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Predictive Scenarios of LULC Changes Supporting Public Policies: The Case of Chapecó River Ecological Corridor, Santa Catarina/Brazil

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Abstract: The studies of spatial-temporal land use and land cover (LULC) change patterns, supported by future scenarios and simulation methods based on the assumption of natural socio-economic and territorial driving forces, allow us to go beyond an accurate diagnosis of the dynamics that have occurred so far, providing a picture of possible alternative futures, and are fundamental in assisting with the planning and policy-making in the territory. In this paper, we use LULC maps and explanatory variables aggregated in five dimensions (physical/natural, economic, sociocultural, technological, and demographic) to identify which are the main drinving forces in the evolution process and the simulation of LULC dynamics for 2036, using as a case study the Chapecó River ecological corridor (Chapecó EC) area. The Chapecó EC was created by the state government in 2010 with the goal of combining nature conservation with local and regional development. In this region, in the last two decades, the loss of areas of natural grassland and forest was on average five times higher than the average recorded in the state. Based on scenario-building methods using artificial neural networks, six predictive scenarios were elaborated, based on three socioeconomic scenarios (current conditions, growth, and socioeconomic recession) and two territorial intervention options (actions). This includes an action based on maintaining the current LULC, and another action of a conservationist nature with the recovery of forest and natural grassland areas to the proportions of areas found in 1990. The results indicate that if the current LULC is maintained, forest, pasture and agriculture areas tend to increase, while silviculture and natural grassland areas decrease, driven by economic and physical/natural driving forces. If there is a conservationist action, natural grassland and pasture areas tend to increase and silviculture and agriculture tend to lose area due to economic, technological, and physical/natural driving forces. These trends have revealed that the natural grassland preservation/restoration, the encouragement of conservationist agricultural practices combined with economic strategies, and the technological development of the rural sector seem to form the basis of economic development combined with biodiversity conservation.

Keywords: spatial modelling; predictive scenarios; artificial neural networks; good farming practices; agricultural technological development; spatial planning

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1. Introduction

The term land use and land cover (LULC) refers to the different categories of land use and land cover. Land use relates to human manipulation to meet certain needs, while land cover refers to the physical condition of the surface [1–3]. Land use impacts the environment mainly through its coverage, which may change as a result of a change in its use [4].

Historically, human populations have been modifying the landscape, and currently this process is occurring in a more accelerated way due to the extraction and appropriation of natural resources as well as the expansion of territories. Negative effects on the environment and social disturbances associated with the intensification of land use are documented in a number of studies that point to agriculture as the main force of land cover transformation on the planet [5–8]. It is estimated that one third of the surface of the earth is used for crops or livestock, and such lands are converted from natural forests, grasslands, and swamps [8].

The study of land use and land-cover (LULC) dynamics stands out as a fundamental topic in the context of the challenges that humanity is facing—e.g., global urbanisation, climate change, food security, global health, and pandemics—since they influence and are influenced by various systems, namely environmental, social, and economic. Therefore, knowledge about these processes and their impacts is crucial in various fields, namely environmental monitoring, land use development and planning, and political and economic evolution trends [9].

Studies on LULC dynamics involve two key steps: identifying changes in the landscape and assigning to those changes a set of causal factors [10] or driving forces. The driving forces are forces that provoke changes and create dynamics in the territory [8,11–13]. They are usually represented by a set of variables [14] classified in different dimensions of analysis, i.e., physical/natural, demographic, economic, technological, social, cultural, and political [15].

In Brazil, the expansion of urban areas (including roads/highways) and areas dedicated to agriculture, cattle raising, and forestry (silviculture) are important driving forces of natural vegetation suppression [7,16–20]. As with urban population growth, the expansion of urban areas and the export of agricultural products are cited as the leading causes of rainforest loss in 41 countries [7].

In that context, it becomes relevant to analyse these processes of change and to explain that LULC dynamics analysis models are tools to support planning and policy decisions in the territory [18–20]. They can include the dynamic simulation of natural and socioeconomic processes and the identification of indicators and predictors [21]. The integration of environmental and human sciences, geographic information systems, and remote sensing has enabled the improvement of techniques for measuring LULC changes and the development of predictive models [22].

The literature presents a set of models that have been widely used in simulation studies of LULC dynamics relating it with their driving forces. There are a variety of models based on different empirical techniques. One of the most used approaches is CA, ANN and ABM [23]. Examples include MOLAND, SLEUTH, FLUS, SECOA, Dynamic EGO, CLUE-S, and the Desakota models [24–30]. Since the decisions and choices made in the scope of land use development and planning processes always address issues related to the future, the construction of scenarios represents an essential tool. Uncertainties about that future increase [31,32], and scenarios provide alternative visions of possible futures, providing insights into the creation of risk management plans, and anticipate action measures that can avoid the potential problem and/or mitigate it, within a cost-effectiveness rationale.

The term 'scenario' adopted in this paper denotes a coherent story or narrative of what might happen in the future [31]. The scenarios resulting from the models illustrate potential and plausible descriptions of the future based on 'if/then' assumptions [33]. The independent variables in the model are altered to compose the desired scenario. The scenarios allow us to measure and evaluate what is more likely to occur, allow for the identification of the driving forces that can influence the results, and offer support to the formulation of public policies [11,32,34–37].

From the model's point of view, the driving forces are the main uncertainties and trends that will influence changes in the baseline scenarios (i.e., business as usual) and allow us to explore plausible futures (scenarios) under a 'what if' approach by changing the values of the main uncertainties. This type of scenario is called a probabilistic predictive scenario and addresses the question, 'What will happen?' [33].

Predictive scenarios are composed of scenarios that represent plausible futures—where the values of one or more independent variables are deliberately changed to compose the future narrative to be considered—and actions, i.e., any policies, projects and territorial restrictions considered to be implemented in the study area. To this end, the actions are carried out in the dependent variable [11,31,33].

The literature highlights some scenario-building methods, e.g., cellular automata (CA), CA and fuzzy analysis, artificial neural networks (ANN), and multicriteria decision analysis (MCDA) [11,32–34,38–40]. In this research, we adopted an artificial neural network modelling approach for its flexibility, which permits the inclusion of express rules that incorporate specialised knowledge, operator experience, and the participation of different interests in addressing 'what if' questions [11,17,32,35,41–43].

In the last two decades, the state of Santa Catarina registered a loss of 15% of grassland and approximately 2% of forest [44]. While our study area, located in the Western region of the state, the Chapecó EC, registered for the same period, includes losses of these areas considerably higher than the state average. Natural grassland lost 55% of its cover to the expansion of agriculture, and forest lost 13% of its area to forestry (silviculture) [17].

The region is seen as an economic influence area and a tug of war between family farming and the agro-industrial complex. This territory is a bone of contention since the situation has not been defined either in terms of a hegemonised production pattern favoured by the agro-industrial complex or the capacity of family farmers to resist or adapt to new scenarios [45].

In 2010, the government of the state of Santa Catarina enacted by State Decree No. 2957 of 20 January [46] the creation of the Chapecó River EC (Chapecó EC), whose principal objective is: *'Developing and implementing a model for the promotion, marketing and leveraging of native forests (and other natural environments) as environmental assets, promoting the maintenance and improvement of the permeability of the landscape'* [47].

Currently, another important territorial policy operates in the region. The Development Plan of the State of Santa Catarina 2018–2030, called the SC2030 Plan, aims to reduce inequalities and promote social equity, seek sustainable regional development, and boost innovative development and the entrepreneurial capacity of Santa Catarina [48].

Furthermore, we identified a lack of information about the LULC change, its drivers and possible future implications in the region of the Chapecó CE, in a way that can subsidize, guide and support territorial and environmental policies.

Thus, this study was aimed at counterposing different predictive scenarios of changes in LULC, taking into account the guidelines of both public policies. Specifically we sought to: (i) build six predictive scenarios of LULC for 2036 from the guidelines of two public policies; (ii) identify the main LULC change between the predictive scenarios and the reference year (2018); (iii) discuss the influence of the main driving forces in each predictive scenario; and (iv) understand the importance of adopting these policies in the region.

This paper is organized as follows: Section 2 describes the study area, data, and methods used for this purpose. Section 3 introduces the main results of LULC changes expected for 2036 and the main driving forces. Section 4 approaches the discussion on the main LULC changes related to the driving forces and the effects of public policies on LULC dynamics. Finally, Section 5 introduces the main conclusions, implications, and limitations of the research.

2. Materials and Methods

2.1. Study Area

The study area is 7242.33 km^2 and is located between the geographical coordinates 27°5′0″ and 26°20′0″ South latitude and 53°0′0″ and 51°10′0″ West longitude. It is located Northwest of the state of Santa Catarina in the Southern region of Brazil (Figure 1). It shelters a preservation area called Chapecó EC, created in 2010 by the Government of the State of Santa Catarina/Brazil [46].

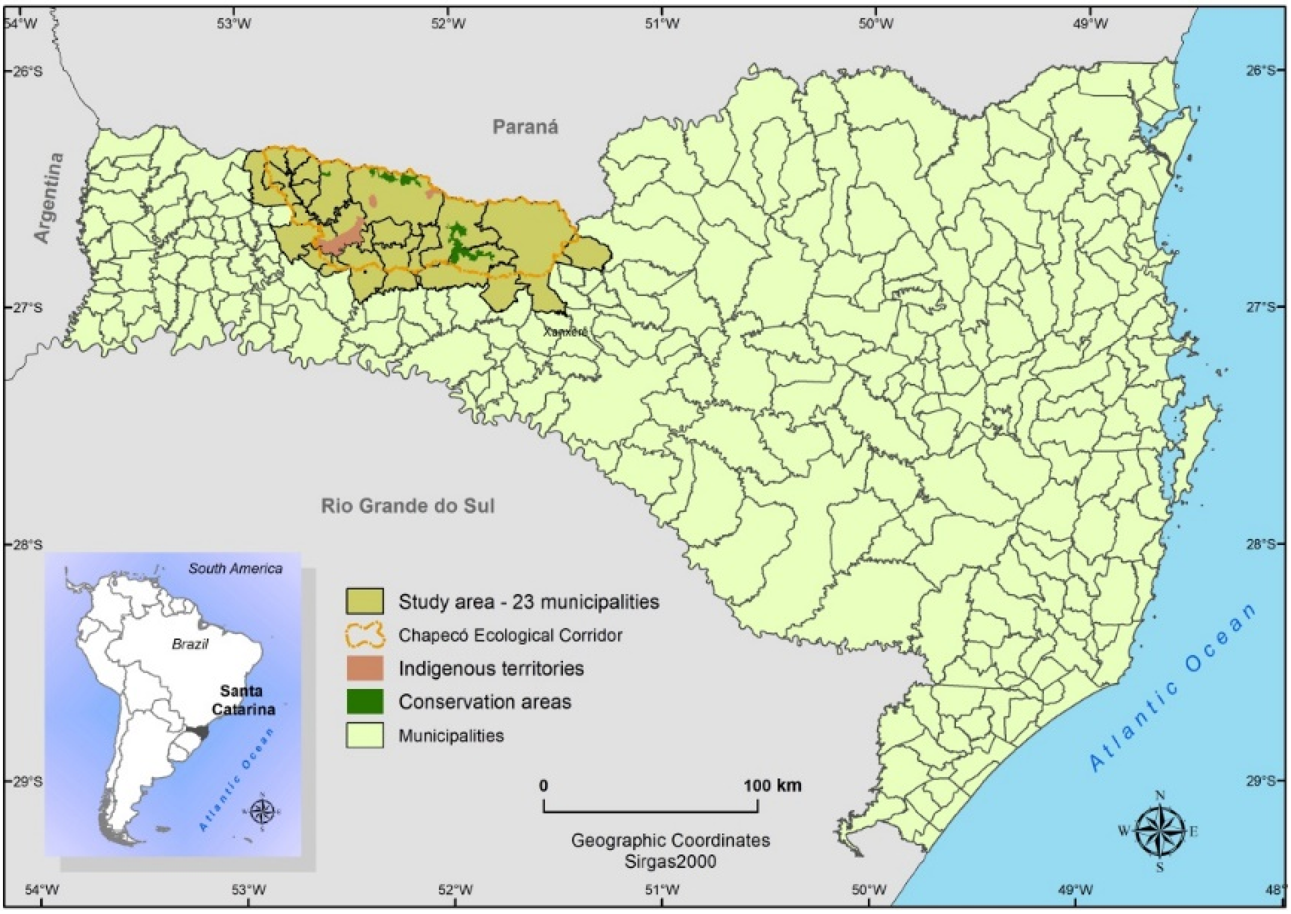

Figure 1. Location of the study area.

This area has different social arrangements with four main segments: indigenous populations, family farmers (plus settlers), employing farmers (grain and cattle ranchers), and foresters. It stands out with the economic activities of soybean cultivation, beef and dairy cattle raising, and wood production [47]. This complex social arrangement, together with land use and land cover changes [16] and territorial conflicts [45], makes this region of great environmental, social, and economic appeal for the state of Santa Catarina.

The Chapecó EC is formed by 23 municipalities, occupying approximately 7.6% of the total area of the state of Santa Catarina. It had an estimated population of 185,000 inhabitants in 2018, in addition to a demographic density and urbanization rate lower than the state average. The municipalities are small, with agricultural and cattle raising traditions. The area dedicated to agriculture and cattle-raising in the region, as well as the Gross value added of agriculture and cattle-raising (GVA) are expressive, which reveals the agricultural aptitude of the region. It exhibits twice as much area dedicated to agriculture and cattle-raising compared to Brazil and participates with 2.2% of the Gross Domestic Product (GDP) of the state (Table 1).

Table 1. Socioeconomic indicators.

Indicators	Chapecó EC	Santa Catarina	Brazil
Area (km^2)	7242 *	95,346	8,516,000
Estimated population (2018)	185,300 *	7,075,500	211,755,692
Demographic density (2018) (inhab./km^2)	25.6	74.2	24.9
Urban population (2010) %	64.6 *	84.0	84.3
Agricultural area (2018) %	67.6 *	48.9	30.6
GVA of agriculture and cattle-raising (2018) %	31.3 **	5.51	5.15
GDP (2018) BRL 1000	6,603,755 *	298,227,090	7,004,141,000

Source: IBGE/SIDRA [49]. Values referring to the sum (*) and average (**) of the 23 municipalities that are part of the Chapecó EC.

The Chapecó EC area is located in the Atlantic Forest biome composed of mixed ombrophilous forest (Araucaria forest), deciduous seasonal forest, and gramineous steppe (natural grassland) [47,50]. Figure 2 shows the phytogeographic composition of the region.

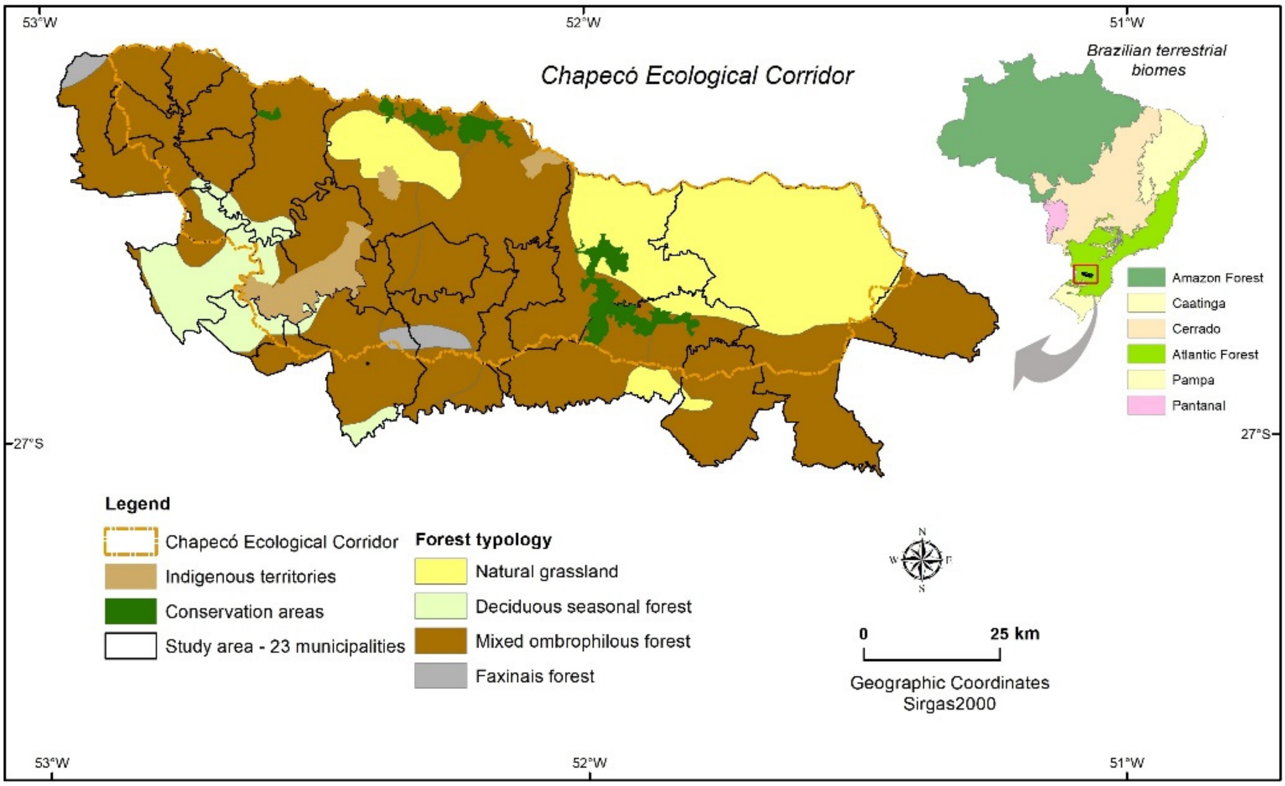

Figure 2. Forest tipology (Atlantic Forest biome) in CHapecó CE.

Geomorphologically, it is formed by the Campos Gerais Plateau and the Dissected Plateau. In the Campos Gerais Plateau, the altitude varies between 800 m and 1200 m, and the area is higher than the surrounding areas, which belong to the Dissected Plateau. The latter has a great topographic contrast with the Campos Gerais Plateau area, with a strongly dissected relief of deep valleys and terraced hillsides. The main types of soil found in the Chapecó EC are latosoil, nitosoil, cambisoil, and litholic soil, where cambisoil is the predominant soil type [45,51,52].

Regarding the climate, in areas below 800 m, the climate is of the humid mesothermal type with hot summers (Cfa), and in areas above that altitude, the climate is of the humid mesothermal type with cool summers (Cfb). The average annual temperature ranges from 15 °C to 18 °C [53], with well-distributed rainfall throughout the year, varying between 1640 and 2035 mm [52,53].

2.2. Methodological Framework

Figure 3 illustrates the methodological framework used to simulate future LULC changes and identify the main driving forces acting under different predictive scenarios [11,32]. The development of the work can be divided into four steps.

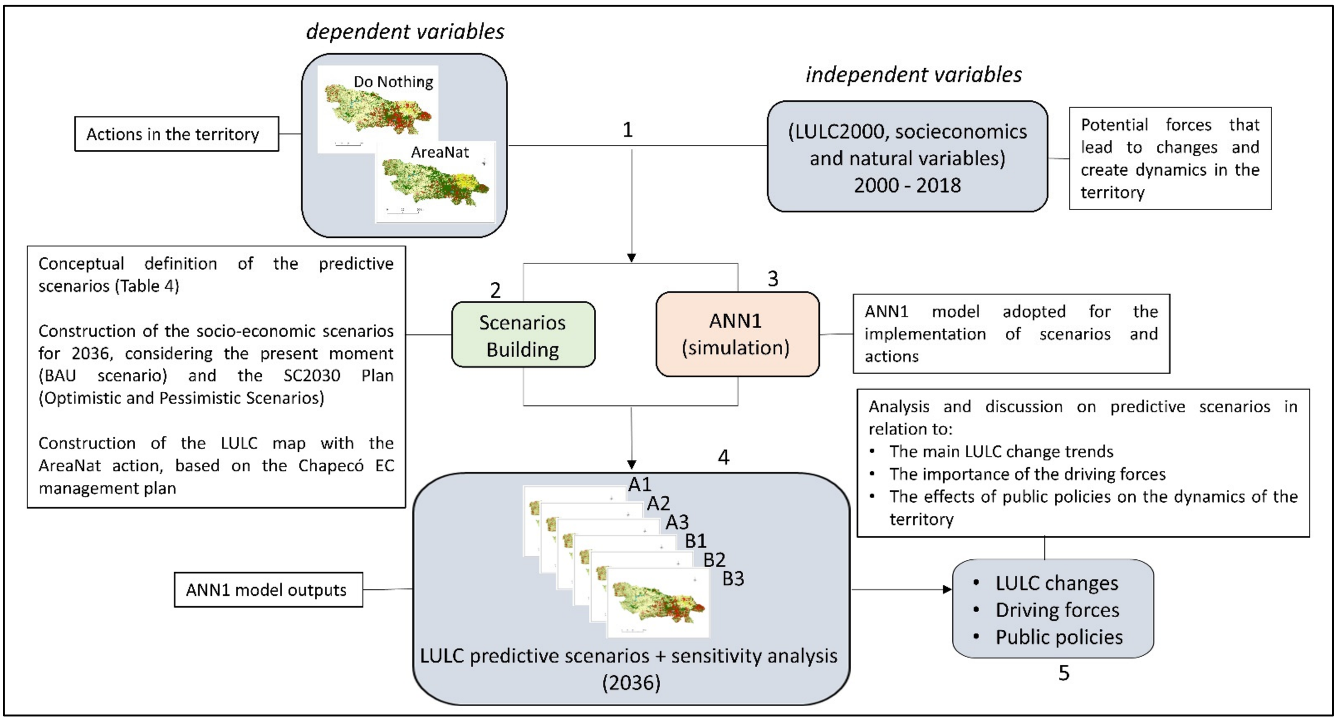

Figure 3. Methodological framework. Step 1—variable selection and systematisation; Step 2—predictive scenario-building; Step 3—LULC dynamics simulation based on artificial neural networks for 2036; Step 4—ANN1 model outputs, and Step 5—analysis and discussion.

In the first step, the representative variables of the scenarios and actions were selected, and the database used in the model was structured. In the second step, the predictive scenarios were conceptually defined based on the combinations between scenarios and possible actions. In the third step, scenarios and actions were implemented, and the model was run. The fourth and fifth steps introduce the results of the predictive model and the analysis and discussion on the trends of LULC dynamics, the main driving forces identified, and the effects of the selected public policies [11,32,41].

2.3. Database

The data used in this work include land use and land cover, physical, social, and economic data; they were selected from available online databases [44,49,53–57].

The whole database was organised in a GIS (Geographic Information System) environment, stored in raster format with 100 m of spatial resolution, and referenced to the SIRGAS UTM 22S system. For the simulation of LULC changes and the sensitivity analysis based on artificial neural networks, the software SPSS 24 [58] was used, and the software ArcGis 10.7 [59] was used for specialisation and LULC change analysis in the different scenarios.

2.3.1. Land Use and Land-Cover Data

The LULC data used in this research comprise maps from 2000 and 2018 from the MapBiomas Project, collection 4.1 [44]. The LULC classes are: forest, silviculture, grassland, pasture, agriculture, mosaic, artificial area, and water bodies. The description of the LULC classes can be seen in Table 1, in the classification key adopted in the Mapbiomas Project [44] and in the phytogeographic typologies of Santa Catarina [50] (Table 2).

Table 2. Land use and land cover description.

LULC Class	Description
Forest (forest formation)	Dense, open and mixed ombrophilous forest, semi-deciduous and deciduous seasonal forest, and pioneer formation.
Silviculture (forest plantation)	Planted tree species for commercial use (e.g., Eucalyptus, Pinus and Araucaria).
Natural grassland	Savannas, park and grassland steppe savannas, steppe and shrub and herbaceous pioneers.
Pasture	Pasture areas, natural or planted, related with farming activity.
Agriculture (annual and perennial crop)	Areas predominantly occupied with annual crop (short to medium-term crops, usually with a vegetative cycle of less than one year, which after harvest needs to be re-planted) and in some regions with perennial crops (Areas occupied with crops with a long cycle (more than one year), which allow successive harvests without the need for new crop).
Mosaic (mosaic of agriculture and pasture)	Farming areas where it was not possible to distinguish between pasture and agriculture.
Artificial Area (urban infrastructure + other non vegeteded area)	Urban infrastructure: urban areas with predominance of non-vegetated surfaces, including roads, highways and constructions and other non vegetated areas Non-permeable surface areas (infrastructure, urban expansion or mining) not mapped into their classes and regions of exposed soil in natural or crop areas.
Water bodies (river, lake and ocean)	Rivers, lakes, dams, reservoir and other water bodies.

2.3.2. Variable Selection

In this paper, the selection of variables was based on the literature review, the historical context of territorial, demographic, socioeconomic, and environmental dynamics in the region [45], as well as the availability of information, both concerning the period of analysis (2000–2018) and its spatial representativeness [16,17,39].

The physical/natural (biophysical) dimension consists of the biotic and abiotic variables which define the natural capacity and/or environmental conditions for land use changes. The economic and technological dimensions can be represented by variables that directly affect the land managers's decision-making process [12,60].

The Chapecó EC region is part of the economic influence zone and region of family farming and agro industrial complex [45]. Therefore, the variables of the economic and technological dimension were selected in order to measure the evolution of the main productive sectors in the region, the participation of family agriculture in the state economy, the rural agro-industries and the technological development in the rural sector.

The analysis of the region's economic structure shows a tendency towards the growth of agribusiness, aimed at the external market. The rate of employment in the industrial sector shows growth in the sector and retraction in the agriculture and cattle raising and forestry production activities. Formal employment in the transformation industry grew 35%, almost twice as much as the state average (19%). Employment in the farming, livestock, and forestry sectors fell 24% in the period [57].

Among the industrial sectors, the slaughtering and meat products sector stands out, measured by the herd size variables. The region presented an increase in the chicken herd (4%) [49]. Chicken meat participates with 36% of the total export of agribusiness in Santa

Catarina, ranking first, followed by wood, swine, soybeans, and tobacco (2019) [61]. The increase in the use of pesticides, the production yield of the main crops in the region and mechanization point to an intensification of agricultural activity, supported by technlogical development. The use of pesticides in the study area (17%) was almost twice the increase in the state (10%). The increase in the average yield of soy and corn production was 105%, while the state registered an increase of 90%, and high mechanization in the region, an increase of 165% in relation to the state, reinforcing the importance of the region in the state and national economic and agricultural context.

The demographic and sociocultural variables, rural population and age of the rural producer sought to portray the dynamics of rural exodus and the aging of the rural population and family succession, seen with concern in the public policies used [47,48]. The rural population in Santa Catarina, between 2000 and 2010, decreased by 24% and in the study area by 15%. In Santa Catarina, 33% of the rural producers in charge are 55 years old or older, and in the study area this problem is even greater than in the state, with 48% at retirement age [49].

Table 3 shows the relation of the variables, both dependent and independent, representing the set of driving forces inputted in the ANN1 model, organised into five dimensions of analysis. The full description of the variables is available in the Supplementary Material Repost S1: Variable description.

Table 3. ANN model variables.

Dimension	Dependent Variables	Unit	Format	Scala/ Spatial Resolution
Physical/natural	Land use and land cover (do nothing)	class	raster	30 m
Physical/natural	Land use and land cover (AreaNat)	class	raster	30 m
Dimension	**Independent Variables—Year**	**Unit**	**Format**	**Scala/ Spatial Resolution**
Physical/natural	Land use and land cover—2000	class	raster	30 m
	Temperature—2002	°C	vector	1:500,000
	Accumulated precipitation—2002	mm	vector	1:500,000
	Type of soil—2004	class	vector	1:250,000
	Type of relief—2000	class	raster	30 m
	Altitude—2000	m	raster	30 m
	Road network—2018	km/km^2	vector	municipality
Economic	Rural agribusiness—2006 and 2017	%	table	municipality
	Cattle herd—2000 and 2018	%	table	municipality
	Swine herd—2000 and 2018	%	table	municipality
	Chicken herd—2000 and 2018	%	table	municipality
	Formal employment (commerce/service)—2006 and 2018	n°	table	municipality
	Formal employment (industry)—2006 and 2018	n°	table	municipality
	Formal employment (agriculture)—2006 and 2018	n°	table	municipality
	Financing (Pronaf)—2006 and 2017	%	table	municipality
	Processing industries—2006 and 2018	n°	table	municipality
	Gross Domestic Product (GDP)—2002 and 2017	R$	table	municipality
	Agricultural land price—2000 and 2018	R$/ha	table	municipality
	Per capita income—2000 and 2010	R$	table	municipality
	Log Production—2000 and 2018	m^3	table	municipality
	Gross value added of agriculture and cattle-raising—2000 and 2017	%	table	municipality
	Milk production value—2002 and 2017	%	table	municipality
Sociocultural	Family agriculture—2006 and 2017	%	table	municipality
	Schooling of the head farmer—2006 and 2017	n°	table	municipality
	Age of the head farmer—2006 and 2017	n°	table	municipality
	Municipal Human Development Index (HDI)—2000 and 2010	index	table	municipality
	Rural workers—2006 and 2017	n°	table	municipality
	Land structure—2006 and 2017	ha	table	municipality
Technological	Use of agrochemicals—2006 and 2017	%	table	municipality
	Mechanization in the rural property—2006 and 2017	tractors/km^2	table	municipality
	Technical orientation—2006 and 2017	%	table	municipality
	Maize yield—2002 and 2017	kg/ha	table	municipality
	Soybean yield—2002 and 2017	kg/ha	table	municipality
	Bean yield—2002 and 2017	kg/ha	table	municipality
	Tobacco yield—2002 and 2017	kg/ha	table	municipality
Demographic	Population density—2000 and 2018	inhab/km^2	table	municipality
	Rural population—2000 and 2010	%	table	municipality

2.4. Scenario Building

The construction of the predictive scenarios for the year 2036 for the Chapecó EC region was based on the method presented by the European Environment Agency (EEA) report [31] and applied by Morgado et al. [11,33].

Table 4 summarises how the six predictive scenarios proposed in this paper were constructed to assess LULC change trends and their main driving forces. The full table of scenario construction is available in the Supplementary Material Repost S2: Scenario building.

Table 4. Scenario building schema.

		Scenarios		
		BAU	**Optimistic**	**Pessimistic**
Action	Do Nothing	A1	A2	A3
	AreaNat	B1	B2	B3

A1—'do nothing and business as usual'—this is the predictive status quo scenario to which the others refer. It considers no action in the territory in the current social and economic condition.

A2—'do nothing and optimistic scenario'—this predictive scenario represents the socioeconomic expansion over the last analysis period (2018) and no action in the territory.

A3—'do nothing and pessimistic scenario'—this predictive scenario represents socioeconomic recession and climate change over the last analysis period (2018) and no action in the territory.

B1—'AreaNat and business as usual'—this scenario describes the counterfactual case of forest and grassland restoration. It considers the recovery of natural areas in the territory in the current social and economic conditions.

B2—'AreaNat and optimistic scenario'—this scenario reports socioeconomic expansion over the last analysis period (2018) and the recovery of natural areas in the territory.

B3—AreaNat and pessimistic scenario'—this scenario assumes socioeconomic recession, social crisis in the countryside and climate change in the last period of analysis (2018) and the recovery of natural areas in the territory.

To define the scenarios and actions, some of the agricultural and environmental guidelines were considered, according to the problematic of the study area, of two public policies, the *Development Plan of Santa Catarina State 2030—SC 2030 Plan* and the *Management Plan of the Ecological Corridor of Chapecó* [47,48], as well as state climate projections [62–65] and socio-economic indicators [49].

Table 5 presents the list of guidelines and target defined in the policies, related to the variables for the construction of the predictive scenarios.

Table 5. Summary of public policy guides used to build scenarios.

Public Policy	General Objective		
SC2030 Plan	*To reduce inequalities and promote social equity, seek sustainable regional development, boost innovative development and the entrepreneurial capacity of the Santa Catarina society*		
Guidelines	**Indicators**	**Targets**	**Variables**
Protect, restore, and promote the sustainable use of terrestrial ecosystems	Percentage of territory with native vegetation cover	+1%	AreaNat action
Combat climate change and its effects	Projections of increased temperature and precipitation [62–65]	+4 °C +84 mm	Temperature Accumulated precipitation
Add value to family farming	Number of family farming agroindustry enterprises Municipal GDP growth [49]	+55% +54	Family agriculture GDP
Revitalize the rural world	Rural credit—participation of Pronaf in the total number of contracts	+0.3%	Financing (Pronaf)
Ensure sustainable production	Maize yield (kg/ha) Soybean yield (kg/ha)	+45% +53%	Maize yield Soybean yield
Social problems in rural areas: rural exodus, aging of head farmers and family succession	Age of the head farmer [49] Rural population [49]	+70% −20%	Age of the head farmer Rural population
Public Policy	**General Objective**		
Management Plan of the Chapecó EC	*Developing and implementing a model for the promotion, marketing and leveraging of native forests (and other natural environments) as environmental assets, promoting the maintenance and improvement of the permeability of the landscape'*		
Guideliness	**Indicators**	**Targets**	**Variables**
Combat the expansion of productive areas (pasture, agriculture and silviculture) over areas of natural vegetation Combat the loss of natural vegetation Conservation of natural grasslands	LULC map	Natural areas recovered to the conservation status of the year 1990	AreaNat action

2.4.1. Scenarios

The business as usual (BAU) scenario represents a narrative of current conditions in the study area. This scenario assumes, for the period of the analysis, that political, economic, demographic, environmental, and social conditions remain as they have been. These are represented by the independent variables observed between 2000 and 2018 and analyzed in Section 2.3.2.

To build the optimistic and pessimistic scenarios, the targets of the rural development policy indicators, historical data from official sources, and climate projections were considered. For the pessimistic scenario, the authors considered it reasonable to adopt only 1/3 of the increase applied to the optimistic scenario.

The optimistic scenario represents social and economic growth, guided by some goals and objectives of the Economic Development axis: Agriculture and Fishing, the Development Plan of the state of Santa Catarina 2030, and the SC2030 Plan [48]. The optimistic scenario foresees an increase in productivity in the agricultural sector (soybean and maize crops), the support for family agriculture with an increase in the participation of Pronaf in the total number of contracts (rural credit), and increased participation of family agriculture in the rural agribusiness. For this scenario, a GDP per capita increase was also considered, since this is a synthetic indicator of the local economy. For this scenario, five independent variables were altered.

For maize and soy yields, the increase applied was 45% and 53%, respectively, an increase of 0.3% in the number of agricultural sites with Pronaf financing and by 55% in the participation of family farming in rural agribusiness according to the SC2030 Plan [48]. The average GDP growth rate in Santa Catarina for the years 2002 to 2017 was 2.5% per annum [49]. Thus, an increase of 54% in the GDP per capita was considered, referring to an increase of 3% per annum multiplied by the number of years of the scenario period (18 years).

The pessimistic scenario, as opposed to the optimistic scenario, reflects conditions of economic recession, social crisis in the rural sector, and climate change. A total of eight independent variables were altered: maize and soybean yields, participation of family farming in the rural agribusiness, GDP, rural population, producer age, temperature, and accumulated precipitation.

The variables 'maize and soybean yields' and 'participation of family farming in rural agribusiness' were considered to grow by only one-third of the target projected in the SC2030 Plan. An increase of only 0.75% per annum was considered for the GDP. Thus, the correction was increased by 15%, 17.5%, 18%, and 13.5%, respectively.

Additionally, in this scenario, we considered a climate of social crisis in the rural sector, where according to the latest censuses and the Management Plan of the Ecological Corridor of the Chapecó River [47,49,66], there is a tendency for the rural population to decrease and age. Thus, a negative variation of 20% was considered for the rural population variable, based on the trend calculated by the variation rate for the 2000 to 2010 period [49]. To characterise the problem regarding the lack of succession in the command of rural property and the ageing of the leading producers [47,48,67] a 70% increase in the number of farmers over 55 was projected.

In the pessimistic scenario, we introduced changes to the variables temperature and precipitation based on different global and regional climate change studies [62–65,68]. To this end, we considered an increase in the average air temperature of 4 °C and an increase in the accumulated precipitation of 84 mm in the study region and the period under analysis.

Table 6 shows the increased values of the independent variables used to prepare optimistic and pessimistic scenarios.

Table 6. Increase in the independent variables used for the construction of optimistic and pessimistic scenarios.

Scenarios			
Optimistic		Pessimistic	
Independent Variable	**Increase**	**Independent Variable**	**Increase**
Family agriculture—2017	+55%	Family agriculture—2017	+18%
Financing (Pronaf)—2017	+0.3%	GDP—2017	+13.5%
GDP—2017	+54%	Maize yield—2017	+15%
Maize yield—2017	+45%	Soybean yield—2017	+17.5%
Soybean yield	+53%	Temperature—2002	+4 °C
		Accumulated precipitation—2002	+84 mm
		Age of the head farmer—2017	+70%
		Rural population—2010	−20%

2.4.2. Actions

For the case study of this research, two actions were considered of relevance since they are pervasive in the discussions of territorial changes due to the implementation of the Chapecó EC, namely, (i) the lack of any forecast action in the territory (do nothing); and (ii) the action of recovery of natural areas (AreaNat).

As the 'do nothing' action does not provide for intervention in the territory, the 2018 land use and land-cover map was used as the dependent variable in the model.

The AreaNat action was elaborated based on the guidelines of the Ecological Corridor Zoning, which defined priority areas for the recovery of permanent preservation areas according to their vocation for conservation and/or direct or indirect use [47]. In addition, another management instrument used as a reference was the SC2030 Plan, which stipulated an increase by 1% of the area with native vegetation cover in the state of Santa Catarina as a goal for 2030 [48]. The details of the guidelines for this action in the territory can be seen in Table 5 (synthesis of public policies). The AreaNat action was considered in the predictive scenarios in order to evaluate the likely effects on future LULC dynamics when a public conservation policy is adopted.

However, due to a spatial scale limitation of the LULC maps, the action was generalised by cross-referencing the 1990 and 2018 LULC maps, restoring the natural areas (forest and natural grassland) that existed in 1990, and conserving those that existed in 2018.

In the study area between the years 2000 and 2018 there was a growth of 190% in areas dedicated to silviculture (forestry) [17] and 79% for soybean [69]. Thus, we adopted as a reference the year 1990, because it represents a reality of LULC dynamics prior to this growth. Government incentives and policies, due to market demands, boosted silviculture activity in the region [70] and the expansion of agricultural commodities [71].

2.5. Simulation Model Based on Artificial Neural Networks

For the simulation of predictive LULC change scenarios for 2036, the type of machine learning adopted was artificial neural networks (ANN), the multilayer perceptron (MLP) method, and the backpropagation algorithm. This is the type of model most widely used in works of this nature [11,17,32,35,41–43].

The simulation is done for the year 2036, because the literature recommends that the predictive scenarios should follow the same time interval as the model input data [11]. In this case, it was from 2000 to 2018, totaling 18 years.

In this study, we used the ANN1 model [17] to simulate the six predictive scenarios (Table 7). Predictive scenario A1 represents the baseline scenario, which is based on extrapolating the trends in LULC dynamics and the current socio-economic scenario between the years 2000 and 2018. The others consider different predictive scenario assumptions (A2, A3, B1, B2 and B3).

Table 7. ANN1 model parameters used to simulate the predictive scenarios.

Parameter	Parameterisation Object	Parameterisation Adopted
Input layer	Independent variables Rescaling method	67 Normalised
Sample	Training Testing Holdout Iterations	70% 20% 10% 500
Hidden layer	Number of hidden layers Number of units (neurons) Activation function	1 56 Hyperbolic tangent
Output layer	Dependent variable Activation function Error function	LULC map* Softmax Cross-entropy

LULC map*: LULC 2018 for scenarios A and AreaNat for scenarios B.

According to the ANN1 model, the classification matrix showed approximately 70% overall accuracy. Individually, the forest class represented 89.5% of the validation sample correctly classified, silviculture represented 38.0%, natural grassland represented 9.5%, pasture represented 57.0%, agriculture represented 79.6%, mosaic represented 20.0%, articicial area represented 56.1%, and water bodies represented 42.6% [17].

Model validation was supported by the area under the curve (AUC) measure derived from the relative operating characteristic (ROC) [72]. The AUC value informs how well the model can distinguish between the classes [42,73–75].

Based on the classification of AUC, the model has excellent accuracy capacity in the following classes: forest, natural grassland, agriculture, artificial area, and water bodies (>90%). The classes silviculture and pasture, with values between 80 and 90%, are classified as having 'very good' quality, and the mosaic class was classified as 'acceptable' (79.4%) [17].

2.6. LULC Dynamics and Sensitivity Analysis

From the transition matrix between the LULC maps of the year 2018 and the LULC maps of the predictive scenarios for 2036 (A1, A2 A3, B1, B2, and B3), the LULC dynamics were verified [76–78].

The transition matrix presents, diagonally, the persistence of each LULC class from the beginning to the end of the period. The column total denotes the proportion of the landscape occupied by each LULC class at the end of the period, and the row total is the proportion occupied by each LULC class at the beginning of the period. The values outside the diagonal represent the transitions between classes from the beginning of the period to its end [76].

The sensitivity analysis presented the relationship between the input variables of the model in a rank format [79]. It allowed us to observe which variables (driving forces) are relatively more influential in the changes seen in the territory [32].

To this effect, first, the contribution of each dimension to the composition of scenarios was verified by considering the sum of the importance of each driving force inputted into the model. Subsequently, the driving forces' influence was analysed based on the average of the normalised importance of the first ten driving forces.

3. Results

In this section we present the six predictive scenarios, considering first the 'no action' in the territory (do nothing—A) and following the conservation action (AreaNat—B), associated with three socioeconomic scenarios (BAU—1, optimistic—2, pessimistic—3). The six predictive scenarios (A1, A2, A3, B1, B2, B3) provide the main LULC changes predicted for 2036, compared to the LULC reference year 2018. For each scenario, according to the sensitivity analysis, we present the list of the ten most important driving forces with an average of the normalized importance of these 10 driving forces organized by dimension.

3.1. Predictive Scenario A ('Do Nothing')—LULC Changes and Key Driving Forces

LULC trends for the different predictive scenarios A1, A2, and A3 for the year 2036 obtained by the ANN1 model can be seen in Figure 4 and Table 8.

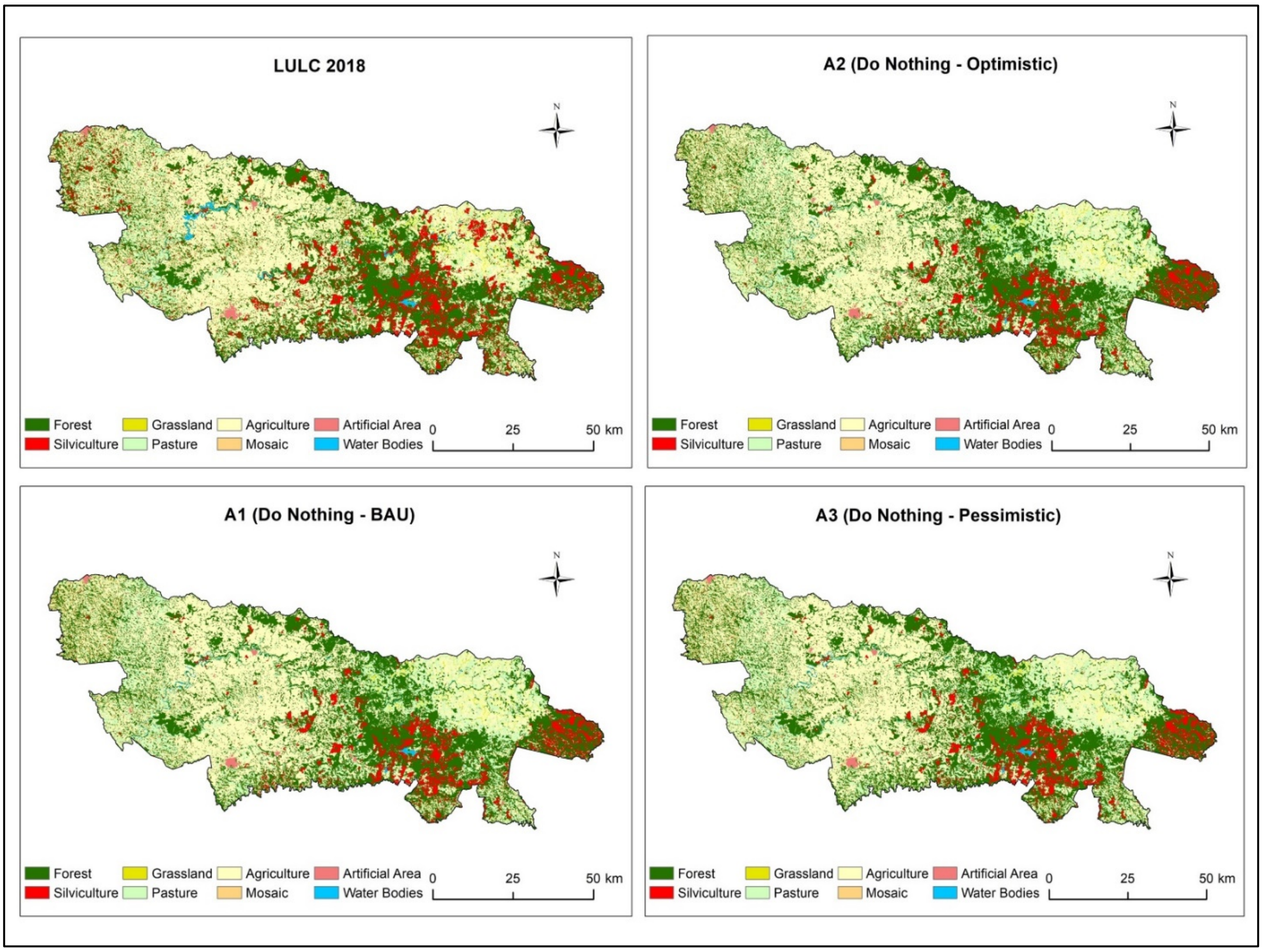

Figure 4. Scenario A—LULC evolution trends of the predictive scenarios for 2036—Chapecó River EC/SC—Brazil.

Table 8. LULC evolution trends of the predictive scenarios A.

LULC	Area (km^2)	Predictive Scenarios (2036)		
	Base Year (LULC2018) (Do Nothing)	A1	A2	A3
Forest	2097.6	2418.2	2418.4	2418.6
Silviculture	914.0	422.9	418.8	409.1
Natural grassland	149.0	34,2	36.5	18.3
Pasture	886.3	1306.1	1322.2	1324.3
Agriculture	2416.3	2637,9	2661.8	2670.0
Mosaic	677.7	363.7	327.2	340.7
Artificial Area	50.1	31.6	31.9	31.9
Water bodies	51.2	27.7	25.4	28.7
Total	7242.3	7242.3	7242.3	7242.3

Table 9 presents, for each scenario, the top ten driving forces responsible for the LULC changes presented in Table 8. The arrows indicate whether the driving force represents a positive (↑) or negative (↓) variation over the period. In Supplementary Material Repost S3: Sensitivity Analysis, one can observe the complete ranking of the driving forces for each scenario.

Table 9. The ten most important driving forces in predictive scenarios A.

Predictive Scenarios	Driving Force	Normalized Importance (%)
A1	Land use and land cover—2000	100.0
	Type of soil—2004	44.8
	Road network—2018	31.6
	Type of relief—2000	30.1
	Per capita income—2010 ↑	21.9
	Agricultural land price—2000 ↓	20.8
	Cattle herd—2018 ↑	20.3
	Processing industries—2006 ↓	19.8
	Rural population—2000 ↑	19.0
	Chicken herd—2000 ↑	18.7
A2	Land use and land cover—2000	100.0
	Type of soil—2004	38.5
	Road network—2018	38.2
	Type of relief—2000	26.1
	Processing industries—2006 ↓	19.3
	Use of agrochemicals—2017 ↑	18.7
	Agricultural land price—2000 ↓	18.7
	Cattle herd—2018 ↑	16.3
	Per capita income—2010 ↑	15.5
	Maize yield—2017 ↑	15.3
A3	Land use and land cover—2000	100.0
	Type of soil—2004	44.8
	Road network—2018	43.5
	Type of relief—2000	24.9
	Financing (Pronaf)—2017 ↓	21.3
	Gross value added of agriculture and cattle-raising—2002 ↑	21.2
	Gross Domestic Product (GDP) –(pessimistic) ↑	20.2
	Agricultural land price—2018 ↑	19.2
	Land structure—2017↑	18.0
	Swine herd—2018 ↓	17.9

Table 10 introduces the normalized importance average per analysis dimension of the ten first driving forces for each scenario.

Table 10. Statistics per analysis dimension of normalized importance of the ten first driving forces in LULC dynamics for the predictive scenarios A.

Predictive Scenario	Dimension	Average Normalized Importance (%)	N° of Driving Forces
A1	Physical/natural	51.6	4
	Economic	20.3	5
	Demographic	19.0	1
	Total		10

Table 10. *Cont.*

Predictive Scenario	Dimension	Average Normalized Importance (%)	N° of Driving Forces
A2	Physical/natural	50.7	4
	Economic	17.4	4
	Technological	17.0	2
	Total		10
A3	Physical/natural	53.3	4
	Economic	19.9	5
	Sociocultural	18.0	1
	Total		10

3.2. Predictive Scenario B ('AreaNat')—LULC Changes and Key Driving Forces

LULC trends for the different predictive scenarios B1, B2, and B3 for the year 2036 can be seen in Figure 5 and Table 11.

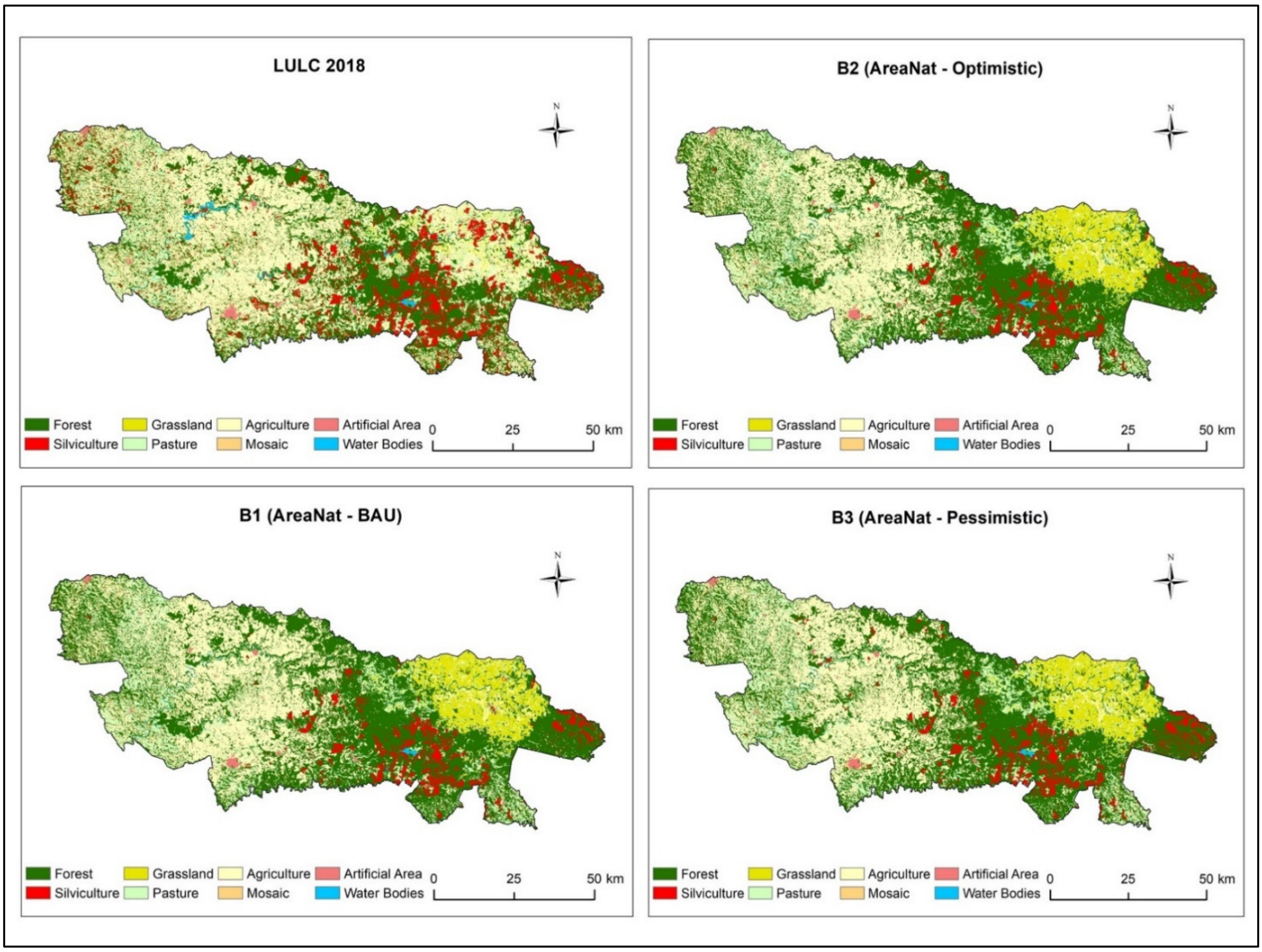

Figure 5. Scenario B—LULC evolution trends of the predictive scenarios for 2036—Chapecó River EC/SC, Brazil.

Table 11. LULC evolution trends of the predictive scenarios B.

LULC	Area (km^2)	Predictive Scenarios (2036)		
	Base Year (LULC2018) (Do Nothing)	**B1**	**B2**	**B3**
Forest	2097.6	3129.2	3151.8	3116.5
Silviculture	914.0	304.8	314.8	338.8
Natural grassland	149.0	624.0	628.3	622.2
Pasture	886.3	944.0	930.8	916.1
Agriculture	2416.3	2052.7	2033.8	2080.6
Mosaic	677.7	135	130.9	113.4
Artificial Area	50.1	31.4	32.9	34.1
Water bodies	51.2	21.2	19.1	20.6
Total	7242.3	7242.3	7242.3	7242.3

Table 12 presents, for each scenario, the top ten driving forces ranked according to their importance. The arrows indicate whether the driving force represents a positive (↑) or negative (↓) variation over the period. In Supplementary Material Repost S3: Sensitivity Analysis, one can observe the complete ranking of the driving forces.

Table 12. The ten most important driving forces in predictive scenarios B.

Predictive Scenarios	Driving Force	Normalized Importance (%)
B1	Land use and land cover—2000	100.0
	Type of soil—2004	43.8
	Road network—2018	30.2
	Type of relief—2000	23.6
	Use of agrochemicals—2017 ↑	20.8
	Technical orientation—2017 ↓	20.4
	Agricultural land price—2000 ↓	19.4
	Gross Domestic Product (GDP)—2017 ↑	18.6
	Tobacco yield—2002 ↑	18.3
	Formal employment (agriculture)—2006 ↑	18.1
B2	Land use and land cover—2000	100.0
	Road network—2018	51.1
	Type of soil—2004	38.6
	Type of relief—2000	23.8
	Formal employment (commerce/service)—2006 ↓	21.4
	Altimetry—2000	20.9
	Agricultural land price—2000 ↓	19.9
	Swine Herd—2018 ↓	17.2
	Gross value added of agriculture and cattle-raising—2017 ↓	17.0
	Tobacco yield—2017 ↓	16.8
B3	Land use and land cover—2000	100.0
	Road network—2018	49.5
	Type of soil—2004	40.3
	Type of relief—2000	26.9
	Altimetry—2000	22.6
	Agricultural land price—2000 ↓	21.8
	Cattle herd—2018 ↑	17.4
	Use of agrochemicals—2017 ↑	16.6
	Maize yield—2017 ↑	16.6
	Rural population—2010 ↓	15.4

Table 13 introduces the normalized importance average per analysis dimension of the ten first driving forces for each scenario.

Table 13. Statistics per analysis dimension of normalized importance of the ten first driving forces in LULC dynamics for the predictive scenarios B.

Predictive Scenario	Dimension	Average Normalized Importance (%)	N° of Driving Forces
B1	Physical/natural	49.4	4
	Technological	19.8	3
	Economic	18.7	3
	Total		10
B2	Physical/natural	46.9	5
	Economic	18.9	4
	Technological	16.8	1
	Total		10
B3	Physical/natural	47.9	5
	Economic	19.6	2
	Technological	16.6	2
	Demographic	15.4	1
	Total		10

4. Discussion

The main guidelines of public policies for rural development and management of the Chapecó ecological corridor (Table 5) point to objectives that must be achieved in an integrated manner through actions that favor socioeconomic advances, maintenance of native vegetation, and rehabilitation of degraded natural areas. An artificial neural network-based LULC dynamics model was used to simulate different socioeconomic scenarios and create predictive scenarios with a desired level of recovery and maintenance of natural areas.

Three possible socioeconomic scenarios were simulated through the manipulation of nine independent variables (Table 6). The first scenario considered that the model would not suffer any interference from the independent variables (BAU). Following some achievements theorized in public policies (Table 5), the optimistic scenario included potentially realistic increments to family farming, Pronaf, GDP, and productivity gains for soybean and maize. In the pessimistic scenario, the values of these variables were changed to lower gains, and an aging population and a rural exodus were simulated. Also, the climate scenarios of increase in average temperature and precipitation were simulated in the pessimistic scenario.

Three predictive scenarios (A1, A2, and A3) (Figure 3, Table 8) were obtained as a first result. Comparing them to the 2018 LULC map, regardless of the socioeconomic gains achieved, a recovery trend was observed in relation to forest areas until 2036, mainly through the reduction of silviculture areas. On the other hand, natural grasslands tend to continue suffering significant losses of areas due to the expansion of pasture areas for livestock activities, which presents the higher expansion rate (48%) in the region. Although at a lower rate (10%), the expansion of agriculture may also be responsible for advances over native grassland areas (Table 8).

In socioeconomic terms, the first two predictive scenarios (A1 and A2) suggest favoring rural development as the driving forces that most influence LULC dynamics indicate economic gains, productivity gains, and the expansion of agricultural activities. On the other hand, the expressive trend of loss of natural grasslands is even more visible in case of economic recession, social crisis involving the rural sector, and climate changes (scenario A3). In this pessimistic scenario, the trend of area loss is twice as high as in the other scenarios, indicating a trend of loss of 87% of natural grassland areas for 2036 compared to 2018 (Table 8). The predictive scenario A3 is the least favorable to the recovery and conservation of natural grasslands, which is one of the main guidelines of the Management Plan of the Chapecó EC (Table 5).

The most active forces that cause this even greater loss of natural grasslands are related to a greater concentration of land, represented by the driving force land structure; the weakening of public policies to support rural producers, indicated by Financing (Pronaf); low economic growth, represented by the GDP; and the expansion of agricultural activities, represented by the driving force gross value added of agriculture and cattle-raising (Table 9). In addition to reflecting that low socioeconomic development has a negative impact on the conservation of natural resources, this result corroborates the importance of the social aspect represented by the mischaracterization of a land structure, represented by small rural properties. The average size of rural properties in the EC area between 2003 and 2017 presented an increase of 22%, while in the state of Santa Catarina this increase reached 12.5% [61].

The promotion of agriculture and preservation of natural resources combined with economic mechanisms aimed at promoting social equity and sustainable regional development (SC2030 Plan) is not sufficient to meet the guidelines for the conservation and recovery of natural areas. The trend towards a growing demand for agricultural and pasture areas demonstrates the importance of agrobusiness for the economy of the state. It reflects a rural development policy that is still ineffective in terms of sustainability, tending to favor large agro-industrial complexes (soybean and animal production complexes), as agrobusiness accounts for more than 70% of the exports of the state [61].

It is necessary to move forward and guarantee continuity in the materialization of the different economic mechanisms aimed at the conservation of natural resources proposed in the ecological corridor management plan, including conservation credits, financial support, and integration systems for agro-industry and local productive arrangements. In addition, it is necessary to engage local agents, investors, public and private institutions, and partners in the implementation of the action mechanisms specified in the plan [47].

Given the environmental inefficiency of the predictive scenarios generated from the simulations of socioeconomic variables, a simulation of the return to the vegetation cover similar to that observed in 1990, prior to the period of promotion of silviculture and agricultural commodities was presented [70,71].

Considering the same socioeconomic conditions of the three first scenarios, with this action in the territory three predictive scenarios were simulated (B1, B2, and B3), in which an environmental variable (AreaNat) was incorporated into the model with the aim of determining the preservation and recovery of natural areas.

As a result, significant gains of natural grassland areas were obtained, as well as a recovery in forest areas and gains of pasture areas. In predictive scenarios B (1, 2, and 3), agriculture tends to suffer a loss of approximately 15% of area compared to the 2018 LULC reality (Table 11). This simulation demonstrated the importance of territorial action policies for the preservation and recovery of natural areas. The advance of human activities on the natural environment, especially in areas of natural grasslands, can only be suppressed by means of actions such as the definition of areas of environmental preservation and legal reserves, the definition of conservation units or creation of ecological corridors [80,81].

The territorial intervention promotes direct actions in the landscapes, whose elements are represented in the model by the four first driving forces of greater importance in the LULC dynamics. These driving forces belong to the physical/natural dimension (Tables 9 and 12), presenting the greatest influence among the main driving forces in LULC dynamics. The greatest influence associated with physical-natural driving forces is present in most articles with similar approaches [13,27,38,82–85].

Thus, the adoption of actions that favor the desired changes in the driving forces of the physical/natural dimension is essential to achieve preservation and recovery objectives.

The significant influence of the driving forces of the technological dimension was also observed for predictive scenarios B (1, 2, and 3) (Table 12), indicating the importance of investing in technology and innovations in order to create a dynamic balance between the socioeconomic needs of rural areas and environmental preservation. Agricultural research in Brazil has always been synonymous with technology and innovation [86–88].

However, precisely due to the search for this dynamic balance between production, revenue, and environmental preservation, there is currently a trend towards a paradigm shift.

This change has been taking place in the state of Santa Catarina. In the 1970s and 1980s, research and technological developments in rural areas were focused on productivist models that emerged from the "green miracle" (genetic research, development and massive use of chemical fertilizers and pesticides, and a focus on increasing productivity). Currently, the new paradigm seeks to maintain the productive capacity of food for a still growing population, but with greater integration with ecosystems and natural dynamics (agroecology, agroforestry systems, organic agriculture, and direct sowing) [89].

Thus, the technological innovation necessary to achieve sustainable agriculture must undergo a process of adaptation and change.

The area of the Chapecó River Ecological Corridor is part of a region pointed out as an economic influence zone and force field for family farming and the agro-industrial complex. It is a territory of multiple interests to the extent that things are not defined either in terms of hegemonization of the productive pattern favored by the agro-industrial complex or in terms of resistance or adaptability to new scenarios by family farmers [45].

If, on the one hand, there is an area of importance for agroindustry and agrobusiness of the state of Santa Catarina, on the other hand there is an area of important biological diversity, with substantial diversity of social agents, such as cattle farmers, soybean producers, silviculturists, small family farmers descended from immigrants, small resettled family farmers, and indigenous peoples from the Guarani and Xokleng ethnic groups, defending different interests related to land ownership and use [47].

The territorial actions established by the ecological corridor management plan, such as the recovery of permanent preservation areas and the environmental suitability of rural properties proposed by the Management Plan of the Chapecó EC [47] should be strengthened.

In addition, new ways of doing agriculture should be encouraged, such as agroforestry systems, which are essential to ensuring economic development combined with environmental sustainability [90,91].

High levels of productivity in a smaller proportion of area and maximum environmental preservation may be achieved through the integration of modern techniques and knowledge from forestry, agricultural, and environmental sciences, such as agroforestry systems [91]. In the search for alternatives in response to the technical, globalized agriculture [92], the reconciliation of the development of rural environment (economic and social) with the conservation of biodiversity requires a broader participation of the government in the elaboration and implementation of public policies, offering greater prominence to local agents.

5. Conclusions

The adoption of LULC dynamics modelling through artificial neural networks proved to be a very useful tool to build predictive scenarios based on public policy guidelines that integrate rural development and environmental preservation and recovery.

Driving forces of a physical/natural are those with the greatest influence on LULC dynamics, regardless of the proposed socioeconomic scenarios.

For predictive scenarios generated from actions in the territory, technological driving forces are identified as the most important following the physical/natural ones.

One of the paths pointed out by these driving forces consists of investing in new agricultural technologies generated from productive systems integrated to nature.

Depending on the scope of the guidelines adopted in public policies, different predictive scenarios of land use and land cover may be expected. Public policies for social and economic development applied in isolation tend to generate future scenarios of low effectiveness in preserving and restoring natural environments.

Public policies for territorial intervention are required so that preservationist objectives are achieved in parallel with social and economic objectives.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/land12010181/s1, Report S1: Variable description. A summary table of the construction of the predictive scenarios is available online, Report S2: scenario building. Sensitivity analysis results are available online, Report S3: Sensitivity analysis.

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