Modeling Land-Use and Land-Cover Change in the Pensacola Metropolitan Area Using CA–Markov and Machine Learning Techniques

Introduction

1.1 Global Background of Land-Use and Land-Cover Change

Land use and Land Cover (LULC) are two words closely related but have different conceptual aspects in regards to the earth's surface (Mahta Maleki Doborji, Hasani, & Mobarghei Dinan, 2020). Land use refers to the utilization and management of land resources by humans for the purpose of production and development whereas land cover refers to physical and natural elements present on the earth's surface (Coffey, 2013). Understanding LULC provides a comprehensive illustration of the earth surface and its modification carried out by human activities (Mahta Maleki Doborji, Hasani, & Mobarghei Dinan, 2020). According to Hasan, Makhtoumi, and Chen (2023), LULC changes are the primary determinants of environmental transformation which has the capacity to directly affect the landscapes providing vital ecosystem services. Growing population, socio-economic development, demand for limited natural resources is impacting the land use patterns on both ground and global level. According to Afuye et al. (2024) an estimation of 62% of the world land area has been transformed into agricultural lands, urban settlements, and infrastructural or built-up areas. These changes can cause various environmental issues, such as deforestation, food security, and ecosystem malfunction. Out of all, urbanization is the most accelerated process driven by population growth, infrastructure development, shifting human land-use demands to the notable degradation of the environment.

1.2 Urbanization and Environmental Change

Generally, the transition of an area from being a rural area to a city area is the process of urbanization (Boundless 2016). Over the last century there has been a gradual increment in urbanization. Many cities all over the world have gone through some major changes as they grew and were developed by the end of the nineteenth century. Industrial revolution was the major driving factor for these changes which also focused on economic growth, better commute, employment opportunities for the people shifting from rural to urban/city areas. This scenario resulted in forming dense urban areas and speeding up the process of urbanization. This caused a direct impact on the environment in many regions (Fawaz, 1980). With the rapid growth of cities their impact on natural disasters also grows which directly threatens life and assets. According to the United Nations, there is an expected rise to 6.3 billion of the global urban population by 2050 (Wu, Li, & Yu, 2021). Between 1982 and 1997, the total amount of land used for urban and built-up has increased by

34% in the US. Moreover, a significant jump of 13% in urban population has been reported by the US Census between the years 1980 to 2020 (Shrestha et al., 2021).

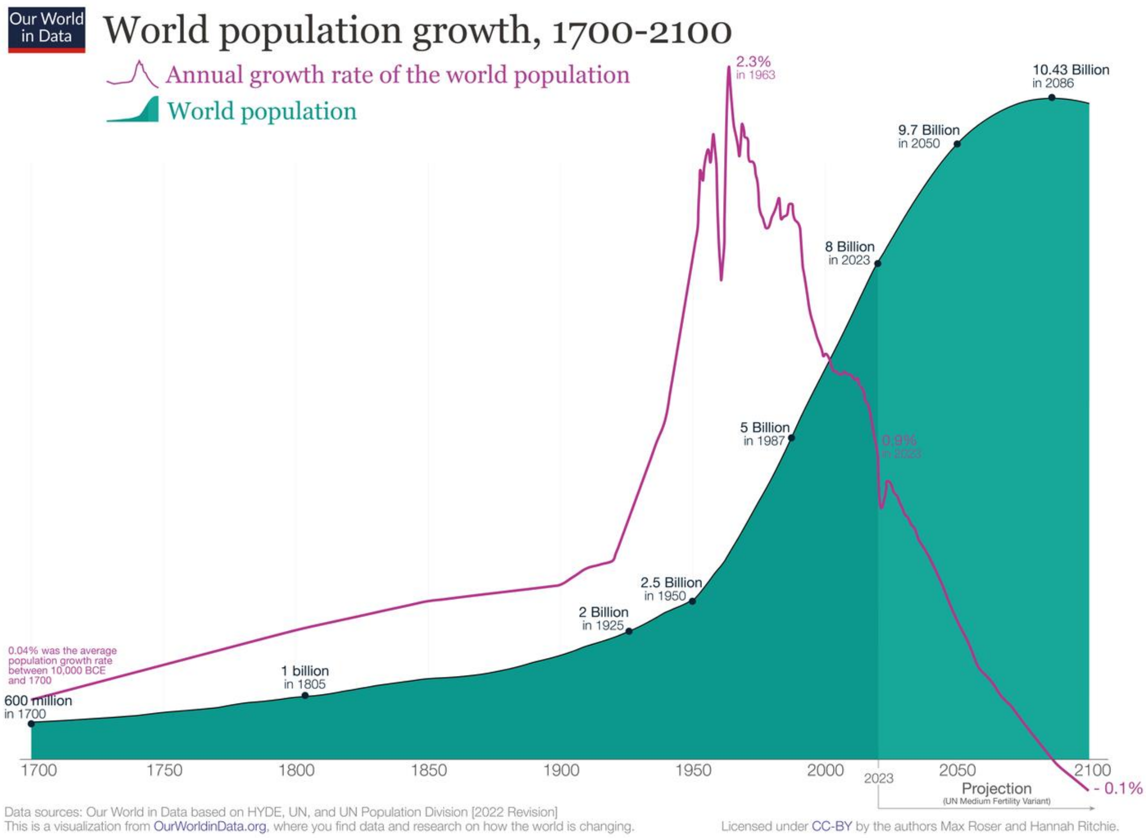

Figure 1. World population and population growth rate (1700–2100).

(Data source: UN Population Division, 2022)

1.3 Urbanization Trends in the United States

On a global scale urban land use changes have become a topic for discussion because of their impact on the ecosystem (Nuissl & Siedentop, 2021). According to Alig, Kline, & Lichtenstein (2004), the US Census Bureau reported an increase in the urban area between the years 1960 and 2000. In comparison to the USDA NRCS 2001 the data shows that the developed land in the United States has increased by more than 34% from the year 1982 to 1997.The Southeast U.S. has seen rapid urban growth. Over the past 60 years, this region has experienced a population of about 40%, making it one of the major hotspots of urbanization in the country (Terando et al., 2014). Population growth, transportation expansion, and economic development have been recognized as dominant forces driving land-use transformation in the United States. The post–World War II era marked a period of unprecedented suburbanization, as economic prosperity and rising population density prompted large-scale conversion of agricultural and forested lands into residential and commercial zones (U.S. Geological Survey, 2013; Alig, Kline, & Lichtenstein, 2004). These interrelated dynamics of demography, mobility, and economy have collectively restructured the American landscape. Within this national context, Florida exemplifies a major hotspot of rapid land-cover change, where population growth, coastal urbanization, and tourism-driven economic activity continue to transform natural ecosystems and land resources (Terando et al., 2014).

Figure 2. Urbanization map of the U.S. derived from city lights data (2009 data). (Data source: U.S. Geological Survey 2013, LCMAP)

1.4 Urban Growth and Land-Use Transformation in Florida

Florida is home to a population of 21.9M out of which 91.1% are U.S citizens (U.S. Census Bureau, 2023. The diverse history of Florida's land use and human settlement has seen a substantial change in land use patterns and land cover which are influenced by the rapid population growth, built-up areas expansion, and urbanization. Between 1936 and 1995, the state experienced a dramatic rise in the number of households—from 1.7 million to 14.1 million—which intensified the demand for land for human settlement and contributed to widespread depletion of natural land cover; during this period, agricultural land increased by 60% and urban land expanded by 63.2% (Volk et al., 2017).This change has impacted various key environmental assets of the state, particularly causing wetland loss, flood regulation, groundwater recharge and sea-level-rise. Most of the studies are carried out focusing particularly on South and Central Florida. However, the Florida panhandle hasn't been researched or studied often despite its growing urban centers such as Pensacola and Tallahassee. Research on this area needs to be done which are critical to regional sustainability and climate-resilience planning.

1.5 The Florida Panhandle

Northwestern part of Florida is known as Florida panhandle (also called West Florida or Northwest Florida). It consists of 10 counties, from Escambia County in the west to Gulf County in the east. The total population covered by Northwest Florida is 1,554,392 as of 2024. Due to coastal cities, commercial interest, and fishing and tourism, Florida panhandle is one of the most rapidly developing regions in the entire state (Wolfe, Reidenauer, & Means, 1988). Installation of military forces such as Eglin Air Force Base, Naval Air Station Pensacola and Hurlburt Field has also played an important role on regional development and land-use policies while occupying significant portions of land (Northwest Florida Sentinel Landscape, 2024).

1.6 LULC Dynamics in the Study Area - Pensacola metropolitan area

Urbanization and LULCC are inter-related to each other. According to Wang and Maduako (2018), urban areas cannot maintain their own population. They are supported by many other factors such as employment opportunities, tourism, industrial growth, and migration of people for quality life. As there is rapid expansion of population and economic activities, there is a significant change in the land cover such as agricultural land, forest, vegetation, barren land, and wetlands. This change will not only affect nature but also affects the social dimensions. Over time, such transformations will lead to increased population density and spatial expansion of urban footprints, reshaping the regional landscapes and ecosystems.

In the context of Northwest Florida, Escambia and Santa Rosa Counties are experiencing continuous population growth and urban development (Northwest Florida Sentinel Landscape, 2024; Kyzar et al., 2025). As Kyzar et al. (2025) explained, within the Florida panhandle, Pensacola metropolitan area including those two counties is the most urbanized area. Compared to other metropolitan regions of Florida, Pensacola metropolitan area remains less developed, but it is experiencing rapid expansion in urban extent and growth in commercial, residential and infrastructure development. There have been many questions that are raised with this development regarding the environmental concerns which need to be addressed by proper land-use planning to balance economic growth and urbanization (Kyzar et al., 2025). The expansion of urban areas in these counties exerts growing pressure on natural and agricultural resources, creating competition for land and intensifying environmental stress (Volk et al., 2017). The land use/cover change (LULCC) dynamics need to be explored and studied in this region. Therefore, analyzing and predicting LULC changes are crucial steps toward formulating strategies for efficient resource management, sustainable urban planning, and environmental protection (Seto, Güneralp, & Hutyra, 2012). Furthermore, urban development is a continuous process, and modeling, simulation and prediction of cities future growth play an important role in implementing suitable and effective planning policies to minimize human activities on the environment (Norman, Feller, & Guertin, 2009).

1.7 Geospatial Framework for Analysis and Modeling Land-Use and Land-Cover Change

With growing technologies many tools have been introduced for the collection and management of spatial-temporal data. The application of remote sensing and GIS have proved their efficiency in the field of urban and environmental planning including various spatial modelling tools such as Markov Chain model, logistic regression model, artificial neural network (ANN) model, cellular automata (CA) model, a modified cellular automata-based SLEUTH model and conversion of land use and its effects (CLUE) model. These models not only help in providing quantitative analysis but also help in future prediction of the land covers with their influential driving factors (Wang and Maduako 2018).

Understanding land-use and land-cover (LULC) dynamics requires an integrated framework that combines spatial data, environmental variables, and predictive modeling tools. This study adopts a geospatial framework designed to analyze past LULC trends and model possible future scenarios for the Pensacola metropolitan area. The framework integrates remote sensing, Geographic Information Systems (GIS), and spatial modeling techniques to quantify historical changes, identify driving factors, and simulate future land transformations under current development trends (Behera et al., 2012; Eastman, 2023).

In this study, raw multi-temporal Landsat satellite imagery was used for 2006,2016, and 2021 which were pre-processed by USGS representing corrected surface reflectance. This was further used for generating the primary LULC classifications. These datasets provide consistent, comparable land-cover classifications that enable long-term monitoring of urban expansion, forest loss, agricultural transitions, and other landscape processes (Homer et al., 2020). Complementary geospatial variables such as slope, distance to roads, population density, and proximity to urban centers are incorporated as drivers of change, representing both biophysical and socio-economic influences on land development (Aduah et al., 2020; Moghadam & Helbich, 2013).

The Land Change Modeler (LCM) in Terr Set is employed as the central analytical platform for modeling and prediction. It provides a comprehensive environment where LULC changes are first detected through change analysis and then modeled using a Multilayer Perceptron (MLP) neural network coupled with Markov chain analysis. This integration allows the framework to evaluate both the spatial probability of future transitions (through MLP) and the quantity of change (through Markov probabilities) (Eastman, 2023; Pontius & Schneider, 2001). The resulting simulations generate both soft prediction maps, representing the likelihood of change, and hard prediction maps, illustrating categorical forecasts such as urban-growth patterns for the year 2030.

Overall, this geospatial framework provides a systematic and replicable approach to understanding how human and environmental factors interact across space and time. It supports spatial decision-making for sustainable land management and advances predictive modeling practices in regional landscape analysis (Behera et al., 2012; Hasan et al., 2020).

2. Research Gap and Objectives

2.1 Research Gap Statement

Like many of Florida, Escambia and Santa Rosa counties in the Northwest have seen significant urban development. According to the U.S. Census Bureau (2010) data, 24.19% of Escambia County's total land area and 8.1% of Santa Rosa County's land area were classified as urban in 2010. As of 2024 both counties have seen significant increase in residential development with approval of over 6000 new homes, large-scale developments projects stretching from Perdido to cantonment, light industrial zones, OLF-8 (Naval Outlying Landing Field in Beulah, Escambia County) community development, industrial growth, development of I-10 Coastal Commerce Center covering an area of 181,000 square feet, 67,000-square foot of commercial development of outdoor storage yard, and economic development of 113,000 square foot facility at whiting aviation park (Pensacola News Journal, 2023).

Many studies have been carried out monitoring the LULC changes and the pattern of urbanization across Florida's developing regions mostly covering the south and central part. However, the Pensacola metropolitan area has received comparatively little scholarly attention despite their increasing population growth and infrastructural development. This gap underscores the need for predictive spatial modeling in emerging urban zones where socio-economic and physical conditions suggest high potential for rapid urbanization.

2.2 Research Purpose

The purpose of this study is to integrate the Cellular Automata–Markov (CA–Markov) model with a Multilayer Perceptron (MLP) neural network to analyze, evaluate, model, and predict the spatial and temporal patterns of past land-cover transitions using multi-temporal satellite data (2006–2021) and generate projections for the year 2030 urban expansion and landscape transformation of Escambia and Santa-Rosa counties.

2.3 Research Objectives

1. To classify raw Landsat imagery and generate seven-class LULC maps for 2006, 2016, and 2021.

2. To analyze the dynamics of LULC changes and trends.

3.To identify the driving factors responsible for influencing the change in LULC including urban growth.

4. To model and predict LULCC for the year 2030.

2.4 Research Questions

1. What are the land use and cover patterns in 2006, 2016 and 2021?
2. What driving factors are most influential in determining the LULCC and urban growth according to the CA–Markov and MLP models?
3. What will future land use/cover pattern and urban extent look like in the future till 2030 based on the prediction of the integrated CA-Markov and MLP models?

2.4 Significance to Study

This study is significant because the findings will not only help us understand the changing patterns of the natural landscape due to rapid urbanization but also help us identify the most affected areas by land-cover transformations. Each year the local county governments allocate a budget for infrastructure and community growth. The outcomes of this research can help both the local and state government to build and balance the development needs with a long-term vision for sustainable growth not affecting the environment. The approach of using integrated CA-Markov and MLP modelling framework will provide insights on how the land will change in the future and what can be the best approach that can guide the local planners, environmental agencies and policymakers in managing future growth. Furthermore, this study will fill the gap by applying advanced geospatial modeling in a region that has received limited attention compared to Central and South Florida.

3. Data and Methodology

3.1 Study Area

The Pensacola Metropolitan Area (Figure 4) is also known as Pensacola-Ferry-Pass-Brent Metropolitan Statistical Area (PMSA) encompasses Escambia and Santa Rosa counties. It covers a total area of 2,049 sq. miles with a total population of 538.928 thousand persons, with a population density of about 323 persons per square miles represented in square miles in the table 1 (U.S. Census Bureau, 2024).

Table 1. Area Characteristics of the Pensacola Metropolitan Area (U.S. Census Bureau, 2022)

County	Land Area	Water Area	Total Area
Escambia	656.99	165.67	822.66
Santa Rosa	1012.40	213.91	1,226.31
Pensacola Metropolitan Area	1,669.4	379.6	2,049.0

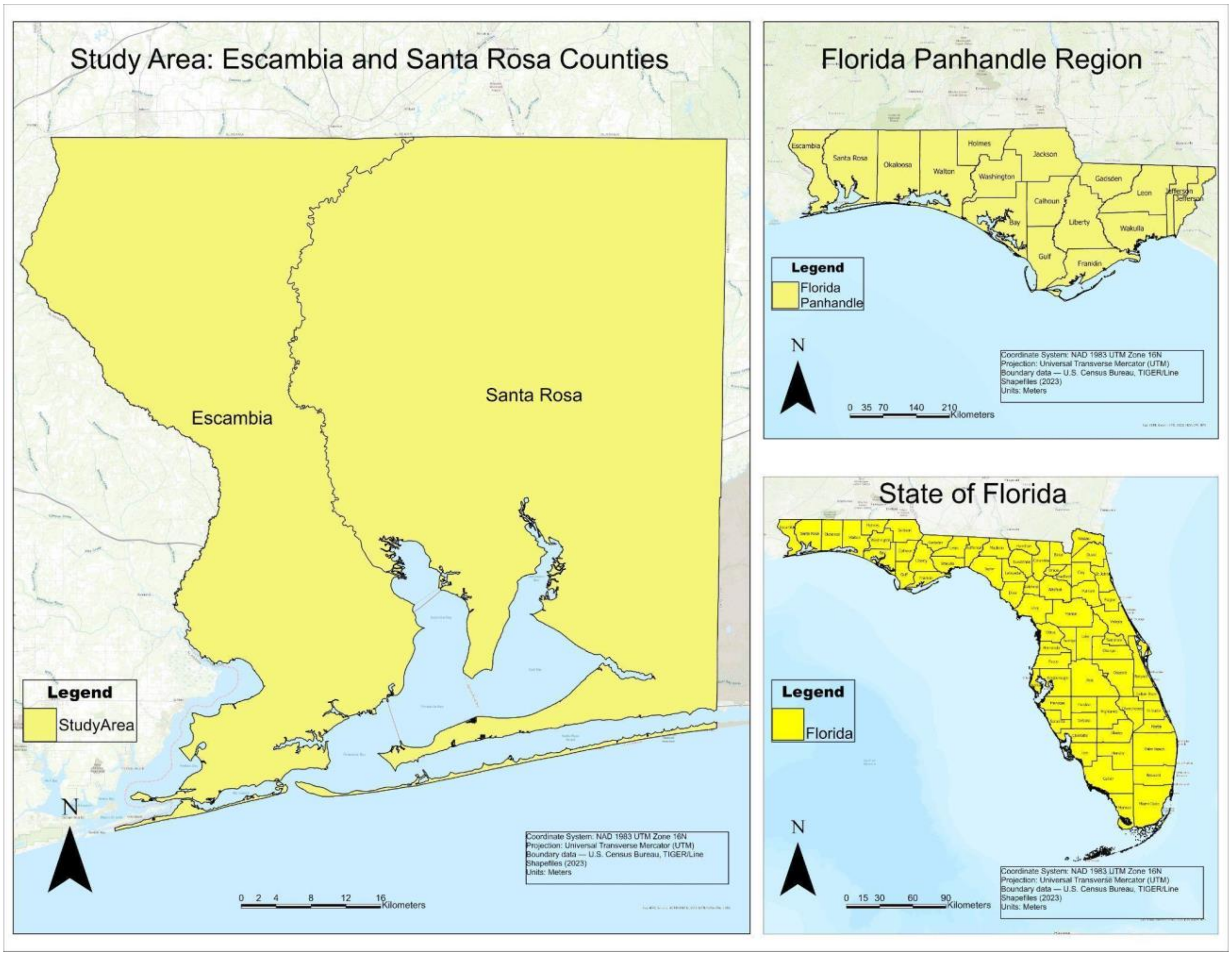

Figure 3: Study Area: Pensacola Metropolitan Statistical Area

3.2 Geography and Climatic Condition

PMSA is geographically diverse and consists of environmentally sensitive coastal regions. Located between the 30°18′ N and 31° N latitude and 86°52′ W to 87°36′ W longitude, the area includes coastal plains, barrier islands, wetlands, estuaries and forested areas. This region has a humid subtropical climate with hot, humid summers and mild winters. The most dominant soil type is sandy coastal plain soil, which is more acidic, poor in nutrients which are very influential to vegetation patterns, groundwater recharge and land-use dynamics.

3.3 Demography

PMSA has the oldest historical importance as the site of the first European Settlement in the United States. It has a mix of diverse people of different cultures, races and identities. Culturally, the area blends southern traditions, Spanish heritage, military influence and coastal character. Because of this unique heterogeneous mix PMSA shapes its own identity being the most dynamic and developing metropolitan area in Northwest Florida Panhandle.

3.4 Economy and Cultural Attractions

The area has a growing economy, supported by major contributors like military, tourism, and manufactures. This place is very famous for Naval Air Station Pensacola which serves as a primary training center for many people in the U.S. Navy, Marine Corps, and Coast Guard. It also has a very famous historical, cultural, and touristic landmark museum called National Naval Aviation Museum where many tourists come to see the historical naval ships and aircraft from World War eras. The military base, coastal tourism, and rich historical cultural heritage, all together, contribute to the regional economy.

3.5 Education

This region is also well known for its several educational institutions. University of West Florida, the major higher education institute, not only provides higher education to the residents but also attracts students from the neighboring places with its academic quality, research and innovation.

3.6 Transportation

PMSA also has well-connected highways such as Interstate 10, US highways 29,90 and 98. It also consists of both waterways and airways named Port of Pensacola and Pensacola International Airport respectively for serving both local and non-local travelers. Local commute facilities are supported by Escambia County Area Transit (ECAT) bus services.

4. Material and Methods

4.1 Land Use/Land Cover Data

In this study two Landsat images from U.S. Geological (USGS) for 2006, 2016, 2021 was obtained which were used to map and detect LULC for over a 15-year period. The first image for the year 2006 was Landsat 5 Thematic Mapper Collection 1 level 1 while Landsat 8 OLI/TIRS Collection 1 level 1 were obtained for 2018 and 2021. Each of these satellite images from USGS had a spatial resolution of 30m, containing less than 20% of cloud cover and was atmospherically corrected. These datasets were then clipped to the study area and projected to UTM Zone 16N to ensure its consistency.

The satellite images were classified into seven land-use and land-cover categories: forest, urban/built-up, agriculture, water, barren land, open/green space, and wetlands shown below (Table 2). To generate the LULC maps, a hybrid classification strategy was employed that combines a traditional supervised Random Forest (RF) classifier with a modern deep learning semantic segmentation model (UNet). Landsat imagery obtained for different years and sensors often exhibit differences in the spectral, radiometric, and landscape complexities which influence the performance of classification and result in the difference of accuracies. Deep learning semantic segmentation UNet was applied for the year 2016 and 2021 datasets which ensure to recognize the land cover shapes, heterogeneous pixels, and scattered urban areas resulting in significantly higher classification accuracy Ma et al., 2019). Traditional classifiers such as Random Forest were included to provide a comparative baseline, as they rely primarily on spectral information and therefore serve as an important reference point for evaluating how much improvement deep learning offers over older methods (Belgiu & Draguț, 2016). Using both methods allowed this research to demonstrate the performance differences between the conventional pixel-based approach and an advanced semantic-segmentation method, highlighting the accuracy gains associated with modern deep learning models (Ma et al., 2019). For the year 2006, 350 polygon-based training samples were collected all over the study area and a supervised Random Forest (RF) classifier, a traditional approach was applied.

The accuracy assessment of these LULC classifications were generated using a stratified equalized sampling approach where 350 accuracy points for year 2006 and 2016, 2021 were taken and distributed evenly across the study area. Validation of each point was manually done using the high-resolution Google Earth imagery to establish ground truth labels. Confusion matrix for every year was conducted to calculate the overall accuracy, user's accuracy and producer's accuracy that evaluates the performance between traditional and Modern methods of classification.

Table 2. Land Use/Land Cover Classification Scheme

Class Value	Class Name	Class Description
1	Forest	Natural or planted tree cover.
2	Urban/Built-up	Residential, industrial, roads, commercial areas.
3	Agriculture	Croplands, pasture, hay fields.
4	Water	Open water bodies like lakes, rivers, ponds.
5	Barren Land	Sand, bare rock, land with less or no vegetation.
6	Open/Green Space	Grasslands, parks, natural open areas.
7	Wetlands	Woody and herbaceous wetlands.

4.2 Selection and Collection of Potential driver variables

Explanatory variables also called driver variables are independent variables that influence LULC change. Drivers range from bio-physical, proximity, demographic, socio-economic, economic to institutional factors which answer the questions of how they will influence the prediction of where, when, and why LULCC occurs. This means the transition of land use/cover status of a place at a certain point in time to the next step is influenced by those driving variables (Kolb, Mas, & Galicia, 2013).

In this study, the driving variables encompass multiple dimensions of environmental and human factors reflecting the physical landscape, human accessibility, and population pressure. According to Gaur and Singh (2023), the importance of explanatory variables varies from region to region, underlying the need to select drivers based on the local importance and the relevance of the study area rather than adopting a standardized set of factors depicted below table 3. All the variables will be calculated from the datasets using ESRI ArcGIS Pro 3.4.

Table 3. Potential Driver Variables and data sources

Category	**Driver Variable**	**Year**	**Data Source**
Topographic	Slope Elevation	2023	www.usgsearthexplor.go
Proximity	Distance to Major Roads	2021	OpenStreetMap (OSM)
Proximity	Distance to Urban Area	2006	Derived from 2006 Classified LULC data
Environmental	Distance to Coastline/Bay	2021	https://coast.noaa.gov
Socio-Demographic	Population Density	2010	https://data.census.gov

Slope is included because flat areas and gently elevated areas are likely to be more suitable for built-up land whereas steep slopes make the construction difficult and less likely to happen (Aduah et al., 2020; Moghadam & Helbich, 2013). Slope will be calculated from a 30-m USGS Digital Elevation Model (DEM) using the Slope tool.

The distance to major roads were computed by clipping the transportation network to the study area and applying the Euclidean Distance tool, producing a continuous surface representing straight-line distance (in meters) from each pixel to the nearest major road segment. Proximity to roads increases development potential by enhancing accessibility, making nearby areas more susceptible to land-use conversion (Ruan et al., 2015). Similarly, distance to existing built-up areas were derived from a binary map created using the 2006 LULC data, where built-up pixels were assigned a value of 1 and all other classes were coded as 0. Applying the Euclidean Distance tool to this binary layer produces a proximity surface reflecting urban diffusion pressures from existing developed clusters. The coastline and bay boundary data were used to derive the distance-to-coastline variable were obtained from the NOAA National Shoreline Dataset through the Shoreline Data Explorer (NOAA, 2021). The distance to shoreline were also computed by clipping the shoreline shapefile to study area and then Euclidean Distance tool was used to generate a raster showing the straight-line distance (in meters) from each pixel to the nearest coastal or bay boundary using the 2006 LULC data The output raster was aligned to the 2006 LULC data. Population density was created using U.S. Census Bureau, 2010 Decennial Census data. First, the total population in each census area was divided by its area to calculate people per square kilometer. Then, the Feature to Raster tool in ArcGIS Pro was used to convert this information into a 30-meter raster so that each pixel represents population density. Finally, the raster was matched to the same projection, resolution, and extent as the other LULC map to make it consistent with the other driver variables. All the driver variable maps are presented in (Figure 4).

4.3 Selecting the Most Influential Drivers

The explanatory power of all these variables in relation to different LULC transitions will be computed and examined by using Cramer's V (Wang et al., 2016). Also known as Cramer's Coefficient (V), this method will be used for quantifying the explanatory power of each variable, which is an optional quick test used to determine whether the variables are worthy of consideration in the model (Megahed et al., 2015). The final variables used for the modeling will be considered based on specific criteria for this value.

4.4 GIS Mapping

Thematic maps of all spatial variables, including driver variables (including socio-economic factors, and proximity-based environmental and demographic drivers) and land-use/cover, land use/cover changes, and urban growth will be created.

5. Land Use/Cover Change (LULCC) modeling

Land Change Modeler (LCM) in the Terrset libera GIS Geospatial Monitoring and Modeling Software will be used to model, simulate, and predict land use/cover changes (LULCC) and urban growth. LCM is an integrated software tool within the Terrset liberal GIS Geospatial Monitoring and Modeling System developed by Clark Labs (Clark Labs, 2020). The modeling framework consists of sub-models of Markov Chain, Cellular Automata (CA), and Multilayer perceptron (MLP) neural network techniques to simulate and predict future land-use transitions. This hybrid approach will be selected for its ability to incorporate both temporal probabilities and spatial relationships among multiple driving factors influencing land transformation. The following are the detailed workflow which will

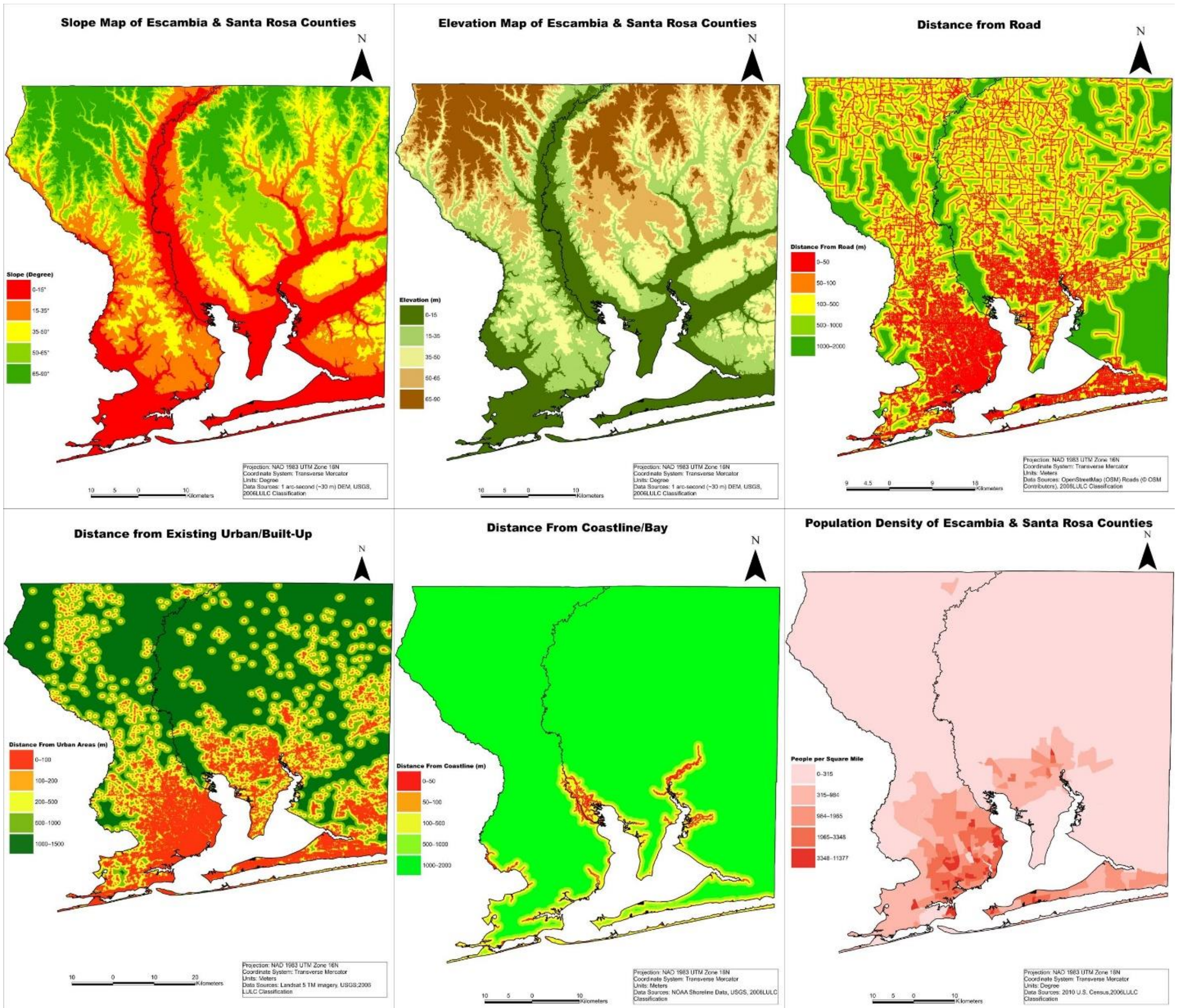

Figure 4. Overview of the driver variables used in the study

be performed in this study to conduct the land-change simulation and prediction using the Terr Set LCM.

4.4 GIS Mapping

Thematic maps of all spatial variables, including driver variables (including socio-economic factors, and proximity-based environmental and demographic drivers) and land-use/cover, land use/cover changes, and urban growth will be created.

5. Land Use/Cover Change (LULCC) modeling

Land Change Modeler (LCM) in the Terrset libera GIS Geospatial Monitoring and Modeling Software will be used to model, simulate, and predict land use/cover changes (LULCC) and urban growth. LCM is an integrated software tool within the Terrset liberal GIS Geospatial Monitoring and Modeling System developed by Clark Labs (Clark Labs, 2020). The modeling framework consists of sub-models of Markov Chain, Cellular Automata (CA), and Multilayer perceptron (MLP) neural network techniques to simulate and predict future land-use transitions. This hybrid approach will be selected for its ability to incorporate both temporal probabilities and spatial relationships among multiple driving factors influencing land transformation. The following are the detailed workflow which will be performed in this study to conduct the land-change simulation and prediction using the Terr Set LCM.

5.1. Change Analysis (what changed, where, and how much)

The first step in the modeling process is to perform the LULCC analysis to identify what is changing, where the change is happening and how much change took place between the study year (2006-2016) (Eastman, 2023). Land cover raster maps of 2006 and 2016 provided by the LULC datasets will be compared and analyzed to provide comprehensive information on quantitative change with the outcome showing gains and losses by the land cover categories. The change analysis will also calculate the net change, losses (the total area each land use/cover class has lost) and persistence (areas that remain unchanged). A class-to-class transition matrix will also be generated which will give information on how one land-cover type has changed into another. The resulting change map visually represents the spatial distribution and intensity of these land-cover transitions, highlighting the major areas of transformation within the study area.

5.2. Land Transition Potential Modeling

The next step after change analysis is land transition potential modeling. It is a process that determines the probability of a specific land cover class transitioning into another class. It automatically detects all transitions between 2006 and 2016. There are various tools to model the transition, including Multi-layer Perceptron (MLP) neural network, Decision Forest (DF) machine learning, Logistic Regression, Weighted Normalized Likelihood (WNL), Support Vector Machine (SVM), or a Similarity-weight instance-based machine learning tool (Simweight). This study will use an MLP neural network which analyzes the relationships between the past land-cover changes and a set of driving variables and answers how influencing each variable is in the changes (Eastman, 2009).

MLP is a type of Artificial Neural Network (ANN) designed to model the complex behavior and pattern which consists of one or more layers between the input and output layers based on a feed-forward neural network. The structure of the MLP includes three primary layers: Input layer, Hidden layers and Output Layer. In the Input layer, each neuron represents one driving variable. Hidden layers consist of one or more layers of the weighted combinations of the inputs processed through an activation or transfer function. The output layer produces a single probability value that ranges from 0 to 1, indicating the likelihood of a pixel transitioning from one land use/cover class to another which in this study is the urban class. During model training, the network employs the feed-forward and back-propagation algorithms to iteratively adjust the internal connection weights, thereby minimizing prediction errors and improving accuracy (Gibson et al., 2018). The model automatically divides the dataset into training and testing samples. For this study, we will use 50% of data for training, and 50% reserved for model validation. Table 4 summarizes the workflow of MLP in the transition sub-model. The training samples will be used to teach the model how variable combinations influence the changes, while testing samples are used for independent validation to ensure model generalization and avoid overfitting (Pontius, Huffaker, & Denman, 2008).

Table 4: summarizes the workflow of MLP in the transition sub-model.

Stage 1: Data Input
Stage 2: Weighted Processing
Stage 3: Feed Forward Propagation
Stage 4: Error Calculation
Stage 5: Back-Propagation of Error
Stage 6: Training, Testing and Validation
Stage 7: Prediction and Mapping

5.3 Change Prediction

The final step of the workflow is to execute the prediction of the future using the past rates of changes from the Change Analysis and the transitional potential modeled with MLP. The future prediction target date is specified. The Change Prediction stage in the Land Change Modeler (LCM) uses the results from the Markov Chain Analysis and Transition Potential Maps to forecast future land-cover patterns. The Markov-Chain model first estimates the quantity of change expected for each class based on the transition probabilities calculated from historical land-cover maps (2006–2016 and 2016–2021). The quantities are then combined with the spatial transition potential maps generated by the Multi-Layer Perceptron (MLP) neural network to determine where those changes are most likely to occur. This integration allows the model to allocate predicted changes to locations with the highest suitability for transition, such as areas near existing urban centers, major roads, or flat terrain. LCM then produces two types of predictive output: soft and hard predictions. The soft prediction output represents the likelihood of change for each pixel as a continuous value between 0 and 1, creating a probability surface that highlights vulnerable or high-potential zones for urban expansion. The hard prediction, on the other hand, converts these probabilities into a final Predicted Land-Cover Map using the Multi-Objective Land Allocation (MOLA) module, which assigns each pixel to the class with the highest probability of occurrence. The hard prediction map provides a categorical visualization of how the landscape is expected to appear in the target year, while the soft prediction map helps interpret the spatial uncertainty and intensity of future change.

6. Accuracy Assessment

The accuracy of the LULCC simulation will be assessed through a validation procedure that compares the modeled 2021 LULC map with the reference 2021 map obtained from the National Land Cover Database (NLCD). The modeled 2021 map will be generated using LULC maps of 2006 and 2016 and the same set of driving variables applied to the LULC maps of 2006 and 2021 for the LULC prediction of the year 2030. This hindcasting approach is used to evaluate how well the model could reproduce a known land-cover pattern before projecting future changes. In this process, the 2006–2016 period served as the calibration phase, while the 2021 NLCD LULCC map will be used as an independent reference for validation of predicted 2021 LULC. The procedure output accuracy assessment indices if Kappa and Relative Operating Characteristic (ROC). According to Sahalu (2014), Kappa values above 0.75 indicate strong agreement, values between 0.40 and 0.75 represent moderate agreement, and values below 0.40 reflect low accuracy (Sahalu, 2014). ROC values range between 0 to 1, where one shows a perfect pit and 0.5 shows a random fit. The ROC curve was used to assess the accuracy of the Multilayer Perceptron (MLP) model during the Transition Potential Modeling stage. The ROC curve evaluates the model's ability to correctly discriminate between changed and unchanged areas by comparing the predicted transition probabilities with the actual observed transitions (Pontius & Schneider, 2001).

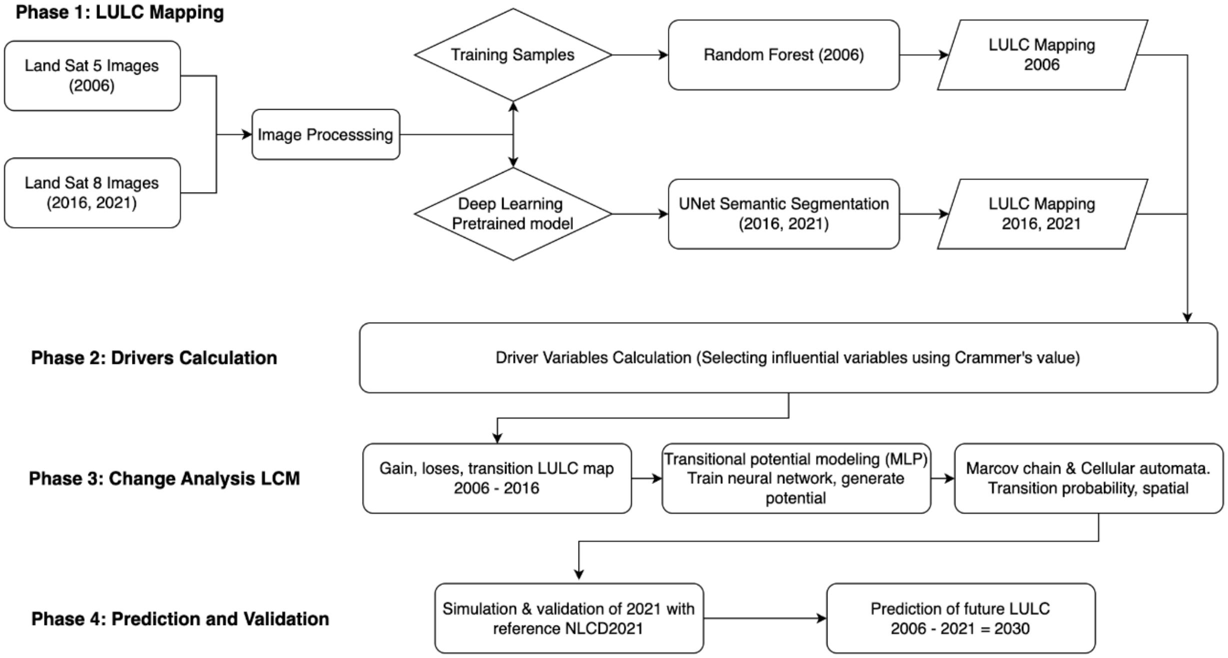

Figure 4. Methodological Framework of the Study

7. Preliminary Results

7.1 Land Use/Land Cover Classification

The LULC maps produced from Landsat 5 TM and Landsat 8 OLI imagery as shown in the (Figure 5) was classified into seven major categories: forest, urban/built-up, agriculture, water, barren land, open/green space, and wetlands. This classification was based on the approach of Classification schema of seven classes was based on the structure of Escambia and Santa Rosa counties which gives a clear representation of the area ensuring a consistent comparison of the LULC changes across all time periods. The hybrid approach for the classification results demonstrated an overall accuracy of LULC maps developed for the year 2006 using a Random Forest classifier was 61.43%, whereas for 2016 and 2021using UNet semantic segmentation model applied to Landsat 8 OLI imagery of 61.43 %, 84.86 % and 78.57% respectively and corresponding Kappa coefficient of 0.55, 0.82, and 0.75. This accuracy indicates that even after using a different method the classification remains consistent and reliable across all three years which depicts that the combination of traditional and modern techniques is suitable for multi-temporal LULC mapping and can effectively handle the differences in sensor quality and landscape conditions.

It can be observed from the (Table. 5) that the change in LULC pattern across the study area shows a clear and dynamic shifts from 2006 to 2016 and 2021 mostly to the urban/built up and agriculture class. Forest area has declined from 2006 to 2016 from 618.25 km² to 583.43 km² in Escambia County whereas in Santa Rosa there is an upward trajectory from 997.71 km² (2006) to 1203.57 km² (2016). In 2021 both the counties area increased to 631.79 km² and 1350.67 km² from 2016. Urban/Built-up area illustrates a clear pattern how both the counties with a time span of 15years has an explosive growth in rapid population and urbanization. Escambia county expanded from 134.97 km² in 2006 to 362.99 km² in 2016 and a slower increment to 364.87 km² in year 2021. In contrast, Santa Rosa County shows a slight yet smooth patterns of increasing Urban/Built-up area from 82.08 km² (2006) to 249.40 km² (2016) and then to 262.15 km² (2021). The agricultural land in Escambia County shows a decline from 399.82 km² in 2006 to 227.28 km² in 2016, whereas from 2016 to 2021 the pattern remains the same and shows a decline to 219.11 km² compare to Santa Rosa County showed a slight different pattern beginning with 689.20 km² (2006), sharply declining to 298.82 km² (2016) and shifting up with 308.71 km² (2021) same goes to barren land in Escambia it got reduced from 148.89 km² (2006) to 22.94 km² (2016) and again to 19.94 km² (2021), Santa Rosa also got decreased from 331.26 km² (2006) to 10.87 km² (2016) and then to 12.05 km² (2021). Moreover, the open/greenspace decreased in Escambia County from 189.31 km² (2006) to 136.38 km² (2016) and further to 113.09 km² (2021) while in Santa Rosa it got increased from 97.35 km² (2006) to 353.77 km² (2016) and decreasing to 235.87 km² (2021). Furthermore, Escambia County wetlands rose from 204.80 km² (2006) to 366.49 km² (2016) and then declined slightly to 347.91 km² (2021). Santa Rosa County showed a similar increase from 420.91 km² (2006) to 511.62 km² (2016) before decreasing to 457.38 km² (2021) whereas water in Escambia County ranged from 22.30 km² (2006) to 23.24 km² (2016) and then slightly decreased to 21.75 km² (2021). Santa Rosa shows a similar pattern, shifting from 30.30 km² (2006) down to 22.80 km² (2016) and slightly to 22.58 km² (2021).

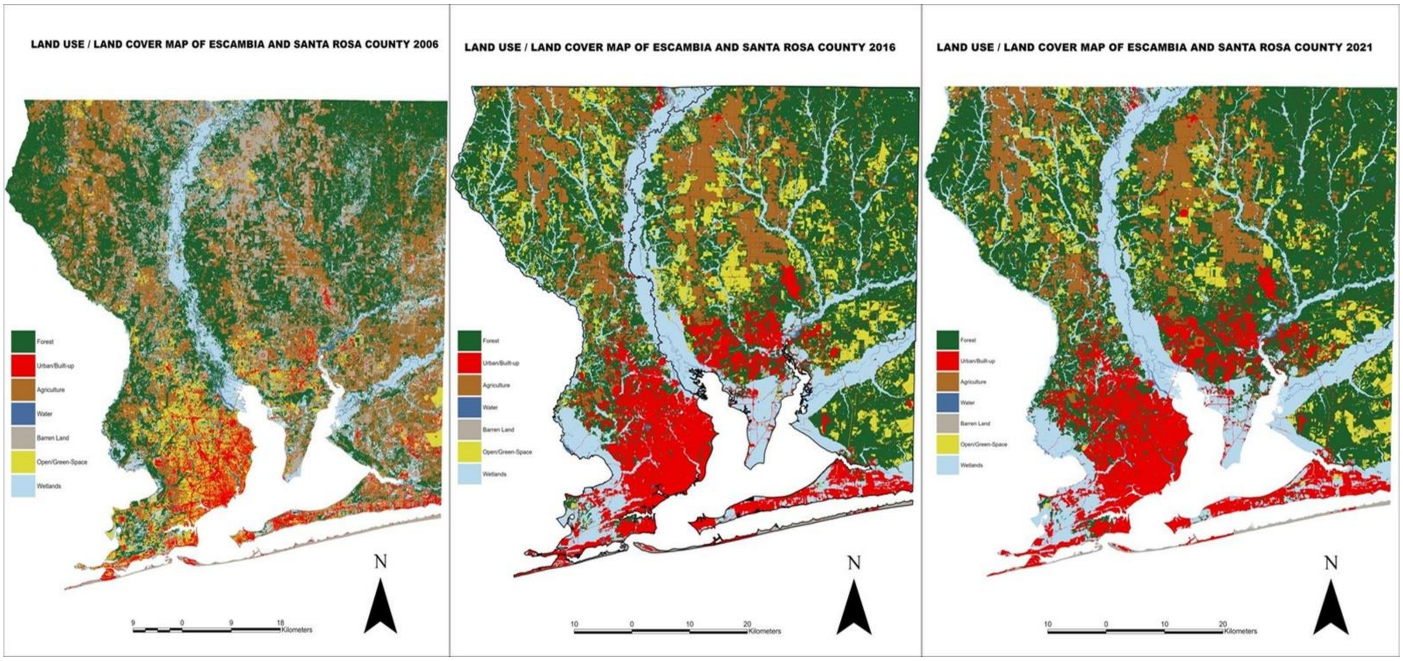

Figure 5. Classified land use/cover maps for 2006, 2016, and 2021.

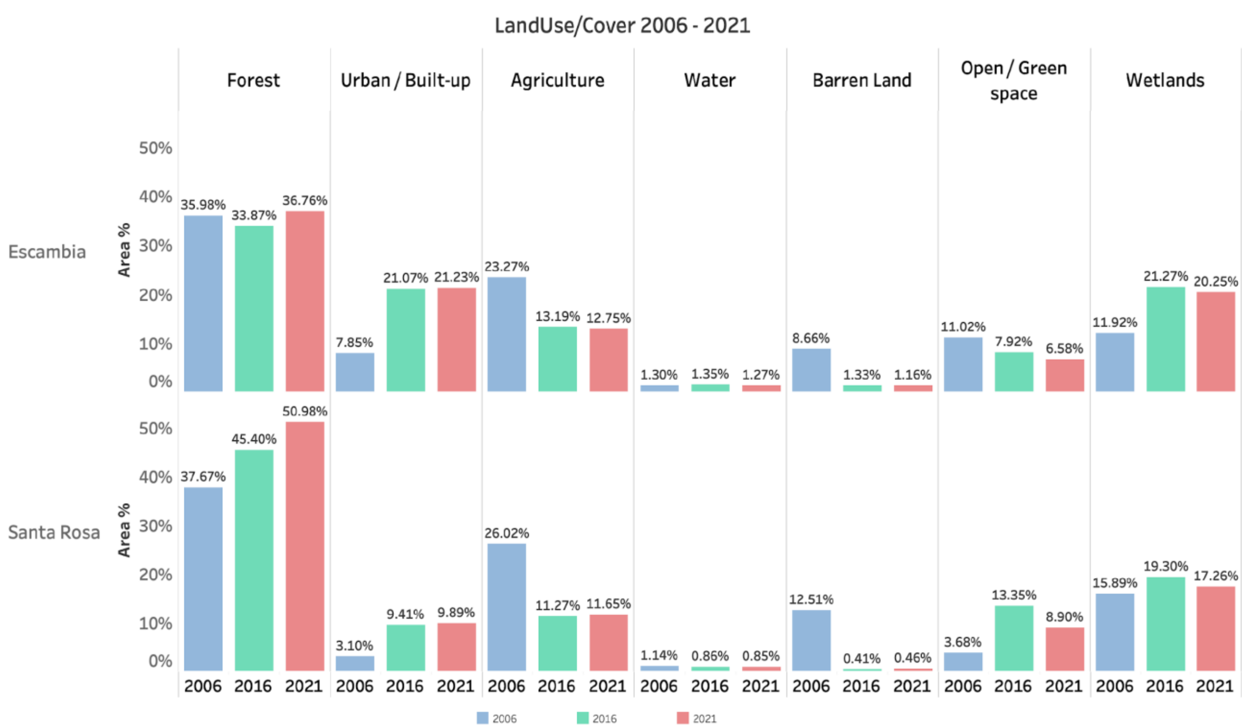

Figure 6. Bar Diagram of land use/cover maps for 2006, 2016, and 2021.

Table 6. LULC Change Statistics for the Period 2006–2016

County	LULC Classes	Area 2006 (km²)	Area 2016 (km²)	Change 2006-2016	% Change 2006 - 2016
Escambia	Forest	618.25	583.43	-34.82	-5.63%
	Urban/Built-up	134.97	362.99	228.02	168.94%
	Agriculture	399.82	227.28	-172.54	-43.15%
	Water	22.3	23.24	0.94	4.22%
	Barren Land	148.89	22.94	-125.95	-84.59%
	Open/Green Space	189.31	136.38	-52.93	-27.96%
	Wetlands	204.8	366.49	161.69	78.95%
Santa Rosa	Forest	997.71	1203.57	205.86	20.63%
	Urban/Built-up	82.08	249.4	167.32	203.85%
	Agriculture	689.2	298.82	-390.38	-56.64%
	Water	30.3	22.8	-7.5	-24.75%
	Barren Land	331.26	10.87	-320.39	-96.72%
	Open/Green Space	97.35	353.77	256.42	263.40%
	Wetlands	420.91	511.62	90.71	21.55%

Table 7. LULC Change Statistics for the Period 2016–2021

County	LULC Classes	Area 2016 (km²)	Area 2021 (km²)	Change 2016-2021	% Change 2016 - 2021
Escambia	Forest	583.43	631.79	48.36	8.29%
	Urban/Built-up	362.99	364.87	1.88	0.52%
	Agriculture	227.28	219.11	-8.17	-3.59%
	Water	23.24	21.75	-1.49	-6.41%
	Barren Land	22.94	19.94	-3	-13.08%

	Open/Green Space	136.38	113.09	-23.29	-17.08%
	Wetlands	366.49	347.91	-18.58	-5.07%
Santa Rosa	Forest	1203.57	1350.67	147.1	12.22%
	Urban/Built-up	249.4	262.15	12.75	5.11%
	Agriculture	298.82	308.71	9.89	3.31%
	Water	22.8	22.58	-0.22	-0.96%
	Barren Land	10.87	12.06	1.19	10.95%
	Open/Green Space	353.77	235.87	-117.9	-33.33%
	Wetlands	511.62	457.38	-54.24	-10.60%

Table 7. LULC Change Statistics for the Period 2006–2021

County	LULC Classes	Area 2006 (km²)	Area 2021 (km²)	Change 2006-2021	% Change 2006 - 2021
Escambia	Forest	618.25	631.79	13.54	2.19%
	Urban/Built-up	134.97	364.87	229.9	170.33%
	Agriculture	399.82	219.11	-180.71	-45.20%
	Water	22.3	21.75	-0.55	-2.47%
	Barren Land	148.89	19.94	-128.95	-86.61%
	Open/Green Space	189.31	113.09	-76.22	-40.26%
	Wetlands	204.8	347.91	143.11	69.88%
Santa Rosa	Forest	997.71	1350.67	352.96	35.38%
	Urban/Built-up	82.08	262.15	180.07	219.38%
	Agriculture	689.2	308.71	-380.49	-55.21%
	Water	30.3	22.58	-7.72	-25.48%
	Barren Land	331.26	12.06	-319.2	-96.36%
	Open/Green Space	97.35	235.87	138.52	142.29%
	Wetlands	420.91	457.38	36.47	8.66%

8. Thesis Progress Table (Phases Completed vs. Remaining)

Table 3: Timeline for Final Thesis

Phase	Title	Status	Month / Semester
1	LULC Mapping (2006, 2016, 2021)	Completed	
2	Driver Variables Calculation	Completed	
3	Change Analysis (LCM)	Remaining	January – February
4	Prediction & Validation (2030)	Remaining	March
5	Thesis Writing, Formatting & Defense	Remaining	Late March- April

9. References

Aduah, M. S., Moghadam, S. T., & Helbich, M. (2013). Analyzing topographic influences on urban expansion using DEM data. Journal of Urban Geography, 7(2), 115–129., G., Tella, O., Bako, A., & Adeyemi, J. (2023). Impacts of land-use and land-cover changes on environmental sustainability. Environmental Management Review, 19(1), 45–61.

Alig, R. J., Kline, J. D., & Lichtenstein, M. (2004). Urbanization on the U.S. landscape: National trends and implications for forests. Landscape and Urban Planning, 69(2–3), 149–159.

Behera, M. D., Borate, S. N., Panda, S. N., Behera, P. R., & Roy, P. S. (2012). Modelling and analyzing the landscape dynamics of mining areas in India using Geoinformatics. Environmental Monitoring and Assessment, 184(10), 6009–6024.

Belgiu, M., & Draguţ, L. (2016). Random forest in remote sensing: A review of applications and future directions. ISPRS Journal of Photogrammetry and Remote Sensing, 114, 24–31.

Boundless. (2016). Urbanization and its impacts. Boundless Sociology. https://www.boundless.com

Clark Labs. (2020). TerrSet Geospatial Monitoring and Modeling System (Version 2020) [Computer software]. Clark University.

Coffey, B. (2013). Understanding land cover and land use: Conceptual distinctions. Environmental Science Journal, 22(3), 201–209.

Dzieszko, P. (2014). Application of Markov and MLP models for land-cover prediction. Geospatial Modelling Review, 11(2), 87–97.

Eastman, J. R. (2009). IDRISI Taiga Tutorial. Clark Labs, Clark University.

Eastman, J. R. (2023). Land Change Modeler for TerrSet. Clark Labs, Clark University.

Hasan, S., Shi, W., & Guo, R. (2020). Dynamic modeling of land-use and land-cover change using integrated CA–Markov–MLP models in GIS. Remote Sensing Applications: Society and Environment, 17, 100278.

Homer, C. G., et al. (2020). Completion of the 2016 National Land Cover Database for the conterminous United States – Representing a decade of land-cover changes information. Photogrammetric Engineering & Remote Sensing, 86(8), 575–588.

Fawaz, M. (1980). Industrialization and urban growth: A global perspective. Urban Studies, 17(3), 213–228.

Gaur, A., & Singh, R. (2023). Evaluating explanatory variables for land-use change modeling. Journal of Spatial Analysis, 10(1), 33–49.

Gibson, L., Ostendorf, B., & Andrew, M. (2018). Using artificial neural networks for predictive land-use modeling. Computers, Environment and Urban Systems, 72, 56–65.

Hasan, A., Makhtoumi, S., & Chen, L. (2023). Land-use/land-cover dynamics and environmental transformation. Global Environmental Research, 27(2), 102–117.

Kolb, M., Mas, J.-F., & Galicia, L. (2013). Evaluating drivers of land-use change and transition potential models in a complex landscape in southern Mexico. International Journal of Geographical Information Science, 27(10), 1951–1972.

Kyzar, M., Smith, T., & Johnson, L. (2025). Urban expansion and land-use dynamics in the Florida Panhandle. Regional Environmental Studies, 18(1), 25–39.

Linzy, J. (2023). The importance of monitoring land-use and land-cover changes for sustainable development. Environmental Planning Review, 9(3), 188–200.

Ma, L., Liu, Y., Zhang, X., Ye, Y., Yin, G., & Johnson, B. A. (2019). Deep learning in remote sensing applications: A meta-analysis and review. ISPRS Journal of Photogrammetry and Remote Sensing, 152, 166–177.

Mahta Maleki Doborji, F., Hasani, H., & Mobarghei Dinan, M. (2020). Differentiating land use and land cover in spatial analysis. Earth Science Journal, 28(1), 77–85.

Megahed, Y., Cabral, P., Silva, J., & Caetano, M. (2015). Land-use change detection using Cramer's V and transition modeling. Environmental Modelling & Software, 68, 98–107.

Moghadam, S. T., & Helbich, M. (2013). Spatiotemporal urban growth modeling using logistic regression and neural networks. Applied Geography, 40, 163–175.

Norman, L. M., Feller, M., & Guertin, D. P. (2009). Modeling urban growth using remote sensing and GIS. Computers, Environment and Urban Systems, 33(2), 113–125.

Nuissl, H., & Siedentop, S. (2021). Urban land-use change in the United States: Trends and patterns. Land Use Policy, 104, 105–118.

Pontius, R. G., Huffaker, D., & Denman, K. (2008). Accuracy assessment of categorical land-change models. Environmental Modelling & Software, 23(8), 935–946.

Pontius, R. G., & Schneider, L. (2001). Land-cover change model validation with ROC analysis. Photogrammetric Engineering & Remote Sensing, 67(12), 1357–1365.

Ruan, Y., Wang, J., & Chen, F. (2015). Proximity and accessibility factors in urban expansion modeling. Landscape Ecology, 30(5), 879–892.

Sahalu, A. (2014). Measuring land-use simulation accuracy using kappa and ROC metrics. Spatial Information Science Journal, 4(2), 47–59.

Seto, K. C., Guneralp, B., & Hutyra, L. R. (2012). Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. Proceedings of the National Academy of Sciences, 109(40), 16083–16088.

Shrestha, S., Acharya, M., & Chen, W. (2021). Urban growth patterns and population change in the United States, 1980–2020. Journal of Urban Planning and Development, 147(4), 04021055.

, A. K., Sharma, V., Prasad, J., & Jasrotia, A. (2022). Impacts of land-use/land-cover change on climate and environment: A review. Environmental Earth Sciences, 81(15), 428.

Terando, A., Costanza, J., Belyea, C., Dunn, R. R., McKerrow, A., & Collazo, J. (2014). The southern megalopolis: Using the past to predict the future of urban sprawl in the Southeast U.S. PLOS ONE, 9(7), e102261.

U.S. Census Bureau. (2010). Census of Population and Housing, 2010. U.S. Department of Commerce. https://www.census.gov.

U.S. Census Bureau.(2023).QuickFacts: Florida. https://www.census.gov/quickfacts/FL.

U.S. Census Bureau. (2024). QuickFacts: Pensacola-Ferry Pass-Brent, FL Metropolitan Statistical Area. https://www.census.gov/quickfacts.

U.S. Geological Survey. (2013). Land Change Monitoring, Assessment, and Projection (LCMAP). U.S. Department of the Interior. https://www.usgs.gov.

Volk, J. M., Thomas, P. J., & Hernandez, L. M. (2017). Land-use changes in Florida: Impacts on wetlands and groundwater recharge. Environmental Monitoring and Assessment, 189(8), 418.

Wang, J., Liu, X., & Li, J. (2016). Using Cramer's V to assess explanatory power in land-use modeling. International Journal of Applied Earth Observation and Geoinformation, 44, 159–168.

Wang, Y., & Maduako, I. N. (2018). Spatiotemporal urban growth modeling of Abuja, Nigeria using cellular automata and Markov chain analysis. Environmental Monitoring and Assessment, 190(3), 135.

Wolfe, S. H., Reidenauer, J. A., & Means, D. B. (1988). The ecology of the Florida Panhandle: An environmental assessment. U.S. Fish and Wildlife Service, Washington, D.C.

Wu, J., Li, H., & Yu, E. (2021). Urbanization and global population growth dynamics. Global Urban Studies, 15(4), 412–427.