

---

# Deep learning for monthly precipitation prediction in mountainous terrain

**Manuel Ricardo Pérez Reyes**

Marco J. Suárez Barón · Óscar J. García Cabrejo

UPTC · Pedagogical and Technological University of Colombia

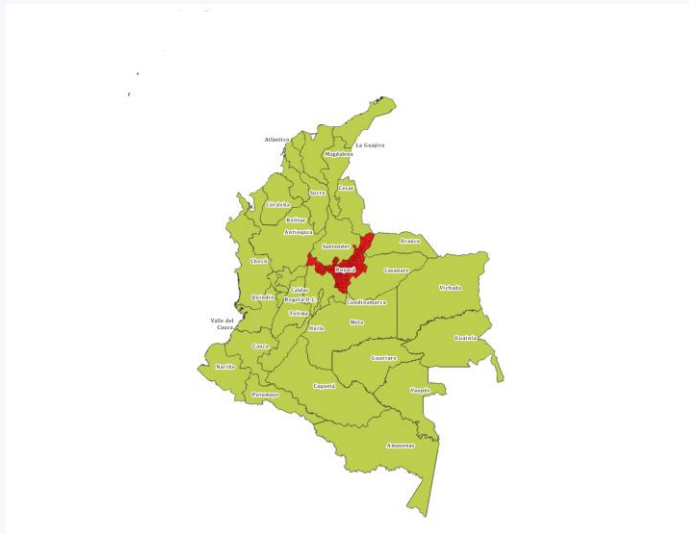
## HEADLINE RESULT

**$R^2 = 0.655$**

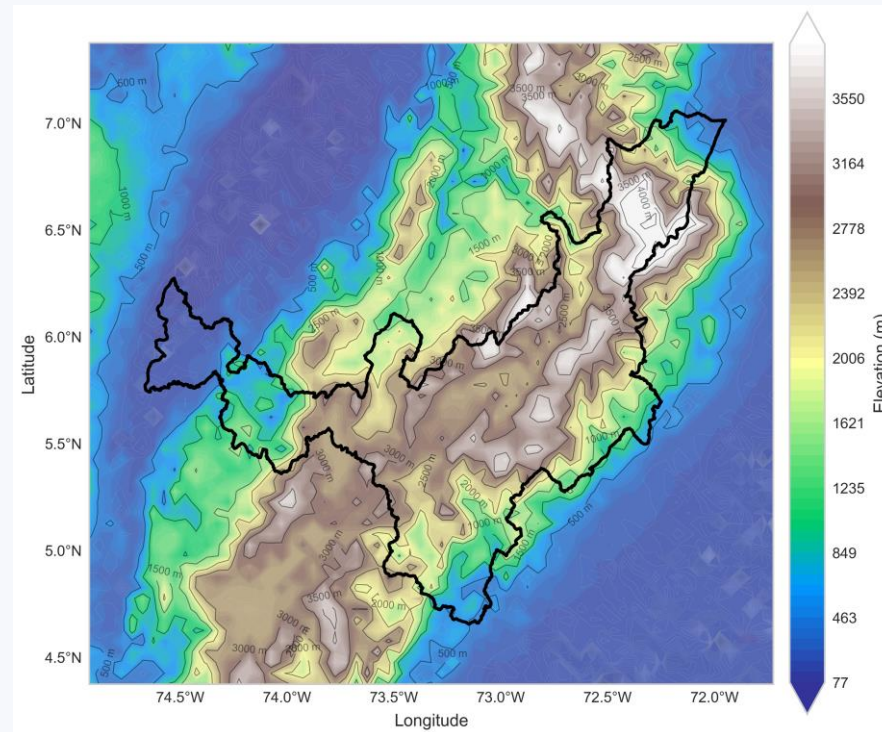
±0.018 (3-seed mean)

Late Fusion (Ridge) of two deep models beats every single architecture across all 12 forecast horizons.

# Boyacá, Colombian Andes: extreme orographic gradients



Boyacá department (red) in Colombia.



SRTM elevation: 145 m (valleys) → 5,500 m (páramo).

## ELEVATION

**145 to 5,500 m**

single watershed range

## GRID

**3,965 cells**

61 × 65 CHIRPS lattice

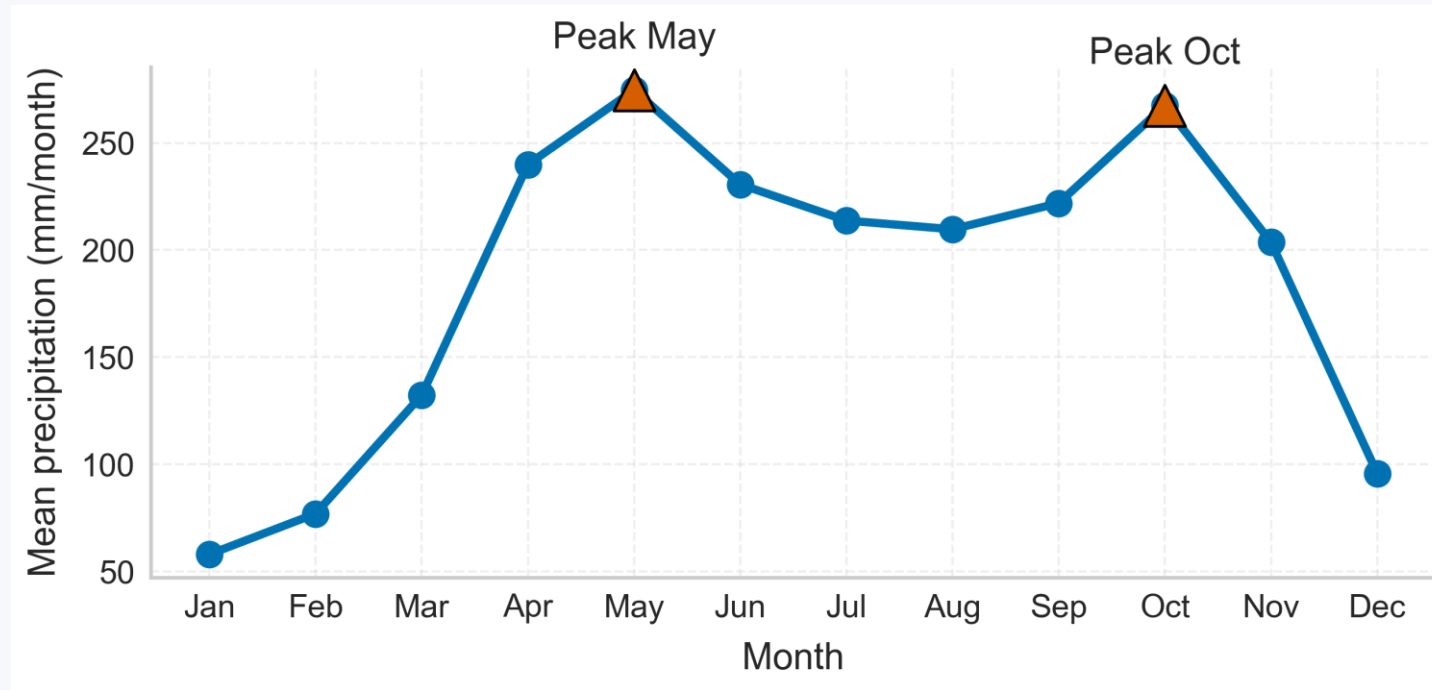
## HISTORY

**35 years**

monthly · 1985–2022

**Bimodal regime: Apr–May & Oct–Nov peaks**

# Two rainy seasons motivate temporal feature engineering



Mean monthly precipitation over Boyacá (1982–2025). Peaks at May (275 mm) and October (267 mm).

**PEAK 1**

**May · 275 mm**

first wet season

**PEAK 2**

**October · 267 mm**

second wet season

**MOTIVATES**

**$\sin/\cos + t-12$**

temporal features in PAFC

**Why it matters: a single sinusoid cannot capture twin peaks 5 months apart. This motivates the  $\sin/\cos$  month +  $t-12$  lag in the PAFC bundle.**

# Three deep-learning families, comparable performance

## CONVLSTM

### Convolutional LSTM

$R^2 = 0.628$  · 148K params · BASIC features

## FNO

### Fourier Neural Operator

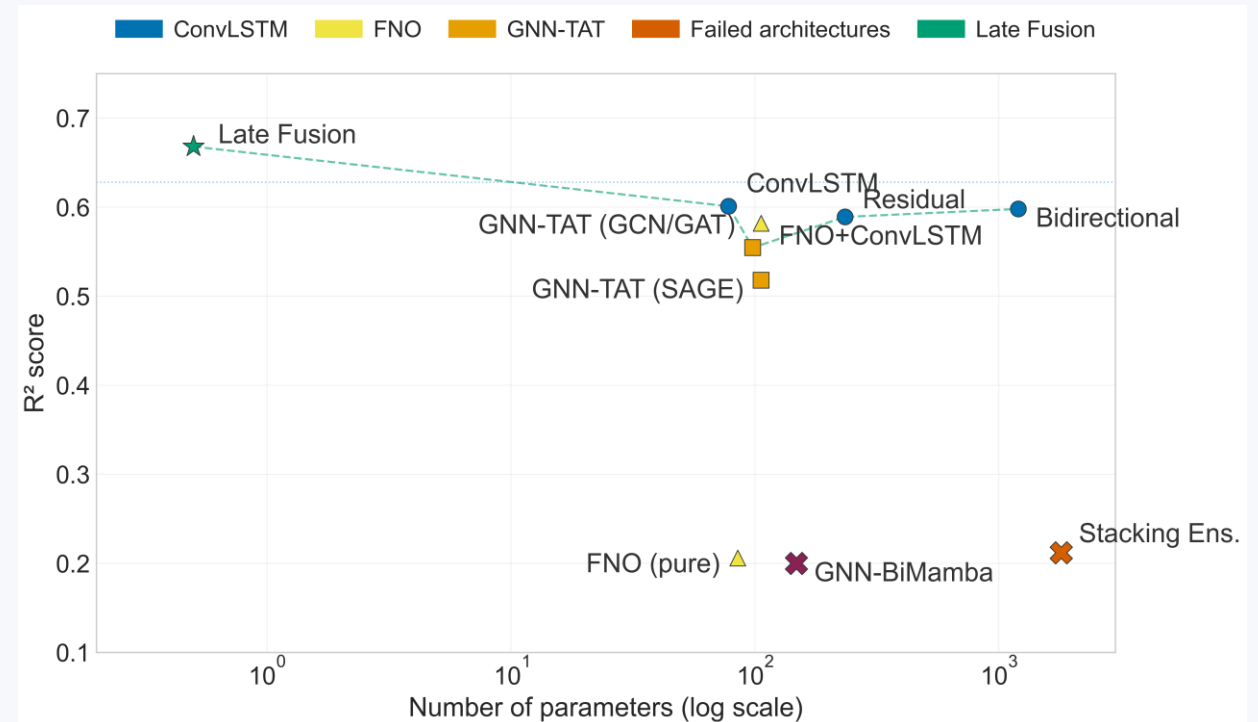
$R^2 = 0.582$  · FNO–ConvLSTM hybrid (rescue effect)

## GNN-TAT

### Graph NN + Temporal Attention

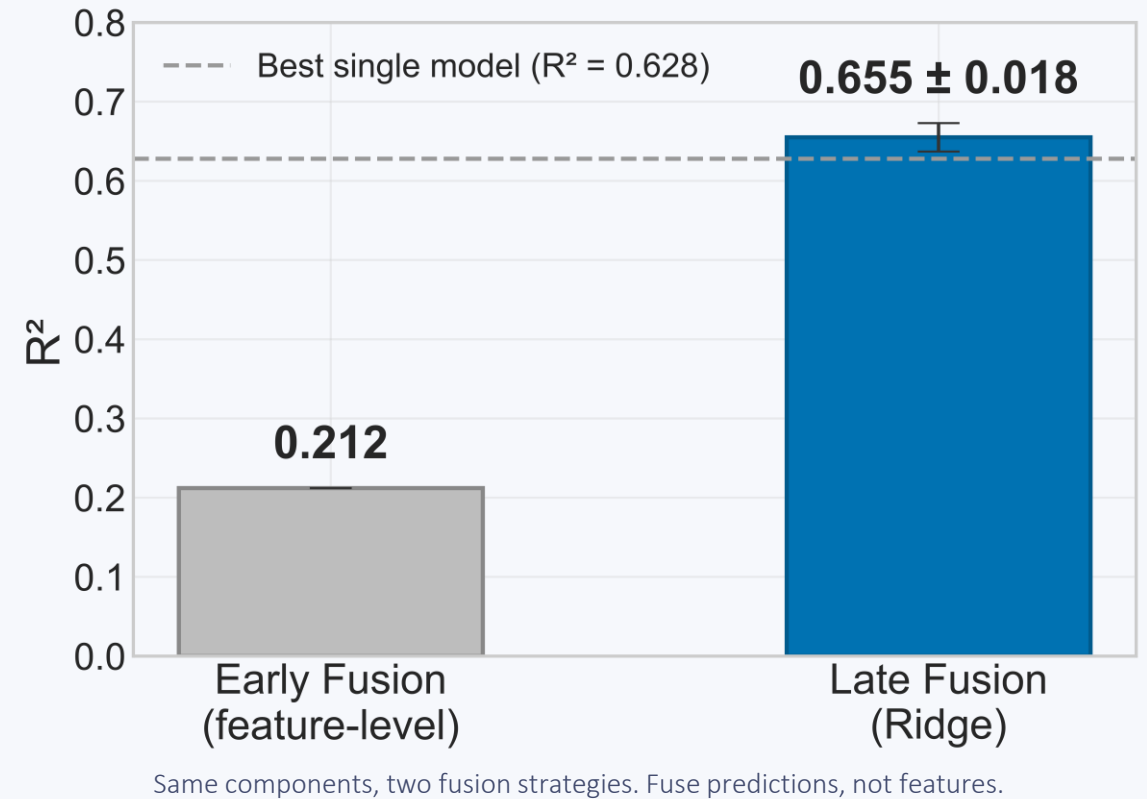
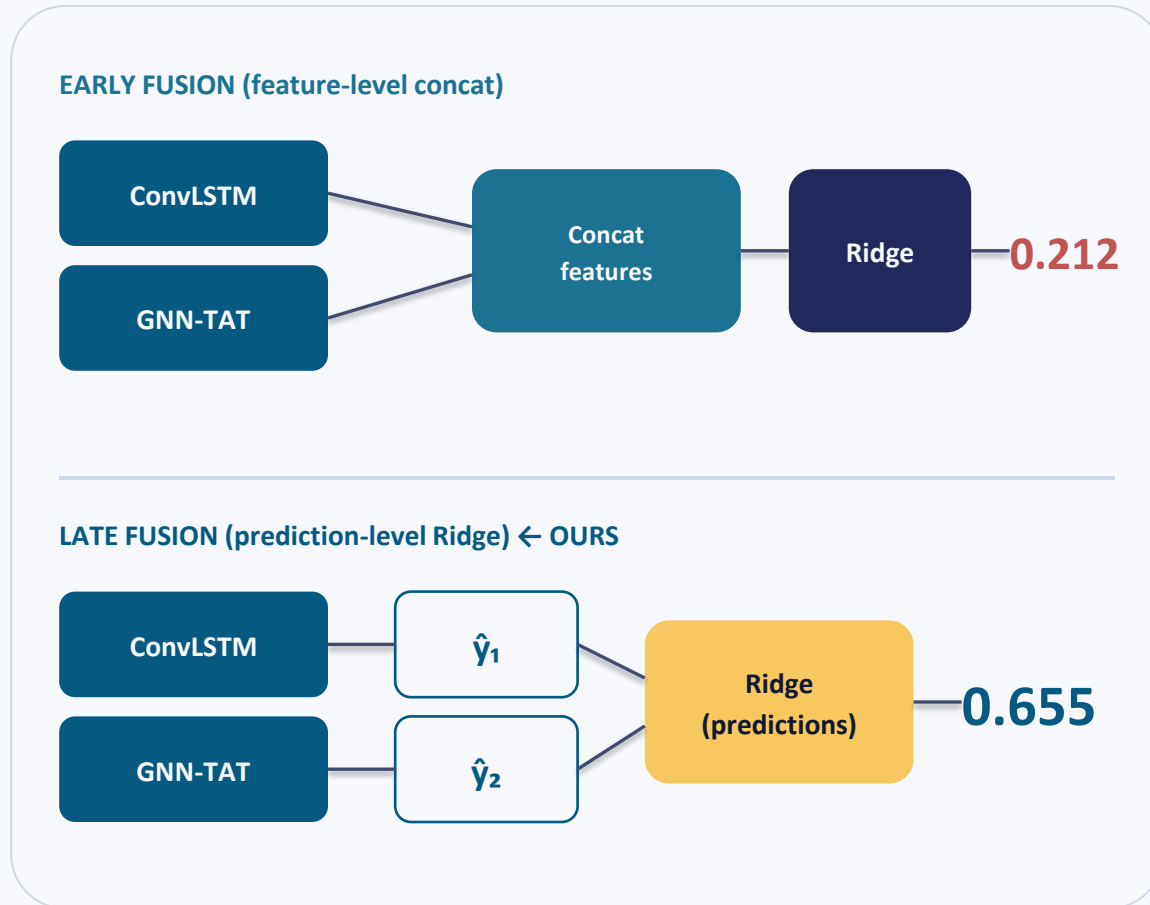
$R^2 = 0.628$  · 98K params · 34% fewer than ConvLSTM

BASIC = temporals + topography · KCE = BASIC + elevation clusters · PAFC = KCE + precipitation lags

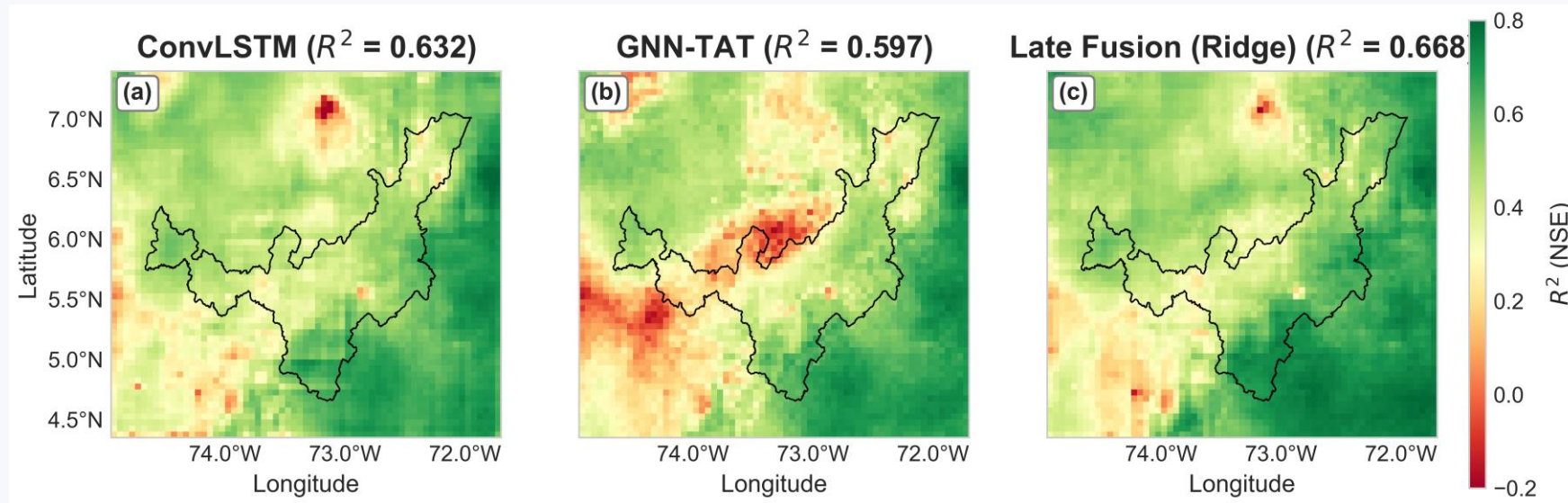


Parameters vs  $R^2$ . Late Fusion delivers the best score with the smallest footprint.

# Late Fusion wins. Early Fusion fails. Same components.



# Why fusion works: complementary failure modes

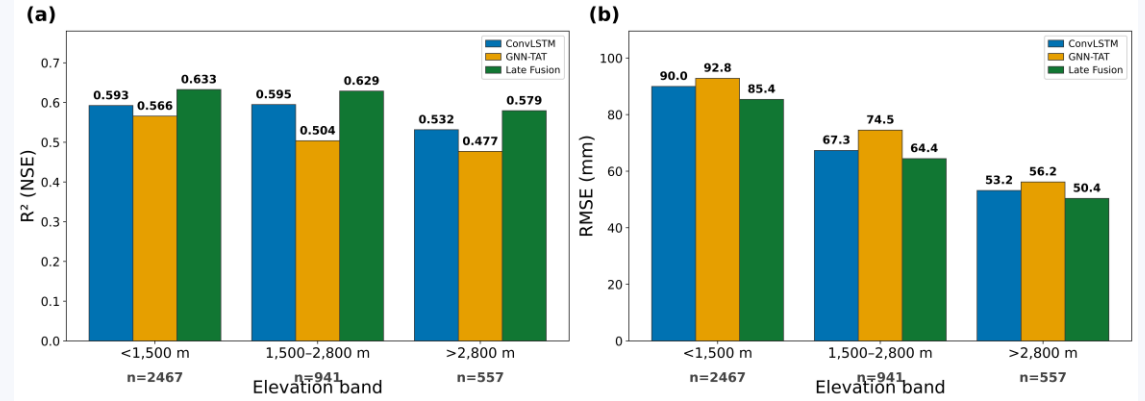
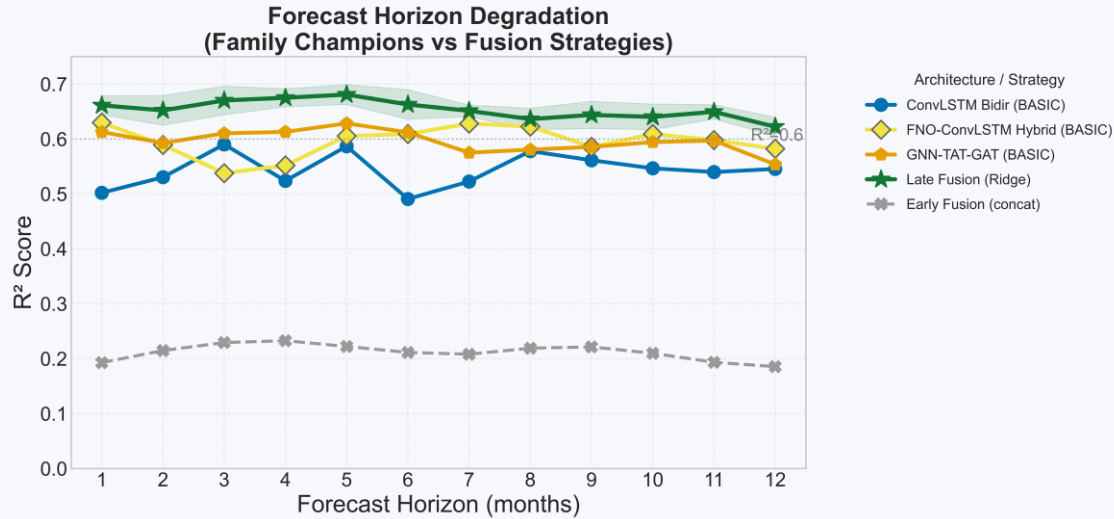


Per-cell  $R^2$  maps. ConvLSTM and GNN-TAT fail in different places; Late Fusion absorbs both.

## THE FUSION INTUITION

Each model corrects the other's spatial blind spots. Ridge learns the per-cell weighting that combines two flawed predictors into one reliable forecast.

# Stable across horizons, KCE-aligned bands, and ENSO years



Forecast horizon (1–12 months): Late Fusion leads at every step.

Elevation bands: gain holds from valleys to páramo.

**12/12 horizons**

Late Fusion best at every H

**16% drop**

low → high (KCE bands, n=2467/941/557)

**Med ≈ High**

transition zone is hardest, not páramo

# What this means and where we go next

01

## Predictability ceiling

Three families converge to  $R^2 \approx 0.580\text{--}0.630$ .  
Limit may be data, not model.

02

## Fusion beats the ceiling

+6.4% with only  $\sim 1,000$  extra parameters. Cost is low, gain is real.

03

## Strategy > architecture

Where you combine matters more than which models you pick.

## NEXT

Wider seed ensembles · physics-guided Mixture of Experts · operational deployment with IDEAM

### COMPANION OUTPUTS

Benchmark · Hydrology 2026, 13(3), 98 | Methodology · Journal of Hydrology (in review) | Code · [github.com/ninja-marduk/ml\\_precipitation\\_prediction](https://github.com/ninja-marduk/ml_precipitation_prediction)

THANK YOU

---

# Fuse predictions, not features.

Combining ConvLSTM and GNN-TAT predictions with Ridge regression improves accuracy at every forecast horizon, by up to +6.4%.

## CONTACT

Manuel R. Pérez Reyes · [manuelricardo.perez@uptc.edu.co](mailto:manuelricardo.perez@uptc.edu.co)

ORCID 0009-0003-2963-1631 · Pedagogical and Technological University of Colombia



Paper · code · poster