Testing a Bayesian Joint Probability modelling approach to bias correct seasonal forecasts for drought risk management in Spain

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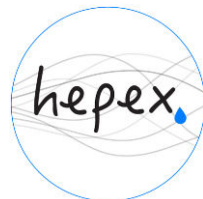[1] IHE Delft for Water Education

[2] Complutense University of Madrid

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1. BACKGROUND

- Climate services create an opportunity to proactive drought risk management
- Essential to identification of **user needs to build user-tailored CS & the potential added value**

Picture of Barrios de Luna reservoir, the main reservoir in the studied region, during the 2017 drought (Martin, 2017)

Orbigo system, Douro River Basin, Spain

Reservoir

0 10 20 30 km
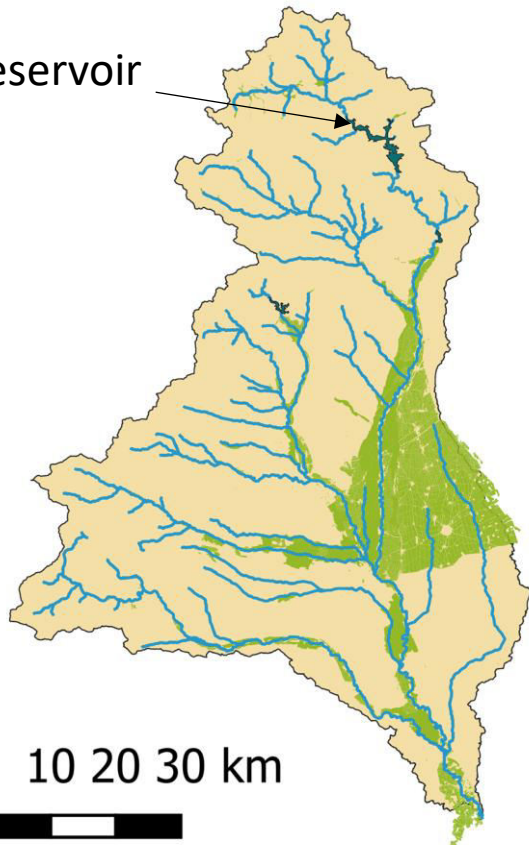
Objective

Value of user-tailored (AI-enhanced) climate services for sustainable drought risk management
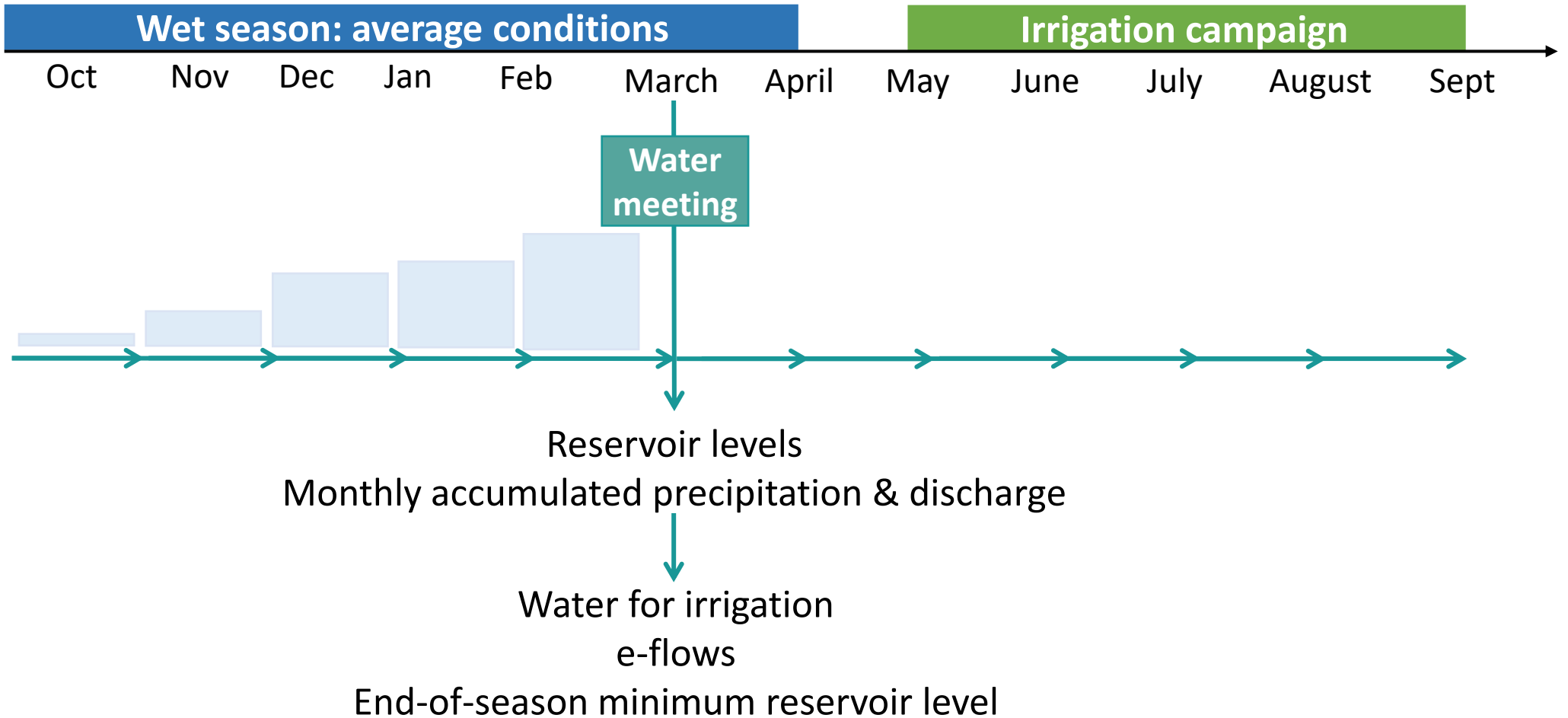
Characteristics

90% water use irrigation vs. **e-flows**
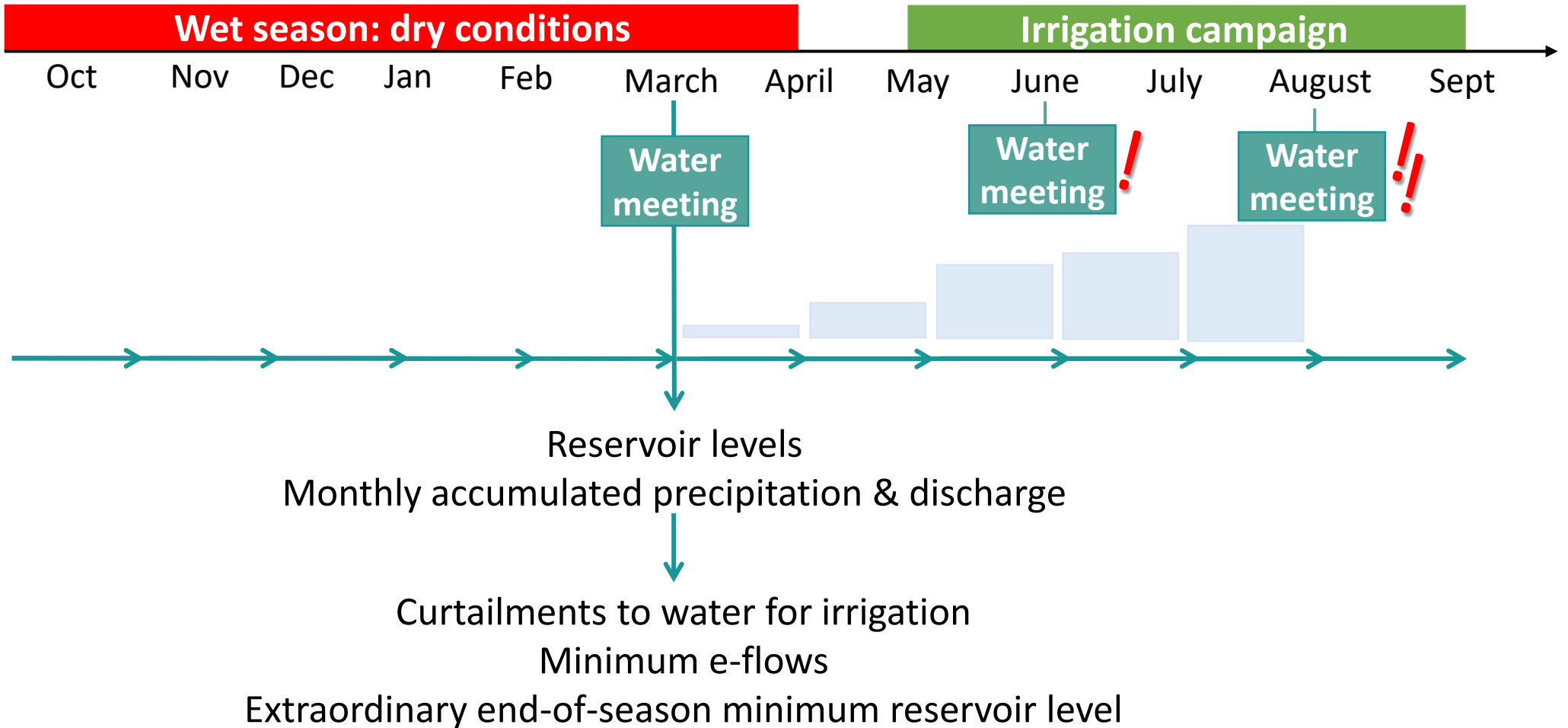
During droughts:

- **Reduction of minimum e-flows**

- **Water curtailments to irrigation**

- **Extraordinary drops of reservoir level**

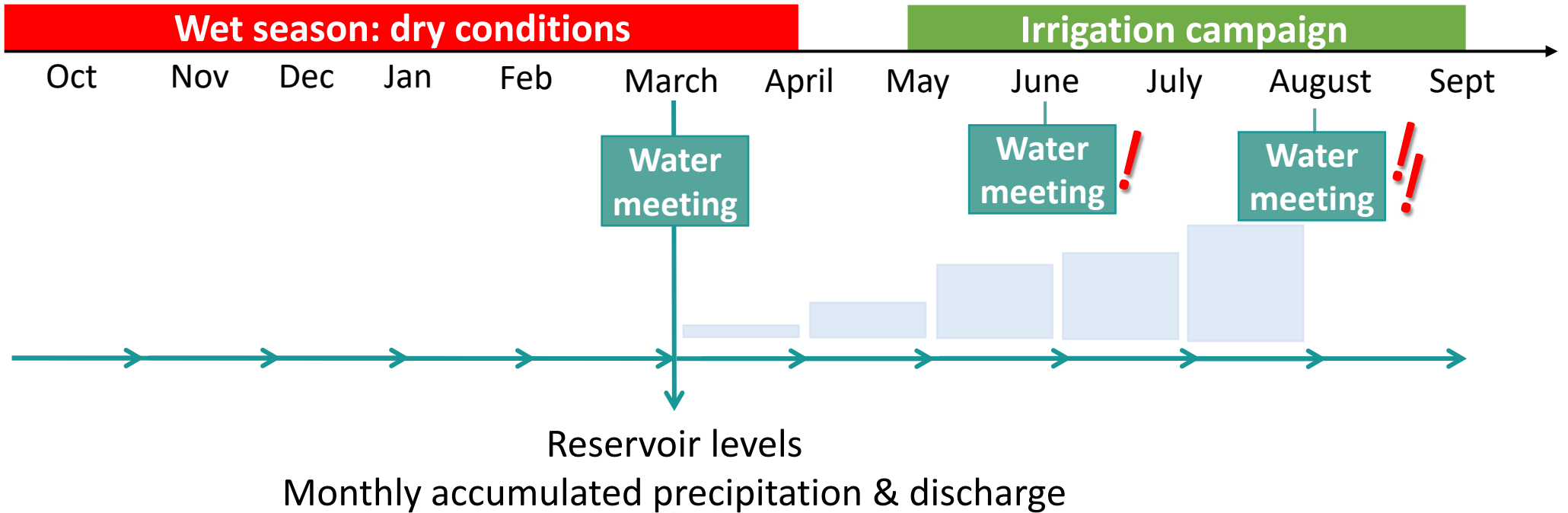**Decisions** based on **drought indicators** that do **not use seasonal forecast**

3. IMPORTANCE OF DECISION-MAKING PROCESS

Wet season: dry conditions

Irrigation campaign

Oct Nov Dec Jan Feb March April May June July August Sept

Water meeting

Water meeting

Water meeting

Reservoir levels
Monthly accumulated precipitation & discharge

Curtailments to water for irrigation
Minimum e-flows
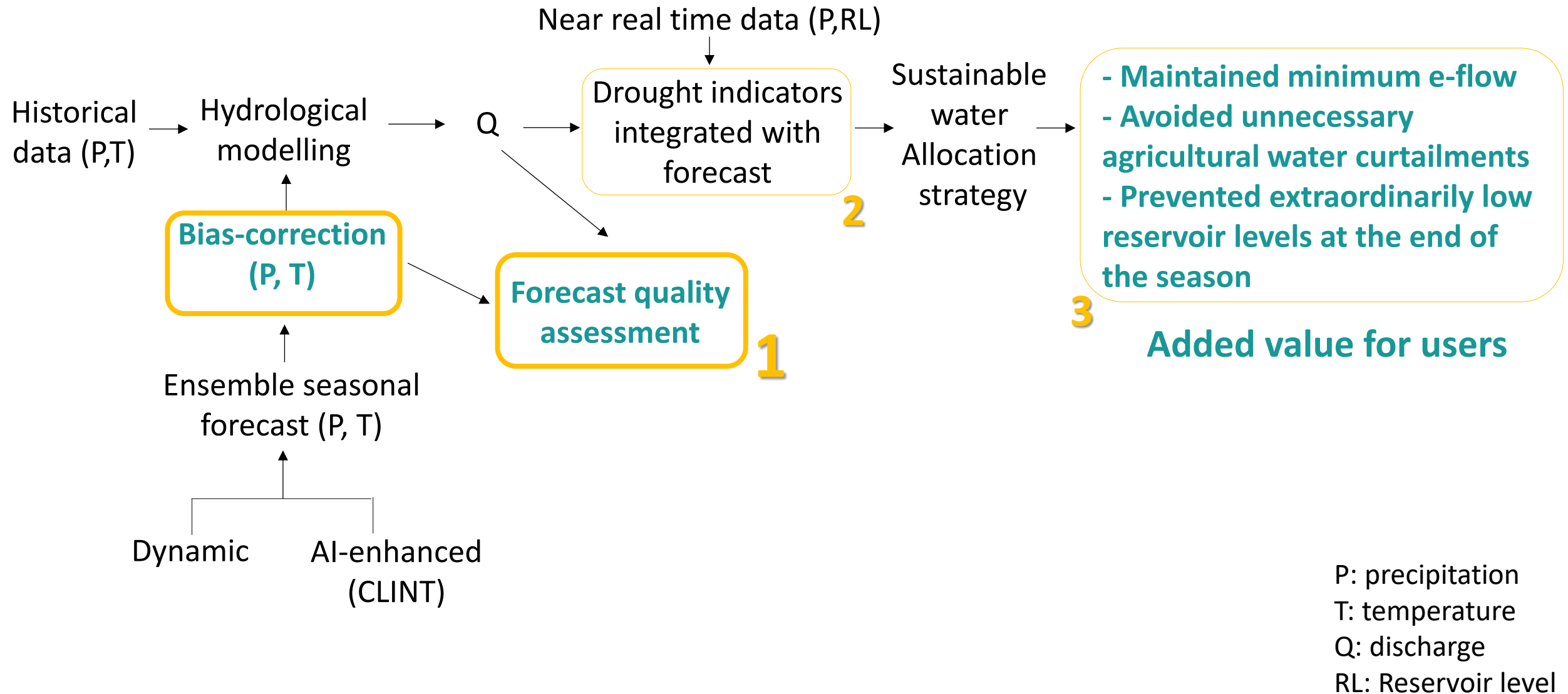Extraordinary end-of-season minimum reservoir level

3. IMPORTANCE OF DECISION-MAKING PROCESS

- Limited capacity of existing drought indicators to trigger **anticipatory actions**
- **Competition** between e-flows and agricultural water uses
- User's trust on their current hydrological model & skepticism to forecasts
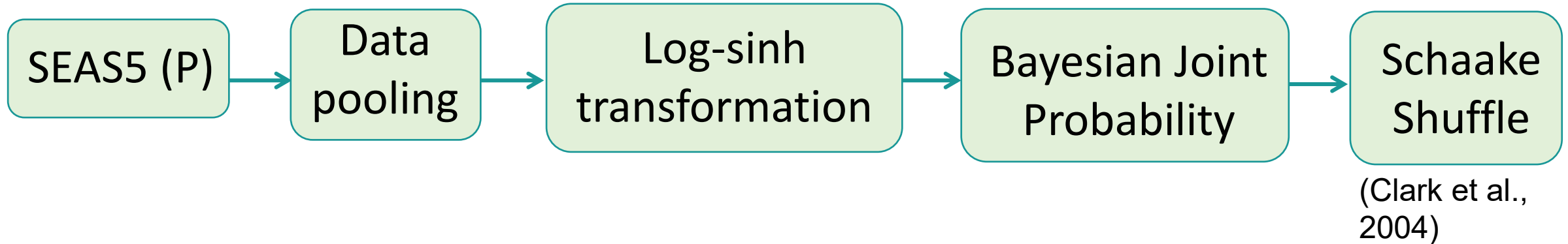- Differences between data needs in terms of modelling and user's needs

Near real time data (P,RL)

Historical data (P,T) → Hydrological modelling → Q → Drought indicators integrated with forecast → Sustainable water Allocation strategy →

Bias-correction (P, T)

Forecast quality assessment **1**

Ensemble seasonal forecast (P, T)

Dynamic   AI-enhanced (CLINT)

2

- **Maintained minimum e-flow**
- **Avoided unnecessary agricultural water curtailments**
- **Prevented extraordinarily low reservoir levels at the end of the season**

3

Added value for users

P: precipitation
T: temperature
Q: discharge
RL: Reservoir level

BJP approach (Schepen et al. 2018)

- BJP considers correlation between forecasts & observations
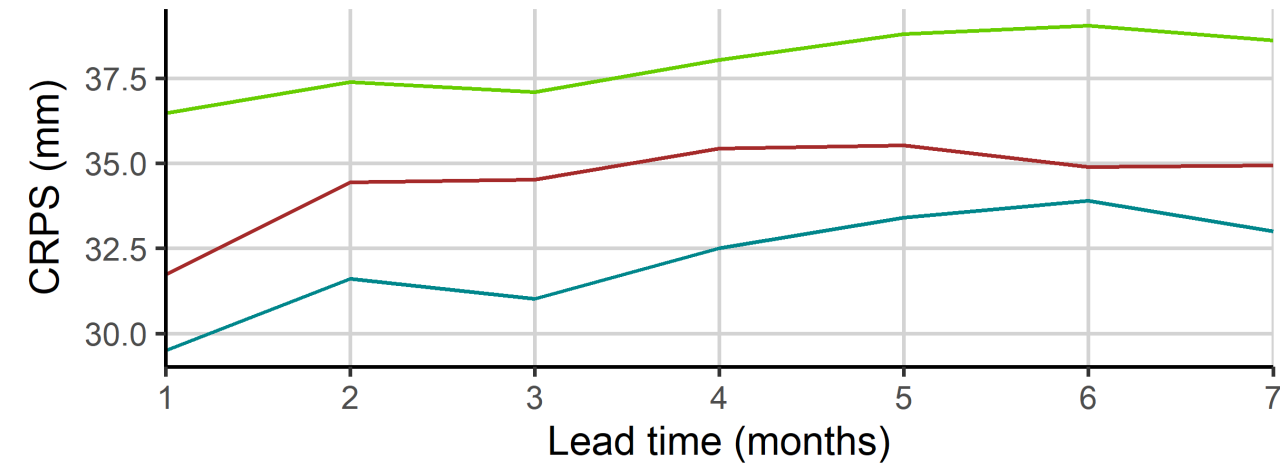- It provides good results for accumulated total and intra-seasonal aggregations

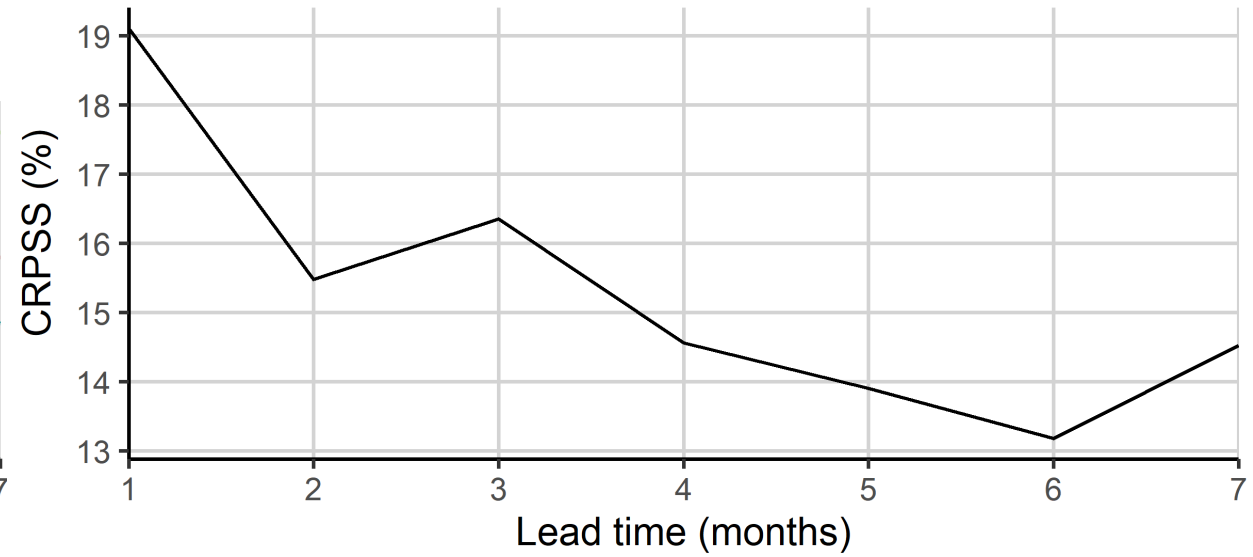SEAS5 (P) → Data pooling → Log-sinh transformation → Bayesian Joint Probability → Schaake Shuffle
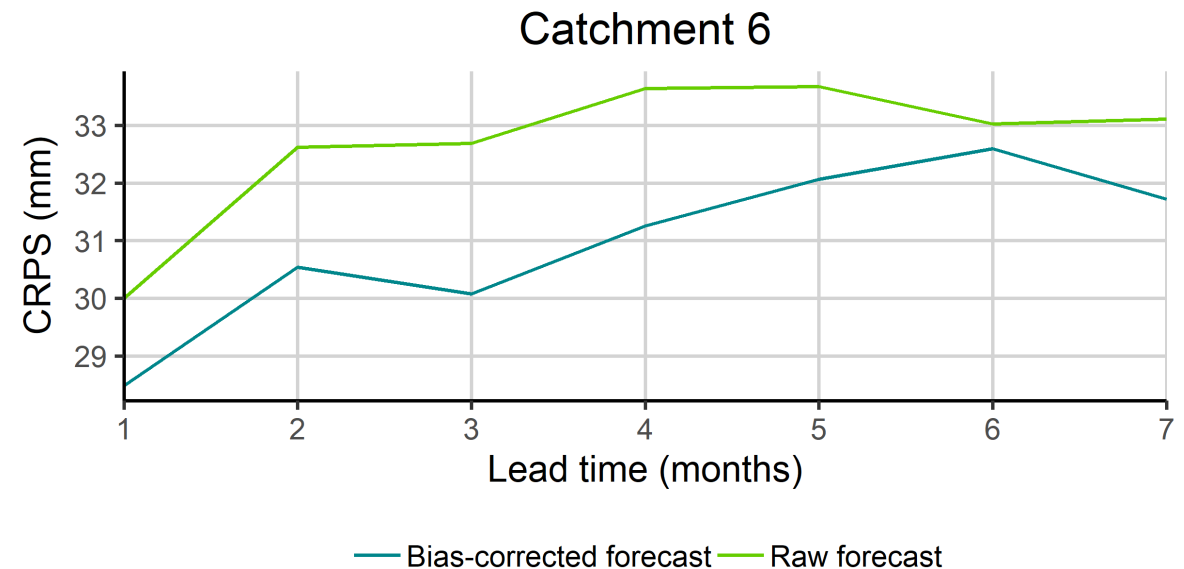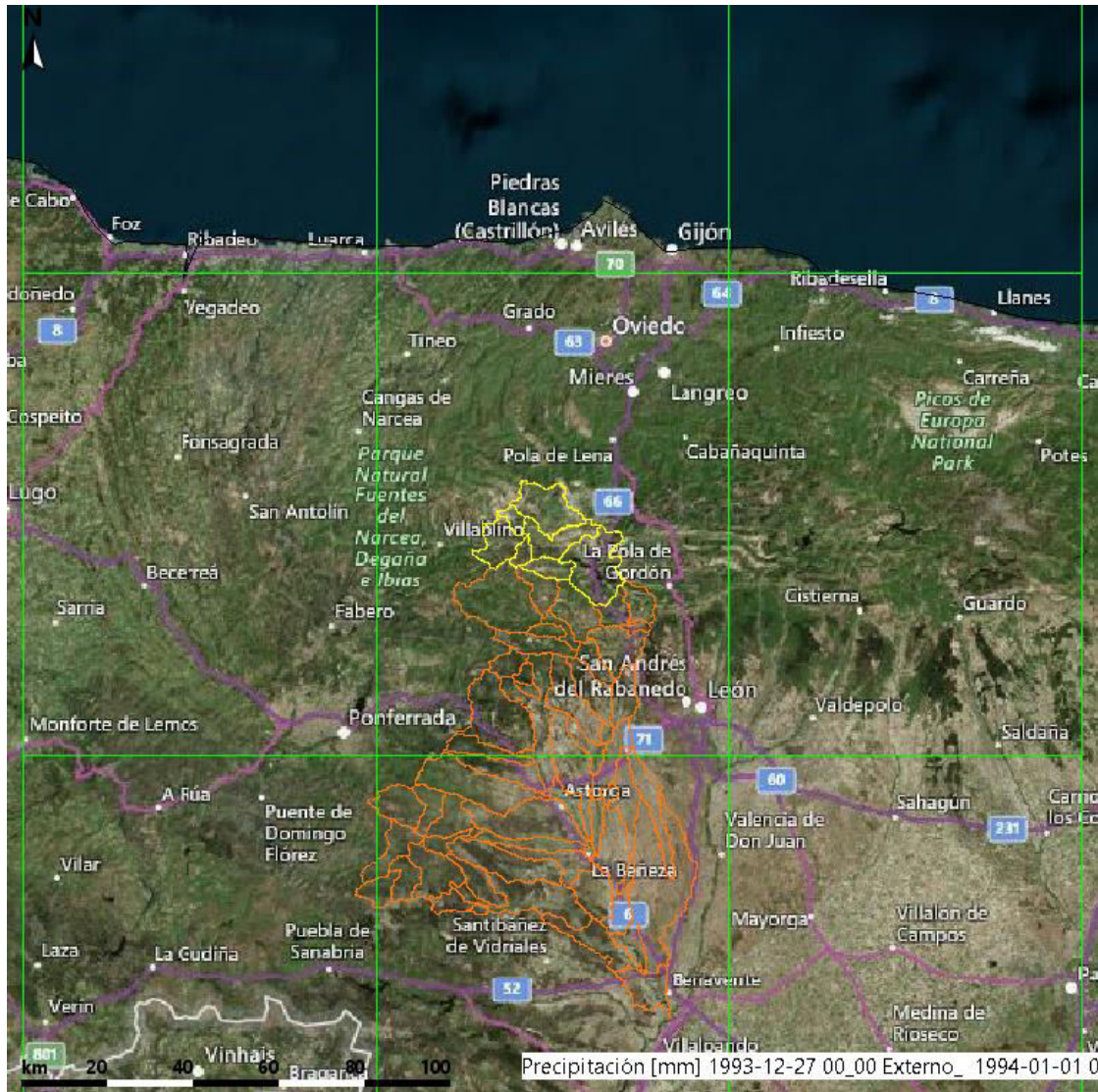
(Clark et al., 2004)

Work in progress

Catchment 22

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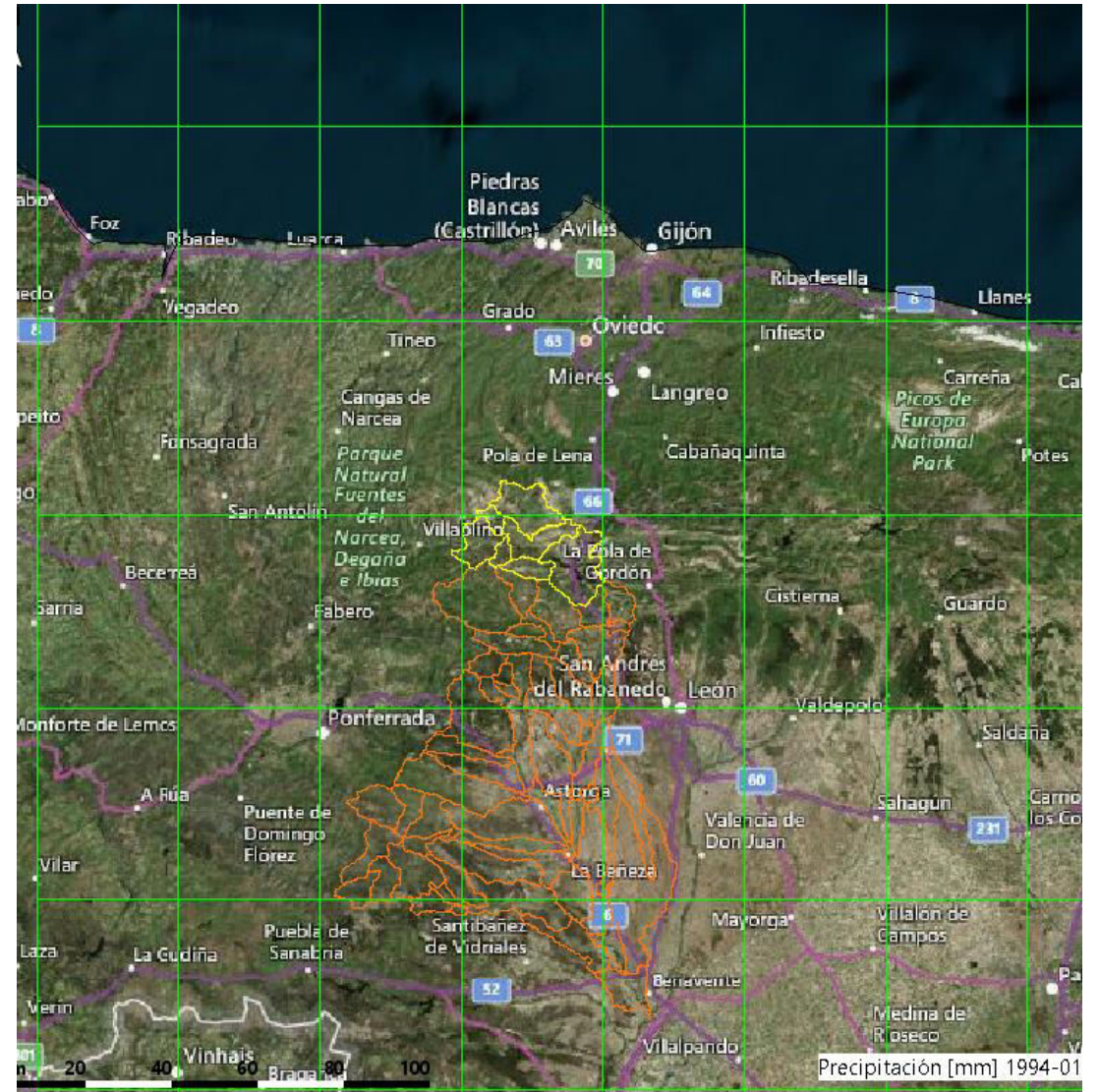
Where does the skill come from?

- Meteorological forcing skill vs hydrological skill
- Spatial resolution - 1 degree vs 0.4 degrees
- Temporal aggregation - Schaake Shuffle
- Bias-correction methods - QM vs BJP vs AI?

Catchment 6

1 degree

0.4 degree

8. NEXT STEPS

- Completing the bias correction process

- Estimating the added value of (AI-enhanced) climate services for drought management

- Showing forecast quality to users, making it interpretable and exploring how this uncertainty can influence decisions and **can contribute to forecast value.**
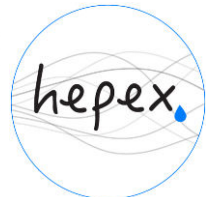
Thanks!

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