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# Evaluation of several cumulus parameterization schemes for daily rainfall predictions over Palembang City

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# Evaluation of several cumulus parameterization schemes for daily rainfall predictions over Palembang City

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**Abstract**. The daily rainfall prediction calculated from four Cumulus schemes i.e.: Kain-Fritsch (KF), New Tiedtke (NT), Grell 3D ensemble (G3D), and Betts-Miller-Janjic (BMJ) had been tested for compliance with daily observation data for 90 days (1 Dec 2018 to 28 Feb 2019) from three observer stations in Palembang city: BMKG-Kenten (Kenten), BMKG-SMB2 (SMB2) and Unsri Bukit Besar (UBB). The test results show that the BMJ cumulus scheme provides better suitability for 19 out of 45 unique indicators for rainfall event indicator (REI) groups and for as many as 13 out of 27 unique indicators for rainfall intensity indicator (RII) groups. The four schemes are able to provide the good performance for each on different indicators and stations, however, in general the BMJ scheme gives the best performance in predicting daily rainfall over Palembang city.

## 1. Introduction

Weather and climate give deep impacts to human life, therefore, understanding their behaviours is essential. Rainfall is one of important factors in defining climate. In the extreme condition, lack of rainfall can lead to the drought, while excess of it can make flood. Forecasting rainfalls is important that man can overcome its impacts.

Scientists have developed numerical weather prediction (NWP) model to predict weather including rainfall events and intensity. The Weather Research and Forecasting-Advanced Research WRF (WRF-ARW) is one of the NWP models that is widely used now days. However, this model cannot completely solve the atmospheric equation explicitly. In order to increase its ability in predicting weather parameters including rainfalls, some cumulus parameterization schemes are introduced such as: Kain Fritsch (KF) [1, 2], New Tiedtke (NT) [3, 4], Grell 3D Ensemble (G3D) [5] and Betts Miller Janjic (BMJ) [6, 7]. These schemes are the most widely used to predict rainfall estimations especially in tropic regions. The KF and NT schemes represent a group of low-level convective control schemes related to how parcels overcome convective inhibition (CIN) and activate convective available potential energy (CAPE), while the G3D and BMJ represents a group of deep-layer convection control schemes, which limit the amount of deep convection to change in CAPE [8].

Many studies on rain prediction had been carried out, ranging from short time (per hour or three hours), daily, monthly, seasonal (3 months) or even yearly. On a spatial scale the study can cover the scope of the local (city), province, regional or even global scope. Especially for WRF utilization with cumulus parameterization schemes, some writings had been published in discussing the performance of each scheme. Examined the Anthes–Kuo, Betts–Miller, Grell, and Kain–Fritsch schemes using six precipitation events over the continental United States for both cold and warm seasons. They found that Kain-Fritsch gave better performance [9, 10]. Examined Kain-Fritsch (KF), New-KF, Grell-Devenyi ensemble and BMJ schemes in simulating three heavy rainfall episodes over the southern peninsular Malaysia during the winter monsoon of 2006/2007 dividing into three episodes starting at 1200 UTC 17 December 2006, 1200 UTC 24 December 2006 and 1200 UTC 11 January 2007, respectively. It was shown that BMJ only over-performed others scheme in the second and third episodes. It seemed that suitability of the scheme is case dependent [11]. Kurniawan et.al. (2012) compared 3 cumulus parameterizations to evaluate predictions of the 3 hourly rainfall data, and the 12 hourly wind data during August 2011 and February 2012 period at the Juanda-Surabaya and Cengkareng-Jakarta stations. A BMJ scheme outperformed GD and KF scheme in rainfall forecasting, while for wind speed and direction forecasting, BMJ and GD scheme gave better result that KF scheme [12]. Other authors such as Fatmasari et.al. (2017), Lorenzo et.al. (2020), and Steeneveld and Peerlings (2020) did the some efforts to examine the performances of some cumulus parameterizations which gave different results [13, 14, 15].

The purpose of this paper is to evaluate several cumulus parameterization schemes in order to find the scheme which gives the best daily rainfall predictions over Palembang city.

## 2. Method

Daily rainfall data from 1 December 2018 to 28 February 2019 (90 days) were used as test data. The data comes from three stations for field observers in the city of Palembang, each of which is the BMKG Climatology Station in Kenten (Kenten: 104,770 E, 2,930 S, 11 masl), BMKG Meteorological Station at Sultan Mahmud Badaruddin II airport (SMB2: 104,700 E, 2,890 S, 10 masl) and Sriwijaya University Bukit Besar campus (UBB: 104,730 E, 2,990 S).

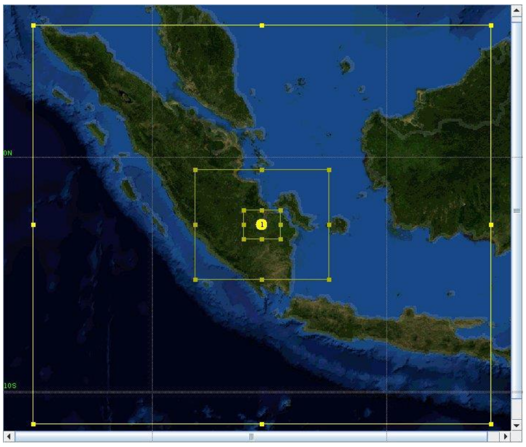

**Figure 1.** Research Domain for WRF-ARW

Global Forecasting System (GFS) data from the determined domain have been processed by adjusting the parameter suit to the selected schemes. The results are appeared as the predicted data of rainfall. Rain prediction calculations were carried out using WRF-ARW version 4.0 in 2019 [16]. WRF was run using the configuration settings as stated in Table 1.

**Table 1.** WRF Configuration for Rainfall Prediction for Palembang City

| Index | Descriptions |
|---|---|
| WRF version | WRF v4.0 |
| Map projections | Mercator |
| Model data period | 1 December 2018 – 28 February 2019 |
| Number of domain | 1 main domain, 2 nests (total 3 domai |
| Temporal resolution | 3 hour |
| Spatial resolution<br>Domain 1<br>Domain 2<br>Domain 3 | <br>27 km<br>9 km<br>3 km |
| Graphic data resolution<br>Domain 1<br>Domain 2<br>Domain 3 | <br>10 m<br>2 m<br>30 s |
| Parameterization schemes<br>1. Cumulus parameterizations | <br>a) Kain-Fritsch (KF)<br>b) Betts-Miller-Janjic (BMJ)<br>c) Grell 3D ensemble<br>d) New Tiedtke (NT) |
| 2. Microphysics parameterization<br>3. Radiation parameterization<br>a. Long wave radiation<br>b. Shot wave radiation<br>4. Surface layer parameterization<br>5. Soil surface parameterization<br>6. Planetary boundary layer parameterization | WRF Single Moment 3-class<br>Rapid Radiative Transfer Model (RR<br>Dudhia<br>Revised MM5<br>Unified Noah Land Surface Model<br>Yonsei University (YSU) |

In terms of the performance test, the indicators used in determining the accuracy of rain predictions can generally be divided into two major groups, namely the rainfall event indicator group (REI) and the rainfall intensity indicator group (RII). REI is based on a more qualitative dichotomy analysis which is described by some indicators such as the Index Bias Factor (FBI), Accuracy (ACC), Threat Score (TS), Probability of Detection (POD), and False Alarm Ratio (FAR). Rainfall intensity indicators (RII) are based on basic statistical calculations such as Correlation Coefficients (CC), Mean Error (ME), and Mean Absolute Error (MAE) [9].

*Dichotomous Test*

For precipitation, a standard analysis namely the dichotomous test will be conducted as shown in Table 2 below to obtain the rainfall event indicator group (REI).

**Table 2**. A Contingency Table

| | | Observed | | |
|---|---|---|---|---|
| | | Yes | No | Total |
| | Yes | Hits | False Alarms | forecast yes |
| Forecast | No | Misses | Correct Negatives | forecast no |
| | Total | observed yes | observed no | Total |

Note: A contingency table is used to see the occurrences of rainfall events.
Hits = The event that is predicted to happen actually happened
False Alarm = The predicted event did not occur
Missed = The event that was predicted did not happen, happened
Correct Negatives = Events that were predicted not to occur, did not occur.

Then calculations will be done with equations below:

$$\text{Frequency Bias Index (FBI)} = \frac{\text{Hits+False Alarm}}{\text{Hits+Misses}} \quad (1)$$

$$\text{Accuration (ACC)} = \frac{\text{Hits+correct negatives}}{\text{Total}} \quad (2)$$

$$\text{Threat Score (TS)} = \frac{\text{Hits}}{\text{Hits+Misses+False Alarms}} \quad (3)$$

$$\text{Probability Of Detection (POD)} = \frac{\text{Hits}}{\text{Hits+Misses}} \quad (4)$$

$$\text{False Alarm Ratio (FAR)} = \frac{\text{False Alarm}}{\text{Hits+False Alarm}} \quad (5)$$

The range and best values for REI indicators are shown in Table 3 below.

**Table 3**. REI Indicator values

| REI Indicators | Range Value | Best Value |
|---|---|---|
| FBI | 0 - ∞ | 1 |
| ACC | 0 - 1 | 1 (max) |
| TS | 0 - 1 | 1 (max) |
| POD | 0 - 1 | 1 (max) |
| FAR | 0 - 1 | 0 (min) |

Rainfall intensity indicators (RII) are based on basic statistical calculations such as Correlation Coefficients (CC), Mean Error (ME), and Mean Absolute Error (MAE) [9].

The Pearson product-moment Correlation Coeffiicient (CC):

$$r = \frac{\overline{F'V'}}{\sqrt{(F')^2}.\sqrt{(V')^2}} \quad (6)$$

With : F : Forecast data
V: Observation data

The Mean Error (MAE): ME = <F-V> (7)

The Mean Absolute Error (MAE): $MAE = \langle |F-V| \rangle$

Correlation coefficient values between from -1 to +1. The best values is +1. Mean error is used to see whether the forecast data are under-estimate or over-estimate the actual data, so, the best value is zero or the minimum value. While mean absolute error (MAE) is used to see the bias between the forecast data and the actual data. Its best value is zero or the available minimum value.

The calculation of the above indicators was carried out for each month as well as the cumulative three months of the observation period.

## 3. Result and Discussion

### *3.1. Rainfall event Indicator (REI) Group*

Table 4 states the results of the rainfall event calculations, for each month and cumulative three months. For different stations and months, for each scheme, there are 45 unique indicators. If the data is calculated for three months cumulatively, there are only 15 unique indicators. The corresponding unique indicator values of each of these schemes will be compared in order to find the best scheme among them.

**Table 4.** Rainfall Event Indicator (REI) Calculation Results.

| Station | Scheme | Dec | | | | | Jan | | | | | Feb | | | | | Dec-Feb | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | FBI | ACC | TS | POD | FAR | FBI | ACC | TS | POD | FAR | FBI | ACC | TS | POD | FAR | FBI | ACC | TS | POD | FAR |
| Kenten | KF | 1.56 | 0.61 | 0.59 | 0.94 | 0.39 | 0.90 | 0.42 | 0.38 | 0.52 | 0.42 | 1.32 | 0.61 | 0.57 | 0.84 | 0.36 | **1.29** | 0.56 | 0.52 | 0.78 | 0.39 |
| | NT | **1.50** | 0.58 | 0.55 | 0.89 | 0.41 | 1.10 | 0.55 | 0.52 | 0.71 | 0.35 | **1.26** | **0.71** | **0.65** | **0.89** | **0.29** | 1.31 | **0.61** | 0.57 | 0.84 | **0.36** |
| | Grell3D | 4.14 | 0.29 | 0.24 | **1.00** | 0.76 | **1.00** | 0.55 | 0.50 | 0.67 | 0.33 | 1.32 | 0.61 | 0.57 | 0.84 | 0.36 | 1.33 | 0.58 | 0.54 | 0.82 | 0.38 |
| | BMJ | 1.56 | **0.68** | **0.64** | **1.00** | **0.36** | 1.14 | **0.65** | **0.61** | **0.81** | **0.29** | 1.37 | 0.52 | 0.50 | 0.79 | 0.42 | 1.38 | **0.61** | **0.58** | **0.87** | 0.37 |
| SMB2 | KF | **1.41** | 0.52 | 0.46 | 0.76 | 0.46 | **0.90** | 0.55 | 0.48 | 0.62 | 0.32 | **1.39** | **0.65** | **0.59** | **0.89** | **0.36** | **1.25** | 0.57 | 0.51 | 0.75 | 0.39 |
| | NT | 1.71 | 0.55 | 0.53 | 0.94 | 0.45 | 1.14 | 0.58 | 0.55 | 0.76 | 0.33 | 1.39 | 0.58 | 0.54 | 0.83 | 0.40 | 1.43 | 0.57 | 0.54 | 0.85 | 0.41 |
| | Grell3D | 4.14 | 0.29 | 0.24 | **1.00** | 0.76 | 0.86 | 0.52 | 0.44 | 0.57 | 0.33 | 1.56 | 0.55 | 0.53 | **0.89** | 0.43 | 1.38 | 0.56 | 0.52 | 0.81 | 0.41 |
| | BMJ | 1.53 | **0.58** | **0.54** | 0.88 | **0.42** | **1.10** | **0.74** | **0.69** | **0.86** | **0.22** | 1.39 | 0.52 | 0.48 | 0.78 | 0.44 | 1.38 | **0.62** | **0.58** | **0.87** | **0.37** |
| UBB | KF | **3.57** | 0.35 | 0.23 | 0.86 | 0.76 | **1.90** | **0.52** | **0.32** | 0.70 | **0.63** | **1.64** | **0.58** | **0.48** | 0.86 | **0.48** | **2.20** | **0.49** | 0.35 | 0.83 | **0.62** |
| | NT | 3.86 | 0.29 | 0.21 | 0.86 | 0.78 | 2.60 | 0.35 | 0.29 | 0.80 | 0.69 | 1.71 | 0.35 | 0.31 | 0.64 | 0.63 | 2.50 | 0.34 | 0.28 | 0.77 | 0.69 |
| | Grell3D | 3.71 | **0.39** | **0.27** | **1.00** | **0.73** | 2.30 | 0.45 | **0.32** | 0.80 | 0.65 | 1.86 | 0.48 | 0.43 | 0.86 | 0.54 | 2.43 | 0.46 | **0.36** | 0.90 | 0.63 |
| | BMJ | 4.00 | 0.26 | 0.21 | 0.86 | 0.79 | 2.70 | 0.39 | **0.32** | **0.90** | 0.67 | 1.93 | 0.52 | 0.46 | **0.93** | 0.52 | 2.70 | 0.39 | 0.34 | **0.93** | 0.65 |

Note that the numbers in bold in Table 4 represent the best unique indicator values that can be attributed to the existing schemes. From these figures it can be concluded that the BMJ scheme has the advantage of 19 out of 45 (42%) and 8 out of 15 (53%) best unique indicator scores, respectively for the calculation of 3 months apart and 3 months cumulatively. In the three-month calculation, the BMJ scheme is also absolutely superior in POD for all stations, while a large dominance is also shown in four indicators (ACC, TS, POD and FAR) at SMB2, three indicators (TS, POD and FAR) at Kenten, however, only POD at UBB. Meanwhile, in general, the BMJ scheme is weak in the FBI.

It is interesting to show that all the REI indicators, except for POD, at Kenten and SMB2 stations have better quality than the corresponding indicators at the UBB station. This means that the four schemes may be more appropriate to the natural conditions in the first two stations (Kenten and SMB2) but less suitable for the natural conditions in UBB. It is necessary to study the more basic reasons for this fact.

### *3.2. Rainfall Intensity Indicator (RII) Group*

Table 5 shows the results of the RII calculation, for each month and cumulative three months. For different stations and months, there are a total of 27 unique indicators for each scheme. If the data is calculated for three months cumulatively, there are only 9 unique indicators. The numbers in bold in Table 5 represent the best unique indicator values for this group.

**Table 5.** RII Calculation Results

| Station | Scheme | Dec | | | Jan | | | Feb | | | Dec-Feb | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | CC | ME | MAE | CC | ME | MAE | CC | ME | MAE | CC | ME | MAE |
| Kenten | KF | -0.13 | 6.94 | 16.62 | -0.10 | 1.62 | 7.58 | 0.01 | -3.15 | 11.39 | -0.06 | 1.97 | 11.88 |
| | NT | -0.16 | 4.96 | 15.48 | -0.23 | 4.78 | 10.33 | -0.18 | 5.39 | 19.58 | -0.12 | 5.03 | 14.98 |
| | Grell3D | 0.18 | 8.44 | 14.74 | 0.10 | 6.58 | 9.98 | 0.19 | 13.40 | 23.83 | 0.21 | 9.34 | 15.93 |
| | BMJ | -0.20 | 3.92 | 13.95 | 0.35 | 1.56 | 4.63 | -0.19 | 2.50 | 19.07 | -0.10 | 2.67 | 12.33 |
| SMB2 | KF | -0.01 | 10.53 | 23.42 | 0.04 | -2.99 | 10.87 | 0.17 | -2.34 | 10.04 | 0.04 | 1.87 | 14.93 |
| | NT | -0.05 | 2.67 | 14.81 | -0.15 | 1.08 | 14.64 | 0.27 | 5.80 | 14.86 | 0.05 | 3.10 | 14.77 |
| | Grell3D | -0.10 | 10.69 | 23.60 | 0.04 | -3.36 | 9.90 | 0.43 | 11.85 | 17.69 | 0.10 | 6.21 | 17.04 |
| | BMJ | -0.17 | 4.54 | 17.99 | 0.47 | -2.70 | 7.73 | -0.03 | 3.02 | 17.75 | 0.02 | 1.57 | 14.38 |
| UBB | KF | -0.10 | 4.74 | 22.22 | -0.16 | -1.73 | 11.57 | 0.00 | -1.26 | 9.18 | -0.08 | 0.65 | 14.49 |
| | NT | -0.15 | 5.46 | 22.36 | -0.14 | 4.63 | 17.03 | 0.05 | 1.75 | 11.50 | -0.09 | 4.02 | 17.14 |
| | Grell3D | -0.11 | 4.48 | 21.85 | 0.23 | 3.64 | 13.34 | -0.16 | 17.48 | 25.26 | -0.03 | 8.24 | 19.98 |
| | BMJ | 0.47 | 2.84 | 14.54 | -0.20 | -0.10 | 12.71 | 0.27 | 5.76 | 12.49 | 0.29 | 2.74 | 13.27 |

It is seen from the table that, thirty of 36 (83%) and 6 of 9 (67%) pairs of prediction and observation data have negative correlation or below +0.25. This indicates that in terms of the pattern of changes in rainfall, the four schemes are generally not sufficiently able to predict it well. However, of the 6 correlation indicators with a value of >= 0.25, 4 indicators come from the BMJ scheme.

From monthly ME values, only 8 out of 36 (22%) rainfall predictions are under-estimated observation data. Accumulative rainfall predictions from each scheme are over-estimated. Based on the MAE values, it can also be concluded that the deviations between predictions and observations of rainfall are generally still quite large, greater than the average daily rainfall values.

It can be seen from the results that the BMJ scheme is dominant at 13 out of 27 (48%) and 4 out of 9 (44%) the best unique indicator values, respectively for monthly and cumulative three months calculations, while the performance of the other schemes is below this value.

The results of the data analysis in the two tables above show that, according to the indicators used, basically each scheme has its own strengths and weaknesses. In fact, there is still no consistency between the advantages and disadvantages of one another when it is seen from the different time (months) and observation stations. However, in general the BMJ scheme gives the best performance.

## 4. Conclusion

From the description above, it can be concluded that although the four schemes are able to provide the good performance for each on different indicators and stations, in general the BMJ scheme gives the best performance in predicting daily rainfall over Palembang city. However, the above conclusions have not consistently applied to certain observation locations and/or at certain times. It is still necessary to do more study involving additional test data through observations in several consecutive years.

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**References**

[1] Kain J S, Fritsch J M 1993 Convective Parameterization for Mesoscale Models: The Kain-Fritsch Scheme *Meteorogical Monographs* **24** (46) pp.165-169

[2] Kain J S 2004 The Kain–Fritsch convective parameterization: An update *J. Appl. Meteor* **43** pp.170–181

[3] Tiedtke M 1989 A Comprehensive Mass Flux Scheme for Cumulus Parameterization in Large-Scale Models *Monthly Weather Review* **117** pp. 1779-1800

[4] Zhang C, Wang Y and Hamilton K 2011 Improved Representation of Boundary Layer Clouds over the Southeast Pacific in ARW-WRF Using a Modified Tiedtke Cumulus Parameterization Scheme *Monthly Weather Review* **139** pp. 3489-3513

[5] Grell G A, Devenyi D 2002 A generalized approach to parameterizing convection combining ensemble and data assimilation techniques *Geophys. Res. Lett* **29** 1693

[6] Janjic, Zavisa I 1994 The Step–Mountain Eta Coordinate Model: Further developments of the convection, viscous sublayer, and turbulence closure schemes Mon. Wea. *Rev*. **122** 927–945

[7] Baldwin M E, Kain J S and Kay M P 2002 Properties of the Convection Scheme in NCEP’s Eta Model that Affect Forecast Sounding Interpretation *Weather and Forecasting* **17** pp. 1063-1079

[8] Stensrud, D J 2007 Parameterization Schemes: Keys to Understanding Numerical Weather Prediction Models *Cambridge University Press, Cambridge, UK*.

[9] Stull R 2017 Practical Meteorology: An Algebra-based Survey of Atmospheric Science *University of British Columbia 2020-2207 Main Mall Vancouver, BC, Canada*

[10] Wang W and Seaman N L 1997 A Comparison Study of Convective Parameterization Schemes in a Mesoscale Model *Monthly Weather Review* pp. 252-278

[11] Ardie W A, Sow K S, Tangang F T 2012 The performance of different cumulus parameterization schemes in simulating the 2006/2007 southern peninsula Malaysia heavy rainfall episodes, *J. Earth Syst. Sci.* **121** ( 2) pp. 317-327

[12] Kurniawan R, Hanggoro W, Anggraini R 2014 Penggunaan Skema Konvektif Model Cuaca WRF (Betts Miller Janjic, Kain Fritsch dan Grell 3D Ensemble). Studi Kasus: Surabaya dan Jakarta *Jurnal Meteorologi dan Geofisika* **15** (1) pp. 25-36

[13] Fatmasari D, Saragih I J A, Putra W 2017 Sensitivity Test of Betts Miller Janjic and Grell 3D Schemes on WRF-ARW Model to Simulate the Heavy Rainfall Event in Lampung (Case Study: 20 February 2017) *Proc. of International Conference: Problem, Solution and Development of Coastal and Delta Areas Semarang*

[14] Lorenzo M S, Morlot A B, Artola A D C 2020 Assessment of Different WRF Configurations Performance for a Rain Event over Panama *Atmospheric and Climate Sciences* **10** 280-297

[15] Steeneveld G J and Peerlings E E M 2020 Mesoscale Model Simulation of a Severe Summer Thunderstorm in The Netherlands: Performance and Uncertainty Assessment for Parameterised and Resolved Convection, *Atmosphere* **11**, 811; doi:10.3390/atmos11080811

[16] Wang W, Bruyere C, Michael D 2019 Weather Research & Forecasting Model, User´s Guide *National Center for Atmospheric Research*