Nat. Hazards Earth Syst. Sci., 22, 1857–1862, 2022
https://doi.org/10.5194/nhess-22-1857-2022

Natural Hazards and Earth System Sciences
Open Access

Preface: Recent advances in drought and water scarcity monitoring, modelling, and forecasting

Brunella Bonaccorso[1], **Carmelo Cammalleri**[2], **Athanasios Loukas**[3], **and Heidi Kreibich**[4]

[1]Department of Engineering, University of Messina, St Agata, Messina, Italy
[2]Joint Research Centre (JRC), European Commission, Ispra, Italy
[3]Department of Rural and Surveying Engineering, Aristotle University of Thessaloniki, Thessaloniki, Greece
[4]GeoForschungsZentrum Potsdam (GFZ), Section Hydrology, Telegrafenberg, 14473 Potsdam, Germany

Correspondence: Brunella Bonaccorso (bbonaccorso@unime.it)

Published: 2 June 2022

1 Introduction

Drought is considered one of the most complex weather-related phenomena due to the considerable variety of causes and impacts. As a recurrent feature of climate, it occurs almost everywhere but with different characteristics from region to region.

Recent publications, based on observational and modelling evidence, suggest that human emissions have substantially increased the probability of drought years in the Mediterranean region (Gudmundsson and Seneviratne, 2016; Gudmundsson et al., 2017). Other recent studies have identified an increase in the frequency of compound events, defined as the co-occurrence of different climate events, such as droughts and heat waves (AghaKouchak et al., 2014; Martius et al., 2016; Zscheischler and Seneviratne, 2017). These compound events have usually amplified effects compared to the single climate events.

These outcomes have been confirmed by the Intergovernmental Panel on Climate Change (IPCC) Working Group 1 contribution to the 6th Assessment Report (AR6) (IPCC, 2021). The report also points out the role of human-induced climate change in increases in the intensity and frequency of agricultural and ecological droughts in drying regions due to increased land evapotranspiration, showing that projected changes become larger with every additional increment of global warming.

While the projected increase in the severity and frequency of droughts due to climate change can already lead to water scarcity situations, overexploitation of available water resources can further exacerbate the consequences of droughts, particularly in those regions that are already water-stressed. In the worst case, this can lead to long-term environmental and socio-economic impacts.

Drought monitoring and forecasting, drought vulnerability and impact assessment, as well as drought preparedness, mitigation and response are the key building blocks of an effective drought management policy (Wilhite, 2011). The enhancement of both monitoring and sub-seasonal to seasonal forecasting of droughts and water availability as well as the development of innovative indicators and methodologies that translate the information provided into effective drought early warning and risk management are therefore essential steps for an operative integrated drought management process.

To this end, many studies have addressed statistical, remote-sensing, and physically based techniques, aimed at monitoring, modelling and forecasting hydro-meteorological variables relevant to drought and/or water scarcity (i.e. precipitation, snow cover, soil moisture, streamflow, groundwater levels and extreme temperatures) (Mishra and Singh, 2011; Fung et al., 2020; Brunner et al., 2021; Prodhan et al., 2022). Some other studies have addressed the development and implementation of drought indicators meaningful for decision-making processes, i.e. tools able to synthetically depict drought conditions for the needs of water managers, policy makers and other stakeholders (Mishra and Singh, 2010; Zargar et al., 2011; Rossi and Cancelliere, 2013; Hao and Singh, 2015; Wu et al., 2021).

This special issue presents a series of contributions on recent advances and future challenges in drought and water scarcity monitoring, modelling and prediction capabilities to improve risk management, adaptation strategies and resilience to such adverse events. The special issue was encouraged by the growing interest in the latest editions of EGU session HS4.2/NH1.15 "Drought and water scarcity: monitoring, modelling and forecasting to improve hydrometeorological risk management". This session gathers scientists, practitioners and stakeholders in the fields of hydrology and meteorology as well as in the field of water resources and drought risk management.

Table 1 summarizes all the papers published in the special issue according to five main topics, illustrating some of the multi-faceted aspects of research studies related to drought and water scarcity.

2 Assessment of past drought features and spatio-temporal evolution

Brunner et al. (2019) investigated the extremeness of the 2018 drought event in Switzerland compared to the 2003 and 2015 events by looking at four variables, i.e. observed precipitation, modelled discharge, soil moisture, and low-flow storage. The latter variables were simulated using the PREVAH hydrological model for 307 medium-sized catchments in Switzerland for the period 1981–2018. This dataset extended the observed discharge dataset in space and time and added the variables soil moisture and low-flow storage. For each of these variables, the two characteristics deficit and deficit duration were considered. The variables were first considered separately in a univariate frequency analysis; pairs of variables were then investigated jointly in a bivariate frequency analysis using a copula model for expressing the dependence between the two variables under consideration. Their findings demonstrated that the use of univariate and bivariate analyses can lead to different severity estimates for individual catchments and divergent conclusions on the extremeness of individual events, which depend on location, variable(s), and the problem under consideration (i.e. the type of return period chosen).

Longobardi et al. (2021) assessed drought features in the Campania region (southern Italy) through an analysis of the spatial and temporal patterns of standardized precipitation index (SPI) time series, based on an in situ measurement database which covers a centennial period from 1918 to 2019. SPI time series were reconstructed for different accumulation timescales (from 3 to 48 months), and the modified Mann–Kendall and Sen tests were applied to identify SPI changes over time. SPI time series were mostly affected by a negative trend, significant for a very large area of the region. Concerning the spatial pattern, negative trends appeared to occur along a northwest–southeast transect, whereas positive trends were observed along a west–east transect at the middle latitude of the region. Those two regions are quite different in terms of orography, which likely influences both the average precipitation spatial distribution and the relevant temporal variability. Also, the accumulation timescale was proven to affect the spatial patterns of the drought characteristics.

Yue et al. (2022) explored the effects of large reservoirs on drought resistance in the Hun River basin (HRB). The standardized runoff index (SRI) was adopted to evaluate the evolution of hydrological drought from 1967 to 2019. Meanwhile, the joint probability of drought duration and severity, identified by the run theory, was computed using the copula function with the highest goodness of fit in order to calculate the return period of hydrological drought events. The authors also evaluated the delay between meteorological and hydrological droughts by calculating the Pearson correlation coefficients between a 1-month SRI and a multi-timescale standardized precipitation index (SPI). Finally, based on the cumulative precipitation deficit thresholds for triggering hydrological drought, the impact of large reservoirs on drought resistance of the basin was revealed. Among the various results, they found that the operation of large reservoirs strengthened the drought resistance in the lower reaches, while it is slightly weakened in the upper reaches of large reservoirs.

Ansari and Grossi (2022) investigated the spatial and temporal evolution of wet–dry events collectively, their characteristics and transition (wet to dry and dry to wet) in the Upper Jhelum basin (UJB)-in South Asia, dominated by two precipitation patterns: westerlies in the north-facing slopes and monsoon in the south-facing slopes of the Himalaya mountain range, crossing the basin in the middle. The standardized precipitation evapotranspiration index (SPEI) at the monthly timescale was applied to detect and characterize wet and dry events for the period 1981–2014. The analysis of the temporal variations of the SPEI showed a strong change in basin climatic features associated with El Niño–Southern Oscillation (ENSO) at the end of 1997, with the prevalence of wet and dry events before and after 1997, respectively. The results of the spatial analysis show a high susceptibility of the monsoon-dominated region towards wet events, whereas the westerlies-dominated region was found to be the hotspot of dry events with higher duration, severity, and intensity. Moreover, the region surrounding the Himalaya divide line and the monsoon-dominated part of the basin were found to be the hotspots of rapid wet–dry transition events.

3 Development of new drought indices

Monteleone et al. (2020) proposed a new composite index for agricultural drought monitoring, namely the probabilistic precipitation vegetation index (PPVI). This new index accounts for both meteorological and agricultural drought conditions by combining in a probabilistic framework the SPI and the vegetation health index (VHI). In addition, they developed and implemented a set of rules to objectively identify drought events. Both the index and the set of rules have been applied to a case study in Haiti. The performance of the PPVI

Table 1. Main topics of the special issue contributions.

References	Assessment of past drought features and temporal evolution	Development of new drought indices	Potential of RCMs in climate and drought simulation	Drought hazard and impact forecasting	Linking drought hazard and impacts
Brunner et al. (2019)	×				
Richardson et al. (2020)				×	
Shukla et al. (2020)				×	
Monteleone et al. (2020)		×			
Wang et al. (2020)					×
Sutanto et al. (2020)				×	
Peres et al. (2020)			×		
Hasan et al. (2021)					×
Popat and Döll (2021)		×			
Longobardi et al. (2021)	×				
Felsche and Ludwig (2021)				×	
Yue et al. (2022)	×				
Ansari and Grossi (2022)	×				

has been evaluated by means of a receiver-operating characteristic (ROC) curve and compared to that of the SPI and VHI considered separately. Comparisons between observed and modelled drought events showed that the new index outperforms SPI and VHI in terms of properly identified and characterized drought events, thus revealing the potential for an effective implementation within drought early-warning systems. The main advantages of the PPVI are that (1) it requires few input data (i.e. only precipitation and the VHI), (2) it is a remote-sensing product and therefore easily transferable and scalable over the entire globe, and (3) it is suitable for a timely implementation of drought mitigation strategies due to the relatively short latency time (less than 1 week) of the datasets employed.

Popat and Döll (2021) proposed two drought indices: the soil moisture deficit anomaly index, SMDAI, based on a simplification of the drought severity index, DSI (Cammalleri et al., 2016), and the streamflow deficit anomaly index, QDAI. The first index describes the drought hazard for vegetation, while the second one specifically quantifies the hazard that drought poses for water supply from rivers. Both indices are computed and analysed at the global scale, with a spatial resolution of roughly 50 km, for the period 1981–2010, using monthly time series of variables computed by the global water resources and the WaterGAP model. Although the two indices are broadly similar to values of purely anomaly-based indices, the deficit anomaly indices provide more differentiated spatial and temporal patterns that help to distinguish between the degree and nature of the actual drought hazard to vegetation health or water supply. In particular, the QDAI can serve as a tool for informing water suppliers and other stakeholders about the joint drought hazard for water supply for both humans and the river ecosystem. Like all hydrological drought indicators that reflect the streamflow anomaly, the QDAI needs to be interpreted carefully in case of highly intermittent streamflow regimes.

4 Potential of RCMS in climate and drought simulation

Peres et al. (2020) proposed a statistical methodological framework to assess the quality of 19 EURO-CORDEX RCMs at 0.11° ($\sim$ 12.5 km) grid spatial resolution, mainly focusing on their ability to simulate climate and drought characteristics (duration, accumulated deficit, intensity, and return period) under current climate forcing. The proposed methodology exploits comparisons with high-density and high-quality ground-based observational datasets, and it was applied to the Sicily and Calabria regions (southern Italy), where long historical precipitation and temperature series were recorded by the ground-based monitoring networks operated by the former regional hydrographic offices. Results show that, among the more skillful models able to reproduce precipitation and temperature variability as well as drought characteristics, several are based on the CCLM-Community RCM, particularly in combination with the HadGEM2 global circulation model (GCM). The proposed study reveals insight into RCM performances in small-scale regions, which are often the target of impact studies but have so far received less attention. It also provides some guidance to select the best models before addressing projection changes in the evolution of extreme hydro-meteorological events, such as drought characteristics.

5 Drought hazard and impact forecasting

Richardson et al. (2020) compared the performance of a dynamical sub-seasonal forecast system (EPS-WP) and a first-order Markov model in predicting European weather pattern (WP) occurrences over a range of lead times, showing that the dynamic model is always more skillful, although the difference in skill reduces with lead time. The proposed forecast system was applied in UK meteorological drought prediction. After post-processing mean sea-level pressure forecasts from the European Centre for Medium-Range Weather Forecasts Ensemble Prediction System (ECMWF-EPS) into probabilistic WP predictions, precipitation estimates were derived, and dichotomous drought event probabilities were estimated by sampling from the conditional distributions of precipitation given the WPs. Model estimates were compared with the direct precipitation and drought forecasts from the ECMWF-EPS and with a baseline Markov chain WP method by using a range of skill diagnostics. They found that the Markov model was the least skillful, while the dynamical WP model and direct precipitation forecasts have similar accuracy regardless of lead time and season. However, drought forecasts are more reliable for the dynamical WP model.

Shukla et al. (2020) tested the suitability of the operational root zone soil moisture (RZSM) products from the recently developed NASA Hydrological Forecasting and Analysis System (NHyFAS) for supporting early warning of droughts in southern Africa (SA). The results indicated that the NHyFAS products can effectively support food insecurity early warning in the SA region. In particular, February RZSM forecasts available in early November (4–5 months before the start of harvest and about 1 year before the start of the next lean season) can explain the interannual variability in regional crop yield production with moderate skill (correlation coefficient of 0.49). The February RZSM monitoring product, available in early March (1–2 months before the start of harvest and 8–9 months before the start of the next lean season) can explain the variability in regional crop yield with high skill (correlation coefficient of 0.79). Furthermore, the February RZSM monitoring product can provide “out-of-sample” crop yield forecasts with higher skill than DJF ENSO (38 % reduction in mean error relative to DJF ENSO), whereas the February RZSM forecasting product, available in early November, can provide crop yield forecasts with comparable skill (∼6 % increase in mean error relative to DJF ENSO). Since the datasets and models used to implement the NHyFAS are available globally, a similar seasonal RZSM monitoring and forecasting framework can potentially be developed at a global scale to support food insecurity early warning in other rainfed regions across the globe.

Sutanto et al. (2020) evaluated the skills of both drought hazard and impact forecasts, which were developed using observed and re-forecast hydro-meteorological data and drought impact reports retrieved from the European Drought Impact Report Inventory (EDII). Empirical drought impact functions were developed by using machine learning approaches (logistic regression and random forest) to predict drought impacts with lead times up to 7 months ahead. The observed and forecasted hydrometeorological drought hazards – in terms of the SPI, SPEI, and SRI – were obtained from the EU-funded Enhancing Emergency Management and Response to Extreme Weather and Climate Events (ANYWHERE) Drought Early-Warning Systems (DEWS). Results show that hydrological drought hazard represented by the SRI has higher skill than meteorological drought represented by the SPI and SPEI for the same accumulation period due to the memory represented in initial hydrological conditions and storage in the hydrological system. For German regions, impact functions developed using random forests indicate a higher discriminative ability to forecast drought impacts than logistic regression. Moreover, skill is higher for cases with higher spatial resolution and less lumped impacted sectors.

Felsche and Ludwig (2021) applied artificial neural networks to predict the drought occurrence in Munich and Lisbon with a lead time of 1 month. The approach takes into account a list of 28 atmospheric and soil variables as input parameters from a single-model initial-condition large ensemble (CRCM5-LE). The data were produced with the Canadian Regional Climate Model (CRCM5) driven by 50 members of the Canadian Earth System Model (CanESM2). Drought occurrence is defined as an SPI-1 less than -1 at the given site. The best-performing machine learning algorithms manage to obtain a correct classification of drought or no drought for a lead time of 1 month for around 55 %–57 % of the events of each class for both domains. Variables like the North Atlantic Oscillation index and air pressure 1 month before the event prove to be essential for the prediction.

6 Linking drought hazard and impacts

Wang et al. (2020) explored the link between drought indices and drought impacts by using correlation and random forest methods. In particular, the study identified which indices link best to a comprehensive database of reported drought impacts for prefectural-level cities in Liaoning Province (northeastern China) and proposed a drought vulnerability assessment method to study the contribution of various socioeconomic factors to drought vulnerability. The results show that the standardized precipitation evapotranspiration index with a 6-month accumulation (SPEI-6) had a strong correlation with all categories of drought impacts. Among the impact datasets, “drought-suffering area” and “drought impact area” had a strong relationship with all drought indices in Liaoning Province, while “population and number of livestock with difficulty in accessing drinking water” had weak correlations with the indices. Overall, population and crop-cultivated area were strongly associated with drought vulnerability, suggesting these factors are good proxy variables of drought vulnerability. However, the complexities of these relationships with drought vulnerability require further investigation.

Hasan et al. (2021) investigated the low-flow characteristics and the river storage draft rates in Selangor (Malaysia), based on the long-term streamflow data from seven stations. In particular, the mass curve was used to quantify the minimum storage draft rate required to maintain the 50 % mean annual flow for the 10-year recurrence interval of low flow. The low-flow conditions were analysed using the 7 d mean annual minimum, while the drought events were determined using the 90th percentile as a threshold level. The study reveals September to December to be a critical period in river water storage to sustain the water availability during low flow in a 10-year occurrence interval. This finding indicated that hydrological droughts have generally become more critical for the capability of rivers to sustain water demand during low-flow periods.

7 Concluding remarks

The consequences of past drought disasters have raised awareness about the need to manage drought risk through integrated tools, such as early-warning and decision support systems. Nowadays, the need for integrated drought risk management is even more urgent due to the fact that water-related inter-sectoral conflicts are likely to be exacerbated in the future, mainly because of the concurrency of increasing severity and frequency of droughts due to climate change and ongoing socio-economic and demographic trends (MedECC, 2020).

In light of these perspectives, several scientific efforts have been carried out to better understand the drought phenomena, their evolution in space and time, and the expected related socio-economic and environmental impacts.

The papers collected in this special issue provide an overview of recently developed tools to cope with drought and water scarcity, such as

- drought monitoring tools able to merge multiple information sources, also including satellite-based data describing vegetation and evapotranspiration conditions,
- land surface hydrologic models driven by remote-sensing data, reanalysis datasets, or climate forecasts to investigate current or future drought impacts on water resources,
- teleconnection influence of internal ocean–atmosphere variability on the occurrence and magnitude of drought events,
- potential of climate models to investigate drought spatio-temporal evolution under climate change scenarios, and
- statistical approaches for drought characterization coupled with uncertainty analyses.

Despite the numerous advances, there are still important limitations to our understanding of drought and our ability to mitigate its various negative impacts. Besides, improving predictions of drought events requires a better understanding of how water, vegetation, and energy interact and propagate through the ocean–atmosphere land system. Shedding light on the predictability of the various physical quantities related to drought, such as precipitation, temperature, soil moisture, snow and runoff, is essential (Funk and Shukla, 2020).

The EGU HS4.2/NH1.15 session will keep on providing an opportunity for scientists and practitioners to meet and discuss and start new collaborations to enhance the state-of-the-art knowledge on drought and water scarcity.

Acknowledgements. We warmly thank all the authors and reviewers who were involved in this special issue, and we hope the readers will enjoy it.

References

AghaKouchak, A., Cheng, L., Mazdiyasni, O., and Farahmand, A.: Global warming and changes in risk of concurrent climate extremes: Insights from the 2014 California drought, Geophys. Res. Lett., 41, 8847–8852, https://doi.org/10.1002/2014gl062308, 2014.

Ansari, R. and Grossi, G.: Spatio-temporal evolution of wet–dry event features and their transition across the Upper Jhelum Basin (UJB) in South Asia, Nat. Hazards Earth Syst. Sci., 22, 287–302, https://doi.org/10.5194/nhess-22-287-2022, 2022.

Brunner, M. I., Liechti, K., and Zappa, M.: Extremeness of recent drought events in Switzerland: dependence on variable and return period choice, Nat. Hazards Earth Syst. Sci., 19, 2311–2323, https://doi.org/10.5194/nhess-19-2311-2019, 2019.

Brunner, M. I., Slater, L., Tallaksen, L. M., and Clark, M.: Challenges in modeling and predicting floods and droughts: A review, WIRes Water, 8, e1520, https://doi.org/10.1002/wat2.1520, 2021.

Cammalleri, C., Micale, F., and Vogt, J.: A novel soil moisture-based drought severity index (DSI) combining water deficit magnitude and frequency, Hydrol. Process., 30, 289–301, https://doi.org/10.1002/hyp.10578, 2016.

Felsche, E. and Ludwig, R.: Applying machine learning for drought prediction in a perfect model framework using data from a large ensemble of climate simulations, Nat. Hazards Earth Syst. Sci., 21, 3679–3691, https://doi.org/10.5194/nhess-21-3679-2021, 2021.

Fung, K. F., Huang, Y. F., Koo, C. H., and Soh, Y. W.: Drought forecasting: A review of modelling approaches 2007–2017, J. Water Clim. Change, 11, 771–799, 2020.

Funk, C. and Shukla, S.: Drought Early Warning and Forecasting. Theory and Practice, Elsevier, https://doi.org/10.1016/C2016-0-04328-0, 2020.

Gudmundsson, L. and Seneviratne, S. I.: Anthropogenic climate change affects meteorological drought risk in Europe, Environ. Res. Lett., 11, 044005, https://doi.org/10.1088/1748-9326/11/4/044005, 2016.

Gudmundsson, L., Seneviratne, S. I., and Zhang, X.: Anthropogenic climate change detected in European renewable freshwater resources, Nat. Clim. Change, 7, 813–816, https://doi.org/10.1038/nclimate3416, 2017.

Hao, Z. and Singh, V. P.: Drought characterization from a multivariate perspective: A review, J. Hydrol., 527, 668–678, 2015.

Hasan, H. H., Mohd Razali, S. F., Muhammad, N. S., and Mohamad Hamzah, F.: Assessment of probability distributions and analysis of the minimum storage draft rate in the equatorial region, Nat. Hazards Earth Syst. Sci., 21, 1–19, https://doi.org/10.5194/nhess-21-1-2021, 2021.

IPCC: Summary for Policymakers, in: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, edited by: Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M. I., Huang, M., Leitzell, K., Lonnoy, E., Matthews, J. B. R., Maycock, T. K., Waterfield, T., Yelekçi, O., Yu, R., and Zhou, B., Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 3–32, https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_SPM.pdf (last access: 31 May 2022), 2021.

Longobardi, A., Boulariah, O., and Villani, P.: Assessment of centennial (1918–2019) drought features in the Campania region by historical in situ measurements (southern Italy), Nat. Hazards Earth Syst. Sci., 21, 2181–2196, https://doi.org/10.5194/nhess-21-2181-2021, 2021.

Martius, O., Pfahl, S., and Chevalier, C.: A global quantification of compound precipitation and wind extremes, Geophys. Res. Lett., 43, 7709–7717, https://doi.org/10.1002/2016gl070017, 2016.

MedECC: Climate and Environmental Change in the Mediterranean Basin – Current Situation and Risks for the Future. First Mediterranean Assessment Report, edited by: Cramer, W., Guiot, J., and Marini, K., Union for the Mediterranean, Plan Bleu, UNEP/MAP, Marseille, France, 632pp., https://doi.org/10.5281/zenodo.4768833, 2020.

Mishra, A. K. and Singh, V. P.: A review of drought concepts, J. Hydrol., 391, 202–216, 2010.

Mishra, A. K. and Singh, V. P.: Drought modeling – A review, J. Hydrol., 403, 157–175, 2011.

Monteleone, B., Bonaccorso, B., and Martina, M.: A joint probabilistic index for objective drought identification: the case study of Haiti, Nat. Hazards Earth Syst. Sci., 20, 471–487, https://doi.org/10.5194/nhess-20-471-2020, 2020.

Peres, D. J., Senatore, A., Nanni, P., Cancelliere, A., Mendicino, G., and Bonaccorso, B.: Evaluation of EURO-CORDEX (Coordinated Regional Climate Downscaling Experiment for the Euro-Mediterranean area) historical simulations by high-quality observational datasets in southern Italy: insights on drought assessment, Nat. Hazards Earth Syst. Sci., 20, 3057–3082, https://doi.org/10.5194/nhess-20-3057-2020, 2020.

Popat, E. and Döll, P.: Soil moisture and streamflow deficit anomaly index: an approach to quantify drought hazards by combining deficit and anomaly, Nat. Hazards Earth Syst. Sci., 21, 1337–1354, https://doi.org/10.5194/nhess-21-1337-2021, 2021.

Prodhan, F. A., Zhang, J., Hasan, S. S., Pangali Sharma, T. P., and Mohana, H. P.: A review of machine learning methods for drought hazard monitoring and forecasting: Current research trends, challenges, and future research directions, Environ. Modell. Softw., 149, 105327, https://doi.org/10.1016/j.envsoft.2022.105327, 2022.

Richardson, D., Fowler, H. J., Kilsby, C. G., Neal, R., and Dankers, R.: Improving sub-seasonal forecast skill of meteorological drought: a weather pattern approach, Nat. Hazards Earth Syst. Sci., 20, 107–124, https://doi.org/10.5194/nhess-20-107-2020, 2020.

Rossi, G. and Cancelliere, A.: Managing drought risk in water supply systems in Europe: A review, Int. J. Water Resour. D., 29, 272–289, 2013.

Shukla, S., Arsenault, K. R., Hazra, A., Peters-Lidard, C., Koster, R. D., Davenport, F., Magadzire, T., Funk, C., Kumar, S., McNally, A., Getirana, A., Husak, G., Zaitchik, B., Verdin, J., Nsadisa, F. D., and Becker-Reshef, I.: Improving early warning of drought-driven food insecurity in southern Africa using operational hydrological monitoring and forecasting products, Nat. Hazards Earth Syst. Sci., 20, 1187–1201, https://doi.org/10.5194/nhess-20-1187-2020, 2020.

Sutanto, S. J., van der Weert, M., Blauhut, V., and Van Lanen, H. A. J.: Skill of large-scale seasonal drought impact forecasts, Nat. Hazards Earth Syst. Sci., 20, 1595–1608, https://doi.org/10.5194/nhess-20-1595-2020, 2020.

Yue, S., Sheng, X., and Yang, F.: Spatiotemporal evolution and meteorological triggering conditions of hydrological drought in the Hun River basin, NE China, Nat. Hazards Earth Syst. Sci., 22, 995–1014, https://doi.org/10.5194/nhess-22-995-2022, 2022.

Wang, Y., Lv, J., Hannaford, J., Wang, Y., Sun, H., Barker, L. J., Ma, M., Su, Z., and Eastman, M.: Linking drought indices to impacts to support drought risk assessment in Liaoning province, China, Nat. Hazards Earth Syst. Sci., 20, 889–906, https://doi.org/10.5194/nhess-20-889-2020, 2020.

Wilhite, D. A.: Essential elements of national drought policy: moving toward creating drought policy guidelines, Proceedings of an Expert Meeting, 14–15 July 2011, Washington, D.C. USA, edited by: Sivakumar, M. V. K., Motha, R. P., Wilhite, D. A., and Qu, J. J., World Meteorological Organization, Geneva, 96–107, 2011.

Wu, D., Li, Y., Kong, H., Meng, T., Sun, Z., and Gao, H.: Scientometric analysis-based review for drought modelling, indices, types, and forecasting especially in Asia, Water-Sui., 13, 2593, https://doi.org/10.3390/w13182593, 2021.

Zargar, A., Sadiq, R., Naser, B., and Khan, F. I.: A review of drought indices, Environ. Rev., 19, 333–349, 2011.

Zscheischler, J. and Seneviratne, S. I.: Dependence of drivers affects risks associated with compound events, Sci. Adv., 3, e1700263, https://doi.org/10.1126/sciadv.1700263, 2017.