

# **Climate Risk Assessment and Management**

James Doss-Gollin

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# Welcome

Welcome to Climate Risk Assessment and Management, an online textbook **under construction** by [James Doss-Gollin](#).

## ! Under Construction

This textbook is a work in progress. Currently it's largely a brain dump, but I am building it out incrementally for use in my own classes. As I add and organize content, I will update the chapter status codes: (*planning*), (*draft*), (*revision*), and (*ready*). [Contributions are welcome!](#)

## Motivation and Scope

### History

This project emerged from two courses taught at Rice University by [James Doss-Gollin](#): [CEVE 543](#) focused on climate hazard and extremes and [CEVE 421/521](#) focused on risk management.

### Aim

The book is motivated by questions like

- What is the probability distribution of wind speeds that a building structure might experience?
- What will the probability distribution of extreme rainfall be in 2050, and what drives uncertainty in this estimate?
- What is the probability distribution of tropical cyclone losses across a regional portfolio?
- When, and how high, should a house be elevated to proactively manage future flood risk?
- What are robust, efficient, and equitable strategies for reducing flood risk in an urban area?

These questions span scales and sectors, yet they share fundamental challenges: characterizing extreme events, quantifying uncertainty, assessing risks, and making robust decisions when probability distributions are unknown or contested. Moreover, there is not a single correct answer to these questions, or a single method that will incontrovertibly answer them.

## How to Use This Resource

The book is designed to be useful for practitioners, students, and teachers. Teachers may use individual chapters in their courses. Students may use it as a class text or reference. Practitioners may focus on specific chapters relevant to their work. Each chapter includes learning objectives and can be read independently, though some chapters build on concepts introduced in others.

### Structure

- [The Preface](#) introduces the book’s motivation and frames key challenges
- [Part 1](#) introduces key topics in probability, inference, Bayesian methods, optimization, machine learning, and Earth science. Rather than providing a comprehensive treatment, this part focuses on essential concepts and links to further resources.
- [Part 2](#) focuses on hazard **assessment**, namely modeling climate hazards and extremes. Material is organized around thematic applications and predictive tasks. The foundational idea is integrating information from noisy and/or biased sources to estimate the joint probability distribution of relevant hydroclimatic variables.
- [Part 3](#) risk management, which involves both mapping hazard to risk and designing interventions to manage these risks. Key ideas include the sequential nature of decisions, the pursuit of unclear and/or contested objectives, and the need to account for the sensitivity of estimated probability distributions (of hazard and of other relevant physical, social, and economic variables) to underlying models and assumptions.
- [Computational notebooks](#) written in [Julia](#) illustrate and complement the methods and concepts discussed in the text. While notebooks are referenced in the text, they are designed as standalone and self-contained resources.

### Prerequisites

Basic probability and multivariate calculus, along with linear algebra, are sufficient mathematical foundations for this textbook. Some exposure to Earth science, hydrology, water resources, or related topics is strongly encouraged for context, though not strictly necessary for understanding methods. This book builds on a wide range of topics and methods in statistics, machine learning, optimization, and Earth science, and expertise in any of these areas may deepen your understanding, but is not necessary. No programming is required to read the book, but going through computational examples and applying methods to your own problems, which can substantially strengthen your understanding, does require programming.



## **Part I**

# **About this book**

# License

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# Contributing

This textbook is a work in progress, and we welcome your contributions. Whether it's fixing a typo or proposing a new module, every suggestion helps. The easiest way to contribute is to fork the repository and submit a pull request. If you're not comfortable with that workflow, please open an issue [on GitHub](#).

# Citing

Please cite this resource as

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  author = {Doss-Gollin, James},  
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}
```

In the future, we will move to stable releases with numbered versions.

## Further Reading

Climate risk assessment and management are complex and interdisciplinary topics, and we are by no means comprehensive here. This page provides some helpful resources (textbooks, detailed online tutorials, and class websites) for your continued and supplementary study.

## Inspiration

This textbook draws inspiration and content from several courses and lecture notes, and I am grateful to the instructors who have shared their materials with me.

- Upmanu Lal’s Environmental Data Analysis course at Columbia
- Vivek Srikrishnan’s [Environmental Systems Analysis](#) and [Climate Risk Analysis](#) classes at Cornell
- R. Balaji’s Advanced Data Analysis Techniques (Statistical Learning Techniques for Engineering and Science) [course](#) at CU Boulder
- Alberto Montanari’s [collection of open course notes and lectures](#)
- **Applegate and Keller (2015)** motivates this project and demonstrates problem-based learning.

## Stats + ML basics

This book assumes familiarity with these topics, but these resources may be helpful as a refresher.

- **Blitzstein and Hwang (2019)** provides a thorough introduction to key concepts and ideas in probability. The book accompanies a free online course, [Stat 110](#), which is a great resource for learning probability and statistics. Practice problems and solutions, handouts, and lecture videos are all available online.
- **Downey (2021)** offers an introduction to Bayesian statistics using computational methods. It’s not environment focused but provides code and a clear explanation of core concepts.
- **Gelman (2021)** is a textbook designed for a first course on applied statistics. Clear and well-worked examples underpin discussion of fundamental ideas in statistical analysis and thinking about data.

## Applications

There are lots of related books on catastrophe modeling, water resources research, geostats, statistical hydrology and related topics. Here is an incomplete list of some core references.

- **Naghattini (2017)** is a textbook on statistical hydrology that covers many of the same topics as this course. The statistical hydrology literature often obfuscates key ideas with complex notation and terminology, but this book is a helpful introduction to the field.
- **Helsel et al. (2020)** is a comprehensive introduction to water resources and hydrology, focusing on statistical methods for analyzing hydrologic data. Its methods are traditional, with less emphasis on machine learning or Bayesian methods and more attention to null hypothesis significance testing, but its case studies are well-worked and thoughtfully described.
- **Abernathey (2024)** is an excellent resource covering introductory topics in Earth and climate data science using Python, with an emphasis on foundational computations. These core computational concepts serves as a recommended prerequisite for more advanced material in this book.
- **Pyrz (2024)** is a textbook focused on applied machine learning, with a particular focus on geostatistics. There's less focus on extremes, hydroclimate, and decision-making, but it provides very clear and interpretable explanations of many machine learning methods, including some that are not directly covered in this book.
- **Mignan (2024)** is a modern introduction to catastrophe risk modeling that covers a wide range of hazards, including hydroclimatic extremes, from a physics-based perspective. It provides a structured framework for quantifying hazard, exposure, and vulnerability, following industry-standard CAT modeling approaches. While broader in scope and more introductory in level, it complements this book's focus by illustrating foundational principles of probabilistic risk modeling in practice.

## More Stats + ML

This book covers a broad set of topics in statistics, machine learning, and optimization. Most chapters could be a textbook of their own, and in fact many exist.

- **Friedman, Hastie, and Tibshirani (2001)** is a classic introduction to machine learning, which complements the Bayesian perspective nicely.
- **Jaynes (2003)** is a classic text on probability theory that you should read if you're interested in questions like "what is probability?"
- **Gelman et al. (2014)** and **McElreath (2020)** are the classic textbooks on Bayesian inference and provide a wealth of insight and detail. The Gelman textbook is a bit more dense while the McElreath book has a more conversational tone, but both cover similar topics.
- **Cressie and Wikle (2011)** provides a detailed exploration of hierarchical space-time models. There have been some computational advances since then that are worth keeping in mind before you apply these models directly, but it's a clearly written and overview.
- **Thurey et al. (2024)** is a new textbook on physics-based deep learning, which is a rapidly growing area of research. It provides a comprehensive overview of the field, including theoretical foundations and practical applications. It covers topics, including neural operators and diffusion models, that are not covered in this course, but which are increasingly used in the climate risk space.
- **Bishop and Bishop (2024)** is a comprehensive, modern, and accessible start-to-finish textbook covering machine learning from basic probability through diffusion models.
- Michael Betancourt's [writing page](#) has detailed and mathematically rigorous explanations of many topics in Bayesian data analysis and probabilistic modeling.

# Preface

## What is climate risk?

Climate risks arise at the intersection of climate hazards, exposed systems, and vulnerability. They manifest when extreme or changing climate conditions—floods, droughts, extreme temperatures, sea-level rise, or shifting precipitation patterns—impact human and natural systems that are exposed and vulnerable to these conditions. The financial sector terms these “physical risks” to distinguish them from transition risks related to policy and market changes.

Climate risks span scales from the hyperlocal (a single building’s flood exposure) to the global (climate impacts on agricultural productivity). They encompass immediate acute risks from individual extreme events and longer-term chronic risks from gradual climate changes. Crucially, climate risks are not solely natural phenomena but emerge from the complex interactions between climate hazards and the human systems—infrastructure, institutions, communities, and economies—that experience their impacts.

Climate risk is often defined as the product of hazard (probability that something will happen) and consequences (exposure and vulnerability). However, it’s often helpful to start with the decisions we care about.

## Risk management

The goal of assessing climate risks is to manage them, as is the focus of Part III. We manage climate risks by

- **building infrastructure**, such as seawalls, stormwater pipes, oyster beds, green roofs, dams
- **designing policy**, such as water pricing, land-use regulations, building codes
- **responding** to climate disasters through disaster response and recovery. While emergency management is beyond the scope of the book, disaster prevention (through infrastructure, policy, etc) and preparation (planning evacuation routes, assessing resource needs, etc) are problems that the tools of this class can inform.

A key insight from considering these applications is that climate risks are not natural phenomena, but occur at the intersection of natural and human systems. A second insight is that decisions about how to manage climate risks do not depend only on climate hazard, but also on human systems and values.

## Exposure and vulnerability

Hazards do not create consequences by themselves. Hazards affect things that we care about, whether natural ecosystems, human homes, infrastructure systems, or something else. Quantitatively these are often described as exposure and vulnerability. However, this is not always a helpful framing because everything is exposed, to at least some degree, to climate hazards.

## Climate hazard

Climate hazards have several key characteristics:

- **Location-specific impacts:** Specific weather patterns cause different things in different places—tropical cyclones cause extreme winds on the Gulf Coast, while persistent intense rainfall causes flooding in major rivers
- **Require Earth science and data:** Understanding hazards requires both physical process knowledge and empirical data
- **Variable focus on extremes:** Some applications care about extremes, but others (e.g., water management) care about shifts in the whole distribution
- **Multi-scale variability:** Characterized by variability across multiple spatial and temporal scales

## What are good strategies?

### The simple story

In principle, managing climate risks should be straightforward. If we had clear objectives and well-characterized uncertainty, there are **established mathematical formalisms for decision-making under uncertainty**. Notably, Bayesian Decision Theory provides an elegant framework: find the action  $a$  that maximizes expected utility

$$\mathbb{E}[U(a)] = \int U(a, s)p(s)ds,$$

where  $U(a, s)$  is the utility of action  $a$  given  $s$ , and  $p(s)$  is the over states of the world. The  $\mathbb{E}[U(a)]$  represents the average utility we would expect from action  $a$  across all possible future states, weighted by their probabilities (see [Chapter on Probability and Statistics](#) for mathematical foundations).

With this framework and modern advances in operations research and optimization, we could frame climate risk management as a large-scale optimization problem. This might still be a challenging problem, requiring sophisticated optimization methods, large-ensemble Monte Carlo simulation, high-performance computing, and more, but fundamentally **there would be a right answer** that we could identify, at least seek to approximate.



## Why this isn't enough

In practice, climate risk management defies this idealized approach for several fundamental reasons:

1. **Deep uncertainty:** Unlike textbook optimization problems, we rarely have well-defined probability distributions over future states. Climate risks involve poorly characterized, multiple, and interacting uncertainties spanning physical processes (climate projections), socioeconomic factors (development patterns, institutional capacity, human behavior), and their complex dependencies. The probability distributions we need span climate hazards, exposure patterns, vulnerability functions, and policy effectiveness—all evolving in ways that resist precise characterization.
2. **Large and poorly defined decision spaces:** The solution space includes not just individual projects but entire systems: infrastructure networks, policy portfolios, risk transfer arrangements, and adaptive management sequences. These decisions interact across scales, sectors, and time horizons in ways that resist comprehensive optimization.
3. **Contested objectives:** Different stakeholders hold different values about what we should optimize for—economic efficiency, equity, robustness, or flexibility. These objectives often conflict, and their relative importance is itself contested and evolving.

This brings us to a crucial insight: **we cannot simply frame climate risk management as a big optimization problem.** The field has witnessed an explosion of computational tools—climate models with ever-finer resolution, machine learning algorithms for processing vast datasets, and sophisticated visualization platforms for rendering complex projections. While these advances represent genuine progress, their proliferation has created new challenges for practitioners seeking to manage real-world climate risks.

The abundance of available tools does not automatically translate to better decisions. Indeed, the sophistication of modern computational approaches can obscure fundamental questions about problem framing, uncertainty characterization, and appropriate methods selection. Without solid conceptual foundations, practitioners may find themselves applying powerful tools inappropriately or mistaking methodological novelty for substantive insight.

## The stakes of getting it wrong

The consequences of inadequate climate risk management are severe and diverse. **Infrastructure failures** occur when designs based on historical extremes prove insufficient for future conditions—leading to flooded neighborhoods when storm drains are undersized, or to costly over-design when extreme projections are treated as certainties. **Policy mistakes** compound these problems: development policies that ignore flood risks concentrate vulnerable populations in harm's way, while overly conservative regulations can stifle economic development without commensurate risk reduction benefits.

**Financial miscalculations** affect both public and private sectors. Insurance companies that underestimate climate risks face catastrophic losses, while those that overestimate risks price themselves out of markets. Infrastructure investors struggle to balance climate resilience against cost constraints, often erring toward solutions that prove either inadequate or prohibitively expensive. These failures cascade across scales: a poorly designed local drainage system contributes to regional

flood management challenges, while flawed national climate risk assessments misguide infrastructure investment priorities across entire countries.

## This book

This book develops both the technical tools and conceptual frameworks needed for climate risk management:

- **Part I** provides the statistical, optimization, and machine learning foundations that enable rigorous analysis of climate risks and decision alternatives
- **Part II** focuses on characterizing climate hazards and their uncertainties, emphasizing the integration of multiple imperfect information sources
- **Part III** addresses the transition from hazard to risk and the design of management strategies under deep uncertainty

Throughout, we emphasize that technical sophistication must be coupled with conceptual clarity about the nature of climate risks and the limits of optimization approaches. The goal is not to abandon quantitative analysis, but to use it more wisely—focusing computational power where it adds most value while acknowledging the irreducible uncertainties that require adaptive, robust approaches to climate risk management.

This book aims to teach readers how to **apply** tools from applied mathematics, statistics, and machine learning to answer questions such as

- What is the probability distribution of some relevant hazards or variables, such as (rainfall, wind, flood, temperature, streamflows) at a specific location?
- How do these probability distributions change in the next 50 years?
- How uncertain are these estimates and what specific mechanisms drive these uncertainties?
- What is the distribution of annual losses of a portfolio of assets exposed to one or many climate risks?
- What are trade-offs between up-front costs and future damages for decisions like how high to elevate a house?
- What are robust strategies for sequentially hardening infrastructure against climate risks?
- What are trade-offs between flood and drought protection for managing a reservoir?

While Part I does provide building blocks, they are intended to be self-contained references rather than a comprehensive overview to applied math, statistics, computer science, machine learning, and operations research. Instead, it aims to give you “just enough” context to think carefully about how to apply tools from these fields to climate risk management challenges.

## What this book is not

This book focuses on the technical foundations of climate risk assessment and quantitative decision-making under uncertainty. While we address design requirements, social dimensions, and stakeholder considerations throughout—recognizing that technical tools can significantly inform these challenges—there are important aspects of climate risk management that require specialized expertise beyond our scope.

This book will **not** primarily teach you how to:

- **Manage reputational and transition risks:** While we focus on physical climate risks and their quantitative assessment, organizations also face complex risks from changing policies, markets, and stakeholder expectations that require specialized risk management expertise
- **Design and implement adaptive organizations:** While we cover adaptive management strategies and robust decision-making frameworks, the organizational design and management expertise needed to implement these approaches in practice requires additional specialized knowledge
- **Facilitate stakeholder processes:** While the quantitative tools we teach can strongly support consensus building by clarifying trade-offs and uncertainties, the facilitation, negotiation, and collaborative governance skills needed to lead stakeholder processes require specialized training
- **Develop communication strategies:** While we emphasize how to interpret and present quantitative risk assessments, developing effective communication strategies for diverse audiences—policymakers, communities, investors—requires specialized expertise in science communication and public engagement
- **Navigate implementation challenges:** While we address policy design and infrastructure planning from an analytical perspective, the practical challenges of construction management, regulatory processes, and community engagement require domain-specific expertise

This is an interdisciplinary text that draws insights from multiple fields and acknowledges the social, political, and institutional contexts that shape climate risk management. However, our primary focus remains on the quantitative and analytical foundations that can inform—but not replace—the broader expertise needed for effective practice.

## **Part II**

# **I: Foundations**

# 1 Climate science

## Learning objectives

After reading this chapter, you should be able to:

- Understand why climate science is essential for risk assessment
- Identify key climate science topics you should study for effective risk management
- Navigate to appropriate resources for learning climate science fundamentals

## 1.1 Why climate science matters for risk assessment

Climate hazards don't occur in isolation. A hurricane's intensity depends on sea surface temperatures and atmospheric conditions. Droughts emerge from large-scale circulation patterns and ocean-atmosphere interactions. Floods reflect not just local rainfall but also broader weather systems and seasonal cycles.

Understanding these connections is crucial for risk assessment because climate science helps us answer three fundamental questions:

1. **What physical processes create hazardous weather patterns?** Understanding the mechanisms behind hurricanes, droughts, heat waves, and floods helps us identify when and where they're most likely to occur.
2. **How do these patterns vary naturally over time?** Climate systems exhibit variability on multiple timescales—from seasonal cycles to multi-decadal oscillations—that affect the frequency and intensity of extreme events.
3. **How might climate change alter these patterns?** As greenhouse gas concentrations rise, the statistical properties of weather and climate are shifting, requiring us to account for non-stationarity in our risk assessments.

## 1.2 Essential climate science topics

1. Climate models and modeling
2. Multi-scale variability
3. Specific weather patterns
4. Climate change and sensitivity
5. Hydrologic cycle

## Further reading

- Mudelsee (2020): statistical approaches to climate extremes
- Merz et al. (2014): flood risk methods connecting climate to impacts
- Ghil et al. (2011): physical processes and extreme value behavior

## 2 Probability and inference

### 2.1 Key terms and ideas

- Probability as an axiomatic language for uncertainty
- Joint, conditional, and marginal distributions
- Bayes' rule
- Likelihood functions
- Maximum likelihood

### Further reading

For deeper study of probability and statistics:

- Blitzstein and Hwang (2019) provides excellent intuition with computational examples
- Downey (2021) emphasizes Bayesian thinking with practical applications
- Gelman (2021) connects regression to broader statistical modeling
- [Mosquito Example](#) demonstrates simulation-based statistical testing with concrete data analysis

# 3 Optimization

## Learning objectives

After reading this chapter, you should be able to:

- Understand the components of optimization problems: decision variables, objectives, constraints
- Apply optimization methods to climate policy and decision problems
- Recognize trade-offs between problem complexity and solution accuracy
- Connect optimization techniques to statistical inference and policy search

## 3.1 Essential optimization concepts

1. Decision variables, objective functions, and constraints
2. Gradient-based optimization methods
3. Stochastic and sequential optimization
4. Policy optimization in climate risk management
5. Trade-offs between problem formulation and solution methods

## Further reading

- Sutton and Barto (2018): Reinforcement learning and sequential decision-making



# 4 Monte Carlo methods

## Learning objectives

After reading this chapter, you should be able to:

- Apply Monte Carlo methods to approximate integrals and expectations
- Use Markov Chain Monte Carlo (MCMC) techniques for Bayesian inference
- Understand parameter uncertainty propagation in decision-making
- Implement Monte Carlo simulation for climate risk assessment

## 4.1 Essential Monte Carlo concepts

1. Monte Carlo integration and expectation approximation
2. Bayesian inference and posterior sampling
3. Markov Chain Monte Carlo (MCMC) methods
4. Parameter uncertainty propagation
5. Sensitivity analysis and global uncertainty quantification

## Further reading

- Gelman et al. (2014): Bayesian data analysis with computational focus

# 5 Machine learning and nonparametric methods

## Learning objectives

After reading this chapter, you should be able to:

- Apply fundamental supervised learning concepts to climate hazard assessment problems
- Understand nonparametric and semiparametric methods for flexible modeling
- Critically evaluate machine learning applications in climate risk literature
- Understand bias-variance tradeoffs and model validation approaches

## 5.1 Essential machine learning concepts

1. Supervised and unsupervised learning paradigms
2. Parametric vs nonparametric methods
3. Bias-variance tradeoff and regularization
4. Cross-validation and model selection
5. Tree-based methods and ensemble learning

## Further reading

# 6 Correlation and dimensionality

## Learning objectives

After reading this chapter, you should be able to:

- Model and interpret spatial dependence in climate fields
- Apply time series analysis methods to detect trends and patterns in climate data
- Use dimension reduction techniques for high-dimensional climate datasets
- Integrate spatial and temporal methods for spatiotemporal climate analysis

## 6.1 Essential concepts

1. Spatial statistics and geostatistical methods
2. Time series analysis and trend detection
3. Principal component analysis and empirical orthogonal functions
4. High-dimensional methods for climate data
5. Spatiotemporal integration approaches

## Further reading

For spatial and temporal analysis in climate science:

- Cressie and Wikle (2011): Comprehensive treatment of spatial statistics

# 7 Model validation and comparison

## Learning objectives

After reading this chapter, you should be able to:

- Apply graphical diagnostic methods to assess model fit quality
- Use information criteria (AIC, DIC, BIC) for quantitative model comparison
- Understand the relationship between model selection and predictive accuracy
- Recognize the subjective nature of model selection and make transparent choices

## 7.1 Essential model validation concepts

1. Graphical diagnostic methods and model checking
2. Information criteria for model comparison
3. Predictive accuracy and cross-validation
4. Model selection philosophy and transparency
5. Ensemble methods and model averaging

## Further reading

- Piironen and Vehtari (2017): Technical treatment of predictive accuracy

## **Part III**

# **II: Hazard Assessment**

# 8 Extreme value theory

## See first

This chapter builds on concepts from [Probability and Statistics](#).

## Learning objectives

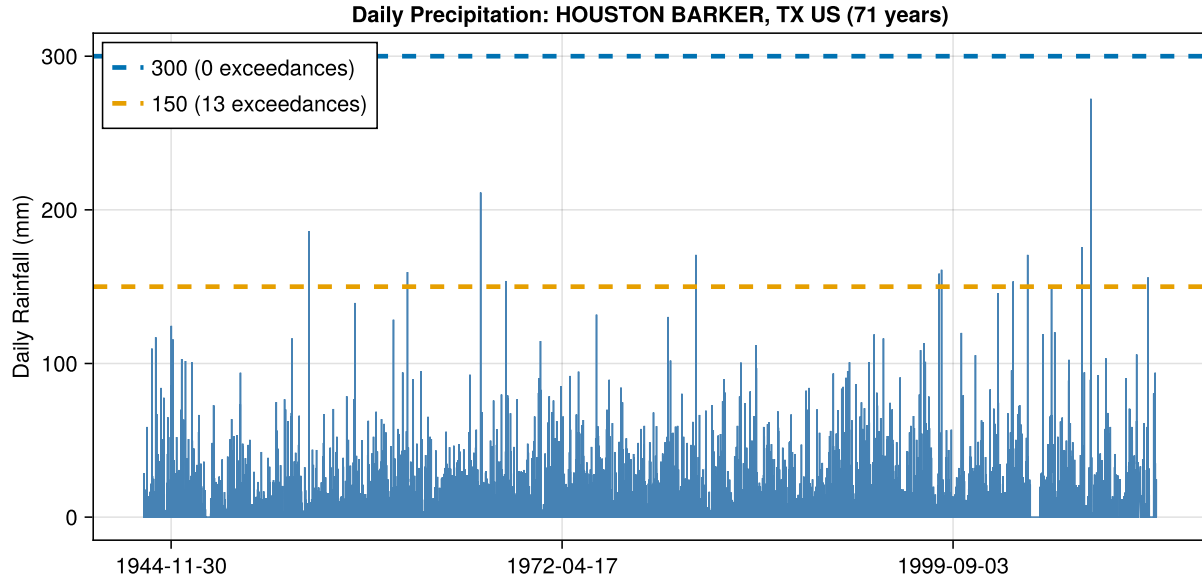
After reading this chapter, you should be able to:

- Understand the motivation for extreme value theory in climate risk assessment.
- Distinguish between block maxima and peak-over-threshold approaches.
- Select and fit appropriate extreme value distributions (GEV, GPD).
- Calculate return periods, return levels, and exceedance probabilities.
- Quantify and interpret different sources of uncertainty in extreme value analysis.
- Recognize the challenges posed by non-stationarity and climate change.
- Apply extreme value methods to real-world case studies.

## 8.1 Motivation

The design of reliable infrastructure, such as stormwater systems in Harris County, Texas, depends on a quantitative understanding of extreme environmental events. Engineers must characterize the magnitude and frequency of rare phenomena. For example, they might need to determine the expected recurrence interval of a daily rainfall total that exceeds a critical design threshold, such as 300 mm.

An initial, intuitive approach is to analyze the historical record.



Analysis of over 70 years of daily precipitation data from a station in Houston reveals 13 days where rainfall exceeded 150 mm. This allows for a simple empirical estimate of the event’s frequency. Thirteen exceedances in 71 years suggests an average recurrence interval of approximately 5.5 years. For the 300 mm threshold, however, the historical record contains zero events. An empirical estimate of the probability is therefore zero, which is uninformative for risk assessment and infrastructure design. We require a method for extrapolating beyond the range of observed data.

A natural extension would be to fit a standard parametric probability distribution—such as a Gamma distribution, which is commonly used for precipitation—to the entire set of daily rainfall observations. One could then use the extreme upper tail of the fitted distribution to estimate the probability of exceeding 300 mm.

This approach, however, is fundamentally unreliable. The goodness-of-fit of a parametric model is driven by its ability to describe the bulk of the data, where observations are plentiful. Minor model misspecifications in this high-density region can translate into substantial errors in the far tails of the distribution, where data are sparse or nonexistent. As stated by Coles (2001), the foundational text on this topic, “very small discrepancies in the estimate of  $F$  can lead to substantial discrepancies for  $F^n$ ”, where in our example  $F$  is the cumulative distribution function (CDF) of daily rainfall while  $F^n$  is the CDF of the maximum daily rainfall over  $n$  days.

The models that best describe the central tendency of a process are not necessarily suitable for describing its extremes. This fragility of tail extrapolation necessitates a theoretical framework developed specifically for modeling the behavior of extreme values.

A naive empirical estimator for the exceedance probability of a value  $x$  based on  $n$  observations  $X_i$  is the simple proportion of exceedances:

$$\hat{P}(X > x) = \frac{1}{n} \sum_{i=1}^n \mathbf{1}(X_i > x)$$

where  $\mathbf{1}(\cdot)$  is the indicator function. This is useful when the number of exceedances is large, but fails for extrapolation when the sum is zero, as was the case for the 300mm threshold. This mathematically demonstrates the limitations of simple empirical methods and motivates the specialized approaches that follow.

## 8.2 Approaches for modeling extreme values

Extreme Value Theory (EVT) provides such a framework. Rather than modeling the entire distribution of a process, EVT focuses on the distribution of its extreme values. There are two primary methods for extracting these values from a time series.

### 8.2.1 Block maxima

In this method, the period of observation is divided into non-overlapping blocks of equal duration (e.g., years). For each block of size  $n$ , we define the block maximum as  $M_n = \max\{X_1, \dots, X_n\}$ . This yields a new time series of block maxima. A crucial conceptual point is that we are not studying a single maximum possible value of the process. Instead, we are studying the distribution of the sample maximum,  $M_n$ , which is itself a random variable. This is why a distribution like the GEV is needed to describe its behavior. This approach is intuitive and directly relates to concepts of annual risk, but it can be inefficient as it discards other potentially extreme events within a block.

### 8.2.2 Peaks-over-threshold

The peaks-over-threshold (POT) method defines a set of exceedances over a high threshold  $u$  as  $\{X_i : X_i > u\}$ . The variable of interest is the value of the **excesses** themselves,  $Y = X_i - u$ , for all  $X_i$  in the set of exceedances. The GPD is a model for these excess amounts, not the raw values. This approach is more data-efficient than the block maxima method. Its primary challenge lies in selecting an appropriate threshold, which involves a trade-off between bias (if the threshold is too low) and variance (if the threshold is too high, yielding too few data points). In practice, exceedances may occur in clusters (e.g., during a multi-day storm event). Therefore, a declustering algorithm is often applied to the raw exceedances to ensure that the events being modeled are approximately independent.

## 8.3 Asymptotic theory for extremes

The statistical justification for both the block maxima and POT approaches comes from asymptotic theorems that describe the limiting distributions of extreme values.



### 8.3.1 Theory for block maxima: The GEV distribution

The theoretical justification for the block maxima approach is the **Extremal Types Theorem**. This theorem states that for a large class of underlying distributions, if a stable, non-degenerate limiting distribution for the block maximum  $M_n$  exists, it must be the **Generalized Extreme Value (GEV)** distribution.

A critical point is that the theorem applies to a *linearly rescaled* or *normalized* maximum. Consider the raw maximum,  $M_n$ . As the block size  $n$  increases, the expected value of  $M_n$  will also increase (or stay the same)—its distribution drifts towards larger values and does not converge. A similar issue arises in the Central Limit Theorem (CLT), which describes the convergence of a sample mean. The CLT does not apply to the raw sum of random variables, but to a normalized version of it.

The Extremal Types Theorem is the direct analog of the CLT for maxima. It states that there exist sequences of normalizing constants, a location parameter  $b_n$  and a scale parameter  $a_n > 0$ , such that the distribution of the normalized maximum,  $(M_n - b_n)/a_n$ , converges to the GEV distribution as  $n \rightarrow \infty$ .

In practice, we do not need to know the specific functional forms of  $a_n$  and  $b_n$ . Instead, for a fixed, large block size  $n$  (e.g., one year of daily data), we fit the GEV distribution directly to the series of block maxima. The GEV's location and scale parameters,  $\mu$  and  $\sigma$ , effectively absorb and account for the normalization that the theory requires. The GEV is a flexible three-parameter family with a cumulative distribution function (CDF) given by:

$$G(z) = \exp \left\{ - \left[ 1 + \xi \left( \frac{z - \mu}{\sigma} \right) \right]^{-1/\xi} \right\}$$

This is defined on the set  $\{z : 1 + \xi(z - \mu)/\sigma > 0\}$ . The parameters are location ( $\mu$ ), scale ( $\sigma > 0$ ), and shape ( $\xi$ ). These parameters implicitly depend on the block size  $n$ .

### 8.3.2 Theory for threshold exceedances: The GPD

The corresponding theory for the POT approach is the **Pickands–Balkema–de Haan Theorem**. It states that for a wide range of distributions, the distribution of excesses over a high threshold  $u$  can be approximated by the **Generalized Pareto Distribution (GPD)**. Conceptually, if the GEV describes the behavior of the maximum of a large block, the GPD describes the behavior of the distribution's tail that produced that maximum. It is the distribution one would expect to see by “zooming in” on the tail of a distribution above a high threshold.

The GPD is a two-parameter family with a CDF for **excesses**  $Y = X - u$  given by:

$$H(y) = 1 - \left( 1 + \frac{\xi y}{\sigma_u} \right)^{-1/\xi}$$

This is defined on  $\{y : y > 0 \text{ and } (1 + \xi y/\sigma_u) > 0\}$ . The parameters are the shape,  $\xi$ , and a scale parameter  $\sigma_u$  that depends on the threshold  $u$ . If the parent distribution's maxima are GEV-distributed with parameters  $(\mu, \sigma, \xi)$ , then the GPD scale parameter is given by  $\sigma_u = \sigma + \xi(u - \mu)$ .

This key result shows that the GPD scale parameter is a linear function of the threshold  $u$ , a property that is used in advanced diagnostics for threshold selection.

### 8.3.3 The shape parameter ( $\xi$ ): A unifying concept

The **shape parameter**,  $\xi$ , is the most critical parameter in extreme value analysis and has the same interpretation in both the GEV and GPD. It governs the tail behavior of the distribution.

- $\xi = 0$  (**Gumbel-type tail**): The tail decays exponentially (light tail).
- $\xi > 0$  (**Fréchet-type tail**): The tail decays as a polynomial (heavy tail), with no upper bound.
- $\xi < 0$  (**Weibull-type tail**): The distribution has a finite upper bound.

### 8.3.4 Connection between GEV and GPD

The GEV and GPD models are intrinsically linked. If the block maxima of a process follow a GEV distribution with parameters  $(\mu, \sigma, \xi)$ , then for a high threshold  $u$ , the threshold excesses follow a GPD with the same shape parameter  $\xi$ . This provides a theoretical consistency between the two primary modeling approaches.

## 8.4 Return periods and return levels

### 8.4.1 Definitions and Calculation

The output of an extreme value analysis is typically expressed in terms of **return periods** and **return levels**. The **N-year return level**,  $z_N$ , is the level expected to be exceeded on average once every  $N$  years. It corresponds to the quantile of the distribution with an annual exceedance probability of  $p = 1/N$ .

For the GEV distribution, it is calculated by inverting the CDF:

$$z_N = \mu - \frac{\sigma}{\xi} [1 - (-\ln(1 - p))^{-\xi}]$$

Calculating return levels from a GPD model requires an additional step. If  $\zeta_u$  is the rate of threshold exceedances (e.g., the average number of exceedances per year), the  $N$ -year return level is the value  $z_N$  that is exceeded with probability  $1/(N\zeta_u)$ . It is calculated by adding the threshold back to the corresponding quantile of the GPD:

$$z_N = u + \frac{\sigma_u}{\xi} [(N\zeta_u)^\xi - 1]$$

### 8.4.2 Return level plots

A standard diagnostic and visualization tool is the return level plot. This plot graphs the estimated return level  $z_N$  against the return period  $N$ , with  $N$  typically plotted on a logarithmic scale. The curvature of the fitted line is a direct visualization of the shape parameter,  $\xi$ : a straight line implies  $\xi = 0$ , a concave curve implies  $\xi > 0$ , and a convex curve implies  $\xi < 0$ .

[Placeholder for a Return Level Plot showing a fitted GEV or GPD curve with confidence intervals.]

## 8.5 Plotting positions

To visually assess model fit, the fitted model is plotted against the observed maxima. For this purpose, we require a method to assign a non-exceedance probability (and thus a return period) to each observed maximum. For a sample of  $n$  block maxima, let  $z_{(1)} < z_{(2)} < \dots < z_{(n)}$  be the ordered values. We estimate the probability  $P(Z \leq z_{(k)})$  using a plotting position formula. These formulas generally take the form:

$$p_k = \frac{k - a}{n + 1 - 2a}$$

where  $k$  is the rank of the observation and  $a$  is a parameter. Common choices include:

- **Weibull:**  $a = 0$ , giving  $p_k = k/(n + 1)$ .
- **Gringorten:**  $a = 0.44$ , giving  $p_k = (k - 0.44)/(n + 0.12)$ . This is often recommended as an unbiased choice for Gumbel-type distributions.

The empirical return period for the  $k$ -th observation is then estimated as  $1/(1 - p_k)$ .

## 8.6 Modeling assumptions and considerations

Application of these models requires careful consideration of underlying assumptions.

- **Stationarity:** The classical GEV and GPD models assume **stationarity**: the parameters are constant in time. This implies that the statistical properties of extreme events do not change. In the context of climate change, this assumption may be invalid and requires more advanced non-stationary models.
- **Practical Choices:** The chosen methodology dictates key practical decisions. For the BM approach, the **block size** must be large enough for the asymptotic theory to hold but small enough to retain a reasonable sample size. For the POT approach, the **threshold selection** is a critical step that balances bias and variance.

## Further reading

- (Coles 2001): Canonical extreme value textbook with mathematical rigor and practical examples

# 9 Downscaling and Bias Correction

## Learning objectives

After reading this chapter, you should be able to:

- Distinguish between supervised and distributional downscaling approaches
- Understand the motivation for downscaling climate model outputs
- Apply bias correction and quantile-quantile mapping techniques
- Recognize the stationarity assumption and its implications
- Evaluate different downscaling methods for specific applications
- Understand modern machine learning approaches to climate downscaling

## Further reading

- Lanzante et al. (2018) for comprehensive review of downscaling challenges
- Lafferty and Sriver (2023)
- Farnham, Doss-Gollin, and Lall (2018)

# 10 Stochastic weather generators

## Learning objectives

After reading this chapter, you should be able to:

- Understand the principles of stochastic weather generation
- Apply statistical models for synthetic weather data
- Use weather generators for downscaling climate model output
- Evaluate the performance of weather generation models

## 10.1 Essential concepts

1. Hidden Markov models for weather state modeling
2. Multi-site and multi-variable generation
3. Statistical downscaling applications
4. Synthetic data validation and evaluation
5. Integration with physical models

## Further reading

# 11 Physics-based models and calibration

## Learning objectives

After reading this chapter, you should be able to:

- Navigate trade-offs between model complexity, interpretability, and computational cost
- Characterize and communicate within- and between-model uncertainty
- Use surrogate models to approximate complex model output
- Apply model calibration techniques for climate applications

## 11.1 Essential concepts

1. Physics-based vs data-driven modeling spectrum
2. Model chaining and uncertainty propagation
3. Calibration methods and parameter estimation
4. Surrogate modeling for computational efficiency
5. Model structure uncertainty quantification

## Further reading

For physics-based modeling in climate applications:

- Rackauckas et al. (2020): Scientific machine learning for differential equations

# 12 Optimal sampling methods

## Learning objectives

After reading this chapter, you should be able to:

- Apply sampling techniques to generate synthetic event sets
- Use importance and stratified sampling to improve efficiency in hazard modeling
- Evaluate how sampling choices affect estimates of extreme risk
- Balance computational cost vs accuracy in climate risk estimation

## 12.1 Essential sampling concepts

1. Monte Carlo sampling and variance reduction
2. Importance sampling for rare events
3. Stratified sampling strategies
4. Synthetic event generation methods
5. Computational efficiency optimization

## Further reading



# 13 Global sensitivity analysis

## Learning objectives

After reading this chapter, you should be able to:

- Understand the role of sensitivity analysis in climate risk modeling
- Apply variance-based sensitivity methods (Sobol indices) to identify key parameters
- Use Morris screening methods for initial parameter importance ranking
- Interpret sensitivity analysis results for model simplification and uncertainty reduction

## 13.1 Essential sensitivity analysis concepts

1. Global vs local sensitivity analysis approaches
2. Sobol indices and variance decomposition
3. Morris elementary effects for screening
4. Multi-model sensitivity analysis
5. Implementation strategies for complex model chains

## Further reading

For global sensitivity analysis:

- Saltelli et al. (2008): Comprehensive introduction to GSA methods
- Herman and Usher (2017): Practical implementation guide with software tools

## **Part IV**

# **III: Risk Management**

# 14 Exposure and Vulnerability

## 14.1 Learning objectives

By the end of this chapter, you should be able to:

- Define exposure and vulnerability in the context of climate risk assessment
- Distinguish between different types of vulnerability (physical, social, economic)
- Understand methods for quantifying and mapping exposure
- Apply vulnerability assessment frameworks to real-world scenarios
- Integrate exposure and vulnerability data with hazard information for risk assessment

## 14.2 Further reading

# 15 Cost-Benefit Analysis and Net Present Value

## Learning objectives

After reading this chapter, you should be able to:

- Understand the theoretical foundation of cost-benefit analysis and Bayesian decision theory
- Apply net present value calculations with appropriate discount rates
- Quantify costs and benefits using utility functions for climate risk decisions
- Handle uncertainty in cost-benefit frameworks using expected value
- Recognize the limitations and appropriate applications of cost-benefit analysis
- Evaluate economic trade-offs over different time horizons and scenarios

## Further reading

## 16 Policy Search & Optimization

# 17 Risk Transfer

## See first

This chapter builds on concepts from: - [Exposure and Vulnerability](#) - [Expectations and Discounting](#)

## Learning objectives

- Explore financial instruments (insurance, reinsurance, catastrophe bonds) for spreading or transferring climate risk.
- Understand parametric insurance triggers and how they differ from indemnity-based approaches.
- Assess the role of public-private partnerships in risk transfer mechanisms.

### 17.1 Insurance/reinsurance fundamentals

### 17.2 Parametric vs. indemnity coverage

### 17.3 Catastrophe bonds, index-based schemes

### 17.4 Challenges in emerging markets and vulnerable regions

## Further reading

# 18 Deep Uncertainty and Model Structure

## See first

This chapter builds on concepts from: - [Probability and Statistics](#) - [Model Validation and Comparison](#)

## Learning objectives

- Distinguish between aleatory and epistemic uncertainty in climate risk assessment
- Understand the challenges posed by structural uncertainty and model disagreement
- Apply Bayesian Model Averaging (BMA) and stacking approaches to combine multiple models
- Recognize when deep uncertainty invalidates traditional decision frameworks
- Identify sources of deep uncertainty in exposure and impact modeling

## Further reading

## 19 Robustness



# 20 Adaptive Planning and Flexibility

## See first

This chapter builds on concepts from: - [Deep Uncertainty](#) - [Robustness](#)

## Learning objectives

- Plan for uncertainty with adaptive management and iterative risk strategies.
- Develop adaptation pathways that evolve with new information (e.g., climate data, impacts).
- Incorporate monitoring and feedback loops into long-term climate policy.

## Further reading

## 21 Working with People: Values, Participation, and Communication

### Learning objectives

- Understand and communicate how decision analyses are necessarily influenced by subjective value judgements
- Explain common ethical frameworks for decision analysis
- Be familiar with multiple frameworks for stakeholder engagement and participatory methods
- Design effective approaches for communicating uncertainty in climate risk assessments
- Recognize the social and political dimensions of climate risk management

### Further reading

**Part V**

**Computational Case Studies**

# Overview

This collection of computational notebooks demonstrates the methods and concepts discussed in the main text through practical applications. Each notebook is designed to be standalone and self-contained, using the Julia programming language for all computations.

# Statistics Without the Agonizing Details

## Learning Objectives

- Compare simulation-based and parametric statistical tests
- Understand the logic of permutation testing
- Apply computational methods to hypothesis testing
- Interpret p-values through simulation

In this class we will use computation and simulation to build fundamental insight into statistical processes without dwelling on “agonizing” details. Here we implement the excellent example problem from John Rauser. First, watch the video:

We will recreate his analysis to answer the fundamental question:

Does drinking beer reduce the likelihood of being bitten by mosquitos?

## Data

First, we will create the data. Here is the data for the beer drinkers:

```
beer = [
    27, 20, 21, 26, 27, 31, 24, 21, 20, 19, 23, 24, 28, 19, 24, 29, 18, 20, 17, 31, 20, 25, 28
]
```

Using Julia, we can learn more about the data through exploratory analysis.

```
typeof(beer)
length(beer)
size(beer)
sum(beer) / length(beer) # the sample average
```

23.6

We can do the same for water drinkers:

```
water = [21, 22, 15, 12, 21, 16, 19, 15, 22, 24, 19, 23, 13, 22, 20, 24, 18, 20]
```

## A simple analysis

Following Rauser, let's calculate the difference between the average number of bites in each group.

```
using StatsBase: mean
observed_diff = mean(beer) - mean(water)
observed_diff
```

## The skeptic's argument

The skeptic asks whether this might be random chance.

1. We could answer this with a  $T$  test:

- Determine if there is a significant difference between the means of two groups
- Assumes (approximate) normality
- Assumptions hidden behind a software package

2. Simulation approach:

- Suppose the skeptic is right – the two groups are sampled from the same distribution
- Shuffle the data (randomly divide into two groups by assuming that there is no difference between the two groups)
- Calculate the difference between each group
- Repeat many times and examine the distribution of differences

## Implementation

We can code up the simulation approach in Julia.

```
using Random: shuffle

function get_shuffled_difference(y1, y2)
    y_all = vcat(y1, y2)
    y_shuffled = shuffle(y_all)
    N1 = length(y1)
    ynew1 = y_shuffled[1:N1]
    ynew2 = y_shuffled[(N1+1):end]
    difference = mean(ynew1) - mean(ynew2)
    return difference
end

get_shuffled_difference(beer, water)
```

We want to learn about the *sampling distribution* of the group differences: repeat this experiment many times over and plot the results.

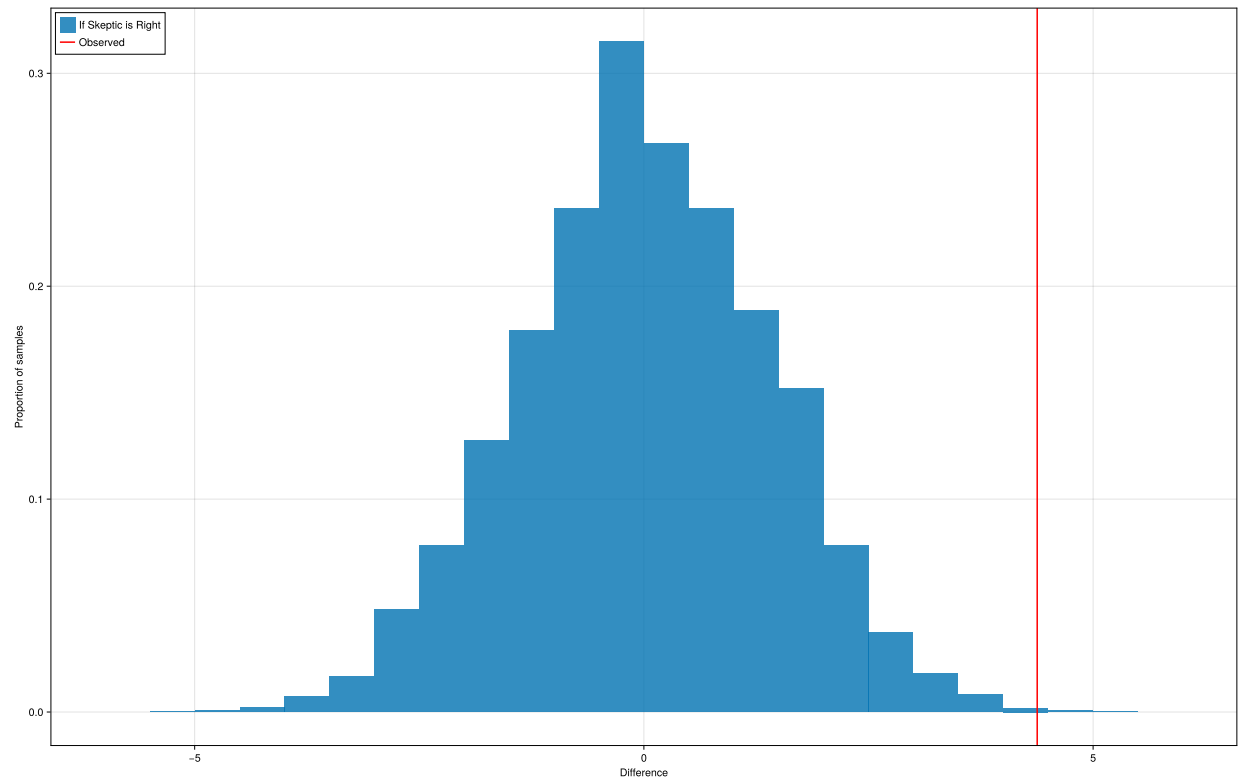
```
simulated_diffs = [get_shuffled_difference(beer, water) for i in 1:50_000]  
length(simulated_diffs)
```

50000

## Plotting

```
using CairoMakie  
  
#| label: fig-plot-diffs  
function plot_diffs(diffs, obs)  
    fig = Figure()  
    ax = Axis(fig[1, 1], xlabel = "Difference", ylabel = "Proportion of samples")  
    hist!(ax, diffs, bins = range(-6, 6, step = 0.5), normalization = :pdf, label = "If Skeptics")  
    vlines!(ax, [obs], label = "Observed", linewidth = 2, color = :red)  
    axislegend(ax, position = :lt)  
    return fig, ax  
end  
  
fig, ax = plot_diffs(simulated_diffs, observed_diff)  
fig
```

Warning: Found `resolution` in the theme when creating a `Scene`. The `resolution` keyword for  
@ Makie ~/.julia/packages/Makie/Q6F2P/src/scenes.jl:238



## Alternative

We could have done this with a parametric test

```
using HypothesisTests

t1 = HypothesisTests.EqualVarianceTTest(beer, water)
t2 = HypothesisTests.UnequalVarianceTTest(beer, water);

mean(simulated_diffs .>= observed_diff)
```

0.00056



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# A Software Setup

If you want to run the computational notebooks in this book, or apply a similar workflow, then these instructions are for you.

## A.1 Quick start

This section provides step-by-step instructions to get your development environment set up and running.

### A.1.1 Installation steps

1. Install **Visual Studio Code** - your code editor
  - There are other good IDEs out there, and you can absolutely use one.
  - VS Code is a good and well-supported starting point
2. Install **Quarto** - for creating documents with code
  - For step 1, choose your operating system
  - For step 2, choose VS Code as your tool
3. Install **Julia** using **JuliaUp** - the programming language
  - Follow the directions on the GitHub page based on your operating system
  - Don't worry about the Continuous Integration (CI) section or anything below it
  - Install Julia 1.11 using `juliaup add 1.11`
  - Set this to be your default version using `juliaup default 1.11`
  - You should get a message that says something like `Configured the default Julia version to be '1.11'`
4. In **VS Code**: Install extensions from the Extensions marketplace
  - Install the **Julia** extension (provides syntax highlighting, code completion, and integrated REPL)
  - Install the **Quarto** extension (provides syntax highlighting and preview capabilities for `.qmd` files)
5. Install **GitHub Desktop** - for version control
  - This is optional if you prefer to use git through the command line or another app, but GitHub Desktop is a good default recommendation

### A.1.2 Verification

After installation, you should be able to:

- Open VS Code and see the Julia and Quarto extensions listed
- Open a terminal and type `julia` to start the Julia REPL
- Create a new Quarto document (`.qmd` file) in VS Code with syntax highlighting

## A.2 Dig deeper

### A.2.1 Julia

[Julia](#) is a fast, modern programming language designed for scientific computing. Its syntax closely mirrors mathematical notation, making it intuitive for researchers while delivering performance comparable to C and Fortran.

JuliaUp is the official Julia version manager. It simplifies installation, allows you to maintain multiple Julia versions simultaneously, and keeps your installation current with the latest releases. This is especially useful as the Julia ecosystem evolves rapidly.

See the [Julia page](#) for more.

### A.2.2 Quarto

Quarto is a scientific publishing system that enables you to combine code, results, and narrative text in reproducible documents. Think of it as the next generation of R Markdown, but with multi-language support (Julia, Python, R, and more).

This textbook is written in Quarto. Unlike traditional notebooks, Quarto documents are plain text files that render to multiple output formats (HTML, PDF, Word, presentations) while maintaining computational reproducibility.

You can learn more at:

- Official [Tutorial: Hello, Quarto](#) - basic document creation
- Official [Tutorial: Computations](#) - integrating code
- Comprehensive [Quarto documentation](#)

#### A.2.2.1 Writing with Markdown and math

Quarto uses Markdown syntax with LaTeX math notation. Essential references:

- [Markdown Cheatsheet](#) - basic text formatting
- [LaTeX Cheatsheet](#) - mathematical notation
- [Mathpix Snip](#) - convert equation images to LaTeX code (free tier available)
- [Detexify](#) - draw symbols to find LaTeX commands

### A.2.3 Visual Studio Code

Visual Studio Code is a free, open-source code editor developed by Microsoft. Its strength lies in its extensibility—thousands of extensions add language support, debugging capabilities, and productivity tools.

For our workflow, the Julia extension transforms VS Code into a full Julia development environment with syntax highlighting, intelligent code completion, integrated debugging, and a built-in REPL. The Quarto extension provides similar capabilities for computational documents, including live preview and cell execution.

You can learn more at [the official tutorial](#).

### A.2.4 Git and GitHub

Git is a distributed version control system that tracks changes in your code over time. GitHub is a cloud-based platform that hosts Git repositories and adds collaboration features like issue tracking, pull requests, and project management.

Version control is essential for reproducible research—it allows you to track changes, collaborate with others, recover from mistakes, and share your work publicly. This textbook itself is maintained on GitHub.

You can learn more at:

- [Git and GitHub for Poets](#) - beginner-friendly video series
- [GitHub Hello World](#) – official docs
- [Version Control](#) - comprehensive guide from MIT’s “Missing Semester”

## B Julia Learning Resources

The computational examples in this textbook use the Julia programming language.

### B.1 Why Julia?

Julia is a fast, modern, open-source programming language designed for scientific and numerical computing. The language is designed to be fast, dynamic, and easy to use and maintain.

Key advantages for this textbook include:

- **High-Level Syntax:** Julia has a clean and expressive syntax that closely parallels mathematical notation.
- **Performance:** Julia compiles to efficient machine code, achieving speeds comparable to low-level languages like C and Fortran. This solves the “two-language problem,” where you might prototype in a high-level language but need to rewrite for performance.
- **Simplified Dependencies:** Eliminates or reduces the need for dependencies on C and Fortran libraries, which simplifies installation and maintenance.
- **Open-Source and Shareable:** Julia is completely open-source with excellent package management for reproducible research environments.
- **Strong Ecosystem:** Despite being newer, Julia has a rapidly growing ecosystem of high-quality libraries for scientific domains.

While Julia is powerful for computational thinking and research, many ecosystems remain stronger in other languages (like Python’s deep learning and climate data analysis tools), so a well-rounded programmer benefits from learning multiple languages.

You can read more about Julia’s design philosophy:

- [Julia Data Science](#) textbook is didactic and clear
- [Why We Created Julia](#) from the founders
- [Why Julia Manifesto](#) is more comprehensive

### B.2 Learning resources

This textbook aims to never reinvent the wheel. There are lots of exceptional resources for learning Julia, or for learning computational concepts with Julia. Here are some favorites:

- MIT’s [Introduction to Computational Thinking](#): Julia-based course covering applied mathematics and computational thinking
- [Julia for Nervous Beginners](#): free course for people hesitant but curious about learning Julia

- [Julia Data Science](#): comprehensive introduction to data science with Julia
- [FastTrack to Julia cheatsheet](#)
- [Comprehensive Julia Tutorials](#): YouTube playlist covering Julia topics
- [Matlab-Python-Julia Cheatsheet](#): helpful if you're experienced in one of these languages

### **B.2.1 Specialized topics**

Here are some additional resources for specific Julia tools and packages developed in this class

- Plotting: [Makie Tutorials](#) and [MakieCon 2023 YouTube Channel](#)
- Statistical Modeling: [Turing.jl tutorials](#) has detailed examples of using Turing for modeling

## C Large Language Models (“AI”)

Coding is an integral part of real-world climate-risk analysis, and large language models (LLMs; often referred to as “AI” models) are rapidly changing how some kinds of coding happen. Beyond web-based chatbots, you may have used tools like [GitHub Copilot](#) (free for students and educators) or Claude Code (see free [Deeplearning.AI Course](#)). LLMs use powerful new technologies that can support learning and replace tedious tasks, but they can also threaten your intellectual growth and skill development (Kosmyna et al. 2025; Bastani et al. 2025).

It is clear that there are some tasks that should be delegated to these models and some tasks that must remain human-driven. However, there are tremendous differences of opinion about how most tasks in the middle can or should be allocated. As you wrestle with these questions for yourself, you should explore resources like:

- [AI Snake Oil](#) is a blog that seeks to dispel hype, remove misconceptions, and clarify the limits of AI. The authors are in the Princeton University Department of Computer Science.
- [AI software assistants make the hardest kinds of bugs to spot](#) from Pluralistic is a thoughtful and deep blog post about the perils of (mis)using LLMs for coding.
- [One Useful Thing](#) is a newsletter about AI focused on implications for work and education. The authors’ [prompt library](#) is also a good resource for working with LLMs.
- [Ed Zitron’s Where’s Your Ed At](#) is a newsletter that takes a critical perspective on the business models and hype narratives around AI.