COMPARISON OF DATA ASSIMILATION USING SURFACE OBSERVATION, UPPER AIR, AND SATELLITE RADIATION DATA ON RAINFALL PREDICTION IN THE JAMBI REGION (Case Study of Heavy Rain October 20TH, 2020)

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Abstract. Weather Research and Forecasting (WRF) is a mesoscale numerical weather prediction model that can provide good rainfall prediction information. The accuracy of the initial conditions and the parameterization scheme used in the WRF model affect the quality of the resulting rainfall prediction. Therefore it is necessary to assimilate to optimize the accuracy of the initial conditions in the model using the Three Dimensional Variational (3DVAR) assimilation technique. The purpose of this study was to determine the effect of applying the 3DVAR assimilation technique with the surface, upper air, and satellite radiation observations in predicting the occurrence of heavy rain on October 20, 2020, in the Jambi region by first conducting a parameterization test of the cumulus and microphysical schemes. In this study, four experimental methods were used, namely no assimilation (NON), observation data assimilation (OBS), satellite radiation data assimilation (SAT), and satellite radiation and observation data assimilation (BOTH). Each experimental model result was then verified statistically and spatially to determine the effect of the applied data assimilation. The results of this study indicate that the combination of Grell-3D and Thompson schemes shows the best performance in predicting rainfall. Then based on the spatial analysis of the SAT experiment, it is known that it can improve the model's initial conditions on the temperature and pressure parameters. Meanwhile, based on statistical verification, the SAT experiment improved the accuracy of rainfall predictions with a better forecast skill score than other experiments tested.

Keywords: *heavy rain, parameterization, data assimilation, WRF*

1 INTRODUCTION

Temporal and spatial estimation and rainfall prediction are essential for many users in various sectors, such as tourism and flood prediction (Bauer et al., 2015). The current rainfall's accuracy continues to improve from time to time to obtain adequate weather forecasting and early warning information. Various ways and methods are used to get accurate weather information, one of which is to use the fundamental equations of numerical weather prediction (NWP) (Golding, 2013). NWP is currently still being developed to meet the need for accurate high-resolution weather forecasts.

Weather Research and Forecasting (WRF) is a mesoscale numerical weather prediction model widely used in research and operational needs for weather forecasting (Burrahman et al., 2019). According to Cardoso et al. (2013), the WRF model can provide good information about rainfall. The atmospheric simulation stage by the WRF model consists of two stages: the configuration of the domain model, processing of the input data, and preparing the model's initial conditions, and the running forecast model (Powers et al., 2017). It should be noted that the initial and boundary conditions of a model that is run depend on the global interpolation model, which has low resolution and uncertainty and several sources of error. The existence of uncertainty from the initial conditions of this model has a substantial effect on the growth of errors generated by a model (Leutbecher and Palmer, 2008). Therefore, the accuracy of the model's initial conditions is something that needs to be considered as a determinant of the existing prediction results.

One way to improve the initial conditions of a numerical model is to perform data assimilation (Skamarock et al., 2008). Data assimilation is a technique in which observational data are combined with NWP product, and their respective error statistics better estimate atmospheric conditions (NCAR, 2017). The application of assimilation in the WRF model consists of various techniques, one of them is the Three Dimensional Variational (3DVAR). The 3DVAR technique performs better in producing a rational analysis of hydrometeorological events with greater computational efficiency than other techniques (Barker et al., 2004). Various types of observational data can be assimilated into the model's initial conditions, including synoptic, buoy, radiosonde, satellite, and radar observations (Skamarock et al., 2008).

In the last decade, many studies on the assimilation of observational data have been carried out and have yielded promising results for improving model predictions. Assimilation of surface observation data during heavy rains in India can improve initial conditions characterized by increased accuracy of the location and amount of rainfall in the Indian monsoon region (Routray et al., 2010). significant effect on wind parameters and a rain pattern close to the observation data, especially in the dry season (Rahma, 2020). These two studies show that the assimilation of surface and upper air observation data can improve the model's ability to predict rainfall.

In addition to surface and upper air observation data, assimilation using satellite radiation data can also improve the prediction results of the model. The assimilation of the Advanced Microwave Sounding Unit-A (AMSU-A) and Microwave Humidity Sounder (MHS) satellite radiation is considered to improve model performance. It can provide valuable information related to temperature profiles that can increase the coverage of heavy rainfall predictions (Xie et al., 2018). According to Sagita et al. (2017), assimilation of AMSU-A and MHS satellite radiation data improves rainfall prediction in northwest Java, where the accuracy of rainfall prediction is better than the model without assimilation.

To get better rainfall prediction results before carrying out the assimilation process, first, test the cumulus and microphysics parameterization to increase the model's sensitivity in predicting rainfall. According to Stensrud et al. (2015), parameterization is the most crucial component in the model, which influences the model output. Therefore, this study aims to determine the effect of improving the model's initial conditions by assimilation of surface, upper air, and satellite observation data in predicting rainfall in the Jambi region by first conducting parameterization tests for cumulus and microphysics schemes. The location and time of the incident were chosen during heavy rains in Jambi, as will be explained in more detail in the research methods section.

2 MATERIALS AND METHODOLOGY

2.1 Location and Data

This research was conducted in Jambi and surrounding areas, with the boundaries of the research area covering 0.143°-3.116°S and 100.924° - 104,826°E (Figure 2-1). Meanwhile, the research was conducted on October 20, 2020, when heavy rains up to 84 mm/day were recorded on AWS Staklim Muaro Jambi.

The data used in this study is Global Forecasting System (GFS) with a spatial resolution of 0.25° × 0.25° and a temporal resolution of 3 hours which is used as the initial condition. GDAS Satellite Radiance Data (AMSU-A and MHS) data in BUFR format and upper air and surface observation data from Global Upper Air and Surface Weather Observations in PREBUFR format as input for assimilation data provided by NCEP. Observation data from AWS Staklim Muaro Jambi, AWS Tj. Jabung Barat, AWS Bukit Baling, and AWS Stamet Sultan Thaha on October 20, 2020, with a temporal resolution of 10 minutes.

2.2 Research Method

Data processing in this study was carried out using the WRF-ARW and WRF-DA models version 4.2. The model is run for 24 hours, starting from 00.00 – 24.00 UTC on October 20, 2020, with the first 12 hours used as spin-up time. Spin-up time is the time required for the model to reach a stable condition. According to Montavez et al. (2017), the spin-up time is optimal if the model provides the most representative results within the shortest period. In this study, the model was run in 3 domains obtained through downscaling technique with a ratio of the model's resolution used is 1:3:3. The first domain has a resolution of 27 km, the second domain is 9 km, and the third domain is 3 km with a center point using coordinates from AWS Staklim Muaro Jambi, namely 1.60111° South Latitude and 103.4944° East Longitude as shown in Figure 2-1.

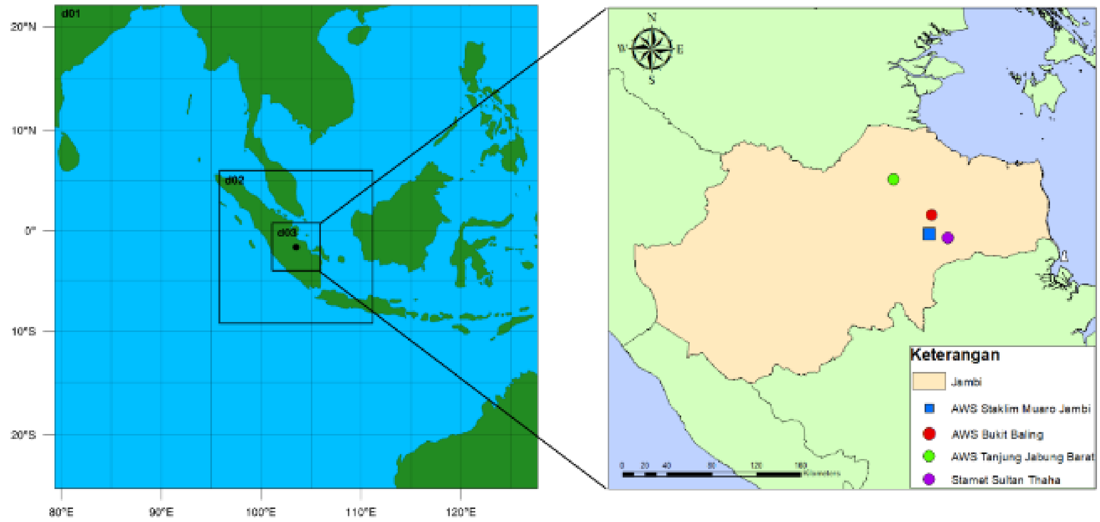

Figure 2-1: Research location

Table 2-1: Model configuration

Configuration	Domain 1	Domain 2	Domain 3
Horizontal Resolution	27 km	9 km	3 km
Temporal Resolution	180 minutes	60 minutes	10 minutes
Central Coordinates	AWS Muaro Jambi (1.60111°S and 103.4944°E)		
Spin-up Time	12 jam		
Microphysics Schematics	[1] Thompson [2] Lin	[1] Thompson [2] Lin	[1] Thompson [2] Lin
Cumulus Schematics	[1] BMJ [2] Grell-Devenyi [3] Grell-3D	[1] BMJ [2] Grell-Devenyi [3] Grell-3D	-
Longwave Radiation Schematics	RRTM	RRTM	RRTM
Shortwave Radiaton Schematics	Dudhia	Dudhia	Dudhia
PBL Scheme	YSU	YSU	YSU
Land Surface Scheme	Noah	Noah	Noah

Parameterization of cumulus and microphysics schemes were tested to obtain the best configuration scheme. The cumulus parameterization schemes tested were Grell-Devenyi (GD), Betts-Miller-Janjic (BMJ), and Grell-3D (G3D), while the microphysics parameterization schemes were Thompson and Lin. The cumulus GD parameterization scheme was adopted from research conducted by Fadianika and Hariadi (2015). The GD scheme has the best sensitivity in predicting rain in almost all areas of East Java. Then the BMJ scheme was chosen because this scheme is suitable for use in humid environments, does not require many calculations, is the most efficient scheme to protect the microphysics scheme from creating convective clouds, and treats high convection better than other schemes (Kurniawan et al., 2014). The selection of the G3D scheme was based on research by Fatmasari et al. (2017), where this scheme is quite good at representing the dynamics of the atmosphere causing heavy rain in the Lampung region and producing rain predictions with good accuracy.

In this study, verification was gained statistically by comparing the model output of rainfall parameters with a 10-minute temporal resolution to the rainfall data from four selected AWS. The statistical verification used includes correlation coefficient (CC), root mean square error (RMSE), accuracy, probability of detection (POD), bias score, false alarm ratio (FAR), and probability of false detection (POFD). Then, to determine the effect of the application of data assimilation on the model's initial conditions, an analysis of atmospheric conditions was carried out. Further analysis of atmospheric conditions was also carried out to determine fluctuations in atmospheric conditions before and during heavy rains. By comparing the four experiments tested, it will be known which experiments with atmospheric dynamics conditions best represent the occurrence of heavy rain in this study.

3 RESULT

3.1Parameterization Scheme Verification

The best parameterization scheme was chosen based on the error value (RMSE) and the correlation value of the observations and predictions of model rainfall. According to Zhou and Mu (2018), the model error threshold value for rainfall parameters is divided into three categories, namely low (< 10 mm), medium (10-20 mm), and high (> 20 mm). Meanwhile, the correlation value ranges from -1 to +1, where the value of -1 is an excellent value indicating a negative linear relationship, and a value of 0 indicates no correlation. In contrast, a value of +1 is an excellent value indicating a positive linear relationship (Wilks, 2006). The higher the correlation value indicates that the model can follow the observed data fluctuations.

Table 3-1: Test results of the parameterized scheme using CC and RMSE values. The yellow cells show the lowest error and highest correlation.

Locations	Index	Schema					
		1	2	3	4	5	6
Stamet Sultan Thaha	CC	0.937	0.922	0.934	0.921	-0.628	0.978
	RMSE (mm)	15.341	18.521	16.019	22.224	25.215	6.702
AWS Stakli Muaro Jambi	CC	0.701	0.695	0.817	0.273	-0.235	0.878
	RMSE (mm)	10.598	10.585	8.365	12.080	13.534	10.288
AWS Bukit Baling	CC	0.319	0.126	0.312	0.029	-0.546	0.362
	RMSE (mm)	3.363	3.631	6.329	10.739	3.924	4.119
AWS Tj. Jabung Barat	CC	-0.114	-0.078	-0.130	-0.147	-0.081	0.038
	RMSE (mm)	1.738	1.736	1.738	1.748	2.203	7.678

Based on the comparison of the results of the parameterization scheme test in Table 3-1, it can be seen that the prediction of rain on October 20, 2020, has different error and correlation values at each observation point. The lowest error value of 1,736 mm is found on AWS Tj. Jabung Barat with a correlation of -0.078 using Scheme 2. Meanwhile, the highest error value of 25,215 mm is found at the Sultan Thaha Meteorological Station with a correlation of -0.628 using Scheme 5. The correlation value generated by all schemes on AWS Tj. Jabung Barat is negative, except for Scheme 6. Negative correlation values are also found in rainfall predictions using Scheme 5 at the four verifier points. The negative correlation indicates that the scheme cannot capture very little rainfall (Fatmasari, 2018). In addition, the negative correlation also indicates that the model cannot follow the fluctuations in the observed rainfall data.

Overall, Scheme 6, a combination of Grell-3D and Thompson schemes, is considered the most capable of producing good rain predictions compared to other five schemes. The highest correlation value indicates this at the four verification points obtained using Scheme 6. In addition, the error value in the rainfall prediction in Scheme 6 is low and meets the error threshold value, which is < 10 mm (Zhou and Mu, 2018). Furthermore, scheme six will be used in the process of assimilation and analysis in the next sub-chapter.

3.2 Rain Verification by Point Observation

On October 20, 2020, heavy rain had different intensities at the four verifier point locations, as shown in Figure 3-1. The intensity of rain produced by the SAT experiment shows a value close to the observed results, except for AWS Bukit Baling, where the measured rainfall intensity is minimal. Meanwhile, for the NON-experiment, the rainfall intensity on AWS Bukit Baling showed a much higher value than the observed results, but on AWS Tj. West Jabung NON and BOTH experiments did not detect any rainfall. Among the four experiments tested, the SAT experiment was considered more capable of producing rain intensity close to the observed results, especially at the Sultan Thaha Meteorological Station.

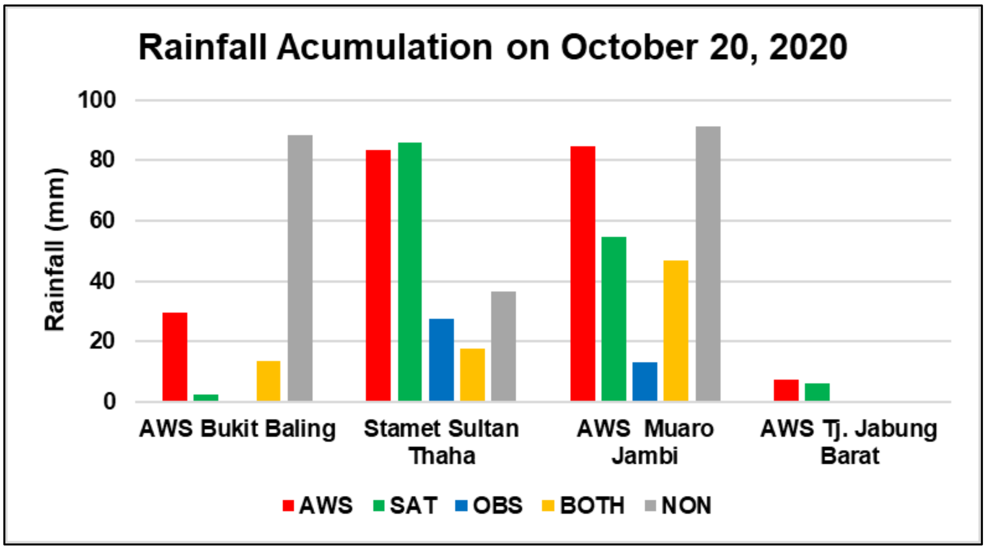

Figure 3-1: Histogram of rainfall accumulation on October 20, 2020, at four locations verifier

Table 3-2 shows the correlation and RMSE values between the observed rainfall and the model output using the SAT, OBS, BOTH, and NON-experiments at four verifier points. Except for AWS Tj, the SAT experiment has a reasonably high correlation value. AWS Tj. Jabung Barat and AWS Bukit Baling are negative. Meanwhile, in the OBS and BOTH experiments, all correlations were negative. A negative correlation indicates that the model cannot capture much less rainfall (Fatmasari, 2018). When viewed from the overall error value, the SAT experiment has a minor error value at the four verifier points, which is < 10 mm (Zhou and Mu, 2018). This shows that the influence of satellite assimilation can improve the model's ability to predict rainfall, seen from the high correlation and low error values.

Table 3-2: Comparison of data assimilation test results for NON, SAT, OBS, and BOTH experiments using CC and RMSE values. The yellow cells show the lowest error and highest correlation

Locations	Index	SAT	OBS	BOTH	NON
Stamet Sultan Thaha	CC	0.969	-0.327	-0.328	0.994
	RMSE (mm)	6.021	27.124	25.776	12.836
AWS Muaro Jambi	CC	0.708	-0.155	-0.156	0.171
	RMSE (mm)	1.567	2.491	3.414	2.844
AWS Bukit Baling	CC	-0.004	-0.119	-0.086	0.618
	RMSE (mm)	1.037	1.046	1.406	3.539
AWS Tj. Jabung Barat	CC	0.026	-0.016	-0.016	0.018
	RMSE (mm)	0.782	0.736	0.734	0.734

Based on the histogram of the forecast skill score shown in Figure 3-2, it is known that the SAT experiment has an immense accuracy value, which is 0.82. This indicates that 83% of all SAT experimental forecasts are accurate. For the POD parameter, it can be seen that the SAT and NON-experiments have a POD value of 1, which indicates that all observed rainfall events were predicted correctly by the two experiments. Meanwhile, for the FAR parameter, the smallest value is owned by the SAT experiment, which is 0.27. This shows that 27% of the predicted rain events did not occur. In this study, the determination of the experiment with the best performance was carried out by referring to the research conducted by Rahma (2020). The best investigation was obtained in this study by determining one stable experiment occupying the top 3 positions on each index. The experiment with the best performance in predicting rainfall in this study is the SAT experiment. The investigation has the highest accuracy and POD and the lowest FAR compared to other experiments.

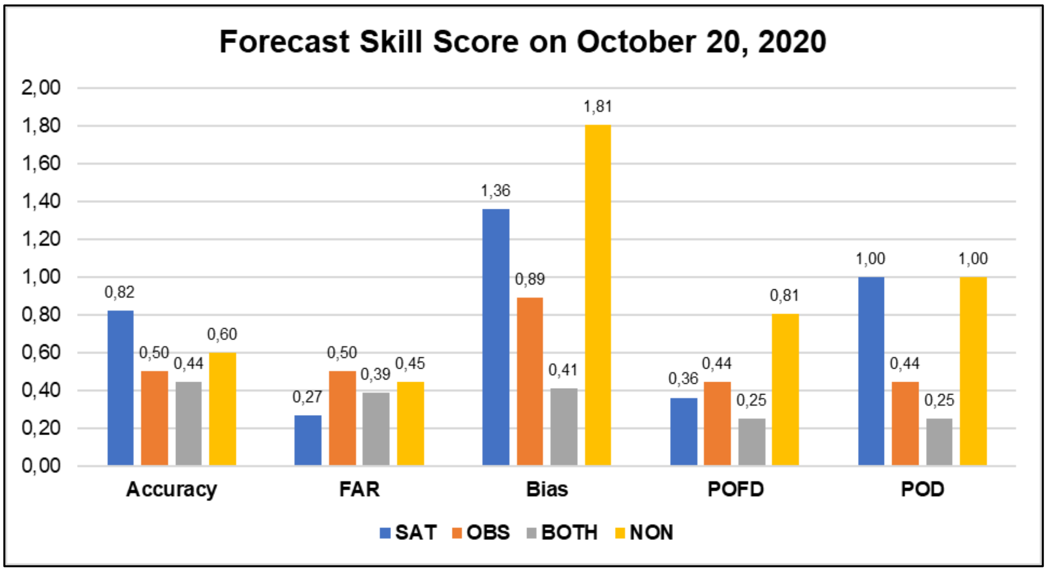

Figure 3-2: Histogram forecast skill score on October 20, 2020 on AWS Staklim Muaro Jambi

3.3 Increment Analysis

Incremental analysis was conducted to determine the effect of assimilation on the model's initial conditions. The increment is obtained from the difference between the assimilated model's initial conditions and those without assimilation. A positive value in the increment analysis indicates a change in the form of an increase in the value of a parameter. In contrast, a negative value indicates a decrease in the value.

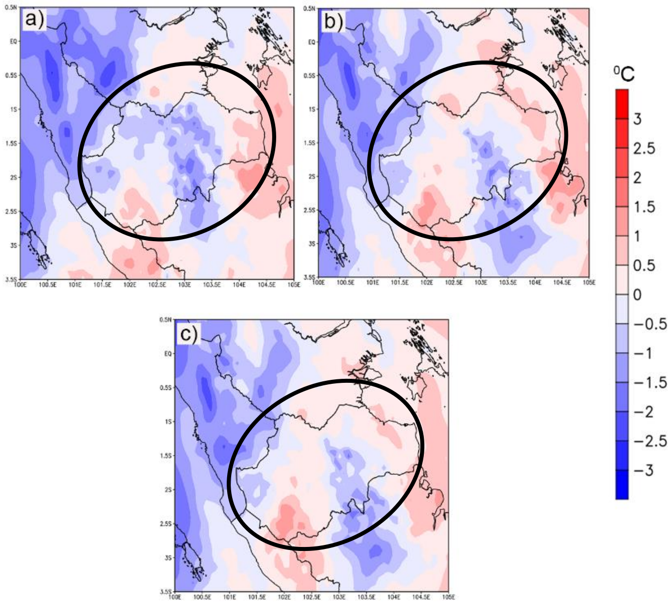

Figure 3-3: Increment of air temperature 700 mb on October 20, 2020 at 15.00 UTC for a) SAT; b) OBS; and c) BOTH. The black circle indicates the Jambi region

Figure 3-3 shows the results of the increment calculation for the 700 MB layer air temperature parameter on October 20, 2020, at 15.00 UTC. Based on the three experiments, it is generally seen that there is an increase in air temperature in the Jambi coastal area of 0.5°C – 2.0°C. While in the central part of Jambi, there was a decrease in air temperature of 0.5°C – 1.5°C. The most significant change in air temperature among the schemes tested occurred in the SAT experiment. The increment of the SAT experiment showed an increase in temperature of 1.0°C – 2.0°C in the Jambi coastal area and a decrease in air temperature of up to 1.5°C in the central Jambi region. Meanwhile, the OBS and BOTH experiments showed almost the same pattern of temperature changes, where the resulting temperature changes were not as significant and as broad as the temperature changes in the SAT experiment. For the Jambi coastal area, the OBS and SAT schemes show a temperature increase of 0.5°C – 1.0°C, and for the central Jambi region, there is a 0.5°C – 1.0°C decrease in temperature.

Based on the analysis of the 700 MB layer of air humidity increment, as shown in Figure 3-4, it can be seen that, in general, there is an increase in air humidity in the central part of Jambi and a decrease in air humidity in parts of the western part of Jambi. The SAT experiment showed a significant change in air humidity for the Jambi region, which increased by up to 20% in the central part of Jambi and decreased by up to 12% in the western part of Jambi. Meanwhile, the OBS and BOTH experiments experienced less significant changes in air temperature than the SAT experiments, where the temperature changes that occurred were relatively small within a narrow area.

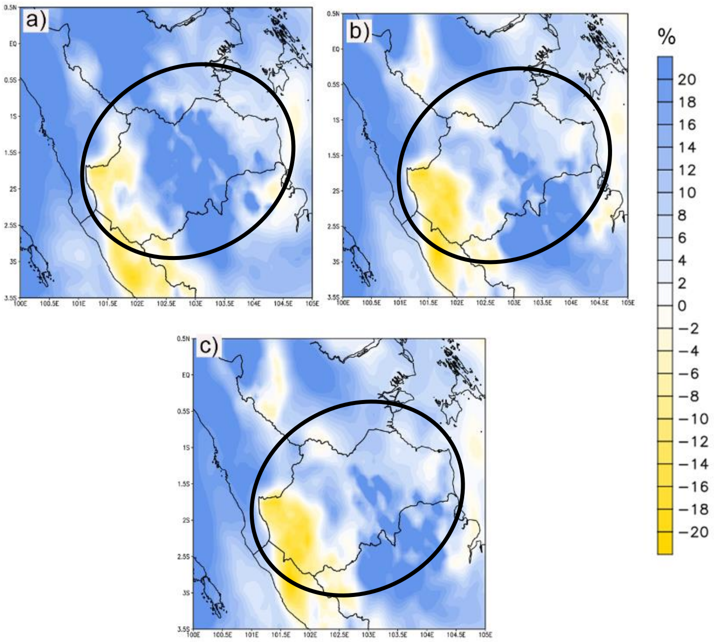

Figure 3-4: Increment of 700 mb layer humidity increment on October 20, 2020 at 15.00 UTC for a) SAT; b) OBS; and c) BOTH. The black circle indicates the Jambi region.

The analysis of temperature and humidity increments shows that the SAT experiment produces more significant changes than the OBS and BOTH experiments, following research conducted by Kutty and Wang (2015), which states that the assimilation of satellite radiation data can change the profile of temperature and humidity. In the tropics, significantly. Meanwhile, the OBS and BOTH experiments showed less significant results because, in the Jambi region, there were no upper air observations; this is based on Fatmasari (2018). In this study, the OBS experiment could not produce significant changes in air temperature and humidity parameters because no additional upper-air data could provide further information on the vertical air temperature and humidity profile.

3.4 Atmospheric Condition Analysis

Relative humidity (RH) measures the relative value of water vapor in the air, where the higher the humidity value, the more saturated the air quality will be. If a particular area has high saturation or water content, it will support cloud growth activity (Tjasyono and Harijono, 2006). The vertical RH condition on October 20, 2020, at 17.00 – 22.00 UTC in Figure 3-5 shows that the NON and SAT experiments tend to have the same RH state where the RH value before and during heavy rain is relatively high, namely 75 - 100% up to a layer of 300 MB. This means that the air contains a lot of water vapor and has the potential to form convective clouds. While the OBS and BOTH experiments generally have almost the same pattern, at 14.00 – 16.00 UTC, the RH value of 75 - 95% occurs from the surface to the 700 MB layer. Then when it rains, at 17.00 – 22.00, the RH value of 80-100% happens from the surface layer to a layer of 700 MB.

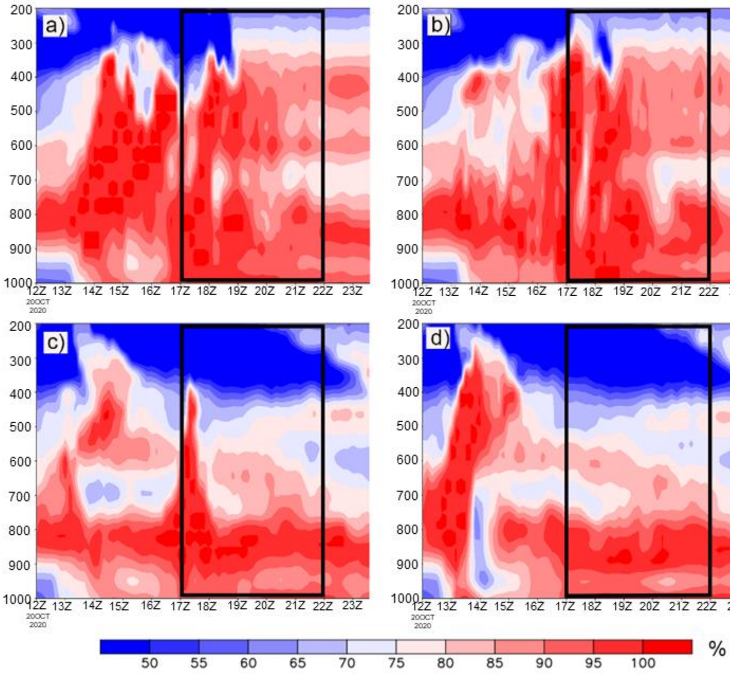

Figure 3-5: Timeseries RH of surface layer up to 200 mb on October 20, 2020 at 12.00 – 23.00 UTC for a) NON; b) SAT; c) OBS; and d) BOTH. The black square line shows the time of heavy rain.

The following parameter to be analyzed is convective available potential energy (CAPE). CAPE is an air parcel's energy when lifted vertically in the atmosphere. The CAPE value can indicate that the atmosphere is stable or unstable. The higher the CAPE value, the more unstable the atmosphere. The Timeseries CAPE at an altitude of 1000 - 500 MB in the NON, SAT, CTRL, and BOTH experiments (Figure 3-6) showed an increase in CAPE values up to a height of 800 MB before the rain at 17.00 UTC and continued to decrease when it rained at 17.00 - 22.00 UTC. It shows a reduction in the removal of energy when it rains. Satellite assimilation results show that the CAPE value is the most significant compared to other non-assimilation and assimilation, where the value reaches 1700 J/kg at 14.00 - 15.00 UTC.

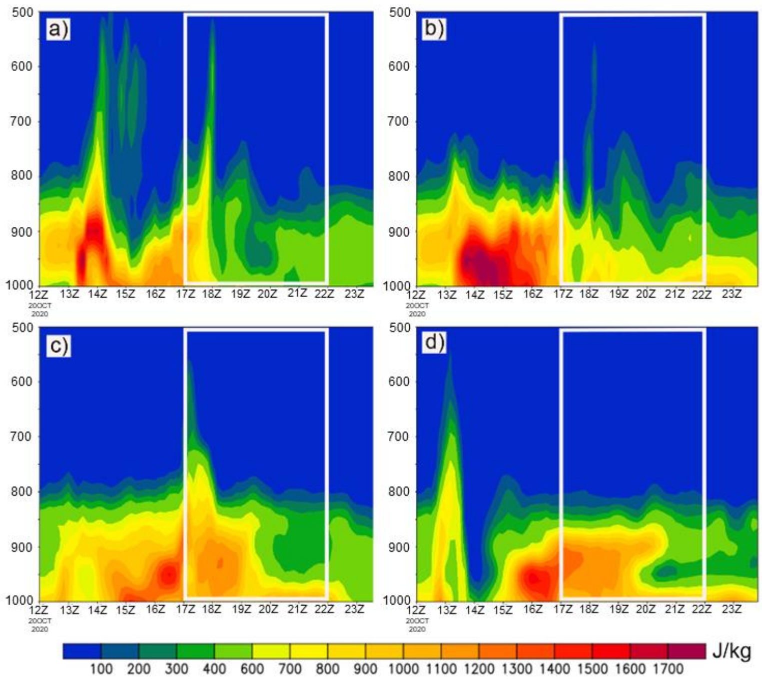

Figure 3-6: Timeseries CAPE of surface layer up to 200 mb on October 20, 2020 at 12.00 – 23.00 UTC for a) NON; b) SAT; c) OBS; and d) BOTH. The white square line shows the time of heavy rain.

The following parameter to be analyzed is the divergence. A positive divergence indicates a downward airflow movement, while a negative divergence indicates an upward trend of airflow. From October 20, 2020, from 17.00 UTC to 19.00 UTC, shown in Figure 3-7, it can be seen that the NON and SAT experiments from the surface layer to the 700 MB layer were dominated by upward airflow with a value of -0.5x10-5 s-1 to -2x10-5 s-1 to support the growth of convective clouds that reach that height. While in the layer above, the higher the layer, the value of negative divergence decreases. Furthermore, in OBS and BOTH, no significant airflow was observed. This is in line with research conducted by Rahma (2020), wherein the surface layer up to a layer of 200 MB and negative divergence values were observed, indicating convection activity.

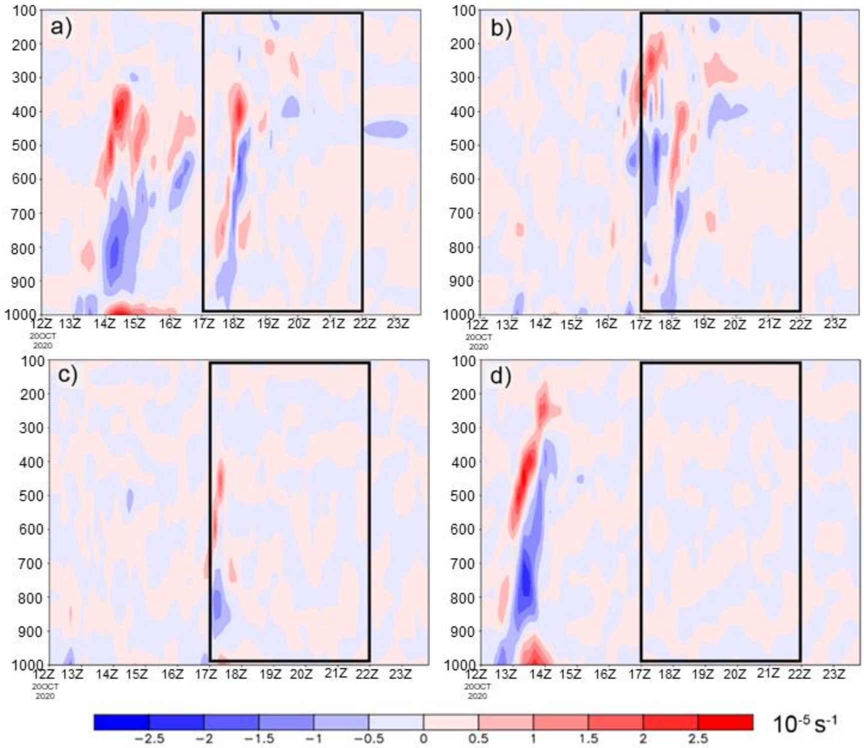

Figure 3-7: Timeseries of surface layer divergence to 200 mb on October 20, 2020, 12.00 – 23.00 UTC for a) NON; b) SAT; c) OBS; and d) BOTH. The black square line shows the time of heavy rain.

The last parameter to be analyzed is cloud fraction. Cloud fraction is the percentage of each pixel in a satellite image or each grid box in a weather or climate model covered by clouds. Figure 3-8 shows that before the rain (at 13.00-16.00 UTC), the four experiments showed a cloud cover of up to 100%. This is under the analysis of air humidity, CAPE, and divergence, which indicate conditions that support cloud growth.

However, it can be seen that the NON-experiment has more significant cloud cover than the other schemes because it shows cloud cover from 900 MB to 300 MB layers. Meanwhile, when it rains (17.00 – 22.00 UTC), the NON and SAT experiments show the same pattern. In both experiments, it was seen that there was cloud cover from the surface layer up to 200 MB at 17.00 – 18.00 UTC. Then it began to decay at 19.00 UTC, marked by an increase in the lowest cloud base height observed. Meanwhile, the OBS and BOTH experiments showed the absence of low clouds when it rained.

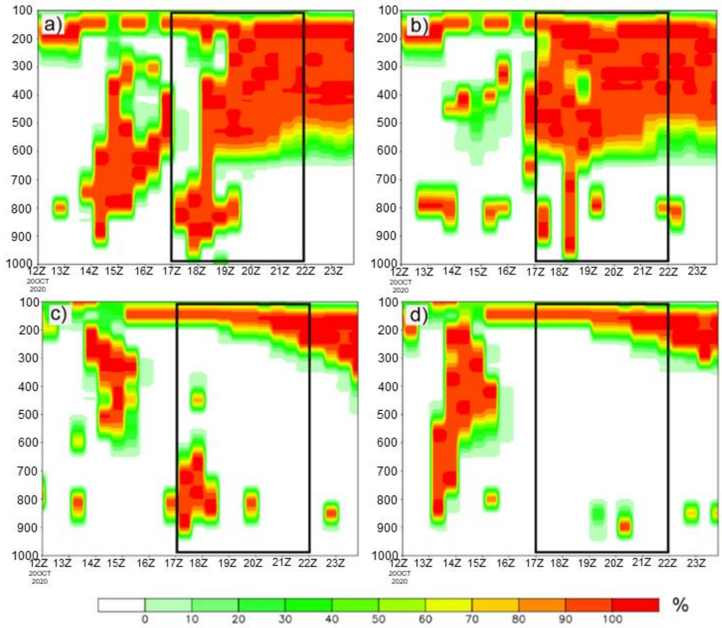

Figure 3-8: Timeseries cloud fraction of surface layer up to 200 mb on October 20, 2020, 12.00 – 23.00 UTC for a) NON; b) SATs; c) OBS; and d) BOTH. The black square line shows the time of heavy rain.

4 CONCLUSIONS

Based on research conducted by comparing the experimental outputs of NON, SAT, OBS, and BOTH in the case of rain on October 20, 2020, in the Jambi region, it can be concluded that the best scheme for predicting heavy rain is the combination of Grell-3D and Thompson schemes. The combination of these schemes can produce predictions with high correlation and low error values compared to the other five schemes tested. Then the SAT experiment was judged to have better rainfall predictions than the other three experiments. The prediction results from the SAT experiment resulted in lower RSME and higher correlation and forecast skill scores. The increment analysis showed that the SAT experiment could significantly influence the temperature and humidity parameters compared to the other two experiments. In the analysis of atmospheric dynamics using the parameters of RH, CAPE, divergence, and cloud fraction, it is known that the SAT experiment can produce atmospheric dynamics that best represent heavy rain in the Jambi region

This study only uses one case of heavy rain in the Jambi area. In future research, it is hoped that it will be able to select rain cases that are more evenly distributed in space and time scales. In choosing a parameterization scheme, long data is obtained and can represent rain events well. Dense in the Jambi region. Then in this study, only the assimilation of observational data and assimilation of satellite data with AMSU-A and MHS sensors. In future research, it is possible to assimilate satellite data by adding other sensors and adding assimilation of radar data to obtain better rainfall predictions.

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