A Performance-Based Approach to Quantifying Atmospheric River Flood Risk in Northern California

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CONTEXT

Motivation

Atmospheric rivers (ARs) cause well over three-quarters of all extreme precipitation events in California and over 90% of the state's record floods[1], leading to almost $300M in average annual losses[2]. Previous research has identified the need for an "end-to-end stochastic model of severe weather, physical impacts, and socioeconomic consequences" for AR-induced flooding to avoid a statewide catastrophe[3].

Research Concept

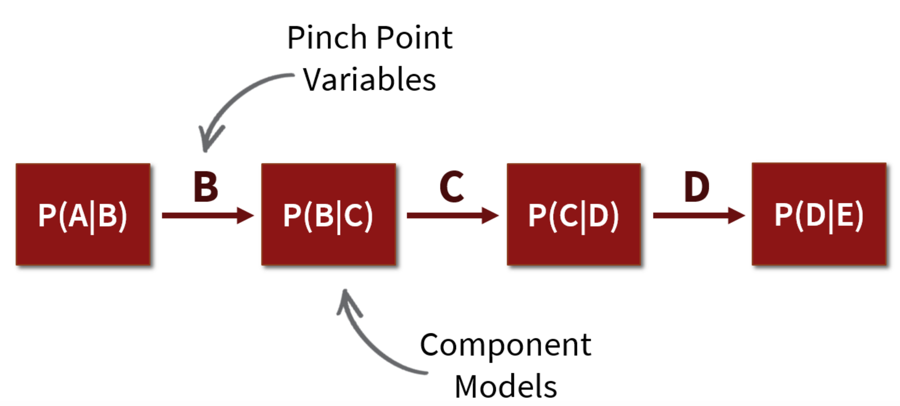
We propose a **Performance-based Atmospheric River Risk Analysis (PARRA)** framework that adapts existing concepts from probabilistic risk analysis and performance-based engineering for AR-driven fluvial flooding. The framework defines a series of conditionally independent ***component models*** linking atmospheric forcings, hydrologic impacts, and economic consequences at specified ***pinch point variables.*** This approach has four key benefits, as described below.

PHYSICALLY BASED
framework supports precise modeling of the sequence of processes from AR inception to impacts

PROBABILISTIC
uncertainty at each step is carried through the full model sequence to quantify confidence in the final results

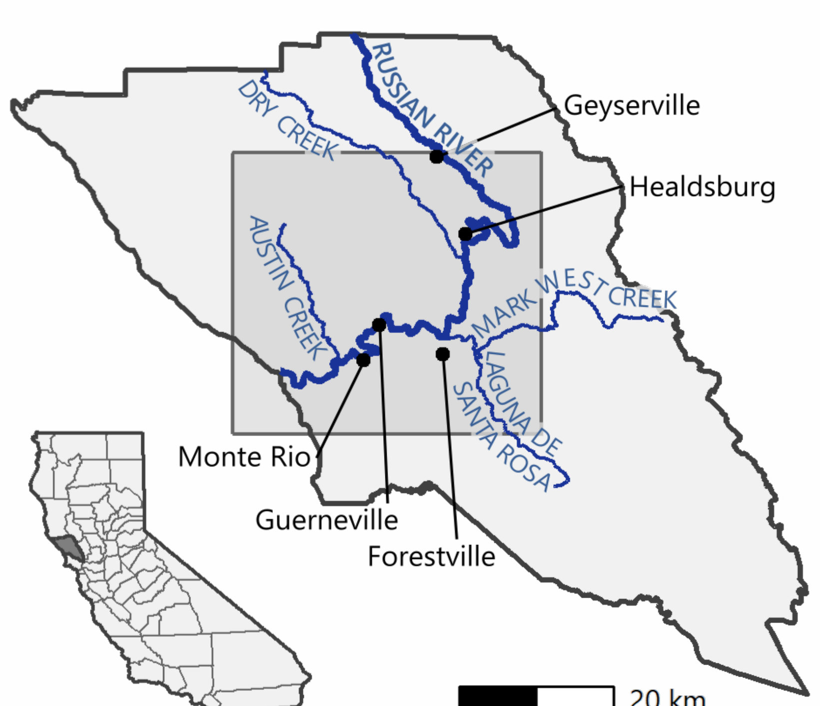
MODULAR
individual component models can be modified without affecting the rest of the sequence

PROSPECTIVE
framework can be used to assess "what-if" questions about events that have not yet occurred



Case Study Location: Russian River

We demonstrate the use of the PARRA framework through a series of analyses along the lower Russian River in Sonoma County, California, which has overtopped its banks 36 times in the last 80 years. The spatially repetitive, locally severe flooding seen on the Russian River is typical of ARs affecting this region.

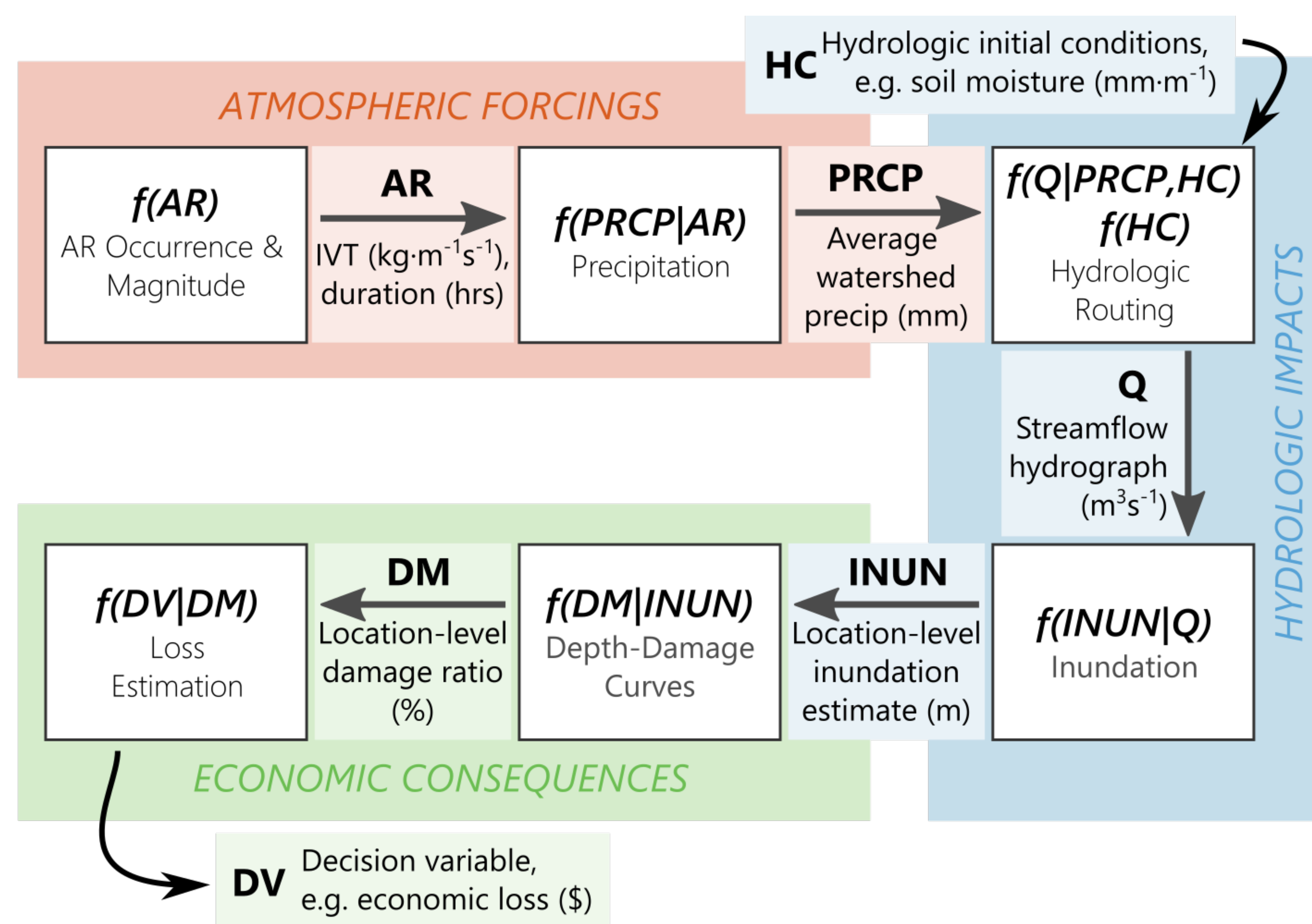


METHODS

The PARRA Framework

The **Performance-based Atmospheric River Risk Analysis (PARRA)** framework has six component models and seven pinch point variables, as described by the equation and the figure below. It is implemented by generating Monte Carlo realizations of the parameters of interest and propagating those realizations through the model sequence to construct an empirical estimate of expected loss.

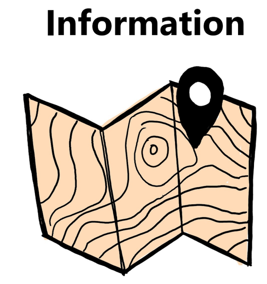
$$\lambda(DV > x) = \iiint \iiint P(DV > x \mid DM) * f(DM \mid INUN) * f(INUN \mid Q) * f(Q \mid PRCP, HC) * f(HC) * f(PRCP \mid AR) * \lambda(AR)\, dDM\, dINUN\, dQ\, dHC\, dPRCP\, dAR$$



Implementation

A hindcast evaluation of a severe AR event from February 2019 shows that the component model implementations accurately capture the observed distributions of precipitation (*PRCP*), streamflow (*Q*), inundation (*INUN*), and damage (*DM*).

Site-specific Information

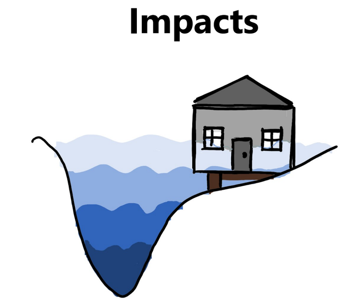


We generated a historic catalog of ARs occurring in Sonoma County from 1987-2019[4,5] and used open-source datasets to determine hazard characteristics for each event.

Atmospheric Forcings

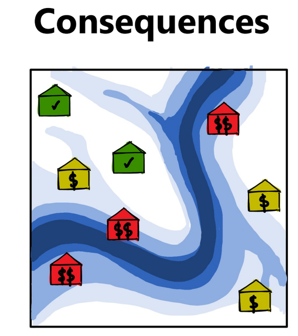
We fit a weighted regression to precipitation based on the historic catalog and used soil moisture as a proxy for antecedent hydrologic conditions.

Hydrologic Impacts



We fit a regression to streamflow, then ran the hydrodynamic software LISFLOOD[6] to generate a suite of floodplain inundation predictions. We implemented a low-dimensional surrogate model to dramatically improve computation efficiency.

Economic Consequences

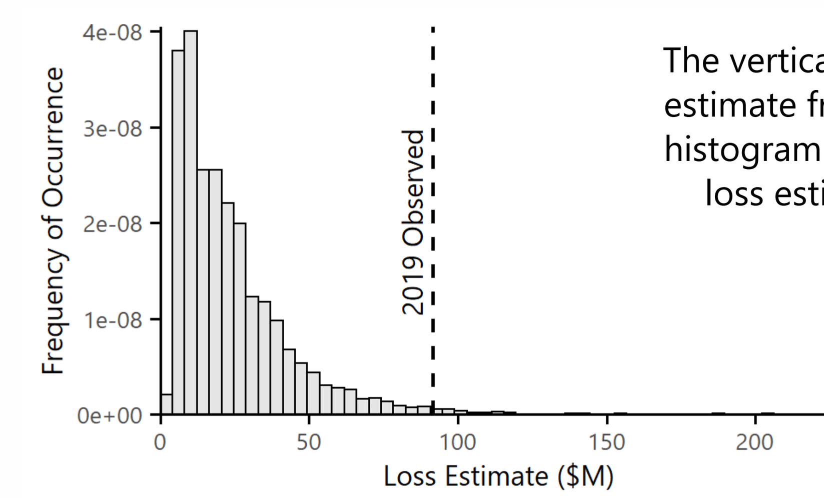


We used both deterministic and stochastic depth-damage curves to capture uncertainty in the damage[7,8], then estimated household-level loss as a function of damage ratio and tax assessor property valuation.

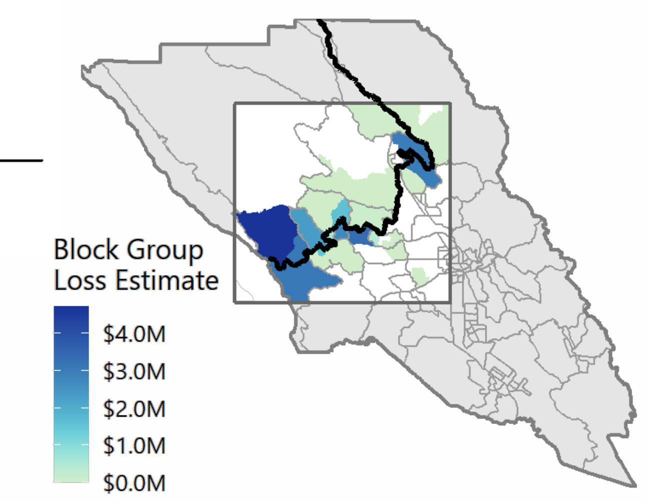
RESULTS

Scenario Event

We generated Monte Carlo realizations of loss from the PARRA framework for the 2019 AR event to characterize the spectrum of potential outcomes, i.e. flood losses that could have occurred due to this event if any of the other pinch point variables had been different.



The vertical dashed line marks the reported loss estimate from the 2019 event ($91.6M), and the histogram represents the probabilistic range of loss estimates from the PARRA framework.



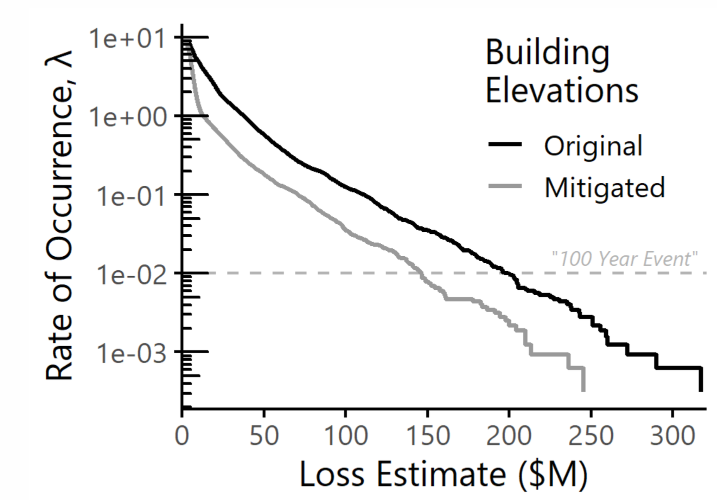
The map shows the average spatial distribution of loss estimates from the PARRA framework. The locations of concentrated loss are consistent with warnings and evacuation orders issued during the 2019 event.

Stochastic Catalog

We move beyond individual scenarios and capture the full distribution of AR-driven fluvial flood losses by generating Monte Carlo realizations of the entire historic catalog. We summarize the results with two loss metrics: average annual loss (AAL) and the loss exceedance curve. The AAL due to AR-driven flooding along the Russian River was found to be $163M, and the loss exceedance curve for the full catalog is plotted as the black line on the figure below.

Mitigation Action

We show the performance-based capabilities of the PARRA framework by defining a loss reduction target of $81M, or half of the AAL, and estimating how many homes would need to be elevated above the 100-year floodplain to meet this target. We found that elevating 150 homes in order of increasing distance from the Russian River was sufficient, and the new mitigated loss exceedance curve is plotted as the gray line.



Research Availability

This manuscript is currently under review at Natural Hazards and Earth System Sciences and is available as a preprint at *https://doi.org/10.5194/nhess-2021-337* (see QR code). All files and code to produce these results are available at *www.github.com/corinnebowers/PARRA*. If you are interested in using the PARRA framework for your own research, or would like to collaborate on an extension of this work, please contact Corinne Bowers at cbowers@stanford.edu.

Acknowledgements

[1] Lamjiri et al. (2018). *San Franc. Estuary Watershed Sci.*, 16(4). **[2]** Corringham et al. (2019). *Sci. Adv.*, 5. **[3]** Porter at al. (2011). USGS Report 2010-1312. **[4]** Gelaro et al. (2017). *J. Clim.*, 30(14), 5419–5454. **[5]** Rutz et al. (2014). *Mon. Weather Rev.*, 142(2), 905–921. **[6]** Bates & De Roo. (2000). *J. Hydrol.*, 236(1–2), 54–77. **[7]** FEMA. HAZUS-MH Technical Manual Flood Model. **[8]** Wing et al. (2020). *Nat. Commun.*, 11(1), 1444.

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