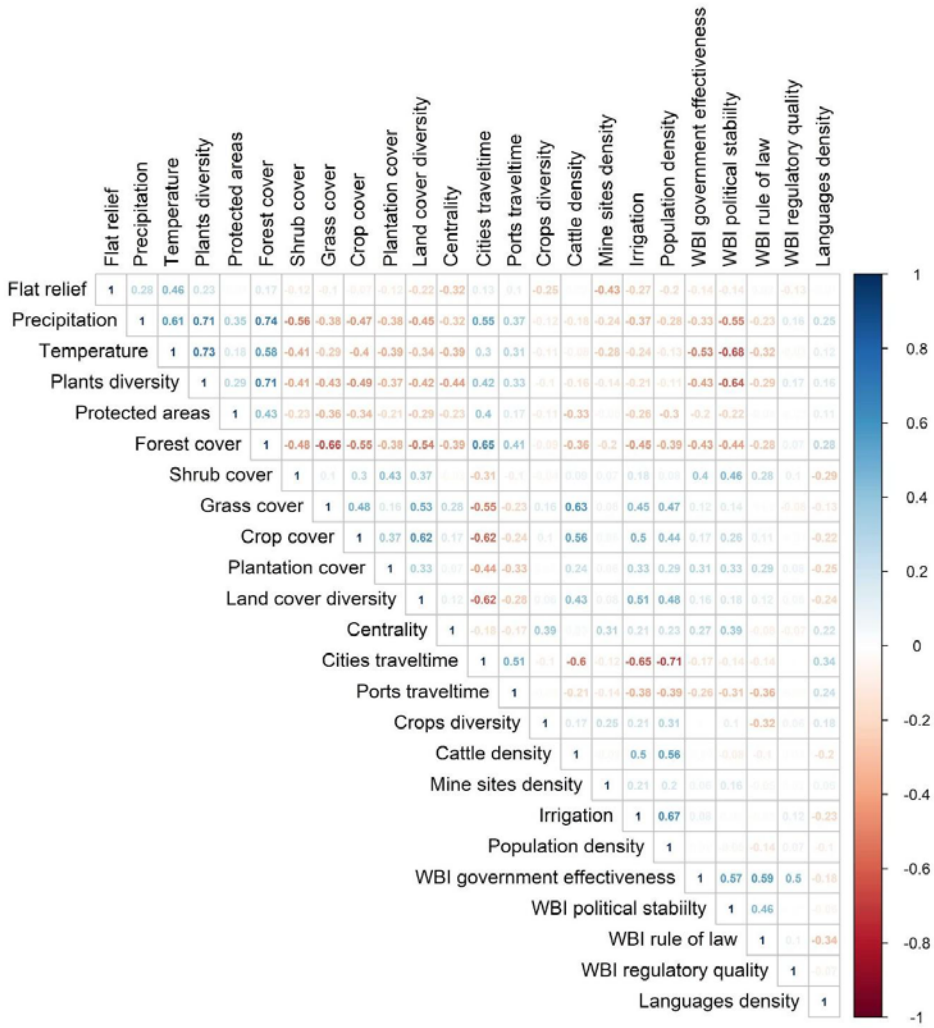

Figure A1.2. Variables correlation matrix. Spearman correlation between all 24 numeric variables considered for the analysis. Positive correlations are in blue, negative correlations are in red, and the strength of the color reflects the strength of the correlation (white color corresponds to correlation coefficients close to zero, therefore not relevant for this purpose).

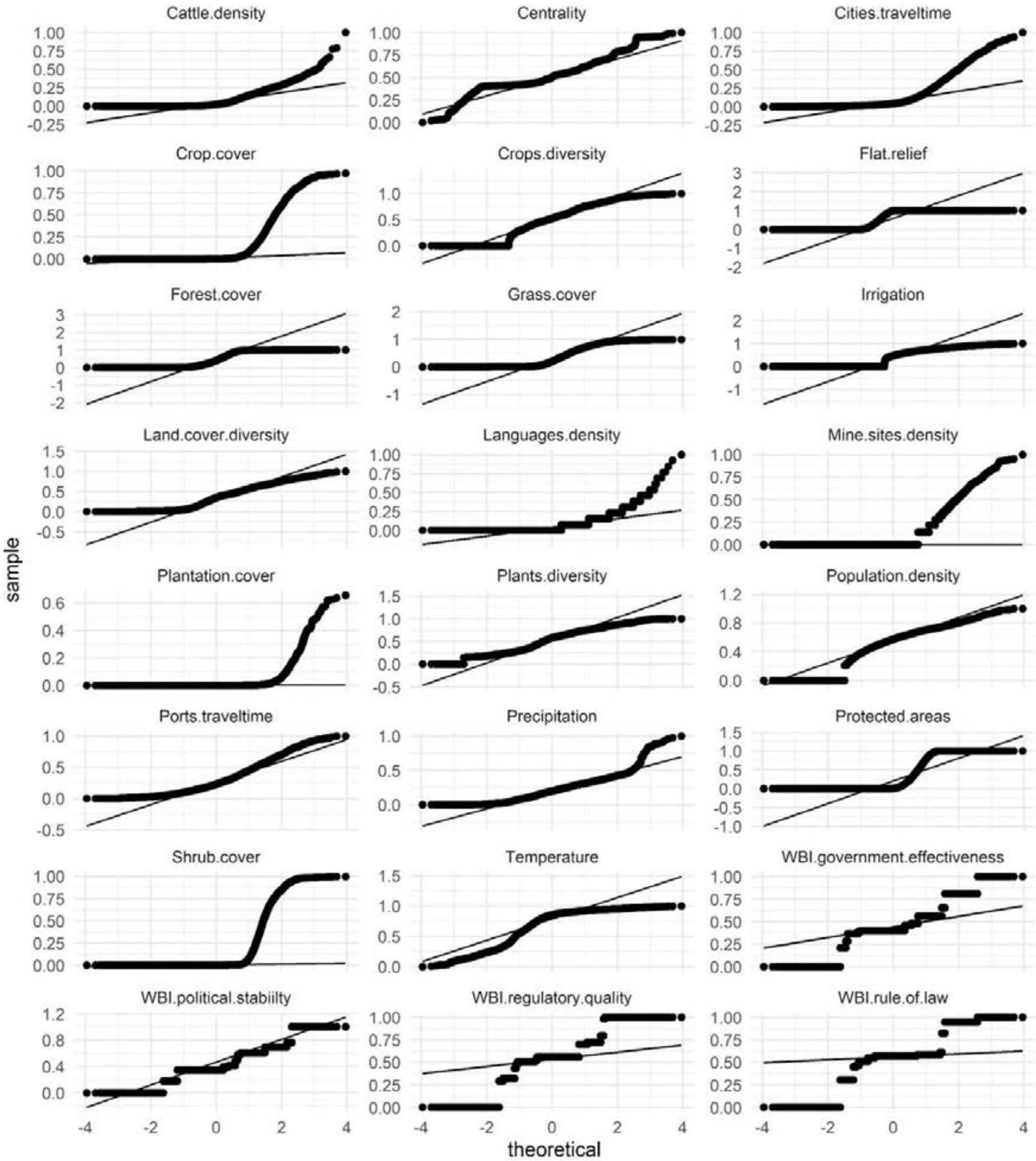

Figure A1.3. Variables Quantile-Quantile plots. These plots allow us to visualize the deviation of each continuous variable from a theoretical normal distribution. If the values (thick dots) lie along the thinner line the distribution has the same shape as the theoretical normal distribution.

3. Clustering analysis.

We analyzed 26 variables across a grid of 13287 hexagonal cells (40 km side to side, area ~1,400 km^2) covering the entire continent of South America in order to identify general typologies of social-ecological land systems (SELS). The process required to calculate the statistical distances between all pairs of hexagons along the multidimensional space and arrange them into groups based on such distances. All calculations were performed in R statistical software (R Core Team 2019) and the scripts are available through this link. https://github.com/luciazarba/SELS-SA.

Statistical distance

Two of our input variables were ordinal: *urbanization type* and *anthropization century*, which represented a major constraint due most distance calculation algorithms only accept continuous data. We followed the Gower distance method (Gower 1971) since it is the recommended algorithm for mixed data (Kassambara 2017, Boehmke and Greenwell 2019). As calculated in R with the *daisy* function (*cluster* package, Maecheler et al. 2019) the dissimilarity between two rows is computed as the weighted mean of the contributions of each variable. Contributions for numeric variables are defined as the absolute difference of both values, divided by the total range of that variable. For ordinal variables' the contribution calculation function applies "standard scoring" (replacement of the variable's levels by their integer codes); similar to using their ranks but avoiding ties.

Several of our input variables did not follow a normal distribution (Fig. A1.3). Despite many data analysis algorithms require specific data distributions, the reference literature for gower (Gower 1971) and DIANA (Kaufman and Rousseeuw 1990) algorithms do not mention particular requirements or considerations regarding data distributions. We found in more recent literature that the Gower distance algorithm is the appropriate metric when clustering non-normally distributed data (Kassambara 2017, Boehmke and Greenwell 2019) since it is less sensitive to outliers and non-normal distributions than other popular methods like Euclidean distances (Boehmke and Greenwell 2019). Furthermore, searching through the gray literature we found a very interesting statement in a scholarly blog discussing the applicability of normality tests for machine learning techniques. One user pointed out that he/she was not aware of any clustering method that assumes normality, and that the cluster-structured data implies a multimodal (and thus non-normal) distribution (Cross Validated blog entry "How to Cluster with Non-normal data" https://stats.stackexchange.com/questions/373404/how-to-cluster-with-non-normal-data).

To account for potential issues with non-normally distributed data we deliberately used the Gower distance metric. Nevertheless, to mitigate the effect of data artifacts on the distance calculations we applied logarithmic transformation to those variables that presented highly exponential distributions (Table 1), and min-max standardization to all variables (forcing them to range between 0 and 1) to avoid unequal impact of variables on the distance measures due their different scales of values.

Clustering Method

We decided *a priori,* based on conceptual adequation, that the most appropriate clustering algorithm for the purpose of this study was Divisive Hierarchical Clustering (DIANA).

As defined in the software vignette (sensu stricto Maechler et al. 2019 page 33): “The DIANA algorithm constructs a hierarchy of clusterings, starting with one large cluster containing all n observations. Clusters are divided until each cluster contains only a single observation. At each stage, the cluster with the largest diameter is selected. The diameter of a cluster is the largest dissimilarity between any two of its observations. To divide the selected cluster, the algorithm first looks for its most disparate observation (i.e., which has the largest average dissimilarity to the other observations within the same cluster). This observation initiates the "splinter group". In subsequent steps, the algorithm reassigns observations that are closer to the "splinter group" than to the "old party". The result is a division of the selected cluster into two new clusters.”

Most methods build their clusters starting from their terminal nodes (leaves), considering local patterns or proximate neighbors to make decisions. Instead, DIANA starts from the root of the tree, taking into consideration the overall distribution of the data points for the initial splits, gaining in accuracy and favoring larger groups coherence rather than smaller groups purity (Kassambara 2017, Dey 2019, Boehmke and Greenwell 2020). The first step of the algorithm involved consideration of all possible divisions of the data into two subsets (and so forth in every iteration), which is computationally demanding for large datasets, but allows to capture the main structure of the data (Kaufman and Rousseeuw 1990).

Since this study is not about sorting elements into distinct natural units that exist in the field but classifying the landscape into general typologies of similarity along a multidimensional continuum, we consider DIANA to be the most appropriate approach. Anyways, for the sake of exploration and following the recommendations of an anonymous reviewer, we tested alternative clustering methodologies (Table A1.2) and compared them through a series of clustering stability and internal validation metrics

(Table A1. 3). The endeavor was not straightforward since many clustering algorithms were not compatible with mixed data nor gower distances, therefore we had to make adaptations: the two ordinal variables in our data set were converted to numeric (equidistant fractions of 1) and similarities were calculated with the Manhattan method, one of the most popular methods that is capable of dealing with outliers and no-normal distributions (similar to Gower). The results do not show any of the methods to be definitely better than the others (Fig. A1.4), therefore we found no reason not to use DIANA. Disclaimer, due the mentioned modifications the results of this experiment are incommensurable with the results of other analysis of our study.

Table A1.2. Clustering algorithms

Method	Definition
Hierarchical agglomerative[1]	each observation is initially considered as a cluster of its own (leaf). Then, the most similar clusters are successively merged until there is just one single big cluster (root).
K-means[1]	partition the points into *k* groups such that the sum of squares from points to the assigned cluster centres is minimized. At the minimum, all cluster centres are at the mean of their Voronoi sets (the set of data points which are nearest to the cluster centre).
PAM[1]	it is based on the search for k representative objects or medoids among the observations of the data set, instead of using the mean, for partitioning a data set into k groups or clusters.
SOM[2]	type of artificial neural network that is trained using unsupervised learning to produce a low-dimensional, discretized representation of the input space of the training samples, called a map, and is therefore a method to do dimensionality reduction.
DIANA[1]	the inverse of agglomerative clustering. It begins with the root, in which all objects are included in one cluster. Then the most heterogeneous clusters are successively divided until all observations are in their own cluster.

[1] Kassambara A. 2017 Practical Guide To Cluster Analysis in R - Unsupervised Machine Learning, *STHDA Edition 1*.

[2] Wehrens R., and J. Kruisselbrink. 2018. Flexible Self-Organizing Maps in kohonen 3.0. *Journal of Statistical Software*, 87(7), 1–18. doi: 10.18637/jss.v087.i07

Table A1.3. Cluster validation metrics

Metric	Definition
APN[1]	measures the average proportion of observations not placed in the same cluster by clustering based on the full data and clustering based on the data with a single column removed
AD[1]	computes the average distance between observations placed in the same cluster by clustering based on the full data and clustering based on the data with a single column removed
ADM[1]	computes the average distance between cluster centers for observations placed in the same cluster by clustering based on the full data and clustering based on the data with a single column removed
FOM[1]	the figure of merit measures the average intra-cluster variance of the observations in the deleted column, where the clustering is based on the remaining (undeleted) samples. This estimates the mean error using predictions based on the cluster averages.
Connectivity[2]	reflects the extent to which items that are placed in the same cluster are also considered their nearest neighbors in the data space - or, in other words, the degree of connectedness of the clusters. And yes, you guessed it, it should be minimised.
Dunn index[2]	represents the ratio of the smallest distance between observations not in the same cluster to the largest intra-cluster distance. As you can imagine, the nominator should be maximised and the denominator minimised, therefore the index should be maximized.
Silhouette width[2]	defines compactness based on the pairwise distances between all elements in the cluster, and separation based on pairwise distances between all points in the cluster and all points in the closest other cluster. Values as close to (+) 1 as possible are more desirable.
avg. within[3]	average distance within clusters.

[1]Brock, G., V. Pihur, and S. Datta. 2008. clValid: An R Package for Cluster Validation. Journal of Statistical Software, 25(4), 1-22. URL https://www.jstatsoft.org/v25/i04/

[2]Kulma, K. 2017. Cluster Validation In Unsupervised Machine Learning. https://kkulma.github.io/2017-05-10-cluster-validation-in-unsupervised-machine-learning/

[3]Hennig C. 2020. fpc: Flexible Procedures for Clustering. R package version 2.2-7. https://CRAN.R-project.org/package=fpc

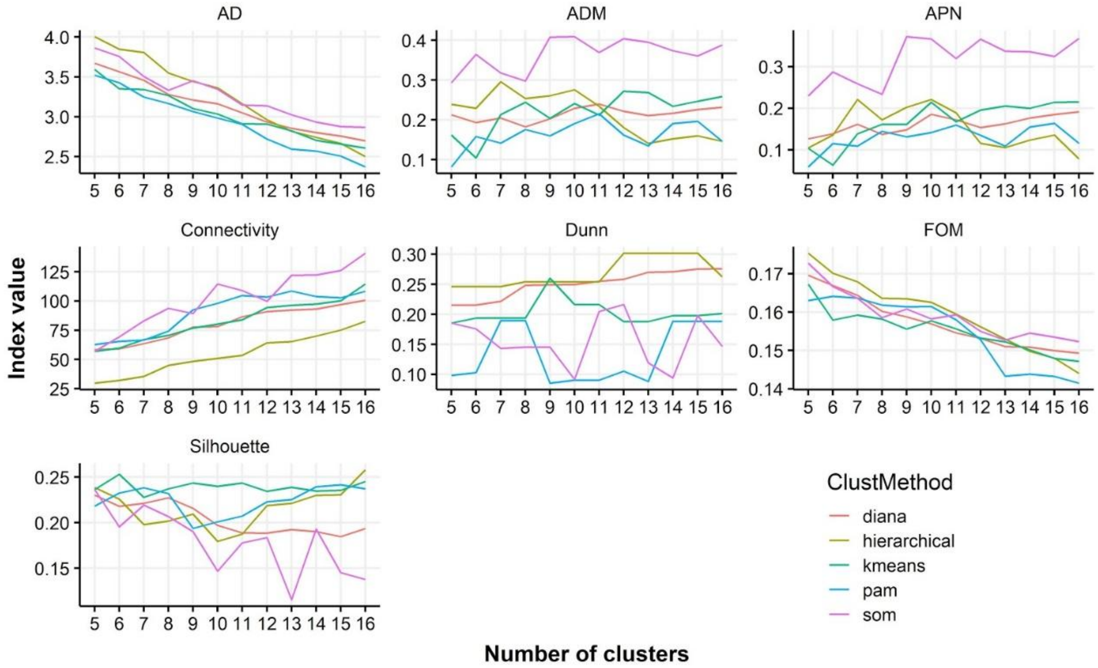

Figure A1.4. Comparison of clustering methods for reference. Performance of alternative clustering methods (line colors, Table A1.2) are compared in terms of stability and internal validation metrics (boxes, Table A1.3) along a gradient of number of clusters (K). Note the distance calculation algorithm for these analyses was Manhattan distance. Disclaimer: due the mentioned modifications the results of this experiment are incommensurable with the results of other analysis of our study.

4. Clustering results

In this section we describe how we analyzed the results of the DIANA analysis and agreed on a clustering output as the best SELS representation according to the specialists group's territorial knowledge. This included the decision on the number of clusters and its map layout, examination of the spatial representativity of the SELS across their territory, and evaluation of the relative contribution of each input variable to the classification.

Number of clusters

The output of DIANA is a dendrogram of hierarchical clusters. To decide at which height to cut the dendrogram we considered quantitative validation metrics (Figure A1.5) and analyzed the resulting spatial layout and clusters' statistics at the successive dendrogram cuts in relation to our territorial knowledge to agree on the optimal number of clusters. We disregarded clustering outputs with less than 5 or more than 16 clusters since we considered them not informative or too complex for the purpose of this study, respectively. As shown in Figure A1.5, alternative validation metrics did not converge into one unique "optimal number of clusters", therefore the decision was made based mostly on expert's knowledge. After analyzing the output maps and variable's statistics the authors agreed the map depicting thirteen clusters was the most adequate representation of smaller-size SELS for the purpose of this study, and we found no evidence in the quantitative validation metrics to contradict that decision.

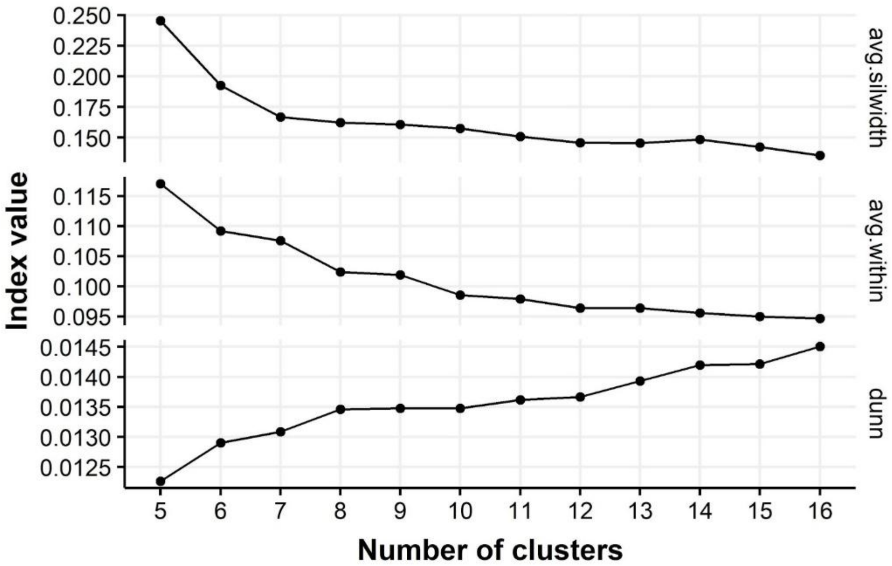

Figure A1.5. Identification of optimal number of clusters. Representation of three internal validation metrics performance: average silhouette width, average within distance, and dunn index (y axis) along the gradient of number of clusters (x axis).

5. Input variable's relative contributions

To measure the input variable's relative contribution we used Boosted Regression Trees. Regression trees are a regression/classification technique from machine learning where a model is trained to relate a response to their predictors by recursive binary splits. In boosted regression trees (BRT) the model accuracy is improved by repeating the regression tree algorithm adjusting the parameters in each iteration, similar to the "functional gradient descent" concept (Elith et al 2008). BRTs have very little restrictions, can handle different types of variables with no need of data transformation or outlier elimination, and can fit complex non-linear relationships. Through BRTs we can estimate the relative contribution of each input variable to the classification, measured as the number of times a variable is selected for splitting the tree, weighted by the model improvement by that split, and averaged across all trees (Elith et al. 2008).

We fitted 15 BRT different models in total, seeking to unravel the relative contribution of each variable in defining different target clusters: one multinomial for the 13 SELS simultaneously, one multinomial for the 5 SER simultaneously, and then individual binary models for each of the 13 SELS classes. Calculations were performed in R with the *gbm* function (*gmb* package, Greenwell et al. 2019) for the multinomial models and *gbm.step* function for the binomial models (*dismo* package, Hijmans et al. 2017). Model parameters are shown in Box A1.1. To evaluate how well the BRT models fit for each case we monitored the evolution of the holdout deviance along the iterations (Figure A1.6).

Box A1.1 BRT model parameters

Multinomial models:	**Binary models:**
learning rate (shrinkage) = 0.005	learning rate: 0.005
tree complexity (interaction depth) =1	tree complexity: 1 (default)
bag fraction: 0.5	bag fraction: 0.5
number of trees: 5000	number of trees: varies along the models

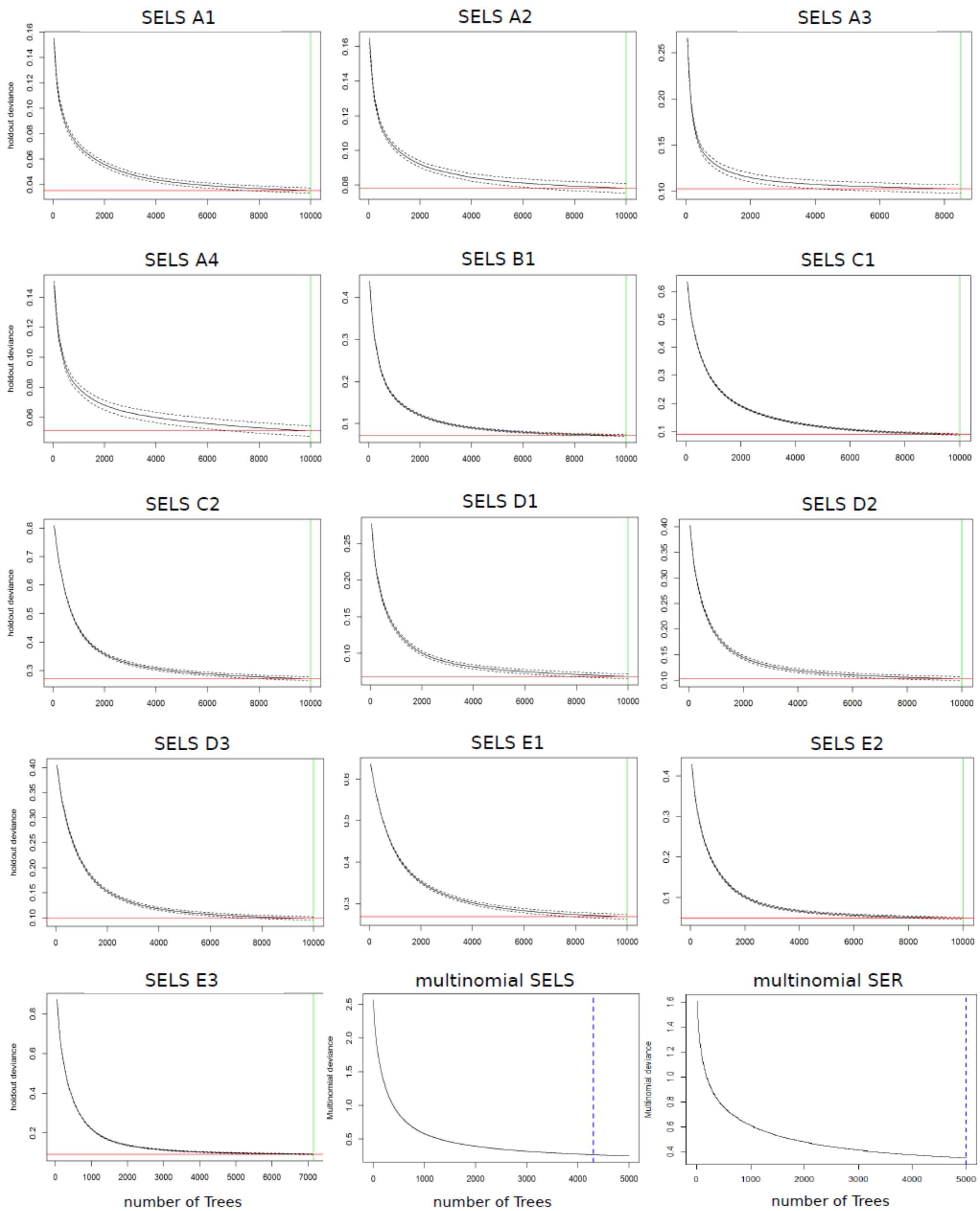

Figure A1.6. Holdout deviance along the iteration of the BRTs for the individual binomial models (SELS A1 to SELS E3) and the multinomial SELS and SER models.

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Appendix 2. Classification Uncertainty

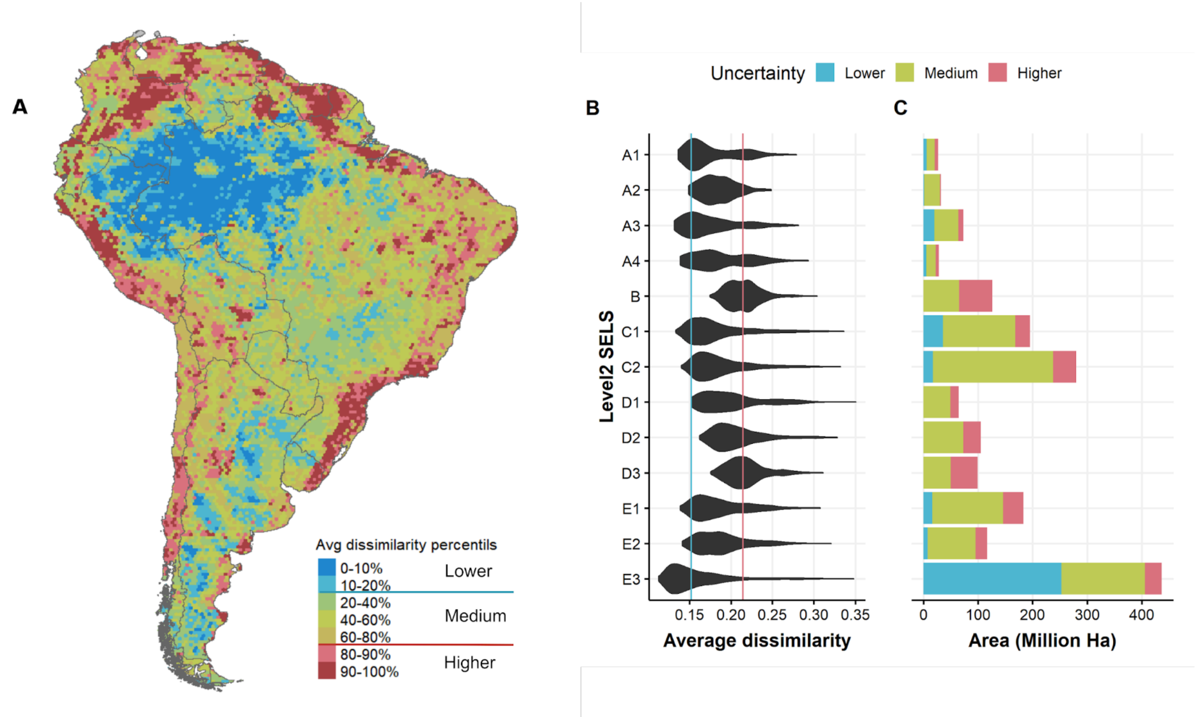

Fig. A2.1. Classification uncertainty map (A), the distribution of uncertainty values by SELS (B), and the area under each category (C). The level of uncertainty for a hexagon belonging to a SELS was calculated as the average dissimilarity between that hexagon and the rest of hexagons within the same SELS. Greater dissimilarity means greater deviation of that hexagon respect to the average SELS characteristics. These figures help distinguishing areas where the classification was more consistent from those where it was less representative due to the heterogeneity of the territory. We labeled the 20% of hexagons with lower uncertainty (blue), the 20% of higher uncertainty (red), and the rest 60% medium uncertainty (green).

Appendix 3. Variables' Contribution to the Classification

Table A3.1. Ranking of variables' contribution to a series of general and specific classification models. The numbers represent the order of contribution of the variables (rows) to each of the different models (columns), where 1 means the most relevant and 26 the least relevant variable for that particular model.

Variable	BRT Model														
	SER	SELS	A1	A2	A3	A4	B1	C1	C2	D1	D2	D3	E1	E2	E3
Forest cover	1	1	11	16	2	6	9	6	1	9	11	6	1	2	1
Flat relief	2	2	-	5	13	10	6	3	3	3	1	2	4	1	2
Plants diversity	3	4	3	3	1	2	13	2	13	26	19	11	17	16	9
Cities traveltime	4	5	13	21	16	-	22	11	4	15	2	13	2	12	3
Temperature	5	3	1	1	5	17	1	10	2	10	12	10	3	9	19
Cattle density	6	16	15	15	11	18	17	4	16	21	3	9	7	19	11
Population density	7	19	5	17	14	11	12	15	15	4	7	5	15	20	12
Irrigation	8	8	6	22	8	9	10	12	5	2	15	7	9	8	5
Anthropization century	9	6	14	7	-	7	5	7	6	1	4	4	11	7	6
Mine sites density	10	11	19	8	9	19	2	-	26	14	21	19	25	22	-
Crop cover	11	7	-	10	-	20	21	1	12	19	5	23	21	23	-
Crops diversity	12	10	16	14	15	5	3	20	21	6	14	20	23	15	20
Urbanization type	13	21	17	-	-	15	15	17	17	8	10	17	12	14	16
Precipitation	14	9	4	2	4	8	4	14	23	18	20	15	6	11	8
WBI regulatory quality	15	13	2	9	6	13	7	19	25	12	-	16	24	5	-
Grass cover	16	15	12	19	7	4	18	8	7	7	6	3	5	21	10
WBI political stabiilty	17	18	-	12	-	21	-	9	9	5	8	22	-	-	-
WBI gov. effectiveness	18	23	-	11	-	-	-	-	19	22	17	25	14	4	14
Languages density	-	26	-	-	-	-	-	-	24	25	-	26	18	10	18
Centrality	-	14	8	13	-	3	16	13	8	16	13	14	10	13	4
Ports traveltime	-	17	7	4	17	14	19	5	10	23	22	18	13	6	13
Protected areas	-	20	9	18	10	16	-	-	18	24	-	21	16	3	7
Shrub cover	-	12	-	20	3	1	14	16	14	20	18	1	20	24	-
Plantation cover	-	24	10	-	-	-	8	-	20	17	16	8	19	-	-
Land cover diversity	-	22	18	6	12	12	11	18	11	13	9	12	8	18	15
WBI rule of law	-	25	-	-	-	-	20	-	22	11	-	24	22	17	17

Model SER: classification into the five SER; Model SELS: classification into the 13 SELS; Models from A1 to E3 consist in distinguishing one particular SELS from the rest as a whole. While SER and SELS models are comparing several classes simultaneously, the others are binary models focused in one SELS at a time. Hyphens means less than 0.01 % relative importance.

Appendix 4. SELS Descriptions by Regional Specialists

SER A. Sparsely populated southern cold lands

SELS A1. Sparsely populated cold extra-tropical Andes

It includes the coldest areas of the sub-continent (area= 27 million hectares), both mountainous dry (Puna) and humid (Patagonia) terrain (Matteucci 2012, Grau et al. 2019). The region has a very low population density, associated with limitations for human agency due to a rigorous climate, which explains why it is separated from the northern Altiplano. Traditional land uses (i.e., extensive sheep raising and marginal agriculture) are experiencing dis-intensification. Tourism, in contrast, is on the rise, with less conventional forms prevailing (e.g., ecotourism, cultural tourism). Mining has strong potential, with both ongoing active expansion (e.g. Lithium salt brines in the Puna) and socio-environmental conflicts resulting from advanced planned projects (e.g. Gold mines in Patagonia). Protected areas are extensive, widespread, and with comparatively few conflicts, but in some areas invasive species are expanding their range. Wildlife is generally in good shape and often recovering. Most of the SELS occurs along the Chilean-Argentine border, which implies some associated social dynamics (e.g. government investments associated with infrastructure, military and bureaucratic jobs, and relatively mild international conflicts during the 20th century).

SELS A2. Remote cold ecotonal extra-tropical Andes

It includes areas bordering SELS A1 to the east, in the ecotone with places at lower elevation, both in the Puna highlands and in the southern temperate forests (area=32 million hectares). Temperature and human population are low, but higher than SELS A1, and rainfall is never as high as in SELS A1. Protected areas are common, and there are relatively small but prosperous urban centers, often associated with tourism and small-scale intensive agriculture. With a more mesic environment than SELS A1, vegetation alternates grasslands, shrublands and forest woody patches. Fire is a relatively common component of ecological functioning and of human-environment relationships (Veblen et al. 1999). This region has high travel time to ports, hence qualifying as "remote".

SELS A3. Low-diversity cold and temperate grassy rangelands

Dominated by a shrub–grass steppe, with low plant diversity, low forest cover, and medium shrub cover (area= 73 million hectares). The northern part corresponds to the "Monte-Arid Chaco-Espinal" and the southern part corresponds to the "Patagonian Steppe". The climate of this region is arid and semi-arid, and cold or seasonally cold, reaching freezing temperatures throughout the region. Plant diversity is low. Human population is also low and concentrated in humid valleys with irrigated agriculture. The rural inhabitants depend mainly on livestock grazing, such as sheep and goats. Overgrazing has led these systems to show signs of desertification, which intensifies the low productivity in the region (Jobbágy and Sala 2000), including the decreasing of low-cover palatable species and increasing relative cover of unpalatable grass species (Perelman et al. 1997).

SELS A4. Low-diversity low-populated shrubby rangelands

Located at the interphase between the "Monte" and the "Patagonian steppe" (area= 29 million hectares). It includes the well-developed irrigated valleys of northern Patagonia (Negro and Colorado rivers with important production of fruits such as apple and vineyards), and the surrounding drylands. It is characterized by a high coverage of shrubs, very low population density and extensive livestock grazing (Pol et al. 2005). There is also oil exploitation and irrigated production in the valleys, favored by good access to ports (e.g. San Antonio Oeste, Madryn). The dominant vegetation is grasses, shrubs, and small scattered trees (Cabrera 1976). In addition to its biogeographical core of Southern Monte shrublands, this SELS seems to capture shrub-encroached areas elsewhere, like in the Chaco plains. This SELS has higher shrub and cattle density compared to SELS A3. These differences between both SELS are useful to highlight the dynamism of the system in the Monte-Espinal transition, as overgrazing or abundance of fires can transform a portion of SELS A3 into SELS A4.

SER B. Arid and semi-arid highlands and adjacent coast, with a long history of agriculture and mining

SELS B1. Arid and semi-arid highlands and adjacent coast, with long history of agriculture and mining

This is the only SELS integrating the homonymous SER B, which spans over the Southern and Central Andes (area= 126 million hectares). It has a cool and overall dry climate which limits agriculture to irrigated areas in valleys and coastal areas and seasonal rainfed cultivation in higher lands. This SELS ranks highest in crop diversity due to its rough geomorphology, high climatic diversity but also its ancient settlement history (before 1700) and relatively high population density (including some large cities such as Lima and Santiago). Therefore, it represents a hotspot of agro-biodiversity linked to both biological and cultural diversity (Mathez-Stiefel et al. 2012, Sietz and Feola 2016). The combination of urbanization, subsistence agriculture, seasonal rainfall and rough topography makes the highland areas very sensitive to climate change and to land use change (Ochoa-Tocachi et al. 2016, Mathez-Stiefel et al. 2017, Tito et al. 2018). The narrow semi-arid Pacific coast is characterized by export-oriented, irrigated agriculture and concentrates most of the economic and political power, especially in Peru. Overall short travel time to ports implies high influence of the overseas trade on regional processes. It ranks highest in mining density, highlighting its social-ecological impact including the ongoing and potential conflicts between extractive activities, traditional and commercial agriculture, environmental conservation and tourism (Tovar et al. 2013, Pérez-Rincón et al. 2019).

SER C. Consolidated large scale agropastoral plains

SELS C1. Urbanized large scale agricultural plains

Covers the grasslands, savannas and shrublands of Uruguay, central east Argentina, and east Paraguay, in addition to patches in south Brazil, Bolivia, Colombia and Venezuela (area= 196 million hectares). This SELS is defined by the presence of agriculture in flat sedimentary landscapes. It is dominated by highly productive rainfed agriculture (e.g. wheat, maize, soybean, sunflower) and outstanding cattle production, but also includes places with irrigated crops. There is internal heterogeneity, with gradients of anthropization levels and different histories of agricultural expansion. In general, these are densely populated areas, with the presence of large farmers and economical power concentration. Land use and land cover changes have transformed the landscape structure and dramatically altered the original vegetation cover (Baldi and Paruelo 2008, Gasparri and Grau 2009, Vallejos et al. 2015). These changes have a major impact on the provision of ecosystem services, and have also generated asymmetries in the use and access to natural resources between stakeholders.

SELS C2. Consolidation of agropastoral lands in savannas and semi-deciduous forest

Located mainly in central Brazil (e.g. Cerrado), to some extent in the llanos of Colombia and Venezuela, the Pantanal, and areas of recent deforestation in western Brazil and in the Chaco (Bolivia, Argentina and Paraguay) (area= 280 million hectares). This SELS is characterized by regions that are flat, hot, with intermediate rainfall, low to intermediate forest cover, and high grass cover. It includes large-scale agriculture (e.g. soybeans and maize) but cattle ranching is dominant, with varying population density and relatively short travel time to cities. Historic deforestation for cattle ranching and agricultural operations, and frequent fires in Central Brazil have created the savanna landscapes that we know today as the Cerrado (Banda-R et al. 2016, Nobre et al. 2016). In more recent times, similar dynamics are occurring in the frontiers between this SELS and the Amazon and Chaco regions. Many areas of SELS E2 are interspersed within this SELS, with similar conditions but more recent deforestation (Silvério et al. 2013). Areas of “natural” savannas, such as the Pantanal, Roraima, and parts of the llanos of Colombia and Venezuela have a different set of native species, but similar land use (e.g. cattle ranching). This SELS represents a transition or intermediate stage between the historical agriculture plains of SELS C1 and the new agricultural frontiers of SELS E2.

SER D. Historically populated tropical areas with low potential for mechanized agriculture

SELS D1. High density montane populations with agropastoral activity
Mainly spans the Northern Andes from northern Peru to Venezuela and to a lesser extent, the more humid eastern slope of the Central Andes (area= 65 million hectares). There is also a small sector in the Serra do Mar north of Rio de Janeiro, Brazil. This SELS is characterized by mountains, sometimes extending into neighboring coastal lowlands (e.g. Ecuador), warm and temperate temperatures, and intermediate levels of precipitation. They include a long history of human intensive land use, as precolonial civilizations occupied much of this area. This SELS includes the highest current population density of all SELS and many medium and large size cities (Parés-Ramos et al. 2013). Political instability (e.g. conflict in Colombia) with important impacts on land use (Sánchez-Cuervo and Aide 2013) is common, including the abandonment of some agricultural activities and the secondary forest recovery (Nanni et al. 2019, Aide et al. 2019). Grass, for cattle grazing, is the dominant cover, followed by trees, and crops. Important crops in the region include coffee and cacao (Rueda and Lambin 2013), and irrigation helps to support a high diversity of Andean crops. Legal and illegal coca plantations are an important feature.

SELS D2. Intensive, market-connected hilly agropastoral systems with long colonization history
It is dominantly located in hilly to partly mountainous terrain, but with excellent access to larger markets and economic hubs (area= 105 million hectares). These areas have a long history of early colonial occupation, and experienced several periods of political instability (Dean 1997, Joly et al. 2014). Land use is diverse and heterogeneous, yet agricultural systems are characteristic for this SELS, dominated by high-intensity cattle husbandry and croplands. The grassland cover is oftentimes composed of planted pasturelands. Croplands are of relative low diversity (i.e. monocultures) and include annuals (e.g., soybean, maize), perennials (e.g., coffee, orange, eucalyptus), and semi-perennials (e.g., sugar cane). Population density is among the highest on the continent, with many communities living in medium-sized cities, but also in metropolitan regions such as Sao Paulo and Rio de Janeiro. The main contiguous area is dominated by fragmented tropical rainforest corresponding to the biome “Mata Atlântica” (i.e., Atlantic Forest) in Brazil (Ribeiro et al. 2009). To the northwest of this main area still within Brazil, climate is dryer and vegetation transitions to the “Cerrado.” The most northern regions encompass parts of the Colombian and Venezuelan Llanos.

SELS D3. Highly populated and biodiverse historical semi-arid areas
Corresponds mostly to the Caatinga and some parts of the Cerrado in Eastern Brazil and includes dry valleys in the eastern slopes of the tropical-Andean valleys of Peru and

Bolivia (area= 99 million hectares). It also includes the Santa Catarina area in Southern Brazil and some portions of Central Colombia and NW Ecuador. These areas seem not to fit this description (being more rather humid areas) which is supported by the high classification uncertainty associated with some of these regions. The definition of this SELS appears to be a result of high deforestation and a long history of landscape transformation. It is characterized by a semi-arid climate with very high temperatures, a rough topography and is covered by dry forests and shrublands. This historical settlement area (before 1700) still maintains densely populated areas and has high levels of both plant and crop diversity, including irrigated agriculture.

SER E. Tropical forests with low anthropization

SELS E1. South American lowlands: new agropastoral frontiers

This SELS corresponds to agricultural frontier regions located in the flat warm lowlands of South America, and includes biomes such as the Amazon, Cerrado and Chaco (area= 183 million hectares). While this SELS is dominated by forested landscapes, some other areas include naturally open ecosystems (e.g. the Bolivian Llanos de Moxos, or the Humid Chaco ecoregions). Although the landscape is mainly dominated by natural vegetation, many areas have been subject to active land use changes throughout the past five decades (e.g. the colonization of Brazilian states of Pará, Mato Grosso, and the Argentinian East Chaco began around the 1970's along highway constructions, indicating many of these settlements have been long established and are no longer "active" frontiers). Accessibility levels are intermediate, and while the population is predominantly rural, small and medium cities are growing in importance as the service economy develops, especially in association with agricultural production. Conflicts around land use are common, involving clashes between existing populations, landless people, and new settlers and between agribusiness and subsistence agriculture (Caldas et al. 2010, Aldrich et al. 2020). These conflicts are related to vast inequities in land distribution and associated production opportunities; and an overall pressure on natural resources for the production of global commodities (Simmons et al. 2010). Thus, this is a highly dynamic SELS where some regions may currently be in transition, with an unstable equilibrium of natural landscapes affected by different land use practices (e.g. extensive cattle ranching, commodity crop production, fires), and climate change (Silvério et al. 2013, Nobre et al. 2016).

SELS E2. Remote and mountainous tropical lands

This SELS is mainly located in the very humid foothills and lower montane areas of the Amazon and Orinoco basins (area= 117 million hectares). It also includes the Guiana highlands of Venezuela, Guyana, Suriname, and Brazil, the Eastern slope of the Andes (upper Amazon in Ecuador, Perú and Bolivia), as well as a few other scattered forested highlands in Argentina, Bolivia, Brazil and Colombia. The SELS is mainly characterized by high levels of forest cover or natural vegetation; however, it also includes some agricultural land uses such as coffee and cacao plantations. It is characterized by rugged/mountainous geomorphology, and low levels of accessibility. It has the largest proportion of protected area, which includes high profile conservation areas reflecting the importance of this SELS for biodiversity and related ecosystem services. The management of many of these lands is tied to national systems of protected areas as well as widespread and vast indigenous territories (Achtenberg 2013, Rodriguez 2017). This SELS should not be mistaken with intact "wilderness". Instead, it exemplifies a Social-Ecological system where many traditional communities co-exist with conservation, tourism, forestry, and other extractive activities. These extractive activities are also relevant for SELS E3.

SELS E3. Tropical forests with low anthropogenic conversion

This SELS mainly covers the most isolated regions of the Amazon basin, plus other highly forested regions, such as the deciduous forests of northern Argentina, northern Paraguay and eastern Bolivia (area= 437 million hectares). The spatial extent of this SELS overlaps with old growth or minimally disturbed forests by post-Columbian populations (Tyukavina et al. 2016, Potapov et al. 2017). Environmental characteristics include vast, relatively flat areas often flooded, high temperatures, high precipitation, and high forest cover. Human settlements tend to be small and sparsely distributed along rivers, with low levels of accessibility by roads. Overall, this SELS has fewer anthropogenic pressures on the environment, but also lower levels of monitoring, enforcement, and governance. While some regions of this SELS do include small-scale subsistence agriculture, other land uses related to extractive activities exist, yet are difficult to detect with current remote sensing technologies, as they do not necessarily coincide with extensive land cover changes. Some of these extractive activities might include forest degradation, forest fires and burned areas, defaunation processes catalyzed by rural and indigenous communities that practice hunting or poaching (Benítez-López et al. 2019), and artisanal and small-scale alluvial artisanal and gold mining (Alvarez-Berríos and Aide 2015). In addition to these activities, changes in size and status of conservation areas also threaten environmental conditions in these areas, adding to the political and social challenges of the SELS (Alvarez-Berríos and Aide 2015).

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Appendix 5. SELS Diagnostic Plots

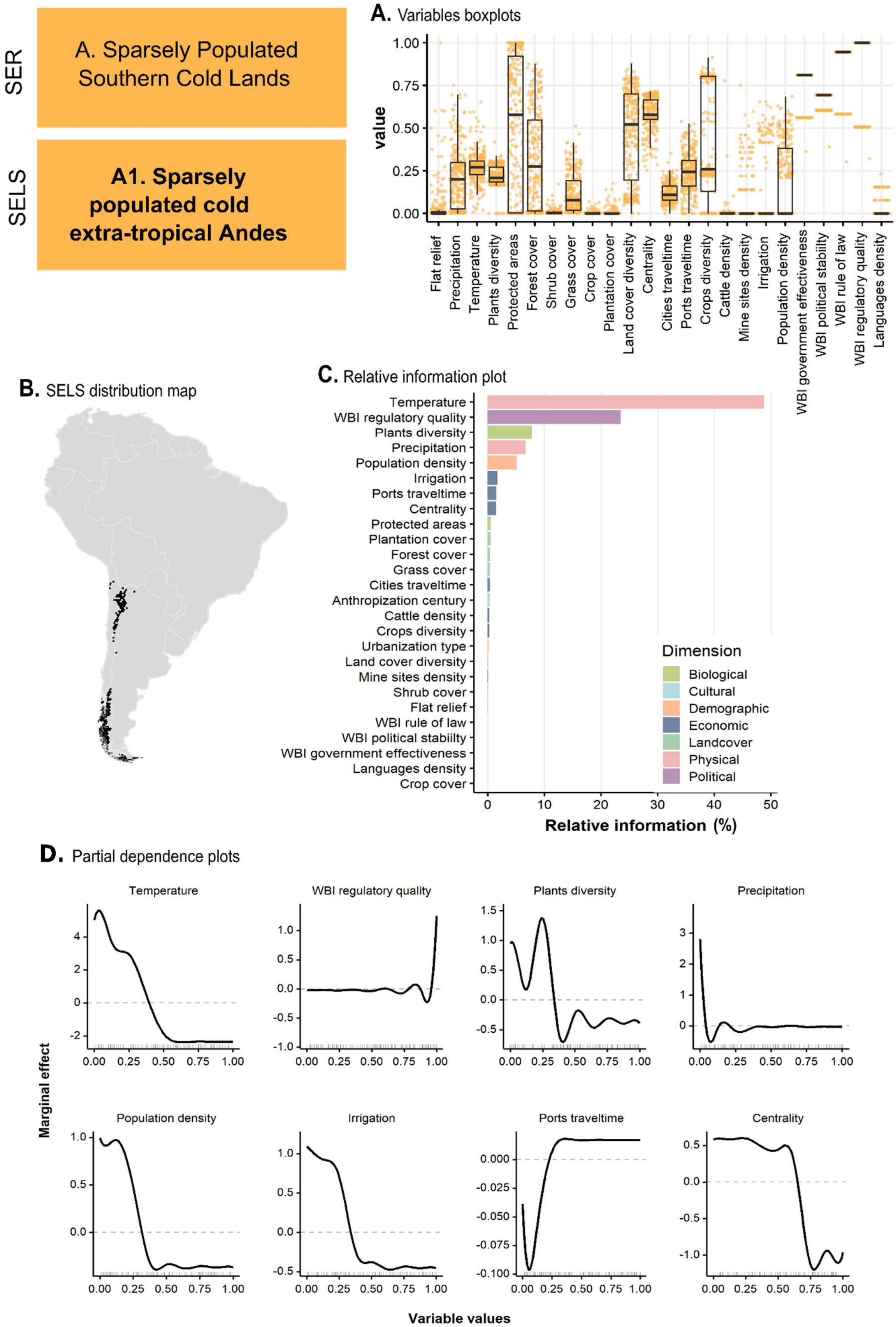
In this section we provide a graphical characterization of the SELS by displaying (in one page per SELS):

A. **Variables boxplots** showing the quartiles summary (boxes) and individual values (dots) of hexagons within the SELS for the 24 quantitative input variables. Box limits represent 2nd and 3rd quartiles, vertical lines the 1st and 4th quartiles, and the thicker line in the middle of the boxes indicates the median value.

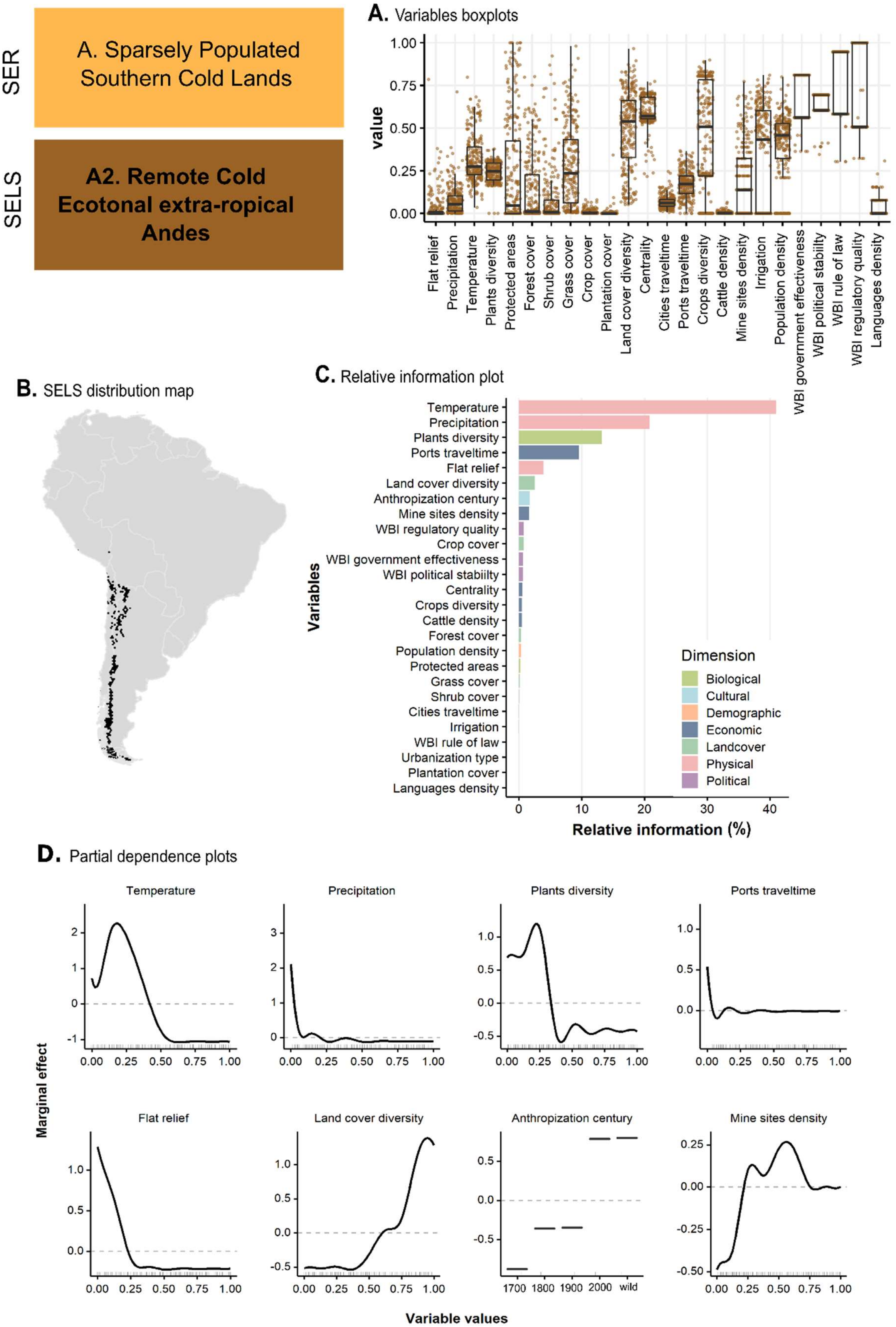
B. **SELS distribution map** with the location of the hexagons classified within that SELS (black), the continent as a background (grey) and the national political boundaries (white).

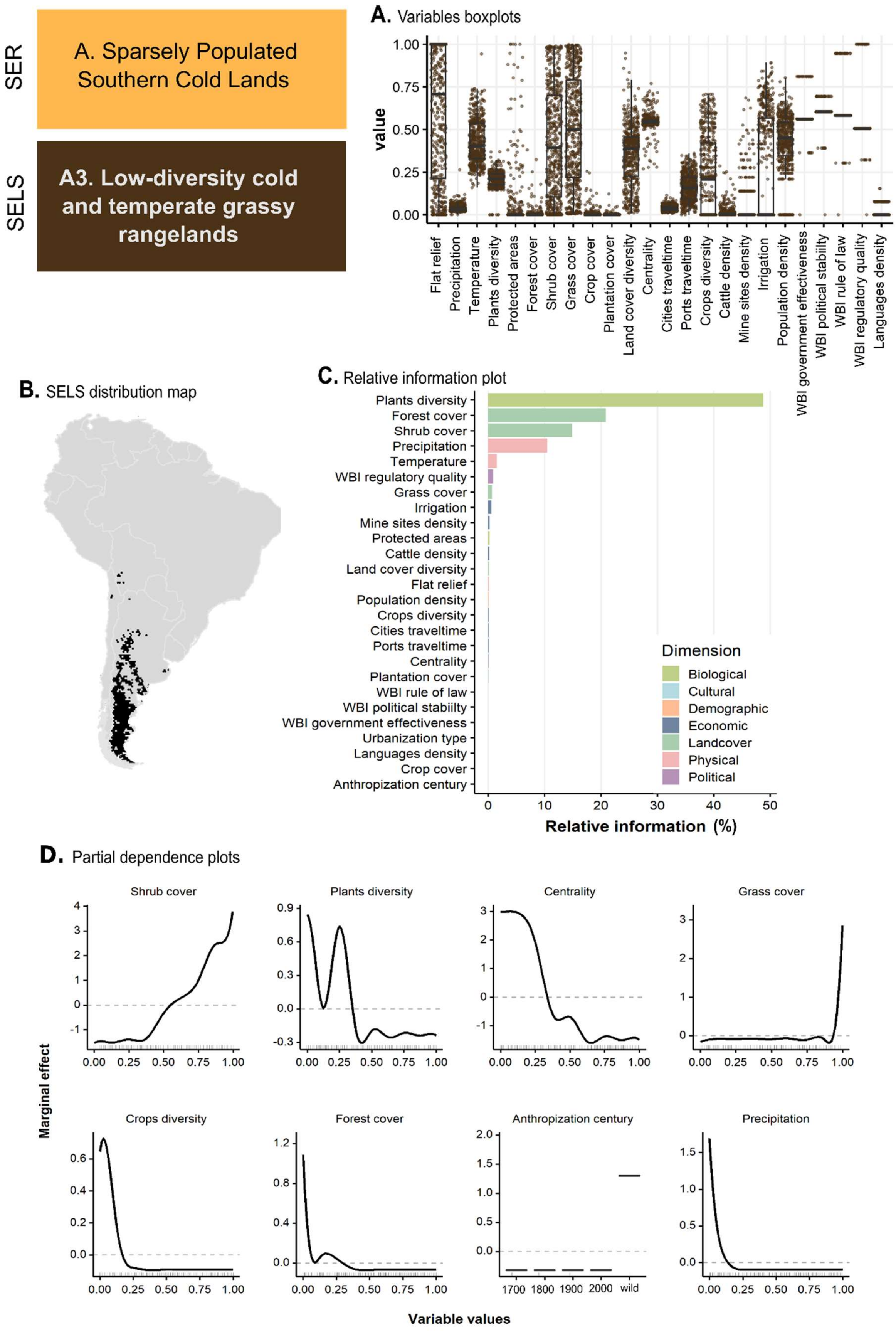
C. **Relative information plot** or variable's "contribution" to the model based on the results of the boosted regression trees analyses. In this section the models consist in distinguishing one particular SELS from the rest as a whole.

D. **Partial dependence plots** of the eight most informative variables for defining the SELS. These plots are a product of the boosted regression trees, and show the distribution of the fitted function (y axis) along the variables' values (x axis) informing on the marginal effect of the variable when you move along its value range (while holding everything else constant). Interpretation: for y-values larger than zero indicate that the SELS category is present in this value range, for y-values smaller than zero that it is absent in this value range. The larger the deviation from zero, the higher the probability of presence (positive values) or absence (negative values).

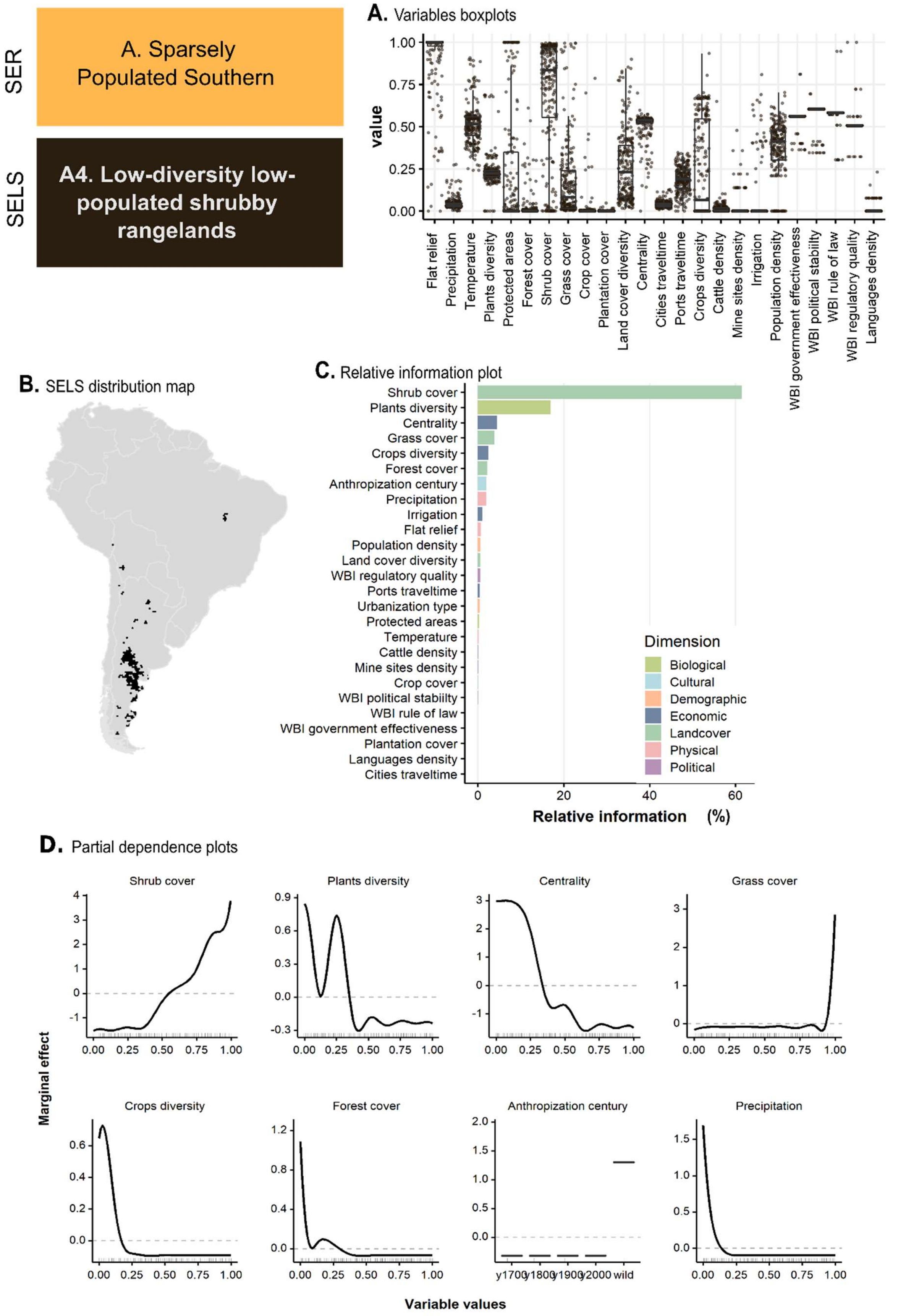


SER
A. Sparsely Populated Southern Cold Lands
SELS
A1. Sparsely populated cold extra-tropical Andes
A. Variables boxplots
value
1.00
0.75
0.50
0.25
0.00
Flat relief
Precipitation
Temperature
Plants diversity
Protected areas
Forest cover
Shrub cover
Grass cover
Crop cover
Plantation cover
Land cover diversity
Centrality
Cities traveltime
Ports traveltime
Crops diversity
Cattle density
Mine sites density
Irrigation
Population density
WBI government effectiveness
WBI political stability
WBI rule of law
WBI regulatory quality
Languages density
B. SELS distribution map
C. Relative information plot
Temperature
WBI regulatory quality
Plants diversity
Precipitation
Population density
Irrigation
Ports traveltime
Centrality
Protected areas
Plantation cover
Forest cover
Grass cover
Cities traveltime
Anthropization century
Cattle density
Crops diversity
Urbanization type
Land cover diversity
Mine sites density
Shrub cover
Flat relief
WBI rule of law
WBI political stabiilty
WBI government effectiveness
Languages density
Crop cover
Dimension
Biological
Cultural
Demographic
Economic
Landcover
Physical
Political
0 10 20 30 40 50
Relative information (%)
D. Partial dependence plots
Temperature
WBI regulatory quality
Plants diversity
Precipitation
Population density
Irrigation
Ports traveltime
Centrality
Marginal effect
Variable values


SER
A. Sparsely Populated Southern Cold Lands
SELS
A2. Remote Cold Ecotonal extra-ropical Andes
A. Variables boxplots
value
Flat relief
Precipitation
Temperature
Plants diversity
Protected areas
Forest cover
Shrub cover
Grass cover
Crop cover
Plantation cover
Land cover diversity
Centrality
Cities traveltime
Ports traveltime
Crops diversity
Cattle density
Mine sites density
Irrigation
Population density
WBI government effectiveness
WBI political stabiilty
WBI rule of law
WBI regulatory quality
Languages density
B. SELS distribution map
C. Relative information plot
Variables
Temperature
Precipitation
Plants diversity
Ports traveltime
Flat relief
Land cover diversity
Anthropization century
Mine sites density
WBI regulatory quality
Crop cover
WBI government effectiveness
WBI political stabiilty
Centrality
Crops diversity
Cattle density
Forest cover
Population density
Protected areas
Grass cover
Shrub cover
Cities traveltime
Irrigation
WBI rule of law
Urbanization type
Plantation cover
Languages density
Dimension
Biological
Cultural
Demographic
Economic
Landcover
Physical
Political
Relative information (%)
D. Partial dependence plots
Temperature
Precipitation
Plants diversity
Ports traveltime
Flat relief
Land cover diversity
Anthropization century
Mine sites density
Marginal effect
1700 1800 1900 2000 wild
Variable values



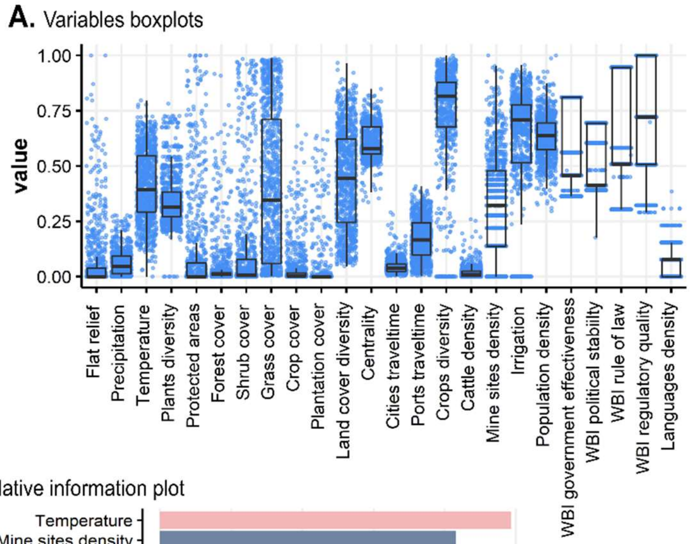
SER
A. Sparsely Populated Southern Cold Lands
SELS
A3. Low-diversity cold and temperate grassy rangelands
A. Variables boxplots
value
Flat relief
Precipitation
Temperature
Plants diversity
Protected areas
Forest cover
Shrub cover
Grass cover
Crop cover
Plantation cover
Land cover diversity
Centrality
Cities traveltime
Ports traveltime
Crops diversity
Cattle density
Mine sites density
Irrigation
Population density
WBI government effectiveness
WBI political stabiilty
WBI rule of law
WBI regulatory quality
Languages density
B. SELS distribution map
C. Relative information plot
Plants diversity
Forest cover
Shrub cover
Precipitation
Temperature
WBI regulatory quality
Grass cover
Irrigation
Mine sites density
Protected areas
Cattle density
Land cover diversity
Flat relief
Population density
Crops diversity
Cities traveltime
Ports traveltime
Centrality
Plantation cover
WBI rule of law
WBI political stabiilty
WBI government effectiveness
Urbanization type
Languages density
Crop cover
Anthropization century
Dimension
Biological
Cultural
Demographic
Economic
Landcover
Physical
Political
Relative information (%)
D. Partial dependence plots
Shrub cover
Plants diversity
Centrality
Grass cover
Crops diversity
Forest cover
Anthropization century
Precipitation
Marginal effect
Variable values

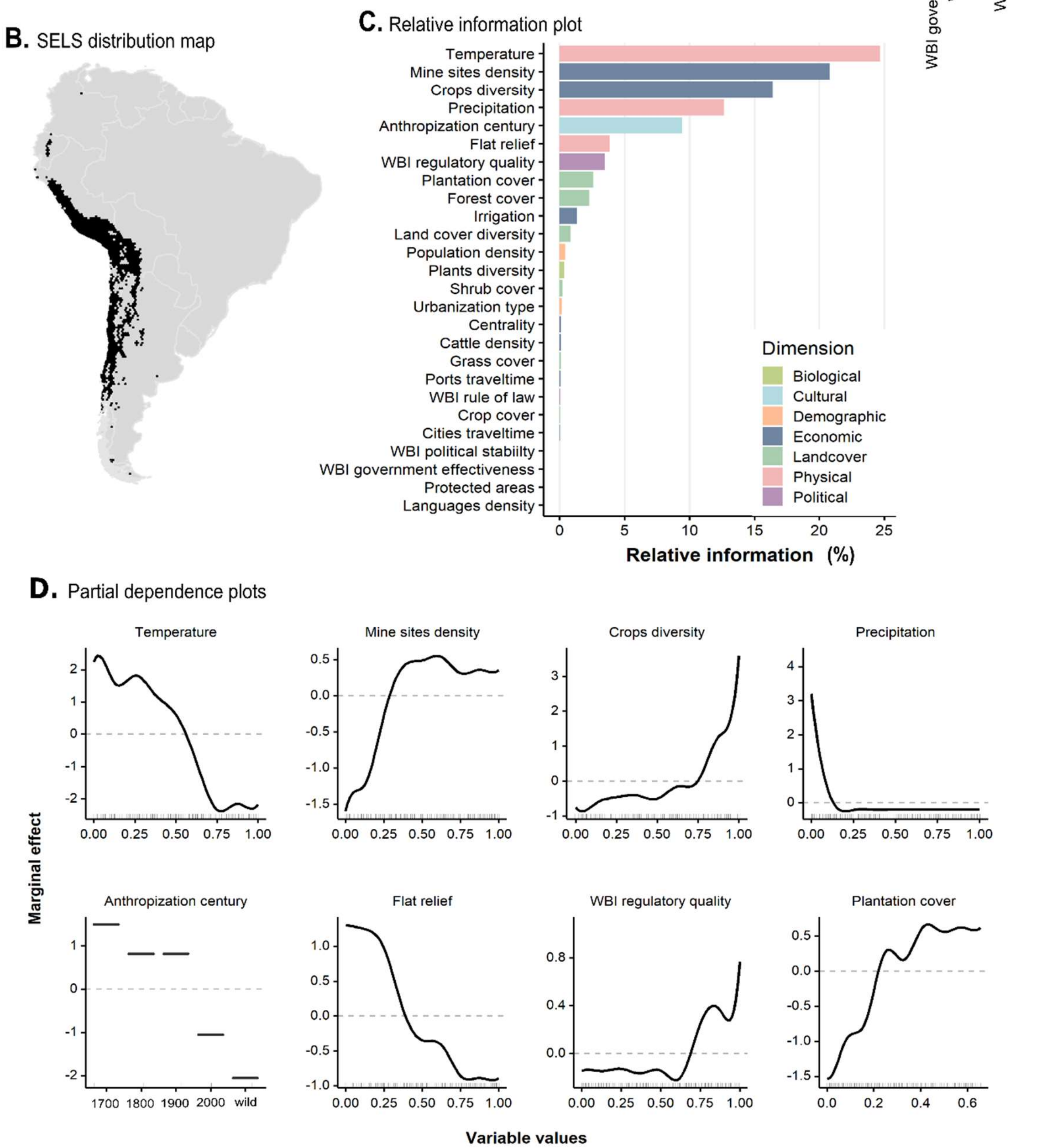

SER
A. Sparsely Populated Southern
SELS
A4. Low-diversity low-populated shrubby rangelands
A. Variables boxplots
value
Flat relief
Precipitation
Temperature
Plants diversity
Protected areas
Forest cover
Shrub cover
Grass cover
Crop cover
Plantation cover
Land cover diversity
Centrality
Cities traveltime
Ports traveltime
Crops diversity
Cattle density
Mine sites density
Irrigation
Population density
WBI government effectiveness
WBI political stability
WBI rule of law
WBI regulatory quality
Languages density
B. SELS distribution map
C. Relative information plot
Shrub cover
Plants diversity
Centrality
Grass cover
Crops diversity
Forest cover
Anthropization century
Precipitation
Irrigation
Flat relief
Population density
Land cover diversity
WBI regulatory quality
Ports traveltime
Urbanization type
Protected areas
Temperature
Cattle density
Mine sites density
Crop cover
WBI political stabiilty
WBI rule of law
WBI government effectiveness
Plantation cover
Languages density
Cities traveltime
Dimension
Biological
Cultural
Demographic
Economic
Landcover
Physical
Political
Relative information (%)
D. Partial dependence plots
Shrub cover
Plants diversity
Centrality
Grass cover
Crops diversity
Forest cover
Anthropization century
Precipitation
y1700 y1800 y1900 y2000 wild
Marginal effect
Variable values

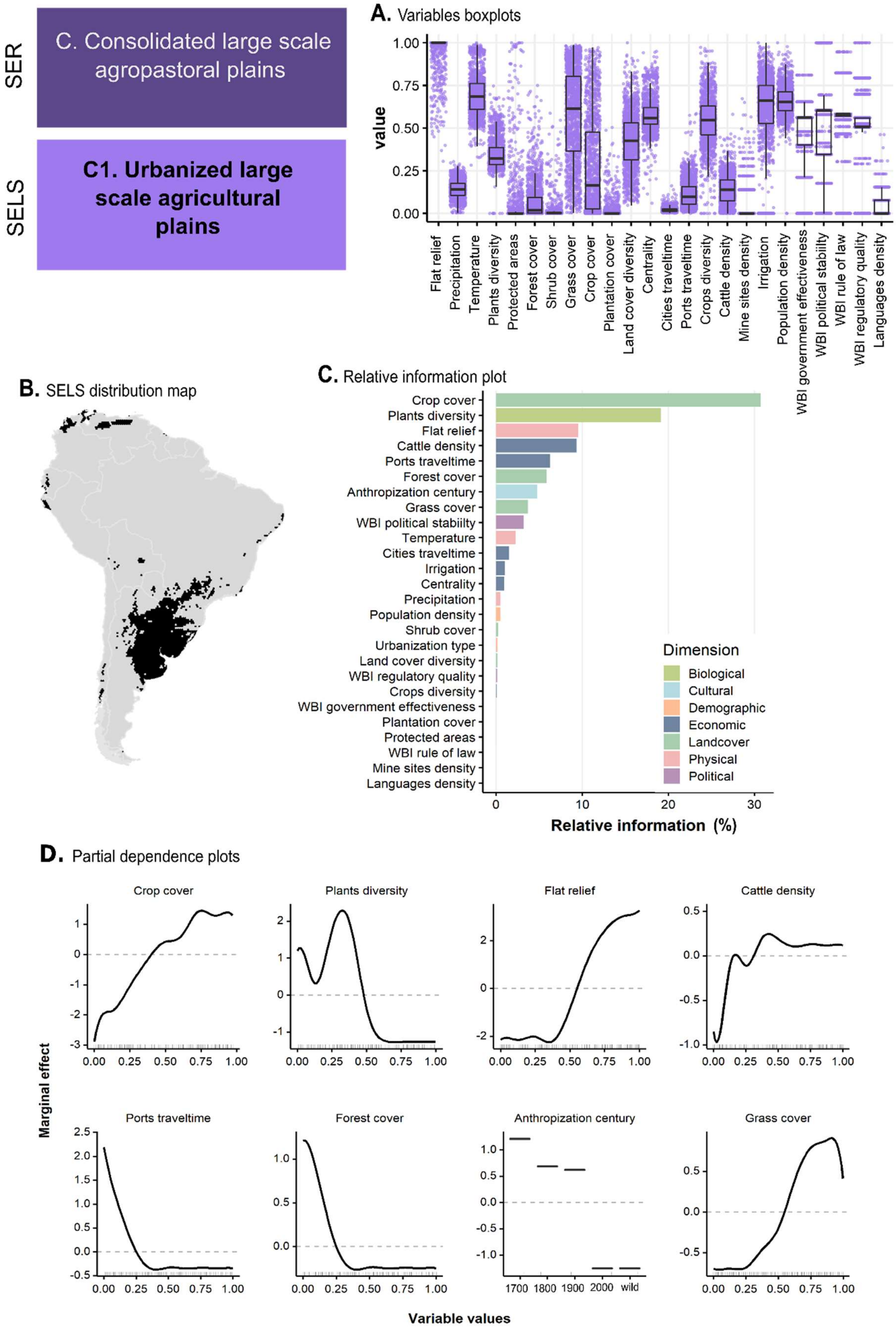
SER

SELS

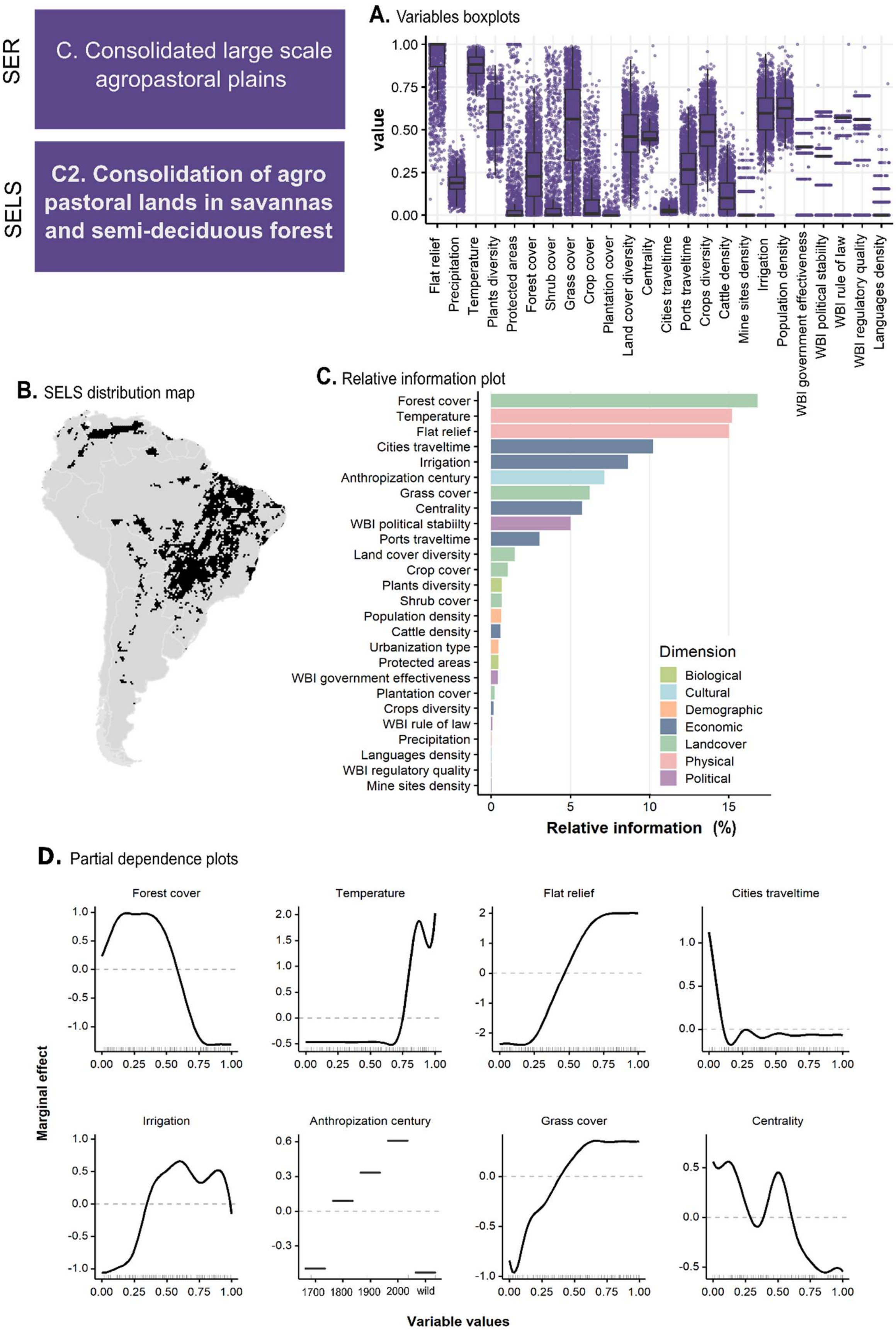
B1. Arid and semi-arid highlands and coast, with long history of agriculture and mining

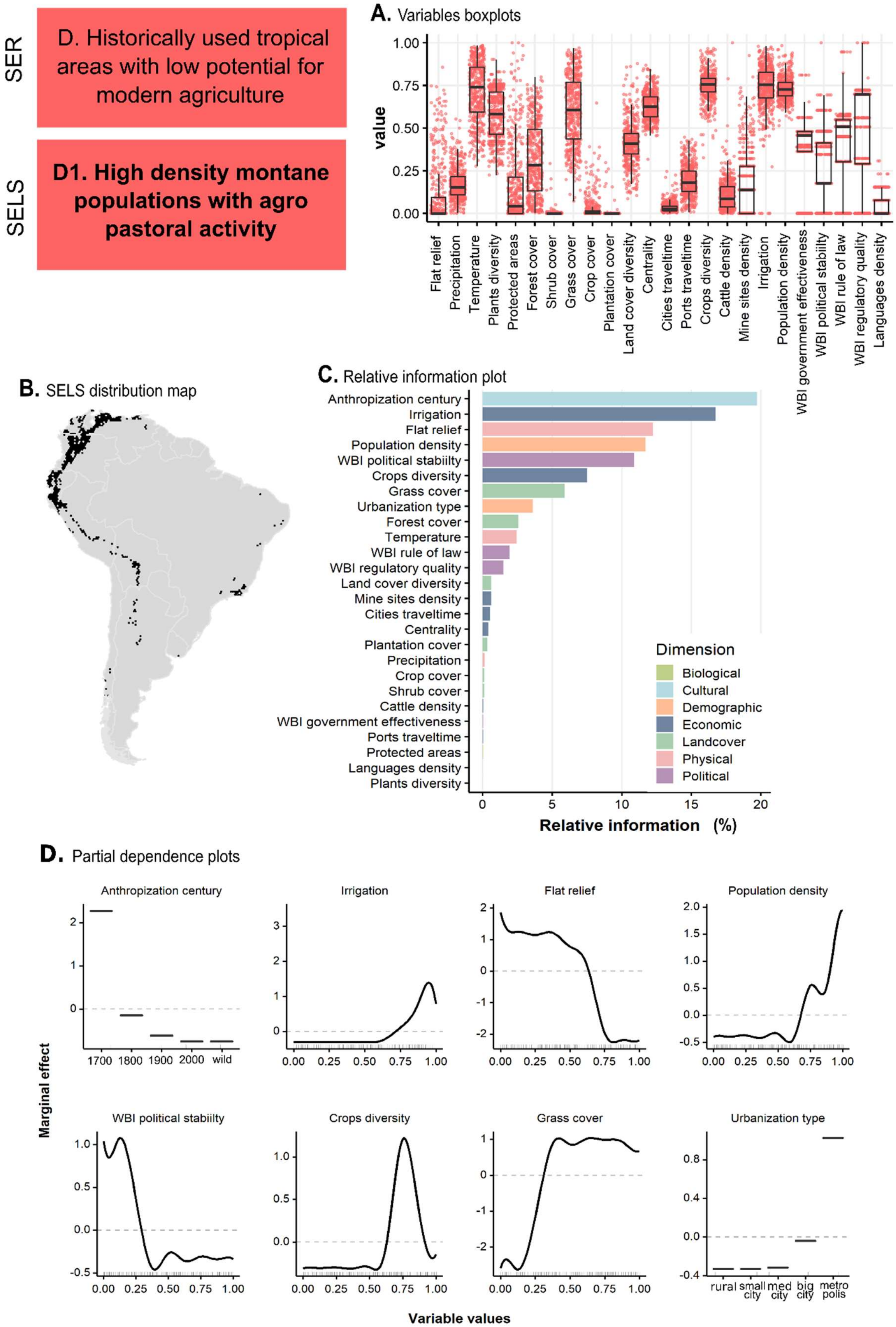


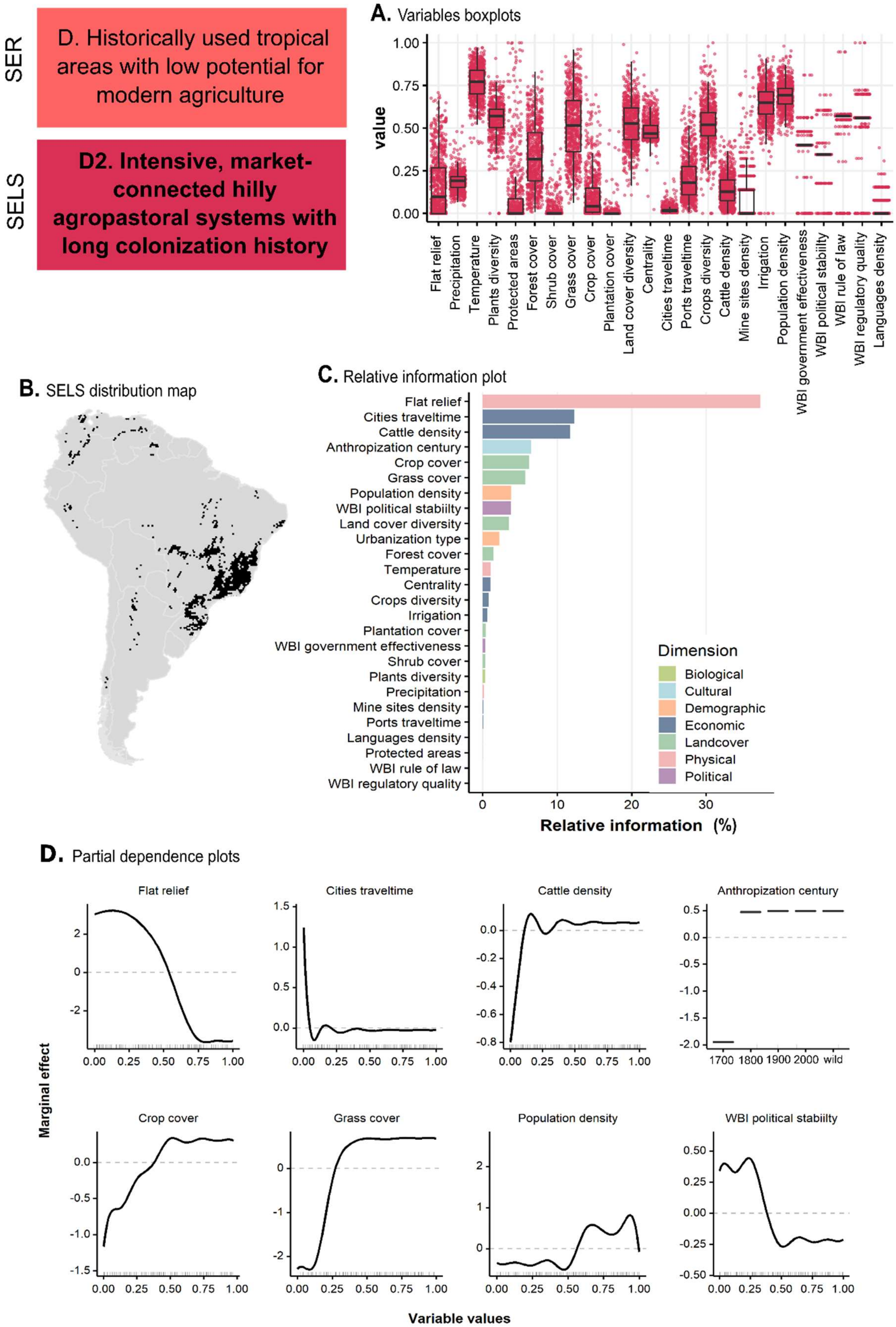


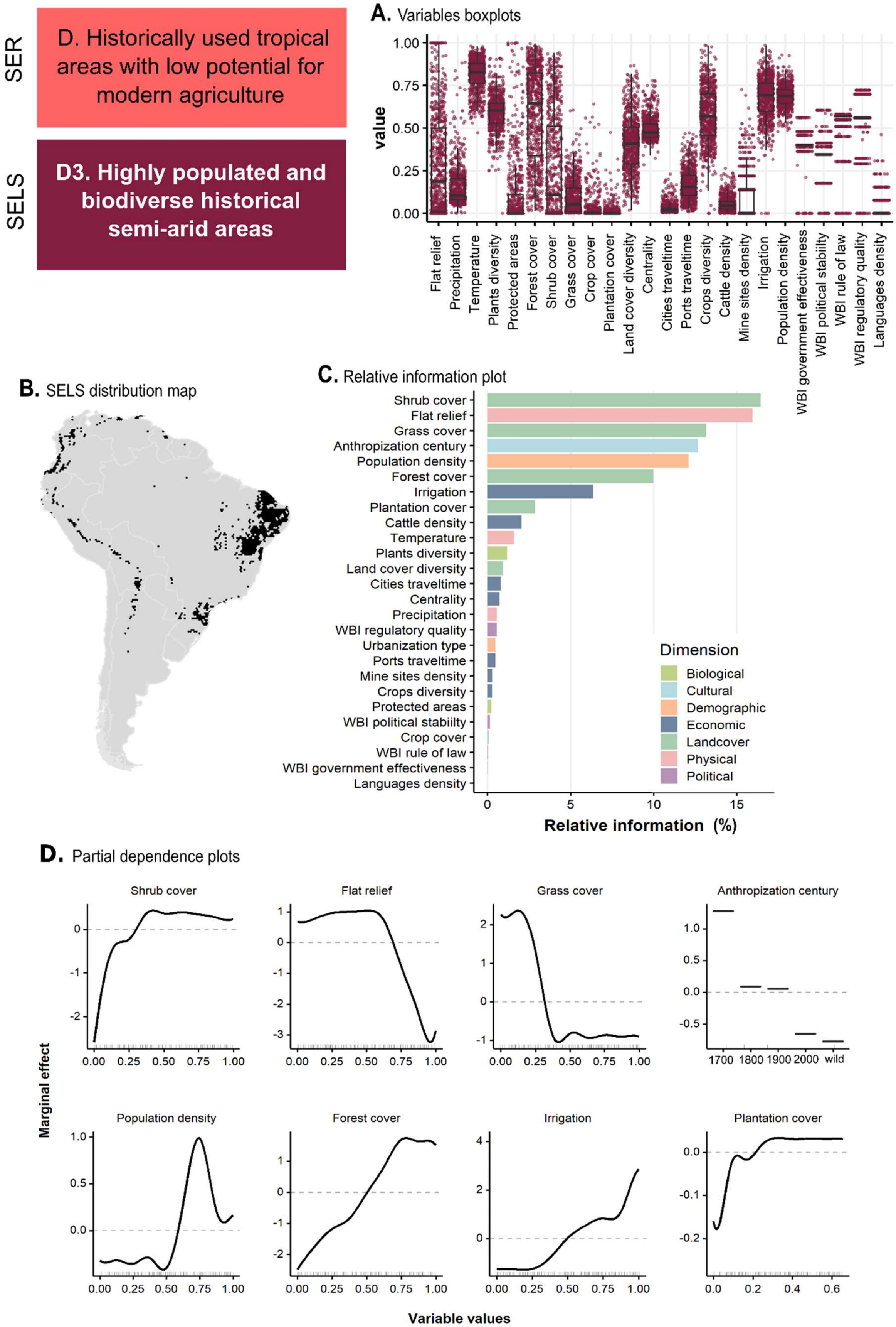


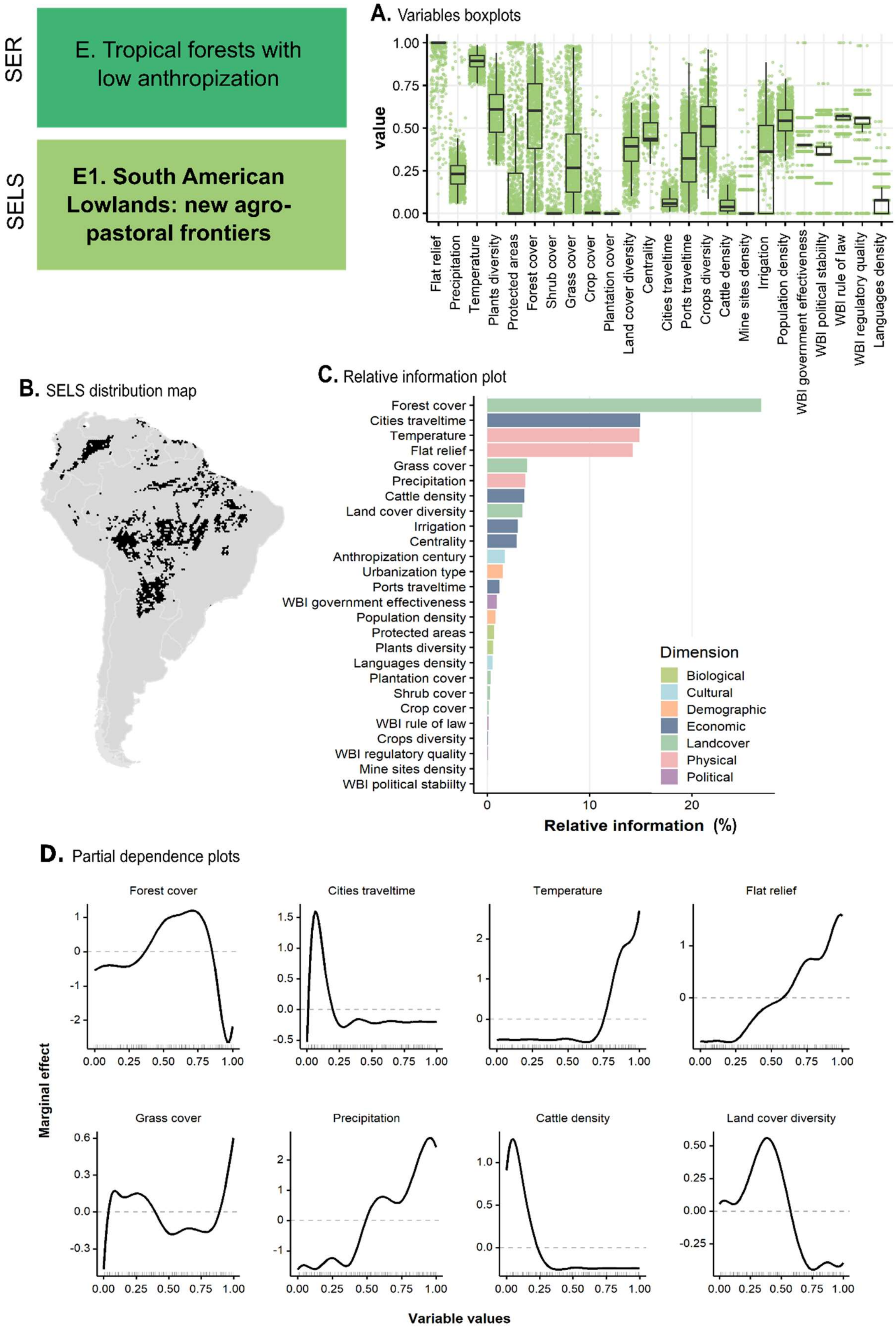
SER
C. Consolidated large scale agropastoral plains
SELS
C1. Urbanized large scale agricultural plains
A. Variables boxplots
value
Flat relief
Precipitation
Temperature
Plants diversity
Protected areas
Forest cover
Shrub cover
Grass cover
Crop cover
Plantation cover
Land cover diversity
Centrality
Cities traveltime
Ports traveltime
Crops diversity
Cattle density
Mine sites density
Irrigation
Population density
WBI government effectiveness
WBI political stabiilty
WBI rule of law
WBI regulatory quality
Languages density
B. SELS distribution map
C. Relative information plot
Crop cover
Plants diversity
Flat relief
Cattle density
Ports traveltime
Forest cover
Anthropization century
Grass cover
WBI political stabiilty
Temperature
Cities traveltime
Irrigation
Centrality
Precipitation
Population density
Shrub cover
Urbanization type
Land cover diversity
WBI regulatory quality
Crops diversity
WBI government effectiveness
Plantation cover
Protected areas
WBI rule of law
Mine sites density
Languages density
Dimension
Biological
Cultural
Demographic
Economic
Landcover
Physical
Political
Relative information (%)
D. Partial dependence plots
Crop cover
Plants diversity
Flat relief
Cattle density
Ports traveltime
Forest cover
Anthropization century
Grass cover
Marginal effect
Variable values
1700
1800
1900
2000
wild

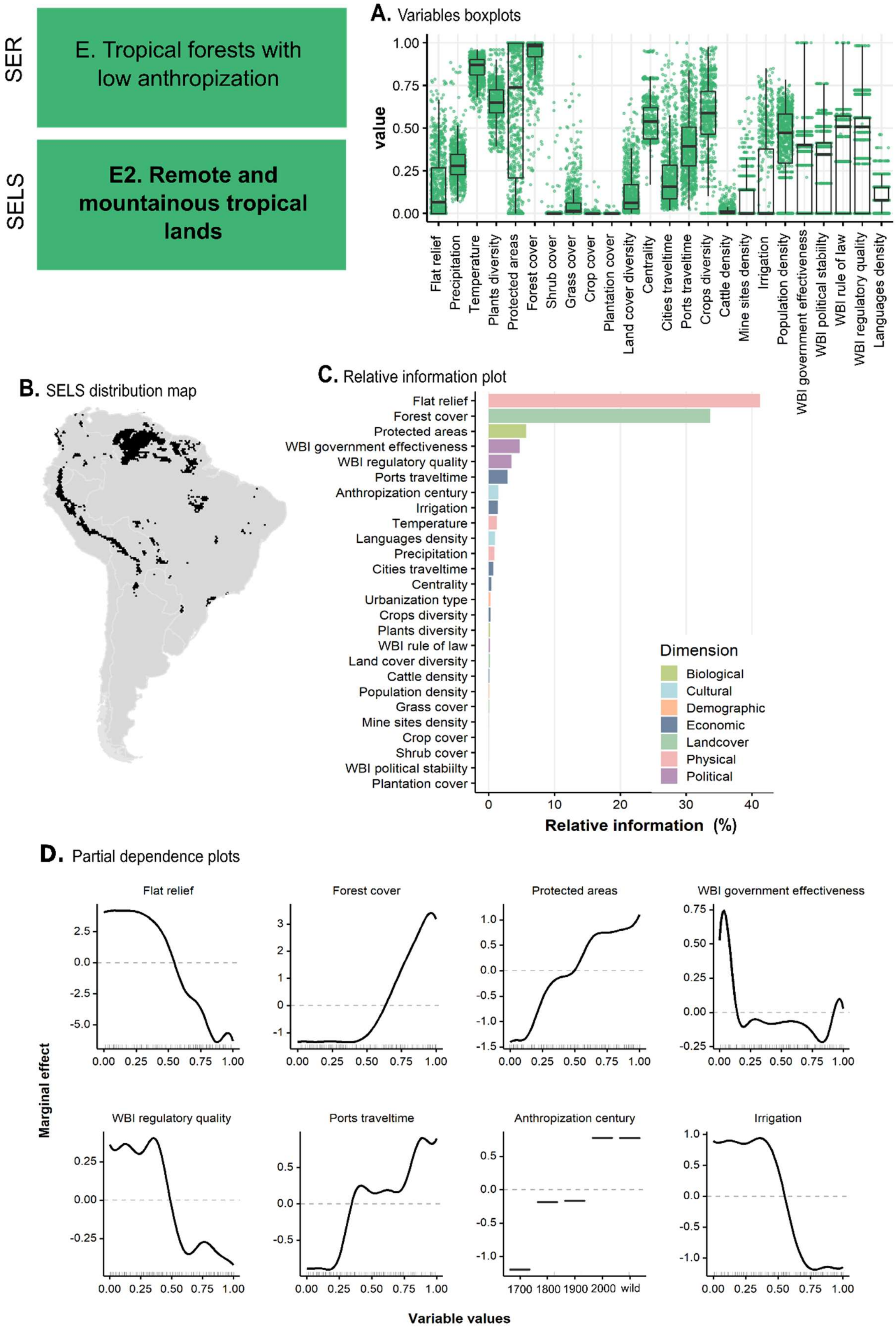

SER
C. Consolidated large scale agropastoral plains
SELS
C2. Consolidation of agro pastoral lands in savannas and semi-deciduous forest
A. Variables boxplots
value
Flat relief
Precipitation
Temperature
Plants diversity
Protected areas
Forest cover
Shrub cover
Grass cover
Crop cover
Plantation cover
Land cover diversity
Centrality
Cities traveltime
Ports traveltime
Crops diversity
Cattle density
Mine sites density
Irrigation
Population density
WBI government effectiveness
WBI political stabilty
WBI rule of law
WBI regulatory quality
Languages density
B. SELS distribution map
C. Relative information plot
Forest cover
Temperature
Flat relief
Cities traveltime
Irrigation
Anthropization century
Grass cover
Centrality
WBI political stabiilty
Ports traveltime
Land cover diversity
Crop cover
Plants diversity
Shrub cover
Population density
Cattle density
Urbanization type
Protected areas
WBI government effectiveness
Plantation cover
Crops diversity
WBI rule of law
Precipitation
Languages density
WBI regulatory quality
Mine sites density
Dimension
Biological
Cultural
Demographic
Economic
Landcover
Physical
Political
Relative information (%)
D. Partial dependence plots
Forest cover
Temperature
Flat relief
Cities traveltime
Irrigation
Anthropization century
Grass cover
Centrality
Marginal effect
Variable values

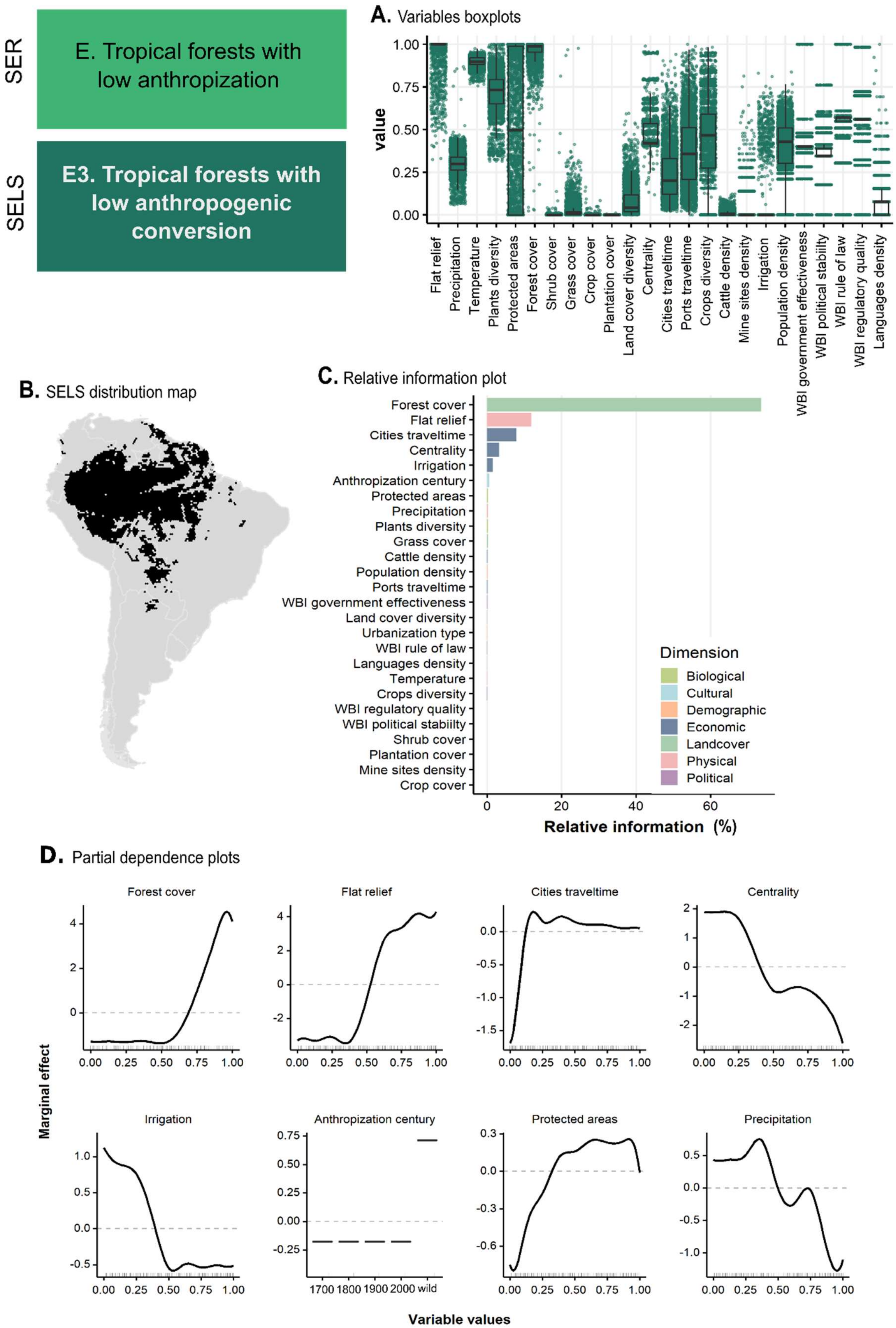

SER
D. Historically used tropical areas with low potential for modern agriculture
SELS
D1. High density montane populations with agro pastoral activity
A. Variables boxplots
value
1.00
0.75
0.50
0.25
0.00
Flat relief
Precipitation
Temperature
Plants diversity
Protected areas
Forest cover
Shrub cover
Grass cover
Crop cover
Plantation cover
Land cover diversity
Centrality
Cities traveltime
Ports traveltime
Crops diversity
Cattle density
Mine sites density
Irrigation
Population density
WBI government effectiveness
WBI political stabiilty
WBI rule of law
WBI regulatory quality
Languages density
B. SELS distribution map
C. Relative information plot
Anthropization century
Irrigation
Flat relief
Population density
WBI political stabiilty
Crops diversity
Grass cover
Urbanization type
Forest cover
Temperature
WBI rule of law
WBI regulatory quality
Land cover diversity
Mine sites density
Cities traveltime
Centrality
Plantation cover
Precipitation
Crop cover
Shrub cover
Cattle density
WBI government effectiveness
Ports traveltime
Protected areas
Languages density
Plants diversity
Dimension
Biological
Cultural
Demographic
Economic
Landcover
Physical
Political
0
5
10
15
20
Relative information (%)
D. Partial dependence plots
Anthropization century
1700 1800 1900 2000 wild
Irrigation
Flat relief
Population density
WBI political stabiilty
Crops diversity
Grass cover
Urbanization type
rural
small city
med city
big city
metro polis
0.00 0.25 0.50 0.75 1.00
Marginal effect
Variable values


SER
D. Historically used tropical areas with low potential for modern agriculture
SELS
D2. Intensive, market-connected hilly agropastoral systems with long colonization history
A. Variables boxplots
value
Flat relief
Precipitation
Temperature
Plants diversity
Protected areas
Forest cover
Shrub cover
Grass cover
Crop cover
Plantation cover
Land cover diversity
Centrality
Cities traveltime
Ports traveltime
Crops diversity
Cattle density
Mine sites density
Irrigation
Population density
WBI government effectiveness
WBI political stabiilty
WBI rule of law
WBI regulatory quality
Languages density
B. SELS distribution map
C. Relative information plot
Flat relief
Cities traveltime
Cattle density
Anthropization century
Crop cover
Grass cover
Population density
WBI political stabiilty
Land cover diversity
Urbanization type
Forest cover
Temperature
Centrality
Crops diversity
Irrigation
Plantation cover
WBI government effectiveness
Shrub cover
Plants diversity
Precipitation
Mine sites density
Ports traveltime
Languages density
Protected areas
WBI rule of law
WBI regulatory quality
Dimension
Biological
Cultural
Demographic
Economic
Landcover
Physical
Political
Relative information (%)
D. Partial dependence plots
Flat relief
Cities traveltime
Cattle density
Anthropization century
Crop cover
Grass cover
Population density
WBI political stabiilty
Marginal effect
Variable values


SER
D. Historically used tropical areas with low potential for modern agriculture
SELS
D3. Highly populated and biodiverse historical semi-arid areas
A. Variables boxplots
value
Flat relief
Precipitation
Temperature
Plants diversity
Protected areas
Forest cover
Shrub cover
Grass cover
Crop cover
Plantation cover
Land cover diversity
Centrality
Cities traveltime
Ports traveltime
Crops diversity
Cattle density
Mine sites density
Irrigation
Population density
WBI government effectiveness
WBI political stabiilty
WBI rule of law
WBI regulatory quality
Languages density
B. SELS distribution map
C. Relative information plot
Shrub cover
Flat relief
Grass cover
Anthropization century
Population density
Forest cover
Irrigation
Plantation cover
Cattle density
Temperature
Plants diversity
Land cover diversity
Cities traveltime
Centrality
Precipitation
WBI regulatory quality
Urbanization type
Ports traveltime
Mine sites density
Crops diversity
Protected areas
WBI political stabiilty
Crop cover
WBI rule of law
WBI government effectiveness
Languages density
Dimension
Biological
Cultural
Demographic
Economic
Landcover
Physical
Political
Relative information (%)
D. Partial dependence plots
Shrub cover
Flat relief
Grass cover
Anthropization century
Population density
Forest cover
Irrigation
Plantation cover
Marginal effect
Variable values

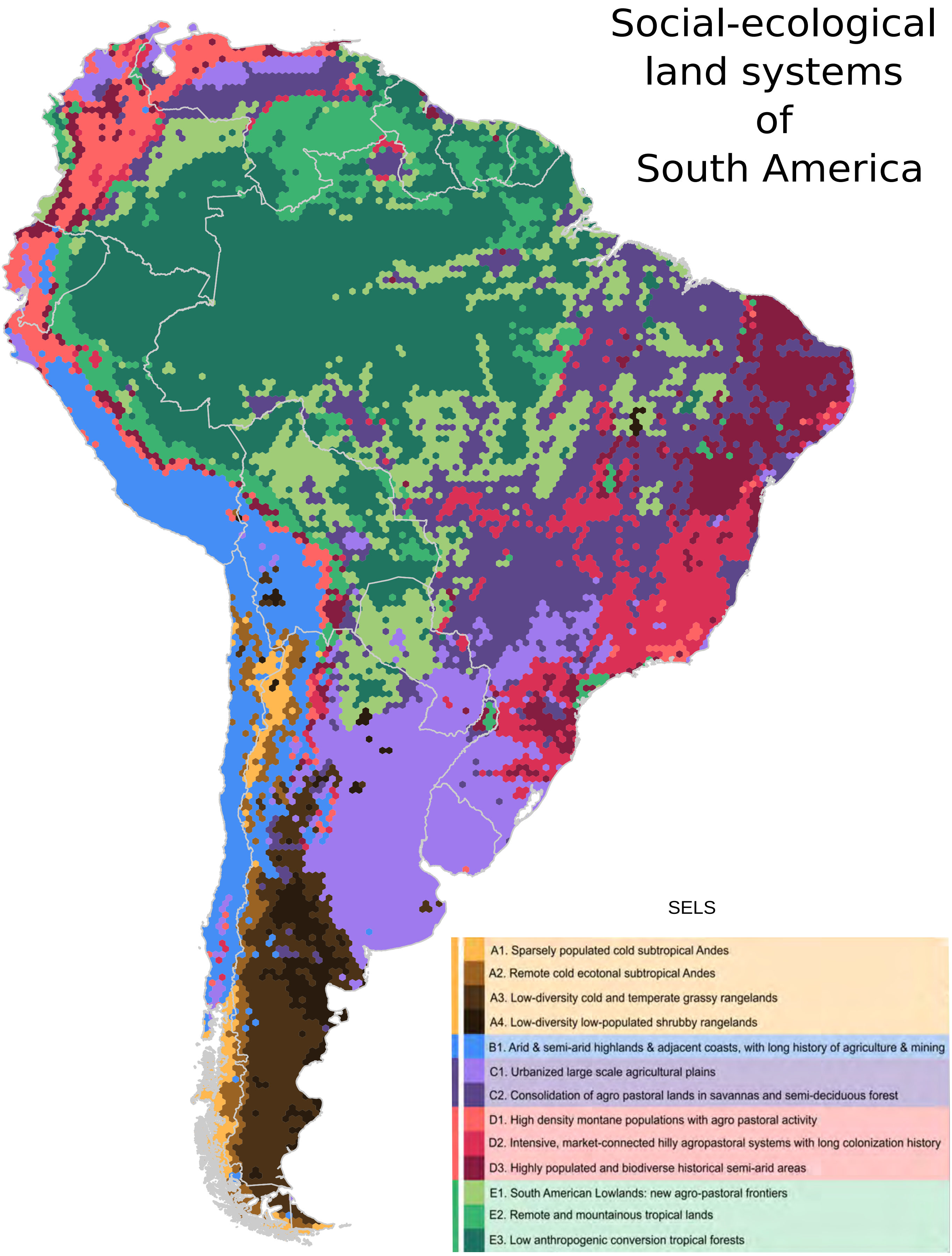

SER
E. Tropical forests with low anthropization
SELS
E1. South American Lowlands: new agro-pastoral frontiers
A. Variables boxplots
value
1.00
0.75
0.50
0.25
0.00
Flat relief
Precipitation
Temperature
Plants diversity
Protected areas
Forest cover
Shrub cover
Grass cover
Crop cover
Plantation cover
Land cover diversity
Centrality
Cities traveltime
Ports traveltime
Crops diversity
Cattle density
Mine sites density
Irrigation
Population density
WBI government effectiveness
WBI political stability
WBI rule of law
WBI regulatory quality
Languages density
B. SELS distribution map
C. Relative information plot
Forest cover
Cities traveltime
Temperature
Flat relief
Grass cover
Precipitation
Cattle density
Land cover diversity
Irrigation
Centrality
Anthropization century
Urbanization type
Ports traveltime
WBI government effectiveness
Population density
Protected areas
Plants diversity
Languages density
Plantation cover
Shrub cover
Crop cover
WBI rule of law
Crops diversity
WBI regulatory quality
Mine sites density
WBI political stability
0
10
20
Relative information (%)
Dimension
Biological
Cultural
Demographic
Economic
Landcover
Physical
Political
D. Partial dependence plots
Forest cover
Cities traveltime
Temperature
Flat relief
Grass cover
Precipitation
Cattle density
Land cover diversity
Marginal effect
Variable values


SER
E. Tropical forests with low anthropization
SELS
E2. Remote and mountainous tropical lands
A. Variables boxplots
value
1.00
0.75
0.50
0.25
0.00
Flat relief
Precipitation
Temperature
Plants diversity
Protected areas
Forest cover
Shrub cover
Grass cover
Crop cover
Plantation cover
Land cover diversity
Centrality
Cities traveltime
Ports traveltime
Crops diversity
Cattle density
Mine sites density
Irrigation
Population density
WBI government effectiveness
WBI political stability
WBI rule of law
WBI regulatory quality
Languages density
B. SELS distribution map
C. Relative information plot
Flat relief
Forest cover
Protected areas
WBI government effectiveness
WBI regulatory quality
Ports traveltime
Anthropization century
Irrigation
Temperature
Languages density
Precipitation
Cities traveltime
Centrality
Urbanization type
Crops diversity
Plants diversity
WBI rule of law
Land cover diversity
Cattle density
Population density
Grass cover
Mine sites density
Crop cover
Shrub cover
WBI political stabiilty
Plantation cover
0
10
20
30
40
Relative information (%)
Dimension
Biological
Cultural
Demographic
Economic
Landcover
Physical
Political
D. Partial dependence plots
Flat relief
Forest cover
Protected areas
WBI government effectiveness
WBI regulatory quality
Ports traveltime
Anthropization century
Irrigation
Marginal effect
1700 1800 1900 2000 wild
0.00 0.25 0.50 0.75 1.00
Variable values



SER
E. Tropical forests with low anthropization
SELS
E3. Tropical forests with low anthropogenic conversion
A. Variables boxplots
value
Flat relief
Precipitation
Temperature
Plants diversity
Protected areas
Forest cover
Shrub cover
Grass cover
Crop cover
Plantation cover
Land cover diversity
Centrality
Cities traveltime
Ports traveltime
Crops diversity
Cattle density
Mine sites density
Irrigation
Population density
WBI government effectiveness
WBI political stability
WBI rule of law
WBI regulatory quality
Languages density
B. SELS distribution map
C. Relative information plot
Forest cover
Flat relief
Cities traveltime
Centrality
Irrigation
Anthropization century
Protected areas
Precipitation
Plants diversity
Grass cover
Cattle density
Population density
Ports traveltime
WBI government effectiveness
Land cover diversity
Urbanization type
WBI rule of law
Languages density
Temperature
Crops diversity
WBI regulatory quality
WBI political stabiilty
Shrub cover
Plantation cover
Mine sites density
Crop cover
Dimension
Biological
Cultural
Demographic
Economic
Landcover
Physical
Political
Relative information (%)
D. Partial dependence plots
Forest cover
Flat relief
Cities traveltime
Centrality
Irrigation
Anthropization century
Protected areas
Precipitation
Marginal effect
1700 1800 1900 2000 wild
Variable values

Appendix 6. High resolution SELS map



Mapeando y caracterizando sistemas territoriales socio ecológicos de Sudamérica

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RESUMEN

Los humanos ejercemos una fuerte presión en el uso del suelo, y hemos modificado al rededor del 75% de la superficie terrestre del planeta. En ese contexto, ecorregiones y biomas, definidos meramente en base a sus propiedades biofísicas, son caracterizaciones incompletas del territorio. La ciencia de sistemas territoriales requiere un esquema de clasificación que incorpore ambas dimensiones, la biofísica y la social.

En este estudio, definimos tipologías espacialmente explícitas de sistemas territoriales socio-ecológicos (SELS por sus siglas en inglés) para Sudamérica, con una metodología híbrida que combina análisis automatizados de datos espaciales con evaluaciones basadas en el conocimiento por un grupo interdisciplinario de especialistas regionales. Nuestro enfoque hace una consideración holística de los sistemas territoriales socio-ecológicos, reuniendo un set de datos de 26 variables cubriendo un abanico de siete dimensiones: física, biológica, cobertura del suelo, económica, demográfica, política y cultural.

Identificamos trece SELS anidados en cinco regiones socio-ecológicas (SER) más abarcativas. Cada SELS fue discutido y descripto por grupos de especialistas específicos para esa región. Mientras cuatro variables ambientales, y una socio-económica explicaron la mayor parte de la distribución de la clasificación en los SER a escala gruesa, una variedad de 15 variables mostraron ser esenciales para definir varios de los SELS, resaltando características específicas que los distinguen.

La clasificación espacial de los SELS que presentamos aquí es una caracterización sistemática y operativa de los sistemas territoriales socio-ecológicos de Sudamérica. Proponemos que su uso puede contribuir como un marco de referencia espacial para un amplio rango de aplicaciones como analizar observaciones enmarcados en contextos más amplios, diseñar soluciones sistema-específica para el desarrollo sustentable, o estructurar el testeo de hipótesis y comparaciones a través del espacio.

INTRODUCCIÓN

A medida que los sistemas naturales (sistemas no afectados por actividades humanas) son cada vez menos abundantes en el planeta (Allan et al. 2017, Riggio et al. 2020), hay una creciente necesidad de analizar y entender el territorio a través de la lente de sistemas acoplados humano-naturaleza. Los humanos no somos meros habitantes de los ecosistemas, sino que influenciamos fuertemente los procesos ecológicos (Ellis y Ramankutty 2008, Maxwell et al. 2016). Biomas y ecorregiones son unidades geográficas muy útiles para representar patrones coherentes de características biofísicas. Sin embargo, para caracterizar la configuración actual de sistemas territoriales, que necesariamente involucran actividad humana (Verburg et al. 2009), necesitamos un esquema de clasificación que integre ambas dimensiones, la biofísica y la social.

Con una disponibilidad de datos creciente surgen nuevas oportunidades para investigación de síntesis de gran escala. Sin embargo, comparar descubrimientos de diferentes localidades y conectarlas con procesos globales o distantes son todavía un desafío (Rocha et al. 2020), en parte por la falta de marcos espaciales apropiados a grandes escalas para ubicarlos en contexto (Huemmerle et al. 2013). La ciencia de sistemas territoriales, como campo de investigación, está en rápido crecimiento y se están diversificando y consolidando abordajes metodológicos para cubrir este vacío (GLP 2016). Un ejemplo es el análisis de sindromes y arquetipos (Mayfroidt et al. 2018, Oberlack et al. 2019, Sietz et al. 2019), que analizan los sistemas socio-ecológicos a través de la identificación de patrones recurrentes de características y procesos de uso del suelo, y que han sido usadas para detectar la ocurrencia de determinados sistemas socio-ecológicos a través del territorio, como así también para generar clasificaciones de sistemas territoriales.

Muchos proyectos aplicaron la lógica de arquetipos para generar clasificaciones a gran escala de sistemas territoriales socio-ecológicos. Una de las primeras iniciativas por Ellis y Ramankutty (200) combinaron cobertura del suelo con irrigación y datos poblacionales para generar los *Biomas antropogénicos del mundo*. Esfuerzos subsiguientes incluyeron datos más detallados en actividades productivas. Letourneau et al. (2012) generaron el *mapa global de sistemas de uso del suelo*, van Asselen y Verburg (2012) produjeron una *representación a escala global de sistemas territoriales*, y Václavík et al. (2013) desarrollaron los *arquetipos globales de sistemas territoriales*. A una escala continental, Levers et al. (2018) analizaron *patrones arquetípicos y trayectorias de sistemas territoriales en Europa*.

Estos estudios cambiaron data de diferente naturaleza (por ejemplo cobertura del suelo, intensidad de uso del suelo, factores biofísicos) usando métodos de clasificación computarizada (por ejemplo procesos empíricos multi-nivel, agrupamiento jerárquico, mapas auto-organizantes). Para producir mapas de resolución espacial media (aproximadamente de 10 a 20 km). No obstante, las clasificaciones se centraron en el uso del suelo, particularmente identificando diferentes tipos de producción agropecuaria. En la mayoría de los casos se usó información sobre las características de las comunidades sociales fue representada sólo a través de densidad de población o accesibilidad (distancia a ciudades), como indicadores de intensidad de uso del suelo. Factores políticos, ambientales y socio-económicos fueron usados en algunos casos *a posteriori* para describir las clases, pero no para generarlas. La cultura y gobernanza son importantes para reflejar el comportamiento complejo de agentes influenciando el paisaje (Lambin et al. 2001, Verburg et al. 2009, Rounsevell et al. 2012) y son muy difíciles de incluir en modelos globales (Václavík et al. 2013). Los *arquetipos globales de sistemas territoriales* es el más abarcador de estos proyectos. Produjeron una clasificación exhaustiva que consideró varias variables físicas, actividad fotosintética (NDVI), producto bruto interno (GDP) y estabilidad política.

Clasificaciones a escala global son ideales para representar patrones generales a través del mundo, pero se quedan cortas para entender los sistemas territoriales a escalas local o regional. Por ejemplo, la clasificación de Václavík y colaboradores (2013) agrupó aproximadamente la mitad del continente Sudamericano (12.000 km^2) como la misma clase: “forest systems in the tropics”. Trabajar a escalas espaciales más finas permite más detalle en la descripción de las clases, la inclusión de variables de relevancia regional, trabajar con un rango de valores específico, y mayor probabilidad de encontrar sets de datos completos y coherentes para variables específicas, como por ejemplo las culturales y políticas.

América del Sur tiene características particulares que justifican tener un esquema de clasificación específico para el continente que mejore el entendimiento dentro y entre sistemas territoriales locales. Por ejemplo una baja densidad poblacional, con más del 80% de la población concentrada en áreas urbanas; una historia de uso del suelo influenciada fuertemente por grupos sociales en regiones del altura, seguida por un período de colonización Europea altamente transformador, incluyendo el reemplazo masivo de herbívoros salvajes por ganado; numerosas comunidades indígenas con un legado cultural diverso; economía y producción agrícola orientada hacia la exportación y vinculada a una de las tasas de deforestación más altas del mundo.

En un primer esfuerzo por integrar conocimiento socio-ecológico en la caracterización de sistemas territoriales para Latinoamérica, Boillat y colaboradores (2017) propusieron “tipologías simplificadas a nivel bioma de sistemas territoriales socio-ecológicos (SELS por sus siglas en inglés)”. Describieron siete SELS basados en datos biofísicos, económicos, organización urbana, instituciones, tecnología, legados históricos y potenciales tendencias futuras. No obstante, estas tipologías fueron basadas exclusivamente en conocimiento de expertos y carece de un mapa que los conecte con una representación espacial específica, lo que limita su uso y aplicación.

En este trabajo, hacemos operativo el concepto de SELS con una clasificación espacial sistemática y precisa para Sudamérica. Nuestro objetivo principal era contribuir al desarrollo de un marco de referencia espacial para facilitar la contextualización de la discusión de resultados y estudios en ciencias de sistemas territoriales y planeamiento territorial. Específicamente, (1) creamos un mapa de tipologías de SELS para Sudamérica, (2) analizamos las variables clave que diferenciaron las tipologías, y (3) describimos y discutimos el mapa de SELS resultante en cuanto a la representación de nuestro conocimiento territorial y adecuación a las descripciones conceptuales de los SELS en el trabajo de Boillat y colaboradores (2017). Adicionalmente, resaltamos vacíos de datos clave que permitirían profundizar más en caracterizaciones de este tipo.

MÉTODOS

Generamos una clasificación de Sudamérica en tipologías generales de sistemas territoriales socio-ecológicos mediante el análisis de patrones espaciales de diversas características a lo largo de un espacio multidimensional, identificando áreas con perfiles similares (Meyfroidt et al. 2018, Sietz et al. 2019). Nuestro objetivo de investigación puede no tener una única solución correcta, por lo que priorizamos un mayor valor de aplicación dando prevalencia a la experiencia colectiva de investigadores trabajando en la región.

Diseñamos una metodología híbrida combinando técnicas de aprendizaje computarizado para analizar un set de datos espaciales social y ambiental, con una evaluación basada en el conocimiento por un grupo interdisciplinario de especialistas regionales (autores). El análisis espacial computarizado permite replicabilidad y detalle espacial, mientras que la perspectiva basada en conocimiento contribuye con una criterio colectivo mejorado para tomar decisiones en el diseño del análisis como en la interpretación de los resultados. Decidimos no confiar exclusivamente en los análisis de datos automatizados ya que reconocemos que hay limitaciones en los datos (por ejemplo el uso de proxies para cubrir vacíos de información, ver la sección *Limitaciones metodológicas*), que impactaban de manera diferencial sobre los tipos de variables, afectando en mayor medida a los aspectos sociales que a los biofísicos. Bajo este escenario, las soluciones matemáticamente óptimas pueden no siempre ser las más significativas temáticamente. Por lo tanto, aplicamos el conocimiento de experto para favorecer una coherencia de los clusters con el conocimiento territorial, tomando decisiones subjetivas sobre la evidencia aportada por los resultados de los análisis. El potencial sesgo de estas decisiones subjetivas fue minimizado a través de la diversificación de perfiles del grupo de especialistas regionales.

Los especialistas regionales estuvieron involucrados a lo largo de los 22 meses de duración del estudio. Tuvimos tres instancias de encuestas individuales sobre las variables a considerar y resultados parciales, un taller presencial durante el congreso GLP Open Science Meeting en abril de 2019, una instancia de trabajo en subgrupos específicos para discutir cada uno de los SELS en profundidad, y finalmente la revisión integral del manuscrito. El grupo de especialistas consistió en 21 investigadores de diferentes perfiles, filiaciones, disciplinas, perfil técnico, género y nacionalidades, con una extensa experiencia local y regional, cubriendo la diversidad territorial y geográfica de Sudamérica. Muchos de ellos fueron autores de la publicación de Boillat et al. (2017). Los perfiles disciplinares representados en nuestro grupo incluyen ecología, etnobiología, geografía, agronomía, ecología económica, antropología y forestal.

Seguimos un proceso iterativo (Figura A1.1) que incluyó: (1) definir las variables relevantes y la escala de análisis, (2) generar los mapas e identificar las principales variables explicativas, (3) discutir los productos del análisis y describir los SELS resultantes. Los detalles de cada paso metodológico están documentados exhaustivamente en el Apéndice 1 a lo largo de sus cuatro secciones: *Variables, Bases de datos, Análisis de agrupamiento* y *Resultados del agrupamiento*.

Marco conceptual y selección de variables

De acuerdo a la definición de Boillat et al. (2017), entendemos a los SELS como sistemas complejos, dinámicos y anidados, que se desarrollaron con los humanos como el principal agente de cambio, pero que dependen de las características y oportunidades ecológicas subyacentes. Cada SELS es definido por su configuración particular de condiciones sociales y ambientales, patrones de urbanización, dinámicas de uso del suelo y factores de contexto. Para guiar el proceso de selección de variables tomamos como referencia las características de las tipologías de SELS a nivel bioma enunciadas en la Tabla 1 de Boillat et al. (2017; a los que nos referiremos como SELS conceptuales). En el proceso de operativizar las definiciones teóricas nosotros (1) desviamos el foco de patrones de cambio de uso del suelo hacia las condiciones estáticas que los reflejarían, (2) estructuramos las descripciones organizándolas según la clasificación de componentes para la investigación de sistemas socio-ecológicos (Winkler et al 2018), y (3) descartamos y agregamos variables en base a la disponibilidad de sets de datos apropiados y teniendo en cuenta el balance de representación de las diferentes aristas de los sistemas socio-ecológicos (Tabla A1.1).

Para ser incluido en nuestro análisis requerimos que todos los sets de datos cubran la totalidad de la superficie continental (dejando fuera a las islas) con una metodología consistente y una resolución espacial menor al tamaño de nuestra grilla de celdas (con excepción de los *indicadores de gobernanza* a escala nacional, y la *diversidad de plantas* con una resolución de 110 km), y de preferencia representativos del año 2010 (o lo más cercano disponible). Finalmente el set de datos que utilizamos para los análisis (Tabla 1) consistió en 26 variables, organizadas en siete dimensiones (variables por dimensión: 3 físicas, 2 biológicas, 6 de paisaje, 7 económicas, 2 demográficas, 4 políticas y 2 culturales), 11 de las cuales correspondieron al dominio ambiental y 15 al dominio socio-económico.

Tabla 1. Set de datos considerados.

Variable	Medición	Resolución	Año
Físicas:			
Relieve llano †	percent non-mountain cover	250m	-
Temperatura †	median of mean annual temperature ‡	1km	1981-2010
Precipitación †	median of mean annual rainfall ‡	1km	1981-2010
Biológicas:			
Diversidad de plantas	vascular plant species richness ‡	110km	-
Áreas protegidas	percent of PA	polygons	2019
Cobertura del suelo:			
Bosque	percent cover	250m	2001 - 2014
Arbustales	percent cover	250m	2001 - 2014
Pastizales	percent cover	250m	2001 - 2014
Cultivos	percent cover	250m	2001 - 2014
Plantaciones	percent cover	250m	2001 - 2014
Diversidad de cobertura	diversity index of 9 land cover classes ‡	250m	2001 - 2014
Económicas:			
Centralidad	national centrality index ‡§	1km	2012
Densidad de ganado	density of cattle production ‡	1km	2010
Densidad de minas	number of mining sites ‡§	point data	2011
Diversidad de cultivos	diversity index of 175 crops areas ‡	10km	2000
Irrigación †	percent area equipped for irrigation ‡	polygons	2005
Tiempo de viaje a ciudades †	mean travel time to the nearest city ‡	250m	2000
Tiempo de viaje a puertos †	mean travel time to the nearest port ‡	250m	2018
Demográficas:			
Densidad poblacional	mean environmental population ‡§	2.5 arc-minutes	2012
Tipo de urbanización	category of biggest city in 100km buffer	point data	2000
Políticas:			
WBI efectividad de gob †	government effectiveness ‡|	country	2015
WBI estabilidad política†	political stability, absence of violence ‡|	country	2015
WBI aplicación de la ley †	rule of Law ‡|	country	2015
WBI calidad de regulación †	regulatory quality ‡|	country	2015
Cultural:			
Densidad de idiomas	number of languages in 100km buffer ‡	polygons	2007
Siglo de antropización	century reaching 30% anthropic land cover	1km	1700-2000

Variables con un † fueron incorporadas durante el presente estudio en relación a Boillat et al. (2017)
Transformaciones de datos: ‡ = min-max standardización, § = log transformación y |= peso menor (0.25)

Nuestro set de datos incluyó datos tanto cuantitativos como cualitativos, ya que dos de nuestras variables estaban representadas por datos categóricos: *Tipo de urbanización* y *Siglo de antropización*.

Análisis de agrupamiento espacial

Nuestro diseño de análisis estuvo fuertemente marcado por dos características de nuestro set de datos: tenemos datos mixtos categóricos y cuantitativos, y la mayoría de nuestras variables no presentaron una distribución normal (Figura A1.3). Para mapear los SELS usamos el enfoque de agrupamiento jerárquico, que es ampliamente usada para identificación espacial de tipologías socio-ecológicas (FAO 2011, Letourneau et al. 2012, van Asselen y Verburg 2012, Václavík et al. 2013, Sietz et al. 2019, Rocha et al. 2020). Para ello (1) dividimos la superficie de Sudamérica en un grillado continuo de celdas hexagonales de 40 km de lado a lado (área ~1400 km^2, n=13.287), (2) agregamos las variables a nivel de hexágono, que luego utilizamos para (3) calcular las distancias estadísticas entre cada par de hexágonos a lo largo del espacio multidimensional, y finalmente (4) corrimos un análisis de agrupamiento jerárquico divisivo (DIANA, Kaufman y Rousseeuw 1990) para agrupar hexágonos en grupos de acuerdo a la similitud de sus características.

Las distancias estadísticas o (dis)similitudes fueron calculadas mediante el método de distancias de Gower (Gower 1071), ya que es el algoritmo de preferencia para agrupamientos con datos mixtos (Gower 1971, Kaufman y Rousseeuw 1990, Kassambara 2017, Boehmke y Greenwell 2019) y es menos sensible a outliers y distribución de datos no normal que otros métodos populares como el Euclideano (Kassambara 2017, Boehmke y Greenwell 2019). Si embargo, aplicamos transformación logarítmica a aquellas variables que presentaron una distribución fuertemente exponencial (ver Tabla 1), y estandarizamos todas las variables para ajustar sus valores a un rango 0-1 para mitigar potenciales efectos derivados de la distribución de valores de los datos.

El agrupamiento jerárquico divisivo (DIANA) es un método de análisis no supervisado que genera dendrogramas, una organización jerárquica de grupos partiendo desde su raíz (todos las hexágonos en un mismo cluster) e iterativamente va dividiendo un grupo en dos hasta que todos los hexágonos constituyen su propio cluster (Maechler et al. 2019). En cada iteración el grupo más heterogéneo (el que contiene el valor de disimilitud más grande entre cualquier par de hexágonos) es dividido en dos nuevos grupos, donde el “grupo particional” es iniciado a partir del hexágono más dispar (mayor disimilitud promedio).

La mayoría de los métodos confeccionan sus grupos a partir de los nodos terminales (hojas), seleccionando el hexágono inicial al azar y considerando sólo los patrones locales o vecinos más próximos para informar las divisiones. En cambio, DIANA, al iniciar a partir de la raíz del árbol, toma en consideración la distribución completa de todos los hexágonos para las divisiones iniciales, ganando precisión y favoreciendo la captura de la estructura principal de los datos priorizando la coherencia de los grandes grupos por sobre la pureza de los grupos pequeños (Kaufman y Rousseuw 1990, Kassambara 2017, Boehmke y Greenwell 2019).

Consideramos los resultados del agrupamiento en dos niveles de detalle espacial anidados (1er nivel corresponde a las Regiones Socio-Ecológicas -SER- y el 2do nivel a los Sistemas Territoriales Socio-Ecológicos -SELS-) ya que los diferentes niveles aportan información complementaria y mejoran la robustez del análisis (Sietz et al. 2017, 2019, Vallejos et al. 2020). Los autores analizamos los productos del agrupamiento (distribución espacial, estadísticas de los grupos, y métricas de desempeño del método) en cortes sucesivos del dendrograma (árbol) en relación a su conocimiento territorial para acordar en el número óptimo de grupos. Para más detalles referirse al Apéndice 1.

Para analizar cuáles de las variables aportaron más información al agrupamiento utilizamos árboles de regresión potenciados (boosted regression tres, BRTs, Elith et al. 2008) sobre el producto del agrupamiento. Los BRT son una técnica de regresión-clasificación en la órbita del aprendizaje computarizado donde se entrena un modelo para relacionar una respuesta a las variables predictoras mediante divisiones binarias iterativas, donde la contribución relativa de las variables puede medirse como el número promedio de veces que esa variable se elige para las divisiones del árbol. Para poder examinar fluctuaciones en la relevancia de variables entre los diferentes grupos, este análisis se repitió varias veces, con diferentes grupos objetivo: dos análisis multi-nominales con el objetivo de diferenciar todos los grupos simultáneamente en la clasificación de SER y SELS, más *n* análisis binarios específicos, donde en cada uno el objetivo fue diferenciar un SELS particular del resto de los SELS como un todo unificado (*n*= número de grupos en la clasificación SELS). Para más especificaciones sobre los modelos y sus parámetros referirse al Box A1.1.

Lejos de ser unidades homogéneas, los grupos incluyen cierta heterogeneidad interna. Para identificar variaciones geográficas en la representatividad de los grupos evaluamos la heterogeneidad interna de los grupos (mediante la disimilitud promedio de los hexágonos que los componen) y generamos un mapa que representa zonas de mayor representatividad y zonas de representatividad marginal). Proponemos esta métrica como un indicador de la variación espacial de la incertidumbre en la clasificación. El nivel de incertidumbre para cada hexágono fue calculado como el promedio de los valores de disimilitud entre ese hexágono y todos los otros pertenecientes a su mismo SELS. Mayor disimilitud indica un mayor desvío de ese hexágono en relación a las características promedio del SELS al que pertenece.

Todos los análisis se realizaron en el programa R 3.6.1 (R Core Team, 2019). Para el agrupamiento utilizamos la función *daisy* (cálculo de distancias estadísticas) y la función *diana* (agrupamiento) del paquete *cluster* (Maechler et al. 2019). Los árboles de regresión fueron calculados con la función *gbm* (modelos multinomiales) del paquete *gbm* (Greenwell et al. 2019) y la función *gbm.step* (modelos binarios) del paquete *dismo* (Hijmans et al. 2017).

Interpretación de los SELS

Para garantizar una interpretación profunda de los SELS, los autores de este trabajo se organizaron en paneles de entre cuatro y siete especialistas regionales específicos para cada SELS. Los paneles discutieron meticulosamente la consistencia entre los SELS y su conocimiento territorial, describieron las características de ese sistema territorial socio-ecológico, propusieron un nombre y evaluaron su alineamiento con los SELS conceptuales.

RESULTADOS

Nuestra clasificación dividió al continente en cinco tipologías a escala gruesa, las Regiones Socio-Ecológicas (SER), que reflejaron los biomas principales y usos del suelo dominantes (Figura 1A). Anidadas en los SER, identificamos 13 Sistemas Territoriales Socio-Ecológicos (SELS), cada uno con características distintivas que representan propiedades más específicas de sus territorios (Figura 1B). La incertidumbre en la clasificación de los SELS fue más baja en las porciones centrales y llanas del continente que en las costas y zonas aledañas (incluyendo la Cordillera de los Andes) (Apéndice 2). Algunas regiones con mayor incertidumbre incluyeron: la ladera este de la porción Norte de los Andes, la costa este de Venezuela, la porción central de las Guayanas y las regiones de los extremos norte y sur de la costa brasilera.

Influencia de las variables en la clasificación de SELS

Las variables más relevantes para caracterizar las clases variaron dependiendo de la escala de análisis. Las variables relevantes para separar las cinco SER fueron un subset de aquellas relevantes para separar los trece SELS (Figura 2), lo que indica que la diversidad de variables facilitó la especificidad de la clasificación de SELS. Esto fue incluso más evidente cuando analizamos las variables más relevantes para diferenciar cada SELS individual del resto (Tabla A3.1). Muchas variables que

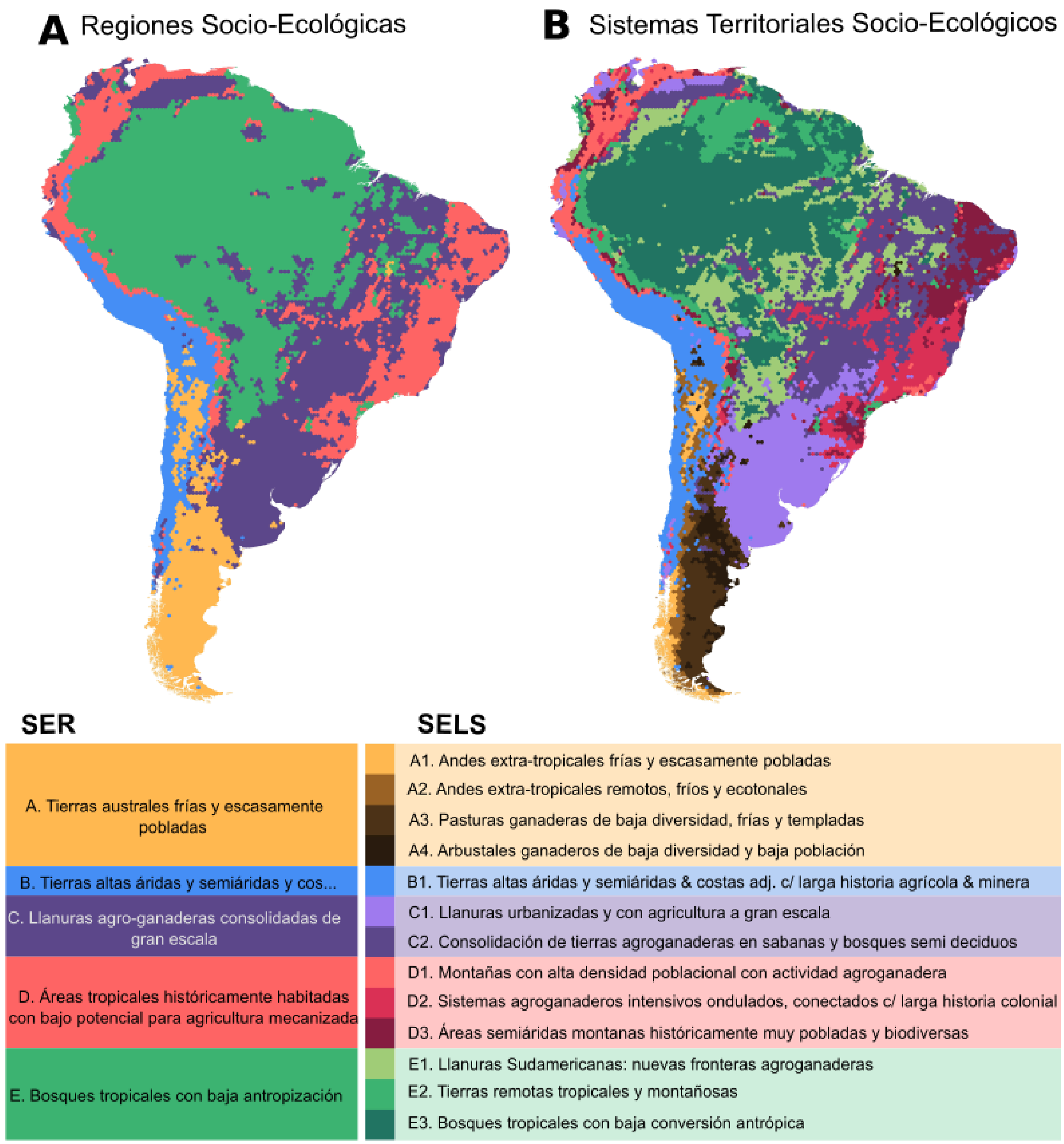

Figure 1. Mapa de las Regiones Socio-Ecológicas (A) y Sistemas Territoriales Socio-Ecológicos (B) de Sudamérica. El mapa representa la distribución espacial de las clases descriptas en la sección 3.2. En el material suplementario encontrarán una versión del mapa en alta resolución.

mostraron muy baja influencia sobre la clasificación general de SER, resultaron entre las variables más informativas para definir algunos SELS individuales.

Las cinco variables más relevantes en definir la clasificación fueron compartidas por ambos niveles SER y SELS: *cobertura de bosque, porcentaje de tierras planas, diversidad de plantas, tiempo de viaje a ciudades* y *temperatura* – sumando un 70.60% (SER) y un 65.58% (SELS) de la varianza explicada

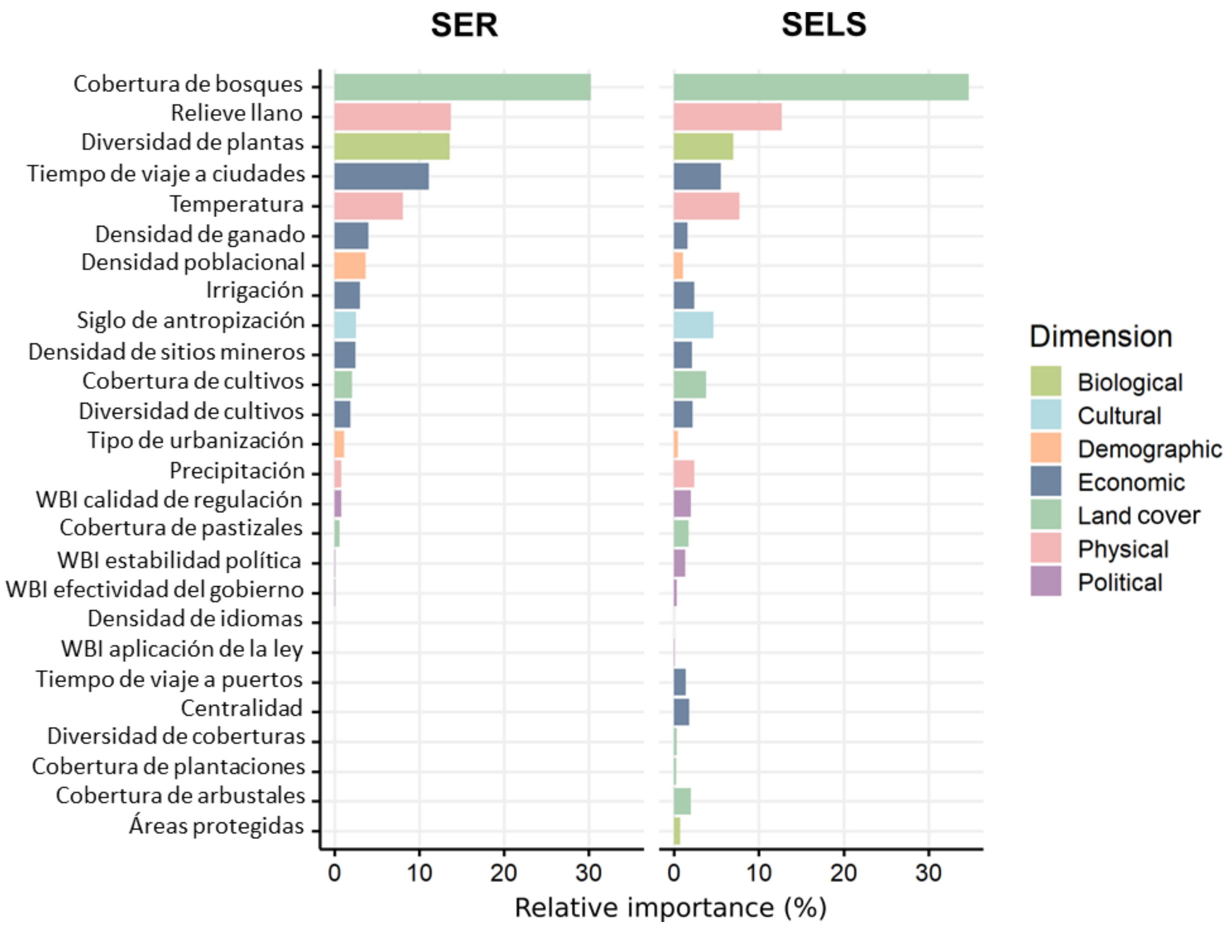

Figura 2. Gráficos de importancia relativa para los SER (izquierda) y SELS (derecha). Los valores indican el porcentaje de la contribución de las variables para cada uno de los dos modelos de clasificación generados a través de árboles de regresión independientes. Los colores de las barras indican a qué dimensión pertenecen las variables.

de la distribución de los clusters (Figura 2). La cobertura de bosque fue dominante, representando aproximadamente un tercio de la varianza explicada, más del doble que la segunda variable en el ranking en ambos niveles de clasificación. Las diferencias aparecieron entre la quinta y décima posición en el ranking de contribución de información relativa: el modelo SER se basó más en *densidad de población* y *ganado*, mientras que el modelo SELS en *cobertura de cultivos* y *siglo de antropización* (Figura 2). Excepto por la dimensión política, las otras seis dimensiones estuvieron representadas entre las 10 variables más relevantes en ambos niveles (modelos SER y SELS). Sin embargo, hubo un cambio de dominancia con más variables ambientales ocupando las posiciones más altas del ranking y más variables socio-económicas hacia la porción central.

En el otro extremo del ranking de importancia relativa, cinco variables rankearon en posición 6 o menor en todos los 15 modelos que examinamos (Tabla A3.1): *Cobertura de plantaciones, diversidad de coberturas del suelo, Indicador del Banco Mundial Acatamiento de la ley, Tipo de urbanización y Diversidad de idiomas.*

Tipologías de sistemas territoriales socio-ecológicos de Sudamérica

En esta sección describimos las cinco tipologías al nivel de SER. Debido a limitaciones de espacio, las descripciones de los trece SELS y los gráficos diagnósticos asociados están en el Apéndice 4 y 5, respectivamente.

SER A. Tierras australes, frías y escasamente pobladas

Incluye ecosistemas boscosos y no boscosos, que a pesar de esta diferencia ecológica clave (provocada principalmente por diferencias en la humedad) comparten importantes características socio-ecológicas: (1) clima cálido asociado a ciclos biogeoquímicos lentos (reflejado por ejemplo en la existencia de turberas conocidas como “mallines” y “bofedales”), (2) relativamente bajos niveles de diversidad biológica, pero altos niveles de endemismo asociados con su historia biogeográfica, (3) bajo potencial para el cultivo fuera de los valles fluviales, (4) baja población humana y áreas muy extensas sin población, (5) ganadería extensiva de animales chicos (cabras y ovejas) y ganado bovino, frecuentemente en declive, (6) actividad minera muy extendida en la zona (con frecuencia sub desarrollada), típicamente asociada con la industria energética (gas, aceite, carbón, litio), (7) creciente importancia del turismo, (8) áreas protegidas extensas, y ocurrencia de procesos espontáneos de recuperación de la fauna nativa (por ejemplo guanacos en la Patagonia, vicuñas en la Puna y sus predadores asociados). Los sectores de bosque templados se caracterizan por una biota muy distintiva que deriva de linajes Gonduánicos con alto nivel de endemismo, en parte amenazadas por la expansión de especies invasoras exóticas (por ejemplo castores, ciervos, pinos, muchas especies de plantas ornamentales). Este SER incluye cuatro SELS, detallados en la Tabla 2.

SER B. Tierras altas áridas y semiáridas y costas adyacentes, con una larga historia agrícola y minera.

Corresponde a los Andes centrales de Perú, Bolivia, Chile y Argentina, los valles secos inter-Andinos de Ecuador, las costas áridas del Pacífico de Perú y Chile, y los Andes mediterráneos. Se caracteriza por una geomorfología irregular, amplio rango altitudinal, gran diversidad climática (en general seco y templado), una antigua historia de ocupación humana y relativamente alta densidad poblacional (incluyendo algunas grandes ciudades). Como un área costera está ampliamente influenciada por la economía de comercio transoceánico. Debido a las condiciones climáticas, la agricultura está limitada a las zonas irrigadas en valles y costas, o cultivos estacionales de secano en las tierras altas. Con alta diversidad biológica y cultural, este SER lidera el ranking de diversidad de cultivos, pero también en densidad minera. Este SER incluye un sólo SELS, detallado en el Apéndice 4.

SER C. Llanuras agro-ganaderas consolidadas de gran escala

Corresponde a llanuras y tierras de baja resistencia al rodaje con suelos mayormente fértiles dominados por paisajes productivos principalmente en Argentina, Uruguay, Brasil, Paraguay y, en un bloue separado, Venezuela y Colombia, pero también incluye parches más pequeños dentro del Amazonas. Este SER incluye las mayores y más productivas áreas de producción y exportación de granos y carnes del continente, como también algunas de las ciudades más grandes y la infraestructura de transporte y exportación de *commodities*. La biodiversidad fluctúa pero es mediana in la mayor parte de la región, con muy pocas áreas protegidas. El área incluye ecorregiones naturales de vegetación abierta, como las Pampas y Campos de pastizal, pero también sectores de bosques tropicales y subtropicales como el Amazonas, Chaco y el Espinal. Aquellos sectores embebidos en el bosque están representados por conglomerados de agricultura consolidada comúnmente desarrolladas en torno a centros urbanos de mediano tamaño, o caminos principales que facilitan su conexión a las principales ciudades y puntos de exportación. Una gran fracción de los *commodities* agrícolas exportado por el continente se originan en el área cubierta por este SER. Este SER incluye dos SELS, detallados en el Apéndice 4.

SER D. Áreas tropicales históricamente habitadas con bajo potencial para agricultura mecanizada

Incluye la región sud-este de Brasil, regiones montañosas de Colombia y Ecuador, y una angosta franja a lo largo de las laderas orientales de los Andes tropicales (ambos, húmedos y secos). En general, estas áreas han sido las bases de la ocupación prehispánica y etapas tempranas de la colonia. La densidad poblacional continúa siendo alta, sin embargo, su área agrícola se convirtió en marginal comparativamente, ya que tienen baja aptitud para la expansión de la agricultura mecanizada moderna debido a las pronunciadas pendientes, accesibilidad limitada, suelos comparativamente pobres o degradados, condiciones climáticas con frecuencia subóptima y una tenencia de la tierra caracterizada por alta fragmentación y parcelas pequeñas. La región presenta una alta diversidad biológica y endemismos. En fuerte asociación con la topografía escarpada, muchas áreas experimentan recuperación de bosques. Los SELS incluidos en este SER incluyen un gradiente de accesibilidad a puertos, con el SELS D2 (Sudeste Brasilero) siendo el más conectado y, en consecuencia, el más desarrollado económicamente con las ciudades más grandes. Este SER incluye tres SELS, detallados en el Apéndice 4.

SER E. Bosques tropicales con baja antropización

Incluye el bioma amazónico completo, extendido hacia el sur sobre Bolivia, el oeste Paraguayo y el norte Argentino. Corresponde a paisajes llanos y ondulados dominados por bosque natural con alta biodiversidad y un enorme stock de biomasa. Se extiende sobre climas cálidos y húmedos, con suelos mayormente ácidos y pobres, incluyendo un gradiente de transformación humana que abarca bosques relativamente inalterados (SELS E3), transición a zonas con fronteras de deforestación activa (SELS E1) y áreas con alta fracción de áreas protegidas (SELS E2). Una historia dinámica de expansión agrícola sobre llanuras y terrenos ondulados del continente sugiere que, en el futuro, la zona de contacto entre este SER y el SER C van a experimentar desplazamientos, y zonas con características del SER C pueden expandirse sobre áreas actualmente clasificadas como E. Este SER incluye tres SELS, detallados en el Apéndice 4.

DISCUSIÓN

Maneras innovadoras para utilizar los datos y métodos que mejoren nuestro entendimiento de los sistemas territoriales están entre las innovaciones destacadas necesarias para avanzar áreas temáticas de investigación claves en la ciencia de sistemas territoriales (GLP 2016), especialmente al combinar ciencias sociales y naturales, como así también datos cualitativos y cuantitativos (Rounsevelle et al. 2012). Nuestro enfoque de SELS mejora la comprensión de características, extensión y ubicación de interacciones humano-natural operando a escalas regionales en Sudamérica, moldeados a lo largo de siglos de intervención humana en el ambiente. Como tal, nuestro enfoque ofrece conocimientos nuevos sobre el Antropoceno, como así también, un marco geográfico transferible que facilita contextualizar la investigación en ciencias territoriales.

Relevancia de variables en definir los SELS

Ambos niveles de clasificación (SER y SELS) se basaron en las mismas cinco variables principales según su poder explicativo sobre los patrones de SELS. Unas pocas variables concentraron la mayor parte de la información relativa de la clasificación, especialmente para la clasificación en tipologías más gruesas, SER. Sin embargo, es a escalas más chicas/detalladas cuando vemos la contribución real de incorporar un set de variables más extenso y deversificado, que resalta las características individuales que diferencian las tipologías de SELS. Por ejemplo, la variable siglo de antropización fue clave para diferenciar los SELS pertenecientes al SER D, distinguiendo las áreas con historia de uso más larga (SELS D1 and D3) de las de ocupación más reciente (SELS D2); densidad de sitios mineros fue la segunda variable más relevante para el SER B; la cobertura de arbustales fue la variable más relevante para los SELS D3 y D4 (Tabla A3.1 y Apéndice 5).

Muchas de las variables más relevantes para la clasificación (por ejemplo *cobertura de bosque, relieve llano, diversidad de plantas, temperatura*) correspondieron al dominio de lo natural. Por lo tanto nuestros resultados sugieren que, similar a un esquema de clasificación de biomas y ecorregiones, las características físicas y biológicas a esa escala continúan prevaleciendo sin importar el impacto humano. Esto sugiere que tienen el poder de determinar, o poner límites a las posibilidades de establecimiento de ciertas actividades socio-económicas.

La variable más relevante en definir la distribución de los SELS fue *cobertura de bosques* (que acaparó un tercio de la varianza explicada). Tanta relevancia es razonable considerando que los bosques ocupan una gran área del continente con una distribución desigual (FAO and UNEP 2020), y que la *cobertura de bosques* es una variable compleja y sintética. Resume la combinación de variables físicas como *altitud, precipitación* y *temperatura*, pero también informa indirectamente sobre la historia antrópica y el uso del suelo. Por ejemplo, en casos donde las condiciones físicas son apropiadas para bosques, su ausencia en ciertas áreas divide una región físicamente homogénea entre deforestada y bosque no convertido.

La segunda variable más relevante fue el relieve, aquí representado como porcentaje de terreno llano, no sólo para los modelos multinomiales generales SER y SELS, sino que también estuvo entre las cinco variables más relevantes en nueve de los trece SELS (Tabla A3.1). La topografía es una de las diferencias más relevantes entre los tipos de uso del suelo actuales y potenciales en Sudamérica, ya que determina en gran medida la aptitud para agricultura mecanizada. En nuestros análisis, la diferenciación entre montañas *versus* planicies fue crítica y probablemente sostiene múltiples propiedades biofísicas y socio-económicas. La tercera variable explicatoria más relevante fue *diversidad de plantas* que, al igual que *cobertura de bosques*, resume aspectos preponderantes de las condiciones climáticas y disponibilidad de recursos (Kreft and Jetz 2007). lo que con frecuencia se asume como la variable organizativa más importante para la diversidad biológica en el continente. La cuarta fue *tiempo de distancia a ciudades*, la única variable socio-económica en el top cinco en el ranking de relevancia. La presencia de ciudades grandes incluye dos propiedades geográficas interconectadas. Por un lado, representan acceso a infraestructura y oportunidades económicas, generando una suerte de poder gravitatorio sobre las actividades humanas (Lambin et al. 2001, Grimm et al. 2008). Por otro lado, la mayor parte de las ciudades fueron fundadas siglos atrás estratégicamente para servir a la Sudamérica colonial (por ejemplo el conflicto bélico con pueblos indígenas y trasportar productos a Europa) y la persistencia de su ubicación pueden haber influenciado la distribución de usos del suelo antrópicos en el presente. La quinta fue temperatura, lo que no representa una sorpresa considerando el amplio rango de temperaturas en el continente (temperatura del aire promedio entre 6 y 24° Celsius, Collins et al. 2009), variando principalmente con la latitud y altitud.

Precipitación, que es asumida frecuentemente como una de las variables más relevantes en determinar la diversidad biofísica en el continente apareció en el puesto 14 del ranking, en lugar de destacarse entre las principales variables físicas como relieve y temperatura. Sin embargo, sí ocurrió en el top cinco de aquellos SELS particularmente relacionados al clima árido (A1, A2, A3 y B).

La *densidad de ganado* fue una variable vinculada a lo humano importante, más aún que la cobertura de cultivos. El ganado está entre los principales herbívoros en el mundo, y su relevancia es desproporcionalmente alta en Sudamérica (Bar-On et al. 2018). Tres de los cinco países en el mundo con mayor proporción entre ganado y personas ocurren en esta región (Argentina, Brasil y Uruguay; FAOSTATS). La *densidad de ganado* permite caracterizar tanto la producción intensiva (por ejemplo, sistemas intensivos que compiten con cultivos en las Pampas o el Cerrado) pero también para discriminar entre regiones no agrícolas, ya que la producción de ganadería extensiva caracteriza los sistemas mésicos que no son tan secos (donde las ovejas y cabras dominan la herbivoría) y no tan húmedos como la selva lluviosa amazónica donde el ganado no ocurre fuera de áreas deforestadas (Seo et al. 2010).

La dimensión política tuvo en general una influencia baja a intermedia en caracterizar a los SELS, posiblemente debido a su resolución espacial tan burda (nivel de países) de los datos. Sin embargo, algunos aspectos políticos fueron relevantes en localidades particulares (por ejemplo, *calidad de regulación* fue la segunda variable más relevante en separar los SELS A1). El bajo impacto de la densidad de idiomas en la clasificación de SELS fue notable, y contraria a las expectativas de los especialistas y la literatura (Maffi 2005, Gorenflo et al 2012). Es posible que la unidad de medida que empleamos (número de idiomas que se hablan dentro de un radio de 100 km) puede haber sido poco apropiada, aunque difícil de contrastar debido a la ausencia de referencias guía de otras publicaciones. Animamos a trabajos futuros a examinar más en profundidad esta preocupación y buscar variables alternativas para reflejar la diversidad cultural.

En la década pasada ocurrió una clara evolución en la clasificación de sistemas territoriales hacia la incorporación de la complejidad de las interacciones humana-natural. Comparado con clasificaciones previas, en este trabajo profundizamos en la consideración de los sistemas territoriales socio-ecológicos. Ampliamos la diversificación de las variables consideradas alcanzando representar siete dimensiones complementarias de los sistemas socio-ecológicos: físico, biológico, cobertura del suelo, demográfico, económico, político y cultural. Además, priorizamos la inclusión de atributos más pertinentes para este continente, como la minería y distancia a puertos. Nuestro esfuerzo para incorporar explícitamente aspectos sociales más profundos de las sociedades humanas representa un paso hacia un salto cualitativo en el campo, de mapear sistemas de uso del suelo hacia mapear sistemas socio-ecológicos. Sin embargo, una serie de limitaciones (discutidas en la sección *Consideraciones metodológicas*) necesita ser atendida para poder alcanzar dicha meta, especialmente considerando los vacíos de información y variación en la calidad de los datos.

Alineamiento con los SELS conceptuales

Las definiciones de SELS producida en este estudio permitieron un refinamiento de los SELS conceptuales basados en criterios de expertos descriptos por Boillat et al. (2017). Algunas regiones socio-ecológicas tuvieron una alta correspondencia con los SELS conceptuales (Figura 3). Estos incluyeron: 1) las *Llanuras agro-ganaderas de gran escala consolidadas* (SER C), que correspondieron con los SELS conceptuales *Mesetas Sudamericanas: áreas agroganaderas históricas*, y 2) los *bosques tropiclaes con baja antropización (SER E)*, que corresponde con el SELS conceptual *Llanuras Sudamericanas: nuevas áreas agroganaderas*. En esta última categoría, nuestro estudio agrega tierras tropicales más remotas, que no habían sido consideradas por Boillat et al. (2017) dado su foco primario en cambio de uso del suelo. Correspondencias tan altas muestran la importancia de la ocupación histórica en moldear características socio-ecológicas en las llanuras de Sudamérica.

En la región andina y patagónica encontramos correspondencias medias. Las *Tierras altas áridas y semiáridas y costas adyacentes, con una larga historia agrícola y minera* (SER B) cubrieron los Andes Centrales áridos y aproximadamente están dentro del SELS conceptual *Altiplano y tierras altas de Sudamérica*. Se diferencia porque incluye del Chile mediterráneo y excluye los Andes septentrionales. En cambio, los Andes septentrionales fueron incluidos en el SER D *Áreas tropicales históricamente* *habitadas con bajo potencial para agricultura mecanizada*, que *se* corresponde con el SELS conceptual *Tierras agrícolas costeras con larga historia de colonización* cubriendo el bosque atlántico brasilero y las costas pacíficas del Caribe. Finalmente, las áreas más altas y frías de los Andes Centrales ocurrieron dentro de las *Tierras australes, frías y escasamente pobladas* (SER A), mostrando más afinidad a los Andes Patagónicos por el clima y la baja población. Al margen de esta inclusión, el SER A se correspondió fuertemente con el SELS conceptual *Bosques templados y tierras áridas del Sur.*

Las zonas áridas fueron las más desafiantes en términos de correspondencia en nuestros análisis. El SELS conceptual *Tierras áridas y mediterráneas* apareció dividido en tres SER diferentes: 1) los Andes

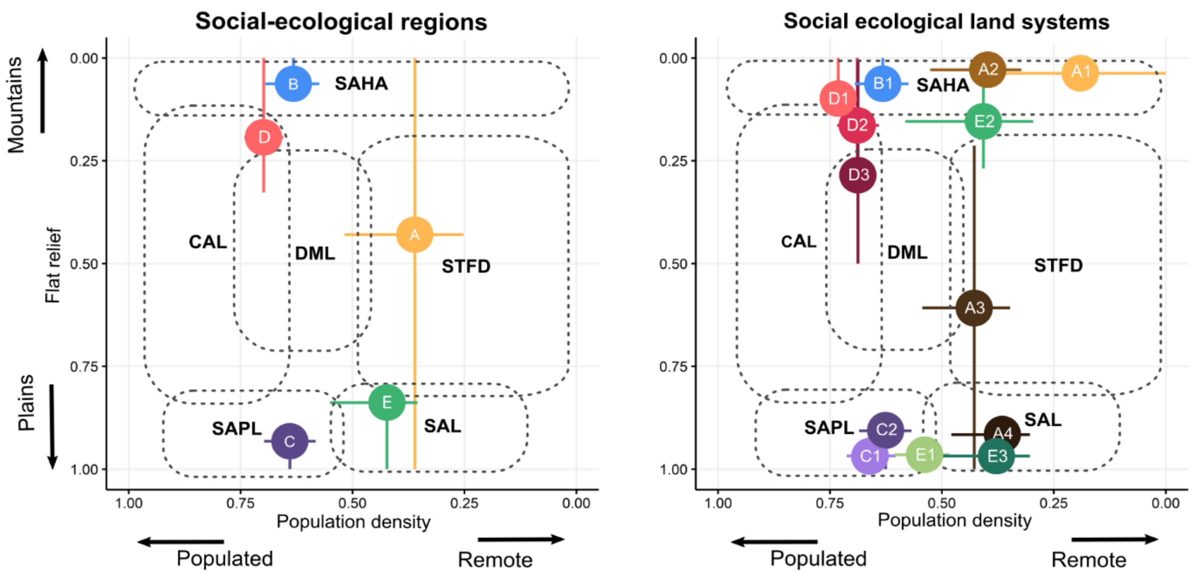

Figura 3. Diagrama de solapamiento entre los SELS conceptuales (Boillat et al. 2017) con los SER (izquierda) y SELS (derecha) a lo largo de dos gradientes de población y relieve. Los círculos representan el promedio de valores y las barras el rango entre el primer y tercer cuantil del porcentaje de tierras llanas (eje y) y la densidad poblacional (eje x). Las líneas de puntos muestran la distribución hipotética de los SELS conceptuales a lo largo de los ejes. Los acrónimos refieren a los nombres en inglés de los SELS conceptuales: SAHA - Altiplano y tierras altas de Sudamérica; CAL - Tierras agrícolas costeras con larga historia de colonización; DML - Tierras áridas y mediterráneas; SAL - Llanuras Sudamericanas: nuevas áreas agroganaderas; SAPL - Mesetas Sudamericanas: áreas agroganaderas históricas; STFD - Bosques templados y tierras áridas del Sur.

Mediterráneos, que tienen más afinidad con los Andes Centrales dentro del SER B, 2) la Caatinga Brasilera, que se correspondió con SER D, representando áreas tropicales históricamente ocupadas, y 3) Oeste Argentino, que fue asignada al SER A, que cubre incluso la Patagonia. Esto mostró la ambigüedad de la categoría tierras áridas que generó configuraciones socio-ecológicas dependiendo de la ubicación geográfica e historia de ocupación. Esto sugiere que los humanos interactúan diferente con las tierras áridas dependiendo de factores tanto biofísicos como socio-económicos en juego.

Sin embargo, dado las diferencias en los enfoques metodológicos, la similitud de ambas clasificaciones es destacable. Sobre todo, considerando la disparidad en el set de variables consideradas en ambos casos. Mientras hacemos avances en rigor cuantitativo, reproducibilidad, operabilidad y definición espacial, es pertinente notar que los atributos mencionados por Boillat et al. (2017) no fueron obstaculizados por disponibilidad de datos y por lo tanto fueron más consistentes con el entendimiento de los sistemas por parte de los autores. Más aún, el rol de las tendencias en ciencia de cambio de usos del territorio fue central para los SELS conceptuales, mientras que en este estudio consideramos únicamente el estado actual, dejando para trabajos futuros el mapear transiciones y cambios en el territorio.

Consideraciones metodológicas

Los modelos son, inherentemente, simplificaciones de la realidad, y como tal, nuestros mapas no reproducen con precisión todas las características de un territorio en toda su extensión. Son muchos los compromisos al mapear sistemas complejos, y discutimos algunos en los siguientes párrafos. Destacamos la metodología híbrida como una fortaleza de este trabajo. La opinión interdisciplinaria de los especialistas contribuyó enormemente al evaluar el desempeño de los procesos automatizados, colaborar en la búsqueda de posibles fuentes de datos y discutir los resultados sobre la base de un conocimiento territorial sólido.

Limitaciones de los datos

La mayor desventaja de los enfoques basados en datos es que están limitados por la poca disponibilidad de sets de datos adecuados. Frecuentemente la disponibilidad y calidad de los datos restringen la caracterización de aspectos importantes de los sistemas. En esta sección destacamos y discutimos un breve resumen de los principales vacíos de información que encontramos al realizar este trabajo que potencialmente lo podrían haber enriquecido, esperando que puedan ser resueltos en el futuro.

(1) *Conflictos socio-ambientales*: el único set de datos que encontramos fue por Scheidel et al. (2020), quienes están desarrollando una base de datos espacial muy completa, aunque actualmente se basan en casos auto-reportados en lugar de un registro sistemático. Una fuente potencial que vale la pena explorar es la minería de datos a través de *Google searches*. (2) *Degradación de ecosistemas naturales*: la degradación modifica procesos ambientales y servicios ecosistémicos con variados impactos en la sustentabilidad (Sasaki and Putz 2009, Garrett et al. 2019). La degradación ecosistémica es un concepto

complejo, en parte porque es basado en valores y con situaciones extremadamente variables. La falta de consenso en su definición (Schoene et al. 2007) dificulta su evaluación. (3) *Gobernanza*: influencia los sistemas territoriales en un esquema multinivel parcialmente jerárquico. Frecuentemente están disponibles variables sólo a nivel nacional, pero subestiman la importancia de reglas de gobernanza locales formales e informales, las que en ocasiones pueden tener mucha influencia en el uso del suelo (Tucker 2020, Rajão et al. 2020). (4) *Exportaciones*: gran parte del uso del suelo en Sudamérica apunta a la exportación de alimentos (UN Comtrade | International Trade Statistics Database). Contar con datos de exportación a una resolución subnacional representaría una enorme mejora. Iniciativas como TRASE pueden ayudar a rellenar este vacío, aunque aún no ofrecen sets de datos que cubran toda Sudamérica completa. (5) *Variables culturales:* Este es posiblemente la dimensión menos representada dentro de las variables consideradas para este análisis. Algunos países como Bolivia, Brasil y Colombia tienen buenos registros espaciales de comunidades indígenas, pero no encontramos ningún set de datos unificado que cubra todo el territorio continental. Otros aspectos de la diversidad cultural que reflejen la cohesión comunitaria o prácticas de uso del suelo serían muy importantes también. Esta sería una prioridad para poder sintetizar mejor el proceso de toma de decisiones sobre uso del suelo en ciencias del territorio en conexión con la gobernanza local. (6) *Tenencia de la tierra (o tamaño de parcela)*: informa sobre el tipo de manejo agrícola más probable, como también el grado en que pequeños productores tienen acceso a la tierra. Las bases de datos que pudimos encontrar para representar esta variable fueron parciales (no cubrieron el continente completo; Graesser y Ramankutty, 2017), tenían resolución a nivel país, o combinaban metodologías heterogéneas (compendio de estadísticas nacionales).

Bordes irregulares, detalle espacial y píxeles aislados

Enfatizamos la importancia de considerar el mapa de incertidumbre en la clasificación (Apéndice 2) para asistir la interpretación y aplicación del mapa de SELS.

En nuestro mapa de SELS las observaciones son hexágonos de 1385 km^2, que incluyen una buena cantidad de heterogeneidad resumida en un sólo valor por hexágono. Un mapa puede tener una apariencia borrosa o de bordes irregulares debido a artefactos de la clasificación o a propiedades del paisaje que pueden difuminar la apariencia general, pero al mismo tiempo pueden presentar información importante. Algunos eventos espacialmente sucintos, como la presencia de una ciudad o un valle húmedo, puede diferenciar la clasificación de un hexágono de sus alrededores, generando patrones dispersos. Regiones montañosas o paisajes heterogéneos también pueden mostrar una clasificación de bordes irregulares. Nosotros decidimos mostrar el producto de la clasificación sin filtrar pixeles aislados ni suavizar los bordes de los SELS debido a que perderíamos la información que pudieran contener. En el otro extremo, algunas regiones que aparentan ser homogéneas en el mapa (por ejemplo Chile y el Oeste Amazónico) pueden no necesariamente tener paisajes uniformes. Aparente homogeneidad debería interpretarse como el compartir características únicas que hacen a esos hexágonos más similares entre sí que al resto de hexágonos en el continente.

Dinámica temporal y SELS

Para este estudio consideramos únicamente variables estáticas, priorizando consistencia de la estructura del modelo., sin embargo, las tendencias y direcciones de cambio son características muy importantes de los sistemas territoriales socio-ecológicos que podrían incluso usarse para diferenciarlos. Incentivamos a estudios futuros a generar una clasificación de SELS que incorpore regímenes de cambio. Adicionalmente, los cambios potencialmente podrían modificar las características de regiones suficientemente como para ameritar una futura revisión de las tipologías asignadas en este estudio, como lo describimos para los SELS dentro del SER A y los SELS dentro del SER E (Apéndice 4).

CONCLUSIÓN

Este estudio presenta tres mayores contribuciones: (1) provee una caracterización razonable e inclusiva de los Sistemas Territoriales Socio-Ecológicos (SELS), (2) ofrece una representación espacial de los SELS en un formato fácilmente operativo y disponible gratuitamente y (3) su perspectiva metodológica sortea algunos desafíos de las clasificaciones socio-ecológicas, como la combinación de datos cuantitativos y cualitativos, y la articulación entre perspectivas basadas en datos y conocimiento de especialistas.

La metodología híbrida representa una fortaleza de este trabajo. La inclusión de un grupo interdisciplinario de especialistas fue crucial para guiar la búsqueda de datos y para contrastar las los productos de las clasificaciones automatizadas con el conocimiento territorial. Adicionalmente, esto mejora la utilidad del mapa resultante ya que aumenta su coherencia y relevancia para la comunidad académica y de planeamiento territorial.

La clasificación en SELS es una caracterización reproducible, bien fundamentada y operativa de los sistemas territoriales socio-ecológicos de Sudamérica que facilitan la incorporación del contexto regional al analizar las realidades locales en el Antropoceno. Esperamos que el mapa de SELS provea un marco geográfico orientativo para analizar patrones observados dentro de un contexto mayor y designar soluciones para la sustentabilidad específica.

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DISPONIBILIDAD DE DATOS

Los datos y códigos que apoyan los resultados de este estudio están disponibles para descarga libre en GitHub https://github.com/luciazarba/SELS-SA.

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