

Conceptualizing and implementing an agent-based modeling framework to examine the hurricane evacuation dynamics. Authors: Austin Harris, Dr. Paul Roebber, Dr. Rebecca Morss.

1. Introduction

The 3-10-day forecasts for Hurricane Irma (2017) called for landfall as a major hurricane near Miami, likely spurring the largest evacuation in US history (FDEM 2017). However, the forecasts then shifted westward, with eventual landfall near Tampa Bay–St. Petersburg, a common evacuation destination in the event, while leaving Miami largely unscathed (Cangialosi et al. 2018; Wong et al. 2018). Similarly, uncertainties in Hurricane Rita’s (2005) track and intensity forecasts, combined with the aftermath of Hurricane Katrina, led to mass evacuations and severe traffic jams in Houston–Galveston. The worst of the storm missed the area, but had Rita struck Houston–Galveston directly, the consequences could have been severe, as many evacuees were stranded on area roads (Zhang et al. 2007; Knabb et al. 2006).

The events are relevant since the forecasts were fairly accurate, with the westward shift of Irma’s track falling within the National Hurricane Center’s (NHC) cone of uncertainty (Cangialosi et al. 2018), and Rita’s forecast track being less erroneous than most (Knabb et al. 2006). However, forecasts were less successful in providing useful guidance for many affected by the events, and they demonstrate how evacuations – the primary means of protective action from hurricanes – are a complex process involving many physical-social parts and uncertainties that evolve over time (e.g., Morss et al. 2017; Barton 2014; Trainor et al. 2012; Miller and Page 2007). Because of these complex dynamics, preventing loss of life remains a formidable challenge.

Empirical studies provide key insight to different aspects of hurricane evacuations, such as how evacuation decisions are made (e.g., Huang et al. 2016; Lindell and Perry 2012; Baker 1991). However, it’s difficult to empirically study the full evacuation system, in all of its complexity, across multiple cases. Thus, computational models provide a complementary tool where empirical knowledge can be codified and used to run virtual experiments for a variety of hurricane scenarios, real and imagined (e.g., Morss et al. 2017, Watts et al. 2019). Along those lines, recent coupled-model experiments demonstrate the potential to model the complete hurricane evacuation system in one framework (e.g., Watts et al. 2019; Blanton et al. 2018; Fossell et al. 2017). Theoretically, the framework – particularly one involving agent-based simulations (Barton 2014; Miller and Page 2007) – could examine the hurricane evacuation system dynamics holistically, which has not yet been done.

This article details a new agent-based modeling platform for investigating the complex dynamics of the integrated hurricane evacuation system. Specifically, empirically-informed models are built representing three interwoven elements relevant to hurricane evacuations: the natural hazard (hurricane, forecasts, warning information), the human system (information flow, evacuation-related decisions), and the built environment (infrastructure, evacuation traffic). NHC products represent the hurricane, forecasts, and

warning information. Two agent-based models replicate the flow of information, evacuee decision-making, and evacuation infrastructure, routing, and traffic. By integrating the models into a unified, agent-based framework, we create a virtual laboratory uniquely positioned to advance fundamental knowledge of the system's behavior (Figure 1).

The philosophy guiding the model's development is to represent key aspects of real-world hurricane evacuations established in the literature, while remaining sufficiently idealized to explore system dynamics and build fundamental knowledge (e.g., see Watts et al. 2019; Sun et al. 2016). The model is implemented for and validated against data from two past hurricanes affecting the Florida peninsula, Hurricane Irma (2017) and Hurricane Dorian (2019). However, the model can be extended to a variety of hurricane scenarios, real or imagined, and additional regions or landscapes beyond the one described herein.

One core feature of the model involves representing dynamic and uncertain forecast information about the hurricane as it moves across the virtual landscape. Heterogeneous household agents combine the warning information with knowledge of the built environment to generate complex evacuation decisions. Another core feature involves vehicle agents fleeing across an idealized road network and interacting to produce evacuation traffic. Each of these features combine to produce complex evacuation phenomena which are impossible to detect using empirical methods.

Previous modeling studies of the hurricane evacuation system are fragmented, meaning they sufficiently represent some features while ignoring and oversimplifying others. For example, one body of work uses agent-based modeling to study evacuation planning for hurricanes (e.g., Madireddy et al. 2011; Zhang et al. 2009; Chen 2008, 2012; Zhan and Chen 2008; Chen and Zhan 2004, 2006). Such work focuses primarily on the evacuation traffic while oversimplifying the forecasts, warning information, and evacuation decision-making. Another body of work uses agent-based models to study warning information flow and evacuation decision making (see, e.g., Dixon et al. 2017; Yin et al. 2014; Widener et al. 2013; Watts et al. 2019; Morss et al. 2017; Czajkowski 2011; Hasan et al. 2013). However, these studies do not represent the evacuation traffic or the built environment. Arguably the most comprehensive model of the hurricane evacuation system is Blanton et al. (2018) and Davidson et al. (2018), as they integrate the forecast, evacuation-decisions, and evacuation traffic into one system. However, the evacuation models are non-agent-based, as they were designed for operational use instead of knowledge-building and experimentation.

Building on previous work, here we describe the conceptualization and implementation of a new agent-based modeling laboratory which integrates the natural hazard, the human system, and the built environment together in a unified, agent-based framework. As such, the model is uniquely positioned to examine the hurricane evacuation dynamics holistically. That is, to establish the relative importance of factors, interactions between systems, and the broader emergent patterns. After describing the model components, we present results from experiments illustrating how large-scale patterns of evacuation can emerge from the individual decisions of many heterogeneous agents as they interact with each other, and

with their physical and informational environments. For the model development and research shown here, simulations are performed on a simplified representation of Florida – a place frequently visited by tropical systems and with notable mass evacuations like Irma (Keim et al. 2007). The model was designed to be flexible, however, and thus the modeling framework can be modified to study other regions and hurricanes.

The paper's structure is similar to the Watts et al. (2019) publication in *Environmental Modeling & Software*. Section 2 provides an overview of the new model and its key components (i.e., its conceptualization and implementation). Section 3 describes the experimental design and the intended data analysis. Section 4 presents the results, including the spatial and temporal patterns in evacuation decisions and evacuation traffic. It then investigates the sensitivity of the model's behavior to changes in key parameter sets (e.g., the agents' weighting of different types of information, the timing of evacuation orders, the geographic distribution of the agent population, and use of contraflow to improve traffic) and compares results for two different hurricanes, Irma (2017) and Dorian (2019). Section 5 summarizes key results, discusses implications of this work, and proposes future research.

2. Conceptual model and implementation

This section describes the major model components and key design elements. The model code was created using the Fortran programming language. This was preferred over existing agent-based software as it provides full control over all model parameters and thus creates a virtual laboratory well suited to perform experiments. For further details, the commented code, an ODD specification (a formal, detailed model description), and supporting input files are available for download at the CoMSES model library (Paul/Rebecca: I will look into this soon).

The model system includes a spatially explicit virtual world representing a geographical area of interest (described in section 2.1); a dynamic hurricane – and forecast information about it – that passes through that world (section 2.2); a multi-agent model where information is interpreted by millions of heterogeneous agents and used to make evacuation decisions (section 2.3); and a traffic model where agents evacuate across the virtual world as the hurricane approaches (section 2.4). These components are conceptually and numerically interconnected as shown in Figure 1. The simulations shown here use a 30 minute time step for the evacuation decision-making model (Figure 1b), a 1.2 second time step for the traffic model (Figure 1c), and run for 144 and 184 hours in the cases of Irma and Dorian, respectively.

To design and implement the model, we integrate expertise in agent-based modeling, social science, and meteorology with knowledge and data from meteorology, emergency management, protective decision making, risk communication, social vulnerabilities, and traffic modeling. As in any modeling effort, numerous aspects of the model are simplified and some real-world processes are not represented. Decisions about what to include in the model were based on our research questions (e.g., to explore the broad system dynamics), review of relevant literature, and discussions among our research team. That said, elements of

the model presented here could be modified (or expanded upon) to address research questions other than the ones described here.

2.1. The virtual world

The virtual world is a cellular representation of a geographic area of interest. In this modeling framework, that world represents the north-south axis of Florida (US) abstracted as a 10 x 4 geographical domain. Florida is selected as it is an area highly susceptible to hurricanes, and has experienced notable mass evacuations such as Irma (2017). The grid spacing is coarse by design (40 grid spaces) as the project's goal is to explore the broader system dynamics, and to provide a starting point for more complex experiments. Census data informs the spatial distribution of agent households on the abstracted grid, while social vulnerability information is used to prescribe household characteristics known to influence evacuations (section 2.3). For the built infrastructure, virtual highways and interstates designed to mimic Florida's road network are overlaid on the model grid (section 2.4). Details regarding the construction of each model system – the natural hazard, the human system, and the built environment (Figure 1) – is provided in the next three subsections.

2.2. The natural system (hurricane, forecasts, and warning information)

The modeled world includes a hurricane that approaches the model domain. The storm and its forecasts can be real or synthetic; here we simulate real, historical storms using archived NHC products (available at <https://www.nhc.noaa.gov/gis/>). These products track the storm's location, size and intensity via wind radii at 34, 50, 64+ knot intervals, and forward speed as it progresses across the virtual world (Table 1a). Forecast products used include the forecast track, storm category, current and forecast wind radii (34, 50, 64+ knot intervals), cone of uncertainty, and the arrival time of tropical storm force winds (Table 1b). The current and forecast information update every 6-hours, and when taken together, the products capture the critical forecast elements (e.g., storm's track, intensity, size, forward speed, amount of uncertainty) and their evolution with time. NHC products are preferred over ensembles (Blanton et al. 2018; Davidson et al. 2018) as they more closely resemble forecasts seen by the public (Demuth et al. 2012), and can be manually perturbed to assess the evacuation's sensitivities to the forecast (section 4.6). Note: the products are a starting point, but the model can be extended to include additional forecast and warning information, if desired. In this article, NHC forecast products are obtained for Hurricanes Irma (2017) and Dorian (2019), which represent forecast scenarios with different tracks, speeds, forecast errors, and subsequently, different evacuation behaviors (e.g., Wong et al. 2018, Mongold et al. 2020).

Products are synthesized into a "light system" forecast of the three major hazards known to drive evacuation: wind, surge, and rain. The approach resembles the Meteoalarm web platform (<http://www.meteoalarm.eu>) where hazard risk are displayed in traffic-light color-coding (green, yellow, orange, red). Reds are reserved for severe and rare events, while also capturing some degree

of immanency (i.e., reds are warnings, yellows are watches) (Alfieri et al. 2012). The light system is advantageous as it (1) synthesizes the forecast for public consumption like TV personnel do (Demuth et al. 2009), and (2) provides means to connect forecast products with the agent-based model grid where evacuation decisions are made (Figure 1b).

Light system forecasts are created in GIS by overlaying products onto the 10 x 4 agent-based model grid. At each of the 40 grid cells, wind forecasts are made by combining the storm's expected category, forecast wind radii, the cone of uncertainty, and the expected time of arrival products for that location. The mathematical process of combining the information is described in Table 2. The same inputs determine surge forecasts, plus the storm's approach angle and inundation susceptibility, which is estimated using NHC's potential storm surge inundation products (Table 3). Rain forecasts are made using the storm's forward speed, wind radii (to approximate the size of the rain field), the cone of uncertainty, and the expected time of arrival of tropical storm force winds (Table 4). For each hazard, inputs are weighted with values informed by the literature (e.g., Rezapour and Baldock 2014), and team expertise in meteorology and risk perception. Though the ideal weighting is unknown, sensitivity tests on the light system weighting (not shown) suggest the weights do not change the forecasts (and subsequent evacuations) in any meaningful way.

Figure 2 presents the light system forecasts for Hurricane Irma (2017) at 24 hour intervals. The early NHC forecasts depict the most likely scenario as a landfalling major hurricane near Miami. However, the forecasts and actual track eventually shifted westward as confidence increases, with a first landfall in the Florida Keys and a second near Tampa Bay. The light system captures the gradual westward shift in threats. Moreover, the threats increase with time as confidence grows, at least for areas inside the narrowing cone of uncertainty. Because of these features, and because of the sensitivity tests on the system weighting (not shown), the light system appears capable of representing the hurricane and hurricane forecasts in the integrated modeling system. As a result, the model becomes the first to use synthesized NHC products in an agent-based modeling framework, and alongside Watts et al. (2019) and Morss et al. (2017), contains one of the most sophisticated representations of hurricane forecast information to date in models of the hurricane evacuation system.

2.3. The human system (information flow, evacuation-related decisions)

With the synthesized light system forecasts as inputs, an agent-based model simulates the “human system” i.e., information flow and evacuation-related decisions (Figure 1b). This includes two types of agents: emergency management agents who issue evacuation orders, and household agents (i.e., the public) who collect information, assess risks, and make protective decisions. An overview of the agents and their decision-making algorithms is described below.

As the hurricane approaches the coastline, emergency management agents (EMs) in the model decide whether to issue evacuation orders for each grid cell. The decision-making process is as follows: EMs issue evacuation orders when (1) the surge forecast is yellow-orange-red, and (2) when the estimated arrival time of tropical storm force winds equals the grid cell's clearance times, which is the estimated time needed to safely evacuate the area. This process is represented schematically in Figure 3 and is based on research by Demuth et al. (2012), Dye et al. (2014), and Bostrom et al. (2016) as well as the analysis in Cutter (2019). Clearance times are based on the Florida Statewide Regional Evacuation Study Program (2019) and are influenced by the available road networks and the number expected to evacuate, which is determined by population density and the surge forecasts. For example, the highest clearance times (40–60 hours) are located in Miami and Tampa Bay during red surge forecasts; lower clearance times (5–20 hours) occur in rural areas upstate with yellow surge forecasts. Since surge is not expected inland, only coastal counties can issue evacuation orders. Future versions of the model could include more complex decision making processes, including variations in how EMs make decisions and/or weight various pieces of information.

The second type of agent, household agents, represent groups of four individuals. These agents collect information about the hurricane, assess risk posed by the storm, and decide whether the risk warrants evacuation. The design of the evacuation decision-making algorithms prescribed to these agents was adapted from conceptual models of protective decision-making for hazards, such as the Protective Action Decision Model (PADM; Lindell and Perry, 2012; see hurricane applications in Lazo et al. 2015; Huang et al. 2017; Watts et al. 2019), and findings from empirical research on decision-making for hurricanes (e.g., Baker, 1991; Dow and Cutter, 2002; Dash and Gladwin, 2007; Morss and Hayden, 2010; Bowser and Cutter 2015; Huang et al., 2016, Morss et al., 2016, Demuth et al., 2016; Cuite et al., 2017; Bostrom et al., 2018; Demuth et al., 2018). As noted in Watts et al (2019), a major challenge is to synthesize the conceptual PADM model and information from empirical analyses into simple yet sufficiently specific instructions for agents. For the purposes of our model, we are not seeking a perfectly realistic algorithm; but one that captures the main processes so we can examine the broader evacuation dynamics holistically. To do so, we synthesized the relevant literature which suggests that people evacuate when they believe the hurricane poses a risk, that different people perceive risk differently and have different evacuation barriers (e.g., Baker, 1991; Dash and Gladwin, 2007; Lazo et al., 2015), and that factors with the strongest influence on evacuation decisions are forecast information, evacuation orders, and household characteristics such as age, socioeconomic status, and car ownership. Thus, we construct the decision-making algorithms by combining information obtained from these key sources (i.e., forecast information, evacuation orders, age, mobile home residence) into a risk assessment, which is then compared with evacuation barriers (i.e., socioeconomic barriers, car ownership) that vary across the agent population. Undecided agents seek information and update decisions every 30 minutes, making agents active participants in the risk communication process (Watts et al. 2019; Morss et al. 2017; Mileti and Sorensen 1990, Sadri et al. 2017). The decision-making algorithm is depicted schematically in Figure 4; specific mathematical formulation is provided in Table 5.

Household agent characteristics are prescribed by subjectively translating county-level census and social vulnerability data (Flanagan et al. 2011) regarding mobile home ownership, age, car ownership, and socioeconomic status onto the model. Grid cells in the model are ranked between 1–5 (Figure 5), with higher values representing variables which increase evacuation intentions (e.g., a 5 in mobile home ownership indicates a grid cell has high rates of mobile homes, relative to other grid cells). Once the geographical distribution of variables is sorted between cells, specific characteristics are stochastically assigned to individual households (Table 6). Again, the idea is to not perfectly represent the real-world characteristics, but to generally capture its geographical distribution, and to have a wide range of characteristics within grid cells. This results in many heterogeneous agents – 4.1 million households total (Figure 6) – with unique preferences and characteristics.

To account for complexities in how people process and value different information, factors influencing risk perception and evacuation barriers are weighed differently between households (Figure 4; Table 7). For example, some agents are concerned about evacuation orders while others are not; some are concerned about their mobile home's durability while others are not, and so on. Varying the weights captures this effect. In addition, varying the weights indirectly represents other factors such as culture and worldviews, which are sometimes important (Lazrus et al. 2020; Morss et al. 2020). In the model, weight distributions are stochastically generated for each household with specified ranges informed by the literature (e.g., Senkbeil et al. 2019; Bostrom et al. 2018; Petrolia et al. 2011; Meyer et al. 2014; Morss and Hayden 2010; Brommer and Senkbeil 2010; Peacock et al. 2005).

One noteworthy simplification of the decision-making algorithm is that households do not share forecast information with other agents. Another is that they do not consider social cues, such as seeing other people evacuate, which can increase one's risk perception. Although these processes are known to influence people's risk assessments and behaviors (e.g., Dash and Gladwin, 2007; Lindell and Perry, 2012; Demuth et al., 2018), we do not include them as the added detail further complicates the interpretation of results. However, such features could be added in future model versions, depending on the intended research goals.

2.4 The built environment (infrastructure, evacuation routing, and traffic)

Once evacuees decide to depart, a second idealized, agent-based model simulates the infrastructure, evacuation routing, and traffic (Figure 1c). The model's road network (Figure 6) consists of two northbound, five-lane interstates (blue lines) – representing Florida's I-75 and I-95 – situated on the edges of the grid i.e., along the “coasts.” Meanwhile eight, two-lane highways (red arrows) move inland residents onto the outer interstates where they flee northward to safety (blue arrows). Additionally, two east-west running, three-lane interstates (purple arrows) – representing Florida's I-75 and I-4 – allow residents to move horizontally across the grid (e.g., from Miami towards Tampa Bay, or inland towards Orlando). Though

idealized, the built infrastructure should capture the main elements of Florida's real world road network. However, future ABMs could add complex road structures, if desired.

If a household decides to evacuate, evacuating agents are instructed to depart within twelve hours of the evacuation decision (Huang et al. 2012, Lindell et al. 2005, Murray-Tuite 2019). Departure times are generated stochastically. Evacuees are also assigned a destination where late and low income evacuees move to local shelters. The rest seek accommodations where the forecast hazard risk is lower and where accommodations are available (i.e., upstate, out-of-state, inland, and in metropolitan areas; Table 8).

Departing households are assigned a vehicle and look for available spots on the nearest highway (Figure 6; red/purple arrows). If spots are unavailable for a period of time due to traffic, evacuees lose patience, abandon the evacuation and shelter in-place instead. For those who enter the road, rules governing vehicle movement are simple: drivers accelerate when they can, slow down if they must, and do not accelerate at the speed limit (70 mph on interstates, 50 mph on roads) or behind another car. Lane switching is not permitted in this model for simplicity but could be added in future models. Some drivers exhibit erratic behaviors by randomly braking, which can cause significant traffic jams. Accidents are stochastically generated, with a frequency based on Robinson et al. (2009). In regard to route selection, we simplify the complex process by assigning agents the shortest route to their destination (Sadri et al. 2014). Once assigned, evacuee routes do not change. The default settings for the parameters is described in Table 8.

A segment of evacuation traffic generated by the agent-based model is shown in Figure 7. Congestion (blue streaks) occurs from abrupt slowdowns by erratic drivers. Similar congestion (not shown) happens at intersections, in densely populated regions, and by accidents or gas shortages. For example, in the experiments shown in section 4.1, considerable traffic occurs along I-75 and I-95 northbound due to the Miami-Tampa Bay metropolitan areas being in the storm's path. Similar traffic patterns were observed during Irma's actual evacuation (e.g., Zhu et al., 2020; Cava 2018). Because of the model realism – both at micro-scales and in aggregate – we believe the agent-based model represents the traffic dynamics at a sufficient resolution to achieve the proposed goals.

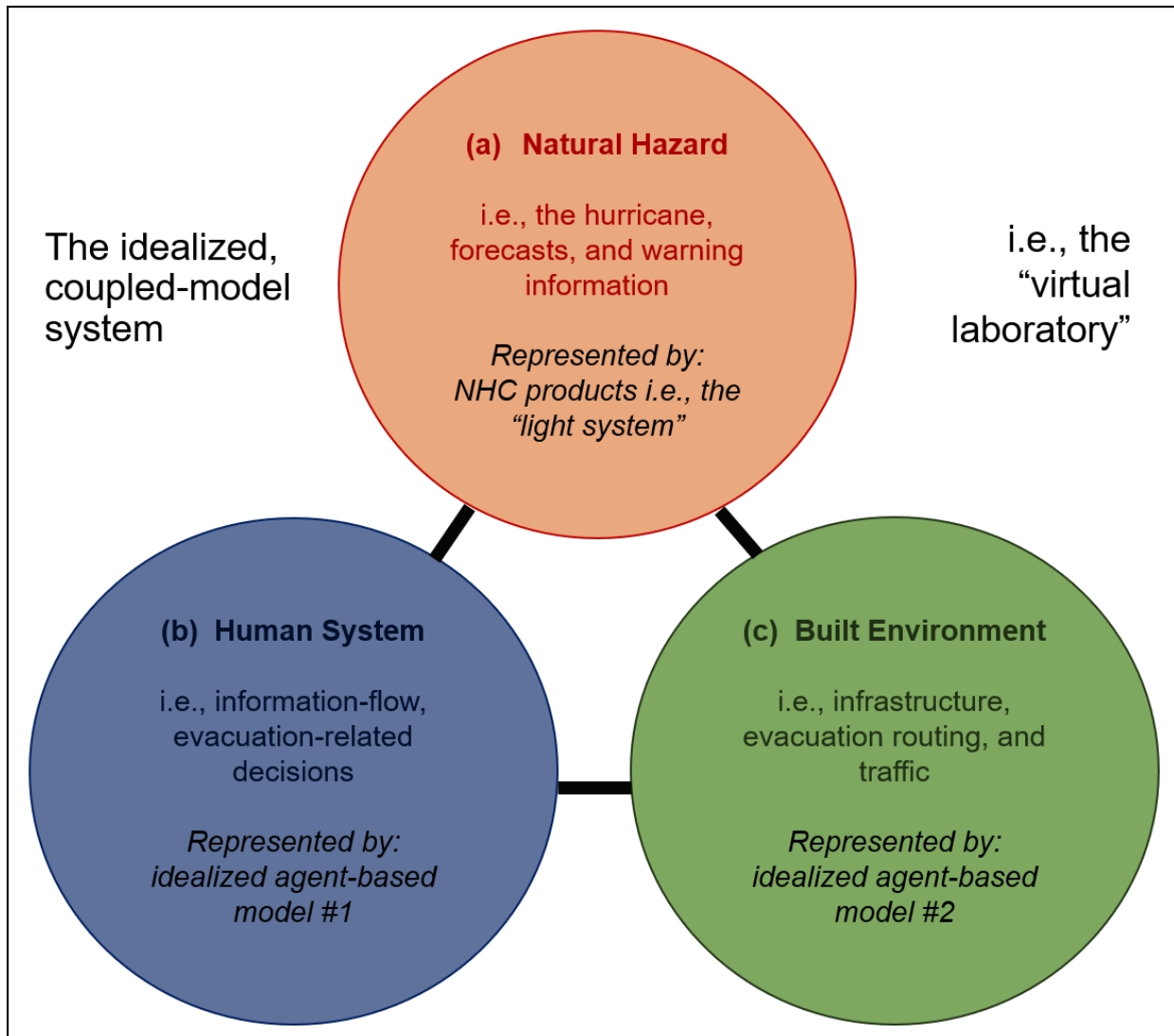


Figure 1: The conceptualized model system developed for the study, which includes three interconnected systems of hurricane evacuations: (a) the natural hazard (b) the human system, and (c) the built environment, represented by NHC forecast products and two agent-based models, respectively (italics). Coupling the idealized models creates a virtual laboratory uniquely positioned to perform experiments which are impossible to conduct in the real-world. For example, model components are perturbed in different ways to see how elements interact in the system context. In this way, they advance our understanding of the hurricane evacuation system dynamics.

a) Current storm characteristics	b) Forecast information
(updated every 6 hours)	(updated every 6 hours)
Current wind radii (i.e., 64, 50, and 34 knot wind speeds in each of 4 quadrants)	Forecast track
Current maximum sustained winds (i.e., current storm category)	Forecast maximum sustained winds (i.e., forecast storm category)
Current forward speed	Forecast wind radii (i.e., 64, 50, and 34 knot wind speeds in each of 4 quadrants)
	Cone of uncertainty
	Expected arrival time of tropical storm force winds

Table 1: Archived NHC products used to depict the (a) current storm characteristics and (b) forecast information in the model framework. Storm characteristics and forecast information update every 6 hours. Consistent with the wind speeds in the NHC data, winds are discussed here in the unit knots (nautical miles per hour, equivalent to approximately 1.15 mph or 1.85 km/h). When taken together, the products capture the hurricane size and location and critical forecast elements (e.g., storm's track, intensity, size, forward speed, amount of uncertainty, evolution with time). Information was downloaded from <https://www.nhc.noaa.gov/gis/>.

Wind risk	*Forecast category	Forecast wind field	Location in cone of uncertainty	*Expected arrival time
1	<TS	None	Fully outside	Outside cone
2	TS-1	>34 kts	Partially outside	>96 h
3	2-3	>50 kts	Partially inside	48-96 h
4	4-5	>64 kts	Fully inside	<48 h
Weight	15%	50%	20%	15%
*Conditional upon being in the cone of uncertainty and/or within forecast wind radii (=1 otherwise)				

Table 2: Wind risk forecasts are calculated for each grid cell by assigning a risk score (1-4) based on the storm's forecast category, forecast wind field (34, 50, 64+ knot intervals), location in the cone of uncertainty, and forecast arrival time of tropical storm force winds. The scores are weighted, summed, and rounded to the nearest integer to provide an overall wind threat score (1-4) expressed as green-yellow-orange-red, respectively. Note: scores for the forecast category and expected arrival time are set to 1 if the grid cell is not situated within the cone of uncertainty and/or any forecast wind radii. When taken together, the products capture the wind's critical forecast elements (e.g., storm's track, intensity, size, forward speed, amount of uncertainty, evolution with time).

Surge risk	*Inundation potential	*Forecast category	Forecast wind field	*Approach angle**	*Location in cone of uncertainty	*Expected arrival time**
1	None	<TS	None	Outside cone	Fully outside	Outside cone
2	Weak	TS-1	>34 kts	Left	Partially outside	>96 h
3	Moderate	2-3	>50 kts	Right and parallel	Partially inside	48-96 h
4	High	4-5	>64 kts	Right and perpendicular	Fully inside	<48 h
Weight	12%	12%	25%	16%	20%	15%
*Conditional upon being along shoreline (i.e., =1 inland) ** Conditional upon being inside cone of uncertainty and/or within forecast wind radii (=0 otherwise)						

Table 3: Surge risk forecasts are calculated by assigning a risk score (1-4) based on the cell's inundation potential (estimated using NHC's potential storm surge inundation products), expected category at that location, location within the forecast wind field (34, 50, 64+ knot intervals), the storm's approach angle, the location in the cone of uncertainty, and the expected arrival time of tropical storm force winds. The scores are weighted, summed, and rounded to the nearest integer to provide an overall surge threat score (1-4) expressed as green-yellow-orange-red, respectively. Note: scores for the expected category and expected arrival time are set to 1 if the grid cell is not situated within the cone of uncertainty and/or the forecast wind radii. Likewise, the values are only calculated for areas along the shoreline, as storm surge does not occur inland.

Rain risk	*Storm speed	Forecast wind field	Location in cone of uncertainty	*Expected arrival time
1	Fast	None	Fully outside	Outside cone
2	Medium	>34 kts	Partially outside	*>96 h
3	Slow	>50 kts	Partially inside	*48-96 h
4	Nearly stationary	>64 kts	Fully inside	*<48 h
Weight	30%	35%	20%	*15%
*Conditional upon being inside cone of uncertainty and/or within forecast wind radii (=1 otherwise)				

Table 4: Rain risk forecasts are calculated for each grid cell by assigning a risk score (1-4) based on the storm speed, location within the forecast wind field (34, 50, 64+ knot intervals), location in the cone of uncertainty, and the expected arrival time of tropical storm force winds. The scores are weighted, summed, and rounded to the nearest integer to provide an overall rain threat score (1-4) expressed as green-yellow-orange-red, respectively. Note: scores for the expected category and forecast period are set to 1 if the grid cell is not situated within the cone of uncertainty and/or the forecast wind radii. When taken together, the products capture the rain's critical forecast elements (e.g., storm's track, size, forward speed, amount of uncertainty, evolution with time).

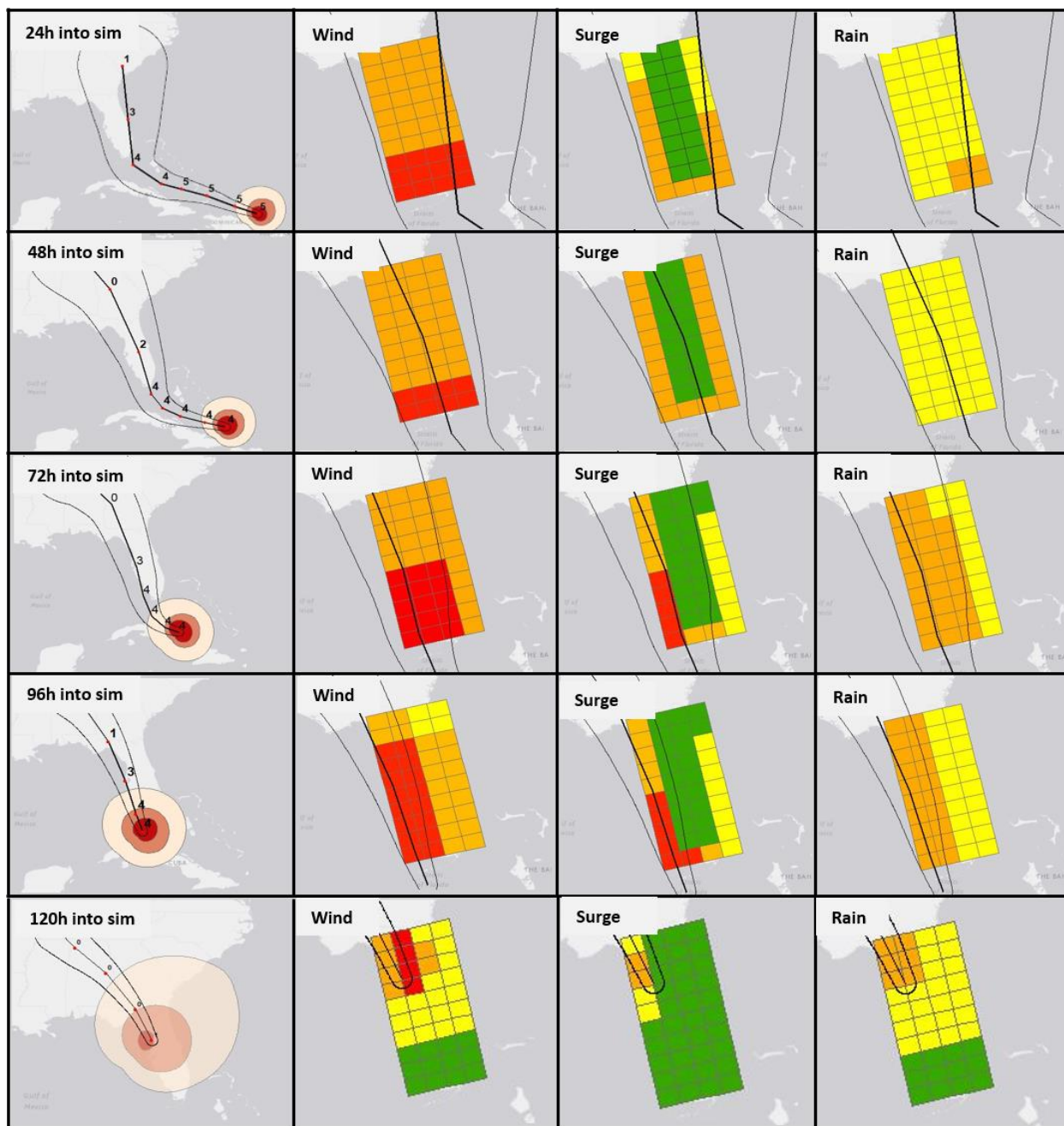


Figure 2: Example “light system” forecast for Hurricane Irma (2017) approaching the Florida-like, agent-based model grid. Forecasts are shown at 24 hour intervals, but update every 6 hours (not shown). Left column: Evolving NHC forecast track (black center line), category (numbers), cone of uncertainty (edges are outer black lines), and current wind radii at 34 (white), 50 (pink), and 64+ (red) knot intervals. Right three columns: The light-system threats for wind, surge, and rain are shown for equivalent times in the simulation, with the forecast track (center black line) and cone of uncertainty (outer black lines) included for reference. Note: threats are highest when near the center of the forecast cone and when hazards are most imminent, among other factors.

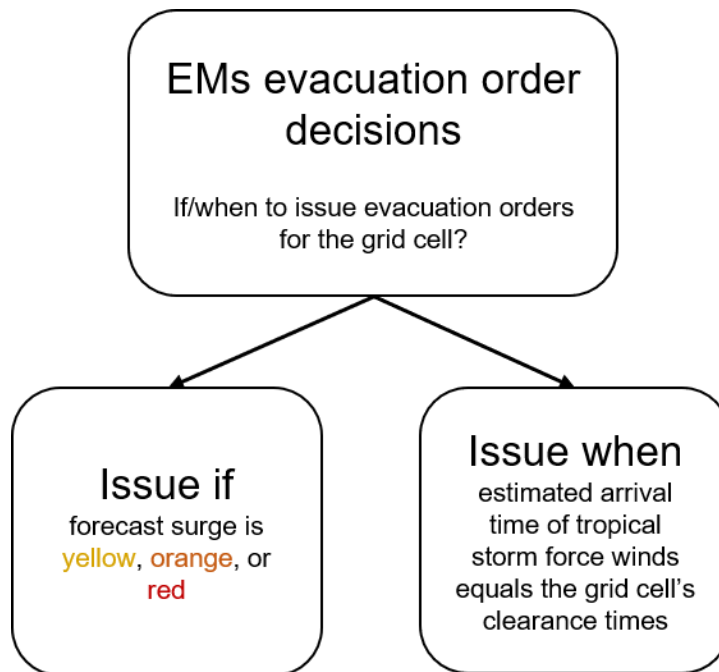


Figure 3: The evacuation order decision-making algorithm prescribed to emergency management agents (EMs) along the coastline. Information used by EMs include the surge light system forecasts (Section 2.2), estimated arrival time of the storm, and clearance times for each grid cell. Note, clearance times are based on the Florida Statewide Regional Evacuation Study Program (2019) and are influenced by available road networks and the number expected to evacuate i.e., based on population density and surge forecasts. For example, the highest clearance times (40-60 hours) are located in Miami and Tampa Bay during red surge forecasts; lower clearance times (5-20 hours) occur in rural areas upstate with yellow surge forecasts.

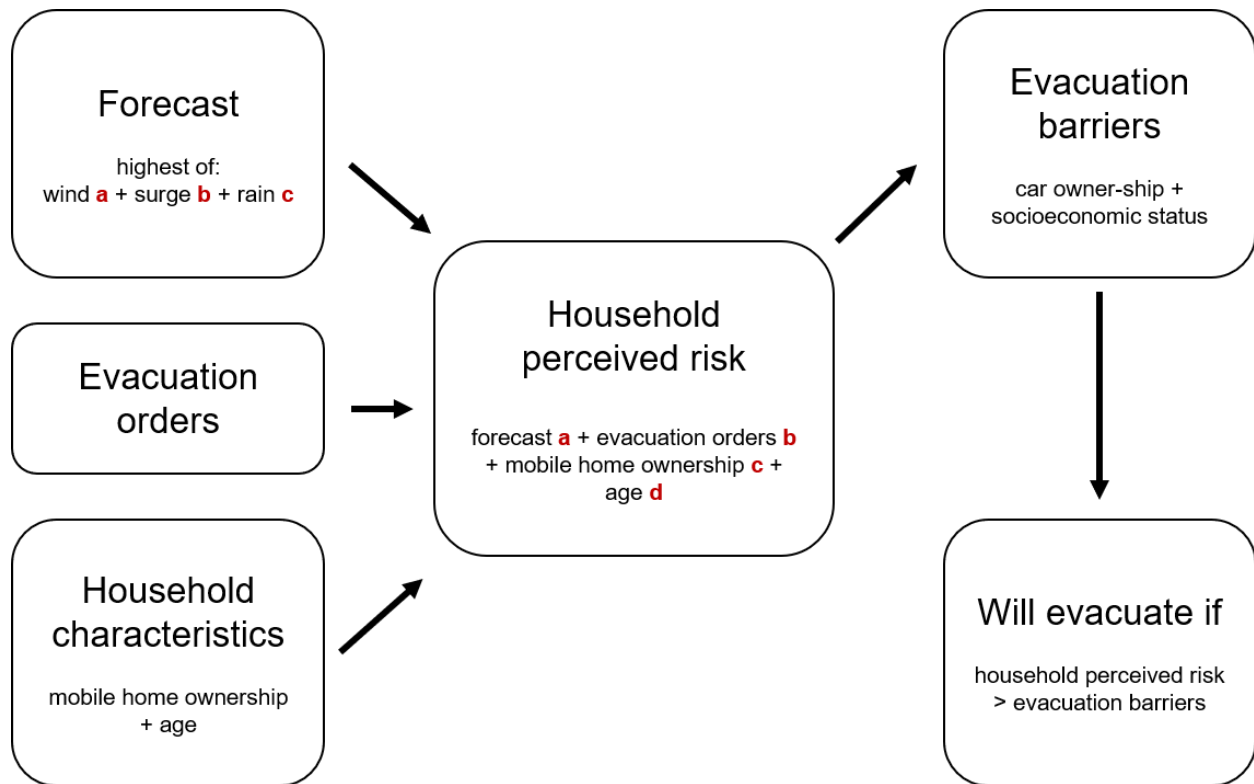


Figure 4: The evacuation decision-making algorithm for household agents in the model. Based on the PADM of Lindell and Perry (2012), the process begins when agents combine information obtained from multiple sources (e.g., forecast information, evacuation orders, and household characteristics) into a household perceived risk assessment, which is then compared with evacuation barriers (i.e., socioeconomic barriers, car ownership) that vary across the agent population. The factor weights (red) vary between households, as different people perceive risk differently. Prescribed values for the weights are detailed in Table 7. The exact mathematical process of combining and processing information to produce evacuation decisions is detailed in Table 5.

Variable	Type	Definition	Notes
Wind Threat	Dynamic	Score from light system normalized to a 0-100 scale	Green = 0, Yellow = 33, Orange = 66, Red = 100
Surge Threat	Dynamic	Score from light system normalized to a 0-100 scale	Green = 0, Yellow = 33, Orange = 66, Red = 100
Rain Threat	Dynamic	Score from light system normalized to a 0-100 scale	Green = 0, Yellow = 33, Orange = 66, Red = 100
Forecast	Dynamic	The highest score from the wind, rain, and surge threats. This is used to calculate a household's perceived risk	Values range from 0-100
Evacuation Orders	Dynamic	Is an evacuation order issued for the household's grid cell (yes/no)? This is used to calculate household perceived risk	If yes = 100. If no = 0
Mobile Home Ownership	Static	Is the household residing in a mobile home (yes/no)? This is used to calculate household perceived risk	If yes = 100. If no = 0
Age	Static	1-5 score from grid cell (Figure 7) normalized to 0-100 scale. This is used to calculate household perceived risk	If 1=20, If 2=40, If 3=60, If 4=80, If 5=100
Household perceived risk	Dynamic	The sum of the forecast, evacuation orders, mobile home ownership, age factors (each normalized to a 0-100 scale) multiplied by their respective weights (see Table 7)	Values can range from 0-400
Evacuation barrier	Static	Evacuation barrier is determined by car ownership/socioeconomic status. If household has a car and household perceived risk > socioeconomic barrier, household will evacuate	If socio=1, barrier = 5-105 If socio=2, barrier = 10-110 If socio=3, barrier = 15-115 If socio=4, barrier = 20-120 If socio=5, barrier = 25-125

Table 5: Mathematical formulation of the evacuation decision-making algorithm illustrated in Figure 4. The algorithm's inputs (i.e., forecasts, evacuation orders, mobile home ownership, age) are normalized onto a 0-100 scale, weighted (see Table 7 for weights), and summed to produce household risk perception. Risk perception is weighted against the potential evacuation barriers (i.e., if household has car, barriers are determined by one's socioeconomic status); if the household's perceived risk perception exceeds the evacuation barriers, a household will evacuate. Dynamic variables update throughout; static variables are assigned at the beginning of the simulation and do not change.

socioeconomic status				car ownership				age				mh ownership			
5	4	4	3	4	3	3	4	5	3	3	3	5	5	5	1
5	4	4	1	3	4	3	1	5	3	3	5	5	4	3	3
4	4	2	1	2	2	4	1	3	3	3	3	4	3	4	2
4	4	3	2	2	1	2	3	1	1	5	3	3	3	2	3
3	1	3	2	3	3	3	2	3	3	1	3	3	3	1	3
2	3	3	3	4	4	2	2	5	5	1	3	2	3	2	3
1	5	5	3	2	2	2	3	1	1	5	3	3	4	4	3
3	5	5	1	2	5	4	3	1	3	3	3	2	5	2	1
1	2	2	2	2	2	4	4	3	5	3	3	1	1	1	1
1	1	3	3	3	4	5	5	5	5	3	3	2	2	1	1

Figure 5: The geographical distribution of household characteristics identified by Huang et al. (2016) as being most important determinants of hurricane evacuations. The spatial distribution is informed by census and social vulnerability data for the state of Florida (Flanagan et al. 2011); specifically, by subjectively projecting the county-level data onto the abstracted, Florida-like agent-based model grid shown here. Values are ranked on a 1-5 scale, with higher values increasing evacuation intentions e.g., a 5 in mobile home ownership indicates that grid cell has high rates of mobile home ownership, relative to other grid cells. These values are used to assign characteristics to individual households (Table 6).

Variable	Type	Definition	Notes
Socioeconomic status	Static	Establishes the evacuation barrier threshold. Low (high) values indicate grid cell has less (more) financial obstacles to evacuate	If = 1, barrier = random between 5-105 If = 2, barrier = random between 10-110 If = 3, barrier = random between 15-115 If = 4, barrier = random between 20-120 If = 5, barrier = random between 25-125
Car ownership	Static	Establishes whether a household owns a vehicle. Carless households do not evacuate	If = 1, 96% of households own car If = 2, 94% of households own car If = 3, 93% of households own car If = 4, 91% of households own car If = 5, 89% of households own car
Mobile home ownership	Static	Establishes whether a household lives in a mobile home. If home is mobile, will increase risk perception	If = 1, 5% of houses are mobile If = 2, 10% of houses are mobile If = 3, 20% of houses are mobile If = 4, 33% of houses are mobile If = 5, 46% of houses are mobile
Age	Static	Indicates how age will influence evacuations. High values increase perceived household risk	These values are not translated down to the household level i.e., everyone in the grid cell has the same 1-5 value.

Table 6: The mathematical process of translating the geographical distribution of household characteristics to individual households. At the beginning of the simulation, the model checks the agent's location and subsequent values in Figure 7, then stochastically assigns household characteristics at the rates established above. These variables are static, meaning they are assigned at the beginning of the simulation and do not change, but serve as inputs into the agent decision-making algorithm described in Figure 4 and Table 5.

Weight	Type	Definition	Notes
Evacuation order	Static	Trust in evacuation orders from EMs	Random between 0-1
Forecast	Static	Trust in forecast information i.e., the light system	Random between 0-0.8
Mobile home	Static	Agent belief in whether their housing type influences perceived risk	Random between 0-10
Age	Static	Agent belief in whether household age influences perceived risk	Random between 0-0.1
Wind	Static	Household's perceived vulnerability to wind	Random between 0.1-1
Surge	Static	Household's perceived vulnerability to surge	Random between 0-1
Rain	Static	Household's perceived vulnerability to rain	Random between 0-0.9

Table 7: The weighting of key variables in the household evacuation decision-making algorithms illustrated in Figure 4. Weights are designed to reflect the relative importance of each factors (e.g., evacuation orders, forecast information, mobile home ownership, and age, in that order) as established in Huang et al. (2016). For the individual hazards, Senkbeil et al. (2019) show that households typically perceive wind as the primary threat over surge and rain.

Variable	Type	Definition	Notes
Departure times	Static	Time between when an agent decides to evacuate and when they actually leave	Random between 0-12 hours
Erratic drivers	Static	Percent of moments in which a driver may act “erratically” by randomly slowing down	5%
Patience threshold	Dynamic	Household patience i.e., the amount of time a household is willing to spend waiting to get onto a heavily trafficked road	Random between 0 and the estimated time of arrival of tropical storm force wind.
Left/right	Static	Agents in the bottom row of tiles can choose between moving left/right on the lower interstate	40% westward, 60% eastward
Destinations (out-of-state)	Static	The number of evacuees in the bottom 4 rows of tiles who evacuate out-of-state (top six rows all evacuate out-of-state)	50%
Destinations (inland)	Static	The number of accommodations available to in-state-evacuees	½ of each grid cell's overall population
Random accident frequency	Static	The frequency of accidents along the two outer interstates i.e., I-95 and I-75. These stop traffic for 10 minutes	1-3 random accidents per hour

Table 8: Key variables for vehicle agents and their implementation in the experiments discussed in this article. These parameters are the default settings for the experiments detailed in Section 4.1. Static variables are assigned once a vehicle decides to evacuate and does not change, whereas dynamic variables do change throughout the simulation.

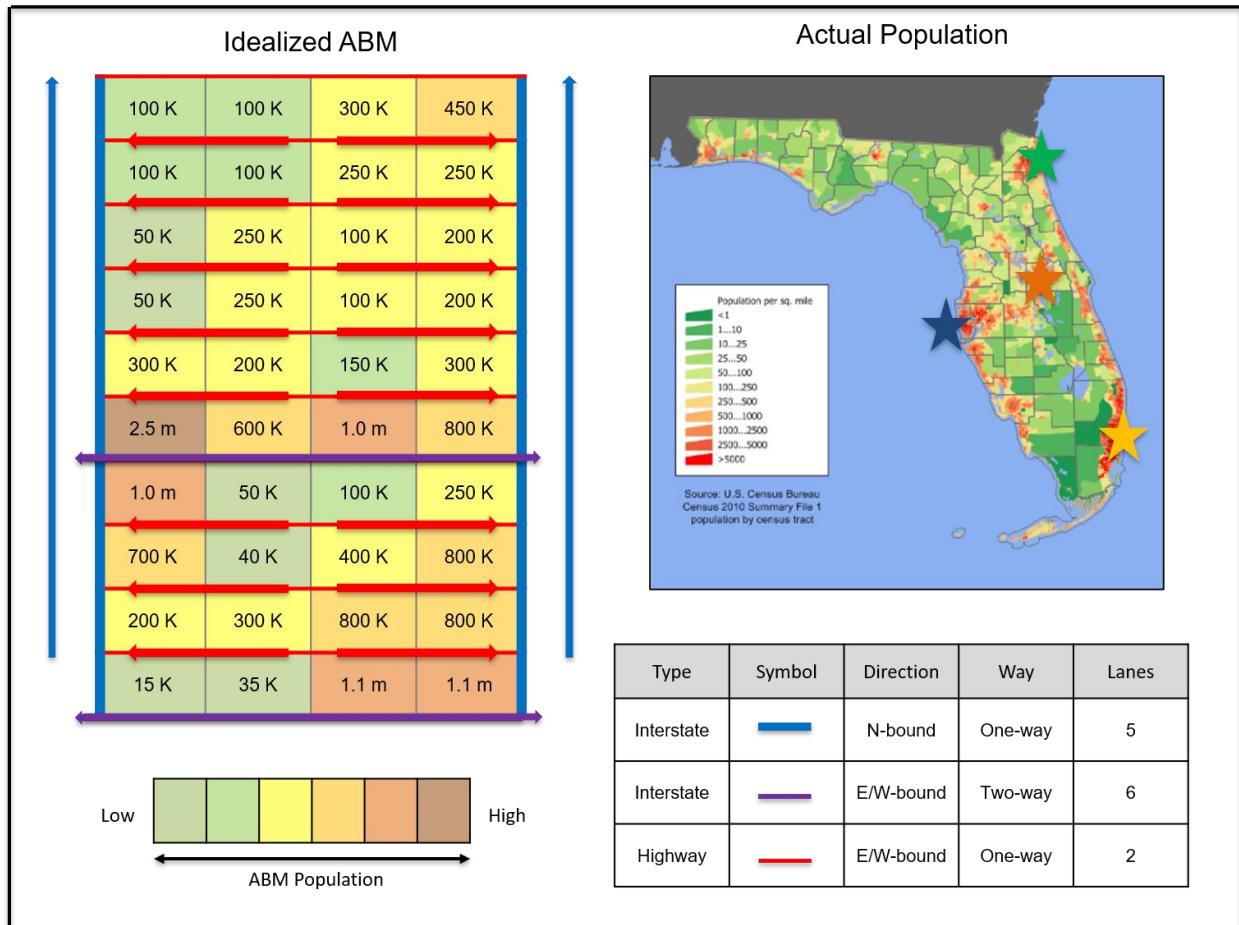


Figure 6: The agent-based model is depicted as a 10 x 4 grid representing the north-south axis of Florida. Agents inside the grid are subjectively populated and characterized based on 2019 census data (left: color filled). Note there are 16.4m agents total, which equates to 4.1m households. Major cities depicted include Miami-Ft. Lauderdale (yellow star), Tampa Bay-St. Petersburg (blue star), Jacksonville (green star), and Orlando (orange star). The available road network (e.g., road type, direction, number of lanes) is shown (left) with supporting table (bottom right). Agents are generally instructed to flee northward and to areas of lower risk.

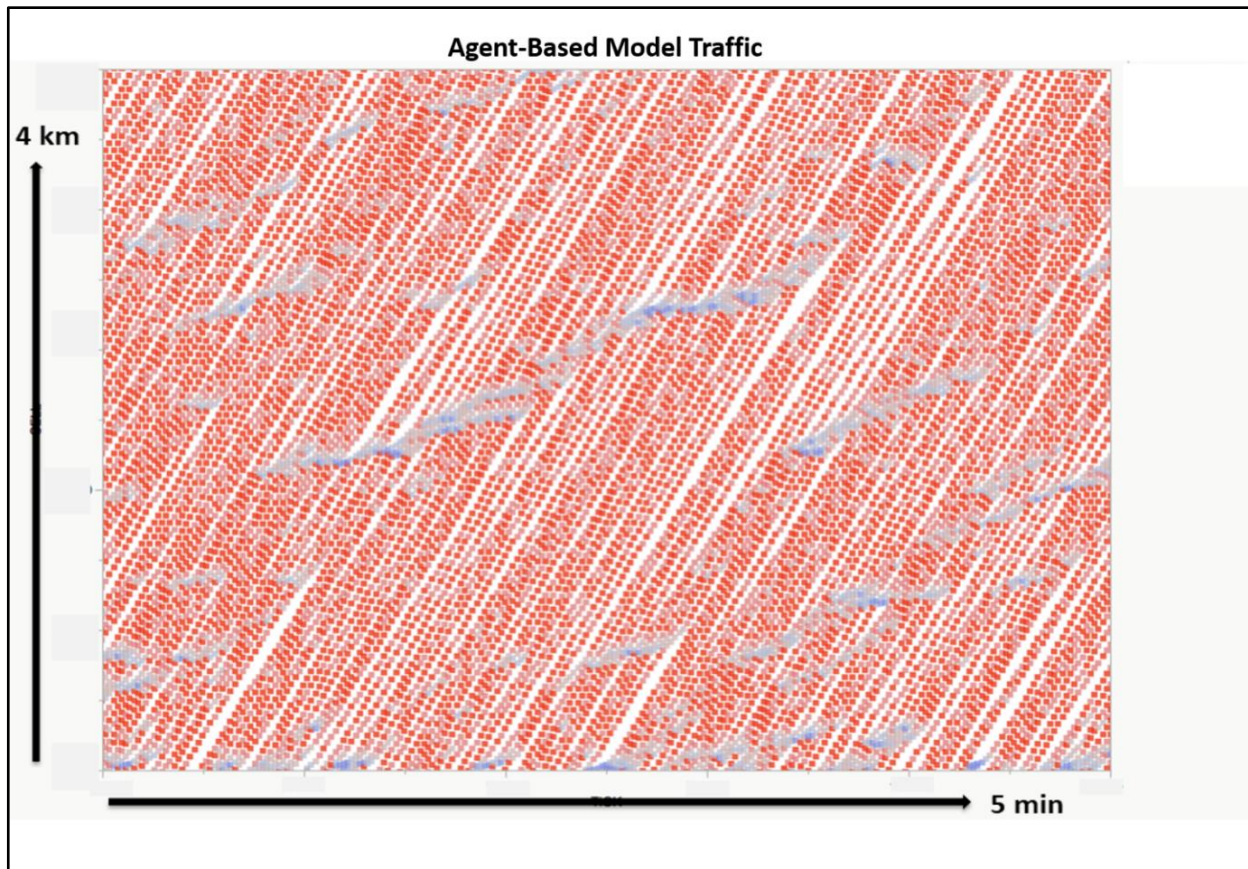


Figure 7: Sample of evacuation traffic generated by the agent-based traffic model during Hurricane Irma (2017). Agents are vehicles (dots) which progress along a 4-km segment of highway (y-axis) over a 5-minute period (x-axis). Colors depict vehicle speed – full speed traffic (red dots) moves unobstructed, while erratic drivers trigger abrupt slowdowns and traffic (blue dots) which builds over time.

Experiment	Storm	Goal	Run details
a) Default	Irma	To establish a baseline of the spatial and temporal patterns of evacuation decisions and traffic (section 4.1)	1: Inputs described in Tables 1-8
b) Evacuation decision-making inputs	Irma	Turn “off” each decision-making input one-by-one and determine influence of each (section 4.2)	1: Forecast weight = 0 2: Evacuation order weight = 0 3: Age weight = 0 4: Mobile home weight = 0
c) Varying evacuation order timing	Irma	Adjust clearance times at each grid cell to examine the influence of changing evacuation order timing (section 4.3)	1: Evacuation orders 10 h earlier 2: Evacuation orders 10 h later 3: Clearance times equal 4: Clearance times equal and 10 h earlier
d) Varying population density	Irma	Adjust population distribution to examine the influence of population density of evacuations (section 4.4)	1: Uniform population distribution
e) Implementing contraflow	Irma	Adjust the number lanes on various highways to examine the influence of contraflow on evacuations (section 4.5)	1: +1 lane on I-95 2: +1 lane on I-75 3: +1 lane on both I-95/I-75
f) Default	Dorian	To examine how the default parameter values carry over to a new storm scenario (section 4.6)	1: Default inputs (Tables 1-8) but with Dorian light system forecasts

Table 9: The different sets of experiments reported in this article. The main goals are to establish the broader spatial and temporal patterns of evacuation behaviors for Hurricane Irma (2017). We then intentionally perturb the model system (i.e., our virtual laboratory) to assess the relative importance and general response of key factors in the model, including the model's response to a new storm, Hurricane Dorian (2019).