

An early warning indicator of hydrological drought for enhancing reservoir operation rules

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INTRODUCTION & AIM

Drought monitoring and early warning are critical for managing water resources and mitigating hydrological risks in Mediterranean basins. Traditional meteorological indicators such as the Standardized Precipitation Index (SPI) capture short-term rainfall variability but often fail to represent soil and hydrological conditions that control water availability (Sadri et al., 2018).

The Joint Drought Index (JDI) offers an integrated framework for drought assessment by merging precipitation and soil moisture anomalies into a single probabilistic indicator, similar to the approach proposed by Monteleone et al. (2021) using VHI. In this study, we assess the JDI's ability to predict streamflow deficits using two soil moisture sources: Copernicus satellite-derived data and DREAM model outputs.

Tab 1. Main Characteristics of the Reservoir

Reservoir Characteristics	
Year of completion	1968
River basin	F. Basento
Catchment area	350 km ²
Purpose	Multipurpose (irrigation, flood control, water supply)
Dam height	54 m
Crest elevation	536.6 m a.s.l.
Total storage	28.9 × 10 ⁶ m ³
Useful storage	23.6 × 10 ⁶ m ³
Flood control volume	5.2 × 10 ⁶ m ³
Max water level	534.6 m a.s.l.
Surface area (max)	1.82 km ²
Max discharge capacity	1.100 m ³ /s

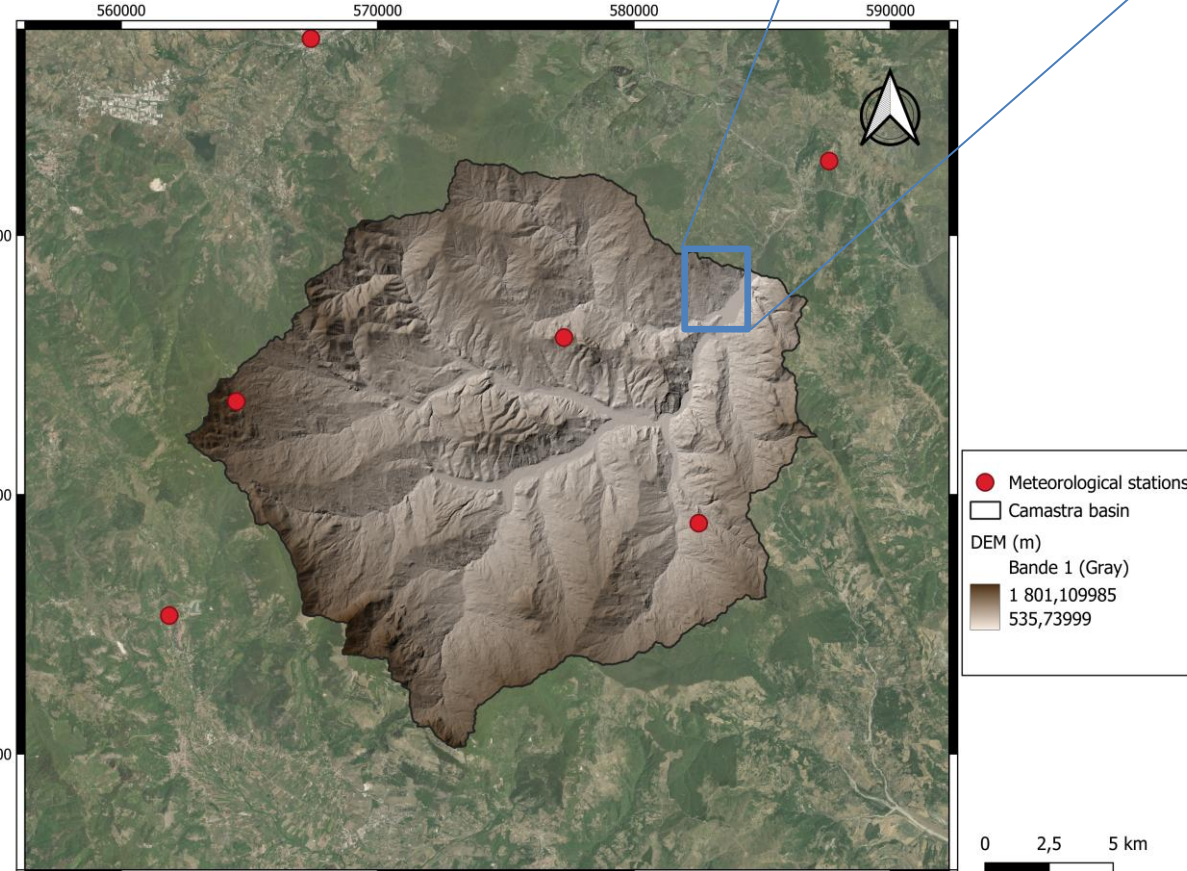


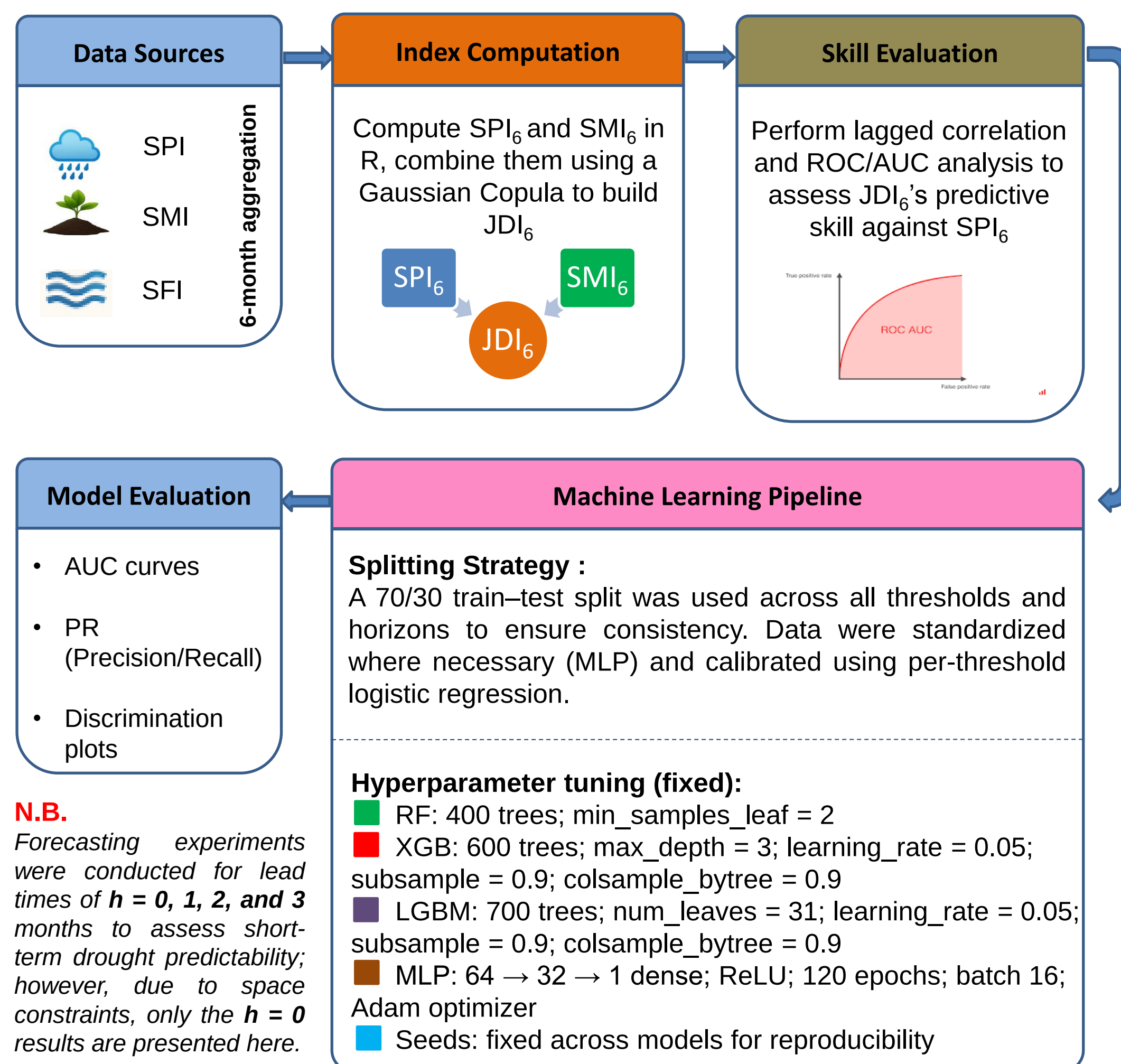
Fig 1. Location of Camastra basin and Camastra Reservoir (*)

METHOD

Meteorological, soil moisture, and discharge data were combined to assess drought propagation and early-warning performance using the Joint Drought Index (JDI).

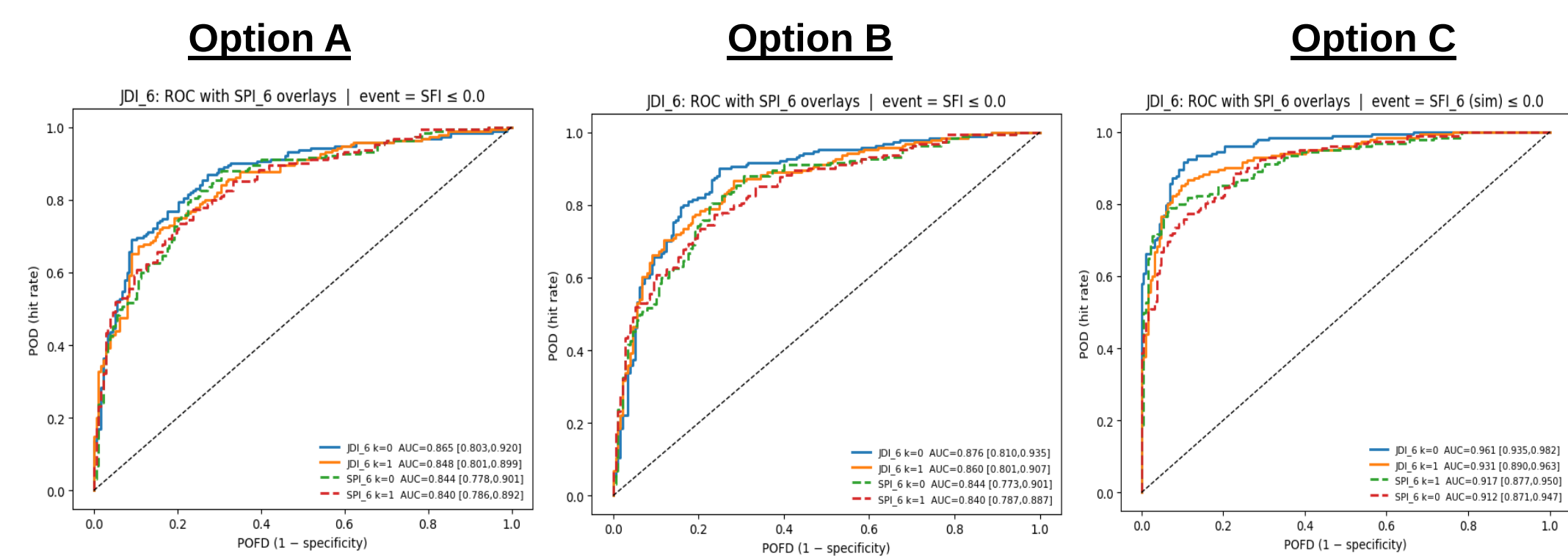
Three configurations of JDI₆ were tested to evaluate how different soil moisture sources and discharge datasets influence drought prediction skill. In **Option A**, JDI₆ was built using Copernicus soil moisture combined with observed streamflow (SFI). **Option B** used DREAM-derived soil moisture with the same observed discharge data, while **Option C** relied entirely on the DREAM model, employing both simulated soil moisture and streamflow to ensure full physical consistency within the modeling chain.

The workflow included five main stages:



N.B. Forecasting experiments were conducted for lead times of $h = 0, 1, 2$, and 3 months to assess short-term drought predictability; however, due to space constraints, only the $h = 0$ results are presented here.

RESULTS & DISCUSSION



The three JDI₆ configurations highlight the influence of soil moisture and discharge data sources on drought early-warning skill.

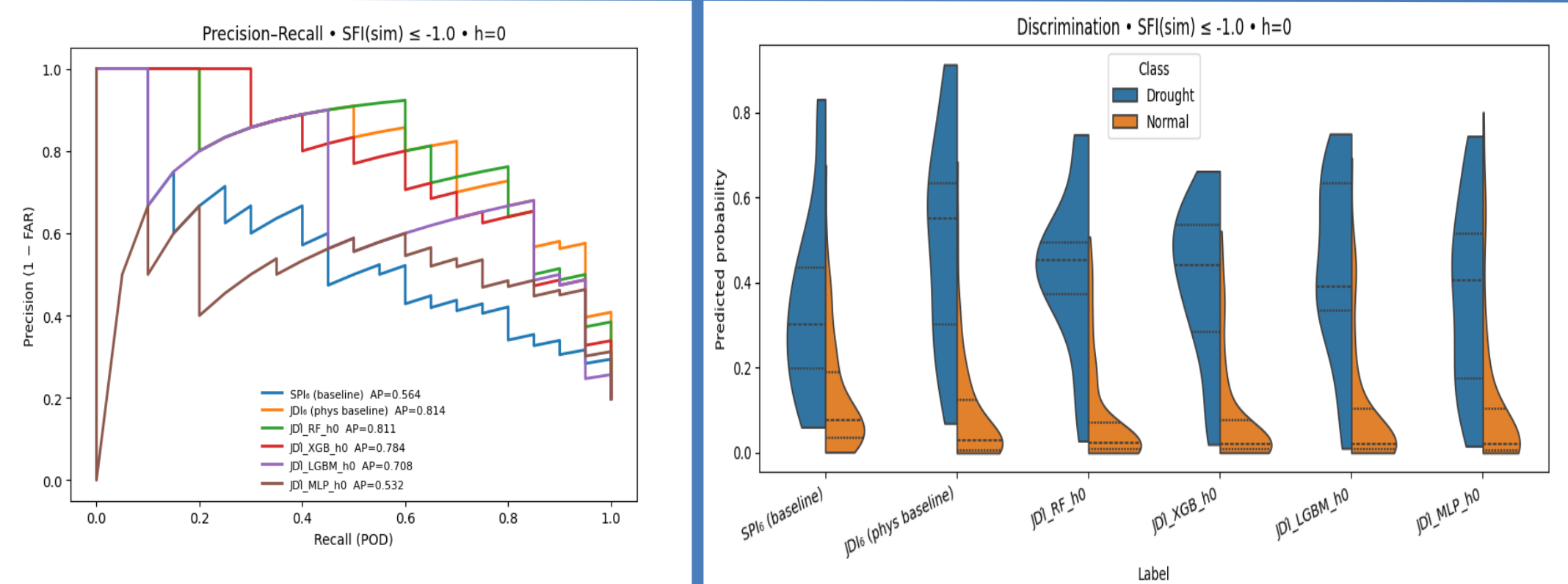
•**Option A (Copernicus + observed SFI):** JDI₆ shows slightly higher skill than SPI₆, mainly for mild droughts.

•**Option B (DREAM + observed SFI):** Overall correlation and AUC values increase, indicating stronger soil–streamflow coupling.

•**Option C (DREAM + simulated SFI):** JDI clearly dominates across thresholds. Typical AUCs are around 0.95 for (SFI₆ ≤ 0), 0.93 for (SFI₆ ≤ −1), 0.96 for (SFI₆ ≤ −1.5), and 0.99 at the rare SFI₆ ≤ −2 tail, it outperforms in every scenario the previous two options and SPI only results.

Takeaway: The DREAM JDI₆ configuration delivers the highest predictive skill, improving early drought detection and serving as the foundation for ML forecasting.

Machine learning models provided a modest performance improvement, particularly for RF and XGB. At $h = 0$, both RF and XGB achieved results comparable to or slightly below the physical JDI₆ model, with AUC values between 0.92 and 0.94, while LGBM showed similar accuracy and MLP performed less effectively. At $h = 1$, RF slightly outperformed physical JDI₆ at the −1 threshold (**AUC = 0.946 vs 0.931**), though for threshold = 0, the physical JDI₆ model remained the best performer.



The Precision–Recall curves confirm that JDI₆-based ML models outperform the SPI₆ baseline, especially for rarer drought events. RF and XGB achieve the highest average precision (**0.784 < AP < 0.811**), closely matching the physical JDI₆ baseline (**AP = 0.814**), while MLP performs less effectively.

All models display a clear separation between drought and normal conditions, with RF and XGB achieving the most distinct class differentiation. The physical JDI₆ baseline already performs well, but ML models slightly enhance discrimination, indicating improved reliability in probabilistic drought classification.

CONCLUSION

The Joint Drought Index (JDI) effectively integrates precipitation and soil moisture signals, improving drought early-warning skill—especially with DREAM soil data.

Machine learning models (RF, XGB) further enhance short-term drought forecasts, confirming the value of combining physical indices with data-driven methods for operational monitoring.

REFERENCES

- Sadri S., Wood E. F. & Pan M. (2018). *Developing a drought-monitoring index for the contiguous US using SMAP*. Hydrology and Earth System Sciences, 22, 6611–6626.
- Monteleone B, Bonaccorso B, Martina M (2020) A joint probabilistic index for objective drought identification: the case study of Haiti. Nat Hazards Earth Syst Sci 20:471–487