

Satellite radiance data assimilation for rainfall prediction in Java Region

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Abstract. This study examined the influence of satellite radiance data assimilation for predicting two days of heavy rainfall in the Java region. The first case occurred from 22 to 23 on January 2015 while the second case occurred from 1 to 2 on February 2015. The analysis examined before and after data assimilation in the two cases study. The Global Forecast System (GFS) data were used as initial condition which was assimilated with several data such as surface observation data, radiance data from AMSUA sensor, radiance data from HIRS sensor, and radiance data from MHS sensor. Weather Research and Forecasting Data Assimilation (WRFDA) is a tool which is used in this study for assimilating process with Three Dimensional Variation (3D-Var) method. The Quantitative Precipitation Forecast (QPF) skill was used to evaluate influence data assimilation for rainfall prediction. The result of the study obtained different rainfall prediction with different data assimilation. In general, the surface observation data assimilation has lower QPF skill than the satellite radiance data assimilation. Even though radiance data assimilation has slightly contribution on rainfall prediction, but it gave better accuracy on rainfall prediction for two heavy rainfall cases.

1. Introduction

One of problem on weather modeling is inaccuracy in initial condition data. According to some previous studies, the solution of inaccuracy in initial condition can be solved by data assimilation [1]. Data assimilation is a combination of various data in order to determine as accurately as possible state of nature [2]. This study combined Global Forecast System (GFS) model data with observation data for rainfall estimation. In this study, data assimilation was used in numerical weather prediction with observational data for increasing accuracy of rainfall prediction [3][4]. Many sources of observational data for data assimilation, e.g. surface observation data, radiance satellite data, and radar data. Combining observation data from many sources with the GFS model use the data assimilation technique. There are two approaches of data assimilation namely sequential assimilation and non-sequential assimilation. Sequential assimilation is data assimilation consider observation data from past until time analysis. Non-sequential assimilation is data assimilation considers observation data from past until future time analysis [5].

Nowadays, improving accuracy of numerical weather prediction for heavy rainfall event is widely required for warning information for operational purposes. The heavy rainfall condition is rainfall which



has intensity 50 millimeter/day or 10-20 millimeter/hour [6]. This study examines two cases of heavy rainfall events in Java i.e. on 22–23 January 2015 (first case) and 1-2 February 2015 (second case). Those heavy rainfall events were identified as severe flood in Jakarta and surrounding area. The early analysis used wind analysis, to know characteristic of rainfall event and potential location of cloud growth. Figures 1 show the wind vector at 850 hPa at 00.00 UTC of 22 January 2015 and 00.00 UTC of 01 February 2015 derived from JRA-55 reanalysis. Figure 1a shows wind vector and convergence pattern over the Java Sea. This condition influence strong convective process along the Java Region.

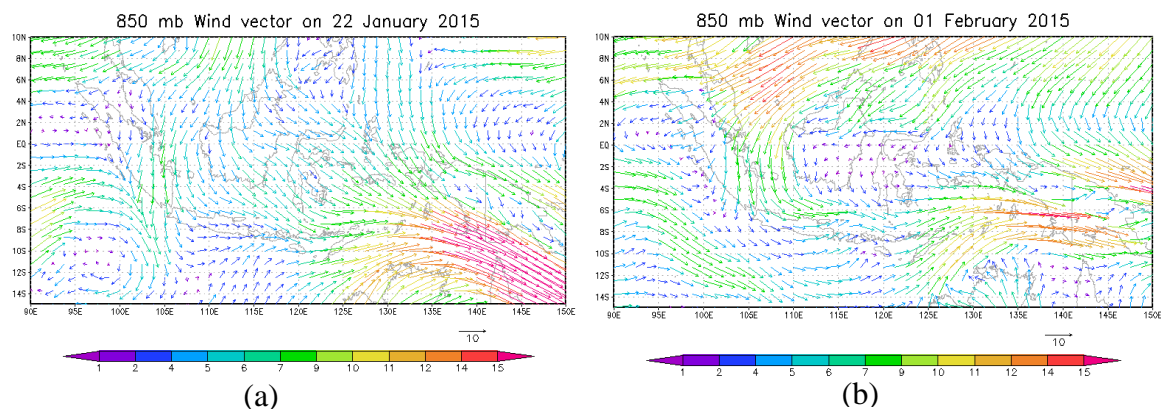


Figure 1. Gradient Wind Analysis on 22th January 2015 (a) and 01th February 2015 (b) [7].

Figure 1b shows wind vector on Java Sea, so it can generate highly cloud growth in the along Southern Sumatra until Western Java. The extreme rainfall event occurred 22-23 January 2015 and 1-2 February 2015 at Java region especially Jakarta area. The daily rainfall reached 134 mm on 22-23 January 2015 and 75 mm on 1–2 February 2015. The object of this study examined influence surface observation data and satellite radiance data assimilation for prediction of rainfall.

2. Data and Methodology

Weather Research and Forecast Data Assimilation (WRFDA) [8][9] is a tool for data assimilation. This study uses Global Forecast System (GFS) data with resolution $0.5^\circ \times 0.5^\circ$ [10], surface observation data in the BUFR format [11], satellite radiance data from many sensors (AMSUA, HIRS, MHS) [11]. This study used rain rate data from GSMAP product for verifying the output of the models. The domain of this study is a Java region with resolution 9 kilometers (figure 2). Red circles on domain map are location of surface observational stations which data are used for data assimilation and data verification. The rainfall physical parameterization schemes were used that is the Thompson graupel microphysical parameterization [12], and the Betts-Miller-Janjic scheme cumulus parameterization [13].

Satellite radiance data were used from NOAA, METOP, and EOS satellite. This study used three kinds sensor of radiance data: AMSU-A, HIRS, MHS.

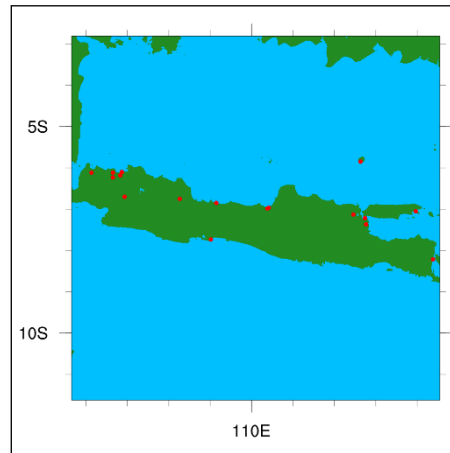


Figure 2. The domain used to model simulation

AMSU-A is The Advanced Microwave Sounding Unit-A. HIRS is a 20-channel infrared scanning radiometer that performs operational atmospheric sounding. Microwave Humidity Sounder (MHS) is a self-calibrating, cross-track scanning, five-channel microwave, full-power radiometer, operating in the 89 to 190 GHz region [14].

The method that was used for the data assimilation is a three-dimensional variation analysis (3D-Var). Formula of 3D-Var is [9]:

$$J(x) = \frac{1}{2}(x - x_b)^T B^{-1}(x - x_b) + \frac{1}{2}[y - H(x)]^T R^{-1}[y - H(x)] \quad (1)$$

$J(x)$ is a function that calculates the cost function between models with observational data surface. The calculation of the cost function $J(x)$ describes in equations 1 where x and x_b is an analysis of expected data and the background data.

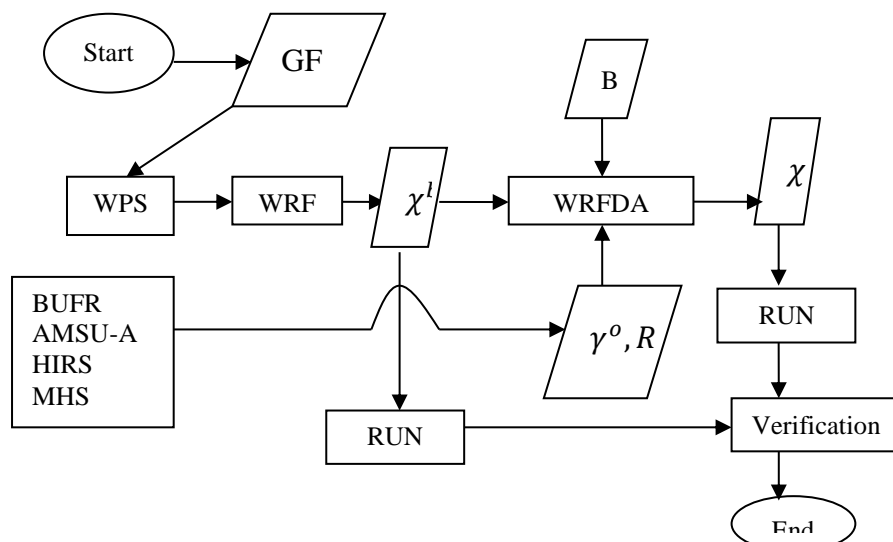


Figure 3. Flowchart.

H is the observation operators include Radiative Transfer Model, R is the observation error covariance operator, and y^o is an observation data in the model grid.

The flowchart of this study can be seen in figure 3. Earlier, this study sets the domain of research on WRF Processing System (WPS) which used GFS as input data. To get initial condition, this study run

output WPS on WRF. Three components are required on WRFDA such as initial condition χ^b , observation data γ^o, R , and background data (B). This study used the data assimilation with the background of global error that has been provided in the application WRFDA. An observation data will be assimilated. Observation data has an error value that was shown by the parameter R. The output of WRFDA is second guess of initial condition χ^a . The first guess of initial condition and second guess of initial condition were used in the forecast process which resulted without data assimilation and data assimilation. The last is verify process by comparing QPF skill between without data assimilation, surface observation data assimilation, AMSU-A radiance data assimilation, HIRS radiance data assimilation, and MHS radiance data assimilation. QPF method used threat score (TS) and false alarm ratio (FAR).

The TS was defined in equation 2 as:

$$\text{Threat Score (TS)} = \frac{\text{Hits}}{\text{Hits} + \text{False Alarm} + \text{Misses}} \quad (2)$$

The FAR score defined in equation 3 as :

$$\text{False Alarm Ratio (FAR)} = \frac{\text{False Alarm}}{\text{Hits} + \text{False Alarm}} \quad (3)$$

Hits are amounts of the event that are detected by observation and forecasting, false alarm is the amount of no event detected by observation, but event detected by forecasting, and misses is the amount of event detected by observation, but no event detected by forecasting.

3. Result

Figure 4 here shows six maps of 24 hours accumulated rainfall in Java region on 22 – 23 January 2015. Figure 4 (a) is 24 hours accumulated rain rate from GSMAP data. GSMAP data is accumulated rainfall that is measured by many satellites. Five maps others are accumulated rainfall prediction from (a) without data assimilation, (b) surface observation data assimilation, AMSU-A data assimilation, HIRS data assimilation, and MHS data assimilation. The severe weather happened in Northern West Java on 22 – 23 January 2015. This was indicated by heavy rainfall more than 80 mm. Comparing rainfall predicted from WRF model, WRF model without data assimilation (b) result heavy rainfall smaller area than others (c, d, e, f). Without data assimilation analysis gave result rain in most of area domain, but observation data from GSMAP gave information there was no rain in many Indian Ocean areas. Improvement result has been produced from surface observation data assimilation and MHS data assimilation, many areas in the Indian Ocean were no rain. This was better than without the data assimilation scheme. Whereares forecasting rainfall by data assimilation still gave overestimate rainfall like without data assimilation, but data assimilation reduced overestimate rainfall.

Figure 5 presents 24 hours accumulated rainfall between 00.00 and 24.00 UTC on 22 January 2015 from both observation data from GSMAP product (a) and scheme of experiments: without data assimilation (b) surface observation data assimilation (c), AMSU-A data assimilation (d), HIRS data assimilation (e), and MHS data assimilation (f). According observation data from GSMAP product (a), Northern West Java was an area where was main heavy rainfall happened (Figure 5a). Compared with observation, the main heavy rainfall region in most areas in Java sea generated from all experiments (Figure 5b, 5c, 5d, 5e, 5f). All experiments have resulted that main heavy rainfall prediction in land is smaller region than the sea. HIRS data assimilation (Figure 5e) reduced overestimation rainfall in Java Sea. Evenly, all experiments have resulted overestimate rainfall.

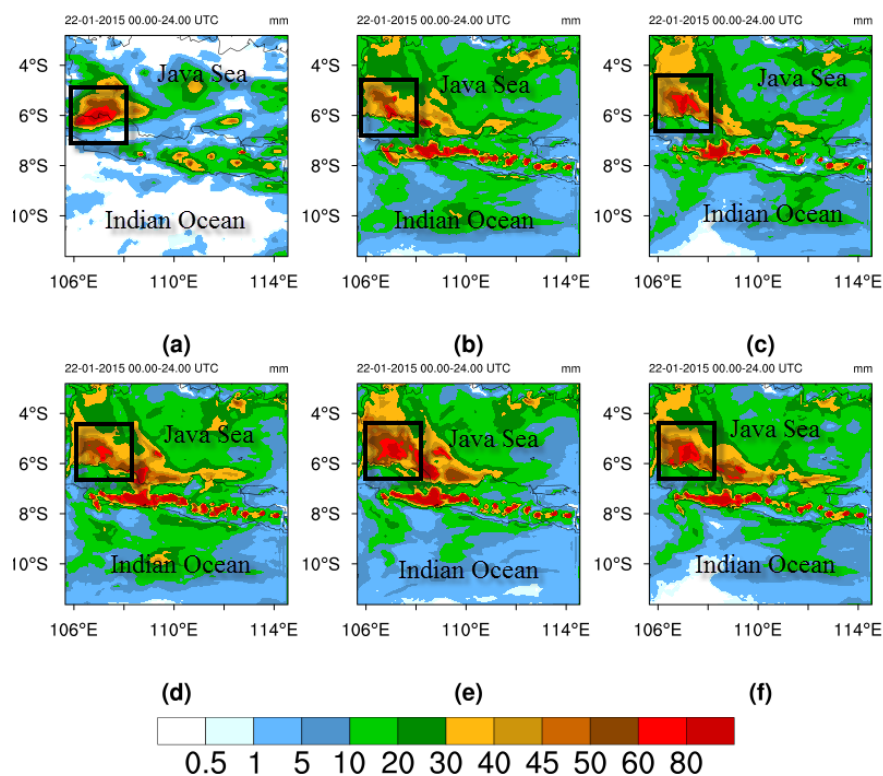


Figure 4. Map of 24 hours accumulated rainfall on 22 – 23 January 2015: (a) GSMAP, (b) without data assimilation, (c) surface observation data assimilation, (d) AMSU-A data assimilation, (e) HRS data assimilation, and (f) MHS data assimilation.

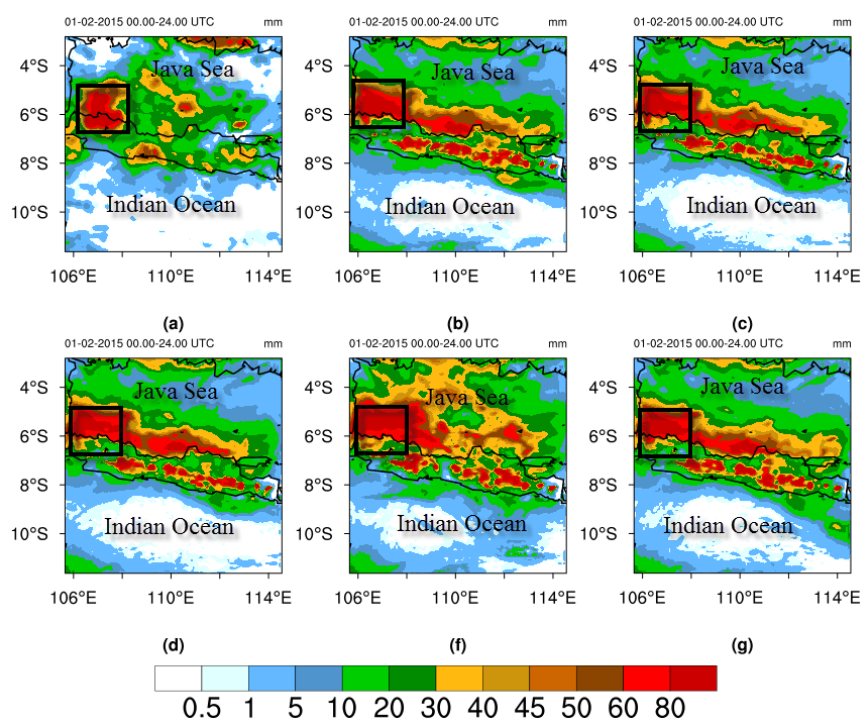


Figure 5. Map of 24 hours accumulated rainfall on 1-2 February 2015: (a) GSMAP, (b) without data assimilation, (c) surface observation data assimilation, (d) AMSU-A data assimilation, (e) HRS data assimilation, and (f) MHS data assimilation.

Quantitative Precipitation Forecast (QPF) skill used threat score (TS) and false alarm ratio (FAR) score for evaluating all experiments result on rainfall prediction. A higher TS indicates a more skillful rainfall prediction. A lower FAR score indicates a few error rainfall predictions. The range value of TS and FAR score are between 0 and 1. The maximum value of TS and FAR are 1.

Figure 6 shows threat score (TS) (figure 6a) and false alarm ratio (FAR) (figure 7.a) for 24-hourly accumulated rainfall with threshold of 1 mm, 5 mm, and 10 mm from all experiments for case 22 – 23 January 2015. For the verifications in all thresholds, the TS in MHS data assimilation experiment are bigger than other experiment (figure 6a). Verification in 1 mm threshold, the TS in AMSU-A data assimilation is smaller than others experiment. Verification in 5 mm threshold, the TS in HIRS data assimilation is smaller than others experiment. Verification in 10 mm threshold, the TS in AMSU-A and HIRS data assimilation are smaller than others experiment. For the verifications in all thresholds, the FAR score in MHS data assimilation is smaller than another experiment. It was indicated MHS data assimilation has the smallest error. Verification in 1 mm threshold, the FAR score in AMSU-A data assimilation is higher than others experiment. Verification in 5 mm threshold, the FAR score in AMSU-A and HIRS data assimilation is higher than others experiment. Verification in 10 mm threshold, the FAR score in AMSU-A and HIRS data assimilation is higher than others experiment. MHS data assimilation for case 22 – 23 January 2015 was the best rainfall prediction that was indicated by the highest TS and smallest FAR score.

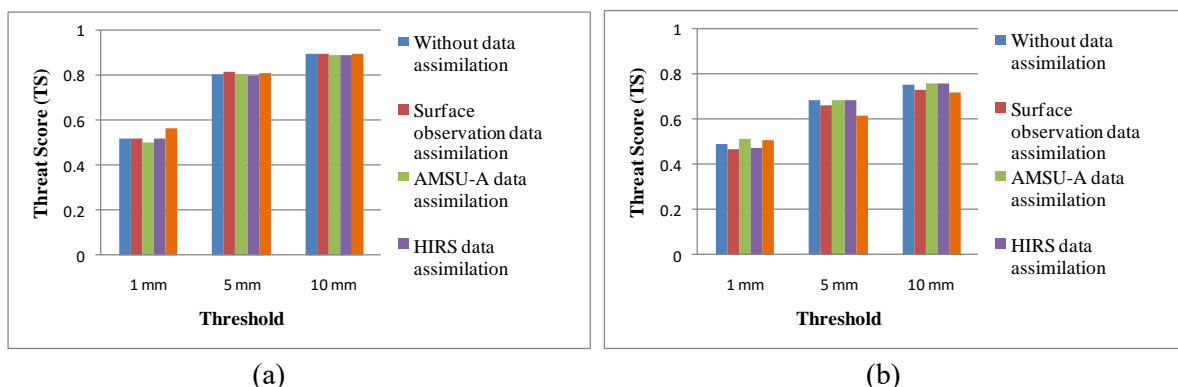


Figure 6. Threat Score (TS) for 3-hourly accumulated rainfall with threshold of 1 mm, 5 mm, and 10 mm from five experiments for case study 22 – 23 January 2015 (a) and case study 1-2 February 2015.

Figure 7 shows threat score (TS) (figure 6b) and false alarm ratio (FAR) (figure 7b) for 3-hourly accumulated rainfall with a threshold of 1 mm, 5 mm, and 10 mm from all experiments for case study 1–2 February 2015. Verification in 1 mm threshold, the TS in AMSU-A and MHS data assimilation is higher than others experiment. Verification in 5 mm threshold, the TS in AMSU-A and HIRS data assimilation is higher than others experiment. Verification in 10 mm threshold, the TS in AMSU-A and HIRS data assimilation are smaller than others experiment. For the verifications in all thresholds, the FAR score in MHS data assimilation is smaller than others experiment. It was indicated MHS data assimilation have smallest error. Verification in 1 mm threshold, the FAR score in AMSU-A data assimilation is smaller than others experiment. Verification in 5 mm and 10 mm threshold, the FAR score in AMSU-A and HIRS data assimilation is smaller than others experiment 11 August 2016. Generally, all radiance data assimilation experiments have given improving rainfall prediction in all rain threshold for case 1-2 February 2015.

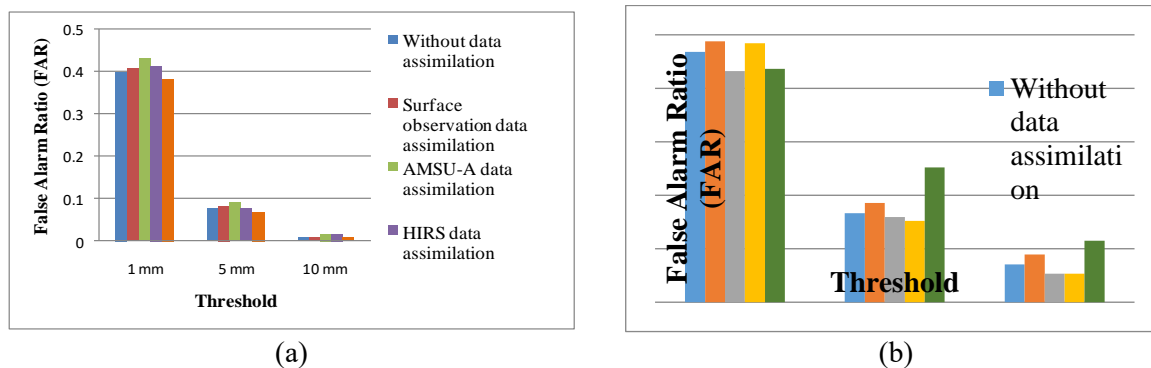


Figure 7. False Alarm Ratio (FAR) (a) score for 3-hourly accumulated rainfall with threshold of 1 mm, 5 mm, and 10 mm from five experiments for case study 22–23 January 2015 (a) case study 1-2 February 2015 (b).

4. Summary and Conclusions

This study was one of the effort to improve rainfall prediction of Weather Research and Forecasting (WRF) model. Data assimilation experiments for 22 – 23 January 2015 and 1 – 2 February 2015 heavy rainfall event over Northern West Java was performed. This study was emphasized in evaluating the additional influence of radiance data assimilation on rainfall prediction. Data assimilation for all experiments still indicated overestimate rainfall prediction. Radiance data assimilation generated slight influence, but generally positive influence on region main heavy rainfall area. On 22 – 23 January 2015 MHS data assimilation was better than other experiment data assimilation showed by the smallest FAR score and highest TS. On 1 – 2 February 2015 AMSU-A data assimilation better than others experiment data assimilation showed by higher TS than others and smaller HIRS than others. The different of the best radiance data assimilation was caused different amount daily radiance data which was collected by satellite.

Acknowledgments

The author would like to express many thanks to Japan Aerospace Exploration Agency, Earth Observation Research Center (JAXA / EORC) for providing GSMAP data and to Indonesia agency for Meteorology, Climatology, And Geophysical Agency (BMKG) for providing surface observation data.

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