Integrative Modeling of Housing Recovery as a Physical, Economic, and Social Process

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ABSTRACT: This paper presents a novel approach to modeling housing recovery through the formulation of recovery-based fragility functions built on empirical data collected longitudinally after a recent flood disaster. Previous community resilience frameworks have not addressed social and economic considerations in engineering-based recovery modeling. In doing so, this work takes an important step forward, advancing the use of probability and statistics in civil engineering applications and facilitating their role in interdisciplinary analysis of post-disaster recovery. To address community housing recovery after a flood event, two recovery-based limit states were analyzed: repair completion and re-occupancy. Two least squares regression models identified the variables most strongly associated with each limit state. These variables included household race and ethnicity, whether the household received post-disaster financial recovery assistance, and physical damage to the home. The analyses provide evidence of the simultaneous and interconnected social, economic, and physical processes that take place in a community and influence recovery progress, further demonstrating the need for multi-disciplinary teams and analytic approaches in modeling resilience and recovery.

Recently, it has become more common in research and practice for the scope of civil engineering analyses to extend beyond hazard modeling and infrastructure design to include repair considerations, interfacing with other infrastructures, and socioeconomic concerns, including fatalities, dislocation, and downtime. Modeling the intersection of physical infrastructure with social and economic systems is complex and requires social and economic expertise. This paper presents a simple, yet novel approach to model housing recovery through the formulation of recovery-based fragility functions and regression models built on longitudinally collected empirical data.

Post-disaster housing recovery is a complex and highly variable process that takes between weeks to years for different households. In this paper, housing recovery is defined as the point at which daily routines are reestablished and the household is able to call the place “home”; this requires meeting four conditions: repair, re-occupancy, restoration of critical services that are accessible to the household, and stability. Housing recovery varies based on a variety of factors including damage, financial resources, and pre-disaster vulnerabilities. It is interdependent with recovery of infrastructure, local economy, and other sectors of a community. The reasons behind differences in recovery time remain largely unexplored, particularly as they unfold over time. In November 2016 and January 2018, researchers at the U.S. National Institute of Standards and Technology (NIST) and the NIST-funded Center for Risk-Based Community Resilience Planning (CoE) conducted a series of field studies in Lumberton, North Carolina following Hurricane Matthew. Among the household-level data collected were information on initial damage level to the home, repair progress, availability and timing of various types of financial recovery resources, dislocation time, and household socio-demographics.

The breadth of data collection was driven by the goal of measuring the complex process of community recovery, including but not limited to the recovery of housing, schools, and businesses. The analyses presented herein utilize an integrated statistical and probabilistic approach to quantify the impact of physical damage to homes, socio-demographic characteristics, and financial recovery resources on a household’s re-occupancy and repair completion, two critical indicators of housing recovery.

1. POST-DISASTER DATA COLLECTION

In October 2016, Hurricane Matthew struck the South Atlantic Coast of the United States, including North Carolina. The Lumber River reached flood stage in Lumberton, North Carolina on October 3rd, 2016 due to local heavy rains. On October 11th, 2016 the river crested at almost 6.7 m (22 feet) above the gage datum. The water level slowly fell, dropping below flood stage on October 23rd, 2016.

The Lumber River runs through the middle of Lumberton, a small in-land community of approximately 21,000 residents (U.S. Census Bureau 2010). The diverse socio-demographic makeup of Lumberton consists of primarily three race and ethnic groups (White, Black, and American Indian) with 34.8% living at or below poverty (U.S. Census Bureau 2010). Thus, selecting Lumberton as a case study for examining the recovery process enables an in-depth understanding of the role social, economic, and physical factors jointly play in community resilience and recovery.

In November 2016, a multi-disciplinary team of CoE and NIST researchers entered the field to collect information on physical damage to housing, and disruption and dislocation to households. In January 2018, a multi-disciplinary team of CoE and NIST researchers returned to Lumberton to collect information on the recovery progress for the same housing sample.

For the original sample, a two-staged non-proportional stratified cluster sample was used to select housing units in Lumberton. Details on the sampling methodology are provided in van de Lindt et al. (2018). Samples were pulled 3:1 from census blocks with the greater proportion of housing units selected from areas with a high probability of flooding. For the first wave of data collection, a total sample of 568 housing units was drawn. These housing units and the households living in these units were the primary sample units for the 2016 survey and the target sample units for the 2018 survey in the longitudinal study. Due to one refusal, the 2018 survey had a sample of 567 housing units.

Data were collected from three types of respondents: continuous residents, new residents, and when the resident was not available, a neighbor or property manager. New residents are those who moved into the housing unit after Hurricane Matthew and the flooding. Continuous, or original, residents are those who lived in the housing unit at the time of Hurricane Matthew and the flooding. These residents were asked the longest set of survey questions. Taking into account only complete surveys of new and original residents, the response rate was 40%, which is above the anticipated response rate of other survey modes (e.g., mail, phone, internet).

To account for the proportioned sample (i.e., 3:1 oversampling of high probability flooding areas), the data were weighted such that the low flooding probability housing units appear three times more frequently in the final dataset. By weighting the data, the total number of housing units increases from 567 to 861. This post-collection weighting is necessary to draw accurate conclusions about the distribution of impact and recovery progress across the community.

Housing units in the sample consisted of single-family housing (77%), multi-family housing (11%), duplexes (11%), and manufactured (mobile) homes (2%). The subsequent analyses are restricted to single-family homes (n = 664 units), where the sample size differs based on how many of those 664 answered the respective questions on the survey.

2. HOUSING DAMAGE, REPAIR, AND RECOVERY MEASUREMENT

2.1. Housing Damage

As repeatedly observed, physical damage to housing is a primary cause for household dislocation after a disaster, and therefore a necessary variable for understanding the housing recovery process (Milch et al. 2010). Engineering research on housing has focused on development of damage-based fragility functions for building systems, sub-systems, and components (e.g., Sutley and van de Lindt 2015; Bahmani et al. 2015). A common approach in building-level investigations is to apply assembly-based vulnerability, which aggregates component fragilities to formulate a system-level fragility (Porter et al. 2001). Probabilistic performance modeling accounting for aleatory and epistemic uncertainties is an important tool used in engineering analyses. Similarly, in community-level investigations it is common to take building-level fragility functions and aggregate to represent building portfolios for the community (Sutley et al. 2016; Lin and Wang 2017). These damage functions have been used to predict economic loss, e.g., repair costs and business downtime, and social disruption, including fatalities and dislocation, where these relationships have been mostly based on expert opinion. The lack of longitudinal and cross-disciplinary data has hindered the accuracy of these relationships until now.

2.2. Housing Repair

As with the extent of damage, the time for housing repair is a primary factor in explaining why households relocate after a disaster. Limited information is available in the literature regarding the time and overall process for repairing damaged structures. As pointed out by Mitrani-Reiser (2007), the repair process is complex and includes much more than reconstruction; it also includes the time to understand and evaluate damage, hire a contractor, get materials on site, develop a design, obtain a permit, and reconstruct or repair. The time to repair is extended when considering that the portfolio of damaged buildings and other infrastructure in the community all need repair simultaneously with limited resources available. Furthermore, homeowners or landlords can spend a considerable amount of time obtaining financial resources and deciding whether they want to rebuild or relocate (Nejat and Damnjanovic 2012).

Previous studies of housing recovery have conflated housing repair with housing recovery. Hirayama (2000) measured the rate of housing recovery after the 1995 Kobe Earthquake as rebuilding the same number of pre-event residential units without consideration of the households that previously occupied the units. Tafti and Tomlinson (2015), who studied housing recovery in Bam, Iran noted that six years after the earthquake, the number of residential units reached the pre-earthquake level. However, 7,510 households were still living in temporary housing or tents even eight years after the earthquake (SCI 2011). In Bam, many low-income renters and homeowners could not achieve housing recovery, while higher income groups accumulated new assets (Tafti and Tomlinson 2013). Thus, housing recovery was not universally achieved despite the reconstruction and repair of the pre-event number of housing units. Therefore, repair is a critical but not sufficient condition for housing recovery. Though rarely, if ever, captured in the engineering literature, re-occupancy is an additional condition for housing recovery.

2.3. Housing Recovery

Temporal and social aspects of the recovery process are often absent in modeling studies. In some cases, recovery time estimates have been employed where recovery is modeled as physical repair, restoration of infrastructure functionality, and in one case, time to treat injuries and post-traumatic stress disorder diagnosis (DHS 2003; FEMA 2012; Sutley et al. 2016; Lin and Wang 2017). In general, analysis of recovery times have not included social and economic considerations that for decades have been shown in the social sciences to influence the time in which repair and overall recovery actually take place for buildings, including housing (Cutter et al. 2003; Fothergill and Peek 2004; Zhang and Peacock 2010).

Various definitions have been proposed in the literature to guide measurement of housing recovery. For example, housing recovery has been defined as the repair of physical damage, re-occupancy of the housing unit, restoration of functionality, and restoration of pre-disaster monetary value (Hamideh, et al. 2018; Sutley and Hamideh 2017). For the purpose of this analysis, the working definition of housing recovery is limited to two conditions - repair and re-occupancy. There is a body of literature on modeling housing damage and repair through the use of limit states. In fact, many of the established engineering and decision frameworks for community resilience rely on the development of fragility functions that capture the exceedance of such limit states. For this study, two housing recovery indicators, repair completion and re-occupancy, are examined as housing recovery limit states with fragility functions for integration into community resilience frameworks.

3. INTEGRATED PHYSICAL AND SOCIAL HOUSING RECOVERY MODELING

In addition to physical damage and repair, socio-demographic and economic factors such as race, ethnicity, income, and financial recovery resources help explain the disparate recovery processes across households in a community. This study moves beyond physical damage and repair, to include social and economic considerations in order to examine the post-disaster housing recovery process holistically.

3.1. Empirical Analysis of Recovery Limit States

Considering the 2018 housing survey, information on occupancy status was recorded for the weighted sample of 664 single family homes, including responses from the occupant or a neighbor. Of the sample, 379 houses were confirmed occupied; 127 houses appeared occupied, but could not be confirmed; 1 house was confirmed unoccupied and unrepaired; 127 houses appeared abandoned or otherwise unoccupied and unrepaired; and 30 houses were not accessible or met other exclusion criteria. A subsample of 132 housing units had additional information from the household having completed a survey where respondents reported on repair progress. Of the subsample, 47 households stated that their home was "still not repaired". Based on these data collected 14 months after the initial flooding, the majority of housing units reached one or more indicators of housing recovery, but were still recovering, while 19% of the 664 houses in the sample made no progress towards housing recovery. As evident from this report, repair completion and re-occupancy are not necessarily sequential nor mutually exclusive. A proportion of the sample met one, both, or neither recovery limit state.

A series of linear regression models were applied to the data to examine which factors explain variation in recovery outcomes using two dependent variables: number of days to complete repairs (RS1), and number of days until re-occupancy (RS2). Independent variables in the models include (1) initial damage state where DS0 is undamaged, DS1 is minor damage, DS2 is moderate damage, and DS3 is severe damage, (2) race and ethnicity as a binary variable where 1 is Not-Hispanic White and 0 is all of the minority groups, (3) insurance, (4) insurance payout after the floods, (5) financial recovery assistance from the government, (6) financial recovery assistance from a non-governmental organization (NGO), all used as binary variables, and (7) self-reported combined annual income as a categorical variable. Variables 2 through 7 were recorded through the household survey. Only the statistically significant variables in each model are discussed and used in the fragility functions.

Table 1: Least square linear regression models

Variable	Model 1 Number of Days to Repair Completion	Model 2 Number of Days to Re-Occupancy
Damage State 1	-	-15.5
Damage State 2	96.03	36.5*
Damage State 3	135.93*	173.1***
Not-Hispanic White	-103.28*	-9.4
Has Insurance	115.09	19.2
Received Insurance	-155.81**	-25.6
Received Gov. Funds	65.74	16.3
Received NGO Funds	81.50	113.7***
Income $20k-$50k	-130.89*	-32.9
Income $50k-$100k	-103.37	-74.8***
Income $100k+	-107.24	-42*
_constant	293.41***	56.2***
R^2	0.39	0.72

Note: Model1 n = 58; Model2 n=104 from 664 observations
*$p \leq 0.05$ (one-tailed)
**$p \leq 0.05$ (two-tailed)
***$p \leq 0.01$ (two-tailed)

The first column in Table 1 provides the coefficients from the least square linear regression model where the dependent variable is number of days to repair completion. For Model 1, 39% ($R^2 = 0.39$) of the variance in this outcome variable is accounted for by the factors included. Shorter repair time is better, thus negative coefficients in Table 1 indicate a positive effect on recovery time. Having severe damage (DS3), race and ethnicity, and having an annual income between $20,000 and $50,000 were all significant predictors for longer repair completion times. For example, for Model 1, the coefficient for severe damage (DS3) indicates that on average, homes with severe damage took 136 days longer to repair than homes with minor damage (DS1).

The second column in Table 1 provides coefficients from the least square linear regression model where the dependent variable is the number of days until re-occupancy. For Model 2, 72% ($R^2 = 0.72$) of the variance in this outcome variable is accounted for by the factors included. Similar to Model 1, shorter length of dislocation is a better outcome, thus negative coefficients in Table 2 indicate a positive effect on recovery. In this model, moderate (DS2) and severe (DS3) damage, receiving NGO funds, and having annual incomes higher than $50,000 were significant predictors of the time for a household to re-occupy after initial dislocation caused by the floods.

3.2. Predicting Housing Recovery States

Physical damage-based fragility functions are developed using statistical hazard levels and physics-based or empirical models. Each damage state is independent and possesses unique distribution parameters representing sequential, mutually exclusive events. Recovery is a process that occurs over time and is contingent on many social and economic factors outside of the hazard. Therefore, the probability of each recovery limit state, *RS*, is conditioned on the significant physical, social, and economic variables, *V*, presented in Table 1. Furthermore, unlike physical damage states, the recovery limit states of repair time and re-occupancy may not be sequential. Rather, the two recovery-based limit states investigated here are assumed to be independent and not mutually exclusive.

The probability of reaching and exceeding a recovery limit state, RT, at some point in time after the disaster, t, is quantified using a lognormal cumulative distribution function, expressed as

$$P[RT \geq t | V = v] = \Phi\left(\frac{\ln(t/\theta_i)}{\beta_i}\right) \qquad (1)$$

where θ_i is the median and β_i is the logarithmic standard deviation of the distribution of the ith recovery limit state, $RS(i)$. Conditioning the recovery-based limit state functions with the significant physical, social, and economic variables separately allows for comparisons on differential recovery rates across different damage levels, and different types of houses and households by isolating the influential variables for specific examination.

Using Eq. (1), the probability of reaching or exceeding the specified limit states of repair completion and re-occupancy are presented in Figures 2 and 3, respectively.

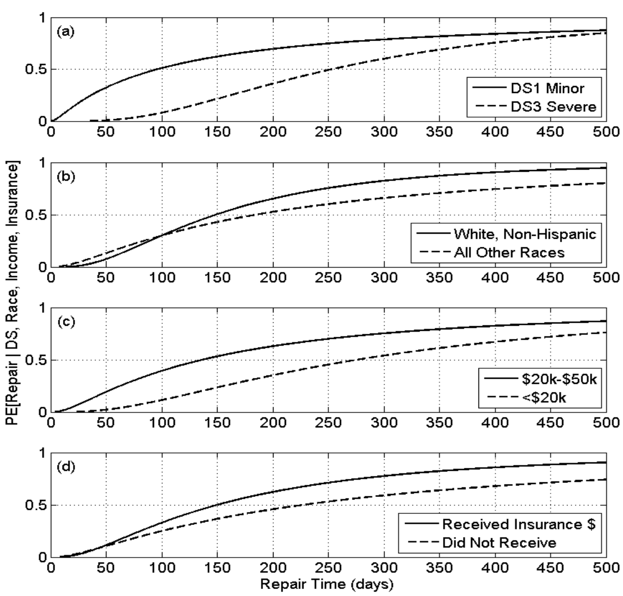

Figure 2: Probability of Reaching or Exceeding Repair Completion given (a) damage state; (b) race; (c) receipt of insurance payout; (d) receipt of insurance payout.

Looking at Figure 2, and examining 50th percentile values, the recovery state functions predict severely damaged homes (DS3) take 156 days longer to repair than homes with minor damage (DS1), non-Hispanic white households require 41 days longer to complete repairs, households whose annual income is between \$20,000 and \$50,000 were able to repair their homes 76 days sooner than households with annual incomes less than \$20,000. Lastly, as shown in Figure 2d, households who do not receiving an insurance payout take 76 days longer to complete repairs.

Looking at Figure 3, and examining 50th percentile values, the recovery state functions predict households with severely damaged homes (DS3) and moderately damaged homes (DS2) took 157 and 38 days longer, respectively, for re-occupancy when compared to households whose homes experienced minor damage (DS1). Households who received NGO funds were re-occupied 138 days later than households who did not received such funds, and households with an annual household income higher than \$50,000 were re-occupied 73 days sooner than households with annual incomes less than \$20,000.

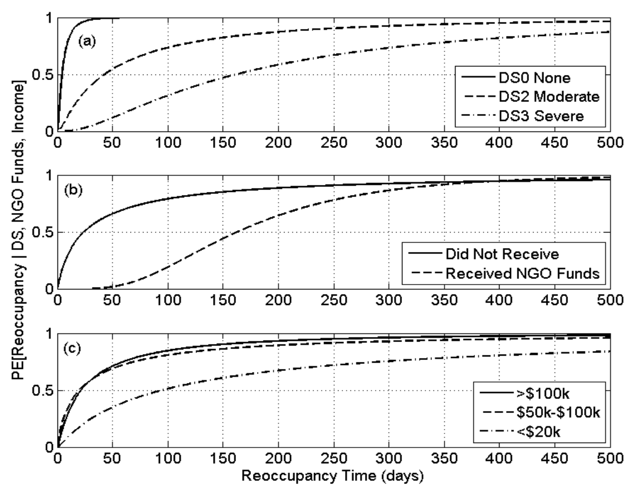

Figure 3: Probability of Reaching or Exceeding Re-Occupancy given (a) damage state; (b) receipt of NGO funds; (c) income level.

4. DISCUSSION AND CONCLUSIONS

The housing recovery limit states and fragility analysis presented here capture physical, social, and economic components of the housing recovery process. While the literature contains many variables that may influence recovery, this study identified four statistically significant variables as impacting time to repair completion and time to re-occupancy. The regression analysis demonstrated that social and economic variables can be strong predictors of recovery progress alongside physical variables such as damage (each being responsible for months of time until repair completion or re-occupancy); thus all three variable types – social, economic, and physical - are imperative to include in recovery analyses.

For the two regression models on repair completion and re-occupancy, having less damage, a higher income, being White, and receiving an insurance payout were significant in shortening the expected duration for repair completion. In analyzing re-occupancy, receiving NGO funds was a predictor for slower recovery progress. This may be attributed to NGO funds being a last resort, so only households with the greatest needs and fewest resources are eligible for and/or seek out NGO funds. The results of the regression analysis closely align with observations discussed for the recovery-based fragility functions, where differences are attributed to the different type of analysis, small sample sizes, and significance levels of individual predictors.

It is important to note that the information collected in the 2018 field study includes an inherent selection bias in that the data represent only households who returned sometime during the 15 months following the flood. Thus, findings should be interpreted with an understanding of the limitation of recovery prediction. These interim findings do not allow for prediction of the recovery times for all households given that some permanently dislocate to other communities. Such households may have dislocated due to the factors included in Models 1 and 2 or because of other factors. Future data collection in this community will provide for ongoing analyses of the complex process of housing recovery.

Probabilistic models, or fragility functions, of housing recovery, such as those presented here, can be used in community resilience and recovery modeling to capture a more holistic picture of recovery. One of the potentials of such integrative probabilistic models is that they can be used and understood much like damage-based fragility functions. Hence, these models both capture the complexity of recovery and present it through methods compatible and useful to engineering analysis. By shifting away from purely physical models of recovery, the reality of housing recovery is more accurately captured (i.e. housing recovery is more than repair). In turn, integrative probabilistic models of recovery improve the likelihood of identifying policy options that shorten recovery time across the community, for all households.

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