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Land use and land cover scenarios: An interdisciplinary approach integrating local conditions and the global shared socioeconomic pathways

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ABSTRACT

Land Use and Land Cover (LULC) changes have profound impacts on the functioning of (agro)ecosystems and have potential to mitigate global climate change. However, we still lack interdisciplinary methods to project future LULC scenarios at spatial scales that are relevant for local decision making and future environmental assessments. Here we apply an interdisciplinary approach to develop spatially explicit projections of LULC at a resolution of 30×30 m informed by historic relationships between LULC and their key drivers, within the context of the four qualitative scenarios of global shared socioeconomic pathways. We apply this methodology to a case study in the Zona da Mata, Brazil, which has a history of major LULC changes. The analysis of LULC changes from 1986 to 2015 indicates that pasture area decreased from 76 to 58 % of total area, while forest areas increased from 18 to 24 %, and coffee from 3 to 11 %. Environmental protection legislation, rural credit for smallholder farmers, and demand for agricultural and raw products were identified as main drivers of LULC changes. Projected LULC for 2045 strongly depends on the global socioeconomic pathway scenarios, and forest and coffee areas may increase substantially under strong government measures in the environmentally conscious Green Road scenario or decrease in the high consumption Rocky Road scenario. Our study shows that under the set of drivers during the past three decades reforestation can go hand in hand with increase of agricultural production, but that major and contrasting changes in LULC can be expected depending on the socioeconomic pathway that will be followed in the future. To guide this process, LULC scenarios at the local scale can inform the planning of local and regional development and forest conservation.

1. Introduction

Land Use and Land Cover (LULC) changes have profound impacts on the functioning of (agro)ecosystems and have potential to mitigate global climate change (Foley et al., 2005), but there is a lack of interdisciplinary methodological approaches to project future LULC scenarios at local scale based on global socioeconomic scenarios. Local LULC may change in response to economic drivers, social dynamics and environmental factors, and can have ecological, economic and social impacts at regional and even global scales (Lambin et al., 2001; Zhao et al., 2006). Exploring potential impacts of LULC changes on (agro) ecosystems by scenario analysis can inform decision making and supporting land use planning to strengthen socioeconomic development and nature conservation (Peterson et al., 2003).

Scenario analysis is widely used to explore pathways towards more sustainable land management (Duinker and Greig, 2007), and has been applied worldwide to build LULC scenarios in qualitative (Oduro et al., 2014; Wesche and Armitage, 2014) and quantitative terms (Han et al., 2015; Sleeter et al., 2012). Qualitative scenarios describe narratives or storylines of different socioeconomic and/or environmental developments for the future (Tapinos, 2012). These scenarios are useful to engage with experts, land managers and policy makers to develop strategies to guide spatial planning and decision making at local and regional scales (Welp et al., 2006). However, the analysis of future scenarios of LULC can be enhanced when qualitative scenarios are coupled with quantitative modelling, resulting in a spatially explicit

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representation of LULC.

Spatially explicit modelling of LULC scenarios can inform how contrasting socioeconomic and environmental developments may play out in different landscape settings. A two-step process is often used for the projection of spatially explicit LULC scenarios: i) the assessment of future percentages of LULC classes, and ii) the allocation of LULC to landscape units (e.g., Verburg et al., 2002, 2006, Verburg and Overmars, 2009; Mas et al., 2014; Liu et al., 2017; Lin et al., 2011). The future LULC demand can be estimated by the story and simulation approach (Alcamo, 2008; Mallampalli et al., 2016), and spatial allocation of land use types using models, such as the Conversion of Land Use and its Effect (CLUE-S) and Dynamics Land Systems (DLS) models (Verburg et al., 2002; Deng et al., 2008). LULC scenarios are often derived from global/regional qualitative or quantitative socioeconomic scenarios (e.g., IMAGE model; Global Europe 2050), which describe different trajectories of the economy, population, environment and agriculture of selected regions over time (Rounsevell et al., 2006; Sleeter et al., 2012). However, the coarse resolution of global LULC scenarios are not ideal for local applications.

Global narratives of socioeconomic and climate developments may be useful to inform the development of socioeconomic scenarios at the local scale, integrating local conditions in a global context (Nilsson et al., 2017). The global Shared Socioeconomic Pathways (SSPs) consist of five contrasting qualitative scenarios: Sustainability (Green Road), Regional Rivalry (Rocky Road), Inequality, Fossil-Fueled Development, and Middle of the Road (Kriegler et al., 2012; O'Neill et al., 2014). These scenarios describe future changes in human dynamics, economy, policies and institutions, technology, environment, and natural resources at the global level (O'Neill et al., 2017; Riahi et al., 2017). For instance, under the Green Road scenario there will be global cooperation, a limited growth of consumption, policies orientated toward sustainable development, and strong regulation of land use to avoid environmental externalities. On the other hand, under the Rocky Road scenario there will be a deglobalisation process with weak governance and low priority for environment issues, and limited regulation of land use. While these scenarios allow a meaningful analysis of potential implications at global level, the relatively coarse resolution make these scenarios less suitable to study LULC changes at the regional scale and below (Doelman et al., 2018; Popp et al., 2014; Riahi et al., 2017). Therefore, there is a need for plausible LULC scenarios, which reflect the local socioeconomic and environmental conditions, and are in accordance with global socioeconomic and climate projections.

Brazil is one of the world's biggest suppliers of agricultural products, such as coffee, soybeans, meat, and raw material as iron mineral, and has witnessed intense LULC changes. The Atlantic Forest biome is the fifth hotspot of biodiversity in the world (Myers et al., 2000). It supports 70 % of the Brazilian population and, due to this anthropogenic pressure, the forested area has been reduced to only 12.5 % of its original area (Sosma and INPE, 2019). In this biome, the region Zona da Mata of Minas Gerais was deforested in the 18th century. Over time, socioeconomic activities and public policies influenced the development of this region, which now consists of a mosaic of pastures, coffee fields and fragments of secondary forests, with a predominance of family farmers (Cardoso et al., 2001; Giovanini and Matos, 2004). The region is one of the three main areas of coffee production in Brazil and represents an interesting case study to analyse past socioeconomic development and to project future scenarios.

The aim of this study was to apply an interdisciplinary methodological approach to project plausible spatially explicit LULC scenarios at relevant spatial scales to support local land use policy making and future environmental assessments. Specifically, our objectives were (*i*) to assess LULC changes from 1986 to 2015, a period of profound changes in land use, in a selected area in the Zona da Mata region of Minas Gerais; (*ii*) to identify the main drivers of these changes, and, (*iii*) to create qualitative and quantitative socioeconomic scenarios and spatially explicitly projections of LULC for 2045 for the studied area within the context of SSPs scenarios.

2. Material and methods

2.1. Study area

The study area covers 11,119 km^2 and is located in the Zona da Mata of Minas Gerais state, Brazil. It borders the states of Espírito Santo and Rio de Janeiro in the Brazilian Atlantic Rainforest biome (Fig. 1). The study area includes the Caparaó National Park and the Serra do Brigadeiro State Park, which are protected areas for conservation and tourism. The climate is classified as humid subtropical, with hot and rainy summers and a well-defined dry season, and average annual precipitation of 1300 mm (Alvares et al., 2013). The relief is hilly and mountainous, and the predominant soils are Ferrasols and Acrisols. The main LULCs in the region are pasture, forest, coffee, and since the 2000's eucalyptus plantations were introduced for wood biomass production. Forest areas consist typically of small and fragmented patches on hill tops. The pasture areas consist mostly by *Brachiaria* spp., to raise beef and dairy cattle in extensive systems. Coffee is mainly produced in monoculture/unshaded *Coffea arabica* systems, but there are also some agroecologically managed agroforestry coffee systems (Souza et al., 2010).

The far majority of farmers in the study region are smallholders with 90 % of the farmers having less than 16 ha of land (IBGE, 2018; Teixeira et al., 2018). At the end of the 1980's the political and socioeconomic conditions had a negative impact on family farmer livelihoods and many farmers were struggling to maintain their agricultural activity (Cardoso and Ferrari, 2006). Since 2000, the national government has made efforts to financially support family farmers with the National Program for Strengthening Family Agriculture (Pronaf) and create a market for their produce with the Brazil's National School Feeding Program (Ghinoi et al., 2018; Valencia et al., 2019). In addition, over the last 30 years a strong social movement, integrating family farmers' organizations, has strived to implement agroecological practices, such as agroforestry systems, that reconcile nature conservation and agriculture production. In 1996, the 15,000 ha Serra do Brigadeiro State Park was created in a unique case of collaboration of social movements, non-governmental organizations (NGO), researchers and the state government.

2.2. Methodological framework

A methodological approach was applied to generate spatially explicit scenarios of LULC for 2045 (Fig. 2; Verburg et al., 2006, 2008). First, we created maps of historic LULC (Section 2.3). Next, we identified the drivers of LULC changes through workshops with local stakeholders and historical data (Section 2.4) to build qualitative and quantitative scenarios (Section 2.5). Finally, we used a spatial allocation model to build maps of LULC for 2045 (Section 2.6). More specifically, the approach comprised five main steps: (1) map the LULC changes from 1986 to 2015; (2) identify the main socioeconomic drivers of these LULC changes in this period; (3) build and translate qualitative socioeconomic scenarios into quantitative estimates, with subsequent assessment of future LULC demands; (4) use biophysical variables to develop a predictive allocation model for the LULC classes to landscape units; and (5) allocate LULC classes to landscape units by combining the future LULC area demand and the allocation model.

2.3. Modelling past land use and land cover

To assess LULC changes in the study area we used images of Landsat 5 and 8 from 1986, 1995, 2007 and 2015. We selected this period because major LULC changes took place in the study area and Landsat

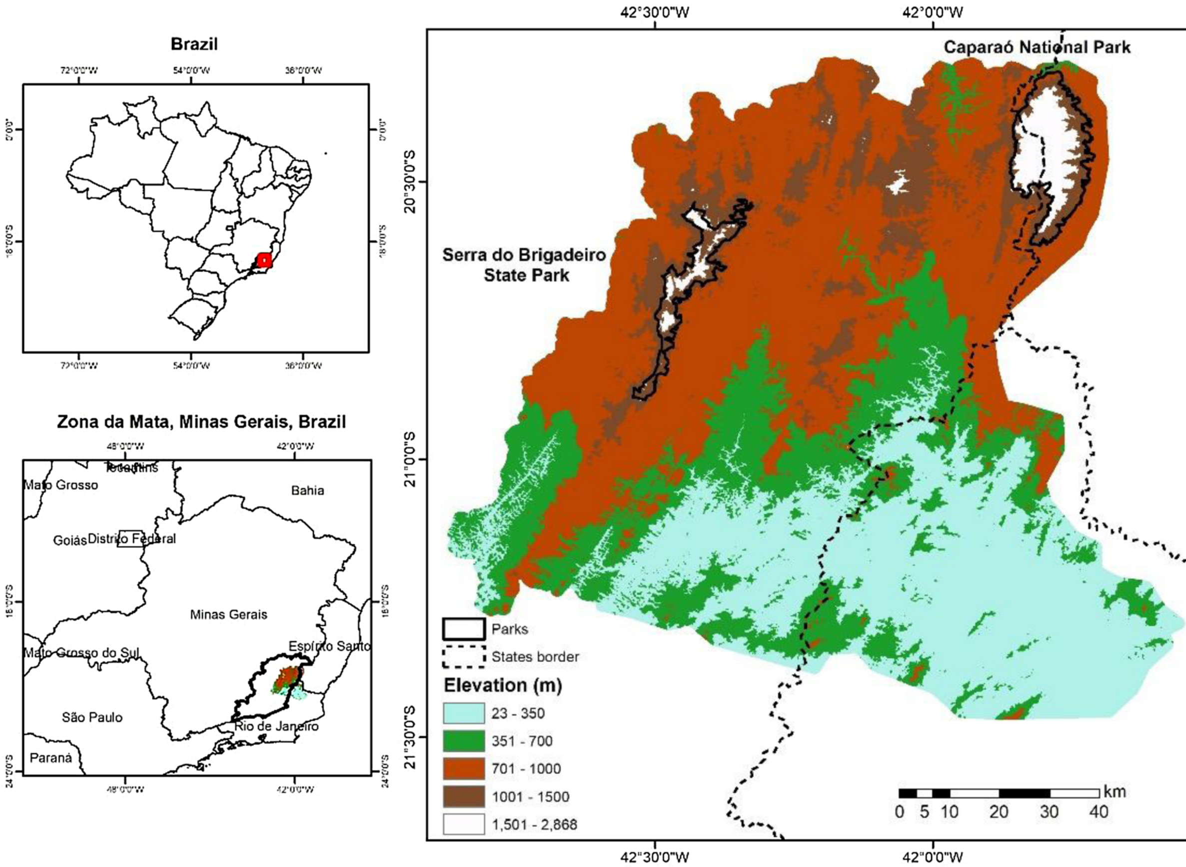

Fig. 1. Zona da Mata, state of Minas Gerais, and its border with the states of Espírito Santo and Rio de Janeiro, Atlantic Forest biome, Brazil.

images with relatively little cloud cover were available for these years, allowing a meaningful assessment of the LULC changes across approximately a 30-year time period. The images were obtained from the United States Geological Survey Earth Resources Observation and Science Center with a resolution of 30 × 30 m (http://earthexplorer.usgs.gov/).

The images were processed using ArcGIS and were classified in six LULC classes: Forest, Coffee, Pasture, Urban Areas, Campo Rupestre (scrub-grassy vegetation on rocks) and Eucalyptus. To classify the images, we collected sampling polygons (12 pixels each) for each LULC by visual interpretation of the Landsat images. The strategic sampling approach based on polygons allowed a better representation of the diversity of spectral characteristics from the same LULC type than an analysis based on a single pixel samples. This process created a database with about 2000 sampling polygons (24,000 pixels), which reflects the area proportion of each LULC class in the study region. To separate the LULC classes we used the Landsat image bands (1–9), Normalized Digital Vegetation Index (NDVI) and Soil Adjusted Vegetation Index (SAVI) as predictor variables (Chakraborty et al., 2016). In addition, to further improve the separation of LULC classes in mountainous terrain we also included the distance from urban centre, the Digital Elevation Model (DEM), geomorphological variables derived from the DEM (e.g. slope, curvature) and solar radiation (Stathakis and Faraslis, 2014). The DEM was obtained from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) dataset with a resolution of 30 × 30 m (http://earthexplorer.usgs.gov/). Then we extracted the values of explanatory variables for the location of pixel samples, generating a database of pixels with LULC types and associated explanatory variables. Next, we used the Random Forest algorithm to randomly select 75 % of the data to train a predictive model, while keeping 25 % of the data as an independent dataset to test the accuracy of the model using the Kappa index. LULC changes were assessed by the construction of a transition matrix of the images between 1986 and 2015, and an annual trend of each LULC was obtained by interpolation the data from the maps of 1986, 1995, 2007 and 2015.

2.4. Drivers of land use cover change

To identify the main drivers that may have influenced these changes in LULC, we organized three workshops in the municipalities of Espera Feliz, Divino and Araponga that are representative for the study area in the Zona da Mata of Minas Gerais. The workshops were attended by 94 participants, which included family farmers, part-time farmers and the directors of the farmer's union of the three municipalities. The workshops focussed on the identification of the historic development of LULC changes in the study region and their main drivers. Participants were asked to report their perceptions of changes in the percentage of forest, coffee, urban area and eucalyptus from 1986 to 2015 in a round table setting. This was followed by a discussion about the major socioeconomic and environmental drivers associated with the reported changes in LULC.

The identification of the main socioeconomic and environmental drivers of changes in LULC in the study region was informed by the outcomes of the workshop (Appendix A1). For instance, from the workshop it became clear that government measures to protect the environment, such as monitoring and high fines for deforestation, was an important driver for the changes in forest areas in the last decades. We used secondary data to triangulate and underpin the drivers that were identified in the workshop in a quantitative way. We used the annual deforestation rate data of the Atlantic Forest biome (Sosma, 2017) as a quantitative indicator for the effectiveness of government measures for forest protection (National Forest Code; Brasil, Lei, 4771/, 1965). Likewise, to underpin drivers related to changes in the area of urban areas, coffee and eucalyptus we used data on trends of rural and

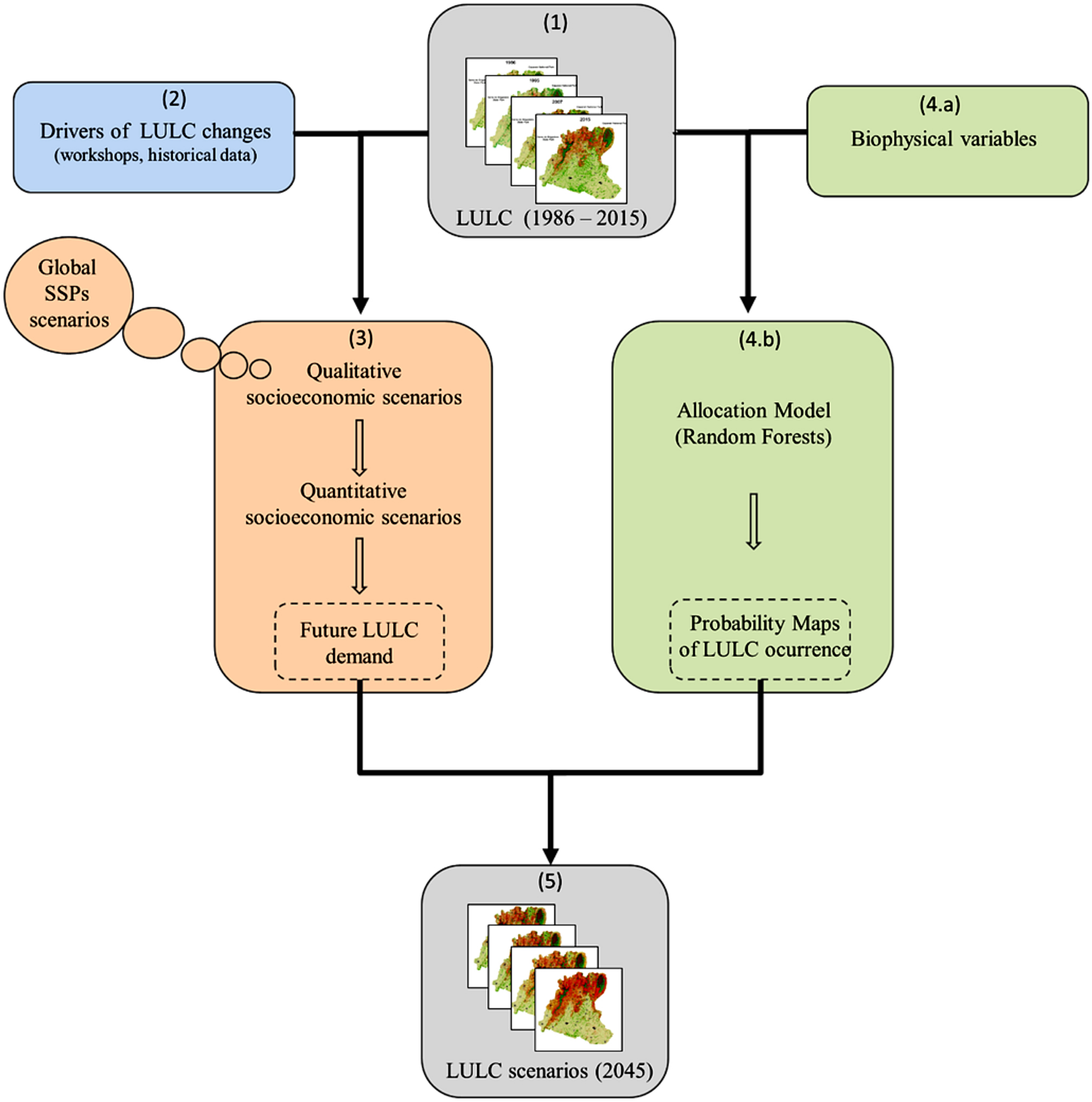

Fig. 2. Methodological framework applied to build the spatially explicit future scenarios of Land Use and Land Cover (LULC).

urban population sizes from the Brazilian Institute of Geography and Statistics (IBGE, 2018) and from the population census of 1980, 1990, 2000 and 2010, data of the Rural Credit by the National Program to Strengthen Family Farming (PRONAF; Banco Central do Brasil, 2017), and coffee export data from the International Coffee Organization (ICO, 2017). National data on the production of coal and cellulose were derived from IBGE (2018). These socioeconomic and environmental data were interpolated to obtain a dataset with an annual resolution between 1986 and 2015.

The annual socioeconomic and environmental data from 1986 to 2015 were considered drivers for LULC change and used to explain changes in forest, coffee, eucalyptus and urban area LULC classes. We used multiple regression models with the annual percentage of each LULC class as the dependent variable and the drivers of LULC change (e.g., rural credit, urban population size) as independent variables (Appendix A2). These regression models were then used to predict the future LULC demands based on the future developments of the socioeconomic and environmental drivers (Reginster and Rounsevell, 2006).

2.5. Qualitative and quantitative scenarios

LULC changes are governed by local, regional and global drivers (Lambin et al., 2001). To develop qualitative scenarios that capture this diversity of drivers we combined a scenario development technique and the global socioeconomic SSP scenarios (O'Neill et al., 2014; Tapinos, 2012). This combination allows to create scenarios that capture local characteristics (e.g., national public policies, local population dynamics), but still align with the global SSP scenarios. Scenario Development involved three steps: (*i*) defining the scope of the scenario exercise, (*ii*) identifying the two most important drivers of LULC changes to define the dimensions for the scenarios (i.e. x and y axes in Fig. 6), and (*iii*) developing qualitative scenarios based on projected trajectories of the two main drivers. This approach resulted in four contrasting qualitative narratives (Fig. 6) as outlined below.

In the first step, we projected scenarios of LULC from 2015 to 2045, mirroring the temporal range of our 30-year historic dataset (1986–2015). In the second step, we analysed the results from the workshops and the secondary data to select the two key drivers that most influenced the changes in LULC. In the third step, we created a matrix of four contrasting local scenarios based on the two key drivers of LULC change (Wulf et al., 2010). For each of the four local scenarios we developed a storyline with qualitative descriptions of contrasting future socioeconomic and environmental developments. To build the four local scenarios in accordance with global future projections, we described the local socioeconomic and environmental developments following the assumptions of the four global SSPs scenarios (Green Road, Rocky Road, Inequality, Fossil-Fueled Development) (O'Neill et al., 2017). For instance, the Green Road SSP scenario describes a future development with low pressure on natural resources and effective international cooperation. Then, one of the four local scenarios was described in this context, with the socioeconomic and environmental developments focused on nature conservation and sustainable agricultural production. We applied the same process to develop the other three scenarios storylines. Specifically, the SSPs scenarios describe the future developments of public policies, socioeconomic and environmental factors in terms of relative scales (e.g., strong, weak, low, high, medium) (O'Neill et al., 2017). Based on the SSPs qualitative descriptions, we categorized the future tendencies to increase/decrease of each local socioeconomic and environmental driver in five classes: very low, low, moderate, high and very high. For instance, in the Rocky Road SSP scenario the global environment will be under "serious degradation" and for land use there will be "hardly any regulation; continued deforestation due to competition over land and rapid expansion of agriculture" (O'Neill et al., 2017). We used these global scenario assumptions to describe the socioeconomic and environmental factors in the local context (e.g., very high increase in deforestation rate), which enabled us to derive a local scenario in line with the global Rocky Road scenario.

To achieve the future demands of each LULC class (expressed in area units), we translated the socioeconomic qualitative scenarios into quantitative terms in a two steps process. First, we translated the future qualitative dynamic of each driver to quantitative estimates using Bayesian parameter estimation (Kemp-Benedict, 2010). Annual relative changes of each driver (e.g., rural credit) between 1986 and 2015 were assessed and rescaled to 5 class percentiles: very low (0.025); low (0.150); moderate (0.500); high (0.850) and very high (0.975) rates. Then we assigned relative driver rates (very low to very high) for each driver according to its description of future dynamics in the qualitative scenarios. Next, we extrapolated the future annual growth rate of each driver from the baseline year 2015–2045. For instance, a socioeconomic driver indexed as 100 in 2015 and has an annual growth rate of 1%, will amount 101 in 2016, 102.01 in 2017, and 134.78 in 2045. In the second step, we use these projected values of socioeconomic and environmental drivers in the multiple regression equations for each LULC class (Section 2.4) to predict the future LULC demands in 2045 for forest, coffee, eucalyptus and urban area. For the area of Campo rupestres vegetation, which is not likely to change over time, we assumed that the area in 2045 will be the same as in 2015. Finally, we assumed that the percentage area that was not allocated to the above land use classes was pasture because in the workshop's farmers indicated even though pastures represent a major land use type, these are hardly managed and are not a priority in land use planning.

2.6. Spatial allocation of future LULC

The spatial allocation of future LULC was conducted using a predictive model (Fuchs et al., 2013; Moulds et al., 2015) and involved four steps. First, we generated a transition matrix of the changes in LULC between 1986 and 2015. Second, we selected a set of spatially explicit socioeconomic and environmental variables (digital elevation model, slope, Euclidian distances from cities centers and rivers, precipitation and temperature from WorldClim database (Fick and Hijmans, 2017)), which are plausible explanatory variables for the spatial distribution of LULC classes. Third, we selected a stratified random sample of 37,800 pixels containing data from LULC classes and we used these to extract the respective values of explanatory variables corresponding to each LULC class. With the LULC class and associated explanatory variables as dependent and independent variables, respectively, we used the Random Forests algorithm to create a probability map of LULC based on the suitability of each pixel for the respective LULC classes. Fourth, the allocation algorithm was used to create a map of LULC based on the probability maps of LULC and the demand for the area per LULC class. The decision rules for LULC transitions in the allocation algorithm were based on the assumption that the transition matrix of LULC changes between 1986 and 2015 are representative for the period 2015–2045, and that new urban areas should expand only in the neighbourhood of existing urban areas. The analysis was conducted using the LULCC package in R (Moulds et al., 2015; R Development Core Team, 2014).

To validate the allocation model, we created a predictive model from 1986 to 2007 and simulated the future LULC for 2015. The performance of the model was assessed by generating three-dimensional contingency tables, which compared the map of 1986, the simulated and actual map of 2015 (Pontius et al., 2011). This method allows to quantify and differentiate the allocation disagreement/agreement between observed and simulated maps within multiple resolutions. For instance, this method allows to distinguish between correctly predicted persistence of land use and correctly predicted changes in land use. Here, we compared the model performance at a 2 × 2 and a 256 × 256 pixel resolution. The agreement between the observed and simulated maps of 2015 was 67 % at a 2 × 2 pixel resolution, consisting of the accurate prediction of 60 % of the pixels with correctly simulated persistence of LULC, and 7% of all pixels with correctly simulated changes of LULC (Appendix A5). At a 256 × 256 pixels resolution the agreement increased to 92 % (with an accurate prediction of 79 and 13 % for correctly simulated persisting and changed pixels, respectively). This procedure strengthened our confidence that the performance of the model was satisfactory and that it can be used to make plausible projections of LULC in the study area. The model was used to generate LULC maps of 2045 for each of the four quantitative scenarios, and a reference scenario (RS), which was based on the extrapolation of LULC trends from 1986 to 2015 without scenario assumptions.

3. Results

3.1. Past LULC changes

The classification of past LULC change resulted in maps of the years 1986, 1995, 2007 and 2015 with a pixel resolution of 30 × 30 m with a high accuracy (Kappa index > 0.81) (Fig. 3; Appendix A3). The covariates Digital Elevation Model, NDVI and SAVI indexes, satellite bands and solar radiation were selected as the most important predictors of LULC classes. The LULC maps indicated that the percentage pastures decreased from 76 to 58 % between 1986 and 2015, while forest area increased from 18 to 24 %, coffee from 3 to 11 %, and urban and eucalyptus increased as well (Fig. 3 and 4). The LULC changes from 1986 to 2015 were most profound for forest and coffee with 41.3 % and 75.2 % of the forest and coffee area in 2015 being converted from pasture. The majority of eucalyptus plantations (63 %) were established in pasture, while 27 % of eucalyptus replaced forest between 1986 and 2015 (Fig. 4; Appendix A4).

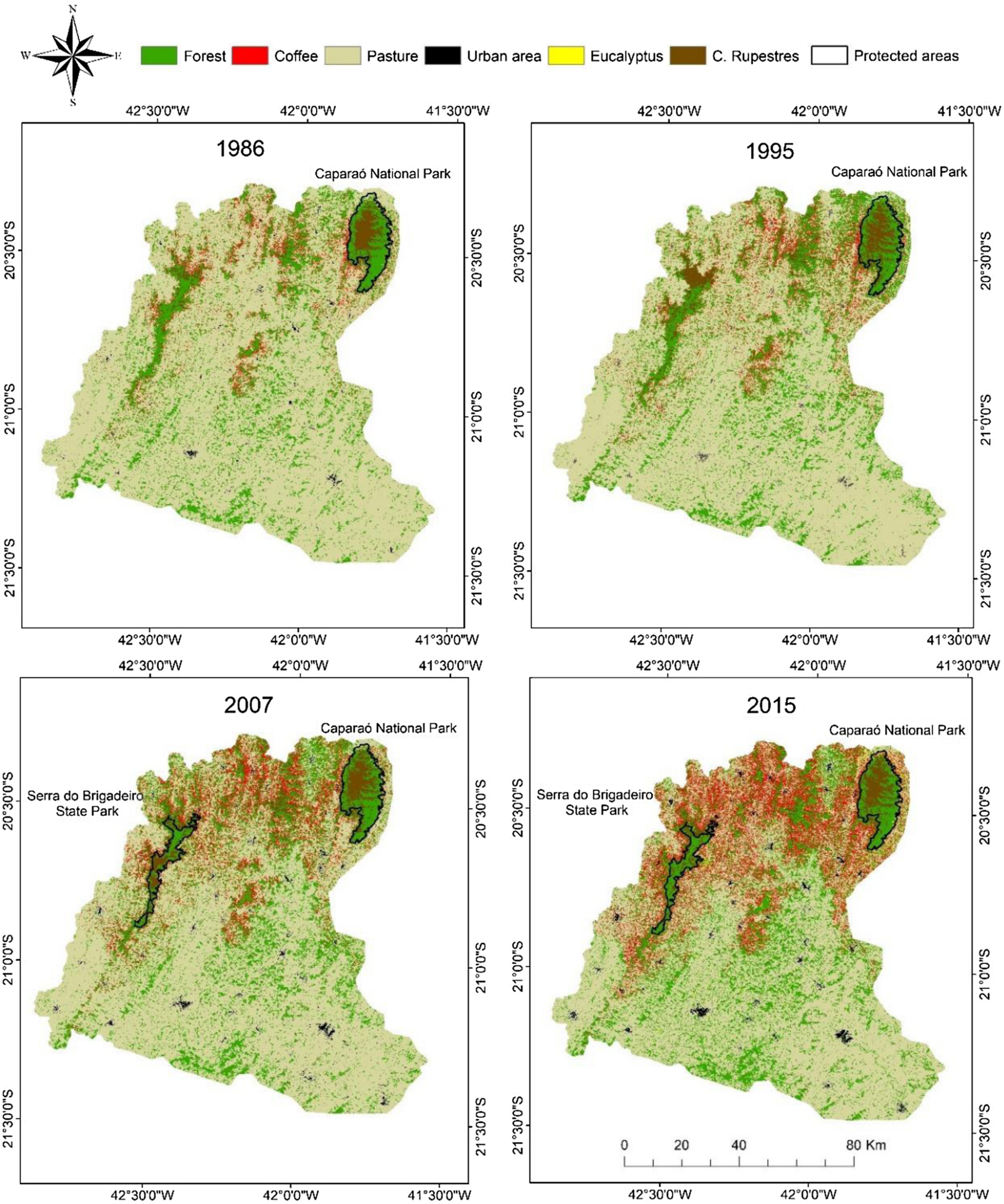

Fig. 3. Land use and land cover maps in the Zona da Mata region, Brazil, of 1986, 1995, 2007 and 2015.

3.2. Drivers of LULC changes

A major outcome of the workshops was that participants perceived that government measures against deforestation (e.g., monitoring and surveillance), providing credit for family farmers, migration from rural areas to urban centers, and the founding of the Serra do Brigadeiro State Park were the main drivers of changes in LULC between 1986 and 2015. Deforestation rate of the Atlantic Rainforest biome decreased about 90 % in this period, reflecting the effectiveness of the intensive monitoring programs by national environmental agencies. At the same time the rural population size decreased from 50.2%–25.1% of the total population (Fig. 5). Government credits for investment in the coffee production and livestock by family farmers increased steadily, amounting to almost 1 billion reais (Brazilian currency) per year in 2015. The export of coffee increased by approximately 380 %, along with increases in the production of charcoal (265 %) and cellulose (268 %).

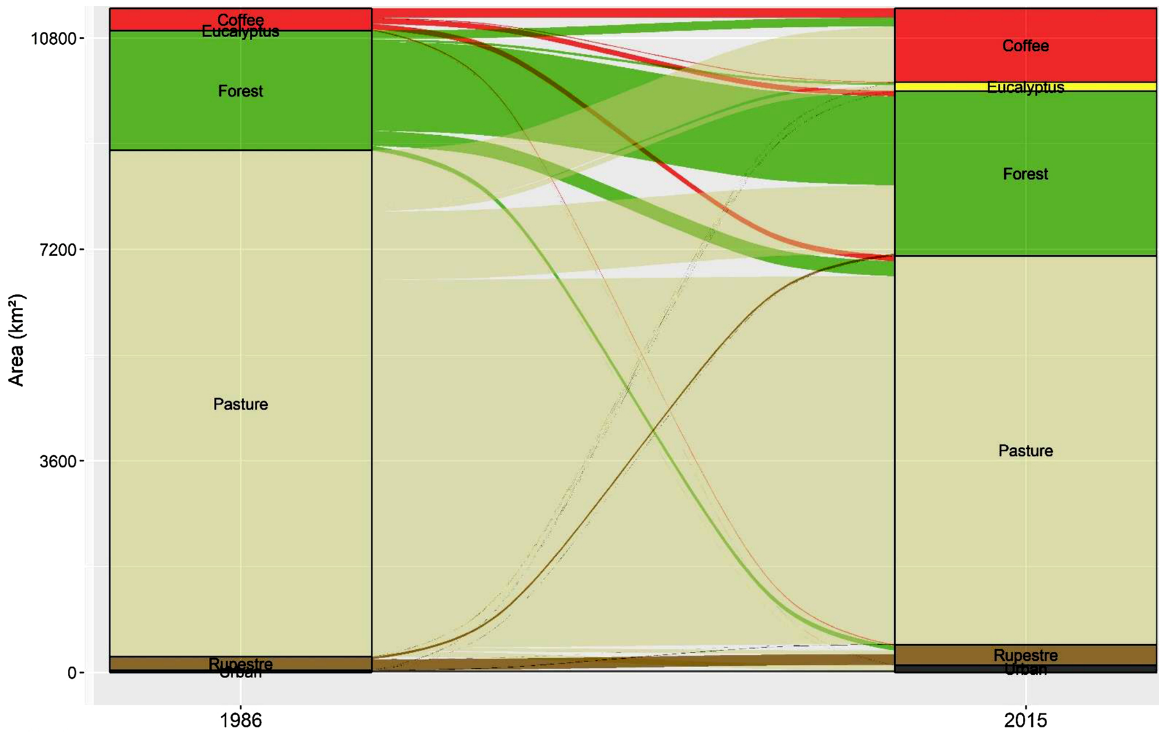

Fig. 4. Transitions of land use and land cover for forest, coffee, pasture, urban, Eucalyptus and campos rupestres vegetation between 1986 and 2015. Each line represents one pixel (30 × 30 m) in the study area.

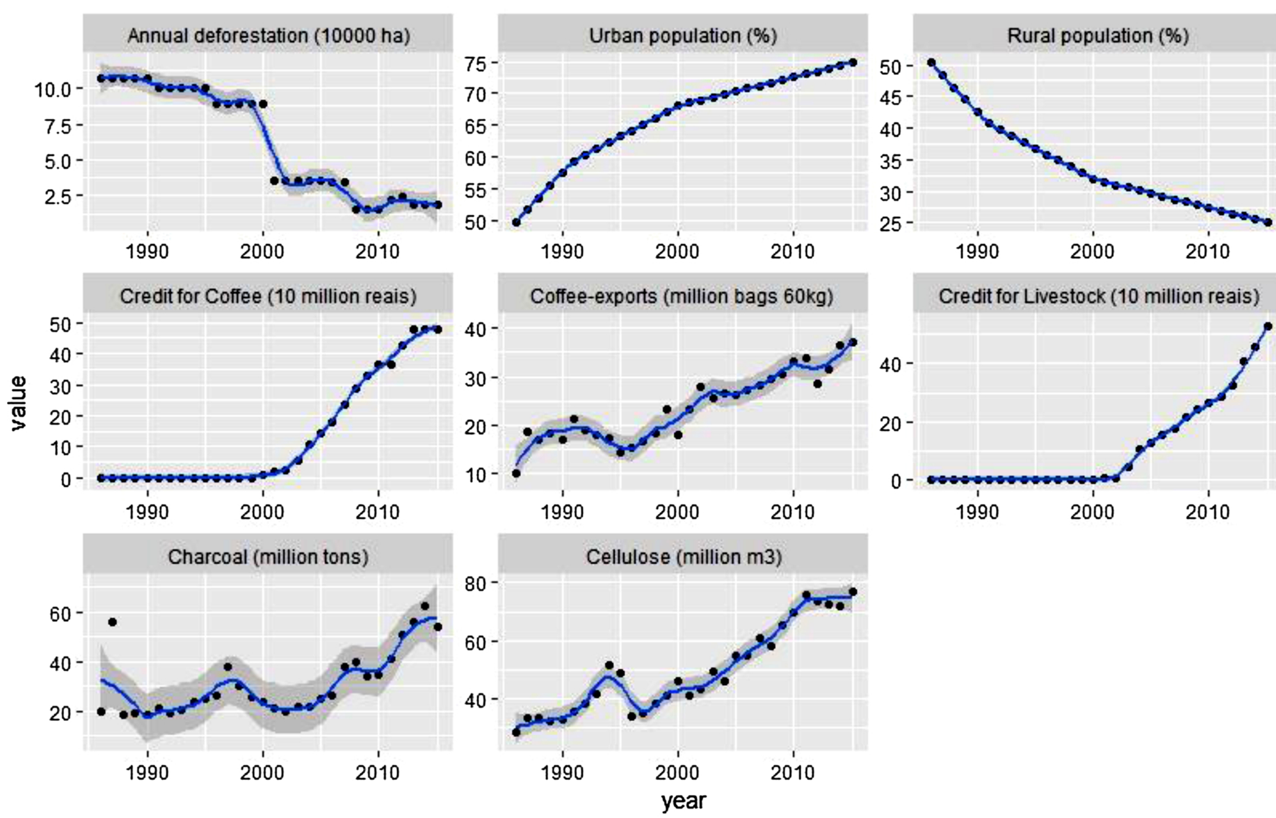

Fig. 5. Trends of the main drivers of land use land cover changes from 1986 to 2015, with multi-annual trends indicated by the blue smoothing lines. Reais is the Brazilian currency.

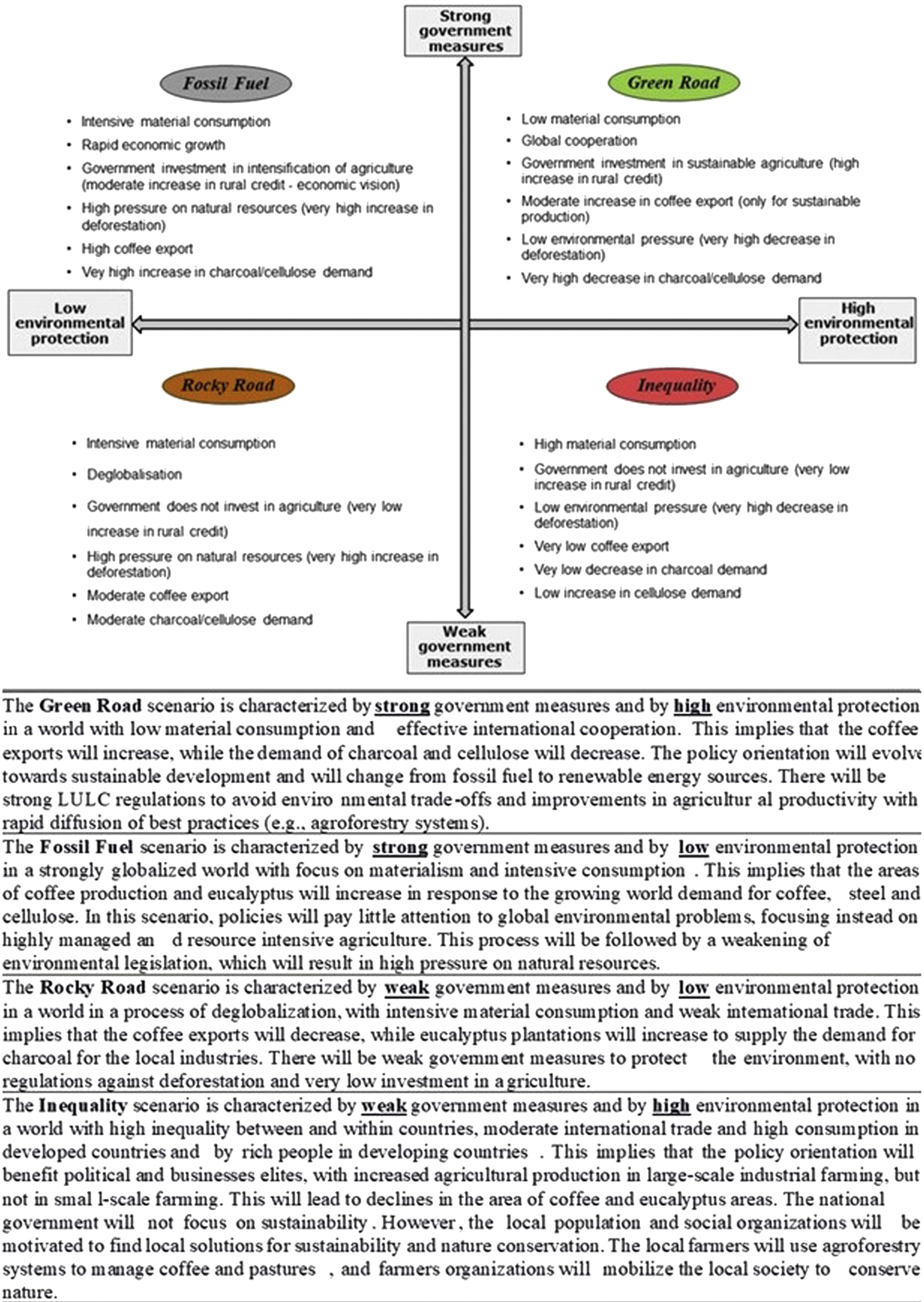

Fig. 6. Qualitative future scenarios (Green Road, Fossil Fuel, Rocky Road and Inequality) of Land Use Cover of 2045 in the context of shared socioeconomic pathways (SSPs).

Table 1
Projected annual rates for the drivers of Land Use and Land Cover (LULC) derived from Bayesian analysis for four contrasting future scenarios.

LULC	Drivers of LULC	Annual growth rates (%) - Bayesian parameters			
		Fossil Fuel	Green Road	Rocky Road	Inequality
Forest	Deforestation	8.947	−17.754	8.947	−17.75
	Credit for livestock and coffee	1.175	7.317	−6.734	−6.734
Coffee	Credit for coffee	1.222	2.94	0.008	0.008
	Coffee Export	4.46	2.97	0.5	0.3
Urban area	Urban Population	0.669	0.669	0.669	0.614
Eucalyptus	Charcoal	3.902	−1.5	3.265	−1.5
	Cellulose	3.533	−2.918	3.533	−2.918

The temporal association of the socioeconomic and environmental drivers with the LULC classes resulted in multiple regressions that define the specific effect of each driver in each LULC class (Appendix A2). For instance, forest area was negatively associated with deforestation rates in the Atlantic Forest biome and public policies for rural credit for coffee and livestock production ($R^2 = 0.84$), while the coffee area was positively associated with rural credits for coffee production and annual rates of coffee exports ($R^2 = 0.94$). Urban area was positively associated with the increase of urban population size ($R^2 = 0.84$), and the demand of charcoal and cellulose explained the establishment of eucalyptus plantations ($R^2 = 0.84$).

3.3. Qualitative narratives and quantitative scenarios

Overall, the results from workshops and the analysis of historical data indicated that the government measures (e.g., credit for farmers) and the degree of environmental protection were the most influential drivers of the LULC changes. Based on these two main drivers we created four scenarios (Fossil Fuel, Green Road, Rocky Road, Inequality) in the context of SSP scenarios, with the vertical axis representing the high and low government measures and the horizontal axis representing low high and low environment protection (Fig. 6).

The four qualitative scenarios (Green Road, Fossil Fuel, Rocky Road and Inequality) gave rise to different estimates of future annual rates for the socioeconomic and environmental drivers (Table 1). Adopting 2015 as a baseline, deforestation rates increased by 8.9 % per year in the Fossil Fuel and Rocky Road scenarios, and decreased by 17.8 % per year in the Green Road and Inequality scenarios. The investment in credit for coffee and livestock reached the highest rate in the Green Road scenario (7.3 % per year) and the lowest values for the Rocky Road and Inequality scenarios with an annual decrease of -6.7 % per year. Coffee export tended to increase in all scenarios, with the annual rate ranging from 4.46 % (Fossil Fuel) to 0.3 % (Inequality). The demand of charcoal and cellulose increased by about 3.6 % per year in the Fossil Fuel and Rocky Road scenarios, and decreased about 2.3 % per year in the Green Road and Inequality scenarios.

3.4. Predictive allocation model and future scenarios

The LULC demand for 2045 indicated that forest area is expected to increase by 52.4 % in the environmental scenario Green Road, and decrease by 41.7 % in the scenario Rocky Road compared to 2015 (Table 2; Fig. 7). On average the coffee area is expected to grow by 111 % in the Green Road, Fossil Fuel, and Reference scenario, while decreasing by 3.6 % in the Rocky Road and Inequality scenarios. In contrast to coffee area, pasture area tends to decrease on average by 32 % in the Green Road, Fossil Fuel, and Reference scenarios, and increase 8% in the Rocky Road and Inequality scenarios. The area of eucalyptus is expected to increase by 257 % in the Reference, Fossil Fuel and Rocky Road scenarios, while decreasing by 99 % in the Green Road and Inequality scenarios.

4. Discussion

4.1. Effects of drivers on LULC changes and future scenarios

Between 1986 and 2015 the area of forest, coffee, eucalyptus, and urban areas has increased in the Zona da Mata, which are likely driven by government measures and economic dynamics at local and global scales, among other drivers. However, these trends may change depending on the socioeconomic scenario that will unfold in the future. For instance, forest and agricultural areas may decrease in the Rocky Road scenario, and increase in the Green Road scenario.

Forest recovery was associated with government law enforcement against deforestation and public policies, and a declining rural population size. During the last two decades the policies have increasingly restricted deforestation, increasing the surveillance in the rural areas with real time monitoring, rural patrols and high fines. The effectiveness of public policies to decrease the deforestation has been reported as a key factor to protect the forest in Amazon biome (Arima et al., 2014). Another factor that contributed to decreasing the pressure on forest areas were the public policies for investments in agriculture, especially in coffee production and livestock (Fig. 5). The sustainable intensification of agriculture enables the increase of the productivity per unit area, reducing the need to convert forest into farmland (Garrett et al., 2018; Tilman et al., 2011). In the study region, the rural population decreased by 50 % between 1986 and 2015 as a result of the large-scale migration of family farmers to urban centers in Brazil in the 1980' and 1990's, with the promise of jobs and a better life in the cities (Lobo, 2016). The recovery of forest provides an inspiring example of how public policies against deforestation and financial support of farmers can be effective in reconciling agricultural production and environmental protection.

The 7% increase of forest area, after many years of deforestation, is an indication of the Forest Transition phenomenon (Mather, 1992;

Table 2
Projected land use and land cover areas in the Reference (RS), Green Road, Rocky Road, Fossil Fuel, and Inequality scenarios in 2045, and the percent change as compared to the base year 2015.

Land Use/Cover	Base year (2015)	Future Scenarios (2045)				
		RS	Fossil Fuel	Green Road	Rocky Road	Inequality
	Area*1000 ha (Gain/Loss %)					
Forest	280.8	368.6 (31.3)	188.2 (−32.9)	427.9 (52.4)	163.5 (−41.7)	270.4 (−3.6)
Coffee	125.7	310.2 (146.7)	247.6 (96.9)	239.5 (90.5)	123.4 (−1.8)	120.6 (−4.0)
Pasture	662.0	335.3 (−49.3)	590.6 (−10.7)	411.4 (−37.8)	743.0 (12.2)	688.3 (3.9)
Urban area	12.2	22.5 (84.2)	16.7 (35.9)	16.6 (35.9)	16.6 (35.9)	16.1 (31.5)
Eucalyptus	14.98	58.9 (293.1)	52.6 (251.4)	0.09 (−99.3)	49.0 (227.2)	0.09 (−99.3)
Rupestre	34.82	34.8 (0.0)	34.8 (0.0)	34.8 (0.0)	34.8 (0.0)	34.8 (0.0)

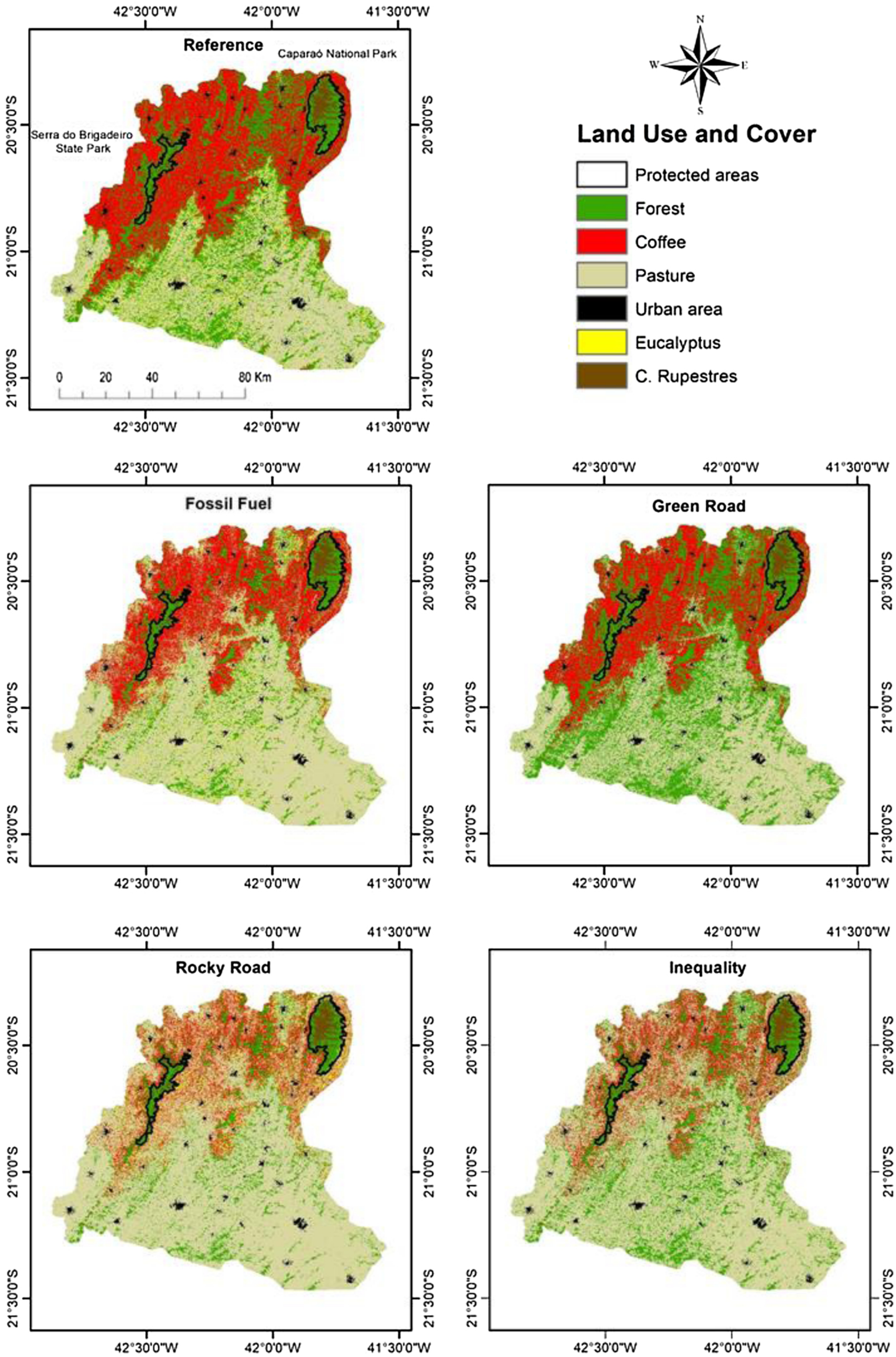

Fig. 7. Projected land use and land cover of the Reference, Green Road, Rocky Road, Fossil Fuel, and Inequality scenarios in 2045, Zona da Mata of the Minas Gerais state, Brazil.

Rudel, 1998). This phenomenon has been reported for developed countries, while in many developing countries the deforestation rates are still accelerating (Rudel et al., 2005). Our study is the first one to highlight, with satellite images, that the forest recovery may be an indication of Forest Transition in this region of the Atlantic Forest biome. However, should policies stop the protection of the environment and support for farmers, our scenarios project a decrease in forest area by 41.7 % by 2045 in the Rocky Road scenario. On the other hand, in the Green Road scenario, forested areas are projected to increase by 52.4 %, due to additional regulations to protect forests and increased investments in agriculture. While these scenarios project major changes in forest cover, the local-scale drivers of forest dynamics in the study region are still ambiguous due to the scarcity of pertinent data, such as subsidies for reforestation or fines imposed for deforestation. We addressed this information gap by using credit for agriculture and deforestation rate as proxies for the drivers of forest temporal dynamics. The identification of the main drivers of forests dynamics at local scale and the analysis of future scenarios can orient local, regional and global measures to protect and expand forest.

Government investment in coffee production and livestock in the last two decades supported the increase of the area of coffee from 3 to 11 %, and cattle stock from 600,000–830,000 animals from 1986 to 2015 in the study area (Statistical yearbooks-IBGE), despite an 18 % decrease pasture area. Public policies (especially the PRONAF) that provide credit specifically for coffee production are one of the main reasons of the consistent increase of coffee area, making it possible for the small farmers to invest in machinery (e.g. brushcutter, coffee dryer, harvest machine, mechanical shakers), and management of the coffee plantations. Global demand for coffee increased over the last 30 years and this is projected to continue for the foreseeable future (ICO, 2017). The study region has ideal growing conditions for coffee production, and the introduction of agroforestry systems, already established in the region, has potential to maintain coffee production in the future (de Souza et al., 2012; Gomes et al., 2020). The scenario analysis indicated (without accounting for impacts of climate change) that coffee areas may expand by almost 100 % in the Fossil Fuel and Green Road scenarios due to public policies, while a 3.6 % reduction is expected in absence of government measures in the Rocky Road scenario. Therefore, this region can contribute to supply the increase in the global demand for coffee under the Fossil Fuel and Green Road scenarios.

Land use changes are often driven by international commodity chains that support the global consumption (Lambin and Meyfroidt, 2011), highlighting the complexity and cross-scale interactions of drivers of local LULC. In our study area the global demand of iron mineral and cellulose in the last decades coincided with the increase of eucalyptus plantations. The fast growth of the economy of China in the early 2000's boosted the global demand for steel (Holloway et al., 2010) and fueled the export of iron ore from Brazil. Unlike other countries that use mineral charcoal to process iron minerals, in Brazil the charcoal made from wood is mostly used, especially from eucalyptus. The world demand for steel therefore increased the value of eucalyptus wood and government agencies and private companies encouraged farmers to plant eucalyptus. Furthermore, the global decline of coffee prices in the 2000's, resulting from increased production in Brazil and Vietnam, also motivated farmers in the study region to plant eucalyptus. Indeed, in the scenario of Fossil Fuel and Rocky Road with higher global demand of steel, an increase of eucalyptus area up to 251 % may be anticipated. Our study suggests that the context of global drivers, such as expressed in SSPs scenarios, can have profound and case study specific impacts on local drivers of LULC and the associated LULC change.

Developing qualitative and quantitative socioeconomic and environmental scenarios at the local scale is important to detect local characteristics (e.g., specific crops), which are extremely important to local LULC changes, but may be overlooked when analysing at national or global level. Moreover, the advantage of creating future scenarios of LULC consistent with the global SSPs assumptions is the possibility to explore the future impact of LULC changes on ecosystem services (e.g., water availability) in line with well-established scenarios for environmental variables (e.g., temperature, precipitation).

4.2. Methodological considerations

We applied an interdisciplinary methodological approach to develop spatially explicit scenarios at the local scale by integrating historic LULC changes, qualitative and quantitative socioeconomic scenarios inspired by global SSP scenarios, with subsequent estimation of LULC demand and the spatial allocation of LULC classes. Our interdisciplinary methodology follows the same steps as the multi-model CLUE-S approach (e.g. Verburg et al., 2002, 2006, 2008) that has been extensively applied worldwide to project LULC scenarios at different scales (Kucsicsa et al., 2019; Lin et al., 2007; Henríquez-Dole et al., 2018). In the CLUE-S methodology local LULC scenarios can be generated based on LULC maps and future socioeconomic scenarios (Verburg et al., 2006). However, this may pose a problem in situations where there is a scarcity of LULC data and socioeconomic scenarios at regional or local scales, such as in many developing countries. To overcome this information gap, we generated LULC scenarios at the local scale using open access methods and data. For instance, we used freely available Landsat images and the Random forest algorithm to classify past LULC trends. In addition, we applied a scenario development technique to develop local future narratives (Tapinos, 2012), and we used Bayesian regression analysis (Kemp-Benedict, 2010) to translate these qualitative socioeconomic scenarios into quantitative terms. The methodology has and weaknesses and strengths, which will be discussed below.

The applied approach has several limitations. The first is that identification of LULC changes by contrasting two independently created maps can give rise to inaccuracies due to map error classification, and therefore resulting LULC maps need to be interpreted with care. Second, while our study demonstrates that combining local scenario development and global SSPs scenarios is a promising way to develop plausible local future scenarios consistent with global future projections, the translation of the implications of global scenarios to local drivers of LULC entails many uncertainties. The participation of farmers in the workshops was essential to identify and understand the drivers of historical LULC changes, since farmers are key actors that make land use decisions and have a good awareness of the associated socioeconomic and environmental impacts (Ariti et al., 2015). The participatory component and on the ground impact of our methodology could still be further improved by discussing the outcomes of our analysis with relevant stakeholders, farmers, civil society and policy makers, and explore implications for future landscape planning and rural development (Nilsson et al., 2017; Palazzo et al., 2017; Häfner et al., 2018; Gullino et al., 2018).

The estimation of the future LULC demands using the Bayesian regression analysis allows to translate qualitative scenarios to quantitative terms in a systematic way. Expert judgment is the most commonly used method to translate narratives to numerical values, but is dependent on expert knowledge (Mallampalli et al., 2016). Using Bayesian statistics, we derived annual future rates for the socioeconomic drivers without the subjectivity of a translation process. We linked quantitative estimates of drivers to LULC demand using regression analysis, which has been widely used to assess the effect of drivers on specific LULC classes, such as the urban areas in Europe (Reginster and Rounsevell, 2006), and multiple LULC classes using dynamic system models (Liu et al., 2017). In our study we made the simplifying assumption that historic relationships between the main drivers and LULC changes will remain unchanged in the future. However, recent advances in non-stationary modelling of future LULC scenarios (McGarigal et al., 2018; Wang et al., 2019) open opportunities for accounting for the complexities of feedbacks and further improve land use models (Verburg et al., 2019). Yet, despite these technical advances, uncertainty about the interactions between drivers and wider developments in society in the future is a general yet unresolved issue in LULC scenarios studies, and therefore these need to be interpreted with care. Our methodology can be useful for scenario analysis in regions where historical LULC maps and future projections of socioeconomic and environmental developments are lacking. For future studies and depending on data availability, we also suggest including more assumptions of SSPs, related to demography, health and economy, which can further improve the quality of integrative future scenarios.

5. Conclusions

In this paper we show that in the past three decades forest and agriculture areas have expanded at the expense of pasture area in the Zona de Mata, Brazil, and that these LULC changes were likely driven by government measures. The projected LULC for 2045 strongly depends on the global socioeconomic pathway scenarios. The Green Road scenario indicates that government measures to protect the environment, such strong regulations and monitoring, and agricultural credit for family farmers may contribute to balancing forest conservation and agricultural production. In contrast, the high consumption Rocky Road scenario may result in substantial deforestation.

Contrasting socioeconomic narratives leading to different LULC configurations may inform local and regional policy making for forest and nature conservation by identifying areas that are prone to land use change in the future. Furthermore, spatially explicitly LULC scenarios combined with climate change scenarios may be useful to explore the effects of socioeconomic measures on biodiversity and ecosystem services, such as water regulation. While the prediction of future LULC changes is fraught with uncertainties, LULC scenario analysis can assist in planning of socioeconomic development to achieve a more sustainable future.

CRediT authorship contribution statement

L.C. Gomes: Conceptualization, Methodology, Writing - original draft, Formal analysis, Funding acquisition. **F.J.J.A. Bianchi:** Conceptualization, Supervision, Writing - review & editing. **I.M. Cardoso:** , Conceptualization, Supervision, Writing - review & editing, Funding acquisition. **R.P.O. Schulte:** Conceptualization, Supervision, Writing - review & editing. **B.J.M. Arts:** , Conceptualization, Supervision, Methodology, Writing - review & editing. **E.I. Fernandes Filho:** Conceptualization, Supervision, Methodology, Writing - review & editing.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.landusepol.2020.104723.

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