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Comparative Analysis of Machine Learning-based Forest Fire Characteristics in Sumatra and Borneo

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ABSTRACT

Sumatra and Borneo are areas consisting of rainforests with a high vulnerability to fire. Both areas are in the tropics which experience rainy and dry seasons annually. The long dry season such as in 2019 triggered forest and land fires in Borneo and Sumatra, causing haze disasters in the exposed areas. This indicates that climate variables play a role in burning forests and land in Borneo and Sumatra, but how climate affects the fires in both areas is still questionable. This study investigates the climate variables: temperature, humidity, precipitation, and wind speed in relation to the fire's characteristics in Borneo and Sumatra. We use the Random Forest model to determine the characteristics of forest fires in Sumatra and Borneo based on the climate variables and carbon emission levels. According to the model, the fire event in Sumatra is slightly better predicted than in Borneo, indicating a climate-fire dependence is more prominent in Sumatra. Nevertheless, a maximum temperature variable is seemingly an important indicator for forest and land fire in both domains as it gives the largest contribution to the carbon emission.

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1. INTRODUCTION

During the fire situation in 2019, the air quality in Borneo and Sumatra was worsening and harmful for people's health. The number of hotspots was increasing during the dry season. Thick and hazardous smoke also drifted over neighboring Singapore and Malaysia. This situation was quite comparable to the situation in 2015 when a strong El Nino occurred. The Meteorology, Climatology and Geophysics Agency (BMKG) said, during September 2019, the concentration of airborne particles, PM10, showed below the threshold value (NAV), but the daily concentration continued to increase according to data released (ispu.menlhk.go.id) at that time. Especially on 12-13 September 2019, the concentration was already very dangerous not only for people's health, but all forest habitat is also under threat.

Wildfire in Indonesia throughout 2019 produced more carbon dioxide emissions than fires that occurred in the Amazon Forest, Brazil, based on the European Union's Copernicus Atmosphere Monitoring Service (CAMS) report on 12th December 2019. The report estimated that forest and land fires in Indonesia had released about 708 megatons of carbon dioxide into the air, much more than the average of 2003–2018. Based on data from the SiPongi Karhutla Monitoring System belonging to the Ministry of Environment and Forestry, the total carbon dioxide emissions in Indonesia in 2019 reached 624,113,986 tons with Sumatra and Kalimantan as the areas experiencing fires with the highest emissions. Fire dynamics are driven by various factors like climate, human activities (anthropogenic), and other natural factors [1-4]. El Nino's experiences in 2015 and 2019 inducing extreme fires is a fact that climate contributes to burning forests, particularly in Borneo and Sumatra [5-6]. Not only El Nino event, but positive IOD (Indian Ocean Dipole) index also gives a higher potential for forest fires [7]. Study from [8] estimated the possibility of extreme fires in Sumatra during the positive IOD and in Borneo during the El Nino period. Moreover, low rainfall and relative humidity as well as high air temperature and strong wind speed make the severity of forest fires increase [9]. Moreover, the fire vulnerability of the peatlands of Sumatra and Kalimantan increases when strong El Nino occurs [10]. Previous research explained that peatland fires are the main cause of carbon emissions, smog, and environmental degradation in those zones [6,11-12].

Humans also drive fire occurrences. Human activities have increased the chances of fires, such as converting forested areas to non-forested land for human use, when land uses changes to more fire-prone areas, such as African savannas turning to plantation areas, or a reduction in fire activity can occur as in the eastern US when land clearing turned into closed canopy forest [13-15]. Central Kalimantan has a high probability of fires in bushland areas on peatlands close to roads, settlements, and oil palm plantations [16]. Moreover, population density, rainfall, and topography were the most critical variables for expecting fires in Sumatra [17].

A machine learning-based model, namely Random Forest (RF) can help to investigate how climate influences fire over Borneo [18]. The random forest has been used as a method for fire prediction in recent years and has shown good performance [19-21]. Another study in [22] also used RF model and described that the climate variables dominate fires compared to environmental and population density variables in southern Borneo. Different areas may behave differently in facing forest fire. As the two areas with the most hazardous fires, the behavior of Borneo and Sumatra on climate related fire should be investigated. This paper aims to study the forest fires characteristics related to climate in Sumatra and Borneo by applying the Random Forest method. In addition to the climate variables used in [18] which are precipitation, relative humidity, wind speed, and temperature, we add a maximum temperature as one of the predictor variables. Further, we investigate the climate variables dependence of forest fire in both Sumatra and Borneo according to the prediction models.

2. METHOD

2.1. Study Area

Borneo (109˚ 7′ - 118˚ 52′ E and 3˚ 52′ S- 6˚ 52′ N) with an area of 748, 168 km^2 is the second-largest island in the Malay Archipelago. The mainland of Borneo is mostly covered by primary and secondary tropical forests. The World Wildlife Fund (WWF) has grouped areas on the island into seven different classifications, namely lowland rain forest that covers most of the island, peat swamp forest, heath forests, freshwater swamp forests, self mangroves, montane rain forests, and shrublands, savannas, the tropical and subtropical grasslands on Southern Borneo. Based on Köppen-Geiger climate classification, Borneo has a tropical rainforest climate which is usually found at 10 to 15 degrees of equatorial latitude with a mean temperature of 26.33°C, precipitation of 8.22 mm, and 83.81% of mean humidity.

Sumatra (94˚ 52′ - 106˚ 7′ E and 5˚ 52′ S- 4˚ 52′ N) with an area of 473, 481 km^2 is the third largest island in Indonesia and is the sixth largest in the world. It is discovered in the western Indonesia. Sumatra is mostly covered with dense primary tropical forests and secondary tropical forests. 30.4% of the surface was permanent primary forest cover in 2010, with almost half of primary forest area over the 20 years study period [23]. Sumatra has three types of climates, namely tropical monsoon climate, oceanic climate, and is dominated by tropical rainforest climate, based on the Köppen-Geiger climate classification. The mean temperature and precipitation are 26.58°C and 8.47 mm, respectively, and 82.2% of mean humidity.

2.2. Dataset

This study uses emission data to represent forest fire with the unit of gC/m^2. The data with a spatial resolution of 0.25 degrees was derived from Global Fire and Emission Data (GFED) version 4 and available from 1997 to 2019 (Giglio et al. 2013). GFED is satellite data obtained from information on the rate of fire and vegetation index to determine the area burned and carbon emissions. For the historical monthly climate data, precipitation from the Tropical Rainfall Measuring Mission (TRMM) project created by Goddard Earth Sciences Data and Information Services Center (GES DISC) was used in this study. The humidity, wind speed, average and maximum surface air temperature data from the ERA5 dataset [24] were retrieved from the European Centre for Medium Range Weather Forecasts (ECMWF). ERA5 is the fifth generation ECMWF atmospheric re-analysis of global climate which yields detailed information on the global atmosphere, ocean waves, and land surface from 1950 onwards. The overview of the climate variables over Borneo and Sumatra from 1998 to 2019 is described in Table 1.

We use the dataset in the period of 1998-2017 for the training data of the Random Forest model and the prediction period is in the last two years of the dataset (2018 and 2019). Figure 1 describes the monthly average of each variable from June to November in 2018 and 2019 when fire usually occurs. In 2018, rainfall and humidity in Borneo and Sumatra were low in June and steadily increased until November. Differently, Borneo and Sumatra experienced a longer drought in 2019. This can be seen from the very low humidity until September and the rain started late in October.

Table 1. Statistics Descriptive of the climate variables during 1998-2019

Variables (unit)	Min		Mean		Max	
	Borneo	Sumatra	Borneo	Sumatra	Borneo	Sumatra
Precipitation (mm/day)	0	0	8.22	8.47	44.72	54.47
Relative Humidity (%)	55.66	48.72	83.81	82.21	92.29	92.75
Average Temperature (0C)	19.67	17.40	26.33	26.58	30.83	30.43
Maximum Temperature (0C)	25.79	23.53	30.88	29.94	40.46	39.64
Wind Speed (knots)	0.68	0.72	2.53	3.03	10.21	9.08

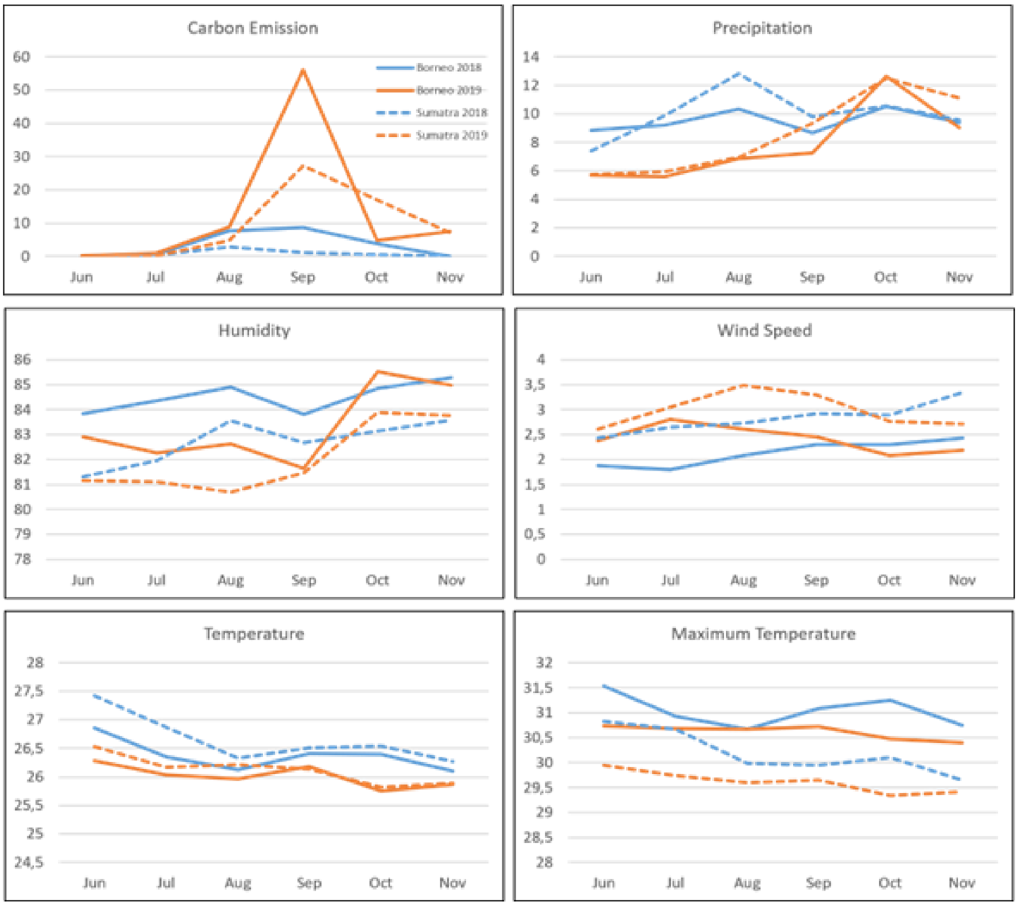


Figure 1. Monthly average of climate variables in the testing period (2018 and 2019)

2.3. Random Forest Model

We built the model using the Random Forest (RF) algorithm, a machine learning method for regression and classification problems [25]. Building the random forest involves a random and uncorrelated forest of decision trees at training time. The implementation of random forest required three parameters, namely the number of trees, the node size, and the sample features' number. The algorithm of random forest starts with performing the bootstrap method to the training dataset to

generate the subsets. Each subset grows an individual decision tree. The node of the tree is divided using the split criterion based on the type of attribute to the same class. At each node, the best split is chosen from a random sample of variables, rather than among all variables. For result, the decisions from individual trees are averaged for regression problem and the most votes are counted for classification. In this simulation, the number of trees is 50 with mean square error (MSE) as the split criterion.
Simulation using the RF model for regression is performed to predict the emission level in each grid of domains using five climate factors as the independent variables. The monthly dataset of emission level and climate factors from 1998 to 2017 is used for the training phase and the next two years of 2018 and 2019 are the testing phase for the prediction and evaluation model. All simulations are implemented in the Python language with scikit-learn libraries.

2.4. Permutation Feature Importance

Feature importance is a technique for ranking input features based on how much importance of each feature on the target variable prediction. It measures the strength of the dependence between the predictors and the target. This technique calculates a mean decrease in impurity by averaging the estimates of the predictive ability of several random trees thereby reducing the variance of the estimates. This technique can be used as a basis for feature selection and dimension reduction to increase the efficiency and effectiveness of the model.

Permutation feature importance is steps to solve the problem of feature importance by rearranging the data set on features. The process starts with training the prediction model, then permuting the feature data, and finally re-evaluating the model. If a feature is reorganized, the feature that contributes the most will affect the performance. On the other hand, if a feature does not contribute significantly to the performance of a model, it will have no effect when the data structure is changed.

2.5. Evaluation Method

Root Mean Square Error (RMSE) and percentages of error are applied to measure the error of a predictive model. This formula is commonly used to evaluate regression-based machine learning systems. The prediction results would be most accurate when the RMSE value is minimum. A prediction perfectly matches the actual data when the RMSE value is zero. Comparisons between data sets or models with different scales can be calculated by normalizing RMSE or normalized root mean square error (NRMSE). In this study, the RMSE is normalized by the range of the actual data. The percentage error (%Error) is calculated by comparing the difference between the regression model and actual data against the latter. We calculate evaluation metrics with the following formula:

$$NRMSE = \frac{\sqrt{\frac{1}{N}\sum(X_{model}-X_{actual})^2}}{max\,(X_{actual})-min\,(X_{actual})} \tag{1}$$

$$\%Error = \frac{1}{N}\sum_1^N \left|\frac{X_{model}-X_{actual}}{X_{actual}}\right| . 100\% \tag{2}$$

where X_{actual} is the total monthly emissions for actual and X_{model} for a predicted model. The number of the data is notated by N. The $\%Error$ and $NRMSE$ values are calculated from August to November which is the month when forest fires often occur.

3. RESULT AND DISCUSSION

This study applied the Random Forest model in Python through RandomForestRegressor from scikit-learn library. Parameters were set with 50 trees and 10 maximum depths of the tree. Moreover, the minimum number of samples required to split an internal node was 3, the minimum number of samples required to be at a leaf node was 4 , and the number of jobs to be executed in parallel is -1. Other parameters were set by default. Then, we evaluate the performance of RF model by comparing the model prediction results and the observation data from GFED, during the normal year (2018) and El Nino (2019). We compare the variability of the total carbon emissions, both temporally and spatially. We implement a permutation feature importance method to identify which climate variable mainly drives the forest fire.

3.1. Temporal variability of fire

We compare the annual cycle of the forest and land fire between the model prediction and GFED. Figure 2 presents the capability of the RF model to represent the seasonal cycle of total carbon emission and provides a comparable pattern to the GFED data. The model describes that the total carbon emission of both domains during a normal year (2018) are much lower than when El Nino occurred (2019). The model can capture the peak of the total carbon emission quite well, even though there is still a substantial underestimation of the peak value for Borneo in 2019. It can predict the peak of fires in Borneo 2019 with total emissions nearly four times greater than in 2018, which is around 60.000 g C/m2, while GFED gives 100.000 g C/m2. While in Sumatra, the model can estimate the peak in 2019, nearly nine times higher than in 2018. In Sumatra, it can correctly capture the peak time of fire in both years, while in Borneo 2018, the model predicts the peak of fires in August (one month earlier than GFED). In comparison between the fire events in 2018 and 2019, we can also observe that during the normal year the highest carbon emission occurs approximately in August and then decreases gradually, while during El Nino the fire continues increasing in September as the peak time. This correlates with the climate condition at that moment, see Figure 1. High rainfall and humidity in August 2018 seemingly helped suppress the carbon emission afterward. Differently, drier conditions in August 2019 caused high carbon emissions and extreme fires in September 2019.

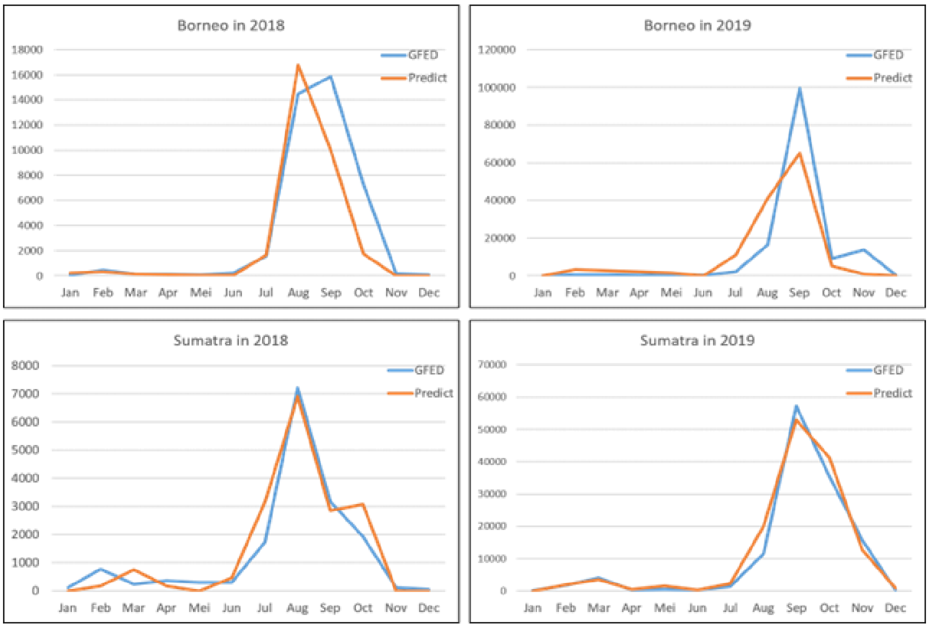


Figure 2. Shown the total monthly emission over Borneo (top) and Sumatra (lower)

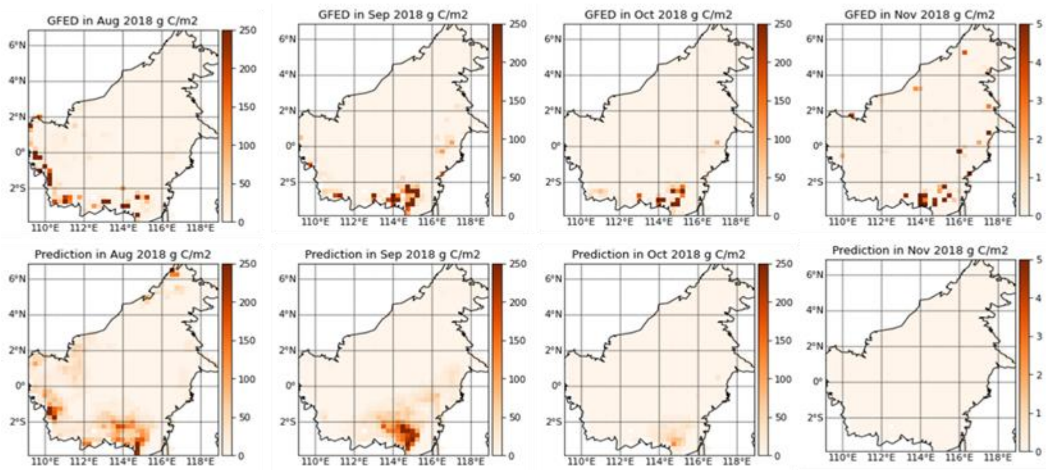
We evaluate the result of the model prediction using the RF regression model against the actual data GFED by calculating the NRMSE and percentage error. The result is presented in Table 2. It can be observed that Sumatra has a smaller error than Borneo in both 2018 and 2019. The NRMSE shows that Sumatra has an error value of about four times smaller than Borneo in 2018 and almost half in 2019. Likewise, Sumatra has a smaller percentage error value than Borneo for both years. The percentage error in Borneo is relatively high, around 35% in the normal year (2018) and 54% during El Nino 2019. This indicates that not only the climatic factors burn the fires in Borneo, but anthropogenic factors and environments also contribute mostly to burning forest as described in [16].

Table 2. Evaluation of the temporal variability of fires

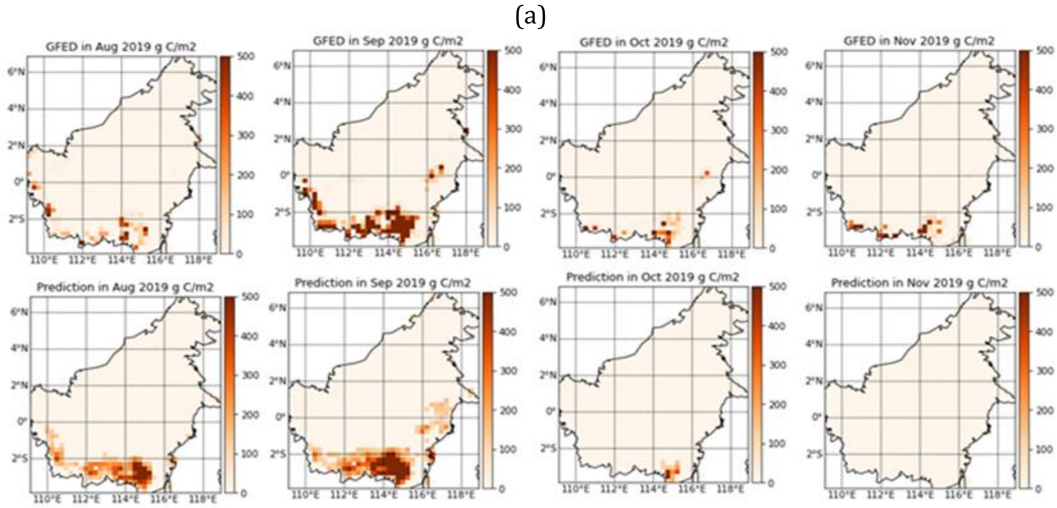
Metric	Borneo		Sumatra	
	2018	2019	2018	2019
NRMSE	0.2577	0.2445	0.0604	0.1479
%Error	35.52	54.68	11.25	18.73

3.2. Spatial variability of fire

This section describes the comparison of the spatial map representing the carbon emission levels between the RF model as a predicted result and satellite data from GFED. Figure 3-4 shows the level of total carbon emission in 2018 and 2019 over Borneo and Sumatra, respectively. In general, the model can spot the high emission level in the southern part of Borneo and the southern east part of Sumatra. However, the RF model could not predict the existence of fires when a very low carbon emission occurred in both domains, see Figure 3 in November 2018-2019 and Figure 4 in November 2018.



(a)



(b)

Figure 3. Total carbon emissions over Borneo from GFED and the RF r in August-November 2018 (a) and 2019 (b)

Figure 3 shows that the RF model estimates the high emission over Borneo occurring in August and September. The estimation values are slightly lower than the GFED data, except in August 2019 showing that the emission level predicted by the model was overestimated. Conversely, the RF model shows an underestimation in October and November, and it hardly captures the high carbon emission levels. The fires mostly occur in the monsoonal southern areas where most land is covered by peatland. The areas face one rainy season from December to February, the dry season from June to August, and the other six months are transitional periods. So, the high carbon emissions in Borneo seemingly occur at the end of the dry season.

Figure 4 shows the spatial distribution of the total carbon emission over Sumatra. Based on the observation data GFED, the high emission levels occur in the southern and eastern part of the domain. However, we observed that the RF model mostly captures the high emission level only in the southern part of Sumatra, while the eastern part is hardly spotted. In both years, the RF model predicts much wider areas in the southern part with a higher emission than the GFED data. In the eastern part, the RF model does not catch the areas with high carbon emission. This may relate to the different climate

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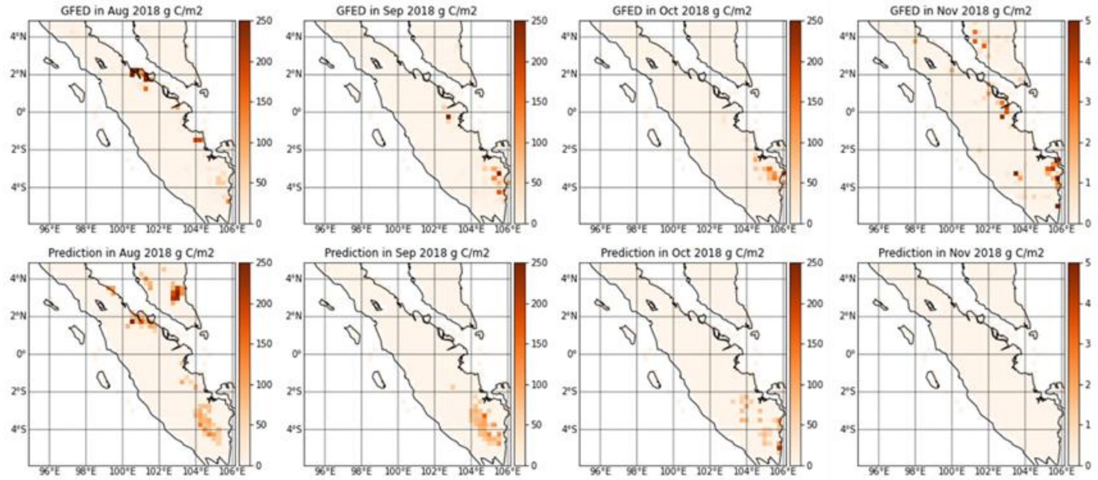
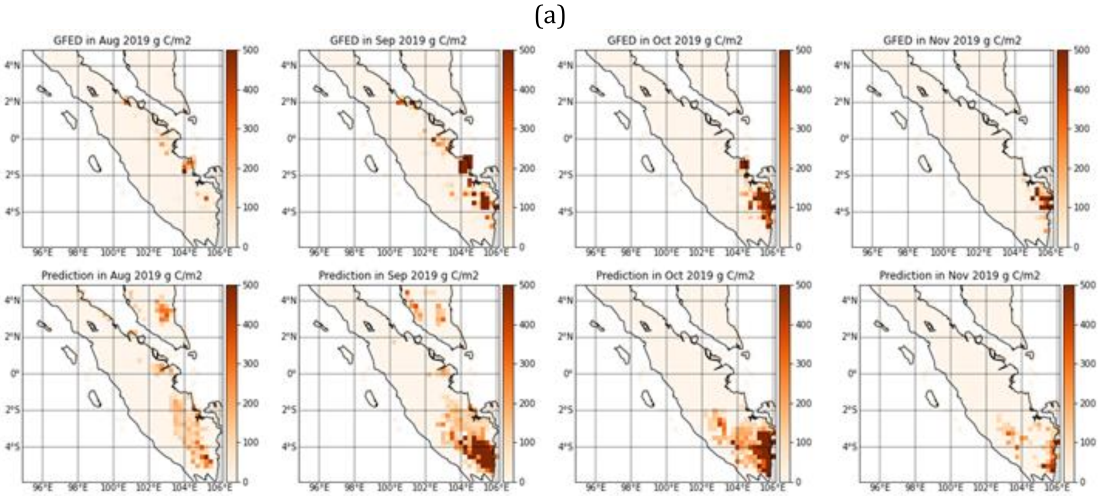
characteristics between the southern and eastern parts of Sumatra. Southern Sumatra is a monsoon climate region while the central to the north part is an equatorial climate area [26], with two rain peaks occurring around March and October. The different climate characteristics might affect the model result. The RF model seemingly better captures the carbon emission level in the area with monsoon than equatorial climate.



(a)



(b)

Figure 4. Total carbon emissions over Sumatra from GFED and the RF model results in August-November 2018 (a) and 2019 (b)

3.3. Impact of climate variables on the fire prediction

We quantify the climate impact on forest and land fires by a permutation importance method. The permutation importance value refers to how much a climate variable's contribution affects the fires based on the RF model, see Figure 5. The maximum temperature has the highest effect on carbon emissions in both Borneo and Sumatra, while the average temperature contributes the lowest. This indicates that an extreme maximum temperature event can be used as an indicator of fire event. The high temperature and dry environment over tropical areas with forest land cover has a very high fire potential and can destroy forests quickly. Even though Borneo and Sumatra have similar characteristics about the most and the least dominant climate variable affecting the fires, the precipitation and wind conditions behave differently in both domains. Wind conditions are the second-highest score in influencing fire prediction results in Borneo and fourth in Sumatra. In contrast, the second-highest permutation score in Sumatra is precipitation, the fourth feature contributing to Borneo's prediction results.

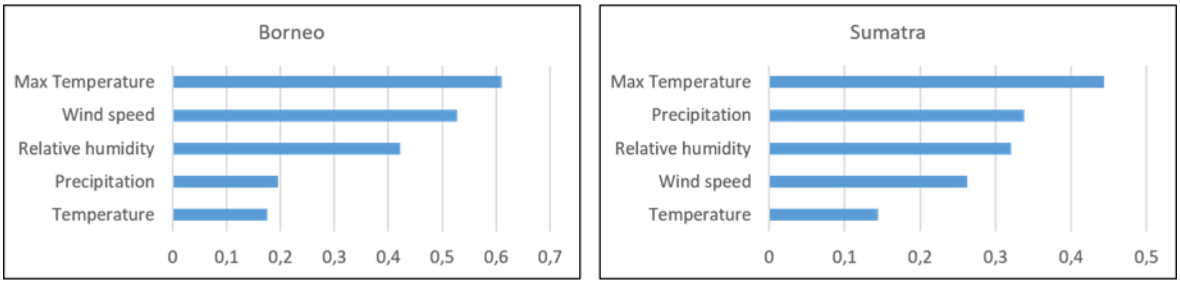


Figure 5. Climate variable's importance of the RF model prediction

4. CONCLUSION

This study compared the characteristics of forest fire prediction affected by climate variables in Sumatra and Borneo. We implemented Random Forest (RF) model to estimate the fires occurring in both domains. Using the historical data from 1998-2017, the model predicted the fire in 2018 and 2019. The total monthly carbon emissions represented the fire. Then the performance of the RF model was measured by evaluating the prediction results against the satellite data from GFED. The RF model can predict fires quite well, both spatially and temporally. In 2018 and 2019, Borneo released carbon emissions from forest and land fires approximately twice as large as Sumatra. A massive jump in carbon emissions from 2018 to 2019 indicates an extreme climate event that the model can also catch, even though the model estimates the fire more precisely during a normal year. Based on the model evaluation, the model prediction performs better in Sumatra than in Borneo. This demonstrates that climate factors give more effect to the fire in Sumatra, while many other factors influence the fires in Borneo. As mentioned in the study [16], forest fires in Borneo are also mainly affected by soil type, land use, and human activities. Nevertheless, both Sumatra and Borneo show a similar characteristic of the climate variable that mainly affects the fire. The permutation of the feature importance method reveals that the maximum temperature significantly contributes to fire prediction in Borneo and Sumatra. Thus, this climate variable can be an early warning indicator of forest and land fire disasters to prevent more severe impacts.

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