Robust Adaptation to Multi-Scale Climate Variability

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At a Glance

Assessing the utility of a particular risk mitigation instrument involves projecting the climate hazard against which the instrument protects over the M-year planning period.

- Climate risk varies in time over a project's finite planning period, M, which may be 1-5 years for a financial risk mitigation instrument and 30-100 years for a structural instrument.
- Cyclical climate variability (anthropogenic climate change) dominates near-term (long-term) climate risk
- Successful climate adaptation requires prediction of short- and long-term climate variability over the finite planning period M

An often neglected point is that the sources of predictability differ between projects with long and short planning periods. *We present a set of stylized experiments to assess how well one can identify and predict risk associated with cyclical and secular climate signals for the design life (M years) and the probability of over- or under-design of a climate adaptation strategy based on these projections.*

Observed LFV

Our analysis is motivated by analysis of historical and paleo records of hydroclimate systems, which often show key modes of variability on interannual to multidecadal time scales [6, 9]. The following time series and wavelet global spectra are representative of this low-frequency climate variability (LFV).

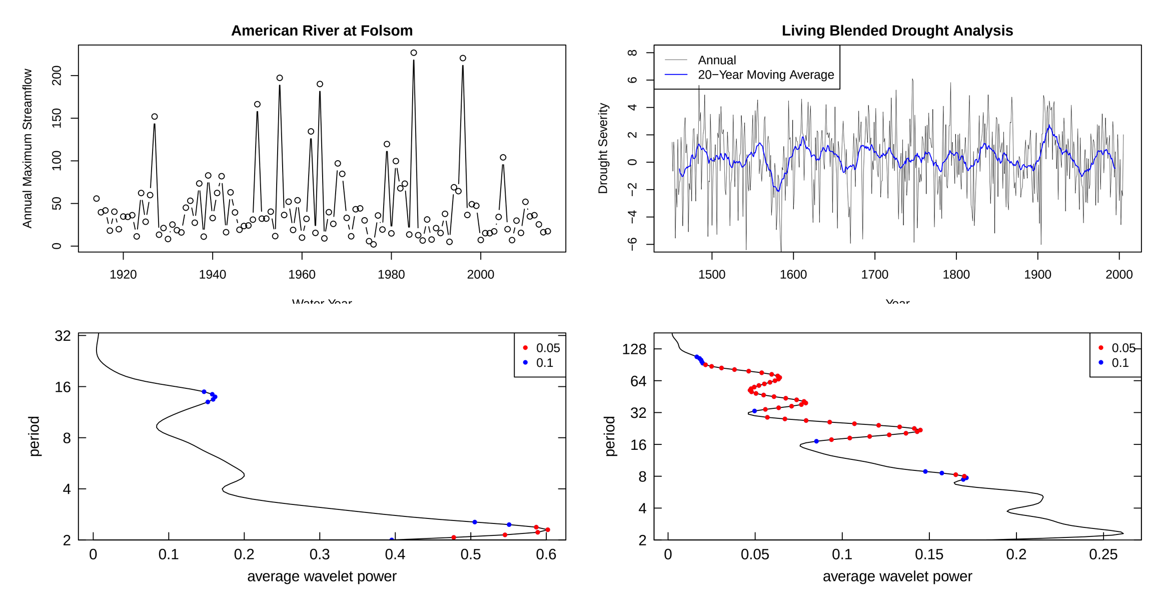

Figure 1: Hydroclimate time series vary on many time scales. (a) A 100 year record of annual-maximum streamflows for the American River at Folsom. (b) A 500 year reconstruction of summer rainfall over Arizona from the living blended drought analysis (LBDA) [1]. (c) the wavelet global (average) spectrum of the LBDA time series (a). (d) like (c), for the LBDA data.

Secular Change

Risk, defined as the product of *hazard* and *exposure*, is changing ("nonstationarity"):

- anthropogenic climate change (ACC) affects the intensity, location, and frequency of hydroclimate extremes [2, 7]
- changes in land use, river channels, and water use affect local hydrologic cycles [6]
- urbanization and development drive increasing exposure to floods [5] and hurricanes [8]

Types of Uncertainty

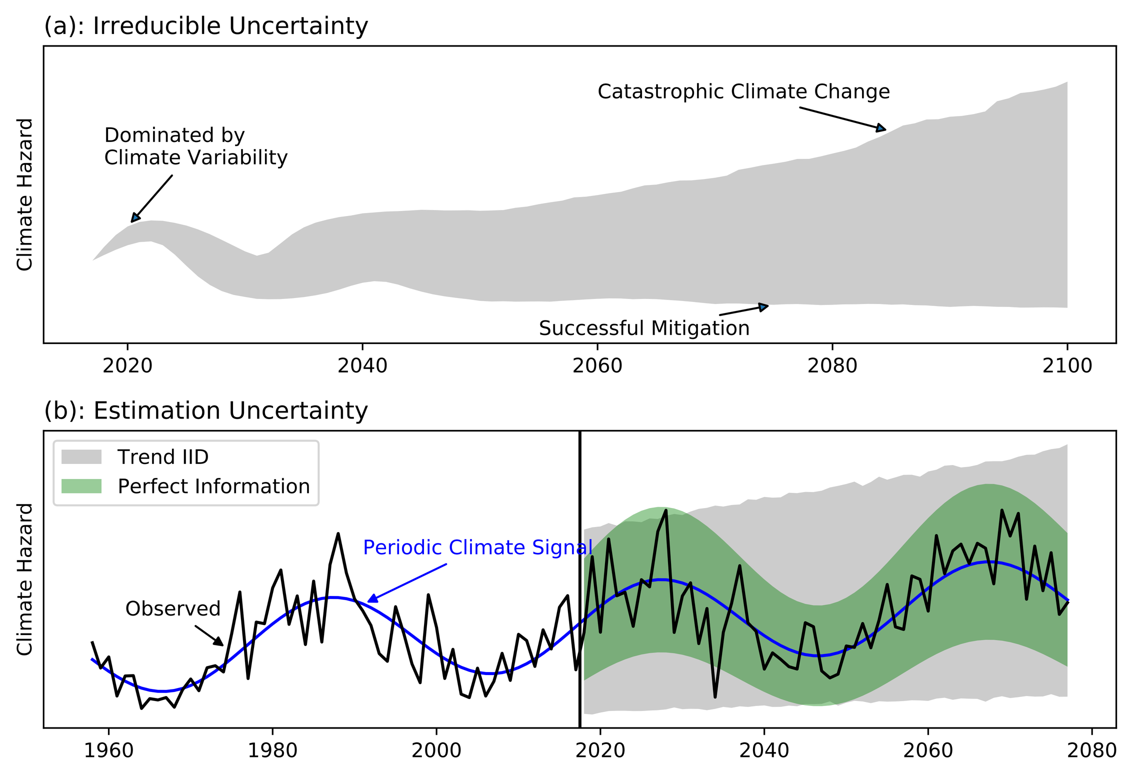

Figure 2: A stylized illustration of (a) irreducible and (b) estimation uncertainty.

Irreducible uncertainty cannot be resolved with better models or data and is dominated in the short term by chaotic behavior of the climate, and in the long term by the uncertainty in future anthropogenic climate change (fig. 2a)

estimation uncertainty: the length of a historical record limits the potential to identify different climate signals (fig. 2b)

Estimation Bias and Variance

The insurance premium for a financial risk mitigation instrument on event X can be parameterized as

$$P = \mathbb{E}[X] + \lambda \sigma[X]$$

Thus, if an estimate has a positive bias and overestimates uncertainty, the instrument may be too expensive for the user. Conversely, if an estimate has negative bias and underestimates uncertainty, it will be likely to fail (fig. 3). A key question is thus *whether the limited information in an N-year observational record permits the identification and projection of cyclical climate variability and secular change, and what the resulting bias and uncertainty portends for risk mitigation instruments with a planning period ranging from a few years to several decades.*

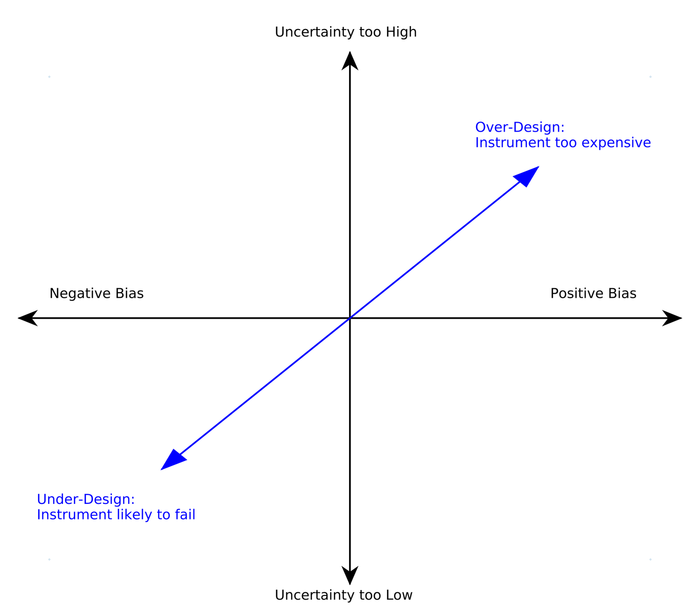

Figure 3: Consequences of model bias or incorrect model representation of uncertainty.

Experiment Design

Stylized experiment design:

1. For each, generate many synthetic streamflow sequences embedded with one of
   - 1.1 Secular trend only
   - 1.2 LFV from the El Niño-Southern Oscillation (ENSO) only
   - 1.3 both LFV and secular trend

   plus stochastic variability.
2. Fit using probabilistic model:
   - 2.1 Bayesian log-normal model
   - 2.2 Bayesian log-normal model with linear trend
   - 2.3 Two-state hidden Markov model (HMM)
3. Evaluate estimation bias and variance across all synthetic streamflow sequences
4. Repeat for many combinations of N (length of historical record: proxy for informational uncertainty) and M (project planning period)

This approach is illustrated in fig. 4

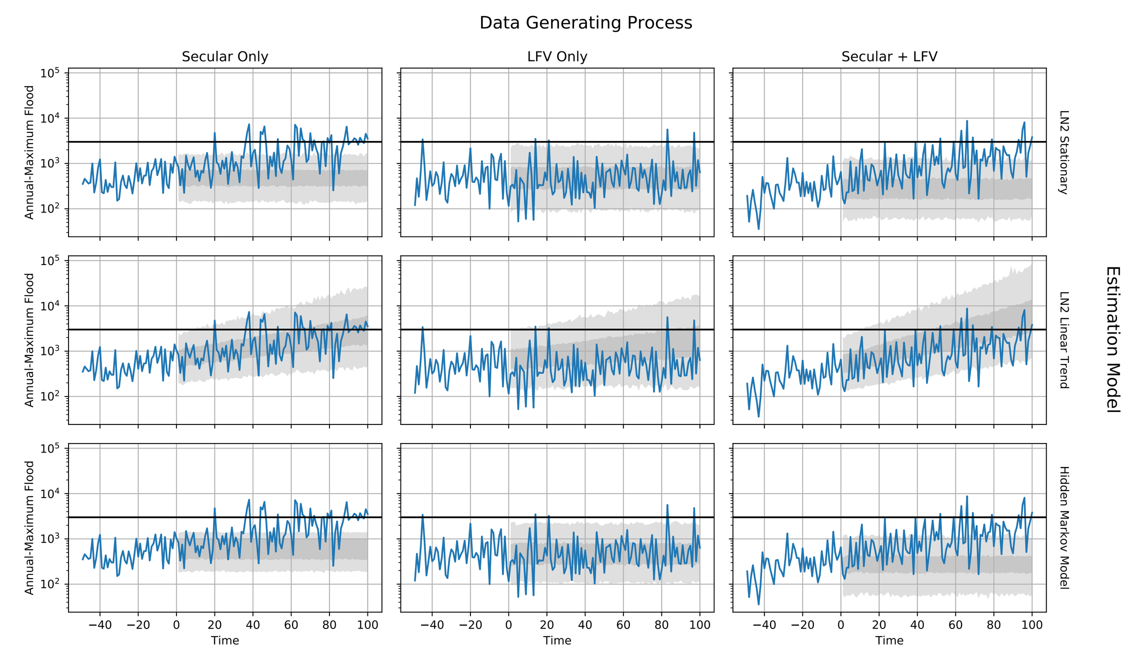

Figure 4: An illustration of the estimation procedure. A single streamflow sequence with $N = 50$ and $M = 100$ is shown for each of the three cases (secular only, LFV only, and secular plus LFV) considered. The blue line shows the observed sequence. The gray shading indicates the 50% and 95% confidence intervals using each of the three fitting methods discussed. The horizontal black line indicates the flood threshold.

Key Findings

Depending on the specific climate mechanisms that impact a particular site, and the predictability thereof, the cost and risk associated with a sequence of short-term adaptation projects may be lower than with building a single, permanent structure to prepare for a worst-case scenario far into the future:

- If uncertainty increases into future then adaptation strategies with short planning periods are preferred
- Risk profile of short-M projects dominated by low-frequency climate variability [3, 4]
- Even though the HMM is an imperfect analog for ENSO, it performs well for short planning periods
- When the planning period is long, trends must be estimated explicitly (requiring more data)

Experiment Results

We evaluate bias and variance as a function of M, N, and estimation method for three scenarios.

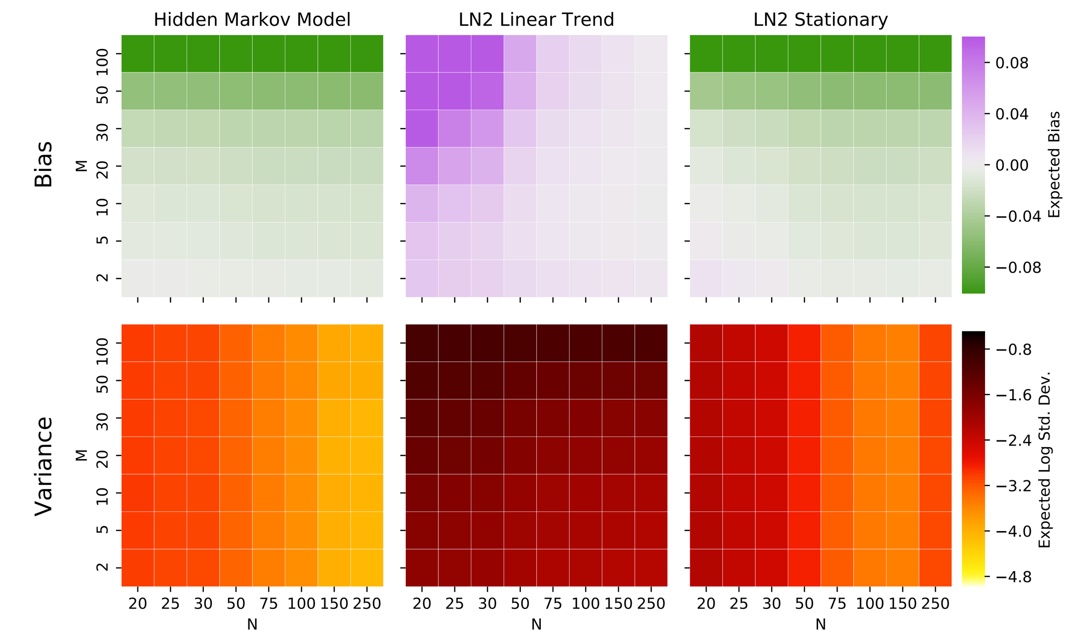

Figure 5: Expected estimation bias and variance for sequences with secular change only (no LFV).

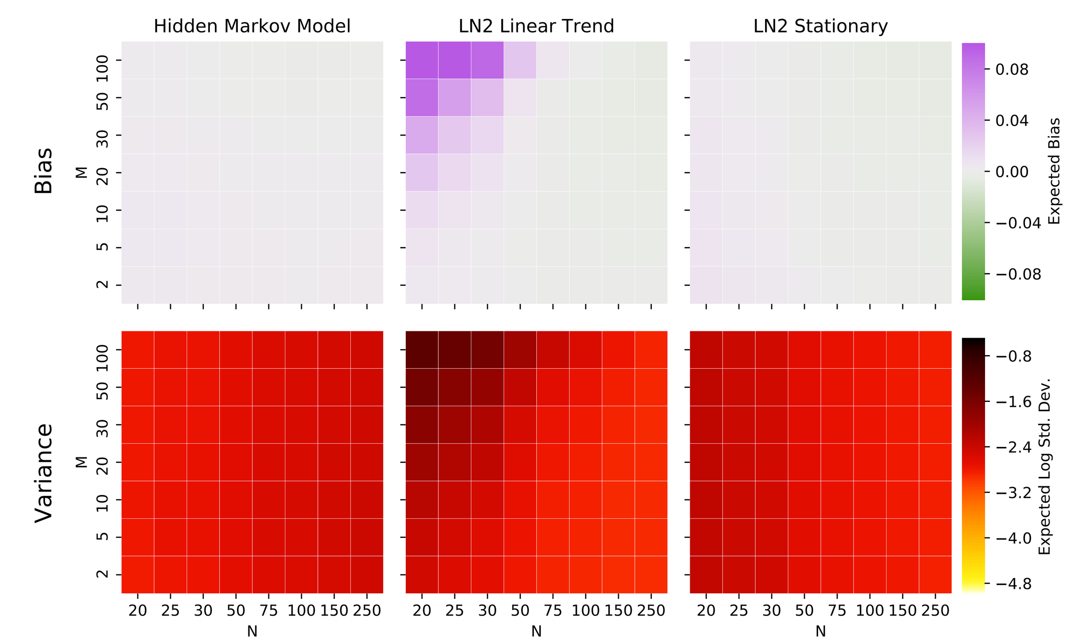

Figure 6: As fig. 5 but for sequences generated with zero secular change and LFV from the ENSO index.

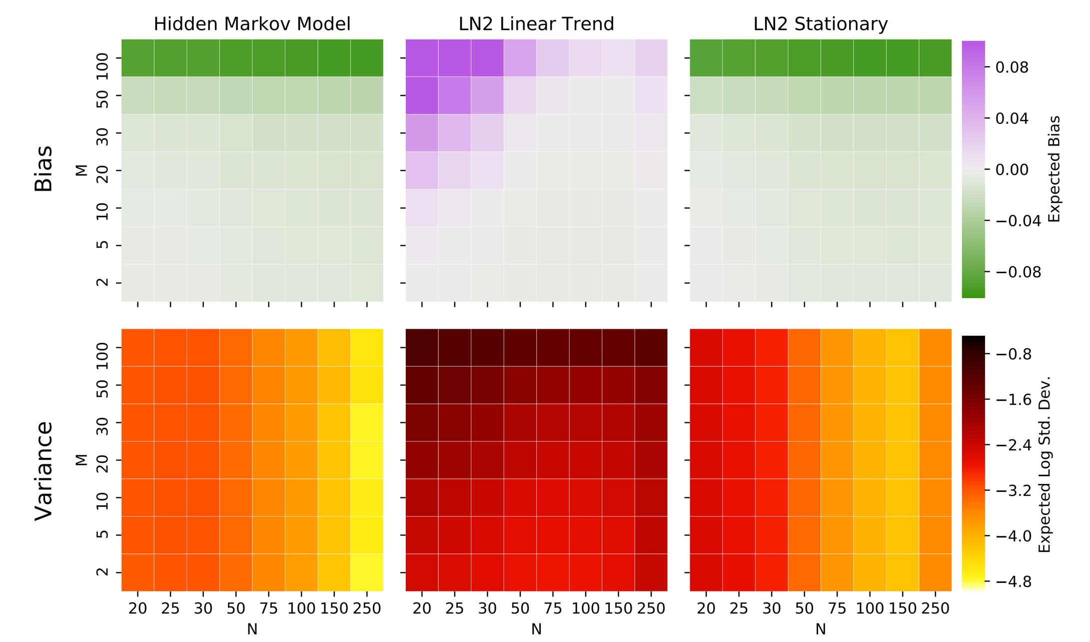

Figure 7: As fig. 5 but for sequences generated from the NINO3 model with both LFV and secular change.

References

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