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RESEARCH ARTICLE

Improving Numerical Weather Prediction of Rainfall Events Using Radar Data Assimilation

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Abstract Data assimilation is a method to improve initial atmospheric conditions in numerical weather prediction. This study aims to investigate the effect of assimilation of Doppler weather radar data in Weather Research Forecasting (WRF) numerical model for the prediction of heavy rain events in the Jabodetabek area with dates representing four seasons respectively on 20 February 2017, 3 April 2017, 13 June 2017, and 9 November 2017. The reflectivity (Z) and radial velocity (V) data from Plan Position Indicator (PPI) product and reflectivity (Z) data from Constant Altitude PPI (CAPPI) product were assimilated using WRFDA (WRF Data Assimilation) numerical model with 3DVar (The Three Dimensional Variational) system. The output of radar data assimilation and without assimilation of the numerical model of WRF is verified by spatial with GSMaP data and by point with precipitation observation data. In general, WRF radar assimilation provides a better simulation of spatial and point rain events compared to the WRF model without assimilation. Moreover, improvements in rain prediction would be more visible in areas close to radar sources, not echo-blocked from fixed objects, and during the rainy season.

1. Introduction

According to Nugroho (2002), most of the flooding that occurred in Jabodetabek was caused by heavy rain. The prediction of accurate heavy rain is important in order to build a flood early warning system. However, operational weather prediction capabilities of Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG) are only good at forecasts of rain or not rain dichotomies, while predictions of heavy and hefty rainfall have low predictive abilities (Gustari et al., 2012).

Predicting rain is not a simple matter. The accurate predictions of rain require in-depth knowledge of the weather system of a region which includes characteristics, physical processes, and dynamic weather processes. Comprehensive understanding of the weather system is necessary to get accurate predictions. Furthermore, understanding a complete weather system can be done objectively by using modeling that requires formulations that describing the weather system as a function of time.

One of the weather modeling systems is Numerical Weather Prediction (NWP) which answers the challenges related to scientific methods needed to predict the weather through physical calculations in simulating sophisticated atmospheres (Sagita, 2017). In the last few years, That NWP has often used are mesoscale models of Weather Research and Forecasting (WRF).

The advantages of WRF are that they are efficient and flexible because they can be used on supercomputers to laptops to study various dynamic interactions on a scale of meters to thousands of kilometers (Skamarock et al., 2008). Besides, WRF is included as open-source so that the configuration of the model can be adjusted and adjusted with research needs. In the WRF model, there are three ways to improve the accuracy of weather predictions, namely improving initiation data (initial conditions and boundaries), numerical techniques, and parameterization. Due to limited costs and time, the improvement of initiation data is the main focus. One way to fix this is to assimilate the data. Data assimilation is a method of improving initiation data as an input model by calculating observational data into a grid model system (Skamarock et al., 2008).

WRF Data Assimilation (WRFDA) is a specific WRF program for assimilation data. WRFDA has several assimilation techniques, including The Three-Dimensional Variational (3DVar), The Four-Dimensional Variational (4DVar), and Ensemble Kalman Filter (EnKF). From various studies, 4DVar and EnKF show good potential in assimilating data, but this technique requires high computational costs.

Meanwhile, 3DVar is considered to have the best performance of all types of methods in analyzing hydrometeorological elements with excellent computational efficiency (Liu et al., 2013).

Assimilated data in WRFDA are surface air observation data, upper-air observations, satellites, and radar. One of the most frequently conducted researches is the assimilation of radar data. The advantage of radar data compared to other data is that it has a high resolution (the resolution is higher than the resolution of the mesoscale model) with full coverage. Based on this, the assimilation of radar data is expected to improve the ability to predict rain significantly.

Xiao et al. (2005) assimilated doppler radial velocity from Korean Jindo radar, Li et al. (2010) assimilated doppler radial velocity in Space and Time Analysis System (STMAS) project at ESRL (Earth System Research Laboratory). The studies stated that the radial velocity (V) PPI (Position Plan Indicator) data assimilation could improve quantitative rainfall prediction capabilities or short-term Quantitative precipitation forecasting (QPF). Furthermore, research on the assimilation of 3DVar radar data uses two data, namely product radial velocity data PPI (V PPI) and reflectivity (Z) of PPI products (Z PPI) (Xiao and Sun, 2007; Sugimoto et al., 2009). Based on these studies, the assimilation of data from the combination of Z and V PPI had a positive impact on the ability of QPF rather than using one of the two flats. In addition, assimilation of combination Z and V PPI data is more stable and does not cause significant errors.

In Indonesia, Satrya (2012) conducted a study on the assimilation of data on the combination of Z and V PPI 3DVar methods in the Bandung region. Based on the conclusion, the biggest sampling technique on Z PPI data as WRFDA input is the best in simulating heavy rain. In addition, Paski et al. (2017) also conducted the same study in Lampung region. Paski et al. (2019) also did a new experiment with the latest engineering research on the assimilation of radar 3DVar data in Jakarta using Z data of Constant Altitude Plan Position Indicator (CAPPI) products as the results provide better spatial rain distribution simulations

The use of CAPPI Z data in radar assimilation is new in Indonesia. Therefore, it is interesting to research the assimilating 3DVar technique radar data using Z CAPPI data. The difference with previous research is that there is a comparison test between the performance of the assimilation model of Z CAPPI, Z PPI, V PPI, and the combination of Z and V PPI in terms of improving initiation data on the WRF model for heavy rain events in Jabodetabek. Improvements to the best models are expected to increase the accuracy of predictions of heavy rainfall and temporal variations.

2. The Methods

In this study, some primary data are used. Global Forecast System (GFS) used as an initial data model, and C-Band Doppler Radar (CDR) data used as observation data. The used data for model verification in this research are data Global Satellite Mapping of Precipitation (GSMaP) for spatial analysis and observational data from the meteorological station owned BMKG around Jakarta region includes Cengkareng, Ponbet, Kemayoran, Tanjung Periuk, and Citeko for point analysis.

WRF model for research use three domains configuration. The third domain has a resolution of three kilometers and covering the Jabodetabek area (in Figure 1). Model parameterization configuration uses the best configuration conducting from Gustari et al. (2014) in WRF 3.9.1. Weather assimilation model obtained from the package of WRFDA with 3DVar technique using radar data as an observation. A brief description of the weather assimilation simulations provided in Table 1.

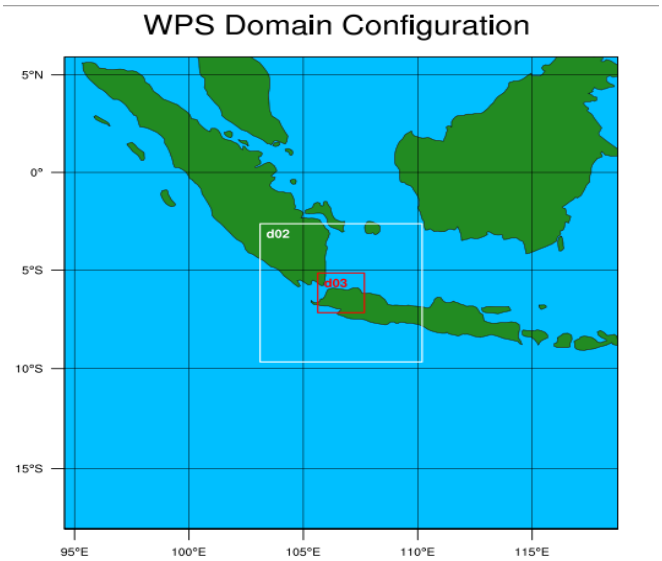

Figure 1. Domain configuration for WRF models

Table 1. Brief description of the scenario assimilations carried out.

Code	Experiment Name	Z CAPPI	Z PPI	V PPI
S1	CTL	no	no	no
S2	ZCAPPI	yes	no	no
S3	ZPPI	no	yes	no
S4	VPPI	no	no	yes
S5	ZVPPI	no	yes	yes

Radar volumetric (.vol) volumetric data is converted into two types of formats, the polar coordinates netCDF and CSV using EDGE applications. Then, both types of radar data formats will each go through different processes. The polar coordinates netCDF radar data will be processed with the wradlib-python application to convert the format into netCDF cartesian coordinates, as well as process the data into a netCDF format CAPPI product. The CAPPI calculation specifications that have been designed following research Permana et al. (2016). Furthermore, CAPPI netCDF format data is processed from the maximum sampling value in one grid model of 3 km x 3 km (according to the domain of previous *.ctl) using the R Studio application. The output data of the R application will result in the output of radar data in ASCII format or according to the WRFDA application input format.

In CSV format data, separate data based on elevation or sweep. In each sweep, the data is also separated based on reflectivity (Z), radial (V), spectral width (W) and filter unfilled (U) reflectivity. This research uses Z PPI and V PPI data as assimilation data. CSV radar data formats will be processed in numerical data analysis to combine Z PPI and V PPI data in one .txt format file. Then, the combined data Z PPI and V PPI (.txt) will be processed with the biggest value sampling technique on a 3 km x 3 km grid (according to the domain of previous *.ctl) using numerical data analysis and computation applications (Paski et al., 2017). The output data of the R application will result in the output of radar data in ASCII format or according to the WRFDA application input format. See Figure 2 for details.

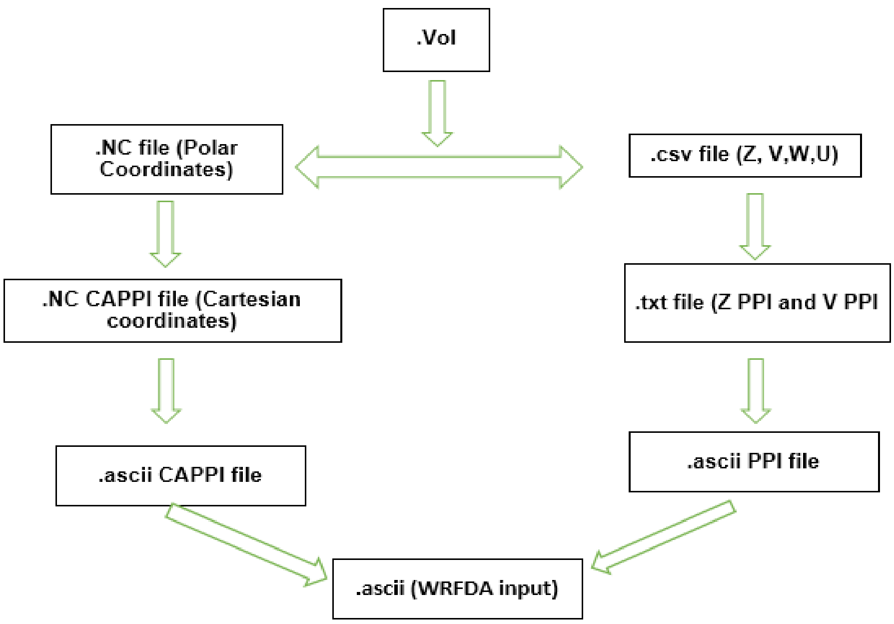

Figure 2. Flowchart for making radar data input on WRF models

The analysis carried out in this study begins by knowing the impact of radar data assimilation on changes in weather parameters on the input data. Furthermore, spatial and temporal verification of the model prediction results is done using comparative data from GSMap and surface observation results. The verification was carried out to determine the performance of the WRF model without assimilation and with assimilation using prediction skills. POD, FAR by using a contingency table on the dichotomy of rainfall events or not and looking for the percentage of hits, underestimates, and overestimations based on the category of light rain, moderate rain, heavy rain, and hefty rain.

3. Result and Discussion

The Effect of Radar Data Assimilation on WRF Initial Parameter Data

Based on table 2, which discussed the effects of each assimilation scenario, showed that the significant impact of radar data assimilation on the initial WRF data occurred in the ZCAPPI and ZVPPI simulations by modifying four initial data parameters (temperature, humidity, water vapor mixing ratio, and wind). Meanwhile, the ZPPI simulation only modified three parameters (temperature, humidity, and mixing ratio of water vapor) while the least is the VPPI simulation which only modified one parameter (wind).

In essence, Z CAPPI and Z PPI data have the same type of data, namely Z data, only in Z CAPPI data is Z data at certain fixed altitudes from data every scanning elevation, while Z PPI data is Z data from one scanning elevation. In this study, ZCAPPI simulations turned out to have a higher value than ZPPI simulations (Fig. 3). So, it was able to change wind parameters through a negative temperature change scheme, while ZPPI simulations were unable to change wind parameters (Wang et al., 2016).

Temperature Parameter

In the 3DVAR WRF assimilation, initial temperature data increments are calculated from warm-rain schemes using Z data (Wang et al., 2012). Temperature parameters play a role in the convection process where the higher the temperature, the greater the convection process that is likely to the occurrence of heavy rain (Jo Han et al., 2010).

Figure 3 shows the difference of WRF initial data for surface temperature parameters between 5 simulations on February 20^{th,} 2017. In the southeast-to-west study area, the temperature of ZCAPPI simulation is warmer than CTL assimilation, ranging from 22-24^{0} C to 26-27° C, moreover at Kemayoran, Tanjung Periuk, Ponbet, and Cengkareng, area of warmer temperatures are widespread. In Z PPI simulation also changes ~~the~~ temperature to more temperate in the southeast to the west of the study area. However, temperature of study areas such as Kemayoran, Tanjung Periuk, Ponbet, and Cengkareng is getting colder. Meanwhile, there is no difference between ZVPPI simulation and ZPPI simulation. Besides, VPPI assimilation does not change at all the temperature parameters.

Humidity Parameter

The humidity parameter is the concentration of water vapor in the atmosphere. In this study, we examine the 850 mb humidity because if the value is high in WRF initial data, then it indicates the moisture content is large enough for convective cloud growth process that has the potential to cause moderate to heavy rain (Liu et al., 2018). Figure 4 shows the initial data difference on the 850 mb humidity parameters between 5 simulations on February 20, 2017. Compared to CTL simulation, the humidity of ZCAPPI and ZPPI simulations don't change significantly. However, generally, the air gets damper so it can be ascertained that rainfall will be high as well. Location of value changes occurring in areas near radar such as Kemayoran, Tanjung Periuk, Ponbet, and Cengkareng by 84% to 86%. Similarly, areas far from radar such as Citeko, the humidity value is getting higher, for example 96% to 98%. Meanwhile, humidity increments in ZVPPI simulation are similar to ZPPI simulation, while VPPI simulation shows no change at all or equal to CTL simulation.

Table 2. Effect of radar data assimilation on WRF initial parameter data

WRF Assimilation	Weather Parameter in WRF			
	Temperature	Humidity	Mixing Ratio	Wind
ZCAPPI	√	√	√	√
ZPPI	√	√	√	-
VPPI	-	-	√	-
ZVPPI	√	√	√	√

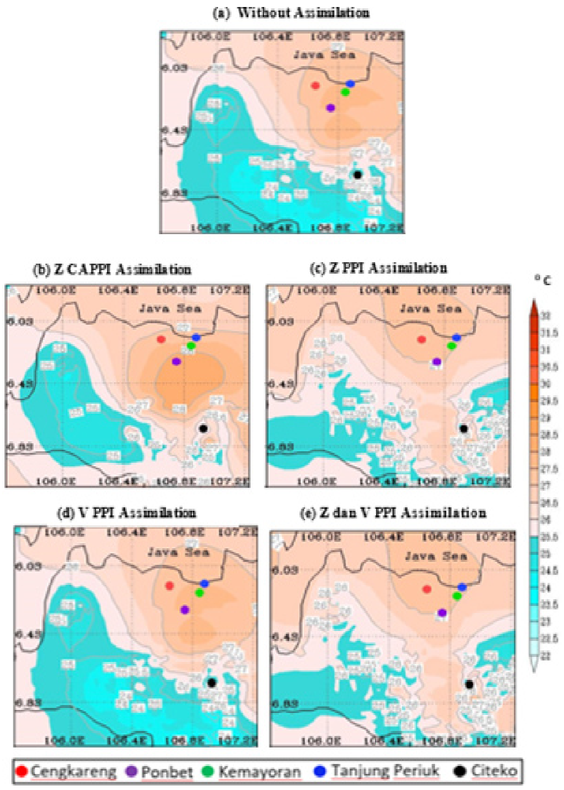

Figure 3. Initial data of surface air temperature parameter

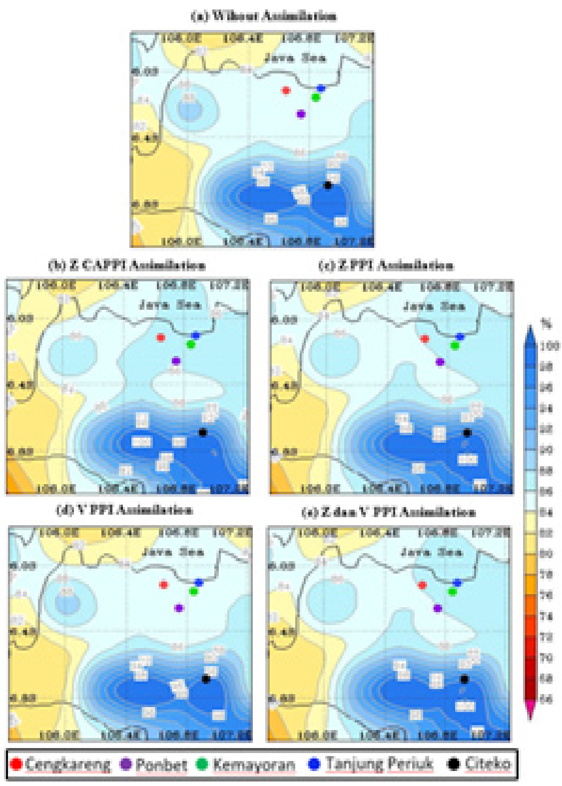

Figure 4. Initial data of humidity parameter

Water Vapor Mixing Ratio Parameters

The parameter of the water vapor mixing ratio is the ratio of moisture mass to the dry air mass present in one particular volume (Wang et al, 2013). The mixing ratio also represents the moisture content of the moisture present in the air so that with the higher the mixing ratio, the greater the chance of rain (Jones et al, 2014).

Figure 5 shows the initial data difference for water vapor mixing ratio parameter between 5 simulations on February 20, 2017. Compared to CTL simulation, there is a significant change in water vapor mixing ratio of ZCAPPI, ZPPI, and ZVPPI simulations in western region study. In areas close to radar sites such as Kemayoran, Tanjung Periuk, Ponbet, and Cengkareng, there was an increase in mixing ratio from 0.0132 to 0.0136 in ZPPI and ZVPPI simulations, whereas 0,014 in ZCAPPI experiment. This increase indicates the higher moisture content of the water or wetter conditions so that there is more potential for heavy rains. In contrast, areas far from radar such as Citeko there was a decrease in the value of mixing ratios, from 0.0152 to 0.014 in ZCAPPI, ZPPI, and ZVPPI simulations. Furthermore, VPPI simulation did not change at all in mixing ratio.

Wind Parameter

The wind parameter acts as a mass vapor supply from the outside or as a humidity transport (Ma et al, 2018). In WRF 3DVAR assimilation, the initial wind data increment comes from ZCAPPI and radial velocity data. ZCAPPI assimilation through negative temperature change (Wang et al, 2016), while assimilation of radial velocity data is directly from wind parameter element u, v, w (Routray et al., 2010)

Figure 6 shows the initial data difference on 850 mb layer wind parameters between 5 scenarios of assimilations on February 20, 2017. Spatially, ZCAPPI, VPPI, and ZVPPI simulations significantly alter the wind parameters, shows that CALM wind speed is widespread in most Southwest Jabodetabek. This indicates that convective cloud growth is not hindered by the wind. Wind speed of Kemayoran, Tanjung Periuk, Ponbet, and Cengkareng area (near radar location) also weakened, namely Cengkareng and Ponbet from 10 knots to 8 knots and Kemayoran and Tanjung Periuk areas from 14 knots to 10 knots. Meanwhile, Citeko which far away from radar location did not change significantly, for example, wind speed CALM on CTL and assimilated simulations. Meanwhile, wind direction parameters did not change significantly in each assimilation experiments. Furthermore, ZPPI simulation does not occur at all wind changes in both direction and speed.

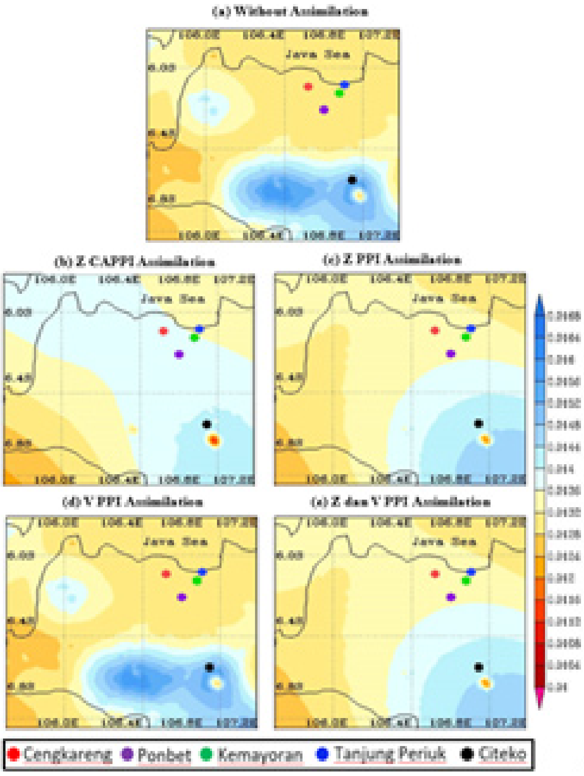

Figure 5. Initial data of water vapor mixing ratio parameter

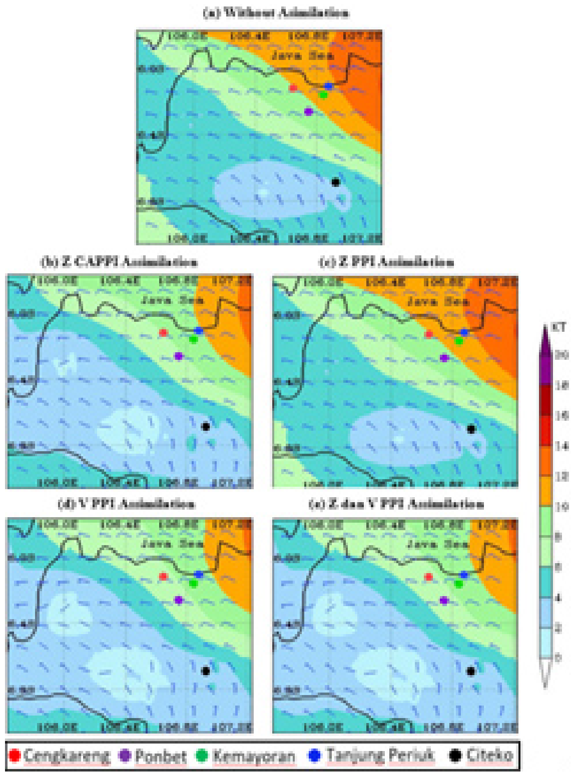

Figure 6. Initial data of 850 mb layer wind parameter

Lapse Rate

The Lapse rate is defined as a decrease in temperature against the height of the atmosphere or a negative vertical temperature gradient (Tyasjono, 2007). The value of the lapse rate is related to the cooling of the ambient temperature quickly. This significant and positive lapse rate initial data effects on the WRF calculation and prediction process (Janiskova, 2015). In general, from table 3, it can be seen that CTL and assimilated simulations on February 20, 2017, has a significant difference in temperature lapse rate at atmospheric altitudes of 1000 - 10000 km. The highest lapse rate occurs in ZCAPPI simulation. Then, the second-highest lapse rate occurred in ZVPPI simulation, then followed by ZPPI, VPPI, and CTL simulations. Meanwhile, VPPI simulation has not changed. This is due to the VPPI simulation cannot improve temperature. Besides, the lapse rate at atmospheric altitude 1000 - 10000 km in all WRF models is positive, so there is no inversion in the atmosphere layer.

Table 3. Lapse Rate

Layer (km)	Without	Z CAPPI	Z PPI	V PPI	Z & V PPI
1000-2000	4.307	6.674	7.304	4.307	8.304
2000-3000	5.84	5.499	4.286	5.84	4.286
3000-4000	6.448	5.219	4.882	6.448	4.882
4000-5000	6.512	5.699	5.42	6.512	5.42
5000-6000	5.996	4.903	6.192	5.996	6.192
6000-7000	5.083	6.091	5.362	5.083	5.362
7000-8000	5.368	5.96	6.071	5.368	6.071
8000-9000	6.901	8.038	6.763	6.901	6.763
9000-10000	8.512	8.013	8.765	8.512	8.765
10000-11000	8.794	8.998	9.274	8.794	8.274
Lapse Rate	6.1074	*6.2328*	6.1161	6.1074	6.227222

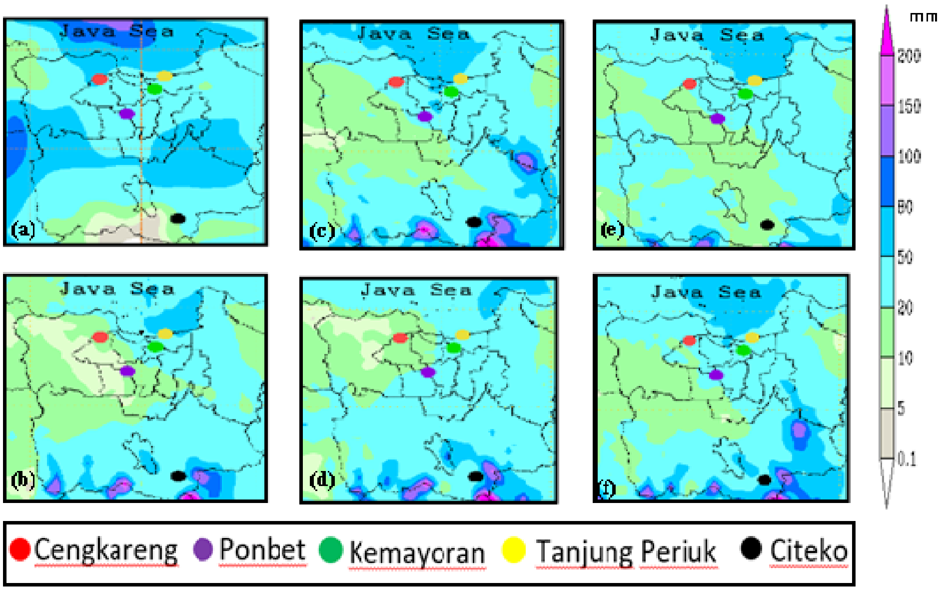

Figure 7. Spatial rain distribution on February 20, 2017, between (a) GSMaP, (b) Without Assimilation, (c) Z CAPPI Assimilation, (d) Z PPI Assimilation, (e) V PPI Assimilation, (f) Z & V PPI Combination Assimilation

Analysis and Verification of Spatial Rain Distribution

Based on Figure 7, it shows the rainfall simulation results and rainfall accumulation between GSMaP observation data and the simulation results using CTL, ZCAPPI, ZPPI, VPPI, and ZVPPI on 20 February 2017. In GSMAP data, shows rainfall of Jabodetabek area dominated by moderate rain (20 - 50 mm). However, the southern part of Bogor area happened light rain (<20 mm). Moreover, the western and eastern parts of Jabodetabek are heavy rains (50 to 100 mm), such as southwestern Tangerang, northern Bogor, eastern Depok, eastern Bekasi, southwestern Bekasi and most of Java Sea.

Compared to GSMaP observation data, the moderate rainfall area of CTL simulation is narrow. As a result, the area of light rain increases to northwest and northeast of Jabodetabek, in Tangerang, West Jakarta, South Jakarta, western Depok, and the southeast and northeast of Bekasi. Likewise, the area of heavy rain also changed places and slightly narrowed in the southern region of Greater Jakarta, which is in Bogor.

Compared to the CTL experiment, spatial rainfall of assimilated simulations does not change significantly, but generally, the broad-range rainfall area in assimilated simulations is wider than CTL, as well as with higher rainfall. It's just that the area of moderate-heavy rain remains narrower than GSMaP data. The highest rainfall is in ZCAPPI and ZVPPI simulations occur in the southeastern part of Jabodetabek, the northeastern Bogor and southeastern Bekasi. In addition, the light rain area's ZCAPPI and ZVPPI simulations in northwest Jabodetabek also appear to be narrowing.

In ZPPI simulation, the light rain area decreases in the northwest part of Jabodetabek while the heavy rain area is seen in the southeastern part of Jabodetabek, Bogor and surrounding areas. Meanwhile, the light rain area in VPPI simulation extends to the south of Jabodetabek, for example in most areas of Bogor. However, the area of heavy rain on VPPI simulation is almost absent in Jabodetabek area. In general, the simulated GSMAP rain-simulation results similar to assimilated simulations differ only in rain intensity with the most superior models are ZCAPPI and ZVPPI simulations because it is more susceptible to heavy rainfall than other assimilated simulations.

Verification of time series predictions for rainfall accumulation for three hours

Figure. 8a shows the time series of accumulated rainfall for three hours in CTL or assimilated simulations at the Soekarno Hatta Cengkareng Meteorological station on February 20^{th,} 2017 tends not to be similar to observational data, namely rain starting at 12.00 UTC, whereas according to observation data occurs around 18.00 UTC. In addition, the rainfall accumulation in the observation data is underestimated, especially CTL simulation, and then there is an improvement in accumulation of rain which is closest to the observation data, those are Z CAPPI and ZVPPI simulations.

Figure. 8b shows the time series of accumulated rainfall for three hours in CTL or assimilated simulations at Ponbet climatological station tends not to be similar to observation data. Based on observation data it appears no more rain after at 09.00 UTC, but on CTL or assimilated simulations, the rain returned where there was an increasingly rising line pattern. In addition, the rain accumulation of the WRF model is entirely overestimate compared to observation data, especially CTL simulation, and then there is an improvement in rainfall accumulation which is the closest to the observation data, that is ZPPI simulation.

Figure. 8c shows the time series of accumulated rainfall for three hours in CTL or assimilated simulations at Tanjung Periuk tends to be similar to observational data with the same start of rain starting at 00.00 UTC, then there was heavy rain at 18.00 UTC. However, the accumulation of rain that occurred in the WRF simulations was entirely underestimating, especially CTL simulation and then there was an improvement in rainfall accumulation which is closest to the observation data with the lowest underestimation occurring in ZCAPPI and ZVPPI simulations.

Figure. 8d shows a time series of accumulated rainfall for three hours in WRF without assimilation or WRF assimilation of radar data at Citeko meteorological station tends not to be similar to observation data. It can be seen from the graph that rainfall distribution at observational data occurs continuously at 00.00 - 06.00 UTC, then returns to rain starting at 18.00 UTC, whereas in WRF without assimilation and radar assimilation rain occurs at 03.00 UTC continuously with different intensities. Moreover, the accumulation of daily rainfall occurs in each WRF is overestimate, with the highest ~~being~~ is in WRF V PPI assimilation.

Rain Dichotomy Verification (yes / no)

To compare the numerical experiments, three statistical indicators PC, POD, and FAR (Jakubiak, 2014) are evaluated using rain dichotomy (yes / no) (Wiegand, 2015; Fatkhuroyan et al, 2019). Radar observation distance will have a significant influence on the accuracy of the radar parameters used to assimilate the data. The evaluation methodology based on the point-to-point comparison between model-generated variables and observations. This is a two-dimensional matrix where each element counts the number of occurrences in which the gauge measurements and the model forecasts exceeded or failed to reach a certain threshold for a given forecast period. The table elements are defined as: A-model forecast and gauge measurement exceeded the threshold; B-model forecast exceeded the threshold but measurement not; C-model forecast did not reach the threshold but measurement exceeded it; and D-model forecast and measurement did not reach the threshold, see Table 4. Based on the above elements, the Proportion Correct is defined as PC = (A+D)/N, with N holding the total number of observations being verified (N=A+B+C+D). The Probability of Detection is defined as POD = A/(A+C), the False Alarm Ratio is defined as FAR = B/(A+B).

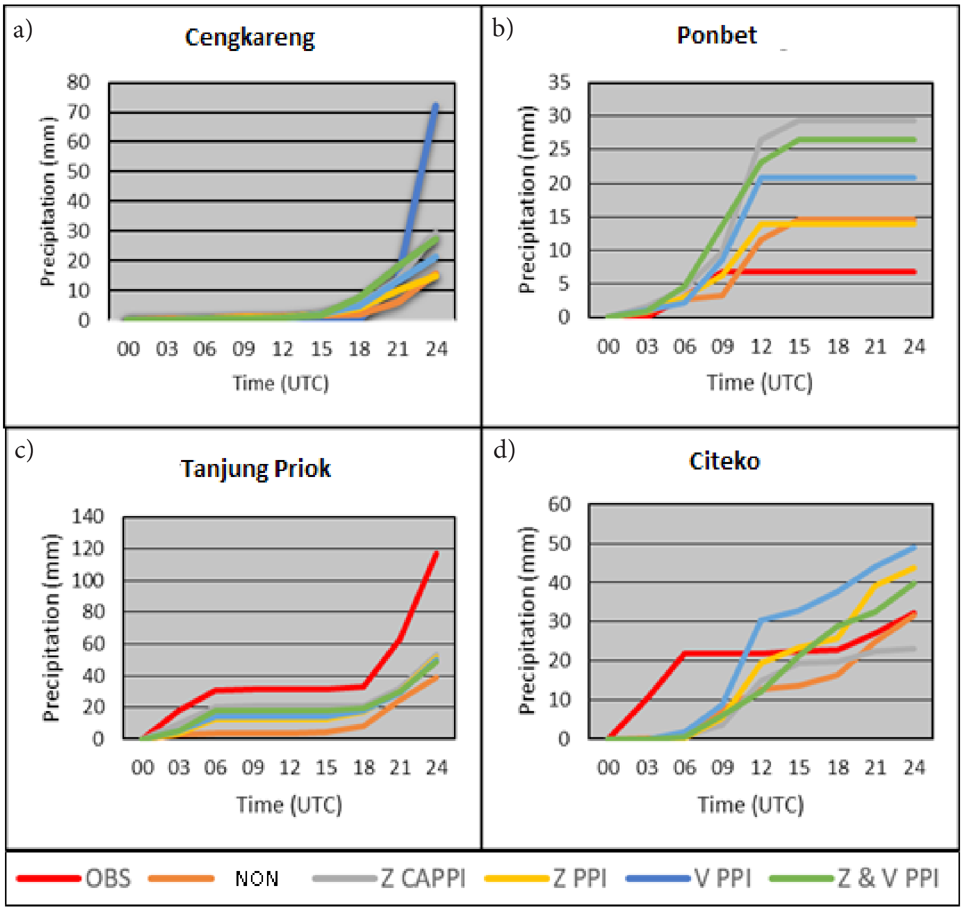

Figure 8. Time series of accumulated rainfall for three hours based on 4 rainfall observed data's meteorological stations

Table 4. 2x2 Contingency Tabel

	Observation: Yes	Observation : No
Forecast: Yes	A	B
Forecast: No	C	D

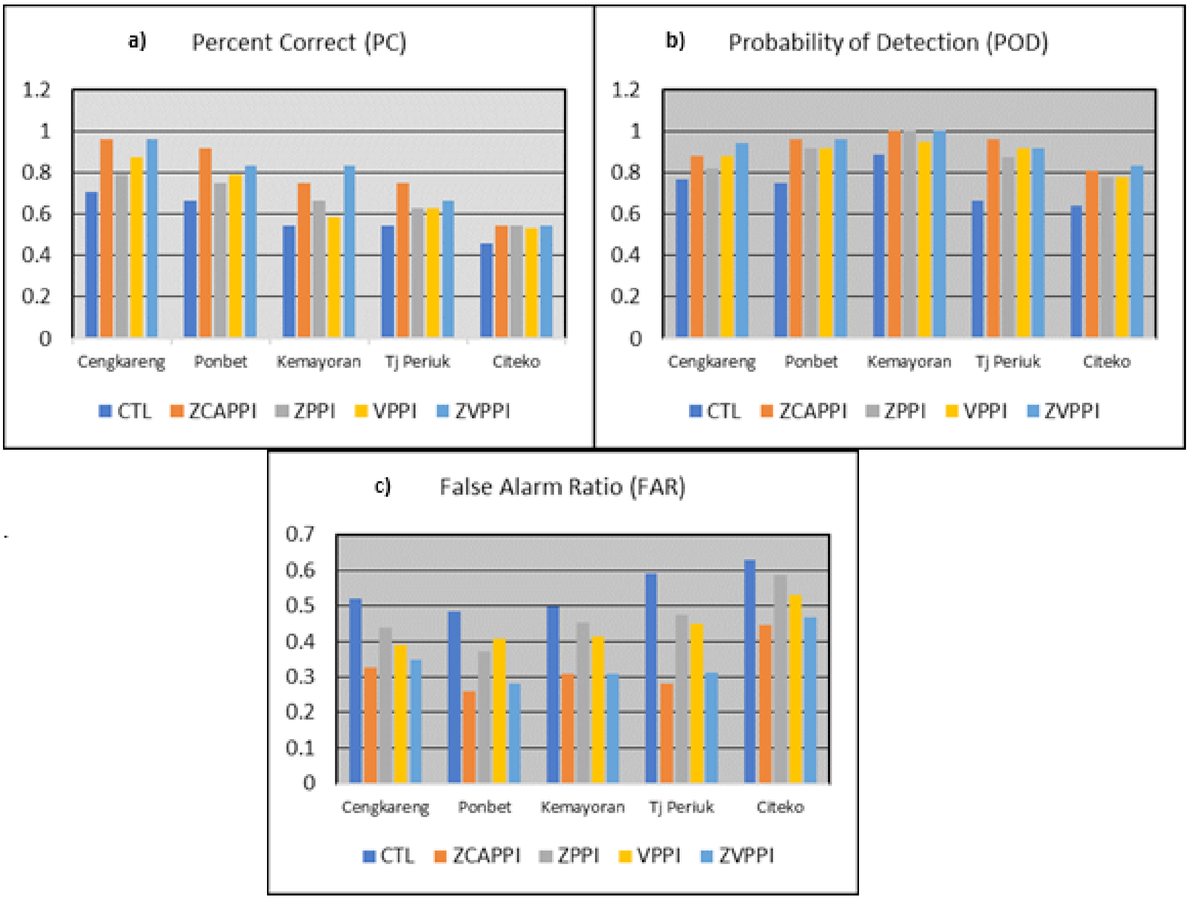

Figure 9. Histogram of Skill forecast (a) PC, (b) POD, (c) FAR

Based on figure 9a, it can be seen that all WRF model scenarios are assimilating radar data improve PC skills. The highest PC value occurred at the Cengkareng area observation point of 0.95, which occurred ZCAPPI and ZVPPI simulations. Furthermore, at Ponbet observation point, the highest PC value which occurred in ZCAPPI simulation is 0.91. At the Kemayoran observation, the highest PC value of 0.83 occurred in ZVPPI simulation. At Tanjung Periuk observation point, the highest PC value of 0.75 occurred in ZCAPPI simulation. Finally, at Citeko observation point, the highest PC value of 0.75 occurred in ZCAPPI, ZPPI, and ZVCAPPI, but this value is lowest compare to PC value at other observation points. Meanwhile, the lowest PC value always occurs in CTL simulation at all observation points followed by VPPI or ZPPI simulation.

Based on figure 9b, it can be seen that assimilated radar simulations improve POD skills. The highest POD value occurred at Kemayoran observation point with an absolute value of 1.00, which occurred in ZCAPPI, ZPPI, and ZVPPI simulations. Furthermore, at Ponbet observation point, POD the highest value of 0.95 occurs in ZCAPPI and ZVPPI simulations. Likewise, at Tanjung Periuk observation, the point highest POD value of 0.95 also occurs in ZCAPPI simulation. At Cengkareng observation point, the highest POD value of 0.94 occurs in ZVPPI simulation. And finally, at Citeko observation point, the highest PC value of 0.83 occurs in ZVPPI simulation, which is this value is the lowest than the highest POD value at other observation points. Meanwhile, the lowest PC value occurred in CTL simulation at all observation points followed by ZPPI or VPPI simulation.

Based on figure 9c, it is clearly seen that assimilated radar simulations improve FAR skills. The lowest FAR value occurred at the Ponbet observation point, which arises in ZCAPPI simulation by 0.25 and ZV PPI simulation by 0.28. Furthermore, at the Tanjung Periuk observation point also had a low FAR value of 0.28, which occurred in ZCAPPI simulation and as much as 0.31 in ZVPPI simulation. At the Kemayoran observation point, the lowest FAR value occurred in ZCAPPI and ZVPPI simulations by 0.3. At the Cengkareng observation point, the lowest FAR value of 0.32 occurred in ZCAPPI simulation. Finally, at the Citeko region observation point, the lowest FAR value of 0.44 occurred in ZCAPPI simulation, where this value is the highest than the lowest FAR value at other observation points. Meanwhile, the highest FAR value occurred in WRF without assimilation at all observation points, followed by ZPPI or VPPI simulations.

Prediction Verification based on Rain Category

Moreover, rain category verification is investigated to see improvement of simulations (Ricciardelli et al., 2018). Generally, from table 5, the percentage of assimilated simulations performance is better than CTL simulation. This can be seen from the best sequence always on assimilated simulations. Simulation performance is best in the light rain category, because the average percentage of *hits* is better than the other rain categories, with the most superior model is ZCAPPI simulation. For the moderate rain category, the rate of *hits* also looks dominant with the best model is ZVPPI simulation. The performance of assimilated model is quite good for the moderate rain category, while in the category of heavy rain and very heavy, underestimate conditions are still very dominant. Furthermore, the average underestimates percentage reached 76.4% in the heavy rain category with the most superior model is ZCAPPI simulation, while the category of very heavy rain - the average underestimate percentage reached 99.48% with the most superior model is ZCAPPI simulation.

Discussion

In this study, the most significant modification of the parameters of temperature, humidity, and water vapor mixing ratio occur in ZCAPPI simulation, then followed by ZVPPI simulation, and ZPPI simulation. The most significant modification of wind parameter values occurs in VPPI simulation, then followed by ZVPPI and ZCAPPI simulations. This result is consistent with the research of Sun and Wang (2013), which states that assimilation of V data has a significant impact on wind analysis, while analysis of temperature, humidity, and water vapor mixing ratio are secondary. Conversely, assimilation of Z data has a direct effect on the analysis of temperature, humidity, and water vapor mixing ratio while wind analysis is secondary.

Based on the summary ranking of skill prediction (see table 6), it can be clearly stated that ZCAPPI and ZVPPI simulations are the best rain prediction both spatially and periodically. It was clearly seen from the 1st best sequence only in the two assimilated simulations. This is consistent with the effects on the initial WRF data, where those both assimilated simulations can improve WRF performance. This is consistent with the research of Sun and Wang (2013), which states that when physical parameters (air temperature, air humidity, water vapor mixing ratio) and dynamic parameters (wind) are calculated in the 3DVar WRF assimilation system, errors can be minimized in order to predict more accurate rainfall.

Table 5. Ranking and Percentage Average of Skill Prediction Based on Rain Category

Category*	The Best Order					Percentage Average		
	1	2	3	4	5	Underestimate	Hits	Overestimate
Light	S1	S4	S3	S2	S0	0 %	89,6 %	10,4 %
Moderate	S4	S1	S2	S3	S0	2,8 %	86,6%	8,6 %
Heavy	S1	S4	S2	S3	S0	75,8 %	23,4 %	0,8 %
Very Heavy	S1	S4	S3	S2	S0	99,8 %	0,2 %	0 %

* The rain category based on Perka BMKG NO: KEP. 009 (2010)

Table 6. Summary Ranking of Skill Prediction by Spatial and Point

WRF Models	Spatial	Point		
		Time Series	Rain Dichotomy	Rain Category
CTL	5	5	5	5
ZCAPPI	1	2	1	1
ZPPI	3	3	4	4
VPPI	4	4	3	3
ZVPPI	2	1	2	2

4. Conclusion

Generally, the WRF model of radar data assimilation provides a better simulation of spatial and point rainfall events than the WRF model without assimilation. The improvement of rainfall predictions will be more visible in areas close to the radar source, that is not blocked by echo from fixed objects such as mountains or hills, and during the rainy season. From the four assimilation model scenarios carried out in this study, it can be concluded that the best sequence of WRF scenarios is ZCAPPI, ZVPPI, VPPI, and ZPPI simulations, respectively.

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