STATISTICAL MODELING OF ON-SITE WASTEWATER TREATMENT SYSTEM LIFE CYCLE PERFORMANCE AND RISK

by

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The final copy of this thesis has been examined by the signatories, and we find that both the content and the form meet acceptable presentation standards of scholarly work in the above mentioned discipline.

ABSTRACT

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Statistical Modeling of On-Site Wastewater Treatment System Life Cycle Performance and Risk

Thesis directed by Professor JoAnn Silverstein

By 2050, it has been estimated that 70 percent of the world's population will live in cities, concentrating waste as well as local environmental stresses. At the same time, decentralized approaches to sanitation are projected to grow due to the capital cost of sewers and centralized treatment facilities. Yet the common belief that technology will assure the performance of on-site systems over their life cycle may lead to significant underestimation of the actual risks to public and environmental health from owner-operated residential sanitation systems. Safe on-site storage, transformation and disposal of human waste require knowledge of how factors such as individual ownership, operations and management, and scale impact wastewater treatment reliability, risk and resilience under both normal and extreme conditions.

This dissertation research is developed to fill a gap in performance-based knowledge of OWTS function, especially the likelihood of system failure over lifetime operation. As such, a data-based investigation of highly decentralized and privatized wastewater management represented by on-site wastewater treatment systems (OWTS) was conducted using data from OWTS located in Boulder County, Colorado. Data were acquired from County maintained repair permit application records, inspection documentation, and property attributes. Methods are developed to quantitatively diagnose

components that determine OWTS life cycle performance such as reliability, risk, fragility, and resilience by applying commonly used statistical modeling approaches based on the Generalized Linear Model regression method. Statistical modeling is then applied to analyze two conditions not controlled by current OWTS design and siting regulations: owner behavior and weather-related hazards.

Statistical model results confirm that owner-operations significantly affect life cycle OWTS functionality. Specifically, the results indicate the significant benefit of regulated inspections and maintenance as means to ensure that once installed, these systems continue to perform reliably and cost-effectively over their lifetime. Although a significant public information campaign (SepticSmart) has been maintained by the Boulder County Public Health Department, it is evident from the regression analysis that relying solely on public education about the importance of practices such as regular inspection and maintenance is insufficient to positively influence private owners' decisions and prevent generation of externalities such as contaminant release from failed OWTS.

A resilience framework is developed to demonstrate the degree to which decentralization influences systematic OWTS vulnerability to weather – both wetter-than-average conditions and extreme storm events, independent of individual OWTS operations. Widespread natural hazards such as flooding are found to affect the frequency and degree to which OWTS function is lost, and more importantly delay their recovery, attributable in part, to a demand surge for both materials and repair services when multiple systems fail simultaneously. Longer recoveries are likely to have environmental and public health consequences due to the prolonged release of contaminants as well as secondary costs related to homeowner losses resulting from a failed OWTS.

Ultimately, the findings of this dissertation contribute to the decisions of planners, regulators and community stakeholders concerned with varying levels of wastewater treatment reliability, risk and resilience along the sanitation continuum from highly centralized and regulated collection and treatment infrastructure to relatively unregulated onsite systems operated by their owners. This research has demonstrated the importance of factors representing two heretofore unrecognized dimensions of OWTS life cycle performance – behavior of individual owners and enhanced vulnerability to natural hazards, and thus enables planners to decide if large-scale deployment of user-owned and operated sanitation is the best means to achieve health and environmental benefits with an acceptable degree of certainty.

AKNOWLEDGEMENTS

If you had asked me as a little girl where I imagined myself in 20 years, I would have never guessed I would be pursuing a doctoral degree focused on providing reliable sanitation. I did not start out dreaming of work with toilets, latrines, and septic systems, but rather dedicated academics, professionals, and opportunities opened my eyes to a path that I now love and know to be necessary. It is my hope that my research and future work has the same reach and excites others to tackle the challenge that is global access to safe and functional sanitation.

To that end, I have several people that I would like to acknowledge that have guided me in the ways of graduate school, supported my ideas, and helped me sculpt my sanitation curiosities into a completed dissertation. First, I would like to recognize my committee chair and advisor, JoAnn Silverstein. I met JoAnn when I first visited CU. She agreed to meet with me when my scheduled appointments fell through, ever since JoAnn has consistently and selflessly made time for me. JoAnn has supported my interest to better understand the complexities of on-site sanitation operations, by helping develop a winning NSF GRFP proposal and then guiding/influencing me in my educational and life-related pursuits. It has been such a pleasure to learn from and work with such an amazing professional and academic.

Additionally, each member of my committee has played a crucial role in my success over the last 4 plus years. I met Jessica Kaminsky during my first year at CU. Her particular research path motivated me in my own pursuit of sanitation research. Jessica dedicated hours to me and my NSF and EPA STAR grant proposals and provided guidance on how to think about research projects and questions by introducing me to Cifi HorseShoe. If I had not had that guidance early on, I would not be here today. Rita Klees to date, to me, is the guru of sanitation. I was first exposed to the challenges of sanitation in her WASH class my first year at CU. Over the years, Rita has provided feedback on research ideas and provided many connections in the sanitation sector, especially when I first started looking for data to do this research. Paul Chinowsky first introduced me to Civil Systems Engineering. Paul provided me with a home during my time here, by inviting me to be part of the Civil Systems cohort. Any improvements in speaking and writing, I owe to his guidance and to my one-on-one rehearsals with JoAnn. Lastly, but certainly not least, Balaji Rajagopalan has helped me with the substance of this research. Only Balaji can attest to the many hours we have spent talking about R codes, statistical methods, and results interpretation. Thank you for being so patient with me and offering me so much of your time.

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LIST OF ACRONYMS AND TERMS USED

AIC	Akaike Information Criteria
ANOVA	Analysis of Variance
BCPH	Boulder County Public Health
BSS	Brier Skill Score
EPA	Environmental Protection Agency
EVA	Extreme Value Analysis
EVA-POT	Extreme Value Analysis- Points Over Threshold
GAIC	Generalized Akaike Information Criteria
GIS	Geographical Information System
GLM	Generalized Linear Models
GAMLSS	Generalized Additive Models for Location, Scale & Shape
NOAA	National Oceanic and Atmospheric Administration
OWTS	On-site wastewater treatment systems
POTW	Publically owned treatment works
RMSE	Root Mean Squared Error
STU	Soil treatment unit

CHAPTER 1: INTRODUCTION

MOTIVATION

Since the 17th century, several sanitation management strategies and technologies to insure the public good by preventing infectious disease and environmental degradation have been employed. These are part of a continuum of solutions with highly centralized, publically owned treatment works (POTWs; e.g. Deer Island Treatment Works receiving 8.7 million m^3/day) at one extreme and small cluster systems and residential scale on-site sanitation installations, which in the U.S. are typically limited to less than 8 m^3/day, at the other (Zimmerman 2002). Unregulated on-site systems for collection, passive treatment and storage such as privies, vaults, and cesspools were replaced in the later half of the 19th century by centralized sewers better able to handle increasing wastewater flows as residential piped water supply and use of flush toilets became widespread and as the association of fecal waste with outbreaks of cholera and other water borne diseases became known (Cosgrove, 1909; Burian *et al*., 2000). Decentralized solutions—cluster and on-site systems—remained alternatives in communities where public sewer services were physically impractical or costly. While tradeoffs exist for every solution on the continuum, scientific knowledge, tradition, and prevailing public opinion has led many engineers, public officials and users to continue to favor centralized alternatives (Etnier *et al.*, 2007; Pinkham *et al.,* 2004; Nelson *et al.*, 2000). One result is that research and development has been directed toward support of centralized wastewater systems.

Today, there is renewed interest in wider use of on-site wastewater treatment systems (OWTS) to provide sanitation coverage. Over the next 20 years, U.S. EPA estimates funding shortfalls of $122 and $148 billion for capital improvement and operations and maintenance of existing facilities, respectively (EPA 2002a). This gap has motivated greater attention to decentralized wastewater treatment, including OWTS, as a permanent part of sanitation infrastructure planning. In the U.S., in addition to the 25% of the population already served by OWTS, 30% of new developments use on-site wastewater treatment. Whereas traditionally OWTS served predominantly rural communities, over 47% of the OWTS population now exists in suburban, higher density areas and 3% in cities (EPA, 2008). Outside of the U.S., OWTS are leveraged to provide sanitation services in both rural and urban communities that either currently use unimproved facilities or have no access altogether (WHO/UNICEF JMP 2015).

While these systems are becoming more widely used, their performance is not necessarily as widely understood. In spite of well-developed on-site wastewater technologies, between 10% nationally and upwards of 50% of OWTS in some individual states fail (EPA, 2002b; Nelson *et al.*, 1999). While environmental and public health risks associated with service disruptions and failure are assumed to be managed through dispersion and dilution under the historic paradigm, the aggregate potential impact of denser OWTS networks may, in fact, be comparable to centralized facilities (Weirich *et al.*, 2011). Of course, OWTS performance estimates are largely speculative or based on anecdotal since no monitoring or reporting of treated water quality is required as it is for centralized systems.

OBJECTIVE

The growing application of OWTS technologies, in addition to a lack of information about their performance variability drives my focus in sanitation research and my interest to add to the body of knowledge about OWTS performance. Consequently, the objective of this research is to develop statistical modeling approaches to quantitatively understand the life-cycle performance of highly decentralized, owner-operated sanitation systems. In addition to providing a quantitative basis to assess OWTS reliability, I have the goal of diagnosing conditions associated with OWTS failure and incorporating such information in decisions to guide the development of effective management strategies to improve reliability and promote sound economic choices. This required consideration of the human factors, heretofore largely ignored, that may predispose a system to failure, as well as individual weather and climate-related events that affect OWTS operations.

CONTRIBUTION

The contribution of this dissertation is two-fold: First, I develop methodologies applying statistical modeling approaches commonly used to evaluate the performance of other infrastructure systems to quantitatively diagnose components that determine OWTS life cycle performance. Second, these data-driven approaches improve the quality, availability, and accessibility of information for decision makers. After installation, which is regulated by permits issued to assure compliance with site and equipment criteria, OWTS are largely unregulated. Yet, their operable life may be 50 years or longer. Given the general acknowledgement that an appreciable number of OWTS in fact fail after installation, a life cycle assessment of performance could play a large role in considering approval of their use and regulation of their operation after installation (Etnier *et al.*, 2005; Fane *et al.*, 2004)

DISSERTATION SUMMARY

Three concepts support this dissertation and the development of the statistical modeling approaches to better understand various system properties characteristic of OWTS life cycle performance. **Chapter 2** provides an overview of the relevant literature to these foundational concepts and clarifies the point of departure for this research.

The first concept is life cycle performance, which provides systems framework to evaluate OWTS deterioration, repairs and replacements as related to inspection, and management strategies, which affect individual owner/operators and communities. The premise of this research is that life cycle performance attributes, namely reliability, risk, fragility, and resilience— which have been developed to assess defined infrastructure networks (transportation, water supply, electric power supply) can be applied to highly decentralized wastewater infrastructure, including OWTS. Each chapter of this dissertation will focus on one of these performance attributes to allow multidimensional comparison of sanitation alternatives along the centralization continuum. The second concept is the structure of performance models, including the model scale, sample selection, data collection, variable identification and statistical methods, which are described in more detail in Chapters 3 (Methods) through 7. The third component addresses the role of (private) ownership of OWTS, one of the hypothesized determinants of OWTS life-cycle performance.

Chapter 4 is a description of the first phase of my research, including results of fitting a continuous distribution to OWTS data of documented repairs and replacements significant enough to require a permit and inspection, using a Generalized Additive Model for Location, Scale and Shape (GAMLSS). As stated above, in the absence of post-installation requirements for monitoring and reporting, OWTS operation and maintenance is largely done at the discretion of the owner, except in the event of a catastrophic failure. **Chapter 4** explores the relationship between owner-related factors and indicators of physical OWTS status; factors include the degree of community or institutional control; owner economic status; owner knowledge and owner self-interests. Since most household systems are not consistently maintained, the functionality of the system decreases over the system's life affecting its reliability (EPA, 2002a). The study highlights the benefit of enforced inspections to reduce the annualized expected costs over a 40-year period due to repairs and replacements.

While the first model illustrates the benefit of, for example, enforced inspections to OWTS function, public resistance to increasing regulation of OWTS in the U.S., including obligatory inspections and upgrades demonstrates the challenges associated with communicating residential and community level risks. Determining appropriate and enforceable performance measures in an industry with little history of performance-based regulation is challenging. Therefore, **Chapter 5** reports the use of Extreme Value Analysis-Points Over Threshold to communicate the risk of a poorly performing OWTS in terms of expected dollars lost, again relating the probability of poor performance (high risk OWTS) to a selection of user-operation practices. **Chapter 5** highlights the trade-off between an enforced inspection management strategy versus 'business as usual' to illustrate the benefit of observing OWTS instabilities through inspection before a catastrophic failure occurs.

Transitioning from performance deterioration factors such as neglected management, **Chapter 6** focuses on vulnerability, here called *fragility*, in response to external stressors such as annual weather and climate variation. **Chapter 6** uses a GLM statistical approach to quantify the relationship between the total number and type of repairs in an OWTS sample and weather variation in each year.

Poor management, in addition to aging and deterioration mechanisms can adversely affect the on-going function of OWTS, rendering them more vulnerable or fragile and less resilient to external stressors such as natural hazards. This relationship between reliability, fragility, time to recovery and overall system resilience motivates the research in the final chapter, **Chapter 7,** which connects measurement of fragility and repair recovery (rapidity) to determine OWTS resilience before and after the 2013 Boulder flood. It has become clear through the first phases of my research that consistent treatment (reliability) depends on human and societal variables that govern operation and maintenance in addition to science and technology factors. In **Chapter 7**, the variables that affect resilience under normal environmental conditions are in fact different from those after an environmental hazard event. Chapter 7 highlights the aggregate impact of OWTS failure on the recovery durations due to an effect called demand surge. In the case of OWTS, the demand for repair services affecting also material availability surpasses the supply, causing recovery delays. These recovery delays have additive cost due to the inconvenience of a failed, unusable system that fall on directly on system owners, in addition to environmental costs associated with the release of untreated wastewater. **Chapter 7** also explores methods to estimate these costs to more accurately represent the risk of OWTS failure for future hazard events.

Figure 1.1 visually summarizes the work completed for this dissertation. More detailed contributions are illustrated in **Chapters 4, 5, 6 and 7** and are summarized in the conclusion section.

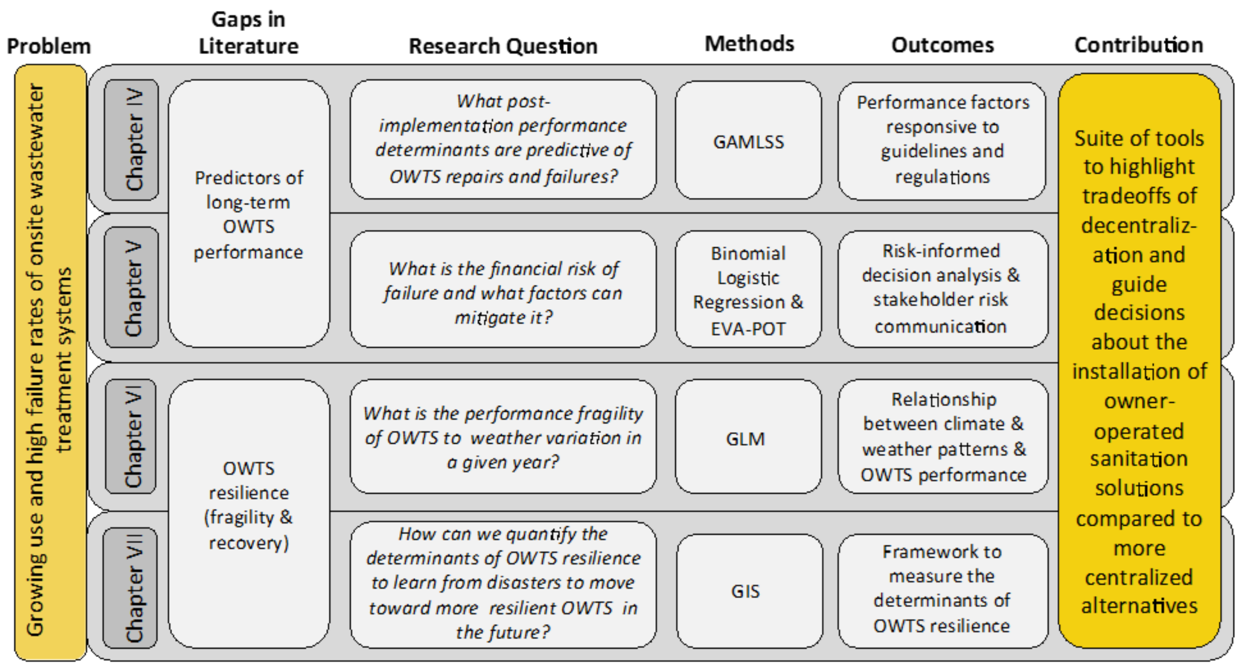

Figure 1.1 Research Design

RESEARCH CONTEXT

The data for this dissertation is from OWTS in Boulder County Colorado. This focus on Boulder County is practical for several reasons. One, data are available from the repair permit documentation process that has been in place since the late 1940s; whereas no comprehensive treated water or ground water quality monitoring data exist for OWTS that are sufficient to form a sample. Furthermore, measures of performance vary because there is no universal definition of ‘failure’. Repair permits were selected to serve as a reasonable proxy measure of failure in this dissertation.

Second, the data available captures variability in geography with systems existing in the mountains and plains communities, affluence based on structural property value that varies greatly across the sample, and the density of OWTS from rural to more suburban areas in Boulder County.

Lastly, wider application of OWTS technology has been accompanied by greater expectations of performance and consideration of new regulations that recognize the risks of denser networks of OWTS as mentioned earlier. A transfer of title inspection regulation was instated in 2008 and in 2014 Boulder County-specific regulations adapting permit terms, OWTS inspections stages, licensing of system contractors and cleaners, detailed soil evaluation procedures, design flow requirements and variance procedures, among other requirements were adopted in April and effective in May. Given the state guidelines for regulations, Boulder County has considered performance-based regulations such as renewable permits. This research directly addresses some of the uncertainties highlighted by the County about such regulations and their benefits.

While the models herein are based on data from U.S. treatment systems, I propose that identified relationships between decentralization, owner operation, economic factors, and the degree of OWTS monitoring and regulation over the system life are broadly applicable to performance-based planning and management over a wide range of communities and cultures.

DISSERTATION FORMAT

This dissertation follows a journal article format. **Chapters 4, 5, 6 and 7** are independent articles, which are related through topics described in this section but are formatted individually per journal publication requirements. **Chapter 4** was published in February 2016 issue of *Environmental Engineering Science*, while other chapters have been submitted for review. I respectfully ask that citations to the work in **Chapter 4-7** reference the published versions and not this dissertation. References are listed both separately with each chapter/publication as well as in the bibliography at the end of this document. Finally, the appendices include the data and R codes for the models presented in each chapter.

CHAPTER 2: FUNDAMENTAL CONCEPTS

LIFE CYCLE PERFORMANCE

The system operations—often involving inspections, repairs and replacements—necessary to insure the safety of and benefits to users can be identified through conducting a holistic assessment of the system and its performance over time. This notion of performance over time is often referred to as life cycle performance, commonly considered to better manage structures and infrastructure systems such as buildings, roads, and bridges, among others (Rackwitz, 2000; Frangopol *et al.,* 2001; Frangopol *et al.*, 2004; Frangopol, 2010; Kumar & Gardoni, 2013, Bonstrom *et al.*, 2014). Assessing a system's performance over its life cycle can help determine its life span; reliability and the costs and benefits of different operation strategies; and the time and resources necessary to recover function after a disaster. Such analyses ultimately inform and aid complex planning and management decisions (Rackwitz, 2000). As such, these decision support assessments should integrate the uncertainties of all life cycle performance behaviors such as natural deterioration due to age and use, management-related reliability, and the occurrence and influence of hazardous events. The literature indicates that probabilistic approaches are both popular and appropriate for this type of assessment, especially as they relate to structure and infrastructure systems (Kumar & Gardoni, 2013).

Life cycle performance applications for structure and large-scale infrastructure systems continue to grow. In 1976, Yang included the effects of deterioration on the development and spread of cracks on aircraft. The analysis incorporated the cost of aircraft inspections and necessary repairs to avoid serviceability failures—meaning the failure of the system to meet certain performance criteria rather than an ultimate failure—due to crack propagation influenced by age (Yang, 1976). The focus on serviceability failures is crucial for age- and management- dependent deteriorating systems because the long term reliability of such systems can decrease with time and result in multiple serviceability failures over the system's life or even inhibit system resilience given a more catastrophic event (Kumar & Gardoni, 2013).

In addition to serviceability failures, ultimate failures described as the complete collapse or breakdown of systems—are also of concern and occur often as the result of external stressors such as climate related events—for instance, hurricanes, earthquakes, fires, and flooding—or neglected system management (Kumar & Gardoni, 2013). While ultimate failures may have low probability, they are high consequence events, therefore understanding the factors/events influencing ultimate failures to estimate occurrence probabilities and losses is important. Research by Oswald & Schuller (1984) and Mori & Ellingwood (1993) proposed methods that could be used to predict the time to a serviceability or ultimate failure, but not both at the same time. Later, Noortwijk & Frangopol (2004), Neves & Frangopol (2005), Kim *et al*. (2011) and Kumar & Gardoni (2013) developed approaches to include them simultaneously, approximating more closely the performance complexity of the systems.

In terms of performance recovery after a failure event, Bruneau *et al.* (2003) established one of the first conceptual frameworks to measure resilience. Bruneau *et al*. (2003) suggested that resilience could be characterized based on four system properties: robustness, rapidity, redundancy, and resourcefulness. Robustness has been defined as the ability to withstand or absorb stressors. Rapidity is the time to restored performance after an event. Resourcefulness is the capacity to mobilize resources in response to a loss in performance and system redundancy refers to the system components that can satisfy some level of function in the event of a hazard-induced disruption (Bruneau *et al.* 2003). Employing these system properties, Bonstrom & Corotis (2014; 2015) applied a time-dependent reliability approach to quantify seismic resilience based on the robustness and restoration time of a building portfolio after an earthquake event. The integration of prior performance reliability and how it affects disaster resilience provides life cycle performance information helpful to prioritize cost-effective mitigation strategies to improve resilience.

Life cycle reliability studies related to specifically decentralized sanitation services are less common. Weirich *et al.* (2011) employed a modeling approach to determine the impact of decentralization on a wastewater facility's ability to meet NPDES discharge standards. The study used statistical modeling to compare the performance of centralized and decentralized treatment facilities, analyzing the relationships between treatment plant capacity and effluent quality. The model confirmed that treatment plant capacity and loading influence the reliability, stability and resilience of facilities treating between 40 and 400,000 m^3/day (Weirich *et al.,* 2011). Life cycle analyses of competing technology configurations for decentralized wastewater treatment, e.g. constructed wetlands versus anaerobic digestion, compare the environmental impact over the systems service life—resources consumed and emissions produced such as CO_2 and Nitrogen (Emmerson *et al.*, 1995; Dixon *et al.,* 2003; Machado *et al.*, 2007; Foley *et al.*, 2009; Fuchs *et al.*, 2011). These studies primarily focus on manufacturing, the initial installation, and input energy costs due to assumed on-going performance and prescribed maintenance tasks under hypothetical and typically ideal performance conditions (Dixon *et al.,* 2003; Machado *et al.*, 2007; Fuchs *et al.*, 2011). Since OWTS do not exist in controlled laboratories, these 'simple' systems gain complexity in practice at the user interface, where seemingly simple operation and maintenance tasks necessary for system functionality are neglected due to the high uncertainties inherent in human behavior. Furthermore, external stressors such as those related to weather and climate that may be less disruptive in larger systems have unknown effects on performance at the very decentralized (single residence) scale. Even fewer studies exist related to OWTS disaster resilience (Johannessen *et al.* 2014) and probabilistic studies relating time- and management-related reliability (potentially dictated by ownership) and resilience as seen in Bonstrom & Corotis (2014; 2015) are non-existent.

CURRENT APPROACHES TO EVALUATE OWTS LIFE-CYCLE PERFORMANCE

Given this added complexity, part of the challenge in applying a holistic approach to attain useful information about OWTS stems from uncertainties, due in part to the lack of data, about the extent to which ownership, user-practices and external stressors influence OWTS life cycle performance.

A number of OWTS studies model performance but do so by estimating failure risks based on initial design and siting factors, rather than actual system operation. This section discusses existing methodologies used for modeling OWTS properties related to life cycle performance.

OWTS treatment performance has been widely studied in the lab and at the field scale. Some of the studies have produced tools to quantify the risks of on-site wastewater systems failure. To date there exist several well-developed OWTS treatment models. **Table 2.1** summarizes existing models, their input variables, and the intended contribution with regards to planning and managing OWTS.

Table 2.1 Existing OWTS performance models

Risk Based Model & Description	Variables
Onsite Sewage Risk Assessment System (OSRAS) • Assesses, using GIS management methodology, individual system contributions to the additive risk of sewage contamination in sensitive environments • Spatial landscape and infrastructure data is used to rank the risk of each land parcel and analyse the spatial data layers to identify areas with a higher probability of system failure	*Independent* • Technology classification • Catchment configuration • Soil characteristics • Slope • Climate • Hydraulic Loading • Lot size • Maintenance frequency • Management practices *Dependent* • 'Failure' defined as unacceptable surcharge or seepage of effluent from a designated land application area References: (Brown & Root Service, 2001; Kenway & Irvine, 2001)
Development Assessment Module (DAM) • Extracts the relevant GIS data for a location of the proposed onsite effluent management system to predict the extent and direction of an OWTS effluent plume to evaluate its potential impact on water quality • Determines the level of risk associated with installing an OWTS in a particular area	*Independent* • Soil characteristics • Slope • Climate *Dependent* • Magnitude and direction of OWTS effluent plume References: (McGuinness & Martens, 2003)
Trench TM 3.0 • Asses sites for absorption trench/bed suitability • Uses water balance or nutrient balance methods to size disposal systems	*Independent* • Catchment configuration (location, land use, etc.) • Soil characteristics • Slope • Climate • Hydraulic loading • Aspect • Setback distances • Floodplain • Wastewater characteristics *Dependent* • Site capability (i.e. expected design area, disposal system, slope, surface discharge, flood potential, wastewater volume, etc.) • Environmental sensitivity • Size and design References: (Cromer 1999a, Cromer 1999b)
Methods for Assessment, Nutrient Loading and Geographic Evaluation of Watersheds (MANAGE) • Identifies potential at risk areas using relatively simple GIS-based vulnerability mapping • Examines surface runoff and infiltration; and acknowledges the influence of soil type and riparian areas on pollutant transport	*Independent* • Technology classification • Catchment configuration • Soil characteristics References: (Joubert, *et al.* 2004)
Integrated Risk Framework for Onsite Wastewater Treatment Systems • A risk framework based on the Australian Standard AS4360: 1999 Risk Management	*Independent* • Soils renovation ability • Lot size • Slope • Suitable setback distances from water resources • Development with the identified floodplain

(AS/NZS 4630. 1999) to identify low, medium, and high risk areas to better manage OWTS in a regional or catchment scale	*Dependent* • Hydraulic Failure • Groundwater and surface water contamination with chemical pollutants • Microbial contamination of ground/surface water References: (Carroll, *et al*. 2006)
Better Assessment Science Integrating Point and Non-point Sources (BASINS) • Performs TMDL studies for larger river basins that can be subdivided into multiple smaller watersheds • Consists of Hydrological Simulation Program Fortran (HSPF) and Soil Water Assessment Tool (SWAT)	*Independent* • Catchment configuration (land cover, land permeability, reach length, etc.) (Using HSPF) • Climate • Snow, surface & groundwater hydrology References: (USEPA) (Chen & Herr, 2002)
Watershed Analysis Risk Management Framework (WARMF) • Simulates the hydrology and calculated the nutrient TMDL to estimate water quality impact at a *watershed* scale	*Independent* • Catchment configuration (land cover, reach length, slope, width, aspect, etc.) (Using USGS DEM) • Climate • Snow, surface and soil hydrology References: (EPRI) (Chen & Herr, 2002)

First the models tend to be deterministic, with outputs based on the forward evaluation of failure given both physical and operational factors, rather than long-term performance data. Furthermore, virtually no studies that quantify OWTS resilience, including recovery, exist. The general conclusion is that poor performance (frequent failures) is attributed to inadequate site and soil assessment and characterization. Onsite Sewage Risk Assessment System (OSRAS), Development Assessment Module (DAM), Methods for Assessment, Nutrient Loading and Geographic Evaluation of Watersheds (MANAGE), TrenchTM 3.0 and the Integrated Risk Framework models identify potential risk areas, wherein placing an OWTS may result in failure given a site's soil, topographical, and hydrological characteristics (Brown & Root Services, 2001; Kenway & Irvine, 2001; McGuinness & Martens, 2003; Cromer, 1999a, 1999b; Joubert, *et al.*, 2004; Carroll *et al.*, 2006). Better Assessment Science Integrating Point and Non-point Sources (BASINS) and Watershed Analysis Risk Management Framework (WARMF) differ in that they are used primarily to estimate the nutrient TMDL and overall water quality impact on a watershed, based on treatment assumptions stemming from controlled experiments or limited field data (Chen & Herr, 2002).

While the risk models provide useful insight for OWTS design and permitting practices and are often integrated into regulations, OWTS continue to fail indicating that a purely physical-technological basis for predicting performance ignores significant factors related to ownership such as system maintenance, owner knowledge, and usage.

OWTS OWNERSHIP AND MANAGEMENT CHALLENGES

The ownership, operation and management challenges of OWTS are distinct from those of centralized wastewater systems. For OWTS, the cost and upkeep are typically the responsibility of homeowners, concentrating the financial risk of failure and adding a level of operation and maintenance complexity to outwardly simple technologies. This user-ownership characteristic must be recognized for accurate prediction of OWTS performance.

Technological advances have been introduced to enhance OWTS reliability and treatment (e.g., pressure systems, subsurface drip systems, Glendon Biofilter® systems, sand filter systems, mound STUs, sand-lined drain fields, ATU (Aerobic Treatment Unit) systems, and recirculating filter systems). While they are more effective in removing pathogens and nutrients, many of these advances demand even more of system owners due to the added maintenance of mechanical components such as aerators, pumps, valves, recirculation equipment and effluent filters. These practices at the user/technology interface directly influence the life cycle performance of technologies (D'Amato *et al.*, 2008) to suggest that more technology is not sufficient to address performance instability.

Policies to address poor OWTS management and system failures typically have centered on user-educational initiatives. The results from a keyword search for "education" and "septic system OR tank" illustrate the customary role of education as a means to address failing OWTS (Mohamed, 2009). The search returned over 1.1 million hits relating to government initiatives to provide information to homeowners based on the belief that homeowners neglect maintenance because their systems are "out of sight and out of mind" (Mohamed, 2009; Schueler, 2000; McKenzie, 2002). Nevertheless, even where educational interventions are in place, OWTS continue to fail. A study in Ohio evaluated homeowner responses to OWTS education programs by comparing homeowner behavior before and after the program. The results show an increase in knowledge but only a slight change in operation behavior (Silverman, 2005).

A 2009 study provides insight on why homeowners do not maintain their septic systems theorizing that users do not properly operate and maintain their systems because it is not in their economic self-interest to do so and that educating households on the consequences is a deficient response (Mohamed, 2009).

Part of the challenge of ensuring OWTS functionality stems from their characteristic as *impure* public goods which have attributes of both *common property resources* (CPRs) associated with public goods such as environmental quality and *open access resources* (OARs), which have undefined ownership, such as the right to discharge contaminants into the environment, and are often privatized. As an OAR, an OWTS creates externalities that generate public costs associated with environmental degradation or threats to public health (Turvev, 1963; Hardin, 1968). Regulatory mechanisms are difficult to impose on *impure* goods. Consequently, without regulations, the private responsibility of OWTS operation and maintenance necessary for the protection of the public resource, i.e., the environment, creates an incentive to opt out of potentially costly maintenance activities, since opting in may offer no immediate benefit to the individual owner/user and opting out is seen as having a small and even undetected impact (Hardin, 1968). This theory concludes that “the divergence between private and public costs points to policies in which households should be required to internalize the externalities of utilizing septic systems” to prevent the general degradation of environmental quality (Mohamed, 2009, 48).

RESEARCH GOALS

No matter how well designed and managed a system is, all systems including those for wastewater treatment are vulnerable to instability and failure, although small decentralized wastewater systems may be overall less reliable and less resilient (Weirich *et al*., 2011). Despite the fact that many inoperative OWTS remain in use beyond a design life on the order of 30 to 40 years (EPA, 2002b), design lives are, in fact, finite and result from an aging process whereby slow degradation, poor management and sudden environmental hazards contribute to their failure and performance recovery (Kumar & Gardoni, 2013). The process of performance, degradation, failure and repair or replacement over time describes OWTS life cycle performance and is the basis of this dissertation.

As described in the previous section, existing approaches to quantify the life cycle properties of performance focus primarily on the technological components as a means to identify prescriptive siting and installation controls. The existing models however, do not incorporate post implementation performance, except as a projection of initial design. While the importance of ownership as it relates to operation and maintenance over the system's lifetime is mentioned, factors related to system operations and maintenance are not represented in the models. Furthermore, the existing models do not incorporate uncertainty, which is necessary to describe highly variable OWTS function over a life cycle.

To address the gap, this dissertation uses probabilistic methodologies and performance-related data to better understand the life cycle properties commonly required for planning and management decisions of larger structure and infrastructure systems such as long-term reliability (discussed in **Chapters 4 and 5**) and resilience to external stressors such as extreme weather events (discussed in **Chapters 6 and 7**). To visualize the relationship of these components, I have adapted a conceptual framework for resilience measurement proposed by Bonstrom & Corotis (2014), which abstracts building portfolio resilience to earthquake hazards. **Figure 2.1-a** is a resilience curve where resilience is characterized by the four properties from Bruneau *et al*. (2003)—robustness (which hereafter will be referred to as 'fragility' or the inability to withstand or absorb stress), rapidity, redundancy and resourcefulness. **Figure 2.1-b** plots actual data from well- (low risk) and poorly-performing (high risk) OWTS from Boulder County to illustrate the prior performance variability before an extreme event, for example, the 2013 Boulder Flood. **Figure 2.1-b** shows the relative loss in performance with each type of repair recorded by the County—minor repairs (with an estimated loss of 25%), moderate (reducing functionality by 50%) and major repairs (causing an arbitrary reduction in OWTS function of about 75%). The purpose of the detail in **Figure 2.1-b** is to show that even under "normal" conditions, OWTS performance is variable. **Chapters 4 and 5** of this dissertation focus on the private ownership attribute of OWTS and specific practices at the user/technology interface to better understand that variability over time. Fragility and rapidity as they relate to disaster resilience are investigated in **Chapters 6 and 7**. The overarching objective is to provide information to support informed decisions about OWTS as an appropriate sanitation solution as well as management strategies as the number of OWTS continues to grow.

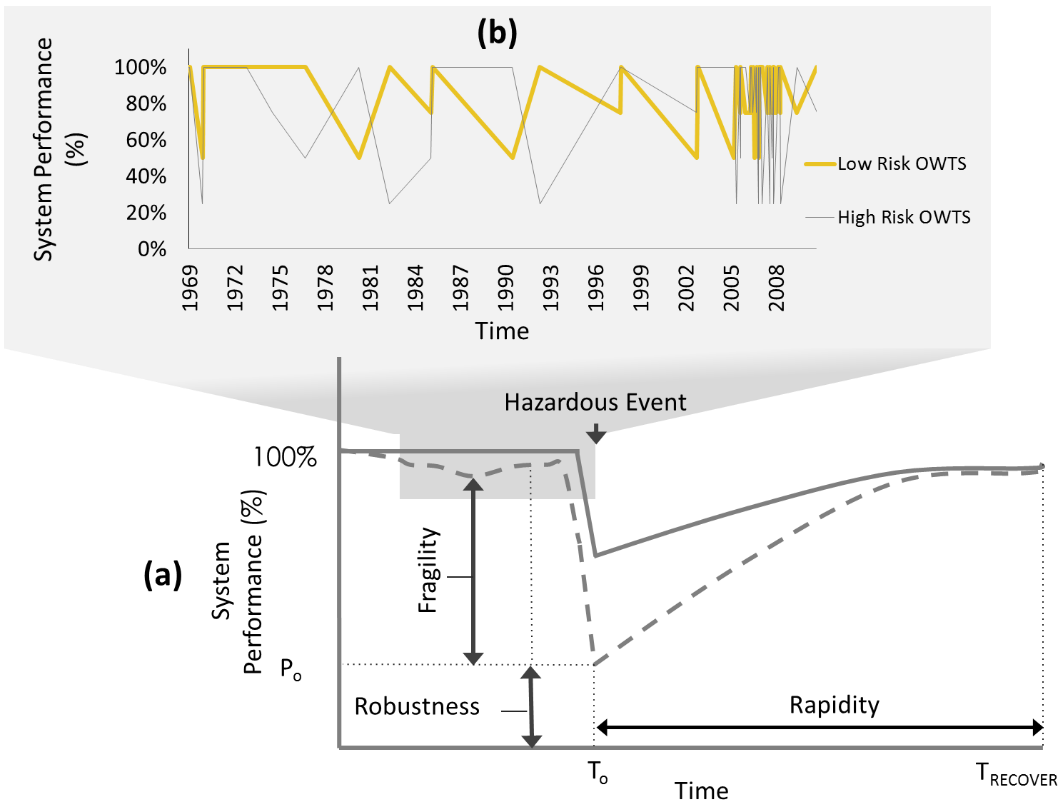

Figure 2.1 Conceptualization of OWTS life-cycle performance (based on graphic from Bonstrom & Corotis, 2014) where minor repairs constitute a 25% loss in function, moderate repairs a 50% loss, and major repairs a 75% loss. The purpose of this figure is to show the deviation from 100% performance over a sample of 39 high and low risk systems' lives. The percentages are mere estimations of performance loss to illustrate the point.

CHAPTER 3: RESEARCH METHODS OVERVIEW

This section presents an overview of the data collection and quantitative analysis methods used to address my research questions. These methods include data collection and organization, variable identification, and a summary of methods of data analysis that are elaborated in **Chapters 4-7**.

DATA COLLECTION AND ORGANIZATION

Because OWTS operation and maintenance are not regulated, practices vary widely and performance and failure data are scarce. Most performance-based data are limited to failure events that directly impact public health or are obtained from homeowners' applications for permits to replace or repair failing systems (EPA, 2002b). While the reported inspections and permits provide insight to actual system performance, they are still limited in that they only identify failures according to codes and do not measure groundwater contamination resulting from onsite system failures (EPA, 2002b). Furthermore, their assimilation requires a significant effort. As a result, many of the models listed in Table 2.1 above are limited to interpolation and extrapolation of sparse data (Brown & Root Services, 2001). Moreover, their output is expected contaminant discharges to the subsurface environment rather than the status of the on-site installation itself.

I selected Boulder County, Colorado as the study site. The County is located in the Boulder Creek-St. Vrain Creek watersheds in the northeastern part of the State. The County has a population of approximately 295,000 residents (121,500 households) in an area of

195,000 hectares (1.5 persons/hectare). The geographic terrain, which stretches from the Continental Divide to the Plains (Figure 3.1); economic activities, which include professional services, manufacturing and farming; and the income status of residents are diverse. Just over 62% of the population lives in owner-occupied units, with a median value of $358,000 (2014 dollars). The educational level of the residents is high with 94% holding a high school degree or higher and 58% of residents over 25 years old holding a Bachelor's degree or higher. In 2010, the median household income was $69,407 (2014 dollars) but over 13% of the population had income below the poverty level (U.S. Census Bureau, 2014).

There are 14,300 OWTS serving approximately 50,000 residents in the County as well as 21 treatment facilities with NPDES permits serving the rest of the population, with design flow rates ranging from 6 to 49,000 m^3/d (Weirich *et al.*, 2015). Permitted wastewater discharge from POTWs total 110,000 m^3/d. Estimated flow from the 14,300 OWTS is approximately 27,000 m^3/d, based on an estimated capacity of 2 m^3/d. I have collected data to produce a performance measure from public records such as legal documents, OWTS repair permit applications, and Boulder County Tax Assessor's data to determine the life-cycle costs and risks of residential sanitation systems.

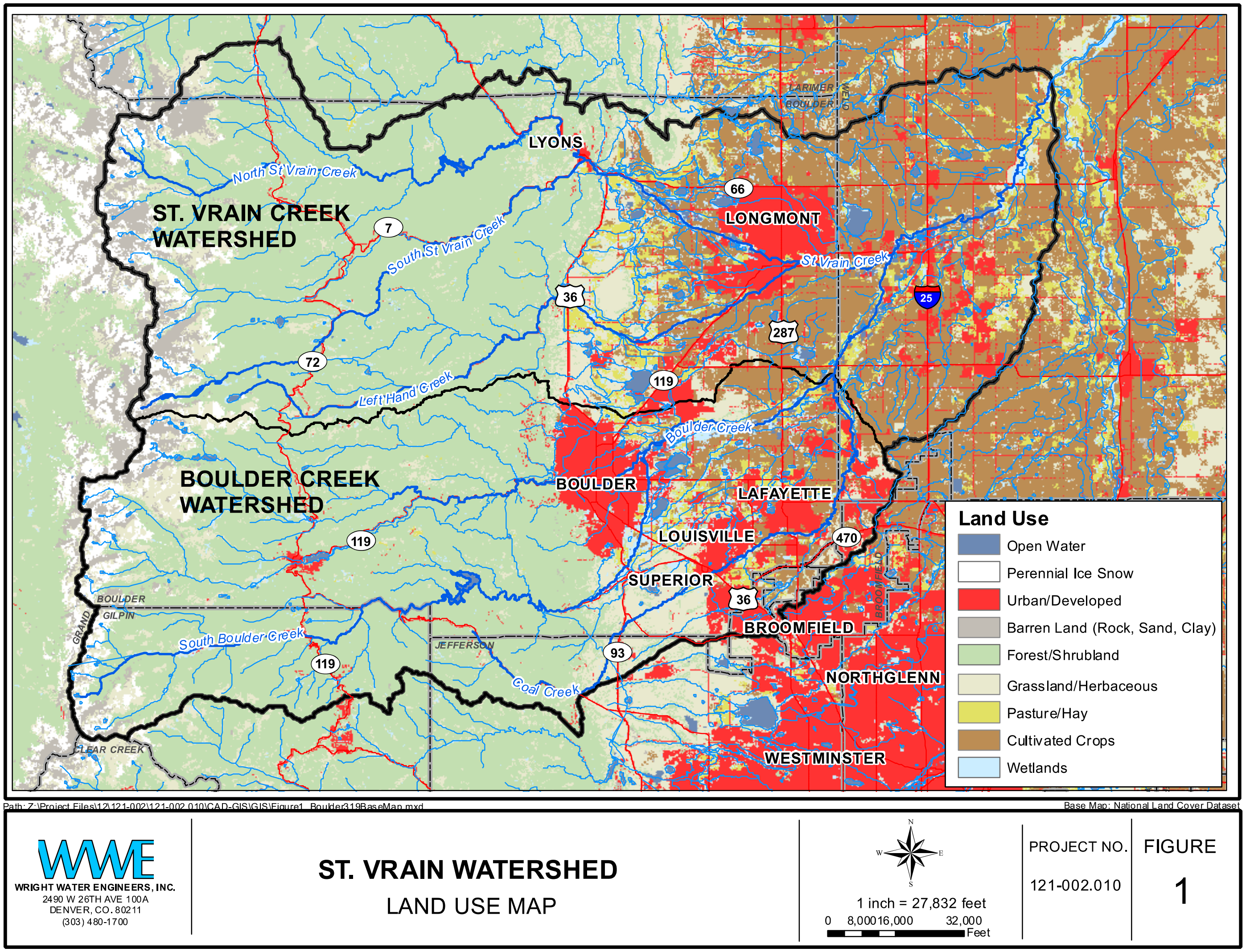

Figure 3.1 Boulder County map. Wright Water Engineers, cited in https://blogs.svvsd.org/water/colorado-watersheds/

Data

The Boulder County Public Health Department has a robust process for issuing permits for installation of OWTS, and has undertaken efforts to inspect systems installed without permits, many of them 50 or more years old (Colorado Department of Public Health and the Environment, 2013). The County also has maintained records dating back to the late 1940s documenting minor and major OWTS repair permits, legal documents, and inspections. The database of the County's repair permits was queried to create three input data sets—one consisting of repair and replacement documentation for permitted OWTS and each system's residential attributes which are described and used in **Chapters 4 and 5**, another which enumerates annual sample repair frequency and is described in detail in **Chapter 6**, and the third which focuses on flood-impacted OWTS and is described in **Chapter 7**.

Dependent Variable

For **Chapters 4 and 5**, the product of frequency and magnitude (costs) of repairs over the period of record forms the performance measure. While not all repairs are associated with a failure and/or contaminant release, exceeding some lifetime cost of repair implies performance instability sufficient to trigger significant intervention by County Health Department staff and/or certified OWTS servicers.

Each County record of a repair is classified by severity into minor, moderate, and major categories, following the determination of BCPH staff, and assigned an associated cost based on the County's posted estimates for the various categories of repairs, as described in **Chapter 4.** The dependent variable, *repair severity*, is the sum of all repair costs over the expected OWTS service life of 40 years, which is the sample average number of years from the final inspection date recorded on the installation permit to the date of the most recent recorded failure. The 40-year reference life is the minimum timeframe to capture approximately 80-90% of all major infrastructure expenditures (Pitterle *et al.*, 2008). For **Chapter 6**, the total number of each type of repair was enumerated for each year from 1979-2015 to correlate repairs to variations in climate/weather variables in each year. Lastly, for **Chapter 7**, the dependent variable is a measure of performance recovery calculated from the time an owner submits a repair permit application to the date of the final inspection.

Independent Variables

Using the Boulder County Assessor's Tax database, property inspection documents, and repair/replacement applications, ten independent variables were defined – which are described in **Chapter 4** and used in both **Chapters 4 and 5**. The independent variable data for each OWTS were coded and stored along with the corresponding *repair severity* values, and a unique location based on the latitude and longitude of the land parcel. The climate and weather independent variables from National Oceanic and Atmospheric Administration (NOAA) and stream flow independent variable from U.S. Geological Survey (USGS) are used and further described in **Chapter 6**.

DATA ANALYSIS

This dissertation uses a suite of statistical methods to observe relationships between the defined dependent and independent variables of the sample OWTS population to identify trends that can then be applied to answer questions about the life-cycle performance of the larger OWTS population (Dowdy *et al.*, 2004).

Various degrees of regression analysis and hierarchical or multilevel modeling have been used in this dissertation, including Generalized Linear Models (GLM), Generalized Additive Models for Location, Shape, and Scale (GAMLSS), and Extreme Value Analysis-Points Over Threshold (EVA-POT). Hierarchical models consist of several models organized in a tree or tiered structure where each model is connected to the other models through a link and where the additive model typically improves the overall model's ability to capture the sample characteristics. The hierarchical structure can capture both the impact of traditional covariates and the influence of geographical space and time. Individual methods will be discussed in the chapters where they are applied.

CHAPTER 4: MODELING ON-SITE SYSTEM RELIABILITY DEPENDENCE ON OWNER BEHAVIOR

Kohler, L., Silverstein, J. and Rajagopalan, B. (2016) **Predicting Life Cycle Failures Of On-Site Wastewater Treatment Systems Using Generalized Additive Models**. *Environmental Engineering Science.* 33(2): 112-124. doi:10.1089/ees.2015.0275.

Keywords: generalized linear model; on-site wastewater treatment; performance-based regulation, sanitation

ABSTRACT

Poor performance of on-site wastewater treatment systems (OWTS) poses local and regional risks to public health and environmental quality. In the US, local regulations control system design via permits issued at the time of installation. However, regulatory focus on one-time controls does not account for factors that influence performance after installation, notably asset management choices made by residential property owners. We develop a statistical method to predict performance over the OWTS life cycle in order to identify vulnerabilities and potential controls that reduce the risk of failure and contaminant release. A regression model based on Generalized Additive Models for Location, Scale and Shape (GAMLSS) uses data from public records of reported OWTS failures, repairs and replacements, inspections, and assessed property values from Boulder County, Colorado, which has 14,300 OWTS. Severity of required system repairs and replacements over a 40-year period was associated with five factors: structural value, house square footage, the number of required inspections, the homeowner expenditures and the frequency of OWTS upgrades. Model results suggest that mandatory inspections

through a mechanism such as renewable permits would significantly reduce life cycle repair/failure frequency and severity, lowering OWTS costs to owners and reducing public exposure to wastewater contaminants.

INTRODUCTION

In the U.S. the array of strategies and technologies for wastewater collection, treatment, and discharge form an organizational continuum from centralized publically owned wastewater collection and treatment works (POTWs) to owner-operated on-site wastewater treatment systems (OWTS). POTWs treat wastewater flows from 10 to over 10^6 m^3/day and operate with discharge permits issued through the National Pollutant Discharge Elimination System (NPDES) that require regular monitoring and reporting of compliance. The capacity range of OWTS serving a family or small commercial enterprise is much narrower, with flows typically less than 8 m^3/day (Crites and Tchobanoglous, 1998). Permits are typically issued by local agencies at the time of installation with no requirements for monitoring or reporting of performance unless the OWTS fails and triggers regulatory action.

POTWs and OWTS have a historical relationship. As the association of faecal waste with outbreaks of cholera and other water borne diseases became known in the latter half of the nineteenth century, unregulated on-site systems for collection, passive treatment and storage using privies, vaults, and cesspools were replaced by centralized sewer systems better able to handle increasing wastewater flows as residential piped water supply and use of flush toilets became widespread (Cosgrove, 1909; Burian *et al.*, 2000). As a result, centralization and modernization of wastewater treatment have been linked, and while the technologies for on-site systems have improved, scientific knowledge, tradition, and prevailing public opinion lead many engineers, public health officials, policy makers and the general public to favor centralized infrastructure over owner/user operated systems (Burian *et al.*, 2000; EPA 1997, 2002b; Etnier *et al.*, 2005, 2007). Because of this history, OWTS may be inaccurately associated with isolated rural residences or considered a temporary solution to be replaced by centralized collection and treatment.

In fact, reliance on OWTS to provide a significant portion of global sanitation is growing especially in regions where no sanitation infrastructure exists. Currently, decentralized, typically user-owned and maintained on-site wastewater treatment systems serve approximately 25% of the population in the U.S. (EPA, 2003, 2008a) with over 25 million OWTS installed in suburban, high population density areas (EPA, 2008a). Due to continued land development outside existing collection system boundaries, limited treatment plant capacity, and the cost of new centralized wastewater infrastructure, approximately 30% of new residential developments in the U.S. are constructed with septic systems (EPA, 1997, 2002a, 2002b, 2003). In 2005 it was estimated that OWTS served approximately 26 million homes, many in urbanized communities, discharging four billion gallons of effluent per day (U.S. Census Bureau, 2006). The City of Los Angeles, for instance, has over 11,500 residential OWTS and many are located near impaired water bodies with elevated levels of nitrate and coliform indicator bacteria ("LA Sewers", 2013).

However, unlike centralized facilities operating with NPDES permits, the performance of OWTS is not routinely documented, since monitoring of operations or discharged water quality is not required. The U.S. EPA estimates that 10 to 20% of OWTS in fact do not treat wastewater to acceptable levels (EPA, 2003) and some states estimate failure rates to be as high as 50% (EPA, 2002b). While one individual system failure may not pose a public health threat because the impacts are localized, the aggregate contaminant release from a cluster of poorly performing OWTS can have negative local and watershed-scale consequences. A survey of state water quality agencies ranked OWTS as the third greatest threat to groundwater quality, behind underground storage tanks and landfills (EPA, 1998).

Part of the challenge of ensuring OWTS functionality stems from their characteristic as *impure* public goods which have attributes of both *common property resources* (CPRs) associated with public goods such as environmental quality and *open access resources* (OARs), which have undefined ownership and are often privatized. As an OAR, an OWTS creates externalities that generate public costs associated with environmental degradation or threats to public health (Turvev 1963; Hardin 1968). Without controls, the private responsibility of OWTS operation and maintenance required for the protection of the public resource, i.e., the environment, creates an incentive to opt out of potentially costly maintenance activities, since opting in may offer no immediate benefit to the individual owner/user and opting out is seen as having a small and even undetected impact. Public Goods Theory implies that some regulation of the private right to use the environment as a waste sink is necessary to prevent the general degradation of environmental quality (Mohamed, 2009).

A comprehensive review of state-based OWTS regulations conducted by D'Amato *et al.* (2004), found that while most states regulate OWTS, regulations are by no means uniform. Furthermore, those states that have more extensive controls focus on installation, siting and design factors contributing to OWTS failure, which have been widely studied.

Existing OWTS performance models incorporate spatial, topographical, hydrologic, and other physical characteristics to identify locations where installing an OWTS may result in a high risk of failure (Oosting and Joy, 2011; Carroll *et al.,* 2006; Hudson, 1986; Brown and Root Services, 2001; Kenway *et al.*, 2001; McGuinness and Martens, 2003; Cromer, 1999a, 1999b; Joubert *et al.*, 1996; Chen and Herr, 2002). However, a significant fraction of properly designed OWTS fail, indicating that technology-based design standards are not the only factors influencing system performance over what is presumed to be a very long life cycle on the order of 30 years or more (EPA, 2002b). OWTS may be designed and operated in a way that optimizes treatment performance and decreases both the frequency and resulting reparative costs of OWTS malfunctions, ultimately improving the overall system performance life (McKinley and Siegrist, 2011).

The premise of this research is that reliance on design-based standards is insufficient to insure OWTS performance over the system life, and that the role of factors associated with system maintenance, owner knowledge, and usage must be considered. Moreover, as demand for use of increasingly sophisticated OWTS technologies for removal of nutrients or emerging trace contaminants grows; the number and complexity of owner-dependent operations will likely increase. Increasing dependence on OWTS as a global sanitation strategy underscores the need to understand how human/social variables such as organization, user motivation and knowledge influence operation of OWTS (Kaminsky and Javernick-Will, 2013).

Statistical modelling has been applied only recently to performance-based diagnostics of wastewater systems. Multivariate regression analysis using Generalized Linear Models (GLM) has been used to model treatment system response to water quality and wastewater variables (e.g., Weirich et al., 2011, 2015; Towler et al., 2013) adapting an approach used more widely in stochastic weather generation (e.g., Verdin et al., 2015; Kleiber et al., 2012, 2013; Furer and Katz, 2007). Weirich *et al.* (2011) used GLM to predict the likelihood of POTW compliance with NPDES permit discharge limits using Discharge Monthly Report data in the U.S. EPA Integrated Compliance Information System (ICIS) (EPA, 2008b). Applying a similar inductive statistical approach to characterize OWTS performance would allow us to observe what practices, if any, differentiate well- and poor-performing OWTS based on the historical performance of real systems over a defined life.

OBJECTIVES

The objective of this study is to i) identify user-associated factors that affect lifetime OWTS performance and ii) develop a predictive model to guide effective management of these systems by owners, environmental and public health agencies, and servicers.

Since no public data analogous to ICIS are available for on-site systems, the first component of this study is acquisition of data from OWTS permit and tax assessment records. In the absence of effluent quality data, information on costs associated with inspection, maintenance, repair and replacement of OWTS components, which are public records, serve as a surrogate measure of poor performance. It should be noted that modelled outcomes based on this type of data also may provide highly communicable cost/benefit information to stakeholders, especially OWTS owners.

Because OWTS records are typically collected and maintained by county health departments, Boulder County Colorado was chosen as the site for data collection. The Boulder County Public Health Department oversees permitting for 14,300 OWTS and also conducts comprehensive permit and public education programs (“SepticSmart Program”, 2015). Variables generated from collected data are then subjected to a regression modelling approach, Generalized Additive Models for Location, Scale and Shape (GAMLSS) (Rigby and Stasinopoulos, 2005) in order to select the post-installation factors associated with the level of OWTS performance over the system’s expected life. The predictive model will enable regulators to define actionable management guidelines for post-installation practices that can be incorporated into county or state regulations to improve OWTS reliability and save owners the costs of catastrophic failure. Additionally, the model will provide a means to communicate wastewater management alternatives and associated financial trade-offs to communities in a quantifiable and comparable way.

METHODS

The methods of this study are discussed in the three following sections: (1) data collection; (2) selection of the performance indicator and ten user-associated independent variables; and (3) development of the GAMLSS method for simulation of OWTS performance.

Data collection

The Boulder County OWTS study site is located in the Boulder Creek-St. Vrain Creek watershed in northeastern Colorado, encompassing an area of approximately 190,000 hectares and 300,000 residents (U.S. Census Bureau, 2015). There are over 14,300 OWTS in the County serving approximately 50,000 residents as well as 21 POTWs with a total capacity of 110,000 m^3/d serving the rest of the population (BCPH, 2013; EPA, 2008b).

Estimated flow from the 14,300 OWTS is approximately 27,000 m^3/d, based on a residential flow of 2 m^3/d (EPA, 1980). OWTS are located in highly variable terrain including mountain communities at elevations exceeding 2600 m and residents on the eastern plans at 1600 m. Approximately two-thirds of the OWTS for which the County has any records received permits at the time of installation.

The OWTS sample consisted of failed or poorly functioning systems selected by searching the database of repair permits maintained by the Boulder County Public Health (BCPH) Department. Repair permits were screened to select for OWTS having conditions associated with visible failures such as wastewater surfacing, odor or mechanical malfunctions resulting in system repairs, replacement or reported functional breakdown. The search returned 215 properties with reported OWTS failures from 2003 to 2013. While the permit database contains applications dating back over 50 years, records of specific reasons for permits did not begin until 2003, limiting the documented failures to post-2003 repair permits. That said, many of the early repair permits available documented visible failures, but the evidence exists in the form of hand written notes on the permit applications and therefore was not searchable in the database. From 215 OWTS in the original sample, only systems that had a County-approved inspection at the time of installation were selected for analysis. This reduced the number of properties in the sample from 215 to 120. Using only permitted sites provides a control for siting and design criteria set by the County. The fact that over half the failed systems in the County met initial design and siting standards supports the premise of this study that design standards are not sufficient to ensure performance.

The selected OWTS sample is distributed throughout the County area (See **Figure 4.1**) and captures variability in neighborhood/community affluence, housing density, and distance to professional OWTS servicers. The breadth of geographic and demographic attributes of the sample is selected to enable the application of results in other communities/regions.

Information in the repair permit applications for each of the 120 OWTS, primarily scanned hand-written originals, was coded to define a failure measure and quantified attributes of the properties and the owners' operation and maintenance history.

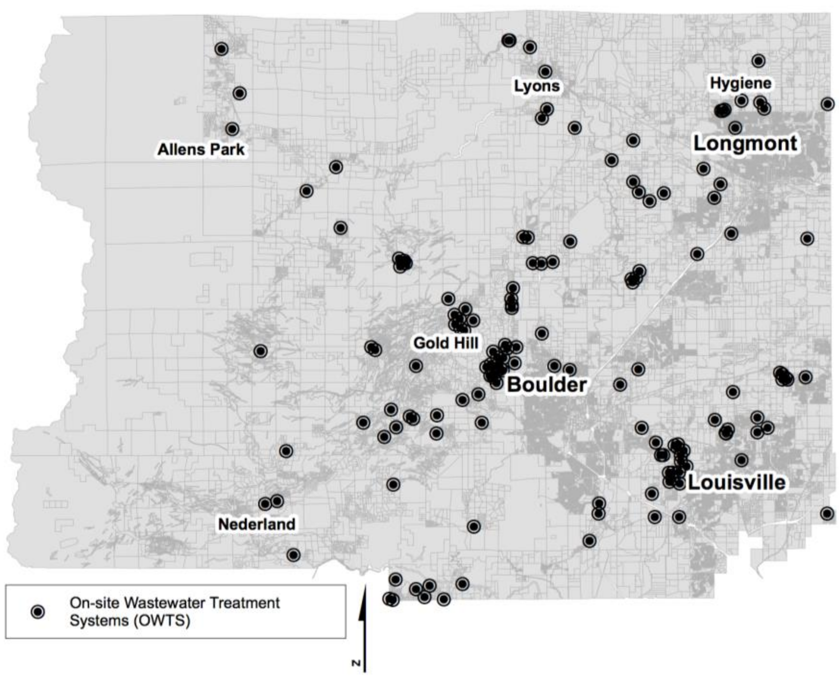

Figure 4.1 Geographic distribution of sampled OWTS repair permits in Boulder County, Colorado. Source: Boulder County Public Health (2013)

Variable definition

Dependent variable

Failure has been generally defined as not meeting some designated performance standard (Etnier *et al.*, 2005). However, there is no recognized definition of OWTS failure.

Failure has been commonly used in the OWTS industry and in the literature to specify major operational faults described above and loss of equipment integrity such as cracking of septic tanks and/or piping. For this study the failure measure for each OWTS is the sum of the estimated cost of all repairs requiring a permit, annualized to a 40-year period of record from 1973 to 2013. Thus failure incorporates both the frequency of major repairs and their magnitude, producing the dependent variable (Y) of ***annual repair severity*** expressed in U.S. dollars.

Repairs were classified into minor, moderate, and major, using cost estimates provided by BCPH staff, as described in the next section. The 40-year life cycle was selected based on the average length of time between the installation inspection and the date of the most recent repair permit.

For this study, a minor repair, defined by BCPH, is any repair to the septic tank or pipes. Moderate repairs refer to extraordinary maintenance or replacement of the soil treatment unit (STU). Failure of both the septic tank and STU constitutes a major repair often requiring replacement of all OWTS components.

The cost estimates for minor, moderate and major repairs are based on the results of an informal survey of OWTS installers and servicers conducted by the BCPH over 10 years ago. Due to property slope, size, water table levels, soil substrate, and location, the cost of any type of repair can vary widely. For example, the BCPH estimated cost of a moderate repair of the STU ranged from $4,860 to $21,800. However, the estimates provide relative benchmarks for minor, moderate and major repair costs adequate for modelling the severity distribution, which can be updated as new cost information is available. The average of the range of estimated repair costs for each category were: minor, $3,066; moderate, $9,173; and major, \$14,866. The repair cost does not include the cost of the repair permit, which is uniform for all repairs, or the cost to hire an engineer for more significant restorations. Engineering costs were excluded from this study because they vary greatly based on attributes associated with the system's location and design complexity. While this information affects the total cost of repair, the infrastructure and labour costs of each repair type included in our analyses differentiate between the types of failures and their relative severity.

Figure 4.2 shows the sample distribution of the annualized repair severity variable as a histogram along with admissible probability density functions, which will be further discussed in the *OWTS Repair Severity Model* section. The data appear to be categorical in nature even though cost of repair is a continuous variable. Approximately 60% of the sample has a repair severity value estimated to be \$372 per year.

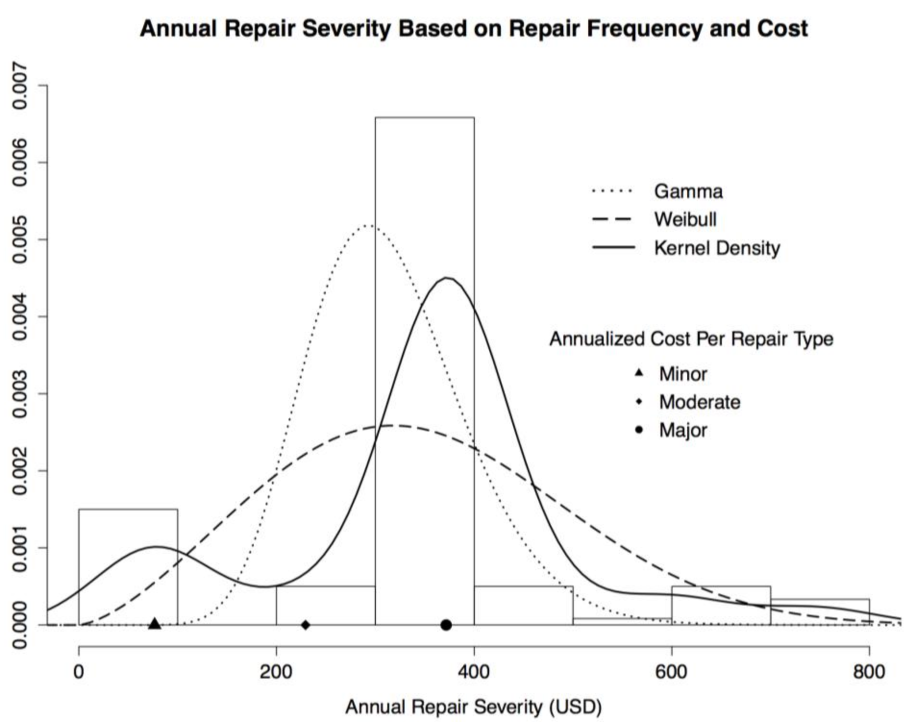

Figure 4.2 Distribution of OWTS *annual repair severity* data measured as cost (USD) compared to the Weibull and Gamma regressions for the 120 OWTS in the sample.

Independent variables

Using information from the Boulder County Assessor's property tax database, property inspection documents, and repair/replacement applications, ten independent variables were defined, which map to six categories that previous researchers have related to long-term OWTS performance (Kaminsky and Javernick-Will, 2013). The categories are technical, referred to herein as physical status (PHYS); organizational (ORG) related to the degree of community or institutional control; economic status of owner (ECON); owner knowledge of system operation (KNOW); user motivation (UM), related to interests affecting owner choices, and other (OTHER). The ten variables related to these categories are described in **Table 4.1**. The independent variable values for each OWTS for the 40-year period from 1973 – 2013 are coded and stored with the associated *annual repair severity* values, and unique land parcel ID for each OWTS site.

Table 4.1 Independent variables hypothesized to influence OWTS performance with definitions, sources and category type.

Variable	*Symbol*	*Variable definition*	*Relation to Variable*	*Category*
Property transfer inspections	**PT**	The number of property transfers after-2008 with documented inspections.	The Property Transfer regulation effective since 2008 states that prior to property sale or title transfer, the owners of the dwelling have to obtain a certified inspection and disclose any system issues to the buyer. The value represents the frequency of regulated system inspection.	**ORG**
Property sales (after 2008)	**PS**	Total number of times a property changed ownership after 2008		**UM/ KNOW**
Property sales (before 2008)	**EPS**	Frequency of title transfers and sales between 1973 and 2008		**UM/ KNOW**
Loan inspections	**LI**	Total number of documented OWTS inspections that occurred as a result of a loan application.	Prior to 2008, Boulder County recorded non-mandatory OWTS inspections recommended by some mortgage lenders, such as. USDA, VA and FHA, with further tests and repairs if problems were found.	**ORG**
Water supply	**WS**	0=private water supply (i.e. wells and cisterns) 1=public water supply (i.e. supplied by municipality or water district)	Availability of private water supplies may be associated with greater demand and OWTS loading (Nauges and Van den Berg, 2006). OWTS owners with private wells may be more likely to protect their water source.	**UM/ OTHER**
Structural value	**SV**	Assessed value of structure, excluding land value, in USD	The structural value of the house is used as a proxy for income and ability to pay for repairs and maintenance (Nieswiadomy and Molina, 1989).	**ECON**
Living area	**LA**	Living area in square feet	Statistically, larger homes consume more water, increasing the wastewater load to the system (Mayer and DeOreo, 1999).	**ECON/ PHYS**
Change in bedroom count	**RC**	The difference between the number of bedrooms when the permit was issued and at the time of the last repair	The number of bedrooms is considered to be associated with OWTS loading and typically is used to specify OWTS sizing.	**PHYS**
Change in bathroom count	**BC**	The difference between the number of bathrooms when the permit was issued and at the time of the last repair	Number of bathrooms is a greater factor in OWTS loading than the number of bedrooms, although then two are often related.	**PHYS**
Upgrades	**UP**	Cost of OWTS upgrades resulting from added bedrooms	Upgrades can be systems retrofitted to accommodate increased hydraulic loading.	**PHYS**

OWTS Repair Severity model

We used a variation of the Generalized Linear Model (GLM) regression method to evaluate the relationship between the *annual repair severity* of the sample OWTS population and the independent variables in **Table 4.1**. The application of the identified relationships is then used to predict the estimated *annual repair severity* of the larger OWTS population (Dowdy *et al.*, 2004).

The GLM provides a more flexible approach to regression than a standard linear regression model. In the GLM, the response variable, *Y,* is assumed to be a realization from any distribution in the exponential family.

$$Y \sim G(\boldsymbol{\theta}) \tag{1}$$

where $G(.)$ is any exponential type distribution and $\boldsymbol{\theta}$ is the set of parameters that define G. A link function, η, relates the expected value of $\boldsymbol{\theta}$ and consequently that of $Y(\boldsymbol{\theta})$, as a linear function of independent variables or covariates $\boldsymbol{X}$, as follows:

$$\eta\big(E(\boldsymbol{\theta})\big) = \boldsymbol{X}\boldsymbol{\beta}^T \tag{2}$$

where $\eta\ (.)$ is the link function, $\boldsymbol{\beta}^T$ is the vector of model parameters, and $\boldsymbol{X}$ is the set of covariates. The residuals are defined as:

$$\varepsilon = Y - E\ (Y) \tag{3}$$

They are assumed to be normally distributed and uncorrelated as with a standard linear regression (McCullagh and Nelder, 1989). $E(Y)$ is the expected value of the Y determined from the model.

Standard linear models require Y to be from a Normal distribution. Consequently, to model variables which are non-negative, positively skewed, discrete, or binary violates the normality assumption and thus cannot be readily modeled using a standard linear model.

Assuming a binomial distribution for the response variable reduces the GLM to a logistic regression; a Poisson distribution makes it a Poisson regression model, etc. (McCullagh and Nelder, 1989). Of course, a Normal distribution assumption reduces this to a standard linear regression. The ability to model a variety of distributions in the exponential family is the major advantage of GLM (McCullagh and Nelder, 1989). Replacing *G(.)* with an extreme value distribution allows this approach to model extremes as shown in the modeling of extremes in water turbidity by Towler *et al.* (2013).

Since every OWTS in the sample was repaired at least once, the response variable Y for all 120 systems is greater than zero and a positively skewed distribution – as displayed in Figure 2. The gamma distribution has been used in a GLM of POTW compliance data that also are positively skewed (Weirich *et al.,* 2011). However, the OWTS data have long tails due to members of the sample with extremely high or low values of repair severity, and the Weibull distribution is better suited to capture tail behavior compared to the Gamma distribution (e.g., Katz *et al*., 2002). While GLM provides computational flexibility, the assumption that the dependent variable Y must be represented by a distribution in the exponential family restricts its ability to model data using, for example, a Weibull distribution, which is not part of this family. Further, the GLM framework is largely for modeling a single parameter of the distribution with a link function. To overcome this limitation, Rigby and Stasinopoulos (2005; 2001) and Akantziliotou *et al.* (2002) introduced generalized additive models for location, scale, and shape (GAMLSS). GAMLSS relaxes the exponential family distribution constraint for the response variable and allows a larger distribution family, including those with long tails such as Weibull. Furthermore, it can admit additive functions of the independent variable that can be linear or nonlinear, providing more flexibility in modeling.

Like GLM, for GAMLSS, a smooth link function, $g_k(.)$, transforms the expectation of each parameter in the representative Y distribution, $f(y_i|\theta^i)$, to a set of predictors. The probability distribution function is conditional on θ^i where $\theta^i = (\theta_{i1}, \theta_{i2}, \ldots, \theta_{ik})$ is a vector of k parameters, where k depends on the distribution type.

$$g_k(\theta_{ik}) = \eta_k = \boldsymbol{X}_k\beta_k + \sum_{j=1}^{J_k} h_{jk}x_{jk} \tag{4}$$

Each parameter, θ_{ik}, is related to the set of explanatory variables, $\boldsymbol{X}_k$, and a parametric vector, $\boldsymbol{\beta}_k$. The term $\sum_{j=1}^{J_k} h_{jk}x_{jk}$ represents the random component and can be either a semi-parametric or non-parametric additive model (Rigby and Stasinopoulos, 2005).

To determine the impact of user operations on the expected *annual repair severity* of OWTS over a 40-year period, all independent variables and variable interactions were incorporated in the GAMLSS model using the GAMLSS package in the open-source statistical program R (http://www.r.project.org)), and all combinations of variables were tested to determine the distribution parameters, θ^i, using the Akaike Information Criteria (AIC, Akaike, 1974). AIC selects a best model by considering all the possible subsets of the independent variables from the fit model. For each model, the generalized Akaike Information Criteria (GAIC), specific to GAMLSS, is calculated as:

$$GAIC = -2\hat{\ell}(\theta) + (N * k) \tag{5}$$

where $\hat{\ell}(\theta)$ is the logarithm of the model likelihood function reflecting the subset of explanatory variables that are obtained from iterated weighted least squares method (IWLS), N is the penalty for additional parameters, which has a default value of 2, typical for AIC, and k is the number of model parameters. The model with the lowest GAIC is selected as the 'best model' (Stasinopoulos *et al.,* 2008).

Cross validation

To evaluate the model performance on an independent data set, a random number of observations, ~15% of the total data set or about 18 points, are dropped. The model is fitted to the remaining ~85% of the data and used to predict the dropped values and performance measure such as R^2 (square of the correlation coefficient between the observed and model predicted values) and RMSE (root mean squared error) are computed. This is repeated a thousand times and the measures are displayeyd as boxplots to provide insights into the variability of the model skill.

Sensitivity Analysis

The range of cost estimates for minor, moderate, and major repairs motivated us to consider the sensitivity of the Weibull model to changing costs. Because the BCPH cost estimates are over 10 years old, the possibility of underestimating the *annual repair severity* is the greater concern. Therefore the sensitivity analysis consists of generating two new models using the following repair cost conditions. Model II: sensitivity to the cost of major repairs only by retaining the average cost for the minor and moderate repairs used in the original model (Model I), but increasing the cost for the major repairs to the high value of the range; and Model III: increasing the cost of repairs for all repair categories to the high value in the range.

RESULTS

A GAMLSS model belonging to the Weibull distribution family was fit to the dependent variables and *annual repair severity* data, using the log link function. The GAMLSS model of repair severity is represented as

$$Y \sim WEI(\mu, \sigma) \tag{6}$$

where Y is the response variable, *annual repair severity*, and μ and σ are the scale and shape parameters, respectively, of the Weibull distribution (WEI). The best model of the scale and shape parameters based on GAIC resulted in the following expressions.

$$log\,E(\mu) = 5.96 + 7.54e - 8 * SV + 2.96e - 5 * LA - 0.05 * UP - 1.4 * PT - 0.10 * PS - 1.21 * (UP * PT) - 0.001 * (SV * PT) - 1.40e - 6 * (SV * PT) - 1.64 * (PT * PS) \tag{7}$$

$$log\,E(\sigma) = 1.023 \tag{8}$$

Equations 6 and 7 indicate that OWTS performance is related to five of the ten individual independent variables and four combinations of the variables. The individual factors selected are the assessed structural value of the home (SV), square footage of the home (LA) — both are considered proxies for household affluence or ability to pay, the number of complete required system inspections (PT) as a result of the 2008 Boulder County Property Transfer regulation for OWTS, the total number sales after 2008 where a property transfer inspection was not documented (PS), and the frequency and cost of OWTS upgrades resulting from adding a bedroom (UP).

The expected value of the shape parameter $E(\sigma)$ is a constant estimated by fitting a Weibull distribution to the observed data. It is common in these models with smaller number of data such as the case here, that the GAIC criteria keeps the shape parameter constant, as varying the shape parameter can make the model fit highly variable and the results difficult to interpret. The nonlinear combination of the five variables describing both the scale and shape parameters creates the Weibull distribution for each observation; therefore, each OWTS observation has a unique scale with a constant shape.

The Analysis of Variance (ANOVA) table (*model I* in **Table 4.2**) shows the significance of each variable in the model based on its p-value.

Table 4.2 Reliability model (Model 1) ANOVA table and model sensitivity to repair cost estimates.

μ coefficients								
	Model I				**Model II**		**Model III**	
GAIC	1533.79				1769.30		1766.75	
Covariate	*Influence*	*Estimate*	*Std. Error*	*P-value*	*Estimate*	*P-value*	*Estimate*	*P-value*
(Intercept)	+	5.96	0.09	<0.001	*6.62*	*<0.001*	*6.85*	*<0.001*
RC		--	--	--	*0.13*	*0.082*	--	--
SV	+	7.54e-7	3.23e-7	0.82	*4.99e-7*	*0.197*	--	--
LA	+	2.96e-5	5.02e-5	0.56	--	--	--	--
UP	-	0.05	0.08	0.53	*0.38*	*0.122*	*-0.05346*	*0.59*
PT	-	1.4	0.42	0.001	*-0.32*	*0.054*	*-0.36371*	*0.02*
PS	-	0.10	0.08	0.20	*-0.12*	*0.336*	*-0.06832*	*0.47*
UP*PT	-	1.21	0.40	0.003	*-1.99*	*<0.001*	*-1.84926*	*0.003*
PT*PS	-	1.64	0.44	<0.001	*-2.00*	*<0.001*	*-1.83440*	*<0.001*
LA*PT	-	0.001	2.08e-4	<0.001	--	--	--	--
SV*UP		--	--	--	*-2.60e-6*	*0.001*	--	--
UP*PS		--	--	--	*0.37*	*0.091*	--	--
SV*PT	+	1.40e-6	3.16e-6	<0.001	--	--	--	--
σ coefficients								
(Intercept)		1.023	0.07	<0.001	*0.776*	*<0.001*	*0.853*	*<0.001*

* Shaded entries are the variables that are consistently associated with repair severity in all three scenarios

The significance threshold was set at 0.1 (i.e. 90% confidence) for this study. The four combined variables: UP*PT, LA*PT, SV*PT, and PT*PS are significant at greater than 90% confidence. Of the individual variables, only the number of property transfers after 2008 when a full inspection was required met the significance criterion. While not all of the individual variables are significant at 90% confidence or higher (i.e. p-value < 0.01) in the best model, the best model from GAIC or other such criteria selects the group of variables that jointly improve the estimation of *annual repair severity.* However, the variables that are not significant tend to have coefficient values close to zero. With one exception, an increase in the value of individual and combined factors including the variable number of required inspections after 2008, PT, was associated with a **decrease** in annual repair severity, as reported under *model I* in **Table 4.2**, column 2.

Model Diagnostics

The GAMLSS model (**Equations 6 and 7**) provides the best estimate of the two parameters of the Weibull distribution describing the repair severity for each observation as a function of the selected independent variables. Consequently, the median and the 95% confidence intervals can be obtained from the estimated sample distribution. While a predictive model encompassing both extreme and the median results would be ideal, the primary concern is whether the model is a good predictor of *annual repair severity* for the average OWTS. Average system performance as reflected by the expected *annual repair severity* over the system's life is a potential decision factor for homeowners and can aid community and regional planning and management decisions when comparison of the costs of on-site and centralized systems is desirable.

The observed values and the predicted *annual repair severity* costs have an R^2 of 0.406 indicating that the model captures ~40% of the overall variability. R^2 values less than 50% are acceptable in behavioral and social science fields where typically the precentage of variance accounted for is smaller given the inherent variability of human nature (Hunter and Schmidt, 2004). Futhermore, even with a low R^2 value, the presence of statistically significant predictors still allow important conclusions to be drawn about how variations in the predictor values are associated with changes in the *annual repair severity*.

Figure 4.3 shows the *annual repair severity* in dollars for each system in the sample compared to the model expected value and 95% confidence interval.

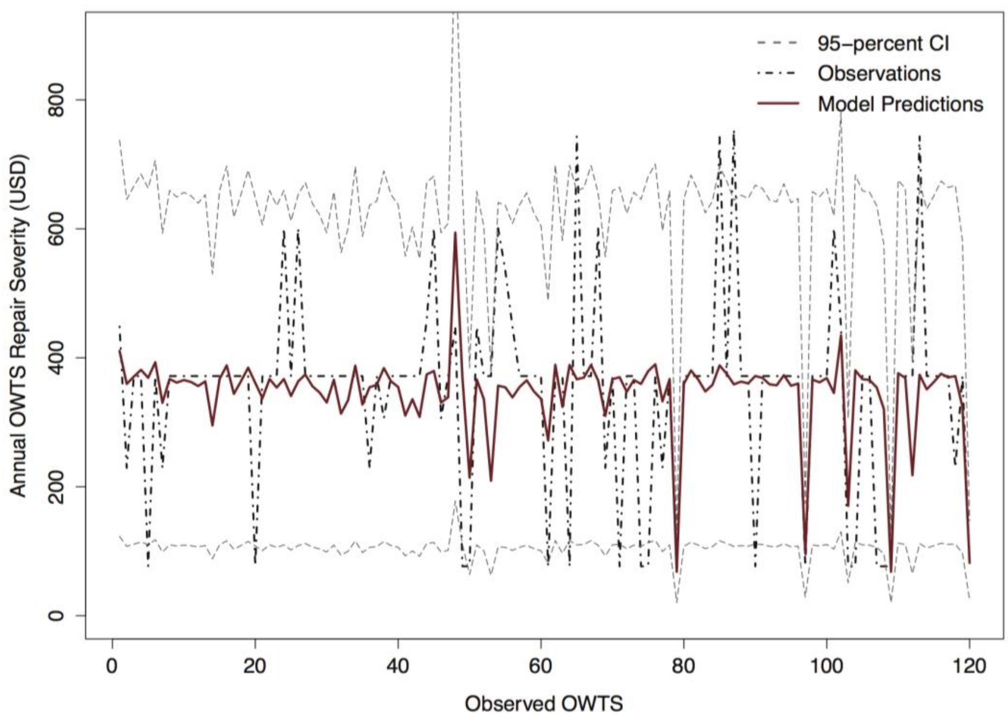

Figure 4.3 Predicted *annual repair severity* (USD) and 95% confidence limits using the fitted Weibull distribution parameters compared to the observed values for all 120 OWTS in the sample.

The figure shows that the model under-predicts the extremes and predicts well near the central values for *annual repair severity*. This suggests that there are additional variables that potentially contribute to the likelihood of either highly performing systems–those requiring few repairs—, and systems requiring frequent and costly major repairs that are ultimately more vulnerable to failure. The confidence intervals (**Figure 4.3**) are asymmetric and shifted in the same direction as the repair severity, suggesting that they are able to capture the variability well – unlike traditional regression approaches, which provide symmetric intervals. **Figure 4.4** shows the observed and modeled values for *annual repair severity* as boxplots as a function of the significant and highly influential variable, of number of property transfers after 2008 with required inspections (PT). No property had more than one required inspection after 2008; however even one inspection had a clear beneficial impact on *annual repair severity*, as captured in the Weibull regression.

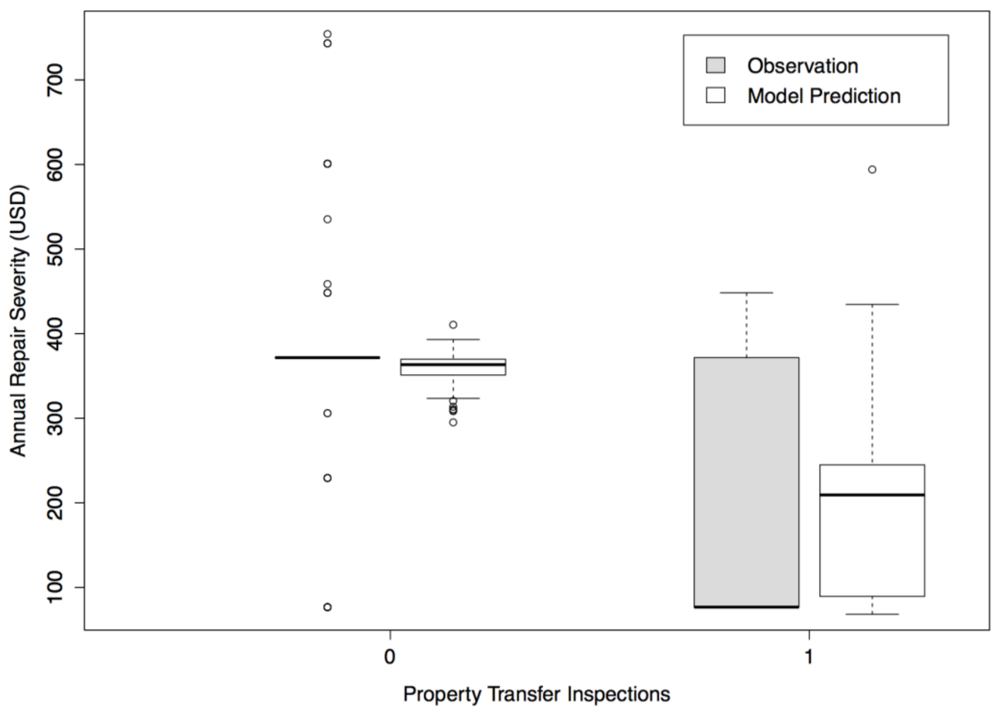

Figure 4.4 Relationship between predicted (Weibull) and actual annual repair severity costs and the number of property transfer inspections for 120 OWTS.

Figure 4.5 has spatial plots of the observed and predicted values of *annual repair severity*. While OWTS requiring moderate to major repairs are distributed throughout the County, the model does capture some spatial clustering of systems that had a history of higher-cost repairs.

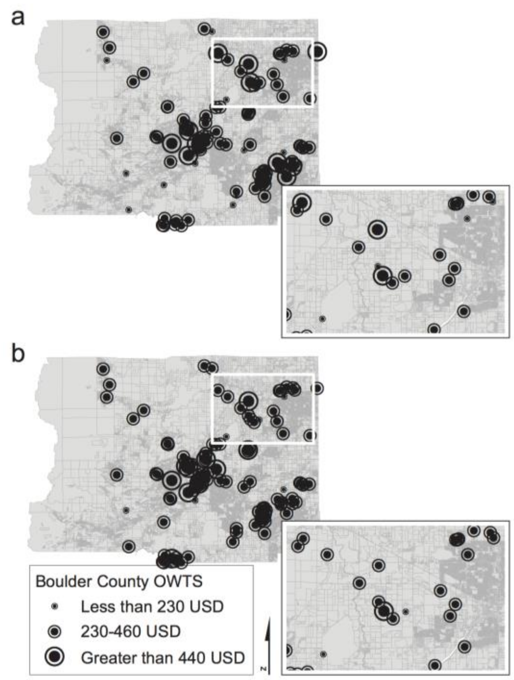

Figure 4.5 GIS map of observed *annual repair severity* (a) compared to the model estimates of *annual repair severity* (b). The windows zoom in on a selection of OWTS in and around the city of Boulder (refer to Figure 1) to highlight the model's ability to capture *annual repair severity* based on the selected covariates.

As mentioned in the model description, the model residuals have to satisfy the assumption of normality, independence and constant variance (i.e. homoscedasticity). These provide a set of measures for testing the model adequacy shown in **Figure 4.6**. The histogram supports the assumption of normally distributed residuals, and the ACF is minimal suggesting independence of the residuals. The heteroscedasticity plot shows no clear trend in residuals as a function of the estimated value of *Y.* Some of the structure in this latter plot is perhaps due to the categorical nature of the data. From the autocorrelation plot it is apparent that while the correlation appears to be minimal, there is significant autocorrelation at the first lag – i.e., one residual is correlated with the other, indicative of spatial correlation. This could be due to local factors such as topography, age of the neighborhood, etc. Hierarchical models where in the residuals are modeled as a spatial Gaussian process are attractive alternatives to capturing the residual structure.

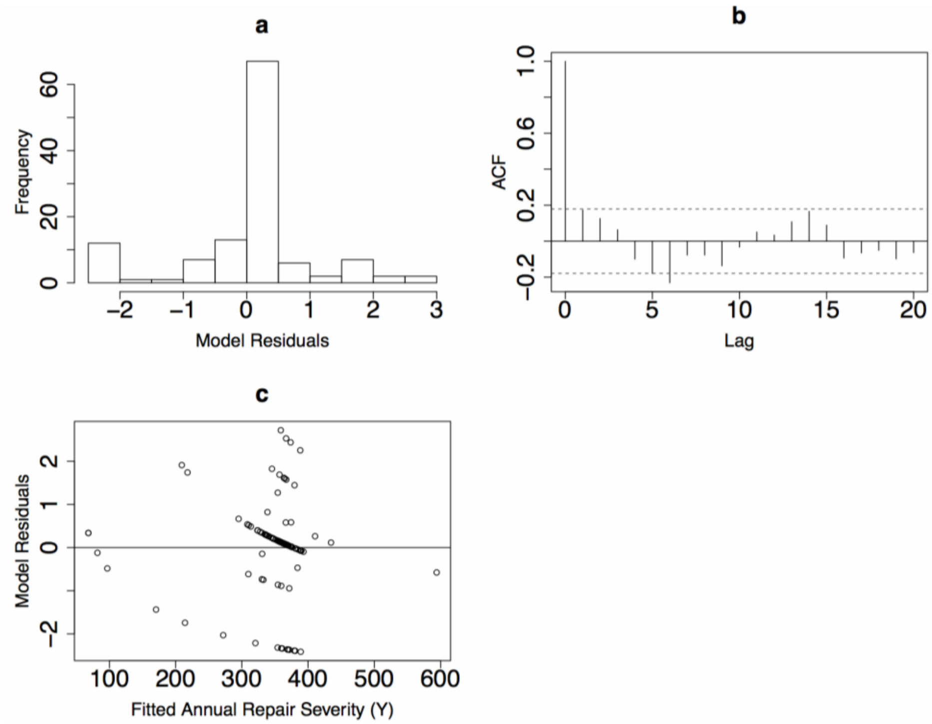

Figure 4.6 GAMLSS model diagnostic plots. (a) residuals histogram showing Normality, (b) Autocorrelation Function (ACF) distribution, and (c) constant variance plot of residuals testing for error heteroscedasticity.

Model Cross Validation

The variability of the predicted RMSE and R^2 skill measures during cross-validation are shown as boxplots in **Figure 4.7.** The relatively large variability in R^2 and RMSE is to be expected since the extremes cannot be modelled well without including them in the model fitting. The spread of both the skill indicators illustrates that the model is best applied to prediction within the original sample range and is least efficient in predicting extreme values of annual repair/replacement severity. The R^2 values of the cross-validation models ranges from approximately 0.1 to 0.8. and reflects the possibility that in each simulation some number of extreme values could be dropped resulting in under- or over-prediction of *annual repair severity*. However, the low median RMSE value of approximately $134 indicates that a significant portion of the predictions differ only slightly from the *annual repair severity* observations even after dropping 15% of the data.

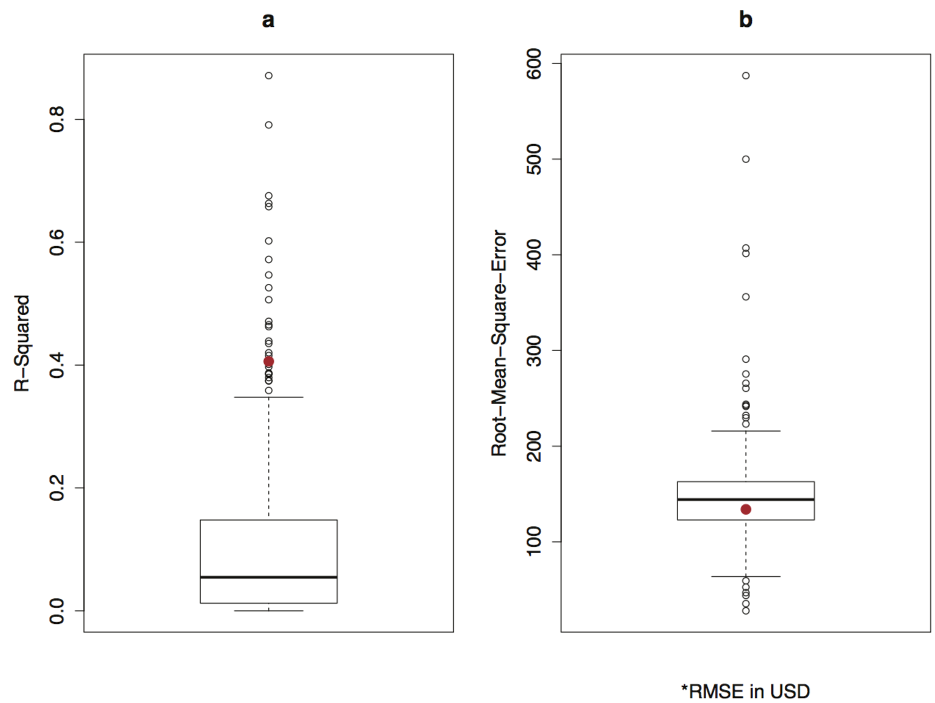

Figure 4.7 Skill of Wiebull model of *annual repair severity* model skill as distributions of R^2 (a) and RMSE (b) of iterated regressions with 15% of observations dropped RMSE in hundreds of dollars.

Model Sensitivity to Cost Estimates

Table 4.2 has the results of the sensitivity analysis comparing the original simulation (model I), based on the average cost in each repair category to results from simulations using cost estimates in models II and III. The covariates consistently associated with *annual repair severity* are UP, PT, PS and the interaction between the number of upgrades and property transfer inspections (UP:PT). Additionally, their influence on the likelihood of a high cost *annual repair severity* is consistently negative with one exception in model II where the likelihood of a high *annual repair severity* increases with an increased number of system upgrades. As the severity weighting is shifted using higher repair cost estimates, some of the covariates relevant in the initial GAMLSS model, e.g., LA, become insignificant to determining *annual repair severity*. However, the coefficient estimates of those variables in the initial model (model I) are approximately zero indicating that even in the initial model they have a lesser influence on *annual repair severity* than the highlighted more robust variables. **Figure 4.8** shows the adjusted *annual repair severity* distributions based on the different cost estimates as well as the representative Weibull fit to each distribution.

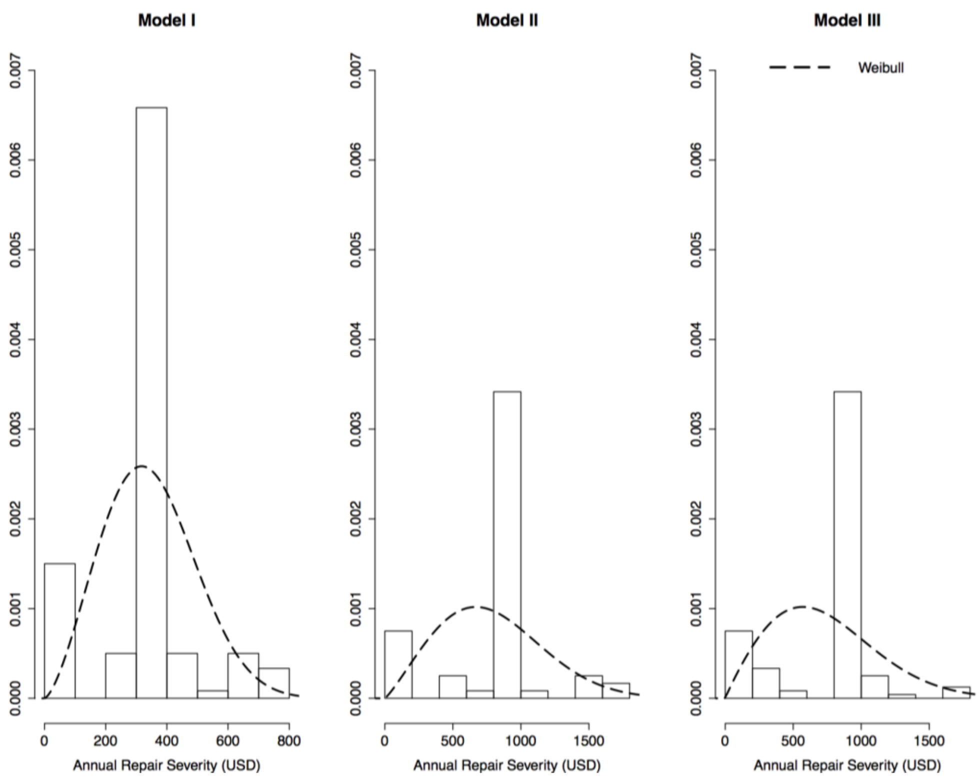

Figure 4.8 Estimated cost distributions for Models I, II and III and their Weibull representation.

Figure 4.9 illustrates the sensitivity of the residuals of the GAMLSS model to changes in cost estimates. Positive residuals in **Figure 4.9** indicate an overestimation of *annual repair severity*; whereas, negative residuals reveal an underestimation of repair/replacement costs. Residuals based around zero demonstrate where the predicted value is close to the real *annual repair severity* value.

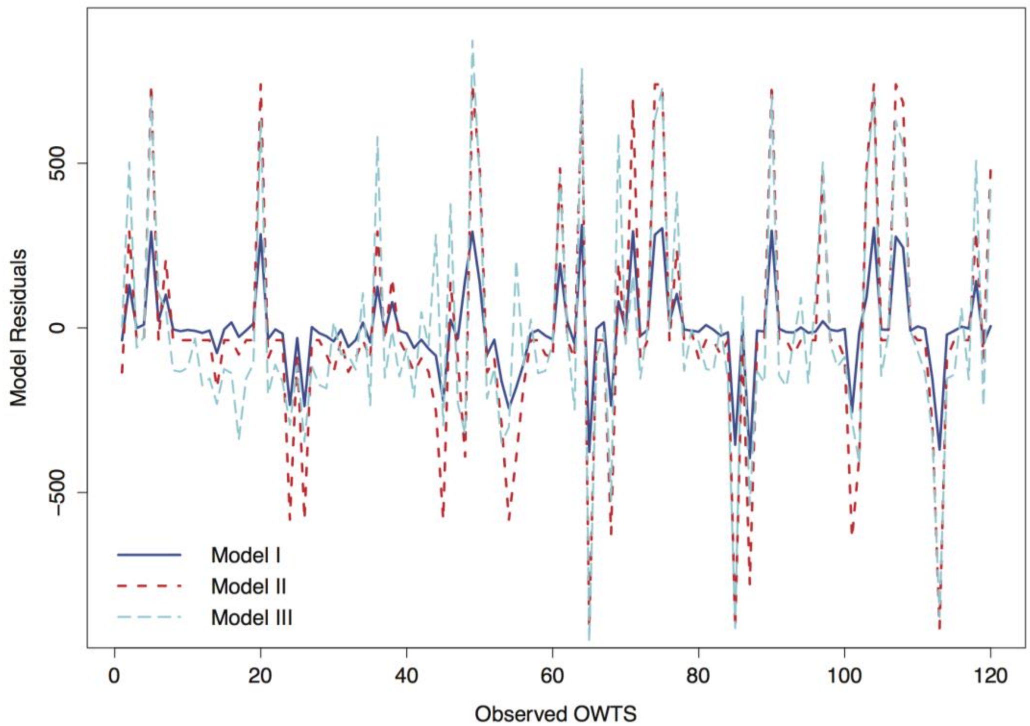

Figure 4.9 Sensitivity of model skill to repair cost estimates used to calculate *annual repair severity.* Model I is the original Weibull regression using the average of BCPH cost ranges for all repair categories; Model II is the Weibull regression substituting a higher cost estimate for major repairs; Model III is the Weibull regression with the higher cost estimate for all three categories of repairs.

In general, both positive and negative residuals increased along with cost estimates for both major and all repairs implying greater uncertainty in predictions of repair severity. This is not unexpected as the predicted *annual repair severity* values also increases as a function of higher costs.

DISCUSSION

Public Good theory provides a policy framework for recommending increased regulation of OWTS (Mohamed, 2009). Health and environmental impacts of appreciable levels of OWTS failure and repair, aggravated by the growing density of these systems, is additional motivation for new regulations requiring regular inspection and maintenance.

However, new regulations have associated costs for both individual owners and for local health departments charged with maintaining records and processing permits. Results of this study provide data-based support for mandatory inspections that reduce repair frequency and cost over the OWTS life, and a credible estimate of the benefits of increased oversight. In fact, the predicted benefit of inspections is conservative, since the Boulder County inspection/repair requirement only takes effect when a property is transferred. It may well be the case that a universal requirement for regular OWTS inspections through means such as a renewable permit would have an even larger benefit in improving OWTS reliability.

Two factors, SV and LA, have been considered as indicators of household affluence (Harlan *et al.*, 2009). The GAMLSS model showed a slight positive association of both with *annual repair severity*. Interestingly, this result goes against the common assumption that an increased ability to pay increases the likelihood of homeowner attention to maintenance and system performance. This counterintuitive result could be attributed to the location of these homes. In Boulder County many larger high-value homes outside POTW service areas are located in mountainous areas far from maintenance services. Some may have soil treatment units located in terrain where a failure may not be noticed by either residents or neighbors. Additionally, more expensive homes may be sold less often, so that structural value is negatively related to mandatory inspections.

Finally, UP was associated with a decrease in predicted *annual repair severity* for OWTS. One explanation is that when a home's size is increased through remodeling and construction, the County requirement for expanded or appropriately upgraded systems would have an effect similar to property transfer inspections resulting in less frequent and less severe repairs. The relationship suggests that increasing system capacity also may benefit performance.

While individual variables such as inspections and repairs associated with property transfers, sales after 2008 and system upgrades decrease the likelihood of a high *annual repair severity,* inclusion of combined variables, especially those containing post-2008 property transfers, improved the Weibull model skill. An interaction between individual variables with the same influence on the likelihood of a high *annual repair severity* amplifies those individual performance effects and increases the overall skill of the model. However, the small coefficient values for some of the combined variables such as structural value and regulated property transfers indicates that their effect on the expected value of *annual repair severity* was small. In general, LA and SV in combination with PT allow the model to discriminate between what might be considered a moderate range and a high range *of annual repair severity* values. While removing the two variables is an option given their p-values, they not only improve the skill of the model but also minimize GAIC compared to model versions without them. This indicates that while household affluence may not directly relate to *annual repair severity*, both indicator variables provide a non-arbitrary amplification of the highly significant covariate, PT, and capture the non-linear effect of the interaction on OWTS performance.

Some spatial clustering of OWTS repair severity (**Figure 4.5**) and autocorrelation of residuals (**Figure 4.6**) suggest that not all factors determining OWTS failure are captured in the Weibull regression. Both geographic clustering and autocorrelation may be explained by factors such as weather, soil and groundwater conditions, distance from OWTS servicers and from other residences. As an attractive extension of this research, the relationship between OWTS repair severity and location can be explored using spatial modeling of the GAMLSS model residuals in a hierarchical modeling approach or a Bayesian method (e.g., Verdin et al., 2015). Another potential extension of this study exists in the discretized characteristic of the data (**Figure 4.2**), which lends itself to a categorical modeling approach using a binomial or multinomial logistic regression analyses (e.g., Towler et al., 2013) to estimate risk, particularly quantifying the likelihood of high repair severity occurrences.

SUMMARY

As the use of owner-operated on-site sanitation technologies increases, life cycle costs and long-term sustainability, including environmental and health impacts become more relevant to reducing the risk of human and environmental exposure to wastewater contaminants. This research identified factors unique to minimally regulated OWTS that may guide future planning to enable better OWTS management over the system life. In the absence of comprehensive monitoring data, the product of the cost and frequency of system repairs and replacement, annualized over a 40-year lifetime, denoted as "annual repair severity", is proposed as a measure of system failure. Data from 120 OWTS in Boulder County, Colorado are fit by regression (GAMLSS) modelling, with the best fit provided by the Weibull distribution. In general, variables associated with conscientious owner management of OWTS were predictive of long-term system integrity. The most important was the frequency of inspections by professional servicers, typically accompanied by maintenance and minor repairs. This result suggests that mandatory inspections through a mechanism such as renewable permits would significantly reduce life cycle repair/failure frequency and severity, lowering OWTS costs to owners and reducing public exposure to wastewater contaminants. The statistical model is skilled at predicting repair severity in the mid-range of the data distribution with an expected annual repair/replacement cost between $350 and $400 per year, over the 40-year life cycle. The observed and modelled annual repair severity values were correlated with an R^2 value of 0.406, with larger discrepancies at the high values of annual repair severity, which fell in the range of $600 to $800 per year. The model dependence on inspection frequency as a principal determinant of repair severity was not sensitive to the cost estimates assigned to each category, indicating general applicability of the model results.

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CHAPTER 5: MODELING RISK OF FAILURE USING EXTREME VALUE ANALYSIS

Kohler, L., Silverstein, J. and Rajagopalan, B. (Out for Review) **Risk-Cost Estimation Of On-Site Wastewater Treatment System Repairs Using Extreme Value Analysis**. *Water Environment Research.*

Key words: on-site wastewater treatment systems, failure risk, extreme value analysis, decision analysis

ABSTRACT

Owner resistance to increasing regulation of on-site wastewater treatment systems (OWTS), including obligatory inspections and upgrades, moratoriums and cease-and-desist orders in communities around the U.S. demonstrate the challenges associated with managing risks of inadequate performance of owner-operated wastewater treatment systems. As a result, determining appropriate and enforceable performance measures in an industry with little history of these requirements is challenging. To better support such measures, we develop a statistical method to predict lifetime failure risks, expressed as costs, in order to identify operational factors associated with costly repairs and replacement. A binomial logistic regression is used to fit data from public records of reported OWTS failures, in Boulder County, Colorado, which has 14,300 OWTS. High-performing OWTS with repairs and replacements below the threshold of $9,000 over a 40-year life are associated with more frequent inspections and upgrades following home additions. OWTS with a high risk of exceeding the repair cost threshold of $18,000 are analyzed in a variation of extreme value analysis (EVA), Points Over Threshold (POT) where the distribution of risk-cost exceedance values are represented by a generalized

Pareto distribution. The resulting estimated costs for OWTS in the high-risk category over a 40-year expected life ranged from $18,000 to $44,000.

INTRODUCTION

Over the next 20 years, the U.S. EPA estimates $122 billion and $148 billion in funding shortages for capitalization of new wastewater infrastructure and continued operation and maintenance of existing facilities, respectively (EPA 2002a). The gap in available funds in part may account for greater interest in more decentralized wastewater treatment, including user operated on-site wastewater treatment systems (OWTS), as a permanent part of sanitation infrastructure planning both in the U.S. and globally. In the U.S., approximately 25% of the population is currently served by OWTS, and 30% of new housing developments have OWTS.

In regions of the U.S., wider application of OWTS technology has been accompanied by greater expectations of performance and consideration of new regulations that recognize the risks of denser networks of OWTS (e.g., State of Colorado recommended transfer of title inspection and renewable permit policy for County level adoption and control (Colorado Department of Public Health and the Environment, 2013), State of California Proposed New Statewide Policy (California Water Boards, 2011) officially adopted in 2012 (California Water Boards, 2012)). Yet in spite of well-developed on-site wastewater technologies, the U.S. Census Bureau estimated OWTS failure rates between 10% and 20% (EPA 2002b), while in some individual states failure rates are upwards of 50% (Nelson, Dix and Shepard 1999).

Existing risk management

OWTS primarily rely on oversized septic tanks and soil treatment units to produce extended waste residence times that enable slow processes like fine-particle sedimentation and ambient temperature anaerobic digestion for the separation and transformation of contaminants, especially pathogens, with no energy or mechanical inputs (Crites and Tchobanoglous 1998). However, OWTS conditions are highly dynamic on multiple time scales of days, months, seasons, and years, and even conservative designs are unlikely to obviate the resulting variability of OWTS performance, especially over the longer time scale associated with factors such as solids overflow, loss of tank integrity, and clogging of the soil treatment unit (STU) (McKinley and Siegrist, 2011). Furthermore, under the historic paradigm that OWTS serve isolated rural residences the environmental and public health risks associated with either intermittent service disruptions or even catastrophic failure are assumed to be managed through dispersion and dilution. Yet, with increasing use, the aggregate impact of denser networks of OWTS may in fact be comparable to or exceed that of centralized facilities, especially when considering poorly removed constituents such as nutrients.

Technological advances may reduce some OWTS performance variability, but those advances alone have not addressed failure rates observed in systems that meet design standards. Safe on-site storage, transformation and disposal of fecal waste require knowledge of how factors such as monitoring, inspection, maintenance, costs and owner knowledge influence performance. These owner-dependent operational factors are different from design and permit-based standards but greatly influence the functionality of OWTS (D'Amato *et al.*, 2008).

Although OWTS are often characterized as passive processes requiring infrequent, if any, operation and maintenance, regular maintenance activities such as pumping solids, repairs and replacements require owner management. In addition to logistical demands, financial responsibility falls on individual residents. Unlike centralized collection and treatment systems, there is no mechanism for distributing the costs of significant repairs or replacement. For example, if a catastrophic failure occurs in a centralized service, the connection fee and monthly rates often include anticipated system repairs and replacements. In the event these are exceeded, public utilities are able to issue tax-guaranteed bonds and while wastewater rates may increase, the cost is still spread over a larger number of ratepayers and over time. Pearson (2007) reported that residential customers of very small community water systems serving 25 to 100 people paid 89% of the revenue for operations, while residents served by larger systems with more than 100,000 people paid only 50% of the operating revenue. If an OWTS fails, 100% of the cost of replacement falls on a single homeowner—typically as a lump sum cost.

Some home insurance policies may cover damage as a result of surfacing effluent, but rarely pay the costs for repair and replacement of OWTS components. Special policies covering septic system repair cost hundreds of dollars per year and do not cover many failures or repairs due to extreme weather, neglected maintenance, construction accidents or misuse (Pro-Sept™, 2014). In any case, the financial risk of failure is transferred to the homeowner with or without insurance. Moreover, the likelihood of choosing to purchase insurance is further reduced without a clear understanding of the financial risks and effective avoidance measures.

The risk of one or more high-cost repair has been defined for other systems as the product of the probability of loss of service and the consequence. In the case of an essential service such as an OWTS, a monetized consequence is the dollar amount for system repairs and/or replacements (Pinkham *et al*., 2004; Fane *et al*., 2004). In previous research we found an association between more frequent OWTS maintenance and the annualized cost of lifetime repairs (Kohler *et al*., 2015). However, there is a strong incentive for homeowners to postpone even basic maintenance services because they are costly, failures in subsurface components are not apparent, and OWTS are not subject to monitoring and reporting regulations. Public education may encourage owners to be proactive in managing their OWTS, but the combination of the economic disincentive and the belief that an individual system failure had little impact on others outweighs persuasion in many instances (Mohamed, 2009).

Study objective

From an asset management standpoint, a goal for decentralized wastewater services is to install and manage systems that deliver treatment to protect receiving water quality for the lowest overall cost (AMSA, 2002). Many of these, including design, manufacturing, installation, routine maintenance, and salvage, may be reliably estimated based on known equipment costs and professional service fees. However, the likelihood of OWTS failures over the system life and the associated costs – a so-called risk-cost model, does not exist. In a study of OWTS near the Chesapeake Bay, asserted the benefit of moving away from lumped safety factors to account for performance uncertainty and measure reliability towards a more objective way of assessing and communicating risk to stakeholders and assigning financial responsibility (Gujer, 2006).

The goal of this study is to quantify risks of OWTS service disruption and enable incorporation of risk associated OWTS failure as a factor in land use planning, regulatory activities and owner engagement. In previous research, we showed that a statistical approach using Generalized Additive Models for Location, Scale and Shape (GAMLSS) fit to data from OWTS repair permit applications, system inspection documentation, and tax assessor's information in Boulder County, Colorado was able to predict life cycle repair/replacement costs for a county-wide OWTS sample (Kohler *et al*., 2015). However, the GAMLSS model skill was relatively low in modeling cost-based failure risks at the extreme ranges of the sample for either the poorest (highest risk) or best (lowest risk) performing systems. Yet characterizing the risk factors for these two populations may have the greatest value for risk communication and decision-making, especially decisions by owners who assume the burden of a cost-based risk. We therefore apply extreme value analysis-peak over threshold (EVA-POT) analysis of the Boulder County OWTS data to improve the estimates of risk at the extremes of OWTS failure profiles. The risk model also provides an economic basis of comparison with other sanitation/wastewater management technologies incorporating uncertainty. Finally, many OWTS failures such as STU clogging, ponding, overflow and septic tank leakage represent uncontrolled release of contaminants to the environment and/or human exposure. While quantifying discharges from failing OWTS is beyond the scope of this study, the cost-based risk model may provide a secondary measure of water quality and health impacts.

METHODS

Data

The input data consisted of coded OWTS permit information, including repair and replacement documentation, residence descriptions and assessed value for 120 sites described in an earlier paper (Kohler *et al.*, 2015). The geographical distribution of the 120 systems encompasses the full range of topographic and demographic characteristics of the Boulder County, and represents an overall OWTS population of 14,300 OWTS.

Variable definition

Dependent variable

For this study, the product of frequency and magnitude (costs) of repairs over the period of record forms the performance measure. While not all repairs are associated with a failure and/or contaminant release, exceeding some lifetime cost of repair implies performance instability sufficient to trigger significant intervention by County Health Department staff and/or certified OWTS servicers.

Each County record of a repair is classified by severity into minor, moderate, and major categories, following the determination of BCPH staff, and assigned an associated cost based on the County's posted estimates for the various categories of repairs, as described by Kohler *et al.* (2015). The dependent variable, *repair severity*, is the sum of all repair costs over a service life of 40 years, which is the sample average number of years from the final inspection date on the installation permit to the date of the most recent recorded failure. Other researchers have suggested that a 40-year life cycle captures approximately 80-90% of the range of wastewater infrastructure expenditures for initial capital and major replacement costs (Pitterle, 2009).

Figure 5.1 shows the histogram of the total *repair severity* variable along with a kernel density estimation of the probability density function. Although, the continuous distribution is shown, the data has clear grouping with approximately 60% of the sample with repair severity value estimated at approximately $15,000 over the 40-year service life. Visually, threshold values of < $9,000 and > $18,000 were used to define the high- and low-risk subpopulations that have extreme values of *repair severity*. The high- and low risk extremes were represented by a subset of 17 and 24 systems, respectively. The basis for the choice of these thresholds is described in the *Extreme Value Analysis* section.

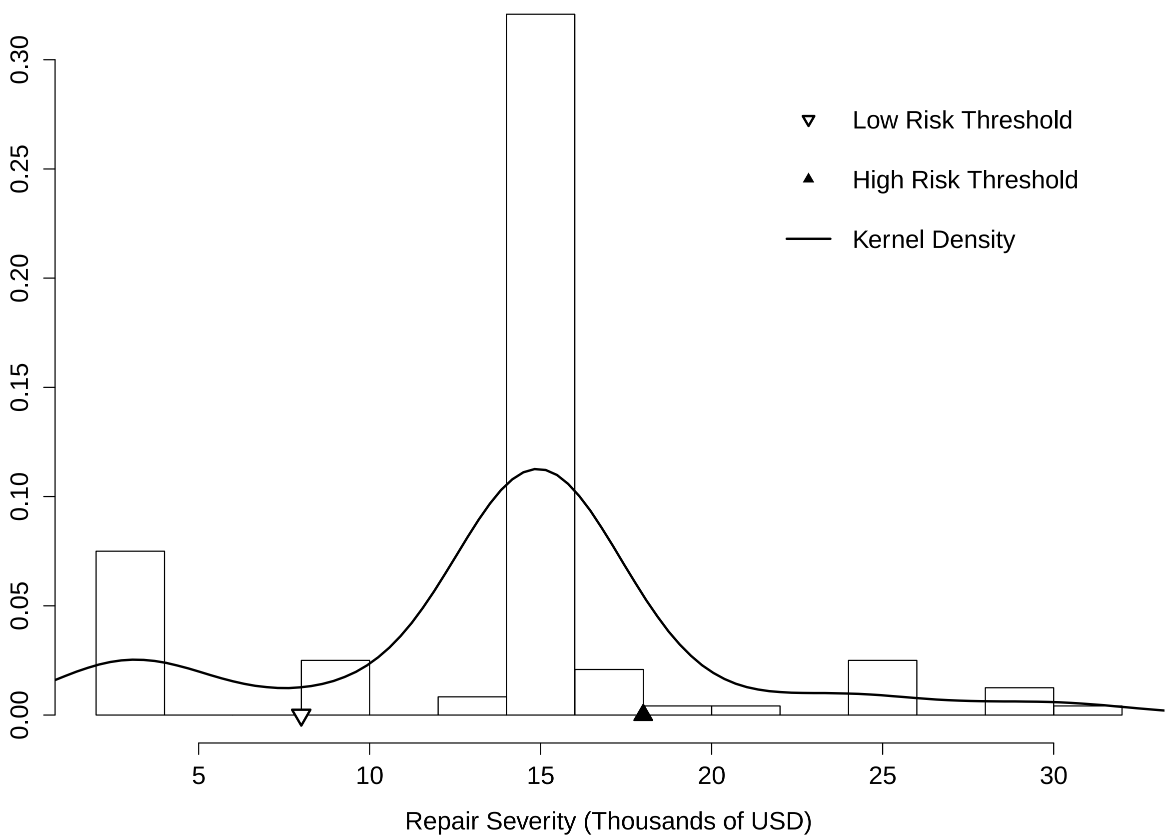

Figure 5.1 Distribution of OWTS *repair severity* data measured as cost (USD) of the 120 sample observations.

Independent variables

From the Boulder County Assessor's Tax database, property inspection documents, and repair/replacement applications, ten independent variables were used – which are described in Kohler *et al.* (2015); and also listed in **Table 5.1** along with their abbreviations. The independent variable data for each OWTS were coded and stored with the corresponding *repair severity* values, and a unique location based on the latitude and longitude of the land parcel.

Table 5.1 Independent variables hypothesized to influence OWTS performance risk.

Variable	*Symbol*
Property transfer inspections	**PT**
Property sales (after 2008)	**PS**
Property sales (before 2008)	**EPS**
Loan inspections	**LI**
Water supply	**WS**
Structural value	**SV**
Living area	**LA**
Change in bedroom count	**RC**
Change in bathroom count	**BC**
Upgrades	**UP**

Extreme Value Analysis

Extreme Value Analysis (EVA) is used to model extreme events (Coles, 2001), i.e. the events in the tails of the distribution, which are often underestimated by regression techniques that rely on the exponential family of distributions. One EVA model, Peaks-Over-Threshold, is used to model events that are outside a selected threshold. Once a threshold is selected two components are modeled - (i) the probability of exceedance (over or under) the threshold and (ii) the magnitude of exceedance. The probability of exceedance is modeled using a logistic regression – which is a Generalized Linear Model (GLM), and a Generalized Pareto Distribution (GPD) for the magnitude of exceedance, together forming the method EVA-POT (Coles, 2001). These two components are described below.

The cumulative distribution function of the GPD for values exceeding the threshold, μ, is specified by three parameters: location, μ – the threshold, scale, σ, and shape, ξ. Generally, the cumulative distribution function of the GPD is:

$$F_{(\xi,\mu,\sigma)}(x) = \begin{cases} 1 - \left(1 + \frac{\xi(x)}{\sigma}\right)^{-1/\xi} & for\ \xi \neq 0 \\ 1 - \exp\left(-\frac{x}{\sigma}\right) & for\ \xi = 0 \end{cases} \quad (1)$$

The threshold can be user-specified - e.g. one with significance in a decision-making context or it can be selected in a quasi-objective manner. In the latter, different thresholds are selected and for each, the scale and shape parameters are estimated. The parameters are plotted against the threshold value and the region where the parameters remains stable is used to select the threshold. Selecting a threshold that is both relevant to the user and falls with the stable region of the plot is preferred (Coles, 2001).

The threshold converts the observed data, in this case the *repair severity* cost, to a binary series of 0 and 1, with one representing an exceedance event. This binary response variable series is modeled as a Poisson process or logistic regression (Coles, 2001) as a function of covariates (independent variables). We use the logistic regression, which is one of the GLMs (McCullagh and Nelder, 1989) with a Binomial parent distribution:

$$G(E(Y_i/n_i)) = G(p_i) = X\beta + \varepsilon \quad (2)$$

where *G(.)* is the logit link function, *X* is the set of predictors or independent variables, $E(Y_i/n_i)$ is the expected value of the proportion of Y_i taking on the value one (also referred to as p_i or the probability of event *i*), and $\boldsymbol{\varepsilon}$ is the error, assumed to be normally distributed. *G(.)* takes the form:

$$G(.) = logit(p_i) = \log\left(\frac{p_i}{1-p_i}\right) \quad (3)$$

The best combination of logistic regression predictors is selected based on minimizing Akaike Information Criteria (AIC), which is a standard approach (Akaike, 1974).

The performance of the logistic regression model, which estimates the probability of the two categories is typically quantified using the Brier skill score (BSS). BSS is a special case of Ranked Probability Skill Score (RPSS), which is widely used to evaluate weather and climate forecasts (Weigel *et al.*, 2007). BSS takes the form:

$$BSS = -\frac{BS - BS_{ref}}{BS_{ref}} \quad (4)$$

which specifies the mean-squared error of probability forecasts (BS) for a dichotomous event compared to a reference forecast (BS_{ref}), also referred to as constant climatology forecast, which is often an unskilled estimate of the outcome. The constant climatology or unskilled forecast is the proportion of the sample count in each risk category. For example, the proportion of OWTS in the high risk category, above threshold, is (17/120) and that of the lower risk, below threshold, is 103/120. The BSS can take on values from $-\infty$ to 1; a BSS of 1 indicates perfect forecast, a value of 0 indicates the model is no better than the constant climatological or unskilled forecast and negative values indicate worse performance (Brier, 1950).

To capture non-stationarity of the magnitude of exceedance, the parameters of the GPD can also be allowed to vary as a function of independent variables or covariates. It is common to vary the scale parameter using a GLM of the form:

$$\log\big(\sigma(x)\big) = \beta_{0,\sigma} + \beta_{1,\sigma}x_1 + \cdots + \beta_{n,\sigma}x_n \quad (5)$$

where the variables x_1, x_2, …, x_n are the covariates which can include time in order to consider a temporal trend, and $\boldsymbol{\beta}$ are the coefficients. The shape parameter is generally not varied as it tends to be sensitive especially for short data sets with variability, but it too can be varied if desired (Katz *et al.*, 2002).

The best combination of covariates for the GPD parameter is selected based on likelihood ratio test (Katz *et al*., 2002; Gilleland, 2015). In this, the likelihood value is calculated for two candidate models and compared using a theoretical F-distribution for significance to select the better model. This is repeated until for possible pairs of models and the last model left standing is the best.

The EVA-POT method has been applied to model hot spells and heat waves (e.g., Furrer *et al*., 2010; Khaliq *et al*., 2005) and in stochastic weather generators (e.g., Furrer and Katz, 2007) to generate precipitation extremes.

Risk models such as those described by Young and Belz (2003) and CSIRO Urban Water (2003) have been developed for centralized water and wastewater asset management. These models estimate the risk of pipe failure under various management scenarios (Pinkham *et al*., 2004*).* We employ an analogous method to evaluate risk and performance uncertainties over a defined time period for OWTS infrastructure. For each facility the estimates of the categorical probability combined with the expected value of the GPD, from the EVA-POT analysis, can be combined to estimate the expected risk.

RESULTS

The EVA-POT was implemented in the statistical programming language R (R Core Team, 2013), using specifically the *extRemes* package and library (Gilleland and Katz, 2011). The selection of thresholds is first presented, followed by the probability of threshold exceedance considering both the lower and upper thresholds to identify user operational factors characteristic of well- and poorly- performing OWTS. Lastly, the magnitude of threshold exceedance associated with high risk OWTS is presented along with the financial risk in terms of dollars lost due to frequent and severe system repairs and failures.

Repair Severity Cost Thresholds

Lower Threshold

Figure 5.2a shows that the shape and scale parameters for the low risk OWTS are stable for expected 40-year repair costs of approximately $9,000 and the data exhibits a break around this value, thus, we selected this as the lower threshold. The monthly wastewater utility charge for the City of Boulder provides a basis of comparison for the OWTS annual *repair severity* threshold values. The current wastewater utility billing rate for City residents is $5.76 per 1,000 gallons of water use, based on an "average winter consumption" (AWC) scale, which omits most outdoor use (City of Boulder, 2015). For Boulder, the AWC for a household is approximately 5,000 gallons/month (Mayer *et al.*, 1999) producing a bill of $28.80/month or just over $345 per year. The City wastewater rate reflects a recent increase for capital cost of collection system replacement, and also includes costs of capital bond servicing and is therefore not precisely comparable to OWTS repair costs, which do not include the cost of initial installation. However, in comparison, the low severity threshold of $225 per year, 35% below the local average wastewater utility rate, appears to be a reasonable indicator of a low risk-cost OWTS.

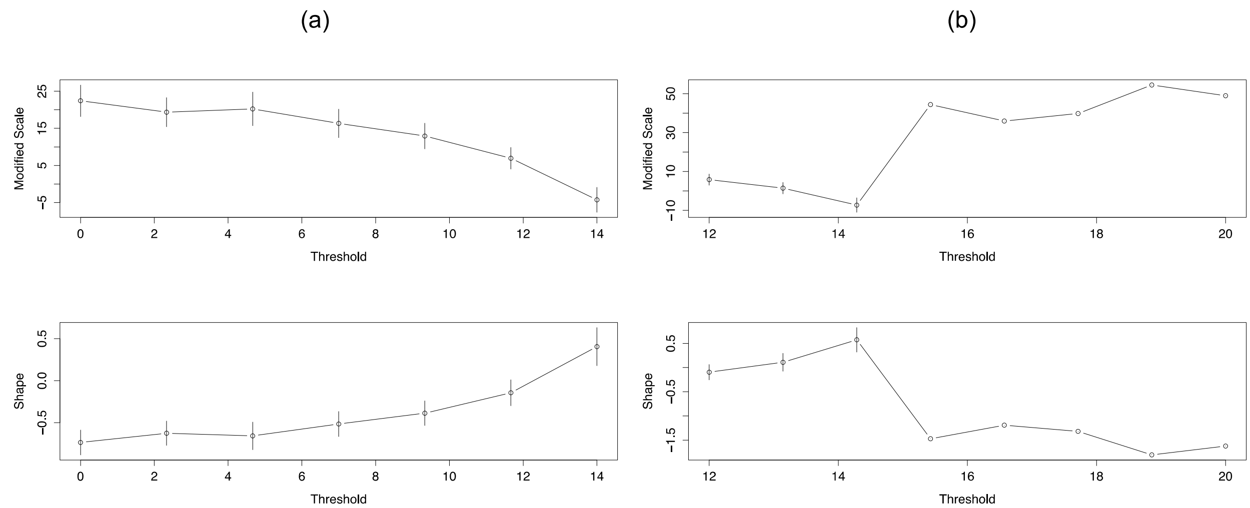

Figure 5.2 Analysis of model parameters given different thresholds for the POT method. (a) Lower-end *repair severity* threshold evaluation. (b) Upper-end *repair severity* threshold evaluation. The threshold axis is in thousands of U.S. dollars.

Upper Threshold

For the upper (high risk) threshold the stable region appears to start at ~$18,000 (**Figure 5.2b**), and includes approximately 15% of the Boulder County OWTS sample. The high risk-cost threshold ($450/year over a 40-year life) is 30% higher than the local average wastewater utility service rate.

Threshold Exceedance Probabilities

In determining risk, we considered both the probability of being below the lower *repair severity* threshold and above the upper threshold to identify those owner maintenance practices and residence attributes (referred to in Kohler *et al.,* 2015) and their influence on well- and poorly- performing OWTS.

The best binomial logistic regression models for the lower and upper thresholds were obtained separately and are shown in **Tables 5.2 and 5.3**, respectively. Referring to

Tables 5.2 and 5.3, the *estimate* column indicates the change in the log-likelihood of a low- or high- risk category of *repair severity*, given unit changes in the relevant explanatory variables. For ease of interpretation we use the risk ratio or odds ratio which is the ratio of the probability of the risk category versus the non-risk category, these are show in the *risk ratio* columns of **Tables 5.2 and 5.3**. Odds ratio values less than 1 decrease the odds of the OWTS being in the risk category, while values greater than 1 increase the likelihood. For example, a unit increase in the number of bedrooms added (RC) to the home decreases the likelihood of being below the low threshold or being in the lowest risk category while it increases the likelihood of repair costs exceeding the high *repair severity* threshold. The significance of increasing house size it supported by the result that relationship for RC is consistent for the high- and low-risk models. An increase in sales after 2008 accompanied by a certified inspection (PS) and property transfer inspections (PT) over the 40-year period respectively decreases the risk of high OWTS repair and replacement costs (**Table 5.3**) and increase the likelihood of OWTS falling in the low risk population (**Table 5.2**), also a consistent result for the high- and low-risk regression models.

Table 5.2 Binomial logistic regression model coefficients, odds ratios, and model significance to determine likelihood of an OWTS being experiencing low repair severity costs. The p-values indicate that each of variables is significant at > 90%.

Coefficients	Variable Notations	Estimate	Odds Ratio	Pr(>|z|)
(Intercept)		-1.42		<0.001
Change in No. Bedrooms	RC	-1.25	0.30	0.082
No. Property Transfer Inspections	PT	2.10	8.20	0.002

Table 5.3 Binomial logistic regression model coefficients, odds ratios and model significance that are characteristic of exceeding a high *repair severity* cost threshold. The p-values indicate that each of variables is significant at levels of 88% or above

Coefficients	Variable Notations	Estimate	Odds Ratio	Pr(>|z|)
(Intercept)		-2.46		<0.001
Change in No. Bedrooms	RC	0.60	1.82	0.121
Property Transfer Before 2008	EPS	0.33	1.39	0.082
Property Transfers After 2008	PS	-1.65	0.19	0.121

Model Skill and Cross-validation

Figure 5.3 demonstrates the skill of the logistic regression models. **Figure 5.3a** shows the histogram (i.e. distribution) of the model estimated probability of being below the low *repair severity* threshold for the subset of OWTS observed in the low risk category, while **Figure 5.3b** illustrates the probability distribution for exceeding the high-risk threshold for the subset of systems observed in the high risk category. The vertical red line in each histogram of specifies the constant climatological or unskilled estimate based on the portion of the total OWTS population in the low- and high- risk categories. The climatological probability for the low-risk category is 0.2, suggesting that an OWTS has a 20% chance of being in the low risk category based purely on the sample fraction. For the high-risk model the climatology is 0.14 or a 14% chance of being in the high-risk category. The fact that the bulk of the distribution of model predictions of cost risk are below 0.2 for low-risk systems and above 0.14 for the high-risk population, confirms that the chance of incurring either significantly lower or higher lifetime repair costs is not random and moreover is accounted for by the two covariates noted above. The calculated BSS for the low- and high- risk models are 0.61 and 0.70, respectively, supporting the graphs in **Figure 5.3.**

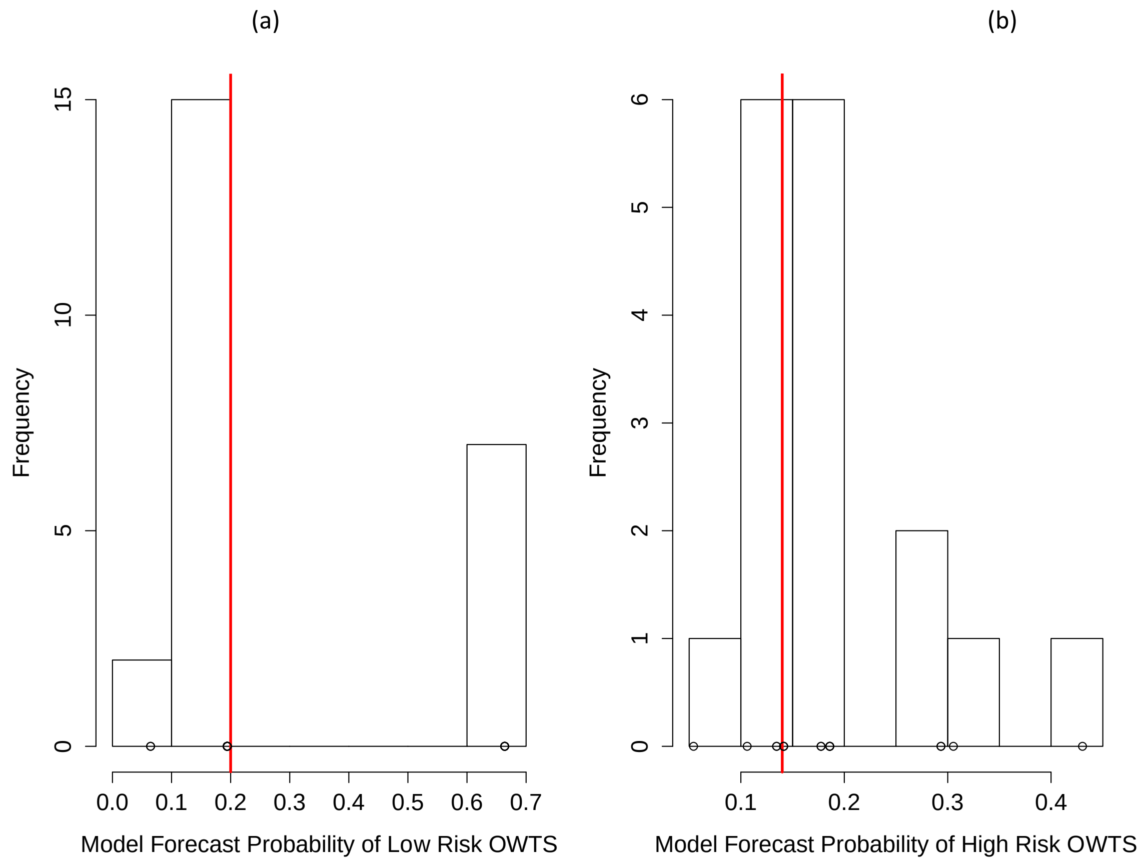

Figure 5.3 Each histogram illustrates the forecasted probability of being below the low (a) and above the high (b) repair and replacement cost threshold for the subset of OWTS actually observed as low- and high- risk, respectively. The red line specifies the constant climatology for each model as a reference for communicating each model's performance.

To evaluate the regression model's performance in a predictive mode or on independent data set - 15% of the observations are dropped at random. The models are fitted on the rest of the data and the dropped points are predicted. The BSS is then computed for the predictions. This method is also known as drop-15% cross validation. A thousand cross validation simulations were performed and the BSS values are displayed as boxplots in **Figure 5.4.** The median BSS value close to 1 for both models illustrates each model's ability to forecast OWTS risk better than an unskilled or average estimate of risk of 20% and 14% for the low risk OWTS and high risk OWTS, respectively. However, the variability of each model's predictive skill is apparent. The spread in the BSS values suggests the need to include additional variables in the model. For instance, OWTS location-related factors that may contribute to some of the model uncertainty are not incorporated. However, both logistic models show good predictive skill and thus are useful for identifying high-risk systems or clusters of systems to target management strategies using a risk-based approach.

Exceedance Magnitude for High-Risk OWTS

Whereas the operational characteristics of OWTS below the lower threshold offer information about how homeowners might mitigate their risk, OWTS above the upper threshold and their estimated magnitude of threshold exceedance provide a means to communicate OWTS performance risk to homeowners paying for OWTS repairs and replacements and to planners making risk-informed decisions. Therefore, for the exceedance magnitude we show results only for the sample set exceeding the upper threshold.

The degree to which an individual OWTS exceeds the repair and replacement cost threshold offers a means to estimate the consequence of performance uncertainty or risk through financial range of costs associated with poorly-performing OWTS. Based on the \$18,000 repair and replacement cost threshold, the OWTS repair severity cost exceedances where modeled using the GPD, described in the previous sections. The best model for the scale parameter of the GPD, based on the likelihood ratio test is shown in **Table 5.4** – the

AIC and BIC values for all the eight combinations are also shown confirming the best model with the minimum values of these criteria.

Table 5.4 The scale parameter of the GPD was related to various independent variable combinations while the shape parameter was held constant. The GPD that minimized both the AIC and BIC was selected as the 'best fit' model.

Variables combinations making up the scale parameter of the GPD		AIC	BIC
Null	(a)	82.24	83.21
RC	(b)	84.24	85.69
RC + PT	(c)	86.24	88.18
RC + PT + PS	(d)	88.24	90.67
PT + PS	(e)	86.24	90.67
PT*PS	(f)	88.24	90.67
PT*PS + SV + LI	(g)	58.58	61.98
PT*PS +SV+ LI + EPS	(h)	74.60	78.48

The scale parameter of the GDP for the best-fit model is a function of the product of the number of property transfer-related inspections (PT) and property sales after 2008 when inspections were mandated (PS), along with home structure value (SV) and loan inspections (LI) (see configuration (g)). No property had more than one required inspection after 2008; however even one inspection had a clear beneficial impact on approximating the *repair severity* cost distribution with more certainty. The four variable combinations enable the model to predict the magnitude by which each system exceeds the $18,000 repair and replacement cost threshold with more accuracy, i.e. produces a narrower range of costs. For each OWTS the scale parameter is estimated from the above model and thus, the corresponding GPD, from which the median threshold exceedance repair cost is estimated. The boxplot in **Figure 5.5** shows the quartile distribution of

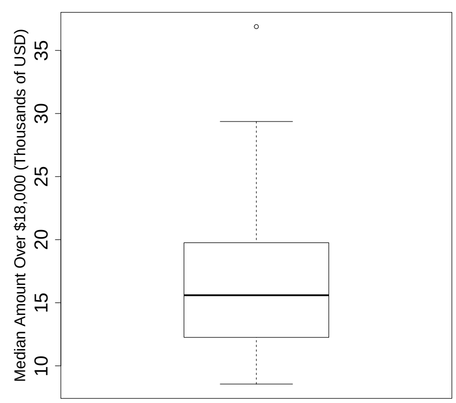

Figure 5.5 Median threshold exceedance cost (in USD) from the GPD distribution for each OWTS.

magnitude from each OWTS exceedance distribution, with a median value of over $15,000, or a median total cost risk of over $33,000 in lifetime repairs. The quantile-quantile (Q-Q) plot of the historic repair costs versus the model estimates are shown in **Figure 5.6**, along with the unit slope line and confirm the predictive skill of the GPD model.

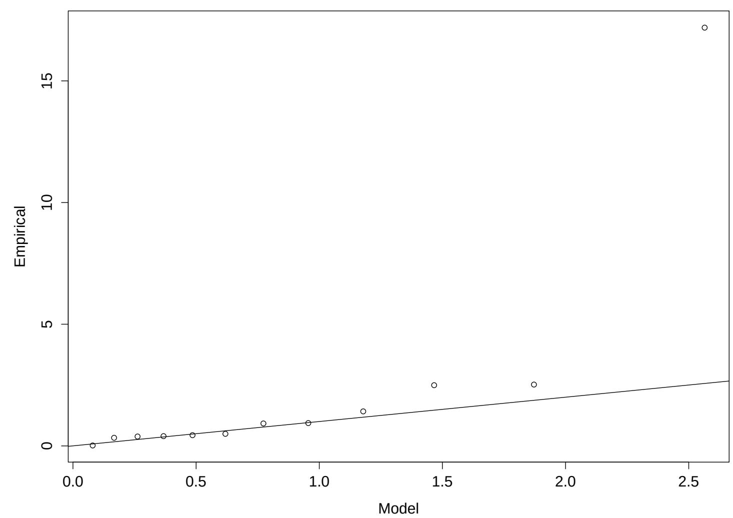

Figure 5.6 Quantile-quantile plots for the 'best-fit' POT model where the scale parameter of the GPD is a function of property transfer inspections, property sales after 2008, structural value, and the number of loan inspections (see (g) in **Table 5.4**).

Cost-based Risk for High Risk OWTS

Regulation of OWTS management over the system life is a substantial change to the approach of existing regulation in the U.S. Public resistance to new regulations, such as obligatory OWTS upgrades, moratoriums on installation of new systems, and in extreme cases cease-and-desist orders demonstrate the challenges associated with communicating residential and community level OWTS performance risks (e.g. State of California: Bolina (Bolinas Community Public Utility District (BCPUD), 2001; 2011) Monte Rio (Kahn, 2007); State of Colorado: Eldorado Springs (Oulton, 2001; Bain, 2002). As a result, determining appropriate and enforceable performance measures in an industry that has been long established to focus on equipment design, siting and installation is challenging. Households that have always been connected to OWTS may be motivated to push back on new regulations that interfere with how they maintain their systems, especially if they add cost.

Therefore the ability to evaluate the benefits and costs of regulatory changes and provide support for community planning decisions is useful to public health agencies, owners and the public.

Combining both the binomial logistic regression and the GPD model provides a basis for communicating the risk of financial losses due to OWTS repairs and replacement. The probability of exceeding the high repair severity threshold from the binomial logistic regression multiplied by, for example the median value from the GPD exceedance magnitude distribution, specifies the risk of the system in terms of dollars lost. The combined model not only predicts the number of *repair severity* threshold excesses in a community but also enables a planner to approximate with some degree of certainty the range of repair and replacement costs associated with the exceedance. Together the frequency and cost specify the distribution of risk for each system. Risk-costs in addition to common life cycle cost serve as tool to enable a quantitative comparison of WWTPs of different sizes and scales. **Figure 5.7** illustrates financial loss distribution for the 120 OWTS in Boulder County based on the model compared to the actual financial losses due to system repairs and replacements. The expected financial loss is calculated as:

$$Expected\ Loss = p_1 * (\$18{,}000 + exc) + p_0 * \ nonexc \qquad (6)$$

where p_1 is the probability of exceeding the high-cost threshold, *exc* is the median cost by which the repair/replacement cost is estimated to exceed the \$18,000 cost threshold, and p_0 is the probability of not exceeding the threshold multiplied by the consequence of non-exceedance, *nonexc*. The actual repair severity costs range between \$3,066 and \$18,000; therefore, three levels of non-exceedance where used for comparison and seen in **Figure 5.7**.

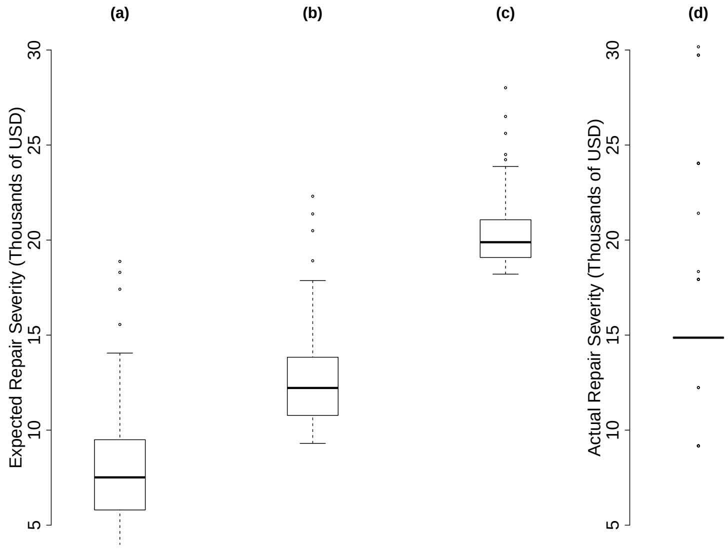

Figure 5.7 Based on the median cost prediction from the GPD, the left boxplots illustrate the spread of the expected financial losses for the 120 OWTS in Boulder County. The financial loss is calculated as the probability of exceeding the high-cost threshold multiplied by the magnitude of the exceedance plus the probability of not exceeding that threshold multiplied by the magnitude associated with non-exceedance. Boxplot **(a)** uses the lower-end magnitude of non-exceedance = \$3,066, **(b)** uses the median magnitude = \$9,000, and **(c)** applies the high-end magnitude associated with not exceeding = \$18,000. The right boxplot shows the actual repair severity distribution for the OWTS sample.

Figure 5.8 shows the spatial distribution of the expected losses predicted for each OWTS in the sample. Interestingly, clusters of high-risk OWTS are located in two neighborhoods, Eldorado Springs and near Crestview Estates subdivision (BCPH, 2004,

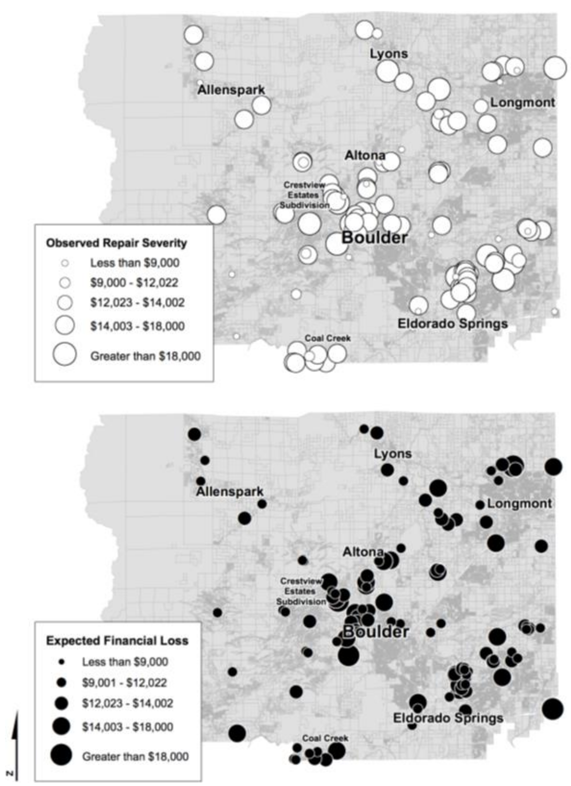

Figure 5.8 Spatial plot of OWTS in Boulder County and each system's expected financial loss based on the probability and financial consequence of exceeding the high-end threshold in addition to the probability and consequence of not exceeding the threshold.

2016). Boulder County identified both areas as high-risk based on risk factors such as age, density, slope and undocumented performance of OWTS in those areas. The figure also demonstrates the model's potential for targeting OWTS performance-based management strategies as well as longer term sanitation planning decisions.

Since inspections and resulting minor repairs are associated with reduced risk, we can estimate the financial trades-off between management strategies, i.e., between inspections enforced through a renewable permit and the no action alternative. **Table 5.5** compares the cost of regular inspections, the life cycle expected financial loss range for low and medium risk OWTS, and the expected financial loss of high risk OWTS. With a regulated inspection every 5 years, the cost associated with OWTS repairs and replacements would be expected to be less than the expected costs in **Table 5.5**. While OWTS inspections cannot prevent all system repairs, recurrent inspections do provide an opportunity to reduce the likelihood of a catastrophic failure and associated high repair/replacement costs.

Table 5.5 40-year life cycle cost comparison of OWTS inspections, the *repair cost severity* range for low and moderate-risk systems and the expected costs associated with high-risk systems.

Cost of Inspection*	Property Transfer Certificate	Expected Repair Costs of Low and Moderate Risk OWTS	Expected Costs for High Risk OWTS
$3,000	$50	$3,066 - $17,932	>$18,000 - $28,000

***At $375 per inspection, once every five years for 40 years (ABC Septic Inspection, 2012)**

DISCUSSION

We have developed a new approach to relate the risk of failure of OWTS in terms of expected life cycle costs to homeowners as a function of owner/user-related factors such as maintenance practices.

Data from 120 OWTS in Boulder County, Colorado was fit to a GLM where the response variable, *repair severity* measured as cost, was modeled as a binomial distribution based on two repair cost thresholds, which defined categories of OWTS as being at very low or high risk of failure. We found an inverse relationship between high *repair severity* (costs) and inspections, which is consistent with a 2015 study characterizing the performance variability of OWTS where required inspections associated with property transfers and sales decreased the likelihood of extremely high life cycle costs annualized over a 40-year life cycle (Kohler *et al.*, 2015). The opposite relation was found when property was transferred without an inspection, which suggests that one benefit of inspections is education of new owners. (e.g., Boulder County, Colorado, “SepticSmart” Program). While property transfer inspections are not a comprehensive form of regulation in Boulder County, their efficacy suggests a potential benefit of mandating inspections through some instrument like a renewable permit to protect individual homeowners and the general public from the cost of catastrophic failure of OWTS. In general, variables associated with effective maintenance practices were predictive of low-risk OWTS. The skill of the regression models produced Brier Skill Scores of 0.69 and 0.7 for the low-risk and high-risk OWTS categories, respectively.

Characterizing high-risk OWTS in terms of their probability of occurrence combined with an estimated cost magnitude offers a means to communicate the risk of performance instability to relevant stakeholders, both homeowners and local public health agencies that make community level sanitation decisions.

When dealing with extremes, the occurrence of the event—such as with weather events or natural disasters—may have a low probability of occurrence but the consequence of occurrence is large. In applying this principle to OWTS, we modeled the overall risk of significant system failure as measured by expected costs using a Points Over Threshold (POT) method of extreme value analysis where the distribution of cost exceedances was represented by the generalized Pareto distribution. We find that while the probability of exceeding the repair and replacement cost threshold of $18,000 is low, the financial consequences associated with failure are as large as $35,000 for OWTS life cycle repair and replacement costs, ten times the cost of a low-risk system.

CONCLUSION

We expect that communicating the magnitude of the risk expressed as expected costs may have a greater impact on homeowners' maintenance decisions and acceptance of greater regulatory oversight than educational messages based on environmental protection. Another premise of this research is that failure risk based on readily available data from existing public records of repairs and replacements should be a good surrogate for environmental and public health effects for which data are much more difficult to obtain on a scale large enough to enable predictive models. Identification of high risk on-site wastewater systems based on costs also can help public health agencies deploy limited enforcement resources more effectively and assist planners in making decisions about siting and permitting OWTS in new developments.

ACKNOWLEDGEMENTS

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CHAPTER 6: FRAGILITY OF ON-SITE SYSTEMS RELATED TO CLIMATE/WEATHER VARIABLES

Kohler, L., Silverstein, J. and Rajagopalan, B. (In Preparation) **Modeling On-Site Wastewater Treatment System Performance Fragility To Hydroclimate Stressors**. *Water Science and Technology.*

Key words: on-site wastewater treatment systems, resilience, weather effects

ABSTRACT

Climate projections throughout the U.S., for this century, indicate increasing variability and extremes of rainfall, temperature and stream flow, which poses risks to subsurface infrastructure such as on-site wastewater treatment systems (OWTS). We propose a new approach to assessing the climate-induced OWTS *fragility* - the degree to which an OWTS loses functionality, as a step to characterizing the resilience of decentralized, owner operated wastewater treatment systems. We used the frequency and severity of OWTS failures (i.e. repairs) as a measure of fragility and modeled them as a function of hydroclimate variables, which include precipitation, temperature and stream flow attributes. In this, the frequency of each type of repair (minor, moderate and severe) was modeled using a generalized linear model (GLM) with a Poisson distribution link function... We demonstrate this model using OWTS failure data from Boulder County in Colorado. The results show that precipitation events influence OWTS fragility (minor repairs) and loss of OWTS functionality (severe repairs) is impacted by high temperatures, incidences of wetter-than-normal months, and the magnitude of peak stream flow in the watershed. These results offer the unique prospects of using climate information for modeling OWTS

fragility and consequently resilience, to enable their efficient management by owners and town planners.

INTRODUCTION

Natural hazards associated with changing climate and related weather events threaten both the physical and functional integrity of infrastructure including wastewater collection and treatment systems. Subsurface components of these systems are particularly vulnerable to flooding and stresses from saturated soils. Moreover, delays in recovery from disruptive events pose risks to the public and environment through exposure to wastewater constituents through direct contact with released wastewater, groundwater and drinking water contamination. During Hurricane Sandy, for instance, 11 billion gallons of untreated and partially treated sewage flowed into rivers, bays, canals, and in some cases, city streets, a consequence of record storm-surge flooding (Kenward *et al.,* 2013). U.S. EPA and local authorities issued advisories warning citizens of the known health implications of contaminated waters and how to prevent exposure (New York City Department of Environmental Protection, Connecticut Department of Public Health & EPA, 2012). However, no information has been available on storm damage to on-site wastewater treatment systems including those that serve 10-40% of the populations in Sandy-affected states (EPA, 2002). While the association is widely acknowledged, the connection between weather and OWTS failure has yet to be demonstrated (Amador *et al.,* 2014; Morales *et al.,* 2015; UNICEF & GWP, 2014).

OWTS make up approximately 25% of the sanitation infrastructure in the U.S., with over 30% of new developments served by on-site technologies (EPA, 2002). Outside of the

U.S., on-site technology is leveraged to provide sanitation services in communities that either currently use unimproved facilities or have no access to safe disposal of fecal waste (WHO & UNICEF, 2015). Even under normal environmental conditions, the failure rate of OWTS is significant – as high as 50% in some regions of the US. Climate change projections of trends toward more frequent precipitation and flooding events could heighten the risk of failure of sanitation systems dependent on buried storage tanks and subsurface discharge through unsaturated soil (Kirtman *et al.,* 2013). Understanding the response of OWTS to weather-related risks and their recovery behavior should therefore be considered in future planning and design of these systems. Because of widespread and growing reliance on decentralized on-site wastewater treatment, we propose a resilience framework for decision making with regard to acceptance and regulation of this technology.

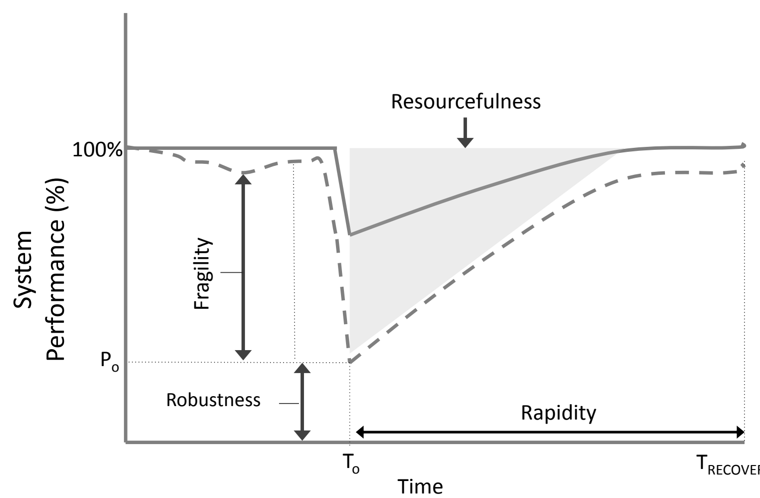


Figure 6.3 Conceptual framework for resilience measurement (adapted from Bonstrom & Corotis (2014)

Bruneau *et al.* (2003), suggests that resilience is characterized by four system properties: robustness, rapidity, redundancy, and resourcefulness. Rapidity is the time required to restore performance ($T_{RECOVER}$ - T_O in Figure 1, where T_O is the time of the initiating event and $T_{RECOVER}$ is that time when system performance is restored). Resourcefulness is the capacity to mobilize resources during recovery and is a determinant of rapidity. These attributes are relevant to assessing OWTS resilience (Bruneau *et al.,* 2003). Redundancy also is a component of system resilience, related to robustness as well as rapidity (McDaniels et al., 2008); however this attribute is not typically a strong component of highly decentralized systems such as OWTS (Rocky Mountain Institute, 2004). While all four properties affect resilience, system vulnerability to stressors—both extreme and non-extreme—and the degree a system loses functionality can directly affect the time and resources required to recover performance. Therefore, we define *fragility* as the difference between 100% of the expected level of OWTS performance and robustness, which is the level of performance after a significant perturbation (refer to **Figure 6.1**). McDougall (2009) further breaks down fragility into *Design* and *Natural fragility*. *Natural fragility* describes the distribution of infrastructure system performance outcomes, i.e. failure frequency and the degree of failure, when operations are outside of conditions assumed by the engineer. *Natural fragility* reflects performance reliability under real world conditions, compared to reliability under purely designed conditions (i.e. *Design fragility*) (McDougall, 2009).

We propose to assess OWTS *Natural fragility* in order to evaluate resilience of decentralized, owner operated wastewater treatment systems to climate-related stressors. In this investigation, we hypothesize that OWTS *Natural fragility*—expressed as the frequency distribution of failure—is associated with annual hydroclimate patterns. We use a surrogate measure of OWTS failure, using severity-based categories of documented OWTS repairs. Using repair permit records, climate and weather data collected from the U.S. National Oceanic and Atmospheric Administration (NOAA) and the U.S. Geologic Survey (USGS), a Generalized Linear Model (GLM) regression method is used to characterize *Natural fragility* and its association with temperature, rainfall and stream flow conditions. Since we examine only *Natural Fragility* in this investigation, to simplify we will refer to it here within as merely *fragility*.

METHODS

Data

Repair permit data were collected for 225 OWTS in the Boulder-St. Vrain Creek watershed in northeastern Colorado, regulated by the Boulder County Public health Department. The geographic distribution shown in **Figure 6.2** encompasses the full range of topographic and demographic characteristics of Boulder County, and represents an overall OWTS population of 14,300.

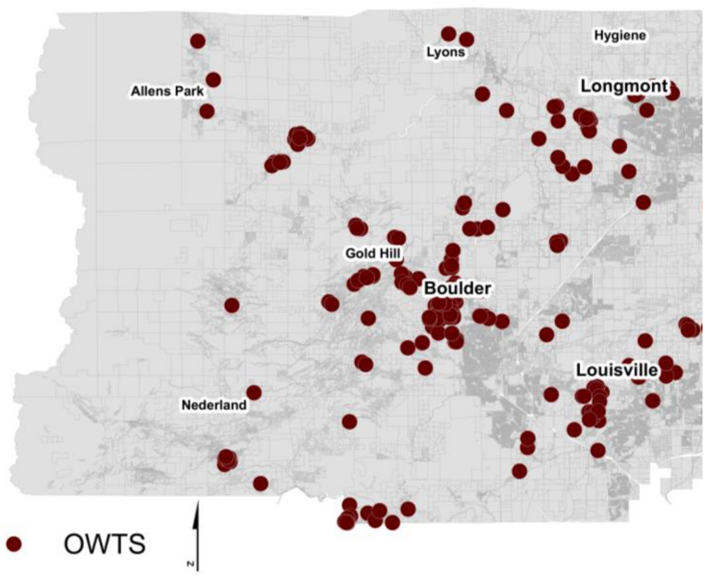


Figure 6.4 Geographic distribution of OWTS in Boulder County Colorado

Variable definition

Dependent variable

The frequency of repairs over the period of record from 1979 to 2015 is the fragility measure. While not all repairs are associated with a complete failure and associated visible contaminant release, the frequency and the severity of repairs provides a measure of decrease in system performance.

Each documented repair is classified into minor, moderate, and major categories, based on a rating system used by the Boulder County Public Health (BCPH) Department (Kohler *et al.,* 2016) and recorded for the 225 OWTS in the sample. A minor repair is any repair to the septic tank or lateral pipes. Moderate repairs refer to extraordinary maintenance to or replacement of the soil treatment unit (STU). Failure of both the septic tank and STU constitutes a major repair often requiring replacement of the entire system. The dependent variable, *annual repairs*, is the annual sample frequency of each type of repair. The distribution of each type of repair serves as an indicator of fragility for the sample population. Failures associated with minor and moderate repairs exhibit partial losses of function and lower degrees of fragility; whereas, major repairs result from a near complete loss of performance, representing the highest degree of fragility. Similar to Kohler *et al.* (2016), the sample consists of only permitted OWTS to control for compliance with siting, design, and installation criteria set by the County.

Figure 6.3 shows the distribution of each category of repair over the period of record from 1979 to 2013, indicating an increased repair frequency starting in 2007. Between 2007 and 2008, Boulder County Public Health (BCPH) reformed their practices regulating OWTS installation, permitting and maintenance. The county initiated the EPA Septic Smart program with a goal to inspect and approve permits for all OWTS in the County by December 31, 2023. More important, in 2008, the County adopted a new regulation, enforcing professional system assessments and required repairs at the time of any property sale ("Septic Smart Program", 2015). We concluded that the rise in repairs after 2007, apparent in **Figure 6.3**, reflects increased frequency of reporting after the County's initiative to permit systems and add a regulation. The association of this factor with repair severity was determined earlier (Kohler *et al.*, 2016). Thus for fragility modeling we use data until 2006, removing the period of the trend that is a mainly a result of policy actions and not climate related.

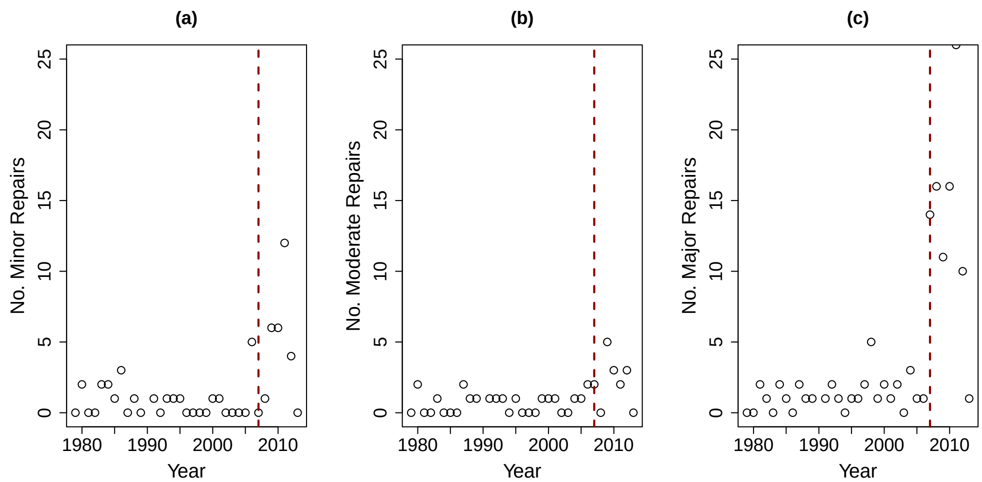


Figure 6.3 Frequency distribution of minor (a), moderate (b), and major (c) repairs from 1979-2015. The dashed vertical line indicates the introduction of Septic Smart and a new inspection regulation.

Independent Variables

Both temperature and precipitation have recognized effects on OWTS performance. Temperature extremes can affect biological activity, flow and mixing within the primary treatment unit (septic tank or vault) and treatment processes in the biomat of the STU. For example, when temperatures are less than 5 ^{o}C the bacterial removal rate of *E.coli* in the STU has been estimated at less than 20%; whereas temperatures closer to 20 ^{o}C have three times the removal rate (Morales *et al.,* 2015). Precipitation can have a physical and therefore visible impact from excess hydraulic loading during high rainfall and snowmelt events above the level set out in design criteria for the STU. Groundwater infiltration and inflow through inadequately sealed covers can cause septic tank overflows resulting in STU clogging as well as physical damage to the STU (Morales *et al.,* 2015). Less visible impacts include the reduction of vertical separation distances between the OWTS and water table as well as increased transport of nutrients and pathogens through soil.

Annual temperature and precipitation profiles for the study location were obtained from the National Climatic Data Center of NOAA. The number of months with precipitation totals over 10.16 cm (4.0 inches) was included to represent uncharacteristically wet conditions and the potential soil saturation effects on OWTS performance. As a reference, in Boulder County April and May are typically the wettest months with precipitation totals of 6.22 cm (2.45 inches) and 7.75 cm (3.05 inches), respectively, from 1948 to 2005 (Desert Research Institute, 2005). Monthly rainfall totals over 10.16 cm have occurred only 43 times in a 38-year period (a less than 10% probability of occurrence). The frequency of days over 1.2 cm were included to capture the effects due to severe single rainstorm events that occur over a shorter period of time and impact the system through surface runoff. Return periods based on storm duration calculated using precipitation measurements from the Boulder Station indicate that while 1.2 cm seems small, the average recurrence intervals for 1.2 cm rainfall event in Boulder County ranges between 10-20 years for a storm enduring 5-min to 1-2 years for a 30-min storm (NOAA, 2013).

Annual stream flow is selected as another independent variable based on its contribution to shallow groundwater levels through interflow (data from USGS gage 06730500). While the interaction mechanisms between ground and surface water are complex, hydrographs are commonly used to estimate ground water recharge either directly or using water balance models (Mau & Winter, 1997; Sophocleous, 2002; Yeh *et al.,* 2007). Stream flows being an integrator of precipitation, soil moisture and watershed response, is an excellent surrogate for subsurface conditions.

Table 6.1 lists each variable. The variables coded with "*_S*" are recorded from April to October to capture rainfall precipitation versus the annual total, which includes snow equivalents.

Table 6.1 Annual frequency and severity precipitation and temperature independent variables

	Code	Explanation
Frequency of Temperature Extremes	DT90	No. of days per year with maximum temperature greater than or equal to 32 °C (90°F)
	DT00	No. of days per year with minimum temperature less than or equal to -18 °C (0°F)
Frequency and Magnitude of Precipitation	DP05_S	No. of days per year with precipitation greater than or equal to 1.2 cm (0.5 in) (Apr-Oct)
	TPCP	Total annual precipitation in centimeters (inches)
	MR40_S	No. of months per year with monthly precipitation totals above 10.16 cm (4.0 inches) (Apr-Oct)
Surface/groundwater Flows	PEAK_FL	Annual peak flow in m^3/s (cubic feet per second)

Model Development

We propose to use a generalized linear model (GLM) to model the fragility, i.e., response repair frequency, *Y,* as a function of hydroclimate variables identified above. GLMs are finding wide application due to their flexibility in modeling non-Gaussian features and ease of implementation – such as for space-time weather generation (Verdin *et al.,* 2014); wastewater quality modeling and resiliency (Weirich *et al.*, 2011; 2015) and recently to OWTs repair magnitude (Kohler *et al*., 2016).

Since the time of introduction of Septic Smart and the inspection regulation are known, we instead break the time series data into two regions—pre- and post- Septic Smart, as mentioned above. Assuming the repair reporting requirements were constant before 2007, we consider the occurrence of OWTS repairs in each year from 1979 to 2006 for all 225 systems, the response variable *Y* for all 225 systems is, consequently, an annual count of repairs

In the GLM, the response variable, Y, is allowed to be a realization from any distribution in the exponential family.

$$Y \sim G(\boldsymbol{\theta}) \tag{1}$$

where $G(.)$ is any exponential type distribution and $\boldsymbol{\theta}$ is the set of parameters that define G. Assuming a Poisson distribution reduces the GLM to a Poisson regression model with parameter μ (McCullagh & Nelder, 1989). The canonical link function for the Poisson distribution, the log link, is as follows:

$$Log(\mu) = \alpha + \boldsymbol{\beta X} \tag{2}$$

where μ is the expected value of Y, $E(Y)$. The log of μ is then a linear function of the explanatory variable(s), $\boldsymbol{X}$, and a random component α. Consequently, μ is a multiplicative function of $\boldsymbol{X}$.

$$\mu = e^{\alpha} e^{\boldsymbol{\beta X}} \tag{3}$$

The residuals of the model are assumed to be normally distributed and uncorrelated as with a standard linear regression (McCullagh & Nelder, 1989).

The best combination of GLM predictors is selected based on minimizing Akaike Information Criteria (AIC), which is a standard approach (Akaike, 1974).

RESULTS AND DISCUSSION

It can be seen from Table 3 the expected number of repairs in a given year in each category is modulated by a combination of precipitation, temperature and precipitation-related attributes, namely the frequency of extreme temperatures (days over 32 ^{o}C), incidences of wet months (months with rainfall totals over 10.16 cm) and the magnitude of peak flows in Boulder Creek. **Table 6.2** highlights the significant variables at 90% for each category of repair.

Table 6.2 Significant model coefficients

	Minor			Moderate			Major		
R^2	*0.38*			*0.53*			*0.70*		
	Est	e^{β}	***p***	***Est***	e^{β}	***p***	***Est***	e^{β}	***p***
Intercept (α)	-1.862	0.155	0.008	-0.932	0.394	0.074			
DT90	0.047	1.048	0.007						
DT00									
TPCP									
DP05_S									
MR40_S							0.527	1.694	0.025
PEAK_FL				0.001	1.001	0.056	-0.001	0.999	0.022

Given the log link function, a unit change in x has a multiplicative effect on μ. For ease of interpretation we included e^{β} in **Table 6.2**. Where $e^{\beta} > 1$, the variable increases the expectation of Y and where $e^{\beta} < 1$, it decreases the expectation. If e^{β} is close or equal to 1, this means that the expected outcome is not related to the covariate, x. For instance, for minor repairs, a unit increase in the number days with temperatures exceeding 32 °C increases the expectation or mean number of repairs in a given year by a factor of 1.048. Therefore, the expectation of minor OWTS function losses can be described as:

$$\mu_{minor} = e^{-1.862} * e^{0.047 x_{DT90}} \quad (4)$$

Temperature extremes have been recognized for their effects on OWTS performance. Researchers describe increased digestion during warmer months due to "spring turnover" increasing both the amount of solids accumulation in the tank as well as the amount that leave the tank due to interrupted settling (D'Amato, 2008). While solids increase in warmer temperatures, settling and solids removal decrease often due to gas eruption during increased digestion. Water demanding activities, which often increase seasonally, can overwhelm septic tanks and increase the amount of solids entering the STU

(Crites & Tchobanoglous, 1998). Temperature extremes may not directly affect the integrity of the primary treatment unit; however, the physical consequences of temperature on septic tank processes leading to clogging and/or solids overflow—often require maintenance services. Furthermore, service providers typically assess the integrity of the system upon their visit, which may explain the correlation between minor repairs and temperature in that more damage is identified during these periods— tank and/or sewer damages, which would have potentially gone unnoticed.

Moderate performance losses seem to be associated with one variable, peak stream flow (PEAK_FL), which is an indicator of surface and subsurface moisture conditions through interflow. The GLM expectation of moderate function losses is:

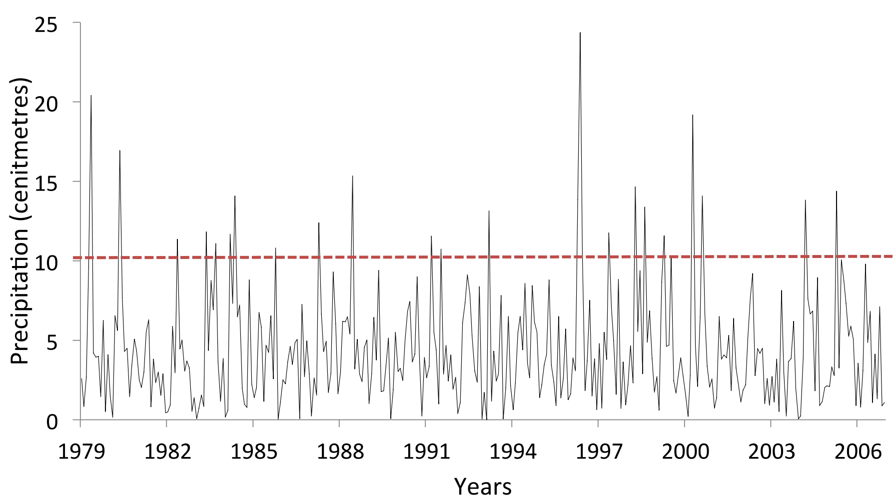
$$\mu_{moderate} = e^{-0.932} * e^{0.001*PEAK\_FL} \qquad (5)$$

The influence of flow on moderate fragility is relatively small. Since $\boldsymbol{e^{\beta}}$ is nearly 1, this indicates that, in fact, the covariate has little influence on the expected number of moderate repairs in a year. Only when the peak flow is substantially high would we see an effect on expected repair. This is a reasonable relationship, given that the highest flows would influence the groundwater table level and in turn compromised performance of the STU. Surface runoff related to a high annual peak flow event may also influence the performance of the secondary treatment unit.

The highest degree of fragility—represented by major repairs—is associated with two variables, the occurrence of wet months, MR40_S, and PEAK_FL. The variables describe the expected number of major repairs in each year as:

$$\mu_{major} = e^{0.527*MR40\_S} * e^{-0.001*PEAK\_FL} \qquad (6)$$

A unit increase in the number months with rainfall exceeding 10.16 cm increases the mean number of repairs in a given year by 1.694, where a unit increase in the peak flow of Boulder Creek dampens the expectation by a factor of 0.999, which is nearly 1 indicating that peak flow has little effect on the expected number of repairs. In extremely wet months, saturated soil conditions impact infiltration of septic tank effluent. **Figure 6.4a** shows the total precipitation each month from 1979 to 2006 and the 10.16-cm threshold. The most significant association of OWTS fragility and weather was with systems requiring major repairs – typically equivalent to replacement, and suggests that OWTS are especially vulnerable to an extended period (month) of higher than normal precipitation. **Figure 6.4b** is a time series of the observed major repairs representing the near complete loss of OWTS performance in each year and the expected major repairs predicted by the GLM. In years with at least one month where rain exceeded 10.16 cm, OWTS failures occur also at a higher frequency. Over the 27 year period, considering only April to October for rainfall events, 23 months (of 189 months) surpassed 10.16 cm. **Figure 6.4b** shows that OWTS fragility is associated with frequency of high rainfall months (e.g. 1995 was a wet year and high monthly rainfall conditions account for 3 of the 5 reported OWTS failures that year.



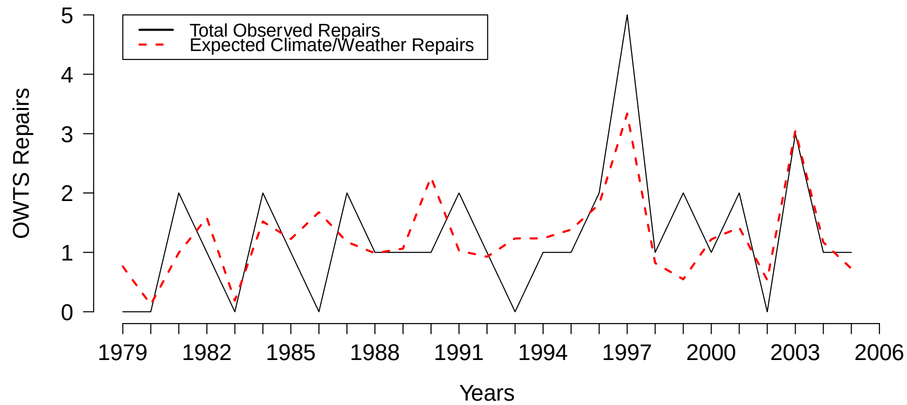


Figure 6.4 Monthly rainfall totals from 1979 to 2006 (a). Observed major repairs over that same period and expected repairs as determined by the GLM, indicating major fragility.

Figure 6.5 has quantile-quantile scatter plots for each repair category. The GLM model of expected repair frequency, μ, in each category as a function of weather related covariate accounts for approximately 38%, 53% and 70% of the variability in the number of minor, moderate and major repairs, respectively, from 1979 to 2006.

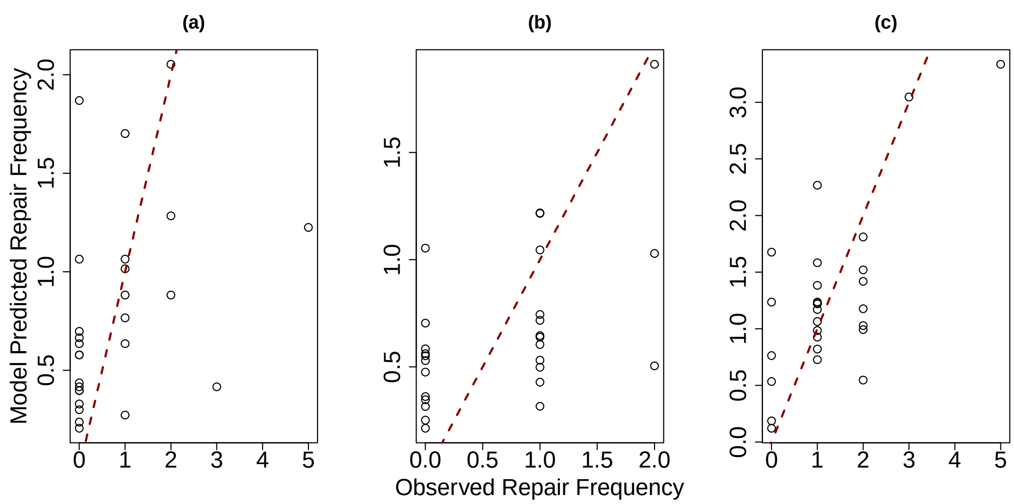


Figure 6.5 Quantile-Quantile plots for the minor (a), moderate (b) and major (c) repairs (fragility) models.

While hydroclimate-related variables capture a significant portion of the variability of repairs year to year, other variables such as OWTS user-operational variables identified previously by Kohler *et al.* (2016) also influence the observed variability. The GLM results indicate that hydroclimate attributes exert a significant influence on OWTS fragility, measured as the degree to which a system loses function, which is represented here by categories of repair.

CONCLUSION

A statistical method based on GLM was developed for modeling the effect of hydroclimate on the degree of OWTS fragility over a period of uniform regulation of OWTS systems in Boulder County, Colorado, from 1979 to 2006. The relationship between the frequency of minor, moderate, and major repairs and high temperature and precipitation was evaluated using a generalized linear model (GLM) where a Poisson distribution represented the number of repairs in a given year. The results show that variability in the frequency of OWTS repairs and replacements each year can be attributed, in part, to weather, particularly uncharacteristically wet months with rainfall over 10.16 cm and annual peak stream flow. The principal outcome of this study is a validated foundation for the relationship between OWTS performance/failure and weather variability, with implications for siting, design and vulnerability assessment. Furthermore, using future projections of hydroclimate, this method provides the foundation to estimate the changes in fragility due to climate and explore potential insurance options to mitigate the risk of future extremes.

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CHAPTER 7: RESILIENCE OF ON-SITE SYSTEMS: CHARACTERISTICS OF RECOVERY FROM A MAJOR STORM EVENT

Kohler, L., JoAnn Silverstein and Rajagopalan, B. (In preparation) **Resilience of On-site Wastewater Treatment Systems After an Extreme Storm Event**

Key words: on-site wastewater treatment systems; resilience; flooding; recovery

ABSTRACT

In 2013, record rainfall in the Front Range area of Colorado led to what was estimated as a 1000-year storm, which resulted in a 100-year flood event. As a result, Boulder County Public Health reported 34 OWTS failures directly attributed to the flood and over 400 failures and subsequent repairs occurring after 2013, which also may have been flood-related. The 2013 Front Range Colorado flood provides a unique opportunity to assess OWTS resilience at the watershed scale after an extreme storm-flooding event. A resilience framework is developed to demonstrate the degree to which decentralization influences systematic OWTS vulnerability to weather, independent of individual OWTS operations. Here resilience is characterized by three system prosperities: the degree to which systems lose function (fragility), time necessary to restore performance (rapidity), and costs incurred while performance is compromised (resourcefulness). The findings illustrate that widespread natural hazards such as flooding are found to affect the frequency and degree to which OWTS function is lost, and more importantly delay their recovery, attributable in part, to a demand surge for both materials and repair services when multiple systems fail simultaneously. Longer recoveries are likely to have environmental and public health

consequences due to the prolonged release of contaminants as well as secondary costs related to homeowner losses resulting from a failed OWTS.

INTRODUCTION

In 2013, record rainfall in the Front Range area of Colorado led to what was estimated as a 1000-year storm, which resulted in a 100-year flood event. Three episodes of torrential rain on September 11-12 and September 15 measured more than 17 inches in the climatology favored upslope areas of the Front Range, which is approximately 85% of the annual average. A large area in eastern Colorado also received between 8 to 17 inches of precipitation during the peak of the event (NOAA, 2014). As a result, 14 Colorado counties including Boulder—the hardest hit county—experienced significant flooding causing damages to infrastructure including those for wastewater collection and treatment (MacClune *et al*. 2014; CBDG_DR, 2015).

The wastewater treatment facilities in Lyons, Longmont and Boulder experienced various degrees of failure ranging from complete shutdown to restricted operations in the Boulder facility (MacClune *et al*. 2014). Due to the resourcefulness of its operators, the Boulder facility remained functional, partially treating 190,000 m^3/d (50 MGD) wastewater augmented by infiltration and inflow from surcharging of sewers, a significant increase from typical flows of 53,000 m^3/d (14 MGD), and double the rated capacity of the plant (95,000 m^3/d) (MacClune *et al*. 2014). During the event, on-site wastewater treatment systems (OWTS), which serve over 14,000 properties in Boulder County, were also disrupted to varying degrees. OWTS reliance on buried storage tanks and subsurface discharge through unsaturated soil makes them particularly vulnerable to high rates of precipitation and flooding. In addition to soil saturation impeding effluent percolation, over 1,100 debris flows and 200 landslides after September 2013 were triggered on slopes where soils were over 100% saturated, resulting in three deaths and significant property and road damage. It was estimated that as much as 1,000 years of accumulated sediment deposited in the Boulder County foothills was washed away in the flood equivalent to scouring depth of 0.2 to 0.5 m, often down to bedrock (Gentes, 2015; Anderson *et al.*, 2015; Ebel *et al*., 2014). Boulder County Public Health (BCPH) reported 34 OWTS failures directly attributed to the flood and over 400 failures and subsequent repairs occurring after 2013, which also may have been flood-related. (Erin Dodge, personal communication, February 15, 2016).

The extensive damage: 19,000 homes destroyed, over the State, and subsequent dislocation, 11,000 people evacuated, not only add to the total amount necessary for reconstruction in terms of materials, equipment, and labor costs, but they also transfer social and environmental costs (MacClune *et al*. 2014). Delays in OWTS restoration pose threats to public and environmental health through exposure to wastewater constituents, and a complete OWTS failure can prevent the occupant from using the system – effectively rendering the property uninhabitable, until it has been repaired (Boulder County, Colorado, 2014a, 32). These added risks make understanding OWTS failure and recovery critical to anticipating secondary impacts related to health risks, prolonged evacuation, and strain on limited material and labor resources. Especially severe social impacts occurred in Boulder County among displaced low-income households due to the lack of affordable or even available rental properties (CDBG_DR, 2015).

As use of OWTS continues to grow along with the likelihood of extreme precipitation events, widespread failures of systems that discharge to the subsurface and associated costs would be expected to increase as well. The 2013 Front Range Colorado flood provides a unique opportunity to test this relationship and assess OWTS resilience at the watershed scale after an extreme storm-flooding event.

Quantifying the concept of network resilience

Bruneau *et al*. (2003) developed one of the first conceptual frameworks for quantifying community resilience after a seismic event based on four system properties: robustness, redundancy, rapidity and resourcefulness. Later studies (Norris *et al*., 2008; Argonne, 2010; Bonstrom & Corotis, 2014) used similar determinants to quantify resilience of networked resources, critical infrastructure, and building portfolios, respectively. Kohler et al. (2016) proposed an approach based on the Bruneau *et al*. (2003) framework to assess OWTS *fragility,* an attribute which is a complement to robustness, defined as the degree to which an OWTS loses function after an initiating extreme event. This was a first step to characterizing the resilience of decentralized, owner operated wastewater treatment systems exposed to severe climate-related stressors. However, the study did not incorporate the other components of resilience: rapidity, resourcefulness or redundancy (Kohler *et al.*, 2016). The challenge for a complete evaluation of OWTS resilience is the lack of an accepted methodology and readily available performance data to assess OWTS performance resilience in the aftermath of hazards such as floods to guide OWTS design and planning decisions.

This study has two objectives. The first is to adapt the conceptual framework proposed by Bruneau *et al.* (2003) to analyze Boulder County OWTS resilience after the

2013 flood in terms fragility, rapidity and resourcefulness. The second is to test one of the proposed benefits of decentralized wastewater systems, namely that risk is dispersed by decentralization, which rests on the implicit assumption that failures of decentralized systems are independent (Booz Allen & Rocky Mountain Institute, 2004). However, in a regional disaster when loss of function is widespread and simultaneous, restoration of decentralized facilities such as buildings or OWTS may be far more difficult, impeding recovery and increasing associated costs (Olsen & Porter, 2011). We have used spatial analysis (Geographical Information System (GIS)) to assess resilience of a regional OWTS network after an extreme event.

METHODS

The methods employed in this study include: (1) OWTS sample data collection from Boulder County, Colorado; (2) definitions and coding of the OWTS resilience dimensions: fragility, rapidity, and resourcefulness; and (3) Geographical Information System (GIS) programming used to integrate the dimensions to determine resilience for the OWTS in Boulder County.

Data

Data used in this study of the 14,300 OWTS located in the Boulder-St. Vrain Creek watersheds were obtained from a permit database maintained by the Boulder County Public Health (BCPH) Department. The sample represents the portion of OWTS, which received permits either at the time of installation or later for repairs. (Approximately one-third of the OWTS in the County do not have any permits on record.) Two sample cohorts were selected from the permit database as a basis for comparison of performance before and after the 2013 flood. Information about each OWTS and their corresponding property can be assessed either directly through a "check septic system records" search on the BCPH webpage by entering the property ID as well as through the Boulder County Tax Assessor's property search tab on their webpage.

The first cohort consisted of 150 OWTS based on a selection provided by BCPH of 588 OWTS requiring permits between 2003 and 2013. Based on 588 properties, a preliminary selection was made for those permitted systems requesting repairs because they explicitly 'Found out my system [was] failing'. Similar to the total population, approximately 30% of the sample of reported failed systems was also NOT permitted and was omitted resulting in a sample of 150 permitted systems, which is about 25% of 2003-2013 cohort sample. We have reported the results of statistical modeling of the risk of individual OWTS failures associated individual owners' monitoring (inspection) and maintenance practices using this data set (Kohler *et al.*, 2016). The second cohort included 490 properties whose owners filed applications for repair or replacement after the flood of September 2013, between January 2014 and February 2016. Thirty-four of these were specifically designated as flood damaged, which exempted them from the typical repair permit application fee of $1,023 (Boulder County, 2016a). To achieve equal representation of this second cohort, a random selection of 25% of the OWTS in the original 2014 to 2016 subset were selected, resulting in 123 OWTS.

Figure 7.1 shows specifically the post-flood OWTS population (490 total OWTS), where the red points specifically identify the flood damaged OWTS (34 OWTS). The added layer shows the spatial distribution of peak rainfall values over the storm period from

September 9 to September 13, 2013. The repair permits specifically documented for flood damage tended to be located in areas that received rainfall of 8 – 10 inches or greater (Erin Dodge, personal communication, February 15, 2016) though a statistical comparison of the spatial distributions on the entire post-2014 OWTS data sets and their association with rainfall levels would be important to support this inference. An exception was OWTS located near the town of Lyons, which is located on St. Vrain Creek and while the rainfall totals were low that region experienced severe surface flooding.

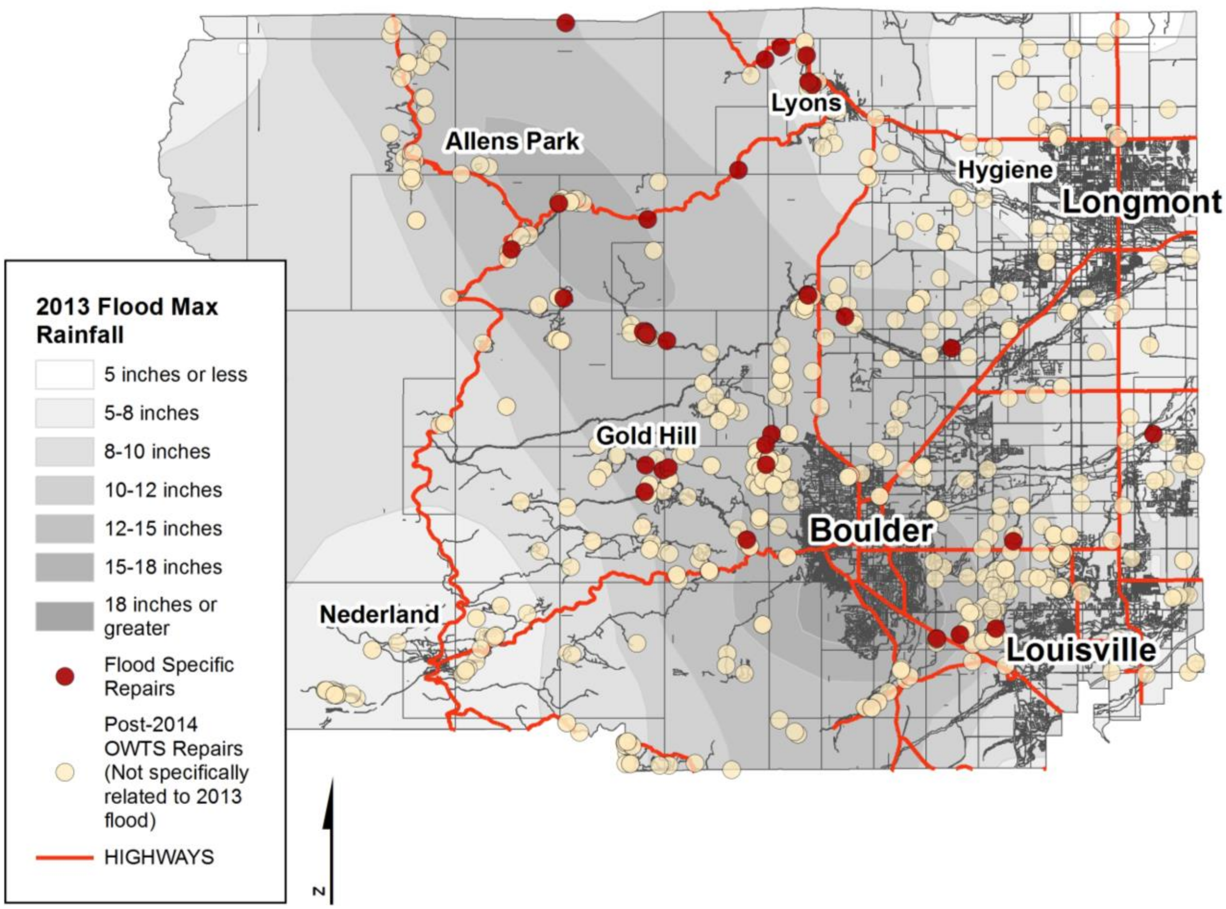


Figure 7.1 Hardest hit areas during the 2013 flood event layered with failed OWTS in Boulder County.

The resilience study is therefore based on the combination of the two cohorts, 150 and 123, making the total sample size for this investigation 273. For each of the 273, the permit application date, final inspection date, and repair type for *each repair* for *each* of the 273 OWTS in the sample were recorded from scanned hand-written repair permit applications found the Boulder County Assessor's tax database. The similar geographic distribution of the permit sample and the two study sub-sample in **Figure 7.2** indicates that the resilience sub-sample is a reasonable geographic representation of the repair permit sample encompassing the pre- and post-flood period between 2003 and 2016.

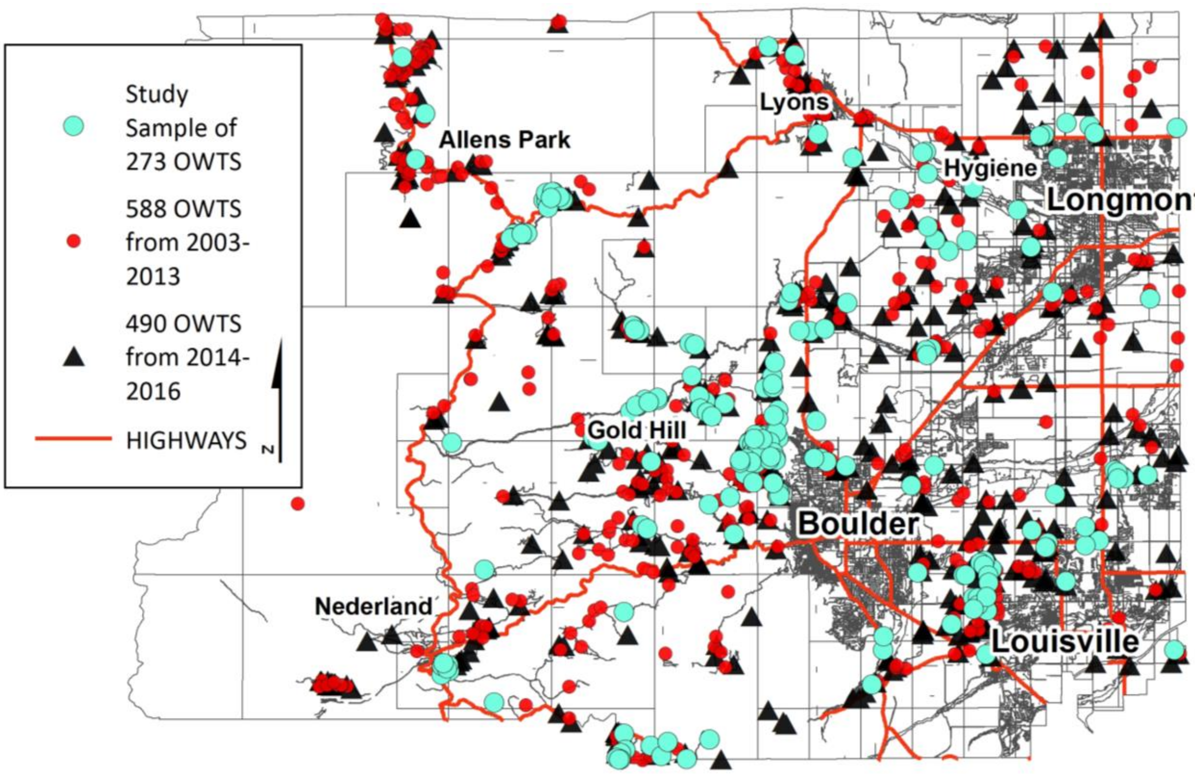


Figure 7.2 Spatial distribution of sample OWTS from the County Public Health Department repair permit database from 2003 to 2016 and sub-sample OWTS randomly selected for the resilience analysis.

Although the County OWTS permit database dates back to the 1940's, the occurrence of permitted repairs is affected by regulations. Starting in 2007, BCPH made a significant change to OWTS regulations to require inspection and necessary repairs during property transfer, resulting in more frequent issuance OWTS repair permits Kohler *et al.* (2016a). We therefore selected the resilience comparison sample to cover a pre-flood period of 2007 to 2013, assuming the frequency of repair permit applications remained constant after that year. While each of the 273 sample OWTS initially belonged to a subset of OWTS queried based on the date of one repair application, *every* repair from 2007 to 2016 for *each* system was recorded, resulting in a history of repair over the two time periods, 2007-2013 and 2014-2016. For example, some systems that were selected in the post-2014 cohort also had repairs earlier between 2007 and 2013.

Variable Definition

Methods for quantifying fragility, rapidity and resourcefulness are described in the following. As noted earlier, we define OWTS vulnerability to stressors and the degree a system loses functionality after a singular event as *fragility*; the time required for restoration of the pre-event level of performance is rapidity; and costs incurred while performance is compromised, including material, labor and costs associated with inconvenience to residents who cannot occupy their homes without a functional wastewater system is *resourcefulness*. **Figure 7.3** depicts the conceptualization adapted from Bruneau *et al*. (2003) highlighting the three dimensions relevant to OWTS resilience.

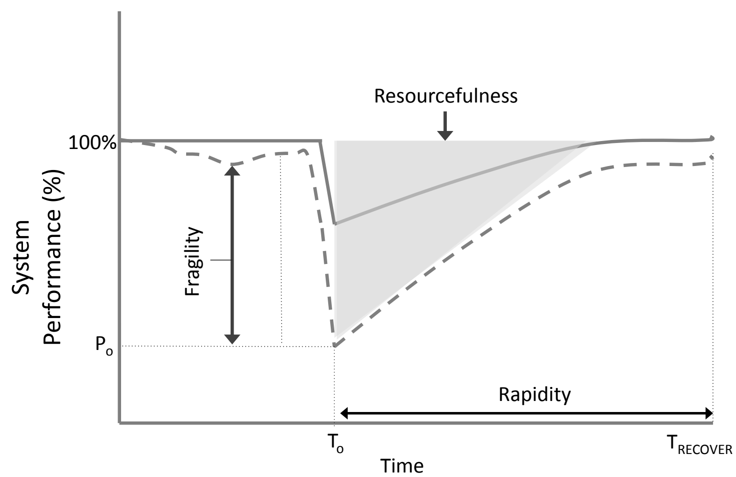
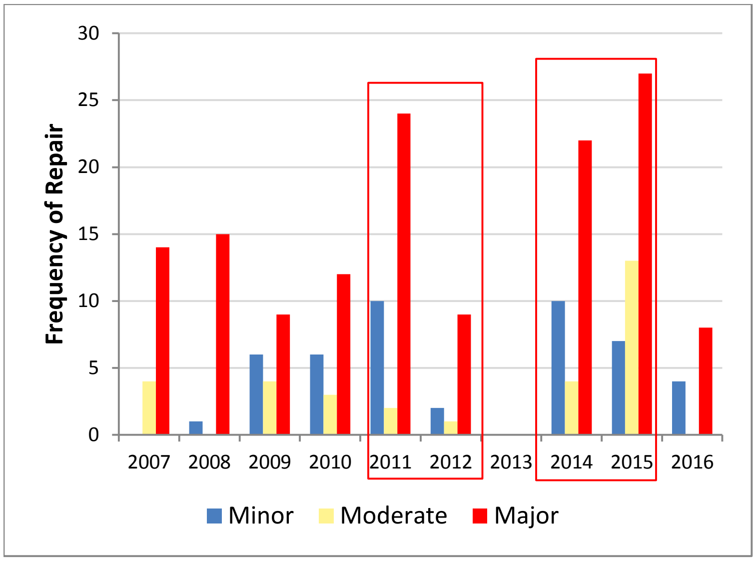


Figure 7.3 Conceptual framework for OWTS resilience showing temporal aspects of fragility, resourcefulness and rapidity.

Fragility

One measure of fragility we considered is frequency of OWTS repair permits over the pre-and post-flood periods. However, with three exceptions, OWTS in both sub-samples had no more than one repair. Instead, the severity of the repair was chosen as a measure of fragility to test the hypothesis that the OWTS network fragility was greater during the 2013 flood. Repair types were classified into minor, moderate, and major depending on the components requiring repairs. Failures associated with minor and moderate repairs resulted partial losses of function and were assigned lower degrees of fragility, 1 and 2, respectively; whereas, major repairs result from a near complete loss of function, representing the highest degree of fragility, assigned the value 3. Systems with more than one repair were assigned a 4 as the highest degree of function loss. The ranked values were normalized based on the maximum value of the fragility ranking. **Table 7.1** lists each repair type associated with a level of lost function, its ranking and the scaled fragility score that was calculated for each of the 273 systems during the pre- and post- flood period. The histogram in **Figure 7.4** shows the frequency of each type of repair over the full 2007 to 2016 period based on the 273 OWTS in the sample (this figure does not include the 3 systems with more than one repair). After the flood, there were consecutive years with a high frequency of OWTS requiring major repairs due to near complete loss of function. To assess the fragility of OWTS over an equivalent time period, the repair total from 2011 and 2012 was compared to the total from 2014 and 2015. The boxplots in **Figure 7.5** illustrate the shift in fragility after the countywide flood event compared to the loss of individual OWTS function that occurred through mechanisms such as age deterioration, poor management, and isolated weather events during the 2 years prior.



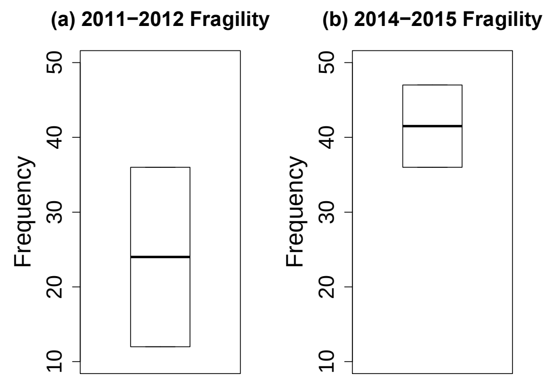


Figure 7.4 Illustrates the degree of OWTS functional loss from 2007 to 2016 based on the 273 OWTS in the study sample

Figure 7.5 Fragility for the 2-year period before and after the flood

Rapidity

Rapidity—a dimension not currently addressed in OWTS literature but covered in structure and infrastructure resilience literature—is the time required to restore performance represented by $T_{RECOVER} - T_0$ in **Figure 7.3**, where T_0 is the time of the initiating event and $T_{RECOVER}$ is that time when system performance is fully restored) (Bruneau *et al.*, 2003; McDaniels *et al.*, 2008; Bonstrom & Corotis, 2014). A study of 209 wastewater treatment facilities in the U.S., operating with National Pollutant Discharge Elimination System (NPDES) permits, modeled the recovery time after a permit violation using effluent water quality data. The study found that *rapidity* ranged from two to five months, with small facilities more likely to experience the longest recovery time, typically making them less resilient after a process upset resulting in a permit violation (Weirich *et al.*, 2011). Comparable information about the post-failure recovery of OWTS under either normal or extreme environmental conditions based on treated water quality does not currently exist.

In this study, *rapidity* is measured by the duration between the date of issue for the OWTS repair permit, T_0, and the date of final inspection of the system, $T_{RECOVER}$, certifying that the OWTS was repaired in accordance with County design guidelines in the regulations. Over 50 OWTS had incomplete repairs as of March 1, 2016. Since we did not want to discard them from the study because their existence in itself is an interesting finding, they were assigned the date March 5, 2016 (the date the information was entered) to represent the duration of the recovery period to date, recognizing that many of the OWTS will not be fully repaired until later in 2016. The permit application dates for these 54 incomplete repairs range between June 2014 and February 2016. Approximately 63%, 20%, and 17% of the 54 had applied for major, moderate, and minor repairs, respectively.

Table 7.1 Fragility Score

Repair Type	Ranking	Scaled Fragility
Minor	1	0.25
Moderate	2	0.50
Major	3	0.75
> 1 Repair	4	1

Table 7.2 Rapidity Score

Recovery Duration	Ranking	Scaled Rapidity
< 60 days	1	0.2
61-180 days	2	0.4
181-270 days	3	0.6
271-365 days	4	0.8
> 365 days	5	1

Table 7.1 presents the categories of rapidity using an ordinal scale. Rapidity ranges and their rankings were based on typical pre-flood recovery durations where recovery periods extending over 6 months specify longer than typical durations under normal

environmental conditions. The ranked values were then normalized based on the highest value for the ranking to calculate each OWTS's scaled value for rapidity.

Resourcefulness

Bruneau *et al.* (2003) and more recently Norris *et al*. (2008) define *resourcefulness* as the capacity to identify problems and mobilize resources (i.e. monetary, physical, technological and informational). While *resourcefulness* is complex and goes beyond monetary resources to recover, here resourcefulness is determined by both OWTS fragility and rapidity. We define it as the ability to anticipate the monetary resources necessary to mitigate all consequences of OWTS failure, including costs associated with displacement during OWTS repair, in addition to physical repair costs in the event of a future natural hazard. The shaded area under the recovery curve in **Figure 7.3** represents *resourcefulness*, with the consequences of fragility monetized as the dollar amount assigned to loss of OWTS performance over the recovery period as well as estimated repair/replacement costs of material and labor. Environmental costs resulting from the release of wastewater into the environment also accrue, but the estimation of those costs is outside of the scope of this study.

To calculate *resourcefulness,* we focus on the major repairs where a near complete loss of OWTS function occurred. Here we make the assumption that for the period the system is not functioning, the owners are displaced or a temporary alternate – a portable chemical toilet, is required (University of Minnesota Extension, 2011).

The insurance industry provides what is referred to as loss-of-use coverage when the residence is not livable due to an insured loss from a flood or other catastrophic event

(American Insurance Association, 2009). However, flood insurance does not provide money for renting temporary housing unless the main structure is damaged or destroyed, and septic systems are not covered in flood insurance policies (FEMA, 2012). FEMA may provide some assistance through the Direct Housing Assistance Program covering rentals up to 18 months after the date of disaster declaration after which tenants are expected to have a permanent housing plan (CDBG-DR, 2015). The 18–month FEMA end date was March 15, 2015 for Boulder County, so relocation costs for repairs after that are responsibility of the tenants. The Department of Housing and Urban Development (HUD) has provided assistance through the final of three Community Development Block Grants for Disaster Recovery (CDBG-DR) allocated to Boulder County since 2013. CDBG_DR can grant up to $50,000 for the repair or replacement of flood-impacted OWTS, including the connection to municipal utilities or 2 years of temporary rental assistance or up to $20,000. However, allocations are based Area Median Income (AMI) and currently only 20% of the funds have been granted for OWTS repair and 16% for housing assistance (Boulder County, 2014b; 2015). As such, predominantly the finance of reconstruction of a failed septic system after the flood and any related inconvenience falls directly on the homeowner (Boulder County, 2015), making an estimation of this cost critical to communicate the true cost of OWTS failure after a natural disaster.

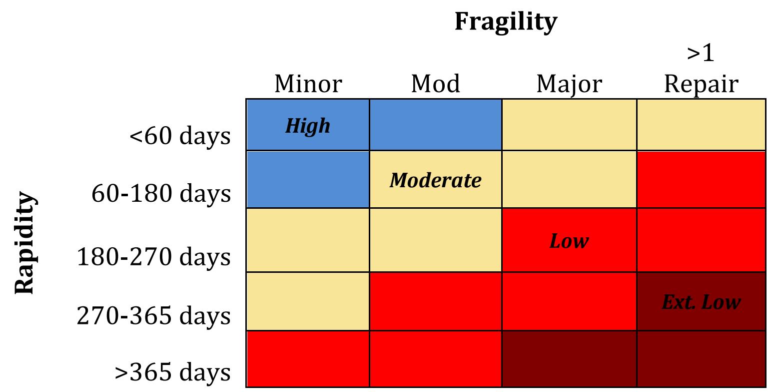
To estimate this cost, = *resourcefulness*, we apply loss-of-use method used by insurers, which determines the amount granted to a particular property owner to relocate based on the property's monthly mortgage rate plan (American Insurance Association, 2009). The monthly mortgage rate for residences with flood-related OWTS repairs is calculated using the BankRate Mortgage Calculator, an interest rate of 4.5 %, and a 30-year term.

For those OWTS requiring major repairs *before* the flood, we estimate the *resourcefulness* per month required to recover performance as the average cost for the repair, $14,866 as determined by BCPH (2013), and the cost of the property's mortgage rate based on the total assessed value of the property from the Assessor's tax database. For those major repairs *after* the flood, *resourcefulness* per month of recovery is comprised of the monthly mortgage, the average cost of the repair plus a 10% repair cost increase. The increase is based on a survey of 5 Boulder County OWTS installers who suggested costs increased between 10-20% after the flood (OWTS Service Provider Survey, 2014). Olsen & Porter (2011) similarly found that demand surge increases reconstruction costs after disasters by 20% or more.

As a secondary measure of the occupancy-related costs in *resourcefulness* estimates, we calculate the minimum cost to the resident for a portable toilet rental as an alternative to temporary relocation. Then the rental cost of a portable chemical toilet per month of recovery is added to the physical repair cost described above. Monthly rental of chemical toilets are estimated to range between $100-300, though prices vary based on service requirements and overall rental duration (United Site Services, Inc., 2015). For this study, we chose to apply the minimum rental value, $100 per month, as a conservative estimate for recovery resources.

Resilience Assessment

Combining the fragility and rapidity dimensions produces a multi-faceted definition of resilience and provides an opportunity to estimate the resourcefulness necessary to improve OWTS resilience.



Resilience		Additive Range
High		< 0.95
Moderate		0.95-1.15
Low		1.15-1.5
Extremely Low		> 1.5

Figure 7.6 Resilience levels based on the fragility and rapidity scores of each OWTS.

The fragility and rapidity scaled scores were combined to specify four levels of post-disaster resilience. Using Geographical Information System (GIS) queries in ArcGIS, the spatial distribution of each OWTS attribute—fragility, rapidity and the resulting measure of resilience—were plotted based on the parcel ID and geographical coordinates of each of the sample OWTS in Boulder County. The lowest ranking corresponds with the highest level of resilience with minor to moderate OWTS failure and rapid recovery, while the highest ranking (lowest resilience) relates generally to severe failure and slow recovery (**Figure 7.6**). **Figure 7.7** illustrates the occurrence of high, moderate, low and extremely low resilient OWTS based on the 273 OWTS in the study sample after the 2013 flood event compared to a pre-flood baseline recovery measurement. While both the pre- and post-flood values are calculated similarly, the pre-flood failure events are considered independent of each other, whereas the failures after 2013 are attributed to the countywide disaster.

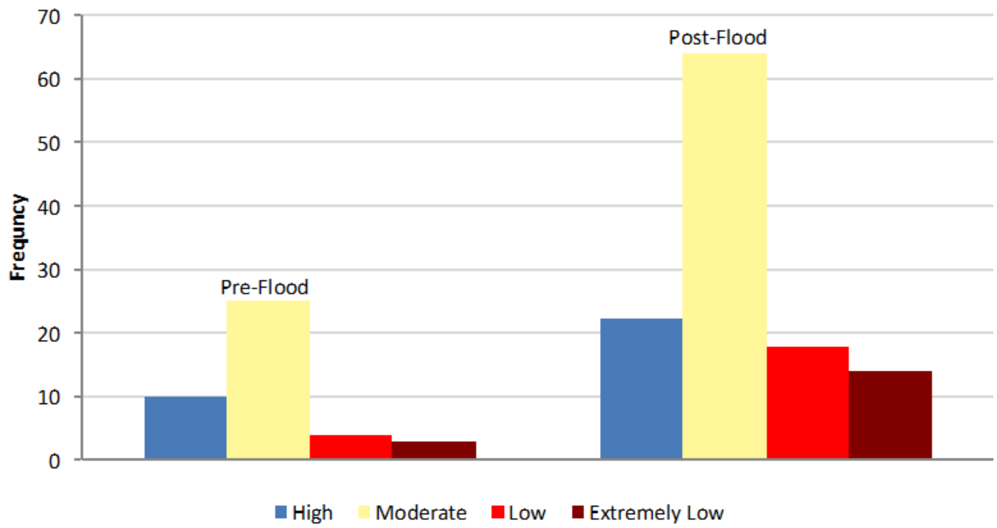


Figure 7.7 Occurrence of OWTS in each category of resilience after the 2013 Flood compared to a baseline measure of recovery for independent failures, repairs and replacements before 2013.

RESULTS AND DISCUSSION

For each of the 273 OWTS in the study sample, fragility and rapidity were calculated both for repairs before and after the 2013 flood. The two dimensions were then combined to determine the resilience level of each system after the flood event as well as estimate the resourcefulness required to mitigate the burden of major or complete OWTS failure in the future. Each section below describes each determinant—fragility and rapidity—and their combination.

Fragility

Figure 7.8a and 7.8b below show the distribution of failure type throughout the county before and after the 2013 flood. Visually, the total number of required OWTS repairs and their fragility distributions before and after the flood appear to be consistent, though the post-flood period of record is less than 3 years while the pre-flood period is 7 years. An important distinction between pre- and post-flood fragility is that independence between each failure occurrence can be assumed before the flood, but this assumption of independence does not apply to the post flood population. Generally, it appears that OWTS that have lost near complete function (major repairs) tend to dominate each population. This may be due to the fact that these repairs are associated with visible failure, while minor and moderate repairs may be more difficult to identify without an inspection, resulting in fewer identifications overall.

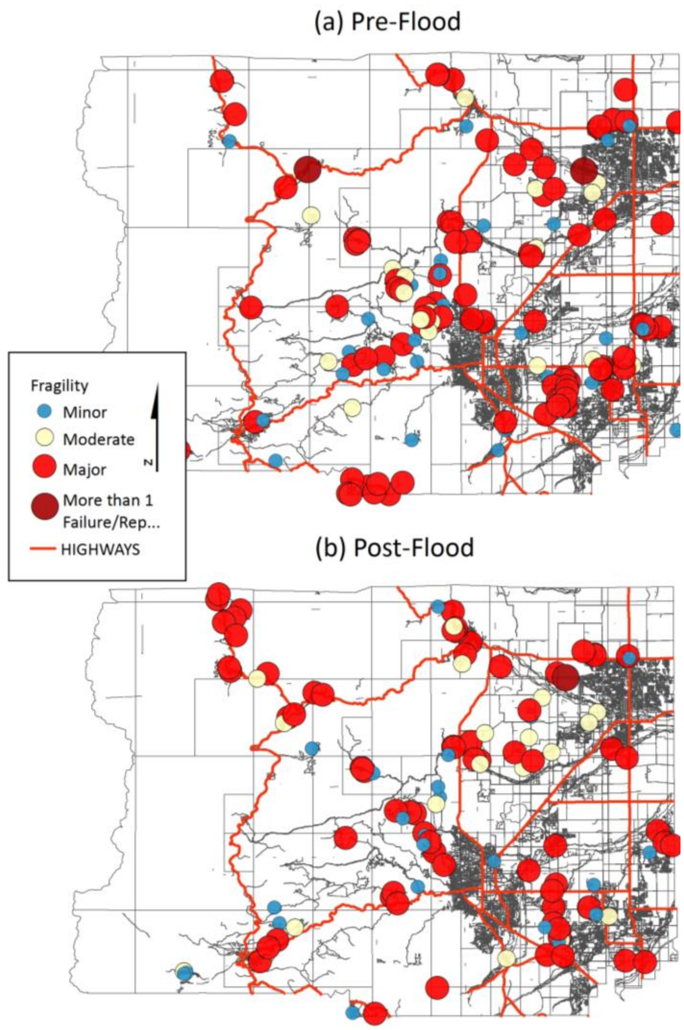


Figure 7.8 Distribtion of fragility before and after the flood.

Rapidity

Unlike the fragility distribution, across the sample rapidity shifts significantly after the 2013 flood to longer recovery times as compared to the more rapid recovery of OWTS from 2007 to 2013. **Figure 7.9a and 7.9b** show the distribution of OWTS throughout Boulder County pre- and post-flood, respectively. A series of boxplots also compare the median recovery duration across the entire sample and their variation after 2013. The recovery distribution for repairs from 2003-2013 are in **Figure 7.10a**, where **Figure 7.10b and 7.910c** show rapidity for the sample of the 34 flood-related repairs based on the permit application date (i.e. the date the owner applied for a repair permit to address the failure) and from the actual date of the flood (i.e. the date the damage occurred) to the final inspection date, respectively. To be consistent for the sake of comparison, we define rapidity as the duration between the permit issue date and the final inspection, though it is interesting to see that for the

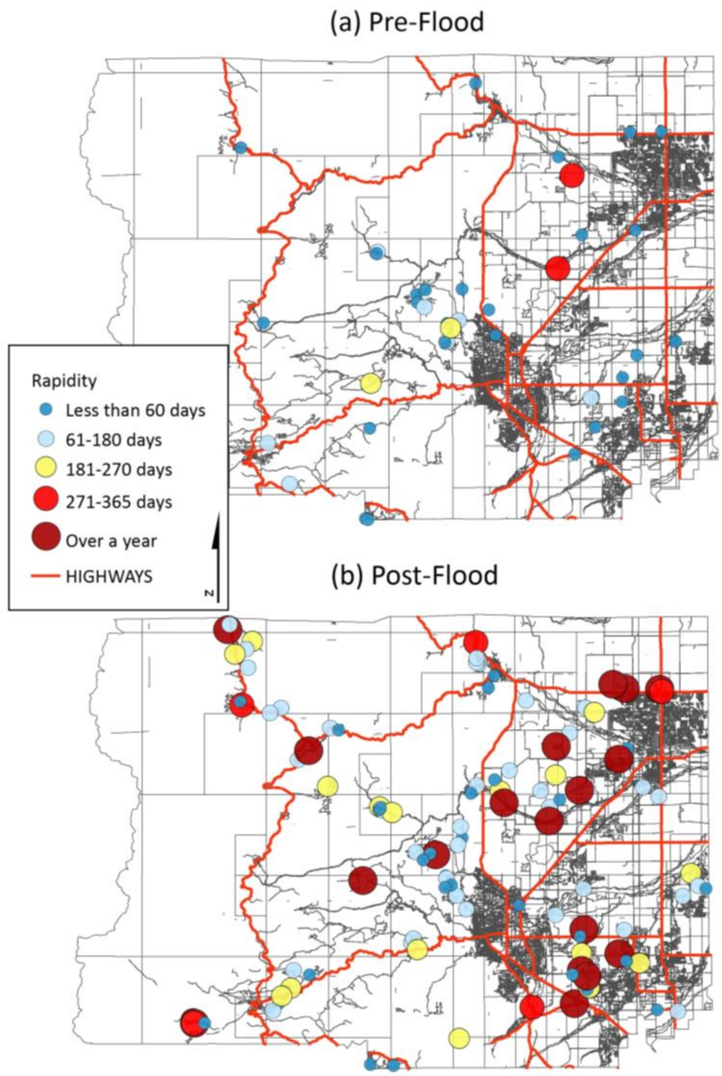


Figure 7.9 Distribution of rapidity before and after flood.

population of systems directly affected by the flood, the true recovery period was significantly longer. This relationship indicates that there not only exists a recovery delay but as well a reporting or permitting delay. Furthermore, **Figure 7.9d** indicates that not only directly flood-impacted OWTS suffered from recovery delays but also all repairs after 2013 up to the present day still undergo significant delays.

To verify the statistical significance of the difference at 95%, we used a simple t-test, which confirmed that, on average, recovery after the flood has been slower or rather rapidity has been lower compared to the recovery durations before the flood.

The increased number of repair calls, reconstruction delays related to backlog and inaccessible properties, and increased demand of material and equipment affecting their costs and availability all influence recovery time. After the flood, delays were attributed to initial debris removal, identified as critical in order for reconstruction to begin. For example, Mosqueda & Porter (2007) reported that the storm surge in Hurricane Katrina moved considerable quantities of debris onto properties near the shore along the Mississippi coast, limiting access to the properties for repair. Though the amount of debris as a result of the 2013 flood may not have been equivalent to the quantity associated with Katrina, many of the OWTS with long recovery durations were located in the canyons, where roads, bridges and culverts were damaged limiting access to properties (MacClune *et al*. 2014). In addition to debris, persistent floodwaters, elevated groundwater levels and shifts in the 100-year and 500-year flood plains have delayed the issue of both building and OWTS repair permits in certain areas (Boulder County, 2015). Areas where these hydrological and topographical transformations occurred, once suitable for OWTS, may no longer be appropriate for decentralized buried sanitation solutions, therefore repair permits have been withheld so alternatives can be discussed. Lastly, these physical challenges in addition to the shear number of applications after the flood overwhelm permitting and inspections offices, restricting the number of permits issued and the rate of final repair inspections.

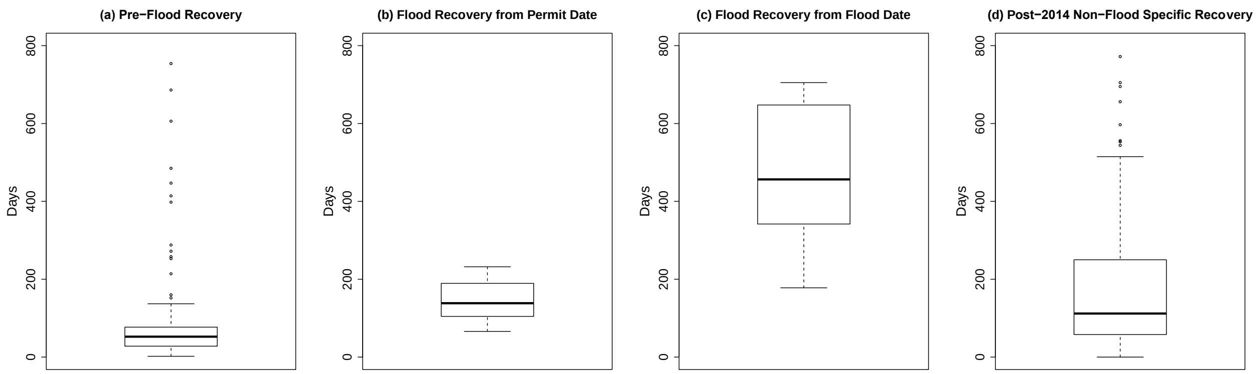


Figure 7.10 Recovery durations for (a) OWTS repairs from 2007-2013, (b) flood-specific repairs based on the permit issue date, (c) flood-specific repairs based on the approximate date of the system failure (entered as September 12, 2013, the peak of the storm event), and (d) all other repairs from 2014-2016.

Resilience

Figure 7.11a and 7.11b display the resilience rankings for each of the 273 OWTS after the flood compared to a baseline measurement of recovery for repair before 2013. As mentioned, the distribution of fragile OWTS before and after the flood appears to be random throughout the county with a total repair increase during the post-flood period. Rapidity, on the other hand, decreases significantly. The dominance of the rapidity dimension as a determinant of resilience is apparent in **Figure 7.11**. Minor to moderate failures with slow recovery rates lead to less resilient OWTS, whereas, major failures that are addressed rapidly specify highly resilient systems.

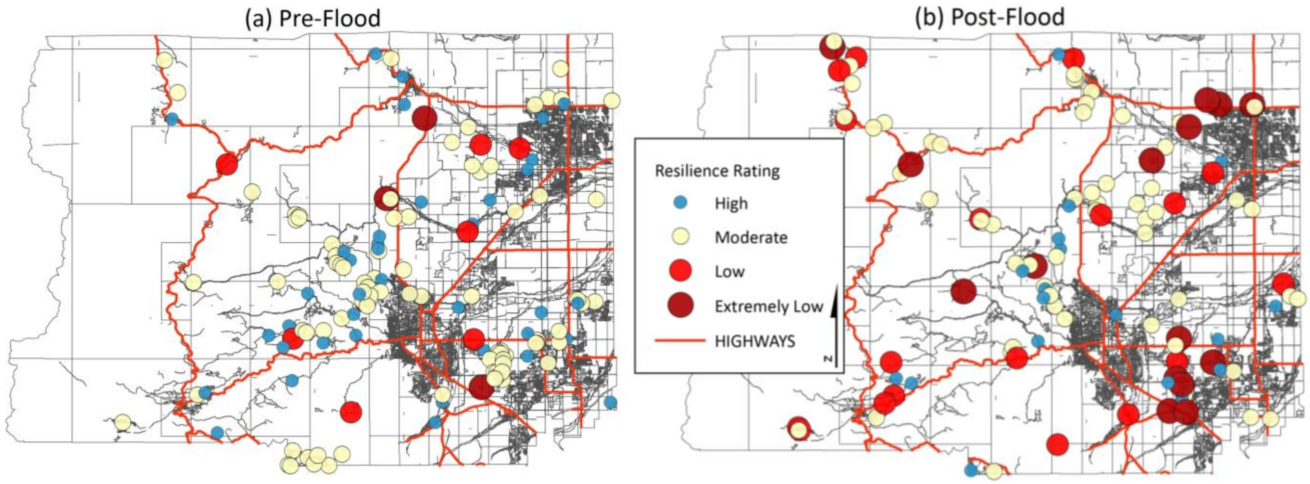


Figure 7.11 Distribution of OWTS resilience before and after

Resourcefulness

Demand surge among the other factors mentioned affect OWTS resilience after a widespread disaster. Olsen and Porter (2011) describe demand surge to include demand increases in materials, labor, equipment, financing, or some combination that outpace their supply after a natural disaster. Major catastrophes, such as earthquakes, hurricanes, and wildfires often create a demand surge for materials and labor, resulting in increased costs to replace damaged property (Federal Alliance for Safe Homes and The Actuarial Foundation 2006). Here the overburdened supply may also be the number of certified service providers in the county to address OWTS failures. Increased repairs over a short period of time can cause backlog stressing the services available, in part delaying recovery and causing OWTS after the flood to be less resilient.

This lack of OWTS resilience, however, has a distinct financial consequence for homeowners. While some resources exist to mitigate the financial burden of OWTS failure through CDBG-DR, both the costs of OWTS repair as well as costs associated with a delayed recovery primarily fall directly on the individual system owners. Information about the degree of failure—here we focus on major fragility—and the duration of recovery create a foundation for estimating resourcefulness to anticipate costs of future disasters in terms of their cost to system owners. The costs to occupy another residence during the restoration of the failed OWTS compared to the cost of renting a portable chemical toilet are plotted in **Figure 7.11 and 7.12**, respectively.

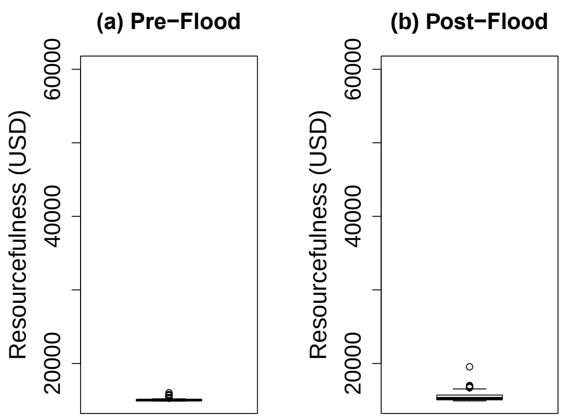


Figure 7.12 Resourcefulness based on displacement

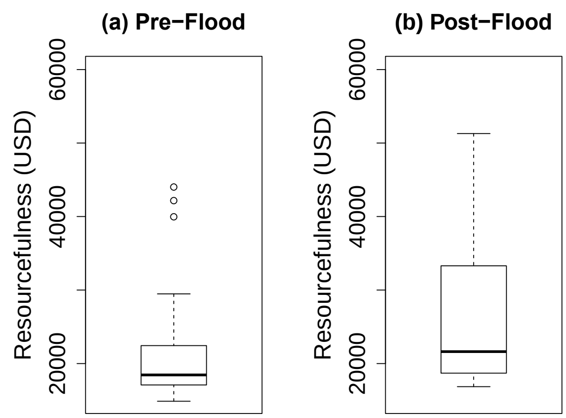


Figure 7.13 Resourcefulness based on a rented toilet

Recognizing the resourcefulness increase after the 2013 flood illustrates recovery response of OWTS given a widespread disaster and their financial burden in comparison to failures that result from smaller isolated events, poor management, or slow system degradation. While these values are merely estimates, they illustrate the severity of a widespread disaster such as the Boulder flood and its affect on immediate recovery, as well as its impact on recovery and costs up to four years after the event.

CONCLUSION

This study examines the effects of decentralization on the resilience of wastewater treatment systems in the face of extreme events and develops a framework to quantify

OWTS resilience based on an overlay of resilience determinants, namely the time and costs required for an OWTS to restore operation after varying degrees of failure. Widespread natural hazards such as flooding were found to affect the frequency and degree to which OWTS function is lost, and more importantly delay their recovery. Flood impacts to not only OWTS but also other infrastructure systems stress the resources available both directly after the event and for several years into the future. Olsen and Porter (2011) describe these stresses and consequent cost increases as demand surge where the supply—for materials and services—is overburdened by a sudden and widespread demand when multiple systems fail simultaneously. The longer recoveries of OWTS have costs related to homeowner losses resulting from a failed OWTS as well as likely have environmental and public health consequences due to the prolonged release of contaminants. This investigation evaluated the costs associated with displacement when a property was rendered unlivable due to a failed sanitation system. The amount necessary to cover the costs of a completely inoperative OWTS including displacement costs or the rental costs of a temporary facility, range between $15,000 and $60,000 after the flood--costs which are directly related to OWTS repair delay. Where there does exist some financial support for OWTS repairs and relocation cost through CDBG-DR grants, the totals allotted are limited to up to $50,000 and $20,000 for OWTS repairs and relocation assistance, respectively. Approximately, 20% and 16% of the CDBG-DR grants have been distributed for OWTS repairs and relocations costs in Boulder since the 2013 event, leaving a large portion of the cost and inconvenience to be managed by homeowners.

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CHAPTER 8: SUMMARY & CONCLUSIONS

SUMMARY

Chapters 4-7 of this research each address the dimensions that describe life cycle OWTS performance, motivated by the growing reliance on decentralized sanitation and the dearth of knowledge about its reliability. The ultimate purpose of this study is to provide guidance for better-informed OWTS regulatory policies and a more complete representation of the risks associated with these systems. In general, OWTS are regulated through a permit issued at the time of installation insuring compliance with equipment design and physical siting criteria for subsurface discharge through a soil treatment unit (STU). Unlike centralized treatment facilities, which must monitor and report water quality data under NPDES permit requirements, there is no monitoring of treated water quality or even system physical integrity. In order to carry out performance-based diagnostic monitoring of OWTS performance, a secondary measure, the frequency of system disruptions severe enough to require repair/replacement actions and associated costs over a 40-year assumed life cycle, *repair severity*, was designated as the performance response variable.

Chapter 4 focuses on quantifying OWTS *repair severity* as a function of owner behavior and policy-related factors operative after installation. A multiple regression method, Generalized Additive Models for Location, Scale and Shape (GAMLSS), was used to simulate OWTS repair/failure data in Boulder County Colorado between 1973 and 2013. A Weibull distribution provided the best fit to estimate annual repair costs between $200 for systems with a record of inspection and maintenance to over $370 for OWTS with no prior inspections. The most significant predictor variables were either property transfer inspections alone or combinations of inspections with permitted upgrades and property sales made under a new regulation promulgated by the County in 2008. The result highlights the importance of requiring owners to obtain professional inspections in determining long-term OWTS functionality. In general, monitoring is an important component of infrastructure reliability. Public health and environmental agencies have sponsored numerous efforts to provide public information on best inspection and maintenance practices for OWTS, including one campaign in initiated by the U.S. EPA and adopted by Boulder County called "Septic Smart." However, the relative invisibility of OWTS fixtures and the cost of inspections and maintenance are incentives for homeowners to opt out of voluntary inspections until significant system failures such as sewage ponding or backups occur. The results of **Chapter 4** support the economic model proposed by Mohammed (2009), that the mixed private-public nature of OWTS constitutes an impure public good where private economic choices often outweigh public interests in environmental quality. In Boulder County, even the less-than-universal requirement for inspection during a property transfer had a beneficial effect on homeowner costs. It can be expected that wider coverage through a system of renewable permits or mandatory maintenance contracts would obtain even greater benefits in terms of environmental quality and homeowner costs.

Chapter 5 presents new methods to communicate failure risk to OWTS owners, in order to incentivize good management practices at the household level by communicating tradeoffs between the preemptive costs of monitoring and maintenance required by performance-based regulations and the costs of system failure, major repair and replacement. Homeowners in many communities have resisted the imposed costs of active OWTS regulation due to their added financial burden unaccompanied by evidence of their benefit. In the end, **Chapter 5**, using Extreme Value Analysis –Points Over Threshold, determines failure risk in terms of the probability of an OWTS performing poorly resulting in repair costs above a selected threshold ($18,000) signifying that the system is high-risk and the consequence in terms of the dollar amount of threshold exceedance. It was found that increasing the number of bedrooms in a home with an OWTS increases the risk of the system incurring a major repair replacement with costs over the threshold, while required inspection at the time of property transfer significantly decreases the risk of over-the-threshold repair costs. **Chapter 5** results highlight the benefit of inspection and maintenance in a risk framework. The model also enables comparison of the cost of regular monitoring through a mechanism such as a renewable permit to the risk-cost of the no action alternative. Overall, the added cost of inspection appears to be advantageous in two respects: the lifetime risk of repair/failure costs is less than the cost of inspections over the same period and also smaller regular maintenance costs are less than the financial burden of a single large expenditure after failure.

In addition to owner behaviors, OWTS are vulnerable to other factors exerted after installation, which are not typically considered in design and siting guidelines. Most notable of these is weather. Buried septic tanks may receive infiltration and inflow through cracks or inadequately sealed risers and subsurface treatment and discharge through the soil treatment unit can be impaired by saturated soil conditions after significant rainfall. **Chapter 6** covers a study of the fragility of an OWTS population measured as predicted repairs/replacements attributable to annual variations in precipitation, stream flow and temperature.

A Generalized Linear Model (GLM) method was used to test the association between weather-related variables and the frequency of OWTS failures in Boulder County, measured as frequency and magnitude of repairs over the period of 1979 to 2006, by fitting permit data to a Poisson distribution. The significant predictor variables (significant at 90% with p values ≤ 0.1) for major OWTS repairs were the number of months in any year that rainfall exceeded 10.16 cm (4 in) and the peak recorded stream flow in the major County watershed, Boulder Creek. For comparison, the average monthly rainfall in the Boulder Creek drainage is 4.39 cm (1.73 in), so the 10.16-cm threshold of the independent variable signifies a much wetter than average month. The R^2 value for the GLM fitted to major repair permit data was 0.70.

A method for evaluating the resilience of OWTS in response and recovery from an historic (1,000-year) storm event that occurred in Boulder County in September 2013 is proposed and demonstrated in **Chapter 7.** Severe flooding and erosion resulted in multiple simultaneous OWTS failures, and the analysis therefore considered OWTS resilience as an attribute of the aggregated County systems damaged by the flood. Resilience is comprised of *fragility*, here, the sudden loss of system function after a hazard event, and measured as repair and replacement frequency between January 2014 and February 2016 and the time to recover OWTS function, measured as the time between the flood event and the final inspection of the restored OWTS (*rapidity*). It was found that there was a significant increase in the annual frequency of major OWTS repairs in the two years following the flood, compared with the period 2003 – 2013. Moreover, the time to recover is significantly increased after the flood disaster when multiple systems are damaged. Extended recovery time after the flood can be attributed to demand surge, a phenomenon in which the demand—in this case materials, labor, and overall OWTS repair services—surpasses the supply (Olsen & Porter, 2011). In addition to recovery time, a survey of OWTS installers revealed that their post-flood charges to owners increased by approximately 10%. **Chapter 7** also estimated the financial consequences of a demand surge for individual homeowners monetized as the cost of relocating residents over the extended recovery period, and as a less-acceptable alternate, the rental cost of a portable toilet. The total amount of each alternative over the recovery duration plus the cost of repair makes up a third component of resilience, *resourcefulness*, which represents the estimated costs associated with recovery that falls directly on system owners. These estimates illustrate the expected cost associated with OWTS failure and delayed recovery as the result of a widespread disaster that are currently not included in the communication of OWTS risk to homeowners. Given increasing probability of extreme storm-related hazards, consideration should be given to these system owner costs associated with the difficulty of maintaining resilient wastewater systems. There exists a great opportunity to develop insurance policies, either as flood insurance or home insurance add-ons, that would alleviate some of financial risk for individual system owners. Policies could be mandated but subsidized based on proof of maintenance records or signed management contracts from certified service providers.

CONTRIBUTION

Overall, this research contributed to the quality, availability, and accessibility of information about key components of OWTS life cycle performance for decision makers.

Figure 8.1 summarizes the contributions made in each chapter of this dissertation.

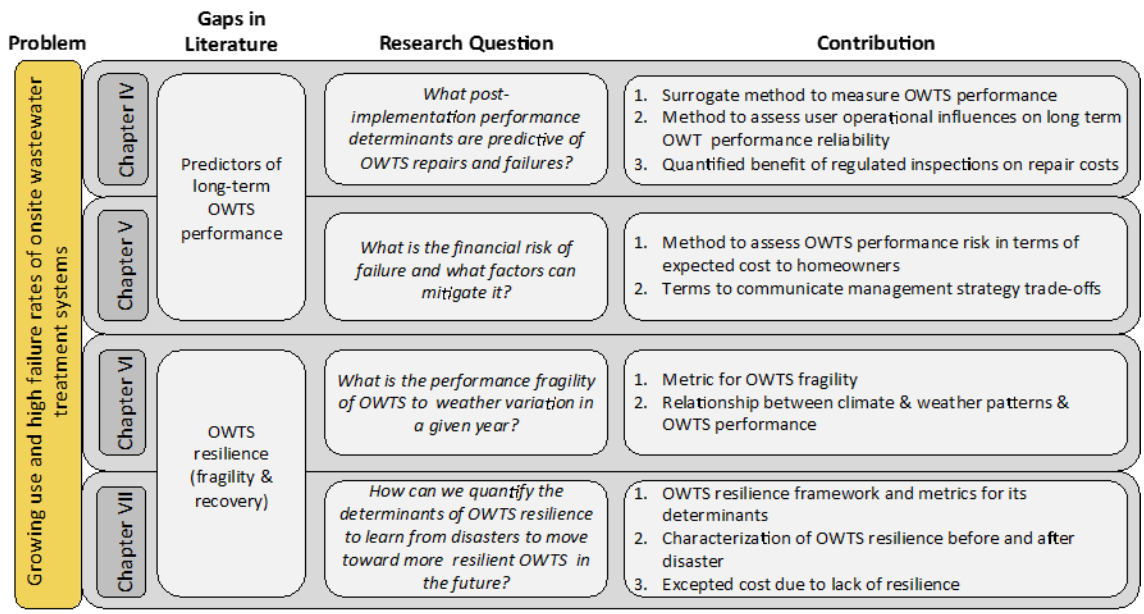

Figure 8.1 Dissertation summary of knowledge needs, related research questions and contributions of results to understanding OWTS life-cycle performance.

An important contribution of this dissertation is the data-driven performance-based methodologies described in **Chapters 4-7** that identify connections between post installation factors such as owner operational practices and weather events and wastewater treatment outcomes expressed as risk of failures and related repair costs. Dependence of OWTS function on both design and operational characteristics has been recognized previously, but not formally analyzed due to a lack of the most common treatment performance measure, water quality.

Use of a secondary measure, repair/replacement frequency and cost data documented in public records produced two benefits. First is a quantitative means of measuring lifetime failure risk as a function of common owner behaviors, and second is producing an effective means of communicating best practices in the form of economic risks that are especially persuasive to two key stakeholders – private OWTS owners and regulators. Results of the study indicate that merely publicizing environmental and public health risks of OWTS failure have not been effective at incentivizing owner best practices. The use of cost provides an alternative that illustrates the tradeoffs between properly operating OWTS and long-term costs related to repairs and replacements.

Modeling OWTS reliability as *repair severity* in **Chapters 4 and 5** illustrates the economic benefits of embedding best practices for lifetime OWTS operation in regulations and other policy measures. A variety or proscriptive mechanisms such as renewable permits and required maintenance contracts between owners and installers and incentives such as access to State Revolving Fund money or rebates for upgrades and subsidized insurance similar to government-subsidized flood insurance.

The impact of weather, especially extreme weather, on OWTS function has never been reported or analyzed in a resilience framework, such as is presented in **Chapters 6 and 7**. Yet in many locations where these systems are now or will be relied on for universal sanitation, resilience to extreme weather events that can severely disrupt decentralized wastewater systems on a large geographic scale should be considered in wastewater system needs assessment and planning. Consideration of fragility and resilience characteristics of OWTS exposed to extreme weather events can motivate improved emergency planning, technological advances and even changes to land use and development practices.

The singular outcome of this dissertation is that reliable treatment of wastewater in OWTS systems cannot be achieved by existing design regulations enforced only at installation. Rather dynamic conditions such as owner behavior and weather conditions exerted over the system lifetime must be considered. By incorporating the influence of ownership as well as the consequence of scale when it comes to natural hazards, we can enable risk-informed decisions related to OWTS management and planning that ultimately result in more sustainable sanitation solutions.

LIMITATIONS & SUGGESTIONS FOR FUTURE RESEARCH

The limitations of this dissertation relate to availability, quality and quantity of OWTS data. Because OWTS operation and maintenance are not regulated, practices vary widely and performance and failure data are scarce. In this investigation, performance-based data were obtained from homeowners' applications for permits to replace or repair failing systems (EPA, 2002b). While the reported inspections and permits offer insight to actual system performance, they are still limited in that they only identify compromised function exceeding a relatively high threshold. They do not consider less disruptive degraded performance that still results in groundwater contamination and possible health risks. Permit applications are hand written documents, many of which date back to the late 1940s. **Chapters 4 and 5** analyses incorporate permit applications and inspection reports dating back to 1973 and required coding to allow quantitation of independent variables. Some counties have considered electronic submission of inspection and permit applications, as has been done in many states for NPDES Discharge Monthly Report data from municipal treatment facilities. Such a system would greatly improve reliability and accessibility of OWTS data to researchers as well as public agencies.

Repair/replacement costs were a component of the severity measure reported in **Chapters 4 and 5**. Variability in site slope, vegetation, soil characteristics, setbacks from surface water bodies, water table levels, and accessibility repair costs can vary widely, for example, from $4,860 to $21,800 for a moderate repair that includes replacing the soil treatment unit. Repair costs were estimated using an informal survey conducted by the Boulder County Health Department in the 1990's and have not been updated. Although a sensitivity analysis revealed that raising costs did not change the statistical model skill, more accurate cost data would be a great benefit to homeowners, insurers and public agencies charged with risk communication.

CONCLUSIONS

The goal here has not been to discredit OWTS as a desirable sanitation solution, but rather to characterize the challenges and costs associated with their long-term sustainability. No doubt OWTS will continue to play a role in the future of sanitation in the U.S. as well as more globally. As an engineer, I believe it to be my responsibility to characterize the risks associated with treatment of domestic wastewater in OWTS and identify those factors that cause OWTS failure and reduce their resilience in order to guide technology innovations and management decisions producing cost-effective performance and minimizing public health and environmental risks. Statistical modeling in this research has enabled identification of the challenges associated with ensuring a public good within the constraints of private ownership.

In the absence of treated water quality data, performance of OWTS over a life cycle of 40 years has been quantified as the *repair severity*, using failure-associated repair permit data from a sample representing 14,300 OWTS in Boulder County, Colorado.

Statistical methods using the GAMLSS multivariate regression method and extreme value analysis indicated that regulation requiring inspection and maintenance significantly reduced both the probability and magnitude of OWTS failures. Both regulation and financial incentives should be considered to insure a desirable level of OWTS performance over their lifetime.

Improved monitoring and reporting requirements will enable more accurate life-cycle assessment of OWTS performance in a sustainability context that considers economic, social and environmental outcomes of privatized and decentralized wastewater management.

OWTS in general are highly vulnerable to weather conditions, particularly precipitation leading to saturated soil and, in the extreme, flooding. The annual frequency of months where rainfall was approximately two times the Boulder Creek drainage monthly average and peak stream flow in the watershed were significantly associated with major repairs in that year, accounting for 70% of repair data variability.

An extreme flood in 2013 resulted in greater than normal OWTS damage requiring major repair and significantly longer time required for restoring damaged OWTS possibly the result of a demand surge, which has been reported to delay recovery of other infrastructure from earthquakes and floods.

It is in the public interest to reduce heightened economic risks to OWTS owners resulting from natural hazards such as floods, possibly by publicly-subsidized insurance and emergency planning that reduces the system recovery time.

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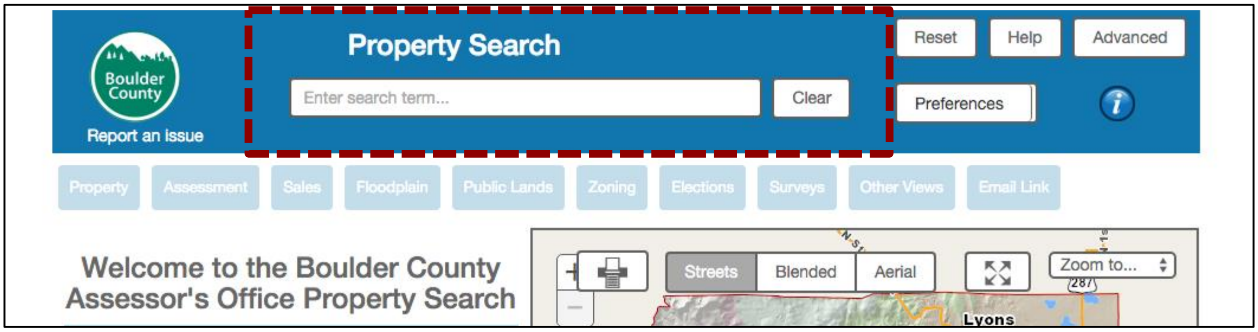
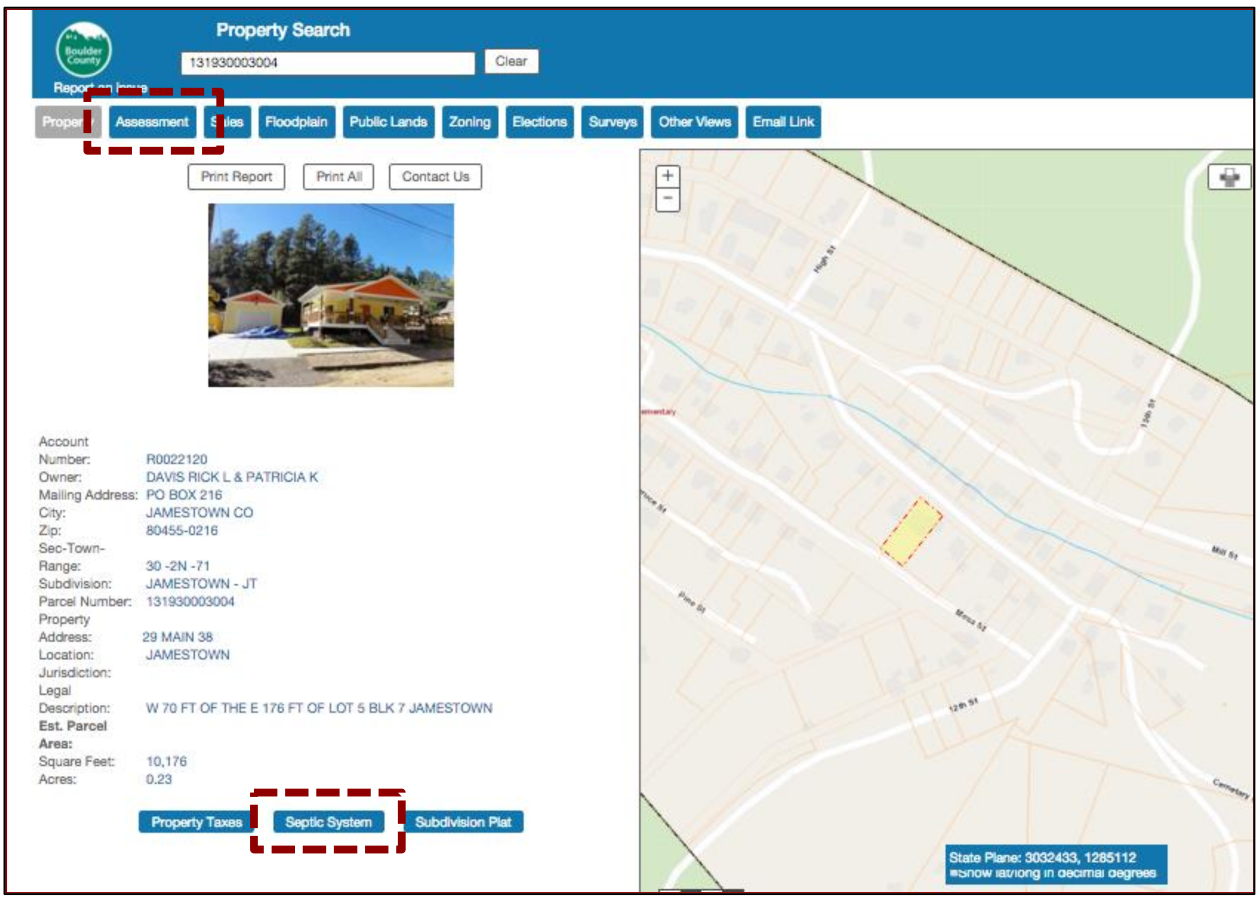
APPENDIX A: DATA COLLECTION

Data was collected from: http://maps.bouldercounty.org/boco/PropertyViewer

1. Each property ID, provided by the Boulder County Public Health (BCPH) department permit database search, was entered into the *property search* bar as pictured below.





2. Under the *assessment* tab for the property, there is information about each property deed, the actual and assessed structural value of the home, the living area, and the assessed number of bedrooms and bathrooms for the property. Clicking the *septic system* tab leads to the permit record for the system. This record has information about

the permit type as well as the permit date and final inspection date. Since BCPH categorizes permit types into only minor and major repairs, I had to differentiate major repairs further by going into the *wastewater system documents for this system* tab.

Property Information

Parcel ID 131930003004

Property Address 29 MAIN ST, JAMESTOWN

Wastewater system documents for this property

Permit Record

Permit #	Structure/Building Type	Permit Type	System Sized for (Bedrooms)	Tank Size (Gallons)	Final Approval Date	Permit Issue Date	Type of System
ON0048587	Primary Dwelling/Structure	OWTS FLOOD MAJOR REPAIR	2	1000	06/15/2015	01/16/2015	System Type 1: Ripped Absorption Field System Type 2: Lift Station
ON0021400	Primary Dwelling/Structure	OWTS MAJOR REPAIR (FULL FEE)	2	1000	09/15/1997	06/09/1997	System Type 1: Septic Tank/Chamber Distribution
ON0021399	Primary Dwelling/Structure	OWTS UPGRADE (FULL FEE)	2	1000	10/07/1992	12/19/1990	System Type 1: Septic Tank/Chamber Distribution
ON0038461	Primary Dwelling/Structure	OWTS NEW SYSTEM (FULL FEE)	2			06/13/1972	System Type 1: Vault

3. The *wastewater system document for this system* tab leads to the any file documents associated with that property ID, including: scanned, hand-written permit documents, design drawings, loan inspection documents, legal documents, property transfer certificates, and miscellaneous.

4. Here I have accessed one of the permits to illustrate the source of certain independent variables.

Onsite Wastewater System documents associated with 29 MAIN ST, JAMESTOWN

Document Type	Permit Number
Permits	
Permits	
Permits	
Designs and Drawings	
Designs and Drawings	
Designs and Drawings	
Legal	
Legal	
Legal	
Miscellaneous	
Miscellaneous	
Blueprints	
Legal	ON0021400
Permits	ON0048587

~~New~~
Repair Shapes X
Upgrade X
Addition
Renewal
Change of Owner

Permit Type

Receipt Number

BOULDER COUNTY HEALTH DEPARTMENT
3450 Broadway, Boulder, CO 80304
441-1190

APPLICATION AND PERMIT TO INSTALL, CONSTRUCT, ALTER OR REPAIR INDIVIDUAL SEWAGE DISPOSAL SYSTEM (SEPTIC TANK)
CERTIFICATION TO BOULDER COUNTY LAND USE DEPARTMENT (COUNTY BUILDING INSP. DEPT.)

Owner RICK DAVIS Mailing Address P.O. Box 216
City JAMESTOWN State CO Zip 80455 Home Phone 444-2430 Work Phone
Agent Street City Zip Phone
Site Address 29 MAIN ST JAMESTOWN Installer MIKE IKELER / Mike SAPP
Legal Description (short) LOT 5 BLOCK 7 TOWNSITE of JAMESTOWN

TO BE FILLED OUT BY APPLICANT
1. Existing Buildings 1

Number of bedrooms and bathrooms at the time of permit; therefore, can track change across permits

4. No. of bedrooms 2 No. of baths 1
~~No. of persons~~ 3
5. Basement plumbing: yes no ✓ type
6. Area of lot (acres) less than .7
7. Subsoil draintile (yes) (no)
8. Type of sewage disp. system requested: Septic tank ✓ vault other

Water Source

9. Well (proposed) (installed)
10. Water District JAMESTOWN

DEPARTMENT USE ONLY
1. Slope <5% Waterlines 25 feet
2. Soil Type Sand/rock
3. Soil perc rate 13.3 minutes/inch (over.)
4. Water table depth 2.17 ft Bedrock 2.34 ft
5. Location of central sewer > mile
6. Sized for 2 bedrooms (2) persons/bedroom)

Please locate on the plot plan below the well location or other type of individual water supply including the house, waterlines, proposed septic area and any streams, ditches, or steep banks on the site.

DETAIL DIRECTIONS TO PROPERTY | DETAIL PLOT PLAN

Owner Signature (Authorized Agent) R. K. Davis Date 5/15/97

DEPARTMENT USE ONLY
Permission is hereby granted to the owner or his agent to perform the work indicated below in accordance with the Boulder County I.S.D.S. Regulations. This permit is to remain in full force for **one year from date,** unless revoked for non-compliance. Plans and specifications of proposed sewage-disposal system when reviewed and attached to this permit have been considered satisfactory. Approval is given if this building site meets existing Zoning and/or Subdivision regulations of Boulder County as they apply in this specific case.

MINIMUM REQUIREMENTS

Install { Septic Tank 1000 gals. / Vault / Other }

Absorption Field Raised bed 273 sq. ft., OR
0 feet of trench three feet wide.
No one trench/line may exceed 100 feet.

Installation Instructions
ABOVE REFERENCED FIELD SIZE REPRESENTS A 40% ADJUSTMENT FOR INSTALLING INFILTRATOR UNITS. Install system per Mike Ikeler design dated 5-21-97 and revision dated 6-4-97, and all BCHD ISDS regulations. System must be re-installed in the area of previous ISDS, and at least two feet above original grade. A minimum of 21 infiltrators must be installed. An engineer must verify suitability, compaction, perc rates of fill soils, and submit new perc rates. Construct a barrier per engineer design to prevent surface run-off. Final inspection by the design engineer and this dept. is required before final approval and use of this system. THIS SYSTEM MUST BE INSTALLED BY A CONTRACTOR LICENSED BY THE BCHD.

Authorized Signatures
Approved by Board of Health
Permit Date

Permit Date 6-9-97
Date X 6-22-97
Final Inspection

Owner or Agent X R. Davis
Installer D. Sapp
Repair Date
Engineer Approval
Final Approval 9-15-97
(Health Officer—Sanitarian Signature)

TO OWNER: Leave entire sewage-disposal system uncovered for final inspection. A final inspection is required for all system installations unless otherwise specified. **THE HEALTH OFFICER SHALL ASSUME NO RESPONSIBILITY IN CASE OF FAILURE OR INADEQUACY OF A SEWAGE DISPOSAL SYSTEM BEYOND CONSULTING IN GOOD FAITH WITH THE PROPERTY OWNER OR REPRESENTATIVE.**

Environmental Health (9/86)

BOULDER COUNTY HEALTH DEPARTMENT
3450 Broadway Boulder, CO 80304
441-1190

INDIVIDUAL SEWAGE DISPOSAL SYSTEM
FINAL INSPECTION

PROPERTY OWNER Davis

LOCATION LOT 5, Block 7; Jamestown; 29 Main St.
(Legal and Property Address)

INSTALLER Mike Ikeler

Installed in area of tests YES at

Since BCPH typically specifies minor and major repairs, this notation helps specify whether the repair is actually major (septic tank and STU) or moderate (only STU). If the tank is not added to, restored, or replaced, then the repair is moderate.

Septic Tank/Aeration Unit Size 1 Ext. 1000

Company Eric Precast Watertight YES Risers NO —

Lift Station Installed YES Watertight YES Size 180 gal.

Warning Device Operating Yes Location In home Type Audial

Minimum Area Required 21 inf units 3x7 Area Installed 21 inf. unit 3x7

Indicates the Engineer Requirements and what was actually installed and assessed during the final inspection. Here the repair applies purely to the STU therefore it is a moderate repair per the definition in this dissertation

Distribution Lines 3 Capped YES Looped — Level YES

BOULDER COUNTY HEALTH DEPARTMENT
3450 Broadway Boulder, CO 80304
441-1190

INDIVIDUAL SEWAGE DISPOSAL SYSTEM
SITE INSPECTION WORK SHEET

PROPERTY OWNER DAVIS

LOCATION LOT 5 JAMESTOWN
(Legal and Property Address)

TYPE OF SYSTEM REQUESTED RAISED BED

Further indicating repair type

Proposed Structure 2 BEDROOM house Water Supply JAMESTOWN

APPENDIX B: DATA

RELIABILITY DATA (For CHAPTER 4)

BOULDER COUNTY OWTS ATTRIBUTE DATA

PARCEL_NO2	PRE2008_DEED	H2O	STRUCT_VAL	DELTA_BED	DELTA_BATH	LIVE_AREA	PROP_YR	LOAN_INSP	MIN	MOD	MAJ	NO_ADD/UPGRADE	TOT_REPAIR	RS	RS_ANN	RS_CATEG	PROP_TRANS_INSP	POST2008_DEED	POST2008_SALES
146336000022	0	0	465100	1	0	4813	1900	0	1	0	1	0	2	17.932	448.3	3	0	0	0
146130007003	1	0	185800	0	0	1040	1976	0	0	1	0	0	1	9.173	229.325	1	0	0	0
146114002011	1	1	400000	0	0.75	1547	1969	2	0	0	1	0	1	14.866	371.65	2	0	0	0
146114009003	2	1	480400	0	0	2280	1972	0	0	0	1	0	1	14.866	371.65	2	0	0	0
146103007006	3	0	309700	0	0	1612	1972	1	1	0	0	0	1	3.066	76.65	1	0	0	0
131727405008	2	0	270200	2	2	3840	1972	0	0	0	1	0	1	14.866	371.65	2	0	0	0
120112000025	2	0	342300	0	0.75	1352	1942	0	0	1	0	2	1	9.173	229.325	1	0	0	0
119711100032	2	0	224400	0	0.5	1648	1968	0	0	0	1	0	1	14.866	371.65	2	0	0	0
131727404005	2	1	212900	0	1	1163	1972	0	0	0	1	0	1	14.866	371.65	2	0	0	0
146102002010	0	1	244500	0	0	1450	1963	0	0	0	1	0	1	14.866	371.65	2	0	0	0
131711000020	1	0	217400	1	0.25	1246	1970	0	0	0	1	0	1	14.866	371.65	2	0	0	0
131919004003	0	1	97633	0	0	960	1971	0	0	0	1	0	1	14.866	371.65	2	0	0	0
120520414003	0	1	157100	0	0	1484	1965	0	0	0	1	0	1	14.866	371.65	2	0	0	0
146123011004	3	1	434500	0	0	2597	1972	4	0	0	1	1	1	14.866	371.65	2	0	2	2
157701107006	0	0	235200	0	0	1626	1966	1	0	0	1	0	1	14.866	371.65	2	0	0	0
157716200003	3	0	200800	0	1	3599	1958	5	0	0	1	0	1	14.866	371.65	2	0	0	0
120111000007	0	0	284393	0	0	1102	1947	3	0	0	1	1	1	14.866	371.65	2	0	0	0
146514009009	3	1	157500	0	0	1510	1966	2	0	0	1	0	1	14.866	371.65	2	0	0	0
132109000004	3	0	275000	0	1.75	3097	1949	0	0	0	1	0	1	14.866	371.65	2	0	0	0
158129000008	5	0	115100	0	0	1364	1974	2	1	0	0	0	1	3.066	76.65	1	0	0	0
146104006005	0	0	260600	0	0	2240	1960	0	0	0	1	0	1	14.866	371.65	2	0	1	1
146111006007	3	0	270000	0	0.25	1526	1978	2	0	0	1	0	1	14.866	371.65	2	0	0	0
131933000006	6	0	128400	0	0	660	1962	0	0	0	1	0	1	14.866	371.65	2	0	0	0
146533100037	1	1	137500	1	0	1864	1900	0	0	1	1	0	2	24.039	600.975	3	0	0	0
158136002002	1	0	117500	0	0.5	1200	1972	2	0	0	1	1	1	14.866	371.65	2	0	0	0
157504001003	3	0	257000	0	0	1222	1963	2	0	1	1	0	2	24.039	600.975	3	0	0	0
157701109002	0	0	258500	0	0	2197	1966	0	0	0	1	0	1	14.866	371.65	2	0	0	0
145912009002	0	0	101182	0	0	915	1914	1	0	0	1	0	1	14.866	371.65	2	0	0	0
157701306014	3	0	163200	0	0.5	1613	1962	4	0	0	1	1	1	14.866	371.65	2	0	0	0
158136001009	1	0	160200	0	0.5	3606	1960	0	0	0	1	1	1	14.866	371.65	2	0	1	1
146111001001	1	0	350400	0	0	1220	1965	0	0	0	1	0	1	14.866	371.65	2	0	0	0
146104004006	3	0	216700	0	0.5	1660	1972	2	0	0	1	1	1	14.866	371.65	2	0	1	1
157701306010	2	0	222300	1	0.75	2044	1963	1	0	0	1	0	1	14.866	371.65	2	0	1	1
157712203003	2	0	521100	1	1.25	2742	1969	1	0	0	1	0	1	14.866	371.65	2	0	0	0
120520414013	3	1	160000	0	0	1488	1964	1	0	0	1	0	1	14.866	371.65	2	0	1	1

158112000009	1	0	136900	1	0	684	1968	0	0	1	0	0	1	9.173	229.325	1	0	0	0
146514016021	1	1	162800	0	0	960	1969	1	0	0	1	0	1	14.866	371.65	2	0	0	0
131506000005	0	1	564500	0	0	4098	1976	0	1	1	0	1	2	12.239	305.975	2	0	0	0
131726309001	1	0	172600	0	0	1456	1966	0	0	0	1	0	1	14.866	371.65	2	0	0	0
146307000002	1	0	205300	2	0	2334	1948	0	0	0	1	1	1	14.866	371.65	2	0	0	0
145907000030	1	0	300100	0	0	1117	1915	3	0	0	1	1	1	14.866	371.65	2	0	1	1
157712203019	3	0	392800	2	0.75	1733	1967	1	0	0	1	0	1	14.866	371.65	2	0	1	1
131930004005	3	1	200000	0	1	1139	1962	2	0	0	1	1	1	14.866	371.65	2	0	1	1
157702000002	5	0	211000	0	0	2334	1975	3	0	2	0	0	2	18.346	458.65	3	0	0	0
146115001007	1	1	382900	0	0.75	2372	1974	1	0	1	1	0	2	24.039	600.975	3	0	0	0
146527000013	1	1	287400	0	0	1488	1960	0	1	1	0	0	2	12.239	305.975	2	0	1	1
158136101015	2	0	180200	0	1	2587	1965	1	0	0	1	0	1	14.866	371.65	2	0	1	1
131935013004	3	1	271000	1	1.25	1859	1966	3	1	0	1	0	2	17.932	448.3	3	1	0	1
146127000011	4	0	456600	1	1.5	1218	1965	3	1	0	0	0	1	3.066	76.65	1	0	0	0
120522311004	3	1	143700	0	0	1092	1972	1	1	0	0	0	1	3.066	76.65	1	1	0	1
146112000041	2	0	200350	0	0	1644	1964	2	1	0	1	0	2	17.932	448.3	3	0	0	0
146314000014	3	1	237000	1	0.25	2146	1967	2	0	0	1	0	1	14.866	371.65	2	0	1	1
146515005004	2	0	165200	0	0	1417	1963	0	0	0	1	0	1	14.866	371.65	2	1	0	1
120524000037	3	1	121100	1	0	950	1973	1	0	1	1	0	2	24.039	600.975	3	0	0	0
146118000029	3	0	129127	0	0	2474	1905	0	1	2	0	1	3	21.412	535.3	3	0	0	0
132103000011	0	0	131800	1	0	951	1940	0	1	0	1	1	2	17.932	448.3	3	0	0	0
157933000014	1	0	99800	2	0	816	1971	1	0	0	1	0	1	14.866	371.65	2	0	0	0
146336004009	2	1	199700	0	0.75	1525	1967	0	0	0	1	0	1	14.866	371.65	2	0	0	0
157931003002	3	0	127800	0	0	1872	1970	3	0	0	1	1	1	14.866	371.65	2	0	0	0
146115004002	4	1	438800	1	0.5	1685	1977	4	0	0	1	0	1	14.866	371.65	2	0	1	1
131935009011	4	1	214500	0	0	1848	1966	2	1	0	0	0	1	3.066	76.65	1	1	0	1
146104017001	1	0	481400	0	0	2965	1973	0	0	0	1	0	1	14.866	371.65	2	0	0	0
146532101001	2	1	119400	0	0	1222	1965	2	0	0	1	0	1	14.866	371.65	2	0	1	1
146122000022	2	0	516100	0	0.75	2852	1966	3	1	0	0	0	1	3.066	76.65	1	0	0	0
131711000012	2	1	355500	0	0	1288	1971	0	0	0	2	0	2	29.732	743.3	3	0	0	0
146114012010	3	1	329300	0	0.75	1587	1974	0	0	0	1	0	1	14.866	371.65	2	0	0	0
120521000006	1	1	260000	1	1.75	3493	1965	0	0	0	1	0	1	14.866	371.65	2	0	0	0
146104023001	3	0	365800	2	0	2880	1966	1	0	1	1	1	2	24.039	600.975	3	0	0	0
131930003003	3	1	201500	0	0	1303	1911	2	0	1	0	1	1	9.173	229.325	1	0	1	1
146515003004	2	1	178900	1	0.25	1750	1963	0	0	0	1	0	1	14.866	371.65	2	0	0	0
146520000017	2	0	673200	0	1.25	2556	1919	4	1	0	0	1	1	3.066	76.65	1	0	0	0
157701411002	0	0	399000	0	1.25	2860	1964	0	0	0	1	0	1	14.866	371.65	2	0	1	1
146104017008	1	0	298100	1	0	1320	1966	2	0	0	1	0	1	14.866	371.65	2	0	0	0
119725000028	1	0	125000	0	0	1200	1977	1	1	0	0	0	1	3.066	76.65	1	0	0	0
157702000004	2	0	371200	0	0	2378	1915	2	1	0	0	0	1	3.066	76.65	1	0	0	0
157712102005	1	0	534300	0	0	2896	1966	2	0	0	1	0	1	14.866	371.65	2	0	0	0
157931001031	4	0	162800	0	0	1996	1953	3	0	1	0	0	1	9.173	229.325	1	0	1	1
146317304001	1	0	221400	0	0	1612	1950	1	0	0	1	0	1	14.866	371.65	2	0	0	0
131720000042	0	1	320000	0	0.25	2964	1977	2	1	0	0	0	1	3.066	76.65	1	1	1	2
146528400016	1	1	689300	0	0.25	3323	1969	0	0	0	1	0	1	14.866	371.65	2	0	1	1
146336014005	1	0	236200	0	0	2819	1965	2	0	0	1	0	1	14.866	371.65	2	0	0	0
146336011001	0	1	219000	0	0.5	1604	1968	0	0	0	1	0	1	14.866	371.65	2	0	0	0

120522305005	3	1	165000	2	0	1775	1967	3	0	0	1	1	1	14.866	371.65	2	0	0	0
146514010002	1	1	145000	0	0	1004	1969	2	0	0	1	0	1	14.866	371.65	2	0	0	0
120334000001	3	0	457200	0	0	2944	1974	1	0	0	2	0	2	29.732	743.3	3	0	0	0
131730003002	1	1	255500	2	0.5	2303	1965	0	0	0	1	0	1	14.866	371.65	2	0	0	0
120319011005	3	1	151000	0	0	1064	1973	3	2	1	1	0	4	30.171	754.275	3	0	0	0
146130003018	0	0	214600	0	0	1305	1973	0	0	0	1	0	1	14.866	371.65	2	0	0	0
120520414010	0	1	120000	0	0	1292	1964	1	0	0	1	0	1	14.866	371.65	2	0	0	0
157720000016	0	0	323300	0	1.25	1824	1973	1	1	0	0	0	1	3.066	76.65	1	0	0	0
131508301001	2	1	183300	0	0	1919	1964	2	0	0	1	0	1	14.866	371.65	2	0	0	0
157932002016	1	0	86900	0	0	1232	1973	1	0	0	1	0	1	14.866	371.65	2	0	0	0
157932000036	2	0	132100	1	0.75	2771	1961	1	0	0	1	1	1	14.866	371.65	2	0	0	0
131524000001	0	1	242300	2	0.5	2139	1900	0	0	0	1	0	1	14.866	371.65	2	0	0	0
146532103021	3	1	121000	0	0	944	1965	2	0	0	1	0	1	14.866	371.65	2	0	0	0
131517000019	0	1	249500	2	0	936	1964	1	0	0	1	0	1	14.866	371.65	2	0	0	0
157513403003	6	1	356600	0	0	4878	1976	0	1	0	0	0	1	3.066	76.65	1	1	0	1
119724000003	0	0	183600	1	0.25	1664	1967	0	0	0	1	0	1	14.866	371.65	2	0	0	0
146318100032	0	0	251900	0	0	1104	1961	0	0	0	1	0	1	14.866	371.65	2	0	0	0
157711002013	2	0	575000	0	1.75	4426	1966	2	0	0	1	0	1	14.866	371.65	2	0	1	1
146121000020	2	0	411500	1	0.25	2649	1965	2	0	1	1	0	2	24.039	600.975	3	0	1	1
131935001010	2	1	212500	0	0.25	1350	1973	1	1	0	1	0	2	17.932	448.3	3	1	0	1
146515010001	0	1	151200	0	0	1426	1964	0	1	0	0	0	1	3.066	76.65	1	1	0	1
146322203006	0	1	338400	0	0	2569	1966	2	1	0	0	0	1	3.066	76.65	1	0	0	0
145911001002	0	0	178200	0	0	1746	1900	0	0	0	1	0	1	14.866	371.65	2	0	0	0
146114008003	1	1	250000	1	0	1436	1967	2	0	0	1	0	1	14.866	371.65	2	0	0	0
131925000002	1	1	113800	0	0	699	1953	1	1	0	0	0	1	3.066	76.65	1	0	0	0
145932000023	3	0	130800	0	0.25	832	1970	0	1	0	0	0	1	3.066	76.65	1	0	1	1
157716200009	1	0	164500	0	0	1260	1960	0	1	0	0	1	1	3.066	76.65	1	1	0	1
131730000006	4	0	373400	0	1.25	2086	1972	2	0	0	1	0	1	14.866	371.65	2	0	0	0
120334000014	2	0	202400	0	0	1860	1969	2	0	0	1	0	1	14.866	371.65	2	0	0	0
131712001004	3	1	255900	0	0.75	2651	1975	0	0	0	1	0	1	14.866	371.65	2	1	0	1
146529002005	1	0	285600	1	0.5	2091	1971	1	0	0	2	0	2	29.732	743.3	3	0	0	0
146114016002	4	1	400000	0	1.25	3233	1967	5	0	0	1	0	1	14.866	371.65	2	0	1	1
157713001006	2	0	187600	0	0	1320	1962	1	0	0	1	0	1	14.866	371.65	2	0	0	0
146114011005	1	1	423500	1	0	1888	1967	1	0	0	1	0	1	14.866	371.65	2	0	0	0
146532101010	2	0	148300	0	0.75	2090	1965	3	0	0	1	0	1	14.866	371.65	2	0	0	0
131703006005	1	1	199000	0	0	2122	1978	2	0	1	0	0	1	9.173	229.325	1	0	0	0
120329401001	1	0	148300	0	0	1104	1972	0	0	0	1	0	1	14.866	371.65	2	0	1	1
120528330001	0	1	125700	0	0.5	1801	1967	0	1	0	0	0	1	3.066	76.65	1	1	0	1

RISK DATA (For CHAPTER 5)

OWTS RISK CATETGORY DATA

PARCEL_NO2		RS_CATEG_303_528	RS_CATEG_200_400	RS_BI_LOW	RS_BI_HIGHa	RS_BI_HIGHb	
146336000022	See GAMLSS Date for variables: Pre2008_deeds through RS_ANNUAL	2	3	0	1	0	See GAMLSS Data for variables: PROP_TRANS_INSP through POST2008_SALES
146130007003		1	2	1	0	0	
146114002011		2	2	0	0	0	
146114009003		2	2	0	0	0	
146103007006		1	1	1	0	0	
131727405008		2	2	0	0	0	
120112000025		1	2	1	0	0	
119711100032		2	2	0	0	0	
131727404005		2	2	0	0	0	
146102002010		2	2	0	0	0	
131711000020		2	2	0	0	0	
131919004003		2	2	0	0	0	
120520414003		2	2	0	0	0	
146123011004		2	2	0	0	0	
157701107006		2	2	0	0	0	
157716200003		2	2	0	0	0	
120111000007		2	2	0	0	0	
146514009009		2	2	0	0	0	
132109000004		2	2	0	0	0	
158129000008		1	1	1	0	0	
146104006005		2	2	0	0	0	
146111006007		2	2	0	0	0	
131933000006		2	2	0	0	0	
146533100037		3	3	0	1	1	
158136002002		2	2	0	0	0	
157504001003		3	3	0	1	1	
157701109002		2	2	0	0	0	
145912009002		2	2	0	0	0	
157701306014		2	2	0	0	0	
158136001009		2	2	0	0	0	
146111001001		2	2	0	0	0	
146104004006		2	2	0	0	0	
157701306010		2	2	0	0	0	
157712203003		2	2	0	0	0	
120520414013		2	2	0	0	0	
158112000009		1	2	1	0	0	
146514016021		2	2	0	0	0	
131506000005		2	2	0	0	0	
131726309001		2	2	0	0	0	
146307000002		2	2	0	0	0	
145907000030		2	2	0	0	0	

157712203019	2	2	0	0	0
131930004005	2	2	0	0	0
157702000002	2	3	0	1	1
146115001007	3	3	0	1	1
146527000013	2	2	0	0	0
158136101015	2	2	0	0	0
131935013004	2	3	0	1	0
146127000011	1	1	1	0	0
120522311004	1	1	1	0	0
146112000041	2	3	0	1	0
146314000014	2	2	0	0	0
146515005004	2	2	0	0	0
120524000037	3	3	0	1	1
146118000029	3	3	0	1	1
132103000011	2	3	0	1	0
157933000014	2	2	0	0	0
146336004009	2	2	0	0	0
157931003002	2	2	0	0	0
146115004002	2	2	0	0	0
131935009011	1	1	1	0	0
146104017001	2	2	0	0	0
146532101001	2	2	0	0	0
146122000022	1	1	1	0	0
131711000012	3	3	0	1	1
146114012010	2	2	0	0	0
120521000006	2	2	0	0	0
146104023001	3	3	0	1	1
131930003003	1	2	1	0	0
146515003004	2	2	0	0	0
146520000017	1	1	1	0	0
157701411002	2	2	0	0	0
146104017008	2	2	0	0	0
119725000028	1	1	1	0	0
157702000004	1	1	1	0	0
157712102005	2	2	0	0	0
157931001031	1	2	1	0	0
146317304001	2	2	0	0	0
131720000042	1	1	1	0	0
146528400016	2	2	0	0	0
146336014005	2	2	0	0	0
146336011001	2	2	0	0	0
120522305005	2	2	0	0	0
146514010002	2	2	0	0	0
120334000001	3	3	0	1	1
131730003002	2	2	0	0	0
120319011005	3	3	0	1	1
146130003018	2	2	0	0	0

120520414010	2	2	0	0	0
157720000016	1	1	1	0	0
131508301001	2	2	0	0	0
157932002016	2	2	0	0	0
157932000036	2	2	0	0	0
131524000001	2	2	0	0	0
146532103021	2	2	0	0	0
131517000019	2	2	0	0	0
157513403003	1	1	1	0	0
119724000003	2	2	0	0	0
146318100032	2	2	0	0	0
157711002013	2	2	0	0	0
146121000020	3	3	0	1	1
131935001010	2	3	0	1	0
146515010001	1	1	1	0	0
146322203006	1	1	1	0	0
145911001002	2	2	0	0	0
146114008003	2	2	0	0	0
131925000002	1	1	1	0	0
145932000023	1	1	1	0	0
157716200009	1	1	1	0	0
131730000006	2	2	0	0	0
120334000014	2	2	0	0	0
131712001004	2	2	0	0	0
146529002005	3	3	0	1	1
146114016002	2	2	0	0	0
157713001006	2	2	0	0	0
146114011005	2	2	0	0	0
146532101010	2	2	0	0	0
131703006005	1	2	1	0	0
120329401001	2	2	0	0	0
120528330001	1	1	1	0	0

FRAGILITY DATA (For CHAPTER 6)

REPAIR FREQUNCY IN EACH YEAR

YEAR	MINOR	MODERATE	MAJOR	TOTAL
1973	0	1	1	2
1974	0	1	1	2
1975	0	0	0	0
1976	0	0	1	1
1977	1	1	0	2
1978	0	0	0	0
1979	0	0	0	0
1980	2	2	0	4
1981	0	0	2	2
1982	0	0	1	1
1983	2	1	0	3
1984	2	0	2	4
1985	1	0	1	2
1986	3	0	0	3
1987	0	2	2	4
1988	1	1	1	3
1989	0	1	1	2
1990	0	1	1	2
1991	1	1	1	3
1992	0	1	2	3
1993	1	1	1	3
1994	1	0	0	1
1995	1	1	1	3
1996	0	0	1	1
1997	0	0	2	2
1998	0	0	5	5
1999	0	1	1	2
2000	1	1	2	4
2001	1	1	1	3
2002	0	0	2	2
2003	0	0	0	0
2004	0	1	3	4
2005	0	1	1	2
2006	5	2	1	8
2007	0	2	14	16
2008	1	0	16	17
2009	6	5	11	22
2010	6	3	16	25
2011	12	2	26	40
2012	4	3	10	17
2013	0	0	1	1
2014	3	0	2	5
2015	4	1	3	8

ANNUAL CLIMATE DATA FROM NOAA

YEAR	DT90	DT00	DP05	DP10	TPCP	TPCP_SI	DP05_S	DP10_S	TPCP_S	TPCP_W	MR25_S	MR30_S	MR40_S	MR50_S
1979	30	7	14	5	22.51	57.18	10	4	15.59	6.92	2	2	1	1
1980	55	5	6	1	22.91	58.19	5	1	18.63	4.28	0	0	0	0
1981	28	2	8	1	23.65	60.07	7	1	20.02	3.63	1	1	1	0
1982	20	4	10	6	22.26	56.54	9	5	19.82	2.44	4	3	2	0
1983	45	8	12	3	22.22	56.44	4	2	12.98	9.24	4	1	1	1
1984	37	5	8	3	18.03	45.8	7	2	13.58	4.45	2	1	1	0
1985	40	10	9	2	15.33	38.94	6	2	8.94	6.39	1	0	0	0
1986	21	2	9	3	16.83	42.75	6	3	12.08	4.75	3	2	1	0
1987	31	5	11	4	15.98	40.59	6	3	6.19	9.79	2	1	1	1
1988	37	3	12	1	16.59	42.14	6	1	9.61	6.98	1	1	0	0
1989	21	10	9	0	15.84	40.23	7	0	12.41	3.43	2	0	0	0
1990	22	7	7	1	14.98	38.05	6	1	12.63	2.35	1	1	1	0
1991	15	3	11	2	13.45	34.16	10	2	8.51	4.94	3	2	0	0
1992	6	1	7	3	12.65	32.13	2	1	3.41	9.24	1	1	0	0
1993	12	7	12	1	12.22	31.04	10	1	6.2	6.02	3	2	0	0
1994	30	2	8	2	13.35	33.91	4	1	6.77	6.58	2	1	0	0
1995	34	1	19	4	12.34	31.34	4	1	7.2	5.14	4	3	3	1
1996	20	13	15	3	14.33	36.4	11	3	7.89	6.44	3	2	1	0
1997	9	4	15	4	15.76	40.03	14	4	9.95	5.81	4	3	2	2
1998	28	1	10	3	16.23	41.22	8	1	11.52	4.71	2	2	2	0
1999	16	0	10	3	16.51	41.94	8	3	14.69	1.82	3	1	1	1
2000	51	0	9	1	16.78	42.62	7	1	12.2	4.58	1	0	0	0
2001	41	1	9	4	17.46	44.35	8	4	12.48	4.98	2	1	0	0
2002	53	3	8	2	16.53	41.99	7	2	12.72	3.81	1	1	0	0
2003	41	4	9	6	16.91	42.95	7	4	8.22	8.69	4	1	0	0
2004	14	5	19	5	16.74	42.52	17	4	11.18	5.56	4	3	1	1
2005	32	2	13	2	16.66	42.32	11	2	12.96	3.7	3	1	0	0
2006	44	4	13	2	14.96	38	8	1	7.97	6.99	2	1	0	0
2007	45	5	7	2	14.13	35.89	5	1	7.33	6.8	0	0	0	0
2008	33	5	9	4	14.31	36.35	8	4	10.29	4.02	2	1	1	0
2009	13	6	9	4	14.27	36.25	7	3	9.17	5.1	3	2	1	1
2010	33	2	11	7	15.75	40.01	8	6	9.71	6.04	3	2	0	0
2011	40	8	16	7	17.27	43.87	13	7	12.06	5.21	3	1	1	1
2012	59	1	10	3	20.18	51.26	9	2	17.06	3.12	1	1	1	0
2013	43	8	11	7	20.33	51.64	10	7	16.44	3.89	3	2	2	1
2014	18	10	11	2	21.64	54.97	8	2	15.42	6.22	3	2	2	0
2015	5	3	11	3	21.16	53.75	9	3	16.71	4.45	2	2	2	1

BOULDER CREEK AT LONGMONT FLOW DATA

agency_cd	site_no	peak_dt	peak_tm	peak_va	peak_va_si	peak_cd	gage_ht
USGS	6730500	7/29/27	6:00	407	11.52495656	5	3
USGS	6730500	6/4/28	9:00	694	19.65189153	5	3.84
USGS	6730500	7/23/29	15:00	530	15.00792869	5	3.4
USGS	6730500	8/18/30	5:00	353	9.995846847	5	2.94
USGS	6730500	5/29/31	9:00	369	10.44891639	5	2.88
USGS	6730500	7/13/32	10:00	128	3.624556364	5	1.86
USGS	6730500	5/4/33	NA	670	18.97228722	5	NA
USGS	6730500	5/10/34	NA	388	10.98693648	5	3
USGS	6730500	5/28/35	NA	1110	31.43169972	5	4.62
USGS	6730500	6/17/36	NA	366	10.36396585	5	2.99
USGS	6730500	6/26/37	NA	680	19.25545568	5	3.97
USGS	6730500	9/3/38	NA	4410	124.8772935	5	6.94
USGS	6730500	4/24/39	NA	390	11.04357017	5	3.23
USGS	6730500	7/3/40	NA	174	4.927131307	5	2.34
USGS	6730500	6/22/41	NA	738	20.89783278	5	3.78
USGS	6730500	4/24/42	NA	1790	50.6871554	5	4.81
USGS	6730500	5/19/43	NA	553	15.65921617	5	3.44
USGS	6730500	4/14/44	NA	970	27.46734119	5	4.13
USGS	6730500	5/30/45	NA	702	19.87842631	5	3.51
USGS	6730500	7/19/46	NA	178	5.040398693	5	2.39
USGS	6730500	6/23/47	NA	2040	57.76636705	5	5.22
USGS	6730500	10/15/4 7	NA	721	20.41644639	5	3.55
USGS	6730500	6/7/49	NA	2020	57.20003012	5	5.2
USGS	6730500	8/3/51	NA	1540	43.60794375	5	5
USGS	6730500	5/24/52	NA	1990	56.35052472	5	5.45
USGS	6730500	5/29/53	NA	247	6.994261108	5	3.15
USGS	6730500	1/14/54	12:30	26	0.736238011	2,5	NA
USGS	6730500	8/19/55	NA	336	9.514460455	5	3.66
USGS	6730500	6/10/79	NA	1040	29.44952046	5	4.23
USGS	6730500	5/1/80	NA	1990	56.35052472	5	5.04
USGS	6730500	5/29/81	NA	387	10.95861963	5	2.74
USGS	6730500	5/13/82	NA	770	21.80397188	5	3.6
USGS	6730500	5/19/83	NA	2090	59.18220938	5	4.82
USGS	6730500	4/24/84	NA	560	15.85743409	5	2.92
USGS	6730500	6/10/85	NA	448	12.68594727	5	2.85
USGS	6730500	6/9/86	NA	508	14.38495807	5	2.86
USGS	6730500	6/9/87	NA	981	27.77882651	5	3.57
USGS	6730500	5/20/88	NA	540	15.29109716	5	2.71
USGS	6730500	6/4/89	NA	623	17.64139543	5	2.9
USGS	6730500	6/12/90	NA	392	11.10020386	5	2.4
USGS	6730500	6/20/91	NA	NA	17.24495957	NA	NA
USGS	6730500	8/24/92	NA	609	40.20992216	5	2.92
USGS	6730500	6/18/93	NA	1420	14.07347276	5	4.23
USGS	6730500	10/18/9	NA	497	65.12874716	5	2.76

		3					
USGS	6730500	5/17/95	NA	2300	39.64358523	5	5.29
USGS	6730500	5/26/96	NA	1400	49.83765	5	4.51
USGS	6730500	6/7/97	8:15	1760	16.02733517	5	5
USGS	6730500	4/26/98	13:15	566	41.62576449	5	3.17
USGS	6730500	5/1/99	1:00	1470	34.82972131	5	4.58
USGS	6730500	7/17/00	7:00	1230	10.67545117	5	4.33
USGS	6730500	5/6/01	0:15	377	6.739409489	5	2.75
USGS	6730500	5/24/02	9:15	238	35.11288977	5	2.6
USGS	6730500	5/31/03	12:15	1240	21.94555611	5	4.34
USGS	6730500	7/24/04	3:45	775	21.37921918	5	3.77
USGS	6730500	5/24/05	14:30	755	34.26338438	5	3.75
USGS	6730500	7/9/06	20:15	1210	17.92456389	5	4.31
USGS	6730500	4/25/07	7:30	633	19.25545568	5	3.51
USGS	6730500	8/16/08	22:00	680	23.87110168	5	3.64
USGS	6730500	6/2/09	23:30	843	40.20992216	5	3.81
USGS	6730500	6/14/10	11:15	1420	32.28120511	5	4.53
USGS	6730500	7/13/11	18:45	1140	20.52971378	5	4.63
USGS	6730500	7/8/12	7:15	725	252.3031031	5	3.89
USGS	6730500	9/13/13	NA	8910	36.81190057	1,2	NA
USGS	6730500	6/1/14	15:45	1300		5	12.74
USGS	6730500	2/17/15	NA	NA		NA	NA

RESILIENCE DATA (For CHAPTER 7)

Prop_ID	PRE_RECOV	PRE_RECOV_R	POST_RECOV	POST_RECOV_R	PRE_FRAG	PRE_FRAG_R	POST_FRAG	POST_FRAG_R	RESIL_PRE	RESIL_POST
131919001042	137	2	0	0	Major	3	0	0	5	0
146130007003	77	2	0	0	Moderate	2	0	0	4	0
146114002011	77	2	0	0	Major	3	0	0	5	0
146114009003	97	2	0	0	Moderate	2	0	0	4	0
146103007006	20	1	0	0	Minor	1	0	0	2	0
145936000034	12	1	0	0	Minor	1	0	0	2	0
119711100032	17	1	0	0	Major	3	0	0	4	0
131727404005	53	1	0	0	Major	3	0	0	4	0
146132000023	7	1	0	0	Minor	1	0	0	2	0
131711000020	20	1	0	0	Major	3	0	0	4	0
131924007011	853	5	0	0	Major	3	0	0	8	0
146123011004	109	2	0	0	Moderate	2	0	0	4	0
157701107006	34	1	0	0	Major	3	0	0	4	0
157716200003	92	2	0	0	Major	3	0	0	5	0
120111000007	60	0	0	0	Major	3	0	0	3	0
146514009009	14	1	0	0	Major	3	0	0	4	0
132109000004	253	3	0	0	Major	3	0	0	6	0
120318203002	59	1	0	0	Moderate	2	0	0	3	0
146104006005	49	1	0	0	Major	3	0	0	4	0
131933000006	97	2	0	0	Moderate	2	0	0	4	0
146114033001	53	1	0	0	Major	3	0	0	4	0
146533100037	58	1	0	0	Major	3	0	0	4	0
157504001003	76	2	0	0	Major	3	0	0	5	0
157701109002	13	1	0	0	Major	3	0	0	4	0
145912009002	73	2	0	0	Major	3	0	0	5	0
157701306014	22	1	0	0	Major	3	0	0	4	0
158136001009	36	1	0	0	Major	3	0	0	4	0
146111001001	28	1	0	0	Major	3	0	0	4	0
131519000026	49	1	0	0	Major	3	0	0	4	0
145925000001	40	1	0	0	Minor	1	0	0	2	0
157701306010	20	1	0	0	Major	3	0	0	4	0
157712203003	84	2	0	0	Major	3	0	0	5	0
131505008001	47	1	0	0	Moderate	2	0	0	3	0
120520414013	41	1	0	0	Major	3	0	0	4	0
145926000026	47	1	0	0	Moderate	2	0	0	3	0
146514016021	83	2	0	0	Major	3	0	0	5	0
131726309001	58	1	0	0	Major	3	0	0	4	0
120330005002	0	0	104	2	0	0	Moderate	2	0	4
157712203019	14	1	0	0	Major	3	0	0	4	0
157702000002	9	1	0	0	Major	3	0	0	4	0
146115001007	28	1	0	0	Moderate	2	0	0	3	0
146527000013	57	1	0	0	Moderate	2	0	0	3	0

158136101015	48	1	0	0	Major	3	0	0	4	0
132115002008	63	2	0	0	Moderate	2	0	0	4	0
131935013004	8	1	0	0	Minor	1	0	0	2	0
146129000003	26	1	0	0	Major	3	0	0	4	0
146112000041	2	1	0	0	Minor	1	0	0	2	0
146335400003	13	1	0	0	Minor	1	0	0	2	0
146326006011	606	5	0	0	Moderate	2	0	0	7	0
146314000014	20	1	0	0	Major	3	0	0	4	0
120524000037	64	2	0	0	Major	3	0	0	5	0
146118000029	6	1	0	0	Minor	1	0	0	2	0
157933000014	62	2	0	0	Major	3	0	0	5	0
157931003002	59	1	0	0	Major	3	0	0	4	0
131935009011	21	1	0	0	Minor	1	0	0	2	0
146532101001	69	2	0	0	Major	3	0	0	5	0
146122000022	43	1	0	0	Minor	1	0	0	2	0
131711000012	72	2	0	0	Moderate	2	0	0	4	0
146114019011	78	2	0	0	Moderate	2	0	0	4	0
131726303012	52	1	0	0	Moderate	2	0	0	3	0
120521000006	28	1	0	0	Major	3	0	0	4	0
131930003003	52	1	0	0	Moderate	2	0	0	3	0
131924007071	96	2	0	0	Major	3	0	0	5	0
146515003004	55	1	0	0	Major	3	0	0	4	0
157701411002	99	2	0	0	Major	3	0	0	5	0
146104017008	78	2	0	0	Major	3	0	0	5	0
157702000004	52	1	0	0	Minor	1	0	0	2	0
157931001031	43	1	0	0	Major	3	0	0	4	0
146317304001	56	1	0	0	Major	3	0	0	4	0
131720000042	61	2	0	0	Minor	1	0	0	3	0
146528400016	15	1	0	0	Major	3	0	0	4	0
146336014005	37	1	0	0	Major	3	0	0	4	0
146336011001	24	1	0	0	Major	3	0	0	4	0
120522305005	56	1	0	0	Major	3	0	0	4	0
146514010002	98	2	0	0	Major	3	0	0	5	0
131730003002	8	1	0	0	Major	3	0	0	4	0
131930010001	41	1	0	0	Major	3	0	0	4	0
120319011005	135	2	0	0	Minor	1	0	0	3	0
146130003018	50	1	0	0	Major	3	0	0	4	0
120510000011	105	2	0	0	Major	3	0	0	5	0
157720000016	17	1	0	0	Minor	1	0	0	2	0
131508301001	48	1	0	0	Moderate	2	0	0	3	0
157932002016	53	1	0	0	Major	3	0	0	4	0
157932000036	125	2	0	0	Major	3	0	0	5	0
131524000001	48	1	0	0	Major	3	0	0	4	0
146532103021	62	2	0	0	Major	3	0	0	5	0
157513403003	12	1	0	0	Minor	1	0	0	2	0
119724000003	53	1	0	0	Major	3	0	0	4	0
157711002013	398	5	0	0	Major	3	0	0	8	0

146121000020	55	1	0	0	Major	3	0	0	4	0
131935001010	27	1	0	0	Minor	1	0	0	2	0
158107000052	21	1	0	0	Minor	1	0	0	2	0
146515010001	24	1	0	0	Minor	1	0	0	2	0
146322203006	39	1	0	0	Minor	1	0	0	2	0
145911001002	7	1	0	0	Minor	1	0	0	2	0
146114008003	258	3	0	0	Moderate	2	0	0	5	0
131925000002	4	1	0	0	Major	3	0	0	4	0
145932000023	0	0	485	5	0	0	Minor	1	0	6
157716200009	62	2	0	0	Minor	1	0	0	3	0
131730000006	43	1	0	0	Major	3	0	0	4	0
120334000014	49	1	0	0	Major	3	0	0	4	0
131712001004	38	1	0	0	Major	3	0	0	4	0
146114016002	214	3	0	0	Major	3	0	0	6	0
157713001006	0	0	754	5	0	0	Major	3	0	8
157922003002	447	5	0	0	Minor	1	0	0	6	0
146114011005	98	2	0	0	Major	3	0	0	5	0
146532101010	30	1	0	0	Major	3	0	0	4	0
120329401001	414	5	0	0	Major	3	0	0	8	0
120528330001	6	1	0	0	Minor	1	0	0	2	0
120111000008	60	0	60	0	Major	3	Minor	1	0	1
131506000005	62	2	0	0	Moderate+Minor	4	0	0	6	0
146127000011	14	1	31	1	Minor	1	Minor	1	2	2
132103000011	65	0	0	0	Minor_Major	4	0	0	0	0
146336000022	74	2			Moderate	2			4	
131727405008	278	4			Major	3			7	
120112000025	14	1	285	4	Major	3	Major	3	4	7
146102002010	54	1			Major	3			4	
131919004003	146	2			Major	3			5	
120520414003	55	1			Major	3			4	
158129000008	123	2			Minor	1			3	
146111006007	39	1			Major	3			4	
158136002002	33	1			Major	3			4	
158136001009	24	1			Major	3			4	
146104004006	36	1			Major	3			4	
158112000009	51	1			Moderate	2			3	
146111000024	120	2			Major	3			5	
146307000002	60	1			Major	3			4	
145907000030	50	1			Major	3			4	
131930004005	35	1			Major	3			4	
146114005011	51	1			Moderate	2			3	
120522311004	7	1			Minor	1			2	
157714000012	60									
145925001001	225	3			Major	3			6	
146515005004	3	1			Major	3			4	
146336004009	45	1			Major	3			4	
146115004002	22	1			Major	3			4	

146104017001	44	1			Major	3			4	
146114012010	99	2			Major	3			5	
146104023001	67	2			Moderate	2			4	
146520000017	49	1			Minor	1			2	
119725000028	15	1			Minor	1			2	
157712102005	14	1			Major	3			4	
120334000001	26	1			Major	3			4	
120520414010										
146104001004	33	1			Moderate	2			3	
131517000019	36	1			Major	3			4	
146318100032	37	1			Major	3			4	
146529002005	56	1			Moderate	2			3	
131703006005			1405	5			Major	3		8
158107000034	64	2			Major	3			5	
146114008003	252	3			Major	3			6	
131913005005			39	1			Major	3		4
131719001002			55	1			Major	3		4
120113000025			61	2			Moderate	2		4
131919002010			214	3			Major	3		6
131913005004			120	2			Major	3		5
120113000061			130	2			Major	3		5
131930002008			47	1			Major	3		4
131930000015			221	3			Minor	1		4
131930003004			150	2			Moderate	2		4
120336000001			267.5	4			Major+Minor	4		8
120319102004			50	1			Major	3		4
119711400050			150	2			Major	3		5
132104003007			642	5			Major	3		8
146133000024			64	2			Major	3		5
131724002003	35	1	383	5	Minor	1	Moderate	2	2	7
146114021001			77	2			Major	3		5
146104013010			61	2			Major	3		5
131722207006			147	2			Major	3		5
146103006030			439	5			Major	3		8
146114010015			49	1			Major	3		4
146133001014			72	2			Major	3		5
119702000054			611	5			Major	3		8
131930000009			68	2			Major	3		5
157926201005			181	3			Major	3		6
157515000007			18	1			Major	3		4
119930000012			80	2			Moderate	2		4
120113000059			68	2			Major	3		5
146325000035			589	5			Major	3		8
131718000007			19	1			Major	3		4
120520411004			385	5			Major	3		8
157701305002			550	5			Major	3		8
158109003011			35	1			Moderate	2		3

146102000004			111	2			Moderate	2		4
146513000030			79	2			Major	3		5
119711400073			189	3			Major	3		6
146133007009			251	3			Major	3		6
146532004003			502	5			Major	3		8
120522316003			441	5			Major	3		8
119726409006			342	4			Major	3		7
119702000038			85	2			Major	3		5
131702000029	350	4	90	2	Major	3	Moderate	2	7	4
145912000122			382	5			Major	3		8
131508301018			449	5			Moderate	2		7
158118017009			50	1			Moderate	2		3
157712202012			449	5			Major	3		8
146512300008			249	3			Major	3		6
120519000033			410	5			Major	3		8
157931004005			47	1			Major	3		4
157712304002			21	1			Major	3		4
157714000017			373	5			Major	3		8
158321209009			319	4			Moderate	2		6
120522000006			345	4			Minor	1		5
119713000007			148	2			Major	3		5
120113000058			65	2			Major	3		5
158321221003			304	4			Minor	1		5
158118001006			181	3			Major	3		6
146124210002			75	2			Major	3		5
146336000050			196	3			Major	3		6
119930002002			124	2			Major	3		5
120520408005			96	2			Major	3		5
146532004004	7	1	296	4	Minor	1	Major	3	2	7
119935000017			51	1			Major	3		4
131505009004			55	1			Moderate	2		3
119726008001			50	1			Major	3		4
119712000034			214	3			Major	3		6
131715000019			221	3			Moderate	2		5
131522002002			116	2			Major	3		5
146111006009			27	1			Major	3		4
120328000001			151	2			Major	3		5
157712308022			243	3			Moderate	2		5
131719000034			243	3			Moderate	2		5
157523000004			179	2			Major	3		5
158108005002			211	3			Major	3		6
157504004003			196	3			Moderate	2		5
119712000103			157	2			Major	3		5
131723000005			57	1			Major	3		4
131720000030			135	2			Major	3		5
131521000007			85	2			Major	3		5
158321220002			155	2			Minor	1		3

146313200011			172	2			Major	3		5
119934415002			114	2			Major	3		5
131717001007			117	2			Moderate	2		4
158321003010			60							
146322400020			114	2			Major	3		5
120325000030			80	2			Major	3		5
131727000010			80	2			Moderate	2		4
132108002002			67	2			Moderate	2		4
132109002003			22	1			Major	3		4
146103004003			16	1			Major	3		4
120319011001			16	1			Major	3		4
120112000051			19	1			Major	3		4
146513000037			23	1			Major	3		4
146325000033			12	1			Major	3		4
131720000017			597	5			Moderate	2		7
157716000052			310	4			Moderate	2		6
158118012009			74	2			Major	3		5
157712308017			8	1			Minor	1		2
146514014006			70	2			Minor	1		3
131935009013			7	1			Minor	1		2
158105004004			91	2			Minor	1		3
158136008005			7	1			Minor	1		2
146115002002			20	1			Minor	1		2
131710003001			68	2			Minor	1		3
132115007009			221	3			Minor	1		4
146111007001			121	2			Minor	1		3
146529005004			165	2			Minor	1		3
131924007047			11	1			Minor	1		2
157711000046			1	1			Minor	1		2
131727407001			546	5			New			5
120520414014			14	1			Minor	1		2
146320100020			26	1			Minor	1		2
146104022001			37	1			Minor	1		2
157505004003			18	1			Minor	1		2
131930004013			1	1			Minor	1		2
158118013005			14	1			Minor	1		2
158321219007	152	2	530	5	Major	3	Minor	1	5	6
131935003002			114	2			Minor	1		3

NON-FLOOD SPECIFIC REPAIR RECOVERY DURATIONS

PARCEL_NO2	APP_DATE	FINAL_INSP	DAYS_RECOV_PERM
146521000011	1/6/14	3/18/14	71
146119000002	1/6/14	2/18/16	773
146531000006	1/10/14	3/18/14	67
120336000001	1/10/14	4/21/14	101
146527003003	1/21/14	4/22/14	91
146122008011	1/22/14	12/4/14	316
131704001001	1/23/14	2/18/16	756
131704001001	1/23/14	2/18/16	756
157505000027	2/25/14	9/2/14	189
120319102004	2/26/14	4/7/14	40
120319012004	2/27/14	6/16/14	109
131522000007	2/28/14	3/19/14	19
157712306002	3/6/14	2/18/16	714
119711400050	3/11/14	3/31/14	20
157710002001	3/17/14	7/31/15	501
146124214002	3/28/14	2/18/16	692
145934000015	3/31/14	2/18/16	689
146318402001	4/3/14	7/22/15	475
132104003006	4/10/14	2/18/16	679
132104003007	4/10/14	2/18/16	679
119735000025	4/10/14	7/16/14	97
146336011009	4/11/14	4/24/14	13
146304000006	4/14/14	5/5/14	21
131532001001	4/15/14	7/14/14	90
146133000024	4/16/14	5/27/14	41
119712000049	4/18/14	6/16/14	59
146114006008	4/24/14	9/10/14	139
131724002003	4/24/14	5/4/15	375
158108007007	4/28/14	12/9/14	225
120517000039	4/29/14	9/29/14	153
146114021001	4/30/14	7/16/14	77
146322400003	5/2/14	2/18/16	657
132104002007	5/7/14	6/16/14	40
146104013010	5/8/14	11/3/14	179
146516008001	5/8/14	2/18/16	651
131928000016	5/12/14	8/25/14	105
131722207006	5/12/14	6/16/14	35
131722207006	5/13/14	2/18/16	646
157515000009	5/13/14	12/16/14	217
146103006030	5/14/14	7/27/15	439
157702001001	5/14/14	1/23/15	254
157702001001	5/14/14	1/23/15	254
158127008001	5/15/14	11/19/15	553
146114010015	5/19/14	7/9/14	51
146133001014	5/20/14	6/5/14	16
119702000054	5/21/14	8/28/14	99
131930000009	5/22/14	8/11/14	81
157926201005	5/22/14	10/28/14	159
146115005002	5/23/14	11/3/14	164
131508000030	5/28/14	2/18/16	631
146334402004	5/29/14	8/21/14	84
157701300032	6/3/14	10/31/14	150
146306002002	6/20/14	9/29/14	101
146306002001	6/20/14	9/29/14	101
131935014001	6/24/14	10/20/14	118
146532000004	6/30/14	2/18/16	598
158321219008	7/8/14	2/18/16	590
158115001006	7/9/14	10/7/14	90
157515000007	7/10/14	8/11/14	32
146335400022	7/16/14	12/9/14	146
119930000012	7/17/14	12/15/14	151
120113000059	7/17/14	10/2/14	77
146325000035	7/17/14	2/18/16	581

131718000007	7/21/14	8/27/14	37
157504002003	7/22/14	10/16/14	86
146336010004	7/24/14	10/1/15	434
146522000019	7/28/14	2/18/16	570
158112000027	7/29/14	11/13/14	107
120520411004	7/30/14	8/24/15	390
157701300028	8/11/14	12/16/14	127
157721000010	8/11/14	11/25/14	106
119934305004	8/11/14	2/18/16	556
146120000015	8/21/14	12/16/14	117
146506000002	8/21/14	12/9/14	110
132118011001	8/21/14	2/18/16	546
146530001014	8/22/14	7/30/15	342
157701305002	8/27/14	2/18/16	540
158109003011	8/28/14	10/23/14	56
146102000004	8/29/14	11/26/14	89
146513000030	9/10/14	11/14/14	65
131930003001	9/11/14	3/30/15	200
158321220001	9/22/14	5/5/15	225
119735000020	9/26/14	11/12/14	47
119711400073	9/26/14	12/8/14	73
119711400075	9/26/14	12/8/14	73
119712000052	9/26/14	11/26/14	61
146133007009	10/2/14	6/12/15	253
146325000037	10/3/14	10/20/15	382
158108012002	10/3/14	6/23/15	263
146532004003	10/7/14	2/18/16	499
157915000021	10/9/14	12/16/14	68
119724000006	10/10/14	2/18/16	496
158136100019	10/20/14	8/20/15	304
157926403003	10/20/14	1/15/15	87
120115001003	10/21/14	2/2/15	104
119726409004	10/21/14	12/10/14	50
131721000010	10/22/14	1/5/16	440
146132000021	10/23/14	2/18/16	483
157711002012	10/29/14	2/18/16	477
146134000041	11/6/14	12/2/14	26
120330005002	11/10/14	2/3/15	85
131723001002	11/13/14	2/18/16	462
119701000016	11/13/14	12/22/14	39
120522316003	11/14/14	12/8/15	389
131519000022	11/17/14	4/13/15	147
119714000001	11/18/14	6/25/15	219
120517000018	11/19/14	2/18/16	456
158136113003	11/20/14	10/18/15	332
119726409006	11/21/14	8/31/15	283
119702000038	11/24/14	1/21/15	58
131702000029	11/25/14	2/18/15	85
145912000122	12/2/14	2/18/16	443
131508301018	12/4/14	2/18/16	441
158118017009	12/4/14	12/23/14	19
146114011004	12/4/14	3/30/15	116
157712202012	12/4/14	2/18/16	441
120332000016	12/9/14	2/18/16	436
146512300008	12/9/14	8/13/15	247
146102002004	12/9/14	2/18/16	436
146118000084	12/11/14	12/30/14	19
146334102004	12/15/14	1/20/15	36
146126002001	12/16/14	3/26/15	100
120519000033	12/24/14	2/18/16	421
131512000022	1/5/15	2/18/16	409
131527000003	1/6/15	2/23/15	48
131527000003	1/6/15	2/18/15	43
157931004005	1/6/15	2/19/15	44
119711400013	1/8/15	7/20/15	193
146534100010	1/16/15	2/9/15	24

146336012002	1/20/15	3/10/15	49
157712304002	1/27/15	2/12/15	16
120325000060	2/2/15	3/18/15	44
158136004001	2/17/15	3/10/15	21
120503000011	2/18/15	2/18/16	365
157714000017	2/18/15	2/18/16	365
157721000043	2/18/15	2/18/16	365
157701300033	2/20/15	2/18/16	363
158321209009	3/3/15	2/18/16	352
158136109009	3/3/15	2/18/16	352
146506000020	3/4/15	2/18/16	351
120326000031	3/4/15	4/13/15	40
120522000006	3/5/15	9/14/15	193
132108003004	3/10/15	6/3/15	85
119713000007	3/13/15	2/5/16	329
131514000034	3/25/15	2/18/16	330
120113000058	3/30/15	6/15/15	77
157501000023	4/3/15	6/23/15	81
158321211012	4/6/15	6/2/15	57
146336000024	4/10/15	4/29/15	19
132300000011	4/14/15	7/28/15	105
120520412004	4/14/15	6/22/15	69
146336006021	4/14/15	6/17/15	64
158321221003	4/16/15	2/18/16	308
120336000025	4/17/15	2/18/16	307
157915000013	4/20/15	5/12/15	22
158118001006	4/21/15	8/6/15	107
146124210002	4/23/15	4/23/15	0
146336000050	4/23/15	9/24/15	154
120113000044	4/30/15	7/22/15	83
119930002002	4/30/15	2/18/16	294
120520408005	5/5/15	8/24/15	111
146532004004	5/7/15	2/18/16	287
119935000017	5/11/15	8/26/15	107
157721000022	5/12/15	9/23/15	134
132109002006	5/13/15	8/14/15	93
146514017002	5/13/15	6/9/15	27
146336014007	5/13/15	2/18/16	281
146126000020	5/14/15	8/17/15	95
131505009004	5/18/15	7/20/15	63
146127000025	5/19/15	2/18/16	275
146104004020	5/29/15	8/14/15	77
158321217011	6/2/15	2/18/16	261
119726008001	6/5/15	8/3/15	59
119726008003	6/5/15	8/3/15	59
119726008004	6/5/15	8/3/15	59
119712000034	6/5/15	8/19/15	75
158321220004	6/9/15	7/30/15	51
146309005002	6/10/15	2/18/16	253
131935015004	6/11/15	8/28/15	78
131715000019	6/11/15	2/18/16	252
157505002002	6/12/15	2/18/16	251
157710002005	6/12/15	2/18/16	251
131522002002	6/16/15	11/16/15	153
146111006009	6/17/15	7/27/15	40
146115002004	6/19/15	2/18/16	244
119900000030	6/22/15	2/18/16	241
120328000001	6/22/15	2/18/16	241
119713000010	6/23/15	8/3/15	41
146315000036	6/29/15	2/18/16	234
146529004001	6/29/15	7/28/15	29
157712308022	6/29/15	2/18/16	234
157931006006	6/29/15	7/14/15	15
146108000089	6/29/15	2/18/16	234
131719000034	6/29/15	2/18/16	234
157523000004	6/30/15	2/18/16	233

157932000045	7/1/15	8/10/15	40
158321217007	7/9/15	11/10/15	124
146317303003	7/17/15	2/18/16	216
158108005002	7/27/15	2/18/16	206
158118016011	7/29/15	10/6/15	69
131512000022	7/30/15	2/18/16	203
120112000008	8/3/15	9/28/15	56
119735000068	8/5/15	2/18/16	197
145701429001	8/5/15	2/18/16	197
146114019003	8/6/15	9/2/15	27
120112000027	8/6/15	2/18/16	196
157926402008	8/10/15	2/18/16	192
158321008001	8/12/15	2/18/16	190
131936000003	8/12/15	2/18/16	190
157504004003	8/13/15	2/18/16	189
157915002010	8/13/15	2/18/16	189
132104002010	8/17/15	2/18/16	185
119712000103	8/17/15	2/18/16	185
119712000103	8/17/15	2/18/16	185
131723000005	8/24/15	2/18/16	178
157701301004	8/24/15	2/18/16	178
119935003003	8/24/15	11/2/15	70
131900000107	8/25/15	2/18/16	177
131720000030	8/25/15	10/26/15	62
131521000007	8/25/15	2/18/16	177
158321220002	8/26/15	2/18/16	176
146313200011	8/27/15	2/18/16	175
131926000006	8/28/15	2/18/16	174
146315204001	9/1/15	2/18/16	170
120503003003	9/1/15	2/18/16	170
119726413011	9/4/15	2/18/16	167
146114022001	9/4/15	2/18/16	167
158115002008	9/8/15	2/18/16	163
132109000018	9/10/15	2/18/16	161
146506000024	9/11/15	2/18/16	160
157713001009	9/15/15	12/29/15	105
120113000031	9/15/15	2/18/16	156
146316000019	9/15/15	2/18/16	156
146531002003	9/16/15	2/18/16	155
132129003021	9/17/15	2/18/16	154
120325000009	9/18/15	11/17/15	60
157701103013	9/23/15	2/18/16	148
145928001021	9/23/15	2/18/16	148
146510001001	9/23/15	12/21/15	89
132127006001	9/25/15	2/18/16	146
120330001004	9/28/15	2/18/16	143
146530001006	9/30/15	2/18/16	141
146503000009	10/5/15	2/18/16	136
131924007053	10/6/15	2/18/16	135
157701201004	10/12/15	2/18/16	129
119934415002	10/13/15	2/18/16	128
146129001001	10/14/15	2/18/16	127
120131000013	10/15/15	2/18/16	126
146111006006	10/19/15	2/18/16	122
158136112003	10/22/15	2/18/16	119
131717001007	10/22/15	2/18/16	119
158321003010	10/23/15	2/18/16	118
120530000013	10/26/15	2/18/16	115
146130003009	10/26/15	2/18/16	115
119711300033	10/30/15	2/18/16	111
158118012005	10/30/15	2/18/16	111
146322400020	11/3/15	12/1/15	28
131511000024	11/3/15	1/12/16	70
158320002004	11/3/15	2/18/16	107
157933000040	11/3/15	2/18/16	107
119934402002	11/9/15	2/18/16	101

120325000030	11/10/15	2/18/16	100
146114006008	11/10/15	2/18/16	100
131520000035	11/12/15	12/17/15	35
157711000047	11/13/15	2/18/16	97
131727000010	11/13/15	2/18/16	97
120524003003	11/17/15	2/18/16	93
146529001006	11/17/15	2/18/16	93
146334414004	11/18/15	2/18/16	92
132108002002	11/19/15	2/18/16	91
131505013001	11/20/15	2/18/16	90
119726400033	11/20/15	2/18/16	90
119723000040	11/20/15	2/18/16	90
146314000029	12/2/15	2/18/16	78
157714000002	12/3/15	2/18/16	77
120507001005	12/4/15	2/18/16	76
146316000035	12/7/15	1/14/16	38
146531000017	12/8/15	10/15/96	-6993
119935000015	12/16/15	2/18/16	64
131913005001	12/17/15	2/18/16	63
119712000093	12/18/15	2/18/16	62
132124000009	12/23/15	2/18/16	57
131726000006	12/29/15	2/18/16	51
132109002003	12/29/15	2/18/16	51
146103004003	12/29/15	2/18/16	51
120319011001	1/5/16	2/18/16	44
120112000051	1/7/16	2/18/16	42
132127005001	1/12/16	2/18/16	37
146512300007	1/27/16	2/18/16	22
157510300004	1/28/16	2/18/16	21
158311000012	2/1/16	2/18/16	17
146513000037	2/1/16	2/18/16	17
120507000034	2/4/16	2/18/16	14
132104001002	2/8/16	2/18/16	10
146324000035	2/8/16	2/18/16	10
146325000033	2/8/16	2/18/16	10
120320100018	1/9/14	4/16/14	97
146132000008	2/6/14	4/15/14	68
157712306007	4/16/14	7/15/14	90
131720000017	5/19/14	2/18/16	640
146532105023	8/11/14	9/26/14	46
119726400010	10/20/14	1/21/15	93
157716000052	3/16/15	2/18/16	339
157501301005	4/27/15	2/18/16	297
158108004005	6/25/15	2/18/16	238
132124004003	7/17/15	8/31/15	45
131730002004	11/9/15	2/18/16	101
131934002001	1/17/14	2/18/16	762
146119000002	2/10/14	2/18/16	738
157501000005	2/19/14	6/2/14	103
146114008011	2/20/14	2/23/15	368
132300000011	3/3/14	2/18/16	717
120516000006	3/7/14	5/20/15	439
157712308009	3/12/14	8/18/15	524
145926000004	3/19/14	9/23/14	188
158313203002	3/25/14	6/24/14	91
146318400027	3/31/14	2/18/16	689
146513000001	4/18/14	2/18/16	671
157931007001	4/18/14	2/18/16	671
132121006003	4/18/14	2/18/16	671
157701300015	4/29/14	2/18/16	660
146114018008	5/8/14	10/21/14	166
158128000015	5/9/14	6/17/14	39
157701301016	5/28/14	10/6/14	131
146104013006	5/29/14	2/18/16	630
131727000019	6/25/14	2/18/16	603
145701000028	7/17/14	2/18/16	581

131934009003	8/26/14	2/18/16	541
132121002001	9/11/14	2/18/16	525
157712306006	9/17/14	10/30/14	43
158118012009	9/22/14	11/20/14	59
131521000003	9/29/14	9/24/15	360
157926403007	10/2/14	2/18/16	504
146325000037	10/3/14	10/20/15	382
146511201002	10/9/14	9/22/15	348
146127000033	11/14/14	2/18/16	461
131727006003	1/9/15	2/18/16	405
120125001007	1/26/15	2/18/16	388
119735000038	3/9/15	2/18/16	346
119726004012	3/11/15	2/18/16	344
158107000037	3/12/15	2/18/16	343
157702000033	3/19/15	2/18/16	336
132129006006	4/14/15	2/18/16	310
146117000106	4/20/15	2/18/16	304
120317000050	4/23/15	2/18/16	301
158136100052	5/8/15	1/5/16	242
145725000006	5/21/15	2/18/16	273
132115004003	5/29/15	2/18/16	265
146511203002	6/8/15	2/18/16	255
131703000025	7/31/15	2/18/16	202
119725007006	8/7/15	2/18/16	195
146520000022	8/12/15	2/18/16	190
131713005002	8/13/15	2/18/16	189
157701311002	8/25/15	2/18/16	177
158136100048	8/27/15	2/18/16	175
158313104001	9/11/15	12/22/15	102
146522007004	9/11/15	2/18/16	160
145928003004	9/15/15	2/18/16	156
157926201002	9/30/15	2/18/16	141
158117000003	10/9/15	2/18/16	132
157712100003	10/15/15	2/18/16	126
146521007009	10/19/15	2/18/16	122
146118000046	10/21/15	2/18/16	120
157932000065	10/23/15	2/18/16	118
146322200001	10/26/15	2/18/16	115
146104019007	10/28/15	2/18/16	113
131732001088	11/2/15	2/18/16	108
146114032002	12/3/15	2/18/16	77
120509005001	1/27/16	2/18/16	22
146121000052	9/9/14	8/27/15	352
131930011005	11/19/15	2/18/16	91
131722204001	1/7/14	2/18/16	772
131924009003	1/9/14	1/22/14	13
145922000004	2/5/14	5/1/14	85
146529000011	2/11/14	4/22/14	70
157712308017	3/3/14	3/20/14	17
131728000015	3/12/14	7/17/14	127
146514014006	3/25/14	6/19/14	86
146114024001	4/8/14	5/7/14	29
146119000092	4/8/14	4/29/14	21
146532103003	4/14/14	5/15/14	31
131518301003	4/14/14	5/5/14	21
146108000078	4/24/14	5/20/14	26
131935009013	5/16/14	6/4/14	19
120335001005	5/20/14	7/23/14	64
131930000029	5/20/14	12/17/14	211
145911003013	5/20/14	2/18/16	639
131933000011	5/23/14	7/2/14	40
146336006020	6/11/14	6/24/14	13
145900000040	6/11/14	2/18/16	617
145914000011	6/11/14	2/18/16	617
158105004004	6/18/14	9/16/14	90
146132000006	7/1/14	8/22/14	52

146130000030	7/9/14	7/29/14	20
146315200005	7/9/14	8/19/14	41
131935009010	7/10/14	10/8/14	90
158315000034	7/16/14	10/21/14	97
158136105005	7/23/14	9/11/14	50
119735000014	7/29/14	1/28/15	183
146513000007	8/4/14	2/18/16	563
158321219011	8/11/14	10/21/14	71
119711400010	8/14/14	9/2/14	19
157729000030	8/25/14	12/23/14	120
158136008005	8/28/14	9/15/14	18
146116000004	8/29/14	2/18/16	538
158321221001	9/3/14	2/18/16	533
146531003004	9/4/14	12/4/14	91
132121002001	9/10/14	2/19/15	162
146117000055	9/12/14	10/30/14	48
146133007010	10/2/14	6/12/15	253
119934409003	10/7/14	8/31/15	328
158127000034	10/10/14	7/9/15	272
158136118008	10/28/14	1/13/15	77
146532103014	11/6/14	11/21/14	15
146112000057	11/24/14	12/3/14	9
131530013002	12/15/14	1/12/15	28
146536000012	12/19/14	1/15/15	27
157720003003	1/20/15	4/2/15	72
146308003004	1/30/15	2/2/15	3
146114010006	2/3/15	4/2/15	58
145914003001	2/13/15	6/23/15	130
145701405008	2/23/15	2/18/16	360
146127002008	3/11/15	4/7/15	27
131713005001	3/13/15	3/18/15	5
146115002002	3/16/15	4/15/15	30
157501304008	3/27/15	4/7/15	11
131520000036	4/3/15	5/18/15	45
119934305003	4/6/15	6/15/15	70
158136109008	4/17/15	2/18/16	307
146133007006	4/20/15	7/9/15	80
146114009005	4/24/15	9/22/15	151
146130001001	4/24/15	5/14/15	20
120336000001	5/7/15	2/18/16	287
146114015005	5/17/15	9/28/15	134
158104008006	5/18/15	6/23/15	36
157729002001	5/18/15	5/21/15	3
131710003001	5/18/15	2/18/16	276
120509005002	5/27/15	7/1/15	35
120332002001	6/8/15	7/31/15	53
146529004018	7/6/15	10/6/15	92
145921000005	7/7/15	8/4/15	28
146114004015	7/8/15	9/23/15	77
146322400006	7/8/15	8/11/15	34
146532105006	7/8/15	9/1/15	55
131702005005	7/13/15	2/18/16	220
146127000011	7/13/15	1/25/16	196
146103002001	7/15/15	2/18/16	218
132115007009	7/17/15	2/18/16	216
120313000002	7/17/15	11/24/15	130
146114007005	7/20/15	2/18/16	213
131508304013	7/21/15	8/12/15	22
146318431001	7/31/15	9/2/15	33
146111007001	8/4/15	12/7/15	125
146519001004	8/13/15	2/18/16	189
146123002005	8/24/15	2/18/16	178
132127005003	8/27/15	2/18/16	175
131526001013	8/31/15	9/14/15	14
146529005004	9/4/15	2/18/16	167
146135105003	9/8/15	2/18/16	163

157900100012	9/8/15	2/18/16	163
146532101006	9/14/15	2/18/16	157
131924007047	9/14/15	10/29/15	45
158107000003	9/15/15	10/1/15	16
145926000026	9/29/15	11/5/15	37
120329400003	10/2/15	12/9/15	68
145905000001	10/8/15	1/6/16	90
146114018013	10/9/15	2/9/16	123
120516000005	10/15/15	2/18/16	126
146114018007	10/15/15	12/2/15	48
146114005010	10/19/15	2/18/16	122
131703000012	10/21/15	2/18/16	120
157711001005	11/5/15	12/9/15	34
157716000020	11/9/15	12/10/15	31
132127006003	11/12/15	2/18/16	98
131514000034	11/18/15	2/18/16	92
158136100055	11/19/15	2/18/16	91
157711000046	12/1/15	12/2/15	1
131727407001	12/8/15	2/18/16	72
120520414014	12/11/15	1/5/16	25
146320100020	12/14/15	1/28/16	45
146104022001	12/17/15	2/10/16	55
131719000004	12/23/15	2/18/16	57
120112000002	12/23/15	1/20/16	28
146532104020	12/29/15	2/18/16	51
157505004003	1/28/16	2/18/16	21
158320002003	2/1/16	2/18/16	17
131722207006	2/1/16	2/18/16	17
157513407007	2/4/16	2/18/16	14
146532101014	2/8/16	2/18/16	10
131930004013	4/7/14	4/9/14	2
146114010012	4/30/14	8/18/14	110
158118013005	6/17/14	7/8/14	21
146118000077	6/24/14	7/24/14	30
131924007058	7/10/14	9/17/14	69
132300000011	7/30/14	5/15/15	289
158321219007	9/8/14	2/18/16	528
157513405003	10/14/14	2/18/16	492
131935003002	10/26/15	2/18/16	115

FLOOD SPECIFIC REPAIR RECOVERY DURATIONS

PARCEL_NO2	APP_DATE	FINAL_INSP	DAYS_RECOV_PERM	DAYS_RECOV_FLOOD
131913005005	1/3/14	3/10/14	66	173
146118000036	1/24/14	9/8/15	592	720
131719001002	3/14/14	6/6/14	84	261
131906000001	4/25/14	7/9/14	75	294
146127000010	5/5/14	7/2/15	423	652
120113000025	5/7/14	12/18/14	225	456
131726304003	5/12/14	9/3/14	114	350
120112000025	6/24/14	4/13/15	293	572
119903004005	8/1/14	11/10/14	101	418
131919002010	8/6/14	12/9/14	125	447
146117000101	8/8/14	10/8/14	61	385
119934305005	8/11/14	6/29/15	322	649
120100000046	9/10/14	12/22/14	103	460
131913005004	10/7/14		NA	NA
146530001028	11/10/14	6/30/15	232	650
146111000016	11/25/14	3/23/15	118	551
146114008016	1/12/15		NA	NA
131930003004	1/12/15	6/15/15	154	635
146111017002	1/16/15	7/27/15	192	677
120111000020	1/21/15	4/13/15	82	572
157712302005	3/11/15		NA	NA
120111000008	3/30/15	8/19/15	142	700

120113000061	7/15/15		NA	NA
132115006008	7/30/15		NA	NA
146511000009	10/20/15		NA	NA
132109006004	11/3/15		NA	NA
131919004007	12/3/15		NA	NA
131930002008	12/3/15		NA	NA
146118000018	12/9/15		NA	NA
157711002002	12/18/15		NA	NA
157710000005	1/13/16		NA	NA
120336000022	6/23/14	11/5/14	135	413
131930000015	7/24/15		NA	NA
146119000032	10/27/15		NA	NA

PRE_FLOOD REPAIR RECOVERY DURATIONS

PARCEL_NO2	APP_DATE	FINAL_INSP	DAYS_RECOV_PERM
146336000022	7/26/11	10/11/11	77
131919001042	6/5/03	10/20/03	137
146130007003	8/23/06	11/8/06	77
146114002011	9/13/06	11/29/06	77
146114009003	9/27/06	1/2/07	97
146103007006	10/24/06	11/13/06	20
131727405008	10/30/06	8/14/07	288
145936000034	11/2/06	11/14/06	12
120112000025	2/7/07	3/23/07	44
119711100032	2/16/07	3/5/07	17
131727404005	4/20/07	6/12/07	53
146132000023	5/8/07	5/15/07	7
146102002010	5/11/07	8/29/07	110
131711000020	5/17/07	6/6/07	20
131919004003	5/17/07	10/16/07	152
120520414003	6/11/07	10/8/07	119
131924007011	8/1/07	12/1/09	853
146123011004	8/10/07	11/27/07	109
157701107006	8/29/07	10/2/07	34
157716200003	8/30/07	11/30/07	92
120111000008	10/12/07	12/11/07	60
120111000007	10/12/07	12/11/07	60
146514009009	10/19/07	11/2/07	14
132109000004	10/23/07	7/2/08	253
158129000008	12/12/07	5/20/08	160
120318203002	12/18/07	2/15/08	59
146104006005	1/29/08	3/18/08	49
146111006007	4/10/08	5/23/08	43
131933000006	6/6/08	9/11/08	97
146114033001	6/13/08	8/5/08	53
146533100037	6/24/08	8/21/08	58
158136002002	6/26/08	8/4/08	39
157504001003	7/1/08	9/15/08	76
157701109002	8/13/08	8/26/08	13
145912009002	8/19/08	10/31/08	73
157701306014	9/2/08	9/24/08	22
158136001009	9/3/08	10/9/08	36
146111001001	9/10/08	10/8/08	28
131519000026	9/11/08	10/30/08	49
145925000001	9/18/08	10/28/08	40
146104004006	9/30/08	11/12/08	43
157701306010	10/8/08	10/28/08	20
157712203003	11/18/08	2/10/09	84
131505008001	1/21/09	3/9/09	47
120520414013	3/3/09	4/13/09	41
158112000009	3/24/09	6/5/09	73
145926000026	4/15/09	6/1/09	47
146514016021	4/17/09	7/9/09	83
146111000024	4/20/09	8/20/09	122

131506000005	4/22/09	6/23/09	62
131726309001	4/28/09	6/25/09	58
146307000002	5/26/09	7/27/09	62
120330005002	11/13/14	2/25/15	104
145907000030	6/1/09	7/28/09	57
157712203019	6/2/09	6/16/09	14
131930004005	6/15/09	7/27/09	42
157702000002	6/23/09	7/2/09	9
146115001007	6/24/09	7/22/09	28
146527000013	6/30/09	8/26/09	57
158136101015	7/16/09	9/2/09	48
146114005011	7/22/09	9/17/09	57
132115002008	7/27/09	9/28/09	63
131935013004	9/1/09	9/9/09	8
146127000011	9/1/09	9/15/09	14
120522311004	9/3/09	9/16/09	13
157714000012	11/10/09	1/11/10	62
146129000003	11/12/09	12/8/09	26
146112000041	12/16/09	12/18/09	2
145925001001	12/18/09	9/16/10	272
146335400003	1/6/10	1/19/10	13
146326006011	1/21/10	9/19/11	606
146314000014	2/16/10	3/8/10	20
146515005004	3/3/10	3/11/10	8
120524000037	3/8/10	5/11/10	64
146118000029	3/12/10	3/18/10	6
132103000011	4/5/10	6/9/10	65
157933000014	4/6/10	6/7/10	62
146336004009	4/7/10	5/28/10	51
157931003002	4/9/10	6/7/10	59
146115004002	4/27/10	5/20/10	23
131935009011	5/5/10	5/26/10	21
146104017001	5/7/10	6/23/10	47
146532101001	5/21/10	7/29/10	69
146122000022	6/2/10	7/15/10	43
131711000012	6/7/10	8/18/10	72
146114012010	6/18/10	9/28/10	102
146114019011	6/30/10	9/16/10	78
131726303012	7/9/10	8/30/10	52
120521000006	7/28/10	8/25/10	28
146104023001	7/29/10	10/12/10	75
131930003003	8/17/10	10/8/10	52
131924007071	8/25/10	11/29/10	96
146515003004	9/28/10	11/22/10	55
146520000017	10/1/10	11/30/10	60
157701411002	10/6/10	1/13/11	99
146104017008	10/25/10	1/11/11	78
119725000028	11/12/10	12/8/10	26
157702000004	11/15/10	1/6/11	52
157712102005	11/17/10	12/2/10	15
157931001031	11/29/10	1/11/11	43
146317304001	12/17/10	2/11/11	56
131720000042	12/29/10	2/28/11	61
146528400016	1/3/11	1/18/11	15
146336014005	1/31/11	3/9/11	37
146336011001	3/14/11	4/7/11	24
120522305005	3/23/11	5/18/11	56
146514010002	4/8/11	7/15/11	98
120334000001	4/18/11	5/17/11	29
131730003002	4/26/11	5/4/11	8
131930010001	4/29/11	6/9/11	41
120319011005	5/2/11	9/14/11	135
146130003018	5/5/11	6/24/11	50
120520414010	6/10/11	7/27/11	47
120510000011	6/20/11	10/3/11	105
157720000016	6/21/11	7/8/11	17

131508301001	6/30/11	8/17/11	48
157932002016	7/11/11	9/2/11	53
146104001004	7/19/11	8/30/11	42
157932000036	7/28/11	11/30/11	125
131524000001	7/28/11	9/14/11	48
146532103021	8/3/11	10/4/11	62
131517000019	8/10/11	9/22/11	43
157513403003	8/12/11	8/24/11	12
119724000003	8/18/11	10/10/11	53
146318100032	8/26/11	10/5/11	40
157711002013	8/31/11	10/2/12	398
146121000020	10/6/11	11/30/11	55
131935001010	10/13/11	11/9/11	27
158107000052	10/18/11	11/8/11	21
146515010001	10/24/11	11/17/11	24
146322203006	10/21/11	11/29/11	39
145911001002	10/21/11	10/28/11	7
146114008003	10/27/11	7/11/12	258
131925000002	11/28/11	12/2/11	4
145932000023	6/17/13	10/15/14	485
157716200009	1/18/12	3/20/12	62
131730000006	1/18/12	3/1/12	43
120334000014	1/24/12	3/13/12	49
131712001004	1/27/12	3/5/12	38
146529002005	2/2/12	4/6/12	64
146114016002	3/12/12	10/12/12	214
157713001006	3/23/12	4/16/14	754
157922003002	4/4/12	6/25/13	447
146114011005	4/17/12	7/24/12	98
146532101010	4/17/12	5/17/12	30
131703006005	4/26/12	4/30/12	4
120329401001	5/1/11	6/18/12	414
120528330001	5/2/12	5/8/12	6
158107000034	6/1/12	8/9/12	69
157701405003	6/8/12	4/25/14	686

RESOURCEFULNESS ESTIMATES BASED ON DISPLACEMENT COSTS AND TEMPORARY CHEMICAL TOILET RENTALS

PROP_ID	RESOURCE_POST	RESOURCE_PORT_POST	RESOURCE_PRE	RESOURCE_PORT_PRE
146336000022				
131727405008			42164.4	15792.67
120112000025	33594.63	15816	15712.98	14912.67
146102002010			19838.41	15046
131919004003			19755.83	15352.67
120520414003			17564.52	15049.33
158129000008				
146111006007			17632.5	14996
158136002002			16271.09	14976
158136001009			16273.78	14946
146104004006			17589.33	14986
158112000009				15036
146111000024			27614.2	15266
146307000002			27080.16	15066
145907000030			17419.7	15032.67
131930004005			16343.83	14982.67
146114005011				15036
120522311004				14889.33
157714000012				15066
145925001001			44013.1	15616
146515005004			15062.95	14876
146336004009			18834.1	15016
146115004002			17805.11	14939.33

146104017001			20628.3	15012.67
146114012010			24242.92	15196
146104023001				15089.33
146520000017				15029.33
119725000028				14916
157712102005			17181.11	14912.67
120334000001			16994.45	14952.67
120520414010				14866
146104001004				14976
131517000019			18671.01	14986
146318100032			18537.98	14989.33
146529002005				15052.67
131703006005	118153.28	19549.33		14866
158107000034			19453.46	15079.33
146114008003			39964.53	15706
131913005005	19375.27	14996		
131719001002	21374.36	15049.33		
120113000025				
131919002010	19822.4	15579.33		
131913005004	19960.2	15266		
120113000061	23940.7	15299.33		
131930002008	18623.69	15022.67		
131930000015				
131930003004				
120336000001	33091.59	15757.67		
120319102004	18627.62	15032.67		
119711400050	17588.9	15366		
132104003007	30914.87	17006		
146133000024	21412.42	15079.33		
131724002003			29474.08	14982.67
146114021001	25795.47	15122.67		
146104013010	21625.48	15069.33		
131722207006	33294.94	15356		
146103006030	51297.15	16329.33		
146114010015	22692.74	15029.33		
146133001014	21897.78	15106		
119702000054	43121.32	16902.67		
131930000009	18456.63	15092.67		
157926201005	23135.15	15469.33		
157515000007	17599.05	14926		
119930000012				
120113000059	19676.33	15092.67		
146325000035	36139.07	16829.33		
131718000007	18258.75	14929.33		
120520411004	39702.98	16149.33		
157701305002	69357.02	16699.33		
158109003011				
146102000004				
146513000030	18724.94	15129.33		
119711400073	20655.56	15496		
146133007009	33224.9	15702.67		
146532004003	73854.02	16539.33		
120522316003	32038.68	16336		
119726409006	20852.29	16006		
119702000038	19496.58	15149.33		
131702000029			14866	16032.67
145912000122	20765.59	16139.33		
131508301018				
158118017009				
157712202012	82889.31	16362.67		
146512300008	33536.26	15696		
120519000033	35492.49	16232.67		
157931004005	18245.82	15022.67		
157712304002	18695.97	14936		
157714000017	49130.35	16109.33		
158321209009				

120522000006				
119713000007	20619.49	15359.33		
120113000058	19838.18	15082.67		
158321221003				
158118001006	21650.41	15469.33		
146124210002	35604.1	15116		
146336000050	29058.69	15519.33		
119930002002	21307.72	15279.33		
120520408005	22082.62	15186		
146532004004	39279.38	15852.67		14889.33
119935000017	18691.21	15036		
131505009004				
119726008001	17819.45	15032.67		
119712000034	21116.31	15579.33		
131715000019				
131522002002	36007.14	15252.67		
146111006009	18799.13	14956		
120328000001	249978.59	15369.33		
157712308022				
131719000034				
157523000004	69733.62	15462.67		
158108005002	23622.53	15569.33		
157504004003				
119712000103	27224.38	15389.33		
131723000005	18044.08	15056		
131720000030	34746.04	15316		
131521000007	21796.43	15149.33		
158321220002				
146313200011	20384.74	15439.33		
119934415002	18587.99	15246		
131717001007				
158321003010				
146322400020	22255.9	15246		
120325000030	21632.95	15132.67		
131727000010				
132108002002				
132109002003	16858.68	14939.33		
146103004003	17505.41	14919.33		
120319011001	17073.04	14919.33		
120112000051	17781.89	14929.33		
146513000037	17744.45	14942.67		
146325000033	17213.76	14906		
131720000017				
157716000052				
158118012009	18258.59	15112.67		
157712308017				
146514014006				
131935009013				
158105004004				
158136008005				
146115002002				
131710003001				
132115007009				
146111007001				
146529005004				
131924007047				
157711000046				
131727407001				
120520414014				
146320100020				
146104022001				
157505004003				
131930004013				
158118013005				
158321219007			18349.69	15372.67
131935003002				

APPENDIX C: RELIABILTY R CODE

```
#### GAMLSS/ WEIBULL USING ANNUAL REPAIR SEVERITY ####

install.packages("MASS")
install.packages("fitdistrplus")
insall.packages("sm")
install.packages("stats4")
install.packages("gamlss")
install.packages("car")
install.packages("scatterplot3d")

library(ADGofTest)
library(MASS)
library(fitdistrplus)
library(sm)
library(stats4)
library(gamlss)
library(car)
library(scatterplot3d)


#### DATA ####
owts<-
read.csv("/Users/laurakohler/Documents/CU_Research/OWTS_Data/CSV/OWTS_CSV_GAMLSS_MULT_3_10_2015.csv",na.string
s="NA",header=TRUE)
OWTS <- owts[1:120,]

#### VISUAL GOODNESS OF FIT FOR Y ####
ydata=OWTS$RS_ANNUAL[1:120]
N=length(ydata)
N1=N-1

xeval=seq(min(ydata)-sd(ydata), max(ydata)+sd(ydata),length=120)
neval=length(xeval)

# Gamma
zgamma=fitdist(ydata, "gamma", optim.method="L-BFGS-B",lower=0.05)
xdensitygamma=dgamma(xeval,shape=zgamma$estimate[1],scale=1/zgamma$estimate[2])

# Weibull
zweibull=fitdist(ydata, "weibull", optim.method="L-BFGS-B",lower=0.05)
xdensityweibull=dweibull(xeval,shape=zweibull$estimate[1],scale=zweibull$estimate[2])

# Nonparametric Kernel Density Estimation
kernelpdf = sm.density(ydata,eval.points=xeval,add=FALSE, lty=1, lwd=4)

# plot the histogram and overlay the PDFs
par(mfrow=c(1,1))
hist(ydata,xlab="Annual Repair Severity (USD)", ylab="", probability=T, main="",ylim=range(c(0, 0.007)),breaks=nds)
title(main="Annual Repair Severity Based on Repair Frequency and Cost")
lines(xeval,xdensitygamma,lwd=2,lty=3, col="black")
lines(xeval,xdensityweibull,lwd=2,lty=5,col="black")
lines(xeval,kernelpdf$estimate,lwd=2,lty=1,col="black")

points(76.65,0,pch=17,cex=1.6,col="black")
#abline(v=76.65,col="darkgreen",lwd=2)

points(229.33,0,pch=18,cex=1.6,col="black")
#abline(v=229.33,col="orange",lwd=2)

points(371.65,0,pch=19,cex=1.6,col="black")
#abline(v=371.65,col="darkred",lwd=2)

legend(500,0.006, c("Gamma","Weibull","Kernel Density"),lty=c(3,5,1), lwd=c(2.5,2.5),bty="n")

legend(445,0.004,c("Minor","Moderate","Major"),pch=c(17,18,19),
col=c("black","black","black"),title="Annualized Cost Per Repair Type",bty="n")
```

```
#### GOODNESS OF FIT ####
# Empirical or SAMPLE quantiles and Empirical Percentiles.
emppercent = 1:N/(N+1)    # Weibull plotting position

# Get the quantiles corresponding to the empirical percentiles from # the fitted PDF model. Also get the model percentiles corresponding # to the empirical quantiles.
ydatasort = sort(ydata)    # Sorted original data

# IF GAMMA
modquant2=qgamma(emppercent,shape=zgamma$estimate[1],scale=1/zgamma$estimate[2])
modpercent2=pgamma(ydatasort,shape=zgamma$estimate[1],scale=1/zgamma$estimate[2])

op <- par(mfrow=c(1,3))

# Plot the Empirical CDF with the Model CDF (Gamma)
plot(ydatasort, emppercent, xlab="Repair Severity", ylab="CDF (F(x))", main="")
lines(ydatasort, modpercent2, col="red")

# Quantile plot (Gamma)
plot(modquant2, ydatasort, xlab="Model (or Theoretical) Quantiles", ylab="Emp. Quantiles", main="")
lines(modquant2, modquant2)

# Probability Plot (Gamma)
plot(modpercent2, emppercent, xlab=" Model (or Theoretical) Percentiles", ylab="Emp. Percentiles", main="")
lines(modpercent2, modpercent2)

par(op)


# IF WEIBULL
modquant3=qweibull(emppercent,shape=zweibull$estimate[1],scale=zweibull$estimate[2])
modpercent3=pweibull(ydatasort,shape=zweibull$estimate[1],scale=zweibull$estimate[2])

op <- par(mfrow=c(1,3))

# Plot the Empirical CDF with the Model CDF (Weibull)
plot(ydatasort, emppercent, xlab="Repair Severity", ylab="CDF (F(x))", main="")
lines(ydatasort, modpercent3, col="red")

# Quantile plot (Weibull)
plot(modquant3, ydatasort, xlab="Model (or Theoretical) Quantiles", ylab="Emp. Quantiles", main="")
lines(modquant3, modquant3)

# Probability Plot (Weibull)
plot(modpercent3, emppercent, xlab=" Model (or Theoretical) Percentiles", ylab="Emp. Percentiles", main="")
lines(modpercent3, modpercent3)

par(op)


#### GAMLSS ####
# By semi-parametric, we mean they need a parametric distribution
# for the response variable,
# although they can cope with a wide range of distributions such as # Poisson, negative binomial,
# lognormal, Weibull, etc. These GAMLSS models are thus "semi" in
# the sense that the modeling of the actual
# parameters, such as the mean or location (as functions of the
# explanatory variables), may involve
# using non-parametric smoothing functions, such as for example,
# cubic smoothing splines.

# The data is fit to a Gamma (GA) and a Weibull (WEI) distribution
op <- par(mfrow=c(2,1))

mGA <- histDist(ydata, "GA", density=TRUE, main="(a)", ylim=c(0,0.008), xlab="Annual Repair Severity", ylab="")

mWEI <- histDist(ydata, "WEI", density=TRUE, main="(b)", ylim=c(0,0.008), xlab="Annual Repair Severity", ylab="")
```

```
par(op)

GAIC(mGA, mWEI)

# According to the GAIC, the Weibull is the best fit for the data


#### WEIBULL MODEL VISUAL DIAGNOSTICS ####
plot(mWEI)

#### K-S Test
fitdistr(ydata,"weibull")
ks.test(unique(ydata),"pweibull",scale=390.3910213,shape=2.4976403)
ad.test(ydata,pweibull,scale=390.3910213,shape=2.4976403)
fitdistr(ydata,"gamma")
ks.test(unique(ydata),"pgamma",rate=0.010730424,shape=3.738835369)
ad.test(ydata,pgamma,rate=0.010730424,shape=3.738835369)

# The test is a one-sided test and the hypothesis that the
# distribution is of a specific form is rejected if the test
# statistic, A, is greater than the critical value.


#### GAMLSS MODEL WITH WEIBULL ####
# The Weibull fitting function WEI() uses the log link for mu and
# sigma;
# therefore, the standard errors are for log(mu) and log(sigma).

#### MODEL 1 #### (Constant Sigma)
# Fitting a model with 11 preliminary explanatory variables
m01 <- gamlss(RS ANNUAL~ PRE2008 DEED + H2O + DELTA BED + STRUCT VAL + LIVE AREA +
        LOAN_INSP + NO_ADD.UPGRADES + PROP_TRANS_INSP + POST2008_DEED,data=na.omit(OWTS),family=WEI)

# m01 <- gamlss(RS ANNUAL~ PRE2008 DEED + H2O + DELTA BED + log(STRUCT VAL) + log(LIVE AREA) +
# LOAN_INSP + NO_ADD.UPGRADES + PROP_TRANS_INSP + POST2008_DEED,data=na.omit(OWTS),family=WEI)

# The commented out command tests variable significance the of
# LIVE_AREA and STRUCT_VAL considering their magnitude by taking the
# log.

# stepGAIC.VR() is based on stepAIC() with the additional property that allows selection of terms for any selected distributional
parameter.

model1 <- stepGAIC.VR(m01,scope=~PRE2008 DEED + H2O + DELTA BED + STRUCT VAL + LIVE AREA + LOAN INSP +
NO ADD.UPGRADES + PROP TRANS INSP + POST2008 DEED + (STRUCT_VAL + LIVE_AREA + PROP_TRANS_INSP +
POST2008_DEED + NO_ADD.UPGRADES)^2) # Sigma (shape) is held constant

# model1 <- stepGAIC.VR(m01,scope=~PRE2008_DEED + H2O + DELTA_BED + # log(STRUCT_VAL) + log(LIVE_AREA) +
LOAN_INSP + NO_ADD.UPGRADES +
# PROP TRANS INSP + POST2008 DEED + (STRUCT VAL + LIVE AREA +
# PROP TRANS INSP + POST2008_DEED + NO_ADD.UPGRADES)^2)
# Sigma (shape) is held constant

residuals1=residuals(model1)
mu mod1=exp(predict(model1, what="mu"))
sigma_mod1=exp(predict(model1, what="sigma"))

expY1<-vector(length=N)
for (i in 1:N){
expY1[i] = mu_mod1[i]*gamma((1/sigma_mod1[i])+1)

}

cor(ydata, expY1)


# MANUAL DIAGNOSTICS (MODEL 1)
par(bg = 'white')
op <- par(mfrow=c(2,2),cex.axis=1.5, cex.lab=1.15, cex.main=1.5, mar=c(5,5,4,2))
```

```
# QQnorm
# qqnorm(ydata-expY1, main="Normal Q-Q Plot of Model Residuals")
# qqline(ydata-expY1)

# qqnorm(residuals1, main="Q-Q Plot")
# qqline(residuals1)


# Histogram of residuals
# hist(ydata-expY1, xlab="Model Residuals", main="Normality of the
# Residuals")

hist(residuals1, xlab="Model Residuals", main="a")


# Autocorrelation
# acf(ydata-expY1, main="Autocorrelation of Model Residuals")

acf(residuals1, main="b")

# plot(expY1, (ydata-expY1), xlab="Fitted Annual Repair Severity (Y)", ylab="Model Residuals")
# abline(0,0)

plot(expY1, (residuals1), xlab="Fitted Annual Repair Severity (Y)", ylab="Model Residuals", main="c")
abline(0,0)

par(op)


# R2 plot (Obs vs Expected Value)
plot(ydata,expY1,xlab="Observed Annual Repair Severity (USD)",ylab="Predicted Annual Repair Severity (USD)", main="")
abline(a=0,b=1)
r2=0.406
mylabel = bquote(italic(R)^2 == .(format(r2, digits = 3)))
text(x = 600, y = 240, labels = mylabel)


#### MODEL VS OBSERVATION PLOTS (to show model skill) ####
# CI line plot (USING expY2)
op <- par(mfrow=c(1,1))
Yu<-vector(length=N)
Yl <-vector(length=N)

for (i in 1:N){
  expY1[i]=mu mod1[i]*gamma((1/sigma mod1[i])+1)
  Yl[i]=qweibull(0.025,sigma mod1[i], mu mod1[i])
  Yu[i]=qweibull(0.975,sigma_mod1[i], mu_mod1[i])
}

plot(OWTS$RS ANNUAL, type="l", xlab="Observed OWTS",ylab="Annual OWTS Repair Severity (USD)",ylim=c(0,900),
col="9",lwd=2, lty=4)
lines(expY1, col="2",lty=1,lwd="2.5")
lines(Yu,col="8",lty="longdash",lwd="1")
lines(Yl,col="8",lty="longdash",lwd="1")
legend("topright", c("95-percent CI","Observations","Model Predictions"),lty=c(2,4,1), lwd=c(2,2,2.5),col=c("8","9","2"),bty="n") #
gives the legend lines the correct color and width
par(op)

#### Scatter Plot ####

boxplot(OWTS$RS_ANNUAL~OWTS$PROP_TRANS_INSP,col = "gainsboro",boxwex = 0.25, at = 0:1-0.15 , xlab = "Property
Transfer Inspections",
       ylab = "Annual Repair Severity (USD)",xaxis=c(0,1),xaxt='n',ann=FALSE)
boxplot(expY1~OWTS$PROP_TRANS_INSP,add = TRUE,
       boxwex = 0.25, at = 0:1+0.15 ,col = "white",xaxt='n',ann=FALSE)
legend(0.70,753, c("Observation", "Model Prediction"),
      fill = c("gainsboro", "white"))
axis(side=1, at=c(0,1))
```

```
#### CROSS VALIDATION ####
# Get the cross validated estimates ...
Y<-ydata
X<-as.matrix(cbind(OWTS$STRUCT VAL, OWTS$LIVE AREA, OWTS$NO ADD.UPGRADES, OWTS$PROP_TRANS_INSP,
OWTS$POST2008 DEED, OWTS$NO ADD.UPGRADES*OWTS$PROP TRANS INSP,
OWTS$LIVE AREA*OWTS$PROP_TRANS_INSP, OWTS$STRUCT_VAL*OWTS$PROP_TRANS_INSP, OWTS$PROP_TRANS_I
NSP*OWTS$POST2008_DEED))

# Drop some % of points, fit the model and predict the dropped
# points ...
library(arules)
nsim = 1000
rmseskill = 1:nsim
corskill=1:nsim
N = length(Y)

N15 = round(0.15*N)          # Drop 15% of points
index=1:N

for(i in 1:nsim){
  drop=sample(c(1:N), N15)
  keep=setdiff(index,drop)

  x=X[keep,]
  y=Y[keep]

  zz<-gamlss(y~x, family=WEI)

  x = as.matrix(X[drop,])
  y=Y[drop]

   Nx=length(y)
   mu zz<-vector(length=Nx)
  sigma zz<-vector(length=Nx)
  yhat<-vector(length=Nx)


  for (j in 1:Nx){

mu zz[j]=exp(coef(zz)[1]+coef(zz)[2]*x[j,1]+coef(zz)[3]*x[j,2]+coef(zz)[4]*x[j,3]+coef(zz)[5]*x[j,4]+coef(zz)[6]*x[j,5]+coef(zz)[7]*(x[j,3]*
x[j,4])+coef(zz)[8]*(x[j,2]*x[j,4])+coef(zz)[9]*(x[j,1]*x[j,4])+coef(zz)[10]*(x[j,4]*x[j,5]))
    sigma zz=exp(getElement(zz,"sigma.coefficients"))
    yhat[j]=mu_zz[j]*gamma((1/sigma_zz)+1)

  }

  yhat=as.vector(yhat)
  #yhat=predict(zz,newdata=data.frame(x),type="response")
  #rmseskill[i]=mean((Y[drop]-yhat)^2)
  #rmseskill[i]=mean(((Y[drop]-yhat)/sd(Y[drop]))^2)
  rmseskill[i]=rmse(Y[drop],yhat)
  corskill[i]=cor(Y[drop],yhat)
}

# Plot fitted R2 and fitted RMSE on boxplots ...
op <- par(mfrow=c(1,2))
boxplot(corskill^2, ylab="R-Squared", main="a")
points(0.406, col="red3", pch=19,cex=1.5)
boxplot(rmseskill, ylab="Root-Mean-Square-Error", main="b",xlab="*RMSE in USD")
points(133.9259, col="red3", pch=19,cex=1.5)
par(op)

#### MODEL 2 #### (Mu and Sigma both vary)
m02 <- gamlss(RS_ANNUAL~ PRE2008_DEED + H2O + DELTA_BED + DELTA_BATH + STRUCT_VAL + LIVE_AREA +
LOAN_INSP + NO_ADD.UPGRADES + PROP_TRANS_INSP + POST2008_DEED,data=na.omit(OWTS),family=WEI)

# Selection of terms for selected distributional parameter, in this # case both scale (mu) and shape (sigma)
m mu2 <-stepGAIC.VR(m02, what="mu",scope=~PRE2008 DEED + H2O + DELTA BED + DELTA BATH + STRUCT VAL +
LIVE_AREA + LOAN_INSP + NO_ADD.UPGRADES + PROP_TRANS_INSP + POST2008_DEED + (STRUCT_VAL + LIVE_AREA
+ PROP_TRANS_INSP + POST2008_DEED +NO_ADD.UPGRADES)^2)
```

```
m sigma2 <- stepGAIC.VR(m mu2, what="sigma", scope=~PRE2008 DEED + H2O + DELTA BED + DELTA BATH +
STRUCT_VAL + LIVE_AREA + LOAN_INSP + NO_ADD UPGRADES + PROP_TRANS_INSP+POST2008_DEED)

model2=m sigma2
residuals2=residuals(model2)

# Compared to Model 2 (modeling mu (Scale) and sigma (Shape))
op <- par(mfrow=c(2,2))
plot(model2)
par(op)

op <- par(mfrow=c(2,2))
plot(model2, ts=TRUE)
par(op)

# Model 2 (model both mu and sigma)
mu mod2=exp(predict(model2, what="mu"))
sigma_mod2=exp(predict(model2, what="sigma"))

zz2=qweibull(0.5, shape=sigma_mod2, scale=mu_mod2)
cor(zz2, ydata)

op <- par(mfrow=c(1,1))
plot(ydata, zz2, xlab="Repair Severity Observations", ylab="Repair Severity Model Predictions (Median)")
abline(a=0, b=0)
par(op)

# Y pred compared to E(Y) using the expected value equation and each # mu and sigma determined from each observation
n=length(mu_mod2)

expY2<-vector(length=n)
for (i in 1:n){
  expY2[i]=mu_mod2[i]*gamma((1/sigma_mod2[i])+1)

}

cor(ydata, expY2)


# MANUAL DIAGNOSTICS (MODEL 2)
par(bg = 'white')
op <- par(mfrow=c(2,3))


# QQnorm
qqnorm(ydata-expY2, main="Normal Q-Q Plot of Model Residuals")
qqline(ydata-expY2)

qqnorm(residuals2, main="Normal Q-Q Plot of Model Residuals")
qqline(residuals2)


# Autocorrelation
acf(ydata-expY2, main="Autocorrelation of Model Residuals")

acf(residuals2, main="Autocorrelation of Model Residuals")


# Histogram of residuals
hist(ydata-expY2, xlab="Model Residuals", main="Normality of the Residuals")

hist(residuals2, xlab="Model Residuals", main="Normality of the Residuals")


# R2 plot (Obs vs Expected Value)
plot(ydata, expY2, xlab="Annual Repair Severity Obs (USD)", ylab="Annual Repair Severity Predict (USD)")
abline(a=0, b=1)
r2=0.408
mylabel = bquote(italic(R)^2 == .(format(r2, digits = 3)))
```

```
text(x = 600, y = 240, labels = mylabel)

plot(expY2, (ydata-expY2), xlab="Fitted Annual Repair Severity (Y)", ylab=" Model Residuals")
abline(0,0)

plot(expY2, (residuals2), xlab="Fitted Annual Repair Severity (Y)", ylab=" Model Residuals")
abline(0,0)

par(op)


#### MODEL VS OBSERVATION PLOTS (to show model skill) ####

# CI line plot (USING expY2)
op <- par(mfrow=c(1,1))
Yu<-vector(length=N)
Yl <-vector(length=N)

for (i in 1:N){
  expY2[i]=mu_mod2[i]*gamma((1/sigma_mod2[i])+1)
  Yl[i]=qweibull(0.025,sigma_mod2[i], mu_mod2[i])
  Yu[i]=qweibull(0.975,sigma_mod2[i], mu_mod2[i])
}

plot(OWTS$RS_ANNUAL, type="l", xlab=" Observed OWTS",ylab="Annual OWTS Repair Severity (USD)",ylim=c(0,900),
col="blue4",lwd="2")
lines(expY2, col="darkred",lwd="2")
lines(Yu,col="darkred",lty="longdash",lwd="1")
lines(Yl,col="darkred",lty="longdash",lwd="1")
legend("topright", c("95-percent CI"," Observations"," Model Predictions"),lty=c(2,1,1),
lwd=c(1,2,2),col=c("darkred","blue4","darkred"),bty="n") # gives the legend lines the correct color and width
par(op)


#### MODEL 3 #### (Mu and Sigma Vary; No DELTA_BATH)
m03 <- gamlss(RS_ANNUAL~ PRE2008_DEED + H2O + DELTA_BED + STRUCT_VAL + LIVE_AREA + LOAN_INSP +
NO_ADD.UPGRADES + PROP_TRANS_INSP + POST2008_DEED,data=na.omit(OWTS),family=WEI)


# Selection of terms for selected distributional parameter, in this case both scale (mu) and shape (sigma)
m_mu3 <-stepGAICVR(m03, what="mu",scope=~PRE2008_DEED + H2O + DELTA_BED + STRUCT_VAL + LIVE_AREA +
LOAN_INSP + NO_ADD.UPGRADES + PROP_TRANS_INSP + POST2008_DEED + (PROP_TRANS_INSP +
POST2008_DEED+LOAN_INSP+STRUCT_VAL + LIVE_AREA +                                    LOAN_INSP +
NO_ADD.UPGRADES)^2)

m_sigma3 <-stepGAICVR(m_mu3, what="sigma",scope=~PRE2008_DEED + H2O + DELTA_BED + STRUCT_VAL + LIVE_AREA
+ LOAN_INSP + NO_ADD.UPGRADES + PROP_TRANS_INSP+POST2008_DEED)

model3=m_sigma3
residuals3=residuals(model3)


#### MODEL 3 DIAGNOSTIC PLOTS ####
# Compared to Model 3 (modeling mu (Scale) and sigma (Shape))
op <- par(mfrow=c(2,2))
plot(model3)
par(op)

op <- par(mfrow=c(2,2))
plot(model3, ts=TRUE)
par(op)

# Model 3 (model both mu and sigma)
mu_mod3=exp(predict(model3,what=" mu"))
sigma_mod3=exp(predict(model3, what="sigma"))

zz3=qweibull(0.5, shape=sigma_mod3, scale=mu_mod3)
cor(zz3,ydata)

op <- par(mfrow=c(1,1))
```

```
plot(ydata,zz3, xlab="Repair Severity Observations",ylab="Repair Severity Model Predictions (Median)")
abline(a=0,b=0)
par(op)

# Y pred compared to E(Y) using the expected value equation and each # mu and sigma determined from each observation
n=length(mu_mod3)

expY3<-vector(length=n)
for (i in 1:n){
  expY3[i]=mu_mod3[i]*gamma((1/sigma_mod3[i])+1)

}

cor(ydata, expY3)


# MANUAL DIAGNOSTICS (MODEL 3)
par(bg='white')
op <- par(mfrow=c(2,3))


# QQnorm
qqnorm(ydata-expY3, main="Normal Q-Q Plot of Model Residuals")
qqline(ydata-expY3)

qqnorm(residuals3, main="Normal Q-Q Plot of Model Residuals")
qqline(residuals3)


# Autocorrelation
acf(ydata-expY3, main="Autocorrelation of Model Residuals")

acf(residuals3, main="Autocorrelation of Model Residuals")


# Histogram of residuals
hist(ydata-expY3, xlab="Model Residuals", main="Normality of the Residuals")

hist(residuals3, xlab="Model Residuals", main="Normality of the Residuals")


# R2 plot (Obs vs Expected Value)
plot(ydata,expY3,xlab="Annual Repair Severity Obs (USD)",ylab="Annual Repair Severity Predict (USD)")
abline(a=0,b=1)
r2=0.380
mylabel = bquote(italic(R)^2 == .(format(r2, digits = 3)))
text(x = 600, y = 240, labels = mylabel)

plot(expY3, (ydata-expY3), xlab="Fitted Annual Repair Severity (Y)", ylab="Model Residuals")
abline(0,0)

plot(expY3, (residuals3), xlab="Fitted Annual Repair Severity (Y)", ylab="Model Residuals")
abline(0,0)

par(op)


#### MODEL VS OBSERVATION PLOTS (to show model skill) ####
# CI line plot (USING expY3)
op <- par(mfrow=c(1,1))
Yu<-vector(length=N)
Yl<-vector(length=N)

for (i in 1:N){
  expY3[i]=mu_mod3[i]*gamma((1/sigma_mod3[i])+1)
  Yl[i]=qweibull(0.025,sigma_mod3[i], mu_mod3[i])
  Yu[i]=qweibull(0.975,sigma_mod3[i], mu_mod3[i])
}
```

```
plot(OWTS$RS ANNUAL, type="l", xlab="Observed OWTS",ylab="Annual OWTS Repair Severity (USD)",ylim=c(0,900),
col="blue4",lwd="2")
lines(expY3, col="darkred",lwd="2")
lines(Yu,col="darkred",lty="longdash",lwd="1")
lines(Yl,col="darkred",lty="longdash",lwd="1")
legend("topright", c("95-percent CI","Observations","Model Predictions"),lty=c(2,1,1),
lwd=c(1,2,2),col=c("darkred","blue4","darkred"),bty="n")
par(op)
```

SENSITIVITY ANALYSIS (USING MODEL 1 (ABOVE))

```
library(gamlss)
library(fitdistrplus)

#### DATA (ORIGINAL) ####
owts1<-
read.csv("/Users/laurakohler/Documents/CU_Research/OWTS_Data/CSV/OWTS_CSV_GAMLSS_MULT_3_10_2015.csv",na.string
s="NA",header=TRUE)
OWTS1 <-owts1[1:120,]

# Fitting a model with 11 preliminary explanatory variables
m01a <- gamlss(RS_ANNUAL~ PRE2008_DEED + H2O + DELTA_BED + STRUCT_VAL + LIVE_AREA + LOAN_INSP +
NO_ADD.UPGRADES + PROP_TRANS_INSP + POST2008_DEED,data=na.omit(OWTS1),family=WEI)

# stepGAIC.VR() is based on stepAIC() with the additional property
# that allows selection of terms for any selected distributional
# parameter.

model1a <- stepGAIC.VR(m01a,scope=~PRE2008 DEED + H2O + DELTA BED + STRUCT VAL + LIVE AREA + LOAN INSP +
NO ADD.UPGRADES + PROP TRANS INSP + POST2008 DEED +(STRUCT_VAL + LIVE_AREA + PROP_TRANS_INSP +
POST2008_DEED +NO_ADD.UPGRADES)^2) # Sigma (shape) is held constant

residuals1a=residuals(model1a)
mu mod1a=exp(predict(model1a,what="mu"))
sigma_mod1a=exp(predict(model1a, what="sigma"))

expY1a<-vector(length=N)
for (i in 1:N){
  expY1a[i]=mu_mod1a[i]*gamma((1/sigma_mod1a[i])+1)

}
residuals1a.1=expY1a-OWTS1$RS_ANNUAL


#### DATA (MAX VALUES USED FOR RS) ####
owts2<-
read.csv("/Users/laurakohler/Documents/CU_Research/OWTS_Data/CSV/OWTS_CSV_GAMLSS_MULT_MAX_ALL.csv",na.strings
="NA",header=TRUE)
OWTS2 <-owts2[1:120,]

m01b <- gamlss(RS ANNUAL~ PRE2008 DEED + H2O + DELTA BED + STRUCT VAL + LIVE AREA + LOAN_INSP +
NO_ADD.UPGRADES + PROP_TRANS_INSP + POST2008_DEED,data=na.omit(OWTS2),family=WEI)


# stepGAIC.VR() is based on stepAIC() with the additional property
# that allows selection of terms for any selected distributional
# parameter.

model1b <- stepGAIC.VR(m01b,scope=~PRE2008_DEED + H2O + DELTA_BED + STRUCT_VAL + LIVE_AREA +
                    LOAN INSP + NO ADD.UPGRADES + PROP TRANS INSP + POST2008 DEED +(STRUCT_VAL + LIVE_AREA
+ PROP_TRANS_INSP + POST2008_DEED +NO_ADD.UPGRADES)^2) # Sigma (shape) is held constant

residuals1b=residuals(model1b)
mu_mod1b=exp(predict(model1b,what="mu"))
sigma_mod1b=exp(predict(model1b, what="sigma"))

expY1b<-vector(length=N)
for (i in 1:N){
  expY1b[i]=mu_mod1b[i]*gamma((1/sigma_mod1b[i])+1)
```

```
}

residuals1b.1=expY1b-OWTS2$RS_ANNUAL


#### DATA (MAX VALUE OF REPAIR USED FOR MAJOR REPAIRS IN RS) ####
owts3<-
read.csv("/Users/laurakohler/Documents/CU_Research/OWTS_Data/CSV/OWTS_CSV_GAMLSS_MULT_MAX_MAJOR.csv",na.str
ings="NA",header=TRUE)

OWTS3 <-owts3[1:120,]

m01c <- gamlss(RS_ANNUAL~ PRE2008_DEED + H2O + DELTA_BED + STRUCT_VAL + LIVE_AREA + LOAN_INSP +
NO_ADD.UPGRADES + PROP_TRANS_INSP + POST2008_DEED,data=na.omit(OWTS3),family=WEI)


# stepGAIC.VR() is based on stepAIC() with the additional property
# that allows selection of terms for any selected distributional
# parameter.

model1c <- stepGAIC.VR(m01c,scope=~PRE2008_DEED + H2O + DELTA_BED + STRUCT_VAL + LIVE_AREA + LOAN_INSP +
NO_ADD.UPGRADES + PROP_TRANS_INSP + POST2008_DEED +(STRUCT_VAL + LIVE_AREA + PROP_TRANS_INSP +
POST2008_DEED +NO_ADD.UPGRADES)^2) # Sigma (shape) is held constant

residuals1c=residuals(model1c)

mu_mod1c=exp(predict(model1c,what="mu"))
sigma_mod1c=exp(predict(model1c, what="sigma"))

expY1c<-vector(length=N)
for (i in 1:N){
  expY1c[i]=mu_mod1c[i]*gamma((1/sigma_mod1c[i])+1)

}
residuals1c.1=expY1c-OWTS3$RS_ANNUAL

op <-par(mfrow=c(1,1))
plot(residuals1a.1,type="l",xlab="Observed OWTS", ylab="Model Residuals",ylim=c(-900,900), col="4",lwd=2.5, lty=1)
lines(residuals1b.1, col="2",lty=2,lwd="2.5")
lines(residuals1c.1,col="5",lty=5,lwd="2.0")
legend("bottomleft", c("Model I","Model II","Model III"),lty=c(1,2,5), lwd=c(2.5,2.5,2),col=c("4","2","5"),bty="n") # gives the legend
lines the correct color and width

par(op)

op <-par(mfrow=c(1,1))
plot(residuals1a,type="l",xlab="Sample OWTS", ylab="Normalized Quantile Model Residuals", col="4",lwd=2, lty=1)
lines(residuals1b, col="2",lty=2,lwd="2")
lines(residuals1c,col="3",lty=5,lwd="1.5")
legend("topleft", c("Model I","Model II","Model III"),lty=c(1,2,5), lwd=c(2,2,1.5),col=c("4","2","3"),bty="n") # gives the legend lines the
correct color and width

par(op)

### Data Hist with Weibull Fit for each model
ydata1=OWTS1$RS_ANNUAL[1:120]
Na=length(ydata1)
N1=Na-1

xeval1=seq(min(ydata1)-sd(ydata1), max(ydata1)+sd(ydata1),length=120)
neval1=length(xeval1)

# Weibull
zweibull1=fitdist(ydata1, "weibull", optim.method="L-BFGS-B",lower=0.05)
xdensityweibull1=dweibull(xeval1,shape=zweibull1$estimate[1],scale=zweibull1$estimate[2])

ydata2=OWTS2$RS_ANNUAL[1:120]
Nb=length(ydata2)
N2=Nb-1
```

```
xeval2=seq(min(ydata2)-sd(ydata2), max(ydata2)+sd(ydata2),length=120)
neval2=length(xeval2)

# Weibull
zweibull2=fitdist(ydata2, "weibull", optim.method="L-BFGS-B",lower=0.05)
xdensityweibull2=dweibull(xeval2,shape=zweibull2$estimate[1],scale=zweibull2$estimate[2])

ydata3=OWTS3$RS_ANNUAL[1:120]
Nc=length(ydata3)
N3=Nc-1

xeval3=seq(min(ydata3)-sd(ydata3), max(ydata3)+sd(ydata3),length=120)
neval3=length(xeval3)

# Weibull
zweibull3=fitdist(ydata3, "weibull", optim.method="L-BFGS-B",lower=0.05)
xdensityweibull3=dweibull(xeval3,shape=zweibull3$estimate[1],scale=zweibull3$estimate[2])

# plot the histogram and overlay the PDFs
par(mfrow=c(1,3))
hist(ydata1,xlab="Annual Repair Severity (USD)", ylab="", probability=T, main="",ylim=range(c(0, 0.007)),breaks=nds)

title(main="Model I")
lines(xeval1,xdensityweibull1,lwd=2,lty=5,col="black")

hist(ydata2,xlab="Annual Repair Severity (USD)", ylab="", probability=T, main="",ylim=range(c(0, 0.007)),breaks=nds)

title(main="Model II")
lines(xeval2,xdensityweibull2,lwd=2,lty=5,col="black")

hist(ydata3,xlab="Annual Repair Severity (USD)", ylab="", probability=T, main="",ylim=range(c(0, 0.007)),breaks=nds)

title(main="Model III")
lines(xeval3,xdensityweibull3,lwd=2,lty=5,col="black")

par(op, xpd=TRUE)
legend("topright", "Weibull",lty=5, lwd=2.5,bty="n")

op <- par(mfrow=c(1,3))
hist(expY1a, main="Model I", xlab="Annual Repair Severity (USD)")
hist(expY1b, main="Model II", xlab="Annual Repair Severity (USD)")
hist(expY1c, main="Model III", xlab="Annual Repair Severity (USD)")
par(op)
```

APPENDIX D: RISK R CODE

```
#### BINOMIAL LOGIT USING GLM ####
install.packages("MASS")
install.packages("verification")

library(MASS)
library(verification)
library(arules)


#### DATA ####
owts<-
read.csv("/Users/laurakohler/Documents/CU_Research/OWTS_Data/CSV/OWTS_CSV_MULT.csv",na.strings="NA",header=TRUE)
owts[1:5,]
OWTS <-owts[1:120,]

ydata=OWTS$RS_ANNUAL[1:120]
N=length(ydata)
N1=N-1

#### MODEL 1: LOWER THRESHOLD (LOW RISK OWTS) ####
# RS<303 -->1; Severity < 9.173
# OWTS$RS_BI_LOW<-cut(OWTS$RS_ANNUAL, breaks=c(0,303,755), labels=c(0,1))

hist(OWTS$RS_ANNUAL,xlab="Annual Repair Severity (USD)", main="", probability=FALSE, breaks=16)
points(303,0,pch=17)

N = length(OWTS$RS_BI_LOW)
p1 <- length(OWTS$RS_BI_LOW[OWTS$RS_BI_LOW == 1])/N
p0 <- length(OWTS$RS_BI_LOW[OWTS$RS_BI_LOW == 0])/N
climo <- c(p1, p0)

glm.out = glm(RS_BI_LOW~ PRE2008_DEED + H2O + DELTA_BED + STRUCT_VAL + LIVE_AREA + LOAN_INSP +
NO_ADD.UPGRADES + PROP_TRANS_INSP + POST2008_DEED, data = OWTS, family=binomial(logit))
summary(glm.out)
anova(glm.out, test="Chisq")

model1=stepAIC(glm.out,scope=~PRE2008_DEED + H2O + DELTA_BED + STRUCT_VAL + LIVE_AREA + LOAN_INSP +
NO_ADD.UPGRADES + PROP_TRANS_INSP + POST2008_DEED +PROP_TRANS_INSP*POST_DEED, direction="backward")
summary(model1)
anova(model1, test="Chisq")

yfit1=predict(model1,type="response")

#### BRIER SKILL SCORE (MODEL 1: LOWER THRESHOLD) ####
brier(as.numeric(OWTS$RS_BI_LOW),yfit1, baseline=climo)$bs
# Perfect Score is 0
brier(as.numeric(OWTS$RS_BI_LOW),yfit1, baseline=climo)$ss
# Perfect Skill is 1

## HIST OF PROBABILTY OF BEING BELOW THRESHOLD ##
hist(model1$fitted,xlab="Probability of Exceedance", main="Probability Distribution of Low Threshold Exceedance")

## HIST OF LOW RISK OWTS ##
combo1<-cbind(OWTS$RS_BI_LOW, model1$fitted)
fitted_sub<-subset(combo1, OWTS$RS_BI_LOW==1)
hist(fitted_sub[,2], xlab="Model Forecast Probability of Low Risk OWTS", main="")
abline(v=0.2,col="red",lwd=2.5)
points(fitted_sub[,2],rep(0,24))

## HIST OF LOW RISK OWTS COMPARED TO COVARIATES ##
covrelate<-cbind(OWTS$RS_BI_LOW, model1$fitted, OWTS$PROP_TRANS_INSP, OWTS$POST2008_SALES)
covrelate_sub<-subset(covrelate,OWTS$RS_BI_LOW==1)

hist(covrelate_sub[,3],xlab="No. of Property Transfer Inspections",ylab="Count of Low Risk OWTS with Attribute", xaxt='n', main="")
axis(side=1, at=seq(0,1), labels=seq(0,1))
hist(covrelate_sub[,4],xlab="No. of Sales after 2008",ylab="Count of Low Risk OWTS with Attribute",xaxt='n',main="")
```

```
axis(side=1, at=seq(0), labels=seq(0))
axis(side=1, at=seq(1,2), labels=seq(1,2))

## Drop some % of points, fit the model and predict the dropped points ...
Y<-OWTS$RS_BI_LOW
X<-as.matrix(cbind(OWTS$PROP_TRANS_INSP, OWTS$DELTA_BED))

nsim = 1000
bs1 = 1:nsim
bss1=1:nsim
N = length(Y)

N15 = round(0.15*N)   #drop 15% of points
index=1:N

for(i in 1:nsim){
  drop=sample(c(1:N), N15)
  keep=setdiff(index,drop)

  x=X[keep,]
  y=Y[keep]

  zz<-glm(y~x, family=binomial(logit))

  x = as.matrix(X[drop,])

  yhat=predict(zz,newdata=data.frame(x),type="response")

  bs1[i]=(yhat-Y[drop])^2/length(yhat)
  bss1[i]=(1-(bs1[i])/dimo[1])
}


#### MODEL 2: UPPER THRESHOLD (HIGH RISK OWTS) ####
# RS > 448 -->1; Severity > 17.932 (~18)
# OWTS$RS_BI_HIGHa<-as.factor(cut(OWTS$RS_ANNUAL,breaks=c(0,448,755), labels=c("0","1")))

hist(OWTS$RS_ANNUAL,xlab="Annual Repair Severity (USD)", main="", probability=FALSE, breaks=16)
points(448,0,pch=17)

N = length(OWTS$RS_BI_HIGHa)
p1 <- length(OWTS$RS_BI_HIGHa[OWTS$RS_BI_HIGHa == 1])/N
p0 <- length(OWTS$RS_BI_HIGHa[OWTS$RS_BI_HIGHa == 0])/N
dimo.a <- c(p1, p0)

glm.out.a = glm(RS_BI_HIGHa~ PRE2008_DEED + H2O + DELTA_BED + STRUCT_VAL + LIVE_AREA + LOAN_INSP +
NO_ADD.UPGRADES + PROP_TRANS_INSP + POST2008_DEED, data = OWTS, family=binomial(logit))
summary(glm.out.a)
anova(glm.out.a, test="Chisq")

model2a=stepAIC(glm.out.a,scope=~PRE2008_DEED + H2O + DELTA_BED + STRUCT_VAL + LIVE_AREA + LOAN_INSP +
NO_ADD.UPGRADES + PROP_TRANS_INSP + POST2008_DEED +PROP_TRANS_INSP*POST2008_DEED,
direction="backward")
summary(model2a)
anova(model2a, test="Chisq")

yfit2a=predict(model2a,type="response")

#### BRIER SKILL SCORE (MODEL 2: UPPER THRESHOLD) ####
brier(as.numeric(OWTS$RS_BI_HIGHa),yfit2a, baseline=dimo.a)$bs
# Perfect Score is 0
brier(as.numeric(OWTS$RS_BI_HIGHa),yfit2a, baseline=dimo.a)$ss
# Perfect Skill is 1
## HIST OF PROBABILTY OF BEING BELOW THRESHOLD ##
hist(model2a$fitted,xlab="Probability of Exceedance", main="Probability Distribution of High Threshold Exceedance")

## HIST OF HIGH RISK OWTS ##
combo2<-cbind(OWTS$RS_BI_HIGHa, model2a$fitted)
fitted_sub2<-subset(combo2, OWTS$RS_BI_HIGHa==1)
hist(fitted_sub2[,2], xlab="Model Forecast Probability of High Risk OWTS", main="")
```

```
abline(v=0.14,col="red",lwd=2.5)
points(fitted_sub2[,2],rep(0,17))

## Drop some % of points, fit the model and predict the dropped points ...
library(arules)
Y<-OWTS$RS_BI_HIGHa
X<-as.matrix(cbind(OWTS$POST2008_DEED, OWTS$PRE2008_DEED, OWTS$DELTA_BED))

nsim = 1000
bs2 = 1:nsim
bss2=1:nsim
N = length(Y)

N15 = round(0.15*N)    #drop 15% of points
index=1:N

for(i in 1:nsim){
  drop=sample(c(1:N), N15)
  keep=setdiff(index,drop)

  x=X[keep,]
  y=Y[keep]

  zz<-glm(y~x, family=binomial(logit))

  x = as.matrix(X[drop,])

  yhat=predict(zz,newdata=data.frame(x),type="response")

  bs2[i]=(yhat-Y[drop])^2/length(yhat)
  bss2[i]=(1-(bs2[i])/dimo.a[1])
}


#### BRIER SKILL SCORE BOXPLOTS FOR LOWER- AND UPPER- THRESHOLD ####
op <-par(mfrow=c(1,2))
boxplot(bss1, ylab="Brier Skill Score", main="(a)")
boxplot(bss2, ylab="", main="(b)")
par(op)
title(main="Model Predictions Skill")


#### TESTING OTHER THRESHOLDS ####
#### UPPER THRESHOLD (With Only 10% In High Risk Category)
# RS > 458 -->1
OWTS$RS_BI_HIGHb<-as.factor(cut(OWTS$RS_ANNUAL,breaks=c(0,448,755), labels=c("0","1")))

N = length(OWTS$RS_BI_HIGHb)
p1 <- length(OWTS$RS_BI_HIGHb[OWTS$RS_BI_HIGHb == 1])/N
p0 <- length(OWTS$RS_BI_HIGHb[OWTS$RS_BI_HIGHb == 0])/N
dimo.b <- c(p0, p1)

glm.out.b = glm(RS_BI_HIGHb~ PRE2008_DEED + H2O + DELTA_BED + STRUCT_VAL + LIVE_AREA + LOAN_INSP +
NO_ADD.UPGRADES + PROP_TRANS_INSP + POST2008_DEED, data = OWTS,family=binomial(logit))
summary(glm.out.b)
anova(glm.out.b, test="Chisq")

model2b=stepAIC(glm.out.b,scope=~PRE2008_DEED + H2O + DELTA_BED + STRUCT_VAL + LIVE_AREA + LOAN_INSP +
NO_ADD.UPGRADES + PROP_TRANS_INSP + POST2008_DEED, direction="backward")
summary(model2b)
anova(model2b, test="Chisq")

yfit2b=predict(model2b, type="response")

brier(as.numeric(OWTS$RS_BI_HIGHb),yfit2b, baseline=dimo.b)$bs
# Perfect Score is 0
brier(as.numeric(OWTS$RS_BI_HIGHb),yfit2b, baseline=dimo.b)$ss
# Perfect Skill is 1

# Too few OWTS fall above the 458 threshold to draw any conclusions
```

```
#### LOW RISK OWTS Model Forecasts ####
New_RS_BI_LOW<-cbind(OWTS$RS_BI_LOW, yfit1, OWTS$PARCEL_NO2)
New_RS_BI_LOW1<-subset(New_RS_BI_LOW, OWTS$RS_BI_LOW==1)
hist(New_RS_BI_LOW1[,2], xlab="Probability of Low Risk OWTS", ylab="", main="Risk Forecast for OWTS Observed in Low Risk Category")
write.csv(New_RS_BI_LOW,"New_RS_BI_LOW.csv")

#### HIGH RISK OWTS Model Forecasts ####
New_RS_BI_HIGH<-cbind(OWTS$RS_BI_HIGHa, yfit2a, OWTS$PARCEL_NO2)
New_RS_BI_HIGH1<-subset(New_RS_BI_HIGH, OWTS$RS_BI_HIGHa==1)
hist(New_RS_BI_HIGH1[,2], xlab="Probability of High Risk OWTS", ylab="", main="Risk Forecast for OWTS Observed in High Risk Category")
write.csv(New_RS_BI_HIGH,"New_RS_BI_HIGH.csv")
#### THRESHOLD PLOT ####

library(sm)
ydata=OWTS$Severity[1:120]
N=length(ydata)
N1=N-1
xeval=seq(min(ydata)-sd(ydata), max(ydata)+sd(ydata),length=120)
neval=length(xeval)

# Nonparametric Kernel Density Estimation
kernelpdf = sm.density(ydata,eval.points=xeval,add=FALSE, lty=1, lwd=4)

par(mfrow=c(1,1))
hist(OWTS$Severity,xlab="Repair Severity (Thousands of USD)", ylab="", probability=T, main="",breaks=16)
points(8,0,pch=25,cex=1.60,lwd=2,bg="white")
points(18,0, pch=24,cex=1.60,lwd=1.5, bg="black")
lines(xeval,kernelpdf$estimate,lwd=2,lty=1,col="black")

legend(22,0.3, c("Low Risk Threshold","High Risk Threshold","Kernel Density"),pch=c(25,17, NA), lty=c(NA, NA,1), lwd=2,bty="n") # gives the legend lines the correct color and width
```

EXTREME VALUE ANALYSIS – POINTS OVER THRESHOLD

```
install.packages("extRemes")
install.packages("ismev")

library(extRemes)
library(ismev)
library(MASS)

#### LOAD DATA ####
owts<-
read.csv("/Users/laurakohler/Documents/CU_Research/OWTS_Data/CSV/OWTS_CSV_MULT.csv",na.strings="NA",header=TRUE)
owts[1:5,]
OWTS <-owts[1:120,]

#### THRESHOLD SELECTION ####
# Choose a threshold low enough (lower variance), but high enough that the
# assumptions for the GPD are valid (lower bias)
op <-par(mfrow=c(2,2))
gpd.fitrange(OWTS$Severity,umin=0,umax=14,nint=7)
gpd.fitrange(OWTS$Severity,umin=12,umax=20,nint=8)
par(op)
#### PLOT TOTAL SEVERITY OVER 40 YR ####
op <-par(mfrow=c(1,1))
plot(OWTS$Severity, xlab = "Sample Systems",ylab = "Annual Repair Severity (Thousand USD)", pch = 1,cex=0.75)
abline(h=18, col="darkred")
par(op)


#### FIT MODEL USING extRemes ####
op <-par(mfrow=c(2,4))
```

```
fit0 <- fevd(Severity, OWTS, threshold=18, type="GP")
plot(fit0,type="qq", main="(a)")

fit1 <- fevd(Severity, OWTS, threshold=18, type="GP", scale.fun=~DELTA_BED)
plot(fit1,type="qq", main="(b)")

lr.test(fit0,fit1)
# If the p-value is smaller than alpha, then the decision is to reject the
# null hypothesis in favor of the model with more parameters.

fit2 <- fevd(Severity, OWTS, threshold=18, type="GP", scale.fun=~DELTA_BED+PROP_TRANS_INSP)
plot(fit2,type="qq", main="(c)")

lr.test(fit0,fit2)

fit3 <- fevd(Severity, OWTS, threshold=18, type="GP", scale.fun=~DELTA_BED + PROP_TRANS_INSP + POST2008_DEED)
plot(fit3,type="qq", main="(d)")

lr.test(fit0,fit3)

fit4 <- fevd(Severity, OWTS, threshold=18, type="GP", scale.fun=~PROP_TRANS_INSP + POST2008_DEED)
plot(fit4,type="qq", main="(e)")

lr.test(fit0,fit4)

fit5 <- fevd(Severity, OWTS, threshold=18, type="GP", scale.fun=~PROP_TRANS_INSP* POST2008_DEED)
plot(fit5,type="qq", main="(f)")

lr.test(fit0,fit5)

fit6 <- fevd(Severity, OWTS, threshold=18, type="GP", scale.fun=~PROP_TRANS_INSP* POST2008_DEED + STRUCT_VAL +
LOAN_INSP)
plot(fit6,type="qq", main="")

lr.test(fit5,fit6)
lr.test(fit0,fit6)

fit7 <- fevd(Severity, OWTS, threshold=18, type="GP", scale.fun=~PROP_TRANS_INSP* POST2008_DEED +STRUCT_VAL+
LOAN_INSP + PRE2008_DEED)
plot(fit7,type="qq", main="(h)")

lr.test(fit5,fit7)

look0 <- summary(fit0, silent=TRUE)
look0 <- c(look0$AIC, look0$BIC)
look1 <- summary(fit1, silent=TRUE)
look1 <- c(look1$AIC, look1$BIC)
look2 <- summary(fit2, silent=TRUE)
look2 <- c(look2$AIC, look2$BIC)
look3 <- summary(fit3, silent=TRUE)
look3 <- c(look3$AIC, look3$BIC)
look4 <- summary(fit4, silent=TRUE)
look4 <- c(look4$AIC, look4$BIC)
look5 <- summary(fit5, silent=TRUE)
look5 <- c(look5$AIC, look5$BIC)
look6 <- summary(fit6, silent=TRUE)
look6 <- c(look6$AIC, look6$BIC)
look7 <- summary(fit7, silent=TRUE)
look7 <- c(look7$AIC, look7$BIC)

# Lower AIC/BIC is better.
names(look0) <- names(look1) <- names(look2) <- names(look3) <- names(look4) <- names(look5) <- c("AIC", "BIC")
look0
look1
look2
look3
look4
look5
look6
look7
```

```
#### PLOT BEST FIT (6) ####
op <- par(mfrow=c(1,1))
fit6 <- fevd(Severity, OWTS, threshold=18, type="GP", scale.fun=~PROP_TRANS_INSP*POST2008_DEED + STRUCT_VAL +
LOAN_INSP)
plot(fit6,type="qq", main="")
par(op)


#### MODEL VS OBSERVATION PLOTS (to show model skill) ####
shape_fit6=findpars(fit6)$shape
scale_fit6=findpars(fit6)$scale

# CI line plot (USING expY2)
op <- par(mfrow=c(1,1))
med<-vector(length=N)
Yu<-vector(length=N)
Yl<-vector(length=N)

for (i in 1:N){
  med[i]=qevd(0.50,scale=scale_fit6[i],shape=1,type="GP")
  Yl[i]=qevd(0.25,scale=scale_fit6[i],shape=1,type="GP")
  Yu[i]=qevd(0.75,scale=scale_fit6[i],shape=1,type="GP")
}

#### RS > 448 -->1 #### Severity > 17.932 (~18) ####
# OWTS$RS_BI_HGHa<-as.factor(cut(OWTS$RS_ANNUAL, breaks=c(0,448,755), labels=c("0","1")))

N = length(OWTS$RS_BI_HGHa)
p1 <- length(OWTS$RS_BI_HGHa[OWTS$RS_BI_HGHa == 1])/N
p0 <- length(OWTS$RS_BI_HGHa[OWTS$RS_BI_HGHa == 0])/N
dimo.a <- c(p1, p0)

glm.out.a = glm(RS_BI_HGHa~ PRE2008_DEED + H2O + DELTA_BED + STRUCT_VAL + LIVE_AREA + LOAN_INSP +
NO_ADD.UPGRADES + PROP_TRANS_INSP + POST2008_DEED, data = OWTS,family=binomial(logit))
summary(glm.out.a)
anova(glm.out.a, test="Chisq")

model2a=stepAIC(glm.out.a,scope=~PRE2008_DEED + H2O + DELTA_BED + STRUCT_VAL + LIVE_AREA + LOAN_INSP +
NO_ADD.UPGRADES + PROP_TRANS_INSP + POST2008_DEED +PROP_TRANS_INSP*POST2008_DEED,
direction="backward")
summary(model2a)
anova(model2a, test="Chisq")

yfit2a=predict(model2a,type="response")


#### PLOT PROBABILITY OF EXCEEDANCE ####
emed<-yfit2a*med
eYu<-yfit2a*Yu
eYl<-yfit2a*Yl

plot(emed, type="l", xlab="Observed OWTS", ylab="Expected Repair Severity of Exceedance (Thousands of USD)",
ylim=c(0,25), col="navy",lwd=2, lty="solid")

lines(eYu,lty=1,lwd=2, col="olivedrab")
lines(eYl,lty=1,lwd=2, col="olivedrab3")
legend("topright", c("Upper Quartile","Median","Lower Quartile"),lty=c(1,1,1),
lwd=c(2,2,2),col=c("olivedrab","navy","olivedrab3"),bty="n") # gives the legend lines the correct color and width
par(op)

#### DATA FOR GIS ####
write.csv(emed,"MED_SEV.csv")


#### BOX PLOT OF EXCEEDENCE SEVERITY ####
emed<-yfit2a*(med+18)
eYu<-yfit2a*(Yu+18)
eYl<-yfit2a*(Yl+18)
```

```
ExpRisk<-emed+(18*(1-yfit2a))
ExpRisk_low<-emed+(3.6*(1-yfit2a))
ExpRisk_High<-emed+(9*(1-yfit2a))
write.csv(ExpRisk,"ExpRisk.csv")
write.csv(ExpRisk_High,"ExpRisk_High.csv")

op <- par(mfrow=c(1,4), mar=c(5,6,4,0))
boxplot(ExpRisk_low,ylab="Expected Repair Severity (Thousands of USD)", main="(a)",ylim=c(5,30))
par(bty="n",cex.lab=1.75,cex.main=1.5,cex.axis=1.75)
boxplot(ExpRisk_High,ylab="", main="(b)",ylim=c(5,30),axes=F)
par(bty="n",cex.main=1.5,cex.axis=1.75)
boxplot(ExpRisk,ylab="", main="(c)",ylim=c(5,30),axes=F)
par(bty="n",cex.main=1.5,cex.axis=1.75)
boxplot(OWTS$Severity,ylab="Actual Repair Severity (Thousands of USD)", main="(d)",ylim=c(5,30))
par(bty="n",cex.lab=1.75,cex.main=1.5,cex.axis=1.75)
par(op)

op <- par(mfrow=c(1,1))
RS<-cbind(ExpRisk, OWTS$Severity)
boxplot(RS, ylab="Repair Severity (Thousands of USD)",names=c("Expected","Actual"))
par(op)

op <- par(mfrow=c(1,1))
par(cex.lab=1.25,cex.axis=1.5,bty="o", mar=c(4,10,4,10))
boxplot(med,ylab="Median Amount Over $18,000 (Thousands of USD)")
par(op)
```

APPENDIX E: FRAGILITY R CODE

```
#### UPLOAD ANNUAL FREQUENCY OF MINOR, MODERATE AND MAJOR REPAIRS ####
REPAIR_TS<-read.csv("/Users/laurakohler/Documents/CU_Research/OWTS_Data/RESILIENCE
/OWTS_REPAIR_TS_CSV.csv",na.strings="NA",header=TRUE)

#### UPLOAD BC PEAK STREAM FLOW(LONGMONT) ####
PEAK_FLOW<-read.csv("/Users/laurakohler/Documents/CU_Research/OWTS_Data/RESILIENCE
/BC_PeaK_Long.csv",na.strings="NA",header=TRUE)

#### UPLOAD NOAA CLIMATE DATA ####
NOAA_CLIM<-read.csv("/Users/laurakohler/Documents/CU_Research/OWTS_Data/RESILIENCE
/NOAA_ClimateDATA2.csv",na.strings="NA",header=TRUE)

install.packages('MASS')
install.packages('verification')
install.packages('msm')
install.packages('locfit')

library(MASS)
library(verification)
library(msm)
library(locfit)


LAG_TPCP<-c(23.1,NOAA_CLIM$TPCP)
LAG2_TPCP<-c(13.5,23.1,NOAA_CLIM$TPCP)

MIN_DATA<-
as.data.frame(cbind(REPAIR_TS$YEAR[7:34],REPAIR_TS$MINOR[7:34],NOAA_CLIM[1:28,2:13],PEAK_FLOW$peak_va[29:56],L
AG_TPCP[1:28],LAG2_TPCP[1:28]))
MIN_DATA<-na.omit(MIN_DATA)
colnames(MIN_DATA)<-
c("YEAR","R_MIN","DT90","DT00","DP05","DP10","TPCP","DP05_S","DP10_S","TPCP_S","TPCP_W","MR25_S","MR30_S","MR40
_S","PEAK_FL","PREV_TPCP","LAG2_TPCP")

MOD_DATA<-
as.data.frame(cbind(REPAIR_TS$YEAR[7:34],REPAIR_TS$MODERATE[7:34],NOAA_CLIM[1:28,2:13],PEAK_FLOW$peak_va[29:
56],LAG_TPCP[1:28],LAG2_TPCP[1:28],REPAIR_TS$MINOR[6:33]))
MOD_DATA<-na.omit(MOD_DATA)
colnames(MOD_DATA)<-
c("YEAR","R_MOD","DT90","DT00","DP05","DP10","TPCP","DP05_S","DP10_S","TPCP_S","TPCP_W","MR25_S","MR30_S","MR4
0_S","PEAK_FL","PREV_TPCP","LAG2_TPCP","R_MIN_LAG")

MAJ_DATA<-
as.data.frame(cbind(REPAIR_TS$YEAR[7:34],REPAIR_TS$MAJOR[7:34],NOAA_CLIM[1:28,2:13],PEAK_FLOW$peak_va[29:56],L
AG_TPCP[1:28],LAG2_TPCP[1:28]))
MAJ_DATA<-na.omit(MAJ_DATA)
colnames(MAJ_DATA)<-
c("YEAR","R_MAJ","DT90","DT00","DP05","DP10","TPCP","DP05_S","DP10_S","TPCP_S","TPCP_W","MR25_S","MR30_S","MR4
0_S","PEAK_FL","PREV_TPCP","LAG2_TPCP")

TOT_DATA<-
as.data.frame(cbind(REPAIR_TS$YEAR[7:34],REPAIR_TS$TOTAL[7:34],NOAA_CLIM[1:28,2:13],PEAK_FLOW$peak_va[29:56],L
AG_TPCP[1:28],LAG2_TPCP[1:28]))
TOT_DATA<-na.omit(TOT_DATA)
colnames(TOT_DATA)<-
c("YEAR","R_TOT","DT90","DT00","DP05","DP10","TPCP","DP05_S","DP10_S","TPCP_S","TPCP_W","MR25_S","MR30_S","MR4
0_S","PEAK_FL","PREV_TPCP","LAG2_TPCP")


#### MINOR REPAIRS ####
plot(MIN_DATA$R_MIN~MIN_DATA$YEAR,ylab="No. Minor Repairs Each Year",xlab="year")

## Fit GLM
glm_min0<-
glm(R_MIN~DT90+DT00+TPCP+DP05+DP05_S+DP10+DP10_S+TPCP_S+MR25_S+MR30_S+MR40_S+PEAK_FL+PREV_TPC
P+LAG2_TPCP, data=MIN_DATA,family="poisson",na.action = na.exclude)
```

```
glm_min1<-stepAIC(glm_min0,
scope=~DT90+DT00+TPCP+DP05+DP05_S+DP10+DP10_S+TPCP_S+MR25_S+MR30_S+MR40_S+PEAK_FL+PREV_TPCP+L
AG2_TPCP, direction="backward")
summary(glm_min1)

## RISK Ratios
exp(0.04694)   # DT90

ypt_minor=predict(glm_min1, type="response")

plot(ypt_minor, MIN_DATA$R_MIN,xlab="Model Predicted Repair Frequency", ylab="Observed Repair Frequency")
cor(ypt_minor, MIN_DATA$R_MIN)



#### MODERATE REPAIRS ####
plot(MOD_DATA$R_MOD~MOD_DATA$YEAR, ylab="No. Moderate Repairs Each Year",xlab="year")
## Fit GLM
glm_mod0<-
glm(R_MOD~DT90+DT00+TPCP+DP05+DP05_S+DP10+DP10_S+TPCP_S+MR25_S+MR30_S+MR40_S+PEAK_FL+PREV_TPC
P+LAG2_TPCP, data=MOD_DATA,family="poisson", na.action = na.exclude)
glm_mod1<-stepAIC(glm_mod0,
scope=~DT90+DT00+TPCP+DP05+DP05_S+DP10+DP10_S+TPCP_S+MR25_S+MR30_S+MR40_S+PEAK_FL+PREV_TPCP+L
AG2_TPCP, direction="backward")
summary(glm_mod1)

## RISK Ratios
exp(0.0007118)   # PEAK_FL

ypt_mod=predict(glm_mod1, type="response")

plot(ypt_mod, MOD_DATA$R_MOD,xlab="Model Predicted Repair Frequency", ylab="Observed Repair Frequency")
cor(ypt_mod, MOD_DATA$R_MOD)


#### MAJOR REPAIRS ####
plot(MAJ_DATA$R_MAJ~MAJ_DATA$YEAR, ylab="No. Major Repairs Each Year",xlab="year")

## Fit GLM
glm_maj0<-
glm(R_MAJ~DT90+DT00+TPCP+DP05+DP05_S+DP10+DP10_S+TPCP_S+MR25_S+MR30_S+MR40_S+PEAK_FL+PREV_TPC
P+LAG2_TPCP, data=MAJ_DATA,family="poisson", na.action = na.exclude)
glm_maj1<-stepAIC(glm_maj0,
scope=~DT90+DT00+TPCP+DP05+DP05_S+DP10+DP10_S+TPCP_S+MR25_S+MR30_S+MR40_S+PEAK_FL+PREV_TPCP+L
AG2_TPCP, direction="backward")
summary(glm_maj1)

## RISK Ratios
exp(0.5765813)  # MR40_S
exp(-0.0010120) # PEAK_FL

ypt_maj=predict(glm_maj1,type="response")

plot(ypt_maj, MAJ_DATA$R_MAJ, xlab="Model Predicted Repair Frequency", ylab="Observed Repair Frequency")
cor(ypt_maj, MAJ_DATA$R_MAJ)


#### TOTAL REPAIRS ####
plot(TOT_DATA$R_TOT~TOT_DATA$YEAR, ylab="Total No. OWTS Repairs",xlab="Year")

## Fit GLM
glm_tot0<-
glm(R_TOT~DT90+DT00+TPCP+DP05+MR40_S+PEAK_FL+PREV_TPCP+LAG2_TPCP, data=TOT_DATA,family="poisson", na.ac
tion = na.exclude)
glm_tot1<-stepAIC(glm_tot0,
scope=~DT90+DT00+TPCP+DP05+MR40_S+PEAK_FL+PREV_TPCP+LAG2_TPCP, direction="backward")
summary(glm_tot1)

ypg_tot=predict(glm_tot1)
```

```
ypt_tot=ypg_tot
write.csv(ypt_tot,"ModelPredRFrequency.csv")

plot(ypt_tot,TOT_DATA$R_TOT, xlab="Model Predicted Repair Frequency", ylab="Observed Repair Frequency")
cor(ypt_tot,TOT_DATA$R_TOT)

op <- par(mfrow=c(1,3))
plot(MIN_DATA$R_MIN,ypt_minor,ylab="Model Predicted Repair Frequency", xlab="Observed Repair Frequency",
cex.lab=1.25,cex.axis=1.2, main="(d)")
abline(0, 1, col="dark red", lty=2)
cor(ypt_minor, MIN_DATA$R_MIN)

plot(MOD_DATA$R_MOD,ypt_mod,ylab="Model Predicted Repair Frequency", xlab="Observed Repair Frequency",
cex.lab=1.25,cex.axis=1.2, main="(e)")
abline(0, 1, col="dark red", lty=2)
cor(ypt_mod, MOD_DATA$R_MOD)

plot(MAJ_DATA$R_MAJ,ypt_maj, ylab="Model Predicted Repair Frequency", xlab="Observed Repair Frequency",
cex.lab=1.25,cex.axis=1.2, main="(f)")
abline(0, 1, col="dark red", lty=2)
cor(ypt_maj, MAJ_DATA$R_MAJ)

par(op)
```

APPENDIX F: RESILIENCE R CODE

RAPIDITY

```
#### DATA ####
PRE_FLOOD<-read.csv("/Users/laurakohler/Documents/CU_Research/OWTS_Data/RESILIENCE/Boulder County Data/RecovTIME_PreFLOOD.csv", na.strings="NA", header=TRUE)
POST_FLOOD<-read.csv("/Users/laurakohler/Documents/CU_Research/OWTS_Data/RESILIENCE/Boulder County Data/RecovTIME_PostFLOOD.csv", na.strings="NA", header=TRUE)
POST_FLOOD_NONFLOOD<-read.csv("/Users/laurakohler/Documents/CU_Research/OWTS_Data/RESILIENCE/Boulder County Data/RecovTIME_NonFloodPostFLOOD.csv", na.strings="NA", header=TRUE)

PRE<- PRE_FLOOD$DAYS_RECOV_PERM
POST<- POST_FLOOD$DAYS_RECOV_PERM
POST_FL<- POST_FLOOD$DAYS_RECOV_FLOOD
POST_NF<- POST_FLOOD_NONFLOOD$DAYS_RECOV_PERM

op <- par(mfrow=c(1,4), mar=c(5.1,5.1,4.1,2.1))
boxplot(PRE, ylim=c(0,800), ylab="Days", main="(a) Pre-Flood Recovery", cex.lab=1.25,cex.axis=1.2)
boxplot(POST, ylim=c(0,800), ylab="Days", main="(b) Flood Recovery from Permit Date", cex.lab=1.25,cex.axis=1.2)
boxplot(POST_FL, ylim=c(0,800), ylab="Days", main="(c) Flood Recovery from Flood Date", cex.lab=1.25,cex.axis=1.2)
boxplot(POST_NF, ylim=c(0,800), ylab="Days", main="(d) Post-2014 Non-Flood Specific Recovery", cex.lab=1.25,cex.axis=1.2)
par(op)

## NOTE: 235 OWTS in the Post-2014 Repairs Subpopulation have not actually been repaired;
## used date of data entry 2/18/2016 to show some of the delay but many of them may take much longer

var.test(PRE, POST)
## p-value greater than 0.05 was obtained, so can assume that the two variances are homogeneous


## Find tabulated value of F
qf(0.95, 149, 19) ## computed =0.9496 and tabulated =1.9203
## The value of F computed is less than the tabulated value of F, which leads us to accept the null hypothesis of homogeneity of variances.

## T-test ##
t.test(PRE, POST, var.equal=TRUE, paired=FALSE)
## p-value less than 0.05 was obtained, so conclude that the averages of two groups are significantly different (reject that null that they are similar)

## Find tabulated value of t (0.975 instead of 0.95 because a 2 tailed test)
qt(0.975, 168)

## t-computed is less (more?) than the tabulated t-value for 18 degrees of freedom, which
## confirms that we reject the null


## COMPARISON: Time to recover from repair permit application vs. flood event
op <- par(mfrow=c(1,2))

boxplot(POST, ylim=c(0,800), ylab="Days", main="Permit Application")
boxplot(POST_FL, ylim=c(0,800), ylab="Days", main="Flood (September 13, 2013)")
par(op)
```

RESOURCEFULNESS

```
#### DATA ####
RESOURCE<-read.csv("/Users/laurakohler/Documents/CU_Research/OWTS_Data/RESILIENCE/Boulder County Data/RESOURCE_PRE_POST.csv", na.strings="NA", header=TRUE)

PRE_MAX<- RESOURCE$RESOURCEFULNESS_PRE
POST_MAX<- RESOURCE$RESOURCEFULNESS_POST
PRE_MIN<- RESOURCE$RESOURCEFULNESS_PORT_MIN_PRE
POST_MIN<- RESOURCE$RESOURCEFULNESS_PORT_MIN_POST

op <- par(mfrow=c(1,2), mar=c(5.1,5.1,4.1,2.1))
```

```
boxplot(PRE_MAX, ylab="Resourcefulness (USD)",ylim=c(15000,85000), main="(a) Pre-Flood", cex.lab=1.25,cex.axis=1.2)
boxplot(POST_MAX, ylab="Resourcefulness (USD)",ylim=c(15000,85000), main="(b) Post-Flood", cex.lab=1.25,cex.axis=1.2)
par(op)

op <- par(mfrow=c(1,2), mar=c(5.1,5.1,4.1,2.1))
boxplot(PRE_MIN, ylab="Resourcefulness (USD)",ylim=c(14866,17100), main="(a) Pre-Flood", cex.lab=1.25,cex.axis=1.2)
boxplot(POST_MIN, ylab="Resourcefulness (USD)", ylim=c(14866,17100), main="(b) Post-Flood", cex.lab=1.25,cex.axis=1.2)
par(op)
```