Community Resilience Group | Materials and Structural Systems Division | Engineering Laboratory

A DECISION-SUPPORT TOOL FOR COASTAL COMMUNITY RESILIENCE: FUTURE IMPACTS FROM SEA LEVEL RISE AND SELF-LEARNING AGENTS

Dylan Sanderson*, Terri McAllister, Jennifer Helgeson, and Rithika Dulam

dylan.sanderson@nist.gov

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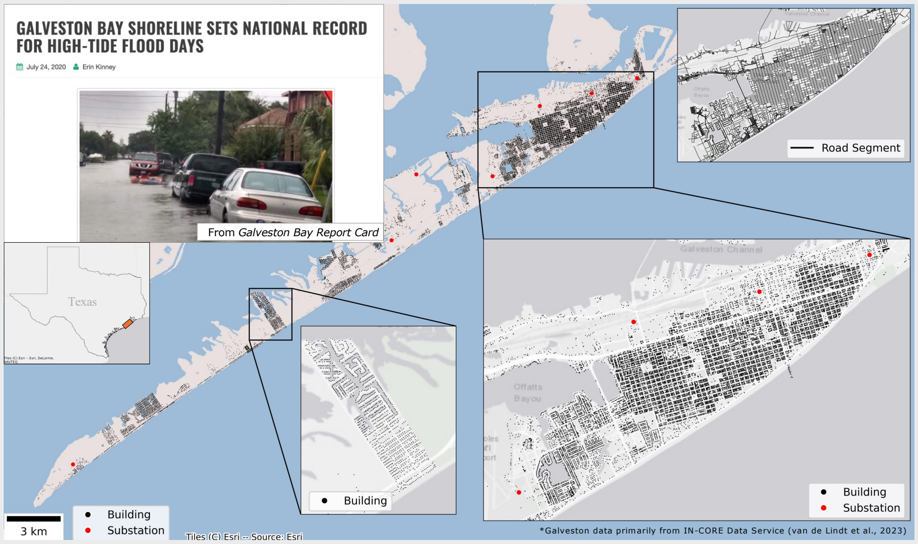
Presenting Author at Poster: 1:40p-3:00p EST



*Galveston data primarily from IN-CORE Data Service (van de Lindt et al., 2023)

MOTIVATION

Community resilience – Ability of communities to:

- *Prepare* for anticipated hazards
- *Adapt* to changing conditions
- *Withstand* and *recover* rapidly from disruptions

Community resilience models need to consider acute hazards, e.g., earthquakes, tsunamis, tornadoes, hurricanes, as well as chronic hazards, e.g., flooding from sea-level rise (SLR).

Need research and decision-support tools that:

- Help communities prepare for future chronic hazards.
- Consider time-varying impacts to buildings *and* infrastructures systems.
- Concurrently consider built, natural, and human systems.

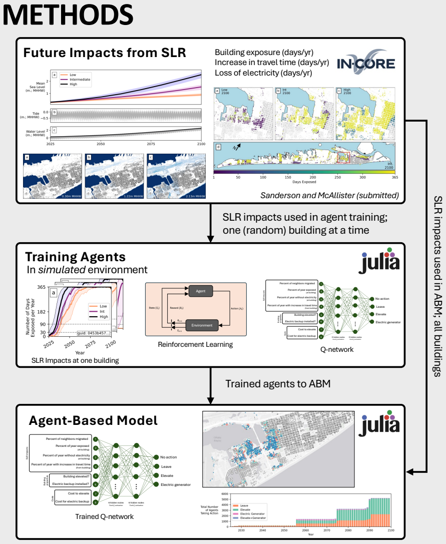
What's novel?

- An agent-based model that considers future SLR impacts to multiple infrastructure systems.
- Agents use reinforcement learning to decide *which* action to take and *when*.

Why is it important?

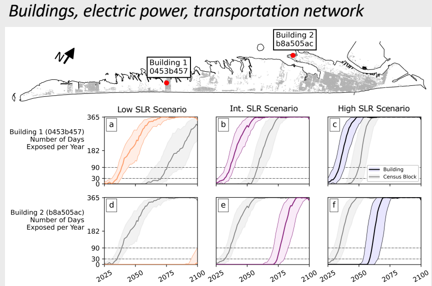
- SLR will impact not just building exposure, but also multiple infrastructure systems (electric, transportation, water, etc.).
- Reinforcement learning results in agents that are proactive and an easy to communicate reward signal.

METHODS



SEA LEVEL RISE IMPACTS

Buildings, electric power, transportation network



At each building, identify days per year:

- With building exposure
- Without electricity
- With increase in travel time to Galveston exit
- With increase in travel time to hospital

Sanderson, D., and McAllister, T. (submitted). Quantifying future local impacts of sea level rise on buildings and infrastructure. Submitted to *ASCE Natural Hazards Review.*

HOUSEHOLD DECISIONS

Use reinforcement learning to simulate household decisions.

Benefits of using reinforcement learning:

1. Agents are proactive, not reactive.
2. Agent, not modeler, decides *which* action to take and *when*.
3. Reward functions are easier to communicate than decision-rules.

Reward Function

$$\underbrace{r_t = PR}_{\text{Place reward}} - \underbrace{(NP + BP + EP + TP)}_{\text{Penalty terms}}$$

Neighbor Migration Penalty

$NP = w_{np} \cdot p_{mg}$

p_{mg}: percent of neighbors migrated at time t

Building Exposure Penalty

$$BP = \begin{cases} w_{bp} & \text{if } p_{be} < 0.1 \\ 2 \cdot w_{bp} & \text{if } 0.1 \le p_{be} < 0.3 \\ 3 \cdot w_{bp} & \text{if } p_{be} \ge 0.3 \end{cases}$$

p_{be}: percent of year with building exposed

Electric Penalty

$EP = w_{ep} \cdot p_{el}$

p_{el}: percent of year without electricity at time t

Transportation Penalty

$TP = w_{tp} \cdot p_{tr}$

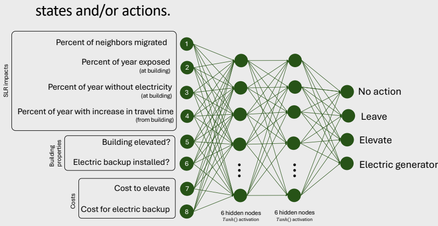
p_{tr}: percent of year with increase in travel time to Galveston exit or hospital at time t

If elevating house $r_t = -c_{elv}$

If installing generator $r_t = -c_{gnrtr}$

Agents' Q-Network

- Used to determine which action (right-hand side) to take based on a given input state (left-hand side).
- Very easy to expand network to account for additional input states and/or actions.



RESULTS

Agent Types

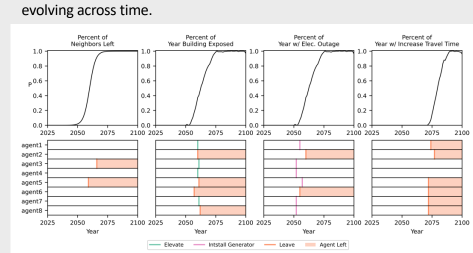
Consider 8 different agent types with variations in reward function weights and discount factor, γ.

Agent	Comparison to baseline agent (agent1)	PR	w_{NP}	w_{BP}	w_{EP}	w_{TP}	γ
agent1	-	1	1	1	1	1	0.9
agent2	Lower discount; near-term focused	1	1	1	1	1	**0.75**
agent3	Higher discount; long-term focused	1	1	1	1	1	**0.98**
agent4	Higher place reward	**3**	1	1	1	1	0.9
agent5	Higher neighbor penalty	1	**3**	1	1	1	0.9
agent6	Higher building exposure penalty	1	1	**3**	1	1	0.9
agent7	Higher electric penalty	1	1	1	**3**	1	0.9
agent8	Higher transportation penalty	1	1	1	1	**3**	0.9

γ: discount factor controls how far ahead agent is planning.

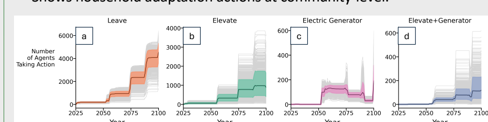
Single Agent Type – One building

Demonstrate how 8 different agent types respond to a single input state evolving across time.



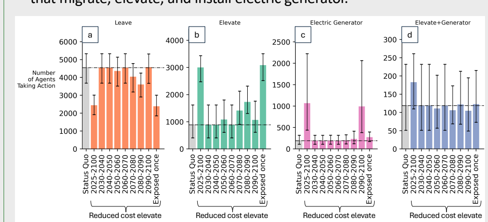
Multiple Agent Types – All Buildings

Weighted sample from different agent types (Dirichlet distribution for weights)
Randomly assign agents to buildings in Galveston.
Shows household adaptation actions at community-level.



Reducing cost to elevate

Run model with variations in incentive program to elevate home.
Assume cost to elevate is reduced by 50% of normal price.
Can see impact that home elevation program has on number of agents that migrate, elevate, and install electric generator.



DATA AND MODELS USED

Data:

- Galveston building and infrastructure inventories from IN-CORE (Fereshtehnejad et al., 2021).
- Sea-level rise data from Interagency Task Force on SLR (Sweet et al., 2022).
- Inundation layers from NOAA Digital Coast (NOAA, 2024).

Models/Methods

- SLR impacts from Sanderson and McAllister (submitted)
    - Jupyter Notebook accompanying above manuscript (Sanderson, 2024)
    - IN-CORE used for building and infrastructure exposure (van de Lindt et al., 2023)
- RL and ABM codes written by Dylan Sanderson using Julia language.

REFERENCES

Fereshtehnejad, E., Gidaris, I., Rosenheim, N., Tomiczek, T., Padgett, J., Cox, D., Van Zandt, S., and Peacock, W. (2021). Probabilistic Risk Assessment of Coupled Natural-Physical-Social Systems: Cascading Impact of Hurricane-Induced Damages to Civil Infrastructure in Galveston, Texas. ASCE Natural Hazards Review, 22(3). https://doi.org/10.1061/(ASCE)NH.1527-6996.0000459

National Oceanic and Atmospheric Administration (NOAA) (2024). Digital Coast. Office for Coastal Management, NOAA, US Department of Commerce. https://coast.noaa.gov/digitalcoast/

Sanderson, D. (2024). Quantifying future local impacts of sea-level rise on buildings and infrastructure. (Jupyter Notebook). https://doi.org/10.5281/zenodo.11402964

Sanderson, D., and McAllister, T. (submitted). Quantifying future local impacts of sea level rise on buildings and infrastructure. Submitted to *ASCE Natural Hazards Review.*

Sweet, W., Hamlington, B., Kopp, R., Weaver, C., Barnard, P., Bekaert, D., Brooks, W., Craghan, M., Dusek, G., Frederikse, T., Garner, G., Genz, A., Krasting, J., Larour, E., Marcy, D., Marra, J., Obeysekera, J., Osler, M., Pendleton, M, … Zuzak, C. (2022). *Global and regional sea level rise scenarios for the United States.* NOAA Technical Report, NOS 01. National Oceanic and Atmospheric Administration, US Department of Commerce. https://oceanservice.noaa.gov/hazards/sealevelrise/noaa-nos-techrpt01-global-regional-SLR-scenarios-US.pdf

van de Lindt, J., Kruse, J., Cox, D., Gardoni, P., Lee, J., Padgett, J., McAllister, T., Barbosa, A., Cutley, H., Van Zandt, S., Rosenheim, N., Navarro, C., Sutley, E., and Hamideh, S. (2023). The interdependent networked community resilience modeling environment (IN-CORE). Resilient Cities and Structures, 2:57-66. https://doi.org/10.1016/j.rcns.2023.07.004

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