# Advancing Real-Time Flood Monitoring Using Artificial Intelligence to Improve Hydroclimatic Decision Support in Complex Terrain Regions

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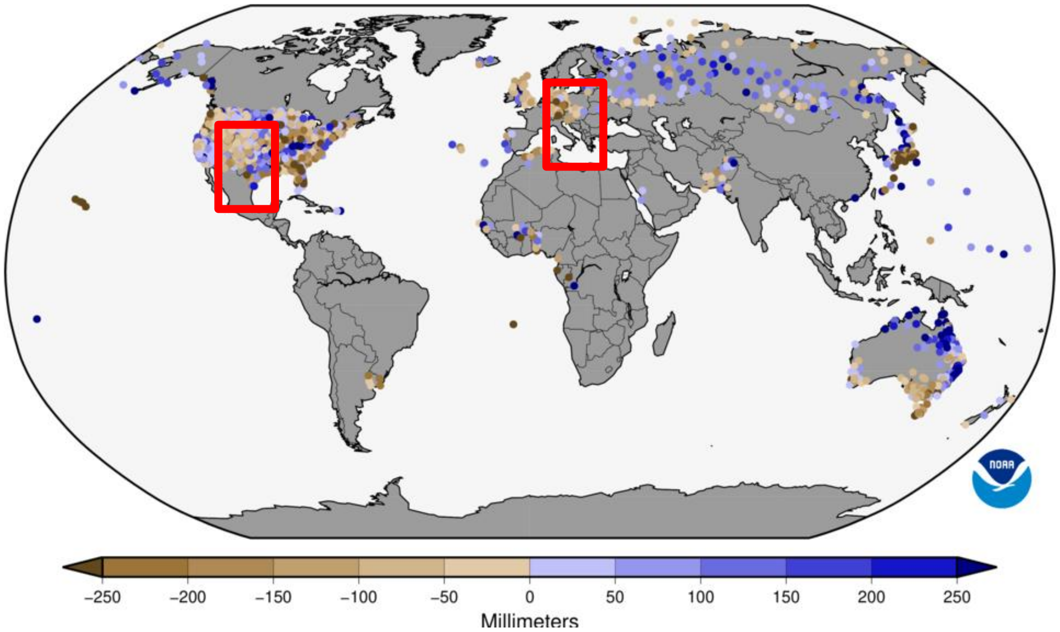
# Motivation

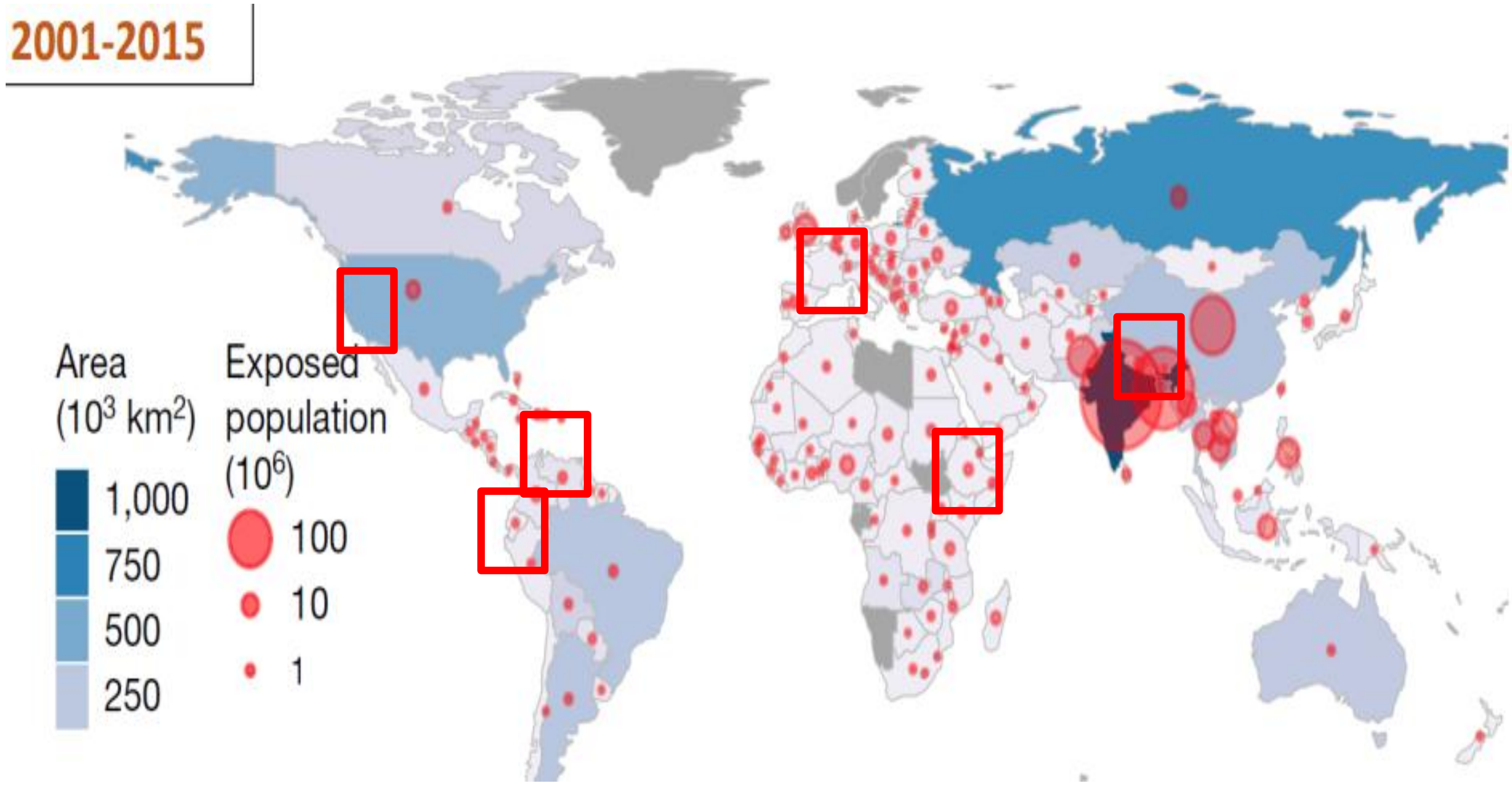
- Estimating extreme hydrological events, such as floods at ungauged locations, specifically in complex terrain regions, remains a significant hydrological challenge.
- The conventional flood flow estimation schemes suffer from considerable drawbacks, such as random and systematic error, which limit their accuracy in water resources applications
- Transferability of the model.

January-December 2025 Precipitation Anomalies




Above-average precipitation was observed across western contiguous U.S., India, southern South America, and part of Africa

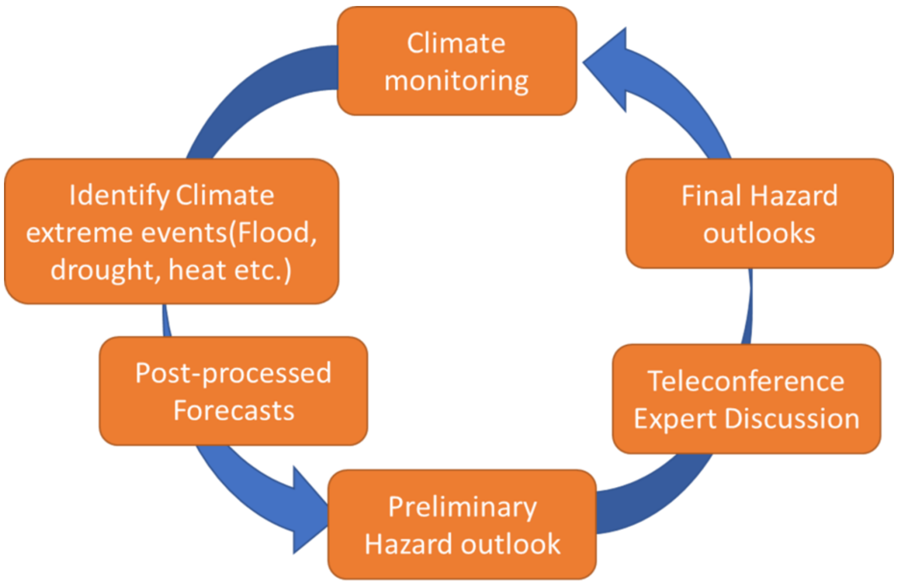
# Global Flood Exposure Map




[Tellman et. al, 2021, Nature]

Large-scale flash floods bring fast-moving and rapid-rising water with force, resulting in tremendous life and property losses as well as social disruption worldwide.

# Flood Monitoring Framework

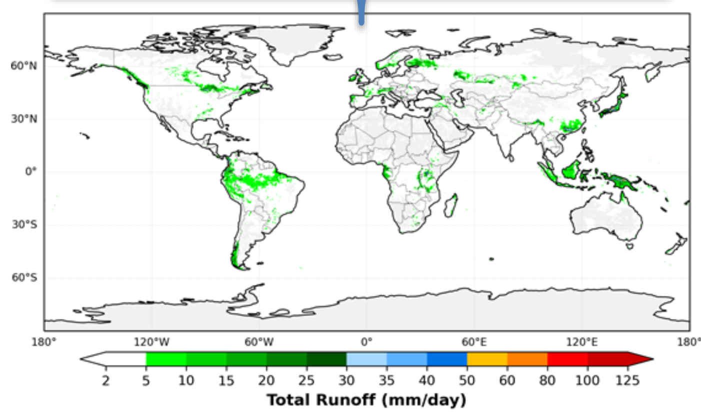



**Bias Correction of GEFS precipitation with high-resolution observations.**

**Applying Artificial Intelligence (AI)algorithm**

**Real-Time Flood Prediction utilized by Bias Correction of GEFS and Historical runoff**

**Investigating Flood model globally**




One vital question :

How "transferable" is this type of framework i.e. can we use the framework over a region without ground reference?

# Physical Models vs. Statistical Models For hydrologic modeling

## Physical Models:

Equations derived from Conservation of Mass, Momentum, Energy, etc.

Pros: "The way the universe works"

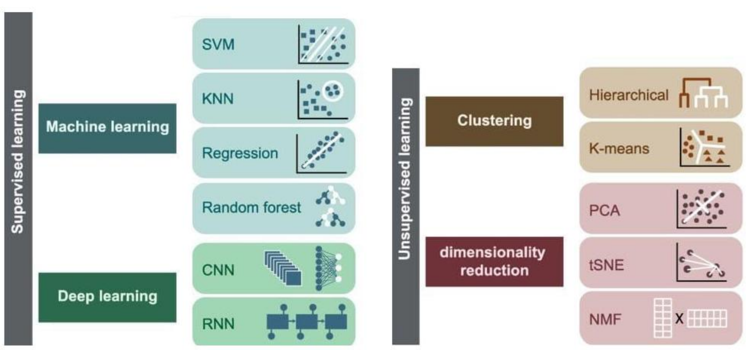
Cons: Difficult to use, requires ample time and resources

## Statistical Models:

Data driven models that embody a set of statistical assumptions

Pros: Simple, convenient, accurate

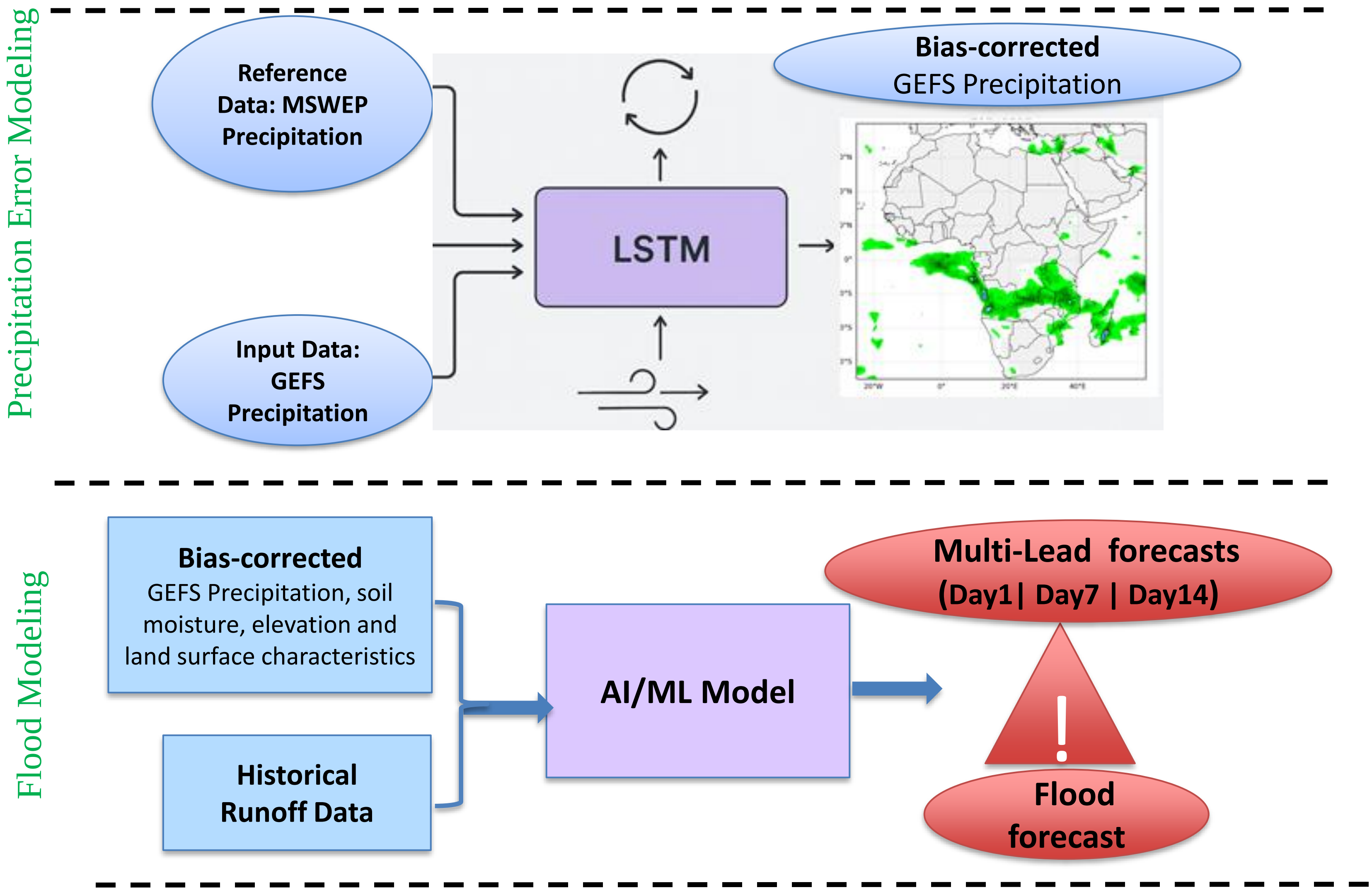
Cons: Makes assumptions, relies purely on historical data




- Deep Neural Network (DNN)
- Recurrent Neural Networks (RNN)

*If we use statistical models, how do we properly account for climate change?*

# AI-Based Flood Prediction Workflow




***Our trained ML models can be effectively transferred to other hydroclimatologically similar regions.***

# Research Framework

Dataset:

- AI technique utilized historical runoff datasets (1991-current)from the European Centre for Medium-range Weather Forecasting (ECMWF) along with dynamic variables (e.g., precipitation) to generate flood flow predictions.

- Date period: 1991-current

Methodology:

- LSTM Model setup
- Model optimization
- Model evaluation:
  - validation period: 2025
  - Systematic/random error

# Performance Evaluation – Error Metrics

Quantitative error statistics:

- Random Error: Normalized Centered Root Mean Square error (CRMSE)
- Systematic Error: Mean Absolute Relative Error (MARE)

$$\mathrm{NCRMSE} = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[\hat{y}_i - y_i - \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)\right]^2}}{\frac{1}{n}\sum_{i=1}^{n} y_i}$$

$$\mathrm{MARE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right|$$

- Kling–Gupta efficiency (KGE) skill scores

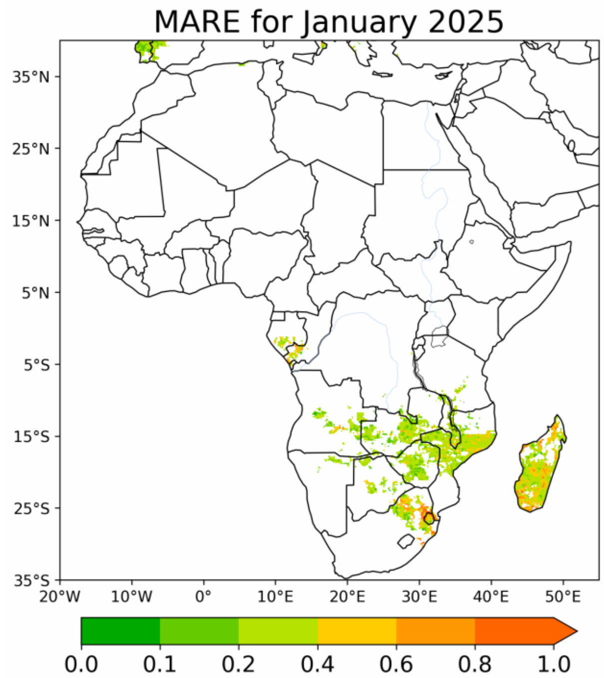
$$\mathrm{KGE} = 1 - \mathrm{ED},$$

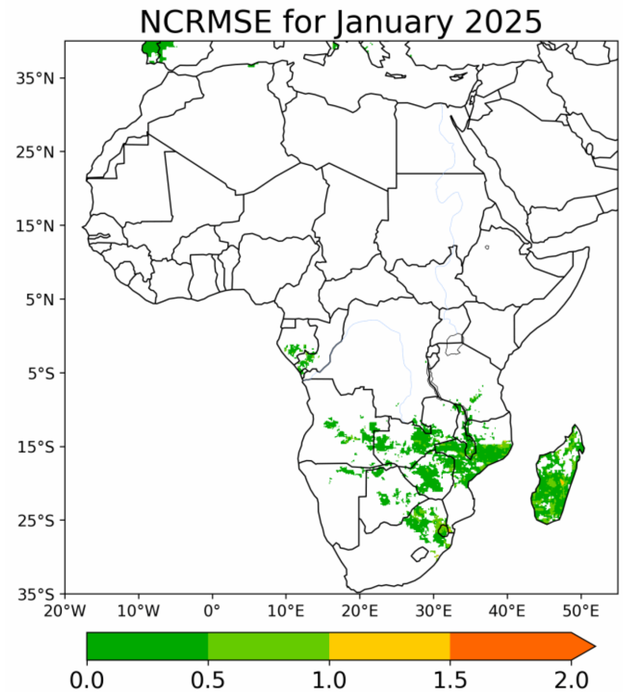
$$\mathrm{ED} = \sqrt{(r-1)^2 + (\alpha-1)^2 + (\beta-1)^2}.$$

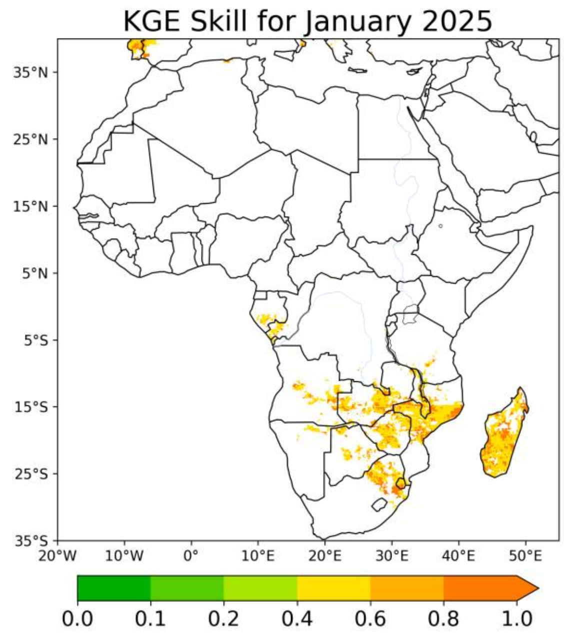
*$\alpha$ and $\beta$ indicate the variability error and the bias error*

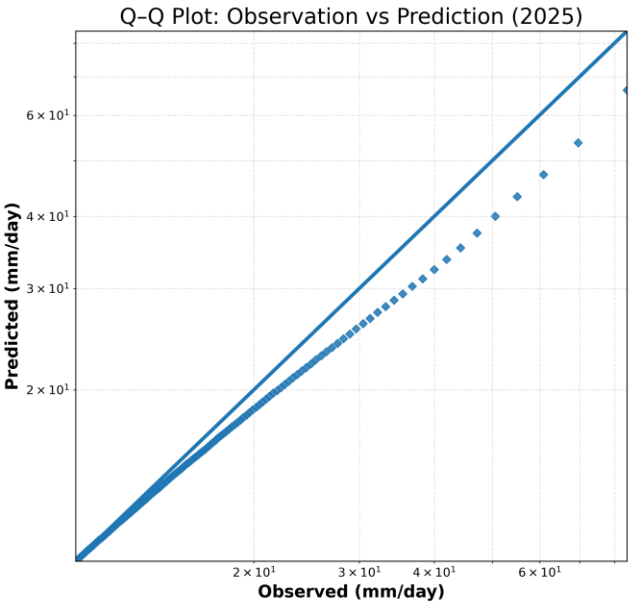
*KGE represents the difference between unity and the Euclidian distance (ED) from the ideal point in the three-dimensional criteria space*

# Model Evaluation



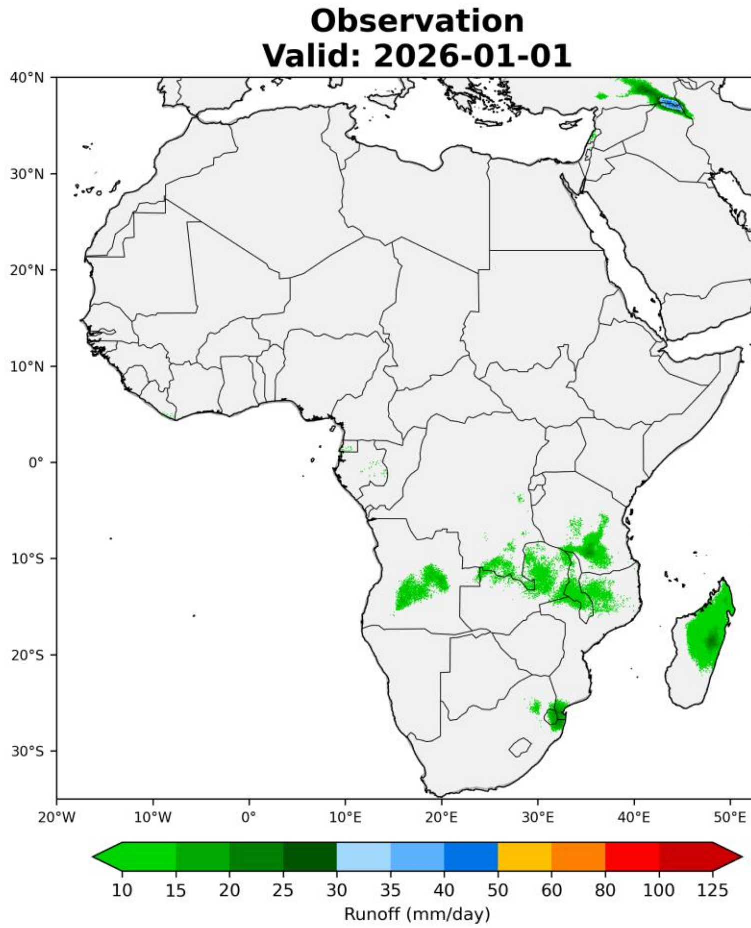



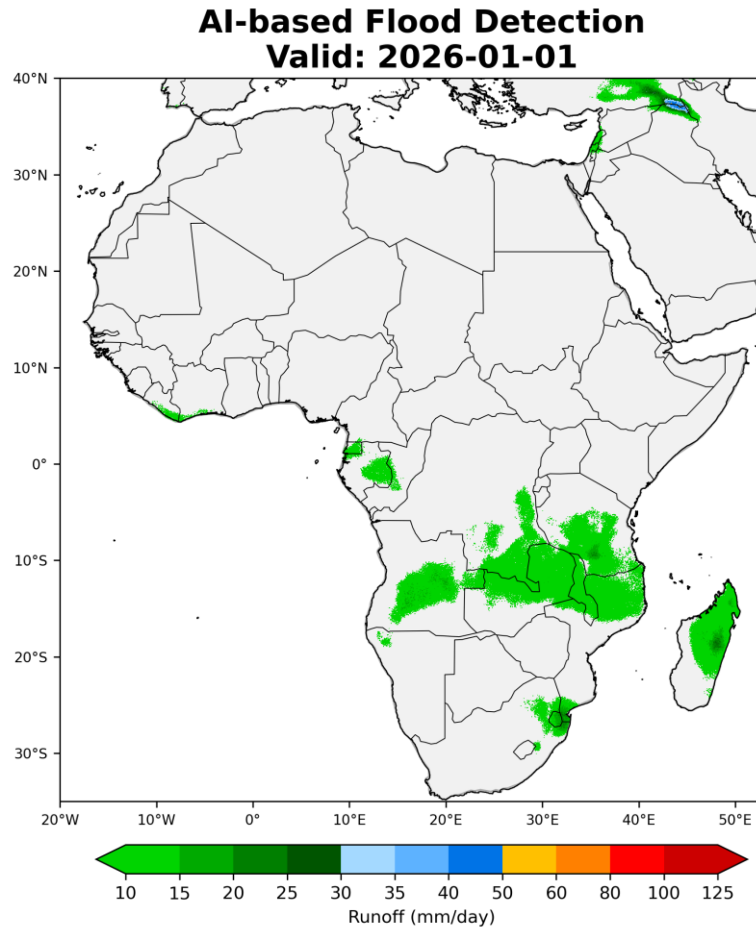



Flood Monitoring
2026-01-01 to 2026-01-14

# Week 1 Flood Prediction: Jan 01–Jan 07, 2026

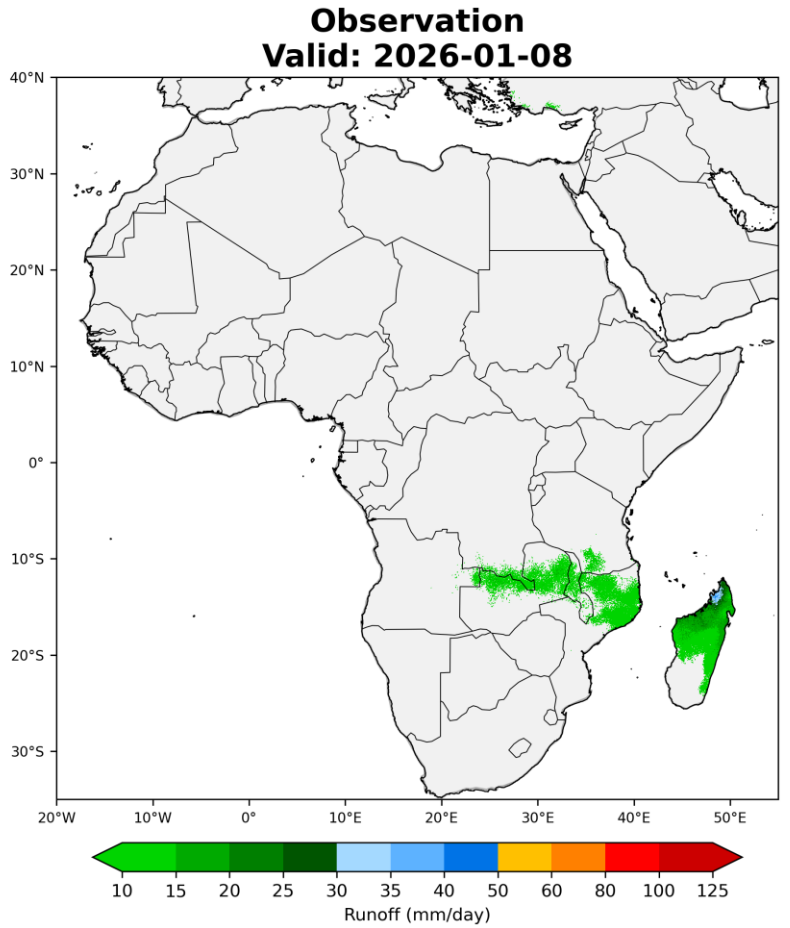


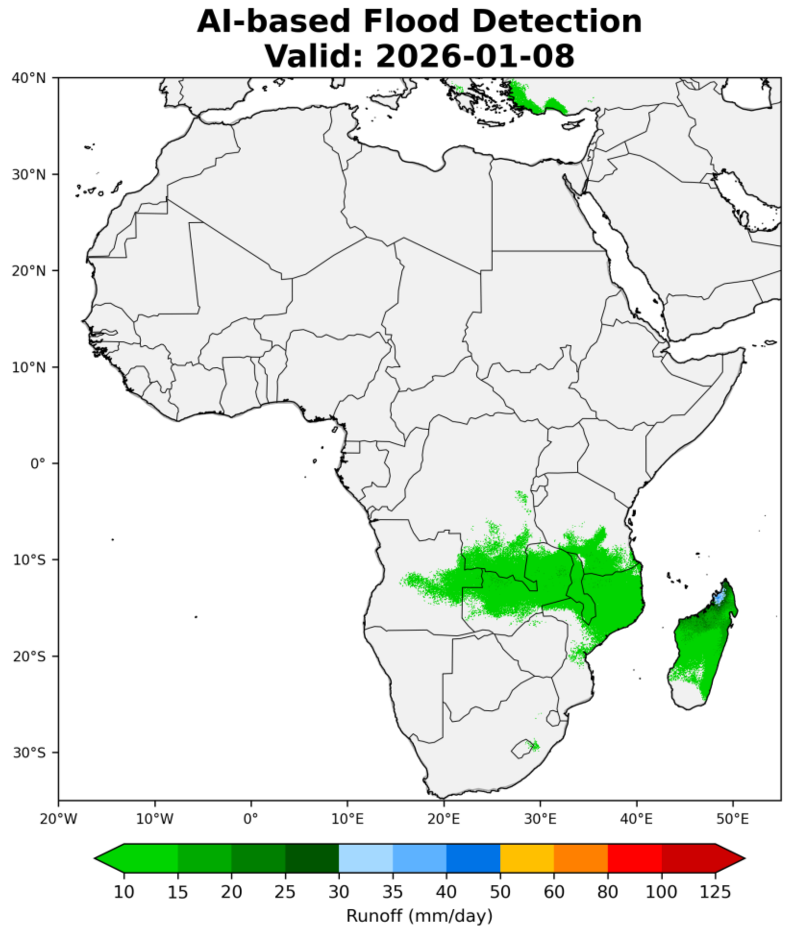




**Bias = 0.47 mm/day, RMSE = 2.49 mm/day, $R^2$ = 0.66**

**Model Evaluation**

# Week 2 Flood Prediction: Jan 08–Jan 14, 2026



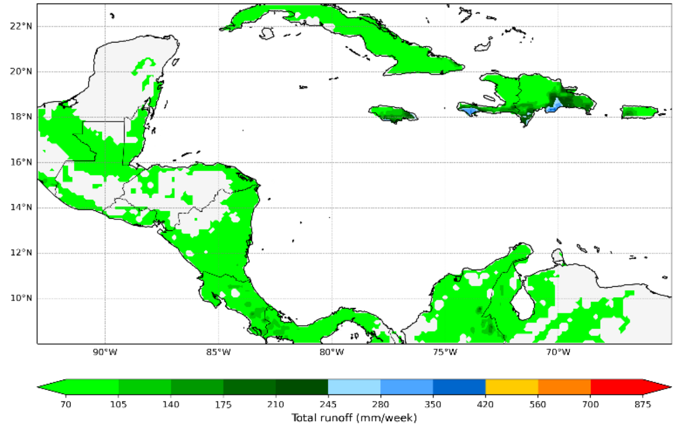

**Bias = 0.74 mm/day, RMSE = 3.67 mm/day, $R^2$ = 0.51**

## Model Evaluation

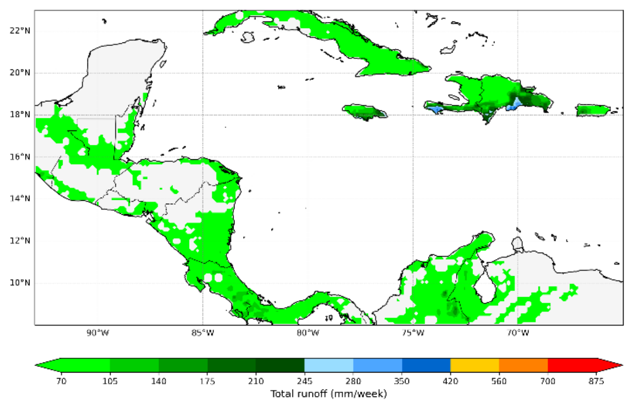
# Model evaluation and skill (14-day lead)

# Hurricane Mellissa (Oct 21–Nov 3, 2025)

**Observation**
**Valid: 2025-10-21 to 2025-10-27**

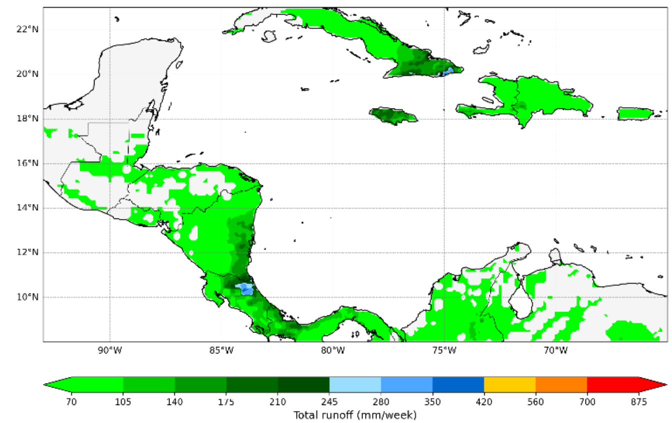



**AI-based Flood Detection**
**Valid: 2025-10-21 to 2025-10-27**

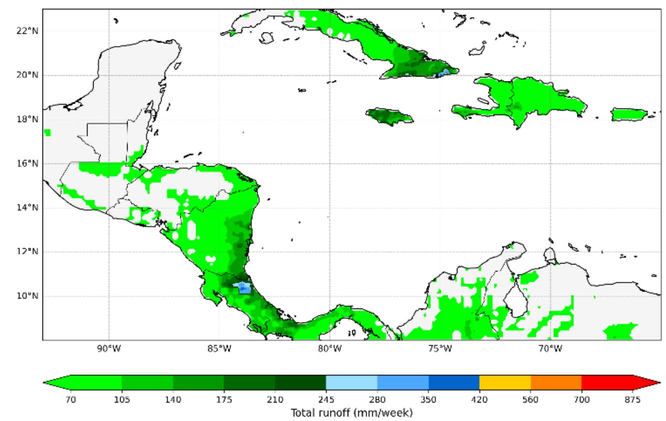



Week 1: $R^2$ = 0.72, HSS = 0.79

**Observation**
**Valid: 2025-10-28 to 2025-11-03**



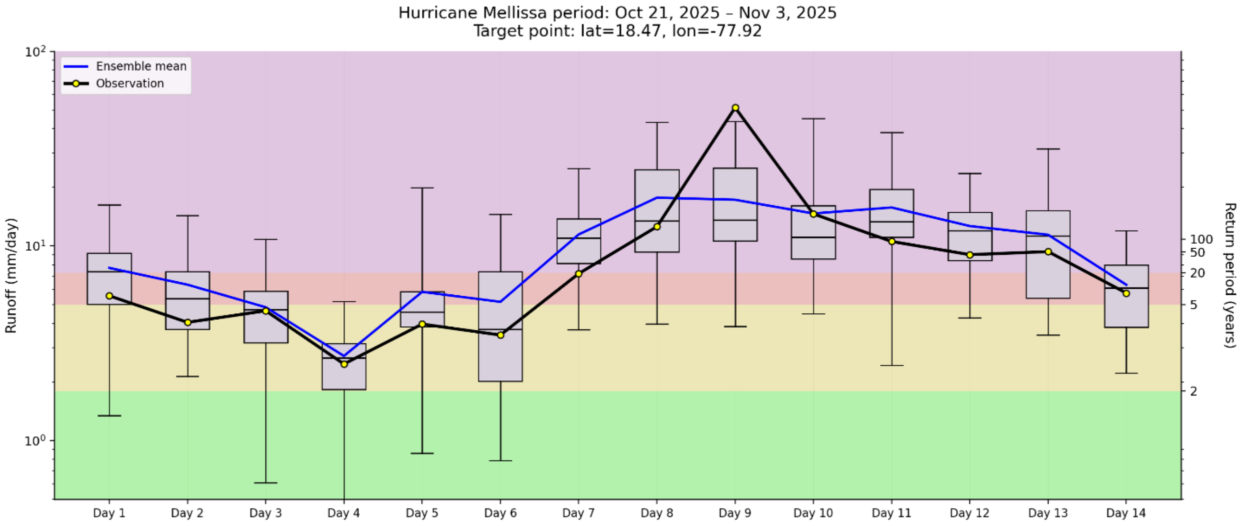

**AI-based Flood Detection**
**Valid: 2025-10-28 to 2025-11-03**



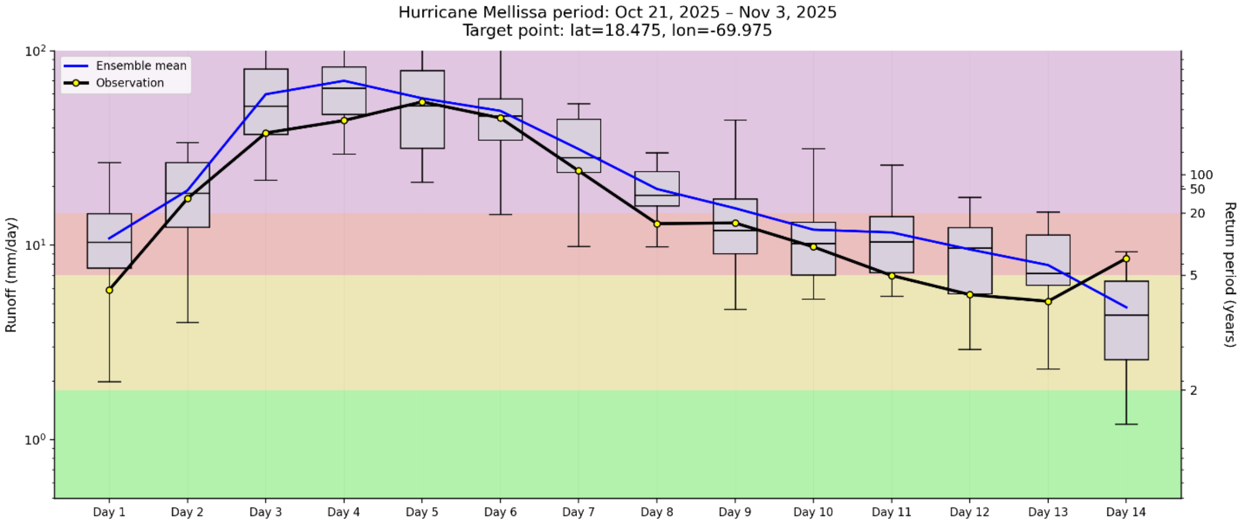

Week 2: $R^2$ = 0.69, HSS = 0.71

These results indicate good agreement with observed flood runoff at extended lead times.

# Flood Severity




**Stats: $R^2$ = 0.61, Bias = -0.671, MAE = 9.065, RMSE = 19.026**

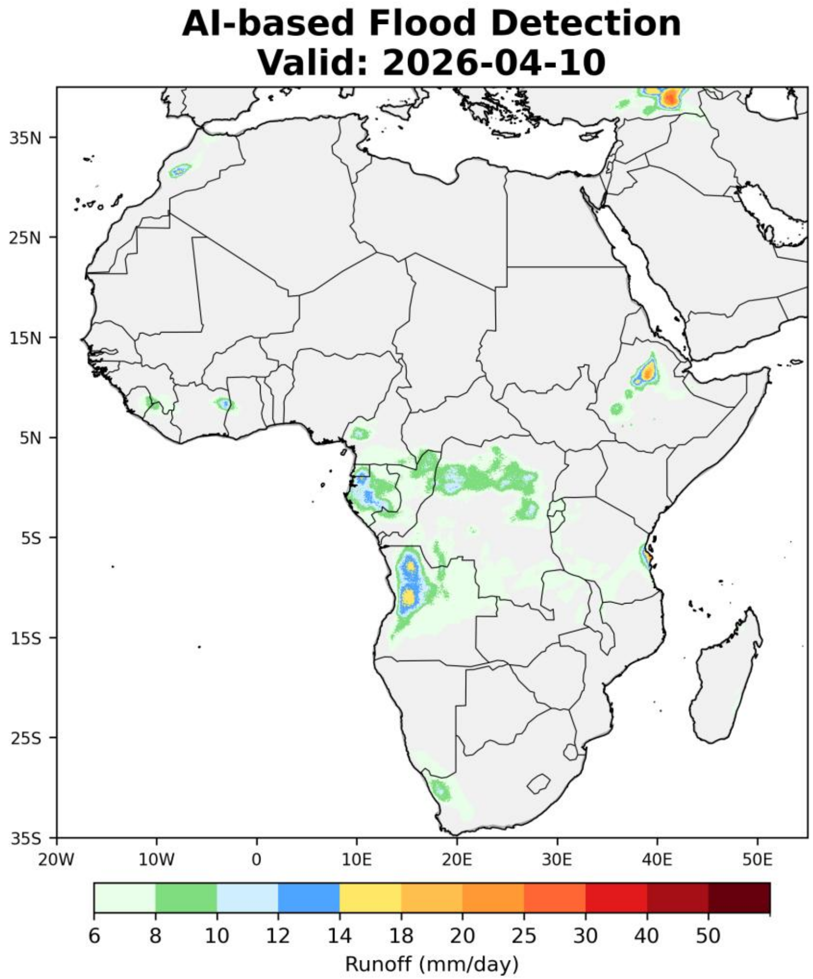


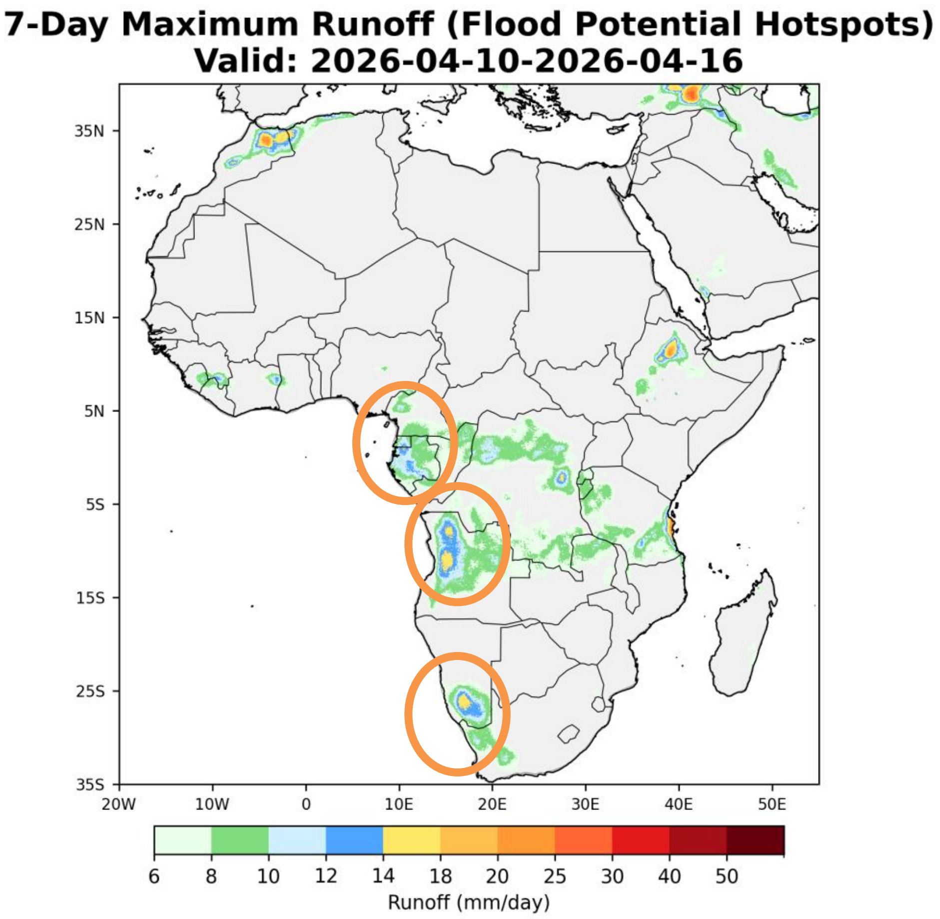

**Stats: $R^2$ = 0.69, Bias = 12.448, MAE = 13.9881, RMSE = 19.991**

- model captures the overall trend of runoff reasonably well ($R^2$: 0.6–0.7), meaning timing and pattern are fairly good.
- In the top case, the bias is slightly negative (−0.67), so the model slightly underestimates runoff, but overall error is moderate (MAE~ 9 mm).

Real-Time Prediction
2026-04-10 to 2026-04-24

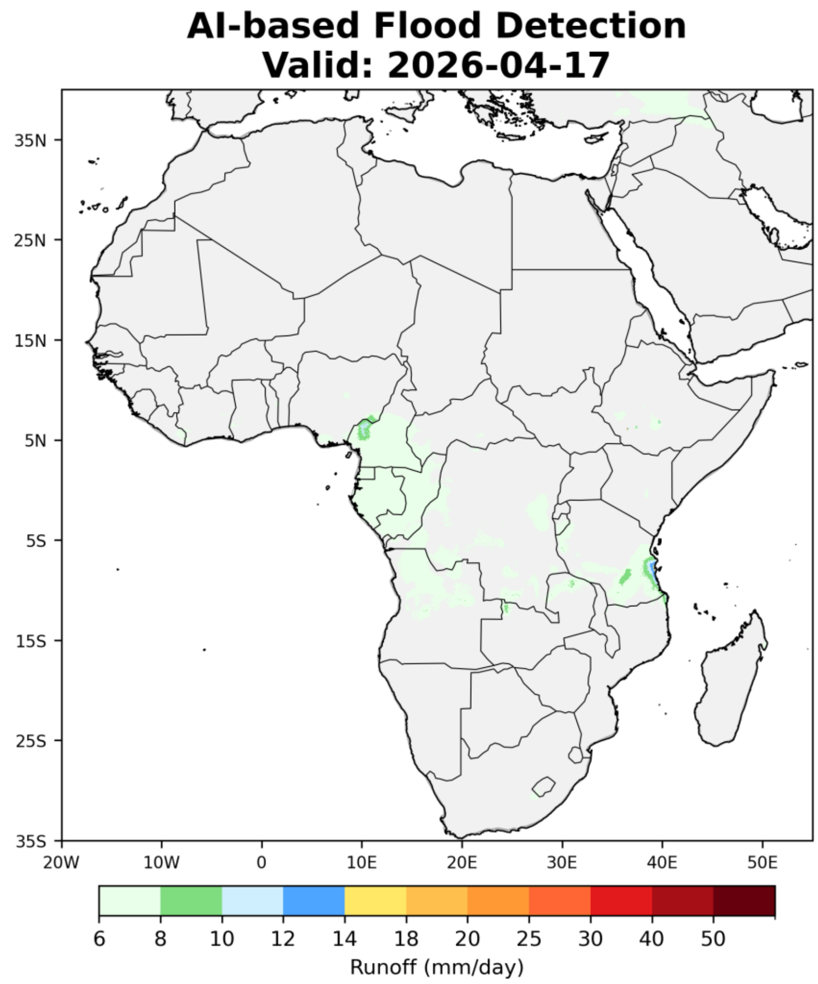
# Week 1 Flood Prediction: Apr 10–16, 2026

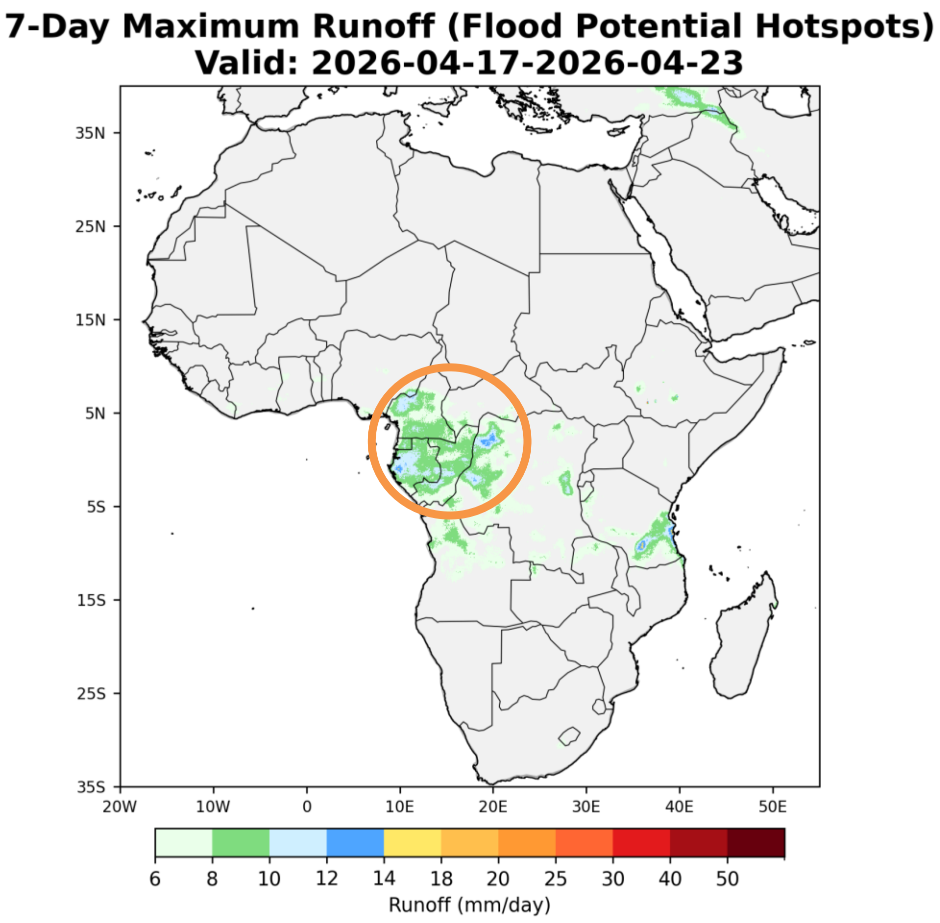



Week-1 Heat Hazards Outlook

# Week 2 Flood Prediction: Apr 17–Apr 23, 2026




Week-2 Heat Hazards Outlook

# Summery & Future Work

- The model evaluation results indicated that the AI/ML technique was able to reduce significantly the random and systematic error with high correlation coefficients.

- Realtime -14-days  forecast results indicated the deep learning-model to be capable of forecasting the flood well in advance with excellent skills.

- Flood severity spatial map will be assessed using return periods of daily runoff, indicating the likelihood of extreme flood events.