Learning, Catastrophic Risk, and Ambiguity in the Climate Change Era

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Introduction

Climate is the probability distribution over weather outcomes. Actors seeking to manage weather risks – whether by regulating the location of new development, investing in protection against weather hazards, or the use of financial instruments (such as insurance policies) that transfer weather risk – need to somehow infer the climate distribution in order to evaluate possible actions. If the climate is known to be stationary, then the historical weather record can be used directly as a proxy for the climate distribution. If the climate is known to be non-stationary, however, then actors face a more challenging inference problem. This is particularly the case if – as is likely for most decision-relevant highly-localized weather variables – the exact nature of the non-stationarity is unknown.

A number of papers have described the learning required for climate change adaptation as an inference problem (Kelly et al. 2005; Kolstad & Moore 2020; Moore 2017)[1]. However, these have almost universally been both motivated by, and applied to, inference over weather variables with normal (i.e. symmetric and thin-tailed) distributions, such as average global or local temperatures. In fact many significant, decision-relevant weather varibales, including temperature maxima and rainfall intensity can exhibit rightward skew (e.g. Figure 1 for rainfall maxima). The expected value of these distributions will be heavily influenced by the non-vanishing possibility of unlikely but highly-consequential outcomes.

The skewed nature of important weather variables interacts with non-linear damage functions to produce even more heavy-tailed damage distributions (Conte & Kelly 2018). Societies are best-prepared for weather events that occur with some regularity, or at least have some precedent in the historical record (Barreca et al. 2015; Carleton et al. 2022; Hsiang & Jina 2014). Conversely, the costs (whether measured in financial or non-monetary terms) of events that are extremely rare or that have no precedent in the historical record can be very much larger than the costs of more frequent events. The convolution of long-tailed climate distributions with steeply non-linear damage functions can produce distribution over *damages* where expected values are dominated by the possibility of unlikely but highly consequential events (i.e. catastrophes, illustrated in Figure 1). This poses a challenge for any actor attempting to manage weather risks as these catastrophic events are, by definition, rare in the historic record.

[1] This is related to a much larger literature that attempts to distinguish between the short- and long-run impacts of weather variation driven by adaptive responses (Burke & Emerick 2016; Carleton et al. 2022; Deschênes & Greenstone 2011; Merel & Gammans 2021; Taraz 2017). Although mostly not formally posed as inference problems, these embed inference within them, since any difference between short- and long-run impacts of weather variation depends on the implicit or explicit recognition of a changing weather distribution prompting actors to take defensive activities in response.

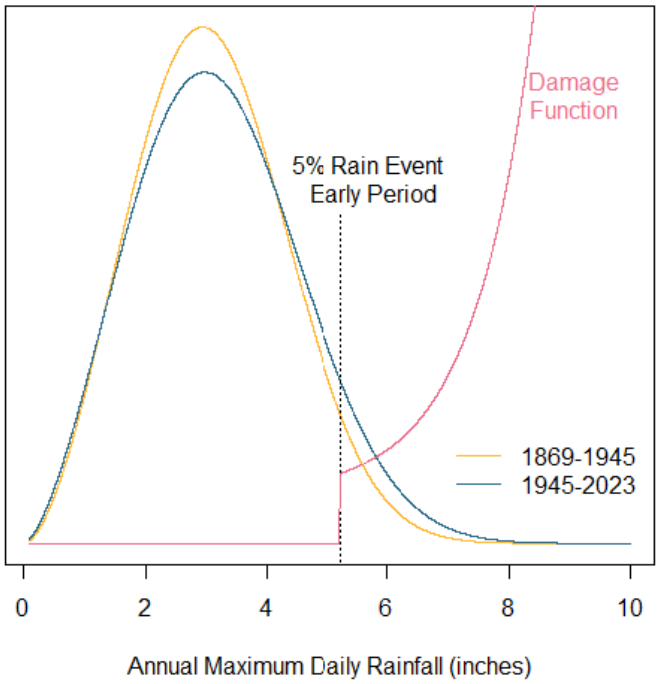


Figure One: Fitted distributions (Weibull) over annual maximum daily rainfall for two periods at the Central Park, NY weather station. Overlaid is a a hypothetical damage function with a threshold at the historic 5% event (for instance related to drainage system design standards) and an exponential increase above that threshold. The probability of a damaging event (i.e. above the damage threshold) has increased from 5% to 8% and annual expected losses from heavy rainfall (under this hypothetical damage function) have almost doubled.

Climate change introduces substantial additional uncertainty and therefore cost into this problem. Under climate change, the past distribution of weather risks cannot be assumed to be representative of current or future risks, undermining a key assumption in standard "catastrophe modeling" approaches. Morevoer, General Circulation Models (GCMs), the standard tools for projecting effects of anthropogenic climate change, are singularly poorly suited for the near-term, high-resolution modeling of weather extremes needed to characterize current weather risks. Changing costs of weather extremes, and the costs of uncertainty in extreme damages introduced by climate change, could constitute an important, but as yet unquantified, component of climate change damages. Moreover, highly-uncertain and dynamic extreme weather risks likely plays an important role in explaining the volatility in property insurance markets observed in states with substantial natural hazard risks in recent years.

Illustration: Climatological Inference Under Stationarity and Non-Stationarity

The climate distribution at any given point in time is not directly observed. Instead it must be inferred, typically from past experience of weather in a particular location. Figure 2a shows annual maximum rainfall over the last 30 years, a period historically treated as a relvant climatology, from the NY Central Park station. If the climate is known to be stationary over this period, then this sequence of observations can be used to estimate the climate distribution and therefore quantify the expected losses under a particular damage function. However, even under favorable learning conditions (i.e. known stationarity of the distribution, optimal Bayesian updating, informative priors, and known shape parameter (see

details in Appendix)) uncertainty over the scale parameter of the distribution creates substantial uncertainty in expected losses purely due to sampling variation in the historic weather data (Figure 2b). Given the right-skew of the distribution and the concentration of damages in the right tail, expected losses differ by over a factor of 5 between the lower and upper confidence bounds.

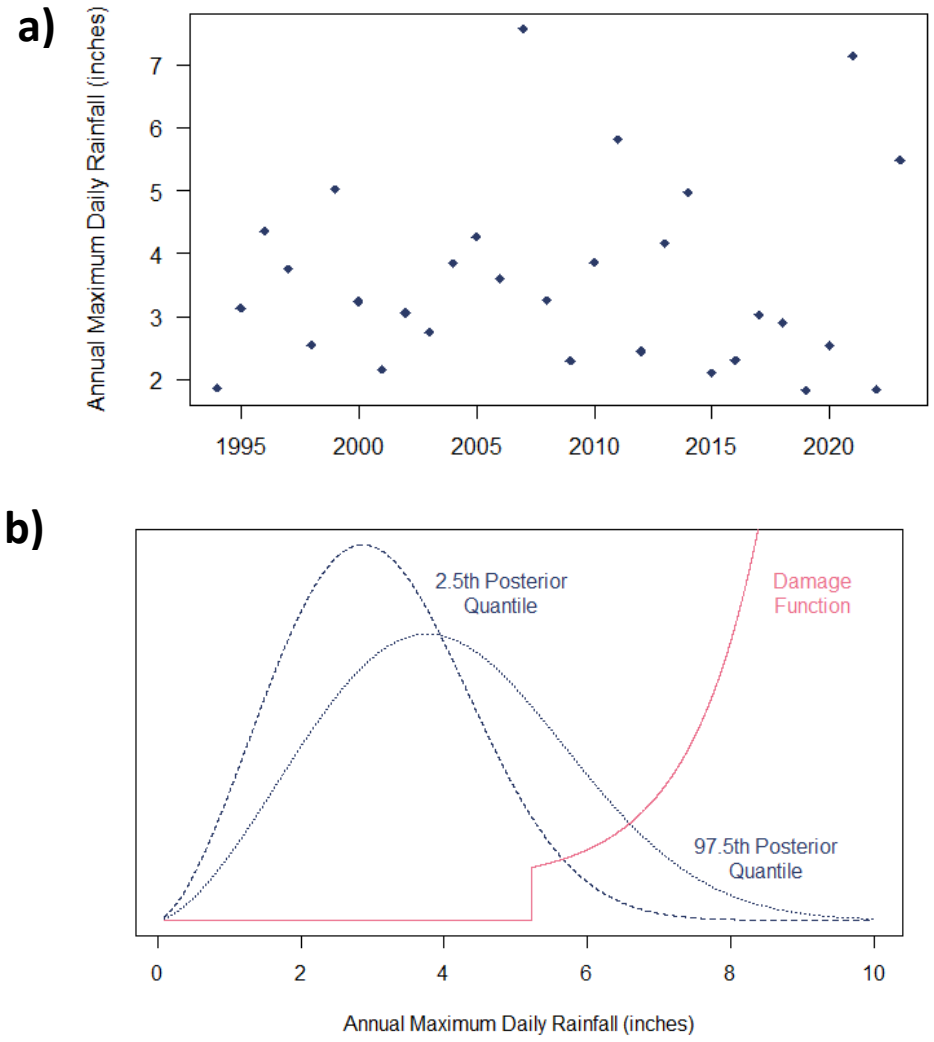


Figure 2: a) Observations of annual maximum daily rainfall at the Central Park, NY station over the 30-year period 1994-2023. b) Two possible rainfall maxima distributions spanning the 95% confidence interval for the inferred Weibull scale parameter based on observations over the 30-year climatology. The same damage function from Figure 1 is overlaid for reference. Under this hypothetical damage function, the expected losses differ by a factor of 5.6 between the two distributions

Note that stationarity in the climate distribution is an important characteristic of the inference problem. If the climate is known to be stationary, there is no reason to limit inference to only the last 30 years of observations. Rainfall records at Central Park go back to 1869: if all of the 155 years of the record can be

assumed to come from the same distribution, then uncertainty over possible maxima can be more tightly constrained. Figure 3 shows posterior distributions over the unknown parameter under different lengths of weather records (Figure 3a), as well as relative uncertainty in expected damages once this posterior uncertainty is propagated through the damage function shown illustratively in Figures 1 and 2 (Figure 3b).

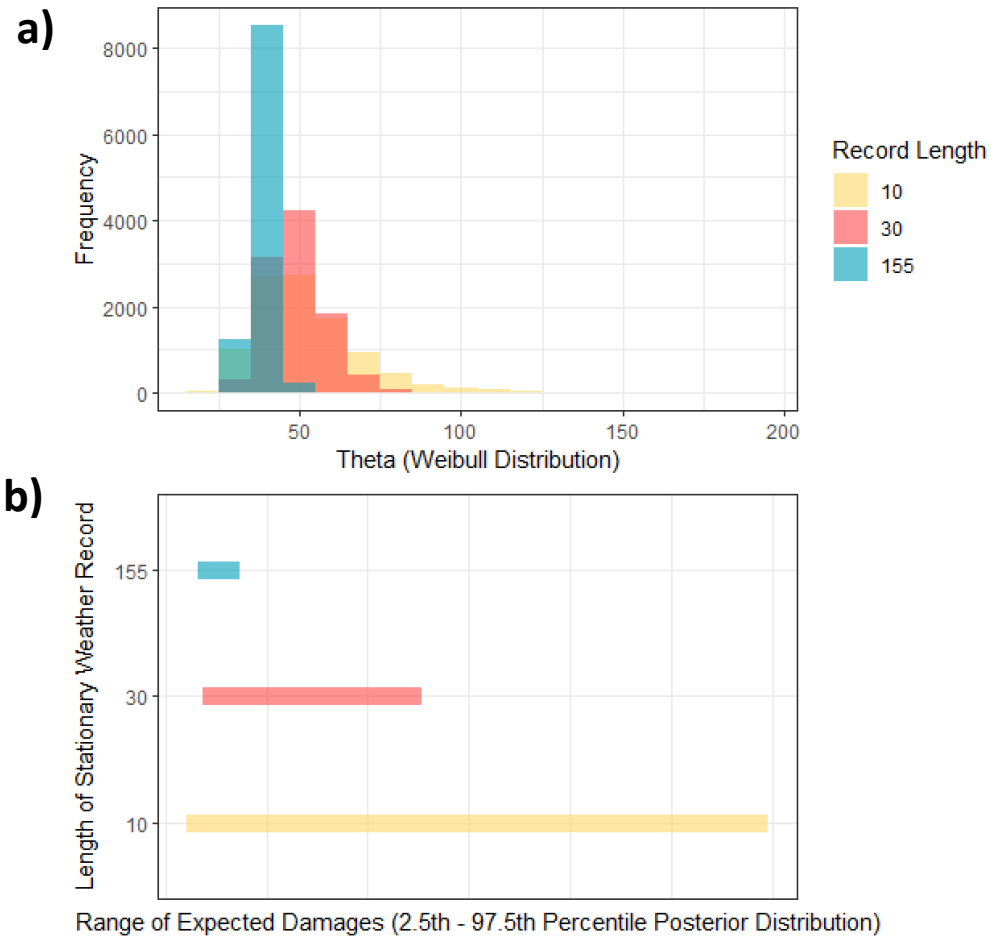


Figure 3: Posterior distribution over parameter using the same prior but integrating weather records of 3 different periods (a) and the associated 95% range in expected damages using the hypothetical damage functions shown in Figures 1 and 2 (b).

Because additional years of information help to constrain the right tail, where potential damages are concentrated, a longer record has a substantive effect in limiting the range of expected damages, particularly at the upper end (Figure 3b). Conversely, if the climate is non-stationary and older records are determined to be not representative of current risks then the record is effectively shortened, the sampling uncertainty in weather observations is much larger, and the associated uncertainty in expected damages increases by almost a factor of 3 from the 30 year to the 10 year record.

This illustration is for extreme rainfall, but the essential insight that non-stationarity *itself* can add substantial uncertainty, and therefore substantial costs, to the management of weather risks is more

general. Any setting in where a skewed weather hazard variable interacts with a steeply non-linear damage function (thought to be characteristic of many weather responses, from agriculture to mortality to flood damage (Carleton et al. 2022; Schlenker & Roberts 2009; Wing et al. 2020)) would be expected to exhibit these tendencies. Moreover, real-world settings exhibit even more inference challenges since the damage function also exhibits both uncertainty and non-stationarity (for instance associated with changes in the location and vulnerability of assets as well as adaptive investments).

Proposed Paper

The proposed paper would build on the illustrative case described here to more fully develop:

1. Theoretical intuition for the interaction of sampling uncertainty, non-stationarity, and non-linear damage functions in driving changes in climate-realted risks
2. An empirical quantification using extreme rainfall, flood-hazards, and empirically-derived depth-damage functions for the U.S. (e.g from Wing et al. 2020)
3. Implications of this risk for policy applications, including costs of insurance premiums and insurer behavior including limiting exposure through withdrawl of coverage

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Appendix: Application of Bayesian Learning over Extreme Rainfall Statistics

For the Case of a Stationary Climate

Assume the annual maxima of daily rainfall are distributed with a Weibull distribution with likelihood:

$$L(x|\alpha,\theta) = \frac{\alpha}{\theta}x^{\alpha-1}e^{-\frac{x^\alpha}{\theta}}$$

Where the shape parameter (α) of the distribution is known precisely (i.e. based on the 30 year climatology).

Define a prior distribution over θ with an inverse gamma distribution:

$$p(\theta|a,b) = \frac{b^a e^{-\frac{b}{\theta}}}{\Gamma(a)\theta^{a+1}}$$

For $\theta > 0$

Chose a diffuse prior with hyperparameters $a = 1.5$ (a heavy-tailed distribution with finite mean but undefined variance) and b chosen so that the mean of the distribution ($\frac{b}{a-1}$) is equal to the estimated θ parameter from the prior 30-year climatology.

The posterior distribution over θ given the vector of data $\boldsymbol{x_1}:\boldsymbol{x_n}$ is then given by an inverse gamma distribution with hyperparameters $a' = a + n + 1$ and $b' = b + \sum_i x_i^\alpha$