Assessing uncertainties in water stress index forecasts

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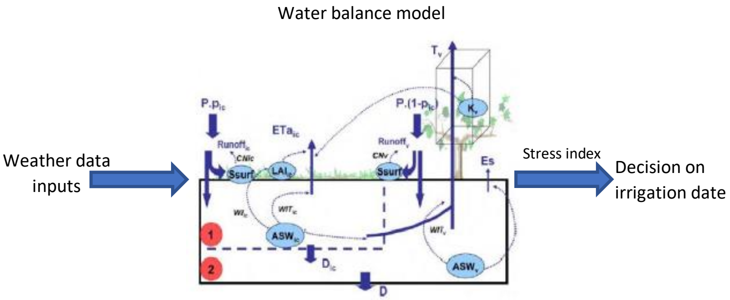
Context: Crop irrigation

- Agriculture accounts for 70% (ref. world bank) of all freshwater withdrawals globally
- Drought is more frequent due to global climate change
- $\Rightarrow$ Crop irrigation is more often a necessity
- The management of water use in irrigation is important

Context: Irrigation management using decision support tools (DSTs)

- DSTs are real-time models that schedule irrigation using daily updated actual weather data and forecasts.



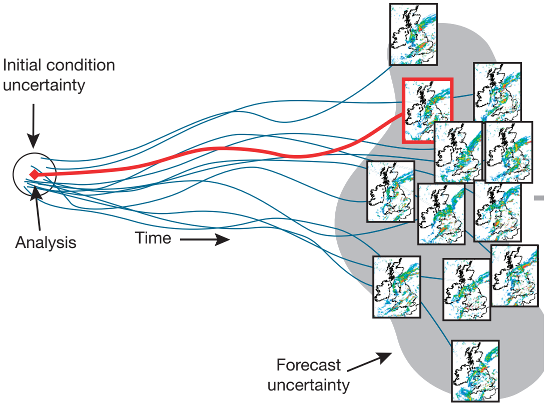
- Uncertainty could either come from the water balance model or from the weather data inputs

Numerical weather prediction uncertainty

Sources of uncertainty:

1. Numerical weather model formulation uncertainties
2. Uncertainty in initial conditions of the atmosphere ⇒ uncertainty in the predictions made

Ensemble prevision approach:

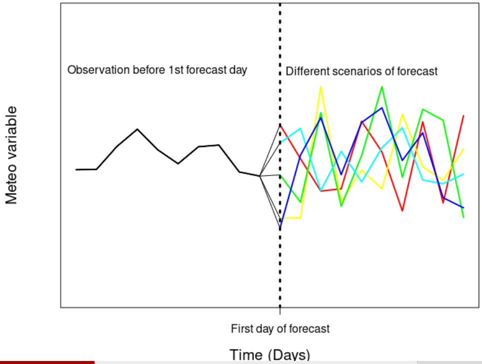


Application to the DSTs

State of the art:

- The current use of these DSTs mostly based on deterministic weather forecasts (i.e single value forecast that does not account for uncertainty)
- Or the use of ensemble of historical weather data (accounts for uncertainty but is it the best way?).

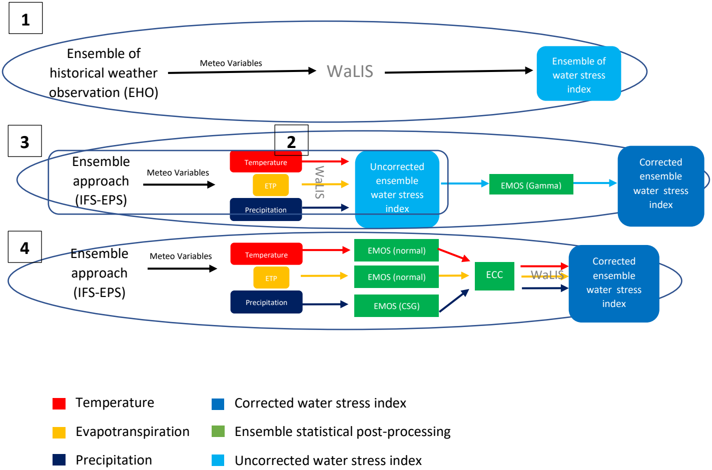
Concept of the use of Ensemble prevision as input in DSTs:



The current study: objective, materials and methods

Objectives of the study:

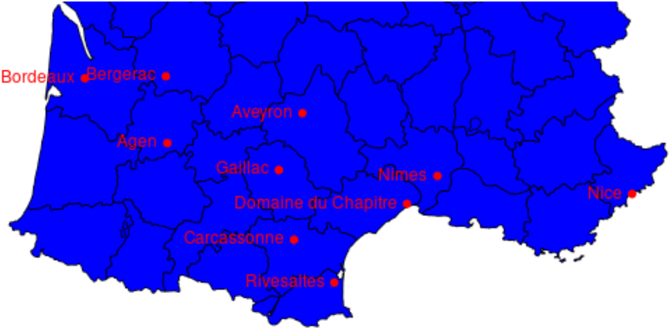
- Compare the performance of ensemble water stress predictions using either state-of-the-art ensemble weather forecasts or an ensemble of historical weather observation (1 vs 2).
- Investigate the effect of post-processing on the probabilistic skill of the water stress index (3 vs 4).



The current study: objective, materials and methods

Materials and methods:

- Numerical weather prevision used is **IFS-EPS** (zone: World, validity period: 15 days, size: 51 members, horizontal resolution: 18Km)
- WaLIS water balance model (developed by Inrae and IFV) for vines irrigation
- Summer period (June to September), years 2018-2019-2020-2021
- 10 sites in the south of France

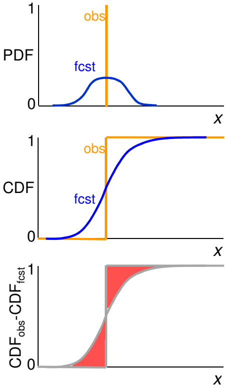


The current study: objective, materials and methods

How to evaluate the performance of an ensemble prevision ?
Many characteristics: Accuracy, reliability, sharpness etc ..

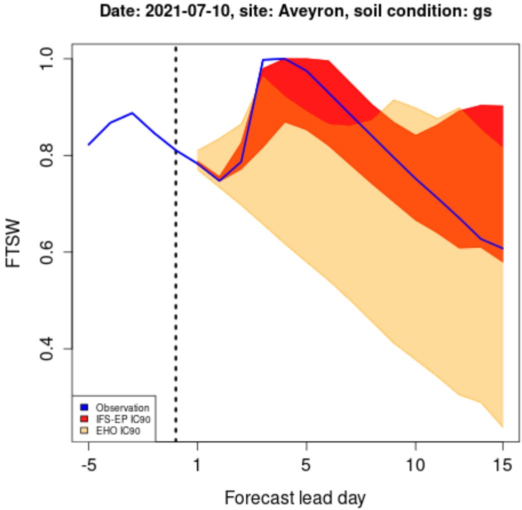
Scores: many scores ! In this study we use the continuous ranked probability score (CRPS):

$$CRPS = \int_{-\infty}^{+\infty} (F_{\text{fcst}}(x) - F_{\text{obs}}(x))^2 \, dx$$



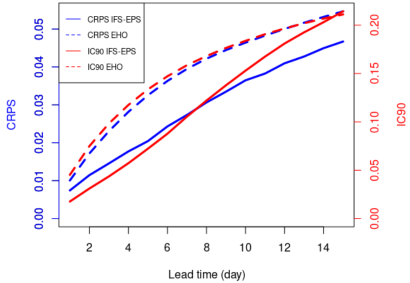
N.B: In our case the obs is the stress index computed by running the WaLIS model using the observation of the meteo variables.

Results (comparison IFS-EPS vs EHO)



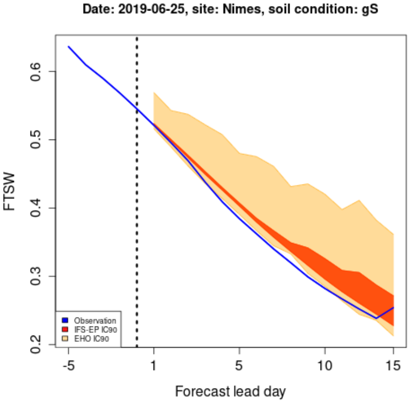
Results (comparison IFS-EPS vs EHO)

	Ensemble forecast (IFS-EPS)					Ensemble of historical observations (EHO)				
Lead	**IC50**	**IC90**	**% in IC50**	**% in IC90**	**CRPS**	**IC50**	**IC90**	**% in IC50**	**% in IC90**	**CRPS**
1	0.006	0.017	13.792	32.500	0.007	0.008	0.045	41.282	70.876	0.010
2	0.012	0.031	19.850	42.622	0.011	0.018	0.074	42.158	72.003	0.017
3	0.017	0.043	22.403	48.979	0.014	0.028	0.098	41.752	72.516	0.023
4	0.022	0.057	25.470	53.766	0.0177	0.037	0.117	41.116	73.162	0.028
5	0.028	0.072	27.435	57.270	0.020	0.045	0.133	40.368	73.205	0.032
6	0.033	0.087	27.948	59.978	0.024	0.053	0.147	39.166	73.579	0.036
7	0.039	0.105	28.878	62.377	0.027	0.059	0.158	31.717	74.091	0.039
8	0.046	0.122	30.165	64.273	0.030	0.064	0.168	38.397	74.113	0.042
9	0.051	0.137	31.255	65.918	0.033	0.068	0.176	37.980	74.326	0.044
10	0.057	0.152	33.044	68.392	0.036	0.072	0.183	37.777	74.989	0.046
11	0.063	0.167	34.385	69.599	0.038	0.076	0.190	37.441	75.048	0.048
12	0.068	0.181	35.876	71.282	0.040	0.079	0.196	37.793	75.048	0.050
13	0.074	0.192	36.442	72.307	0.042	0.082	0.201	37.863	74.636	0.051
14	0.078	0.203	37.537	73.675	0.044	0.084	0.206	35.857	74.444	0.053
15	0.084	0.214	38.488	74.380	0.046	0.087	0.211	37.948	74.487	0.0546



Why to post-treat ensemble previsions ?

- Existence of systematic bias error in the prediction sometimes
- Dispersion error in the ensemble sometimes



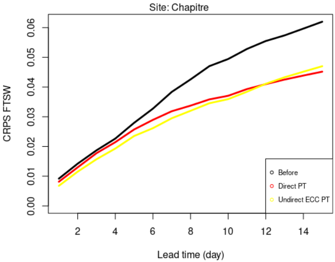
- EMOS is a statistical post-processing method that addresses these issues

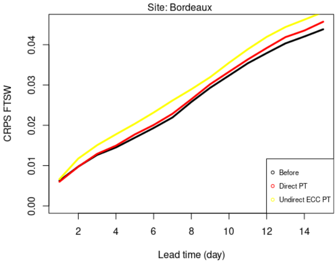
EMOS method for post-treatment of ensemble prevision

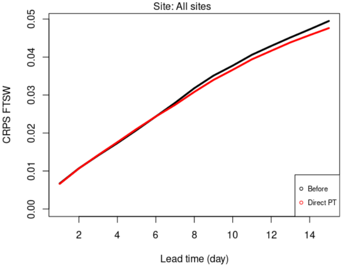
Let $X_1, X_2, ..., X_N$ be the members of the ensemble X.

- Assumption on the distribution of the ensemble to post-treat (e.g normal distribution).
- Fit the parameters of predictive distribution $N(a + b\overline{X}, c + dV(X))$ by minimizing the CRPS on a training data set.
- Usually the training data set is a moving window consisting in T training days before the day J of the prevision to post-treat.

Results (Post treatment EMOS)







Results (Post treatment EMOS)

- Locally: 4/10 sites present improvement after post-treating.
- The improvement becomes significant (p-value < 0.05) starting leads 5-6-7.
- Globally averaged on all sites tiny improvement.
- No significant difference between direct and indirect post-treatment.

Take home messages:

- The use of ensemble prevision in irrigation DSTs is promising and has better results in comparison with the use of historical weather observations.
- Post-treatment of ensemble water stress index could show improvement in ensemble previsions locally in some sites.
- Globally on all sites post-treating the water stress index ensemble prevision could improve the predictions by reducing the dispersion error and the bias.
- No advantage in post-treating directly the water stress index.

Perspectives:

- Investigate the uncertainty that comes from the DST model itself.

Thank you for your attention !