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CLIMATE & WEATHER SYSTEMS

Group - 15

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Probabilistic Monsoon Rainfall Prediction for Agricultural Planning

Real-world context of the problem:

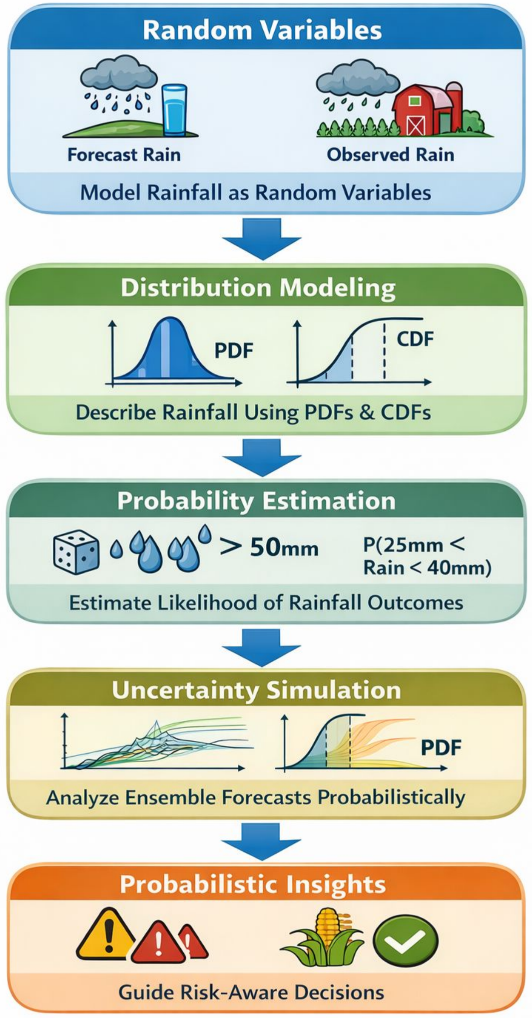
- Agricultural decisions depend strongly on monsoon rainfall
- Irrigation planning depends on expected rainfall amounts
- Flood or drought risk analysis needs reliable rainfall prediction.

Why is uncertainty intrinsic to this problem:

- Rainfall is a stochastic and variable natural process
- Same forecast conditions can result in different rainfall outcomes

Project Objective and Scope

- To model rainfall forecasts probabilistically rather than deterministically
- To develop a probabilistic model for rainfall forecasting
- To represent rainfall uncertainty using random variables
- To build intuition about uncertainty using PDF and CDF analysis
- Analysis of rainfall uncertainty using PDF and CDF plots



Project System Overview

End-to-End System Pipeline

Deterministic rainfall forecast → Observed rainfall data → Joint probabilistic modeling → Conditional inference of rainfall uncertainty → PDF/CDF computation

Major System Components:

- Bayesian Joint Probability (BJP) modeling framework
- Conditional probability estimation P(Observed | Forecast)
- Distribution parameter estimation
- PDF/CDF computation for uncertainty quantification

Sources of Uncertainty in the Project

Measurement Noise:

- Rain gauge measurement errors
- Spatial sampling limitations
- Instrument precision and recording errors

Environmental / Contextual Variability:

- Natural variability in monsoon dynamics
- Spatial heterogeneity of rainfall
- Temporal fluctuations in rainfall intensity

Modeling / Data Uncertainty:

- Structural limitations of NWP models
- Limited historical data for distribution estimation
- Parameter estimation uncertainty in Bayesian modeling

Key Random Variables and Their Roles

Forecast Rainfall (X):

- Rainfall forecast from the NWP model
- Modeled as a continuous random variable $X:\Omega \to R$
- Represents uncertainty in model-based rainfall prediction

Forecast Rainfall (Y):

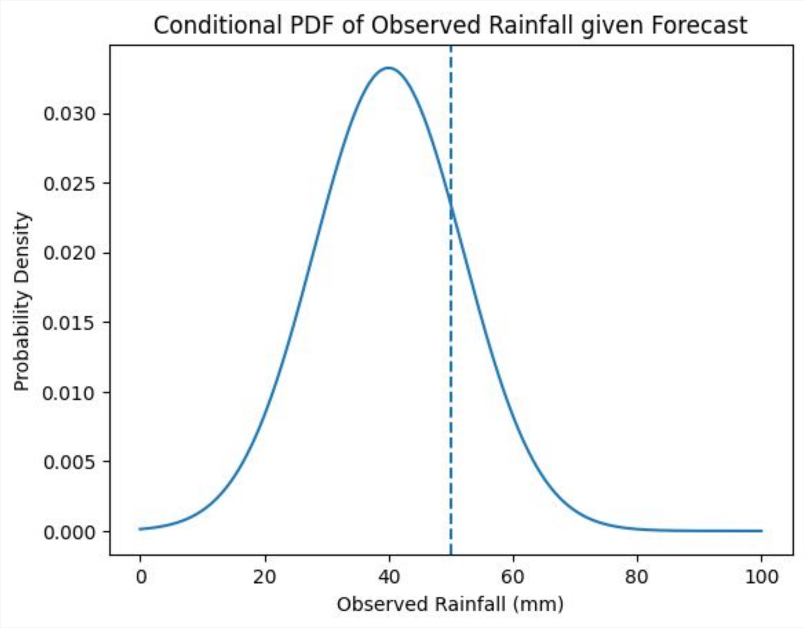
- Modeled as a continuous random variable $Y:\Omega \to R$
- Represents the actual rainfall that occurs
- Transformation helps reduce skewness and enable probabilistic modeling

Threshold Exceedance Event (Z):

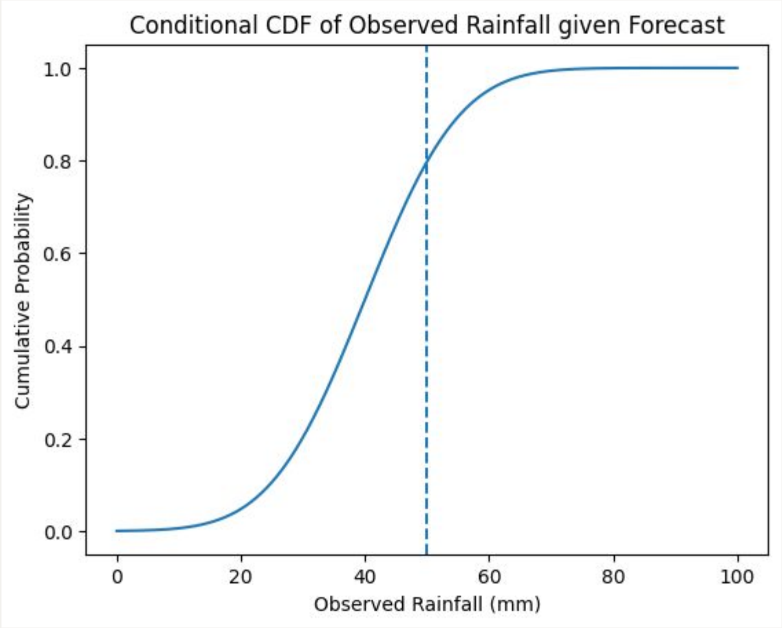
- Binary random variable defined as $Z=1(Y>t)$
- Represents whether rainfall exceeds a critical threshold
- Used to quantify risk and support decision-making

Probabilistic Models and Assumptions

- Forecast rainfall X is modeled as a **continuous random variable**
- Assume X~N(μ=40 mm,σ=20 mm)



PDF: Shows relative likelihood of different rainfall amounts



CDF: Gives probability that rainfall is less than or equal to a value

Assumptions

- Forecast rainfall uncertainty is modeled using a normal (Gaussian) distribution
- Rainfall outcomes are treated as continuous random variables

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Probabilistic Reasoning and Inference Logic

Step 1: Joint Modeling

$$(X, Y) \sim N_2(\mu, \Sigma)$$

Forecast (X) and Observed Rainfall (Y) are jointly modeled.

Step 2: Conditional Inference

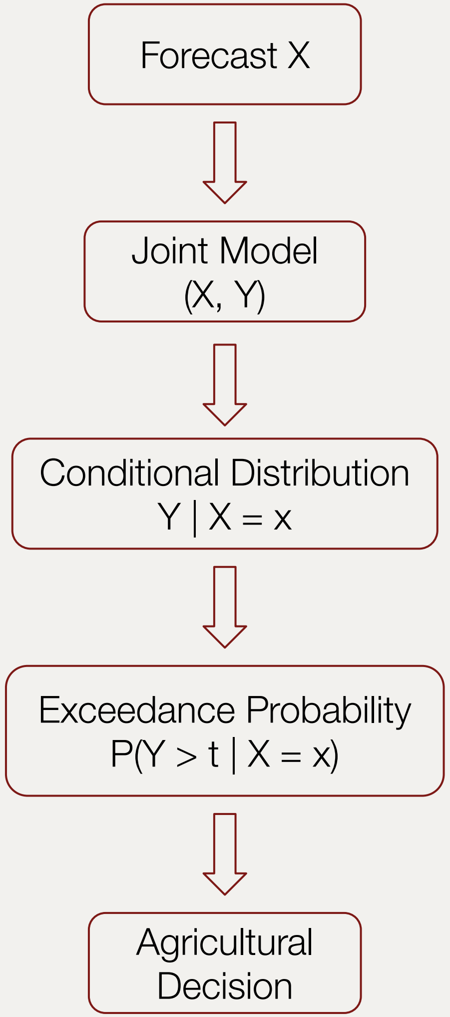
$$Y|X = x \sim N(\mu_{Y|x}, \sigma^2_{Y|x})$$

Forecast information shifts the mean and reduces variance.

Step 3: Exceedance Risk

$$P(Y > t|X = x)$$

Transforms prediction into decision-relevant probability.



Operationalizing Probabilistic Reasoning

Reasoning is Implemented :

- Estimate parameters:

  $\theta = (\mu X, \mu Y, \sigma X^2, \sigma Y^2, \rho)$

- Compute analytical conditional distribution
- Evaluate exceedance probability
- Validate using historical rainfall data

Simplifying Assumptions :

- Gaussian after transformation
- Linear dependence via correlation ρ
- Stationary parameters
- Monte Carlo sufficiently converged

These enable tractable conditional inference.

Evaluation Metrics & Their Meaning

Metric	Probabilistic Interpretation
Bias %	Systematic shift in distribution
CRPS	Full distribution accuracy
RMSE	Mean squared predictive error
ROC / AUC	Event discrimination ability
Spread–Skill	Calibration of uncertainty

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Current Limitations and Conceptual Gaps

1. Tail Behavior

- Extreme rainfall may be heavier-tailed than Gaussian
- Risk underestimation possible

2. Stationarity Assumption

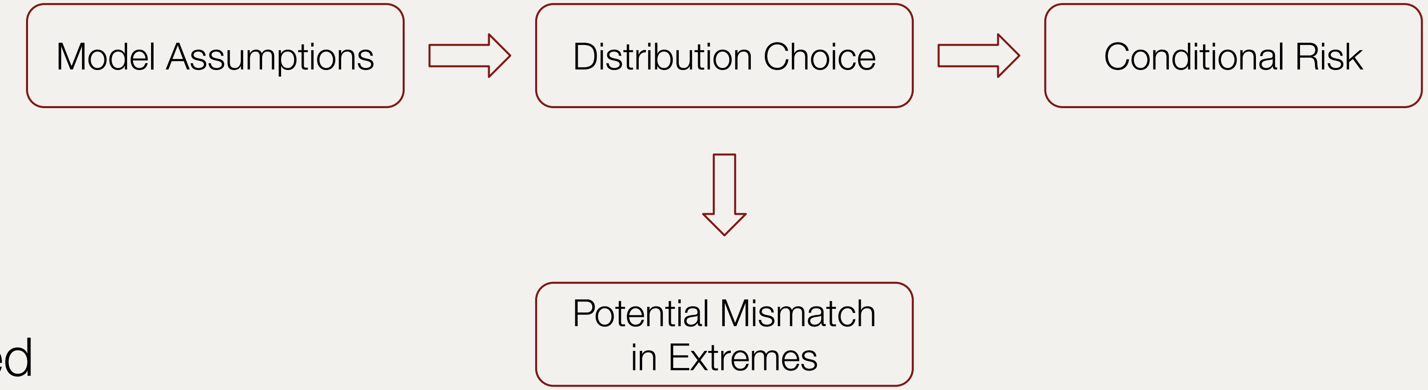
- Parameters assumed constant
- Monsoon dynamics may evolve

3. Dependence Structure

- Only linear correlation modeled
- Nonlinear rainfall dependence not captured

4. Parameter Uncertainty

- Bayesian framework introduced
- Full predictive uncertainty still under refinement



Planned Refinements and Role Coordination

- **Next steps**

1. Refine probabilistic model assumptions
2. Improve extreme rainfall modeling
3. Enhance conditional inference framework
4. Integrate agricultural decision context

- **Roles**

1. Model Team : Improve joint distribution & dependence structure
2. Data Team : Validate historical data & preprocessing
3. Inference Team : Work on conditional probability & exceedance
4. GitHub Manager / Reviewer : Version control, integration, coordination

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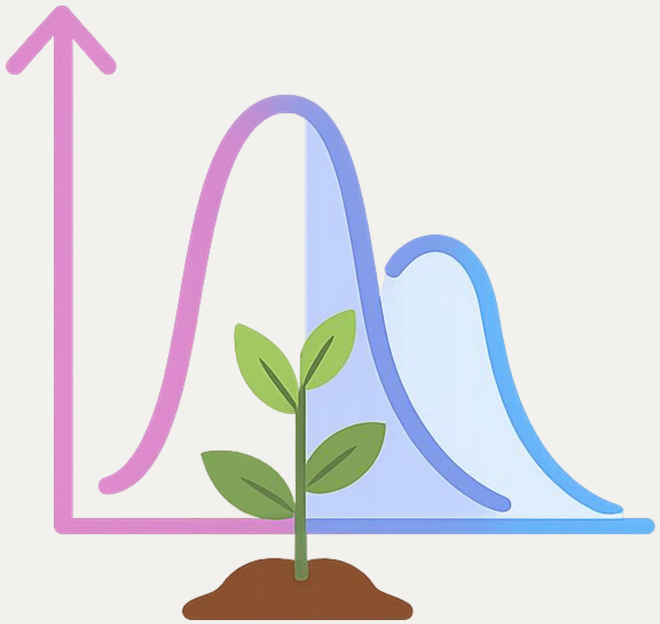
Summary of Group-Level Understanding

Our framework formalizes rainfall uncertainty into a structured probabilistic decision system.

- Joint modeling captures dependence between forecast and observation
- Conditional inference translates forecast signals into predictive distributions
- Exceedance probability enables actionable agricultural risk assessment



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Thank You