

Cloud-Based and AI-Enhanced Earth Observation for Mapping and Forecasting Hydrological Extremes and Irrigation Demand across Selected Catchments in Malawi

Progress presentation



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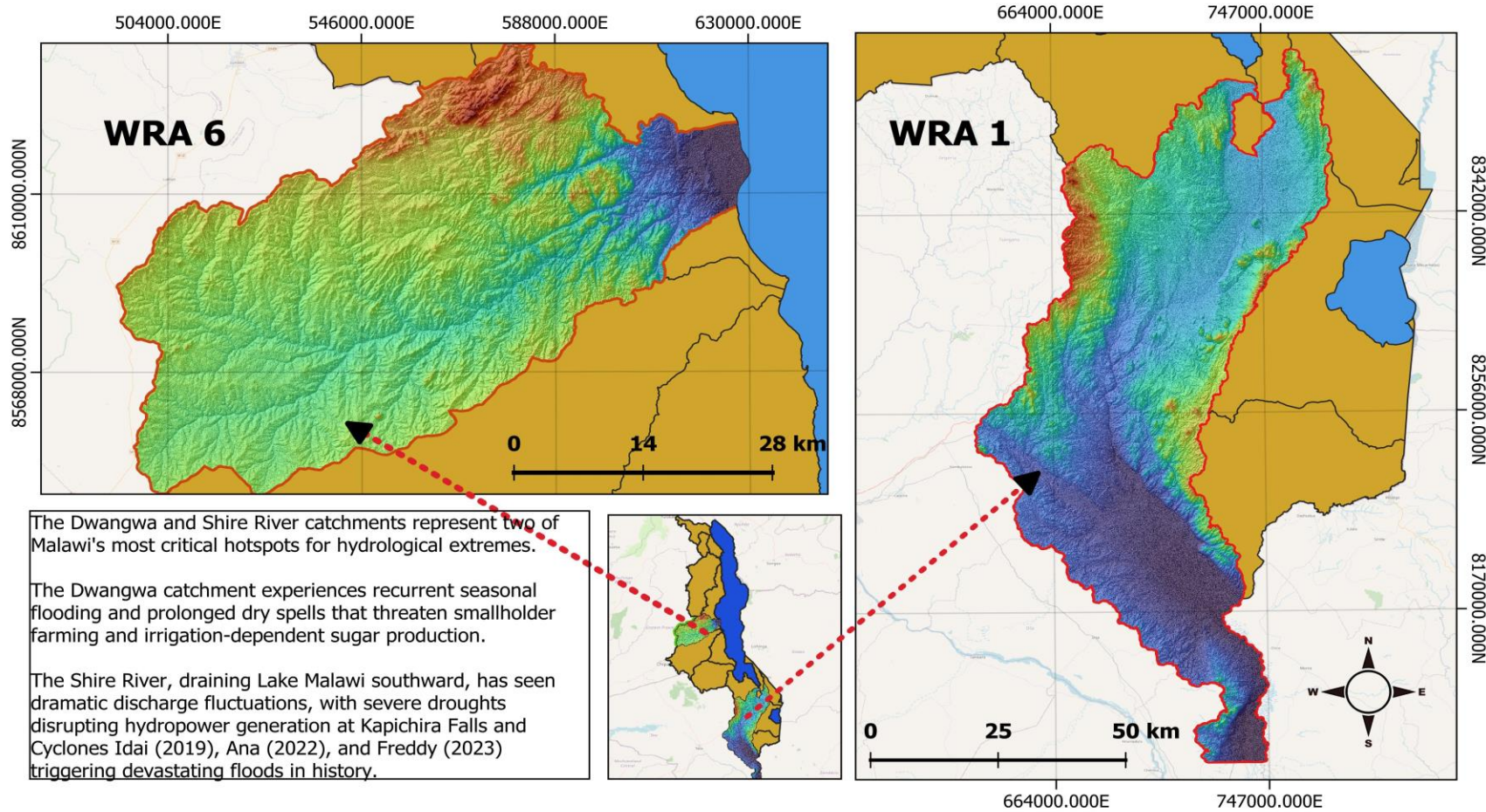
- Malawi ranks in the top 10 of the 2021 Global Climate Risk Index despite contributing less than 0.01% to global emissions
 - floods, droughts and cyclones severely disrupt food and water security, and livelihoods
 - Cyclones Idai, Ana, Freddy, and Jude, alongside recurrent droughts, caused widespread damage to rainfed agriculture and rural communities across the country.
 - Existing early warning systems such as CREWS remain limited by coarse spatial resolution (4 km), sparse monitoring networks, and weak predictive capability for hydrological extremes and irrigation demand
- need for high-resolution, AI-driven tools to accurately forecast and classify hydrological extremes in Malawi

Objective :

- Develop a cloud-based, open-source AI algorithm using Earth Observation data to map historical and near-real-time hydrological extremes and forecast irrigation demand across selected catchments in Malawi



DWANGWA AND SHIRE CATCHMENTS

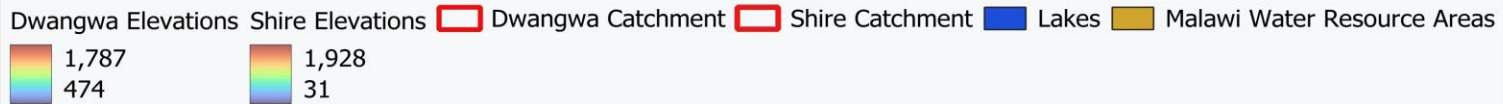


The Dwangwa and Shire River catchments represent two of Malawi's most critical hotspots for hydrological extremes.

The Dwangwa catchment experiences recurrent seasonal flooding and prolonged dry spells that threaten smallholder farming and irrigation-dependent sugar production.

The Shire River, draining Lake Malawi southward, has seen dramatic discharge fluctuations, with severe droughts disrupting hydropower generation at Kapichira Falls and Cyclones Idai (2019), Ana (2022), and Freddy (2023) triggering devastating floods in history.

Key



Phase 1 — Literature review

Historical flood periods · optimal RF flood features · SAR change detection methods

Phase 2 — Collection & Data Processing

Terrain features

Copernicus DEM Slope
· TWI.
HAND.
Curvature

SAR Features (2018–2024)

Sentinel-1 through Planetary Computer and CREODIAS via EODAG
Speckle filter: 3×3 rolling median
Threshold: $\Delta\text{dB} > 3-4$ & peak $< -16 -18$ dB
JRC permanent water mask
Events: 2019, Ana 2022, Gombe 2022, 2024

Rainfall Features

CHIRPS dataset
Antecedent
Precipitation Index (API)
Daily maximum rainfall
3-day cumulative total

Phase 3 — Training data sampling & field validation

Stratified random sampling · 5,000 samples per year. Balanced flood / non-flood classes · field visit for label validation

Phase 4 — Random Forest model training & validation

Training Years
2018–2022
Terrain + SAR
+ rainfall

Validation Years
2023–2024 Held-out
seasons
Cross-year
generalisation

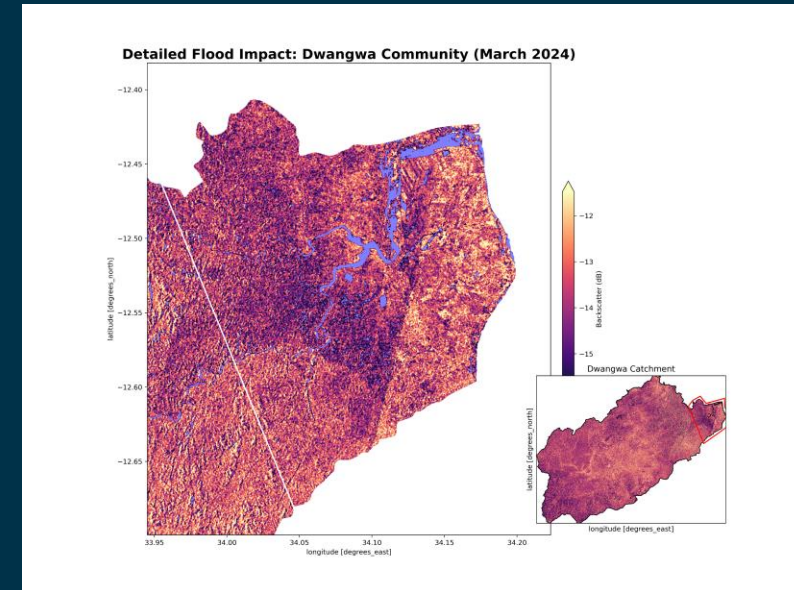
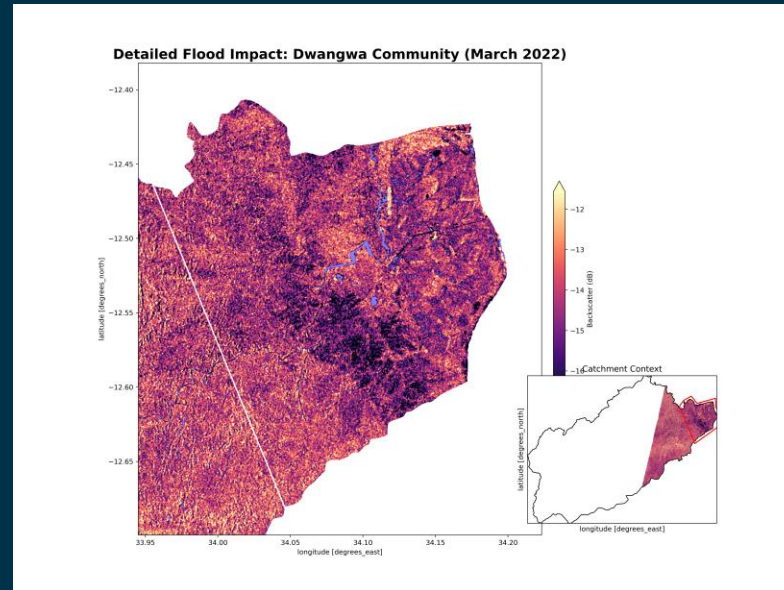
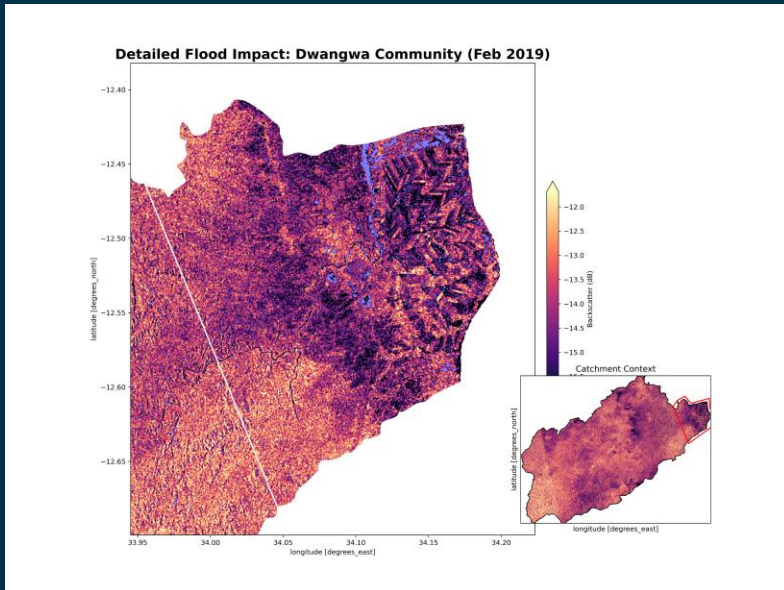
**Testing 2025
flood event**
Fully unseen data
Real-world
deployment

Phase 5 — Performance assessment

AUC-ROC · Precision · Recall · F1-Score · Overall accuracy. Evaluated across training and validation splits

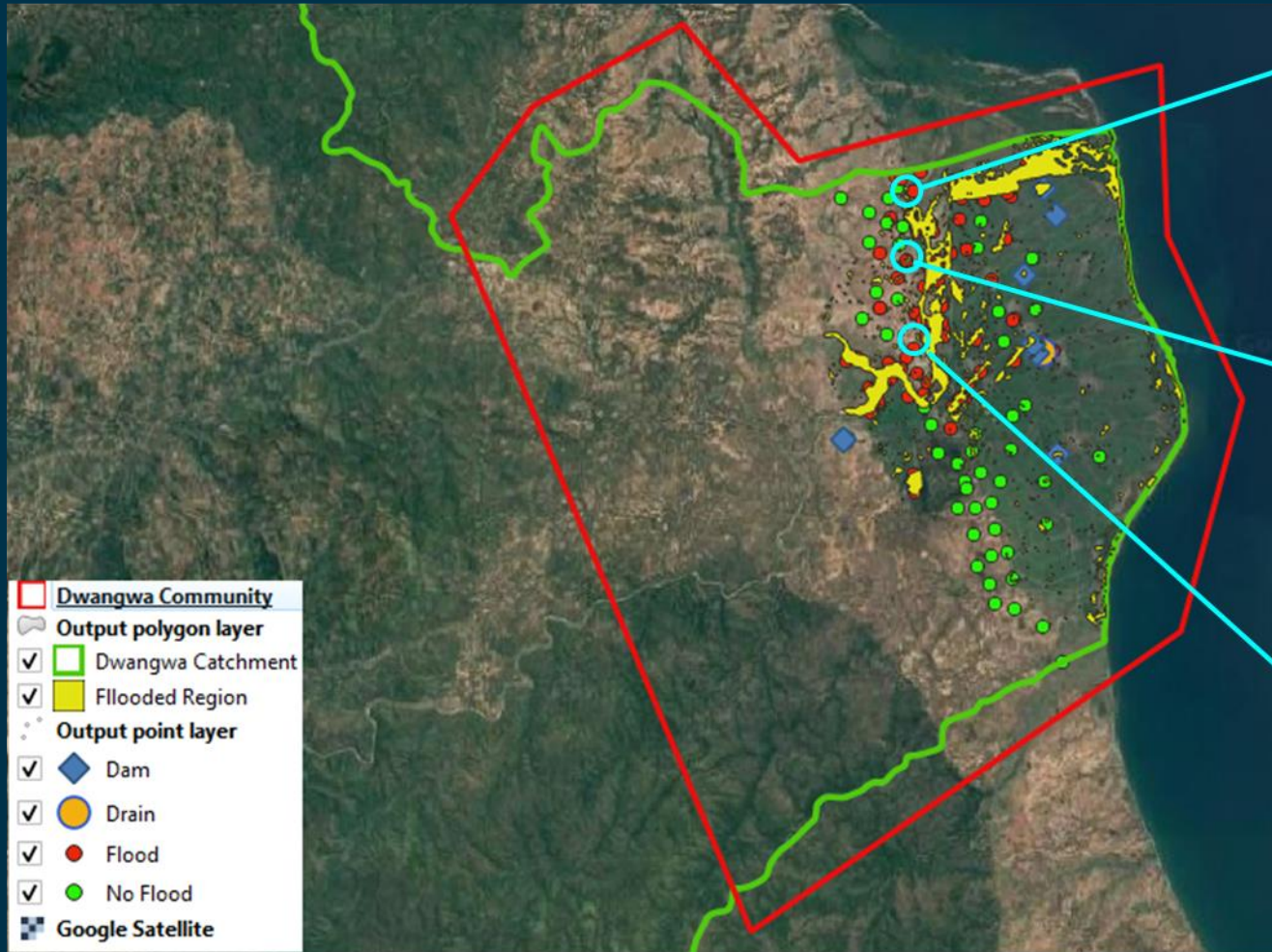
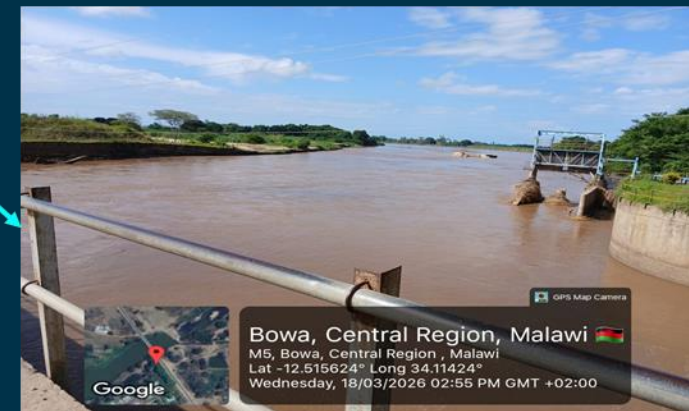
Phase 6 — Model application (Shire catchment)

Apply trained RF model to unseen catchment. Generate flood susceptibility map · assess spatial transferability

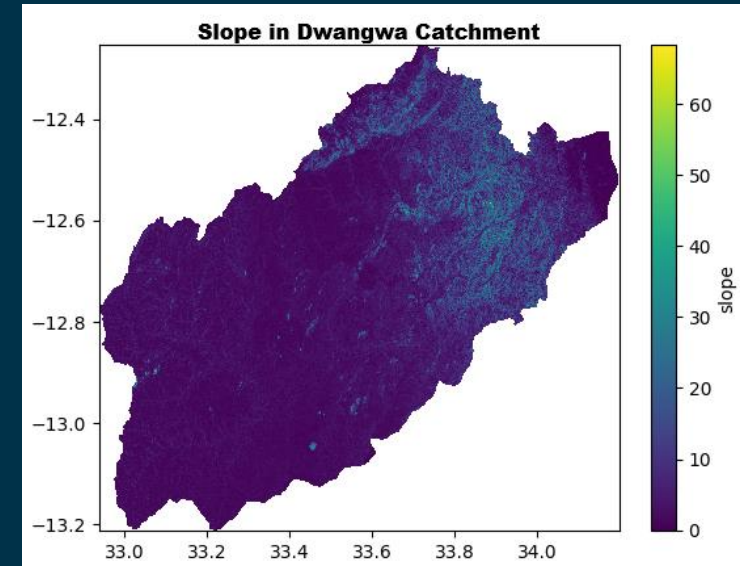
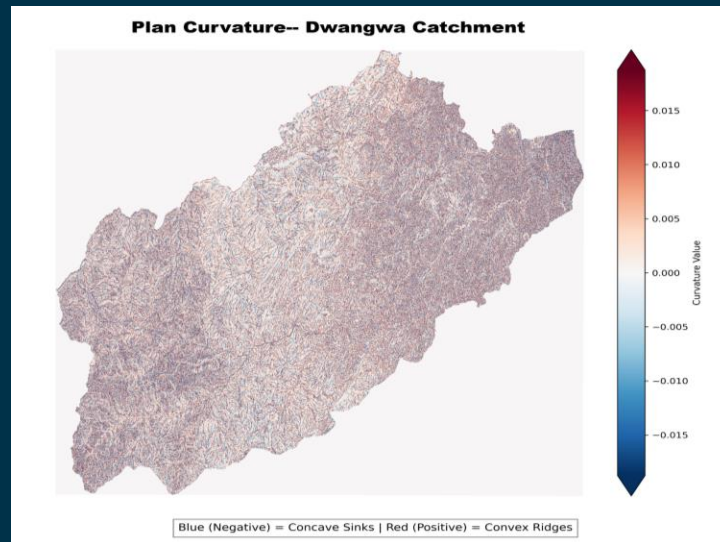
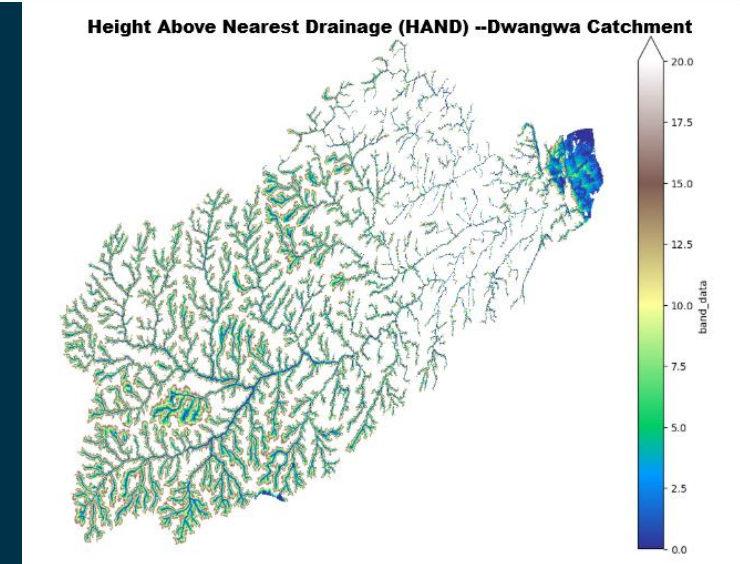
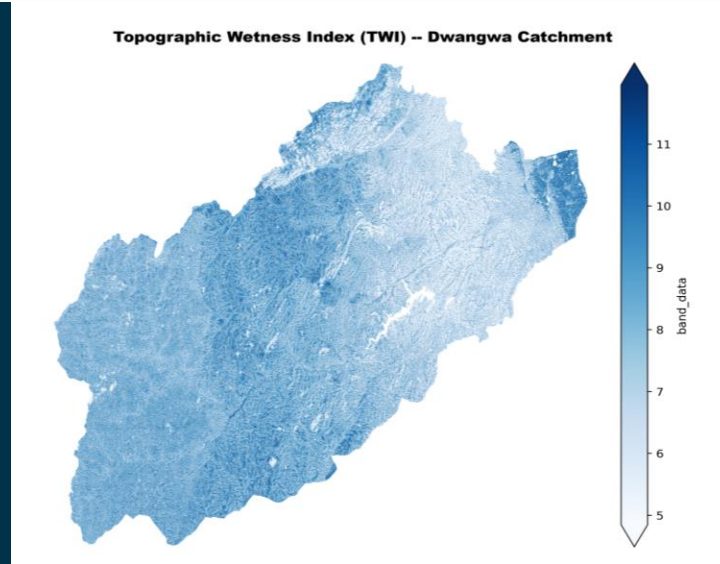


- Flood masks created for 2019, 2022 (Cyclone Anna), 2022 (Cyclone Gombe), and 2024 floods
- JRC's Global Surface Water data used to filter out permanent water
- Due to lack of validation data, a field visit was done to validate frequently flooded areas

Validation of Flood Masks

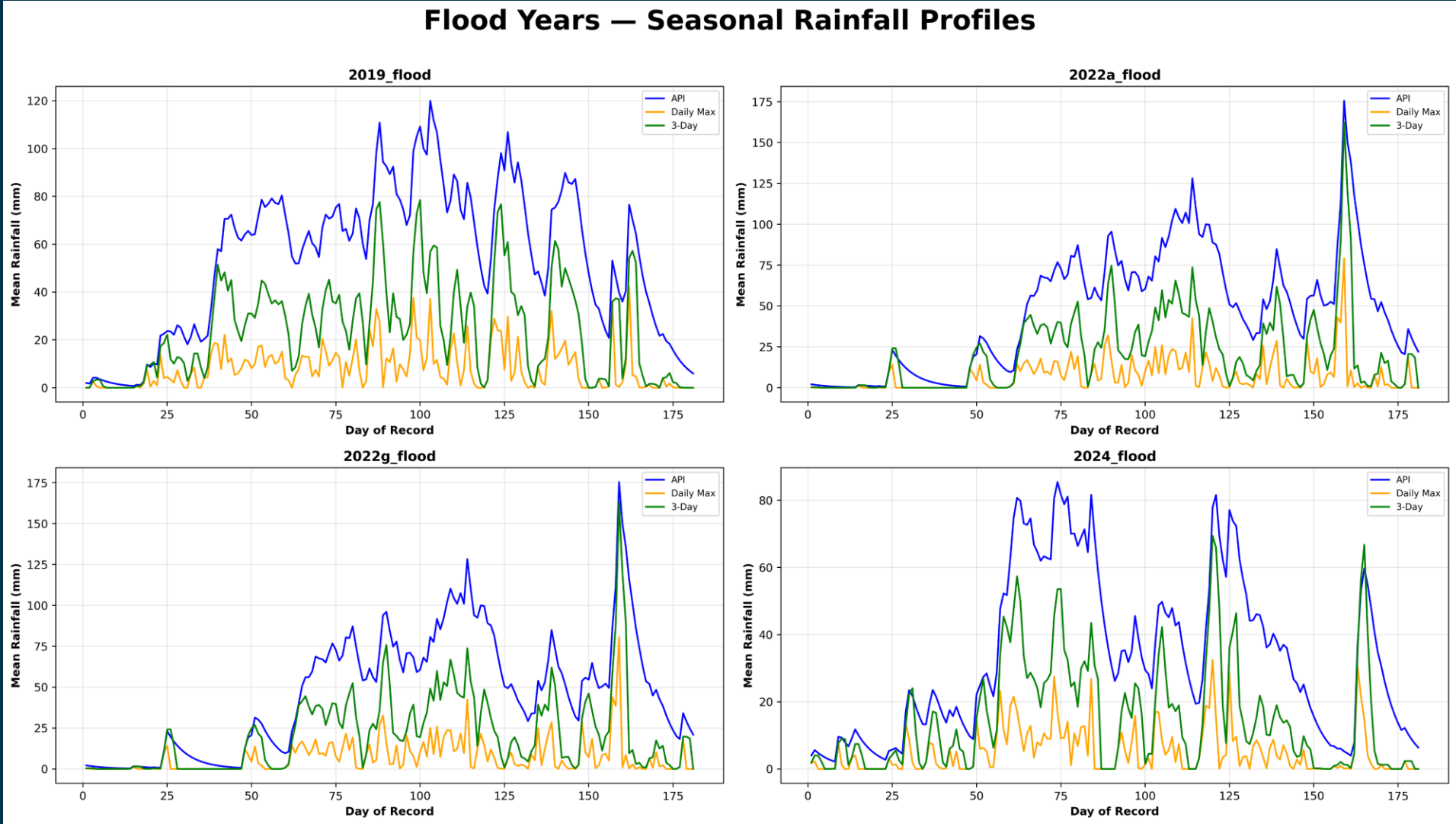


- Topographic Wetness Index (TWI)
- Height Above Nearest Drainage (HAND)
- Plan Curvature
- Slope



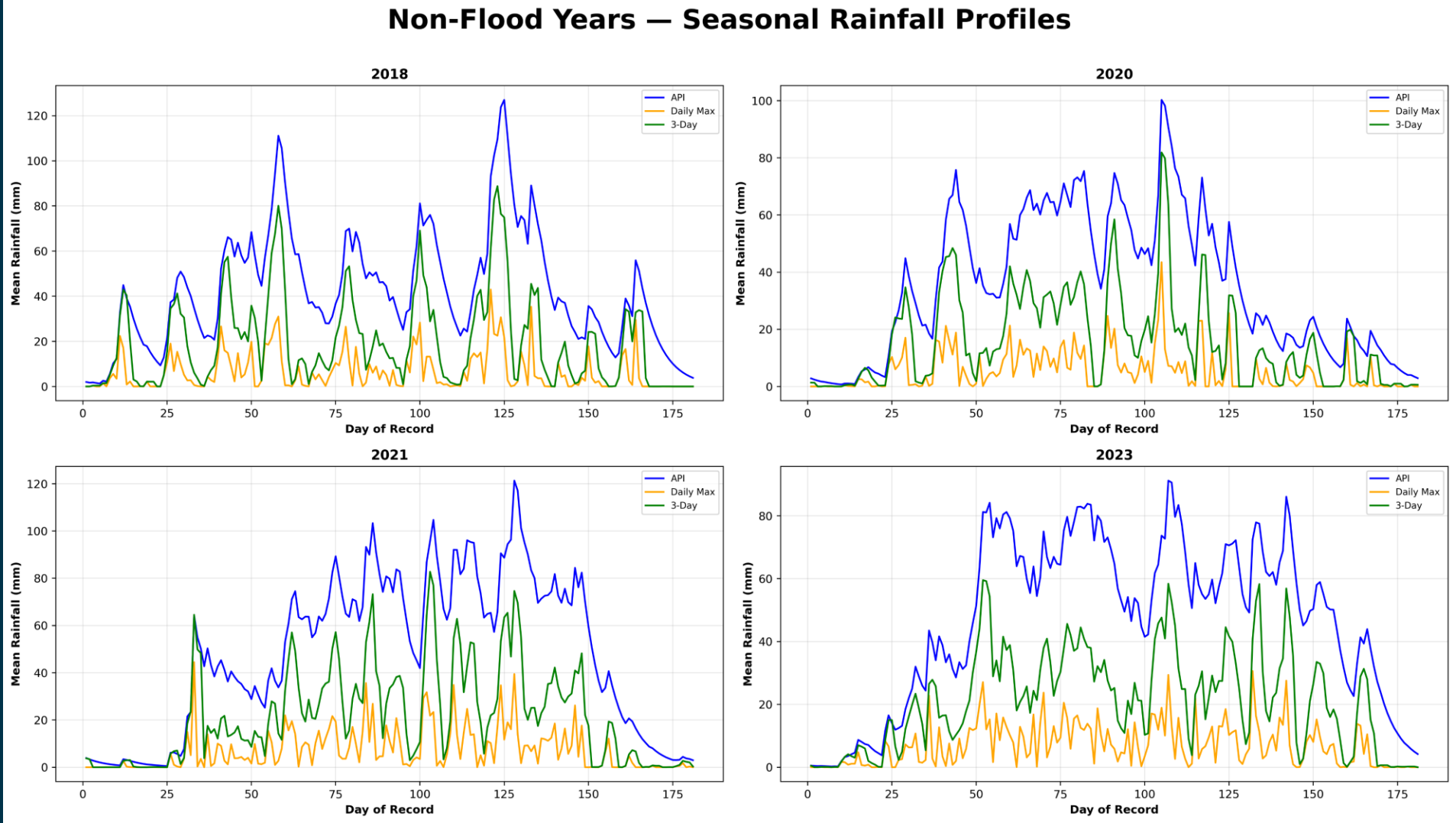
Rainfall Season Profiles

- Rainfall features:
 - Daily Max
 - API
 - 3-Day Total



Rainfall Season Profiles

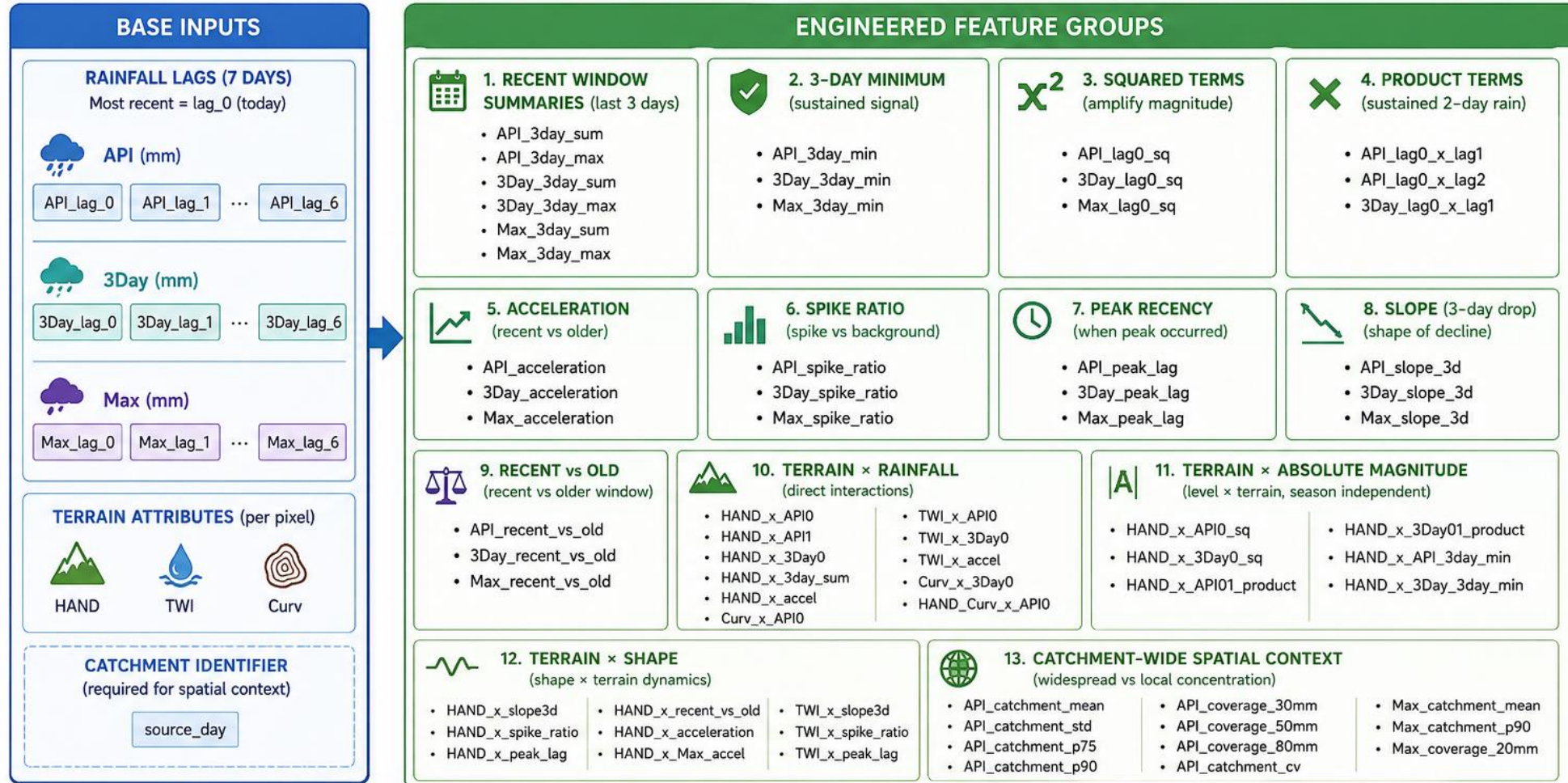
- Despite having higher rainfall features, 2018 and 2021 were non-flood years
→ initial model learned that higher rainfall features do not lead to floods



- Since isolated sub-catchment storms can produce locally high API without triggering widespread network-scale flooding, catchment-wide spatial context features were computed from the CHIRPS rainfall grid for each day in the record.
- These included the coefficient of variation of API across all catchment pixels, areal coverage fractions at 30mm, 50mm and 80mm thresholds, and the 75th and 90th percentile of catchment-wide API and maximum daily rainfall, each joined to every pixel observation for that day.
- These features provided each pixel with contextual awareness of how spatially extensive a rainfall event was across the catchment

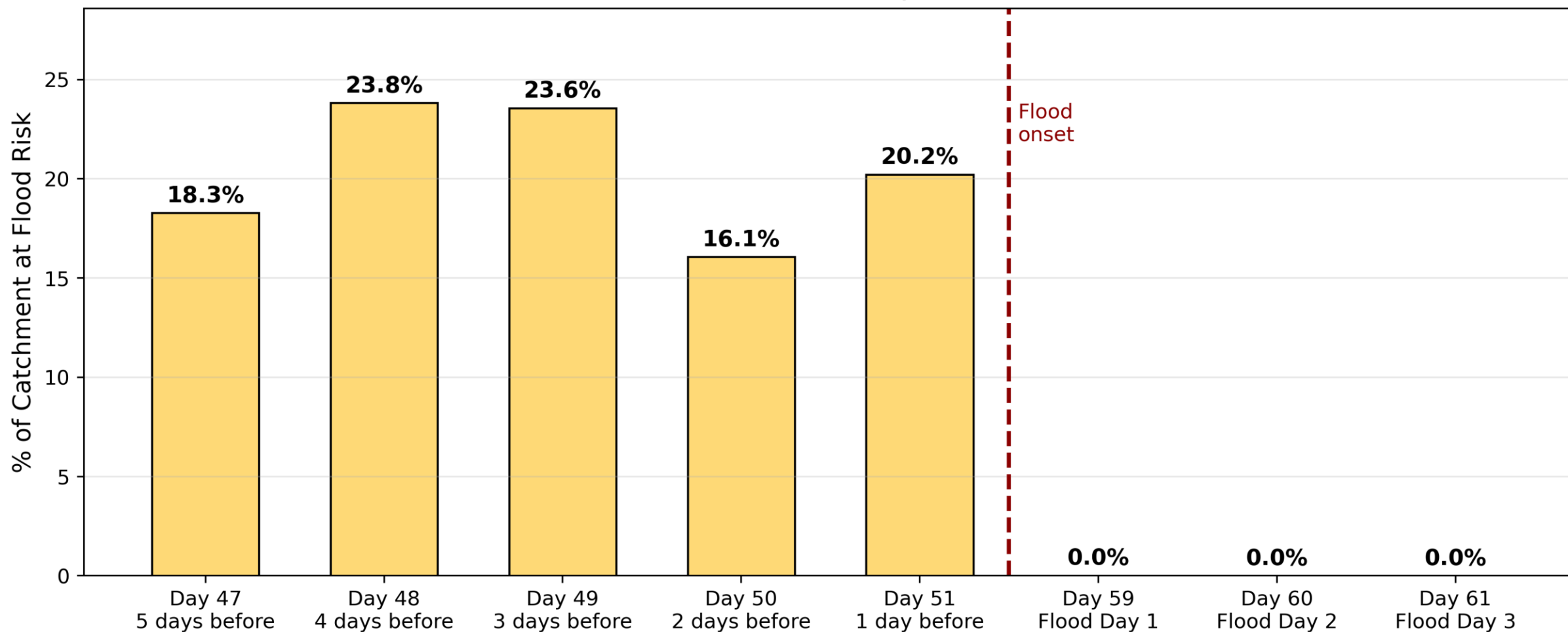
ENGINEERED FLOOD MODEL FEATURES

Built from 7 days of rainfall history (lags 0–6) + terrain attributes + catchment-wide context



INITIAL FLOOD PROGRESSION

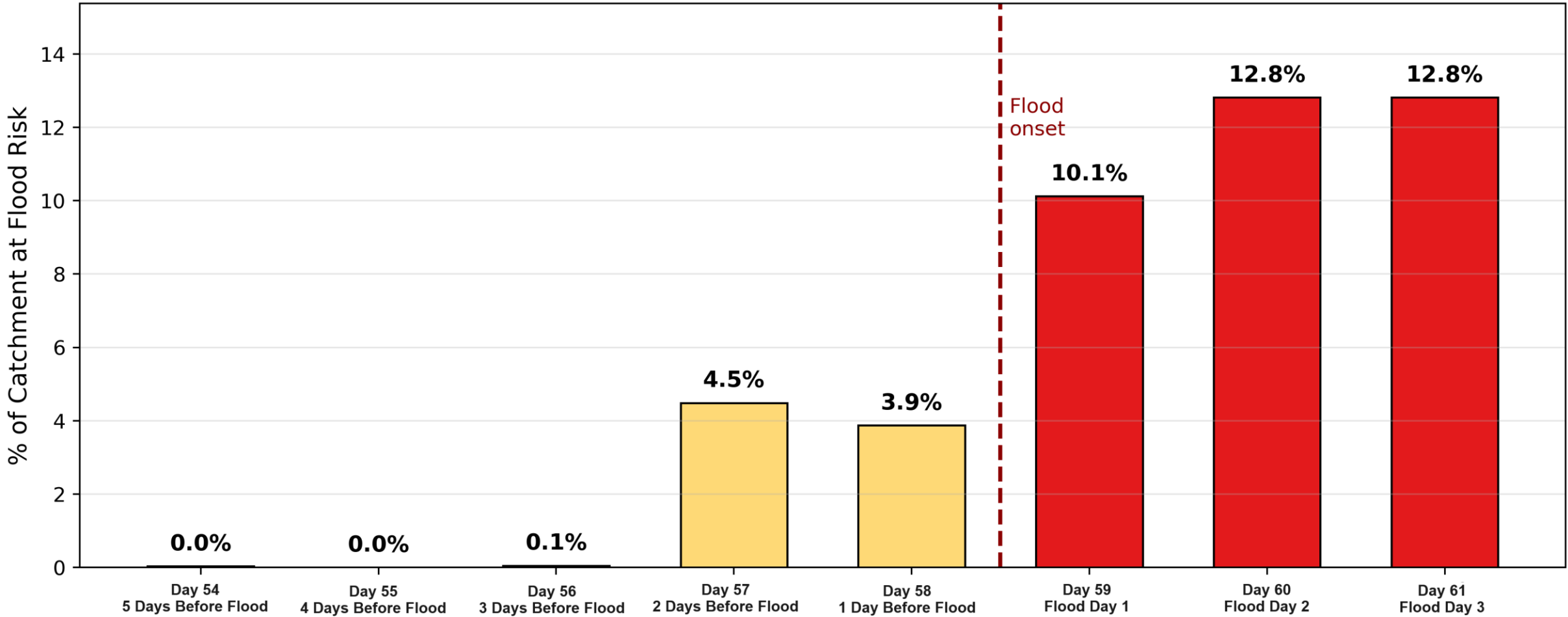
Dwangwa Flood Extent Progression (Initial Model) Dec 27 - Dec 31, 2025



FINAL FLOOD PROGRESSION

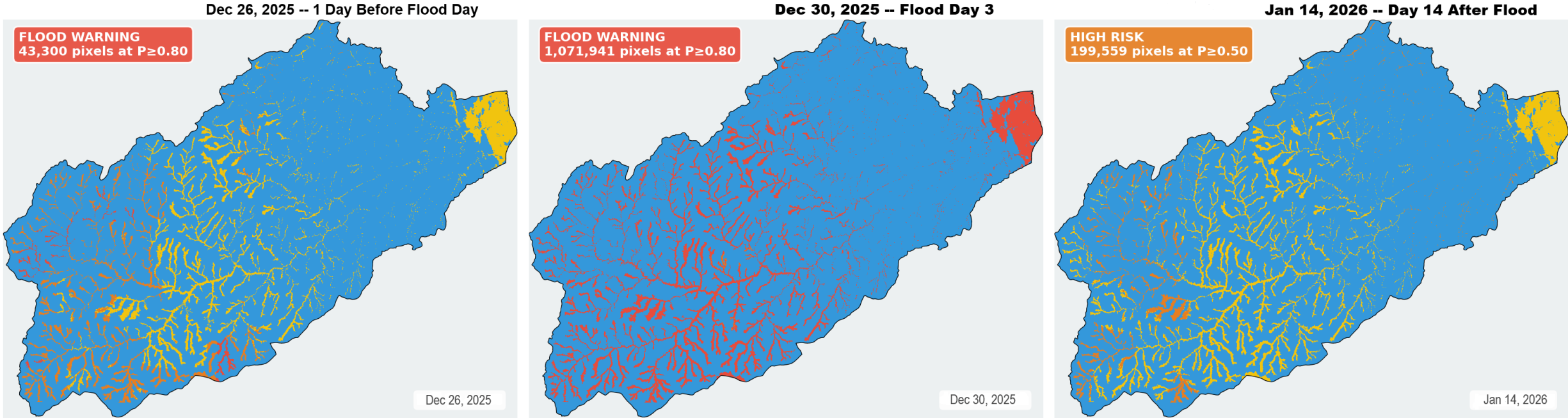


Dwangwa Flood Extent Progression Dec 27 - Dec 31, 2025



Model Performance on December 2025 Floods

Dwangwa Catchment — Flood Alarm Level Progression December 2025 | Dwangwa Flood Model



■ Normal ($P < 0.20$)
 ■ Elevated (0.20 - 0.50)
 ■ High risk (0.50 - 0.80)
 ■ Flood warning ($P \geq 0.80$)

NEXT COURSE OF ACTION

Phase	Activities	Timeline
Phase 3: Model Design & Training	<ul style="list-style-type: none"> LSTM model development and hyperparameter tuning Continued Random Forest hyperparameter tuning Testing both models on unseen environment (Shire Basin) 	Months 4–9
Phase 4: Validation & Calibration	Model accuracy testing, stakeholder feedback integration	Months 9–11
Phase 5: System Deployment	Cloud-hosted dashboard and interface development	Months 11–13
Phase 6: Capacity Building & Dissemination	Training, outreach, documentation, publication	Months 13–15





Thank You
