Future flood risk assessment: Comparing ML-based and traditional hydrologic modeling approaches

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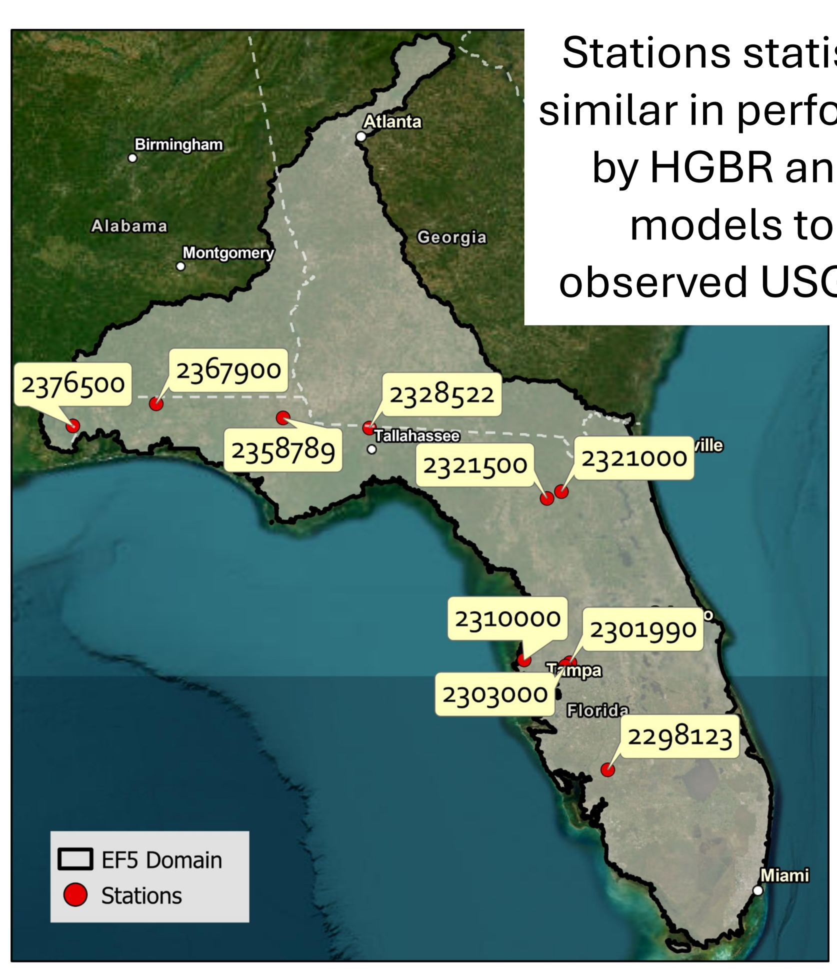
INTRODUCTION

Future flood risk assessments has risen in locations across the globe particularly for vulnerable populations that lack the financial resources to design large-scale flood mitigation structures. Conventionally, hydrologic models are calibrated and used to optimize mitigation strategies. The data and computational demands of these models implemented across large spatial scales make them an inefficient tool for resource-limited countries to access and utilize. *Machine learning (ML) based models are a viable alternative that counters these drawbacks. The potential exists for employing ML models to spatially inform on future flood risk under various climate scenarios.*

OBJECTIVE

To investigate the level of agreement that ML models have with traditional models to evaluate changes in future flood risk

STUDY AREA/ DATA



Stations statistically similar in performance by HGBR and EF5 models to the observed USGS AMS

DATASETS

Variables	Model	Dataset	Resolution	Reference
Meteorological, streamflow & static	HGBR (Train)	CAMELS-CONUS	Catchment-averaged; daily 2000 – 2018	Addor et al. 2017; Newman et al. 2015
Observation Precipitation & Temperature (HGBR only)	EF5 (Calibrate)	MULTI-RADAR MULTI-SENSOR (MRMS) QPE - Current	1-km, hourly 2016 - 2023	Zhang et al. 2019
	HGBR (Train)	Daymet-North America (Ver 4)	1-km, daily; 1980-2023	Thornton et al. 2022
	EF5 & HGBR (Test)	NOAA Climate Prediction Center (CPC)	0.25 deg, daily; 1948 – 2023	Xie et al. 2007; Chen et al. 2008
GCM-based Precipitation & Temperature	EF5 & HGBR	Localized Constructed Analogs (Ver 2) – Coupled Model Intercomparison Project (LOCA-CMIP6)	6-km, daily 1950 – 2014 (historic); 2015 – 2100 (future)	Pierce et al. 2015
Annual Peak Stream Flow	GEV-HGBR & GEV-EF5	U.S. Geological Survey	Annual Max Values across gauges	U.S. Geological Survey, NWIS

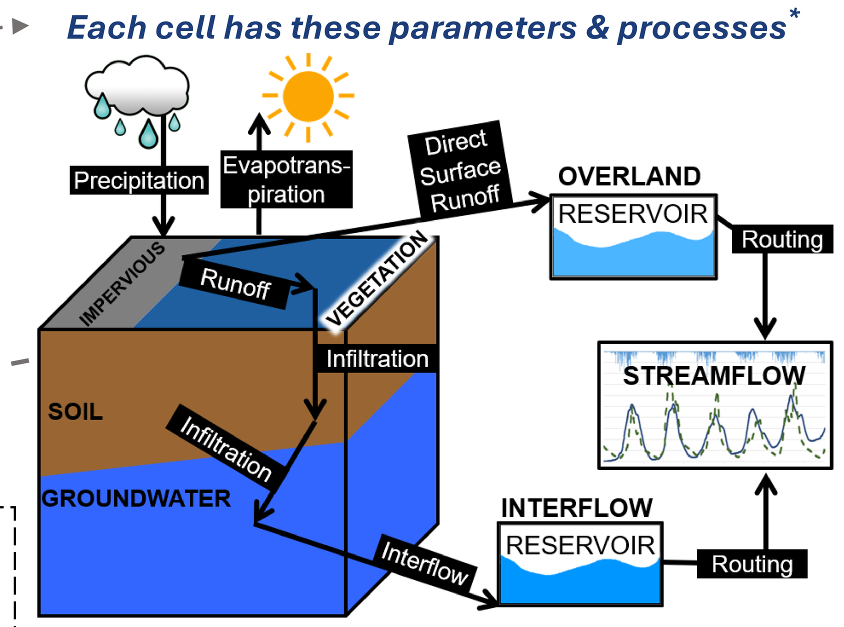
METHODOLOGY

EF5 is a hydrologic model – **Ensemble Framework For Flash Flood Forecasting**

CREST — KINEMATIC WAVE

Forcing → Water Balance → Routing → Output

*Each cell has these parameters & processes**



Observed Climate Data, CPC

Future Climate Data, LOCACMIP6

Calibrated Hydrologic Model, EF5

Trained ML Model, HGBR

Validation of models with USGS (AMS)

Extract AMS

Return Periods (yr): **10** | **20** | **50** | **100**

Compute RPs based on GEV-LMOM

GEV-LMOM: **G**eneralized **E**xtreme **V**alue Distribution with **L-moment** approach for GEV parameter estimate (Hu et al. 2020)

Compare the relative changes in flood frequency

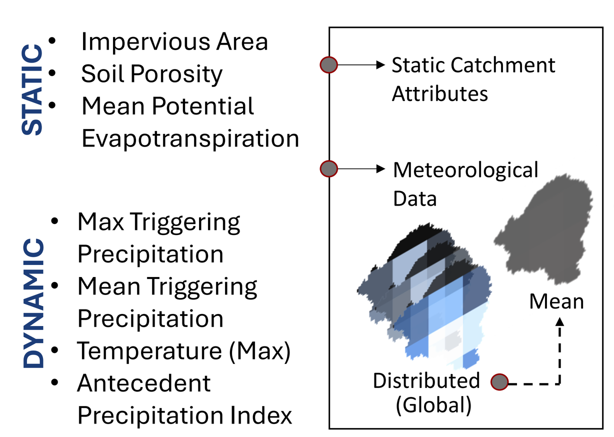
MID-CENTURY (2030-2064)
END-CENTURY (2065-2100)

SSP 2.45 (LOW)
SSP 5.85 (HIGH)

Future Perspectives

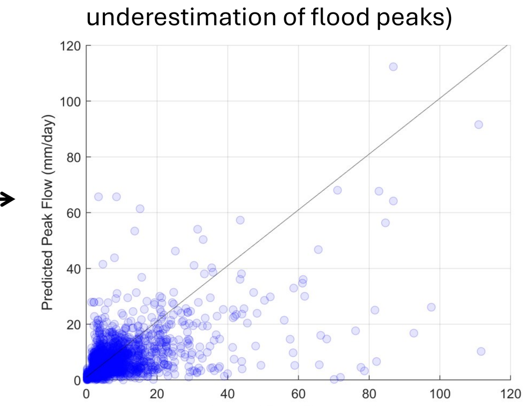
HGBR model trained on FLOOD PEAKS

(Rasheed et al., 2022, 2024)



For each peak, static-catchment & storm triggering characteristics are identified and used for training

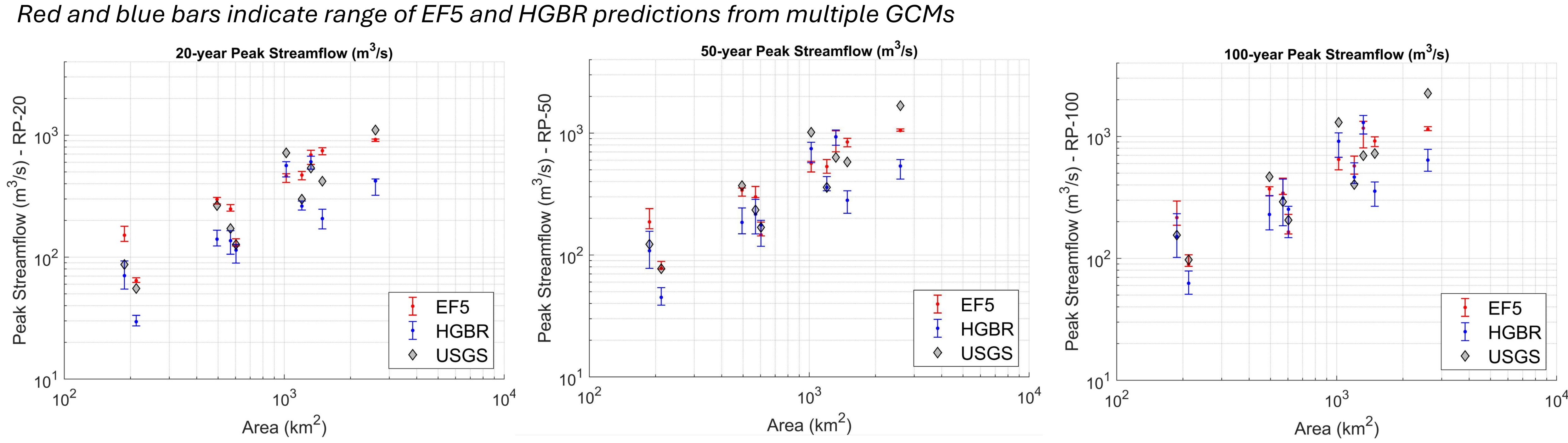
PRD = -6.17% (This indicates a slight underestimation of flood peaks)



*Credit: Module 1.2 Introduction to Hydrological Models (Slide 35); EF5

HISTORIC COMPARISON

Red and blue bars indicate range of EF5 and HGBR predictions from multiple GCMs

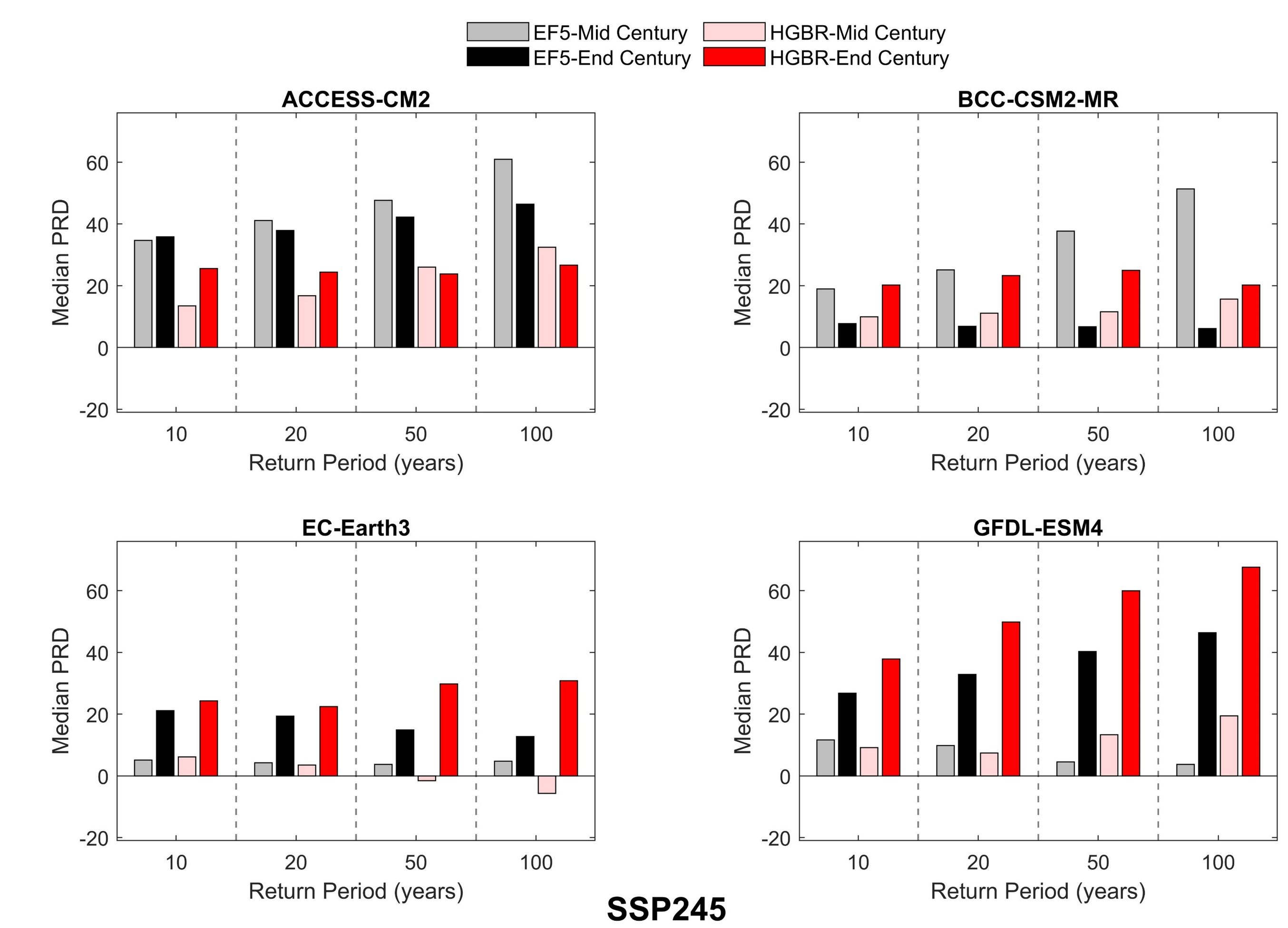


FUTURE FLOOD RISK COMPARISON

The HGBR is a viable ML approach for providing the relative change in future floods in an ungauged catchment

Global Climate Models	SSP*	MID-CENTURY 10-yr	MID-CENTURY 20-yr	MID-CENTURY 50-yr	MID-CENTURY 100-yr	END-CENTURY 10-yr	END-CENTURY 20-yr	END-CENTURY 50-yr	END-CENTURY 100-yr
ACCESS-CM2	***2.45***	0.401	0.501	0.390	0.341	0.020	0.010	0.068	0.178
	5.85	0.256	0.493	0.723	0.718	0.354	0.605	0.740	0.877
BCC-CSM2-MR	***2.45***	0.050	0.081	0.095	0.211	0.965	0.968	0.845	0.967
	5.85	1.000	0.730	0.436	0.287	1.000	0.855	1.000	0.909
EC-Earth3	***2.45***	0.137	0.087	0.147	0.200	0.141	0.772	0.933	0.818
	5.85	0.005	0.061	0.050	0.138	0.890	0.839	0.938	0.822
GFDL-ESM4	***2.45***	1.000	0.798	1.000	0.847	0.458	0.472	0.461	0.499
	5.85	0.348	0.340	0.340	0.398	0.036	0.155	0.292	0.359

Brunner-Munzel test for similarity in relative change (in future flood w.r.t. historic) between the two models



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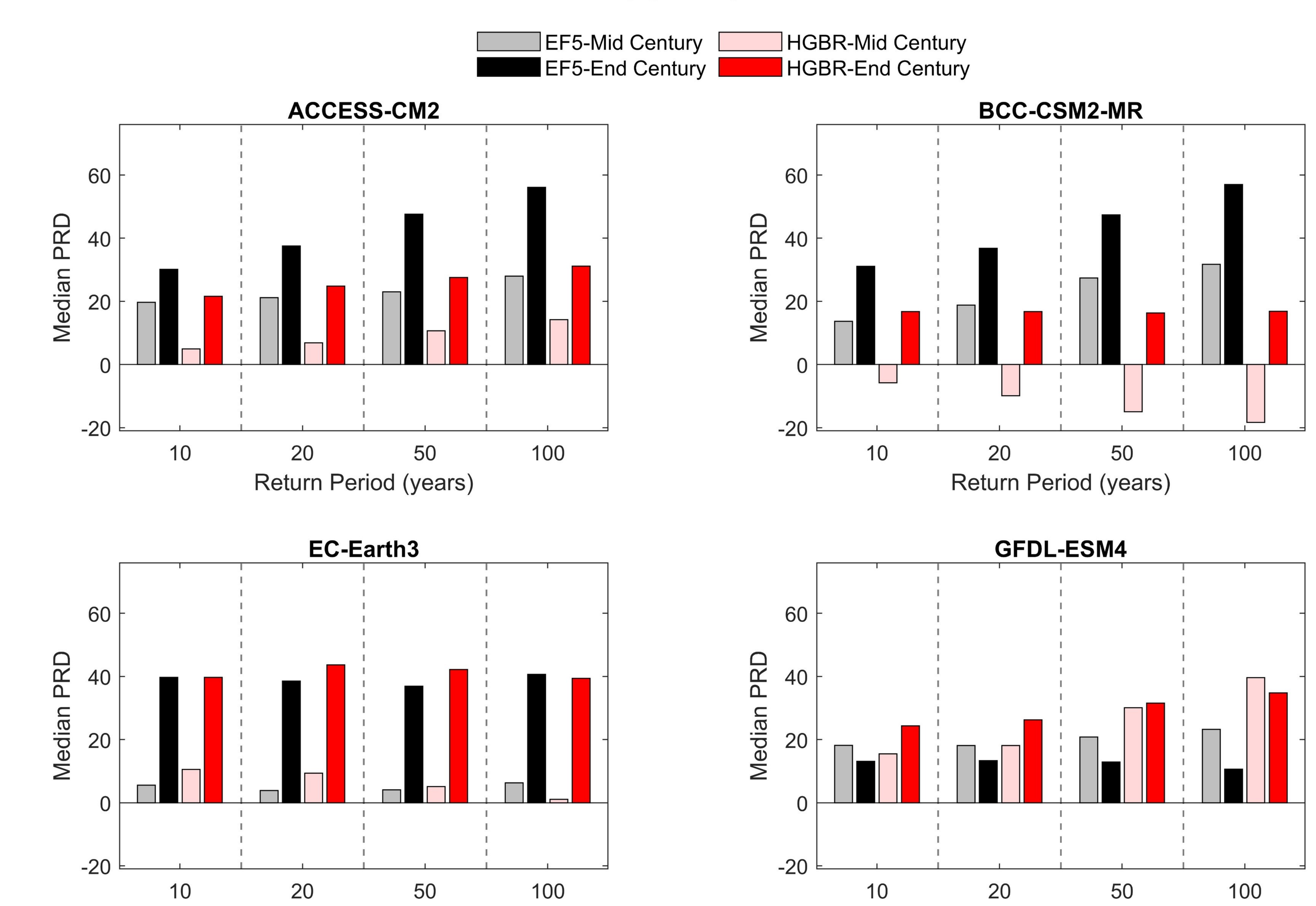

SSP585

CONCLUSIONS

ML models may serve as efficient and proactive tools toward flood prediction and mitigation strategies catering to a changing climate - especially for vulnerable communities that are resource-deficient and data-scarce or ungauged

- ❑ Uncertainty in future flood projections are dominated by climate-forcing uncertainty
- ❑ Some GCMs indicate the greatest percentage flood change as soon as mid-century

REFERENCES & ACKNOWLEDGEMENTS

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- Addor, N., Newman, A. J., Mizukami, N., & Clark, M. P. (2017). The CAMELS data set: catchment attributes and meteorology for large-sample studies. Hydrology and Earth System Sciences, 21(10), 5293–5313. https://doi.org/10.5194/hess-21-5293-2017
- Chen, M., Shi, W., Xie, P., Silva, V. B. S., Kousky, V. E., Higgins, R. W., & Janowiak, J. E. (2008). Assessing objective techniques for gauge-based analyses of global daily precipitation. Journal of Geophysical Research: Atmospheres, 113(D4). https://doi.org/10.1029/2007jd009132
- CPC Global Unified Gauge-Based Analysis of Daily Precipitation data provided by the NOAA PSL, Boulder, Colorado, USA, https://psl.noaa.gov. DATA RETRIEVED: June-September, 2024
- Flamig, Z.L., Vergara, H. and Gourley, J.J., 2020. The ensemble framework for flash flood forecasting (EF5) v1. 2: Description and case study. Geoscientific Model Development, 13(10), pp.4943-4958.
- Hu, L., Nikolopoulos, E.I., Marra, F., Anagnostou, E.N., 2020. Sensitivity of flood frequency analysis to data record, statistical model, and parameter estimation methods: An evaluation over the contiguous United States. J. Flood Risk Manag. 13 (1). https://doi.org/10.1111/jfr3.12580.
- Huffman, G.J., E.F. Stocker, D.T. Bolvin, E.J. Nelkin, Jackson Tan (2019), GPM IMERG Early Precipitation L3 Half Hourly 0.1 degree x 0.1 degree V06, Greenbelt, MD, Goddard Earth Sciences Data and Information Services Center (GES DISC), Accessed: [01-APR-2022], 10.5067/GPM/IMERG/3B-HH-E/06
- Kratzert, F., Klotz, D., Shalev, G., Klambauer, G., Hochreiter, S., & Nearing, G. (2019). Towards learning universal, regional, and local hydrological behaviors via machine learning applied to large-sample datasets. Hydrology and Earth System Sciences, 23(12), 5089–5110. https://doi.org/10.5194/hess-235089-2019
- Muñoz Sabater, J., (2021): ERA5-Land hourly data from 1950 to 1980. Copernicus Climate Change Service (C3S) Climate Data Store (CDS). (Accessed on Jun-Aug., 2022), 10.24381/cds.e2161bac
- Newman, A. J., Clark, M. P., Sampson, K., Wood, A., Hay, L. E., Bock, A., Viger, R. J., Blodgett, D., Brekke, L., Arnold, J. R., Hopson, T., & Duan, Q. (2015). Development of a large-sample watershed-scale hydrometeorological data set for the contiguous USA: data set characteristics and assessment of regional variability in hydrologic model performance. Hydrology and Earth System Sciences, 19(1), 209–223. https://doi.org/10.5194/hess-19-209-2015
- Pierce, D. W., D. R. Cayan, E. P. Maurer, J. T. Abatzoglou, and K. C. Hegewisch, 2015: Improved bias correction techniquesx for hydrological simulations of climate change. J. Hydrometeorology, v. 16, p. 2421-2442. DOI: http://dx.doi.org/10.1175/JHM-D-14-0236.1
- Rasheed, Z., Aravamudan, A., Sefidmazgi, A.G., Anagnostopoulos, G.C., Nikolopoulos, E. I., 2022. Advancing flood warning procedures in ungauged basins with machine learning. J. Hydrol. 609, 127736. https://doi.org/10.1016/j.jhydrol.2022.127736.
- Rasheed, Z., Aravamudan, A., Zhang, X., Anagnostopoulos, G. C., & Nikolopoulos, E. I. (2024). Combining global precipitation data and machine learning to predict flood peaks in ungauged areas with similar climate. Advances in Water Resources, 192, 104781. https://doi.org/10.1016/j.advwatres.2024.104781
- Thornton, M.M., R. Shrestha, Y. Wei, P.E. Thornton, and S-C. Kao. 2022. Daymet: Daily Surface Weather Data on a 1-km Grid for North America, Version 4 R1. ORNL DAAC, Oak Ridge, Tennessee, USA. https://doi.org/10.3334/ORNLDAAC/2129
- Xie, P., A. Yatagai, M. Chen, T. Hayasaka, Y. Fukushima, C. Liu, and S. Yang (2007), A gauge-based analysis of daily precipitation over East Asia, J. Hydrometeorol., 8, 607. 626.
- Zhang, Jian et al. (2016). MULTI-RADAR MULTI-SENSOR (MRMS) QUANTITATIVE PRECIPITATION ESTIMATION Initial Operating Capabilities. 97(4). https://doi.org/10.1175/bams-d-14-00174.1

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