Seasonal Prediction of Midsummer Extreme Precipitation Days over Northeast China

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ABSTRACT

Northeast China (NEC) has sustained economic losses in recent years because of extreme precipitation events. Despite many efforts, it remains very difficult to predict these extreme events. In this study, we documented the characteristics of extreme precipitation days (EPD) over NEC and established a seasonal prediction model using a year-to-year increment (DY) approach. The results show that most of the EPD over NEC occurred during midsummer, along with large values concentrated over the Greater and Lesser Khingan Mountains and Changbai Mountain. Two variables—the preceding early spring soil moisture DY over central Asia and the sea surface temperature DY in the tropical Atlantic Ocean—were used to construct the statistical model to predict the EPD DY over NEC. These two factors influenced the EPD by modulating the moisture transport over NEC. Cross-validation tests for the period from 1962 to 2016 and independent hindcasts for the period from 1997 to 2016 indicated that the two variables gave good predictions of the EPD over NEC. The observed and predicted year-to-year increments in EPD were well correlated, with a correlation coefficient of 0.65 for the period from 1962 to 2016 in the cross-validation test. In addition, the EPD DY covaried coherently with the midsummer precipitation amount DY over NEC, and those two predictors also gave good predictions for the midsummer precipitation amount over NEC. The correlation coefficient is 0.68 between the observed and predicted year-to-year increment in the amount of midsummer precipitation from 1962 to 2016 in a cross-validation test.

1. Introduction

Extreme precipitation events, including drought and floods, have a heavy impact on society, economy, ecosystems, and human life at regional and global

scales. Observed data and models both show that the maximum daily precipitation amounts have increased in dry and wet regions worldwide (Donat et al. 2016). There is therefore a need for in-depth scientific analysis to support an improved understanding and better predictions of extreme precipitation events, so that national stakeholders receive timely and reliable

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information to support the development of disaster mitigation and adaptation strategies.

Considerable efforts have been devoted to the changes in extreme precipitation over China in recent decades (Zhai et al. 2005; Tu et al. 2010; Chen and Sun 2015; Chen et al. 2017). For example, researchers have shown that extreme precipitation is the main contributor to the year-to-year variability in the annual precipitation over China, and accounts for about one-third of the total precipitation based on the overall mean in China (Sun 2012). The intensity of heavy precipitation has increased significantly over most of China in the past five decades (Wang et al. 2012b). Previous works have documented the changes in extreme precipitation over different parts of China (Zhou et al. 2016; Zhang et al. 2019; Zhou et al. 2018). The frequency of extreme precipitation events increased over the Yangtze River basin, Southeast and South China, Northwest China, and the Tibetan Plateau from 1961 to 2009 (Fu et al. 2013), while the annual maximum number of consecutive dry days increased in the middle-lower reaches of the Yellow River basin and South China from 1961 to 2011 (Wang and Fu 2013). Zeng and Lu (2015) indicated that the amount of summer extreme precipitation mainly changes because of changes in the frequency of events over most of China. Moreover, both the intensity and frequency of heavy precipitation show distinct decadal variability over eastern China (Chen et al. 2012). Researchers have also investigated the main influences on extreme precipitation over China. For example, Tian and Fan (2012) and Lü et al. (2017) reported that anomalous atmospheric circulation (i.e., the North Atlantic Oscillation, the Eurasian pattern, and the Pacific–Japan teleconnection) influences extreme precipitation over East China. Using regional climate models, Gao et al. (2002) explored the effect of doubled greenhouse gases on the number of heavy precipitation days over China. Also, researchers have recently revealed that anthropogenic forcing has contributed to the intensification of extreme precipitation over China, and consider that this forcing may strengthen with warming in the future (Zhou et al. 2014; Wu et al. 2015; Chen and Sun 2017; Li et al. 2017; Xu et al. 2018).

Northeast China (NEC), at the mid- to high latitudes, is among the subregions of China that is most affected by climate changes (Zuo et al. 2004). Over NEC, the rainy season occurs in summer and precipitation is influenced by circulations at mid- to high latitudes and in the tropics, such as anticyclones or blocking highs at high latitude (Yao and Dong 2000), sea surface temperature (SST) anomalies in the critical seas (Feng et al. 2006), the activities of cold vortices (Hu et al. 2010), anomalies

in Arctic Sea ice cover (Han et al. 2015; Li et al. 2018), and the East Asian summer monsoon systems (Sun et al. 2017). Recently, extreme summer precipitation has resulted in economic losses and casualties over NEC (Xue and Cao 2018). Previous studies have shown that the intensity of rainstorms over NEC has increased significantly since the 1990s, especially over the central, southern, and northwestern portions (Sun et al. 2007; Sun et al. 2010; Zou and Ding 2010). However, the issue remains that there is still a lack of understanding about what drives extreme precipitation over NEC, and an inability to give good predictions of extreme precipitation days from the latest datasets and available methods.

The year-to-year increment approach, initially used by Fan et al. (2007), has been utilized in short-term East Asian climate prediction in recent decade. The year-to-year increment is defined as the year-to-year difference in a variable between current year and the previous year (referred to as DY). The year-to-year increment approach treats DY of a variable as the direct predictand, compared with anomalies relative to climatology in conventional prediction method. And the predicted variable is obtained by adding the predicted DY to the observed value in the previous year. For example, the predicted $Y(\text{current year}) = \text{the predicted DY}(\text{current year}) + \text{the observed } Y(\text{preceding year})$. This approach is based on the quasi-biennial oscillation (QBO) in the variability of East Asian summer monsoon, temperature and precipitation (Chen et al. 2006). Considering the contribution of QBO to climate variables, the anomalies of a given variable in the current year (referred to as y_i) and in the previous year (referred to as y_{i-1}) can be respectively presented as $y_i = C + D_i$ and $y_{i-1} = -C + D_{i-1}$. Both D_i and D_{i-1} are disturbances in C . Therefore, $y_i \approx C$, and the DY of the variable is expressed as $\text{DY} = y_i - y_{i-1} \approx 2C$. The year-to-year increment of a given variable is approximately 2 times the anomaly of the variable (Wang et al. 2012a), which suggests that the predicted DY could amplify the prediction signals. In addition, the observed value in the previous year is real and credible and contains the interannual and interdecadal variation. Thus, this approach could well capture interannual and interdecadal variability of the variable. This method has significantly improved the prediction on summer precipitation and air temperature over eastern China (Fan et al. 2007; Fan and Wang 2010; Zhu 2011), the frequency of typhoons over the northwestern Pacific Ocean (Fan and Wang 2009), crop yields over NEC (Zhou and Wang 2014), the Asian–Pacific Oscillation (Huang et al. 2014), and the number of winter haze days on the North China Plain (Yin and Wang 2016).

Previous studies have suggested that this new approach has improved the prediction of East Asian mean climate. In addition, using the year-to-year increment approach, [Fan and Tian \(2013\)](#) provided an effective climate prediction model for heavy snow days over Northeast China. Given the severe impacts of extreme precipitation events and the urgent need for the prediction of extreme precipitation events, the DY approach is used to predict the seasonal variation in the extreme precipitation days during summer over NEC in this study.

The data and methods used in this study are introduced in [section 2](#). The characteristics of the extreme precipitation days, and the seasonal prediction model of the extreme precipitation days during midsummer and of the midsummer precipitation amount in NEC are described in [section 3](#). [Section 4](#) illustrates the comparison between the DY approach and traditional prediction method on extreme prediction days (EPD). The main conclusions and discussion are provided in [section 5](#).

2. Data and methods

An advanced gridded daily precipitation dataset for China, “CN05.1” ([Wu and Gao 2013](#)), for the period from 1961 to 2016 was used in this study. This dataset was constructed by interpolating data from more than 2400 observation stations in China and has a resolution of $0.25^\circ \times 0.25^\circ$. In this study, NEC is defined as the area of China that is east of 115°E and north of 38°N .

The monthly atmospheric data (resolution of $2.5^\circ \times 2.5^\circ$), such as the geopotential height, for the period from 1948 to 2017 were taken from the global atmospheric reanalysis dataset of the National Centers for Environmental Prediction and the National Center for Atmospheric Research (NCAR; [Kalnay et al. 1996](#)). The monthly global soil moisture dataset for the period from 1948 until 2017, at a resolution of $0.5^\circ \times 0.5^\circ$, was provided by NCAR ([Fan and Dool 2004](#)). The monthly mean SST data were the HadISST1.1 dataset with a resolution of $0.5^\circ \times 0.5^\circ$ ([Rayner et al. 2003](#)). All of the data covered the period from 1961 to 2016.

Traditionally, a heavy precipitation event is defined as one with a daily precipitation amount that exceeds 50 mm. Because there were significant regional differences, an absolute precipitation threshold was not applied to each grid, but rather a percentile-based method was used to determine the EPDs in this study. For a given station, the EPD were defined as the days with daily precipitation amounts greater than the

90th-percentile threshold of all the rainfall records (daily precipitation greater than 0.1 mm) for the period from 1961 to 2016.

The DY of a given variable is defined as the difference between the current year and the previous year. All variables in form of year-to-year increment are expressed as DY (such as SST DY). The predictand of a year-to-year increment prediction model is the year-to-year increment of the variable. And then the predicted variable is obtained by adding the predicted DY of the variable to the observation of the preceding year. The time span of the actually available dataset is 56 years, covering 1961–2016.

Multiple linear regression method was used to build the statistical prediction model. The predictive ability of the model was assessed using some statistics that expressed the predicted values relative to the observations, including the correlation coefficient (CC) and the percentage of cases with the same sign anomaly between the observed and simulated increment time series (Perc), the relative percentage of the error (RE), and the root-mean-square error (RMSE). The coefficient of efficiency E is also used to evaluate the performance of the predictive model ([Nash and Sutcliffe 1970](#)).

3. Results

a. Characteristics of EPD over NEC

Precipitation over NEC mainly occurs during the summer half-year (i.e., months from May to September). The climatological monthly mean EPD over NEC from May to September are plotted ([Fig. 1](#)). The climatological EPD are large from June to August and are particularly large during July and August (JA). The climatological seasonal cycle of monthly EPD averaged over NEC is shown in [Fig. 2a](#). Most EPD over NEC occur in JA, and approximately 65% of the total EPD occurs during midsummer (as shown in [Fig. 2b](#)). Therefore, the months of July and August are considered as the local extreme precipitation season over NEC, so the EPD during midsummer are predicted in this study.

The geographic distribution of the climatological EPD over NEC during JA is shown in [Fig. 3a](#). The spatial distribution is closely related to topography, and EPD with large values are concentrated over the Greater and Lesser Khingan Mountains and Changbai Mountain. The ratio of the extreme precipitation amount during JA to the annual mean precipitation is greater than 25% over most of NEC ([Fig. 3b](#)).

To facilitate analysis, an EPD index is defined by averaging the EPD within NEC. As shown in [Fig. 4a](#), precipitation extremes occur frequently over NEC

FIG. 1. The climatological monthly mean extreme precipitation days in (a) May, (b) June, (c) July, (d) August, and (e) September over Northeast China, measured in days.

FIG. 2. (a) Climatological seasonal cycle of monthly EPD averaged over NEC, in days. (b) The ratio of monthly EPD to total EPD during the summer half-year as a percentage.

during the 1960s, 1980s, and 1990s but have decreased since the 2000s. The interdecadal trend is removed in the year-to-year increment of the EPD (referred to as EPD DY) (Fig. 4b). Wavelet analysis shows that the EPD displays a significant period of 2–4 yr (Fig. 5). This implies that the year-to-year increment approach is appropriate to predict the extreme precipitation days over NEC during midsummer.

b. Physical predictors of EPD

The transport of moisture plays an important role in extreme precipitation processes (Sun and Wang 2013). Consistent with previous research (Sun et al. 2016), there are two dominant water vapor transport paths contributing to the EPD over NEC, including a southeasterly or southwesterly current that originates from the subtropical western Pacific across the southern boundary of NEC, and the other moisture flow that is transported from inland areas to NEC

across the western boundary with the westerly winds (Fig. 6).

The seasonal march of the western Pacific subtropical high promotes the propagation of a precipitation belt from southern to northern China during the summer months. The DY of geopotential height at 500 hPa (Z500 DY) and the EPD DY are significantly and positively correlated in the tropics from late winter to midsummer, especially over the subtropical western Pacific Ocean (Fig. 7). Hence, a western Pacific subtropical high index (referred to as x_1) is defined as the regionally averaged geopotential height DY (10°–35°N, 105°–135°E; as shown in the rectangle in Fig. 7a) at 500 hPa during late winter when the correlation coefficient is the strongest. The CC between x_1 and the EPD DY is 0.50, significant at the 99% confidence level. The subtropical western Pacific Ocean is an important moisture source for extreme precipitation events over NEC (Ma et al. 2017). The southwesterly at

FIG. 3. (a) The climatological mean EPD over NEC during midsummer (July and August), in days. (b) The ratio of the midsummer extreme precipitation amount to the annual mean precipitation amount over NEC, expressed as a percentage.

FIG. 4. (a) Time series of the EPD index (solid line) and its 7-yr running mean (dotted line) from 1961 to 2016. (b) Time series of the year-to-year increment of EPD index from 1962 to 2016.

the northwestern flank of the western Pacific subtropical high transports warm moist air along eastern China, then moves further northward, and then facilitates intensive precipitation over NEC.

With a longer memory than the atmosphere, soil moisture can influence climate and has been previously used to predict short-term changes in climate (Zhu 2011; Fan and Tian 2013). The EPD DY and the soil moisture DY are significantly and positively correlated over western Asia during late winter, and over central Asia from early spring onward (Fig. 8). The soil moisture over central Asia is closely related to the EPD over NEC from early spring (March–April) to midsummer. A soil moisture DY index (referred to as x_2) is defined

as the average increment in soil moisture within central Asia (36° – 45° N, 56° – 75° E) during early spring (as shown in the rectangle in Fig. 8b), and the CC between x_2 and the EPD DY is 0.54. As shown in Fig. 6, the westerly airflow, which generally prevails in the middle troposphere, is an important channel for transporting water vapor for extreme precipitation events over NEC (Ma et al. 2017). The increase in the soil moisture over central Asia is followed by an enhanced westerly winds along the 40° N parallel over China, causing an increase in the precipitable water content over NEC (Fig. 9).

Anomalies in sea surface temperature can contribute to predictions of summer climate over East Asia (Tian and Fan 2013; Wang et al. 2013; Sun and Wang 2019),

FIG. 5. Wavelet analysis of the EPD over NEC for the period 1961–2016. The slashed regions indicate significant variability at the 90% significance level estimated by a red-noise process, and the parabola indicates the “cone of influence.”

FIG. 6. The correlation coefficients between the EPD DY and vertically integrated moisture flux DY during midsummer from 1962 to 2016. Vectors indicate the moisture flux DY correlated with EPD DY. The rectangle represents the NEC. Dark and light shadings respectively indicate values that significantly exceeded the 95% or 90% confidence level, estimated with the Student's t test.

and, as reported previously, anomalies in SST can influence summer precipitation over large areas of the NEC (e.g., Han et al. 2017, 2018). The increase in the EPD is correlated with a significant positive SST anomaly in the tropical Atlantic Ocean from late winter to midsummer, and the correlations are strongest during early spring. However, the correlations between these two variables in the Pacific and Indian Oceans are strong

during late winter and early spring but are not significant during summer (Fig. 10). Therefore, a SST_DY index (referred to as x_3), is defined as the early-spring area-averaged SST DY in the tropical Atlantic Ocean (20°S – 10°N , 20° – 60°W ; as shown in the rectangle in Fig. 10b), and the CC between x_3 and the EPD DY is 0.65. Yu et al. (2016) found that the tropical Atlantic SST anomalies influence the anomalous circulation over the northwestern Pacific via the Indian Ocean relaying effect, with implications for the anomalous moisture current along eastern China and NEC. Consistently, warming SST anomalies in the tropical Atlantic Ocean are followed by significant anticyclonic wind anomalies over the subtropical western Pacific (Fig. 11a). Enhanced southerly anomalies over East China transport moisture originating from the subtropical western Pacific into NEC crossing the southern boundary. Correspondingly, significant moisture divergence is centered over the western Pacific Ocean, and moisture convergence centers NEC (Fig. 11b).

The correlations between the EPD DY and the three indexes mentioned above are displayed in Table 1, all significant at the 99% confidence level. The correlation between the EPD DY and x_3 is the strongest, indicating that SST DY in the tropical Atlantic (x_3) should be included when predicting the EPD over NEC. With the goal of achieving the best prediction ability from the fewest predictors, fitting equations for the EPD DY are built with one, two, and three factors and the statistics of the resulting predictive models are listed in Table 2.

FIG. 7. The correlation coefficients between the EPD DY and geopotential height DY at 500 hPa during (a) January–February (label JF), (b) March–April (MA), (c) May–June (MJ), and (d) July–August (JA) from 1962 to 2016. The rectangle represents the selected region (10° – 35°N , 105° – 135°E) in (a) for predictor x_1 . Dark and light shadings respectively indicate values that significantly exceeded the 95% and 90% confidence level, estimated using the Student's t test.

FIG. 8. The correlation coefficients between the EPD DY and soil moisture DY during (a) JF, (b) MA, (c) MJ, and (d) JA from 1962 to 2016. The rectangle represents the selected region (36° – 45° N, 56° – 75° E) in (b) for predictor x_2 . Dark and light shadings respectively indicate values that significantly exceeded the 95% or 90% confidence level, estimated using the Student's t test.

The fitting results are best when x_2 and x_3 are used, and do not improve significantly when all three predictors are used. The soil moisture DY over central Asia (x_2) and SST DY in the tropical Atlantic (x_3) are independent of each other and are used in the model to predict seasonal variability in the EPD DY over NEC: $\text{EPD DY} = -0.0394 + 0.2657x_2 + 0.4516x_3$.

The CC between the observed and simulated EPD incremental time series is 0.70 from 1962 to 2016 (Table 3). The coefficient of efficiency (i.e., E) is 0.49, implying that the prediction model is a better predictor than the observed average. In addition, the Perc is 72.7%, and the 55-year mean RE and RMSE are 14.3% and 17.8%, respectively. The EPD are calculated by

FIG. 9. The correlation coefficients between the soil moisture DY index and (a) zonal wind DY at 700 hPa and (b) precipitable water content DY during midsummer from 1962 to 2016. The rectangle represents the NEC. Dark and light shadings indicate values that significantly exceeded the 95% or 90% confidence level, estimated using the Student's t test.

FIG. 10. The correlation coefficients between the EPD DY and sea surface temperature (SST) DY during (a) JF, (b) MA, (c) MJ, and (d) JA from 1962 to 2016. The rectangle represents the selected region (20°S – 10°N , 20° – 60°W) in (b) for predictor x_3 . Dotted areas indicate values that significantly exceeded the 95% confidence level, estimated using the Student's t test.

adding the fitted increment to the observed EPD in the previous year. The CC between the observed and fitted EPD is 0.58, significant at the 99% confidence level.

Cross validation is used to estimate the model's skill and stability (Michaelson 1987). The cross-validation tests show that the CC between the observed and predicted incremental time series of EPD is 0.65 for the period from 1962 and 2016, and the Perc is 70.9%

(Fig. 12a; Table 3). The CC between the observed and simulated EPD is 0.53, significant at the 99% confidence level (Fig. 12b). The interdecadal trend is captured well in the predicted EPD, with more extreme precipitation days over NEC during the 1980s and 1990s and fewer values during the 1970s and 2000s.

In addition, the model also provides good hindcasts for the period from 1997 to 2016 (Figs. 12c,d; Table 3). The CC between the observed and predicted incremental

FIG. 11. The correlation coefficients between the SST DY index during early spring and (a) horizontal wind at 850 hPa and (b) vertically integrated moisture flux divergence DY during midsummer from 1962 to 2016. Vectors indicate the horizontal wind at 850 hPa DY correlated with SST DY. The rectangle in (a) and (b) represents NEC. Dark and light shadings in (a) respectively indicate values that significantly exceeded the 95% or 90% confidence level, estimated using the Student's t test. Dotted areas in (b) indicate values that significantly exceeded the 95% confidence level, estimated using the Student's t test.

TABLE 1. The correlation coefficients between the EPD DY over NEC with the predictors during 1962–2016. All correlation coefficients are significant at the 99% confidence level.

Predictors	Meaning	CC
x_1	Late-winter Z500 DY over subtropical western Pacific Ocean	0.50
x_2	Early-spring soil moisture DY over Central Asia	0.54
x_3	Early-spring SST DY in the tropical Atlantic Ocean	0.65

time series is 0.70. The CC between the observed and predicted EPD is 0.46, significant at the 95% confidence level.

c. Model for predicting midsummer precipitation over NEC

There is consistent year-to-year variation between the EPD DY and the DY of midsummer precipitation amount over NEC (Fig. 13). The CC of 0.97 between these two variables implies that the two factors are derived from similar sources. Because the midsummer precipitation over NEC displays a predominant period of 2–4 yr (figure not shown), the year-to-year increment method with x_2 and x_3 is considered suitable for predicting the amount of midsummer precipitation over NEC: $\text{PRCPDY} = -0.0279 + 0.2692x_2 + 0.4553x_3$.

The coefficient of efficiency for the forecasting model is 0.52, which indicates that such prediction model is superior to the observed average. For the period from 1962 to 2016, the CC, Perc, RE, and RMSE between the observed and simulated increments in the amount of midsummer precipitation are 0.72, 76.4%, 14.3%, and 11.7%, respectively. The CC between the observed and simulated midsummer precipitation amounts is 0.60 ($p < 0.01$).

In addition, the cross validation of the prediction model is robust. The CC between the observed and predicted increments in the midsummer precipitation amount over NEC is 0.68, and Perc is 74.5% (Fig. 14a). The fitted and observed amounts of midsummer precipitation covary

consistently, and the CC is 0.56 from 1962 to 2016 ($p < 0.01$) (Fig. 14b). These both have significant negative linear trend. The model also reflects the decadal variation, and captures the decreasing shifts around the 1970s and the late-1990s.

The prediction model also provides good hindcasts of midsummer precipitation over NEC for the period from 1997 to 2016 (Figs. 14c,d). The CC between the observed and predicted incremental time series is 0.75 ($p < 0.01$). The CC between the observed and predicted midsummer precipitation is 0.56 ($p < 0.05$).

4. Comparison of year-to-year increment approach and traditional prediction method on EPD

For traditional prediction method, it is the anomalies with respect to climatology that are directly predicted. We compared the predictions on EPD from the year-to-year increment approach and conventional prediction method in this section.

As shown in Figs. 8b and 15a, the correlation between the soil moisture over central Asia and the EPD is only significant when year-to-year increments are considered; the relationship is insignificant when the anomalies are used. The significant correlation coefficients between SST anomalies in the Atlantic Ocean and EPD are spatially broader and quantitatively larger in Fig. 10b (year-to-year increments) than in Fig. 15b (anomalies). It suggests that the year-to-year increment approach can capture more significant predictive signals.

In addition, we also established model 0 using the SST and soil moisture anomalies instead of their year-to-year increments in previous early spring. The two predictors that were used are the soil moisture over the northern Asia ($60^\circ\text{--}65^\circ\text{N}$, $100^\circ\text{--}140^\circ\text{W}$; as shown in the rectangle in Fig. 15a) and the averaged SST over the tropical Atlantic Ocean ($10^\circ\text{S}\text{--}5^\circ\text{N}$, $40^\circ\text{W}\text{--}0^\circ$; as shown in the rectangle in Fig. 15b), respectively. The CC between the observed and model 0–predicted EPD time series is 0.55 during 1961–2016, and E is -28.17 (Table 4). By comparison, the CC between the observations and simulated

TABLE 2. Statistics (defined in the text) of models using different numbers of predictors. All correlation coefficients are significant at the 99% confidence level.

No. of factors:	1	2	2	3
Predictors	x_3	x_3 and x_1	x_3 and x_2	x_3 , x_2 , and x_1
E	0.42	0.46	0.49	0.50
CC for increment	0.65	0.68	0.70	0.71
CC for original values	0.54	0.57	0.58	0.59
Perc	72.7%	72.7%	72.7%	74.5%
RE	14.9%	14.3%	14.3%	14.2%
RMSE	18.9%	18.4%	17.8%	17.7%

TABLE 3. Statistics of models. One and two asterisks indicate values that significantly exceeded the 95% and 99% confidence level, respectively, estimated using the Student's *t* test.

Predicted variable	Extreme precipitation days over NEC during midsummer		Midsummer precipitation amount over NEC	
	CC for increment	CC for original values	CC for increment	CC for original values
CC between the obs and fitted variables 1962–2016	0.70**	0.58**	0.72**	0.60**
Cross-validation 1962–2016	0.65**	0.53*	0.68**	0.56**
Hindcasts 1997–2016	0.70**	0.46*	0.75**	0.56**
<i>E</i>		0.49		0.52

EPD by year-to-year increment approach (referred to as model 1) is 0.58 during 1962–2016, with an *E* of 0.49. Moreover, the cross-validation test on model 0 shows that the CC between the observed and predicted EPD is 0.48 for 1961–2016, and the *E* is -28.36 (Table 4). Comparatively, the CC between the observed and predicted EPD is 0.53 for 1962–2016, and *E* is 0.49 in the cross-validation test for model 1. The *E* value ranges from minus infinity to 1.0, with higher values indicating better agreement between the model simulations and the observations.

To further verify the skill of prediction models with respect to interdecadal variability, we calculated an 11-yr running average from observations and predicted EPD, as shown in Fig. 16. The CC between the observed

and predicted interdecadal EPD using model 1 is 0.95, whereas the CC between the observed and predicted interdecadal EPD by model 0 is 0.64. Model 1 shows a higher skill than model 0 in capturing interdecadal variation, especially after the 1990s. These results imply that model 1 (based on the year-to-year increment approach) is superior to model 0 (the prediction method on the anomaly of EPD directly).

5. Conclusions and discussion

This study documents the characteristics of the EPD over NEC during midsummer and the associated precursors. A statistical model is established to predict the

FIG. 12. (a) Temporal variation in the observed (red) and cross-validation-fitted (blue) EPD DY over NEC from 1962 to 2016, in days. (b) Temporal variation in the observed (red) and cross-validation-fitted (blue) EPD NEC from 1962 to 2016, measured in days. (c) Temporal variation in the observed (red) and hindcast (blue) EPD DY over NEC from 1997 to 2016, in days. (d) Temporal variation in the observed (red) and hindcast (blue) EPD NEC from 1997 to 2016, measured in days.

FIG. 13. Time series of the midsummer EPD increment (red line) and midsummer precipitation increment (Pre_JA_DY; blue line) over NEC from 1962 to 2016, both of which are normalized.

EPD using the year-to-year increment approach and its validity is assessed. The three main findings are as follows:

- 1) Over NEC, EPD occur most frequently in midsummer and account for approximately 65% of the total EPD that occurs during the summer half year from May to September. The spatial distribution of the EPD during

midsummer is closely related to topography, with large values mainly concentrated over the Greater and Lesser Khingan Mountains and Changbai Mountain.

- 2) Two main moisture transport paths for the EPD over NEC during midsummer are detected, namely, the water vapor transport from the subtropical western Pacific across the southern boundary of NEC and the transport of moisture from the westerly that crosses the western boundary. The preceding early-spring soil moisture DY over central Asia and the early-spring SST DY in the tropical Atlantic Ocean are chosen as variables for the model to predict the EPD DY over NEC, based on the year-to-year increment approach. The former of these predictors influences the moisture conditions over NEC by modulating the intensity of the westerly flow along 40°N, and the latter impacts anomalous circulation over the northwestern Pacific (Yu et al. 2016) and then influences the southeasterly or southwesterly moisture current that crosses the southern boundary of NEC. Cross-validation tests for the period from 1962 to 2016 and independent hindcasts for 1997 to 2016 indicate that these two variables give good predictions of the EPD over

FIG. 14. (a) Temporal variation in the observed (red) and cross-validation-fitted (blue) midsummer precipitation DY over NEC from 1962 to 2016, in days. (b) Temporal variation in the observed (red) and cross-validation-fitted (blue) midsummer precipitation from 1962 to 2016, measured in days. The red and blue dotted lines are respectively the linear trend of the observed and cross-validation-fitted midsummer precipitation. (c) Temporal variation in the observed (red) and hindcast (blue) midsummer precipitation DY over NEC from 1997 to 2016, in days. (d) Temporal variation in the observed (red) and hindcast midsummer precipitation from 1997 to 2016, measured in days.

FIG. 15. (a) Map of correlation coefficients between the anomalies of EPD over NEC and soil moisture for 1961–2016. Dark and light shadings respectively indicate values that significantly exceeded the 95% and 90% confidence level, estimated using the Student's t test. (b) Map of correlation coefficients between the anomalies of EPD over NEC and SST for 1961–2016. Dotted areas indicate values that significantly exceeded the 95% confidence level, estimated using the Student's t test.

NEC. The cross-validation result show that the CC between the observed and predicted EPD DY for the period from 1962 to 2016 is 0.65, and the CC between the observed and predicted EPD is 0.53, both of which are significant at the 99% confidence level.

- 3) The EPD DY covaries consistently with the midsummer precipitation amount DY over NEC, with a CC of 0.97 for the period from 1962 to 2016. The cross-validation tests show that those two variables also give good predictions of the amount of midsummer precipitation over NEC. The CC between the observed and predicted midsummer precipitation amount DY for 1962 to 2016 is 0.68, and the CC between the observed and predicted EPD is 0.56, both of which are significant at the 99% confidence level.

It remains a big challenge to forecast extreme precipitation owing to its irregular and complicated occurrence over

eastern China. Located in the mid- to high latitudes, precipitation over Northeast China is affected by the atmospheric anomalies over East Asia as well as circulation systems over mid- to high latitudes and moisture transport from tropical oceans, which makes it more complex to explore the predictability and the mechanisms of precipitation variation over NEC than over other subregions over eastern China. Previous studies

TABLE 4. Statistics of model 0 (predicting the anomaly of EPD directly) and model 1 (using a year-to-year increment approach). Two asterisks indicate values that significantly exceeded the 99% confidence level, estimated using the Student's t test.

Predictors	Model 0 (model 1)	Cross validation on model 0 (cross validation on model 1)
E	−28.17 (0.49)	−28.36 (0.49)
CC	0.55** (0.58**)	0.48** (0.53**)

FIG. 16. Time series of 11-yr running mean of observed EPD (black line), model 1-fitted EPD (using the year-to-year increment approach; red line) and model 0-fitted EPD (predicting the anomaly of EPD directly; blue line).

have devoted much effort to explore the prediction of extreme precipitation particularly over South China, the Yangtze River basin, and North China (Gao and Zhao 1999; Zhao and Liu 2003; Li and Wang 2018), whereas few refer to the prediction of extreme precipitation events over Northeast China. Thus, this manuscript attempted to predict the extreme precipitation days during midsummer over NEC, which may provide a reference and lay a foundation for prediction research in the future.

In addition, the interannual increment approach, proposed by Fan et al. (2007), is based on the variability of the year-to-year increment of variables and the associated physical processes. Importantly, this approach utilizes the previous year's observation that contains interdecadal variation. Therefore, the year-to-year increment predictions not only amplify the prediction signal but also capture the interannual and interdecadal variability. Studies have demonstrated that the year-to-year increment approach has a high forecast skill in summer precipitation and wintertime heavy snow over Northeast China (Zhu 2011; Fan and Tian 2013). The present study shows good performance of this approach to predict the extreme precipitation days during midsummer over NEC.

Although this study provides a climate prediction model for extreme precipitation days and precipitation amount during midsummer over Northeast China, we also found that the EPD prediction signal is not as significant as that of EPD DY, based on the SST in the tropical Atlantic Ocean and soil moisture over central Asia. These two factors may involve important air-sea interactions and land surface processes, which possibility hinders the forecasting of the EPD. Correspondingly, in-depth scientific analysis is urgently required on the physical mechanisms of the extreme precipitation and on identifying new predictors to improve the forecasting

of interannual variability of midsummer EPD over NEC. In addition, it is necessary and useful to develop a prediction model at a finer spatial scale for Northeast China, and that goal will be the focus of a future follow-up study.

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