

Uncertainties in calculating precipitation climatology in East Asia

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Abstract. This study examines the uncertainty in calculating the fundamental climatological characteristics of precipitation in the East Asia region from multiple fine-resolution gridded analysis datasets based on in-situ rain gauge observations and data assimilations. Five observation-based gridded precipitation datasets are used to derive the long-term means, standard deviations in lieu of
5 interannual variability and linear trends over the 28-year period from 1980 to 2007. Both the annual and summer (June–July–August) mean precipitation is examined. The agreement amongst these precipitation datasets are examined using two metrics including the signal-to-noise ratio (SNR) defined as the ratio between long-term means and the corresponding standard deviations, and Taylor diagrams which allows examinations of the pattern correlation, the standard deviation, and the centered
10 root mean square error. It is found that the five gauge-based precipitation analysis datasets agree well in the long-term mean and interannual variability in most of the East Asia region including eastern China, Manchuria, South Korea, and Japan, which are densely populated and have fairly high density observation networks. The regions of large inter-dataset variations include Tibetan Plateau, Mongolia, northern Indo-China, and North Korea. The regions of large uncertainties are typically lightly
15 populated and are characterized by severe terrain and/or extreme high elevations. Unlike the long-term mean and interannual variability, agreements between datasets in the linear trend is weak, both for the annual and summer mean values. In most of the East Asia region, the SNR for the linear trend is below 0.5, i.e., the inter-dataset variability exceeds the multi-data ensemble mean. The uncertainty in the spatial distribution of long-term means among these datasets occurs both in the spatial pattern
20 and variability, but the uncertainty for the interannual variability and time trend is much larger in

the variability than in the pattern correlation. Thus, care must be taken in using long-term trends calculated from gridded precipitation analysis data for climate studies over the East Asia region.

1 Introduction

Long-term means, standard deviations in lieu of interannual variability, and trends calculated from
25 observed data are among the fundamental fields in representing the characteristics of regional cli-
mates. These climatological properties play crucial roles in defining climatological norms, occur-
rence of extreme events, detection of climate change, and projecting future climate variations and
change as well as their impacts (Giorgi et al., 1994; Groisman et al., 2001; Kim, 2005). For example,
reliability of the climate change detection is examined by comparing the long-term means and trends
30 calculated from observations against those simulated in climate model sensitivity experiments (e.g.,
IPCC, 2001, 2007). In addition, the changes in key local hydrological fields such as precipitation
are frequently measured relative to their climatological means. Thus, calculating reliable values of
these properties is a critical step in climate research for identifying regional climate characteristics,
through quantification of their changes due to external and/or internal forcings such as emissions of
35 anthropogenic greenhouse gases, and the impacts of such changes on regionally important sectors.

Gridded representations of observed data on the basis of a variety of instruments, locations, plat-
forms, retrieval algorithms and analysis schemes are widely employed in climate research with vari-
ous goals (Legates and Willmott, 1990; Mitchell and Jones, 2005; Shige et al., 2006; Schneider et al.,
2014). Typically, only a limited number of such datasets were available, and most climate studies
40 employed a single dataset which includes features needed for their analyses. Recently, a number
of researchers and institutions have introduced newly developed observation-based gridded analysis
datasets of global or regional coverage with fine spatial resolutions (Legates and Willmott, 1990;
Adler et al., 2003; Mitchell and Jones, 2005; Shige et al., 2006; Yatagai et al., 2012; Pai et al.,
2013; Schneider et al., 2014). These newly introduced analysis datasets provide precipitation and/or
45 surface air temperatures over extended periods of multiple decades at spatial resolutions of 0.5°
or finer, which are substantial improvements from previous generation datasets that are typically at
much coarser horizontal resolutions, for example, the 2.5° resolution GEWEX Global Precipitation
Climatology Project (Adler et al., 2003). These recent fine-scale datasets allow us to better examine
the regional precipitation and temperature climatology and to perform more reliable evaluations of
50 today's high-resolution climate simulations, especially over the regions of complex terrain, that are
important for climate-change impact assessments and climate model evaluations (Kim et al., 2013).
These new datasets also introduce uncertainties in calculating regional climate characteristics be-
cause of the differences amongst them. Based on these concerns, two recent studies by Prakash et al.
(2014) and Kim et al. (2015) examined uncertainty in calculating precipitation climatology over In-
55 dia and its surrounding regions using multiple precipitation analysis datasets. These two studies have

revealed independently that there exist substantial amounts of differences amongst today's gridded precipitation datasets resulting in uncertainties in the calculated precipitation climatology and that the uncertainty or the spread amongst multiple datasets vary according to regions as well as seasons. Kim et al. (2015) further revealed that uncertainties in the calculated precipitation climatology defined relative to their climatological means are generally larger in the dry regions and/or local dry seasons. These two studies strongly suggest that uncertainty due to the differences between various datasets needs to be examined and quantified in all climate studies because the absolute accuracy of individual datasets cannot be quantified in practice.

In this study, we investigate the uncertainty in calculating fundamental properties in representing regional climate characteristics of precipitation over the far east Asian region due to the differences amongst today's fine-resolution gridded datasets based on analyses of observed data. This study examines for the first time the uncertainty in calculating the standard deviation, a widely-used first-order statistical moment, and linear trend against that in calculating the average, the zero-order statistical moment. Examining the uncertainty in assessing the key precipitation characteristics from the current available precipitation data can help interpret future precipitation projections. In East Asia, with huge populations and frequent hydrologic extremes, assessing long-term variations in precipitation has been an important concern. However, the effects of inter-dataset differences on such assessments have not been studied so far. The uncertainty analysis for the East Asia region in this study is also applicable to any other parts of the world. The methodology and data are presented in Sect. 2, and results are given in Sect. 3. Section 4 summarizes and discusses the implications of the findings in this study.

2 Methodology and data

In this study, spatial variations in the long-term means, interannual variabilities, and linear trends over the region of interest are examined in terms of inter-dataset variability measured using signal-to-noise ratio (SNR) and the similarity with reference data.

Five gridded precipitation datasets are used to estimate the uncertainty in constructing regional climate characteristics over East Asia for the entire year and for the summer season (June–July–August). Only the datasets that cover more than 25 years are selected for analysis for reliable calculations of the temporal variability in lieu of interannual variability and linear trends. The period of the recent three decades examined in this study corresponds to the period of quite steady (near monotonic) and large increases in the global mean temperature. The analysis was limited to the 28-year period (1980 ~ 2007) due to the length of the available data. Examination of the precipitation trend in the period of clear warming trend is a major scientific interest related to the link between the changes in precipitation and temperature.

90 Based on the selection criterion, five high-resolution gridded datasets are selected, including the
Climate Research Unit of the University of East Anglia (CRU), University of Delaware (UDEL),
Global Precipitation Climatology Center (GPCC), the Asian Precipitation – Highly Resolved Ob-
servational Data Integration Towards Evaluation of water resources (APHRODITE), and the Mod-
ern Era Retrospective-analysis for Research and Applications (MERRA) land, that are either based
95 on rain gauge data or assimilations. These datasets and references are summarized in Table 1. We
also examined uncertainties including the coarse resolution Global Precipitation Climatology project
(GPCP) data (Adler et al., 2003) to get essentially the same conclusions that are obtained with the
original five datasets only; thus, the results including the GPCP data are not presented here to focus
on fine-resolution datasets.

100 Note that there are some factors leading to differences among the datasets – e.g., the horizon-
tal and/or vertical resolutions, the gridding procedure, the analysis methods, etc. Such inter-dataset
differences may be an unavoidable source of uncertainty in this study. As seen in Table 1, obser-
vational data are available in various resolutions and discretizations. In fact, datasets of the same
horizontal resolution can be defined in different grid structures. The gridding procedure might also
105 be different for different dataset. The analysis datasets are usually based on different sets of station
(observational) data, depending on the data availability at the time of analysis and specifics of the
quality control procedures (e.g., Mitchell and Jones, 2005; Yatagai et al., 2012; Pai et al., 2013).
Furthermore, the analysis methodology, essentially the interpolation scheme that varies for different
analysis datasets, can contribute to the inter-dataset differences. However, assessing the effects of
110 different datasets and/or the analysis schemes on the inter-dataset differences used here is beyond
the scope of this study.

To alleviate the uncertainty related to the inter-dataset differences, we have interpolated all datasets
onto a common grid so that we can compare all datasets at the same locations. The spatial interpo-
lation procedure can affect the characteristics of spatial variability of the interpolated data. This can
115 be an important concern in deriving the characteristics of horizontal variability, e.g., spatial power
spectra, but is not expected to have serious effects on deriving temporal variability of the interpo-
lated data. Because all of the properties we concern in this study are related to the temporal variability
(e.g., temporal means, standard deviations, and trends), we expect the differences in the horizontal
resolutions and subsequent spatial interpolation have minimal impacts on the results. We have also
120 created a multi-dataset ensemble by simple averaging of all observational datasets included in the
analysis, using equal weights. The equal weighting is employed because the accuracy of individual
datasets cannot be determined objectively.

Uncertainties in representing precipitation climatology due to the spread amongst today’s obser-
vational data are examined in terms of the SNR. The SNR has been a key property in a number of
125 climate studies in which the uncertainty of climate signals are estimated against noises stemming
from various sources (e.g., Giorgi and Mearns, 2002; Covey et al., 2003; Meehl et al., 2005; Tebaldi

and Knutti, 2007; Duan and Phillips, 2010). In climate and weather forecast research based on ensembles of multiple model or observation datasets, the SNR has been used to measure the reliability of the multi-dataset ensemble mean against the spread of the datasets in the ensemble. Within this context, the signal and noise are defined as the associated mean and standard deviation, respectively, of multiple datasets. The definition of “noise” can be complicated when the data reliability varies among datasets and the weighting factor in constructing multi-dataset ensemble can vary for different dataset (Duan and Phillips, 2010). Such complications in calculating “noise” frequently occur in climate projections where outputs from various models of varying performance are used to construct an ensemble mean using the variable weighting (e.g., Giorgi and Mearns, 2002). Because it is practically impossible to rank the selected observational datasets in terms of their accuracy, the ensemble is constructed using an equal weighting.

The similarity between individual datasets and the reference data defined as the multi-dataset ensemble is measured in terms of the pattern correlation and the standard deviation of individual datasets relative to the reference datasets. Measurements of these two properties are presented using Taylor diagrams (Taylor, 2001; Gleckler et al., 2008). Taylor diagram was first introduced by Taylor (2001) to provide a way to intuitively present two properties simultaneously; the correlation coefficient of a dataset with the reference data are presented in the azimuth angle (the angle for perfect agreement is zero) and the relative magnitude of the standard deviation of a dataset with respect to that of the reference data is expressed as the radial distance (e.g., see Fig. 5a). Thus, the radial distance of 1 and the azimuthal angle of 0° implies that a sample data has the same pattern and variability as the reference data. In addition, the distance between the point (0° , 1.0) and a data point in this diagram corresponds to the centered root mean square error (RMSE). This diagram has become one of the most widely used methodologies in climate studies for presenting the evaluations of multiple models and/or variables or intercomparison of multiple datasets (IPCC, 2001; Taylor, 2001; Duffy et al., 2006; Gleckler et al., 2008; Kim et al., 2013, 2015).

3 Results

3.1 Regional climatology

Figure 1 presents the three basic characteristics of the annual and summer (June–July–August) precipitation climatology over East Asia – long-term means, interannual variability and trends, calculated from the ensemble mean of the multiple datasets in Table 1. The annual mean precipitation in the region is characterized by the wet regions in southeastern China and Japan (Fig. 1a). Precipitation over the Korean Peninsula is characterized by maxima in the southwestern and central regions and a rapid decrease towards the northwestern part of the peninsula bordering with Manchuria. The driest region covers southern Mongolia, the Gobi desert, and northern Tibetan Plateau. Interannual variability of the annual mean precipitation (Fig. 1b) also shows similar distribution as the annual

means. Linear trend of the annual precipitation varies substantially according to geography (Fig. 1c). The most notable features include the positive trend in the driest region, including southern Mongolia, the Gobi desert and northern Tibetan Plateau, and the negative trend along the wet Yangtze River. Strong positive trends are also found in much of the Korean Peninsula, the coastal region of northern China to the west of the Shandong Peninsula, most of southern China, and eastern Japan. Decreasing precipitation trends also occur in the region between 45 and 50° N and extending from central Mongolia to far-eastern Russia. The summer rainfall climatology (Fig. 1d–f) resembles the annual mean climatology but with larger magnitudes. This shows that the precipitation climatology over the East Asia region is primarily determined by the summer rainfall.

3.2 Uncertainties in precipitation climatology

The climatology presented in Fig. 1 varies for different datasets. This is inevitable because each dataset utilizes different raw data, data quality control, and analysis methodology (Xie and Arkin, 1995). Because it is practically impossible to determine which dataset is more accurate, assessing the reliability of climatological properties calculated from various datasets as well as the expected range of uncertainty due to the diversity of these datasets is crucial in calculating regional climatology (Kim et al., 2015). In this section, the range of uncertainty in the three precipitation characteristics is measured in terms of the SNR and the agreement between individual datasets and the multi-data ensemble mean in terms of the spatial pattern correlation and the magnitude of spatial variability following the methodology of Kim et al. (2015), using the Taylor diagram.

The SNR is calculated as the ratio between the multi-data ensemble mean and the inter-dataset variability, i.e., a measure of the magnitude of the multi-dataset ensemble mean relative to that of the inter-dataset variations. Thus, as SNR increases, these datasets agree more closely with each other. There is no established threshold value of SNR to distinguish “good” from “bad”. However, we may use some subjective guidance to interpret the SNR values. For instance, if $\text{SNR} < 1$ the signal is smaller than the noise, and it becomes a clear case that the signal is not reliable. The case with $\text{SNR} > 5$ may indicate that the spread amongst the multiple datasets may be small enough so that we can take the multi-data ensemble as the representative value for the included datasets.

The SNRs for the annual mean precipitation (Fig. 2a) and its interannual variability (Fig. 2b) over the 25-year period exceeds 5 in most of the study domain. Hence, the five datasets examined in this study agree well in terms of the annual mean precipitation and its interannual variability in the East Asia region. The regions of small SNR, i.e., showing poor agreements amongst the selected datasets, are located in the western part of the domain that include eastern Tibetan Plateau, the Gobi desert, and northern Indochina bordering with China. It is notable that the station density is relatively low in these regions. The SNR for the interannual variability is generally smaller than that for the mean; thus, uncertainty in calculating the interannual variability is larger than in calculating the mean climatology. Unlike the annual mean and its interannual variability, the SNR for the linear

tendency of the annual precipitation (Fig. 2c) is generally below 5 in most regions. Thus, long-term annual precipitation trend in the region is highly uncertain except in a few small areas.

200 Figures 2d–f show the SNR for the summer mean precipitation. Overall, the reliability of the three characteristics of the summer precipitation calculated from these five datasets is similar to that of the annual precipitation. The SNRs for the summer precipitation climatology is somewhat smaller than those for the annual precipitation climatology, but still largely exceed 5 in about the same region as for the annual precipitation. For the interannual variability (Fig. 2b vs. Fig. 2e) and linear trend
205 (Fig. 2c vs. Fig. 2f), the five datasets agree more closely for the summer mean values than for the annual mean values. It is noteworthy that the positive tendency of the summer rainfall in southern China (Fig. 1f) is highly reliable as all five datasets agree closely (i.e., relatively smaller inter-dataset variations compared with the multi-dataset ensemble mean).

To evaluate the statistical significance of trends, we have plotted the p -values from each dataset in
210 calculating the linear trend of the annual-mean precipitation and the summer-mean precipitation (see Figs. 3 and 4, respectively). The regions of large SNR correspond to the regions of small p -values in calculating the linear trend. This suggests that some of the uncertainty in the multi-dataset ensemble may be inherited from the uncertainty in calculating the trend from individual datasets. Still, a significant portion of the region of small p -values shows small SNR values. Thus, inter-dataset
215 differences are the main cause of the uncertainty in calculating long-term trends.

Figure 5 measures the spatial variations in the three climatological properties represented by the five observational datasets using the Taylor diagrams and the simple multi-dataset ensemble as the reference. In these diagrams, the areas encompassed by the red polylines may be regarded as the range of uncertainty (see Kim et al., 2015). Thus, as the area is smaller, the uncertainty due to the
220 differences between the examined datasets is smaller. The spread in the azimuthal and radial direction indicates the spread in the spatial pattern and in the magnitude of spatial variability, respectively. Similarly as from Fig. 2, the uncertainties in the spatial variations of the annual and summer mean precipitation and their interannual variability are much less than the uncertainty in the spatial variations of the linear trend. The distances from the reference data at the point indicated by a star (i.e.,
225 the reference point with both standardized deviation and correlation being equal to 1.0) to individual datasets for the means (Figs. 5a and 5d) are similar to those for their interannual variability (Figs. 5b and 5e), indicating similar level of spread amongst these datasets in representing these two properties of the precipitation climatology in the region. Regarding the linear trend (Figs. 5c and 5f), compared to the means and their interannual variabilities, the distances between the reference point
230 and individual datasets are much larger. This is another indication of the larger uncertainties in the linear trend represented by these datasets.

One interesting feature in the examination of the uncertainties in the spatial variability in Fig. 5 is that the spreads in these datasets occur in both the spatial pattern and the magnitude for the annual and summer mean values; however, these datasets show more consistency in the spatial pattern than

235 in the variability. Figures 5b and 5e show that the five datasets show similar spatial correlations with
the reference data and that the predominant spread among these datasets are in the radial direction,
i.e., the magnitude of the spatial variability. This feature is more pronounced for the linear trend
(Figs. 5c and 5f) which shows nearly linear distribution of the data points in radial directions, i.e.,
much smaller spread in the azimuthal direction (pattern correlations) than in the radial direction
240 (magnitude of variability relative to the reference data).

4 Summary and discussions

The uncertainties in three fundamental climatological characteristics of the precipitation over East
Asia due to the differences among available fine-scale observation-based gridded analysis datasets
have been examined using the metrics selected for objectively measuring the spread of these proper-
245 ties calculated from individual datasets. The three climatological characteristics include the means,
interannual variabilities, and linear trends in the annual and summer mean precipitation, which are
key fundamental climatological characteristics widely used in studies for examining regional climate
characteristics and model evaluations. The spread or the magnitude of disagreements amongst the
selected datasets are measured using the signal-to-noise ratio (SNR) and examined visually using
250 the Taylor diagrams which allows simultaneous evaluations of three properties – pattern correlation,
standard deviations and the centered mean square errors between multiple datasets and a reference
dataset.

The SNR values calculated from the five selected precipitation datasets show that the mean cli-
matology of the annual and summer mean precipitation values and their interannual variability are
255 highly reliable in much of East Asia except in southern Mongolia, the Gobi desert, and the Tibetan
Plateau – the regions of sparse population and complex terrain. Precipitation measurements in re-
gions of dry climate and complex terrain require high density networks (e.g., Kim et al., 2015).
Unlike the climatological mean values and interannual variability, linear trends calculated over the
28-year period are highly uncertain except in a few limited areas. It is striking that reliable estima-
260 tions of the temporal trend of the annual mean precipitation (Fig. 2c) is very low compared to that
for the means and the variability (Fig. 2a and b, respectively). Reliable calculation of linear trends is
only possible over the southern China region for the summer mean precipitation. Thus extra caution
must be taken when analyzing precipitation trends over the East Asian region.

The uncertainty characteristics also vary according to the climatological properties. Figures 1 and
265 2 discussed above show that the reliability of calculating temporal variabilities is much lower than
that of time mean values, especially for linear trends. In addition, the spatial pattern and variability of
the calculated linear trend (Fig. 5c) show much larger spread (i.e., uncertainty) among these datasets
compared to the annual means (Fig. 5a) and interannual variability (Fig. 5b). The consistency in the
spatial pattern between individual datasets and the reference data measured in terms of the corre-

270 lation are near or over 0.95 for the temporal means and variability whilst it barely exceeds 0.8 for
the linear trend. The range of spatial variability measured in terms of the standardized deviation (the
ratio between the standard deviation of a datasets and the reference dataset) for the linear trend is
over 0.5 which is more than twice of the range of the means and the variabilities. It is also observed
that uncertainties in the spatial distribution of the annual and summer mean precipitation (Fig. 5a
275 and 5d, respectively) occur in both the spatial pattern and the magnitude of variability. For the in-
terannual variability and linear trends, the spread in the standardized deviation (i.e., the magnitude
of variability) is much larger than that in the spatial pattern. These may suggest that all of these
datasets are affected by some common factors in determining the characteristics of these datasets.
For example, the station datasets included in each analysis dataset may provide high consistency
280 in the spatial distribution pattern, but different analysis schemes may lead to a larger spread in the
magnitude of their variability because of different basis functions employed in different interpolation
schemes (e.g., Xie and Arkin, 1995; Prakash et al., 2014). This is just a hypothesis and needs close
examinations in future studies.

The uncertainty in calculating precipitation climatology in the regions including southern Mon-
285 golia, the Gobi desert, and the Tibetan Plateau is of a special concern. These regions can respond
sensitively to climate change because of disproportionately larger impacts of global warming on high
elevation regions and snow-ice processes (e.g., IPCC, 2007; Waliser et al., 2011). Because of rapid
variations in the spatial precipitation distributions according to terrain during storms, accurate mea-
surement of precipitation in the regions of extreme terrain requires high gauge network (Xie and
290 Arkin, 1995). The sparse population density in these regions may require higher cost to build and
maintain additional gauges to reduce the uncertainties. Remote sensing of precipitation will play
important roles in monitoring precipitation over these regions of sparse observations in addition to
the investments for installing and maintaining additional surface observing stations.

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Table 1. The precipitation datasets employed in this study.

Dataset name	Source	Resolution	References
CRU	Rain gage	$0.5^\circ \times 0.5^\circ$	Mitchell and Jones (2005)
UDEL	Rain gage	$0.5^\circ \times 0.5^\circ$	Legates and Willmott (1990)
APHR	Rain gage	$0.25^\circ \times 0.25^\circ$	Yatagai et al. (2012)
GPCC	Rain gage	$0.5^\circ \times 0.5^\circ$	Schneider et al. (2014)
MERRA-Land	Assimilation	$2/3^\circ \times 0.5^\circ$	Reichle et al. (2011)

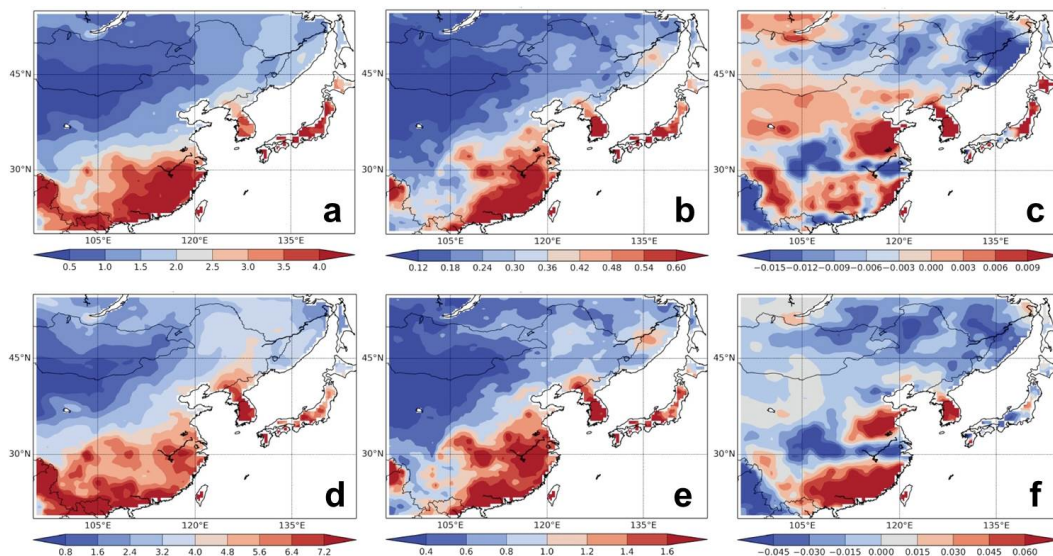


Figure 1. The climatological properties of the annual (upper panels) and summer (lower panels) precipitation for the period 1980–2007 over East Asia: **(a, d)** the mean climatology, **(b, e)** the standard deviation, and **(c, f)** the linear trend of precipitation. These properties are derived from the ensemble of the corresponding properties calculated from the datasets in Table 1.

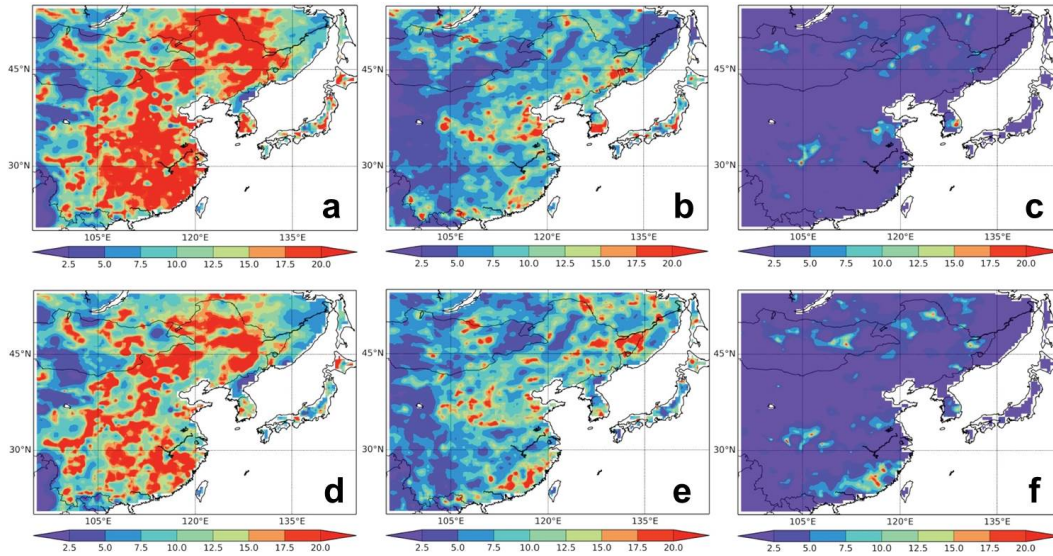


Figure 2. The signal-to-noise ratio (SNR) for the properties shown in Fig. 1, calculated from the corresponding properties of the five precipitation analysis datasets in Table 1.

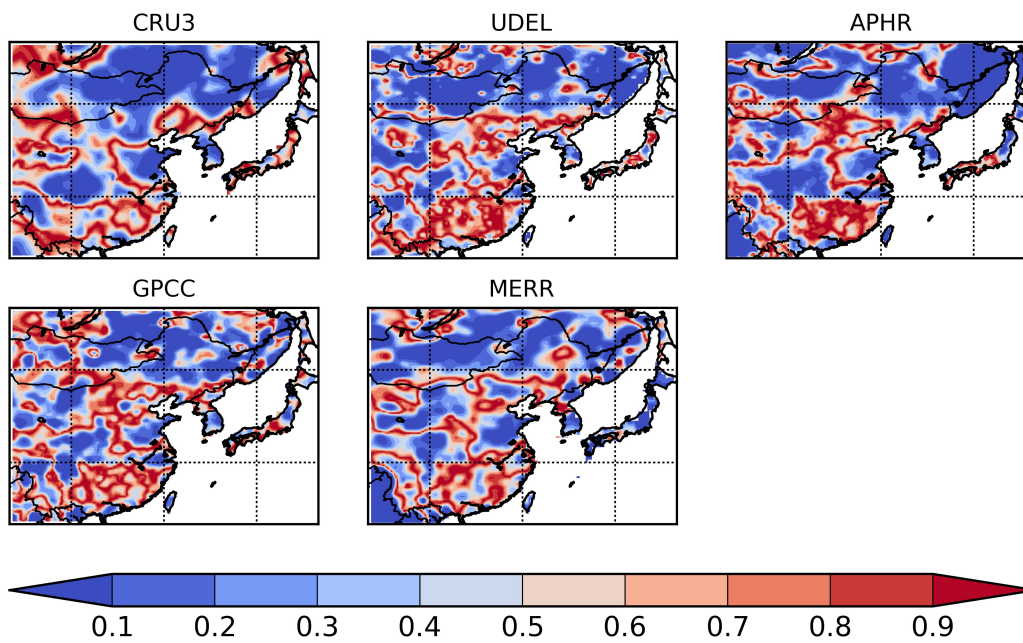


Figure 3. The p -values in calculating the linear trend of the annual-mean precipitation from each dataset.

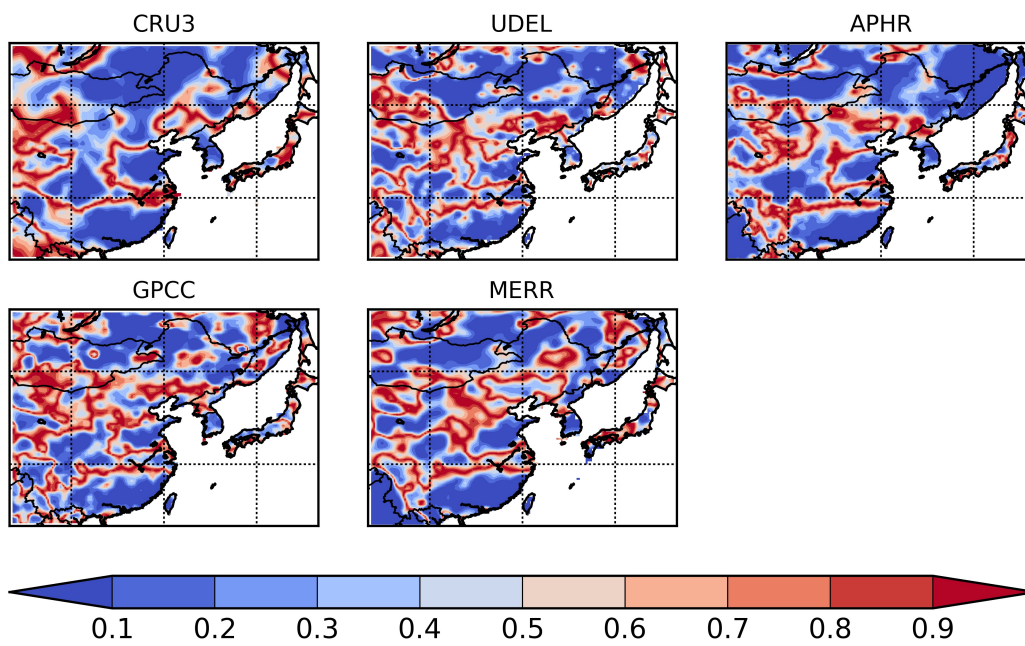


Figure 4. Same as in Fig. 3, but for the summer-mean precipitation trend.

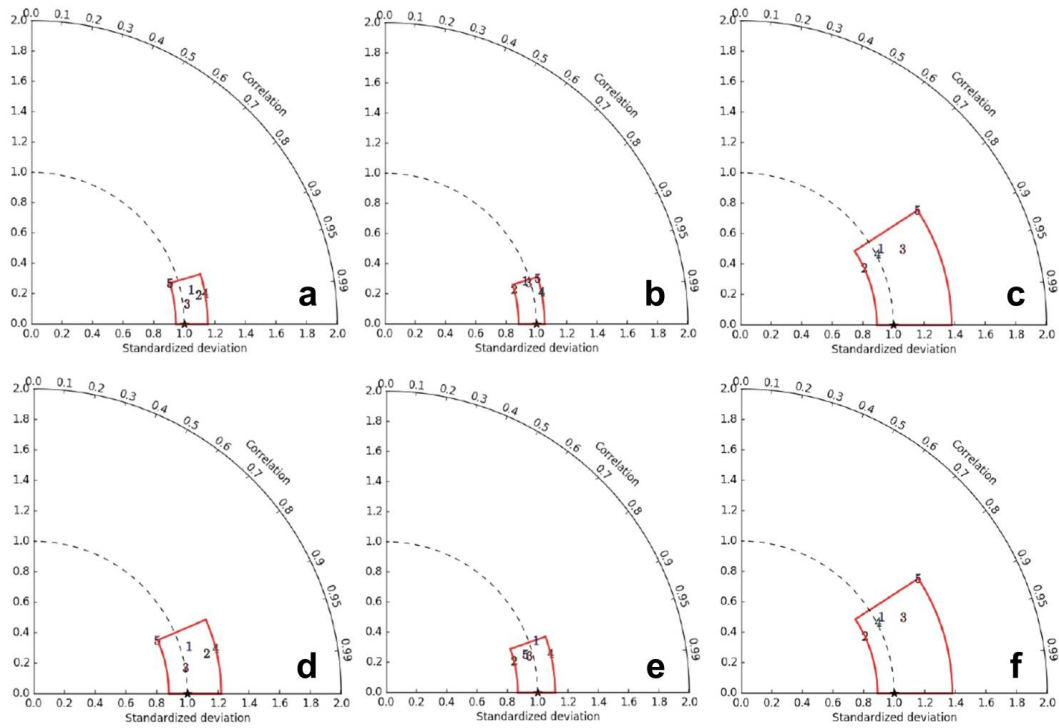


Figure 5. The spread amongst the five precipitation datasets in representing the spatial variability of the three climatological properties of the annual (upper panels) and summer (lower panels) precipitation over East Asia: **(a, d)** the mean, **(b, e)** the interannual variability, and **(c, f)** the trends of precipitation. They are presented in terms of their spatial pattern correlations (the azimuthal direction), the standardized deviation, and the standard deviation of individual datasets normalized by that of the reference data (the radial direction). The area within the red polyline represent the range of spread amongst these datasets.