Evaluation of Probabilistic Forecasts of Consecutive Days Without Measurable Rainfall Over Taiwan

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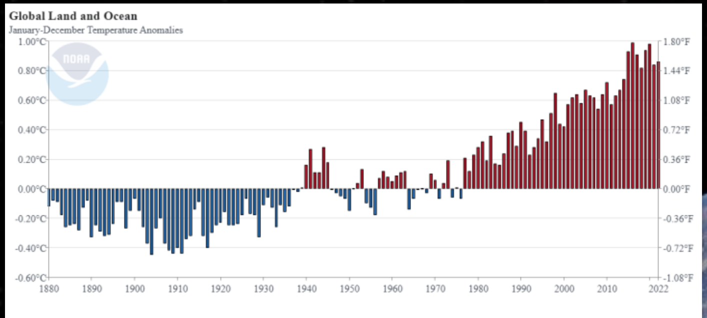
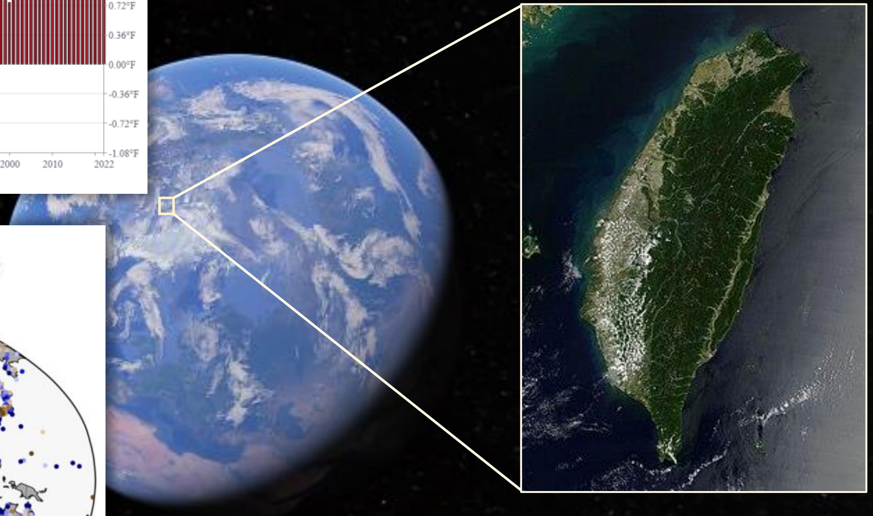
Background Knowledge

It's an indisputable fact that global warming is causing severe climate change.



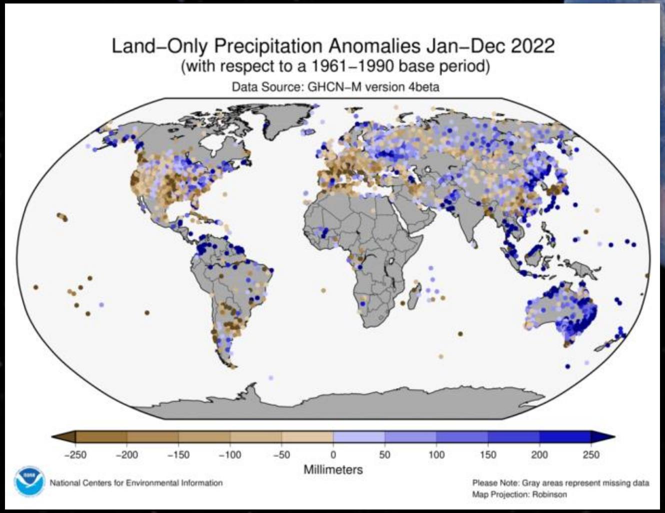
Temperature

Taiwan | complex terrains
unique geographical location



Seasonal characteristics of rainfall in Taiwan

- Summer (Jul-Sep)
  convectional, typhoon rainfall
- Winter (Oct-Apr)
  frontal rainfall (cold front)
- Mei-Yu (May-Jun)
  frontal rainfall (stationary front)



Precipitation

- *extreme precipitation*
- *drought*

ref.: https://www.ncei.noaa.gov/access/monitoring/monthly-report/global/202213

what — *past*

livestock industry in Taiwan

Predicament

Taiwan is suitable for cultivating tropical grass, but during the winter, it is prone to experiencing slow growth.

Goal

It's possible to harvest and process the grass into hay when its yield is high in the summer.

Challenge

In the process of preparing hay, excessive rainfall can lead to mold formation on the grass.

ref.: https://eng.moa.gov.tw/ws.php?id=9162

how — *present*

EPS

Purpose

Assist in weather-related behavioral decision-making

Forecasts of Consecutive Days Without Measurable Rainfall

⇩

Probabilistic Forecasts (calibrated)

⇩

Evaluation

Evaluation of Probabilistic Forecasts of Consecutive Days Without Measurable Rainfall Over Taiwan

why — *future*

cross-field cooperation
environment resilient

Predicament

Taiwan's major grass import countries also face extreme drought conditions leading to insufficient grass yields.

Goal (challenge)

Supported domestic production of grass and silages to increase domestic fodder supply and quality

Methodology

Statistical Post-Processing for calibrating | **Analog Post-processing (AP)**

Current forecast

single forecast
ensemble mean

pattern matching

historical forecast $_1$ ⇒ historical observation $_1$

historical forecast $_2$ ⇒ historical observation $_2$

historical forecast $_3$ ⇒ historical observation $_3$

⋮ ⋮

historical forecast $_{20}$ ⇒ historical observation $_{20}$

fct-to-obs correspondence

calibrated ensemble members

Similarity (Schefzik 2016)

variable: accumulated rainfall

$$\Delta^{t_d}(x^t, x^{t_d}) = \sqrt{\frac{1}{L}\sum_{l=1}^{L}(\bar{x}^{l,t} - \bar{x}^{l,t_d})^2 + \frac{1}{L}\sum_{l=1}^{L}(s^{l,t} - s^{l,t_d})^2}$$

$\bar{x}$: ensemble mean s : ensemble spread

Observation & Forecast Data

Variable: precipitation

Verification period: Jan 2000 - Dec 2019

	Data source	Spatial resolution	Update frequency	Forecast time length (output frequency)
Observation	**precipitation grid analysis** (produced by CWB)	1 km	daily	
Forecast	**GEFS v12 Re-forecast** (10 members without control run on Wednesday)	0.5 deg	4 times (00/06/12/18 UTC)	0-840 hour (6-hourly)

threshold of
consecutive days without measurable rainfall

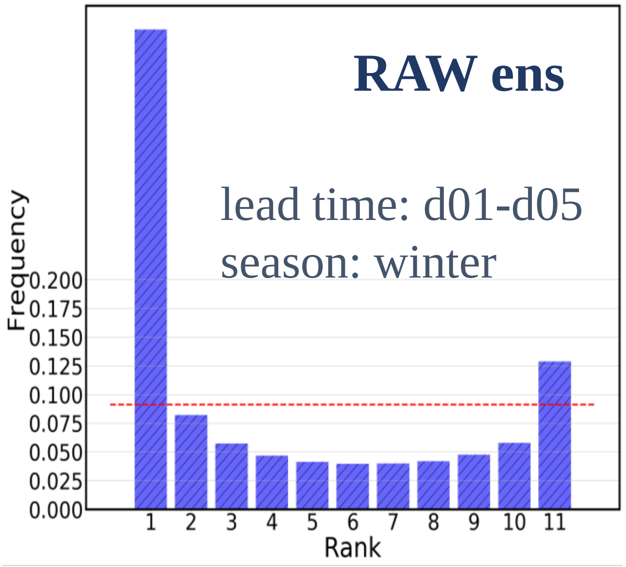
probabilistic forecast

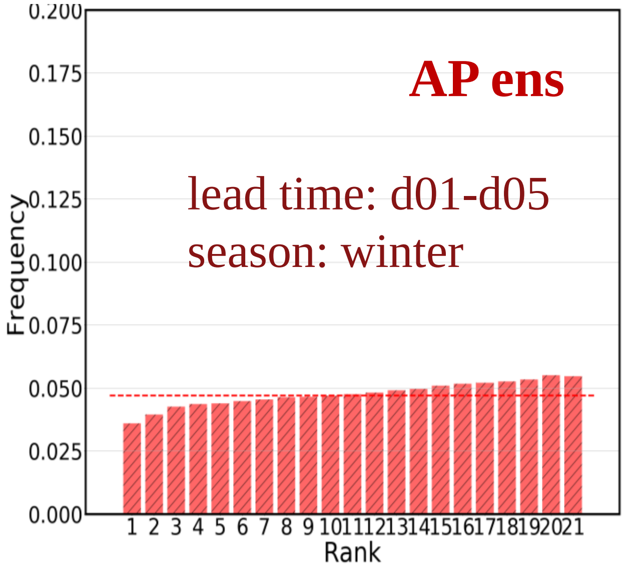
Results

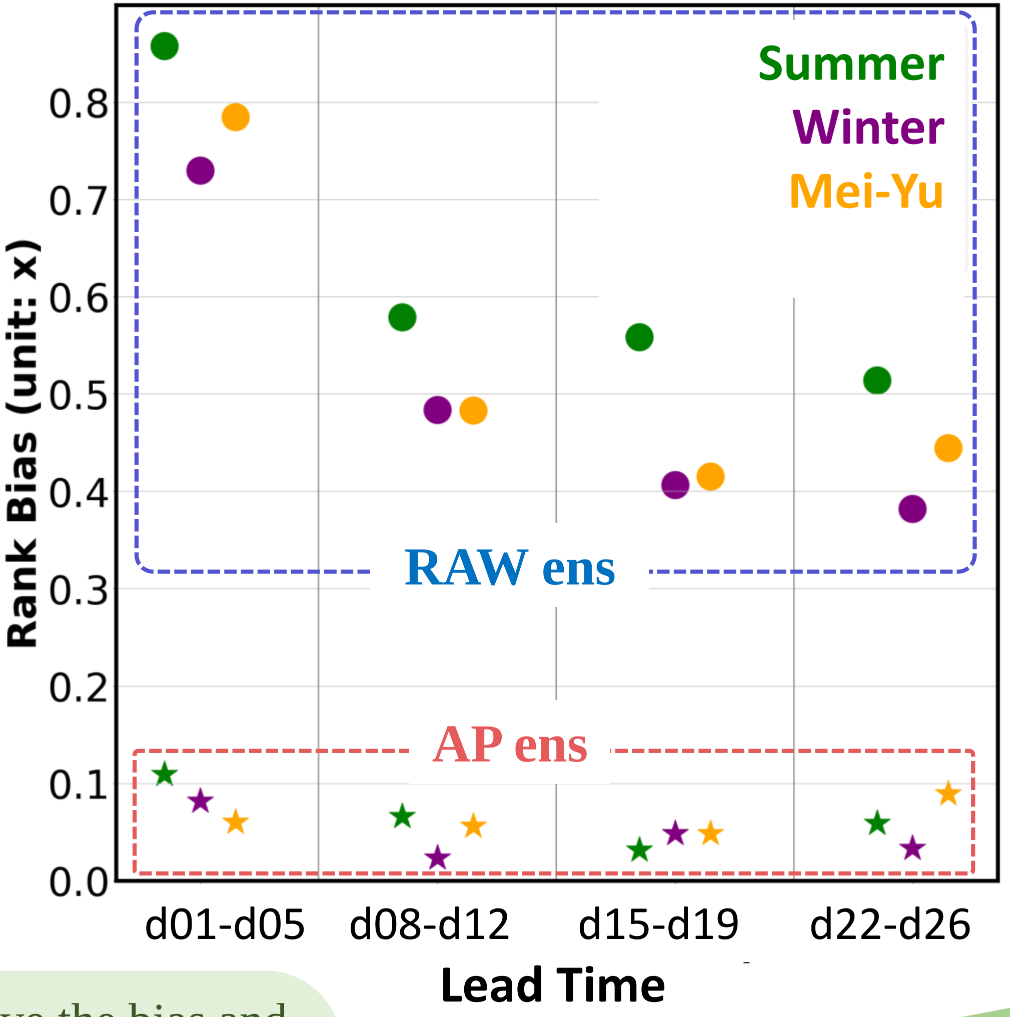
- **ensemble quality of EPS**
- **reliability and discrimination of probabilistic forecast**
- **forecast value**

Results | ensemble quality

variable: 5-day accumulative rainfall







Rank histogram — *is the most common approach to evaluating whether a collection of ensemble forecasts for a scalar predictand satisfies the consistency condition.*

Rank bias — *is the sum of the difference from the frequency of actual rank and the ideal situation*

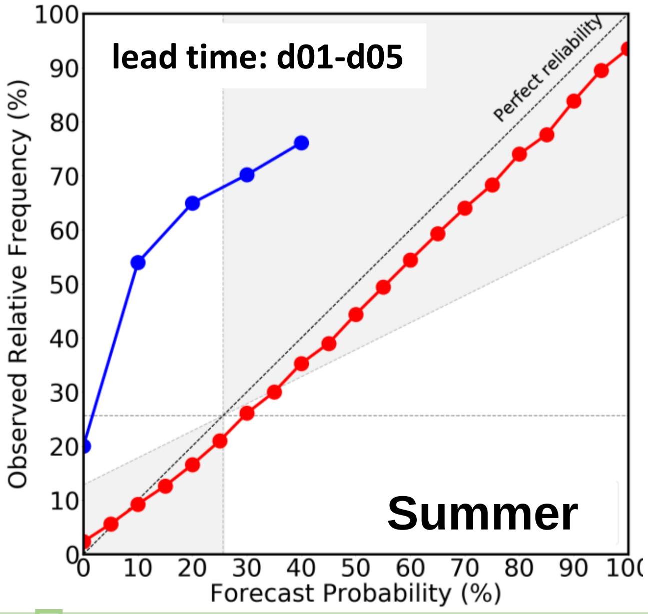
The AP ensemble improve the bias and dispersion of the raw ensemble.

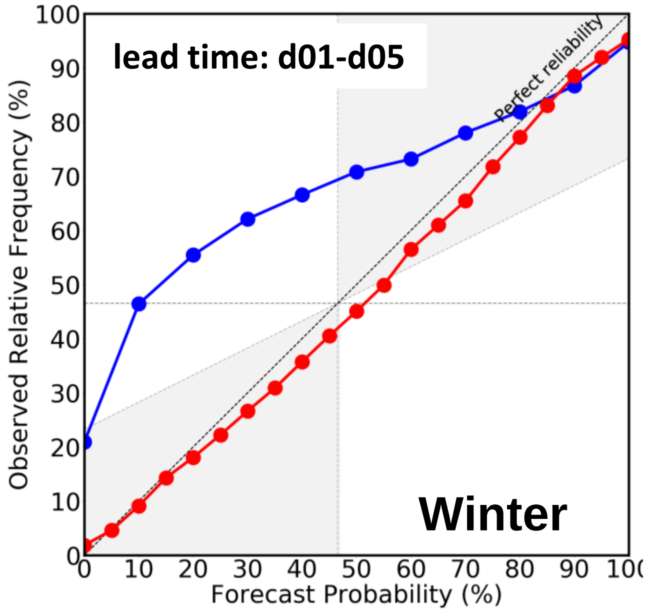
Results | reliability of probabilistic forecasts

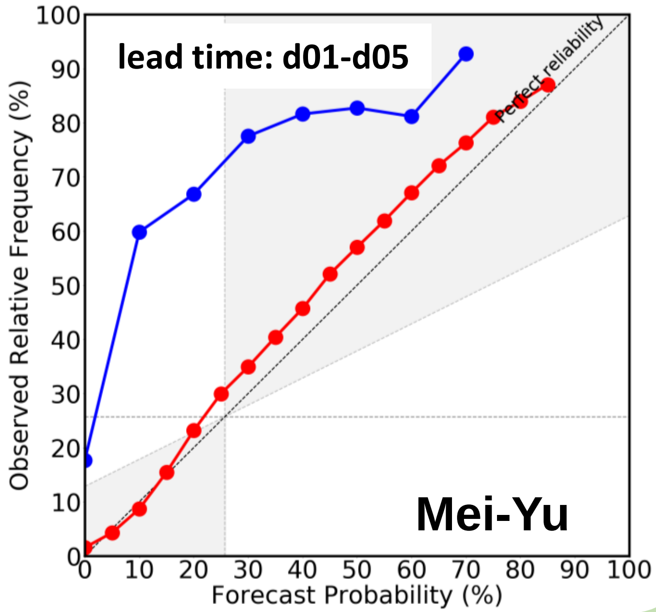
variable: 5-day accumulative rainfall
Threshold: < 3mm/5days

Reliability diagram — *plots the observed frequency against the forecast probability*

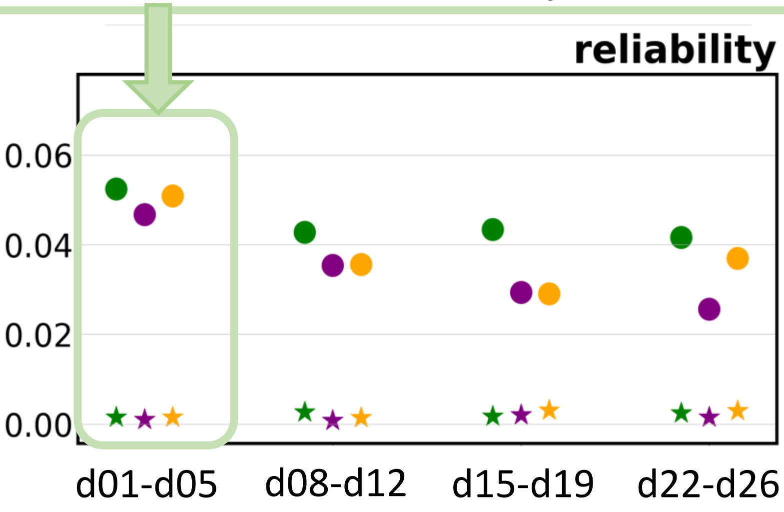
The AP probabilistic forecasts have good reliability.

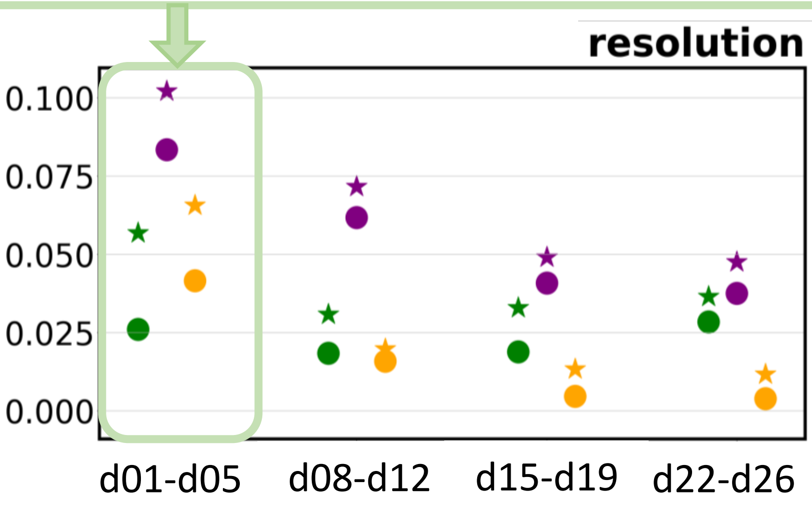






Reliability — *agreement between forecast probability and mean observed frequency*

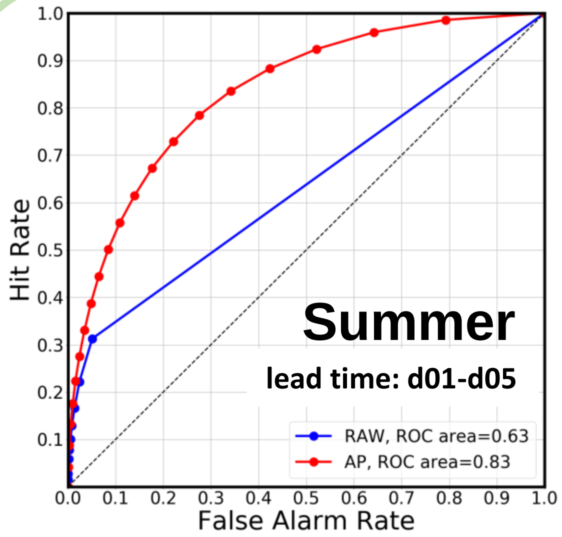


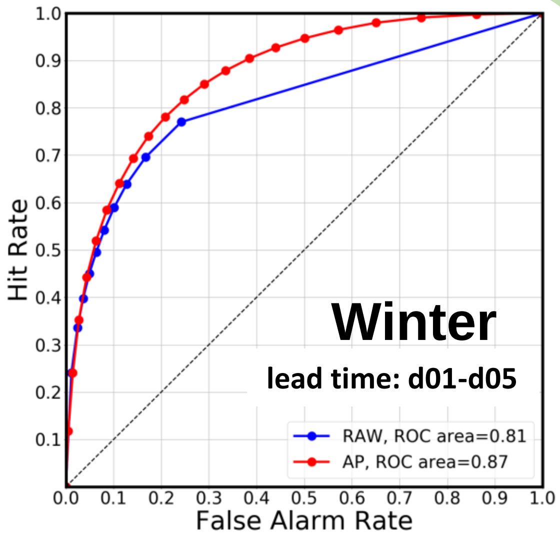


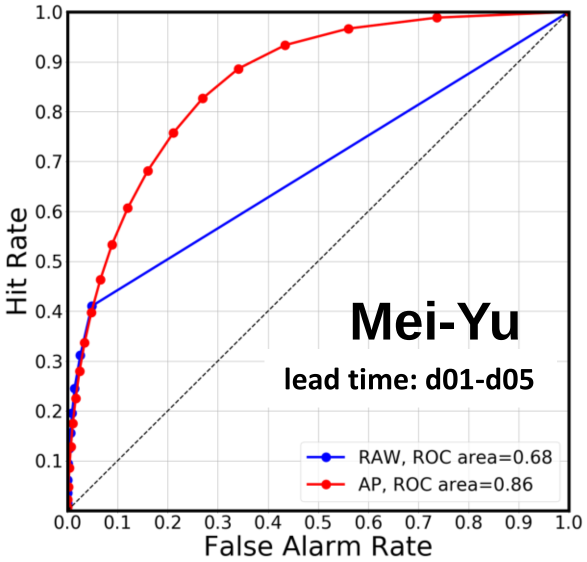
Resolution — *ability of the forecast to resolve the set of sample events into subsets with characteristically different outcomes*

Results | discrimination of probabilistic forecasts

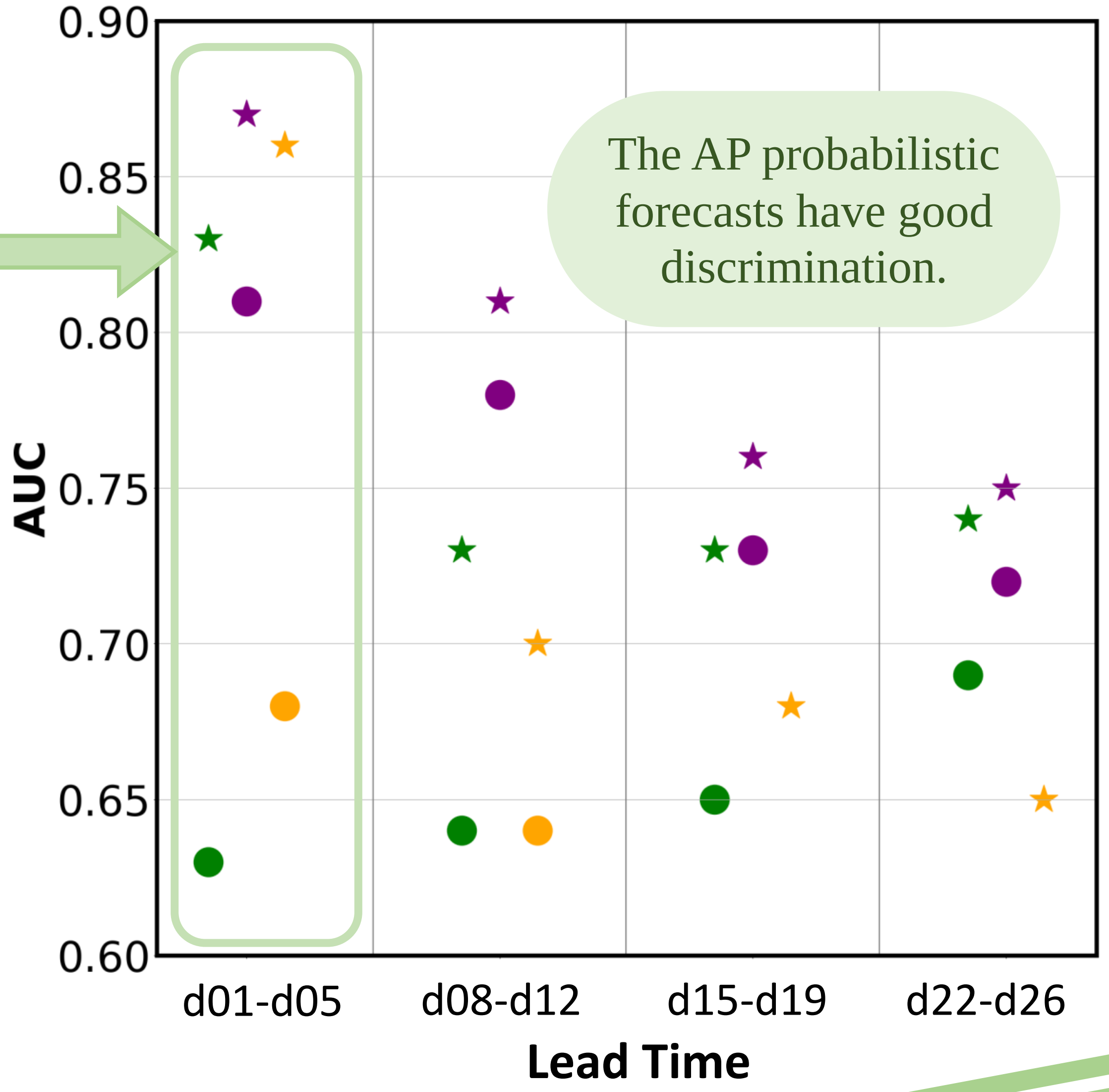
variable: 5-day accumulative rainfall
Threshold: < 3mm/5days







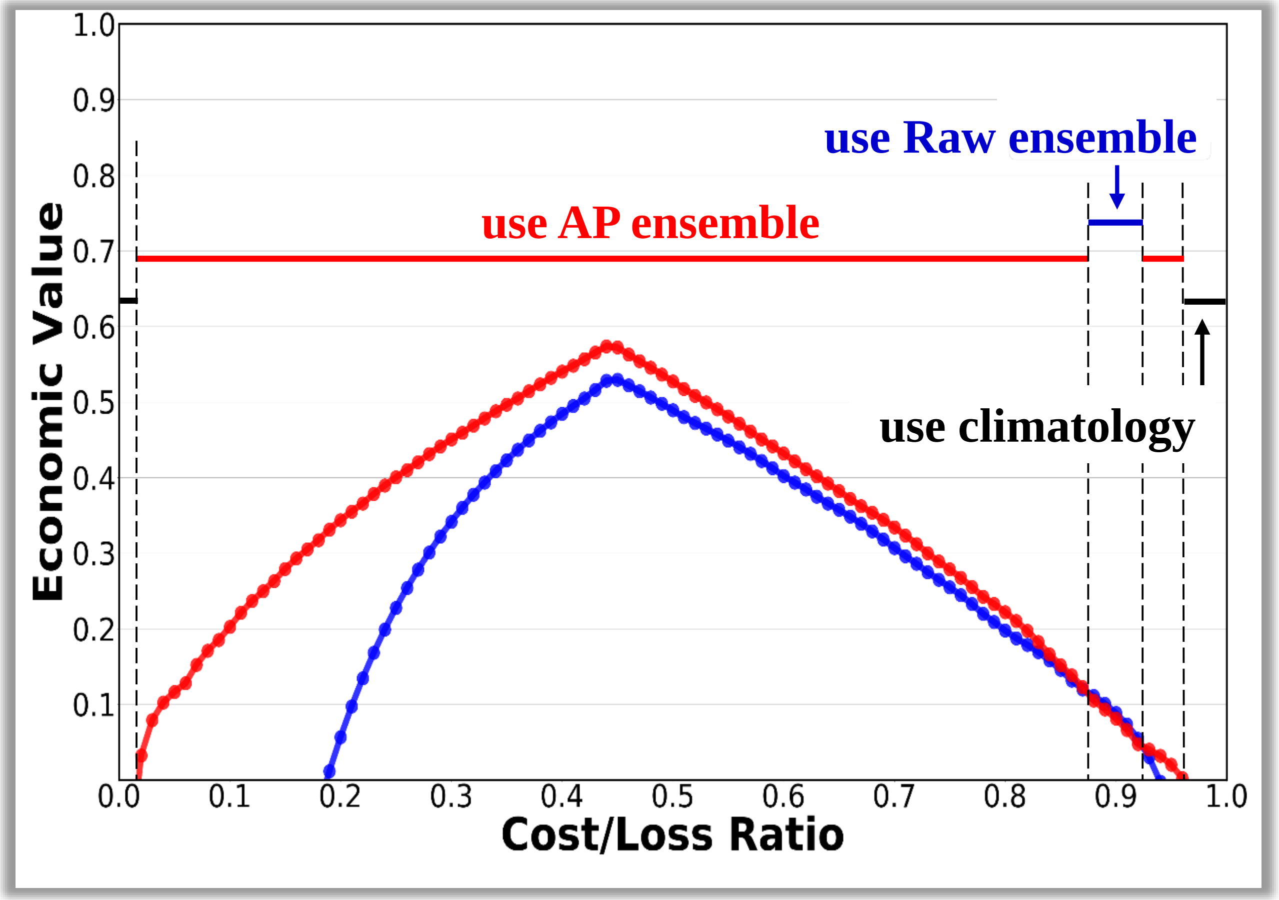
ROC — *plots hit rate (HR) vs false alarm rate (FAR), using a set of increasing probability thresholds to make the yes/no decision*

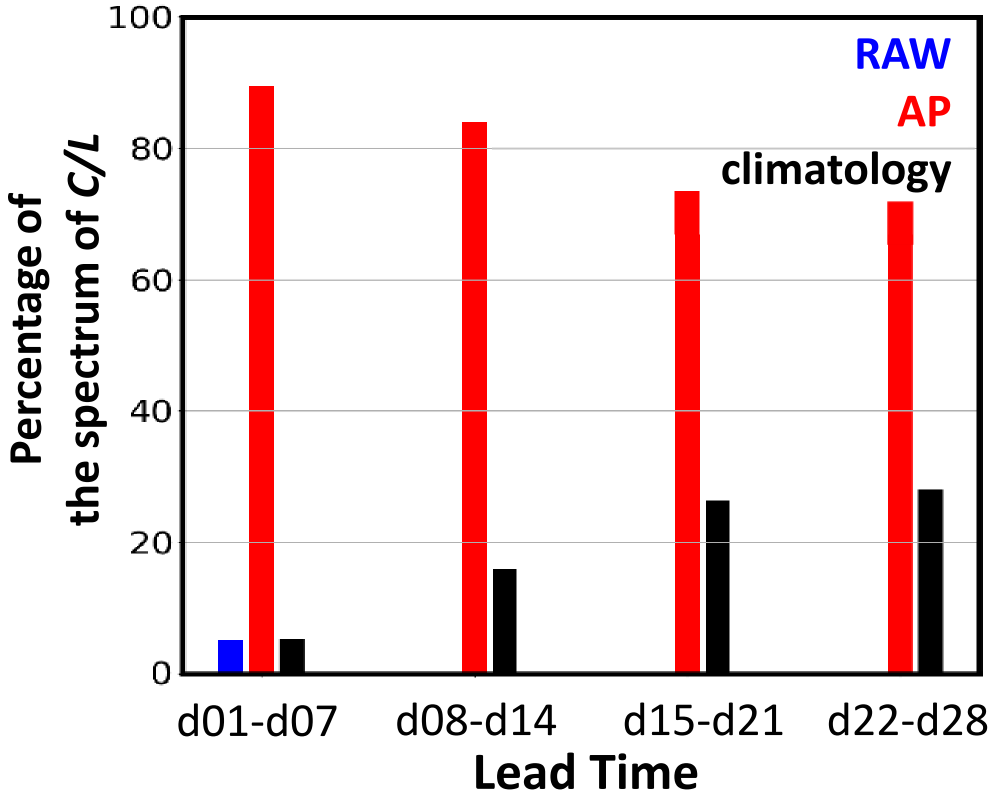


The AP probabilistic forecasts have good discrimination.

Results | relative Economic Value

variable: 7-day accumulative rainfall
Threshold: < 5mm/7days
Season: winter





relative Economic Value — *is a skill score of expected expense, with climatology as the reference forecast.*

The AP ensembles provide **higher** economic value for users with a wider spectrum of cost/loss ratio as compared to the raw forecast.

Summary

The purpose of this study is to generate **calibrated** probabilistic forecasts of consecutive days without measurable rainfall using Analog Post-processing (**AP**) technique:

(1) The AP ensemble improve the bias and dispersion of the raw ensemble

(2) The AP probabilistic forecasts

- have good reliability and discrimination up to four weeks of lead time
- provide higher economic value for a wider range of users as compared to the raw forecast.

Success rate of hay production increased from 60% to 90%, increasing hay production by more than 33%.

Future Opportunities

building resilience through better water management

With any given threshold, the probability forecasts can be derived separately

calibrated probabilistic forecast → forecast information

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Thank you for listening !