CHANGES IN TENNESSEE LAND USE

A Thesis Presented for the
Master of Science
Degree
The University of Tennessee, Knoxville

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May 2024

ACKNOWLEDGEMENTS

Thank you to my parents, Billy and Suzanne Hopper.

ABSTRACT

Urbanization and rural development make agricultural and forest land susceptible to conversion. In Tennessee, there has been an increase in the rate of agricultural and forestry land conversion over the past two decades. In this study, we will be conducting a geo-spatial analysis, on 86 of the 95 Tennessee counties, to identify farm, agricultural, and forest parcels that have converted to some other land classification. Additionally, we provide a statistical analysis on the Eastern Tennessee region to identify drivers that are influencing conversion. From the geo-spatial analysis, we show farm, agricultural, and forestry parcels that have converted to some other land type, the type of land parcel converted to, and the amount in acres that were converted. From the statistical analysis, we find that farm, agricultural, and forest parcels with public or private utility hook-ups and urban paved or curb road types had an increased likelihood of conversion, compared to their respective baselines. We also find that as land value increases the likelihood of conversion increases. We find that parcels located on rolling, mountainous, and high elevation topography were less likely to convert, compared to the baseline of level topography. We also find that parcels with interchange, state highway, paved, gravel, dirt, and private/none road types were less likely to convert, compared to the baseline of U.S. highway. Finally, we find that parcels with out-of-state owners were less likely to convert, compared to parcels owned by Tennessee residents. Understanding the drivers for agricultural and forestry land loss is useful for local and government officials, policy makers, and stakeholders. Smart development is a way for Tennessee to balance

agricultural productivity and urban growth so that Tennessee's economy can grow efficiently.

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CHAPTER ONE
INTRODUCTION AND RESEARCH OBJECTIVE

Introduction

From 2001 to 2016, American Farmland Trust estimated that 11 million acres of agricultural land had been fragmented or converted to non-agriculture uses (American Farmland Trust, 2020). Approximately 4.4 million acres of this conversion was classified as low-density residential (LDR) or urban and high density (UHD) land (American Farmland Trust, 2020). According to Knox County Planning, LDR land is a tract of land that is primarily residential property and consists of five or less dwellings per acre (Knoxville-Knox County Planning, 2024). Likewise, high-density residential can be classified as land that contains mixed use development, such as apartments and housing, with twenty-four or more dwellings per acre (Knoxville-Knox County Planning, 2024). LDR and UHD increasing agricultural land conversion results in diminished food supply, reduced economic opportunity, and negative environmental impacts (American Farmland Trust, 2020; Brown, 1995; Naab et. al., 2013; Zhang et. al., 2023). As of 2020, the American Farmland Trust ranked Tennessee fourth in the nation for agricultural land loss (Sallet, 2020).

For Tennessee, the agriculture and forestry industry are impactful contributors to the economy. In 2021, the agri-forestry industry directly and indirectly contributed approximately $89 billion to Tennessee’s economy, approximately 11% of total economic activity (University of Tennessee [UT] Boyd Center, 2024). Tennessee encompasses approximately 26.4 million square acres. From 1997 to 2017, it was estimated that 1.1 million acres of agriculture and forestry land in Tennessee was converted to some other land classification (United States [U.S.] Census Bureau, 2023). This is equivalent to 55,601 acres/year, 152 acres/day, and 6.3 acres/hour. Additionally, from 2017 to 2022, it was estimated that Tennessee lost an additional 432,941 acres in agriculture and forestry land. This is equivalent to 86,588 acres/year, 237 acres/day, and 9.8 acres/hour (UT Boyd Center, 2024). Overall, this approximately 1.5 million acres of converted agriculture and forestry land is equivalent to the size of six Tennessee counties. Seeing that the rate of conversion is increasing in Tennessee, the expectation is farmland conversion rates will continue to remain constant or increase, due to development in the state such as Blue Oval City and increased solar farm expansion (UT Boyd Center, 2024). Xie et. al. (2023) estimated that Tennessee will see 250,000 – 300,000 acres convert to UHD land and 900,000 – 1,500,000 acres convert to LDR land by 2040.

Although Tennessee offers agriculture and forest preservation programs, such as Greenbelt, which offers landowners (minimum of 15 acres up to a maximum of 1,500 acres) tax break incentives by maintaining their land in agricultural production (agriculture or forest production), Tennessee is still witnessing high conversion rates in agriculture and forestry land. Understanding the drivers for this conversion is important for local and government officials, policy makers, and stakeholders, so Tennessee can encourage smart conversion and balance agricultural and developmental economic growth. Recognizing the importance of smart conversion in Tennessee is important because of the economic contribution the industry provides to the state. Development is expected to happen due to urban sprawl and population increases, and it is imperative that

Tennessee handle the development in a way that is not detrimental to the agricultural and forestry industry.

Research Objective

The objective of this research is to identify farm, agriculture, and forestry parcels that have converted to a different land classification, as well as identify the drivers that are influencing this conversion.

CHAPTER TWO
LITERATURE REVIEW

Modeling for Land Conversion

There are several different models that could be implemented to analyze land-use change. To identify drivers of land change, land use change models are used to understand spatial relationships and predict changes based on historical changes (Meiyappan, et.al., 2014). Land use change models allow testing of the linkage between social and ecological systems (Veldkamp and Lambin, 2001).

In a study by Lui et. al. (2010), the researchers studied urban land conversion in Hangzhou, China using a logistic regression. The objective of this paper was to understand the drivers that contribute to urbanization. The regression for this study was ran twice, for time periods 1995-2003 and 2003-2009 (Lui et. al. 2010). The researchers created a dummy dependent variable where one equals land converted to urban and zero equals otherwise. For independent variables, the researchers included distance variables including distance to the central business district, industrial centers, roads, and the Qiantang River, as well as variables such as frequency to neighboring urban areas, neighboring land availability, intensity of market points, and planned as built-up areas (Lui et. al., 2010).

Their results show that for every one kilometer (km) increase in distance from a central business district, there was a 14.3% and 7.9% decrease in likelihood of conversion from 1995-2003 and 2003-2009, respectively. For every one km increase in distance from industrial centers, there was a 15.6% and 13.1% decrease in the likelihood of conversion from 1995-2003 and 2003-2009, respectively. For every one km increase in distance from roads, there was a 27.5% and 41.2% decrease in likelihood of conversion from 1995-2003 and 2003-2009, respectively. For every 1% increase in built-up neighborhoods, there was a 2.3% and 1.2% increase in likelihood of conversion from 1995-2003 and 2003-2009, respectively. For every one point per km^2 increase in market density there was a 371.1% and 108.6% increase in likelihood of conversion from 1995-2003 and 2003-2009, respectively. For every 1% increase in the amount of available land, there was a 1.4% and 0.9% decrease in likelihood of conversion from 1995-2003 and 2003-2009, respectively. Lastly, for every one km increase in distance from the Qiantang River, there was a 3.3% decrease in likelihood of conversion from 2003-2009. There was no statistical significance for the Qiantang River variable from 1995-2003 (Lui et. al., 2010).

In a different study, Li, Wu, and Deng (2013) used a spatial multinomial logit model to determine drivers for land use change in China from 1988 to 2005. For this study, the researchers combined data on land use, weather conditions, land quality, topographic features, and economic variables into a geographic information system (GIS) database to analyze the spatial interaction between land use choices with an econometric land use model (Li et. al., 2013). Since this study focuses on the spatial interaction between land parcels, the researchers assume that the net benefits of an alternative use on a land parcel influenced the net benefits of alternative uses of a neighboring parcel (Li et. al., 2013). Land was classified into six categories: farmland, forests, grassland, water area, urban land, and unused land. Since policy regulation in China differed over the years, the researchers ran the model in three conversion time periods: 1988-1995, 1995-2000, and 2000-2005(Li et. al., 2013). Their results show that farmland with high yield potential was more likely to stay in agricultural production in the first two time periods, farmland with higher elevation was less likely to stay in farmland or convert to urban land and more likely to convert to forests or grassland, and farmland with steeper slopes were more likely to convert to forest land (Li et. al., 2013). For the weather variables, the results found that farmland was less likely to convert to grassland or unused land if they were in areas of high precipitation and more likely to stay in farmland in the first two time periods (Li et. al., 2013). From 1995-2005, farmland was more likely to convert to urban use in areas that had higher urban land value, and from 1988-1995, as per hectare agricultural GDP increased, farmland was less likely to convert to urban land (Li et. al., 2013). The researchers found that as rural income increased farmland was more likely to convert to forests, grasslands, and water areas (Li et. al., 2013). Along with these results, the researchers found that increasing road density and public agricultural investment were drivers for farmland expansion, increased urban income and urban land value were drivers for urban development, deforestation was influenced by increasing road density and urban income, and rising rural income increased forest and grasslands conversions (Li et. al., 2013).

Variables Impacting Agricultural Land Conversion

Agricultural land conversion (ALC) is influenced by incentives (Rondhi et. al., 2018). Farah et. al. (2019) utilized a logit model to determine drivers for land conversion in Faisalabad, a highly urbanized city, and Sahiwal, a city in the initial stages of urbanization, in Pakistan, and found that physical and economic factors were drivers for ALC in both locations. In Faisalabad, the results found that as the age of the owner increased, the likelihood of conversion decreased by 26.2%, as agricultural income decreased, the likelihood of conversion increased by 69.7%, as the costs of agriculture inputs increased, the likelihood of conversion increased by 74.3%, as agricultural commodity prices decreased, the likelihood of conversion increased by 76.9%, as land value increased the owner was 95.4% more likely to sell their land, for every 1 km decrease in distance from a main road, increased famers willingness to sell by 83.2% , and access to irrigation increased the willingness of the farmer to sell by 97.4% (Farah et. al., 2019).

In the lesser developed city, Sahiwal, the results showed that for every additional year of education the farmer had, the likelihood of conversion increased by 91%, as agricultural income decreased, the likelihood of conversion increased by 74.4%, urban land in the surrounding area increased farmers willingness to sell by 46%, and access to irrigation increased the willingness of the farmer to sell by 94.3% (Farah et. al., 2019). These results showed the similarities and differences in conversion drivers between highly and lowly urbanized areas in Pakistan.

Each of the studies in this section evaluated how different variables impact land conversion. Given that these studies are conducted in different countries, and China having government regulations, the methods used here model the research done in this paper. Like this study, Farah et. al. (2019) evaluated ALC to determine variables that are driving urbanization. Using similar methods, with variables and data specific to

Tennessee, will allow us to evaluate agricultural and forestry land conversion tailored to a specific region.

CHAPTER THREE
DATA AND METHODS

Data

From 1997-2022, Tennessee lost approximately 1.5 million acres in agricultural and forestry land (UT Boyd Center, 2024). With the rate of conversion increasing, understanding the drivers that are impacting this conversion will be beneficial to state government, county officials, policy makers, and Tennessee landowners. From the literature above, we can see variables that are affecting land conversion in other countries and the methods used to evaluate the data. By pinpointing exactly what land parcels are being converted out of agriculture and forestry land, we can show what land classification the parcels are converting to, the amount in acres that are being converted, and what variables are driving these parcels to change.

For this study, we will be analyzing data that was provided by the Tennessee Comptroller of the Treasury and Tennessee Property Assessors' data. These sources provided shapefiles and attribute tables that contained 142 variables describing every land parcel in 86 of the 95 Tennessee counties. The counites that were not included in the data set are counties that keep independent records (do not report to the state) or have inefficient data records. This project was conducted using a geo-spatial analysis and a statistical analysis. For the statistical analysis, we ran the logistic regression using Eastern Tennessee counties. This regression contained 31 counties and did not include Knox, Hamilton, and Bradley counties. Figures 1 and 2 show the three Tennessee grand regions (West, Middle, and East) and the percent change in farm, agricultural, and forest land in each county, respectively. All tables and figures can be found in the appendix. For context, parcels labeled as agriculture could be used for farm or forestry purposes; however, agricultural parcels are enrolled in Tennessee's Greenbelt program and farm and forest parcels are not. Since this data set was so large, we only have the computational power to run one region at a time. East Tennessee contained 486,028 farm, agricultural, and forest observations. We chose East Tennessee due to the high rates of conversion, as shown in figure 2. Figure 3 shows the steps taken to accomplish this research.

Methods and Procedures

Each of the 86 county geo-spatial analyses were ran independently, following the same methods. The geo-spatial analysis was conducted using ArcGIS Pro. For the majority of the counties, we were able to compare 2014 data to the newest 2023 data; however, occasionally we had to compare 2015 or 2019 data to the 2023 data. The geo-spatial analysis focuses on identifying farm, agricultural, and forestry parcels that were converted to some other land type by 2023. Other land types include residential, city, county, state, federal, religious, education/science/charity, other exempt, commercial, industrial, state assessed, and local utility. We started by joining and intersecting the starting year data (2014, 2015, or 2019) with the 2023 data, so we could compare the parcel classifications for both years and isolate the converted parcels. We were also able to calculate the geometry of the converted parcels in terms of U.S. survey acres, so we can see how many acres are being converted. We extracted all isolated farm, agricultural, and forest parcels, along with the 142 variables for each county and organized them by region for the statistical analysis. After compiling the results from the geo-spatial analysis, we saw a trend of farm, agricultural, and forest parcels converting to residential land.

For the statistical analysis, we ran a logistic regression. The formula for this analysis is generally described as

$$\boldsymbol{Y = \sum_{i=1}^{k} \beta_i X_i + \varepsilon}$$

where *Y* represents the binary dependent variable of Conversion, where one equals if the farm, agricultural, or forest parcel converted to some other land type, zero otherwise. Since we noticed a trend in residential development, we selected variables, of the 142 available, that we believe influence residential developers' decisions when choosing what land to buy. These variables are represented by *X* in the equation and include types of utility hook-ups (Water/Sewer, Electric, Gas), size of parcel (in acres), land value, road type, topography, and if there were preexisting buildings on the property, and if so, how many buildings. We also created dummy variables such as county dummies, state owner (where one equals if the farm, ag, or forest parcel was owned by a non-Tennessee resident, zero otherwise), structure (where one equals it there was a preexisting structure on the property, zero otherwise), and AgeIn20xx to represent the age of the structure, if there was one present. In the equation above, *k* represents the total number of independent variables in the equation, *i* represents each independent variable, and β represents the parameter estimate for each independent variable. The error term, ε, contains all variables that were not used in the equation and is a logistic distribution. Logistic distributions are often found in probability models and have tails that are asymptotes that approach but never touch zero. We also ran marginal effects to be able to interpret the results in percent form. Since there were so many categorical variables in this regression, table 1 provides a summary of the variables Water/Sewer, Electric, Gas, Road Type, and Topography.

CHAPTER FOUR
RESULTS AND DISCUSSION

Geo-spatial Analysis

Figure 4 and Table 2 shows an example of the geo-spatial analysis results. This example depicts Jefferson County, Tennessee, which is located in the Eastern region. Overall, Jefferson County lost 5.8% of its farm, agricultural, and forest land from 2014 to 2023. From the map in figure 4, we can see that the land parcels highlighted in red were classified as farm, agricultural, or forest land in 2014 but have been converted to some other classification by 2023. Table 2 provides a summary of what land classification the parcels converted to, as well as the amount in acres that were converted. Jefferson County is representative of what we were seeing across the state, that being high rates of conversion to residential land. Of the 6,601.6 acres of farm, agricultural, and forest parcels that were converted in Jefferson County, 6,257.6 acres converted to residential land, 163.8 acres converted to commercial land, and 180.2 acres converted to "other" land classifications. "Other" classifications means that a farm, agricultural, or forest parcel was converted to a land classification other than residential or commercial. For example, if an agriculture parcel converted to an industrial parcel, this would fall into the category of "Agriculture – Other". Across the 31 counties analyzed, East Tennessee lost approximately 221,935 acres of farm, agricultural, and forestry land with 54% converting to residential land, 2% converting to commercial land, and the remaining 44% converting to other land classifications.

Statistical Analysis

The logistic regression ran on East Tennessee contained 486,028 observations. Table 3 summarizes the variables, standard error, parameter estimates and significance levels, and marginal effects of each variable. Each of the statistically significant variables were significant at the 0.1%, 1%, or 5% level. For interpretation, the categorical variables were all compared to their baselines, as defined by the state. These baselines were Public/None Water/Sewer, None Electric, None Gas, U.S. Highway Road Type, and Level Topography.

For utility hook-ups, we find that farm, agriculture, and forest parcels with Public/Public, Public/Private, and Private/None Water/Sewer hook-ups were 17%, 6.2%, and 4.7%, respectively, more likely to convert compared to the baseline of Public/None Water/Sewer hook-ups. We also find that similar parcels with Private/Private, Individual/None, Individual/Individual, None/None, None/Public, None/Private, and None/Individual Water/Sewer hook-ups were 4.2%, 9.7%, 6.7%, 9.4%, 14.9%, 14.9%, and 4%, respectively, less likely to convert compared to parcels with Public/None Water/Sewer hook-ups. Farm, agriculture, and forest parcels with Private electrical hook-ups were 5% more likely to convert compared to parcels with no electrical hook-ups. Private electrical hook-ups are privately owned electrical companies that still follow federal regulations. Lastly, we find that parcels with Public-Natural Gas hook-ups were 2.6% more likely to convert compared to parcels with no gas hook-up, and parcels with Private-Manufactured Gas hook-ups were 4.5% less likely to convert compared to parcels with no gas hook-up.

For topography and road type, we find that farm, agriculture, or forest parcels located on Rolling, Mountainous, and High Elevation topography were 0.8%, 4.6%, and 2.3%, respectively, less likely to convert compared to parcels that were located on Level topography. Farm, agriculture, and forest parcels with Interchange, State Highway, Paved, Gravel, Dirt, and Private/None road types were 8.2%, 1.2%, 2.1%, 7.4%, 11.9%, and 8.7%, respectively, less likely to convert compared to parcels with a U.S. Highway road type. However, we also find that farm, agriculture, and forest parcels with Urban Paved and Curb/Gutter Paved road types were 6.3% and 18.3%, respectively, more likely to convert compared to similar parcels with a U.S. Highway road type.

Other variables that were statistically significant were State Owner and Land Value. We find that farm, agriculture, and forest parcels with out-of-state owners were 1.7% less likely to convert compared to parcels owners that were Tennessee residents. We also find that as land value increases, the likelihood of conversion increases. Figure 5 shows a chart that entails how the likelihood of conversion is impacted based off the land value of the parcel. For example, if the land value of a parcel is $100,000 above the average land value, the likelihood of conversion increases by 0.4%. Figure 5 shows scenarios for land values increase in likelihood of conversion for parcels ranging from $100,000 to $2,000,000 above average land value, in increments of $100,000.

Discussion

Given the geo-spatial analysis results show high rates of conversion to residential land, the results from the statistical analysis are logical and intuitive. According to the Tennessee Department of Health, Tennessee’s population increased from 6,549,201 in

2014 to 7,051,355 in 2022, resulting in 502,154 additional residents (Tennessee [TN] Department of Health, 2024). Farm, agriculture, and forest parcels with public water, sewer, and gas hook-ups and private electrical utility hook-ups showed increased likelihoods of conversion compared to individual and no utility hook-up access. From a residential development standpoint, public and private utility hook-up access is convenient and decreases the cost of converting these parcels. Farm, agriculture, and forest parcels with access to urban paved and curb road types increase the likelihood of conversion, indicating that these parcels are closely located to other developed land and are drivers that influence urban sprawl. We also find that parcels located on rolling, mountainous, and high elevation topography were less likely to convert compared to the baseline of level topography. Although level land is the most convenient and economical for residential development, this is also the primary land type for agricultural use.

Although the literature looks at a variety of variables, a common variable we observed is land value. Farah et. al. (2023) also find that as land value increases the likelihood of conversion increases. Overall, it seems that money and locality are drivers for conversion. From the literature review, we see that distance to neighboring cities, roads, and marketplaces increase the likelihood of conversion (Farah et. al., 2023; Lui et. al., 2010). In this study, we find that road type, topography, and utility hook-ups are main drivers for conversion. All of these variables provide a level of convenience to people interested in developing agricultural or forestry land. For locality purposes, being closer the developed areas are more appealing for development purposes; likewise, in our findings, we see that U.S. highway road types are preferred, so not only being close to developed areas are important, but being able to easily access them via road type is important as well. For monetary purposes, we see from Farah et. al. (2023) that access to irrigation increased the chances of farmers seeing their land, which may seem counterintuitive; however, when this study finds that water/sewer and electrical hook-ups increase likelihood of conversion, it seems as though these irrigated land tracts are more valuable, because they are already equipped with water and electric hook-ups that are being used for irrigation purposes. It is also interesting to note that, per the results of Jefferson County and many counties across the state, parcels that were reclassified from agriculture to residential highly contribute to the amount of land that was converted. Seeing that parcels classified as agriculture are enrolled in Tennessee's Greenbelt program, it appears that the tax incentive program is not slowing the rate of conversion like planned. When land is removed from the Greenbelt program, rollback taxes are applied (Tennessee Comptroller of the Treasury, 2024). Under the assumption that residential developers are purchasing the land for conversion, the seller of the land would include the rollback taxes in the price of the land, and large residential developers would be willing to pay the taxes for access to the land.

CHAPTER FIVE
CONCLUSION AND IMPLICATIONS

Conclusion

The data and results for this analysis are specific to Tennessee and allow policy makers, local and state government, and stakeholders to understand the drivers that are influencing agricultural and forestry land conversion. Understanding land conversion provides information needed to enact policies, conserve land, and optimize economic development in Tennessee, while recognizing the contribution that the agriculture industry provides to the Tennessee economy. From the results, utility hook-up type, topography, road type, the state in which the parcel owner resides, and land value all influence agricultural and forestry land conversion. Although urbanization and development are inevitable, and in some cases economically beneficial, recognizing variables that threaten agricultural and forestry land conversion is valuable for conservation and smart conversion.

It is significant to point out that not having access to data for the largely populated Tennessee counties, in this regression Knox and Hamilton counties, is a limitation for this analysis. These counties contain urbanized cities, such as Knoxville and Chattanooga. Having access to these counties would give us a better understanding of variables contributing to urban sprawl in areas that are surrounding major Tennessee cities.

Implications and Future Research

The results from the statistical analysis indicate the variables that increase and decrease the likelihood of a farm, agriculture, or forest parcels converting to some other land type. Seeing that Tennessee lost approximately 1.5 million acres of agricultural and forest land from 1997-2022, understanding the drivers that cause this conversion is beneficial to state and local government, policy makers, and stakeholders (UT Boyd Center, 2024). Converting agricultural land to other high value uses, in turn, increases the land value of surrounding agriculture land and increases the likelihood of conversion. This is important to note, because after agriculture or forestry land is converted to some other land type, the land is degraded and results in uncultivable surfaces for future productivity (Xie et. al., 2023). To preserve the remaining agriculture and forestry land from urbanization and development, smart conversion is a way to manage urban sprawl and protect productive agriculture and forest land. One way to do this is to understand what type of land is being converted and focus on developing low-productivity land areas.

To further this research, the same statistical analysis on Middle and West Tennessee could be studied and compared to the East Tennessee results. Additionally, expansion of the geo-spatial analysis could include Tennessee's Crop Productivity Index (CPI). The Natural Resources Conservation Service created a raster file that displays the CPI that categorizes productivity ranges on a scale of zero to one, where zero is the least productive land and one is highly productive land. By overlaying the CPI file with the results from our geo-spatial analysis, one would be able to see the productivity level of the farm, agriculture, and forest parcels that were converted. The CPI layer will provide more insight into what type of land is being converted and highlight where both the lowly and highly productive agricultural land is located in the state. By showing the areas of low productivity land, this gives government officials and policy makers the option to focus urban development in these areas, rather than urbanizing highly productive agricultural or forestry land. Given that Tennessee’s population increased by over 500,000 from 2014 to 2022, development is to be expected (TN Department of Health, 2024). However, due to the impact that the agri-forestry industry has on Tennessee’s economy, it is important for Tennessee to balance urban development and agriculture and forestry land preservation.

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APPENDIX

Tables

Table 1: Categorical variables classifications for Water/Sewer, Electric, Gas, Topography, and Road Type

Water/Sewer**	Electric	Gas	Topography	Road type
Public/None*	None*	None*	Level*	U.S. Highway*
Public/Public	Public	Public	Rolling	Interchange
Public/Private	Private	Private	Mountainous	State Highway
Public/Individual	Individual	Individual	High Elevation	Paved
Private/None			Low Elevation	Gravel
Private/Public			Gully/Waste	Dirt
Private/Private				Urban paved
Private/Individual				Curb/Gutter Paved
Individual/None				Private/None
Individual/Public				
Individual/Private				
Individual/Individual				
None/None				
None/Public				
None/Private				
None/Individual				

*, Variables that were dropped from the regression and were considered the baseline for the logistic regression.
**, Where the description before the backslash represents the water hook-up and the description after represents the sewer hook-up. For example, Public/None represents public water hook-up and no sewer hook-up.

Table 2: Jefferson County conversion statistics

Jefferson County 2014-2023	Number of parcels converted	Acreage
Ag-Residential	6,501	4,561.5
Ag-Commercial	168	81.0
Ag-Other	255	157.7
Farm-Residential	2,272	1,494.4
Farm-Commercial	43	5.4
Farm-Other	60	22.5
Forest-Residential	396	201.7
Forest-Commercial	13	77.4
Total	**9,708**	**6,601.6**

Table 3: Logistic regression and marginal effect estimates demonstrating land conversion in Tennessee (n=486,028).

Variable	Standard Error	Estimate	Marginal Effect
Public/Public Water/Sewer	2.278e-02	7.458e-01 ***	0.170
Public/Private Water/Sewer	4.258e-02	2.591e-01 ***	0.062
Public/Individual Water/Sewer	1.384e-02	1.284e-02	0.003
Private/None Water/Sewer	7.270e-02	1.980e-01 **	0.047
Private/Public Water/Sewer	4.399e-01	2.787e-01	0.066
Private/Private Water/Sewer	3.866e-02	-1.730e-01 ***	-0.042
Private/Individual Water/Sewer	5.365e-02	4.889e-02	0.012
Individual/None Water/Sewer	2.472e-02	-4.089e-01 ***	-0.097
Individual/Public Water/Sewer	8.733e-02	-1.071e-01	-0.026
Individual/Private Water/Sewer	1.267e-01	-1.759e-01	-0.042
Individual/Individual Water/Sewer	1.373e-02	-2.815e-01 ***	-0.067
None/None Water/Sewer	1.567e-02	-3.926e-01 ***	-0.094
None/Public Water/Sewer	1.425e-01	-6.354e-01 ***	-0.149
None/Private Water/Sewer	2.713e-01	-6.028e-01 *	-0.149
None/Individual Water/Sewer	7.796e-02	-1.681e-01 *	-0.040
Public Electric	1.831e-02	-2.791e-03	-0.001
Private Electric	1.058e-01	2.129e-01 *	0.050
Individual Electric	8.077e-02	-1.149e-01	-0.027
Public – Natural Gas	1.568e-02	1.090e-01 ***	0.026
Public – Manufactured Gas	1.267e-01	1.443e-01	0.034
Private – Natural Gas	6.258e-02	-1.224e-01	-0.029
Private – Manufactured Gas	7.734e-02	-1.919e-01 *	-0.045
Individual – Natural Gas	6.504e-02	1.160e-01	0.027
Individual – Manufactured Gas	4.056e-02	-3.987e-02	-0.009
Land Value	6.267e-09	1.669e-07 ***	3.911e-08
Buildings	1.620e-03	-1.551e-03	0.0004
Rolling Topography	1.622e-02	-3.581e-02 *	-0.008
Mountainous Topography	1.927e-02	-1.698e01 ***	-0.046
High Elevation Topography	2.835e-02	-9.807e-02 ***	-0.023
Low Elevation Topography	6.261e-02	-4.557e-02	-0.011
Gully/Waste Topography	2.052e-01	1.210e-01	0.029
Interchange Road Type	1.432e-01	-3.475e-01 *	-0.082
State Highway Road Type	2.270e-02	-5.026e-02 *	-0.012
Paved Road Type	2.049e-02	-8.992e-02 ***	-0.021
Gravel Road Type	2.172e-02	-3.116e-01 ***	-0.074
Dirt Road Type	2.83e-02	-5.088e-01 ***	-0.119
Urban Paved Road Type	7.113e-02	2.688e-01 ***	0.063
Curb/Gutter Paved Road Type	1.097e-01	8.149e-01 ***	0.183
Private/None Road Type	2.342e-02	-3.688e-01 ***	-0.087
Acres	2.552e-06	-3.630e-07	-8.506e-08
State_Owner	9.603e-03	-7.428e-02 ***	-0.017
Structure	9.392e-03	1.443e-03	0.0003
AgeIn20xx	1.332e-04	-1.371e-04	-3.212e-05

*, **, *** significant at 5%, 1%, and <0.1%, respectively

Figures

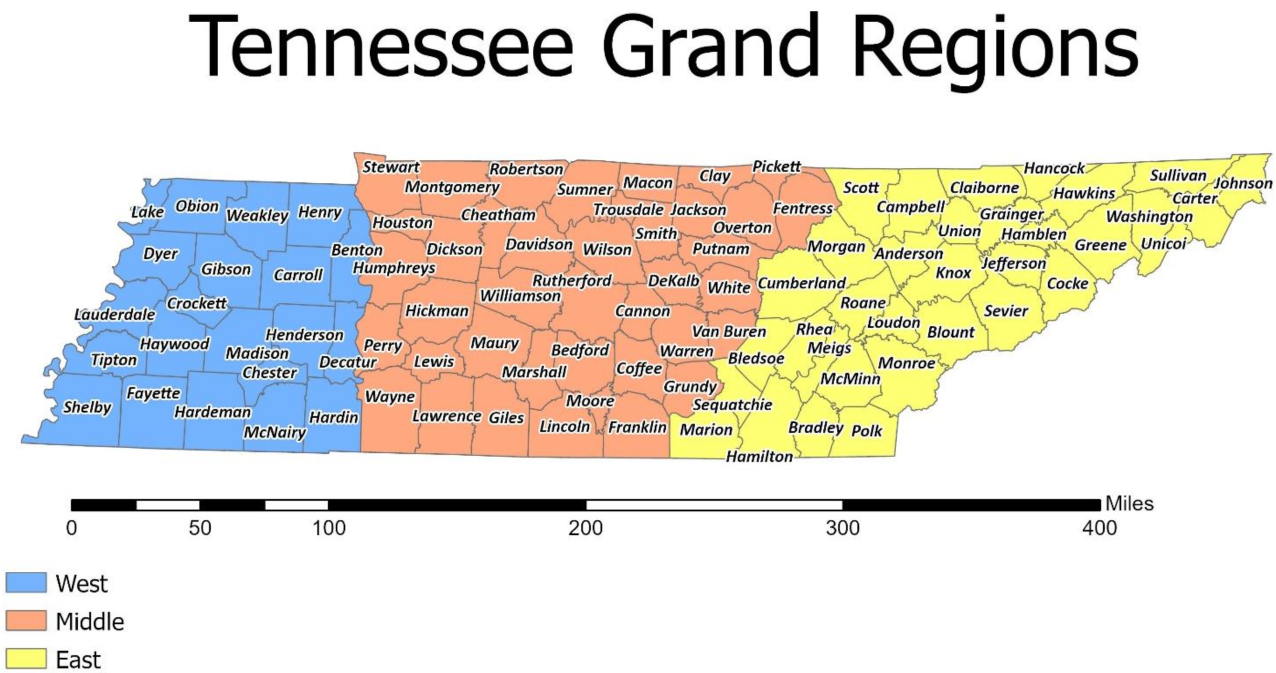

Figure 1: Tennessee Grand Regions

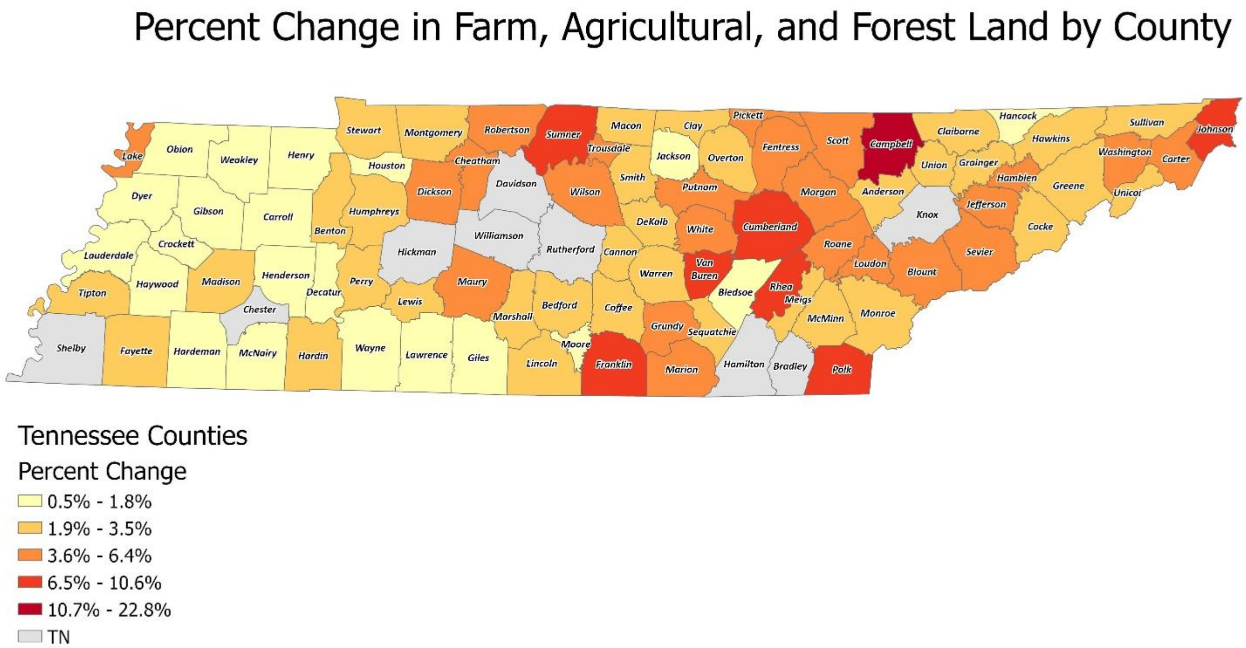

Figure 2: Percent change in farm, agricultural, and forest land by county

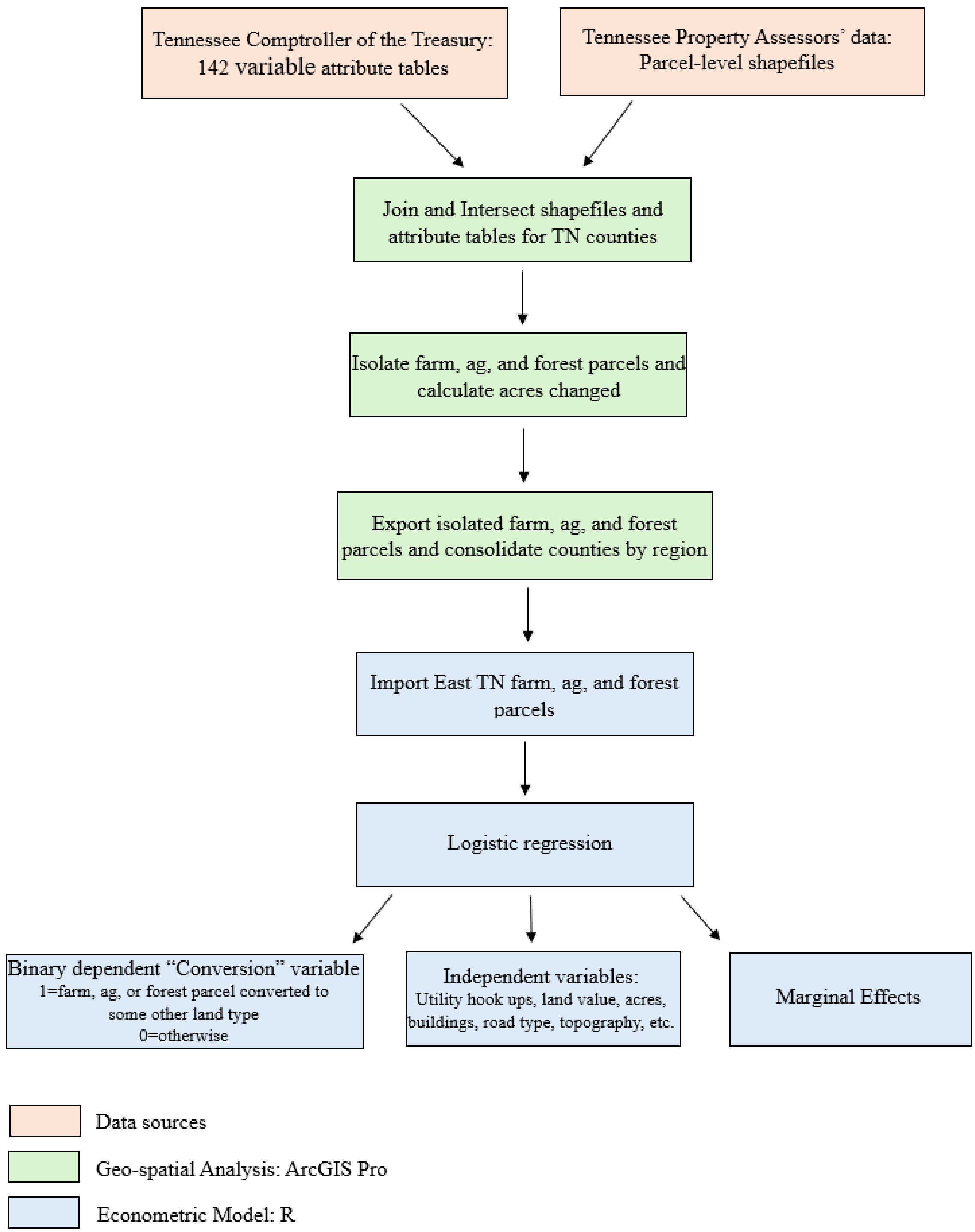

Figure 3: Analysis framework

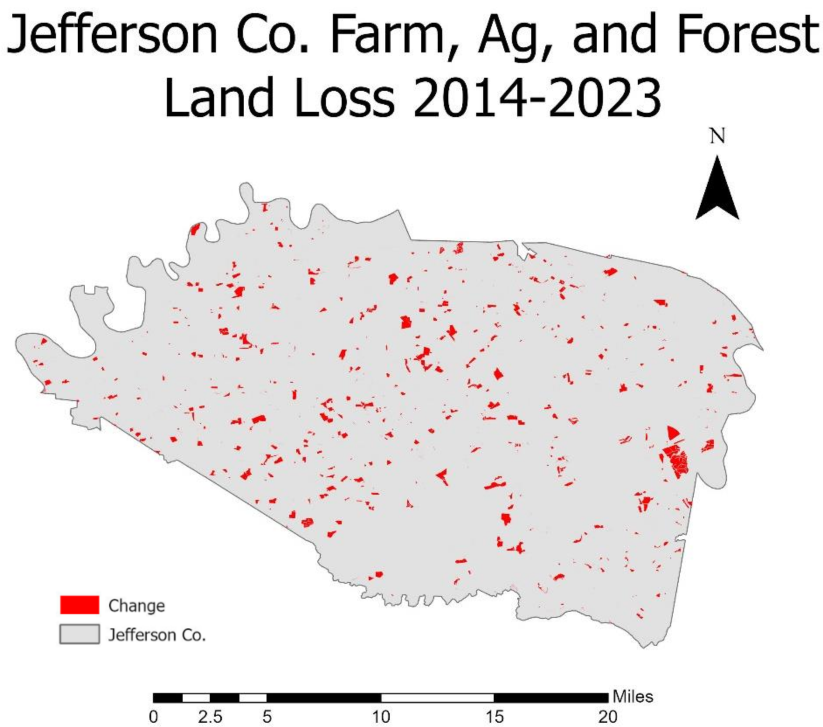

Figure 4: Jefferson County geo-spatial analysis results

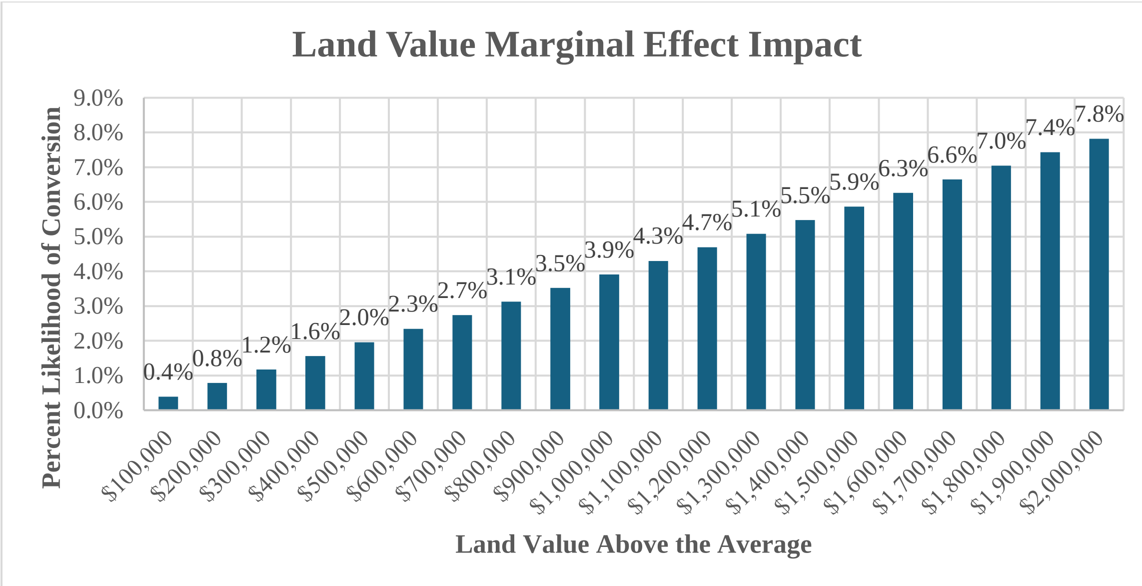

Figure 5: Percent likelihood of conversion based on land value

VITA

Leann Hopper is from Troy, Tennessee, where she graduated from Obion County Central High School in 2018. In 2021, Leann graduated *cum laude* with a Bachelor of Science degree from the Department of Agricultural Economics at Mississippi State University, having majored in Agribusiness with a minor in Economics and concentration in Policy and Law. Leann decided to pursue her Master of Science degree from the University of Tennessee in the Department of Agricultural and Resource Economics. She spent much of her time analyzing land conversion, conducting geo-spatial analyses, and working with eye-tracking studies. After graduation, Leann will be returning to Mississippi State University to work as a Research Program Manager at the Geosystems Research Institute.