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Quantifying the reliability of precipitation datasets for monitoring large-scale East Asian precipitation variations

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ABSTRACT: Early detection of extreme drought and flood events either over the whole globe or a broad geographical region, and timely dissemination of this information, is indispensable for mitigation and disaster preparedness. Recently, the APEC Climate Center (APCC) has launched a global precipitation variation monitoring product based on the Climate Anomaly Monitoring System-Outgoing Longwave Radiation Precipitation Index (CAMS-OPI) data. Here we quantify the reliability of CAMS-OPI, as well as other gauge-satellite-merged and reanalysis precipitation datasets, for the purpose of monitoring large-scale precipitation variability in East Asia. The ground truth is the newly available gauge-based data from the project titled 'Asian Precipitation – Highly-Resolved Observational Data Integration Towards Evaluation (APHRODITE) of the Water Resources'. It is found that the seasonal-to-interannual rainfall deficit and surplus given by various reanalysis systems sometimes do not match the spatial patterns seen in the APHRODITE data. Moreover, maps showing the Standardized Precipitation Index (SPI) become less and less reliable as the time scale based on which values are calculated increases. In contrast, the performance of gauge-satellite-based rainfall datasets is satisfactory and the quality of SPI maps does not decay as the time scale increases. Overall, CAMS-OPI is found to be reliable for monitoring large-scale precipitation variations over the East Asian sector.

KEY WORDS hydrological index; precipitation; reliability; Standardized Precipitation Index (SPI)

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1. Introduction

Extreme droughts and floods result in tremendous economic, social, and environmental losses. Monitoring these precipitation variations is essential for developing a good prediction and warning system. It is also crucial to have a quantitative classification of these events so that policy makers and stakeholders can facilitate better mitigation measures. As such, a number of National Hydrological and Hydrometeorological Services are providing monitoring products on the national level, such as those by the Colorado Climate Center (CCC), the Western Regional Climate Center (WRCC) and the National Drought Mitigation Center (NDMC) in the United States, and Beijing Climate Center (BCC) in China. However, most of these products cover only a limited geographical region, despite the fact that impacts from prominent climate drivers such as the El Nino and Southern Oscillation (ENSO) are global in nature.

In view of the important need for real-time or near-real-time monitoring of precipitation over a wide region, the APEC Climate Center (APCC) has recently launched an experimental global drought monitoring product using the Climate Anomaly Monitoring System-Outgoing Longwave Radiation Precipitation Index (CAMS-OPI; Janowiak and Xie, 1999). Because it is available in real-time (http://www.cpc.ncep.noaa.gov/products/global_precip/html/wpage.cams_opi.html), CAMS-OPI is preferred to the Global Precipitation Climatology Project (GPCP; Huffman *et al*., 1997; Adler *et al*., 2003) data or the Climate Prediction Center Merged Analysis of Precipitation (CMAP; Xie and Arkin, 1997), even though the latter two products use both IR and microwave-based satellite estimates and are probably better quality-controlled. (GPCP and CMAP data are usually not uploaded until a few months later.) Here in this current paper, we assess the reliability of using CAMS-OPI, as well as other readily available global precipitation data, for monitoring East Asian precipitation changes in the large scale. Besides CMAPS-OPI, GPCP, and CMAP data, precipitation products from the National Centers for Environmental Prediction – Department of Energy (NCEP-DOE) Atmospheric Model Intercomparison Project (AMIP-II) reanalysis (R-2; Kanamitsu *et al*., 2002), the European Centre for Medium-Range

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Weather Forecasts (ECMWF) 40 Year Re-analysis (ERA-40; Uppala *et al*., 2005) and the Japanese 25-year Reanalysis (JRA-25; Onogi *et al*., 2007) are also assessed in this study. Our 'ground truth' is the newly available gauge-based high-quality precipitation dataset from the Asian Precipitation – Highly-Resolved Observational Data Integration Towards Evaluation of the Water Resources (APHRODITE's Water Resources; Yatagai *et al*., 2009). The seasonal-to-interannual precipitation variability from these aforementioned products will be examined. More importantly, the fidelity of maps of the Standardized Precipitation Index (SPI; McKee *et al*., 1993) – a widely used index adopted by WMO for drought monitoring (WMO Press Release No. 872, available at http://www.wmo.int/pages/mediacentre/press_releases/pr_872_en.html) – computed based on various precipitation products will be assessed. It is hoped that, through these intercomparisons, the reliability of these precipitation data can be better quantified, and further improvements of the datasets can be brought about in the future.

2. Precipitation datasets and SPI

The APHRODITE v0902, with which all other precipitation data are compared in this study, is a daily gridded precipitation dataset covering the Middle East, Russia, and monsoon Asia, and is available on $0.5^\circ \times 0.5^\circ$ and $0.25^\circ \times 0.25^\circ$ grids. The dataset, which covers the period of 1961–2004, was created by collecting rain gauge observation data across Asia through the APHRODITE project. The number of valid stations was between 5000 and 12 000, representing 2.3–4.5 times the data available through the Global Telecommunication System (GTS) network for precipitation products. In particular, besides GTS data, precompiled, and data collected for APHRODITE, rainfall records from hydrological–meteorological organisations of many countries in the region (including Japan, Korea, China, Mongolia, Taiwan, Philippines, Vietnam, Laos, Thailand, Cambodia, Myanmar, Malaysia, Indonesia, Bhutan, Bangladesh, India, Sri Lanka, Nepal, Pakistan, Uzbekistan, Kyrgyzstan, Iran, Turkey, and Israel) were also colleted by this project. After quality control, which includes screening and geographic location checks, the gauge-based dataset was then interpolated onto a 0.05° grid using the weighted mean method based on Spheremap (Willmott *et al*., 1985), and then re-gridded to 0.25° and 0.5° products using the area-weighted mean.

Regarding the quality of the APHRODITE dataset, Rajeevan and Bhate (2009) recently compared APHRODITE v0804 (based on about 2000 station observations over the Indian subcontinent) with the rain gauge network from the India Meteorological Department (IMD) (comprising more than 6000 stations). They showed that APHRODITE does, in general, correlate highly and significantly with the IMD rainfall data over most of India. Krishnamurti *et al*. (2009) also recommended the use of APHRODITE, as an improvement to the Tropical Rainfall Measuring Mission (TRMM), over India. These studies, and also the validation work carried out by Yatagai and Xie (2006), Yatagai *et al*. (2005; 2009) give us confidence that APHRODITE is a reliable dataset for studying rainfall variations over Asia. Finally, it is the only long-term product that incorporates measurements from a dense network of rain gauges in the Himalayas and mountainous areas in the Middle East, over which very scanty data were included in the GTS network. In a sense, APHRODITE can be considered as 'observations' and 'ground truth' around the Himalayas, the Middle East and Central Asia regions (Yatagai *et al*., 2007; 2009).

For the CAMS-OPI, GPCP, and CMAP datasets, over land they are dominated by rain gauge observations, and the difference between them is less than 10% nearly everywhere and greater than 10% only in regions where the rain gauge density is relatively sparse (Janowiak and Xie, 1999). On the other hand, precipitation products from NCEP-DOE R-2, ERA-40, and JRA-25 are model outputs, and strongly depend on the model physics. In this study, analyses are performed for the period from January 1979 to December 2001 (the continuation of ERA-40 has allowed for extension of the record up to 2001), the common period over which all data are available. Since the length of the record could affect the SPI calculation due to the changes in the shape and scale parameters of the gamma distribution (Wu *et al*., 2005), a common data period is used. Only terrestrial data within the region of 1.25–53.75 °N, 61.25–148.75 °E is considered in our analyses. All datasets are interpolated onto a $2.5^\circ \times 2.5^\circ$ grid for comparison.

There are several indices that measure the deviation of precipitation from historically established norms at a point for a given period of time. SPI (McKee *et al*., 1993) is one such index adopted to identify precipitation deficit and surplus for the most recent 1-month, 3-month, 6-month, and 12-month periods. SPI is found by first fitting the long-term precipitation record to a Gamma distribution; it is then transformed into a standardized normal distribution on an equal probability basis. The value of SPI for a particular time scale is then the 'z-score' from which the probability of occurrence of the corresponding anomalous precipitation can be calculated under the assumption of a normal distribution (McKee *et al*., 1993; Edwards 1997). On the basis of this index, extreme droughts and floods can be categorized accordingly (Table I). The advantage of using SPI is that it recognizes a variety of time scales, and provides information on precipitation deficit, percentage relative to the average, and probability. Because SPI is normalized, wetter and drier climates can be represented in the same way, and wet periods can also be monitored using SPI. Depending on the purpose, SPI can also be computed in a similar way with alternative inputs such as snowpack, stream flow, reservoir storage, soil moisture, and ground water.

Table I. Flood/drought conditions categorized according to the SPI value.

SPI values	Category
>2.0	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
−0.99 to 0.99	Near normal
−1.0 to −1.49	Moderately dry
−1.5 to −1.99	Severely dry
< −2	Extremely dry

3. Seasonal-to-interannual variability from different precipitation products

First, the quality of each dataset in terms of its seasonal-to-interannual variability of precipitation over East Asia is assessed. To represent the skills of various precipitation datasets in the whole East Asian region, temporal correlation values are averaged over all grid points. (In addition, monthly correlations for each of the 12 calendar months are further averaged to arrive at a single representative value; correlation on the 3-, 6-, and 12-month time scales are treated in a similar way.) Figure 1 shows the averaged correlation as a function of the time scale, based on the gauge-satellite-based datasets as well as reanalysis products. It can be seen that GPCP, CMAP, and CAMS-OPI all have superior skills compared to the reanalysis datasets. CMAP and CAMS-OPI results are very close to each other, probably due to the fact that the OPI satellite estimation method has been trained based on the CMAP analyses. It is noteworthy that their skills are relatively stable and do not decrease noticeably as the time scale increases. On the other hand, all reanalyses give poorer correlation, especially for longer time scales. Finally, we note that JRA-25 is better than NCEP-DOE R-2 and ERA-40 over East Asia, consistent with the observation that the performance of the long time series of the global precipitation is the best among all the reanalyses (Onogi *et al.*, 2007).

The temporal correlation coefficients between APHRODITE and CAMS-OPI, and those for JRA-25 based on the various timescales, are given in Figure 2. Both sets of results show relatively low correlation in Mongolia, western China to the Himalayas. The latter may be attributed to the orographical precipitation along the Himalayas, which is specially treated in the APHRODITE data (Yatagai and Xie, 2006). Overall, it is remarkable that CAMS-OPI correlates well with APHRODITE data on the time scales from 1 to 12 months over most regions (although it gives low correlation in Burma; e.g. Figure 2(a) and (c)). Compared with CAMS-OPI, it is obvious that JRA-25 gives lower correlation on all time scales. On the monthly-to-seasonal scale, the 'skill' of JRA-25 is especially low in Southeast Asian regions such as Indochina and the Philippines during the wet season (Figure 2(d) and (h)). This may

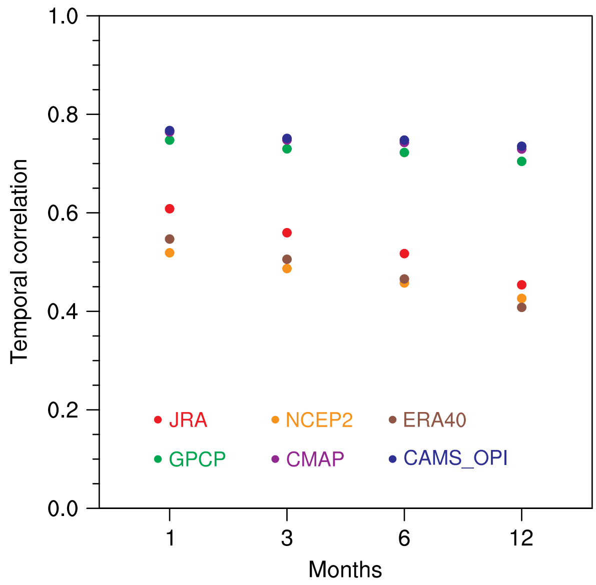

Figure 1. Temporal correlation of anomalous rainfall between APHRODITE and JRA-25 (marked in red), NCEP-DOE R-2 (orange), ERA-40 (brown), GPCP (green), CMAP (purple), and CAMS-OPI (blue) based on different timescales. Correlation coefficients are averaged over all grid points over East Asia.

be related to the bias of the JRA-25 rainfall over East Asia, which is the largest in the wet season (figures not shown). Onogi *et al.* (2007) also noticed that JRA-25 overestimates the magnitude of the summer monsoon precipitation, especially in the region covering India and the Bay of Bengal. Comparing the JRA-25 1-month (or 3-month) with the 12-month correlation maps, it can also be discerned that the overall correlation in the whole region decreases as the time scale increases. On the other hand, there is no decay of skill for CAMS-OPI as the time scale increases.

4. Impact on monitoring precipitation deficit and surplus

Figure 3 gives the pattern correlation between SPI maps based on APHRODITE data and those from other datasets for various time scales. (For each particular time scale, SPI results are averaged over all calendar months, similar to the procedure outlined above for the regionally averaged temporal correlation.) It shows that the gauge-satellite-based data are superior in capturing the spatial patterns of precipitation deficit and surplus in East Asia; all of them give average pattern correlation of above 0.6 (as relative reference value for pattern correlation; Hollingsworth *et al.*, 1980; Wilks, 1995). CAMS-OPI is found to be slightly better than GPCP and CMAP in reproducing the SPI patterns for all time scales. Again, the skill of the reanalysis products in capturing the SPI patterns shows degradation as the time scale increases, consistent with the previous analysis (Figure 1). Among the reanalysis datasets, the performance of JRA-25 is the best and is more reliable on the short (1–3 month) than on the long time scales (e.g. 12 months). With the

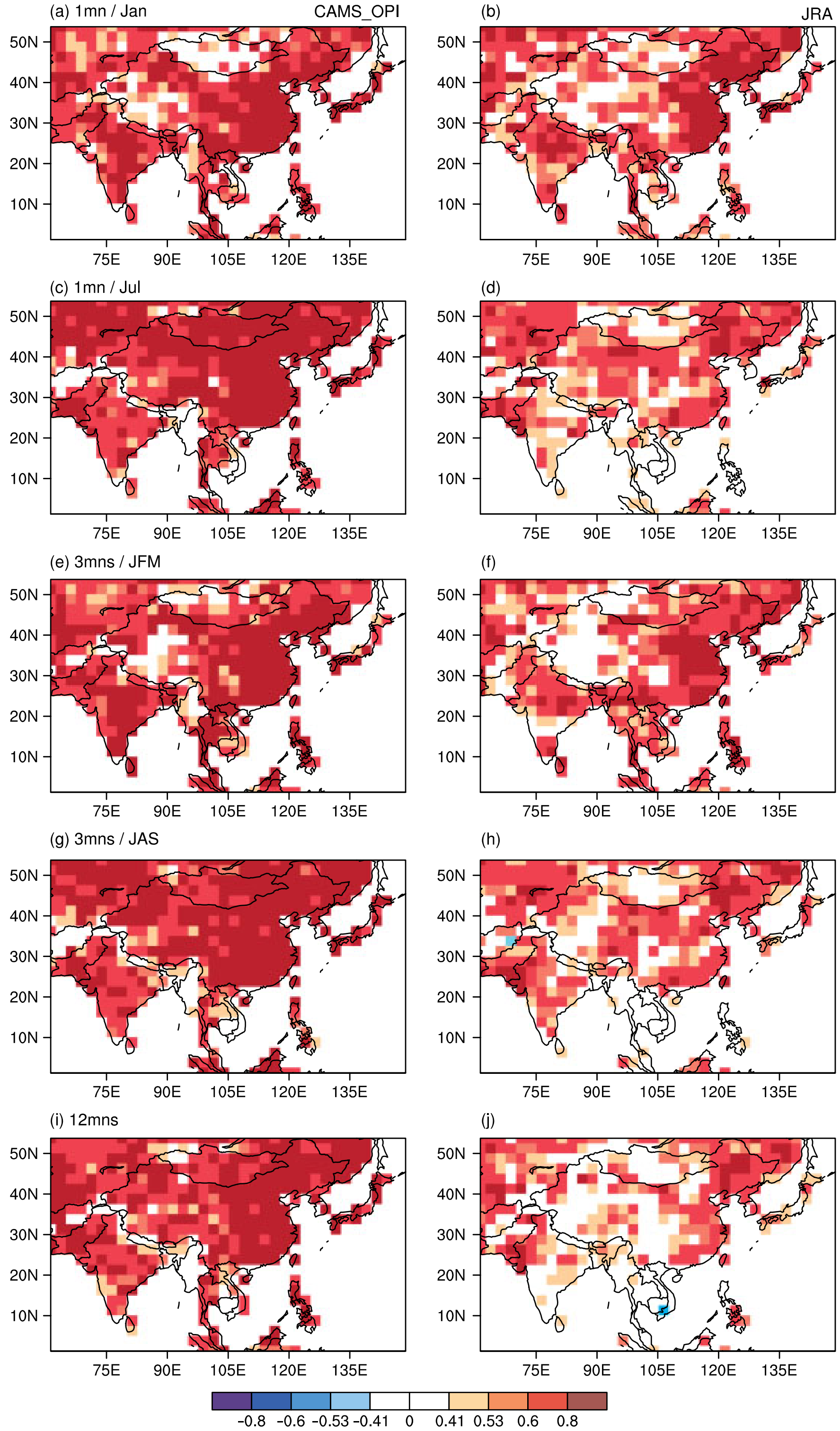

Figure 2. Temporal correlation coefficients between anomalous rainfall based on (a, c, e, g, i) APHRODITE and CAMS-OPI, and between (b, d, f, h, j) APHRODITE and JRA-25, based on the timescales of (a, b, c, d) 1 month for (a, b) January and (c, d) July, (e, f, g, h) 3 months for (e, f) JFM and (g, h) JAS, and (i, j) 12 months. The correlation values of 0.41 and 0.53 correspond to the 5 and 1% levels of significance, respectively.

exception of JRA-25 on the 1-month time scale, none of the reanalysis datasets give a pattern correlation (with APHRODITE) higher than the value of 0.6.

The previous discussion focuses on the average performance of each dataset over the entire period. However, it is also of interest to see how well they capture individual drought or flood episodes. In particular, we have calculated SPI maps based on APHRODITE, CAMS-OPI, and JRA-25 for some specific cases. In general, it is found that both CAMS-OPI and JRA-25 are very capable in capturing ENSO impacts, Indian summer monsoon rainfall variations over land (which are generally related

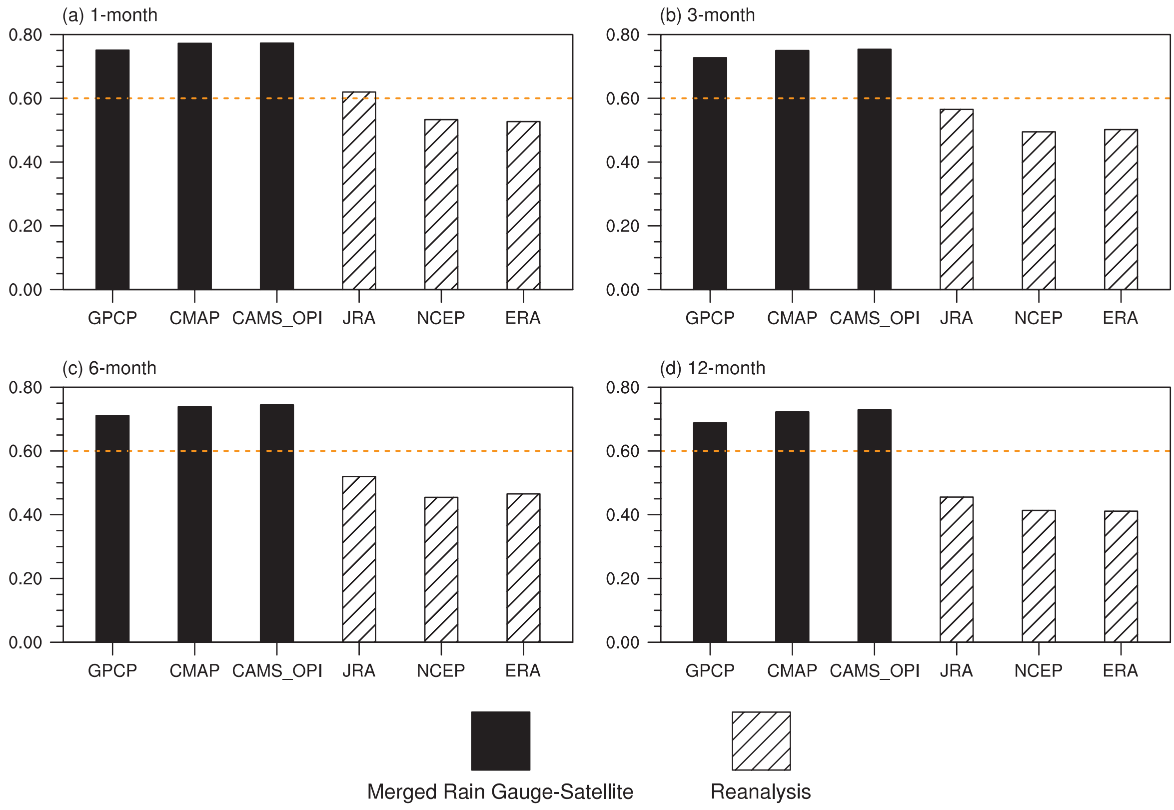

Figure 3. Pattern correlation coefficients between SPI maps based on APHRODITE and those using various rainfall products, for the timescale of (a) 1 month, (b) 3 months, (c) 6 months, and (d) 12 months. Solid bars denote merged rain gauge-satellite products and hatched bars denote reanalyses. The dotted line indicates the relative reference value for pattern correlation. This figure is available in colour online at wileyonlinelibrary.com/journal/joc

to ENSO; Adler *et al.*, 2003) (figures not shown). The lowest skill given by *both* satellite-based estimates and reanalyses was found in the year 1980, when the pattern correlation for the 3-month SPI can be as low as 0.4 (0.2) based on the CAMS-OPI (JRA-25) data. This might be due to the influence from major volcanic eruptions during that year (e.g. those from St Helens; Adler *et al.*, 2003). In Figure 4 we compare the SPI maps from CAMS-OPI and JRA-25 with those based on APHRODITE, for the drought event in East Asia during May 2001. This was the most severe drought that struck Korea in the last 100 years. On the 1-month to 12-month timescale in May 2001, both CAM-OPI and JRA-25 shows good agreement with APHRODITE in East Asia. On the 1-month timescale, dry conditions in eastern Kazakhstan are obvious in APHRODITE and CAMS OPI, but these signals do not appear in the reanalysis. On the other hand, JRA-25 shows better performance for 3-month than 1-month time scale, but it tends to overestimate the intensities of dry signal over East Asia and wet signals over western Mongolia and southwestern China. For the 6-month and 12-month SPI, JRA-25 gives very wet signals in the vicinity of Lake Balkhash and over western Mongolia, compared to those from APHRODITE. The wet conditions in western Mongolia were persistent from 3- to 12-month time scale. It appears that those erroneous signals (for this case) persistently show up in maps with longer and longer timescale, probably leading to the erosion skill of SPI maps as the time scale increases.

5. Summary

We have quantified the reliability of three gauge-satellite-merged precipitation products and three reanalysis precipitation datasets for monitoring East Asia precipitation variations. The ground truth is the gauge-based precipitation data from the APHRODITE project. CAMS-OPI, which is now used in the APCC global extreme drought/flood monitoring, is able to represent large-scale precipitation variations reasonably well on time scales from 1 to 12 months. In fact, SPI maps given by CAMS-OPI are found to be slightly better that those computed using GPCP or CMAP data. Among the different reanalysis products, the performance of JRA-25 is the best for monitoring precipitation variations in East Asia. However, its skill is acceptable only for extreme events of short time scales (from 1 to 3 months); for longer time scales, there is an appreciable decrease of skill in the SPI maps. A noticeable decay of skills is also found in other reanalysis products, but not in the gauge-satellite-based precipitation datasets.

The aforementioned problem of degradation of skill could be related to the accumulation of errors, which seems to be particularly serious in the reanalysis rainfall. In some cases, the erroneous signals persistently show up

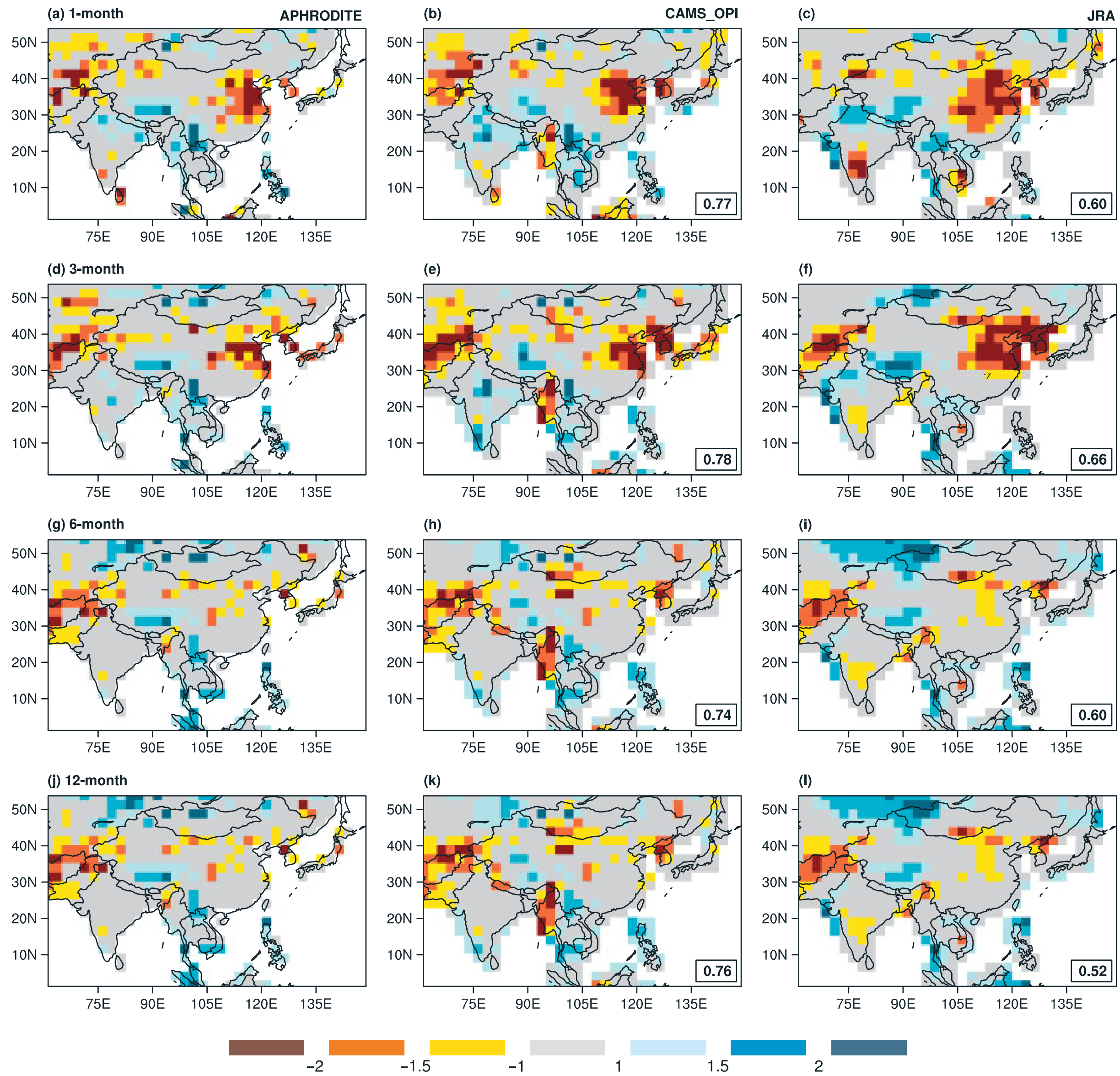

Figure 4. SPI maps based on (a, d, g, j) APHRODITE, (b, e, h, k) CAMS-OPI, and (c, f, i, l) JRA-25 data, for (a, b, c) the 1-month, (d, e, f) the 3-month, (g, h, i) the 6-month, and (j, k, l) the 12-month ending in May 2001. Pattern correlation coefficients between CAMS-OPI and APHRODITE, and those between JRA-25 and APHRODITE, are shown at the bottom right of the middle and right panels, respectively.

Table II. Pattern correlation coefficients between mean fields based on APHRODITE and those using various rainfall products, for the timescale of 1, 3, 6, and 12 months.

Month Data	Satellite-Gauge Merged Products			Reanalyses		
	GPCP	CMAP	CAMS−OPI	JRA-25	NCEP-DOE R-2	ERA-40
1	0.89	0.86	0.88	0.79	0.72	0.74
3	0.92	0.88	0.90	0.82	0.76	0.78
9	0.92	0.90	0.91	0.83	0.77	0.79
12	0.93	0.91	0.92	0.84	0.78	0.81

in the SPI maps as the timescale increases, thus eroding the skill of the SPI patterns. We have also examined the pattern correlation between the climatological mean precipitation from reanalysis, and that from APHRODITE, based on various timescales. Interestingly, the monthly, seasonal, and annual rainfall maps from reanalyses all correlate well with those from the APHRODITE data (Table II). In particular, there is no decay of the pattern correlation coefficients as the time scale increases. This suggests that such a degradation problem is not directly related to the mean rainfall bias in the reanalyses. (In other words, removal of the mean bias cannot solve this problem.) Apparently, more work needs to be done to improve the quality of reanalysis products for the latter to be useful for monitoring (especially long-term) drought/flood events.

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