

# The performance of the weather research & forecasting model (WRF) using ensemble method to predict weather parameters

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**Abstract.** The performance of the WRF model is evaluated using different physical options for the Riau Province. There are 12 members, and the ensemble mean method is used to evaluate the temperature, humidity, wind direction, and wind speed. The primary purpose of this study is to determine the appropriate parameterization for the study area. In this study, two nested domains have been used for performance analysis, with the resolution of the coarser domain set at 9 km and the inner domain set at 3 km. The model was run for five days in 2019 during a forest fire episode in Riau Province. The analysis was carried out by looking at the values of the correlation coefficient, root mean square error (RMSE), and bias. From the weather forecast, WRF, with the sixth parameterization member, produces a better value than the others. RRTM and Dudhia parameterization gave better results for temperature parameters. Meanwhile, the parameterization of Yonsei University (YSU) produces better results for the parameters of wind direction and wind speed.

## 1 Introduction

Weather parameters have an essential role in human life. They include rainfall, wind direction and speed, humidity, pressure, temperature, and radiation. The availability of accurate weather forecasts is needed for various purposes, such as disaster adaptation and mitigation, hydrology, and agriculture. Weather forecasting is intricate and challenging since the atmosphere is difficult to anticipate because to its dynamic and nonlinear characteristics [1]. Despite its intricacy, various methodologies are available to assist in weather forecasting, including statistical and numerical weather prediction (NWP) techniques. Moreover, NWP models yield significantly more realistic and precise outcomes as they address the atmospheric equations more effectively than statistical methods [1]. A numerical weather model is one of the tools being developed around the world for predicting and simulating current and future weather conditions. One of the models being developed is the WRF-ARW (Weather Research and Forecasting Model—Advanced Research WRF) model.

WRF is a mesoscale numerical weather forecast model that is used and utilized for atmospheric research and weather forecast operational purposes worldwide [2]. The basis of the WRF model is the solution of the model's mathematical equations. In this case, the WRF product has an uncertainty value because there are different kinds of errors that can cause different forecasts. The low quality of the initial data and the choice of boundary conditions cause the error to change, which leads to a loss

of skills. Also, an increase in projection time is one of the things that makes the predicted skill less accurate. The longer the prediction is made, the higher the level of uncertainty will be. This is due to dynamic and chaotic weather conditions, so at any time, it can interfere with the quality of the forecast [3]. Determining the size of the resolution of the simulation domain also has a significant role in generating model uncertainty. A high-domain selection must be supported by high-resolution data, such as topographic data (if available) [4]. Atmospheric dynamics occur at diverse geographical and temporal scales. The meteorological models, such as WRF, are not intended to accurately represent these physical processes. Unresolved processes are addressed using physical parameterization approaches, including cumulus, microphysics, boundary layers, radiative transfer, soil interaction, and vegetation interaction [4]. The parameterizations incorporate numerous assumptions and approximations to elucidate unsolved processes. Moreover, for numerical weather prediction, such as WRF in a specific location, it is essential to identify the optimal mix of physical parameterizations within the selected modeling framework [5].

The ensemble method is one of the methods currently being worked on to deal with uncertainty in the model. Basically, Ensemble systems may vary not only in their simulation of initial uncertainties (i.e., analytical errors) and the nature of model prediction errors, but also in ensemble size and their capacity to represent the probability distribution function of analysis and forecast states [6]. The examination of ensemble methodologies

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indicates that some combinations of physics correspond effectively with observations, notably the new GFS-simplified Arakawa-Schubert and the modified Tiedtke cumulus parameterizations when integrated with Thompson and Morrison microphysics for precipitation forecasting [5]. Moreover, to optimize WRF performance, stochastic parameterizations alone are inadequate for capturing model uncertainty and must be supplemented by a multi-physics suite [7].

Riau Province is an area in Indonesia that is always hit by forest fire events. One of the bad effects of these forest fires is the decline in air quality in the area, which has the potential to spread to surrounding areas such as Padang, Jambi, Batam, and Palembang. Meteorological variables, including wind direction and velocity, significantly influence the advection of pollutants. To predict the bad effects of forest fires, it is important to have accurate weather prediction data. Several WRF tests for wind speed and direction have been done in many places using different numerical and physics options. The testing of WRF in Portugal suggests that the wind simulation error can be kept to a minimum by testing and choosing a numerical and physical configuration that works well for the area of interest. In the research, the combination parameterization of WRF, Yonsei University, and Noah is the most suitable for that site [4]. Research on the sensitivity of WRF physical parameters on the island of Sumatra and the Maritime Continent has been tested several times. The combination of parameterization schemes Eta Scheme (microphysical), GD Scheme (cumulus), and MYJ Scheme (planetary boundary layer) is one of the best parameterization combinations for predicting rainfall in tropical peatland areas, one of which is Sumatra Island [8].

The primary objective of this study is to determine the optimal method to configure the WRF model's physical parameters. For this purpose, the performance of WRF from various simulations with specific configurations is assessed by comparing the results to the observational data in Padang, Pekanbaru, and Batam. The best parameterization is determined by carrying out statistical analysis, including the Pearson correlation method, RMSE, and bias. The examination of the WRF model's sensitivity in relation to alterations in configuration options is a significant evaluative task, and this sensitivity study will substantially enhance other research aimed at revealing which model parameters are most effective [1].

## 2 Materials and method

The simulation of weather prediction has been done using the WRF-ARW model. The model was executed from September 21–25, 2019. Basically, in this study, two kinds of data are used. The data are from the global forecast system (GFS) and the observation data from automatic weather stations (AWS).

### a. GFS Data

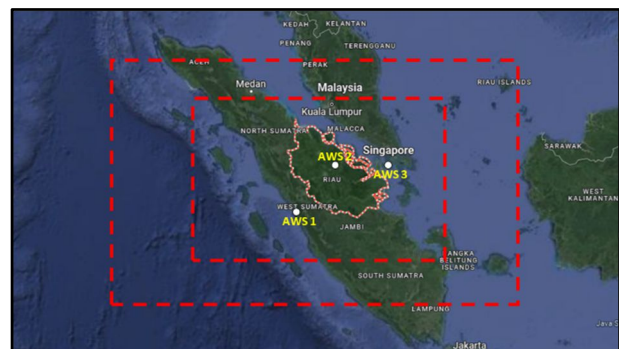
This study uses the GFS data for the initial conditions and input to the WRF model. This data has 0.25 degrees by 0.25 degrees for the spatial resolution and 3 hours for time resolution. The GFS

data can be downloaded at <https://rda.ucar.edu/datasets/ds084.1>

### b. AWS Data

The observation data was obtained from an automatic weather station that is installed at three locations and operated by the Indonesian Ministry of Environment and Forestry. These locations are Padang (0.939° S, 100.363° E), Pekanbaru (0.511° N, 101.459° E), and Batam (1.045° N, 103.942° E). The weather parameters that are used for evaluating the model result are wind speed and direction, surface temperature, and relative humidity.

The initial phase in configuring the WRF model involves establishing a domain design. The domain's design is seen in Fig. 1. The study encompasses a parent domain (D1) with a spatial resolution of 9 km and a secondary, nested domain (D2) with a spatial resolution of 3 km. In this study, 3 AWS (automatic weather stations) are used in the cities of Padang, Pekanbaru, and Batam. These stations are in the same domain in the WRF simulation. So, it can be used to evaluate parameterization, especially domain 2 (fine domain). The simulation domain of WRF is shown in Fig. 1.



**Fig. 1.** Simulation domain of WRF. The outer domain is set to 9 km, and the inner domain is set to 3 km. The white circle marked shows the location of the AWS.

In WRF models, the mathematical representation of atmospheric processes is frequently streamlined based on the model's objectives, resolution, and focus. The dynamical core solves the governing equations on a discrete grid, neglecting terms of minimal significance [9]. Unresolved processes, including radiation, deep and shallow cumulus convection, cloud microphysics, precipitation, and turbulence, influence the resolved scales via a parameterized representation in WRF [9]. There are five physical parameters: cloud microphysical, cumulus, the planetary boundary layer (PBL), and longwave and shortwave radiation. This study examines the combination of parameterization schemes. The examination was conducted with 12 members and one method of the ensemble mean. The combination of parameterization schemes can be seen in Table 1. In running the WRF model, a simulation is carried out for five days, where one day is used for the model spin-up time, and the other four days are the results of the model predictions. Table 1 shows that GD (Grell Devenyi), Grell Freitas, and Grell 3D parameterization dominate in this simulation for cumulus parameterization. This refers to

research conducted by [8] in tropical peatlands, one of which is Sumatra Island [8]. Furthermore, the research done by [10] in Riau Province, [11] in Pekanbaru for the forest fire episode, and [12] also used one of the parameterizations in table 1 [10–12]. Grell Freitas applies the stochastic methodology from Grell Devenyi within the cumulus framework and modifies the scale awareness for the convective eddy transport equation [9]. Grell 3D is a combination of multiple physical schemes (Kain Fritsch, Betts and Miller, and Grell Devenyi) [5]. Cumulus schemes attempt to assess a mesoscale convective system; microphysics, on the other hand, attempts to evaluate a warm frontal zone with stratiform precipitation [9]. The microphysical parameterizations tested were the WRF single moment3 class (WSM3), Eta Scheme, Lin, and Kessler scheme. The boundary layer aims to illustrate the statistical properties of turbulence phenomena and their

average effects on grid-scale fields [13]. The transfer of energy (momentum, heat, moisture) to the upper atmospheric layers is crucial and serves as a feedback mechanism in atmospheric circulation [14]. We selected Yonsei University (YSU) and Mellor-Yamada-Janjic (MYJ) due to their potential impact on model outcomes, based on a review of the available literature and an analysis of the scheme formulas [13]. The radiation scheme comprises two parameters, namely short wave and long wave. These schemes play a crucial role in simulating temperature, precipitation, and global radiation. Shortwave (SW) and longwave (LW) radiation transfer were modeled using the Dudhia scheme, the Rapid Radiative Transfer Model (RRTM), and the Rapid Radiative Transfer Model for General Circulation Model (RRTMG). The parameterization schemes used in simulation are shown in Table 1.

**Table 1.** Parameterization schemes used in simulation

Member	Parameterization Scheme				
	Cumulus	Microphysics	Short Wave	Long Wave	Boundary Layer
Member 1	Grell-Devenyi	WSM3	Dudhia	RRTM	YSU
Member 2	Grell-Devenyi	Eta Schema	New Goddard	RRTM	MYJ
Member 3	Grell-Devenyi	WSM3	RRTMG	RRTMG	YSU
Member 4	Grell-Devenyi	Eta Schema	New Goddard	RRTMG	MYJ
Member 5	Kain Fritsch	Lin	CAM	CAM	YSU
Member 6	Grell 3D	Lin	Dudhia	RRTM	YSU
Member 7	Grell Freitas	Kessler	Goddard	New Goddard	YSU
Member 8	Grell 3D	Lin	RRTMG	RRTMG	MYJ
Member 9	Grell Freitas	WSM3	Goddard	FLG	YSU
Member 10	Grell 3D	Eta Schema	New Goddard	RRTM	MYJ
Member 11	Grell 3D	Thompson	Dudhia	New Goddard	MYJ
Member 12	Grell 3D	Lin	RRTMG	RRTMG	YSU

The ensemble prediction method is a way to determine the value of the accuracy of the prediction results by comparing the results from several weather prediction models (members). This ensemble prediction method performs the running process several times using the same initial time. The results of the running process are called ensemble members. The ensemble mean forecast is defined as the average of all members of the ensemble forecast [6]. The following is the equation for the ensemble mean:

$$em^{xx}(t) = \frac{1}{(N_{xx}+1)} \sum_{j=0, N_{xx}} f_j^{xx}(t) \quad (1)$$

Where xx denotes weather forecast parameters, and  $N_{xx}$  is the total number of ensemble members.

Numerical weather prediction (NWP) models such as WRF need to be verified. Verification is carried out on observational data collected in the field. In this case, it is carried out using observation data from Padang City, Pekanbaru City, and Batam City. The main purpose of this verification is to find the appropriate parameterization for

real conditions. The statistical parameters used to validate the results of the WRF model are the Pearson correlation coefficient, root mean square error (RMSE), mean error (BIAS), and Lavdaz validation.

The correlation coefficient is used to measure the level of linearity between the results of the model and observation data [8]. The coefficient ranges from -1 to +1. The negative sign indicates that the correlation between the model findings and observational data is inversely proportional. To determine the strong, moderate, and weak categories of correlation coefficients. The categories of correlation coefficients are shown in Table 2.

**Table 2.** The category of correlation coefficient

Coefficient Interval	Correlation
$0.00 < r < 0.20$	No correlation
$0.20 \leq r < 0.40$	Weak
$0.40 \leq r < 0.70$	Intermediate
$0.70 \leq r < 0.90$	Strong
$0.90 \leq r < 1.00$	Very Strong

The following is the equation to determine the Pearson correlation coefficient (R)

$$r = \frac{\sum(F_i - \bar{F}_i)(O_i - \bar{O}_i)}{\sqrt{\sum(F_i - \bar{F}_i)^2} \sqrt{\sum(O_i - \bar{O}_i)^2}} \quad (2)$$

Where F denotes forecasting data, and O is the observation data.

The RMSE quantifies the deviation of data points from the observation data. As the forecast and observation data diverge, the RMSE value fluctuates, increasing and decreasing as they converge. The subsequent information is utilized for RMSE computations.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (F_i - O_i)^2} \quad (3)$$

The mean error is calculated by dividing the total discrepancies between the observational data and the WRF model findings by the number of observations. The mean error count facilitates the observation of data trends. If positive, the simulated value is likely an excess of the actual values; if negative, it is likely an underestimate of the actual value [15].

$$BIAS = \frac{\sum_{i=1}^n (F_i - O_i)}{N} \quad (4)$$

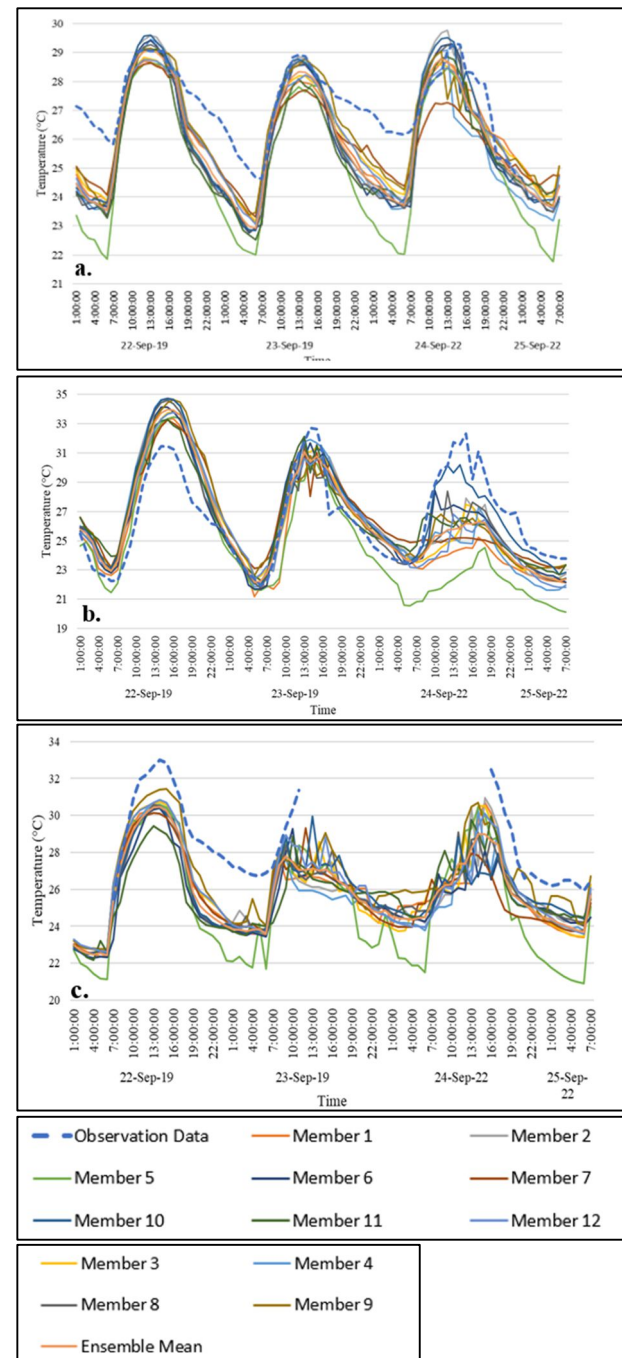
The Lavdas method can be used to verify wind direction. In this method, the wind directions from the model are grouped into eight wind directions : north-east (45 degrees), east (90 degrees), south-east (135 degrees), south (180 degrees), southwest (225 degrees), west (270 degrees), north-west (315 degrees), and north (360 degrees). In this method, calm winds are omitted from the calculation. If the observed wind originated from the accurately predicted direction, specifically the nearest eight-point compass direction, the forecast was classified as a direct hit for that hour. A forecast was deemed a near miss to the left if the wind-borne smoke's trajectory was approximately one compass point to the left of the forecasted direction. For instance, with a northeast forecast and a 350-degree observation, the forecasted wind would direct smoke southwestward, while the observed wind would direct smoke southward (to the nearest compass point), as south is adjacent to the left of southwest when facing southwest. Consequently, the forecast is categorized as a near miss to the left for that hour. A similar assessment was conducted for forecasts that were near misses to the right. Forecasts classified as a direct hit, a near miss to the left, or a near miss to the right were aggregated into a near or direct-hit category; the remaining forecasts were designated as missed forecasts. [16].

### 3 Results

Riau Province is one area that often experiences forest fires and other hydrometeorological disasters. These disasters are closely related to various meteorological parameters. Therefore, the requirement for and availability of meteorological data becomes very important. In this study, verification of the prediction results of the WRF model was carried out on

meteorological observation data for parameters of humidity, temperature, wind speed, and wind direction.

#### 3.1 Temperature parameter



**Fig. 2.** WRF model temperature comparison with observational data in (a) Padang, (b) Pekanbaru, and (c) Batam

Temperature quantifies the thermal state of an environment, indicating its degree of coldness or heat. This situation can be affected by the duration of sunlight, the angle of sunlight, cloud cover, and the condition of the Earth's surface. Fig. 2 shows a comparison between the results of the WRF model and the observation data for the temperature parameter.

According to Fig. 2, the WRF model has a similar pattern to the observational data. The maximum

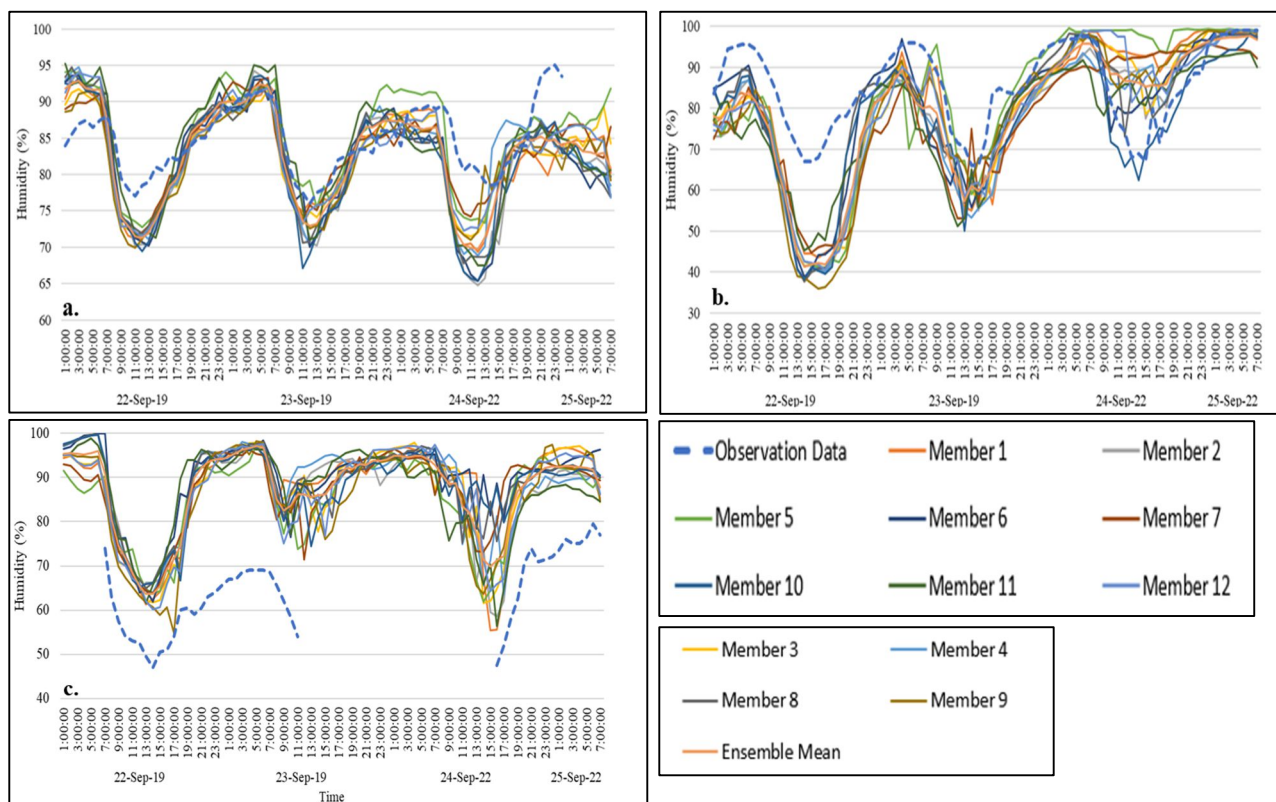
temperature occurs between 13.00 and 16.00 local time (LT) during the day, while the minimum temperature occurs between 04.00 and 05.00 LT in the early morning. In general, the WRF model has a high linearity value for the Padang, Pekanbaru, and Batam observational data (Table 3). This is indicated by the average correlation value between 0.70 and 0.89. The member with the highest correlation value was member 6, with a value of 0.89 for the city of Padang, followed by member 10, with a value of 0.87 for the city of Pekanbaru, and member 11, with a value of 0.87 for the city of Batam, and member 11,

with a value of 0.91 for the Batam region. While the typical error generated in the Padang region is 0.18, it is 0.19 in the Pekanbaru region and 2.11 in the Batam region. Temperature parameters are typically underestimated by the WRF model. Consequently, a negative bias value is observed (less than 0). For the ensemble mean, the temperature prediction results for the Padang, Pekanbaru, and Batam regions show good agreement with the observation data, particularly in terms of linearity and error patterns.

**Table 3.** Validation of correlation coefficient, RMSE, and BIAS from the WRF model against temperature observations in Padang, Pekanbaru and Batam

Member	Padang			Pekanbaru			Batam		
	Corr	RMSE	BIAS	Corr	RMSE	BIAS	Corr	RMSE	BIAS
Member 1	0.86	0.29	-1.18	0.67	0.04	-0.77	0.87	3.31	-2.81
Member 2	0.88	0.26	-1.19	0.72	0.02	0.07	0.90	0.35	-2.81
Member 3	0.86	0.03	-1.06	0.72	0.04	-0.21	0.87	0.50	-2.64
Member 4	0.86	0.03	-1.49	0.70	0.38	-0.06	0.86	3.75	-3.08
Member 5	0.85	0.16	-2.01	0.62	0.67	-1.78	0.88	3.22	-3.56
Member 6	0.89	0.31	-1.45	0.82	0.03	-0.09	0.89	0.88	-3.09
Member 7	0.88	0.24	-1.25	0.62	0.22	0.10	0.83	0.39	-2.92
Member 8	0.88	0.01	-1.38	0.76	0.35	-0.10	0.90	0.44	-2.78
Member 9	0.85	0.18	-0.92	0.70	0.10	0.07	0.88	3.36	-2.01
Member 10	0.88	0.26	-1.20	0.87	0.10	0.55	0.83	3.62	-2.72
Member 11	0.88	0.08	-1.57	0.76	0.08	-0.04	0.91	3.88	-2.96
Member 12	0.87	0.14	-1.20	0.70	0.41	-0.26	0.88	0.43	-2.55
Ensemble Mean	0.88	0.31	-1.33	0.74	0.13	-0.21	0.91	3.31	-2.83

### 3.2 Humidity parameter



**Fig. 3.** WRF model humidity comparison with observational data in (a) Padang, (b) Pekanbaru, and (c) Bata

Air humidity is a measure of the amount of moisture in the air that is affected by temperature, air pressure, wind speed, duration of sunlight, and categories of vegetation.

Fig. 3 depicts a comparison between the WRF model's humidity results and observational data.

Figure 3 shows that the WRF model reveals a similar pattern to the observational data. Maximum humidity occurs between 01:00 and 04:00 LT in the early morning, while minimal humidity occurs between 11:00 and 15:00 LT in the afternoon. For the Padang, Pekanbaru, and Batam regions, the WRF model has a linearity value that tends to be moderate to strong in relation to the observed data for the humidity parameter (Table 4). This is indicated by the average correlation value between 0.55 and 0.89. The maximum correlation value was shown by member 7 for the city of Padang, member 10 for the city of Pekanbaru, and member 12 for the Batam region. While the typical error generated in the Padang region is 0.33, it is 1.64 in the Pekanbaru region and 10.07 in the Batam region. In general, the Padang and Pekanbaru regions are underestimated by the WRF model, whereas Batam is overestimated. This is indicated by a negative bias value (less than 0) for Padang and Pekanbaru and a positive bias

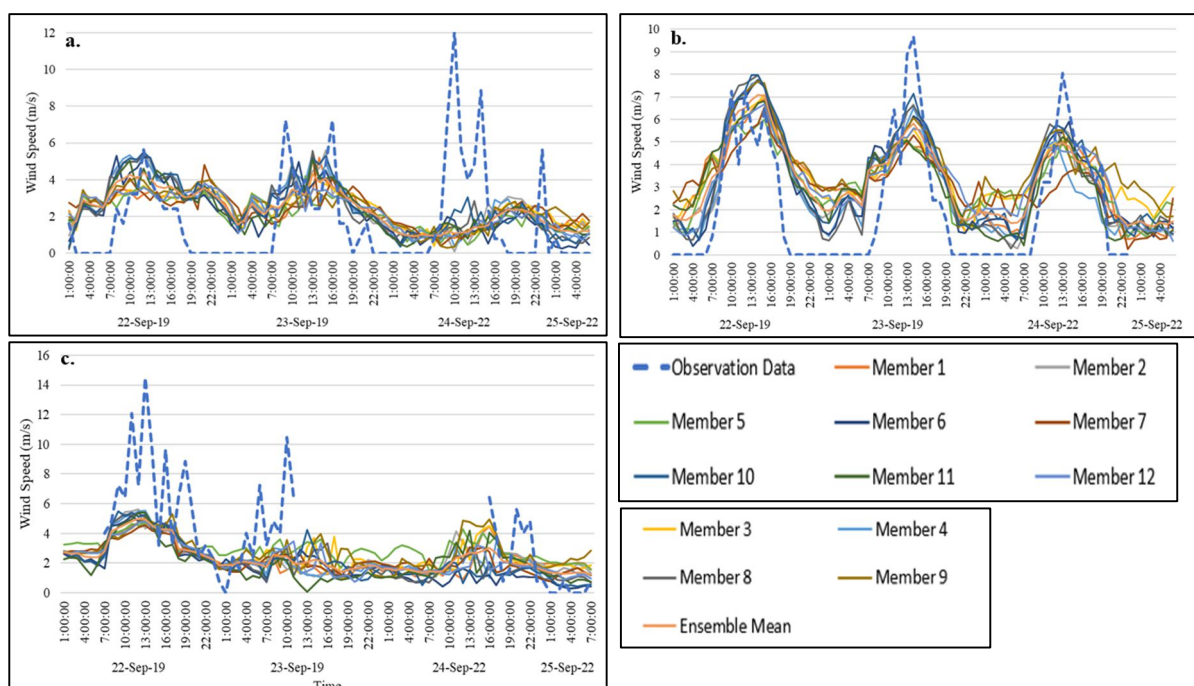
value (greater than 0) for Batam. Table 4 demonstrates that Batam has greater error and bias than Padang and Pekanbaru. This is because there are a large number of missing observational values for the humidity parameter in the Batam region. In the Padang, Pekanbaru, and Batam regions, the ensemble mean humidity prediction result exhibits a similar pattern to the observation data, particularly the linearity pattern.

Figures 2 and 3 illustrate that the correlation between temperature and humidity is inversely proportional. Relative humidity indicates the quantity of water vapor present in the atmosphere. A high humidity level signifies a substantial presence of water vapor in the atmosphere. Basically, Temperature and humidity are influenced by seasonal fluctuations; during the dry season, temperatures are elevated and humidity is diminished [17]. During the rainy season, temperatures decrease and humidity rises [17].

**Table 4.** Validation of correlation coefficient, RMSE, and BIAS from the WRF model against humidity observations in Padang, Pekanbaru, and Batam

Member	Padang			Pekanbaru			Batam		
	Corr	RMSE	BIAS	Corr	RMSE	BIAS	Corr	RMSE	BIAS
Member 1	0.69	0.66	-2.31	0.64	1.53	-5.22	0.81	13.79	23.96
Member 2	0.73	0.002	-2.98	0.69	0.70	-8.30	0.78	2.42	23.48
Member 3	0.72	0.21	-2.29	0.70	0.89	-6.18	0.83	4.14	23.25
Member 4	0.68	0.64	-2.04	0.70	2.92	-8.46	0.72	13.99	24.39
Member 5	0.72	0.17	0.24	0.56	3.43	-3.22	0.84	13.53	21.70
Member 6	0.72	0.48	-2.62	0.78	0.63	-5.61	0.79	12.00	26.25
Member 7	0.78	0.34	-1.65	0.54	2.00	-8.14	0.75	2.28	23.32
Member 8	0.70	0.49	-2.65	0.73	3.05	-5.40	0.76	4.01	24.96
Member 9	0.70	0.19	-2.93	0.65	0.48	-6.42	0.81	13.98	21.83
Member 10	0.74	0.33	-3.19	0.85	0.58	-8.83	0.72	13.95	24.31
Member 11	0.68	0.12	-1.53	0.67	1.15	-8.44	0.70	13.27	23.14
Member 12	0.71	0.03	-1.93	0.69	2.32	-5.96	0.84	9.47	23.15
Ensemble Mean	0.74	0.69	-2.16	0.71	1.68	-6.68	0.83	14.06	23.65

### 3.3 Wind speed parameter



**Fig. 4.** WRF model wind speed comparison with observational data in (a) Padang, (b) Pekanbaru, and (c) Batam

The wind is the horizontal movement of air masses due to pressure differences. Basically, air masses transition from regions of high pressure to regions of low pressure. Fig. 4 presents a comparison of the WRF model findings with the observational data for wind speed parameters.

Figure 4 illustrates the similarity between the WRF model and the observations, particularly in the Padang and Batam regions. The maximum wind speed occurs between 10:00 and 16:00 LT during the day, while the minimum temperature occurs between 3:00 and 5:00 LT in the early morning. In general, the WRF model exhibits moderate to strong linearity with the observational data, particularly in the Padang and Batam regions. (Table 5). This is indicated by the average correlation value between 0.55 and 0.89. In the Pekanbaru region, the linearity value

between WRF model data and observation data demonstrates a weak correlation (no correlation). Member 10 demonstrated the highest correlation with a value of 0.86 for the city of Padang, while member 12 demonstrated the lowest correlation with a value of 0.75 for the Batam region. While the average error is 0.28 in the Padang region, it is 0.19 in the Pekanbaru region and 0.34 in the Batam region. In general, the WRF model results for wind speed in Padang and Pekanbaru are higher than the observational data, whereas the results for Batam are sluggish. The ensemble means wind speed prediction result displays a similar pattern, particularly the linearity and error patterns derived for the Padang and Batam regions.

**Table 5.** Verification value of correlation coefficient, RMSE, and BIAS from WRF model against observation in Padang, Pekanbaru, and Batam for wind speed

Member	Padang			Pekanbaru			Batam		
	Corr	RMSE	BIAS	Corr	RMSE	BIAS	Corr	RMSE	BIAS
Member 1	0.76	0.14	1.06	-0.04	0.08	0.61	0.60	0.41	-1.89
Member 2	0.84	0.21	1.01	0.12	0.21	0.91	0.60	0.72	-1.79
Member 3	0.81	0.43	1.42	-0.01	0.22	0.75	0.70	0.16	-1.65
Member 4	0.79	0.23	0.84	0.19	0.08	0.83	0.66	0.17	-1.92
Member 5	0.79	0.36	1.05	0.00	0.46	0.45	0.67	0.44	-1.22
Member 6	0.85	0.17	0.96	0.32	0.13	0.57	0.71	0.10	-2.30
Member 7	0.66	0.27	1.01	-0.09	0.13	0.71	0.73	0.80	-1.94
Member 8	0.84	0.25	1.03	0.26	0.13	0.70	0.70	0.07	-2.04
Member 9	0.79	0.33	1.76	-0.15	0.30	0.75	0.66	0.40	-1.46
Member 10	0.86	0.19	1.22	0.36	0.10	0.84	0.72	0.23	-2.05
Member 11	0.76	0.44	0.90	0.24	0.30	0.68	0.66	0.07	-2.18
Member 12	0.82	0.41	1.13	0.03	0.38	0.62	0.75	0.47	-1.95
Ensemble Mean	0.84	0.21	1.12	0.14	0.02	0.70	0.73	0.39	-1.87

### 3.4 Wind direction parameter

The wind's direction is essential, especially in ascertaining the dispersion of air contaminants. As forest fires are a common occurrence in the province of Riau, it is crucial to collect data on wind direction. Table 6 depicts a contrast between the results of the WRF model and the observational data for wind direction parameters.

In the Padang, Pekanbaru, and Batam regions, the average WRF model is able to detect wind direction

accurately, as shown in Table 6. The WRF model's average ability to detect wind direction is greater than 60%, with an average number of errors below 30%. The ability with the highest percentage of near or direct hits is worth 74.7% in the Padang region (member 8), 72.2% in the Pekanbaru region (member 4), and 84.7% in the Batam region (member 10). For the ensemble mean, the wind direction prediction reveals positive results. This is indicated by the near or direct strike percentage exceeding 65%.

**Table 6.** Percentage of near/direct hit against miss of wind direction each member

Category	Member												
	1	2	3	4	5	6	7	8	9	10	11	12	En
<b>Padang</b>													
Near/Direct Hit (%)	53.2	64.6	63.3	69.6	72.2	73.4	65.8	74.7	62.0	69.6	62.0	69.6	68.4
Miss (%)	46.8	35.4	36.7	30.4	27.8	26.6	34.2	25.3	38.0	30.4	38.0	30.4	31.6
<b>Pekanbaru</b>													
Near/Direct Hit (%)	65.8	72.2	65.8	72.2	69.6	68.4	63.3	70.9	69.6	70.9	62.0	68.4	68.4
Miss (%)	34.2	27.8	34.2	27.8	30.4	31.6	36.7	29.1	30.4	29.1	38.0	31.6	31.6
<b>Batam</b>													
Near/Direct Hit (%)	82.6	80.4	78.3	71.7	80.4	73.9	82.6	78.3	78.3	84.8	71.7	78.3	80.4
Miss (%)	17.4	19.6	21.7	28.3	19.6	26.1	17.4	21.7	21.7	15.2	28.3	21.7	19.6

## 4 Discussion

From the WRF simulation, member six is found to be the greatest predictor of the temperature parameter. Member 6 employs the RRTM and Dudhia schemes to parameterize longwave radiation and shortwave radiation. The WRF model is generally good at estimating the pattern and value of temperature at three different places. In the coastal regions of northern China, a combined Dudhia and RRTM scheme also demonstrates the greatest model performance among longwave and shortwave radiation schemes [18]. Not only temperature parameters but the humidity parameter also show a good output against the pattern and value of the observation data at three locations. In general, the pattern of meteorology parameters shows a diurnal pattern in Padang, Pekanbaru, and Batam.

This simulation additionally incorporates an assessment of the wind speed and direction characteristics. Wind speed exhibits the most sensitivity to PBL schemes, followed by longwave or shortwave radiation schemes, and microphysics schemes, whereas wind direction demonstrates reduced sensitivity to modifications in physical parameterization [18]. Using Yonsei University's PBL parameterization, the WRF simulation results indicate that the strongest member is member 6 (YSU). The YSU PBL scheme is a nonlocal first-order K-profile model that incorporates a countergradient term to account for the influence of large-scale eddies on the overall flow [13]. The YSU scheme demonstrates a greater capacity for aligning with daytime wind observations, while the MYNN scheme tends to align more effectively with nighttime observations [13]. According to the simulation results, the correlation value of wind speed in the Pekanbaru region is very low. This is due to the fact that nighttime observation data is limited or nonexistent, whereas daytime observation data appears to have an excellent pattern. Regarding wind direction parameters, the WRF model can make accurate predictions. This is evidenced by the high percentage of near or direct strikes, which is 65%. The evaluation of wind direction across the Persian Gulf using various PBL parameterization schemes reveals that the YSU scheme, in conjunction with Interim reanalysis data, yields the most accurate wind speed estimation, while the YSU scheme paired with NCEP-FNL data produces the least error in wind direction [19].

## 5 Conclusion

This paper investigates the evaluation of 12 member parameterizations and one ensemble mean from September 21 to September 25, 2019. For all simulations using GFS data, the model was initialized at 00 UTC. A comparison is made between the model results and Automatic Weather Station (AWS) datasets for the same time series. Based on the simulations, we discovered that WRF generates plausible simulated meteorological parameters (humidity, temperature, wind direction, and wind speed) over the Riau Province. All ensemble

members and the ensemble mean generate a good to strong correlation with the observational data for temperature and humidity parameters, but the values of the parameters are slightly underestimated for temperature and overestimated for the majority of humidity values. Regarding wind speed, the WRF model generates a poor correlation in the Pekanbaru region, but a strong correlation in Padang and Batam. In general, the WRF generates an overestimated value for the wind speed parameter in Padang and Pekanbaru, but an underestimated value in Batam.

The simulation also revealed that the sixth member corresponds closest to the observation data. It is due to the fact that almost all parameters in the three regions are consistent (above average correlation of 65 % and low RMSE). It employs RRTM and Dudhia to parameterize longwave and shortwave radiation (LW/SW) and Yonsei University (YSU) to parameterize the planetary boundary layer (PBL). According to the simulation results, the correlation value of wind speed in the Pekanbaru region is very low. This is due to the fact that nighttime observation data is limited or nonexistent, whereas daytime observation data appears to have an excellent pattern. Regarding wind direction parameters, the WRF model can make accurate predictions. This is evidenced by the high percentage of near or direct strikes, which is 65%.

In addition, the results of this study can be used to predict the typical direction of pollution dispersal in the province of Riau. In the process of pollutant advection, meteorological variables such as wind direction and speed, temperature, and humidity play a significant role. Consequently, it is possible to estimate the magnitude of the influence or contribution caused by forest fires in the affected areas.

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