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Landscape-scale analysis of changes in forest land use/land cover across Puerto Rico, 1990-2020

By

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List of Abbreviations

LULC – Land use Land cover

LULCC – Land Use Land Cover Change

LCMS – Landscape Change Monitoring System

GWR – Geographically Weighted Regression

GIS – Geographic Information System

PR – Puerto Rico

FIA – Forest Inventory Analysis

GEE – Google Earth Engine

OLS – Ordinary Least Squares

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Abstract

Land use/land cover (LULC) change is a global phenomenon that greatly impacts the extent of forest cover, particularly in tropical countries which face increasing pressures related to agriculture, production of timber and non-timber materials, urbanization, and other anthropogenic drivers. There is a need for research focused on post-agricultural societies in tropical urbanizing landscapes to assess LULC change where forest regeneration is occurring due to both passive and active management strategies. The Caribbean archipelago of Puerto Rico is an ideal place to explore such change. It has experienced drastic changes in forest cover over the course of the past century, in response to changing socio-economic and conservation trends. This study analyzes decadal changes in forest land use (as a proxy for LULC) in Puerto Rico from 1990 to 2020 at the island scale to accomplish the following objectives: 1) explore temporal trends in forest loss and gain; 2) calculate transition probabilities between land use categories; 3) analyze the spatial distribution of forest loss and gain; and 4) examine spatial autocorrelation of changes in forest loss/gain at the block group scale in relation to select social variables. The analyses were conducted using land use data derived from 30 m x 30 m Landsat imagery and obtained from the Landscape Change Monitoring System (LCMS), together with social data representing population density and forestry/agricultural occupation density at the census block scale. Trends in forest loss/gain, transition probabilities, spatial clustering, and geographically weighted regression analyses (GWR) were performed using ArcGIS Pro software and spatial analysis tools.

The results showed that forest land use in Puerto Rico during the study period remained relatively constant, representing approximately 62%-64% of total area. This result was higher than the various estimates provided by previous studies that analyzed data within similar time frames and calculated a low of 32% forest area (1990) and a high of 57% (2003). This difference between the estimates is due to differences in classification methods and forest definitions between LCMS and other approaches. Results show that forest represents the largest fraction among the land use classes and represents the lowest percentage of overall (30-year) loss of 1.4%. Prominent forest losses were observed in coastal peri-urban areas adjacent to major cities and interior mountainous areas in eastern central Puerto Rico. Among the decadal intervals evaluated, the period 1990-2000 was marked by a dominant forest loss equivalent to about 520.9 km^2, while the dominant period of forest gain was 2000-2010 and equivalent to 443.7 km^2. The results also show that Forest land use is the most resilient to change and therefore the most stable among the land use classes. This stability is evidenced by a probability of 86% (30-year) of remaining forest. The relatively small areas of Forest that did change tended to convert to Developed and Rangeland or Pasture. Additionally, areas classified as Developed, Rangeland or Pasture, and Agriculture also converted to Forest. The observed expansion of Forest in urban areas is likely due attributed to increases in tree canopy cover rather than actual land conversion, thus indicating that urban forests are a key contributor to overall forest cover.

At the census block group scale, significant clusters of forest loss were found in many coastal areas and the expanding peri-urban areas around urban centers. Significant clusters of forest gain were in mountainous areas, eastern central Puerto Rico, and select certain coastal areas. Our analyses using GWR models revealed the presence of several spatially-variable relationships between Forest loss and gain with population density and to a lesser extent forest/agricultural occupation density. The strength of these relationships varied from weak to strong and in sign (positive vs negative) across geographical space and from one decadal interval to the next. Population density had a stronger influence on forest losses in densely urbanized areas. The focus on census block groups provided an innovative way to assess LULC changes in Puerto Rico but was also limiting in the variables for which data were available at that scale. The results of this study are useful to understand at the landscape scale the long-term effects of land use change and socio-economic factors on forest-related gains and losses in an urbanizing tropical environment and their implications for ecosystem function and the provision of services. Future research should include other relevant variables like road density and precipitation, and other socio-economic data which could also have very large influences on LULC change.

Keywords: tropical forest, long-term forest trends, landscape change, cluster analysis, census block groups, transition probability, geographically-weighted regression

Introduction

The earth has an estimated forest area of about 4.06 billion ha, or 31% of total land area (Keenan et al., 2015). This equates to approximately 0.52 ha per person (Morales-Hidalgo et al., 2015). However, forests are not distributed equitably among the peoples of the world or geographically (Heynen et al., 2006). The tropical zone has the largest proportion of the world's forests, about 45%, followed by the boreal, temperate and subtropical zones (Payn et al., 2015). Tropical forests broadly encompass woody vegetation types ranging from primary to secondary forests and have immense carbon sequestration rates (Banda et al., 2006; Poorter et al., 2016). Located almost entirely in the less developed regions of the world, they are an important resource, both from the point of view of production and conservation (Rannikko, 1999). Because of their economic and environmental importance, tropical forests are continuously monitored at different national, regional, and global levels of planning, monitoring, and management (Melo et al., 2013). Due to increasing pressures on forest lands for timber and non-timber based forest products, clearing for agriculture, and urbanization, land use and land cover change (LULC) has become particularly intense in developing tropical countries (Momo et al., 2018; Wright, 2010). This has raised concerns about their resilience to disturbance and capacity to continue supporting human communities (Poorter et al., 2016).

Exploring changes in LULC can provide insight into ecosystem processes that affect biological communities, including humans (Tran et al., 2017). For example, urbanization transforms natural land surfaces to include covers such as buildings and roads, fragmenting the ecosystems of urban landscapes and affecting the livability of cities (Benton-Short & Short, 2013; Long et al., 2014). This can lead to increases in urban heat islands (Kardinal Jusuf et al., 2007) as well as urban flooding (Huong & Pathirana, 2013), both of which are anticipated to have exacerbated impacts on society due to climate change (Hans-Otto Pörtner et al., 2022; Rodríguez-Caballero et al., 2022). These can also affect biomass, carbon pools, and the provision of regulating ecosystem services such as carbon sequestration (Chave et al., 2014) and have unprecedented consequences for biodiversity (Lambin et al., 2001; Ramachandran et al., 2018; Titeux et al., 2016). Many forms of LULC change are likewise associated with increases in food and fiber production, resource efficiency, wealth, and well-being (Geist et al., 2006; Lambin et al., 2006; Ramankutty et al., 2006). Agriculture has spread to savannas, steppes, and forests in all regions of the world to meet the demand for food and fiber, in some cases causing desertification (Mazoyer & Roudart, 2006; Tappan et al., 2004). Thus, changes in LULC can both result in increased production of resources for human societies and also augment the vulnerability of places and people to climatic, economic, or socio-political disturbances (Lorencová et al., 2013; Minale & Belete, 2017; Nottage & New Zealand Climate Change Centre, 2010).

Understanding the patterns, causes and consequences of LULC change has been an important research topic in recent decades (Ozsahin et al., 2018; Turner et al., 1996). Human activity is a driving force affecting spatial and temporal changes in land use (Prăvălie et al., 2020). Land use changes are associated with agricultural expansion/intensification, urbanization, deforestation, and conversion of forests to agricultural and urban land (Laurance et al., 2014; Mailafiya, 2015). Consequently, forest lands are identified as one of the globally threatened ecosystems (Camacho-Valdez et al., 2014). Indeed, in the tropics, forest lands are converted for the benefit of urban expansion, as well as the extraction of wood for furniture and charcoal (Beven & Cloke, 2012; Pauleus & Aide, 2020; Shukla & Mintz, 1982). For example, in Sri Lanka, forest cover represented about 42.5% of the total land area but approximately 19% of the forest has been converted during the last 30 years, primarily to cropland (Vijitharan et al., 2022). A case study in Haiti showed an estimated reduction in forest cover from 26.5% in 2000 to 21.3% by 2015. These forest losses are mainly due to land transition to mixed agriculture/pasture, which has largely occurred on private lands surrounding several national parks and protected areas. In addition, forest losses have increased in Haiti due to wood extraction for charcoal production as a source of income (Pauleus & Aide, 2020). More permanent land transitions away from forest occur in response to the processes of urban expansion (Güneralp et al., 2020) which includes the construction of roads, building, and related infrastructure as has been reported in tropical forests of Malaysia (Nourqolipour et al., 2016).

In contrast, other tropical regions have experienced forest growth in recent years, due to changing socio-economic pressures on natural resources. Panama, for example, has largely experienced a significant forest transition over the past 20 years, its total forest cover averaging 61% of land area, with an annual increase of 0.36%. This increase is due to agricultural abandonment and conversion of crops or pastures to tree plantations, some of which is actively promoted via tax incentives (Wright & Samaniego, 2008). In addition, rural-urban migration creates opportunities for new forests to regenerate spontaneously or with active regeneration on marginal and abandoned agricultural land. For example, in Argentina in the Misiones province, new forests have regenerated as plantations mainly on land owned by large corporations. Logging in this area has also decreased in protected areas, due to government restrictions, and together these practices have contributed to the extension of forest cover (Wilson et al., 2017). Moreover, in Guanacaste province, Costa Rica, widespread deforestation that reduced forest cover to 23.6% by 1975 was followed by a period of very low rates of deforestation and an increase in forest cover to 47.9% by 2005. This reversion is attributed to the decline of the cattle industry and a high decline in agricultural employment, urbanization, in combination with retention policies including creation of protected areas, payments for the ecosystem services, and restrictions on timber extraction and forest clearing and encouraged tree plantations (Wilson et al., 2017). Thus, tropical forest transitions occur through both natural and assisted reforestation activities that passively or actively support regeneration, thereby helping to increase forest cover (Sloan et al., 2019; Wilson et al., 2017).

In the Caribbean archipelago of Puerto Rico, drastic changes in land use and land cover have occurred in the 500+ years since European colonization. It is estimated that in the 16th century most of Puerto Rico's land area was forested (Birdsey & Weaver, 1987), with more than 7,000,000,000 cubic feet of wood (Wadsworth, 1950). However, by the beginning of the 19th century, the cutting of trees and the development of non-forest lands reduced the extent of forests to 587,000 ha (Birdsey & Weaver, 1982, 1987; Wadsworth, 1950). Cultivation of coffee in the late 19th century further reduced forest land to 187,000 ha (Birdsey & Weaver, 1987). By the early 20th century there were 81,000 ha of forest, representing approximately 9% of land area (Birdsey & Weaver, 1987, Gill, 1931), and it is estimated that forest cover dropped to as low as 6% by the late 1930s (Koenig, 1953; Wadsworth, 1950).

Since that time, and over the past 80 years, Puerto Rico has transitioned from an agricultural-based economy toward industrialization, accompanied by widespread agricultural abandonment, urban expansion and more recently the development of a service-based economy (Eileen Helmer et al., 2002; Martinuzzi et al., 2007a; Pascarella et al., 2000). Post-WWII industrialization led to migration to cities (Grau et al., 2003a) and urban development, often via the conversion of agricultural land (Del Mar López et al., 2001; Thomlinson et al., 1996). For example, falling market prices for coffee led farmers to abandon their coffee plantations and between 1959 and 1974 the total area used for agricultural (e.g., sugarcane, tobacco, and coffee) declined from around 285,000 ha to 139,000 ha (Rudel et al., 2000). The rapid reduction in agricultural sparked an equally rapid forest recovery across the island (Gould et al., 2020; Grau et al., 2003; Turner et al., 1996). In addition, in recent decades, some governmental and non-governmental organizations have been involved in initiatives to establish nature reserves and promote forest conservation (Rivera-Collazo, 2015). Between 1959 and 1980, the percent of forest land increased from 13 to 34% of total area (Rudel et al., 2000). A further increase was also observed between 1980 and 1985 when forest cover grew from 279,000 ha to 300,000 ha (Birdsey & Weaver, 1982, 1987). By 2003, forest cover in Puerto Rico had expanded to an area of approximately 505,993 ha (Brandeis et al., 2007). Forest area decreased slightly to 474,469 ha about a decade later in 2014 (Marcano-Vega, 2017). A recent study by Brandeis and Marcano-Vega (2021) estimated the forest cover was 467,320 ha for the year 2019.

Concurrent changes in the extent and distribution of vegetation cover have also been observed in Puerto Rico's urban areas. In the city of San Juan, Ramos-González (2014) found an overall value of 42% green cover based on 2002 satellite imagery, 26% of which were trees, with larger blocks of forest in the southern part of the city than in the denser northern sector where development is concentrated. While vegetation cover in middle- and upper-class suburban neighborhoods of San Juan was observed to increase between 1960 and 2010, lower income neighborhoods experienced an overall loss of vegetation during the same time period (Ramos-Santiago et al., 2014). Thus, changes in LULC do not occur uniformly. Recent challenges, including a prolonged economic recession and two major hurricanes in 2017 (Irma and María), have contributed to an ongoing population decline throughout Puerto Rico that influences long-term land-use patterns (Santos-Lozada et al., 2020). At present, forest cover exceeds 50% of the total land area (Gould et al., 2020). As demographic trends continue to shift in Puerto Rico, it is important to understand the effects of these changes on forest cover, as gains or losses in population and urban development trends can directly influence the extent of forest resources, with consequences for biomass, and the provision of many ecosystem services related to carbon, water, and other functional processes (Brandeis et al., 2006; Liao et al., 2019; Lugo, 2008).

1- Research objectives

This investigation sought to understand the geographic patterns and implications of LULC associated with forest cover in the Caribbean archipelago of Puerto Rico over a recent thirty (30) year period and interpret those patterns in the context of related LULC work and general socio-economic trends that overlap with the study period. The primary goal of this project was to analyze decadal changes in forest LULC from 1990 to 2020 at the island scale and accomplish the following objectives: 1) explore temporal trends in forest loss and gain; 2) calculate transition probabilities between LULC categories; 3) analyze the spatial distribution of forest loss and gain; and 4) examine spatial autocorrelation of changes in forest loss/gain at the block group scale in relation to select social variables.

2- Research Questions and hypotheses

In the context of indirect and direct drivers related to changing climatic patterns and socio-economic activities that can affect forest cover in Puerto Rico, we formulated the following research questions:

1) How has forest LULC changed in PR at decadal intervals from 1990-2020 in terms of total land area and representative percentages, and how well do the results align with other forest LULC studies using distinct datasets?

2) What are the important transition trends and probabilities among the categories of LULC?

3) What are the spatial patterns of forest losses and gains, as clustered across the landscape at the block group scale?

4) What is the spatial relationship between clusters of forest loss and gain and concurrent social variables?

3- Hypotheses

In this study, we expect to observe directional changes in forest cover during the study period and that changes will not be spatially uniform across Puerto Rico but rather there is variability in forest gains and losses that fluctuate at decadal intervals and are concentrated geographically in different areas in relation to social variables. Specifically, we propose the following hypotheses:

1) Island-wide forest LULC has increased from 1990 to 2020.

2) Forest is the most stable LULC during the study period, and the probability of non-forest LULC categories changing to forest is greater than that of forest changing to non-forest LULC classes.

3) Percent forest LULC losses and gains are clustered non-uniformally throughout Puerto Rico at the block group scale.

4) Forest loss and gain vary spatially in relation to social variables that describe human population and natural resource-related occupations at the census block group scale.

4- Intellectual merit of this study

LULC changes in tropical countries have experienced great fluctuations during the last 30 years and continue to be influenced by the increase and decrease in population growth associated with socio-environmental factors. Research in the subtropical region of Guangxi China demonstrated that long-term forest change trends are important for detecting and assessing ecosystem production and services provided by forests (Hu et al., 2019). South American countries such as Brazil, Argentina, and Paraguay also have an extensive long-term experience where land use changes in the Paraná Atlantic Forest ecoregion have been attributed through grazing or livestock, to the cultivation of soybeans and cotton leading to the increase of protected areas and are also a major source of regional biodiversity (Mohebalian et al., 2022). Similarly, Caribbean countries such as Haiti have also presented a declined in forest over the past 40 years, including Forest des Pins, an important area for carbon storage (Pauleus & Aide, 2020). Yet there remains a need for study in post-agricultural societies in tropical urbanizing landscapes such as Puerto Rico to assess LULC change where forest regeneration is occurring due to both passive and active management strategies. This includes the patterns of forest LULC change, the long-term effects of socio-environmental drivers of LULC change dynamics, and the implications for ecosystem processes and provision of services.

This work builds on previous assessments of land cover and forest extent in Puerto Rico using a recently produced, long-term dataset derived from Landsat satellite imagery that spans a 30-year period. The research provides an unprecedented opportunity to study island-wide changes in forest cover using medium-resolution, remotely sensed LULC data that spans multiple decades. In addition to exploring temporal trends in forest cover across several decades, we examine the spatial configuration of forest gain and loss and their relation to social variables that may be driving those patterns. While significant prior work has been done looking at landscape scale changes in forest change across Puerto Rico (Foster et al., 1999; López-Marrero et al., 2019; Lugo & Helmer, 2004; Wang et al., 2017), to our knowledge there have not yet been spatial analyses examining the patterns and clustering of such change at the island scale nor the relation of forest cover loss and gain to census data aggregated at the scale of census block groups.

In this study we will obtain robust information about forest extent, distribution, clustering patterns and transitional trends through time, and interpret those data in the context of other island-wide studies of forest cover and contemporary socio-economic trends. Other lines of research have used administrative boundaries to analyze geographic trends in both ecological and socio-economic phenomena. For example, one study conducted in Tainan, the fourth largest city in Taiwan, highlighted the clustered impact of urban land use change on the environment at the district scale in protected coastal areas to the east and south of the city center (Kuo & Tsou, 2017). Another study conducted in 37 cities in the United States linked the distribution of HOLC (ethnic classification/segregation) levels to city-wide forest cover, including socio-economic factors such as poverty; the results showed that low-income urban areas and areas where racial minorities live have less tree cover compared to wealthier communities (Locke, 2020; Locke & Grove, 2016). Furthermore, Meléndez-Ackerman et al. (2016) examined patterns of vegetation at the household scale in San Juan, PR, and observed that socio-demographic profiles of residents and watershed-scale characteristics are related with vegetation patterns within urban yards. Strong relationships have also been observed between development patterns and conserved forest lands. For example, Castro-Prieto et al. (2017) reported that lands around protected areas in Puerto Rico are extremely vulnerable to residential development despite declining human population, although there is considerable spatial variation in housing and population near each individual protected area. Taking a similar approach to this study of LULC change in Puerto Rico, analysis at the demographic unit of census block groups can help identify significant spatial clusters of forest gains and loss and link them to relevant socio-demographic phenomena that can subsequently be quantified, analyzed and used to develop probabilistic models at the island scale. It can also help inform strategies and policies to mitigate or amplify the causes and consequences of such change in different parts of the island in the future.

Furthermore, anticipated changes in climate for the Caribbean region include an increase in the frequency and severity of extreme atmospheric events, as well as reduced annual precipitation (Reyer et al., 2017). Therefore, understanding long-term trends in forest cover across Puerto Rico can provide insight into potential landscape-scale changes in forest productivity and ecosystem services under future climate scenarios (Gould et al., 2020; Saatchi et al., 2011; Vihervaara et al., 2013). Understanding how forest lands change over time concerning demographic and climate drivers is an important part of addressing sustainability issues in tropical environments and developing appropriate measures to maintain social-ecological resilience.

Methodology

1- Study area

The study area for this project encompasses the archipelago of Puerto Rico (18.22◦ N and 66.59◦ W), the smallest of the Greater Antilles islands which is located in the eastern Caribbean. Total land area is approximately 8950 km^2 including the main island and several smaller islands and cays (Wang et al., 2017). The island has a tropical marine climate with an annual average temperature ranging from 21.1 to 26.7 ◦C and a rainy season from April to November (Wang et al., 2017). The island includes rocks and sediments of volcanic origin, but current geological evidence suggests the most recent active volcanism dates back 30 million years (Gould et al., 2020; Wang et al., 2017). Parts of the island contain uplifted carbonate sediments that developed during a period when much of the current island was submarine, with recent uplift (5 mya) resulting in the current configuration of mountains and narrow coastal plains (Hobbs et al., 2013; Vihervaara et al., 2013). Precipitation on the island varies greatly depending on altitude, distance from the ocean, and wind direction, with the prevailing trade winds blowing from the northeast, and precipitation values generally ranging from 2 to 5 m per year (Gould et al., 2020; Martinuzzi et al., 2007). However, a topographic rain shadow effect results in less than 1000 mm annually in the southwest leeward side. As a result, a very heterogeneous landscape was formed with abrupt changes in climate and vegetation over short geographic distances. Moist tropical forests dominate in the northern part of the island and central cordillera, while dry forest is prominent in the south. Differences in precipitation and temperature across the island result in six distinct subtropical life zones (Ewel & Whitmore, 1973), categorized into (dry, moist, rain, wet, rain forest lower montane, wet forest lower montane; Fig 1) (Brown & Lugo, 1982; Gould et al., 2006).

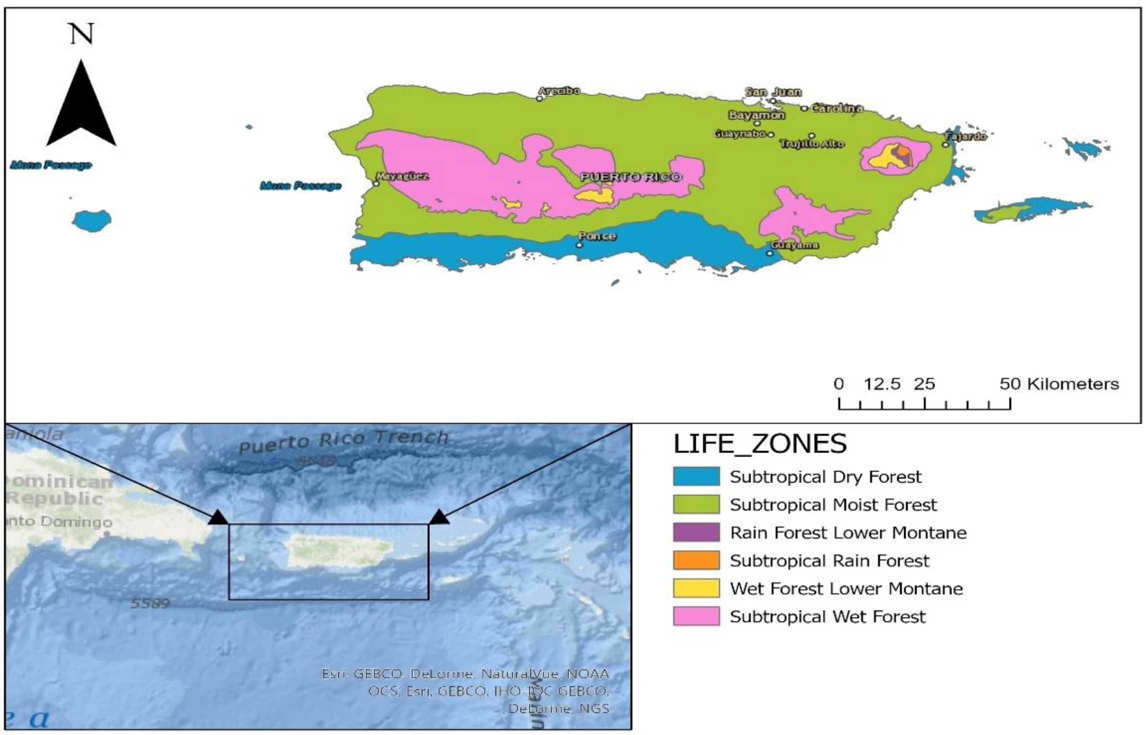

Figure 1: Location of the study area and ecological life zones of Puerto Rico, following (Ewel & Whitmore, 1973).

The human population is estimated at around 3.1 million, with a population density of 344 people per km^2 (García et al., 2021). Most of the population is concentrated in coastal areas around several highly developed urban centers, the largest of which is the San Juan metropolitan area. The dominance of human communities directly affects the vegetative land cover of Puerto Rico. Post-agricultural land abandonment beginning in the 1950s and continuing to the present has been concentrated in rugged mountainous areas where agriculture was difficult to sustain due to steep slopes and severe soil erosion (Weaver & Gillespie, 1992). According to Forest Inventory and Analysis (FIA) surveys conducted in Puerto Rico by the USDA Forest Service, Puerto Rico's proportion of forest cover was 54.7% in 2010 (Gray et al., 2012; Housman et al., 2022). The forests were found to have over 1.6 billion trees over 2.5 cm in diameter, 10.6 million m^2 of basal area, and 36.6 million Mg of sequestered carbon (Brandeis & Turner, 2013).

2- LULC and census spatial datasets

There are several large-scale, publicly accessible databases available for use in examining the status and trends in forest cover. For this project, the primary data source was curated LULC data from the USDA Forest Service's Landscape Change Monitoring System (LCMS) (https://data.fs.usda.gov/geodata/rastergateway/LCMS/index.php) (Housman et al., 2022). LCMS uses Google Earth Engine (GEE) under a corporate agreement between the USFS and Google for all remote sensing raster data acquisition and processing (Gorelick et al., 2017). GEE is a parallel computing environment that provides access to many publicly available Earth observation datasets (Housman et al., 2022). LCMS incorporates 30 m x 30 m Landsat satellite pixel imagery and classifies values to produce annual maps depicting land cover, land use, and change (vegetation loss and vegetation gain) from 1985 to 2020. Additionally, LCMS uses Scikit-Learn for sample design, selection of model predictor variables, and model validation. Models are calibrated using the TimeSync attribution tool, a web-based application that allows users to view a time series of Landsat images, as well as high-resolution images available in Google Earth Pro and other auxiliary data to assign the annual land cover, land use, and process of change to each training point location (Cohen et al., 2010). Model outputs for the Puerto Rico and US Virgin Islands (PRUSVI) region include calibration data from 2000-2020, due to a lack of available Landsat imagery over the entire region prior to 2000 (Housman et al., 2022). All supervised classifications for LCMS use the random forest modeling method (Breiman, 2001). Random forest randomly selects a subset of predictor variables and training sites across many classifications and regression trees. Each of the many trees predicts a class, which is then aggregated and used to determine the final modeled class. LCMS uses the GEE instance of random forests called "smileRandomForest" for all classifications. The local processing used for the selection of variables and the validation of the card uses the sklearn.ensemble. RandomForestClassifier method (Housman et al., 2022).

We used LCMS data from the PRUSVI dataset for the period 1990-2020. Three 10-year intervals from 1990 to 2020 (1990-2000; 2000-2010; 2010-2020) and the entire 30-year period (1990-2020) were considered. The LCMS land use datasets include six categories (agriculture, developed, forest, non-forest wetland, rangeland or pasture, and others; Table 1), while the land cover datasets include 14 categories, broken down into various types of woody and herbaceous vegetation. Both LCMS land use and land cover datasets include non-classified data as well, representing pixels that do not have a cloud or cloud shadow free value for a given year (Fig 2).

Land use classes	**Land cover classes**
1. Agriculture	1. Trees
2. Developed	2. Shrubs & Trees Mix
3. Forest	3. Grass/Forb/Herb & Trees Mix
4. Non-Forest Wetland	4. Barren & Trees Mix
5. Rangeland or Pasture	5. Shrubs
6. Others (includes lands which are perennially covered with water, salt flats and other undeclared classes. Water includes rivers, streams, canals, ponds, lakes, reservoirs, bays, or oceans. This assumes permanent water (which can be in some state of flux due to ephemeral changes brought on by climate or anthropogenic)	6. Grass/Forb/ & Shrubs Mix
	7. Barren & Shrubs Mix
	8. Grass/Forb/Herb
	9. Barren & Grass/Forb/Herb Mix
	10. Barren or impervious
	11. Snow or ice
	12. Water

Table 1: Land use and Land cover classes for PRUSVI from LCMS. See (Housman et al., 2022) for additional descriptions of classes.

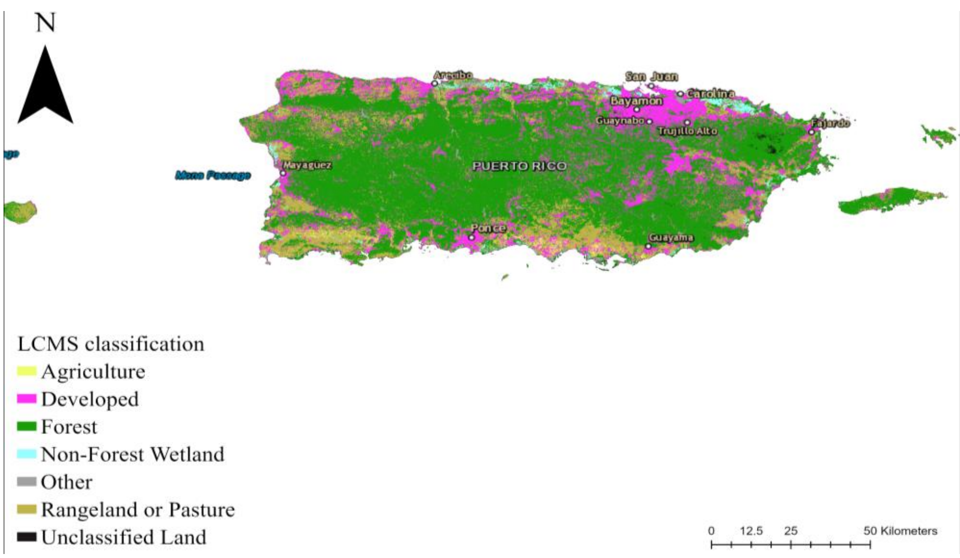

Figure 2: Land use classification of Puerto Rico for 2020 LCMS.

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Given that LCMS data products were only released in 2022 and have not been extensively validated against other published LULC datasets, we acquired additional forest data from the Hansen Global Forest Change dataset v1.9, which is available for download at https://glad.earthengine.app/view/global-forest-change. The Hansen data are derived from time series of Landsat images of 1 arc-second per pixel, or about 30 m spatial resolution, and can be used for characterizing global forest change from 2000 to 2021. Among the available datasets, Percent Tree Cover was available for the year 2000 only, and this dataset was included as a reference against which to compare outputs derived from the LCMS for that same year.

Socio-economic variables can also influence LULC patterns over time. Census block group boundaries were downloaded from the US Census Bureau (https://data.census.gov/) for the year 2020 (Fig 3). The dataset contains 2515 block group units.

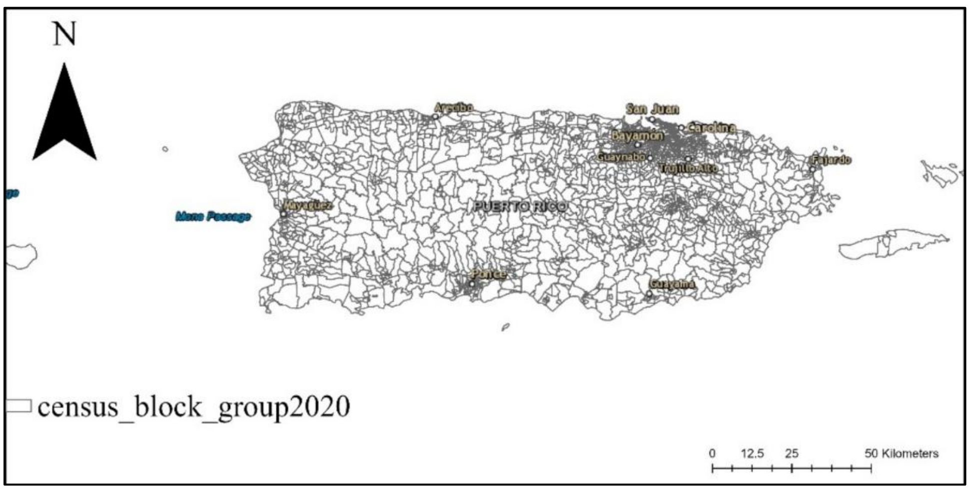

Figure 3: 2020 Census block groups for Puerto Rico.

We extracted population and occupation data available at the block group level from the US Census Bureau (https://data.census.gov/) for the end year of the three decadal time intervals (i.e., 2000, 2010, and 2020). The population data were obtained from American Community Survey tables, H002 (2000), P2 (2010) and P2 (2020). The occupation data represented a subset specific to agricultural, forestry, and farmland practices, which the US Census Bureau considers to be the primary activities where people/professionals/organizations occupy one or more parcels of land for the purpose of productive use. These data were obtained from American Community Survey tables P049 (2000), C24030 (2010), and C24030 (2020). We used these variables because

LULC change has been linked in tropical developing countries with socioeconomic and demographic factors related to agricultural activities (Grau et al., 2003), and they therefore may have a direct or indirect relationship with changes in forest cover. Furthermore, both variables were available for the full 30-year study period, facilitating analysis of their relationship with LULC over time. To normalize for differences area at the block group scale, we converted these data variables to data to population density, and occupation density.

3- Spatio-temporal analysis of LULC change.

We used LCMS data from the PRUSVI dataset for the period 1990-2020, and extracted land areas that pertain to Puerto Rico. To analyze LULC change over time, we followed the methods outlined by Hu et al. (2019). Annual datasets of land use were downloaded from the LCMS data viewer for the years 1990, 2000, 2010, and 2020 (https://apps.fs.usda.gov/lcms-viewer/) and imported in a GIS using ArcGIS Pro software (version 10.3). Then we removed pixels with no data (identified within the LCMS dataset as unclassified pixels due to clouds and lack of data). We also removed pixels that were unclassified in the previous year and became classified in subsequent years. The number of unclassified pixels represented < 1% of the available for any given year and excluding them did not have a meaningful effect on the analyses; we found our Kappa statistic results to be very similar to those of the LCMS Kappa statistic. Thus, the final dataset included only the pixels for which land use was assigned for all four focal years (1990, 2000, 2010, 2020), and this dataset was used for all subsequent analyses (Figure 4).

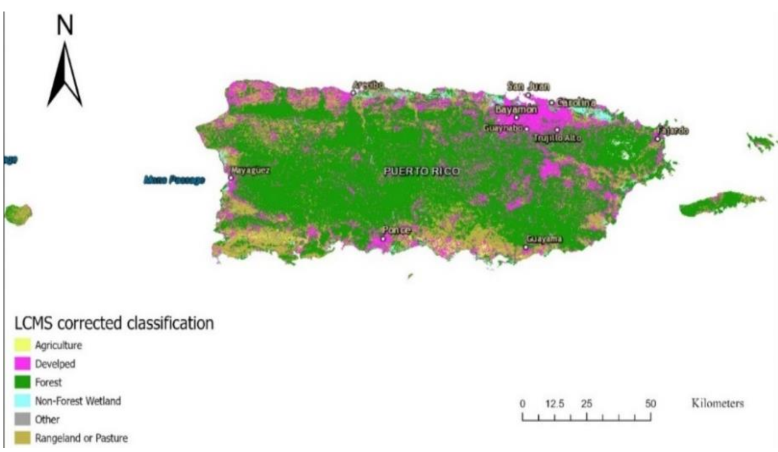

Figure 4: Map of corrected land use classification for 2020 after removal of unclassified pixels.

We exclusively used the LCMS land use datasets as a proxy for LULC, because they specifically include a ‘forest’ category, which allowed for consistent comparison throughout the island and across the focal years. In the LCMS context, ‘forest’ is defined as “land that is planted or naturally vegetated and which contains (or is likely to contain) 10% or greater tree cover at some time during a near-term successional sequence. This may include deciduous, evergreen, and/or mixed categories of natural forest, forest plantations, and woody wetlands.” This definition is derived from and similar to the FIA definition of ’forest’ cover, but differs in that it is based on a standard Landsat pixel size of 30 m x30 m whereas FIA has a minimum area of 1 acre (Housman et al., 2022). The number of pixels associated with each land use category was summed for 1990, 2000, 2010, and 2020. Using spatial analysis and spatial statistics tools in ArcGIS Pro, we calculated for each focal year the total area (km^2) and percentage cover for forest land use and the other five land use categories. Previous work in the region by Pauleus & Aide (2020) used the Hansen Global Forest Change dataset to validate the estimation of forest cover in Haiti. Following their methodology, we used Hansen data to calculate forest cover in Puerto Rico and compare the outputs with our LCMS forest cover results for the year 2000.

Next, we used the Compute Change Raster tool to calculate the area (km^2) and the percent of each land use category (LCMS dataset only) that changed to forest, as well as forest that changed to other categories of land use. We followed the formula from Banerjee et al. (2020) to calculate the net percent change in forest area and other land use categories per period in terms of absolute and net gains and losses:

$$A = (I - F) / F \times 100$$

where A = net percentage of change, F= first date, and I = reference date.

Excel spreadsheets were used to calculate absolute and net land use gains and losses between focal years, as well as to generate tables and graphs.

3.1 Transition trends and probabilities of LULC

Using the outputs of the absolute gains and losses for each land use , we built a transition matrix according to methods described by Pontius et al. (2001). Then, following Iacono et al.

(2016), we calculated the transition possibilities (TPs) for each land use type, as described by Markov chain models to provide the important stability and transition among land use categories. The expression of the TPs matrix can be described using the following equation:

$$P = P_{ij} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ P_{m1} & P_{n2} & \cdots & P_{mn} \end{bmatrix} \left(\sum_{j=1}^{n} P_{ij} = 1,\ 0 \leq P_{ij} \leq 1\right)$$

Equation 1: transition probability

where *P* represents the transition probability of the system from state *i* at time *t* to state *j* at later time *t+1*, and m, n represent the number of land use types (Iacono et al., 2016).

3.2 Cluster Analysis of forest losses and gains

Among the methods of spatial autocorrelation analyses, there are two crucial methods (Pravitasari et al., 2019; Zhang et al., 2008). The first concerns Global Moran's I. It is used to analyze the overall spatial autocorrelation among data values. In general, the larger the absolute value of Moran's I, the stronger a spatial autocorrelation, and the larger the absolute value of normalized Moran's I, the more significant a spatial pattern (Niu et al., 2018; Pravitasari et al., 2019). At the global level, the value of Moran's I must be in the interval [-1, 1] in order to predict the existence and the significance of spatial autocorrelation (Hu et al., 2019; Niu et al., 2018; Pravitasari et al., 2019). This autocorrelation could be positive if the value of Moran's I is greater than 0, and negative if the value of Moran's I is less than 0 (Hu et al., 2019; Pravitasari et al., 2019). The Global Moran's I tool in ArcGIS Pro is generally used to provide spatial autocorrelation analysis and Moran's I value. These methods have been widely used in landscape-scale ecological and social research. For example, Fu et al. (2014) used Moran's I to study the spatial variation of carbon density within leaf litter of forested in the forest ecosystems, and Fu et al. (2011) also examined the spatial variation of nutrients such as soil phosphorus. In northeastern Thailand, Suwanlee & Som-ard (2020) utilized Moran's I to examine the effect of spatial interaction on population density patterns as related to the provision of social services in 20 provinces. In our study we used Global Moran's I tool in ArcGIS Pro to measure the degree of spatial autocorrelation of percent change in Forest loss and gain throughout the entire study area. For the conceptualization of spatial relationships, we selected the option of contiguity edges only.

However, Global Moran’s I does not provide detail at the spatial scale the geographic regions where the autocorrelations are concentrated (i.e., clustered) and/or dispersed. It also does not provide spatial diagrams relating to the spatial map of clusters and see for the case of use of census block group. This scale is an integral part of our spatial analysis.

This can be accomplished using the second method, Anselin Local Moran's I, which is used to identify the presence of spatial clusters and outliers (Overmars et al., 2003; Zhang et al., 2008). It is therefore useful in studying spatial patterns of environmental variables, such as comparing significant spatial patterns among different variables or of the same variable (Overmars et al., 2003; Zhang et al., 2008). This method takes into consideration the spatial scale and shows the areas or geographic regions where clustering is statistically significant and grouped together (Niu et al., 2018; Overmars et al., 2003; Zhang et al., 2008). The result of Local Moran's I provides spatial clusters indicated as HH (cluster of high values), LL (cluster of low values), HL (outlier in which a high value is surrounded primarily by low values), LH (outlier in which a low value is surrounded primarily by high values), as well as values that are not significantly clustered (Overmars et al., 2003; Zhang et al., 2008). Many studies have used this method. Jukneliėnė & Mozgeris (2015) used Local Moran’s I to examine the spatial variation in the distribution of forest cover change as related to agricultural land use suitability in Lithuanian municipalities over a 63-year period . Zhang et al. (2008) also examined the identification of pollution hotspots using lead concentrations in urban soils in the city of Galway in Ireland using Local Moran’s I. Thus, these studies demonstrate the utility of such analysis tools for identifying regions or geographic areas where data are spatially clustered. In a similar manner, in addition to Global Moran’s I we used the Local Moran's I tool in ArcGIS Pro to assess for the presence of significant clustering of the percent forest gain and loss at the block group scale for each time interval, as well as to identify the geographical regions where they are grouped.

4- Statistical analyses with social variables

We carried out preliminary tests to evaluate the statistical strength of the association between percent forest loss and gain and social variables that we hypothesized were related. For the explanatory variables we chose two social variables for which data were readily available at the block group scale for the focal years and which represented demographic characteristics of human communities that can influence LULC patterns: 1) population density and 2) occupation density of individuals who work in agricultural and natural resource fields. Case studies such as that of Cartagena-Colón et al. (2022) have analyzed the effects of population density factors on LULC change at Jobos Bay in the municipality of Guayama in Puerto Rico between 1990 and 2010. López Marrero (2003) for her part studied the effects of population density on LULC change in the eastern portion of the Puerto Rico between 1977 and 1995 with the aim of explaining the evolution of land use linked to human factors. Other previous works have also analyzed the factors of population density and occupation on LULC change at several spatial scales (Gould et al., 2020; Grau et al., 2003; Martinuzzi et al., 2018; Parés-Ramos et al., 2008). These studies have shown that changes in forest cover (losses or gains) are particularly linked to demographic factors such as population density and occupation. However, most of these studies have assessed these interactions at the municipal or regional level; few studies have assessed these dynamics at the census block group spatial scale for the entire island of Puerto Rico.

In ArcGIS Pro we conducted some preliminary analyses to examine the relationships between forest loss and gain and the explanatory variables at the block group scale for each focal year using Ordinary Least Square (OLS) models and Geographically Weighted Regression (GWR) models. OLS is useful to describe the significant relationship between one or more independent quantitative variables and a dependent variable in order to predict the effects of a phenomenon depending on the external factors (Lechner et al., 2016; Ou et al., 2015). The output value of R^2 indicates overall model fit and provides a measure of how much of the variation of the dependent variable is explained by the independent variables of the model (Gallo & Owen, 1998; Minasny & McBratney, 2007). On the other hand, GWR is also useful for predictive purposes and identifying the nature of the relationships between several explanatory variables and one or more explained variables (Mohammadinia et al., 2019; Shaker & Ehlinger, 2014; Windle et al., 2010). Like OLS, it provides the R^2 value which indicates the significant degree of the relationship and fit of the model (Maimaitijiang et al., 2015; Mohammadinia et al., 2019; Shaker & Ehlinger, 2014). One important difference, however, is that GWR also assesses if there are meaningful spatial relationships among explanatory and dependent variables by taking into account cartographic aspects of the data that may vary across regions (Shaker & Ehlinger, 2014; Wu & Zhang, 2013). Previous studies have also used GWR to evaluate for spatial pattern. (Shaker & Ehlinger, 2014) examined the spatial dependence as a measure of aquatic ecological status at two basin scales in southern Wisconsin. Wu and Zhang (2013) used GWR to analyze the probability of occurrence of orographic cloud cover in the Luquillo Experimental Forest in northeastern Puerto Rico, considering variables such as slope, aspect, and the difference between elevation and lifting condensation level. Another study by Chen et al. (2016) utilized GWR to study the impact of land use and population density on surface water quality in the Wen-Rui Tang River watershed in East China. The authors compared the outputs of both OLS and GWR models and found that GWR provided a much higher R^2 and demonstrated better prediction accuracy, while the OLS models neglected spatial features (Chen et al., 2016). Similarly, a study by Zhu et al. (2020) also used both OLS and GWR models, finding that GWR has greater ability to show the spatial relationships between variables and make accurate predictions.

Based on this prior literature, and considering the results of the preliminary tests that we performed using both models which indicated a higher R^2 value for GWR compared to OLS, we selected GWR as the model to use for studying spatial relationships with Forest loss and gain. We relied on the method provided by Fotheringham et al. (2017) using the GWR tool in ArcGIS Pro to provide the relational model between the dependent variable (percent forest loss and gain) and the social predictors (population density and agricultural/forest occupation density). For the GWR models we first explored the relationship using logistic data in which the values of percent forest loss and gain were converted into a binary format of 0 and 1, where 0 represents absence of loss/gain and 1 represents presence loss/gain. Subsequently we explored the relationship using a continuous (Gaussian) GWR model. Between these two different models, the R^2 values of the continuous GWR model were greater than those of the logistic model, and moreover, the AIC value was lower. Prior work by Pineda Jaimes et al. (2010) also reported the robustness and superior performance of the Gaussian GWR model. Thus, we proceeded with the Gaussian GWR model for our analyses. The GWR model generates the global and local values of R^2. The global model analyzes the spatial relationships between the explanatory variables together with the dependent variables by taking into account the set of all variables at the census block scale across the landscape to produce the R^2 values. On the other hand, the local model analyzes spatial relationships by considering each explanatory variable separately at each point of a landscape. Thus, the local R^2values are generated by taking into account each of the variables separately for each block group and its geographical characteristics. This is also interesting in the case of our study. We assessed the relative strength of the relationships between Forest loss and gain and the two explanatory social variables at the block group scale for the different time periods based on the R^2_{adj} value of the different models. The GWR also allows for generating maps of the spatially explicit raster surfaces of coefficient values that help visualize regional variation in the strength of the relationship between each of the explanatory variables and dependent variable separately. These surfaces are generated independently for each location in the study area by establishing a fixed neighborhood around each raster cell. Distance based weights are calculated from the center of the raster cell to all the input features falling within the neighborhood (bandwidth). These weights are used to calculate a unique regression equation for that raster cell and create coefficient raster surfaces for the model intercept and each explanatory variable. The coefficients vary from raster cell to raster cell because the distance-based weights change, and potentially different input features will fall within the neighborhood(bandwidth) (https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatialstatistics/how-geographicallyweightedregression-works.htm) (Sisman & Aydinoglu, 2022). In addition, the raster coefficients generated by the GWR model make it possible to see the regions where the relationships with the predictors taken separately are negative and positive.

The results of the analyses were summarized in tables and maps using Excel, and ArcGIS Pro software to show the spatial distribution of forest gain and loss, categories of land use change, and spatial clusters at the block group level. The results have been interpreted in the context of related LULC work regarding forest cover and general socio-economic trends in Puerto Rico that overlap with the study period.

Results

1- Summary of land use classes from 1990 to 2020

The LCMS land use data used in this study ranged temporally from 1990 to 2020 and encompassed an area of 8,941 km^2. Three classes, Forest, Developed, and Rangeland or Pasture consistently accounted for greater than 95% of the total area throughout the 30-year period. The Forest class represented the largest fraction. There were 5,710.7 km^2 (64.1% of total area) of Forest in 1990, a low of 5,581.1 km^2 (62.7%) in 2000, a high of 5,729.5 km^2 (64.3%) in 2010, and then 5,628.5 km^2 (63.3%) in 2020. The Developed class ranged from a minimum of 1,509.2 km^2 (16.9% of total area) in 2010 to a high of 1,656.7 km^2 (18.6%) in 1990. Rangeland or Pasture exhibited a minimum value of 1,204.4 km^2 (13.5% of total area) in 1990 and maximum of 1,449.7 km^2 (16.3%) in 2000 (Table 2; Figure 5). At the same time, our calculations using the Hansen global forest dataset resulted in 6,917.8 km^2 of Tree cover for Puerto Rico, close to 76% of total land area. Thus, the estimated forest area for 2000 using the Hansen dataset was about 13% more than the area derived from the LCMS dataset.

	1990		2000		2010		2020	
Land Use	**Area (km^2)**	**(%)**	**Area (km^2)**	**(%)**	**Area (km^2)**	**(%)**	**Area (km^2)**	**(%)**
Agriculture	72.2	*0.8%*	78.9	*0.9%*	56.3	*0.6%*	70.6	*0.8%*
Developed	1656.7	*18.6%*	1573.8	*17.7%*	1509.2	*16.9%*	1536.6	*17.3%*
Forest	5710.7	*64.1%*	5581.1	*62.7%*	5729.5	*64.3%*	5628.5	*63.3%*
Non-Forest Wetland	188.4	*2.1%*	166.8	*1.9%*	137.8	*1.5%*	125.2	*1.4%*
Other	72.3	*0.8%*	75.2	*0.8%*	74.3	*0.8%*	79.6	*0.9%*
Rangeland or Pasture	1204.4	*13.5%*	1432.5	*16.1%*	1401.6	*15.7%*	1449.7	*16.3%*

Table 2: Area (km^2) and percent of total land area (italics) of LCMS-derived land use for Puerto Rico from 1990 to 2020. Percent totals do not sum to 100% due to rounding.

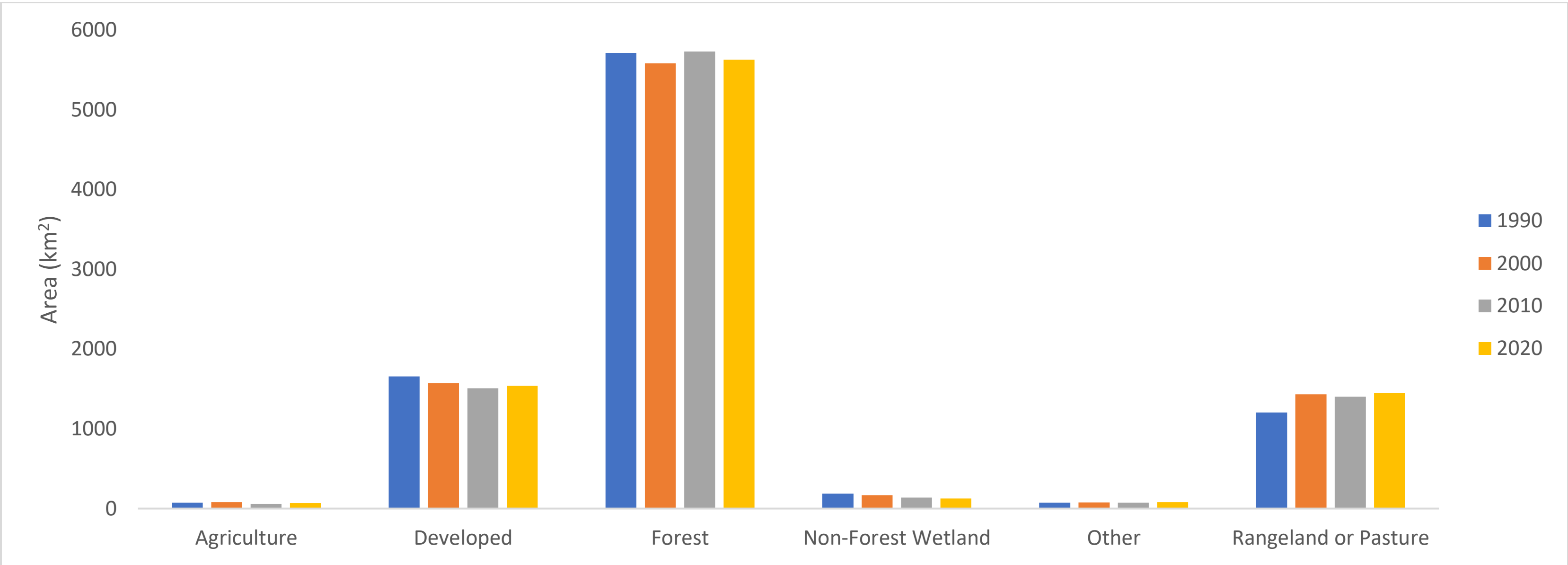

Figure 5: Bar graph summarizing LCMS-derived land use area (km^2) per class from 1990 to 2020.

2- Land use change trends from 1990 to 2020

The land use classes experienced within-class changes in area during the study period, with some classes showing generally increasing trends, others showing decreasing trends, and others oscillating between increases and decreases in area (Figure 6). Looking more closely at decadal variability within individual land-use classes, Forest showed relatively minor changes from decade to decade, with a maximum 10-year loss of 129.7 km^2 (-2. 3% change) from 1990 to 2000, and a maximum annual gain of 148 km^2 (2.7% change) between 2000 and 2010 (Table 3; Figure 6). For the entire 30-year period there was a slight overall Forest loss of 82.2 km^2 (1.4% change).

The Developed and Other classes showed slightly larger relative changes in area. Between 1990-2020 Developed had an overall loss of 120.1 km^2 (7.2% change) and only exhibited a small gain during the 2010-2020 interval of 27.4 km^2 (1.8% change). Other, which includes lands perennially covered in water, salt flats, and undeclared classes, increased by a total of 7.3 km^2 (10.1%) during the 30-year period, and only showed a slight decrease of -0.9 km^2 (1.2% change) during the 2000-2010 interval (Table 3; Figure 6).

Rangeland or Pasture showed much greater variability in area gains. There was an overall total increase of 245.3 km^2 (20.4% change) during the entire 30-year period, most of which occurred during the 1990-2000 interval. There were much smaller losses and gains in this class between 2000-2010 (-30.9 km^2, 2.2% change) and 2010-2020 (48.1 km^2, 3.4% change), respectively (Table 3; Figure 6) for each of them. Non-Forest Wetland showed losses during each time interval and throughout the study period, as well as the largest relative percentage reduction of all land use classes, losing 63.2 km^2 (33.6% change) between 1990-2020 (Table 3; Figure 6).

	1990-2000		2000-2010		2010-2020		1990-2020	
Land Use	**Δ Area (km²)**	**Δ %**	**Δ Area (km²)**	**Δ %**	**Δ Area (km²)**	**Δ %**	**Δ Area (km²)**	**Δ %**
Agriculture	6.6	*9.2%*	-22.6	*-28.6%*	14.3	*25.4%*	-1.7	*-2.3%*
Developed	-82.9	*-5.0%*	-64.6	*-4.1%*	27.4	*1.8%*	-120.1	*-7.2%*
Forest	-129.7	*-2.3%*	148.4	*2.7%*	-101.0	*-1.8%*	-82.2	*-1.4%*
Non-Forest Wetland	-21.6	*-11.5%*	-29.0	*-17.4%*	-12.6	*-9.2%*	-63.2	*-33.6%*
Other	2.9	*4.0%*	-0.9	*-1.2%*	5.3	*7.1%*	7.3	*10.1%*
Rangeland or Pasture	228.2	*18.9%*	-30.9	*-2.2%*	48.1	*3.4%*	245.3	*20.4%*

Table 3: Change in area (km^2) and percent change (italics) of each land use category per decadal interval and from 1990 to 2020.

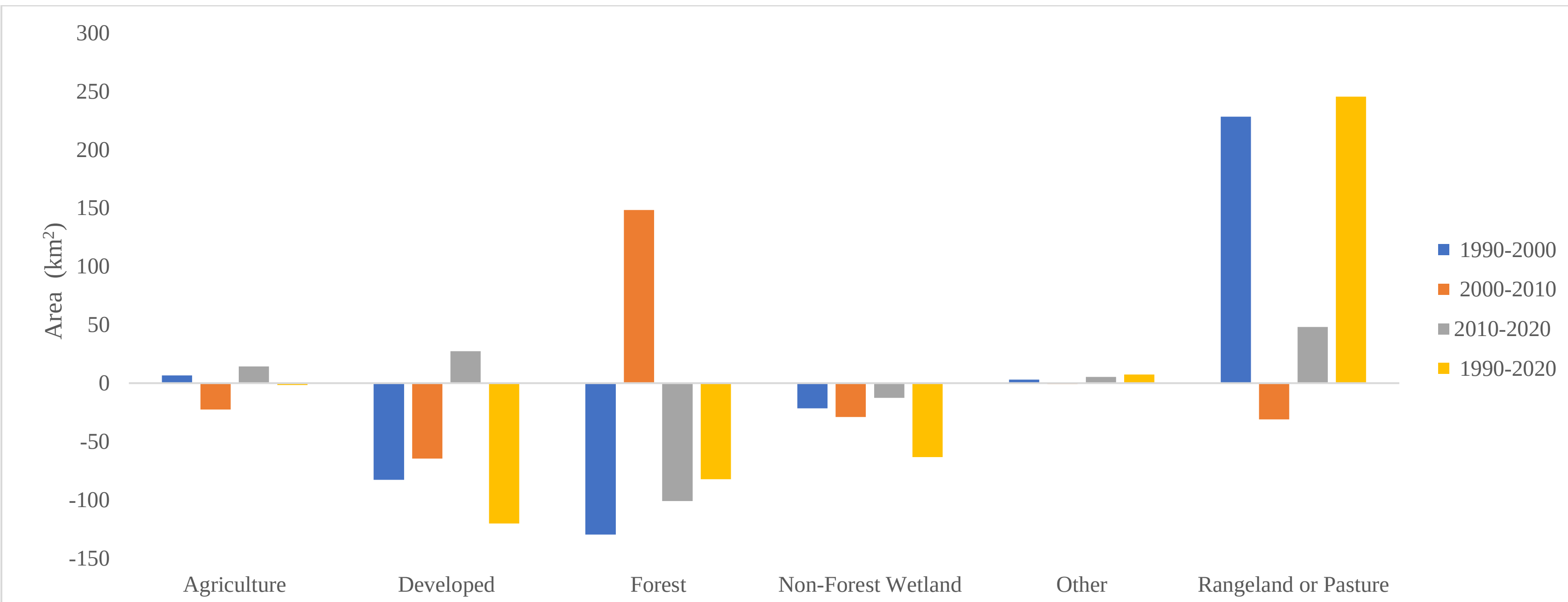

Figure 6: Bar graph showing net changes in area (km^2) per land use class for each decadal interval and from 1990-2020.

3- Change trends in Forest land use area from 1990 to 2020.

With respect to Forest land use specifically, this class experienced both an expansion of area (gain) and conversion to other categories (loss). For each of the 10-year intervals, the observed changes from and to Forest varied in absolute and proportional terms, but there were several important trends. Overall, Developed and Rangeland or Pasture were most frequently converted to Forest throughout the study period, accounting for greater than 90% of the observed change regardless of the decade. Depending on the decade, conversion values from Developed to Forest ranged from 108.1 km^2 (30.5% of decadal change) in 2010-2020 to 194.1 km^2 (49.6% of decadal change) in 1990-2000, with a 30-year change value of 331.8 km^2 (46.9% of change). Conversion from Rangeland or Pasture to Forest ranged from 159.8 km^2 (40.8% of decadal change) to 256.0 km^2 (57.7% of decadal change) and a 30-year change value of 318.3 km^2 (45.1% of change) (Table 4). Rangeland or Pasture showed the greatest proportional change to Forest for a single 10-year interval (61.9% in 2000-2010). Smaller absolute and proportional changes to Forest occurred from Agriculture, Non-Forest Wetland, and Other land uses, with change values of approximately 1-5% for all three classes. The greatest total absolute change occurred during 2000-2010, with a total of 443.4 km^2 converted to Forest (Table 4).

The conversion was not unidirectional, however. We also observed that Forest was most often converted to Developed and Rangeland or Pasture throughout the study period, again accounting for over 90% of the observed change in all three-time intervals (Table 4). Depending on the decade, Forest to Developed conversion values ranged from 92.3 km^2 (31.2% of decadal change) in 2000-2010 to 187.6 km^2 (36.0% of decadal change) in 1990-2000 with an overall 30-year change value of 257.5 km^2 (32.7% of change), while the conversion from Forest to Rangeland or Pasture ranged from 178.8 km^2 (60.6% of decadal change) in 2000-2010 to 281.3 km^2 (61.7% of decadal change) in 2010-2020, and a 30-year change value of 455.7 km^2 (57.8% of change). Forest showed the greatest proportional change to Rangeland or Pasture for a single 10-year interval (61.7% in 2010-2020). Similar to conversion to Forest, smaller absolute and proportional changes were observed from Forest to Agriculture, Non-Forest Wetland, and Other land uses, with change values of approximately 2-6% for all three classes. The great total absolute change occurred during 1990-2000, with a total of 521.1 km^2 converted from Forest to other land uses (Table 4).

	Δ to Forest								Δ from Forest							
	1990-2000		**2000-2010**		**2010-2020**		**1990-2020**		**1990-2000**		**2000-2010**		**2010-2020**		**1990-2020**	
Land Use	**Δ Area (km²)**	**Δ %**	**Δ Area (km²)**	**Δ %**	**Δ Area (km²)**	**Δ %**	**Δ Area (km²)**	**Δ %**	**Δ Area (km²)**	**Δ %**	**Δ Area (km²)**	**Δ %**	**Δ Area (km²)**	**Δ %**	**Δ Area (km²)**	**Δ %**
Agriculture	8.1	*2.1*	8.6	*1.9*	3.5	*0.9*	9.7	*1.4*	14.1	*2.7*	5.9	*2.0*	8.8	*1.9*	15.9	*2.0*
Developed	194.1	*49.6*	149.8	*33.8*	108.1	*30.5*	331.8	*46.9*	187.6	*36.0*	92.3	*31.2*	122.8	*26.9*	257.5	*32.7*
Non-Forest Wetland	20.2	*5.2*	22.3	*5.0*	18.2	*5.1*	33.1	*1.6*	30.2	*5.8*	13.7	*4.6*	19.4	*4.3*	28.2	*3.6*
Other	6.8	*1.8*	6.7	*1.5*	5.4	*1.5*	11.0	*1.6*	9.7	*1.9*	4.6	*1.6*	9.7	*2.1*	17.1	*2.2*
Rangeland or Pasture	159.8	*40.8*	256	*57.7*	219.6	*61.9*	318.3	*45.1*	279.5	*53.6*	178.8	*60.6*	281.3	*61.7*	455.8	*57.8*

Table 4: Area (km^2) and proportional percent changed (italics) from individual land use classes to and from Forest for each decadal interval and from 1990 to 2020. Percent change doesn't sum to 100 due to rounding errors.

Looking at conversion to and from Forest in aggregate, there were overall Forest losses between 1990-2000, 2010-2020 and the entire period 1990-2020. The greatest loss for a single 10-year interval occurred between 1990-2000, representing about a 33% difference between loss relative to gain. In contrast, only the period 2000-2010 showed overall forest gain, with approximately 50% more forest gained than lost during that decade (Table 5; Figure 7).

Forest area (km^2)	1990-2000	2000-2010	2010-2020	1990-2020
Loss	520.9	295.3	455.7	788.7
Gain	391.3	443.7	354.7	706.5

Table 5: Changes (loss / gain) in Forest area (km^2) for each decadal interval and from 1990 to 2020.

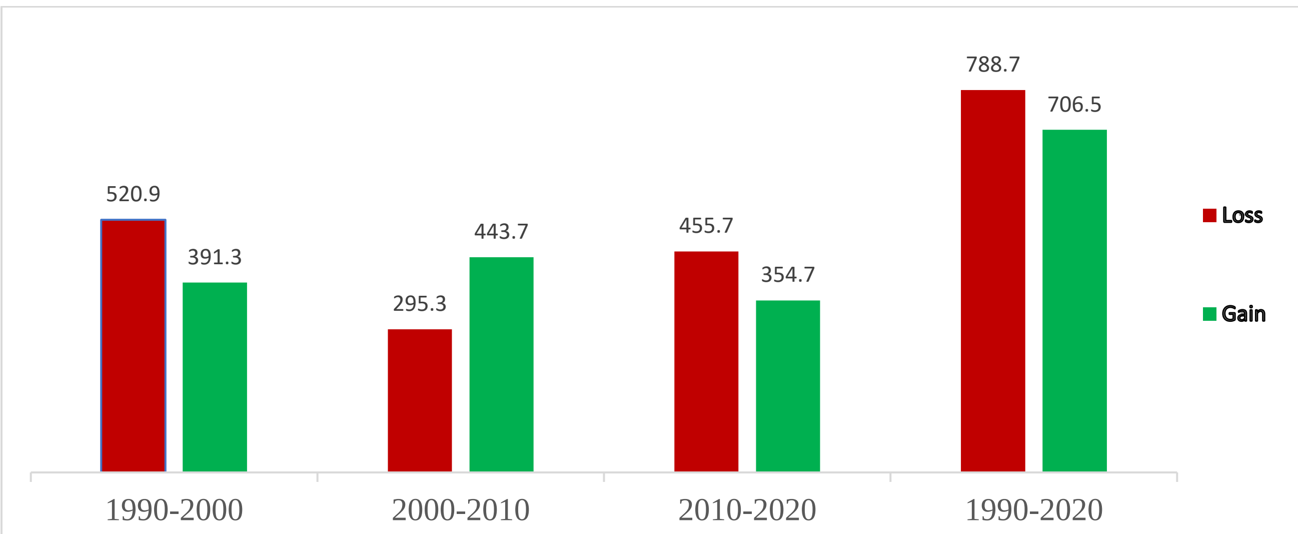

Figure 7: Bar graph summarizing change in Forest area loss / gain (km^2) for each decadal interval and from 1990 to 2020.

4- Transition Matrix and Transition Probabilities

The transition matrix for each time interval was calculated to take stock of the gains and losses of the land use classes. The main diagonal of the matrix represents unchanged areas of LULC classes from one to another including the most important transitions between classes. For its part, the probability of transition, which is derived from the transition matrix, was also calculated to detect classes that exhibit a high degree of persistence of a land use class and resistance to change over time. The results of the transition matrix showed that land uses classes such as Developed, Forest, and Rangeland or Pasture had the greatest absolute changes across the three decadal intervals (1990-2000; 2000-2010; 2010-2020) and the entire 30-year period (1990-2020) (Tables 6 and 7). Regarding transition probabilities, however, Forest land use was the most stable among the classes, showing a consistent probability of remaining forest during the three decadal intervals (consistently >90%) and during the entire 30-year period (about 86%) (Tables 8 and 9). In contrast, Agriculture consistently showed transition probabilities below 50% for all decadal intervals (i.e., relatively low resistance to change), and the lowest 30-year stability value of just 21%. Non-Forest Wetland also had a relatively lower resistance to change as compared to Forest, Developed, Rangeland or Pasture, and Other land uses classes.

Transition Matrix

1990-2000	Agriculture	Developed	Forest	Non-Forest Wetland	Other	Rangeland or Pasture	**Gross Loss**
Agriculture	**34.3**	7.7	8.1	0.9	0.3	21.1	38
Developed	9.8	**1277.1**	194.1	6.9	1.6	167.2	379.6
Forest	14.1	187.6	**5189.8**	30.2	9.7	279.5	521
Non-Forest Wetland	2.2	10	20.2	**123.8**	4.3	28	64.6
Other	0.2	4.9	6.8	0.8	**58.9**	0.7	13.4
Rangeland or Pasture	18.3	85.5	159.8	4.3	0.5	**936**	268.4
Gross Gains	44.6	296.7	391.3	43	16.3	496.6	1288.5

Transition Matrix

2000-2010	Agriculture	Developed	Forest	Non-Forest Wetland	Other	Rangeland or Pasture	**Gross Loss**
Agriculture	**29.9**	11.8	8.6	0.9	0.3	27.2	48.9
Developed	6.8	**1297.8**	149.8	4.9	1.7	112.8	275.9
Forest	5.9	92.3	**5285.8**	13.7	4.6	178.8	295.3
Non-Forest Wetland	0.8	4.6	22.3	**107.8**	2.2	29.2	58.9
Other	0.2	2.1	6.7	0.8	**65.1**	0.3	10.1
Rangeland or Pasture	12.6	100.6	256	9.7	0.4	**1053.2**	379.3
Gross Gains	26.3	211.4	443.7	30	9.2	348.4	1069

Table 6: Transition matrix (km^2) of land use types for the period 1990-2000 and 2000-2010.

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Transition Matrix

2010-2020	Agriculture	Developed	Forest	Non-Forest Wetland	Other	Rangeland or Pasture	**Gross Loss**
Agriculture	**25.5**	10.2	3.5	0.4	0.2	16.4	30.8
Developed	8.8	**1275.5**	108.1	3.2	1.9	107.6	233.7
Forest	8.8	122.8	**5273.8**	19.4	9.7	281.3	455.7
Non-Forest Wetland	0.7	3.8	18.2	**86.6**	2.3	26.2	51.2
Other	0.3	2.4	5.4	0.7	**64.8**	0.8	9.5
Rangeland or Pasture	26.6	121.9	219.6	14.9	0.6	**1017.4**	384.2
Gross Gains	45.1	261.1	354.7	38.6	14.8	432.3	1165.1

Transition Matrix

1990-2020	Agriculture	Developed	Forest	Non-Forest Wetland	Other	Rangeland or Pasture	**Gross Loss**
Agriculture	**15.4**	15.4	9.7	0.9	0.3	30.6	56.8
Developed	12.2	**1078.7**	331.8	6.6	2.3	221.8	578
Forest	15.9	257.5	**4922.1**	28.2	17.1	455.8	788.7
Non-Forest Wetland	1.8	12	33.1	**84.2**	7.2	49.9	104.2
Other	0.2	6.8	11	0.9	**51.9**	1.5	20.4
Rangeland or Pasture	25.1	165.2	318.3	4.6	0.8	**689.9**	514.4
Gross Gains	55.2	457.9	706.5	40.9	27.7	759.7	2066.4

Table 7: Transition matrix (km^2) of land use types for the period 2010-2020 and 1990-2020.

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Transition Probability

1990-2000	Agriculture	Developed	Forest	Non-Forest Wetland	Other	Rangeland or Pasture
Agriculture	47.4	10.7	11.1	1.2	0.3	29.2
Developed	0.6	77.1	11.7	0.4	0.1	10.1
Forest	0.2	3.3	90.9	0.5	0.2	4.9
Non-Forest Wetland	1.2	5.3	10.7	65.7	2.3	14.9
Other	0.3	6.7	9.5	1.1	81.4	0.9
Rangeland or Pasture	1.5	7.1	13.3	0.4	0	77.7

Transition Probability

2000-2010	Agriculture	Developed	Forest	Non-Forest Wetland	Other	Rangeland or Pasture
Agriculture	38	14.9	11	1.2	0.4	34.5
Developed	0.4	82.5	9.5	0.3	0.1	7.2
Forest	0.1	1.7	94.7	0.2	0.1	3.2
Non-Forest Wetland	0.4	2.7	13.4	64.6	1.3	17.5
Other	0.2	2.8	8.9	1.1	86.6	0.4
Rangeland or Pasture	0.9	7	17.9	0.7	0	73.5

Table 8: Transition probabilities of land use categories for the period 1990-2000 and 2000-2010.

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Transition Probability

2010-2020	Agriculture	Developed	Forest	Non-Forest Wetland	Other	Rangeland or Pasture
Agriculture	45.3	18.1	6.2	0.7	0.4	29.2
Developed	0.6	84.5	7.2	0.2	0.1	7.1
Forest	0.2	2.1	92.0	0.3	0.2	4.9
Non-Forest Wetland	0.5	2.7	13.2	62.8	1.7	19
Other	0.4	3.2	7.2	0.9	87.2	1
Rangeland or Pasture	1.9	8.7	15.7	1.1	0	72.6

Transition Probability

1990-2020	Agriculture	Developed	Forest	Non-Forest Wetland	Other	Rangeland or Pasture
Agriculture	21.3	21.3	13.4	1.1	0.4	42.4
Developed	0.7	65.1	20	0.4	0.1	13.4
Forest	0.3	4.5	86.2	0.5	0.3	8
Non-Forest Wetland	0.9	6.4	17.6	44.7	3.8	26.5
Other	0.3	9.4	15.2	1.2	71.8	2
Rangeland or Pasture	2.1	13.7	26.4	0.4	0.1	57.3

Table 9: Transition probabilities of land use categories for the period 2010-2020 and 1990-2020

5- Spatial distribution of Forest loss and gain

Figure 8 shows spatial distribution maps of forest area loss and gain for the three focal decades and the entire study period. The red pixels represent areas with loss of Forest land use, i.e., change of Forest into other land use classes. The green pixels refer to the gain of forest area, i.e., the change of other land use classes to Forest. Forest losses and gains appear to be both spatially variable (non-uniformly distributed across the island) and temporally variable (the distribution gain and forest loss as represented by the pixels changes from one decade to the next). Also, while forest loss and gain can be observed in both coastal and interior areas, there is an overall dominance of Forest loss in coastal areas in the proximity of major urban areas and Forest gain in interior mountainous areas. Notably, many areas where there is neither Forest loss nor gain overlap spatially with protected areas that are conserved from land use change, such as El Yunque National Forest, the northern karst belt, and several national parks in the Central Cordillera (Figures 8 and 9).

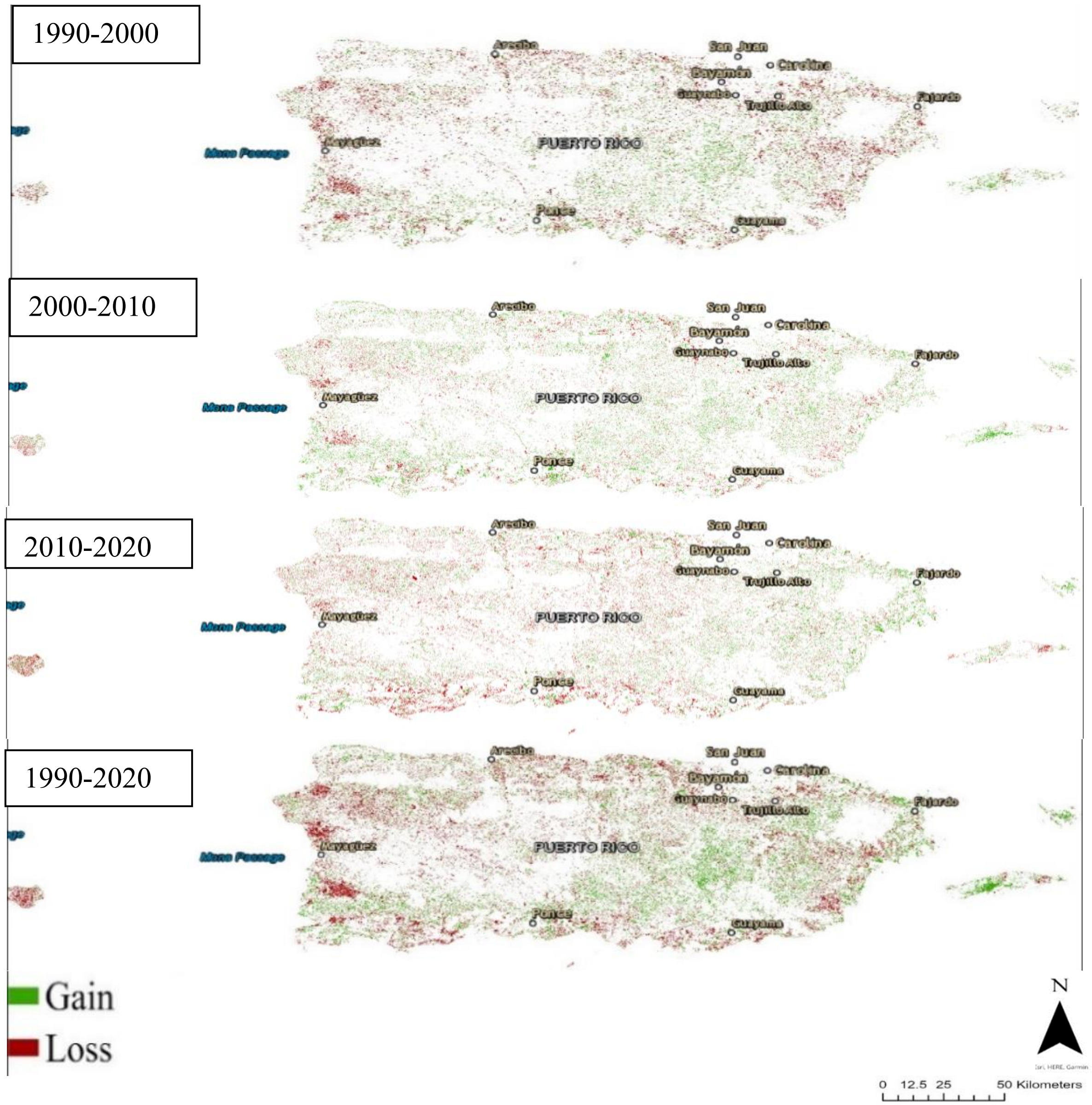

Figure 8: Spatial distribution of forest change (loss/gain) for each decadal interval and for the entire period 1990-2020.

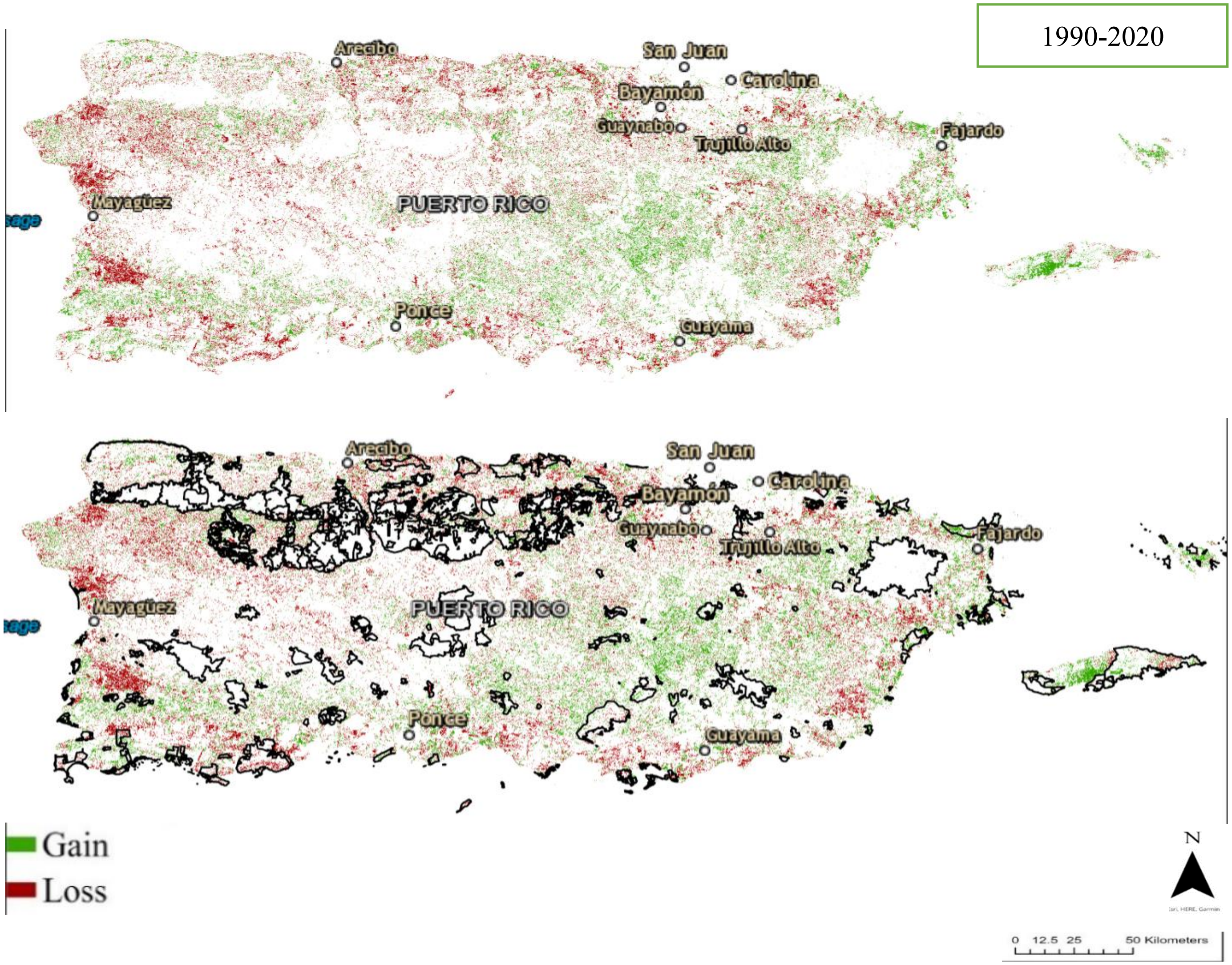

Figure 9: Spatial distribution of forest change (loss/gain) within the protected areas for the entire period 1990-2020.

6- Spatial distribution of change in land use types (loss/gain)

Figures 9 and 10 show the spatial distribution of change in all land use types (including Forest) in terms of loss and gain. As presented earlier, Forest, Developed and Rangeland or Pasture are the three major dominant classes most affected by land use conversion in terms of both losses and gains for the three decadal intervals (1990-2000; 2000-2010; 2010-2020) and for the entire period 1990-2020. Similar to the distribution of Forest loss and gain, changes in land use type are spatially and temporally variable across the island.

The most dominant losses of Developed are in less urbanized and interior mountain areas in east-central Puerto Rico and in and around select urban centers, and range in total area from 233.7 km^2 to 379.6 km^2 for the three decadal intervals and 578 km^2 for the entire period (Table 10). The most dominant losses of Forest are also in densely populated peri-urban areas adjacent to urban centers, particularly in the coastal plains, and range in total area from 295.3 km^2 to 520.9 km^2 for the three decadal intervals and 788.7 km^2 for the entire period. The most dominant losses of Rangeland or Pasture are also in northern and southern coastal areas and range in total area from 268.4 km^2 to 384.2 km^2 for the three decadal intervals and 514.4 km^2 for the entire period.

Conversely, the most dominant gains of Developed are found either in urban areas or in adjacent peri-urban areas, particularly along the north coast. These gains range in total area from 211.4 km^2 to 296.7 km^2 for the three decadal intervals and 457.9 km^2 for the entire period (Table 10). Similarly, the most dominant areas of Forest gain are found in mountainous areas in east central Puerto Rico, often areas farther far from major urban centers, and in select coastal locations such as along the east coast. Forest gains range in total area from 354.7 km^2 to 443.7 km^2 for the three decadal intervals and 706.4 km^2 for the entire period. Finally, the most dominant gains of Rangeland or Pasture are found in certain coastal areas, most prominently in the south, and range in total area from 348.4 km^2 to 496.6 km^2 for the three decadal intervals and 759.7 km^2 for the entire period.

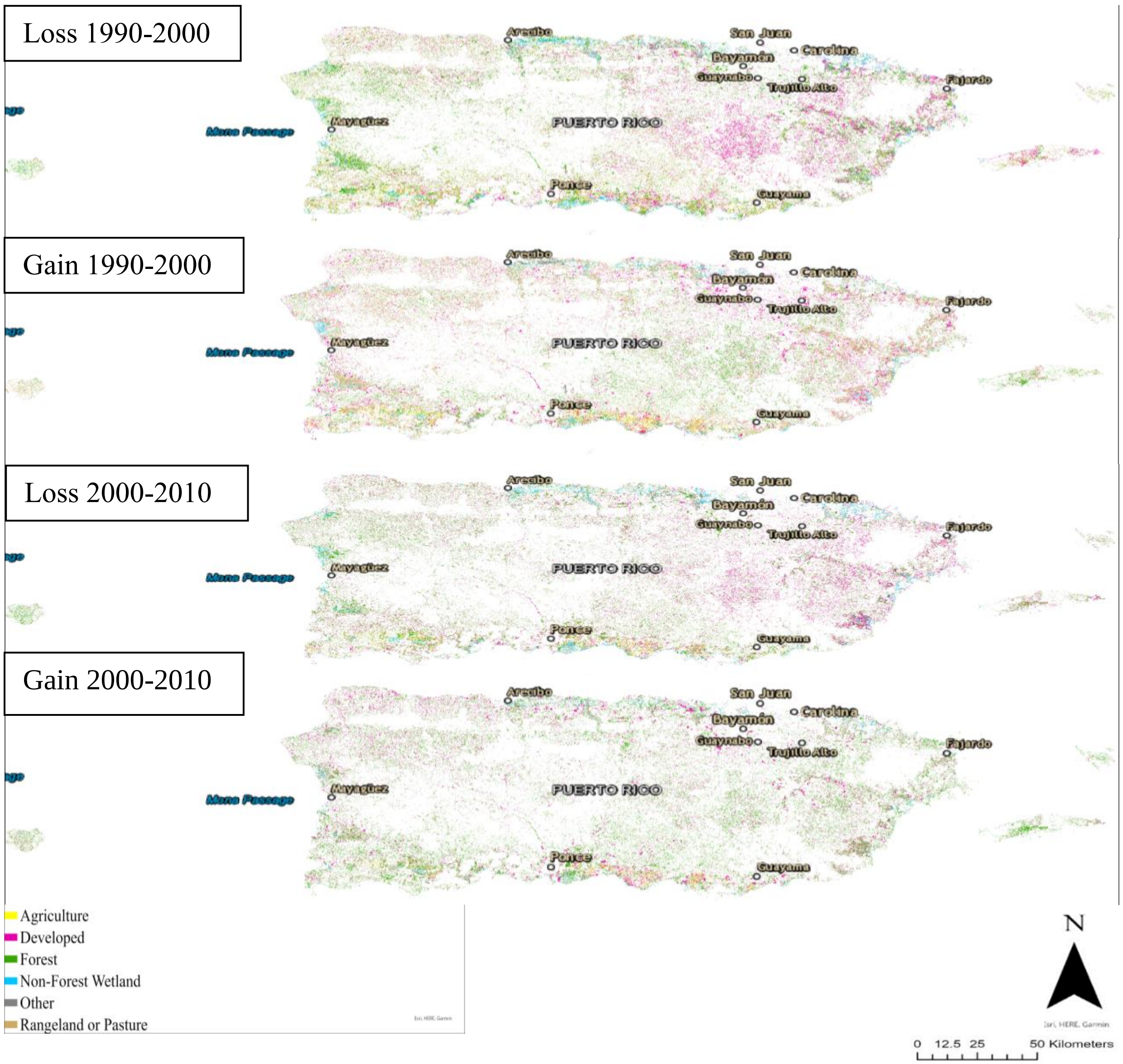

Figure 10: Spatial distribution of land use types (loss/gain) for the periods 1990-2000 and 2000-2010.

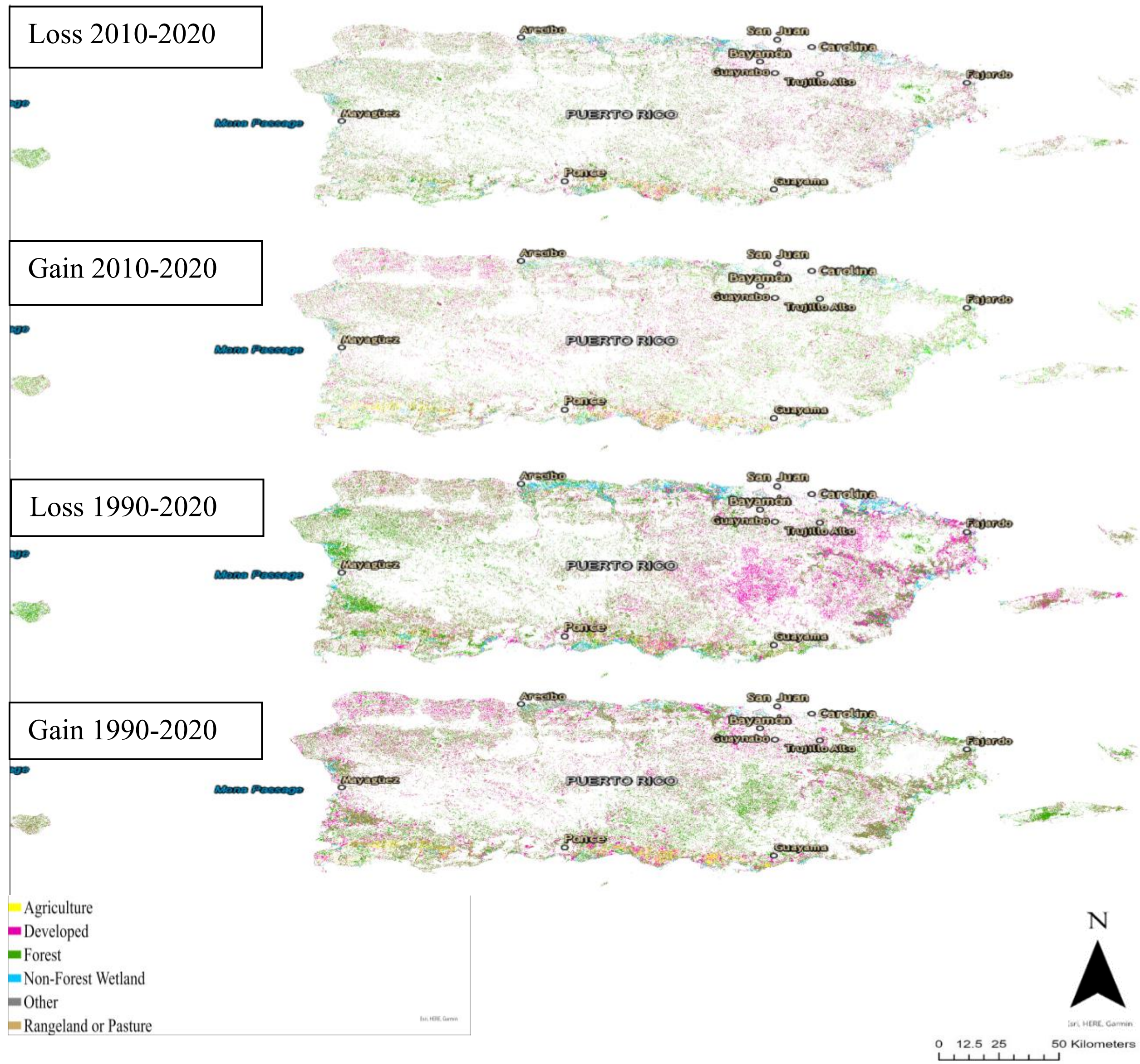

Figure 11: Spatial distribution of land use types (loss/gain) for the periods 2010-2020 and 1990-2020.

	Gross Loss				Gross Gain			
Land Use	**1990-2000**	**2000-2010**	**2010-2020**	**1990-2020**	**1990-2000**	**2000-2010**	**2010-2020**	**1990-2020**
Agriculture	37.9	48.9	30.8	56.8	44.6	26.3	45.1	55.2
Developed	379.6	275.9	233.7	578.0	296.7	211.4	261.1	457.9
Forest	520.9	295.3	455.7	788.7	391.3	443.7	354.7	706.4
Non-Forest Wetland	64.6	58.9	51.2	104.2	43.0	30.0	38.6	40.9
Other	13.4	10.1	9.5	20.4	16.3	9.2	14.8	27.7
Rangeland or Pasture	268.4	379.3	384.2	514.4	496.6	348.4	432.3	759.7

Table 10: Gross loss and gain in total area (km^2) per land use type for each decadal interval and the entire period.

7- Spatial autocorrelation and cluster analysis of Forest losses and gains

The outputs of the Global Moran's I analysis indicated the presence of significant patterns of spatial autocorrelation among percent change in both Forest losses and gains throughout Puerto Rico (Table 11). The values of Global Moran's I are positive, with p-values less than 0.05 for the three-decade intervals and for the entire period. Subsequent cluster analysis (Anselin Local Moran's I) at the scale of the census block group revealed where statistically significant concentrations of losses and gains are located. Results varied considerably from one time period to the next, but some general patterns are visible. For the interval 1990-2000 there are HH significantly high clusters of percent Forest loss in many coastal areas, particularly in peri-urban areas and municipalities adjacent to (but not directly within) major metropolitan centers like San Juan, Ponce, and Mayagüez and in east-central Puerto Rico, while several LL (significantly low) clusters of Forest loss are concentrated closer to those same cities (Figure 11). For 2000-2010 and 2010-2020 HH clusters of Forest loss appear more prominently in the Central Cordillera and western Puerto Rico. There are also small patches where either clusters of high Forest loss are surrounded by areas of low loss or low Forest loss is surround by high loss, and their spatial distribution is quite variable depending on the time interval.

As for clusters of percent forest gain, there was again much spatial and temporal variability. Significantly high clusters (HH) were found in the Central Cordillera and select coastal areas, though not typically those associated with major urban areas like San Juan, Ponce or Mayagüez but rather smaller urban centers such as Fajardo and Guayama (Figures 11 and 12). Many significantly low (LL) clusters of forest gain were found in or adjacent to major urban areas and a few mountainous areas in central Puerto Rico. The distribution of small patches of high Forest gain surrounded by low gain and likewise low Forest gain surrounded by high gain varied considerably throughout the 30-year period.

Global Moran's I	Percent Forest loss	Percent Forest gain
1990-2000	I_{value} = 0.84 P_{value} = 0.00	I_{value} = 0.88 P_{value} = 0.00
2000-2010	I_{value} = 0.32 P_{value} = 0.00	I_{value} = 0.0.43 P_{value} = 0.00
2010-2020	I_{value} = 0.32 P_{value} = 0.00	I_{value} = 0.34 P_{value} = 0.00
1990-2020	I_{value} = 0.34 P_{value} = 0.00	I_{value} = 0.47 P_{value} = 0.00

Table 11: I and p-values of Global Moran's I of percent forest loss and gain between decadal intervals.

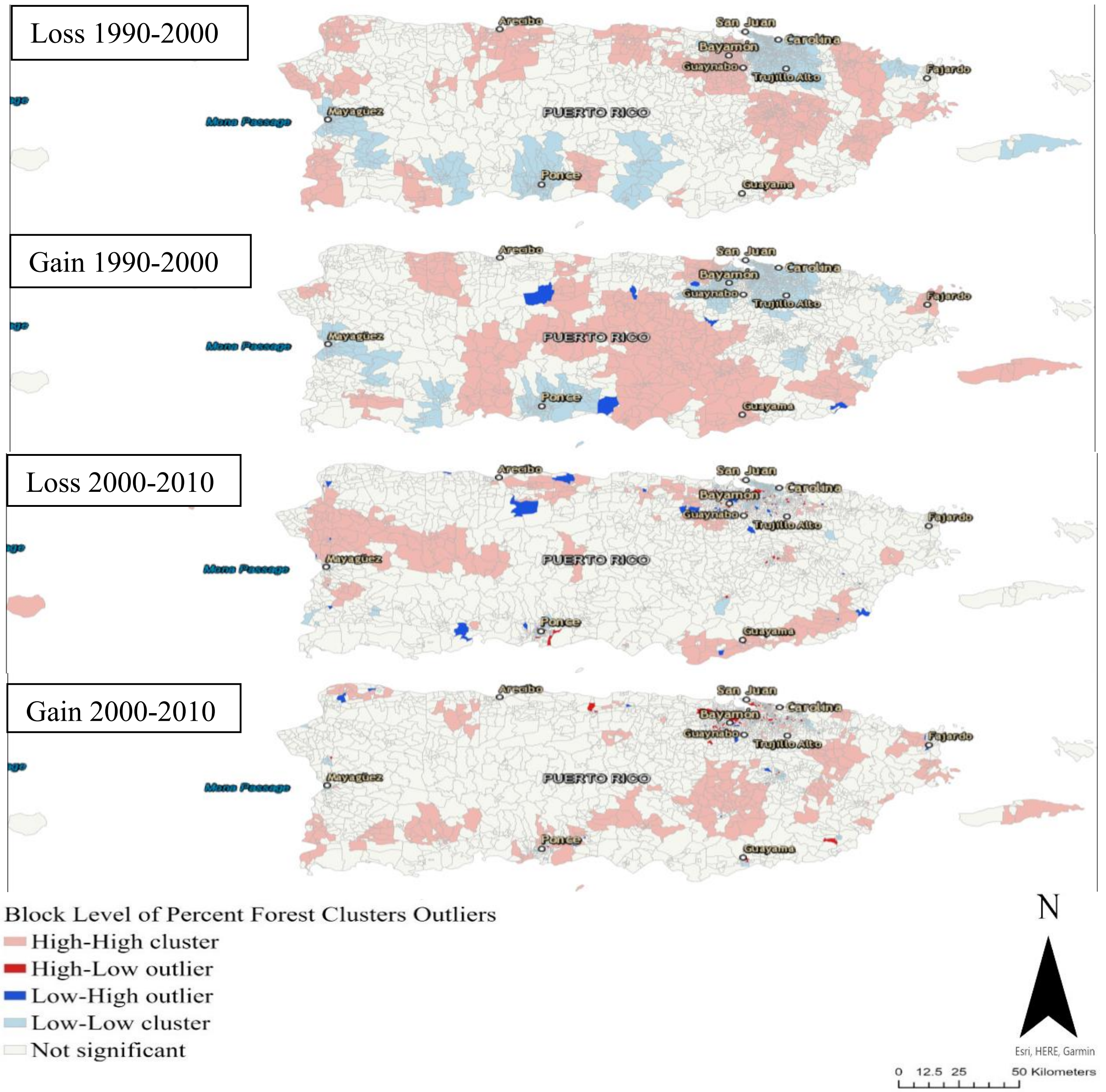

Figure 12: Spatially-significant clusters of percent forest loss and gain for the periods 1990-2000 and 2000-2010.

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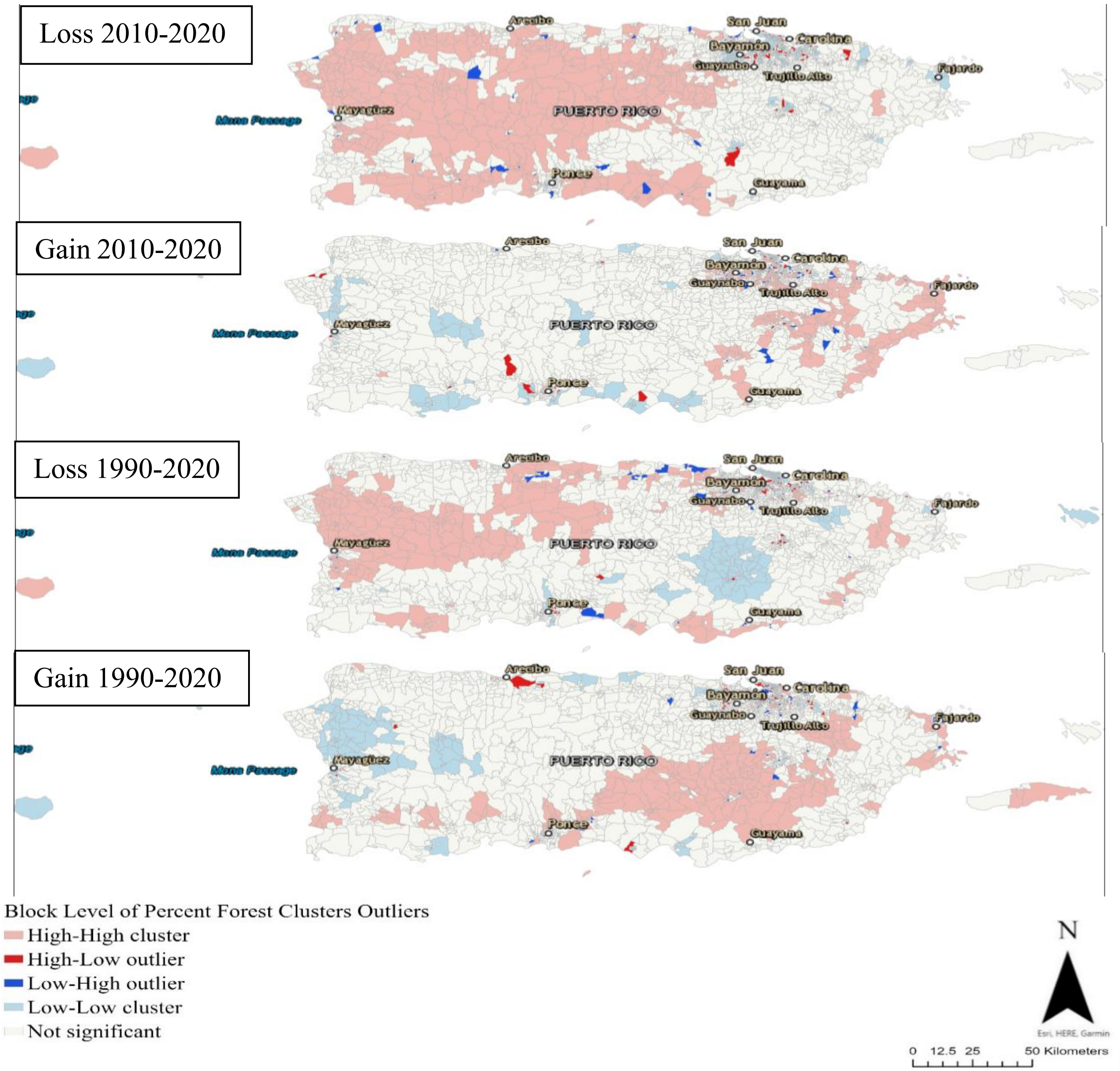

Figure 13: Spatially-significant clusters of percent forest loss and gain for the periods 2010-2020 and 1990-2020.

8- Statistical analysis of social variables with GWR model

The results of the continuous (Gaussian) GWR model revealed the presence of several spatial relationships between Forest gain and loss and the social predictor variables we evaluated (population density and forest/agricultural occupation density), and these relationships varied from one time period to the next. For both Forest loss and gain, the strongest relationship for the global models was observed for the period 1990-2000: the forest gain model had an R^2_{adj} value of 0.62, while the Forest loss model had an R^2_{adj} of 0.74, indicating moderate to strong positive correlations, respectively (Table 12). For 2000-2010 and 2010-2020, as well as for the entire period of 1990-2020, the global model relationships were less robust, with weak-to-moderate correlations being observed for Forest loss (R^2_{adj} ranging from 0.26 to 0.45) and weak associations with Forest gain (R^2_{adj} ranging from 0.22 to 0.25). The results of the local models which examined spatial relationships between individual predictor variables and Forest loss and gain at the scale of individual block groups showed weak correlations for all time periods. R-squared values for population density ranged between 0.08 (1990-2000) and 0.24 (2010-2020) for the Forest loss model, and between 0.04 (1990-2000) and 0.12 (2000-2010) for the Forest gain model. R-squared values for forest/agricultural occupation density were effectively zero for both Forest loss and gain local models for all time periods (Table 12).

The GWR outputs also included maps of the spatially explicit raster surfaces of coefficient values that exhibit regional variation in the strength of the relationship (positive or negative) between forest loss and gain and each of the explanatory variables separately. These surfaces show that the nature of the relationships varied considerably in both time and space. There were weak to moderate coefficient values for population density as related to Forest loss in several coastal urban areas, which varied with the different time periods. These include Humacao (1990-2000), Aguadilla (2010-2020; 1990-2020), and Yauco (1990-2020). Several inland areas along the central cordillera also had showed weak to moderate positive coefficient values for the relationship between Forest loss and population density at different time periods. There are also moderate to strong negative coefficient values between population density and Forest loss around Fajardo (1990-2000), Caguas (2000-2010), much of the central cordillera (2010-2020) and Arecibo (1990-2020) (Figures 13 and 14). Regarding Forest gain, we observed moderate to strong positive coefficient values in coastal areas near Fajardo and Guayama (1990-2000), Mayagüez (2000-2010;

1990-2020), the southwestern coast of PR including Cabo Rojo and surrounding areas (2000-2010), and near Yauco and parts of the central cordillera (2010-2020) (Figures 13 and 14). There were moderate to strong negative coefficient values between population density and Forest gain around Humacao (1990-2000), Cayey (2010-2020; 1990-2020) and Yauco (2000-2010), and Aguadilla (2010-2020).

As for forest/agricultural occupation density, although the results of the regression models showed that the variable occupation density did not explain any of the variance in the forest loss and gain at the block group scale, there is still regional variation in the occupation density variable and its relationship to Forest loss and gain. Weak to moderate positive coefficient values with Forest loss were observed around Yauco (1990-2000), Aguadilla (2000-2010), Mayagüez (2010-2020) and Arecibo (2010-2020; 1990-2020), while weak to moderate negative relationships were observed around Humacao (1990-2000), Caguas (2000-2010), and Ponce (2010-2020; 1990-2020) (Figures 15 and 16). Weak to strong positive coefficient values for occupation and Forest gain were observed in the areas of Humacao (1990-2000), Fajardo (2010-2020), Caguas (2000-2010) and Guayama (1990-2020), while weak to moderate negative relationships were observed around Humacao (2000-2010), Arecibo and Cayey (2010-2020) and Aguadilla (1990-2020) (Figures 15 and 16). Coefficient values for Forest loss and occupation in inland areas along the central cordillera varied in both sign and magnitude from one time period to the next.

GWR Continuous (Gaussian) Model	Percent Forest loss vs (Population density + Occupation density)	Percent Forest gain vs (Population density + Occupation density)
1990-2000	R^2_{global}=0.76 AdjR^2=0.74 $R^2_{local\ Popdensity}$=0.08 $R^2_{local\ Occupdensity}$=0.01	R^2_{global}=0.64 AdjR^2=0.62 $R^2_{local\ Popdensity}$=0.04 $R^2_{local\ Occupdensity}$=0
2000-2010	R^2_{global}=0.30 AdjR^2=0.26 $R^2_{local\ Popdensity}$=0.1 $R^2_{local\ Occupdensity}$=0	R^2_{global}=0.27 AdjR^2=0.23 $R^2_{local\ Popdensity}$=0.12 $R^2_{local\ Occupdensity}$=0
2010-2020	R^2_{global}=0.50 AdjR^2=0.45 $R^2_{local\ Popdensity}$=0.24 $R^2_{local\ Occupdensity}$=0	R^2_{global}=0.30 AdjR^2=0.25 $R^2_{local\ Popdensity}$=0.05 $R^2_{local\ Occupdensity}$=0
1990-2020	R^2_{global}=0.40 AdjR^2=0.34 $R^2_{local\ Popdensity}$=0.13 $R^2_{local\ Occupdensity}$=0	R^2_{global}=0.27 AdjR^2=0.22 $R^2_{local\ Popdensity}$=0.08 $R^2_{local\ Occupdensity}$=0

Table 12: R^2 and R^2_{adj} values of GWR relationship between population density and forest/agricultural occupation density and Forest loss and gain for the three decadal intervals and the entire period 1990-2020.

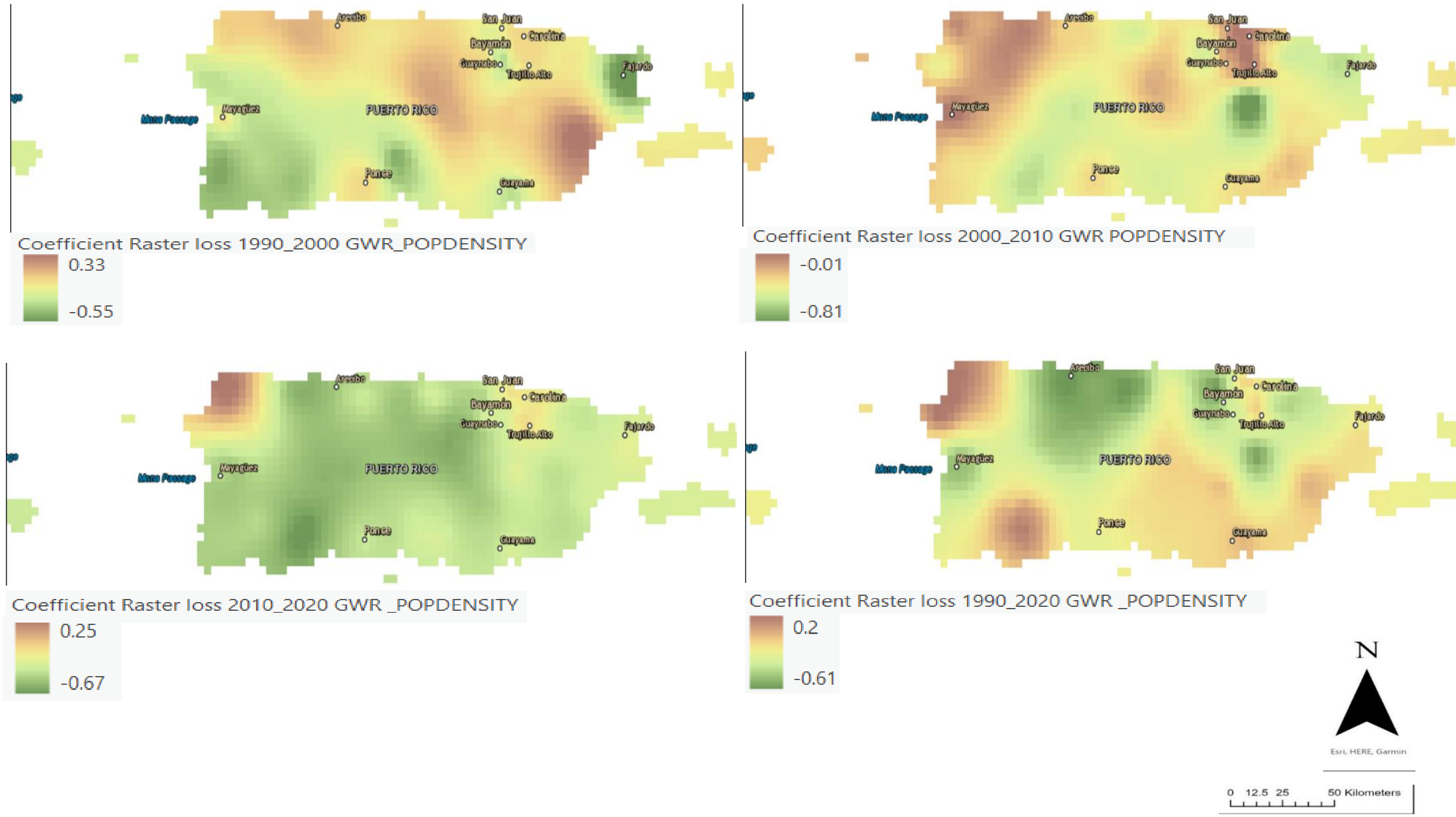

Figure 14: Raster coefficient rasters of spatial relationship between percent forest loss and population density for the three decadal intervals and the entire period 1990-2020.

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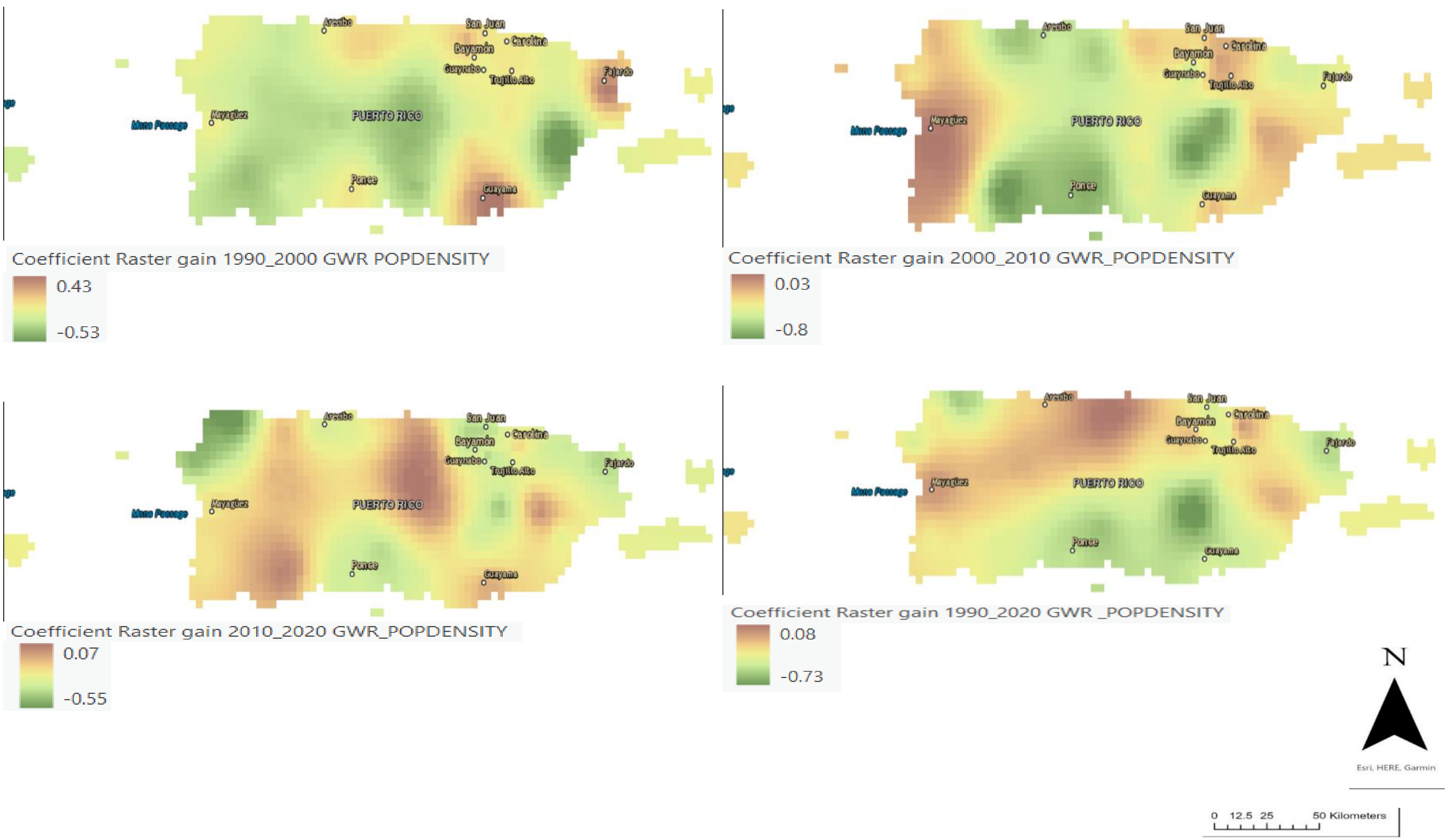

Figure 15: Raster coefficient rasters of spatial relationship between percent forest gain and population density for the three decadal intervals and the entire period 1990-2020.

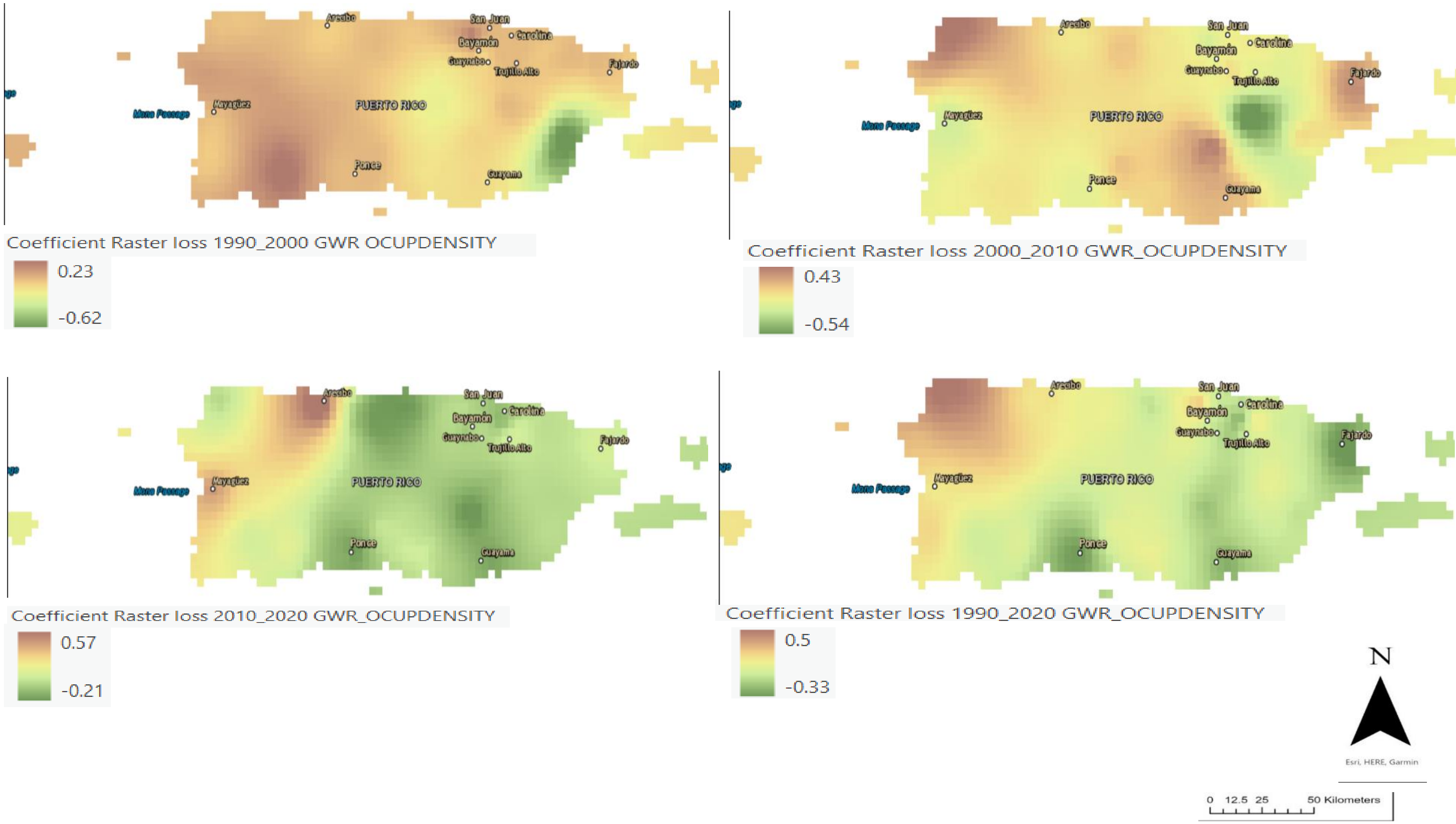

Figure 16: Raster coefficient rasters of spatial relationship between percent forest loss and occupation density for the three decadal intervals and the entire period 1990-2020.

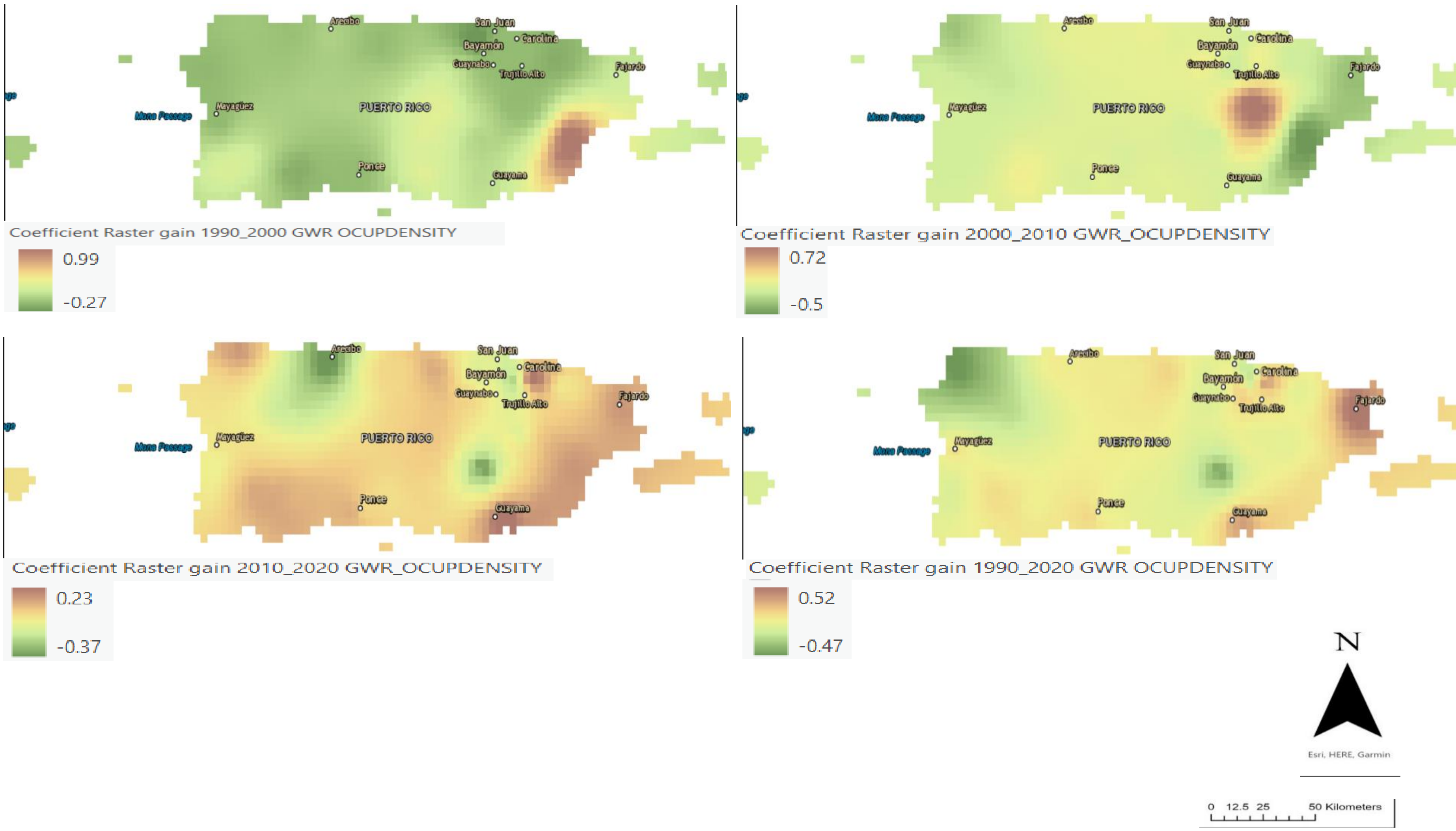

Figure 17: Raster coefficient rasters of spatial relationship between percent forest gain and occupation density for the three decadal intervals and the entire period 1990-2020.

Discussion

1- Forest trends in Puerto Rico

Our analyses revealed that Forest land use, as derived from the LCMS data, was relatively constant, remaining between 62% and 64% during the 30-year study period. This was surprising to us because we had anticipated larger proportional increases in forested area (Hypothesis 1). Previous studies of forest cover in Puerto Rico using data collected at different times during the same decades have reported greater variability. Franco et al. (1997) estimated forest cover of about 287,000 ha in 1990, representing 32% of total area, much less than the value of 64% that we calculated for that year. Another study by Kennaway and Helmer (2007) analyzed land cover change from 1991 to 2000 based on Landsat image classification and reported that forest cover expanded during that period from 385,219 ha to 389,552 ha, representing approximately a 1% increase to a total of approximately 45% of the land area. Again, these values differ considerably from the total and percent of forest land use we calculated for 1990 and 2000 (Table 2; Figure 5). Wang et al. (2017), for their part, estimated the land cover of Puerto Rico for the year 2000 using Landsat TM/ETM+ products data and PALSAR, with different window sizes of 0.75 km × 0.75 km, 1.5 km × 1.5 km, and 3 km × 3 km and found a total forest area of 399,400 ha (45%), similar to the value reported by Kennaway & Helmer (2007). In contrast, the 2003 FIA analysis for Puerto Rico estimated forest area of 505,993 ha, representing 57% of the total land area (Brandeis et al., 2007). This value is much more comparable to the 62% of Forest land use we calculated with LCMS for the year 2000.

Another FIA estimate that incorporated aerial photograph interpretation and classified satellite imagery data concluded that forest cover was about 54.7% for the year 2010 (Brandeis & Turner, 2013). The most recent island-wide FIA data available is from 2019, with forest covering 467,320 ha (52.7%) of the total area (Brandeis and Marcano-Vega, 2021). Furthermore, a study conducted by Yuan et al. (2017) using Landsat Paths 4-5 data at 30 m spatial resolution estimated that Puerto Rico's forest cover for the year 2014 was 405,000 ha (45.7%). Lastly, the reference analysis we conducted using the Hansen global dataset (Hansen et al., 2013) for the year 2000 resulted in total Forest cover of around 76%, which is considerably higher than the value derived from the LCMS dataset in this study.

The principal reasons for these marked differences in estimates of forested land is the variability in sampling area as well as the sampling approach. For example, the Franco et al. (1997) study of 1990 forest cover mentioned above was conducted by the USDA Southern Forest Inventory and Analysis Research (SOFIA) Work Unit that used a slightly smaller total area estimate for Puerto Rico (8,900 km^2 vs 8,940 km^2 in our study). During the 1990 survey, the FIA used a square sampling grid with lines spaced 3 km apartwhich only included mainland PR. Subsequent FIA surveys after 1990 have included mainland PR, Vieques, Culebra and Mona and have used a hexagonal sampling grid with a sampling point every 67 ha for forest area estimation. Furthermore, the FIA protocol defines Forest as areas of at least 0.4 ha that have a least 10% canopy of living plants, and requires that roadside, streamside, and shelterbelt strips of trees must be at least 36 m wide to qualify as forest land. The Landsat study by Kennaway and Helmer used an even higher minimum cover of 25% woody vegetation (including trees or trees plus shrubs). In contrast, the LCMS defined forest as land that is planted or naturally vegetated, and which contains (or is likely to contain) 10% or greater tree cover within a 30 m x 30 m pixel and may include deciduous, evergreen and/or mixed categories of natural forest, forest plantations, and woody wetlands (Housman et al., 2022). Thus, the FIA approach and Kennaway and Helmer's study were more conversative in their definition of forest than LCMS, which helps account for many of the differences in estimated forest area compared to our study. Furthermore, the FIA methodology includes ground-truthing to validate the results while LCMS uses a remote approach to validate land use models using group training points. This reveals some of the potential trade-offs in data quality between using satellite imagery vs field sampling.

As for the Hansen dataset, forest is defined as all vegetation taller than 5 m in height with >25% canopy that includes all plantation (trees, palm, and coconut tree). This can include large shrubs as well, which in the LCMS are often associated with the Rangeland or Pasture land use class, and that may help explain the observed difference in Forest area between the two datasets. Despite the observed differences, there are general similarities in the spatial patterns between the LCMS and Hansen data, which helps validate the results for the methods we used. Additional analysis is required to determine if the results from the LCMS data are reliable. All in all, there is not always a consensus when defining forests and estimating forest LULC in reports and the literature due to the difference in the images used, classification methods, spatial resolution, study scales and methods of validation. It is therefore important to make comparisons using data derived from consistent methods. The results of this study also highlight the need for harmonization regarding the definition of forest to facilitate better comparison among landscape scale analyses. Such efforts are being explored by a network of national forest inventory experts who have outlined a consistent and coherent approach for monitoring trends in forest cover and implementing sustainable management as specified in the document *National Forest Inventories of Latin America and the Caribbean* (*National Forest Inventories of Latin America and the Caribbean*, 2022).

2- Spatiotemporal patterns of land use change

Our results revealed that during the first (1990-2000) and third (2010-2020) decadal intervals and the entire 30-year period there were greater overall losses in forest area relative to forest gains, and only during the second period (2000-2010) did forest total forest gains exceed losses. During each decade the land use category to which most Forest area transitioned was Rangeland or Pasture, and the second most common transition category was Developed. In the opposite direction, Rangeland or Pasture pixels exhibited the greatest transition to Forest during the latter two decades of the study. Interestingly, however, it was Developed land that experienced the greatest relative transition to Forest during the first decade and for the entire period of study.

Previous studies in Puerto Rico have focused on natural disturbances such as hurricanes (Hall et al., 2020), ecological impacts (Grau et al., 2003) and landslides (Wang et al., 2017) in relation to changes in forest cover. Others have looked at intense agriculture (Parés-Ramos et al., 2008) and population dynamics (Martinuzzi et al., 2007). Likewise, socio-economic drivers processes are contributory factors to the change in land use over longer time periods and have become highly influential (Álvarez Martínez et al., 2011). Despite a decline in the urban population of Puerto Rico over the last thirty years due to the effects of economic recession and hurricanes (Santos-Lozada et al., 2020), the development model of the last seventy years has been focused on an architecture of large urban centers, peri-urban agglomerations, industrial areas, isolated residential complexes, ports, and airports (Martinuzzi et al., 2007). This expansion of infrastructure, coupled with inefficient urban planning, has generated an ongoing dependence on land that is likely responsible, at least in part, for the conversion of Forest to Developed that we observed (Martinuzzi et al., 2007). According to our results, more forest loss occurs in coastal areas, in the south, east, and in municipalities adjacent to core urban areas such as San Juan, Arecibo and Caguas which also coincide with areas of suburban expansion in recent decades (Parés-Ramos et al., 2008). Even if the population has experienced a decline during the three decades analyzed, the need for land for commercial and residential development is considerable, as illustrated by the high population density estimate of 438 people/km^2 (US Census Bureau, 2000). Thus, urbanization disproportionately affects forest cover around urban centers, particularly in low-lying coastal areas.

On the other hand, the observed expansion of Forest in urban areas can likely be attributed to increases in tree canopy cover rather than actual land conversion. In other words, developed areas did not suddenly become undeveloped; rather, pixels that were previously dominated by non-woody vegetation or development eventually exceeded the minimum LCMS threshold of 10% tree cover to be classified as forest. This conclusion is supported by prior land cover analyses that have documented the importance of urban tree cover in Puerto Rico. For example, the San Juan metropolitan area was estimated to have about 26% tree coverage in 2002 (Ramos-González, 2014) and Martinuzzi et al. (2018) found that most urbanized neighborhoods in San Juan had at least 10% tree canopy cover. Furthermore, urban tree inventory work conducted by Brandeis et al. (2014) reported relative increases in percent tree cover for commercial/industrial, institutional, and residential areas of the San Juan Bay Estuary Watershed between 2001 and 2011. Notably, we did not analyze changes in forest land use directly around the years prior to and after Hurricane Maria in 2017 and consequently our results do not specifically address the effects of the storm on changes in tree cover. Prior analysis by Feng et al. (2018) using pre- and post-Maria Landsat data found a dramatic island-wide reduction in green leaf canopy cover immediately following the storm. Likewise, Melendez-Ackerman et al. (2018) reported immediate post-storm decreases in tree area cover of approximately 25%, 6%, and 4% for the metropolitan areas of San Juan, Ponce and Mayagüez, respectively. Additional research is necessary to determine if similar results can be observed using the LCMS datasets.

The results of the transition and probability matrices also support Hypothesis 2. They showed that for each of the decadal intervals Forest land use was more stable than other land use categories and had a probability of more than 90% remaining as forested. Furthermore, the probability of non-forest classes changing to forested area was greater than that of forest changing to non-forest classes. Many areas of Agriculture, Developed and Rangeland or Pasture were converted during the study period to Forest land as well, with between 6-18% probability of conversion per each of these land use types, depending on the time period. Indeed, agricultural land becomes forest in most cases due to abandonment of agricultural practices (Parés-Ramos et al., 2008) and this has resulted in net reforestation across the island, consistent with previous studies that examined forest transitions in Puerto Rico since the 1950s (Brandeis et al., 2009; Geist et al., 2006; Helmer et al., 2008). Our findings also highlight that Forest pixels tend to appear in small, fragmented patches within surrounding Agricultural, Developed, and Rangeland or pasture matrix rather than large contiguous patches. Additional quantitative analysis is required to describe the size and distribution of such patches. Previous work by Lugo and Helmer (2004) has also underscored the highly fragmented nature of emerging forest patches on abandoned agricultural land in Puerto Rico. It is also worth noting that Non-Forest Wetland was one of the least stable land use types during the study period. This may reflect ongoing trends of urbanization and development in coastal areas which constrain wetlands in Puerto Rico (Yu et al., 2019).

3- Cluster analysis of percent forest loss/gain

We also examined the significant cluster of percentage forest gain/loss using Anselin Local Moran's I at the block group level, which provided the basis for the existence of heterogeneously-distributed Forest land use loss and gain clusters. This finding is in alignment with Hypothesis 3. Prior studies have initiated cluster analyses to assess physiogenomic properties and infer population structure and ancestry in the Puerto Rican population (Ruaño et al., 2009), physical characteristics trends of watersheds (Santos-Román et al., 2003), and the chemical and microphysical properties of dust particles from Africa (Reid, 2003), yet to date there have not been previous analyses that examined geographic clustering of forest gains/losses at the scale of census block groups in Puerto Rico. In that regard, our study provides a novel examination of the relationship between LULC and socio-demographic census data.

Clustering was observed around several urban areas during each of the decadal intervals, and the overall 30-year period. Many of the places where concentrations of forest loss were significantly high were in coastal areas and the expanding peri-urban areas around major urban centers and in the smaller urban centers that developed over time such as, Humacao, Arecibo and Barceloneta, among others. Moreover, these geographical regions with high clustering of forest loss and in particular the greater metropolitan area of San Juan are marked by periods of high urban growth rates (7% from 1991 to 2000; (Martinuzzi et al., 2007) and high population density approaching almost 1,000 people/km^2 (Martinuzzi et al., 2007). In addition, sprawling construction outside of urban centers and along major connecting routes between major cities and in peri-urban settlements results in large areas of land consumption (Martinuzzi et al., 2007). Parés-Ramos et al. (2008) noted that population decline increased dramatically in urban centers of 90% of the municipalities in Puerto Rico between 1990 and 2000, and indeed the places where forest loss was significantly low were in certain core urban centers such as Ponce, San Juan, and Mayagüez. At the same time, this was accompanied by the construction of over 200,000 new housing units in suburban and exurban barrios outside of urban cores, especially in coastal areas, more than double the rate of population growth for the same period. Thus, the spatially clustering we observed tracks with concurrent patterns of land use development throughout the study period.

The places where Forest gain was significantly high were in the mountainous areas, in eastern central Puerto Rico, and certain coastal areas such as around Fajardo and surrounding areas. As previously mentioned, other studies argue that forest gains are linked to the abandonment of agriculture as the driving forest of conversion to forest. Indeed, most of these areas where we observed forest gains were previously agricultural lands that have been abandoned over the past 50 years and have been in the process of forest regeneration (Aide et al., 2000). Other reasons for forest gain include population decline and migration. Wang et al. (2017) reported that the rate of forest cover loss was reduced by 42% in 2000–2010 compared to 1991–2000, which is largely attributable to agricultural land abandonment rural-to-urban migration. Furthermore, Wang et al. (2017) also observed clusters of reforestation in the eastern central part of the island during 2000-2010, speculating that some of this gain might be attributable to forest regrowth following Hurricane Georges. Notably, there were many areas in Puerto Rico that did not experience Forest loss or gain but rather remained stable as forested area throughout the study period. These include several large intact blocks of conserved land where human activities have been limited such as the Luquillo Mountains, the largest remaining tract of forested area on the island (Zimmerman et al., 2021) and several national parks in the Central Cordillera. While Forest land within protected areas remained stable, changes in Forest land use were observed in areas adjacent to protected areas. Although we did not quantify the magnitude of these changes, previous research by Castro-Prieto et al. (2017) for the period 2000-2010 has shown that such lands are vulnerable to the impacts of residential development. Further study is needed to better understand the spatial patterns of forest fragmentation in Puerto Rico across longer time periods and in relation to changing socio-demographic variables.

4- Spatial relationship between Forest loss/gain and social predictors

Our results of statistical analyses using the GWR model globally showed spatially variable relationships between percent Forest loss and gain and social predictors, as anticipated in Hypothesis 4. We observed areas where the raster coefficients of the predictor variables were positive, that is to say areas where the explanatory power of those variables was high, as well as areas where the raster coefficients were negative. The strength of these relationships varied spatially from one decadal interval to the next. Nevertheless, we found that the correlation between population density and percent forest loss and gain was consistently stronger than that between forest/agricultural occupation density and forest loss and gain. Other studies in Puerto Rico have found that population densities are related to deforestation (Thomlinson et al., 1996; Yackulic et al., 2011) which aligns with our results. For example, former agricultural areas in the municipality of Luquillo urbanized rapidly during the 1970s and 1980s, resulting in a loss of forested areas (Grau et al., 2003). Martinuzzi et al. (2018) also showed strong relationships between patterns of vegetation cover and socioeconomic (e.g., population density, building age, detached homes) and environmental variables (e.g., topography) in the San Juan Metropolitan area. Similar case studies in Mexico have also shown that forest loss is strongly correlated partly with population density and especially in urbanized and densely populated cities (Pineda Jaimes et al., 2010). Therefore, throughout our study period, population density is one of the dominant factors acting on the conversion to and from Forest land use.

The fact that we did not observe a robust relationship with occupation does not necessarily signal that it is not an important driver of land use change. It may be difficult to link occupation with Forest loss and gain at the block group scale because people in forestry and agricultural occupations do not necessarily work in immediate proximity to where they live. By using block groups as our focal unit to examine clustering, we were also limited in choosing variables included in the census for all four focal years (1990, 2000, 2010, 2020). In addition, the census occupation density data used as one of the explanatory variables integrates several sectors such as forestry and agriculture and has very low values in some blocks groups, which can make the correlation weak or absent in some places. It may be that the census block group is not the best scale at which to observe spatial relationships with forestry and agricultural occupations and Forest loss and gain. Recent research about the impact of Hurricane Maria on food security in Puerto Rico examined variables such as farm size and farm production based on the municipality where farmers reported their farming operations (Rodríguez-Cruz et al., 2022). There may also be other socio-economic and environmental factors driving spatial patterns of forests throughout Puerto Rico, including income, road density, farm density, development policies, topography, soil type, precipitation, and landslide density, among others. Further research is needed to examine the individual and interacting relationships among these variables and LULC change and the scales at which they manifest themselves.

Conclusion

This study used LCMS data classified from medium resolution Landsat optical images to evaluate changes in forest area in Puerto Rico over three decadal intervals within a 30-year period from 1990-2020. We found that Forest land use varied only slightly between approximately 62-64% of total land area and was remarkably stable during the study period. We had anticipated greater proportional increases in forested area as have been observed over similar spans of time in previous decades. There were relatively small areas of Forest that converted from or to Developed, Rangeland or Pasture, and Agriculture and these tended to occur in small patches. In urban areas, Forest gain was probably due to growth of tree canopy cover. The extent of area classified as Forest was higher than previously found using other methods. This is likely due to differences in classification methods and forest definitions. We also examined patterns of autocorrelation of forest loss and gain at the census block group scale and found clusters of loss associated with coastal and suburban areas adjacent to core urban centers, and gain in rural mountainous areas, notably in the eastern central part of the island and in select coastal areas. We also found social factors such as population density to be related to changes in forest cover both in terms of loss or gain. Our analysis was limited to only two social factors due to their availability at the census block group scales. We did not integrate other socio-economic variables due to unavailability and quality of data over time and at the scale of census block groups in our case study. Nevertheless, the results of this study are useful to understand at the landscape scale the long-term effects of land use change and socio-economic factors on forest-related gains and losses in an urbanizing tropical setting and their implications for ecosystem function and the provision of services. In addition, they can help inform policies and programs to address the drivers of forest loss and improve existing forest conservation practices. Future research with higher resolution of demographic and additional socio-economic and environmental data can provide more nuanced results and identify additional factors associated with forest LULC change.

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