Human Influence on the Increasing Drought Risk Over Southeast Asian Monsoon Region

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Abstract Southeast Asian monsoon region is regularly stricken by drought, but less attention is paid due to its slow-onset and less visual impact. This study investigated the observed drought changes over Southeast Asian monsoon region and impacts of anthropogenic forcing using the Coupled Model Intercomparison Project Phase 6 models. We revealed an increasing drought risk for 1951–2018 due to more frequent and wide-spread droughts. The influence of anthropogenic forcing is successfully detected, which has increased the likelihood of the extreme droughts in historical simulation by reducing precipitation and enhancing evapotranspiration. The time of emergence of anthropogenic forcing in extreme drought occurrence and affected area occurs around the 1960s. The future projected severe and extreme drought risks are still beyond natural only forced changes under all scenarios. Our findings demonstrate a robust impact of anthropogenic forcing on drought risk over Southeast Asia, and highlight the importance of future pathway choice.

Plain Language Summary As a humid region, drought in Southeast Asian monsoon region is often underestimated due to its slow rate of onset and less visual impact. Here we revealed a significant increasing trend of drought occurrence and affected area over Southeast Asian monsoon region since the 1950s. The impact of human influence is successfully detected using the Coupled Model Intercomparison Project Phase 6 models. Anthropogenic forcing has increased the likelihood of the extreme droughts for 1951–2014 by suppressing water supply and enhancing evaporation demand. The time of emergence of anthropogenic forcing in extreme drought frequency and affected area first appeared around the 1960s. Even though drought risk will start to decrease since the 2030s in the future under the lowest emission scenario of CMIP6, the projected drought risks are still beyond natural only forced changes.

1. Introduction

Southeast Asian monsoon region falls in the warm and humid tropics modulated by Asian monsoon. It is home to nearly 15% of the world’s tropical forests and 8.5% population in 3% earth’s total land area, and also one of the biodiversity hotspots in the world (Sodhi et al., 2010; Stibig et al., 2014). With the unprecedented urbanization and population growing rate, water scarcity issues have already posed a serious challenge for sustainable development in Southeast Asian monsoon region (Kumar et al., 2015). As a humid region, drought in this region is often underestimated due to its slow rate of onset and less visual impact. However, drought can have devastating cumulative impacts, especially on the countries which are poor and less developed but heavily depend on agriculture (Polpanich, 2010). Thus, understanding the drought changes and their mechanism is of great importance.

This study focuses on the Southeast Asian monsoon region, including the mainland Southeast Asian countries and South China (10°N–30°N, 90°E–120°E) (Figures 1a and 1b), because this region has the longest wet season and the strongest interannual variability in the monsoon length in the Asian monsoon region (Misra & DiNapoli, 2014). Decreasing trends in annual precipitation from the 1950s to 2000s were observed in Myanmar, Thailand, and northern Vietnam (Endo et al., 2009), and the number of rainy days significantly decreased from 1961 to 1998 (Manton et al., 2001). Drought has affected over 66 million people in Southeast Asian countries for the past 30 decades (UNESCAP and ASEAN, 2020). The 2020 drought started from 2019 has caused water levels in Southeast Asia’s Mekong River to drop to its lowest in more than 100 years (https://www.nationalgeographic.com/environment/2019/07/me Kong-river-lowest-levels-
100-years-food-shortages/), affecting 13 provinces in the Mekong Delta region (https://reliefweb.int/report/viet-nam/viet-nam-drought-and-saltwater-intrusion-office-resident-coordinator-flash-update-1). The 2020 drought also spread to Southwest China, the upstream of Mekong River, and over one million people were lack of accessing drinking water (https://news.cgtn.com/news/2020-04-05/Drought-affects-over-one-million-people-in-SW-China-province-PrpBkhJok/index.html). South China, adjacent to the Southeast Asian countries, has been frequently stricken by droughts in recent decades (Chen & Sun, 2015; Xin et al., 2006; Zhang et al., 2020). The two adjacent regions share the same climate and are facing similar drought risk. Thus, we study the drought changes over the traditional Southeast Asian countries and South China together in this study.

Climate change could further aggravate drought by either enhancing evapotranspiration or suppressing precipitation (Dai, 2011; Trenberth et al., 2014), and Southeast Asian monsoon region is one of the hotspots with strong drying under global warming (Cook et al., 2020). The effect of black carbon aerosol radiative forcing can partly explain the observed drying trend of Southeast Asian spring precipitation (Lee &

**Figure 1.** The spatial distribution for observed linear trend of drought from 1951 to 2018 for (a) SPEI (unit: 68 years^{-1}) (b) extreme drought (SPEI ≤ −2.0) occurrence (unit: month (68 years)^{-1}). The temporal changes of (c) occurrence (unit: month yr^{-1}) and (d) affected area fraction (unit: %) for different drought categories averaged over Southeast Asian monsoon region (10°N–30°N, 90°E–120°E). The yellow, orange, brown and red lines represent abnormally dry (SPEI ≤ −0.5), moderate drought (SPEI ≤ −1.0), severe drought (SPEI ≤ −1.5), and extreme drought (SPEI ≤ −2.0), respectively. SPEI, Standardized Precipitation-Evapotranspiration Index.
The optimal fingerprinting attribution shows a dominant role of anthropogenic aerosols forcing in the declining trend since the 1950s of northern hemispheric monsoon precipitation, including Southeast Asia (Polson et al., 2014). Compared with present-day, drought events are projected to increase in the future over mainland Asia based on the regional climate model (Ammuolajaren & Chanvichit, 2019) and CMIP5 multimodel simulations (Lu et al., 2019). As for the droughts associated with El Niño events, drought would cover more area over Southeast Asia in the near future even with less severe El Niño events, and droughts associated with severe El Niño would be more extreme and more widely spread in the near and far future (Hariadi, 2017).

The Coupled Model Intercomparison Project Phase 6 (CMIP6) with improved climate models and more modeling groups is expected to provide more reliable information on the regional climate response to anthropogenic forcing (Eyring et al., 2016; Ukkola et al., 2020). This study aims to answer the following questions by examining observation and CMIP6 multimodel output: (a) How does the observed drought over Southeast Asian monsoon region change since the 1950s? (b) Whether anthropogenic forcing plays any role in the drought changes? (c) How would drought change under different scenarios in the future?

2. Data and Method

2.1. Observation and CMIP6 Model Simulations

We use monthly observational precipitation and potential evapotranspiration data set from the Climatic Research Unit of the University of East Anglia (CRU TS v.4.03) for 1951–2018 at a horizontal resolution of 0.5° (Harris et al., 2020). To verify the observed drought changes revealed by simple drought index, surface (0–10 cm) soil moisture from Global Land Data Assimilation System Version 2 (GLDAS-2.0, Rodell et al., 2004) for 1951–2014 is also used. We employ the pre-industrial control simulation (piControl), historical simulation (Hist) and four future scenarios projections from 14 coupled models underpin CMIP6 to explore the role of anthropogenic forcing and the scenario dependence of drought changes in future projection (Tables S1 and S2). The four scenarios chosen in this study are the Shared Socioeconomic Pathways (SSP) 1–2.6, 2–4.5, 3–7.0, and 5–8.5 (O’Neill et al., 2016). The piControl (preindustrial control) is employed to estimate internal variability of the unforced drought. All model outputs are interpolated onto the same resolution of 1.5° × 1.5° using the first-order conservative interpolation. We use Hargreaves equation to calculate reference evapotranspiration (ET) (Hargreaves, 1994), which has a good agreement with Penman-Monteith method (Droogers & Allen, 2002).

This study chooses the Standardized Precipitation-Evapotranspiration Index (SPEI) (Vicente-Serrano, Beguería, & López-Moreno, 2010, Vicente-Serrano, Beguería, López-Moreno, Angulo, & Kenawy, 2010) to investigate the changes in drought intensity, occurrence or frequency defined as drought months per year and affected area fraction. To verify the observed drought changes revealed by SPEI, self-calibrating Palmer Drought Severity Index (sc-PDSI, Wells et al., 2004) is also employed. In observation, SPEI and sc-PDSI are both calculated based on the CRU TSv.4.03 precipitation and evapotranspiration data set (Schrier et al., 2013; Vicente-Serrano, Beguería, López-Moreno, Angulo, & Kenawy, 2010). As monthly sc-PDSI is not able to depict drought on time scales shorter than 12 months, we use SPEI at a 12-months time scale to estimate drought changes in the observation. In each model simulation, SPEI is calculated using a Log-Logistic distribution (Vicente-Serrano, Beguería, & López-Moreno, 2010), the parameters of which are derived by fitting it to the piControl simulations of that model.

2.2. Estimate of Internal Variability and Time of Emergence

Following Zhang and Delworth (2018), internal variability is estimated from the preindustrial control simulations. For drought occurrence and affected area changes, we first calculate the drought occurrence at each grid and the drought affected area of the study area. The running-mean drought affected area and area-averaged drought frequency for a 20-years period over the target region are then calculated. Internal variability is defined as the range between the maximum and minimum values across the entire piControl runs. The ranges of drought area and area-averaged frequency in piControl simulation are only due to internal climate variability. To estimate the ranges of decadal changes in precipitation, ET and their difference caused by internal variability, we first randomly select two nonoverlapping 20-years periods from the piControl
simulation. Then, we calculate the difference between these two 20-years periods. Next, we repeat these 14 times (to mimic the 14 models ensemble) to form the ensemble and compute ensemble average. Finally, we repeat the above process 5000 times to gain a probability density function (PDF), which is seen as the ranges resulting from internal variability.

The time of emergence (TOE) is defined as the time when external forcing signal, which is represented by multimodel ensemble mean (MME), exceeds internal variability first and lasts at least 2 decades (Zhang & Delworth, 2018). To estimate the spread of TOE, we calculate the time when the MME exceeds ranges of internal variability of each model, and define this time as the TOE for each model. The spread of TOE is the range of ±1 standard deviation of TOE across the 14 models.

3. Results

3.1. Observed Drought Changes for 1951–2018

In observation, an overall drying trend over the Southeast Asian monsoon region is observed since the 1950s, with the strongest drying trend over Yunnan Province in China, northern Thailand and Myanmar (Figure 1a). SPEI has decreased by −0.75 at the maximum from 1951 to 2018. The occurrence of extreme drought, defined as month with SPEI ≤ −2.0 per year, has been significantly increasing over the regions with significant decreasing trend of SPEI (Figure 1b). It is centered over the Southwest China and Burma. In contrast, Viet Nam, along the west coast of Pacific Ocean, shows significant wetting trends. Significant increasing trends in the drought occurrence and affected area are seen from the temporal changes averaged over Southeast Asia (Figures 1c and 1d). For the past 68 years, the severe and extreme drought occurrence (affected area) has increased by 0.8 and 0.2 months per year (7.1% and 3.1%), respectively, ~23% and 8% (85% and 142%) of climate mean. In contrast, the linear trend in drought intensity is insignificant (Figure S1a). It indicates that the mean severity of drought may not change significantly when droughts occur, although droughts are becoming more frequent and more widely spread over the Southeast Asian monsoon region. So, we will mainly focus on the changes in drought occurrence and affected area in the following sections.

The results based on sc-PDSI (Figures S1b and S2) and surface soil moisture (Figure S3) both confirm the increasing drought risk over Southeast Asian monsoon region. Following Cook et al. (2014), we recalculate SPEI by removing the linear trend of ET for 1901–2018 to estimate contribution of precipitation changes to the drought risk trend (Figure S4). Over the centers with strongest decreasing trend of SPEI and increasing trend of drought occurrence, the contribution of precipitation changes is higher than 50%, reaching 90% at maximum, demonstrating the importance of precipitation changes. Given the high consistency between sc-PDSI and SPEI, we will use SPEI to investigate the impact of anthropogenic forcing in the following discussion.

3.2. Responses of Droughts to Historical Anthropogenic Forcing

By comparing PDF distributions of drought indices averaged over the study region in Hist and piControl, a detectable role of anthropogenic forcing can be seen from the leftward (rightward) shift in SPEI, precipitation and surface soil moisture (ET, drought occurrence and affected area) under anthropogenic forcing (Figure 2). The likelihood of a 1-in-20-years drought event defined by extreme drought occurrence and affected area in piControl is estimated to increase to 24% (6%–49% for 10–90 confidence level) and 32% (25%–45%) in Hist, respectively. It indicates anthropogenic forcing has increased the risk of such event by 5-time (3–25-time) and 6-time (4–9-time) estimated from risk ratio (P_Hist/P_piControl), respectively. Human influence can intensify the drought risk by changing both standard deviation and climate mean of precipitation, ET and SPEI (horizontal lines Figures 2a–2c). Specifically, standard deviation for SPEI, precipitation anomaly and ET anomaly in Hist increases to 0.44, 0.81 mm day⁻¹, and 0.15 mm day⁻¹ from 0.40, 0.77, to 0.13 mm day⁻¹ in piControl.

3.3. ToE of Anthropogenic Forcing

To investigate when the human influence forced signal exceeds natural variability, we estimate the TOE of anthropogenic forcing here. Because estimation of TOE is sensitive to the simulated ranges of climate
variability, we first evaluate the models’ capability in simulating the variability of drought occurrence and affected area over Southeast Asian monsoon region. Most CMIP6 models and MME underestimate the variability of occurrence of extreme drought, but overestimate the extreme and severe drought affected area fraction (Figure S5). To avoid the model biases, we scale the simulated variability of internal variability using the ratio between the standard deviation of observation and of Hist of each model for the period 1950–2014.

Figure 2. Probability distribution function (PDF) of drought changes in piControl and Hist. (a) SPEI averaged over the land area of Southeast Asian monsoon region. (b) and (c) are same as (a), but for monthly precipitation (mm day$^{-1}$), ET (mm day$^{-1}$) and surface soil moisture (0–10 cm) (kg m$^{-2}$) anomalies relative to piControl. (e) and (f) are for extreme drought occurrence and affected area fraction over the Southeast Asian land monsoon region. The solid lines are the multi-model ensemble (MME) mean of piControl (black line) and Hist for 1950–2014 (red line), and the shadings denote the range of 10th to 90th across models. The vertical blue dash lines denote the return value of 20-years period. The horizontal lines and dots denote the range of standard deviation and the mean value of PDFs, respectively. The mean value and the inter-model 10–90 range are shown in the right corner of each plot. SPEI, Standardized Precipitation-Evapotranspiration Index.
Consistent with the observation, a significant increasing trend for the drought occurrence and affected area fraction since the early 20th century is clearly simulated in Hist. The TOE of climate change induced extreme drought occurrence and affected area emerges around 1967 (1928–2006) and 1967 (1941–1993), close to that of severe drought events 1969 (1935–2003) and 1967 (1939–1995). We also investigate whether future changes in drought risk under different scenarios will return to natural only forced variability (colored lines in Figure 3). The extreme and severe drought occurrence and area fraction start to decrease around the 2030s under SSP1-2.6 and keep stable since the 2030s under SSP2-4.5, while continue to increase through the whole 21st century under SSP3-7.0 and SSP5-8.5. The anthropogenic forced higher drought risks are still beyond the ranges of natural variability of piControl under the four scenarios, although a decrease is shown in SSP1-2.6. The largest increase is seen from SSP3-7.0, which has the greatest anthropogenic aerosol loadings in the future (Wilcox et al. 2020). The drought will become more frequent and more widespread in the future compared with piControl under all scenarios, but a slight decrease relative to present day is projected under the lowest emission scenarios. The earliest TOE has appeared over the Southwest China before the 1990s, followed by the Mekong river basin countries (Figure S6a). For the drought occurrence changes averaged over the 20 years around TOE relative to piControl, extreme drought increases by 0.4–0.8 months per year over the Southwest China and 0.4–1 month over Thailand (Fig. S6b).

As for the future projection, precipitation shows a recovery since the 2020s in all scenarios except SSP3-7.0 under which it recovers from the 2030s. Changes in precipitation return to the ranges of natural variability around 2030 (2025–2035), 2037 (2031–2043), 2059 (2054–2064), 2039 (2032–2046) in SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5, respectively. The black vertical dash lines denote the time of emergence (TOE).

We also present the changes of precipitation, ET and their difference (PmE) relative to piControl to see their impact on drought risk changes (Figure 4). In the 20th century, the ensemble mean precipitation of the 14 CMIP6 models shows very similar evolution to those in drought, decreasing with time from the early 21st century to present, reaching its minimum recently. The TOE of precipitation occurs around 1980 (1973–1987) (Figure 4a). Meanwhile, the anthropogenic activity forced ET increases with time and goes beyond natural variability around 1999 (1968–2030), with much weaker magnitude than precipitation (Figure 4b). The combination of decrease in water supply (precipitation) and increase in evaporation demand (ET) contributes to the decreasing trend in PmE (Figure 4c).

As for future projection, precipitation shows a recovery since the 2020s in all scenarios except SSP3-7.0 under which it recovers from the 2030s. Changes in precipitation return to the ranges of natural variability around 2030 (2025–2035), 2037 (2031–2043), 2059 (2054–2064), 2039 (2032–2046) in SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5, respectively. The changes in PmE under SSP2-4.5 and SSP3-7.0 do not return to the ranges of internal variability because of faster ET increase and moderated recovery of precipitation with global warming (Table S3). The changes in precipitation, ET and PmE demonstrate that future global warming benefits a recovery of Southeast Asian monsoon precipitation, but faster ET increase could overwhelm its recovery and contribute to a further decrease in PmE and higher drought risk.

Enhancement of precipitation in the future projection is closely related to radiative forcing. In Hist, reduction in precipitation is dominated by anthropogenic aerosol forcing by reducing atmospheric humidity and
weakening the monsoon circulation, although the thermodynamic effect from greenhouse gases forcing can partly offset the impact of anthropogenic aerosol forcing (Zhou et al., 2020). In the future projection, greenhouse gases (GHGs) keep on increase but anthropogenic aerosol forcing declines (O’Neill et al., 2016), which intensifies the impact of GHGs on precipitation through the thermodynamic response (Chen et al., 2020; Wilcox et al., 2020), and enhances ET as well. Higher scenarios result in faster warming, and faster recovery in precipitation and enhancement in ET. Only under SSP1-2.6 and SSP5-8.5, the recovery of precipitation exceeds enhanced ET, favorable of less drought risk and a return to the variability in a natural world.

4. Summary and Conclusion Remarks

As a slow-onset extreme event, drought over Southeast Asian monsoon region is paid less attention so far. We examined drought changes over this region in the observation from 1950 to 2018, and showed that Southeast Asian monsoon region has been undergoing more frequent and more widespread drought for 1951–2018 in the observation, centered Southwest China, northern Thailand and Myanmar. The extreme drought affected area fraction is almost doubled during 1951–2018 over the study region.

The impact of anthropogenic forcing and projected changes in drought under different scenarios were investigated by comparing Hist and future projections with piControl from the CMIP6 multimodel output. We found a detectable role of anthropogenic forcing on the increasing drought risk over the Southeast Asian monsoon region. Human influence has increased the occurrence and affected area fraction of extreme drought during 1951–2014. Consistent with the observation, significant increasing trends for the drought occurrence and affected area fraction in Hist are simulated since the early 20th century. The TOE of extreme drought occurrence and affected area appeared around 1967 (1928–2006) and 1967 (1941–1993), respectively. The anthropogenic forced precipitation decrease dominates the increasing drought risk in the past century. In the future, the projected changes in extreme and severe drought risk would start to decrease around the 2030s under SSP1-2.6, while keep on increasing through the whole 21st century under SSP3-7.0 and SSP5-8.5. However, the projected changes in drought risk under all scenarios are still beyond the ranges of natural variability.

Our study demonstrated a distinguishable role of anthropogenic forcing in the increasing drought risk over Southeast Asian monsoon region, and the TOE of anthropogenic forcing on drought has occurred in the past. Both higher aerosols loading and higher radiative forcing in the future are important for the drought changes, and SSP3-7.0, which bears the largest anthropogenic loadings in the future and second high radiative forcing among the four scenarios, projects the most frequent and most widespread drought for the mid- and long-term projections. Although precipitation over Southeast Asian monsoon region will recover since the 2050s due to more atmospheric humidity with global warming, the evapotranspiration enhancement could offset and even overwhelm the precipitation recovery, increasing the drought risk.

Southeast Asian monsoon region, particular over the Mekong river Basin, will be the hotspot of frequent and widespread drought risk in the future. It would greatly threaten the agriculture, heightened fire risks and lead to acute shortages of drinking water. ASEAN and the United Nations Economic and Social Commission for Asia and the Pacific proposed to build resilience to drought in Southeast Asia mitigate the impacts of drought (UNESCAP and ASEAN, 2020). Here, we demonstrate the choice of pathways is also
crucial for the drought risk changes over Southeast in the future. It is urgent to take actions to reduce an-
thropogenic aerosol loading and greenhouse gases emissions to reduce the Southeast Asian drought risks.

Data Availability Statement
The authors also thank University of East Anglia Climatic Research Unit (CRU) for providing the obser-
vational precipitation data sets (https://catalogue.ceda.ac.uk/uuid/10d3e3640f004c5784034191ac167d82).
The SPEI and sc-PDSI data sets can be freely accessed from the websites (https://digital.cscis.es/handle/10261/202305 and https://crudata.uea.ac.uk/cru/data/drought/). Surface soil moisture from GLDAS is available from https://disc.gsfc.nasa.gov/datasets/GLDAS_NOAH2015_M_2.1/summary.

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