

Appendix: Overview, Design concepts, and Details (ODD)

The model description presented in this appendix follows the Overview, Design concepts, Details (ODD) protocol for describing individual- and agent-based models (Grimm et al. 2006), as updated by Grimm et al. (2020).

1. Purpose and patterns

The purpose of this model is to explain the post-disaster recovery of households residing in their own single-family homes and to predict households' recovery decisions from drivers of recovery. Herein, a household's recovery decision is repair/reconstruction of its damaged house to the pre-disaster condition, waiting without repair/reconstruction, or selling the house (and relocating). Recovery drivers include financial conditions and functionality of the community that is most important to a household. Financial conditions are evaluated by two categories of variables: costs and resources. Costs include repair/reconstruction costs and rent of another property when the primary house is uninhabitable. Resources comprise the money required to cover the costs of repair/reconstruction and to pay the rent (if required). The repair/reconstruction resources include settlement from the National Flood Insurance (NFI), Housing Assistance provided by the Federal Emergency Management Agency (FEMA-HA), disaster loan offered by the Small Business Administration (SBA loan), a share of household liquid assets, and Community Development Block Grant Disaster Recovery (CDBG-DR) fund provided by the Department of Housing and Urban Development (HUD). Further, household income determines the amount of rent that it can afford. Community conditions are assessed for each household based on the restoration of specific anchors. ASNA indexes (Nejat, Moradi, & Ghosh 2019) are used to identify the category of community anchors that is important to a recovery decision of each household. Accordingly, households are indexed into three classes for each of which recovery of infrastructure, neighbors, or community assets matters most. Further, among similar anchors, those anchors are important to a household that are located in its perceived neighborhood area (Moradi, Nejat, Hu, & Ghosh 2020; Nejat 2018).

The ratio of repaired/reconstructed houses was the main pattern for evaluating the ability of the model in reproducing households' recovery decisions from their financial conditions and recovery of their perceived neighborhood. The significant role of these drivers in post-disaster recovery has been highlighted in various studies. Financial aids provided through insurance policies, disaster loans, and public funds enhance the progress of restoration (Nejat & Ghosh 2016). Distribution of these resources affects the pattern of recovery such that regions with less assistance may experience a higher rate of relocation (Kamel & Loukaitou-Sideris 2004). Households' recovery decisions are influenced by their neighbors. Recovery of neighbors relays a positive message on the restoration of neighborhood and encourages other residents to repair/reconstruct (Nejat & Damjanovic 2012; Rust & Killinger 2006). Further, infrastructure and community assets, such as transportation systems, commercial features, schools, and healthcare facilities, provide services that are vital to the residents for addressing their regular and recovery-specific needs (Comerio 2014; Miles & Chang 2011; Ronan & Johnston 2005; Xiao, Wu, Finn, & Chandrasekhar 2018). Besides, post-disaster functionality of infrastructure and community assets influences households' perception of their neighborhood reestablishment and can impact their decisions in favor of or against repairing/reconstruction (Moradi 2020).

2. Entities, state variables, and scales

The model includes the following entities: agents representing households, agents representing community assets, and global environment representing the study area and its conditions.

Households are represented by agents called *lots*. A lot represents a single-family homeowner and is placed on the centroid of the house lot polygon drawn using the shapefile of properties. There are 74,604 agents of this type in the model. This research focuses on owner-occupied single-family detached houses. The rationale behind this selection was the prevalence of this type of housing in the United States' residential sector. Moreover, other housing types have different and complicated recovery behaviors, stemmed from their sophisticated ownership patterns, which require a different research methodology (Zhang & Peacock 2009). Table A.1 presents the state variables associated with lots.

Community assets are represented by *cass*. A *cas* is an agent located on the centroid of its associated polygon

drawn from shapefile of community assets. The model includes 135 agents of this type. Nejat et al. (2019) indexed households into three categories (infrastructure-aware, social-networks-aware, and community-assets-aware). The rationale for including cass agents is to capture the effect of recovery of community assets on recovery decisions of the community-assets-aware households. Table A.2 describes the state variables related to cass.

Several variables describe the environment. The data on the amount of money reimbursed to each zip code from the National Flood Insurance (*NFI*), FEMA Housing Assistance (*FEMA-HA*), SBA disaster loan (*SBA*), and HUD's Community Development Block Grant Disaster Recovery fund (*CDBG-DR*) and the maximum amount that could be reimbursed to a household (*cap*) are of the model inputs. This data is provided for each of the 12 residential zip codes in the study area. Another input data is the average damage to the infrastructure in every quarter. This data is used to incorporate the effect of infrastructure recovery on decisions of infrastructure-aware households (Nejat et al. 2019). Census data on liquid assets and data from HUD on Fair Market Rent are also of global variables. Other variables are those that identify probabilities and thresholds, for example, thresholds that reflect households' perception of adequate recovery of their community, probability of selecting between possible recovery options, habitability threshold, and probability of availability of vacant rental units. The state variables associated with the environment are presented in Table A.3.

The spatial extent of the model is a square of 6000×6000 square cells. With each cell (patch) representing $9.20 \text{ ft} \times 9.20 \text{ ft}$, the NetLogo world is equivalent to a total area of 109.4 square miles in the real world. The relatively fine resolution of the model was selected to accommodate the research scope regarding developing a model at the household level. The world in NetLogo does not wrap. i.e. the space is not toroidal. Each time step in the model is equivalent to one quarter of a year (three months). While coarser time steps could not adequately reflect the dynamics of recovery, finer time steps may unnecessarily increase the running time without providing additional insights.

Table A.1. State variables associated with *lots* (household agents)

Variable name	Type, units, and range	Meaning
<i>asna_i_org</i>	Integer, static; 1, 2, or 3	Households' ASNA index predicted from their attributes
<i>bbl</i>	Integer, static; positive	Borough-Block-Lot (BBL) of a house
<i>bgsf</i>	Integer, static; ft ² ; positive	Gross square footage of a house
<i>dmg_flg_y2</i>	Boolean, static; 0 or 1	A flag indicating that a house was still damaged 2 yrs after disaster (1) or not (0)
<i>fldz</i>	String, static; "A", "AE", "AO", "VE", "X", "0.2% annual chance"	Flood zone in which a house is located
<i>imp_y0</i>	Integer, static; USD; any value	Discounted improvement values of houses in the fiscal year after disaster
<i>imp_yb</i>	Integer, static; USD; any value	Discounted improvement values of houses in the fiscal year before disaster
<i>inc_25k</i>	Boolean, static; 0 or 1	Household income if it is less than \$25,000
<i>inc_50k</i>	Boolean, static; 0 or 1	Household income if it is \$25,000 - \$49,999
<i>inc_75k</i>	Boolean, static; 0 or 1	Household income if it is \$50,000 - \$74,999
<i>inc_100k</i>	Boolean, static; 0 or 1	Household income if it is \$75,000 - \$99,999
<i>inc_125k</i>	Boolean, static; 0 or 1	Household income if it is \$100,000 - \$124,999
<i>inc_150k</i>	Boolean, static; 0 or 1	Household income if it is \$125,000 - \$149,999
<i>inc_200k</i>	Boolean, static; 0 or 1	Household income if it is \$150,000 - \$199,999
<i>inc_200kplus</i>	Boolean, static; 0 or 1	Household income if it is above \$200,000
<i>p_radius</i>	Real, static; ft; positive	Radius of perceived neighborhood
<i>zp</i>	Integer, static; positive	Zip code in which a house is located

Table A.2. State variables associated with *cass* (community-asset agents)

Variable name	Type, units, and range	Meaning
<i>bbl</i>	Integer, static; positive	Borough-Block-Lot (BBL) of a community asset
<i>cas_dmg_qi</i>	Real, static; non-negative	Damage to community assets in quarter <i>i</i>

Table A.3. State variables associated with the global environment

Variable name	Type, units, and range	Meaning
<i>adq_cas</i>	Real, static; 0 to 100	Threshold for adequacy of recovery of community assets
<i>adq_infr</i>	Real, static; 0 to 100	Threshold for adequacy of recovery of infrastructure
<i>adq_nbr</i>	Real, static; 0 to 100	Threshold for adequacy of recovery of neighbors
<i>cdbg_cap</i>	Real, static; USD; positive	Maximum limit for CDBG-DR assistance
<i>cdbg_dollar_i</i>	Real, static; USD; non-negative	Dollar amount of CDBG-DR assistance available in zip code <i>i</i>
<i>fema_cap_r</i>	Real, static; USD; positive	Maximum limit for FEMA-HA
<i>fema_dollar_i</i>	Real, static; USD; non-negative	Dollar amount of FEMA-HA available in zip code <i>i</i>
<i>infra_dmg_i</i>	Real, static; non-negative	Average damage to infrastructure in quarter <i>i</i>

Variable name	Type, units, and range	Meaning
<i>insurance_cap_r</i>	Real, static; USD; positive	Maximum limit for flood insurance
<i>insurance_penetration</i>	Real, static; non-negative	Percentage of National Flood Insurance penetration
<i>net_worth_i</i>	Real, static; USD; non-negative	Discounted median net worth for household in quintile <i>i</i> of income
<i>pcnt_holding_assets_i</i>	Real, static; 0 to 100	Percent holding assets for household in quintile <i>i</i> of income
<i>r_asna</i>	Probability, static; 0 to 100	Probability of which a household's ASNA class is equal to its predicted class
<i>r_cdbg</i>	Probability, static; 0 to 100	Probability of which a household is reimbursed its eligible amount of CDBG-DR
<i>r_fema</i>	Probability, static; 0 to 100	Probability of which a household is reimbursed its eligible amount of FEMA-HA
<i>r_hbt</i>	Real, static; 0 to 100	Threshold for habitability of houses
<i>r_ins</i>	Probability, static; 0 to 100	Probability of which a household is reimbursed its eligible amount of NFI
<i>r_prds</i>	Probability, static; 0 to 100	Probability of which a household's perceived neighborhood radius is equal to its estimated value
<i>r_rent</i>	Probability, static; 0 to 100	Probability of which a household's rent power is equal to its estimated value
<i>r_rlqa</i>	Probability, static; 0 to 100	Random multiplier of a household's liquid assets considered for recovery
<i>r_sba</i>	Probability, static; 0 to 100	Probability of which a household is reimbursed its eligible amount of SBA loan
<i>r_vac</i>	Probability, static; 0 to 100	Probability of which a vacant rental unit is available
<i>r₀</i>	Real, static; 0 to 100	Probability of which buyers may decide to repair/reconstruct rather than wait/sell
<i>r₁</i>	Real, static; 0 to 100	Probability of which households may decide to wait rather than sell
<i>r₂</i>	Real, static; 0 to 100	Probability of which households may decide to recover rather than sell
<i>rnt_1bd_fyi</i>	Real, static; USD; positive	Fair Market Rent for 1-bedroom residence in fiscal year <i>i</i>
<i>rnt_2bd_fyi</i>	Real, static; USD; positive	Fair Market Rent for 2-bedroom residence in fiscal year <i>i</i>
<i>rnt_3bd_fyi</i>	Real, static; USD; positive	Fair Market Rent for 3-bedroom residence in fiscal year <i>i</i>
<i>rnt_4bd_fyi</i>	Real, static; USD; positive	Fair Market Rent for 4-bedroom residence in fiscal year <i>i</i>
<i>rnt_eff_fyi</i>	Real, static; USD; positive	Fair Market Rent for efficiency residence in fiscal year <i>i</i>
<i>sba_cap_r</i>	Real, static; USD; positive	Maximum limit for SBA disaster loan
<i>sba_dollar_i</i>	Real, static; USD; non-negative	Dollar amount of SBA disaster loan available in zip code <i>i</i>

3. Process overview and scheduling

The model is developed to simulate recovery of households within two years after Hurricane Sandy. The model includes two main processes: one related to estimating the amount of financial resources available to households for repair/reconstruction, and the other on the evaluation of recovery criteria and making the decision. Each of these processes consists of several subprocesses that are described here and more in detail in Submodels.

It was assumed that insurance settlements, FEMA-HA, and SBA loans were distributed within the first three months. These assumptions were made based on the reports and guidelines available on the distribution of financial resources in the absence of more specific data. Further, since CDBG-DR funds for post-Sandy recovery of New York city were allocated more than one year after the hurricane (HRO 2016), households were assumed to spend a share of their liquid assets in the first three months to cover the repair/reconstruction gap after receiving assistance from NFI, FEMA, SBA, but before reimbursement of CDBG-DR. Therefore, the program updates households' NFI, FEMA-HA, SBA, and liquid assets in the second time step while CDBG-DR is updated in the fifth time step. Further, while NFI, FEMA, SBA, and liquid assets are assigned in the same time step, they are updated in sequence to cover the repair/reconstruction gap after receiving preceding assistance and to avoid duplicating one amount by the other. Moreover, recovery criteria are evaluated every three months, meaning that households' decisions are updated in every time step.

Figure A.1 shows the steps of evaluating the recovery criteria and predicting households' decisions. The algorithm starts with targeting damaged houses and reimbursing financial aids to eligible households. These aids include NFI settlements, FEMA-HA, SBA loans, the share of liquid assets that households spend on recovery, and CDBG-DR assistance. The resources are reimbursed in sequence in order not to duplicate each other. Next, the model compares each households' available financial resources to the damage cost. If the financial criterion is not satisfied, i.e. the available financial resources are not enough to cover the repair/reconstruction costs, the model checks whether the house is habitable or not. If it is, the household would be expected to wait, but it also has the alternative of selling the property. If the house is uninhabitable, two additional conditions are evaluated. If the household can afford to pay for the rent of another property and a vacant rental unit is available, the options would be waiting or selling (like the previous case), but if either is not met, the only option would be selling the house.

The financial criterion is evaluated first because repair/reconstruction cannot be initiated without the availability of monetary resources. If the financial criterion is satisfied, the community criterion is evaluated. Based on the ASNA index of a household, restoration of infrastructure, neighbors, or community assets is compared to its desirable threshold. If the perceived community has adequately recovered, the household would be expected to decide in favor

of repair/reconstruction, though it would also have the alternative of selling. However, if community recovery is inadequate, the model proceeds like the situation in which the financial resources were not enough. The community criterion is built into the model to capture the important effect of recovery of perceived community on households' recovery decisions.

If a house is sold, the buyer could decide to repair/reconstruct the house or wait (or sell again). This process is to address the decisions of households that, whether their recovery criteria have been met or not, may decide to sell their property rather than to wait or repair/reconstruct.

The activation of household agents for each process is random. However, the program does not proceed to the next process once the current process is completed for all agents. For example, in the subprocess of reimbursing NFI (under the process of financial criterion evaluation), eligible household agents are selected randomly and are paid an insurance settlement. When all subprocess completed for all eligible households, the program advances to the next subprocess, i.e. reimbursing FEMA-HA.

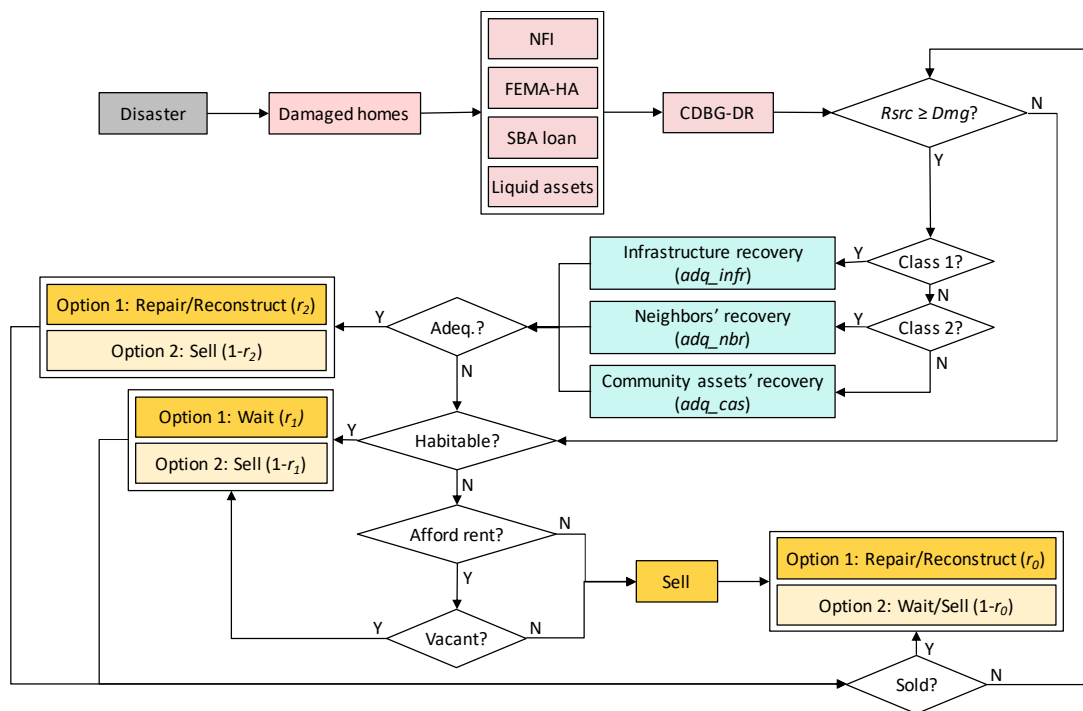


Figure A.1. RecovUS algorithm.

4. Design concepts

4.1. Basic principles

Recovery models aim to abstract and simulate the real world by including factors that affect the phenomenon of recovery. Households' recovery decisions, however, are impacted by many parameters that their complete inclusion in a single model is infeasible. Although several models for housing recovery have been developed, (de Koning & Filatova 2020; Filatova, Parker, & van der Veen 2011; Haer, Botzen, & Aerts 2016; N. Magliocca, Safirova, McConnell, & Walls 2011; N. R. Magliocca & Walls 2018; Miles 2017; Miles & Chang 2006, 2011; Nejat & Damjanovic 2012), there are still gaps in the full understanding of post-disaster recovery and of how individual, communal, and organizational decisions interact to result in the overall recovery output. Further, integrating spatial aspects of recovery into models is an essential but under-researched subject. Therefore, this model aims to bridge the gap by 1) including various types of financial resources and predict their impacts on homeowners' recovery decisions, and 2) capturing the role of post-disaster functionality of infrastructure, recovery of neighbors, and functionality of community assets in the recovery of households with heterogeneous preferences.

The current model directly involves insurance companies and public agencies by providing housing financial assistance and indirectly engages the latter via the restoration of infrastructure and community assets. Besides, the model includes spatial aspects of recovery by capturing the effect of recovery of neighbors and neighborhood community assets on households' recovery decisions. This research focuses on owner-occupied single-family detached houses. The rationale behind this selection was that housing restoration influences overall recovery of a community through a ripple effect (Nejat & Damjanovic 2012; Peacock, Dash, & Zhang 2007a, 2007b) due to its primary role in peoples' lives, constituting the major share of building stock, and its significant effect on shaping the built environment (Bratt 2002; Comerio 1998). Additionally, this type of housing was selected because of its prevalence in the United States' residential sector as well as complicated recovery behavior of other housing types stemmed from their sophisticated ownership patterns that necessitate a different set of assumptions (Zhang & Peacock 2009).

4.2. Emergence

The primary outcome of this model is the ratio of damaged houses that repair/reconstruct. This outcome emerges from how households respond to different financial and community conditions by repairing/reconstructing, waiting, or selling and from decisions of buyers for repair/reconstruction or waiting.

The maximum total amount of financial resources including FEMA-HA, SBA loan, and CDBD-DR fund, the regions in which houses may be reimbursed with NFI, and recovery progress of infrastructures and community assets are imposed to the model by input data.

4.3. Adaptation

Household agents have two adaptive behaviors: 1) they may decide to repair/reconstruct or wait, 2) they may decide to wait or sell their property. If a household sells its property, then the buyer has one adaptive behavior: decide to repair/reconstruct or wait/sell.

Households' decisions are modeled as a combination of direct and indirect objective seeking. A household first decides between the two adaptive behaviors based on whether its objective measures (recovery criteria) are met or not (see Objectives). Then, the decision between the alternatives in each adaptive behavior (repair/reconstruct or wait in the first adaptive behavior, and wait or sell in the second) is modeled using indirect objective seeking; i.e. stochastic rules cause a household to select between alternatives with a probability (frequency threshold) identified by model calibration. The threshold for deciding between repair/reconstruct or wait is named r_2 , and the threshold for selecting the wait or sell alternative is called r_1 .

Buyers' decisions are modeled as indirect objective seeking; a buyer decides in favor of repair/reconstruction (rather than the wait/sell alternative) with a probability of r_0 . This threshold is a model parameter that its value is determined by calibration.

4.4. Objectives

Households select between the adaptive behaviors using two objective measures: 1) financial resources and 2) recovery of the perceived community. The objective measure for financial resources represents the amount of money that is available to a household at the end of every time step for repair/reconstruction: $total_money = reimbursed_ins_value + reimbursed_fema_value + reimbursed_sba_value + spent_rlqa_value + reimbursed_cdbg_value$, where $total_money$ is the objective measure, $reimbursed_ins_value$ is the NFI settlement, $reimbursed_fema_value$ is the amount of FEMA-HA reimbursed to a household, $reimbursed_sba_value$ is the reimbursed SBA loan, $spent_rlqa_value$ is the amount of a household's liquid assets that is spent on repair/reconstruction, and $reimbursed_cdbg_value$ is the reimbursed CDBG-DR fund.

The objective measure that households use to evaluate the recovery of their community at the end of every time step is the ratio of recovered perceived community anchors. Perceived community anchors are identified by the ASNA index of each household (Nejat et al. 2019). Based on a household's index (1, 2, or 3), this objective measure calculates the average recovery of infrastructure ($infr_rec$), average recovery of neighbors residing within the household's perceived neighborhood radius (nbr_rec), or average recovery of community assets located within the household's perceived neighborhood radius (cas_rec).

4.5. Learning

No learning is included in the decision process.

4.6. Prediction

The objective measures for households are based on the explicit prediction that when financial conditions and community recovery are satisfactory, most households decide to repair/reconstruct their damaged houses. However, when one or both of the criteria are not met, households with habitable houses or those with uninhabitable houses who can rent another place wait in the hope of better conditions in the next time step.

Adaptive behavior of buyers is based on the implicit prediction that repair/reconstruction of many sold houses does not happen shortly after the ownership transfer and can take several months or years.

4.7. Sensing

Of their own state variables, households sense the amount of money that they need for repair/reconstruction (amount of damage), amount of their liquid assets that they will spend on repair/reconstruction, and the amount that they can pay for rent if required. Of other entities, the households sense the amount of available financial assistance (NFI, FEMA-HA, SBA loan, and CDBG-DR), availability of rental units and their cost, and recovery status of the perceived community. Households sense average recovery of infrastructure, average recovery of neighbors residing within the household's perceived neighborhood radius, or average recovery of community assets located within the household's perceived neighborhood radius depending on their ASNA index (*asna_index*) to be 1, 2, or 3. ASNA index is constant over time and space but different among households. Radius of perceived neighborhood (*p_radius*) is estimated based on a household's ASNA index with the inclusion of stochasticity. Therefore, this radius is constant over time and space but different among households, though households with the same index are more likely to have radii with closer values. Please see Initialization, Input data, and Submodels for more explanation.

4.8. Interaction

The model includes two types of interactions between agents: between households with ASNA index 2 and their neighboring households, and between households with ASNA index 3 and their neighboring community assets. Households with index 2 interact directly with the households residing in their perceived neighborhood radius to find out whether they have not been damaged by the disaster or if damaged, whether they have repaired/reconstructed or not. Households with index 3 interact directly with the community assets located within their perceived neighborhood radius to realize whether they are functioning or not. Both types of interactions are local since households sense the agents within a radius. However, this radius is different based on the index of a household and the applied stochasticity.

4.9. Stochasticity

The model uses stochasticity in five ways. First, the model uses stochasticity in the initialization of some variables including households' ASNA indexes, their perceived neighborhood radius, and liquid assets. While these variables are calculated/assumed based on households' attributes, stochasticity is also included to count for variability caused by other possible factors that have not been explicitly considered (see Initialization, Input data, and Submodels).

Second, selecting the households in each step of the model is stochastic. For example, to assign FEMA-HA, a household from the pool of eligible households is selected and reimbursed with an amount of FEMA-HA. Then, the total money available for FEMA-HA is updated by deducting the reimbursed amount and the process is repeated until the total money is exhausted or all eligible households are paid. This stochastic process allows for a more realistic simulation where delayed applications may not be paid due to the unavailability of resources.

Third, stochasticity is included in the reimbursement of financial resources. Once the amount of FEMA-HA, for example, that a household is eligible to receive is identified, the reimbursed amount is estimated as the product of the eligible amount and a random number between r_fema and 100%. This stochasticity is to account for possible factors of variability that have not been explicitly included in the model.

Fourth, the availability of rental units is partly stochastic as the model assumes that a vacant rental property is available to a household if a random number between 1 and 100 is equal or less than r_vac . This stochasticity was used to simplify the modelling of market capacity.

Finally, stochasticity is used to select between recovery alternatives of an adaptive behavior. Three parameters r_0 , r_1 , and r_2 represent the thresholds below which a household selects the first alternative of an adaptive behavior. For example, a household whose objective measures have been satisfied decides in favor of repair/reconstruction (rather than wait) if a random number between 1 and 100 is equal or less than r_2 . The use of this stochasticity is to include the nature of human decisions and to avoid deterministic decisions which contradict with the real-world observations.

4.10. Collectives

Agents do not belong to any collectives.

4.11. Observation

The purpose of the model is to simulate and predict homeowners' recovery decisions affected by financial and community conditions. Accordingly, the key output of the model is the ratio of damaged houses that are repaired/reconstructed at the end of every time step (equivalent to 3 months). Another primary output, which is mostly used for model calibration, is the ratio of repair/reconstruction predicted by the model divided by an estimation of the same ratio in the real world (estimated from tax assessment data). This ratio is calculated at the end of the 4th and 8th time steps (12 and 24 months after the disaster, respectively). These outputs are provided via monitor boxes on the interface as well as output files.

There are also other nonprimary but worth-noting outputs. The share of each ASNA index among all households is shown as a histogram on the interface. The total amount and number of NFI, FEMA-HA, SBA loan, and CDBG-DR assistance reimbursed to households, the total amount of liquid assets spent by households, the total amount of financial resources spent on repair/reconstruction, and the maximum amount of the resources among households are displayed in monitor boxes on the interface. The amount of FEMA-HA, SBA loan, and CDBG-DR fund reimbursed in each zip code can be output to files using the buttons on the interface.

5. Initialization

The model is initialized via running several submodels. The initialization is generic, though the input data are related to the recovery of Staten Island after Hurricane Sandy. Therefore, initialization of a different case uses its specific input data but applies the same initialization procedure. While this section provides a brief overview of the process, the detailed explanation of the data and submodels are provided in the Input data and Submodels sections.

Submodel *load-lots* loads the shapefile of properties using the GIS extension, draws their boundary polygons, creates household agents (lots), and assigns them the data on household attributes, Discounted Improvement Market (DIMP) values in the fiscal year before the disaster and immediately after it, and recovery status in the second post-disaster year estimated from tax assessment data.

Submodels *load-fema*, *load-sba*, and *load-cdbg* import zip-code level data on FEMA-HA, SBA loan, and CDBG-DR, respectively. Submodel *load-lqa* loads the data on percent holding assets and median net worth for each quintile i of income. Submodel *load-rent* imports HUD's Fair Market Rents (FMR) for efficiency and 1- to 4-bedroom units for two fiscal years after the disaster. Submodel *load-infra* loads data on the average quarterly damage of infrastructure, starting immediately after the disaster to eight subsequent quarters. These data are imported into the model and saved as global variables.

Submodel *load-cas* imports the shapefile of community assets using NetLogo GIS extension, creates agents representing community assets, and assigns them the data on their quarterly damage.

Submodel *asna* handles two tasks. First, with a probability of r_asna (default value = 80%), it keeps the predicted index as a household's ASNA index, but randomly assigns one of the other two indexes in the other cases. The submodel then assigns each household its radius of perceived neighborhood calculated as the product of the median radius corresponding to its ASNA index and randomness of $\pm r_prds\%$ (default value = ± 20).

Submodel *assign-rlqa* estimates the number of households that hold assets for each quintile of income by multiplying percent holding assets (from the census) in number of households in that quintile. Then, the product is applied to randomly select households whose income is in the quintile and assign them a share of their net worth (up

to r_{rlqa} %) as the maximum amount of liquid assets that they may spend on recovery. The default value for r_{rlqa} in the model is 20% (i.e. the model considers 1-20% of households' net worth as their liquid asset).

Submodel *divide-dataset* sets up the whole dataset or one of the options for training/testing the data. The application of this submodel is for the scenarios that differ in initialization. If the model is to be trained (calibrated) on the whole dataset or be applied to predict the effect of different recovery drivers, the *all* dataset is selected. If test error is to be calculated, one of the other sets is selected accordingly.

Submodel *est-bdrm* estimates the number of bedrooms for a house based on its building gross square foot. Submodel *habitability* identifies whether a house is habitable after the disaster or not. Stemmed from the FEMA's standardized degrees of damage (see the submodel *reimburse-fema* below), properties with damage less than 10% (r_{hbt}) of their pre-disaster improvement value were assumed to be habitable. Submodel *rent-power* estimates the amount that a household can afford for rent as a percentage of its income and a random number between r_{rent} to 100% (default $r_{rent} = 80\%$). Submodel *rent-afford* determines if a household with an uninhabitable house can afford to rent another residence by comparing its rent power with the FMR. Proper FMR is identified by the number of bedrooms that a household needs and the fiscal year at which the program is running. These submodels assign the generated data to the household agents.

6. Input data

The input data consist of:

1. Housing attributes including Staten Island single-family detached houses, their spatial location, level of damage caused by Hurricane Sandy, and restoration status after two years.
2. Household attributes including household income and ASNA index.
3. Financial resources including distribution of NFIP, FEMA-HA, SBA loan, CDBG-DR, and liquid assets.
4. Households' financial ability to pay for rent.
5. Damage to infrastructure and community assets and their restoration progress.

Housing attributes

Housing attributes were extracted from the New York City tax assessment data for the fiscal years 2013 to 2019 (NYC 2019a). This period corresponds to one year before Sandy (2011), disaster year (2012), and five subsequent years after the hurricane (2013-2017). Cleaning the data to include only single-family detached houses of Staten Island resulted in 74,604 houses as the input for RecovUS. Improvement market values for each house was calculated in different years by subtracting its land market value from total market value. The improvement value gives the worth of additions to the land, mainly brought in by the structure. The improvement values were further discounted back to a common time (August 2011) using monthly Consumer Price Indexes (CPIs) for housing in New York, Newark, Jersey City (BLS 2019) to have the same basis for comparison. The discounted improvement market (DIMP) values were used to estimate the damage to the properties. If the DIMP value of a house showed a decrease in the first post-Sandy year compared to the pre-Sandy year, the house was assumed damaged and the amount of damage was estimated as the difference of the pre- and post-sandy DIMP values. Additionally, once the DIMP value of a damaged house in the subsequent years reached or exceeded its pre-Sandy DIMP value, the house was assumed to have been completely restored to its pre-disaster condition. The results summarized in Table A.4 and Figure A.2 estimate that 57% of the single-family detached houses were damaged by Sandy (Y1). While this ratio dramatically decreased in the next year (Y2), damage continued to exist by the sixth year of the analysis period, i.e. 2017 (Figure A.2.a). It is worth to mention that although the values were analyzed for seven years to investigate the restoration progress, RecovUS needs the data of three years only (Y0 to Y2) since the model is to simulate the recovery in two years after the disaster. The data were then joined to the shapefile of the lots' polygons (NYC 2019b) using ArcGIS Desktop 10.3.1 (ESRI 2015) to provide the input file for RecovUS (Figure A.3). Since RecovUS is intended to simulate two post-disaster years, the DIMP values before the disaster (Y_0) and two years after the disaster (Y_2) are of interest to the model. Another housing attribute as input to the model is gross square footage (see Rent).

Table A.4. Estimated damage and recovery.

Year	% Damaged	Mean DIMP value	Median DIMP value
Y0	-	178,322	160,848
Y1	57.16	173,035	159,706
Y2	12.08	247,845	226,320
Y3	9.83	251,672	229,193

Y4	7.75	264,961	239,501
Y5	5.28	256,591	233,337
Y6	3.58	267,548	246,116

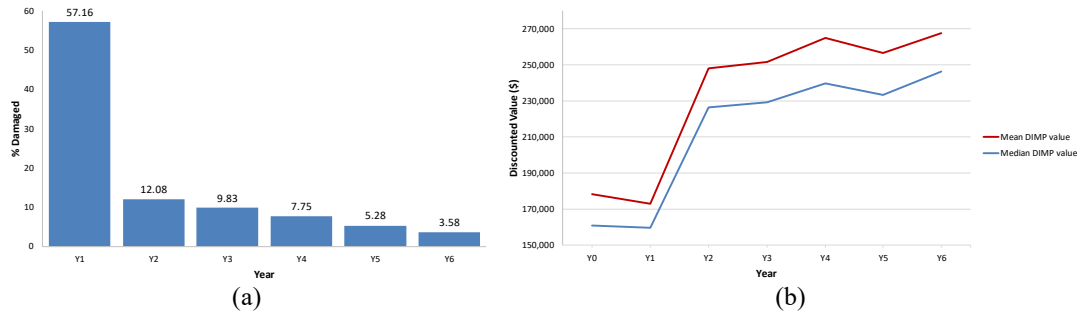


Figure A.2. Estimated damage: (a) ratio of damaged single-family detached houses; (b) changes in mean and median of DIMP values.

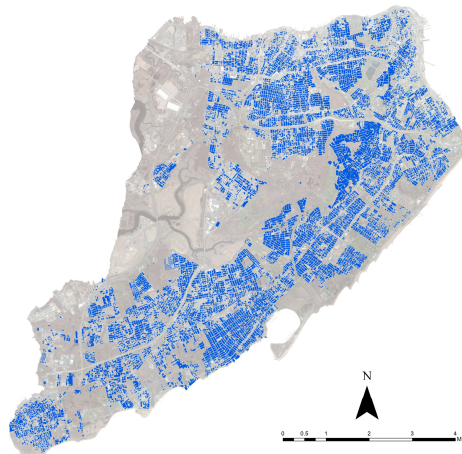


Figure A.3. 74,604 single-family detached houses inputted to the program.

Household attributes

Household income and householder ASNA index are of the input data. Income is applied to estimate household liquid assets and renting power and to control the eligibility criteria for financial assistance. Furthermore, household income together with the population density of county of residence, householder educational attainment, and householder race is used to estimate ASNA indexes. This estimation was based on the latent class regression model introduced by Nejat et al. (2019) in which the odds of belonging to index 2 versus index 1 and belonging to index 3 versus index 1 are estimated using five significant covariates: logarithm of population density (LPD), householder education (HED.3 and HED.4), race (White), and income (INC.3).

Table A.5. Latent class regression coefficients (Nejat et al. 2019)

	Intercept	LPD	HED.3 ^a	HED.4 ^b	White	INC.3 ^d
Index 2	-2.885	-1.614	8.008	5.904	4.135	-5.579
Index 3	-1.353	-0.367	1.117	0.819	1.092	-1.115

The reference category is index 1.

^a Undergraduate degree

^b Graduate or professional degree

^d \$100,000 and up

While population density is simply calculated, data on the other three covariates are not generally available at the household level. In the current research, these data were synthetically generated via Iterative Proportional Fitting (IPF) of the 2013 census data on household income, educational attainment, and race (USCB 2013a, 2013b, 2013c).

The code, developed by the authors in NetLogo 6.1.0, generated household-level education and race by randomly selecting households in each block group and assigning their characteristics proportional to the census ratios for that block group. A block group is a contiguous area generally having a population size between 600 and 3,000 people and 240 240 and 1,200 housing units. Block group is the smallest geographic unit for which the United States Census Bureau tabulates sample data. A higher-level geographic delineation is census tract (USCB 2019, 2020).

Generation of household-level income was partly different. Since the total market value of the properties were available from tax assessment data, a positive relationship was assumed between income and property value of 90% of the households. In each block group, 90% of the households were randomly selected, sorted based on their houses' pre-Sandy total market value, and assigned an income level proportional to the census ratios for that block group such that higher incomes owned the more expensive properties. For the other 10% of the households, income was assigned randomly like education and race.

After generating the household-level attributes from the census block-group level data, the results were validated by aggregating the income and education of white householders to tract level and comparing them to similar data from the census (USCB 2013d, 2013g). Census tract is a higher-level geographic delineation that consists of one or several block groups and contains 1,200 to 8,000 people, with an optimum size of 4,000 people and 1,600 housing units (USCB 2019, 2020). Generation, aggregating, and comparison of the attributes were repeated 1,000 times. The set of household-level attributes that yielded the minimum Mean Square Error (MSE = 0.001909) was selected as the households' attributes (Moradi 2020; Moradi & Nejat 2020).

To reduce the runtime of RecovUS, ASNA indexes were estimated from attributes in advance (rather than estimating within the program) using the following equations:

$$\Pr(Y_i = 2) = e^{\beta_2 \cdot X_i} / (1 + \sum_{k=2}^3 e^{\beta_k \cdot X_i}) \quad (\text{A.1})$$

$$\Pr(Y_i = 3) = e^{\beta_3 \cdot X_i} / (1 + \sum_{k=2}^3 e^{\beta_k \cdot X_i}) \quad (\text{A.2})$$

$$\Pr(Y_i = 1) = 1 - (\Pr(Y_i = 2) + \Pr(Y_i = 3)) \quad (\text{A.3})$$

where $\Pr(Y_i = j)$ is the probability of household i belonging to ASNA index j , β_k is the set of latent class regression coefficients associated with ASNA index k (Table A.5), and X_i is the set of covariates associated with household i . For each household i , class membership probabilities $\Pr(Y_i)$ are estimated. The household is then indexed according to the highest estimated probability.

Households' income and ASNA index were joined to the shapefile of the lots using ArcGIS to provide the input file to the model. The ASNA index identifies the community anchors that matter most to a household with specific characteristics. Additionally, the index is used to estimate a geographical proxy for the perceived neighborhood within which the community anchors are deemed important. Table A.6 shows the median of perceived neighborhood area (classified by the ASNA indexes) that were calculated from the data collected by Nejat (2018). In the absence of more detailed data, a circular shape was assumed for the perceived neighborhoods and the median perceived neighborhood radii were calculated accordingly. The program assigns each household its radius of perceived neighborhood calculated as the product of the median radius corresponding to its ASNA index and a randomness of $\pm 20\%$.

Table A.6. Median area and median radius of perceived neighborhood

ASNA index	Median perceived area (m ²)	Median perceived radius (m)	Median perceived radius (ft)
1	565150.64	424.14	1391.53
2	457425.71	381.58	1251.90
3	516833.02	405.60	1330.72

Financial resources

The National Flood Insurance Program (NFIP) paid 32,360 losses (totaling \$8.80 billion) in the 16 states impacted by Hurricane Sandy (III 2019a, 2019b). However, higher-resolution data on the distribution of settlements is not publicly available to the best of the authors' knowledge. Therefore, FEMA's Flood Insurance Rate Map (FIRM) (FEMA 2015) was used to estimate this data. While flood insurance in areas with low to moderate risk of flooding

is recommended to owners and renters, it is mandatory for all homeowners who are residing in high-risk areas and have mortgaged their properties with federally-regulated or insured lenders (FEMA 2019a; Shawnee County 2019). As Figure A.4.a shows, Staten Island consists of six zones from which three zones are at high risk of flooding: A, AE, and VE. These zones correspond to the Special Flood Hazard Areas (SFHA) with a 1% annual chance of flooding, i.e. below the limits of the 100-year floods (FEMA 2019b; Shawnee County 2019). The households' dataset (Figure A.3) was spatially joined to the shapefile of the flood zones to assign the zone tags and identify the houses located in high-risk flood areas. As of 2013, 71.2% of Staten Island owner-occupied housing units had mortgage (USCB 2013f). Therefore, insurance penetration was assumed 80% to accommodate mortgaged and a share of non-mortgaged properties insured. The maximum limit for flood insurance was calculated by discounting the NFI cap, i.e. \$250,000 (III 2018, 2019a) to the base date (August 2011). Based on insurance guidelines, this research assumes that insurance settlement was reimbursed within the first 3 months after Sandy.

FEMA approved \$1.01 billion for 117,643 Individual Assistance (IA) applications under the Individuals and Households Program (IHP) in the 13 counties of New York State affected by Sandy (FEMA 2012). Figure A.4.b shows the distribution of the IHP assistance at the zip-code level (FEMA 2019c) which totals the amounts for repair/replacement, rental, and other needs assistance. As shown, the east and south shores had the major share of applicants and reimbursements which indicates the severity of damage in these regions. The data in the interest of this study is the amount of FEMA-HA reimbursed to single-family households for repair/replacement. However, since FEMA does not categorize the payment based on housing type, the percentages of single-family houses in each zip code (USCB 2013h) were used to estimate the share of repair/replacement HA to these properties. The amounts were also discounted back to the base date (August 2011) to have the same basis for comparison. The results are presented in Table A.7 (column a). The maximum limit of FEMA-HA was assumed \$33,000 (FEMA 2019d) and was discounted back to the base date. FEMA's home repair assistance is not intended to return a home to its pre-disaster condition but to make it safe, sanitary, and functional (FEMA 2016a, 2016b, 2017). In order to quantify *safe, sanitary, and functional*, FEMA's standardized degrees of damage were applied. FEMA classifies level of damage into four categories of affected, minor, major, and destroyed, among which only *affected* is habitable (FEMA 2016a). Accordingly, the affected level was considered as the safe, sanitary, and functional level. However, since a clear quantitative threshold between affected and minor has not been explicitly provided, 10% of pre-Sandy DIMP value was assumed as the threshold. FEMA-HA was assumed to be reimbursed within the first 3 months but after the NFI in order not to duplicate the amounts paid by insurance (FEMA 2018).

As of November 2013, SBA approved 32,542 disaster home loans, totaling \$2.1 billion (OIG 2016). Figure A.4.c shows the amount of disaster loans (consisting of real estate and content) approved at each zip code (SBA 2014). Like FEMA assistance, the east and south shores received the major share of loans. The real-estate share of SBA loan approved for single-family houses was used by the model. Moreover, since the SBA data does not specify the housing type, the percentage of single-family houses in each zip code was used to estimate the required data. The amounts were further discounted back to the base date (Table A.7 - column b). Further, the maximum limit of SBA disaster loan for repair/replacement, i.e. \$200,000 (SBA 2018b), was discounted back to the base date. SBA disaster loan may be used if insurance and FEMA assistance do not fully cover the damage cost (SBA 2018a). Therefore, SBA loan was assumed to be reimbursed within the first 3 months, but after NFI and FEMA-HA. Eligibility of households for SBA loan is evaluated based on a combination of household income and credit score (SBA 2018c). However, since to the best of the authors' knowledge, a formal instruction has not been publicly provided, households with annual income of \$50,000 or more who still need recovery assistance after being paid by the NFIP and FEMA-HA were assumed eligible for SBA loan.

Another type of recovery assistance is the CDBG-DR fund. CDBG-DR assistance is to help with recovery needs that have not been met by other assistance programs (HUD 2017). Build It Back program is the local CDBG-DR authority that helps with post-Sandy recovery of homeowners, landlords, renters, and tenants in New York City (NYC 2018). The reimbursements associated with the Build It Back program started in early 2014, more than one year after the hurricane (HRO 2016). Distribution of CDBG-DR funds to single-family houses as of June 30, 2019, is depicted in Figure A.4.d (NYC 2019c). Like FEMA assistance and SBA loan, east and south shores received the major share of the CDBG-DR fund. The amounts were discounted back to the base date (Table A.7 - column c). In the absence of explicit information, the maximum limit for CDBG-DR was assumed equal to the average of discounted CDBG-DR funds reimbursed among Staten Island single-family applicants, i.e. \$140,000. City of New York was required to expend at least 50 percent of its CDBG-DR funds on low-and moderate-income populations, i.e. households with income equal or less than 80% of the Area Median Income (AMI) for the region (NYC 2014). Since the 2013 AMI for the five counties of New York City (Bronx, Kings, Queens, New York, and Richmond) was

Appendix to: Moradi, Saeed and Nejat, Ali (2020) 'RecovUS: An Agent-Based Model of Post-Disaster Household Recovery' Journal of Artificial Societies and Social Simulation 23 (4) 13 <<http://jasss.soc.surrey.ac.uk/23/4/13.html>>. doi: 10.18564/jasss.4445

\$57,001 (USCB 2013i), households with annual income equal or less than $0.8 \times \text{AMI} = \$45,601$ were prioritized by the model.

Table A.7. Financial assistance to single-family houses (discounted USD): (a) FEMA-HA for repair/replacement; (b) SBA disaster loan for real estate; (c) CDBG-DR assistance.

<u>Zip code</u>	<u>(a) FEMA-HA</u>	<u>(b) SBA loan</u>	<u>(c) CDBG-DR</u>
10301	96,470	89,790	833,851
10302	63,849	68,534	432,610
10303	161,144	93,886	1,768,411
10304	48,761	141,366	877,622
10305	3,143,263	5,579,297	55,034,874
10306	12,408,726	20,612,502	177,627,236
10307	759,883	2,300,454	6,261,660
10308	772,210	1,457,226	14,265,580
10309	168,574	310,741	1,032,531
10310	77,207	130,872	580,245
10312	636,364	1,172,095	4,745,478
10314	160,083	214,430	1,483,167

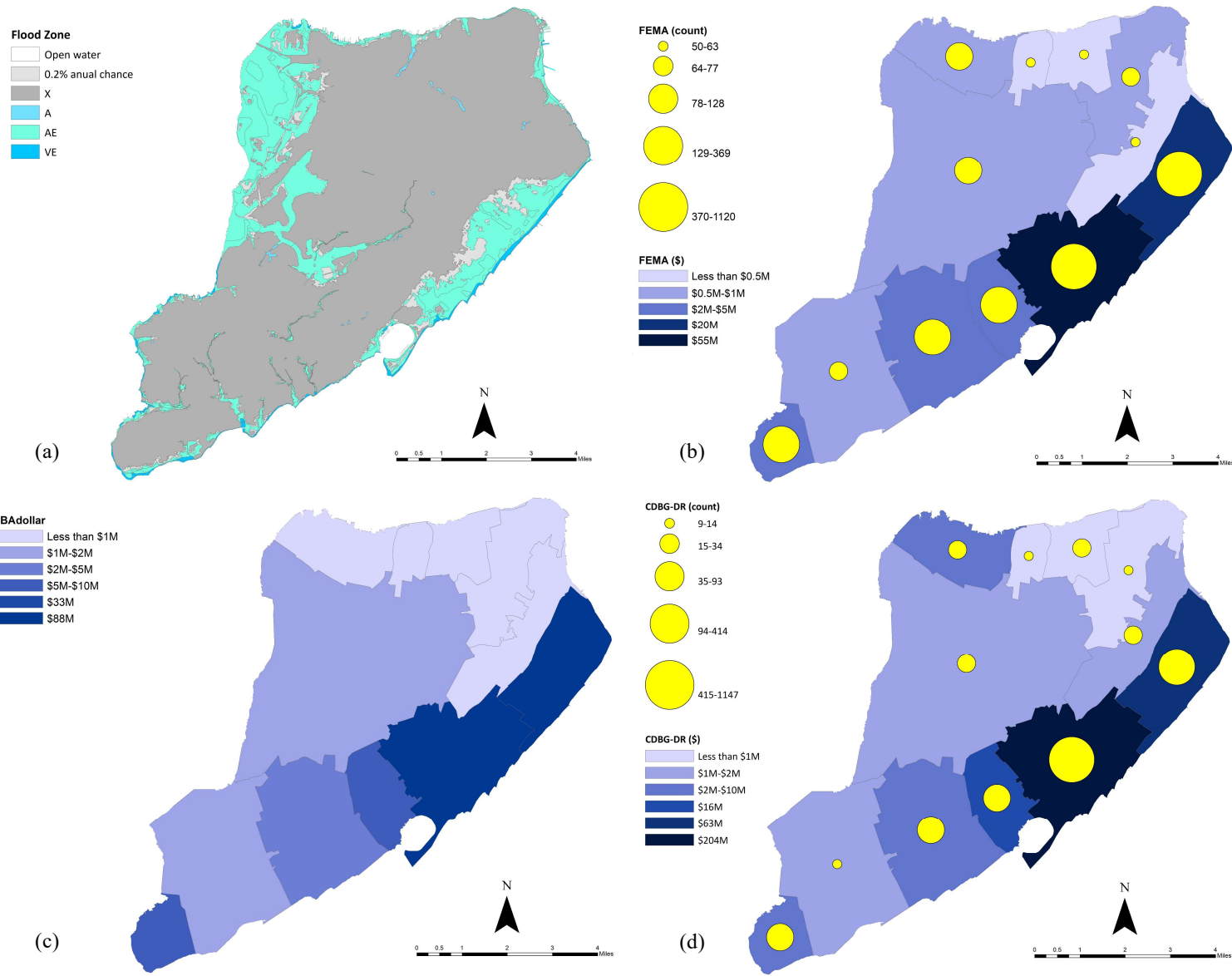


Figure A.4. Financial assistance to single-family houses: (a) FEMA flood zones; (b) FEMA IHP assistance; (c) SBA disaster loan; (d) CDBG-DR assistance

The 2013 census data on households' wealth was used (USCB 2014) to estimate the share of liquid assets that a household may consider for recovery. Given an attribute such as household income, householder race, householder age, or highest educational attainment in the household, the census data gives an estimation of the median and mean values of household assets and percent of households holding assets. In this research, household income was selected to obtain the median net worth and percent holding assets. The median net worth was discounted back to the base date (Table A.8). Since after Sandy, the first round of CDBG-DR was reimbursed in early 2014 (HRO 2016), households were assumed to spend a share of their net worth (1-20%, see *assign-rlqa* below) in the first three months (before CDBG-DR) but after NFI, FEMA-HA, and SBA loan.

Table A.8. Household median net worth (discounted USD) and percent holding assets

Household income	Median net worth	% holding assets
Lowest quintile	3,484	71.5
Second quintile	23,655	87.2
Third quintile	63,595	93.3
Fourth quintile	138,090	96.2
Highest quintile	401,930	98.0

Rent

According to the model algorithm, if recovery criteria are not met, a household will have the option of waiting. If a household decides to wait while the house is uninhabitable, it will have to rent another residence. Stemmed from the FEMA's standardized degrees of damage, properties with damage above 10% of their pre-disaster improvement value were assumed to be uninhabitable. In this case, RecovUS checks whether the household can afford to pay for rent by comparing its financial power to the amount of rent.

Household financial power for rent was estimated as the product of 40% of household income and a random number less than 100%. Estimation of the 40% ratio was based on the 2013 census data on gross rent as percentage of household income in Staten Island (USCB 2013e). This data gives the number of surveyed households (Count) along with the share of income that they spent on rent (Table A.9). For example, 3502 of the survey households spent 10% to 14.9% of their income on rent. Weighted average of rent as the percentage of income was calculated using the data and considering the upper bound of rent intervals (e.g. 14.9% for the 10%-14.9% interval) and number of households in each interval (e.g. 3502). The rationale behind selecting the upper bound (rather than the midpoint, for example) was to accommodate the possible effect of disaster in inflating rents (FEMA 2016b) due to supply-demand imbalance. The weighted average was calculated to be equal to 38.54%. It is worth noting that a share of 30% of yearly income is commonly considered as the affordable rent in normal conditions (LendKey 2015; Quintana 2018). Therefore, in post-disaster conditions where prices can be inflated, the larger ratio of 38.54% is reasonable. This value was rounded up to 40% and was considered as the *base* percentage. Additionally, the percentage for each household was multiplied by a random number between r_{rent} and 100% (default $r_{rent} = 80\%$) to account for possible factors of variability that have not been explicitly included in the model. Therefore, the program estimates the rent power of each household by multiplying its income (midpoint of the income interval synthesized by IPF) by 40% by a random number between r_{rent} and 100%.

Table A.9. Gross rent as a percentage of household income, Staten Island (USCB 2013e).

Rent as % of household income	Count
Less than 10.0 percent	2233
10.0 to 14.9 percent	3502
15.0 to 19.9 percent	5825
20.0 to 24.9 percent	5576
25.0 to 29.9 percent	4255
30.0 to 34.9 percent	3945
35.0 to 39.9 percent	2697
40.0 to 49.9 percent	3845
50.0 percent or more	15474

The amount of rent was estimated using the HUD's Fair Market Rent (FMR) for Staten Island (HUD 2019). Table A.10 shows the FMR in fiscal years 2013 and 2014 per number of bedrooms. To identify the proper FMR for each household, it was assumed that a household will need a rental property with the same number of bedrooms as its primary home. Housing characteristics, reported in the tax assessment data (NYC 2019a), were applied to estimate the number of bedrooms. However, since this data contains gross square footage of buildings rather than number of

bedrooms, the number of bedrooms in a house was estimated from its gross square footage using various space planning criteria and guidelines (APA 1952; DoD 2015). Table A.11 shows the estimated equivalencies. Given the number of bedrooms of a household's pre-disaster residence and FMRs, the corresponding amount of rent is included by the program.

Table A.10. HUD's Fair Market Rents, Staten Island (HUD 2019).

Fiscal year	Monthly rent (\$)				
	Efficiency	1-bedroom	2-bedroom	3-bedroom	4-bedroom
2013	1,191	1,243	1,474	1,895	2,124
2014	1,163	1,215	1,440	1,852	2,075

Table A.11. Estimated equivalency between gross square feet and number of bedrooms

Gross sq. ft	No. of bedrooms
Less than 750	Efficiency
Equal or greater than 750 but less than 1,000	1-bedroom
Equal or greater than 1,000 but less than 1,150	2-bedroom
Equal or greater than 1,150 but less than 1,400	3-bedroom
Equal or greater than 1,400	4-bedroom

Infrastructure and community asset

Qualitative reports were used to estimate quantitative values for damage and restoration of infrastructure and community assets. The east and west shores of Staten Island, which correspond to the regions with greater inundation depth (Figure A.5.a), were damaged most by Sandy (Figure A.5.b) (NYC 2013).

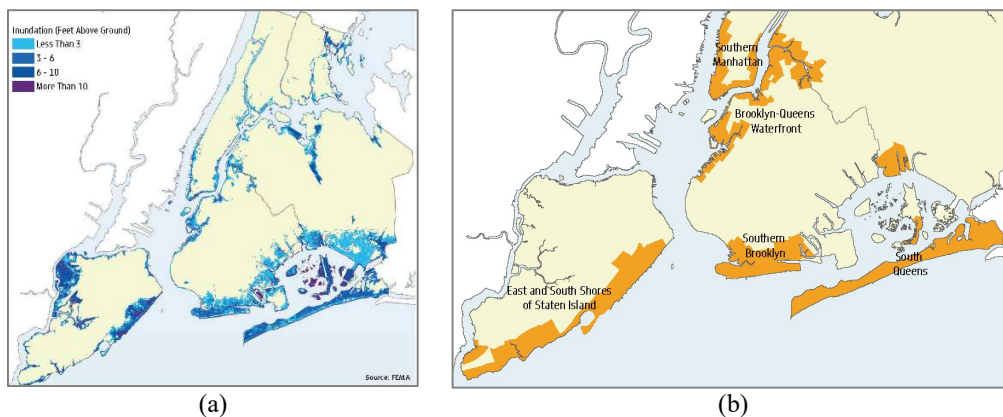


Figure A.5. Hurricane Sandy: (a) inundation depth; (b) most-damaged neighborhoods (NYC 2013)

Infrastructure-aware households (ASNA index 1) are characterized by transportation (e.g. highways and streets) and geographical features (e.g. bodies of water and terrain types) (Nejat et al. 2019). A report published by the City of New York lists the important infrastructures and community assets and qualitatively explains what happened in Hurricane Sandy (NYC 2013). For instance, the report describes the important transportation infrastructure: “The area’s transportation assets include Hylan Boulevard. Running the length of the shoreline—approximately 14 miles, from the North Shore neighborhood of Rosebank to the South Shore neighborhood of Tottenville—the roadway is highly trafficked, with 44,000 vehicles and 32,000 bus riders traveling it on a typical weekday...”; “Another transportation asset on the East and South Shores is the SIR, a 14-mile commuter rail line operated by the Metropolitan Transportation Authority (MTA)...”; “Yet another transportation corridor in the area is Father Capodanno Boulevard...” (NYC 2013). Then, it explains what happened in Sandy: “As for the area’s transportation assets, Hylan Boulevard was inundated in many areas during Sandy, causing severe delays in express and local bus service. Major damage also occurred at the SIR’s operations and maintenance facilities, limiting service in the days after the storm (ultimately, full service was only restored in mid-December)” (NYC 2013). These descriptions were used to estimate the damage to the infrastructure in every three months after Sandy. For example, it was assumed that Hylan Boulevard was 80% unfunctional immediately after the hurricane but was completely restored within the

first 3 months (i.e. damage = 0). Table A.12 summarizes the results. Since the items in the report are major infrastructures that affected most of the residents, the average damage to the infrastructure system (rather than individual infrastructures) was calculated and fed in RecovUS. The estimated damage is also consistent with other documents that report complete recovery of transportation infrastructure in two months (Kaufman & Shaby 2013).

Table A.12. Estimated damage to infrastructure

Infrastructure	Months after Hurricane Sandy								
	0	3	6	9	12	15	18	21	24
TRA: Hayden Blvd.	0.8	0	0	0	0	0	0	0	0
TRA: SIR	0.8	0	0	0	0	0	0	0	0
TRA: Father Capodanno Blvd.	1	0	0	0	0	0	0	0	0
GEO: Bluebelt	1	0.5	0	0	0	0	0	0	0
Average damage	0.9	0.125	0	0	0	0	0	0	0

A similar approach was applied to estimate the damage to the community assets, i.e. the anchors which are preferred by households of index 3. As an example, the report mentions Hylan Boulevard as a major commercial location: “A primary commercial corridor for both the East and South Shores is Hylan Boulevard, a major north-south artery...” (NYC 2013). Then, it explains the effect of Sandy: “The Hylan Boulevard commercial corridor, roughly between Seaver Avenue and New Dorp Lane in the East Shore, was flooded with many businesses, including large-format retailers, forced to close for days.” (NYC 2013). Accordingly, it was assumed that the commercial centers and retail stores along Hylan Boulevard, between Seaver Avenue and New Dorp Lane, were 100% damaged/unfunctional after the disaster. However, since they were closed “for days” (not months), it was assumed that they were completely restored at the end of the 3rd month after Sandy. This procedure resulted in the estimation of damage and recovery for 135 community assets. The data were then joined to the community assets shapefile (NYC 2019b) to obtain their spatial location (Figure A.6). RecovUS evaluates recovery of community assets for index-3 households based on the geographic location of the assets since they were assumed to mostly serve the local residents.

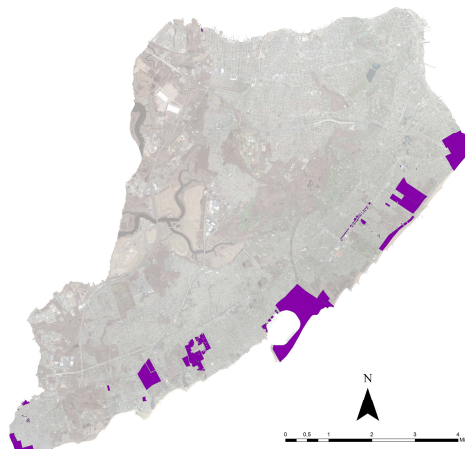


Figure A.6. Community assets on the east and south shores affected by Hurricane Sandy

7. Submodels

The model is implemented by two major submodels: *setup* and *go*. Submodel *setup* loads the data and initializes the environment. Once setup is completed, *go* implements the program in 8 time-steps each of which represents a 3-month interval.

Submodel setup

setup consist of several sub-submodels: *load-lots*, *load-fema*, *load-sba*, *load-cdbg*, *load-lqa*, *load-rent*, *load-infra*, *load-cas*, *asna*, *assign-rlqa*, *divide-dataset*, *est-bdrm*, *habitability*, *rent-power*, and *rent-afford* (Figure A.7).

Since these submodels were described mostly in Initialization and Input data, only complementary explanations and pseudocodes are presented here.

```
to setup
  load-lots
  load-fema
  load-sba
  load-cdbg
  load-lqa
  load-rent
  load-infra
  load-cas
  asna
  assign-rlqa
  divide-dataset
  est-bdrm
  habitability
  rent-power
  rent-afford
end
```

Figure A.7. *setup* pseudocode

load-lots

Data on Staten Island houses were mined from New York City tax assessment data (NYC 2019a). The submodel *load-lots* loads the shapefile, draws the property polygons, creates household agents (*lots*), and assigns them the data. The submodel uses NetLogo GIS Extension to load the shapefile of Staten Island single-family detached houses and projects it to *NAD 1983 StatePlane New York Long Island* spatial reference. Each polygon is drawn as a set of patches which are colored in red if the house was damaged by Sandy and green if not. The color scheme has a visualization purpose and does not carry any value in the calculation process. As explained before, a house is assumed damaged if its post-Sandy DIMP value showed a decrease compared to its pre-Sandy value. Further, the damage cost that the household needs to provide for recovery is calculated as the difference of the mentioned values.

Then, an agent is created for each house and placed on the polygon's centroid to represent the household. Finally, discounted improvement values in the fiscal year before Sandy and immediately after Sandy, the observed recovery of the lot in the second year after Sandy, household income, and its ASNA index are assigned to the agent from the attribute table joined to the imported shapefile. The pseudocode of the submodel has been provided in Figure A.8. Figure A.9 shows the 74,604 lots imported by the submodel. For a more detailed explanation please see Input data.

```
to load-lots
  ;;project
  coordinate-system = NAD_1983_StatePlane_New_York_Long_Island_FIPS_3104_Feet.prj
  ;;load shapefile
  lots_dataset = lots_shapefile.shp

  ;;draw the lots and color them based on damage
  for i = 1 to 74604
    draw lots_dataset(i)
    if dmg_value(i) > 0
      color = red
    else
      color = green
  ;;sprout an agent at centroid of each polygon and assign its attributes
  sprout 1 lot
    assign attributes
end
```

Figure A.8. *load-lots* pseudocode

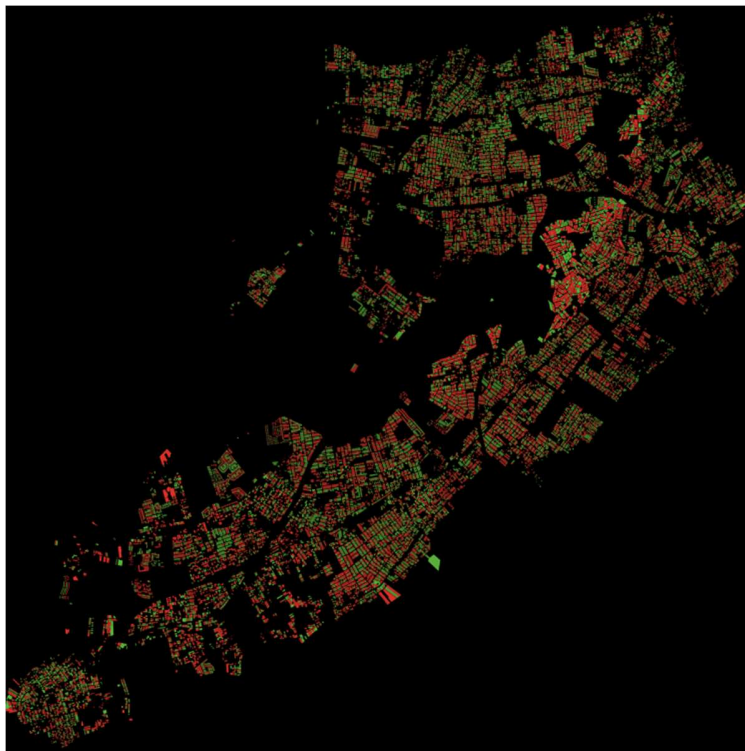


Figure A.9. Staten Island single-family detached houses imported by the model

load-fema

load-fema imports zip-code level data on the discounted amount of FEMA-HA (Figure A.10). Description of the data has been provided in Input data.

```
to load-fema
  for i = 10301 to 10310, 10312, 10314 ;;zip codes
    fema_dollar(i) = file-read ;;total amount of fema-ha available in zip code i
  end
```

Figure A.10. *load-fema* pseudocode

load-sba

load-sba loads the data on the discounted amount of SBA loan for real estate in each zip code (Figure A.11). Description of the data has been provided in Input data.

```
to load-sba
  for i = 10301 to 10310, 10312, 10314 ;;zip codes
    sba_dollar(i) = file-read ;;total amount of sba loan available in zip code i
  end
```

Figure A.11. *load-sba* pseudocode

load-cdbg

load-cdbg imports the data on the discounted amount of CDBG-DR in each zip code (Figure A.12). Description of the data has been provided in Input data.

```
to load-cdbg
  for i = 10301 to 10310, 10312, 10314
    cdbg_dollar(i) = file-read ;;total amount of cdbg-dr available in zip code i
  end
```

Figure A.12. *load-cdbg* pseudocode

load-lqa

load-lqa imports data on percent holding assets and discounted median net worth for each income quintile (Figure A.13). Description of the data has been provided in Input data.

```
to load-lqa
  foreach quintile i = 1 to 5
    pctnt_holding_assets(i) = file-read ;;holding assets
    net_worth(i) = file-read ;;median net worth
  end
```

Figure A.13. *load-lqa* pseudocode

load-rent

load-rent imports HUD's Fair Market Rents for efficiency, and 1- to 4-bedroom units for fiscal years 2013 and 2014 (Figure A.14). Description of the data has been provided in Input data.

```
to load-rent
  for year i = 2013 to 2014
    rnt_eff_fy_i = file-read ;;fair market rent for efficiency residence
    rnt_1bd_fy_i = file-read ;;fair market rent for 1-bedroom residence
    rnt_2bd_fy_i = file-read ;;fair market rent for 2-bedroom residence
    rnt_3bd_fy_i = file-read ;;fair market rent for 3-bedroom residence
    rnt_4bd_fy_i = file-read ;;fair market rent for 4-bedroom residence
  end
```

Figure A.14. *load-rent* pseudocode

load-infra

load-infra imports the data on the average quarterly damage of infrastructure, starting immediately after Sandy to eight subsequent quarters (Figure A.15). Description of the data has been provided in Input data.

```
to load-infra
  for i = 0 to 8
    infra_dmg(i) = file-read ;;average infrastructure damage in quarter i
  end
```

Figure A.15. *load-infra* pseudocode

load-cas

Similar to *load-lots*, *load-cas* imports the shapefile of community assets, creates agents representing community assets, and assigns data on their quarterly damage (Figure A.16). Description of the data has been provided in Input data.

```
to load-cas
  ;;project
  coordinate-system = NAD_1983_StatePlane_New_York_Long_Island_FIPS_3104_Feet.prj
  ;;load shapefile
  cass_dataset = cass_shapefile.shp

  ;;draw the lots and color them based on damage
  for i = 1 to 135
    draw cass_dataset(i)
    if dmg_value(i) > 0
      color = red
    else
      color = green
    ;;sprout an agent at the centroid of each cas polygon
    sprout 1 cas
    assign attributes
  end
```

Figure A.16. *load-cas* pseudocode

asna

asna identifies the ASNA index and perceived neighborhood of a household based on the assumptions and data provided in Initialization and Input data. Figure A.17 presents the pseudocode.

```

to asna
  ask lots
  ;;assign asna class by including randomness
  if ((random 100) + 1) < r_asna
    asna_index = asna_i_org
  else
    if asna_i_org = 1
      if ((random 100) + 1) < 80
        asna_index = 2
      else
        asna_index = 3
    if asna_i_org = 2
      if ((random 100) + 1) < 80
        asna_index = 1
      else
        asna_index = 3
    if asna_i_org = 3
      if ((random 100) + 1) < 50
        asna_index = 1
      else
        asna_index = 2

  ;;assign radius of perceived neighborhood
  rprd_rt = ((100 + r_prds) - (random (2 * r_prds + 1))) / 100
  if asna_index = 1
    p_radius = rprd_rt * (1391.53 / patch-gis-scale)
  if asna_index = 2
    p_radius = rprd_rt * (1251.90 / patch-gis-scale)
  if asna_index = 3
    p_radius = rprd_rt * (1330.72 / patch-gis-scale)
end

```

Figure A.17. *asna* pseudocode

assign-rlqa

assign-rlqa (Figure A.18) assigns households a share of their net worth as the amount of liquid assets that they consider for recovery. The assumptions and data are presented in Initialization and Input data

```

to assign_rlqa
  for i = 1 to 5
    quintile_no (i) = (pcnt_holding_asset(i) / 100) * count lots with income = quintile (i) ;;number of
    households holding assets w/ income in quintile i
  ask quintile_no(i) of lots with income = quintile(i)
    rlqa_rt = random (r_rlqa + 1) / 100 ;;randomness
    rlqa(j) =rlqa_rt * net_worth(i) ;;recovery liquid assets
end

```

Figure A.18. *assign-rlqa* pseudocode

divide-dataset

Once the model is calibrated using the whole dataset, generalizability of the model is evaluated using the k -fold cross-validation method ($k = 4$). The submodel *divide-dataset* (Figure A.19) sets up the dataset that the program uses in the next steps: all data or one of the 4 training or test sets (9 options). The submodel divides the dataset into 4 subsamples, constituting four training and test sets. Since RecovUS captures spatial aspect of recovery by evaluating recovery of neighbors and community assets, subsamples are four geographic regions of the dataset (zip codes) with almost the same number of damaged houses rather than completely random sparse samples. Table A.13 and Figure A.20 show the sets.

```

to divide-dataset
  for i = 1 to 4
    if selected_dataset = train(i)
      ask lots in test(i)
      die
    if selected_dataset = test(i)
      ask lots in train(i)

```

```
end
die
```

Figure A.19. *divide-dataset* pseudocode

Table A.13. Training and test sets for *k*-fold cross-validation

Dataset	Train		Test	
	Count	Ratio (%)	Count	Ratio (%)
All	42645	100.00	-	-
Set 1	30771	72.16	11874	27.84
Set 2	32617	76.48	10028	23.52
Set 3	31430	73.70	11215	26.30
Set 4	33117	77.66	9528	22.34

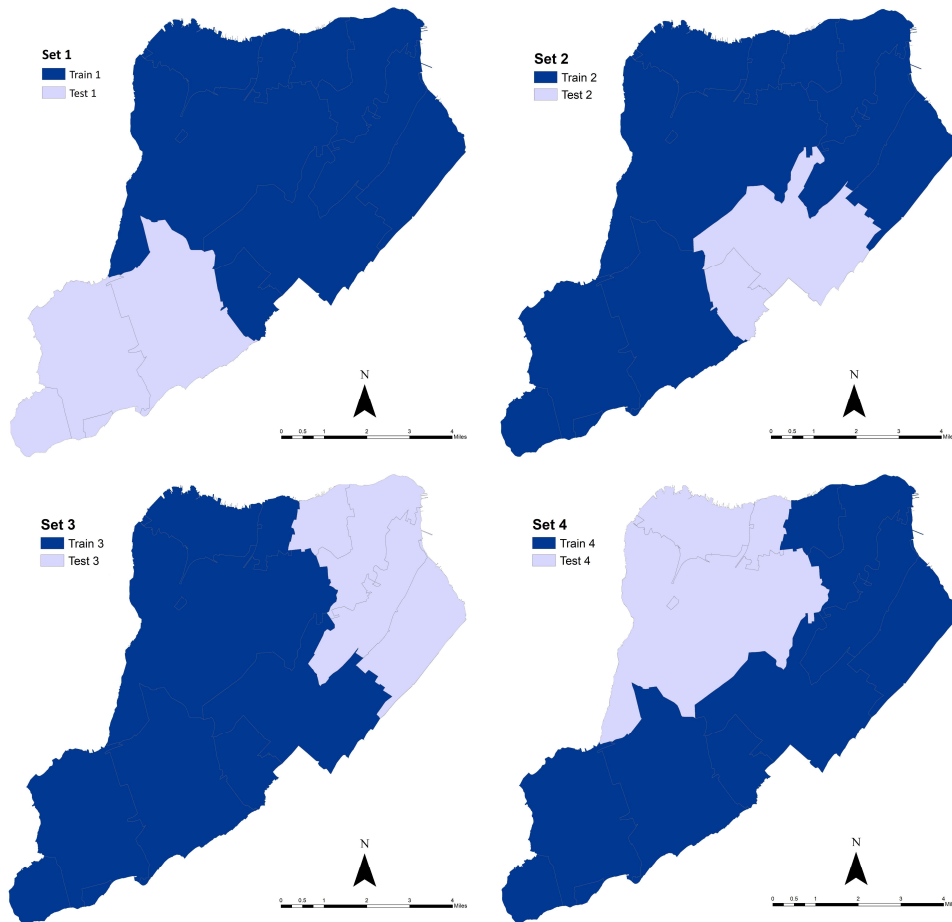


Figure A.20. Training and test sets for *k*-fold cross-validation

est-bdrm

est-bdrm (Figure A.21) estimates the number of bedrooms based on the building gross square feet and the procedure and data described in Initialization and Input data.

```
to est-bdrm
  ask lots
    if bgsf < 750 ;;if building gross square footage is less than 750 square feet, assume Efficiency
      bdrm = 0
```

```

if bgsf >= 750 & bgsf < 1000
  bdrm = 1
if bgsf >= 1000 & bgsf < 1150
  bdrm = 2
if bgsf >= 1150 & bgsf < 1400
  bdrm = 3
else
  bdrm = 4
end

```

Figure A.21. *est-bdrm* pseudocode

habitability

habitability identifies if a house is habitable after the disaster (Figure A.22). Stemmed from the FEMA's standardized degrees of damage (see submodel *reimburse-fema*), habitable houses were assumed those properties with damage cost less than 10% of the pre-disaster improvement value.

```

to habitability
  ask lots
    if dmg_value < (r_hbt / 100) * imp_yb ;;r_hbt = 10%
      hbt = 1 ;;the house is habitable
    end
  end
end

```

Figure A.22. *habitability* pseudocode

rent-power

rent-power (Figure A.23) estimates the amount of rent that households can afford to pay based on the assumptions explained in Initialization and Input data. For simpler coding, habitable houses were assigned an extreme rent power (\$1M).

```

to rent-power
  ask lots with hbt = 0
    rnt_rt = (r_rent + random (101 - r_rent)) / 100 ;;randomness
    rnt_pwr = rnt_rt * 0.4 * middle_of_income_level / 12
  ask lots with hbt = 1
    rnt_pwr = 1000000
  end
end

```

Figure A.23. *rent-power* pseudocode

rent-afford

rent-afford determines if a household with an uninhabitable house can afford to rent according to the procedure and data described in Initialization and Input data. The pseudocode of the submodel is presented in Figure A.24.

```

to rent-afford
  for each bdrm i = eff to 4bd
    ask lots with bdrm = i
      if rnt_pwr >= rnt_i_fy13
        rnt_aff_1 = 1 ;;if a household can afford the rent in the 1st year
      if rnt_pwr >= rnt_i_fy14
        rnt_aff_2 = 1 ;;if a household can afford the rent in the 2nd year
      end
    end
  end
end

```

Figure A.24. *rent-afford* pseudocode

Submodel go

Submodel *go* evaluates the recovery criteria and predicts households' decisions. This submodel is a set of sub-submodels including *reimburse-insurance*, *reimburse-fema*, *reimburse-sba*, *spend-rlqa*, *reimburse-cdbg*, and *decide-for-recovery* (Figure A.25).

```

to go
  if ticks = 8 ;;i.e. maximum time steps (8 quarters) reached
    stop
  else
    reimburse-insurance
    reimburse-fema
    reimburse-sba
    spend-rlqa
    reimburse-cdbg
    decide-for-recovery
  end
end

```

```

tick ;;next time step
end

```

Figure A.25. *go* pseudocode

reimburse-insurance

The settlement received from the National Flood Insurance Program is the first recovery assistance that is assigned to eligible households by the submodel *reimburse-insurance*. The model assumes that the insurance settlement was reimbursed within the first 3 months after Sandy. An assumption that was made based on available guidelines related to the process of insurance reimbursement. Therefore, the submodel is activated in the second time step. The maximum limit for flood insurance was calculated by discounting the NFI cap (*insurance_cap_r*), i.e. \$250,000 (III 2018, 2019a) to the base date of August 2011.

The pseudocode for *reimburse-insurance* is presented in Figure A.26. The submodel first estimates the number of insurance policies as the number of properties located within areas at the high risk of flooding (zones A, AE, and VE) multiplied by the ratio of insurance penetration (*insurance_penetration*). In high-risk areas, purchase of flood insurance is mandatory for properties with federally regulated or insured lenders (FEMA 2019a; Shawnee County 2019). Further, as of 2013, 71.2% of Staten Island owner-occupied housing units had a mortgage (USCB 2013f). Therefore, insurance penetration was assumed 80% to accommodate mortgaged houses as well as a share of non-mortgaged but insured properties. The estimated number of policies is next used to randomly select lots within the high-risk areas to assume them as insured properties. Then, the amount of settlement that an insured house is eligible to receive is calculated as the minimum of damage cost and insurance cap. Finally, the eligible amount is multiplied by a random number between *r_ins* and 100% to estimate the reimbursed amount of insurance settlement. The default value for *r_ins* in the model is 80%.

```

to reimburse-insurance
  if ticks = 1 ;;run the submodel if the program is in the first 3-month
  ;;number of lots (damaged/undamaged) with flood insurance
  number_insured = (insurance_penetration / 100) * count lots with high_risk

  ;;assign insurance
  ask number_insured of lots with high_risk
  insured_flg = 1

  ;;set insurance cap
  insurance_cap = discount insurance_cap_r

  ;;reimburse insurance settlement
  ask lots with dmg_value > 0 & insured_flg = 1 ;;lots having insurance
  eligible_ins_dollar = min (dmg_value, insurance_cap) ;;eligible amount
  reimb_rt ((r_ins + random (101 - r_ins)) / 100) ;;randomness
  ins = reimb_rt * eligible_ins_dollar ;;reimbursed insurance
end

```

Figure A.26. *reimburse-insurance* pseudocode

reimburse-fema

Submodel *reimburse-fema* distributes the zip-code level FEMA-HA to eligible households. FEMA-HA was assumed to be reimbursed within the first 3 months. Therefore, *reimburse-fema* is activated in the second time step. Further, because FEMA assistance cannot duplicate the amounts paid by insurance (FEMA 2018), the submodel is run after *reimburse-insurance*, hence the amount of reimbursed insurance is deducted from the total amount of money required for repair/reconstruction. The assumptions of timing and sequence of FEMA-HA is based on FEMA guidelines (FEMA 2018). The maximum limit of FEMA-HA (*fema_cap_r*) was assumed \$33,000 (FEMA 2019d) and was discounted to the base date. FEMA's house repair assistance is not intended to return the house to its pre-disaster condition but to make it safe, sanitary, and functional (FEMA 2016a, 2016b, 2017). 10% of pre-Sandy DIMP value was assumed as the threshold for *safe, sanitary, and functional*.

Figure A.27 illustrates the pseudocode. In each zip code, the submodel randomly selects an eligible house one at a time. Eligible houses are the damaged properties that, once insurance settlement and limit of habitability is deducted from their damage cost, still need money for repair/reconstruction. The amount of FEMA-HA that the household is eligible to receive is equal to the minimum of the mentioned gap, FEMA cap, and the total FEMA money remained for that zip code. The eligible amount is then multiplied by a random number between *r_fema* and 100% to give the amount of reimbursed FEMA-HA (default *r_fema* = 80%). Then, the amount of FEMA-HA remained for the zip code is updated and the process is repeated until either the total FEMA-HA in each zip code is

exhausted or all eligible households are paid.

```

to reimburse-fema
  if ticks = 1 ;;run the submodel if the program is in the first 3-month
  ;;set fema cap
  fema_cap = discount fema_cap_r

  ;;reimburse fema-ha assistance
  For i = 10301 to 10310, 10312, 10314 ;;zip codes
    while fema_dollar(i) > 0
      ask one-of lots with (dmg_value - ins - (r_hbt / 100) * imp_yb) > 0
        eligible_fema_dollar = min (dmg_value - ins - (r_hbt / 100) * imp_yb), fema_cap,
          fema_dollar(i) ;;eligible amount
        reimb_rt = (r_fema + random (101 - r_fema)) / 100 ;;randomness
        fema = reimb_rt * eligible_fema_dollar ;;assign reimbursement

      ;;update remaining money
      fema_dollar(i) = fema_dollar(i) - fema
    end
  end

```

Figure A.27. *reimburse-fema* pseudocode

reimburse-sba

Submodel *reimburse-sba* reimburses the zip-code level discounted SBA loan for real estate. Based on the SBA guidelines, it was assumed that SBA loan is reimbursed within the first 3 months, thus, *reimburse-sba* is activated in the second time step. SBA disaster loans can be used if insurance and FEMA assistance do not fully cover the damage cost (SBA 2018a). Therefore, the submodel is run after *reimburse-insurance* and *reimburse-fema*. Further, the maximum limit of SBA disaster loan for repair/replacement (*sba_cap_r*), i.e. \$200,000 (SBA 2018b), was discounted to the base date.

The pseudocode is shown in Figure A.28. In each zip code, the submodel randomly selects an eligible house one at a time. The households with an annual income of \$50,000 or more who still needed recovery assistance after being paid by the NFIP and FEMA-HA were assumed eligible for SBA loan. The amount of loan that the household is eligible to receive is calculated as the minimum of the gap, SBA cap, and the total SBA money remained for that zip code. The eligible amount is then multiplied by a random number between *r_sba* and 100% to give the amount of reimbursed loan (default *r_sba* = 80%). Next, the amount of SBA loan available for the zip code is updated and the process is repeated until either exhausting the total SBA loan in each zip code or paying all the eligible households.

```

to reimburse-sba
  if ticks = 1 ;;run the submodel if the program is in the first 3-month
  ;;set sba cap
  sba_cap = discount sba_cap_r

  ;;reimburse fema-ha assistance
  For i = 10301 to 10310, 10312, 10314 ;;zip codes
    while sba_dollar(i) > 0
      ask one-of lots with (income >= 50k & dmg_value - ins - fema > 0)
        eligible_sba_dollar = min (dmg_value - ins - fema, sba_cap, sba_dollar(i)) ;;eligible
          amount
        reimb_rt = r_sba + random (101 - r_sba) / 100 ;;randomness
        sba = reimb_rt * eligible_sba_dollar ;;assign reimbursement

      ;;update remaining money
      sba_dollar(i) = sba_dollar(i) - sba
    end
  end

```

Figure A.28. *reimburse-sba* pseudocode

spend-rlqa

Submodel *spend-rlqa* assigns the amount of liquid assets that households spend on recovery. Since after Sandy, the first round of CDBG-DR was reimbursed in early 2014 (HRO 2016), households were assumed to spend a share of liquid assets before CDBG-DR. Therefore, the submodel *spend-rlqa* is run in the second time step, but after reimbursement of NFI, FEMA-HA, and SBA loan.

The submodel estimates the amount of liquid assets that a household *spends* for recovery as the minimum of damage cost minus the mentioned aids, and the recovery liquid assets estimated before by *assign-rlqa* (Figure A.29).

```

to spend-rlqa
  if ticks = 1 ;;run the submodel if the program is in the first 3-month

```

```

;;spend share of liquid assets considered for recovery
ask lots with (dmg_value - ins - fema - sba > 0 & rlqa > 0)
  spent_rlqa = min (dmg_value - ins - fema - sba, rlqa)
end

```

Figure A.29. *spend-lqa* pseudocode

reimburse-cdbg

Submodel *reimburse-cdbg* reimburses the zip-code level data on the discounted amount of CDBG-DR. Reimbursement of CDBG-DR funds to New York City was initiated in April 2014 under the Build It Back program (HRO 2016). Therefore, *reimburse-cdbg* is activated in the fifth time step to help with recovery needs that have not been met by other assistance programs (HUD 2017). In the absence of explicit information, the maximum limit for CDBG-DR (*cdbg_cap*) was assumed to equal the average of discounted CDBG-DR funds reimbursed among Staten Island single-family applicants, i.e. \$140,000. The City of New York was required by law to expend at least 50 percent of its CDBG-DR funds on low-and moderate-income populations, i.e. households with income equal or less than 80% of the Area Median Income (AMI) for the region (NYC 2014). Since the 2013 AMI for the five counties of New York City (Bronx, Kings, Queens, New York, and Richmond) was \$57,001 (USCB 2013i), households with an annual income equal or less than $0.8 \times \text{AMI} = \$45,601$ were prioritized by the submodel.

Figure A.30 shows the pseudocode of the submodel. In each zip code, *reimburse-cdbg* randomly selects a prioritized eligible household one at a time. Prioritized eligible households are those with an annual income of \$50k or less who still need recovery assistance after including NFI, FEMA-HA, SBA, and recovery liquid assets. The amount of CDBG-DR assistance that the household is eligible to receive is calculated as the minimum of the gap, CDBG-DR cap, and the total CDBG-DR money remained for that zip code. The eligible amount is then multiplied by a random number between *r_cdbg* and 100% to estimate the amount of reimbursed assistance (default *r_cdbg* = 80%). Next, the amount of CDBG-DR fund available for the zip code is updated and the process is repeated until either the fund in each zip code is exhausted or all prioritized applicants are paid. If all the prioritized households are paid but CDBG-DR has remained, the submodel continues to reimburse higher-income eligible households.

```

to reimburse-cdbg
  if ticks = 5 ;;run the submodel if the program is in the fifth 3-month
  ;;reimburse cdbg_dr assistance
  For i = 10301 to 10310, 10312, 10314 ;;zip codes
  ;;reimburse cdbg_dr assistance to lower-income households
  while cdbg_dollar(i) > 0
    ask one-of lots with (income < 50k & dmg_value - ins - fema - SBA - spent_rlq > 0)
      eligible_cdbg_dollar = min (dmg_value - ins - fema - SBA - spent_rlq), cdbg_cap,
        cdbg_dollar(i) ;;eligible amount
      reimb_rt = (r_cdbg + random (101 - r_cdbg)) / 100 ;;randomness
      cdbg = reimb_rt * eligible_cdbg_dollar ;;assign reimbursement

      ;;update remaining money
      cdbg_dollar(i) = cdbg_dollar(i) - cdbg

  ;;reimburse remaining cdbg_dr assistance (if any)to other households
  if cdbg_dollar(i) > 0
    while cdbg_dollar(i) > 0
      ask one-of lots with (dmg_value - ins - fema - SBA - spent_rlq > 0 & cdbg = 0)
        eligible_cdbg_dollar = min (dmg_value - ins - fema - SBA - spent_rlq), cdbg_cap,
          cdbg_dollar(i) ;;eligible amount
        reimb_rt = (r_cdbg + random (101 - r_cdbg)) / 100 ;;randomness
        cdbg = reimb_rt * eligible_cdbg_dollar ;;assign reimbursement

        ;;update remaining money
        cdbg_dollar(i) = cdbg_dollar(i) - cdbg
  end
end

```

Figure A.30. *reimburse-cdbg* pseudocode

decide-for-recovery

The submodel *decide-for-recovery* is the heart of RecovUS. The pseudocode of this submodel is presented in Figure A.31. In each time step, the submodel implements the following procedure:

- 1) Available financial resources for the households who have not repaired/reconstructed and have not sold their properties is calculated by summing the NFI, FEMA-HA, SBA loan, share of liquid assts for recovery, and CDBG-DR assistance. Since recovery resources are assigned in the 2nd and 5th time steps, the amount is updated only in these steps.

- 2) Then, the submodel evaluates financial conditions by comparing a household's available money to the damage cost. If financial resources for repair/reconstruction are not enough, the program evaluates habitability of the house. If it is habitable, with a probability of $r_1\%$, the household decides to wait, and with a probability of $(100-r_1)\%$, it decides to sell the house. If the house is uninhabitable, the program checks whether the household affords to pay for the rent of another property. If it affords, the program checks if the household can find a vacant rental unit. The probability of finding a vacant rental unit was assumed 80% (r_{vac}). If the household can find a vacant unit, the decision is made like the previous case where the house was habitable, i.e. the household decides to wait or sell the property. However, if the household does not afford the rent or cannot find a vacant unit, it sells the house.
- 3) If financial resources for repair/reconstruction are enough, community recovery is evaluated by comparing the recovery of community anchors that are important to a household to their thresholds representing a desirable recovery. If a household index is 1, the average recovery of infrastructure in the current time step is compared with the threshold for adequate recovery of infrastructure (adq_infr). But if the household index is 2, the average recovery of neighbors residing within the household's perceived neighborhood radius is computed and compared with the threshold for adequate recovery of neighbors (adq_nbr). Finally, if the household index is 3, the average recovery of community assets located within the household's perceived neighborhood radius is compared with the threshold for adequate recovery of community assets (adq_cas). If the comparison shows that the perceived community has adequately recovered, the community criterion is satisfied. In this case, with a probability of $r_2\%$, the household decides to repair/reconstruct, and with a probability of $(100-r_2)\%$, it decides to sell. However, if the criterion is not satisfied, the decision is made like the previous case where a household did not have enough money, i.e. habitability, rent affordability, and vacancy are checked, and the household decides to wait or sell the house.
- 4) If a household sells its house (and relocate), the buyer may decide to repair/reconstruct, wait, or sell the house again. RecovUS assumes that with a probability of $r_0\%$, a buyer decides to repair/reconstruct, and with a probability of $(100-r_0)\%$, it decides to wait or sell.

The thresholds adq_infr , adq_nbr , adq_cas , r_0 , r_1 , and r_2 are the model parameters and their values are determined through calibration. Calibration of the model with the aforementioned data resulted in $adq_infr = 50\%$, $adq_nbr = 40\%$, $adq_cas = 50\%$, $r_0 = 35\%$, $r_1 = 95\%$, and $r_2 = 95\%$.

```

to decide-for-recovery
  ;;households who have not recovered and have not sold their properties
  ask lots with rec_status = 0 & sell = 0
  ;;update available money when new money is expected
  if ticks = 1 or ticks = 5
    all_money = ins + fema + sba + spent_rlqa + cdbg
  ;;check financial conditions
  if all_money < dmg_value ;;if household does not have enough money for recovery
    if hbt = 1 ;;if habitable
      if ((random 100) + 1) <= r1
        wait ;;does nothing
      else
        sell = 1 ;;sell the house
    else ;;if uninhabitable
      if rnt_aff = 1 ;;if household affords rent
        if ((random 100) + 1) <= r_vac ;;if vacant rental unit is available
          decide like if hbt = 1
        else ;;if vacant rental unit is unavailable
          sell = 1
      else ;;if household does not afford rent
        sell = 1
    else ;;if household has enough money for recovery
      ;;check community conditions
      if asna_index = 1 ;;if household ASNA class is 1
        infr_rec = 1 - infra_dmg(tick) ;;average recovery of infrastructure
        if infr_rec >= adq_infr / 100
          pnhd_rec = 1 ;;infrastructure has adequately recovered
      if asna_index = 2 ;;if household ASNA class is 2
        nbr_rec = mean [rec_status] of other lots in-radius p_radius ;;average recovery of perceived
          neighbors
        if nbr_rec >= adq_nbr / 100
          pnhd_rec = 1 ;;neighbors have adequately recovered
      if asna_index = 3 ;;if household ASNA class is 3
        cas_rec = (1 - mean [cas_dmg(tick)] of cass in-radius p_radius ;;average recovery of perceived
          community assets

```

```
    if cas_rec >= adq_cas / 100
        pnbhd_rec = 1 ;;community assets have adequately recovered

    if pnbhd_rec = 1 ;;if perceived neighborhood has adequately recovered
        if ((random 100) + 1) <= r2
            rec_status = 1 ;;repair/reconstruct
        else
            sell = 1 ;;sell the house
        else ;;if perceived neighborhood has not adequately recovered
            decide like if all_money < dmg_value

    ;;houses that have not been recovered but have been sold
    ask lots with rec_status = 0 & sell = 1
        if ((random 100) + 1) <= r0
            rec_status = 1 ;;repair/reconstruct
        else
            wait or sell
end
```

Figure A.31. *decide-for-recovery* pseudocode

Appendix to: Moradi, Saeed and Nejat, Ali (2020) 'RecovUS: An Agent-Based Model of Post-Disaster Household Recovery' *Journal of Artificial Societies and Social Simulation* 23 (4) 13 <<http://jasss.soc.surrey.ac.uk/23/4/13.html>>. doi: 10.18564/jasss.4445

References

- APA. (1952). Minimum requirements for lot and building size. In: The American Planning Association (APA), Chicago, IL.
- BLS. (2019). *Housing in New York-Newark-Jersey City*.
- Bratt, R. G. (2002). Housing and family well-being. *Housing Studies*, 17(1), 13-26.
- Comerio, M. C. (1998). *Disaster hits home: New policy for urban housing recovery*: Univ of California Press.
- Comerio, M. C. (2014). Disaster recovery and community renewal: Housing approaches. *Cityscape*, 16(2), 51-64.
- de Koning, K., & Filatova, T. (2020). Repetitive floods intensify outmigration and climate gentrification in coastal cities. *Environmental Research Letters*, 15(3), 034008.
- DoD. (2015). DoD space planning criteria - Chapter 130: Net to gross conversion factors. In: Department of Defense (DoD) - Defense Health Agency Facilities Division.
- ESRI. (2015). ArcGIS Desktop Release 10.3.1. Redlands, CA: Environmental Systems Research Institute (ESRI).
- FEMA. (2012, 11/19/2012). New York Hurricane Sandy (DR-4085). Retrieved from <https://www.fema.gov/disaster/4085>
- FEMA. (2015). Digital Flood Insurance Rate Map database, City of New York, New York. from The Federal Emergency Management Agency (FEMA) <http://www.region2coastal.com/view-flood-maps-data/view-preliminary-flood-map-data/>
- FEMA. (2016a). *Damage assessment operations manual: A guide to assessing damage and impact*. Retrieved from
- FEMA. (2016b). *Individuals and Households Program Unified Guidance (IHPUG)*. Retrieved from
- FEMA. (2017). Public Assistance: Local, State, Tribal and Private Non-Profit. *The Federal Emergency Management Agency (FEMA)*. Retrieved from <https://www.fema.gov/public-assistance-local-state-tribal-and-non-profit>
- FEMA. (2018). Individual Disaster Assistance. *The Federal Emergency Management Agency (FEMA)*. Retrieved from <https://www.fema.gov/individual-disaster-assistance>
- FEMA. (2019a, 04/04/2018). FEMA flood maps and zones explained. Retrieved from <https://www.fema.gov/disaster/updates/fema-flood-maps-and-zones-explained>
- FEMA. (2019b, 03/18/2019). Flood zones. Retrieved from <https://www.fema.gov/flood-zones>
- FEMA. (2019c). OpenFEMA dataset: Housing assistance data owners - V1. Retrieved Sep. 19, 2019, from The Federal Emergency Management Agency (FEMA) https://www.fema.gov/media-library-data/1510759434562-dfb20c9a88200a9b6eae4a8e26443b75/FactSheet_Flooding_Am_I_At_Risk.pdf
- FEMA. (2019d). *What is FEMA's Individual Assistance Program?* Retrieved from https://www.fema.gov/media-library-data/1461689021638-cfcfd7f6c263635802fa7a76a19e00ea/FS001_What_is_Individual_Assistance_508.pdf
- Filatova, T., Parker, D. C., & van der Veen, A. (2011). The implications of skewed risk perception for a Dutch coastal land market: insights from an agent-based computational economics model. *Agricultural and Resource*

Appendix to: Moradi, Saeed and Nejat, Ali (2020) 'RecovUS: An Agent-Based Model of Post-Disaster Household Recovery' *Journal of Artificial Societies and Social Simulation* 23 (4) 13 <<http://jasss.soc.surrey.ac.uk/23/4/13.html>>. doi: 10.18564/jasss.4445

Economics Review, 40(3), 405-423.

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., . . . Huse, G. (2006). A standard protocol for describing individual-based and agent-based models. *Ecological Modelling*, 198(1-2), 115-126.

Grimm, V., Railsback, S. F., Vincenot, C. E., Berger, U., Gallagher, C., DeAngelis, D. L., . . . Groeneveld, J. r. (2020). The odd protocol for describing agent-based and other simulation models: A second update to improve clarity, replication, and structural realism. *Journal of Artificial Societies and Social Simulation*, 23(2), 1-7.

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

HRO. (2016). *Build It Back progress update*. Retrieved from New York, New York, U.S.:

HUD. (2017). *Programs of HUD: Major mortgage, grant, assistance, and regulatory programs*. Retrieved from <https://www.hud.gov/sites/dfiles/Main/documents/HUDPrograms2017.pdf>:

HUD. (2019). Fair Market Rents. Retrieved Sep. 22, 2019, from The United States Department of Housing and Urban (HUD)

III. (2018). Spotlight on: Flood insurance. Retrieved from <https://www.iii.org/article/spotlight-on-flood-insurance>

III. (2019a). Facts + Statistics: Flood insurance. Retrieved from <https://www.iii.org/fact-statistic/facts-statistics-flood-insurance>

III. (2019b). Facts + Statistics: Hurricanes. Retrieved from <https://www.iii.org/fact-statistic/facts-statistics-hurricanes>

Kamel, N. M., & Loukaitou-Sideris, A. (2004). Residential assistance and recovery following the Northridge earthquake. *Urban Studies*, 41(3), 533-562.

Kaufman, C., & Shaby, B. (2013). The role of the range parameter for estimation and prediction in geostatistics. *Biometrika*, 100(2), 473-484.

LendKey. (2015, May 13, 2015). How much of your income should you spend on housing? Retrieved from <https://www.lendkey.com/blog/personal-finance/how-much-of-your-income-should-you-spend-on-housing/>

Magliocca, N., Safirova, E., McConnell, V., & Walls, M. (2011). An economic agent-based model of coupled housing and land markets (CHALMS). *Computers, Environment and Urban Systems*, 35(3), 183-191.

Magliocca, N. R., & Walls, M. (2018). The role of subjective risk perceptions in shaping coastal development dynamics. *Computers, Environment and Urban Systems*, 71, 1-13.

Miles, S. B. (2017). DESaster: A discrete event disaster recovery simulation built on top of the Simpy discrete event simulation Python library. Retrieved from <https://github.com/milessb/DESaster>

Miles, S. B., & Chang, S. E. (2006). Modeling community recovery from earthquakes. *Earthquake Spectra*, 22(2), 439-458.

Miles, S. B., & Chang, S. E. (2011). ResilUS: A community based disaster resilience model. *Cartography and Geographic Information Science*, 38(1), 36-51.

Moradi, S. (2020). *RecovUS: An Agent-Based Model of Post-Disaster Housing Recovery*. (Ph.D.), Texas Tech

Appendix to: Moradi, Saeed and Nejat, Ali (2020) 'RecovUS: An Agent-Based Model of Post-Disaster Household Recovery' *Journal of Artificial Societies and Social Simulation* 23 (4) 13 <<http://jasss.soc.surrey.ac.uk/23/4/13.html>>. doi: 10.18564/jasss.4445

University, Lubbock, TX.

Moradi, S., & Nejat, A. (2020). Post-disaster housing recovery: The case of Staten Island after Hurricane Sandy. *International Journal of Disaster Risk Reduction, Under Review*.

Moradi, S., Nejat, A., Hu, D., & Ghosh, S. (2020). Perceived neighborhood: Preferences versus actualities. *International Journal of Disaster Risk Reduction, Under Review*.

Nejat, A. (2018). Perceived neighborhood boundaries: A missing link in modeling post-disaster housing recovery. *International Journal of Disaster Risk Reduction*, 28, 225-236.

Nejat, A., & Damnjanovic, I. (2012). Agent - based modeling of behavioral housing recovery following disasters. *Computer-Aided Civil and Infrastructure Engineering*, 27(10), 748-763.

Nejat, A., & Ghosh, S. (2016). LASSO model of postdisaster housing recovery: Case study of Hurricane Sandy. *Natural Hazards Review*, 17(3), 04016007.

Nejat, A., Moradi, S., & Ghosh, S. (2019). Anchors of social network awareness index: A key to modeling postdisaster housing recovery. *Journal of Infrastructure Systems*, 25(2), 04019004. doi:[https://doi.org/10.1061/\(ASCE\)IS.1943-555X.0000471](https://doi.org/10.1061/(ASCE)IS.1943-555X.0000471)

NYC. (2013). *A stronger, more resilient New York*. Retrieved from <https://www1.nyc.gov/site/sirr/report/report.page>:

NYC. (2014). *One city, rebuilding together: usA report on the City of New York's response to Hurricane Sandy and the path forward*. Retrieved from https://www1.nyc.gov/assets/housingrecovery/downloads/pdf/2017/sandy_041714.pdf:

NYC. (2018). About The Mayor's Office of Housing Recovery Operations. *New York City (NYC) Housing Recovery*.

NYC. (2019a). *Assessments*.

NYC. (2019b). *Department of Finance Digital Tax Map*.

NYC. (2019c). Sandy funding tracker. Retrieved Sep. 27, 2019

OIG. (2016). *Early-defaulted hurricane Sandy disaster loans*. Retrieved from Washington, D.C.:

Peacock, W. G., Dash, N., & Zhang, Y. (2007a). Sheltering and Housing Recovery Following Disaster. In H. Kaplan (Ed.), *Handbook of disaster research* (pp. 258-274). New York: Springer.

Peacock, W. G., Dash, N., & Zhang, Y. (2007b). t. In H. Kaplan (Ed.), *Handbook of disaster research* (pp. 258-274). New York: Springer.

Quintana, M. (2018, Nov. 30, 2018). Rent to income ratio: How much can i afford to spend on rent? Retrieved from <https://www.nakedapartments.com/blog/rent-to-income/>

Ronan, K., & Johnston, D. (2005). *Promoting community resilience in disasters: The role for schools, youth, and families*. New York: Springer Science & Business Media.

Rust, E. B., & Killinger, K. (2006). *The financial services roundtable blue ribbon commission on mega-catastrophes: A call to action*. Retrieved from

SBA. (2014). SBA disaster loan data superstorm Sandy. Retrieved Sep. 27, 2019, from The United States Small

Appendix to: Moradi, Saeed and Nejat, Ali (2020) 'RecovUS: An Agent-Based Model of Post-Disaster Household Recovery' *Journal of Artificial Societies and Social Simulation* 23 (4) 13 <<http://jasss.soc.surrey.ac.uk/23/4/13.html>>. doi: 10.18564/jasss.4445

Business Administration (SBA) <https://www.sba.gov/funding-programs/disaster-assistance>

SBA. (2018a). Disaster assistance. *The United States Small Business Administration (SBA)*. Retrieved from <https://www.sba.gov/funding-programs/disaster-assistance>

SBA. (2018b). Disaster loan assistance: Home and personal property loans. *The United States Small Business Administration (SBA)*. Retrieved from <https://disasterloan.sba.gov/ela/Information/HomePersonalPropertyLoans>

SBA. (2018c). The three step process: Disaster loans. In *The United States Small Business Administration (SBA)*.

Shawnee County. (2019). Definitions of FEMA flood zone designations. In. <http://snmapmod.snco.us/fmm/document/fema-flood-zone-definitions.pdf>.

USCB. (2013a). *B02001: Race*.

USCB. (2013b). *B15003: Educational attainment for the population 25 years and over*.

USCB. (2013c). *B19001: Household income in the past 12 months (in 2013 inflation-adjusted dollars)*.

USCB. (2013d). *B19001A: Household income in the past 12 months (in 2013 inflation-adjusted dollars) (white alone householder)*.

USCB. (2013e). *B25070: Gross rent as a percentage of household income in the past 12 months*.

USCB. (2013f). *B25081: Mortgage status*.

USCB. (2013g). *C15002A: Sex by educational attainment for the population 25 years and over (white alone)*.

USCB. (2013h). *DP04: Selected housing characteristics*.

USCB. (2013i). *S1903: Median income in the past 12 months (in 2013 inflation-adjusted dollars)*.

USCB. (2014). Wealth, Asset Ownership, & Debt of Households Detailed Tables: 2013. Retrieved Sep. 27, 2019, from The United States Census Bureau (USCB)

USCB. (2019). Glossary. Retrieved from <https://www.census.gov/programs-surveys/geography/about/glossary.html>

USCB. (2020). Glossary. Retrieved from <https://www.census.gov/glossary/>

Xiao, Y., Wu, K., Finn, D., & Chandrasekhar, D. (2018). Community businesses as social units in post-disaster recovery. *Journal of Planning Education and Research*, 0739456X18804328.

Zhang, Y., & Peacock, W. G. (2009). Planning for housing recovery? Lessons learned from Hurricane Andrew. *J. Am. Plann. Assoc.*, 76(1), 5-24.