Spatial Patterns of Rural and Exurban Residential Settlement and Agricultural Trends in the Intermountain West

Saleh Ahmed

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SPATIAL PATTERNS OF RURAL AND EXURBAN RESIDENTIAL SETTLEMENT
AND AGRICULTURAL TRENDS IN THE INTERMOUNTAIN WEST

by

Saleh Ahmed

A thesis submitted in partial fulfillment
of the requirements for the degree

of

MASTER OF SCIENCE

in

Sociology

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Logan, Utah

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ABSTRACT

Spatial Patterns of Rural and Exurban Residential Settlement and Agricultural Trends in the Intermountain West

by

Saleh Ahmed, Master of Science
Utah State University, 2014

Major Professor: Douglas Jackson-Smith
Department: Sociology, Social Work and Anthropology

In recent years, counties in the Intermountain West (CO, ID, MT, UT, WY) have experienced rapid population growth and housing development, and much of this growth is occurring outside of urban areas. Residential development can have negative impacts on farmlands, farm viability, and environmental services provided by working landscapes. In this study, I use county-level data to explore the association between residential settlement patterns and trends in farm numbers, cropland acres, and farm sales between 1997-2012 in this region. Results from traditional ordinary least-squares and spatial regression models demonstrate that population pressure (e.g. rural population density), socioeconomic structure (e.g. median household income), and biophysical resources (e.g. length of growing season) are related to different types of farm trends, but that accounting for the spatial pattern or arrangement of rural and exurban residential development can improve models to explain agricultural change. Since spatial dependencies are present among different variables, this study also demonstrates that
spatial regression methods are appropriate and useful to use when modeling county-level processes of socioeconomic change.
Spatial Patterns of Rural and Exurban Residential Settlement and Agricultural Trends in the Intermountain West

Population growth is often linked to negative impacts on agriculture. However, the effects of residential development likely depends on the spatial pattern of development, such as whether housing is clustered or dispersed, and whether it is located near or away from important farmland. For several decades, rural and urban planners have advocated policies to encourage consolidated forms of development as one strategy to protect agriculture and preserve open space. To date, relatively little empirical research has been conducted on the actual effects of different spatial patterns of residential settlement on agricultural. This study aims to fill that gap with a regional focus on the Intermountain West.

The five state Intermountain West region (Colorado, Idaho, Montana, Wyoming, and Utah) is experiencing rapid population growth, and much of that growth takes the form of low-density development outside the urban core. Rural and exurban housing has been identified as a particularly damaging form of development for agriculture. This study uses county-level data between 1997-2012 to explore how different patterns of residential development in the rural and exurban areas affect farm trends in the Intermountain West.

The study found that traditional county-level measures of population pressure (e.g. county population growth rate) are not systematically related to farm trends in the region. However, by controlling for biophysical resources and indicators of socioeconomic opportunities, several indicators of the spatial pattern or distribution of development are statistically associated with trends in farm numbers, farm sales, and cropland acreage in this region. Areas with higher rural population density had consistently more negative trends in all three farm trends. Measures of land use heterogeneity (where development is intermingled with farming) were linked to more robust trends in farm. Contrary to expectations, greater clustering or aggregation of development was not linked to positive farm trends. The overall findings of this study have importance with particular relevance to planners, policy makers, farmers and rural community leaders. It suggests that efforts to protect farming using growth management tools can work, but should focus on separation of agriculture and potentially conflicting land uses.

Saleh Ahmed
ACKNOWLEDGMENTS

First and foremost I need to thank Douglas Jackson-Smith for the patient way he mentored me through my entire academic training and experience here at Utah State University. His impact on my academic career reaches far beyond this thesis and I thank him for cultivating my interests and skills in natural resource sociology. I also thank Richard Krannich, whose encouragements and inputs in developing my skills and knowledge about the regional growth and change in the Intermountain West have been invaluable. I am grateful to Carlos Licón, whose constant encouragements, interests, and input helped me to finish this work in a timely manner. In addition, I am thankful to Molly Cannon, who helped substantially for all the required geospatial analyses. In this opportunity, I also thank all the faculty and staff members in the Department of Sociology, Social Work and Anthropology, particularly Leon Anderson. It has been my privilege and honor to meet a person like him. My graduate school experience has been greatly enhanced by my friendships with many other students across the campus. Particularly, I want to thank all the graduate students in sociology collectively, and former graduate school colleagues Andrew Burger and Beth Kiester individually. Thank you Andrew and Beth for everything that both of you have done for me and my family.

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CHAPTER I
INTRODUCTION

The five states in the Intermountain West (IW) region – Idaho, Montana, Wyoming, Colorado, and Utah – have experienced rapid population growth over the last twenty years, a trend that is associated with dramatic patterns of social, economic, and landscape change (Krannich, Luloff, and Field 2011; McGranahan 1999; Travis 2007). A major component of this growth is taking place on rural and agricultural landscapes and has contributed to significant land use changes and impacts on agriculture and other environmental services. During much of the last 20 years, counties with the highest rates of population growth were associated with the most rapid expansion of developed land and with the subsequent loss of farmlands (Jackson-Smith, Jensen, and Jennings 2006). Overall, the IW region is losing almost 50 acres of farmland every hour due to the conversion to different forms of development (Biodiversity Project 2010). However, trends in agriculture vary widely among counties in this region, with some areas experiencing growth, while others are in serious decline (Jackson-Smith et al. 2006).

While overall rates of population growth at the county level are clearly linked to trends in agriculture, the spatial arrangement and location of residential development can also be important. The growth of rural and exurban residential developments outside of urban areas are often identified as a particularly damaging form of housing growth for farming and reflect growing tensions between people and nature (Travis 2007). Exurban settlements refer to housing patterns that are located between rural and suburban areas, and are characterized by dispersed, relatively low-density residential land uses and
pockets of small-scale commercial development (Herbers 1986). Because much of the landscape in the IW is in public ownership (and hence unavailable for development), both rural and exurban forms of residential development take place mostly on productive agricultural lands and working landscapes. In addition, the per-capita footprints of rural and exurban growth are also much higher than growth in urban or suburban areas because of larger lot sizes (Theobald 2001), and while they contain a relatively small portion of new population growth, they may very well turn out to be the most impactful type of population change in the region (Travis 2007).

Aside from recognizing the importance of non-urban residential growth overall, few scholars have examined the impacts of different spatial arrangements of rural and exurban housing, (such as dispersed vs. clustered) on agriculture and other rural industries. This study fills that gap by exploring how different patterns of residential settlement affect trends in the agricultural sector. Specifically, my research question is:

**How do spatial patterns of rural and exurban residential development impact agricultural trends?** I use county-level data to assess how information about spatial patterns of housing can improve our ability to account for variation in rates of change in three indicators of farm sector well-being: farm numbers, cropland acres, and gross farm sales.
CHAPTER II
LITERATURE REVIEW

Demographic and Economic Change in the Intermountain West

This study focuses on a five state region – including Idaho, Montana, Wyoming, Colorado, and Utah – that is often referred to as the Intermountain West (IW). These states comprise the majority of the ‘interior’ West, and are dominated by high and relatively inaccessible mountain ranges interspersed with irrigated valleys in which most agriculture and urban development takes place (McNabb and Avers 1994).

The IW region is experiencing one of the fastest population growth rates in the nation. Over a 30-year period, from 1980 to 2010, the population of the West increased by 66.6 percent compared to 29.1 percent in the remainder of the U.S. (WDRC 2010). Even though the majority of growth is occurring in big metropolitan regions, a sizeable portion of growth is also occurring outside of the urban core (Otterstrom and Shumway 2003), particularly in counties with high natural amenities and adjacent to metropolitan areas. Census experts expect that in coming years in the IW will experience higher population growth rate than the national average (Figure 1).

What is taking place in the IW is related to larger trends in urban and rural migration across the United States over the last 40 years. In-migration has been the principle contributor fueling the growth in many nonmetropolitan areas across the nation (Beale and Johnson 1998). Rising middle class wealth enabled a growing number of people to act on a longstanding preference for residential settlement in less dense and more rural areas (Brown et al. 2005). Most Americans feel some affinity for the
Jeffersonian ideal of living in a small agrarian rural community with open space, large lots, etc. (Kusel and Fortman 1991). Simultaneously, there is growing evidence that residential migration decisions are increasingly linked to the availability of natural amenities associated scenic vistas, outdoor recreational and leisure opportunities, and favorable climate conditions (McGranahan 1999). Meanwhile improved transportation and communication infrastructure helped people relocate to ever more distant nonmetropolitan areas to get away from urban disamenities like traffic congestion, pollution, crime, and high cost of living.

The West presents a unique regional demographic profile since its strong growth crosses all age cohorts, and the region has strong net positive domestic and international immigration as well (Travis 2007). Both natural increases and net migration are the major drivers of population growth in the IW. The change in population since 1970 was strongly associated with the presence of natural amenities which likely played a greater
role in attracting new residents (often called ‘amenity migrants’) than the availability of jobs (Rudzitis 1999). People came first for their lifestyles choices driven by scenic and cultural amenities and then jobs followed them (Beyers and Nelson 2000; Vias 1999).

Population growth in this region is positively associated with local employment growth and economic well-being (Krannich et al. 2011; Wall and Mathieson 2006). Since the new migrants often come with new sources of income, wealth, and occupational, organizational and leadership skills, they can contribute to the promotion of local entrepreneurship and employment (Krannich and Petzelka 2003; Kruger 2005).

The history of the American West is tied to farming, ranching, mining and other extractive industries (Power and Barrett 2001). In recent years, the region has experienced a steady transition to a “post-cowboy” economic era, which is defined less by the traditional mining, logging, and ranching, and more by a postindustrial, service- and amenities-based economy (Power and Barrett 2001). This regional economic transition is often viewed as a shift from the “Old West” to the “New West” (Krannich et al. 2011; Shumway and Otterstrom 2001; Winkler et al. 2007). The Old West is characterized by extractive industries and dependence on federal government expenditures, while the New West is distinguished by environmental amenities, recreation-based economies, and retirement destination communities. The New West reflects a maturing and economic diversification combining the elements of local and regional entrepreneurial skills, technology, and investment (Travis 2007). Through this process of regional change, peoples’ historical ties to the land – both through work and recreation – have been transformed (Nelson 2001).
Agricultural Restructuring in the West

Agricultural trends in the West are related to broader patterns of structural change in agriculture in the United States (Jensen 2005). These include: increasing farm output along with consolidation of production in the hands of fewer large commercial operations; increasing average farm size overall, but with the emergence of a bi-modal farm structure characterized by growth in numbers of both very large and very small (hobby or recreation) farms, and a corresponding decline in mid-sized operations; replacement of labor through intensive mechanization; growing levels of capital investment and debt; and growing reliance on off-farm income to support the viability of farm households (Buttel 2003; Cochrane 1993; Lobao and Meyer 2001).

A range of social, economic, and technological forces are driving farm structural change. These include increasing technical economies of scale, rewards to specialization of production, consolidation of ownership in the input supply and farm output processing sectors, and the growing role of global markets for agricultural commodities (Bonano and Constance 2006). While economic forces are critical, the role of social factors is also important (Jackson-Smith 2004). The quality of life benefits associated with farming helps explain the persistence of family-labor midsized farms and ranches in the face of below-market rates of return, as well the growth of ‘lifestyle’ farming operations (Bartlett 1993; Jackson-Smith 1999).

Farm structural change can have significant impacts on farm families, rural communities, and working landscapes. The declining economic viability of mid-sized, full-time commercial farms has led to increased financial and psychological stress for farm operators and family members (Armstrong and Schulman 1990; Belyea and Lobao
1990; Jacob, Bourke, and Luloff (1997), and farm structural change has been linked to
debates in local spending (Foltz, Jackson-Smith, and Chen 2002; Foltz and Zeuli 2005)
and in the quality and types of farm community social ties and patterns of engagement
(Goldschmidt 1978; Jackson-Smith and Gillespie 2005). Declining local ownership of
farmland, decision-making and control over production and distribution system
contribute to the unfavorable outcomes for the community and the quality of social
relationships and interactions within the community (Petrzelka, Ma, and Malin 2013).
Changes from farming and ranching to housing development can impact wildlife
populations, open space and landscape amenities, and local government finances
(Theobald, Miller, and Hobbs 1997).

Impacts of Demographic Change on Agriculture

While the growing significance of non-farm (and ‘New West’) sectors of the
economy of the IW is undeniable, research suggests that the links between regional
demographic and economic changes and agricultural trends are complex (Jackson-Smith
et al. 2006). The most urban and rapidly growing counties have seen the most negative
trends in farming overall. However, some forms of agriculture can also thrive in the
urban shadow, particularly when they raise high-value commodities that can be marketed
directly to urban customers (Jackson-Smith and Sharp 2008). Moreover, the growth of
the New West economy has actually been associated with growth in farm numbers and a
more moderate rate of farmland loss (Jackson-Smith et al. 2006). In addition, sluggish
growth in farm sales in these counties suggests a gradual shift from commercial-scale
operations to hobby farming, mostly by the amenity in-migrants who engage in farming
as a lifestyle choice. In contrast, Old West counties have experienced a rapid decline in farm numbers and farmland acres, but significant growth in farm sales.

The complexity of urban growth’s impacts on agriculture can be better understood by recognizing the different mechanisms through which residential development and farm trends are connected. Among these are losses of farmlands by increasing land consumption, increasing farmland prices, increasing cost of community services, local land use conflicts, fragmentation of landscapes, declining agriculture infrastructure, and competition for water. Each of these is explored in more detail below.

Loss of Farm Lands:

Nationwide, the cumulative effect of thousands of individual land use decisions is changing the countryside by converting at least 1.4 million acres of rural land into residential uses each year. This result includes loss of agricultural production, water pollution, increases in local runoff and flooding and loss of habitat and biodiversity (Mylott 2009). Nonmetropolitan rural population growth comes with the loss of thousands of acres of prime farmland into residential and commercial land areas (Jackson-Smith 2002; Travis 2007). New houses in rural areas typically utilize much larger parcels of land per capita than more urban forms of development, and are disproportionately responsible for the conversion of farmland and forests to development each year (Heimlich and Anderson 2001; Riebsame, Gosnell, and Theobald 1996).

As development spreads, it competes with agriculture for land (Mylott 2009). Counties with the highest rate of population growth are associated with the most rapid expansion of developed land (Jackson-Smith et al. 2006). The competition for land from
amenity purchasers makes it more difficult for commercial farmers to capture productivity increases by increasing farm scale purchasing farmland and expanding their farm holdings. To remain competitive farmers must intensify their farm operations within the existing land area. Not all farm managers can, or wish to, implement this option though. This means they must choose between selling and moving where land is cheaper, taking off-farm work, or living within the constraints of declining farm income (Barr 2008).

The scenario in IW is not very different than the national picture. The region is experiencing a rapid and sustained loss of available farmlands (Krannich et al. 2011). Between 1982 and 2007, the USDA reports the loss of farmland was over 200 acres per day as it is converted to different forms of development (Table 1). In the present changing landscape, non-ranchers are buying much of the cowboy’s historic range, and all these changing phenomena are also contributing to the loss or conversion of farmlands as well as to shape new community fabric in Intermountain West.

*Increasing Farm Land Prices:*

Another mechanism through which residential growth impacts farming is through land price inflation. When development spreads to rural areas, the price of farmland is often driven above its economic value for farm use (ERS 2002). Nonfarm amenity buyers typically pay much more than what ranchers and the farmers reliant on commodity markets can afford. In states and counties where farmland is in great demand for conversion to developed and rural residential uses, a relatively large proportion of the market value of farmland is attributable to nonfarm demand. Ranchlands even in less
Table 1: Conversion of Land between 1982 and 2007 in the Intermountain West

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<th>CO</th>
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<th>UT</th>
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<td>acres</td>
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<td>Total rural land</td>
<td>765,400</td>
<td>363,800</td>
<td>246,200</td>
<td>321,400</td>
<td>160,000</td>
<td>1,856,800</td>
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<td>converted to</td>
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<td>developed land</td>
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<td>Converted land</td>
<td>605,200</td>
<td>289,500</td>
<td>192,800</td>
<td>301,300</td>
<td>156,000</td>
<td>1,544,800</td>
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<td>Percent of</td>
<td>79.1%</td>
<td>79.6%</td>
<td>78.3%</td>
<td>93.7%</td>
<td>97.5%</td>
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<td>Prime</td>
<td>70,200</td>
<td>124,400</td>
<td>22,800</td>
<td>66,800</td>
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<tr>
<td>Percent of</td>
<td>11.6%</td>
<td>43.0%</td>
<td>11.8%</td>
<td>22.2%</td>
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Source: USDA NRCS National Resources Inventory (2007)

attractive landscapes across the West now go for twice to ten times than their agricultural value (MacLaren et al. 2005).

The inflated land value associated with development pressure can be both a blessing and a curse for local farmers and ranchers (Daniels and Bowers 1997). Appreciating land values enable farmers to realize significant financial gains when they sell their farmland assets and often this is the only source of retirement funds for older farm families. On the other side, rising farmland values can attract nonfarm land speculators (Lins 1994) and can make it difficult for new farmers to buy or even rent a
farm for their own agricultural practices (Daniels 1999). Similarly, increases in farmland prices can raise rental rates and make it difficult for farmers to expand their operations.

The temptation of potential windfall incomes from the sales of farmland to developers is also a major push factor encouraging farm operators to abandon farming activities. Rising farmland values can also reduce incentives for farmers to make investments in their own operations, since they may be expecting to sell for development in the future. This “impermanence syndrome” can accelerate patterns of agricultural decline near urban areas (Berry 1978).

*Declining Agricultural Infrastructure:*

The nonmetropolitan areas that are experiencing rapid population growth often lack critical mass of farming activity both in relative and in absolute terms. Farms in these areas are relatively small in acres operated, volume in sales and cattle inventories (Jackson-Smith and Jensen 2009). Declines in the number and economic scale of commercial farming enterprises in the face of urban pressure can create challenges for businesses, like farm input suppliers, bankers, and commodity processors and handlers, that rely on agriculture as a primary source of their economic activity. Farm supply dealers need a “critical mass” of farm operation to remain viable within an area (Jackson-Smith 2003). All these together force a gradual decline in agricultural infrastructures. As this infrastructure crumbles, a vicious cycle can ensue through which farmers lose access to important input and marketing infrastructure, which can in turn reduce the viability of local farms.


**Fragmentation of Landscapes:**

Often population growth in nonmetropolitan rural areas fragments agricultural parcels and makes carrying out farming operations more complicated and less efficient (Johnson 1999). As land gets split into smaller parcels due to population growth, remaining farmers are forced to deal with more landlords and travel longer distances to access rented fields. Therefore, with some little exceptions, landscape fragmentation usually comes with the increasing complexity of social and administrative sides of rural life (King and Burton 1982). Fragmentation also increases the number of people involved in implementing decisions about a particular area, and makes it more difficult to negotiate access or cooperate with neighboring landowners (King and Burton 1982).

**Local Land Use Conflicts:**

Another way that rural and exurban growth can impact agriculture reflects the increased potential for land use conflicts between agricultural and non-agricultural residents. The influx of nonfarm people into farming areas can increase the incidence of complaints and conflicts over the dust, noise, and smells associated with modern agricultural activities (Daniels 1999; Jackson-Smith 2003). Conflicts can arise between growers and new neighbors over early morning noise and ultimately can create a climate of distrust and uncertainty for some types of agricultural operations (particularly large livestock farms). Increased traffic associated with population growth can also hinder farmers’ ability to move their equipment between fields on crowded rural roads (Heimlich and Anderson 2001). These conflicts present important practical and
economic challenges to commercial farmers and ranchers, but also diminish the quality of life benefits associated with the farming way of life (Zollinger and Krannich 2002).

**Increasing Costs of Community Services:**

Similarly, growth in residential land use in rural and exurban areas can increase the costs to local governments of providing important community services. New residents not only increase the amount of population who has to be served by local authorities, but they typically have higher expectations for the number, scope, and quality of those services (Zolnik 2011). Growing evidence indicates that residential developments dispersed across farmland and rangelands require more expenditures on local roads, schools, fire and police protection, and solid waste disposal services than they generate in new tax receipts (Carruthers and Ulfarsson 2003, 2008). This creates financial burdens on the ranchers and farmers, since local property taxes are often the primary mechanism to pay more for expanded community services.

**Competition for Water:**

In the arid landscape of American West, water is always critical in shaping region’s growth and change. Currently, agriculture uses upwards of 74% of all freshwater withdrawals from surface and groundwater purposes in this region (Gollehon and Quinby 2000). Due to relatively low annual rainfall in the Intermountain West, farmers rely heavily on irrigation to support their crop and livestock operations. Population growth and residential development in the nonmetropolitan IW can create competition for the available water supply. In the coming years agriculture is likely to be the source of most water that is transferred to nonfarm urban uses. The aggregate impact on agriculture and
rural communities of water transfers to meet other nonfarm (e.g., urban and environmental) uses is an important policy and local livelihoods/lifestyle question. New nonfarm residential development can also impact local hydrologic processes and water quality (DeFries and Eshleman 2004).

Spatial Configurations (Patterns) of Development

The impacts of population growth on agriculture depend on more than the sheer volume of new residents, but are likely mediated by the form and location of new housing construction on the landscape. For example – growth within the boundaries of existing urbanized areas is less likely to cause challenges for agriculture, while growth that takes place within the working landscape will have more noticeable effects.

Previous literature has identified several major types of residential development that affect rural landscapes (Heimlich and Anderson 2001). The first reflects a classic form of “urban sprawl” (Williams 2000). It is characterized by growth in suburban residential developments close to the edge of existing urban and metropolitan areas, typically on larger than average lot sizes and associated with the development of extensive transportation, employment, and retail networks to provide services for an increasingly dispersed population (Benfield, Raimi, and Chen 1999; Rome 2001). A second residential development pattern consists of a mix of large-lot residential or recreational housing developments located further away from the boundaries of existing urban areas. This ‘rural sprawl’ or ‘exurban’ development is less well understood and documented (Daniels 2000). It usually involves far fewer numbers of people but significantly increased consumption of land per person. This form of development can
consist of the houses placed on relatively large parcels of rural land, the purchase of existing housing on relatively large parcels of (rural) land, and the purchase of large acreages for use as seasonal recreational, vacation, or hunting properties, often without any building construction (Jackson-Smith 2003). Finally, some new housing growth takes place in decidedly rural areas located far from urban centers. Much of this type of ‘rural’ growth in the IW consists of second homes built for vacations, hunting, and other recreational uses.

Geographers often distinguish exurban from suburban (or rural) areas based on a population density threshold (Berube et al. 2006; Clark et al. 2009; Wolman et al. 2005). A common criteria used to define ‘exurban’ involves population densities between 100 to 1000 people per square mile (or roughly 40-400 persons km$^{-2}$). Densities above that level are seen as urban (and suburban), while densities less than this threshold are considered rural.

The conflict between housing growth and agriculture can be particularly acute in the Intermountain West, where a large fraction of the land base is in public (mainly federal) ownership, which forces new residential growth to occur within the areas originally settled by pioneers in the 19th and early 20th century. By the nature of how this region was settled, the private land base tends to consist of the most productive agricultural soils with good access to irrigation water and comparatively flat topography. Nearly all of the major population centers in the IW are located along the base of mountain ranges, where winter snow accumulates and runs off to provide critical water supplies in the hot dry summer months.
As noted above, even though the majority of growth in the IW happens in metropolitan counties, a substantial number of new residents are settling in the lower-density exurban fringes of these urban counties, or in the rural or exurban parts of nonmetropolitan counties. Many in-migrants to the region are seeking to take advantage of unusually high natural amenities found in non-metropolitan counties. In these lower-density areas, new homes are likely to be built on larger lots (increasing the amount land consumed per new resident) and are often built in disconnected or dispersed patterns, which leads to greater penetration into and potential conflicts with operators of local working farmland.

Exurban landscapes are the scene of some of the IW’s greatest tensions between development and agriculture, and exurban housing growth has been identified as a significant threat to the region’s long-run social and ecological sustainability (Travis 2007). Both rural and exurban types of residential development tend to be fragmented and are often located in areas that lack any serious commitment to public land use planning or zoning. This form of growth is often criticized for being less economically and ecologically efficient and produces a larger human footprint on the environment per capita and overall (MacLaren et al. 2005; Theobald, Gosnell, and Riebsame 1996). For example, dispersed development can alter and/or disrupt local coupled human and natural systems. It usually fragments landscapes, isolates habitat patches, hampers natural habitats, changes landforms and drainage networks, and often introduces exotic species as well as controls and modifies disturbances and disrupts energy flow and nutrients (Alberti 2005). In this context, many planners recommend consolidating housing development in aggregated or clustered patterns (Pasakarnis and Maliene 2010), a goal
that is often achieved by adopting plans and local land use policies to protect local agricultural and rural landscapes (Clark, Inwood, and Jackson-Smith 2014).

Little is known about the explicit spatial configuration of most rural or exurban areas and subsequent impacts on agricultural outcomes. However, several recent studies have used available data to develop indicators to capture differences in the density and spatial arrangements of housing development. Theobald (2001) used census housing counts at the block group level to identify exurban landscapes in the US. Some of his work uses this approach to track changes in housing densities and a range of ecological outcomes over time. Similarly, Berube et al. (2006) used census tract data to define and locate exurban settlement. Clark et al. (2009) used data in 1 km pixels from the global ‘LandScan’ estimates of population density to identify the location of settlements in exurban areas across the lower 48 states. LandScan is treated as the finest resolution global population distribution data, with a representation of an ambient population (average over 24 hours). It has approximately 1 kilometer resolution (30" X 30").

Aside from density, a number of scholars have relied on indicators developed in the field of landscape ecology to characterize changing landscape patterns (Palmer 2004). These landscape indicators or landscape pattern metrics can identify and describe complex landscape into identifiable patterns and explore associated ecosystem properties, which are not directly noticeable (Antrop and Van Eetvelde 2000; Turner, Gardner, and O’Neill 2001). The most common use of landscape metrics (also widely known as spatial or landscape pattern metrics) is to quantify the shape and pattern of natural vegetation or landscapes (Gustafson 1998; Hargiss, Bissonette, and David 1998). However, in recent years, scholars have used landscape pattern metrics for quantifying changes and patterns
in human settlement. In doing that, they discussed: implications of different patterns of residential, population, urban growth (clustered or dispersed) and subsequent impacts on landscape change (Luck and Wu 2002; Theobald et al. 1997; Weng 2007;); impacts of landscape change on ecological functions and processes (Turner et al. 2001); and the linkages between landscape fragmentation and process of urbanization (Irwin and Bockstael 2007). One of the common goals of these studies is to document the ‘footprint’ of population growth based on the size of parcels converted into residential settlements (Alberti and Waddell 2000). Another goal is to capture whether residential settlements are clustered or dispersed in nature (Fagan et al. 2001). Sources of data have included the use of Landscan data (at 1 km resolution) and the National Land Cover Database (NLCD) developed by the Multi-Resolution Land Characteristics Consortium. NLCD is a land cover classification of 16-class (additional 4-class in Alaska only), and has been applied consistently in all 50 states and Puerto Rico at a spatial resolution of 30 meters (MLCC 2013). Where available, more fine grained and accurate land use datasets have been used at the state level. For example, Irwin and Bockstael (2007) demonstrated that high resolution land use change information provided by the State of Maryland provided a more accurate and detailed foundation to analyze rural and exurban housing development than the NLCD.

**Role of Spatial Process in Social Sciences**

Another empirical challenge in the study of spatial patterns of housing development relates to the unit of analysis at which patterns are measured. Many studies have relied on county-level data to aggregate information about demographic and
economic trends and impacts on agriculture and wildlife. County-level approaches make sense to the extent that many of the underlying processes operate at this scale. For example, decisions by a farmer to expand or make investments in his or her operation are likely to be shaped both by the larger agricultural, economic, and demographic context in their valley (or county) and by the changes taking place on their operation or on immediately adjacent parcels. Similarly, the effects of urban proximity can extend beyond the boundaries of individual counties; nonmetropolitan counties that are adjacent to metropolitan counties have distinctive employment opportunities and real estate market dynamics, and experience different trends and outcomes in the agricultural sector (Jackson-Smith et al. 2006). As explored in this thesis, spatial patterns describing how residential development is arrayed across the agricultural landscape can be thought of as a county-level trait of the local farming context that affects outcomes at the individual farm and aggregate farm community level.

At the same time, what happens in one county is related to things that are going on in neighboring counties. This concept of spatial interdependence stems from Tobler’s (1970) first law of geography. Tobler mentions that on space everything is related to everything else; however things that are near to one another are expected to be more related than distant things. This theoretical assumption is the founding principle upon which the contemporary understanding and corrective measures for spatial autocorrelation have been based, in which statistical information about neighboring units of analysis can be used to explain trends in the unit of interest (Anselin 1999). Space is an ever-present element in human interactions and interdependence (Hawley 1950). Human behavior shapes space, and at the same time, space also shapes human behavior (Burch
1965). Therefore, space is a key dimension of the biophysical environment that sets the stage for human activities (Krannich et al. 2011). This growing awareness of the potential importance of spatial patterns and processes has contributed to a surge of interest in research and analysis methods that are appropriate to answer questions related to natural resources social science in recent years.
CHAPTER III
METHODS

Approach

This research contributes to the literature by examining the associations between different patterns of residential settlement and agriculture trends in the Intermountain West. I use spatially explicit measures of growth patterns and spatial analysis methods to capture the role of within- and across-county spatial processes. There are usually two opposite approaches towards dealing with spatially referenced data: data–driven and model–driven approaches (Anselin 1986). A data-driven approach allows the data to ‘reveal’ the spatially important patterns or processes, often without the use of a theoretical framework. Meanwhile, a model-driven approach starts from a theoretical specification, and uses theory to guide the selection of measurement and analysis approaches (Anselin 1980, 1988; Cliff and Ord 1981).

This study follows a model-driven approach that builds on prior empirical and theoretical literature. Based on the literature summarized above, I use a theoretical conceptual model (Figure 2) that recognizes spatial patterns of development as an important independent variable that could help improve our understanding of variation in trends in a range of agricultural outcomes. In this theoretical model the major drivers of variation in farm change in the IW fall into three basic categories: population pressure, socioeconomic structural contexts, and biophysical resources. Each of these had been shown to affect the nature and trajectory of changes in agriculture in the United States,
and was expected to help explain why some parts of the IW are witnessing growth, while others were seeing the rapid decline in their farming sectors.

Figure 2: Theoretical Model.

To this basic model of farm change, I add a new factor – the spatial pattern of residential settlement. I argued that spatial patterns could have their own impact on agricultural trends, but also mediate the impacts of population pressure and socioeconomic structure.

Selection of Units of Analysis

In studies of land use change and subsequent impacts on agriculture, the selection of appropriate spatial unit of analysis is a crucial component. In social science research on trends in agriculture, empirical research has often relied on aggregate county-level
data (Jackson-Smith and Jensen 2009; Jackson-Smith et al. 2006). Counties have also been the basis to examine trends in rural economies and communities more broadly (Beale and Johnson 1998; Cromartie 1998; Frey and Johnson 1998; Frey and Speare 1992; Fuguitt 1985; Johnson and Fuguitt 2002; McGranahan 1999; Overdevest and Green 1995; Rudzitis 1999). The use of counties as a unit of analysis is partly explained by the widespread availability of census and other secondary data at the county-level (Irwin 2007). County is a standard census administrative unit and data are replicable and easy to compare with other counties.

Many local social and economic processes operate at scales larger than the local household or community, and aggregate county-level data allow for the analysis of those broader relationships between population growth and changes in agriculture (Jensen 2005). Farmers who live in the same county share a similar set of social, demographic, economic, and environmental opportunities and challenges, regardless of their individual personal or farm enterprise characteristics. Changes on a single farm operation are always shaped by changes that are taking place in this broader local context.

This study focused on the five state IW region (Idaho, Montana, Wyoming, Colorado, and Utah), and included counties that have sufficient agricultural activity to enable an analysis of farm sector trends. Of the 216 total counties in these five states, data on key farm sector characteristics from the U.S. Census of Agriculture were available for all but 26. The proposed research thus included 190 counties (shown in Figure 3 below).
Operationalizing Key Theoretical Concepts

This study proposed to use a range of different data from secondary sources to operationalize the key theoretical concepts outlined in Figure 2 above.

Dependent Variables: Indicators of Agricultural Change

This study focuses on explaining variation in the changes taking place in agriculture in the Intermountain West at the county level between 1997 and 2012. This time period took advantage of the availability of detailed county-level data from the U.S. Census of Agriculture, which takes place every 5 years. Agricultural census reporting methods changed in 1997 (incorporating adjustments based on statistical sampling) which makes comparisons to earlier periods potentially problematic. The study period extends
through 2012, the most recent available census wave. A fifteen year time period of change is also more robust than shorter 5-year change windows since it is more likely to reflect enduring long-term processes and be less susceptible to the effects of unusual events or market shifts associated with just one census.

I use three indicators to capture different aspects of the process of farm structural change. First, I examine changes in the number of farming operations through time. To qualify as a farming operation, a person only needs to produce (or have the potential to produce) $1000 worth of agricultural goods in a typical year. This low threshold means that the count of farms includes many operations that are relatively small. Indeed, in the IW roughly 56.93% of all farms sold less than $10,000 of produced goods in 2012 (US Census of Agriculture 2012). Nevertheless, growth and decline in the number of farming operations is a good indicator of changes in the human face of the farm sector – whether large or small, each farm family represents an important component of the social fabric of most rural communities.

Second, I look at trends in the acres used as cropland in this region. Because of the widespread use of rangeland and pasture for grazing livestock, cropland represents a relatively small fraction (roughly 26%) of the overall reported ‘farmland’ base in the IW (Table 2). However, cropland represents the most productive lands (best soils, best access to irrigation) and is responsible for the overwhelming majority of economic output associated with agriculture in these five states. Trends in cropland thus reflect some of the most substantively meaningful indicators of land use change from agriculture to other types of land use.
Table 2: Importance of Land in Farms and Cropland in 5-state Region, 2012.

<table>
<thead>
<tr>
<th></th>
<th>CO</th>
<th>ID</th>
<th>MT</th>
<th>UT</th>
<th>WY</th>
<th>TOTAL</th>
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<tbody>
<tr>
<td>Acres (unless otherwise noted)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Land in Farms</td>
<td>31,886,676</td>
<td>11,760,109</td>
<td>59,758,917</td>
<td>10,974,396</td>
<td>30,363,641</td>
<td>144,743,739</td>
</tr>
<tr>
<td>Cropland</td>
<td>10,649,747</td>
<td>5,793,347</td>
<td>17,022,177</td>
<td>1,645,898</td>
<td>2,418,931</td>
<td>37,530,100</td>
</tr>
<tr>
<td>CL as % of land in farms</td>
<td>33%</td>
<td>49%</td>
<td>28%</td>
<td>15%</td>
<td>8%</td>
<td>26%</td>
</tr>
<tr>
<td>Harvested Cropland</td>
<td>5,182,628</td>
<td>4,504,676</td>
<td>9,533,929</td>
<td>1,054,369</td>
<td>1,440,605</td>
<td>21,716,207</td>
</tr>
<tr>
<td>HC as % of cropland</td>
<td>49%</td>
<td>78%</td>
<td>56%</td>
<td>64%</td>
<td>60%</td>
<td>58%</td>
</tr>
<tr>
<td>HC as % of land in farms</td>
<td>16%</td>
<td>38%</td>
<td>16%</td>
<td>10%</td>
<td>5%</td>
<td>15%</td>
</tr>
<tr>
<td>Irrigated Land</td>
<td>2,516,785</td>
<td>3,365,292</td>
<td>1,903,019</td>
<td>1,104,257</td>
<td>1,435,710</td>
<td>10,325,063</td>
</tr>
<tr>
<td>IL as % harvested CL</td>
<td>49%</td>
<td>75%</td>
<td>20%</td>
<td>105%</td>
<td>100%</td>
<td>48%</td>
</tr>
<tr>
<td>IL as % cropland</td>
<td>24%</td>
<td>58%</td>
<td>11%</td>
<td>67%</td>
<td>59%</td>
<td>28%</td>
</tr>
<tr>
<td>IL as % land in farms</td>
<td>8%</td>
<td>29%</td>
<td>3%</td>
<td>10%</td>
<td>5%</td>
<td>7%</td>
</tr>
</tbody>
</table>

Third, I included measures of trends in gross farm sales between 1997 and 2012. Change in gross sales is a good measure of the overall economic contribution of farming to the well-being of farm households and the regional economy. Because inflation can distort the real spending value of a dollar through time, I used the consumer price index (CPI) to adjust all reported gross sales to reflect 2010 dollars.

Maps for the study counties illustrating spatial patterns in agricultural trends are included in Figures 4 to 6 below. These maps highlight that county-level variation in agricultural trends can be quite dramatic – with some areas experiencing growth and others decline in all three indicators. Moreover, the trends in one indicator in a given county are not always tied to trends in the other indicators.
Figure 4: Spatial Variation in the Rates of Change in Farm Number.

Figure 5: Spatial Variation in the Rates of Change in Cropland.
Independent Variables: Population Pressure

I use data from the U.S. Census of Population to develop measures of population pressure at the county level (US Census Bureau 2014a). First, I capture the various components of population growth during my study period. One is a reflection of the net change in county population (or the number of new residents minus outmigration) between 2000 and 2010. Another is a measure of the rate of population change over the same time period.

Second, I include a measure of rural population density in 2000 to capture variation in the degree to which rural (or non-urbanized) parts of each study county are already populated. This indicator is calculated using several key adjustments to a typical county-wide estimate of population density. Initially, because residential housing
development generally cannot occur on public lands, I exclude federal lands from the land base denominator used to calculate population density. Spatial data on the location of federally owned lands was obtained from USGS Protected Areas Data Portal (U.S. Geological Survey 2014). I also exclude areas within study counties that consist of open water or barren lands (as noted in the National Land Cover Database described below). Finally, I only include the ‘rural’ residents of each county in the numerator, and divided this rural population by the area of non-federal, non-water private developable lands (PDL) that were located outside of officially designated census urbanized areas or urban clusters.

Third, I included a measure to capture the degree of urban influence in each study county. The USDA Economic Research Service develops a formal ‘urban influence code’ (UIC), a classification scheme that distinguishes metropolitan counties by size and nonmetropolitan counties by size of the largest city or town and proximity to metro and micro areas (USDA ERS 2014). Scores on the UIC range from 12 to 1, and higher values are associated with a smaller degree of urban influence. I utilize the 2003 version of the UIC scale in my analysis to capture urbanization levels in the middle of my study period.

**Independent Variables: Socioeconomic Structure**

I also use several variables in my analysis that capture differences in the socioeconomic structure surrounding farmers in each study county. First, I include two measures to capture differences in the types of farms (or farm structure) that were prevalent in each of the study counties. These included an estimate of the percent of farm sales that comes from crops (instead of livestock) and a measure of the percent of farms
that are classified as ‘retirement’ or ‘lifestyle’ operations. Over the 1997-2012 period, crop farming was much more profitable and successful than livestock farming (in the US and global markets), so I expected places with crop farms to have fared differently than areas with predominantly livestock operations (net the effects of other variables). The \textit{percent crop sales} variable reflected the types of farming operations that were present in a county at the outset of the study period (from the 1997 census of agriculture). Since data on retirement and lifestyle farms were not reported in the census until 2007, I use that year to estimate the degree to which local agriculture consists of this type of farm (which I expect to be more compatible with or resilient in the face of population growth pressures).

In addition to measures of farm structure, I include three indicators to capture the broader socioeconomic opportunity structure in each study county at the outset of the study period. Specifically, I include a measure of median household income in 1999 (from the 2000 Census), with the idea that areas with higher overall levels of household income might provide more opportunities for farms to market their products locally or for farm households to generate off-farm income. Median household income is likely to be higher in New West places than Old West places, which reflects the relatively higher level of economic opportunities and diversification of local economies and more urban nature of New West places (Winkler et al. 2007).

I also include variables to capture whether or not a county is (a) agriculturally important (as defined in Jackson-Smith and Jensen 2009), and (b) located in an area with relatively high natural amenities (as classified in a standardized scale by McGranahan 1999). For agriculturally important counties, I use a dummy variable with values of 0 or
1. I expect that places with a critical mass of commercial agricultural production will have different agricultural trajectories than places where agriculture is a less important economic activity. To capture the relative quality of natural amenities, I use the natural amenity scale developed by McGranahan (1999) that sums the standardized Z-scores for a set of indicators of natural amenities (topographic variation, climate, proximity to water bodies, etc.). The result is an indicator of how a county’s natural amenities compares to other counties in the U.S. The scale ranges from -6 to +11, with positive values reflecting higher natural amenity quality. I would expect that the presence of unusually positive natural amenities would provide a basis for non-farm rural economic growth linked to a New West or tourism and recreation economy. Such growth might compete with agriculture, or alternatively, provide opportunities for non-farm income that can help sustain farm households during agricultural downturns.

**Independent Variables: Biophysical Resource Quality:**

Since long growing seasons and good soil quality contribute to competitive advantages for farmers, I include two measures of county ‘biophysical resource quality’ in my analysis. In both cases, I drew upon measures developed by Jill Clark and Douglas Jackson-Smith that provide a mean soil quality index score and typical number of growing days between frosts for each county in the region. The methods use USDA soil maps and associated information from the USDA/NRCS STATSGO soils database to calculate an area-weighted average county value for two indicators of suitability for farm production: average number of frost-free days (essentially a proxy for the length of the growing season) and percent of land in the top three ‘land capability classes’ (which are
considered best for agricultural production). In each case, integrated geospatial data layers were used to exclude urbanized areas, lands covered with surface water, and lands owned and managed by federal agencies (Jackson-Smith et al. n.d.). Data layers were rasterized and geographically weighted average were calculated for each variable for the private lands, non-urban areas in each study county.

**Key Explanatory Variables: Spatial Patterns of Residential Settlement**

The core of my research explores how spatial patterns or the distribution of rural and exurban development are associated with agricultural trends. I expect that spatial patterns provide information that is lacking in simple aggregate statistics on county population growth rate or number. To assess this question, I use several metrics of spatial patterns drawn from the field of landscape ecology. I utilize spatially explicit data on the location of nonfarm development to calculate four key explanatory variables to capture the heterogeneity of rural and exurban residential patterns in the IW.

I begin by using the National Land Cover Database (NLCD), a 16-class land cover classification scheme that is available across all 50 United States and Puerto Rico at a spatial resolution of 30 meters (MLCC 2013). It is publicly available data, and was the first nationwide initiative that provided consistent land cover inventory for the United States. NLCD data are available for several time periods (1992, 2001, 2006 and – just released – 2011) and have been widely used to study issues like spatial patterns of growth, change, and landscape fragmentation.

Because I am interested primarily in rural and exurban patterns of development, I also restrict my analysis to areas outside of formal urban areas. Formal urban areas are
the census-designated places that have population densities more than 1,000 persons per square mile, as well as contiguous areas with population densities of more than 500 persons per square mile. There are also two subtypes of urban areas: (1) urban areas – populations greater than 50,000, and (2) urban clusters – areas with population between 2,500 and 50,000 (US Census Bureau 2014b).

At the outset, I clipped census urban areas using boundaries from the 2000 Census of Population. Next, because 46 percent of the land base in the IW is publicly owned (Headwaters Economics 2012), private development cannot take place on much of this landscape. For this reason, I removed federal lands from my analysis. Finally, some counties include major water bodies or barren lands that are also unavailable for settlement, and these were excluded from my analysis. The result is a spatial raster layer that only includes privately owned (non-federal) developed and undeveloped lands that are outside of official urban areas in the study area. All metrics reported below are based on this restricted study landscape.

Since the NLCD ‘developed lands’ layer captures both residential and commercial development as well as other forms of developed land cover that are not residential housing (particularly roads), I worked with Molly Cannon (a GIS consultant at Utah State) to systematically identify and exclude pixels that overlay major public roads or oil and gas well pads and pipelines. The remaining areas were considered ‘developed’ pixels in the metrics described below.

Most landscape metrics rely on analysis of ‘patches’ of homogenous types of land use or land cover to estimate quantitative indicators of spatial patterns (Eiden, Kayadjmian, and Vidal 2000). These patches are the landscape elements that define an
overall landscape structure (Forman 1995). Landscape metrics measure spatial structure or patterns and provide useful information about the composition or configuration of a landscape. Common themes in landscape analysis are documenting the size of patches, the degree to which patches are clustered together or fragmented or dispersed, connectivities between patches, and the degree of overall patch heterogeneity in the landscape (Botequilha Leitao et al. 2006). The size and shape of patches determines to a large degree their ecological and functional characteristics (Botequilha Leitao et al. 2006). When landscape structures change, functions also change and vice versa.

For measuring the landscape metrics, I used Fragstats, a widely used software program used for quantifying landscape patterns (McGarigal, Cushman, and Ene 2013). Landscape metrics often measure multiple aspects of landscape pattern. Some metrics are inherently redundant because they provide alternative ways of representing the same basic information (e.g. mean patch size and patch density). In other words, metrics may be empirically redundant; not because they measure the same aspect of landscape pattern, but because for the particular landscapes under investigation, different aspects of landscape pattern are statistically correlated (Botequilha Leitao et al. 2006).

To examine the rural and exurban residential development impacts on agriculture, I identified a set of landscape pattern metrics that capture different dimensions of the arrangement of housing within largely agricultural rural PDL landscapes at the county-level. I selected four different metrics to capture different aspects of spatial heterogeneity: Patch Density (PD), Largest Patch Index (LPI), Aggregation Index (AI), and Total Edge Contrast Index (TECI).
Patch Density (PD):

PD describes the number of patches of a given land use type in a landscape, divided by the total landscape area. I used metric units in my analysis, measuring area using hectares (ha), as 10,000 square meters (100 m by 100 m).

\[
PD = \frac{n_i}{A} (10,000)(100)
\]

where,

\(n_i\) = number of patches in the landscape of patch type (class) i

\(A\) = total landscape area (in square meters, or m²)

Higher values of PD occur when there are a greater number of patches within a reference area (Eiden et al. 2000). In my study, PD reflected the number of distinct patches of residential settlement in rural or exurban areas for each county divided by the total corresponding landscape area. Often scholars use PD to identify the changes of landscape patterns (Botequilha Leitao et al. 2006; Weng 2007). Weng (2007) identified a positive relationship between PD and the number of residential units in a particular landscape. This implies that as the population grows, PD also tends to reach a higher value (=more fragmentation). In most cases, this high value PD is a strong indicator of greater landscape heterogeneity and fragmentation (Palmer 2004).

Largest Patch Index (LPI):

LPI is the ratio of the area of the largest single patch to the total area of the landscape (Wu, Shen, Sun and Tueller 2002). In other words, LPI equals the percentage
of the landscape comprised by the largest patch. It is a measurement of patch type dominance (Luck and Wu 2002).

The formula for LPI is:

\[
LPI = \frac{\max_{i,j}(a_{ij})}{A} \times 100
\]

where,

\[a_{ij} = \text{area (m}^2\text{)} \text{ of patch } ij\]

\[A = \text{total landscape area (m}^2\text{)}\]

LPI approaches 0 when the largest patch of the corresponding patch type is increasingly small relative to the size of the area. In that case, there is no single patch that dominates the landscape. This could either reflect the fact that there are not many patches in the county’s rural PDL or that they are highly fragmented. When LPI equals 100, it indicates that the entire landscape consists of a single patch of the corresponding patch type (McGarigal et al. 2013). Ghosh et al. (2012) attempted to analyze the changes in forests of the Himalayan Foothills using LPI in their analysis. Their results found a lower value of LPI for agricultural landscape, since agricultural land covered a small percentage of total studied area.

Aggregation Index (AI):

The Aggregation Index (AI) is a direct measure of the degree of clustering and consolidation for particular patch types. AI is calculated by assessing the number of ‘like adjacencies’ involving cells in a given land use class, divided by the maximum possible
number of like adjacencies achieved if the class were in a single clump. To identify the
degree of aggregation of a particular patch class on a particular landscape, it compares
the number of shared edges with the total possible number of shared edges (Rutledge
2003).

The formula for AI is:

\[
AI = \left( \frac{g_{ii}}{\text{max} \rightarrow g_{ii}} \right) \times 100
\]

where,

- \( g_{ii} \) = number of like adjacencies (joins) between pixels of patch
type (class) i based on the single-count method
- \( \text{max} \rightarrow g_{ii} \) = maximum number (roughly % of maximum possible) of
like adjacencies between pixels of patch type i based on the
single-count method

The AI varies with varying spatial resolution, but the index value for individual
classes will not be affected by changes in the other classes (Rutledge 2003). AI equals 0
when the focal patch type is maximally disaggregated (i.e., when there are no like
adjacencies). AI increases as the focal patch type is increasingly aggregated and equals
100 when the patch type is maximally aggregated into a single, compact patch.

There are not many landscape pattern metrics that measure clustering and
consolidation for particular patch types. Most other metrics have certain limitations
measuring aggregation of landscape patterns (He, DeZonia, and Mladenoff 2000.).
Therefore, He et al. (2000) argue that AI provides a quantitative basis to correlate
landscape patterns with processes that are typically a class-specific phenomenon. Based
on this argument, Liu and Weng (2013) also used AI as one of their metrics to analyze urbanization-induced land change and land cover changes. In their studies they demonstrated that higher aggregation of lands (or patches) often implied a clustered development.

*Total Edge Contrast Index (TECI):*

The Total Edge Contrast Index (TECI) reflects the amount of heterogeneity in the overall landscape. Unlike the three indicators above, which only look at patterns of a ‘focal’ land use class, TECI requires information about all types of land use throughout the landscape. TECI is estimated by comparing land uses on both sides of the edges of all of the pixels in a landscape. It equals the sum of the lengths (m) of each edge segment involving the corresponding patch type multiplied by a corresponding contrast weight (equal to 1 if neighboring land uses are different, or 0 if the uses are the same and does not contain any edge). This sum is then divided by the sum of the lengths (m) of all edge segments. In TECI, edge segments along the landscape boundary (e.g., along county lines) are ignored since the neighboring pixel is outside of the landscape of interest.

\[
TECI = \frac{\sum_{k=1}^{m} (e_{ik} \cdot d_{ik})}{\sum_{k=1}^{m} e_{ik}^*} \tag{100}
\]
where,

\[ e_{ik} = \text{total length (m) of edge in landscape between patch types (classes) } i \text{ and } k; \text{ includes landscape boundary segments involving patch type } i. \]

\[ e_{ik} = \text{total length (m) of edge in landscape between patch types (classes) } i \text{ and } k; \text{ includes the entire landscape boundary and all background edge segments, regardless of whether they represent edge or not.} \]

\[ d_{ik} = \text{dissimilarity (edge contrast weight) between patch types } i \text{ and } k. \]

In simple words, TECI captures the degree of structural contrasts along the edges of corresponding patches (Nonaka and Spies 2005), and TECI is one of the major landscape metrics for measuring fragmentation. Pechanec et al. (2013) used TECI to measure land use fragmentation across time in selected steppe sites in the Pannonian region of the Czech Republic. They found that landscape fragmentation is linked to population growth and urban development. Apart from identifying the landscape heterogeneity, scholars like Botequilha Leitão and Ahern (2002) also argue that TECI can give better understanding to conceptualize goals for or outcomes of locally relevant sustainable landscape planning.

Considering all these metrics’ properties and functions, I generated hypotheses about how I believed different spatial patterns would affect agricultural trends in the region (Table 3). First, if in a particular landscape, the number of patches is high, that tells us the areas are more fragmented. In usual circumstances, evidence supports higher level of fragmentation of lands is bad for agriculture (Dirimanova 2006; Hung, MacAulay, and Marsh 2007). Therefore, I argue that a higher PD index score is bad for
agriculture. Second, LPI is the measurement of patch type dominance, and a single contiguous patch of a particular land use category dominates the landscape when the LPI is high. This indicates less fragmentation, which is considered favorable to sustaining commercial agricultural activity. Third, AI identifies the degree of clustering and consolidation of particular patch types. If the patches are consolidated, it signals less fragmentation. Less clustering or consolidation indicates the opposite. Therefore, I argue that higher values of AI are good for agriculture. Furth, TECI captures the degree of contrast or intermixing among land use categories. More contrast is found when in a particular landscape there are more land use types, and these types are intermixed to a significant extent, which signals the existence of higher fragmentation of landscape. For this reason, I argue that higher values for TECI could be detrimental for agriculture.

Table 3: Theoretical Expectations of Landscape Metrics.

<table>
<thead>
<tr>
<th>Spatial Pattern Variable</th>
<th>Direction</th>
<th>Expectation</th>
</tr>
</thead>
<tbody>
<tr>
<td>PD</td>
<td>-</td>
<td>Higher PD is bad for agriculture</td>
</tr>
<tr>
<td>LPI</td>
<td>+</td>
<td>Higher value of LPI is good for agriculture</td>
</tr>
<tr>
<td>AI</td>
<td>+</td>
<td>Higher value of AI is good for agriculture</td>
</tr>
<tr>
<td>TECI</td>
<td>-</td>
<td>Higher value of TECI is bad for agriculture</td>
</tr>
</tbody>
</table>

Since all these metrics deal with the varying degree and aspects of landscape heterogeneity (as well as fragmentation), my research tests whether these landscape pattern metrics are associated with three types of farm trends: change in farm numbers, cropland acres and farm sales. In general, trends in cropland and farm sales are thought to follow an overall pattern where lower overall levels of development and greater clustering of residential housing is associated with relatively positive trends. Conversely, more fragmentation and land use heterogeneity is viewed as predicting negative
outcomes. However, since the number of hobby farms in the IW had increased in last couple of years and is linked to amenity- or lifestyle-oriented population growth, I am also open to the possibility that greater land use fragmentation and heterogeneity could be associated with positive growth in farm numbers. These study expectations are tested using a series of regression analyses as described below.

Descriptive Statistics for Study Variables

A list of and descriptive characteristics for all the variables I include in my analysis is provided in Table 4 and Figure 7. Among the 190 counties included in this study, the average rate of population growth between 2000-2010 was 10 percent, but ranged from negative 18 percent to a high of 73 percent. The mean household income in 1999 was roughly US $35,500, ranging from $24,690 to $82,580. In addition, the average proportion of retirement or lifestyle farms in 2007 was 53 percent, but ranged from minimum 24 percent to maximum 72 percent. During the study period, the average rate of farm number change was approximately 10 percent and that ranged from a low of -29 percent to a high of 162 percent. The average county saw cropland decline by 17 percent, but ranged from -73 percent to one county where cropland expanded by 37 percent. Finally, the average rate of change in farm sales (adjusted for inflation) was 36 percent, but ranged from -67 percent to +245 percent.

Methods of Analysis

This work involved statistical analysis (using Excel and SPSS) and some fairly sophisticated geospatial data manipulation and analysis - including the use of ArcMap (ESRI 2014), Fragstats, and spatial regression modeling using GeoDa (GeoDa Center
At first, I prepared the input data for Fragstats by using ArcMap’s Spatial Analysis Tools. Then with Fragstats, I calculated the four landscape pattern metrics for every county in this region. After preparing these spatial pattern variables, I estimated a set of regression models to explain variation in the three dependent variables. I began by

<table>
<thead>
<tr>
<th>Variables (type &amp; name)</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>St.Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Independent Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><em>Population Pressure</em></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Net Change in Population 2000-2010 (1000s)</td>
<td>-1.93</td>
<td>148.28</td>
<td>8.07</td>
<td>22.51</td>
</tr>
<tr>
<td>Population Growth Rate 2000-2010</td>
<td>-17.71</td>
<td>73.09</td>
<td>9.89</td>
<td>15.44</td>
</tr>
<tr>
<td>Rural Population Density 2000</td>
<td>0.36</td>
<td>118.78</td>
<td>13.34</td>
<td>17.49</td>
</tr>
<tr>
<td>Urban Influence Code</td>
<td>1.00</td>
<td>12.00</td>
<td>7.60</td>
<td>3.53</td>
</tr>
<tr>
<td><strong>Socio-Economic Structure</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median HH Income 1999 (1000s)</td>
<td>24.69</td>
<td>82.58</td>
<td>35.55</td>
<td>8.62</td>
</tr>
<tr>
<td>Percent of Sales from Crop 1997</td>
<td>2.47</td>
<td>93.46</td>
<td>38.39</td>
<td>25.37</td>
</tr>
<tr>
<td>Percent Retirement or Lifestyle farms 2007</td>
<td>24.00</td>
<td>72.30</td>
<td>53.23</td>
<td>10.91</td>
</tr>
<tr>
<td>Agriculturally Important (Dummy variable)</td>
<td>0.00</td>
<td>1.00</td>
<td>0.19</td>
<td>0.39</td>
</tr>
<tr>
<td>Natural Amenity Scale Score</td>
<td>-3.82</td>
<td>7.47</td>
<td>2.53</td>
<td>1.98</td>
</tr>
<tr>
<td><strong>Biophysical Resource Quality</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Length of Growing Season</td>
<td>53.58</td>
<td>157.74</td>
<td>106.70</td>
<td>22.59</td>
</tr>
<tr>
<td>Soil Quality Index</td>
<td>0.00</td>
<td>70.76</td>
<td>14.75</td>
<td>15.84</td>
</tr>
<tr>
<td><strong>Spatial Pattern Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Patch Density (PD)</td>
<td>0.01</td>
<td>3.21</td>
<td>0.46</td>
<td>0.53</td>
</tr>
<tr>
<td>Largest Patch Index (LPI)</td>
<td>0.00</td>
<td>1.88</td>
<td>0.07</td>
<td>0.16</td>
</tr>
<tr>
<td>Aggregation Index (AI)</td>
<td>36.40</td>
<td>84.00</td>
<td>60.08</td>
<td>9.13</td>
</tr>
<tr>
<td>Total Edge Contrast Index (TECI)</td>
<td>0.43</td>
<td>62.75</td>
<td>15.03</td>
<td>12.06</td>
</tr>
<tr>
<td><strong>Dependent Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Farm Number Change (integer)</td>
<td>-29.09</td>
<td>162.15</td>
<td>10.16</td>
<td>21.66</td>
</tr>
<tr>
<td>Cropland Change (integer)</td>
<td>-73.16</td>
<td>37.07</td>
<td>-17.01</td>
<td>19.57</td>
</tr>
<tr>
<td>Farm Sales Change (integer)</td>
<td>-67.34</td>
<td>244.60</td>
<td>35.58</td>
<td>42.92</td>
</tr>
</tbody>
</table>
estimating standard ordinary least squares (OLS) linear regression models using SPSS (Statistical Package for Social Sciences). Since data might be spatially dependent, I assessed evidence for spatial autocorrelation and dependence, and when appropriate, conducted spatial regression modeling using GeoDa. A more detailed explanation of the analysis approach follows.

**Step 1: Standard Linear Regression – Ordinary Least Squares (OLS):**

The general purpose of linear regression analysis is to find a linear relationship between a dependent variable and a set of explanatory (independent) variables. I

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**Figure 7: Values of Spatial Pattern Metric Variables by County.**
conducted hierarchical OLS regression analyses. In the first step, I conducted the OLS regression by estimating a base model that included indicators for population pressure, socioeconomic structural characteristics and biophysical resource quality. As second step, I added the four spatial pattern variables to this base model.

This approach helps explore whether adding the spatial pattern variables improves our ability to explain variation in agricultural trends in the Intermountain West. In comparing these two models, I also examine if the second ‘full’ model reduced errors improved fit, provided stronger parameter estimates, and better met the assumptions of regression models.

**Step 2: Determining Spatial Dependence – Spatial Regression Modeling:**

To understand the role of spatial patterns and processes, I also conducted a spatially-explicit analysis. A model is spatially explicit when the variables, inputs or processes have explicit spatial locations and information about spatial location and relationships is incorporated into the modeling process. Nearly all landscape models have the potential to be spatially explicit, since landscapes are fundamentally spatial entities (McGarigal 2001). I use spatial regression modeling techniques as a key tool to analyze my spatially explicit data.

Spatial regression models are often appropriate when there is evidence of spatial relationships among the errors or residuals in traditional ordinary least squares regression models. To assess whether spatial autocorrelation or dependence was present in my data, I first utilized GeoDa to rerun my OLS models with spatial location information and calculated a Moran's Index, which quantifies the level of correlation in regression
residuals among neighboring counties. The presence of spatial autocorrelation of regression residuals is often considered a violation the OLS regression model assumption of independence of errors. A Moran’s I value near +1.0 indicates positive clustering while an index value near -1.0 indicates systematic dispersion in the distribution of regression residuals. Either high or low values of Moran’s I are evidence of the presence of spatial dependence.

Spatial dependence is "the propensity for nearby locations to influence each other and to possess similar attributes" (Goodchild 1992: 33). In simple terms, when a value observed in one location depends on the values observed at neighboring locations, then there is a spatial dependence (Logan 2005). Spatial dependence can be caused by two distinct processes: (1) spatial error – where the error terms across different spatial units are correlated, which indicates the possibility of omitted (spatially correlated) covariates that if left unattended would affect inference; and (2) spatial lag – a situation in which the dependent variable in one place is affected by levels of the independent variables in a neighboring place (Logan 2005). Spatial lag models are often used to analyze diffusion processes across the spaces where events in one place predict an increased likelihood of similar events in neighboring place.

In these analyses, I estimate both spatial lag and spatial error models for all variables in the full OLS model using GeoDa, which provides a range of regression diagnostics to detect spatial dependence.
Step 3: Selecting Appropriate Regression Model:

It was expected that both spatial lag and spatial error model would improve the original OLS model. To assess which model was better – OLS, spatial lag or spatial error, I used three criteria. First, I used theoretical arguments to inform the choice. If there are strong theoretical reasons for one form of model specification instead of another, it is generally preferred. Second, when theory does not provide a good guide, one can also examine the performance of variables in the models and identify model specifications that have more significant coefficients.

Finally, one can compare the model performance by using different measures of model Goodness-of-Fit: $R^2$, adjusted $R^2$, overall model F-test, F-test for change in $R^2$, Log–likelihood and Akaike Information Criterion (AIC). $R^2$ is widely used Goodness-of-Fit measure in any regression analysis, and directly reflects how well the linear regression equation fits the data (strictly speaking, it quantifies the proportion of variation in the dependent variable that is explained by the independent variables in the model). Because $R^2$ can be inflated by adding variables that have weak relationships to the dependent variable, most scholars use an adjusted form of $R^2$ that controls for the number of variables in the model. The F-test statistic is the ratio of the explained variability (as reflected by $R^2$) and the unexplained variability (as reflected by $1 – R^2$), divided by the corresponding degrees of freedom. The statistic can be used to determine if any single model is significantly better than a ‘null model’ in which dependent variables are predicted at random. The F-statistic can also be used to test whether adding a new block of variables to an existing model provides a statistically meaningful improvement over the previous model.
Two additional measures of model fit are reported in the analysis below. These reflect growing interest among statisticians in alternative (non-$R^2$) measures of fit based on comparing models (as opposed to strict assessment of ‘goodness’ of fit). The Log-likelihood (LL) statistic reflects the likelihood of a particular model fitting the observed data, and is useful when compared to a LL statistic for an alternative model applied to the same data (either a null model or a model with different parameters included). Higher Log-likelihood values demonstrate that a model is a better fit than the comparison model, though the absolute values of LL statistics do not in themselves convey a clear statistical meaning and cannot be compared to models developed using different datasets (Allison 1999). Meanwhile, the Akaike Information Criterion (AIC) provides a measure of the relative quality of a statistical model for a given set of data, or the tradeoff between goodness of fit and the complexity of a model. AIC offers a relative estimate of the information lost when a given model is used to represent the process that generates the data. The formula for the AIC statistic is: \[ AIC = 2k + n(\text{LnRSS}/n) \]

Finally, in the spatial regression models reported below, I report estimates of two distinct ‘spatial’ coefficients. In the spatial lag models, the spatial lag coefficient reflects the degree spatial dependence among dependent variables for neighboring counties that is inherent in my sample data, and measures the average influence on observations by their neighboring counties (Logan 2005). Meanwhile, the spatial error model reports a Lambda coefficient, which captures the spatial autoregressive properties in the residuals. Lambda values range from 0 (meaning the error terms are independent) to 1 (meaning the error terms are highly correlated). A significant lambda coefficient confirms the evidence of spatial dependence that was suggested by the Moran’s-I test.
CHAPTER IV

RESULTS

To assess the impact of spatial arrangements of residential development on agriculture in the Intermountain West, I estimate a series of regression models using data at the county level. My approach is to begin with a ‘base model’ that includes indicators of county-level population pressure, socioeconomic structure and biophysical variables, then explore whether adding a block of spatial pattern variables improves model fit. I also start with ordinary least squares regression models, but test whether a spatial regression model (which utilizes information about the spatial relationships among counties in the region) is a more appropriate statistical approach to address my research questions. I utilize this approach to estimate three different sets of models that seek to account for variation in county-level trends in farm numbers, cropland acres, and total farm sales (adjusted for inflation) between 1997-2012.

Explaining Farm Number Change, 1997-2012

The regression models for farm number change are shown in Table 5. The first model shows regression coefficients and model fit statistics for the base model (which does not yet include variables capturing spatial patterns of development). The second model presents results of a “full” model that incorporates spatial pattern measures. These two OLS regression models are then compared using several different indicators of model-fit.
Model Fit:

Based on all the indicators of fit, the full model is a significantly better model than the base model and explains a significantly larger amount of the variation in the rate of county-level farm number change. After adding the spatial pattern variables, the adjusted $R^2$ improved in the full model from 0.328 (32% of the variation in rate of farm number changes) to 0.401 (which explained almost 7% more of the variation). Moreover, F-tests for overall model fit as well as the F-test for change $R^2$ values (between the base and full model) were highly significant ($p<0.001$). Log-likelihood and AIC measures also suggest that the full model is preferable to the base model, Log-likelihood improved from -815.7 to -804.8, which suggests an improvement in model performance. Finally, the full model had a lower AIC value (1641.6) than the base model (1655.4), indicating that less information is lost in the full model.

Taken as a whole, model fit statistics confirmed that adding spatial metrics (spatial pattern variables) improves our understanding of variation in rate of farm number change at the county level in the IW region. In other words, the spatial pattern of residential development has a significant association with county-level trends in farm numbers, net the effects of other variables in the model.

Because I am using county-level data, and events or processes in one county could affect outcomes in neighboring counties, I calculated a Moran’s I statistic to test for evidence of spatial auto-correlation in regression residuals in both of the OLS (base and full) regression models. The Moran’s I (error) value is statistically significant in the base model, but the full model does not appear to have statistically significant spatial
Table 5: Regression Outcomes for Dependent Variable % Change in Farm Number (1997-2012)

<table>
<thead>
<tr>
<th>Population Pressure</th>
<th>Dependent Variable (% change in Farm Number 1997-2012)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-64.783 15.880 0.000 *** -60.747 16.805 0.000 *** -49.329 15.833 0.002 ** -51.324 16.949 0.002 **</td>
</tr>
<tr>
<td>Population Growth Rate County Net Change</td>
<td>-0.026 0.080 -0.027 0.745 0.072 0.087 0.075 0.409 0.076 0.081 0.248 0.088 0.083 0.287</td>
</tr>
<tr>
<td>Rural Population Density 2000-10</td>
<td>-0.250 0.097 -0.202 0.011 ** -0.191 0.100 -0.155 0.037 * -0.167 0.093 0.074 * -0.174 0.096 0.071 *</td>
</tr>
<tr>
<td>Urban Influence Code 2003</td>
<td>0.245 0.518 0.040 0.637 0.533 0.506 0.087 0.284 0.392 0.473 0.407 0.337 0.503 0.504</td>
</tr>
<tr>
<td>Socio-economic Structure</td>
<td>0.593 0.220 0.236 0.008 ** 0.630 0.218 0.254 0.004 ** 0.490 0.206 0.017 * 0.552 0.217 0.011 *</td>
</tr>
<tr>
<td>Percent Sales from Crop 1997</td>
<td>-0.023 0.062 -0.027 0.705 0.028 0.065 0.033 0.667 0.022 0.060 0.717 0.020 0.066 0.761</td>
</tr>
<tr>
<td>Percent Retirement/Lifestyle Farms 2007</td>
<td>0.514 0.175 0.259 0.004 ** 0.602 0.171 0.304 0.001 ** 0.571 0.161 0.000 *** 0.613 0.166 0.000 ***</td>
</tr>
<tr>
<td>Agriculturally Important County</td>
<td>-13.057 3.799 -0.237 0.001 ** -13.726 3.716 -0.249 0.000 *** -12.010 3.496 0.001 ** -12.753 3.670 0.001</td>
</tr>
<tr>
<td>Natural Amenity Scale Score</td>
<td>2.834 0.936 0.259 0.003 ** 2.830 0.899 0.259 0.002 ** 2.123 0.853 0.014 * 2.514 0.910 0.006 **</td>
</tr>
<tr>
<td>Biophysical Resource Quality</td>
<td>0.227 0.076 0.237 0.003 ** 0.246 0.074 0.257 0.001 ** 0.199 0.070 0.005 ** 0.226 0.076 0.003 ***</td>
</tr>
<tr>
<td>Length of Growing Season (days)</td>
<td>-0.044 0.117 -0.032 0.799 -0.133 0.118 -0.097 0.264 -0.082 0.112 0.464 -0.119 0.120 0.323</td>
</tr>
<tr>
<td>Spatial Pattern Variables</td>
<td>-4.027 3.557 -0.099 0.289 -3.557 3.333 0.286 -4.252 3.530 0.288</td>
</tr>
<tr>
<td>Patch Density (PD)</td>
<td>-32.430 11.041 -0.236 0.004 ** -29.205 10.321 0.005 *** -28.277 10.604 0.008 ***</td>
</tr>
<tr>
<td>Largest Patch Index (LPI)</td>
<td>-0.214 0.187 -0.090 0.255 -0.213 0.175 0.225 -0.244 0.185 0.185</td>
</tr>
<tr>
<td>Aggregation Index (AI)</td>
<td>0.057 0.150 0.032 0.702 0.011 0.140 0.936 -0.024 0.148 0.873</td>
</tr>
<tr>
<td>Total Edge Contrast Index (TECI)</td>
<td>0.232 0.087 0.006 ** 0.155 0.101 0.127</td>
</tr>
<tr>
<td>Spatial Regression Variables</td>
<td>0.232 0.087 0.006 ** 0.155 0.101 0.127</td>
</tr>
</tbody>
</table>

Test of Spatial Autocorrelation
Moran's I 0.005 ** 0.096 * n.a. n.a.

MODEL FIT STATISTICS
R² 0.328 0.401 0.428 0.302
Adjusted R² 0.286 0.349 n.a. n.a.
Overall Model F-test (significance) 0.000 *** 0.000 *** n.a. n.a.
F-test for Change in R² (significance) n.a. n.a. n.a. n.a.
Log-Likelihood (LL) -815.723 -804.818 -801.524 -820.367
Akaike Information Criterion (AIC) 1655.450 1641.640 1637.050 1672.730

Note: Significance denoted by *** = p<0.001, ** = p<0.01, * = p<0.05, † = p<0.10
dependence among the regression residuals. In any case, the results suggest the potential for spatial dependence, so I estimate two spatial regression models: a spatial lag (lagged dependent variable) and a spatial error model. Overall these models appear to fit the underlying data better than the OLS full model, though the spatial lag model is clearly the better fit. The value of $R^2$ increases from 0.401 in the OLS full model to 0.428 in the spatial lag model, but drops to 0.302 in the spatial error model. Log-likelihood values are highest and the AIC statistic is lowest in the spatial lag model. The spatial lag coefficient is positive (0.232) and statistically significant ($p=0.008$), and suggests that trends in farm numbers in neighboring counties are positively related to trends in each study county. Meanwhile, the Lambda coefficient (available for the spatial error model) is not significant ($p=0.127$). These results suggest that our model fit improved when we accounted for the spatial effects of trends in neighboring counties, but there is not a clear need to control for spatial autocorrelation in the error terms.

**Exploring Key Variables in the Spatial Lag Model:**

These findings support using the spatial lag model as the best model for examining the associations between the rest of the independent variables and trends in farm numbers across counties in the IW. More particularly, this model explains more variation than the spatial error model, and there are theoretical and empirical arguments for the importance of capturing the effects of trends in neighboring counties.

Population pressure: The role of population pressure is captured in the first block of 4 variables in the models. With respect to trends in farm number change, none of the variables are statistically significant. This is something of a surprise because it is
commonly thought that population growth (in absolute and percentage terms) and rural population density would all be negatively related to agricultural viability. However, rural population density is weakly associated with the trends of farm number change, though it is statistically not very significant.

Socioeconomic structure: All the indicators of socioeconomic structure, except the percent of sales from crop 1997, are associated with trends in farm numbers: median HH income ($p=0.017$), percent farms retirement or lifestyle farms ($p<0.001$), an indicator of a county being agriculturally important ($p=0.001$), and natural amenity score (0.014). The unstandardized coefficient of median HH income is positive and weakly significant (0.490; $p=0.017$), which means each $1,000 increase in median HH income is associated with an increase of 0.49 percent in the predicted rate of farm number change. The percent of county farms classified as retirement or lifestyle farms is strongly and positively linked (0.571) to predict farm number changes such that each 10 percent increase in the proportion of hobby farms is associated with a 5.7 percent more positive rate of change. Meanwhile, counties that were agriculturally important in 1997 were associated with a dramatically lower (-12%) predicted rate of change in farm numbers change ($p=0.001$). Finally, counties with high scores on the natural amenity scale were positively associated with trends in farm number. Each additional point on that scale was linked to a 2.1 percent more positive rate of change.

Biophysical resource quality: Because agricultural productivity is linked to climate and soil quality, a pair of variables was included to account for differences in the biophysical resource base in each of the study counties. The results suggest that an indicator of the average length of the growing season is positively related to estimates of
change in farm numbers ($p<0.01$). Specifically, each additional 10 days of growing season is associated with the 2 percent higher prediction of the percent change of cropland. The coefficient for soil quality was not significant.

Spatial pattern variables: While the results for these three blocks of background variables are interesting (and consistent with expectations), the core of the analysis was to explore whether indicators that capture the fine-grained spatial arrangements of residential development within non-urban areas of the study counties could contribute to the explanation of variation in cropland change. The findings suggest that only one spatial pattern variable is important. The coefficient for the Largest Patch Index (LPI), a measure of the degree of clustering in developed land uses, is both negative (-29.265) and highly significant ($p=0.005$). This suggests that higher levels of LPI (which reflect more clustering of development per unit land area) are associated with a more negative predicted rate of farm number change. Conversely, more fragmented settlement patterns are associated with growth in farm numbers. While contrary to my expectations, it is likely that growth in hobby farms could be both a cause and effect of fragmentation in rural housing development. Meanwhile, the coefficients for the other spatial pattern metrics (PD, AI, and TECI) are not significantly related to the rate of farm number change in my study counties.

**Explaining Cropland Change, 1997-2012**

The regression models for cropland change are shown in Table 6. Again, the first two models shows regression coefficients and model fit statistics for an OLS base model
as well as a ‘full’ model that incorporates measures of within-county spatial patterns of development.

Model Fit:

A comparison of model fit statistics suggests that both the base and full OLS models explain a significant amount of the variation in the rate of county-level cropland change. Adding the spatial pattern variables in the full model improves the adjusted $R^2$ from 0.295 (explaining 29% of the variation in rate of cropland changes) to 0.335 (which explained 4% more of the variation). Moreover, F-tests for overall model fit as well as the F-test for change in $R^2$ values (between the base and full model) are statistically significant ($p < 0.001$). Both Log-likelihood and AIC measures demonstrate that the full model is a better and more efficient way to explain variation in cropland trends. In other words, the spatial pattern of residential development has a significant association with county-level cropland trends net the effects of the other variables in the model.

Table 6 also presents Moran’s I statistics to test for evidence of spatial autocorrelation in regression residuals in both of the OLS (base and full) regression models. In this instance, the Moran’s I values are statistically significant in both models. This indicated that there are persistent spatial dependencies among the variables, which raises questions about whether the underlying assumptions of standard OLS regression models have been met. Such dependencies can lead to inconsistent and biased coefficient estimates for an OLS model (Getis 2007).

To address this problem, I estimated two spatial regression models: a spatial lag (lagged dependent variable) and a spatial error model. Overall, both of these models
appear to fit the underlying data better than the OLS full model. The value of $R^2$ increases from 0.388 (OLS – full) to 0.410 (spatial lag model) and 0.411 (spatial error model). Log-likelihoods also improved across the models from -787.6 in the full OLS model, to -785.0 and -785.2 in the spatial lag and error models. Finally, AIC statistics decreased from 1607.2 (OLS – full) to 1604.0 and 1602.5 in the spatial lag and error models. This gradual decline of AIC demonstrated that our model fit improved when we accounted for spatial dependency issues.

This is further supported by the fact that spatial regression coefficients were significant in both lag and error models. Specifically, the spatial lag coefficient (available for spatial lag model) was positive (0.208) and statistically significant ($p=0.022$), and reflects the average influence in each county from trends in cropland in their neighboring counties. For example, counties surrounded by counties with positive cropland trends are predicted to have more positive cropland trends (holding other variables constant), and vice versa. Meanwhile, the Lambda coefficient was positive (0.251) and significant ($p=0.009$), suggesting that residuals are not spatially independent, and the variable controlling for spatial autocorrelation makes a statistically significant difference in overall model fit.

*Exploring Key Variables in the Spatial Lag Model:*

The spatial lag model is theoretically and empirically the best model since explains virtually the same amount of variation as the spatial error model, and there are theoretical arguments for why one might expect cropland trends in one county to influence farm in their neighboring counties. Moreover, while accounting for spatial
Table 6: Regression Outcomes for Dependent Variable % Change in Cropland Acres (1997-2012)

<table>
<thead>
<tr>
<th>Model 1: OLS Base Model</th>
<th>Model 2: OLS Full Model</th>
<th>Model 3: Spatial Lag Model</th>
<th>Model 4: Spatial Error Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-61.832</td>
<td>14.263</td>
<td>0.000</td>
</tr>
</tbody>
</table>

### Population Pressure

| Net Change County Pop 2000-10 (1000s) | -0.189 | 0.072 | -0.218 | 0.009 | ** | -0.098 | 0.079 | -0.113 | 0.218 | -0.090 | 0.074 | 0.226 | -0.099 | 0.074 | 0.184 |
| County Population Growth Rate 2000-10 | -0.025 | 0.106 | -0.020 | 0.811 | -0.043 | 0.104 | -0.034 | 0.677 | -0.008 | 0.098 | 0.931 | 0.018 | 0.100 | 0.658 |
| Rural Population Density 2000 | -0.326 | 0.088 | -0.292 | 0.000 | *** | -0.227 | 0.091 | -0.203 | 0.014 | * | -0.222 | 0.086 | 0.099 | ** | -0.215 | 0.087 | 0.014 | * |
| Urban Influence Code 2003 | 0.722 | 0.465 | 0.130 | 0.122 | | 1.071 | 0.462 | 0.193 | 0.022 | * | 0.856 | 0.439 | 0.051 | 0.893 | 0.466 | 0.056 |

### Socio-economic Structure

| Median HH Income 1999 (1000s) | 0.337 | 0.198 | 0.148 | 0.091 | † | 0.318 | 0.199 | 0.140 | 0.112 | | 0.260 | 0.187 | 0.164 | 0.175 | 0.201 | 0.384 |
| Percent of Sales from Crop 1997 | 0.163 | 0.055 | 0.211 | 0.004 | ** | 0.213 | 0.059 | 0.276 | 0.000 | *** | 0.199 | 0.056 | 0.000 | 0.210 | 0.061 | 0.001 | ** |
| Percent Retirement/Lifestyle Farms 2007 | -0.098 | 0.157 | -0.055 | 0.531 | 0.020 | 0.156 | 0.011 | 0.898 | 0.040 | 0.147 | 0.788 | 0.020 | 0.151 | 0.894 |
| Agriculturally Important County | 3.466 | 3.412 | 0.170 | 0.014 | * | 9.124 | 3.994 | 0.183 | 0.008 | ** | 7.800 | 3.192 | 0.015 | ** | 6.533 | 3.377 | 0.053 | * |
| Natural Amenity Scale Score | 0.962 | 0.841 | 0.097 | 0.254 | 0.872 | 0.821 | 0.088 | 0.290 | 0.749 | 0.771 | 0.332 | 0.538 | 0.853 | 0.528 |

### Biophysical Resource Quality

| Length of Growing Season (days) | 0.248 | 0.068 | 0.286 | 0.000 | *** | 0.259 | 0.068 | 0.299 | 0.000 | *** | 0.216 | 0.065 | 0.001 | ** | 0.241 | 0.072 | 0.002 | ** |
| Soil Quality Index | 0.133 | 0.105 | 0.107 | 0.209 | | 0.040 | 0.108 | 0.033 | 0.710 | | 0.034 | 0.102 | 0.736 | 0.077 | 0.113 | 0.492 |

### Spatial Pattern Variables

| Patch Density (PD) | -8.770 | 3.249 | -0.239 | 0.008 | ** | -7.502 | 3.077 | 0.015 | ** | -8.074 | 3.263 | 0.013 | * |
| Largest Patch Index (LPI) | -4.574 | 10.084 | -0.037 | 0.651 | | -4.804 | 9.481 | 0.612 | | -6.323 | 9.594 | 0.510 |
| Aggregation Index (AI) | -0.273 | 0.171 | -0.127 | 0.112 | | -0.261 | 0.160 | 0.104 | | -0.232 | 0.170 | 0.172 |
| Total Edge Contrast Index (TECI) | -0.089 | 0.137 | -0.055 | 0.518 | | -0.103 | 0.129 | 0.423 | | -0.109 | 0.136 | 0.423 |

### Spatial Regression Variables

| Spatial Lag Coefficient | 0.208 | 0.091 | 0.022 | ** | 0.251 | 0.096 | 0.009 | ** |

### Test of Spatial Autocorrelation

| Moran's I | 0.002 | ** | 0.006 | ** | n.a. | n.a. |

### MODEL FIT STATISTICS

| R^2 | 0.336 | 0.388 | 0.410 | 0.411 |
| Adjusted R^2 | 0.295 | 0.335 | n.a. | n.a. |
| Overall Model F-test (significance) | 0.000 | 0.000 | n.a. | n.a. |
| F-test for Change in R^2 (significance) | n.a. | 0.007 | n.a. | n.a. |
| Log-Likelihood (LL) | -795.322 | -785.598 | -785.000 | -785.247 |
| Akaike Information Criterion (AIC) | 1614.640 | 1604.000 | 1602.490 |

Note: Significance denoted by *** = p<0.001, ** = p<.01, * = p<0.05, † = p<0.10
dependence in the disturbance term (in the error model) was significant, it did not identify any new variables that are more or less significant in the overall model (which is one goal of using controls for spatial dependence in the errors). While I focus my discussion on the spatial lag model coefficients, it is worth noting that these coefficients are quite similar to those estimated in the full OLS and spatial error models as well.

Population pressure: The role of population pressure is captured in the first block of 4 variables used in the model. With respect to trends in cropland change, only the variable capturing rural population density 2000 at the county level is statistically significant ($p=0.009$), each one unit increase on the rural population density index (controlling for the other independent variables in the equation) is associated with a decrease of 0.22% in the predicted rate of cropland change. This says that increasing rural population density contributes to lowering the rate of cropland change, which is favorable to farm outcomes.

Socioeconomic structure: The next block of five variables captures differences in a county's socioeconomic structure. Two variables had statistically significant coefficients: percent of sales from crops ($p<0.001$) and an indicator of a county being agriculturally important ($p=0.015$). The unstandardized coefficient of percent of sales from crops is 0.199, which means each increase of one percent in the share of sales from crops is associated with an increase of 0.199 percent in the predicted rate of cropland change. Meanwhile, counties that were agriculturally important in 1997 were associated with predicted cropland change that was 7.8 percent more positive. The other indicators of socioeconomic structure (median HH income, percent of farm retirement or lifestyle
farms, or high amenity county) were not significantly linked to variation in the rate of change in croplands in the region.

Biophysical resource quality: The results suggest that an indicator of the average length of the growing season is positively related to estimates of cropland change $(p<0.001)$. Specifically, each additional 10 days of growing season is associated with the 2 percent higher prediction of the percent change of cropland. Somewhat surprisingly, measures of soil quality did not play any significant role in explaining variation in cropland change in the region.

Spatial pattern variables: The findings suggest that only one spatial pattern variable is important. The coefficient for Patch Density (PD) is both negative (-7.502) and statistically significant $(p=0.015)$. This suggests that higher levels of PD (which reflect more patches of development per unit land area) are associated with a more negative rate of cropland change. Meanwhile, the largest patch index (LPI; another measure of clustering), aggregation index (AI; measure of aggregated or clustered forms of development) and total edge contrast index (TECI; a measure of landscape heterogeneity) variables were not significantly related to the rate of cropland change in my study counties.

**Explaining Farm Sales Change, 1997-2012**

The regression models for farm sales change are shown in Table 7. Again, model coefficients and fit statistics for five model specifications are reported: Two OLS regression models and two spatial regression models.
**Model Fit:**

As in the previous two sections, the full model is a significantly better model than the base model when explaining trends in farm sales. Adding the spatial pattern variables improved the adjusted $R^2$ in the full model from 0.281 (explaining 28% of the variation in rate of farm sales changes) to 0.306 (which explained 2% more of the variation).

Moreover, F-tests for overall model fit and for change in $R^2$ values (between the base and full model) were highly significant ($p < 0.01$). Log likelihood and AIC statistics also demonstrate an improvement in model performance for the full OLS model.

Taken as a whole, model fit statistics confirmed that adding spatial metrics (spatial pattern variables) improves our understanding of variation in rate of farm sales change at the county level in the IW region. In other words, the spatial pattern of residential development has a significant impact on county-level farm sales trends net the effects of the other variables in the model.

Results for the Moran’s I statistic test demonstrate positive evidence of spatial auto-correlation in the regression residuals in both OLS models. The two spatial regression models provide new estimates of model coefficients that control for spatially lagged dependent variables (lag model) and spatially autocorrelated errors (error model). Assessing indicators of $R^2$, log-likelihood ratios, and AIC statistics suggest that both spatial models fit the underlying data better than the OLS full model. Spatial regression coefficients were also significant in both the lag and error models. Specifically, the Spatial Lag coefficient (available for spatial lag model) was positive (0.369) and highly significant ($p < 0.001$), and suggests that counties surrounded by counties with positive farm sales trends are predicted to have more positive farm sales trends (holding other
variables constant), and vice versa. Meanwhile, the Lambda coefficient (available for spatial error model) was also positive (0.393) and significant \( (p<0.001) \). Values greater than 0 suggest that residuals are not independent, and the variable controlling for spatial autocorrelation makes a statistically significant difference in overall model fit.

Exploring Key Variables in the Spatial Lag Model:

Based on these results, I use the spatial lag model as the best model for accounting for changes in farm sales in counties in the Intermountain West. I select this model since it explains virtually the same amount of variation as the spatial error model, and there are theoretical arguments for why it is likely that trends in most counties are likely to influence farm trends in their neighboring counties. Moreover, while accounting for spatial dependence in the disturbance term (in the error model) was significant, it did not identify any new variables that are more or less significant in the overall model (which is one goal of using controls for spatial dependence in the errors). While I focus my discussion on the spatial lag model coefficients, it is worth noting that these coefficients are quite similar to those estimated in the full OLS and spatial error models as well.

Population pressure: With respect to trends in farm sales change, only the variable capturing population density in rural privately available land is statistically significant \( (p=0.037) \). Higher values of the population density in rural privately available land are associated with lower levels of change in farm sales, so a negative coefficient (-0.384) suggests that each 1-person increase per square mile in rural population density is associated with a decrease of 0.384\% in the predicted rate of farm sales change. None of
## Table 7: Regression Outcomes for Dependent Variable % Change in Farm Sales (1997-2012).

### DEPENDENT VARIABLE (% change in Farm Sales 1997-2012)

<table>
<thead>
<tr>
<th></th>
<th>Model 1: OLS Base Model</th>
<th>Model 2: OLS Full Model</th>
<th>Model 3: Spatial Lag Model</th>
<th>Model 4: Spatial Error Model</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Constant</strong></td>
<td>81.608</td>
<td>31.570</td>
<td>0.011</td>
<td>*</td>
</tr>
<tr>
<td><strong>Population Pressure</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Net Change County Pop 2000-10 (1000s)</td>
<td>-0.043</td>
<td>0.159</td>
<td>-0.023</td>
<td>0.788</td>
</tr>
<tr>
<td>County Population Growth Rate 2000-10</td>
<td>0.218</td>
<td>0.235</td>
<td>0.078</td>
<td>0.354</td>
</tr>
<tr>
<td>Rural Population Density 2000</td>
<td>-0.550</td>
<td>0.194</td>
<td>-0.224</td>
<td>0.005</td>
</tr>
<tr>
<td><strong>Socio-economic Structure</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median HH Income 1999 (1000s)</td>
<td>0.010</td>
<td>0.438</td>
<td>0.002</td>
<td>0.982</td>
</tr>
<tr>
<td>Percent of Sales from Crop 1997</td>
<td>** 0.203</td>
<td>0.122</td>
<td>** 0.120</td>
<td>0.009</td>
</tr>
<tr>
<td>Percent Retirement/Lifestyle Farms 2007</td>
<td>** -0.625</td>
<td>0.348</td>
<td>** -0.159</td>
<td>0.074</td>
</tr>
<tr>
<td>Agriculturally Important County</td>
<td>7.713</td>
<td>7.552</td>
<td>0.071</td>
<td>0.309</td>
</tr>
<tr>
<td><strong>Biophysical Resource Quality</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Length of Growing Season (days)</td>
<td>-0.063</td>
<td>0.150</td>
<td>-0.033</td>
<td>0.676</td>
</tr>
<tr>
<td>Soil Quality Index</td>
<td>-0.111</td>
<td>0.233</td>
<td>-0.041</td>
<td>0.633</td>
</tr>
<tr>
<td><strong>Spatial Pattern Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Patch Density (PD)</td>
<td>-5.595</td>
<td>7.278</td>
<td>-0.032</td>
<td>0.722</td>
</tr>
<tr>
<td>Largest Patch Index (LPI)</td>
<td>-1.041</td>
<td>22.591</td>
<td>-0.004</td>
<td>0.963</td>
</tr>
<tr>
<td><strong>Aggregation Index (AI)</strong></td>
<td>** -0.745</td>
<td>0.383</td>
<td>** -0.159</td>
<td>0.053</td>
</tr>
<tr>
<td>Total Edge Contrast Index (TECI)</td>
<td>** -0.813</td>
<td>0.307</td>
<td>** -0.228</td>
<td>0.009</td>
</tr>
<tr>
<td><strong>Spatial Regression Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatial Lag Coefficient</td>
<td>0.369</td>
<td>0.082</td>
<td>0.000</td>
<td>***</td>
</tr>
<tr>
<td>LAMBDA Coefficient</td>
<td>** 0.393**</td>
<td>0.087</td>
<td>0.000</td>
<td>***</td>
</tr>
</tbody>
</table>

**Test of Spatial Autocorrelation**
- Moran’s I: 0.000 **
- LAMBDA Coefficient: 0.000 **

**MODEL FIT STATISTICS**
- R²: 0.323
- Adjusted R²: 0.281
- Overall Model F-test (significance): 0.000
- F-test for Change in R² (significance): n.a.
- Log-Likelihood (LL): -946.287
- Akaike Information Criterion (AIC): 1916.570

**Note:** Significance denoted by *** = p<0.001, ** = p<.01, * = p<0.05, † = p<0.10
the other measures of population pressure are significantly associated with farm sales trends between 1997-2012 in the IW region.

Socioeconomic structure: Three indicators of socioeconomic structure in a county had statistically significant coefficients: percent of sales from crop ($p=0.014$), agriculturally important county ($p=0.086$), and an indicator of a high amenity county ($p=0.008$). The unstandardized coefficient of percent of sales from crops is 0.292, which means each increase of one percent in the share of sales from crops is associated with an increase of 0.292 percent in the predicted rate of farm sales change. Meanwhile, higher scores on the agriculturally important county index is associated with more positive predicted farm sales, while higher scores on the natural amenity index is associated with more negative predicted farm sales trends. The other indicators of socioeconomic structure (median HH income and percent of farm retirement or lifestyle farms) were not significantly linked to variation in the rate of change in farm sales in the region.

Biophysical resource quality: Neither soil quality nor the length of growing season appear to play a significant role in explaining variation in trends in farm sales in the region.

Spatial pattern variables: The findings suggest that two spatial pattern variables are associated with farm sales trends. Initially, the indicator for Aggregation Index (AI) is both negative (-0.643) and significant ($p=0.062$). This suggests at a relationship in which more aggregated or clustered forms of residential development were weakly associated with a more negative rate of farm sales change. In addition, total edge contrast index (TECI; a measure of landscape heterogeneity) is both negative (-0.688) and statistically significant ($p=0.013$). This hints at a relationship in which more
heterogeneity of residential development is weakly associated with a more negative rate of farm sales change in my study counties.

**Comparing Results Across the Models:**

It is worth noting that the estimated coefficients on nearly all significant variables do not change notably between the OLS full model and the SLM and SEM models for a given dependent variable. This suggests that regardless of the statistical modeling approach, the relationship between the independent and dependent variables are relatively robust. The spatial models help explain additional variation in the dependent variables associated with trends and patterns in neighboring counties. At the same time, the specific variables that were associated with farm changes in this region between 1997-2012 differed significantly depending on whether I was explaining change in cropland, farm numbers, or aggregate farm sales. I review some of these differences below.

**Population Pressure:**

Contradictory to conventional assumptions, most variables related to population pressure were not consistently related to farm trends in the region. Only rural population density was significant in predicting change in farm numbers, cropland and farm sales trends.

**Socioeconomic Structure:**

There was variation in which measures of socio-economic structure were linked to different types of farm trends. Agricultural importance (which identifies counties that had commercially significant levels of agricultural activity) was positively linked to
cropland change, but negatively related to changes in farm numbers. Counties with high amenity scores had more negative rates of change in farm sales, but more positive trends in farm numbers (perhaps recreation or hobby farms). Greater dependence on crops (or less reliance on livestock) for farm sales was positively linked to both rates of cropland change and growth in farm sales during the study period, but unrelated to trends in farm numbers. Higher levels of median household income and the indicator for higher prevalence of lifestyle and hobby farms were associated with more positive trends in farm numbers, but not related to the other two dependent variables.

**Biophysical Resource Quality:**

Only one of the two variables used to capture biophysical resource quality were statistically associated with farm trends. Length of growing season was positively linked to trends in farm numbers cropland, but not predictive of trends in sales. Soil quality was never statistically related to agricultural trends in this region.

**Spatial Pattern Variables:**

Overall – in each set of models, the inclusion of indicators of spatial development patterns significantly improved the fit of the models. The addition of spatial pattern variables also improved fit without substantively changing the role of ‘base’ model variables in these models. Moreover, each of the four spatial development pattern variables – PD, LPI, AI, and TECI – played a significant role in at least one of the models. Some results were as predicted. Areas with higher patch density (or more distinct developed ‘patches’ on the landscape) were linked to more negative trends in cropland. Areas with greater land use heterogeneity (TECI) also had lower rates of
growth in farm sales. At the same time, two results contradicted the research expectations. Counties that had greater clustering (as captured by the largest patch index or LPI) had more negative trends in farm numbers. Also, areas with more aggregated residential development (higher AI score) experienced more negative trends in farm sales.
CHAPTER V

DISCUSSIONS AND CONCLUSIONS

In this thesis I examined how spatial patterns of rural and exurban residential development are associated with agricultural trends in the Intermountain West between 1997 and 2012. During this time period, the region has experienced one of the fastest population growth rates in the country (Krannich et al. 2011; Otterstrom and Shumway 2003; WDRC 2010). Evidence suggests that even though the majority of growth and change occurred in large metropolitan regions (e.g. Salt Lake City, Boise, Denver etc.), a sizeable portion of growth is also occurring outside of the urban core (Carruthers and Vias 2005; Otterstrom and Shumway 2003). This is because decisions about residential migration are increasingly linked to the availability of natural amenities, such as favorable climatic condition, natural beauty, and opportunities for outdoor recreation (Krannich et al. 2011; McGranahan 1999).

However with this changing pattern of population growth, the region is also exposed to different development challenges. Even though the region is famous for its vast open space, much of the landscape is in public ownership and hence not available for development (Nickerson et al. 2011; Rengert and Lang 2001). As a result, exurban and rural landscapes in the IW are the scenes for some of the region’s greatest tensions between population growth, housing development and agriculture (Travis 2007).

Farming, ranching, mining or other types of extractive industries are tied to the history of the Intermountain West (Power and Barrett 2001; Shumway and Otterstrom 2001). While some might argue with the extent of importance of agriculture in the
contemporary West (Donahue 1999; Power 1996), farming and ranching are still widely treated as the important parts of Western identity and culture (Jensen 2005). However, there are complex relationships as well as dependencies between trends in population and economic growth, on the one hand, and changes in agriculture (Jackson-Smith et al. 2006). To date, there have been limited studies of the role that the spatial configuration of development plays in shaping opportunities for or barriers to the agricultural sector. Drawing upon knowledge and methods from different social science disciplines, this thesis aimed to address that research gap.

Implications for Academic Research on Agricultural and Land Use Change in the IW

Impact of Development on Agriculture:

Traditionally, population growth is seen as presenting challenges for agriculture because it increases land consumption for non-agricultural purposes and reduces lands available for farming. In addition, population growth reduces farm viability due to the increased land prices, land use conflicts, and the loss of critical mass and infrastructure. Pressure on farms and ranches can contribute to declines in farm numbers, loss of working cropland, and diminishing agricultural economic activity (e.g., farm sales).

Finding #1: Traditional measures of population pressure are not systematically related to farm trends in this region

Net population changes, the overall county growth rate and indicators of urban influence are not systematically related to farm trends in the IW between 1997-2012. However, rural population density, which is not often used in studies of farm change, was
significant in my models and acted as expected. Specifically, areas with more people living in non-urban portions of western counties per unit area tend to have more negative rates of change in farm numbers, croplands and farm sales. The significance of rural population density points to the importance of growth which takes place outside of urban areas in shaping farm trends (discussed more below).

The lack of a consistent relationship between overall county-level urbanization and farm trends may reflect the fact that some forms of agriculture often survive (or even thrive) near urban areas. Studies show that a substantial portion of country’s agricultural production is located at the rural-urban interface (Jackson-Smith and Sharp 2008). Urban agriculture tends to reflect two types of farms: intensive producers of high value commodities that do not require large amounts of land as well as smaller hobby or lifestyle oriented farms that serve as rural residential properties for people who commute to work in urban areas. Conversely, because many farmers rely on off-farm income to sustain their households, a lack of population growth (or even population decline) can be associated with diminishing local employment opportunities, and thus contribute to agricultural decline. For example, many remote rural places in the United States are experiencing declines in farm numbers.

Finding #2: Socioeconomic opportunity structure is linked to farm trends

Several indicators of socioeconomic opportunity structure Yet higher ‘agricultural importance’ (reflecting critical mass of commercial farms) and greater reliance on crop income all are associated with faster declines in farm numbers, but more positive trends in cropland and farm sales. In this regard, critical mass of commercial farmers seems to
be important to sustaining economic viability of farming and resisting land use
conversions. Similarly, the lack of a consistent relationship between farm trends and
indicators of the growing New West recreational and service economy in the region
confirm some previous studies that suggest New West growth is not always in conflict
with Old West economic activity (Jackson-Smith et al. 2006; Nelson 2001). In this case,
extensive livestock operations and hobby, lifestyle, or retirement farming can be both
compatible with (and even reflect the landscape aesthetic preferences) of amenity
migrants to many western rural communities.

Meanwhile, counties with higher natural amenities and higher median household
income (both indicators of ‘new west’ counties) experienced more positive trends in farm
numbers, more negative trends in farm sales, and no systematic relationship to cropland
trends. In general, the lack of a consistent relationship between farm trends and indicators
of the growing New West recreational and service economy in the region confirm some
previous studies that suggest New West growth is not always in conflict with Old West
economic activity (Jackson-Smith et al. 2006; Nelson 2001). In this case, extensive
livestock operations and hobby, lifestyle, or retirement farming can be both compatible
with (and even reflect the landscape aesthetic preferences) of amenity migrants to many
western rural communities. While commercial scale agriculture may be in decline in
many high amenity wealthy places in the IW, the growth in lifestyle farms and a
preference for working open landscapes by amenity migrants leads these areas to be no
more or less likely to be losing cropland than other places.
Finding #3: Spatial pattern or distribution of development clearly matters

Taken as a whole, accounting for the spatial pattern of population growth and development within county boundaries explains more variation in regional farm trends between 1997-2012. As noted above, counties with higher population density in rural areas experienced more negative trends in all three agricultural outcomes. High rural population density is a reflection of historical trends where population growth was more likely to occur outside of urban areas (one broad indicator of spatial patterns of development. Meanwhile, full models including ecological landscape metrics for spatial development patterns performed than base models. All four landscape metrics related to at least one of the outcome measures. Areas with higher patch density (PD) or more distinct developed ‘patches’ per square mile on the landscape were linked to more negative trends in cropland, which was consistent with the theoretical expectation. In addition, areas with greater land use heterogeneity (TECI) had lower rates of growth in farm sales, which was also consistent with the theoretical expectation.

Interestingly, while statistically significant, the coefficients associated with the two landscape metrics that measured clustering/aggregation were not consistent with expectations. Counties that had greater clustering (as captured by the largest patch index or LPI) had more negative trends in farm numbers. To the extent that housing growth is related to growth in hobby or recreational farming, rural development related to amenity migration could result in a less aggregated pattern of housing development, but growth in farm numbers.

However, counties with higher Aggregation Index scores (which reflect more concentrated patterns of rural settlement) experienced more negative trends in farm sales.
This result is more difficult to explain from a rise in small-scale hobby farming. Since they are not pursuing commercial farming, growth in small farms would not be expected to also boost farm sales. More research is needed to explain why consolidated patterns of rural housing development are negatively related to farm economic trends.

In addition to demonstrating the importance of including variables designed to capture spatial patterns of housing development, the results illustrate that conventional ordinary least squares models have significant spatial correlation in regression residuals. The use of a spatial lag regression model helps address this potential problem by estimating a direct measure of how farm trends in a county are affected by similar farm trends in neighboring counties. The spatial lag coefficients in the three spatial lag regression models suggest that farm changes in one particular county are significantly and positively related to trends in their neighboring counties. Future studies of the impacts of growth and development on agriculture should be attentive to these cross-border effects.

Implications for Planners

Most planners think consolidation of development and protection of open space is good for protecting agriculture and rural landscapes, and also for reducing fiscal costs to local governments associated with growth (Daniels 1999). My results suggest that two related dimensions of rural growth patterns – heterogeneity and consolidation – actually have different effects on farm outcomes. Specifically, heterogeneity in land use – defined as places where different types of land use are highly intermixed – were significantly and negatively associated with trends in both cropland and farm sales. Conversely, places where farming and development land uses are physically separated experienced more
positive agricultural trends. These results are consistent with ideas that development in close proximity to agricultural operations can lead to greater conflict between farmers and nonfarm residents, and that fragmentation of farmland can make it more expensive and difficult to sustain commercial farming operations.

Meanwhile, consolidation measures the degree to which housing development is clumped in aggregated clusters in rural landscapes. While indicators of land use heterogeneity performed as expected, the indicators of consolidation or clustering in this region (AI and LPI) were not only unrelated to cropland trends, but significantly associated with worsening trends in sales & farm numbers.

These combined results suggest that rural land use planning efforts designed to encourage clustered or consolidated blocks of housing development may not produce the benefits for farmland preservation or protection of working farms that are intended. What might matter more than simple ‘clustering’ are efforts to keep large blocks of agricultural land clear of development, and to direct housing development (whether clustered or not) into areas within a county where they will conflict less with working farm and ranch operations.

**Implications for Farmers and Rural Community**

Farmers, ranchers, and rural community residents and leaders in the Intermountain West tend to share a desire to achieve three goals: (a) protecting the viability of commercial farming and the overall farm economy, (b) reducing a perceived decline in farm numbers and ensuring opportunities for new entry by facilitating the transfer of farms across generations, and (c) protecting the rural character of the
landscape through preservation of farmland and open space. The results of this study have several implications for farmers and rural community leaders pursuing these goals.

(a) Protecting viability of farming and overall farm economy: Most farm and ranch groups and organizations in the west frequently express concern about protecting commercial agriculture from perceived threats associated with population growth, urbanization, and other forces (e.g., environmental regulation or high rates of taxation). Similarly, rural community leaders often appreciate agriculture for the contributions it can make to local economic activity. For these groups, the models highlighting predictors of trends in farm sales may produce the most salient results. For example, preservation of a critical mass of farmers (agricultural important counties) and greater reliance on crop farming (or less dependence on livestock) can help sustain farm sales, while higher rural population densities and greater land use heterogeneity (or mixing) can depress rates of change in farm sales.

(b) Concerns about loss of farms: The social fabric of many rural communities in the IW region is linked to their identity as a farm or ranch community and a commitment to an agricultural lifestyle. As such, concerns about losing farmers and ranchers (as reflected in trends in farm numbers) are equated with a fear about the loss of rural community vitality and character. The model exploring trends in farm numbers described above suggest that ‘New West’ forms of growth were actually linked to more positive trends in farm numbers, but particularly to expansion of retirement, recreational, or lifestyle farms, which may not present same social advantages to rural communities. Although popular or rural farm community discourse frequently focuses on a perceived ‘loss’ of farms, statistics suggest that in this region farm numbers are actually growing
(particularly due to an increase in the number of these retirement/lifestyle farms). This disconnect may reflect the fact that traditional farmers and ranchers do not consider small-scale, sub-commercial operations to be ‘real farms’. Since this analysis did not explore trends in the number of large scale farms (per se), the results of the farm number trend models may not fully speak to the concerns of these rural communities. Therefore, a separate analysis of impacts on ‘commercial’ scale farm numbers would be necessary to know if effects are different for this group.

(c) Protecting ‘farmland’ and open space: Farmers and rural communities also care about sustaining working landscapes. For farmers, access to affordable cropland in sufficiently large blocks can be important to their ability to survive in an increasingly competitive global economy. For local community residents, the open spaces and rural aesthetic that come with a working agricultural landscape can provide important quality of life benefits. Results from this analysis suggest that sustaining a strong farm economy (agricultural importance), lower levels of reliance on livestock sales, and minimizing rural population density are associated with more robust trends in cropland acreage.

Possible Limitations of This Study

Even though county-level information is readily available and easy to compare, I am aware that not all social processes involved in demographic agricultural change operate at this scale. Particularly in very large rural counties, spatial patterns in one part of the county may be too far away to have much impact on farmers in another part of the county. Moreover, farmers and farm households may be tied to areas that are further away than their neighboring county (though long-distance commuting, investment
earnings, government program payments, etc.). Following the administrative boundaries of counties may fail to capture the meaningful spatial boundaries that shape patterns of human interaction, economic linkages, social structures and environmental processes (Beckley 1995; Endter-Wada, Blahna, Krannich, and Brunson 1998; Redman, Grove, and Kuby 2004). For instance, Beckley (1998) noted that the nature and effects of forest dependency changes at a finer scale, and suggested the importance of scale for the development of appropriate forest management plans and other public policies.

In addition, micro-level dynamics are often overlooked/masked by the aggregate county-level information (Jackson-Smith 1999). Even though census data provided a consistent source of information of farm conditions in 1997 and 2012, they still provided little or no information of the nature of changes at the individual and/or sub-groups levels during the intervening period. Micro-level dynamics can be fairly different than the overall pattern (Jackson-Smith 1999) or can be overshadowed by or disguised within the aggregate trends. This type of “ecological fallacy” – a problem when we infer information about an individual case based on aggregate data – can be detrimental to interpretation of local dynamics.
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APPENDIX
Table 8: Correlation Matrix Among the Variables Used in the Models.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Farm Number Change (integer)</th>
<th>Cropland Change (integer)</th>
<th>Farm Sales Change (integer)</th>
<th>NetChgPop0010 (in thousands)</th>
<th>PopGrowth0010_INTEGERS</th>
<th>RuralPopDensity2000</th>
<th>UrbInf08</th>
<th>MedianHHInc1999_1000s</th>
<th>PersistCrop97A</th>
<th>PersistLifestyleFarms_07_INTEGRERS</th>
<th>AgImp_1997</th>
<th>Natural Amenity Scale (Z-score)</th>
<th>FrostFreeNFNUNW</th>
<th>PercyC12S0NFNUNW</th>
<th>PD_NLCD</th>
<th>LPI_NLCD</th>
<th>AI_NLCD</th>
<th>TECI_NLCD</th>
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