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DO THE IMPACTS OF NATURAL AMENITIES ON POPULATION CHANGE DIFFER IN NEW WEST VERSUS OLD WEST PLACES?

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By

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Chairperson: Katrina Mullan

This research examines how location-specific amenities affect rural population growth given demographic and cultural differences found in New West and Old West census tracts in the mountain west. In the 1970s, the United States experienced an unexpected turnaround in migration patterns as households began moving from urban to rural areas. Identifying different drivers of rural population growth is necessary for planning for and managing future growth in ways that optimize economic benefits while minimizing potential environmental degradation. Using cross-sectional, specially constructed, spatially explicit data, this research identifies how determinants of population growth differ in New West versus Old West census tracts. Marginal effects from an OLS model with interaction terms identifies that drivers of population change, namely natural amenity preferences, in New West versus Old West do differ.

1 Introduction

In the 1970s, the US experienced an unexpected turnaround in migration patterns as households began moving from urban to rural areas. In particular, rural areas rich in natural amenities and with amenable climates experienced rapid population growth (Dearien et al. 2005; Deller et al. 2001; Rickman and Rickman 2011). Traditional economic theory asserts that migration results from utility-maximizing households seeking higher wages and greater employment opportunities. However, technological advances in telecommuting and economic restructuring towards a service economy loosened geographic constraints on household location choices. Additionally, rising wages led to an increase in household preferences for natural amenities, shifting population migration patterns as households considered quality of life factors when making location choices. I examine how location-specific amenities affect population growth given demographic and cultural differences between New West and Old West census tracts in the mountain west.

Empirical research identifies natural amenities as significant drivers of population growth (McGrannahan 1999, 2008; Deller et al. 2001; Rickman and Rickman 2011; Chen et al. 2013; Johnson and Beale 2002). Migrants are drawn to natural amenities, like mountains, rivers, and forests, for their recreational and aesthetic value (Waltert and Schlapfer 2010; Bastian et al. 2002; Cragg and Kahn 1997; Johnson and Beale; 2002). From 1970-2000, counties rich in natural amenities experienced greater rates of population growth than counties with few natural amenities (McGranahan 1999; Rickman and Rickman 2011; Dearien et al 2005; Johnson and Beale 2002). Rapid population growth is especially prevalent in amenity-rich rural west (McGranahan 1999).

Some empirical evidence demonstrates that not all amenity-rich areas equally attract migrants (Deller et al. 2001; Chen et al. 2013). For instance, Deller et al. (2001) find that rural counties, rich in both natural amenities and man-made amenities (e.g. ski resorts), experience higher rates of population growth than amenity-rich rural counties without man-made amenities. Changes in rural population have economic and environmental consequences. Rural areas experiencing rapid population growth may also experience environmental degradation if they are unable to manage and plan for such rapid growth. Conversely, rural areas experiencing population decline may be interested in identifying what attracts migrants to an area to induce growth. Researchers have investigated this disproportionate population growth using the concept of the “New West” (Rudzitis 1998; Shumway and Otterstrom 2001; Winkler et al 2007). New West and Old West locations differ in demographic and cultural composition. New West locations have economies focused on professional services and tourism and have relatively high levels of cultural amenities, like art galleries and restaurants. Old West locations tend to depend on resource extraction for economic development.

The New West conjures images of cattle ranches being converted to hobby ranches by footloose transplants. Places like Bozeman, MT exemplify the New West. Bozeman has attracted migrants from around the world who come for the access to Yellowstone National Park, several national forests, world-class ice climbing, and two ski resorts. A community trail system runs through Bozeman, easing access to downtown restaurants, parks, art galleries. The presence of such amenities draws certain types of people to the area.

The demographic composition of New West and Old West places fundamentally differ. White Sulphur Springs, MT, located 80 miles north of Bozeman, is considered Old West. The 2010 Census reports that approximately 50% and 12% of the population, 25 years old and over, in Bozeman and White Sulphur Springs respectively have a Bachelor's degree or higher. In 2010, the median household income in Bozeman was $42,218 relative to $30,541 in White Sulphur Springs. Relative to White Sulphur Springs, the residents of Bozeman tend to be more educated, earn more money, and tend to be younger, with a 2010 median age of 27.2 compared to median age of 45.6 in White Sulphur Springs.

Prior research examining the drivers of rural population growth has largely been at the county-level and on a national scale (Chen et al. 2013; Beale and Johnson 1998; McGranahan 1999; Partridge et al. 2008; Rickman and Rickman 2011; Rupasingha et at. 2015; Deller et al. 2001). Specific to the New West research, Shumway and Otterstrom (2001) found that population growth was associated with New West counties in the Mountain West region while Winkler et al. (2007) explored the distribution of New West census places in the Inter-Mountain West and found that New West places are concentrated along the Rocky Mountains. However, these studies did not explore the different drivers of population change in New West areas. I fill this gap by examining how location-specific amenities affect population growth given demographic and cultural differences between New West and Old West census tracts in the mountain west.

A better understanding of the mechanisms that drive population migration can help identify rural areas prone to rapid population growth. Population growth, and associated land development, may jeopardize the location-specific amenities that initially draw migrants to these regions. This is particularly important in this region as mountain ecosystems are especially vulnerable. Additionally, rural areas experiencing economic decline may be interested in identifying ways to attract migrants to revitalize their economies. Identifying rural areas prone to growth, and subsequent development, is necessary to maximize potential economic benefits while minimizing environmental degradation.

The study area encompasses Washington, Oregon, western Montana and Wyoming, northwestern Colorado, and northeastern Utah. This region offers dramatic topography, an abundance of public lands, mountain ranges, and undeveloped rivers, lakes, and coastline. The abundance of natural amenities offers exemplary scenic and recreational opportunities in places like Yellowstone and Olympic National Parks, the Sawtooth Mountains, and the Columbia River. All states in the study area, apart from Montana, have experienced higher rates of population growth from 1970-2015 than the national average (Headwaters Economics 2016). From 1970-2015, the national average percent change in population was 57.7% compared to 109% in Washington, 130% in Idaho, 91% in Oregon, 75% in Wyoming, 45.1% in Montana, and 181% and 145% in Utah and Colorado respectively. Also, on average, this region contains more public land, 46.3%, than the national average of 28% (Headwaters Economics 2016). Natural amenities clearly attract migrants but it is less clear how the impacts of natural amenities vary in New West versus Old West census tracts in attracting migrants (McGranahan 1999, 2008; Rappaport and Sachs 2003).

I construct a New West index to quantify the degree to which a census tract is New West versus Old West. Old West areas tend to rely on extractive industry employment (e.g. mining or logging) or are areas that remain relatively undeveloped (Winkler et al. 2007). Winkler et al. (2007) characterize the New West as areas with relatively high employment in the arts, professional services, and tourism rather than extractive industries; income and education levels, prevalence of second home ownership, and relatively high median housing values. Thus, the New West index captures a combination of cultural and demographic determinants of population migration. These demographics are highly correlated with employment opportunity, urban cultural amenities, and natural amenities (McGranahan and Wojan 2007; Winker et al. 2007). To better understand the circumstances in which natural amenities drive population migration, I compare the impact of individual amenities in New West versus Old West locations.

I estimate rural population growth between 1990-2010 at the census tract level as a function of remoteness, initial population level, and variation in climate and natural amenities. I use spatially explicit measures of amenities, capturing distance to different types of public lands and water bodies, topographic complexity and land cover, and travel time to ski areas. Migrants' location choices are also influenced by climate so the following variables are included: average and extreme summer and winter temperatures, precipitation (rain and snow), and hours of sunshine (Albouy et al. 2013; Deller et al. 2001; McGranahan 1999, 2008; Rappaport 2007; Rappaport and Sachs 2003). Using the New West index, I create a binary New West indicator variable, which categorizes census tracts as New West or Old West. I then interact the New West indicator variable with a climate factor variable, a vector of natural amenities, and remoteness factor variable. Interacted variables reveal the heterogeneous effects of location-specific characteristics on population change in New West versus Old West locations.

2 Literature Review

2.1 Traditional Drivers of Population Migration

Traditional microeconomic theory views migration as a response to spatial disequilibria resulting from differences in economic opportunities. In other words, households migrate to areas with higher real wages or greater job opportunities while firms locate to areas with lower wages and rents (Carlino & Mills, 1987). Thus, in order to maximize utility, a household must first consider the costs of moving, including potential psychological costs (Sjaastad, 1962), and make decisions between alternative locations while lacking complete information.

Traditional models failed to reveal the drivers of population migration from urban to rural areas that occurred in the 1970s because they did not account for location-specific natural amenities. This shift is largely attributed to an increase in overall wages, increasing households' demand for quality of life factors like natural amenities (Rappaport 2007). This prompted economists to consider models accounting for quality of life factors, like natural amenities, in understanding drivers of population migration.

Expanding the traditional location choice model, Graves and Linneman (1979) developed a consumption theory of migration, which distinguished between traded and non-traded goods. They hypothesized that location specific, non-traded goods (e.g. weather and crime rates) influence household migration patterns. In this model, total utility is spatially constant. Generally, areas rich in natural amenities are expected, at equilibrium, to have lower levels of real wages. Households living in areas with low levels of non-traded goods are compensated through adjustments in real wages until locational indifference is achieved. In this view, migration is a product of a change in demand for non-traded goods that can be satisfied by moving to an alternative location. Additionally, households may earn higher wages by working for firms in low-amenity areas while living in high-amenity areas. Graves (1980) found that including climate variables, like humidity and temperature, greatly improved the predictive power of gross migration flows into US cities. Graves' (1980) findings demonstrate that differences in income and employment may not reflect utility differentials but capture the compensation required for locational indifference to be reached in the presence of location-fixed, non-traded goods like climate.

Advancing the compensation differential model, Roback (1982) theorized that land constraints, and thus housing markets and land values, also determine the locational distribution of workers and firms. If firms and workers have identical preferences, they cannot occupy the same space; thus, both land and labor markets must clear as households and firms compete for scarce sites. In other words, Roback's spatial equilibrium model asserts that utility is equalized across locations through wage differentials, land costs, or housing (i.e. rent or wages or both). Accounting for climate variables, like number of clear days and total snowfall, Roback (1982) finds that regional wage differences in the US are largely explained by local amenities. These theoretical equilibrium models are critical in highlighting the importance of including amenity variables when considering drivers of population migration.

2.2 Natural Amenity Drivers of Population Migration

In the early 1900s, firms relied heavily on the location of raw materials and transport links, like ports and rivers, in making location choices. In areas of high population density, where housing costs were higher, firms offered higher wages. In turn, households making location decisions began moving from rural to urban areas seeking higher wages and better employment opportunities. However, rising incomes led to shifts in household preferences for quality of life factors, like natural amenities. The advent of air conditioning also shifted migration patterns as air conditioning allows people to comfortably reside in areas with hot or humid climates (Rappaport 2007). Additionally, technological advances enabling telecommuting, make firms and households less location dependent and allow households to earn higher wages while living in high amenity areas.

These developments, paired with the economic decline in natural resource extraction, have transformed demographic composition of the US as people migrate to areas rich in natural amenities. In the early 1990s, rural areas experienced population growth of over one million people (Deller et al. 2001). From 1970-2000, counties rich in natural amenities experienced greater rates of population growth than counties with few natural amenities (McGranahan 1999; Rickman and Rickman 2011; Dearien, Rudzitis, and Hintz 2005).

An abundance of empirical literature identifies natural amenities as critical drivers of population change (McGrannahan, 1999; Deller et al., 2001; Rickman & Rickman, 2011). Researchers have explored the role of natural amenities on quality of life (Rappaport 2007), economic development (Deller et al. 2001), and population change (McGranahan 1999). Some efforts have been made to develop a standard set of natural amenities in explaining the aforementioned phenomena. Notably, in investigating population growth in rural US counties, McGranahan (1999) developed a now widely used natural amenity index identifying counties rich in natural amenities, while Deller et al. (2001) designed five broad indices to explain the role of amenities on population change and rural economic growth in rural US counties. McGranahan's (1999) index identifies mild climate, varied topography, and proximity to surface water as the primary variables driving population change. Deller et al (2001) finds that all five indices; climate, developed recreational infrastructure, land, water, and winter variables influence population change, with the climate index accounting for 46% of the variation in population change.. McGranahan (1999) does warn that the natural amenity index performs better across US regions rather than within US regions.

While natural amenity indices may be a useful approach in investigating population migration patterns across large geographic regions, researchers generally focus on particular types of amenities of smaller geographic areas. Natural amenities may vary considerably by geographic region but key natural amenity variables are climate, water, topography, land cover, and public lands.

Climate Amenities

Households derive nonpecuniary utility from natural amenities. Economists calculate the value of climate amenities as total wages a household is willing to forego plus additional costs they are willing to pay to live in a place with a desirable climate. Estimating a household's trade-off of wages for climate amenities reveals that households have an affinity for moderate temperatures, like cooler and less humid summers (Rappaport 2007; Sinha and Cropper 2013; Albouy et al. 2013; Cragg and Kahn 1999). Sinha and Cropper (2013) found that households were willing to pay for less snowfall, reinforcing Rappaport's (2007) findings that population growth increases as average daily maximum winter temperatures rise above the sample mean of 41ºF. However, some aspects of climate are perceived as disamenities. While rain is a disamenity, researchers find that its impact on population change is not as significant as increases in summer temperature and humidity (Rappaport and Sachs 2003; Rappaport 2007). Individuals' preferences for moderate temperatures contribute to population growth along coasts, which tend to moderate extreme temperatures (Rappaport and Sachs 2003).

Coasts & Water Bodies

The empirical literature finds that coastal proximity is strongly correlated with population growth (Rappaport and Sachs 2003). Historically, population densities were concentrated along the coast as firms located there for access to raw materials and transportation routes. However, after controlling for initial conditions, weather, and topography Rappaport and Sachs (2003) find that coastal population density, though historically driven by a productivity effect, are becoming more concentrated due to quality of life effects. Specifically, they find that counties adjacent to the Pacific Ocean have an expected population density of 1.4 times that of other counties (where the Pacific coast is the closest coast). Investigating household climate preferences, Sinha and Cropper (2013) and Albouy et al. (2013) use distance measures to the nearest coast. Sinha and Cropper (2013) find that distance to coast is sensitive to the model specification while Albouy et al. (2013) find that proximity to coasts contributes to a household's quality of life.

In addition to coastal proximity, access to lakes and rivers provide migrants with aesthetic and recreation value. McGranahan (1999, 2008) and Poudyal et al. (2007) use the proportion of water area in each county and find that water is highly correlated with county-level population change. Using principal component analysis, Deller et al. (2001) develop a vector of water variables and find that counties with highly developed water resources (e.g. marinas and guide services) tend to score higher on the water variable measure, suggesting these counties are more likely to experience population growth.

Topography

Topographic variation represents the variation in land formations ranging from plains and grassland to hills and mountains (Deller et al. 2001; McGranahan 1999). Empirical research finds that topography variation or complexity, positively influences population change (McGranahan 1999, 2008; Deller et al. 2001; Rappaport and Sachs 2003; Rappaport 2007; Rickman and Rickman 2011). In fact, in ranking counties by presence of natural amenities, Rickman and Rickman (2011) find that topographic variation is most correlated with a high amenity ranking. Rappaport and Sachs (2003) found that topography and coastal proximity were highly correlated, thus; topography significantly contributed to the high population density on the Pacific coast. Given the demonstrated importance of topographic variation, it is reasonable to expect this amenity to be a significant driver of population change in the northwestern United States, which is particularly mountainous.

Public Lands

In a survey of migrants to high-amenity counties, Rudzitis (1996) found that counties with Wilderness Areas experienced three times the population growth relative to the national average. Rasker and Hansen (2001) find that Wilderness Areas, National Parks, and wildlife refuges are significant drivers of population change in rural counties. Johnson and Beale's (2002) finding reinforce the importance of National Parks. They find that non-metropolitan counties with National Parks experience higher rates of population growth than the national average. Deller et al. (2001) finds that mountains, Forest Service land, and National Forest are positively associated with population growth.

Land Cover

There is evidence that inmigrants are drawn to particular types of land cover. Deller (2001) finds a positive correlation between grasslands and population growth. Using a simple measure of forest cover, percent of county with forest cover, Rasker and Hansen (2000) find positive correlation with forest cover and population growth in rural counties in the Greater Yellowstone Area. Exploring a more nuanced measure of forests, McGranahan (2008) finds that the impact of forests on population change is quadratic. For instance, counties with little to no forests generally experienced out-migration while counties composed of more than 90% forest experienced low rates of inmigration. It appears that households prefer moderate levels of forest mixed with open land; counties that were 45-60% forest experienced higher rates of inmigration. Thus, the simple presence of an amenity is not always a sufficient measure of its significance.

2.3 Cultural and Demographic Drivers of Population Migration

Location-specific natural amenities contribute to quality of life factors, influencing population migration. Similarly, cultural and demographic characteristics of a place may drive population change. Certain types of migrants may be attracted to areas with art galleries and restaurants or areas with people who share similar political views, education levels, or cultural backgrounds.

In introducing the ideas of the "creative class" and the bohemian index, Florida (2002a; 2002b) asserts that regional development in metropolitan areas is influenced by innovative ideas and knowledge, which are more prevalent in certain occupations (e.g. finance and entertainment). Florida (2002b) finds that the presence of the bohemian class, a subset of the creative class, is a strong predictor of population growth. Furthermore, Florida (2002b) argues that the bohemian index (a measure of authors, musicians, artists, etc.) is a superior measure of cultural amenities than museums and restaurants, as it accounts for the actual producers of cultural amenities. Thus, Florida argues that a certain demographic mix may improve quality of life in a given location, promoting population growth.

Other demographic indices have also been developed to capture the complex composition of location-specific attributes that make a place interesting and “cool” to live. For instance, ethnic diversity and melting pot indices capture the cultural diversity of a region, which some migrants view as an amenity because greater ethnic diversity is associated with a broader range of foods, experiences, and entertainment (Florida 2002a; Olfert and Partridge 2011). Ultimately, these demographic indices represent the mix of people that create interesting places to live, contributing to quality of life and attracting further inmigration.

Extending Florida’s work, McGranahan and Wojan (2007) and Olfert and Partridge (2011) more narrowly define the creative class and extend their analysis to include both rural and urban counties. Olfert and Partridge (2011) find that ethnic diversity has a positive and significant relationship to employment shares of the culture class, a subset of the creative class, but only in urban areas in Canada and not rural areas. However, this analysis, while incorporating climate variables, does not account for natural amenity variables, which also influence location choices. Accounting for natural amenities, McGranahan and Wojan (2007) find that the creative class is indirectly related to net migration in rural counties in the US. In fact, the authors find that the creative class is drawn to areas rich in natural amenities, particularly in the Mountain West. Specifically, the authors find the creative class is growing most rapidly in counties with mountains, a mix of forest and open area, little cropland, and sunny winters. Given this trend, it is reasonable to expect rural areas in my study area with both natural amenities and creative class demographic mix to experience population growth.

The New West

In the past several decades areas in the western US have witnessed an economic shift away from natural resource extraction and manufacturing towards a service economy (Brown and Deavers 1988). The New West framework also accounts for industry composition of a location’s economy. While New West locations are rich in natural amenities, they are not dependent on resource extraction for economic development (Winkler et al. 2007). Old West areas tend to rely on extractive industry employment (e.g. mining or logging) or are areas that remain relatively undeveloped (Winkler et al. 2007).

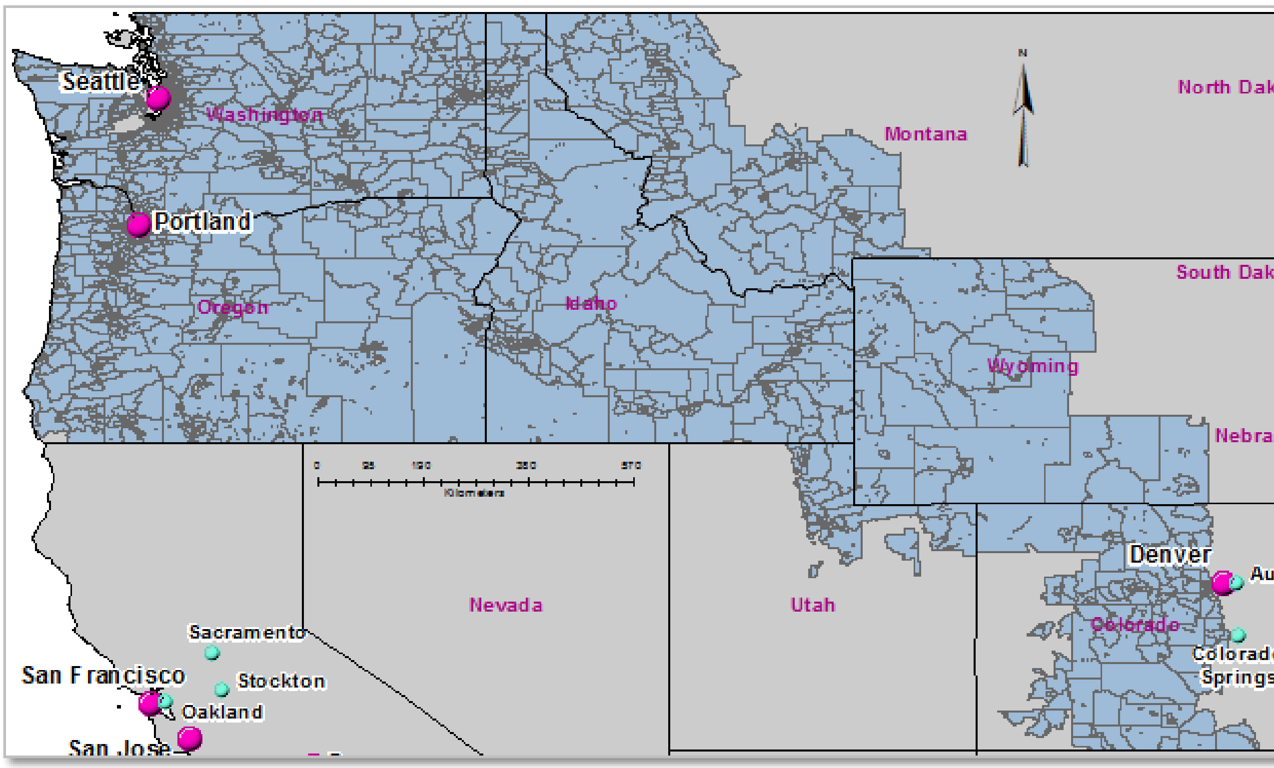
Another distinguishing characteristic of these categories is the demographic composition of New West and Old West. New West areas tend to attract migrants with higher education levels, higher income levels, and work in the professional services industry. Relative to New West areas, Old West areas tend to have populations with lower incomes and lower educational attainment. In categorizing areas as New West or Old West, Winkler et al. (2007) use a set of variables in defining the New West that overlap with attributes of the creative class. Namely, New West places tend to have people employed in finance, insurance, real estate (FIRE) and tourism industries. The creative class, as defined by both Florida (2002a) and McGranahan and Wojan (2007), include individuals employed in finance and arts and entertainment. Additionally, in both the New West and in the creative class, individuals tend to be college educated with preferences for amenity-rich areas, particularly areas containing public lands (Florida 2002a, 2002b; McGranahan and Wojan 2007; Winkler et al. 2007). This suggests that the drivers of population change in New West places, relative to Old West places, are in part influenced by the contribution of demographic diversity, which provides additional quality of life, thereby inducing population growth.

Spatial disequilibrium models, which account for location-specific amenities assume quality of life factors are equalized across space. Migration is induced by a change in preferences for location-specific amenities that contribute to quality of life. Natural amenities are well-established drivers of population growth but what remains unclear are the impacts of natural amenities on population growth in areas with different demographic and cultural compositions, or New West and Old West places. Given that demographic and cultural mixes differ in New West and Old West locations, it is reasonable to assume that these groups of people have heterogenous preferences of location-specific amenities. Drivers of population growth in New West places versus Old West places may be due to a new type of rural growth induced by a specific mix of natural and cultural amenities.

3 Study Area

The study area (Figure 1), in the northwestern United States, consists of 2,836 census tracts in Washington, Oregon, Idaho, Wyoming, Colorado, Utah, and Montana. The study area contains several ecoregions, which vary in biophysical conditions, climate, and topographic complexity (USGS). The largest tracts of wildlands in the contiguous US, the Rocky Mountains and Cascade Ranges, are found in our study area (Wade and Theobald 2009). This region is rich in natural amenities and offers exemplary scenic and recreational opportunities in like the Columbia River, Yellowstone National Park, Sawtooth Mountains in Idaho, and Olympic National Park in Washington. These natural resources support biodiversity and provide ecosystem services to this region. The boundaries of the study area are ecological, rather than municipal, because I am interested in capturing the effects of natural amenities on population growth in rural mountainous areas. Eastern Montana, Colorado, and Wyoming are not mountainous and are thus excluded from the study area.

Figure 1: The Study Area Located in the Northwestern US.



4 Data

I use spatial data from multiple sources to measure the influence of climate, remoteness, demographic, and natural amenity variables on population change at the census tract-level. Census tract boundaries are standardized to 2010 census tract boundaries, allowing intertemporal comparisons across decades. Analysis at the census tract-level reduces aggregation bias often associated with county level analysis, as counties tend to be more heterogeneous than census tracts (Crandall and Weber 2004). I use GIS software, ESRI ArcGIS, R, and Stata to link demographic, economic, and amenity data to census tract boundaries, capturing characteristics of resident households and biophysical and geographic features of land. Spatially explicit data allow for econometric analysis that captures spatial relationships of attributes. All spatial variables and indices included in my model are mapped and presented in the Appendix.

The full study area contains 2,836 census tracts and is approximately 1,052,164 square kilometers in size. However, because public lands constitute roughly 60% of the study area, this inherently restricts where individuals may migrate. For example, an individual cannot migrate to Yellowstone National Park. Thus, only private land in the study area was used for analysis. I used an Albers equal-area conic projection which provides a more accurate measure of area by minimizing distortion, particularly for lands extending east to west, like my study area. I calculated census tract average values for all spatial variables, like forest complexity and distance to a national park, and population density using private land area in ArcGIS. Calculating variables using private land area provides a more precise measure of the characteristics of places where people may live. Private land area was calculated by fitting the private land data to the study area, yielding 2,803 census tracts with a total area of 416,401 square kilometers (Figure 2). Raster files are spatial files that contain data stored in pixels. A given census tract may contain thousands of pixels, translating to thousands of data points. For instance, a raster file measuring the distance to the Pacific Coast contains millions of pixels for this study area. Each pixel has a value measuring the distance, in minutes, to the Pacific Coast. This raster layer is then fitted to the private land area of a census tract where the average distance to the Pacific Coast is then calculated using the Spatial Analyst tool in ArcGIS. This process is repeated for all spatial variables used in the model.

My research focuses on rural population growth; as such, urban census tracts are omitted from my study area. The Economic Research Service of the USDA provides a rural-urban continuum which identifies areas as urban or rural. However, this continuum is only available at the county level and not the census tract level (Figure 3). So, I dropped census tracts with initial population density in 1990 that were greater than 500/km^2. The 500/km^2 population density threshold eliminates highly urban census tracts from the study area, leaving 1,513 total census tracts (Figure 4).

Figure 2: Distribution of Private Land Area.

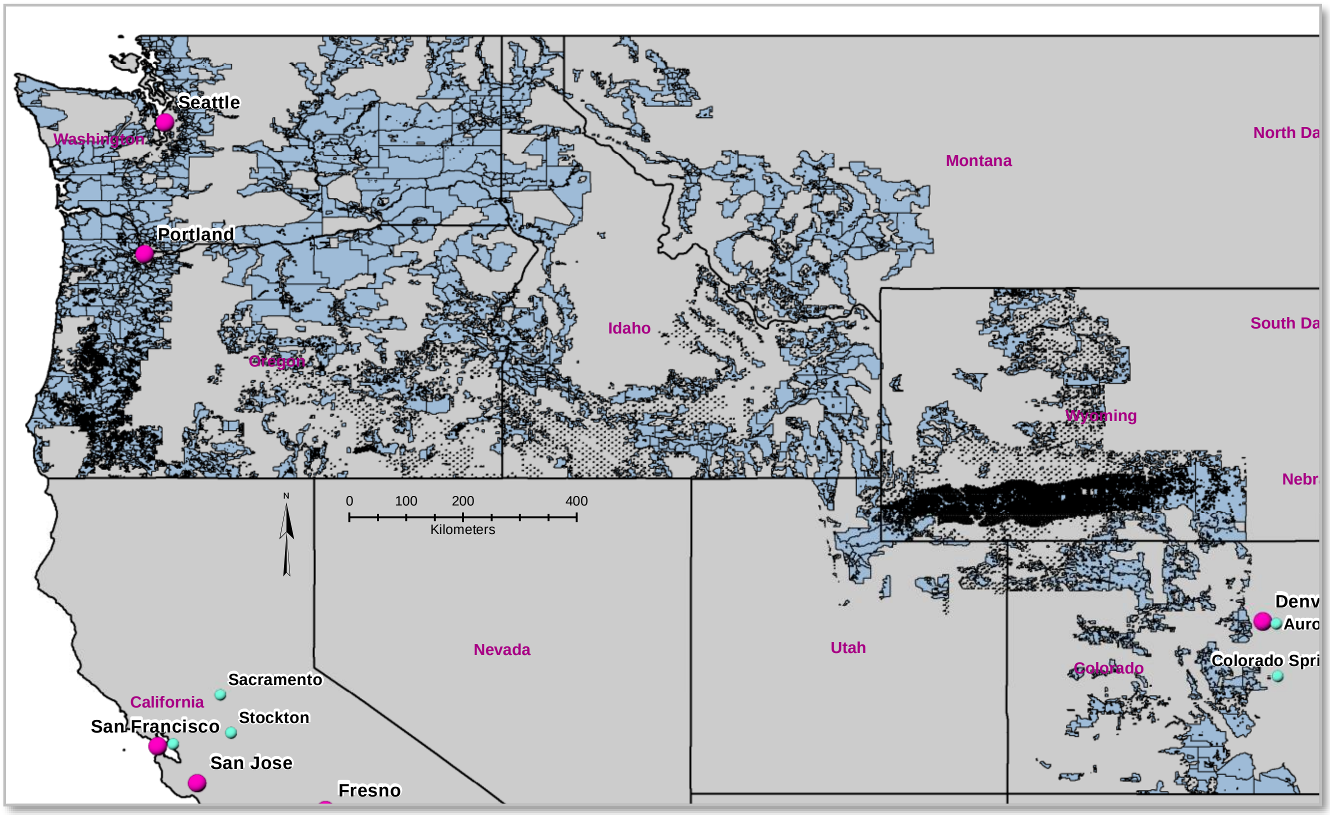


Figure 3: County-level distribution of the rural-urban continuum.

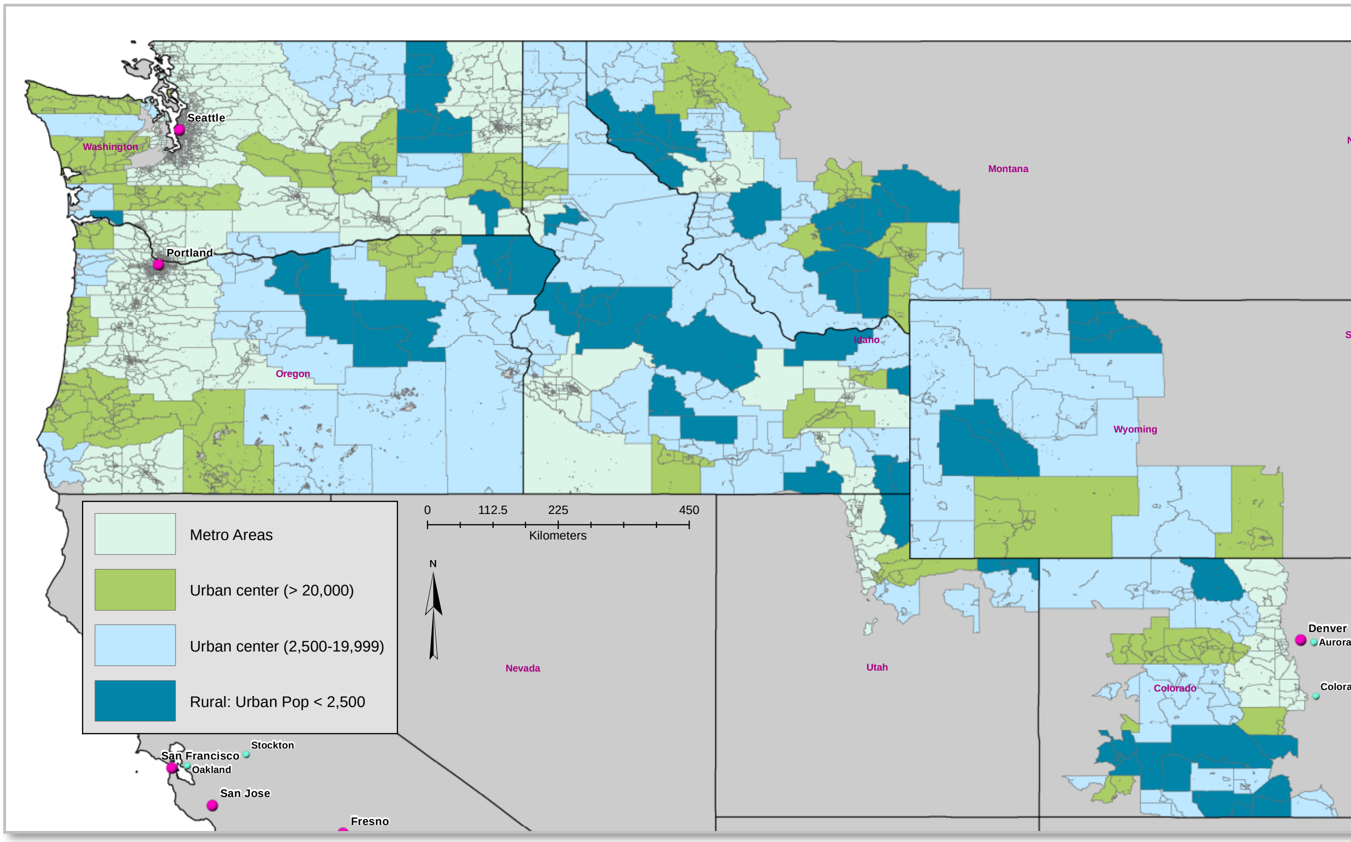
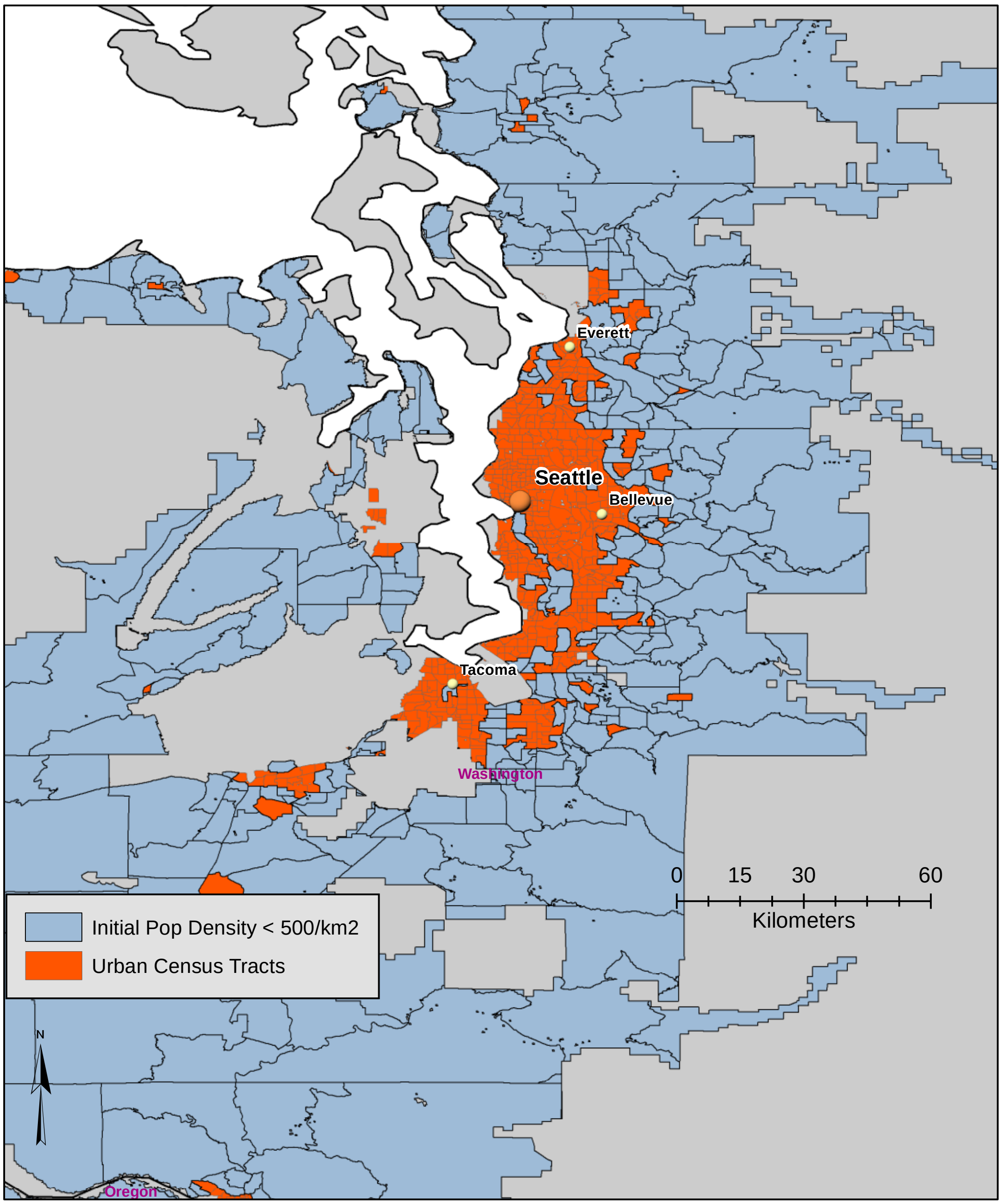


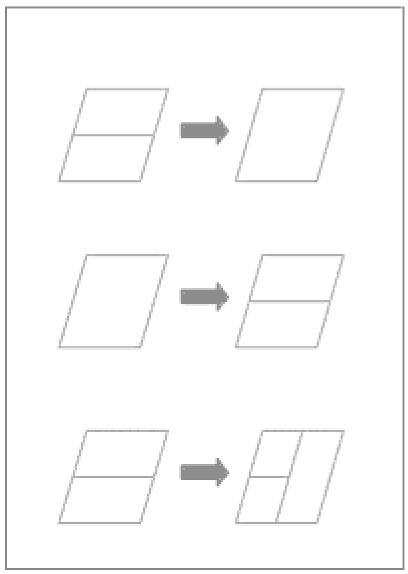
Figure 4: Distribution of Urban Census Tracts Removed from the Sample.



5 Variables

Demographic and economic data for 1990 and 2000 are purchased from Geolytics. Census tract boundaries are adjusted, consolidated or split, every ten years according to population growth or decline, with the optimum population of 4,000 people (US Census Bureau 2010). Approximately 35% and 31% of all US census tract boundaries changed from 1990-2000 and 2000-2010 respectively (Logan, Xu, and Stults 2015). For example, a census tract in 1990 or 2000 that experienced population growth may be divided into two separate tracts in 2010. Conversely, if a census tract in 1990 or 2000 experienced population decline, it is consolidated into another tract(s). Figure 5 illustrates the different ways a given census tract change over time. Changing boundaries clearly complicates analysis at the census tract-level.

Figure 5: Three ways census tracts may merge or split.



The Geolytics data are normalized to 2010 census tract boundaries, allowing intertemporal comparisons. Geolytics normalizes the 1990 and 2000 census data at the census block group level, the smallest geographic level where the full US Census Long Form data is available. Census blocks, which are smaller than census block groups, are used to track merges or splits within a census block group. When census blocks split, the demographic information must be reallocated between these two blocks. A weight is created to determine the distribution of demographic values by analyzing the presence of streets of a census block in 1990. Street presence is used because it is assumed that this is where people are located. So, if a census block splits, the half that had more streets in 1990 is assumed to have a higher population density and is weighted more heavily. Census blocks with greater weights will be allocated more of the demographic values. The weight is then used to split or merge demographic data for blocks that have changed from 1990 to 2000. This same method is for census tracts.

5.1 Dependent Variable

The dependent variable is percent change in total tract population from 1990 to 2010. Population data are obtained from Geolytics, which estimate population data using the U.S. Census Bureau (Long Form: SF3). The log of population levels is used to calculate the percent change in population of a given census tract. Population densities, measured as the population per square kilometer of private land are reported in Table 1. While the median population densities of census tracts in 2000 and 2010 are less than the 1990 median value, the standard deviation is much greater, meaning the variation in population densities of census tracts was greater in 2000 and 2010.

Table 1: Summary Statistics of Population Density.

Population Density (km^2)	Mean	Median	Std. dev.	Min	Max
Pop density: 1990	161.06	154.47	74.73	0.1	432.1
Pop density: 2000	158.96	50.14	247.18	0.0	2365.3
Pop density: 2010	213.21	57.50	359.16	0.0	4217.0
Observations	1513	1513	1513	1513	1513

5.2 Independent Variables

Table 2 describes the climate variables included in the model. Climate variables were obtained from the PRISM database for the year 1989, as 1990 was not available (PRISM Climate Group). Quadratics for climate variable are included, as nonlinear relationships often exist. For instance, population may increase in areas with warmer summers but beyond a temperature threshold warmer summer temperatures become a disamenity, deterring population growth. The winter temperature variable is the mean *minimum* temperature for January averaged over all days in the month while the summer temperature variables is the mean *maximum* temperature for July, averaged over all days in the month. Humidity is a measure of the daily minimum vapor pressure deficit, averaged over all days in the month, measured in kilopascals (kPa) with a kPa greater than 1.0 representing low humidity.

Table 2: Climate Variables Description and Summary Statistics.

Climate Variable	Description	Unit of measurement	Mean	Std. dev.	Min	Max
Winter temperature	Mean minimum temperature for January	˚C	-4.51	5.47	-19.1	3.9
Summer temperature	Mean maximum temperature for July	˚C	26.22	3.06	0.0	32.9
Humidity	Mean minimum vapor pressure deficit	Kilopascal pressure unit (low value -> high humidity)	0.82	0.72	-0.5	3.4
Summer precipitation	Mean precipitation for June-Sept	Millimeters	35.85	16.22	0.0	111.0
Annual precipitation	Mean annual precipitation	Millimeters	843.83	554.03	0.0	3320.1
Observations			1513	1513	1513	1513

The literature demonstrates that migrants prefer more moderate temperatures (McGranahan 1999: Sinha and Cropper 2013; Rappaport 2007; Poudyal et al. 2008; Deller et al 2001; Albouy et al 2013). It is common to use a simple mean to measure winter and summer temperatures (Koirala and Bohara 2014; Sinha and Cropper 2013; Deller et al. 2001; McGranahan 1999). However, measuring the extremes of winter and summer temperatures may reveal household's preferences or distaste (disamenity) for more extreme temperatures.

Using factor analysis, a climate amenity index is created to capture different types of climates in the study area. Factor analysis uses observable and correlated variables to capture latent characteristics of the study area while reducing a set of explanatory variables to a single scalar measure. Factor analysis assumes observed variables are linearly related to underlying factor variables and are thus weighted linearly. An eigenvalue measures the amount of variance that is accounted for by the factor. Generally, an eigenvalue greater than 1.0 suggests a sufficient relationship between latent factors and observed variables. Factor 1, with an eigenvalue of 3.2, suggests that Factor 1 explains more of the variation of the climate index than the other factors, which have significantly lower values (Table 3). Factor loadings represent how variables are weighted. All the climate variables included in the index are weighed heavily, with summer temperatures and humidity being negative. Table 3 shows that a negative factor analysis score is associated with more moderate, humid, and wet climates while positive scores capture drier, warmer climates. This is expected as the study area contains coastal areas, where higher rates of precipitation and more moderate temperatures are expected relative to the rest of the study area. The distribution of climate types, illustrated in Figure 4, demonstrate clear spatial patterns among census tracts with more wet and moderate climates concentrated near the Pacific Coast and drier, cooler climates dominating the inland area.

Table 3: Climate variable factor loading and scores for private lands with pop density < 500.

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	3.19295	2.62932	0.8546	0.8546
Factor2	0.56363	0.34558	0.1509	1.0055
Factor3	0.21805	0.31356	0.0584	1.0638
Factor4	-0.09550	0.04744	-0.0256	1.0383
Factor5	-0.14294	.	-0.0383	1.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Uniqueness
Annual precip	0.8939	0.0483	0.2756	0.1227
Summer precip	0.7214	-0.4928	0.1470	0.2150
Summer temp	-0.8414	0.1336	0.2536	0.2098
Winter temp	0.6468	0.5414	0.0821	0.2818
Humidity	-0.8644	-0.0864	0.2223	0.1960

Scoring coefficients (method = regression)

Variable	Factor1	Factor2	Factor3
Annual precip	0.40746	0.20296	0.87694
Summer precip	0.11483	-0.70132	0.12672
Summer temp	-0.25538	0.14652	0.48366
Winter temp	0.08906	0.51536	0.00798
Humidity	-0.24724	-0.13075	0.52840

Natural Amenities

Proximity to a natural amenity, like a national park, does not always translate to accessibility, particularly in mountainous regions with few roads. For instance, a park entrance may be located hours from an individual's home despite Euclidean proximity. Rather than using a simple Euclidean measure of distance, distances were calculated using cost distance. Cost distance of travel time, in minutes, was calculated in ArcGIS using Dijkstra's cost distance algorithm, which calculates the shortest path between a given point and all other points. Cost distance calculations assume: a) travel in a car, assuming speed limits are followed, b) anisotropic frictions, whereby travel time may vary according to slope (e.g. takes longer to travel uphill than downhill). Thus, cost distance provides a more accurate measure of access to a natural amenity. Cost distances were measured by clipping raster data to 2010 census tract boundaries. Each pixel in the raster data contains a value for travel time. The raster data were clipped to the private land area and average travel time for a census tract was calculated using the Spatial Analyst Tool in ArcGIS. All natural amenity variables, except for distance to ski resorts, were calculated and measured using this approach.

Public land variables are derived from Theobald's (2014) National Land Use dataset. Public lands provide attractive viewsheds and opportunities for recreation and have been demonstrated to attract migrants (Dearien et al. 2005; Rudzitis and Johansen 1989; Deller et al. 2001). As such, Forest Service (USFS), Fish and Wildlife Service (USFWS), and National Park Service (NPS), and some Bureau of Land Management (BLM), lands are included in the model. BLM lands tend to have small, if any, impacts on population change (Deller et al. 2001). However, National Monuments and Wilderness Areas fall under the jurisdiction of the BLM and so these BLM lands are included. Cost distance to public lands were calculated in the methods described in the preceding paragraph.

Topographic complexity, derived from a USGS digital elevation map, captures the variation of land formations within a tract. Topographic complexity is calculated as the standard deviation of elevation of the center cell from the mean of all cells within a moving radius of 5.6km. A radius of 5.6km was used as it represents an ecologically relevant scale (Theobald et al. 2015). In other words, this radius captures the nuances of a location; a larger radius would smooth out heterogeneous features. More varied landscapes are considered attractive regions for migrants (McGranahan 1999). As such, tracts with greater topographic complexity are expected to experience higher rates of population growth relative to tracts with less topographic complexity.

Forest pattern is derived from the 1992 National Land Cover Database (Vogelman et al. 2001) and calculated as the standard deviation of the center cell to the mean of all cells within a moving radius of 5.6km. Since 1990 forest pattern data are not available, the closest year, 1992, was used to capture forest pattern conditions. Average values for forest complexity were calculated at the census tract level at a 90-meter resolution; cells were classified as forested or not forested. Larger standard deviations represent greater variation in forest pattern. Forest classes include no forest, coniferous, deciduous, and mixed forest (some combination of coniferous and deciduous). McGranahan (2008) finds that individuals are not simply attracted to the mere presence of a forest but rather a dynamic forest landscape, including composition of different tree species and heterogeneous patterns of forest and non-forest. Measuring the forest pattern of a tract, rather than a simple percent measure, provides a more nuanced understanding of how forest amenities influence population migration.

Average tract cost distances to water bodies equal to or greater than $1km^2$ in size are calculated as travel time in minutes. Water body data are obtained from the USGS: National Hydrography Dataset (https://nhd.usgs.gov). Past research measures the water bodies as a percent of water in a given area (McGranahan 2008). However, using a simple area measure does not account for accessibility of water amenities or water in other tracts. Cost distance measures to water bodies will provide a more nuanced understanding of how migrants value water amenities like lakes and rivers.

Ski resorts provide recreational opportunities and are expected to influence population growth (Deller et al. 2001). Distance to ski resorts is measured as the Euclidean distance, in meters. Again, census tract averages for distance were calculated by clipping the ski resort raster data to the study area polygons and calculating tract averages using the Spatial Analyst Tool in ArcGIS. Though cost distance measures are preferred, time constraints did not allow for this calculation. Ski resort data are derived for 2007, the most recent available, from the National Weather Service: National Operational Hydrologic Remote Sensing Center (http://www.nohrsc.noaa.gov/gisdatasets).

Table 4: Natural Amenity Variable Description.

Natural Amenity	Description	Data Source and Year
Pacific coast	Cost distance to the Pacific coast (minutes)	USGS: TIGER
Water bodies	Cost distance to water bodies 1km^2 or larger (minutes)	USGS: TIGER
Topographic Complexity	Captures landscape complexity using variation in elevation within a tract	USGS
Forest Complexity	Captures the heterogeneity of a forest pattern by accounting for different forest types	USGS: National Land Cover Data (1992)
Ski Resorts	Euclidean distance to nearest ski resort in meters	National Weather Service: NOAA (2007)
Public Land	Cost distance to BLM, FS, and USFWS land (minutes)	Theobald (2014)
NPS	Cost distance to National Parks (minutes)	Theobald (2014)

Table 5: Summary Statistics of natural amenity variables.

Natural Amenity Variables (Measured as Distance in Minutes)	Mean	Std. dev.	Min	Max
Public Land	47.39	39.10	0.3	262.8
NPS	244.97	132.82	2.0	804.2
Ski Resort	70338.60	43473.74	1436.8	254965.0
Forest Complexity	32.47	15.66	0.1	49.0
Topographic Complexity	5498.39	4125.32	105.9	24215.0
Waterbody	70.12	76.02	0.5	743.2
Observations	1513	1513	1513	1513

The Pacific Coast raster data, measuring cost distance to the Pacific Coast, did not extend beyond 300,000 meters (Figure 6). Thus, to measure the impact of coastal proximity on population change for the entire study area, a categorical variable was created. The categorical variable for Pacific Coast ranges from 0-4: 4 representing census tracts less than 166 minutes to the coast; 3 being 166-370 minutes, 2 being 371-746 minutes, 1 being 746-22,821 minutes; and 0 being greater than 22,821 minutes. Areas without data for coastal proximity were categorized as having no effect on population change, category 0. These distance thresholds were based on reasonable cost distances an individual would travel to the coast. The distribution of the categorical Pacific Coast variable is illustrated in Figure 7 with frequencies reported in Table 6.

Figure 6: Original Measure of Proximity to Pacific Coast (Cost Distance in Minutes).

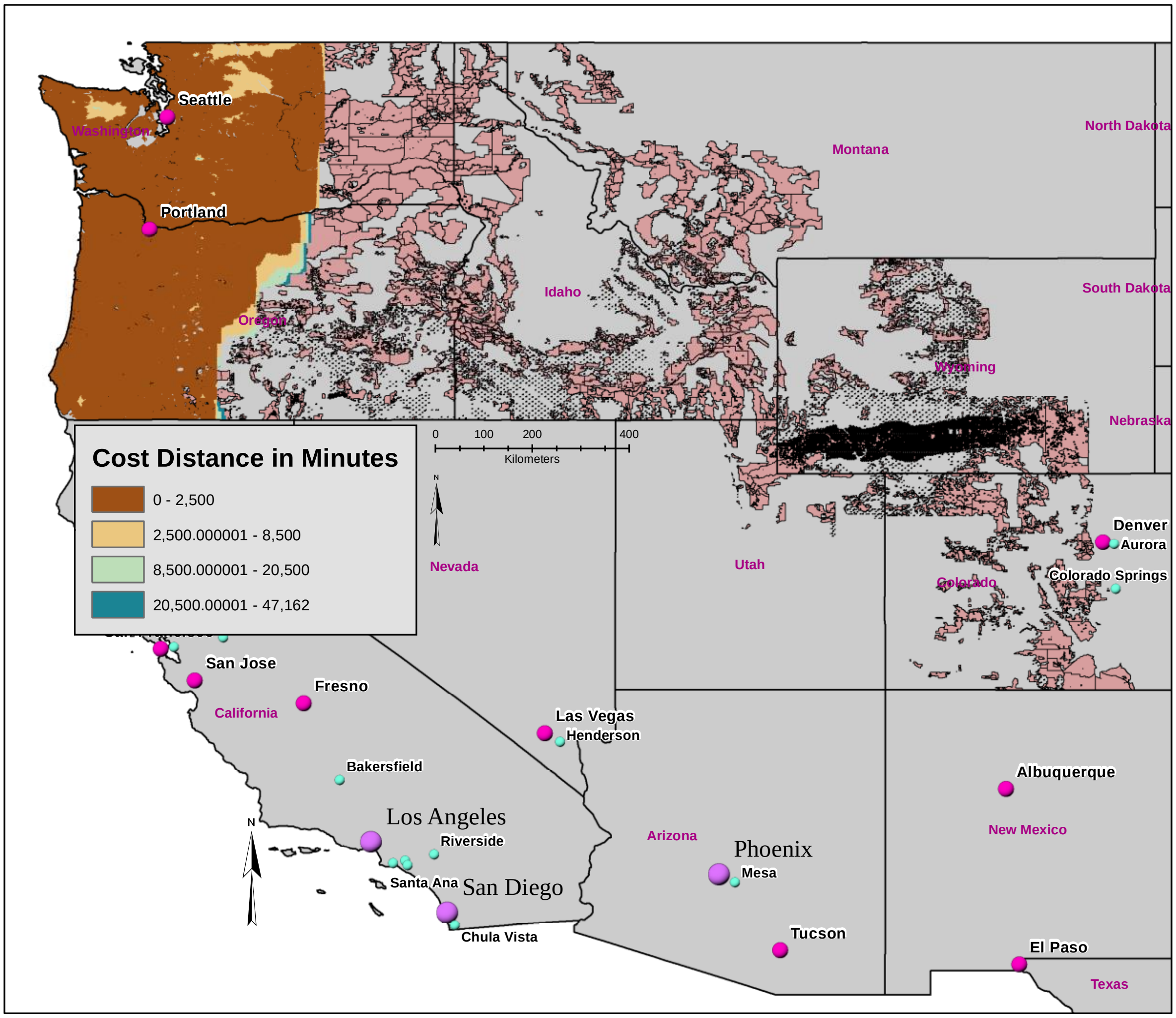
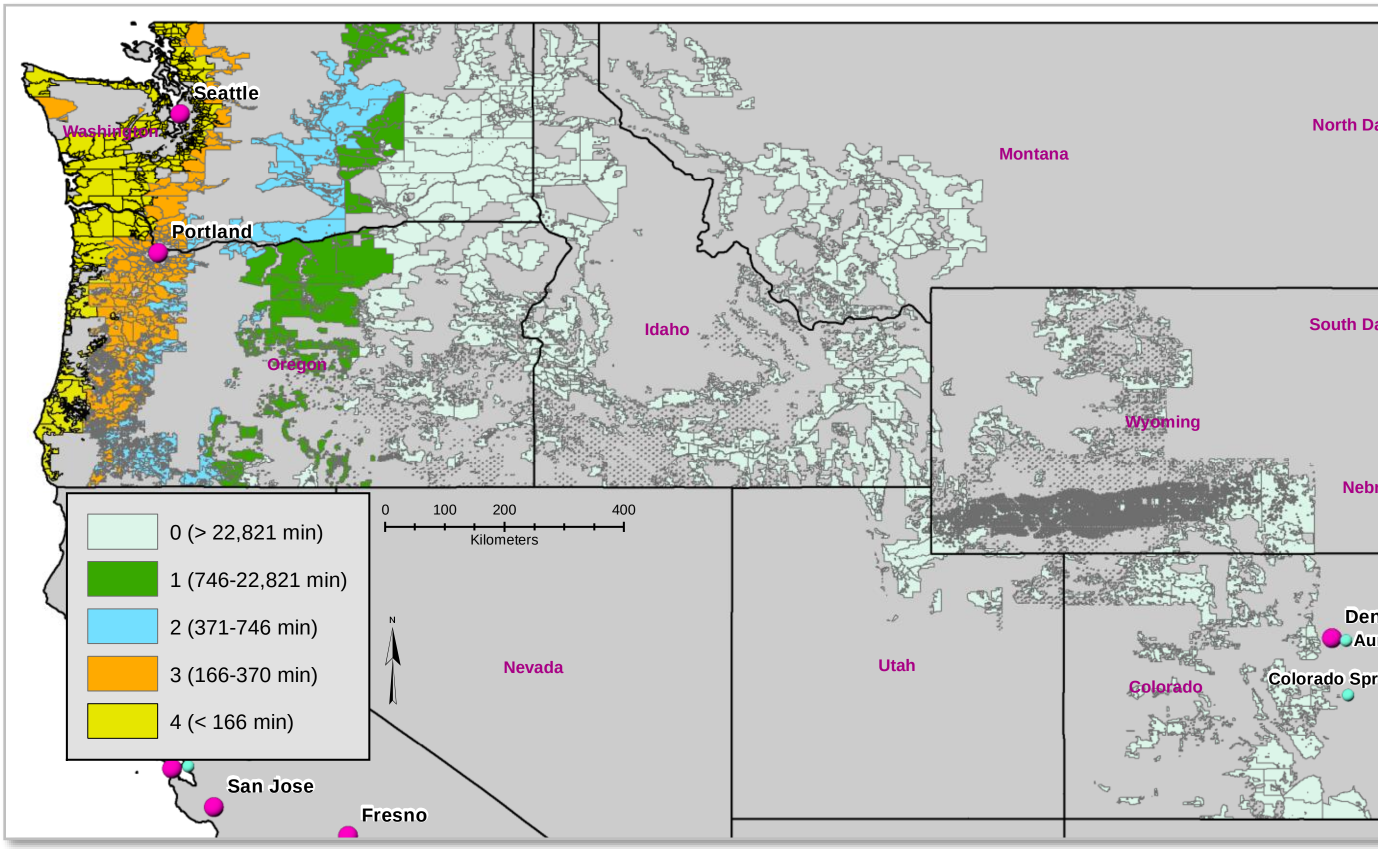


Table 6: Frequency of Pacific Coast Categories at the Census Tract Level.

Pacific Coast Category	**Frequency**	**Percent**
4 (less than 166 min)	377	24.92
3 (166-370 min)	263	17.38
2 (371-746 min)	116	7.67
1 (746-22,821 min)	53	3.50
0 (greater than 22,821 min)	704	46.53
Total	1513	100

Figure 7: Distribution of Pacific Coast Categorical Variable: Cost distance in minutes.



Following Winkler et al. (2007) I created a New West index using the following variables: 1) Percent of inmigrants from out-of-state; 2) percent of workers employed in finance, insurance, or real estate (FIRE); 3) percent of workers employed in extractive industries; 4) percent of all housing units used for seasonal or recreational use; 5) percent of all specified owner occupied housing units valued at $200,000 or more; 6) percent of people age 25 and over with a Bachelor's degree or more; and 7) percent of workers employed in tourism industry (arts, recreation, food service). New West variables are derived from the US Census Bureaus (Long Form: SF3). Housing values are divided into four ranges and five homeowner-use categories with the expectation that higher housing values will be associated with New West tracts. The FIRE industry (finance, Insurance, Real Estate, and Rental and Leasing) and tourism industry variables identify New West tracts while the extractive industry variable is associated with Old West tracts. New West tracts are expected to experience higher rates of inmigration from out of state migrants while having higher levels of educational attainment, seasonal housing, and people employed in FIRE industries.

Following Winker et al. (2007), I create a New West continuum, ranging from Classic Old West to Model New West, to categorize each census tract. Table 7 describes explanatory variables used to determine how population growth may vary between New West and Old West census tracts. The New West Index captures the demographic and housing characteristics, and economic emphasis of a tract (e.g. extractive industry, finance, etc.).

I used factor analysis to construct a New West factor score for each census tract. Using the factor scores, I created two New West indicator variables, 1) a binary New West variable that identifies a tract as either New West or Old West and 2) a four-level New West variable that identifies a tract as either Classic Old West, Old West, New West, and Model New West. Factor analysis results are reported in Table 8. All variables in the New West index yield positive scoring coefficients except percent of individuals employed in extractive industries. Percent of individuals with Bachelor's degrees or higher has the strongest effect on the factor score, followed by percent of individuals employed in FIRE industries and housing value greater than $200,000. Thus, census tracts with positive factor scores represent New West tracts while negative factor scores capture Old West tracts.

Table 7: Descriptive and Summary Statistics for New West Variables: 1990.

New West Variables	Measure (Percent %)	Description	Mean (%)	Std. dev.	Min	Max
Education Attainment	Percent of population with a bachelor's degree or higher	Highest level of education attained	25.20	15.09	3.6	100
Housing Value	Percent of housing values > $200,000 : home owner use categories: Owner-occupied, Vacant, Seasonal, Occasional Use, Recreational	Housing Value Ranges: 1. $200,000-$299,999 2. $300,000-$499,999 3. $500,000-$999,999 4. ≥ $1,000,000	49.71	11.70	14.0	100
Extractive Industry	Percent of population employed in the extractive industry	Employment in Agriculture, Forestry, Fishing, Hunting, or Mining	5.44	11.71	0.0	98.4
FIRE Industry	Percent of population employed in the FIRE industry	Employment in Finance, Insurance, Real Estate, Rental and Leasing	4.71	2.62	0.0	16.4
Tourism Industry	Percent of pop employed in tourism	Employed in Arts, Entertainment, Recreation, Accommodation, Food Services	9.77	9.97	0.0	100
Housing Units	Percent of houses being used seasonally	Housing units being used occasionally or seasonally	1.38	1.49	0.0	17.6
Inmigration Out of State	Percent of population that have moved from a different state	People that lived in a different house in 1995 (in the US)	26.13	28.78	0.0	100
Observations			1,513			

Table 8: New West factor loadings and scores.

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.89414	1.43327	1.0551	1.0551
Factor2	0.46087	0.39487	0.2567	1.3118
Factor3	0.06599	0.11998	0.0368	1.3485
Factor4	-0.05399	0.09770	-0.0301	1.3185
Factor5	-0.15168	0.03518	-0.0845	1.2340
Factor6	-0.18686	0.04631	-0.1041	1.1299
Factor7	-0.23318	.	-0.1299	1.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Uniqueness
Pct Seasonal Housing	0.1216	0.4571	-0.0340	0.7751
Pct Employed Tourism	0.4293	0.2647	-0.0918	0.7372
Pct Employed Extraction	-0.4501	0.3214	0.1203	0.6797
Pct Employed FIRE	0.6538	-0.2019	-0.0529	0.5290
Pct Housing Value > 200k	0.6294	0.0386	0.1441	0.5816
Pct Born out State	0.4014	0.1901	-0.0846	0.7956
Pct Bachelor's Degree	0.7126	0.0096	0.1060	0.4809

Scoring coefficients (method = regression)

Variable	Factor1	Factor2	Factor3
Pct Seasonal Housing	0.04362	0.32944	-0.04062
Pct Employed Tourism	0.14118	0.21578	-0.11141
Pct Employed Extraction	-0.14808	0.25899	0.14308
Pct Employed FIRE	0.27089	-0.19981	-0.09293
Pct Housing Value > $200k	0.23692	0.04478	0.18586
Pct Born out State	0.12160	0.14935	-0.09652
Pct Bachelor's Degree	0.32498	0.02352	0.15633

I used factor analysis to calculate a measure of remoteness for each census tract. Remoteness captures the degree to which a census tract has access to urban centers and transportation networks. Census tract averages of cost distances, in minutes, to roads, and urban centers of different sizes are included to account for traditional drivers of population growth. Railway data for 2015 are obtained from the Department of Transportation and measured as average Euclidean distance, in meters. Time constraints prevented me from calculating the average cost distance to railways. Access to railways are expected to be important in areas economically dependent on natural resource extraction (http://osav.usdot.opendata.arcgis.com). Highway and interstate data are obtained from the US Census Bureau (2010 TIGER shapefiles). Cost distances are calculated from the centroid of an urban center. Urban centers of one million; 250,000; 50,000; and 2,500 people are considered for the year 2010 and obtained from the US Census Bureau. A single variable captures the shortest cost distance to urban centers of 250,000 people or 1 million people. In other words, if a pixel is located near an urban center of 250,000 and an urban center of 1 million people, this variable will account for the urban center with the shortest cost distance. Table 9 provides variable descriptions and summary statistics.

Table 9: Summary Statistics: Market Access measured in cost distance (minutes).

Remoteness Variables	Description	Mean	Std. dev.	Min	Max
Pop center: 2,500	Average cost distance from centroid of urban center of 2,500	116.04	120.80	2.7	1411.5
Pop center: 50k	Average cost distance from centroid of urban center of 50,000	135.74	183.16	2.4	1257.8
Pop center: 250k or 1 million	Average cost distance from centroid of urban center of 250,000 or 1 million	492.50	882.47	5.0	17348.0
Highway	Average cost distance from a highway	27.50	35.09	0.0	325.2
Interstate	Average cost distance from an interstate	110.59	142.21	1.4	1015.6
Rail	Average Euclidean distance from a railway (meters)	9603.38	14962.32	150.5	129834.3
Observations		1,513			

Logged values of the remoteness variables created a more normal distribution of the data. Table 10 reports the factor analysis results for the remoteness index using logged values of remoteness variables. Factor 1 is used as it has the largest eigenvalue and thus accounts for the greatest amount of variation. All remoteness variables are positive and weighed heavily in the factor loading. Log distance to urban centers of 50,000 people has the largest coefficient followed by log distance to highways and interstates. Thus, a positive remoteness factor score captures areas that are remote while negative scores capture areas close to urban areas and transportation links.

Table 10: Remoteness factor loading and scores of private lands.

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	4.17574	4.00289	1.0105	1.0105
Factor2	0.17285	0.14451	0.0418	1.0524
Factor3	0.02835	0.07208	0.0069	1.0592
Factor4	-0.04374	0.02649	-0.0106	1.0486
Factor5	-0.07022	0.06055	-0.0170	1.0316
Factor6	-0.13077	.	-0.0316	1.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Uniqueness
Highway	0.9001	-0.1679	-0.0451	0.1597
Interstate	0.8475	0.2307	0.0085	0.2284
Rail	0.7095	0.0731	0.1339	0.4734
Pop: 2,500	0.8337	-0.1535	-0.0095	0.2812
Pop: 50k	0.9270	-0.1383	0.0160	0.1213
Pop: 250k or 1 million	0.7679	0.2083	-0.0892	0.3590

Scoring coefficients (method = regression)

Variable	Factor1	Factor2	Factor3
Highway	0.22659	-0.41274	-0.24298
Interstate	0.21042	0.62326	0.05283
Rail	0.07502	0.11136	0.24276
Pop: 2,500	0.12981	-0.20289	-0.01059
Pop: 50k	0.33906	-0.38866	0.18069
Pop: 250k or 1 million	0.11043	0.34623	-0.20970

6 METHODS

Following Rappaport (2007), the theoretical approach for identifying the drivers of population migration is based on a spatial equilibrium model. I assume utility is spatially constant and migration occurs when household preferences for location-specific amenities change. I estimate the percent change in population from 1990 to 2010. The percent change in population (Δpop) is a function of remoteness (*R)*, natural amenities (*NA*), climate variables (*C)*, and New West characteristics (*NW*):

$$\%\Delta pop_{90to10} = f(R, NA, C, NW)$$

However, factor mobility is imperfect and can require decades to adjust from one steady state to another, meaning current population density may differ from steady-state population density (Rappaport 2004). So, a positive partial correlation between current population density and independent variables may capture past, in addition to current, impacts of these variables on population change. Including initial population density accounts for agglomeration effects, allowing me to identify changes in preferences for natural amenities. Omitting initial conditions would bias the coefficients of explanatory variables by overstating the impact they have on population change [1].

6.1 Ordinary Least Squares

A cross-sectional ordinary least squares (OLS) regression model estimates the average impacts of natural amenities, climate, remoteness, and the degree to which a census tract is New West on population change from 1990-2010 (Eq. 1). The model includes the log of population density in 1990, $lnpopden_{90}$, to account for delayed agglomeration effects.

Eq. (1)

$$\%\Delta Pop_{90to10i} = \beta_0 + \beta_1 lnpopden_{90i} + \beta_2 newwest_{90i} + \beta_3 amenity_i + \beta_4 climate_{89i} + \beta_5 remoteness_i + \beta_6 states_i + \varepsilon_i$$

[1] Initial conditions of population density in 1990 and a vector of climate variables for 1989 are included in the model. Ideally these variables would capture initial conditions for 1990; however, not all variables were available for that year.

The $newwest_{90}$ variable is a continuous index, created using factor analysis, that captures differences in demographic compositions of census tracts by identifying a census tract as Classic Old West, Old West, New West, or Model New West. *Amenity* is a vector of natural amenity variables. Natural amenity variables measured as cost distances, like average cost distance to public lands, are incorporated into the model as logged values. Topographic and forest complexity are also included in the vector of natural amenities. The *climate* variable is a continuous index, created using factor analysis, that captures two major climate types found in the study area: a) wetter areas with moderate summer and winter temperatures and b) drier areas that experience greater fluctuations in summer and winter temperatures. *Remoteness* is also a continuous index created using factor analysis. This index includes the logged values of market and transportation access variables measured as cost distance in minutes, like distance to urban centers and highways. The coefficients of natural amenity variables estimate the *changes* in preferences for natural amenities on changes in population.

The *states* variable is a vector of dummy variables for each state in the study area. State dummy variables are included to minimize endogeneity resulting from omitted variable bias. Endogeneity occurs when unobserved variables in the error term, ε, are correlated with independent variables and the dependent variable, resulting in a biased an inconsistent estimator. State fixed effects help reduce omitted variable bias by accounting for unobserved, time-invariant characteristics of a state, like state-level conservation and taxation policies, that may be correlated with the explanatory variables and influence population growth. This model also assumes that the error term is homoscedastic and does not suffer from autocorrelation. Robust standard errors are used to correct for heteroskedasticity. Even if the error term is homoscedastic, robust standard errors will simply yield OLS standard errors. The issue of autocorrelation is discussed later in this section.

6.2 OLS with Interaction Terms

I then added interaction terms to the base model to identify potential differences in population growth in New West versus Old West census tracts (Eq. 2). I interacted the binary New West variable, which identifies a census tract as New West or Old West, with the climate and remoteness indices and each individual natural amenity in the amenity vector. The average marginal effects of these interactions are computed using the margins command (dydx) in Stata. The marginal effects describe the impacts explanatory variables (remoteness, amenities, and climate) have on percent population change in New West versus Old West census tracts. For instance, the coefficient of the marginal effect of the binary New West variable interacted with forest complexity ($\beta_2 binary\_newwest_{90} * forest\ complexity$) describes how forest complexity impacts the percent change in population from 1990-2010 in New West versus Old West census tracts. I run the same interaction model using a four-level New West variable, *four_newwest*$_{90}$, to explore how explanatory variables impact percent change in population in Classic Old West, Old West, New West, and Model New West census tracts (Eq. 3).

Eq. (2)

$$\%\Delta Pop_{90to10i} = \beta_{0i} + \beta_1 lnpopden_{90i} + \boldsymbol{\beta_2 binary\_newwest_{90i} * amenity} + \boldsymbol{\beta_3 binary\_newwest_{90i} * climate_{89i}} + \boldsymbol{\beta_4 binary\_newwest_{90i} * remoteness} + \beta_5 states_i + \varepsilon_i$$

Eq. (3)

$$\%\Delta Pop_{90to10i} = \beta_{0i} + \beta_1 lnpopden_{90i} + \boldsymbol{\beta_2 four\_newwest_{90i} * amenity} + \boldsymbol{\beta_3 four\_newwest_{90i} * climate_{89i}} + \boldsymbol{\beta_4 four\_newwest_{90i} * remoteness} + \beta_5 states_i + \varepsilon_i$$

Complications in estimating the drivers of population change arise due to spatial autocorrelation. Tobler's (1970) first law of geography, "Everything is related to everything else, but near things are more related than distant things" best describes the basic tenet of spatial autocorrelation. However, before I test for spatial autocorrelation, I must determine how to define "near".

6.3 Spatial Weight Matrices

Spatial weight matrices are constructed to capture weighted averages of data by measuring the spatial relationship, or correlation, between all pairs of locations. For instance, the first row of the spatial weight matrix represents the spatial relationship between the centroid of one census tract and all other census tracts.

However, spatial relationships can be defined in different ways. A Rook's case adjacency (Fig. 8) requires census tracts to share an edge, or border, with another census tract to be considered adjacent; whereas a Queen's case adjacency (Fig. 9) allows census tracts to share a corner, in addition to edges. Because census tracts are irregularly shaped, and due to limitations on matrix sizes in Stata, I use an inverse-distance spatial weight. Let us assume the matrix in Figure 10 uses an inverse-distance spatial weight. If each element, w_{ij}, depends on the distance between locations i and j, then the spatial weight is calculated as $1/w_{ij}$. A threshold distance is often used to identify a distance at which weights no longer have an impact. However, with only 1,513 census tracts in the study area, and therefore 1,513 centroids, I allow the weight matrix to account for all other centroids from a given location.

Fig 8.

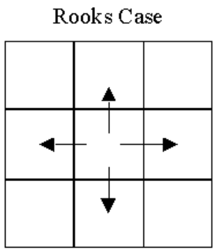


Fig. 9

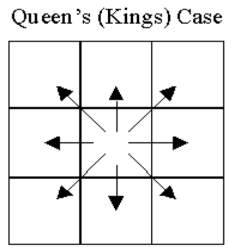
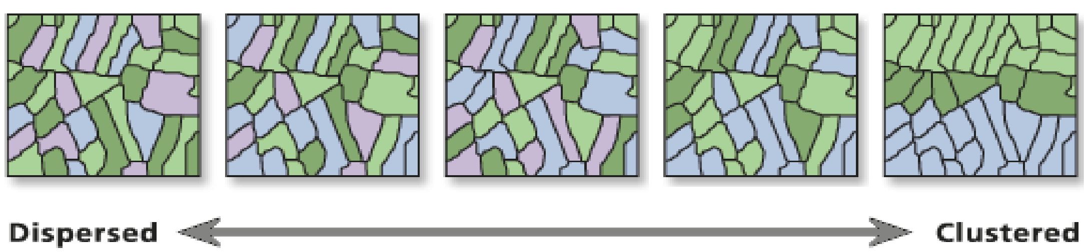


Fig. 10 $\mathbf{W} = \begin{bmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{bmatrix}$

It is common practice to experiment with different weight matrices and so I use inverse distance, queen adjacency, and rook adjacency spatial weight matrices to estimate SAR, SEM, and mixed spatial regression models. Researchers often experiment with different spatial weight matrices to determine the best fit model.

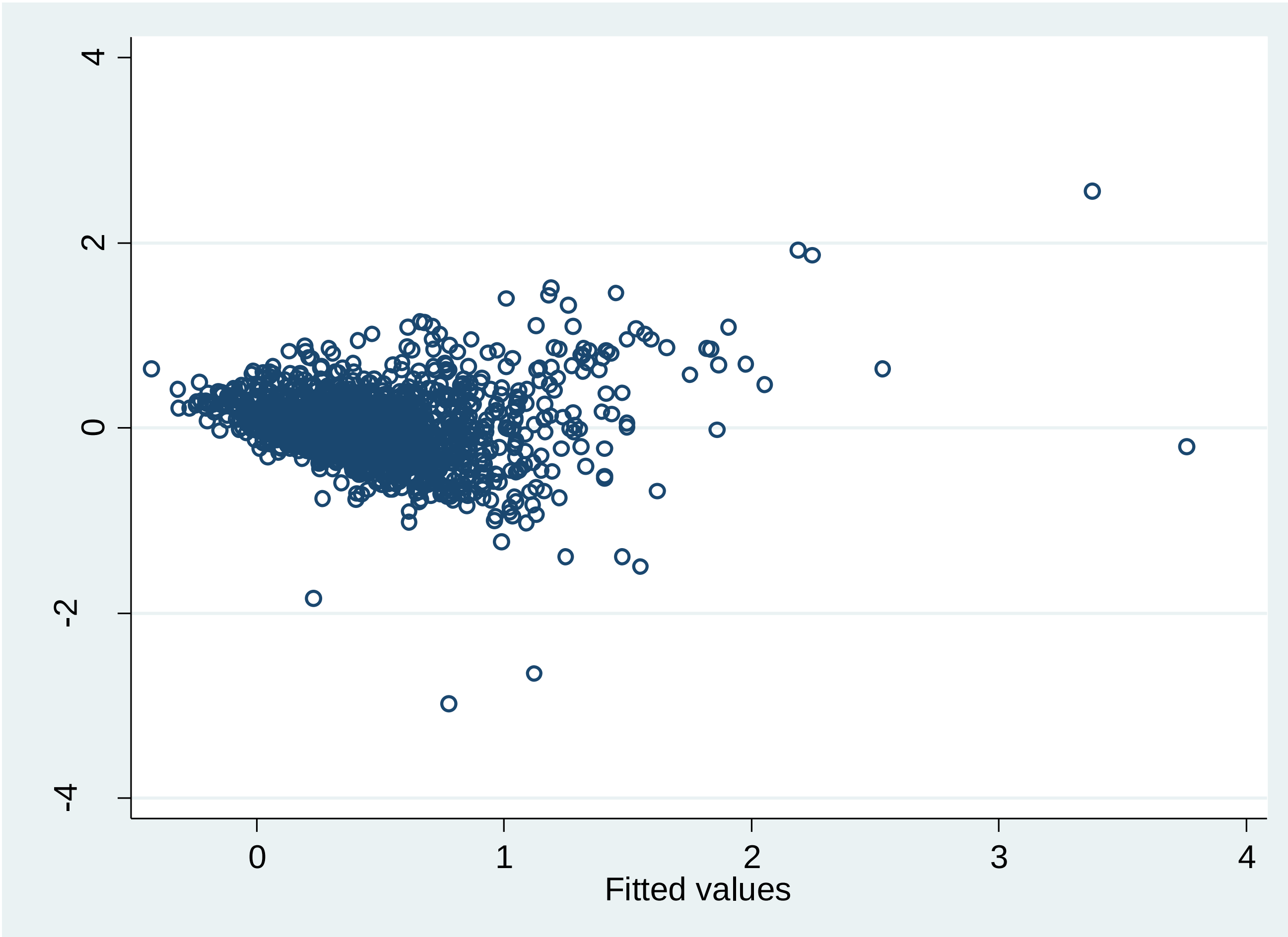
Spatial autocorrelation measures the correlation of the same measurement taken in different points or locations. The most widely used test for spatial autocorrelation is Moran's-I, where the null hypothesis assumes no spatial association. Figure 11 is useful in visualizing spatial relationships captured by Moran's I. Generally speaking, Moran values greater than .30 indicate clustering, values less than -.30 indicate dispersion, and a value of zero indicates no spatial relationship.

Figure 11: Illustration of Spatial Patterns Accounted by in the Moran's I Test.



It is especially important to test and account for spatial autocorrelation as many of the variables in the model are spatially explicit. Figure 12 illustrates the distribution of the residuals of Equation 3 which clearly demonstrates a relationship among the residuals. The presence of spatial autocorrelation violates the assumption of independence among the error terms. While estimators are still unbiased and consistent, they are no longer efficient resulting in biased standard errors. Spatial autocorrelation biases the standard errors, thereby biasing t-values.

Figure 12: Distribution of the residuals: OLS regression with four-level New West Indicator.



6.4 Spatial Regression Models

To account for spatial autocorrelation of the dependent variable, percent population change from 1990-2000, a spatial autoregressive model (SAR) is used. A spatial autoregressive model is simply a standard linear regression model with a spatially lagged dependent variable where ρ is the autoregressive parameter and W is the spatial weights matrix. The formal SAR model states that the dependent variable, y, is dependent on y in neighboring areas (Eq. 4):

Eq. (4)

$$y=\lambda Wy + X\beta + \mu$$

A spatial error model (SEM) is used to account for spatial autocorrelation of the error term where

λ is the autoregressive parameter and W is the spatial weight matrix. The formal spatial error model accounts for spatial relationships in the error term (Eq. 5):

Eq. (5)

$$y = X\beta + u$$
$$u = \rho W u + v$$

A mixed autoregressive spatial model is simply a spatial error model with a spatially lagged dependent variable. However, it is common practice to run a mixed model (Eq. 6) which incorporates a spatially lagged dependent variable and an autoregressive parameter in the error term.

Eq. (6)

$$y = \lambda W y + X\beta + u$$
$$u = \rho W u + v$$

Thus, a mixed spatial model would be estimated using Equation 7:

Eq. (7)

$$\%\Delta Pop_{90to10i} = \beta_0 + \rho W \%\Delta Pop_{90to10i} + \beta_1 lnpopden_{90i} + \beta_2 newwest_{90i} + \beta_3 amenity_i + \beta_4 climate_{89i} + \beta_5 remoteness_i + \beta_6 states_i + \varepsilon_i, \quad where\ \varepsilon_i = \lambda W \varepsilon + \mu$$

Ideally, I would have estimated the spatial models of equations 2 and 3 to reveal how impacts of explanatory variables differ in New West versus Old West census tracts. However, I was unable to run spatial models with interaction terms in Stata and while I could run the spatial models with interaction terms in R, I was unable to estimate the marginal effects. Additionally, I was not able to calculate the Moran's I for the inverse distance spatial models as the Stata spatial package did not have this option. Table 11 reports the results for spatial autocorrelation and goodness of fit of the four models discussed above. In all three spatial models the Moran's test shows that the residuals area spatially independent. This suggests that the spatial models sufficiently accounted for the spatial autocorrelation. While I could not run a Moran's test for the OLS models, I used robust standard errors and found that the standard errors and t-statistic improved. The Akaike Information Criteria is a measure of goodness of fit and often used to compare model performance. A lower AIC is associated with a better fit model and I find that the AIC scores are similar. While the spatial models tend to have lower AIC scores, I use a cross-sectional OLS regression with interaction terms to estimate the marginal effects of the primary explanatory variables. Specifically, I am interested in the marginal effects of the interaction terms to identify if the drivers of population growth have different impacts in New West versus Old West census tracts. I was not able to calculate the marginal effects of the interaction terms of the spatial models due to limitations of Stata and R. However, I could calculate the marginal effects of the interaction terms using an OLS regression and the AIC scores of the OLS regressions are not substantially different from the AIC scores of the other models. As such, I used the OLS equations, 1 and 2, to estimate the models using robust standard errors and state dummy variables to account for time-invariant unobserved state characteristics.

Table 11: Testing for Spatial Autocorrelation and Goodness of Fit.

Model		Equation	Queen Contiguity		Rook Contiguity		Inverse Distance	No Weight Matrix
			Moran's-I	AIC	Moran's-I	AIC	AIC	AIC
OLS	Indices	1	n/a	n/a	n/a	n/a	n/a	1496.58
	Binary NW Interaction	2	n/a	n/a	n/a	n/a	n/a	1489.01
	Four-level NW Interaction	3	n/a	n/a	n/a	n/a	n/a	1484.41
SAR	Indices	1	-0.0131	1462.1	-0.0154	1455.8	1453.41	n/a
	Binary NW Interaction	2	-0.1113	1464.6	-0.0144	1458.6	n/a	n/a
	Four-level NW Interaction	3	-0.0133	1462.8	-0.0162	1456.8	n/a	n/a
SEM	Indices	1	-0.0070	1485.3	-0.0071	1482.2	1422.25	n/a
	Binary NW Interaction	2	-0.0064	1486.2	-0.0065	1484.2	n/a	n/a
	Four-level NW Interaction	3	-0.0069	1485.8	-0.0070	1483.4	n/a	n/a
Mixed	Indices	1	-0.0036	1473.8	-0.0036	1467.5	1423.92	n/a
	Binary NW Interaction	2	-0.0051	1485.0	-0.0055	1480.1	n/a	n/a
	Four-level NW Interaction	3	-0.0063	1481.7	-0.0069	1478.5	n/a	n/a

7 RESULTS

Table 12 reports the percent change in population from 1990-2010 by New West category. The median percent change in population is positive for all four categories of the New West indicator with the median percent change of Model New West more than twice as large as Classic Old West. Rural census tracts in the study area overwhelmingly experience growth with 96% of New West tracts and 90% of Old West tracts experiencing increases in population. This supports previous research identifying a trend in rural population growth in the West (Dearien et al. 2005; Deller et al. 2001; Rickman and Rickman 2011). However, New West census tracts are growing at a faster rate than Old West census tracts.

Table 12: Summary Statistics of Dependent Variable by New West Indicator.

% Change Population (1990-2010)	Obs.	Median	Std. Dev.	Min	Max
Classic Old West	380	0.20	0.33	-0.29	2.61
Old West	526	0.31	0.41	-1.61	2.55
New West	229	0.45	0.62	-1.53	4.11
Model New West	378	0.51	0.70	-2.21	5.93

Table 13 presents estimation results for all four models using equation 1. The sign and significance of remoteness, a traditional driver of population change, is negative and statistically significant at the one percent level across all four models. As expected, an increase in the average cost distance, in minutes, to urban centers and transportation links is associated with slower rates of population growth from 1990-2010. The sign and significance of initial population density in 1990 is also negative and statistically significant at the one percent level in all four models. Thus, census tracts with higher initial population density experience lower rates of agglomeration.

Table 13: Regression of Indices and Natural Amenity Variables (OLS is the preferred model).

Dep Var: Log Population Change: 1990-2010	**OLS** (1)	**SAR** (2)	**SEM** (3)	**MIX** (4)
Initial Pop Density: 1990	-0.48463***	-0.44964***	-0.45590***	-0.44985***
	(0.03916)	(0.01772)	(0.01749)	(0.01751)
NPS	0.02949	0.05241***	0.05189**	0.05223***
	(0.02552)	(0.01763)	(0.02227)	(0.02010)
Public Land	0.01136	0.00152	0.01857	0.01139
	(0.01754)	(0.01244)	(0.01330)	(0.01293)
Waterbody	-0.01639	-0.02026	-0.01686	-0.02248
	(0.02535)	(0.02289)	(0.02447)	(0.02357)
Ski resort	0.02049	0.02525	-0.00518	-0.00074
	(0.02086)	(0.01952)	(0.02296)	(0.02128)
Forest complexity	0.00257**	0.00214**	0.00371***	0.00299***
	(0.00104)	(0.00097)	(0.00113)	(0.00105)
Topographic complexity	-0.00001***	-0.00001**	-0.00001***	-0.00001***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Pacific Coast	0.02534*	-0.00433	0.05007**	0.03465*
	(0.01483)	(0.01563)	(0.02275)	(0.01994)
Climate	-0.08449***	-0.08219***	-0.08021***	-0.08435***
	(0.02141)	(0.02113)	(0.02471)	(0.02267)
Remoteness	-0.14651***	-0.09239***	-0.12950***	-0.09666***
	(0.02839)	(0.02784)	(0.02957)	(0.02896)
New West Factor	0.10335***	0.08384***	0.08539***	0.07652***
	(0.01857)	(0.01454)	(0.01597)	(0.01522)
Washington	-0.02968	-0.08246	-0.02618	-0.04127
	(0.07481)	(0.06097)	(0.08623)	(0.07208)
Oregon	-0.07886	-0.12258**	-0.14492*	-0.12830*
	(0.07822)	(0.06127)	(0.08647)	(0.07245)
Idaho	0.07517	0.01402	0.00285	0.01487
	(0.08163)	(0.06134)	(0.08038)	(0.06922)
Montana	-0.00813	-0.02033	-0.03336	-0.00537
	(0.08152)	(0.06528)	(0.08585)	(0.07382)
Wyoming	-0.12647	-0.14846*	-0.07820	-0.07196
	(0.09131)	(0.07916)	(0.09397)	(0.08574)
Colorado	-0.10165	-0.07880	-0.07539	-0.05155
	(0.08539)	(0.06317)	(0.08375)	(0.07158)
Observations	1513	1513	1513	1513
R2	0.47			

Standard errors in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

The coefficient of the climate factor is negative and statistically significant at the one percent level. Thus, census tracts with drier, more extreme temperatures experience higher rates of population growth than warmer, more wet census tracts.

Proximity to the Pacific Coast is positive and statistically significant in all but one model, the SAR model. Positive coefficients for proximity to the Pacific Coast indicate that closer proximity to the Pacific Coast is associated with higher rates of population growth from 1990-2010. This is consistent with the findings of Rapapport and Sachs (2003). Though not statistically significant, the coefficients on the average distance to a waterbody greater than $1km^2$ maintains the expected sign in all four models. That is, an increase in the cost distance to a water body is associated with slower rates of population growth from 1990-2010.

While other studies have found that topographic complexity is associated with an increase in population migration (Deller et al 2001, McGranahan 1999), I find that the coefficients measuring average topographic complexity of a census tract is statistically significant and negative in all four models. Though inmigrants prefer areas with a complex and varied landscape, very high levels of topographic complexity represent steep, mountainous areas which prohibit development, thereby limiting inmigration to these areas. Thus, these negative coefficients likely represent geographic constraints.

The coefficients for average cost distance from public lands are counter-intuitive. An abundance of empirical evidence exists that suggests public land is a significant driver of population change (Deller et al 2001). Yet, I find that the coefficients for the average cost distance to a public land are positive and statistically insignificant in all four models. This suggests that as the cost distance, in minutes, to public lands increase, population is expected to increase. A lack of significance may be explained by the abundance of public land in the study area. Roughly 60% of the study area comprises public lands, potentially diminishing the importance of public lands on an individual’s natural amenity preferences.

The coefficients for the average cost distance to a National Park are positive and statistically significant for all models, except OLS. Thus, it is expected that census tracts with higher average cost distances, in minutes, to a National Park will experience high rates of population growth from 1990-2010. These results run counter to other findings in the literature (Deller et al 2001, Rasker and Hansen, 2000). It is possible that areas adjacent to National Parks are more likely to have policies in place that restrict development. So, the National Park variable may be correlated with an omitted variable, like a zoning policy regulating development.

The coefficients of average forest complexity for a census tract are positive and statistically significant in all four models. An increase in the average level of forest complexity is associated with higher rates of population growth from 1990-2010. These results are consistent with other empirical findings (McGranahan 1999).

The coefficients for Euclidean distance to a ski resort are inconsistent and statistically insignificant. Positive coefficients, in the OLS and SAR models, suggest that census tracts near ski resorts will experience slower population growth while negative coefficients, in the SEM and Mixed models, suggest that census tracts far from ski resorts will experience faster rates of population growth. The former results run counter to the findings of Deller et al. (2001). However, Deller et al. use principal component analysis to create a "winter" index which includes "acres of mountains", "acres of forestland", "acres of Federal land", and the ski resort variable, which is measured as skiable acreage. Thus, it is possible that these conflicting results are a result of methodology and measurement. Measuring distance to ski resorts as cost distance rather than Euclidean distance may change the coefficients of the ski resort variable. It is also possible that ski resorts are correlated with things that restrict development, like steep terrain.

The coefficients for the New West factor variable are positive and highly statistically significant at the one percent level in all four models. Thus, higher New West factor scores are associated with faster rates of population growth in 1990-2010. These results support existing empirical evidence that New West census tracts experience faster population growth than Old West census tracts (Winkler et al 2007, Rudzitis 1999, Shumway and Ottterstrom 2001).

The preceding four models provide basic insight of population growth in the rural mountainous northwest. Exploring how results vary by New West and Old West census tracts provides a more nuanced understanding how drivers of population growth in rural areas may vary.

Table 14 reports the marginal effects of each of the explanatory variables from a model using an interaction between a binary New West variable and these explanatory variables. Table 15 reports the marginal effects from a model interacting a four-level New West indicator variable with the explanatory variables.

The binary New West model finds that the effect of remoteness is twice as strong in Old West census tracts than New West census tracts. The effect is negative and statistically significant with remoteness being associated with a .20% and .07% decrease in the rate of population growth from 1990-2010 in Old West and New West census tracts respectively. The four-level New West model reveals a more nuanced impact of remoteness on population growth. Remoteness is negative and statistically significant in Classic Old West, Old West, and New West census tracts. Interestingly, the magnitude of the effect increases as a census tract moves towards Classic Old West, having no statistical impact in Model New West census tracts. This suggests that individuals moving to Model New West census tracts do not prioritize access to urban areas.

The marginal effects of climate are negative and statistically significant in both New West and Old West census tracts. These results suggest that census tracts with drier, more volatile temperatures experience faster rates of growth than census tracts with more moderate and wet climates, regardless of the New West factor score.

The coefficients measuring the average cost distance, in minutes, to the Pacific Coast are positive for all Pacific Coast and New West categories. The binary New West model finds that proximity to the Pacific Coast has a greater effect in New West census tracts when census tracts are 166 to 370 minutes from the coast (Pacific Coast =3) relative to census tracts that are greater than 22,821 minutes from the Pacific Coast (Pacific Coast=0). The four-level New West model finds the strongest effects in this category as well, with the greatest statistical significance in New West census tracts and no significance in Classic Old West census tracts. Proximity to the Pacific Coast of less than 166 minutes is statistically significant for New West census tracts and nearly significant in Old West census tracts, relative to census tracts that are greater than 22,821 minutes from the Pacific Coast. It is possible that Pacific Coast category 3 outperforms category 4 because there is a significant amount of public land along coastal areas, prohibiting development. Thus, it appears that Old West, New West, and Model New West census tracts with an average cost distance of 166-370 minutes, relative to average cost distance greater than 22,821 minutes, experience faster rates of population growth. For census tracts very distant from the coast (746-22,821 minutes), relative to census tracts greater than 22,821 minutes from the coast, the binary New West model finds the coefficient is only statistically significant in Old West census tracts. However, the four-level New West model reveals that the coefficients of very distant census tracts are positive and statistically significant for Old West and New West census tracts, while being nearly significant for Classic Old West census tracts.

The coefficients for average cost distance to a waterbody of 1km^2 behave as expected. That is, in the four-level New West model, the coefficients for New West and Model New West census tracts are negative and statistically significant for Model New West census tracts and nearly significant for New West census tracts. The coefficients are positive for Old West and Classic Old West census tracts while only statistically significant for Classic Old West census tracts.

Thus, Classic Old West census tracts experience faster rates of population growth as the average cost distance to a waterbody increases. A decrease in the average cost distance to a waterbody is associated with faster rates of population growth in Model New West census tracts.

The coefficients for average topographic complexity are negative in both models and for all New West categories while distance to ski resorts was statistically insignificant. Topographic complexity is only statistically significant in the four-level New West model for Old West census tracts. As mentioned before, it is likely that these negative coefficients represent areas that are not conducive to development or timber harvesting while the ski resort variable may be capturing uninhabitable areas with very steep terrain.

The coefficients for average cost distance to public lands is statistically insignificant in both models and for all New West categories. It may that the abundance of public land, roughly 60%, in the study area diminishes the effect of public lands on population change. Distance to a National Park is positive for both models but only statistically significant in Old West census tracts. A 1% increase in the distance to a National Park is associated with a .05% point increase in population change in Old West census tracts. The uniqueness of this study area, which is roughly 60% percent public land and contains eight unique National Parks, may attract a very specific type of migrant to New West areas that the model is not capturing.

Forest complexity has a positive and statistically significant impact on population change in Old West tracts, with the largest impact on Classic Old West tracts. Forest complexity is not statistically significant for New West or Model New West tracts in either model. The strong effects of forest complexity in Classic Old West and Old West tracts may result from historical or current dependence on natural resource extractive industries, like timber harvesting. Thus, Old West tracts may be more likely to be located near forests relative to New West tracts. Additionally, it may be the case that an abundance of public land results in massive swaths of forests rather than complex compositions of forests (e.g. forests mixed with grasslands).

These results demonstrate that natural amenities impact population change differently in New West versus Old West census tracts. Specifically, proximity to waterbodies and the Pacific Coast are important drivers of population growth in New West census tracts while increased forest complexity and distance to a National Park were important drivers of population change in Old West census tracts. An increase in remoteness significantly decreased population growth rates in Old West tracts but was less significant in New West census tracts. Thus, it appears the impact of natural amenities on population growth do vary in the presence of different demographic and cultural mixes which distinguish New West and Old West areas.

Table 14: Marginal effects of the explanatory variables when interacted with a binary New West variable.

Dep Var: Pop Change 1990-2010 (log) (500 Robust)						
	dy/dx	Std. Err.	t	P>|t|	[95% Conf. Interval]	
NPS						
nw_tract						
0	.0443849	.0185412	2.39	0.017	.008015	.0807548
1	.055641	.0502362	1.11	0.268	-.0429007	.1541827
Public Land						
nw_tract						
0	.0102633	.0173451	0.59	0.554	-.0237602	.0442869
1	.0191929	.0280266	0.68	0.494	-.0357831	.074169
Waterbody						
nw_tract						
0	.0287961	.0283414	1.02	0.310	-.0267975	.0843897
1	-.0881462	.0437493	-2.01	0.044	-.1739634	-.0023291
Ski Resort						
nw_tract						
0	.0163666	.025837	0.63	0.527	-.0343144	.0670476
1	-.0373848	.0318862	-1.17	0.241	-.0999317	.0251621
Forest Complexity						
nw_tract						
0	.0051542	.001039	4.96	0.000	.0031161	.0071923
1	-.0024869	.0022138	-1.12	0.261	-.0068294	.0018556
Topographic Complexity						
nw_tract						
0	-6.82e-06	4.41e-06	-1.55	0.122	-.0000155	1.83e-06
1	-9.91e-06	7.89e-06	-1.26	0.209	-.0000254	5.56e-06

Pacific Coast (1: far)

nw_tract						
0	.1520519	.0618725	2.46	0.014	.0306848	.2734189
1	.1850955	.1325547	1.40	0.163	-.0749196	.4451106

Pacific Coast (2)

nw_tract						
0	.0553729	.049173	1.13	0.260	-.0410833	.1518292
1	.0576237	.0619671	0.93	0.353	-.0639291	.1791764

Pacific Coast (3)

nw_tract						
0	.1679595	.0632091	2.66	0.008	.0439705	.2919485
1	.3344343	.10018	3.34	0.001	.1379244	.5309442

Pacific Coast (4:close)

nw_tract						
0	.1125844	.0808622	1.39	0.164	-.0460323	.2712012
1	.1876108	.1068662	1.76	0.079	-.0220145	.3972362

Climate

nw_tract						
0	-.0895047	.0327699	-2.73	0.006	-.153785	-.0252244
1	-.1033876	.0406532	-2.54	0.011	-.1831315	-.0236436

Remoteness

nw_tract						
0	-.2035375	.0362599	-5.61	0.000	-.2746638	-.1324113
1	-.071769	.0460461	-1.56	0.119	-.1620916	.0185537

Table 15: Marginal effects of the explanatory variables when interacted with a 4-level New West variable.

Dep Var: Pop Change 1990-2010 (log) (500 Robust)						
	dy/dx	Std. Err.	t	P>|t|	[95% Conf. Interval]	
NPS						
nw_indicator_90						
0	.0408705	.024411	1.67	0.094	-.0070134	.0887544
1	.047423	.0192994	2.46	0.014	.0095659	.08528
2	.0539754	.0363594	1.48	0.138	-.0173461	.1252969
3	.0605279	.0586901	1.03	0.303	-.0545967	.1756524
Public Land						
nw_indicator_90						
0	-.0025496	.020932	-0.12	0.903	-.0436092	.03851
1	.0088788	.0154568	0.57	0.566	-.0214407	.0391983
2	.0203072	.0206836	0.98	0.326	-.0202651	.0608794
3	.0317355	.0316993	1.00	0.317	-.0304448	.0939159
Waterbody						
nw_indicator_90						
0	.0782783	.0369692	2.12	0.034	.0057608	.1507959
1	.0117556	.0241115	0.49	0.626	-.0355407	.059052
2	-.0547671	.0294789	-1.86	0.063	-.112592	.0030578
3	-.1212898	.0472191	-2.57	0.010	-.2139134	-.0286663
Ski Resort						
nw_indicator_90						
0	.0472038	.032546	1.45	0.147	-.0166374	.111045
1	.017829	.0223417	0.80	0.425	-.0259958	.0616537
2	-.0115459	.0224689	-0.51	0.607	-.0556201	.0325284
3	-.0409207	.0328077	-1.25	0.212	-.1052752	.0234338
Forest Complexity						
nw_indicator_90						
0	.0053639	.0013212	4.06	0.000	.0027723	.0079556
1	.0028806	.0009794	2.94	0.003	.0009594	.0048017

2	.0003972	.0015261	0.26	0.795	-.0025964	.0033908
3	-.0020862	.0024198	-0.86	0.389	-.0068327	.0026604

Topographic Complexity

nw_indicator_90

0	-7.49e-06	5.52e-06	-1.36	0.175	-.0000183	3.35e-06
1	-8.04e-06	4.01e-06	-2.01	0.045	-.0000159	-1.77e-07
2	-8.58e-06	5.61e-06	-1.53	0.126	-.0000196	2.42e-06
3	-9.13e-06	8.76e-06	-1.04	0.298	-.0000263	8.06e-06

Pacific Coast (1:far)

nw_indicator_90

0	.1352878	.0684699	1.98	0.048	.0009794	.2695962
1	.1759568	.0627436	2.80	0.005	.0528809	.2990326
2	.2166257	.0986592	2.20	0.028	.0230989	.4101525
3	.2572947	.1485893	1.73	0.084	-.0341734	.5487627

Pacific Coast (2)

nw_indicator_90

0	.0675385	.0543039	1.24	0.214	-.0389824	.1740594
1	.0617199	.0431248	1.43	0.153	-.0228725	.1463122
2	.0559012	.0494831	1.13	0.259	-.0411633	.1529657
3	.0500826	.0686688	0.73	0.466	-.0846159	.1847811

Pacific Coast (3)

nw_indicator_90

0	.1137279	.0780222	1.46	0.145	-.039318	.2667738
1	.2089547	.0546868	3.82	0.000	.1016828	.3162266
2	.3041815	.0718169	4.24	0.000	.1633077	.4450553
3	.3994083	.1121987	3.56	0.000	.1793229	.6194936

Pacific Coast (4:close)

nw_indicator_90

0	.1095112	.1013485	1.08	0.280	-.0892908	.3083131
1	.1363611	.0696327	1.96	0.050	-.0002282	.2729504
2	.1632111	.078668	2.07	0.038	.0088984	.3175238

3	.190061	.1195464	1.59	0.112	-.0444374	.4245595
Climate						
nw_indicator_90						
0	-.093186	.0359251	-2.59	0.010	-.1636555	-.0227165
1	-.099779	.0269978	-3.70	0.000	-.1527371	-.046821
2	-.106372	.0332599	-3.20	0.001	-.1716136	-.0411305
3	-.1129651	.0492202	-2.30	0.022	-.2095139	-.0164163
Remoteness						
nw_indicator_90						
0	-.2507807	.0453477	-5.53	0.000	-.3397333	-.1618281
1	-.1728758	.0299333	-5.78	0.000	-.2315921	-.1141596
2	-.094971	.0328765	-2.89	0.004	-.1594605	-.0304815
3	-.0170661	.0510979	-0.33	0.738	-.1172982	.083166

8 Discussion

In the mountainous northwestern US, dry and more extreme climates and access to urban areas and transportation links drive population growth while public lands and topographic complexity deter growth. Overall, New West census tracts experienced higher rates of population growth than Old West census tracts.

Determinants of population growth in New West versus Old West census tracts do differ to some extent. Remoteness, a traditional driver of population change, was a very strong driver in Old West census tracts, suggesting that access to urban areas is particularly important to individuals in the Old West. Thus, it is reasonable to expect that remote Old West census tracts will experience slower rates of growth or even population decline. Interestingly, remoteness is statistically insignificant in Model New West tracts which suggests that access to urban areas is not be valued by migrants to these areas. This also suggests that, counter to traditional economic theory, even remote places may experience population growth. It appears that individuals drawn to Model New West areas are significantly different from not only individuals drawn to Old West area but perhaps even New West areas.

Proximity to waterbodies, the Pacific Coast, and ski resorts were more important in New West areas than Old West areas. Individuals in New West areas place a higher premium on access to these amenities for their recreational and scenic value relative to individuals in the Old West. However, forest complexity only drove population growth in Old West census tracts. Old West areas were historically dependent on natural resource extraction, like timber harvesting. It is possible the positive association between forest complexity and population growth in these areas is due to past dependence on forests for timber. Theoretically, inmigrants to New West tracts would be positive but it is possible that this study area lacks the type of forest complexity that New West migrants seek. This may be attributed to the abundance of public land which may preserve large swaths of forests rather than patches of forest and grassland. Again, it appears that migrants to New West and Old West areas have different natural amenity preferences driving population growth.

The study area contains two primary climate types: moderate climates in areas near the Pacific Coast and more extreme climates found east of the Cascade Mountains. Both New West and Old West census tracts in inland areas, which experience more volatile temperatures and tend to be dry, experienced higher rates of population growth than areas with more moderate climates. Migrants appear to be drawn to inland areas for the drier, warmer summer temperatures and low humidity.

The negative and statistically significant coefficients on public lands and National Parks run counter to the expected impact on population change. The initial study area was restricted to private land to capture the impacts of the explanatory variables on developable land, areas where people could live. New West tracts tend to be clustered around urban centers and near National Parks. As such, it is possible that this proximity to both urban centers and National Parks is confounding the impacts of National Parks on population growth.

These results suggest that traditional drivers of population growth, like access to markets and transportation links, are still important in Old West places while becoming less important in New West places. It may be that migrants to Model New West places represent a different type of rural rebound in that individuals are willing to forgo cultural amenities found in urban areas because they themselves are willing to generate these cultural amenities in more remote areas. This aligns with McGranahan and Wojan's (2007) research which suggests that the "creative class" are attracted to high-amenity areas that need not be metropolitan.

9 Conclusion

In the 1970s, the US experienced an unexpected turnaround in migration patterns as households began moving from urban to rural areas. In particular, rural areas rich in natural amenities and with amenable climates experienced rapid population growth (Dearien et al. 2005; Deller et al. 2001; Rickman and Rickman 2011). Relative to New West areas, Old West areas tend to have populations with lower incomes and lower educational attainment (Winkler et at. 2007). Old West areas tend to rely on extractive industry employment (e.g. mining or logging) or are areas that remain relatively undeveloped (Winkler et al. 2007). Winkler et al. (2007) characterize the New West as areas with relatively high employment in the arts, professional services, and tourism rather than extractive industries; income and education levels, prevalence of second home ownership, and relatively high median housing values.

The New West variable captures the variation impacts of location-specific natural amenities on population growth change given differences in the demographic and cultural compositions of those places. This research affirms that drivers of population growth in New West and Old West census tracts do differ. Using more accurate measures of cost-distance to natural amenities, I found that proximity to waterbodies, the coast, and ski resorts promote growth in New West areas while access to markets and forest complexity promote growth in Old West areas.

As incomes rise and employment becomes increasingly less location-dependent, households' mobility increases as do their preferences for natural amenities. Thus, identifying rural areas prone to experience rapid population growth is critical if communities wish to plan for such growth. New West areas may be interested in protecting the natural amenities drawing people to the area. This is of particular interest in mountainous areas where fragile ecosystems are sensitive to disturbances, like development. Additionally, Old West areas experiencing economic decline may be interested in understanding that natural amenities and cultural and demographic amenities are needed to rapidly increase population growth.

It is possible that other location-specific amenities are driving population growth in New West areas. For instance, some effort has been made to capture the uniqueness of an area by measuring ethnic diversity, the density of gay people, and even a "coolness" index (Florida 2002, Olfert and Partridge 2011). The inclusion of variables that capture these characteristics may improve the predictive power of my models and provide a more robust picture of what drives growth in these areas. Further research is required to understand the different drivers of population change so policy makers and land managers can anticipate and plan for future growth while protecting natural amenities that attract people to these areas.

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APPENDIX

Figure 13: Distribution of the Climate Index: Negative scores represent drier more extreme temperatures while positive scores represent more wet areas with moderate temperatures.

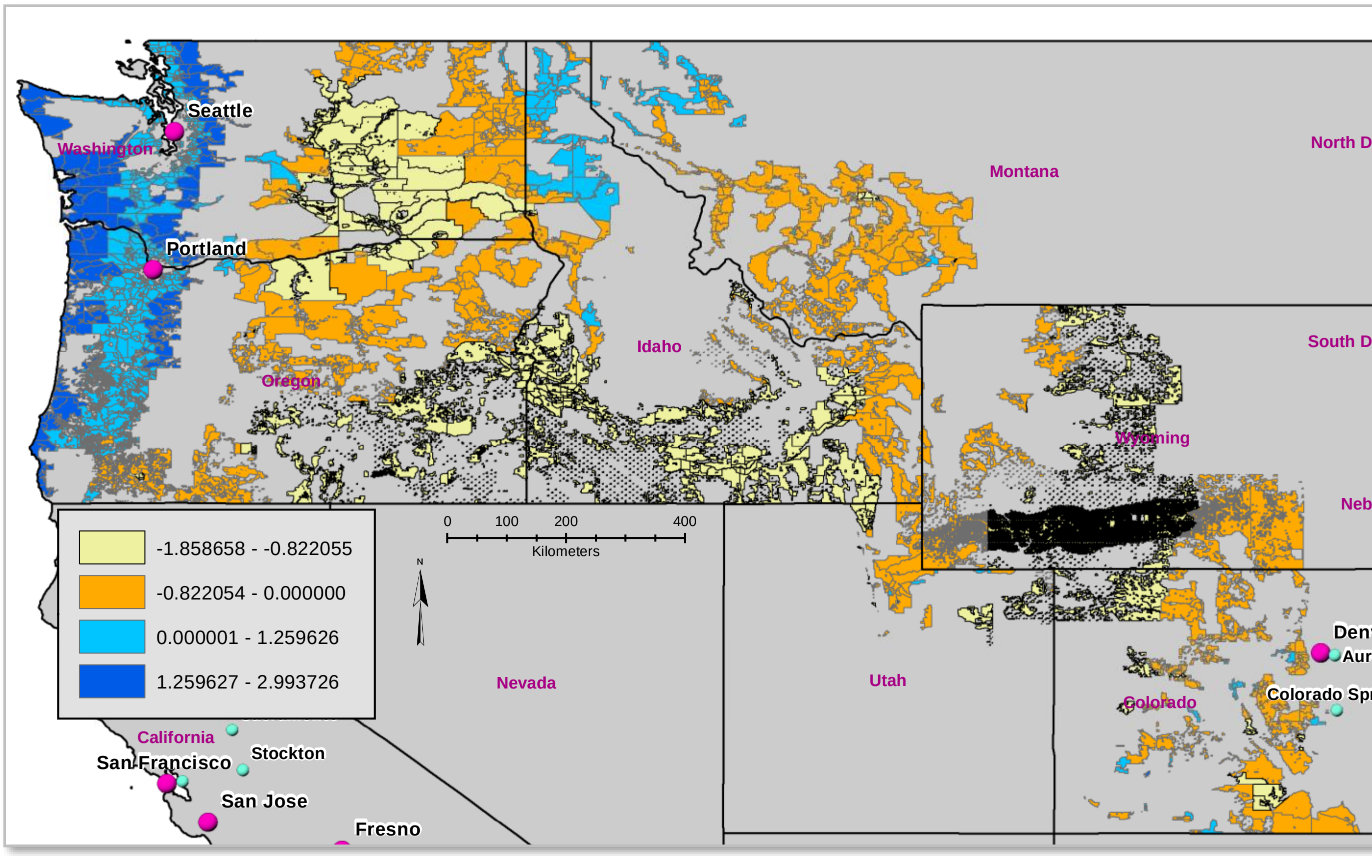

Figure 14: Distribution of Distance to Public Land in Minutes.

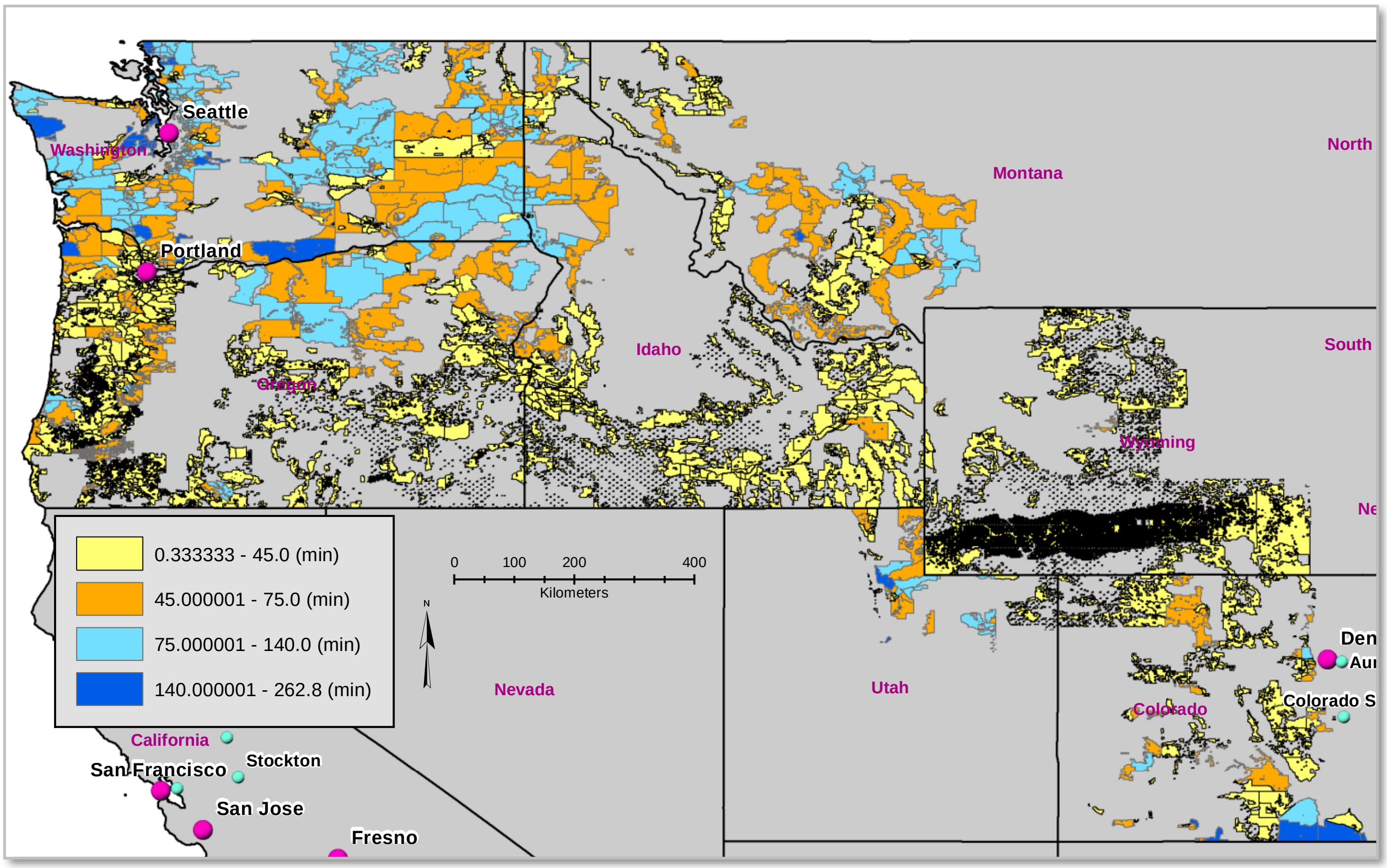

Figure 15: Distribution of Distance to National Parks in Minutes.

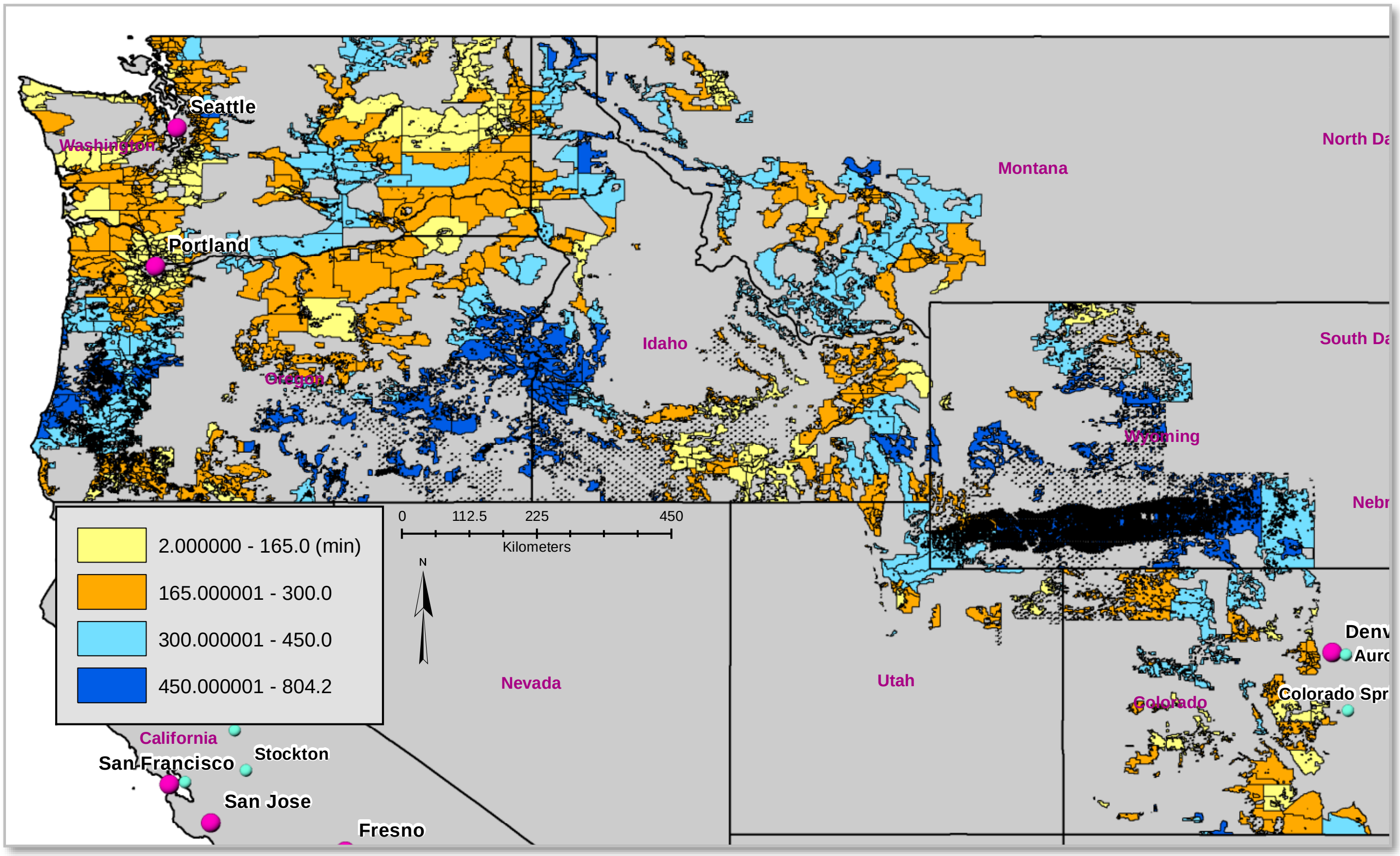

Figure 16: Distribution of Topographic Complexity: Higher values represent areas with greater topographic complexity.

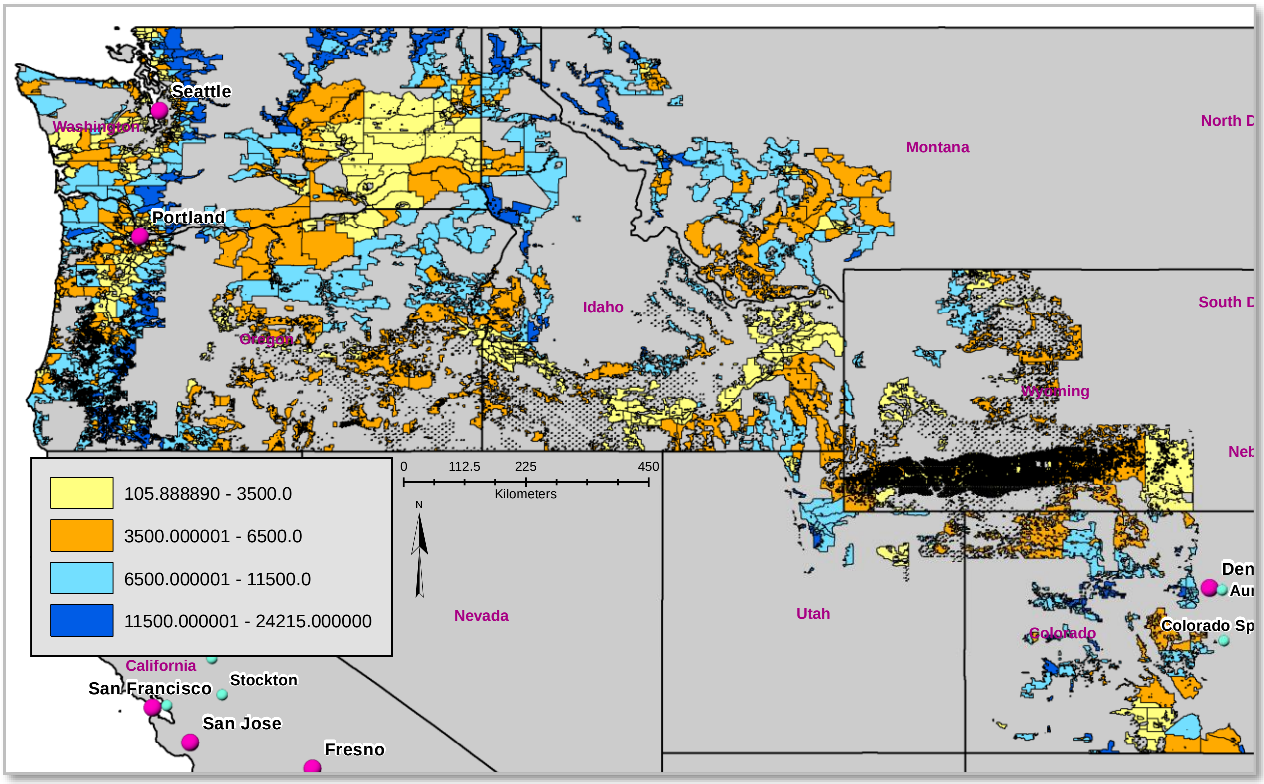

Figure 17 : Distribution of Forest Complexity: Higher values represent areas with greater forest complexity.

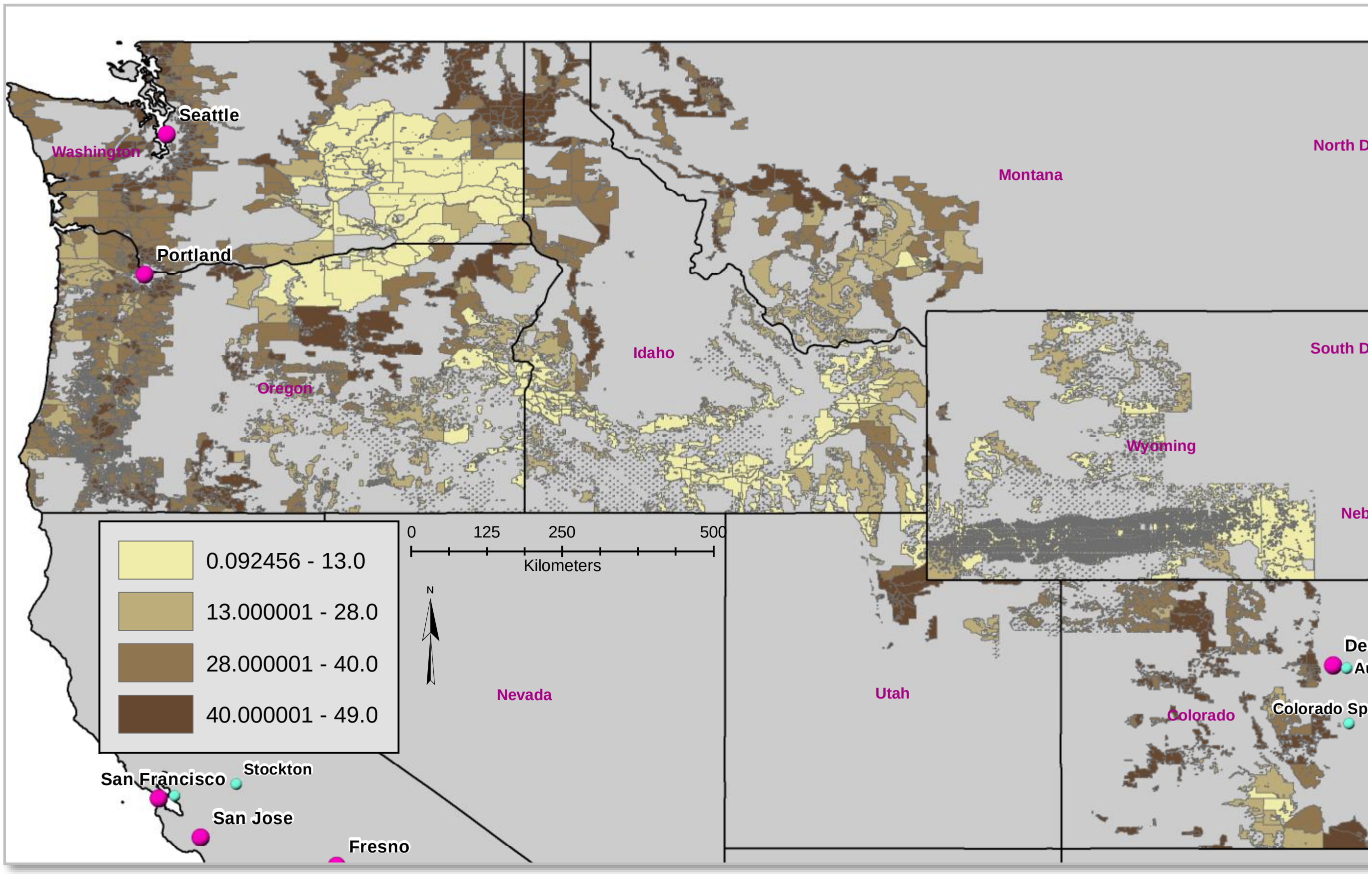

Figure 18: Distribution of Distance to Waterbodies.

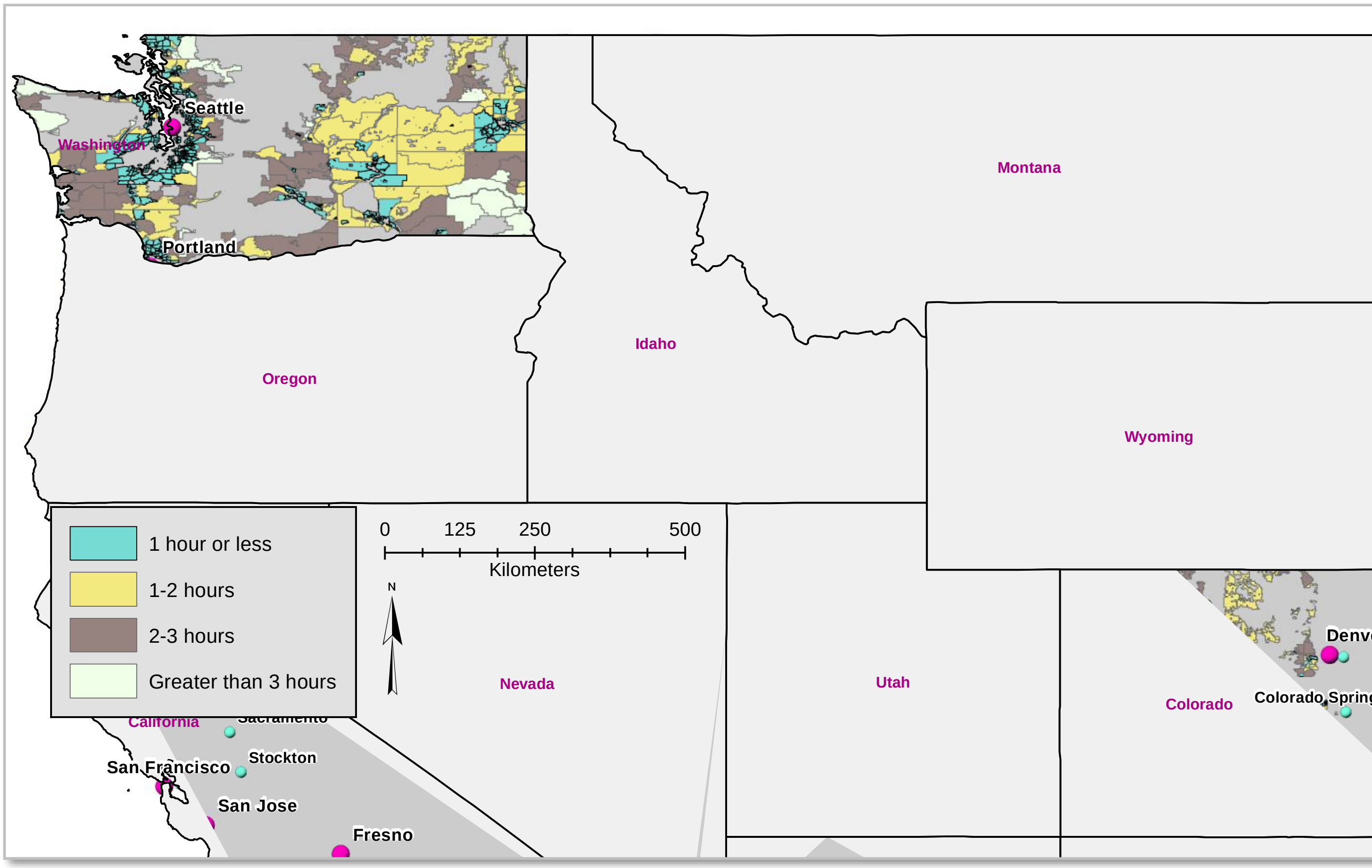

Figure 19: Euclidean Distance to a Ski Resort in Meters.

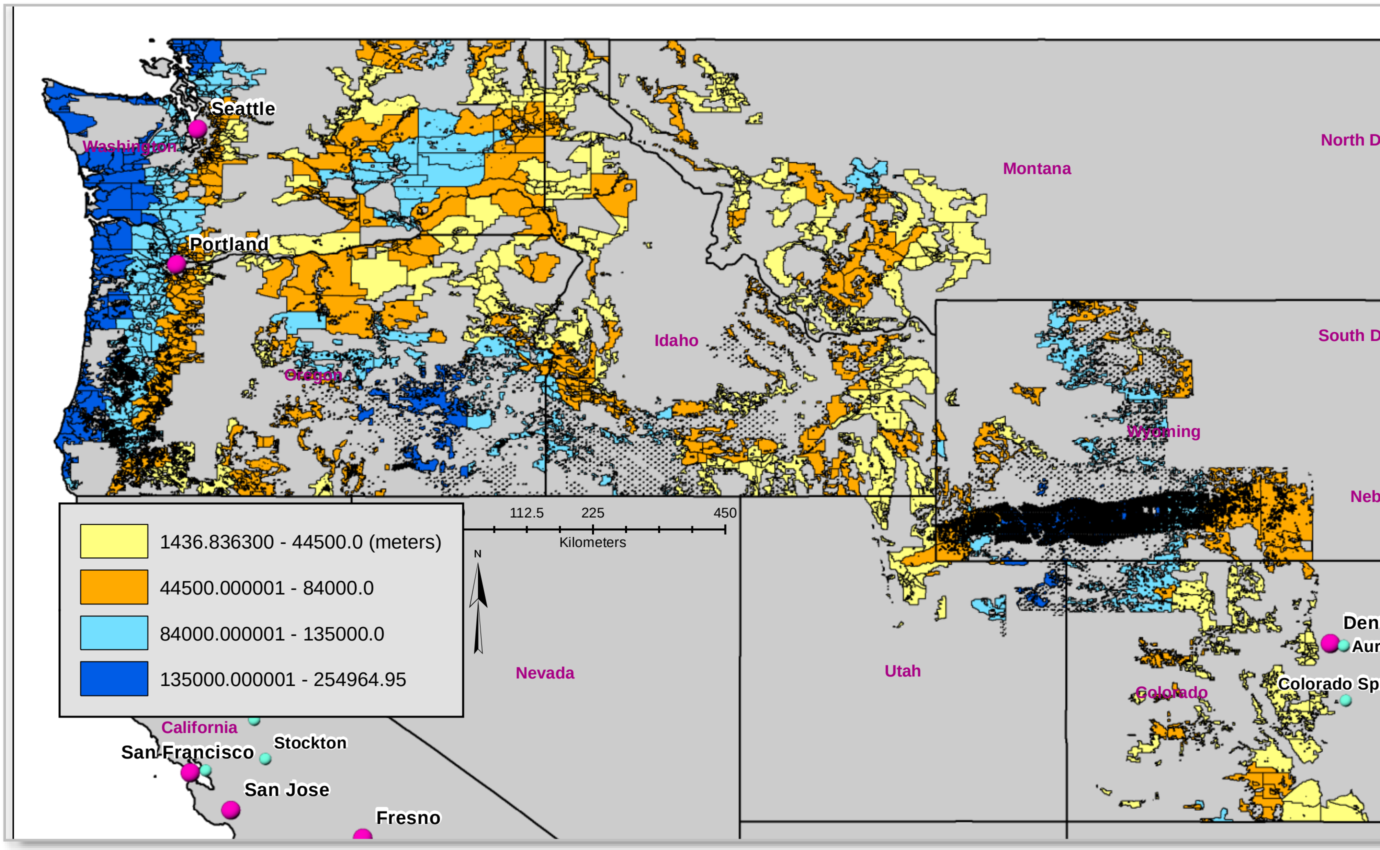

Figure 20: Distribution of the Four-Level New West Indicator Variable.

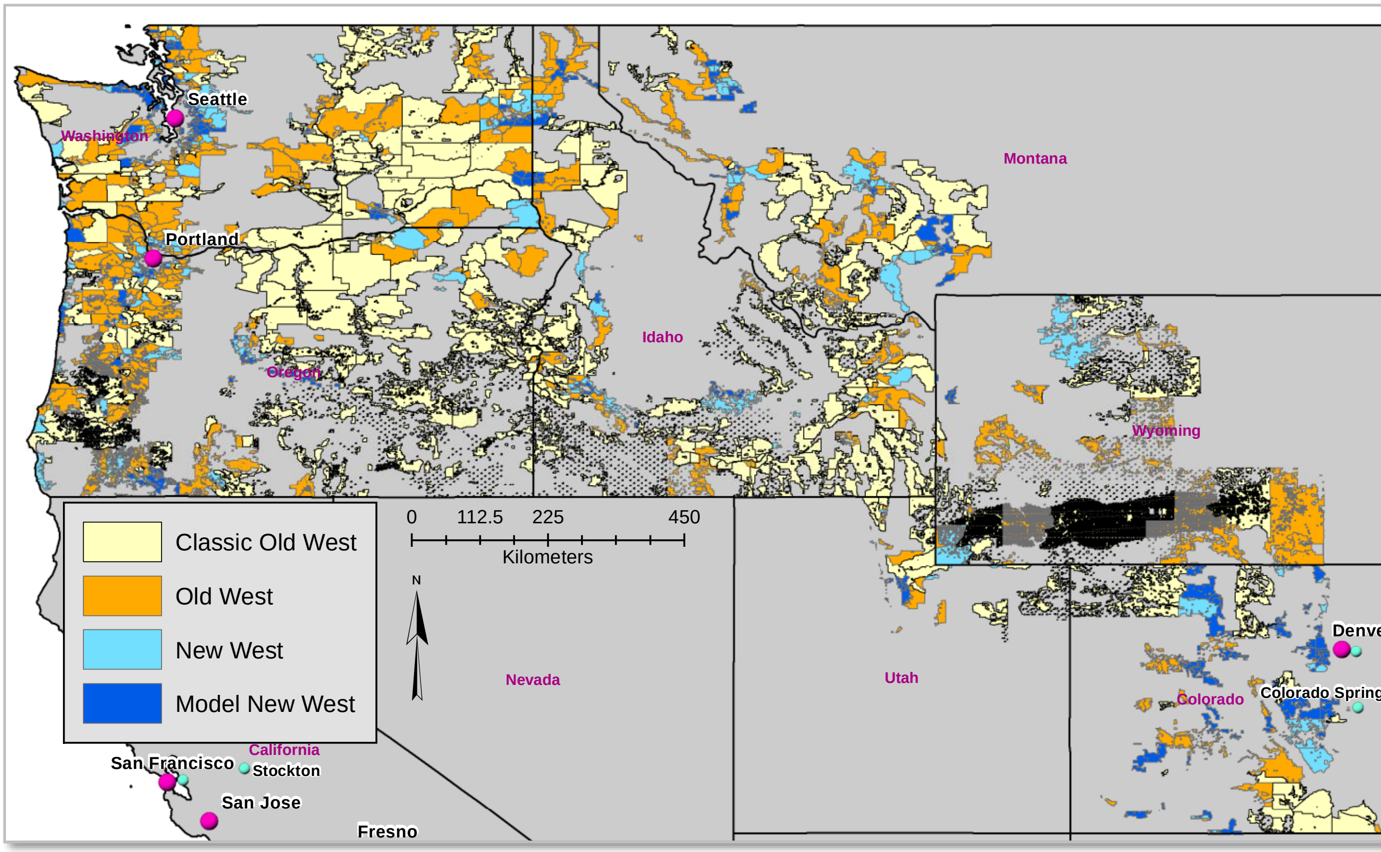

Figure 21: Distribution of the Remoteness Index: Higher values represent more remote areas.