SERVICIOS CLIMÁTICOS PARA GESTIÓN DEL REGADÍO
CLIMATE SERVICES FOR IRRIGATION MANAGEMENT

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SUMMARY

AEMET is contributing with the provision of climate services related with seasonal forecasts to the MOSES (Managing crOp water Saving with Enterprise Services) EU H2020 project. The main objective of MOSES project is to put in place and demonstrate at the real scale of application an information platform devoted to planning of irrigation water resources, to support water procurement and management agencies (e.g. reclamation consortia, irrigation districts, etc.). Its main goals are saving water, improving services to farmers and reducing monetary and energy costs. MOSES is a multi-disciplinary project involving 16 partners and the AEMET main contribution consists of producing weather and climate forecasts up to seasonal timescale for two demonstration areas over Spain and another one over Morocco selected for their agricultural value.

Introduction

The main objective of project EU H2020 MOSES (Managing crOp water Saving with Enterprise Services) is “to put in place and demonstrate at the real scale of application an information platform devoted to water procurement and management agencies to facilitate planning of irrigation water resources”.

Within this objective, the project contributes to improve critical aspects like flood and drought risk management, decision support, monitoring systems and water governance. The first of these aspects, flood and drought risk management, is among the main priorities of the EU environmental policy (see, for example, directive 2007/60/EC).

There are 16 participating partners including environmental agencies, universities, research institutes, space associations, water consortia, irrigation associations, small and medium enterprises and industries from 5 European countries and 3 continents. 3 stakeholders are also involved in the project. Operational products are being developed for 4 demonstration areas located in Italy, Spain, Romania and Morocco.

Among the list generated products are: i) pre-season information products from remote sensing (early crop mapping); ii) seasonal information products from remote sensing; iv) seasonal forecasts (of irrigation water requirements) and v) in-season information products from remote sensing and weather forecasts (crop mapping, crop status monitoring, short term crop water demand forecast).

AEMET contribution

The contribution of AEMET involves the provision of climate services suited to the needs of the irrigation community based on forecasts ranging from short term to seasonal time scales. Downscaled forecasts are provided for two demonstration areas over Spain and another one over Morocco. The two Spanish demonstration areas are BembézarMD (circa 12 000 ha) and Sector-BXII (circa 15 000 ha) and both lie on the Guadalquivir river basin. The Moroccan one is Doukkala (96 000 ha) located between the Atlas Mountains and the cost.

The forecasts range from short and medium term (up to seven days) to seasonal, although it is optional the generation of forecasts covering the extended medium term (up to two weeks) and monthly ranges.

Forecasted variables are, basically, temperature, precipitation and reference evapotranspiration (hereinafter ET_0). The two first ones are direct model outputs, whereas the last one is derived. Reference evapotranspiration is of special interest for the irrigation schedule.

These tailored products are based with some manipulation on operational numerical models running at AEMET and ECMWF. Additionally, seasonal forecasts generated by global models, are spatially and temporally downscaled in order to be used as input for the water balance model, which produces the irrigation forecast.

We have followed two different procedures to generate products for Spanish and Moroccan demonstration areas, due to the different availability of observations and forecasts for both countries.

Short and medium term forecasts (up to seven days)

Short term products for Spanish demonstration areas, come from the "Base de Datos Digital de Predicción" (hereinafter called BDDP). This is an internal product aiming to assist predictors in their routinely work, and consist of the postprocessed (improved) output from some numerical models (Hirlam and Harmonie) to predict up to the second day, and the deterministic model of the ECMWF to complete up to the seventh day. The output of these models is postprocessed using also observations to obtain a better tuned result. Therefore, the BDDP products outperforms the direct model output from the models. Both, the spatial and temporal resolution provided by the BDDP is suited for our purposes, so there is no need to make any spatial or temporal downscale.

Insolation is taken from the ECMWF model for all forecast ranges, as this variable is not included in the BDDP. Calculation of the reference evapotranspiration follows FAO Penman-Monteith method, slightly modified to use forecast data instead of observational data as the method assumes. Therefore, whereas the FAO recommends calculating daily mean value of several variables using their extreme values (maximum and minimum), we have used the average of forecasted values at least 6 hourly separated. For the Moroccan demonstration area, all variables are taken from the Harmonie model output up to two days and from the deterministic model of the ECMWF for the remaining days up to the seventh one. No postprocessing is applied to these data, so in principle they are expected to be less accurate than those coming from the BDDP. All short and medium term forecasts are produced daily, and are delivered via an FTP server.

Seasonal predictions

The seasonal forecast is probabilistic and therefore it is provided as an ensemble of forecasts. Each member of the ensemble consist of two physically consistent daily time series, one for temperature and another one for precipitation.

Two methods are used for the provision of seasonal forecasts: a) one (referred as "common method") is used by all meteorological services of all participating countries, b) the other one is a specific method of each meteorological service. AEMET will apply these two methods in the Spanish and the Moroccan demonstration areas.

The common method makes use of dynamical seasonal prediction models from the EUROSIP project, spatially downscaled and calibrated by the quantile mapping technique (Piani et al 2010). A time downscaling is made by means of a weather generator after the quantile mapping has been applied.

The specific method applied by AEMET is based on different preexisting products that depend on the country where the DA is located. For Spanish DAs, our MOSES seasonal forecasts are based on the operational terciles seasonal forecasts issued monthly for the following three months. For the Moroccan DA, our MOSES seasonal forecasts are based on EUROSIP. Both forecasts are spatially and temporally downscaled and calibrated using a time series analogue method.

Common method

The common method produces climate indices for the following season, making use of daily forecasts provided by EUROSIP models members.

These indices are:

- total cumulated precipitation,
- wet day frequency,
- frequency of a wet day after a wet day,
- average minimum temperature,
- average maximum temperature and
- difference between mean maximum temperature in dry days (less than 1.0 mm precipitation) and the same mean maximum temperature in wet days (precipitation greater/equal than 1.0 mm).

Then, these climate indices are locally bias corrected using the Quantile mapping technique (herein after, QM). Finally, a weather generator provides physically consistent daily time series of temperature and precipitation.

The rest of this section is devoted to briefly explain the QM technique. More information can be found in Piani et al. (2010) and papers there referred. Figure 1 shows graphically the mapping correction applied to the each model index for a certain hindcast period. The correction is conducted percentile by percentile using the accumulated frequencies. Then the bias corrected new value is used as input for the weather generator producing physically consistent daily time series of temperature and precipitation. Finally, the weather generator output feeds a water balance model, which produces the forecast of irrigation needs.

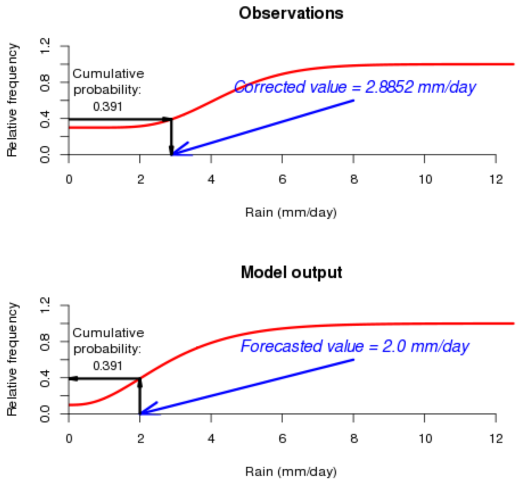

Fig. 1 – Illustration of the quantile mapping correction. The red line in both graphics represents the accumulted frequency of daily rain. Both have been calculated in the same hindcast period. The one above is calculated from the observations and the one below from the hincast of the model.

AEMET specific method

The AEMET specific method is based on AEMET operational forecasts and EUROSIP products.

AEMET operational forecasts is made by consensus using a collection of selected climate models, relevant drivers at seasonal scale and input from the RAVI RCC LRF[1], and produces a different forecast for each of four quadrants in which is divided the Iberian Peninsula. We can see an example of these predictions for temperature, in Fig. 2.

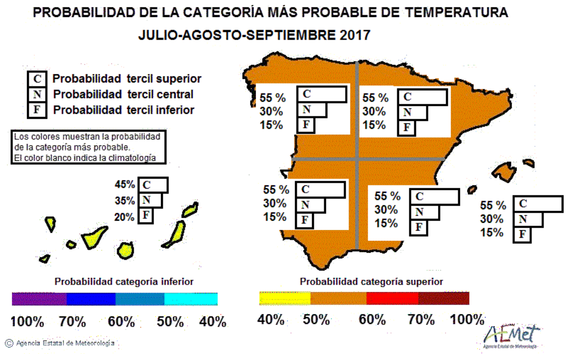

Fig. 2 – Example of seasonal prediction operative at AEMET. A prediction for temperature is issued for each quadrant.

The EUROSIP forecasts are based on the multimodel ensemble of five seasonal models: ECMWF, Met Office, Météo-France, NCEP and JMA.

Both seasonal forecasts are spatially and temporally downscaled and calibrated by means of the Time Series Analogue method, that yields an ensemble of daily time series of the required meteorological variables. This method is simpler than other downscaling methods operational at AEMET and allows us the straightforward use of the operational seasonal forecast. Additionally, it circumvents the application of weather generator algorithms to provide physically consistent daily data of precipitation and temperature. One additional advantage of this method is its immediate application. However, its main drawback is the provision of a variable number of members for the ensemble of time series, typically between 15 and 40, for each meteorological variable.

The Time Series Analogue method consists of a selection of daily time series for the season to be predicted of the required meteorological variables, obtained from the observed time series of a meteorological station. In this way, starting from a number of time series equal to the years of observations (for each variable), we proceed to classify each year as belonging to one tercile of temperature and one tercile of precipitation. We want then to select a number of members (time series) so that their distribution among the terciles of precipitation is as close as possible to that provided by the large-scale operational seasonal forecast, and at the same time with respect to the temperature terciles. We define the terciles using the same climatology used by the large-scale seasonal prediction.

[1]RAVI: Regional Associacion VI. (The area of the Regional Association VI (RAVI) of the World Meteorological Organisation (WMO) extends over millions of square kilometres, from Iceland to Kazakhstan and from Spitsbergen to the Levant).
RCC: Regional Climate Centre.
LRF: Long-range Forecasting.

Suppose, for example, that we have 55 years of daily observations and we have a seasonal forecast for next winter of 33%, 33%, 33% (below normal, normal and above normal) for temperature and 25%, 35%, 40% for precipitation. If the observatory is not too far away from the place for which we want to downscale the prediction, we can consider that the weather is the same in both places.

In each of the observed years, we select only the days pertaining to the season to be forecasted, in this example, for winter. Then we calculate the mean temperature and the total accumulated precipitation in that season for each year. The temperature will lie on a certain tercile of temperature and the precipitation will lie on a certain tercile of precipitation.

We have a total of nine possibilities to classify a year according to the combination of tercile for temperature and precipitation, gathered in the matrix of occupancies in table I, where T1, T2 and T3 mean first, second and third tercile of temperature, respectively, and P1, P2 and P3 mean first, second and third terciles of precipitation respectively.

The absolute and relative frequencies of occupation of both temperature and precipitation are shown in the grey cells.

Table I

	T1	T2	T3	Abs. freq.	Rel. freq.
P1	6	6	2	14	25%
P2	9	9	1	19	35%
P3	2	8	12	22	40%
Abs. freq.	17	23	15		
Rel. freq.	31%	42%	27%		

Table I – Number of years that lie in each combination of temperature and precipitation (white) and marginal frequencies (grey). T1, T2 and T3 are the terciles of temperture, and P1, P2 and P3 are the terciles of precipitation.

The aim then is to select a number of years out of the total of 55 in table I, so that the relative frequencies of occupation both of temperature and precipitation are as close as possible to the probabilities provided by the large scale seasonal forecast.

In order to solve this constrained optimization problem we carried out an exhaustive search algorithm, which given the number of years here was computationally feasible in a reasonable time. We first defined a metric for each possible table of occupation numbers. That metric measured the distance from the objective stated. To define it, we start from the six elements vector formed by concatenating the temperature and precipitation tercile relative frequencies (the last column and last row in table I). Then, we calculate the sum of the squares of this vector. The number obtained is the value of the metric (note that this is an Euclidean metric).

Therefore, we start from the vector of relative frequencies shown in Table I: (31, 42, 27, 25, 35, 40). Then, we have to select some (or none) of the years (of observations) in each white cell of Table I in order to have a vector of relative frequencies equal (or the most possible approximated) to the vector of forecast likelihoods: (33, 33, 33, 25, 35, 40).

Let i = P1, P2, P3 and j = T1, T2, T3. Let also be f_{ij} the absolute frequency in cell i, j. For i =P1 and j = T1, we have a set of 6 years, so $f_{P1,\ T1} = 6$, and we can choose, from this cell, 0, 1, … or 6 years in order to make the relative frequencies be as close as possible to the forecast likelihoods. Therefore, for each cell we can choose any of $(f_{ij}+1)$ subsets. Moreover, the total number of possible combinations of subsets of all cells is $\Pi\ (f_{ij}+1)$ where the product extends over the 9 occupancy cells of table I. In our example, this number is of the order of 10^7.

From all these possible combinations, the one that minimised the metric was finally chosen (see table II). If the number of years were considerably greater, the total number of combinations would grow exponentially and then a Monte Carlo technique could be applied.

Table II

	T1	T2	T3
P1	4	5	2
P2	9	6	1
P3	2	4	12

Table II – Number of years that we take from each combination of temperature and precipitation. These occupancy numbers have been found by the algorithm that minimizes the metric.

Comparing tables I and II, we can see for example that, from cell (P1,T1), we had 6 years, among we choose only 4 years. Which of the initial 6 years are chosen does not matter because any of the options will lead to the same vector of frequencies. However, it is also true that if we apply a criterion, we are making a decision on the data. For example, if we choose the first 4 years, perhaps they are less influenced by the climate change than the last 4 years, so that the same mean temperature is achieved by more heat waves than in the last 4 years. This leads to a time series of temperature with a structure that can be very different from the time series of the last 4 years and this can be good or not. So, in order to not to make any decision when choosing the data, we choose the 4 years randomly.

Table III summarizes the occupancy frequencies for: the objective (seasonal prediction), initial of table I and final of table II. The algorithm achieved a considerable reduction in the metric, from 11 for the initial matrix to 1.4 for the final matrix.

Table III

	P Terciles (%)		
Objective	25	35	40
Initial	25	35	40
Final	24	36	40
	T Terciles (%)		
Objective	33	33	33
Initial	31	42	27
Final	33	33	33

Table III – Relative frequency of occupation of each tercile of temperature and precipitation. The "objective" is the large-scale operational seasonal forecast. The "initial" are the relative frequencies in Table I, and the "final" are the relative frequencies of the years selected by the algorithm.

Then, we take each daily time series of each year (temperature and precipitation) as a member of an ensemble prediction. By construction, each of these time series is physically consistent between precipitation and temperature so that it is not necessary to use a weather generator.

These time series are used as input to the water balance model, producing the irrigation needs forecast.

Verification of short and medium term forecasts

Short and medium term forecasts of all variables (except precipitation) have been verified using the correlation coefficient between observations and forecasts and the RMSE (root of mean square error) between observations and forecasts. The verification period goes from 2017-01-01 to 2017-06-14. You can see this verification in Fig. 2.

The short and medium term precipitation forecasts have been verified using the absolute frequency of wet days, and the total accumulated precipitation in the verification period (from 2017-01-01 to 2017-06-14). You can see this verification in Fig. 3.

Conclusions

- We have developed a tailored climate service for support needs of agriculture end-users. This climate service makes use of accurate weather forecasts for short and

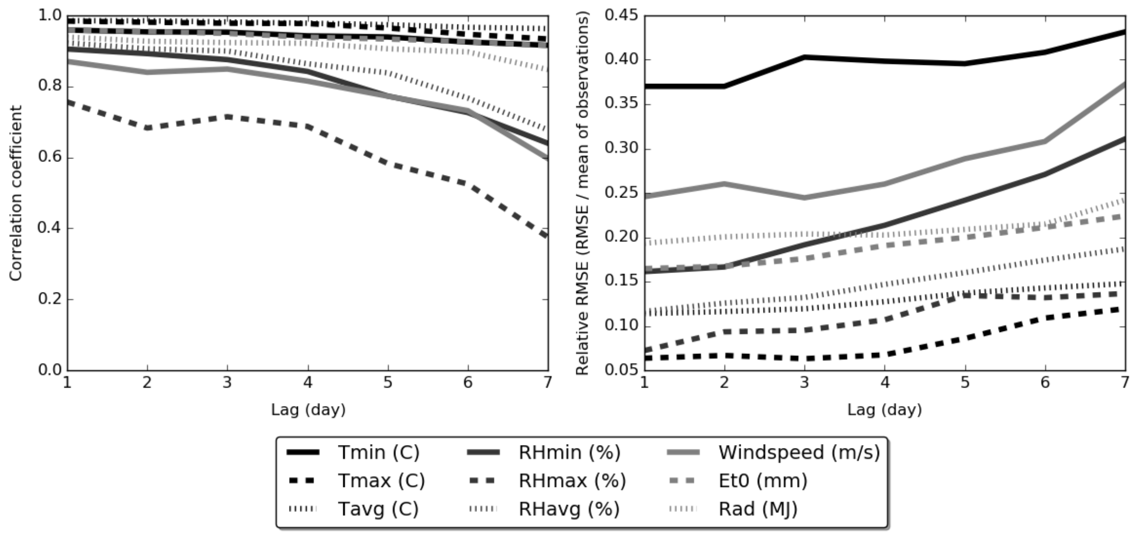

Fig. 2 – Verification of all variables exept rain, at observatory Lebrija I. On the left, correlation coefficient between observed and forecasted daily values, is represented for each range in the prediction. On the right, the relative (divided by observations average) RMSE is represented allowing the representation of all variables in the same graphic. The verification period is 165 days.

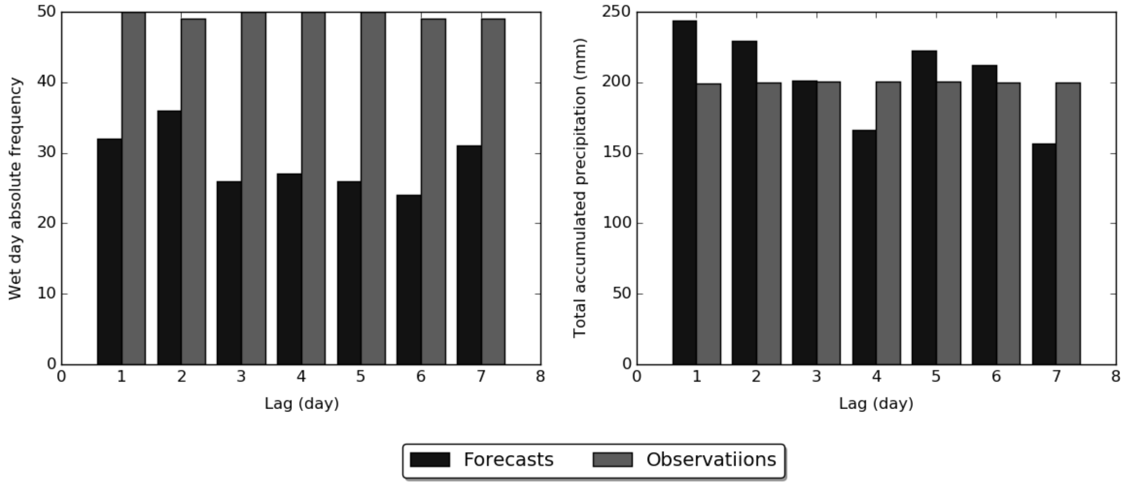

Fig. 3 – Verification of rain predictions. On the left, comparison between observed and foreccasted absolute wet day frequency. On the right, total accumulated precipitation (observed and forecasted) for the verification period (from 2017-01-01 to 2017-06-14).

medium range and of downscaled seasonal forecasts.

- Ancillary information on soil and vegetation state can improve the limited skill of atmospheric seasonal forecasts and add some skill to the final products requested by end-users.

- A new downscaling algorithm based on analogues has been developed and applied to operational seasonal forecasts for the provision of an ensemble of daily temperature and precipitation time series serving as input to the application models.

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