Maize Drought Hazard in the Northeast Farming Region of China: Unprecedented Events in the Current Climate

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ABSTRACT

The Northeast Farming Region (NFR) of China is a critically important area of maize cultivation accounting for ~30% of national production. It is predominantly rain fed, meaning that adverse climate conditions such as drought can significantly affect productivity. Forewarning of such events, to improve contingency planning, could therefore be highly beneficial to the agricultural sector. For this, an improved estimate of drought exposure, and the associated large-scale circulation patterns, is of critical importance. We address these important questions by employing a large ensemble of initialized climate model simulations. These simulations provide 80 times as many summers as the equivalent observational dataset and highlight several limitations of the recent observational record. For example, the chance of a drought greater in area than any current observed event is approximately 5% per year, suggesting the risk of a major drought is significantly underestimated if based solely on recent events. The combination of a weakened East Asian jet stream and intensified subpolar jet are found to be associated with severe NFR drought through enhanced upper-level convergence and anomalous descent, reducing moisture and suppressing precipitation. We identify a strong 500-hPa geopotential height anomaly dipole pattern as a useful metric to identify this mechanism for relevance to seasonal predictability. This work can inform policy planning and decision-making through an improved understanding of the near-term climate exposure and form the basis of new climate services.

1. Introduction

The Northeast Farming Region (NFR) of China is a critically important area of maize production, accounting for ~30% of national production (NBSC 2018) and just over 5% of global production (FAO 2018). The requirement for a high rate of self-sufficiency in grain production and the large human population in China means that, as the largest rain-fed maize-producing region, it is a crucial component of the national food system (Meng et al. 2006; Ghose 2014; Du et al. 2014; Cui and Shoemaker 2018; Qin et al. 2015).

Maize production in the NFR has increased significantly over the past 30 years, with a threefold increase in the sown area since the 1980s, to just under 12 million ha in 2015 (Fig. 1; NBSC 2018). It is the largest crop in the NFR by sown area and in recent years accounted for 50%–60% of the total cropland across the region. Drought is the dominant cause of agrometeorological disasters in the region (Fig. 1); droughts occur more frequently than other hazards, have the longest duration, and cover the largest area, all of which contribute to the greatest loss to agricultural production and economy (Zhang 2004; Xie et al. 2014; Xu et al. 2013).

Providing an improved estimate of drought exposure can provide highly relevant information to policy planners and decision-makers who have responsibility for building a resilient agricultural system, and ensuring food security for China's population. This crucial hazard information can provide a platform for assessing and developing near-term climate services and provide

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FIG. 1. Maize area across eastern China and reported agrometeorological hazard area in the NFR: (left) maize area in hectares across China (Monfreda et al. 2008), with the NFR provinces outlined by the thick lines and values < 1000 masked, and (right) reported areas affected by drought, flood, and other (hail, low temperature, and typhoons) hazards across all cropland in Liaoning, Jilin, and Heilongjiang Provinces. The dashed black line shows the reported sown area for corn. Data sources: Guo et al. (2018) and NBSC (2018).

additional context to longer-term adaptation planning (Hewitt et al. 2012; Hewitt and Golding 2018), including regional risk assessments (Zhang 2004; Xu et al. 2013), agricultural insurance services (Zhang et al. 2017), or identifying disaster losses (Xie et al. 2014). Furthermore, natural climate variability is one of the main drivers of uncertainty within regional climate projections over the next 20–30 years (Hawkins and Sutton 2009). Thus, building resilience to the present-day climate exposure is likely to be a significant step in adapting to climate variability and change over the next few decades.

As noted above, food production across the region is vulnerable to climate variability and change (Zhao et al. 2015). The NFR is located at the northern edge of the East Asian summer monsoon's influence and exhibits significant seasonality (Sun et al. 2017). For example, June–August (JJA) typically accounts for 70%–80% of the annual rainfall and coincides with the main crop growing period (Meng et al. 2006). However, because of their rarity, our understanding of significant agricultural production losses associated with weather and climate events is poor. In particular, some of the most severe droughts recorded—such as the northern China drought in 1928–30 (Qian et al. 2012) and the East China drought of 1965–66 (Shen et al. 2007)—occurred prior to the 1980s and the advent of high-quality monitoring data. Datasets that include improved temporal and spatial coverage therefore do not capture these megadroughts and thus only represent a fraction of the known climate variability.

In this study, we use a large climate model ensemble to overcome the limitations of the observational record and explore the dynamics of extreme drought events

across the NFR. This builds on recent advances in near-term climate prediction, using ensembles to provide a novel approach for assessing the risk of unprecedented climate extremes (Thompson et al. 2017; Kent et al. 2017; Thompson et al. 2019). The “unprecedented simulated extremes using ensembles” (UNSEEN) method assumes that observations provide only one realization of the plausible climate conditions and initialized climate model ensembles allow the exploration of a wider range of possible states. These are spatially coherent and physically plausible but did not happen to have occurred due to the chaotic evolution of the observed climate system.

This approach provides a wealth of highly relevant information for exploring the near-term risk. However, it is important to note that models (and the observations) are imperfect, exhibiting a range of biases in space and time. Thus, the fidelity of the model needs to be tested fully and taken into consideration when presenting hazard information and risk (Thompson et al. 2019).

Here we employ a large ensemble initialized climate model simulations to characterize drought across the NFR. We quantify the annual likelihood of drought area and we assess the probability of record-breaking conditions. We then utilize the ensemble to identify key large-scale circulation patterns associated with rainfall variability, from the maize production perspective, to inform future development of new climate services.

The structure of the paper is as follows: section 2 describes the methods and datasets. Section 3 presents the results derived from the climate model ensemble in terms of both drought area and severity. The large-scale patterns of relevance to new climate services are then

detailed in [section 4](#), and [section 5](#) provides an initial exploration of the atmospheric features associated with unprecedented dry summers. [Section 6](#) concludes with the key findings.

2. Methods

a. Maize and crop production

The harvested area for maize across the NFR is extracted from [Monfreda et al. \(2008\)](#). This provides an estimate of the geographical distribution of yield, production, and area harvested around the year 2000. Changes in cropping areas over time are therefore not incorporated and represent an unquantified source of uncertainty in this region, although the impact on the subsequent analysis is expected to be small.

b. Climate observations

Gridded precipitation data for JJA, covering the period from 1981 to 2010, from the Global Precipitation Climatology Centre dataset, version 5/6 (GPCC v5/6; [Schneider et al. 2011](#)), were extracted from the Water and Global Change (WATCH) Forcing Data ERA-Interim (WFDEI) dataset ([Weedon et al. 2014](#)) in which the dataset has been quality checked and regridded onto a $0.5^\circ \times 0.5^\circ$ global grid. Additional precipitation datasets were extracted from ERA-Interim ([Dee et al. 2011](#)), JRA-55 ([Kobayashi et al. 2015](#)), APHRODITE ([Yatagai et al. 2012](#)), and CRU-TS ([Harris et al. 2014](#)). Comparison among these precipitation datasets indicates that there can be large discrepancies in terms of mean, variability, and extremes across the NFR (see the online supplemental material). We therefore utilize these five datasets, which include different resolutions and cover slightly different periods, to assess the climate model fidelity.

We select the GPCC dataset for the analysis within this study, to characterize drought events and provide a comparison to the model. This dataset strongly correlates with the other datasets, compares well in terms of mean climate conditions and interannual variability, and provides a consistent record throughout the period at a high spatial resolution of 0.5° .

To examine the large-scale atmospheric circulation patterns associated with NFR rainfall variability zonal and meridional winds (850 and 250 hPa) and geopotential height anomalies at 500 hPa were also extracted from the ERA-Interim reanalysis dataset for JJA ([Dee et al. 2011](#)).

c. Initialized climate model simulations

Simulations of the present-day climate (1981–2010) are ensemble predictions from the Met Office Decadal Prediction System (DePreSys3; [Dunstone et al. 2018](#)).

The Hadley Centre Global Environment Model (HadGEM3-GC2; [Williams et al. 2015](#)), is initialized on 1 November (1 May) each year from 1980 (1981) and run for 16 (11) months. Precipitation totals for JJA represent forecasts at lead times of 2–4 and 8–10 months, for the May and November ensembles, respectively. With 40 ensemble members per start date, this provides 2400 simulations of JJA rainfall between 1981 and 2010, 80 times as many samples of interannual variability as were observed over the period.

This climate model has been used in a range of studies focusing on the climate of East Asia (e.g., [Li et al. 2016, 2018](#)). In this study, fidelity testing of the model follows [Kent et al. \(2017\)](#) (see also [Thompson et al. 2017, 2019](#)) and is assessed by determining if the observations and model data are drawn from the same underlying distribution. A large number of randomly selected subsamples of length equal to the observations (i.e., 30 years) are taken from the model ensemble, for which the mean, standard deviation, kurtosis and skewness are calculated. The model is deemed to be indistinguishable from the observations if the statistical characteristics of the observations fall within the 2.5th–97.5th range of 10 000 model subsamples at a given grid box. Furthermore, we perform the fidelity tests across five datasets of historical climate conditions (GPCC, CRU, ERA-Interim, APHRODITE, and JRA-55) and record the number of test passes for each grid cell.

The climate model shows good agreement with the observational datasets for the period 1981–2010 across the NFR, as well as much of East China and the Yangtze basin ([Fig. 2](#)). This likely reflects the performance of the model in capturing the mean state, variability and interactions between features such as the subtropical jet (see the online supplemental material), the East Asian summer monsoon (EASM; [Bett et al. 2017; Li et al. 2016; Martin et al. 2019](#)), the northwest Pacific subtropical high (NWPSH; [Camp et al. 2019](#)) and tropical sea surface temperature anomalies ([Hardiman et al. 2018](#)), which directly influence climate over the NFR. The fidelity tests pass for generally three or four of the observational datasets across the NFR (thick outline in [Fig. 2](#)). Across the North China Plain (and the southwestern parts of Liaoning Province) the model exhibits a slight wet bias and the interannual variability is too large (gray region in [Fig. 2](#)). Overall, we cannot distinguish the model and observations in this region, and we proceed to use the model data for assessing the characteristics of drought across the NFR.

d. Definition of drought

Here we use the standardized precipitation index (SPI; [McKee et al. 1993](#)), which provides a simple measure of meteorological drought relative to a location's

FIG. 2. Climate model fidelity for (a) mean and (b) standard deviation of JJA precipitation for 1981–2010. Results are shown for the November start-date ensemble. Colors indicate the number of observational datasets from which the climate model is statistically indistinguishable. Stippling shows areas where the model climatology falls outside all of the observational constraints. Observational datasets are GPCC (Schneider et al. 2011), JRA-55 (Kobayashi et al. 2015), ERA-Interim (Dee et al. 2011), Aphrodite (Yatagai et al. 2012), and CRU-TS (Harris et al. 2014).

climatological rainfall characteristics (mean and variability). The SPI is a common measure of meteorological drought (WMO 2012; Hao et al. 2017) that relies only on precipitation and is widely used within operational drought monitoring and evaluation, for example, in the United States (<http://droughtmonitor.unl.edu/>) and United Kingdom (<https://eip.ceh.ac.uk/droughts>).

The simplicity of the index makes it easy to apply to climate model data but can limit its applicability when temperature and other factors are important, such as when considering the impact of long-term climate changes or comparing different climatic zones. Despite this limitation, the 3-month SPI is highly correlated with more complex indices such as the standardized precipitation evapotranspiration index (Vicente-Serrano et al. 2010) over the NFR during the period 1981–2010 (correlation coefficient $r > 0.95$). Furthermore, by using only atmospheric conditions the SPI avoids surface and soil calibration issues that can affect other indices (e.g., Trenberth et al. 2014).

Within the GPCC dataset, JJA precipitation is found to be indistinguishable from a Gaussian distribution (Shapiro–Wilks test; 99% confidence level) across the NFR and thus we obtain the SPI by removing the climatological mean and dividing by the standard deviation at each grid cell. Following WMO (2012) an SPI threshold of -1 is used to classify drought conditions across the NFR each summer. This corresponds to precipitation more than one standard deviation below the mean and implies a drought occurs approximately every 6 years.

Applying the threshold to GPCC precipitation for the period 1981–2010, and weighting the results by the spatial area of cropland from Monfreda et al. (2008) for

each province, is found to be strongly correlated ($r \approx 0.65$ – 0.75) with the reported drought hazard area by NBSC (2018) and Guo et al. (2018). This provides confidence that this drought threshold does capture agricultural impacts, despite the large uncertainties in the reported statistics and changes in the maize area over time.

3. Quantifying present-day drought exposure

Analyzing the occurrence of drought events within such a large ensemble allows the spatial characteristics of drought across the region to be quantified. Here we show the annual probability that different extents of maize area experience drought, in both absolute and cumulative forms (Fig. 3). This information enables the likelihood of severe impact scenarios to be assessed, such as the probability that at least 50% of the maize area experiences meteorological drought simultaneously.

While the profile of drought exposure for GPCC and the climate model are similar, providing further confidence that there is no significant bias within the model, there are several key differences.

First, the paucity of observations of simultaneous events results in a poorly represented exposure profile with gaps and jumps (Fig. 3, black bars). For example, recent observations indicate that the annual likelihood of 40% and 60% of the maize area experiencing drought are statistically indistinguishable. The model provides much more clarity on these estimates, indicating that the annual chance halves between these two affected impact levels.

Second, the GPCC profile has a much larger uncertainty range compared to the model, due to the smaller

FIG. 3. Spatial characteristics of summer drought across the NFR in terms of absolute [in (a)] and cumulative [in (b)] areas: (a) Annual probability (%) of drought area based on GPCC (black; $n = 30$) and the initialized climate model (red; $n = 2400$; dark red indicates overlap with black bars) (the y axis is limited to 15% for clarity). (b) Cumulative probability (%) that x or more percent of the maize area experiences seasonal (JJA) drought. Shading represents the 95% confidence interval based on 1000 random resamples of 90% length. Each sample is therefore of length $n = 27$ and $n = 2160$ for the GPCC and climate model ensemble, respectively. Dashed lines indicate the maximum area recorded.

sample size of 30. The observation-based estimate is highly sensitive to the sample size; one or two more/fewer years can significantly alter the derived probabilities. For example, the annual probability of at least 40% of the maize area experiencing drought is approximately 5%–25% within the GPCC dataset but only 14%–18% in the model.

Third, the climate model ensemble produces scenarios that are unprecedented in the observations. In particular, the maximum maize area affected by drought within the observations is 65.4%. In contrast, the model indicates that almost the entire NFR maize area (99.4%) could be simultaneously affected by drought. This scenario occurs only once within the 2400 member ensemble, whereas 13 realizations exhibit areal extents that are greater than 90%, and 123 show record drought extents (56 and 67 from the November and May start dates, respectively). The probability of a more widespread drought than observed over the last 30 years is therefore approximately 5% each year. Assuming each year is independent, it is more likely than not that an unprecedented drought events will occur in the next 10–20 years.

The largest droughts (by area) are, by definition, associated with drier than average conditions across the NFR region. In terms of area-average summer precipitation the climate model ensemble contains 81 occurrences of unprecedented dry conditions (Fig. 4)—summer precipitation less than the GPCC minimum (1981–2010)—36 and 45 events from the November and May start dates, respectively. These events occur throughout the time series and thus do not appear related to the initial conditions; however, not all of the important drivers, such as soil

moisture (Gao et al. 2014b), are fully initialized in this ensemble. As a final demonstration of the type of information of relevance to policy and decision-makers that can be extracted from this approach, the severity of dry summers as a function of the return period can be derived from the 81 unprecedented events (Fig. 4b). For example, the climate model ensemble estimates that a 1-in-100-year event (1% annual probability) is approximately 15% (12%–17%) drier than the GPCC 1981–2010 minimum of 264 mm.

4. Large-scale circulations associated with NFR rainfall variability

Given the high risk of unprecedented drought events in the current climate, as well as the generally low predictability (at seasonal time scales) across the region (e.g., Bett et al. 2017), in this section we identify key circulation patterns associated with summer rainfall variability, through the focus of maize in the NFR, which could support the development of new climate services.

NFR summer precipitation is found to be positively correlated with the 850-hPa meridional and zonal wind anomalies south of the region (Fig. 5; see also the ERA-Interim correlations in the online supplemental material), with significant (95% level; $n = 2400$) Pearson correlation scores of approximately 0.5–0.6. This is in line with previous analyses (Zhao et al. 2018; Sun et al. 2017) and represents the importance of moisture transport from the tropical south (i.e., via the EASM) as well as the tracking of rain-bearing systems along the western edge of the NWPSH. Northeasterly wind anomalies

FIG. 4. Unprecedented dry summer rainfall over the NFR: (a) Time series of NFR summer precipitation from the initialized climate model (boxplots and black line) and GPCC (blue line). The boxplots show the distribution across all 80 members, with boxes covering the 25th–75th range. The red circles highlight model realizations that contain record-low precipitation totals. Over the period 1981–2010, there are 81 unprecedented dry events (red circles) in the climate model ensemble. (b) Corresponding annual probability of summer rainfall events lower than the minimum observed within GPCC (1981–2010). Shading represents the 95% confidence interval based on 1000 random resamples of 90% length.

across East Asia, with reduced moisture transport are, therefore, strongly associated with drought in the NFR.

In the upper troposphere, the East Asian jet stream (EAJS; a regional component of the wider subtropical jet) is one of the most important upper-level atmospheric circulation phenomena for the Asia–Pacific region—its intensity and position are key drivers of EASM rain belt variability and rainfall across northeast China (Lin and Lu 2005; Zhao et al. 2018; Yan et al. 2019).

The climate model utilized here captures this behavior well, with an intensification of the EAJS associated with increased summer NFR precipitation (Fig. 5). Conversely, a weakened jet corresponds to drought conditions across the NFR (Lin and Lu 2005; Shen et al. 2011). In terms of the physical mechanism, Sun et al. (2017) highlight that a weakened westerly subtropical jet can enhance upper-level convergence, reducing vorticity (anticyclonic circulation), and causing anomalous descent over the region. In the mid- and lower-troposphere humidity is reduced, cloud formation and precipitation are suppressed, and surface temperature increases. A corresponding increased subpolar jet (Fig. 5) in combination with a weakened EAJS would also enhance anomalous descent over the NFR and contribute this mechanism for reduced NFR rainfall.

The correlation analysis also highlights a strong dipole pattern of significant correlations between north China and Japan for geopotential height anomalies at 500 hPa (Fig. 5), driven by the weakened EAJS. The two nodes of the dipole (dashed boxes in Fig. 5), which are similar to previously identified regions (Zhao et al. 2018; Lu 2002; Sun et al. 2017), are correlated with NFR rainfall with coefficients of approximately 0.3, while the difference between them is negatively correlated at -0.44

($n = 2400$). Given the considerable intraseasonal variability of rainfall across the region (Zhao et al. 2018; Shen et al. 2011), this is a very high correlation score based on seasonal mean indices alone. Thus, despite the complexity of precipitation variability across the NFR, here we have highlighted the potential for new seasonal climate services based on large-scale circulation patterns, which appear to be captured well within climate model utilized in this study.

5. Atmospheric dynamics of extremely low NFR summer rainfall

A key benefit of using dynamical climate models is the ability to explore the corresponding circulation patterns and dynamics associated with extreme climate events (Thompson et al. 2019), something that cannot be done using statistical methods and observations. While a full dynamical assessment is out of the scope of this study, in this section we provide an initial assessment of the atmospheric patterns associated with record dry conditions within the climate model ensemble. To explore the large-scale features present within the 81 unprecedented dry events here we assess consensus across the model realizations, in terms of the sign of the anomalies, and combine this with statistical significance testing. However, it is also important to note that some extreme events will have been driven by subseasonal variability (Shen et al. 2011), which is not explored here.

The consensus plots of unprecedented dry events (Fig. 6; $n = 81$) highlight similar spatial patterns to those seen in the correlation maps (see Fig. 5; $n = 2400$). Approximately 70%–80% of the events exhibit a weekend EAJS, which can induce anomalous descent and

FIG. 5. (a)–(e) Significant correlation scores (95%) between NFR summer mean precipitation and circulation anomalies within the initialized climate model ensemble ($n = 2400$). Insignificant correlation scores are masked. (f) The frequency of differences in geopotential height between the dashed squares in (e) against the normalized NFR precipitation. Corresponding maps based on ERA-Interim are provided in the online supplemental material.

suppress precipitation across the region, with a strong north China–Japan 500-hPa dipole pattern occurring in 80%–90% of the events. In the lower-troposphere almost all events show significantly reduced zonal and meridional 850-hPa wind components over East Asia, highlighting the strong relationship to the EASM. These consensus maps indicate that any improvement in the predictability of the general atmospheric patterns associated with NFR rainfall variability would also translate well into prediction of extreme drought events.

Given the strong relationship between unprecedented dry events and the 500-hPa geopotential height anomaly gradient between north China and Japan, we can explore the possible remote drivers further by categorizing subsets of events based on the magnitude of the gradient. Of the 81 unprecedented events, 13 exhibit a very

strong gradient (greater than 2 standard deviations away from the mean) and 14 exhibit negative, or approximately average (less than +0.5 standard deviations), pressure gradients.

Event consensus maps for these two subsets (Fig. 7 and the online supplemental material) highlight two potentially separate large-scale patterns. First, the strong gradient subset exhibits a weakened EAJS, extending from the jet's western core (dashed line on Fig. 7b) across East Asia and directly over the NFR. The events also exhibit wave train patterns in the upper-level meridional wind field (Fig. 7), indicating that circumglobal wave trains such as the Silk Road pattern (Hong and Lu 2016) may also be relevant to NFR climate anomalies. A potential wave train pattern relating to the subpolar jet is also apparent and highlights the possible connection

FIG. 6. Unprecedented dry summer event consensus. The panels show the proportion of unprecedented dry events ($n = 81$) that show a positive anomaly relative to the climatological mean [shown in (e) and (f) in meters per second, with dashed lines representing negative values]. Stippling indicates that the mean anomaly is significantly different from 0 (95% level). The black-outlined boxes in (e) and (f) represent the active regions of the EAJ and subpolar jet (Huang et al. 2014).

between NFR summer precipitation and the hemispheric-wide circulation (e.g., Huang et al. 2014; Yan et al. 2019). In addition, an El Niño response is seen within the surface temperature and 500-hPa geopotential height fields (see the online supplemental material). While El Niño–Southern Oscillation is known to be a key driver of the EASM (e.g., Sun et al. 2017), a key topic of current research focuses on the asymmetry of the relationship (Hardiman et al. 2018), as well as the exact location and phasing of tropical SST anomalies (Zhou et al. 2014), both of which could affect the precipitation response as far north as the NFR.

In contrast, the subset without a strong pressure gradient exhibits very little consensus in terms of anomalies

along the subtropical and subpolar jets. Instead, the subset shows a stronger relationship to the upper atmospheric conditions over the northwestern Pacific, possibly driven by the northward extent of the NWPSH, more localized surface wind anomalies, or subseasonal factors.

It is evident that interannual climate variability across the NFR is complex. Nevertheless, here we have identified potential hemisphere-wide teleconnection patterns associated with severe drought in the NFR. These patterns require further investigation but could form the basis for seasonal or near-term climate services as well as new metrics to assess within climate change scenarios irrespective of any predictability across the region (Gao et al. 2014a; Lin et al. 2018; Bett et al. 2017).

FIG. 7. Unprecedented dry NFR precipitation event consensus maps for (a),(c),(e) strong ($n = 13$) and (b),(d),(f) weak ($n = 14$) 500-hPa geopotential height anomaly gradients between northern China and Japan. The panels show the proportion of unprecedented dry events that show a positive anomaly relative to the climatological mean [shown in (c)–(f) in meters per second, with dashed lines representing negative values]. Stippling indicates that the mean anomaly is significantly different from 0 (95% level). The black-outlined boxes in (c)–(f) represent the active regions of the EAJS and subpolar jet (Huang et al. 2014).

6. Conclusions and discussion

The NFR is an important agricultural region of China and is a crucial part of ensuring China's national food security. Drought represents the most frequent and widespread meteorological hazard in the region; however, quantifying its spatial characteristics is severely limited by a relatively short observational record. Here we make use of a state-of-the-art ensemble prediction system to better sample interannual variability and characterize drought across the NFR. This provides new assessments on the likelihood of drought events and the probability of record-breaking conditions. The large model ensemble was then used to identify key large-scale circulation patterns associated with NFR rainfall variability, from the maize production perspective, to inform future development of new climate services.

Our analysis highlights multiple challenges with estimating exposure using limited observational records. These include a paucity of events (i.e., data gaps), a large uncertainty in annual likelihoods (sampling uncertainty), and a limited range of plausible climate conditions. To support

risk-planning activities we present hazard information in cumulative form and estimate the probability of experiencing unprecedented drought to be $\sim 5\%$ each year. We, therefore, estimate that it is more likely than not a record drought event will occur during the next 10–20 years. Through this analysis it is clear that drought exposure may be significantly underestimated if based solely on recent observations.

A significant benefit of our approach is the ability to assess large-scale dynamics and circulation patterns associated with severe drought in the NFR. Variations of the subtropical and subpolar jets, and in particular a weakened EAJS combined with an intensification of the subpolar jet, can lead to anomalous descent over the region, reducing moisture transport from the tropical south as well as rain-bearing systems along the western edge of the NWPSH, and suppress precipitation. In the midtroposphere, we find a strong 500-hPa geopotential height anomaly dipole pattern between north China and Japan as a useful metric to identify this mechanism (alongside variations in the NWPSH) and which would

be applicable for use within new seasonal climate services. Initial analysis indicates perturbations along the subpolar and subtropical jet streams can drive these circulation patterns, providing a link to the hemispheric-wide circulation, as well as SST anomalies in the tropical Pacific, and this is a key area for future research.

In terms of caveats, it is important to note that our analysis is based on a single climate model and thus provides no assessment of model structural uncertainty (e.g., Knutti et al. 2010). However, the model has been shown to produce climate variability in the NFR that is statistically indistinguishable from observations across a number of metrics, and has been thoroughly tested and used for a number of applications across a range of time scales and locations in China (Lu et al. 2018; Li et al. 2016, 2018), providing confidence in its performance. Last, this analysis is focused on seasonal climate anomalies. Therefore, we do not provide information on subseasonal or higher-frequency extreme events, particularly if their occurrence is not associated with the larger-scale seasonal conditions.

Interannual climate variability across northeast China is complex and influenced by multiple factors, both local and remote. Nevertheless, here we have identified clear circulation patterns that could form the basis for seasonal/near-term climate services, as well as new metrics to explore in climate change scenarios. This work builds on a growing area of research using climate models to explore extremes and applies these methodologies to inform policy planning and decision-making through improved understanding of the near-term climate risk. In particular it could be used to assess the likelihood of region-specific impacts and support food security risk assessments for China.

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