Towards operational drought impact-based forecasting in Europe:
Trade-offs between indicators and impacts

Anastasiya Shyrokaya [1]

Florian Pappenberger [2], Gabriele Messori [1], Ilias Pechlivanidis [3] Hannah Cloke [4], Giuliano Di Baldassarre [1]

[1] Centre of Natural Hazards and Disaster Science (CNDS), Department of Earth Sciences, Uppsala University, Uppsala, Sweden
[2] European Centre for Medium-Range Weather Forecasts (ECMWF), Reading, UK
[3] Swedish Meteorological and Hydrological Institute (SMHI), Norrköping, Sweden
[4] Department of Geography and Environmental Science, University of Reading, Reading, UK

Why do we need impact-based forecasting?

Despite the progress in seasonal drought forecasting, it remains challenging to identify suitable drought indices for accurately predicting the impacts of a future drought event. Impact-based forecasting establishes impact functions that connect drought indicators with impacted sectors, considering vulnerability factors. By inputting forecasted drought indicators into impact functions, this approach allows to forecast impacts, identify vulnerable areas, and prioritize aid. **For more details, refer to the paper ->**

Shyrokaya, A., Pappenberger, F., Pechlivanidis, I., Messori, G., Khatami, S., Mazzoleni, M., & Di Baldassarre, G. (2024). **Advances and gaps in the science and practice of impact-based forecasting of droughts.** *WIREs Water 11(2), e1698*).

1 Link between drought indicators and impacts

Number of studies assessed the link between drought indicators and impacted sectors;

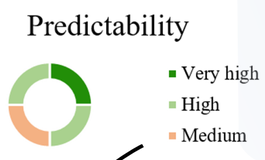
Used results from [1] for the UK and Germany;

Step 1
Link between Drought Indicators and Impacted Sectors

Step 2
Forecasting Performance of Drought Indicators

Step 3
Total Predictability Score

Range (from low (1) to high (5))	Correlation Coefficients	Total score
1,2	Below 0.4 (low)	Low
3	0.4 – 0.6 (medium)	Medium
4	0.6 – 0.8 (high)	High
5	Above 0.8 (very high)	Very High



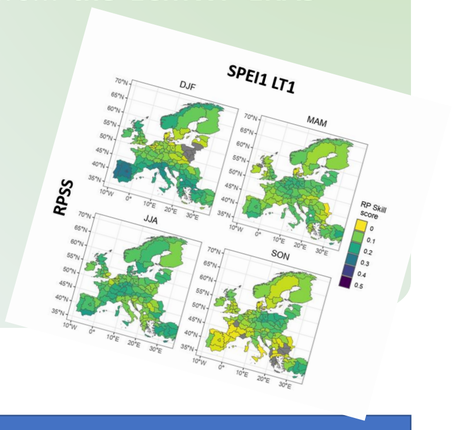
2 Forecasting Performance of drought indicators

Assessing the predictability of drought indices by computing various drought indicators from:

a. **ECMWF SEAS5 seasonal forecasts**;
b. evaluated by computing the same indices from **the ECMWF ERA5 reanalysis data;**

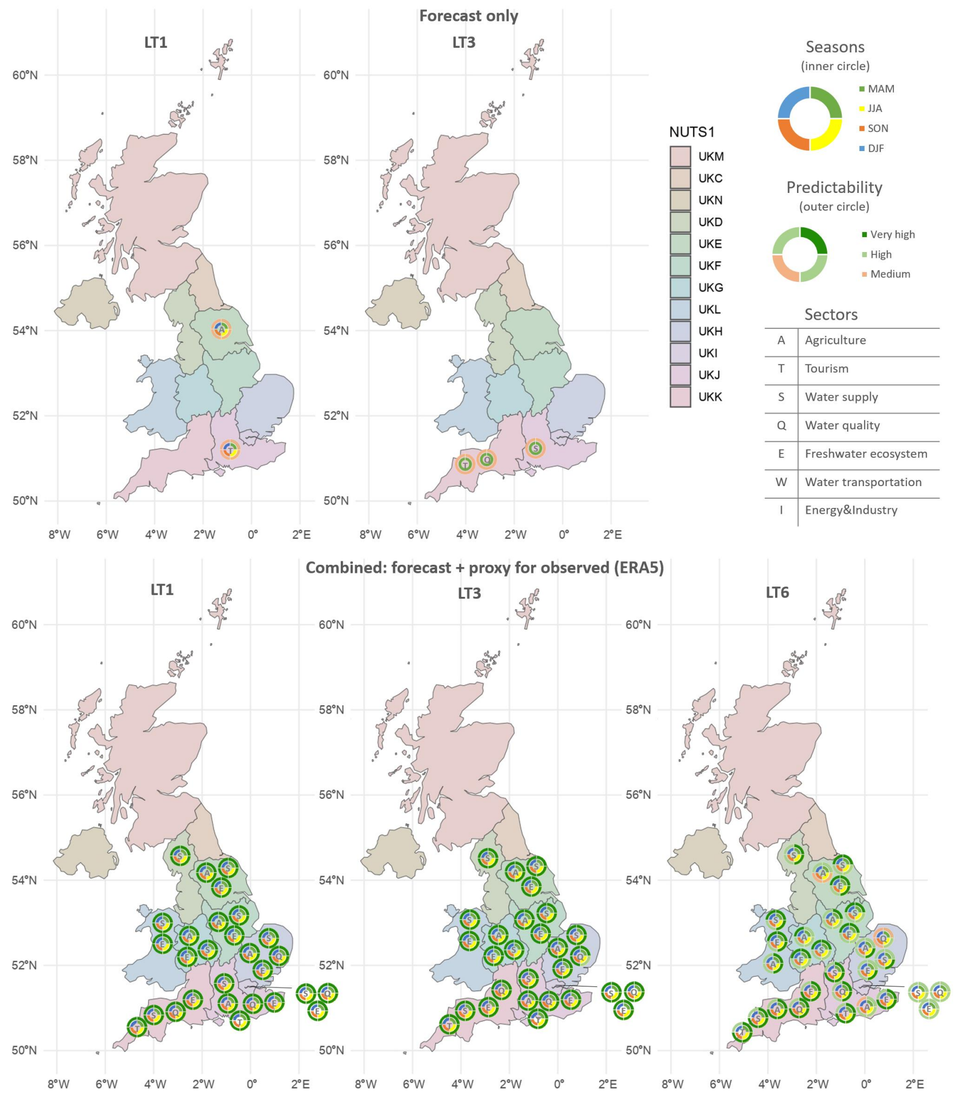
Assessment is conducted across various:

- Drought indices (SPI, SPEI)
- Accumulation periods (1 to 12)
- Lead times (1 to 6 months ahead)
- Seasons (DJF, MAM, JJA, SON)
- Forecasting scores (used corr coeff for step 3)



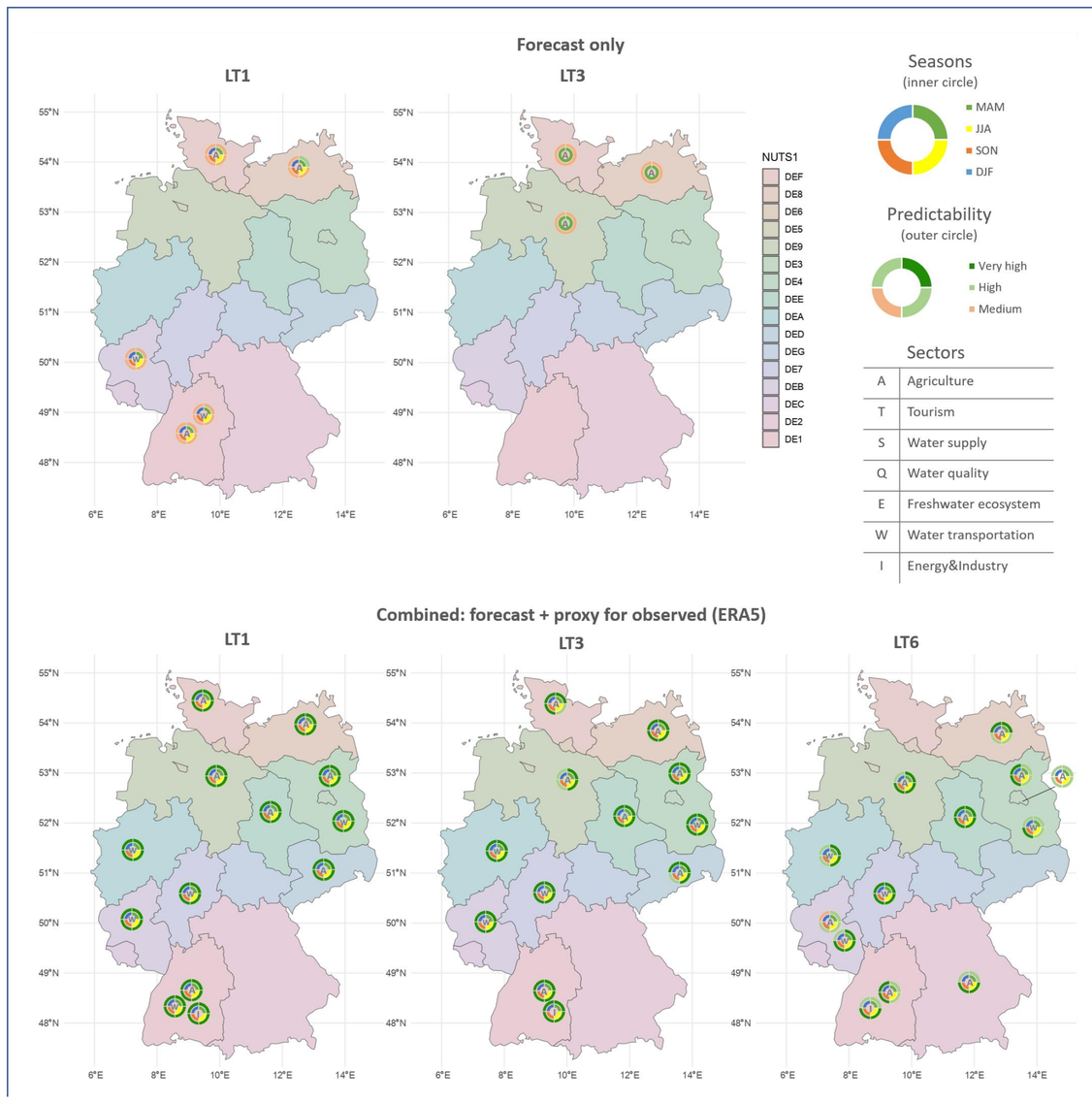
3 Total predictability of impacted sectors

UK case study



Sectors	
A	Agriculture
T	Tourism
S	Water supply
Q	Water quality
E	Freshwater ecosystem
W	Water transportation
I	Energy&Industry

Germany case study



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Figures 1 and 2: The total predictability scores for impacts on various sectors across different NUTS1 regions in the UK (left) and Germany (right). The analysis is split between two approaches: forecast only (upper panel) and combined forecast + proxy for observed ERA5 (lower panel). For each approach, predictability is evaluated at three lead times (LT1, LT3, and LT6) and across different seasons (MAM: Spring, JJA: Summer, SON: Autumn, DJF: winter).

The verification of forecast-only data for the UK (Fig.1, upper panel) indicates that the impacts on Agriculture in Yorkshire and the Humber (UKE) and on Energy and Industry in the South East (UKJ) can be predicted with moderate accuracy at LT1 across all seasons. Similarly, the impacts on Water Supply in the South East and on Water Quality and Tourism in the South West (UKK) exhibit moderate predictability at LT3, but this is limited to the spring season.

When combining forecast data with observational (Fig. 2, lower panel) across multiple sectors—such as Agriculture, Water Supply, Water Quality, Freshwater Ecosystems, and Tourism—predictability increases to a very high level across all seasons at LT1 and LT3. However, by LT6, different sectors exhibit varying levels of predictability (still mostly very high) depending on the NUTS1 region and season. For example, in Mecklenburg-Vorpommern, Agriculture shows higher predictability in winter and spring, with predictability slightly lower but still high in summer and autumn.

Policy recommendations and implications

- **Based on two case studies (the UK and Germany), we showcase how information on the seasonal predictability of drought indicators can be integrated into an impact-based forecasting framework to predict drought impacts across various affected sectors;**
- **Our analysis highlights the need to account for seasonal trends and spatio-temporal patterns in the (seasonal) predictability of drought indices across Europe;**
- **This research contributes to establishing the emerging field of operational impact-based forecasting and operational drought early warning services, aimed at improving preparedness and reducing the impacts of droughts.**

[1] Bachmair, S., Svensson, C., Hannaford, J., Barker, L. J., & Stahl, K. (2016). A quantitative analysis to objectively appraise drought indicators and model drought impacts. Hydrology and Earth System Sciences, 20(7), 2589-2609. https://doi.org/10.5194/hess-20-2589-2016

Contact: Anastasiya Shyrokaya
anastasiya.shyrokaya@geo.uu.se

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