Earth and Space Science

RESEARCH ARTICLE

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Key Points:

- Nonstationary extreme value model with northeast cold vortex (NECV) is first used to study mechanism of extreme precipitation in Northeast China.
- Northeast cold vortex index and the synergies make a significant contribution, accounting for 29.41% of all best nonstationary models.
- Extreme precipitation in Northeast China can be explained by humidity field anomalies, wind field anomalies, and their divergences at 850 hPa.

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Abstract

The northeast cold vortex (NECV) is one of the major synoptic systems affecting Northeast China. The activity of NECV is an important reason for severe convective storms. However, research on extreme precipitation over Northeast China and their associations with the northeast cold vortex index (NECVI) is limited. Based on nonstationary generalized extreme value models, we analyze and quantify the contribution of the NECVI and the multiscale synergistic indices. Then, we verify the necessity of the NECVI by the likelihood ratio test and the blank control experiment, and further verify the impact of the NECVI on the extreme precipitation over Northeast China in combination with the climate index atmospheric circulation analysis. Results suggest that the models established with East Asian summer monsoon index, Southern Oscillation Index, and NINO3.4 index as covariates the most common. The NECVI and the synergies also make significant contribution and have passed the likelihood ratio test at 80% confidence. Especially in late summer, accounting for 18.69% of the 10 selected best models and 29.41% of the nine selected best nonstationary models. Based on the blank experiments, the models with the NECVI have a maximum reduction of 4.72% than those without the NECVI in the Akaike information criterion values in late summer. In early summer and late summer, the center of the high values of the water vapor anomaly is mainly located in southwestern in the strong NECVI years. These findings help to understand the genetic mechanism of extreme precipitation over Northeast China and provide reference for risk management.

Plain Language Summary

Precipitation over northeast China is often influenced by NECVI defined by monthly meteorological indices. We applied the methodology and the algorithm for calculating daily NECVI values in early summer and late summer, which is used as a parameter in nonstationary generalized extreme precipitation value models for the first time. Then, statistical analysis and case study show the significance of NECVI. The correlation between NECVI and humidity field anomalies, wind field anomalies and their divergences at 850 hPa helps to reveal the mechanism of the influence of NECVI on extreme precipitation over northeast China.

1. Introduction

With global warming, the increasing number and intensity of extreme precipitation events are a global trend. The IPCC AR5 (2012) points out that the global average temperature has increased by 0.12°C every 10 years in the past 60 years (1951–2012). The temperature in Northeast China has increased by 1.75–2.5°C and is one of the most sensitive regions to climate change in the world (IPCC, 2012; Qin and Stocker, 2014). Northeast China is the most important area for food production in China and is also an important base for national security. Therefore, it is particularly important to study the mechanism of the formation of extreme precipitation in Northeast China.

Extreme value theory (EVT) can successfully characterize climatic and hydrological extremes and has been widely used in meteorology and hydrology (Gao et al., 2016; Gu et al., 2019; Katz et al., 2002; Li et al., 2013, 2019; Soukissian & Tsalis, 2015; Um et al., 2017). In previous studies, EVT has generally been considered
to be stationary in meteorology and hydrology (Katz et al., 2002). However, due to human activities and climate change, the assumption of stationarity has been increasingly questioned by scholars (Gao & Zheng, 2018; Gao et al., 2016; Katz, 2013; Salas & Obeysekera, 2014; Wi et al., 2016). Considering the nonstationary characteristics of EVT in meteorology and hydrology, adding climate factors (e.g., El Nino-Southern Oscillation [ENSO] and North Atlantic Oscillation [NAO]) as covariates into EVT has recently become a widely discussed topic in extreme precipitation research (Coles, 2001; Gao et al., 2016, 2018; Renard & Thyer, 2019). However, few studies have considered the establishment of nonstationary extreme models based on multiscale meteorological indices to detect the nonstationary effects due to the synergy of multiple climatic indices. Therefore, a nonstationary generalized extreme value (GEV) model based on the multiscale synergistic indices was implemented to detect the changes in extreme precipitation in Northeast China caused by the nonstationary effects of one or more climatic indices.

Northeast China is located in East Asia, where the climate is strongly influenced by important subsystems of the East Asian monsoon (Shen et al., 2011; Yuan et al., 2017). The ENSO meteorological phenomenon is recognized as the strongest interannual variation signal in the coupled ocean-atmosphere system. It mainly affects the East Asian monsoon, resulting in effects on many meteorology anomalies, such as precipitation, heat waves, and hurricanes, and is especially impactful on precipitation (Gao et al., 2016; Min et al., 2011; Mondal & Mujumdar, 2015; Qiao et al., 2018; Tan & Shao, 2016; D. D. Zhang et al., 2015). In addition, precipitation in Northeast China is also influenced by the cut-off lows (COLs), especially in summer. The northeast cold vortex (NECV) is the most common COL in East Asia and is also the product of the large-scale circulation situation under specific conditions in Northeast China. The activity of the NECV is an important cause of the strong convective weather processes in Northeast China, such as thunderstorms, gales, and rainstorms (Liu et al., 2012a; G. Liu et al., 2015; Sun et al., 2002).

The objectives of this study are to better understanding the most significant physical indices of the nonstationary of annual maximum precipitation (AMP) time series. Especially, the contribution of the northeast cold vortex index (NECVI) and multiscale synergistic indices to AMP time series is verified and quantified. The first step of this study is to establish nonstationary GEV models based on multiscale synergistic indices that are currently used in Northeast China. The procedure was developed to study the relationship between climatic indices and extreme precipitation through Pearson correlation and quantile regression. And thereby, the climatic indices that affect extreme precipitation in the early and late summer in Northeast China were selected. Based on this, the synergistic climatic indices were selected by principal component analysis, and a nonstationary GEV model of the multiscale synergistic indices was established. The formation mechanism analyzes the summer extreme precipitation events in Northeast China based on the best statistical models, which were chosen by the Akaike information criterion (AIC), and the aim was to identify the significant individual physical indices that influence extreme precipitation in Northeast China. The model provides a reference for risk management and engineering designs to mitigate the effects of extreme precipitation over Northeast China.

2. Study Area and Data

2.1. Study Area and Precipitation Data

The study area is located at 115°52′E-135°09′E, 38°72′N-53°55′N, including the provinces of Liaoning, Jilin, Heilongjiang, and the cities of Hulun Buir, Hinggan League, Tongliao, and Chifeng in eastern Inner Mongolia (Du et al., 2013). The daily precipitation data from 116 meteorological sites across Northeast China during 1951–2017 were collected and provided by the National Meteorological Information Center of China Meteorological Administration (CMA). Some meteorological sites are missing values from the early period of 1951–1959. Considering the consistency and completeness of the data set, data from 107 sites in the same gauged period (1959–2017, 59 years) were finally selected (Figure 1).

In this study, the contributions of the NECVI and synergistic indices on extreme precipitation in early and late summer in Northeast China have been studied. According to Shen et al. (2011), there is obvious seasonal variation in summer in Northeast China. The seasonal variation of precipitation from May to June is not consistent with that from July to August, so it is necessary to divide into early summer and late summer.
Extreme precipitation in early/late summer every year is often defined as the maximum daily precipitation in the period, recorded as AMP time series (Gao et al., 2016; Jeon et al., 2016; L. L. Zhang et al., 2020).

### 2.2. Data of Covariates

The NECV is one of the main weather systems affecting Northeast China (Lian et al., 2016; Wang et al., 2007; Xie & Bueh, 2014). The activity of the NECV is an important reason for the occurrence of strong convective weather processes such as thunderstorms, gales, and rainstorms in Northeast China (Chen et al., 2018). According to Liu et al. (2012b), the NECVI is calculated by the regional average 500 hPa geopotential height in the key regions (40°N-50°N, 120°E-130°E) that display the main characteristics of NECV activity. The NECVI can accurately characterize the characteristics of the NECV activity.

The East Asian summer monsoon index (the EASMI, Figure 2) is defined by Li and Zeng (2003, 2005) as the regional-averaged seasonally dynamical normalized seasonality of 850 hPa in East Asian monsoon region (10°N-40°N, 110°E-140°E).

![Figure 1](image1.png)

**Figure 1.** Geographical distribution of the 107 meteorological sites in Northeast China (different colors represent different altitudes), distributed in the area of 115°52’E-135°09’E, 38°72’N-53°55’N.

![Figure 2](image2.png)

**Figure 2.** Time series of the four indices from 1959 to 2017 in early summer (left) and late summer (right). (a) and (e) EASMI; (b) and (f) NECVI; (c) and (g) SOI; (d) and (h) NINO3.4.
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The ENSO is a kind of atmospheric component that depicts large-scale fluctuations in atmospheric mass between the tropics and subtropics Indian and Pacific Oceans. It is recognized by the global meteorological community as the strongest interannual variation signal in the coupled ocean-atmosphere system (Capotondi et al., 2015; Trenberth, 1984; Tan & Shao, 2016). The NINO3.4 index and the Southern Oscillation Index (SOI) (Figure 2) were used to represent the ENSO index (Min et al., 2011; Mondal & Mujumdar, 2015; Revadekar and Kulkarni, 2008). The NINO3.4 index is a time series of monthly sea surface temperature anomalies over the NINO3.4 region (17°E-120°W, 5°S-5°N), and SOI was derived from monthly sea level pressure data that were normalized at Tahiti and Darwin.

3. Methodology

3.1. Quantile Regression

Quantile regression is a trend-detection method which is used to identify any percentile value of climate variable over time. It was originally proposed by Koenker and Bassett (1978). In addition, the relationship between extreme climate and large-scale climate patterns can also be detected by quantile regression (Fan & Xiong, 2015; Shiau & Lin, 2016; Tan & Shao, 2016; Tareghian and Rasmussen, 2013). In hydrometeorological studies, the extreme quantiles (the 5th or 95th percentile) or the mean quantiles of quantile regression (the 50th quantile) are similar to the quantiles of response variables, which have been widely concerned by scholars (K. M. Yu et al., 2003). The widely used linear quantile regression minimizes the function, as shown in Equation 1 as follows:

$$
\sum_{i=1}^{n} \rho_\tau(y_i - X_i^T \beta)
$$

where $$\rho_\tau(u) = ruI_{[0,\infty)}(u) - (1 - \tau)ruI_{(-\infty,0)}(u)$$ is a check function; $$I_A(u)$$ is the indicator function that equals 1 if $$u \in A$$ and otherwise equals 0; $$n$$ is the length of the observed time series $$y$$ and $$y$$ is the extreme precipitation in Northeast China in this study; $$X_i = (X_{i1}, \ldots, X_{im})^T$$ where $$m$$ is the number of covariates and $$X_i$$ represents the temporal or climatic indices in this study; $$\beta$$ denotes the parameter vector to be estimated and $$\tau$$ is the quantile level (Koenker, 2005; K. M. Yu et al., 2003). In this study, quantile regression was implemented using the R package “quantreg” (Gao & Zheng, 2018; Koenker, 2013).

3.2. Nonstationary GEV Distribution

Based on the extremal types theorem, if the summer daily precipitations, denoted by $$\{(P_1, \ldots, P_n)\}$$, are independent and identically distributed with a common cumulative distribution function then $$M_n = \max\{P_1, \ldots, P_n\}$$ will follow one of the three distributions (i.e., Gumbel, Fréchet, and Weibull), and the three distributions can be combined into the following GEV distribution (Coles, 2001):

$$
F(m) = \exp \left\{ - \left[ 1 + \varepsilon \left( \frac{m - \mu}{\sigma} \right) \right]^{-1/\varepsilon} \right\}, 1 + \varepsilon \left( \frac{m - \mu}{\sigma} \right) > 0
$$

where $$\mu, \sigma > 0$$, and $$\varepsilon$$ are the location, scale, and shape parameters, respectively. Positive, zero, and negative values of the shape parameter represent different distributions. When one or more of the parameters of the GEV were expressed as a function of temporal or climatic indices, a nonstationary GEV distribution was established (Katz, 2013). In this nonstationary setting, the parameters were expressed as a function of the climatic indices in the following general formula:

$$
\mu(t) = \mu_0 + \mu_V, \sigma(t) = \sigma, \varepsilon(t) = \varepsilon
$$

Then, the nonstationary GEV is in the following form:

$$
F_t(m) = \exp \left\{ - \left[ 1 + \varepsilon \left( \frac{m - \mu(t)}{\sigma} \right) \right]^{-1/\varepsilon} \right\}
$$
where we assume that the shape parameter and the scale parameter are constants. $V$ is one of the four synergistic climatic indices (including the EASM, NECVI, SOI, and NINO3.4). Commonly, the location parameter $\mu(t)$ is linearly dependent on those climatic indices (Gao & Zheng, 2018; Katz, 2013; Wi et al., 2016). All data in the nonstationary GEV distributions were standardized before fitting the annual extreme precipitation for computational simplicity. The maximum likelihood method was primarily used for parameter estimations in both nonstationary GEV distributions. For multiple candidate models, we used one of the popular AIC statistics to select the optimal model (Katz, 2013). The model with the lowest AIC was considered the best model. For extreme precipitation, the most significant covariates were those with a corresponding nonstationary model that minimized AIC. Whether the nonstationary effects of that climatic indices were indeed significant was further tested by the likelihood ratio test. All stationary and nonstationary GEV distributions are listed in Table 2.

4. Results and Discussion

4.1. Climatology of the Summer AMP Time Series in Northeast China

The spatial distribution of the average AMP time series in Northeast China for early summer and late summer are shown in Figure 3. In both periods, the AMP time series has a decreasing trend from the southeast to the northwest in Northeast China, and the AMP time series in the southeast as approximately twice that in the northwest. The topography of Northeast China determines the irregular distribution. The confluence of the mid-latitude westerly flow and the northeastern-southwestern direction of Da Hinggan Mountains in northwestern Northeast China is also the reason why the AMP time series tends to be more westward and less eastward. Beyond that, the AMP time series located in the southeast upwind slope of Northeast China is also affected by the southerly wind in the east of Northeast China, which mainly comes from the air flow rises against the northeastern-southwestern Changbai Mountains.

Generally, the values of the AMP time series in late summer were remarkably larger than those in early summer. In early summer, the values in the AMP time series ranged from 18 to 52 mm. While the values of the AMP time series in late summer, which ranged from 32 to 116 mm, were about twice that in early summer. There were three maximum centers of the AMP time series in early summer, eastern Liaoning Province, southeastern Jilin Province, and the center of Heilongjiang Province. The maximum centers of the AMP time series in late summer were mainly located throughout most of Liaoning Province. The AMP time series centers in early summer and those in late summer were significantly different. Hence, it was necessary to study the AMP time series in the two time periods separately.

Figure 3. The spatial distribution of the average AMP time series in (a) early summer and (b) late summer in Northeast China.
4.2. Correlations Between the AMP Time Series and the Climatic Indices

The relationship between the climatic indices and the AMP time series was investigated to establish the nonstationary extreme value model. Table 1 shows the Pearson correlations between the AMP time series and the climatic indices from the same time period (i.e., EASMI, NECVI, SOI, and NINO3.4) in Northeast China from 1959 to 2017. Because the precipitation pattern was significantly different between the early summer and the late summer in Northeast China, the statistical significance of the correlations between the precipitation and each climate index was separately detected for those two time periods. The climatic indices mostly significantly correlated with the early summer AMP time series included the NECVI and NINO3.4. However, the late summer AMP time series was statistically significantly correlated with the EASMI, NECVI, and SOI. Except for the NECVI, the effects of all other climatic indices on the two seasons were significantly different. In particular, the EASMI and NINO3.4 show the opposite correlation coefficients.

Considering the delayed effect of the ENSO events, this delayed effect was sometimes quite critical for the AMP time series. The Pearson correlation between the AMP time series and ENSO indices (i.e., SOI and NINO3.4) were calculated with lags of 0–12 months, and the value of lag correlation coefficient was selected to draw the lag correlation map between the AMP time series and the ENSO indices. Figure 4 shows the Pearson correlations between the AMP time series and the two ENSO indices (i.e., SOI and NINO3.4) for 1959–2017 in Northeast China with 0–12 month temporal lags.

Table 1
Pearson Correlations Between the AMP Time Series and Climatic Indices (i.e., EASMI, NECVI, SOI, and NINO3.4) in Northeast China for 1959–2017

|                | EASMI | NECVI | SOI  | NINO3.4 |
|----------------|-------|-------|------|---------|
| Early summer   | –0.09 | 0.20* | 0.03 | 0.23*   |
| Late summer    | 0.17* | 0.20* | 0.18*| –0.08   |

Note
*represents the Pearson correlation that is significant at α = 0.1.

*Figure 4.* Absolute values of the Pearson correlations for 0–12 month lags between the AMP time series and two ENSO indices (i.e., SOI and NINO3.4) in Northeast China for 1959–2017 in the (a) early summer and (b) late summer.
and 1-month lags. However, the significant correlation between the late summer AMP time series and the NINO3.4 occurred at 6-, 10-, and 11-month lags.

### 4.3. Quantile Relationships Between the AMP Time Series and the Climatic Indices

The Pearson correlation only focuses on the conditional mean of the dependent variables, but it does not fully consider the complete characteristics of the conditional distribution of the dependent variables. Therefore, the quantile regression was introduced to study the relationship between the extreme precipitation and climatic indices.

Figure 5 shows how the quantile regression can illustrate a full picture of the correlations between the AMP time series in Northeast China and the climatic indices and underscores the limited perspective afforded by the least-squares linear regression. Here, the NECVI is adopted as a covariate in the following quantile regression:

$$ \hat{q}(\tau | \text{NECVI}) = \hat{\beta}_1(\tau) + \hat{\beta}_{\text{NECVI}}(\tau).\text{NECVI} $$

where $\hat{q}(\tau | \text{NECVI})$ is the predicted conditional quantile of the AMP time series, the intercept $\hat{\beta}_1(\tau)$, and the slope $\hat{\beta}_{\text{NECVI}}(\tau)$ were obtained by inference values calculated by the Barrodale and Roberts algorithm.

Compared to the Pearson correlation analysis, in both early summer and late summer, the quantile regression revealed significant correlations between the AMP time series and the ESMI, NECVI, SOI, and the NINO3.4. The quantile correlations between the AMP time series and the EASMI showed significant differences between early summer and late summer. In particular, the AMP time series is dependent on the EASMI at certain quantiles (e.g., $\tau = 0.5$ for EASMI in early summer, $\tau = 0.05$ and 0.5 for EASMI in late summer). As the EASMI increased, the early summer AMP time series at $\tau < 0.5$ decreased, and the magnitude increased with the quantile levels. In contrast, the significantly positive correlations between the EASMI and the late summer AMP time series were detected over all quantile levels. Moreover, the magnitude of the changes varied significantly among the quantile levels.

The quantile correlations between the AMP time series and the NECVI, SOI, and NINO3.4 values showed significant differences among the different quantiles. The trend of the increase in the late summer AMP time series with the NECVI was statistically significant, and the magnitude increased with the quantile levels. Similarly, the NECVI affected the early summer AMP time series, especially when the quantile was at $\tau = 0.05$. In both the early summer and late summer, as the SOI increased (toward La Niña-like conditions), the AMP time series at all quantile levels decreased and the magnitude increased with quantile levels. The largest AMP time series decrease occurred at $\tau = 0.95$. In contrast, there were significantly positive correlations between the NINO3.4 and the AMP time series over all quantile levels, and the magnitude increased with the quantile levels. The extremely high quantiles ($\tau \geq 0.95$) showed the highest increase among all quantile levels, which was more obviously observed in early summer.

Hence, the AMP time series for both early summer and late summer were statistically significantly correlated with the NECVI, SOI, and NINO3.4. Considering the synergy among the climatic indices, principal component analysis was used to calculate the synergy among the climatic indices. The synergistic indices were introduced into the nonstationary extreme value model together with the climatic indices.
formation mechanism of the AMP time series in early summer and late summer was studied with the nonstationary extreme value model.

### 4.4. Modeling and Spatial Distribution of the Best Nonstationary Extreme Values

Previous studies have shown that the risk of the recurrence of extreme precipitation events is significantly correlated with the variation in the mean and the variance of the precipitation series. A small change in the mean may lead to a very large change in the extreme precipitation events. In this study, the location parameter was assumed to be a linear function of the climatic indices to account for the nonstationarity (Equation 4), while the scale and shape parameters were kept constant, meaning that only the nonstationarity with respect to $\mu$ was discussed. The primary reason was that modeling temporal changes in $\sigma$ and $\xi$ requires reliable long-term observations, which were often not available for practical applications (L. Y. Cheng et al., 2014).

In addition, our goal was to determine the significant individual physical indices that influenced the AMP time series in Northeast China. Thus, we did not test whether a combination of any two covariates was better than any individual covariate. Along with the nonstationary statistical modeling of the AMP time series, one of the aims of this study was to assess the physical drivers that significantly affected each of the AMP time series. A linear dependence model was sufficient for this purpose, as the significance of each covariate could be tested through this model for the AMP time series in each observation site. The linear dependence of the parameters on the covariates has been considered in several studies on nonstationary modeling of extreme values of hydrometeorological variables (J. S. Cheng and Xiao, 2019; Katz, 2013; Katz et al., 2002; Mondal & Mujumdar, 2015; Sillmann et al., 2011; X. B. Zhang et al., 2010).

The 12 stationary and nonstationary GEV distributions listed in Table 2 were first fitted to the early summer AMP time series at 107 sites. The potential covariates in the nonstationary GEV distributions were the climatic indices (i.e., EASI, NECV, SOI, and NINO3.4) and the synergistic climatic indices. At each site, the best model, which was the model with the lowest AIC value, was selected from the 12 candidate models. The results of the model selection for the AMP time series are shown in Table 3, and the differences between early summer and late summer are shown graphically in Figure 6. The stationary GEV distribution Model M0 was chosen as the best model at 53 sites for early summer and at 39 sites for late summer. As in early summer, Models M1, M3, and M4 were selected as the best models at sites 11, 17, and 12, respectively. These three nonstationary GEV distributions accounted for 37.38% of the nine selected best models and accounted for 74.07% of the eight selected best nonstationary models. These sites were mainly located throughout most of Jilin Province and in southeastern Heilongjiang Province, southern Liaoning Province, and western Hulun Buir City. They were in areas with moderate rain, areas with moderate to heavy rain, and areas with heavy rain. This finding showed that the optimal extreme value model of the AMP time series was easy to use as a nonstationary model in areas with high-intensity AMP time series (Figure 2). Models M2, M7, M8, M9, and M11 were selected as the best models, and this five nonstationary GEV accounted for 13.08% of the nine selected best models and accounted for 25.93% of the eight selected best nonstationary models. These sites were mainly located in northwestern Liaoning Province and throughout most of Inner Mongolia, which belonged to the region of moderate to the heavy rain.

In the late summer, models M1, M3, and M4 were the main nonstationary models. These three nonstationary GEVs accounted for 44.83% of the 10 selected best models. These sites were mainly located throughout

| Model ID | Number of optimal models |
|----------|--------------------------|
|          | Early summer | Late summer |
| M0       | 53           | 39          |
| M1       | 11           | 14          |
| M2       | 4            | 9           |
| M3       | 17           | 17          |
| M4       | 12           | 17          |
| M6       | 1            | 1           |
| M7       | 1            | 2           |
| M8       | 2            | 6           |
| M9       | 1            | –           |
| M10      | –            | 1           |
| M11      | 6            | 1           |

Note. The quotation marks “–” indicate that the model was not selected.

Table 3. Results of the Model Selection for Extreme Value Modeling of the AMP Time Series in Northeast China.
most of Heilongjiang Province and in northwestern Liaoning Province, most of Inner Mongolia, and the southeastern and northwestern corners of Jilin Province, which are in areas with rain intensity varying from heavy rains to rainstorms. Models M2, M6, M7, M8, M10, and M11 were selected as the best models, and these six nonstationary GEVs accounted for 18.69% of the 10 selected best models and 29.41% of the nine selected best nonstationary models. The sites were located in western Liaoning Province, northwestern Jilin Province, and western Hulun Buir City, which are areas of moderate to heavy rain, heavy rain, and rainstorms. Meanwhile, the results of the model selection for the AMP time series between early summer and late summer showed significant differences. The model selection results between early summer and late summer were different and accounted for 78.50%. The model selection results were similar at only 21.50% sites, and these sites were mainly located in central Heilongjiang Province and central Jilin Province.

Figure 6. Results of the optimal model selection for extreme value modeling of the AMP time series for (a) early summer and (b) late summer in Northeast China. The optimal model selected for each site in early summer (a) or late summer (b) was represented by the different colors, and the parameters of each optimal model are shown in Table 2. (c) The differences in the optimal model selection between early summer and late summer. For each site, the same marker of the optimal model in early summer and late summer was marked as "same optimal model"; otherwise, it was marked as "different optimal model."
4.5. Climatic Indices for Nonstationary Extreme Value Modeling

The best statistical models, which were chosen by AIC for the AMP time series in early summer, are shown in Figure 7. It can be observed that the most significant climatic indices differed among the sites. The stationary model was the best model for the AMP time series at the highest majority (49.53%) of the nine selected best models. The traditional assumptions for assessing the risk of extreme precipitation events was not valid at 50.47% of the locations (54 sites). At some sites, the NECVI was noted to have a positive impact on the AMP time series, which was consistent with our earlier discussion on the correlations between the climatic indices and the AMP time series. These sites were located mainly in southeastern Heilongjiang Province, Tongliao City, Chifeng City, and southeastern Hinggan League and were in areas with moderate and heavy rain. The synergistic indices, that is NECVI and other climatic indices, were also the main indices affecting the nonstationarity of the AMP time series. These five climatic indices accounted for 25.93% of all nonstationary climatic indices. When the NECV circulation interacts with other climate systems such as cyclones, it can promote the occurrence of extreme precipitation in Northeast China. This is consistent with

Figure 7. Grid-wise best statistical models for the early summer AMP time series of the (a) spatial patterns and (b) percentage of locations falling under each category of models. The best statistical models by each site in early summer are represented for different colors.
the conclusions of previous researches (Du et al., 2013; Shen et al., 2011). Therefore, it was reasonable to bring the NECV event into the extreme value model to analyze its influence on the AMP time series.

In addition to the NECVI, the main nonstationary climatic indices also included EASMI and ENSO, which was consistent with our earlier discussion in Figure 5. For the AMP time series, the climate index was significant at ~11.21% of the location as the NINO3.4. These sites were located in central Heilongjiang Province and southwestern Liaoning Province, both of which had moderate rain and moderate to heavy rain in early summer. The physical covariate that was significant at ~15.89% of locations was SOI. These sites were located in central Heilongjiang Province and southwestern Liaoning Province, both of which had moderate and moderate to heavy rain in early summer. The EASMI accounted for 10.28% of the location, which was a significant result. These sites were located mainly in the central part of Liaoning Province, northwestern Jilin Province, most of Heilongjiang Province and the eastern Chifeng City and were in areas with moderate to heavy rain. The NINO3.4 and SOI represent ENSO events, and EASMI was also strongly affected by ENSO events. These three indices were statistically significantly correlated with precipitation in Northeast China. Hence, the global scale variables ENSO and EASMI were thus noted to have the strongest effects on the AMP time series.

The goodness of fit of the chosen models was further tested by the likelihood ratio test at these 54 sites. The null hypothesis of the stationary GEV distribution was tested against an alternative GEV distribution of Equation 3, where the parameter was a linear function of the climatic indices from the best model. Thus, the likelihood ratio test evaluated the null hypothesis against the alternative that it was not zero. At 42 out of the 54 “nonstationary” sites, this null hypothesis could be rejected with a statistical confidence of 77.78% ($p$-value < 0.1). At 80% confidence, this null hypothesis could be rejected at all 54 sites. This shows that the chosen nonstationary models were satisfactory.

Figure 8 shows the best statistical models, which chosen by their AIC values, for the AMP time series in late summer. The color representation of the model is the same as that in Figure 7. The assumption of stationarity in the AMP time series in late summer was more unreasonable than that in early summer, and it was not valid at 63.55% of the locations (68 sites). The NECVI and the synergistic indices (i.e., PNS, PNE, PNNS, PNSE, and PNNSE) between the NECVI and the other climatic indices are significant at ~29.41% of all nonstationary climatic indices. The results indicated that the effect of NECVI on the AMP time series was particularly significant in the late summer. Considering that the regional distribution of the AMP time series was affected by the NECVI in the early summer and the late summer in Northeast China, it can be seen that Heilongjiang Province, Tongliao City, and Chifeng City were affected by the NECVI. These municipalities just were the key areas for NECVI. From early summer to late summer, influenced by the NECVI, the rainfall tended to be patchy in western and eastern Northeast China, and the rainfall was expanding. For the AMP time series, the physical covariate that was significant at ~13.08% of the location was the EASMI. The AMP time series in Heilongjiang Province and Jilin Province in early summer and late summer was greatly affected by the EASMI. From early summer to late summer, affected by the EASMI, the whole rainband showed a southeast-northwest trend, and the range of the rainband was constantly expanding. The NINO3.4 index and SOI represent ENSO events and were significantly correlated with the AMP time series at ~31.78% of sites. For the AMP time series, the climatic indices (i.e., EASMI, SOI, and NINO3.4) were significant at the highest number (44.86%) of locations, and those percentages were significantly higher than early summer. The ENSO and EASMI fluctuation tend to force a great disturbance on the atmospheric circulation, which has an impact on the extreme precipitation in Northeast China. Based on a likelihood ratio test to verify the rationality of the nonstationary model, the null hypothesis can be rejected at all 68 “nonstationary” sites.

To reflect the necessity of adding the NECVI, we also compared the results with the results of the four models (i.e., M0, M1, M3, and M4) that did not include the NECVI. The results showed that the nonstationary model of extreme precipitation in the early and late summer of Northeast China that included the NECVI was better than the nonstationary model without the NECVI. The nonstationary model of extreme precipitation in the early summer of Northeast China that included the NECVI was superior to the nonstationary model without the NECVI at 14 sites, and the AIC value maximum reduction was 3.88%. Additionally, the nonstationary model of extreme precipitation in Northeast China with the NECVI for late summer is better than that without the NECVI at 20 sites, and the AIC value maximum reduction was 4.72%.
The formation of precipitation needs not only water vapor, but also dynamic condition. This paper mainly discusses the water vapor transport and divergence of extreme precipitation over Northeast China in the abnormal years of climate indices. We define the abnormal years based on thresholds of ±0.80 based on standardized climate indices (P. Liu et al., 2020; H. Y. Yu et al., 2019). The year, when the standardized climate index is greater than 0.8, is selected as a positive abnormal year of climate index, while a negative abnormal year is with the standardized climate index less than −0.8.

Figure 9 shows the composite of the 850 hPa specific humidity field anomalies and the 850 hPa wind field anomalies and their divergences in early and late summer for abnormal years of climatic indices. The three climatic indices are analyzed in both periods. The southerly wind anomalies in Northeast China are beneficial to the northward movement of a large quantity of warm and humid air, which is prone to precipitation, especially in the late summer of the EASMI positive abnormal years. The center of high values of the water

4.6. Analysis of Atmospheric Circulation of Nonstationary Climatic Indices

The formation of precipitation needs not only water vapor, but also dynamic condition. This paper mainly discusses the water vapor transport and divergence of extreme precipitation over Northeast China in the abnormal years of climate indices. We define the abnormal years based on thresholds of ±0.80 based on standardized climate indices (P. Liu et al., 2020; H. Y. Yu et al., 2019). The year, when the standardized climate index is greater than 0.8, is selected as a positive abnormal year of climate index, while a negative abnormal year is with the standardized climate index less than −0.8.

Figure 9 shows the composite of the 850 hPa specific humidity field anomalies and the 850 hPa wind field anomalies and their divergences in early and late summer for abnormal years of climatic indices. The three climatic indices are analyzed in both periods. The southerly wind anomalies in Northeast China are beneficial to the northward movement of a large quantity of warm and humid air, which is prone to precipitation, especially in the late summer of the EASMI positive abnormal years. The center of high values of the water
vapor anomaly is mainly located in northwestern Northeast China. Particularly in the late summer of the EASMI positive abnormal years, it spreads throughout most of Northeast China, in the southwestern Northeast China of the NECVI negative abnormal years.

In the negative abnormal years of NECVI index, the negative center of divergence is mainly located in the south of Northeast China, and water vapor converges in Northeast China, corresponding to the enhancement of extreme precipitation in Northeast China. Especially in late summer, the convergence range of water vapor in Northeast China is larger, which is more conducive to the increase of extreme precipitation. In late summer, the effect of NECVI index on extreme precipitation in Northeast China is significantly strengthened, which is consistent with the conclusions in Figures 7 and 8.

In the EASMI positive abnormal years, the southerly wind prevails and the water vapor is the strongest. The water vapor is transported northward along the southerly wind anomaly to Northeast China, which causes the increase of extreme precipitation in Northeast China, especially in late summer. EASMI index is the main factor affecting the extreme precipitation in Northeast China in late summer, which is consistent with the previous researches (Lian et al., 2003; Shen et al., 2011).

5. Conclusions

The nonstationary models of the AMP time series in the early summer and late summer in Northeast China were established by using the large-scale climatic indices, local climatic indices, and their synergistic indices as the covariates of the location parameters. In particular, the NECVI and the synergistic indices between the NECVI and the other climatic indices were added to verify the significant effect for extreme precipitation. In order to further verify the contribution of NECVI, the blank control experiments are done and atmospheric circulation of nonstationary climatic indices of extreme precipitation are analyzed.

In early summer and late summer, the EASMI and ENSO mainly contribute to extreme precipitation, and the NECVI also make a significant contribution based on the best nonstationary extreme models. And, those models have passed the likelihood ratio test at 80% confidence, which shows that the best nonstationary models are reasonable. The contribution of the NECVI account for 25.93% of all nonstationary models in early summer and at ~29.41% of the nine selected best nonstationary models. The results indicated that the effect of NECVI on the AMP time series was particularly significant in the late summer. Considering that the regional distribution of the AMP time series was affected by the NECVI in the early summer and the late summer in Northeast China, it can be seen that Heilongjiang Province, Tongliao City, and Chifeng City were affected by the NECVI. According to Liu et al. (2012b), these municipalities were the key areas for NECVI. From early summer to late summer, influenced by the NECVI, the rainband tended to be patchy in western and eastern Northeast China, and the rainband was expanding.

In the blank control experiments, the nonstationary models with the NECVI are superior in the early summer and late summer. Specially, the nonstationary models with the NECVI for late summer are better than that without the NECVI at 20 sites, and have a maximum reduction of 4.72% than those without the NECVI in the AIC values in late summer. The composite of the specific humidity field anomalies and the wind field anomalies and their divergences in the negative abnormal years of NECVI index were analyzed. In early and late summer, the negative center of divergence is mainly located in southwestern Northeast China in the NECVI negative abnormal years, and water vapor converges in Northeast China, corresponding to the enhancement of extreme precipitation in Northeast China.

Overall, this study verifies and quantifies the contribution of the NECVI and multiscale synergistic indices to the AMP time series by nonstationary GEV model. This study has a clearer understanding of the physical mechanism of extreme precipitation in Northeast China, which is conducive to policy formulation and engineering design.
Data Availability Statement

The authors thank the China Meteorological Administration (CMA) for providing the daily precipitation data across Northeast China, which were obtained online (http://data.cma.cn/data/ccd/detail/dataCode/SURF_CLI_CHN_MUL_DAY_V3.0.html). The authors also thank NOAA for providing the 500 hPa geopotential height data available at https://www.esrf.noaa.gov/psd/data/gridded/data.ncep.reanalysis.pressure.html. Moreover, the annual EASMI time series were collected by Dr. J. P. Li and were available on the following website (http://ljp.gcess.cn/dct/page/65577). The NINO3.4 index and SOI were provided by NOAA and are available at http://www.cpc.ncep.noaa.gov/data/indices/.

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