

STUDY ON QUANTIFICATION OF AREAL MEAN PRECIPITATION USING SATELLITE-GAUGE MERGING PRECIPITATION

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Abstract

Satellite based precipitation product (GSMaP-MVK) can be reliably used to estimate the Areal Mean Precipitation error based on “Sample Design method” (*Esdd*) with the effort to mitigate the problem of sparse data, especially severe in poorly gauged river basins. In addition, the satellite-gauge merging precipitation would reduce significantly the magnitude gaps between the satellite rainfall estimations and the rain gauge data. In this study, the capability of satellite-gauge merging precipitation using GSMaP-MVK and local dense rain gauge data with bias reduction approach to evaluate the AMP is investigated. The main finding is that satellite-gauge blending data which incorporates a dense rain gauge measurements shows the better capability to evaluate AMP using *Esdd* index than the original satellite only precipitation estimations. However, *Esdd* quantification performances of satellite-gauge blending precipitation are inferior to the original satellite only precipitation product GSMaP-MVK when the number of blended rain gauges is not large enough.

Keywords: areal mean precipitation; remote sensed precipitation product; satellite-gauge merging; rainfall runoff simulations.

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1. Introduction

Areal Mean Precipitation (AMP) is the main input of lumped conceptual models. In that sense, the accuracy of AMP would be one of the main factors that control the accuracy of rainfall runoff (RR) modelling. Nandakuman et al. [1] investigated the impact of climate data on RR model performances and concluded that the systematic errors in rainfall impose the most severe effect on flow predictions. Chaubey et al. [2] examined the model outputs uncertainties due to spatial variability of rainfall and founded that highly variations of rainfall over the space leads to large uncertainties in the modeled outputs. Therefore, estimating the AMP error is vitally important. Researches on this problem are necessary to give the guidance to future research work in order to improve the accuracy and robustness of the RR models.

Quantifying the AMP uncertainty is a long concerning issue. The effect of gauge density on the correctness of AMP estimation has been studied intensively. In history, the AMP error was estimated using historical measurements rainfall data set. The relation between AMP error caused by sampling error with the gauge density, storm duration, storm type and season has been studied intensively [3–7]. Moulin et al. [8] has proposed a reliable estimation of AMP uncertainty when AMP is obtained through the interpolation of the rain gauge measurements.

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However, it is difficult to grasp the spatial distribution of precipitation (as well as AMP) properly from limited number of rain gauge. Therefore, Hieu et al. [9] investigated the capability of surrogate global remote sensing precipitation to quantify the AMP. The study concluded that global remote sensing precipitation GSMaP-MVK can be used to estimate AMP uncertainties over a catchment accounting for the gauge number as well as the spatial and temporal discretisation of the rainfall field (i.e. using AMP error index based on sample design method called *Esdd*).

Because of inadequate number or time series of meteorological stations, there have been many research efforts on producing alternative meteorological data including remote sensing precipitation and satellite-gauge merging precipitation. VIC-3L hydrological model forced with the satellite meteorological datasets was applied for simulating the daily river flow of Red River System in Vietnam [10]. In order to improve the quality of satellite only precipitation for RR modelling application, Hieu and Ishidaira [11] assessed numbers of satellite-gauge blending algorithms to produce daily precipitation from remote sensing precipitation and rain gauge observations in different climatic regions. The study blended the global GSMaP-MVK with the local good number of rain gauge number. The conclusion is that the satellite-gauge merging precipitation using bias-reduction method can reduce the magnitude gaps between the satellite rainfall estimations and the rain gauge data, which leads to significant improvement of RR model performance efficiency.

The raising question is that how is the capability of satellite-gauge merging precipitation to grasp the spatial variation of the rainfall field or to evaluate the AMP uncertainty? This study aimed at investigating the ability of satellite-gauge merging precipitation using bias reduction method to estimate the AMP uncertainty with the *Esdd* index, which is based on sample design method. The effects of rain gauge density on the performances of satellite-gauge merging precipitation regarding *Esdd* computations are also investigated.

2. Study area and methodology

2.1. Study area

We included basins in a wide range of latitudes and under different climatic conditions (tropical monsoon and temperate climate) in three different Asian countries (Japan, Vietnam, and South Korea). The Hyeonsan and Fuji basins are located in mid-latitude area of South Korea and Japan, respectively, and they have relatively dense rain gauge networks. On the other hand, the Da and Upper-Cau river basins are located in the northern part of Vietnam in a tropical climate area, and they have much lower rainfall gauge densities. Their details can be found in Table 1.

Table 1. Summary of characteristics of 4 study basins

	Fuji	Da	Upper-Cau	Hyeonsan
Country	Japan	Vietnam	Vietnam	South Korea
Area (km ²)	3570	45900	2760	1167
Gauge number	88	22	7	14
Simulation period	2003–2007	2000–2006	2000–2006	2000–2005

Fuji River (Fig. 1a) is located in central Japan; it originates in the Southern Alps and is surrounded by many high mountains in the west (peaks over 3000 m) and the north (peaks over 2000 m). Because of the geological features are very complex and fragile, the spatial rainfall pattern varies significantly

annual rainfall in the Kofu Basin is as low as 1100 mm. The middle and lower reaches experience more precipitation, with high average values ranging from 2000 to 2500 mm. The whole basin receives mean annual precipitation of around 2100 mm. The basin lies in an inland mid-latitude climate region with hot and humid summers, and cold and dry winters. The temperature differences between summer and winter are extreme, with average temperatures of 26°C and 3°C, respectively.

Da River Basin (Fig. 1b) is a humid catchment (annual relative humidity of 82%; 85–90% in the rainy season) and is the biggest branch of the Red River Basin, which is located in a diverse and complex topographical area. Its climate is tropical monsoonal with two distinct seasons: a warm and humid summer, and cool and dry winter. Rainfall is distributed unevenly over the catchment, in both time and space, which is attributed to many factors such as the elevation of the topography and the orientation of mountains. The annual rainfall in the Hoang Lien Son mountain chain, which includes many high mountains (above 2800 m), is very large, from 2000 to 3200 mm per year because the high mountains in the Pusilang mountain chain block the southwest monsoon that causes high rainfall on the east side of the basin. Meanwhile, the west side of the Da River Basin is sheltered from the wind, which results in a lower annual rainfall, from 1800–2000 mm in Muong Nhe Province and 1200–1600 mm in Son La and Moc Chau Plateaus.

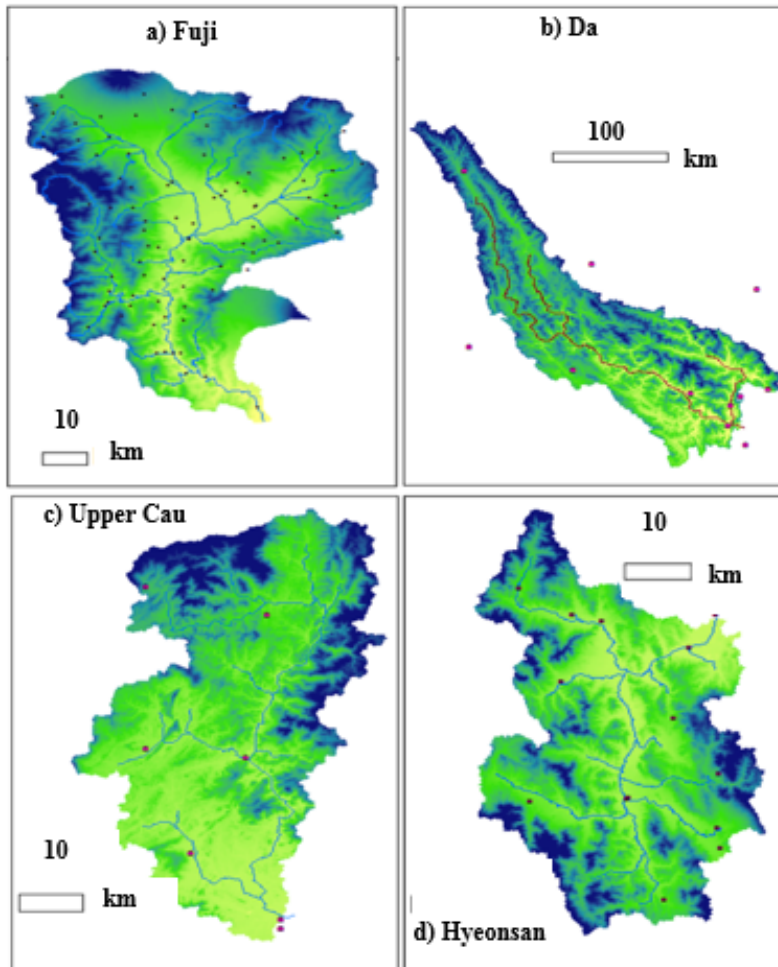


Figure 1. Study area map: a) Fuji; b) Da; c) Upper Cau and d) Hyeonsan

The drainage area covers the Upper-Cau River Basin to the gauging station Gia Bay in Thai Nguyen, with a drainage area of 2,760 km². As with the Da River Basin, it is located in a humid, subtropical climate region with two distinct seasons. The rainy season, which provides more than 80% of the total annual rainfall, usually starts in May and ends in September. The topography of the Upper Cau River Basin (Fig. 1c) includes mountainous areas, with only a few mountain peaks exceeding 1000 m and hilly land that is much less complicated than the Da River Basin. As a result of the less complex topography, the spatial distribution of rainfall there is more even than in the Da River Basin, with the average annual rainfall varying from 1500 to 2000 mm per year.

The Hyeongsan River (Fig. 1d) flows through the southeastern part of Gyeongbuk Province on the Korean Peninsula. It covers an area of 1167 km² and consists of low mountainous relief, the highest peak being 901 m (Mt. Beakwoon) in the upper stream; there is a plain in the lower stream. The average annual precipitation over the river basin is approximately 1117 mm, with a moderate spatial distribution of 1000 to 1700 mm.

2.2. Satellite-Gauge merging precipitation: Bias reduction approach

In this paper, the satellite-gauge merging precipitation method called bias reduction [10] is applied to combine the global satellite data GSMaP-MVK with the local rain gauge measurements. GSMaP-MVK was chosen in this study because it has a very high spatial resolution (0.1°), temporal resolution (1h) and it has been successfully producing fairly good pictures in near real time and shows high comparable results with other high-resolution systems [12].

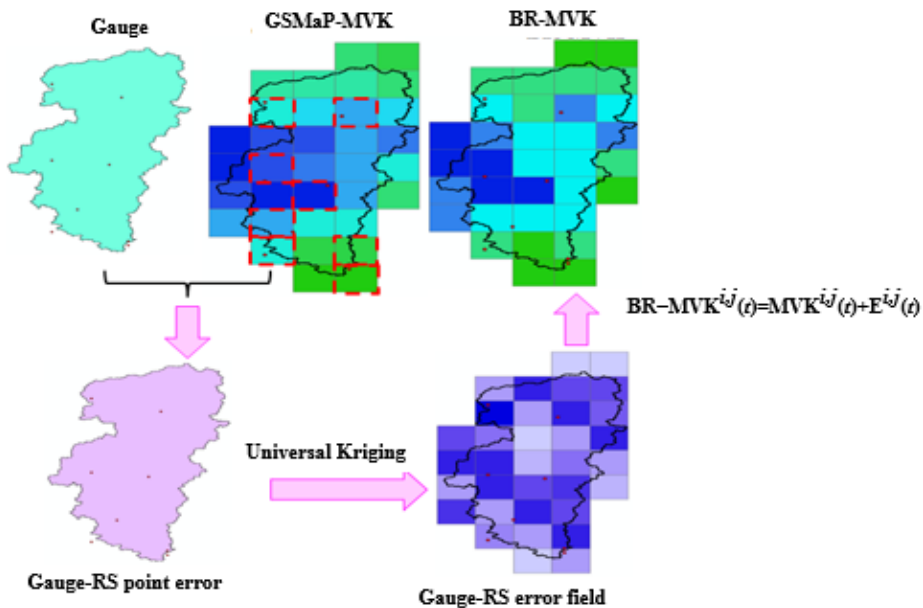


Figure 2. Schematic representation of bias reduction approach

Fig. 2 describes the steps to obtain satellite-gauge merging precipitation GSMaP-MVK. Firstly, with an assumption that the remote sensing precipitation value at each gauge location has the same value of the pixel containing same rain gauge, the differences (or errors) between the observed precipitation and remote sensing data were computed. In the next stage, the Universal Kriging was employed to obtain the daily rainfall error field in a corresponding grid of remote sensing data. The weight value

was computed to obtain the best linear unbiased estimator assuming a local trend model $m(i, j)$. Being the linear combination of the rainfall error values nearby $E(i_\alpha, j_\alpha)$, the predicted rainfall value at location (i, j) representing the longitude and latitude of the center of the remote sensing grid, $E^*(i, j)$ is defined as:

$$E^*(i, j) = m(i, j) + \sum_{\alpha=1}^n \lambda_\alpha(i_\alpha, j_\alpha) [E(i_\alpha, j_\alpha) - m(i, j)] \quad (1)$$

GSMaP-MVK was merged with full set of 88 rain gauge measurements and resampled rain gauge network in order to investigate the effect of rain gauge density on the performances of satellite-gauge merging precipitation. BR-MVK(n) is used as the symbol of satellite-gauge blending precipitation estimation using n number of rain gauges.

2.3. Method for evaluating the AMP error based on Sample Design Method

Because the global remote sensing precipitation product has high spatial-temporal resolution and broad spatial coverage, Hieu et al. investigated the potential use of remote sensing precipitation products to evaluate the AMP uncertainties. The study founded that the global satellite-based precipitation product GSMaP-MVK has the capability to estimate the AMP uncertainties using Esdd(n) index. Esdd(n) index refers to the AMP uncertainties due to the number (density) of the rain gauges and the spatial variability of the rainfall field. The AMP error based on “Sample Design method” is defined by [13]. By assuming normal distribution of precipitation in space, and taking the sample from the distribution, expected error in AMP was defined as the following equation:

$$\text{Esdd}(n) = \frac{C_{vd}}{\sqrt{n}} \quad (2)$$

where C_{vd} is a coefficient of variation of precipitation (an average of daily coefficient of variation on a rainy day), which represents spatial variability calculated on a daily basis. The rainy day is the day with more than 50% of basin area having precipitation. In this study, full set of 88 rain gauge data, satellite only precipitation product GSMaP-MVK and satellite-gauge merging precipitation estimations using resampled rain gauge measurements BR-MVK(n) were used to estimate C_{vd} which are $C_{vd}(g(88))$, $C_{vd}(MVK)$ and $C_{vd}(BR-MVK(n))$ respectively. After obtaining the coefficient of variation of precipitation value, the AMP error indices using reference full rain gauge data, BR-MVK(88) and GSMaP-MVK are computed and named as Esdd($g(88)$), Esdd(BR-MVK(88)) and Esdd(MVK), respectively.

2.4. Approach for eliminating rain gauge from existing network

To investigate the impact of AMP error of different rain gauge network density on satellite-gauge merging performances, streamflow simulation skills of ground measurements, and satellite-gauge precipitation data the different scenarios of rain gauge network based on the existing network of each river basin are needed. The rain gauge network was removed in such a way that the spatial distribution of remaining “ n ” gauges is as uniform as possible. A simple approach was applied in this study as the following rule: among all rain gauges, the nearest pair of gauges is identified. After that, the gauge with lower elevation is eliminated because the gauge at higher elevation gives more direct observations characterizing orographic precipitation than the lower gauge, leading to more accuracy in estimating the AMP.

2.5. Experimental design

The Hydrologiska Byråns Vattenbalansavdelning (HBV) model is a rainfall runoff conceptual model of catchment hydrology, which simulates discharge with AMP as the main input. It is characterized by a relatively simple and robust two-layer tank model structure, with a small portion of parameters, which focus on capturing the most important run-off generating process. Because HBV model has been applied in numerous studies, and adopted as a standard forecasting tool in nearly 200 basins through Scandinavia and has been applied in more than 40 countries [13], it is chosen for this study.

The first stage is to determine the RR model performances using the rain gauge measurements. Firstly, the full available set of precipitation of each river basin was calibrated for parameter identification. Secondly, the number of the rain gauges was resampled (reduced); AMP was calculated using the Thiessen Polygon Method (TPM) and put into hydrological model, where the calibrated parameter at the first step is used. Then the daily rainfall data from both the full rain gauge network and the resample rain gauge network were used as input for rainfall-runoff HBV model to their skills to reproduce stream-flow by using Nash-Sutcliffe efficiency (NS) and Coefficient of Determination (R^2).

At the second stage, AMP uncertainty using *Esdd* index of rain gauge data, BR-MVK(88) and GSMaP-MVK are calculated. At the third stage, the relationship between AMP uncertainty and the RR model simulation efficiency is established. In order to investigate the capability of satellite-gauge merging precipitation BR-MVK(88) for AMP uncertainty estimation using the *Esdd* index, the relationship between model performance (R^2 and NS) and *Esdd*(BR-MVK(88)), *Esdd*(MVK) and *Esdd*(g(88)) was compared.

Fuji river basin, the most densely gauged one among them, was analyzed with several purposes. Firstly, owing to be the highly dense gauged basin, the ground measurements in Fuji basin can capture the rainfall distribution in space. Hence, cross check for coefficient of variation of precipitation between ground measurements and satellite gauge merging data examines the quality of satellite-gauge merging precipitation. The relationship between the AMP error indicators and the model performances with a wide range of gauge density can be the reference for the other study cases. Data in the 3 remaining basins is collected to examine the behavior of satellite gauge merging precipitation for AMP error computation in less dense gauged catchments than Fuji basin. In addition, the effects of rain gauge density on the performances of BR-MVK to estimate AMP error are also taken into account in Fuji river basin.

3. Results

3.1. Evaluation the ability of satellite-gauge merging precipitation BR-MVK to quantify AMP uncertainty

a. Case study: Fuji river basin (well-gauged basin)

Fuji river basin is a very well-gauged basin (approximately 0.025 gauge/km²). The daily discharge in the Fuji river basin is simulated using the conceptual rainfall runoff model with 5 year-period simulation (2003–2007). The two model performance indicators (coefficient of determination and Nash Sutcliffe efficiency) were related to the *Esdd* index corresponding to the resample (reduce) number of the rainfall stations. In Fig. 3 and Fig. 4 each point in the plots represents for the model performance and AMP error corresponding to each resample case of rain gauge network. The curves depict the trends of those points to analyze the behavior of model performances with the change of AMP errors.

In Fuji river basin, the total 88 available rain gauges are involved to compute the satellite-gauge precipitation BR-MVK(88) and the AMP uncertainty index $Esdd(BR-MVK(88))$. Fig. 3 illustrates the relationship between model performances and $Esdd$ index calculated using full set of 88 rain gauges (hollow green squares), BR-MVK(88) (dark blue dots) and GSMaP-MVK (red triangular) in Fuji basin. The declining trends of the model performances along with the increments of AMP error values can be observed obviously in Fig. 3. While GSMaP-MVK follows very similar reduction trends of the rainfall ground measurements, the declining lines of BR-MVK(88) are mostly identical compared with the rain gauges. The almost identical declining lines are the results of minor different of C_{vd} (around 0.7%) obtained by BR-MVK(88) and rain gauges. The $C_{vd}(MVK)$ and $C_{vd}(BR-MVK(88))$ are 0.852 and 0.858, respectively. The ranges of $Esdd(BR_MVK(88))$ are from 0.091 to 0.491, which is almost closed to that of the rain gauges. This results indicate that BR-MVK(88) is capable of not only evaluating the AMP uncertainty using $Esdd$ index but also giving better performances than the original satellite only product.

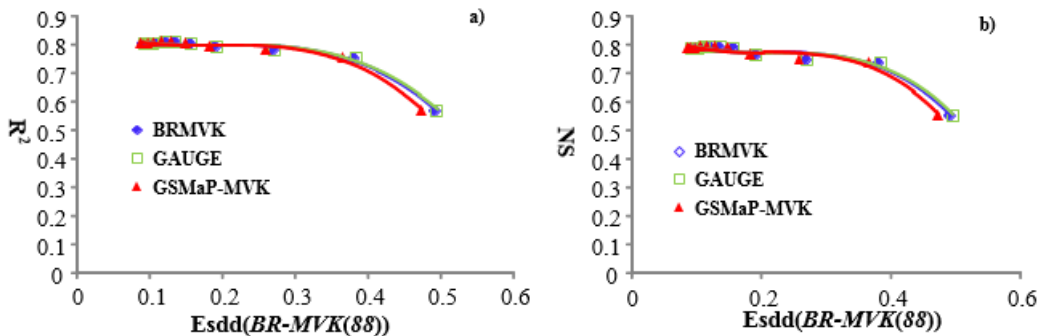


Figure 3. Relation between the model performances (a) R^2 and b) Nash Sutcliffe efficiency with $Esdd$ in Fuji basin

b. Case study: other river basins

In generally, it is very difficult to obtain large number of rain gauge information like in Fuji-river basin. In order to mitigate the limitation of gauge based data availability, and improve the accuracy of satellite based precipitation product, satellite-gauge merging precipitation was used. All the available local rain gauges are used to merge with the satellite only precipitation data GSMaP-MVK used to produce gridded precipitation data with relatively high temporal and spatial resolution.

As shown in Fig. 4, $Esdd(BR-MVK)$ in 3 river basins is capable of capturing the patterns that the model performances are good with the small AMP errors and the model performances get worse with the large errors. Although the number of the point is few due to small rainfall station numbers, the attempt to fit the points with the curves is done to compare the behaviors of model performances reacting with the AMP error values in the less dense gauge basins. The ranges of $Esdd(BR-MVK)$ values are from 0.28 to 0.65 in Da, from 0.24 to 0.52 in Hyeonsan and from 0.3 to 0.49 in Upper-Cau. Interestingly, all the lower values of $Esdd(BR-MVK)$ of three other river basins are less than the lower value of Fuji river basin. This can be explained that there is a large number of the available rain gauges in Fuji catchment that results lesser $Esdd$ value than the limited rainfall stations in other river basins.

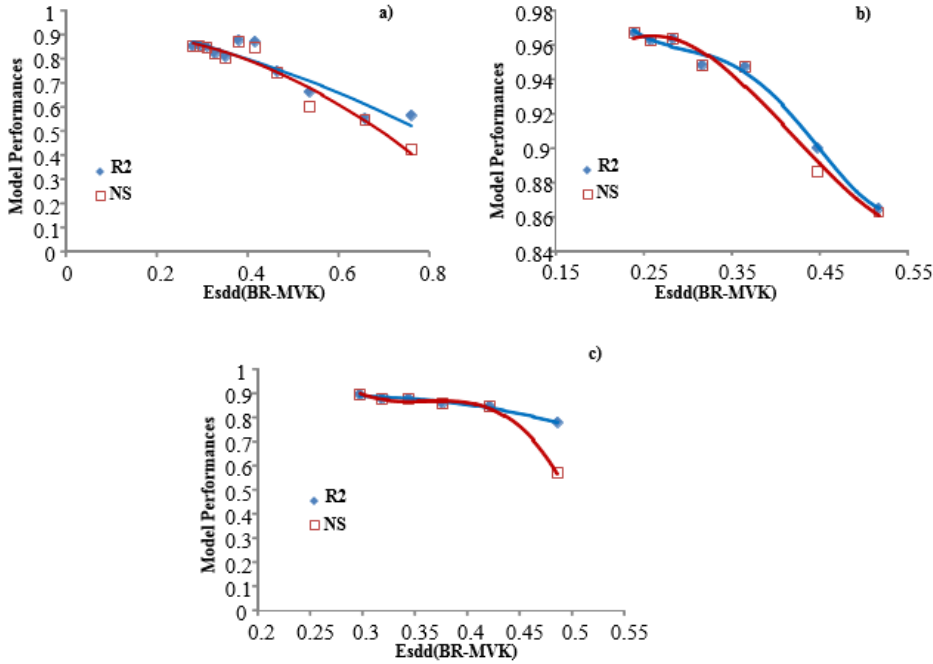


Figure 4. Relation between the model performances (R^2 and Nash Sutcliffe efficiency) with $Esdd(BR-MVK)$ in a) Da basin; b) Hyeonsan basin and c) Upper Cau basin

3.2. Evaluation of the impact of rain gauge density on the performance of satellite-gauge merging precipitation BR-MVK to quantify AMP uncertainty

Because Fuji-river basin is very densely gauged with 88 rain gauges cover the area of about 3570 km^2 , the rainfall station network in Fuji has the ability to grasp the spatial distribution of precipitation field. Therefore, the ground measurements are assumed to be the standard data set to judge the performance of GSMap-MVK and BR-MVK in terms of AMP uncertainty quantifications. The coefficient of variation of precipitation computed using all 88 rain gauges is considered as the reference data to evaluate the coefficient of variation of precipitation computed using $BR-MVK(n)$.

Given a specific number of rain gauge, AMP uncertainty index based on sample design method $Esdd$ solely depends on the spatial variations of the rainfall field. Therefore, the difference of coefficient of variation of precipitation between that of the reference rainfall field and $BR-MVK(n)$ (Eq. (3)) which incorporates the different samples of rain gauge network can be used as a surrogate value to assess the $Esdd$ quantification ability. The smaller difference of coefficient of variation between the reference data and the satellite-gauge merging data indicates the better ability of $BR-MVK(n)$ to grasp the spatial distribution of the rainfall field. In another word, the smaller C_{vd} refers to better ability of $BR-MVK(n)$ to estimate AMP uncertainty.

$$C_{vd} = \frac{|C_{vd}(g(88)) - C_{vd}(BR - MVK(n))|}{C_{vd}(g(88))} \quad (3)$$

It can be observed in Fig. 5 that $BR-MVK(88)$ expresses the best performances among the remaining. When the number of rain gauges n , which is incorporated to create $BR-MVK(n)$, decreases, the performances of $BR-MVK(n)$ declines in general expressing the increment of C_{vd} values. However,

when the rain gauge density becomes very less, C_{vd} tends to decrease. The C_{vd} value of BR-MVK(3) is around 5.2% (slightly higher than that of GSMaP-MVK (around 4.4%)), which could be explained that the remote sensing product has more effects on shaping the satellite-gauge precipitation than the few number of rain gauges in terms of expressing the spatial variations of rainfall field. Most of the BR-MVK(n) shows the C_{vd} values less than 10%, which is encouraging result to sense the overall ability of BR-MVK of capturing the rainfall distribution over the space. However, the highest value of C_{vd} raises the notice to consider the rain gauge density when using the satellite-gauge merging precipitation for *Esdd* evaluations.

Interestingly, $C_{vd}(MVK)$ is only less than $C_{vd}(BR-MVK(88))$. The combination of satellite precipitation with the remaining resampled rain gauge networks is inferior to the original GSMaP-MVK regarding to the capture the spatial variation of rainfall field. This result highlights the strength of remote sensing precipitation with high spatial resolution to grasp the rainfall distribution over the space. Therefore, the satellite-gauge merging precipitation shows superior AMP error estimation performances than the satellite only precipitation product only if the number of blending rain gauges is large enough.

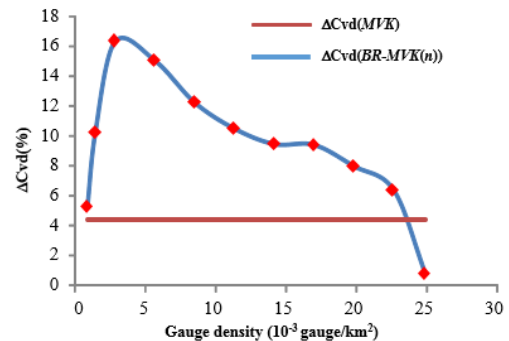


Figure 5. Relation between the gauge density and the difference of C_{vd} between reference rainfall field and the BR-MVK(n)

4. Conclusions

One of the research goals is to examine the ability of satellite-gauge merging precipitation data to estimate the AMP errors using AMP error index based sample design method. This *Esdd* index accounts for not only the gauge density but also the rainfall spatial variability. As shown in the result section, satellite-gauge merging precipitation shows positive capability to evaluate AMP uncertainty using *Esdd* index. This statement is specially demonstrated by almost identical relation of model performance efficiency with *Esdd* index between BR-MVK(88) and the standard ground measurements.

However, the *Esdd* quantification performances of BR-MVK depend upon the rain gauge numbers used for blending with remote sensing product. The worst performance among the resample rain gauge networks shows almost 4 times higher of discrepancy level compared with the reference rainfall data than that of GSMaP-MVK. This result highlights the needs for considering the rain gauge density while investigating the performances of satellite-gauge merging precipitation to measure AMP uncertainty using *Esdd* index.

GSMaP-MVK expresses the better ability to capture the spatial rainfall distribution than the satellite-gauge merging precipitation using the resample rain gauge networks in Fuji river basin. Therefore, the original GSMaP-MVK is recommended for computing the AMP uncertainty the sparse data river basins.

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