Estimation of the Monthly Precipitation Predictability Limit in China Using the Nonlinear Local Lyapunov Exponent

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ABSTRACT

By using the nonlinear local Lyapunov exponent and nonlinear error growth dynamics, the predictability limit of monthly precipitation is quantitatively estimated based on daily observations collected from approximately 500 stations in China for the period 1960–2012. As daily precipitation data are not continuous in space and time, a transformation is first applied and a monthly standardized precipitation index (SPI) with Gaussian distribution is constructed. The monthly SPI predictability limit (MSPL) is quantitatively calculated for SPI dry, wet, and neutral phases. The results show that the annual mean MSPL varies regionally for both wet and dry phases: the MSPL in the wet (dry) phase is relatively higher (lower) in southern China than in other regions. Further, the pattern of the MSPL for the wet phase is almost opposite to that for the dry phase in both autumn and winter. The MSPL in the dry phase is higher in winter and lower in spring and autumn in southern China, while the MSPL values in the wet phase are higher in summer and winter than those in spring and autumn in southern China. The spatial distribution of the MSPL resembles that of the prediction skill of monthly precipitation from a dynamic extended-range forecast system.

Key words: monthly precipitation, nonlinear local Lyapunov exponent (NLLE), predictability, spatial distribution

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1. Introduction

The East Asian monsoon is one of the most important components of the East Asian climate system and causes distinct wet and dry seasons in China (Gao et al., 2014). Anomalous monsoon activity may cause extremes of drought and/or flood, exerting large impacts on the society, economy, and environment in China (Jin et al., 2013). In order to prevent meteorological disasters, reliable climate predictions such as monthly/seasonal predictions are needed. Unfortunately, the widely used method for monthly prediction is still fraught with uncertainties (Wang et al., 2015). Therefore, appropriate assessment of the predictability limit of monthly precipitation may advance our knowledge about prediction uncertainties and assist the end-user in setting up infrastructure for disaster preparedness.

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Some studies have focused on the predictability of monthly to seasonal temperature (Yue et al., 1999; Li and Ding, 2008; Li et al., 2014), but less research has been conducted on the precipitation predictability. Yilmaz and DelSole (2010) assessed the predictability of seasonal precipitation globally using joint probabilities, which provided only a rough assessment of predictability in East Asia. Ying et al. (2014) estimated the seasonal predictability of precipitation in eastern China according to the climatic signal-to-noise ratio, and obtained predictable precipitation patterns only qualitatively. Compared with predictability of temperature, estimation of precipitation predictability is more challenging because the precipitation rate is strongly non-Gaussian and discontinuous.

In general, the predictability of precipitation can be estimated by both statistical and dynamical methods. The former aims to estimate the climatic signal-to-noise ratio (Zhao, 2008; Ying et al., 2013); thus, such methods can be used only for qualitative investigation of predictability. For dynamical methods, numerical models (Koster et al., 2000; Zhao et al., 2000) and nonlinear dynamic system theory are commonly used. However, the performance of numerical models in simulating precipitation variability is generally poor due to complexity of the physical processes responsible for precipitation, indicating that the precipitation predictability derived from model simulations will yield considerable errors (Zhou et al., 2014). Nonlinear dynamic system theory, such as the Lyapunov stability theory, can be applied to observations and used to evaluate the predictability limit quantitatively, and therefore can overcome the errors from climate model simulations. On the basis of the Lyapunov stability theory and criterion of error growth, the predictability limit can be defined as the time over which the errors double (Lorenz, 1965). Li and Ding (2008) developed Lyapunov stability theory by proposing the nonlinear local Lyapunov exponent (NLLE) to quantify the predictability limit of a chaotic system.

The NLLE has been employed to estimate the predictability limit of monthly zonal circulation (Li and Ding, 2008) and monthly surface air temperature in China (Li et al., 2014). In this study, we attempt to quantitatively evaluate the predictability limit of monthly precipitation in China using the NLLE. In addition, we compare the pattern of the monthly standardized precipitation index (SPI) predictability limit (MSPL) derived from observations using the NLLE with that of the dynamical prediction skill of monthly precipitation.

2. Data and method

2.1 Data

Daily precipitation observations at 756 stations in China during 1960–2012 were obtained from the China Meteorological Administration. Missing data were replaced by climatic mean values for 1960–2012, but stations were excluded if values were missing for more than five consecutive days or the number of missing values for the entire time series was more than 60 days. After this process, 537 stations remained. Additionally, we used monthly precipitation hindcast data from the monthly dynamic extended-range forecast operational system version 2 (DERF2.0) of the National Climate Center for 1983–2013 (Wu et al., 2013). The model ran at a T106 (approximately 110 km) horizontal resolution. Four DERF2.0 runs (0000, 0600, 1200, and 1800 UTC) were initialized every day starting on days 22–26 of each month since January 1983 and run for 55 days each. Thus, there were 20 ensembles for each month, and the hindcast monthly precipitation was the ensemble average of all outputs of the 20 ensembles (He et al., 2014). Monthly global precipitation datasets were obtained from the CPC merged analysis of precipitation (Xie and Arkin, 1997) for 1983–2013. The horizontal resolution of the data was 2.5° × 2.5°. Anomalies of monthly precipitation for the observation and hindcast data are given relative to the 1984–2013 average.

2.2 Estimation of the nonlinear local Lyapunov exponent

The NLLE at time t_0 is defined as follows:

$$\lambda(x(t_0), \delta(t_0), \tau) = \frac{1}{\tau} \ln \left| \frac{\delta(t_0 + \tau)}{\delta(t_0)} \right|, \quad (1)$$

where $x(t_0)$ is the initial state of the reference orbit in phase space, i.e., the variable value at time t_0; $\delta(t_0)$ is the initial error, defined herein as the difference in precipitation between t and t_0, and t is determined by the local dynamical analogs (Li et al., 2011); and τ is the time step since t_0. The condition $\lambda > 0$ implies that the distance between initially similar orbits increases with time and their correlation is weakened with time. A larger value of λ indicates more rapid growth of the initial error. When the error growth reaches the saturation level, almost all similarity information from the initial states is lost and the prediction becomes meaningless.

The mean relative growth of initial error can be obtained by

$$\overline{E}(\delta(t_0),\tau) = \exp(\overline{\lambda}(\delta(t_0),\tau)\cdot\tau). \tag{2}$$

On the basis of the nonlinear error growth theory (Ding and Li, 2009), we obtain

$$\overline{E}(\delta(t_0),\tau) \xrightarrow{P} c(N\rightarrow\infty), \tag{3}$$

where the constant c is considered as the theoretical saturation level of $\overline{E}(\delta(t_0),\tau)$ when sample number N tends toward infinity.

In general, precipitation data feature a non-Gaussian distribution and are distributed discretely in both space and time. Therefore, prior to quantitative estimation of the precipitation predictability using the NLLE, a transformation method should be employed to ensure that the data fit a Gaussian distribution. The standardized precipitation index (SPI) defined by McKee et al. (1993) based on observed precipitation has a Gaussian distribution, so it is used in this study instead of the raw precipitation time series to estimate the precipitation predictability. The concept of SPI was first proposed by Mckee et al. (1993) and specific formulae for calculation of SPI were given in Edwards and Mckee (1997). This study follows the latter to obtain the SPI values. Herein, a positive (negative) value of the SPI indicates that the precipitation is greater (less) than the median precipitation.

Finally, the monthly SPI predictability limit is defined as

$$\mathrm{MSPL} = \left\{t|\overline{E}(\delta(t_0),\tau) = 0.99\cdot c\right\}, \tag{4}$$

i.e., MSPL is the time at which the error reached 99% of its saturation level (Li et al., 2014). The physical meaning of the MSPL is the time limit after which the two dynamic similar initial states become absolutely dissimilar (Li et al., 2014). This indicates the lead time for which the monthly precipitation can be predicted. If the MSPL is longer than 30 days, it indicates that the monthly mean is predictable from the beginning of the month. The longer the MSPL, the higher the predictive skill.

A sufficiently large number of samples are required when applying the NLLE (Li and Ding, 2011). In order to obtain enough samples, the SPI was obtained based on daily precipitation with a 30-day moving window day by day. The SPI for each day was calculated by using the 30-day daily precipitation before that day (McRoberts and Nielsen-Gammon, 2011). For example, the SPI for 31 January was calculated by using daily precipitation from 1 to 30 January.

We found that the predictability limit of the SPI depends on its phases. Thus, the SPI was classified into three phases: wet, dry, and neutral (Table 1). The wet and dry phases each constituted one-quarter of the total number of samples, and the neutral phase accounted for half of the total number of samples. The threshold of 0.675 was used because a frequency of 25% corresponds to an SPI value of 0.675 when the SPI time series has a Gaussian distribution.

Previous studies demonstrated that SPI time series usually do not fit a Gaussian distribution in areas where the annual precipitation is relatively low, such as northwestern China (Wu et al., 2007; Svoboda et al., 2012). For example, the peak of the probability distribution frequency (PDF) of the SPI time series for Ruoqiang Station in northwestern China shows an obvious shift to the low index phase, indicating a non-Gaussian distribution (Fig. 1). Therefore, the SPI time series for this station does not satisfy the NLLE requirement.

In contrast, the PDF of the SPI time series for Nanjing Station in central-eastern China fits a Gaussian distribution well (Fig. 2), with approximately 50% of the samples in the neutral phase and 25% in the wet and dry phases.

Table 1. Classification of the SPI phases

	Dry phase	Neutral phase	Wet phase
SPI	SPI $<$ –0.675	$\lvert$SPI$\rvert \leqslant$ 0.675	SPI $>$ 0.675

Thus, we employed a procedure to detect whether the SPI time series fit a Gaussian distribution. The SPI is considered to be a Gaussian distribution if it fits one of the two conditions given below:

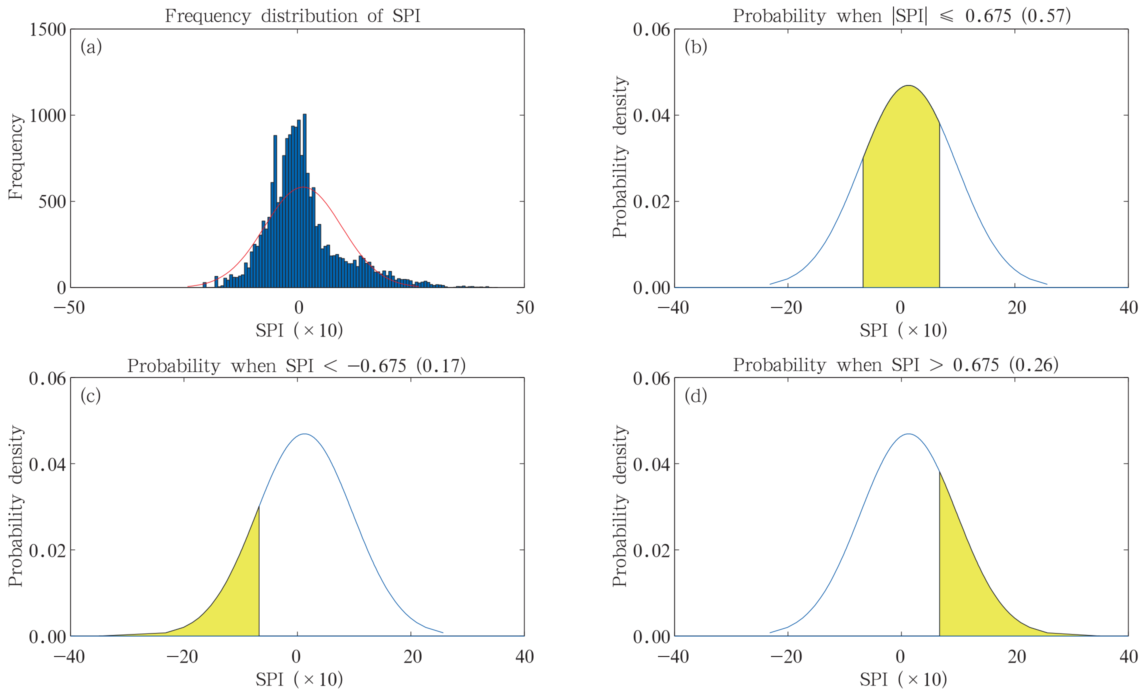

Fig. 1. (a) SPI frequency at Ruoqiang Station, and the accumulated probability with respect to the (b) neutral, (c) dry, and (d) wet phases.

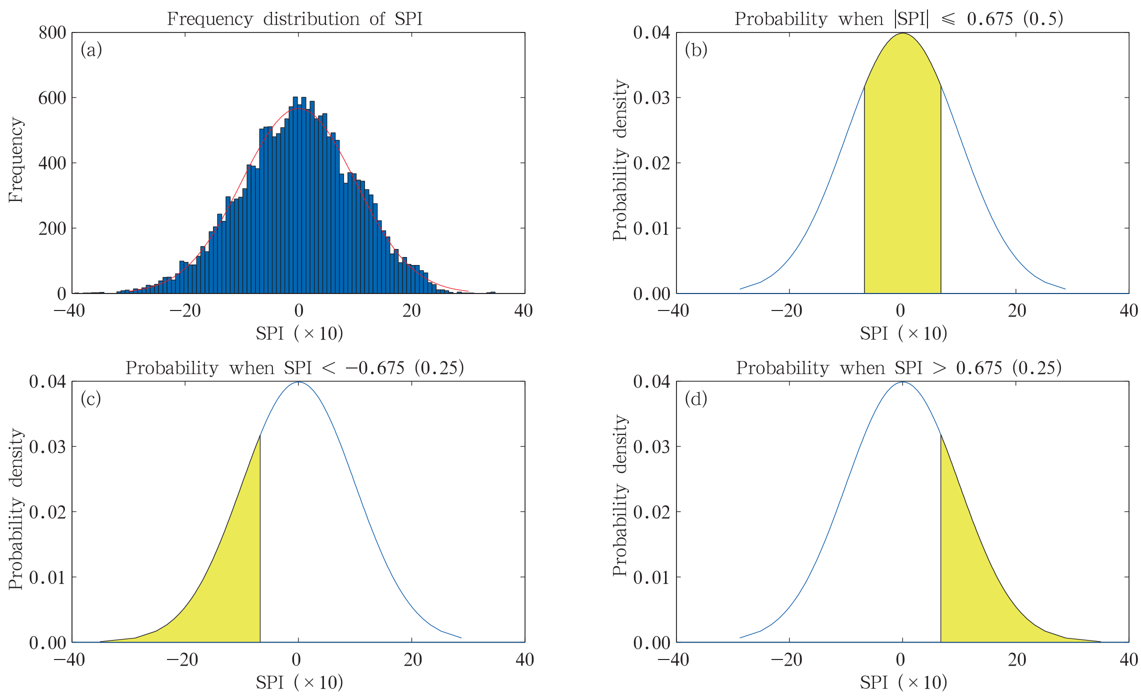

Fig. 2. As in Fig. 1, but for Nanjing Station.

$$\left|\frac{(\text{Days}|\text{SPI} < -0.675) - N}{N}\right| \leqslant 10\%, \tag{5}$$

$$\left|\frac{(\text{Days}|\text{SPI} > 0.675) - N}{N}\right| \leqslant 10\%, \tag{6}$$

where Days|SPI $<$ –0.675 and Days|SPI $>$ 0.675 represent the number of days in the dry and wet phases, respectively; and N denotes the total number of days.

Figure 3 shows the geographical distribution of the 537 stations used in the analysis. There are 37 stations with a non-Gaussian distribution, most of which are located in northwestern China, where the climatological mean of precipitation is less than 200 mm yr^{-1} (Fig. 3). Finally, 500 stations with Gaussian distribution SPI were selected for further analysis.

2.3 Calculation of monthly precipitation prediction skill

Similar to the SPI, we first classified the hindcast monthly precipitation into three phases: wet, dry, and neutral (Table 2). We then calculated the prediction skill (P) of the hindcast monthly precipitation from DERF2.0 for 1983–2013.

The prediction skill of the hindcast monthly precipitation was calculated by using the formula

$$P = \frac{P_s - P_c}{P_c} \times 100\%, \tag{7}$$

where P_s is the prediction score of monthly precipitation. P_s is defined as:

$$P_s = m_p/n_p \times 100\%, \tag{8}$$

where n_p is the number of predicted samples and m_p is the number of observed precipitation samples, which is in the same phase as the n_p predicted samples. The prediction score is reliable only when compared with the stochastic prediction score of monthly precipitation (P_c), which is given by

$$P_c = m_o/n_o \times 100\%, \tag{9}$$

where n_o is the number of observed samples, and m_o is the number of samples in the dry (neutral and wet) phase among these n_o samples.

3. Results

3.1 Spatial distribution of the MSPL

Figure 4a shows the spatial distribution of the annual mean MSPL in China. The annual mean MSPL was approximately 30–35 days over almost the whole of China. However, the patterns of MSPL show distinct differences between the three phases of the SPI (Figs. 4b–d). In the dry phase of the SPI, the MSPL is relatively high in northern China, with a value of about 30–45 days in northeastern China, but less than 30 days in the Huaihe River basin and southern China (Fig. 4b). The pattern of the MSPL in the wet phase of the SPI (Fig. 4d) is almost opposite to that in the dry phase. In the wet phase, the MSPL is less than a month over a large part of northern China, but more than 30 days in the Huaihe River basin and part of southern China. The MSPL values in the dry phase

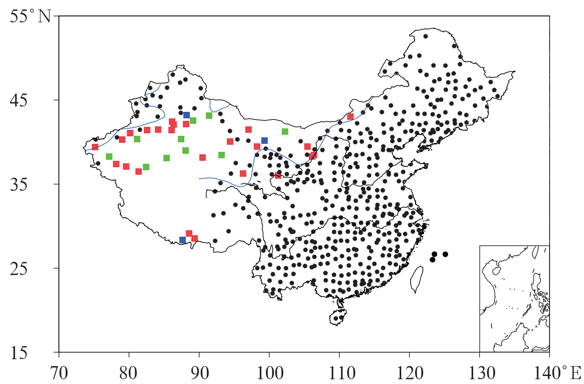

Fig. 3. Distribution of the 537 meteorological stations used in this study. Black spots represent the stations with Gaussian distribution SPI series; red (blue) squares represent the stations that do not fit Eq. (5) (Eq. (6)); green squares represent the stations that do not fit both Eqs. (5) and (6); and the blue line is the annual average 200-mm isohyet.

Table 2. Classification of precipitation phases (He et al., 2014)

	Dry phase	Neutral phase	Wet phase
Precipitation anomaly percentage (PAP; %)	PAP $<$ –20%	|PAP| $\leqslant$ 20%	PAP $>$ 20%

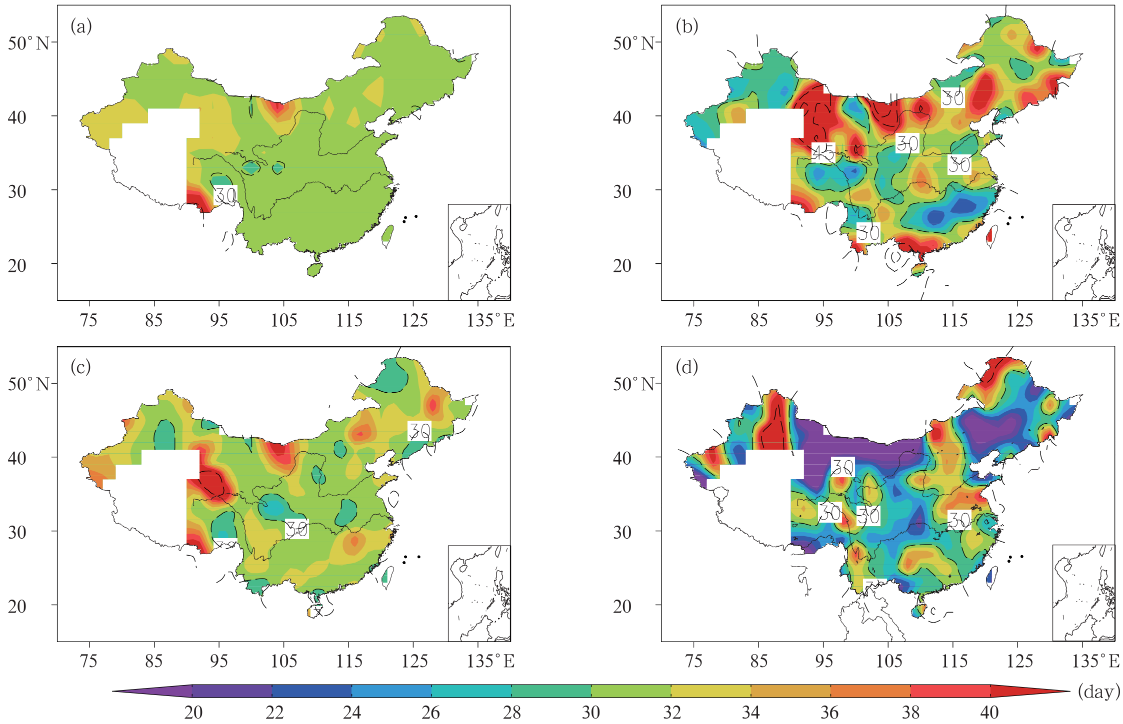

Fig. 4. (a) Annual mean MSPL, and the MSPL for the (b) dry, (c) neutral, and (d) wet phases of the SPI.

are relatively high in arid areas but low in moist areas (Fig. 4b); in contrast, the MSPL in the wet phase is relatively high in moist areas but low in arid regions (Fig. 4d). As a country seriously affected by the East Asian monsoon, the frequency of precipitation in dry (wet) phase is higher in arid (moist) areas. There are more samples in the dry (wet) phase in arid (moist) areas than those in other regions. Thus, it is easier to find better local dynamical analogs, which leads to a higher MSPL in the dry (wet) phase in northwestern (southern) China. In the neutral phase of the SPI, the MSPL pattern (Fig. 4c) resembles that of the total dataset (Fig. 4a), which can presumably be attributed to the opposite spatial distribution of the MSPL between the wet and dry phases.

As the precipitation in China shows large spatial and seasonal variations, we further examined the distribution of the MSPL for the four calendar seasons in terms of the SPI phases (Fig. 5). The MSPL is about 30–45 days in a large part of central-northern China, which is obviously higher than that in southern China (less than 30 days) in the dry phase of the SPI for spring (Fig. 5a). The distribution of the MSPL in the wet phase of the SPI in central-northern China is nearly opposite to that in the dry phase (Fig. 5c). The MSPL pattern in both the dry and wet phases of the SPI in summer is similar to that in spring (Figs. 5d and 5f). The MSPL is more than 30 days in central-northern China in the dry phase (Fig. 5d), and is around 30–40 days in the Huang-Huai River basin and Yunnan Province in the wet phase (Fig. 5f).

In autumn, the MSPL in the dry phase of the SPI is less than 30 days in a large part of southern China and more than 30 days in most areas of northern China (Fig. 5g). In contrast, the MSPL in the wet phase is more than 30 days in southern China but less than a month in northern China (Fig. 5i). In winter, the MSPL is more than 30 days in eastern China in the wet phase of the SPI (Fig. 5l)—the opposite pattern to the same area in the dry phase (Fig. 5j). Of note is that the MSPL in the neutral phase is more than 30 days in most areas of Chinese mainland in all four seasons except for several local regions, such as North China in both spring and autumn (Figs. 5b, 5e, 5h, and 5k).

In summary, the MSPL is higher in the neutral

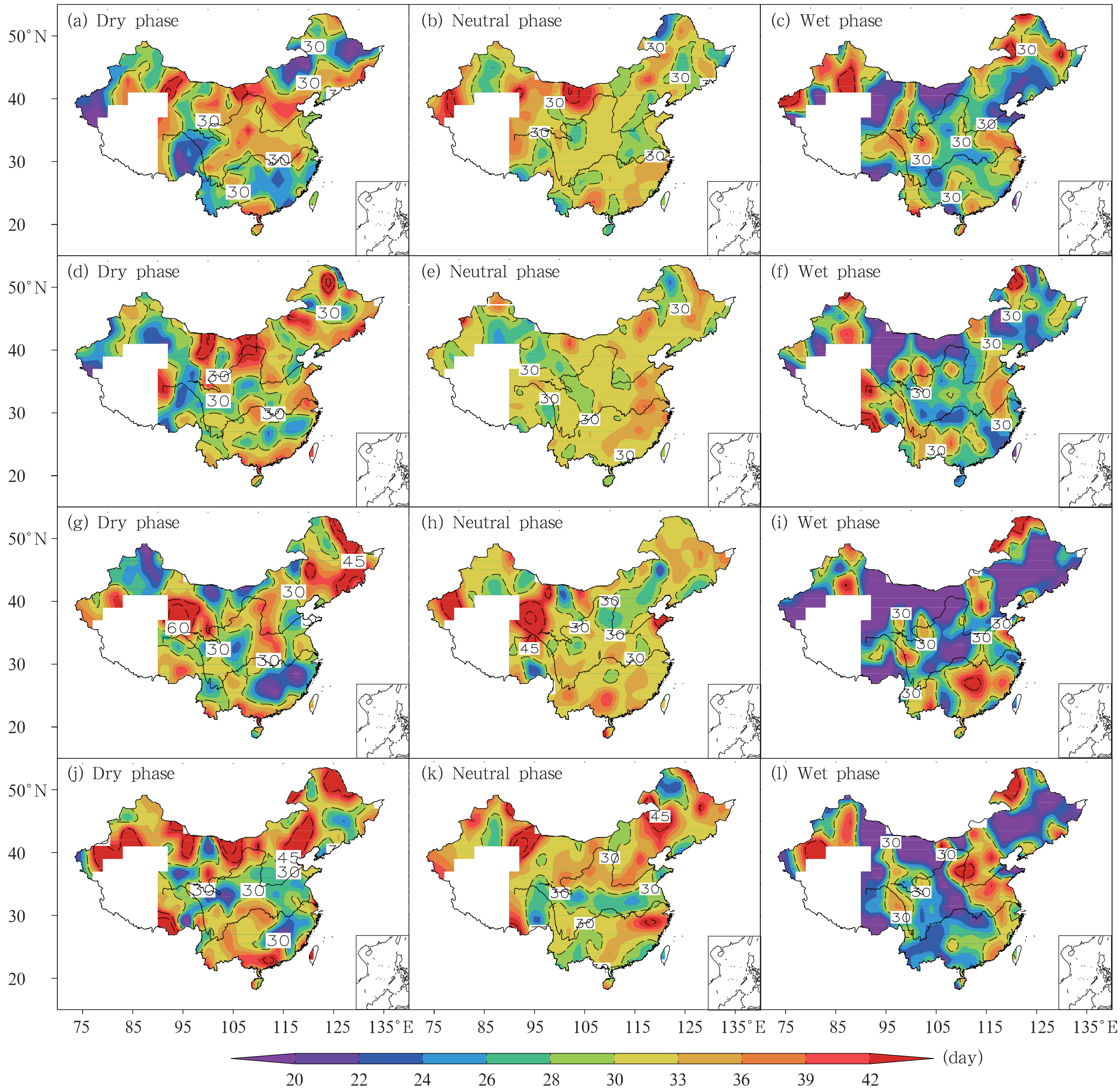

Fig. 5. Spatial distributions of the seasonal mean MSPL: (a–c) spring (March–April–May, MAM), (d–f) summer (June–July–August, JJA), (g–i) autumn (September–October–November, SON), and (j–l) winter (December–January–February, DJF) for (a, d, g, j) dry, (b, e, h, k) neutral, and (c, f, i, l) wet phases.

phase than in the dry and wet phases. This finding implies that prediction of the SPI is more challenging in the dry and wet phases than in the neutral phase. We also determined that the MSPL in the dry phase is higher than that in the wet phase. The spatial distribution of the MSPL in the wet phase is almost opposite to that in the dry phase in both autumn and winter. The MSPL in the dry phase of the SPI in a large part of southern China is higher in winter and lower in both spring and autumn. This finding is consistent with the results of Ying (2013), and supports the notion that the seasonal predictability of precipitation is higher in winter but lower in transitional seasons.

3.2 Comparison with the prediction skill of hindcast monthly precipitation

We investigated the similarity between the MSPL derived from precipitation observations using the NLLE and the prediction skill of the hindcast monthly precipitation. Figure 6 shows the prediction skill of the hindcast monthly precipitation in the three phases for each calendar season. As seen in Fig. 6, the prediction skill of hindcast monthly precipitation in the neutral phase is higher than in the other two phases in each season, which is consistent with the results in Fig. 5. In detail, the prediction skill in the neutral phase in northwestern and southern China is higher than that in the rest of China for spring (Fig. 6b), which strongly resembles the MSPL distribution in Fig. 5b. Prediction skill in the dry phase is relatively low to the south of the Yangtze River for summer (Fig. 6d), which is similar to the MSPL pattern in Fig. 5d. We additionally used the Global Precipitation Climatology Project monthly precipitation (Adler et al., 2003) as the observed precipitation to estimate the prediction skill. For this measure, the distributions of the prediction skill (figure omitted) are similar to those in

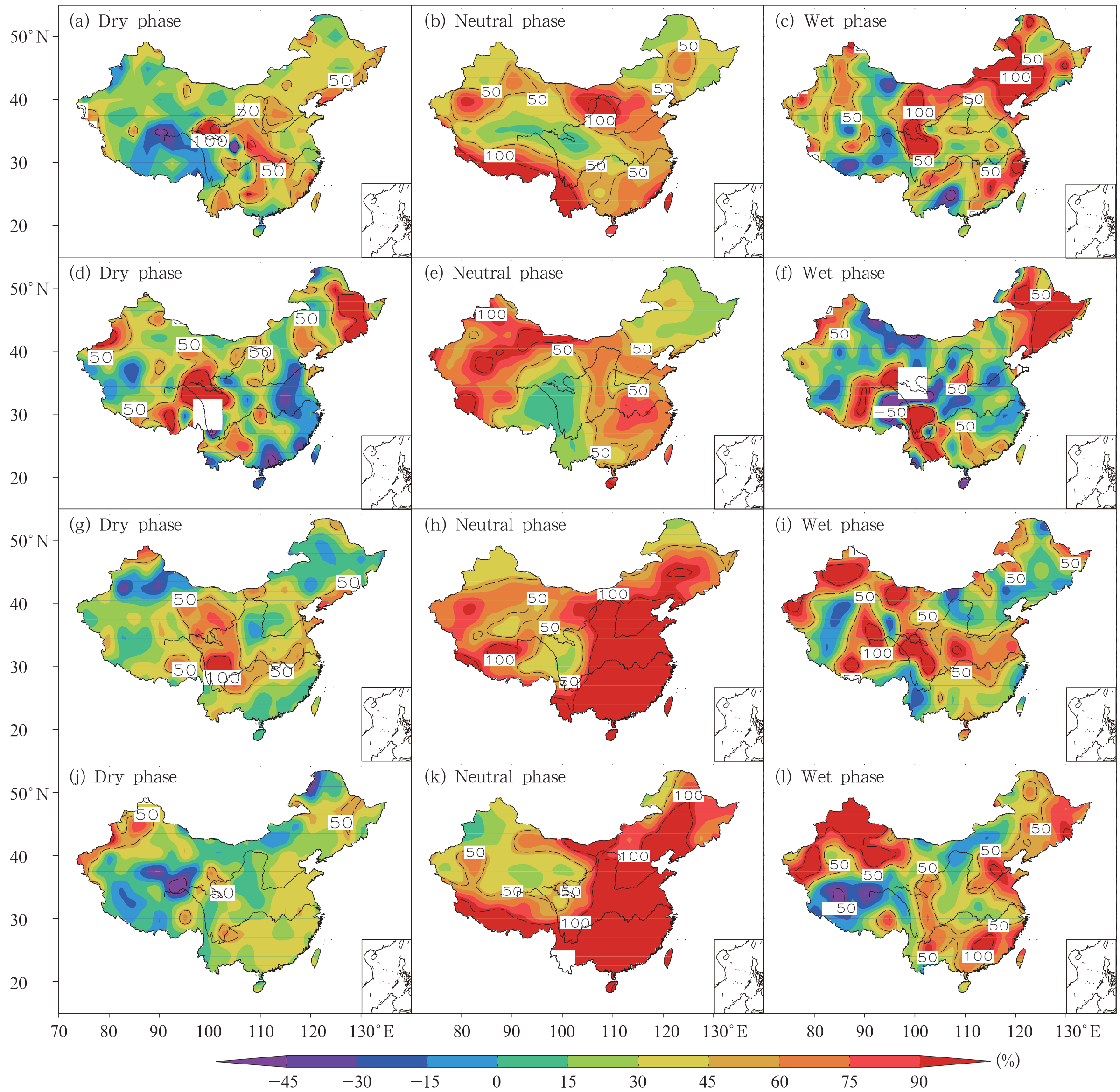

Fig. 6. Spatial distributions of the prediction skill of monthly precipitation from DERF2.0: (a–c) spring (MAM), (d–f) summer (JJA), (g–i) autumn (SON), and (j–l) winter (DJF) for (a, d, g, j) dry, (b, e, h, k) neutral, and (c, f, i, l) wet phases.

Fig. 6. In summary, the distribution of the prediction skill is consistent with the distribution of the MSPL to a great extent. The prediction skill largely depends on the predictability, which is evaluated utilizing a certain method. The MSPL is the intrinsic property gained from the precipitation time series. It can be used to verify whether the model can simulate this intrinsic property. Thus, the distribution of the MSPL is an important reference for model improvement.

4. Conclusion

We quantitatively estimated the monthly precipitation predictability limit using the NLLE, based on observations of daily precipitation from approximately 500 stations in China during 1960–2012. As the daily precipitation data are not continuous in space and time, a transformation was employed to obtain the monthly SPI. The SPI has a Gaussian distribution. The monthly predictability limit of the SPI i.e., the MSPL, was quantitatively estimated for its dry, wet, and neutral phases.

The results indicate that the annual mean MSPL in China varies significantly by region for both wet and dry phases. In particular, the MSPL is higher for the neutral phase than for both the dry and wet phases, implying that prediction of monthly precipitation is more challenging for the dry and wet phases than for the neutral phase. Additionally, the MSPL in the dry phase is relatively high (low) in arid (moist) areas; in contrast, the MSPL in the wet phase is relatively high (low) in moist (arid) areas. Moreover, the MSPL pattern in the wet phase is almost opposite to that in the dry phase in both autumn and winter. The MSPL in the dry phase is higher in winter and lower in both spring and autumn in southern China. The MSPL in the wet phase is higher in summer and winter than in spring and autumn in southern China. Furthermore, we found that the spatial distribution of the MSPL resembles that of the prediction skill of monthly precipitation from a dynamic extended-range forecast system. The prediction skill of precipitation in the neutral phase is highest compared to those in the wet and dry phases for all calendar seasons, which is consistent with the MSPL distribution.

Our results show that monthly precipitation is remarkably predictable in northern (southern) China in the dry (wet) phase. However, the predictability limit of precipitation is markedly smaller than that of the surface air temperature (Wang et al., 2007; Li et al., 2014). The spatiotemporal relations between precipitation and associated boundary conditions remain unknown because the method applied in this study cannot separate predictability induced by initial values and by external forcing.

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