**The ODD protocol**

This model description follows the ODD (Overview, Design, Concepts and Details) protocol by Grimm (2010,2006) to facilitate the reproducibility of agent-based models.

1. **Overview** 
   1. **Purpose**

This purpose of this agent-based model is to understand the micro-level processes contributing to the emerging yet limited diffusion of adaptation practices among transit agencies. It uses the empirical setting of transit agencies adapting to extreme weather events through resilience-enhancing capital investment against extreme weather impacts.

* 1. **Entities, state variables and scales**

This section describes the agent in the model, by defining the state variables and attributes that characterize the agents. It also elaborates the environment and temporal extents of the model.

* + 1. **Agents**

The model contains two types of agents: transit agencies, solutions and regional office of Federal Transit Administration (FTA). From the very beginning, each of transit agencies are attached to a solution which copes the immediate impacts of extreme weather events. Adaptation solutions are randomly distributed across modeling space, with a higher efficacy value than the coping solutions. Agents are heterogenous in their capacity, their natural environment, the level of accepted risk and the number of windows they have access to. There are two types of solutions, indicated by a Boolean attribute of the solutions. The solutions differ in efficacy and costs, based on their type.

The model also contains three types of links: 1) among agencies in the same region; 2) among agencies located in difficult regions; 3) among agencies and the FTA regional offices. The links do not have attributes and are only used in agencies’ search for adaptation solutions. Specifically, when looking out for alternative approaches, an agency can formally access solutions through their network ties within their region, or informally through network ties outside their region. The regional FTA office serves as a hub to garner information about resilience-enhancing capital investment in the region, which they either distribute to member transit agencies in a regular basis or share with agencies upon requests.

The model includes a few global settings to specify the number of initial solutions distributed over the modeling space, the scanning range an agency can reach out to in searching for new solutions, the maximum number of windows an agency can access and the maximum extent to which an organization can mitigate expected impacts from bad weather events through improving coping measure focused on reacting to the immediate impacts in the aftermath of an extreme weather events and recovery to the pre-event status. All agent attributes and their state variables are provided in Table 1, including the description and parameterization of each state variable.

**Table 1. Agent attributes**

|  |  |  |
| --- | --- | --- |
| **Variable** | **Description** | **Initial value** |
| **Agencies** |  |  |
| Extreme weather probability | The probability of having an extreme weather event in a given tick | Floating point ranges from 0 to 0.145. |
| Expected extreme weather probability | The probability at which an agency expects to have an extreme weather event | Initial value equals the objective extreme weather probability |
| Disaster probability | The probability of having a weather disaster in a given tick | Floating point ranging from 0 to 0.111 |
| Declaration rate | The ratio of disasters that are officially declared | Floating point ranging from 0 to 0.076 |
| Capacity | Capacity based on resource endowment and system characteristics to implement a certain solution | Floating point ranging from 0.016 to 4.184 |
| Level of accepted risk | The maximum level of risk acceptable to a given agency | Normal distribution with a certain regional mean and standard deviation of 0.1. The regional mean ranges from 0.4 to 0.7. |
| Expected bad weather severity | The maximum level of weather intensity an organization plans for. | 0.08 |
| Impact reduction rate | The extent to which an agency can reduce the expected bad weather impact through improving coping solutions | Floating point ranging from 0.10 to 0.40 |
| Maximum impact reduction | The maximum extent at which an agency can reduce the expected bad weather impact through improving coping solutions | 0.4 |
| Scanning Range | The range at which an agency can reach out to seek adaptation solutions. | A random integer calibrated to qualitatively match the reference pattern and |
| Minimum number of a certain type of network ties | This specifies the minimum number of ties an agency has within or outside their region, in the algorithm to generate networks where organizations with bigger capacity is better connected. | 1 |
| Number of windows | The number of windows of opportunity for each agency | Randomly generated across the course of the simulation.  The number is calibrated to qualitatively match the reference pattern. |
| **Solution** |  |  |
| Efficacy | Represents the effectiveness of a solution for dealing with the extreme weather impacts. Coping solutions have lower efficacy than adaptation solutions. | Efficacy for coping solutions: Floating point ranging from 0.05 to 1 |
| Efficacy for adaptation solutions: Floating point ranging from 1.5 to 3. |
| Cost | Represents the cost involved in implementing a certain solution. Coping solutions cost less than adaptation solutions. | Cost for coping solutions are initiated as lower than an agency's capacity, so that all agencies are able to implement coping solutions. |
| Cost for adaptation solutions: Minimum is 2, the maximum is controlled by a slider. |
| Adaptation | A Boolean variable representing the two types of solutions (i.e. coping versus adaptation). | Either 0 or o1 |

**1.2.2 Landscape**

The landscape is represented as a grid of four cells, each cell representing one of the four Census regions in the United States. The organizations are distributed in the four regions drawing on the 2016 survey data. The agencies are linked by two networks: 1) networks with agencies in the same region; 2) networks with agencies in other regions.

This model includes a few global settings that influence the number of initial solutions distributed over the modeling space, the damage each extreme weather event can possible cause, the max resilience level of each agency to determine the level of impact per extreme event, an organization’s memory length to filter out older memories, the scanning range which determines an agency’s scope of search for information about alternative problem solving.

* + 1. **Time Scale**

Each time step represents a month, which forms the baseline for parameterization of a few agent attributes, such as the probability of extreme weather events or weather disasters. The number of time steps is not specified but should be about the time it takes to reach an equilibrium beyond which almost no more agencies will adapt to extreme weather.

**1.2.4. Environment**

The model follows Railsback and Grimm (2011) to apply a log-normal distribution to generate the value for weather intensity at each time step, at a mean of 5 and standard deviation that equals the probability at which an extreme weather can occur to a given agency.

To provide a threshold value beyond which the weather intensity becomes extreme or even of disastrous magnitude, the model simulates the weather intensity for each time step over 300 years. The generated values and vectorized and sorted from high to low. The minimum intensity level of an extreme weather event can be matched to the value in the vector based on the extreme weather probability. For example, with an extreme weather probability at 10%, an agency will take the value at the 10 percentiles in the generated vector. It applies the same algorithm to determine the minimum level of intensity for a weather disaster.

When the intensity of weather at a given time step exceeds the minimum threshold intensity value, it becomes extreme or disastrous depending on the probabilities, which in turn triggers a series of organizational behavior to be detailed below.

**1.3 Process overview and scheduling**

At each time step, an agency takes the following steps in the given order as displayed in Figure 1:

1. Check weather intensity. A random value of weather intensity is generated based on the log-normal distributed as aforementioned. If the weather intensity goes beyond the predefined minimum threshold intensity level for extreme weather, the weather is modelled as extreme weather. If it further transcends the threshold intensity for disasters, it is additionally modeled as weather disasters.
2. An agency updates it perceived risk based on the weather conditions. Risk is the product of the consequences of a certain risk and the probability of its occurrence. Perceived risk is defined as:

Perceived Risk = E(Worst weather intensity – solution efficacy ) \* P(worst severe weather probability)

Since organizations cannot plan for every single worst scenario for climatic conditions, the bad weather intensity in this function represents the highest level of weather intensity an organization typically plans for. When an extreme weather occurs, an organization raises its expected probability for the worst severe weather event by five to ten percent. The percentage increases to 0.25 to 0.30 to represent the sharp increase in expected probability of worst severe weather when weather disasters occur. In contrast, in the absence of an extreme weather event, the agency’s expected probability of worst severe weather reduces by a random percentage of one to three.

The operationalization is consistent with the cognitive biases in human evaluation of weather risks. Direct experience plays a crucial role influencing risk perception, a phenomenon related with the availability heuristic (Tversky & Kahneman, 1973). People and organizations tend to underestimate or ignore low probability risks, until being punctuated by some peak events when the risk materializes in significant magnitude and over a short time horizon (Camerer & Kunreuther, 1989; Yohe & Tol, 2002). Experience with dramatic risk event improves the memorability and imaginability of the hazard, thereby intensifying risk perception in a way related to the availability heuristic (Tversky & Kahneman, 1973). On the other hand, they also misconstrue a consecutive series of mild events, such as the absence of extreme weather events, assigning unwarranted low probability of to future extreme events (Haasnoot et al., 2015).

Drawing on the literature on risk communication and perception, the model explicitly considers the interdependence of problem recognition (Kasperson & Kasperson, 1996; Patt & Siebenhüner, 2005). An agency increases expected probability for extreme weather events when any organization in their region experience a disastrous weather event. This is a relatively crude operationalization, given the nuances involved in risk recognition which requires much more refined similarity in geographical attributes and weather patterns. For example, the recent 2019 flood in the Iowa (Smith & Schwartz, 2019) can raise concerns and risk awareness in agencies similarly situated on major rivers, but probably not so much among agencies in the same region located further away from rivers where flash floods are more likely.

1. Agencies assess their risk perception relative to their risk tolerance (i.e. maximum level of acceptable risk). When the perception of risk exceeds the risk tolerance, the agency activates its problemistic search to reduce the level of expected impacts (Cyert & March, 1963). Their first go-to solution is to enhance the efficacy of their coping solution, which is compatible with their current framework and cheaper to implement. The model limits to extent to which an agency can improve the efficacy of its coping measures. When an agency is looking to increase its coping efficacy within the restriction, it improves coping efficacy; otherwise it looks elsewhere for adaptation solutions. The simulation starts the next tick if the perception risks lies under the accepted level of risks.
2. If the “access all” is switched on, then an agency can assess all adaptation solutions in the global environment. When “access through network” is on, the agency initiates its search among its network ties. There are four pools of adaptation solutions an agency can learn of: 1) scanning the environmental at a user-defined range for solutions randomly distributed in the grid; 2) solutions practiced by their regional ties; 3) solutions practiced by their tie outside their region; 4) solutions promoted or share by their regional FTA office. When an agency can find a solution with a higher efficacy than that of its current solution, it attaches this solution as a target solution. Otherwise, it continues the search in the next time step as long as its risk perception stay above its risk tolerance.
3. With a target adaptation solution, the agency assesses its capacity to decide whether the solution is something they can implement at the current time step. If so, it then initiates the implementation and practices the adaptation solution onwards with a higher efficacy to protect the organization after future extreme weather shocks. If not, the agency holds on to the target solution, waiting for windows of opportunities to come by. In the real world, the windows are opened in many forms, some predictably by an organization’s scheduled upgrade, design or new construction or reallocation of internal resources and some unpredictably by the availability of new grants, inter-organizational initiatives or new streams of revenue such as the approval of transit tax.
4. Upon an open window, an agency executes the sequence of assessment: 1) whether its expected risk is above its risk tolerance: 2) whether it has a readily available solution to implement; 3) Is the additional influx of resources sufficient for implementing the target solution. An answer of “no” to any of the evaluations will take the agency to the next time step. Only when an agency meets all three criteria can it successfully implement the adaptation solution.
5. Consistent with evidence that extreme and disastrous weather events are occurring at an accelerated rate (Boustan et al., 2017; Smith, 2017), the probabilities for extreme weather events and weather disasters slightly increase at the end of each time step.

**Figure 1. Flowchart of modeled systems of organizational adaptation**

A close up of a map

Description automatically generated

**1.4 Design concepts**

**1.4.1 Theoretical and empirical background**

**Initialization**

The model is initiated as having zero adapters in order to observe the emergence of adaptive behavior, operationalized as agencies’ capital investment in enhancing system resilience against extreme weather impacts. The configuration of the initial conditions are reported in Table 1.

**Input Data**

The reference pattern is drawn from a 2016 national survey on the largest fixed-route transit agencies in US metropolitan areas. The survey data along with the prior literature are also utilized to inform parameterization of key element in the model. The objective extreme weather probability uses the answer from a survey question asking organizations of the number of extreme weather events they experienced in the past two years, wherein the value is adjusted to match the temporal scale of the model. The frequency of disasters is drawn from the FEMA’s summary data on weather disasters, including both major disaster declarations and special emergencies. In terms of windows of opportunities created by disasters, the model only considers disasters that received the presidential declaration. Using the state-level declaration success rate in Schmidtlein et al (2008) as the baseline, the model applies some random variation in the agency-level declaration rate. Other parameters are either categorically calibrated to the match the reference pattern (Railsback & Grimm, 2011) or are incorporated in sensitivity analysis to determine their relative importance in influencing the model outcome.

**Emergence**

Agent adaptive behavior in coupled socio-environmental systems. Extreme weather from the natural environment constitute the external drivers for organizational risk perception, which when exceeding their accepted level of risk, motivates problemistic search for adaptation solutions with higher efficacy in modulating weather impacts. The search process is informed by the agency’s connections with other agencies, as well as their interaction with the regional FTA office. When a solution is identified, an organization either implements with its current capacity, or wait for windows of opportunities. Upon an open window, if an organization still perceives risk as higher than their tolerance, it will implement the solution to the maximum extent allowable with the boosted capacity.

**Adaptation**

The agents adjust their risk perception based on their experience with extreme weather or the lack thereof. Its behavior changes non-linearly as its perceived risk exceeds it risk tolerance. When the agents successfully implement a solution with better efficacy, be it a more effective coping measure or adaptation measure, they response to the change by lowering their perceived risk.

**Objective**

The ultimate goal of the agents is to reduce the impacts of extreme weather on their systems and operations.

**Sensing**

Agents sense changes in the weather conditions and are able to access the common pool of information about disaster occurrences. They can also detect the solutions practiced elsewhere through their network ties and the FTA regional office.

**Prediction**

The agents predict how much their current practice or target solution can help mitigate the bad weather impacts.

**Learning**

Agents learn about the effectiveness of their current solution in mitigating risks against the typically worst weather scenario and make adjustment when possible.

**Interaction**

In perceiving and adjusting their perception of risk, agents respond to the information about weather disasters experienced by their regional neighbors. They also respond to choices and solutions practiced by organizations they are connected to.

**Stochasticity**

There is stochasticity in the occurrence of extreme weather or weather disasters, the extent to which an organization can reduce the expected impact by enhancing their coping solutions or taking up adaptation solutions. The distribution of windows of opportunities also follows a stochastic process to reflect the uncertain and unpredictable emergency of opportunities in the empirical setting.

**Collectivity**

The FTA regional offices are related to each organization based on their geographical location. The level of risk tolerance is also distributed based on the four Census regions.

**Observation**

The number of agencies taking up adaptation measures against weather impact is the ultimate outcome of this model. The model aims to understand the micro-level mechanisms leading to pattern of organizational adaptation to extreme weather.

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