Supplementary Material

A) LULC data: dependent variables

For the analysis of the LULC changes, we used a data set that was originally produced in Pierri-Daunt and Silva (2019) (data is publicly available at https://zenodo.org/record/2648783), and is described there in detail. In the following, the main steps of data preparation are described, as well the results.

We acquired three Landsat Collection 1 Higher-Level Surface Reflectance images (formerly known as Landsat Climatic Data Record images) distributed by the U.S. Geological Survey (USGS), covering the entire study area (path 76 and 77 row 220, WRS-2 reference system, https://earthexplorer.usgs.gov/). The series included two images acquired by the Landsat 5 Thematic Mapper (TM) sensor on 1985-07-27 and 2000-01-10, and one image from the Landsat 8 Operational Land Imager (OLI) sensor, from 2015-08-15.

We choose the geographic object-based image analysis (GEOBIA) approach as it enables mixed use classification and requires less workload for manual post-classification corrections. We segmented the images into objects with homogeneous spectral responses using the Shepherd segmentation algorithm implemented in the open source library “RSGISlib”, accessible through the Python programming language (Bunting and Clewley, 2013).

We then classified land use and land cover at each imaged date using the Random Forests supervised algorithm (Breiman, 2001) implemented in the “Sci-Kit Learn” Python library (Pedregosa et al., 2012). This algorithm is an ensemble learning method based on classification and regression trees built through randomization of the training data (Breiman, 2001). The training data were the spectral responses of samples with known LULC categories (Table A.i). Homogeneous regions were manually selected as training samples, and delineated separately for each combination of LULC class and each imaged date, distributed as best as possible throughout the study area. The total area sampled for training each class depended on the relative proportion of the class within the scene, varying from

0.13 km² for bare soil to 14.10 km² for mature forest. Selection was based on visual interpretation of the images aided by visual comparison with high resolution datasets, when available.

Table A.i. - Land use and land cover classes used for mapping land cover changes in the Northern Coast of São Paulo State, Brazil, between 1985 and 2015, using Landsat historical data.

Land use / land cover class	Description
Mature forest	Dense forest characterized by advanced successional stages and comprised mainly by primary forest, or occasional old-growth secondary forest.
Regenerating forest	Less dense forest at early to medium successional stages, mostly comprised by regenerating secondary forest.
Non-forest vegetation	Native or exotic vegetation including pastures, grasslands and agriculture.
Bare soil and rock	Exposed soil or rock surfaces lacking vegetation and buildings and including sandy beaches and rocky shores.
Peri-urban	Mixed areas with lower population density and sparse buildings, including a high diversity of rural uses, agroforestry, and small forest fragments.
Dense urban settlements	Dense built-up areas, mostly urban.
Water	Free water surfaces.

To aid image interpretation and support map validation and accuracy assessment, we obtained digital georeferenced colour aerial photographs from 2001 at the 1:10.000 scale, freely available at www.datageo.sp.gov. We also used the GoogleEarth™ platform to assess the accuracy of the most recent classification, based on Landsat 8 OLI. To generate the ground truth dataset, we randomly distributed 40 random points per LULC class for each date, which were then visually interpreted and classified based on the available high-resolution imagery. We then used these sets to build confusion matrices and derive global accuracy, per-class accuracy, the kappa index of agreement, and commission and omission errors (Congalton, 1991) (Table A.ii). After manual revision and correction, land use and land cover maps for 2015 and 2000 had overall accuracies of 0.94 and 0.88, and corresponding Kappa agreement indices were 0.92 and 0.86 respectively.

Table A.ii. Kappa index of agreement and omission and commission errors for each LULC class from 2000 and 2015, after manual correction.

Classes	Kappa Index		Omission Error		Commission Error	
	2000	2015	2000	2015	2000	2015
Non-forest vegetation	0.85	0.94	0.15	0.05	0.13	0.05
Peri-urban	0.79	0.85	0.13	0.07	0.18	0.13
Bare soil/rock	0.83	0.93	0.00	0.09	0.15	0.06
Dense urban settlements	1.00	0.88	0.05	0.03	0.00	0.10
Mature forest	0.85	1.00	0.10	0.06	0.13	0.00
Regenerating forest	0.81	0.93	0.26	0.08	0.15	0.06

Land use and land cover changes were quantified using map algebra, by mathematically adding them together in successive pairs, from 1985 to 2000 (10*LULC2000 + LULC1985) and from 2000 to 2015 (10*LULC2015 + LULC2000). We reclassified the LULC data into the four chosen dominant processes of change from 1985 to 2000 and from 2000 to 2015 (in **bold**, Table A.iii). Different land cover conversions can sum up to the same process; for instance the process "urban growth" consists of conversions from various LC types into the "urban" class; "peri-urban growth" consists of conversions from various cover types into the "peri-urban" class; "forest persistence" consists of no changes in "mature" and "recovery" forest classes; and "deforestation" consists of conversions from both forest classes to any other cover type (Bürgi et al., 2017). We create binary rasters for one of each process of change from 1985 to 2000 and from 2000 to 2015, and this data was considered as the dependent variables of our model.

Table A.iii. Dominant processes aggregated from Pierri-Daunt and Silva (2019). Processes used to construct the model are in **black** other processes and types of changes are in **grey**.

LULC classes	Non-forest vegetation	Peri-Urban	Bare soil	Urban	Mature forest	Regenerating forest
Non-forest vegetation	No change	Non forest vegetation decrease/ **Peri-Urban growth**	Non forest vegetation decrease/ Bare soil increase	Non forest vegetation decrease/ **Urban growth**	Non forest vegetation decrease/ Afforestation	Non forest vegetation decrease Afforestation
Peri-Urban	Peri-Urban decrease/ Non forest vegetation increase	No change	Peri-Urban decrease/ Bare soil increase	Peri-Urban decrease/ **Urban growth**	Peri-Urban decrease/ Afforestation	Peri-Urban decrease / Afforestation
Bare soil	Bare soil decrease/ Non forest vegetation increase	Bare soil decrease/ **Peri-Urban growth**	No change	Bare soil decrease/ **Urban growth**	Bare soil decrease/ Afforestation	Bare soil decrease/ Afforestation
Urban	Urban decrease/ Non forest vegetation increase	Urban decrease/ **Peri-Urban growth**	Urban decrease/ Bare soil increase	No change	Urban decrease/ Afforestation	Urban decrease/ Afforestation
Mature forest	**Deforestation**/ Non forest vegetation increase	**Deforestation / Peri-Urban growth**	**Deforestation**/ Bare soil increase	**Deforestation/ Urban growth**	**Forest persistence**	**Forest disturbance**
Regenerating forest	**Deforestation** / Non forest vegetation increase	**Deforestation / Peri-Urban growth**	**Deforestation**/ Bare soil increase	**Urban growth / Deforestation**	**Forest persistence**	**Forest persistence**

Table Aiiii Land use and cover characterization inside and outside state parks in Northern Coast of São Paulo State (State Park area = 1375.7 km²; Outside State Parks = 572.7 km², % = class percentage of the entire area).

Land use and land cover classes		1985		2000		2015	
		km²	% study area	km²	% study area	km²	% study area
Mature forest	Park	1282.0	91.4	1220.4	87.1	1182.2	84.3
	Outside	181.0	33.9	144.0	27.0	151.9	28.4
	Total	1463	75.5	1365.6	70.4	1335.3	68.9
Recovery forest	Park	78.0	5.6	146.5	10.4	183.4	13.1
	Outside	138.2	25.9	148.3	27.8	127.3	23.8
	Total	216.2	11.2	295.2	15.2	311.3	16.1
Non-forestall vegetation	Park	20.1	1.4	14.5	1.0	12.3	0.9
	Outside	114.1	21.4	98.7	18.5	74.1	13.9
	Total	134.4	6.9	113.4	5.8	86.5	4.5
Bare soil/rock	Park	3.6	0.3	2.3	0.2	1.4	0.1
	Outside	15.5	2.9	9.9	1.8	6.2	1.2
	Total	19.7	1.0	12.6	0.6	8.0	0.4
Peri-urban	Park	16.4	1.2	15.5	1.1	23.1	1.7
	Outside	34.4	6.4	36.8	6.9	41.1	7.7
	Total	50.8	2.6	52.4	2.7	64.3	3.3
Urban	Park	0.1	0.0	0.9	0.1	2.7	0.2
	Outside	45.9	8.6	90.2	16.9	120.4	22.6
	Total	46.3	2.4	91.8	4.7	123.8	6.4

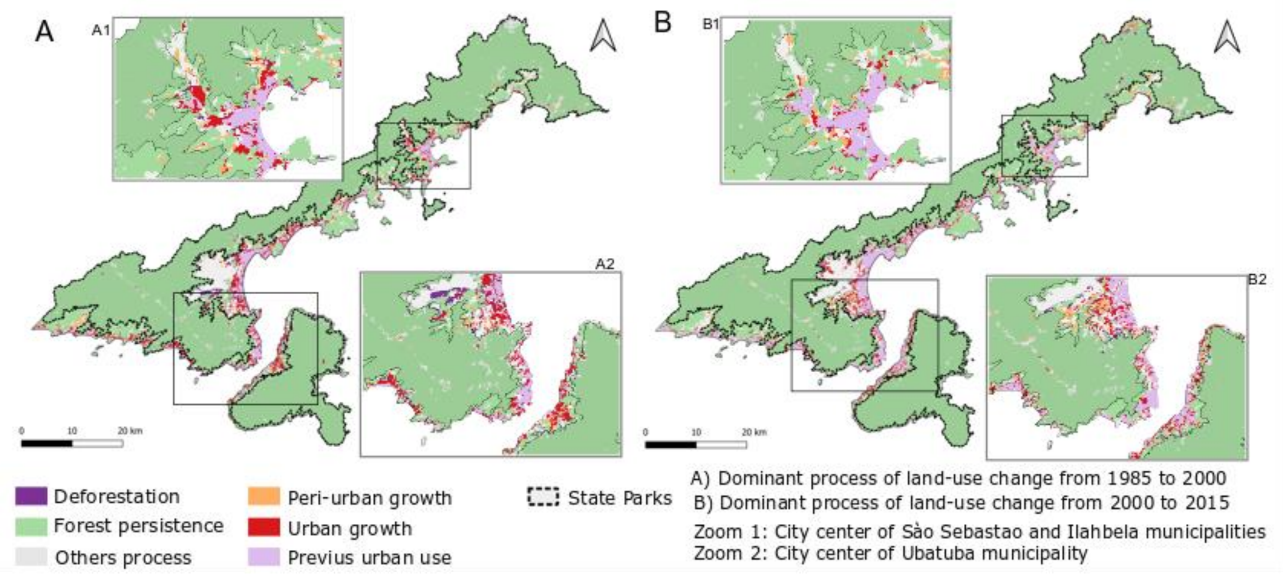

Figure A.i. The most dominant processes between 1985 and 2000 (A) and 2000 and 2015 (B). Adapted from Pierri-Daunt & Silva (2019). Urban growth consists of conversions from various cover types into the cover class urban; the process of peri-urban growth consists of conversions from various cover types into the cover class peri-urban; forest persistence consists of mature and recovery forest maintenance; and the process of deforestation consists of conversions from mature and recovery forest into various cover types; previous urban use consists in no changes in urban use from A) 1985-2000, and B) 2000-2015; other process consist of all other land conversion trajectory.

B) Driving forces: literature review and variables choices

In the following section, we provide rationales and background information from the literature on the driving forces considered and the respective variables selected

The Political driving force (hereby DF) has been broadly described as one of the most important drivers of landscape changes, although it usually acts indirectly on land changes (Hersperger and Bürgi, 2009; Plieninger et al., 2016). Environmental policies can affect land availability, land prices, transport network and therefore determine the land use and landscape stability (Hersperger and Bürgi, 2009; Jepsen et al., 2015). The Atlantic forest at the Northern Coast of São Paulo State (NCSP) is protected by three state parks, the Serra do Mar, Ilhabela and Ilha Anchieta, which protect around 70% of the study area. The presence of state parks is suggested as a driver of forest persistence. Ecological-Economic Zoning (EEZ) was developed in Brazil during the 1980s, and is one of the main instruments that regulate land-use change at NCSP (Figure 3, manuscript). Developing countries are usually characterized to present fast urban sprawl devoid of water access, sanitation and waste service. In order to better understand the role of the public policies in NCSP, we quantified the effect of the attendance of these services on urban and peri-urban growth.

Socio-economic drivers have been broadly described as one of the most important driver of landscape changes (Hersperger and Bürgi, 2009; Silva et al., 2016), and population density and demographic changes have been already discussed as the main cause of LULC changes (Ellis and Ramankutty, 2008) although they are rarely the only or major underlying cause (Lambin et al., 2001). Population density, permanent house density and mean income were previously suggested to be a driver of deforestation, urban and peri-urban growth. Increased in the percentage of access to basic education was suggested to be a driver of forest persistence, but can also be associated with urban growth, since the access to education is frequently higher in urban areas in Brazil.

Topographic measures are frequently modeled as a driver of urban growth (Pazur and Bolliger, 2017; Schneeberger et al., 2007; Silva et al., 2016). Highest slope values and highest TPI values are suggested as drivers of forest persistence, since human settlements are expected to occur at lower densities on these regions. Natural high-risk areas can also influence human settlements. Due to the high escarpment at the study area, the NCSP hosts many landslide-prone areas that can be positively correlated with forest persistence, and should be negatively correlated with urban expansion and peri-urban increase.

Landscape accessibility, considering terrestrial and marine transportation of people and goods, can be considered a very important driver of landscape changes (Antrop, 2005; Bürgi et al., 2017). The ports of Ubatuba and São Sebastião have driven village development since the 16th century (Campos, 2000; Cunha, 2003; Silva, 1975), and the four highway built in the region are suggested as a strong driver of urban expansion since the 1920's (Buzato, 2012; Pierri Daunt and Silva, 2019). At São Sebastião municipality, the presence of the largest Petroleum and Gas Brazilian Company (PETROBRAS) plant and the infrastructure to explore and transport petroleum and natural gas has been also suggested to be an important driver of changes (Carmo et al., 2012; Teixeira, 2013).

Cultural factors were also highlighted as dominant drivers of landscape changes (Plieninger et al 2016), although they are very complex to measure and act indirectly on land changes (Nassauer, 1995). In addition to being an important biodiversity hotspot, the Northern Coast of São Paulo State also has unique historical and cultural characteristics, currently preserved by indigenous and traditional peoples (Ab'Sáber, 1986; São Paulo, 2006), such as the Tupi-Guarani nation and the Caiçara and Quilombola ethnicities, which have historically contributed to landscape sustainability and multifunctionality (Antrop, 2005; Diegues, 2001). The presence of native people is suggested as a driver landscape heterogeneity and diversity increase, and also support a high level of biodiversity (Diegues 2001).

C) Data processing and organization

The explanatory variables for this study were acquired from different sources, reflecting different scales of measures. This required many data preparation steps. The following section is dedicated to clarify these steps in detail.

The official limits of the State Parks and the Ecological Economic Zoning were provided by the Forestry Foundation of São Paulo and by the São Paulo State Environment Plan Division (CPLA-SP) in vector format, respectively. We generated presence-absence raster files (30m resolution) in QGIS. Slope and Topographic Position Index (TPI) were derived from a digital elevation model (30-m resolution) produced by the Japanese Space Agency (JAXA) (available at: eorc.jaxa.jp/ALOS/en/about/about_index.htm), and were considered constant during the study period.

Cumulative Cost Distances from main highways, from the two seaports, from the Ubatuba airport, from industrial infrastructure, from traditional communities, and from flood and landslide high risk areas were calculated in QGIS. The cumulative cost distance data provides the cumulative cost for each cell to the nearest source over a cost surface (Environmental Systems Research Institute, 2016). The source of this dataset is described in Table 1. First, vector files were transformed in presence-absence rasters (30-m resolution). Secondly, we produced a multi-criteria cost surface raster by combining the topography dataset with the LULC categories dataset. The cost surface raster measures the relative cost of traveling through each cell (Environmental Systems Research Institute, 2016). We considered that slope and LULC information were very important to measure the distance from the evaluated drivers. Each of these datasets is in a different measurement system (LULC and slope), and must be reclassified to a common scale (Environmental Systems Research Institute, 2016). We then reclassified slope and LULC from a 1 to 10 scale. To combine both sources of information we gave double of importance (weight) to slope, i.e. an influence of 66% versus LULC influence of 34%. The detailed description to generate a multi-criteria cost surface raster can be accessed at https://pro.arcgis.com/en/pro-app/tool-reference/spatial-analyst/creating-a-cost-surface-raster.htm (Environmental Systems Research Institute, 2016). For the 1985-2000 model we used LULC from

1985, and for the 2000-2015 model, we used LULC from 2000. Finally, we created cumulative cost distance raster maps (one for each time step) in the GRASS 7 environment accessed from QGIS 3.1 software. Additionally, we conduced previous tests with Euclidean Distances and we fund neither substantial differences on the model results nor on the importance of the technological drivers.

Regarding Federal Census data (Table 1, manuscript), we accessed the information for each sector/area in a table. We added this information to a vector file provided by the Brazilian Institute of Geography and Statistics (IBGE), with the spatial limits of the census sectors for 2000 and 2010. For 1991, the census only provided spatial descriptions, i.e. the names of neighbourhoods, and data had to be aggregated into sub-districts. The variables related with numbers per census sector were transformed into density, i.e. population and housing. For each census sector area, we calculate the population/housing density for a pixel size of 30m, which gives us a value of population/housing number per 30m pixel. Regarding the percentage data, i.e. alphabetization and basic services provision, we rasterized them to a 30m pixel raster, and assumed that all pixels inside each census area should have the same value. The Federal Census occurred only in 1991, 2000 and 2010. To address the gap between the time steps, annual rates of change were calculated for 1985–2000 and 2000–2015 to allow comparability between LULC periods. The census sector limits of the Brazilian National Census changed over time, so we addressed it as follows: for 1991, the census only provides spatial descriptions, i.e. the names of neighbourhoods, and data had to be aggregated into sub-districts. For 2000, due to an inconsistency in the census sector vector file, it was likewise necessary to aggregate some sectors to reorganize the spatially explicit data into sub-districts. For 2010, the vector file from IBGE was used to generate the spatially explicit data. The Human Develop Index is available at a municipality level. We attributed the HDI for the vector file with the municipality border, and we rasterized (30 m resolution) this file in QGIS.

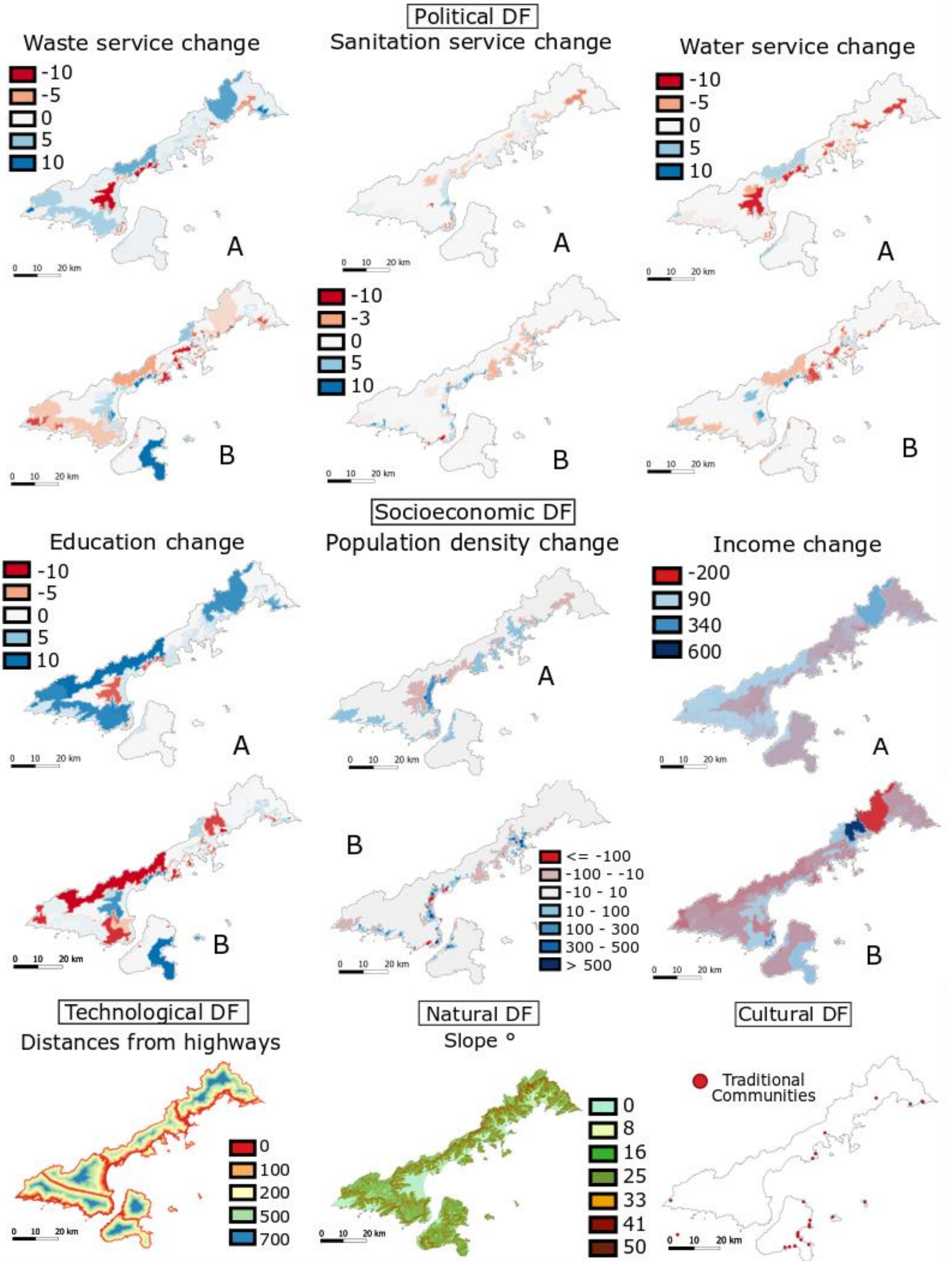

Figure C.i. Examples of the modelled variables in 30 m resolution. A) 1985-2000: B) 2000-2015. Waste: annual rates of change in waste collection service % per census sector; Sanitation: annual rates of change in sanitation service % per census sector; Water: annual rates of change in water service % per census sector; EEZ: 2004 Ecological-Economic Zoning and State parks.; Education: annual rates of change in basic education % per census sector; Population: annual rates of change in population density per census sector; Income: annual rates of change in mean income per census sector (in Reais);

HDI: annual rates of change in Human Development Index per municipality; Highways: cumulative cost distance from principal highways (m); Slope (°). Traditional communities: location of the traditional communities. Description at Table 1 of the manuscript.

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