IMPROVING SHORT-TERM WEATHER FORECASTING USING SUPPORT VECTOR MACHINE METHOD IN NORTH BARITO

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ABSTRACT

Flooding is a recurring issue in North Barito Regency due to the overflow of the Barito River. Weather forecasts in the region rely mainly on Numerical Weather Prediction (NWP) models, which often fail to capture local details due to their grid-based homogenization. To address this limitation, statistical techniques such as Model Output Statistics (MOS) can enhance NWP outputs by representing local conditions more accurately. MOS establishes statistical relationships between response variables (predictands) and predictor variables derived from NWP outputs, enabling operational applications without the need for advanced instruments. This study utilizes rainfall data from 2021-2022 from the Beringin Meteorological Station in North Barito as the response variable, while data from the Integrating Forecasting System (IFS) model serve as the predictor variables. The Support Vector Machine (SVM) method is employed to identify the relationship between predictor and response variables. By integrating the MOS technique with the SVM method, this research aims to improve the accuracy of weather forecasting, particularly for short-term predictions in North Barito. This approach demonstrates the potential to enhance localized weather predictions by addressing the limitations of conventional NWP models. The results indicate a consistent reduction in RMSE across all experiments conducted. Furthermore, the SVM model showed notable improvements in bias values and exhibited a stronger correlation compared to the original outputs from the IFS model. The percentage improvement (%IM) in rainfall forecasts, following correction using the SVM model, increased by 5.03%. The percentage improvement (%IM) in rainfall forecasts, following correction using the SVM model, increased by 5.03% for use as a predictor variable in the applied SVM method. In contrast, a combination of surface pressure, temperature across various layers, and rainfall proved to be the the most effective input variables for enhancing the accuracy of weather forecasting in North Barito using the SVM model.

Keywords: Integrating Forecasting System, Model Output Statistics, Support Vector Machine, Barito Utara, rainfall prediction

1. Introduction

The Regional Disaster Management Agency (BPBD) of Barito Utara Regency, Central Kalimantan, reports that hydro-meteorological disasters occur almost every year, particularly floods caused by heavy rainfall in North Barito Regency. Most flood result from the overflow of the Barito River, the longest river in Central Kalimantan [1] which flows through the region. While much of North Barito consists of lowlands, the region also features small hills and scattered mountains. This geographical variation influences rainfall patterns, as convective precipitation systems interact with diurnal cycles [2,3,4] and impact global atmospheric circulation [5]. The Beringin Meteorological Station is responsible for providing meteorological data for aviation and public weather services to stakeholders in North Barito. However, its observational and weather modeling facilities remain limited. Several global Numerical Weather Prediction (NWP) model datasets currently used by Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG) have been evaluated across 34 locations, each representing a province in Indonesia [6]. The findings indicate that the Integrated Forecasting System (IFS) model from the European Centre for Medium-Range Weather Forecasts (ECMWF) demonstrates the best performance compared to three other models. It consistently outperforms them in most regions of Indonesia. Despite its relative accuracy, IFS performance in Central Kalimantan remains low, with only 33% accuracy. This limitation arises because IFS is a global model, while weather conditions in Central Kalimantan are influenced by phenomena ranging from global to local scales [5,7,8]. NWP models calculate weather conditions by dividing the Earth into grids, with each grid representing a specific area [9]. However, this grid-based approach homogenizes weather values across the grid, making it unable to capture localized details such as topography, vegetation, soil type, and small water bodies. These local features are highly variable and can significantly influence weather patterns [10]. This limitation underscores the need for an efficient computational approach that better represents local conditions in North Barito, particularly for short-term weather forecasting.

Statistical methods, such as Model Output Statistics (MOS), address this issue by establishing relationships between observational data and NWP outputs. MOS has been widely applied to meteorological variables, including rainfall probability estimation [11] and improving model-based rainfall forecasts [10]. As a regression-based model, MOS develops statistical links between the predicted variables (predictands) and predictor variables from NWP outputs at various projection times [12]. Using multiple linear regression, MOS connects response and predictor variables, allowing the estimation of predictands as a linear combination of predictors [11]. The method is operationally efficient and does not require high-specification.

Rainfall being a non-linear weather parameter, necessitates a non-linear method to model the relationship between predictors and the response variable. In this study, rainfall serves as the response variable, with Support Vector Machine (SVM) employed to identify the relationship. SVM is a machine learning technique used for both classification and regression. It effectively handles linear and non-linear problems, making it suitable for meteorological applications [13,14]. Previous studies have applied SVM for tasks such as real-time 39-hour rainfall forecasting to enhance flood prediction accuracy in southwest Japan [15] and monthly average temperature and rainfall prediction at 45 weather stations in Thailand [16]. Comparative studies have shown that SVM outperforms methods like Artificial Neural Networks, Random Forest, and Multivariate Linear Regression in meteorological applications [17,18,19]. This is attributed to its simpler data processing scheme and its ability to find a global optimal solution. Unlike simpler methods such as Naive Bayes, SVM provides optimal results, particularly in cases with limited and high-dimensional data [13,14,20]. Building on this foundation, this study integrates the MOS technique with the SVM method to enhance short-term weather forecasting accuracy in North Barito. The approach aims to address the limitations of existing models and improve the representation of local weather conditions in the region.

2. Data and Methods

This study utilized IFS model data from ECMWF as predictor variables, including air temperature, relative humidity, pressure, rainfall, and wind, for the period of 2021–2022, with a spatial resolution of 0.125° × 0.125°. The response variable was derived from 3-hourly observational rainfall data recorded at the Beringin Meteorological Station in North Barito, Central Kalimantan. Additionally, Global Precipitation Measurement (GPM) rainfall data, with a spatial resolution of 0.1° × 0.1° and a temporal resolution of 30 minutes, was obtained to perform spatial verification of the model's rainfall forecast results. Furthermore, the average weather conditions in North Barito over a 30-year period were analyzed using ERA-5 reanalysis data, which has a spatial resolution of 0.25° × 0.25°. The parameters considered included the U and V components of 10-meter wind, total precipitation, 2-meter air temperature, and mean sea level pressure, with monthly averages from 1994 to 2023.

Table 1 Inclusion of Predictor Variables for Rainfall Response Variables at Each Experiment

Predictor Variables	**Level**	**Experiment**		
		1	**2**	**3**
Pressure	Surface	Yes	Yes	Yes
Rainfall	Surface	Yes	Yes	Yes
Temperature	1000 mb	Yes	Yes	No
	850 mb	Yes	Yes	No
	700 mb	Yes	Yes	No
	500 mb	Yes	Yes	No
U Wind	1000 mb	Yes	No	Yes
	850 mb	Yes	No	Yes
	700 mb	Yes	No	Yes
	500 mb	Yes	No	Yes
	10 m	Yes	No	Yes
V Wind	1000 mb	Yes	No	Yes
	850 mb	Yes	No	Yes
	700 mb	Yes	No	Yes
	500 mb	Yes	No	Yes
	10 m	Yes	No	Yes

The collected data were divided into predictor variables from the IFS model and response variables (ground truth) from observational data, which served as the reference for prediction verification. The predictor variables were categorized into three experimental groups, as outlined in Table 1. Data cleaning was performed to address outlier issues and handle missing values. Additionally, data normalization was conducted to standardize the scale or range of values for each feature in the dataset. This scaling adjustment ensured a uniform format that could be effectively processed by the SVM model. The purpose of data standardization was to ensure that each variable had a balanced influence in the analysis and modeling process. Prior to model development, the data were standardized to have a mean of zero and a standard deviation of one. Once the model was developed, the predicted values were de-standardized using the original mean and standard deviation of the data. After the SVM model generated outputs, these normalized values were converted back to their original scale through a denormalization process.

The standardized data from the preprocessing stage were randomly split into training and test sets in an 80:20 ratio. Specifically, 80% of the total data were used for training, while the remaining 20% were allocated for testing in both the one-year (2021) and two-year (2021 and 2022) experiments. The exact number of data points used in the training and testing phases is presented in Table 2. During the training process, parameter tuning was performed to achieve optimal accuracy by testing multiple parameter combinations. The most suitable parameter values for model development were determined using a random search approach. At this stage, Support Vector Regression (SVR) with a Radial Basis Function (RBF) kernel was applied, utilizing parameters such as C, gamma (γ), and epsilon (ε). The RBF kernel was selected due to its effectiveness in handling non-linear data. By mapping the input data into a higher-dimensional space, the RBF kernel enables the separation of data points that are not linearly separable in the original space [16].

Table 2 The Number of Data Division

Year Length	Year	Training	Testing	Total
1	2021	551	2204	2725
2	2021 to 2022	1053	4210	5263

The SVR model obtained from the training process is then used for regression on the test data. The testing phase evaluates the model's ability to predict or perform regression on previously unseen data. This provides an indication of the model's real-world performance and assesses its generalization capability from the training dataset to new data. Testing is crucial to ensure that the model does not merely memorize the training data but can also make accurate predictions for new inputs.

The next step is to evaluate the test results of the Model Output Statistics (MOS) forecasting using machine learning performance metrics. Several statistical measures are employed to assess the modeled rainfall, including Root Mean Square Error (RMSE), bias, correlation coefficient (R), and percentage improvement. If the performance metrics achieve the desired values, the model can proceed to the next stage. However, if the results are still unsatisfactory, parameter tuning is conducted by experimenting with different parameter combinations to optimize model performance until better results are obtained.

Once the model has demonstrated satisfactory performance, it is applied for rainfall prediction. The model outputs are stored in scalar format, enabling their application to new data. Newly extracted IFS model data is used to obtain meteorological variables that correspond to those utilized in the SVM model training phase. These extracted variables are then processed to generate predictive features, which are compiled into a single dataset organized in a DataFrame format. Subsequently, the dataset is normalized using the previously stored scalar values to ensure consistency with the scale applied during model training.

After normalization, the trained and stored SVR model is used to make predictions. The normalized input data is fed into the model, producing predictive results that estimate rainfall at specific locations and times. These predictions are then transformed back into a two-dimensional format, aligning with the appropriate longitude and latitude grids for visualization. Finally, the predicted rainfall distribution is mapped to provide a spatial representation of forecasted precipitation in the study area. These predictive results serve as the basis for further meteorological analysis, ensuring that the trained model is effectively applied to new data while generating interpretable geographic predictions.

Result and Discussion

This chapter presents the results and analysis of this study, which investigates improvements in short-term weather forecasting using Model Output Statistics (MOS) techniques with Support Vector Machine (SVM) methods. The discussion begins with an analysis of the characteristics of several meteorological parameters at the study location, serving as the foundation for defining predictor input experiments in model development. Next, the evaluation results comparing the original IFS model data with the forecasted outputs are examined. Finally, a short-term weather forecasting experiment is conducted to predict weather conditions for the next 12 hours.

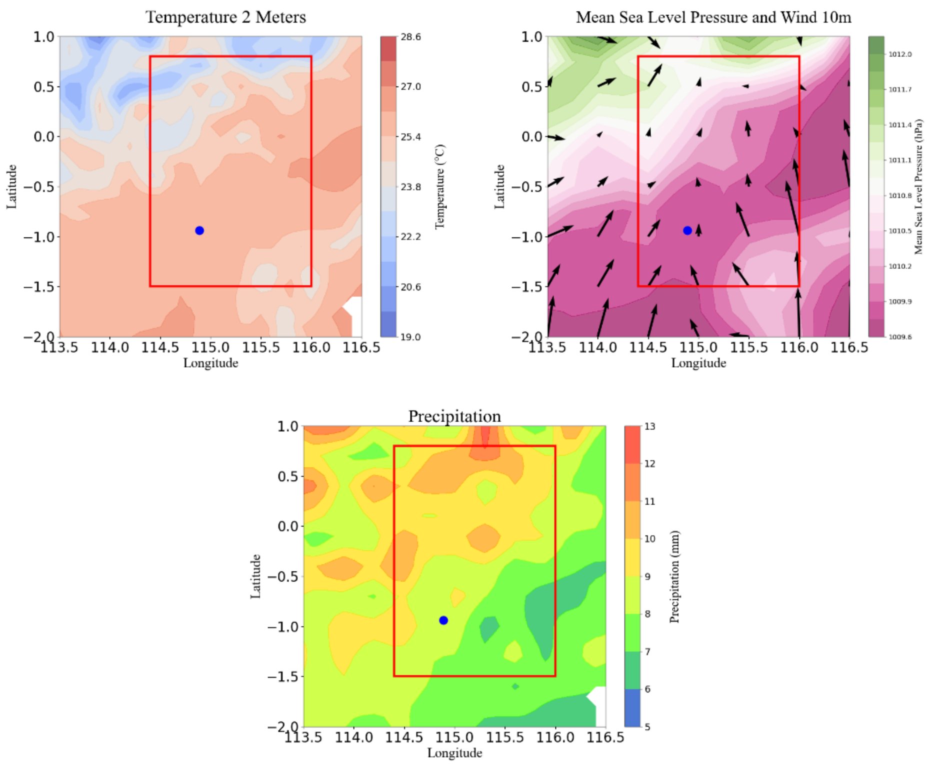

Figure 1 The average (a) 2 meter temperature, (b) sea level pressure, (c) rainfall over 30 years. The red box refers to the study area and the blue dot indicates the location of the Beringin Meteorological Station.

Weather Characteristics at the Study Area. The weather characteristics in the study area were analyzed using ERA-5 reanalysis data over a 30-year period from 1994 to 2023. The average 2-meter air temperature in North Barito reached approximately 28.6°C across most of the region, as illustrated in Figure Ia. This is consistent with North Barito's equatorial location, which contributes to higher temperatures. Warmer air temperatures were observed in the central and southern parts of North Barito, whereas relatively cooler temperatures were found in the northern region.

This temperature distribution exhibits a correlative relationship with the sea level pressure pattern shown in Figure Ib. Areas with lower air pressure values correspond to regions with higher air temperatures. However, the overall pressure differences across North Barito are not substantial, indicating a relatively stable pressure system, particularly during warmer seasons. Figure Ib also illustrates that the average wind speed in the study area remains low, ranging from 1 m/s to 2 m/s. This observation aligns with data from meteorological stations, which consistently record similar values. The topographical characteristics of North Barito, consisting predominantly of lowlands with small hills, do not create significant local wind patterns. Additionally, the presence of extensive vegetation may contribute to reduced wind speeds by obstructing airflow. Rainfall in the study area is frequently influenced by local atmospheric circulation, which triggers convective processes. These conditions can enhance atmospheric instability, particularly during nighttime, thereby impacting precipitation patterns in North Barito [2,4].

In general, experiments using two years of input data demonstrated better performance compared to those utilizing only one year of input data. A longer data period provided a broader representation of weather conditions, allowing the model to capture stronger and more accurate relationships between predictor and response variables. This improved the statistical relationships estimated by the model, making them more representative than those derived from a single year of data.

Moreover, interannual and intra-annual variations in weather patterns can occur. By incorporating a longer dataset, the model can learn to recognize and predict these variations more effectively. Evaluating model performance using two years of test data is also more objective, as it assesses the model's ability to generalize over a longer period rather than being limited to short-term variations.

The average rainfall in the study area, illustrated in Figure Ic, ranges between 7–13 mm. Higher rainfall is predominantly observed in the northern region compared to the southern region, with values ranging from 9–13 mm in the north and 7–10 mm in the south. The higher rainfall in the northern part is consistent with the region's bimodal rainfall pattern, where the rainy season exhibits two peaks annually [1]. Additionally, rainfall in this area is classified as convective, often triggered by the presence of low-pressure cells that develop due to strong solar heating (insolation) [21, 22].

The four meteorological parameters discussed above were used as predictor variables in the SVM model. Several variables from the IFS model data were selected as inputs, including surface pressure, rainfall, temperature, wind components (U and V) at multiple atmospheric levels (1000 mb, 850 mb, 700 mb, and 500 mb), and wind components (U and V) at 10-meter height. These variables were categorized into three experimental groups to determine which parameters were most relevant for short-term weather forecasting in North Barito.

The selection of surface pressure as a parameter in this study is crucial for understanding general atmospheric circulation based on the geostrophic principle. This principle aids in predicting the barotropic component of atmospheric flow, which often dominates the total flow [23]. Additionally, meteorological parameters are commonly analyzed at multiple pressure levels (e.g., 1000 mb, 850 mb, 700 mb) to provide a comprehensive three-dimensional representation of their distribution across different elevations [24]. In this study, wind and temperature were selected as key parameters to examine the vertical structure of the atmosphere at the research location. Winds and temperatures at various pressure levels serve as input variables to represent vertical air movement, capturing both upward and downward circulation in response to temperature variations at each atmospheric layer [25].

Evaluation of Model Outputs with IFS. The evaluation of RMSE, bias, and correlation coefficients was conducted to assess the performance of the SVM-based rainfall forecasts compared to the original rainfall values from the IFS model. The RMSE values for the original IFS model and the SVM-adjusted forecasts are presented in Figure 2. The results indicate a consistent decrease in RMSE when using the SVM model across all three experimental setups, for both the 1-year and 2-year experiments.

For the IFS model data, the RMSE was 9.366 mm in the 1-year experiment and 8.417 mm in the 2-year experiment. The largest RMSE reduction was observed in Experiment 2, with RMSE values decreasing to 8.875 mm (1-year) and 8.347 mm (2-year). Experiment 1 recorded the second-highest RMSE reduction, with values of 8.895 mm (1-year) and 8.328 mm (2-year). Finally, Experiment 3 showed the lowest RMSE reduction, with RMSE values of 8.908 mm (1-year) and 8.380 mm (2-year).

The percentage improvement (%IM) achieved by the SVM model compared to the original IFS values showed positive gains across all experiments. In the 1-year experiment, the highest improvement was observed in Experiment 2 (5.24%), followed by Experiment 1 (5.03%) and Experiment 3 (4.79%). Conversely, in the 2-year experiment, the order of highest improvements differed, with Experiment 1 (1.06%) ranking first, followed by Experiment 2 (0.83%) and Experiment 3 (0.44%). These findings align with the study conducted by Idowu and Rautenbach (2009) [10], which also demonstrated improvements in weather forecasting when applying the MOS technique. The evaluation based on bias values, presented in Figure 3a, also demonstrated improvements in both the 1-year and 2-year experiments. The bias in the original IFS model was -1.493 mm for the 1-year experiment and -0.841 mm for the 2-year experiment. When applying the SVM model, Experiment 2 showed the greatest improvement in bias reduction compared to Experiments 1 and 3 across both experimental periods. The bias values obtained using the SVM model were -0.076 mm for Experiment 1, -0.012 mm for Experiment 2, and -0.161 mm for Experiment 3 in the 1-year experiment. In the 2-year experiment, the values were -0.044 mm for Experiment 1, -0.029 mm for Experiment 2, and -0.167 mm for Experiment 3.

Similarly, the correlation coefficient in the original IFS model was 0.058 in the 1-year experiment and 0.098 in the 2-year experiment. The application of the SVM model led to a notable increase in correlation values, with Experiment 2 again exhibiting the highest improvement compared to the other two experiments. In the 1-year experiment, the correlation values were 0.141 for Experiment 2, 0.120 for Experiment 1, and 0.116 for Experiment 3. In the 2-year experiment, the correlation values were 0.191 for Experiment 2, 0.186 for Experiment 1, and 0.138 for Experiment 3. These findings align with previous research, including studies by Yin et al. (2022) [15] and Aksornsingchai & Srinilta (2011) [16], which also demonstrated improvements in correlation when applying SVM models to weather forecasting.

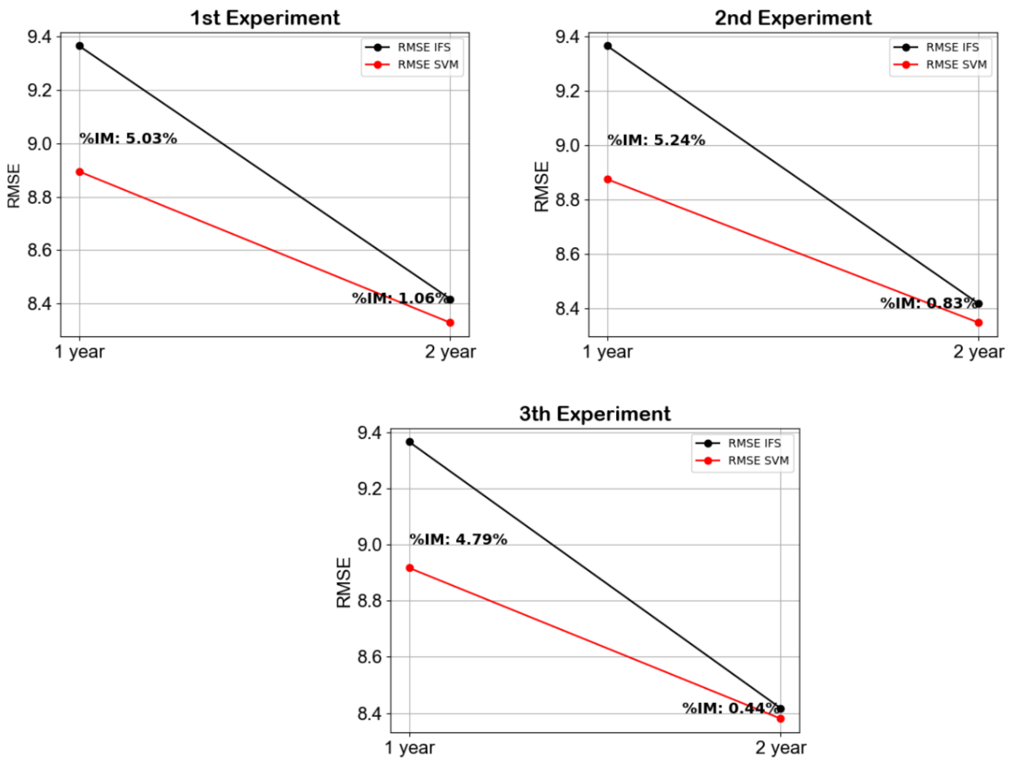

Figure 2. RMSE values between IFS model and SVM model results for three input variable experiments.

Overall, experiments utilizing 2 years of input data exhibited better performance compared to those using only 1 year of data. A longer input period provided a more comprehensive representation of weather variability, allowing the model to capture stronger and more accurate relationships between predictor and response variables. The extended dataset enabled the model to learn weather patterns and variations over a longer period, leading to better statistical relationships than when using only 1 year of data.

A longer training period also improved the model's ability to generalize more effectively, making model performance evaluation more objective when tested over a longer period. This indicates that a greater amount of historical data contributes to better predictive capability and enhances the reliability of the model's rainfall forecasts.

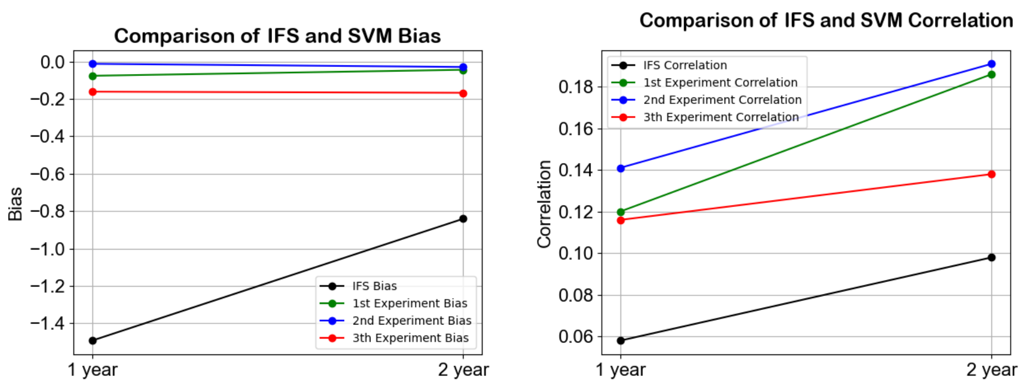

Figure 3 Comparison of bias (left) and correlation (right) values of IFS and SVM model results for 3 input variable Experiments.

Based on the evaluations of RMSE, bias, and correlation, Experiment 2 consistently outperformed the other experiments in improving values from the original IFS model. This experiment utilized input data consisting of surface pressure, temperatures at 1000 mb, 850 mb, 700 mb, and 500 mb layers, along with rainfall. Notably, it did not include wind variables, which suggests that the absence of wind components contributed to its improved performance. This finding aligns with the weather characteristics of

North Barito, where the average wind speed is very low.

The lower model performance observed in Experiment 3 further supports this conclusion. Experiment 3 included surface pressure, U and V wind components at 1000 mb, 850 mb, 700 mb, and 500 mb layers, U and V wind components at 10 meters, and rainfall. The presence of wind variables in this experiment did not enhance the model's predictive capability, leading to a weaker performance compared to the other two experiments. These results indicate that wind variables did not significantly influence the SVM model's predictions in North Barito, reinforcing the idea that temperature and surface pressure are more relevant predictors for rainfall forecasting in this region.

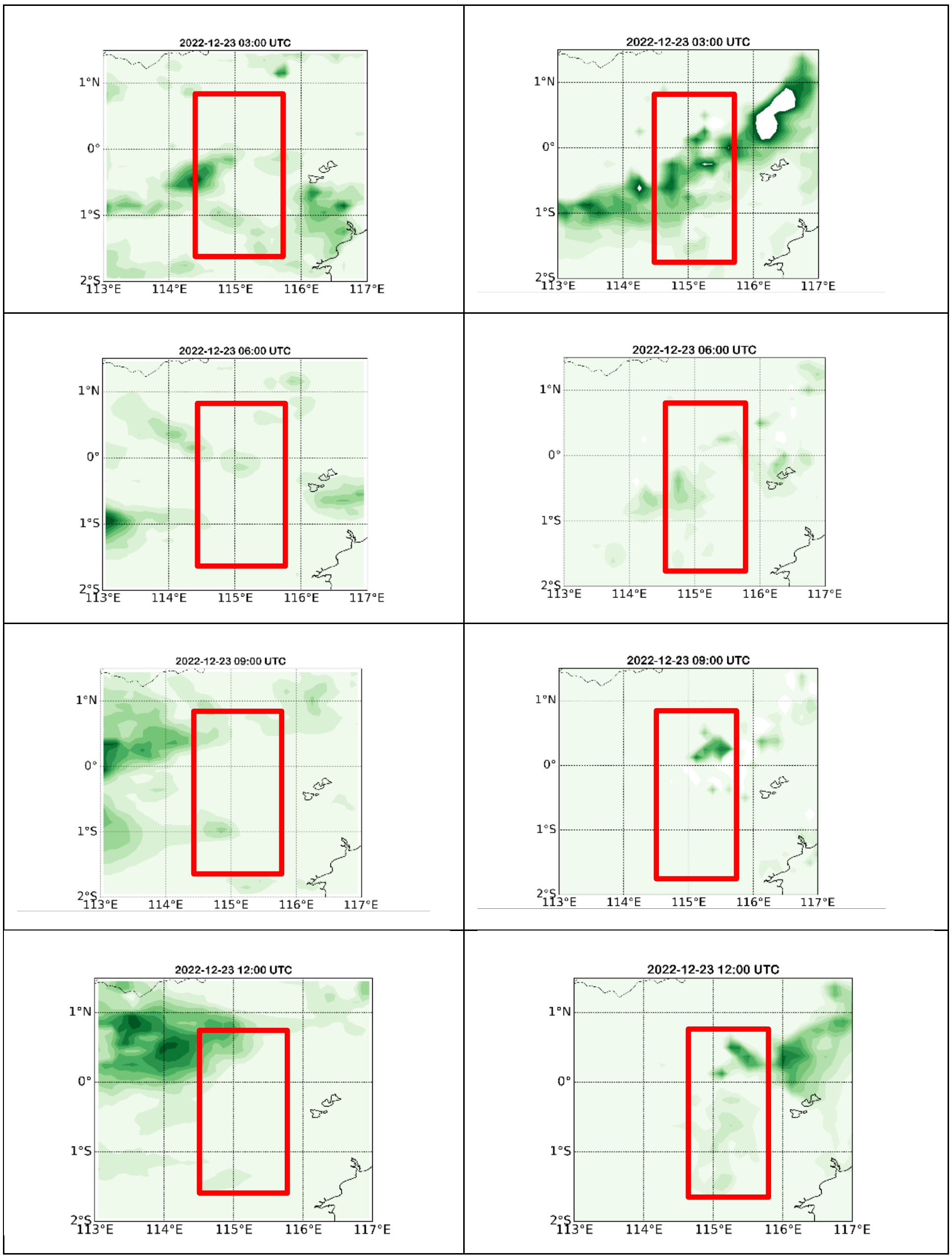

Figure 4 Comparison of 12-hour ahead rainfall forecasts from the GPM data (left) and SVM (right).

Rainfall Forecasting. After obtaining the best-performing model, the next step was to spatially predict rainfall for the next 12 hours. The SVM model was applied to predict IFS data from December 23rd, 2022, at 00:00 UTC for the following 12 hours. The results, shown in Figure 4, present a comparison between rainfall from GPM data and rainfall predicted by the SVM model. During 03:00 UTC, the GPM data reveals notable rainfall activity in the Barito Utara region, particularly concentrated in the eastern part, as highlighted by the red box. This indicates localized heavy rainfall in that area. In contrast, the SVM model predicts a broader distribution of rainfall across most of the study region. This suggests that while the model effectively captures the general rainfall occurrence, it tends to overestimate the spatial extent of the precipitation compared to the actual observations. Moving to 06:00 UTC, both the GPM data and the SVM model output indicate the absence of significant rainfall throughout the region. This alignment suggests that the model is capable of accurately identifying periods of minimal or no rainfall, reflecting its reliability during drier conditions. Turning to 09:00 UTC, the GPM data shows a shift in rainfall patterns, with precipitation detected in the northern and southwestern parts of Barito Utara. However, the SVM model only identifies rainfall in the northern region, failing to capture the southwestern rainfall observed in the GPM data. Despite this limitation, the SVM model demonstrates strong predictive capability by accurately detecting rainfall in the northern area ar 12:00 UTC, as evidenced by the similarity in spatial patterns highlighted by the green features in both datasets. This indicates that while the model has some difficulty capturing all localized rainfall events, it remains effective in identifying major rainfall occurrences within the study area.

3. Conclusion

The implementation of MOS techniques using an SVM model demonstrated that several factors influence model performance, including input variables and the research time period. The SVM model successfully improved rainfall forecasts in North Barito, as indicated by decreased RMSE values across all Experiments. Additionally, bias improvements and increased correlation values were observed when using the SVM model compared to the original IFS model output. Among the three Experiments, Experiment 2 consistently performed the best, although the general prediction pattern aligned well with actual data in all cases. Wind data was found to be less relevant as a predictor variable in the SVM model for North Barito, which aligns with the region's typically low wind speeds. This explains why Experiment 3, which included surface pressure, rainfall, and wind components, yielded the lowest performance among the three Experiments. In contrast, temperature variables, when used alongside surface pressure and rainfall as predictor variables, produced the best model performance. This suggests that the combination of surface pressure, temperature at multiple atmospheric layers, and rainfall is the most relevant set of input variables for SVM-based weather forecasting in this region. Furthermore, experiments using two years of input data consistently outperformed those using only one year, reinforcing the importance of a longer dataset in improving model accuracy and capturing weather variability.

Suggestion

This research needs to undergo further processes to be operationalized in other areas. Some suggestions that can be carried out are adding more study locations around North Barito or other areas, so it is not only using 1 ground truth. Additional input periods are also needed so that the model can learn weather patterns and variations over a longer period of time. It is also necessary to conduct experiments on other predictor variables from NWP models or satellite data that are not available at operational stations to enrich the model input information.

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