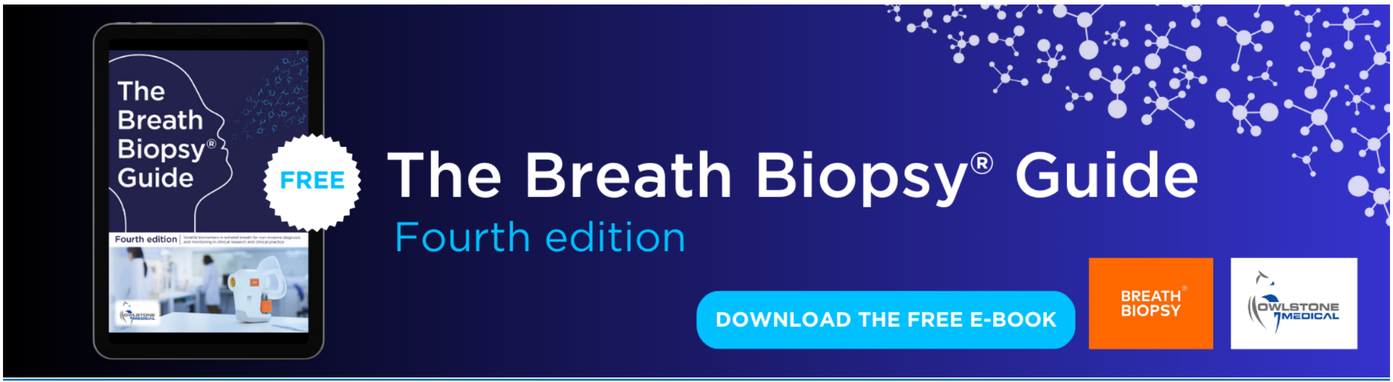
ENVIRONMENTAL RESEARCH
LETTERS

LETTER • OPEN ACCESS

Sub-seasonal to seasonal outlook of the 2022–23 southwestern Korea meteorological drought

To cite this article: Chang-Kyun Park *et al* 2023 *Environ. Res. Lett.* **18** 104039



IOP Publishing Environ. Res. Lett. 18 (2023) 104039 https://doi.org/10.1088/1748-9326/acfb27

ENVIRONMENTAL RESEARCH
LETTERS

OPEN ACCESS

RECEIVED
15 April 2023

REVISED
15 September 2023

ACCEPTED FOR PUBLICATION
19 September 2023

PUBLISHED
3 October 2023

LETTER

Sub-seasonal to seasonal outlook of the 2022–23 southwestern Korea meteorological drought

Chang-Kyun Park[1], **Sangeun Lee**[2], **Hyuncheol Yoon**[3] **and Jonghun Kam**[1,*]

[1] Division of Environmental Science and Engineering, Pohang University of Science and Technology, Pohang 37673, Republic of Korea
[2] Land and Infrastructure Safety Research Center, Korea Research Institute for Human Settlements, Sejong 30147, Republic of Korea
[3] National Integrated Drought Center, National Disaster Management Research Institute, Ulsan 44538, Republic of Korea
[*] Author to whom any correspondence should be addressed.

E-mail: jhkam@postech.ac.kr

Keywords: drought, S2S forecast, Korean Peninsula, scEDI

Supplementary material for this article is available online

Abstract

The southwestern Korean Peninsula had experienced cumulative precipitation deficits from the early spring of 2022, causing a severe meteorological drought in March 2023. As a growing season was forthcoming, the sub-seasonal to seasonal outlook of this ongoing drought came into question. This study aims to investigate a key driver of the ongoing drought and the required precipitation for its termination, and examine the sub-seasonal and seasonal outlooks of the ongoing drought via probabilistic and climate model-based forecasts. Results show a comparable contribution of springtime and summertime precipitation deficits in 2022, indicating that six-month accumulated precipitation deficit of 2022 was a key driver of the ongoing drought. We find that at least 80, 150, and 210 mm (170, 310, and 440 mm) of accumulated precipitation are required for the recovery (full recovery) in March, April, and May 2023, respectively. These required cumulative precipitation are found from 25% and 20% of empirical and dynamic precipitation forecasts, respectively. This study highlights the importance of the collaborative effort of national and local governments and stakeholders on mitigating negative impacts of the ongoing drought.

1. Introduction

The southwestern (SW) Korean Peninsula had experienced long-lasting precipitation deficits since the spring of 2022, resulting in a severe drought in early 2023. Normally, regional dam operation facilities over this region maintain the maximum water level of dam reservoirs in January for a forthcoming crop planting season from late March through early May. In February 2023, however a majority of the large reservoirs showed 50% of the maximum water level or less (K-water 2023). Since then, regional authorities had operated dams following drought contingency plans to mitigate adverse effects of the ongoing drought on regional communities, but the effectiveness of the changes in dam operation remains uncertain due to missing of the sub-seasonal to seasonal (S2S) outlook of the ongoing drought. This region had 95.7 mm in a single day (5 May 2023), which lead to a temporary drought recovery. Heavy rainfalls occurred from late June and through mid-July (over 350 mm of total rainfall), terminating the two year-long drought (figure 1).

While drought monitoring systems (Svoboda *et al* 2002, Begueria *et al* 2014, Sheffield *et al* 2014) and precipitation forecasting operational systems (Kirtman *et al* 2014, Pegion *et al* 2019) are common, the monitoring and forecasting systems of drought recovery are limited. The operational systems of the NOAA National Weather Service (www.weather.gov/serfc/howmuchrain) and United Kingdom (UK) Hydrological Outlook (https://hydoutuk.net/) provide a spatiotemporal outlook of the ongoing drought and also the required amount of precipitation for termination of the ongoing drought. These drought recovery outlooks provide actionable information for proactive drought mitigation plans. However, a severe South Korea drought is often terminated by heavy rainfalls within a short period (Kim *et al* 2009, Park *et al* 2022) that often cause

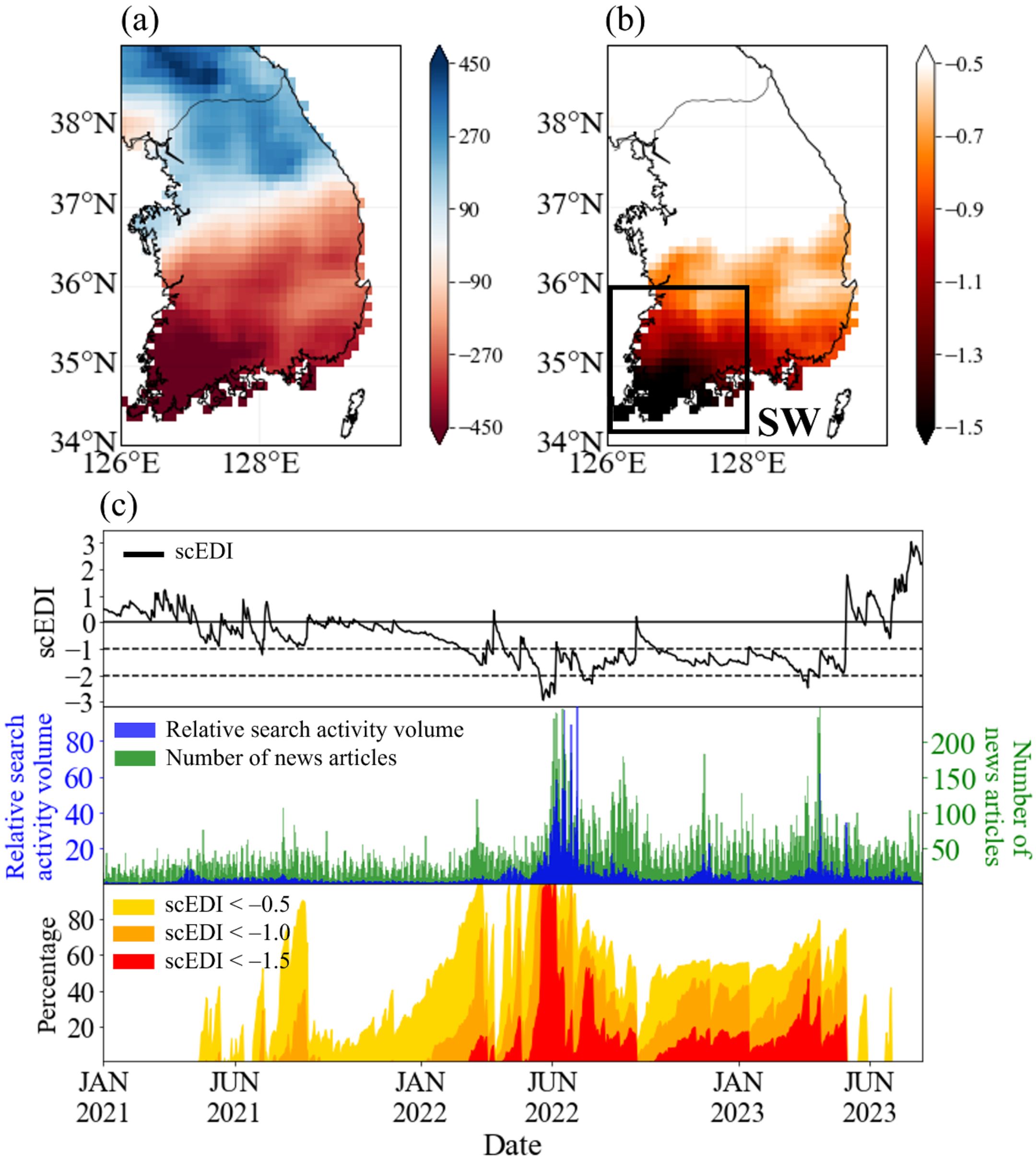


Figure 1. Spatial distributions of (a) accumulated precipitation anomalies (unit: mm) and (b) the mean scEDI during January 2022 through July 2023. A black box in (b) depicts the southwestern (SW) Korean Peninsula region. (c) Daily scEDI values over SW region (lines), relative online search activity volumes (blue bars) and number of news article (green bars) using a search term, 'drought', from NAVER for 2021–2023, and areal fractions of drought-affected area in South Korea.

a severe pluvial flood, which makes the authorities of South Korea more focused on the imporvement of flood forecasting, rather than drought recovery forecasting.

The seasonal forecasting skill of drought recovery remains uncertain due to limited precipitation forecasting skill beyond two weeks. To examine a possibility of drought recovery and its uncertainty range, previous studies quantified the required accumulated precipitation amount and likelihood of the ongoing drought demise using drought index-based methodologies (Antofie *et al* 2015), ensemble deterministic model forecasts (Bell *et al* 2013, Pan *et al* 2013) and statistical methodologies (Parry *et al* 2018, Singh *et al* 2021, Xu *et al* 2023). However, these studies are based on soil moisture and hydrological droughts that has long-term memory in their time series. It is well known that Korea meteorological droughts have a relatively short-term duration with the onset in the spring season (Kim *et al* 2009). The Korean Peninsula has 1200–1300 mm of the annual precipitation on long-term average, with a clear seasonality of precipitation. Most of the total annual precipitation is distributed over the summer months via heavy rainfalls developed by various generating mechanisms of moisture transports from surrounding seas and remote oceans, including atmospheric rivers (e.g. Changma/Maiyu) and tropical cyclones (Ha *et al* 2012, Kim and Jin 2016, Park *et al* 2021). This rapid recovery of the meteorological droughts has been found in the eastern US region (Kam *et al* 2014). The regional climate system of the Korean Peninsula often causes severe summertime pluvial flooding, following a severe springtime meteorological drought. Therefore, monitoring of the stage of the ongoing drought is critical to understand the recovery patterns of Korean Peninsula droughts and generate their sub-seasonal and seasonal outlooks.

The effective drought index (EDI; Byun and Wilhite 1999) is the only drought index that is designed to characterize the drought condition at the daily basis. While standardized drought indices accounts for accumulation of monthly precipitation deficit within a fixed time window, the EDI accounts for the time-varying accumulation of daily precipitation deficit, depending on the severity of the ongoing drought. The EDI can provide the estimate of required precipitation amounts for its demise. Monitoring of the daily condition of the ongoing drought can provide actionable information to water resources managers and local stakeholders (Byun and Wilhite 1999, Kim *et al* 2009, Park *et al* 2022). Previous studies found that EDI detected and characterized the past droughts across the spatial and temporal scales more accurately compared to other standardized indices (e.g. Morid *et al* 2006, Pandey *et al* 2008, Akhtari *et al* 2009, Deo *et al* 2017, Kamruzzaman *et al* 2019, Malik *et al* 2021).

Recently, the self-calibrating EDI (scEDI; Park *et al* 2022) is proposed to compute daily drought index values using 30-year receding yardsticks, instead of the last 30 year yardstick that is used in the EDI calculation, to monitor daily evolutions of the ongoing drought. In other words, the scEDI automatically calibrates the 'optimal climate normal' (Wilks 1996), depending on the period of interest, which leads to the statistical consistency of its index values (e.g. the frequency of −1.0 of scEDI values is 34% of the sample).

Precipitation forecasts of the real-time operation systems can hint the outlooks of the ongoing drought from the perspective of the drought propagation. But they do not provide the actionable information for drought preparation and response plans, which requires specific information for decision making like the required precipitation amount for drought recovery. The Sub-seasonal Experiment (SubX, Pegion *et al* 2019) and North American Multimodel Ensemble (NMME, Kirtman *et al* 2014) forecasting systems provide the sub-seasonal and seasonal forecasts, respectively. They provide multi-model ensemble forecasts of precipitation and other meteorological variables over the globe. Previous literatures suggested that precipitation forecasts of SubX and NMME are reliable over the Asian region (Pegion *et al* 2019, Roy *et al* 2020, Moradian and Yazdandoost 2021, Tiwari and Mishra 2022). A recent study (Park and Kam 2023) found that the predictability of SubX model forecasts for multi-year Korea droughts is event-dependent. Effort to translate dynamical forecast precipitations in the context of drought outlooks remains limited. Furthermore, comparison studies of synthetic/empirical and dynamical precipitation forecasts (Turco *et al* 2017) provide a reliable outlook of the ongoing drought, but they are still lacking. Therefore, this study aims to examine scEDI-based required cumulative precipitation amounts for the drought recovery from ensemble empirical precipitation forecasts and compare the likelihood of the drought demise from empirical and dynamical forecasts. This study will deepen our understanding of the causes of the ongoing drought and the reliability of the sub-seasonal and seasonal outlooks, leading to actionable information to update the contingency plans for the future droughts.

2. Data and methods

This study used the 10-km gridded European Centre for Medium-Range Weather Forecasts reanalysis version 5 Land (ERA5-Land) daily precipitation data over 1950–2023 (Muñoz-Sabater *et al* 2021; www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-v5). ERA5-Land daily precipitation data showed a consistent spatial pattern of scEDI values with that from observational data of the 59 Korean Meteorological Administration weather stations over 2022–2023 (figure S1). The regional averages of daily scEDI values from the ERA5-Land gridded and observational precipitation data over the SW Korean Peninsula showed a high temporal correlation coefficient (about 0.85) for 1980–2023 (figure S1(c)), indicating the reliability of daily ERA5-Land precipitation data for the SW Korean Peninsula.

Increases in online search activity volumes and news articles related to droughts is the social impact of a severe drought. In this study, daily search activity volume data from the NAVER DataLab platform (https://datalab.naver.com) and the number of news article about drought from the NAVER news portal (https://news.naver.com) were used to monitor the public's and mass media's attention to the ongoing drought. These data provided by the NAVER search engine provide a unique opportunity to analyze the dynamic patterns of social response over the temporal evolutions of the ongoing drought. The daily search activity volumes and the number of news articles were collected over 2021–2023. It is worth noting that NAVER occupies about 60% of the Korean Internet web search market in 2023 (Chang 2023).

This study also used multi-ensemble precipitation forecasts of six SubX and six NMME climate forecast models due to available forecasts during the study period (http://iridl.ldeo.columbia.edu/SOURCES/.Models). Forecast precipitation at the four corresponding 100-km grid boxes to the SW Korean Peninsula regions were used to compute the regional averages of precipitation and scEDI values. The forecast initial time of the precipitation forecasts was late February or early March 2023, which is the closest available forecast date to 1 March 2023. Detailed information of the SubX and NMME forecasts were shown in table S1. The forecast range of the SubX (NMME) system is from 32 to 45 days (from 9 to 12 months). Diverse verification metrics show that the SubX and NMME hindcasts are corresponded well to the observation in zero to one month lead time (see figures S2 and S3 in supplementary material), which is consistent with the findings of a recent prediction skill assessment for South Korea droughts (Park and Kam 2023).

In this study, the SubX and NMME models were divided into two groups based on their predictive performances to three historical drought events (see figures S2 and S3 in supplementary material). The high (low) performance model group for SubX consists of ECCC-GEPS7, ESRL-FIMr1p1, and NCEP-CFSv2 (EMC-GEFSv12, GMAO-GEOS_V2p1, and RSMAS-CCSM4). The high (low) performance model group for NMME, these are GEM5-NEMO, GFDL-SPEAR, and NCEP-CFSv2 (CanCM4i, NASA-GEOSS2S, and RSMAS-CCSM4). To generate the distributions of precipitation forecasts of the NMME (SubX) models, precipitation forecasts are randomly sampled with replacement 10 000 times from the 56 and 30 (29 and 44) ensemble runs of the high and low performance models, respectively. For example, the distribution of precipitation forecasts of the NMME model group with the high performance is constructed by randomly sampling with replacement from the 10, 30, and 16 ensemble forecasts of the GEM5-NEMO, GFDL-SPEAR, and NCEP-CFSv2 models, respectively and repeating it 10 000 times.

To detect and characterize historical and ongoing droughts, the scEDI was calculated by using the daily precipitation of the ERA5 over 1950–2023. Using the daily precipitation time series of each grid of ERA5, the scEDI values are calculated following the methods of Park *et al* (2022). Firstly, effective precipitation (EP) is calculated by weighting averaged m-day antecedent precipitation (equation (1))

$$\mathrm{EP}\left(k,y\right)=\begin{cases}\displaystyle\sum_{n=1}^{\mathrm{DS}}\left[\left(\sum_{m=1}^{n}P\left(365+k-m,\ y-1\right)\right)/n\right], & k\leqslant m\\ \displaystyle\sum_{n=1}^{\mathrm{DS}}\left[\left(\sum_{m=1}^{n}P\left(k-m,\ y\right)\right)/n\right], & k>m\end{cases}\tag{1}$$

where DS is the initial duration of antecedent precipitation summation, 365, k is the day number of the climatological year ($k = 1, 2, \ldots, 365$), y is the last year of a 30 year rolling period.

Secondly, the climatology of precipitation using a 30 year rolling period (i.e. the preceding 30 years; rCP) are calculated (equation (2))

$$\mathrm{rCP}\left(k,\ y\right)=\frac{\sum_{y-29}^{y}P\left(k,y\right)}{30}.\tag{2}$$

Thirdly, the mean EP (MEP) values are calculated following the EP calculation but using rCP (k, y), instead of daily precipitation (equation (3)),

$$\mathrm{rMEP}\left(k,\ y\right)=\begin{cases}\displaystyle\sum_{n=1}^{\mathrm{DS}}\left[\frac{\left(\sum_{m=1}^{n}\mathrm{rCP}(365+k-m,\ y-1)\right)}{n}\right], & k\leqslant m\\ \displaystyle\sum_{n=1}^{\mathrm{DS}}\left[\frac{\left(\sum_{m=1}^{n}\mathrm{rCP}(k-m,\ y)\right)}{n}\right], & k>m\end{cases}\tag{3}$$

Then, the deviations of EP (rDEP) are calculated by subtracting rMEP from EP (equation (4)),

$$\mathrm{rDEP}\left(k,y\right)=\mathrm{EP}\left(k,y\right)-\mathrm{rMEP}\left(k,y\right).\tag{4}$$

The DS value (DS(k,y)) is 365 when the rDEP value of the corresponding date is zero or positive. The DS value increases when the rDEP value of the corresponding date is negative, which is time-varying accumulation length of precipitation deficits. By updating the DS values, EDI can account for time-varying summation durations depending on cumulative antecedent precipitation deficit, which can characterize a more realistic drought condition. With the updated DS values, the EP and rMEP values were re-calculated. Lastly, the means and standard deviations of the rDEP values with DS(k,y) are computed and then the scEDI values are computed from standardized rDEP values (equation (5)). For a more detailed description of the scEDI calculation, we refer the reader to Park *et al* (2022),

$$\mathrm{scEDI}\left(k,\ y\right)=\frac{\mathrm{rDEP}\left(k,y\right)}{\mathrm{STD}\left(\mathrm{rDEP}\left(k,y\right)\right)}.\tag{5}$$

In this study, the intensity of drought was defined as the minimum value of scEDI over the drought duration, following the definition used in Kam *et al* (2021a). The threshold values for drought recovery were 0.0 of scEDI, respectively. We defined +1.0 of scEDI as a threshold value for full drought recovery since the drought can still re-emerge when the scEDI value is close to zero. In other words, it is possibly an intermittent period of above-average or normal conditions during the drought development phase (Parry *et al* 2016).

To investigate the contribution of the springtime and summertime precipitation deficits to the ongoing 2022–23 drought, two synthetic historical precipitation data were generated by replacing the observed precipitation with the spring (March–May) and summer (June–August) climatological precipitation individually and calculated the daily scEDI values of each case. Furthermore, the required single-day precipitation amount for drought recovery and full recovery on 1 March 2023 were estimated.

To generate empirical forecasts, observed daily precipitation were randomly sampled 10 000 times with replacement (bootstrapping) from the historical records on the corresponding date (1 March through 31 May) over 1991–2020. For example, empirically forecasted precipitation on 15 May 2023 were generated by randomly sampling with replacement among the observed 30 values of daily precipitation on 15 March over 1991–2020. Synthetic precipitation-based empirical model forecasts were generated by shuffling the historical springtime precipitation over 1991–2020. Synthetic precipitation-based empirical model forecasts were generated by shuffling the historical springtime precipitation over 1991–2020, excluding the study years, 2022 and 2023. Overall, daily scEDI values from the gauge station data and ERA5 reanalysis product were consistent to each other (figure S1).

Past meteorological events are a representative of events that may occur in the near-future (Day 1985, Garbrecht and Zhang 2014). In this study, the synthetic precipitation-based empirical forecasts were a baseline for probabilistic forecast from the climatological perspective. Then, the scEDI index was calculated using the synthetic daily precipitation. Based on the scEDI index values, the drought recovery and full recovery can be detected when the scEDI value is below 0 and −1, respectively. The reliability of the empirical approach-based forecasts can be assessed by checking whether the observed rainfall during the recovery of past droughts is within a certain range (e.g. one-standard deviation) of the required precipitation for drought recovery from the 10 000 empirical approach-based forecasts, rather than whether the timing of the drought recovery is predicted accurately. The accumulated precipitation relating to the recovery of historical droughts were analyzed (figure S2). Over 1980–2021, 12 out of the 16 past drought cases showed observed precipitation for the drought termination were within the one standard deviations of precipitation from 10 000 empirical forecasts, indicating that the empirical forecasting approach used in this study is reliable.

3. Results

The southern and central Korean Peninsula showed a contrast of long-lasting precipitation deficits and surplus over 2022–2023 (figures 1(a) and (b)). In particular, −1.0 of the scEDI value or less on the regional average were found over the SW Korean Peninsula (a black box (34–36° N and 126–128° E) in figure 1(b)). The severe drought condition (close to −1 of scEDI) in the summer of 2021 was the normal condition (close to zero of scEDI) in the late fall of 2021 (figure 1(c)). The 2022–23 drought emerged in the spring of 2022 with the minimum scEDI value close to −3.0 (22 May 2022). In June, drought related news articles abruptly increased reaching 246 news articles on 13 June 2022, which was around 20 days after the occurrence day of the minimum scEDI value. Online information seeking activity volumes about drought increased rapidly in late June with the maximum volume (30 June 2022), which was 17 days after the peak of news article numbers. This reactive pattern of the public drought awareness was also found during the 2011–17 California drought (Kam *et al* 2019). These results indicate that the response of mass media leads the public interest in drought, highlighting an important role of mass media in enhancing the nation level drought awareness (Moeller 2006).

The SW Korean Peninsula has experienced two multi-year drought epochs in mid-1990s and early 2000s, however the 2022–23 drought was the lowest intensity since 1951 (figure S3). The areal fraction under extreme drought (−1.5 of scEDI or below) abruptly increased from 20% to 100% in May, which is a key feature of flash drought (e.g. a rapid expansion) (Mo 2011, Otkin *et al* 2018). Typhoon Hinnamnor made landfall over the Korean Peninsula on 4 September 2023 and brought intense rainfall on the following two days, particularly over the southeastern region of the Korean Peninsula, which resulted in an intermittent period close to the normal condition (zero of scEDI or above). In October, the drought re-emerged and persisted until March 2023.

The synthetic climatological precipitation data showed a comparable contribution of springtime and summertime precipitation deficits to the 2022–23 drought (figure 2). The former showed that the scEDI values gradually increased in the spring month (May, April, and May) and then increased and decreased dramatically from June, reaching −1.2 of scEDI in February 2023. The later showed the scEDI values gradually increased in JJA and then persisted around −0.8 in February 2023. These results indicated that the summer precipitation in 2022 deficits played a relatively important role in the development of the ongoing 2022–23 drought. For both cases, the abrupt increased of scEDI following heavy rainfall in early September is related to the typhoon Hinnamnor which made landfall over the Korean Peninsula, indicating the ameliorating impact of a tropical cyclone landfall on the ongoing drought (Kam *et al* 2013).

Results from the 92-day empirical forecasts showed the range of about 80–170 (130–230), 150–310 (200–380), and 210–440 (280–590) mm of accumulated precipitation are required to recover (fully recover) the ongoing 2022–23 drought in March,

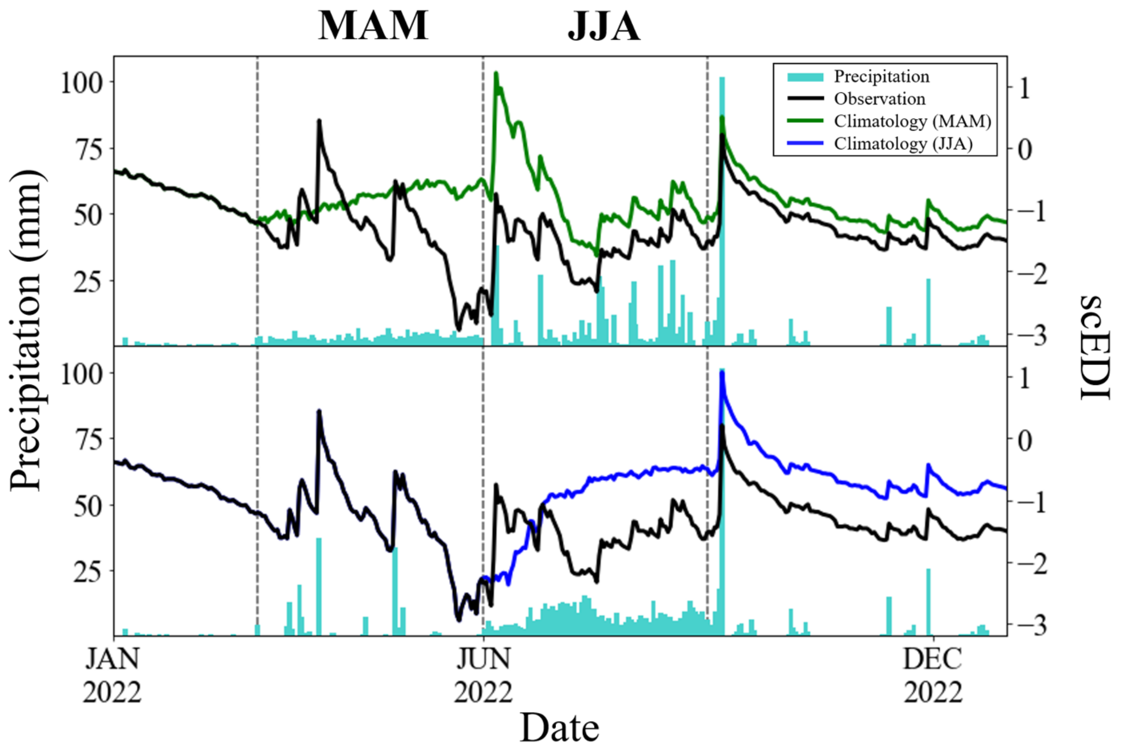


Figure 2. Daily scEDI values for 2022. Green (blue) lines represent the scEDI values calculated by using the March–May (June–August) climatological precipitation of 2022. Cyan bars in the upper and bottom sub-panels depict the daily precipitation combined with the climatological precipitation for March–May and June–August, respectively.

April, and May, respectively (figure 3). A wider range of required accumulated precipitation amounts for the drought recovery/full recovery in May indicate that uncertainties increases when the lead time increases (i.e. the rainy season starts). The chance to terminate the ongoing drought increased slowly from March to May (bars in figure 3). The 25% (5%) of empirical forecasts showed the drought recovery (full recovery) by May. Furthermore, 50, 80, and 110 mm (80, 110, and 140 mm) of the single-day precipitation are required to recover (full recover) the ongoing drought by the end of March, April, and May, respectively (figure S4). However, these required precipitation amounts or above are still rare over the Korean Peninsula in the spring months (Ho *et al* 2003).

Figure 4 shows the distributions of accumulated precipitation from dynamical forecasts of SubX and NMME models by May 2023. Except for May, SubX and NMME model-based forecasts generally showed the drought persistence in March and April 2023 (figures 4(a) and (b)). The mean values (black dot) for both of high and low performance models of SubX and NMME were close to the that of the drought persistence scenario and its related forecast distributions also generally overlapped with that scenario's distribution.

The percentages of dynamical forecasts that predict drought recovery and persistence in March, April, and May were estimated (figure 4(c)). For conservative estimate, the maximum (minimum) accumulative precipitation corresponding to −1 (0) of scEDI values were used as the threshold value for drought persistence (recovery) scenario (below the blue (red) line in figures 4(a) and (b)). 19% of high and low performance NMME models predict recovery of the ongoing 2021–23 drought in May 2023 (figure 4(c)). The probability of persistence kept on decreasing until May 2023 and 16% for both of high and low performance NMME models showed the drought persistency by May 2023. Overall, the forecasts of SubX and NMME suggest that there is a slim chance to recover the ongoing 2022–23 drought till the early summer rainy season.

Considering the fact that the NMME models generally underestimate the precipitation compared to the observation as about 5%–15% (figure S5), the window of opportunity to the drought recovery could be a little bit wider than the range suggested in this study. However, the verification metrics for ensemble forecast indicate a low performance of the NMME models for next 1–3 lead months (figure S6), implying that huge uncertainties are still existed in NMME forecast. The wide range of the SubX and NMME ensemble forecasts might be attributable to the different model physics and parameterizations, which should be improved by better understanding of the prediction skill of other variables, such as sea surface temperature and 2 meter air temperature and

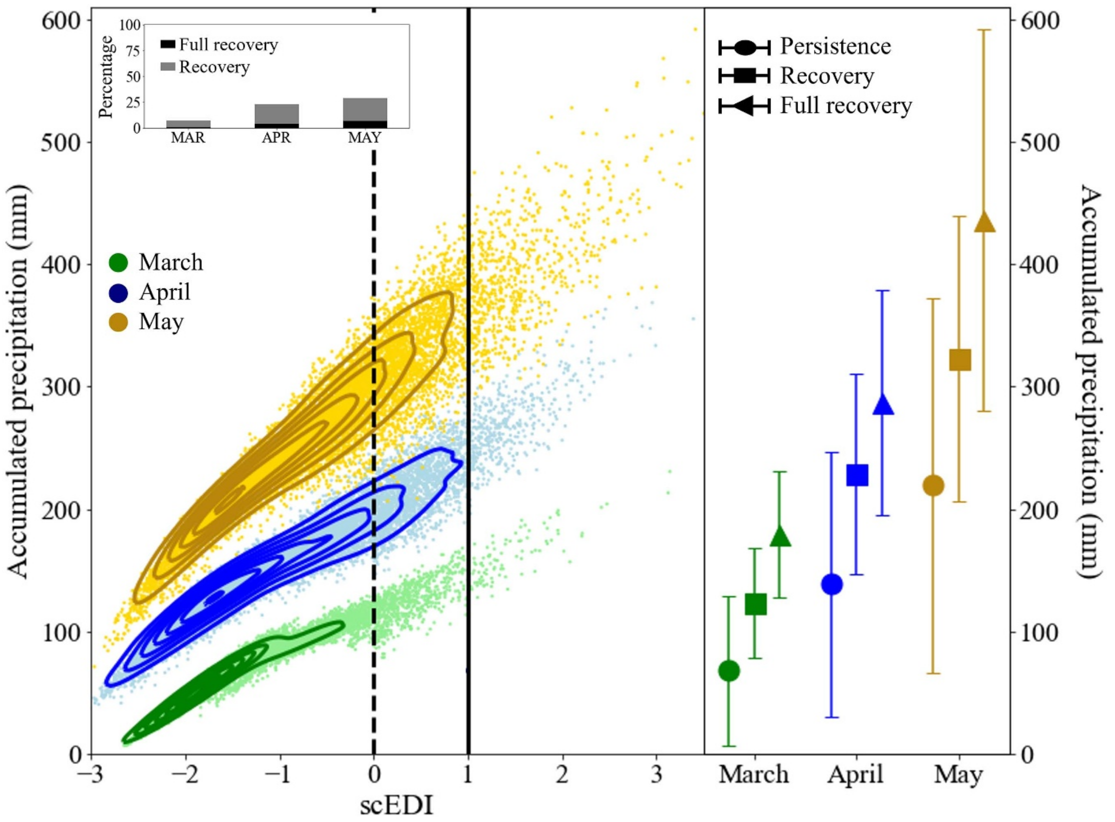


Figure 3. Distributions between the scEDI value and the related accumulated precipitation summed from 1st March to the end dates of March (green), April (blue), and May (dark golden) for 10 000 scenarios. The bar subplot shows proportion (%) of scenarios for drought recovery and full recovery that exceeds 0.0 and 1.0 of scEDI, respectively. Solid lines depict the range of kernel density estimation for the accumulated precipitation. Errorbars in the right sub-panel depict the range of the accumulated precipitation for each scenario and month.

modeled interactions between land, ocean, and atmosphere (Kam *et al* 2014, 2021b).

4. Discussion

This study examined scEDI-based required accumulated precipitation amounts for the drought recovery from ensemble empirical precipitation forecasts and compared the likelihood of the drought demise between empirical and dynamical forecasts. The 2022–23 SW Korea drought was the most intense drought and the 3rd longest drought since 1950. The key driver of the ongoing drought was exceptional six-month precipitation deficits during the spring and summer of 2022. At the time of writing (March, 2023), the required total precipitation for drought recovery was at least 80, 150, and 210 mm by the end of March, April, and May 2023, respectively. This study found that the empirical and dynamical model-based predictions had a low predictability of actual rainfall events in May, 2023 when they forecasted in early March. This finding implied that the actual predictability of empirical and dynamical models for observed intense rainfall in May that lead to the drought recovery was still low, possibly due to atmospheric noise, known as the significant butterfly effect of an initial condition at the seasonal scale. However, the empirical model-based precipitation can provide the required precipitation for drought recovery/full recovery that can be used to interpret forecasted daily precipitation in terms of drought persistency/recovery.

The SW Korean Peninsula is a breadbasket of South Korea, which is vulnerable to a severe drought. The findings of this study suggest that the full mobilization of national water management system and plans is necessary to overcome a crisis of the ongoing drought persistence for the next crop planting season. A possible drought contingency plan is an interbasin transfer project between the central and SW Korea peninsula. Over 2022–23, the central Korean Peninsula experienced exceptionally positive precipitation anomalies. This study also suggests the need to include interbasin transfer projects in the current drought contingency plans.

Interbasin transfer projects however require the nationwide public support to expedite its execution. When interbasin transfer projects are proposed, however federal and local governments and local stakeholders have often faced social conflicts,

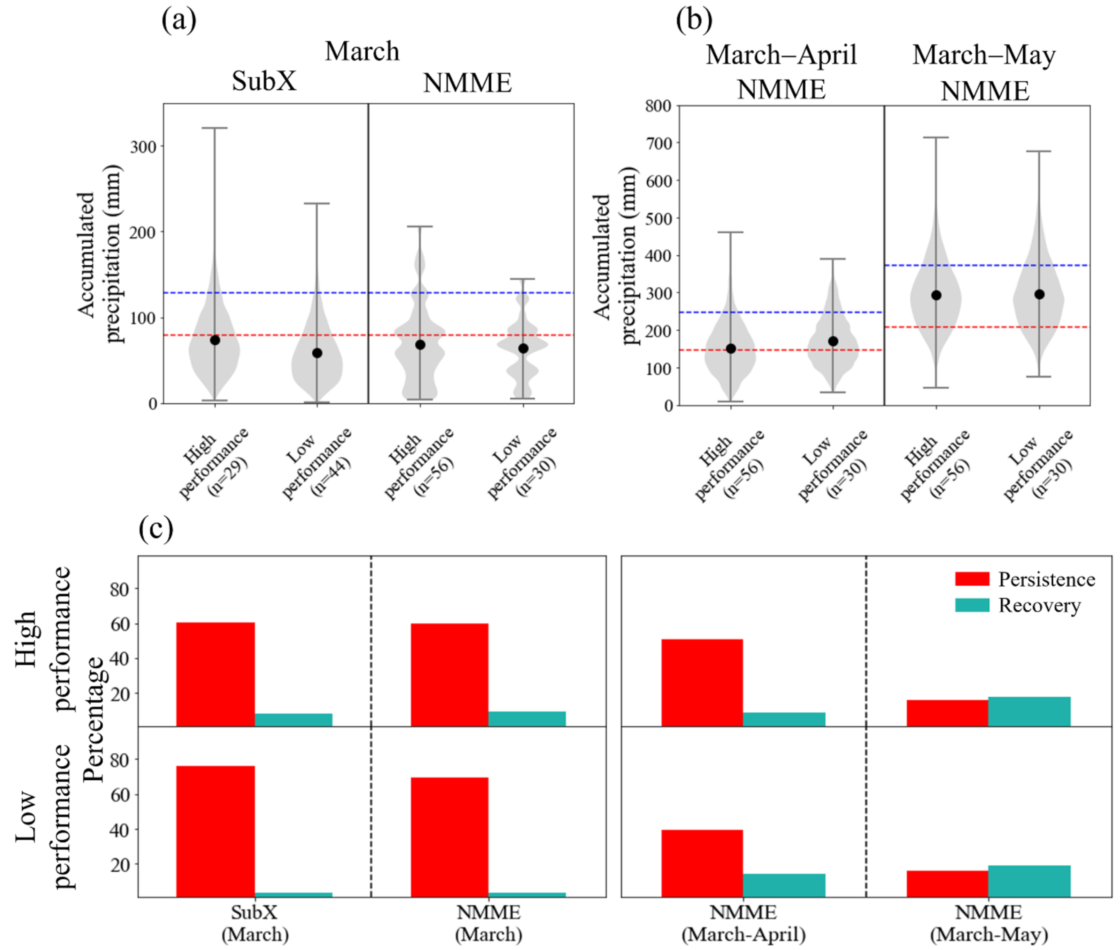


Figure 4. Forecasts of the SubX and NMME models for the accumulated precipitation during (a) March 2023, (b) March–April 2023, and March–May 2023, respectively. The red and blue dashed lines represent the minimum and maximum values of recovery and persistence scenarios in figure 3, respectively. Dots depict the mean value of each forecast distribution. In (c), the percentage (%) of forecasts for the recovery (persistence) is defined by the ratio of the forecasts that have a greater (smaller) accumulated precipitation corresponding to the maximum (minimum) value of persistence (recovery) scenario (blue (red) lines in (a) & (b)).

particularly between water ample and scarce states. According to the NAVER DataLab data, the internet search activity volumes with the search term, 'drought', in 2022 was one-tenths of those in 2017 when the entire Korean peninsula experienced a severe drought (figure S7), indicating a lack of the nationwide awareness of the ongoing SW Korea drought. This study suggests the need of a persistent and collaborative effort of governments and mass media to improve the nationwide awareness of the ongoing drought, eventually leading to the public support for cross-basin water resources management and drought contingency plans.

5. Conclusions

This study presented a prospective evaluation of the sub-seasonal to seasonal forecasting skill of the 2022–23 SW Korea meteorological drought, using sub-seasonal to seasonal outlooks from dynamic model forecasts compared with the synthetic precipitation-based empirical forecasts from the climatological perspective. While the scEDI-based drought propagation scenarios constructed by the SubX forecast models provided a practical guideline for effective drought response and recovery at the sub-seasonal scale, the SubX and NMME forecast models showed still a large uncertainty of the seasonal prediction skill for the ongoing drought evolution. The limited seasonal forecast skill was not able to provide actionable information for the drought response and recovery plans, emphasizing the need to improve the current climate forecast models for reliable seasonal forecasting skill. The proposed methodology in this study can provide the required precipitation for the ongoing drought recovery based on the drought index-based scenarios, which is informative for whether sub-seasonal and seasonal forecast precipitation can recover the ongoing drought or not.

Data availability statements

The ERA5-Land reanalysis product is available at https://cds.climate.copernicus.eu. The SubX and NMME forecast data are available at https://iridl.ldeo.columbia.edu/SOURCES/.Models/.SubX/ and http://iridl.ldeo.columbia.edu/SOURCES/.Models/.NMME/, respectively. The python code for scEDI used in this study are available at https://doi.org/10.7910/DVN/QXINCU. The data used in this study are available at https://doi.org/10.7910/DVN/1SUVFL.

Acknowledgments

We acknowledge the agencies that support the NMME and SubX system, and we thank the climate modeling groups (Environment Canada, NASA, NOAA/NCEP, NRL, and University of Miami) for producing and making available their model outputs. This study was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2021R1A2C1093866) and a Grant (2022-MOIS63-001) of Cooperative Research Method and Safety Management Technology in National Disaster funded by Ministry of the Interior and Safety (MOIS, Korea). Chang-Kyun Park was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2021R1C1C2004711).

Authorship contribution statement

Chang-Kyun Park: Conceptualization, Data curation, Investigation, Formal analysis, Methodology, Software, Validation, Visualization, Writing—original draft, Writing—Review & Editing. Sang Eun Lee: Analysis, Validation, Writing—Review & Editing. Hyuncheol Yoon: Validation, Writing—Review & Editing. Jonghun Kam: Conceptualization, Methodology, Funding acquisition, Project administration, Resources, Supervision, Writing—review & editing.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

ORCID iD

Jonghun Kam https://orcid.org/0000-0002-7967-7705

References

Akhtari R, Morid S, Mahdian M H and Smakhtin V 2009 Assessment of areal interpolation methods for spatial analysis of SPI and EDI drought indices *Int. J. Climatol.* **29** 135–45

Antofie T, Naumann G, Spinoni J and Vogt J 2015 Estimating the water needed to end the drought or reduce the drought severity in the Carpathian region *Hydrol. Earth Syst. Sci.* **19** 177–93

Beguería S, Vicente-Serrano S M, Reig F and Latorre B 2014 Standardized precipitation evapotranspiration index (SPEI) revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring *Int. J. Climatol.* **34** 3001–23

Bell V A, Davies H N, Kay A L, Marsh T J, Brookshaw A and Jenkins A 2013 Developing a large-scale water-balance approach to seasonal forecasting: application to the 2012 drought in Britain *Hydrol. Process.* **27** 3003–12

Byun H-R and Wilhite D A 1999 Objective quantification of drought severity and duration *J. Clim.* **12** 2747–56

Chang S 2023 Search engine market share in Korea 2023 (available at: www.interad.com/en/category/insights/korean-search-engine-market-share.html) (Accessed 11 June 2023)

Day G N 1985 Extended streamflow forecasting using NWSRFS *J. Water Resour. Plan. Manage.* **111** 157–70

Deo R C, Tiwari M K, Adamowski J F and Quilty J M 2017 Forecasting effective drought index using a wavelet extreme learning machine (W-ELM) model *Stoch. Environ. Res. Risk Assess.* **31** 1211–40

Garbrecht J D and Zhang J X 2014 Generating synthetic daily precipitation realizations for seasonal precipitation forecasts *J. Hydrol. Eng.* **19** 252–64

Ha K-J, Heo K-Y, Lee S-S, Yun K-S and Jhun J-G 2012 Variability in the East Asian monsoon: a review *Meteorol. Appl.* **19** 200–15

Ho C-H, Lee J-Y, Ahn M-H and Lee H-S 2003 A sudden change in summer rainfall characteristics in Korea during the late 1970s *Int. J. Climatol.* **23** 117–28

Kam J, Kim S and Roundy J 2021b Did a skillful prediction of near-surface temperatures help or hinder forecasting of the 2012 US drought? *Environ. Res. Lett.* **16** 3

Kam J, Min S-K, Wolski P and Kug J-S 2021a CMIP6 model-based assessment of anthropogenic influence on the long sustained western cape drought over 2015–2019 *Bull. Am. Meteorol. Soc.* **102** S45–S50

Kam J, Sheffield J, Yuan X and Wood E F 2013 The influence of Atlantic tropical cyclones on drought over the eastern United States (1980–2007) *J. Clim.* **26** 3067–86

Kam J, Sheffield J, Yuan X and Wood E F 2014 Did a skillful prediction of sea surface temperatures help or hinder forecasting the 2012 Midwestern summer drought? *Environ. Res. Lett.* **9** 034005

Kam J, Stowers K and Kim S 2019 Monitoring of drought awareness from Google Trends: a case study of the 2011–17 California drought *Weather Clim. Soc.* **11** 419–29

Kamruzzaman M, Hwang S, Cho J, Jang M-W and Jeong H 2019 Evaluating the spatiotemporal characteristics of agricultural drought in Bangladesh using effective drought index *Water* **11** 2437

Kim D-W, Byun H-R and Choi K-S 2009 Evaluation, modification, and application of the effective drought index to 200-year drought climatology of Seoul, Korea *J. Hydrol.* **378** 1–12

Kim T and Jin E K 2016 Impact of an interactive ocean on numerical weather prediction: a case of a local heavy snowfall event in eastern Korea *J. Geophys. Res. Atmos.* **121** 8243–53

Kirtman B P, Min D, Infanti J M, Kinter J L III and Paolino D A 2014 The North American multimodel ensemble: phase-1 seasonal-to-interannual prediction; phase-2 toward developing intraseasonal prediction *Bull. Am. Meteorol. Soc.* **95** 585–601

Korea Water Resources Corporation (K-water) 2023 Water information portal (my water) (available at: www.water.or.kr) (in Korean)

Malik A, Kumar A, Kisi O, Khan N, Salih S Q and Yaseen Z M 2021 Analysis of dry and wet climate characteristics at Uttarakhand (India) using effective drought index *Nat. Hazards* **105** 1643–62

Mo K C 2011 Drought onset and recovery over the United States *J. Geophys. Res.* **116** D20106

Moeller S D 2006 "Regarding the pain of others": media, bias and the coverage of international disasters *J. Int. Aff.* **50** 173–96

Moradian S and Yazdandoost F 2021 Seasonal meteorological drought projections over Iran using the NMME data *Nat. Hazards* **108** 1089–107

Morid S, Smakhtin V and Moghaddasi M 2006 Comparison of seven meteorological indices for drought monitoring in Iran *Int. J. Climatol.* **26** 971–85

Muñoz-Sabater J *et al* 2021 ERA5-Land: a state-of-the-art global reanalysis dataset for land applications *Earth Syst. Sci. Data* **13** 4349–83

Otkin J A, Svoboda M, Hunt E D, Ford T W, Anderson M C, Hain C and Basara J B 2018 Flash droughts: a review and assessment of the challenges imposed by rapid-onset droughts in the United States *Bull. Am. Meteorol. Soc.* **99** 911–9

Pan M, Yuan X and Wood E F 2013 A probabilistic framework for assessing drought recovery *Geophys. Res. Lett.* **40** 3637–42

Pandey R P, Dash B B, Mishra S K and Singh P 2008 Study of indices for drought characterization in KBK districts in Orissa (India) *Hydrol. Process.* **22** 1895–907

Park C-K, Chang M, Ho C-H, Ha K-J, Kim J and Sohn B-J 2021 Two types of diurnal variations in heavy rainfall during July over Korea *Adv. Atmos. Sci.* **38** 2201–11

Park C-K and Kam J 2023 Sub-seasonal experiment (SubX) model-based assessment of the prediction skill of recent multi-year South Korea droughts *Asia-Pac. J. Atmos. Sci.* **59** 69–82

Park C-K, Kam J, Byun H-R and Kim D-W 2022 A self-calibrating effective drought index (scEDI): evaluation against social drought impact records over the Korean Peninsula (1777–2020) *J. Hydrol.* **613** 128357

Parry S, Wilby R L, Prudhomme C and Wood P J 2016 A systematic assessment of drought termination in the United Kingdom, Hydrol *Earth Syst. Sci.* **20** 4265–81

Parry S, Wilby R, Prudhomme C, Wood P and McKenzie A 2018 Demonstrating the utility of a drought termination framework: prospects for groundwater level recovery in England and Wales in 2018 or beyond *Environ. Res. Lett.* **13** 064040

Pegion K *et al* 2019 The subseasonal experiment (SubX): a multimodel subseasonal prediction experiment *Bull. Am. Meteorol. Soc.* **100** 2043–60

Roy T, He X, Lin P, Beck H E, Castro C and Wood E F 2020 Global evaluation of seasonal precipitation and temperature forecasts from NMME *J. Hydrometeorol.* **21** 2473–86

Sheffield J *et al* 2014 A drought monitoring and forecasting system for sub-Sahara African water resources and food security *Bull. Am. Meteorol. Soc.* **95** 861–82

Singh A, Reager J T and Behrangi A 2021 Estimation of hydrological drought recovery based on precipitation and gravity recovery and climate experiment (GRACE) water storage deficit *Hydrol. Earth Syst. Sci.* **25** 511–26

Svoboda M *et al* 2002 The drought monitor *Bull. Am. Meteorol. Soc.* **83** 1181–90

Tiwari A D and Mishra V 2022 Sub-seasonal prediction of drought and streamflow anomalies for water management in India *J. Geophys. Res.* **127** e2021JD035737

Turco M, Ceglar A, Prodhomme C, Soret A, Toreti A and Francisco J D R 2017 Summer drought predictability over Europe: empirical versus dynamical forecasts *Environ. Res. Lett.* **12** 084006

Wilks D S 1996 Statistical significance of long-range "optimal climate normal" temperature and precipitation forecasts *J. Clim.* **9** 827–39

Xu Z, Wu Z, Guo X and He H 2023 Estimation of water required to recover from agricultural drought: perspective from regression and probabilistic analysis methods *J. Hydrol.* **617** 128888