CHANGES IN RURAL PRIVATE LAND OWNERSHIP IN THE SOUTHEASTERN UNITED STATES

A Thesis

by

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ABSTRACT

Changes in the demand for rural land in combination with rapid population growth and rising land market values threatens privately owned farms, ranches and forests (i.e., “working lands”), and the ecosystem services they provide across the United States. These factors collectively facilitate the sub-division and conversion of working lands (i.e., ownership fragmentation). As such, ownership fragmentation can have serious implications for how landscapes are managed, given varying management objectives among landowners and the external pressures they exert on each other.

While most land fragmentation studies are conducted within small spatial scales, focusing on the spatial discontinuity of land or habitat, ownership fragmentation focuses instead on the human aspect of landscapes. I used data reported by the United States Department of Agriculture’s Census of Agriculture and the United States Census Bureau to evaluate ownership fragmentation metrics and social drivers of land ownership change across a large geographic region. I used these data to quantify ownership fragmentation and explanatory variables that are hypothesized to explain variation in ownership fragmentation (e.g., total population, asset value per acre), and to analyze the systematic forces that influence ownership fragmentation of working lands across the southeastern United States. I identified important trends and relationships between ownership fragmentation, population, and land value across the southeastern United States that can be used to inform public and private decision makers, and to evaluate land use policies

in light of conservation and natural resource policy efforts to maintain critical resources and ecosystem services delivered from privately owned land.

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“Count it all joy, my brothers, when you meet trials of various kinds, for you know that the testing of your faith produces steadfastness. And let steadfastness have its full effect, that you may be perfect and complete, lacking in nothing.”

James 1:2-4

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Background

Privately owned farms, ranches, and forests (i.e., "working lands") provide valuable ecosystem services that we rely on for food, clean air, water, fiber, wildlife habitat, recreation, and rural economies (TAMU-IRNR 2014). Rural working lands also preserve scenic landscapes, protect biodiversity, and contribute to flood control (Rissman et al. 2007, Sundberg 2014, Ham et al. 2015). While valuable from an economic and ecological standpoint, working lands are highly susceptible to conversion from one land use type to another (e.g., agricultural to residential). Changing landowner demographics, rapid population growth, increasing market values, and stagnant agricultural values facilitate the sub-division and conversion of working lands (Kjelland et al. 2007). Such divisions can have major impacts on rural landscapes with the potential for loss of open space, localized loss of farm, ranch, and forest production, and a reduction in contiguous wildlife habitat (Collinge 1996, Wilkins et al. 2003).

The process of land use conversion includes ownership fragmentation, or ownership parcelization, which I define here as the division of rural working land under a single ownership into smaller parcels with multiple owners (Wilkins et al. 2000, Drzyzga and Brown 2002, Ko and He 2011). This is different from land and habitat fragmentation, which are generally described as the spatial discontinuity of habitat patches or land cover, because ownership fragmentation focuses on the human aspect rather than the structural dimensions of landscapes. Ownership fragmentation can often serve as a proxy for land and habitat fragmentation because changes in ownership size generally represent external pressures on landowners (e.g., urban development, land tenure and inheritance, changing management objectives, markets, and economies, and rapidly increasing populations), which can result in adjacent properties with different management objectives (Hatcher et al. 2013). As such, ownership fragmentation can have serious implications for how landscapes are managed and how socio-economic changes affect the pattern, composition, and characteristics of the land (Donnelly and Evans 2008).

In some circumstances, ownership fragmentation can result in property sizes that are too small to operate at the economy of scale for traditional farming, ranching, and forestry uses (Wilkins et al. 2000, Germain et al. 2006, Hatcher et al. 2013). Parcelization of larger properties into smaller parcels and their subsequent sale on the market can have significant impacts on the uses available to the new landowner (Kennedy and McFarlane 2009, Haines and McFarlane 2012). As a result, this process often facilitates the transition of land from one land use to another (Donnelly and Evans 2008), as land use and land cover change commonly follow parcel lines (Croissant 2004). In addition, parcelization inhibits the coordination of landowner management to maintain ecological processes and services that extend beyond individual property boundary lines (Collinge 1996), and therefore represents a barrier to effective wildlife management and conservation (Wilkins et al. 2003). The rate and scale of land cover change increases with parcelization (proportional to the number of landowners, and inversely proportional to average parcel size), creating economic pressures (i.e., increased market value, decreased production values, and increased taxation rates) that results in further degradation in natural resource services (Haines et al. 2011). As humans become more dependent on the self-renewing capacity of our ecosystems, the need for integrative land management strategies that address the drivers of this issue is critical (Collinge 1996, Kjelland et al. 2007, Rissman et al. 2007).

Texas Land Trends

The Texas Land Trends project provides a decision support tool that identifies and informs key natural resource and land use issues in Texas. Researchers working on this project publish the Texas Land Trends report every five years following the availability of the quinquennial Census of Agriculture data set (TAMU-IRNR 2014), which includes information from the Texas State Comptroller of Public Accounts (www.comptroller.texas.gov), the United States Department of Agriculture’s National Agricultural Statistics Service Census of Agriculture (https://www.agcensus.usda.gov/), the United States Census Bureau (http://www.census.gov/topics/population/data.html), and the United States Department of Agriculture’s National Resources Inventory (http://www.nrcs.usda.gov/wps/portal/nrcs/main/national/technical/nra/nri/). Ultimately, the Texas Land Trends report illustrates the relationships among land value, land ownership, and land use in Texas working lands, collectively known as privately owned farms, ranches, and forests (TAMU-IRNR 2014).

In Texas and elsewhere, ownership fragmentation is correlated with a number of metrics including changing demographics, rural land values, exurban development, and operational challenges (Conklin and Lesher 1977, Chicoine 1981, Wilkins et al. 2000).

According to a United States Census Bureau study from 2013, Texas contains seven of the 15 most rapidly growing cities in the nation (United States Census Bureau 2012). From 1997 to 2012, the Texas population increased from 19 million to 26 million residents (a 36% increase) with the majority (87%) of this increase occurring within the state's top 25 highest growth counties (TAMU-IRNR 2014). Changes in population density in Texas are significantly spatially correlated with changes in property size and changes in consumptive values of rural land (Kjelland et al. 2007). The 2014 Texas Land Trends report (TAMU-IRNR 2014) indicated that since 1997, Texas sustained a net loss of approximately 1.1 million acres of working lands that were converted to non-agricultural land uses. During the same time period, Texas gained over 21,000 new farms and ranches while the average ownership size declined from 581 acres to 521 acres (TAMU-IRNR 2014).

Ownership or parcel size is inversely proportional to market and production values, indicative of an economic threshold in perceived economic profitability which results in a distributional shift toward smaller parcel sizes over time (Kjelland et al. 2007). In 2012, Texas working lands averaged an appraised market value of approximately $1,573 per acre, a 214% increase since 1997, and a 36% increase since 2007 (TAMU-IRNR 2014). The rising demand for land as a result of rapid population growth has contributed to an increase in land market values, and an increasing gap between the market value (the consumer demand as influenced by location, land use, recreational opportunities, and other characteristics) and the productivity value (the land's capacity to produce commodities such as crops, cattle, and forest products). The increasing gap between the market value and productivity value varies widely by region but is most pronounced in areas dominated by urban centers, the transportation corridors that connect them, or rural areas in close proximity to urban centers that offer outdoor recreational opportunities (Pope III 1985, Shi et al. 1997, Kjelland et al. 2007). Results from a study on agricultural land values under urbanizing influences indicate that both farm income and urban proximity are important factors affecting the value of farmland (Shi et al. 1997). The authors found that the price differential between land use value and market value is inversely related to the distance and directly related to the population density of urban areas (Shi et al. 1997). Trend data from the most recent Texas Land Trends report also suggests the magnitude of the difference between market value and productivity value appears to be a predictor of land use conversion and ownership fragmentation (TAMU-IRNR 2014).

Collectively, population growth, population density, market and production value differentials, and ex-urban development all contribute to the growing epidemic of working land loss and ownership fragmentation. While local and regional differences in natural resources, industry, taxation, socio-economic policy, population demographics, and other factors undoubtedly contribute to anisotropic fragmentation of working lands, it is clear that further research is needed to fully understand the collective influence of these metrics and their predictive power in determining future areas with impending impacts.

Quantifying Ownership Fragmentation

One challenge in studying ownership fragmentation is the lack of an agreed upon measure or metric for judging and comparing the extent to which a landscape has been parcelized, which creates difficulties in determining where and how to prioritize efforts to minimize the effects of ownership fragmentation over broad landscapes (Kilgore and Snyder 2016). Parcel size data constitute the most appropriate level of geographic detail for research and analysis involving ownership fragmentation of private lands (Committee on Land Parcel Databases: A National Vision et al. 2007), however, quantifying fine-scale changes in land use across broad spatial scales and accessing georeferenced parcel data that is consistent, comparable, and historical beyond the extent of a single county or urban area is extremely difficult (Bentley 1987, Irwin and Bockstael 2007, Kilgore et al. 2013).

One feasible option to examine trends in ownership fragmentation across a broad geographic study area is to use information from national data sets compiled by the United States Department of Agriculture's (USDA), National Agricultural Statistics Service (NASS) Census of Agriculture (hereafter, Ag Census). Previous research on ownership parcelization determined that the composition of a landscape, particularly the amount of area covered by working lands, corresponds with parcel boundaries, supporting the hypothesis that parcelization highly influences spatial patterns of land use, land cover, and the configuration of rural lands (Croissant 2004). Some studies have shown a distinct link between ownership fragmentation and increases in land use change (Gustafson and Loehle 2006, Haines et al. 2011), and evidence suggests that ownership parcel size is an indicator of land use, where small, dense parcels are common in urbanized areas and larger land holdings are more associated with rural agriculture (Donnelly and Evans 2008). As such, using the data set that best represents land ownership sizes and changes is important for exploring trends in ownership fragmentation and its impact on the potential loss of working lands through land use and land cover changes (Brown et al. 2000, Kjelland et al. 2007).

The Ag Census ownership data set reports working lands as the number of farms and acres of farms by size class each census year (1997, 2002, 2007 and 2012) for every county in the United States. This data set provides four consistent and extensive data points from which general indicators of ownership fragmentation can be analyzed, including change in average farm size, change in proportion of total agricultural land, change in the area (acres) of small farms, and change in the number of small farms. While average farm size cannot accurately depict the distribution of farm sizes, and can be skewed by a large number of small farms (Kittredge et al. 2008), this metric can provide a relative indicator of changes in farm size over time. For example, if average farm size increases over time, it may indicate that either farm consolidation or a loss of small farms has occurred. Conversely, if average farm size decreases over time, it may indicate that either ownership fragmentation or a loss of large farms has occurred (Kilgore et al. 2013).

Because average farm size does not capture the total amount of agricultural land within a landscape, changes in the proportion of total agricultural land can also be used to characterize ownership fragmentation. This metric quantifies land use change by measuring changes in total area of agricultural land as proportions of total county area. The change in the number and area of small farms are two additional ownership fragmentation metrics that can address the distribution of farm size classes and how they have changed over time. The number and area of small farms generally represents ownership fragmentation as larger farms are sub-divided; an increase in the number or acres of small farms must come from either farms in larger size classes (larger farms fragmented into smaller farms), farms within small size classes (small farms fragmented into smaller farms), or from newly created agricultural land (non-agricultural land use converted to agricultural land). While these small farm metrics ignore the full distribution of size classes and their changes, they are the only measureable areas where we generally know the source of the farm increase. Collectively, these ownership fragmentation metrics can provide insight into the degree of ownership fragmentation occurring across a landscape.

Explaining Patterns in Ownership Fragmentation

Ownership fragmentation can be highly influenced by various socio-demographic factors. The movement and distribution of people on the landscape has a direct impact on how land is used and distributed (Kline et al. 2004). Change in total population and population density, as reported by the United States Census Bureau, are two measures that capture this influence over the landscape. Large increases in population or population density could indicate changes in private, rural ownerships, and subsequent changes on the landscape.

As a result of population increases, high rates of housing growth and accompanying development of suburban amenities threaten all rural lands, but especially small farms directly surrounding urban centers (Berry 1978, Munroe and York 2003, Kjelland et al. 2007). Rapid development creates demand for surrounding open lands leading to rapid spikes in land market values. Working lands may be distinguished by land use, land cover, ownership type, development potential, and geographic location, each of which may be valued differently (Irwin 2002). One method of valuing rural land can be found in the summation of the market and productive values (Pope III 1985), reported by the Ag Census as farm asset value (asset value per acre and asset value per operation) and farm related income (receipts per operation). Analyzing land asset value can identify areas where working lands are in high demand and may indicate encroaching urban growth. One can also consider the difference between the asset value and the income to represent the growing disconnect often found in lands highly susceptible to ownership fragmentation or conversion; as urban areas grow in population, and demand for real estate increases, surrounding rural lands increase in market value while the land's agricultural productivity value remains the same (Pope III 1985). Analyzing the asset value-income differential of privately owned rural lands identifies areas where urban pressures could have greater influence over spatial patterns of land use and ownership.

Relationships between ownership fragmentation and socio-economic and demographic factors, such as population and land asset value, vary by both political and ecological boundaries. The organization of state and local governments varies widely across the United States, as do the ecological conditions that exist within and between them. Ecoregions are defined as broad geographic areas with similar ecological conditions, such as geology, physiography, vegetation, climate, soil, land use, wildlife, and hydrology (United States Environmental Protection Agency 2013). As we are faced with overriding concerns that ownership fragmentation will lead to the development and conversion of our working lands, there is an immediate need for research that evaluates the relationships between ownership fragmentation measures and socio-economic and demographic drivers across multiple states and ecoregions (Engle 2002, Gobster and Rickenbach 2004).

OBJECTIVES

The objectives of my study are to evaluate ownership fragmentation metrics and social drivers of land ownership change beyond a local or regional area (e.g., Texas Land Trends), and to analyze the systematic forces that influence ownership fragmentation of working lands across a large geographic region, the southeastern United States (Clement and Podowski 2013). I will first quantify ownership fragmentation metrics and explanatory variables that are hypothesized to explain variation in ownership fragmentation (e.g., total population, asset value per acre) across states and ecoregions. I will then specifically address the following questions for each ownership fragmentation variable:

1. Does ownership fragmentation, population density, and land value vary across states and ecoregions?
    a. Null hypothesis: State and ecoregion boundaries have no effect on ownership fragmentation, population density, and land value.
    b. Prediction: I predict there will be no difference in ownership fragmentation, population density, and land value across states, as state lines are artificial, political boundaries. I predict ownership fragmentation, population density, and land value to be different across ecoregion boundaries due to the broader land uses and ecological conditions available to a region.

2. Is there a relationship between ownership fragmentation, population density, and land value within and across states and ecoregions?
    a. Null hypothesis: There is no relationship between ownership fragmentation, population density, and land value within and across states and ecoregions.
    b. Prediction: I predict that there will be a positive relationship between population density and each of my ownership fragmentation metrics, and a positive relationship between land value and each of my ownership fragmentation metrics. I predict there will be no difference in both of these relationships between states, and I predict both of these relationships will vary across ecoregions due to the broader land uses and ecological conditions available to a region.

Changes in the demand for rural land in combination with rapid population growth and changing land market values threatens working lands, and the ecosystem services they provide not only in Texas, but across the entire United States. Based on the Texas Land Trends model, an expanded regional study in the southeastern United States could provide a comprehensive data set with timely information to both public and private decision makers on a regional, landscape scale. These trends could then be used to evaluate land use policies in light of conservation and natural resource policy efforts to maintain critical resources and ecosystem services delivered from privately owned land across multiple state boundaries (Kjelland et al. 2007). My southeastern regional study, as an extension of the Texas Land Trends project, will address ownership fragmentation across the region and identify influences that drive the breakup of rural working lands.

METHODS

Study Area

My study area includes Texas, Oklahoma, Arkansas, Louisiana, Alabama, Mississippi, Georgia, South Carolina, and Florida in the southeastern United States (Figure 1, Table 1). These states are characterized by a tradition of rural working land ownership that can be used to compare ownership fragmentation trends at a regional scale, but also represent varying land areas, land use types, average farm sizes, amounts of agricultural land, rates of population growth, land values, and land incomes, among others. Specifically, the Southeast includes multiple ecoregions, which are represented at a county level by the United States Department of Agriculture's (USDA) five Farm Resource Regions. Farm Resource Regions include the Eastern Upland, Fruitful Rim, Mississippi Portal, Prairie Gateway, and Southern Seaboard (Figure 2, Table 1). The USDA's Economic Research Service (ERS) constructed Farm Resource Regions depicting geographic specialization in production of United States farm commodities (Economic Research Service 2000). These county level regions represent areas of similar physiographic, soil, and climatic traits, and reflect a combination of analyses conducted by the USDA, including a cluster analysis of United States farm characteristics, the old Farm Production Regions, the Land Resource Regions, and NASS Crop Reporting Districts (Economic Research Service 2000) (Figure 2). I used the USDA's county level Farm Resource Regions instead of ecoregions described by

Table 1. Total counties, sample sizes (n), and area (acres) for each state and Farm Resource Region (region) in the southeastern United States.

State or Region		**Counties**	***n*[a]**	**Acres**
State				
	Alabama	67	65	33,086,944
	Arkansas	75	75	34,034,430
	Florida	67	63	37,303,560
	Georgia	159	152	37,704,882
	Louisiana	64	60	30,181,950
	Mississippi	82	82	30,516,327
	Oklahoma	77	77	44,735,290
	South Carolina	46	44	19,914,048
	Texas	254	245	169,947,148
Region				
	Eastern Upland	97	97	43,764,473
	Fruitful Rim	145	132	96,609,370
	Mississippi Portal	132	128	55,631,162
	Prairie Gateway	212	211	130,083,902
	Southern Seaboard	305	295	111,335,672
Total				
	Southeast United States	891	863	437,424,579

[a]Sample sizes reflect missing data omissions.

Figure 1. Map of all states, counties, and major cities in the southeastern United States. Includes Texas, Oklahoma, Arkansas, Louisiana, Mississippi, Alabama, Georgia, South Carolina, and Florida.

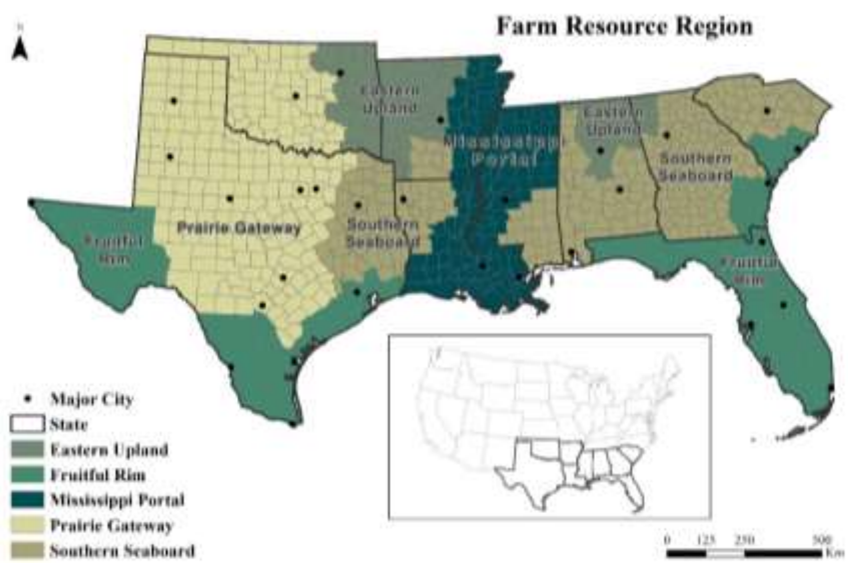


Figure 2. Map of the USDA Economic Research Service's Farm Resource Regions and major cities for all states in the southeastern United States.

other sources, such as Omernik (Omernik 1987), in order to maintain data scale consistency across all data sets.

Data

The data set I used to examine ownership fragmentation and identify the influences that drive the breakup of rural working lands in the southeastern United States includes information obtained from the United States Department of Agriculture (USDA), National Agricultural Statistics Service (NASS), Census of Agriculture (hereafter, Ag Census) (https://www.nass.usda.gov/Quick_Stats/), the United States Census Bureau (hereafter, Census Bureau) (http://www.census.gov/topics/population/data.html), and the USDA's Economic Research Service (ERS) (http://www.ers.usda.gov/) (Table 2). The Ag Census is conducted every five years and provides uniform, comprehensive agricultural data for every county in the United States. This data set provides valuable information on farms and ranches and their operators and is used to make decisions about issues that impact not only farmers and ranchers, but also impact wildlife, water, and natural resources (National Agricultural Statistics Service 2014).

From Ag Census, I used ownership size (acres operated and number of operations by county) data to calculate average farm size, proportion of agricultural land, acres of small farms by size class (<50 acres, <100 acres, <500 acres), and number of small farms by size class (<50 acres, <100 acres, <500 acres) for years 1997 and 2012 and the percent change from 1997–2012 for each county (Table 3). The Ag Census defines farms as any property from which $1,000 or more of agricultural products

Table 2. Sources and descriptions of ownership fragmentation and explanatory data used in a study examining differences in ownership fragmentation across the southeast United States using explanatory land demographic variables.

Data set	**Source**	**Description**
Number of small farms	USDA Census of Agriculture	Number of farms by size class (number of farms)
Acres of small farms	USDA Census of Agriculture	Acres of farms by size class (acres of farms)
Asset value	USDA Census of Agriculture	Land market value including all buildings and improvements ($/acre and $/operation)
Income	USDA Census of Agriculture	Gross income from farm-related sources received before taxes and expenses ($/operation)
Population	US Census Bureau	Census county annual estimates 1997–2012
Farm Resource Region	USDA Economic Research Service	County level geographic specialization of production of U.S. farm commodities

were produced and sold, or normally would have been sold, during the census year (National Agricultural Statistics Service 2013). The number and acres of small farms generally indicates ownership fragmentation as larger farms are sub-divided into small farms, increasing the overall totals for each metric. Because the Ag Census collects and reports personal data provided by farmers and ranchers, some counties in each data set withhold information to protect the privacy and confidentiality of landowners (Table 1). In these cases, I omitted the county from data analyses.

The United States Census Bureau conducts nation-wide surveys every ten years and is the leading source of statistical demographic information in the nation. Subjects include groups such as children, veterans, and the foreign-born, and characteristics such as age, sex, race, Hispanic origin, migration, ancestry, and language use, as well as health, education, employment, income and poverty level (United States Census Bureau 2015). I used population data compiled from Census Bureau county annual estimates (1990–1999, 2000–2010, and 2010–2014) to calculate total population and population density (population/acre) per county for 1997, 2012, and the percent change from 1997–2012 (Table 3).

I also used the land value (asset value and income by county) data set from Ag Census to calculate asset value per acre ($/acre), asset value per operation ($/operation), and the asset value-income difference per operation ($/operation) for 1997, 2012, and the percent change from 1997–2012 for each county (Table 3). The asset value metric ($/acre and $/operation) represents the market value of the land including all buildings and improvements. Total income from farm-related sources ($/operation) includes gross income from farm-related sources received before taxes and expenses from the sales of farm byproducts and other sales and services closely related to the principal functions of the farm business (National Agricultural Statistics Service 2012). I omitted counties with no data from data analyses (Table 1).

Table 3. Names and descriptions for all 8 ownership fragmentation variables and 5 explanatory variables used in initial Spearman's rank correlation analyses. An * indicates the 4 ownership fragmentation variables and 3 explanatory variables used in final analyses.

Variable		**Description**
Ownership Fragmentation		
	AvgFarmSize*	Average farm size 1997, 2012, and % change 1997–2012
	PropAg*	Proportion of total ag land to county acres 1997, 2012, and % change 1997–2012
	AcresLess50	Acres of farm less than 50 acres in size 1997, 2012, and % change 1997–2012
	AcreLess100	Acres of farms less than 100 acres in size 1997, 2012, and % change 1997–2012
	AcreLess500*	Acres of farms less than 500 acres in size 1997, 2012, and % change 1997–2012
	FarmLess50	Number of farms less than 50 acres in size 1997, 2012, and % change 1997–2012
	FarmLess100	Number of farms less than 100 acres in size 1997, 2012, and % change 1997–2012
	FarmLess500*	Number of farms less than 500 acres in size 1997, 2012, and % change 1997–2012
Explanatory		
	Pop	Total population in 1997, 2012, and % change 1997–2012
	PopDens*	Population density 1997, 2012, and % change 1997–2012 (people/acre)
	AssetPerAcre*	Asset value per acre 1997, 2012, and % change 1997–2012 ($/acre)
	AssetPerOp	Asset value per operation 1997, 2012, and % change 1997–2012 ($/operation)
	AVIDiffPerOp*	Asset value-income difference per operation 1997, 2012, and % change 1997–2012

*Final variables chosen for the regression model analyses.

Analysis

Because I thought that many of my ownership fragmentation and explanatory variables could represent the same trends across and within states and Farm Resource Regions, I first used Spearman's rank correlation tests to refine my data set and select variables that represented unique aspects of ownership fragmentation and socio-economic demographics. I visually mapped trends for each ownership fragmentation and explanatory variable using ArcMap 10.3 geospatial software (Environmental Systems, Research Institute, Inc., Redlands [ESRI], CA, USA).

I then calculated two-way analyses of variance (ANOVA) for each of my final ownership fragmentation variables and each of my explanatory variables to assess differences in means across and within states, Farm Resource Regions, and years. My two-way ANOVAs represented interactions between state and year and Farm Resource Region and year for each ownership fragmentation and explanatory variable. When I found no significant interaction ($\alpha < 0.05$), I conducted single-factor ANOVAs to examine variation in my ownership fragmentation and explanatory variables independently across year, state, and Farm Resource Region. I used Tukey's honest significant difference test (Tukey's HSD) to calculate post-hoc comparisons for each variable and to determine which means were significantly different. These analyses served to explore differences over time and space and to determine variation in ownership fragmentation and land demographic variables across states and Farm Resource Regions (Objective 1). I also conducted single factor ANOVAs on all mean percent change (1997–2012) variables across states and regions to explore differences in the rate of ownership fragmentation and in the rate of change in explanatory variables over the 15-year time period (Objective 1). I again used Tukey's HSD tests to identify significant differences in mean percent changes.

I then used a generalized linear model approach to determine which final explanatory metrics best predicted each final ownership fragmentation variable (Objective 2). For each ownership fragmentation variable, I used a candidate model set that included an intercept model, main effects models representing my final explanatory variables, and models representing interactions between my socio-economic variables and state and Farm Resource Region. I chose best-fit models based on Akaike's Information Criterion (AIC_c), a measure of model adequacy that adjusts for small sample sizes and accounts for the number of parameters included in the model, and Akaike Weights (w_i), a measure of relative likelihood of a model (Sugiura 1978, Burnham and Anderson 2002). I selected models with $\Delta AIC_c > 2.0$ and relatively high w_i values as best-fit. For variables with two plausible models (each model contains $\Delta AIC_c < 2.0$), I considered relationships from both, instead of using a model averaging approach, because both model parameters included informative and important variables that aligned with other ownership fragmentation regression results. Using the best-fit models, I estimated regression coefficients to predict values for each of my ownership fragmentation variables given the best explanatory predictors, and calculated 95% confidence intervals for each relationship. Finally, I examined the 95% confidence intervals for each predicted ownership fragmentation variable to determine the statistical and realistic significance of each relationship. I conducted all statistical analyses using R statistical software (R Development Core Team 2016).

RESULTS

Spearman's correlation analyses on all ownership fragmentation variables revealed high, statistically significant correlations (*P* < 0.05) between all size classes (<50 acres, <100 acres, and <500 acres) for both acres and number of farms across states and Farm Resource Regions (hereafter, region) (Appendix A). As such, I selected the following variables to represent unique aspects of ownership fragmentation: average farm size, proportion of agricultural land, acres of farms <500 acres in size, and number of farms <500 acres in size (Table 3). I chose the largest size class, farms 1–500 acres in size, as an inclusive representative of all small farms across the southeast United States because the acres of farms <500 acres in size (hereafter, acres of farms) and number of farms <500 acres in size (hereafter, number of farms) metrics account for diverse small land ownership patterns across the Southeast (mean average farm sizes in 2012 ranged from 238–1,618 acres). Results of Spearman's correlation analyses on all explanatory variables revealed high, statistically significant correlations (*P* < 0.05) between population metrics, population change and population density, and between asset value metrics, asset value per acre and asset value per operation (Appendix A). Because the variables within these two pairs of data were redundant and significantly correlated, I selected population density and asset value per acre to represent unique aspects of population growth and land value (Table 3).

I found statistically significant interactions between state and year and region and year for mean asset value per acre (Figure 3) and mean asset value-income difference per operation (Figure 4). Mean asset value per acre was 78–159% higher in 2012 when compared to 1997 across all states and regions. I observed the largest difference in mean asset value per acre from 1997–2012 in Florida (Δ = \$3,535 per acre, approximately 270% higher than any other state) and the Fruitful Rim (Δ = \$2,261 per acre, approximately 170% higher than any other region) (Figure 3). The state of Florida contained the highest mean asset values per acre in 2012 ($\bar{x}$ = \$6,088 per acre) across the entire Southeast, a 65% difference from second highest mean values in Georgia ($\bar{x}$ = \$3,719 per acre). Similarly, asset value-income difference per operation was 95–185% higher in 2012 than in 1997 across all states and regions. The largest changes in mean asset value-income difference per operation from 1997–2012 were observed in Texas (Δ = \$922,805 per operation) and the Fruitful Rim (Δ = \$997,952 per operation). The mean asset value-income difference per operation was approximately 230% higher in Texas than in any other state. Mean asset value-income differences per operation were approximately 150% higher in the Fruitful Rim than in the Prairie Gateway and Mississippi Portal regions, and approximately 360% higher than in the Eastern Upland and Southern Seaboard (Figure 4). I did not find statistically significant interactions for the following: (1) mean average farm size, state, and year (df = 8, F = 0.02, P = 1.00), (2) mean average farm size, region, and year (df = 8, F = 0.09, P = 0.99), (3) mean proportion of agricultural land, state, and year (df = 8, F = 0.35, P = 0.94), (4) mean proportion of agricultural land, region, and year (df = 4, F = 0.1, P = 0.98), (5) mean acres of farms, state, and year (df = 8, F = 0.44, P = 0.90), (6) mean acres of farms, region, and year (df = 4, F = 0.51, P = 0.73), (7) mean number of farms, state and year

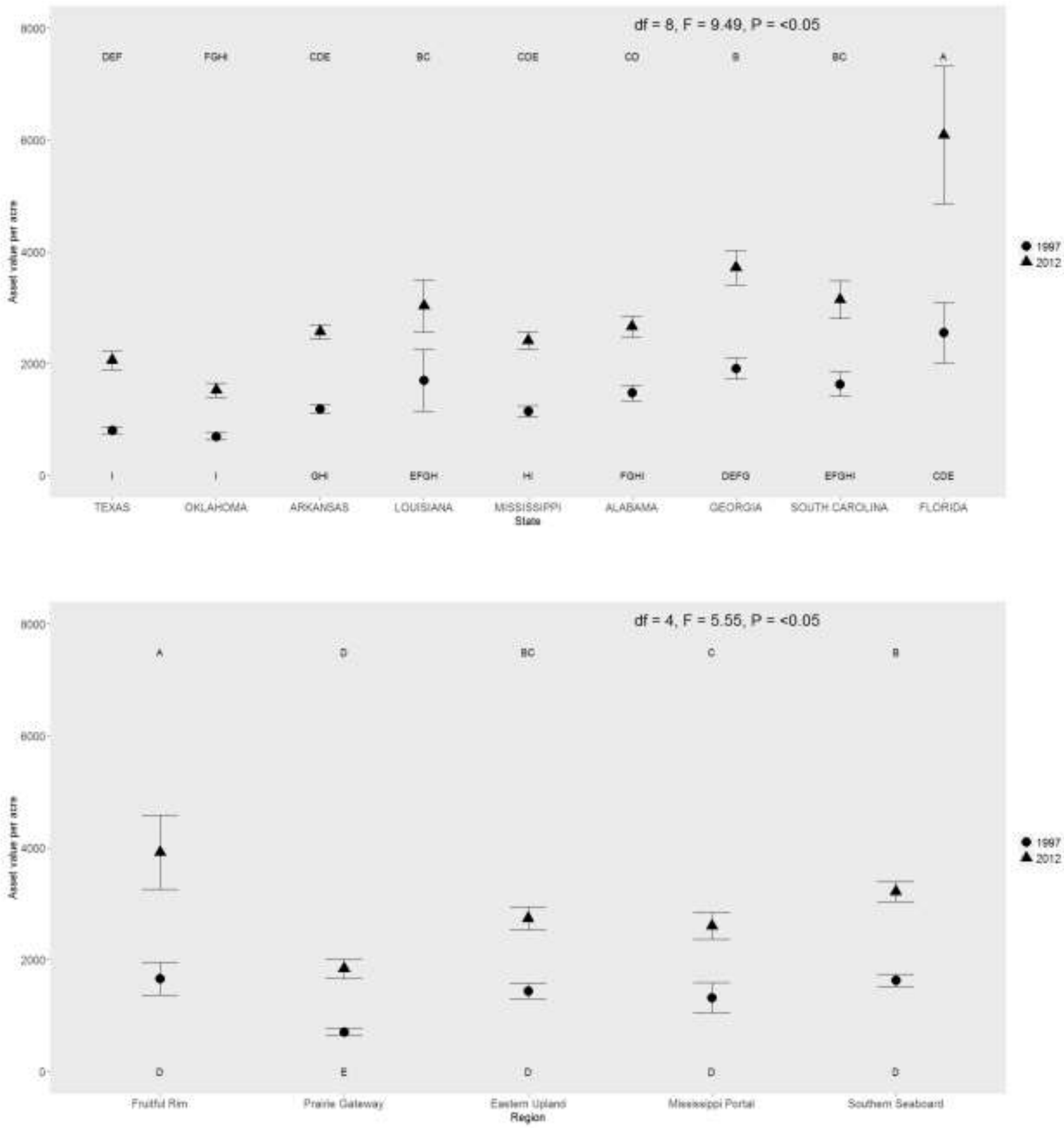


Figure 3. Mean asset value per acre ($/acre) and their associated 95% confidence intervals across states and Farm Resource Regions. Statistics (df = degrees of freedom, *F* = F-ratio, *P* = P-value) represent the results of two-way analyses of variance. Letters represent the results of Tukey's honest significance difference test. Each letter represents significant differences in mean values.

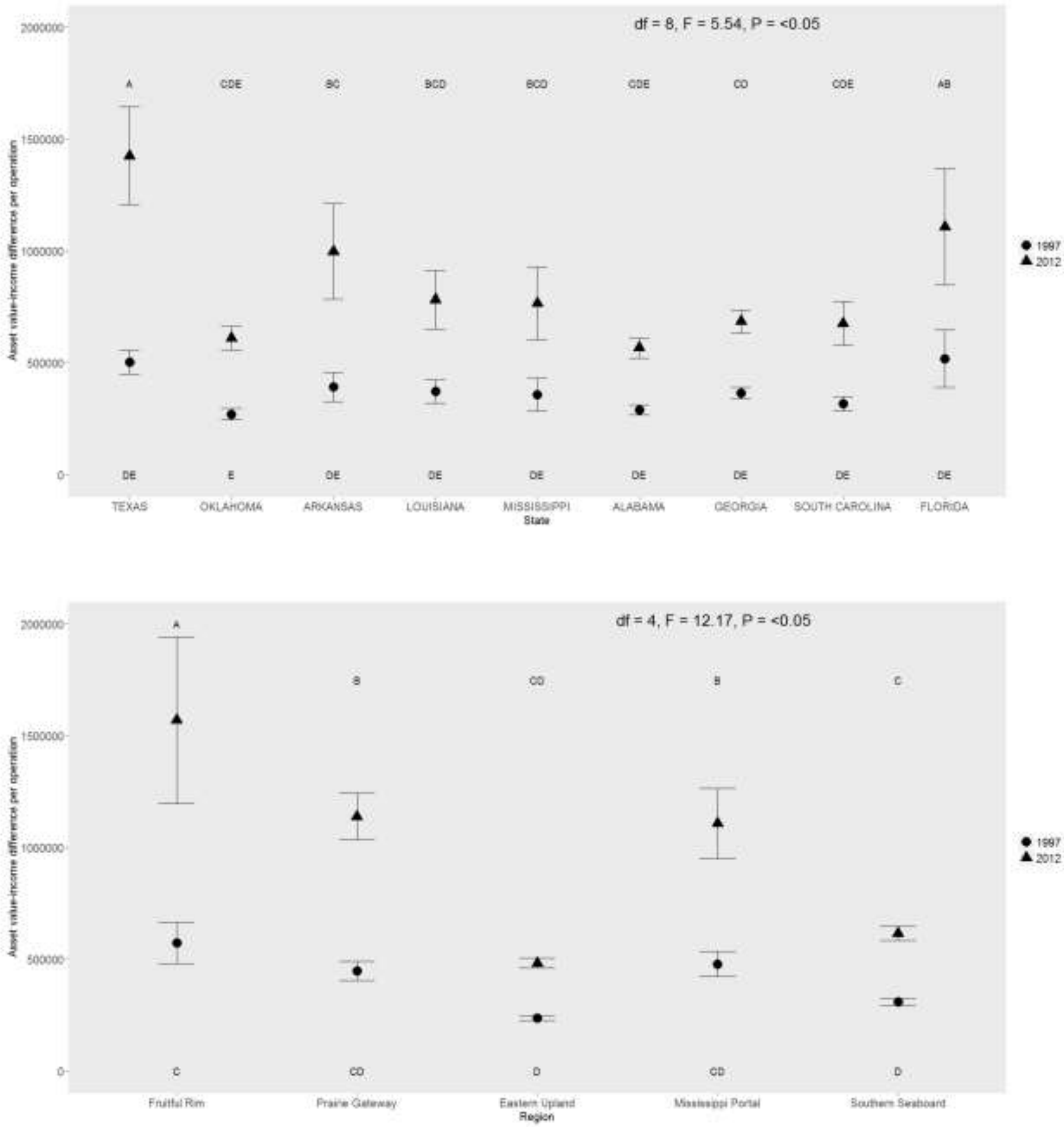


Figure 4. Mean asset value-income difference per acre ($/operation) and their associated 95% confidence intervals across states and Farm Resource Regions. Statistics (df = degrees of freedom, *F* = F-ratio, *P* = P-value) represent the results of two-way analyses of variance. Letters represent the results of Tukey's honest significance difference test. Each letter represents significant differences in mean values.

(df = 8, F = 0.91, P = 0.51), (8) mean number of farms, region, and year (df = 4, F = 0.99, P = 0.41), (9) mean population density, state, and year (df = 8, F = 0.12, P = 1.00), and (10) mean population density, region, and year (df = 4, F = 0.06, P = 0.99).

When I found no statistically significant interaction between year and state or region, I conducted single factor ANOVAs for my ownership fragmentation and explanatory variables. I found statistically significant differences across states and regions for the following: mean average farm size (Figure 5), mean proportion of agricultural land (Figure 6), mean acres of farms (Figure 7), mean number of farms (Figure 8), and mean population density (Figure 9). Mean average farm sizes in Texas ($\bar{x}$ = 1,659 acres) were about 240% higher than in Oklahoma ($\bar{x}$ = 490 acres), and about 475% higher than in Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, and South Carolina ($\bar{x}$ = 290 acres) (Figure 5). Similarly, mean average farm sizes in the Fruitful Rim ($\bar{x}$ = 1,659 acres) were approximately 55% higher than mean average farm sizes in the Prairie Gateway ($\bar{x}$ = 1,075 acres) and approximately 450% higher than in the Eastern Upland, Mississippi Portal, and Southern Seaboard ($\bar{x}$ = 298 acres) (Figure 5). Mean proportions of agricultural land in Texas and Oklahoma ($\bar{x}$ = 0.77) were approximately 145% higher than mean values in all other states ($\bar{x}$ = 0.32) (Figure 6). The Prairie Gateway region ($\bar{x}$ = 0.86) mirrored this trend with mean proportion of agricultural land values 120% higher in 1997 and 2012 than in the Fruitful Rim, Eastern Upland, Mississippi Portal, or Southern Seaboard regions ($\bar{x}$ = 0.40) (Figure 6). Texas and Oklahoma ($\bar{x}$ = 102,463 acres) contained approximately 155% more acres of farms

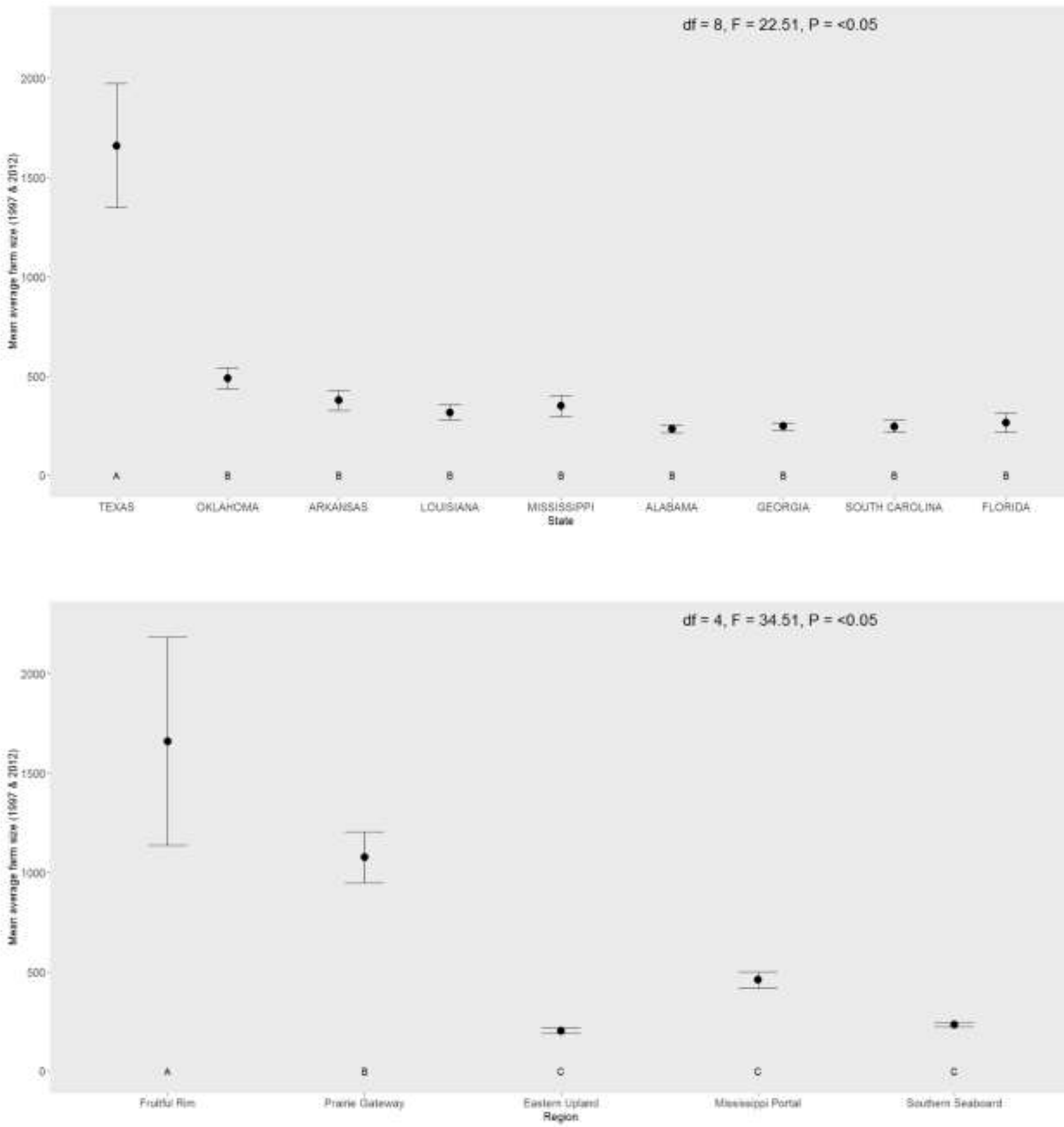


Figure 5. Mean average farm size and their associated 95% confidence intervals across states and Farm Resource Regions. Statistics (df = degrees of freedom, F = F-ratio, P = P-value) represent the results of single factor analyses of variance. Letters represent the results of Tukey's honest significant difference test. Each letter represents statistically significant differences in mean values.

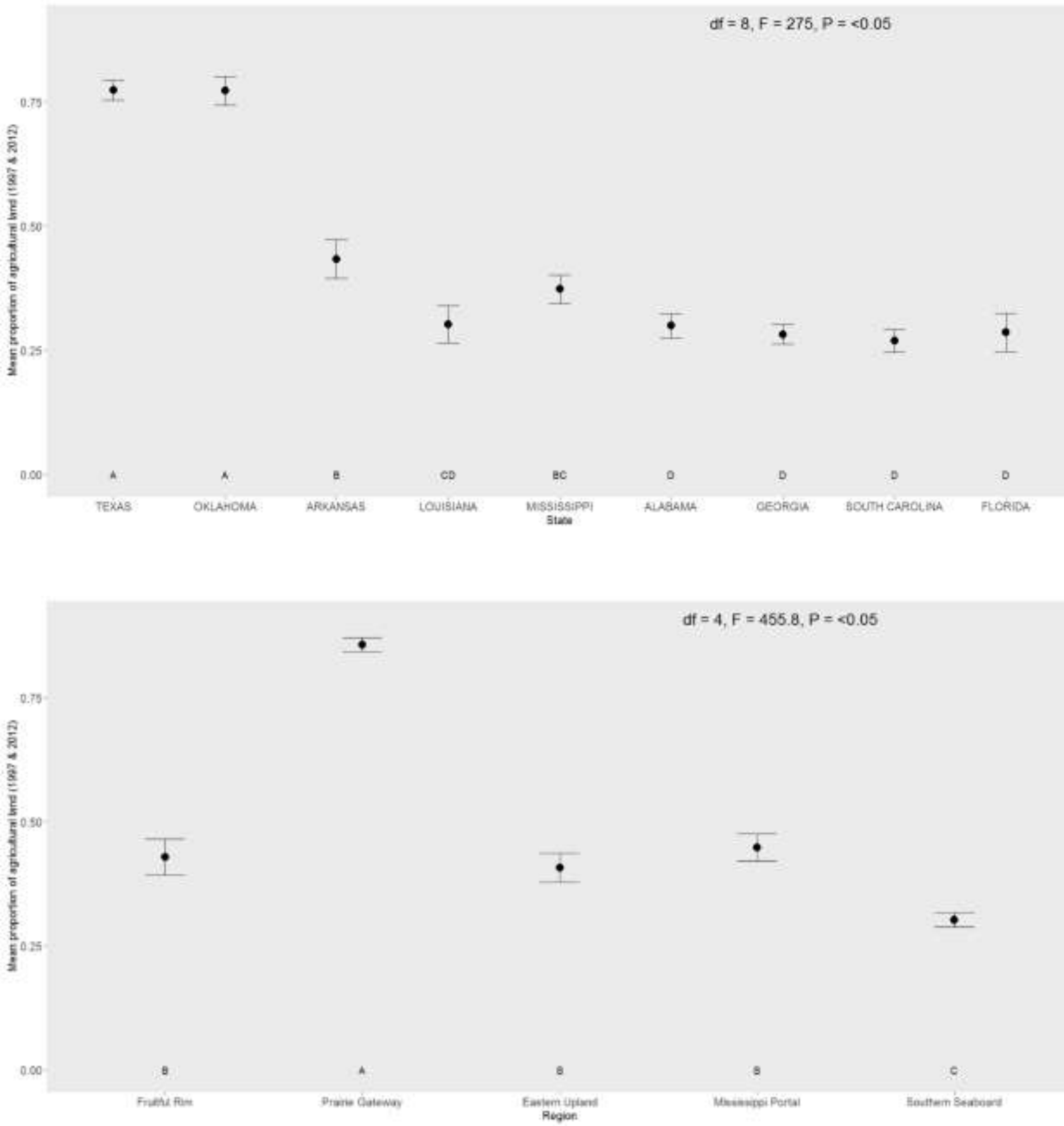
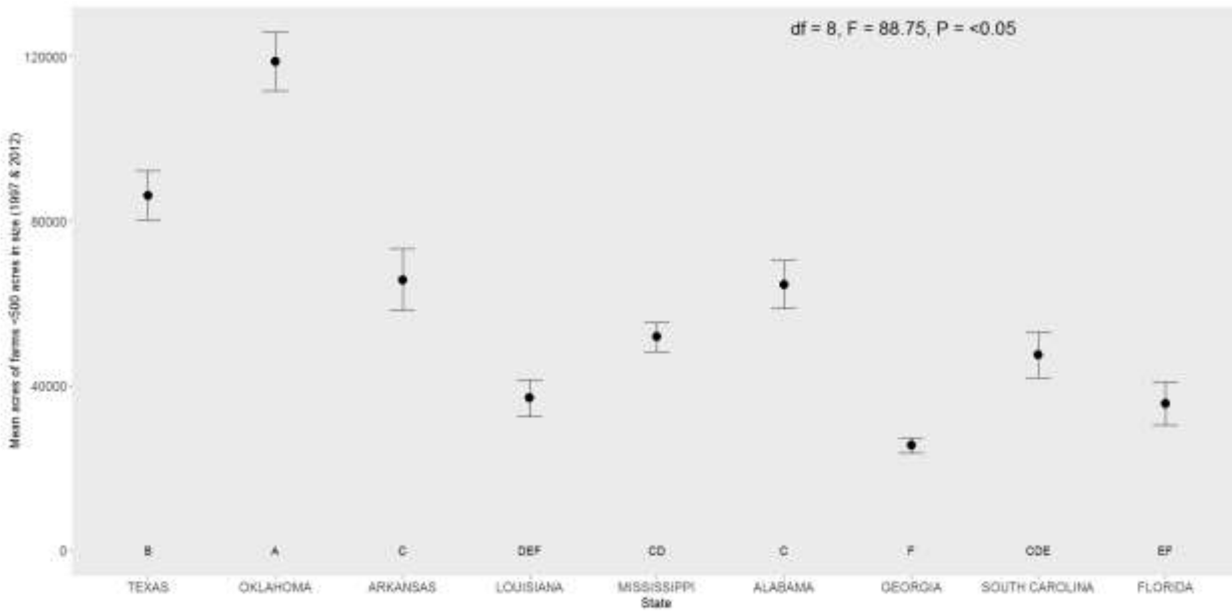


Figure 6. Mean proportion of agricultural land and their associated 95% confidence intervals across states and Farm Resource Regions. Statistics (df = degrees of freedom, *F* = F-ratio, *P* = P-value) represent the results of single factor analyses of variance. Letters represent the results of Tukey's honest significant difference test. Each letter represents statistically significant differences in mean values.



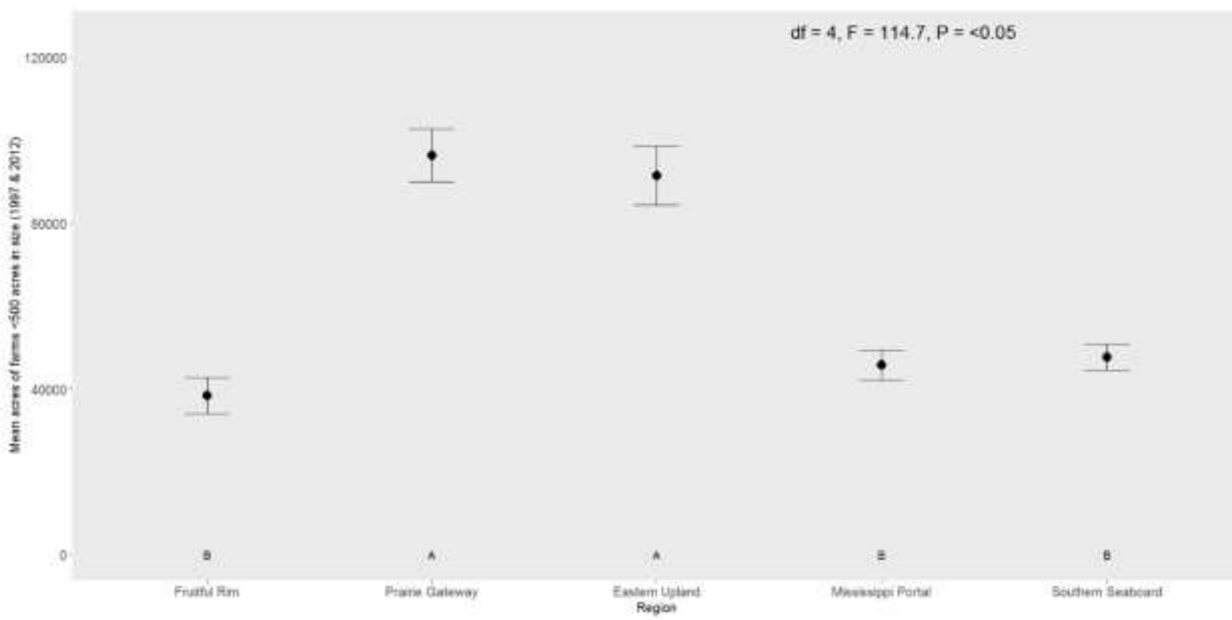


Figure 7. Mean acres of farms <500 acres in size and their associated 95% confidence intervals across states and Farm Resource Regions. Statistics (df = degrees of freedom, F = F-ratio, P = P-value) represent the results of single factor analyses of variance. Letters represent the results of Tukey's honest significant difference test. Each letter represents statistically significant differences in mean values.

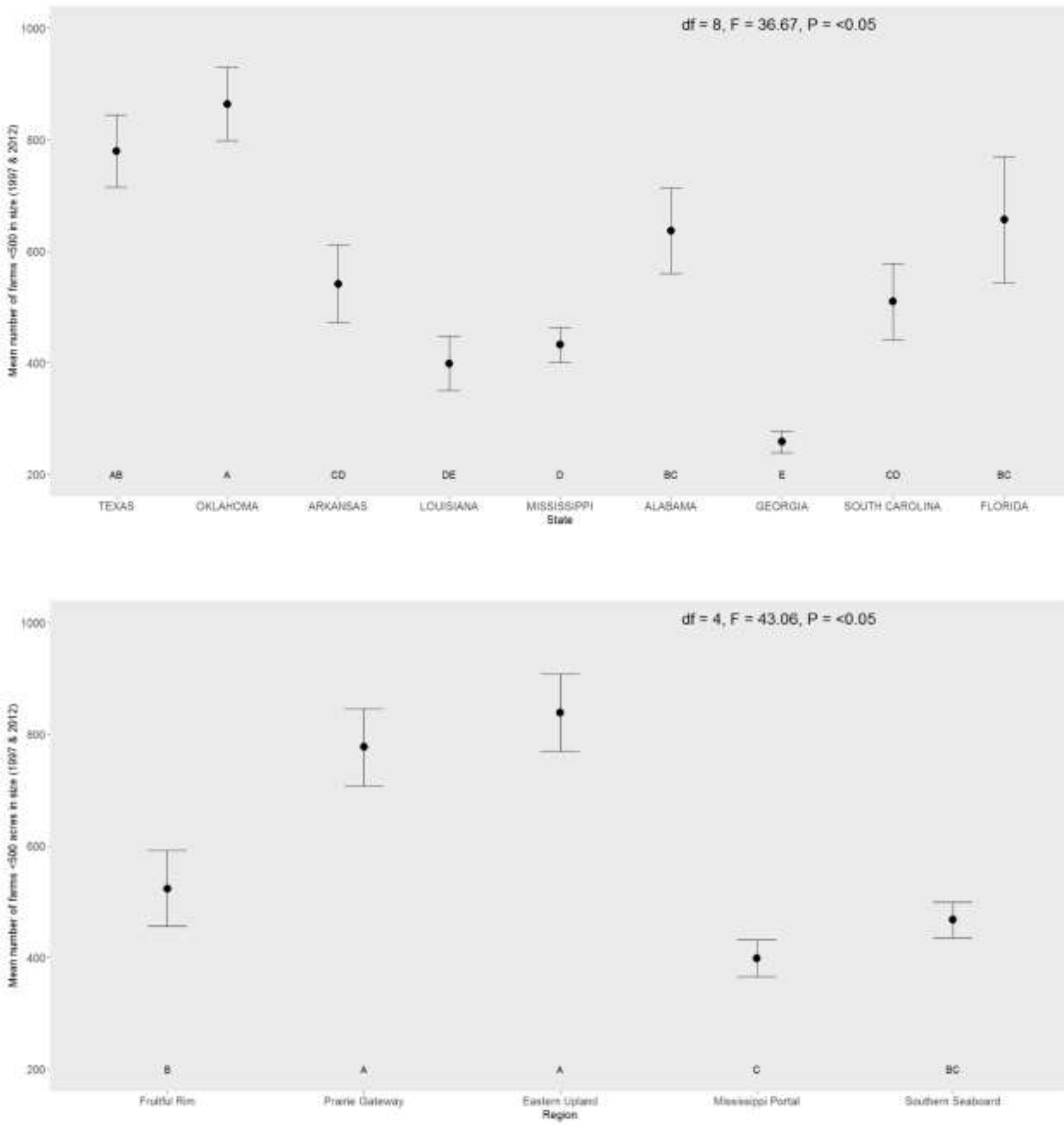


Figure 8. Mean number of farms <500 acres in size and their associated 95% confidence intervals across states and Farm Resource Regions. Statistics (df = degrees of freedom, *F* = F-ratio, *P* = P-value) represent the results of single factor analyses of variance. Letters represent the results of Tukey's honest significant difference test. Each letter represents statistically significant differences in mean values.

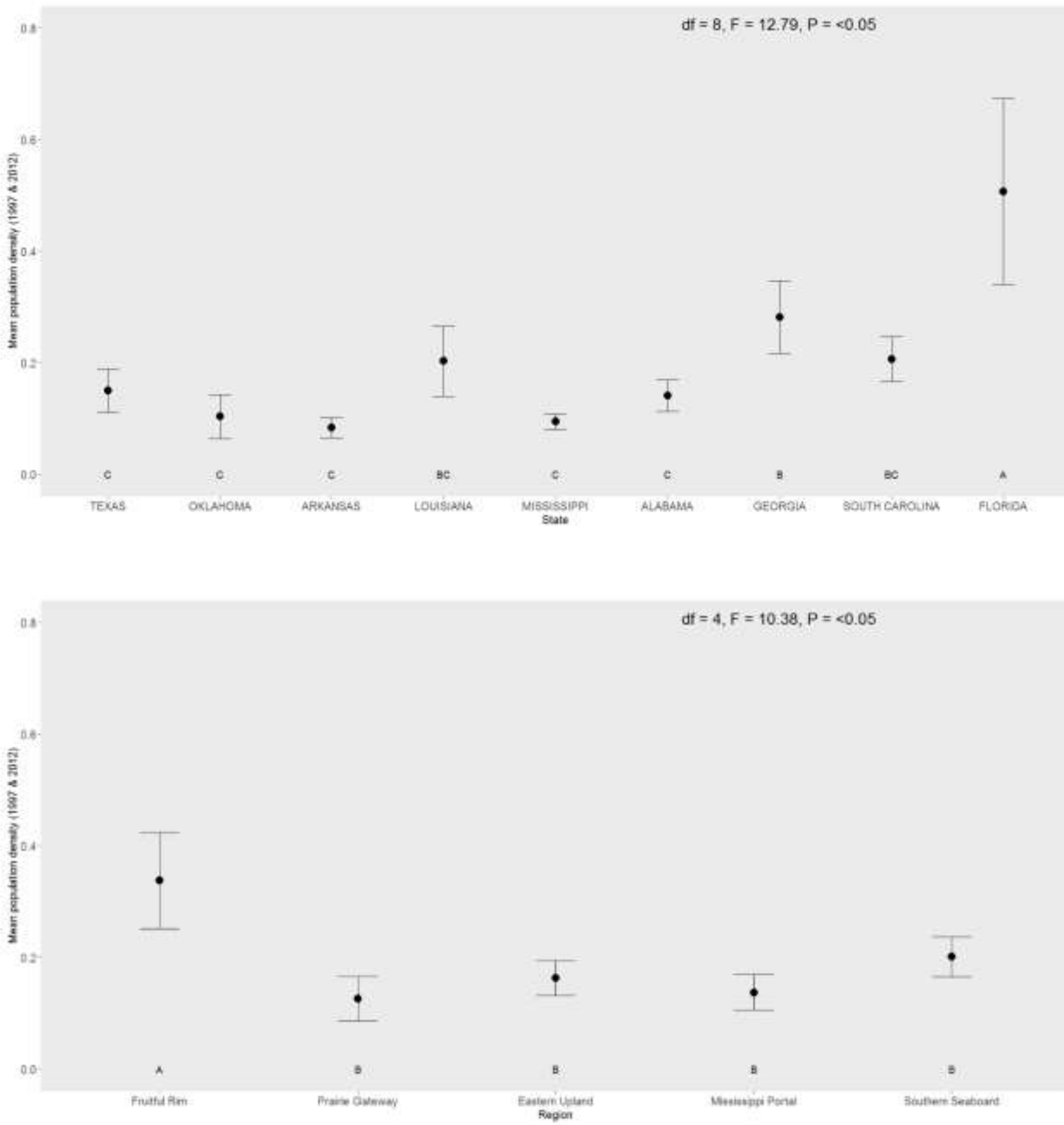


Figure 9. Mean population density and their associated 95% confidence intervals across states and Farm Resource Regions. Statistics (df = degrees of freedom, F = F-ratio, P = P-value) represent the results of single factor analyses of variance. Letters represent the results of Tukey's honest significant difference test. Each letter represents statistically significant differences in mean values.

in 1997 and 2012 than all other states ($\bar{x}$ = 46,792 acres) (Figure 7). The Prairie Gateway and Eastern Upland regions ($\bar{x}$ = 93,949 acres) observed approximately 115% more mean acres of farms in 1997 and 2012 than any other region ($\bar{x}$ = 43,934 acres) (Figure 8). Similarly, Texas and Oklahoma ($\bar{x}$ = 822 farms) contained approximately 70% more mean number of farms than any other state ($\bar{x}$ =490 farms), and the Eastern Upland and Prairie Gateway regions ($\bar{x}$ = 808 farms) contained approximately 45% more mean number of farms than any other region ($\bar{x}$ = 463 farms) (Figure 8). Mean population densities in Florida ($\bar{x}$ = 0.51) were approximately 120% higher than Georgia, Louisiana, and South Carolina ($\bar{x}$ = 0.23), and approximately 345% higher than Texas, Oklahoma, Arkansas, Mississippi, and Alabama (Figure 9). Mean population densities in the Fruitful Rim ($\bar{x}$ = 0.34) were approximately 115% higher than any other region in the Southeast ($\bar{x}$ = 0.16) (Figure 9).

When I conducted single factor ANOVAs examining percent changes from 1997–2012 across states and regions, the following variables were statistically significant: mean percent change in average farm size (Figures 10 and 11), mean percent change in proportion of agricultural land (Figures 12 and 13), mean percent change in acres of farms (Figures 14 and 15), mean percent change in number of farms (Figures 16 and 17), mean percent change in population density (Figures 18 and 19), mean percent change in asset value per acre (Figures 20 and 21), and mean percent change in asset value-income difference per operation (Figures 22 and 23). Mean percent changes in average farm size from 1997–2012 varied from 10% decrease in Florida to 15% increase in Louisiana (Figures 10 and 11). Regional mean percent changes in average farm size ranged from 10% decrease in the Fruitful Rim to a 10% increase in the Mississippi Portal. Mean percent changes in proportion of agricultural land from 1997–2012 varied from 15% decrease in Georgia to 10% increase in Louisiana (Figures 12 and 13). Regional mean percent changes in proportion of agricultural land ranged from 10% decrease in the Southern Seaboard and 2% increase in the Mississippi Portal. Mean % changes in acres of farms from 1997–2012 varied from 20% decrease in Georgia to 15% increase in Florida (Figures 14 and 15). Regional mean percent changes in acres of farms ranged from 15% decrease in the Southern Seaboard to 10% increase in the Fruitful Rim. Mean percent changes in number of farms from 1997 –2012 varied from 15% decrease in Alabama to 15% increase in Texas (Figures 16 and 17). Regional mean percent changes in number of farms ranged from 10% decrease in the Eastern Upland to 10% increase in the Prairie Gateway. Mean percent changes in population density from 1997–2012 varied from 10% decrease in Louisiana to 25% increase in Florida (Figures 18 and 19). Regional mean percent changes in population density ranged from 10% decrease in the Mississippi Portal to 15% increase in the Fruitful Rim. From 1997–2012 mean percent changes in asset value per acre ranged from 90% increase in Alabama to 175% increase in Texas (Figures 20 and 21), and mean percent changes in asset value-income difference per operation ranged from 90% increase in Georgia to 190% increase in Texas (Figures 22 and 23). Regional mean percent changes in asset value per acre ranged from 105% increase in the Eastern Upland to 170% increase in the Prairie Gateway. Regional mean percent changes in asset value-income difference per operation ranged from 110% increase in the Southern Seaboard and 160% increase in the Prairie Gateway.

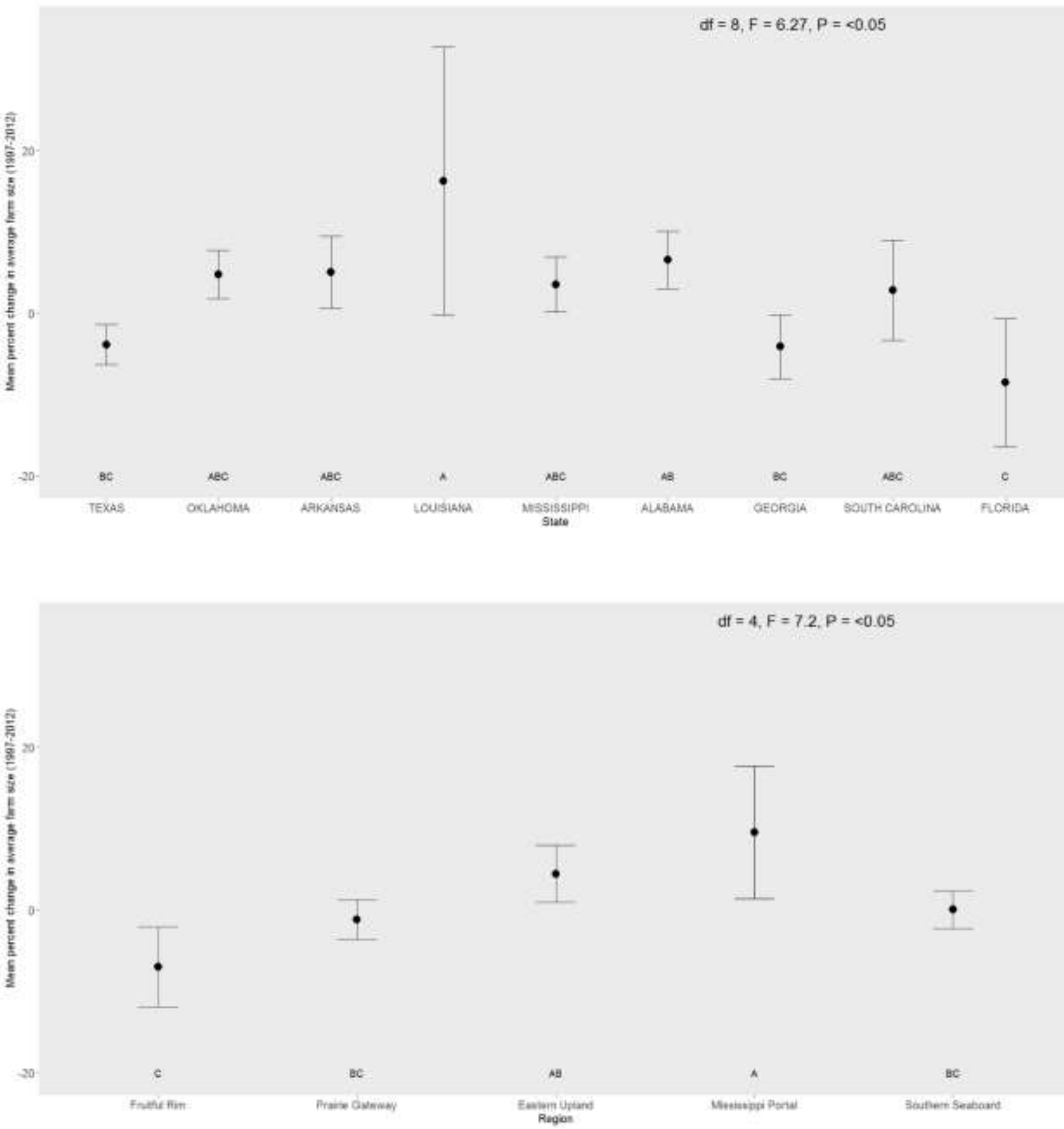


Figure 10. Mean percent change in average farm size and their associated 95% confidence intervals across states and Farm Resource Regions. Statistics (df = degrees of freedom, *F* = F-ratio, *P* = P-value) represent the results of single factor analyses of variance. Letters represent the results of Tukey's honest significant difference test. Each letter represents statistically significant differences in mean percent change values.

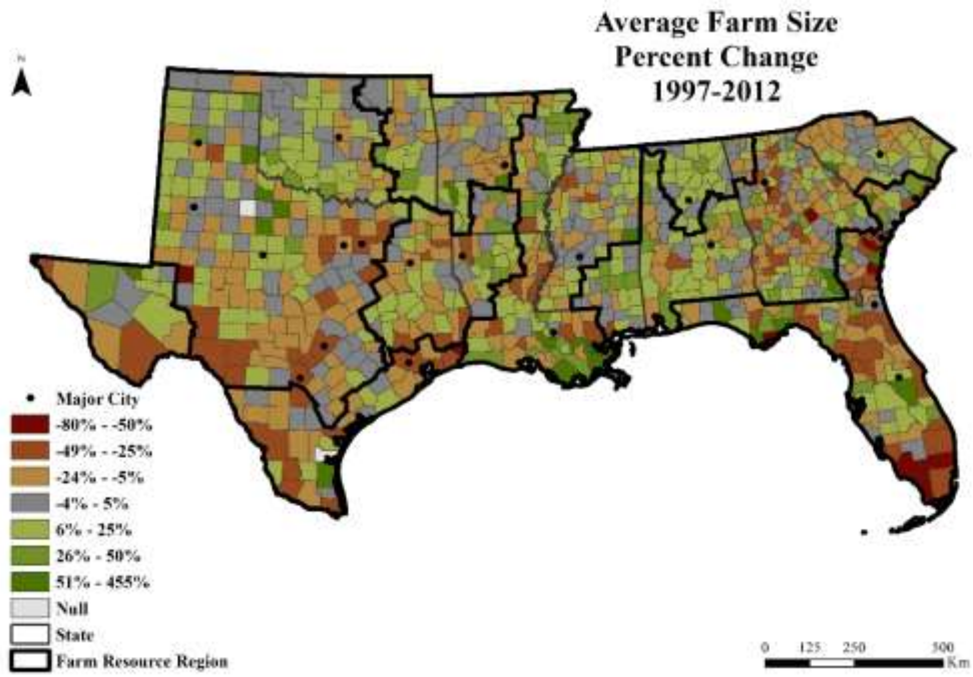


Figure 11. Map of the percent change in average farm size per county from 1997–2012 with major cities across all states and Farm Resource Regions in the southeastern United States. States include Texas Oklahoma, Arkansas, Louisiana, Mississippi, Alabama, Georgia, South Carolina, and Florida. Farm Resource Regions include the Eastern Upland, Fruitful Rim, Mississippi Portal, Prairie Gateway, and Southern Seaboard.

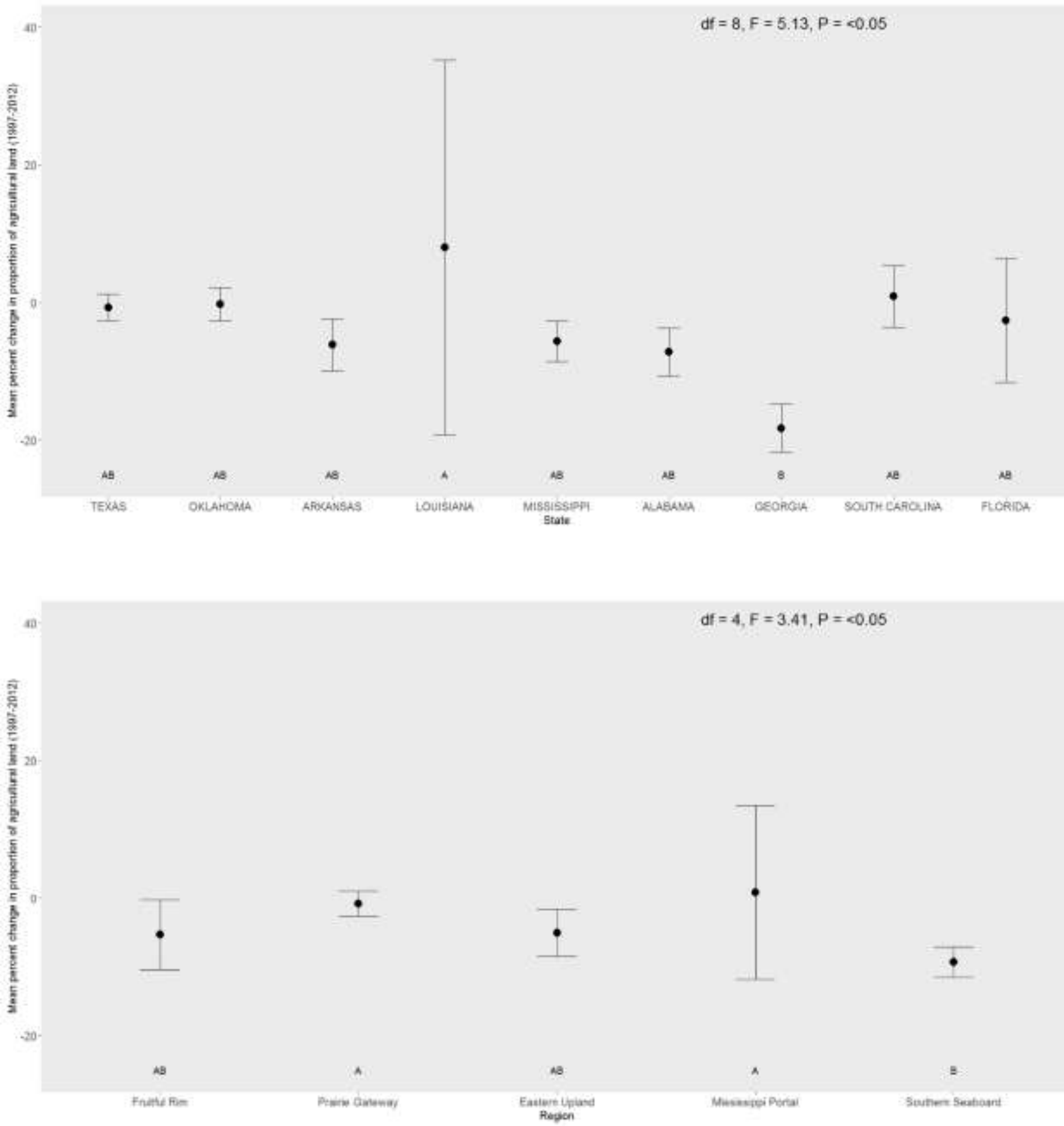


Figure 12. Mean percent change in proportion of agricultural land and their associated 95% confidence intervals across states and Farm Resource Regions. Statistics (df = degrees of freedom, *F* = F-ratio, *P* = P-value) represent the results of single factor analyses of variance. Letters represent the results of Tukey's honest significant difference test. Each letter represents statistically significant differences in mean percent change values.

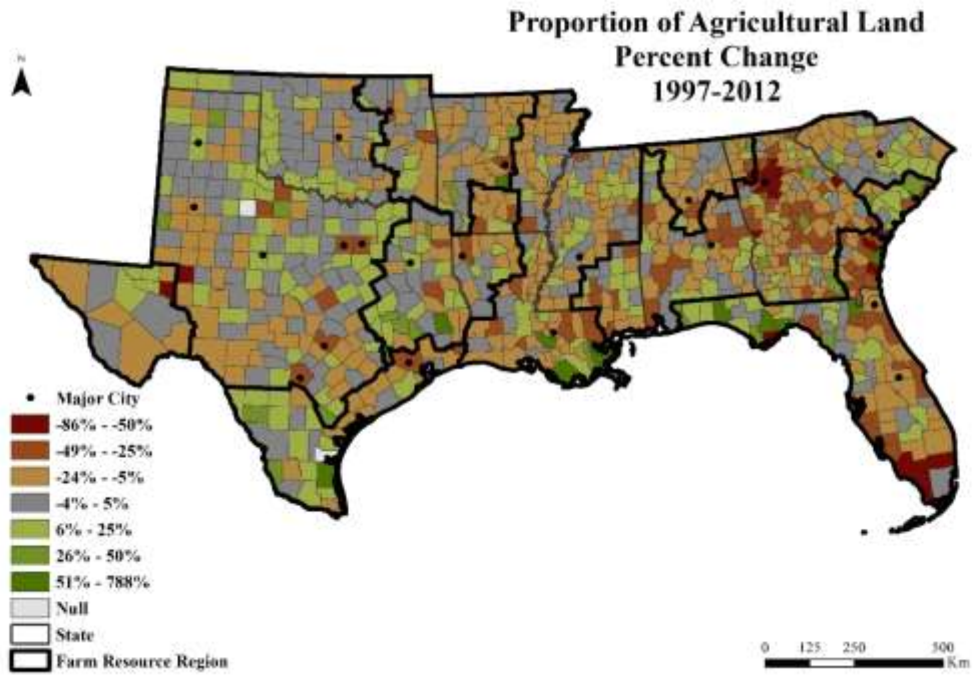


Figure 13. Map of the percent change in proportion of agricultural land per county from 1997–2012 with major cities across all states and Farm Resource Regions in the southeastern United States. States include Texas Oklahoma, Arkansas, Louisiana, Mississippi, Alabama, Georgia, South Carolina, and Florida. Farm Resource Regions include the Eastern Upland, Fruitful Rim, Mississippi Portal, Prairie Gateway, and Southern Seaboard.

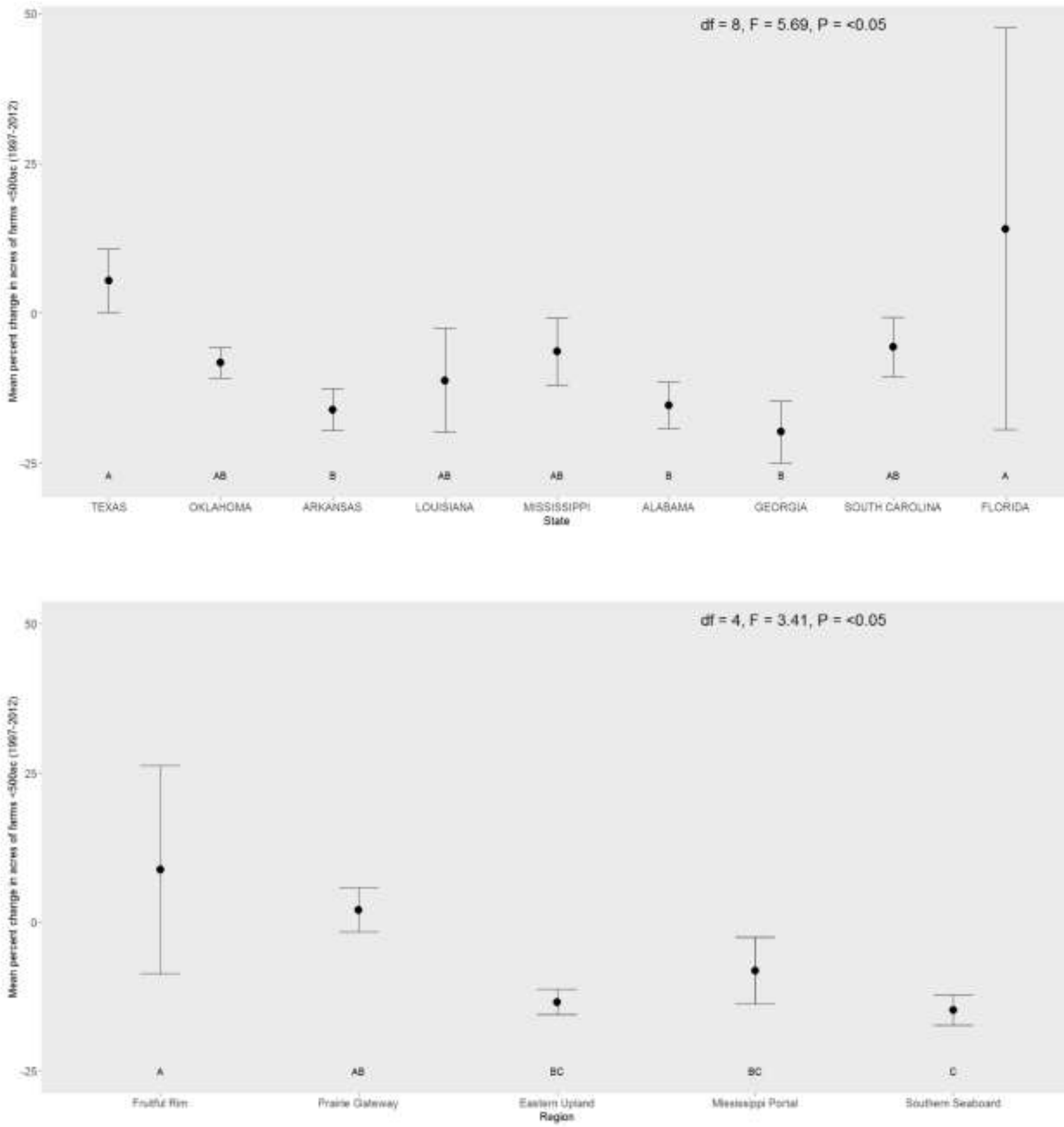


Figure 14. Mean percent change in acres of farms <500 acres in size and their associated 95% confidence intervals across states and Farm Resource Regions. Statistics (df = degrees of freedom, F = F-ratio, P = P-value) represent the results of single factor analyses of variance. Letters represent the results of Tukey's honest significant difference test. Each letter represents statistically significant differences in mean percent change values.

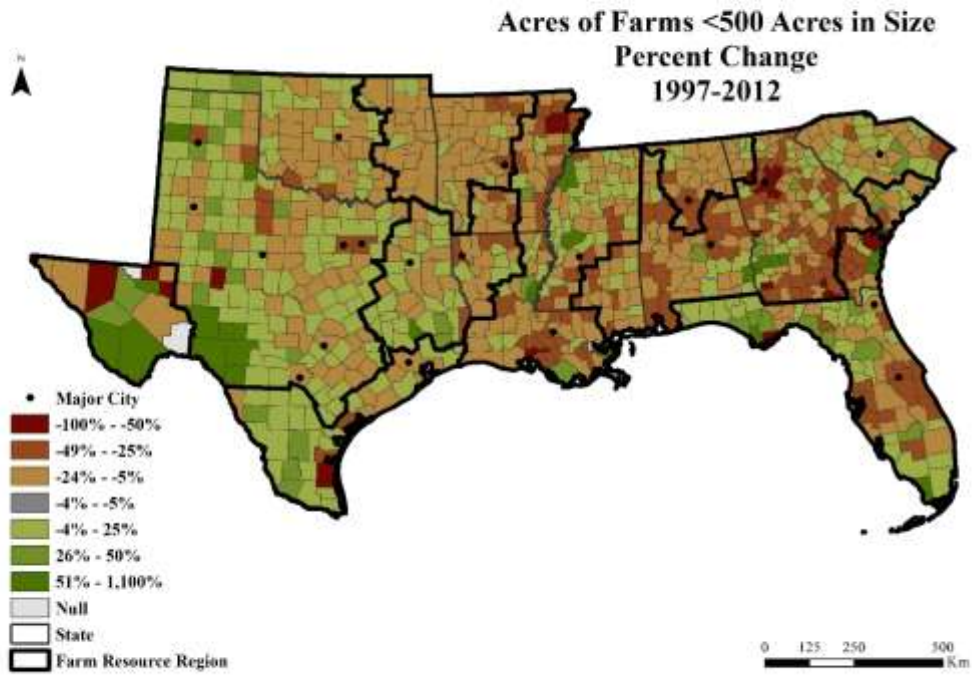


Figure 15. Map of the percent change in acres of farms <500 acres in size per county from 1997–2012 with major cities across all states and Farm Resource Regions in the southeastern United States. States include Texas Oklahoma, Arkansas, Louisiana, Mississippi, Alabama, Georgia, South Carolina, and Florida. Farm Resource Regions include the Eastern Upland, Fruitful Rim, Mississippi Portal, Prairie Gateway, and Southern Seaboard.

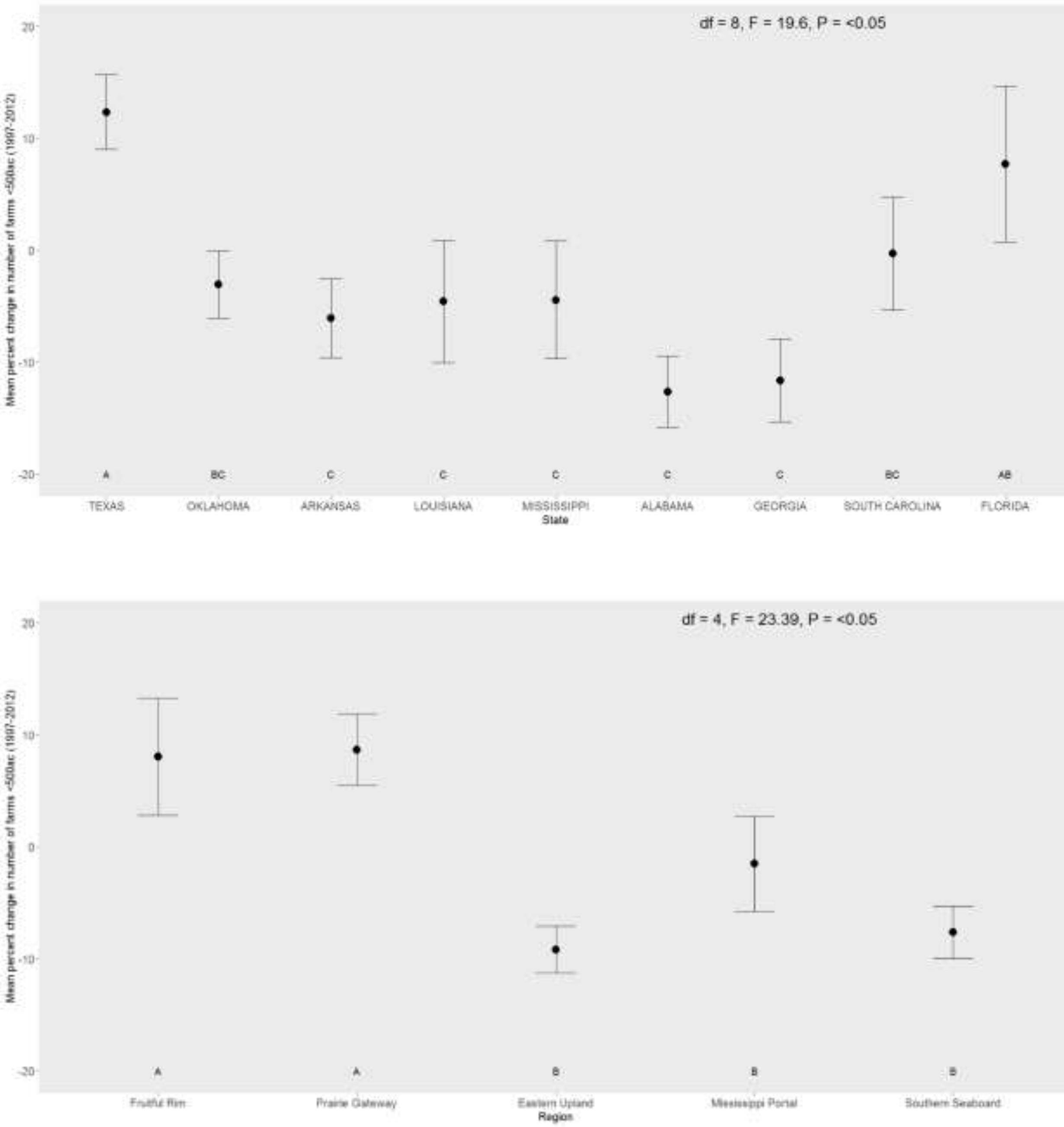


Figure 16. Mean percent change in number of farms <500 acres in size and their associated 95% confidence intervals across states and Farm Resource Regions. Statistics (df = degrees of freedom, *F* = F-ratio, *P* = P-value) represent the results of single factor analyses of variance. Letters represent the results of Tukey's honest significant difference test. Each letter represents statistically significant differences in mean percent change values.

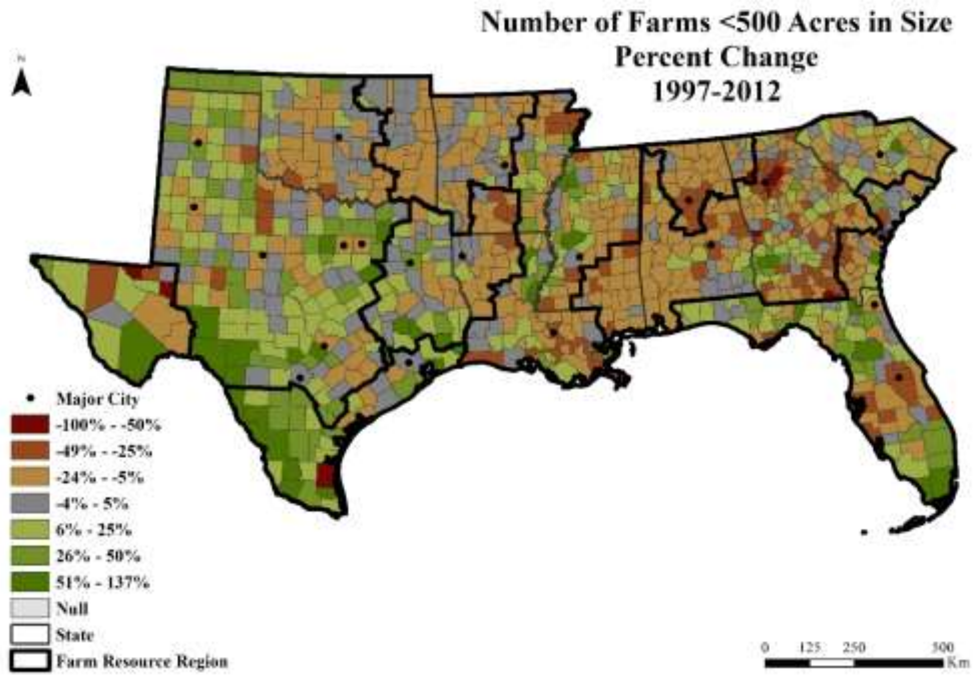


Figure 17. Map of the percent change in number of farms <500 acres in size per county from 1997–2012 with major cities across all states and Farm Resource Regions in the southeastern United States. States include Texas Oklahoma, Arkansas, Louisiana, Mississippi, Alabama, Georgia, South Carolina, and Florida. Farm Resource Regions include the Eastern Upland, Fruitful Rim, Mississippi Portal, Prairie Gateway, and Southern Seaboard.

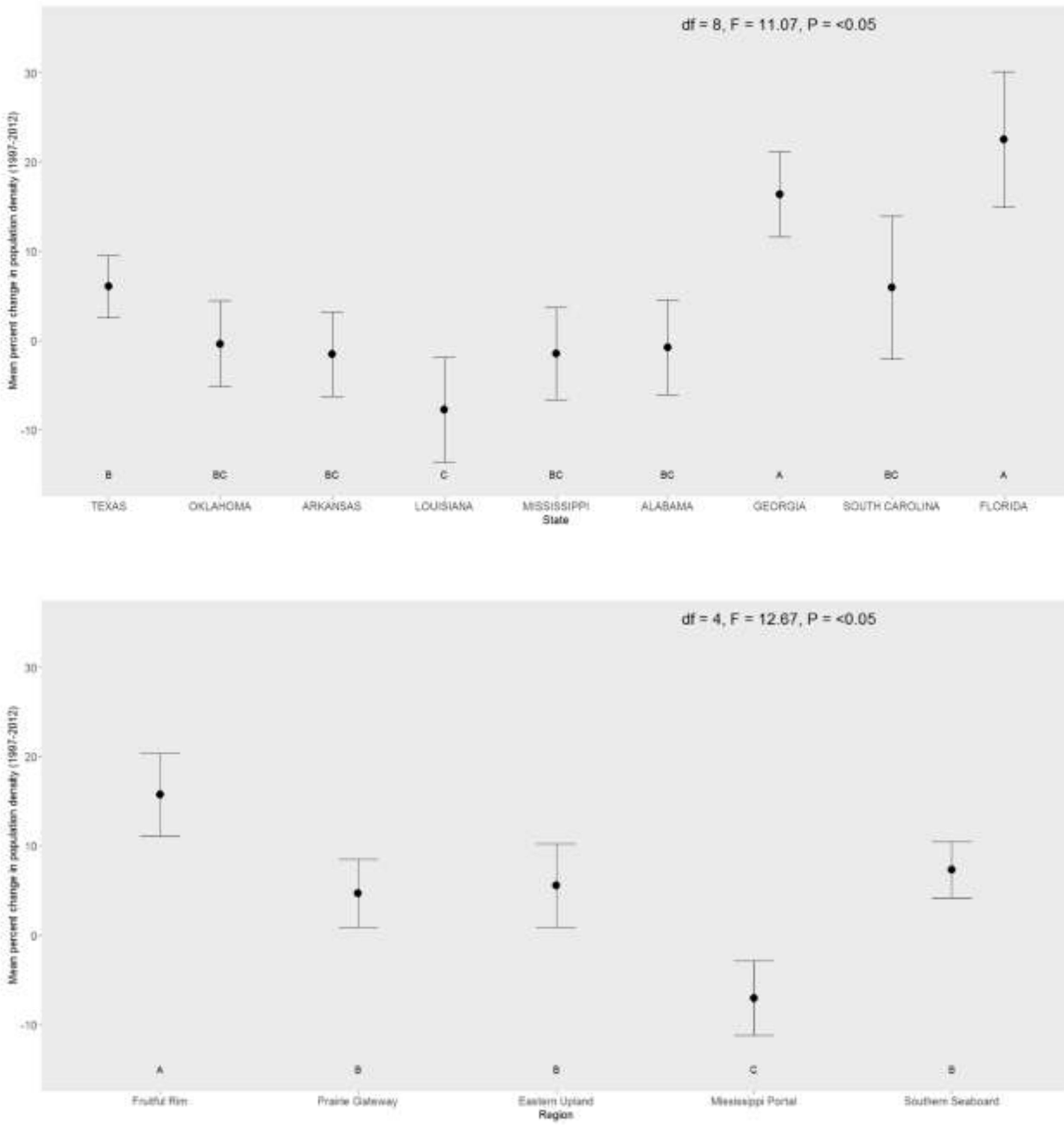


Figure 18. Mean percent change in population density (population/acre) and their associated 95% confidence intervals across states and Farm Resource Regions. Statistics (df = degrees of freedom, *F* = F-ratio, *P* = P-value) represent the results of single factor analyses of variance. Letters represent the results of Tukey's honest significant difference test. Each letter represents statistically significant differences in mean percent change values.

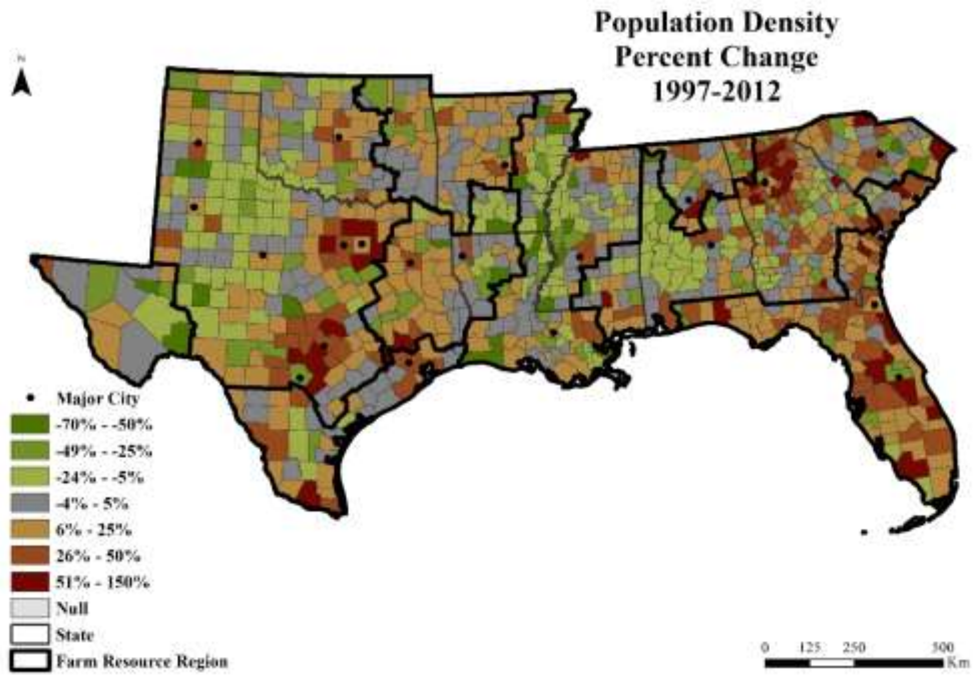


Figure 19. Map of the percent change in population density (population/acre) per county from 1997–2012 with major cities across all states and Farm Resource Regions in the southeastern United States. States include Texas Oklahoma, Arkansas, Louisiana, Mississippi, Alabama, Georgia, South Carolina, and Florida. Farm Resource Regions include the Eastern Upland, Fruitful Rim, Mississippi Portal, Prairie Gateway, and Southern Seaboard.

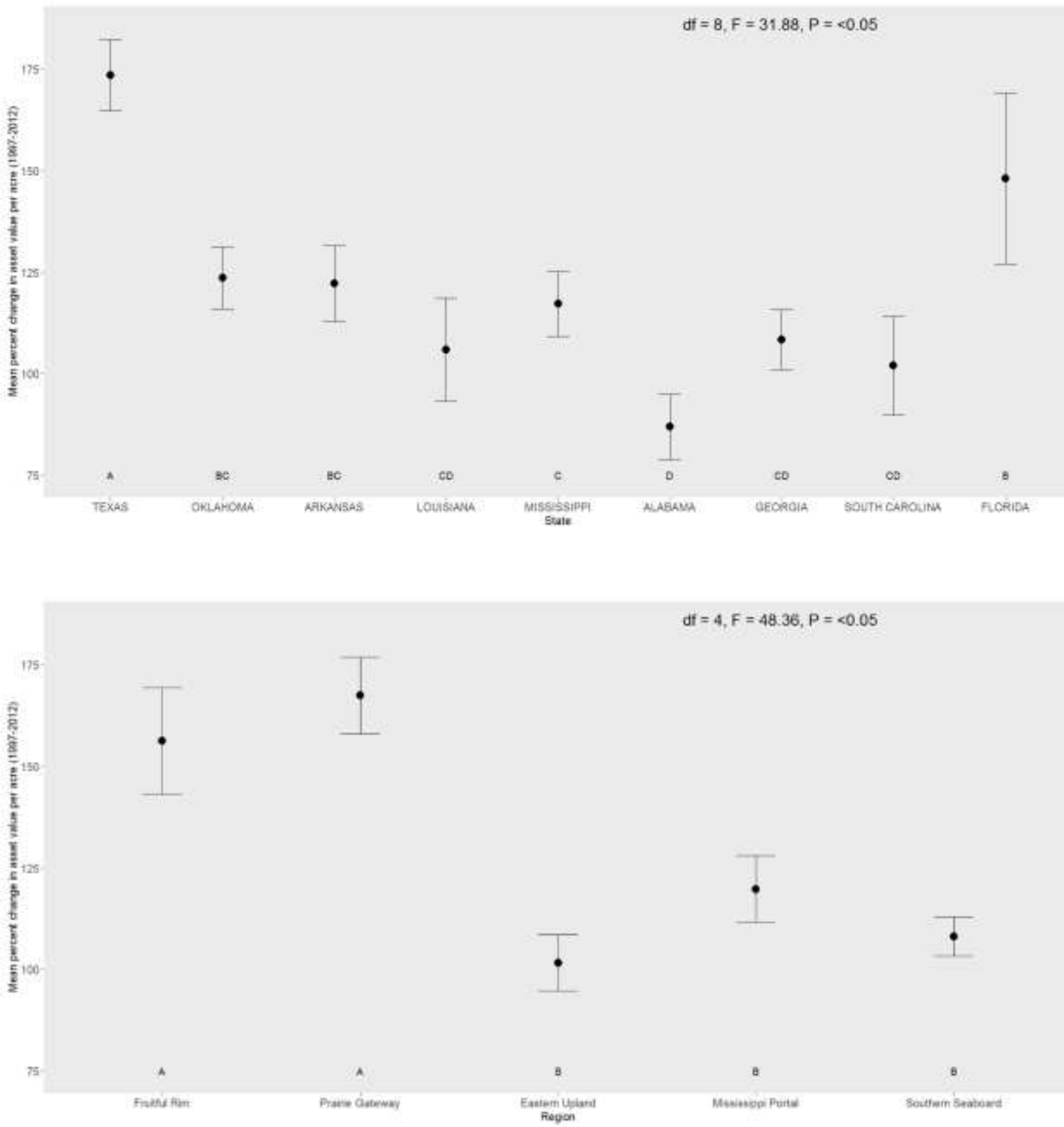


Figure 20. Mean percent change in asset value per acre ($/acre) and their associated 95% confidence intervals across states and Farm Resource Regions. Statistics (df = degrees of freedom, F = F-ratio, P = P-value) represent the results of single factor analyses of variance. Letters represent the results of Tukey’s honest significant difference test. Each letter represents statistically significant differences in mean percent change values.

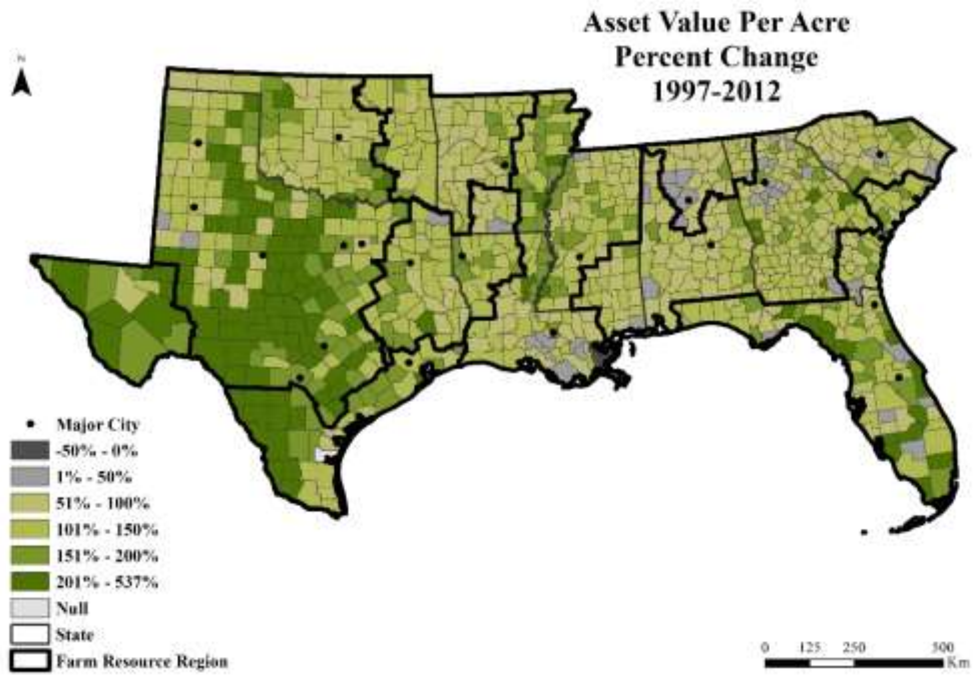


Figure 21. Map of the percent change in asset value per acre ($/acre) per county from 1997–2012 with major cities across all states and Farm Resource Regions in the southeastern United States. States include Texas Oklahoma, Arkansas, Louisiana, Mississippi, Alabama, Georgia, South Carolina, and Florida. Farm Resource Regions include the Eastern Upland, Fruitful Rim, Mississippi Portal, Prairie Gateway, and Southern Seaboard.

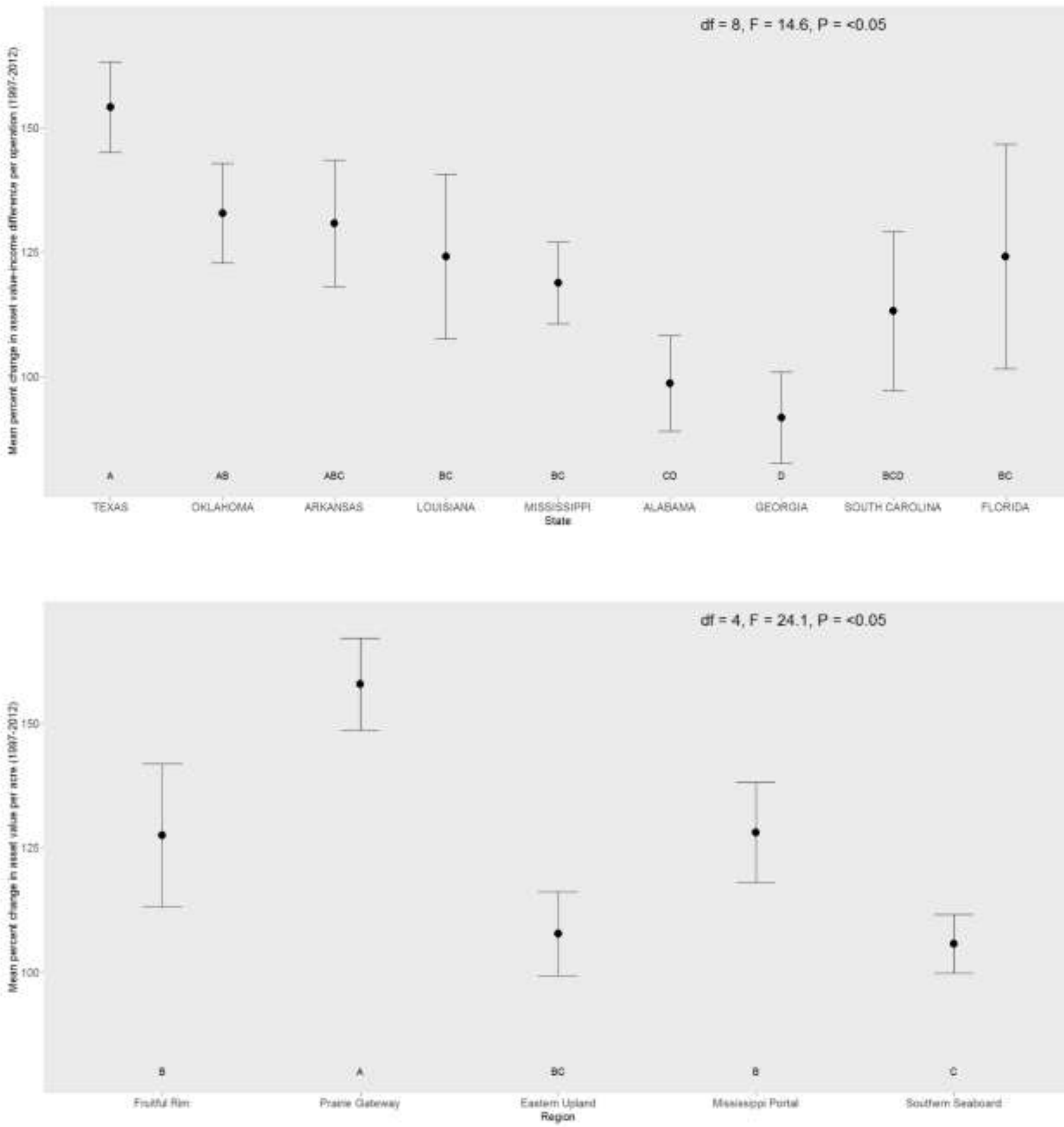


Figure 22. Mean percent change in asset value-income difference per operation ($/operation) and their associated 95% confidence intervals across states and Farm Resource Regions. Statistics (df = degrees of freedom, F = F-ratio, P = P-value) represent the results of single factor analyses of variance. Letters represent the results of Tukey's honest significant difference test. Each letter represents statistically significant differences in mean percent change values.

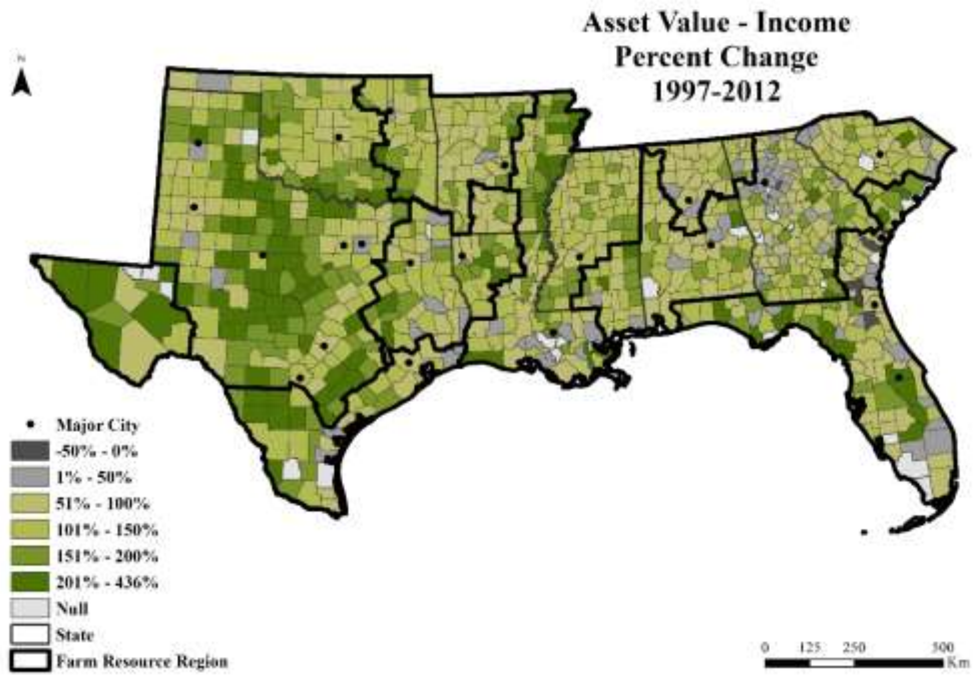


Figure 23. Map of the percent change in asset value-income difference per operation ($/operation) per county from 1997–2012 with major cities across all states and Farm Resource Regions in the southeastern United States. States include Texas Oklahoma, Arkansas, Louisiana, Mississippi, Alabama, Georgia, South Carolina, and Florida. Farm Resource Regions include the Eastern Upland, Fruitful Rim, Mississippi Portal, Prairie Gateway, and Southern Seaboard.

The best-fit model for percent change in average farm size included the interaction between state and percent change in asset value-income difference per operation (Table 4). Because many of my regression lines and confidence intervals were similar across states, I presented only the statistically significant differences and informative predictions in the figures inserted into the main body of my text. Figures representing all of my regression results can be found in Appendix B. The predicted mean percent change in average farm size increased approximately 10% for every 50% increase in percent change in asset value-income difference per operation in Alabama, Arkansas, Florida, Mississippi, Oklahoma, and South Carolina, however, overlapping confidence intervals suggest that there were no differences in these trends across states (represented by the state of Georgia in Figure 24; Appendix B). While Texas was not statistically significantly different from the states of Alabama, Arkansas, Florida, Mississippi, Oklahoma, and South Carolina, it was significantly different from the states of Georgia and Louisiana. I found that for every 50% increase in the percent change of asset value-income difference per operation, the predicted mean percent change in average farm size in Texas increased by approximately 5% (Figure 24). I found statistically significant differences in mean percent change in asset value-income difference per operation for the state of Louisiana (Figure 24). I found for every 50% increase in the percent change in asset value-income difference, the predicted mean percent change in average farm size increased by approximately 20% in Louisiana (Figure 24).

Table 4. Models of ownership fragmentation variables (percent changes of average farm size, proportion of agricultural land, acres of farms <500 acres in size, and number of farms <500 acres in size from 1997–2012) across 9 states and 5 Farm Resource Regions in the southeastern United States.

Ownership Fragmentation[a]	**Model**[b]	***K***[c]	**Log liklihood**	**AIC$_c$**[d]	**ΔAIC$_c$**[e]	***w$_i$***[f]
AvgFarmSize	State * AVIDiffPerOp	19	-3892.74	7824.38	0.00	1.00
	Region * AVIDiffPerOp	11	-3923.86	7870.04	45.65	0.00
	State * AssetPerAcre	19	-3953.26	7945.42	121.03	0.00
	AVIDiffPerOp	3	-3973.44	7952.91	128.53	0.00
	Region * AssetPerAcre	11	-3982.70	7987.71	163.32	0.00
	State * PopDens	19	-3997.38	8033.67	209.28	0.00
	AssetPerAcre	3	-4016.99	8040.00	215.62	0.00
	Region * PopDens	11	-4025.22	8072.76	248.38	0.00
	State	10	-4031.15	8082.55	258.17	0.00
	PopDens	3	-4038.68	8083.40	259.01	0.00
	Region	6	-4039.48	8091.06	266.68	0.00
	Intercept	2	-4052.29	8108.59	284.21	0.00
PropAg	State * AssetPerAcre	19	-4159.33	8357.57	0.00	1.00
	State * AVIDiffPerOp	19	-4180.47	8399.84	42.28	0.00
	State * PopDens	19	-4185.07	8409.05	51.48	0.00

Table 4. Continued

Ownership Fragmentation[a]	Model[b]	*K*[c]	Log liklihood	AIC_c[d]	ΔAIC_c[e]	w_i[f]
PropAg	Region * AVIDiffPerOp	11	-4206.21	8434.73	77.16	0.00
	Region * AssetPerAcre	11	-4207.91	8438.12	80.55	0.00
	AVIDiffPerOp	3	-4219.15	8444.33	86.77	0.00
	Region * PopDens	11	-4225.64	8473.59	116.02	0.00
	State	10	-4235.93	8492.11	134.54	0.00
	PopDens	3	-4247.69	8501.41	143.84	0.00
	AssetPerAcre	3	-4253.09	8512.20	154.63	0.00
	Region	6	-4250.52	8513.14	155.57	0.00
	Intercept	2	-4256.52	8517.05	159.48	0.00
Acres	State * PopDens	19	-4139.16	8317.21	0.00	0.57
	State * AssetPerAcre	19	-4139.49	8317.89	0.67	0.40
	State	10	-4151.46	8323.18	5.97	0.03
	State * AVIDiffPerOp	19	-4144.41	8327.72	10.51	0.00
	Region * AssetPerAcre	11	-4162.02	8346.34	29.13	0.00
	Region * PopDens	11	-4162.90	8348.11	30.90	0.00

Table 4. Continued

Ownership Fragmentation[a]	**Model**[b]	***K***[c]	**Log liklihood**	**AIC$_c$**[d]	**ΔAIC$_c$**[e]	***w_i***[f]
Acres	Region	6	-4172.81	8357.71	40.50	0.00
	AssetPerAcre	3	-4177.12	8360.27	43.06	0.00
	Region * AVIDiffPerOp	11	-4170.81	8363.93	46.71	0.00
	PopDens	3	-4192.26	8390.56	73.34	0.00
	Intercept	2	-4197.86	8399.73	82.52	0.00
	AVIDiffPerOp	3	-4196.92	8399.87	82.65	0.00
Farms	State * AVIDiffPerOp	19	-3849.22	7737.35	0.00	0.68
	State * PopDens	19	-3850.02	7738.94	1.60	0.31
	State * AssetPerAcre	19	-3853.79	7746.49	9.14	0.01
	State	10	-3876.09	7772.43	35.09	0.00
	Region * AssetPerAcre	11	-3880.26	7782.83	45.48	0.00
	Region * AVIDiffPerOp	11	-3893.29	7808.88	71.54	0.00
	AssetPerAcre	3	-3902.20	7810.42	73.08	0.00
	Region * PopDens	11	-3895.82	7813.96	76.61	0.00

Table 4. Continued

Ownership Fragmentation[a]	Model[b]	K[c]	Log liklihood	AIC_c[d]	ΔAIC_c[e]	w_i[f]
	Region	6	-3910.30	7832.69	95.35	0.00
	AVIDiffPerOp	3	-3954.29	7914.61	177.26	0.00
	Intercept	2	-3956.34	7916.69	179.34	0.00
	PopDens	3	-3956.25	7918.53	181.19	0.00

[a]Ownership fragmentation variable abbreviations are as follows: AvgFarmSize= percent change in average farm size, PropAg= percent change in proportion of agricultural land, Acres= percent change in acres of farms <500 acres in size, farms= percent change in number of farms <500 acres in size.

[b]Explanatory variable abbreviations are as follows: Intercept= null model, State= state, Region= Farm Resource Region, PopDens= percent change in population density, AssetPerAcre= percent change in asset value per acre, AVIDiffPerOp= percent change in asset value-income difference per operation.

[c]Number of parameters in the model.

[d]Akaike's Information Criterion corrected for small sample sizes

[e]Difference between the best-fit model (smallest AIC_c) and each model

[f]Model Akaike Weight

The best-fit model for percent change in proportion of agricultural land included the interaction between state and percent change in asset value per acre (Table 4). I found no difference in the mean percent change in proportion of agricultural land associated with percent changes in asset value per acre for the states of Alabama, Arkansas, Florida, Georgia, Mississippi, Oklahoma, South Carolina, and Texas (Appendix B). I found statistically significant differences in percent change in asset value per acre in Louisiana (Figure 25). In Louisiana, I found that for every 50% increase in the percent change of asset value per acre, the predicted mean percent change in proportion of agricultural land decreased by approximately 50% (Figure 25).

Model results for percent change in acres of farms revealed two plausible models in the candidate set based on ΔAIC_c values, including (1) state and percent change in population density, and (2) state and percent change in asset value per acre (Table 4). I considered both models as best-fit, instead of using a model averaging approach. I found no difference in the mean percent change in the acres of farms associated with percent changes in population density for the states of Oklahoma and Florida (Appendix B). The mean percent change in acres of farms decreased with increasing percent change in population density in Alabama, Arkansas, Georgia, Mississippi, South Carolina, and Texas (Appendix B). However, overlapping confidence intervals suggest that there were no differences in these trends across states (Appendix B). The mean percent change in acres of farms increased with increasing percent change in asset value per acre in Alabama, Florida, Georgia, Oklahoma, South Carolina, and Texas, and decreased in Arkansas, however, overlapping confidence intervals suggest that there were no

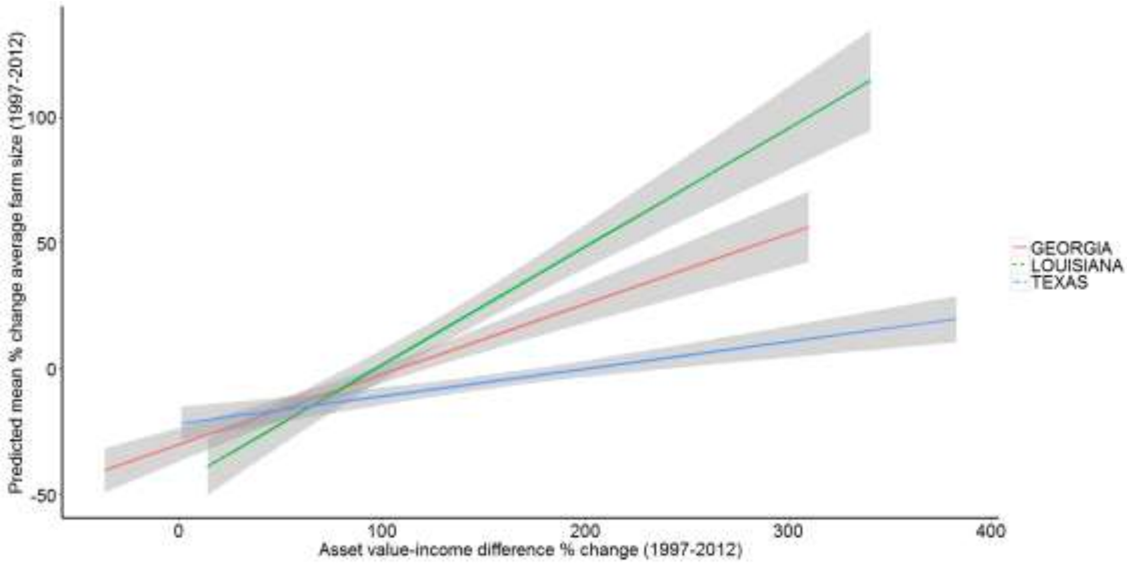


Figure 24. Significantly different predicted means for percent change in average farm size (1997–2012) using the best-fit model (percent change in average farm size = state * percent change in asset value-income difference per operation [1997–2012]).

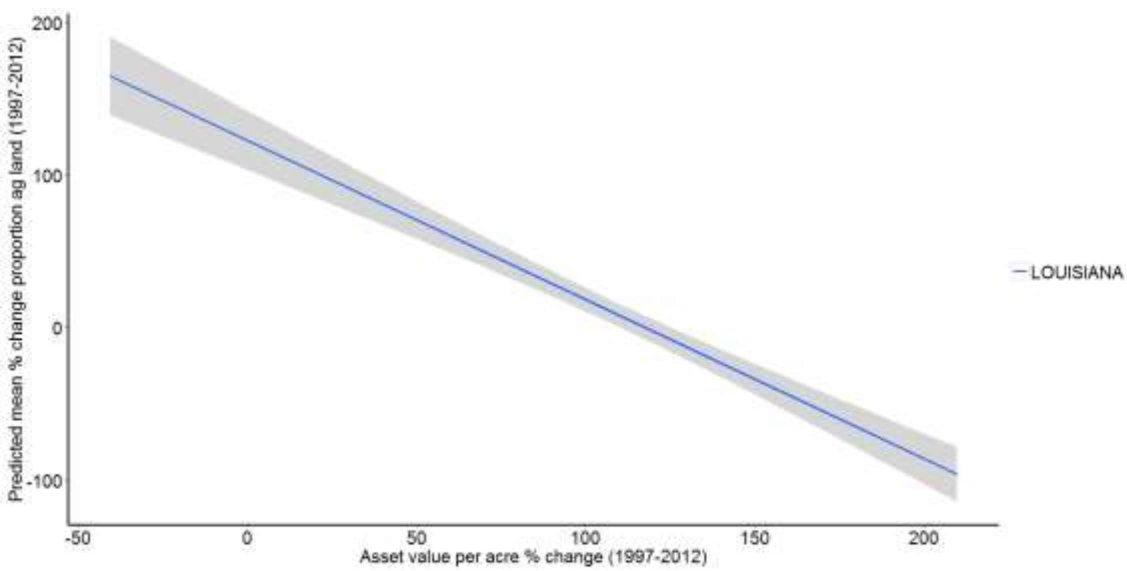


Figure 25. Significantly different predicted means for percent change in proportion of agricultural land (1997–2012) using the best-fit model (percent change in proportion of agricultural land = state * percent change in asset value per acre [1997–2012]).

differences in these trends across states (Appendix B). In Louisiana, I found for every 50% increase in the percent change of population density, the predicted mean percent change in acres of farms decreased by approximately 30% (Figure 26), and for every 50% increase in the percent change in asset value per acre, the predicted mean percent change in acres of farms decreased by approximately 10% (Figures 26 and 27). In Mississippi, I found for every 50% increase in the percent change in asset value per acre, the predicted mean percent change in acres of farms increased by approximately 15% (Figure 27).

Model results for percent change in number of farms also revealed two plausible models in the candidate set based on ΔAIC_c values, including state and percent change in asset value-income difference per operation, and state and percent change in population density (Table 4). I considered both models as best-fit, instead of using a model averaging approach. I found no difference in the mean percent change in the number of farms associated with percent changes in asset value-income difference per operation in Alabama (Appendix B). The mean percent change in the number of farms decreased with increasing percent changes in asset value-income difference per operation in Arkansas, Florida, Georgia, Louisiana, Oklahoma, and South Carolina (Appendix B). However, overlapping confidence intervals suggest that there were no differences in the trends across these states (Appendix B). I found that for every 50% increase in percent change in asset value-income difference per operation, the predicted mean percent change in the number of farms decreased by 5% in Texas, and 10% in Mississippi (Figure 28). I found no difference in the mean percent change in the number of farms

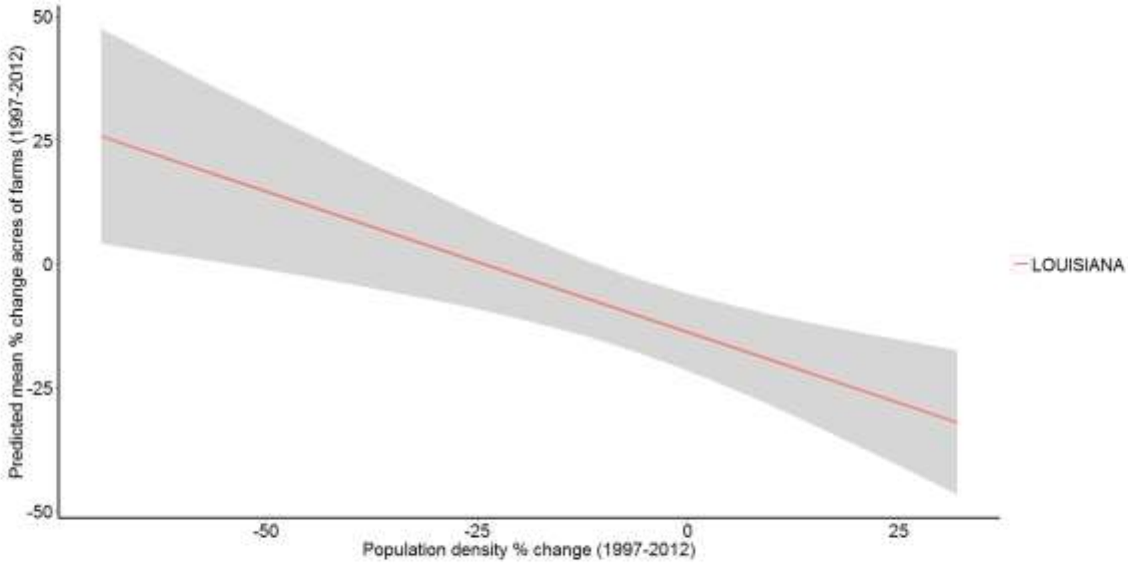


Figure 26. Significantly different predicted means for percent change in acres of farms <500 acres in size (1997–2012) using the first best-fit model (percent change in acres of farms <500 acres in size = state * percent change in population density [1997–2012]).

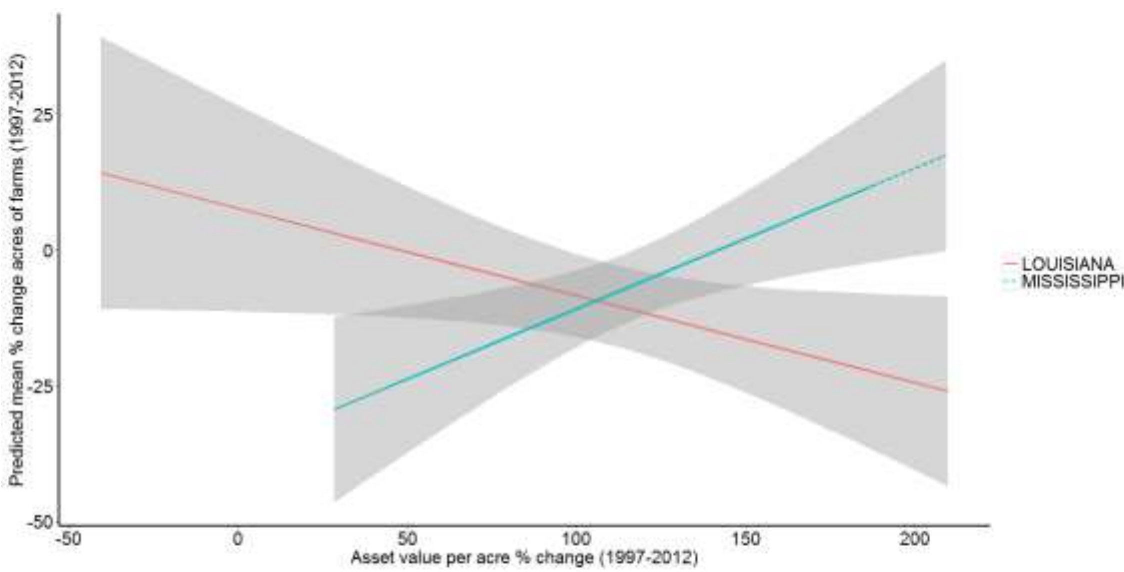


Figure 27. Significantly different predicted means for percent change in acres of farms <500 acres in size (1997–2012) using the second best-fit model (percent change in acres of farms <500 acres in size = state * percent change in asset value per acre [1997–2012]).

associated with percent change in population density for the states of Arkansas and Oklahoma (Appendix B). The mean percent change in the number of farms decreased with increasing percent change in population density in South Carolina, Louisiana, and Alabama (Appendix B). However, overlapping confidence intervals suggest that there were no differences in these trends across states (Appendix B). I found statistically significant differences in mean predictions for percent change in the number of farms associated with percent change in population density for the states of Florida, Georgia, Mississippi, and Texas (Figure 29). I found that for every 50% increase in the percent change of population density, the predicted mean percent change in the number of farms increased by approximately 10% in Texas and approximately 5% in Florida (Figure 29). I found that for every 50% increase in the percent change of population density, the predicted mean percent change in the number of farms decreased by approximately 20% in Mississippi and approximately 10% in Georgia (Figure 29).

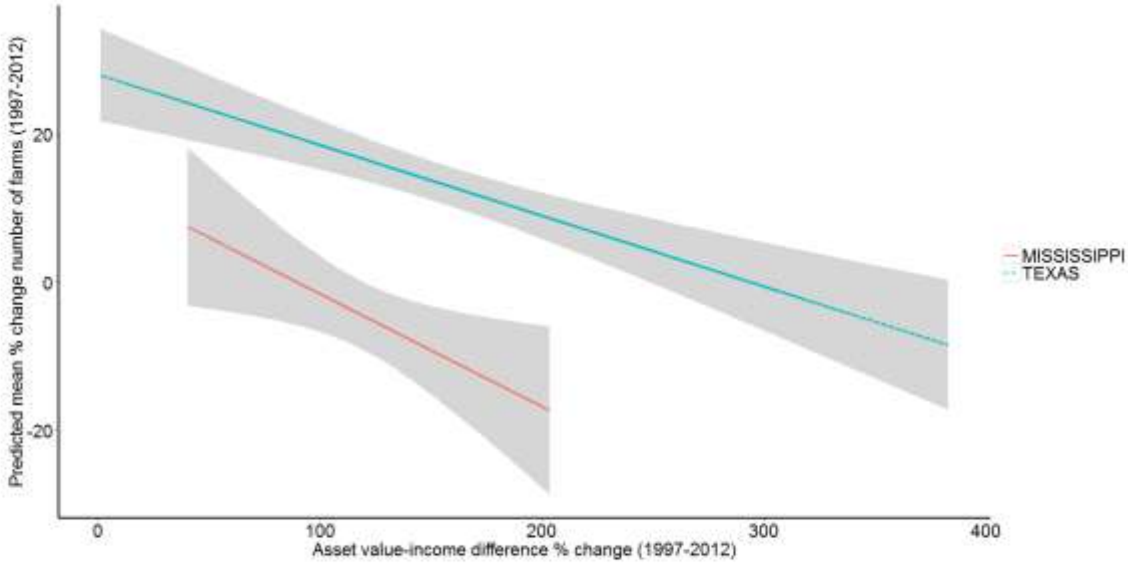


Figure 28. Significantly different predicted means for percent change number of farms <500 acres in size (1997–2012) using the first best-fit model (percent change in number of farms <500 acres in size = state * percent change asset value-income difference per operation [1997–2012]).

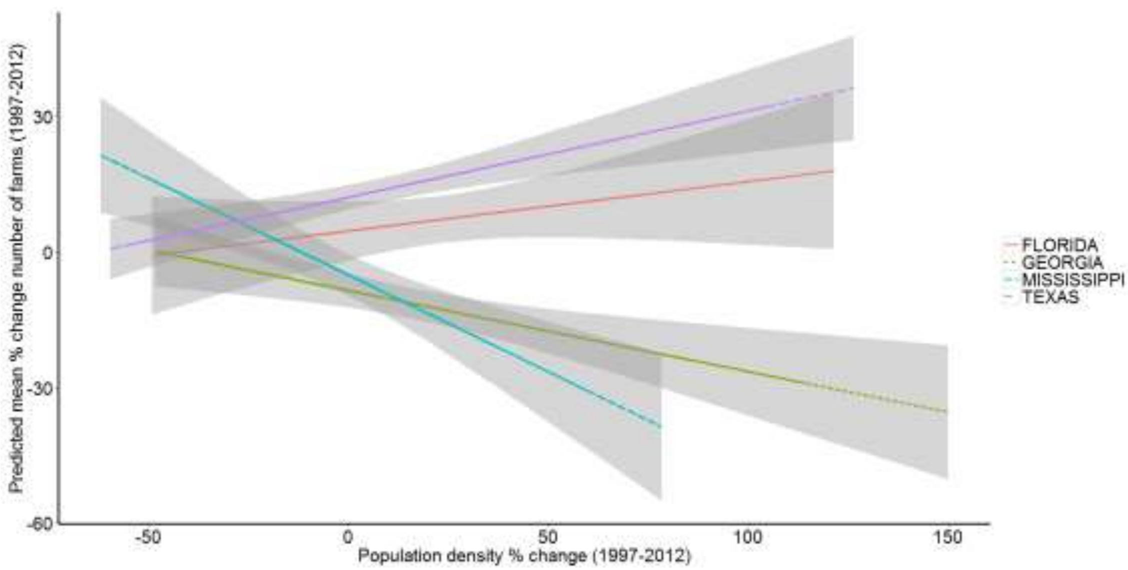


Figure 29. Significantly different predicted means for percent change in number of farms <500 acres in size (1997–2012) using the second best-fit model (percent change in number of farms <500 acres in size = state * percent change in population density [1997–2012]).

DISCUSSION

Land use is a multi-dimensional, equilibrium process in which land value and land ownership are established by physical characteristics (e.g. landform), location (e.g. accessibility), the value of goods and services, and supply and demand (Gobin 2001). I quantified four metrics associated with ownership fragmentation and three metrics that I hypothesized could explain patterns in ownership fragmentation across states and regions, including population density, asset value per acre, and asset value-income difference per operation. Contrary to my hypothesis that ownership fragmentation, population density, and land value would vary more by region than by state boundaries, I found significant differences in ownership fragmentation and land demographics across both states and regions in the southeastern United States, indicating that states and regions vary in average farm sizes, proportions of agricultural land, acres of farms, number of farms, population density, land asset value, and land asset value-income differences and their changes over time. I found significant relationships between ownership fragmentation and interactions between land demographic variables and state, and not regions, contrary to my hypothesis that ecoregion boundaries would better predict ownership fragmentation over state boundaries. The process of ownership fragmentation due to population and land value changes occurs similarly, regardless of geographic or political boundaries, however, the degree to which this process occurs depends on the presence and impact of the factors that cause it. Ownership fragmentation is a chain reaction process: populations increase with economic growth, population growth creates upward pressures on land values and markets, and high land values and demand for land creates incentive for landowners to subdivide and sell their land (i.e. ownership fragmentation).

Mean average farm sizes, mean proportions of agricultural land, mean acres of farms, and mean number of farms were significantly larger in Texas and Oklahoma, and the Fruitful Rim, Eastern Upland, and Prairie Gateway regions than in any other state or region in the Southeast. Texas and Oklahoma are very large in total area, primarily privately owned, and major agricultural producers; Texas leads the nation in cattle and cotton production (Texas Department of Agriculture 2016) and Oklahoma leads the nation in rye production and ranks second in production of cattle and canola (Reese et al. 2015). In addition, Texas and Oklahoma primarily consist of the Prairie Gateway and Fruitful Rim regions, and together these two regions make up about 25% of the nation's cropland and contain the largest share of large and very large family farms (Economic Research Service 2000). This land ownership demographic and the land uses typically found in these states and regions play an influential role in determining average farm sizes, proportions of agricultural land, and the acres and number of small farms (Kjelland et al. 2007). Larger crop and livestock farms and ranches realize better financial performance and are better able to utilize labor and capital more intensively (MacDonald et al. 2013), as illustrated by the significantly larger average farm sizes, proportions of agricultural land, acres of farms, and numbers of farms in each of these states.

The eastern portions of Texas and Oklahoma, and the Prairie Gateway region, transition to the Eastern Upland and Southern Seaboard regions. The Southern Seaboard contains a mix of small and large farms, and the Eastern Upland contains the largest number of small farms compared to any other region (Economic Research Service 2000). These trends are, again, likely attributable to the ecoregional characteristics of the landscapes that dominate much of the southeastern United States. The prevalence of forestlands and small-scale agricultural productions increases across the Eastern Upland and Southern Seaboard regions (Klepzig et al. 2014). As Texas and Oklahoma are considered parts of the “breadbasket” of America because of their agricultural productivity (Garreau 1981), the Southeast’s Eastern Upland and Southern Seaboard regions are often described as the “wood basket” of the nation because of their productive pine forests (Klepzig et al. 2014). Like cropland and livestock farms and ranches, forestland ownership size is a limiting factor in terms of the economies of scale available to a forest owner in the establishment, management, and harvesting of timber (Wear and Greis 2012, Hatcher et al. 2013). Research on forestland ownership sizes identified minimum economies of scale that are generally much smaller than economies scale for crop or livestock production (Rowan and White 1994, Kittredge et al. 1996, Hatcher et al. 2013), as illustrated in my research by the significantly smaller average farm sizes, smaller proportions of agricultural land, and larger acres and numbers of small farms in each of these regions.

While average farm sizes, proportions of agricultural land, acres of farms, and numbers of farms are all impacted by geographic and ecoregional locations, population growth is more impacted by local economic and social factors. Population growth in the southeastern United States from 1997–2012 surrounded major metropolitan areas, economic hubs, and their connecting corridors, especially along the I-35 corridor and Houston metropolitan area in Texas, the Atlanta metropolitan area in Georgia, and the four major metropolitan areas in Florida: Jacksonville, Orlando, Tampa, and Miami (Conklin and Lesher 1977). Ten of the top 15 fastest-growing large cities in the United States from 2010 to 2011 were located in Texas, Georgia, or Florida (United States Census Bureau 2012). The state of Florida contained the highest population densities in 1997 and 2012 across the Southeast, where historically, migration from other states for employment opportunities and tropical climates has been a major source of population growth (Smith 2005). In contrast, the state of Louisiana experienced significant population loss with the lowest percent decrease in population density from 1997–2012 of all states and regions in the southeastern United States. This is likely due, in part, to the catastrophic storms of Hurricanes Katrina and Rita in 2005. According to the Census Bureau, between July 1, 2005 and July 1, 2006, the population of Louisiana decreased by approximately 250,000 persons (Blanchard 2009). Decreases in Louisiana coastline county populations can be attributed to significant population losses in the city of New Orleans alone due to these hurricanes (Wilson and Fischetti 2010).

Population distribution and growth are good indicators of demand for rural land (Brown et al. 2005) and potential land use change and working land loss (Berry 1978). Research in Texas revealed that the value of rural land for consumptive uses is directly correlated with population density (Kjelland et al. 2007), indicating the overall general influence of population density on rural land values and ownership size changes. Asset value per acre increased significantly from 1997–2012 in every state and region, but most notably in Florida and Georgia, and their corresponding regions, the Fruitful Rim and Southern Seaboard. In general, working land values reflect not only agricultural returns, but also other consumptive returns such as potential development to urban land use activities, agricultural program payments, or provision of natural amenities (Borchers et al. 2014). Cumulatively, population growth and attraction to economic opportunities could result in an overall increase in the asset value of rural land, as illustrated in Georgia and Florida. Georgia, in particular, is home to 18 Fortune 500 headquarters, including The Home Depot Inc., United Parcel Service Inc., The Coca Cola Co., and Delta Air Lines Inc., among others (Georgia Department of Economic Development 2016). Additionally, there are 30 Fortune 1000 businesses and over 450 Fortune 500 companies that have a presence in Georgia, leading this state to top rankings for business, workforce training, global access, and infrastructure (Georgia Department of Economic Development 2016). This economic climate in Georgia, that attracts a workforce of more than 6.3 million, plays a major role in increasing land values. This trend was also confirmed in Texas where research revealed that consumptive demands for rural land applied significant upward pressure on rural land values, and played an important role in determining farm and ranch size structure (Pope III 1985, Kjelland et al. 2007). In many areas across the United States, working land values have been found to exceed their use value in agricultural production (Borchers et al. 2014). As development potential is a significant contributor to land market value, the divergence between the agricultural income and land asset value suggests the extent to which urban influences, as a result of population growth, are encroaching upon surrounding rural lands. The state of Texas and the Fruitful Rim exhibited the greatest increase in mean asset value-income difference per operation from 1997–2012, likely due to rapid population and economic growth, and abundant natural resources and land (United States Census Bureau 2012, Bureau of Economic Analysis 2013). The significant increases in both mean asset value per acre and mean asset value-income difference per operation from 1997–2012 across all states and regions, however, indicates that these pressures and processes likely occur not only in Florida, Georgia, and Texas, but also across the Southeast at varying degrees.

I found a positive relationship between average farm size and asset value-income difference per operation. Population growth is a prime factor in regional variations in ownership size, where lower average farm sizes are found in more densely populated regions (Grigg 1995, Donnelly and Evans 2008). This population growth often leads to increasing asset values, creating a divergence between the land value and income. As the asset value-income difference increases, a bimodal distribution in farm sizes frequently occurs. Mid-sized farms are often either fragmented to smaller farms that are no longer viable for large-scale crop production, or consolidated into larger farms with greater capacity to operate at economies of scale (Wilkins et al. 2003, Kjelland et al. 2007). While the asset value-income difference metric is intended to be a measure of encroaching urban pressures, it also captures high land values from larger farms (i.e., larger farms have higher land values than small farms). This could explain the overall increase in average farm sizes with significant increases in asset value-income difference across most states, including Louisiana and Georgia, in the southeastern United States. Texas is the exception to this trend, with overall decreases in predicted average farm sizes with significant increases in asset value-income difference (>200%), likely because Texas contains significantly larger average farm sizes and greater agricultural land area than any other state in the Southeast. Rural land is large and abundant in Texas with more room for the creation and existence of small farms before urban conversion. The results of my study suggest the possibility of a land value threshold, above which, any change in asset value-income difference results only in increasing average farm sizes. This trend is evident as most states, representative of Louisiana and Georgia, experience significant decreases in average farm size with percent increases in asset value-income difference less than 100%.

I found a negative relationship between proportion of agricultural land and asset value per acre. Land under urban uses provides a far higher economic return than other agricultural enterprises, resulting in a common trend where farmland on the edge of cities is converted to residential or industrial purposes (Grigg 1995, Nickerson et al. 2012). Human responses to economic opportunities, as mediated by institutional forces, drives ownership fragmentation and potentially land cover and land use changes, as seen through decreases in the proportion of agricultural land, especially in states such as Louisiana (Lambin et al. 2001). In most states across the Southeast, proportions of agricultural land experienced relatively little change with increases in asset value, indicating that generally proportions of agricultural land have decreased or remained relatively constant over the 15-year time period, regardless of large increases in land markets. This could be a result of the one-way nature of land use change; once open space land is converted it is likely to remain urbanized. The state of Louisiana is the exception to this general trend likely because of its slow economic growth and population losses (Bureau of Economic Analysis 2013).

I found generally negative relationships between acres of farms and population density. This trend confirms the effect of population growth on rural lands and ownership sizes, as population increases often lead to an expansion of urban structure at the expense of surrounding small farms (Engle 2002). Louisiana had the most significant decrease in predicted acres of farms with increases in population density. This state represents an extreme example of trends across the southeastern United States as Louisiana also had the most drastic decreases in population density from 1997–2012. In most states across the Southeast, any increase in population density resulted in a loss of acres of small farms. This trend aligns with and confirms predictions for proportions of agricultural land.

I found generally positive relationships between acres of farms and asset value per acre, however, most states predicted percent decreases in acres of farms even with significant percent increases (>100%) in asset value, especially in Louisiana. This could be an indicator of either, (1) consolidation as a result of bimodal ownership size distributions (small and mid-sized farms are consolidated into larger farms), or (2) rapid land use conversion as small farms in these states are converted and lost to urban uses (Wilkins et al. 2003, Kjelland et al. 2007). Mississippi, Florida, and Texas are the only exceptions to this general trend with predicted increases in acres of small farms with very large increases (>100%) in asset value per acre, likely due to the rapid expansion of major metropolitan areas in these states into surrounding rural and suburban lands.

I found a negative relationship between number of farms and asset value-income difference. Rural land that is more profitable in non-agricultural use has a higher market value than its agricultural use value (Kjelland et al. 2007). This disparity (measured in my study as the asset value-income difference per operation) was found in similar studies to increase with proximity to urban areas because of the demand for consumptive land, serving as a major force in the increasing number of small-scale farms and ranches (Pope III 1985, Shi et al. 1997, Kjelland et al. 2007). This holds true in Texas and Florida, where very large increases in asset value-income difference (up to 200%) resulted in positive mean predictions in number of farms. High demand for land due to rapid population and economic growth in Texas and Florida likely contribute to the fragmentation of large ownerships into smaller farms. Most states, represented by Georgia and Mississippi, did not follow this trend and generally saw decreases in number of farms with increasing asset value-income differences, as small farms were likely converted from rural to urban land uses.

While mean percent changes in number of farms generally decreased with increasing percent changes in asset value-income difference per operation, increasing percent changes in population density had varying reactions in percent changes in number of small farms. In most states, represented again by Georgia and Mississippi, percent increases in population density resulted in percent decreases in number of farms, indicating conversion of rural lands to urban uses. This trend is illustrated by the generally lower proportions of agricultural land found in these two states. In Texas and Florida, however, increases in population density resulted in overall positive predictions in number of farms. As with predictions for acres of farms, this is likely due to the attractive job markets, affordable housing markets, and temperate climates found in Texas and Florida that encourage new growth and development of major metropolitan and economic areas in these two states.

My research establishes that ownership fragmentation and the factors that influence them are different across both states and regions, contrary to my original hypothesis that state boundaries would have no influence over ownership fragmentation or explanatory variables. My results could be, in part, due to reporting differences within the Ag Census, or because of the large scale data sets used for my study. If ownership fragmentation and land value patterns are more influenced by state boundaries, and not the broader ecological conditions represented by Farm Resource Regions, my results provide reason to question the consistency and accuracy of data reporting methods within and between states within the Ag Census, especially in Louisiana. Because each data set was reported at a county scale, some fine-scale differences in ecological and land use characteristics could have been lost and not accurately captured by the broader Farm Resource Region boundaries. Additionally, while the Ag Census provides useful and informative data on ownership sizes across the United States, the results of any analysis using this data are limited by its broad, county-level, scale. To fully understand the fine-scale role of ownership fragmentation on landscapes, consistent and historical, parcel-size data and land cover imagery are needed. To date, understanding the role of ownership fragmentation in the loss of both natural habitat and agricultural lands has been impeded by a lack of this data that captures changes in ownerships and links them with changes in land use and land cover beyond small scale urban extents (Brown et al. 2005). Each of these changes need to be represented and measured as separate processes in order to link socio-economic variables with changes in working land cover (Brown et al. 2000). While my results provide broad, general findings on multiple ownership fragmentation variables across a large study area, they are not able to link these changes with their potential impacts on rural lands and habitats without finer scale data.

The Ag Census definition of a farm is "any place from which $1,000 or more of agricultural products were produced or sold, or normally would have been sold, during the year" (National Agricultural Statistics Service 2013). Land in farms consists of agricultural land used for crops, pasture, or grazing, and also includes woodland and wasteland not actually under cultivation or used for pasture or grazing, provided it was part of the farm operator's total operation (National Agricultural Statistics Service 2013). As forestry is a large part of the southeastern United States, privately owned forestland ownerships might not be wholly represented in this data set. A large part of forest ownership dynamics in the southeastern United States is dominated by transitions between small-family and commercially owned forests (Wear and Greis 2012). Private owners have majority control over forests in the Southeast, however, these ownership patterns are becoming less stable as divestiture of corporate ownership groups shifts to timber management organizations and real estate investment trusts (Wear and Greis

2012). Private forest ownerships are an important factor in the future of forestlands and timber production in the Southeast, and future studies addressing these ownership dynamics are needed to assess the impacts of these trends on ownership fragmentation patterns.

The process of ownership fragmentation is multi-dimensional, and heavily influenced by numerous social, economic, political, environmental, agricultural, and technological factors, that are often difficult to capture at comparable scales. For example, property taxes influence land ownership and management by providing unintentional disincentives to long-term land management. Tax policies can contribute to ownership fragmentation and land development as parcels are often assessed for their "highest and best use", which in most cases is residential development (LaPierre and Germain 2005). At the same time, federal, state, and local policies may affect land ownership structures across multiple fronts, including the impact of lending programs, environmental or food safety regulations, research and development funding, and commodity programs (MacDonald et al. 2013).

Each of these factors has an impact on rural lands and their potential for ownership fragmentation, and additional research that targets local and regional differences in natural resources, agriculture, industry, taxation, socio-economic policy, and population demographics is needed to fully understand the collective influence of these metrics and their predictive power in determining future areas with impending impacts.

CONCLUSION

Ultimately, revealing the effects of human interaction with biological and physical processes, and their roles in driving land ownership change, is critical to understanding national and global landscape change (Hobbs et al. 2008). Although most habitat fragmentation takes place at the land use level, with individual parcels as the unit of study, it is necessary to compare whole landscapes that differ in their patterns of ownership fragmentation to draw inferences about the larger consequences of land ownership change (Bennett and Saunders 2010).

While there are limitations in the Ag Census data set, my study still provides a broad overview of the general trends in ownership fragmentation occurring across a large study area. Conservation managers must manage entire landscapes, not just individual fragments, and therefore require an understanding of the properties and characteristics that influence ownership fragmentation across a broad region of whole landscapes (Bennett and Saunders 2010). The results from my research identified important relationships between ownership fragmentation, population, and land value across the southeastern United States that can be used to inform public and private decision makers, and to evaluate land use policies in light of conservation and natural resource policy efforts to maintain critical resources and ecosystem services delivered from privately owned land.

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APPENDIX A

Table A1. Statistically significant correlations between percent change in acres of farms <50 acres, <100 acres, and <500 acres in size from 1997–2012 across the southeast U.S., states, and Farm Resource Regions.

State or region	**Row**[a]	**Column**[a]	r_s[b]	***P***[c]
Southeast U.S.	AcresLess50PctChg	AcresLess100PctChg	0.67	0.00
Southeast U.S.	AcresLess50PctChg	AcresLess500PctChg	0.42	0.00
Southeast U.S.	AcresLess100PctChg	AcresLess500PctChg	0.56	0.00
Alabama	AcresLess50PctChg	AcresLess100PctChg	0.68	0.00
Alabama	AcresLess50PctChg	AcresLess500PctChg	0.34	0.00
Alabama	AcresLess100PctChg	AcresLess500PctChg	0.45	0.00
Arkansas	AcresLess50PctChg	AcresLess100PctChg	0.73	0.00
Arkansas	AcresLess50PctChg	AcresLess500PctChg	0.05	0.67
Arkansas	AcresLess100PctChg	AcresLess500PctChg	0.10	0.39
Florida	AcresLess50PctChg	AcresLess100PctChg	0.74	0.00
Florida	AcresLess50PctChg	AcresLess500PctChg	0.60	0.00
Florida	AcresLess100PctChg	AcresLess500PctChg	0.65	0.00
Georgia	AcresLess50PctChg	AcresLess100PctChg	0.61	0.00
Georgia	AcresLess50PctChg	AcresLess500PctChg	0.44	0.00
Georgia	AcresLess100PctChg	AcresLess500PctChg	0.47	0.00
Louisiana	AcresLess50PctChg	AcresLess100PctChg	0.69	0.00
Louisiana	AcresLess50PctChg	AcresLess500PctChg	0.31	0.01
Louisiana	AcresLess100PctChg	AcresLess500PctChg	0.46	0.00
Mississippi	AcresLess50PctChg	AcresLess100PctChg	0.55	0.00
Mississippi	AcresLess50PctChg	AcresLess500PctChg	0.45	0.00
Mississippi	AcresLess100PctChg	AcresLess500PctChg	0.57	0.00
Oklahoma	AcresLess50PctChg	AcresLess100PctChg	0.68	0.00
Oklahoma	AcresLess50PctChg	AcresLess500PctChg	0.45	0.00

Table A1. Continued

State or region	**Row**[a]	**Column**[a]	r_s[b]	P[c]
Oklahoma	AcresLess100PctChg	AcresLess500PctChg	0.43	0.00
South Carolina	AcresLess50PctChg	AcresLess100PctChg	0.60	0.00
South Carolina	AcresLess50PctChg	AcresLess500PctChg	0.23	0.12
South Carolina	AcresLess100PctChg	AcresLess500PctChg	0.54	0.00
Texas	AcresLess50PctChg	AcresLess100PctChg	0.64	0.00
Texas	AcresLess50PctChg	AcresLess500PctChg	0.38	0.00
Texas	AcresLess100PctChg	AcresLess500PctChg	0.54	0.00
Eastern Upland	AcresLess50PctChg	AcresLess100PctChg	0.74	0.00
Eastern Upland	AcresLess50PctChg	AcresLess500PctChg	0.23	0.02
Eastern Upland	AcresLess100PctChg	AcresLess500PctChg	0.29	0.00
Fruitful Rim	AcresLess50PctChg	AcresLess100PctChg	0.71	0.00
Fruitful Rim	AcresLess50PctChg	AcresLess500PctChg	0.47	0.00
Fruitful Rim	AcresLess100PctChg	AcresLess500PctChg	0.60	0.00
Mississippi Portal	AcresLess50PctChg	AcresLess100PctChg	0.67	0.00
Mississippi Portal	AcresLess50PctChg	AcresLess500PctChg	0.31	0.00
Mississippi Portal	AcresLess100PctChg	AcresLess500PctChg	0.46	0.00
Prairie Gateway	AcresLess50PctChg	AcresLess100PctChg	0.61	0.00
Prairie Gateway	AcresLess50PctChg	AcresLess500PctChg	0.43	0.00
Prairie Gateway	AcresLess100PctChg	AcresLess500PctChg	0.59	0.00
Southern Seaboard	AcresLess50PctChg	AcresLess100PctChg	0.65	0.00
Southern Seaboard	AcresLess50PctChg	AcresLess500PctChg	0.35	0.00
Southern Seaboard	AcresLess100PctChg	AcresLess500PctChg	0.46	0.00

[a]Acres of farms percent change variable abbreviations are as follows: AcresLess50PctChg = percent change in acres of farms <50 acres in size from 1997–2012, AcresLess100PctChg = percent change in acres of farms <100 acres in size from 1997–2012, AcresLess500PctChg = percent change in acres of farms <500 acres in size from 1997–2012.
[b]Spearman's correlation coefficient
[c]P-value

Table A2. Statistically significant correlations between acres of farms <50 acres, <100 acres, and <500 acres in size in 1997 across the southeast U.S., states, and Farm Resource Regions.

State or region	**Row**[a]	**Column**[a]	r_s[b]	***P***[c]
Southeast U.S.	AcresLess50_97	AcresLess100_97	0.97	0.00
Southeast U.S.	AcresLess50_97	AcresLess500_97	0.73	0.00
Southeast U.S.	AcresLess100_97	AcresLess500_97	0.84	0.00
Alabama	AcresLess50_97	AcresLess100_97	0.97	0.00
Alabama	AcresLess50_97	AcresLess500_97	0.80	0.00
Alabama	AcresLess100_97	AcresLess500_97	0.85	0.00
Arkansas	AcresLess50_97	AcresLess100_97	0.97	0.00
Arkansas	AcresLess50_97	AcresLess500_97	0.82	0.00
Arkansas	AcresLess100_97	AcresLess500_97	0.88	0.00
Florida	AcresLess50_97	AcresLess100_97	0.97	0.00
Florida	AcresLess50_97	AcresLess500_97	0.87	0.00
Florida	AcresLess100_97	AcresLess500_97	0.94	0.00
Georgia	AcresLess50_97	AcresLess100_97	0.95	0.00
Georgia	AcresLess50_97	AcresLess500_97	0.68	0.00
Georgia	AcresLess100_97	AcresLess500_97	0.82	0.00
Louisiana	AcresLess50_97	AcresLess100_97	0.98	0.00
Louisiana	AcresLess50_97	AcresLess500_97	0.86	0.00
Louisiana	AcresLess100_97	AcresLess500_97	0.91	0.00
Mississippi	AcresLess50_97	AcresLess100_97	0.94	0.00
Mississippi	AcresLess50_97	AcresLess500_97	0.67	0.00
Mississippi	AcresLess100_97	AcresLess500_97	0.80	0.00
Oklahoma	AcresLess50_97	AcresLess100_97	0.98	0.00
Oklahoma	AcresLess50_97	AcresLess500_97	0.76	0.00
Oklahoma	AcresLess100_97	AcresLess500_97	0.84	0.00

Table A2. Continued

State or region	**Row[a]**	**Column[a]**	r_s[b]	***P***[c]
South Carolina	AcresLess50_97	AcresLess100_97	0.97	0.00
South Carolina	AcresLess50_97	AcresLess500_97	0.88	0.00
South Carolina	AcresLess100_97	AcresLess500_97	0.94	0.00
Texas	AcresLess50_97	AcresLess100_97	0.98	0.00
Texas	AcresLess50_97	AcresLess500_97	0.86	0.00
Texas	AcresLess100_97	AcresLess500_97	0.92	0.00
Eastern Upland	AcresLess50_97	AcresLess100_97	0.96	0.00
Eastern Upland	AcresLess50_97	AcresLess500_97	0.68	0.00
Eastern Upland	AcresLess100_97	AcresLess500_97	0.82	0.00
Fruitful Rim	AcresLess50_97	AcresLess100_97	0.96	0.00
Fruitful Rim	AcresLess50_97	AcresLess500_97	0.77	0.00
Fruitful Rim	AcresLess100_97	AcresLess500_97	0.89	0.00
Mississippi Portal	AcresLess50_97	AcresLess100_97	0.96	0.00
Mississippi Portal	AcresLess50_97	AcresLess500_97	0.79	0.00
Mississippi Portal	AcresLess100_97	AcresLess500_97	0.89	0.00
Prairie Gateway	AcresLess50_97	AcresLess100_97	0.98	0.00
Prairie Gateway	AcresLess50_97	AcresLess500_97	0.89	0.00
Prairie Gateway	AcresLess100_97	AcresLess500_97	0.94	0.00
Southern Seaboard	AcresLess50_97	AcresLess100_97	0.97	0.00
Southern Seaboard	AcresLess50_97	AcresLess500_97	0.80	0.00
Southern Seaboard	AcresLess100_97	AcresLess500_97	0.88	0.00

[a]Acres of farms 1997 variable abbreviations are as follows: AcresLess50_97 = acres of farms <50 acres in size in 1997, AcresLess100_97 = acres of farms <100 acres in size in 1997, AcresLess500_97 = acres of farms <500 acres in size in 1997.
[b]Spearman’s correlation coefficient
[c]P-value

Table A3. Statistically significant correlations between acres of farms <50 acres, <100 acres, and <500 acres in size in 2012 across the southeast U.S., states, and Farm Resource Regions.

State or region	**Row**[a]	**Column**[a]	$\boldsymbol{r_s}$[b]	$\boldsymbol{P}$[c]
Southeast U.S.	AcresLess50_12	AcresLess100_12	0.96	0.00
Southeast U.S.	AcresLess50_12	AcresLess500_12	0.73	0.00
Southeast U.S.	AcresLess100_12	AcresLess500_12	0.85	0.00
Alabama	AcresLess50_12	AcresLess100_12	0.96	0.00
Alabama	AcresLess50_12	AcresLess500_12	0.77	0.00
Alabama	AcresLess100_12	AcresLess500_12	0.83	0.00
Arkansas	AcresLess50_12	AcresLess100_12	0.95	0.00
Arkansas	AcresLess50_12	AcresLess500_12	0.86	0.00
Arkansas	AcresLess100_12	AcresLess500_12	0.94	0.00
Florida	AcresLess50_12	AcresLess100_12	0.97	0.00
Florida	AcresLess50_12	AcresLess500_12	0.89	0.00
Florida	AcresLess100_12	AcresLess500_12	0.96	0.00
Georgia	AcresLess50_12	AcresLess100_12	0.94	0.00
Georgia	AcresLess50_12	AcresLess500_12	0.77	0.00
Georgia	AcresLess100_12	AcresLess500_12	0.88	0.00
Louisiana	AcresLess50_12	AcresLess100_12	0.97	0.00
Louisiana	AcresLess50_12	AcresLess500_12	0.86	0.00
Louisiana	AcresLess100_12	AcresLess500_12	0.90	0.00
Mississippi	AcresLess50_12	AcresLess100_12	0.91	0.00
Mississippi	AcresLess50_12	AcresLess500_12	0.63	0.00
Mississippi	AcresLess100_12	AcresLess500_12	0.80	0.00
Oklahoma	AcresLess50_12	AcresLess100_12	0.97	0.00
Oklahoma	AcresLess50_12	AcresLess500_12	0.71	0.00
Oklahoma	AcresLess100_12	AcresLess500_12	0.80	0.00

Table A3. Continued

State or region	**Row[a]**	**Column[a]**	r_s[b]	***P***[c]
South Carolina	AcresLess50_12	AcresLess100_12	0.96	0.00
South Carolina	AcresLess50_12	AcresLess500_12	0.81	0.00
South Carolina	AcresLess100_12	AcresLess500_12	0.90	0.00
Texas	AcresLess50_12	AcresLess100_12	0.98	0.00
Texas	AcresLess50_12	AcresLess500_12	0.85	0.00
Texas	AcresLess100_12	AcresLess500_12	0.92	0.00
Eastern Upland	AcresLess50_12	AcresLess100_12	0.94	0.00
Eastern Upland	AcresLess50_12	AcresLess500_12	0.76	0.00
Eastern Upland	AcresLess100_12	AcresLess500_12	0.89	0.00
Fruitful Rim	AcresLess50_12	AcresLess100_12	0.97	0.00
Fruitful Rim	AcresLess50_12	AcresLess500_12	0.79	0.00
Fruitful Rim	AcresLess100_12	AcresLess500_12	0.90	0.00
Mississippi Portal	AcresLess50_12	AcresLess100_12	0.94	0.00
Mississippi Portal	AcresLess50_12	AcresLess500_12	0.76	0.00
Mississippi Portal	AcresLess100_12	AcresLess500_12	0.88	0.00
Prairie Gateway	AcresLess50_12	AcresLess100_12	0.98	0.00
Prairie Gateway	AcresLess50_12	AcresLess500_12	0.87	0.00
Prairie Gateway	AcresLess100_12	AcresLess500_12	0.93	0.00
Southern Seaboard	AcresLess50_12	AcresLess100_12	0.96	0.00
Southern Seaboard	AcresLess50_12	AcresLess500_12	0.83	0.00
Southern Seaboard	AcresLess100_12	AcresLess500_12	0.91	0.00

[a]Acres of farms 2012 variable abbreviations are as follows: AcresLess50_12 = acres of farms <50 acres in size in 2012, AcresLess100_12 = acres of farms <100 acres in size in 2012, AcresLess500_12 = acres of farms <500 acres in size in 2012.
[b]Spearman's correlation coefficient
[c]P-value

Table A4. Statistically significant correlations between percent change in number of farms <50 acres, <100 acres, and <500 acres in size from 1997–2012 across the southeast U.S., states, and Farm Resource Regions.

State or region	**Row**[a]	**Column**[a]	r_s[b]	***P***[c]
Southeast U.S.	FarmsLess50PctChg	FarmsLess100PctChg	0.88	0.00
Southeast U.S.	FarmsLess50PctChg	FarmsLess500PctChg	0.75	0.00
Southeast U.S.	FarmsLess100PctChg	FarmsLess500PctChg	0.87	0.00
Alabama	FarmsLess50PctChg	FarmsLess100PctChg	0.87	0.00
Alabama	FarmsLess50PctChg	FarmsLess500PctChg	0.70	0.00
Alabama	FarmsLess100PctChg	FarmsLess500PctChg	0.84	0.00
Arkansas	FarmsLess50PctChg	FarmsLess100PctChg	0.94	0.00
Arkansas	FarmsLess50PctChg	FarmsLess500PctChg	0.70	0.00
Arkansas	FarmsLess100PctChg	FarmsLess500PctChg	0.74	0.00
Florida	FarmsLess50PctChg	FarmsLess100PctChg	0.96	0.00
Florida	FarmsLess50PctChg	FarmsLess500PctChg	0.93	0.00
Florida	FarmsLess100PctChg	FarmsLess500PctChg	0.98	0.00
Georgia	FarmsLess50PctChg	FarmsLess100PctChg	0.84	0.00
Georgia	FarmsLess50PctChg	FarmsLess500PctChg	0.74	0.00
Georgia	FarmsLess100PctChg	FarmsLess500PctChg	0.85	0.00
Louisiana	FarmsLess50PctChg	FarmsLess100PctChg	0.90	0.00
Louisiana	FarmsLess50PctChg	FarmsLess500PctChg	0.81	0.00
Louisiana	FarmsLess100PctChg	FarmsLess500PctChg	0.89	0.00
Mississippi	FarmsLess50PctChg	FarmsLess100PctChg	0.84	0.00
Mississippi	FarmsLess50PctChg	FarmsLess500PctChg	0.77	0.00
Mississippi	FarmsLess100PctChg	FarmsLess500PctChg	0.87	0.00
Oklahoma	FarmsLess50PctChg	FarmsLess100PctChg	0.83	0.00
Oklahoma	FarmsLess50PctChg	FarmsLess500PctChg	0.71	0.00
Oklahoma	FarmsLess100PctChg	FarmsLess500PctChg	0.85	0.00

Table A4. Continued

State or region	**Row**[a]	**Column**[a]	r_s[b]	*P*[c]
South Carolina	FarmsLess50PctChg	FarmsLess100PctChg	0.88	0.00
South Carolina	FarmsLess50PctChg	FarmsLess500PctChg	0.70	0.00
South Carolina	FarmsLess100PctChg	FarmsLess500PctChg	0.90	0.00
Texas	FarmsLess50PctChg	FarmsLess100PctChg	0.89	0.00
Texas	FarmsLess50PctChg	FarmsLess500PctChg	0.74	0.00
Texas	FarmsLess100PctChg	FarmsLess500PctChg	0.84	0.00
Eastern Upland	FarmsLess50PctChg	FarmsLess100PctChg	0.93	0.00
Eastern Upland	FarmsLess50PctChg	FarmsLess500PctChg	0.83	0.00
Eastern Upland	FarmsLess100PctChg	FarmsLess500PctChg	0.89	0.00
Fruitful Rim	FarmsLess50PctChg	FarmsLess100PctChg	0.94	0.00
Fruitful Rim	FarmsLess50PctChg	FarmsLess500PctChg	0.87	0.00
Fruitful Rim	FarmsLess100PctChg	FarmsLess500PctChg	0.95	0.00
Mississippi Portal	FarmsLess50PctChg	FarmsLess100PctChg	0.89	0.00
Mississippi Portal	FarmsLess50PctChg	FarmsLess500PctChg	0.74	0.00
Mississippi Portal	FarmsLess100PctChg	FarmsLess500PctChg	0.83	0.00
Prairie Gateway	FarmsLess50PctChg	FarmsLess100PctChg	0.85	0.00
Prairie Gateway	FarmsLess50PctChg	FarmsLess500PctChg	0.66	0.00
Prairie Gateway	FarmsLess100PctChg	FarmsLess500PctChg	0.80	0.00
Southern Seaboard	FarmsLess50PctChg	FarmsLess100PctChg	0.86	0.00
Southern Seaboard	FarmsLess50PctChg	FarmsLess500PctChg	0.76	0.00
Southern Seaboard	FarmsLess100PctChg	FarmsLess500PctChg	0.86	0.00

[a]Number of farms percent change variable abbreviations are as follows: FarmsLess50PctChg = percent change in number of farms <50 acres in size from 1997–2012, FarmsLess100PctChg = percent change in number of farms <100 acres in size from 1997–2012, FarmsLess500PctChg = percent change in number of farms <500 acres in size from 1997–2012.
[b]Spearman's correlation coefficient
[c]P-value

Table A5. Statistically significant correlations between number of farms <50 acres, <100 acres, and <500 acres in size in 1997 across the southeast U.S., states, and Farm Resource Regions.

State or region	**Row**[a]	**Column**[a]	r_s[b]	*P*[c]
Southeast U.S.	FarmsLess50_97	FarmsLess100_97	0.99	0.00
Southeast U.S.	FarmsLess50_97	FarmsLess500_97	0.91	0.00
Southeast U.S.	FarmsLess100_97	FarmsLess500_97	0.96	0.00
Alabama	FarmsLess50_97	FarmsLess100_97	0.99	0.00
Alabama	FarmsLess50_97	FarmsLess500_97	0.96	0.00
Alabama	FarmsLess100_97	FarmsLess500_97	0.98	0.00
Arkansas	FarmsLess50_97	FarmsLess100_97	0.98	0.00
Arkansas	FarmsLess50_97	FarmsLess500_97	0.92	0.00
Arkansas	FarmsLess100_97	FarmsLess500_97	0.96	0.00
Florida	FarmsLess50_97	FarmsLess100_97	0.99	0.00
Florida	FarmsLess50_97	FarmsLess500_97	0.95	0.00
Florida	FarmsLess100_97	FarmsLess500_97	0.98	0.00
Georgia	FarmsLess50_97	FarmsLess100_97	0.98	0.00
Georgia	FarmsLess50_97	FarmsLess500_97	0.89	0.00
Georgia	FarmsLess100_97	FarmsLess500_97	0.95	0.00
Louisiana	FarmsLess50_97	FarmsLess100_97	0.99	0.00
Louisiana	FarmsLess50_97	FarmsLess500_97	0.96	0.00
Louisiana	FarmsLess100_97	FarmsLess500_97	0.98	0.00
Mississippi	FarmsLess50_97	FarmsLess100_97	0.98	0.00
Mississippi	FarmsLess50_97	FarmsLess500_97	0.88	0.00
Mississippi	FarmsLess100_97	FarmsLess500_97	0.93	0.00
Oklahoma	FarmsLess50_97	FarmsLess100_97	0.99	0.00
Oklahoma	FarmsLess50_97	FarmsLess500_97	0.95	0.00
Oklahoma	FarmsLess100_97	FarmsLess500_97	0.96	0.00

Table A5. Continued

State or region	**Row**[a]	**Column**[a]	r_s[b]	*P*[c]
South Carolina	FarmsLess50_97	FarmsLess100_97	0.97	0.00
South Carolina	FarmsLess50_97	FarmsLess500_97	0.94	0.00
South Carolina	FarmsLess100_97	FarmsLess500_97	0.99	0.00
Texas	FarmsLess50_97	FarmsLess100_97	0.99	0.00
Texas	FarmsLess50_97	FarmsLess500_97	0.96	0.00
Texas	FarmsLess100_97	FarmsLess500_97	0.98	0.00
Eastern Upland	FarmsLess50_97	FarmsLess100_97	0.98	0.00
Eastern Upland	FarmsLess50_97	FarmsLess500_97	0.88	0.00
Eastern Upland	FarmsLess100_97	FarmsLess500_97	0.94	0.00
Fruitful Rim	FarmsLess50_97	FarmsLess100_97	0.99	0.00
Fruitful Rim	FarmsLess50_97	FarmsLess500_97	0.93	0.00
Fruitful Rim	FarmsLess100_97	FarmsLess500_97	0.97	0.00
Mississippi Portal	FarmsLess50_97	FarmsLess100_97	0.98	0.00
Mississippi Portal	FarmsLess50_97	FarmsLess500_97	0.91	0.00
Mississippi Portal	FarmsLess100_97	FarmsLess500_97	0.96	0.00
Prairie Gateway	FarmsLess50_97	FarmsLess100_97	0.99	0.00
Prairie Gateway	FarmsLess50_97	FarmsLess500_97	0.96	0.00
Prairie Gateway	FarmsLess100_97	FarmsLess500_97	0.98	0.00
Southern Seaboard	FarmsLess50_97	FarmsLess100_97	0.99	0.00
Southern Seaboard	FarmsLess50_97	FarmsLess500_97	0.93	0.00
Southern Seaboard	FarmsLess100_97	FarmsLess500_97	0.97	0.00

[a]Number of farms 1997 variable abbreviations are as follows: FarmsLess50_97 = number of farms <50 acres in size in 1997, FarmsLess100_97 = number of farms <100 acres in size in 1997, FarmsLess500_97 = number of farms <500 acres in size in 1997.
[b]Spearman’s correlation coefficient
[c]P-value

Table A6. Statistically significant correlations between number of farms <50 acres, <100 acres, and <500 acres in size in 2012 across the southeast U.S., states, and Farm Resource Regions.

State or region	**Row**[a]	**Column**[a]	r_s[b]	***P***[c]
Southeast U.S.	FarmsLess50_12	FarmsLess100_12	0.99	0.00
Southeast U.S.	FarmsLess50_12	FarmsLess500_12	0.91	0.00
Southeast U.S.	FarmsLess100_12	FarmsLess500_12	0.96	0.00
Alabama	FarmsLess50_12	FarmsLess100_12	0.98	0.00
Alabama	FarmsLess50_12	FarmsLess500_12	0.92	0.00
Alabama	FarmsLess100_12	FarmsLess500_12	0.96	0.00
Arkansas	FarmsLess50_12	FarmsLess100_12	0.98	0.00
Arkansas	FarmsLess50_12	FarmsLess500_12	0.93	0.00
Arkansas	FarmsLess100_12	FarmsLess500_12	0.97	0.00
Florida	FarmsLess50_12	FarmsLess100_12	0.99	0.00
Florida	FarmsLess50_12	FarmsLess500_12	0.97	0.00
Florida	FarmsLess100_12	FarmsLess500_12	0.99	0.00
Georgia	FarmsLess50_12	FarmsLess100_12	0.97	0.00
Georgia	FarmsLess50_12	FarmsLess500_12	0.91	0.00
Georgia	FarmsLess100_12	FarmsLess500_12	0.97	0.00
Louisiana	FarmsLess50_12	FarmsLess100_12	0.99	0.00
Louisiana	FarmsLess50_12	FarmsLess500_12	0.95	0.00
Louisiana	FarmsLess100_12	FarmsLess500_12	0.99	0.00
Mississippi	FarmsLess50_12	FarmsLess100_12	0.96	0.00
Mississippi	FarmsLess50_12	FarmsLess500_12	0.84	0.00
Mississippi	FarmsLess100_12	FarmsLess500_12	0.93	0.00
Oklahoma	FarmsLess50_12	FarmsLess100_12	0.99	0.00
Oklahoma	FarmsLess50_12	FarmsLess500_12	0.94	0.00
Oklahoma	FarmsLess100_12	FarmsLess500_12	0.97	0.00

Table A6. Continued

State or region	**Row**[a]	**Column**[a]	r_s[b]	*P*[c]
South Carolina	FarmsLess50_12	FarmsLess100_12	0.97	0.00
South Carolina	FarmsLess50_12	FarmsLess500_12	0.93	0.00
South Carolina	FarmsLess100_12	FarmsLess500_12	0.98	0.00
Texas	FarmsLess50_12	FarmsLess100_12	0.99	0.00
Texas	FarmsLess50_12	FarmsLess500_12	0.96	0.00
Texas	FarmsLess100_12	FarmsLess500_12	0.98	0.00
Eastern Upland	FarmsLess50_12	FarmsLess100_12	0.98	0.00
Eastern Upland	FarmsLess50_12	FarmsLess500_12	0.88	0.00
Eastern Upland	FarmsLess100_12	FarmsLess500_12	0.94	0.00
Fruitful Rim	FarmsLess50_12	FarmsLess100_12	0.99	0.00
Fruitful Rim	FarmsLess50_12	FarmsLess500_12	0.95	0.00
Fruitful Rim	FarmsLess100_12	FarmsLess500_12	0.98	0.00
Mississippi Portal	FarmsLess50_12	FarmsLess100_12	0.97	0.00
Mississippi Portal	FarmsLess50_12	FarmsLess500_12	0.90	0.00
Mississippi Portal	FarmsLess100_12	FarmsLess500_12	0.96	0.00
Prairie Gateway	FarmsLess50_12	FarmsLess100_12	0.99	0.00
Prairie Gateway	FarmsLess50_12	FarmsLess500_12	0.96	0.00
Prairie Gateway	FarmsLess100_12	FarmsLess500_12	0.98	0.00
Southern Seaboard	FarmsLess50_12	FarmsLess100_12	0.98	0.00
Southern Seaboard	FarmsLess50_12	FarmsLess500_12	0.93	0.00
Southern Seaboard	FarmsLess100_12	FarmsLess500_12	0.98	0.00

[a]Number of farms 2012 variable abbreviations are as follows: FarmsLess50_12 = number of farms <50 acres in size in 2012, FarmsLess100_12 = number of farms <100 acres in size in 2012, FarmsLess500_12 = number of farms <500 acres in size in 2012.
[b]Spearman’s correlation coefficient
[c]P-value

Table A7. Statistically significant correlations between percent change in population and percent change in population density from 1997–2012 across the southeast U.S., states, and Farm Resource Regions.

State or region	**Row**[a]	**Column**[a]	$\boldsymbol{r_s}$[b]	***P***[c]
Southeast U.S.	PopPctChg	PopDensPctChg	1.00	0.00
Alabama	PopPctChg	PopDensPctChg	1.00	0.00
Arkansas	PopPctChg	PopDensPctChg	1.00	0.00
Florida	PopPctChg	PopDensPctChg	1.00	0.00
Georgia	PopPctChg	PopDensPctChg	1.00	0.00
Louisiana	PopPctChg	PopDensPctChg	1.00	0.00
Mississippi	PopPctChg	PopDensPctChg	1.00	0.00
Oklahoma	PopPctChg	PopDensPctChg	1.00	0.00
South Carolina	PopPctChg	PopDensPctChg	1.00	0.00
Texas	PopPctChg	PopDensPctChg	1.00	0.00
Eastern Upland	PopPctChg	PopDensPctChg	1.00	0.00
Fruitful Rim	PopPctChg	PopDensPctChg	1.00	0.00
Mississippi Portal	PopPctChg	PopDensPctChg	1.00	0.00
Prairie Gateway	PopPctChg	PopDensPctChg	1.00	0.00
Southern Seaboard	PopPctChg	PopDensPctChg	1.00	0.00

[a]Population percent change variable abbreviations are as follows: PopPctChg = percent change in total population from 1997–2012, PopDensPctChg = percent change in population density from 1997–2012.
[b]Spearman's correlation coefficient
[c]P-value

Table A8. Statistically significant correlations between population and population density in 1997 across the southeast U.S., states, and Farm Resource Regions.

State or region	**Row**[a]	**Column**[a]	r_s[b]	**P**[c]
Southeast U.S.	Pop97	PopDens97	0.91	0.00
Alabama	Pop97	PopDens97	0.96	0.00
Arkansas	Pop97	PopDens97	0.97	0.00
Florida	Pop97	PopDens97	0.95	0.00
Georgia	Pop97	PopDens97	0.92	0.00
Louisiana	Pop97	PopDens97	0.88	0.00
Mississippi	Pop97	PopDens97	0.93	0.00
Oklahoma	Pop97	PopDens97	0.94	0.00
South Carolina	Pop97	PopDens97	0.93	0.00
Texas	Pop97	PopDens97	0.96	0.00
Eastern Upland	Pop97	PopDens97	0.93	0.00
Fruitful Rim	Pop97	PopDens97	0.94	0.00
Mississippi Portal	Pop97	PopDens97	0.91	0.00
Prairie Gateway	Pop97	PopDens97	0.97	0.00
Southern Seaboard	Pop97	PopDens97	0.85	0.00

[a]Population variable abbreviations are as follows: Pop97 = total population in 1997, PopDens97 = population density in 1997.
[b]Spearman's correlation coefficient
[c]P-value

Table A9. Statistically significant correlations between population and population density in 2012 across the southeast U.S., states, and Farm Resource Regions.

State or region	**Row[a]**	**Column[a]**	$\boldsymbol{r_s}$**[b]**	***P*[c]**
Southeast U.S.	Pop12	PopDens12	0.10	0.00
Alabama	Pop12	PopDens12	0.47	0.00
Arkansas	Pop12	PopDens12	0.15	0.20
Florida	Pop12	PopDens12	0.07	0.59
Georgia	Pop12	PopDens12	-0.03	0.74
Louisiana	Pop12	PopDens12	0.17	0.19
Mississippi	Pop12	PopDens12	0.34	0.00
Oklahoma	Pop12	PopDens12	0.19	0.10
South Carolina	Pop12	PopDens12	-0.07	0.65
Texas	Pop12	PopDens12	0.05	0.42
Eastern Upland	Pop12	PopDens12	0.31	0.00
Fruitful Rim	Pop12	PopDens12	0.08	0.32
Mississippi Portal	Pop12	PopDens12	0.26	0.00
Prairie Gateway	Pop12	PopDens12	-0.04	0.58
Southern Seaboard	Pop12	PopDens12	0.15	0.01

[a]Population variable abbreviations are as follows: Pop12 = total population in 2012, PopDens12 = population density in 2012.
[b]Spearman’s correlation coefficient
[c]P-value

Table A10. Statistically significant correlations between percent change in asset value per acre and percent change in asset value per operation from 1997–2012 across the southeast U.S., states, and Farm Resource Regions.

State or region	**Row**[a]	**Column**[a]	r_s[b]	***P***[c]
Southeast U.S.	AssetPerAcrePctChg	AssetPerOpPctChg	0.63	0.00
Alabama	AssetPerAcrePctChg	AssetPerOpPctChg	0.60	0.00
Arkansas	AssetPerAcrePctChg	AssetPerOpPctChg	0.64	0.00
Florida	AssetPerAcrePctChg	AssetPerOpPctChg	0.43	0.00
Georgia	AssetPerAcrePctChg	AssetPerOpPctChg	0.56	0.00
Louisiana	AssetPerAcrePctChg	AssetPerOpPctChg	0.44	0.00
Mississippi	AssetPerAcrePctChg	AssetPerOpPctChg	0.46	0.00
Oklahoma	AssetPerAcrePctChg	AssetPerOpPctChg	0.67	0.00
South Carolina	AssetPerAcrePctChg	AssetPerOpPctChg	0.68	0.00
Texas	AssetPerAcrePctChg	AssetPerOpPctChg	0.70	0.00
Eastern Upland	AssetPerAcrePctChg	AssetPerOpPctChg	0.61	0.00
Fruitful Rim	AssetPerAcrePctChg	AssetPerOpPctChg	0.54	0.00
Mississippi Portal	AssetPerAcrePctChg	AssetPerOpPctChg	0.54	0.00
Prairie Gateway	AssetPerAcrePctChg	AssetPerOpPctChg	0.71	0.00
Southern Seaboard	AssetPerAcrePctChg	AssetPerOpPctChg	0.57	0.00

[a]Asset value percent change variable abbreviations are as follows: AssetPerAcrePctChg = percent change in asset value per acre from 1997–2012, AssetPerOpPctChg = percent change in asset value per operation from 1997–2012.
[b]Spearman's correlation coefficient
[c]P-value

Table A11. Statistically significant correlations between asset value per acre and asset value per operation in 1997 across the southeast U.S., states, and Farm Resource Regions.

State or region	**Row[a]**	**Column[a]**	$\boldsymbol{r_s}$**[b]**	***P*[c]**
Southeast U.S.	AssetPerAcre97	AssetPerOp97	-0.17	0.00
Alabama	AssetPerAcre97	AssetPerOp97	-0.14	0.25
Arkansas	AssetPerAcre97	AssetPerOp97	-0.16	0.17
Florida	AssetPerAcre97	AssetPerOp97	0.21	0.10
Georgia	AssetPerAcre97	AssetPerOp97	-0.02	0.83
Louisiana	AssetPerAcre97	AssetPerOp97	-0.09	0.47
Mississippi	AssetPerAcre97	AssetPerOp97	-0.02	0.85
Oklahoma	AssetPerAcre97	AssetPerOp97	-0.31	0.01
South Carolina	AssetPerAcre97	AssetPerOp97	-0.29	0.05
Texas	AssetPerAcre97	AssetPerOp97	-0.59	0.00
Eastern Upland	AssetPerAcre97	AssetPerOp97	0.53	0.00
Fruitful Rim	AssetPerAcre97	AssetPerOp97	-0.26	0.00
Mississippi Portal	AssetPerAcre97	AssetPerOp97	0.07	0.42
Prairie Gateway	AssetPerAcre97	AssetPerOp97	-0.43	0.00
Southern Seaboard	AssetPerAcre97	AssetPerOp97	0.09	0.13

[a]Asset value 1997 variable abbreviations are as follows: AssetPerAcre97 = asset value per acre in 1997, AssetPerOp97 = asset value per operation in 1997.
[b]Spearman's correlation coefficient
[c]P-value

Table A12. Statistically significant correlations between asset value per acre and asset value per operation in 2012 across the southeast U.S., states, and Farm Resource Regions.

State or region	**Row**[a]	**Column**[a]	$\boldsymbol{r_s}$[b]	***P***[c]
Southeast U.S.	AssetPerAcre12	AssetPerOp12	-0.25	0.00
Alabama	AssetPerAcre12	AssetPerOp12	-0.15	0.24
Arkansas	AssetPerAcre12	AssetPerOp12	0.28	0.02
Florida	AssetPerAcre12	AssetPerOp12	0.13	0.30
Georiga	AssetPerAcre12	AssetPerOp12	-0.23	0.00
Louisana	AssetPerAcre12	AssetPerOp12	-0.31	0.01
Mississippi	AssetPerAcre12	AssetPerOp12	0.03	0.76
Oklahoma	AssetPerAcre12	AssetPerOp12	-0.73	0.00
South Carolina	AssetPerAcre12	AssetPerOp12	-0.50	0.00
Texas	AssetPerAcre12	AssetPerOp12	-0.60	0.00
Eastern Upland	AssetPerAcre12	AssetPerOp12	0.04	0.71
Fruitful Rim	AssetPerAcre12	AssetPerOp12	-0.33	0.00
Mississippi Portal	AssetPerAcre12	AssetPerOp12	0.26	0.00
Prairie Gateway	AssetPerAcre12	AssetPerOp12	-0.43	0.00
Southern Seaboard	AssetPerAcre12	AssetPerOp12	-0.08	0.18

[a]Asset value 2012 variable abbreviations are as follows: AssetPerAcre12 = asset value per acre in 2012, AssetPerOp12 = asset value per operation in 2012.
[b]Spearman's correlation coefficient
[c]P-value

APPENDIX B

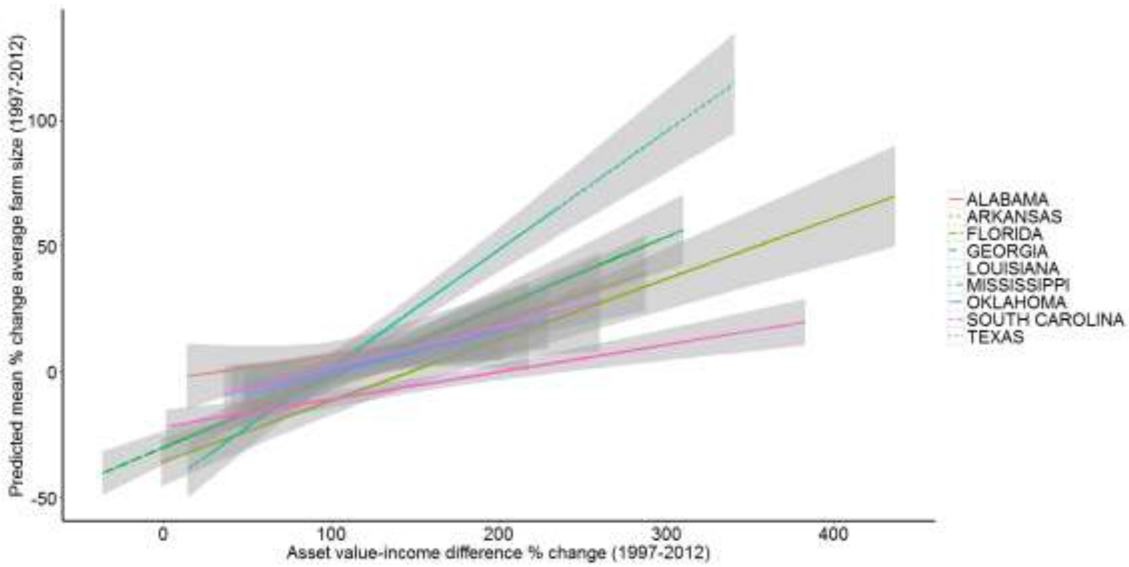

Figure B1. Predicted means for percent change in average farm size (1997–2012) using the best-fit model (percent change in average farm size = state * percent change in asset value-income difference per operation [1997–2012]).

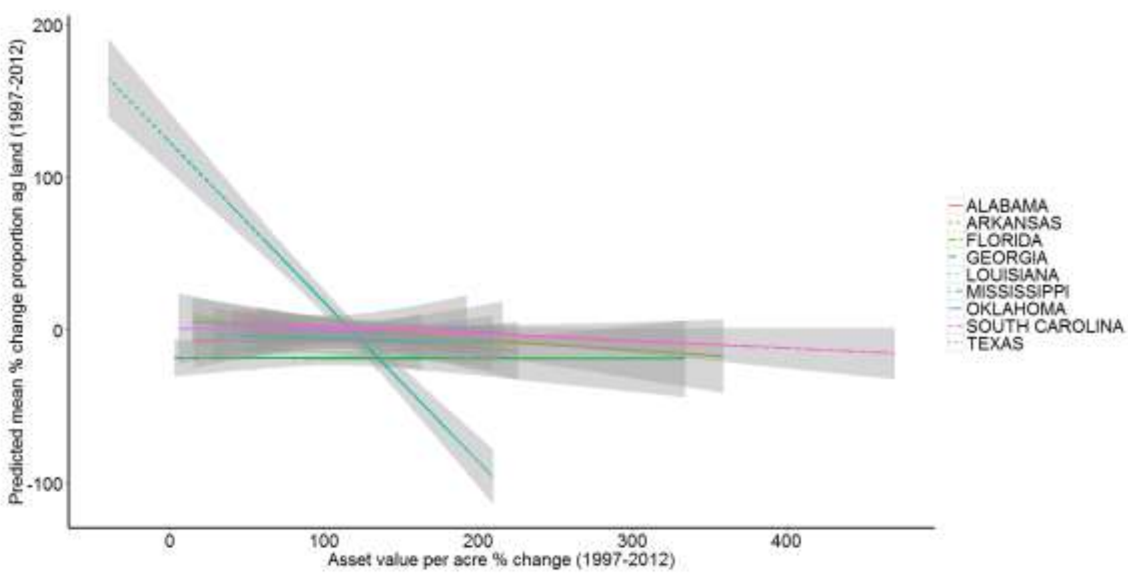

Figure B2. Predicted means for percent change in proportion of agricultural land (1997–2012) using the best-fit model (percent change in proportion of agricultural land = state * percent change in asset value per acre [1997–2012]).

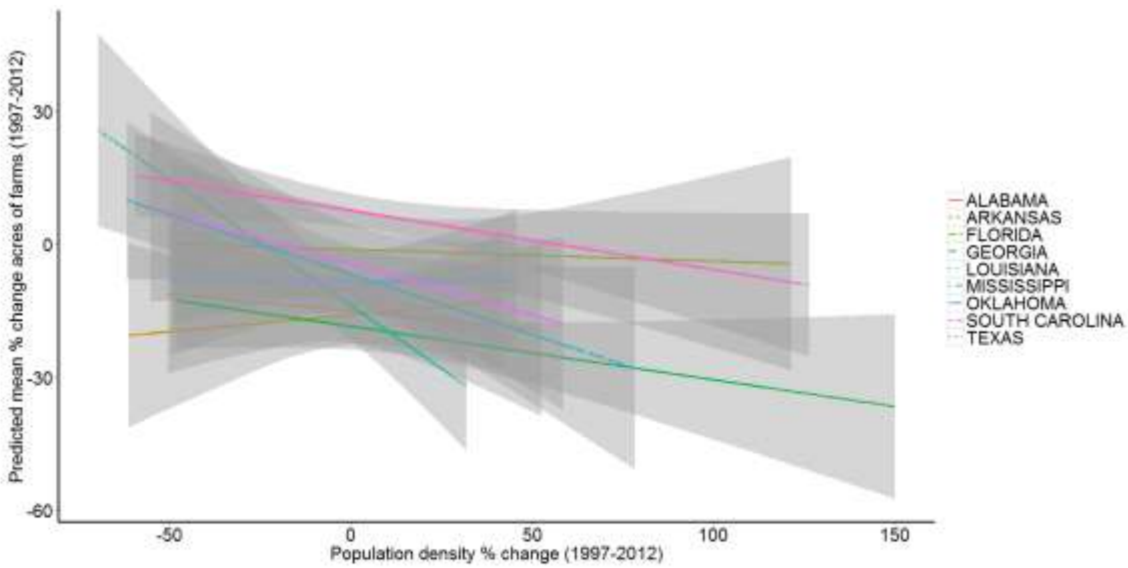

Figure B3. Predicted means for percent change in acres of farms <500 acres in size (1997–2012) using the first best-fit model (percent change in acres of farms <500 acres in size = state * percent change in population density [1997–2012]).

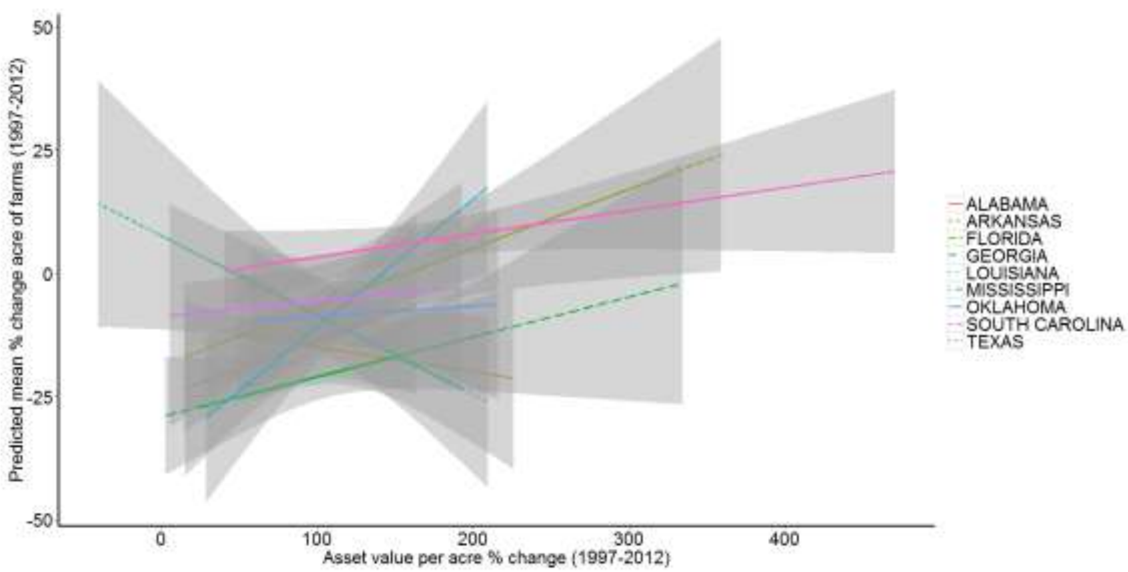

Figure B4. Predicted means for percent change in acres of farms <500 acres in size (1997–2012) using the second best-fit model (percent change in acres of farms <500 acres in size = state * percent change in asset value per acre [1997–2012]).

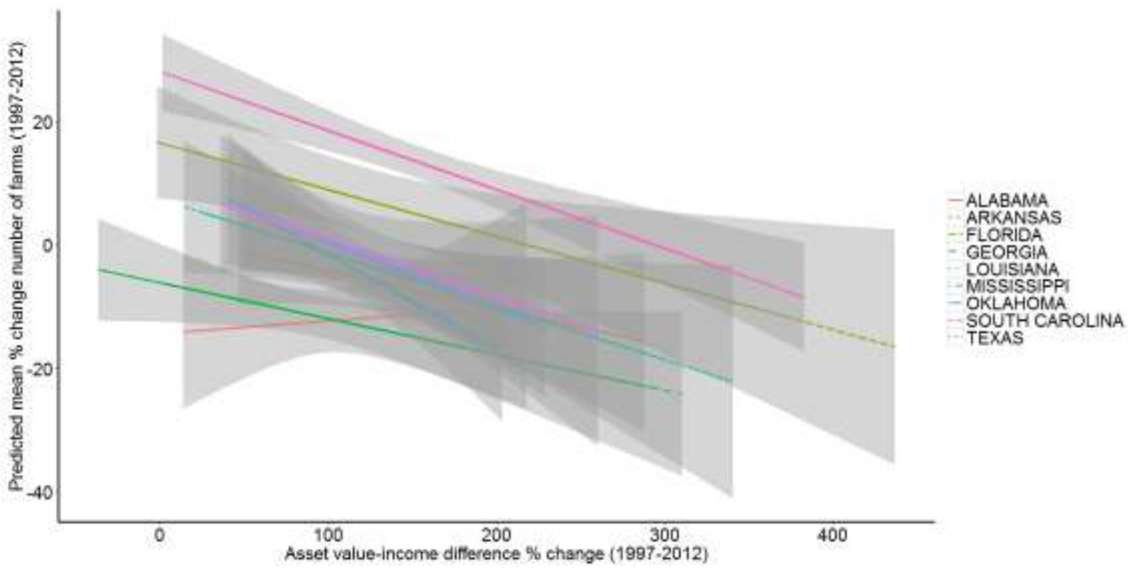

Figure B5. Predicted means for percent change number of farms <500 acres in size (1997–2012) using the first best-fit model (percent change in number of farms <500 acres in size = state * percent change asset value-income difference per operation [1997–2012]).

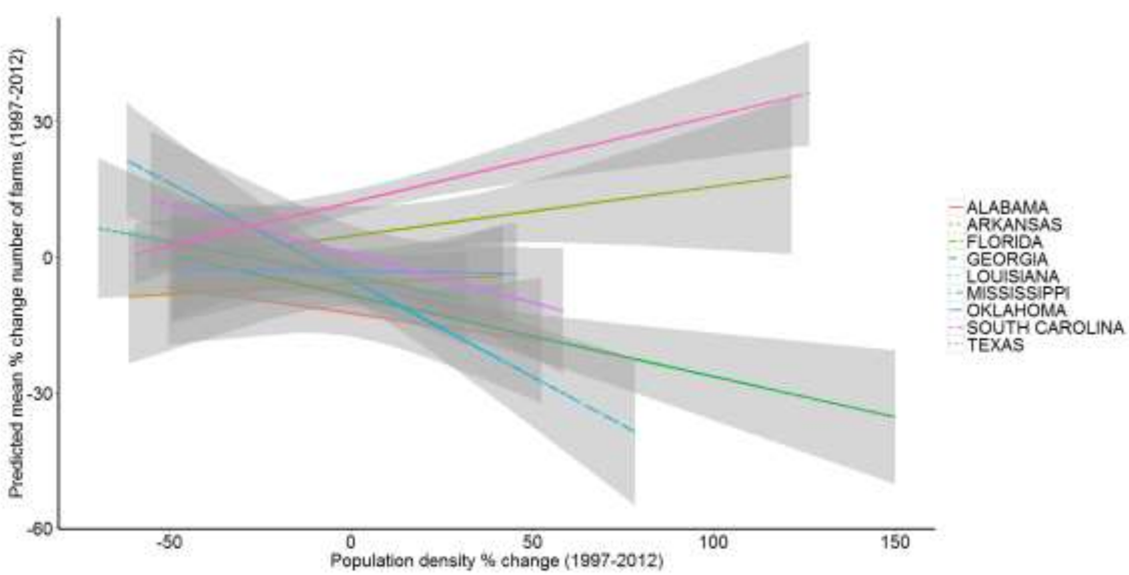

Figure B6. Predicted means for percent change in number of farms <500 acres in size (1997–2012) using the second best-fit model (percent change in number of farms <500 acres in size = state * percent change in population density [1997–2012]).