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Analyzing the Spatial Distribution of NRCS Conservation Programs in West Virginia

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Abstract

The purpose of this paper is to assess the spatial distribution of Natural Resource Conservation Service (NRCS) assistance programs throughout the state of West Virginia. Land cover attributes along with socioeconomic characteristics are used within a Spatial Hierarchical Model to explain regional patterns and to predict the number of applied practices at the census tract level. Based on the observed traits, census tracts are then classified as underserved or overserved by their designated NRCS field office (service center). Amount of agricultural land, amount of stream mileage and the location of a field office have statistically significant effects on the number of applied practices within a census tract. County level data collected from the US Census of Agriculture are also observed within this analysis. Number of farms, average farm size, and number of cattle have significant indirect and total spillover effects on the number of applied practices. By targeting of outreach efforts to underserved regions that should be receiving higher levels of assistance along with exposing external or internal factors impacting the distributional aspects of the assistance programs, the results of this study will assist in illustrating the new priority areas for NRCS.

Keywords: Resource and Environmental Policy Analysis, Rural/Community Development, Natural Resource Economics, Spatial Econometrics, Spatial Analysis

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Introduction

Historically, the state of West Virginia has seen a tremendous amount of resource extraction from its timber, coal, oil, and natural gas resources. Due to this extraction, it is important to address resource concerns to preserve the remaining environmental quality of the land. Conservation programs developed by federal agencies, such as Natural Resource Conservation Service (NRCS), address resource concerns such as water quality, soil quality, water conservation, air quality, as well as wildlife habitats. There are several benefits related to the adoption of these practices, examples include financial incentives with short-term input costs and long-term profits, risk aversion to crop or establishment failure, and an increase in technology or productivity (Pannell et al. 2006). These programs work best with a cooperation of landowners or farmers. Federal agencies, like NRCS, have the objective of building new and existing relationships with landowners and farmers to increase program participation and expand their local audience. The mission of NRCS is 'Help People, Help the Land' (NRCS Farm Bill Program Outreach Strategy). The goal of the agency is consistency in regards to "ensure that all programs and services are made equally accessible to all customers, with emphasis to the underserved". One of the key issues of these agencies related to conservation program participation understands why individuals participate in these programs, and what barriers inhibit participation.

Previous literature has identified influential factors explaining individual or farm level participation in government programs. Lambert et al. (2006) examine the farmer demographics and farm characteristics of participants and non-participants. Farm size, commodity mix, and operator motivation influence the decision to use different types of conservation practices. Ma et al. (2010) incorporate a constrained utility maximization framework to examine farmer responses to enrollment choices for proposed payment for environmental services programs. Reimer and Prokopy (2014) utilized a mixed-method approach including surveys and interviews to identify motivations and social barriers of individual participation in U.S. Farm Bill programs. Heckman and Smith (2004) also observe social demographics in participation of social programs. While the authors identify ethnicity and education level as playing significant parts in participation, they believe that awareness of the social program and program eligibility play a major role in participation throughout various demographic groups.

Ryan et al. (2003) identify that farmers are more intrinsically motivated by the appearance and management of the land rather than economic compensation. They also find farmers are concerned about the effects of their farming practices on downstream neighbors. They make two statements related to importance of our study, “farmers’ sense of obligation to their community may be a new strategy for convincing farmers to engage in conservation” and “[t]he social dimension of farmers’ conservation behavior is a variable worth further exploration in environmental planning and policy research”.

What has not been explored within the literature is government program participation at a regional or community level. We attempt to measure the social aspects highlighted as future work in the Ryan et al. (2003) paper. This study expands from this previous literature by explaining government program participation at an aggregate level (census tract) in order to assess the spatial distribution of applied conservation assistance practices while controlling for socio-economic characteristics and land cover attributes. It is important to observe program participation at a regional level to observe the influence of social interactions and networking. Theories based on social reinforcement include as cascades, entrapment, and tipping (Dixit, A.K. 2003; Gladwell, M. 2000; and Heal, G. and H. Kunreuther 2010). These social interaction effects can help explain the spatial dependence of the applied practices. We want to identify the significance of a social group, like NRCS conservation program participants, on the spatial distribution of practice application throughout the state.

Based on our analysis, we classify census tracts as either overserved or underserved by their local service area (field office) in terms of program participation/implementation. It is important to address spatial inequality of program participation at the state level as areas that are underserved have both landowner and environmental conservation needs that are not being satisfied by NRCS assistance programs. By targeting outreach efforts to underserved regions that should be receiving higher levels of assistance along with exposing external or internal factors affecting the distributional aspects of the assistance programs, the results of this study will illustrate new priority areas for outreach efforts conducted by NRCS. This analysis utilizes NRCS conservation practices of technical assistance and financial assistance that could lead to potential community outreach applied from 2004 to 2015.

The development of this project was based upon an interest of the WV NRCS State office for evaluating program participation and promoting outreach efforts throughout the state. The purpose of this essay is to evaluate the spatial distribution of conservation assistance programs provided by the NRCS. This paper focuses on the first phase of the project is explaining and evaluating program participation at the census tract level based on service provided by the local NRCS service area. The starting point of the second phase of the project, identifying priority areas for future outreach areas, is based upon the results of the analysis conducted within the first phase. We conclude this paper by identifying the new priority areas in West Virginia for future outreach efforts by NRCS.

West Virginia Natural Resource Conservation Service Assistance Programs

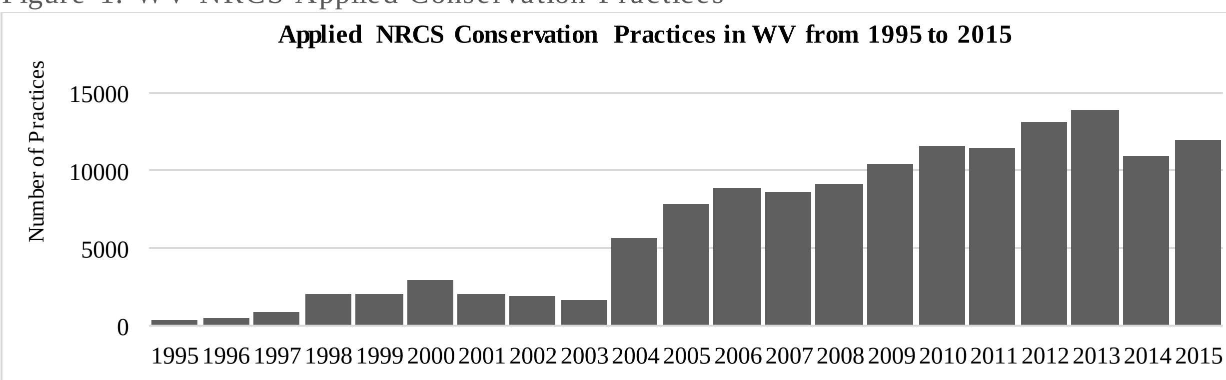
The Natural Resource Conservation Service (NRCS) is a federal agency operating under the United States Department of Agriculture (USDA). This agency provides financial and technical assistance to farmers and landowners for aid in the management and sustainability of natural resources. The agency also provides incentives to farmers and landowners for putting land under long-term easements. This agency is federally regulated but provides assistance at the state and local levels. This analysis focuses on the financial and technical assistance programs offered by NRCS. This section discusses the type of programs offered, as well as participation levels in WV.

Through financial assistance programs, the agency provides cost-share support to projects with landowners such as planning and implementing conservation practices to address resource concerns or to promote ecological preservation on agricultural land and non-industrial private forest land. NRCS financial assistance programs currently include: Agricultural Management Assistance (AMA), Conservation Stewardship Program (CSP), and Environmental Quality Incentives Program (EQIP). AMA helps producers use conservation techniques to manage risk and solve natural resource issues. CSP assists agricultural producers in maintaining and improving their conservation systems. The program also promotes conservation activities to address priority resource concerns. This program incentivizes conservation performance quality with the higher the conservation performance, the higher the payment. EQIP provides both financial and technical assistance to producers to address natural resource concerns and to deliver improved environmental benefits. EQIP has the highest enrollment levels of the financial assistance programs. Information on these programs was collected from the national NRCS website[1].

Conservation Technical Assistance Programs (CTA) do not provide cost-share assistance however, they can provide other resources such as: resource assessment, practice design, resource monitoring, and follow-up consultations of installed practices. Technical assistance is available to a larger audience than financial assistance. Only programs that West Virginia NRCS state office identified as leads to potential outreach to increase program adoption throughout the state were included in this study. CTA-General and EQIP are the most applied conservation practices in WV. Information on technical assistance programs was collected from the national NRCS website[1].

Figure 1 displays the annual number of implemented practices throughout the state of West Virginia from 2005 to 2015. In 2004, there was a sharp increase in the annual number of applied conservation practices in West Virginia. NRCS applied assistance practices was on a steady increase from 2004 to 2013, however in 2014 participation began to decrease.

Figure 1. WV NRCS Applied Conservation Practices



The noticeable increases in the annual number of applied practices are correlated with the installation of the US Farm Bills. During 1995 to 2015, four amendments were made to the US Farm Bill. These amendments include Federal Agriculture Improvement and Reform Act of 1996, Farm Security and Rural Investment Act of 2002, Food, Conservation, and Energy Act of 2008, and the Agricultural Act of 2014. If we assume at least a two-year delay between the introduction of the amendment and its application, we can identify a direct positive effect on the number of conservation practices applied in West Virginia. It is important to identify underserved regions as

[1]USDA NRCS. "NRCS Conservation Programs" Accessed on April 12, 2017 https://www.nrcs.usda.gov/wps/portal/nrcs/main/national/programs/

future target areas for NRCS so that participation levels may once again be on the rise. Our study focuses on the practice installation at the census tract level from 2004 to 2015.

Table 1 below displays the number of applied assistance programs throughout West Virginia. From 2004 to 2015, there was a total number of 123, 659 applied conservation practices throughout the state. Of this total, 57,833 practices were financial assistance programs while 65, 826 practices were technical assistance programs. The CTA-General program has the highest count of technical assistance practices, while the EQIP program has the highest count of financial assistance practices. Prescribed grazing is the most implemented conservation practice in WV.

Table 1. Types of NRCS Assistance Programs Applied in West Virginia

Program	Full Name	Count	Program Type
AMA	Agricultural Management Assistance Program	807	Financial
CBWI	Chesapeake Bay Watershed Initiative	3869	Financial
CRP	conservation Reserve Program	972	Financial
CSP	Conservation Security Program	2937	Financial
CStwP	Conservation Stewardship Program	9399	Financial
CTA-GENRL	Conservation Technical Assistance - General	62330	Technical
CTA-GLC	Conservation Technical Assistance - Grazing Land Conservation	3496	Technical
EQIP	Environmental Quality Incentives Program	34090	Financial
GRP	Grasslands Reserve Program	834	Financial
WF-03	Flood Prevention Operations	318	Financial
WHIP	Wildlife Habitat Incentives Program	4573	Financial
WRP	Wetlands Reserve Program	34	Financial

Programs that will not be included in this study are Agricultural Conservation Easement Program (ACEP), Conservation Technical Assistance- Natural Resource Inventory (CTA-NRI), Emergency Conservation Program (ECP), Emergency Watershed Protection (EWP), and Farm and Ranchland Protection Program (FRPP)[2]. These programs are related to emergency assistance after natural disasters and other rare circumstances. By the removal of these programs, only a total of 13 practices were removed from the dataset. In the future, a sensitivity analysis may be conducted with the removal of programs that are currently, no longer offered by NRCS. Currently the major

[2] During our meeting in December 2016 with the NRCS administrative team, the advisors from NRCS decided these programs should not be included within the study as they do not have outreach potential.

financial assistance programs offered by the WV NRCS include AMA, CSP, and EQIP. Former financial assistance programs include AWEP, CCPI, and WHIP, which has been folded into EQIP.

Agricultural Production in West Virginia

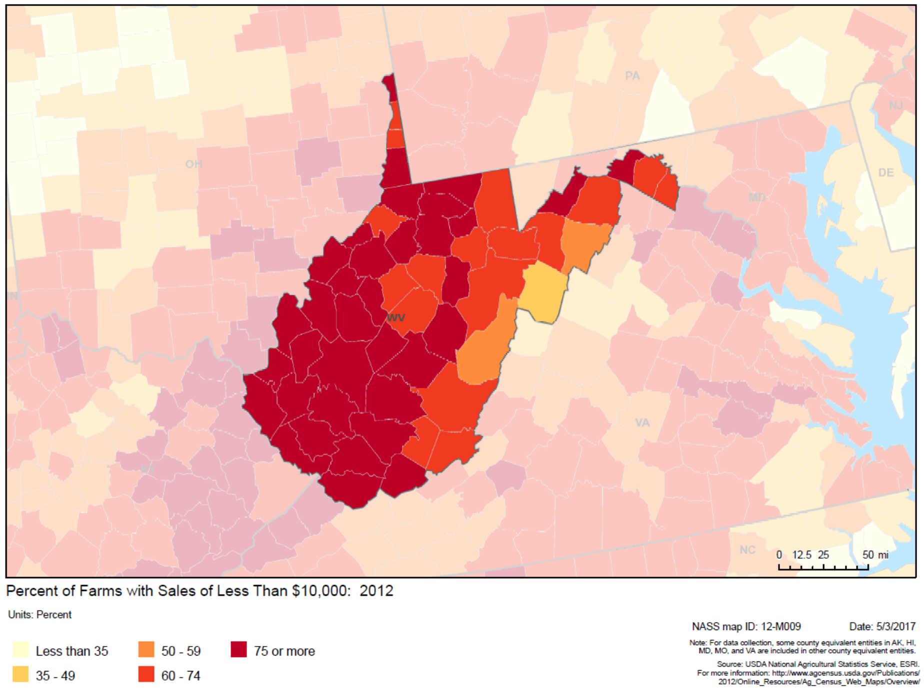
According to the WV Annual Bulletin No. 47, there were 20,900 farms with a majority of these farms as family-owned and operated[3] in 2015. Although the number of farms have decreased over the last five years, the average size of the farm has increased to 172 acres per farm. There is a total of 3.6 million acres of farmland throughout the state of West Virginia.

West Virginia is not an agricultural production dominant state. For an entity to be considered a farm, it only needs to produce $1,000 worth of goods. In 2012, the majority of the farms within the state had sales less than $10,000 for the year. The distribution of percent of farms with sales less than $10,000 is displayed in Figure 2 below. Boone County is the only county where the majority of farm operators list farming as their primary occupation. Since farming operates on a low-income scale throughout the state, many operators treat farming as a secondary/alternative occupation. Figure 3 displays the distribution of the percentage of farm operators in each county that list farming as their primary occupation in 2012. In most of the counties, only 35-44 percent of the operators list farming as their primary occupation in West Virginia.

However, West Virginia's production of crops, livestock, and poultry rank nationally. In 2015, the state's apple production ranked 9th, trout production ranks 10th, peach production ranked 11th, turkey production ranked 14th, and broiler chicken production ranked 18th. The table below is from the WV Annual Bulletin No. 47 and displays the ranking and quantity of production for 2015.

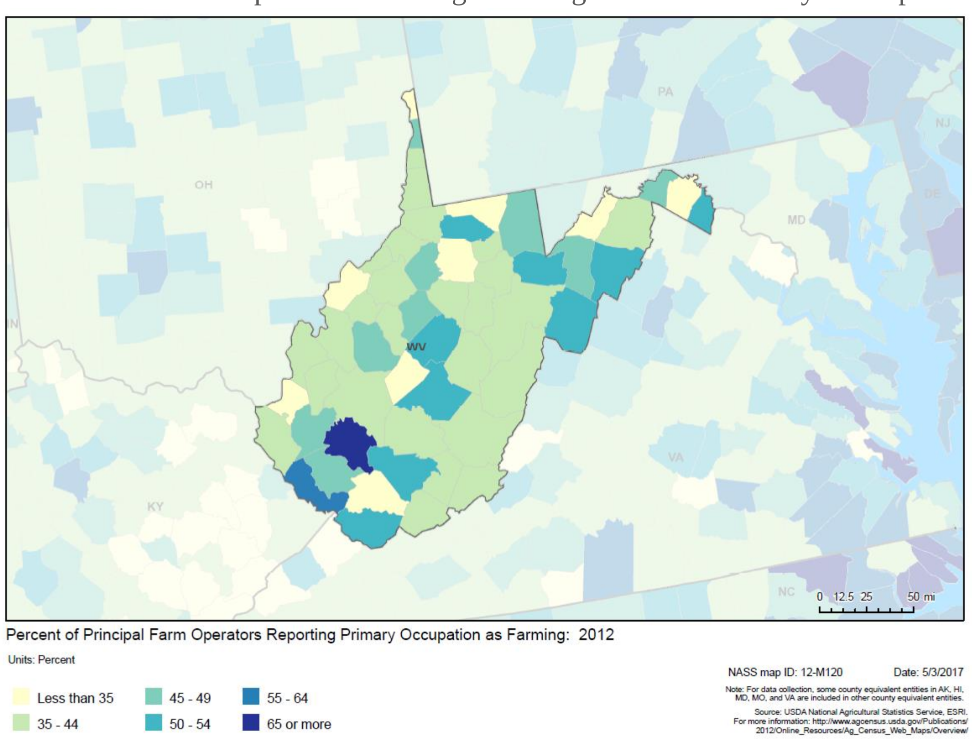
[3] Farms can be operated by partnerships or corporations.

Figure 2. Percent of Farms in WV with Sales Less than $10,000 in 2012



Map was created by the US Census of Agriculture

Figure 3. Percent of Farm Operators Listing Farming as their Primary Occupation



Map was created by the US Census of Agriculture

Table 2. West Virginia's Farm Production Ranking in 2015

GENERAL
West Virginia's Rank in the Nation's Agriculture - 2015

Crops, Livestock and Poultry	West Virginia				United States
	Rank Among States [1/]	Production	Unit	Value of Production (Dollars)	Leading State
Apples [2/]	9	90,000,000	Lbs.	13,532,000	Washington
Broilers	18	356,100,000	Lbs.	191,582,000	Georgia
Cattle & Calves	39	136,673,000	Lbs.	220,334,000	Texas
Chickens, All [3/]	31	2,112,000	Birds	16,474,000	Iowa
Corn for Grain	40	5,180,000	Bu.	20,461,000	Iowa
Corn for Silage	38	252,000	Tons	[4/]	Wisconsin
Eggs	32	274,000,000	Eggs	53,872,000	Iowa
Hay, Alfalfa	32	66,000	Tons	13,530,000	California
Hay, All	37	1,035,000	Tons	134,655,000	Texas
Hay, Other	26	969,000	Tons	121,125,000	Texas
Hogs & Pigs	41	1,420,000	Lbs.	787,000	Iowa
Honey	40	175,000	Lbs.	777,000	North Dakota
Milk	42	141,000,000	Lbs.	24,675,000	California
Peaches [2/]	11	5,700	Tons	6,056,000	California
Soybeans	30	1,248,000	Bu.	11,232,000	Iowa
Trout [5/]	10	[4/]		1,052,000	Idaho
Turkeys	14	90,600,000	Lbs.	73,477,000	North Carolina
Wheat, Winter	41	240,000	Bu.	1,296,000	Kansas
Wool	28	120,000	Lbs.	120,000	California

[1/] Rankings based on production. [2/] Value of production is based on utilized production. [3/] Excludes broilers. [4/] Not available. [5/] Ranking based on total value of fish sold.

Note: Table pulled directly from the WV Annual Bulletin No. 47 in 2016

The commercial broiler chicken and the cattle and calves industries are the leading agriculture production sectors in the state in terms of monetary value. The total value of production in 2015 was roughly $905 million, in which broilers account 21 percent and cattle and calves account for 24 percent of the value in production. Combined, broiler chickens and cattle and calf's production account for 45 percent of the dollar value of production in 2015.

Different regions within West Virginia have diverse focuses on the production of crops, livestock, and poultry. Based on the West Virginia Agriculture State Profile 2014, Greenbrier County is the lead in county in the state for agriculture. Greenbrier leads the state in the most farmland, number of cattle, and hay production. Hardy County is the lead in the state for broiler chicken inventory and agricultural sales. Jefferson County leads the state in corn for grain, and soybean and wheat production. Leading counties in the state for all cattle include Greenbrier Monroe, Hardy, Preston, and Pendleton. Leading counties in the state for chickens include Hardy, Grant, Pendleton, Hampshire, and Mineral. County level data on fruit production was not provided within the Bulletin. However, based on the US Census of Agriculture, McDowell County and the counties in the eastern panhandle have the most acres of land in orchards.

The Influence of Social Networking on the Adoption of Conservation Programs

The decision of adopting conservation practices for an individual is a social process that involves outside parties as part of the decision-making process. By applying a social networking framework, our understanding of the spatial distribution of program participation is increased by allowing for the spillover of knowledge and opinions from nearby landowners. In this section of the paper, the importance of social networking on practice application based on knowledge shared by neighbors or interaction within a social group will be discussed. Previous literature proclaims farmers perceive programs based on neighbors' knowledge and opinion. I will review studies that illustrate the influence of these social interactions, the theory behind these social networking observations, and how it applies to the adoption of NRCS conservation programs.

Social networking is based on individual interaction and the spread of information, which involves channeling personal or media influence, and enabling a change in attitude or behavior (Liu et al. 2003). There has been an abundance of literature on the theory behind this topic. Early work identifying the importance of social reinforcement includes the work of Leibenstein (1950). He identifies the social reinforcement effect, known as the "bandwagon effect" that recognizes how other people's actions can reinforce or influence one's choices. Social networks are motivated and driven through the maximization one's utility based on: the feeling of belonging, contributing to one's community, or dependence on the choice of others (Granovetter 1978).

Heal and Kunreuther (2010) utilized game theory notation to identify social networking behaviors such as cascades, entrapment, and tipping. Cascading behavior is the movement of one behavior in a group to another by a series of individual changes. As individual farmers within a community group starts to implement practices on their own farms, members of that same community group could lean towards also adopting practices on their farms. Entrapment represents participation in a group or activity, even though it makes one worse off. This behavior may produce the equilibrium for the group, but not the individual. Also in this situation, one participant could be better off while making everyone else worse off (Dixit 2003). In this situation, a policy intended on helping a community could also be presenting a negative externality on the residents. Knoot and Rickenbach (2011) conducted a social network analysis on landowner decisions for program enrollment in Best Management Practices. They found that program enrollees had a larger social network than non-enrollees. They also found the program improved the water quality, however it also increased the perceived difficultly of the timber harvest process. Tipping is when a small group in the community moves or changes their behavior, and therefore, 'tips' the equilibrium of the entire community. As community leaders start promoting and adopting conservation strategies, it becomes more attractive for other members to participate.

Previous literature including Morton (2008) investigates how social networking promotes conservation program adoption within a community. He evaluates the roles of social pressure, internal beliefs, and knowledge play in achieving sustainable practices. Within this study, farmers were collectively joined at watershed level to address watershed impairment issues and the role of social networking in tackling water problems and land practices. With the creation of personal networks through community meetings, Morton identifies a connection between "the farmers' quest for knowledge and information to make good on-farm decisions to knowledge, beliefs, and conservation ethics of others in their watershed in ways that reaffirm local practices and/or open them to new ways of doing things because of what they've learned".

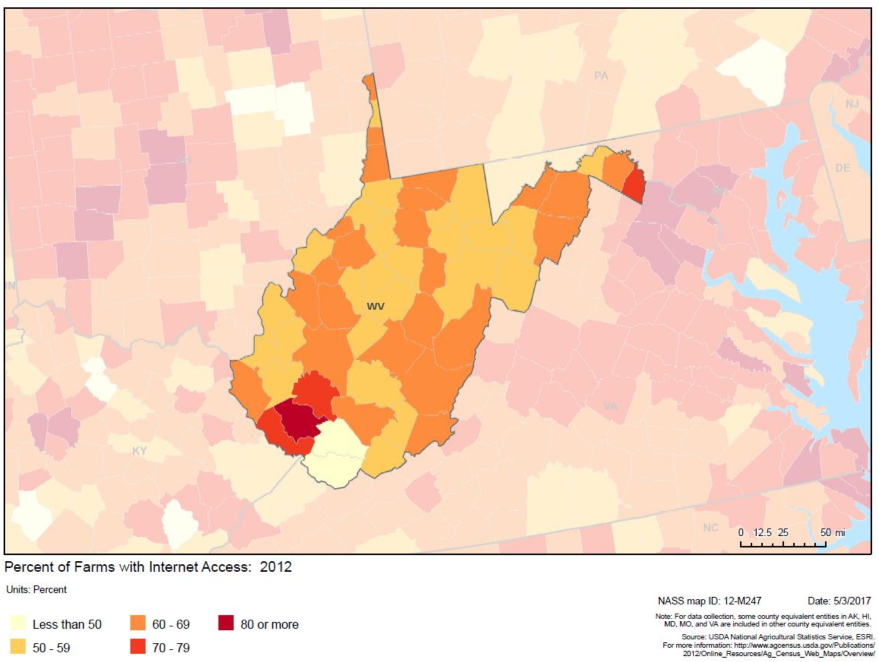
Phillips (1985), more recently discussed in Pannell et al. (2006), observes the social spread of knowledge through dairy farmers. If a farmer lacked knowledge on a certain project, he or she would seek advice from a nearby entity that he or she perceived as an expert of the project. Pannell et al. (2006) summarize key social factors that may influence the adoption decision. These factors include the strength of landowners' networks and local organizations, physical proximity to other adopters, and physical distance to the source of information about these programs. Nearby social factors influence the adoption of practices within a community or regional framework.

Through the use of the National Woodland Owner Survey and Butler et al. (2005), Schubert and Mayer (2012) have found that non-industrial private forest owners get as much information and advice on management and voluntary program enrollment from neighbors and peers as they receive from professional foresters at public agencies. Other members within the non-industrial private forest community influenced roughly half of the owners to some level. Both farm and private forestland owner groups are eligible to participate in NRCS conservation programs.

Social networking can explain why some individuals participate in these programs, and it can explain what barriers may inhibit participation. Breetz et al. (2005) identify that mistrust of government agencies or other regulators will hinder effective communication, and will contribute to farmers' initial unwillingness to participate in conservation programs. They also find that community or social connections such as educational and outreach approaches, third party affiliations, and awareness of existing relationships may relieve these barriers of participation.

Based on the previous literature, it is easy to see how social networking influences conservation practice adoption at the individual or community level. In this study, the significance of these effects at a census tract level, as well as, the spread throughout a NRCS designated service area is investigated. The spatial distribution of farms within each census tract varies throughout the state; the effects of social networking should also vary within a community. There is a large percentage of farms/farmers without access to internet throughout the state (see figure below). This means farmers in these areas may rely more heavily on the advice or information from their neighbors. Areas of isolated farmers with little attachment to the land may not understand the importance of community involvement; this may lead to areas with a lower number of practices.

Figure 4. Percent of Farms without Internet Access



Map was created by the US Census of Agriculture

Spatial Distribution of NRCS Conservation Practices

Before the number of applied NRCS assistance programs is estimated, it is best to observe any spatial patterns that may currently exist. By observing the spatial pattern of the practices, we can identify how the other regional attributes (explanatory variables) may influence the placement of practices. Through spatial analysis techniques in ArcGIS, patterns of spatial clustering or dispersion within the data can be identified. In this analysis, global measures such as the Average Nearest Neighbor (ANN) analysis and local measures such as the Getis-Ord Gi* Hot Spot analysis were utilized to identify if these data are spatially autocorrelated. Also with these techniques, we can identify if the data is spatially auto correlated. If the data is spatially auto correlated, we can control for the spatial dependency in the econometric analysis. Figure 5 presents a map of the existing conservation practices throughout the state of West Virginia. Figure 6 displays the regional distribution of applied practices at the census tract level. Spatial statistics tools such to identify spatial autocorrelation, as well as a hot spot analysis are utilized on the point data of applied practices throughout WV from 2004 to 2015. These tools highlight existing spatial patterns or the spatial autocorrelation of the practices.

Figure 5. Applied NRCS Assistance Practices from 2004 to 2015 in West Virginia

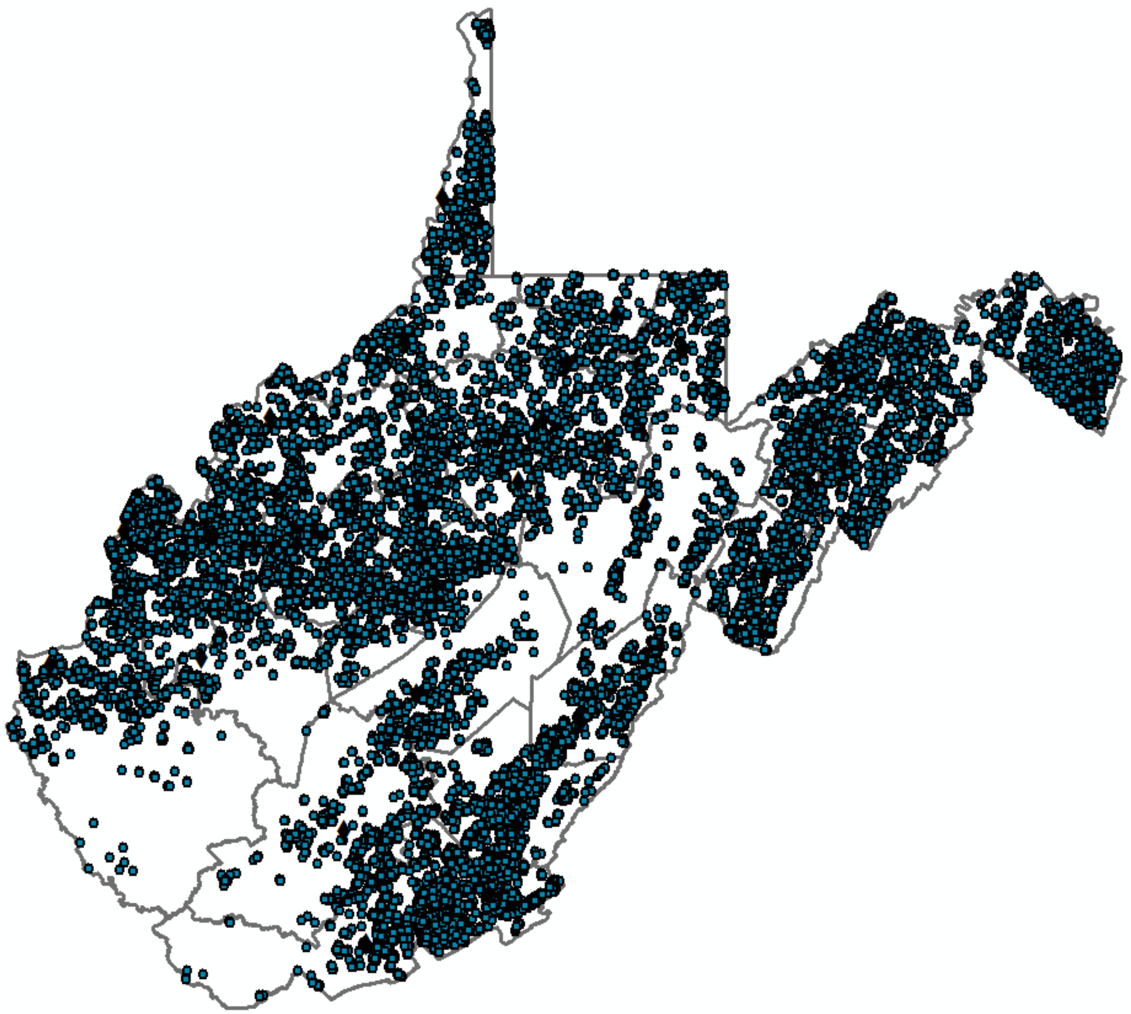
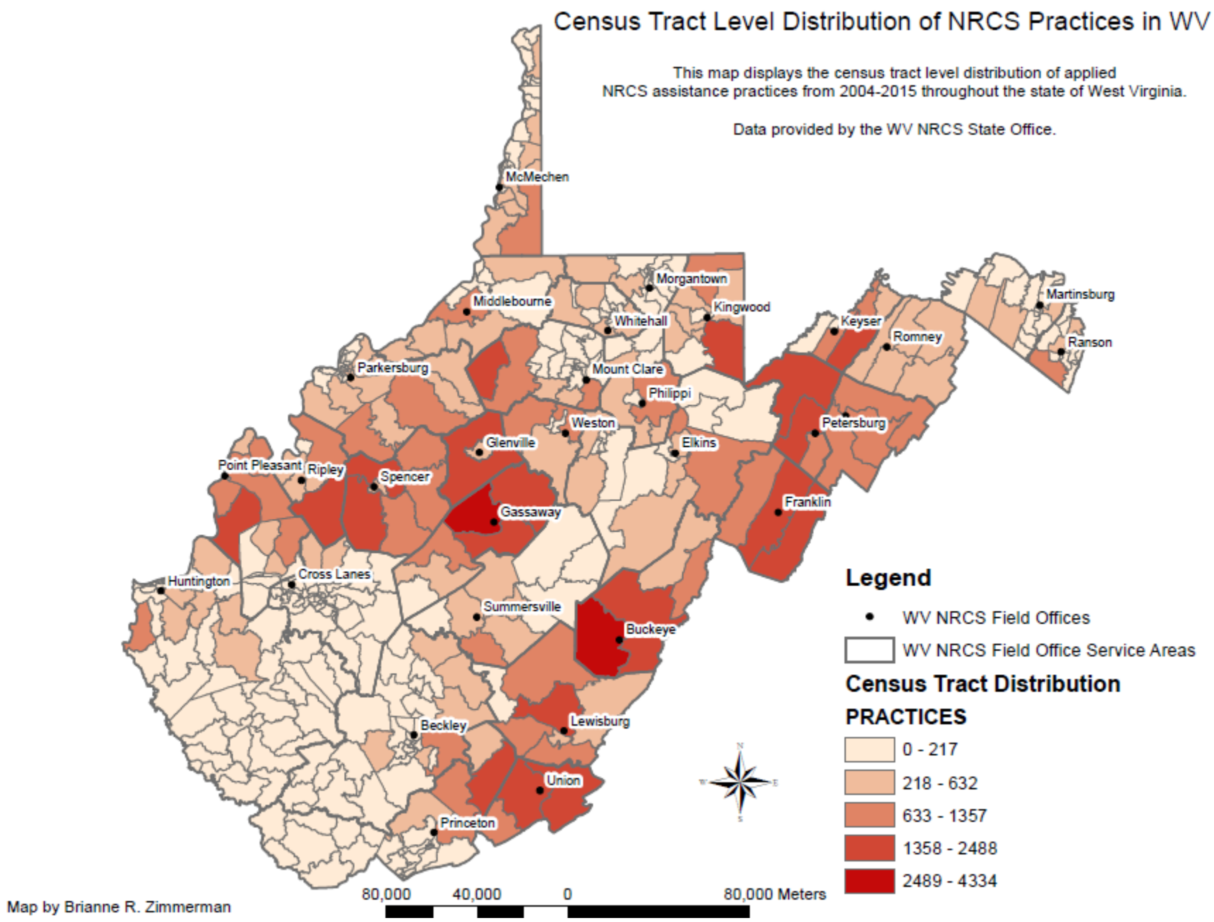
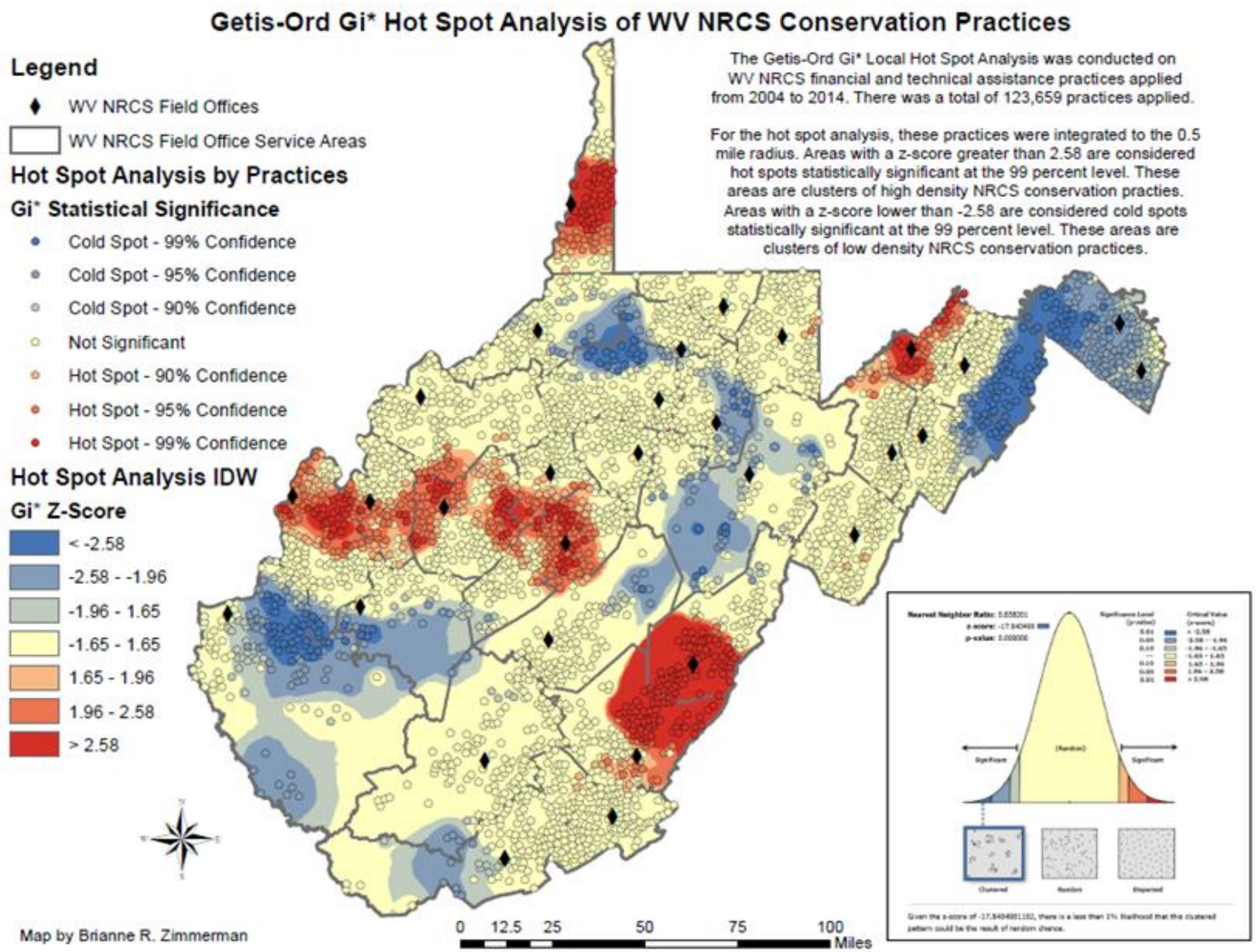


Figure 6. Census Tract Level Distribution of Applied Assistance Programs



The ANN analysis was first conducted as a global measure of spatial autocorrelation. This measure observes the spatial relationship of the location of the features. This test identified a spatial clustering pattern within these data statistically significant at the 99 percent level. The results of this analysis are provided within the bell curve chart on the map in Figure 7 below. To further observe the spatial autocorrelation of these data, a Getis-Ord Gi* Hot Spot analysis was conducted. The hot spot analysis of Getis-Ord G_i* assesses spatial patterns at a local scale (Getis and Ord 1996; Longley and Batty 1996). Through this analysis we can identify statistically significant local 'hot spots' and 'cold spots' clusters throughout the state. Hot spots are areas where there is a high number of practices clustered within a region. Cold spots are areas where there is a low number of practices clustered within a region. Full description of the methodology used for analyzing the spatial distribution of practice level data is included within the Appendix. Based on the results of these analyses we can reject the null hypothesis of random distribution of these data.

Figure 7. Getis-Ord Gi* Hot Spot Analysis on Practice-Level Data



Data & Methodology

The purpose of this analysis is to explain the spatial distribution of NRCS assistance programs throughout the state of WV by identifying significant factors that influence NRCS conservation practice adoption at a regional level. Various socio-economic characteristics such as population, income, and educational attainment and poverty rates were tested within this analysis. Land cover attributes such as agricultural land, hosting a NRCS field office, percent of developed land, percent of state and federally owned land, total stream mileage, and total surface-mined area were also observed. Data was collected from WV NRCS, US Census Bureau, National Land Cover Dataset (NLCD 2011), WV Department of Environmental Protection (DEP), WVU Natural Resource Analysis Center (NRAC), and other WV state and federal datasets. Table 3 below provides a list of the variables used within this analysis and their data sources. Table 4 displays the descriptive statistics of the variables observed in the census tract level analysis.

Table 3. Definitions and Data Sources of Variables

Variable Name	**Definition**	**Data Source**
PRACTICES	Number of applied practices from 2004 to 2015	WV NRCS
AGLAND	Amount of pasture land (NCLD81) and cropland (NLCD82) in square kilometers	NLCD 2011
FIELD OFFICE	Indicator if NRCS field office is located within	WV NRCS
POP2010	Total population in 2010	US Census 2010
INCOME	Household median income in USD	US Census 2010
BACH	Percent of population with Bachelor's degree	US Census 2010
POVERTY	Percent of households below the poverty level	US Census 2010
STATE	Percent of state owned land	WV State and Federal Datasets
FED	Percent of federally owned land	WV State and Federal Datasets
DEVELOP	Percent of developed land (low, medium, & high intensity)	NLCD 2011
MINE	Percent of surface mining land area	WV DEP
STREAM	Total miles of 24K stream length	WVU NRAC

There are 484 census tracts in the state of West Virginia. From 2004 to 2015, nearly 123,659 assistance practices had been applied throughout the state. The census tract hosting the Buckeye service center within Pocahontas County has the highest distribution of practices. Table 2 illustrates the descriptive statistics of the census tract level variables included within the models.

Table 4. Descriptive Statistics of Variables

Variable	Count	Mean	Std. Dev.	Min	Max
PRACTICES	484	255.49	485.82	0.00	4334.00
AGLAND	484	11443.94	18429.73	0.00	122473.80
FIELDOFFICE	484	0.06	0.24	0.00	1.00
POP2010	484	3828.50	1567.94	990.00	11756.00
INCOME	484	41.17	13.68	8.00	108.08
BACH	484	18.68	11.95	1.10	71.40
POV	484	18.95	10.04	1.50	75.10
STATE	484	1.28	3.95	0.00	45.33
FED	484	2.93	10.72	0.00	80.31
DEVELOP	484	19.29	26.50	0.05	100.00
MINE	484	2.02	5.14	0.00	39.82
STREAM	484	113.61	148.20	0.00	794.72

There are three main objectives within this analysis to observe the spatial distribution of the applied practices, identify significance variables that explain practice adoption, and to identify underserved/overserved census tracts. First, global and local measures of spatial autocorrelation were implemented to observe the spatial pattern with these practice-level data. Secondly, econometric techniques will be utilized to highlight significant socio-economic characteristics and land cover attributes that influence conservation practice adoption and to control for the spatial autocorrelation within these data. Lastly, based on the results of the spatial econometric analysis we will identify census tracts that are underserved or overserved by their local NRCS field office.

To identify significant explanatory variables, we first conduct an ordinary least squares (OLS) analysis at the census tract level. The model used for empirical analysis is below:

Equation 1. Census tract level model

$$PRACTICES = \beta_0 + \beta_1 FIELDOFFICE + \beta_2 POP + \beta_3 INCOME + \beta_4 COLLEGE + \beta_5 POVERTY + \beta_6 STATE + \beta_7 FED + \beta_8 DEVELOP + \beta_9 MINE + \beta_{10} AGLAND + \beta_{11} STREAM + \varepsilon$$

Census tract model variables included within the analysis are agricultural land, location of NRCS field offices, population, median household income, educational attainment, poverty rate, state and federally-owned land, developed land, amount of surface mining area, and stream miles. The variable FIELDOFFICE is an indicator variable for if a local field office is located within the census tract (1), or otherwise (0). Pannell et al. (2006) identify the physical distance to an information source, like a local field office, is important, as more distant landholders are less likely to adopt. Information appears less relevant and less feasible due to limited exposure. We include population and the amount of developed land as measures of urbanization, more population and urban development leads to less land for rural or agricultural applications[4]. We include other individual or household characteristics to control for regional heterogeneity. Pannell at el. (2006) have identified a conflicting relationship between education and practice adoption. On one hand, the higher educated are more likely to adopt innovative ideas. On the other hand, limitations brought on by practice adoption may go unrecognized by less educated individuals. We include the amount of state and public land in the analysis as outreach should occur on mostly private lands. However, state-owned land does include wildlife management areas in which would lead to positive correlation with practice application. The amount of land impacted by surface mining within a census tract is expected to decrease the expected number of practices. While the amount of agricultural land and stream miles in a census tract are attractive features for practices.

We expect the amount of agricultural land, hosting an NRCS field office, population, median household income, educational attainment, and stream miles to have a positive effect on the amount of conservation practices applied in a census tract. Our agricultural land observations at the census tract is a proxy measure of pasture land and cropland from the NLCD. However, we expect poverty rate, the amount of state and federally-owned land, the amount of developed land, and the amount of surface mining area to have a negative influence on the number of conservation practices within a census tract. Table 4 above the descriptive statistics of the variables.

The estimated results of the OLS model are displayed in Table 5 on the proceeding page. For the OLS model, 64 percent of the variation in the dependent variable is explained by the variation in the explanatory variables. The amount of agricultural land, hosting a field office, and the amount of stream miles within a census tract has a positive influence on practice application. These variables were all statistically significant at the 99 percent level. Population, household median income, poverty, and the amount of surface mining within a census tract has a negative influence on practice application within a census tract. Population and poverty were statistically significant at the 90 percent level. Income was statistically significant at the 95 percent level and surface mining was statistically significant at the 99 percent level. This model does not account for the spatial autocorrelation within the data nor the omitted variable bias.

[4] In the future, we may consider testing population density instead of raw population numbers.

Table 5. OLS results for census tract practice application

VARIABLES	PRACTICES
AGLAND	0.014***
	(0.001)
FIELDOFFICE	270.041***
	(56.612)
POP2010	-0.016*
	(0.010)
INCOME	-4.152**
	(1.878)
BACH	2.538
	(1.661)
POV	-4.027*
	(2.105)
STATE	3.413
	(3.482)
FED	-0.097
	(1.387)
DEVELOP	-0.221
	(0.719)
MINE	-8.176***
	(2.834)
STREAM	1.050***
	(0.143)
Constant	237.878**
	(106.496)
Observations	484
R-squared	0.648
Adjusted R-squared	0.639
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

Spatial Econometric Analysis

To address the spatial autocorrelation identified earlier within the paper, spatial econometric models were estimated in this analysis. Three spatial econometric models were utilized to identify the spillover effects at the census tract level of program participation: Spatial Durbin Model (SDM), Spatial Durbin Error Model (SDEM), and Spatial Lag of X Model (SLX). By implementing spatial econometrics, we can account for the influence of surrounding regions on program participation in a census tract located within the same NRCS designated service area. For all of the spatial models, the spatial weight matrix (W) is a block diagonal for each of the service areas. For example, if a census tract is located within a service area district then it receives a value of 1 inside the weight matrix, zero if otherwise. Also, we indicated that census tracts can only be 'neighbors' with other census tracts inside of the same service area district. Local field offices can only control practice adoption within census tracts in their designated service area.

Spatial Durbin Model

The spatial Durbin model (SDM) is known as general form for measuring global spillover effects (LeSage 2014). There are three major contributions of the SDM model. First, it produces global spillover effects, which is preferred with a national model. It assumes that the explanatory variable affects (on average) are similar throughout the entire observed region. The estimated spillover effects consider the effects on the counties past the identified weight matrix, somewhat like a ripple effect. While the local spillover effects only consider the effects within the surrounding counties identified within weight matrix. Secondly, it controls for omitted variable bias when omitted variables are correlated with the dependent variable (LeSage and Pace 2009). Since our model is ad hoc in nature without a solid theoretical explanation, omitted variables are likely to occur within our estimation. Lastly, it controls for omitted spatially-correlated variables that are correlated with the explanatory/predictor variable. The structure of the SDM model as discussed in (LeSage 2014) is provided below:

Equation 2. Spatial Durbin Model

$$Y = \rho WY + X\beta + WX\theta + \varepsilon$$

The variable Y (N x 1) is the dependent variable, predicted by our matrix of explanatory variables, described above, represented by X (N X K). The scalar ρ is the measure of spatial dependence between counties, and W (N x N) is the spatial weight matrix. Both β and θ are parameter vectors (K x 1). N represents the number of observations, and K represents the number of explanatory variables included within the model. The residual error term is represented by ε (N x 1). WY measures the spatial lag in the dependent variable, and ρWY represents the spatial autoregressive term. WX measures the spatial lag in the explanatory variables.

The SDM model produces estimates at three levels of spatial effects: direct, indirect, and total effects. These estimates provide an average effect for the entire study region. The direct effect measures, on average, how a change in an explanatory variable in county i, effects the dependent variable in county i. The indirect effect is the difference between the total effect and the direct effect. It measures the average change in an explanatory variable in county i on the dependent variable in county j, also known as the spillover effect. The total effect can be interpreted as the average total impact on the dependent variable in every county resulting from a change in an explanatory variable within county i. Rho, ρ, estimates the level of spatial dependence in the explanatory variable of these data. Results of this model are displayed in Table 6.

For this model, nearly 68 percent of the variation in the number of practices within a census tract is explained by the variation in the explanatory variables. The amount of agricultural land, hosting a field office, and the amount of stream miles within a census tract has a positive and statistically significant direct effect on the number of practices within the census tract. The amount of surface mining within a census tract has a negative and statistically significant direct effect on the number of practices within the census tract. The amount of agricultural land within a census tract has a negative and statistically significant indirect effect, at the 99 percent level. As the amount of agricultural land increases in a census tract, the number of practices within a nearby census tract will decrease. The amount of agricultural land, hosting a field office, and the amount of stream miles within a census tract has a positive and statistically significant total effect on the number of practices within a census tract throughout the total region. Rho is positive and statistically significant at the 99 percent level.

Spatial Durbin Error Model

The spatial Durbin error model (SDEM) is similar to the SDM model, however it does not include the spatial autoregressive term on the dependent variable. It does however include local spillover effects and local error terms (u). The model description in matrix form as discussed by LeSage (2014) is below:

Equation 3. Spatial Durbin Error Model

$$y = X\beta + WX\theta + u$$
$$u = \lambda Wu + \varepsilon$$

The variable Y (N x 1) is the dependent variable, predicted by our matrix of explanatory variables represented by X (N X K). The W (N x N) is the spatial weight matrix. Both β and θ are parameter vectors (K x 1). N represents the number of observations, and K represents the number of explanatory variables included within the model. The residual error term is represent by ε (N x 1). In the SDEM model the spatial autoregressive component, λWu, is controlled for in the error term u. This will allow for global diffusion of shocks to the error or disturbances within the model (LeSage 2014). WX measures the spatial lag in the explanatory variables.

As a local model. the SDEM model only produces estimates for two levels of spatial effects: direct and indirect effects. These estimates provide an average effect for the entire study region. The direct effect measures, on average, how a change in an explanatory variable in county i, effects the dependent variable in county i. The indirect effect is the difference between the total effect and the direct effect. It measures the average change in an explanatory variable in county i on the dependent variable in county j, also known as the spillover effect. Lambda, λ, estimates the level of spatial dependence in the error term. Results of this model are displayed in Table 7.

For the SDEM model, 75 percent of the variation in the dependent variable is explained by the variation in the explanatory variables. The amount of agricultural land, total stream miles, and hosting a field office has a statistically significant and positive direct effect on practice adoption. Total amount of land that has been surface mined has a statistically significant and negative direct effect on the number of applied practice. The percent of population in poverty as well as the amount of federal land have positive indirect effects. As the amount of these attributes increase in a census tract, the number of applied practices in the surrounding census tracts will also increase. The amount of state-owned land, the percent of developed land, and the amount of surface mining and stream miles have negative and statistically significant effects on practice application. Lambda is positive and statistically significant at the 99 percent level.

Spatial Lag of X Model

The Spatial Lag of X (SLX) model is a reduced form of the SDEM model where λ=0. It is a simple, but powerful model that captures the local spillover effects. With the SLX model, the regression estimates of β and θ should be unbiased, even when the true model is SDEM, since spatial dependence in the error term represents only an efficiency problem (LeSage 2014). Below is the model framework:

Equation 4. SLX Model

$$y = X\beta + WX\theta + \varepsilon$$

The matrix interpretation of the SLX model is the same as the SDEM model, however it excludes the spatial autoregressive error term included in the SDEM model. As a local model, it only estimates direct and indirect effects, not the total effects of the explanatory variables. The SLX model does not include a global measure of spatial dependence. The results of the SLX model estimates are displayed in Table 8.

For the SLX model, 68 percent of the variation in the dependent variable is explained by the variation in the explanatory variables. Like the other models, the amount of agricultural land, total stream miles, and hosting a field office has a statistically significant and positive direct effect on practice adoption. However, in this model the amount of state owned land also have a positive and statistically significant direct effect on applied practices. Total amount of land that has been surface mined has a statistically significant and negative direct effect on the number of applied practices. Hosting a field office, and the amount of stream miles and state-owned land have positive and statistically significant indirect effects on the number of applied practices in surround census tracts. The amount of agricultural land and total population have a negative and statistically significant indirect effect on the number of adopted practices within the surrounding census tracts.

The SLX model, rather than the SDEM model, produces results that are more consistent with the SDM model results. All three spatial models have consistent direct effects on practice adoption within a census tract. The local spillover models, SDEM and SLX models, seem to have more significant indirect effects than the global spillover model, the SDM model.

Table 6. Spatial Durbin Model estimates

Spatial Durbin Model Estimates	
Dependent Variable	PRACTICES
R-squared	0.692
Rbar-squared	0.677
sigma^2	63134.497
log-likelihood	-3199.376
Nobs, Nvars	484, 23
# iterations	14
min and max rho	-1.00, 1.00
total time in secs	0.502
time for lndet	0.085
time for t-stats	0.031
time for x-impacts	0.238
# draws used	1000
Pace and Barry, 1999 MC lndet approximation used	
order for MC appr	50
iter for MC appr	30

****************** ********** ********** **************

Variable	Coefficient	Asymptot t-	z-probability
Constant	120.018	0.370	0.711
rho* **	**0.472**	**7.076**	**0.000**

Direct	Coefficient	t-stat	t-prob
AGLAND* **	**0.016**	15.320	0.000
FIELDOFFICE* **	**289.270**	4.177	0.000
POP2010	-0.005	-0.537	0.591
INCOME	-1.965	-1.089	0.277
BACH	0.985	0.616	0.538
POVERTY	-2.367	-1.130	0.259
STATE	5.247	1.503	0.134
FED	-1.741	-1.280	0.201
DEVELOP	0.377	0.573	0.567
MINE **	**-6.332**	-2.382	0.018
STREAM* **	**0.722**	5.228	0.000

Indirect	Coefficient	t-stat	t-prob
AGLAND* **	**-0.010**	-2.942	0.003
FIELDOFFICE	734.784	1.620	0.106
POP2010	-0.062	-1.381	0.168
INCOME	4.905	0.472	0.637
BACH	-5.307	-0.546	0.586
POVERTY	3.676	0.232	0.817
STATE	23.044	0.787	0.432
FED	8.230	1.255	0.210
DEVELOP	-1.746	-0.435	0.664
MINE	-10.184	-0.539	0.590
STREAM	0.389	0.642	0.521

Total	Coefficient	t-stat	t-prob
AGLAND*	**0.006**	1.812	0.071
FIELDOFFICE **	**1024.054**	2.017	0.044
POP2010	-0.067	-1.426	0.155
INCOME	2.941	0.270	0.787
BACH	-4.322	-0.430	0.667
POVERTY	1.309	0.078	0.938
STATE	28.291	0.910	0.363
FED	6.489	0.938	0.349
DEVELOP	-1.370	-0.327	0.744
MINE	-16.515	-0.844	0.399
STREAM*	**1.111**	1.705	0.089

Table 7. SDEM Estimate Results

Spatial Durbin Error Model Estimates
Dependent Variable = PRACTICES
R-squared = 0.7578
Rbar-squared = 0.7462
sigma^2 = 57057.1393
log-likelihood = -3188.8074
Nobs, Nvars = 484, 23
iterations = 0
min and max rho = -0.9900, 0.9900
total time in secs = 1.4530
time for optimiz = 0.3160
time for lndet = 0.2320
time for t-stats = 0.3180
Pace and Barry, 1999 MC lndet approxim
order for MC appr = 50
iter for MC appr = 30
****

Variable	Coefficient
Constant	-850.059
Direct Effects	
AGLAND* **	**0.016**
FIELDOFFICE*	**117.962**
POP2010	0.002
INCOME	-1.576
BACH	0.806
POVERTY	-0.558
STATE	-5.133
FED	0.663
DEVELOP	-0.445
MINE* **	**-8.219**
STREAM* **	**0.552**
Indirect Effects	
W*AGLAND	-0.007
W*FIELDOFFICE	-434.436
W*POP2010	0.053
W*INCOME	16.908
W*BACH	-11.863
W*POVERTY* **	**56.274**
W*STATE* **	**-129.160**
W*FED* **	**31.049**
W*DEVELOP* **	**-16.896**
W*MINE **	**-59.408**
W*STREAM* **	**-1.529**
lambda* **	**0.738**

Table 8. Spatial Lag of X Estimate Results

Spatial Lag of X Model Estimates
Dependent Variable = PRACTICES
R-squared = 0.6927
Rbar-squared = 0.6781
sigma^2 = 75983.7116
Durbin-Watson = 1.3431
Nobs, Nvars = 484, 23
****

Variable	Coefficient
Constant	432.696
Direct Effects	
AGLAND* **	**0.016**
FIELDOFFICE* **	**330.539**
POP2010	-0.007
INCOME	-2.336
BACH	1.218
POVERTY	-3.041
STATE **	**6.824**
FED	-2.100
DEVELOP	0.358
MINE **	**-5.919**
STREAM* **	**0.731**
Indirect Effects	
W*AGLAND* **	**-0.010**
W*FIELDOFFICE* **	**780.574**
W*POP2010* **	**-0.089**
W*INCOME	2.984
W*BACH	-3.800
W*POVERTY	-8.362
W*STATE* **	**54.025**
W*FED	1.390
W*DEVELOP	1.124
W*MINE	2.522
W*STREAM* **	**1.038**

Spatial Hierarchical Model

Along with the assessment of census tract level spatial econometric models, spatial hierarchical econometric models were also estimated within this paper. Through this method of analysis, data collected from a smaller region such as a census tract and a larger region such as a county can be combined for estimation. We can include data that with availability only at the county-level into the estimation of number of applied practices at the census tract level by through the implementation of the spatial hierarchical model. Raudenbush and Bryk (2002) provide the theoretical framework for hierarchical linear models. The county-level data included in this analysis was collected from the US Census of Agriculture including: number of farms, average farm size, and total number of cattle. There are 484 census tracts within the 55 counties in West Virginia. We replicate the modeling approach of Lacombe and Flores (2017) for the Bayesian Hierarchical SLX model provided below[5]:

Equation 5. Hierarchical SLX model

$$y = X\beta + W_1 X\theta + \Delta a + \varepsilon$$
$$a = Z\gamma + W_2 Z\delta + u$$
$$\varepsilon \sim N(0, \sigma^2 I_n)$$
$$u \sim N(0, \tau^2 j)$$

The dependent variable in our case, practices, is represented by y which is an N x 1 vector, and the explanatory variables, X, are represented as an (N x K) matrix. W_1 (N x N) is the census tract level weight matrix, and both β and θ are parameter vectors (K x 1) at the census tract level. $W_1 X$ is the spatialled weighted exogenous explanatory variables. ε is an $N \times 1$ vector of disturbances with mean 0 and variance $\sigma^2 In$. The symbol Δ represents an $N \times J$ (where N represents the total number of observations and J represents the number of groups) matrix that assigns each level 1 observation to a level 2 group. This matrix matches the census tracts with its designated county. The symbol α represents the $J \times 1$ vector of terms which are predicted in the level 2 model.

The dependent variable in the level 2 model, a (Z x 1) vector, is predicted by Z, a (J x m) vector of explanatory variables with γ as the (J x m) vector of coefficients, W_2 as the (J x J) county level spatial weight matrix, and δ is the (m x 1) vector of spatially weighted coefficients of the explanatory variables. The vector of error (J x 1), u, has a variance of $\tau^2 j$ for the county level. We

[5] This type of model was first implemented in Lacombe and Flores (2017) to measure crime levels in Mexico.

assume that ε and u are uncorrelated, u and X are uncorrelated, and u and Z are uncorrelated. These are the standard assumptions of the hierarchical models (Raudenbush and Bryk 2002).

Our model is estimated through Bayesian econometric techniques, in which estimates of the parameters take place on the posterior distribution. The posterior distribution of this model is represented by the equation below. The posterior distribution is proportional to the likelihood times the hierarchical prior, times the priors for all parameters. All the priors utilized in the model are proper leading to a "fully Bayesian" analysis[6]. We utilize the posterior mean to interpret the level 1 effects and the level 2 effects estimated by the Bayesian econometric techniques.

Equation 6. Posterior Distribution of Parameters

$$\pi(\theta,\alpha|y) \propto f(y|\theta,\alpha)\ f(\alpha|\theta)\ \pi(\theta)$$

We estimate the spatial hierarchical SLX model for three county level variables: number of farms, average farm size, and number of cattle (per thousand). The descriptive statistics for the county level variables are provided in the table below.

Table 9. Descriptive Statistics of County Level Variable

	Count	Mean	Std. Dev.	Min	Max
FARMCOUNT	55	429.42	261.31	15	1048
FARMSIZE	55	150.05	52.60	41	313
CATTLECOUNT	55	3.92	3.50	0.05	16.22

We believe local spillover effects are more appropriate for our research question as practice adoption in the southern part of the state will be heterogeneous to practice adoption in the northern panhandle. Since there are only 55 counties in the state of West Virginia, we estimated the effects of each level 2 variable in separate regressions. We employ the Deviance Information Criterion (DIC), developed by Spiegelhalter et al. (2002), to identify the superior model of the three estimated hierarchical SLX models. The model with the lowest DIC value identifies the model of best fit, which is the model estimated with CATTLECOUNT as the level 2 variable.

We implement the same weight matrix as discussed previously for the level 1 (census tract) estimates. For the level 2 (county) estimates we used the nearest neighbor spatial weight matrix. The appropriate number of 'neighbors' for each level 2 variable was identified through the calculation of the DIC value. We tested the nearest neighbor weight matrix from 2-10 neighbors

[6] Full discussion of the posterior distribution for the hierarchical model is provided by Lacombe and Flores (2016).

for each county level variable. We determined the weight matrix of 2 nearest neighbors was superior for the FARMCOUNT and FARMSIZE models, while the 7 nearest neighbors matric was superior for the CATTLECOUNT model. Since the results of the three hierarchical models remain relatively consistent, we only discuss the results of the CATTLECOUNT model below[7].

For the Bayesian analysis, the 95% credible intervals for all the parameters estimated in this model were identified. If the interval does not contain zero, then the parameter is statistically significant and helps to explain the variation in the dependent variable.

Spatial Hierarchical Model Level 1 Effects

The interpretation of the level 1 explanatory variables is the same as the interpretation of the explanatory variables of a regular SLX model. Level 1 results are displayed in Table 10. As mentioned above, since the results of the three models are consistent we will only interpret the output of the model with CATTLECOUNT as the level 2 variable, for the level 1 estimates.

For the level 1 estimates, AGLAND, FIELDOFFICE, MINE, and STREAM had statistically significant direct effect estimates. As the amount of agricultural land within a census tract increases by 1,000 square kilometers, the number of applied practices within the census tract should increase 15 practices. The more agricultural land within a census tract, the more land opportunities for practice adoption. If a field office is located within a census tract, it will likely increase the number of practices in the same census tract by a total of 55 practices. Farmers are more likely to adopt practices if access to assistance through the local office is easily accessible. As the percent of land impacted by surface mining area increases by 1 percent of the total area within a census tract, it will likely decrease the number of practices within a census tract by over 7 practices. Land impacted by surface mining does not provide opportunities for conservation practice adoption as the resources of the land have already been degraded. However, as the total number of stream miles in a census tract increases by 10 miles, the expect number of practices with the census tract will increase by over 7 practices. Based on this estimate, we can say NRCS is motivated to developing practices that protect water quality. Prescribed grazing and nutrient management are the most adopted practices in the state of West Virginia. Both of these practices try to protect/improve stream water quality. Prescribed grazing can improve water infiltration, protect stream banks from erosion, and manage animal waste material away from water bodies.

[7] We utilize the Gibbs sampling algorithm to cycle through each conditional distribution for each of the parameters. We run 100,000 iterations with the first 50,000 as the 'burn-in' process, leaving the remaining 50,000 iterations.

Nutrient management optimizes the placement of fertilizers, manure, etc. to maximize the protection of local air quality, soil quality, and water quality.

The explanatory variables AGLAND, FED, DEVELOP, and MINE have statistically significant indirect effects or spillover effects. The amount of agricultural land within a census tract creates a competitive effect on practice adoption in surrounding census tracts. If the amount of agricultural land in a census tract was greater by 10,000 sq. km., the expected number of practices in nearby census tracts will decrease by 9 practices. Since practices are adopted on mostly private land, the percent of federally-owned land within one census tract will increase the number of practices within surrounding census tracts. If the amount of federally-owned land were to increase by 1 percent, increases the number of conservation practices applied in nearby census tracts by over 9 practices. The percent of developed land within a census tract decreases the amount of conservation practices applied in the nearby census tracts. A one percent increase in developed land, indicates a decrease of 7 practices in surrounding census tracts. This may be an indication of urban census tracts that would have a higher proportion of developed land. Urbanized census tracts have smaller amount of land area, since their size are designated by population levels. The percent of surface mined area within a census tract also has a negative indirect effect. As the amount of surface mining area increases by 1 percent in a census tract, the expected number of practices within nearby census tracts will decrease by 49 practices. We believe this is due to the very small distribution of practices in the areas where surface mining has occurred. With the indirect effects we can identify which attributes effect not only practice application within the same region, but also how those attributes effect practice application in nearby areas.

The total effect can have varying interpretation. In this analysis we will identify how attributes within a census tract influence the number of applied practices within the total region. The explanatory variables AGLAND, DEVELOP, MINE, and STREAM have statistically significant total effects on the region. The amount of agricultural land and stream mileage have positive total effects, while developed land and surface mining have negative total effects. As the amount of agricultural land increases by 1,000 sq. km. in a census tract, conservation adoption will increase by 6 practices in the total region. As stream mileage in a census tract increases by 1 mile, the total number of conservation practices in the total region will increase by 1 practice. Agricultural land and stream mileage are very significant, contributing components for conservation practice adoption in West Virginia. As the amount of developed land increases within a census tract by 1 percent, conservation adopting for the entire region will decrease by 6 practices. As the percent of land degraded by surface mining in a census tract increases by 1 percent, the expected number of practices in the total region will decrease by 57 practices. Surface mining is a very significant, constricting component for conservation practice adoption. The land cover attributes with an inverse relationship have a larger impact on practice adoption, that the effect of the attributes with a positive relationship.

Spatial Hierarchical Model Level 2 Effects

Lacombe and Flores (2015) state the benefit of a hierarchical model is the estimation of level 2 covariates which provides more interpretation that standard models with fixed-effects. With this model we can also identify the significant direct, indirect, and total effects of these variables. The number of farms, average farm size, and total number of cattle (thousand) within a county were estimated as the level 2 variables. Knowler and Bradshaw (2007) create a synthesis of recent research on farmers' adoption of conservation agriculture. They identify farm size and dairy farms were significant attributes of conservation practice adoption. They also indicate farm tenure influences conservation practice adoption; in the future we would like to test this theory.

Based on the DIC values estimated within the spatial hierarchical SLX models, the model with the CATTLECOUNT as the level 2 variable was the superior model. In this discussion we will interpret the effects of this variable. Note the direct and indirect effects were not statistically significant, however we will provide interpretation of these variables for the purpose of the comprehension of the level 2 effects on the smaller region. Results of the variance estimates and the coefficient estimates for each model are displayed in Table 11.

The total number of cattle in a county has positive direct, indirect, and total effects on the number of practices applied in a county. The total effect is statistically significant at the 95 percent confidence interval. If the number of cattle within county increased by 1,000, then conservation within the same county will increase by 14 practices. By the indirect effect, for every 1,000 cattle within a county, the number of conservation practices will increase by 24 practices. The estimate for the total effect indicates as the number of cattle within county increased by 1,000, then conservation within the total region will increase by 39 practices. The positive influence of cattle on conservation practice adoption increases significantly as the impacted region grows.

Table 10. Level 1 Coefficient Estimates for Spatial Hierarchical Models

Farm Count Hierarchical Model

Level 1 Explanatory Variables	Posterior Mean
Direct Effects	
Direct AGLAND**	**0.015**
Direct FIELDOFFICE**	**55.865**
Direct POP2010	0.001
Direct INCOME	-1.729
Direct BACH	1.170
Direct POVERTY	-2.270
Direct STATE	0.069
Direct FED	-1.457
Direct DEVELOP	0.048
Direct MINE**	**-7.113**
Direct STREAM**	**0.720**
Indirect Effects	
Indirect AGLAND**	**-0.009**
Indirect FIELDOFFICE	-3.419
Indirect POP2010	-0.043
Indirect INCOME	-1.322
Indirect BACH	-0.921
Indirect POVERTY	0.306
Indirect STATE	-14.922
Indirect FED	8.716
Indirect DEVELOP**	**-6.908**
Indirect MINE**	**-43.356**
Indirect STREAM	0.507
Total Effects	
Total AGLAND**	**0.006**
Total FIELDOFFICE	52.445
Total POP2010	-0.042
Total INCOME	-3.050
Total BACH	0.250
Total POVERTY	-1.964
Total STATE	-14.853
Total FED	7.259
Total DEVELOP**	**-6.860**
Total MINE**	**-50.469**
Total STREAM**	**1.227**

Farm Size Hierarchical Model

Level 1 Explanatory Variables	Posterior Mean
Direct Effects	
Direct AGLAND**	**0.015**
Direct FIELDOFFICE**	**55.798**
Direct POP2010	0.000
Direct INCOME	-1.721
Direct BACH	1.063
Direct POVERTY	-2.242
Direct STATE	0.258
Direct FED	-1.344
Direct DEVELOP	0.072
Direct MINE	**-7.384**
Direct STREAM	**0.717**
Indirect Effects	
Indirect AGLAND**	**-0.009**
Indirect FIELDOFFICE	-3.023
Indirect POP2010	-0.044
Indirect INCOME	0.201
Indirect BACH	-3.623
Indirect POVERTY	0.607
Indirect STATE	-12.991
Indirect FED	9.104
Indirect DEVELOP	-6.137
Indirect MINE**	**-49.230**
Indirect STREAM	0.452
Total Effects	
Total AGLAND**	**0.006**
Total FIELDOFFICE	52.775
Total POP2010	-0.044
Total INCOME	-1.520
Total BACH	-2.560
Total POVERTY	-1.635
Total STATE	-12.734
Total FED	7.760
Total DEVELOP	-6.065
Total MINE**	**-56.613**
Total STREAM**	**1.169**

Cattle Count Hierarchical Model

Level 1 Explanatory Variables	Posterior Mean
Direct Effects	
Direct AGLAND**	**0.015**
Direct FIELDOFFICE**	**55.884**
Direct POP2010	0.001
Direct INCOME	-1.684
Direct BACH	1.102
Direct POVERTY	-2.188
Direct STATE	-0.273
Direct FED	-1.359
Direct DEVELOP	0.001
Direct MINE**	**-7.441**
Direct STREAM**	**0.719**
Indirect Effects	
Indirect AGLAND**	**-0.009**
Indirect FIELDOFFICE	-3.790
Indirect POP2010	-0.038
Indirect INCOME	-0.656
Indirect BACH	-3.036
Indirect POVERTY	0.013
Indirect STATE	-18.733
Indirect FED**	**9.682**
Indirect DEVELOP**	**-6.953**
Indirect MINE**	**-49.914**
Indirect STREAM	0.436
Total Effects	
Total AGLAND**	**0.006**
Total FIELDOFFICE	52.094
Total POP2010	-0.037
Total INCOME	-2.340
Total BACH	-1.934
Total POVERTY	-2.175
Total STATE	-19.007
Total FED	8.323
Total DEVELOP**	**-6.952**
Total MINE**	**-57.355**
Total STREAM**	**1.155**

Table 11. Level 2 Estimates for Spatial Hierarchical Models

Farm Count Hierarchical Model

Variance Posterior Mean	
sigma^2	241.155
tau^2	256.254

Level 2 Explanatory Variable	Posterior Mean
Constant	21.778
Direct FARMCOUNT	0.204
Indirect FARMCOUNT **	**0.301**
Total FARMCOUNT **	**0.505**

Dbar	pD	DIC
341417.851	31.022	341448.873

Farm Size Hierarchical Model

Variance Posterior Mean	
sigma^2	240.694
tau^2	236.309

Level 2 Explanatory Variable	Posterior Mean
Constant	4.509
Direct FARMSIZE	0.750
Indirect FARMSIZE	0.970
Total FARMSIZE **	**1.719**

Dbar	pD	DIC
341315.948	29.776	341345.724

Cattle Count Hierarchical Model

Variance Posterior Mean	
sigma^2	240.059
tau^2	275.510

Level 2 Explanatory Variable	Posterior Mean
Constant	47.127
Direct CATTLECOUNT	14.289
Indirect CATTLECOUNT	24.830
Total CATTLECOUNT **	**39.119**

Dbar	pD	**DIC**
341175.948	32.526	**341208.474**

Consolidated Discussion of Results

This paper highlights the spatial dependence of participation in NRCS assistance programs. Spillover effects of socioeconomic characteristics and land attributes play significant roles in the application of conservation programs. We estimated the SDM model, the SDEM model, as well as the SDEM model as regular observations of global or local spillover effects. We then implemented the hierarchical SLX model to estimate the effects of county-level data on census tract level observations. Based on the DIC value, the model measuring the total number of cattle as the level 2 variable was the model of best fit. The amount of cattle within a county had positive and statistically significant effects on the total region.

Overall, the amount of agricultural land, hosting a field office, and the amount of stream miles within a census tract have a positive influence on practice application, while surface mining has a negative effect. The percent of developed land also had a negative effect on practice application within the hierarchical SLX model. The number of practices applied in a census tract are constrained by the amount and quality of the land available within the same census tract. The number of practices applied in a census tract are also influenced by the amount of land available for conservation practice application within the surrounding census tracts of the same service area.

Based on the accumulated results of the different spatial models, census tracts were then categorized as overserved or underserved on outreach efforts by NRCS, based on an averaged residual across the different spatial models, and by their local field office. We categorized a consolidated residual value, estimated by an aggregated residual value of all of the estimated models, based on the number of standard deviations from the mean. Tracts with less observed applied practices than the number predicted for that census tract were identified as underserved by their local service area field office. On the other hand, regions that have more applied practices than the predicted number of practices for their region are categorized as overserved by their local service area field office. This study identifies a localized threshold for NRCS field offices to achieve for implementing future conservation practices within their designated service areas.

Evaluation of Census Tracts

By normalizing the residuals of the four spatial models, census tracts were identified as overserved or underserved in terms of applied conservation practices. A consolidated residual value estimate was used to categorize census tracts, displayed in map below. The overserved/underserved classification process of each census tract in West Virginia is based on an aggregated residual value and is described below:

Equation 7. Equation for residual estimates

$$Residual = Actual\ Number\ of\ Practices - Predicted\ Number\ of\ Applied\ Practices$$

- If the residual value was positive (greater than zero), then the actual number of practices was greater than the predicted number of practices, the census tract was designated as an over-served area for conservation practices.
- If the residual value was negative (less than zero), then the actual number of practices was less than the predicted number or practices, the census tract was designated as an under-served area

Figure 8. Spatial Distribution of WV NRCS Financial and Technical Assistance Practices

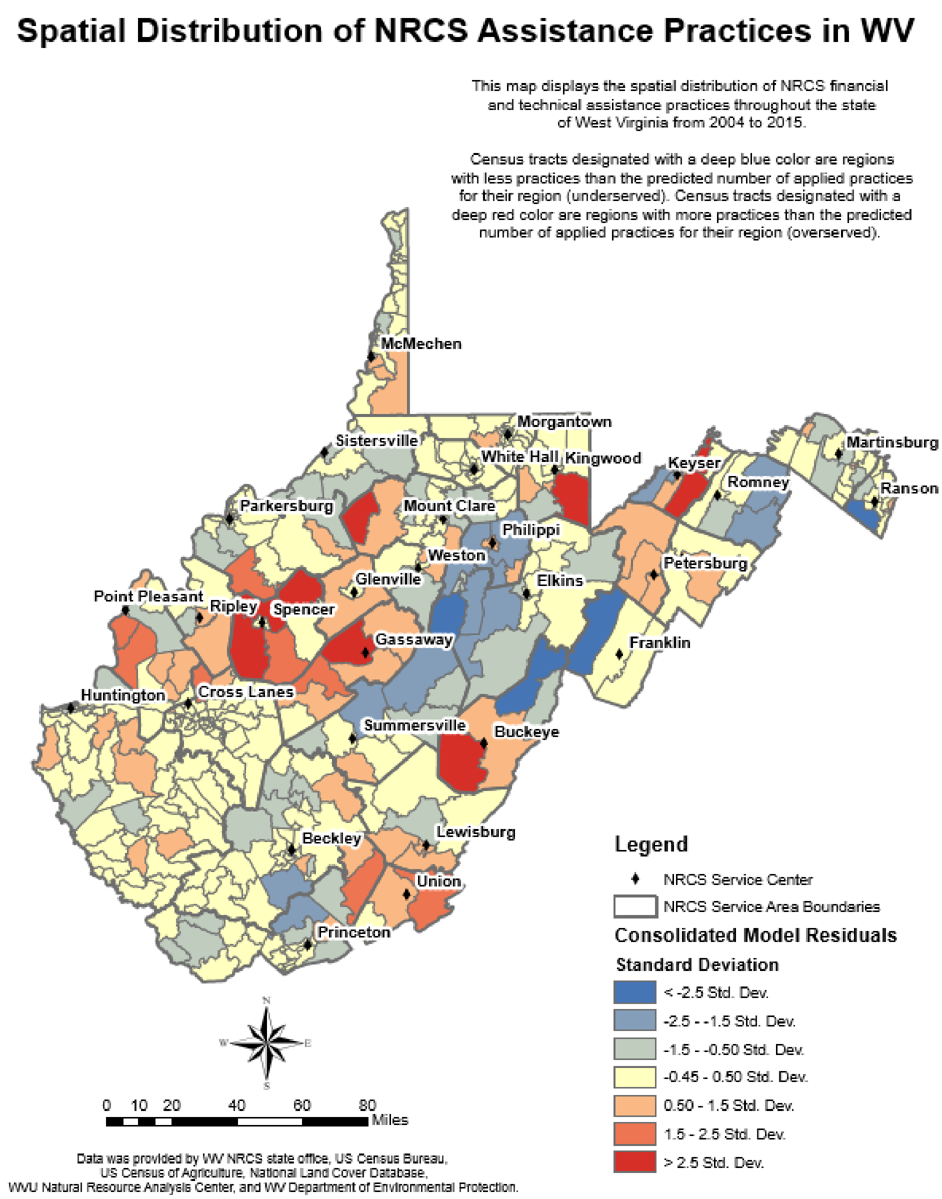
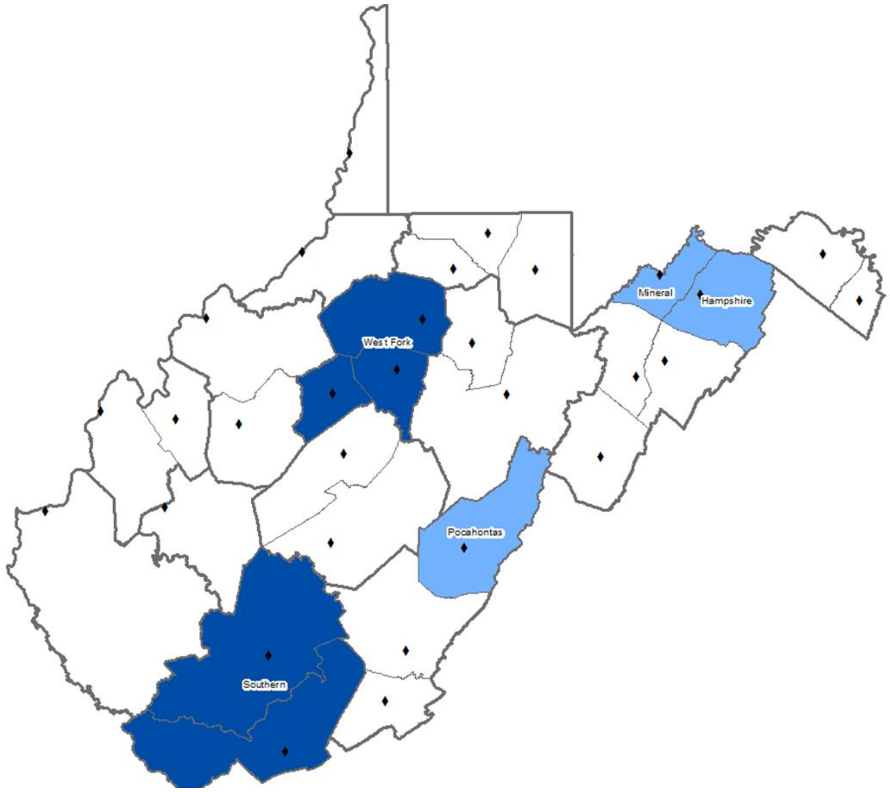


Figure 9. Selected Areas for Future Outreach Efforts



Conclusions

This paper highlights the implication of spatial dependence on participation in NRCS assistance programs. This spillover effects of socioeconomic characteristics and land cover traits play a significant role in the application of conservation programs. Through this analysis, census tracts were identified as being underserved or overserved by their local NRCS field office. In collaboration with the WV NRCS state office, several regions were selected for further observation of outreach efforts. By observing these selected regions in an isolated manner, we can identify localized effects that may influence the number of conservation practices at the census tract level.

A December 2016 meeting between WV NRCS State Administrators, and WVU researchers reviewed the assessment of the spatial distribution of NRCS conservation assistance practices. Based on identification of underserved regions, five areas have been selected as focus for the second phase of the study. Focus areas selected include the Southern Conservation District, the West Fork Conservation District, the Buckeye Service Area, the Keyser Service Area, and the Romney Service Area. The second phase will involve working with farming and landowner communities to implement outreach plans or marketing strategies to increase involvement and awareness of conservation services provided by NRCS.

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