Evaluating staged investments in critical infrastructure for climate adaptation

Interdisciplinary Ph.D. Workshop in Sustainable Development 2019

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The really big picture

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That is not a particularly stretching target. Of Nigeria's many daily headaches, power is perhaps the worst. After years in which state-owned power plants decayed, the government changed course by selling power stations and the distribution grids that carry power to homes and businesses. This bold stroke was meant to turn the lights on, and indeed it has encouraged investors to put millions of dollars into upgrading the battered system. Yet the supply of power has failed to respond as hoped in the two years since privatisation. At the moment the country's big stations produce a pitiful 2,800MW, which is about as much as is used by Edinburgh. Only just over half of Nigerians have access to electricity, and it is still harder for businesses to hook up to the grid than almost anywhere else.

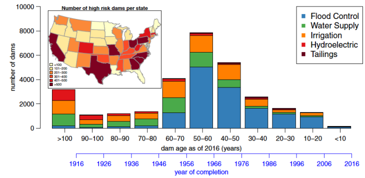

Figure 1. Age of dams in the United States (that meet the criteria of 1. Possible or likely loss of human life in the event of dam failure; 2. Dam height $\geq$ 7.6 m and reservoir storage $\geq 18.5 \times 10^3$ m^3; or 3. Dam height $\geq$ 1.8 m and reservoir storage $\geq 61.7 \times 10^3$ m^3) with primar uses of flood control, water supply, irrigation, hydroelectric, or tailings dams [*U.S. Army Corps of Engineers*, 2015] and (inset) Number of high-risk dams per state (where failure or misoperation would result in the probable loss of human life [*Federal Emergency Management Agency*, 2004]. Data from *Stanford University* [2016].

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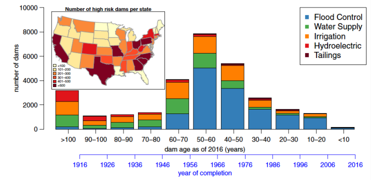

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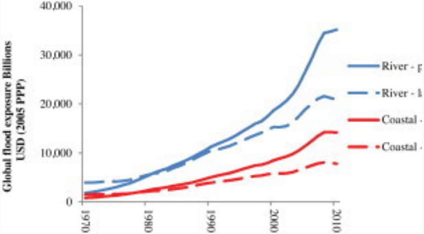
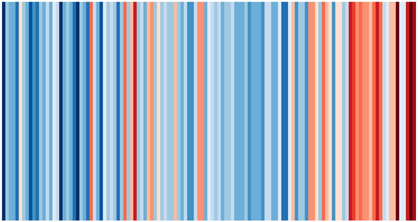


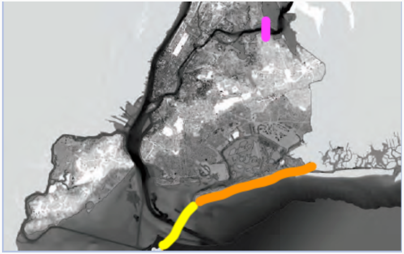
Annual temperature for contiguous USA (1895–2017)

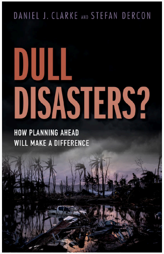


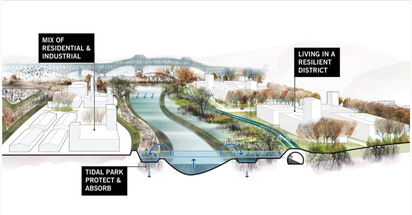
(Ho et al., 2017; Jongman et al., 2012; "Powerless" 2016)

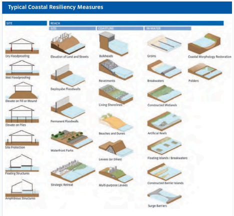
Motivating case study

What to do after Sandy? (City of New York, 2013)









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Paper submitted to Earth's Future; all codes are available at `http://github.com/jdossgollin/2018-robust-adaptation-cyclical-risk`

Hypotheses

Idea 1: Risk Estimates over Finite Future Periods

Typical Approach:

Cost-Benefit Analysis (CBA), probably with discounting, over a finite planning horizon of M years.

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Small M: defer large investment and allow some uncertainties to be resolved

Idea 2: Hydroclimate Systems Vary on Many Scales

Inter-annual to multi-decadal cyclical variability key (for small M)

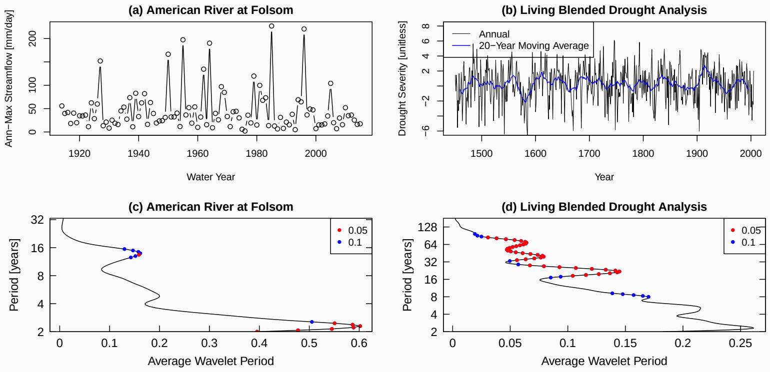
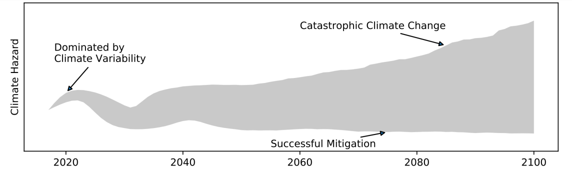


Figure 1: (a) 500 year reconstruction of summer rainfall over Arizona from LBDA (Cook et al., 2010). (b) A 100 year record of annual-maximum streamflows for the American River at Folsom. (c),(d): wavelet global (average) spectra.

Idea 3: Physical Drivers of Risk Depend on M

The physical drivers of hazard depend on the projection horizon (M),



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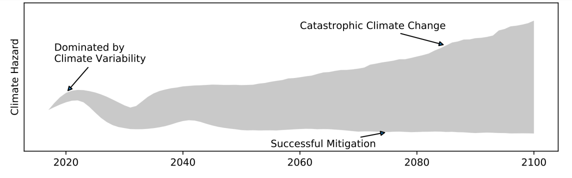
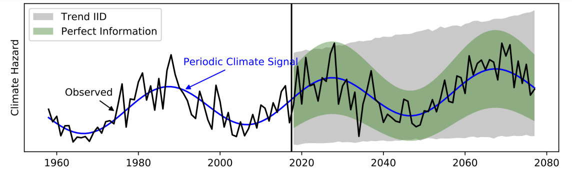


but our ability to identify these mechanisms depends on information available (e.g., the length of an N-year observational record).



Stylized Experiments

Experiment Setup

Research Objective

How well can one identify & predict cyclical and secular climate signals over a finite planning period (M), given limited information?

Let $P^* = \mathbb{P}(X > X^*)$.

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- 3 simple models for projecting risk

Measure bias and variance of P^*.

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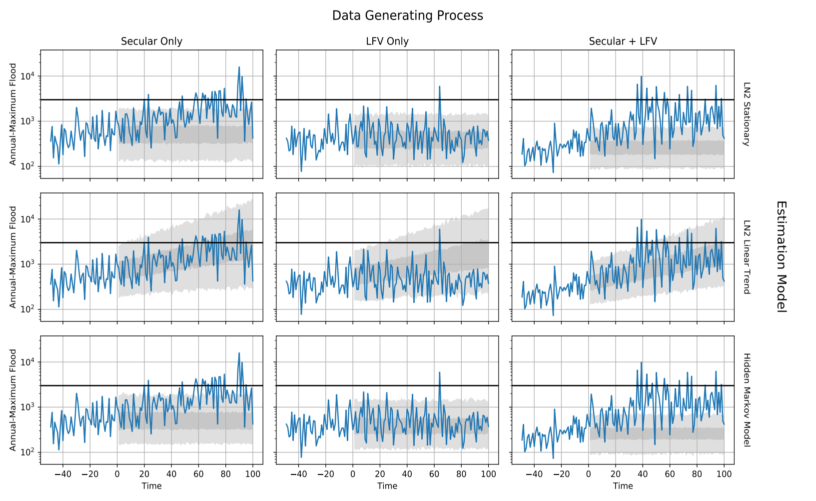
Measure bias and variance of P^*.

Don't use these models for actual estimation!

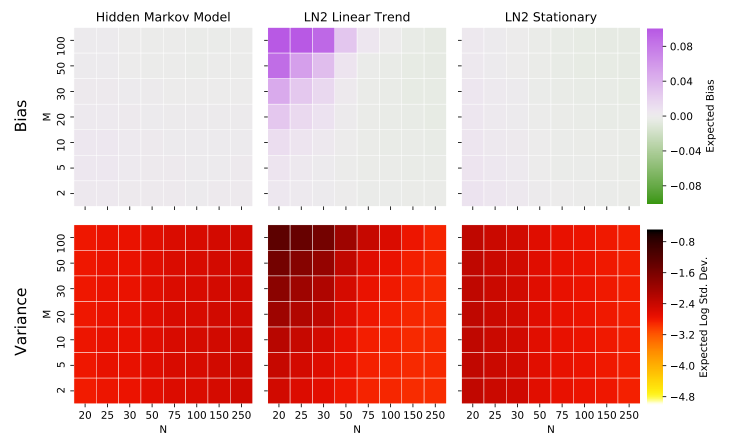
How it works



Data Generating Process
Secular Only
LFV Only
Secular + LFV
Annual-Maximum Flood
10^4
10^3
10^2
LN2 Stationary
LN2 Linear Trend
Hidden Markov Model
Estimation Model
−40 −20 0 20 40 60 80 100
Time

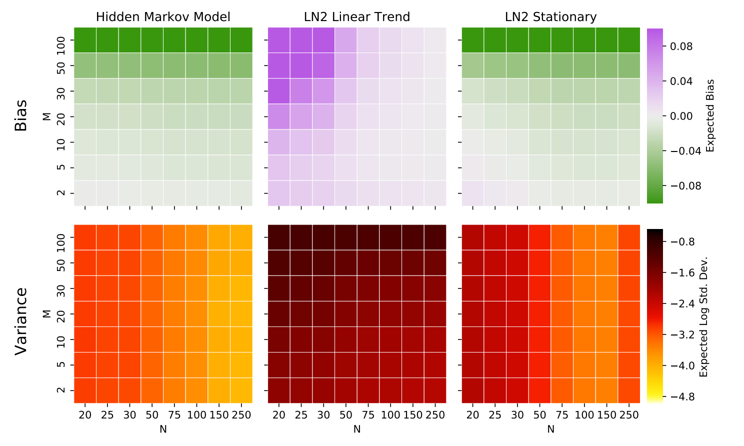
Stationary Scenario (LFV Only)

With limited data, the uncertainties caused by extrapolating from complex models lead to poor performance.



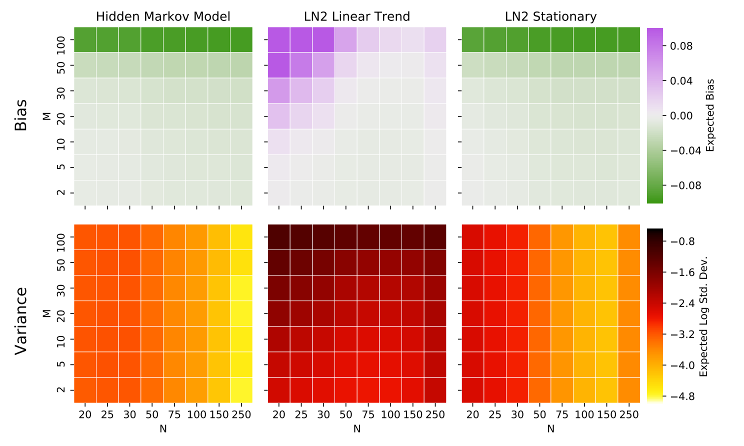
Nonstationary Scenario I (Secular Change Only)

Long planning periods need trend estimation, but this demands lots of information. For short planning periods, simple models may be better.



Nonstationary Scenario II (Secular Change + LFV)

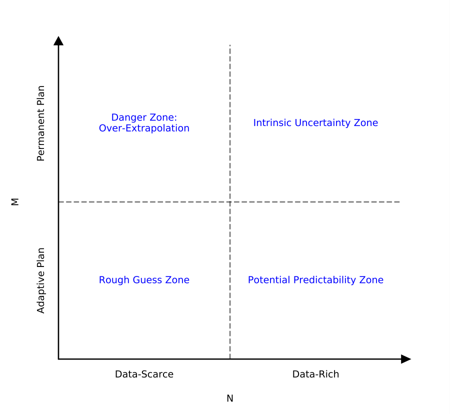
As the system becomes more complex, more data is needed to understand it.



Discussion

Summary

- Investment evaluation depends on climate condition over finite planning period
- Physical hydroclimate systems vary on many scales
- Physical drivers of risk depend on planning period



Conclusions

- Quasi-periodic and secular climate signals, with different identifiability and predictability, control future uncertainty and risk

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- Quasi-periodic and secular climate signals, with different identifiability and predictability, control future uncertainty and risk
- Adaptation strategies need to consider how uncertainties in risk projections influence success of decision pathways
- Stylized experiments reveal how bias and variance of climate risk projections influence risk mitigation over a finite planning period

Next steps

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Thanks for your attention!

Interested in making these ideas more concrete? I'd love to collaborate!

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Supplemental Discussion

Idealized Experiments $\Longleftrightarrow$ Real World

The idealized models used here are analogs:

Analysis	Real World
N-year record	Total informational uncertainty of an estimate
Statistical models of increasing complexity and # parameters	Statistical and dynamical model chains of increasing complexity and # parameters
Linear trends	Secular changes of unknown form
low-frequency climate variability (LFV) from the El Niño-Southern Oscillation (ENSO)	LFV from many sources
LFV and trend additive	LFV and trend interact

Generating Synthetic Streamflow Sequences

Equations for Synthetic Streamflow Generation

First

$$\log Q(t) \sim \mathcal{N}(\mu(t), \sigma(t)). \tag{A1}$$

Where $\sigma(t) = \xi\mu(t)$, with $\sigma(t) \geq \sigma_{\text{min}} > 0$. Then,

$$\mu(t) = \mu_0 + \beta x(t) + \gamma(t - t_0), \tag{A2}$$

and where $x(t)$ is NINO3.4 index from realistic ENSO model (Ramesh et al., 2016; Zebiak and Cane, 1987)

Spectrum of LFV Used

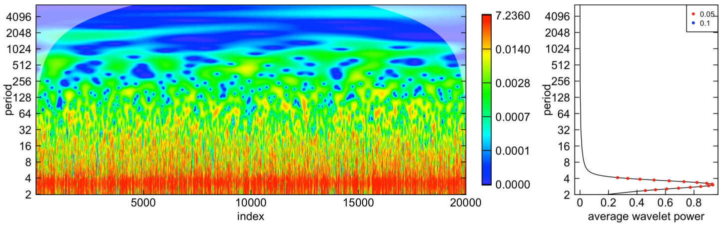

Figure A1: Wavelet spectrum of (sub-set of) ENSO model used to embed synthetic streamflow sequences with low-frequency variability. ENSO data from Ramesh et al. (2016).

Climate Risk Estimation

Stationary LN2 Model

Treat the N historical observations as independent and identically distributed (IID) draws from stationary distribution

$$\begin{aligned} \log Q_{\text{hist}} &\sim \mathcal{N}(\mu,\ \sigma) \\ \mu &\sim \mathcal{N}(7, 1.5) \\ \sigma &\sim \mathcal{N}^+(1, 1) \end{aligned} \tag{A3}$$

where $\mathcal{N}$ denotes the normal distribution and $\mathcal{N}^+$ denotes a half-normal distribution. Fit in Bayesian framework using stan (Carpenter et al., 2017).

Trend LN2 Model

Treat the N historical observations as IID draws from log-normal distribution with linear trend

$$\begin{aligned}
\mu &= \mu_0 + \beta_\mu (t - t_0) \\
\log Q_{\text{hist}} &\sim \mathcal{N}(\mu,\ \xi\mu) \\
\mu_0 &\sim \mathcal{N}(7, 1.5) \\
\beta_\mu &\sim \mathcal{N}(0, 0.1) \\
\log \xi &\sim \mathcal{N}(0.1, 0.1)
\end{aligned} \tag{A4}$$

where ξ is an estimated coefficient of variation. Also fit in stan.

Hidden Markov Model

Two-state Hidden Markov Model (HMM) (see Rabiner and Juang, 1986) implemented using pomegranate python package (Schreiber, 2017). See package documentation for reference.