A Drought Alert system based on seasonal forecasts

E. Arnone[1*], Marco Cucchi[1], Sara Dal Gesso[1], Marcello Petitta[1,2,3]
[1]*Amigo s.r.l., Rome, ITALY*
[2]*ENEA, SSPT-MET-CLIM, Rome, Italy*
[3]*EURAC, Institute for applied remote sensing, Bolzano, Italy*
** e-mail: elisa.arnone@amigoclimate.com*

Introduction

Water resources are under stress in many areas of the world, because of a combination of climatic and anthropogenic factors. The Mediterranean area is one of the regions mostly vulnerable to climate alterations (Forestieri et al., 2018). These alterations have direct impacts on the surface water balance and groundwater recharge (Arnone et al., 2018), and thus changes in the reservoir inputs and the management of water utilities (WUs) are severe challenges for water resources in the future. However, WUs management routines scarcely consider climate information and are based on the stationarity assumption, working on weekly or daily time scale.

The use of seasonal forecasts for guiding a strategic planning of the resources has been increasing across several climate-sensitive sectors, including water management and energy (e.g. De Felice et al., 2015, Viel et al., 2016). This is due to the fact that it is generally preferred to focus on the upcoming season rather than taking decisions on the basis of a 100-year climate projection. The project EUPORIAS promoted the use of climate information for decision support by involving both providers and potential users of seasonal data (Buontempo et al., 2017). It was demonstrated that seasonal forecasts may give important contributions in the fields of drought-risk assessment and mid-term reservoir management (Viel et al., 2016; Crochemore et al., 2017).

This study aims at providing some insights in using seasonal forecasts to derive supporting information for water management decision-makers based on drought assessment. Indeed, the exploitation of climate information as precipitation in a mid-term scale, as the seasonal scale, allows for understanding the possible shifts in water resource availability. We describe some results obtained for a case study in Greece.

Materials and methods

We used the System 5 (SEAS5) Seasonal Forecasts (SF) data released by ECMWF (European Centre for Medium-Range Weather Forecasts), and made available by the data access system Copernicus Climate Change Service (C3S). The SF the ensemble contain 51 members. To estimate the reliability of SEAS5, hindcasts are available from 1981 to 2016, and have 25 ensemble members. For the sake of data understanding, Figure 1 shows a graphical representations of forecast time series for a selected grid point.

The methodology developed in this study exploits the predictions on precipitation for the next few months to evaluate the climate state of the upcoming months compared to the climatology. The proposed procedure aims at targeting the following questions: (i) Are the upcoming months going to be dry? (ii) How confident are we that the upcoming months are going to be either dry or not dry?

At a given month, the climate state which characterizes the upcoming months is evaluated based on the prediction of cumulative precipitation computed over a cumulation period (CP) of given length, i.e. the number of months over which precipitation is cumulated. CP may vary from 1 to 6. Once CP is selected, precipitation is cumulated over a rolling window of CP length that determines the PERIOD of forecast (e.g., CP3 leads to a three-months rolling window of periods JJA, JAS, …).

Predictions for each period are compared with the climatology characterizing the same period, assessed over the hindcast data. The terciles of the distribution identify three classes: 1st 'dry', 2nd 'normal' and 3rd 'wet'. The comparison between predictions and climatology will reveal whether the forecasts will belong to the dry class or not, based on a discriminate threshold frequency.

The procedure evaluates a different monthly responses based on the lead time (LT), which is the temporal distance, in months, between the release of the seasonal forecast and the first month of the CP. LT may vary from 0 to 5. Technically, the procedure applies for all the possible combinations between CP and LT. In this study, based on the specific needs of a water utility, we analyzed the combinations LT0-CP3, LT0-CP5, LT3-CP3, which are representative of a short-term prediction (for the next 3 months), a long-term prediction (for the next 5 months) and of outlook evaluation (for 3 months from next 2 months).

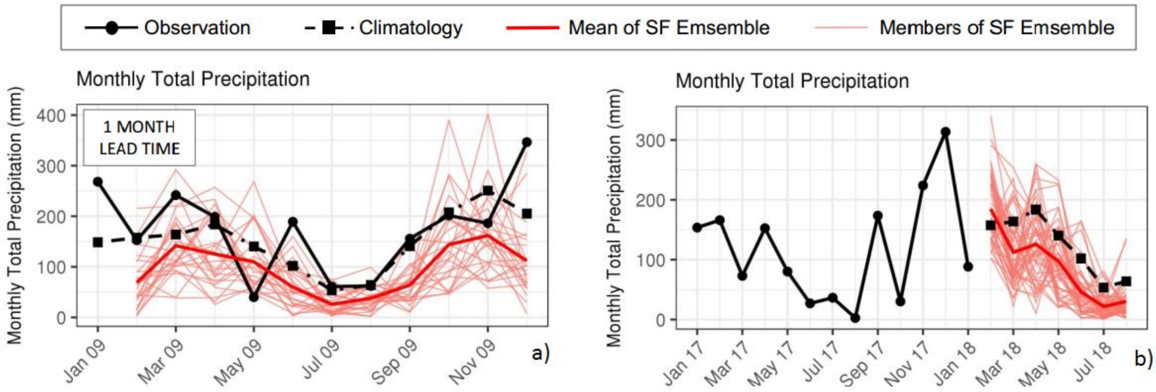

Figure 1 - Forecast time series for a selected grid point: comparison with hindcasts for 2009 of monthly total precipitation (a); observed time series (2017) and future SF time series (2018) of monthly total precipitation (b).

Results and concluding remarks

Table 1 shows the results of the release obtained in November 2018 for the island of Zakynthos, Greece. None of the cases in a 'dry' climate state, based on the statistical comparison between the cumulated rainfall derived from seasonal forecasts and climatic reference. The state of Drought Alert is triggered when predictions fall within the 'dry' class. Conversely, a state of no-alert will be released, i.e. neither normal or wet conditions are contemplated by the procedure. Given the significant uncertainty that can be associated with the prediction, a reliability of the alert/no-alert information will be assessed through the evaluation of the false rate (0-100%) of the current prediction, which derives from the combination of the skill of the prediction system and the grade of predictability of the state of the upcoming months.

Table 1 – Drought Alert: climate state of the upcoming months based on the SF of precipitation.

Current month: November 2018				
Lead Time/Timing		**0/short-term**	**0/long-term**	**3/outlook**
PERIOD		***Nov-Dec-Jan***	***Nov-Dec-Jan-Feb-Mar***	***Feb-Mar-Apr***
Class	Dry			
	Not dry	X	X	X

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