



Climate-informed stochastic hydrological modelling: Incorporating decadal-scale variability using paleo data.

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Objectives

1. Develop a general stochastic framework:
 - (a) Uses climate / paleo–climate data to inform models of decadal variability
 - (b) Simulate impact of decadal variability on hydrological data.

2. Evaluate the impact of decadal variability on drought risk

Motivation

- Reliable estimates of drought risk depend on stochastic models capturing climate variability
- Water supply systems typically have up to 3-5 years carry-over storage
- Vulnerable to decadal-scale droughts
- Understanding of and ability to simulate decadal climate variability is crucial

Data required to identify “true” stochastic model of long-term variability

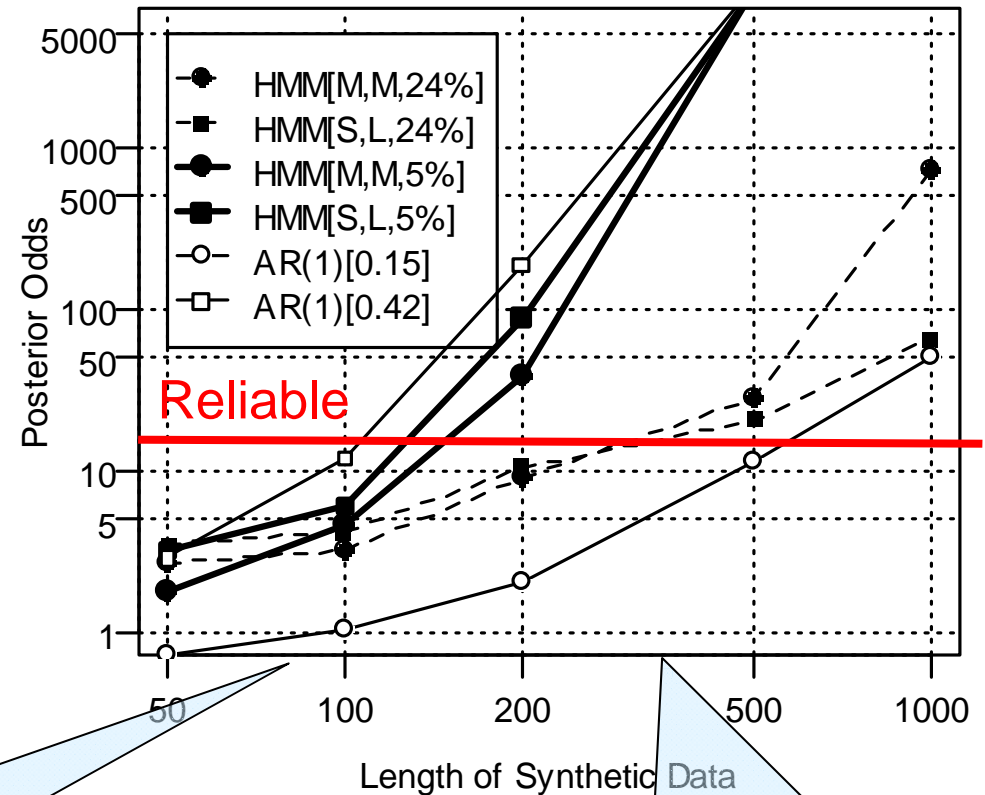
Synthetic Experiments

1. Generate data using model A
2. Fit model A and model B to data
3. Evaluate probability of identifying true model A given data:

$$\frac{P(\text{Model A} | \text{Data})}{P(\text{Model B} | \text{Data})}$$

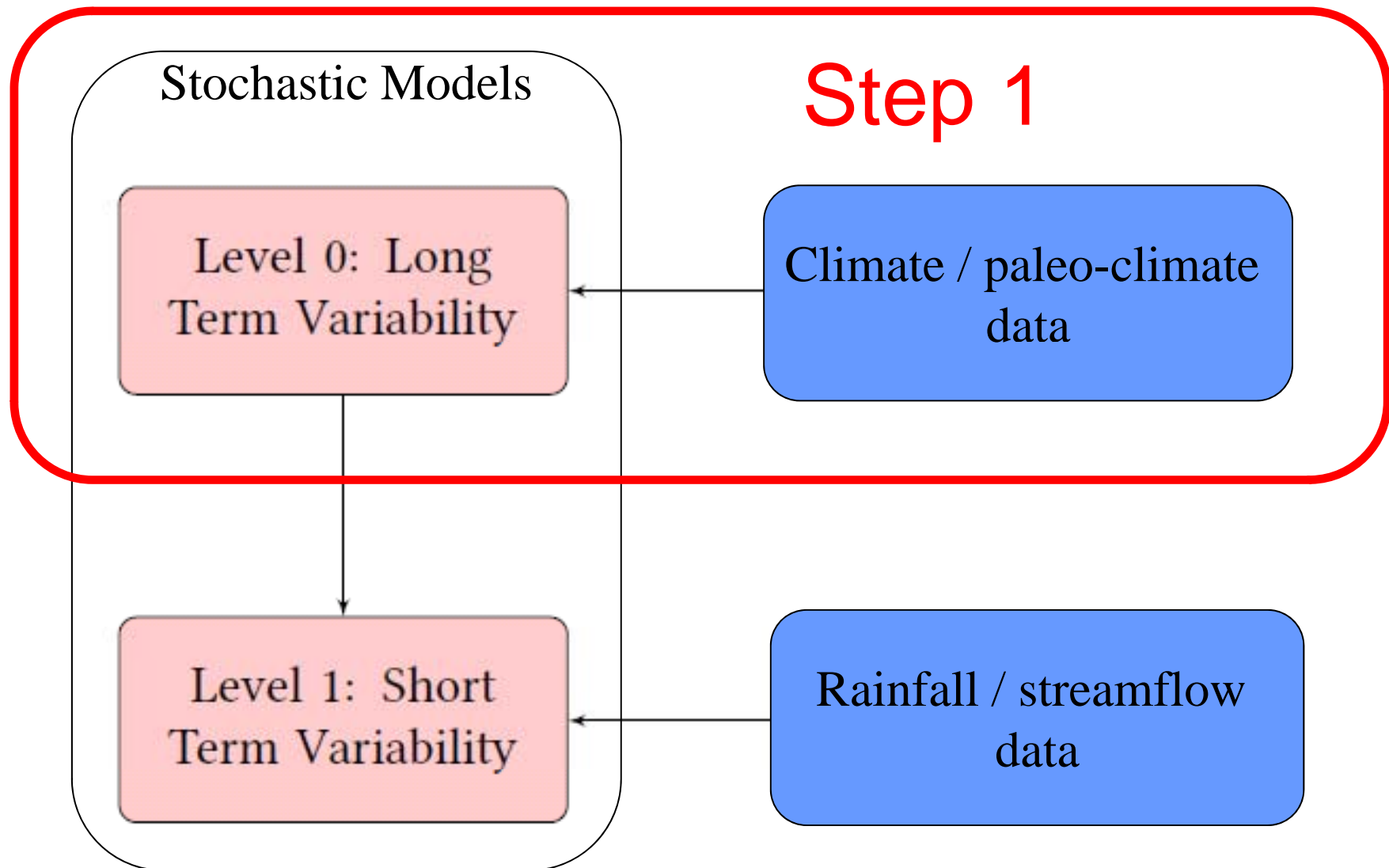
Models: Hidden markov (HMM) and autoegressive (AR(1))

Difficult to identify true model for typical hydrological data lengths (<100 years)

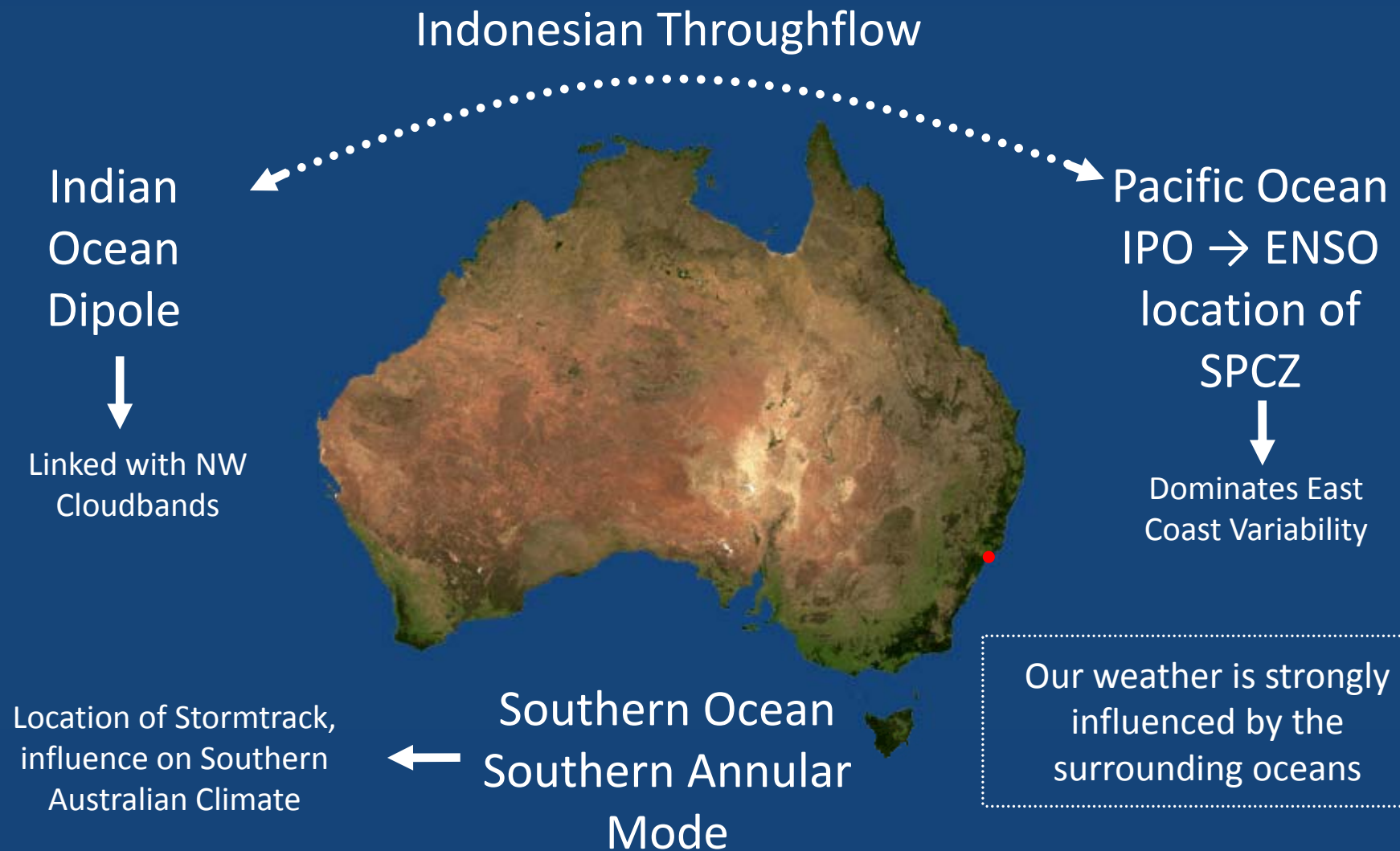


Need approx. 200-500 years for reliable identification
=> **Need paleo-climate data**

CIMSS: Climate-informed multi-time scale stochastic framework

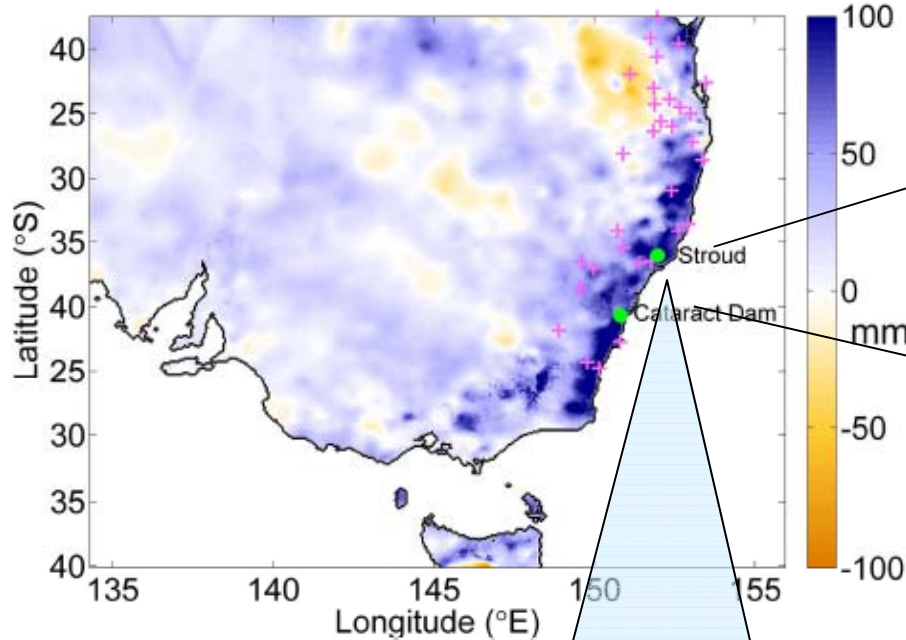


Influence on Australian Climate Variability

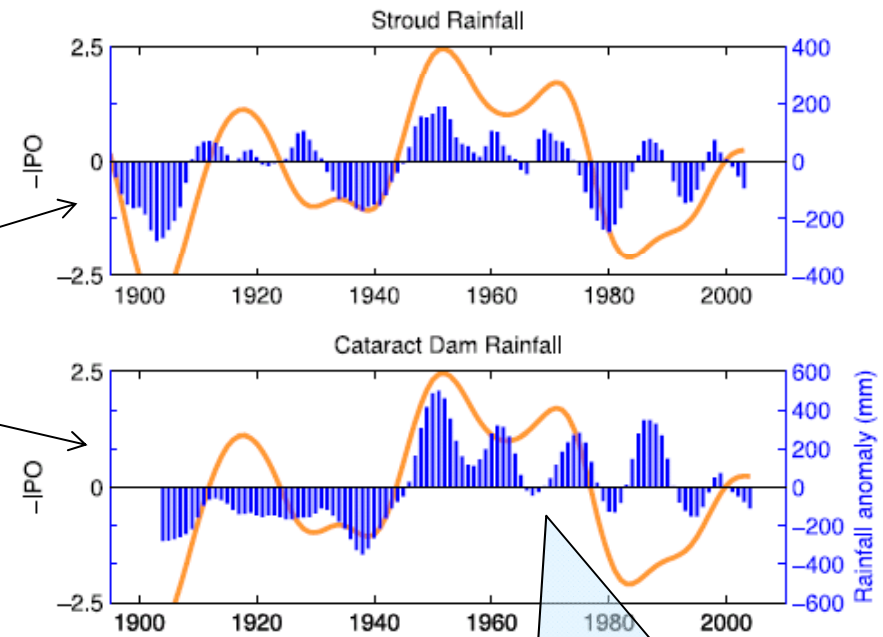


Impact of Interdecadal Pacific Oscillation (IPO) on Australia's Rainfall

Difference in annual rainfall between negative and positive IPO phases

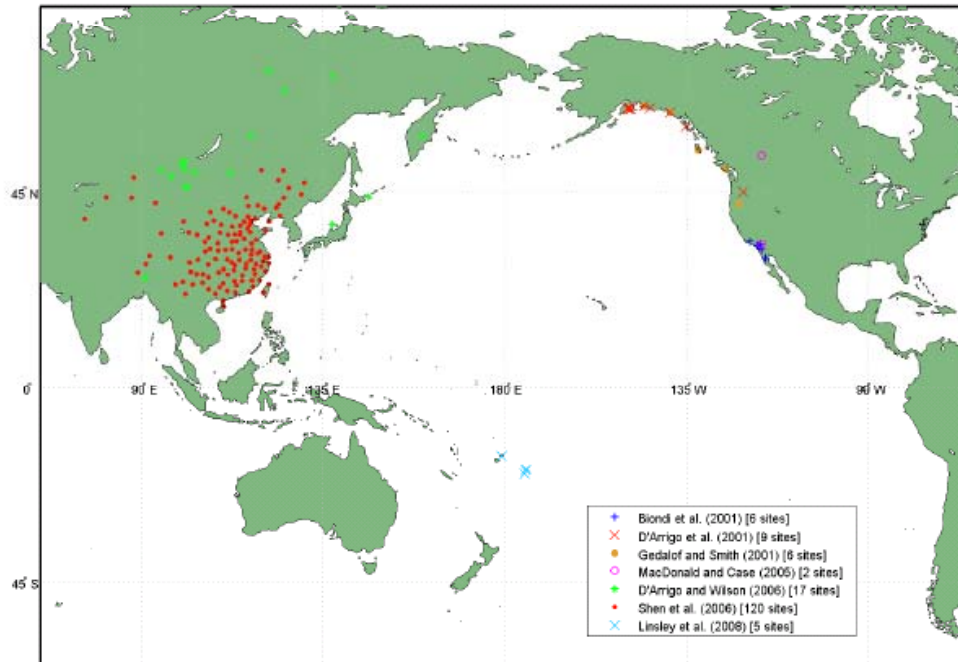


Spatial impact close to coast
=> water supply dams

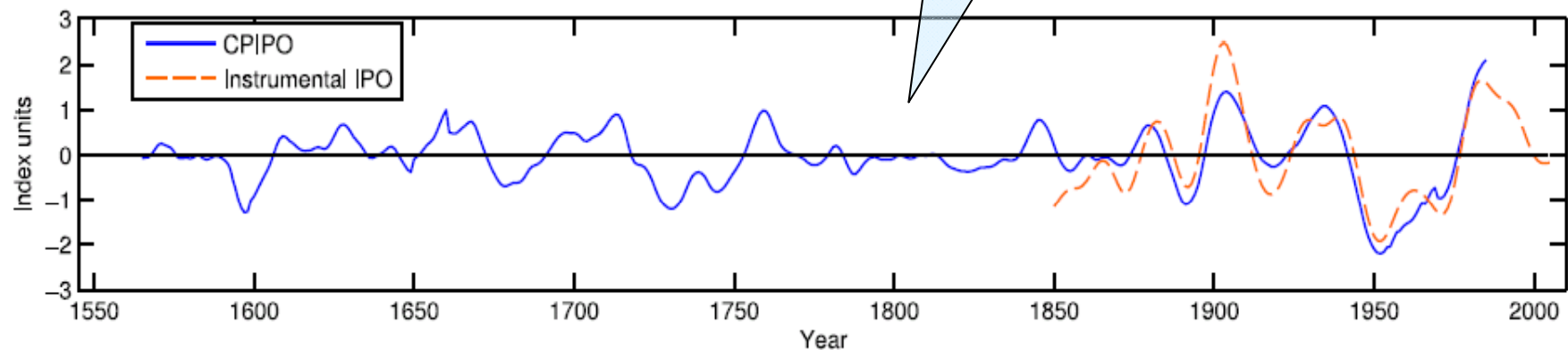


IPO phases last 10-20 years

Multiple paleo sources of IPO/PDO to identify decadal variability

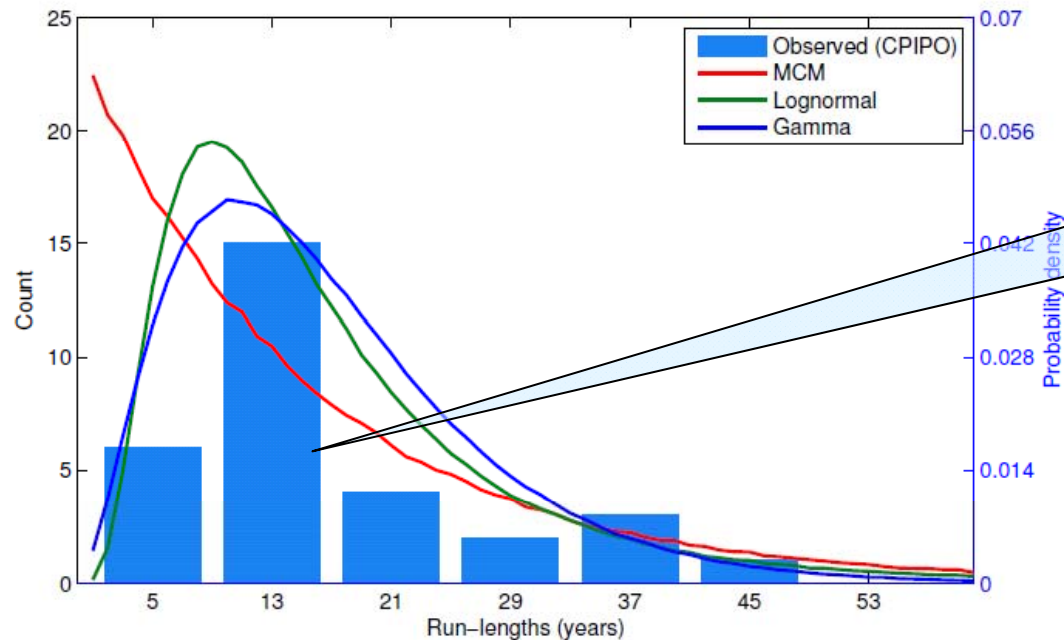


Developed objective approach to combine multi-paleo sources
⇒ **Composite Paleo IPO index (CPIPO) (~500 years)**



Stochastic model for decadal variability

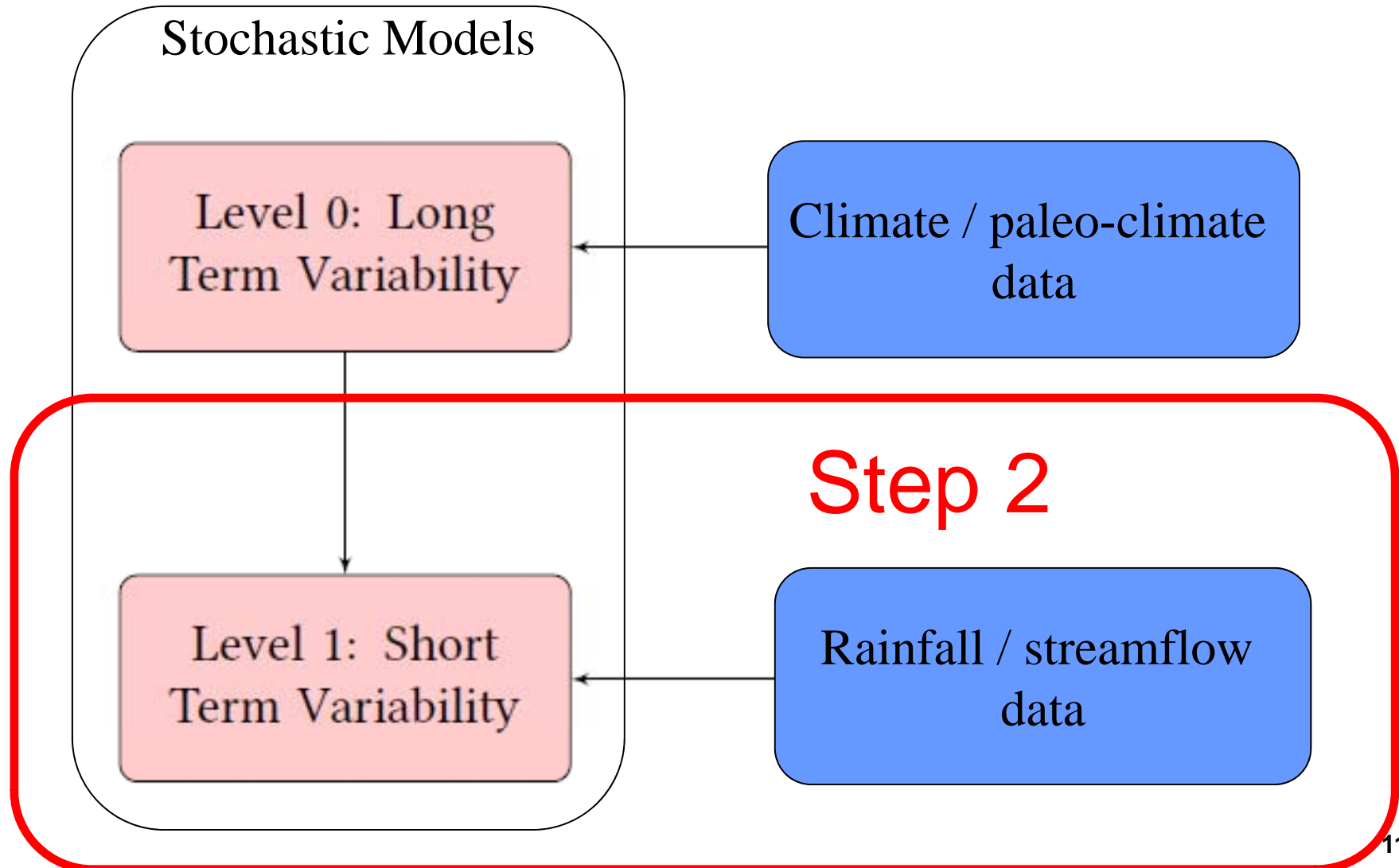
Distribution of run-lengths of CPIPO
positive and negative phases



CPIPO:
Average ~ 15 years
90% : 3 and 33 years

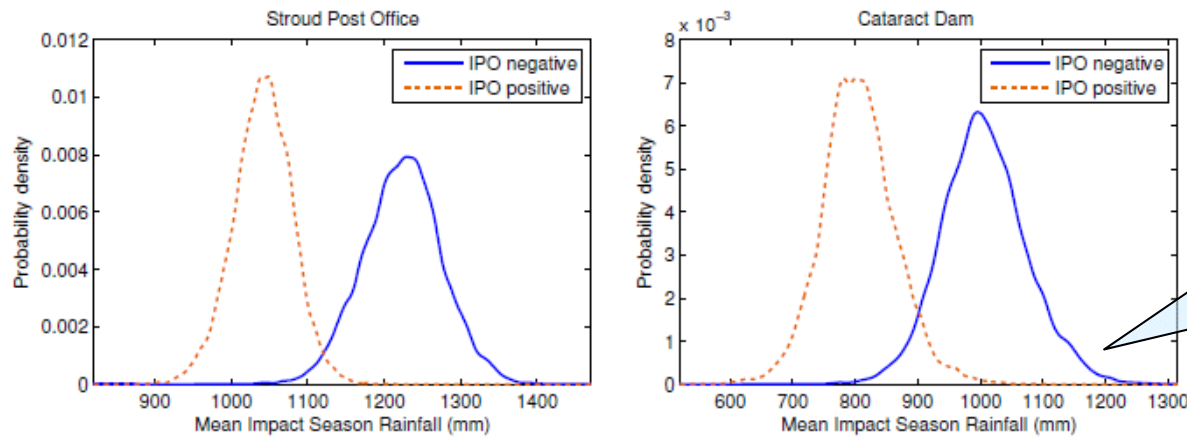
- Two-state model to capture IPO +ve and -ve phases
- Probability model for run-lengths of phases => Bayesian Model selection
- Commonly used Markov models (HMM and AR(1)) were rejected
=> **Do not capture distribution of run-lengths of decadal variability**
- Gamma/Log normal distribution was preferred

CIMSS: Climate-informed multi-time scale stochastic framework



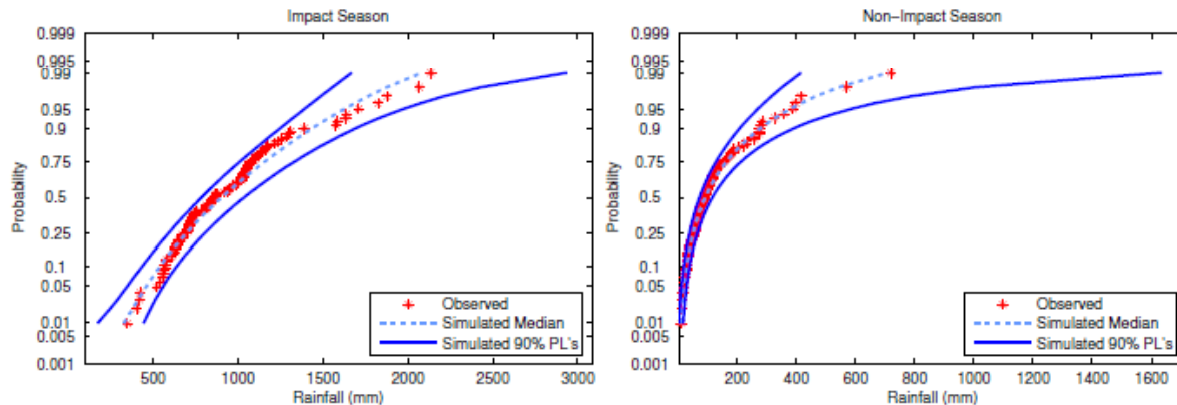
Short-term variability model for rainfall

- Seasonal AR(1) Model with Box-Cox Transformation
- Parameters conditioned on IPO +ve and -ve phases
- Bayesian approach to evaluate parameter uncertainty



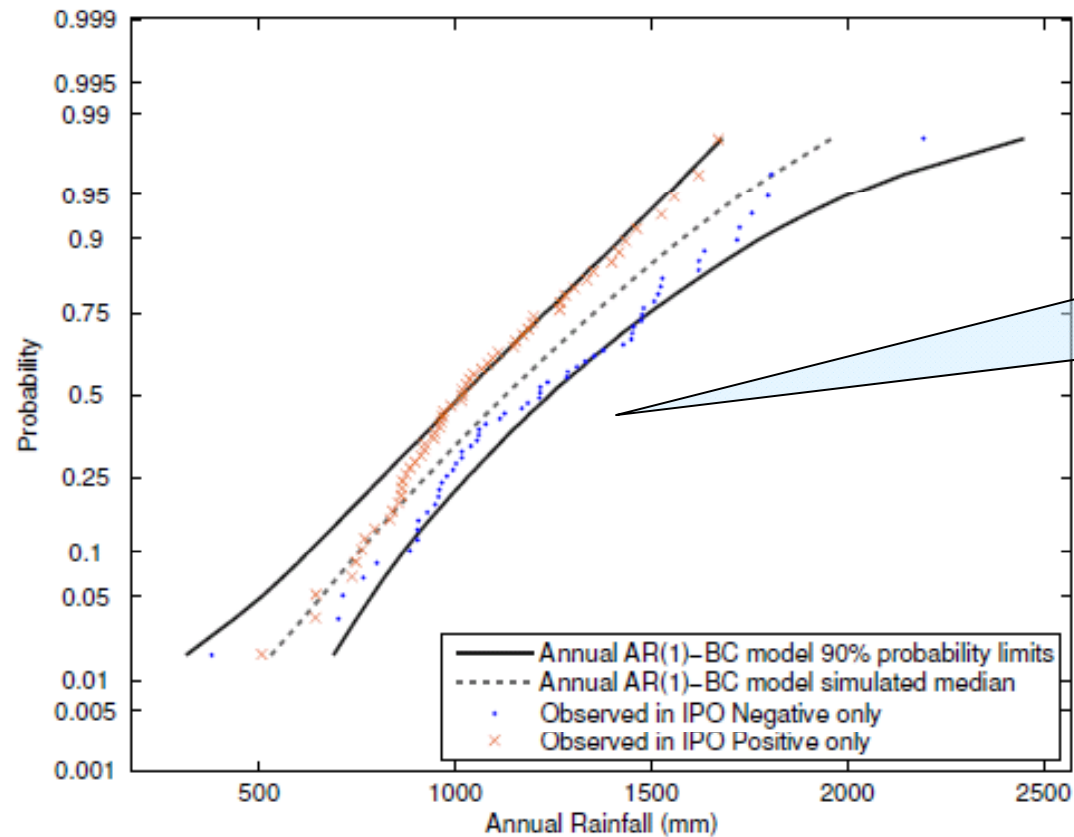
(a) $\mu_{I_{Pos}}, \mu_{I_{Neg}}$

Difference in posterior of mean seasonal rainfall ~15- 30% between IPO phases



Simulated captures observed data

Comparison to non-climate informed AR(1)

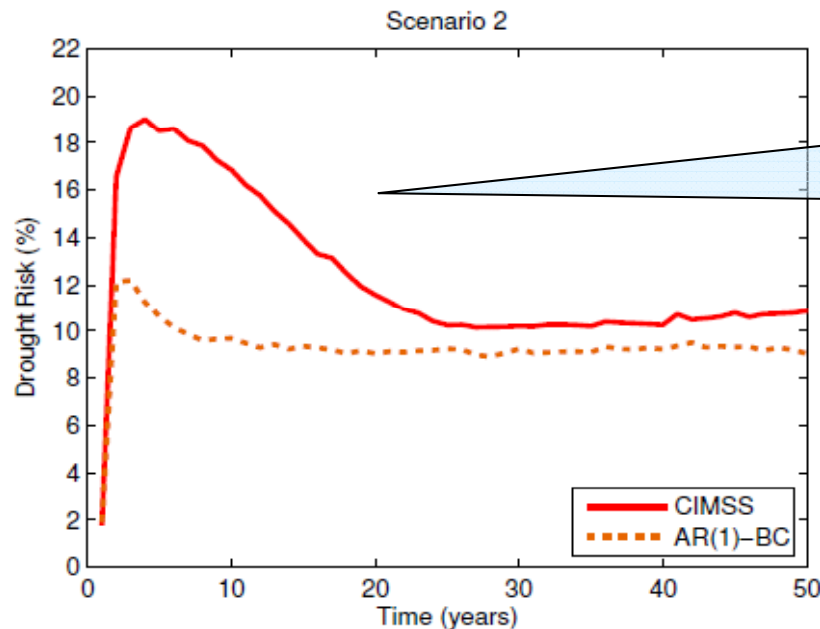


(a) Stroud Post Office

Typical AR(1) is unable to capture IPO influenced rainfall distributions

Impact on Drought Risk

- Simple reservoir simulation model to estimate drought risk
- Compare drought risk using rainfall input from
 - CIMSS and non-climate informed AR(1)
- Long-term drought risk => Differences are minimal
- Short-term drought risk => condition drought risk on initial conditions (previous rainfall, storage, climate phase)



During IPO dry phase, CIMSS drought risk is **double** AR(1) model

Conclusions

- Climate informed multi-time scale stochastic (CIMSS) framework
- Multiple paleo sources => Composite paleo IPO index
 - 500 years - average phase run-length ~ 15 years
- Paleo data inform stochastic models of decadal variability
 - Traditional Markov models do not capture decadal variability
- Conditioned seasonal rainfall model on decadal variability
 - 15-30% difference in mean seasonal rainfall in +ve and –ve phases
- Impact on drought risk
 - CIMSS short-term risk up to double of typical AR(1) model

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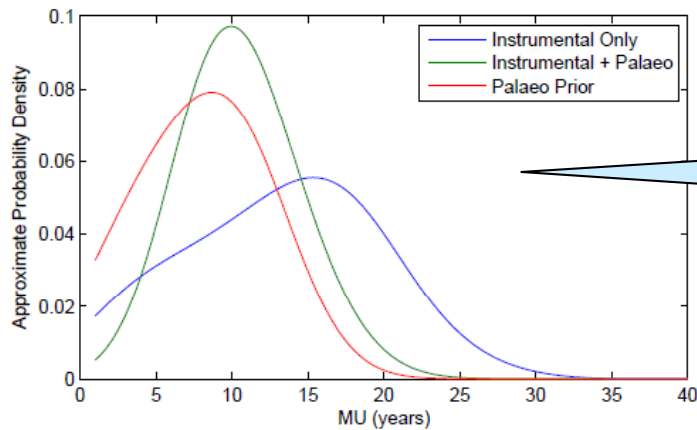
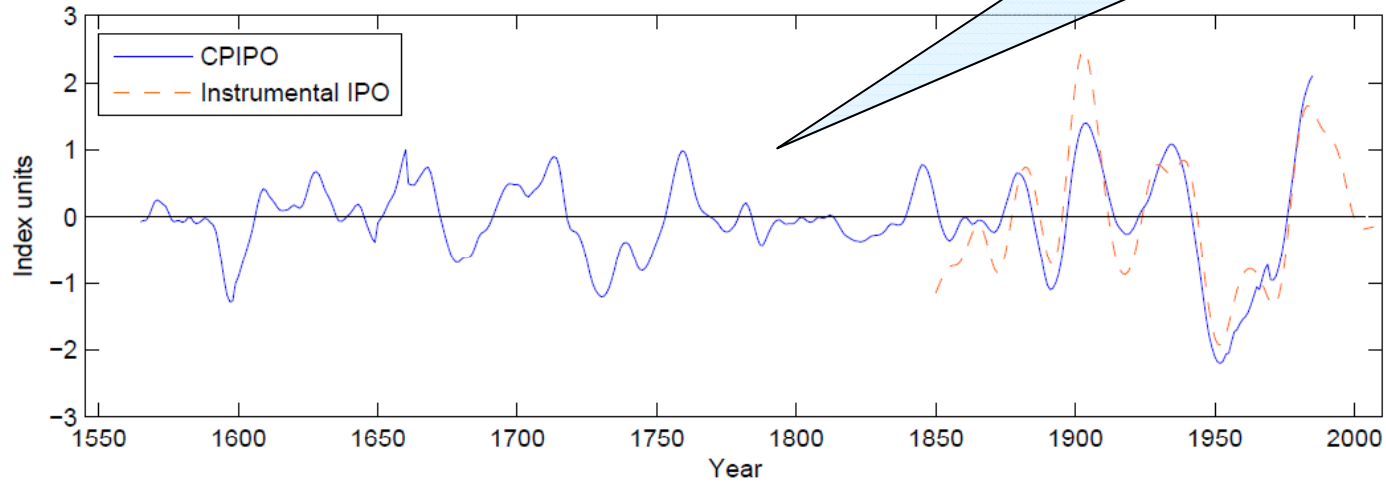
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Paleo Data to Identify Decadal Variability

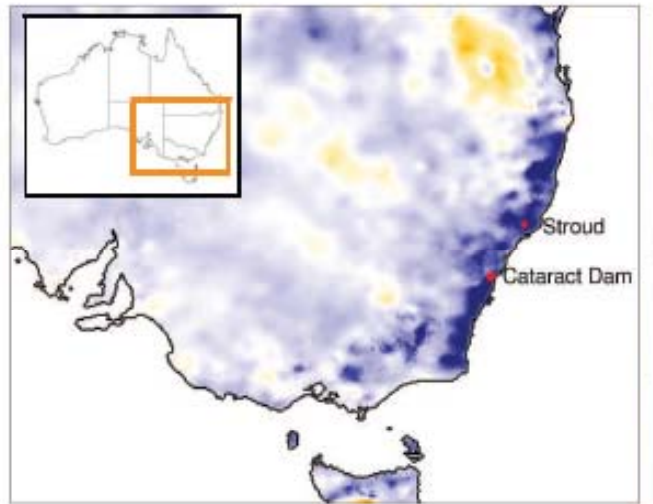
Paleo Series	Proxy for	Length (yrs)	Location of Source
<i>Biondi et al.</i> [2001]	PDO	330	Southern and Baja California ¹
<i>D'Arrigo et al.</i> [2001]	PDO	300	West-coast of North America ¹
<i>Gedalof and Smith</i> [2001]	PDO	400	West-coast of North America ¹
<i>MacDonald and Case</i> [2005]	PDO	1000	California and Alberta ¹
<i>D'Arrigo and Wilson</i> [2006]	PDO	420	East Asia ¹
<i>Shen et al.</i> [2006]	PDO	530	Eastern China ²
<i>Linsley et al.</i> [2008]	IPO	350	Fiji/Tonga ³

Combine paleo data to identify run length of wet/dry periods

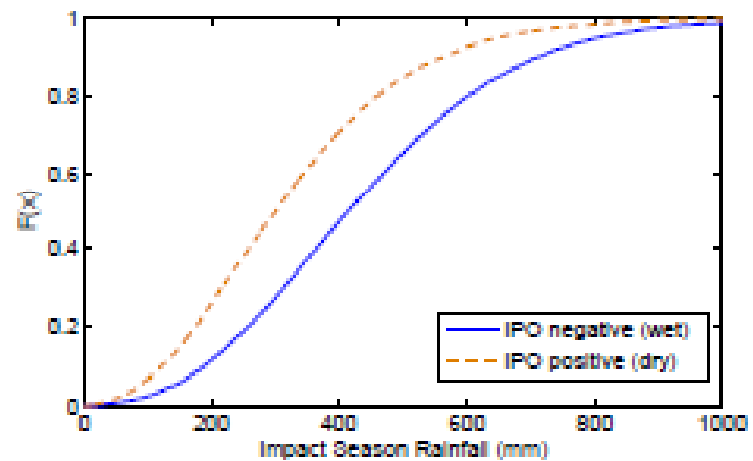
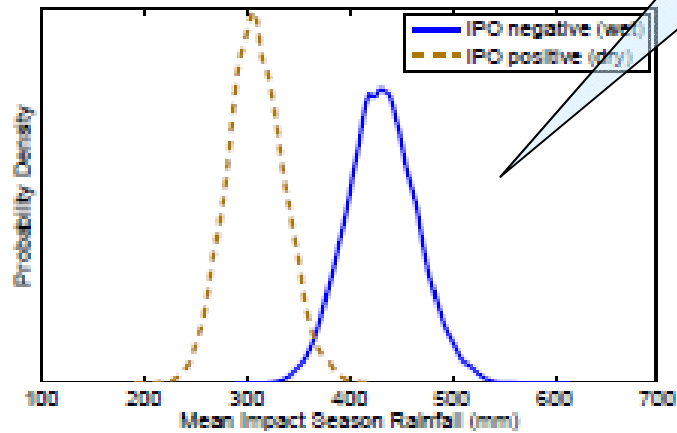


Bayesian Approach to Combine Instrumental/Paleo Data

Impact on Hydrological Data

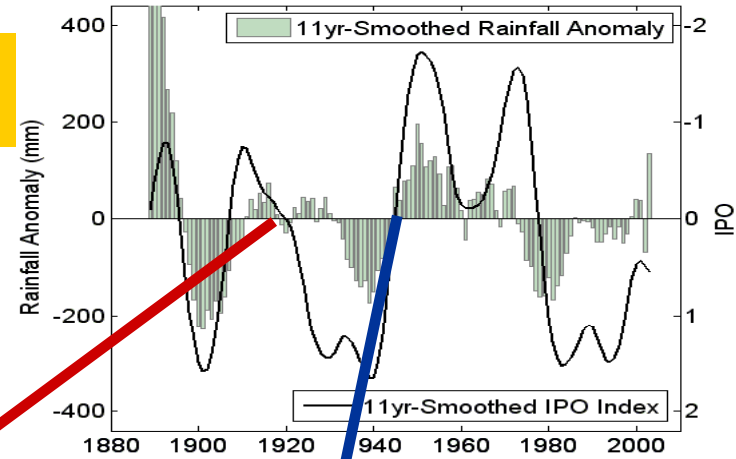


Reduction in mean rainfall of 13%-25%

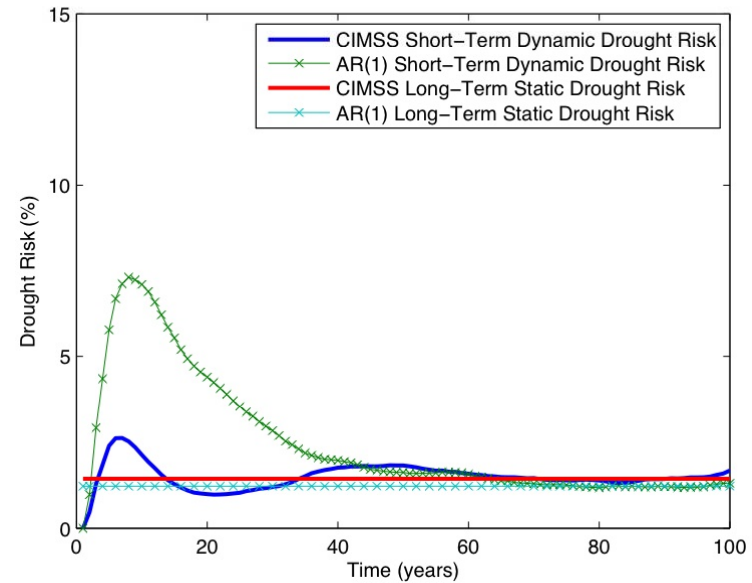
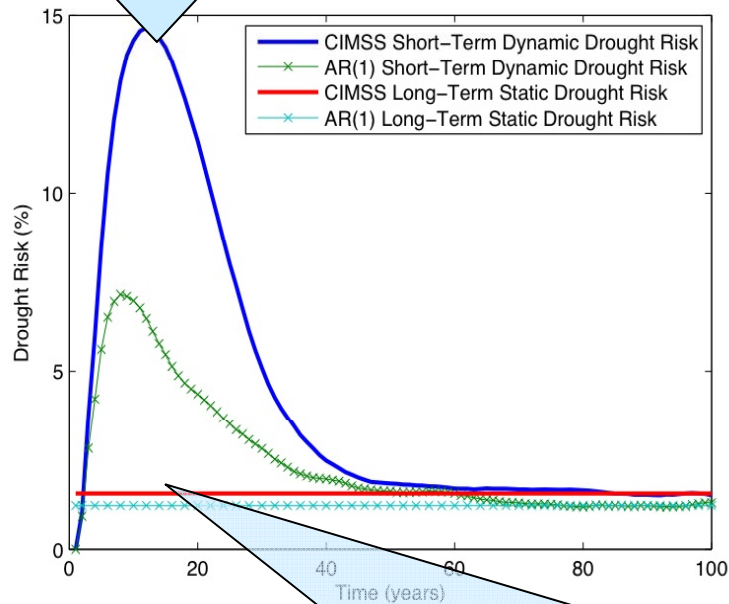


Impact on Drought Risk

- Drought risk is dynamic
 - Conditional on climate state and initial conditions of reservoir



CIMSS dynamic risk is higher than standard models



Short-term dynamic risk is higher than long-term risk

Summary

- Natural climate variability impacts on hydrological data and drought risk
- CIMSS framework incorporates natural climate variability using climate indices/paleo data
- Applied to East Coast of Australia

Future

- Incorporate more climate indices from different oceans
 - Indian Ocean Dipole, Southern Annular Mode
- Investigate impact of climate indices on South Australian hydrology
- Extend CIMSS framework to incorporate climate variability impact on SA.