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A Preliminary Study on the Parameter Configuration of Weather Research Forecasting in Tropical Peatland, Central Kalimantan

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ABSTRACT

Hydrometeorological variables are sensitively regulated by atmospheric dynamics and variability. Weather research and forecasting (WRF) model is the cutting-edge tool for studying and investigating the dynamics of physical atmospheric conditions, but the configuration scheme of WRF parameters remains a research challenge for topical peatland situated in the maritime continent. Here, we evaluated WRF parametrization based on three kalibration configuration schemes, which influence rainfall, temperature, and soil moisture dynamics. We tested the WRF evaluation for Sebangau-Kahayan peatland for a wet-dry season in August 2020. The best configuration was determined based on three statistical metrics namely mean absolute error, percent bias, and coefficient of correlation. Our results showed that WRF forecasts were greatly depend on a bias correction to improve the model performance, in which it was consistently found in all configurations. Rainfall was barely predicted in station level with a low performance in term of weekly spatial distribution. Other findings revealed that all configurations showed a good performance for temperature and soil moisture forecasts. Further, our findings emphasize the important physical parameter of WRF that control rainfall formation and dynamics. Last, we highlight an urgent need of more ground stations in term of spatial distribution to validate the weather forecast.

KEYWORDS
parameterization, rainfall, soil moisture, spatial distribution, temperature

INTRODUCTION

Drought associated fires is one of the driving factors for tropical peatland degradation. Prolonged dry season leading to low monthly rainfall is favorable for fire risk (Taufik et al., 2017). The situation getting worse when it coincides with El Nino event such as in 1997 and 2015 (World Bank, 2016), when fires and smoke-haze become catastrophic events influencing socio-economic activities in Southeast Asia region (Forsyth, 2014; Koplitz et al., 2016; Sheldon and Sankaran, 2017). Efforts have been proposed to mitigate the drought associated fires such as through the establishment of Indonesian peatland agency, which is specifically tasked to restore degraded peatland. Researches also contribute to deal with the drought associated fires by integration of weather research and forecasting model into drought-fire indices (Groot et al., 2006; Lisnawati et al., 2022; Taufik et al., 2023) to mitigate the fire risk.

Weather forecasting is urgently required and is one of the most applicable fields in atmospheric modelling, which has various implications to environment and society. Scientists use the modeling approach combined with observation to study physical atmospheric conditions such as rainfall formation, atmospheric stability, and tornado cyclone. Weather research and forecasting (WRF) model is a state-of-the art of numerical weather prediction that has been widely tested and applied worldwide to study the atmospheric condition. Now its application is not limited to operational weather forecasting only, but expands to weather impact studies such as flood forecast (Patel et al., 2019; Zhou et al., 2018), susceptible to landslide events (Nuryanto et al., 2020), and forest fires prediction (Lisnawati et al., 2022; Shamsaei et al., 2023; Taufik et al., 2023).

A wide application of WRF related to its convenience use of the parameter configuration. One can easily select the configuration of WRF parameters, which suit better to the specific needs. Researches have tested several configurations to study rainfall forecast in subtropics climate (Chinta and Balaji, 2020; Merino et al., 2022; Zhou et al., 2018) by selecting different available schemes of microphysics, cumulus, and planetary boundary layer parameters. Other weather variables also have been investigated based on parametrization (Fernández-González et al., 2018; Varga and Breuer, 2020). Researches showed that the configuration of parameterization schemes of WRF and local eco-region greatly control the output forecasts (Merino et al., 2021; Zhang et al., 2013; Zhou et al., 2018). Therefore, with the unique condition of maritime continent, model configuration of WRF remains a research challenge to forecast rainfall and other weather variables. Further, near surface soil moisture that controls heat and moisture fluxes is barely investigated under WRF research flag.

In this study, peat hydrological unit of Sebangau-Kahayan in Kalimantan, Indonesia is used to test the WRF configuration scheme. We evaluated the configuration for a wet dry season due to La Nina phenomenon. Then, the aims of research are to bias corrected the hydrometeorological forecast, and to determine the best WRF configuration for a wet-dry season. Further, this evaluation will benefit to the choices of WRF parameter configuration, which is a suitable tool to estimate the fire danger at the fire-prone peatland region.

MATERIALS AND METHODS

Study Area

The study site was on the peat hydrological unit (PHU) of the Kahayan River - Sebangau River (Figure 1), Central Kalimantan, where homes for 18% of Indonesia's peatland. Frequent fires were reported in the site and surrounding area as excessive drainage canals development (Konecny et al., 2016). The site in Sebangau was previously used as a logging concession area until 1990s and it was designated as national park in 2006, which keep it remains intact afterwards. Vegetation distribution was dominated by *Dipterocarpaceae, Clusiaceae*, *Myrtaceae* and *Sapotaceae* families (Mirmanto, 2010).

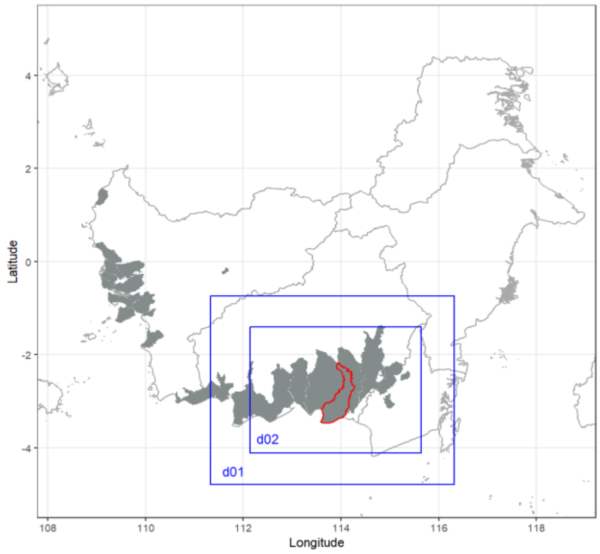

Figure 1. Location of the study area in a red polygon situated in southern part of Borneo. Two blue-polygons represent the domain of model for 5 Km (do2) and 15 Km (do1).

The climate is fully humid tropics according to the Köppen classification with annual rainfall and evapotranspiration is ca. 2400 mm and ca. 1400 mm (Hirano et al., 2015). Monthly rainfall below 100 mm is rarely observed. But during El-Niño, monthly rainfall plummeted to 0, and it caused dry season lasted longer (Susilo et al., 2013). The period of July-August-September is the lowest monthly rainfall, which favors peat fire events (Usup and Hayasaka, 2023).

Model Setup and Input

Weather Research and Forecasting (WRF) is an atmospheric model developed by multi-partnerships of the National Center for Atmospheric Research (NCAR), National Oceanic and Atmospheric Administration (NOAA) for the High-resolution Numerical Weather Prediction (NWP) and other research institutes. For operational use, WRF provides weather forecasts for the next 16 days with the data inputs from the Global Forecast System (GFS). The simulation for weather forecast was perform-ed on two domains with horizontal resolutions of 5 Km and 15 Km (Figure 1), respectively. In the vertical direction, 35 sigma levels were identified for all domains, with the top fixed at 1 hPa. For domain 2, in total, there were 189 horizontal grids that we focused on for further analysis.

WRF is a program for forecasting weather variables using a variety of predetermined physical and dynamic atmospheric scheme options (Powers et al., 2017). There are seven core physics parameters of WRF used in this study: microphysics, cumulus, planetary boundary layer, longwave radiation, shortwave radiation, land surface, and surface layer. Microphysics, cumulus, and planetary boundary layer parameters are crucial for simulating rainfall (Merino et al., 2022, 2021), while longwave radiation, shortwave radiation, land surface, and surface layer parameters are essential for simulating air temperature and soil moisture. The selection of schemes for each WRF parameter will determine the output of forecast data.

We used reanalysis forecast data from the Global Forecast System (GFS) at a spatial resolution of 0.25° and a temporal resolution of 6 hours as the input data for initial and lateral boundary conditions. We tested and parameterized the 3-combination schemes for weather condition in August 2020. In this research, we simulated the 3-combination of scheme options (Table 1), selected from the 7-physics parameters of WRF. We tested the 3-combination to investigate their influence on hydrometeorological variables (rainfall, air temperature, and soil moisture). Also we considered and selected the combination based on the previous researches performed in the maritime continent, Indonesia (Nuryanto et al., 2020; Sanusi et al., 2021; Taufik et al., 2023; Yulihastin et al., 2021).

Data correction

WRF's forecast data were extracted to obtain three variables (air temperature, rainfall, and soil moisture) for fire hazard detection. The variables require a bias-correction with ground observation data. A bias may come from: the systematic error from the calculation in the numerical weather prediction (NWP), imperfect model parameterizations, insufficient length and quality of reference data, and inadequate spatial resolution. We used the Quantile Mapping (QM) bias correction method to rectify bias in the output results of NWP models based on Piani approach (Piani et al., 2010).

The ground observed data comes from three monitoring weather stations in the PHU Kahayan-Sebangau. Three stations provided daily rainfall and air temperature data namely: Tjilik Riwut (113°57'0.00"E, 2°13'12.00"S), Pulang Pisau (114°15'20.88"E, 2°46' 39.72"S), and Pandih Batu (114°9'15.12"E, 3°3'42.26"S), which represent the upstream, middle, and down-stream of PHU. Moisture datasets were from the two nearby stations closed to Tjilik Riwut and Pulang Pisau, which were managed by BRGM.

We assumed that the datasets represented moisture condition in both weather stations. In addition, the corrected forecast will be analyzed on weekly basis to see its spatio-temporal distribution throughout the PHU.

Data Verification

WRF's forecast data were evaluated using three statistical metrics (Moriasi et al., 2015), as presented in Table 2. The first metric is Mean Absolut Error (MAE), which is defined as the mean value of the forecasts' errors in absolute values. The range of MAE value from 0 to ∞, with 0 as an optimal value. Percent Bias (PBIAS) can gauge the estimated bias in overestimating or underestimating data and is expressed as a percentage. The ideal value for PBIAS is 0, with mostly PBIAS $\pm$ 10% is a good performance. The Pearson Correlation Coefficient (r) is a statistical metric used to assess the level of linear relationship between observed and forecast data. This metric has a range from -1 to +1, with 0 is no correlation at all between two pairs of data.

Table 1. The 3-combination of the physical parameters of WRF for the modelling purpose.

No	Parameter	Symbol	Combination 1	Combination 2	Combination 3
1	Microphysics	Mp	WRF Single-Moment 6-class (WSM6)	WRF Single-Moment 3-class (WSM3)	Eta scheme
2	Cumulus	Cu	Betts-Miller-Janjic (BMJ)	Kain-Fritsch (KF)	Grell-Devenyi (GD) ensemble scheme
3	Planetary boundary layer	PBL	Yonsei University (YSU)	Yonsei University (YSU)	Mellor-Yamada-Janjic (MYJ)
4	Long-wave radiation	LR	Rapid Radiative Transfer Model for GCMs (RRTMG)	Rapid Radiative Transfer Model (RRTM)	Rapid Radiative Transfer Model (RRTM)
5	Short-wave radiation	SR	Rapid Radiative Transfer Model for GCMs (RRTMG)	Dudhia	New Goddard
6	Surface layer	SL	5th Generation Penn State/NCAR Mesoscale Model (MM5)	5th Generation Penn State/NCAR Mesoscale Model (MM5)	Monnin-Obukhov
7	Land surface	LS	Noah Land Surface Model	Noah Land Surface Model	Rapid Update Cycle (RUC) Land Surface Model

Table 2. List of statistical metrics as a tool for forecast evaluation.

Metrics	Notation	range	Ideal value	Note
Mean Absolut Error	MAE	0.0 to ∞	0.0	Widely used
Percent BIAS	PBIAS	-∞ to ∞	0.0	It can identify average model simulation bias (overprediction vs. underprediction)
Pearson correlation	r	-1.0 to 1.0	-1.0 (- slope) Or 1.0 (+ slope)	Widely used as a benchmark for performance evaluation

RESULTS

Hydrometeorological Condition

Rainfall

Rainfall in August 2020 was relatively high, in which each station received >100 mm. On average, the August rainfall was 125 mm, with the highest rainfall found in Pulang Pisau (148 mm). Less rainfall (26% lower) was identified in the southern part as shown from Pandih Batu data. The daily maximum rainfall was not distributed evenly throughout the PHU. In the northern part (Tjilik Riwut), the max rainfall event occurred at 12 Aug 2020 (53 mm), whereas in the middle part was reported a-week earlier at 5 Aug 2020 (51.4 mm). The number of rainfall days were 20 days, which were distributed evenly in the monitoring stations.

Air Temperature

The daily temperature ranges from 30.0 to 35.4 ^{0}C. The southern part of the PHU was reported much hotter than the other part. There is a tendency that the closer the location to the beach, the hotter the temperature is.

Soil moisture

Moisture in northern part was relatively wetter compare to the middle one. The moisture varied from 46.9% to 59.7% (mean= 55.6 ± 3 %) in the northern part, whereas it was 20% higher than the moisture reported in the middle (mean= 37.5 ± 0.64 %).

Statistical Verification of forecast

The forecast verification was station based in three weather station for rainfall and temperature, whereas only two stations for moisture. Our analysis showed that inconsistency findings were found for each combination. For rainfall, Comb1 generated a MAE of 5.58 mm, which was slightly higher (8%) compared to Comb3. On contrast, the PBIAS for Comb1 was greatly lower compared to that of Comb3 (Table 3). Other metric r showed very low values. From the three combinations, Comb2 had a lowest PBIAS, which is only 3.7%. This leads Comb1 and Comb2 might be the best parameter schemes in term of bias.

The Comb1 used the WSM6 microphysics and YSU PBL schemes, while Comb2 used the WSM3 microphysics scheme YSU PBL schemes. Both microphysics schemes can be compared based on goodness of fit values (Table 3). The forecast rainfall of Comb1 indicated a low variation as shown by low SD value (4.56), which was 50% lower that the observed rainfall (9.37). The similar findings were found for Comb3. This showed both Comb1 and Comb3 prediction tend to close the average value of rainfall. Overall, the Comb3 is the most unsuitable schemes for rainfall forecast.

For temperature, all combinations showed a good performance in term of error and bias. They have an error < 1 and bias < 1%. But, Comb1 likely performed well with the lowest error (MAE=0.68) and bias. It also has a highest value (Table 3). The forecast temperature values indicated a reasonable prediction as both show comparative SD values. Comb1 which used RRTMG-RRTMG schemes for shortwave and longwave radiations scheme revealed the best combination compared to Dudhia-RRTM and New Godard-RRTM. For soil moisture, all combinations performed well as shown by low values of MAE and high values of r.

Option of Combination Configurations

Based on model performance in Table 2, Comb2 may suitable for rainfall forecast as it has low PBIAS. But Comb1 may be still useful as well as the bias still in acceptable range of performance. Then, we checked weekly spatial distribution of the forecasts whether they fitted to the observed rainfall events. In week_31, all combination schemes showed an overestimated forecast as shown by the amount of rainfall ~20 mm on average, but the observed one was < 2 mm (Figure 2A). Although all combinations revealed an overestimated forecast, Comb1 forecast was the most inaccurate forecasts as shown high rainfall in the upper PHU (Figure 2b).

For week_32 and week_33 the forecast of Comb2 (Figure 2b, middle panel) seemed follow the pattern of observed rainfall (Figure 2a). The Comb2 was able to mimic the high rainfall especially in the middle and upstream PHU. For Comb1, the forecast indicated the average value (~ 20 – 30 mm), whereas the Comb3 was overestimated forecast. For other weeks, the performance of Comb2 scheme seemed much better that the other two, as indicated by low PBIAS (Table 3).

Table 3. List of statistical metrics as a tool for forecast evaluation.

Variable	Combination	MAE [-]	PBIAS [%]	r [-]
Rainfall	Comb1	5.58	-11	0.05
	Comb2	7.08	**3.7**	-0.04
	Comb3	**5.12**	-50.3	-0.05
Temperature	Comb1	**0.68**	**0.4**	**0.69**
	Comb2	0.79	0.8	0.47
	Comb3	0.81	0.8	0.42
Soil moisture	Comb1	**1.16**	-	0.92
	Comb2	1.29	-	0.92
	Comb3	1.27	-	**0.93**

Comb3 was the most unreliable schemes for rainfall forecast in the study site as indicated by dominated high rainfall forecasts (Figure 2b, bottom) and high PBIAS value (Table 3). Comb2 with WRF Single-Moment 3-class and micro-physics of Kain-Fritsch (Table 1) become the best option to forecast rainfall in the study site.

All combination configurations indicated low error and bias in temperature forecast (Table 3), with Comb1 showed as the best configurations with the highest r correlation value. A weekly distribution of forecast is presented in Figure 3. The Comb1 seems to be closed to the observed temperature during week 33 (mean 32.7 ^{0}C and 32.6 ^{0}C for observed and forecast, respectively) and perfectly matched for week 34 (Figure 3), whereas Comb2 forecast was on par with the observed temperature for week 32 (the same mean of 32.9 ^{0}C) and barely made it at week 35 (median= 33.2 and 33.4 ^{0}C for observed and forecast, respectively). From the weekly distribution we suggested Comb1 is the best configuration for assessing temperature in the study site.

DISCUSSION

The research evaluated the applicability of weather and research forecasting for hydrometeorological variable predictions in Central Kalimantan, Indonesia. Three variables included rainfall, temperature, and soil moisture, which were analyzed at daily basis. Three WRF configurations were tested to obtain the best configuration based on their statistical metric values.

Overall, there is no consistency for the models' performance in rainfall forecast at station level. For Comb1 and Comb3 seemed underestimated rainfall as shown in the negative bias value, whereas Comb2 indicated the positive bias (Table 3). Configuration of Comb2 using microphysics parameter of WRF Single-Moment 3 and cumulus parameter of Kain-Fritsch was to be better performed compared to the other two configurations for rainfall forecast during weak La Nina August 2020. This finding confirms the choice of schemes of microphysics and cumulus parameters does matters. Previous researches revealed that micro-physics and cumulus parameters determine thermo-dynamics process in the atmosphere (Merino et al., 2022). Other study in China revealed that the selection of planetary boundary layer parameter may more sensitive to numerical simulation (Wu et al., 2023), and this study also confirmed it as shown in the large difference of bias values between YSU and MYJ schemes (Table 3).

Based on statistical metrics in Table 3, we might not rely on their values independently without considering the rainfall's spatial pattern and distribution of forecasts. Although the model performance is reliable at station level, but there is much discrepancy related to forecasts' spatial distribution and pattern as shown in Figure 2. This issue may rise due to the number of stations for bias correction, which are limited numbers (only 3 stations) and only in the eastern part, that not even spatially distributed in the study site. Research in Iberian Peninsula showed that station density determines in the accuracy of rainfall forecast (Merino et al., 2021).

Air temperature represents a meteorological element that has the potential to initiate peatland fires (Taufik et al., 2023). In tropical maritime, normally temperature exhibits low variability. In WRF parameterization, air temperature is intricately linked to longwave and shortwave radiations, the surface layer, land surface, and the planetary boundary layer (PBL). Our finding revealed that all WRF configurations resulted in inconsistency forecasts at weekly basis (Figure 3), but the error and bias forecast were small. This revealed that any configuration choices work well for temperature forecast. Similar findings were observed for soil moisture forecast.

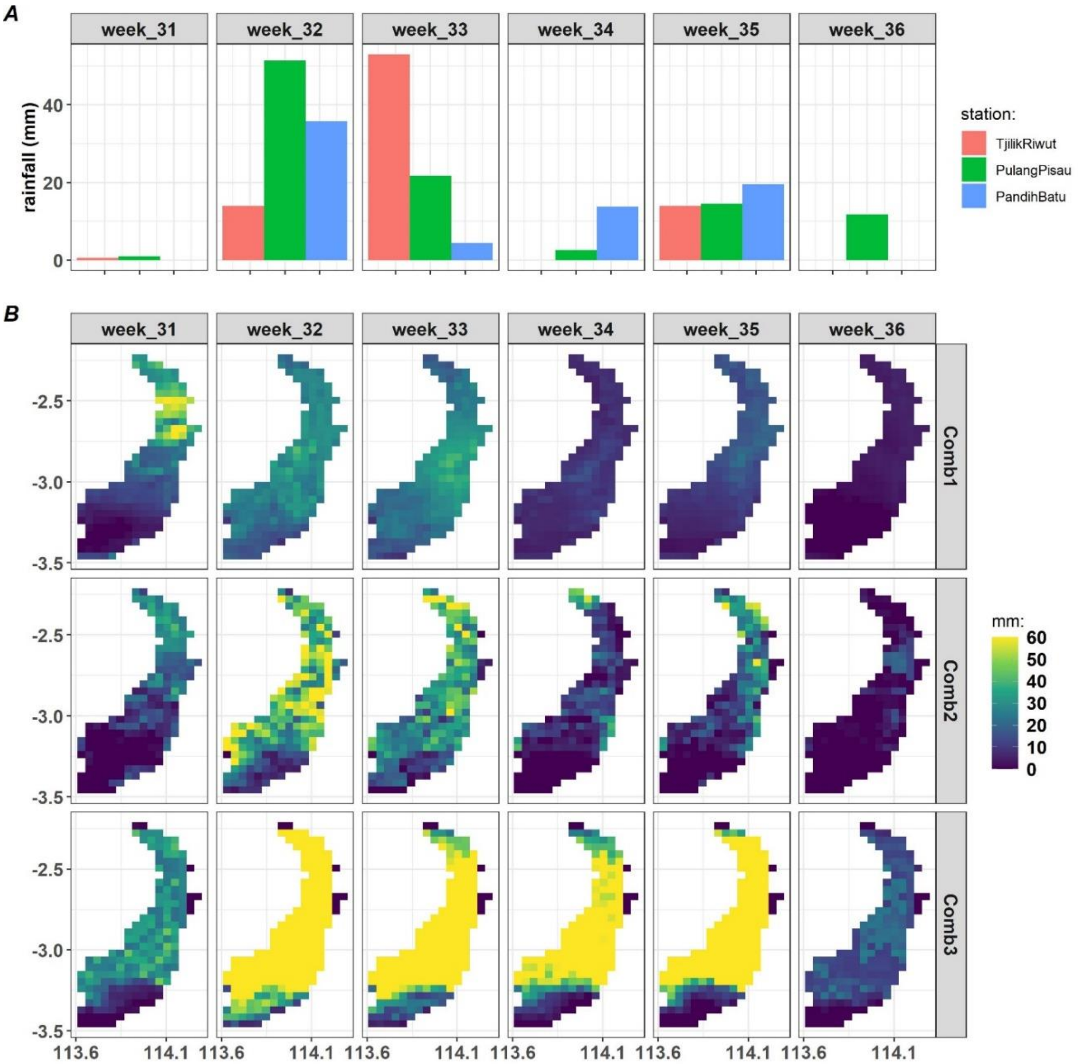

Figure 2. Weekly rainfall distribution: (a) Observed station with Tjilik Riwut (upstream), Pulang Pisau (middle), and Pandih Batu (downstream). (b). Spatial distribution based on corrected forecast WRF for Comb1 (top panel), Comb2 (mid panel), and Comb3 (bottom panel). Note: week_31 has two days, week_32 to week_35 have seven days each, while only one day for week_36.

The research has several drawbacks that shall be considered for further application. First, the number of stations for bias correction was not distributed evenly throughout the study site. This may disregard the influence of sea breeze on rainfall formation (Zhou et al., 2023) and temperature especially in the southern part. During dry season strong winds often occur, which trigger high land temperatures (Usup and Hayasaka, 2023), that is not captured by the available weather stations. Second, other model evaluation may be proposed especially using metrics derived from contingency table (Bennett et al., 2013) such as false alarm ratio, hit rate, and bias score. The use of the contingency based metrics may improve in the applicability of rainfall forecast as they couple real and forecast values (Bennett et al., 2013). Lastly, the choices of WRF configuration and parametrization especially for microphysics, cumulus, and PBL greatly determine the outcome of forecasts, in which we used three configurations (Table 1). More efforts on parametrization with various WRF configurations will improve our understanding on the dominant factors of rainfall formation in maritime continent and the reliability of WRF forecasts.

The findings of research will benefit for further studies such as fire prediction, drought forecasting, and flood research. Severe fire impacts in tropical peatland Indonesia are strongly related to fire management and field operational activities. Being able to accurately predict with reliable weather forecasts, sites with high fire risk condition are easily detected, which leads to pro-active management to minimize the risk. Also, the forecast will benefit to a higher alert phase for emergency purposes (Taufik et al., 2015) that can minimize the ecological and envi-ronmental impacts. Further, researches are more expected to find the suitable WRF configuration for rainfall forecast specific for maritime continent.

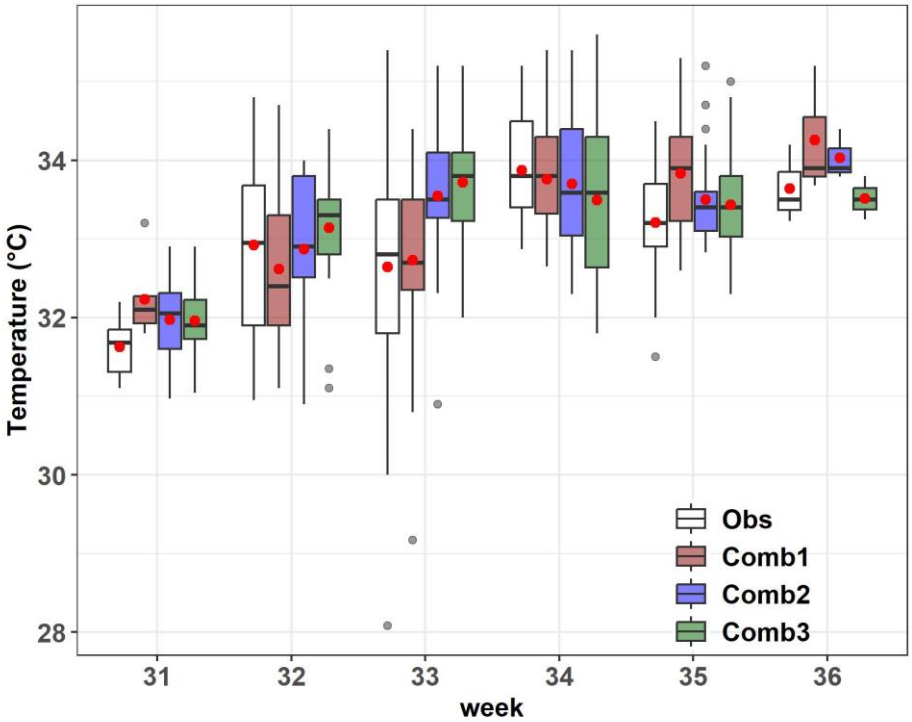

Figure 3. Boxplot of max temperature (°C) for observation (transparent) and forecast data (Comb1 -red, Comb2 –blue, and Comb3 –green). The boxplot represents the median, and the 25 and 75% quantiles. The whisker is 10 and 90% of quantiles, whereas the black dots indicate outliers. Red dots inside the boxplot indicate mean value.

CONCLUSION

This study systematically evaluated the efficacy of the WRF model for predicting key hydrometeorological parameters (rainfall, air temperature, and soil moisture) in Kahayan-Sebangau peatland, Central Kalimantan. Our findings indicated that a bias correction of the forecasts increased the model performance.

Then, we found varying degrees of predictive accuracy across the different configurations, with the configuration Comb2, incorporating the WRF Single-Moment 3-class microphysics scheme and the Kain-Fritsch cumulus parameterization, well demons-trated in rainfall forecast. However, significant spatial discrepancies were observed, underscoring the necessity for a more extensive network of observation stations to enhance bias correction and spatial resolution.

These findings suggest that while the WRF model is a powerful tool for hydrometeorological forecasting, its precision can be significantly improved through enhanced spatial data collection and calibration efforts.

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