Towards Quantitative Assessment of Vulnerability, Resilience, and the Effects of Adaptation on Social-Environmental Systems

By

Katherine S. Nelson

Dissertation

Submitted to the Faculty of the

Graduate School of Vanderbilt University

in partial fulfillment of the requirements

for the degree of

DOCTOR OF PHILOSOPHY

in

Environmental Engineering

June 30, 2018

Nashville, Tennessee

Approved:

Mark Abkowitz, Ph.D.

Janey Camp, Ph.D.

Hiba Baroud, Ph.D.

Jonathan Gilligan, Ph.D.

James Fraser, Ph.D.

ACKNOWLEDGMENTS

I would like to recognize financial support from the National Center for Freight & Infrastructure Research and Education (CFIRE), a consortium of University Transportation Centers funded in part by the United States Department of Transportation (USDOT), the U.S. Army Corps of Engineers (USACE) Research Participation Program, which is administered by an Oak Ridge Institute for Science and Education (ORISE) Graduate Research Fellowship, and Nashville Metro Water Services (MWS), all of which funded significant portions of this work. I am grateful for the feedback of the employees at MWS who helped guide, and provided data in support of, the work presented in the fourth chapter of this dissertation. I am also indebted to fellow collaborators Leslie Marthaler-Gillespie and Emily Burchfield for being amazingly supportive and dedicated co-workers and friends. I am also grateful to my friends and colleagues Leah Dundon and Paul Johnson for both being such reliable collaborators and understanding office-mates. Thanks also go to Mark Abkowitz, Janey Camp, Jonathan Gilligan, Hiba Baroud, and Craig Philip for their generous support and guidance over the past five years. Finally, I would like to acknowledge the support of my family, Tuan, Mira, and Ella, who put everything in perspective.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Figures Page

CHAPTER I: INTRODUCTION

Overview

The concepts of vulnerability and resilience have been gaining attention in the realm of hazards and climate change adaptation in the past couple decades, with a variety of approaches and definitions utilized in their assessment. In recent years, more efforts have been made to link these concepts under the umbrella of sustainability science, and adaptive capacity has emerged as a common factor that holds particular relevance in the context of climate adaptation and management/governance of social-environmental, or socio-environmental, systems (Engle, 2011; Turner et. al., 2003).

Adaptive capacity is often described as the ability to adapt when faced with stressors or shocks that adversely impact a system, and is usually seen to be a universally positive attribute that can be shaped by human actions. From a vulnerability standpoint, adaptive capacity is seen as an attribute that allows the system to prepare for and respond to stressors and shocks, thereby having a moderating effect on the exposure and sensitivity components of vulnerability (Adger, 2006; Engle, 2011). In the resilience literature, adaptive capacity is often seen as the ability of actors to facilitate interactions between the human and environmental components of a system in order to increase the likelihood that a system will be resilient (Engle, 2011). In both cases, governance structures and the ability of humans to act, which is constrained by resource availability, are defining features of adaptive capacity that link the two concepts of resilience and vulnerability.

While there is nearly universal agreement that increased adaptive capacity of social-environmental systems is a positive attribute that should be encouraged, efforts to build adaptive capacity are hampered by a number of ongoing issues. Lack of consensus on the determinants of adaptive capacity and how they relate to concepts of vulnerability and resilience are apparent in climate adaptation and hazard response literature (Eakin & Luers, 2006; Engle, 2011; Gallopín, 2006; Hinkel, 2011). The diversity of ideas and approaches taken towards adaptive capacity, vulnerability, and resilience assessment is in part fueled by the contextual nature of these concepts, but also by a lack of evidence-based measurement (Eakin & Luers, 2006; Engle, 2011; Hinkel, 2011).

The use of composite indices to describe or characterize these concepts is heavily favored in the vulnerability literature as they provide a generalizable inductive approach to indicator selection and simplify complexity to a single value. However, without some sense of the actual effect vulnerability, resilience, and adaptive capacity, as represented by these indices, have on hazardous event outcomes, the usefulness of the indices as a planning tool is questionable (Hinkel, 2011). Evidence-based validation of composite indices is hampered in part by a lack of relevant and appropriately scaled data, by the nature of composite indices, which aggregate complexity to a form from which causal relationships cannot be untangled, and also by the lack of a clearly operationalized framework for assessing relationships between vulnerability, hazard-induced impacts, resilience, and adaptive capacity. This suggests that context-specific deductive selection of indicators, spatial modeling methods, and an operational framework that proposes causal pathways, may be necessary for evidence-based measurement of vulnerability, resilience, and adaptive capacity to bear fruit. While deductive context-specific approaches may reduce the generalizability of results, this may be a necessary sacrifice, as without a clear understanding of the determinants of vulnerability, resilience, and adaptive capacity, and the mechanisms that link them to impacts on communities, the costs of maladaptation remain unquantified, and it becomes difficult to justify expenditures toward increasing a system's adaptive capacity.

Outline of the Dissertation

Several gaps in vulnerability, resilience, and adaptive capacity research continue to linger. The most predominate of these gaps include: (1) continued confusion about the conceptual links between vulnerability, resilience, and adaptive capacity (and sustainability), (2) lack of an assessment framework that can account for the multi-scalar (through space and time) and dynamic processes related to all of these inter-dependent concepts, (3) lack of secondary verification of measurements of the aforementioned concepts and determinants, and (4) lack of quantitative analytical assessment of impacts of these concepts on outcomes to disrupted systems. The work presented in this dissertation attempts to begin addressing these gaps by building theory on adaptive capacity, vulnerability, and resilience, and by developing and demonstrating methods that enable the assessment and verification of qualities that influence the survivability and well-being of complex, adaptive social-environmental systems subject to environmental stressors or shocks. The research objectives for this work are as follows:

- Develop a framework for assessing the connections between the concepts of vulnerability, resilience, and sustainability.
- Develop and/or demonstrate use of a spatial disaggregation technique and a spatial modeling method that can be used to support assessment of vulnerability and resilience for social-environmental systems.
- Apply the developed framework and spatial analysis techniques to empirically assess the effects of an urban flood adaptation strategy.

Chapter II of this dissertation presents a review of the literature on vulnerability, resilience, sustainability, and adaptive capacity and a conceptual synthesis of these topics (Gillespie-

Marthaler, Nelson, Baroud, & Abkowitz, *under review*). Furthermore, a framework for empirical assessment of sustainable resilience, which integrates aspects of vulnerability, resilience, and sustainability concepts in an adaptive cycle is proposed (Nelson, Gillespie-Marthaler, Baroud & Abkowitz, *working paper*). The work presented in Chapter II addresses the confusion about the conceptual links between core concepts (vulnerability, resilience, adaptive capacity, and sustainability) in social-environmental studies (Gap 1) and proposes an assessment framework capable of accounting for multi-scalar dynamic processes in these core concepts (Gap 2).

In Chapter III, a spatial disaggregation technique and a spatial modeling method that may be used to support assessment of sustainable resilience using the framework described in Chapter II are described and demonstrated (Nelson & Burchfield, 2016; Nelson & Burchfield, 2017; Nelson, Camp, & Abkowitz, 2015). In Chapter II, the ability to account for the multi-scalar nature of social-environmental system processes is identified as a critical concern. The work in Chapter III begins to bridge the gap between framework and operationalization by developing and demonstrating an approach for downscaling census data to a spatial scale that is more representative of coincidence with flooding hazards and urban flood adaptation processes, the tax parcel (Nelson et al., 2015). Chapter III also demonstrates the use of hierarchical Bayesian spatiotemporal modeling as a method for empirically validating and investigating relationships between vulnerability and resilience in social-environmental systems (Nelson & Burchfield, 2016; Nelson & Burchfield, 2017).

Chapter IV presents an application of the developed sustainable resilience assessment framework presented in Chapter II and the two spatial analysis methods presented in Chapter III. This work serves as a first demonstration of operationalization of the developed framework for empirical assessment. This "proof-of-concept" work is grounded in a case study of an urban flood event and adaptation strategy in the Nashville, Tennessee, area. Finally, Chapter V synthesizes the findings of the work described in Chapters II through IV, summarizes the contributions of this dissertation, and discusses the broader impacts of the body of work.

CHAPTER II: VULNERABILITY, RESILIENCE, AND SUSTAINABILITY: AN INTEGRATED ASSESSMENT FRAMEWORK FOR COMPLEX ADAPTIVE SYSTEMS

Introduction

Though the concepts of vulnerability, resilience, adaptive capacity, and sustainability are often used independently, a great deal of conceptual overlap exists and assessments of each concept are frequently conducted in similar ways and used to address similar issues. Depending on the framework used and the type of application, the concepts of resilience and vulnerability can be seen as inversely related, interdependent, or intersecting (e.g., vulnerability as a part of resilience or resilience as part of vulnerability) (Engle, 2011; Turner, 2010; Lam, 2015; Gallopín, 2006; Bahadur et al., 2010). Often, decreasing vulnerability is considered to be an approach to increasing resilience (Sahely et al., 2005, Cutter et al., 2008; Bahadur et al., 2010). Some argue that resilience is a subset of vulnerability, and therefore that increasing resilience can be seen as a way of decreasing vulnerability (Gallopín, 2006; Turner et.al., 2003; Adger, 2006), and others consider vulnerability a subset or factor in resilience metrics (Henry & Ramirez-Marquez, 2012; Baroud et al., 2014). Increasing adaptive capacity, on the other hand, is seen as a way to both increase resilience and decrease vulnerability and has been highlighted as a bridging concept between resilience and vulnerability (Engle, 2011).

Resilience and vulnerability concepts are also frequently used within the umbrella of "sustainability science", which usually implicitly considers sustainability concepts in analysis and assessment of resilience and vulnerability by linking adaptive capacity to the availability of resources (Turner, 2010). However, concerns about either the environmental or the social component being under-considered in social-environmental system resilience and vulnerability assessments continue due to difficulties in trying to encompass many different variables and perspectives within a single conceptual framework or multiple frameworks operationalized in parallel. These shortcomings, and the typically short to mid-term temporal horizon and localized spatial window used in vulnerability and resilience assessments, lead to narrowed views that can ultimately result in unsustainable outcomes. In the sections below, I briefly discuss vulnerability, resilience, adaptive capacity, and sustainability concepts, identify challenges in their assessment for social-environmental systems, suggest a framework for thinking about interdependencies between the concepts, and propose an integrated framework for empirical assessment of social-environmental system sustainable resilience.

Core Concepts in Social-environmental Systems Studies

Vulnerability

The concept of vulnerability results from the standard risk concept that specifically addresses differential impacts from disturbances among populations, assets, and systems. Vulnerability is generally described as the extent to which a system is likely to experience losses from some hazard (impactful event), and as such, it is a universally negative quality (Adger, 2006; Turner et. al., 2003). Vulnerability assessment has evolved along two dominant tracks; the natural hazards community and the social science community. Different vulnerability assessment frameworks use quantitative, semi-quantitative, or qualitative methods, and many make use of composite indices to characterize vulnerability. In the natural hazards literature, vulnerability historically uses a risk-hazard model, where vulnerability is described as the combination of a risk factor, and the potential for loss in the system at risk (Turner et. al., 2003; Eakin & Luers, 2006). This approach equates the negative outcome of some hazardous event (typically a physical manifestation) that has been realized to vulnerability (Eakin & Luers, 2006).

In the social science community, vulnerability traditionally focuses on inequities in sensitivity and exposure (social equity) resulting from social-structural characteristics, such as socioeconomic and political status, demographics, culture, and governance (Adger, 2006; Cutter, 2003; Turner et. al., 2003; Eakin & Luers, 2006). In this approach, less emphasis is placed on the physical damage incurred by a specific hazard, with a greater emphasis placed on identifying who may be vulnerable and why they may be vulnerable (Adger, 2006; , 2003; Eakin & Luers, 2006). In both cases, imbalance can occur in assessing either the physical or social aspects of vulnerability, leading to an incomplete understanding of vulnerability within systems (social, ecological, engineered, and coupled social-environmental).

A more recently developed social-ecological systems approach to vulnerability attempts to merge both perspectives and defines vulnerability as the "state of susceptibility to harm from exposure to stresses associated with environmental and social change and from the absence of capacity to adapt" (Adger, 2006). In this application, vulnerability includes three components: exposure, sensitivity, and adaptive capacity. Exposure is simply the magnitude and extent to which a disruption or stress is experienced, sensitivity is the expected degree of impact from a disruption or stress given a certain exposure, and adaptive capacity is the ability to prepare for and respond to disruptions and stress (Adger, 2006; Engel, 2011), which is dependent upon the system's ability to effectively access and use necessary resources. Despite this broad definition of vulnerability, little consensus on the appropriateness of different methods for measuring or characterizing vulnerability across social-environmental systems has arisen.

The lack of consensus around vulnerability assessment mentioned above is due in part to continuing challenges in the ability to operationalize the different components of vulnerability and how to account for the differences between short-term and long-term vulnerability (Engle, 2011;

Gallopín, 2006; Fekete, 2012; Fussel, 2007; Eakin and Luers, 2006; Hinkel, 2011). The dynamic qualities of vulnerability are inextricably tied to adaptive capacity, as the ability to respond is a quality that describes pre-event readiness and immediate response, which occurs on short time scales, while the ability to plan and prepare is a quality that describes post-event learning process and associated change that occur on longer time scales. This dynamism can lead to confusion when selecting indicators of the sensitivity component of vulnerability as an indicator of sensitivity at one time scale (e.g., poverty may be an indicator of sensitivity during an active emergency as fewer resources are immediately available to respond to the crisis at hand), and may be an equally valid indicator of adaptive capacity at another time scale (e.g., poverty may also be an indicator of adaptive capacity as fewer resources are available to adequately prepare for future emergencies).

Resilience

The concept of resilience originates from ecological science, where it was originally defined as a system's ability to "absorb changes of state variables, driving variables, and parameters, and still persist" (Holling, 1973). Resilience is seen in this conceptualization as a property that results in a system's level of persistence. A commonly accepted definition of resilience today is the "capacity of a system to absorb disturbance and re-organize while undergoing change so as to still retain essentially the same function, structure, identity and feedbacks" (Folke, 2006). This conceptualization of resilience considers both system persistence and adaptability, and does so in the context of complex system interactions such as cross-scale dynamics, multiple equilibria, and feedback loops (Folke, 2006; Turner et al., 2003).

The concept of resilience of social-environmental systems is still under development and is used in diverse ways across fields of study. A recent analysis of resilience definitions yielded the following common attributes: 1) most refer to the ability of a system to absorb/respond and adapt to disruptive events, 2) recovery from disturbance is considered a critical component, 3) some require a return to a steady or pre-disturbance state, while others allow for system degradation or the possibility of an enhanced or transformed state, and 4) many include emphasis on preparedness and recovery activities (Hosseini et al., 2016). Recent definitions of resilience associated with social and economic systems incorporate the concepts of coping, adaptive, and transformative capacities (Engle, 2011; Keck & Sakdapolrak, 2013), and the ability to adapt or reconfigure to achieve strategic goals (Martin, 2012). In nearly all cases, the attainment of resilience is linked to a desired end state or functionality. In the case of social, engineered, or coupled systems, that end state is typically some combination of achieving social health and wellbeing.

The concept of resilience is clearly related to the concept of vulnerability, and in some cases resilient systems are even characterized by assessment of other system attributes including robustness, vulnerability, sustainability, and adaptive capacity. Due to the dynamic, multi-scalar, and interdependent nature of resilience of social-environmental systems, as it is currently understood, resilience assessment efforts are hampered by many of the same issues that plague social-environmental system vulnerability assessment.

Adaptive Capacity

The concept of adaptive capacity, as stated previously, is commonly defined as the ability to prepare for and respond to disturbance (Adger et al, 2004; Adger, 2006; Engle, 2011). This concept is less developed than the concepts of vulnerability, resilience, and sustainability, and not widely utilized by practitioners. However, it is gaining traction in social-environmental system assessment as it is commonly recognized as playing a supporting role in both vulnerability and resilience concepts (Engle, 2011). In addition, it is widely recognized that the adaptive capacity of a system is dependent upon the resources available to that system, linking the concept to that of sustainability via the availability of sustainability capital (Adger et al., 2004; Adger & Vincent, 2005; Engle, 2011; Turner, 2010). While the concept of adaptive capacity is not one of the primary concepts commonly used in complex system assessment today, and hence not a focus of this study, it is implicit within any assessment oriented towards understanding adaptive systems, and plays a key role in linking the three aforementioned concepts of vulnerability, resilience, and sustainability (Engle, 2011).

Sustainability

The classic definition of sustainability can be traced to the Brundtland Report, in which sustainable development was described as development that included trans-generational (long-term) equity by requiring that development be able to meet the needs of the present without compromising the ability of future generations to meet their own needs (WCED, 1987). The concept of recognizing present and future needs is related to the interdependence between critical human-centric (social), finance-centric (economic), and ecological-centric (natural) resources. A sustainable social-environmental system is understood as a system with the ability to provide sufficient resources to the human population without endangering the viability of the natural system, and is essentially concerned with, "address[ing] threats to provisioning society and to maintaining life support systems," (Turner, 2010) through management of critical resource capital. Critical resource capital, or sustainability capital, must be managed strategically over appropriate spatial and temporal scales to ensure future viability. In this sense, "capital" refers to the amount of a critical resource (social, economic, or natural) that may be available at a point in time. Strategic management of sustainability capital includes consideration of both risk and opportunity to provide desired outcomes and overall system quality. Sustainability is primarily future-focused and seeks to achieve environmental equity, long-term allocative efficiency, and distributive efficiency (Bithas & Christofakis, 2006) across sustainability capital in order to maintain system viability and wellbeing.

When used to characterize system quality, sustainability assessment without adequate consideration of changes to sub-system/component vulnerability and resilience can lead to sub-optimal system performance and assessment. Where specific applications of sustainability assessment may require that a system is optimized to reduce material flows, the same system may also require an increase in materials to achieve decreased vulnerability and/or increased resilience through protective measures such as robustness and adaptability (Ahern, 2011; Bocchini et al., 2014; Minsker et al., 2015). This is especially true over time and under changing circumstances that may not have been fully anticipated, or may not be fully definable without a high degree of uncertainty (Minsker et al., 2015), such as climate variability, extreme weather events, market trends, and population shifts. While sustainability is inherently multi-generational in scope, typical sustainability assessments offer only a snapshot in time related to a specific set of resource trajectories. This does not allow for evaluation of sustainability over time and under dynamic conditions. However, due to interdependence with vulnerability and resilience concepts, consideration of sustainability dynamics is also bound to be subject to the same limitations and challenges as vulnerability and resilience assessment, where this is expected to be most apparent in evaluation of social resources.

Challenges in Assessment

Assessment of vulnerability, resilience, adaptive capacity, and sustainability of social-environmental systems (SESs) are challenging due to the latent nature of the concepts and the dynamic, multi-scalar, and interdependent qualities of SESs. The latency of the concepts means that they must be represented by indicators suggested by theory. A large number of indicator studies have been conducted for all of these concepts, however the theoretical framing that drives indicator selection is often underdeveloped, and relatively little validation of indicators has been conducted to support indicator choice. In addition, in many cases selected indicators are used to create a composite index that is intended to serve as a measure of the concept in question. However, few validation studies of composite indices using external data sources have been conducted, and analyses of composite indicators have shown they are sensitive to indicator selection and aggregation methods. The lack of validation is, in large part, the result of a lack of external measures of the concepts, but is also hampered by the complexity of SESs and the lack of appropriate tools to model dynamic and interdependent processes through space and time. Below, I discuss the state of the knowledge in indicator selection, the importance of scale of analysis, and emerging tools for spatiotemporal analysis.

Indicator Selection

In the natural hazards literature, vulnerability is often examined as the intersection of social vulnerability and exposure, where exposure is some standardized measure of the magnitude or severity of exposure (e.g., flood inundation depth). In this literature, social vulnerability indices are typically based on a definition of vulnerability that posits that social stratification and local infrastructure factors are the primary contributors to the vulnerability or resilience of a population (Chakraborty, 2005; Cutter, 1996; Cutter, et al., 2003; Rygel, et al., 2006). The vulnerability indicators (such as age, gender, socioeconomic status, living arrangements, access to medical care, and race/ethnicity) used in construction of most social vulnerability indices are heavily based on socio-demographic information measured in census data and are generally consistent from one study to another (Azar, 2007; Cutter, et al., 2003; Rygel, et al., 2006). However, choice of which specific census variable to use to represent a vulnerability indicator and the number of indicators and variables used for an index varies widely, with the number of variables used ranging from less than ten to more than fifty depending on the type of analysis and the index construction method (Chakraborty, 2005; Cutter, et al., 2003; Fekete, 2009; Krishnamurthy, 2011; Rygel, et al., 2006; Shepard et al., 2012; Wilhelmi, 2013).

Often, studies that used the above mentioned framework for construction of vulnerability indices do not specify the relationship of the indicators selected with a specific component of vulnerability (sensitivity or adaptive capacity), suggesting that the index represents vulnerability across time-scales (Cutter, 2003; Fekete, 2009). On the other hand, some studies create separate indices for each component of vulnerability, often using the same indicator more than once (for both sensitivity and adaptive capacity) (Frazier, 2014). The sub-indices are usually combined to create an overall composite index which then represents vulnerability across time scales. In addition to these issues of sensitivity and adaptive capacity confusion, physical environment and governance factors that relate to vulnerability are typically given only cursory attention. While infrastructure is included in these assessments, its inclusion is typically limited, leading to misrepresentation of the interconnectedness of the social and environmental in coupled systems.

In 2007, Eriksen and Kelly emphasized that credible selection of indicators depends on explicating a clear theoretical and conceptual framework, understanding the relationship between indicators and the processes that drive vulnerability, and on verification of indicators against independent measures of vulnerability. This call has been taken up by many researchers in the years since, with a limited response, in part due to the difficulty in obtaining appropriate independent measures of vulnerability (Hinkel, 2011; Engle, 2011; Fekete, 2009; Dominey-

Howes, 2007; Ignacio & Andres, 2016). In addition, multiple studies have drawn attention to possible mischaracterizations of vulnerability in composite index vulnerability assessments (Stafford, 2016; Dominey-Howes, 2007; Tate, 2012). Despite this, composite indices built using loosely justified indicators remain a common way of assessing vulnerability for planning purposes and index verification efforts are rare (Stafford, 2016; Eriksen and Kelly, 2007; Dunning, 2013; Cutter et al., 2013).

Resilience assessments, particularly those that attempt to include aspects of community or social resilience, often rely on similar loose theoretical frameworks, index construction techniques, and indicator sets as social vulnerability assessments (Keck & Sakdapolrak, 2013; Sherrieb, Norris & Galea, 2010; Mayunga, 2009; Burton, 2012). Hence, they are subject to many of the same issues with regards to potential for mischaracterization and lack of verification. The outcome of sustainability assessment is dependent upon the scale of analysis and level of detail included in defining objectives, indicators and performance measures. As with resilience and vulnerability assessment, challenges exist in sustainability assessment when attempting to aggregate indices and metrics across sub-systems and components, especially when considering extended spatial and temporal scales.

Scale of Analysis

The analytical problems associated with coincidence analysis of hazards and populations have been well documented to show that scale does matter, particularly when examining the intersection of two or more areal units of different scales and spatial extents (Chakraborty, 2011; Mennis, 2003). Different interpretations of intersection or overlap of census units with hazard zones have been shown to have a large influence on the results of hazard risk analysis, leading to both overestimation and underestimation of at-risk populations, an issue referred to as the

Modifiable Areal Unit Problem (MAUP) (Maantay, et al., 2007; Mennis, 2002). In particular, the use of census data, which is heavily relied upon for social vulnerability and environmental justice studies, restricts spatial interpretation of socio-demographic data to areal units (e.g., census tracts) that may not correlate well with the spatial scale of the hazard of interest (e.g., floodplains), or with the actual boundaries of spaces in which people are located (e.g., residences).

Dasymetric mapping techniques have recently received attention as a valuable tool for vulnerability and environmental justice analyses as they provide a way to disaggregate socio-demographic data to a finer scale which may be more representative of the area affected by a hazard (Chakraborty, 2011; Maantay, et al., 2007; Mennis, 2003). Dasymetric mapping is a form of areal interpolation that utilizes an ancillary dataset containing supplementary information that can be used to redistribute data to smaller areal units. Land use classification raster data sets are commonly used as an ancillary dataset for this purpose, allowing census data to be redistributed to raster grids of 30m to 100m in edge length by attributing a population density to different land use classifications (Mennis, 2002; Mennis, 2003). An alternative to land use classification rasters as a supplementary dataset is cadastral (tax parcel) data (Maantay, et al., 2007; Tapp, 2010). Using cadastral data as an ancillary dataset allows population data to be redistributed to individual parcels, a spatial unit highly relevant to municipal planning. While dasymetric mapping provides a way to intelligently disaggregate data, and hence remove some of the loss of information that can occur when performing regression analyses on census data, treating disaggregated data as if it is not clustered in regression analyses can lead to biases in the estimates of standard errors.

A complementary approach for analysis of multi-scalar effects is to use a multi-level or hierarchical modeling framework. Wu and David (2002) point out the loose hierarchical structuring of ecosystems, where different levels in the hierarchy correspond to processes that occur at different rates. Like ecosystems, SESs too can be considered to be hierarchal structured systems. Higher levels in the hierarchy typically represent processes that occur at larger spatial scales and longer time scales than lower level processes. The hierarchical modeling approach, multi-level modeling, is widely used in regression studies in the social sciences, as it provides a way to account for variance resulting from grouping (one classic example is students in classrooms). (Note: Hereafter, I will refer to multi-scalar modeling as “multi-level modeling” and reserve the term “hierarchical” for Bayesian analyses where it refers to nested prior distributions.) Use of multi-level modeling approaches for analysis of spatially nested processes has been advancing quickly over the past decade, propelled in large part by the fields of epidemiology and ecology (Arcaya, 2012; Chaix, 2005; da Roza, 2012; Pisano, 2015; Blangiardo et al., 2013).

The complexity of analyses including spatial effects has led many in epidemiology to utilize Bayesian methods that account for complex covariance structures. Increasing demand for more computationally efficient software that can model more complex processes has driven development of software packages that can model effects that exhibit spatial and temporal dependency. One such software package is R-INLA (Blangiardo et al., 2013), a package developed for the free statistical software R that uses an integrated nested Laplace approximation approach to Bayesian analysis of multi-level, spatial, temporal, and spatiotemporal data. Use of the package has been demonstrated for ecological, environmental, social, and epidemiological datasets, and more recently for datasets combining two or more of these data types, subject to different types of spatial and temporal processes (Raghavan et al., 2016; Scott, 2015; Lindgren & Rue, 2015). These studies demonstrate the flexibility of Bayesian multi-level spatiotemporal modeling using the R-INLA package, and provide support for adoption of these methods for examining the concepts of vulnerability, resilience, adaptive capacity, and sustainability.

Conceptual Links

General and widely accepted definitions of the concepts of vulnerability, resilience, sustainability, and adaptive capacity were compiled from the literature and are specified as follows:

- Vulnerability is defined as the likelihood of experiencing loss due to hazard as a function of exposure, sensitivity, and adaptive capacity;
- Resilience is defined as the ability to resist disruption, recover, adapt, and/or transform given a hazardous event in order to maintain desired system performance;
- Sustainability is defined as the long-term ability to operate without failure through balanced management of critical *social*, *economic*, and *environmental capital* (Adger, 2006; Folke, 2006; Hosseini et al., 2016; Minsker et al., 2015).
- Adaptive capacity is defined as the ability to cope with, recover from, and adapt/transform in response to hazardous events (Adger et al., 2004; Adger and Vincent, 2005; Smit and Wandel, 2006).

Drawing from these definitions, and from literature on the theoretical foundations and practical applications of each concept, possible causal relationships relating to cross-scalar processes (e.g. emergence) and time frame of analysis were identified. The suggested links between the concepts are shown in Figure 1.

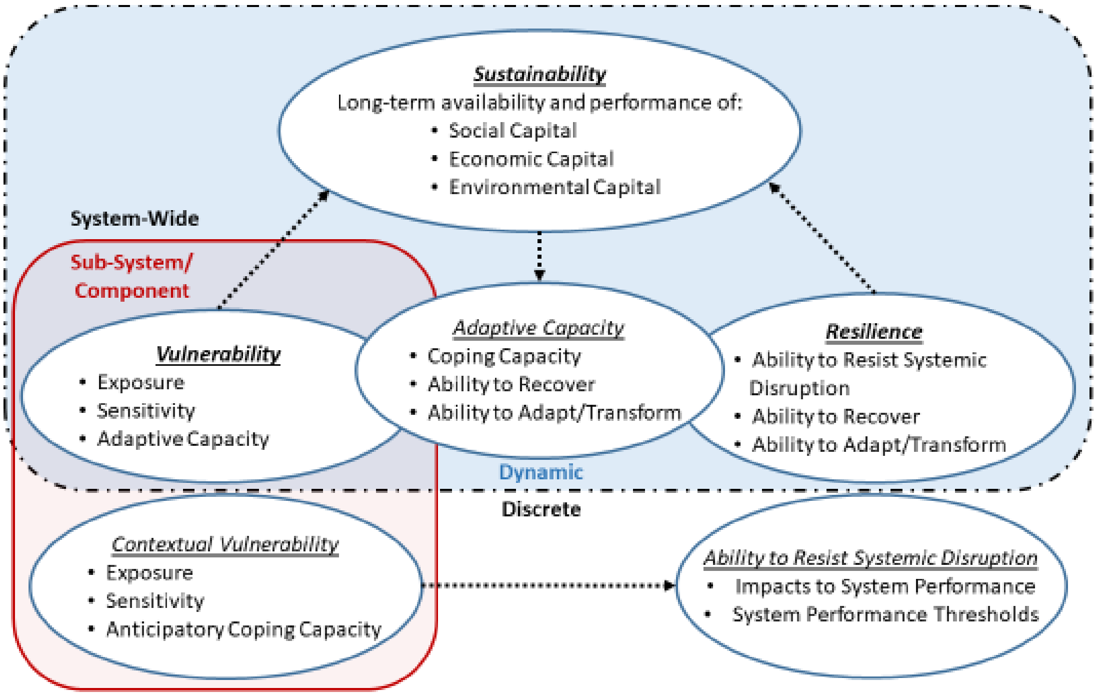

Figure 1: Conceptual interdependencies between vulnerability, resilience, sustainability, and adaptive capacity.

In Figure 1, large arrows indicate relationships between primary and contributing concepts (e.g., adaptive capacity is a key component of both vulnerability and resilience). Dashed arrows indicate conceptual dependencies/interdependencies between concepts. As shown, sustainability is presumed to have a direct impact on adaptive capacity, which is inherently dependent on the availability (access to needed quality and quantities) of sustainability capital. Sustainability is itself seen to be dependent on the ability of the system to resist systemic disruption, recover, adapt, and transform, which we define as resilience, as these abilities directly impact deposits and withdrawals from sustainability capital. This implies that the concept of adaptive capacity has an indirect effect on sustainability (through interactions between sustainability capital and system requirements to maintain desired levels of functionality, performance, and overall quality). In order to sustain functionality, performance, and quality through time, a system should have the ability to cope, recover, adapt, and/or transform, where the capacity to do so is moderated by the vulnerability and/or resilience of the system.

Adaptive capacity is itself seen to be one component in the set of components that comprise vulnerability and resilience. Contextual vulnerability, which is a discrete interpretation of vulnerability at a specific moment in time, also belongs to the complete set of vulnerability. At any discrete moment in time, a sub-system/component has an existing ability (or inability) to cope with change. Contextual vulnerability therefore, takes into account existing plans or capabilities that improve the effectiveness and range of actions available in response to a disruptive event, termed “anticipatory coping capacity” (Cutter, 2008; Gallopín, 2006; Turner, 2003). The ability to resist systemic disruption, a component of resilience, belongs to the complete set of resilience and is presumed to be dependent on contextual vulnerability. The ability to resist systemic disruption is based on interactions between critical sub-systems/components and their relative abilities to cope with a disruptive event, resulting in an overall system ability to either resist or succumb to disruption.

These relationships imply that the concepts of vulnerability and resilience are interdependent, and as formulated, are composed of the same basic building blocks. Despite this, differences in the scale, resolution, and unit of comparison that define the lenses of vulnerability and resilience mean that these concepts are not simple inverses of each other. In addition, both vulnerability and resilience are indirectly dependent upon sustainability capital and its ability to promote or constrain adaptive capacity through availability and effective use of critical resources. Based on these conceptual dependencies, the selection and implementation of system adaptation strategies resulting from an integrated assessment could inform and modify:

- sustainability (capital) through management (withdrawals and investments) in critical resources needed to effect changes in vulnerability and resilience over time;
- exposure, sensitivity, and/or coping through changes in adaptive capacity (increasing and/or decreasing critical sub-system/component vulnerability and system-wide resilience); and
- the need to consider and/or implement system transformation (where transformation strategies may lead to the definition of new hazards and a new set of vulnerability indicators).

Within a risk management framework, the typical end goal of a system assessment is to minimize adverse impacts, such as those addressed in the ability to resist systemic disruption (the discrete representation of resilience as shown in Figure 1). Therefore, evaluation of system resilience should serve as a reasonable focal point for integrated system assessment. Given the discussed conceptual linkages and the suggested use of resilience as a system assessment focal point, we define *sustainable resilience* as the ability of a system to maintain desired system performance by changing in response to expected and unexpected challenges over time, while simultaneously considering intra-system and inter-generational distribution of impacts and sustainability capital.

An Integrated Assessment Framework

The integrated sustainable resilience assessment framework has been developed for application to complex adaptive systems, specifically social-environmental systems. Like any system, social-environmental systems are defined by both their function and structure. As complex adaptive systems, social-environmental systems are expected to be subject to multi-scalar relationships between the system, sub-systems, and external systems where direct and indirect causal relationships, both physical and non-physical in nature, can result in impacts to overall system performance and quality. Complex, coupled social-environmental systems undergo adaptive cycles, where change is triggered by disruptive events (Adger, 2006; Engle, 2011). This is consistent with the characterization of resilience as the ability to resist disruption, recover, adapt, and/or transform given a hazardous event in order to maintain desired system performance. These systems are generally assumed to be metastable, in that adaptive cycles often lead to changes that do not significantly alter the state of the system as defined by its objectives and functional relationships (Adger, 2006; Engle, 2011). However, it is possible that significant change, resulting in transformation can redefine the objectives or functional relationships of the system (Engle, 2011; Martin, 2012; Keck & Sakdapolrak, 2013).

The proposed framework uses a serial and cyclical process, allowing users to assess observed hazard-related impacts (outcomes), evaluate relationships between outcomes and factors that define the contextual vulnerability of the system (drivers), identify resource constraints that influence adaptation options and strategy selection, and simulate the effects of adaptation scenarios on drivers and associated outcomes and resources. While the basic form of the framework may be applied to planning processes (Nelson, et al., *working paper*), the specific process flow and steps described in the section below and illustrated in Figure 2 are intended for empirical assessment of systems using observed hazardous event data and prediction of possible future impacts.

The proposed assessment process begins with a baseline system definition and identification of critical system relationships, followed by an assessment cycle. The system definition includes identification of system goals, and critical system components and sub-systems, given a hazardous event of interest. System goals may refer to both short-term direct impacts and long-term indirect impacts. Critical relationships between system characteristics, or drivers, and direct and indirect impacts of the hazardous event of interest are then evaluated by: (1) identifying and quantifying measurable outcomes of the hazardous event that relate to system goals (Ability to Resist Systemic Disruption), (2) identifying and quantifying characteristics of the system that are expected to affect the outcomes of the hazardous event experienced by the system (Contextual Vulnerability Assessment), and (3) using quantitative modeling (e.g. regression, agent-based simulation, physical process-based) to measure or define the effect of the drivers on the outcomes. These relationships are used within the assessment cycle to simulate the effects of adaptation strategies.

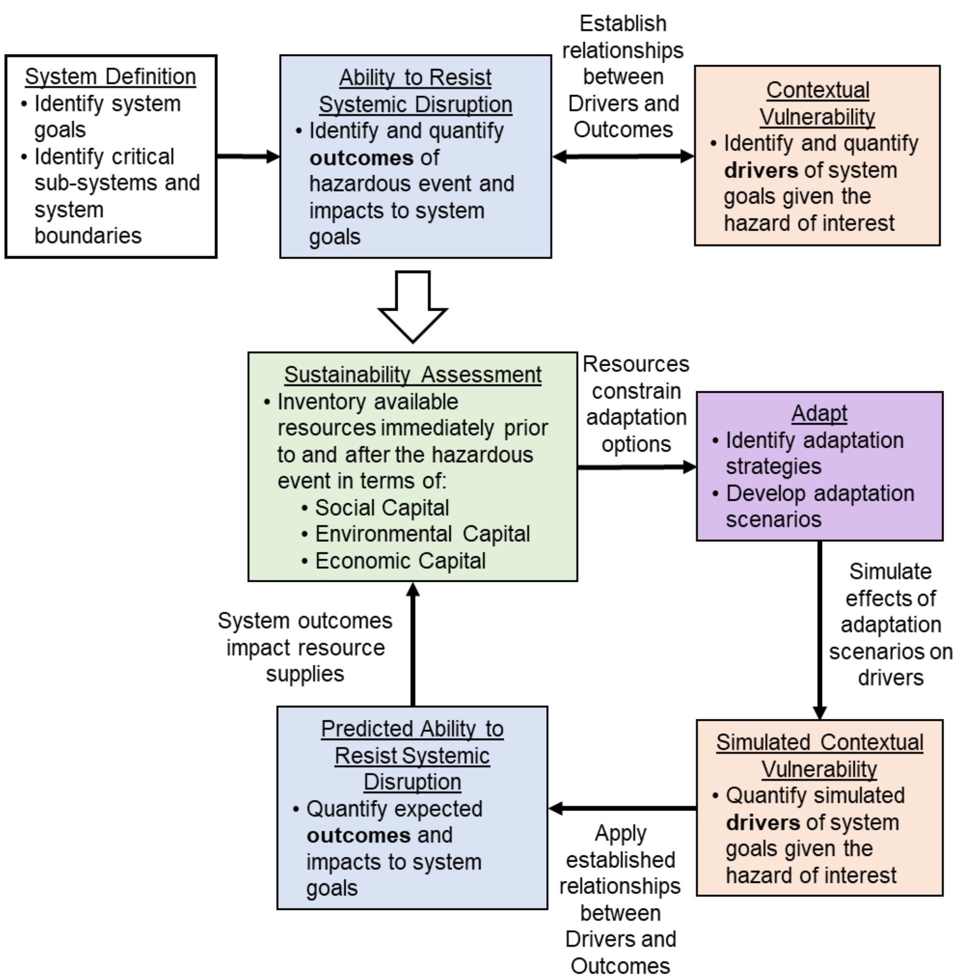

Figure 2: Proposed integrated sustainable resilience empirical assessment framework.

The assessment cycle then begins with a sustainability assessment that quantifies the impacts of the hazardous event and resulting system disruptions on the availability of critical resources including social capital, economic capital, and environmental capital. The availability of resources is assumed to inform the development of adaptation or transformation strategies and constrain the selection of implemented strategies. For systems where an adaptation strategy has been implemented, observed changes to drivers resulting from the adaptation process are quantified and the values of these drivers at some time point following the hazardous event are used, together with the previously established relationships between drivers and outcomes, to estimate the potential impact of a similar hazard post-adaptation. For cases where the evaluation of alternative adaptation scenarios is desirable, potential future values of drivers should be simulated (simulated contextual vulnerability) and used with previously established relationships between drivers and outcomes to predict possible impacts of the hazard of interest given implementation of the adaptation strategy of interest (predicted ability to resist systemic disruption). In both cases, following prediction of hazard outcomes, a second sustainability assessment should be conducted to identify the potential impacts of the adaptation strategies on long-term resource availability.

Given the significant linkages between the concepts of vulnerability, resilience, and sustainability, we conclude that a unifying framework is needed to properly characterize complex adaptive social-environmental systems and assess their behavior in response to short-term disruptions and long-term challenges in the context of decision-making. We suggest that when sustainability and vulnerability are explicitly considered within a resilience assessment framework, resilience becomes a universally positive system quality, as unit-of-analysis based inequities and long-term resource availability are both taken into account, and adaptation strategies are developed within the bounds of pre-defined desired system performance end-states. Within such a framework, a system that is persistent and strongly resists change is not necessarily considered to be resilient. In order to be resilient, the system must also meet stakeholder performance and value expectations, and maintain adequate resource pools to sustain the system for future generations. We refer to this quality as sustainable resilience.

The framework for empirical assessment of sustainable resilience described above is intended to be used to assist in making decisions regarding the prioritization and selection of adaptation strategies and for evaluating the effectiveness of an implemented strategy or set of strategies for systems that have recently experienced, and collected data on, hazardous events. It was intentionally developed to include consideration of multi-scalar and dynamic processes by iteratively considering micro-scale vulnerabilities, meso-scale risks, and macro-scale sustainability. The use of this cyclical and dynamic process enables evaluation of relationships between vulnerability, sustainability, and system performance objectives (and potential changes in these relationships over time), providing information which, from a decision-making standpoint, allows for integration and balancing of priorities from different perspectives and a more effective allocation of resources.

CHAPTER III: SPATIAL MODELING METHODS FOR SOCIAL-ENVIRONMENTAL SYSTEM ASSESSMENT

Introduction

The spatial scale of analysis and multi-scalar processes were identified in Chapter II as areas of critical importance that pose challenges for vulnerability, resilience, and sustainability assessments, as well as environmental justice studies. This is due in part to the reality that many hazards occur at spatial scales that do not coincide with the spatial scales at which social-environmental system data is available. In addition, social and environmental phenomena often exhibit nested structures (Wu & David, 2002). In order to address scalar issues, methods for disaggregating data (particularly social data), and multilevel modeling methods were reviewed.

Within the literature, dasymetry was identified as a growing area of interest in social data disaggregation techniques. However, current dasymetric techniques are primarily limited to redistribution of population counts and provide limited options for disaggregation of specific sub-populations and social factors of interest. The first of two studies described below attempts to overcome spatial mismatches between identification of environmental hazards and socially vulnerable populations by developing a set of logic-based operations for disaggregating sub-populations using tax parcel descriptions to inform spatial data redistribution (Nelson et al., 2015). This technique is expected to add value to vulnerability indicator validation efforts by representing characteristics of interest at spatial scales with greater relevance to hazardous events of concern.

A review of the literature in multilevel spatial modeling techniques also suggested that new advances in Bayesian computing are enabling a growing field of work (currently limited primarily to work in the fields of ecology and epidemiology) in multilevel spatiotemporal modeling of social-environmental systems. The second study described below illustrates the use of multi-level Bayesian regression modeling for conducting a spatiotemporal analysis of the effects of the legal structure of water rights on drought impacts in California (Blangiardo et al., 2013; Nelson & Burchfield, 2017; R-Core Team, 2013).While the subject area of this second study, an agricultural system, differs from that of the previously described study of Nashville, Tennessee, as well as from the subject area of the final case study presented in Chapter IV, this work is intended demonstrate how multilevel spatial Bayesian modeling can be applied to empirically validate and investigate relationships between vulnerability and resilience in social-environmental systems.

Selective Redistribution of Census Demographic Information Using Cadastral Dasymetry

The availability of demographic information from census data has enabled the development of indices that describe the relative social vulnerability of populations at different locations. These indices are often used in conjunction with models of physical exposure to environmental hazards, such as flooding and hazardous waste emission, to identify populations at greatest risk. However, using standard census areal units to calculate social vulnerability can lead to significant underestimation of vulnerable populations as environmental hazards typically occur on a finer spatial scale than census units such as block groups. This study describes a method for disaggregating census demographic information to a higher spatial resolution by taking advantage of ancillary information within tax parcel datasets. Furthermore, the effects of utilization of higher resolution demographic information are illustrated via use of disaggregated census data in the creation of a tax parcel resolution social vulnerability index (SVI). This high resolution social vulnerability index shows notable differences from a standard block-group social vulnerability index with implications for municipal planning processes that address existing or potential environmental justice issues.

Vulnerability, Environmental Justice, and Associated Analytical Challenges

The concept of social vulnerability to environmental hazards has gained increasing interest over the past few decades with many studies proposing composite indices for comparative analysis of vulnerability across spatial extents (Chakraborty, 2005; Cutter, et al., 2003; Krishnamurthy, 2012; Shepard et al., 2012). In the natural hazards literature, social vulnerability indices are typically based on a definition of vulnerability that posits that social stratification and local infrastructure factors are the primary contributors to the vulnerability or resilience of a population (Chakraborty, 2005; Cutter, 1996; Cutter, et al., 2003; Rygel, et al., 2006). The vulnerability indicators (such as age, gender, socioeconomic status, living arrangements, access to medical care, and race/ethnicity) used in construction of most social vulnerability indices are heavily based on socio-demographic information measured in census data and are generally consistent from one study to another (Azar, 2007; Cutter, et al., 2003; Rygel, et al., 2006).

Social vulnerability indices often utilize a hazards-of-place framework, which implies that only human environments, spaces containing human populations, are considered vulnerable, and are often mapped to show spatial relationships between social vulnerability and biophysical vulnerability to environmental hazards such as flooding (Azar, 2007; Cutter, 1996). These indices have been created as planning tools and metrics that can be used to inform policy development, funding allocations and educational efforts, to assist municipal and emergency planners in identifying populations at risk during evacuation scenarios, and to identify potential or existing environmental justice concerns (Burton, 2010; Chakraborty, 2005; Cutter, et al., 2003).

Related to the concept of social vulnerability to environmental hazards is the idea of environmental justice. Derived from the idea of environmental racism, which was focused on discrimination against people of color in environmental policy-making, environmental justice has been generally described as a type of distributive justice concerned in particular with the distribution of benefits and burdens among a population that is affected by decisions and actions made in relation to the environment (Cutter, 2012; Wenz, 1988). As a form of distributive justice, environmental justice analysis involves an assessment of the geographical distribution of environmental hazard burdens among the population. Therefore, it is an inherently spatial problem, and one where scalar mismatches between populations of interest and environmental hazards often hamper precise characterization of the at-risk population (Chakraborty, 2011; Mennis, 2003).

Dasymetric mapping techniques have emerged as an approach for improving the precision of characterization of at-risk populations by facilitating disaggregation of socio-demographic data to a finer scale which may be more representative of the area affected by a hazard (Chakraborty, 2011; Maantay, et al., 2007; Mennis, 2003). A form of areal interpolation, dasymetric mapping, utilizes an ancillary dataset containing supplementary information to inform the redistribution of data from original large areal units to smaller areal units represented by the ancillary information. Land use classification raster data, road networks, imagery and cadastral (tax parcel) data are common sources of ancillary information used in dasymetric mapping (Bhaduri, Bright, Coleman, & Urban, 2007; Maantay, et al., 2007; Mennis, 2002; Tapp, 2010).

Dasymetric mapping techniques that make use of density of development categories in land-use classification rasters as a proxy measure of population density were utilized by Mennis (2002) for analysis of environmental justice risk. In an analysis of the proximity of 'disadvantaged' populations (minorities and those living below the poverty line) to a hazardous facility, Mennis found that the percentage of the population that could be considered ‘disadvantaged’ peaked at a distance from the hazardous facility that is several times smaller than the length of many block groups and census tracts. Without disaggregation of the population to higher resolution sub-units, the relative increase in the percent of the population residing near hazardous facilities that are ‘disadvantaged’, and the environmental justice risk associated with this disproportionate population distribution, would likely not be recognizable.

Cadastral-based dasymetric mapping techniques have also been applied to analysis of environmental justice issues. Maantay and Maroko (2009) investigated the distribution of populations according to racial/ethnic group in New York City in relation to flooding risk. Their analysis found that the use of standard methods for evaluating flood affected populations using census block groups underestimated the at-risk population by as much as 72% when compared with a cadastral-based dasymetric mapping technique. They also found that while minority racial/ethnic groups did not disproportionately reside in high flood risk areas, they were disproportionately undercounted using standard methods for evaluating flood affected populations, indicating that decision-making tools that lack sufficient spatial resolution may provide faulty information that leads to the underestimation of ‘disadvantaged’ at risk populations. Tax parcel data, while less widely available than land-use classification data and not nationally standardized, is available in most urban areas and frequently includes zoning information, property size, and living area (or number of dwelling units) (Maantay, 2007; Tapp, 2010). Cadastral data also often includes information such as property value and land use information (i.e., designated nursing home, single family dwelling, boarding house, etc.) that can provide insight into the makeup of the population within a parcel (Maantay, 2009).

Both of the aforementioned environmental justice studies utilized dasymetric mapping to improve the precision of spatial distribution estimates of various populations relative to an environmental hazard, but examined only a few variables that describe 'disadvantaged' populations to assess environmental justice risk (Maantay, 2009; Mennis, 2003). These 'disadvantaged' populations are groups that are believed to have higher degrees of social vulnerability than the population at-large, and are identified by variables that are often used in the construction of social vulnerability indices (Azar, 2007; Chakraborty, 2005; Cutter, 1996; Cutter, et al., 2003; Rygel, et al., 2006). As the concept of environmental justice commonly used today suggests that all people, regardless of socioeconomic or demographic character, should bear an equitable proportion of the burdens of both man-made and natural environmental hazards, and have equitable access to environmental benefits, and it is commonly accepted that a number of variables such as race, socioeconomic status, and cultural beliefs may interact to increase or decrease the overall extent of the vulnerability of specific sub-groups (Chakraborty, 2011; Cutter, et al., 2003; Maantay, 2009), a tool that provides a more comprehensive characterization of the social vulnerability of populations at high spatial resolution should prove valuable in the assessment of environmental justice risk (Padgett, 2013).

Census Disaggregation Methods

Census block groups from the American Community Survey (ACS 2012 5-year estimates) were used as the original socio-demographic data to be disaggregated to the parcel level, as they are the smallest census unit for which the detailed demographic information needed for construction of social vulnerability indices is available on an annual basis. Detailed parcel data (2013) for Davidson County, Tennessee, was used as the ancillary cadastral dataset. The parcel dataset included information at the parcel level such as property type, building type, living area, dwelling units, and assessed property value. Geoprocessing necessary for dasymetric mapping and selective demographic variable distribution, as well as mapping of social vulnerability indices, was facilitated by ESRI's ArcGIS.

Population Disaggregation

Cadastral dasymetric mapping techniques were adapted from the Cadastral-based Expert Dasymetric System (CEDS) developed by Maantay, Maroko, and Herrmann (2007). This system ensures that the sum of the population of all parcels in a census area is equal to the total population of the census area as defined by the original census data, also referred to as the pycnophylactic property (Mennis, 2002). The system also selects which of two types of ancillary data, living area or number of dwelling units, to use for disaggregation of census data on a block group by block group basis, by determining which data type minimizes errors in aggregation of parcel populations to census tracts (Maantay, et al., 2007). Although living area and/or dwelling unit values were missing for some of the parcels, these values were modified in the parcel data only where other information was available, implying that the accuracy of the dasymetric mapping is limited by the accuracy of the ancillary parcel data.

Unlike the original CEDS, in the adapted version, no adjustments were made to residential areas or number of dwelling units beyond the cases described below due to lack of relevant adjustment information at the parcel level in the tax data (Maantay, et al., 2007). The majority of parcels with designated property type "mobile home" or "mobile home park" were missing both living area and dwelling unit values; for these cases, both dwelling unit and living area values were manually added following examination of current satellite imagery of the parcels. A few block groups contained no parcels with residential property type designations or contained no parcels with residential property type designations that also had dwelling unit or living area information.

In these cases, parcels in the block group that clearly contained residential areas, such as universities with an on-campus population, or that were identified as residential by their property type designation, were assigned a proportion of the block group population relative to the parcel area. Validation of population disaggregation was validated using the method described by Maantay, et al. (2007) in which the disaggregation procedure is replicated for an alternate spatial scale, such as census tracts, and the resulting dasymetrically estimated parcel populations are aggregated back to the original scale (block groups) for comparison with census populations.

Produced dasymetric maps of Davidson County total population were tested for disaggregation errors by aggregating parcel populations to the block group level. Comparison of aggregated values to block group populations from census data confirmed that the pycnophylactic property was retained, indicating that any errors in disaggregation are confined within block groups. While direct validation of data disaggregated from block groups to parcels is generally not feasible, disaggregation from census tracts to block groups was found to be accurate within thirteen percent (based on the sum of the absolute differences between dasymetrically assigned census tract populations and block group level census populations) (Maantay, et al., 2007).

Sub-Population Disaggregation

Sub-populations and physical variables relevant to social vulnerability in the area, as determined from a principal components analysis of social vulnerability indicators at the block group level, were joined with data at the parcel level based on block group identifiers (GEOID). The sub-populations were then disaggregated to residential parcels.

Due to lack of related ancillary information, many of the sub-populations were distributed to parcels as a proportion of the total population at the parcel equal to the ratio of the sub-population value at the block group level to the total population of the block group. Certain sub-populations (age 5 and under, age 65 and older, women, those living in group quarters) were selectively assigned to, or excluded from, certain parcels based on descriptive building type and land use information associated with each parcel (APPENDIX A, Table A 1). In addition, parcel information was utilized to provide parcel-level resolution for other physical and economic characteristics such as property value, residence type (i.e., mobile home, rental, or owner occupied), and access to medical care.

Disaggregation logic for sub-populations was developed to retain the pycnophylactic property whereby the sum of all parcel sub-population values is equal to the block group sub-population value. Using the disaggregation logic, an excluded property (EP) was considered a parcel where none of the sub-population is expected to be found, therefore the sub-population at that parcel was assigned a value of zero. An assigned property (AP) was considered a parcel where nearly the entire population of the parcel was expected to belong to the sub-population. In order to maintain the pycnophylactic property, the sub- population at APs was calculated as follows:

If	$\sum TPop_{AP,BG} \leq SPop_{BG}$,
then	$SPop_{AP} = TPop_{AP}$.
Else if	$\sum TPop_{AP,BG} > SPop_{BG}$,
then	$SPop_{AP} = TPop_{AP}\left(\frac{SPop_{BG}}{\sum TPop_{AP,BG}}\right)$.

where SPopAP is the designated sub-population at an assigned property, TPopAP is the total population at an assigned property, SPopBG is the sub-population value at the block group level, TPopBG is the total population value at the block group level, and TPopAP,BG is the total population of an assigned property in a specified block group. Similarly, the sub-population at all properties that are not EPs or APs was calculated as:

$$SPop_{Parcel} = TPop_{Parcel}\left(\frac{SPop_{BG} - \sum SPop_{AP,BG}}{TPop_{BG} - \sum TPop_{EP,BG} - \sum TPop_{AP,BG}}\right)$$

where SPopParcel is the sub-population at a parcel which is not an excluded or assigned property, TPopParcel is the total population at a parcel which is not an excluded or assigned property, SPopAP,BG is the sub-population at an assigned property in a specified block group, and TPopEP,BG is the total population at an excluded property in a specified block group. Here, the numerator represents the sub-population that is available for distribution to parcels that are not EPs or APs, and the denominator represents the total population in a block group among which the remainder of the sub-population may be proportionally distributed.

Application of Disaggregated Census Data in a Social Vulnerability Index

To illustrate one application of high resolution demographic information and its implications for planning purposes, a standard census block-group scale social vulnerability index (SVI) and a tax-parcel scale SVI using dasymetrically distributed census data were built and contrasted.

Social Vulnerability Index Creation

One widely accepted method for creating a SVI is the SoVI® analysis method, in which principal components analysis (exploratory factor analysis) is used to reduce a large number of demographic variables to a smaller subset of vulnerability factors (Cutter, et al., 2003). The vulnerability factors produced in the principal components analysis are linear combinations of variables that are highly correlated with each other, while the factors themselves are orthogonal to each other. In this way, each factor can be generally described as representing a certain unique characteristic of vulnerability. This methodology was recently adopted by the United States Army Corps of Engineers (USACE) for use in water resources planning (Dunning, 2013).

In order to create the block-group scale SVI (BGSVI) a principal components analysis was conducted on a set of 64 variables derived from ACS 2012 5-year block group estimate census data using the statistics package SPSS Statistics 22.0. This initial set of variables was composed of social vulnerability indicators commonly utilized in principal components construction of social vulnerability indices (Cutter et al., 2003; Kleinosky, 2007; Schmidtlein, 2008). The principal components analysis was conducted following the method generally outlined by Cutter et al. (2003). Block groups with no population values were removed from the dataset and cells with missing values were assigned a value of zero.

An iterative process involving use of different normalization schemes and elimination of variables with low commonality scores, low component loading scores, and/or low measured sampling adequacy scores was applied to reduce the number of variables used in the principal components analysis and increase the amount of variance explained by the extracted components (Cutter, et al., 2003; Rygel, et al., 2006; Wood, 2009). The composite BGSVI was created using a weighted sum method where the percent variance explained by each component was used as the weighting factor for each component (Schmidtlein 2008; Wood, 2009). As in the SoVI® method, directionality was assigned to each component in a manner that leads to high vulnerability being represented by highly positive index scores (+ if significant variables increase vulnerability, - if significant variables decrease vulnerability, or absolute value if the significant variable loadings produce mixed vulnerabilities). The z-scores of the raw BGSVI score were calculated to create a standardized index score and were mapped in ArcGIS as standard deviations.

The principal components analysis of 64 block group census variables at the block group level produced a reduced dataset of 37 variables (APPENDIX A, Table A 2) and yielded 10 components with eigenvalues greater than 1.0 that explain 71 percent of the variance. Based on the loading of the variables, these components can be generally described as representing: 1. Race/Class (14%), 2. Economic Status (12%), 3. Foreign Born (9%), 4. Elderly (8%), 5). Women (7%), 6. Group Living (6%), 7. Families (5%), 8. Housing Quality (4%), 9. Hospice Care (3%), and 10. Rural (3%).

To create the tax-parcel scale SVI (PSVI) a principal components analysis of the parcel dataset including the selectively redistributed demographic data was conducted using the same methodology as described above. The variables used in the parcel level principal components analysis were normalized as described in Table A 3 (this normalization means that values for variables for which selective assignment logic was not used are the same for each parcel in the block group). The resulting PSVI scores were also standardized using z-scores and mapped in ArcGIS as standard deviations.

The principal components analysis of the social vulnerability indicator variables distributed to parcels reduced the number of relevant variables from 37 to 30 (APPENDIX A, Table A 3) and yielded nine components with eigenvalues greater than 1.0 that describe 66 percent of the variance. These nine components are similar in composition to the components extracted from the block group data analysis and generally represent: 1. Economic Status (11%), 2. Foreign Born (10%), 3. Race/Class (10%), 4. Elderly (8%), 5. Women (8%), 6. Families (7%), 7. Group Living (5%), 8. Renters/Population Density (4%), and 9. Mobile Homes (3%). In this case, 1. the Rural component from the block group level analysis drops out as the variability in population density within an analysis unit that is captured by this component is already fully explained by the

Renters/Population Density component, 2. the Housing Quality component from the block group level analysis which included both low value housing and mobile homes is relabeled as Mobile Homes as the number of mobile homes is the only variable that significantly contributes to this component, and 3. the Hospice Care component drops out as the significant variables in this component are incorporated into the Group Living, Race/Class, and Renters/Population Density components. Each component, with the exception of Foreign Born, includes at least one selectively assigned variable with a significant loading. The standardized BGSVI and PSVI scores for central Davidson County are shown in Figure 3.

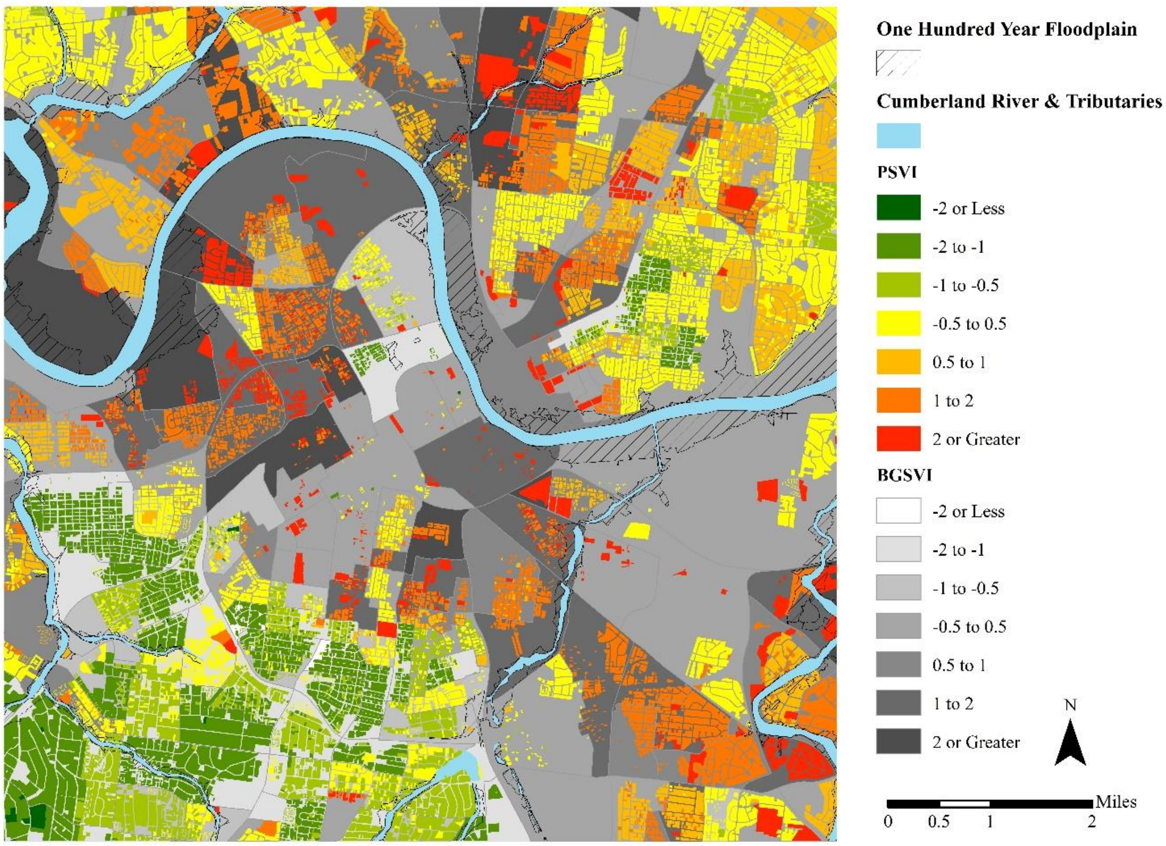

Figure 3: PSVI and BGSVI for the Nashville area.

Comparison of BGSVI and PSVI

In order to compare the distribution and impact of the BGSVI and PSVI, dasymetrically estimated parcel total population, BGSVI values, and PSVI values were joined to parcels by parcel and block group identifier. Numbers of slightly vulnerable (index score greater than 0.5), moderately vulnerable (index score greater than 1), and highly vulnerable (index score greater than 2) parcels, as well as the expected total population at these parcels, were extracted for comparison.

When BGSVI are applied to parcels, it was observed that fewer occupied parcels in the county are considered vulnerable than when the PSVI is used (Table 1). The difference between parcel vulnerabilities using the BGSVI and PSVI in terms of a percent of all parcels in the county is misleadingly small. Using the BGSVI, approximately 2% of all parcels in Davidson County are classified as highly vulnerable. This percentage increases to only 3% when the PSVI is used to identify highly vulnerable parcels. However, as the degree of vulnerability (as indicated by the index score) increases, the proportional difference between the numbers of parcels identified using BGSVI and PSVI increases, with the PSVI ultimately identifying nearly twice as many highly vulnerable parcels than the BGSVI.

Of greater note are the population trends associated with parcels classified as vulnerable (see Table 1 for details). While an estimated 3% of the total population in Davidson County is expected to reside in parcels that the BGSVI identifies as highly vulnerable, more than 22% of the total population is expected to reside in parcels that the PSVI identifies as highly vulnerable. As with the proportional differences between numbers of parcels, the proportional difference between estimated population numbers using the BGSVI and PSVI increases with increasing index score. The proportional difference between estimated resident populations in parcels identified as slightly vulnerable to highly vulnerable using the BGSVI and PSVI increases from a factor of approximately 1.7 times for slightly vulnerable parcels to 7.5 times for highly vulnerable parcels.

As the PSVI is derived primarily from block group level information and disaggregated block group information, the two indices are expected to be highly consistent. That is, it is expected that most parcels that are identified as vulnerable using the BGSVI will also be identified as vulnerable using the PSVI. The Pearson's correlation coefficient for BGSVI and PSVI is 0.906 (significant at the 0.01 level for a 2-tailed test), indicating that the two indices are highly correlated, and thus consistent.

The co-occurrence of slightly vulnerable, moderately vulnerable, and highly vulnerable parcel identifications using both PSVI and BGSVI was also examined (see Table 2 for details); the differences between the two indices increases with increasing index score. All but 7% of parcels that are identified as at least slightly vulnerable using the BGSVI were also identified as at least slightly vulnerable using the PSVI (i.e., 7% of parcels with a BGSVI of 0.5 or more have a PSVI less than 0.5). This percentage of failure of vulnerability identifications to co-occur increases to 36% for parcels identified as highly vulnerable using the BGSVI. However, much of this variance between the BGSVI and PSVI can be attributed to the establishment of analytical cutoff points for differing severities/levels of vulnerability identifications. Nearly all parcels identified as moderately or highly vulnerable using the BGSVI have a PSVI vulnerability identification that is one level removed or less (i.e., more than 99% of parcels with BGSVI of at least 2 have a PSVI of at least 1 and more than 99% of parcels with a BGSVI of at least 1 have a PSVI of at least 0.5). An example of parcels with consistent vulnerability identifiers using PSVI and BGSVI is shown in Figure 4.

Table 1: BGSVI and PSVI comparison for Davidson County.

Vulnerability Based on Index Score	Number of Parcels		Percent of all Parcels in County		Proportional Difference in Parcel Count (PSVI/ BGSVI)	Estimated Resident Population		Percent of Total Population in County		Proportional Difference in Estimated Population (PSVI/ BGSVI)
	BGSVI	PSVI	BGSVI	PSVI		BGSVI	PSVI	BGSVI	PSVI	
Slightly Vulnerable (Index Score > 0.5)	40,665	52,574	22	29	1.3	176,567	297,785	28	47	1.7
Moderately Vulnerable (Index Score > 1)	18,905	30,026	10	16	1.6	91,863	234,190	15	37	2.5
Highly Vulnerable (Index Score > 2)	3,075	5,863	2	3	1.9	18,754	141,250	3	22	7.5

Table 2: Co-occurrence of BGSVI and PSVI vulnerability identifications at the parcel level.

Vulnerability Based on Index Score	Number of Parcels	Percent of all Parcels in County	Percent of BGSVI Parcels with Same Level PSVI	Percent of BGSVI Parcels with PSVI Within 1 Level	Percent of PSVI Parcels with Same Level BGSVI	Percent of PSVI Parcels with BGSVI Within 1 Level
Slightly Vulnerable (Index Score > 0.5)	37,754	21	93	---	74	---
Moderately Vulnerable (Index Score > 1)	17,004	9	90	99	59	96
Highly Vulnerable (Index Score > 2)	1,956	1	64	100	36	94

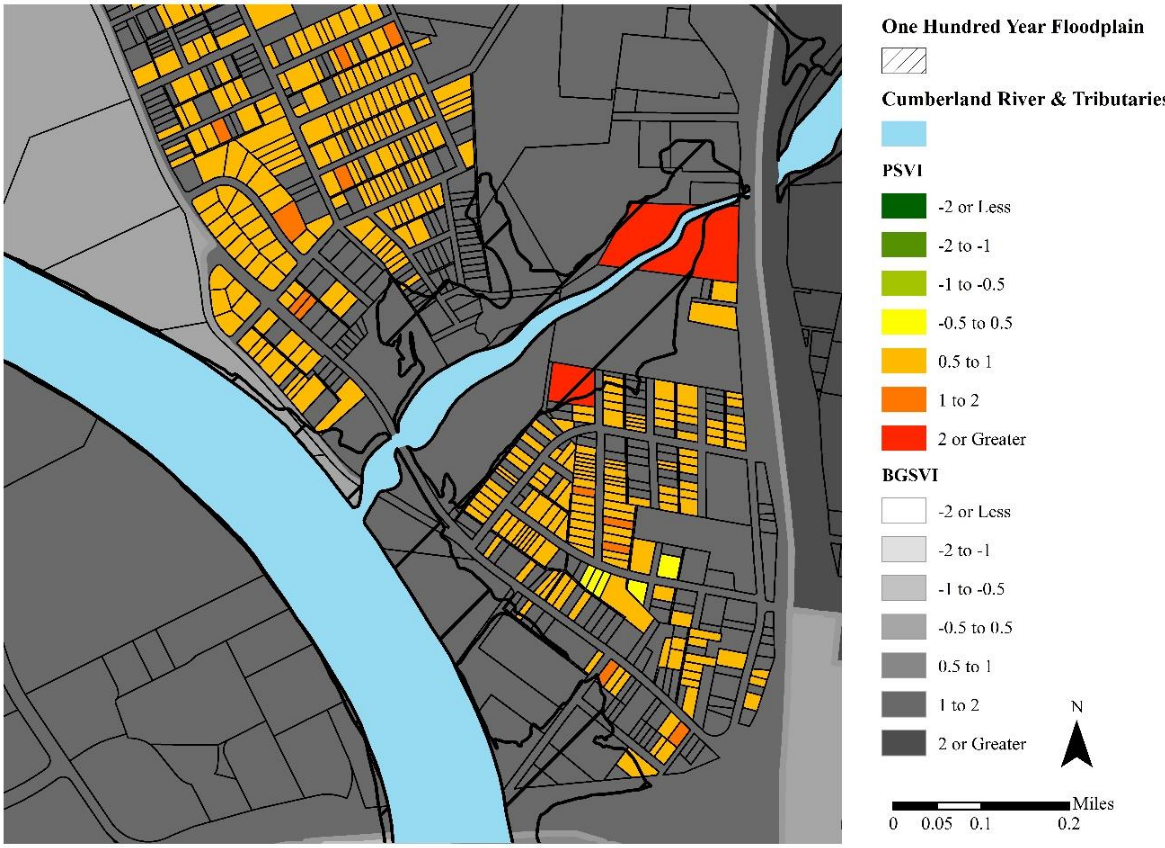

Figure 4: PSVI and BGSVI along the Cumberland River where vulnerability identifications are consistent.

The percent of PSVI identified vulnerable parcels that are also BGSVI identified vulnerable parcels is less than the previously described reverse relationship, as the BGSVI identifies a smaller number of vulnerable parcels overall, but the trend is the same, with co-occurrence decreasing with increasing index score. However, while nearly all BGSVI vulnerable parcels had a PSVI within 1 level of the BGSVI, the reverse does not hold true. While 100% of parcels identified as highly vulnerable using the BGSVI were identified as at least moderately vulnerable using the PSVI, only 94% of the parcels that the PSVI identifies as highly vulnerable are also identified as at least moderately vulnerable using the BGSVI. In fact, more than 2% of parcels identified as highly vulnerable using the PSVI are identified as not vulnerable using the BGSVI (see Figure 5 for an example), indicating that boundary conditions in the vulnerability scale are only part of the picture, and suggesting that the PSVI incorporates additional vulnerability attributes that are sensitive to parcel level spatial resolution and thus not considered using the BGSVI.

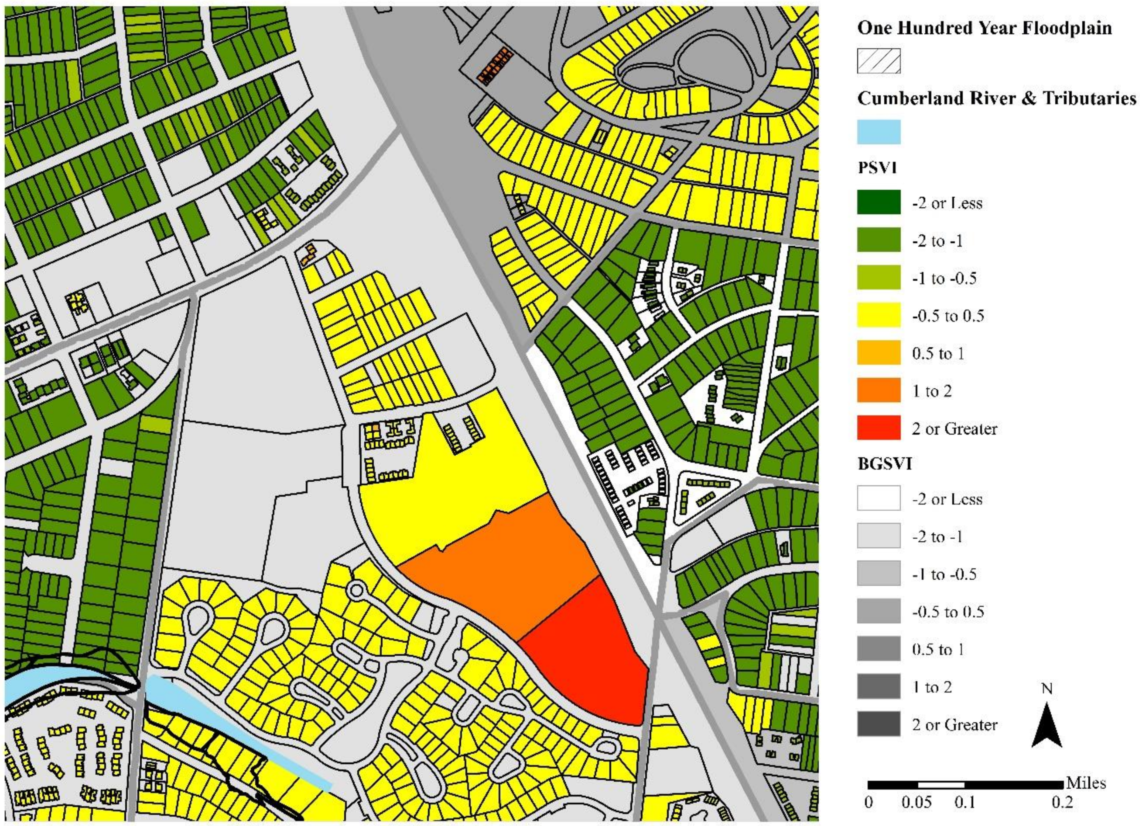

Figure 5: PSVI and BGSVI in central Nashville where discrepancies are seen between the vulnerability identifications.

This conclusion that discrepancies between the PSVI and BGSVI occur due to spatial sensitivity of certain vulnerability attributes is corroborated by examination of the parcel descriptions and associated social vulnerability indicator variables. All of the parcels identified as highly vulnerable using the PSVI and not vulnerable using the BGSVI are residences that are classified as apartments, mobile homes, or some form of group-living quarters, such as boarding houses or nursing homes. These residence classifications are contained within parcel descriptions and were all used in the selective distribution of social indicator variables. In comparison, only 25% of parcels that are identified as highly vulnerable using the PSVI and at least slightly vulnerable using the BGSVI have these same residence classifications.

Comparison of selectively distributed social vulnerability indicator variable values for parcels with discrepancies between PSVI and BGSVI, and parcels for which PSVI and BGSVI are consistent in identifying vulnerability, shows that total population, renter population, group quarters population, senior population, and the numbers of mobile homes are all significantly elevated for parcels with discrepant PSVI and BGSVI. Estimated senior populations at discrepant parcels are about 1.5 times higher than at consistent parcels, estimated group quarter populations are 4 times higher, the number of mobile homes is 15 times higher, estimated total population is more than 20 times higher, and estimated renter populations are more than 25 times higher.

This comparison of selectively distributed variables indicates that the PSVI is sensitive to parcel level population and to the heterogeneous spatial distribution of different types of living arrangements and their associated resident populations. Such sensitivity may prove most useful for urban areas; particularly for areas with mixed residential types, where block group level analyses tend to dilute the effects of non-conformity to the mean within each block group.

Discussion

Application of census data selectively redistributed to tax parcels in a social vulnerability index for the Davidson County, Tennessee, area found that a PSVI is consistent with a BGSVI constructed using standard principal components analysis methodology (Cutter, et al., 2003; Maantay, et al., 2007). However, the high resolution PSVI is also sensitive to parcel level population and to residence type. These added sensitivities make the PSVI useful for urban areas with mixed residential classifications and a high degree of local heterogeneity and illustrate the utility and potential benefits offered by downscaled census data (Chakraborty, 2011; Maantay, et al., 2007; Maantay, 2009). As the PSVI is produced at a spatial scale that is, on average for the case study area, 80 times smaller than block groups, when overlaid with maps displaying exposure to environmental hazards, the PSVI can help to more precisely identify regions where biophysical and social vulnerabilities overlap, creating potential for environmental injustice to occur (Chakraborty, 2011; Maantay, 2009; Mennis, 2003).

It should be noted that despite the high spatial resolution provided, the selective redistribution methodology described is not intended to be used to evaluate or predict the characteristics of individuals, nor would it be desirable to do so. Even when demographic information is interpolated to smaller areal units, the base composition is aggregated survey data that is subject to measurement errors. Nor is the disaggregation methodology immune to errors in assignment as the selective disaggregation logic makes use of generalized assumptions about sub-population locations which may or may not hold true in all cases. Additionally, while areal interpolation is a powerful tool, validation at this scale is difficult, and all disaggregated population data should be utilized as estimates (Maantay, et al., 2007).

Instead, this methodology should be viewed from a municipal planner's perspective as a tool that can provide information about the likelihood that a population residing at a particular parcel is relatively large or small and possesses certain characteristics of interest. This information may serve as supplementary justice-oriented information that can help planners locate areas where residents may lack the means to cope with and recover from the physical, emotional, and economic burdens associated with environmental hazards.

This work highlights the importance of scale and the mischaracterizations possible when using spatially aggregated data. However, this work does not address issues related to measurement error which is a particularly significant issue with U.S. Census American Community Survey (ACS) data. The deterministic disaggregation approach here may lead to mischaracterization of uncertainty in the spatial distribution of the data. This issue may be partially addressed using Monte Carlo approaches that incorporate ACS measurement error with the data disaggregation logic. An alternative approach is to utilize multilevel modeling approaches that account for variance existing at higher levels in the estimates of lower level outcomes. In the following section I describe one application of the multilevel modeling approach for evaluation of the effects of social and physical factors on the performance of a complex social-environmental system during hazardous conditions.

Evaluating Relationships Between Social-Environmental System Hazard Outcomes and Social and Environmental Drivers Using Multi-Level Bayesian Regression

In order to test the effectiveness of multilevel modeling methods for analytical assessment of multi-scalar processes in complex SESs, a study examining the effect of water rights structures on agricultural production in California's Central Valley during drought was undertaken. In this study, the relationships between environmental factors such as drought conditions and groundwater availability, social factors such as competition between different water uses and structured legal access to surface water, and system performance, in terms of agricultural productivity, are evaluated using spatial analysis and multilevel Bayesian regression. This work demonstrates the utility of Bayesian modeling methods for assessing relationships between vulnerability and resilience in complex social-environmental systems.

California's Central Valley region has been called the "bread-basket" of the United States. The region is home to one of the most productive agricultural systems on the planet. Such high levels of agricultural productivity require large amounts of fresh water for irrigation. However, the long-term availability of water required to sustain high levels of agricultural production is being called into question following the latest drought in California. In this study, we use Bayesian multilevel spatiotemporal modeling techniques to examine the relationships between factors influencing the vulnerability of the system and agricultural production during the recent drought, with a specific focus on understanding the influence of the structure of surface water rights. Surface water rights are of particular interest as they are governed by state water policy, and hence are a likely target for intervention in potential adaptation planning.

In this study, Bayesian spatiotemporal modeling is employed to account for spatial processes that have the potential to influence the effects of water right structures on agricultural production. Results suggest that, after accounting for spatiotemporal dependencies in the data, seniority in surface water access significantly improves crop health and productivity on cultivated lands, but does not independently affect the ability to maintain cultivated extent. In addition, agricultural productivity in watersheds with more junior surface water rights show less sensitivity to cumulative drought exposure than other watersheds, however the extent of cultivation in these same watersheds is relatively more sensitive to cumulative drought exposure.

Introduction

California's Central Valley is one of the most productive agricultural systems on the planet (Diffenbaugh & Swain, 2015). This system requires massive amounts of water to function; the agricultural sector accounts for 77 percent of the state's water use (Swain et al., 2014). The Central Valley experienced a state of prolonged drought starting in the mid-2000s that escalated to severe drought conditions lasting from 2011 until 2017 (Howitt, Medellín-Azuara, & MacEwan, 2014; U.S. Drought Monitor, 2017). The persistent drought conditions significantly strained agricultural production throughout the valley with an estimated economic cost of $2.7 billion in 2015 alone (Howitt, MacEwan, Medellín-Azuara, Lund, & Sumner, 2015). Research suggests that future changes in climate will continue to impact surface water availability, ultimately affecting plant growth rates as well as irrigation timing and runoff (Mann & Gleick, 2015; Schwarz, 2015). These changes will likely increase legal mandates curtailing surface water use. In a study of the Sacramento-San Joaquin Delta, Schwartz (2015) estimates that water rights curtailments between 2030 and 2059 may last 20% longer and occur with 10% greater frequency than they have in the past. These changes, coupled with rapidly increasing population growth and shifts in agricultural demand will place significant strain on agricultural systems in the Central Valley in the future, threatening national food security.

In the Central Valley, increased pumping of groundwater has enabled many farmers to continue to cultivate in spite of the current drought (Christian-Smith, Levy, & Gleick, 2015; Famiglietti et al., 2011). Rates of groundwater depletion in the Central Valley have increased dramatically throughout the drought, exceeding groundwater recharge rates and putting future groundwater use at risk (Famiglietti et al., 2011; Howitt, MacEwan, Medellín-Azuara, Lund, & Sumner, 2015; Medellín-Azuara et al., 2015). If current pumping rates continue, the region's groundwater supplies may be over-drafted and the ability of farmers to use groundwater to mitigate surface water shortfalls during drought will be increasingly limited. Farmers have also engaged in water transfers among agricultural users, fallowing of land, and diversification towards less water-intensive crops (Christian-Smith et al., 2015). These farm-level adaptive practices are fairly short-term responses to water scarcity; they leverage current technology, institutions, and infrastructures to address drought. Growing evidence suggests that California may enter a period of prolonged water stress in the future requiring more significant adaptation; therefore, it is important to assess the impact of how the institutions governing resource use impact agricultural responses to water scarcity (Hertel & Lobell, 2012; Zilberman, Dinar, MacDougall, Brown, & Castillo, 2002).

This study focuses on the impact of the legal institutions governing California's surface water on a remotely sensed metric of agricultural productivity and the likelihood of a field being left fallow during the recent drought in California's Central Valley. California is an important place to study these dynamics as it is the only state to recognize the two dominant approaches to surface water management in the United States: riparian and appropriative rights. The unique hierarchical legal structure of these surface water rights in California facilitates exploration of the impact of these distinct ways of managing surface water on agricultural systems. We hypothesize that during periods of extreme water stress, such as the recent drought, seniority in access to surface water significantly improves local capacity to cultivate and maintain crop health, and also decreases sensitivity to increasing precipitation deficits. In what follows, we discuss the nature of surface water rights and groundwater in California and outline the conceptual framing of the analyses conducted. We then describe the methods and novel dataset used in this study, the statistical analyses conducted, and the empirical results. Finally, the implications of the study for water management in a changing climate and limitations of the study are discussed.

Understanding surface water rights in California

Surface water access in the Central Valley is governed by a complex hierarchy of water rights. California is the only state to recognize both riparian and appropriative rights (Schwarz, 2015). Riparian rights are water rights belonging to a land owner and apply to the use of naturally flowing water within, or adjoining, a parcel of land (California State Water Resources Control

Board (CA SWRCB), 2016a). As riparian rights do not require licenses or permits and generally are not lost by non-use or transitions in land ownership, they are considered as “senior” to appropriative water rights (CA SWRCB, 2016b; Sawyers, 2005). However, riparian rights do not entitle a water user to divert water to storage (for use during the dry season) or to apply the water outside of the watershed in which the parcel of land lies (CA SWRCB, 2016b). While water diversion under riparian rights are by law limited to the amount of water which can be put to reasonable and beneficial use, because they are exempt from California State Water Resources Control Board (CA SWRCB) oversight diversion amounts are rarely quantified unless a stream system statutory adjudication process takes place (CA SWRCB, 2016a; Sawyers, 2005; Schwartz, 2015).

Appropriative water rights are rights that divert water from the original stream system for use on land that is not classified as riparian (CA SWRCB, 2016b; Sawyers, 2005). Like riparian rights, appropriative rights are limited to the amount of water which can be put to reasonable and beneficial use, however as permitted and licensed rights, the diverted quantities of water are generally subject to more scrutiny than riparian rights. In addition, any appropriative right may be lost if the right is not exercised for a period of five years (prescriptive period). In times of water shortage riparian water rights holders typically have higher priority access to water than appropriative rights holders, where each riparian right is given equal priority (CA SWRCB, 2016b; Sawyers, 2005).

Appropriative rights are themselves subject to an internal hierarchy that is often described as “first in time, first in right” whereby rights holders with the oldest claim have higher priority access to water (CA SWRCB, 2016b). In California, appropriative rights are divided into two categories, Pre-1914 and Post-1914 rights. Pre-1914 appropriative rights are non-riparian rights for which there is evidence that the right was claimed prior to the creation of a state-wide permitting system in 1914 (CA SWRCB, 2016b; Sawyers, 2005). These rights, similar to riparian rights, are not subject to CA SWRCB oversight and are senior to Post-1914 appropriative rights. Post-1914 appropriative water rights are subject to a great deal of oversight and are granted by the CA SWRCB only after demonstration of both unappropriated water availability and applicant ability to beneficially use that water. Priority of water access among Post-1914 appropriative rights holders is granted based on the date the water right permit application was filed, where the most recent rights are the first to discontinue use in times of water shortage (CA SWRCB, 2016b; Sawyers, 2005).

While some farmers hold the rights to the surface water they use for irrigation, much of the surface water in California is distributed via contracts between a farmer with no legal water rights and a second party who holds the original water right, but does not directly use the water (Medellín-Azuara et al., 2015; Sawyer, 2005). While private water contracting is common, the largest water contractors, and holders of the largest share of water rights, are the state and federal government (California Department of Water Resources (CA DWR), 2017a; Sawyer, 2005). The California Department of Water Resources (CA DWR) and the U.S. Bureau of Reclamation (USBR) collectively hold an estimated 219 water rights with more than one thousand points of diversion across the state, and are estimated to supply approximately 25% of irrigation water in any given year (Medellín-Azuara et al., 2015). This water is diverted to water contract holders via the State Water Project (SWP) or the Central Valley Project (CVP), which are managed by CA DWR and USBR, respectively, and include large-scale water conveyance structures, such as the California Aqueduct (CA DWR, 2017b; Medellín-Azuara et al., 2015; USBR, 2017a).

As the SWP and CVP transport water across watersheds, and sometimes over great distances, water right point of diversion locations for contracted water are not necessarily directly associated with the location of water use. However, it is required that points of rediversion from natural and artificial water ways be reported to the California Water Resources Control Board suggesting that some records do exist that link contracted water to areas near the location of water use (California Water Boards, 2017). Contract water is typically used for municipal and agricultural uses and the contracts are often made with local governments and large irrigation management districts, but may be also held by individuals and small trusts (CA DWR, 2017b; Medellín-Azuara et al., 2015; USBR, 2017b). While those who contract for water with a second party do not have a direct legal claim to water, and their use of water may be restricted by the nature of their contract with the water right holder or a local distributer of water (such as an irrigation management district), the water they receive is associated with a legal water right and is subject to the same restrictions and privileges granted to that class of water rights.

Groundwater in California

Groundwater plays a critical role in the California agricultural system as during a typical year groundwater supplies about 30% of irrigation water, while during drought years this share can increase to over 50% (Medellín-Azuara et al., 2015). However, while increased groundwater extraction has been a prevalent response to recent droughts in California, a growing body of research suggests that this is not a sustainable response to projected future changes in water availability (Famiglietti et al., 2011; Howitt, MacEwan, Medellín-Azuara, Lund, & Sumner, 2015). At present, there is no state-wide groundwater use permitting and regulation process and the only regulation of groundwater use is limited to basin-specific court adjudication in a few regions (CA SWRCB, 2016b). The Sustainable Groundwater Management Act, signed into law in 2014, requires High and Medium Priority basins subject to critical conditions of overdraft to be managed under a groundwater sustainability plan by January 31, 2020, leaving groundwater basins vulnerable to increased pumping rates over the next few years (CA DWR, 2015; Medellín-Azuara et al., 2015). Lack of groundwater monitoring is also a significant issue in the region with about a quarter of High and Medium priority basins inadequately monitored under the California Statewide Groundwater Elevation Monitoring Program (CASGEM) (CA DWR, 2014; Medellín-Azuara et al., 2015). Groundwater use is therefore constrained primarily by groundwater aquifer location and depth, the ability to drill new wells, and pumping costs (Mukherji & Shah, 2005; Schlenker, Hanemann & Fisher, 2007).

Modeling agricultural production during water scarcity

In this study, a farmer's cultivation decision (what and how much to plant) during times of water stress is conceptualized as a function of expectations of water availability, recent weather trends, the portfolio of cultivation options available to the farmer, and expected crop values. Similarly, the health and productivity of cultivated crops is seen to be dependent on the choice of crop grown, weather conditions during the growing season, and access to and availability of water to apply to the cultivated crops. We hypothesize that the legal structure of surface water rights in the state is one of the factors at play in both farmer decision-making and crop productivity.

California water code prioritizes water allocations based on the stated purposes of water use, the type of water right, and the timing of appropriation. The structure of these prioritizations, e.g. domestic use over irrigation; Riparian over Appropriative; Pre-1914 appropriations over recent appropriations, has the potential to inform farmer cultivation decisions and constrain the amount of water available for application to fields, particularly for junior water rights holders. Therefore, we hypothesize that during periods of extreme water stress, such as the recent drought, seniority in access to surface water significantly improves local capacity to cultivate and maintain crop health and productivity. In addition, we predict that access to senior appropriative water rights will decrease agricultural sensitivity to cumulative meteorological drought stress relative to riparian and junior rights. In what follows, we apply Bayesian spatiotemporal modeling to a novel dataset to test these hypotheses.

Methods and Data

That water shortages have a negative impact on agricultural production is a logical and somewhat obvious deduction. However, analysis of the impacts of water shortages on agricultural production, including factors influencing access to water, is a non-trivial task. One of the largest contributors to heterogeneity in water stress impacts on the health and productivity of agricultural systems is location. Vegetation health exhibits strong autocorrelative spatial dependency that can be difficult to account for in regression analyses and which, if not considered, has the potential to bias results. In addition, temporal dependency, differences in crop type, the sources of water used for irrigation, the complexity of the physical water distribution system, and the scale of cultivation activities also contribute to variations in the impacts of drought on agriculture.

In water resources research, simulation models of water use dynamics are commonly employed. There are many examples of agricultural water use models for California's Central Valley that employ simulation strategies. Medellín-Azuara et al. (2015) merge a model of economic and agricultural production (SWAP) with a groundwater use model (C2VISim) to estimate the economic costs of pumping groundwater during the drought, finding higher vulnerability in regions without access to wells and uncertain access to surface water. Schwartz (2015) uses a series of linked models to estimate future water rights curtailments, finding that many more water rights holders will be affected by curtailments in the future. While simulation studies provide valuable information, it is prudent to assess the conclusions of simulations using alternate methods.

Recent advances in computational power and Bayesian empirical modeling techniques, which offer advantages over traditional regression methods in consideration of uncertainty in estimates and the ability to accommodate missing data, have made Bayesian modeling approaches more tractable for analyses of complex systems (Blangiardo & Cameletti, 2015; Gelman & Hill, 2007). Bayesian methods have been found to be particularly useful for analyses of spatial and hierarchically (multi-level) structured data and have been used to examine the space-time dynamics of disease (Schrodle et al., 2011; Raghavan et al., 2016), child malnutrition (Kandala et al., 2001), and wildlife population dynamics (Cosandey-Godin et al., 2015). More recently the expansion of Laplace approximation-based Bayesian analyses, which are more computationally efficient than traditional Markov chain Monte Carlo-based Bayesian analyses, has led to a rapid increase in examination of spatiotemporal phenomenon in large datasets (Mantovan & Secchi, 2010).

In what follows, we present analyses that explore the role of surface water rights in modifying the effects of drought on a remotely sensed metric of agricultural productivity and the likelihood of a field being left fallow throughout the recent California drought. We apply Bayesian multilevel modeling techniques that account for spatial and temporal effects to estimate the variation in the effects of surface water rights structure over the course of the drought. These techniques allow us to quantify the effects of key predictors after accounting for temporal and spatial patterns in the region. The multilevel approach also allows us to explore factors driving agricultural response to drought at both the watershed and field levels.

Area of Interest

In order to investigate the effects of the legal structure of surface water rights on agricultural production over the course of the drought a large spatiotemporal panel dataset was compiled (see Table B 1 in APPENDIX B for additional information on data sources and formats). Annual data for years 2010-2014 of the recent drought were obtained for the Central Valley with outcome, control, and predictor variables available at one of two different spatial scales: field-level (1km pixels) or watershed level (U.S. Geological Survey hydrologic unit code (12-digit designation). For the analyses described below the dataset was clipped to the subset of fields located in the California Central Valley that have been characterized as agricultural land (farmland or grazing land) in any of the biennial California farmland mapping surveys between 2006 and 2014 (California Department of Conservation, 2016). Figure B 1 in the Appendix displays the spatial extent of the area of study, which contains 849 watersheds and 62,050 fields.

Outcome data

The spatiotemporal resolution of existing agricultural production datasets made public by the U.S. Department of Agriculture is at the county-year scale, however, given the size of counties in California, agricultural production data at this level can mask significant spatial variations that occur at the farmland field and watershed scale. In order to more precisely investigate relationships that link agricultural production to water use we opted for outcomes at the field-level. While data limitations inhibit consideration of the legal structure of water rights at the field-level, the use of the field-level outcome allows us to both account for localized factors such as land-use and to explicitly model the full extent of field-level variation within an area.

To capture field-level production dynamics, we computed an index of total vegetative production (TVP) using remotely sensed metrics of vegetation health. TVP is computed as the integral of the annual smoothed Enhanced Vegetation Index (EVI) time series and represents the relative productivity of that pixel for the year of interest. To compute TVP we extracted measures of the observed EVI from a one-kilometer, 16-day resolution dataset from the NASA Moderate Resolution Imaging Spectroradiometer (MODIS) Terra MOD13A2 dataset (NASA LP DAAC, 2015). The EVI is measured as:

$$EVI = G\frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + C_1\ x\ \rho_{RED} - C_2\ x\ \rho_{BLUE} + L}$$

where ρ is atmospherically corrected surface reflectance, L is the canopy background adjustment, and C1 and C2 are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosols in the red band (Huete et al., 2002). EVI values approaching one indicate higher levels of photosynthetic activity over the 16-day period. The MODIS quality mask was applied to the full dataset, dropping low quality observations. Pixels with more than 50 percent of their values flagged as low quality through time were dropped from the analysis. For the remaining pixels, missing observations were linearly interpolated and the full time series was smoothed using a Savitzky-Golay filter before computing the annual integral to obtain TVP (Savitzky & Golay, 1964).

The EVI is highly correlated with both leaf area and vegetation fraction estimates (Gumma, 2011; Huete et al., 2002; Sakamoto et al., 2005; Small & Milesi, 2013; Xiao et al., 2006). A recent study compared MODIS vegetation indices, including EVI, to county-level yield data from the U.S. Department of Agriculture. Crops studied include barley, corn, canola, cotton, potatoes, rice, sorghum, soybeans, sugarbeets and wheat. The EVI was found to correlate strongly with yields across all these crops (Johnson, 2016). As the integral of the EVI time series, TVP serves as a proxy for cumulative annual vegetative productivity. Integrated vegetation indices such as TVP have been shown to be a good measure of productivity and yield in a number of studies (Mkhabela, Bullock, Raj, Wang, & Yang, 2011; Wang, Rich, Price, & Kettle, 2005). Higher values of TVP indicate higher amounts of vegetative health and productivity over a year (Jönsson & Eklundh, 2002; Jönsson & Eklundh, 2004). Figure B 2 in the Appendix provides a representative map of TVP spatial patterns.

In order to probe the effects of the structure of surface water rights on cultivation decisions, a binary, field-level outcome was computed that represents whether a field is barren and fallow. This outcome variable was derived from the National Agricultural Statistics Service CropScape dataset (USDA National Agricultural Statistics Service, 2016). For each year, the mode of the 30-meter resolution CropScape dataset was computed for pixels within each field (1 kilometer TVP pixel) and fields where the mode was categorized as barren and fallow were assigned a value of one while all other fields were assigned a value of zero.

Surface water rights data

Surface water use explanatory variables that describe the structure of water rights were computed at the watershed level. Watersheds are irregular spatial units that define local hydrologic dynamics that are topology dependent and are often the preferred unit of analysis for water use and water quality studies (Ficklin, Luo, Luedeling, & Zhang, 2009; Kollet & Maxwell, 2008). Point data identifying the location of surface water right points of diversion (PODs) and the legal status of each POD were downloaded from the CA SWRCB electronic water rights information management system (eWRIMS) (CA SWRCB, 2016c). Digitized data currently does not exist to link a POD to a specific place of use, so this point data was aggregated to watersheds to reflect watershed-level patterns of surface water access. Use of watershed scale or river basin data aggregations in studies examining access to water and water allocations in relation to water rights are common in the literature, in large part due to the lack of data on water access at the field-level (Grantham and Viers, 2014; Schwarz, 2015; Tidwell et al. 2014).

In this study, the legal structure of water rights is represented by three variables that give the percent of all active agricultural use PODs within a watershed that are classified as Riparian, Pre-1914 Appropriative (henceforth referred to as "Pre-1914") and Post-1914 Appropriative (henceforth referred to as simply "Appropriative") water rights (additional information on water rights data processing and aggregation is provided Text B 1 in the Appendix). We suggest that these newly developed metrics provide a measure of the distribution of legal access to surface water within watersheds. While legally structured differences in field-level access to surface water most certainly exist within watersheds, these metrics provide information about the relationship between the tendency towards certain types of legal access within a watershed that may influence the average level of agricultural production within that watershed. The legal structure of water rights in a watershed is expected to influence famer cultivation decisions by modifying expectations for water availability during the growing season. The legal structure of water rights is also expected to influence agricultural productivity of cultivated fields by modifying the availability of sufficient surface water to maintain cultivated fields during the growing season. Of the 849 watersheds within the study area, 333 have some Riparian water right PODs, 190 have one or more Pre-1914 right PODs, and 486 have Appropriative right PODs. Additional summary statistics can be found in Table 3. Maps of the spatial distribution of water rights can be found in Figure B 3, Figure B 4, and Figure B 5 in APPENDIX B.

As a single water right may be associated with multiple PODs this metric gives greater weight to water rights with multiple PODs. As water rights are frequently not held by individual farmers, but instead by irrigation management districts who then distribute water via multiple PODs to a number of farmers that contract with the district for water supply, the POD based water rights metrics are intended to capture information about the number of farms receiving water associated with water rights and not just the number of water rights holding institutions and individuals (this assumes that the number of PODs is proportional to the number of water users in a watershed). It should also be noted that due to the lack of information on the point of application of water, these metrics assume that the majority of a water rights users are located within the watershed in which the POD is located, which disassociates a water right from use of water associated with that right occurring in other watersheds (see Text B 2 in the Appendix for information on contract water representation in the POD dataset).

Drought severity data

The effect of drought on agricultural production was examined using a measure of cumulative meteorological drought stress which is expected to influence both farmer cultivation decisions (for the following year) and growing-season agricultural productivity (for the current year). This predictor was calculated as the annual sum of the Standardized Precipitation Index (SPI). The SPI is measure of meteorological drought (a deficit in precipitation) that is given over a specified time period (in this case we use 9-month SPI data) and is presented on a normalized scale with a mean of zero and standard deviation of one (AghaKouchak and Nakhijiri, 2012). Negative values of SPI indicate dry conditions while positive values indicate wet conditions. The cumulative annual SPI predictor (henceforth referred to as “SPI”) was computed for each watershed-year using monthly SPI calculated from the NASA North American Land Data Assimilation System (NLDAS) precipitation data and made available by AghaKouchak and Nakhijiri (2012). As SPI is a local measure of precipitation deficit it does not account for changes in water availability that are due to precipitation and water storage occurring outside the study area such as alpine snowpack and reservoir storage. In this case, SPI provides a watershed localized measure of negative forcing on soil moisture and streamflow (Whan et al., 2015).

Crop type data

To account for aspects of field-level agricultural land and water use not attributable to the structure of surface water rights, we included two field-level datasets. The first is a crop type categorical variable derived from the National Agricultural Statistics Service CropScape dataset (USDA National Agricultural Statistics Service, 2016). This land use categorical variable is expected to influence the agricultural productivity of cultivated fields. The CropScape data for each year was aggregated into six generalized categories of land use: barren and fallow, grasses, grains, row crops, fruits and nuts, and uncultivated cover (additional information on CropScape data aggregation is provided in Table B 2). The mode of the 30-meter resolution CropScape data was computed for pixels within each field (1 kilometer TVP pixel) and this land use category was assigned to each field-year. The average farm size in California is 1.3 kilometers, so while this aggregation approach may mask some intra-farm diversity, it largely captures farm-level variations in land use (California Department of Food and Agriculture, 2016). Within the final dataset of 62,050 square kilometers of agricultural fields over 5 years, 7.4% of all fields were classified as barren and fallow, 6.1% were classified as grasses, 11.7% were classified as grains, 5.5% were classified as row crops, 16.1% were classified as fruits and nuts, and 53.1% were classified as uncultivated cover. In addition, 37.2% of all fields were classified as barren and fallow at some time during the drought. Figure B 7 displays the spatial variation in crop type in a representative year.

Groundwater data

The second field-level dataset is the depth to groundwater in January of each cultivation year. This provides an estimate of the accessibility of groundwater at a particular location prior to the start of the growing season. The depth to groundwater is expected to influence both cultivation decisions, by modifying expectations for groundwater availability prior to the growing season, and agricultural productivity, by modifying access to groundwater for irrigation during the growing season. The quality of groundwater extraction data in California and across the U.S. is notoriously poor (CA DWR, 2014). California's Groundwater Information Center monitors well levels for a subset of wells covering the state through the California Statewide Groundwater Elevation Monitoring Program (CASGEM) program, however the temporal and spatial coverage of this monitoring network is lacking, particularly in key critical regions (CA DWR, 2014).

In order to account for reductions in surface water being offset by groundwater use, and in an attempt to avoid omitted variable bias, we applied spatiotemporal kriging to the CASGEM groundwater elevation point dataset using the R package Spacetime to produce a gridded depth to groundwater dataset for the region (GeoTracker GAMA, 2016; Gräler, Pebesma, & Heuvelink, 2016). This method uses an "exact estimator" to interpolate values for spatial locations and time points for which no data is available using the available space-time information and a provided model of spatiotemporal correlation. Following recommended model-fitting procedures as outlined by Gräler, Pebesma, & Heuvelink (2016), we tested the fit of a number of variogram structures to our data and found a simple-sum metric spatiotemporal model to best fit our data.

The point data was then kriged through space-time to generate a 10-kilometer monthly gridded groundwater elevation dataset which was compared to a held-out dataset of groundwater elevation observations for verification purposes. Our model performed well with a mean normalized RMSE of 0.08 against the held-out observations and a Nash-Sutcliffe efficiency of 0.80. To convert the groundwater elevations to depth to groundwater and aggregate this monthly dataset to an annual time-step, we subtracted the groundwater elevation in January of each year from the ground-level elevation using the Elevatr package to estimate depth to groundwater (Hollister and Shah, 2017). This value of depth to groundwater was extracted to each field-year. More information on the groundwater space-time kriging procedure is provided in Text B 3. Figure B 12 displays the spatial distribution of depth to groundwater in a representative year.

Additional control data

To account for agricultural dynamics at the watershed level, we computed an index of agricultural diversity to indicate whether the agricultural system of a watershed tends towards monoculture. This metric captures the complexity of the agricultural system, where areas with less diversity are expected to have a greater amount of permanent or semi-permanent physical irrigation infrastructure in place that might constrain farmer cultivation decisions. The CropScape data from USDA were aggregated for each watershed-year using the diversity indexing method described by Turner, Neill, Gardner, & Milne (1989) where diversity is described as the linear sum of the proportion of a landscape area that is covered by each crop type. As the crop diversity metric is expected to influence pre-season cultivation decisions this variable was lagged by one year.

As access to surface water is expected to influence both farmer cultivation decisions and growing season productivity we also control for physical accessibility and proximity of surface water in each watershed using a measure of the density of agricultural surface water right PODs. This metric was computed by taking the ratio of the total number of agricultural surface water rights PODS in a watershed and the area of all farmland in a watershed and controls for watershed scale variations in agricultural production related to proximity to streams and rivers, where PODs tend to be clustered, that are independent of the legal structure of water rights. In addition, as competition between different types of water uses (e.g. agricultural, municipal, and industrial) during times of water scarcity is expected to influence the availability of surface water for agricultural purposes we computed a metric of completion as the percent of all surface water right PODs in a watershed that are reported to be used for agricultural purposes. This metric is expected to influence both farmer cultivation decisions and growing season productivity within a watershed.

Geographically referenced annual data was unavailable for a number of factors thought to be relevant to cultivation decisions and agricultural health and productivity such as surface water availability, climatic conditions, and changes in crop value. In order to take into consideration these omitted variables categorical indexes for year and watershed were included in the dataset so that omitted variable influences that varied with time but not location, or that varied by watershed but remained constant over time could be controlled for using year and watershed specific effects.

Table 3: Descriptive statistics for continuous variables.

	Spatial Scale	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Total Vegetative Production	field	0.55	0.16	0	1.35
Annual Cumulative SPI	watershed	-2.04	3.15	-12.96	8.76
Percent Riparian	watershed	28.5	33.8	0	100
Percent Pre-1914	watershed	15.6	28.1	0	100
Percent Appropriative	watershed	61.6	38.1	0	100
Depth to Water Table (ft)	field	189.8	242.3	0.02	1731.8
Crop Diversity	watershed	14.6	6.2	0	36.8
Water Rights Density (PODs/square km farmland)	watershed	0.08	0.33	0	35
Percent Agricultural Use	watershed	39.37	35.38	0	100

Statistical Analyses

<u>Multi-level structure</u>

The importance of multi-level structuring on the growing season agricultural productivity outcome variable (TVP) was tested by fitting a three-level null model and calculating the intraclass correlation coefficient (ICC). The null model takes the form,

$$y_{ijk} = \beta_{0jk} + e_{ijk} \tag{1.1}$$

$$\beta_{0jk} = \beta_{00k} + u_{0jk} \tag{1.2}$$

$$\beta_{00k} = \gamma_{000} + u_{00k} \tag{1.3}$$

which can be expressed in reduced form as:

$$y_{ijk} = \gamma_{000} + u_{00k} + u_{0jk} + e_{ijk} \tag{1.4}$$

where y_{ijk} is TVP for a time-ordered measurement during year i, at field j, in watershed k, γ_{000} is the intercept coefficient, u_{00k} is a random effect accounting for variability between watersheds k, u_{0jk} is a random effect accounting for variability between fields j in watershed k, and e_{ijk} is a random effect accounting for the remaining within field variability over time. TVP was modeled using a Gaussian likelihood distribution, and for the null model we model all random effects using a random Gaussian correlation structure (iid). The intraclass correlation coefficient was calculated as the proportion of the total variance attributable to between unit variance at levels i, j, and k. The ICC ranges from 0 to 1 where 0 indicates that grouping conveys no information and 1 indicates that all group members are identical (Gelman & Hill, 2007). The resulting ICCs of 0.2 for level i, 0.3 for level j, and 0.5 for level k indicate that significant variance is found at each level and suggests that dynamics at all three levels should be taken into consideration. Given the large size of the dataset used in this study (5 years, ~62,000 fields, and 849 watersheds) we prioritize consideration of spatial processes occurring at level k to reduce the computational demands of model estimation.

Bayesian model specification

In order to test the hypothesis that seniority in access to surface water improves local capacity to maintain crop health and productivity and reduces agricultural sensitivity to cumulative meteorological drought stress during times of water scarcity the observed TVP was fit to a multi-level mixed-effects model with water right-SPI interactions, which can be expressed generally as:

$$y_{ijk} = \beta_{0jk} + \beta_{10k} SPI + \boldsymbol{\beta}_{20k} \boldsymbol{X} + \boldsymbol{\beta}_{30k} \boldsymbol{X} * SPI + \boldsymbol{\beta}_{4jk} \boldsymbol{C} + s_{00k} + e_{ijk} \qquad (2.0)$$

where, β_{0jk} is an intercept term, β_{10k} represents the linear effect of cumulative meteorological drought stress (SPI) on TVP, β_{20k} is a vector of coefficients that describe the effects of water rights on TVP at the watershed level, X is a vector of water rights predictors (Percent Riparian, Percent Pre-1914, and Percent Appropriative), β_{30k} is a vector of coefficients that describe the effect of interactions between water rights predictors and SPI, β_{4jk} is a vector of coefficients for controlling variables, C is a vector of controlling variables (year, crop type category, water rights density, competing uses, and depth to groundwater), s_{00k} is a watershed level spatial effect, and e_{ijk} is the residual within field variability. Both year and crop type category are modeled as fixed effects while the watershed spatial effect is modeled as a random effect. All continuous variables were scaled to a mean of zero and standard deviation of one to ease interpretation of the intercept and coefficients.

In order to account for spatial effects in the large spatiotemporal dataset modeling was performed using the R package R-INLA, a Bayesian modeling package utilizing integrated nested Laplace approximations that includes a number of models for spatial and non-linear random effects (Blangiardo, Cameletti, Baio, & Rue, 2013). Spatial effects at the watershed level were modeled using an intrinsic conditional autoregressive (iCAR) model coupled with an exchangeable (iid) random effect, also known as a Besag-York-Mollié (BYM) model. The addition of the spatial random effects can be interpreted as a random intercept term that accounts for both spatially random differences across watersheds and autocorrelation between neighboring watersheds.

The fit of the above described model (Model A) was compared to a model of only the described linear predictors and interactions using the calculated DIC (deviance information criterion). The proposed model (Equation 2.0) showed better performance (see Table B 3). In addition, recognizing that the effects of weather are not necessarily linearly related to agricultural production, models adding polynomial terms for SPI were compared with Model A (Schlenker and Roberts, 2006). While polynomial terms for SPI were found to be significant, the linear effect of SPI, and more importantly, the main effects of the water right predictors and their interaction effects with SPI were not significantly different from those observed in Model A (see Table B 4). In addition, the DIC for these models did not offer great improvements over Model A and the range of the full SPI effect for these models remained similar to Model A. Given that the focus of this study is to examine the impacts of the structure of water rights the more parsimonious Model A was selected for further analysis of impacts to agricultural productivity.

In order to test the hypothesis that during periods of extreme water stress, seniority in access to surface water significantly improves local capacity to cultivate crops and decreases the sensitivity of cultivation decisions to cumulative meteorological drought stress, a Bernoulli likelihood model examining the effect of water rights and SPI on the likelihood that a field of agricultural land is classified as barren and fallow was also run. The model (Model B) takes the same basic form as Equation 2.0 (with the addition of the farmland crop diversity control, use of a lagged SPI variable, and minus the land use category control), however, the outcome in this case is binary, where a value of one indicates that a field is barren and fallow and a value of zero indicates the field belongs to some other land use category.

As water use dynamics in the Central Valley are subject to feedbacks and simultaneity that can lead to endogeneity issues, factors whose values in any year are dependent on processes related to other independent variables or the outcomes (e.g., the amount of groundwater applied to fields is dependent on the crop type and amount of surface water applied to fields) were avoided in the above described models. In addition, due to lack of appropriate data for known factors influencing agricultural productions and other unknown excluded factors, endogeneity due to omitted variable bias was also a concern. In order to test the robustness of our models and identify potential biases in coefficient estimates, a series of models were run testing the sensitivity of our estimates of interest (surface water rights predictors) to the inclusion and exclusion of controlling variables and spatial random effects, while holding the crop type and temporal fixed effects constant.

These sensitivity tests were conducted for both Model A and Model B and a subset of the results are provided in Table 4 and Table 5, respectively (complete results are provided in Table B 5 and Table B 6). To test the validity of the random effects assumption (random effects are assumed to be uncorrelated with controlling variables in a regression), Model A was run with fixed effects for watersheds and compared to the same model with spatial random effects. Coefficient estimates for the predictors of interest in the watershed fixed effects and watershed spatial random effects model were not significantly different at the 95% credibility interval, providing confidence that no watershed-scale omitted variables that might significantly bias results remain unaccounted for (see Table B 7). Key results of the Bayesian multi-level spatiotemporal models given as the median estimates of posterior parameters are summarized in Table 4 and Table 5 in the Results section (full model results for Models A and B, including 95% Credibility Intervals, are provided in Table B 8 and Table B 9).

Results

The posterior Bayes estimates for Model A indicate that cumulative meteorological drought stress and one of the three water rights predictors have a significant effect on agricultural production after accounting for crop type, year, and watershed (Table 4). The effect for SPI indicates that when each water right's predictor is at zero (its mean), and cumulative drought stress becomes less severe, total annual vegetative production (TVP) shows, on average, slight increases. The water rights predictor Percent Pre-1914 also shows a positive and significant effect on agricultural productivity, while the effect of Percent Riparian and Percent Appropriative water rights are not significant (Figure 6).

Table 4: Posterior Bayes median effect estimates for models evaluating field level TVP in the Central Valley.

Variable	Model A	Model A.2	Model A.3	Model A.4	Model A.5	Model A.6
Intercept	0.1623*	0.1631*	0.1628*	-0.1000 *	-0.0806*	-0.1016*
SPI	0.0623*	0.0624*	0.0623*	0.1081*	0.1113*	0.1120*
Percent Riparian	-0.0007	0.0014	0.0008	-0.0661*	-0.0587*	-0.0464*
Percent Pre-1914	0.0536*	0.0540*	0.0538*	0.0125*	0.0174*	0.0300*
Percent Appropriative	-0.0062	-0.0050	-0.0062	-0.0377*	-0.0439*	-0.0198*
Percent Riparian*SPI	0.0060	0.0058	0.0060	-0.0515*	-0.0517*	-0.0477*
Percent Pre-1914*SPI	-0.0009	-0.0010	-0.0009	0.0114	0.0109*	0.0166*
Percent Appropriative* SPI	-0.0226*	-0.0228*	-0.0226*	-0.0798*	-0.0763*	-0.0752*
Depth to Groundwater	0.0024	0.0024	0.0024	-0.0213*	-0.0428*	-0.0213*
Water Rights Density	0.0020	0.0020	---	0.0387*	0.0494*	---
Percent Agricultural Use	-0.0042	---	-0.0039	0.1087*	---	0.1157*
Spatial Random Effects	Yes	Yes	Yes	No	No	No
DIC	619551	619552	619552	772393	774797	772950
*Indicates effect estimate is significantly different from zero at a 95% credibility level.						

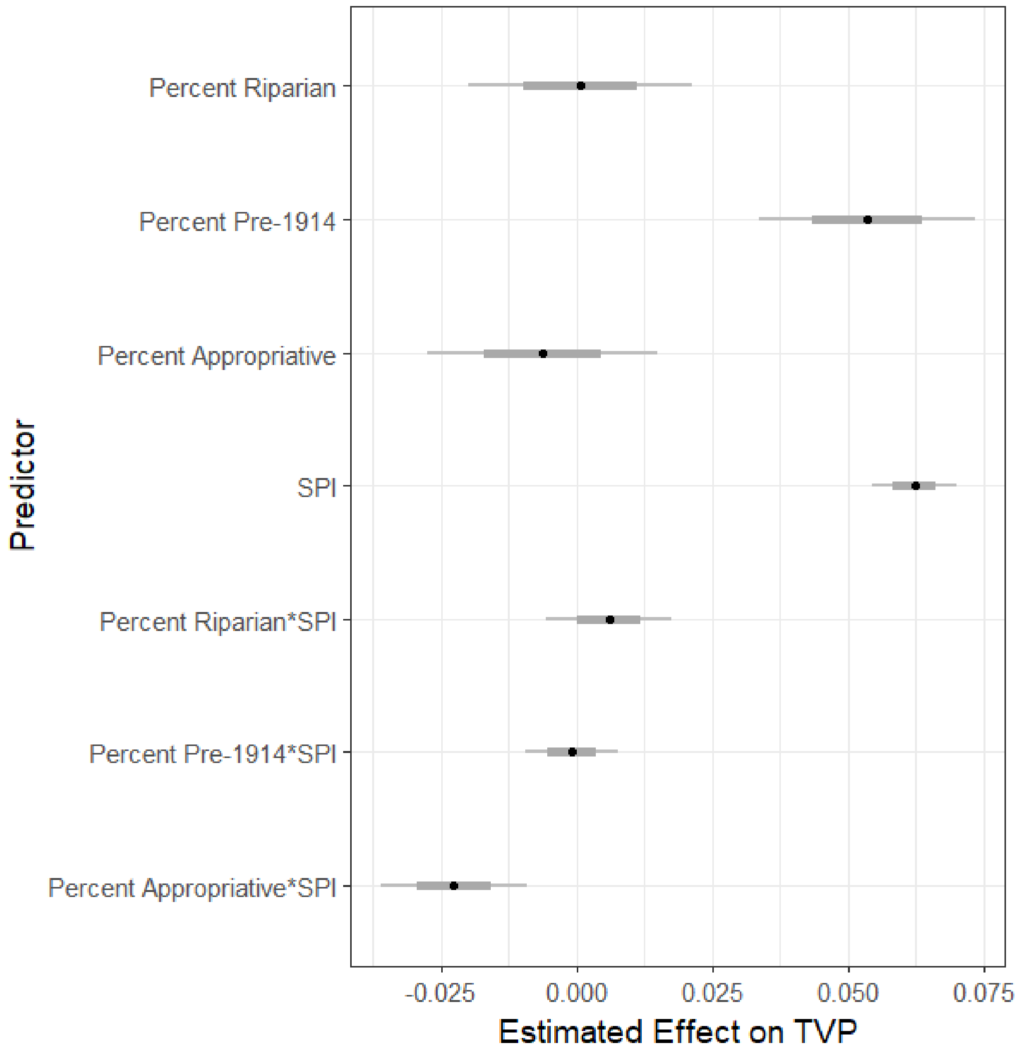

Figure 6: Estimated effect of key predictors on TVP.

The effect for Percent Pre-1914 water rights indicates that when SPI is zero (at its mean) watersheds with a larger proportion of water rights that are classified as Pre-1914 have, on average, higher TVP (indicating better crop health and productivity) than watersheds with a low proportion of Pre-1914 water rights. In addition, Appropriative water rights have a significant interaction effect with SPI, such that the effect of SPI on TVP is reduced from ~0.06 to ~0.04 when the percent of Appropriative water rights in a watershed increases by one standard deviation. Figure 7 illustrates how the effect of SPI on TVP changes as a function of each water right type. These results rather surprisingly indicate that agricultural productivity in watersheds with a higher proportion of Appropriative water rights is, on average, less sensitive to precipitation deficits than watersheds with a higher proportion of Pre-1914 or Riparian water rights.

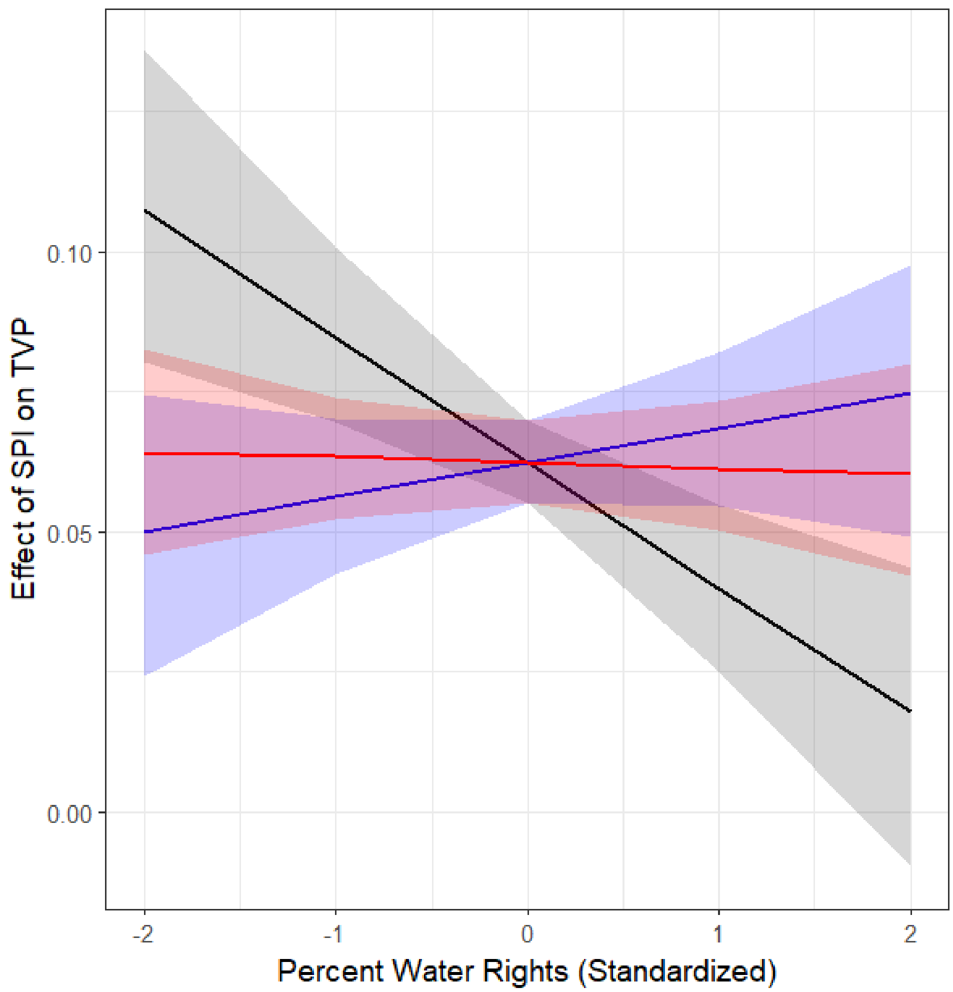

Figure 7: The effect of SPI on TVP as a function of standardized water rights predictors.

Both the primary predictor effect estimates and the interaction effect estimates remain stable in Model A through Model A.3 as control variables are included or excluded when temporal and crop type fixed effects and watershed spatial random effects are held constant, providing some confidence in the robustness of the results. The estimates do shift considerably when the watershed spatial random effects are removed (Models A.4-A.6) suggesting that a significant amount of the variation in the predictors is related to omitted variables correlated with location (e.g. location of contract water districts and volume of water contract allotment).

Surprisingly, the coefficient for the depth to groundwater variable is not significant in Model A. In comparison, the coefficient for depth to groundwater estimated in Model A.4, where watershed spatial random effects are not included, shows that increasing depth to groundwater results in, on average, lower TVP outcomes. This would suggest that after controlling for crop type and year, areas where it may be more difficult or costly to access groundwater are less able to utilize groundwater to offset surface water shortages and maintain crop health. However, variation in this effect seems to occur at the watershed spatial scale and does not vary consistently over time, leading groundwater effects to be soaked up by the watershed spatial effects.

The density of water rights PODs within a watershed is also not significant in Model A. Comparison with Model A.4 where there is no watershed spatial effect indicates that this metric does positively effect TVP outcomes, but that these effects vary primarily across watershed and hence are accounted for with the spatial random effect in Model A. As with the density of water rights and depth to groundwater variables, the percent of all water rights PODs in a watershed that are used for agricultural purposes does not show a significant effect on agricultural productivity in Model A, but does in Model A.4 where its positive effect suggests that watersheds where a greater proportion of water rights go to agriculture are better able to maintain crop health.

Table 5: Posterior Bayes median effect estimates for models of the likelihood of a field being classified as barren and fallow in the Central Valley.

Variable	Model B†	Model B.2†
Intercept	0.0122 *	0.0436*
SPI	0.9198 *	1.0539*
Percent Riparian	0.9804	0.8733*
Percent Pre-1914	1.0577	0.8756*
Percent Appropriative	1.0399	1.0341*
Percent Riparian*SPI	1.1023*	1.2695*
Percent Pre-1914*SPI	1.0956*	1.1163*
Percent Appropriative*SPI	1.2081*	1.2839*
Depth to Groundwater	0.4269*	0.4222*
Water Rights Density	1.0382*	0.9534*
Percent Agricultural Use	1.1430*	1.0989*
Farmland Crop Diversity	0.9629*	1.0868*
Spatial Effects	Yes	No
DIC	130682	156065

†Anti-logit of the intercept estimate and exponentiated predictor effect estimates are reported.
*Indicates effect estimate is significantly different from zero at a 95% credibility level.

The posterior estimates of the marginal distributions for Model B as shown in

Table 5indicate that there is generally a low average likelihood that any agricultural field is classified as barren and fallow. The estimate of the intercept suggests that the chances of a field being barren and fallow given average conditions for SPI in the previous year, water rights predictors, and controls, and after accounting for year and watershed, are about 12 in 1,000. The estimates of the predictor effects can be interpreted as an incremental change in the probability of a field being classified as barren and fallow. The effect of SPI suggests when the water rights predictors equal zero and SPI increases by one standard deviation (decreasing cumulative drought stress), the probability that a field will be barren and fallow decreases by ~8%.

None of the three water rights predictors have a significant main effect on the likelihood that a field is barren and fallow, however all three water rights predictors have significant interaction effects with SPI. The interaction effects can be interpreted as the ratio by which the SPI effect changes due to variations in the water rights predictors. The resulting effect of SPI given an increase of one of the interacting variable can be calculated as the exponentiated sum of the focal predictor (SPI) effect and the interaction effect (this is equivalent to the product of the exponentiated focal effect and interaction effect) (Chen, 2003). This indicates that increasing the value of the Appropriative water rights predictor from zero to one (from the mean to one standard deviation above the mean) modifies the effect of SPI such that a one standard deviation increase in SPI increases the probability of a field being barren and fallow by ~11% instead of decreasing it by ~8%. Conversely, this implies that in watersheds with a lower percentage of Appropriative water rights, as SPI increases, the likelihood of a field being barren and fallow decreases. A one standard deviation reduction in the percent Appropriative rights corresponds to a reduction in the likelihood of a field being barren and fallow of ~24% when SPI also increases by one standard deviation.

The interaction effects for Riparian and Pre-1914 waters are also significant. An increase of one standard deviation in the percent Pre-1914 water rights corresponds to 0.01% increase in the likelihood of a field being barren and fallow when SPI increases by one standard deviation, and an equivalent change in the percent Riparian water rights corresponds to a 1.4% increase in the likelihood of a field being barren and fallow when SPI increases by one standard deviation.

These interaction effects suggest that, on average, when cumulative drought stress is more severe, watersheds with a higher than average proportion of senior water rights will be less likely to have barren and fallow fields than watersheds with more junior rights.

While the main effect estimates for the water rights predictors were not significant in Model B the estimates for all controls were significant. The estimate for depth to groundwater suggests that when the depth to groundwater increases by one standard deviation the likelihood of a field being barren and fallow decreases dramatically (~57% less likely). This result is counterintuitive as it suggests that farmers located in areas where it may be more difficult to access groundwater choose to cultivate a greater extent of crops. In order to investigate whether this result reflects the influence of permanent crops such as Almonds, which cannot be left to fallow as annual crops can regardless of groundwater accessibility, and high value crops which may drive increased groundwater use despite increasing pumping costs, a model including a control for type of crop grown in the previous year was run. The results of this model (Table B 10) show that while crop type grown in the previous year does strongly influence the likelihood of a field being classified as barren and fallow and does significantly change the groundwater effect, it does not produce a meaningful change the groundwater effect. This suggests that the unexpected groundwater effect on cultivation choices is more likely to be related to other factors such as the presence of existing groundwater wells, for which statewide data is not yet publicly available. (As with Model A we note that while we cannot control for all confounding factors in these models the lack of significant movement in the water rights variables of interest when controls are added and removed (see Table B 6 and Table B 10) provides some confidence in their robustness.)

The farmland crop diversity estimate in Model B suggests that increasing crop diversity slightly reduces the likelihood of fields being barren and fallow, and may indicate a shift from cultivation of only a few traditional crops towards cultivation of more acreage of alternative drought-resistant crops in some watersheds. The effects for the controls for surface water access, water rights density and percent agricultural use, indicate that increases in the water rights density and in the amount of water rights associated with agricultural use are correlated with increases in the likelihood of a field being barren and fallow. This suggests that farmers in heavily agricultural watersheds that are reliant on surface water were more likely to cultivate less farmland during the drought. When comparing Model B and Model B.2, which has no watershed spatial random effects, it is clear that unlike the model of agricultural productivity (Model A) the estimates of the control variables in the logistic model are relatively insensitive to the addition of spatial effects, suggesting that they are accounting for variance within watersheds and over time. The effect estimates for the water rights predictors in Model B.2 are all significant and for Percent Riparian and Percent Pre-1914 indicate that watersheds with a higher percentage of Riparian or Pre-1914 water rights are less likely to have fields classified as barren and fallow. That these effects are not significant in Model B suggests that these effects are not strong after accounting for watershed properties that influence cultivation that are consistent over time.

Discussion

Given the importance of governance in creating opportunities to improve the capacity of people to respond to adverse situations, particularly in complex coupled social-ecological systems such as agricultural systems, a better understanding of the impacts of legally institutionalized structures granting and limiting access to surface water may positively inform water managers' decision-making during times of water scarcity. The models presented in this study represent, to our knowledge, the first attempt to investigate the overall impacts of the legal structure of surface water rights in California on total annual vegetative productivity and the likelihood of a field being left barren and fallow for the entire Central Valley. Starting with the assumption that the legal structure of surface water rights in the state affects agricultural productivity, we test the hypotheses that (1) farmers with seniority within the hierarchical legal structure of Californian surface water rights were able to achieve better than average agricultural productivity and maintain cultivated extent during the recent drought and that (2) they experienced less sensitivity to cumulative drought stress than did those with junior access to surface water.

The model results partially support the general hypothesis that the legal structure of surface water rights, as represented by the proposed metrics of watershed-scale distribution of water rights types, in the state affects agricultural production. In line with expectations, the model results suggest that areas with a large proportion of the most senior water rights, Pre-1914, did, on average have better agricultural productivity outcomes during the drought than areas with more junior, Appropriative, water rights. However, contrary to expectations, the model results also suggest that areas with a high proportion of junior water rights exhibit less sensitivity to cumulative meteorological drought stress, as decreases in SPI in areas with a high proportion of Appropriative water rights are associated with less severe decreases in agricultural productivity. Conversely, these same watersheds may not experience significant improvements in TVP when local drought conditions improve, perhaps signaling a reliance on distant water sources or a tendency for short-term increases in available surface water to go to higher priority beneficial water uses or senior water rights holders. Significant effects were not found for the main effects of Riparian and Appropriative water rights in spatiotemporal models of agricultural productivity, indicating that any effects of these predictors did not produce sufficient variation in TVP to be differentiated from watershed spatial effects. This may in part be due to the strong influence of groundwater and contract water use for agricultural irrigation that consistently occurs in many watersheds in the Central Valley.

The estimated effect sizes reported for the models examining effects on agricultural productivity may be small, however, it is important to note that these significant effects remain after accounting for variations in watershed characteristics that may influence agricultural productivity, time-invariant watershed-level factors, space-invariant temporal changes, and after controlling for land use decisions in each field. This implies that neither correlation between water rights and type of crop cultivated nor spatial correlation in locations of water rights contribute to the observed water rights effects, which are a reflection of the legal structures governing farmers' expectations for, and access to, surface water. In addition, it should be recognized that the size of the effect of the water rights predictors on TVP is of a similar magnitude as the linear SPI predictor. That the effect observed for SPI is of such a small magnitude suggests that the short-term capacity of farmers in the Central Valley to mitigate the impacts of drought are considerable. Given likely increases in drought conditions in the area in the future, and state regulations related to sustainable groundwater management, this short-term capacity may be reduced in favor of long-term agricultural system viability, suggesting that the effect of SPI on crop health and productivity may be greater in the future (CA DWR, 2015).

While the results of models examining the role of the legal structure of water rights on agricultural productivity during times of water stress suggest that crop health and productivity was generally higher in areas with a high proportion of Pre-1914 water rights than in other areas, the results of the logistic model examining the likelihood of an agricultural field being left as barren and fallow indicate that the structure of water rights alone does not have a significant direct effect on the likelihood that a field is barren and fallow. However, the interaction effects from the logistic regression suggest that when cumulative meteorological drought stress is more severe, areas with a high proportion of Appropriative water rights are more likely to have barren and fallow fields, while areas with a high proportion of Pre-1914 water rights are least likely to have barren and fallow fields. This finding supports the hypothesis that seniority in access to surface water decreases the sensitivity of cultivation decisions to cumulative meteorological drought stress. Interestingly, the effect of depth to groundwater has a strong and stable effect in the logistic model that indicates that the likelihood of a field being barren and fallow is much less in areas where the depth to groundwater is greater. This finding, may reflect the importance of the locations of existing groundwater wells and lack of groundwater pumping restrictions which were not explicitly controlled for in this model.

Limitations of the study

Accounting for the spatiotemporal dynamics of agricultural response to water availability is a complex task. Despite our best efforts to leverage the power of R-INLA to model complex spatiotemporal error structures, our results remain limited by data resolution and availability (Blangiardo, Cameletti, Baio, & Rue, 2013). Without data clearly linking points of diversion to farmers' fields, we can only approximate vegetative responses and cultivation decisions to the general configuration of water rights in the surrounding watershed, and must rely on spatial effects to control for aspects of the agricultural system such as contract water. In addition, these analyses rely on the assumption that the amount of surface water and groundwater applied to agricultural fields can be approximated by metrics of access, availability, and water right priority. Reduction in surface water availability is assumed to be accounted for by year fixed effects, while issues related to dissociation between water right POD locations and point of water use, and between depth to groundwater and locations of actual groundwater wells, are assumed to be accounted for by the spatial random effects.

While the use of spatial random and fixed effects can be a powerful tool for addressing issues related to incomplete data, applying these controls successfully and without loss of explanatory power can be difficult. In our analyses incorporation of spatial random effects was associated with a reduction in significant effect estimates. However, the stability of the estimates in the spatiotemporal models when control variables are included or excluded provides some confidence in the robustness of the findings. While models without the spatial random effects provided more significant effect estimates the same level of robustness cannot be claimed as effect estimates do vary significantly with inclusion and exclusion of controls.

With higher resolution data linking fields to specific water rights, modeling field-level agricultural responses to surface water institutions would be possible. This data, coupled with increased groundwater monitoring could generate crucial research required to understand the complex dynamics of agricultural water use in the Central Valley. As more data becomes available describing access to groundwater and surface water in the region, research can be developed to explore how specific configurations of surface water rights affect agricultural production, how agricultural groundwater and surface water use interact during periods of drought and during years without drought, and how future groundwater policies such as the Sustainable Groundwater Management Act initiative could impact surface water access in the Central Valley. Additional research is also needed to determine how the portfolio of surface water use (e.g. industrial, domestic and agricultural use) influences agricultural response to drought. Knowledge about the impact of these structures on agriculture may help to support more comprehensive water use planning at the state and national levels and may assist farmers in mitigating the impacts of future drought.

Conclusion

The work described in this study advances the use of Bayesian modeling to control for complex dynamics in large social-environmental datasets. We utilized multilevel Bayesian modeling methods that included consideration of temporal effects and spatially autocorrelated effects to test the hypotheses that farmers with seniority within the hierarchical legal structure of California surface water rights were able to achieve better than average agricultural productivity and maintain cultivated extent during the recent drought, and that they also experienced less sensitivity to cumulative drought stress than did those with junior access to surface water. Our results suggest that:

1. Watersheds with a higher proportion of senior water rights had better agricultural health and productivity during the drought than watershed with less seniority in surface water access;
2. That agricultural productivity in watersheds with a higher proportion of junior water rights was, on average, less sensitive to meteorological drought conditions than other watersheds; and
3. That watersheds with a higher proportion of junior water rights were more likely to reduce the extent of cultivation, by allowing fields to fallow in response to increasingly severe meteorological drought conditions.

These results generally suggest that, as expected, seniority in access to surface water granted via the hierarchical legal structure of water rights in California enables farmers to cultivate more land with healthier crops. However, the finding that crop health and productivity in watersheds with relatively more junior water rights are less sensitive to changes in drought conditions may indicate that farmers in watersheds with a large proportion of junior water rights are better prepared to take action to mitigate the impacts of surface water deficits via groundwater pumping and other mechanisms. Considering that watersheds with more junior water rights are more likely to have more barren and fallow fields but also more improved agricultural productivity outcomes when drought severity increases, it may be inferred that farmers in watersheds with more junior access to surface water prioritize maintaining crop health over increasing the extent of cultivation. The findings of this study provide some evidence that the legal structure of surface water rights in California affects the ability of farmers to cultivate crops and maintain crop health during periods of drought, and suggests that attention to the effects of legal institutions governing access to water for agricultural uses should not be neglected in revisions of current water policies and creation of new water policies and institutions.

The study described above suggests that consideration of spatial and temporal effects in social-environmental systems can significantly alter the results of regression analyses and that it is possible to identify significant effects for processes related to vulnerability and resilience in complex SESs. While complex, Bayesian spatiotemporal modeling has the potential to account for dynamic, multi-scalar processes in SESs, and may lead to greater confidence in the identification of vulnerability, resilience, adaptive capacity, and sustainability indicators. In addition, the ability to model processes through space and time may be used to analyze trends in vulnerability, resilience, adaptive capacity, and sustainability over time.

Implications of Spatial Modeling Methods for Analysis of Social-Environmental Systems

The findings of the two studies described in this chapter confirm that spatial effects and scale of analysis are of considerable importance when evaluating issues related to the vulnerability, resilience, and sustainability of complex social-environmental systems. The first study demonstrates that the scale at which social vulnerability is computed significantly alters conclusions about the number and characteristics of vulnerable persons, where application of aggregated census data underestimates the vulnerability of specific demographic groups such as senior citizens. The second study demonstrates the importance of accounting for underlying spatial processes that shape the characteristics of systems, where models that lacked consideration of watershed-scale autocorrelative spatial effects tended to overestimate the effects of the structure of water rights on vegetative health and cultivation outcomes.

In addition, these two studies demonstrate possible methods for addressing both issues. In the first study a method for downscaling demographic information to a resolution that more accurately reflects intersections between vulnerable populations and hazard exposure is presented and applied to the Nashville, TN case study area. The second study applies multi-level Bayesian spatiotemporal modeling methods to assess multi-scalar processes in an agro-ecosystem, demonstrating the potential of these methods for empirical evaluation of policies and social and physical processes related to system performance. In the following chapter I apply both of these techniques to evaluation of the performance of a community system (Nashville, TN) that has experienced a severe flood event and responded by implementing a home buyout program.

CHAPTER IV: COMMUNITY SUSTAINABLE RESILIENCE TO FLOODING

Introduction

In May 2010, central Tennessee experienced a severe precipitation event where more than 13 inches of rain reportedly fell in Nashville in 32 hours, more than twice the historic record. This storm event led to severe flooding issues across the region, with the highest amount of damage being concentrated in the heavily developed Nashville metropolitan area. Following the 2010 Nashville flood, the City of Nashville took measures to ensure that it would be less vulnerable to extreme flood events by reducing exposures, both personal and property-related, through purchase and removal of flood-damaged properties in some high-risk flood areas. The activities of the Metro Water Services (MWS) buyout program are intended to make Nashville more resilient and sustainable by adding shared community value while decreasing future flood loss through development of new green spaces.

This strategic conversion of developed landscapes from high-loss and liability to enhanced value, multi-benefit, shared spaces can be seen as an adaptive capacity building model for urban centers. However, while many in the community recognize the inherent benefit of reducing high-risk areas and replacing them with such spaces, quantification of those benefits has not yet fully been realized. In-depth evaluation of the relationships between the provision of spaces that may offer these services and economic and other community well-being outcomes is needed in order to accurately assess the value of avoided damage and losses and potential secondary benefits resulting from these actions. In addition, there is a need to go beyond quantification of standard costs and benefits of the program and to also examine the effectiveness of the buyout program in building adaptive capacity by reducing vulnerability, increasing resilience, and increasing sustainability. Such information will provide a measure of less tangible benefits of the program and may provide information to justify replication of similar programs in other areas of both the Nashville community and beyond.

Background

The Nashville Flood Case

In May of 2010, Middle Tennessee and more specifically, the greater Nashville area (Davidson County), experienced catastrophic flooding following a record-setting rainfall event in which more than 13 inches (330 mm) of rain fell within a 48 hour period (NOAA, 2011). This amount of rainfall exceeds expectations for a 1,000 year, 48-hour rainfall event in the area (NOAA, 2018). At least eleven fatalities occurred due to flash flooding of streams and tributaries of the Cumberland River, more than 150 water rescues were conducted and more than 11,000 buildings were damaged at an estimated cost of about $2 billion (NOAA, 2011).

Following the flood, Nashville took steps to improve emergency response and mitigate flood impacts. The Nashville Office of Emergency Management put in place improved emergency communication plans and Nashville Metro Water prepared a Unified Flood Preparedness Plan that assessed the effectiveness of different flood response and mitigation strategies, including modifications to water and wastewater treatment plants and construction of flood walls (MWS, 2013). In addition, Metro Water Services (MWS) utilized FEMA funding to significantly expand the small home buyout program that had been in place since the late 1970s.

The objective of the MWS home buyout program started in the 1970s was to remove homes that had experienced repetitive flood damage. The expansion of the buyout program also targeted areas of repetitive flood damage and high flood risk. Though the primary goals of the program were to remove people and property from direct physical harm, MWS also recognized the additional value provided to the community by increasing riparian buffering along streams and creating greenspace and additional tree cover (ecosystem services). These last points have become especially pressing giving the high rate of development in the Nashville area which has experienced rapid population growth over the past decade (9.4% growth from 2010-2016) and is expected to continue to grow at a rapid pace in the near future (United States Census Bureau b, 2017).

New Directions in Resilience Research

In both sustainability and resilience fields, researchers often examine historical hazardous events to try to gain insight into what characteristics make system resilient, vulnerable, or sustainable, and via which processes this occurs (Redman, 2014). However, it has been recognized that it is critical to go beyond post-ante analysis and try to determine what alternative system forms were possible before the event and how these alternative forms might have changed how the system responded to the event, in other words, to examine alternate histories (Redman, 2014). Analyses of this kind that combine post-ante analysis with prediction may be used to inform adaptation strategies by providing insight into the effectiveness and potential shortcomings of various adaptation options in advance of future hazardous events.

In addition, it has been noted that standard conceptions of resilience do not include value judgments, such that it is possible to have a resilient system that has undesirable qualities. However, as the goal of system planning in the context of resilience is typically to not just maintain current system states, but to simultaneously improve the ability of the system to weather shocks and to maintain or transition towards desirable system states, identification of desired system goals and preferred system performance are often used to guide resilience planning processes (Gillespie-Marthaler et al., *under review*; Olsson, 2006). Finally, system sustainability, which is not necessarily positively correlated with resilience, should be considered in system planning. This may require identification of separate sustainability measures and evaluation of tradeoffs between advances in resilience and in sustainability. (Gillespie-Marthaler et al., *under review*; Walker et al. 2004).

This work aims to address some of the areas of need in resilience research pointed out above. However, in order to accomplish the goals of quantifying the costs and benefits of the buyout program described above, a framework that operationalizes links between contextual vulnerability, hazard impacts, resource availability and the influence of policies and adaptation programs is needed to structure analyses. In addition, spatial disaggregation of census data and use of regression techniques that account for spatial dependency may be necessary in order to identify significant effects. Therefore, this study makes use of the sustainable resilience assessment framework described in Chapter II, and the spatial modeling methods described in Chapter III (Nelson et al., 2015; Nelson et al., *working paper*; Nelson & Burchfield, 2017).

The process flow connection between contextual vulnerability and the ability to resist systemic disruption identified in the sustainable resilience assessment framework will be used as the foundation for spatial and spatiotemporal regression analyses using disaggregated and original scale census data to validate community vulnerability indicators. Observed trends in the vulnerability indicators, observed impact data, and observed sustainability capital trends will be used to provide estimates of changes in community resilience over time within the context of the framework. Lastly, vulnerability indicator effects will be used in predictive spatiotemporal models to estimate flooding impacts incurred and avoided as a result of the MWS buyout program by comparing observed impacts to predicted impacts under buyout restriction and expansion scenarios within the framework. This final step will attempt to provide an accounting of the costs and benefits of an adaptation strategy to the community and estimate the potential for the strategy to build future adaptive capacity.

Conceptual Framing

Drawing from the proposed integrated assessment framework for sustainable resilience and hypothesized conceptual linkages between vulnerability, resilience, adaptive capacity, and sustainability present in Chapter II, I attempt to operationalize the assessment framework using deductively selected indicators, empirical regression, and predictive modeling. In this case, I assume that the goal of system adaptation is to improve system performance.

System performance is not some general directly quantifiable quality, instead it is defined by the goals and purpose of the system (as understood by system stakeholders), and is quantified using proxy measures or indicators of the status of specific system goals and purposes. At any time, system performance is presumably affected by the distribution of social and bio-physical characteristics in the system. During hazardous events system performance is presumed to be strongly affected by bio-physical and social characteristics that suggest increased vulnerability to hazards, and the distribution and coincidence of these characteristics throughout the system.

At any time, system performance is expected to affect future availability of and access to economic resources, natural resources, and social capital, the combination of which I refer to as sustainability capital. During hazards, system performance, and conversely, system failure, are expected to strongly impact sustainability capital. Sustainability capital itself, is expected to constrain adaptation options, and also to directly affect long-term changes in social and bio-physical characteristics of the system.

Adaptation that occurs in response to hazards often uses interventions that directly target bio-physical and social vulnerability, and less frequently interventions that target sustainability capital (see Figure 8). In addition to adaptation to hazards, systems also undergo deliberate changes intended to improve some aspect of system performance. These changes often take the shape of long-term development planning and social welfare systems, and can be implemented at multiple large scales, often outside the bounds of system analysis.

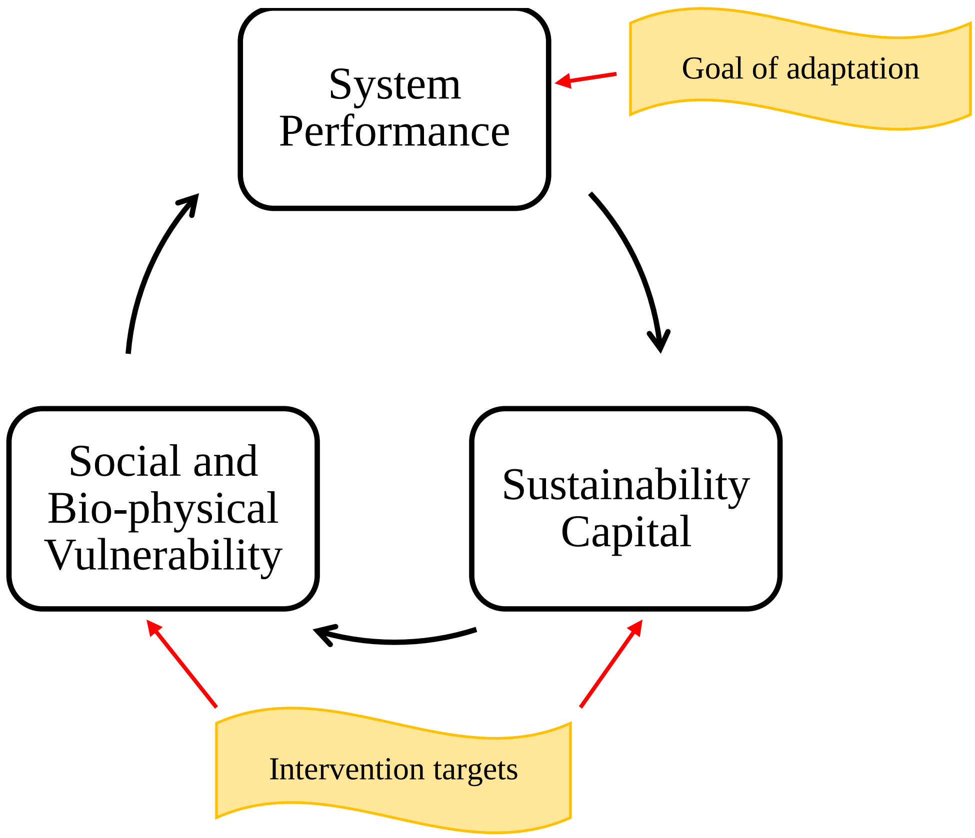

Figure 8: System performance cycle and location of adaptation entry points.

In this work, I draw from the NashvilleNext 2016 report to identify general goals of the Nashville community system (NashvilleNext, 2016). The NashvilleNext 2016 report identifies a series of four foundational pillars (Opportunity and Inclusion; Economic Prosperity; Environmental Stewardship; Efficient Government), seven elements (Land Use, Transportation & Infrastructure; Art, Culture and Creativity; Economic & Workforce Development; Education & Youth; Health, Livability & the Built Environment; Housing; Natural Resources & Hazard Adaptation), and seven guiding principles (Be Nashville; Ensure Opportunity for All; Foster Strong Neighborhoods; Expand Accessibility; Advance Education; Create Economic Prosperity; Champion the Environment) which in many cases have overlapping objectives and which I reduced to the following three broad system goals:

1. Maintain or improve the health and safety of community residents.
2. Maintain or improve the economic prosperity of the community and its residents.
3. Maintain or improve the ability of all residents to live comfortable and productive lifestyles.

These system goals are quite broad and easily tens of proxy measures could be identified for each of these goals. However, for this work, I was most concerned with issues concerning flooding and the home buyout program. Therefore, I relied on the guiding question below when identifying candidates for specific proxy measures of these three system performance goals.

What do you expect the flood and flood adaptations (green space creation) to change or impact in the short term and in the long term?

Table 6 lists all candidate proxy measures for System Performance identified. As the target of adaptation, these measures are assumed to be the outcomes of interest that are dependent on vulnerability and that impact future sustainability capital.

Table 6: System goals and associated candidate measures of system performance.

Health and Safety	Economic Prosperity	Livability and Opportunity
Mortality rate	Per capita municipal net revenue	Net migration rate into the city
Percent population in good health	Per capita infrastructure operations and maintenance costs	Relocation rate to suburbs
Hospitalization rate	Percent of municipal spending on emergency and disaster relief	Percent renters
Emergency room visitation rate	Count of building permits	Percent homes vacant
Hazard deaths	Per capita property taxes	Ratio of population growth to regional population growth
	Per capita sales taxes	Mean length of tenure
	Per capita hours worked	Ratio of income to cost of living
	Unemployment rate	Change in percent population with no post-secondary education
	Ratio of hazard damage to property value	Change in percent population below poverty level
	Percent properties with hazard damage	Change in population age 65 and older
		Change in non-white population
		Change in Hispanic population

The drivers of these outcomes are factors that define local neighborhood, asset, and population contextual vulnerability. As described in Chapter II, contextual vulnerability is a discrete interpretation of vulnerability at a specific moment in time and operationalizes the concept of vulnerability by focusing on pre-hazard characteristics of sub-systems/components that describe the extent to which they may be expected to experience negative impacts of a hazard based on expected exposure, current sensitivity, and current anticipatory coping capacity (Cutter et al., 2008; Gallopín, 2006). In identifying drivers, I consider the following:

- Exposure includes consideration of the magnitude and extent of a hazard.
- Sensitivity includes consideration of the innate characteristics that influence the degree to which impacts will be suffered given a certain level of exposure.
- Anticipatory coping capacity includes consideration of existing plans or capabilities that improve the effectiveness and range of actions available in response to a hazard.

In order to distinguish sensitivity from coping capacity, I suggest that sensitivity include variables related to structure, such as societal factors that influence and limit a system's or component's set of possible actions (e.g., social class, cultural acceptance, aesthetic norms), as well as intrinsic physical characteristics (e.g., physical design, structural integrity, code/legal requirements). On the other hand, variables used to represent anticipatory coping capacity should reflect the ability of the system parts to survive and adjust during a hazardous event via individual actions/choices or systematic policies and programs in place at the time of the disturbance (e.g., flood insurance; emergency notification system; evacuation or shelter-in-place plan; property protection plan) (Adger et al., 2004; Gallopín, 2006; Turner et al., 2003).

Based on the considerations above, several driver classes were identified for each class of system goals. In order to operationalize these driver classes, a set of candidate proxy measures was identified for each driver class. Again, as the focus of the study is on flooding and the buyout program, I relied on the guiding question below in identifying the candidate proxy measures for the drivers of system performance.

What characteristics do you expect to moderate or mediate the short term and long term impacts of the flood and flood adaptations on the system goal of interest?

In addition to this guiding question, additional considerations were made specifically for social aspects contained within the sensitivity and anticipatory coping capacity components of vulnerability. As we would not necessarily expect that an individual's race or ethnicity would directly make them more vulnerable to flooding, social pressures that drive, maintain, and often exacerbate non-institutionalized segregation and disparities in education and socio-economic class often lead to minority groups being forced into the highest-risk areas of a system and left with relative lesser means to cope with and recover from hazards. Drawing on theories of social justice, I identify three types of oppression most relevant to issues of community resilience for the case study area: marginalization, exploitation, and powerlessness (Young, 1990; Harvey, 1992).

Marginalization is the process (intentional or otherwise) of obstructing entrance into or promotion within the labor system based on individual characteristics such as race, ethnicity, and gender. As a consequence, marginalized groups tend to have less material resources that may be used to cope with health issues, economic hardships, community change, and hazardous events. Exploitation is the process of taking advantage of marginalized and needy populations within the workplace by requiring employees to work, for example, in more hazardous conditions or with reduced pay or no benefits. As a consequence, exploited groups tend to struggle to improve their economic situation and are more likely to work in conditions hazardous to their health. Immigrant populations, particularly those that do not speak English well, may be more prone to exploitation than other groups. Powerlessness refers to lack of ability to effect change due to a lack of respect and accompanying disregard for expressed opinions and difficulties in mobilization of a critical mass of lick-minded individuals. In many cases marginalized, exploited, and powerless groups tend to overlap, where minority, immigrant, and high-needs groups such as the disabled and those with low levels of education can fall within either or all of these categories of oppressed groups.

In an attempt to fully consider the social aspects of community resilience, the following questions were used to guide selection of additional measures of vulnerability.

1. Are there minority, immigrant, or high-needs groups that may lack the ability or the means to prepare for and protect their health and safety during hazardous events?
2. Are there minority, immigrant, or high-needs groups that may reside in lower value, poor quality or higher flood-risk housing due to lack of materials resources?
3. Are there minority, immigrant, or high-needs groups that may be more likely to not be able to secure full-time employment or well-paying jobs?
4. Are there minority, immigrant, or high-needs groups that may lack the means to recover from hazardous events, or to respond to changing neighborhood conditions?
5. Are there groups that may lack the power needed to shape local changes in neighborhood conditions?

Table 7, Table 8, and Table 9 list all drivers of the system performance measures identified (column headings) and associated candidate proxy measures for these drivers. These measures are expected to reflect the social and bio-physical vulnerability of the system, to be dependent on sustainability capital, and to be determinants of system performance. As most adaptation interventions target vulnerability, and most frequently bio-physical aspects of vulnerability (exposure), these measures are expected to change significantly in response to implementation of adaptation plans.

Table 7: Drivers of health and safety and associated candidate proxy measures.

Hazard Exposure	Living Conditions	Pre-existing Conditions	Demographics	Health and Social Services	Hazard Planning
Flood zone	Residence age	Prevalence of chronic health conditions (diabetes, asthma, COPD)	Non-English speakers	Proximity to health clinic	Proximity to emergency sirens
Inundation level	Residence quality	Prevalence of obesity	Age over 65	Proximity to hospital	Proximity to emergency shelter
Topography	Persons per bedroom in residence	Prevalence of cancer and heart disease	Age under 18	Proximity to police or fire station	Emergency shelters per 1,000 residents
	Seniors living alone		Disabled	Health service providers per 1,000 residents	
	Rent or own		Income		
			Percent income spent on housing		
			African American		
			Hispanic		
			Gender		

Table 8: Drivers of economic prosperity and associated candidate proxy.

Hazard Exposure	**Infrastructure Quality**	**Community Desirability**	**Spending Capacity**	**External Funding**	**Hazard Planning**
Flood zone	Type of structure	Median Education Level	Income	Federal development grant funds	Residents with flood insurance
Inundation level	Structure quality	Median Age	Individual debt	FEMA individual grants	Municipality flood insurance coverage
Topography	Roadway conditions	Property Sales	Individual wealth	FEMA business grants	
Impermeable surface area		Population Density	Unemployment, SS, and disability support		
Water retention capacity		New businesses			
Tree canopy		New residences			
		Jobs available by sector			
		New jobs created			

Table 9: Drivers of community livability and associated candidate proxy measures.

Hazard Exposure	Access to Services	Affordability	Equity	Community Engagement & Support
Flood zone	Proximity to work	Median rent	Median Income by race	Public welfare spending
Inundation level	Proximity to schools	Median sale value	% Non-white population	# of churches and community groups
Topography	Proximity to healthcare	Median income	% Hispanic population	% population volunteerism
Distance to stream/river	Proximity to public transit		Median income by gender	% population voting for winner of presidential election
	Proximity to greenspace		Access to services by race	
	Proximity to recreation			
	Students per class			
	Auto ownership density			

Sustainability capital of the system is expected to be impacted by system performance (and system failure). It also impacts future vulnerability, and more importantly, constrains adaptation options that can be implemented to improve system performance. In this work, sustainability capital is examined as total system availability of environmental capital, economic capital, and social capital. As with the measures of vulnerability and system performance, sustainability capital measures that directly related to flooding and the home buyout program were identified. Candidate measures are presented in Table 10.

Table 10: Sustainability capital classes and associated candidate measures.

Environmental Capital	**Economic Capital**	**Social Capital**
Impervious surface area	Total property taxes	Total population
Water retention capacity/ Runoff production	Net government revenue	Total number of jobs
Riparian buffer area	Total government encumbrances	Total housing stock
Riparian buffer width	Total disaster damages	Total volunteer hours
Tree canopy	Infrastructure operations and maintenance costs	
Greenspace	Federal government disaster relief and recovery funds	

In order to fully understand the sustainable resilience of the Nashville community system to flooding events and related changes and the impacts of the home buyout program as a flood adaptation strategy, ideally all of the system performance outcome measures, contextual vulnerability driver measures, and sustainability capital measures identified, as well as any number of factors not identified, such as flooding outcomes and drivers related to the transportation network, water infrastructure, and energy infrastructure, would be examined closely. (Note that the system conceptual and analytical model would become unmanageably complex if all possible direct and indirect impacts were considered in detail.) However, restrictions in data availability for both extended time scales and fine sub-system spatial resolution constrains the analytical modeling possibilities. While some of this data can be downscaled using the techniques described in Chapter III, and multi-level modeling can be used to help to account for multiple scales of analysis, these methods cannot be applied for all of the measures of interest. Due to data limitations, evaluation of system performance, vulnerability and sustainability capital was performed on a reduced set of measures that includes the six system performance outcomes, eighteen contextual vulnerability measures, and six sustainability capital measures shown in Table 11.

Table 11: Measures of system performance, contextual vulnerability, and sustainability capital used in analyses of the flood resilience of the Nashville community and effectiveness of the home buyout program as a flood adaptation strategy.

System Performance Measures	Contextual Vulnerability Measures		Sustainability Capital Measures
Hazard deaths	Distance to stream/river	Property size	Impervious surface area
Water rescues	Floodzone	Property type	Runoff Production
Hazard damages	Flood inundation	Median Income	Riparian buffer area
Damaged structures	Depth of inundation	Percent population with no GED	Riparian buffer width
Exposed population	Distance to greenspace	Percent population below poverty level	Total property taxes
Total property value	Total population	Percent population non-white	Net property revenue
	Population age 65 and older	Percent population foreign born	
	Renter population	Percent population that speaks English poorly	
	Property value	Percent households with social security income	

Data and Methods

Data used for the analyses described below was drawn from tax parcel geodatabases, building footprint survey shapefiles, U.S. Census American Community Survey (ACS) 5-year estimate tables, IPUMS National Historical Geographic Information System (NHGIS) time series tables, United States Geological Survey (USGS) earth surface and water system geodatabases, Nashville Metropolitan Government reports, and Nashville Metro Water Services (MWS) internal data. Census data was collected for ACS years 2009-2016 and all other data was collected for years

2005-2016 (Manson, Schroeder, Van Riper, & Ruggles, 2017; United States Census Bureau c, 2017). With the exception of some data provided privately by MWS and publicly available at-cost tax parcel data, all of these data can be downloaded from online sources at no cost (Metro Maps, 2017). In addition, data processing scripts and modeling scripts are openly available at https://github.com/katesnelson/Flood_Adaptation.[1] All scripts were written for, and run in, R on a machine with 72 threads and 100 GB RAM (Team, R. Core, 2013). Spatial data processing was carried out primarily using the R package sf while Bayesian spatial modeling was carried out using the R package R-INLA (Blangiardo, Cameletti, Baio, & Rue, 2013; Pebesma, 2017).

Data Processing

In order to evaluate characteristics relevant to system processes and relationships between characteristics, substantial manipulation of the data was conducted to produce measures at the appropriate scales. For example, hydrological processes governing flooding severity, such as overland runoff production, are most commonly assessed at the watershed or drainage catchment scale, however relevant data on characteristics that impact these hydrological processes was available at a building or tax-parcel scale. In this work, ecosystem and land cover characteristics of the system were computed at the micro-watershed scale, flood damage and inundation were computed at the parcel and building scale, property values and taxes were computed at the parcel scale, flood exposed population was computed at the parcel scale, and demographic and socio-economic characteristics at the census tract scale were utilized.

---

[1] Note that one process, micro-watershed delineation, was performed in the commercial software ArcGIS 10.2.2, and no scripts are available to replicate this process.

Micro-Watershed Delineation

As the home buyout program is conducted at the tax parcel scale, and the amount of area converted from building cover to greenspace is very small in comparison to the size of the county or typical watershed boundaries made available by USGS (there are only twenty-three watersheds that intersect the county using the finest available resolution HUC-12 data), it is likely that no significant effect would be discernable if the buyout program activities were aggregated to USGS watersheds. For these reasons, ecosystem and land cover characteristics were aggregated up to a micro-watershed scale, where 410 micro-watersheds were delineated in ArcGIS 10.2.2 using USGS 1/3rd arc second resolution digital elevation models of the Davidson County area (USGS, 2017). The ArcGIS hydrology toolbox was used to delineate the micro-watershed boundaries using points on the USGS National Hydrology Dataset (NHD) stream and river flow lines where the flow accumulation was more than one standard deviation above the mean as pour points (drainage outlets) in the delineation (USGS b, 2017). The ArcGIS eliminate tool was used to remove excessively small polygons and polygon slivers (polygons with area less than the mean minus one standard deviation of all micro-watershed areas), and waterbodies within each watershed were erased to provide a final shapefile of micro-watershed land areas. Characteristics such as volume of runoff produced, impervious building area, riparian area and riparian width are discussed in terms of micro-watershed and county-wide totals or averages.

Impervious Area

In order to provide annual estimates of impervious land cover, building footprint information provided by MWS was used. Other potential land cover datasets including USGS National Land Cover Datasets (NLCD) were eliminated as viable options due to lack of annually updated information. As the focus of this study was on flooding issues in the context of the home buyout program, impervious land cover from paved areas, which are not impacted by the buyout program (and for which annually information was not available), were not considered in this study. The building footprint shapefiles themselves also lacked annually updated information as building footprint survey results were only available for 2005, 2014, 2015, and 2016, however, via association with annual tax parcel information it was possible to build estimated building footprint shapefiles for each year (Metro Maps, 2017). Building footprint shapefiles for years without original data were constructed by removing buildings on parcels not present in that year from the 2005 building footprint shapefile, and adding building footprints from the 2014 building footprint shapefile for parcels that were newly identified in that year and that remained in the 2014 shapefile (see Figure 9 for a process diagram). This method captures changes in building area that result from demolition of properties and addition of new properties and buildings, but does not capture changes in building area due to construction of additions on existing buildings or construction/removal of new sheds or outbuildings.[2]

[2] Note that while tax parcel data and shapefiles were used to identify removal and addition of parcels and associated buildings the living area attribute included in these files were not used for impervious building area calculations due to inconsistencies in reporting, lack of data for non-residential buildings, and lack of knowledge regarding distribution of living area across multiple building stories.

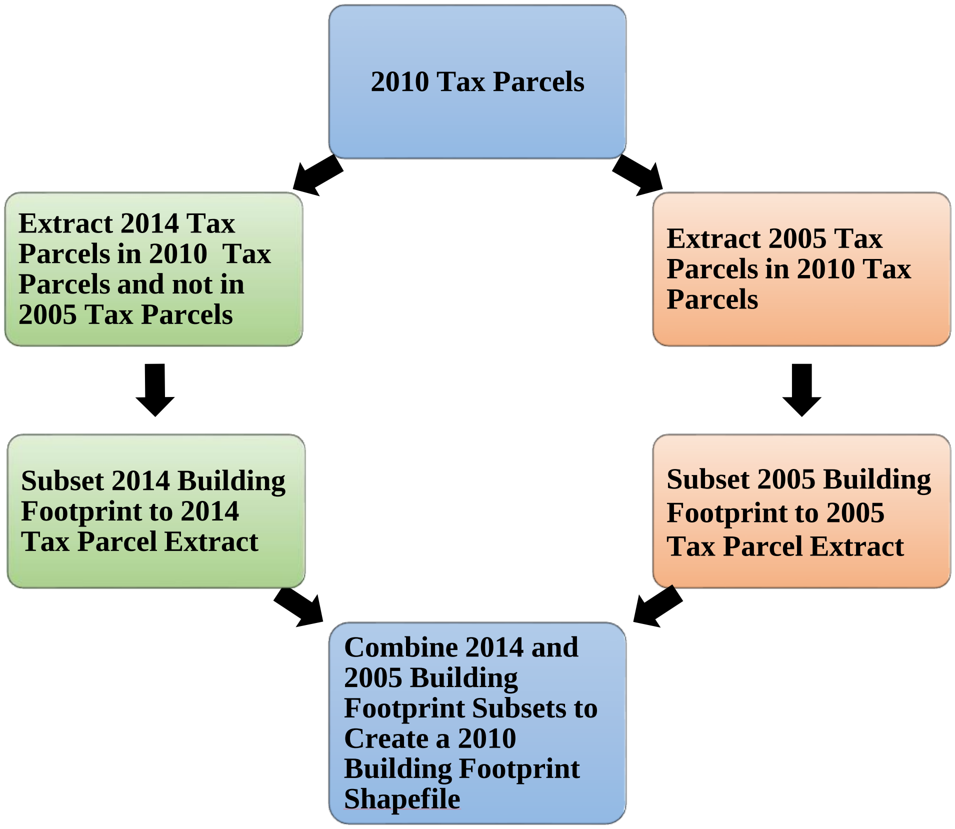

Figure 9: Process for creating an interpolated building footprint shapefile for years for which there is no observed building footprint data using 2010 as an example.

Runoff

The expected runoff produced from impervious building cover and permeable greenspaces was estimated for each micro-watershed using the curve number method for a 100-year, 24-hour, rainfall event (NRCS-USDA, 1986). This estimation assumes unconnected imperviousness (no runoff channeling infrastructure, therefore assume overland flow) and characterizes permeable surfaces as grass/lawn in good condition, and hence, may overestimate runoff depths at locations that are connected to gray infrastructure. The estimates also do not consider accumulation and concentration of runoff at outflow points. The expected runoff in inches was converted to a volume by multiplying the runoff depth in a micro-watershed by the total surface area of the micro-watershed.

Riparian buffers

Riparian buffers around streams and buffers were delineated by first creating a 100 meter buffer around all streams and rivers in Davidson County as provided in the National Hydrologic Dataset NHDAreas (USGS b, 2017). To determine the effective extents of riparian buffering, built-up areas were removed from this buffered area. Built-up areas were delineated by triangulating building footprints in each micro-watershed (Figure 10) and removing triangulations with an area larger than the average area (Figure 11) or edge length longer than the average length (Figure 12) in that micro-watershed. The triangulated polygons for each watershed were merged and areas of intersection with the 100-meter buffer area were erased leaving only non-built-up areas in the riparian buffer.[3] Riparian buffer widths were calculated by computing the shortest straight-line distance from the edge of the riparian buffer to the stream bank at regular intervals across each micro-watershed.

[3] Note that roadways and paved areas were not included in the built areas that were removed from the riparian buffer zone as these remain relatively constant over the time period of interest, are typically not affected by the buyout program, and due to lack of consistently available data on paved areas or a means of interpolating these areas between years. Nor do these riparian buffer areas account for different types of vegetation growth for which limited information is available.

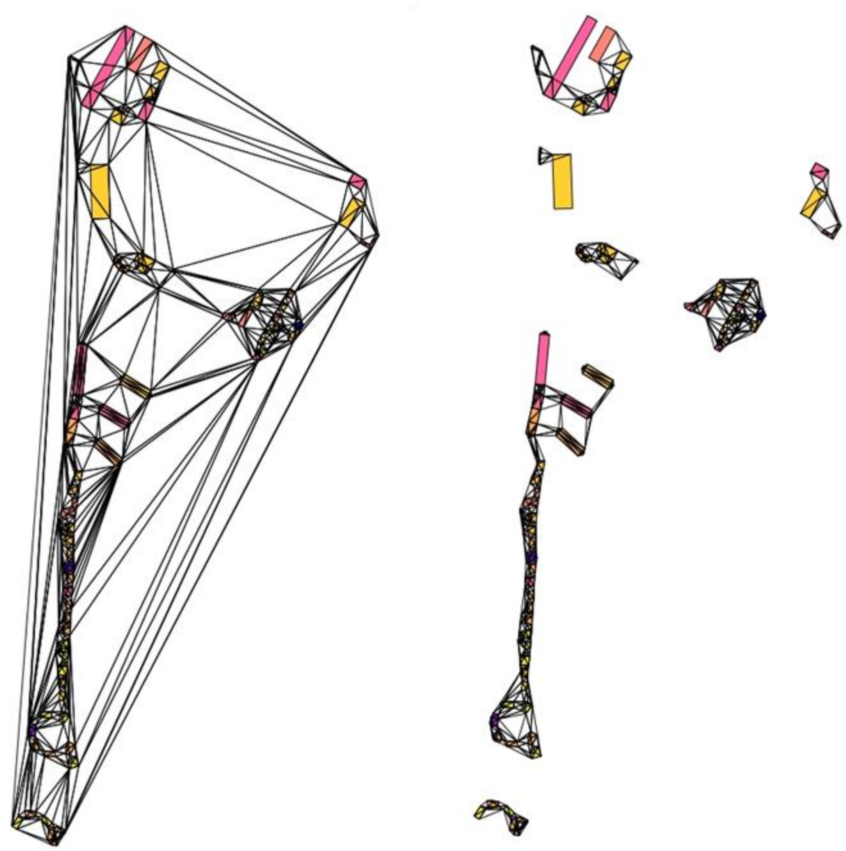

Figure 10: Example of buildings triangulations (black lines) with original building footprints (colored polygons) in a single micro-watershed before (left) and after (right) removal of large triangle areas and large triangle edge lengths.

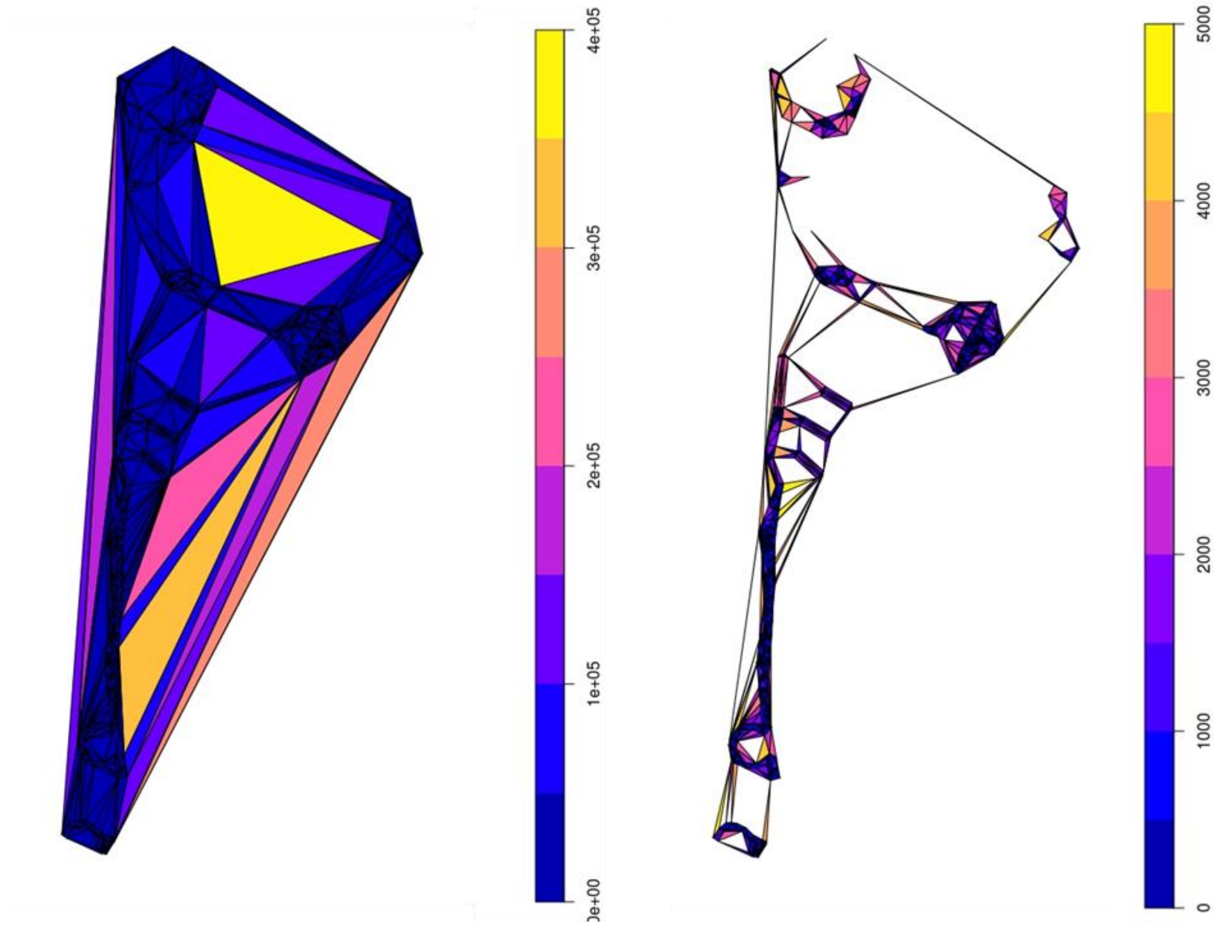

Figure 11: Example of removal of triangulations with large areas in built-up area delineation. All triangulated areas shown on the left and remaining triangulations after removal of large areas on the right. Scale bars correspond to area in square feet.

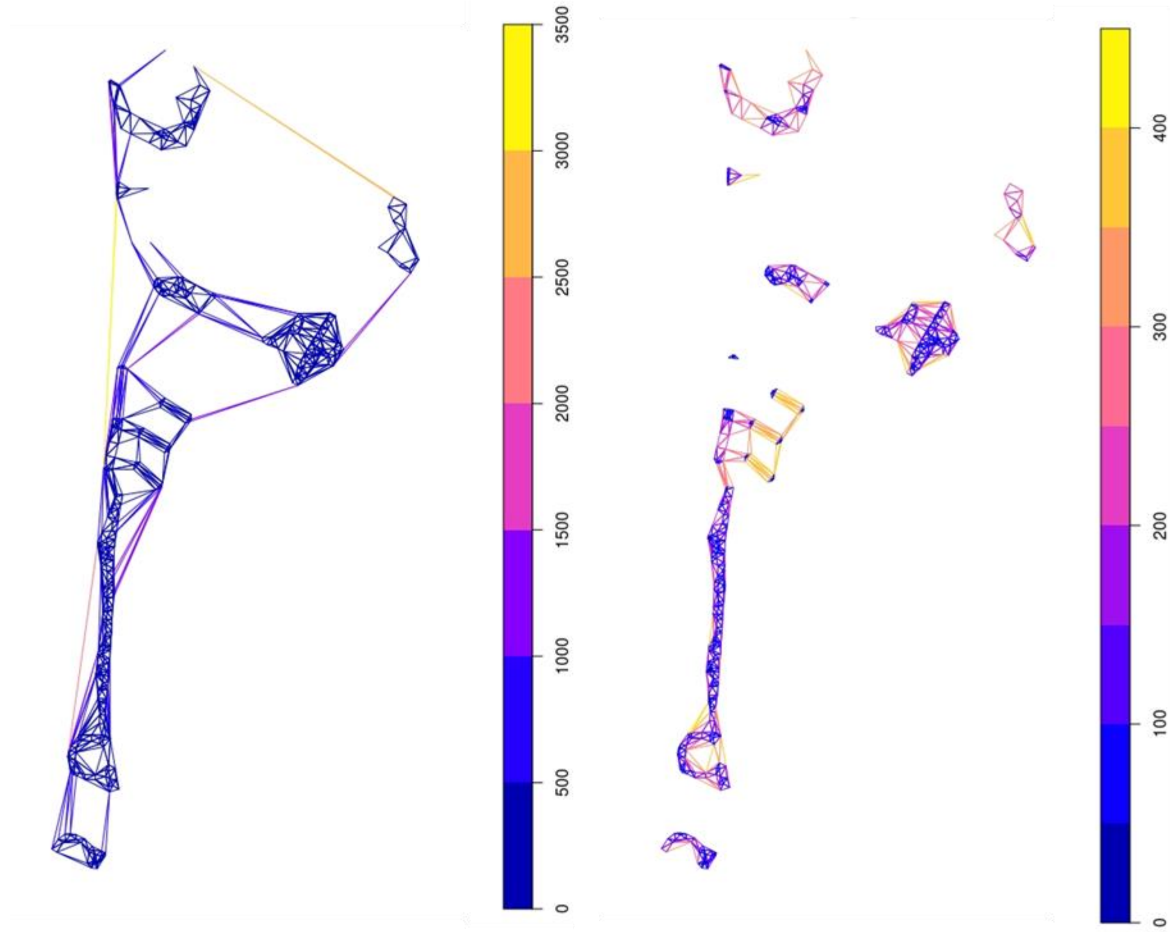

Figure 12: Example of removal of long triangle edge lengths in built-up area delineation process. All remaining triangulated edges shown on the left while the right shows the edges remaining after removal of large edge lengths. Scale bars correspond to edge length in feet.

Damaged Assets and Exposed Populations

Direct flooding impacts in terms of number of inundated buildings, number of inundated properties (tax parcels), and population in inundated buildings were calculated using spatial coincidence of building footprint and tax parcel shapefiles with the 2010 inundation boundaries. As multiple tax parcels may be located in the same building, tax parcel characteristics such as dwelling unit count, living area, and appraisal value were aggregated to buildings prior to spatial coincidence analysis. For impacted population counts, populations from census tracts were distributed to residential tax parcels using the dasymetric mapping techniques described in Chapter III that use information in tax parcel datasets (living area, number of dwelling units, and class of property) to inform redistribution of census tract populations to the finer resolution tax parcels.

For this work, the dasymetric method was further extended to produce a count-based distribution of population instead of a continuous population distribution. This means that the smallest non-zero population assigned to any tax parcel is one. Further information on this extended dasymetric process can be found at https://github.com/katesnelson/Flood_Adaptation, and an example population distribution is plotted in Figure 13. Note that only total population, senior citizen, and renter population were redistributed.[4] As multiple tax parcels may be co-located at the same location in 2-dimensional space, tax parcel count, dwelling unit count, living area, and appraisal value for multiple tax parcels in the same location were aggregated leaving a single record for each unique tax parcel location.

Similarly, metrics for damaged buildings and properties, and population in damaged buildings were calculated based on spatial coincidence of unique tax parcel locations with damage point locations provided from the MWS windshield survey of the 2010 flood damage. As multiple buildings may be located in the same tax parcel boundaries, the count of buildings in each tax parcel was aggregated to unique tax parcel locations.

[4] Senior citizens were prioritized as 8 out of 11 fatalities that occurred in the Nashville area during the 2010 flood were for people aged 65 and older, and the tax parcel data lacked ancillary information that could inform the selective redistribution of vulnerable minority, immigrant, and high needs populations. Renter populations had also been identified as a sub-population of interest by MWS.

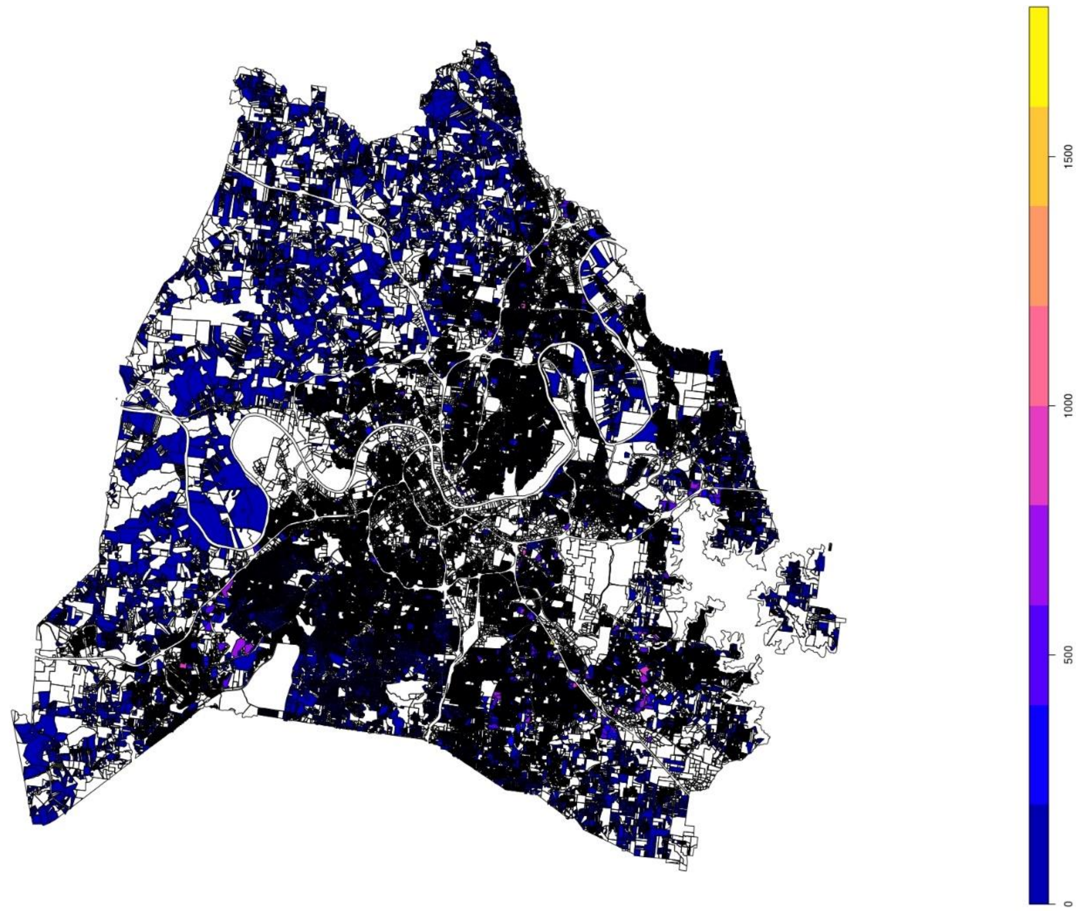

Figure 13: Example of dasymetric count distributed population

Economic Impacts of Direct Damage

To estimate cost of damages incurred due to physical exposure to the flood, the estimated depth of inundation from a *windshield survey*[5] conducted by MWS immediately after the flood, and improvement appraisal values were used together with Federal Insurance Administration (FIA) depth-damage curves used by the Federal Emergency Management Agency in the HAZUS® hazard modeling and loss estimation software (FEMA, 2013). The FIA depth damage curves were

[5] This windshield survey involved MWS employees driving down county roads and noting the estimated inundation depth of each homes as they drove by.

used to estimate structural damage for one story and multiple story buildings and mobile homes. In addition, a second estimate of structure damage was generated using average estimated personal economic losses from a survey conducted by Vanderbilt following the 2010 flood (note that these estimates are based on a very small sample size, n=74, of single-family dwelling owners). The first approach is expected to provide a more conservative (high-end) estimate while the second approach is expected to provide a low-end estimate. These estimates were conducted for all buildings within the county based upon available parcel data.

In addition to structural damages, contents damages, relocation costs and labor costs for debris cleanup and rebuilding were also estimated. Contents damages were estimated using FIA depth damage curves for residential and non-residential building contents and building to content value ratios from HAZUS. Relocation costs were estimated using building areas and depth-restoration time tables and average daily relocation cost per square foot from HAZUS and depth-restoration time relationships and average daily relocation cost per square foot established using data from the Vanderbilt survey. Cleanup and rebuilding labor costs were estimated using a depth to labor hours table built using the Vanderbilt survey results and the average cost of volunteer labor for the state of Tennessee in 2010 (Independent Sector, 2018).

Scenario Development

Redman (2014) suggests that resilience science should strive to examine not only what happened during a hazardous event and what the outcomes of the event were, but to also examine what alternative histories would have been possible and what each would have offered in terms of improved (or worsened) outcomes. Therefore, in order to quantify direct flood damages of the 2010 flood, damages avoided via the home buyout program, and potential damages avoided given expansion of the buyout program, a set of shapefiles representing four buyout program adoption scenarios were created and analyzed in reference to the 2010 flood inundation boundaries and the observed depth of inundation from the Metro windshield survey. The scenarios include: observed conditions (With Buyouts), presumed conditions had no buyouts taken place (No Buyouts), presumed conditions had all completed buyouts (as of 2016) been completed prior to 2010 (All Buyouts), and presumed conditions had all buyouts on the buyout "wish list" (full selection of buyout properties plus proposed MWS buyout expansions) been completed prior to 2010 (Wish List). Shapefiles were produced for each year between 2005 and 2014 in order to track the potential for damage avoidance offered by the buyout program each year.

The shapefiles for the No Buyouts scenario were created by adding building footprints of all homes bought out prior to 2010 from the 2005 building footprint shapefile and adding them to the building footprint shapefile for all other years. For the All Buyouts scenario, shapefiles were created by removing all homes on the buyout list from the 2010 and following years building footprint shapefiles. For the Wish List scenario, all homes on the original buyout list and the proposed expansion list were removed from the 2010 and following years building footprint shapefile. These shapefiles were used in the calculations described above such that more than thirty different annual datasets (at multiple scales: building, parcel, and watershed) were produced and analyzed.

Bayesian Modeling and Prediction

Multilevel Bayesian spatial regression was used on the dataset produced for observed conditions to estimate effects of contextual vulnerability drivers on resilience outcomes and the effects of sustainability capital, particularly ecosystem services, on contextual vulnerability. These models, described in more detail in the Results section, use spatial modeling functions of the `R-INLA` package. Models using the stochastic partial differential equation (spde) approach, model the spatial effect as a Gaussian Markov random field that accounts for continuous spatial processes such as elevation that affect the outcome variable independent of other explanatory variables. Models using an intrinsic conditional autoregressive (iCAR) model coupled with an exchangeable (iid) random effect, also known as a Besag-York-Mollié (BYM) model, as a spatial effect that account for variations in outcomes variables that are based on location within local areas or neighborhoods and accounts for dependency between adjacent areas/neighborhoods.

Estimated effects from some models were used to predict contextual vulnerability, resilience outcomes, and associated sustainability capital levels for the hypothetical scenarios. Predictions of outcome variable values (response) for alternate scenarios was accomplished by taking the linear sum of the posterior effects times the value of the predicting variable and the spatial effect. Sums were computed using 0.025 quantile, 0.5 quantile, and 0.975 quantile posterior effect values to provide a credible range for each response computed. This “naïve”, but computationally efficient, method of building the predicted values was compared with a set of predicted values computed during the estimation process in R-INLA as a consistency check. The predicted results provide an estimate of the annual damage avoidance potential, and the expected net benefits of different buyout program adoptions rates and extents.

Results

This study produced information on individual measures of contextual vulnerability, system performance, and sustainability capital for four different buyout program scenarios and in some cases for seven different years. In this section, I describe the results of models used to determine measure significance and relevance to the processes of interest, the results of deterministic modeling and predictions, and the results of one set of Bayesian model-based predictions describing feedbacks between measures of sustainability capital, contextual vulnerability, and system performance.

Contextual Vulnerability

Proposed contextual vulnerability measures that significantly impacted system performance measures (see Table 11) were retained as valid indicators of the vulnerability of the Nashville community system to flooding.[6] Measures associated with exposure were assumed to be valid based on well established relationships between flood exposure and property damages (FEMA, 2013). The direct relationships between flooding exposure and property damages account for flood inundation boundaries, depth of inundation, type of property (residential or commercial, single-story or multi-story), property value, and property size therefore all five of these characteristics were considered to be valid indicators of contextual vulnerability to flooding. Similarly, total population was assumed to be a valid indicator of vulnerability as it is directly related to exposed population as modeled using dasymetric mapping (which is also based on property size and type) and spatial coincidence with flood inundation boundaries.

[6] Note that while the senior citizen population was not significant in any of the models there is sufficient anecdotal evidence (eight out of eleven people that died during the flooding in 2010 were senior citizens) that suggest that senior citizens have higher health and safety risks during flooding to retain this variable in further analyses.

Regression models were used to determine which of the remaining proposed contextual vulnerability indicators were valid indicators of vulnerability to flooding in the Nashville community system. Models evaluating the effect of proposed vulnerability indicators on system performance measures of property value (economic prosperity), hazard deaths and water rescues (health and safety), and income to cost of living ratio (opportunity) were estimated using multilevel Bayesian spatial regression. Finally, two models estimating the relationships between social characteristics and the depth of inundation in 2010 and between social characteristics and holding flood insurance (social vulnerability models) were estimated to identify social groups that were most severely impacted during the flood and that may have lacked personal means to recover following the flood. While these models do not directly relate to any of the evaluated system performance measures, they do provide information relevant to overall system performance as they relate to the amount of volunteer and social system support needed during the flood recovery phase as well as to long term recovery and issues of neighborhood blight.

Economic Prosperity Models

Economic prosperity models examined the effects of proximity to greenspace and flood risk on residential property values. Two models were run, one for the three years prior to the year of the flood (2007-2009) and one for three post flood years (2011-2013) where the outcome was assessed property value at the tax parcel scale and neighborhood spatial effects were accounted for using a BYM model. As the buyout program only applies to residences, the models were conducted only on the subset of properties in the county that are classified as residential by metro land-use codes.

The pre-flood model examined location in high risk flood zones and proximity to greenspace (metro parks and bought-out parcels). After controlling for year (accounts for changes in property values due to external economic drivers), local neighborhood, and residence characteristics (building size, number of dwelling units, and property acreage), increased proximity to greenspace was found to have a small positive, but not significant effect on residential property value (see Table 12 for model results). In line with the literature, the model also indicates that the property values of homes located in the high risk floodway and FEMA one hundred year floodplain areas are on average lower than homes not located in these areas (Bin, Kruse, & Landry, 2008; Bin & Polasky, 2004). These results suggest that prior to the flood in 2010 the removal of homes from high risk flood areas removed homes that had depressed property values. While there is evidence within the literature that increased proximity to greenspace can increase property values, this effect seems to be non-significant in the Nashville system and the buyout program should not be seen as a way to elevate property values by increasing greenspace (Kroll & Cray, 2010).

The model for the post-flood period from 2011 to 2013 adds consideration of previous flood damage to the pre-flood model. The results of this model suggest that proximity to greenspace has no effect on property values, that property values are increasingly lower in higher risk flood areas, and that properties that were flooded during 2010 have lower values. This again suggests that the buyout program is removing homes that have depressed values, therefore the losses in property tax revenue to the municipal government produced by removal of these homes is minimized.

Table 12: Economic prosperity model results.

Variable	Pre-Flood Model (2007-2009) Posterior Mean and Standard Deviation †	Post-Flood Model (2011-2013) Posterior Mean and Standard Deviation †
Intercept	0.0132* (0.0056)	-0.0053 (0.0137)
Year 2	0.0007 (0.0019)	0.0001 (0.0019)
Year3	0.0007 (0.0019)	0.0009 (0.0019)
Dwelling Units	0.0862* (0.0008)	0.0804* (0.0009)
Living Area	0.7609* (0.0009)	0.7587* (0.0009)
Property Acreage	-0.0124* (0.0008)	-0.0128* (0.0009)
Distance to Greenspace	-0.0032 (0.0023)	0.0007 (0.0024)
Floodway	-0.0451* (0.0089)	-0.047* (0.0093)
100 Year Floodplain	-0.0179* (0.0046)	-0.0079* (0.0052)
Previous Inundation	NA	-0.0188* (0.0053)
Depth of Previous Inundation	NA	-0.0053 (0.0035)

* Indicates effect is significant at a 95% credibility interval.

† Note that all effects for continuous variables are reported for models run on standardized values and are not directly interpretable.

Health and Safety Models

The effects of vulnerability indicators on hazard fatalities and water rescues were estimated using zero-inflated binomial logistic Bayesian spatial models. These models estimated the effects of dasymetrically distributed population, census demographics, watershed runoff production, and flood risk while controlling for location and spatial dependency using the spde approach on reported flood fatalities and water rescues in 2010. The outcome data is available at point locations associated with tax parcels and models were estimated only using tax parcel locations where there was flood damage or inundation. Non-significant indicator variables in preliminary models were removed from the final estimated models.

The final flood fatality model indicates that there was a higher likelihood of flood related fatalities in areas that experience deeper flood inundation, and in watersheds where more runoff is produced (see Table 13 for model results). Dasymetrically assigned population and census demographic characteristics were not found to be significantly associated with flood fatality risk. This suggests that flood fatality risk is primarily associated with physical characteristics of the natural and built environment. Locations in the floodway were found to be negatively associated with increased flood fatality risk, perhaps indicating a higher level of flooding awareness and willingness to evacuate among populations who reside nearest to streams and rivers.

The water rescue model indicates that emergency water rescues were more likely in the FEMA one-hundred year floodplain, in areas with deeper flood inundation, and in watersheds with greater amount of storm water runoff. This model also suggests that water rescues were less likely in locations with higher populations, but greater in locations with higher renter populations, perhaps indicating that tenants in low-density rental properties such as duplexes were more likely to require a water rescue. In addition, emergency water rescues during flooding were found to be more likely in areas where there are relatively high populations of people that do not speak English well, that are foreign born, or that are not White, indicating potential barriers in flood safety communication in immigrant neighborhoods. Finally, the water rescue model indicates that higher poverty levels and lower education levels were not associated with increased risk of a water rescue.

Table 13: Health and safety model results.

Variable	Fatality Model Posterior Mean †	Water Rescue Model Posterior Mean †
Intercept	2.323×10^{-5} *	0.65*
Zero-probability parameter	0.586*	0.708*
Population	1.088	0.732*
Senior Population	0.660	0.908
Renter Population	0.925	1.398*
Median Income	1.012	NA
Population without GED	0.829	0.385*
Population in Poverty	NA	0.569*
Population with Poor English	NA	3.642*
Population that is Foreign Born	NA	1.873*
Population that is White	NA	0.549*
Floodway	1.186×10^{-9} *	0.031*
FEMA 100 year floodplain	NA	3.184*
Distance to Stream	0.004	NA
Depth of Inundation	1.859*	1.721*
Volume Runoff	1.858*	1.569*

* Indicates effect is significant at a 95% credibility interval.

† Note that all effect estimates for continuous variables are reported for models run on standardized values and are presented as exponentiated or anti-logit transformed effects.

Social Vulnerability Models

The relationship between flooding severity (flood inundation depth) and the demographic characteristics of those who were flooded was modeled using an spde model to account for spatial dependency. Only tax parcels which were damaged or within the 2010 flood inundation boundaries were retained for estimation. The model results, as shown in Table 14, suggest that areas with relatively lower populations, lower median income, higher population in poverty, higher white population, and higher population without a GED, on average, experienced greater flood inundation depths. Areas with relatively more foreign born population and population that have Social Security income experienced, on average, less deep flooding.

The relationship between holding flood insurance and demographic characteristics of the population at tax parcels that were damaged or within the flood inundation boundaries was modeled using a binary logistic model with a spde spatial dependency structure. The model results suggest that about fifty percent of the tax parcels that were damaged or within the flood inundation boundaries during the 2010 flood did not have flood insurance. In addition, the results suggest that areas with higher population, with relatively less educated population, and with more foreign born population were less likely to have flood insurance. They also suggest that areas with less people in poverty, higher median incomes, and relatively more people with Social Security income were more likely to have flood insurance. Taken together these models suggest that populations with lower education levels are both more likely to experience more severe flooding and less likely to have flood insurance to assist with flood recovery.

Contextual Vulnerability Indicator Trajectories

In order to evaluate how indicators of contextual vulnerability that effect system performance and that are altered by the buyout program might change over time as a result of the buyout program and different buyout program scenarios, net measures of the indicators at all flood damaged or inundated tax parcels were plotted over time and compared with net measures of the indicators across the county. (Trajectories for census demographic variables that were not dasymetrically distributed were not produced due to lack of information on the direct impacts of the buyout program.)

Table 14: Results of social vulnerability models.

Variable	Flood Inundation Model Posterior Mean †	Flood Insurance Model Posterior Mean ††
Intercept	-0.0216	0.464*
Population	0.0144	0.731*
Senior Population	-0.0032	1.178
Renter Population	-0.0222	1.189
Median Income	-0.1967*	0.678*
Population without GED	0.0448*	0.869*
Population in Poverty	0.1037*	1.382*
Population with Social Security Income	-0.0702*	1.157*
Population with Poor English	-0.0074	0.929*
Population that is Foreign Born	-0.1039*	0.857*
Population that is White Only	0.1207*	1.004

* Indicates effect is significant at a 95% credibility interval.

† Note that all effects for continuous variables are reported for models run on standardized values.

†† Note that all effects for continuous variables are reported for models run on standardized values. The anti-logit of the intercept exponentiated predictor effects are reported.

For example, in Figure 14 it can be seen that while the total population of senior citizens in the county increased between 2010 and 2013, the expected percent of the population that would be exposed to a 2010-like flood that are senior citizens, while somewhat higher than the county average, is relatively stable. This might suggest that relatively more senior citizens are participating in the buyout program and relocating to lower flood-risk areas. In addition, it is seen that the percent of the expected flood-exposed population that are renters is greater than the percent of the total county population that are renters, that this population has increased proportionally with increases in total county renter population, and that the buyout program has actually increased the percent of the exposed population that are renters. This increase in exposed renter population is a natural reflection of the buyout program targeting single family dwellings, and may indicate that there is increased risk for emergency water rescues during flood events as renter populations were positively associated with water rescue risk in the model presented in the preceding section.

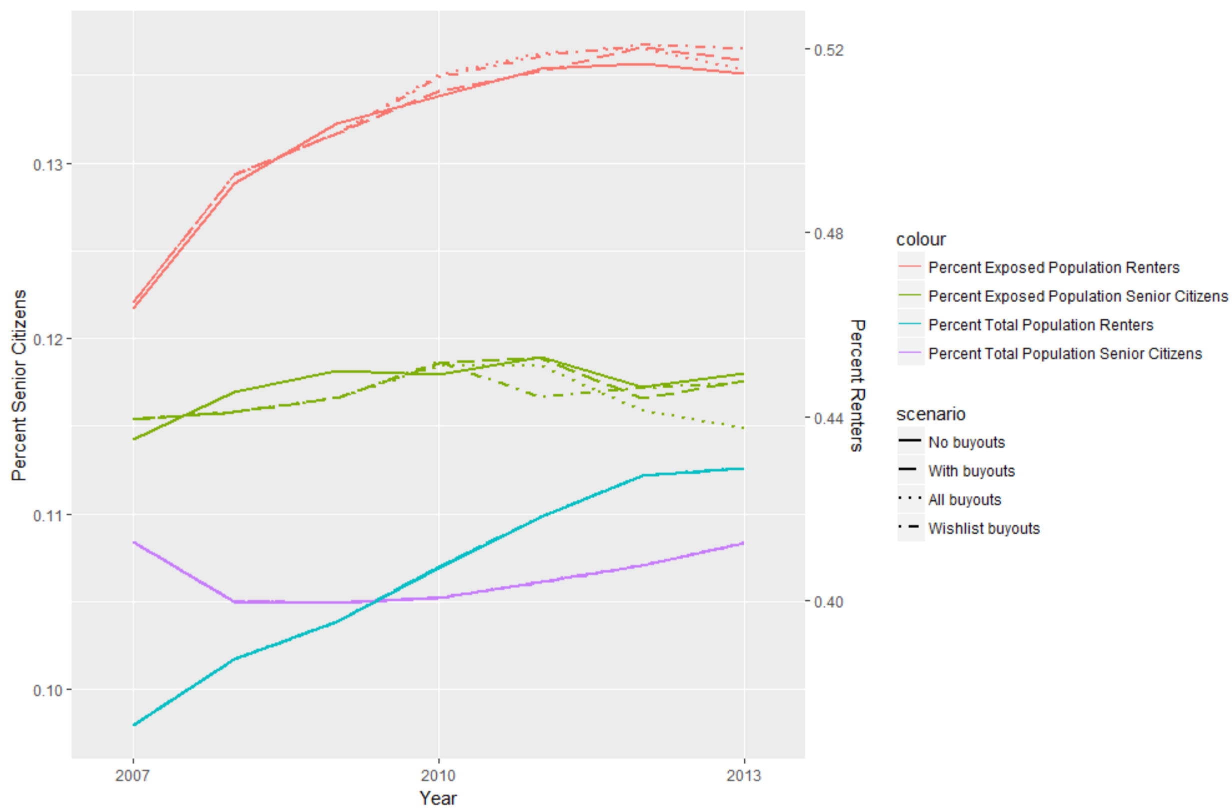

Figure 14: Trajectories for senior citizen and renter populations.

System Performance

The measures of system performance were computed and/or recorded for each scenario and year, where data was available.[7] Hazard damages, damaged structure count, exposed

[7] Note that hazard death (flood fatalities) and water rescue data was only available for a single year (2010) and no deterministic models were available for estimating these values for other years and for the buyout scenarios.

population count, and total property values were estimated for each year for each scenario, where hazard damages were estimated using the deterministic modeling methods described in the Economic Impacts of Direct Damage section.

Hazard Deaths and Water Rescues

There were eleven reported flood-related deaths due to the May 2010 flood. Eight of the eleven who were killed during the flood were senior citizens. In addition, there were more than 150 emergency water rescues conducted during the flood. The locations of each of the reported fatalities and water rescues is shown in Figure 15.

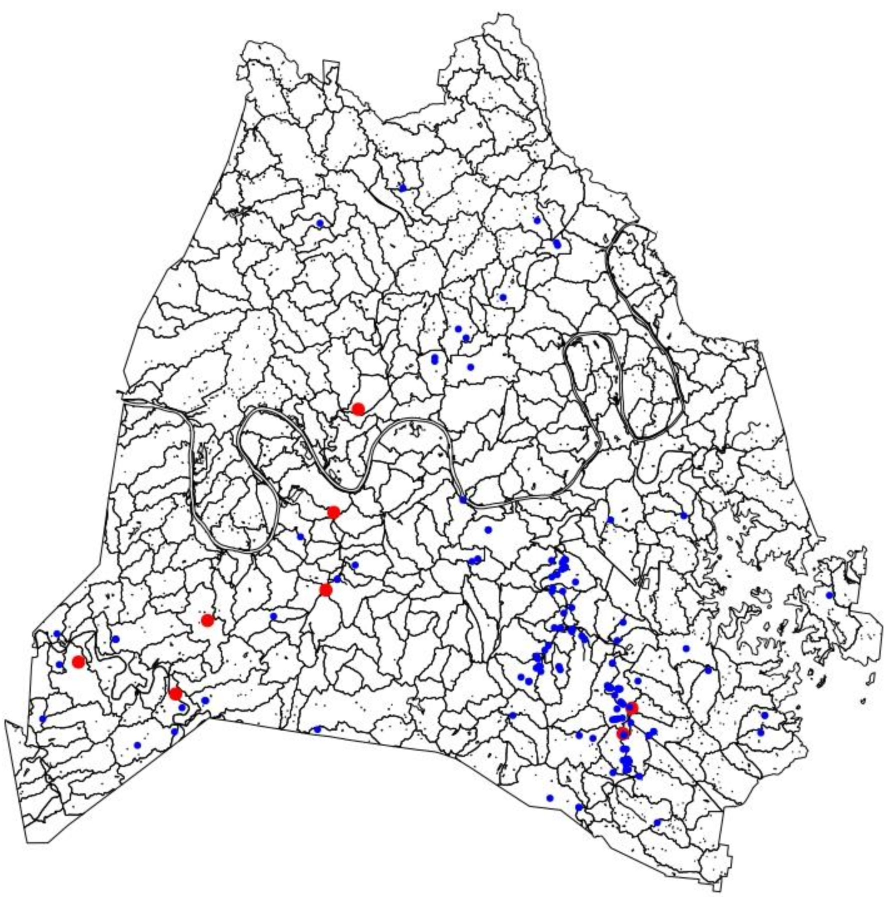

Figure 15: Fatality (red) and water rescue (blue) locations during the May 2010 flood.

Damaged Assets and Exposed Populations

Spatial coincidence analysis indicated that nearly 12,000 tax parcels (both commercial and residential) were either damaged or within the flood inundation boundaries during the May 2010 flood. It is estimated that more than 46,000 people resided within these flood impacted parcels. In comparison, an additional thirty-three properties and estimated twenty-seven people would have been directly impacted by the flood had the buyout program not been active between 2005 and 2010, and about 281 fewer properties and 691 fewer people would have been impacted had all the buyouts been carried out prior to 2010 (see Table 15 for a summary of damage counts in 2010 for the buyout scenarios).

Table 15: Summary of direct flood damage counts in 2010.

Scenario	**Scale**	**Damaged Properties**	**Exposed Population**	**Exposed Senior Population**	**Exposed Renter Population**
No Buyouts	County	11,998	46,703	5,507	23,806
	Micro-watersheds with Buyouts	3,641	16,957	1,652	10,883
	Buyout Parcels	398	980	111	293
With Buyouts	County	11,965	46,697	5,537	23,853
	Micro-watersheds with Buyouts	3,608	16,948	1,654	10,890
	Buyout Parcels	365	953	103	281
All Buyouts	County	11,684	46,091	5,458	23,703
	Micro-watersheds with Buyouts	3,327	16,323	1,601	10,705
	Buyout Parcels	84	262	25	74
Wish List	County	11,600	45,897	5,446	23,576
	Micro-watersheds with Buyouts	3,243	16,130	1,588	10,630
	Buyout Parcels	0	0	0	0

Examination of the trajectories for these measures between 2007 and 2013 (Figure 15), produced using deterministic modeling methods suggest that the number of properties that would be impacted by a 2010-like flood event in each year between 2010 and 2013 would remain the same if buyouts had not taken place (suggests that no new properties were constructed within the flood inundation boundaries between 2010 and 2013). However, due to increases in population the trajectories suggest that the exposed population in any year given a 2010-like flood would be increasingly high.

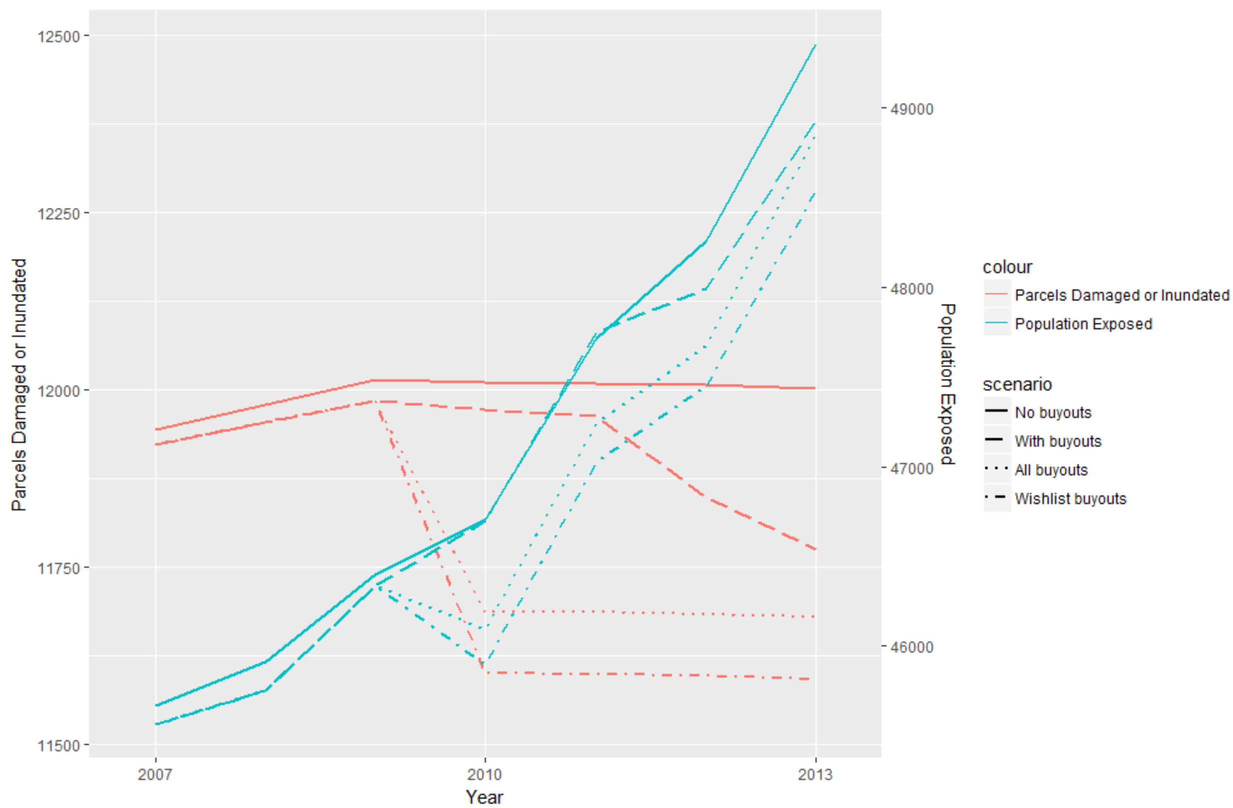

Figure 16: Trajectories for damaged structures and population exposed.

Hazard Damages

The cost of direct damage to structures and structure contents resulting from flood inundation in 2010 was estimated to be between \$1,564M and \$1,740M across the entire county, with damages to buyout properties estimated to be about \$21.9M to \$22.4M. Hazard damage associated with relocation and labor costs at flood damaged properties in 2010 was estimated to be $823M to $1,515M, where the cost of relocation and labor at buyout properties was $19M to $22M. This suggests total direct hazard damages in 2010 were approximately $3,567M to $2,387M. Had no buyout taken place prior to 2010 these damages would have been about $6M more, and had all the buyouts taken place prior to 2010 these damages would have been about $38M less (or total damages avoided of $44M) (see Table 16 for a summary of all damage estimates in 2010 for the buyout scenarios). Given an acquisition cost of $38.88M for all of the buyouts the damages avoided by their removal prior to the 2010 flood would have exceeded the cost of acquisition.

Table 16: Direct damage economic impacts in millions of 2010 dollars.

Scenario	Scale	Structural Damages	Contents Damages	Relocation Costs	Labor Costs	Total Damages	Acquisition Cost	Appraisal Value
No Buyouts	County	1030.75-542.07	1024.9	713.97-19.86	806.11	3575.73-2392.94	NA	NA
	Micro-watersheds with Buyouts	173.08-123.91	132.33	156.08-4.52	180.11	641.6-440.87	NA	NA
	Buyout Parcels	15.94-15.8	8.95	3.45-0.55	21.81	50.15-47.11	38.88	52.46
With Buyouts	County	1029.16-540.13	1024	713.5-19.79	803.21	3569.87-2387.13	NA	NA
	Micro-watersheds with Buyouts	171.49-121.96	131.42	155.6-4.45	177.2	635.71-435.03	NA	NA
	Buyout Parcels	14.35-13.85	8.05	2.98-0.48	18.9	44.28-41.28	31.54	47.12
All Buyouts	County	1017.15-527.74	1017.33	711.08-19.37	786.47	3532.03-2350.91	NA	NA
	Micro-watersheds with Buyouts	159.49-109.58	124.75	153.18-4.02	160.46	597.88-398.81	NA	NA
	Buyout Parcels	2.35-1.47	1.38	0.56-0.05	2.16	6.45-5.06	0	11.42
Wish List	County	1014.81-526.27	1015.95	710.52-19.31	784.31	3525.59-2345.84	NA	NA
	Micro-watersheds with Buyouts	157.14-108.11	123.38	152.62-3.97	158.3	591.44-393.76	NA	NA
	Buyout Parcels	0-0	0	0-0	0	0-0	0	0

Examination of the hazard damage trajectories over time from 2007 to 2013 as shown in Figure 17 suggests that removal of the buyout homes reduced the potential relocation and labor costs associated with a 2010-like flood, but that trends across the county have contributed to a general decline in the potential for relation and labor costs over time. This decline may be the result of reduced building footprint area of flood damaged homes. In contrast, while the buyout program has reduced the potential for structural and contents damages, these values are highly dependent on property values and hence can fluctuate a great deal from year to year. Given the general increase in property values in the Nashville area in recent years the potential for structural and contents damages from a 2010-like flood has increased noticeably since 2010.

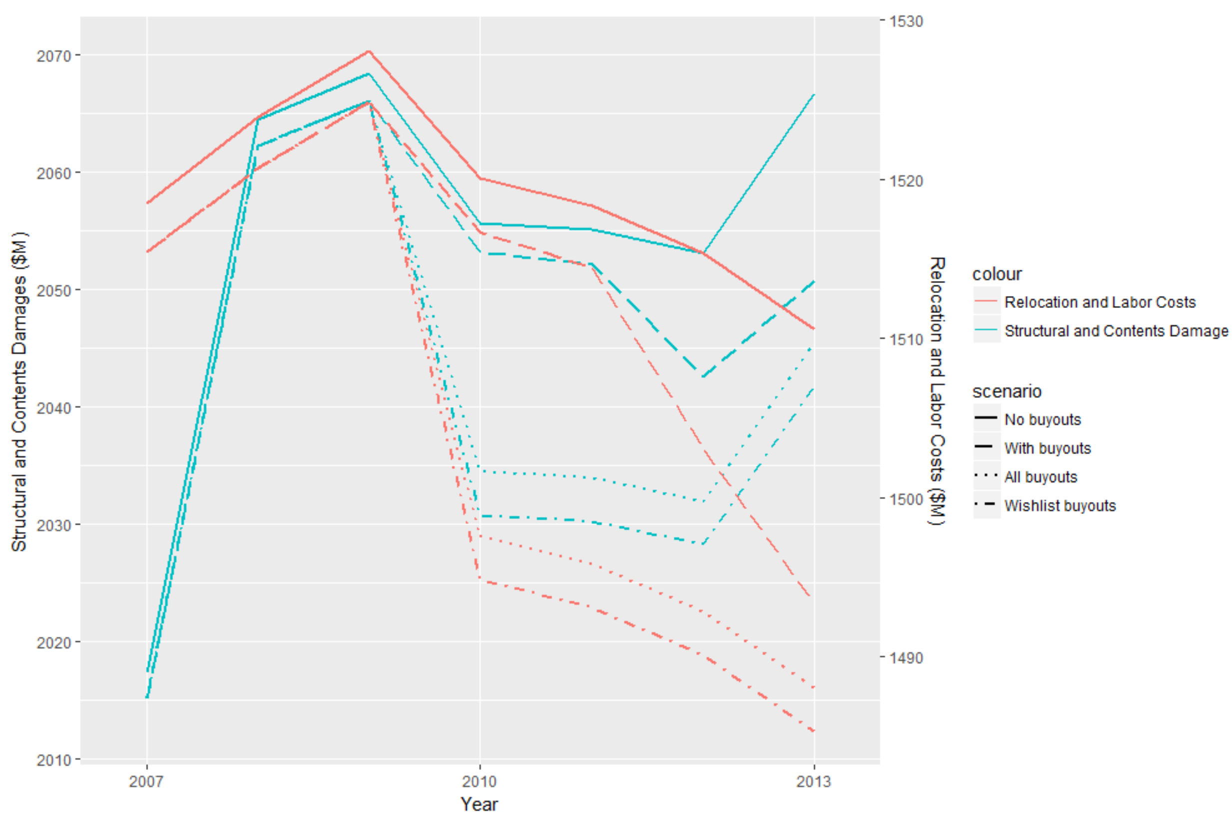

Figure 17: Trajectories for hazard damages.

Property Values

The net county property value was computed using tax parcel information for each year and for each scenario. The trajectories shown in Figure 18 suggest that property values have been steadily increasing since 2009. Removal of buyout properties, as expected, initially produces a noticeable reduction in net property value. When comparing the No Buyouts scenario with the All Buyouts scenario in 2007 this difference is about $0.42M. This difference in net property value for these two scenarios is $0.46M in 2013 (assuming the buyout program did not significantly affect property values of remaining properties). Given the difference between the cost of acquisition of these properties and the damages that would have been avoided, the $5M in economic savings to the system provided by the All Buyouts scenario would be reduced to zero within eleven to twelve years provided no other flooding events occur and no beneficial effects of the buyout program on property values.

Sustainability Capital

Sustainability capital measures relating to ecosystem services and system economic capital were computed for each scenario and year between 2007 and 2013 using deterministic spatial analysis methods as described in the Data and Methods section.

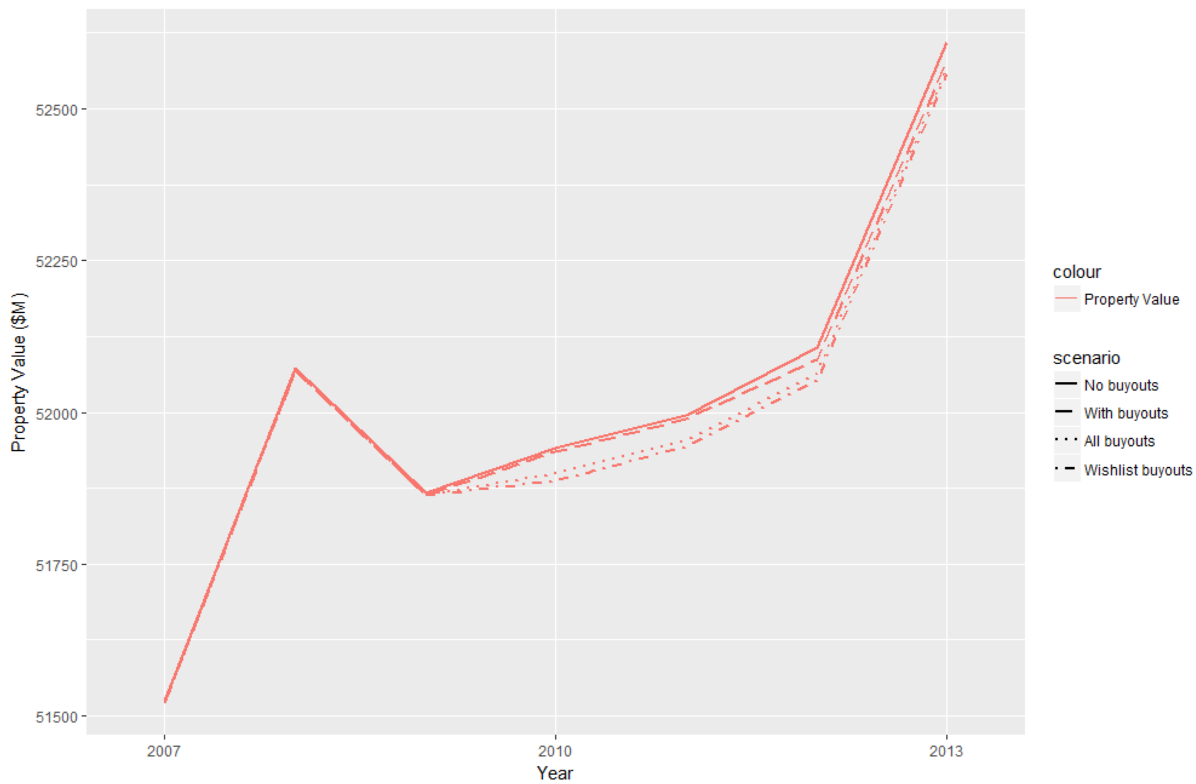

Figure 18: Trajectory of property values.

Impervious Area and Runoff

The analysis of impervious land cover from building footprints in Davidson County demonstrated that high rates of development have driven significant increases in impervious cover in the county. The total increase in observed building cover from 2007 to 2013 was approximately 163 acres. The buyout program removed more than 10 acres of impervious building cover by 2013 and expansion of the buyout program to the wish list would have removed about 18 acres of imperious cover by 2013. This impervious cover is directly related to the expected amount of runoff produced during rainfall events. Increases in impervious cover have led to an increase in total runoff volume of more than seven million gallons (MG) between 2007 and 2013. Buyouts that took place between 2007 and 2013 reduced runoff volumes by an estimated 0.46 MG and expansion of the buyout program to the wish list would have led to a reduction of runoff volumes of 1.02 MG by 2013.

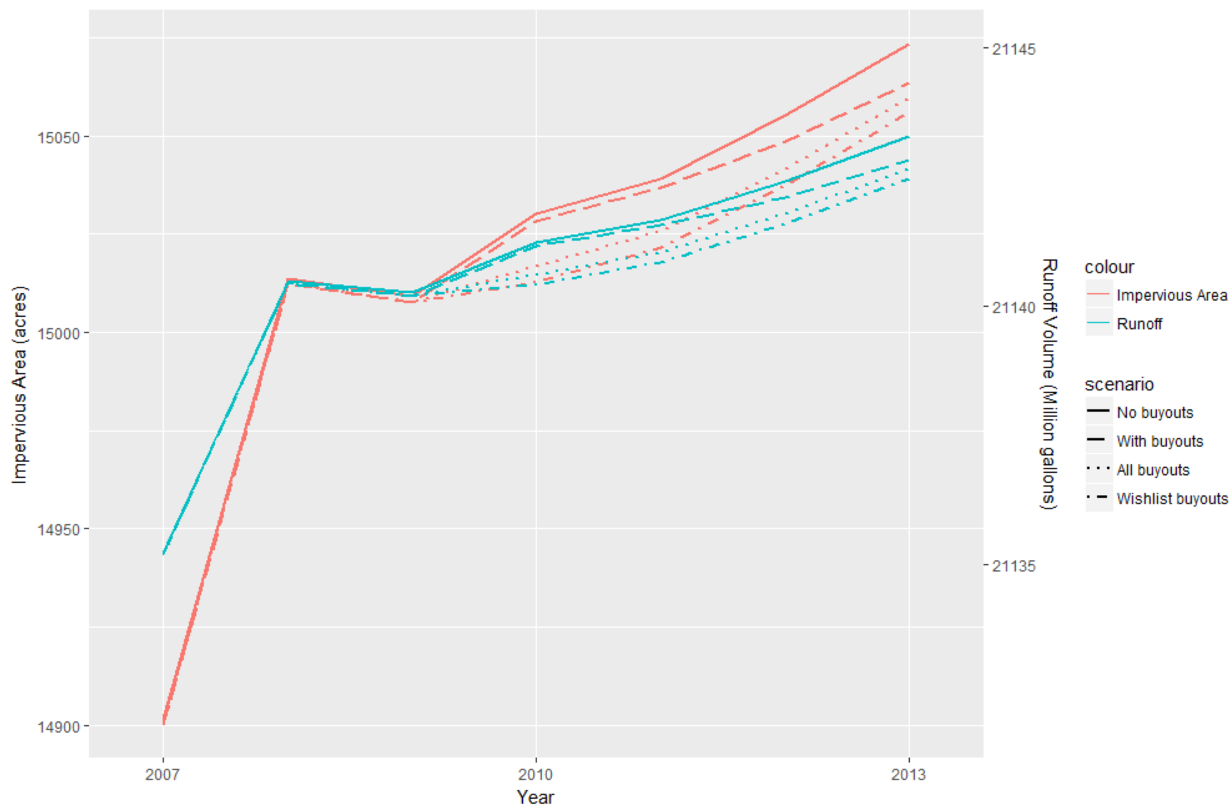

Figure 19: Trajectories for impervious cover and runoff.

Estimated impervious area and storm water runoff volumes for all years and all scenarios are shown in Figure 19. The trends in Figure 19 and the summary for the year 2010 provided in Table 17 indicate that while the buyout program marginally reduces local micro-watershed neighborhood impervious cover and storm runoff, the scale of the program is too small to have a significant effect on system-wide sustainability capital and without massive expansion will not significantly curb development-driven trends in impervious cover and runoff production. This is unfortunate, as one potential pathway for flood mitigation via the buyout program is by reduction of flood severity by decreasing storm water runoff. While it may be possible that the buyout may produce some of these flood mitigating effects in micro-watersheds it is unlikely that they will be significant in the future due to network connectivity of the stormwater conveyance system. As the buyouts typically occur in or near micro-watersheds where stormwater runoff accumulates, increased development in non-buyout micro-watersheds will produce more stormwater that will negatively impact buyout micro-watersheds (see Figure 20 for a map of impervious cover across the county).

Table 17: Landcover and associated runoff characteristics in 2010 for four scenarios.

Scenario	Spatial Unit	Impervious Building Area (Acres)	Percent Area that is Impervious Cover	Runoff Volume (MG)
No Buyouts	County	14,425.875	4.488	21,113.027
	Buyout Micro-watersheds	2,698.152	7.120	2,540.627
With Buyouts	County	14,424.057	4.487	21,112.942
	Buyout Micro-watersheds	2,696.334	7.114	2,540.542
All Buyouts	County	14,412.666	4.484	21,112.410
	Buyout Micro-watersheds	2,684.943	7.083	2,540.010
Wish List	County	14,408.599	4.482	21,112.219
	Buyout Micro-watersheds	2,680.876	7.072	2,539.819

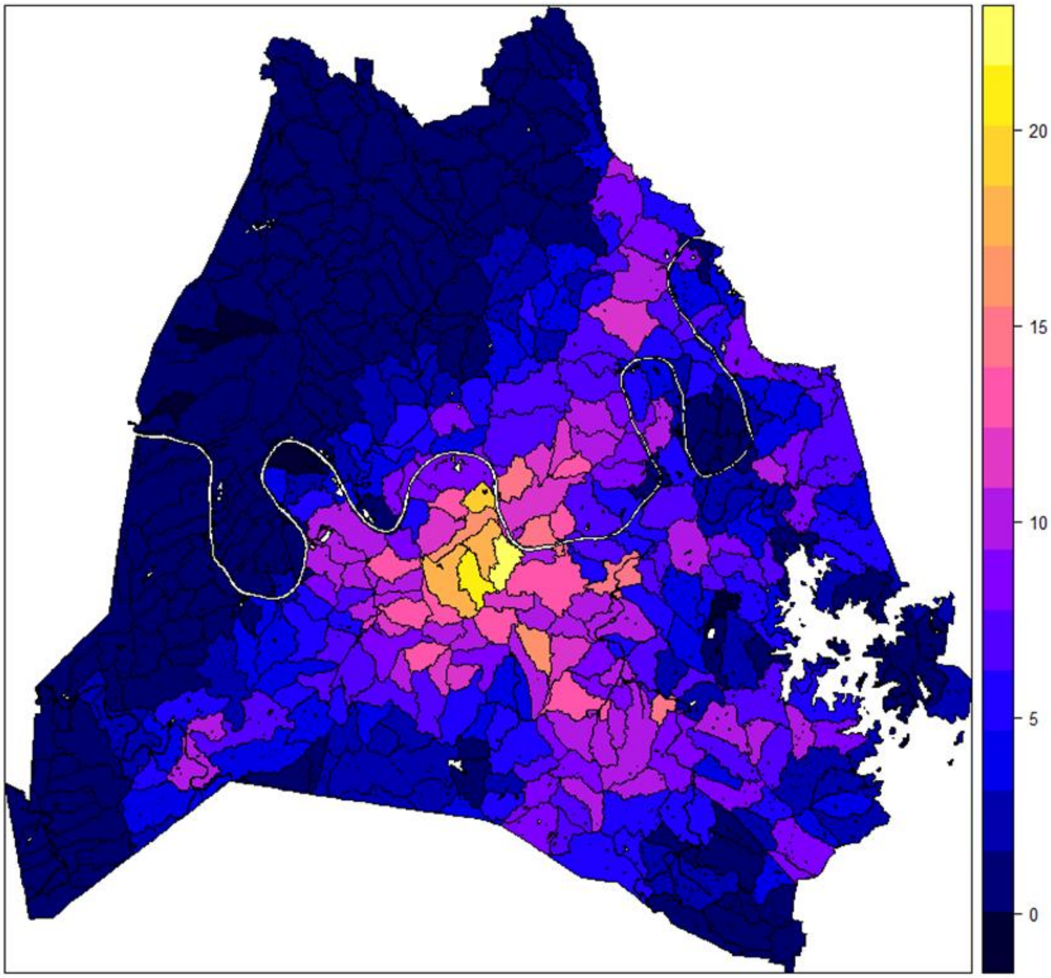

Figure 20: Impervious building cover in 2010 as a percent of total micro-watershed area.

Riparian Buffers

Estimated riparian buffer area and average riparian buffer width for all years and all scenarios are shown in Figure 21. Analysis of riparian buffers in Davidson County demonstrated that the average width of un-built riparian buffer areas around streams and rivers in 2010 was less than 100 meters (328 feet), which was chosen as an initial baseline desired riparian width.[8]

[8] Research suggests for flood attenuation riparian buffer widths of at least 20 to 150 meters are recommended (de Sosa et al., 2018; Hawes & Smith, 2005; NRCS-USDA, 2003)

Indeed, in many micro-watersheds containing riparian areas there are buildings that are located less than 50 feet distant from a stream or river. The average riparian width increased slightly from 291.3 feet in 2007 to 291.7 feet in 2013 (See Figure 21). Expansion of the buyout program to include homes on the "wish list" would have added about 0.3 feet to the average riparian width.

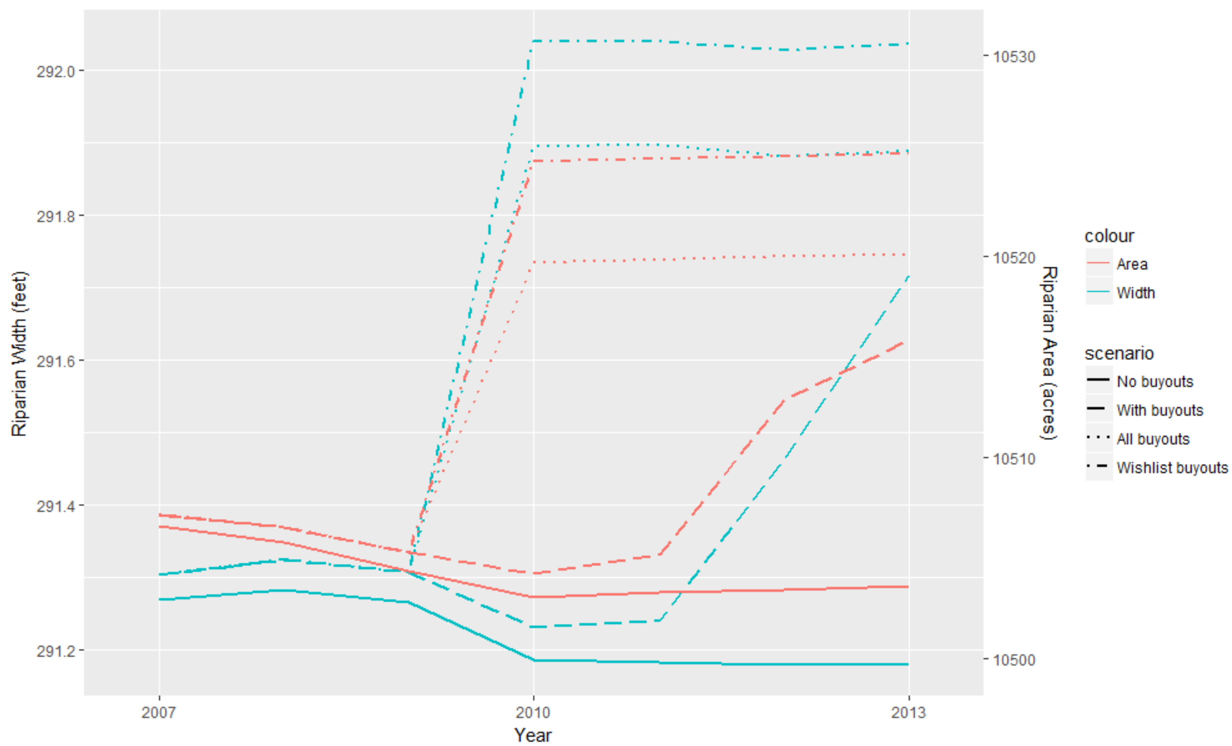

Figure 21: Trajectories for riparian width and riparian area

Within the county there were about 10,504 acres of un-built riparian area in 2010. This area increased by 8 acres from 2007 to 2013. The buyouts conducted prior to 2010 converted one acre of built area in riparian zones to undeveloped riparian buffer area. Completion of buyouts on the Wish List would have created an additional ten acres of riparian buffer area by 2013. As with impervious cover and runoff production, the trends in Figure 21 and summary for the year 2010 provided in Table 18, indicate that the buyout program marginally increases riparian buffer area and average riparian buffer width in local micro-watershed neighborhoods where buyouts take place, but that the scale of the program is too small, and development trends too strong, for a significant effect on county-wide values to be observed. Unlike impervious cover and runoff production though, as the impacts of riparian buffering on flood attenuation are primarily local, negative trends in riparian buffer area in other areas is not necessarily expected to adversely impact flood severity in buyout micro-watersheds. Therefore, changes in local riparian conditions may produce significant positive effects on flood severity within watersheds regardless of county-wide trends (see Figure 22 and Figure 23 for maps of riparian characteristics).

Table 18: Riparian buffer characteristics in 2010 under four buyout program scenarios.

Scenario	Spatial Unit	Riparian Buffer Area (Acres)	Average Riparian Buffer Width (Feet)
No Buyouts	County	10,503.020	291.186
	Buyout Micro-watersheds	1,851.588	269.851
With Buyouts	County	10,504.207	291.231
	Buyout Micro-watersheds	1,852.854	270.158
All Buyouts	County	10,519.636	291.894
	Buyout Micro-watersheds	1,868.164	272.879
Wish List	County	10,524.679	292.039
	Buyout Micro-watersheds	1,873.207	273.907

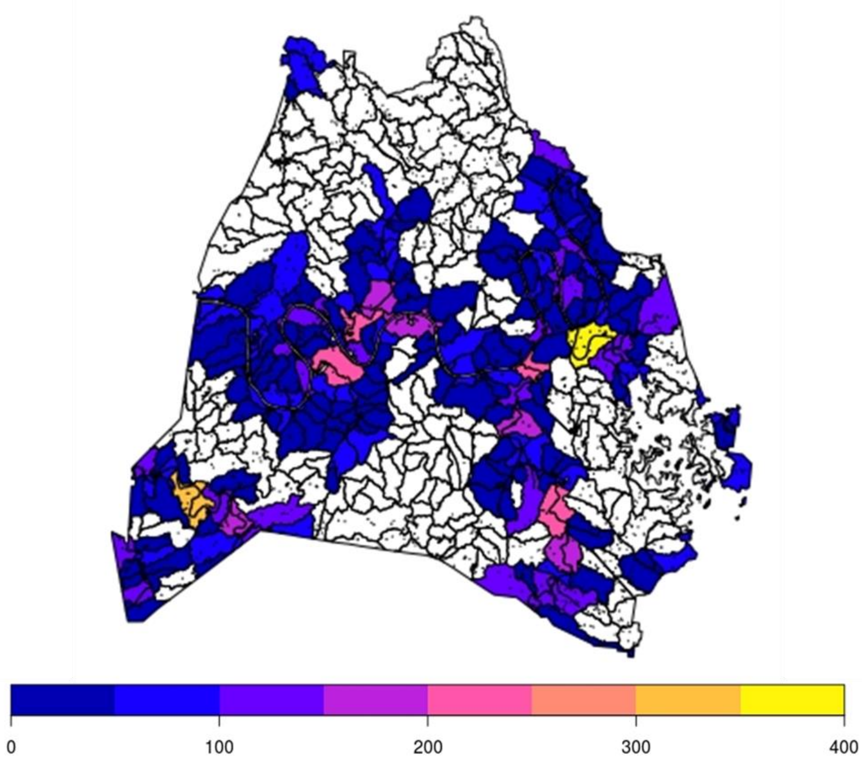

Figure 22: Map of riparian buffer area (in acres) by micro-watershed.

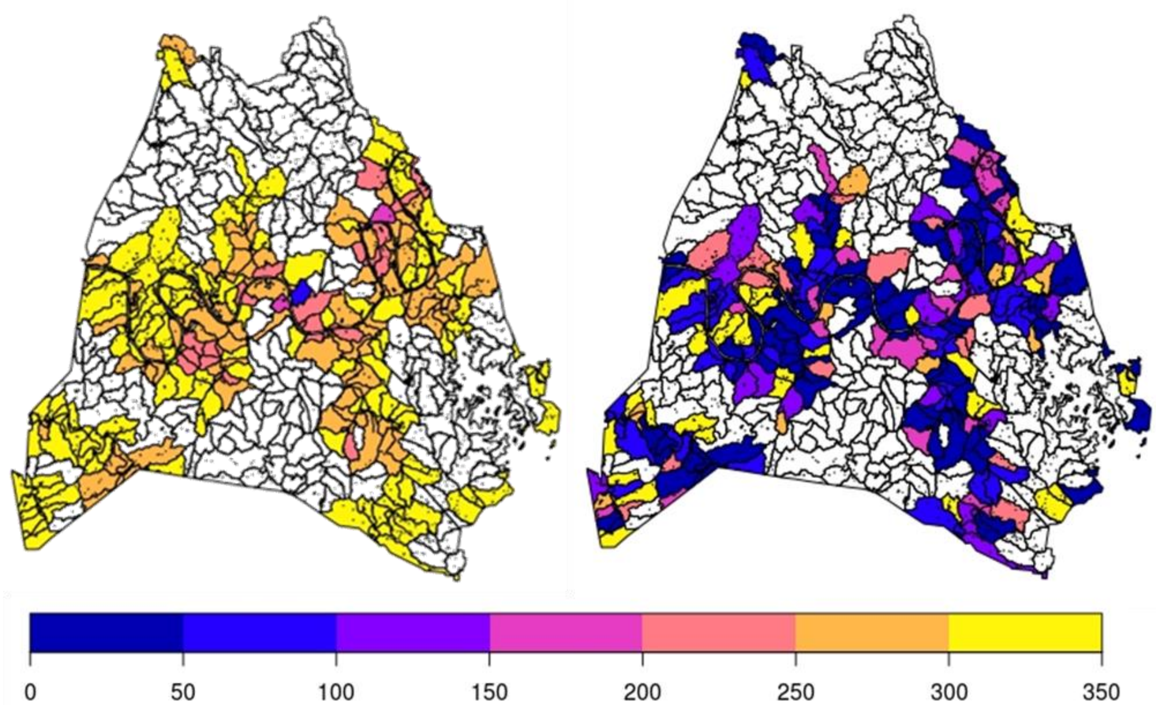

Figure 23: Maps of average (left) and minimum (right) riparian buffer width (in feet) by micro-watershed.

Property Taxes and Net Property Revenue

Total property taxes for the county and the difference between property taxes and hazard damages to properties where calculated for each scenario and year using appraised property values in tax parcel data. The property taxes that are collected by the county government are derived from appraised property values, an assessment ratio, and the annual tax rate set by the county property assessor's office (Property Assessor, 2018). In Davidson County, property taxes constitute approximately forty percent of the metropolitan government's total revenue stream and hence are an important source of economic capital (NashvilleNext, 2016). The net property revenue suggests the potential economic deficit between property-based revenue and property-based damages at the system level which will need to be overcome using other sources of economic capital such as personal funds, federal funds, and credit lines.

As can be seen in Figure 24, property taxes collected by the municipal government are not significantly impacted by the buyout program. The difference between the No Buyout scenario and Wish List scenario in 2010 is $0.54M. Instead, the current tax rate is responsible for most changes in property taxes collected, where about $68M less was collected in 2010 than in 2007 due to changes in the tax rate put in place during the recession. The trajectories in Figure 25, however, show that the buyout program does significantly reduce the potential deficit between property tax revenue and property damages due to a 2010-like flood event. The difference between the No Buyout and Wish List scenarios in 2010 is about $15.4M, where a $15.9M difference in the property losses in the two scenarios is slightly blunted by the $0.5M reduction in property tax income in the Wish List scenario.

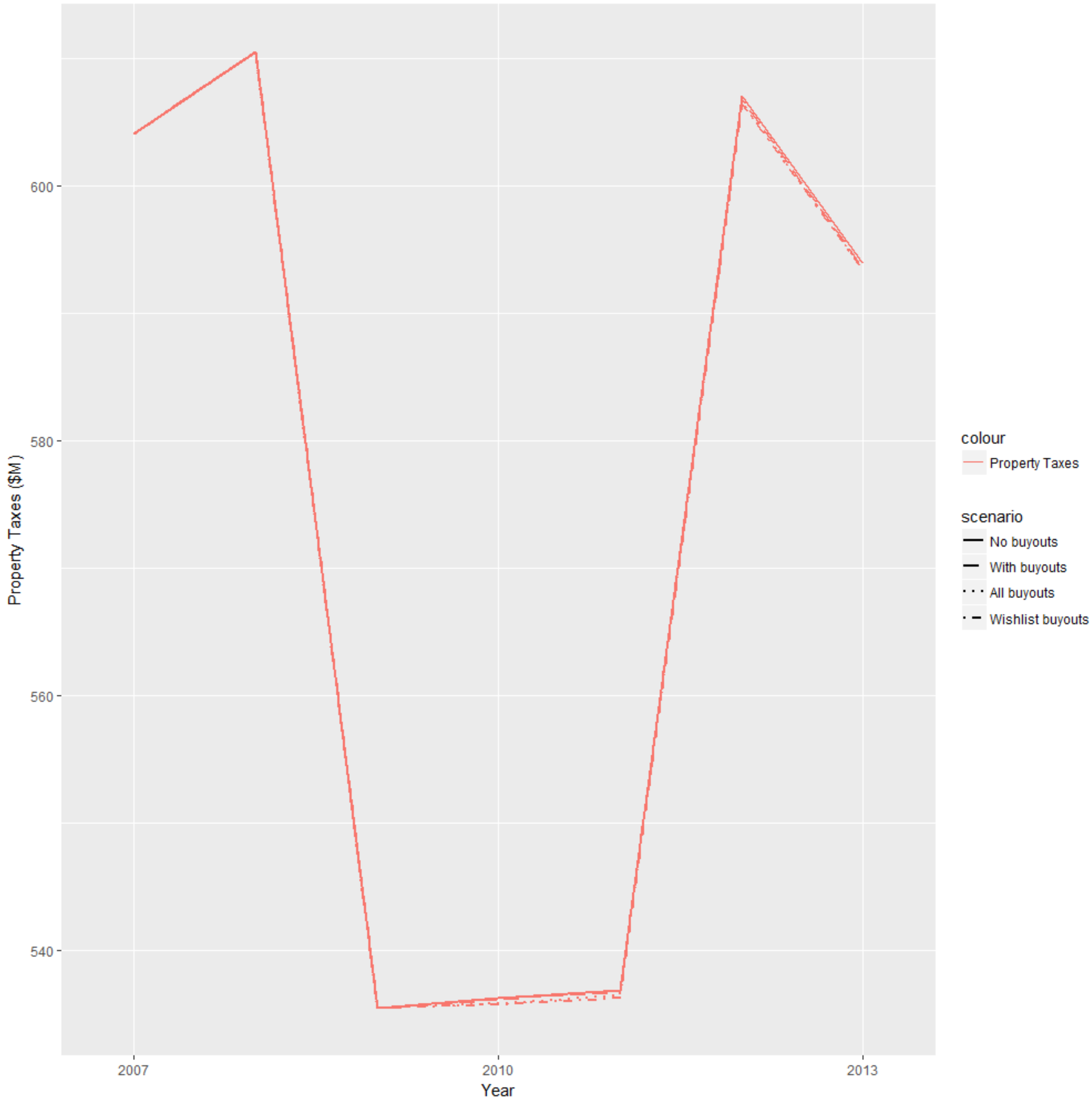

Figure 24: Trajectory for total property taxes.

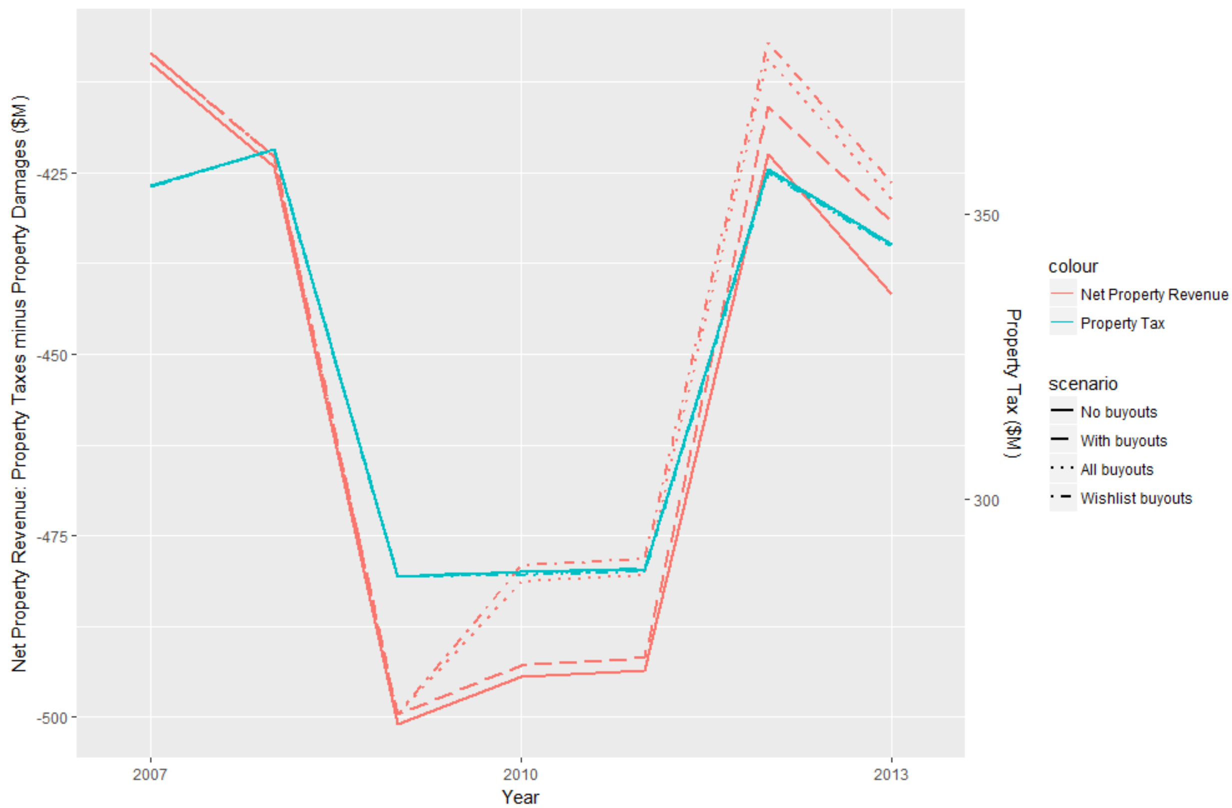

Figure 25: Trajectory for net property revenue.

<u>Feedback from Sustainability Capital to Contextual Vulnerability</u>

One of the primary changes made by the home buyout program, as discussed in the previous section, is an increase in greenspace and an associated reduction in impervious land cover and increase in riparian buffer areal extent and width. These changes are related to natural processes that govern water movement within the Nashville community ecosystem such as surface water runoff production and flood attenuation (ecosystem services). As such, the changes to these ecosystem characteristics produced by the buyout program are expected to impact, even if very slightly, flood severity.

In order to account for changes in ecosystem services produced by the buyout program, regression analysis was used to estimate the relationship between ecosystem services, flood risk, and the depth of inundation observed during the 2010 flood. The analyses use depths estimated from the windshield survey as the outcome and examine the effect of riparian buffer width and extent, impervious building cover, runoff production, and location within the riparian buffer, floodway, or FEMA 100 year and 500 year floodplains on the observed depths. Non-significant predictors in preliminary models were removed for estimation of the final model. These analyses also control for distance from waterways and local spatial characteristics using a spde model. The distance from waterways control accounts for the fact that flooding is more severe nearer to streams and rivers regardless of the ecosystem flood buffering characteristics of micro-watersheds while the spatial effect controls for local characteristics such as elevation that impact flood depths independent of ecosystem characteristics. Models were built using tax parcel scale data, where locations are represented by points at the centroid of each parcel polygon, and only parcels with observed damage were retained for evaluation.

The final model provides evidence that a targeted buyout program has the potential to create both direct benefits in terms of removal of high-risk homes and secondary benefits in terms of providing flood exposure buffering. After controlling for location and distance from streams and rivers I find that riparian buffering and landcover characteristics in micro-watersheds have a significant effect on flood inundation depths reported in the windshield survey. In addition, buildings located within high-risk flood areas are significantly associated with greater flood inundation depths. A summary of final model results is presented in 19 and the spatial effect is plotted in Figure 28.

Table 19: Results of final flood inundation model.

Variable	Mean and Standard Deviation of Posterior Effect Estimate†
Intercept	-0.1655* (0.0179)
Distance to Stream	-0.2698* (0.0103)
Riparian Zone	0.3637* (0.0300)
Floodway	-0.0279 (0.0315)
100 Year Floodplain	0.1305* (0.0191)
500 Year Floodplain	0.1069* (0.0250)
Average Riparian Width	-0.0666* (0.0116)
Percent Building Cover	0.0692* (0.0096)
* Indicates effect is significant at a 95% credibility interval. † Note that all effects for continuous variables are reported for standardized values and are not directly interpretable.	

Model results suggest that the increasing the average riparian buffer widths in micro-watersheds has a positive effect on inundation depth, where an increase in the average riparian width is associated with a reduction in inundation depth. In addition, being located within the baseline 100 meter riparian buffer zone is associated with an increase in inundation depth. Increased impervious cover in micro-watersheds is also associated with increased inundation depth. Finally, the model indicates that buildings located in higher risk flood areas are subject to greater inundation depths, on average. (Note that the effect for buildings located in the floodway is not significant, likely due to collinearity with other locational variables and a small sample size.)

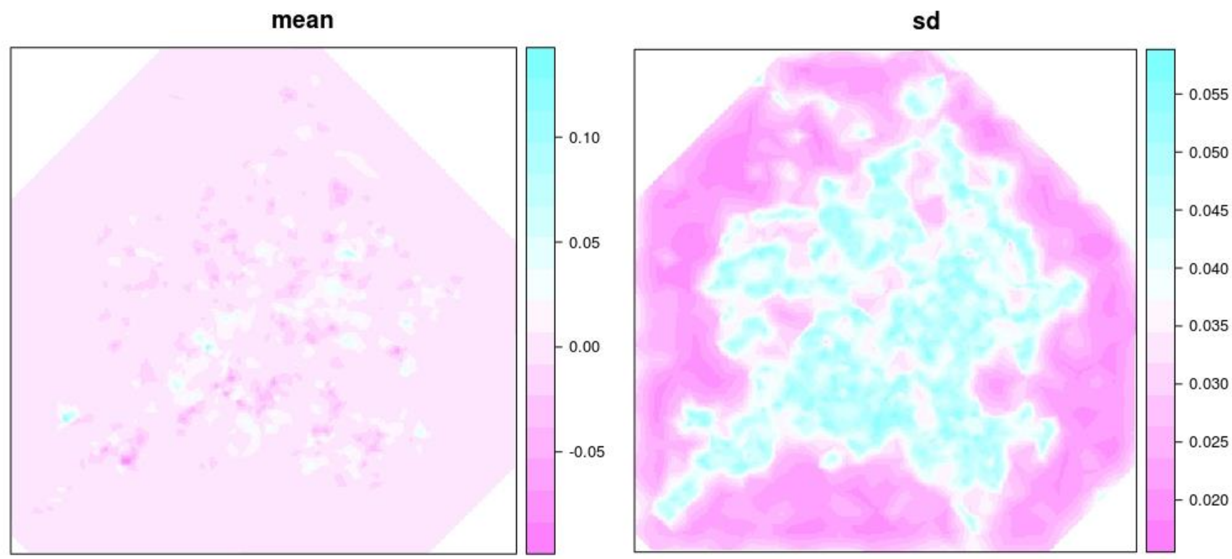

Figure 26: Spatial effect for models of flood inundation depth. Mean of the posterior distribution for the spde spatial effect shown on the left and the standard deviation of the posterior on the right.

The estimated predictor effects and spatial effects were then used to predict the response of flood inundation depth (for a May 2010-like flood event) to changes in watershed and riparian ecosystem service characteristics. The predicted 2.5%, 50%, and 98.5% depths for years 2007, 2010, and 2013 were computed for all four scenarios using the method described in the Bayesian Modeling and Prediction section. An example map of the predicted flood inundation depths is given in Figure 27. Note that as estimation was limited to properties where flood inundation was observed in 2010, the predictions are also limited to locations where flood inundation was previously observed and does not account for increases or reductions in the number of inundated properties. This suggests that the net impacts of the ecosystem service characteristics on flood severity presented in this analysis may be underestimated.

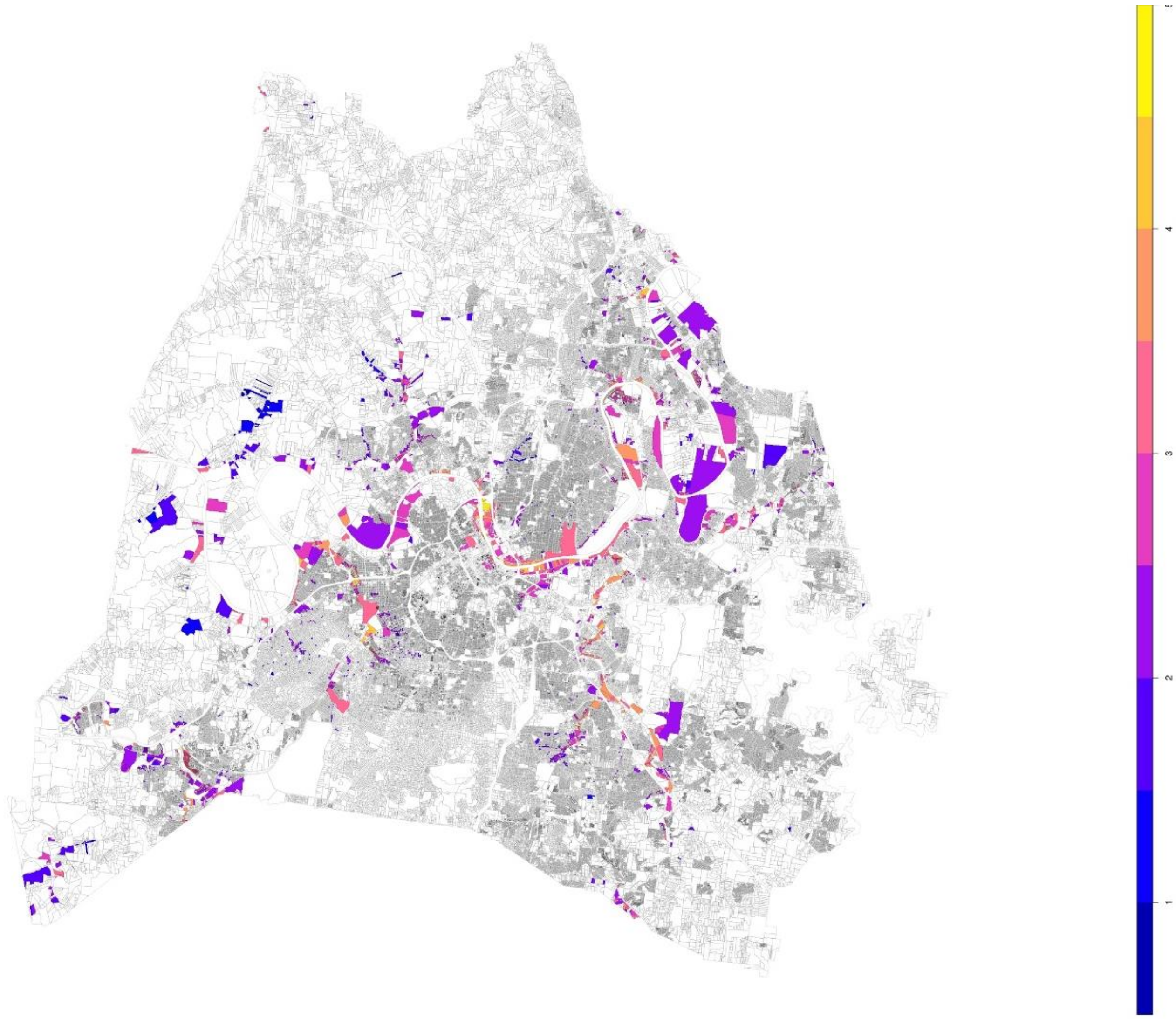

Figure 27: Example of predicted median flood inundation depth (feet) for 2010 all buyouts scenarios.

Feedback from Modified Contextual Vulnerability to System Performance

While damage estimates were previously produced for each scenario and year, these estimates were based on the assumption that only the removal or addition of homes was of importance and that no significant changes in flood severity were produced by the buyout program. However, given the results of models showing significant relationships between ecosystem services and flooding depths the predicted flood inundation depths were used to recalculate the expected hazard damages. This step accounts for changes in expected contextual vulnerability that are the result of changes in sustainability capital produced by the buyout program. The range (95% credibility) of estimated damages based on predicted flood inundation depths for years 2007, 2010, and 2013 for each scenario are shown with the original damage estimates in Figure 28. The predicted damages are skewed towards lower values due to compression of high outlier depths towards the mean in depth prediction models. This compression towards the mean is amplified in damage calculations due to non-linear depth-damage relationships. (Note that this skew towards lower values is of a similar size to alternative damage estimates made using reported damage costs from a Vanderbilt survey of flood impacted households conducted following the May 2010 floods, and also with estimates of damages calculated using a the depth grid from a 1,000 year storm event modeled in HAZUS™, both of which are generally about $1,000M lower than damage estimates using FIA depth-damage curves and observed flooding depths from the windshield survey.) In addition, the predictive models, while skewed towards lower values, suggest that changes in the ecosystem services induced by the buyout program may offset expected increases in flood damages over time due to increasing property values, stabilizing the damages expected from a severe flood similar to the May 2010 flood by improving flood attenuation near streams and rivers.

The difference between the predicted damages for the No Buyouts and Wish List scenarios in both 2010 and 2013 ranges from $75M for the low-end predictions to $141M for the high-end predictions. In comparison the difference between these scenarios using the original damages estimates is only $50M. This suggests that improving flood attenuation via buyout activities may provide more than double the damage savings expected when only considering the value of the home removed from harm’s way.

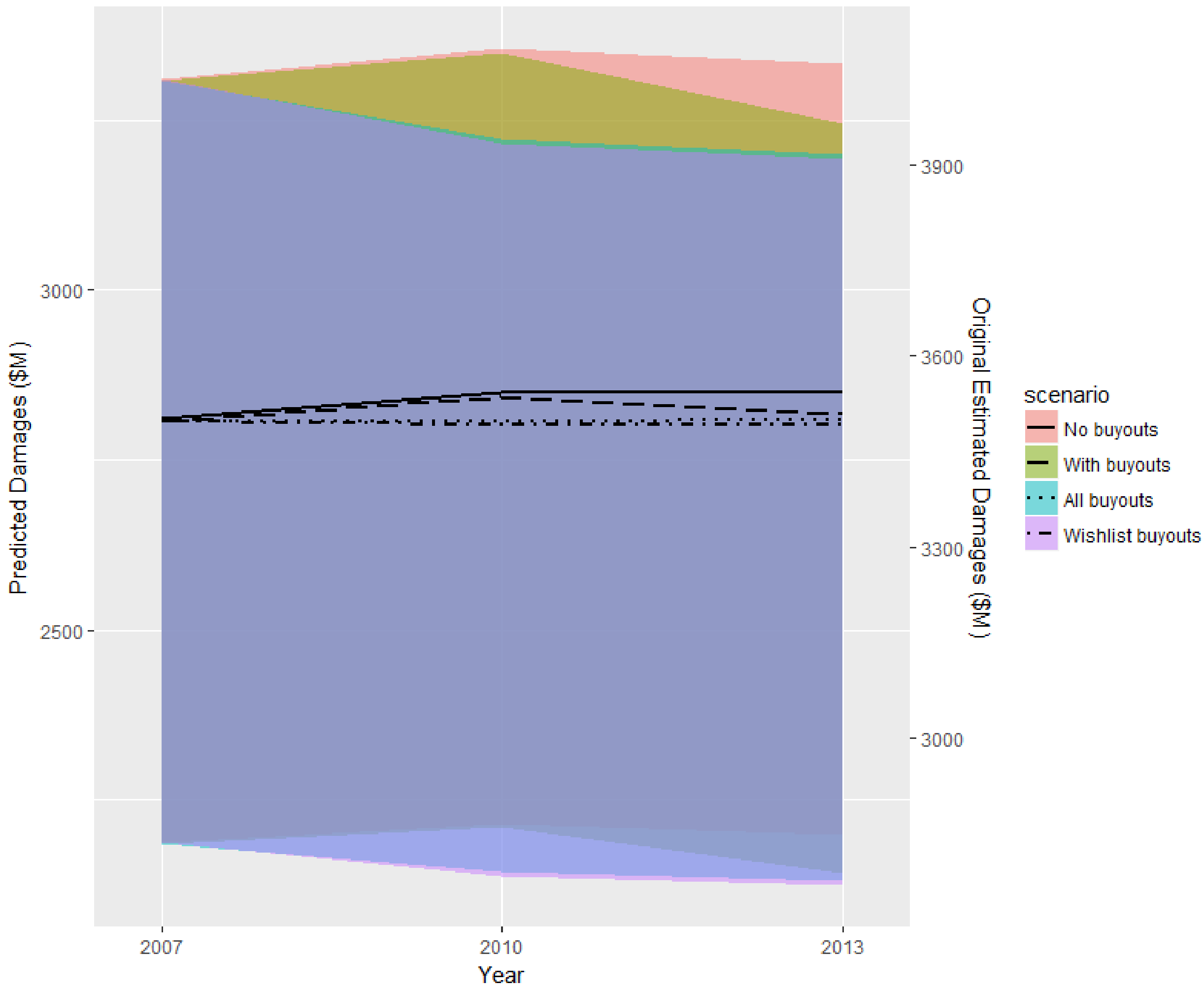

Figure 28: Estimated range of damages given predicted flood depths. Colored bands represent the 95% credibility range for predicted damages while black lines represent the original damage estimations.

The buyout program also directly changes the contextual vulnerability indicators of distance to greenspace, location within flood zones, and flood inundation which affect (although not always significantly) the system performance measures of property value and hazard damages. In addition, the buyout program may directly alter the distribution of contextual vulnerability indicators such as total population and renter population. These indicators, together with inundation depths and runoff production of watersheds, which are also directly and indirectly changed by the buyout program, produce significant effects on health and safety. While generating predictions of changes in these metrics would be interesting and make for a more complete consideration of feedbacks between the concepts of vulnerability, resilience, and sustainability, due to the very broad range of uncertainty and difficulty in producing accurate predictions these models are not conducted in this study.

Feedback from Modified System Performance to Sustainability Capital

Finally, while most of the sustainability capital measures of interest are directly impacted by the buyout program, sustainability capital measures related to economic capital are indirectly impacted via expected changes in property value and hazard damages system performance measures. The net property revenue was recalculated for each scenario for years 2007, 2010, and 2013 using the predicted property damages as estimated in the previous section. Updated net property revenue estimations are plotted with the original calculations in Figure 29. As with the predicted damages in the previous section the values for net revenue are somewhat skewed, in this case towards larger (less negative) values. The trend for net revenue remains the same as seen in the original calculations, however the difference in the property tax-property damage deficit across buyout scenarios is increased such that a difference between the No Buyout and Wish List scenarios in 2010 of about $15M (in the original calculations without the feedback considerations) is increased to about $33M. Again, this difference is due to estimated reduced property damages resulting from reduced flood inundation depths that are the predicted result of increases to ecosystem services provided by the buyout program.

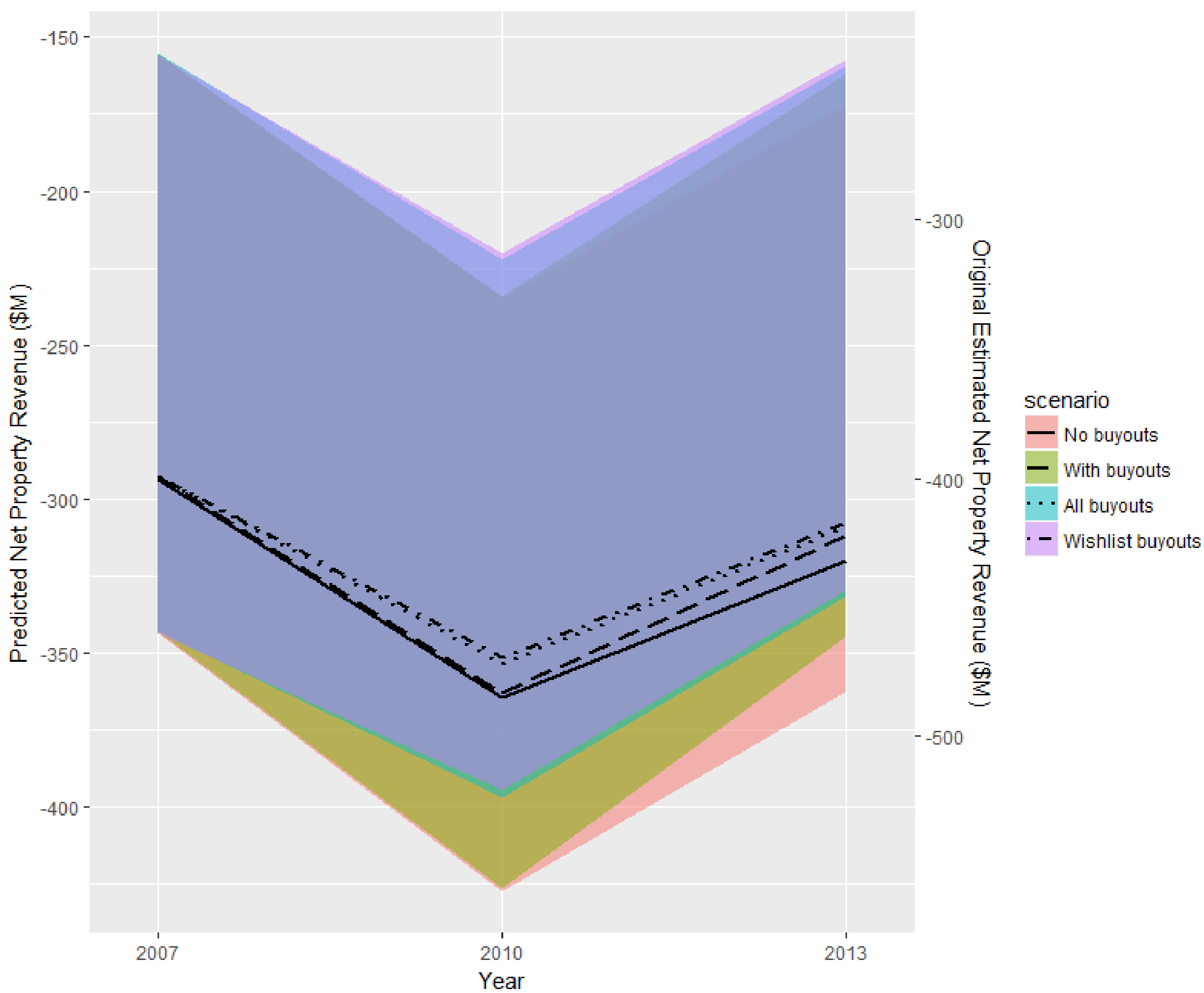

Figure 29: Predicted net revenue. Colored bands represent the 95% credibility range for predicted values while the black lines represent the original estimations.

Discussion

Taken together the results of the analyses conducted in this study suggest that physical exposure to flooding and risk of flood exposure as represented by indicators of flood inundation depth, distance to streams and rivers, and location within flood zones significantly affects system health and safety and economic prosperity in the context of flooding. Model results also indicate that characteristics of the built environment and populations also significantly affect system health and safety and economic prosperity. In addition, the results suggest that certain populations were subjected to relatively high severity of flooding and that likelihood of carrying flood insurance also varied across population types.

These findings suggest that the following measures are valid indicators of the contextual vulnerability of the Nashville community system to flooding: distance to stream/river, flood zone, depth of inundation, total population, renter population, property value, property size, property type, median income, percent population without GED, percent population below poverty level, percent population white only, percent population foreign born, percent population that speaks English poorly, and percent households with Social Security Income. While this is not by any means an exhaustive list of valid indicators of community vulnerability to flooding, these are indicators for which there is observed evidence, either produced in this study or in previous work, that they are related to the level of harm experienced during a hazardous event.

This study also shows how changes in these measures of vulnerability, over time and across hypothetical buyout program scenarios, have the potential to influence the impact of a severe flooding event on system performance measures. The ability of the system to maintain high levels of system performance given a hazardous event is a key characteristic of resilient systems. The results of deterministic and Bayesian predictions indicate that the buyout program does produce significant benefits in terms of reduced numbers of damaged properties and exposed populations, as well as reduced hazard damage costs. These results indicate that while some system performance measures may be slightly negatively impacted by the buyout program (property values), the economic benefits of an expanded buyout program outweigh the negative economic impacts.

In addition, the buyout program produces non-economic benefits in terms of removing people from harm's way. Removal of homes in high-risk flood areas should reduce the risk of flood fatalities and water rescues. However, examination of the trajectory of renter populations also indicates that more renters are likely to be exposed to severe flooding. Together with models indicating an increasing risk of needed a water rescue for renter populations, this might indicate that water rescues may be increasingly likely during future severe flooding events, particularly if steps are not taken to improve flood safety communication and education among non-native English speakers, and that this increase might be negatively impacted by the buyout program.

Finally, this study demonstrates how the buyout program modified sustainability capital in the form of ecosystem services and economic capital. Economic capital is shown to be slightly negatively impacted by expansion of the buyout program, however this impact is minor in comparison to non-flood related factors such as changes in tax rates, which appear to be driven primarily by external economic forces such as the recession. While expansion of the buyout program does improve the level of ecosystem services in the localized micro-watersheds where buyouts take place, at the system-scale these changes are far outweighed by county-wide trends in development. However, model results do indicate that the extent of impervious cover and riparian buffer width are associated with flood inundation depths, suggesting that the buyout program does provide some secondary benefits in terms of localized flood attenuation. The impact of these ecosystem services on flood inundation depths was predicted and used to reevaluate potential flood damages and net property revenue and show that these secondary benefits may produce added economic benefits to the system.

Conclusions

In this study, I show how deterministic modeling, spatial analysis, and Bayesian modeling can be used to show that a home buyout program provides long term benefits to the Nashville community system. In doing so, I utilize a relational framework between the concepts of vulnerability, resilience, and sustainability that posits that there are causal relationships that exist between these concepts and lead to feedback between system properties at different scales and examined from different perspectives. This work is intended to illustrate some of the tradeoffs between different scenarios of a home buyout program as a flood adaptation strategy and tradeoffs across aspects of community vulnerability, resilience and sustainability.

While this work only examined a small subset of factors related to community flooding, the examination of multiple factors across time and across scenarios in addition to modeling of interactions between factors meant that this analysis quickly became very large and complex. Future work should be done to improve predictive capabilities so that the influence of feedbacks between vulnerability, resilience, and sustainability can be more carefully examined. In addition, future work should examine ways in which the multiple factors examined in this analysis can be consolidated to produce single values that represent system vulnerability, resilience, and sustainability, such that tradeoffs between the concepts can be more easily identified. In addition, future work should endeavor to examine additional system performance factors, particularly those related to long-term change, and the vulnerability and sustainability factors related to those system performance factors. This will require acquisition of additional data and or examination of these concepts at a larger spatial scale.

While improvements and expansion of this work is ongoing, the analyses presented thus far illustrate that the home buyout program has produced economic benefits in terms of reduced hazard damage potential and that expansion of the program will continue to offer additional benefits. In short, the cost of buyouts conducted prior to 2010 were nearly paid for solely in direct damages avoided during the 2010 flood, and assuming that these homes were subject to repetitive flooding, a benefit-to-cost ratio for the buyouts of about 3:1 can be expected over a 75-year time frame (NIBS, 2017). In addition, the buyout program has contributed to the creation of greenspaces that provide flood attenuation services that counteract some of the continuing negative trends in ecosystem services provisioning created by high levels of development in the area, and have removed people from high flood-risk areas, preventing future emergency water rescues and flood fatalities. Finally, the results of this study show that the buyout program has had a positive impact on vulnerability, resilience, and sustainability in the Nashville community system, but indicate that early expansion of the program would have produced even greater benefits. This suggests that home buyout programs may be an effective urban flood adaptation strategy for building community sustainable resilience, and that such programs should aim to remove as many homes as possible from flood prone areas, as early as possible, in order to increase program effectiveness.

CHAPTER V: CONCLUSION

With increasing recognition of the negative impacts of natural hazards and the potential for climate change to exacerbate these hazards, an increasing number of nations, states, municipalities, and corporations are attempting to reduce hazard risks by formulating mitigation and adaptation plans. As the natural hazards literature has evolved and begun to interface with climate science, the standard risk formulations have been supplemented with insights from parallel developments in sustainability science, social justice and vulnerability, behavioral psychology and social learning, and systems resilience. From this work, the concepts of adaptive capacity and of social-environmental systems have emerged and grown in recent decades. Social-environmental systems science explicitly considers relationships between human, technological, and natural components of multi-scalar systems to provide information that identifies unexpected and unintended consequences of actions, decisions, and events. Yet, along with the added value that social-environmental systems science brings there is also added complexity and potential for confusion.

As a whole, researchers in social-environmental systems science and related fields, have embraced the concepts of social-environmental system vulnerability, resilience, sustainability, and adaptive capacity. However, it is also apparent that confusion as to the definitions and applications of these concepts is rampant. Nevertheless, research in this area has increased rapidly over the last decade and an increasing number of calls from leaders in the field have been issued trying to draw attention and focus to several areas in need of development. These areas include: elucidation of the links between vulnerability, resilience, sustainability, and adaptive capacity concepts; development of integrated assessment methodologies; validation and empirical verification of the theoretical indicators of these concepts and of assessment methods in wide use today; and translation of complex theories and methods into operational assessment and evaluation methods accessible to researchers and practitioner alike.

Recognizing the potential value that social-environmental systems conceptualizations of vulnerability, resilience, sustainability, and adaptive capacity may provide to our society, as well as some of the shortcomings of social-environmental systems approaches, in this dissertation I attempt to address some of the known gaps in the field. This dissertation work endeavored to provide a solid conceptual framing on which to ground further work; a generic framework for evaluating adaptation options by integrating assessment of vulnerability, resilience, and sustainability over time; demonstrations of spatial analysis and modeling methods that may be applied in empirical analyses; and a case study that applies the aforementioned concepts, framework, and methods. This work provides a foundation on which to build further work on adaptation in social-environmental systems using a micro-scale lens and empirical methodologies. In addition, this work demonstrates ways in which spatial analysis and modeling may be applied in order to approach true validation of vulnerability, resilience, and sustainability indicators and, by association, conceptual understandings.

Chapter II of this work addressed the conceptual underpinnings of social-environmental system vulnerability, resilience, adaptive capacity, and sustainability. A relational diagram for these four key concepts was presented and serves as the basis for development of the proposed framework for integrated assessment of adaptation. Chapter II also identifies some of the barriers and challenges associated with assessment processes in social-environmental systems and suggests possible methods and tools that may be employed to address these issues.

In the following Chapter, I identify two approaches to addressing assessment issues related to scale. I develop a method for downscaling select demographic variables from census data scales to tax parcel scales and demonstrate the use of these downscaled variables in a social vulnerability index. In addition, I demonstrate how Bayesian spatio-temporal modeling may be applied to evaluating process in complex multiscalar social-environmental systems.

Finally, in Chapter IV I demonstrate how the components of conceptual analysis, spatial analysis, and spatial modeling can be brought together and operationalized in the proposed integrated framework for sustainable resilience assessment. As shown in Figure 30 the spatial analysis and modeling techniques described in Chapter III can be leveraged to support use of the integrated framework described in Chapter II by aiding in the definition of *contextual vulnerability* in a system as well as by enabling identification of relationships between *contextual vulnerability* and the *ability to resist systemic disruption*. These same techniques can also be utilized to support simulation of alternate scenarios and prediction of expected consequences of these alternate scenarios.

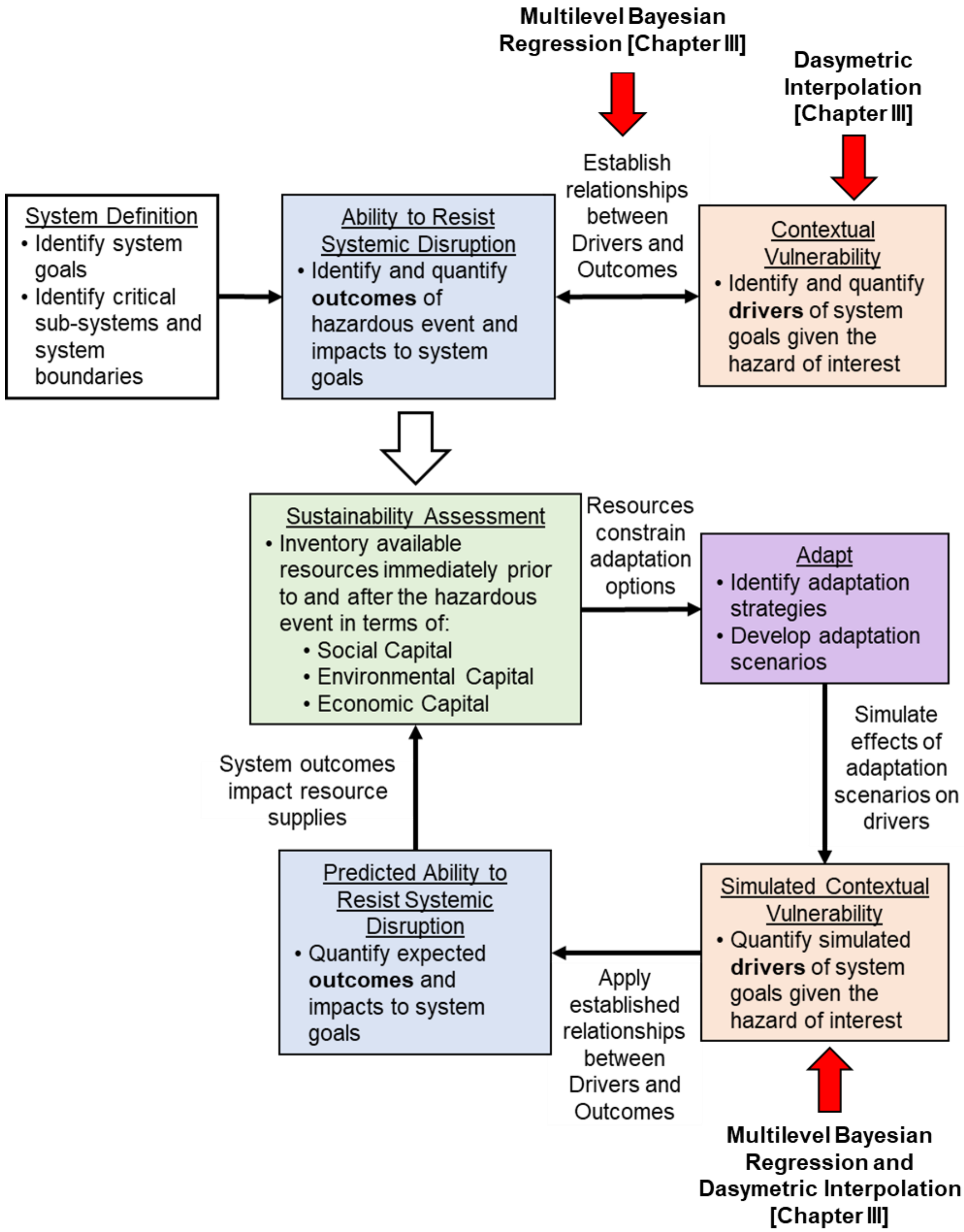

Figure 30: Illustration of the areas of the integrated framework that can be supported by spatial analysis and modeling techniques.

In order to illustrate how the framework and the spatial analysis and modeling techniques might be operationalized Chapter IV presents a micro-scale analysis of flood adaptation for the

Nashville, TN community. This case study uses observed data from the May 2010 flood and data on the home buyout program run by Nashville Metro Water Services to evaluate the benefits offered by the buyout program and predict the value of damages avoided by the program and the value of expansion of the program. Evidence is presented of the effectiveness of one adaptation strategy at building sustainable resilience to flooding, and also serves as a blueprint for other micro-scale, empirically-based assessments of natural hazard adaptation strategy evaluation.

As a body of work, this dissertation offers only glimpses at a few of the numerous areas for expansion in social-environmental system assessment and adaptation strategy evaluation. Further research could focus on methods of spatial interpolation of social, human, and technological information for micro-scale studies; on Bayesian prediction methods for simulation of adaptation strategy effectiveness; on system-dynamics and agent-based models for developing relationships between interdependent components of systems and expected outcomes during hazardous events; on improved consideration of recovery within the proposed integrated assessment framework; or on translation of the framework to multiple scales of analysis. In addition, it is imperative that additional case studies using the same or similar methods be carried out in order to build a body of work that is able to provide some generally applicable findings about adaptation to hazards and factors that contribute to or detract from social-environmental system sustainable resilience. Finally, it is of critical importance that the methods and findings of this work be made accessible to practitioners and policy makers. Areas of expansion of this work related to this concern might include development of open-source tools for adaptation assessment; describing research-practitioner partnerships for implementation of the described methods, frameworks, and tools; and analysis of state and national policies that impact hazard adaptation using cross-sectional and longitudinal data.

REFERENCES

Adger, W.N. (2006). Vulnerability. Global Environmental Change. 16, 268-281.

Adger, W.N. & Vincent, K., (2005). Uncertainty in adaptive capacity. Comptes Rendus Geoscience, 337(4), pp.399-410.

Adger, W.N., Brooks, N., Bentham, G., Agnew, M. & Eriksen, S. (2004). New indicators of vulnerability and adaptive capacity (Vol. 122). Norwich: Tyndall Centre for Climate Change Research.

AghaKouchak A., & Nakhjiri N. (2012). A Near Real-Time Satellite-Based Global Drought Climate Data Record. Environmental Research Letters. 7(4), 044037, doi:10.1088/1748-9326/7/4/044037.

AghaKouchak, A., Feldman, D., Hoerling, M., Huxman, T., & Lund, J. (2015). Water and climate: Recognize anthropogenic drought. Nature, 524(7566), 409–411. http://doi.org/10.1038/524409a

Ahern, J.F. (2011). From fail-safe to safe-to-fail: sustainability and resilience in the new urban world. Landscape Architecture & Regional Planning Graduate Research and Creative Activity, Paper 8.

Allen, C.R., Angeler, D.G., Garmestani, A.S., Gunderson, L.H. & Holling, C.S. (2014). Panarchy: theory and application. Ecosystems, 17(4): 578-589.

Arcaya, M., Brewster, M., Zigler, C. M., & Subramanian, S. V. (2012). Area variations in health: A spatial multilevel modeling approach. Health & place,18(4), 824-831.

Ashley, C., & Carney, D. (1999). Sustainable livelihoods: lessons from early experience. London: Department for International Development (DFID).

Azar, Derek, & David Rain. (2007). Identifying population vulnerable to hydrological hazards in San Juan, Puerto Rico. GeoJournal 69.1-2: 23-43.

Babcicky, P., & Seebauer, S. (2016). The two faces of social capital in private flood mitigation: opposing effects on risk perception, self-efficacy and coping capacity. Journal of Risk Research, 1-21.

Bahadur, A.V., Ibrahim, M., & Tanner, T. (2010). The resilience renaissance? Unpacking resilience for tackling climate change and disasters. Strengthening Climate Resilience Discussion Paper 1. Institute of Development Studies. Brighton, UK.

Bahadur, A.V., Ibrahim, M., & Tanner, T., (2010). The resilience renaissance? Unpacking resilience for tackling climate change and disasters. Strengthening Climate Resilience Discussion Paper 1. Institute of Development Studies. Brighton, UK.

Baroud, H., Barker, K., & Hank Grant, F. (2013). Multiobjective stochastic inoperability decision tree for infrastructure preparedness. Journal of Infrastructure Systems, 20(2), 04013012.

Baroud, H., Ramirez-Marquez, J. E., Barker, K., & Rocco, C.M. (2014). Stochastic Measures of Network Resilience: Applications to Waterway Commodity Flows, Risk Analysis, 34(7): 1317-1335.

Baroud, H., Ramirez-Marquez, J. E., Barker, K., & Rocco, C.M. (2014). Stochastic Measures of Network Resilience: Applications to Waterway Commodity Flows. Risk Analysis, 34(7): 1317-1335.

Biggs, D., Hall, C. M., & Stoeckl, N. (2012). The resilience of formal and informal tourism enterprises to disasters: reef tourism in Phuket, Thailand. Journal of Sustainable Tourism, Vol. 20, Issue 5.

Bin, O., Kruse, J. B., & Landry, C. E. (2008). Flood hazards, insurance rates, and amenities: Evidence from the coastal housing market. Journal of Risk and Insurance, 75(1), 63-82.

Bin, O., & Polasky, S. (2004). Effects of flood hazards on property values: evidence before and after Hurricane Floyd. Land Economics, 80(4), 490-500.

Bithas, K. P., & Christofakis, M. (2006). Environmentally Sustainable Cities. Critical Review and Operational Conditions. Sust. Dev., 14, 177–189.

Blangiardo, M., & Cameletti, M. (2015). Spatial and spatio-temporal Bayesian models with R-INLA. John Wiley & Sons.

Blangiardo, M., Cameletti, M., Baio, G., & Rue, H. (2013). Spatial and spatio-temporal models with R-INLA. Spatial and spatio-temporal epidemiology, 7, 39-55.

Bocchini, P., Frangopol, D. M., Ummenhofer, T., Zinke, T. 2014. Resilience and Sustainability of Civil Infrastructure: Toward a Unified Approach. J. Infrastruct. Syst. 20 (2).

Bocchini, P., Frangopol, D. M., Ummenhofer, T., & Zinke, T., (2014). Resilience and Sustainability of Civil Infrastructure: Toward a Unified Approach. J. Infrastruct. Syst. 20 (2).

Boer, J., Wouter Botzen, W. J., & Terpstra, T. (2015). More Than Fear Induction: Toward an Understanding of People's Motivation to Be Well-Prepared for Emergencies in Flood-Prone Areas. Risk analysis, 35(3), 518-535.

Bossel, H. (2001). Assessing viability and sustainability: a systems-based approach for deriving comprehensive indicator sets. Conservation Ecology 5(2): 12.

Bozza, A., Asprone, D., & Manfredi, G. (2015). Developing an integrated framework to quantify resilience of urban systems against disasters. Nat Hazards, 78, 1729–1748.

Bruneau, M., Change, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M.,... von Winterfeldt, D., A. (2003). Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities. Earthquake Spectra, Volume 19, No. 4, 733–752.

Burton, C., & Cutter, S. L. (2008). Levee failures and social vulnerability in the Sacramento-San Joaquin Delta area, California. Natural Hazards Review, 9(3), 136-149.

Burton, Christopher G. (2010). Social vulnerability and hurricane impact modeling. Natural Hazards Review 11.2: 58-68.

Burton, Christopher G. (2012). THE DEVELOPMENTOF METRICS FORCOMMUNITY RESILIENCE TO NATURAL DISASTERS. Diss. University of South Carolina.

California Department of Conservation. (2016). California Farmland Mapping and Monitoring Program. Accessed January 2016, at http://www.conservation.ca.gov/dlrp/fmmp/Pages/county_info.aspx.

California Department of Food and Agriculture. (2016). California Agricultural Statistics Review 2015-2016. Accessed June 2017 at https://www.cdfa.ca.gov/Statistics/PDFs/2016Report.pdf.

California Department of Water Resources [CA DWR]. (2014). Public Update for Drought Response: Groundwater Basins with Potential Water Shortages, Gaps in Groundwater Monitoring, Monitoring of Land Subsidence, and Agricultural Land Fallowing. Accessed October 2016 at http://water.ca.gov/waterconditions/docs/DWR_PublicUpdateforDroughtResponse_GroundwaterBasins.pdf

California Department of Water Resources [CA DWR]. (2015). Sustainable Groundwater Management Program: Draft Strategic Plan. Accessed October 2016 at http://www.water.ca.gov/groundwater/sgm/pdfs/DWR_GSP_DraftStrategicPlanMarch2015.pdf

California Department of Water Resources [CA DWR]. (2017a). California State Water Project Water Rights. Accessed June 2017, at http://www.water.ca.gov/swp/waterrights.cfm.

California Department of Water Resources [CA DWR]. (2017b). California State Water Project Overview. Accessed June 2017, at http://www.water.ca.gov/swp/index.cfm.

California State Water Resources Control Board [CA SWRCB]. (2016a). Statutory Water Rights Law And Related Water Code Sections (As amended, including Statutes of 2014). Retrieved from: http://www.waterboards.ca.gov/laws_regulations/docs/wrlaws.pdf.

California State Water Resources Control Board [CA SWRCB]. (2016b). The Water Rights Process. Accessed October 2016, at http://www.waterboards.ca.gov/waterrights/board_info/water_rights_process.shtml.

California State Water Resources Control Board [CA SWRCB]. (2016c). Electronic Water Rights Information Management System (eWRIMS). Accessed January 2016, at http://www.waterboards.ca.gov/waterrights/water_issues/programs/ewrims/index.shtml.

California Water Boards. (2017). California Code of Regulations, Title 23, Section 715(c). Retrieved from: http://www.waterboards.ca.gov/laws_regulations/docs/wrregs.pdf.

Camp, J., Whyte, D., & Shaw, A. (2016). “Technical Report: Freight Economic Vulnerabilities Due to Flooding Events.” CFIRE 09-19. National Center for Freight & Infrastructure Research & Education Department of Civil and Environmental Engineering College of Engineering University of Wisconsin–Madison.

Chaix, B., Merlo, J., Subramanian, S. V., Lynch, J., & Chauvin, P. (2005). Comparison of a spatial perspective with the multilevel analytical approach in neighborhood studies: the case of mental and behavioral disorders due to psychoactive substance use in Malmö, Sweden, 2001. American journal of epidemiology, 162(2), 171-182.

Chakraborty, Jayajit, Graham A. Tobin, & Burrell E. Montz. (2005). Population evacuation: assessing spatial variability in geophysical risk and social vulnerability to natural hazards. Natural Hazards Review 6.1: 23-33.

Chakraborty, Jayajit, Juliana A. Maantay, & Jean D. Brender. (2011). Disproportionate proximity to environmental health hazards: methods, models, and measurement. American journal of public health 101.S1: S27-S36.

Chen, J. J. (2003). Communicating complex information: the interpretation of statistical interaction in multiple logistic regression analysis. American journal of public health, 93(9), 1376-a.

Chen, J., Jonsson, P., Tamura, M., Gu, Z., Matsushita, B., & Eklundh, L. (2004). A simple method for reconstructing a high-quality NDVI time-series data set based on the Savitzky-Golay filter. Remote Sensing of Environment, 91(3–4), 332–344. https://doi.org/10.1016/j.rse.2004.03.014

Christian-Smith, J., Levy, M. C., & Gleick, P. H. (2015). Maladaptation to drought: a case report from California, USA. Sustainability Science, 10(3), 491–501. http://doi.org/10.1007/s11625-014-0269-1

Cosandey-Godin, A., Krainski, E. T., Worm, B., & Flemming, J. M. (2014). Applying Bayesian spatiotemporal models to fisheries bycatch in the Canadian Arctic. Canadian Journal of Fisheries and Aquatic Sciences, 72(2), 186-197.

Cumming, G.S., Barnes, G., Perz, S., Schmink, M., Sieving, K.E., Southworth, J.,... Van Holt, T. (2005). An exploratory framework for the empirical measurement of resilience. Ecosystems, 8(8): 975-987.

Cutter, S. L. (2016b). Resilience to What? Resilience for Whom? The Geographical Journal, 182(2), 110-113.

Cutter, S. L. (2016a). Social Vulnerability and Community Resilience Measurement and Tools.

Cutter, S. L., & Gall, M. (2007). Hurricane Katrina: A failure of planning or a planned failure. Naturrisken und Sozialkatastrophen. Berlin, Heidelberg: Springer.

Cutter, S. L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E., Webb, J. (2008). A place-based model for understanding community resilience to natural disasters. Global Environmental Change 18, 598-606.

Cutter, S. l., Boruff, B. J., Shirely, L. W. (2003). Social Vulnerability to Environmental Hazards. Social Science Quarterly, Vol 84, No. 2.

Cutter, S. L., et al. (2013). Integrating social vulnerability into federal flood risk management planning. Journal of Flood Risk Management 6.4: 332-344.

Cutter, Susan L. (1996). Societal responses to environmental hazards. International Social Science Journal 48.150: 525-536.

Cutter, Susan L. (1996). Vulnerability to environmental hazards. Progress in Human Geography 20 : 529-539.

Cutter, Susan L., Bryan J. Boruff, & W. Lynn Shirley. (2003). Social vulnerability to environmental hazards. Social science quarterly 84.2: 242-261.

Davoudi, S., Shaw, K., Haider, L. J., Quinlan, A. E., Peterson, G. D., Wilkinson, C., & Davoudi, S. (2012). Resilience: a bridging concept or a dead end? "Reframing" resilience: challenges for planning theory and practice interacting traps: resilience assessment of a pasture management system in Northern Afghanistan urban resilience: what does it mean in planning practice? Resilience as a useful concept for climate change adaptation? The politics of resilience for planning: a cautionary note: edited by Simin Davoudi and Libby Porter. Planning Theory & Practice, 13(2), 299-333.

de Sosa L.L., Glanville H.C., Marshall M.R., Abood S.A., Williams A.P., & Jones D.L. (2018). Delineating and mapping riparian areas for ecosystem service assessment. Ecohydrology.11:e1928. https://doi.org/10.1002/eco.1928

Diffenbaugh, N. S., & Swain, D. L. (2015). Anthropogenic warming has increased drought risk in California. Proceedings of the National Academy of Sciences, 112(13), 3931–3936.

Dominey-Howes, D. & Papathoma, M. Nat Hazards (2007). 40: 113. doi:10.1007/s11069-006-0007-9

Dunning, C. M., & S. Durden. (2013). Social Vulnerability Analysis: A Comparison of Tools. White Paper. Alexandria, VA: U.S. Army Corps of Engineers, Institute for Water Resources.

Eakin, H., Luers, A. L. (2006). Assessing the Vulnerability of Social-Environmental Systems. Annu. Rev. Environ. Resour. 31, 365–94.

Pebesma, E. (2017). sf: Simple Features for R. R package version 0.5-4. https://CRAN.R-project.org/package=sf

Engle, N.L. (2011). Adaptive capacity and its assessment. Global Environmental Change 21, 647-656.

Eriksen, S.H. & Kelly, P.M. (2007). Mitig Adapt Strat Glob Change 12: 495. doi:10.1007/s11027-006-3460-6

Famiglietti, J. S., Lo, M., Ho, S. L., Bethune, J., Anderson, K. J., Syed, T. H., … Rodell, M. (2011). Satellites measure recent rates of groundwater depletion in California's Central Valley. Geophysical Research Letters, 38(3), 2–5. http://doi.org/10.1029/2010GL046442

Fekete, A. (2012). Spatial disaster vulnerability and risk assessments: challenges in their quality and acceptance. Natural Hazards, 61 (3): 1161-1178.

Fekete, Alexander. (2009). Validation of a social vulnerability index in context to river-floods in Germany. Natural Hazards and Earth System Sciences 9.2: 393-403.

Federal emergency Management Agency (FEMA). (2013). "Hazus MH Technical Manual: Multi-hazard Loss Estimation Methodology, Flood Model." Federal Emergency Management Agency. Retrieved from https://www.fema.gov/media-library-data/20130726-1820-25045-8292/hzmh2_1_fl_tm.pdf.

Ficklin, D. L., Luo, Y., Luedeling, E., & Zhang, M. (2009). Climate change sensitivity assessment of a highly agricultural watershed using SWAT. Journal of Hydrology, 374(1), 16-29.

Fiksel, J. (2006). Sustainability and resilience: toward a systems approach. Sustainability: Science, Practice, & Policy, 2 (2).

Folke, C. (2006). Resilience: The emergence of a perspective for social–ecological systems analyses. Global Environmental Change, 16, 253–267.

Frazier, T.G., Thompson, C.M. & Dezzani, R. J. (2014). A framework for the development of the SERV model: A Spatially Explicit Resilience-Vulnerability model. Applied Geography, 51, 158-172.

Fussel, H. (2007). Vulnerability: A generally applicable conceptual framework for climate change research. Global Environmental Change, 17, 155-167.

Gallopín, G. C. (2006). Linkages between vulnerability, resilience, and adaptive capacity. Global Environmental Change, 16, 293-303.

Gelman, A., & Hill, J. (2007). Data analysis using regression and multilevel hierarchical models (Vol. 1). New York, NY, USA: Cambridge University Press.

Gillespie-Marthaler, L., Nelson, K.S., Baroud, H., & Abkowitz, M.D. Integrating Vulnerability, Resilience, and Sustainability to Achieve Sustainable Resilience: A New Concept for Assessing System Quality. (*under review*)

GeoTracker GAMA. (2016). Groundwater Ambient Monitoring and Assessment: Statewide Depth-to-Water and Groundwater Elevation data. Accessed January 2016, at http://geotracker.waterboards.ca.gov/gama/data_download.asp.

Godschalk, D. R. (2003). Urban hazard mitigation: creating resilient cities. Natural hazards review, 4(3), 136-143.

Gotts, N.M. (2007). Resilience, panarchy, and world-systems analysis. Ecology and Society, 12(1), p.24.

Gräler, B., Pebesma, E., and Heuvelink, G. (2016). Spatio-temporal interpolation using gstat. R Journal.

Grantham, T. E., & Viers, J. H. (2014). 100 years of California's water rights system: patterns, trends and uncertainty. Environmental Research Letters, 9(8), 084012.

Gumma, M. K. (2011). Mapping rice areas of South Asia using MODIS multitemporal data. Journal of Applied Remote Sensing, 5(1), 53547. http://doi.org/10.1117/1.3619838

Gundogdu, K. S., & Guney, I. (2007). Spatial analyses of groundwater levels using universal kriging. Journal of Earth System Science, 116(1), 49-55.

Haer, T., Botzen, W. W., & Aerts, J. C. (2016). The effectiveness of flood risk communication strategies and the influence of social networks—Insights from an agent-based model. Environmental Science & Policy, 60, 44-52.

Haimes, Y. Y. (2009). On the Definition of Resilience in Systems. Risk Analysis, Vol. 29, No. 4.

Hallegate, S., Green, C., Nicholls, R.J., Corfee-Morlot, J. (2013). Future flood losses in major coastal cities. Nature Climate Change, Vol 3.

Hawes, E. & Smith, M. (2005). Riparian Buffer Zones: Functions and Recommended Widths. Retrieved from http://eightmileriver.org/resources/digital_library/appendicies/09c3_Riparian%20Buffer%20Science_YALE.pdf

Henry D. and Ramirez-Marquez J.E. (2012). Generic metrics and quantitative approaches for system resilience as a function of time. Reliability Engineering and System Safety, 99, 114–122

Hertel, T. W., & Lobell, D. B. (2012). Agricultural adaptation to climate change in rich and poor countries: Current modeling practice and potential for empirical contributions (No. Working Paper No. 72).

Hinkel, J. (2011). Indicators of vulnerability and adaptive capacity: Towards a clarification of the science– policy interface. Global Environmental Change, 21, 198-208.

Holling, C. S. (1973). Resilience and Stability of Ecological Systems. Annual Review of Ecology and Systematics, Vol. 4, 1-23.

Holling, C.S. (2001). Understanding the complexity of economic, ecological, and social systems. Ecosystems, 4(5): 390-405.

Hollister, J.W., Tarak Shah (2017). quickmapr: elevatr: Access Elevation Data from Various APIs. CRAN v0.1.2.

Hosseini, S., Barker, K., Ramirez-Marquez, J. E. (2016). A review of definitions and measures of system resilience. Reliability Engineering and System Safety, 145, 47-61.

Howitt, R., MacEwan, D., Medellín-Azuara, J., Lund, R., & Sumner. D. (2015). Economic Analysis of the 2015 Drought for California Agriculture. Center for Watershed Sciences, University of California – Davis, Davis, CA, 16 pp.

Howitt, R., Medellín-azuara, J., & MacEwan, D. (2014). Economic Analysis of the 2014 Drought for California Agriculture. Center for Watershed Sciences. University of California, Davis, California, 20p. Retrieved from http://watershed.ucdavis.edu

Huete, A., Didan, K., Miura, T., Rodriguez, E. ., Gao, X., & Ferreira, L. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sensing of Environment, 83(1–2), 195–213. http://doi.org/10.1016/S0034-4257(02)00096-2

Ignacio, J. Andres F., et al. (2016). Assessing the effectiveness of a social vulnerability index in predicting heterogeneity in the impacts of natural hazards: Case study of the Tropical Storm Washi flood in the Philippines. Vienna Yearbook of Population Research 2015: 91-129.

Independent Sector. (2018). The Value of Volunteer Time — Independent Sector. Retrieved from Value of Volunteer Time by State 2001-2016: https://independentsector.org/wp-content/uploads/2016/05/Value-of-Volunteer-Time-by-State-2001-2016.pdf

Johnson, D. M. (2016). A comprehensive assessment of the correlations between field crop yields and commonly used MODIS products. International Journal of Applied Earth Observation and Geoinformation, 52, 65-81.

Jönsson, P., & Eklundh, L. (2002). Seasonality extraction by function fitting to time-series of satellite sensor data. IEEE Transactions on Geoscience and Remote Sensing, 40(8), 1824–1832. http://doi.org/10.1109/TGRS.2002.802519

Jönsson, P., & Eklundh, L. (2004). TIMESAT—a program for analyzing time-series of satellite sensor data. Computers & Geosciences, 30(8), 833–845. http://doi.org/10.1016/j.cageo.2004.05.006

Kandala, N. B., Lang, S., Klasen, S., & Fahrmeir, L. (2001). Semiparametric analysis of the socio-demographic and spatial determinants of undernutrition in two african countries. Retrieved from https://epub.ub.uni-muenchen.de/1626/

Kaplan, S., & Garrick, B. J. (1981). On the quantitative definition of risk. Risk analysis, 1(1), 11-27.

Keck, M., Sakdapolrak, P. (2013). What is social resilience? Lessons learned and ways forward. ERDKUNDE. Vol. 67, No. 1, 5-19.

Kleinosky, Lisa R., Brent Yarnal, & Ann Fisher. (2007). "Vulnerability of Hampton Roads, Virginia to storm-surge flooding and sea-level rise." Natural Hazards 40.1 (2007): 43-70.

Kollet, S. J., and R. M. Maxwell. (2008). Capturing the influence of groundwater dynamics on land surface processes using an integrated, distributed watershed model. Water Resour. Res., 44, W02402, doi:10.1029/2007WR006004

Krishnamurthy, P. Krishna, & L. Krishnamurthy. (2011). Social Vulnerability Assessment through GIS Techniques: A Case Study of Flood Risk Mapping in Mexico. Geospatial Techniques for Managing Environmental Resources. Springer Netherlands. 276-291.

Kroll, C.A., Cray, A.F. (2010). Hedonic Valuation of Residential Resource Efficiency Variables.

A Review of the Literature. The Center for Resource Efficient Communities (CERC),

University of California, Berkley.

Lam, N. S., N., Reams, M., Li, K., Li, C., & Mata, L. P. (2015). Measuring Community Resilience to Coastal Hazards along the Northern Gulf of Mexico. Natural Hazards Review 17(1).

Lindgren, Finn, & Håvard Rue. (2015). "Bayesian spatial modelling with R-INLA." Journal of Statistical Software 63.19.

Linkov, I., Bridges, T., Creutzig, F., Decker, J., Fox-Lent, C., Kröger, W., & Nyer, R. (2014). Changing the resilience paradigm. Nature Climate Change, 4(6), 407-409.

Luers, A.L. (2005). The surface of vulnerability: an analytical framework for examining environmental change. Global Environmental Change, 15(3): 214-223.

Luers, A.L., Lobell, D.B. Sklar, L.S., Addams, C.L. & Matson, P.A. (2003). A method for quantifying vulnerability, applied to the agricultural system of the Yaqui Valley, Mexico. Global Environmental Change, 13(4): 255-267.

Maantay, J.A., Andrew R. M., & Herrmann, C. (2007). Mapping population distribution in the urban environment: The cadastral-based expert dasymetric system (CEDS). Cartography and Geographic Information Science 34.2: 77-102.

Maantay, J.A., & Maroko, A. (2009). Mapping urban risk: Flood hazards, race, & environmental justice in New York. Applied Geography 29.1: 111-124.

Maantay, J.A. (2007. Asthma and air pollution in the Bronx: methodological and data considerations in using GIS for environmental justice and health research. Health & place 13.1: 32-56.

Mann, M. E., & Gleick, P. H. (2015). Climate change and California drought in the 21st century. Proceedings of the National Academy of Sciences, 112(13), 3858–3859. http://doi.org/10.1073/pnas.1503667112

Manson, S., Schroeder, J., Van Riper, D., & Ruggles, S. (2017). IPUMS National Historical Geographic Information System: Version 12.0 [Database]. Minneapolis: University of Minnesota.

Manyena, S. B. (2006). The concept of resilience revisited. Disasters, 30(4): 433−450.

Martin, R. (2012). Regional economic resilience, hysteresis and recessionary shocks. Journal of Economic Geography, 12, 1–32.

Masterson, J. H., Peacock, W. G., Van Zandt, S. S., Grover, H., Schwarz, L. F., & Cooper, J. T. (2014). Planning for Community Resilience. Island Press. Washington, D.C.

Mayunga, J. S. (2007). Understanding and applying the concept of community disaster resilience: a capital-based approach. Summer academy for social vulnerability and resilience building, 1, 16.

Mayunga, J.S. (2009). Measuring the measure: A multi-dimensional scale model to measure community disaster resilience in the US Gulf Coast region. Diss. Texas A&M University.

McPherson, E. Gregory, J.R. Simpson, P.J. Peper, et al. (2007). *Northeast Community Tree Guide: Benefits, Costs, and Strategic Planning*. US Department of Agriculture, Forest Service. Retrieved from https://www.itreetools.org/streets/resources/Streets_CTG/PSW_GTR202_Northeast_CTG.pdf.

Medellín-Azuara, J., MacEwan, D., Howitt, R. E., Koruakos, G., Dogrul, E. C., Brush, C. F., ... & Lund, J. R. (2015). Hydro-economic analysis of groundwater pumping for irrigated agriculture in California's Central Valley, USA. Hydrogeology Journal, 23(6), 1205-1216.

Mennis, J. (2003).Generating surface models of population using dasymetric mapping∗. The Professional Geographer 55.1: 31-42.

Mennis, J. (2002). Using geographic information systems to create and analyze statistical surfaces of population and risk for environmental justice analysis. Social science quarterly 83.1: 281-297.

Metro Maps. (2017). Nashville Planning Department Property Mapping. http://www.nashville.gov/Planning-Department/Mapping-and-GIS/PropertyMapping.aspx

Miller, F., Osbahr, H., Boyd, E., Thomalla, F., Bharwani, S., Ziervogel, G.,... Nelson, D. (2010). Resilience and Vulnerability: Complementary or Conflicting Concepts? Ecology and Society 15 (3):11.

Milman, A., & Short, A. (2008). Incorporating resilience into sustainability indicators: An example for the urban water sector. Global Environmental Change, 18 (4): 758-767.

Minkser, B., Baldwin, L., Crittendon, J., Kabbes, K., Karamouz, M., Lansey, K.,... Williams, J. (2015). Progress and Recommendations for Advancing Performance-Based Sustainable and Resilient Infrastructure Design. J. Water Resour. Plann. Manage., 141(12).

Mkhabela, M. S., Bullock, P., Raj, S., Wang, S., & Yang, Y. (2011). Crop yield forecasting on the Canadian Prairies using MODIS NDVI data. Agricultural and Forest Meteorology, 151(3), 385-393.

Mukherji, A., & Shah, T. (2005). Groundwater socio-ecology and governance: a review of institutions and policies in selected countries. Hydrogeology Journal, 13(1), 328–345. https://doi.org/10.1007/s10040-005-0434-9

Myers, C. A., Slack,T. & Singelmann, J. (2008). Social vulnerability and migration in the wake of disaster: the case of Hurricanes Katrina and Rita. Population and Environment 29.6: 271-291.

NASA LP DAAC. (2015). *MOD13A2 Vegetation Indices 16-Day L3 Global 1km. Version 5*. NASA EOSDIS Land Processes DAAC, USGS Earth Resources Observation and Science (EROS) Center, Sioux Falls, South Dakota (https://lpdaac.usgs.gov). Accessed January 2016, at http://dx.doi.org/10.5067/ASTER/AST_L1T.003.

Nashville Financial Operations (NFO). (2017). Comprehensive Annual Financial Reports. Available at http://www.nashville.gov/Finance/Financial-Operations.aspx as of February 2017.

Nashville Metro Water Services (MWS). (2009). *Metropolitan Government of Nashville and Davidson County Green Infrastructure Master Plan*. Retrieved from https://www.nashville.gov/Portals/0/SiteContent/WaterServices/Stormwater/docs/reports/GreenInfrastructureRpt101120.pdf.

Nashville Metro Water Services (MWS). (2011). *Long Term Control Plan*. Retrieved from http://www.cleanwaternashville.org/content/resources/pdfs/pdr/LongTermControlPlan.pdf

Nashville Metro Water Services (MWS). (2013). *Unified Flood Preparedness Plan*. Retrieved from http://www.nashville.gov/Portals/0/SiteContent/WaterServices/docs/reports/UFPP%20Final%20report.pdf

NashvilleNext. (2016). *2016 Annual Report, A General Plan for Nashville & Davidson County*. retrieved from http://www.nashville.gov/Portals/0/SiteContent/Planning/docs/NashvilleNext/AnnualReports/2016AnnualReport-Final_v6_web.pdf

National Academies of Sciences, Engineering, and Medicine. (2016). Pathways to Urban Sustainability: Challenges and Opportunities for the United States. Washington, DC: The National Academies Press. doi:https://doi.org/10.17226/23551.

National Infrastructure Advisory Council (US). (2009). Critical Infrastructure Resilience: Final Report and Recommendations. National Infrastructure Advisory Council.

National Institute of Building Sciences (NIBS). (2017). *Natural Hazard Mitigation Saves: 2017 Interim Report*. National Institute of Building Sciences Multihazard Mitigation Council, December 2017.

National Oceanic and Atmospheric Administration (NOAA), National Weather Service. (2011). *Service Assessment. Record Floods of Greater Nashville: Including Flooding in Middle Tennessee and Western Kentucky, May 1 -4, 2010*. Retrieved from https://www.weather.gov/media/publications/assessments/Tenn_Flooding.pdf

National Oceanic and Atmospheric Administration (NOAA) (2018). [Chart of Point Precipitation Frequency Estimates for Nashville, TN]. *National Weather Service Hydrometeorological Design Studies Center Precipitation Frequency Data Server (PFDS)*. Retrieved from https://hdsc.nws.noaa.gov/hdsc/pfds/pfds_map_cont.html?bkmrk=tn

National Research Council. (2012). Dam and levee safety and community resilience: A vision for future practice. National Academies Press.

National Resources Conservation Service United States Department of Agriculture (NRCS-USDA). (1986). Urban Hydrology for Small Watersheds TR-55. Retrieved from https://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/stelprdb1044171.pdf

National Resources Conservation Service United States Department of Agriculture (NRCS-USDA). (2003). Where the Land and Water Meet A Guide for Protection and Restoration of Riparian Areas. Retrieved from https://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/nrcs142p2_010931.pdf

Nelson, K. S. & Burchfield, E.K.. (2016). *Does the Structure of Water Rights Impact Agricultural Production During Droughts? A Spatiotemporal Analysis of California's Central Valley. Panel Paper.* Association for Public Policy Analysis & Management 2016 Fall Research Conference. November 4th, 2016. Washington, D.C. Retrieved from https://appam.confex.com/appam/2016/webprogram/Paper18290.html

Nelson, K. S., & Burchfield, E. K. (2017). Effects of the structure of water rights on agricultural production during drought: A spatiotemporal analysis of California's Central Valley. Water Resources Research, 53, 8293–8309.

Nelson, K. S., Abkowitz, M.D., & Camp, J.V. (2015). A method for creating high resolution maps of social vulnerability in the context of environmental hazards. Applied Geography 63 : 89-100.

Nelson, K.S., Gillespie-Marthaler, L., Baroud, H., & Abkowitz, M.D. An Integrated and Dynamic Framework for Assessment of Sustainable Resilience. (*working paper*)

Ness, B., Urbel-Piirsalu, E., Anderberg, S., & Olsson, L. (2007). Categorising tools for sustainability assessment. Ecological economics, 60(3), 498-508.

Niemeijer, D.,& de Groot, R.S. (2008). Framing environmental indicators: moving from causal chains to causal networks. Environment, Development and Sustainability, 10: 89.

O'Connell, D., Walker, B., Abel, N., & Grigg, N. (2015). The Resilience, Adaptation and Transformation Assessment Framework: from theory to application. CSIRO, Australia.

Padgett, D.A. (2013). Environmental Justice in Emergency Preparedness for Natural Hazards: Are Vulnerable Populations in Nashville/Davidson County Equally Protected? National Environmental Justice Conference and Training Program Presentation. (April 3, 2013).

Pebesma, E. (2017). Simple Features for R. R package version 0.5-4. Available at https://CRAN.R-project.org/package=sf.

Pisano, I., & Lubell, M. (2015). Environmental Behavior in Cross-National Perspective A Multilevel Analysis of 30 Countries. Environment and Behavior: 0013916515600494.

Pope, J., Annandale, D., & Morrison-Saunders, A. (2004). Conceptualising sustainability assessment. Environmental Impact Assessment Review, 24 (6): 595-616.

Property Assessor, Metropolitan Nashville & Davidson County. (2018). Tax Rates & Calculator. Accessed at http://www.padctn.org/services/tax-rates-and-calculator/

Raghavan, R. K., Goodin, D. G., Neises, D., Anderson, G. A., & Ganta, R. R. (2016). Hierarchical Bayesian Spatio–Temporal Analysis of Climatic and Socio–Economic Determinants of Rocky Mountain Spotted Fever. PLOS ONE, 11(3), e0150180. https://doi.org/10.1371/journal.pone.0150180

Redman, C. L. (2014). Should sustainability and resilience be combined or remain distinct pursuits?. Ecology and Society, 19(2).

R-Core Team (2013). R: A language and environment for statistical computing

Roza, D.L., Caccia-Bava, M.D.C.G., and Martinez, E.Z. (2012). Spatio-temporal patterns of tuberculosis incidence in Ribeirão Preto, State of São Paulo, southeast Brazil, and their relationship with social vulnerability: a Bayesian analysis. Revista da Sociedade Brasileira de Medicina Tropical 45.5: 607-615.

Rygel, L., O'Sullivan, D. & Yarnal, B. (2006). A method for constructing a social vulnerability index: an application to hurricane storm surges in a developed country. Mitigation and Adaptation Strategies for Global Change 11, no. 3: 741–64.

Sahely, H. R., Kennedy, C. A., Adams, B. (2005). Developing sustainability criteria for urban infrastructure systems. Canadian Journal of Civil Engineering, 32, 1.

Sakamoto, T., Yokozawa, M., Toritani, H., Shibayama, M., Ishitsuka, N., & Ohno, H. (2005). A crop phenology detection method using time-series MODIS data. Remote Sensing of Environment, 96(3–4), 366–374. http://doi.org/10.1016/j.rse.2005.03.008

Savitzky, A., & Golay, M. J. (1964). Smoothing and differentiation of data by simplified least squares procedures. Analytical Chemistry, 36(8), 1627–1639.

Sawyers, G. W. Esq. (2005). A Primer On California Water Rights. University of California Agricultural Issues Centre 2005 Spring Outlook Forum. Retrieved from: http://aic.ucdavis.edu/events/outlook05/Sawyer_primer.pdf

Schlenker, W., & Roberts, M. J. (2006). Nonlinear effects of weather on corn yields. Applied Economic Perspectives and Policy, 28(3), 391-398.

Schlenker, W., Hanemann, W. M., & Fisher, A. C. (2007). Water availability, degree days, and the potential impact of climate change on irrigated agriculture in California. Climatic Change, 81(1), 19-38.

Schmidtlein, Mathew C., Roland C. Deutsch, Walter W. Piegorsch, and Susan L. Cutter. (2008). A sensitivity analysis of the social vulnerability index. Risk Analysis 28 (4): 1099–1114.

Schrödle, B., & Held, L. (2011). Spatio-temporal disease mapping using INLA. Environmetrics, 22(6), 725-734.

Schwarz, A. M. (2015). California Central Valley water rights in a changing climate. San Francisco Estuary and Watershed Science, 13(2). http://doi.org/10.5811/westjem.2011.5.6700

Scott, T. (2015). Does collaboration make any difference? Linking collaborative governance to environmental outcomes. Journal of Policy Analysis and Management, 34(3), 537-566.

Shepard, C.C., Agostini, V.N., Gilmer, B., Allen, T., Stone, J., Brooks, W., & Beck, M.W. (2012). Assessing future risk: quantifying the effects of sea level rise on storm surge risk for the southern shores of Long Island, New York. Natural Hazards 60, no. 2: 727–45.

Sherrieb, K., Norris, F.H., & Galea, S. (2010). Measuring capacities for community resilience. Social Indicators Research 99.2: 227-247.

Singh, R. K., Murty, H. R., Gupta, S. K., & Dikshit, A. K. (2012). An overview of sustainability assessment methodologies. Ecological Indicators, 15(1), 281-299.

Skøien, J. O., Blöschl, G., & Western, A. W. (2003). Characteristic space scales and timescales in hydrology. Water Resources Research, 39(10).

Small, C., & Milesi, C. (2013). Multi-scale standardized spectral mixture models. Remote Sensing of Environment, 136, 442–454. http://doi.org/10.1016/j.rse.2013.05.024

Smit, B. & Wandel, J. (2006). Adaptation, adaptive capacity and vulnerability. Global environmental change, 16(3), pp.282-292.

Stafford, S., and Abramowitz, J. "An analysis of methods for identifying social vulnerability to climate change and sea level rise: a case study of Hampton Roads, Virginia." Natural Hazards: 1-29.

Swain, D. L., Tsiang, M., Huagen, M., Singh, D., Charland, A., Rajaratnam, B., & Diffenbaugh, N. (2014). The extraordinary California drought of 2013/2014: Character, context, and the role of climate change. Bulletin of the American Meteorological Society, 95(7), S3–S7.

Tapp, A. F. (2010). "Areal interpolation and dasymetric mapping methods using local ancillary data sources." Cartography and Geographic Information Science 37.3: 215-228.

Tate, E., Cutter, S.L., & Berry, M. (2010). "Integrated multihazard mapping." Environment and planning. B, Planning & design 37.4: 646.

Tate, E. (2012). Social vulnerability indices: a comparative assessment using uncertainty and sensitivity analysis. Natural Hazards 63.2: 325-347.

Temmerman, S., Meire, P., Bouma, T., Herman, P., Ysebaert, T., & De Vriend, H. (2013). Ecosystem-based coastal defense in the face of global change. Nature, 504, 79-83.

Tidwell, V. C., Moreland, B. D., Zemlick, K. M., Roberts, B. L., Passell, H. D., Jensen, D., ... & Larsen, S. (2014). Mapping water availability, projected use and cost in the western United States. Environmental Research Letters, 9(6), 064009.

Tscherning, K., Helming, K., Krippner, B., Sieber, S., Paloma, S.G. (2012). Does research applying the DPSIR framework support decision making? Land Use Policy, 29, 102–110.

Turner, B. L., Kasperson, R. E., Matson, P. A., McCarthy, J. J., Corell, R. W., Christensen, L., ... & Polsky, C. (2003). A framework for vulnerability analysis in sustainability science. Proceedings of the national academy of sciences, 100(14), 8074-8079.

Turner, B.L. (2010). Vulnerability and resilience: Coalescing or paralleling approaches for sustainability science? Global Environmental Change 20, 570-576.

Turner, B.L. Kasperson, R. E., Matson, P. A., McCarthy, J.J., Corell, R. W., Christensen, L.,... Schiller, A. (2003). A framework for vulnerability analysis in sustainability science. Proceedings of the National Academy of Sciences of the United States of America, vol. 100, 8074–8079.

Turner, M. G., Neill, R. V. O., Gardner, R. H., & Milne, B. T. (1989). Effects of changing spatial scale on the analysis of landscape pattern. Landscape Ecology, 3, 153–162. http://doi.org/10.1007/BF00131534

U.S. Drought Monitor. (2017). U.S. Drought Monitor Map Archive. Accessed June 2017, at https://droughtmonitor.unl.edu/MapsAndData/MapArchive.aspx.

U.S. Geological Survey. (2012). Alluvial Boundary of California's Central Valley. Available at https://water.usgs.gov/GIS/metadata/usgswrd/XML/pp1766_Alluvial_Bnd.xml (accessed {May 2016}). U.S. Geological Survey, Reston, Virginia.

U.S. Geological Survey (USGS). (2017). [3DEP products and services: The National Map, 3D Elevation Program]. *The National Map.* Retrieved from https://nationalmap.gov/3DEP/3dep_prodserv.html

U.S. Geological Survey b (USGS b). (2017). [National Hydrography Dataset: The National Map] *The National Map.* Retrieved from https://nhd.usgs.gov/index.html

UN General Assembly. (2015). Transforming our world: the 2030 Agenda for Sustainable Development, A/RES/70/1.

United States Bureau of Reclamation [USBR] (2017). Central Valley Project Water Supply. Accessed June 2017, at https://www.usbr.gov/mp/cvp-water/.

United States Bureau of Reclamation [USBR] (2017b). CVP Water Users/Contractors and Other Sources: Ag Contractors. Retrieved from: https://www.usbr.gov/mp/cvp-water/docs/ag-contractors-website.pdf.

United States Census Bureau. (2012). TIGER/Line Shapefiles with 2008-2012 American Community Survey 5-year estimates, Tennessee. Washington, D.C.

United States Census Bureau b. (2017). *U.S. Census Bureau: State and County QuickFacts*. Accessed from http://quickfacts.census.gov/qfd/states/47/47037.html

United States Census Bureau c. (2017). [Summary Tables, 2005 – 2019 to 2011-2015, 5-year estimates] American Community Survey. U.S. Census Bureau's American Community Survey Office. Retrieved from http://factfinder2.census.gov

United States Environmental Protection Agency. (1996). 1996 Environmental Justice Implementation Plan. EPA/300-R-96-004.

Upadhyaya, J. K., Biswas, N., & Tam, E. (2014). A review of infrastructure challenges: assessing stormwater system sustainability. Can. J. Civ. Eng., 41, 483–492.

USDA National Agricultural Statistics Service. (2016). Cropland Data Layer {2007-2015}. Available at https://nassgeodata.gmu.edu/CropScape/ (accessed {January 2016}). USDA-NASS, Washington, DC.

Vale, L. (2007). The resilient city. Sociologia urbana e rurale.

Vale, L. J. (2014). The politics of resilient cities: whose resilience and whose city? Building Research & Information, 42(2), 191-201.

Vale, L. J., & Campanella, T. J. (2005). The resilient city: How modern cities recover from disaster. Oxford University Press.

Walker, B., Holling, C.S., Carpenter, S.R. & Kinzig, A. (2004). Resilience, adaptability and transformability in social--ecological systems. Ecology and society, 9(2).

Wang, J., Rich, P. M., Price, K. P., & Kettle, W. D. (2005). Relations between NDVI, grassland production, and crop yield in the central Great Plains. Geocarto International, 20(3), 5-11.

Warhurst, A. (2002). Sustainability Indicators and Sustainability Performance Management. Mining, Minerals and Sustainable Development, No. 43.

WCED (World Commission on Environment and Development). (1987). Our Common Future. Oxford University Press, Oxford.

Wenz, P. S. (1988). Environmental justice. SUNY Press.

Whan, K., Zscheischler, J., Orth, R., Shongwe, M., Rahimi, M., Asare, E. O., & Seneviratne, S. I. (2015). Impact of soil moisture on extreme maximum temperatures in Europe. Weather and Climate Extremes, 9, 57-67.

Wilhelmi, O.V., & Morss, R.E. (2013). Integrated analysis of societal vulnerability in an extreme precipitation event: A Fort Collins case study. Environmental science & policy 26: 49-62.

Wilkinson, C. (2012). Social-ecological resilience: Insights and issues for planning theory. Planning Theory, 11(2), 148-169.

Wolshon, B. (2006). Evacuation planning and engineering for Hurricane Katrina. Bridge, 36(1): 27-34.

Wood, N.J., Burton, C.G., & Cutter, S.L. (2010). Community variations in social vulnerability to Cascadia-related tsunamis in the U.S. Pacific Northwest. Natural Hazards 52, no. 2: 369–89.

Wu, J., & David, J.L. (2002). A spatially explicit hierarchical approach to modeling complex ecological systems: theory and applications. Ecological Modelling 153.1: 7-26.

Xiao, X., Boles, S., Frolking, S., Li, C., Babu, J. Y., Salas, W., & Moore, B. (2006). Mapping paddy rice agriculture in South and Southeast Asia using multi-temporal MODIS images. Remote Sensing of Environment, 100(1), 95–113. http://doi.org/10.1016/j.rse.2005.10.004

Zilberman, D., Dinar, A., MacDougall, N., Brown, C., & Castillo, F. (2002). Individual and institutional responses to the drought: The case of California agriculture. Journal of Contempory Water Research and Education, 121(1), 17–23.

APPENDIX A

Table A 1: Selectively Distributed Variables

	Variable	Excluded Properties	Assigned Properties
Disaggregated Sub-population	Age 5 and Under	Nursing Home, Elderly Housing, Jail, Women's Jail, Dormitory/Boarding House, School or College, Sanitarium	N/A
	Age 65 and Over	Dormitory/Boarding House (if not also Elderly Housing), School or College	Nursing Homes, Elderly Housing
	Age 65 and Over in Group Quarters	Dormitory/Boarding House (if not also Elderly Housing), School or College	Nursing Homes
	Women	Jail	Women's Jail
	Employed Women	Jail	Women's Jail
	Population in Group Quarters	N/A	Nursing Home, Dormitory/Boarding House, School or College, Orphanage/Charitable Service (unless also Single Family Dwelling), Sanitarium, Jail, Women's Jail
Parcel-Specific Economic or Physical Characteristic	Rental/Semi-Permanent Housing	All Others	Duplex(s), Triplex(s), Quadplex(s), Nursing Home, Parsonage, Orphanage/Charitable Service, Dormitory/Boarding House, Apartment
	Owner Occupied Housing with Value Greater than $200,000	All Others	Single Family Dwelling, Residential Condominium Unit, Residential Zero Lot Line, Mobile Home, Residential Combination, Mobile Home Park, Rural Combination where the total appraisal value was greater than $200,000
	Mobile Homes	All Others	Mobile Home, Mobile Home Park
	Rural	All Others	Single Family Dwelling, Mobile Home, Duplex, Triplex, Combination where also designated as Rural
	Number of Hospitals Within 3 Mile Radius	N/A	All parcels within a 3 mile radius of a Davidson County hospital or medical clinic.
	Property Total Appraisal Value	N/A	All Properties

Table A 2: Block-Group Social Vulnerability Index Variables

Social Dimension	Variable Type	ACS 2012 5yr Block-Group Estimates Variable/s Short Name	Variable Normalization	Component Variable Loads on Significantly
Age	Median Age	B01002e1	None	Elderly
	Age Under 5 Years	B01001e3 + B01001e27	Total Population (B01003e1)	Families
	Age Over 65 Years	B09020e1	Total Population (B01003e1)	Elderly
Gender	Female	B01001e26	Total Population (B01003e1)	Women
	Female Civilian Employed, Age 16 and Up	C24010e38	Total Civilian Employed, Age 16 and Up (C24010e1)	Women
Race/Ethnicity	African American Alone	B02001e3	Total Population (B01003e1)	Race/Class
	Some Other Race/Races	B02001e4+B02001e5+ B02001e6 + B02001e7+ B02001e8	Total Population (B01003e1)	Foreign Born
	Hispanic or Latino	B03003e3	Total Population (B01003e1)	Foreign Born
Employment	Unemployed In Labor Force, Age 16 and Up	B23025e5	Total Civilian Labor Force (B23025e2)	Race/Class
	Participating Civilian Labor Force, Age 16 and Up	B23025e2	Total Population, Age 16 and Up (B23025e1)	Institutional and Group Living
Occupation	Service Workers	C24010e19 + C24010e55	Total Civilian Labor Force (C24010e1)	Race/Class
	Natural Resources, Construction, Maintenance Workers	C24010e30 + C24010e66	Total Civilian Labor Force (C24010e1)	Foreign Born
	Production, Transportation, Material Moving Workers	C24010e34 + C24010e70	Total Civilian Labor Force (C24010e1)	Economic Status & Housing Quality
Medical Services	Healthcare Workers	C24010e16 + C24010e20 + C240101e52 + C240101e56	Total Population (B01003e1)	Institutional and Group Living
	Number of Hospitals	Not Available (Use Tax Info)	Total Population (B01003e1)	Hospice Care
Family Structure	Population in Occupied Housing Units	B25008e1	Total Occupied Housing Units (B25007e1)	Families
	Female Householder, No Husband Present	B09002e15	Total Households with Children (B09002e1)	Race/Class
Housing Quality	Number of Mobile Homes		Total Housing Units (B25001e1)	Housing Quality
Renters	Renter-Occupied Housing Units	B25056e1	Total Occupied Housing Units (B25007e1)	Race/Class

	Median Gross Rent	B25064e1	None	Institutional and Group Living
Education	Over Age 25 with No High School Diploma	B15003e16	Population Over Age 25 (B15003e1)	Foreign Born & Rural
Special Needs	Over Age 65 in Group Quarters	B09020e21	Population Over Age 65 (B09020e1)	Hospice Care
	With a Disability, Age 16-64	C23023e3 + C23023e14	Population Age 16-64 (C23023e1)	Women
	Population in Group Quarters	B09019e38	Total Population (B01003e1)	Institutional and Group Living
Social Dependence	Households with Social Security Income	B19055e2	Total Households (B16002e1)	Elderly
	Households Receiving Food Stamps/ SNAP in Past 12 Months	B22010e2	Total Households (B16002e1)	Race/Class
Immigrants	Households Where No One Age 14 or Older Speaks English Only or English "Very Well"	B16002e4 + B16002e7 + B16002e10 + B16002e13	Total Households (B16002e1)	Foreign Born
Wealth and Income	Per Capita Income (2012 Adjusted $)	B19301e1	None	Economic Status
	Household Income > $100,000	B19001e14 + B19001e15 + B19001e16 + B19001e17	Total Households (B16002e1)	Economic Status
	Population Below Poverty Level in the Past 12 Months	B17021e2	Total Population (B01003e1)	Race/Class
	Median Home Value	B25077e1	None	Economic Status
	Owner Occupied Housing Units with Value < $100,000	B25075e2 + B25075e3 +B25075e4+B25075e5+B25075e6+B25075e7+ B25075e8 +B25075e9+ B25075e10 +B25075e11 +B25075e12+ B25075e13+ B25075e14	Total Owner Occupied Housing Units (B25075e1)	Housing Quality
	Owner Occupied Housing Units with Value $100,000 - $200,000	B25075e15+B25075e16+B25075e17+ B25075e18	Total Owner Occupied Housing Units (B25075e1)	Economic Status
	Owner Occupied Housing Units with Value > $200,000	B25075e19+B25075e20+B25075e21+ B25075e22+B25075e23+B25075e24+ B25075e25	Total Owner Occupied Housing Units (B25075e1)	Economic Status
Transportation	Population Using Public Transportation to Get to Work, Age 16 and Over	B08134e61	Total Worker Population (B08134e1)	Race/Class
	Occupied Housing Units with No Vehicle Available	B25044e3 + B25044e10	Total Occupied Housing Units (B25007e1)	Race/Class
Rural	Land in Farms/Rural Use	Not Available (Use Tax Info)	Total Population (B01003e1)	Rural

Table A 3: Parcel Scale Social Vulnerability Index Variables

Social Dimension	Variable Type	ACS 2012 5yr Block-Group Estimates Variable/s Short Name	Variable Normalization	Component Variable Contributes to Significantly
Age	Age Under 5 Years	B01001e3 + B01001e27	Total Population per Parcel	Families
	Age Over 65 Years	B09020e1	Total Population per Parcel	Elderly
Gender	Female	B01001e26	Total Population per Parcel	Women
	Female Civilian Employed, Age 16 and Up	C24010e38	Total Civilian Employed, Age 16 and Up per Parcel	Women
Race/Ethnicity	African American Alone	B02001e3	Total Population (B01003e1)	Race/Class
	Some Other Race/Races	B02001e4+B02001e5+ B02001e6 + B02001e7+ B02001e8	Total Population (B01003e1)	Foreign Born
	Hispanic or Latino	B03003e3	Total Population (B01003e1)	Foreign Born
Employment	Unemployed In Labor Force, Age 16 and Up	B23025e5	Total Civilian Labor Force (B23025e2)	Families
	Participating Civilian Labor Force, Age 16 and Up	B23025e2	Total Population, Age 16 and Up (B23025e1)	Elderly
Occupation	Service Workers	C24010e19 + C24010e55	Total Civilian Labor Force (C24010e1)	Race/Class
	Natural Resources, Construction, Maintenance Workers	C24010e30 + C24010e66	Total Civilian Labor Force (C24010e1)	Foreign Born
	Production, Transportation, Material Moving Workers	C24010e34 + C24010e70	Total Civilian Labor Force (C24010e1)	Economic Status
Medical Services	Healthcare Workers	C24010e16 + C24010e20 + C240101e52 + C240101e56	Total Population (B01003e1)	Economic Status
	Number of Hospitals in 3 mile radius of parcel	Davidson County Tax Info	None	Race/Class
Family Structure	Population per tax lot/household	B01003e1	Tax Lot Footprint Area	Renters/ Population Density
	Female Householder, No Husband Present	B09002e15	Total Households with Children (B09002e1)	Race/Class
Housing Quality	Number of Mobile Homes per parcel	Tax Info	None	Mobile Homes
Renters	Population in Renter-Occupied parcels	Tax Info	None	Renters/ Population Density
Special Needs	Over Age 65 in Group Quarters	B09020e21	Population Over Age 65 per parcel	Institutional and Group Living

	With a Disability, Age 16-64	C23023e3 + C23023e14	Population Age 16-64 (C23023e1)	Women
	Population in Group Quarters	B09019e38	Total Population per Parcel	Institutional and Group Living
Social Dependence	Households with Social Security Income	B19055e2	Total Households (B16002e1)	Elderly
	Households Receiving Food Stamps/ SNAP in Past 12 Months	B22010e2	Total Households (B16002e1)	Race/Class
Immigrants	Households Where No One Age 14 or Older Speaks English Only or English "Very Well"	B16002e4 + B16002e7 + B16002e10 + B16002e13	Total Households (B16002e1)	Foreign Born
Wealth and Income	Household Income > $100,000	B19001e14 + B19001e15 + B19001e16 + B19001e17	Total Households (B16002e1)	Economic Status
	Population Below Poverty Level in the Past 12 Months	B17021e2	Total Population (B01003e1)	Race/Class
	Parcel Value	Davidson County Tax Info	Total population per parcel	Economic Status
	Owner Occupied Housing with Value > $200,000	Davidson County Tax Info	None	Economic Status
Transportation	Population Using Public Transportation to Get to Work, Age 16 and Over	B08134e61	Total Worker Population (B08134e1)	Race/Class
	Occupied Housing Units with No Vehicle Available	B25044e3 + B25044e10	Total Occupied Housing Units (B25007e1)	Race/Class

APPENDIX B

Summary of the Appendix Material

This study involved compilation of a large spatiotemporal dataset and use of novel Bayesian spatial modeling techniques. Here we provide additional information regarding primary data sources and data transformation in Table B 1. Additional information regarding crop type aggregation is provided in Table B 2. Figure B 1 displays the extents of the study area and individual watershed boundaries. Figures B 2 through B 5, Figure B 7, and Figure B 12 provide visualizations of some of the data described in Table B 1 and in the Methods and Data section of the paper. Additional information on water rights data processing procedures is provided in Text B 1. Text B 2 and Figure B 6 provide additional information on contract water representation within the dataset used for the analyses described in the paper. Additional information on groundwater modeling procedures and results are provided in Text B 3 and Figures B 8 through B 11. In addition, complete model results providing full summaries of marginal posterior effect estimates for all non-spatially varying variables are provided in Tables B 8 and B 9. Additional information used to justify model selection is provided in Tables B 3 through SB 7 and Table B 10. Scripts used for dataset compilation, modeling, and figure creation are available at the authors' GitHub repository (https://github.com/katesnelson/CA_drought) or upon request. Note that model runs are computationally intensive. All models were run on a computer with 72 available threads and > 100 GB RAM. Despite this, model runs in excess of 24 hours of real time were not uncommon.

Table B 1: Summary of data sources, types, and transformations used in the compiled dataset.

Variable	Data Source	Spatial Data Type/ Spatial Resolution/ Temporal Resolution	Data Transformation	Spatial Scale in Analyses	Definition
Agricultural Land	CA Farmland Mapping and Monitoring Program	Spatial Polygons/ Sub-watershed/ Biennial	Spatial union across all years.	NA	Land classified as farmland or grazing land.
TVP	NASA LP DAAC: MOD13A2	Raster/ 1km pixel/ 16 day	Calculated integral of annual time series for each pixel and year.	Field	Total vegetative production. (Proxy for agricultural production.)
Crop Type	USDA CropScape	Raster/ 30m pixel/ Annual	Aggregated categories into six general land use types.	Field	Crop or land cover type.
Depth to Groundwater	GeoTracker GAMA	Point/ NA/ Daily	Spacetime kriging used to interpolate groundwater elevations (in ft above msl) to a 10km grid on a monthly time step. Depth to groundwater in January was calculated for each grid cell and year.	Field	Pre-growing season depth to groundwater (ft).
Water Rights Density	CA SWRCB: eWRIMS	Point/ NA/ Daily	Calculated as the count of all surface water right PODs with stated beneficial uses of irrigation, heat control, and frost protection (agricultural uses) in a watershed per square kilometers of farmland area in a watershed.	Watershed	Density of all agricultural use surface water right PODs associated with farmland in a watershed.
Percent Riparian	CA SWRCB: eWRIMS	Point/ NA/ Daily	Count of Riparian status agricultural use water right PODs in a watershed divided by the count of all agricultural use surface water right PODs in the watershed.	Watershed	Percent of agricultural surface water right PODs in a watershed that have Riparian status.
Percent Pre-1914	CA SWRCB: eWRIMS	Point /NA/ Daily	Count of Pre-1914 status agricultural use water right PODs in a watershed divided by the count of all agricultural use surface water right PODs in the watershed.	Watershed	Percent of agricultural surface water right PODs in a watershed that have Pre-1914 status.
Percent Appropriative	CA SWRCB: eWRIMS	Point /NA/ Daily	Count of Post-1914 Appropriative agricultural use water right PODs in a watershed divided by the count of all agricultural use surface water right PODs in the watershed.	Watershed	Percent of agricultural surface water right PODs in a watershed that have Post-1914 Appropriative status.
Crop Diversity	USDA CropScape	Raster/30m pixel/ Annual	Calculated index of watershed crop diversity. (Turner et.al., 1989)	Watershed	Diversity of crops grown in a watershed.
Percent Agricultural	CA SWRCB: eWRIMS	Point /NA/ Daily	Count of agricultural use water right PODs in a watershed divided by the count of all surface water right PODs in the watershed.	Watershed	Percent of water rights PODs in a watershed that are associated with agricultural water use.
SPI	AghaKouchak and Nakhijiri	Raster/ 1/8th degree grid/ Monthly	Annual sum of monthly records of the 9-month SPI index .	Watershed	Annual cumulative index of the 9 month precipitation deficit.

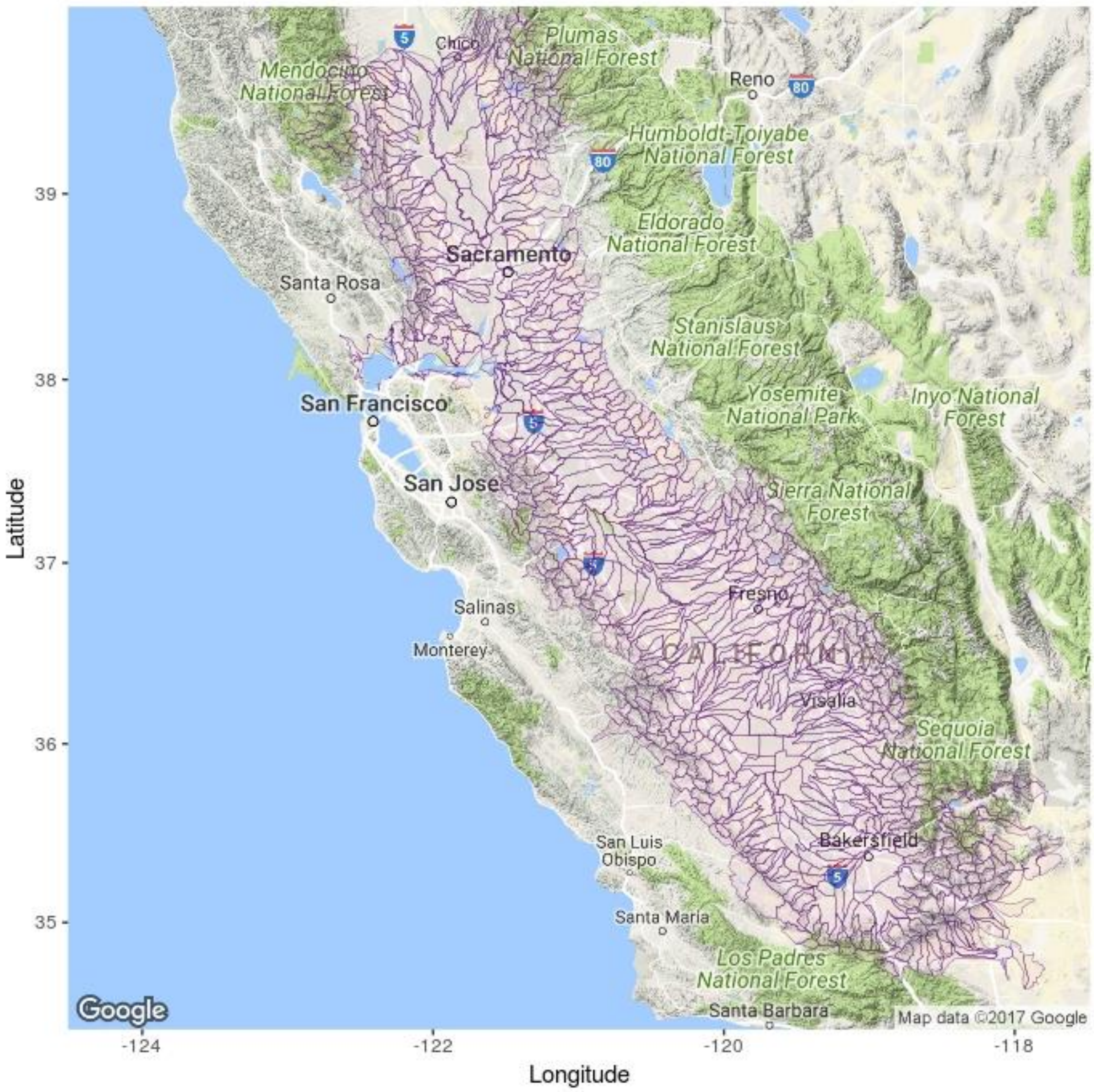

Figure B 1: Spatial extents and watershed boundaries (purple lines) of California Central Valley used in analyses. Spatial extent of the study area was determined as the intersection of watersheds, the alluvial central valley boundary [U.S. Geological Survey, 2012] and the NASA Moderate Resolution Imaging Spectroradiometer (MODIS) tile (NASA LP DAAC, 2015) covering the majority of California.

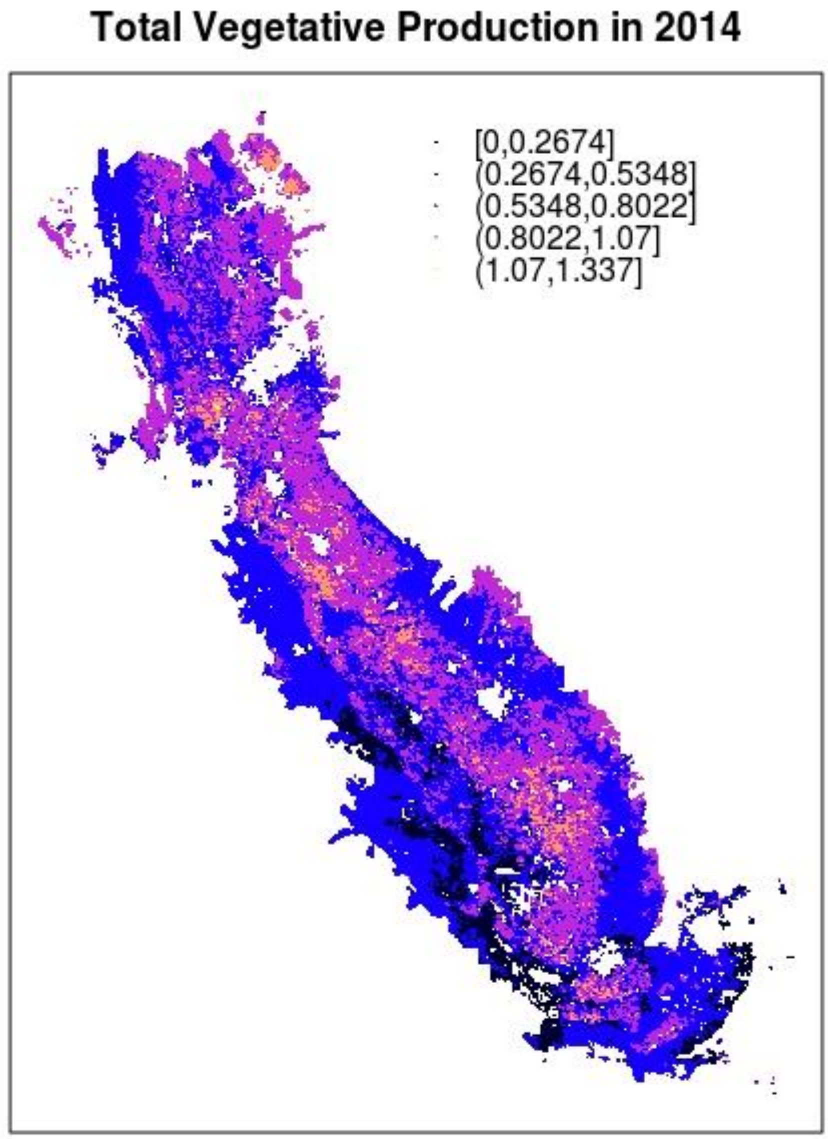

Figure B 2: Spatial pattern of total vegetative production for the area of study in 2014. Lower total vegetative production (TVP) shown as dark colors and higher TVP as light colors.

Text B 1

Water rights data used in this study were obtained from the CA SWRCB electronic water rights information management system (eWRIMS) and aggregated to watersheds for analyses (CA SWRCB, 2016c). All available digitized water rights records were downloaded in Microsoft Excel format from the CA SWRCB electronic water rights information management system (eWRIMS) by their beneficial use category (CA SWRCB, 2016c). Water right descriptive information and point of diversion (POD) information on different worksheets were joined by the water rights application identification number. Water right PODs were then classified according to a simplified beneficial use scheme including categories of agriculture (irrigation, heat control, and frost protection), animal husbandry (stock watering, aquaculture), domestic (domestic, municipal, aesthetic), industrial (industrial, dust control, power, mining, milling, incidental power), fish and wildlife (fish and wildlife preservation and enhancement, fire protection), and recreation (recreational, other, snow making). Duplicate records, records without geospatial location information, and spatial duplicates of water rights POD locations with the same beneficial use were then removed. To create a panel dataset of active water right POD records the dataset was divided into annual sets such that all the water rights in each year's set were classified as active (status not cancelled, closed, inactive, rejected, or revoked) and had a "status date" that corresponding to the current or any previous year. This effectively restricts each year's water right POD records to water rights that were active for all or some part of the year of interest. To aggregate water right PODs to the watersheds a spatial join of the Central Valley watershed polygon shapefile and the water right POD point shapefile was conducted for each of the annual water right POD records. The count of PODs for each type of water right of interest was computed for each watershed-year and the resulting annual watershed water rights datasets were merged by the watershed identification code into a single wide format spatiotemporal dataset. Due to inconsistency in digital records prior to 2010 only data for years 2010-2014 were used in this study.

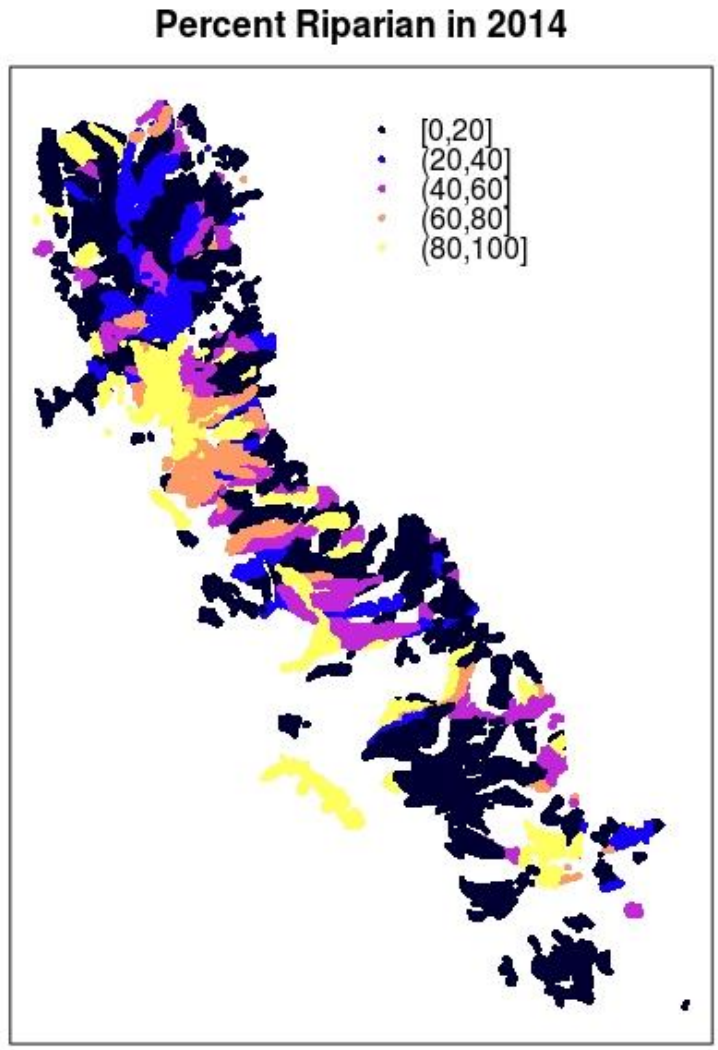

Figure B 3: Spatial distribution of percent Riparian water rights in watersheds for the area of study in 2014.

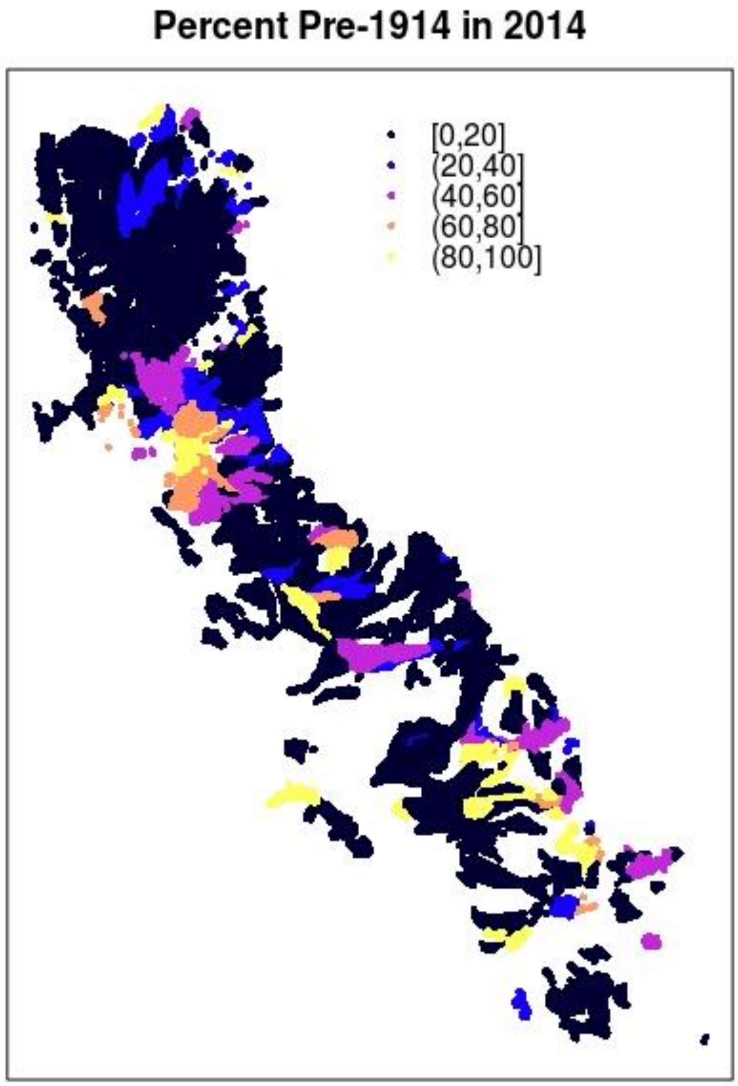

Figure B 4: Spatial distribution of percent Pre-1914 water rights in watersheds for the area of study in 2014.

Percent Appropriative in 2014

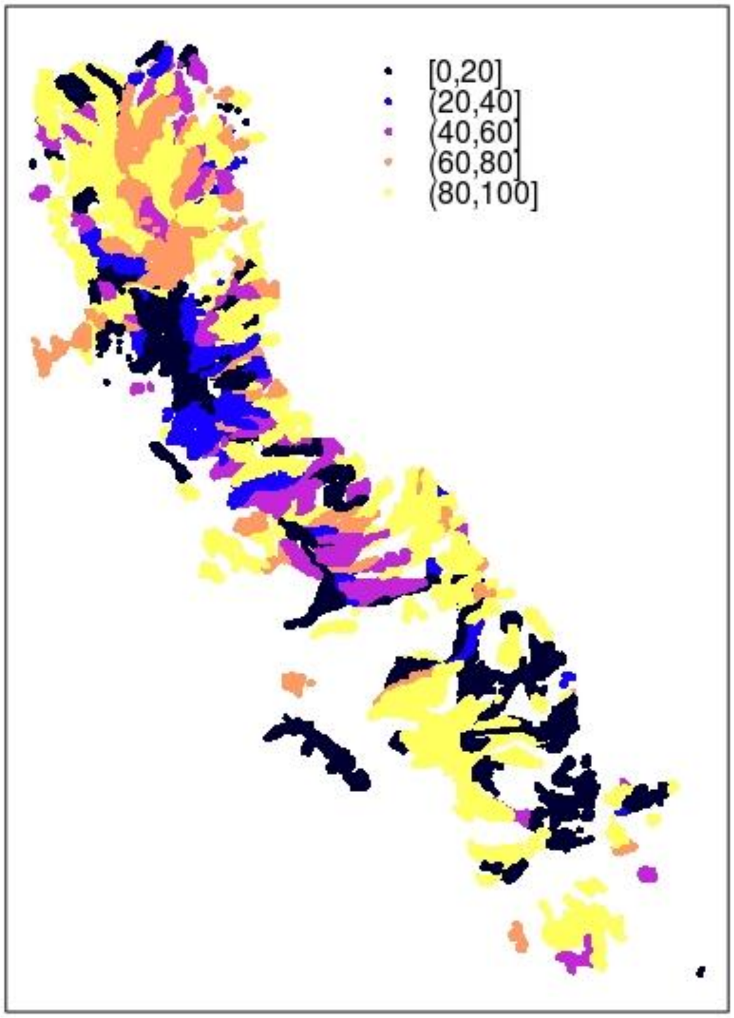

Figure B 5: Spatial distribution of percent Appropriative water rights in watersheds for the area of study in 2014.

Text B 2

The location of water right PODs associated with known State Water Project (SWP) and Central Valley Project (CVP) water contractors was examined to determine the extent of contract water representation within the compiled dataset. Agricultural water contractor names listed by the California department of Water Resources (CA DWR, 2017b) and the U.S. Bureau of Reclamation

(USBR, 2017b) were associated with Primary Owner names for each water right in the water rights data collected from the CA SWRCB electronic water rights information management system (eWRIMS) (CA SWRCB, 2016c). In all, an estimated 103 known water contractors (approximately 40% of all reported water contractors) were associated in some way with a water right within our dataset. The water right points of diversion associated with these water contractors were mapped in order to determine the spatial coverage associated with these rights and is given in Figure B 6.

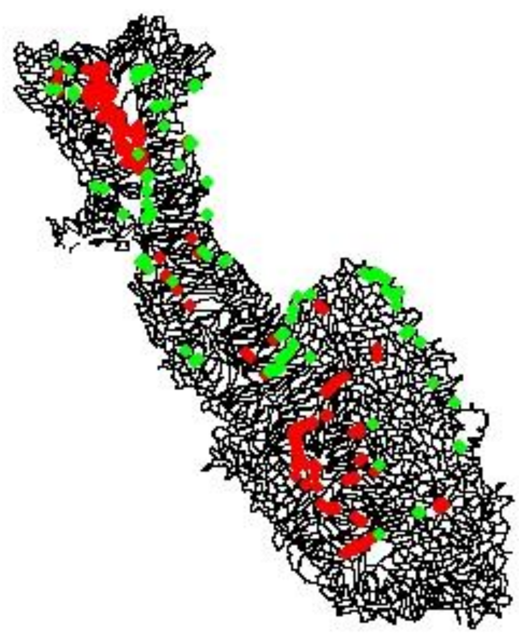

Figure B 6: Spatial distribution of water right points of diversion associated with known SWP and CVP water contractors. Green points indicate the water right is held by either the state or federal government. Red points are all other water right owners who are also identified as water contractors.

Table B 2: Aggregation scheme for USDA CropScape land use classifications based on range of TVP values for each land use type in 2009.

Barren & Fallow		Grasses		Grains		Row Crops		Fruit & Nuts		Uncultivated Cover	
USDA CropScape Land Use Name / Numerical ID											
Barren	131	Sod	59	Triticale	205	Dry Beans	42	Grapes	69	Mixed Forest	143
Fallow	61	Clover	58	Rice	3	Potatoes	43	Almonds	75	Shrubland	152
		Hay	37	Winter Wheat	24	Cotton	2	Walnuts	76	Woody Wetlands	190
		Alfalfa	36	Corn	1	Sunflowers	6	Olives	211	Herb Wetlands	195
				Durum Wheat	22	Safflower	33	Cherries	66	Grassland	176
				Oats	28	Tomatoes	54	Peaches	67		
				Rye	27						

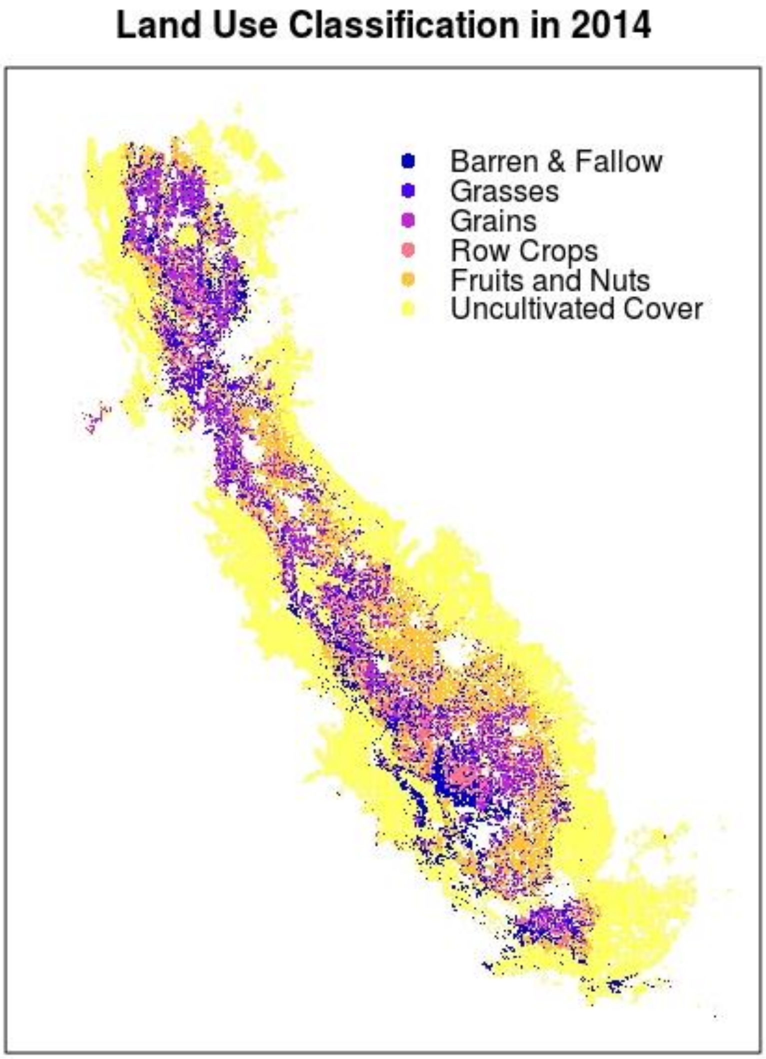

Figure B 7: Spatial distribution of crop types across the Central Valley in 2014.

Text B 3

In order to create a gridded depth to groundwater dataset with consistent time steps we conducted spatiotemporal kriging of groundwater elevations. Wells monitored by the California Statewide Groundwater Elevation Monitoring Program (CASGEM) program and falling within the Central Valley were extracted from the full CASGEM dataset (n = 109,318) (GeoTracker GAMA, 2016). Wells with extremely high or low groundwater elevations were removed from the sample (> - 50 and < 4000 were included; < 2 % of the entire dataset was dropped). The raw elevation data was log transformed so ensure it followed a normal distribution, as high skewness and outliers may have an undesirable impact on semivariogram structure and kriging estimates [Gundogu and Guney, 2007]. We randomly selected 60 % of the data for sample variogram construction (n = 61,675); the other 30% of the data was held out for testing (n = 47,643). Using the spacetime package in R, we plotted empirical variograms for space and time (Figure B 8) and visually assessed each variogram to define boundaries for upper and lower parameters [(Graler et al., 2016).

Our spatial variogram showed a strong Gaussian shape, so we estimated models with spatial Gaussian components. A spatial cutoff of 60 kilometers was included in the variograms, which reduces the risk of over fitting the variogram model to large distances not used for prediction (Graler et al., 2016; Skøien & Blöschl, 2003]). Conversely, a temporal cutoff of 180 days and minimum interval time of 30 days was used for the temporal component of the variogram model in order to avoid over fitting to short-term trends [(Skøien & Blöschl, 2003). Multiple semi-variogram models were fit to the data and the MSE was compared across models. We found that the sum-metric variogram had the lowest unweighted MSE, suggesting better fit (Figure B 9).

Well point data was kriged through space-time onto a 10 kilometer grid at monthly intervals using the sum metric variogram estimated for our dataset. The predicted gridded elevation values were compared to the held out observations at actual wells located within a kriged 10 x 10 kilometer grid cell for each month-time interval. The mean normalized RMSE of the kriged data against the held-out observations is 0.08 and the Nash Sutcliffe efficiency is 0.80. The average differences between observed and predicted elevations across space and time are shown in Figures S10 and S11.

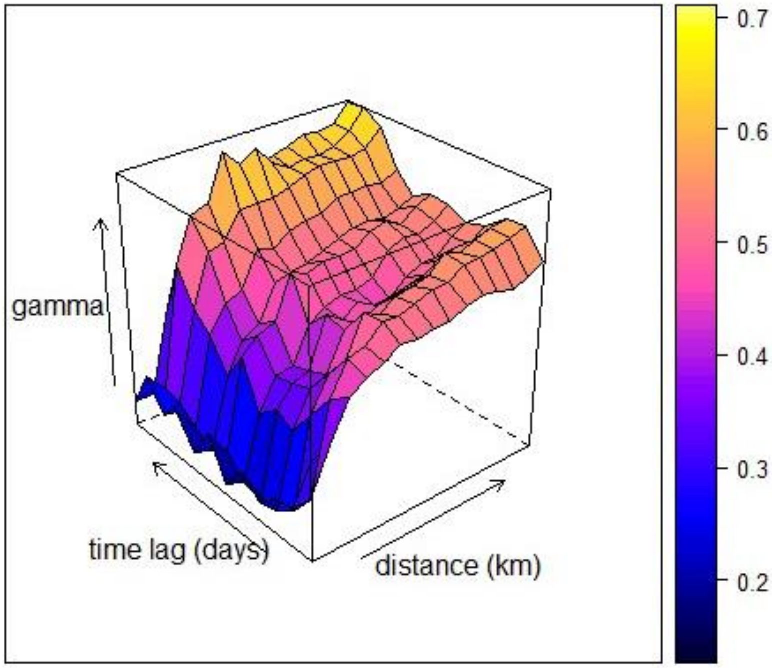

Figure B 8: Empirical space-time variogram of groundwater elevation data for the Central Valley.

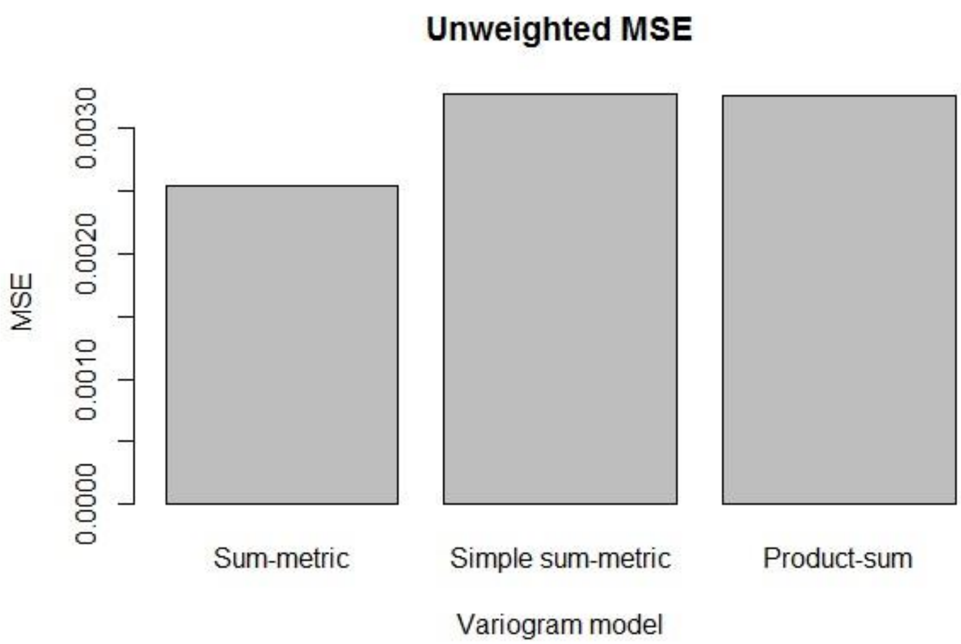

Figure B 9: Unweighted MSE for the fit of different variogram models to the empirical space-time variogram.

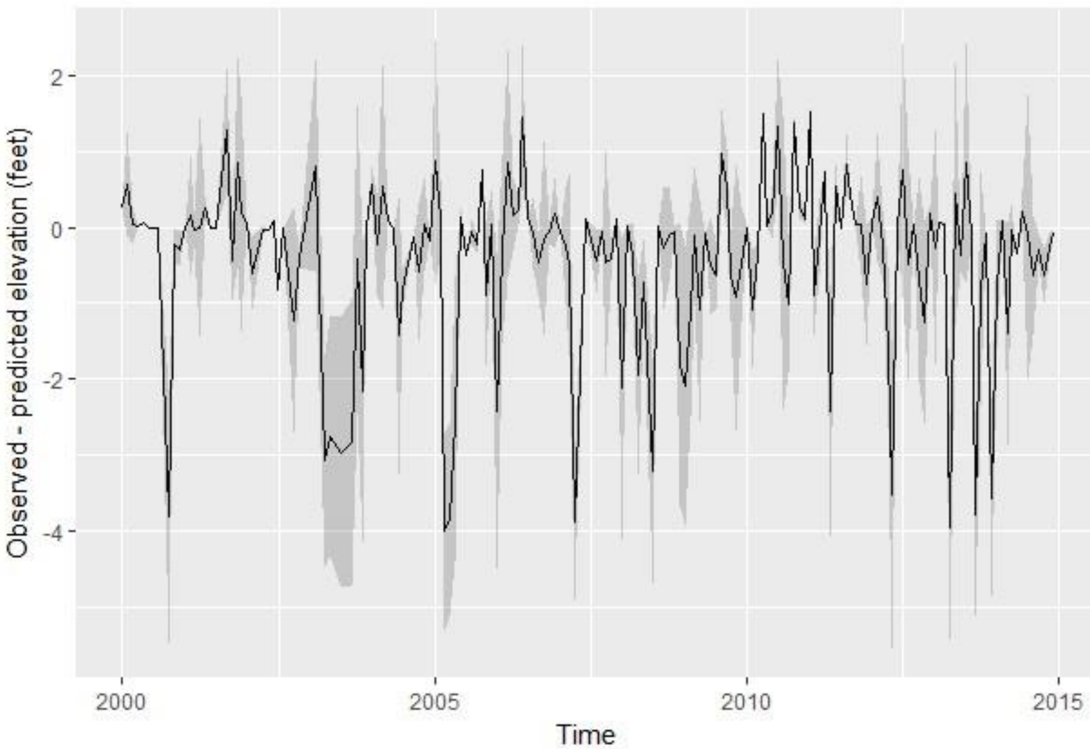

Figure B 10: Average difference between held out observations and predicted estimates across time (monthly intervals).

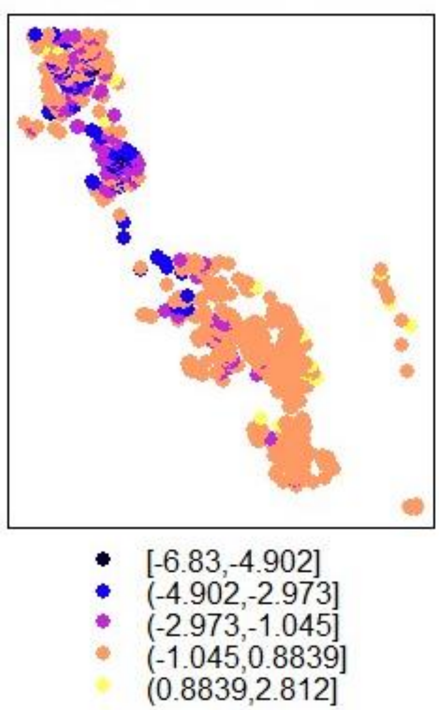

Figure B 11: Average difference between held out observations and predicted estimates (in feet) across space.

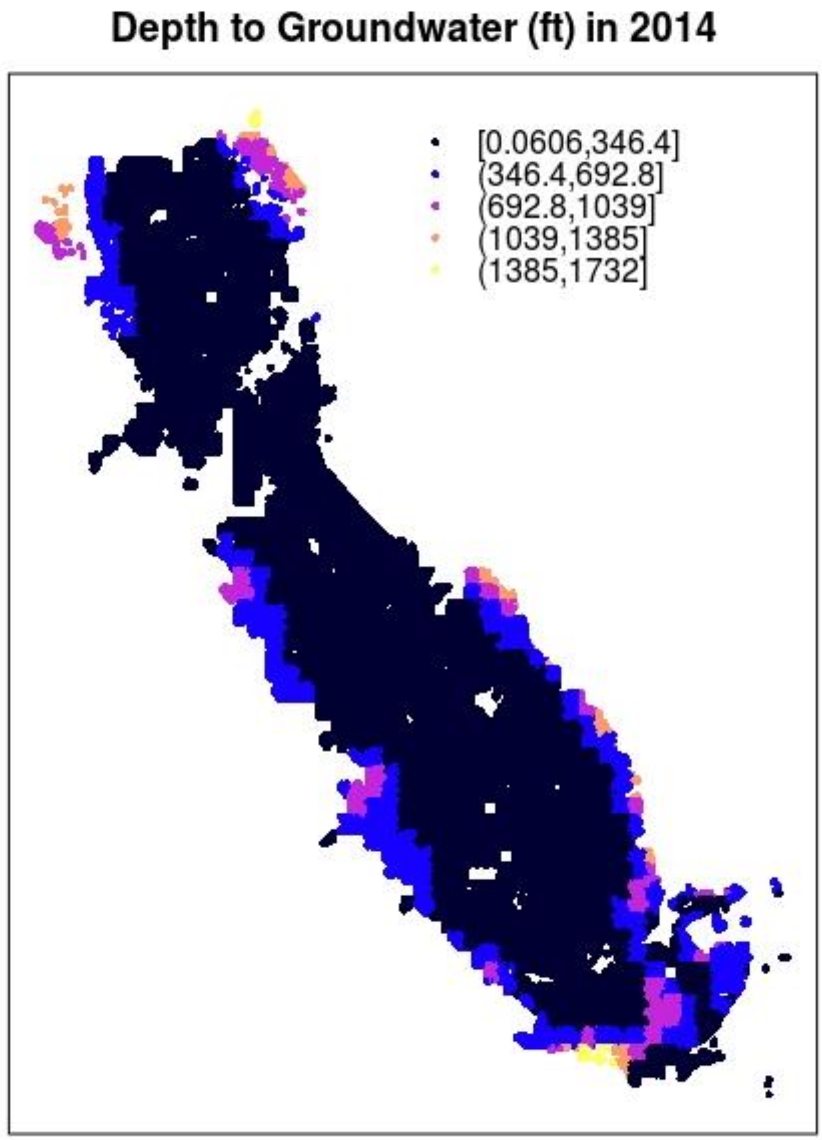

Figure B 12: Estimated depth to groundwater for the Central Valley in 2014.

Table B 3: Model fit for various agricultural production (TVP outcome) models.

Model Description	**Deviance Information Criterion (DIC)**
Model A: Includes SPI and water rights predictors, SPI-Water rights interactions, all controls (including temporal and crop-type effects), and spatial effects.	619551
No spatial effects model: Variation of Model A without the spatial effects.	878882
Quadratic SPI model: Variation of Model A that includes a squared SPI term.	619631
Spatial fixed effects model variation of Model A that uses watershed fixed effects instead of spatial random effects	619476

Table B 4: Summary of marginal posterior effect estimates for all non-spatially varying variables in a model of total vegetative production (TVP) with quadratic SPI.

Variable	Mean	Standard Deviation	0.025 quantile	0.5 quantile	0.975 quantile
Intercept	0.1606	0.0063	0.1482	0.1606	0.1731
Riparian	-0.0007	0.0106	-0.0216	-0.0008	0.0201
Pre-1914	0.0534	0.0103	0.0332	0.0534	0.0735
Appropriative	-0.0065	0.0109	-0.028	-0.0065	0.0149
SPI	0.0785	0.0049	0.0688	0.0785	0.0882
SPI squared	0.0173	0.0032	0.0111	0.0173	0.0235
Depth to Groundwater	0.0016	0.003	-0.0044	0.0016	0.0075
Water Right Density	0.0018	0.0032	-0.0044	0.0018	0.008
Percent Agricultural	-0.0027	0.0112	-0.0247	-0.0027	0.0193
Grasses	0.974	0.0069	0.9604	0.974	0.9877
Grains	0.4516	0.006	0.4398	0.4516	0.4633
RowCrops	0.416	0.0072	0.4018	0.416	0.4302
Fruit&Nuts	0.5339	0.0058	0.5226	0.5339	0.5452
Cover	-0.0006	0.0055	-0.0113	-0.0006	0.0101
2011	-0.1893	0.0046	-0.1984	-0.1893	-0.1802
2012	-0.5542	0.0041	-0.5621	-0.5542	-0.5462
2013	-0.5888	0.0039	-0.5963	-0.5888	-0.5812
2014	-0.7724	0.0041	-0.7805	-0.7724	-0.7644
Riparian*SPI	0.0069	0.0059	-0.0048	0.0069	0.0185
Pre-1914*SPI	-0.0011	0.0044	-0.0097	-0.0011	0.0075
Appropriative*SPI	-0.0244	0.007	-0.0382	-0.0244	-0.0107

Table B 5: Summary of posterior median effect estimates for all non-random variables in spatiotemporal models of total vegetative production (TVP) given inclusion and exclusion of control variables and spatial random effects.

Variable	Model A	Model A.2	Model A.3	Model A.7	Model A.8	Model A.4	Model A.5	Model A.6	Model A.9
Intercept	0.1623	0.1631	0.1628	0.1626	0.1631	-0.1	-0.0806	-0.1016	-0.092
Riparian	0.0007	0.0014	0.0008	0.0006	0.0007	-0.0661	-0.0587	-0.0464	-0.0657
Pre-1914	0.0536	0.054	0.0538	0.0535	0.0538	0.0125	0.0174	0.03	0.0122
Appropriative	-0.0062	-0.005	-0.0062	-0.0063	-0.0063	-0.0377	-0.0439	-0.0198	-0.0364
SPI	0.0623	0.0624	0.0623	0.0625	0.0625	0.1081	0.1113	0.112	0.1071
Depth to Groundwater	0.0024	0.0024	0.0024	---	---	-0.0213	-0.0428	-0.0213	---
Water Right Density	0.002	0.002	---	-0.0043	---	0.0387	0.0494	---	0.0387
Percent Agricultural	-0.0042	---	-0.0039	0.002	-0.0042	0.1087	---	0.1157	0.1145
Grasses	0.9736	0.9736	0.9736	0.9736	0.9736	1.5248	1.5541	1.5278	1.527
Grains	0.4509	0.4509	0.4509	0.4509	0.4509	0.802	0.8346	0.8051	0.8039
RowCrops	0.4157	0.4157	0.4157	0.4157	0.4157	0.5674	0.586	0.5649	0.5695
Fruit&Nuts	0.5341	0.5341	0.5341	0.5341	0.5341	0.9841	0.9991	0.9814	0.9861
Cover	-0.0003	-0.0003	-0.0003	0.0002	0.0002	0.2564	0.2069	0.2582	0.2409
2011	-0.1915	-0.1915	-0.1915	-0.1914	-0.1913	-0.1478	-0.1486	-0.1442	-0.1494
2012	-0.5574	-0.5573	-0.5574	-0.5573	-0.5573	-0.5312	-0.5341	-0.5295	-0.5321
2013	-0.5911	-0.5911	-0.5911	-0.5911	-0.5911	-0.5875	-0.5921	-0.5872	-0.588
2014	-0.7732	-0.7731	-0.7731	-0.7732	-0.7732	-0.7787	-0.7829	-0.7797	-0.7788
Riparian*SPI	0.006	0.0058	0.006	0.0059	0.006	-0.0515	-0.0517	-0.0477	-0.0476
Pre-1914*SPI	-0.0009	-0.001	-0.0009	-0.0009	-0.0009	0.0114	0.0109	0.0166	0.0109
Appropriative*SPI	-0.0226	-0.0228	-0.0226	-0.0226	-0.0225	-0.0798	-0.0763	-0.0752	-0.0762
Spatial Random Effects	Y	Y	Y	Y	Y	N	N	N	N
DIC	619551	619552	619552	619549	619550	772393	774797	772950	772518

Table B 6: Summary of untransformed posterior median effect estimates for all non-random variables in spatiotemporal logistic models of the likelihood that a field is barren and fallow given inclusion and exclusion of control variables and spatial random effects.

Variable	Model B	Model B.3	Model B.4	Model B.5	Model B.6	Model B.2	Model B.7	Model B.8	Model B.9	Model B.10
Intercept	-4.397	-4.4231	-4.3988	-4.4024	-4.5855	-3.0886	-3.0936	-3.0865	-3.0875	-2.9142
Riparian	-0.0197	-0.0552	-0.0166	-0.0203	-0.0241	-0.1354	-0.139	-0.1568	-0.1486	-0.1173
Pre-1914	0.0562	0.039	0.067	0.058	0.0822	-0.1329	-0.137	-0.1517	-0.1339	-0.141
Appropriative	0.0393	-0.0109	0.0414	0.037	0.05	0.0336	0.0155	0.0146	0.025	0.0993
SPI (lagged)	-0.0835	-0.0834	-0.0826	-0.0824	0.0043	0.0526	0.0557	0.0478	0.0553	0.0148
Depth to Groundwater	-0.8512	-0.8542	-0.8499	-0.8524	---	-0.8621	-0.9199	-0.8625	-0.8263	---
Water Right Density	0.0375	0.0379	---	0.0366	0.0294	-0.0477	-0.0278	---	-0.0508	-0.0505
Percent Agricultural	0.1338	---	0.1363	0.1368	0.1908	0.0943	---	0.087	0.0857	0.3495
Crop Diversity (lagged)	-0.0377	-0.0387	-0.0369	---	-0.0441	0.0776	0.0688	0.0785	---	-0.0907
2011	0.5143	0.5123	0.5148	0.5145	0.521	0.4859	0.485	0.484	0.4878	0.4772
2012	0.3228	0.32	0.3238	0.322	0.3832	0.3896	0.3897	0.3858	0.3951	0.3679
2013	0.2771	0.2744	0.2781	0.2758	0.3126	0.3102	0.3089	0.3078	0.3159	0.3047
2014	0.4939	0.4921	0.4945	0.4916	0.4869	0.447	0.4451	0.4466	0.4533	0.4536
Riparian*SPI	0.0975	0.0942	0.0976	0.095	0.0997	0.2388	0.2318	0.2302	0.2288	0.3471
Pre-1914*SPI	0.0914	0.0918	0.0933	0.0916	0.0899	0.11	0.1088	0.1007	0.1104	0.1018
Appropriative*SPI	0.1892	0.1895	0.1901	0.1872	0.1794	0.25	0.2498	0.2398	0.2354	0.3486
Spatial Random Effects	Y	Y	Y	Y	Y	N	N	N	N	N
DIC	130722	130714	130721	130725	131788	156065	156162	156083	156146	160591

Table B 7: Summary of marginal posterior effect estimates for all non-spatially varying variables in a model of total vegetative production (TVP) with watershed fixed effects.

Variable	**Mean**	**Standard Deviation**	**0.025 quantile**	**0.5 quantile**	**0.975 quantile**
Intercept	1.2082	0.0616	1.0873	1.2082	1.329
Riparian	-0.0072	0.012	-0.0308	-0.0072	0.0164
Pre-1914	0.068	0.0123	0.0438	0.068	0.0921
Appropriative	-0.0248	0.0118	-0.048	-0.0248	-0.0016
SPI	0.0613	0.0039	0.0536	0.0613	0.069
Depth to Groundwater	0.0019	0.003	-0.004	0.0019	0.0078
Water Right Density	0.0836	0.0094	0.0651	0.0836	0.1022
Percent Agricultural	-0.0345	0.0139	-0.0617	-0.0345	-0.0073
Grasses	0.9716	0.0068	0.9582	0.9716	0.985
Grains	0.45	0.0059	0.4384	0.45	0.4616
RowCrops	0.4148	0.0071	0.4008	0.4148	0.4288
Fruit&Nuts	0.5323	0.0057	0.5211	0.5323	0.5434
Cover	0.0004	0.0054	-0.0102	0.0004	0.0109
2011	-0.1941	0.0046	-0.2031	-0.1941	-0.1852
2012	-0.5597	0.004	-0.5675	-0.5597	-0.5519
2013	-0.594	0.0038	-0.6014	-0.594	-0.5865
2014	-0.7757	0.0041	-0.7837	-0.7757	-0.7678
Riparian*SPI	0.007703	0.005947	-0.00397	0.007703	0.01937
Pre-1914*SPI	-0.0009	0.004389	-0.00952	-0.0009	0.00771
Appropriative*SPI	-0.02138	0.007017	-0.03516	-0.02138	-0.00761

Table B 8: Summary of marginal posterior effect estimates for all non-random variables in the spatiotemporal model of total vegetative production (TVP) as a function of surface water rights, drought conditions, depth to groundwater, crop type, and other controls (Model A).

Variable	Mean	Standard Deviation	0.025 quantile	0.5 quantile	0.975 quantile
Intercept	0.1623	0.0062	0.15	0.1623	0.1746
Riparian	0.0007	0.0105	-0.0199	0.0007	0.0212
Pre-1914	0.0536	0.0101	0.0337	0.0536	0.0735
Appropriative	-0.0062	0.0108	-0.0274	-0.0062	0.0149
SPI	0.0623	0.0039	0.0547	0.0623	0.07
Depth to Groundwater	0.0024	0.003	-0.0035	0.0024	0.0082
Water Right Density	0.002	0.0031	-0.0041	0.002	0.0082
Percent Agricultural	-0.0042	0.0111	-0.026	-0.0042	0.0176
Grasses	0.9736	0.0068	0.9602	0.9736	0.987
Grains	0.4509	0.0059	0.4393	0.4509	0.4625
RowCrops	0.4157	0.0071	0.4018	0.4157	0.4297
Fruit&Nuts	0.5341	0.0057	0.523	0.5341	0.5452
Cover	-0.0003	0.0054	-0.0108	-0.0003	0.0103
2011	-0.1915	0.0045	-0.2004	-0.1915	-0.1826
2012	-0.5574	0.004	-0.5652	-0.5574	-0.5496
2013	-0.5911	0.0038	-0.5985	-0.5911	-0.5837
2014	-0.7732	0.004	-0.7811	-0.7732	-0.7653
Riparian*SPI	0.006	0.0058	-0.0055	0.006	0.0174
Pre-1914*SPI	-0.0009	0.0043	-0.0094	-0.0009	0.0076
Appropriative*SPI	-0.0226	0.0069	-0.0361	-0.0226	-0.0091

Table B 9: Summary of marginal posterior (untransformed) effect estimates for all non-random variables in the spatiotemporal logistic model of the likelihood that a field is barren and fallow as a function of surface water rights, historic drought conditions, depth to groundwater, and other controls (Model B).

Variable	Mean	Standard Deviation	0.025 quantile	0.5 quantile	0.975 quantile
Intercept	-4.3978	0.0517	-4.5017	-4.397	-4.2988
Riparian	-0.0197	0.0589	-0.1356	-0.0197	0.0958
Pre-1914	0.0563	0.0568	-0.0548	0.0562	0.1679
Appropriative	0.0395	0.0607	-0.0793	0.0393	0.1589
SPI (lagged)	-0.0835	0.0241	-0.1309	-0.0835	-0.0362
Depth to Groundwater	-0.8513	0.0261	-0.9026	-0.8512	-0.8003
Water Right Density	0.0371	0.0117	0.013	0.0375	0.0591
Percent Agricultural	0.1336	0.0494	0.0361	0.1338	0.2301
Crop Diversity (lagged)	-0.0377	0.0155	-0.0682	-0.0377	-0.0072
2011	0.5143	0.0247	0.4659	0.5143	0.5627
2012	0.3228	0.0315	0.2609	0.3228	0.3847
2013	0.2772	0.028	0.2222	0.2771	0.3321
2014	0.4939	0.0246	0.4457	0.4939	0.5422
Riparian*SPI	0.0975	0.0467	0.0058	0.0975	0.1891
Pre-1914*SPI	0.0914	0.0349	0.023	0.0914	0.1598
Appropriative*SPI	0.1892	0.0533	0.0843	0.1892	0.2937

Table B 10: Summary of marginal posterior (untransformed) effect estimates for all non-random variables in the spatiotemporal logistic model of the likelihood that a field is barren and fallow as a function of surface water rights, historic drought conditions, and other controls when previous year crop-type fixed effects are added and the depth to groundwater control is included and excluded.

Variable	Groundwater Included			Groundwater Excluded		
	0.025 quantile	0.5 quantile	0.975 quantile	0.025 quantile	0.5 quantile	0.975 quantile
Intercept	-2.5199	-2.4161	-2.317	-2.6136	-2.5051	-2.4018
Riparian	-0.1131	-0.0029	0.1069	-0.1273	-0.0102	0.1063
Pre-1914	-0.0498	0.0518	0.1541	-0.0373	0.0736	0.1851
Appropriative	-0.0699	0.0464	0.1636	-0.0672	0.0545	0.177
SPI (lagged)	-0.1284	-0.0782	-0.028	-0.0623	-0.0127	0.0368
Depth to Groundwater	-0.7832	-0.7296	-0.6764	---	---	---
Water Right Density	0.0103	0.034	0.0543	0.0014	0.0279	0.0502
Percent Agricultural	0.0678	0.157	0.2451	0.1092	0.2073	0.3039
Crop Diversity (lagged)	-0.0991	-0.0671	-0.0352	-0.1086	-0.0763	-0.044
Grasses	-2.5084	-2.4293	-2.3514	-2.4891	-2.41	-2.3322
Grains	-1.6881	-1.6392	-1.5905	-1.674	-1.6252	-1.5766
RowCrops	-2.0238	-1.9556	-1.888	-1.997	-1.9288	-1.8613
Fruit&Nuts	-2.5645	-2.5064	-2.4489	-2.5537	-2.4957	-2.4382
Cover	-2.0265	-1.982	-1.9377	-2.1292	-2.0852	-2.0413
2011	0.4916	0.5422	0.5928	0.4913	0.5419	0.5925
2012	0.0974	0.163	0.2287	0.1281	0.1935	0.2589
2013	0.0922	0.1505	0.2088	0.1037	0.1619	0.2201
2014	0.3718	0.423	0.4742	0.3526	0.4037	0.4548
Riparian*SPI	-0.0014	0.0933	0.1878	-0.0025	0.093	0.1883
Pre-1914*SPI	-0.0058	0.0634	0.1326	-0.0118	0.0587	0.1294
Appropriative*SPI	0.0429	0.1517	0.2601	0.0315	0.1414	0.251