PREVEDERE, A SCALA STAGIONALE, L'INNESCO E LA PERSISTENZA DI EVENTI ESTREMI DI SICCITA': IL CASO STUDIO DEL BACINO IDROGRAFICO DEL PO

PREDICTING, ON A SEASONAL SCALE, THE TRIGGERING AND PERSISTENCE OF EXTREME DROUGHT EVENTS: THE CASE STUDY OF THE PO RIVER BASIN

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Abstract

In the last 15 years, the northern regions of Italy have experienced some prolonged periods of intense drought. In this context, drought forecasting can be an effective tool for optimizing water resources and activating appropriate adaptation actions. However, the seasonal forecasts for the anticipation of possible drought conditions are challenging, due, in general, to the limited predictive ability of seasonal predictions over the Euro-Mediterranean region and, in particular, to the limited ability of dynamical models in predicting blocking onset and frequency at all forecast timescales, being these the large scale dynamical features leading to the occurrence of local droughts.

For this reason, the identification of the best timeframes and related drought forecasting opportunities can be an innovative and effective approach for the drought risk manager, especially in the agronomic field.

The present work explores potential relationship between the SPI (Standardized Precipitation Index) calculated over multiple time frames (from 1 to 36 months) with an equivalent river discharge indicator, SQI (Standardized Discharge River Index) for the Po river basin from 1961 to 2022. Specifically, pairwise correlations between SPI and SQI of different time frames are explored, with SPI from zero to 4 months ahead of the SQI reference month. The results show significant correlations between SPI and SQI of equivalent time frames, with advances of 1 and 2 months. The explorative approach shown here provides insight into the many forecasting opportunities that can be achieved. For instance, good results were obtained between SPI5 in May and SQI5 in June (i.e., SPI one month early, $R2 = 0.81$) and SPI6 in June and SQI6 in August (i.e., SPI 2 months early, $R2 = 0.84$).

This approach can help to increase the endowment of useful instruments to increase the resilience of the territories, with a strong agricultural vocation and of national importance, in the face of an increasing risk of drought.

Parole chiave italiano

Opportunità di previsione della siccità, previsione della siccità, regioni del nord Italia, dataset ARCIS

Keywords english

Drought forecasting opportunities, Drought forecasting, Northern regions of Italy, ARCIS dataset

Introduction

Rising global temperatures are likely to drastically reduce freshwater availability (by 2-15% for 2°C warming), especially in Mediterranean regions (Antolini et al., 2016, Brunetti et al., 2006, Toreti and Desiato, 2008, Cramer et al. 2018; Gorguner and Levent, 2020). The vulnerability of water resources in the Mediterranean area will call for management plans focused on water uses, including adapting irrigation demand to climate change (Rocha et al, 2020).

Drought is among the major side-effects of climate change for agriculture (Maleka et al, 2018; Nerantzaki et al, 2019; Del Buono, 2021). Currently, Italy has experienced several prolonged drought events and large interannual weather variability, putting the profitability of farmers at risk (García-León, 2021). At the same time, summer droughts, representing a relevant aspect of local climatology, are observed to increase significantly over the last 60 years (Pavan et al, 2019), while surface temperature has been observed to increase significantly particularly in summer (refs). Both these aspects of current observed climate are expected to be exacerbated by future climate change, .which may lead to an increase in the amount of irrigation needed to sustain crop growth (Del Buono 2021). Several attempts have been made to develop a drought index capable of capturing the combined spatial and temporal characteristics of precipitation scarcity and heat waves (Zampieri at al., 2017). The Standardized Precipitation Index (SPI) and Standardized Precipitation-Evapotranspiration Index (SPEI) are among the most well-established examples. These indices cumulate meteorological anomalies over a wide range of time frames, that is, from short to long period (e.g., 1 month, 6 months, 12 months, etc.) so as to **reflect the timescales in the response of different water resources**, such as river discharges and storage. River discharge inevitably reflect the rainfall variability at seasonal scales, but is also an indicator of hydrological droughts and floods as well as of the whole basin water availability. Thus, the ability of predicting seasonal river discharge from seasonal precipitation could provide a new effective early warning system for water management at basin scale. Even if these indices have been extensively used for identifying the development and the characterization of drought events, just a limited studies have examined their potential effectiveness in river discharge estimates and forecasts (Du et al., 2013, Wang et al., 2017). Nevertheless, in the following it is shown that the correlations between a newly developed Standardized River Discharge Index (SQI) and the SPI, the latter computed up to 4 months in advance respect to the SQI reference month, are strong and could enhance the development of actionable services to alert stakeholders of potential drought risks, especially in the agronomic field. These results are meant to be used to set up an operational climate service to provide usable and salient information to support drought risk management over the Mediterranean area. made available by the Drought Observatory (DO) of CNR-IBE (Magno et al., 2019).

Methods

Source data

Po river discharge data (Pontelagoscuro gauging site, monthly averages [$m^3m^{-2}sec^{-1}$]) are available for the period 1961-2022 from Agenzia Regionale per la Prevenzione, l'Ambiente e l'Energia dell'Emilia-Romagna (ARPAE, https://www.arpae.it/it). Let us define as Q the time series of monthly Po river discharge data. On the other hand, SPI was computed by using the ARCIS precipitation dataset (Pavan et al. 2019), a gridded observational dataset of daily precipitation [mm] over North-Central Italy from 1961 to present. To aggregate precipitation data at the river basin scale, the geometries (i.e., shapefile) defining the boundaries of the catchment area at the outlet of Pontelagoscuro site and provided by the European Environment Agency (EEA, https://www.eea.europa.eu/data-and-maps/data/european-river-catchments-1) were used.

Data harmonization to consistent spatial-temporal scale

Daily precipitation data were cumulated on a monthly scale and averaged throughout the grid points within the Pontelagoscuro watershed so as to obtain an average monthly precipitation (P). In this way, a 62-year time series (1961-2022) of monthly values of P that is time- and spatial-wise consistent with the data of Q was obtained. Furthermore, river discharge data were converted into mm of water equivalent dividing the volume of water flowed out (m^3) in each month by the basin area (approximately 70000 Km^2).

SPI and SQI

P was used to calculate the Standardized Precipitation Index (SPI) normalising the precipitation anomaly for a specific time frame with respect to the corresponding climatological reference value. Specifically, SPI was computed for multiple time frames (i.e., from 1 to 36 months) for each month of the period ranging from January 1991 to December 2022, using at climatological reference the period 1961-1990. The joint exploration of multiple time frames at shorter scales is crucial to assess the impacts of short term precipitation anomalies on river discharge. On the contrary, for longer time frames, **the SPI strongly reflect the duration** of precipitation anomalies over the past months and can be used to evaluate the relationship between long term precipitation anomalies and the occurrence of hydrological droughts (Du et al., 2013).

The SPI was computed following the method of Lloyd-Hughes and Saunders (2002)..

Since the World Meteorological Organization (WMO) promotes the standardization of meteorological and hydrological observations to ensure uniform statistics and consistency of hydro-meteorological variables (Rodda, 2011), Q was also standardized following the same methods used for the SPI. The rationale behind our choice relies on the river discharge behaviour, which is typically characterized by asymmetric right-skewed distribution of only-positive values, as P. Moreover, average values of Q may reflect both near and long anomalies in precipitations, depending on the morphology and the extent of the catchment area. Hence, as for SPI, we computed a Standardized River Discharge Index (SQI) for multiple time frames (i.e., from 1 to 36 months) for the reference months ranging from January 1991 to December 2022, whereas the period 1961-1990 were use as baseline.

Pairwise correlation test

SQI and SPI were subjected to a pairwise Pearson correlation test (Dunn & Clark, 1986) to measure the strength of linear relationships at multiple time frames (i.e., 1-36 months). Moreover, since the SQI could be time-lagged correlated to the SPI, the pairwise correlation test was also performed considering the reference months of the SPI up to 4 months ahead of the SQI.

Results and Discussion

The investigation of potential correlation between SQI and SPI at multiple time frames and different time lags results in correlation matrices of shape (36 x 36 x 4) where 36 are the multiple time frames adopted to compute the SQI and SPI, and 4 is the number of time-lags investigated between the reference month of SQI respect that of the SPI. Figure 1 shows the correlation matrix between SPI and SQI at the time-lag 1 (i.e., reference month of SPI in advance of 1 month respect to the SQI) where the maximum correlation (r = 0.92) is achieved with the time frame 18 (red point in the figure). In general, Figure 1 shows that correlations between SQI and SPI are higher alongside the diagonal, suggesting that linear correlation is maximized by considering SQI(t-1) and SPI(t) for every t between 1 and 36 months. These results, obtained from an exploratory approach, allow for a large number of follow-up insights. For illustrative purposes, we report an example: due to evidence of strong correlations between equivalent time frames of SQI and SPI, and given the need of having a forecasting tool on drought and water resources management, in Figure 2 we show the correlations between SQI and SPI computed over equivalent time frames (e.g., SPI1 vs SQI1, SPI2 vs SQI2, etc) ranging from March to September, which is the period when the agriculture irrigation water need is locally at its maximum. Moreover, Figure 2 shows the results for SQI computed up to 4 months-lag with respect to the SPI reference month. The highest correlations (Fig. 2, yellow cells showing the value of r^2) are generally found for SQI with one month-lag (or equivalently SPI one month ahead). In June however, the SPI6 shows the highest correlation with the SQI6 of August. In other words, knowing the SPI6 for June, would let us to predict the SQI6 of August.

A further insight is presented in Figure 3 where timeseries of SPI6-June and SQI6-August are plotted over the whole period (1961-2022, Fig. 3 left panel) and compared through a scatter plot (Fig. 3, right panel). The insight on the case SPI6-June vs SQI6-Aug shows the presence of a significant link between two time series , opening the possibility of predicting SQI6-August peaks by using the SPI6-June index.

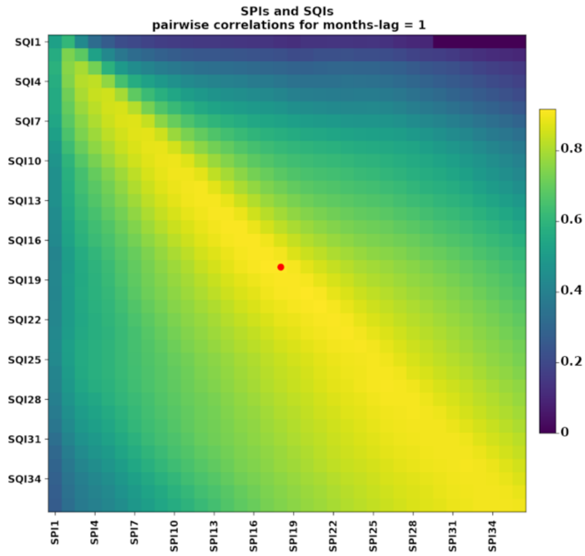

Fig. 1 – Correlazioni (R2) tra SQI e SPI calcolati su periodi temporali da 1 a 36 mesi e sfasati di un mese, SQI(t-1) and SPI(t) – Pairwise correlations (R2) between SQI and SPI computed on time frames from 1 to 36 months at time lag , SQI(t-1) and SPI(t). Correlations (R2) between SQI and SPI calculated on time periods from 1 to 36 months and shifted by one month, SQI(t-1) and SPI(t) – Pairwise correlations (R2) between SQI and SPI computed on time frames from 1 to 36 months at time lag , SQI(t-1) and SPI(t).

Conclusion

Water resource management requires valuable and usable tools for salient information, especially when severe drought hammer key farming regions. The approach described in the present work can contribute to increase the endowment of useful instruments to increase the resilience of the territories, with a strong agricultural vocation and of national importance, in the face of an increasing risk of drought, although it must be remembered that the results on the correlation between basin precipitation and river discharge for the Po river might be significantly affected by the geographical extent and by the morphological and climatological aspects of the geographical area encompassed by the basin

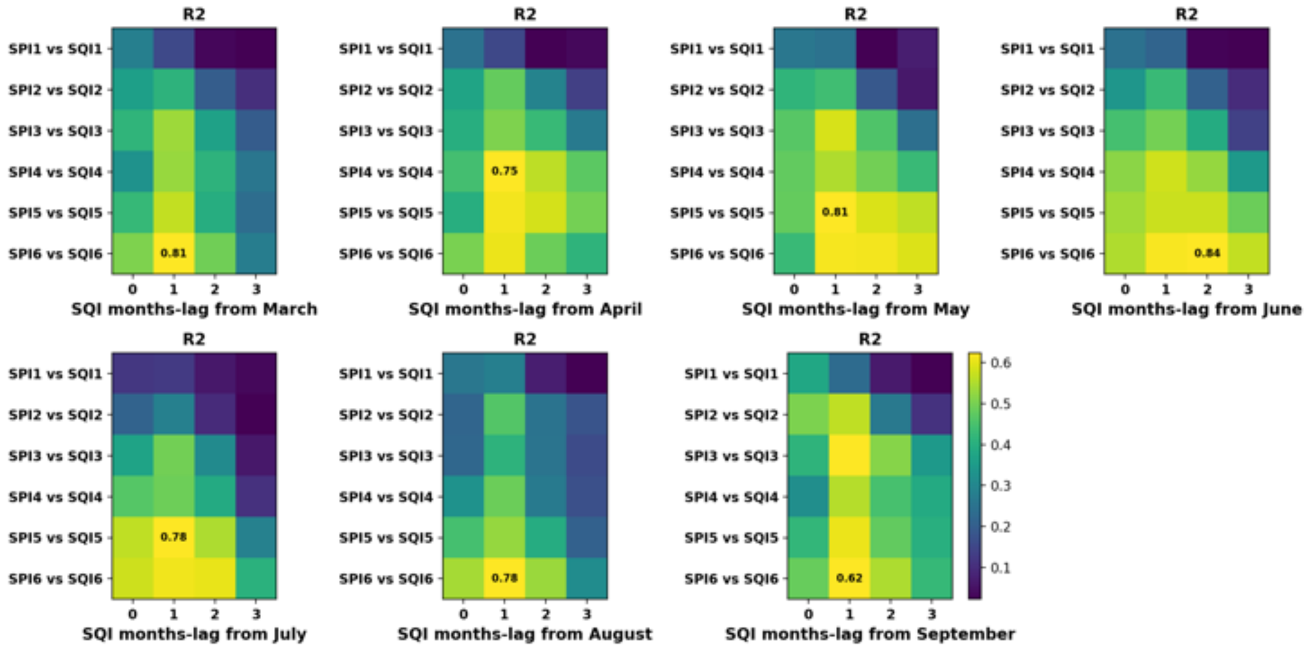

Fig.2 Correlazioni (R2) tra SQI e SPI calcolati su periodi temporali equivalenti da 1 a 6 mesi e considerando fino a 4 mesi anticipo tra il mese di riferimento di SPI e SQI. Le celle con il valore di R2 identificano il risultato migliore tra quelli esplorati - Correlations (R2) between SQI and SPI calculated on equivalent time periods from 1 to 6 months and considering up to 4 months advance between the reference month of SPI and SQI. The cells with the value of R2 identify the best result among those explored.

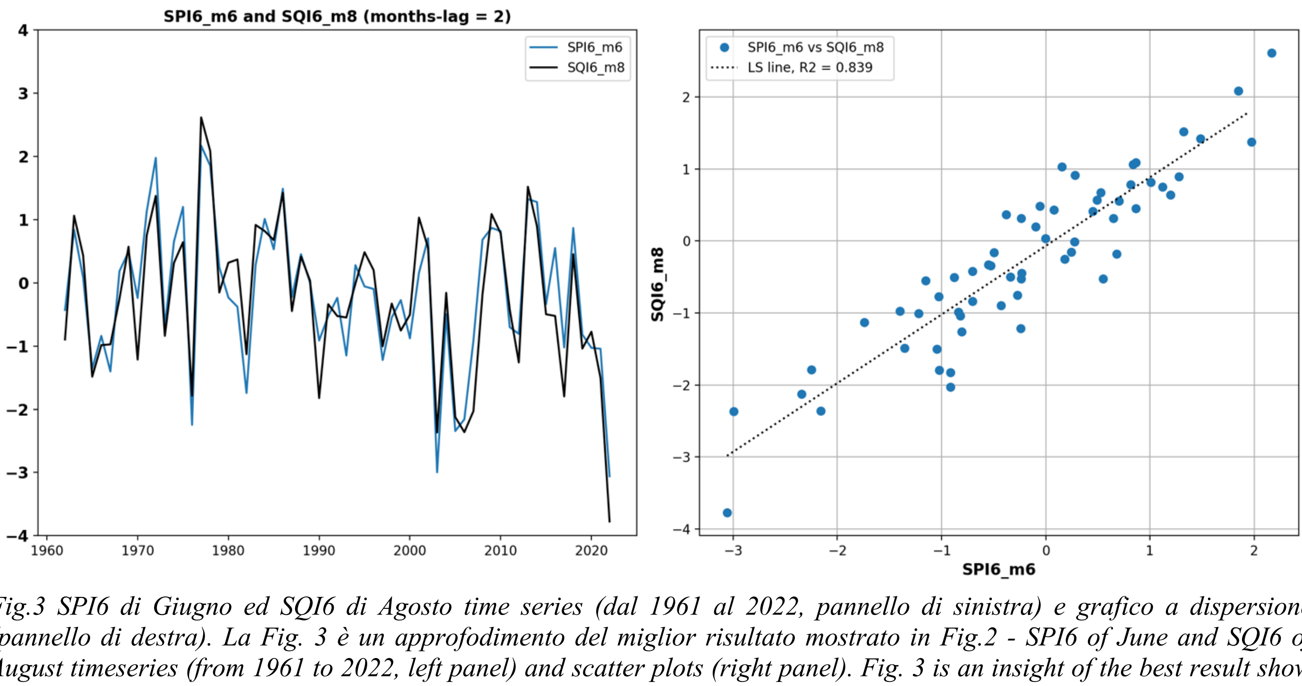

Fig.3 SPI6 di Giugno ed SQI6 di Agosto time series (dal 1961 al 2022, pannello di sinistra) e grafico a dispersione (pannello di destra). La Fig. 3 è un approfodimento del miglior risultato mostrato in Fig.2 - SPI6 of June and SQI6 of August timeseries (from 1961 to 2022, left panel) and scatter plots (right panel). Fig. 3 is an insight of the best result show in Fig.2

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