

A Markov Decision Process Model for Socio-Economic Systems Impacted by Climate Change

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Outline

- Introduction
- MDP Model
- Optimal Policy
- Simulation Results
- Conclusion

Climate Change and Sea Level Rise

The New York Times

Sep. 25, 2018	Saving Scotland's Heritage From the Rising Seas
Sep. 12, 2018	North Carolina, Warned of Rising Seas, Chose to Favor Development
Feb. 23, 2018	What Land Will Be Underwater in 20 Years? Figuring It Out Could Be Lucrative
Aug. 7, 2017	The Sea Level Did, in Fact, Rise Faster in the Southeast U.S.
Mar. 14, 2016	Rising Sea Levels May Disrupt Lives of Millions, Study Says

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The Washington Post

Sep. 20, 2018	At this rate, Earth risks sea level rise of 20 to 30 feet, historical analysis shows
Sep. 6, 2018	Welcome to Virginia Beach, home of the East Coast's fastest-rising sea level
Aug. 20, 2018	Sea level rise is eroding home value, and owners might not even know it
Feb. 13, 2018	Study: Sea-level rise is accelerating, and its rate could double in next century
Sep. 10, 2017	Tampa Bay may escape the worst of its nightmare scenario

BUSINESS INSIDER

Sunny Day Flooding

Jul 16, 2019

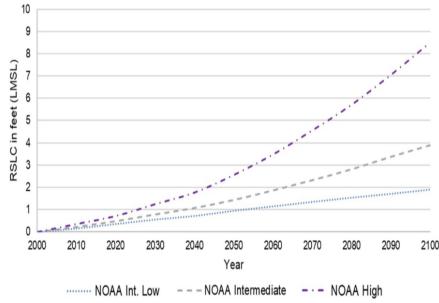
- ☐ In 2018, the number of days with high-tide flooding in the US tied the record set in 2015. In the coming year from May 2019 through April 2020- experts expect that record to be broken.
- ☐ 'Sunny-day flooding' is projected to put parts of the US underwater for at least 100 days per year by 2050.



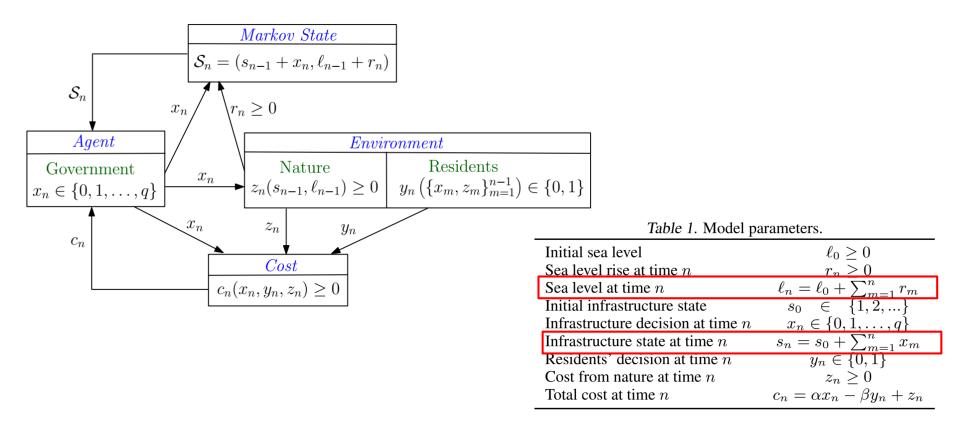
Sea Level Rise in Tampa Bay

- Tampa Bay one of the 10 most at-risk areas on the globe (World Bank study).
- \$175 billion loss in a storm the size of Hurricane Katrina.
- "Flooding in Florida will eventually cost the state regardless of whether a hurricane hits it" (WP, 9/10/17, Report by Risky Business)
- In 12 years, the value of property that will be lost to sinking land and rising water will amount to \$15 billion. By midcentury, that figure is likely to increase to \$23 billion, the report said.

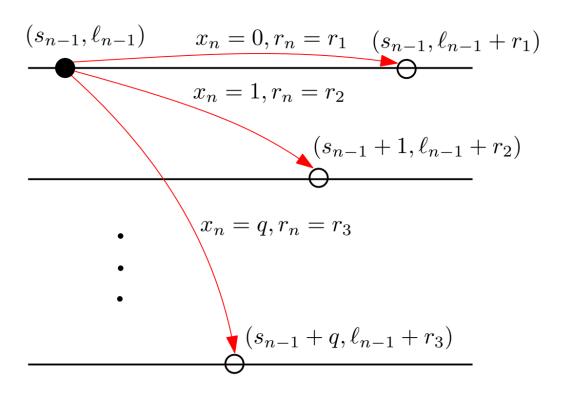
Relative Sea Level Change Projections -Gauge 8726520, St. Petersburg, FL



Markov Decision Process(MDP) Model



MDP Model: State Transition



MDP Model: Government

- Government makes a decision $x_n \in \{0, 1, 2, ..., q\}$ about degree of investment in infrastructure improvement against SLR, e.g., storm water drainage system, sea wall, levee, etc.
- Cost function

$$C_N = \sum_{n=0}^{N} a_g^n [\alpha x_n - \beta y_n + z_n]$$

- $\bullet y_n \in \{0,1\}$ denotes residents' decision to support government's investment
- $z_n \ge 0$ denotes cost from nature, e.g., flooding, storm surge, etc.
- $a_g \in (0,1)$ discount factor defines the weight of future costs in the agent's decisions.
- Time unit could be a year, two years, ... and Cost unit could be \$100 M, \$1 B, ...
- Three different entities in the cost definition are combined by adjusting the parameters lpha, eta .

MDP Model: Nature

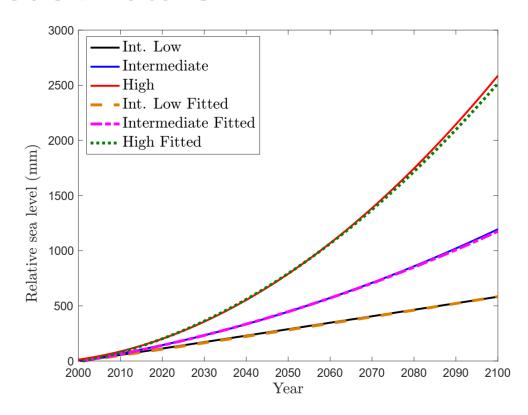
Sea level rise is modeled as

$$r_n \sim \text{Gamma}(\mu, \phi)$$

- $\phi = 0.5$
- μ is set to match the mean SLR to different NOAA projections for St. Pete, FL
- Nature's cost is modeled as

$$z_n \sim \text{GeneralizedPareto}(k, \sigma_n, \theta)$$

$$\theta \ge 0, \ \sigma_n = \frac{\eta(\ell_{n-1})^a}{(s_{n-1})^b}, \ k < 0$$



MDP Model: Residents

Residents' decision governed by $y_n \sim \text{Bernoulli}(p_n)$

$$y_n \sim \text{Bernoulli}(p_n)$$

$$p_n = \sigma(h_n) = \frac{1}{1 + e^{-(h_n - h_0)}}$$
$$h_n = \sum_{m=1}^{n-1} a_r^{n-m} x_m z_m$$

- $a_r \in (0,1)$ denotes residents' cooperation index
- For high probability of support, recently there must be both government investments and some serious cost from nature
- That is, residents are typically followers; they are serious only when both government and nature are serious!

Optimal Policy

- A rational government tries to minimize the expected cost $\mbox{E}[C_N(x_n,y_n,z_n)]$ by choosing its actions.
- Bellman Equation:

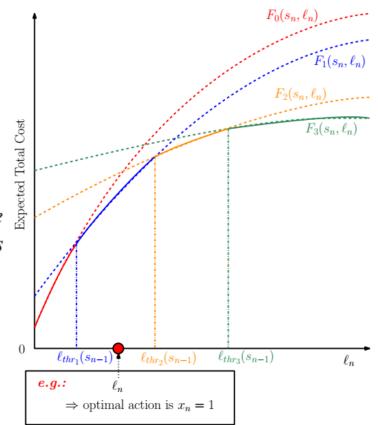
$$\begin{split} V(s_{n-1},\ell_{n-1}) &= \min_{x_n} \mathbb{E}[c_n + a_g V(s_n,\ell_n) | x_n] \\ &= \min \Big\{ \underbrace{ \begin{array}{c} \mathbb{E}[-\beta y_n + z_n + a_g V(s_{n-1},\ell_{n-1} + r_n)], \\ F_0(s_n,\ell_n) \\ \\ \mathbb{E}[\alpha - \beta y_n + z_n + a_g V(s_{n-1} + 1,\ell_{n-1} + r_n)], \\ \\ \mathbb{E}[2\alpha - \beta y_n + z_n + a_g V(s_{n-1} + 2,\ell_{n-1} + r_n)], \\ \\ \mathbb{E}[2\alpha - \beta y_n + z_n + a_g V(s_{n-1} + 2,\ell_{n-1} + r_n)], \\ \\ \cdots, \\ \mathbb{E}[q\alpha - \beta y_n + z_n + a_g V(s_{n-1} + q,\ell_{n-1} + r_n)] \Big\}, \end{split}} \end{split}$$

 $F_a(s_n,\ell_n)$

Optimal Policy

Theorem 1. For m = 0, 1, ..., q, $F_m(s_n, \ell_n)$ is nondecreasing and concave in ℓ_n for each s_n ; and the derivative of $F_m(s_n, \ell_n)$ with respect to ℓ_n is lower than that of $F_{m-1}(s_n, \ell_n)$ for m = 1, ..., q.

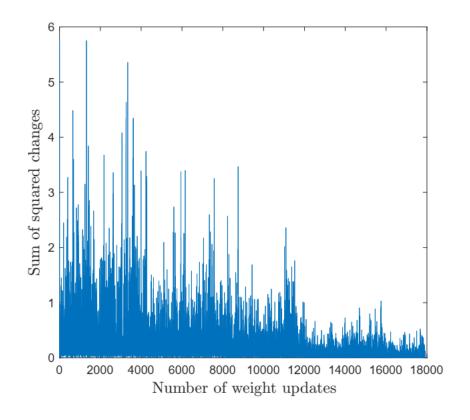
Corollary 1. The optimum policy, at each infrastructure state s_n , compares the sea level ℓ_n with at most q thresholds where each threshold signifies a change of optimal action.



Deep Q Learning (DQN) for Optimal Policy

Algorithm 1 DQN algorithm for finding optimum policy

```
1: Input: a_q, a_r, \alpha, \beta, \theta, k, \eta, a, b
 2: Initialize replay memory \mathcal{D} to capacity N
 3: Initialize action-value function Q with random weights
    w and target action-value function Q' with random
    weights w' = w
 4: for episode = 1, 2, ... do
       Initialize state S_0 = (s_0, \ell_0)
      for n = 1, 2, ..., N do
 6:
          With probability \epsilon select a random action x_n, oth-
          erwise select x_n = \arg\min_x Q(S_n, x; w)
          Execute action x_n and observe cost c_n = \alpha x_n –
 8:
          \beta y_n + z_n (see (2) and (3))
          Store transition (S_n, x_n, c_n, S_{n+1}) in \mathcal{D}
 9:
          Sample random minibatch of transitions
10:
         (S_i, x_i, c_i, S_{i+1}) from \mathcal{D}
          Set target t_i = c_i + a_q \min_x Q'(S_{i+1}, x; w')
11:
          Perform a gradient descent step on [t_j -
12:
          Q(S_i, x_i; w) with respect to the weights w
          Every d steps reset w' = w
13:
          if Q(S, x) converges for all S, x then
14:
            break
15:
          end if
16:
       end for
18: end for
```



Simulation for Tampa Bay Region

$$\beta = 14$$

$$\alpha = 25$$

$$x_n \in \{0, 1, 2, 3\}$$

$$s_0 = 50$$

$$\ell_0 = 100$$

Generalized Pareto parameters

$$k = -0.001$$

$$\theta = 1$$

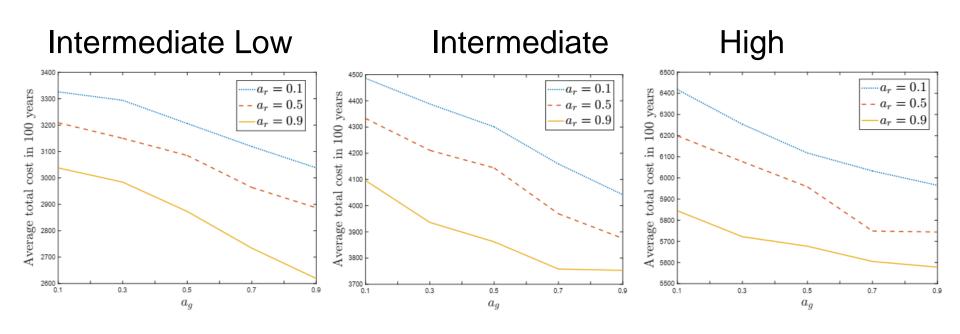
$$\eta = 25$$

$$a = 0.9$$

$$b = 1.1$$

Results:

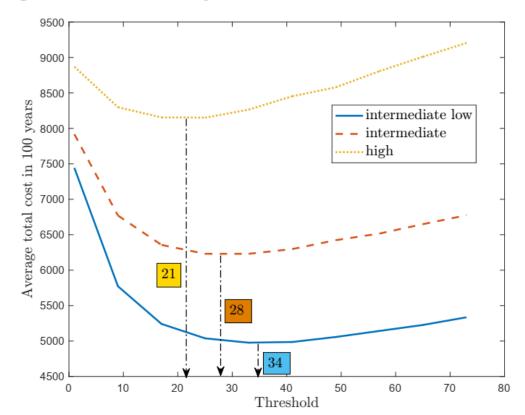
Total cost as a function of cooperation indices for 3 scenaios



Results:

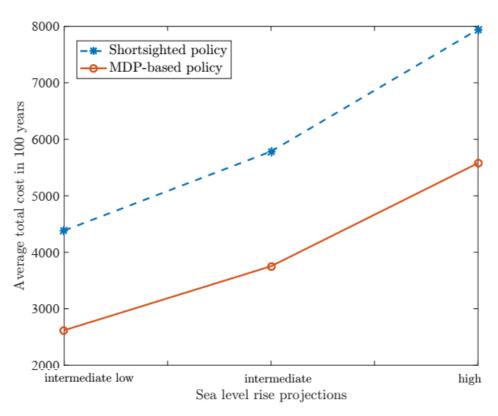
Shortsighted Policy

- An reactive/responsive real-world government improves infrastructure after experiencing a significant cost from the nature.
- Shortsighted government makes yearly investment whenever cost from nature is higher than a predetermined threshold.



Results:

Shortsighted vs. MDP based Policy



Collaboration with policymakers from the Tampa Bay area

- Douglas Hutchens, Deputy City Manager, the City of Dunedin.
- Melissa Zornitta, Executive
 Director, Hillsborough County Planning
 Commission
- Mark Hafen, Member, Tampa Bay Climate. Science Advisory Panel.
- Vik Bhide, Director, Transportation and Stormwater Services at City of Tampa
- Alison Barlow, Executive Director,St.
 Petersburg Innovation District



Concluding Remarks

- •MDP model for government's investment decisions.
- Optimal policy is proactive: monitors sea level.
- Convergence for RL algorithm that finds optimal policy.
- Optimal policy achieves much less cost than shortsighted policy.
- •Cooperation matters: responsive governments and residents significantly decrease the expected cost.



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Thank You