Assessing Social Vulnerability to the Impacts of Climate Change on Forest Ecosystems: A Case Study of the Pacific Northwest

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Abstract

Climate change is expected to alter the composition and distribution of earth's forests. The impacts of these ecological changes will have many social consequences. The individuals and households that will be most affected will likely be those that derive value from forest resources. This thesis proposes a methodology for identifying human populations that may be differentially impacted by forest related climate changes with the use of a social vulnerability framework. Dynamic vegetation change models were used to quantify exposure to climate change related forest changes. Sensitivity and adaptive capacity were calculated using an indicator-based approach. The social (sensitivity and adaptive capacity) and biophysical (exposure) systems were related with a measure of economic forest dependence. The components were combined to produce a measure of vulnerability to forest related climate changes. The results of this assessment are useful for informing management decisions and the proposed methodology allows for the assessment of spatially indirect hazards.

Table of Contents

Authorization to Submit ii

Abstract iii

Table of Contents iv

List of Figures vi

List of Tables vii

1. Introduction 1

2. Background 2

 2.1 Vulnerability 2

 2.2 Vulnerability Assessments 4

 2.3 Climate Change 5

 2.4 Forest Change Vulnerability 7

 2.5 Forest Dependence 10

3. Research Goals/Questions 11

4. Study Area 11

5. Methods 13

 5.1 Exposure 14

 5.2 Sensitivity and Adaptive Capacity 17

 5.3 Forest Dependence 19

 5.4 Vulnerability 22

6. Results/Discussion 22

 6.1 Exposure 26

6.2 Sensitivity 27

6.3 Adaptive Capacity 28

6.4 Forest Dependence..29

6.5 Vulnerability..32

6.5.1 Mid-Century 32

6.5.2 End Century...34

7. Conclusions..35

References...37

Appendices 40

Appendix A: Average percent area occupied by primary and secondary vegetation for the historic, mid-century, and end-century MC2 models......................................40

Appendix B: Z-Scores of the aggregated social and economic data 43

List of Figures

Figure 1: Füssel and Klein's (2006) 2nd generation conceptual framework for assessing vulnerability to climate change 6

Figure 2: Williamson et al.'s (2007) list of key processes and systems affecting community vulnerability 9

Figure 3: Map of the study area, the states of Oregon and Washington.................................12

Figure 4: Conceptual model of social vulnerability to spatially indirect hazards 14

Figure 5: An example of the MC2 data 16

Figure 6: Maps of the z-scores for each vulnerability component 25

List of Tables

Table 1: List of climate models used in the MC2 model data 15

Table 2: Vegetation classes that are important to timber industries.......................................16

Table 3: List of the indicators used for the sensitivity and adaptive capacity analysis 18

Table 4: Industry names and NAICS codes for forest related industries 20

Table 5: The final z-scores for sensitivity, adaptive capacity, FLQ, exposure, and vulnerability 23

Table 6: Results of the factor analysis performed on the sensitivity indicators 27

Table 7: Results of the factor analysis performed on the adaptive capacity indicators..........28

Table 8: Employment in the timber industry reported by county...30

1. Introduction

The goods and services provided by forest ecosystems are essential for human well-being (Seppala, Buck, and Katila 2009). Forests provide humans with direct products such as timber, food, and fuel; and ecosystem services such as soil and water protection, biodiversity conservation, and tourism and recreation opportunities (Easterling and Apps 2005; Kirilenko and Sedjo 2007; Pulhin et al. 2010; Devin et al. 2010; Wear and Joyce 2012). Aside from their importance to human well-being, forest goods and services comprise an integral part of the world economy. Nearly 450 million people in the world are entirely dependent on managed ecosystem services like forests (IPCC 2007). In the U.S. alone, direct forest products account for over $200 billion in sales annually and employ nearly 900,000 people (AFPA 2012).

Earth's forests are expected to undergo a number of changes as a result of global climate change (Easterling et al. 2007). Changing temperature and precipitation patterns are expected to alter the distribution and composition of Earth's forests (Pulhein et al. 2010). In general, tree species are expected to migrate towards the poles, and disease and wildfire will become more prevalent (Easterling et al. 2007; Kirilenko and Sedjo 2007). In the U.S. Northwest, these changes will manifest in the short term as an increased growth in high elevation forests west of the cascades, and as decreased forest growth in the long term (Karl, Melillo, and Peterson 2009). However, the changes in the composition, productivity, and distribution of forests, is more difficult to predict.

Even more difficult to predict, although perhaps more important, are the impacts of forest changes on the well-being of human communities and economies. The impact of forest changes on the U.S. economy as a whole would likely be minimal due to the diversity of the U.S. economy and the relatively low percentage of economic activity attributable to forest industries. However, small, rural communities with economies that are dependent on forest industries could be severely affected by changing forest resources (Williamson et al. 2007). In these communities, the loss of a sawmill, paper mill, or lumberyard may be catastrophic. Additionally, the impact of forest changes would be amplified in communities that possess underlying socioeconomic sensitivity to changes or stresses. For example, those that have a high rate of poverty or unemployment or that have low levels of education may be more sensitive to these stresses. Identifying the communities that are most at risk to forest change can be useful in understanding where the impacts of climate change may be experienced most significantly. With this understanding, policy and management decisions can be informed and can take into consideration the human impacts of forest related climate changes. In fact, the U.S. Forest Service has already identified the need to incorporate social vulnerability into its management practices (Lynn, MacKendrick, and Donoghue 2011). However, comprehensive assessments of community vulnerability to forest change are limited and few. There is a need for large-scale and quantitative vulnerability assessments that are specifically focused to identify social vulnerability to climate-change-induced forest changes.

2. Background

2.1 Vulnerability

The concept of vulnerability arose from risk, hazards, and disasters literature over 30 years ago (Gilbert 1995; Pelanda 1981). These pioneering researchers were the first to consider disaster risk as a product of both sociocultural risks and geophysical risks. Previously, geophysical risks alone were seen as the primary determinant of hazard risk. Considering the underlying social, cultural, and political components of risk was a major conceptual advancement in the hazards and risks literature and is the foundation of modern vulnerability research.

Current conceptualizations of social vulnerability express that the impact of a disturbance on a given individual or community is determined not only by the nature of the disturbance, but by a complex set of interacting geographic, household, social, and economic conditions (Cutter 2003; Fothergill 1996; Fothergill and Peek 2004; Morrow 1999; Wisner et al. 2004). Thus, social vulnerability is seen as an a priori condition of an individual or community. The expression of this condition is the result of the various social and political processes that shape both the built and cultural landscape. Yet, this condition at any given time is only one spatiotemporal expression of vulnerability. Therefore, vulnerability is a dynamic state of being, dictated by the existing patterns of inequality in social, political, and financial capital and influenced by the legacy of historical social marginalization and exploitation (Eakin and Luers, 2006).

To characterize the complex set of conditions affecting vulnerability, researchers have identified the following three vulnerability components: exposure, sensitivity, and adaptive capacity (Adger 2006; Cutter, Boruff, and Shirley 2003; Eakin and Luers 2006; McCarthy et al. 2001; Luers 2005; Turner et al. 2003). Exposure is the degree to which a system experiences a stress or disturbance. Typically, these disturbances are exogenous forces that have the potential to have an adverse effect on a system, such as floods, market fluctuations, or vegetation change (Luers 2005). The magnitude, frequency, duration, and areal extent of these disturbances characterize exposure intensity (Adger 2006). Sensitivity refers to the degree to which a system is affected or harmed by a disturbance, while adaptive capacity is the ability of the system to adjust and respond to the disturbance and increase its capacity to cope. The commonly accepted factors influencing sensitivity and adaptive capacity are access to resources and political power, social capital, beliefs and customs, and physical ability (Cutter 1996; Cutter, Boruff, and Shirley 2003; Tierney, Lindell, and Perry 2001). These concepts identify the ways in which vulnerability is differentially experienced based on the socioeconomic characteristics of an individual or community. By examining the impacts of exposure, sensitivity, and adaptive capacity as separate components of a system, researchers are able to better understand total vulnerability.

2.2 Vulnerability Assessments

Vulnerability assessments have gained popularity in the hazards field as a way of quantifying vulnerability to hazards. Susan Cutter's Social Vulnerability Index (SoVI) was one of the first comprehensive methodologies proposed for assessing vulnerability (Cutter, Boruff, and Shirley 2003). The SoVI model used an indicator-based approach to quantify vulnerability to environmental hazards. The indicators used in the SoVI model were chosen because they provide an estimate of the underlying social characteristics that predispose a population to be vulnerable. Factor analysis was performed in order to account for data redundancy and for indicator reduction. A county's vulnerability score was calculated as the sum of each indicator.

The SoVI model was an important advancement in vulnerability science, but it has a number of shortcomings. In the SoVI model, vulnerability is measured by assessing the social characteristics that predispose people groups to be affected by a hazard. In current conceptualizations of vulnerability, this predisposition of a people group refers to sensitivity. SoVI is therefore an index of sensitivity, not vulnerability. Secondly, using the county as a unit of analysis washes out local level variability in vulnerability. Hazard mitigation decisions often happen at the sub-county scale, so the utility of a county level analysis is limited. The final critique is not specific to SoVI, but to all indicator-based techniques. It is difficult to select indicators that accurately identify vulnerability when indicator selection is limited only to data that are readily available and easily aggregated. Many social characteristics that could identify vulnerability are either unavailable or impossible to measure for large-scale analyses.

There have been a number of advancements in indicator-based vulnerability assessments in the 12 years since SoVI was published. Wood, Burton, and Cutter (2010) have adapted SoVI to operate at the census block level, which has improved the precision and utility of the results. Frazier, Thompson, and Dezzani (2014) also assess vulnerability at the census block level with their Spatially Explicit Resilience-Vulnerability Model (SERV). The SERV model considers and measures the three components of vulnerability, exposure, sensitivity, and adaptive capacity, to produce a holistic measure of vulnerability. This holistic approach is able to capture the spatial variation of a hazard's impact and of the social characteristics of the affected community. These advancements have made significant improvements in the utility and efficacy of vulnerability assessments, yet their application beyond natural hazards is still limited.

2.3 Climate Change

Researchers of global environmental change (GEC) have adopted the vulnerability concept to study the impacts of climate change. Many GEC specific vulnerability frameworks have been proposed that are designed to capture the slow onset and indirect nature of climate change impacts (Füssell 2007; Füssell and Klein 2006; Heltberg, Siegel, and Jorgensen 2009; Ionescu et al. 2009; Luers 2005; Turner et al. 2003). While no one framework is universally accepted, nearly all agree that vulnerability is a function of exposure, sensitivity, and adaptive capacity.

Füssel and Klein's (2006) GEC vulnerability framework provides a clear and comprehensive outline for assessing vulnerability to climate change (Figure 1). The authors' framework, dubbed the 2nd generation vulnerability assessment, conceptualizes vulnerability as the combined effect of physical climate changes, sensitivity to climate changes, and adaptive capacity. An advantage of this framework is the explicit consideration non-climate factors, such as demographic, economic, and sociopolitical conditions in the sensitivity and adaptive capacity components. Overall, this framework provides an ample theoretical foundation for GEC vulnerability assessment, but the application of this theory is often difficult.

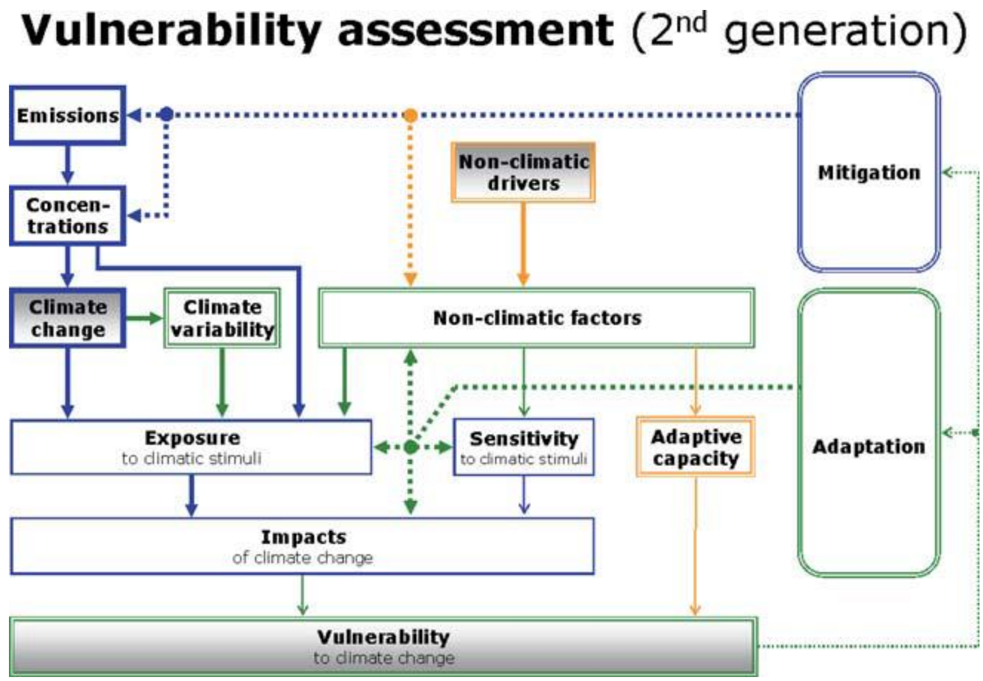

Figure 1: Füssel and Klein's (2006) 2nd generation conceptual framework for assessing vulnerability to climate change.

Other conceptual frameworks regarding vulnerability to climate change take a similar approach as Füssel and Klein (Füssel 2007; Heltberg, Siegel, and Jorgensen 2009; Ionescu et al. 2009). However, as Füssel and Klein (2006) state, the application of these frameworks to vulnerability assessments is "not yet commonplace, in absence of a clear methodology" (pp. 320). This is due partially to the long-term nature and inherent uncertainty of climate change, which makes assessing climate change impacts difficult. Additionally, forecasting climate variations and their impacts relies on assumptions about future human development and political policies, which are inherently uncertain, and the data needed to measure climate changes is often unavailable or unsophisticated (Füssel and Klein 2006; Klein and Nicholls 1999). Even when good climate change models are available, it is typically quite difficult to predict their impacts on humans. These issues are difficult to overcome and could be why so few practical assessments have been performed.

2.4 Forest Change Vulnerability

Climate change vulnerability frameworks outline the ways in which researchers can identify populations that are vulnerable to climate change in a general sense. These studies provide a theoretical foundation for climate change vulnerability assessments, but the applicable use of these frameworks is limited. Climate change will have many consequences, and the impact of these consequences on human populations is varied. Therefore, there is a need for methodologies and assessments that focus on specific climate change impacts.

Assessing vulnerability to forest change requires a different set of considerations than do hazard assessments. Forest changes are not inherently harmful. Therefore, researchers need to understand how forest changes relate with human communities. Forest harvests and human well-being has been researched by Charnley et al. (2008). The authors provides an interesting look at how changing forest harvest impact community well-being. The Northwest Forest Plan, an initiative to manage and limit where and how much timber is being harvested on National Forest lands, provided an opportunity for research on the economic and human impacts of decreased forest yields. Charnley et al. (2008) found that this artificial scarcity of forest resources negatively impacted the human communities that were near federal forest lands. The economic ability of these communities was minimized and employment opportunities were lessened. As a result, the communities suffered. Forests and human well-being are inherently linked. This is especially true for human populations that are situated in or near forest ecosystems. Considering this relationship is important when assessing social vulnerability to forest change.

Very few vulnerability frameworks have been proposed that specifically focus on forest change. One forest specific vulnerability framework has been proposed by a group of researchers with the Canadian Forest Service (Williamson et al., 2007). The authors' framework focuses on outlining a practical methodology for forest specific vulnerability assessments. It identifies the specific systems and processes affecting vulnerability to climate change and shows how each system is related (Figure 2). Many of the social and economic indicators identified by the authors have been borrowed from traditional social vulnerability frameworks, such as jobs, income, property, assets, and heath. However, some are specifically related to forest change, such as timber values, tourism, recreation, and environmental values. An added component of the Williamson et al. (2007) framework is the consideration of ecosystem composition characteristics and ecosystem processes that may affect forest-based communities, such as fire, insects, drought, productivity, and habitat change. This model therefore considers that the vulnerability of forest-based communities to climate change is determined by "exposure to climate, the sensitivity of the forest ecosystem and of the community's social and economic systems, various socioeconomic scenarios, global trends in the markets for forest products, and the community's adaptive capacity" (Williamson et al., 2007 pp. 6). Understanding the state of these components and the ways in which they interact can provide a comprehensive understanding of vulnerability to forest change. This methodology mark a critical step towards the application of vulnerability science in the forest disciplines.

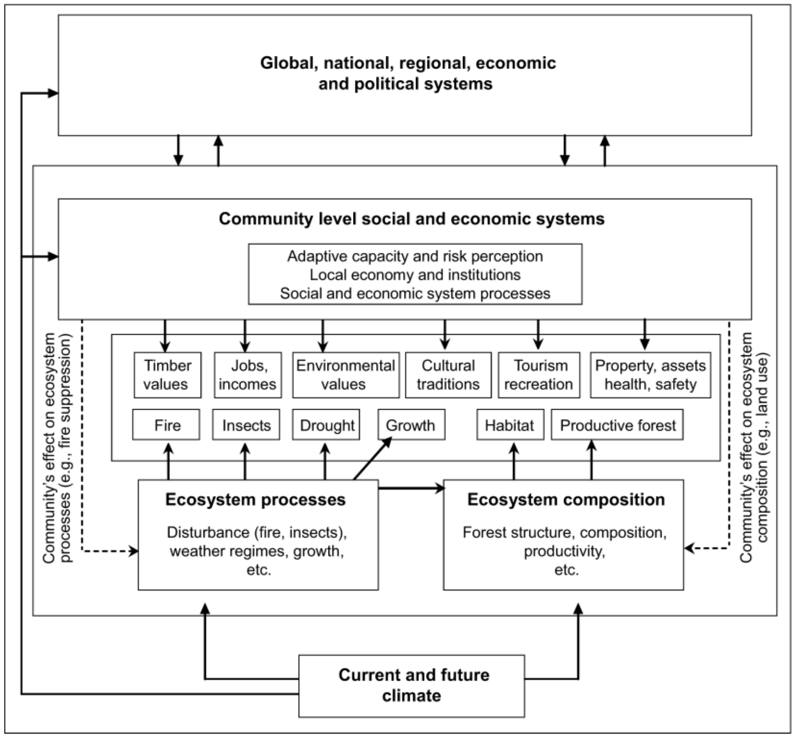

Figure 2: Williamson et al.'s (2007) list of key processes and systems affecting community vulnerability.

A step further was taken by Williamson et al. (2008) in a case study application of the Williamson et al. (2007) framework. This study aimed to assess the vulnerability of a forest-based community, Vanderhoof, Canada, to climate change. To do so, the researchers utilized a four-step process. First, climate change scenarios were developed for the area surrounding the case study community. Then, the impacts of these climate changes on forest productivity, forest composition, and wildfire risk were estimated. Next, these climate change impacts were related to the local economy and community well-being. Finally, an estimate of the combined impact of all the factors was produced. The resulting analysis is a good application of vulnerability concepts to forest related climate changes. The community level scale and qualitative approach of this study allows for a holistic and deep understanding of vulnerability in the case study community. However, it is unable to produce a total measure of vulnerability for the community or compare vulnerability among different regions and communities. Additionally, the qualitative nature of the vulnerability assessment is subject to errors from researcher bias and subjectivity in its interpretation. An improvement in the quantification of vulnerability to forest changes is necessary in order to understand how vulnerability varies across space. Yet, very few forest change vulnerability assessments have been performed that explicitly quantify variations in vulnerability over a large study area.

2.5 Forest Dependence

A necessary consideration of forest-specific vulnerability assessments is the degree to which a region or community is economically dependent on forest industries. In Williamson et al. (2007), the authors suggest the use of general equilibrium models for assessing the economic impact of changing forest resources. General equilibrium models are commonly used in economic impact assessments due to the readily available data and low cost of production. However, these models may be inappropriate for assessing long-term processes like climate change because their components are both spatially and temporally static. They therefore would fail to capture the dynamic nature of climate change.

Another approach to measuring forest industry dependence was proposed in a series of papers by Steadman et al. (Steadman, Parkins, and Beckley, 2004; Steadman, Parkins, and Beckley, 2005; Steadman, Patriquin, and Parkins, 2011). The authors measure forest industry dependence as the proportion of employees in the forest industries to the number of employees in all industries. The use of employment in these studies, as opposed to sales volume or income, allows for better measure of the number of individuals that are dependent on the forest industry, and is therefore a more direct bridge between forests and human communities. Additionally, employment data is readily available and the required calculations are straightforward and simple. These methods, however, are not sensitive to the potential cascading economic effects of changing resources, and, like many other economic measures, provide only one static measurement of forest dependence in time.

3. Research Goals/Questions

This research attempts to advance vulnerability science by developing a climate change specific methodology for vulnerability assessments. Hazard vulnerability models were modified in order to assess vulnerability to climate-change-induced forest changes in a way that explicitly relates the social and the biophysical systems. This relationship will be quantified by measuring the economic dependence of human populations on timber specific forest products. The methodology will then be tested in a case study region, the U.S. states of Oregon and Washington. It will identify regions in the study area that are highly vulnerable to changes in forest ecosystems and will answer the following questions:

1. What is the socioeconomic vulnerability of human populations to climate-change-induced forest changes within the study area?
2. How can vegetation change models and forest specific economic and social indicators be used to quantify exposure, sensitivity, and adaptive capacity to climate-change-induced forest changes?
3. Can social dependence on timber forest products be measured and used to relate the biophysical and social systems?

4. Study Area

The study area includes the U.S. states of Oregon and Washington (Figure 3). These states are geographically situated on a wealth of forest resources. In fact, over 45% of the land area in this region is covered by forests. There are 17 national forests within these states that manage and regulate these forests for timber production. Consequently, the forest industry in this region is diverse and widespread, and changes in the health and productivity of these forests will have significant impacts on the human population in the area. The majority of the population in these states exists within the ‘megacity’ region in the western parts of the states; an area stretching north from Bellevue, WA to Salem, OR. This ‘megacity’ includes the cities of Seattle, WA, Portland, OR, Tacoma, WA, and Olympia, WA. The eastern parts of these states show a stark contrast from their western counterparts in both social and physical characteristics. The western half is defined by high population, ethnic diversity, economic prosperity, and a cool, wet climate. The eastern half, on the other hand, is largely rural and Caucasian, is economically dependent on resource industries, and has a warmer dryer climate. The diversity of this study area will likely lead to significant east-west differences in the vulnerability assessment.

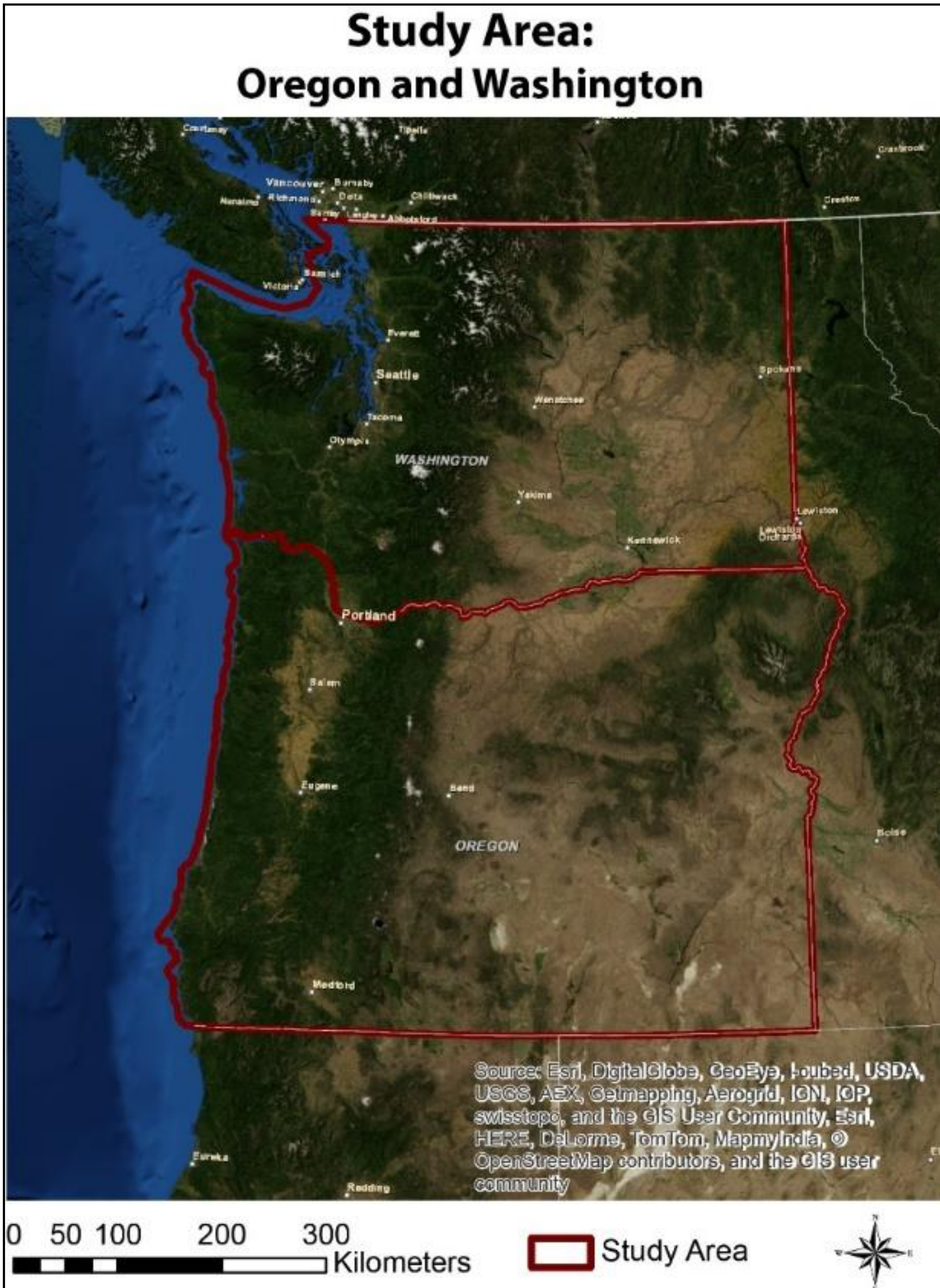

Figure 1: Map of the study area, the states of Oregon and Washington.

5. Methods

This research borrows the vulnerability assessment framework proposed by Frazier, Thompson, and Dezzani (2014). In this framework, vulnerability is measured as the combined effect of exposure, sensitivity, and adaptive capacity, where each component is measured separately and combined using the following equation:

$$\boldsymbol{Vulnerability = (Exposure + Sensitivity) - Adaptive\ Capacity.}$$

In the context of forest change, exposure refers to the degree to which climate change will alter timber related forest vegetation in a region, sensitivity refers to the degree to which changing forest vegetation will affect human communities in a region, and adaptive capacity refers to the degree to which human communities in a region are able to adapt to changing forest vegetation.

The Frazier, Thompson, and Dezzani (2014) framework was developed to assess vulnerability to hurricane induced storm surge. In the case of spatially direct hazards, like storm surge, exposure, sensitivity, and adaptive capacity can be assumed to be directly relatable within a given spatial unit. However, this assumption is not valid when assessing a spatially indirect hazard such as forest change. Changing forest composition has no clear impact on human communities without some understanding of how, or if, the community derives any value, economically or otherwise, from the forest. Introducing a measure of forest dependence into the model is necessary in order to relate the social components (sensitivity and adaptive capacity) with the biophysical (exposure) (Figure 4).

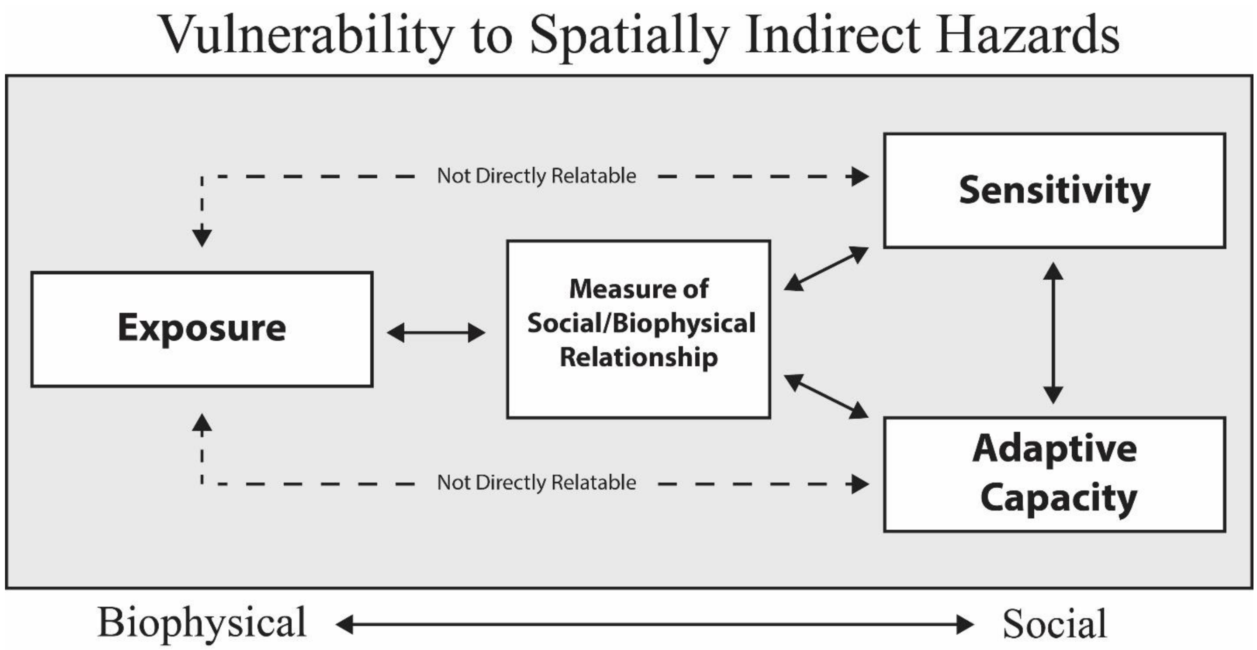

Figure 2: Conceptual model of social vulnerability to spatially indirect hazards. Arrows represent the interactions between vulnerability components.

A modified version of the Frazier, Thompson, and Dezzani (2014) vulnerability equation was used in order to account for human forest dependence. The modified equation is as follows:

$$\boldsymbol{Vulnerability = Forest\ Dependence + Exposure + Sensitivity - Adaptive\ Capacity.}$$

Where forest dependence is equal to some measure of human dependence on resources from forest ecosystems.

<u>5.1 Exposure</u>

In the context of this research, exposure refers to potential climate related changes in resources derived from forest ecosystems. This measure must therefore capture how timber vegetation is expected to change under various climate change scenarios. Dynamic vegetation models (DVM) provide just such a measure.

Dynamic vegetation models combine climate models, biogeography models, biogeochemistry models, and fire disturbance models to produce an estimation of dominant vegetation under future climate scenarios (Bachelet et al., 2001; Bachelet et al., 2011; Daly et al., 2000). They are useful in understanding the broad patterns of vegetation change. However, DVMs only provide an estimate of how conditions for dominant vegetation type may change under different climate scenarios, not how vegetation will actually be altered. Using DVMs for assessing how timber vegetation may change relies on the assumption that changes in climatic suitability for species may result in tree mortality and increased wildfire, insect, and disease risk. These impacts would then affect the productivity of forest ecosystems for resource extraction.

For this research, a recently updated DVM was used called MC2. The MC2 model was developed by Dominic Bachelet at the Conservation Biology Institute. It is a 4km resolution raster data set that represents modal vegetation under a suite of climate scenarios. Two MC2 data sets were obtained for each models listed in Table 1. One for the mid-century (2036-2065) and one for the end-century (2071-2100). A MC2 model derived from historic conditions was also obtained and used as a reference. All models were generated using the most extreme CO_2 emission scenario, representative concentration pathway 8.5. Figure 5 shows an example of the MC2 data.

Table 1:
List of climate models used in the MC2 model data. Two MC2 outputs were obtained for each of these models.

CanESM2	GFDL-ESM2M	HadGEM2-ES	MIROC-ESM	bcc-csm1-1
CCSM4	HadGEM2-CC365	IPSL-SM5A-MR	MRI-CGCM3	MIROC-ESM-CHEM
CNRM-CM5	HadGEM2-CC	IPSL-CM5B-LR	NorESM1-M	IPSL-SM5A-LR
CSIRO-Mk3-6-0	HadGEM2-ES365	MIROC5	bcc-csm1-1-m	GFDL-ESM2G

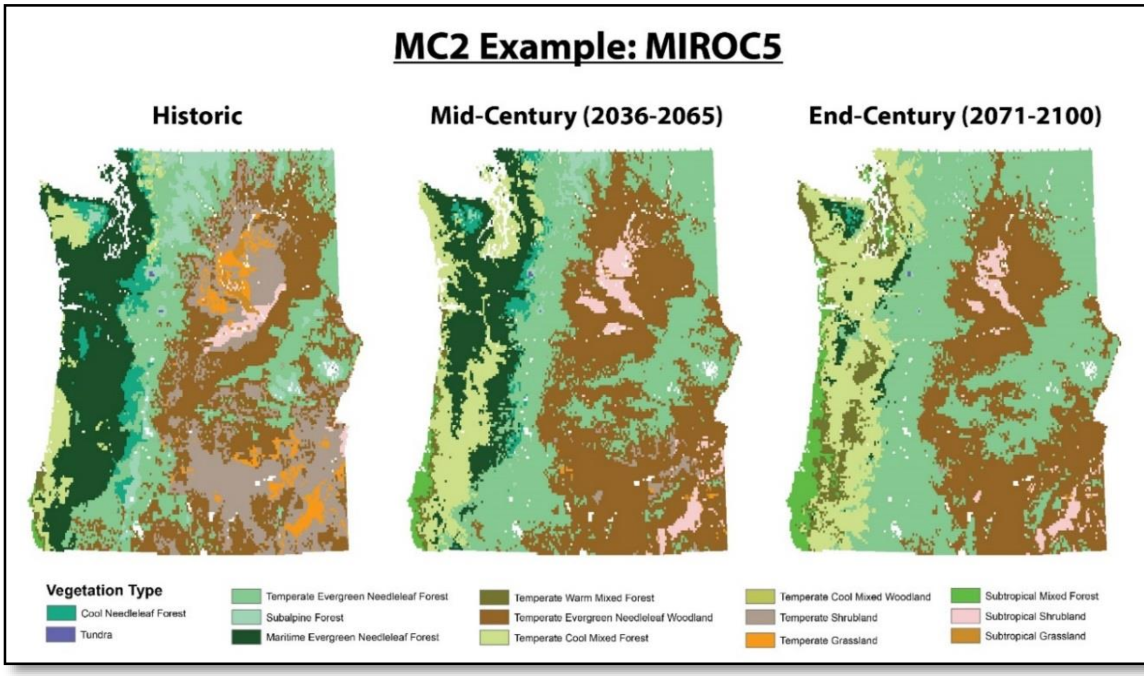

Figure 3: An example of the MC2 data. The mid-century and end-century models shown here were generated using the MIROC5 climate model.

In order to understand how these vegetation changes will impact timber resources, the authors of this paper developed a list of vegetation types that are associated with timber resources in the Pacific Northwest (Table 2). Timber vegetation types were broken down into two categories, those that are of primary importance or secondary importance to timber industry. The analysis performed with the MC2 models focused solely on these vegetation types.

Table 2:
Vegetation classes that are important to timber industries.

Importance Rank	MC2 Code	Vegetation Type
Primary	7	Maritime Evergreen Needleleaf Forest
	8	Temperate Evergreen Needleleaf Forest
Secondary	4	Boreal Evergreen Needleleaf Forest
	6	Subalpine Forest
	9	Temperate Deciduous Broadleaf Forest
	10	Temperate Cool Mixed Forest
	11	Temperate Warm Mixed Forest

To quantify changing timber potential, the researchers used the MC2 models to calculate the number of cells in each county changing from primary vegetation to other vegetation or from secondary vegetation to other vegetation. This measure was then averaged over the suite of climate models and a measure of the percent area in each county experiencing each change was calculated. The final measure of change in timber potential was calculated by weighting and adding the two measures using the following equation:

$$\Delta TP_i = P_i + (0.5 * \ S_i)$$

where delta *TP* is equal to the change in timber potential for county *i*, *P* is equal to the percent of total cells in county *i* lost or gained in primary vegetation types, and *S* is equal to the percent of total cells in county *i* lost or gained in secondary vegetation types. This measure of change in timber potential was calculated for both year ranges, 2036-2065 and 2071-2011, and constituted the measure of exposure.

5.2 Sensitivity and Adaptive Capacity

Sensitivity and adaptive capacity describe the underlying characteristics of a household or individual that predispose them to be either more or less affected or able to respond to stressors. This study utilized an indicator-based approach in order to quantify both the sensitivity and adaptive capacity components. Social and economic indicators were identified from the literature that characterize a population's inherent sensitivity or adaptive capacity to a stress event. The indicators were limited to those that were found in readily available geospatial data sets. Separate lists of indicators were created for sensitivity and adaptive capacity (Table 3).

Table 3:
List of the indicators used for the sensitivity and adaptive capacity analysis.

Data Source	Sensitivity Indicators	Adaptive Capacity Indicators
U.S Census Bureau, 2010	Population under 5 years old Population over 65 years White alone or in combination with one or more other races Any non-white race Median age Female-headed households, with children, no spouse present Renter-occupied housing units	Population under 5 years old Population over 65 years Female-headed households, with children, no spouse present Home ownership
American Community Survey	Population receiving SNAP benefits Per Capita Income Females employed- over 16 Population below poverty line	No high school diploma - over 25 College degree or more Population employed- over 16 Population below poverty line GINI Index
Infogroup Business Data	Critical Facilities Essential Facilities Medical Facilities - response and health facilities Dependent Population Facilities	Churches per capita Schools per capita
GAP Landcover	Percent of total area occupied by forests	

All of the indicators were aggregated to the county level. The percent of each indicator observed in each county was calculated. For example, population over 65 years old was calculated as a percent of total population and critical facilities were calculated as a percent of total facilities. In order to standardize all the data and account for indicators that cannot be converted to percentages, all of the indicators were converted to z-scores using the following equation:

$$Z = \frac{(x - \mu)}{\sigma}$$

where *x* is the raw value, μ is the mean of the population, and σ is the standard deviation of the population.

Factor analysis was performed on both the sensitivity and adaptive capacity indicators. Indicators that did not have significant component loading values, greater than 0.5 or less than -0.5, were removed and the test was re-run. This process was repeated until all indicators had significant component loading values. The component loading values and the percent explained variance of the final factor analysis were used to weight each indicator. This process is outlined in the following equation:

$$S_{ij} = (Z_i * F_i) * V_j$$

where *S* is equal to the score of indicator *i* in factor *j*, *Z* is equal to the value of indicator *i*, *F* is equal to the component score of indicator *i*, and *V* is equal to the percent explained variance of factor *j*. The scores were assigned directionality (positive or negative) based on if they increased or decreased sensitivity or adaptive capacity. Finally, the scores of each indicator were summed by county. The resulting scores were county measures of sensitivity and adaptive capacity.

5.3 Forest Dependence

A measure of forest dependence was calculated in order to relate the social components (sensitivity and adaptive capacity) with the biophysical (exposure). The products and services provided by forests benefit humans with aesthetic, environmental, and economic value. Many of the aesthetic and personal values that forests provide are difficult to quantify and relate to human well-being. However, economic dependence on forest products can be directly related to both human well-being and forest ecosystems. The economic relationship was therefore the focus of this analysis and was quantified by measuring employment in industries that directly harvest or process forest resources.

Infogroup data were used to measure employment in timber industries. These data were chosen because of their high degree of spatial precision (point level), wide array of economic statistics, and use of the North American Industry Classification System (NAICS). Industries relating to forest resource extraction, management, and processing were selected from the dataset by manually searching the NAICS code descriptions for relevant industries (Table 4). The associated economic data were then aggregated to the county level.

Two measures of economic concentration were used to identify regional dependence on the forest industry, the location quotient (LQ) and the focal location quotient (FLQ). The location quotient is a rather simple, but widely used statistic that provides a measure of the concentration of a variable within one spatial unit compared to the concentration of that variable in the study area as a whole. It is given by the following equation:

$$LQ_i = (e_i/E_i)/(e/E)$$

Where the LQ of county *i* is equal to the ratio of forest industry (e_i) to total industry (E_i) in county *i* divided by the ratio of forest industry (e) to total industry (E) in the entire study area. The LQ was calculated using number of employees as the variable representing forest industry as suggested in Steadman, Parkins, and Beckley (2004). A major shortcoming of this measure, however, is that it is calculated without regard to neighboring observations and therefore does not account for spatial effects.

Table 4:
Industry names and NAICS codes for forest related industries.

NAICS Code	Industry Title
113110	Timber Tract Operations
113210	Forest Nurseries and Gathering of Forest Products
113310	Logging
115310	Support Activities for Forestry
321113	Sawmills
321114	Wood Preservation
321211	Hardwood Veneer and Plywood Manufacturing
321212	Softwood Veneer and Plywood Manufacturing
321213	Engineered Wood Member (Except Truss) Manufacturing
321214	Truss Manufacturing
321219	Reconstituted Wood Product Manufacturing
321911	Wood Window and Door Manufacturing
321912	Cut Stock, Resawing Lumber, and Planing
321918	Other Millwork (Including Flooring)
321920	Wood Container and Pallet Manufacturing
321999	All Other Miscellaneous Wood Product Manufacturing
322xxx	Paper Mills/Products
333243	Sawmill, Woodworking, and paper Machinery Manufacturing
423310	Lumber, Plywood, Millwork, and Wood Panel Merchant Wholesalers
71219003	Nature Centers

An improvement of the LQ statistic is called the focal location quotient (FLQ). This statistic, developed by Cromley and Hanink (2012), explicitly incorporates neighboring values and therefore can account for various spatial effects occurring in the study area. It is given by the following equation:

$$FLQ_i = \left(\sum_j w_{ij} e_j \,/ \sum_j w_{ij} E_j\right) / \,(e/E)$$

Where the FLQ of county *i* is equal to the sum of spatial weights *ij* times the forest employment in county *j* (e_j) and divided by the sum of spatial weights *ij* times the total employment in county *j* (E_j). This ratio is then divided by the ratio of forest employment (*e*) to total employment (*E*) in the entire study area. The FLQ was calculated for each county in the study area using number of employees as the variable of choice and 1st order Queen's contiguity to calculate spatial weights.

The FLQ statistic is able to capture neighborhood effects in timber industry employment. In effect, the FLQ is a spatially smoothed LQ that provides a better estimation of where clusters of timber industry employment exist in the study area. These spatial effects are important to consider because timber employment in one county does not necessarily mean that timber resources are derived from that county. It is reasonable to assume that timber industries obtain forest resources from the county they are situated in and in counties nearby. Additionally, employees may live in one county but work in another. The 1st order Queen's contiguity FLQ statistic is able to capture employment in timber industries that may cross over county boundaries.

5.4 Vulnerability

The final step of this research was to combine the exposure, sensitivity, adaptive capacity, and forest dependence components to produce a measure of vulnerability. The modified version of Frazier, Thompson, and Dezzani's (2014) vulnerability equation was used. Each component was converted to Z-score and placed into the equation. Measures of vulnerability were calculated for each year range, 2036-2065 and 2071-2100.

6. Results/Discussion

The results of these analyses identify counties in Oregon and Washington that are vulnerable to climate-related changes in forest ecosystems. The following results show the ways in which vulnerability varies across the study area and can help identify the areas where planners and forest managers may need to focus their attention. In addition, the measures of exposure, sensitivity, adaptive capacity, and forest dependence can offer insight into the underlying factors influencing vulnerability. Scores for vulnerability and each component are listed in Table 5 and mapped in Figure 6. These results can be useful in helping customize planning and management strategies based on the specific conditions in each county.

Table 5:
The final z-scores for sensitivity, adaptive capacity, FLQ, exposure, and vulnerability.

County Name	Adaptive Capacity	Sensitivity	Focal Location Quotient	Exposure Mid-Century	Exposure End-Century	Vulnerability Mid-Century	Vulnerability End-Century
Baker	-0.78	-0.12	1.12	-0.29	-1.15	0.57	0.24
Benton (OR)	0.24	-0.77	0.51	0.08	1.86	-0.16	0.53
Clackamas	0.92	-0.79	-0.64	0.03	0.29	-0.89	-0.80
Clatsop	0.23	-0.63	0.07	1.18	0.86	0.15	0.03
Columbia (OR)	0.08	-0.46	-0.27	0.02	0.51	-0.30	-0.12
Coos	-1.03	0.41	3.72	4.51	2.02	3.70	2.81
Crook	-1.18	0.21	0.51	-0.04	-0.81	0.71	0.43
Curry	-0.89	-0.64	2.79	4.07	1.83	2.72	1.91
Deschutes	0.69	-0.70	0.77	-0.75	-0.85	-0.52	-0.57
Douglas (OR)	-1.16	0.18	1.31	0.58	1.41	1.24	1.59
Gilliam	2.67	-2.47	-0.46	-0.12	-0.98	-2.19	-2.58
Grant (OR)	-0.14	-0.57	0.82	-0.14	-0.90	0.10	-0.20
Harney	0.63	-0.10	0.43	-0.09	-0.87	-0.15	-0.46
Hood River	0.83	-0.36	-0.75	-0.85	-0.80	-1.06	-1.07
Jackson	-0.73	0.43	2.00	-0.18	0.05	1.14	1.26
Jefferson (OR)	-0.98	1.95	-0.02	-0.08	-0.69	1.08	0.87
Josephine	-1.78	0.78	2.09	0.17	1.57	1.84	2.43
Klamath	-0.76	0.43	1.06	-0.28	-0.77	0.75	0.58
Lake	0.76	-0.83	0.49	-0.32	-0.97	-0.54	-0.81
Lane	-0.61	0.21	0.96	0.25	1.00	0.77	1.09

Lincoln (OR)	-0.44	-0.35	0.33	2.97	2.05	1.30	0.97
Linn	-0.25	0.42	0.04	-0.08	0.45	0.24	0.46
Malheur	-1.69	1.52	0.78	-0.01	-0.79	1.52	1.25
Marion	-0.91	1.22	-0.13	-0.08	0.56	0.74	1.01
Morrow	-0.45	0.37	-0.79	-0.12	-1.04	-0.03	-0.39
Multnomah	0.49	0.20	-0.57	0.13	1.02	-0.28	0.06
Polk	0.10	0.21	0.11	0.02	1.35	0.09	0.62
Sherman	1.10	-0.96	-0.47	0.00	-0.59	-0.97	-1.23
Tillamook	-0.27	-0.09	0.20	1.46	1.17	0.71	0.61
Umatilla	-0.72	1.04	-0.57	0.05	-0.48	0.48	0.28
Union	-0.32	-0.07	0.66	-0.43	-0.85	0.18	0.02
Wallowa	1.69	-0.83	0.25	-0.34	-0.79	-1.00	-1.20
Wasco	-0.63	0.38	-0.61	-0.68	-1.02	-0.11	-0.24
Washington	1.34	-0.03	-0.46	0.04	0.70	-0.68	-0.44
Wheeler	1.62	-1.83	1.48	0.00	-0.65	-0.76	-1.03
Yamhill	0.05	0.16	-0.37	0.02	1.17	-0.09	0.35
Adams	-0.66	3.00	-1.08	0.02	-0.59	0.99	0.78
Asotin	-0.81	-0.26	-0.78	-0.39	-0.89	-0.24	-0.44
Benton (WA)	0.50	-0.33	-0.79	0.01	-0.52	-0.62	-0.84
Chelan	-0.17	0.58	-0.89	-3.10	-1.90	-1.24	-0.80
Clallam	-0.34	-0.30	0.42	-0.07	0.33	0.15	0.31
Clark	0.50	-0.03	-0.34	0.02	0.97	-0.32	0.04
Columbia (WA)	0.23	-0.87	-0.81	0.02	-0.52	-0.73	-0.95
Cowlitz	-1.08	0.64	1.03	0.02	0.56	1.06	1.30
Douglas (WA)	-0.45	0.82	-0.86	-0.33	-0.77	0.03	-0.14
Ferry	-0.74	0.47	0.32	-0.47	-1.03	0.41	0.20
Franklin	-1.43	2.74	-1.09	0.02	-0.50	1.19	1.01
Garfield	2.65	-2.85	-0.73	0.02	-0.50	-2.37	-2.64
Grant (WA)	-1.02	1.83	-0.82	0.02	-0.51	0.78	0.60
Grays Harbor	-1.08	0.45	0.09	0.49	1.54	0.81	1.24
Island	1.34	-0.69	-0.71	0.54	0.77	-0.84	-0.77
Jefferson (WA)	0.38	-0.90	-0.22	-0.44	0.30	-0.74	-0.47
King	1.66	-0.20	-0.82	-0.05	0.46	-1.05	-0.87
Kitsap	0.94	-0.32	-0.83	0.48	1.65	-0.62	-0.17
Kittitas	-0.09	-0.29	-0.85	-1.25	-1.22	-0.88	-0.89
Klickitat	-0.23	0.22	-0.64	-0.04	-0.69	-0.08	-0.34
Lewis	-0.38	0.35	-0.01	-0.31	0.33	0.16	0.41
Lincoln (WA)	2.14	-1.40	-0.77	0.04	-0.69	-1.64	-1.96
Mason	-0.89	0.15	-0.51	-0.02	1.00	0.19	0.60
Okanogan	-0.77	1.22	-0.69	-2.05	-1.94	-0.28	-0.25
Pacific	-0.78	-0.20	1.95	0.87	1.34	1.30	1.52
Pend Oreille	-1.23	0.38	-0.70	-0.74	-0.78	0.06	0.05
Pierce	0.44	0.50	-0.80	-0.52	0.39	-0.48	-0.14
San Juan	1.35	-1.77	-0.41	0.51	0.47	-1.16	-1.20
Skagit	0.30	0.01	-0.65	-0.57	-0.24	-0.58	-0.46
Skamania	0.62	-0.76	-0.30	-0.39	-0.59	-0.79	-0.89
Snohomish	1.28	-0.09	-0.91	-0.42	0.21	-1.03	-0.81
Spokane	0.53	-0.37	-0.73	-0.10	-0.70	-0.66	-0.91
Stevens	0.35	-0.07	-0.69	-0.09	-0.59	-0.46	-0.67

Thurston	1.11	-0.42	-0.29	0.03	1.65	-0.68	-0.07
Wahkiakum	0.43	-1.04	2.78	0.16	1.37	0.56	1.05
Walla Walla	-0.41	0.21	-0.99	0.03	-0.51	-0.13	-0.34
Whatcom	0.55	-0.24	-0.58	-1.37	-0.66	-1.04	-0.79
Whitman	-0.31	-0.42	-0.90	0.02	-0.50	-0.38	-0.59
Yakima	-2.14	2.74	-0.81	-1.26	-1.35	1.08	1.07

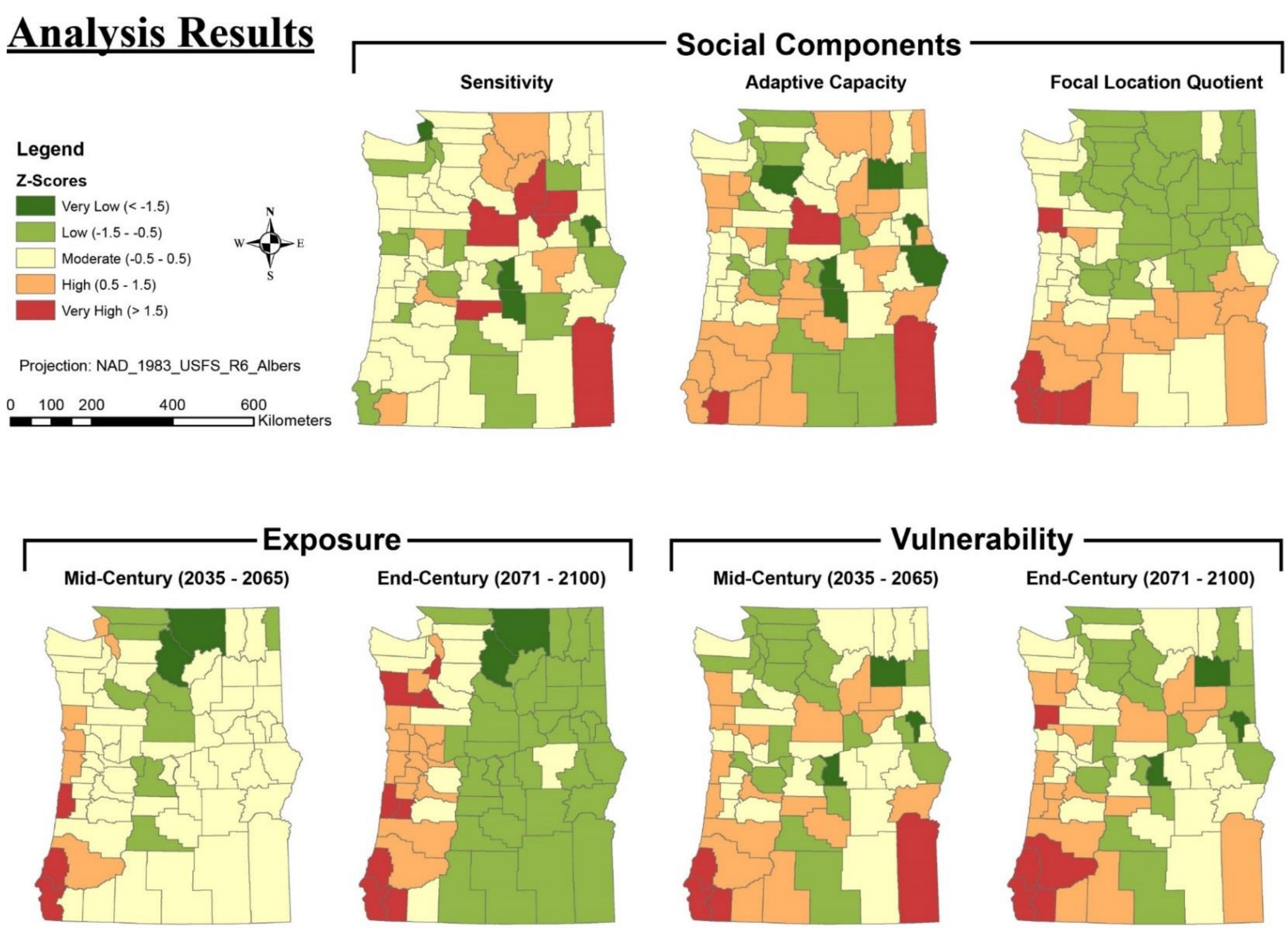

Figure 6: Maps of the z-scores for each vulnerability component. A separate map is shown for sensitivity, adaptive capacity, FLQ, exposure in the mid-century and end-century, and vulnerability in the mid-century and end-century.

6.1 Exposure

Change in timber potential was calculated for every county in the study area. The general spatial trend in the results shows that climate change is expected to more negatively impact timber vegetation in the western counties than it will those in the east. In the mid-century, this trend is less distinct, with moderate exposure in some of the western and eastern counties. However, in the end-century, the difference between the western counties and eastern counties is much more distinct. Most of the counties along the western coast are highly or very highly exposed and all eastern counties have low exposure. In both year ranges, the north central counties have very low exposure. These spatial patterns may be due to the spatial distribution of the vegetation classes chosen in this study. Much of the primary vegetation only exists in the western counties. Therefore, they are the only counties with primary vegetation to lose.

In the mid-century, the counties that are significantly more exposed than the mean are Coos, Curry, and Lincoln (OR). These three counties area are also highly exposed in the end-century, as are Benton (OR), Kitsap, Thurston, Josephine, and Grays Harbor. The analysis showed that these eight counties will experience the most severe decrease in timber vegetation types due to climate change. In the end-century, each of these counties is predicted to lose over 60% of their total area in primary vegetation (Appendix A).

Conversely, the counties of Okanogan and Chelan are the least exposed to climate related changes in timber vegetation. In fact, primary timber vegetation is expected to increase substantially in these two counties and in Yakima, Kittitas, Baker, and Whatcom counties for both the mid-century and end-century (Appendix A). At the same time, these six counties experience a significant decrease in secondary timber vegetation. This pattern, the replacement of secondary vegetation by primary vegetation, was common in the study area.

6.2 Sensitivity

The measure of sensitivity identifies the counties in the study area that would be most affected by a stress event. Results of the factor analysis are shown in Table 6. Four components and 16 indicators were determined to be significant. Overall, the components explained 81.491% of the total observed variance.

Table 6:
Results of the factor analysis performed on the sensitivity indicators.

	Component			
Indicator	**1**	**2**	**3**	**4**
Under5	-0.958	0.028	-0.046	0.087
Minority	-0.957	-0.014	-0.007	0.035
White	0.937	0.04	0.01	-0.033
FemHeadHouse	-0.704	0.079	-0.353	0.068
Over65	0.571	0.147	0.322	0.418
MedianAge	0.534	-0.031	0.242	0.539
ForestArea	0.518	-0.011	-0.518	0.088
BelowPov	0.118	0.947	0.039	-0.366
PerCapIncome	0.043	-0.922	-0.068	-0.028
SNAP	-0.005	0.809	-0.205	0.136
FemEmployed	0.12	-0.619	-0.082	-0.588
Essential	0.072	0.045	0.914	0.129
Critical	0.125	0.055	0.882	0.131
Dependent	0.044	0.005	0.858	-0.051
Medical	0.087	-0.144	0.727	-0.058
RenterHouse	0.004	0.132	0.026	-0.963
Percent Explained Variance	**27.511**	**17.91**	**23.054**	**13.016**

The six counties with very high sensitivity (> 1.5 standard deviations above the mean) are Adams, Yakima, Franklin, Jefferson (OR), Grant (WA), and Malheur. All of these counties are characterized by high levels of poverty, low per capita income, high minority population, and high reliance on SNAP benefits (Appendix B). Yakima, Grant (WA), Adams, and Franklin counties are all located in central Washington. These areas are predominantly rural, with the majority of economic activity coming from agriculture. A possible reason explaining this area of high sensitivity is the large population of immigrant workers who make meager incomes and have little opportunity for economic or social advancement. Jefferson County, Oregon and Malheur County have a similar economic and social context. However, Malheur County has a higher economic dependence on livestock grazing and recreation than do the other sensitive counties.

6.3 Adaptive Capacity

Results of the adaptive capacity analysis show the varying degrees of social adaptability to stress events across the study area. Factor analysis identified 4 significant components and 11 significant indicators (Table 7). The significant factors identified in this analysis explained 87.24% of the total observed variance.

Table 7:
Results of the factor analysis performed on the adaptive capacity indicators.

	Component			
Indicator	**1**	**2**	**3**	**4**
Religious	0.991	0.064	0.016	0.058
Schools	0.967	0.1	0.004	0.099
FemHeadHouse	-0.549	0.648	0.049	0.052
NoHS	0.146	0.912	-0.04	-0.035
Under5	-0.191	0.845	0.127	0.316
CollegeDeg	-0.204	-0.834	0.045	0.307
GINI	-0.035	-0.419	-0.815	0.098
BelowPov	0.029	0.392	-0.808	-0.181
OwnerHouse	-0.001	-0.089	0.506	-0.782
Employed	0.103	-0.164	0.258	0.948
Over65	0.408	-0.368	0.036	-0.56
Percent Explained Variance	**23.557**	**29.116**	**15.128**	**19.438**

In this case, low adaptive capacity values indicate increased vulnerability. Therefore, those counties with the lowest adaptive capacity are of the most interest in this study. Only three counties have very low adaptive capacity (< 1.5 standard deviations below the mean). They are Yakima, Josephine, and Malheur. These three counties have relatively low measures of education and social capital, with a small number of religious institutions and schools per capita, low percentage of population with a college degree, and high percentage of population without a high school diploma. Additionally, these counties have a low percentage of their working age population formally employed and have a large proportion of their population living below the poverty line.

The map of the adaptive capacity results shows clusters of low or very low adaptive capacity in South Western Oregon. This counties comprising this cluster are Lane, Douglass, Coos, Klamath, Jackson, Josephine, and Curry County. All of these counties are rural, resource dependent regions. It is therefore logical to assume that these areas may have lower access to resources and education opportunities. This region of low adaptive capacity warrants additional consideration when making planning and management decisions. Neighborhood effects may exacerbate the impacts of stress events in large regions with low ability to adapt to stress events, such as the region in South Western Oregon.

6.4 Forest Dependence

In the study area as a whole, timber related industries employ 82,848 people of the 4,935,045 total employees reported in the Infogroup data (Table 8). This equates to a 1.68% share in employment. Lane County employs the most people in timber industries, with 6052 employees. However, this makes up only 3.34% of all employees in Lane County. The counties of Crook, Grant (OR), Douglass (OR), Cowlitz, Lake, and Curry all have over 10%

of their employees working in timber industries. Crook County has the highest percent employed in timber industry with 14.67%. The LQ statistic indicates that timber employment is over eight times more concentrated in Crook County than in the study area as a whole. The counties of Grant (OR), Douglass (OR), Cowlitz, Lake, and Curry also exhibit high concentration of timber employment with LQ values of 8.24, 7.55, 6.17, 6.17, and 6.02 respectively.

The FLQ results show counties that are in a region of high timber employment. There were 20 counties that had focal timber employment greater than that of the study area. The six counties with the highest concentration of timber employment were Coos, Curry, Wahkiakum, Josephine, Jackson, and Pacific. The counties of Coos, Curry, Josephine, and Jackson form a cluster of high timber employment in the southwest corner of Oregon. This cluster is surrounded by the counties of Lane, Douglass, and Klamath, all of which have a FLQ value over 2.5. South Western Oregon is therefore a region that derives a large amount of value from forest resources and an area that warrants additional consideration.

Table 8:
Employment in the timber industry reported by county. Spatially weighted employment values and the LQ and FLQ statistic are also included in the table.

	Standard (Without Spatial Weights)				**Spatially Weighted (Queens Contiguity)**			
County Name	**Total Employees**	**Timber Industry Employees**	**Percent in Timber Industry**	**Location Quotient**	**Total Employees**	**Timber Industry Employees**	**Percent in Timber Industry**	**Focal Location Quotient**
Coos	25,326	1,235	4.88%	2.905	79,919	7,915	9.90%	5.90
Curry	9,257	936	10.11%	6.023	110,438	8,873	8.03%	4.79
Wahkiakum	1,301	107	8.22%	4.899	120,654	9,665	8.01%	4.77
Josephine	30,519	958	3.14%	1.870	176,505	11,688	6.62%	3.94
Jackson	91,393	4,050	4.43%	2.640	193,798	12,485	6.44%	3.84
Pacific	9,145	324	3.54%	2.110	90,080	5,709	6.34%	3.78
Wheeler	516	4	0.78%	0.462	36,478	1,969	5.40%	3.22
Douglas (OR)	45,336	5,744	12.67%	7.547	409,500	20,708	5.06%	3.01

Baker	6,908	394	5.70%	3.397	37,939	1,775	4.68%	2.79
Klamath	26,550	1,733	6.53%	3.888	431,508	19,658	4.56%	2.71
Cowlitz	44,423	4,603	10.36%	6.172	249,633	11,240	4.50%	2.68
Lane	181,119	6,052	3.34%	1.990	457,559	19,905	4.35%	2.59
Grant (OR)	3,274	453	13.84%	8.242	82,745	3,372	4.08%	2.43
Malheur	12,564	3	0.02%	0.014	25,557	1,021	3.99%	2.38
Deschutes	84,029	1,760	2.09%	1.248	357,483	14,213	3.98%	2.37
Union	12,082	854	7.07%	4.210	57,756	2,173	3.76%	2.24
Benton (OR)	51,036	959	1.88%	1.119	319,204	11,043	3.46%	2.06
Crook	6,835	1,003	14.67%	8.741	104,855	3,611	3.44%	2.05
Lake	3,081	319	10.35%	6.167	116,471	3,983	3.42%	2.04
Harney	2,811	171	6.08%	3.624	112,594	3,709	3.29%	1.96
Clallam	31,607	1,192	3.77%	2.246	52,055	1,704	3.27%	1.95
Lincoln (OR)	23,821	702	2.95%	1.755	284,287	8,790	3.09%	1.84
Ferry	2,803	137	4.89%	2.911	42,702	1,315	3.08%	1.83
Wallowa	3,111	71	2.28%	1.359	64,041	1,875	2.93%	1.74
Tillamook	10,751	702	6.53%	3.890	343,146	9,718	2.83%	1.69
Polk	17,560	375	2.14%	1.272	329,225	8,733	2.65%	1.58
Grays Harbor	26,179	1,473	5.63%	3.352	215,393	5,635	2.62%	1.56
Clatsop	20,386	1,747	8.57%	5.105	274,280	7,025	2.56%	1.53
Linn	45,668	2,955	6.47%	3.854	529,260	13,314	2.52%	1.50
Lewis	33,069	2,058	6.22%	3.707	644,997	15,508	2.40%	1.43
Jefferson (OR)	7,390	220	2.98%	1.773	298,847	7,135	2.39%	1.42
Marion	142,458	993	0.70%	0.415	426,375	9,268	2.17%	1.29
Jefferson (WA)	11,236	475	4.23%	2.518	208,122	4,110	1.97%	1.18
Columbia (OR)	12,330	826	6.70%	3.990	939,224	17,691	1.88%	1.12
Thurston	119,115	589	0.49%	0.295	498,120	9,189	1.84%	1.10
Skamania	3,267	263	8.05%	4.795	835,765	15,299	1.83%	1.09
Clark	155,243	3,383	2.18%	1.298	689,686	12,079	1.75%	1.04
Yamhill	37,931	2,047	5.40%	3.215	592,484	9,914	1.67%	1.00
San Juan	9,212	37	0.40%	0.239	229,790	3,665	1.59%	0.95
Washington	220,367	3,319	1.51%	0.897	939,605	14,123	1.50%	0.90
Gilliam	1,138	0	0.00%	0.000	27,389	411	1.50%	0.89
Sherman	788	2	0.25%	0.151	21,499	318	1.48%	0.88
Mason	16,649	716	4.30%	2.562	558,480	7,787	1.39%	0.83
Multnomah	474,423	3,004	0.63%	0.377	1,041,375	13,407	1.29%	0.77
Umatilla	32,381	401	1.24%	0.738	163,492	2,103	1.29%	0.77
Whatcom	90,987	1,248	1.37%	0.817	177,241	2,249	1.27%	0.76
Wasco	11,951	200	1.67%	0.997	347,608	4,147	1.19%	0.71
Clackamas	163,417	2,478	1.52%	0.903	1,062,875	12,175	1.15%	0.68

Klickitat	7,622	116	1.52%	0.907	227,121	2,572	1.13%	0.67
Skagit	55,702	677	1.22%	0.724	503,024	5,685	1.13%	0.67
Okanogan	21,340	287	1.34%	0.801	271,481	2,833	1.04%	0.62
Stevens	13,867	887	6.40%	3.810	264,598	2,737	1.03%	0.62
Pend Oreille	3,625	133	3.67%	2.186	257,103	2,596	1.01%	0.60
Island	31,046	36	0.12%	0.069	442,055	4,448	1.01%	0.60
Garfield	995	33	3.32%	1.976	26,666	258	0.97%	0.58
Spokane	239,611	1,576	0.66%	0.392	275,791	2,632	0.95%	0.57
Hood River	12,328	134	1.09%	0.647	673,008	6,195	0.92%	0.55
Lincoln (WA)	4,692	4	0.09%	0.051	346,144	3,046	0.88%	0.52
Asotin	7,239	82	1.13%	0.675	25,341	218	0.86%	0.51
Morrow	5,374	89	1.66%	0.987	129,568	1,093	0.84%	0.50
Benton (WA)	79,263	30	0.04%	0.023	325,909	2,745	0.84%	0.50
Pierce	303,108	4,353	1.44%	0.855	1,823,697	14,990	0.82%	0.49
Yakima	105,390	1,738	1.65%	0.982	1,738,354	14,026	0.81%	0.48
Columbia (WA)	1,325	40	3.02%	1.798	105,225	835	0.79%	0.47
Grant (WA)	42,462	113	0.27%	0.159	314,047	2,444	0.78%	0.46
King	1,148,805	5,195	0.45%	0.269	1,949,601	15,027	0.77%	0.46
Kitsap	82,193	181	0.22%	0.131	1,845,703	13,998	0.76%	0.45
Kittitas	15,368	160	1.04%	0.620	1,668,628	11,926	0.71%	0.43
Douglas (WA)	11,424	9	0.08%	0.047	132,665	927	0.70%	0.42
Chelan	42,071	358	0.85%	0.507	1,547,376	9,728	0.63%	0.37
Whitman	13,996	32	0.23%	0.136	301,966	1,870	0.62%	0.37
Snohomish	252,666	3,042	1.20%	0.717	1,612,483	9,489	0.59%	0.35
Walla Walla	26,682	165	0.62%	0.368	166,386	729	0.44%	0.26
Adams	7,373	10	0.14%	0.081	95,258	252	0.26%	0.16
Franklin	26,735	93	0.35%	0.207	197,836	483	0.24%	0.15

6.5 Vulnerability

The final piece of this research was to combine the previously calculated components to produce a comprehensive measure of vulnerability. Vulnerability measures were calculated at the county level for both the mid-century and the end-century.

6.5.1 Mid-Century

In the mid-century, the counties with very high vulnerability (> 1.5 standard deviations above the mean) are Coos, Curry, Josephine, and Malheur. Coos County has the highest vulnerability score (3.7 standard deviations above the mean). It has very high scores for both exposure and FLQ, 4.51 and 3.72 respectively. This means that timber forest vegetation is expected to experience a significant decrease in Coos County in the mid-century and that a large proportion of employees in the region work in timber related industry. These two factors indicate that the impacts of forest-related climate change will manifest quite severely in Coos County. Compounding this impact is the low level of adaptive capacity in Coos County (-1.03) and the moderate level of sensitivity (0.41). This indicates that the population in Coos County will be moderately sensitive to the forest changes and that it will be poorly able to adapt and respond to these changes. Overall, Coos County is highly vulnerable in the mid-century because its population is highly dependent on timber resources for employment and it lacks the ability to effectively respond to the severe changes in timber vegetation that it will experience. Although not as extreme, similar trends are observed in the very highly vulnerable counties of Curry and Josephine. Malheur County is considered very highly vulnerable primarily because it has very low adaptive capacity and high sensitivity. However, it is only moderately exposed (-0.01). We can therefore interpret Malheur County as being highly socially vulnerable, but with low biophysically vulnerability. These considerations are important to keep in mind when interpreting the vulnerability scores.

Clusters of high vulnerability appear to exist in the study area. Highly vulnerable counties seem to be concentrated in the southwestern portion of the study area. The most obvious cluster consists of seven counties located in the southwest corner of Oregon. Three of the four total counties with very high vulnerability and four of the eighteen counties with high vulnerability are located in this region. This is likely due to the high exposure and forest dependence in this area. Similarly, all but three of the counties located on the Pacific coast are considered very highly or highly vulnerable. These regions should be focused on when making planning or management decisions regarding climate change.

6.5.2 End-Century

The three counties with the highest vulnerability in the mid-century are also the highest in the end-century. They are Coos, Josephine, and Curry counties. Relative exposure in Coos and Curry County has decreased, from 4.51 to 2.02 and 4.07 to 1.83 respectively. While relative exposure in Josephine County has increased, from 0.17 to 1.57. The relative decrease in exposure values for Coos and Curry County could be attributed to an increase in the change in timber potential for other counties in the study area. This could also mean that Coos and Curry will be some of the first counties to experience vegetation change. Josephine County now has a vulnerability score of 2.43, second highest in the study area. It has very low exposure, very high forest dependence and exposure, and high sensitivity. These compounding factors make Josephine County very highly vulnerable in the end-century. Douglass County, Oregon and Pacific County are also very highly vulnerable in the end-century. Both of these counties are similar to Coos, Josephine, and Curry in that they exhibit a similar high level of vulnerability in both the social and biophysical systems.

The spatial pattern of highly vulnerable counties in the end-century is very similar to the mid-century. High vulnerability clusters are still evident in southwestern Oregon and along the Pacific coast, but the vulnerability in these areas appears to have increased. The cluster in southwest Oregon now contains four very highly vulnerable counties and the high vulnerability counties have extended north into west central Oregon. A cluster of one very highly vulnerable county and four highly vulnerable counties is evident in west central Washington. It is clear that the areas most impacted by changes in timber vegetation will be those in southwestern Oregon and in western Washington.

7. Conclusions

This research has served as a way to bring cutting edge hazard vulnerability assessment techniques to the climate change discipline. It has demonstrated how vulnerability components can be separated and compiled using methods from the SERV model and others. In doing so, a reasonably good estimation of vulnerability to forest change has been produced. However, this has not gone without considerable assumptions and generalizations being made. These issues are presented not to undermine the research presented previously, but to bring attention to the need for additional research in this field.

The indicator-based approach used in this research was developed to identify social vulnerability to hazards. Even though most of the hazard specific indicators were excluded in this analysis, there were very few climate change specific indicators that were introduced. The approach the author took was to focus on inherent sensitivity or adaptive capacity to any stress event. While this does introduce an understanding of the general social conditions present in the spatial unit, climate specific considerations are ignored. In order to improve the ability and efficacy of these types of assessments, research must be conducted to identify the socioeconomic characteristics that predispose individuals to be vulnerable to slow onset hazards such as climate change. Additionally, indicators focused on specific impacts of climate change, such as forest change or agricultural change, should be developed for even more focused analyses.

Another issue is the large unit of analysis used in this study. The county is not an ideal spatial unit for assessing variations in social and economic characteristics. This coarse scale washes out a significant amount of the inter-county variability that exists within the study area. However, it is not appropriate to interpret DVMs at fine spatial scales. The impacts of forest changes will not manifest in a spatially direct manner, therefore some method of aggregation is necessary. Improvements in the way vegetation changes are assigned to spatial units could allow for a fine scale assessment. Distance based aggregation techniques that are specific to the social spatial unit could be one method for solving this issue.

A second issue of the scale of this study is the difficulty in capturing local context. Studies, such as the Williamson et al. (2008) paper, focus on one community, and therefore are able to capture the local context to a high degree of precision. However, the research presented in this paper provides only a macro level view of vulnerability. Users of the results of this research should consider this and introduce their own understanding of local context and local level vulnerability where they are able.

This study focused on only one impact of climate change, timber specific forest changes. Within that focus, only the economic or employment impacts were considered. This is far from a comprehensive assessment of vulnerability to climate change, yet it does provide one piece of a larger picture. Other assessments, with other foci, should be performed to complete our understanding of climate change vulnerability.

Despite these issues, this research has presented a novel application of vulnerability assessments. The methods of relating the biophysical and social systems is an important advancement in vulnerability science and has many applications that extend beyond the scope of this research. There are many hazards that manifest impacts in a temporally and spatially complex manner. A similar technique could be used to assess the social vulnerability of climate related agricultural change or of the social impact of regulatory policies. When considered in this manner, vulnerability can be assessed for any event that has the potential to affect human well-being. This not only allows vulnerability science to grow in relevance and utility, but also to help scientists to gain a better understanding of how humans affect and are affected by their world and themselves.

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Appendix A

Average percent area occupied by primary and secondary vegetation types for the historic, mid-century, and end-century MC2 models.

Percent change from historic to mid-century and historic to end-century is also shown.

	Primary Vegetation					Secondary Vegetation				
County Name	**Historic**	**Mid-Century**	**End-Century**	**Change Mid-Century**	**Change End-Century**	**Historic**	**Mid-Century**	**End-Century**	**Change Mid-Century**	**Change End-Century**
Adams	0.23	0.23	0.25	0.00	0.02	0.00	0.00	0.00	0.00	0.00
Asotin	0.64	0.68	0.75	0.04	0.11	0.00	0.00	0.00	0.00	0.00
Baker	0.47	0.52	0.67	0.05	0.20	0.04	0.00	0.00	-0.04	-0.04
Benton (OR)	1.00	0.99	0.26	-0.01	-0.74	0.00	0.01	0.18	0.01	0.18
Benton (WA)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Chelan	0.32	0.74	0.88	0.42	0.57	0.37	0.09	0.01	-0.27	-0.36
Clackamas	0.98	0.98	0.73	0.00	-0.26	0.01	0.01	0.08	0.00	0.07
Clallam	0.61	0.63	0.36	0.02	-0.25	0.03	0.02	0.08	-0.02	0.05
Clark	0.98	0.98	0.50	0.00	-0.49	0.00	0.00	0.16	0.00	0.16
Clatsop	0.78	0.65	0.36	-0.14	-0.43	0.00	0.06	0.11	0.06	0.11
Columbia (OR)	0.97	0.97	0.62	0.00	-0.35	0.00	0.00	0.14	0.00	0.14
Columbia (WA)	0.88	0.88	0.89	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Coos	0.66	0.28	0.04	-0.38	-0.62	0.19	0.12	0.04	-0.07	-0.15
Cowlitz	0.99	0.99	0.64	0.00	-0.35	0.00	0.00	0.12	0.00	0.12
Crook	0.30	0.30	0.38	0.01	0.09	0.00	0.00	0.00	0.00	0.00
Curry	0.67	0.29	0.05	-0.38	-0.62	0.11	0.12	0.05	0.01	-0.06
Deschutes	0.42	0.53	0.56	0.11	0.14	0.08	0.00	0.00	-0.08	-0.08
Douglas (OR)	0.96	0.89	0.38	-0.06	-0.57	0.03	0.05	0.12	0.03	0.09

Douglas (WA)	0.05	0.08	0.13	0.03	0.08	0.00	0.00	0.00	0.00	0.00
Ferry	0.72	0.76	0.86	0.05	0.15	0.00	0.00	0.00	0.00	0.00
Franklin	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Garfield	0.99	0.99	0.99	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Gilliam	0.06	0.08	0.20	0.01	0.13	0.00	0.00	0.00	0.00	0.00
Grant (OR)	0.66	0.68	0.78	0.02	0.12	0.02	0.00	0.00	-0.02	-0.02
Grant (WA)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Grays Harbor	0.88	0.81	0.23	-0.06	-0.65	0.00	0.04	0.17	0.04	0.17
Harney	0.12	0.14	0.23	0.01	0.11	0.00	0.00	0.00	0.00	0.00
Hood River	0.85	0.99	0.98	0.13	0.13	0.11	0.00	0.00	-0.10	-0.10
Island	0.39	0.33	0.02	-0.07	-0.37	0.00	0.04	0.04	0.04	0.04
Jackson	0.97	0.99	0.78	0.02	-0.20	0.00	0.00	0.09	0.00	0.09
Jefferson (OR)	0.58	0.60	0.64	0.02	0.06	0.03	0.00	0.00	-0.03	-0.03
Jefferson (WA)	0.72	0.81	0.49	0.08	-0.23	0.13	0.04	0.14	-0.08	0.01
Josephine	1.00	0.97	0.36	-0.03	-0.64	0.00	0.02	0.14	0.02	0.14
King	0.86	0.89	0.59	0.03	-0.27	0.07	0.03	0.08	-0.04	0.01
Kitsap	0.74	0.68	0.09	-0.07	-0.66	0.00	0.05	0.12	0.05	0.12
Kittitas	0.44	0.63	0.71	0.19	0.27	0.14	0.01	0.00	-0.14	-0.14
Klamath	0.79	0.84	0.89	0.05	0.10	0.05	0.00	0.00	-0.05	-0.05
Klickitat	0.73	0.74	0.78	0.01	0.05	0.00	0.00	0.00	0.00	0.00
Lake	0.27	0.30	0.40	0.04	0.13	0.01	0.00	0.00	-0.01	-0.01
Lane	0.92	0.91	0.47	-0.01	-0.45	0.05	0.03	0.11	-0.02	0.06
Lewis	0.93	0.99	0.68	0.05	-0.25	0.05	0.01	0.10	-0.05	0.04
Lincoln (OR)	0.81	0.48	0.08	-0.33	-0.74	0.02	0.14	0.08	0.12	0.06
Lincoln (WA)	0.24	0.23	0.29	0.00	0.05	0.00	0.00	0.00	0.00	0.00
Linn	0.97	0.99	0.67	0.02	-0.30	0.02	0.00	0.10	-0.02	0.08
Malheur	0.03	0.03	0.11	0.00	0.08	0.00	0.00	0.00	0.00	0.00
Marion	0.97	0.99	0.64	0.02	-0.33	0.03	0.01	0.10	-0.02	0.08
Mason	0.92	0.93	0.44	0.01	-0.48	0.02	0.01	0.15	-0.01	0.14

Morrow	0.35	0.36	0.50	0.01	0.15	0.00	0.00	0.00	0.00	0.00
Multnomah	0.96	0.94	0.47	-0.02	-0.49	0.00	0.02	0.14	0.02	0.14
Okanogan	0.27	0.54	0.79	0.26	0.51	0.24	0.10	0.01	-0.15	-0.23
Pacific	0.80	0.69	0.23	-0.11	-0.57	0.00	0.06	0.12	0.06	0.12
Pend Oreille	0.84	0.98	0.99	0.13	0.14	0.13	0.00	0.00	-0.13	-0.13
Pierce	0.76	0.86	0.55	0.10	-0.21	0.17	0.06	0.10	-0.11	-0.07
Polk	1.00	1.00	0.40	0.00	-0.60	0.00	0.00	0.17	0.00	0.17
San Juan	0.30	0.24	0.02	-0.07	-0.28	0.00	0.04	0.03	0.04	0.03
Sherman	0.28	0.28	0.30	0.00	0.03	0.00	0.00	0.00	0.00	0.00
Skagit	0.73	0.84	0.70	0.11	-0.03	0.17	0.05	0.07	-0.11	-0.09
Skamania	0.90	0.97	0.96	0.08	0.06	0.09	0.01	0.02	-0.08	-0.07
Snohomish	0.84	0.92	0.66	0.08	-0.19	0.11	0.03	0.09	-0.08	-0.02
Spokane	0.93	0.94	0.99	0.01	0.06	0.00	0.00	0.00	0.00	0.00
Stevens	0.91	0.93	0.94	0.01	0.03	0.01	0.00	0.00	-0.01	-0.01
Thurston	0.95	0.95	0.28	0.00	-0.67	0.00	0.00	0.14	0.00	0.14
Tillamook	0.84	0.67	0.32	-0.17	-0.52	0.00	0.07	0.12	0.07	0.12
Umatilla	0.82	0.82	0.82	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Union	0.82	0.89	0.95	0.07	0.13	0.07	0.01	0.00	-0.06	-0.07
Wahkiakum	0.94	0.92	0.34	-0.02	-0.60	0.00	0.02	0.17	0.02	0.17
Walla Walla	0.39	0.39	0.39	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wallowa	0.76	0.83	0.88	0.06	0.12	0.07	0.01	0.00	-0.06	-0.07
Wasco	0.58	0.64	0.72	0.07	0.14	0.00	0.00	0.00	0.00	0.00
Washington	1.00	1.00	0.60	0.00	-0.40	0.00	0.00	0.13	0.00	0.13
Whatcom	0.51	0.76	0.67	0.25	0.16	0.28	0.04	0.05	-0.24	-0.23
Wheeler	0.62	0.62	0.66	0.00	0.04	0.00	0.00	0.00	0.00	0.00
Whitman	0.89	0.89	0.89	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Yakima	0.35	0.54	0.67	0.19	0.32	0.17	0.02	0.01	-0.15	-0.16
Yamhill	1.00	1.00	0.45	0.00	-0.55	0.00	0.00	0.18	0.00	0.18

Appendix B

Z-Scores of the aggregated social and economic data. These data were used to measure sensitivity and adaptive capacity.

County Name	Under 5	Over 65	Median Age	White	Minority	Female Head of Household - No Spouse	Renter Occupied Household	Owner Occupied Household	SNAP	Per Capita Income	GINI	College Degree or More	No High School Diploma
Baker	-0.51	1.05	0.95	1.04	-1.05	-0.51	-0.21	0.21	0.34	-0.41	0.97	-0.17	0.17
Benton (OR)	-1.16	-1.02	-1.49	0.21	-0.27	-1.22	2.00	-2.00	-0.88	0.62	2.24	2.02	-1.48
Clackamas	-0.18	-0.68	-0.18	0.30	-0.33	-0.16	-0.38	0.38	-1.15	1.84	0.27	1.02	-0.94
Clatsop	-0.26	-0.06	0.22	0.62	-0.57	-0.11	1.00	-1.00	0.07	0.15	0.34	0.01	-0.76
Columbia (OR)	-0.21	-0.62	-0.07	0.90	-0.83	0.02	-1.31	1.31	0.13	0.36	-0.55	-0.63	-0.17
Coos	-0.61	0.93	0.86	0.66	-0.54	-0.23	0.27	-0.27	1.09	-0.64	0.51	-0.44	0.23
Crook	-0.42	0.65	0.60	0.74	-0.78	-0.44	-0.73	0.73	0.93	-0.96	-1.22	-1.10	0.75
Curry	-1.62	2.31	1.82	0.87	-0.70	-1.06	-0.38	0.38	0.12	-0.27	-0.47	-0.14	-0.31
Deschutes	0.11	-0.42	-0.24	0.74	-0.68	0.22	0.24	-0.24	-0.50	0.78	0.57	1.18	-1.04
Douglas (OR)	-0.53	0.84	0.67	0.86	-0.77	0.17	-0.23	0.23	0.99	-0.77	-0.49	-0.82	0.41
Gilliam	-0.70	1.10	1.23	0.98	-1.00	-1.65	0.37	-0.37	-1.17	0.41	-1.27	-0.22	-0.07
Grant (OR)	-1.07	1.40	1.28	1.08	-1.12	-0.69	-0.82	0.82	0.44	-0.30	1.50	-0.13	0.05
Harney	-0.40	0.41	0.53	0.77	-0.80	-0.09	-0.28	0.28	1.17	-0.73	-0.52	-0.73	-0.26
Hood River	0.53	-0.91	-0.58	-0.35	1.20	-0.20	0.76	-0.76	-1.62	0.13	-1.47	0.12	1.16
Jackson	-0.05	0.15	0.05	0.41	-0.26	0.59	0.80	-0.80	0.75	-0.05	0.73	0.09	-0.24
Jefferson (OR)	0.89	-0.33	-0.33	-2.13	1.69	1.46	-0.25	0.25	0.90	-0.93	-0.41	-1.23	0.82
Josephine	-0.66	1.12	0.86	0.87	-0.67	0.08	0.07	-0.07	1.19	-0.87	0.63	-0.40	0.10
Klamath	0.05	0.04	-0.01	0.13	-0.02	0.36	0.18	-0.18	1.47	-0.73	0.04	-0.38	0.18
Lake	-0.99	0.73	0.88	0.59	-0.57	-1.09	-0.18	0.18	1.10	-0.40	0.61	-0.17	0.65
Lane	-0.55	-0.40	-0.43	0.45	-0.34	0.29	1.31	-1.31	1.08	-0.12	1.05	0.43	-0.60
Lincoln (OR)	-0.81	0.99	1.22	0.33	-0.32	-0.50	0.45	-0.45	0.60	0.13	0.37	0.39	-0.01

Linn	0.47	-0.31	-0.39	0.63	-0.56	0.48	0.36	-0.36	0.46	-0.66	-1.09	-0.76	-0.18
Malheur	1.08	-0.40	-0.86	-1.09	1.41	1.15	0.83	-0.83	1.21	-1.93	0.39	-1.48	1.55
Marion	1.15	-0.84	-1.03	-0.90	1.03	1.42	1.09	-1.09	1.08	-0.60	-0.11	-0.53	0.83
Morrow	0.87	-0.87	-0.81	-1.13	1.31	-0.14	-0.78	0.78	0.66	-0.88	-0.74	-1.74	1.78
Multnomah	0.26	-1.33	-0.94	-1.05	0.75	0.31	2.24	-2.24	0.32	1.29	1.65	1.86	-0.27
Polk	0.40	-0.44	-0.72	0.09	0.02	0.14	0.16	-0.16	-0.29	0.01	-0.45	0.35	-0.55
Sherman	-0.52	1.01	1.00	0.81	-0.96	-1.65	-0.06	0.06	-1.09	-0.09	-0.20	-0.73	-0.40
Tillamook	-0.43	0.83	0.89	0.64	-0.54	-0.89	-0.41	0.41	-0.12	-0.49	-0.75	-0.47	0.10
Umatilla	1.12	-0.87	-0.94	-0.88	0.93	1.52	0.76	-0.76	1.05	-0.83	-0.71	-1.09	1.02
Union	0.28	-0.04	-0.27	0.84	-0.91	0.49	0.30	-0.30	0.42	-0.56	0.85	-0.32	-0.33
Wallowa	-0.50	1.31	1.36	1.18	-1.22	-1.08	-0.77	0.77	0.75	-0.51	-0.39	0.27	-0.76
Wasco	0.39	0.15	-0.01	-0.05	0.24	0.37	0.53	-0.53	0.57	-0.45	-0.17	-0.28	1.07
Washington	0.95	-1.43	-1.00	-1.07	0.93	0.35	1.05	-1.05	-1.29	1.66	-0.22	1.78	-0.65
Wheeler	-0.88	2.55	1.74	0.86	-0.93	-2.06	0.11	-0.11	-0.80	0.12	0.69	-0.78	0.70
Yamhill	0.41	-0.74	-0.77	-0.03	0.11	0.74	-0.11	0.11	-0.04	-0.24	-0.63	-0.39	0.02
Adams	3.62	-1.39	-1.97	-3.05	3.59	1.76	0.32	-0.32	1.57	-1.96	-1.07	-1.78	3.13
Asotin	-0.09	0.50	0.27	1.00	-1.03	1.34	0.02	-0.02	0.33	-0.07	0.46	-0.63	-0.17
Benton (WA)	1.14	-1.07	-0.95	-0.38	0.49	1.06	-0.20	0.20	-0.74	0.86	-0.60	0.50	-0.35
Chelan	0.63	-0.31	-0.38	-0.88	0.80	0.21	0.64	-0.64	-1.61	0.23	0.39	0.02	0.89
Clallam	-0.94	1.49	1.12	0.21	-0.32	-0.35	-0.79	0.79	-0.68	0.27	-0.47	0.77	-0.59
Clark	0.73	-1.14	-0.78	0.05	-0.09	0.76	0.24	-0.24	-0.43	0.79	-0.51	0.35	-0.74
Columbia (WA)	-0.50	1.26	1.01	0.87	-0.79	-0.23	-0.96	0.96	-0.07	0.52	1.35	-0.21	0.32
Cowlitz	0.34	-0.31	-0.24	0.47	-0.44	1.11	0.24	-0.24	1.07	-0.26	0.03	-0.77	0.26
Douglas (WA)	1.01	-0.57	-0.77	-0.87	1.03	0.71	-0.51	0.51	-0.54	-0.43	-1.70	-0.65	1.29
Ferry	-0.61	0.42	0.86	-1.05	0.49	-0.48	-0.86	0.86	0.65	-1.29	0.74	-0.66	0.07
Franklin	3.51	-2.00	-2.07	-3.26	3.09	2.61	0.16	-0.16	1.15	-1.35	-0.71	-1.63	2.76
Garfield	-1.29	1.13	1.12	0.88	-1.04	-1.97	-1.21	1.21	-2.78	0.62	-2.42	1.16	-1.31
Grant (WA)	2.34	-1.06	-1.49	-1.63	1.95	1.37	0.79	-0.79	1.03	-1.05	-0.34	-1.37	2.00

Grays Harbor	-0.08	-0.13	0.02	-0.04	-0.06	0.58	-0.12	0.12	1.25	-0.66	-0.09	-0.84	0.70
Island	-0.13	0.31	0.22	0.17	-0.17	-0.64	-0.68	0.68	-1.69	1.44	-1.02	1.25	-1.44
Jefferson (WA)	-1.79	1.94	1.88	0.70	-0.75	-1.15	-1.27	1.27	-1.07	0.99	0.31	2.24	-1.06
King	0.21	-1.25	-0.72	-2.03	1.36	-0.46	1.42	-1.42	-1.65	3.64	1.10	2.83	-0.83
Kitsap	-0.04	-0.76	-0.36	-0.14	0.20	0.29	-0.21	0.21	-1.16	1.61	-0.42	0.86	-1.19
Kittitas	-0.74	-0.87	-1.52	0.44	-0.49	-0.99	1.61	-1.61	-0.53	-0.51	0.63	0.13	-0.89
Klickitat	-0.36	0.19	0.55	0.26	-0.29	-0.82	-0.59	0.59	0.71	-0.74	-0.72	-0.44	0.22
Lewis	0.09	0.09	-0.04	0.52	-0.48	0.39	-0.50	0.50	0.90	-0.58	-1.01	-0.82	0.48
Lincoln (WA)	-0.56	0.81	0.91	1.06	-1.13	-0.97	-1.95	1.95	-0.92	0.12	-0.75	-0.04	-1.02
Mason	-0.42	0.29	0.41	0.15	-0.16	-0.27	-1.85	1.85	-0.10	-0.23	-0.65	-0.36	0.07
Okanogan	0.65	0.06	0.18	-1.48	1.05	0.40	-0.23	0.23	0.67	-0.89	0.45	-0.54	1.15
Pacific	-0.90	1.64	1.40	0.23	-0.35	-1.10	-1.03	1.03	0.37	-0.18	0.56	-0.46	0.68
Pend Oreille	-0.44	0.46	0.94	0.70	-0.79	-0.33	-1.78	1.78	1.16	-0.48	1.82	-0.23	-0.25
Pierce	0.79	-1.22	-0.91	-1.11	1.00	1.68	0.73	-0.73	-0.74	0.86	-0.68	0.02	-0.62
San Juan	-1.91	1.31	1.70	0.80	-0.86	-1.19	-0.58	0.58	-2.16	3.39	2.70	3.25	-1.20
Skagit	0.41	-0.16	-0.26	-0.32	0.34	0.25	-0.15	0.15	-0.57	0.67	-0.74	0.34	-0.07
Skamania	-0.37	-0.52	0.35	0.88	-0.78	-0.67	-1.25	1.25	-0.64	0.91	0.65	-0.11	-0.46
Snohomish	0.52	-1.37	-0.72	-0.81	0.56	0.23	0.02	-0.02	-1.23	1.62	-1.36	0.81	-0.70
Spokane	0.35	-0.83	-0.77	0.50	-0.50	0.78	0.46	-0.46	-0.04	0.30	0.47	0.79	-1.10
Stevens	-0.49	0.07	0.50	0.49	-0.63	-0.39	-1.91	1.91	0.24	-0.66	-0.71	-0.07	-0.55
Thurston	0.11	-0.82	-0.50	-0.20	0.20	0.88	0.09	-0.09	-1.17	1.34	-1.17	1.21	-1.07
Wahkiakum	-1.48	1.79	1.63	1.04	-0.99	-1.92	-2.25	2.25	0.58	0.10	-0.62	-0.26	-1.00
Walla Walla	0.02	-0.41	-0.78	-0.18	0.52	0.37	0.67	-0.67	-0.22	-0.23	0.56	0.38	-0.07
Whatcom	-0.24	-0.76	-0.80	0.00	-0.09	-0.34	0.90	-0.90	-0.67	0.45	0.39	1.07	-0.78
Whitman	-1.16	-1.54	-2.69	-0.10	-0.13	-1.65	3.90	-3.90	-1.71	-1.03	3.53	0.95	-2.02
Yakima	2.15	-1.11	-1.48	-2.78	2.79	2.73	0.70	-0.70	1.43	-1.22	0.04	-1.45	2.88

Appendix B (Cont.):

County Name	Employed	Female Employed	Below Poverty	Critical	Essential	Medical	Dependent	Schools	Religious	Forest Area
Baker	-0.66	-0.36	0.85	0.17	0.17	-0.78	0.15	0.18	0.16	-0.25
Benton (OR)	1.03	1.32	1.21	-0.49	-0.56	0.49	-0.68	-0.71	-0.70	0.41
Clackamas	1.28	1.12	-1.62	-0.77	-0.62	-0.34	-0.54	-0.74	-0.88	0.96
Clatsop	1.02	0.99	-0.09	0.48	-0.15	0.98	-0.61	-0.33	-0.08	0.03
Columbia (OR)	0.27	0.31	-0.53	-0.53	-0.48	-1.09	-0.05	-0.38	-0.21	0.08
Coos	-0.68	-0.02	0.30	-0.49	-0.36	-0.69	-0.12	-0.38	0.21	0.70
Crook	-0.73	-1.07	0.38	-0.48	-0.27	-1.17	-0.48	-0.57	-0.39	0.09
Curry	-1.46	-0.65	-0.56	0.89	0.02	1.44	-0.23	-0.27	0.24	0.98
Deschutes	0.80	0.97	-0.74	0.13	-0.57	0.92	-0.10	-0.55	-0.75	0.48
Douglas (OR)	-0.80	-0.32	0.47	-0.13	-0.33	0.11	-0.51	-0.38	0.01	1.27
Gilliam	1.47	-0.31	-0.86	4.50	4.20	4.57	4.52	3.31	2.63	-1.77
Grant (OR)	-0.54	-0.40	-0.07	0.96	0.97	-0.63	0.01	1.54	0.60	1.11
Harney	0.21	0.34	0.78	0.83	0.48	-0.63	1.37	2.62	0.10	-1.31
Hood River	1.74	1.50	-1.51	0.77	-0.11	1.92	0.79	-0.41	0.15	1.31
Jackson	0.29	0.72	0.16	-0.45	-0.57	0.00	-0.05	-0.78	-0.71	1.27
Jefferson (OR)	-0.63	-1.06	0.71	-0.62	-0.27	-1.21	-0.64	-0.02	-0.26	0.87
Josephine	-1.38	-0.94	1.04	-0.79	-0.55	-0.42	-0.12	-0.77	-0.46	1.65
Klamath	-0.19	-0.27	0.66	-0.09	-0.37	0.88	-0.67	-0.55	-0.25	0.92
Lake	0.16	0.26	0.13	1.37	0.93	0.52	0.19	1.93	2.16	-0.76
Lane	0.64	0.95	0.69	-0.63	-0.57	-0.16	-0.56	-0.74	-0.72	1.06
Lincoln (OR)	0.19	0.86	0.00	0.76	0.05	0.82	-0.28	-0.76	0.32	0.44
Linn	-0.22	-0.29	0.18	-0.69	-0.54	-0.81	-0.33	-0.53	-0.17	0.57
Malheur	-1.61	-1.21	1.77	0.01	-0.17	-0.08	-0.09	0.61	-0.04	-1.81
Marion	0.26	0.39	0.45	-0.64	-0.56	-0.50	-0.65	-0.73	-0.84	0.04
Morrow	-0.02	-0.81	-0.08	0.89	0.21	-0.64	-0.45	0.30	0.19	-1.16
Multnomah	2.32	2.41	0.25	-0.70	-0.62	0.49	-0.55	-0.88	-0.82	0.07
Polk	-0.14	0.09	-0.39	-1.24	-0.67	-1.33	-1.03	-0.71	-0.85	-0.03
Sherman	-0.37	0.08	1.68	1.56	3.79	1.14	4.66	2.56	2.06	-1.80
Tillamook	-0.27	-0.04	0.22	0.81	0.12	-0.99	0.45	0.00	0.00	0.78
Umatilla	0.10	-0.02	-0.29	-0.50	-0.37	-0.20	-0.18	-0.38	-0.46	-0.60
Union	-0.22	0.08	0.27	-0.13	0.01	0.55	-0.17	-0.09	-0.03	0.88
Wallowa	-0.30	0.40	-0.38	0.46	0.71	0.93	-0.22	2.88	0.94	0.24
Wasco	0.11	0.05	0.81	0.75	-0.13	0.62	0.36	-0.30	0.30	-0.18

Washington	1.73	1.51	-1.31	-0.84	-0.75	-0.22	-0.72	-0.96	-1.19	-0.03
Wheeler	0.28	-0.07	-1.07	3.92	4.62	2.74	3.79	2.01	4.80	0.51
Yamhill	0.63	0.47	-0.68	-0.63	-0.56	-0.35	-0.31	-0.59	-0.45	0.17
Adams	-0.41	-1.43	1.84	-0.48	0.05	-0.82	-0.14	0.36	0.55	-1.91
Asotin	-0.45	0.54	-0.61	-0.52	-0.40	0.80	0.40	-0.16	-0.31	-1.15
Benton (WA)	0.46	-0.05	-0.79	-0.29	-0.65	1.12	-0.72	-0.85	-0.95	-1.91
Chelan	0.44	0.25	-0.82	-0.36	-0.40	-0.92	0.18	-0.23	-0.31	1.05
Clallam	-1.14	-0.81	-0.69	-0.20	-0.44	0.64	-0.34	-0.52	-0.41	0.09
Clark	0.75	0.68	-1.04	-1.03	-0.69	-0.80	-0.47	-0.95	-1.08	-0.17
Columbia (WA)	-0.69	-0.02	-0.75	1.08	0.99	0.06	0.47	0.69	2.10	-0.52
Cowlitz	-0.52	-0.54	0.50	-0.82	-0.50	-0.71	-0.48	-0.64	-0.45	0.65
Douglas (WA)	0.56	0.12	0.16	-1.25	-0.45	-2.00	-0.52	-0.70	-0.81	-1.84
Ferry	-2.96	-3.50	1.16	1.38	0.53	1.08	-0.70	1.65	0.69	1.00
Franklin	-0.43	-1.19	1.38	-0.70	-0.64	-0.70	-0.81	-0.81	-0.87	-1.90
Garfield	-0.03	0.99	-1.66	1.81	1.69	2.02	-0.91	1.13	1.93	-1.11
Grant (WA)	-0.06	-0.79	1.06	-0.70	-0.43	-1.01	-0.53	-0.18	-0.52	-1.89
Grays Harbor	-0.67	-0.58	0.53	0.05	-0.19	0.38	0.26	-0.25	-0.08	0.07
Island	0.50	0.20	-1.89	-0.94	-0.58	-0.87	-0.31	-0.67	-0.72	-0.91
Jefferson (WA)	-0.83	-0.34	-0.64	0.00	-0.29	0.69	-0.43	0.17	-0.42	0.91
King	2.42	2.07	-1.33	-0.78	-0.67	-0.14	-0.33	-0.81	-1.04	0.56
Kitsap	0.98	0.24	-1.50	-0.89	-0.68	-0.74	-0.35	-0.84	-0.79	0.18
Kittitas	0.75	0.72	1.26	-0.32	-0.15	-0.73	0.42	-0.30	-0.34	0.03
Klickitat	-1.43	-1.40	0.83	-0.29	0.29	-0.48	0.30	0.48	0.57	-0.27
Lewis	-0.60	-0.57	-0.56	-0.36	-0.18	-0.49	0.56	-0.12	0.07	0.88
Lincoln (WA)	-0.44	-0.60	-0.42	1.06	0.67	-0.22	-0.13	2.68	1.84	-1.73
Mason	-1.12	-1.12	0.27	-0.64	-0.57	-0.68	-0.54	-0.88	-0.69	0.68
Okanogan	-0.63	-0.63	1.18	0.43	-0.06	0.25	0.23	0.36	0.20	0.50
Pacific	-1.35	-1.06	0.56	0.99	0.82	-0.21	0.48	0.50	0.98	-0.10
Pend Oreille	-2.47	-2.80	1.62	-0.04	-0.07	-0.38	-0.48	-0.11	0.28	1.46
Pierce	1.07	1.01	-1.10	-0.82	-0.66	-0.04	-0.55	-0.66	-0.86	0.51
San Juan	1.10	1.34	-1.23	0.65	0.40	-0.11	1.46	0.32	0.44	-1.05
Skagit	0.19	-0.04	-0.89	-0.04	-0.40	0.52	0.00	-0.61	-0.41	0.69
Skamania	0.05	-0.24	-0.92	-0.55	0.22	-0.93	-0.21	0.46	0.10	1.07
Snohomish	1.77	1.41	-1.61	-1.05	-0.74	-1.00	-0.67	-0.97	-1.10	1.08

Spokane	0.80	0.98	-0.37	-0.42	-0.62	0.38	-0.27	-0.65	-0.69	-0.71
Stevens	-1.18	-0.92	0.15	-0.42	-0.40	-0.68	-0.59	0.60	0.19	0.91
Thurston	1.20	1.58	-1.28	-0.52	-0.33	0.22	0.03	-0.63	-0.96	0.24
Wahkiakum	-1.10	-1.25	-0.06	0.60	1.17	0.89	0.47	0.29	1.17	0.43
Walla Walla	-0.19	-0.28	0.15	-0.59	-0.40	-0.33	0.02	-0.48	-0.44	-1.76
Whatcom	1.33	1.29	-0.11	-0.72	-0.57	-0.25	-0.36	-0.69	-0.69	0.67
Whitman	0.47	0.23	3.20	-0.09	-0.26	-0.51	-0.25	0.03	-0.15	-1.84
Yakima	-0.45	-0.45	1.61	-0.63	-0.56	-0.17	-0.15	-0.46	-0.63	-0.08