Whitepaper: Calculating Weather Event Return Rates Using Bayesian Parameter Learning

Introduction

Accurately estimating the return rates of extreme weather events is crucial for informed planning and risk management. Traditional methods, which rely on fixed historical averages, often overlook the inherent uncertainty and variability in climate patterns. Using Bayesian parameter learning, we can continually refine our estimates of weather event return rates based on observed data while explicitly accounting for uncertainty. This approach enables planners to make more adaptive and resilient decisions.
This whitepaper outlines the detailed steps for calculating return rates of weather events using Bayesian techniques.

Step-by-Step Calculation

1. Model the Weather Event as a Poisson Process

We model the arrival of extreme weather events, such as floods or storms, as a Poisson process. This is characterized by the parameter λ (lambda), which represents the average event occurrence rate (e.g., storms per year). The Poisson distribution gives the probability of observing a given number of events, k, in a specified time period.

$$P(k|\lambda) = \frac{\lambda^k e^{-k}}{k!}$$

Note even though k is discrete, the λ is continuous. It turns out that the return rate, R, is the reciprocal of the λ.

$$R = \frac{1}{\lambda}$$

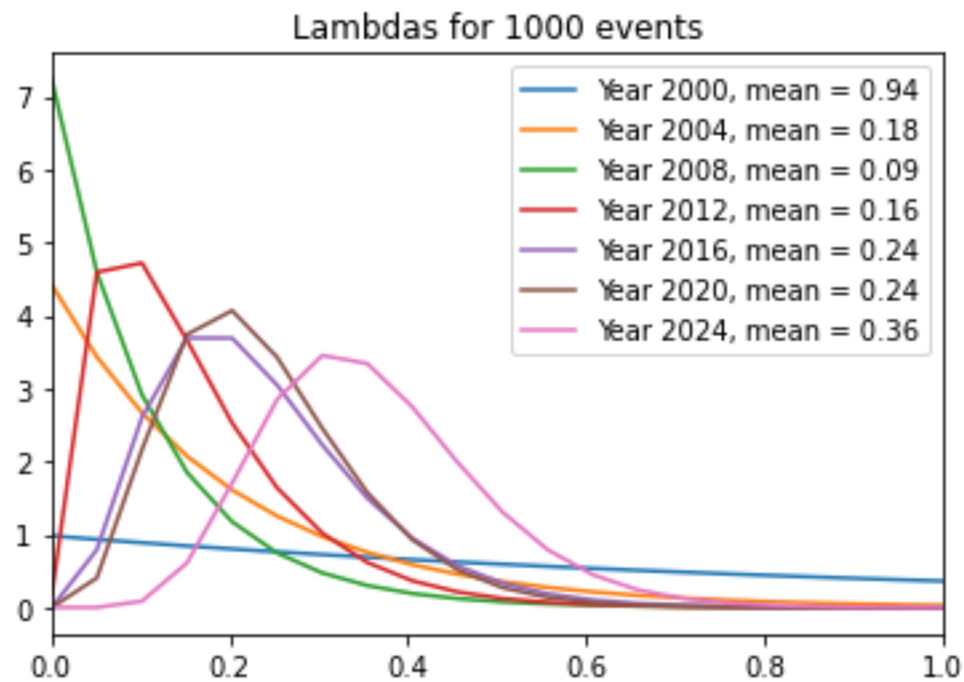
So, the strategy is first to learn the λ and then use Monte Carlo methods to learn the R.

2. Data Collection

Collect historical data on the number of events, k, observed in each year from 2010 to 2022 (1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 2,2).

3. Bayesian Update

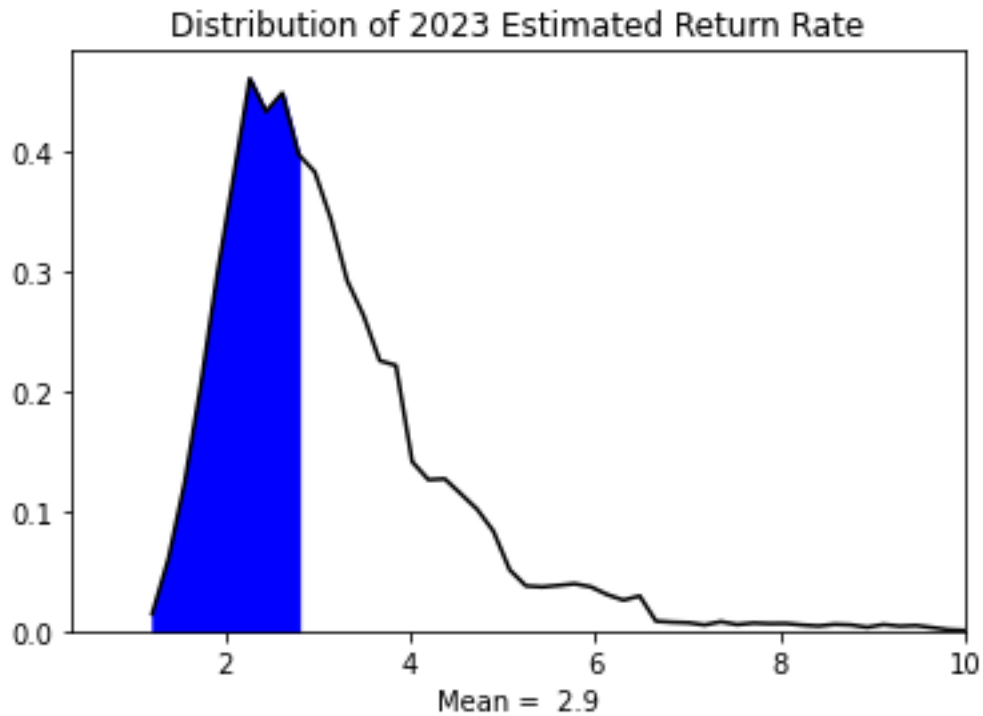
Using Bayesian inference, we update our belief about λ using the Poisson distribution for the likelihood function and the yearly events as the ks. We started with a uniform prior uniform distribution as a minimal assumption. Here are a sampling of the Lambdas:



4. Calculate the Return Rate

The return rate, R, is the reciprocal of λ. We need to compute its PDF. We do this using a Monte Carlo method:

- Take about 50,000 samples of the λ PDF using the inverse CDF method.
- Create an array of the reciprocals of the samples.
- Build a normalized histogram of the array of reciprocals with optimized bin sizes.
- Interpolate the histogram to get the return rate PDF

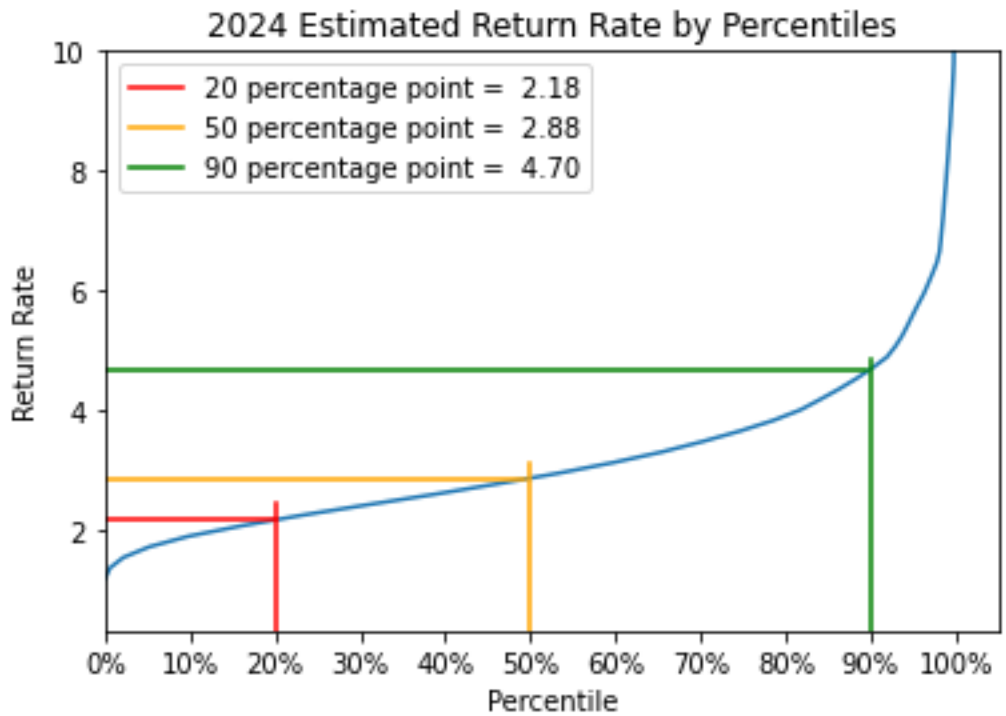


This PDF fully represents the uncertainty in the return rate, allowing planners to see the range of possible return intervals for the weather event.

Risk Tolerance and Decision Making

With the return rate PDF in hand, decision-makers can incorporate their risk tolerance into planning:
- High-Risk Aversion: For organizations with a low-risk tolerance, planning might focus on high percentiles of the return rate distribution (e.g., the 95th or 99th percentile). This ensures preparedness for rare but severe events that could have catastrophic consequences.
Moderate Risk: Planners with higher risk tolerance may focus on median or lower percentiles, accepting that extreme events may occur less frequently but not preparing for the worst-case scenarios.

This chart of the inverse of CDF supports these this decision.



Conclusion

Using Bayesian parameter learning to calculate weather event return rates, we can create more accurate, probabilistic estimates of event frequencies. This method allows for continual updating as new data becomes available, ensuring planners have the most up-to-date information on which to base their decisions. Additionally, by incorporating risk tolerance into the process, decision-makers can better balance cost, preparedness, and the likelihood of extreme weather events, making their strategies more robust and adaptable to future uncertainties.