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LETTER

Increasingly uneven intra-seasonal distribution of daily and hourly precipitation over Eastern China

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Abstract
It has been long appreciated that precipitation falls unevenly in time, but the degree of unevenness and its changes with warming have been seldomly quantified. These quantifications, however, matter to various sectors (e.g. crop and livestock yields) for addressing evolutionary hydro-meteorological hazards. Using gauge observations at hourly- and daily-resolution, precipitation unevenness is measured by the number of wettest days/hours for half of seasonal precipitation totals over Eastern China, a major breadbasket vulnerable to precipitation volatility intra-seasonally. Across the region, half of seasonal totals needs only 11 d or even more unexpectedly just 44 h to precipitate. During 1970–2017, though seasonal precipitation amount changed little, the intra-seasonal distribution of precipitation, in both frequency and amount, has been getting significantly more uneven, with more widespread and faster changes manifesting in hourly records. The regional-scale unevenness increase is unlikely modulated by internal variability alone, suggesting detectable contributions from anthropogenic climate change. The increased unevenness has led to significant lengthening of the longest dry spells, exposing the region to a more volatile precipitation mode—burstier-but-wetter storms with prolonged droughts in-between.

1. Introduction
Evidence is mounting that anthropogenic climate change has altered amount and spatial pattern of total precipitation, as well as frequency and intensity of extremes (Trenberth 2011, Collins et al 2013, Zhang and Zhou 2019). Another core characteristic of precipitation-temporal unevenness (unevenness hereafter)—remains poorly understood, especially at impact-relevant spatiotemporal scales (Rajah et al 2014, Pendergrass and Knutti 2018).

The unevenness informs how asymmetric precipitation is distributed over a period of time. A day or a period could see no precipitation, light-moderate precipitation or downpours. They contribute disproportionately to the total, and also differ in impacts. Steady moderate rains, soaking into soil, benefit plants; while the same amount falling in cluster causes floods. So, even absent significant changes in total amount, a shift in the distribution of precipitation within a period has enormous implications on agriculture, infrastructure service and maintenance, emergency response, stockbreeding, and water management (Asner et al 2004, Huxman et al 2004, Fishman 2016, Sloat et al 2018). Only accounting for changes in precipitation totals yet overlooking unevenness changes may lead to unintended underestimate for impacts and risks from warming-induced precipitation changes.

The current state of knowledge on precipitation unevenness, particularly on the intra-seasonal timescale critical to flood-drought preparedness, is
far from informative for policy-making (Fishman 2016). A fit-for-purpose definition is of priority. Precipitation seasonality indicative of wet- and dry-season precipitation contrast is a common measurement for annual-scale unevenness (Chou et al. 2013). Other indices flexible for various timescales have also been proposed, such as the fraction in total amount from percentile-exceeding extremes (Klein Tank and Konnen 2003, Zolina et al. 2009), the ‘Gini coefficient’ adapted from economic field (Rajah et al. 2014), ‘weighted sum of precipitation’ (Lu 2009), and ‘precipitation concentration index’ (Sloat et al. 2018). Recently, Pendergrass and Knutti (2018) introduced a more intuitive indicator, i.e. ‘the number of days for half of precipitation totals’. All of these metrics used daily-to-monthly precipitation observations and simulations. Nonetheless, the unevenness is expected to manifest more striking in hourly-scale precipitation, as it better characterizes the lifecycle of heavy rain-producing storms (Trenberth et al. 2017, Pendergrass and Knutti 2018). The use of hourly-resolution records may therefore refine and advance our understandings about the degree of unevenness and its response to warming.

Enhanced unevenness of precipitation shows only one side of the coin. The greater intensification of extremes compared to average precipitation is projected to bring more intense yet less frequent rainfall (i.e. more uneven), producing two seemingly-contradictory effects—more floods and longer dry periods (more droughts) (Collins et al. 2013, Lau et al. 2013). Such a ‘boom-or-bust’ mode within a short timespan like a season will quickly exhaust the adaptive capacity of various sectors (Witze 2018, Sloat et al. 2018). Mapping hotspots where this dangerous tendency is emerging or has emerged could spare valuable room for vulnerable regions to better prepare for the challenging hydrological future.

Changing precipitation unevenness is particularly impactful to populous monsoon regions, like Eastern China, a major world breadbasket with agriculture production critically contingent on the behavior of monsoonal precipitation. However, neither the degree of precipitation unevenness over the course of monsoon season nor its long-term changes has been quantified formally for the region. To shed some light on aforementioned gaps, I use high-quality hourly- and daily-scale precipitation observations to quantify the intra-seasonal precipitation unevenness over Eastern China, and estimate their linear trends over 1970–2017. I also investigate implications of changing unevenness on hydro-meteorological extremes. Further, I attempt to pin down the nature of changing precipitation unevenness over Eastern China, as a systematic response to external forcings or random changes dictated by internal variability.

The rest of the paper is organized as follows. Section 2 introduces the data and methods. Main results are presented in section 3. The implication of unevenness on defining precipitation extremes, some candidate mechanism explanations for unevenness changes and the resulting hydro-meteorological risks are discussed in Section 4, followed by a brief summary.

2. Data and methods

2.1. Data

Gauge observations of hourly and daily precipitation over 1951–2017 from 2474 meteorological stations in China are used (http://data.cma.cn/en). It was subject to rigorous quality controls (QC), with a QC code assigned to each record specifying its correctness or type of errors. This dataset represents the spatially-densest, longest-running and highest-quality observation in the country.

A major focus is paid to the extended warm season covering April to October, encompassing the major rainy season and also largely overlapping with the growing season (Ding and Chan 2005). Extra constraints are put on the distance of site relocations and the percentage of missing values such that:

1. missing and problematic/wrong hourly records account for no more than 20% of hours during the season each year;
2. throughout the period, site relocations are restricted within 20 km horizontally and 50 m vertically.

As a trade-off between the network density and record length, 1970–2017 is chosen as the study period, during which 483 stations meet above constraints. The selection of stations and study period refers primarily to hourly records, because gauges operating routine observations for daily precipitation far outnumber those for hourly observations. Requiring lower percentage of missing instead, e.g. 10%, leaves less than 100 stations; while using looser threshold, such as 30% and 40% missing, does not add many to the network (figure omitted). Following the method introduced by Zolina et al (2005), I further scrutinize the structure of missing records. Despite 20% being used as the threshold, it does not necessarily mean that every season contains around 10 ~ 20% missing hours. Instead, the hourly records are fairly complete in time, with missing above 10% occurring in very limited (1 ~ 3) seasons over 1970–2017 in most stations and less than 1% in the remaining seasons. Across the network, more than 89% missing gaps (consecutive missing records) are shorter than 24 h, and around 7% missing gaps persist 24–36 h. Major missing gaps longer than 15 d mainly occur in early April and/or late October before 1975 in some northern stations
(less than 10). Considering the dry conditions in the north during these two months, these occasional long-gap missing should not exert discernable impacts on the characterization of precipitation unevenness.

2.2 Methods
Following the definition developed by Pendergrass and Knutti (2018), the unevenness is quantified by the number of days/hours contributing half of seasonal precipitation totals. Specifically, at each station, precipitation series for each season is sorted by high to low daily/hourly accumulation, and then the number of days/hours till which the accumulated precipitation for first time exactly equals to or exceeds half of the seasonal total that year is counted. Here, using the direct counting instead of fitting the cumulative fraction of seasonal precipitation to the number of wet days/hours (i.e. cumulative density function) avoids yielding a non-integer number (between two neighboring days/hours) ambiguous to the unevenness quantification. The median of multi-year (1970–2017) numbers of days/hours for half of seasonal totals is taken as the climatological unevenness at the station-level (figures 1(b) and (d)). The regional-scale unevenness climatology is further represented by the median of station-level climatological unevenness across the network (figures 1(a)–(b)). By design, a smaller value of the metric indicates higher degree of unevenness, and a decreasing (negative) trend for the metric indicates enhanced unevenness over time.

Compared to existing measurements that put more emphasis on the intensity contrast amongst wet events (Zolina et al 2009, Lu 2009, Sloat et al 2018), this unevenness metric is superior in its simultaneous characterization of the frequency contrast between wet and dry days/hours and the amount (intensity) contrast between heavier and weaker events. Mathematically, the metric could be viewed as the product of $F$—the seasonal total number of wet days/hours and $P$—the proportion (%) of the considered N wettest days/hours in $F$ ($P = N/F \times 100\%$).
Figure 2. Linear trends for unevenness during 1970–2017 based on daily (a) and hourly (b) precipitation, with grey dots showing zero trends. The embedded '+' and '×' indicate the trend significance at the 0.1 level at least for daily and hourly unevenness, respectively. The fraction of stations that registered each sign of trends is specified at lower-right, with the fraction of significant trends displayed in bracket. (c) Consistency and inconsistency in the sign of trends for daily- and hourly-based metrics. In the legend, daily and hourly are abbreviated as letter-D and -H, and symbol '0', '+', '-' indicate no trends, positive trends (less unevenness), and negative trends (more uneven) respectively. The numbers behind symbols indicate the fraction of each configuration. (d) and (e) show domain-averaged series (blue dot-solid line) of unevenness, along with linearly-fitted curves (green solid) and their 95% confidence intervals (green dashed). The values of linear trends, in both absolute and relative manners, are indicated at upper-right, with ‘∗’ meaning the significance at the 0.05 level.

That is,

\[ N = F \times P \]  \hspace{1cm} (1)

\( F \) characterizes the frequency aspect. \( P \) decreases when less fraction of wet events is needed for the same percentage (50%) of seasonal totals, thus suggesting enhanced contrast in precipitation amount between the metric-constituent wet days/hours and the rest events within the season, regardless of the directional change of \( F \). Such a way of characterizing the amount unevenness is similar to the index defined as the fraction of total precipitation from percentile-exceeding extremes (Zolina et al 2009, Leander et al 2014), but by prescribing fraction (50%) of seasonal totals instead of percentiles for extremes (e.g. the long-term 95th). This also makes the used unevenness metric insensitive to the sample size of percentile-based extremes (Zolina et al 2009).

Linear trends for the unevenness are evaluated via the Kendall’s tau slope estimator (Sen 1968), the one being sufficiently insensitive to outliers. In additional to conventional increasing and decreasing trends, the Kendall’s tau slope estimator also provides ‘zero trend’ indicative of no directional changes in essence. All linear trends are converted to percentage
Figure 3. Joint influences of frequency and intensity changes on trends for unevenness based on daily (a) and hourly (b) metrics. Frequency changes (F) are represented by trends for the number of seasonal wet days/hours, binned into 0.5%/decade intervals (y-axis); while intensity changes are represented by trends for fraction (P) of constituent wet days/hours in seasonal wet days/hours, binned into 0.05%/decade (x-axis). The color of each square indicates unevenness trends averaged amongst those stations with their frequency and intensity trends falling into corresponding bins. The meaning of each parameter is detailed in the Method, and the direction of their changes is specified by arrows. In particular, the ‘intensifying’ and ‘weakening’ labelled below x-axis means stronger or weaker intensification of metric-constituent wet days/hours compared to the rest events within the season.

Changes relative to the 1970–1989 climatology to facilitate comparisons. The non-parametric Mann-Kendall test (Mann 1945, Kendall 1975) is employed to accept or reject the null hypothesis that the trend for a station-level series or domain-averaged one is statistically significant.

Changes in dry days and spells are also examined to illustrate the consequence of precipitation unevenness changes. Dry days are defined as the one with daily precipitation accumulation less than 1 mm day$^{-1}$, accounting for the limited accuracy of rain gauges and trivial contributions of below-threshold drizzle in alleviating droughts (Zolina et al 2010). Dry spells are defined as the period of consecutive dry days without interruption.

A ‘spatially-aggregated PDF (probability density function)’ is constructed to examine whether observed changes in precipitation unevenness have already been detectable (Fischer and Knutti 2014). Simply put, station-based differences of mean unevenness between two 24-year slices (1994–2017 vs. 1970–1993) are aggregated (totally 483 samples) to establish the spatial PDF via a kernel density estimate (Worton 1989). The range (5%–95%) of changes potentially induced by random internal variability is mimicked by resampling differences of mean unevenness between randomly sampled 24-year pairs (N = 1000) over 1970–2017. Based on the comparison between PDF for real observations and the mimicked range, I check whether observed unevenness changes above a certain magnitude are more widespread than expected due to internal variability alone. Each bootstrap realization only disturbs the sequencing of the series in time but samples on the same records (the same day or hour) across the network to preserve the spatial dependency inherent to large-scale monsoonal precipitation (Zhang and Zhou 2019).

3. Results

Figure 1 shows the climatology of unevenness. At all gauges combined, it takes only 11 d for half of seasonal totals to fall (figure 1(a)). Treating consecutive wet days as ‘an event’, the half of seasonal totals requires only nine events. Spatially, the unevenness varies from 4 to 6 d in the north where it rains less frequently to 8–20 d in the south where precipitation tends to be spread over many wet days throughout the season (figure 1(b)). From a broader perspective, 25% of seasonal totals falls within only 4 d, and 24 d are enough to contribute three-quarters of seasonal rainfalls. Note that the number of constituent wet days diverges substantially amongst rain gauges when considering percentage beyond 50% (error bars in figure 1(a)). It is therefore suggested that the 50% percentage of seasonal totals is a proper compromise between ensuring the extremity (impacts) of constituent wet days and distilling the unevenness shared by most gauges.

The use of hourly records unearths more uneven intra-seasonal distribution of precipitation. At the regional-scale, 44 wet hours contribute half of the seasonal total. These wet hours tend to aggregate into
31 wet spells of differing durations. More surprising is that only 13 h is needed for a quarter of seasonal totals. Similarly, the hourly-based unevenness exhibits a meridionally contrasting pattern, with the number ranging from 30 h in the north to 30–70 h in the south.

The absolute unevenness (days or hours) is also converted into the form of fraction (%) in total seasonal wet days/hours, to further highlights the non-uniform distribution of precipitation amount amongst wet days/hours (the P item in equation 1, Methods). Spatially, in most stations, half of seasonal totals are contributed by 10% ~ 14% of seasonal wet days (figure S1(b) available online at https://stacks.iop.org/ERL/15/104068/mmedia), while the percentage reduces to 6% ~ 10% in seasonal wet hours with a median at 8.1% (figure S1(c)–(d)).

Unexpectedly, less than 2.5% of wet hours could contribute as large as 25% of seasonal totals, intuitively illustrating the unevenness in precipitation amount.

On daily basis, over 60% gauges did not see any directional changes (zero trends) in precipitation unevenness (figure 2(a)). The daily unevenness has enhanced (negative trends, Methods) mainly in the lower reaches of the Yangtze River, northern South China, parts of Southwest China, and northern Hainan Island, where the seasonal total actually changed insignificantly (figure S2). By contrast, trends for the hourly-scale unevenness exhibit a more spatially-homogeneous pattern, with enhanced unevenness observed in more than three-quarters of stations (figure 2(b)). That is, using daily precipitation records leads to considerable

Figure 4. Linear trends for the number of dry days within the warm season (a) and for the duration of the longest-lasting dry spells (b). The symbols and numbers have the same meaning as those in figures 2. (c) and (d) show the scatter-plot between grid-average (5° × 5°) trends for unevenness (x-axis) and for the duration of the longest dry spells. The linearly-fitted curve and its 95% confidence interval are shown by solid and dashed lines, with the regression equation and the P-value for the regression coefficient presented at the top.
underestimate for the spatial extent—by more than 40% (35.4% stations for daily vs. 76.4% stations for hourly)—of enhanced intra-seasonal unevenness in this typical monsoon region. More specifically, in southern South China and the region north of 30°N (figure 2(c), green dots), though the daily unevenness has changed little, the hour-by-hour contrast in amount and frequency of precipitation within the season has strengthened. As with the regional-mean unevenness, the number of days for half of seasonal totals declined by around 9% (−1.9%/decade) during 1970–2017, while the hourly-based metric gives rise to a faster reduction by around 12% (−2.4%/decade) (figures 2(d)–(e)). Namely, the use of hourly records helps better understand how fast and widespread the intra-seasonal precipitation unevenness has been increasing.

Based on equation (1) (Method), the unevenness metric (N) is decomposed into the frequency item (F), and the intensity item (P), with the latter expressed as the ratio of constituent wet days/hours in the seasonal total number. Over 1970–2017, broad swathes of the region, especially south of 30°N, experienced a reduction in seasonal wet days/hours (figure S3(a)–(b)). Amongst 171 stations that observed increased daily unevenness, around 95% stations saw decline in the number of wet days. Hence, the enhanced unevenness could be preliminarily felt through the sharpened contrast between the occurrence frequency of wet and dry days. Further
focusing on wet days only, in around 88.9% of the 171 stations, a smaller fraction of wet days is needed for half of seasonal totals (figure S3(c)). So in these stations, the enhanced unevenness could be further perceived by strengthened contrasts in precipitation amount between heavier events and the rest weaker events, that is, the rainiest days get rainier (figure S4(a)). For hourly records, amongst the 369 stations observing increased unevenness, 88.9% saw decreases in the frequency of wet hours (figure S3(b)) and 83.2% observed diminishing fractions of hours responsible for half of seasonal amount (figure S3(d)).

From a uni-factor perspective, it seems reasonable to conclude that both frequency and intensity changes are at play in enhancing unevenness (figure S5). The frequency (F, y-axis) -intensity (P, x-axis) joint analysis (figure 3) further brings into prominence the dominant role of the disproportionate intensification amongst events of different intensity levels. In the bi-factor space, regardless of directional changes in F, decreases in fraction of constituent wet days/hours (P) definitely leads to enhanced unevenness (figures 3(a)-(b), quadrat-1 and 2). By contrast, almost all trends toward less uneven fall in the quadrats with growing ratios of constituent wet days/hours (quadrat-3 and 4), even if configured with decreasing seasonal total wet days/hours (quadrat-3). Stronger increases in unevenness result jointly from larger decline in seasonal wet days/hours’ frequency and greater reductions in the fraction of constituent hours/days (figure 3, quadrat-2).

In tandem with increasing unevenness, a sizable portion of stations in this monsoon region recorded more dry days during the warm season, especially in the southern part (figure 4(a)). This elevates the probability of dry days occurring consecutively, and lengthens the longest dry spells (figure 4(b)) that normally spans from two weeks to two months dependent on the geophysical location (figure omitted). The risks of flash droughts and seasonal droughts would be accordingly heightened (Yuan et al 2019). In view of this, I attempt to quantify the role of enhanced unevenness on the elevated risks of droughts/dryness by regressing grid-average (5° × 5°) trends for unevenness onto duration trends for the longest wet spells, considering the spatial contiguity of droughts/dryness. As expected, more uneven precipitation is distributed intra-seasonally, the longer dry conditions have become, with the relationship being stronger and more significant using hourly-scale unevenness (figures 4(c)–(d)). This further points to the added value of hourly records in linking changing precipitation unevenness to evolutionary hydrological hazards.

Consistent with the trend analysis, the spatially-aggregated PDF (see Method) shows that the precipitation becomes increasingly uneven in more stations than it becomes less uneven, at both daily and hourly scales (figure 5). During 1970–2017, regions where the number of days for half of seasonal totals dropped by more than 7% are more widespread than what would be expected by pure chance (figure 5, grey shaded). The pattern for threshold-exceeding stations is also consistent with hotspot distribution in trend analysis. Similarly, at hourly scales, stations that observed reduction in the number of hours for half of precipitation over 6.5% account for 42.5% in the observational network (figure 5(d)), distinguishably larger than the fraction of stations expected from internal variability alone (around 27%). To sum up, without steady external forcings, strong enhancement of intra-seasonal unevenness should not have been as widespread as observed. This conclusion robustly holds by using pairs of shorter slices (e.g. 20-year, 15-year), performing block bootstrapping (5 ~ 10 years, Wilks 1997) to simulate internal variability, or applying the field significance test to trend estimates instead (Westra et al 2013, figure omitted).

4. Discussions

An alternative metric to quantify precipitation unevenness is a given percentage of seasonal amount falling beyond the top-X percentiles. This metric concerns exclusively about the contrast between extreme and non-extreme events in their amount. The 50% is still used as the ‘given percentage’ here for comparison. Considering wet days, half of seasonal precipitation falls in events stronger than the 87.5th ~ 90th percentiles (figure S6); while calculating percentiles using all days (including dry), the key percentiles soar to 92.5th ~ 97.5th. At the hourly-scale, hours wetter than the wet-hour 90th ~ 95th percentiles allow for half of seasonal totals. Referring to all-hour percentiles instead, events heavier than the 99th ~ 99.5th percentiles are needed. These percentiles are critical to distinguish ‘real extremes’ from moderate ones, for the purpose of understanding their differential responses to warming. As the atmosphere moistens with warming, extremes intensify faster than total (average) precipitation, as the latter is additionally constrained by the planetary energy budget (Trenberth 2011). To avoid substantial overlaps with total precipitation, real extremes should constitute a minority—less than half—in total precipitation (Pendergrass and Knutti 2018). Hence, the wet-day (-hour) 90th (95th) percentile or all-day (-hour) 95th (99th) or higher ones are recommended for identifying real extremes over Eastern China. These key percentiles also point to that the participating N wettest days/hours in the unevenness metric largely represent events conventionally considered extreme.
The use of hourly records enables us probing into the finer-resolution structure of precipitation, i.e. distribution within a day or amongst hours in different days. This micro-distribution of precipitation is essentially shaped by activities of short-lived convective storms (Westra et al 2014, Trenberth et al 2017, Schumacher and Rasmussen 2020). As climate warms, heavier hourly extremes intensify more strongly, possibly due to stronger ascending motions invigorated by more latent heat released within wetter convective storms, i.e. the so-called dynamic amplification (Berg et al 2013, Li et al 2019). This dynamic amplification has been found particularly efficient in southeast part of China due to more convective-favorable environments and stronger interactions between convection and large-scale dynamics there (Nie and Fan 2019, Norris et al 2019, Chen et al 2020), leading to more lopsided distribution of hourly precipitation intra-seasonally. This partly explains why the enhancement of unevenness with warming manifests at hourly scale but is absent at daily scale in some stations (figure 2(c) green dots). The regional-specific dynamic amplification also accounts for the preferential occurrence of significant increases in unevenness in the southern sector. Substantially intensified hourly downpours in turn removes much more moisture from the air, so the surface evaporation and moisture advection take longer than previously to replenish the depleted moisture required by the next storm, producing longer dry spells (Dai et al 2018). This process, better characterized by hourly precipitation records, might be one of the underlying mechanisms leading to the relationship between unevenness increases and the lengthening of longest dry spells being stronger and more significant at hourly scale (figures 4(c)–(d)). Based on convection-permitting simulations, more analysis is worthwhile conducting to validate above hypothesis and further advance understanding about the reason for the difference in changes and implications of hourly- versus daily-scale unevenness.

The results suggest that increasing precipitation unevenness has elevated the chance of both floods and droughts. Given the general expectation of more uneven precipitation in the future (Pendergrass and Knutti 2018), dry spells in-between precipitation extremes would further increase in duration (Park et al 2020). This implies that future precipitation extremes will give way to prolonged dry spells more erratically within a season to form so-called ‘precipitation whiplash’ (Swain et al 2018; Chen et al 2020). In a warming climate, extremely-long dry spells are inclined to be confounded by hot extremes to constitute hot-dry compound events (Hao et al 2017, 2018). These cascading and compound extremes substantially increase local communities’ vulnerability and decrease their resilience to the simultaneous/sequential hazards (Ruiter et al 2019, Zscheischler et al 2018). Several years had already suffered from precipitation whiplash in the domain (Shan et al 2018). Projected unevenness changes and the resulting damaging whiplash events in this populous monsoon region are suggested to be factored into future risk assessments and managements.

5. Conclusions

Using gauge observations of daily and hourly precipitation over Eastern China, this study examines the climatology and long-term changes of warm-season (April–October) precipitation unevenness. The unevenness is quantitatively measured by the number of wettest days/hours that constitute half of seasonal precipitation totals. Climatologically, half of the seasonal totals across Eastern China requires only 11 d or 44 h to contribute. During 1970–2017, enhanced unevenness of daily precipitation occurred in patches of southern sectors only; while hourly records unfold a pan-regional enhancement of precipitation unevenness and therefore a greater rate for regional-mean unevenness increase. The enhanced unevenness originated primarily from greater intensification of extremes compared to average events, and secondarily from the decline in the number of seasonal wet days/hours. The more uneven intra-seasonal distribution of hourly precipitation has translated into significant lengthening of the longest dry spells in southern part of Eastern China, putting the region at higher risks from both flash floods and droughts. During the study period, the spatially-aggregated tendency toward enhanced unevenness has already emerged from the range expected due to random internal variability.

These results warn that this populous monsoon region needs to prepare for a challenging future mixing little precipitation most of the season and more-intermittent-but-heavier precipitation.

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Data availability statement

All data that support the findings of this study are included within the article (and any supplementary information files).

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Zscheischler J et al 2018 Nature Clim Change 8