The Vietnam Gridded Precipitation (VnGP) Dataset: Construction and Validation

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Abstract

In this study, daily-observed data from 481 rain gauges were used to build a new gridded rainfall dataset for Vietnam based on the Spheremap interpolation technique. The new dataset, called Vietnam Gridded Precipitation (VnGP) Dataset has the resolution of 0.25° and covers the period 1980–2010. The validation was done for VnGP by assessing the spatial distribution, correlations, mean absolute errors, root mean square errors with gauge observations. Results showed that VnGP had a relatively better performance compared to the datasets that used different interpolation techniques or used less number of input rain gauges. VnGP is currently available at the Data Integration and Analysis System (DIAS) managed by the University of Tokyo, Japan.

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1. Introduction

Understanding rainfall characteristics is very important for monitoring and mitigating water-related disasters around the world. Many countries have so far established a dense rainfall network with the capability of collecting data continuously and automatically. However, several countries, including Vietnam, still have a relatively sparse network with manual collecting procedures (Ngo-Duc et al. 2013).

Besides rainfall data sources at stations, some global/regional combined gridded rainfall datasets have also been used, such as the monthly Climate Research Unit (CRU) data (Harris et al. 2014), the Global Precipitation Climatology Project (GPCP) (Adler et al. 2003), the Global Precipitation Climatology Centre (GPCC) (Schneider et al. 2014), the 6-hourly National Centers for Environmental Prediction (NCEP)/National Center for Atmospheric Research (NCAR) Corrected by CRU (NCC) (Ngo-Duc et al. 2005), the monthly and pentad Climate Prediction Center (CPC) Merged Analysis of Precipitation (CMAP) (Xie and Arkin 1997), the daily Asian Precipitation – Highly-Resolved Observational Data Integration Towards Evaluation (APHRODITE) (Yatagai et al. 2012) datasets. Each dataset has merits and demerits and was built based on different techniques and different input data sources. For example, CRU and APHRODITE, with the resolutions of 0.5° and 0.25°, respectively, were only based on ground stations, whereas GPCP was a combination from surface rain gauges, geostationary and low-orbit satellite data, leading to a set of rainfall data on both land and oceans. The gauge data used in the current global/regional gridded datasets are mainly archived from the World Meteorological Organization (WMO) Global Telecommunication System (GTS) synoptic weather reports (SYNOP) and monthly climate reports (CLIMAT), and from additional data sources provided through bilateral contacts (e.g. Schneider et al. 2014; Yatagai et al. 2012). Therefore, the number of gauges ingested in the currently available global/regional gridded datasets is often limited and much less than the actual existing rainfall stations. Several recent efforts have been conducted in order to build new gridded datasets for specific regions based on a denser observation network. For example, Herrera et al. (2012) used 2756 quality-controlled stations over peninsular Spain and the Balearic islands to build a daily gridded dataset at 0.2° horizontal resolution from 1950 to 2003. Chen et al. (2010) used observed data at 753 stations for the period 1951–2005 to build a daily gridded dataset of 18km × 18km covering China. As part of the APHRODITE project, Kamiguchi et al. (2010) constructed historical (1900–) high-resolution (0.05°) daily precipitation data over Japan.

To build a gridded rainfall dataset, spatial interpolation methods (SIM) are often used. Li and Heap (2014) made a review of popular methods in order to provide guidelines and suggestions regarding the application of SIMs. SIMs are often divided into three categories, including non-geostatistical interpolation methods, geostatistical interpolation method and combined methods. It was found that there is no method that is superior to the others in the general cases. The optimal method can only be identified for a specific case, depending on various parameters such as data density, spatial distribution of samples, data quality, surface characteristics, etc. It is important to note that most methods produce similar results when data density is high (Li and Heap 2014).

Some of the applications of gridded rainfall datasets are to be used to assess the performance of a climate models and/or to validate satellite derived rainfall products. It is worth mentioning that gridded products are generally considered as the true values in most of climate change impact studies (Suyer et al. 2013). However, Juneng et al. (2016), under the framework of the Coordinated Regional Climate Downscaling Experiment (CORDEX) – Southeast Asia, showed notable differences in magnitude among APHRODITE, CRU, GPCC, and the Tropical Rainfall Measuring Mission (TRMM) 3B42 (Huffman et al. 2007) datasets over the Southeast Asian region, including Vietnam. One should note that in the current available gridded datasets covering Vietnam such as APHRODITE, CRU, GPCC, the number of gauges used is less than 100 stations (not shown). Hence, there is a need to build a new reliable gridded rainfall dataset that could incorporate the information from a denser observation network over Vietnam. Such a new gridded dataset could be used to assess specific characteristics of rainfall and can help avoid misleading conclusions with respect to the performance of climate models over Vietnam.
2. Data and methodology

In this study, we initially collected the daily-observed rainfall data from 614 stations of the National Hydro-Meteorological Service of Vietnam (NHMS). Then the data were checked with a 5-sigma rule. The outlier values were consequently identified and reported back to the staffs of the Data and Information Center of NHMS for a manual verification. Finally, only 481 stations among the 614 ones were selected (Fig. 1) so that no stations have missing data for more than 3 years over the study period of 1980–2010 (Supplementary Fig. S1). More precisely, among 481 stations, there are 386 stations (~80.25%) with 0-year missing data, 48 stations (~9.98%) with 1-year missing data, 24 stations (~4.99%) with 2-year missing data, and the remaining 23 stations (~4.8%) with 3-year missing data. The daily data is defined as 24-hour rainfall amount accumulated from 19 LT (12UTC) of the previous day.

To build a new gridded rainfall dataset, the first step is to create datasets at the resolution of 0.25° with the aim to meet the resolution of a standard CORDEX product (Juneng et al. 2016; Ngo-Duc et al. 2016). To interpolate station information to 0.25° gridded datasets, different methods are used including Cressman (Cressman 1959), Inverse Distance Weighted (IDW) (Shepard 1968), ordinary Kriging (Switzer 2014), and Spheremap version 99.8a (Willmott et al. 1985). The different products obtained with the different interpolation methods are named Cressman, IDW, Kriging, and Spheremap, respectively.

The new datasets are generated for the period 1980–2010, except for Cressman. One should note that the Cressman method requires a background grid dataset (Cressman 1959). In this study we used the APHRODITE dataset for the Monsoon Asia (version V1103R1, available for the period 1951–2007) (Yatagai et al. 2012) as a first-guess dataset for Cressman; the radius of influence chosen is 52 km and the overlapping data period is 1980–2007. The number of rainfall stations of Vietnam that were used for APHRODITE varies significantly, depending on month and on year. Thus the observations from the stations used in APHRODITE could be double used for the Cressman method. However, this double usage is acceptable because the Cressman interpolation readjusts the value of a grid point based on the difference between the observation data and background data at the grid point and a weighting function depending on the distance between the station and the grid point. If the grid point value of APHRODITE is already close to the observation data, the adjustment will be consequently small.

The formula of the Cressman method is described as follows:

\[
\text{fout} = \text{fbg} + \sum_{k} \sum_{i} w_{ik} (\text{obs}_{ik} - \text{fbg})
\]

where \(\text{fout}, \text{fbg}\) and \(\text{obs}\) are output, background and observed data, respectively; \(i, k\) are index used for locating grid cells; \(K\) is the number of grids involved in the interpolation; \(w_{ik}\) is a weighted coefficient, given by:

\[
w_{ik} = \left\{ \begin{array}{ll}
\frac{R^2 - r_{ik}^2}{R^2 + r_{ik}^2}, & \text{if } r_{ik}^2 \leq R^2 \\
0, & \text{if } r_{ik}^2 > R^2
\end{array} \right.
\]

where \(R\) is the predefined radius of influence, \(r_{ik}\) is the distance between the \(i^{th}\) grid and the \(k^{th}\) one.

Regarding IDW, the value of an unsampled point is calculated using the 25 nearest stations with the weight of each station estimated as the reciprocal value of the distance from the station to the unsampled point and the power parameter is set to 2. The Kriging method also estimates the weight of each station from the 25 nearest ones that contributes to the final value at an unsampled location. Here, the weight vector is entirely determined by the station configuration and the covariance model between station points, i.e. the geographical distances or directions between the stations and the unsampled location are responsible for the variation of data values on the surface. The ordinary Kriging method, which is used in this study, assumes that data mean is constant in the local neighborhood of each unsampled point, leading the Kriging weights to sum to 1 (Switzer 2014).

In this study, the Spheremap interpolation method is also applied. Spheremap takes into account the spherically-derived distances and angles between the grid points and stations. Spheremap has been implemented at the Global Precipitation Climatology Centre (GPCC) since 1991 (Schneider et al. 2014). Willmott et al. (1985) identified weights \(S_k\) for the interpolation procedures according to three categories of distance as follows:

\[
S_k = \begin{cases} 
\frac{27}{4r_j} \left( \frac{d_{j,k}}{r_j} - 1 \right), & \text{if } d_{j,k} \leq r_j/3 \\
0, & \text{if } d_{j,k} > r_j
\end{cases}
\]

where \(r_j\) is the search radius and \(d_{j,k}\) is the distance from grid point \(j\) to nearby data point \(k\). In this study, the information from 25 nearest stations is used to estimate the search radius, and then the value of each grid point. Thus, the weighting function of Spheremap applied here is more suitable to represent rainfall fields with high locality, for example, over the central region as shown in Fig. 2.

For the IDW, Kriging and Spheremap methods, sensitivities of the results with the number of nearest stations have been conducted. The number of nearest stations has been changed from 15 to 35 with steps of 5. Because box plots and spatial distributions do not display significant differences with different number of stations (not shown), thus 25 nearest stations are used. For Cressman, 52 km is chosen for the radius of influence, so that the information of about 25 stations on average is also used for one grid point.

The APHRODITE dataset has the resolution of 0.25° and covers the period 1951–2007. In Section 3, APHRODITE is also used for comparing with the new gridded datasets for the overlap period 1980–2007.

Fig. 1. Location of 481 rainfall stations. The blue points indicate 15 locations of the stations listed in Table 1 that are discussed in Results Section. The red points indicate the locations of 11 stations at which APHRODITE performs the best, that are also discussed in Results Section.
3. Results

Figure 2 represents the December-January-February (DJF) and June-July-August (JJA) seasonal rainfall averaged for the period 1980–2007 of the gauge observations and the different gridded datasets. In general, the different interpolation methods give quite similar rainfall patterns with APHRODITE as well as with the gauge observations. The gridded products can spatially capture the seasonal variations and the topographical influences on rainfall. One can note the similarity among the datasets at the heavy rainfall centres in South Central in winter, in Northwest areas and in Central Highlands in summer.

However, there are still differences among the datasets. IDW and Kriging tend to smooth out the rainfall patterns. Meanwhile, Cressman and Spheremap clearly show the east-west disparity in South Central and in Central Highlands that are in agreement with the gauge observations. One should note that the smoother characteristic of IDW and Kriging remains with the different choices of the used station numbers (not shown).

Figure 3 shows the cumulative frequency distribution (CDF) of the gridded datasets over 481 stations in comparison with that of APHRODITE and that of gauge-observations. There is a clear difference in the frequency of precipitation values from 50–500 mm per month. For example, one can recognize the higher frequency in the low rainfall ranges of APHRODITE than that of the other gridded datasets, that could be due to the smaller number of rain gauges used in building APHRODITE. It is also noted that the CDF curves of the four interpolation methods resemble well each other; and are closer to the observed CDF in the high rainfall ranges compared to APHRODITE.

To see the similarity of the datasets, the cross-correlation between them for the daily rainfall over the period 1980–2007 is given in Fig. 4. There are high correlations between the interpolation methods, ranging from 0.7 to 1. IDW, Kriging and Spheremap are highly correlated with each other, while the Cressman method shows a relatively lower correlation in Central Highlands. The correlations between APHRODITE and the newly build datasets are relatively low. One point worth noting is that although Cressman used APHRODITE as the first-guess dataset, at the end of the interpolation process, the influence of the background data has been greatly reduced, proven by the low correlation between APHRODITE and Cressman over the area where few station observations were used for building APHRODITE (not shown).

In order to statistically quantify the performance of the datasets, the nearest interpolation method is used to extract time series at 481 stations for the period 1980–2007; then the extracted data are evaluated with gauge observations by using correlation (CORR), mean absolute error (MAE) and root mean square error (RMSE). Figure 5 shows that APHRODITE has a lower CORR,
higher MAE and RMSE compared to the other datasets. IDW is marginally better than Cressman and Kriging; and Spheremap performs the best among the products. There are also cases where the correlations between the interpolation methods and the stations are relatively low. One should note that the grid resolution is 25 km; therefore the rainfall data interpolated for a grid point could be quite different from that observed at the station inside the grid, particularly over a region with a rather complicated topography, of which the rainfall regime could vary sharply from one location to another. These differences explain the low correlations found in Fig. 5.

Note that the above comparisons are not really fair for APHRODITE. The data of 481 stations are used to build the gridded datasets; then the statistical values shown in Fig. 5 are computed at the same set of stations, which gave significant advantages to the newly build datasets in comparison with APHRODITE which used a much less number of stations over Vietnam. Thus a question arises: how about the performance of the different interpolation methods at the stations at which no gauge observations are used for building the datasets?

In order to address the above question, 15 “worst” stations and 11 “best” stations distributed over the 7 sub-climatological regions of Vietnam (Phan et al. 2009; Vu et al. 2014) are respectively removed from the set of 481 stations used in this study (Fig. 1). At the 15 “worst” stations, APHRODITE has either the lowest correlation, the highest MAE, or the highest RMSE with the gauge observations in a sub-climatological region (Table 1). Reversely, the 11 “best” stations are selected based on the opposite criteria. Then, the daily data from the remaining 466 (470) stations are used to build again the gridded datasets by applying the four interpolation methods discussed in Section 2.

Figures 6 and S2 evaluate the performance of the newly obtained products at the stations selected above by comparing to the gauge observations. It is important to highlight that with the dependent data (right panels of Figs. 6 and S2), Spheremap is better than the other three interpolation methods. However with the independent data (left panels), Spheremap is not always the best one. Therefore, there is a possibility that Spheremap is simply able to fit the observation data better, but not necessarily supe-

### Table 1. List of 15 stations at which APHRODITE has either a low CORR, a high MAE or a high RMSE with the gauge observations.

| # | Station name | Lon (°E) | Lat (°N) | CORR | MAE (mm d⁻¹) | RMSE (mm d⁻¹) |
|---|-------------|---------|----------|------|--------------|--------------|
| 1 | TuanGiao    | 103.42  | 22.58    | 0.091| 8.282       | 18.220       |
| 2 | P-ChuMoiTV  | 105.78  | 21.88    | 0.219| 5.919       | 13.105       |
| 3 | BacQuang    | 104.87  | 22.50    | 0.358| 11.05       | 32.144       |
| 4 | VinhYen     | 105.60  | 21.32    | 0.451| 5.037       | 12.490       |
| 5 | P-MaiSuu    | 106.55  | 21.25    | 0.483| 5.114       | 13.639       |
| 6 | P-ThongNhatNT | 105.48  | 20.08    | 0.469| 4.726       | 12.431       |
| 7 | ALuoi       | 107.28  | 16.22    | 0.614| 8.019       | 25.087       |
| 8 | NamDong     | 107.72  | 16.17    | 0.715| 7.281       | 26.722       |
| 9 | P-TanMyTV   | 106.47  | 17.70    | 0.104| 6.773       | 19.407       |
| 10| P-GiaVuc    | 108.57  | 14.70    | 0.418| 9.183       | 28.219       |
| 11| P-NamBan    | 108.33  | 11.85    | 0.371| 5.017       | 10.473       |
| 12| P-DaTeh     | 107.50  | 11.57    | 0.540| 7.526       | 14.387       |
| 13| PhuocLong   | 106.98  | 11.83    | 0.434| 6.657       | 14.966       |
| 14| P-LongSon   | 106.83  | 10.88    | 0.257| 5.633       | 13.019       |
| 15| P-TucTrung  | 107.45  | 11.25    | 0.397| 6.990       | 14.810       |
rior to the other methods. It is also worth to emphasize that the obtained results cannot support that the interpolation method(s) used in this study has advantages over the one used in constructing APHRODITE. However, the use of the dense observation network contributes to improve the accuracy of gridded rainfall.

At P-TanMyTV (station#9, blue dot) (Fig. 6), the correlations between the gridded datasets with the gauge-observations are low. One should note that this station is located in Central Vietnam, close to the coastal line (Fig. 1) and surrounded by a rather complicated topography with mountains. Therefore the rainfall characteristics of this station are different from that of the surroundings (not shown), leading to the fact that the correlations mentioned above are low when the information of the neighbouring stations are taken into account.

4. Conclusions

The different interpolation methods are used in this study to build the different daily gridded rainfall datasets over Vietnam. In general, the built products well represent the spatial pattern and the seasonal variations of rainfall. The IDW and Kriging methods tend to show smoother rainfall patterns compared to that of Cressman and Spheremap. Although Spheremap shows a relatively better performance compared to the other methods with the dependent verification, it is not always the best with the independent data. It is shown that the utilization of more rain gauges improves the accuracy of the gridded rainfall, explaining why APHRODITE has a statistically lower performance over Vietnam compared to the newly built datasets.

As having a relatively better performance with the dependent validation, the Spheremap product is chosen as a final product, called Vietnam Gridded Precipitation (VnGP) dataset, which is released to the community. The VnGP dataset at 0.25 degree of resolution has been registered to the Data Integrated and Analysis System (DIAS) and can be accessible from http://dias-dmg.tkl.iis.u-tokyo.ac.jp/dmm/doc/VnGP_025-DIAS-en.html. A version of VnGP at 0.1 degree of resolution has been also created for the period 1980–2010 by using the same Spheremap technique and been registered to DIAS at: http://dias-dmg.tkl.iis.u-tokyo.ac.jp/dmm/doc/VnGP_010-DIAS-en.html. The VnGP dataset at 0.1 degree of resolution should be used with caution on quality checking before it is used.

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