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Hydrology and Earth System Sciences
Discussions

Interactive comment on "Automatic design of basin-specific drought indexes for highly regulated water systems" *by* Marta Zaniolo et al.

Marta Zaniolo et al.

andrea.castelletti@polimi.it

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The manuscripts provides an excellent contribution to the field for characterizing basin-specific drought conditions within a powerful framework that offers automation, replicability and flexibility. This is particularly useful in applying the approach in management (and planning) decisions at various temporal and spatial scales including reservoir operation, hydropower generation and water allocation among various users and the environment. An fine review on drought types, commonalities and differences is a good compendium to cite for research and educational purposes. The two algorithms presented in the selection of predictors, target variable and index subsets is a great contribution to the field which is often dominated by standardized indicators of droughts that may lack relevance in a local basin context where other confounding factors including

regulations, water rights, environmental constraints and long-time operation rules merit representation. That said, the manuscript would benefit from a better presentation of results, minor editorial improvements and some more detailed explanation of some of the calculations involved in estimating the index. In what follows, I provide some recommendations for improvement.
We thank the referee for the positive comment

Major Issues

1. One of the major issues in the manuscript is presentation of the final step, the drought index. There is a strong disconnect between what is presented in figure 2 and the calculated index? It is clear the at the linear model was a a balanced way to obtain the supply deficit and 'the index'. Is the automated index the supply deficit? Fitness is really good compared to the well-established State Index but how it all fits together considering the different units and how are things calculated? This might seem like an unnecessary question but it is important to present with clarity the fundamental outcome of the approach.
The supply deficit is identified as target variable to guide the construction of the automated index, the index is therefore a proxy of the deficit, not the deficit itself. The supply deficit, in fact, was not obtained by linear model, but was simulated with the AQUATOOL model (Andreu et al., 1996), a Decision Support System developed at the Universidad Politécnica de Valencia (UPV), Valencia, Spain. The model can run in simulation mode with a monthly time step, and it is conceived in the form of a flow network with different types of oriented connections that reproduce water losses, hydraulic connections between nodes, reservoirs and aquifers, and flow limitations based on elevation. Within AQUATOOL, complex processes such as evaporation and infiltration are effectively reproduced. The modeled supply deficit represents the monthly nominal shortage of water conveyed to the irrigation districts, and is only quantifiable a posteriori, when the water shortage has already jeopardized the fields. On the other hand, the automated index can be constantly monitored, and thus represents a valu-

able management tool for containing drought impacts and identifying effective drought management strategies. Numerical results show that FRIDA methodology outperforms the benchmark State Index in the representation of the recorded deficit, and, to assess so, we employed the coefficient of determination R2. R2 is calculated as the ratio of the explained variance (the proportion to which a mathematical model reproduces the dispersion of a given data set) to the total variance, and is a common measure of correlation. As a consequence, the unit in which a variable is expressed has no impact in the computation of R2 and the values of correlation reported are perfectly comparable. We will remark the above points in the text.

2. Likewise for Table 2, how are these weights applicated? Elaborate on the exclusion of Moy in the weight and how is brought back so is taken into account. IF this is too much detail for the main paper consider an appendix for 1 and 2 above.
In the linear case, the index is calculated as a weighted sum of the form:
$Index = weight1 * predictor1 + weight2 * predictor2 + weight3 * predictor3 + (\dots)$
The predictor Moy represents the succession of the months in the year, and is an expression of the seasonality of hydro-meteorological processes. Not surprisingly, it is selected as a relevant variable in the feature selection step. Moy is constructed as the repetition of an array of numbers from 1 to 12 for the length of the considered time horizon, and thus presents a discontinuous shape: a slow and steady increase followed by a steep decrease in correspondence to the onset of a new year. While the non-linear models employed in the feature selection can effortlessly handle such an intermittent vector, linear models struggle with similar shapes. We therefore decided to account for the seasonality in the linear model indirectly, i.e., excluding Moy from the predictors set, but consistently considering seasonality by depurating the predictors of their annual cyclostationary mean.
Following the reviewer suggestion, we will clarify the matter in the text.

3. The set of conclusions are succinct and useful. However, I would highly recommend to comment before (or as part of these) the cases in which this approach may not be

suitable. What are the challenges in obtaining predictors and developing computations, and where the approach presented in the paper which is actually promising moving in the field.
We thank the referee for the good point raised. We find this comment in accordance to the suggestions of referee 1, and, accordingly, we will expand the conclusion section of the paper to substantially improve its clarity, and better elaborate on the mentioned issues.
The efficacy of FRIDA methodology is strongly dependent on the data availability, in terms of predictors diversity and numerosity, and length of the time series. FRIDA is best applicable in contexts where an extensive monitoring system has been in place for long enough to allow a consistent and informative dataset for the index calibration. âĂÍHowever, while some hydro-meteorological variables are easy to monitor and most often available (e.g., precipitation, temperature), the accessibility of other variables such as soil moisture, groundwater table level, snowpack extent, air humidity etc., may represent a problem. When a key drought-driving variable for the context at hand is absent from the input set, the efficacy of FRIDA is undermined. Concerning the computation, FRIDA procedure is mostly automatized. The only step that may require a small degree of manual calibration is the number of ELM to be employed in the feature selection step. An inadequate number of ELM may yield a poor result due to insufficient learning potential (too few ELM), or tendency to overfit the data (too many ELM).

4. Perhaps offer an online supplementary material section in which users can play with the approach. I found it very suitable for an educational setting and in helping basins worldwide in organizing information to characterize drought. Even when some of the algorithms require a fair amount of training from the users, having a pre-processed repository would be of great service to the community.
Following the referee suggestion, we will set up an online repository including all the candidate predictors and the AQUATOOL modeled deficit. A readme text file will detail the nature of the inputs, their sources, and units of measures, as well as the experimen-

tal settings adopted in our experiments. For the codes needed to run the experiments we will refer to the publicly available W-QEISS repository.

5. From what I understand, supply deficit is the target variable. Description of it and its connection with the indicators of the basin is poor. So I encourage the authors to improve it in the paper to make it easier to follow how do we go from predictors, Pareto optimal sets, to index estimation (see 1 above) and and tests.
The supply deficit is the monthly shortage of water conveyed to the irrigation districts with respect to their nominal water demand. As such, it represents the manifestation of a drought as perceived by the water users, i.e., an operational drought. As detailed in the introduction, an operational drought is driven by two factors: water availability due to hydro-meteorological fluctuations, and management of available water resources. An operational drought index must, on the one hand, account for hydro-meteorological predictors, and on the other hand, detect situations of water shortage as perceived by users, i.e., supply deficit. We will make sure this message is conveyed in the introduction of the paper, in order to clarify the relation between supply deficit and operational indicators. In step 1 of FRIDA, possibly relevant hydro-meteorological predictors are identified, and in step 2 those predictors are combined to define Pareto optimal sets. Providing multiple optimal sets we allow the customization of the index, foreseeing its employment as a management tool for the constant monitoring of water resources. The decision maker can identify the preferred subset in accordance to context-dependent needs of accuracy, and agility in the variables monitoring. Finally, in step 3 of the Framework, we tested the potential in constructing meaningful operation drought indexes. To do so, we opted for one of the Pareto optimal sets, we calibrated the relative index on the target deficit, and tested its performance in terms of accuracy and cardinality against the benchmark state index. We here remark that the state index was validated on the same supply deficit, granting a fair comparison between the two indexes. Following the reviewer suggestion, we will make sure to clarify the workflow leading to index design in the section dedicated to present the FRIDA framework.

Minor Issues

1. I through revision of the abbreviations/acronyms in the paper is recommended. Examples: MOEA, ELM, CHJ.
We will extend the table of acronyms to include every acronym included in the manuscript.

2. Abstract, explain how it that traditional drought indexes fail to detect events. Not in the abstract but in the opening of the paper or the contributions section of the paper.
Meteorological, agricultural, and hydrological indexes fail in representing drought conditions in highly regulated basins, where the presence of man-managed water infrastructures (lake dams, groundwater pumps) filter water availability and have a role in magnifying or restraining drought impacts. On the other hand, traditional operational drought indexes are often designed to operate analysis over coarse spatiotemporal resolutions, thus resulting unsuitable for a real time basin level drought detection, characterization, and management. Highly regulated systems need ad hoc index formulations to account for uncontrolled hydro-meteorological conditions (precipitation, temperature…) as well as controllable variables (reservoir and groundwater levels).

3. paragraph line 25, Why is the Jucar index superior to other approaches? What is the basis for comparison?
The State index is a well-established drought monitoring tool currently in use in every Spanish hydrographic confederation (Jucar, Duero, Segura, Ebro, Guadalquivir, Tajo…) to monitor the state of water resources in the basin and trigger drought restraining measures when certain threshold values of the index are reached. Each confederation has designed its customized formulation for the state index which reflects the hydroclimatic conditions and the water uses of the region, and is the outcome of a long participatory process involving basin experts and stakeholders. Since their establishment in 2007, the State indexes have represented the most consistent and extensively applied example of index used for drought management purposes. Thus, Ie represent the state of the art for basin-customized operational drought indexes, and a remarkable

benchmark to test the proposed FRIDA methodology.
We will elaborate on the choice of the State Index as a benchmark in the paper introduction.

4. Line 33, are the \$100 billion for all Europe, over the time period? What does this mean in terms of GDP or other indicators? Put some context to it otherwise is useless. What sectors are included what type of impacts?
As stated in the EU "drought and water scarcity second interim report" (European Commission, 2007), economic impacts of drought amount to \$100 billion for the period 1976-2006. This figure was estimated by aggregating information provided by EU member states on the economic impacts of drought, which, as the report states in page 32, include impacts endured by consumers and households, tourism, industry, energy, and agriculture. No information is provided in terms of GDP units.

5. line 37 what is meant by economic damage?
By economic damage caused by drought we refer to a situation in which a water deficit induced by droughts affects production, sales and business in a variety of sectors (Spinoni et al., 2016). The main economic impacts divided by sectors are detailed in the same report are: socioeconomic impacts; impacts on environmental, forestry, wildfires, and biodiversity; impacts on farming and livestock; impacts on public water supply; impacts on surface and groundwater; impacts on industry; impacts on power generation: hydropower, thermal, and nuclear; impacts on commercial shipping; impacts on tourism and recreation. In the introduction of the manuscript we will mention the matter and refer to Spinoni et al., 2016 for further details.

6. A graphic showing the four types of drought described would be very useful although not the main objective of the paper. Spatial, temporal, supply and demand, and involved sectors in a basin could be outlaid in the infographic.

We will include the infographic in Figure 1 in the paper introduction.

Caption: Development chain of droughts through time. Meteorological drought: defined as a lack of precipitation over a region for a certain period of time; develops in the short term. Agricultural drought: accounts for the plants and crops water stress; develops in the medium term. Hydrological drought: defined as a period of low streamflow in watercourses, lakes and groundwater level below normal; develops in the long term. Operational drought: defined as a period with anomalous supply failures in a developed water exploitation system. Figure adapted from Spinoni et al., 2016 to include Operational drought.

7. Sentence starting in line 93 is awkward please break into more sentences.
We will rephrase as:
Anthropized systems have, in fact, demonstrated the ability to endure meteorological droughts for months or even years without suffering consequences i.e., without incurring in a situation of water shortage perceived by users. The employment of an effective planning and management of water resources system enables such systems to wisely exploit the combined storage capacities of surface and groundwater reserves and restrain drought.

8. The equation below line 230, should it be $f4(Si) >= f(Sj)$?
There is indeed an error in the formula, we thank the reviewer for noticing. The correct formula is
$\mathbf{S}_i \subset \mathbf{S}_j$ and $f_4(\mathbf{S}_i) \geq f_4(\mathbf{S}_j)$.
. We will make sure to fix it in the revised version of the paper.

9. Line 320 as per comment above, elaborate on Ie performance.
According to the reviewer suggestion we will remark the significance of the Spanish experience with State Indexes in this instance, in accordance to what elaborated in the response to minor issue 3.

10. How would a 'traditional index' e.g. SDI would perform in Figure 5? How are we making the case of both Ie and the developed automated index are better? Please

elaborate.

We hereby assume the reviewer intended to mention the traditional SPI index. âĂÍSPI would represent meteorological conditions but won't provide any insight on actual water shortage as perceived by the users. Both Ie and Frida index are operational indexes, and take into account the filtering effect of water management on meteorological fluctuations, thus correlating significantly with the recorded supply deficit.

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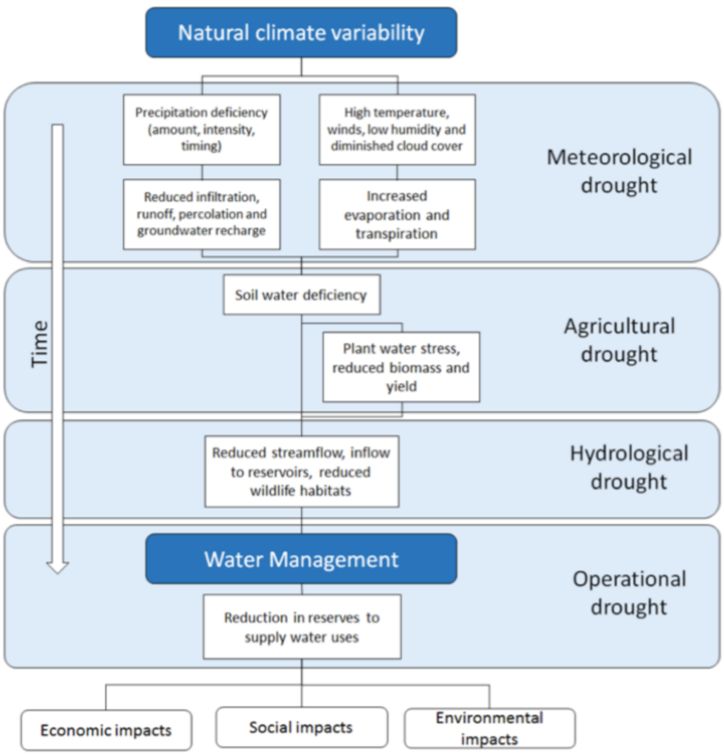

Fig. 1. Drought Evolution infographic