H52F-05H: Robust Adaptation to Multi-Scale Climate Variability

Toward Better Water Planning and Management in an Uncertain World I

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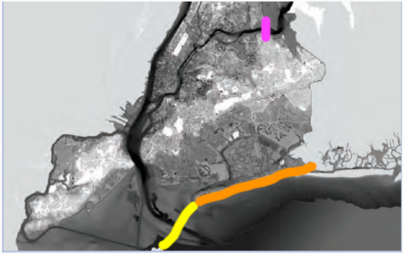
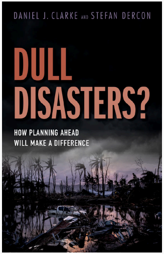
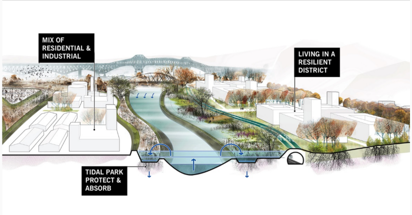
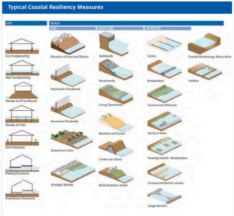
Motivating Example

What to do after Sandy? [*City of New York*, 2013]









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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Project should be evaluated on climate conditions over this finite planning period:

- For "mega-project", $M \geq 50$ years
- For small, flexible project, $M \leq 5$ years

Idea 2: Hydroclimate Systems Vary on Many Scales

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

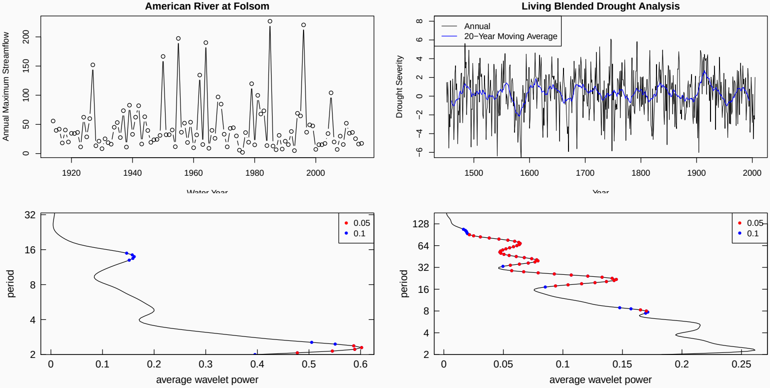
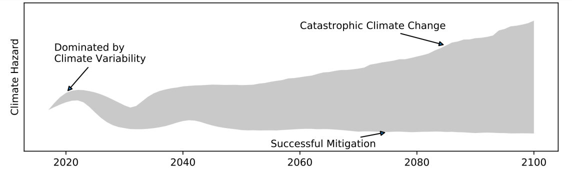


Figure 1: (a) 500 year reconstruction of summer rainfall over Arizona from LBDA [*Cook et al.*, 2010]. (b) A 100 year record of annual-maximum streamflows for the American River at Folsom. (c),(d): wavelet global (average) spectra.

Idea 3: Physical Drivers of Risk Depend on M

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



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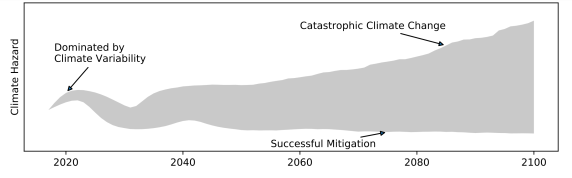
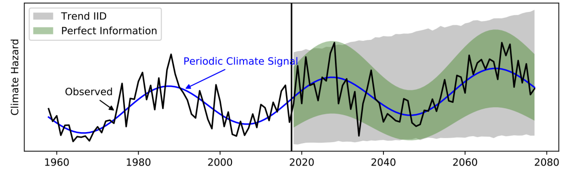


but our ability to identify these mechanisms depends on information available (e.g., the length of an N-year observational record).



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 $P^*(X > X^*)$. Note that the insurance premium (or risk factor) is:

$$R = \mathbb{E}[P^*] + \lambda \mathbb{V}[P^*]$$

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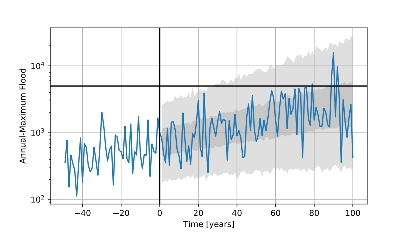
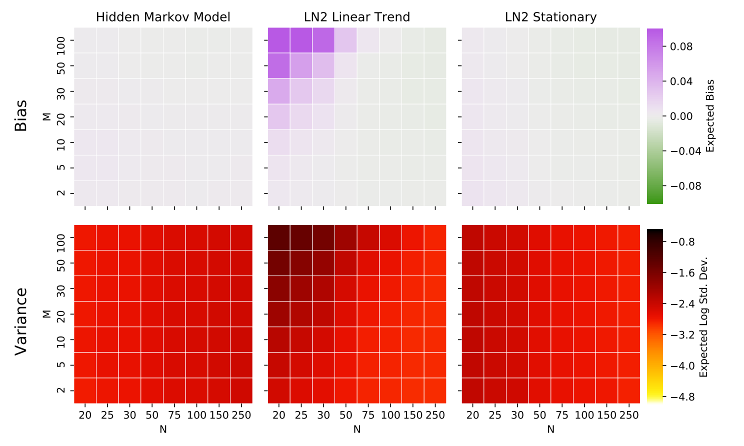


Systematic, stylized experiments: what happens as we vary M, N, climate structure, estimating model?

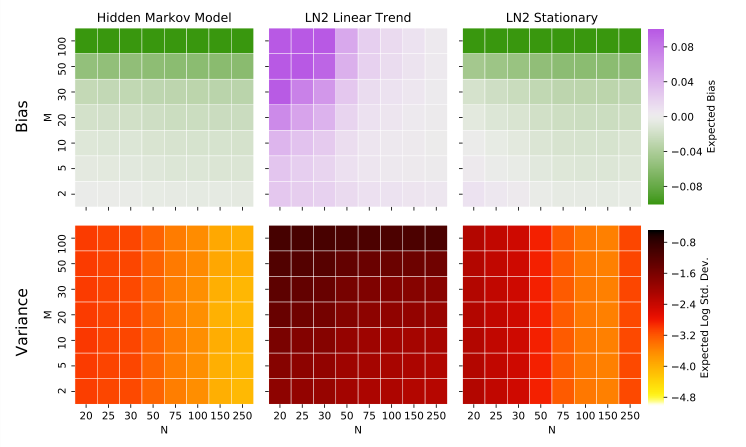
Stationary Scenario (LFV Only)

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



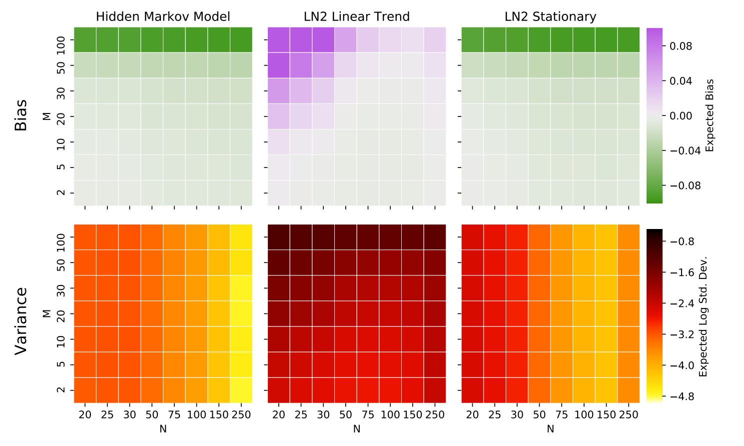
Nonstationary Scenario I (Secular Change Only)

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

Assertions:

- 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

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- *Importance* of predicting different climate signals depends on extrapolation desired (i.e., planning period)

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Implications:

- *Ability* to identify and predict different climate signals depends on information available (e.g., N)
- *Importance* of predicting different climate signals depends on extrapolation desired (i.e., planning period)
- In general, low risk tolerance and/or limited information favor investments with short planning periods.

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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

Example Sequences and Fits

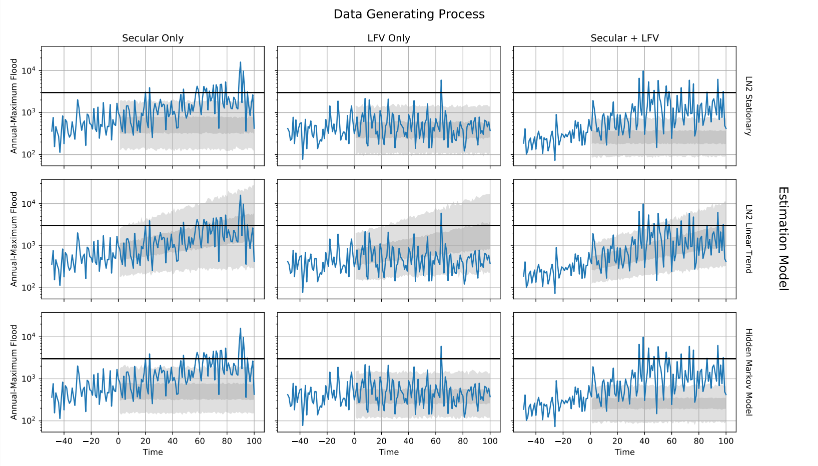

Figure A1: Example of sequences generated with $M = 100$ and $N = 50$

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 [*Zebiak and Cane*, 1987; *Ramesh et al.*, 2016]

Spectrum of LFV Used

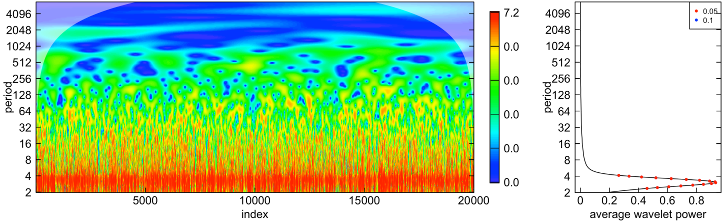

Figure A2: Wavelet spectrum of (sub-set of) ENSO model used to embed synthetic streamflow sequences with low-frequency variability. ENSO data from *Ramesh et al.* [2016].

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.