RADAR-DERIVED QUANTITATIVE PRECIPITATION ESTIMATION BASED ON VERTICAL-RAINCLOUD TRAJECTORY PROFILES

Hanggar G Mawandha[1] and Satoru Oishi[2]

[1]*Graduate School of Engineering, Kobe University, Japan.*
E-mail: mawandha@stu.kobe-u.ac.jp
[2]*Professor, Research Center for Urban Safety and Security, Kobe University, Japan.*
E-mail: tetsu@phoenix.kobe-u.ac.jp

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1 Introduction

Radar-derived precipitation is subject in the hydrological field following an advanced development of remote monitoring system used for many disaster mitigation purposes. A high space-time resolution of radar-based quantitative precipitation estimates (QPE) is appealing features for the spatially characterized hydrological condition. However, its quantification accuracy is a challenging task. A network of rain gauges provides more accurate point-wise measurements however the spatial representativity is limited. In contrast, radar provides proper spatial rainfall distribution, but the possibility to inaccurate determination of ground measured value due to uncertain discrepancy factor is high. Hence, combining radar-rain gauge is one of the solutions for generating better QPE in advance. However, radar-rain gauge-based QPE tends to have less precision when limited rain gauge with sparse spatial distribution existed. In this case, a method based on radar-rain gauge merging algorithms (Cecinati, 2010; Germann, 2006; Lee, 2015) to discriminate discrepancy contained in QPE is no longer appropriate to be used.

This study aims to assess the factor of interspace discrepancy between radar bins and rain gauges to generate better QPE algorithm based on the vertical profile of raincloud. This study is taking the case of a radar set up at Mt. Merapi located in the Southern part of Java Island, Indonesia Country (see Figure 1-a). In a mountainous area, the rain gauge network is usually sparse and sufficient point rainfall measurements are not available, which are often unable to characterize the spatial distribution of highly variable rainfall. On the other hand, the void interspace under the available radar tilting beam due to beam distance or beam blockage has caused some valuable rainfall data missing, which is recognized contributing to discrepancy toward the ground. Furthermore, such discrepancies are known aggravated during the raincloud formation processes under developing, mature, and dissipating stages. The method proposed in this study is considering the correlation between vertically-raincloud profile and their composing physical component. Once its correlation has been recognized, the vertically-trajectory pattern of raincloud above the rain gauge could be depicted in the form of rain intensity. These trajectory fields are then used to estimate the probabilities of rain intensity for lower altitudes. Here, the discrepancy factor contained in QPE product can be discriminated against various raincloud formation stages.

2 Methodology

Generally, trajectory profiling comes up with non-parametric and parametric estimates (Jo, 2014). Non-parametric estimators have no fixed structure and depend upon all the data points to get an estimate while parametric estimators concern the nominal values used for every parameter. The problem to use non-parametric estimators requires many data from the prior trajectories. In this case, to collect an adequate data used for raincloud profiling is difficult since rainfalls mostly occur within a short period with a limited height of the vertical column. Hence, application of parametric model will be emphasized based on a physical component which formulates vertically-raincloud profiles. The atmospheric sounding data generated from radiosonde is used to see the correlation among the physical components and calculate the parametric coefficient values which can describe the relationship of rain rate product with the corresponding atmospheric factors (see Figure 2). Radiosonde observations provide an independent and unique reference for many altitudes meteorological variables such as water vapor content, temperature and humidity profiles. However, they are unevenly distributed. Here, the atmospheric water vapor content and relative humidity data are used to generate parametric regression model. The atmospheric water vapor content can explain the extreme precipitation event through the relationship with the surface air temperature (Fujita & Sato, 2017).

The atmospheric data is retrieved from the University of Wyoming (United States) website: http://weather.uwyo.edu/upperair/sounding.html. The upper air map information about water vapor distribution in the study area is shown in Figure 1-b. Two rainfall events on 20/12/2017 and 11/02/2018 are selected representing the heavy rainfall cases. For checking the consistency of the spatial variance over the radar coverage area, several available rain gauges, representing radar range various distance (i.e., ≤ 10 km and ≥ 15 km), are utilized to validate the result. Statistical variables used to evaluate the model performance are zero phase and maximum phase correlation, lag time, and mean absolute bias value.

In parametric regression, we can model the relationship using any combination of single or multiple predictor variables, and use the least squares approach to estimate the parametric coefficient either linearly or non-linearly. A linear model uses a linear function f(x) to represent the relationship between a dependent random variable $\boldsymbol{Y}$ and a k-dimensional vector of predictor variables $\boldsymbol{X}$ (Ghasemi Hamed et al., 2013). The parameters (different weights for each input and bias) of the regression are adjusted to minimize the difference between the retrieved variables and real variables in the sense of least squares. The following is general equation form of the linear parametric model.

$$\boldsymbol{Y} = \boldsymbol{X}\beta + \varepsilon \tag{2.1}$$

$$\boldsymbol{X} = \begin{pmatrix} 1 & x_{11} \cdots x_{1k} \\ . & . \; .. \; . \\ . & . \; .. \; . \\ 1 & x_{n1} \cdots x_{nk} \end{pmatrix}_{(n\times p)} , \varepsilon = (\varepsilon_1, \dots, \varepsilon_n)^T \tag{2.2}$$

Where $\boldsymbol{Y}$ is the vector of response variables, $\boldsymbol{X}$ represents a matrix of observed values for the predictor variables. In the parameter estimation phase, we are searching for the vector of parameters β through the set of n points in a way to minimize the sum of the squared error function. The most commonly used type of linear regression is the Ordinary Least Square Estimation (OLSE) which is described through as follows.

$$\widehat{\beta} = (X^T X)^{-1} X^T Y \tag{2.3}$$

where $\widehat{\beta}$ is a least square solution function to minimize the error sum of squares $\varepsilon^T \varepsilon$. Once the parametric coefficient value has been obtained, it can be used to generate response value at void interspace through reverse multiplication process. For model validating step, cross-correlation technique is applied into data sets between QPE product and rain gauge data observed along the rainfall duration. By using the Fourier-shift method, correlation at zero phase and phase at a maximum value can be obtained. Also, the lag in time series between the data sets can be seen.

3 Results

3.1 Overall Discrepancy Assessment

Radar-derived precipitation estimate method is commonly generated from Constant Altitude Plan Position Indicator (CAPPI) either a maximum value or lowest altitude value. A maximum CAPPI product is computed from 3-D radar volume scan by projecting the maximum value within a vertical column to a 2-D plane. A lowest CAPPI value is obtained from 3-D volume scan by projecting the first CAPPI containing a value within a vertical column to a 2-D plane. In this study, we have three different QPE methods to be compared namely, “max” stands for maximum CAPPI product, “lowest” for lowest CAPPI product, and “model” for parametric model proposed in this study. The size of radar pixel used in this analysis is 300 x 300 m and time resolution is 2 minutes.

The overall QPE performances from three different methods are summarized in Table 1. All QPE methods are assessed based on radar beam distance factor to see the spatial consistency performance. From the statistical test, it concludes that for radar range less than 10 km the maximum CAPPI or lowest CAPPI method performs better than the parametric model. However, compensate result achieved by the parametric model in case of lag time and maximum phase correlation indicator. Regarding lag time, it shows at what delay/lag values time series are similar. Here, lag=1 represents 2 minutes delay of which positive value means radar time series are shifting step ahead than rain gauge while negative means the opposite. When lag $\neq 0$ it will slight decrease in correlation while lag=0 both datasets will have a perfect correlation. In case of radar beam reach up to 15 km range or more, the parametric model performs much better than two other methods. Although the overall correlation value is not so high, however small lag time (close to 0) performed by parametric model-based QPE indicates a strong correlation on temporal variance toward actual ground value. The QPE showing the spatial outlook generated by each method over the entire radar range is shown in Figure 3.

Table 1: Statistical test-based QPE performance

Radar beam distance factor	≤ 10 km			≥15 km		
QPE method	max	lowest	model	max	lowest	model
zero phase correlation	0.87	0.90	0.84	0.77	0.72	0.79
maximum phase correlation	0.93	0.93	0.93	0.86	0.83	0.86
lag time (2 minutes interval)						
case of 20/12/2017	1	1	1	2	2	1
case of 11/02/2018	0	0	0	-1	-2	0
mean absolute bias (mm)	7.94	8.66	8.53	19.46	20.03	14.89

3.2 Raincloud stages-based Discrepancy Assessment

The purpose of this analysis is intended to verify such discrepancy caused by raincloud formation processes. At this step, we separated rainfall event based on raincloud formation which consists of developing, mature, and dissipating stage. In Figure 4 we have separate windows showing different raincloud formation stage based on the vertical profile of rain intensity. Under the developing stage along 10 minutes rainfall duration, the maximum CAPPI, the lowest CAPPI, and the parametric model obtained 57 mm h^{-1}, 49 mm h^{-1}, and 19 mm h^{-1}, respectively while the rain gauge recorded 29 mm h^{-1}. Under the mature stage, the maximum CAPPI, the lowest CAPPI, and the parametric model obtained 61 mm h^{-1}, 38 mm h^{-1}, and 48 mm h^{-1}, respectively while the rain gauge recorded 47 mm h^{-1}. Under the dissipating stage, the maximum CAPPI, the lowest CAPPI, and the parametric model obtained 17 mm h^{-1}, 12 mm h^{-1}, and 25 mm h^{-1}, respectively while the rain gauge recorded 18 mm h^{-1}.

The results show that the use of the parametric model can reduce the discrepancy showing from less mean bias value obtained. The highest mean bias value exhibits under developing stage phase where radar indicates rainfall in the air, but rain gauge does not. At this stage, the maximum CAPPI and lowest CAPPI value prone to give high discrepancy when is used as QPE. The discrepancy of radar and rain gauge measurement is recognized through discriminating of each stage of raincloud formation process. However, these stages were not always clearly seen especially for raincloud under convective circumstances where horizontal wind drift plays the dominant role than wind updraft and downdraft.

4 Discussion

Radar-derived QPE based on the parametric model has shown a robust performance compared to maximum CAPPI or lowest CAPPI value as currently used for QPE method. It has revealed showing less mean bias value with a lag time close to zero, especially for longer radar range distance condition. Through the use of atmospheric sounding data as a reference for many altitudes, it has proven that water vapor content and relative humidity configuration deals with vertical raincloud profile. In the model, the physical atmospheric data are assumed to be constant over the simulation of rainfall event since it generally does not change dramatically within a short period. Moreover, the parametric model provides a better approach to figure out discrepancy under different raincloud formation process.

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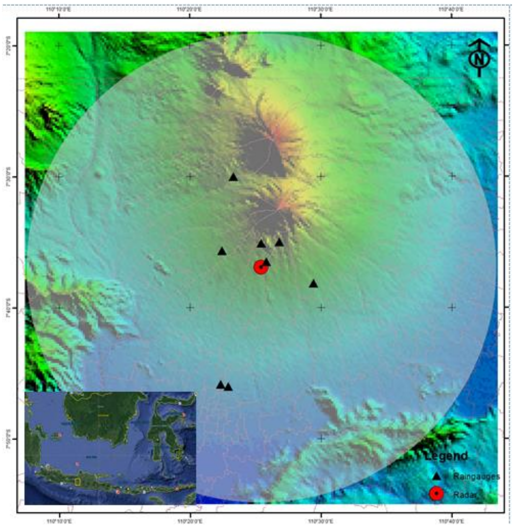
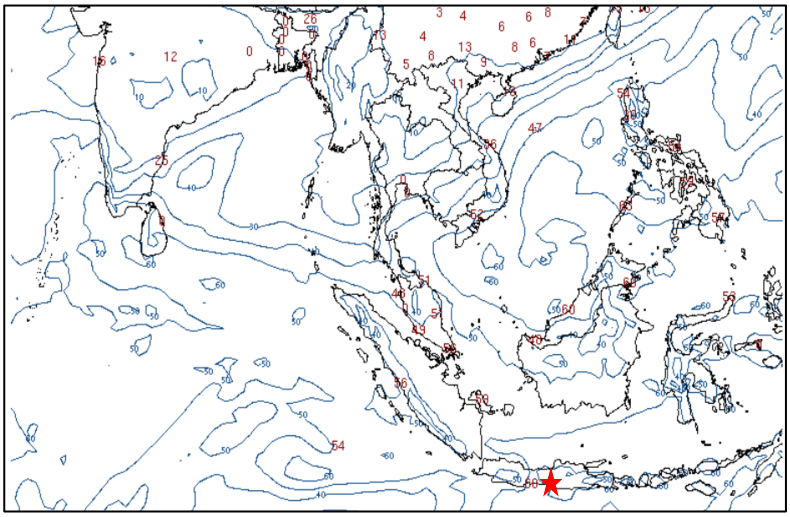


(a)



(b)

Figure 1: (a) Raingauges distribution and radar set up at Mt.Merapi, (b) Precipitable water vapor map at 12Z 20 Dec 2017.

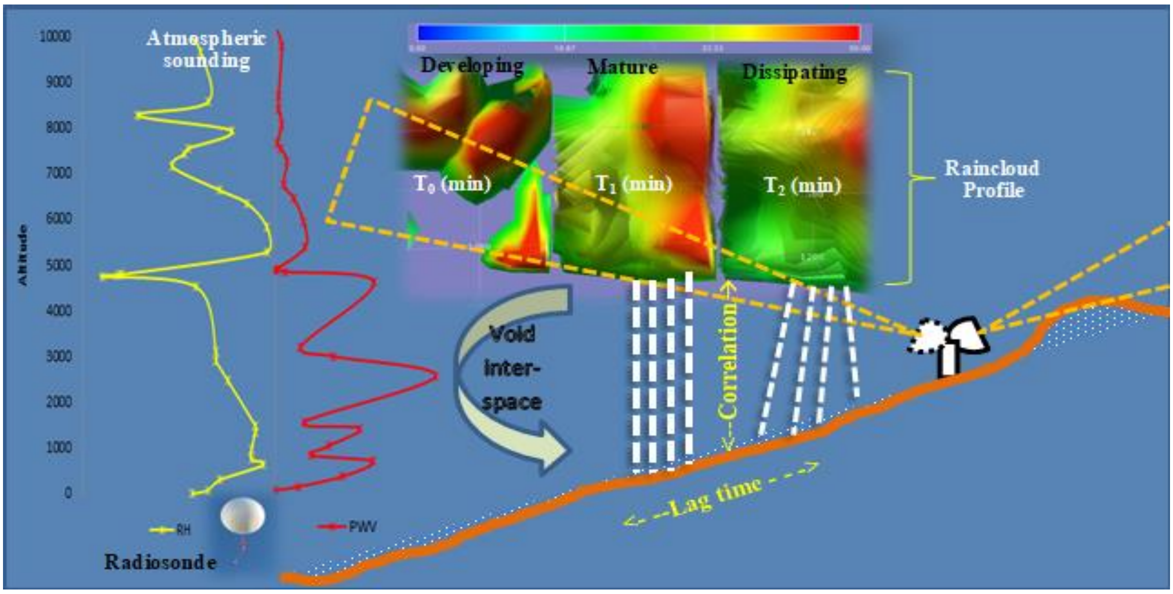
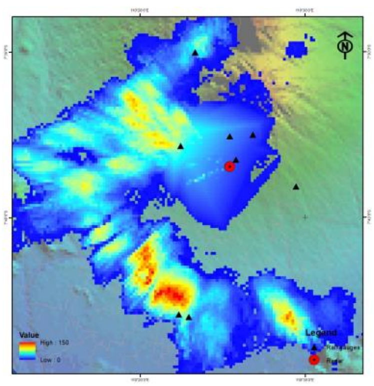


Figure 2: Vertically-raincloud trajectory profiling model scheme.



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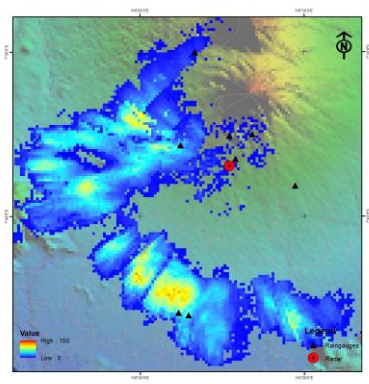

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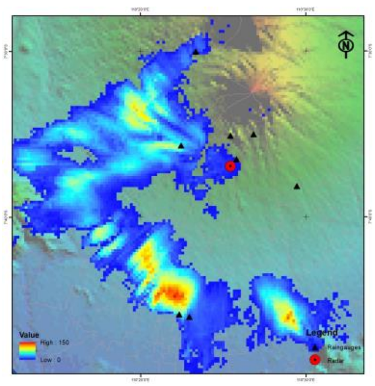
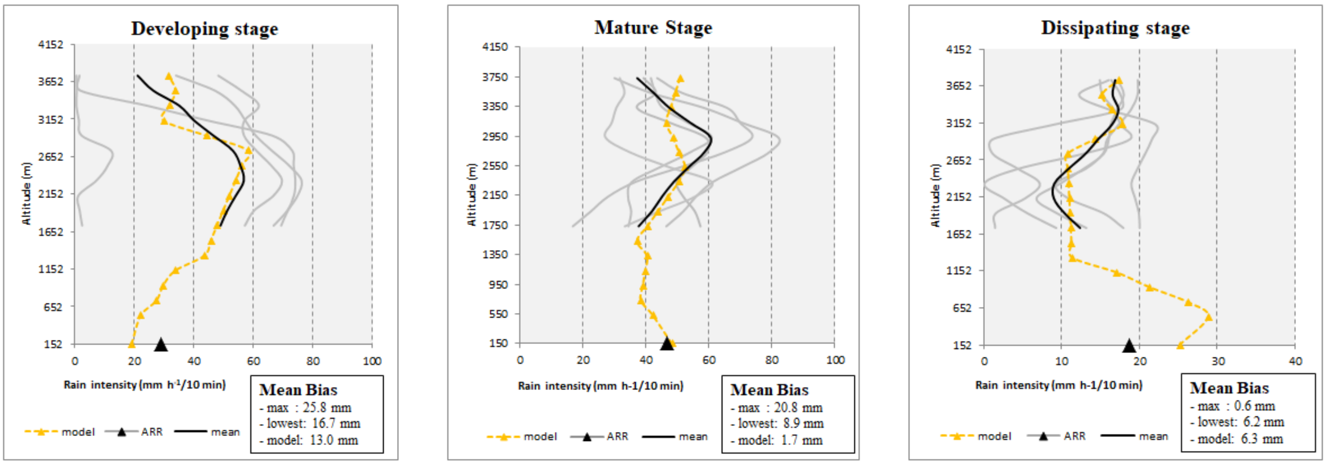


(c)

Figure 3: (a) Maximum CAPPI-based QPE, (b) Lowest CAPPI-based QPE, (c) Parametric model-based QPE.



(a) (b) (c)

Figure 4: (a) Projected rain intensity under raincloud developing stage phase, (b) Projected rain intensity under raincloud mature stage phase, (c) Projected rain intensity under raincloud dissipating stage phase.