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Assessing the Fires Impact on Vegetation Cover Using Remote Sensing Data: Indonesia Case Study

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Abstract: Wildfires in Indonesia have become abnormally frequent due to the human-driven degradation of forest and agricultural lands, as well as climate change. The authors analyze recent studies that provide evidence for an increase in the fire hazard to various ecosystems in Indonesia (forests, peatlands, agricultural lands) considering changes in climatic and meteorological parameters of the environment. This work establishes a relationship between burnt areas, measured by Moderate Resolution Imaging Spectroradiometer (MODIS), and the following parameters, retrieved from the Reanalysis v5 (ERA5) ECMWF dataset: monthly precipitation amount, temperature at a height of 2 m above sea level, soil temperature in the upper layer (0 to 7 cm depth), water content in the upper soil layer (0 to 7 cm depth), specific air humidity, zonal wind speed, meridional wind speed, and a standard deviation of precipitation. The authors reveal a correlation and a direct dependence of wildfires on the potential factors influencing the area: air temperature and soil temperature. It is assumed to be associated with the rainfall type, winds (speed, direction, and oscillations), improper land use, and the El Niño–Southern Oscillation.

Keywords: Indonesian region, fires, temperature, precipitation, moisture, climatic zones, remote sensing, MODIS, ERA5, Google Earth Engine.

1. INTRODUCTION

According to weekly fire alerts, the peak of the fire season in Indonesia typically begins in early August and lasts around 14 weeks. There were 2,303 high-accuracy fire alerts issued by the visible infrared imaging radiometer suite (VIIRS) from December 2019 to November 2020, and 2205 alerts only in 2020. This value does not exceed the normal compared with previous years going back to 2012. The most fires (32,294 fire alerts) were detected by VIIRS in 2015 [10]. The fires caused long-term harm to the forestry and agricultural sector, making 0.5% of the Gross Domestic Product (GDP) loss in Indonesia in the third quarter of 2019, as estimated by the World Bank. In general, it caused reduced GDP rates in Indonesia in 2019 and 2020.

Many factors are contributing to the intensification of wildfires, but it is becoming increasingly apparent that warmer and drier conditions play a large role in exacerbating heat, creating conditions for destructive wildfires. The loss of moisture by the ground cover during evaporation and transpiration occurs under the complex influence of several meteorological factors. The combustibility of forests with high accuracy can be defined only considering all these factors [2]. In addition, there are seasons with different precipitation, air temperature, wind force, and air humidity patterns, which affect the moisture content of the combustible material. Among the main factors influencing the intensity of wildfires, there is terrain morphometry (aspect and slope

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steepness), which affects moisture level in the forest floor by influencing the speed of forest combustible materials drying [22].

The fire rate of the ground cover will be different at the same air temperature or the same moisture deficit if this is preceded by a period of dry and hot weather or by a period of low temperatures and precipitation. It matters in what form the precipitation falls, whether it is not intense but prolonged, or has a stormy character. Thus, the possibility of the ground cover burning is formed due to the complex effect of many factors, and the influence of these factors must be considered not only by their current state but also by the previous period. The research [14] defines that peat soil with a water content of less than 115% will have a high fire risk, between 115 and 135% – a moderate fire risk, and more than 135% – a low fire risk. Active anthropogenic logging actively affects the intensity of forest fires in Indonesia [21].

Deeper degraded peatlands and mixed agricultural lands are the most vulnerable areas, and anthropogenic activity is suggested to be a strong driver of combustion [26]. The main reasons for deforestation in Indonesia are selective logging and conversion to industrial oil palm and pulpwood plantations. Industrial plantations were causing over half of Indonesia's deforestation until 2016 and then it dropped down to 15%. Small-scale farming was a driver for more than one-quarter of all deforestation for two years in 2014-2016. Also, forest fires converted 20% of forests into grass and shrubland lands in 2015 [24].

Improper land use changes the soil water regime, which aggravates soil aridity and makes an ecosystem more vulnerable to fire. One of the impacts resulting from the conversion of peatlands from forest to non-forest lands is drought. It is due to the draining of land for agricultural cultivation purposes [14] because of the increasing bulk density that influences soil moisture.

According to [1], the fire frequency is higher in areas where secondary peat swamp forests were transformed into shrubs or plantations ($0.15\ km{-}2 \times yr{-}1$).

In the [29] authors conducted research on the fire frequency in Indonesia's two largest peatland regions, Sumatra and Kalimantan, during 2001-2018. They explored relationships between burning and land-cover types using MODIS and Landsat satellite data. Peatlands of these two regions burned five times more than other land covers despite covering less area which could lead to Indonesia's peatlands disappearing in the coming decades.

Moreover, the number of identified hot spots is highly dependent on population density; according to [3] high population density reduces the number and probability of a large number of hot spots, which is associated with quick measures to eliminate them.

The groundwater table can be a good indicator for risk zone mapping of peat fire in the peatland area. According to regulations in Indonesia, peatland with a groundwater table of more than 40 cm is defined as a degraded peatland area and has a high potential to fire [30]. Other analyses have also linked water table depth to a fire risk, prompting the Indonesian government to impose regulations regarding drainage based on an allowable water table depth of 40 cm [31].

A strong relationship between burned areas and preceding soil moisture makes the remote sensing of soil moisture a valuable source of information for fire forecasting models and identifying fire-vulnerable locations [5].

The intensity of fires also depends on the type of plant communities and soil profile [26]. The largest carbon loss (94.2 t/ha) occurs on a secondary peat swamp forest and is equivalent to the emission of 345.4 t CO_2eq. The second-largest carbon loss (36.3 t/ha) occurs in secondary dryland forests followed by forest plantation (18.5 t/ha) and bushes swamp (13.5 t/ha). The most extensive carbon loss on secondary peat swamp forest and forest plantation occurs on the aboveground biomass pool, while secondary dry forest and bushes swamp occur on the deadwood pool.

Interannual variability in precipitation associated with the Southern Oscillation of El Niño (ENSO) has been closely linked to fire emissions frequency and duration. From a comparison of fire activities in several areas on both Indonesian islands, it is evident that the most severe peat fires occur in the southern part of Central Kalimantan due to the relatively long dry season (of more than 3 months under ENSO) [12]. The latest studies show no causal relationship between ENSO and the intensity of forest fires in Indonesia. Until 2018, researchers explained fires in

Indonesia's peatlands with the ENSO. However, fires still occurred independently of ENSO in an area of about 16 × 103 km^2 in 2019. Therefore, more suitable indicators and methods are required to analyze, evaluate, and forecast peatland fires [13].

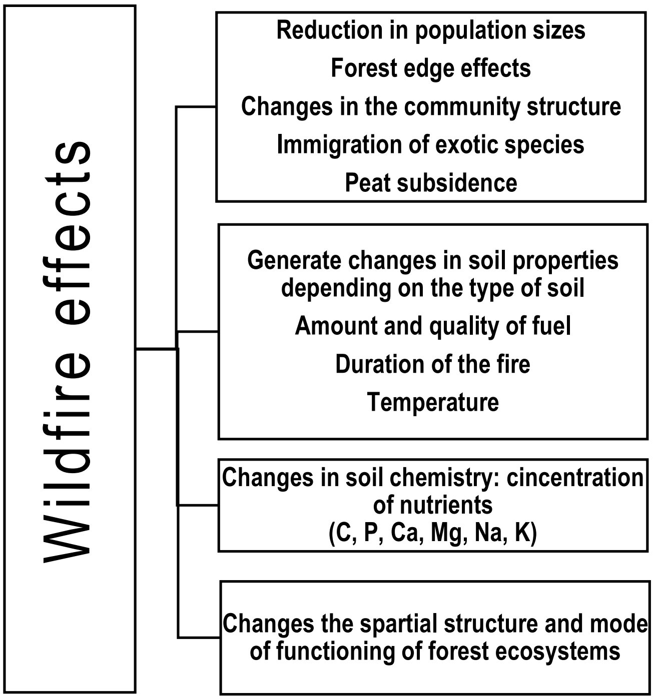


Fig. 1.1. Wildfires effects on forest ecosystems in Indonesia [17]

1. STUDY AREA

As the object of study, we chose the plant communities assigned to three climatic zones: broadleaf evergreen forests (in particular, tropical evergreen forests), broadleaf deciduous forests (especially, deciduous monsoon forests), swamp forests, mangrove and nipa palms, alpine vegetation, grassland and cultivated area of Indonesia.

To better understand the patterns of precipitation preceding and coinciding with the fire season, we based our analysis on a slightly modified division of the three climatic regions (zones) proposed by [15].

The territory of Indonesia can be grouped into three climatic zones:

– Zone 1 – monsoon – has a U-shape. In this case, the rainy season and dry seasons can be clearly differentiated, i.e., November-April for the rainy season, and May-October for the dry season. Precipitation rates are not significantly exceeded over time. Zone 1 includes East Java, Bali, Nusa Tenggara, parts of Sulawesi, Riau, South Sumatra, Aceh, all of Maluku, parts of East Kalimantan, and South Kalimantan;

– Zone 2 – anti-monsoon – has almost the same pattern as the monsoon type, however, the rainfall in the dry season is higher than in the monsoon type. Zone 2 includes the areas of Sulawesi and Papua;

– Zone 3 – semi-monsoonal – monthly precipitation pattern is very similar to the anti-monsoon pattern during rainy seasons and slightly different during dry periods. Zone 3 includes most of the areas in Sumatra, West Java, Central Java, Jakarta, Banten, Yogyakarta, and northern Kalimantan.

Consequently, the division of the studied area into three clusters allows the most complete tracing of the fire severity on plant formations depending on climatic characteristics.

2. DATA AND METHODOLOGY

Based on information about the distribution of precipitation [15], a detailed mapping of climatic zones was carried out. The source of the initial data was the ERA5 climate dataset from the European Center for Medium-range Weather Forecasts (ECMWF), available since 1981 with a grid spacing of 0.25° (approximately 12 km) [7].

ERA5 contains total monthly precipitation: accumulated liquid and frozen water, including rain and snow falling on the Earth's surface, and does not include fog, dew, or precipitation that evaporates in the atmosphere before reaching the surface.

The Earth Engine cloud platform was used to process the ERA5 data and to carry out the geospatial data analysis [11]. To identify three climatic zones in Indonesia, the authors carried out preliminary data processing and its subsequent clustering using the following code [28].

As part of the preliminary processing, 12 maps were obtained – the average values of total precipitation for each month for the period 2000-2020. As a result of the «Reduce» procedure (an ordered procedure for mixing multiple sources of information), these maps were reduced to a raster image consisting of several information channels. Each pixel of the generated image contains the following information at a given point for the years 2000-2020:
– absolute precipitation minimum
– absolute precipitation maximum
– month’s ordinal number when an absolute maximum is registered
– month’s ordinal number when an absolute minimum is registered
– average precipitation
– median precipitation
– standard deviation of precipitation

Further, ERA5 data was used to obtain datasets in GeoTIFF format for each of three zones with the following parameters:
– total monthly precipitation
– temperature at a height of 2 m above sea level
– temperature of the soil in the upper layer (depth from 0 to 7 cm)
– water content in the upper soil layer (depth from 0 to 7 cm)
– specific air humidity
– zonal wind speed
– meridian wind speed.

Obtaining the values of these parameters using the ERA5 dataset was carried out by directly downloading data from the site [6], converting the data into GeoTIFF format, and obtaining raster images containing the parameter value in each pixel.

Also, data from the MODIS instrument, onboard the Terra and Aqua satellites, was used. MODIS provides multispectral detection capabilities in 36 spectral bands ranging in wavelength from 400 nm to 14400 nm. Each platform delivers daily coverage of the entire globe. It offers advantages over other data sources for studying the occurrence and extent of wildfires by providing two essential fire products: active fire detections and burned area estimates. Both are widely used as data sources in many large-scale analyses of wildfire activity and environmental impacts, climate change scenario simulations, and vegetation response projections [16,17,27,32].

The next parameters were used based on MODIS products:
– land cover classification based on MCD12Q1 (University of Maryland classification, USA) [8,19], including the following land cover types:
   a) Evergreen Broadleaf Forests (value 2);
   b) Woody Savannas (value 8);
   c) Savannas (value 9);
   d) Grasslands (value 10);
   e) Permanent Wetlands (value 11);
   f) Croplands (value 12);
   g) Urban and Built-up Lands (value 13);

h) Cropland/Natural Vegetation Mosaics (value 14);

– burned area estimations based on MCD64A1 [29,30];
– assessment of net primary production based on MOD17A3 [31,32].

In this work, for each of the three zones, the parametric Pearson correlation coefficient was calculated using SPSS Statistics software. Pearson's correlation criterion is a parametric statistics method that allows determining the presence or absence of a linear relationship between two quantitative indicators and assessing their closeness and statistical significance. The coefficient was calculated between the parameter representing the burnt area of forest fires and the factors affecting the intensity of the pyrogenic factor: humidity, soil temperature (0-7 cm), air temperature (2 m above the ground), horizontal and vertical components of wind speed (at a height of 10 m), and specific air humidity. To determine the closeness of the relationship, the coefficient of determination was calculated.

3. RESULTS AND DISCUSSION

Firstly, three climatic zones (Fig. 3.1) were identified using the commonly used k-means unsupervised classification method [4]. In this case, the iterative algorithm divides a set of pixels into three zones, determining their centers based on the raster data bands, and assigning each pixel the number of the closest zone.

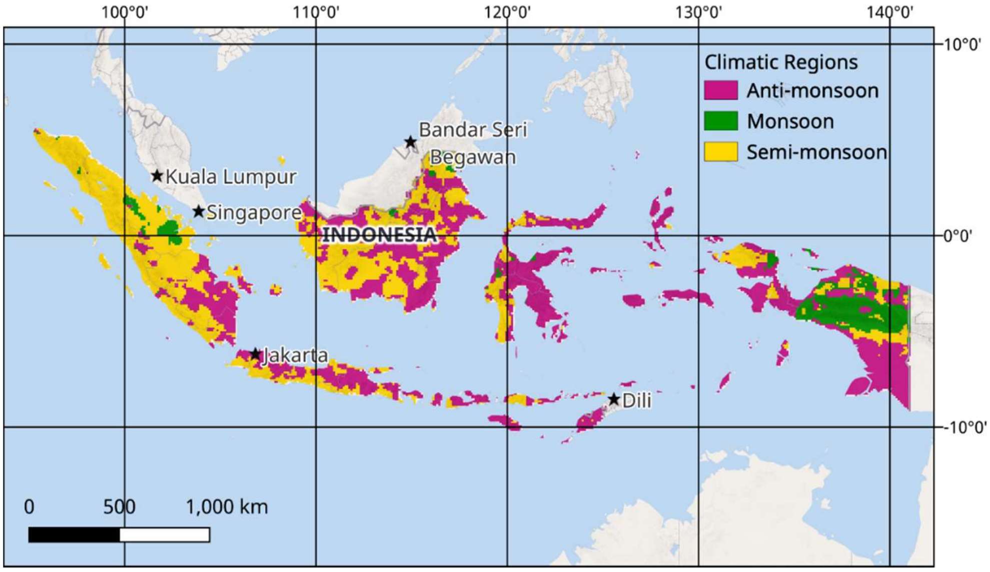


Fig. 3.1. Distribution of zones according to the values of average annual precipitation in Indonesia:
– green area – monsoon type:
P_{min}=8.5 mm in July, P_{max}=39 mm in September, P_{av}=20 mm, P_{med}=19 mm;
– yellow area – semi-monsoonal type:
P_{min}=1.2 mm in August, P_{max}=21.6 mm in October, P_{av}=7.8 mm, P_{med}=7.5 mm;
– pink area – anti-monsoon type:
P_{min}=0.1 mm in October, P_{max}=18.9 mm in March, P_{av}=7 mm, P_{med}=7 mm.

Secondly, for the three zones obtained by clustering by the k-means method, the time series of the fire area's dependence on climatic and meteorological parameters were obtained. The studied parameters were described for each cell with spatial coordinates for each month in the period 2000-2019.

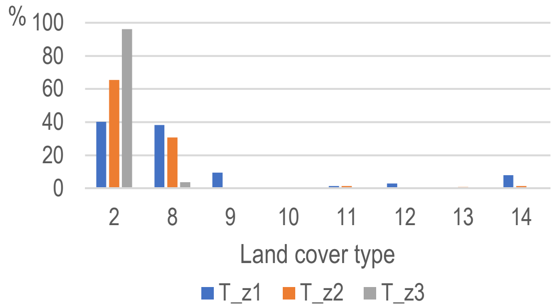
The result of calculating the Pearson coefficient showed the highest correlation between the burnt area and air temperature for the monsoon zone, as well as between soil temperature and wind speed. The drainage greatly increases fire risk in peatlands, which lowers the water table, exposing more dry peat to combustion [14].

It can be explained by the fact that during the years of frequent wildfires in northern Sumatra in the monsoon zone, the most active fires occurred at the beginning of the dry season when air and soil temperatures are the highest.

During the period 2000-2015, an average of 75% of all active fires occurring in northern Sumatra were in peatlands, with the highest numbers of 87% and 88% in 2005 and 2014, respectively. North Sumatra, with approximately 42 000 km^2 of peatlands, had the highest proportion of active fires observed on peatlands – 75% – compared to 61% in South Sumatra. Although South Kalimantan has the largest peatland area with over 500 000 km^2, the number of active peat fires in this region accounted for 50% of all active fires, which is about 100% of all of Indonesia. According to research, it was determined that 120 days of precipitation accumulation before an active fire was the best-correlated time for all fires in South Sumatra and Kalimantan. In the north of Sumatra, this period was less than 30 days. This is partly because the dry season is shorter there. Thus, the dry season determines the temperature of the soil and air, which affects the frequency and intensity of fires. A similar trend is observed for the antimonsoon zone, which is due to a combination of the following factors: soil moisture associated with rainfall, improper land use, and the sensitivity of three zones to ENSO. El Niño combined with Walker reverse circulation leads to drought in most of Indonesia, while La Niña events lead to an increase in rainfall. The correlation analysis between the fire area and the temperature at the level of 2 m above the ground showed the highest correlation in zones 2 and 3 for land cover type 2 – Evergreen Broadleaf Forests. It is important to note that for zone 3, in almost 100% of cases, high correlation values are exclusively in this land cover type, while for zone 2, the maximum correlation values are typical for land cover type 8 – Woody Savannas. Zones 1 and 2 also demonstrate less significant correlation values for these land cover types: 9 – Savannas, 11 – Permanent Wetlands, and 14 – Cropland/Natural Vegetation Mosaics (Fig. 3.2a).

A similar situation is for the correlation analysis between the burnt area and the temperature of the soil in the upper layer (depth from 0 to 7 cm), which is associated with a direct dependence of this parameter on the temperature at the level of 2 m above the ground (Fig. 3.2b).

a)



b)

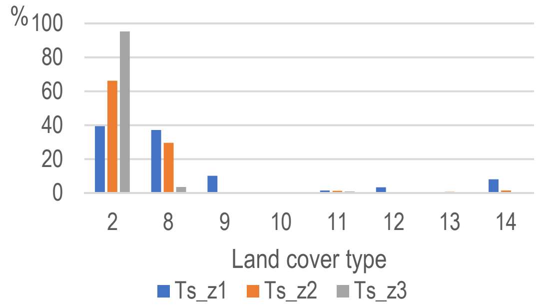


Fig. 3.2. The distribution of significant correlations for the temperature at a level of 2 m above the ground T (a) and for the temperature of the soil in the upper layer Ts (b) by land cover types for zones 1 (z1), 2 (z2), 3 (z3), where: 2 – Evergreen Broadleaf Forests; 8 – Woody Savannas; 9 – Savannas; 10 – Grasslands; 11 – Permanent Wetlands; 12 – Croplands; 13 – Urban and Built-up Lands; 14 – Cropland/Natural Vegetation Mosaics

The correlation analysis between the fire area and the water content in the upper soil layer showed the highest correlation for land cover type 2 – Evergreen Broadleaf Forests – in zone 2, while zone 3 leads in the number of significant correlations for this land cover type (Fig.3.3). Zone 1, in addition to high correlation values for land cover type 2 – Evergreen Broadleaf Forests, has significant values for land cover type 8 – Woody Savannas, 14 – Cropland/Natural Vegetation Mosaics, 9 – Savannas, 12 – Croplands, in descending order.

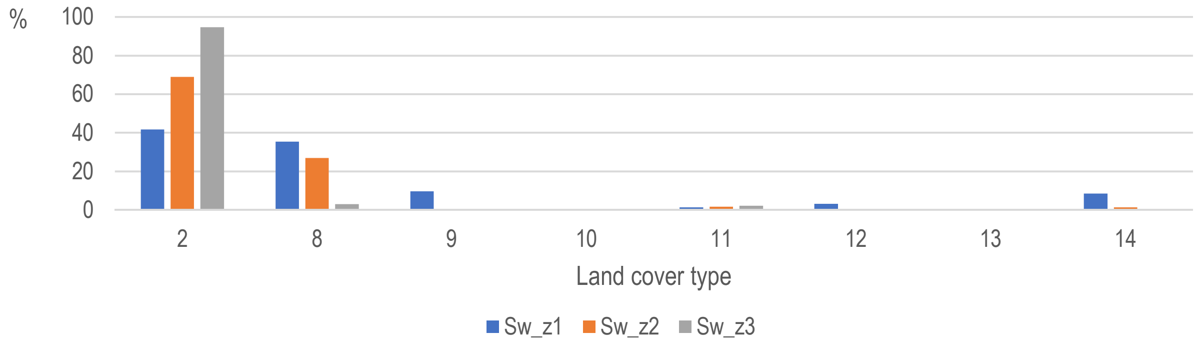


Fig. 3.3. Distribution of significant correlations for the water content in the upper soil layer Sz by land cover types for zones 1 (z1), 2 (z2), 3 (z3), where: 2 – Evergreen Broadleaf Forests; 8 – Woody Savannas; 9 – Savannas; 10 – Grasslands; 11 – Permanent Wetlands; 12 – Croplands; 13 – Urban and Built-up Lands; 14 – Cropland/Natural Vegetation Mosaics

The correlation analysis between the fire area and the specific air humidity (Fig. 3.4) showed the highest correlation for zones 2, 3, and land cover type 2 – Evergreen Broadleaf Forests. In zone 1, a significant correlation is for land cover type 2 – Evergreen Broadleaf Forests, as well as for land cover type 8 – Woody Savannas, 14 - Cropland/Natural Vegetation Mosaics, 9 – Savannas, in descending order.

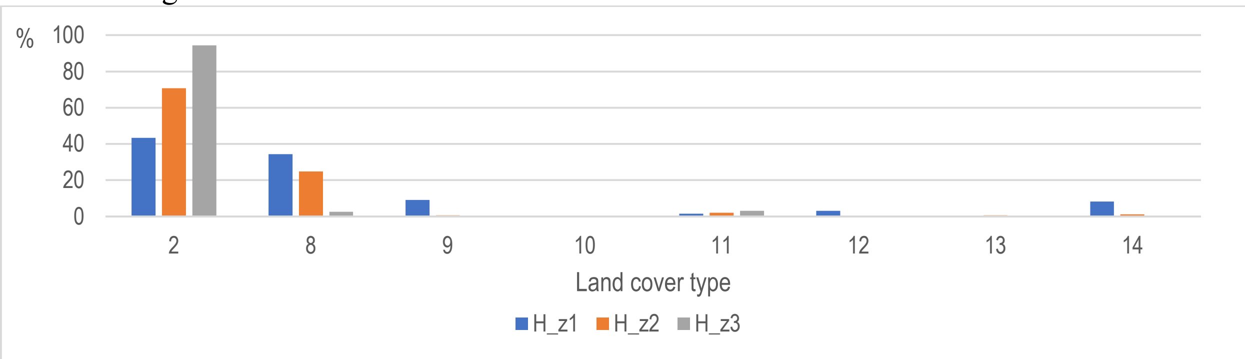


Fig. 3.4. Distribution of significant correlations for the specific air humidity H by land cover types for zones 1 (z1), 2 (z2), 3 (z3), where: 2 – Evergreen Broadleaf Forests; 8 – Woody Savannas; 9 – Savannas; 10 – Grasslands; 11 – Permanent Wetlands; 12 – Croplands; 13 – Urban and Built-up Lands; 14 – Cropland/Natural Vegetation Mosaics

The correlation analysis between the fire area and the zonal wind speed (Fig. 3.5) showed the highest correlation for zone 3 and land cover type 2– Evergreen Broadleaf Forests, then for zone 2 and 1 for the same one. In addition, in zone 1, there is a significant correlation for land cover type 8 – Woody Savannas. The situation is similar for zone 2.

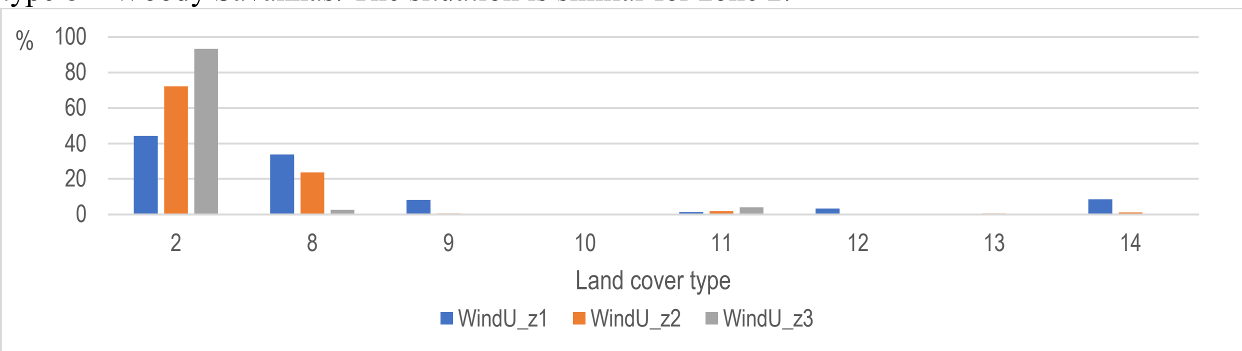


Fig. 3.5. Distribution of significant correlations for the zonal wind speed WindU by land cover types for zones 1 (z1), 2 (z2), 3 (z3), where: 2 – Evergreen Broadleaf Forests; 8 – Woody Savannas; 9 – Savannas; 10 – Grasslands; 11 – Permanent Wetlands; 12 – Croplands; 13 – Urban and Built-up Lands; 14 – Cropland/Natural Vegetation Mosaics

The correlation analysis between the burnt area and the meridian wind speed (Fig. 3.6) showed the greatest number of significant correlations in zone 3 for the land cover type 2 – Evergreen Broadleaf Forests. For zone 1, a higher correlation value is for land cover type 8 – Woody Savannas than for type 2 – Evergreen Broadleaf Forests.

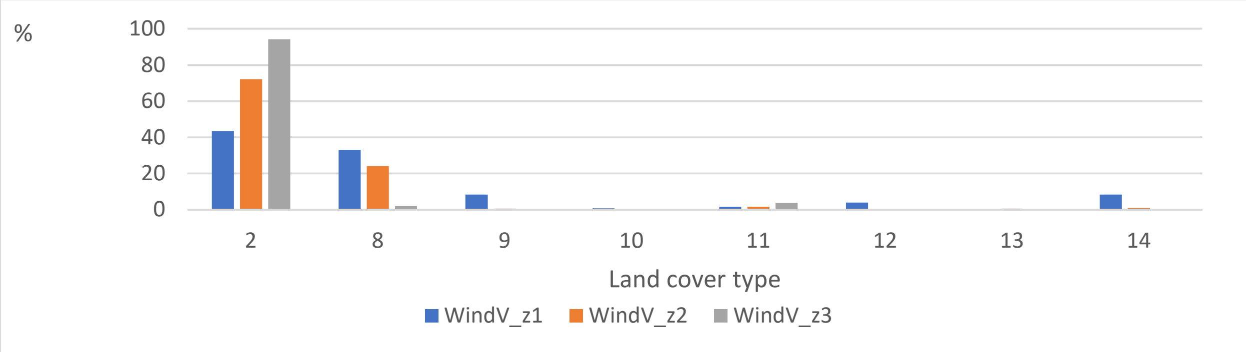


Fig. 3.6. Distribution of significant correlations for the meridian wind speed WindV by land cover types for zones 1 (z1), 2 (z2), 3 (z3), where: 2 – Evergreen Broadleaf Forests; 8 – Woody Savannas; 9 – Savannas; 10 – Grasslands; 11 – Permanent Wetlands; 12 – Croplands; 13 – Urban and Built-up Lands; 14 – Cropland/Natural Vegetation Mosaics

Thus, the analysis showed that predominantly high correlation values between the burnt area and all parameters in all zones are typical for land cover type 2 – Evergreen Broadleaf Forests, the dominant land cover type in Indonesia. At the same time, zone 1 is characterized by the largest scatter of significant correlations for such land cover types as 8 – Woody Savannas, 14 – Cropland/Natural Vegetation Mosaics, 9 – Savannas, 12 – Croplands, and 11 – Permanent Wetlands, in descending order. Zone 3 has almost 100% high correlation values exclusively for land cover type 2 – Evergreen Broadleaf Forests, which is prevailing for this zone, with some inclusions in the statistics of land cover types 8 – Woody Savannas and 11 – Permanent Wetlands. Zone 2 is intermediate between zones 1 and 3, therefore, it is characterized by predominantly high correlation values for land cover type 2 – Evergreen Broadleaf Forests – and a slight scatter of high correlation values for land cover types 8 – Woody Savannas, 14 – Cropland/Natural Vegetation Mosaics, 9 – Savannas, 12 – Croplands, and 11 – Permanent Wetlands, but in a much lower percentage than for zone 1.

4. CONCLUSION

1. The clustering of terrestrial plant communities in Indonesia by the k-means method was carried out based on the data on total precipitation from the ERA5 monthly climate data set. As a result, three zones were identified: monsoon, semi-monsoon, and anti-monsoon.

2. A database was formed using the Google Earth Engine platform to conduct a multivariate statistical analysis on the following parameters for the period 2000-2020: soil moisture and temperature (0-7 cm), air temperature (2 m above the ground), horizontal and vertical components of wind speed (at 10 m height), specific air humidity, and burnt area.

3. The linear Pearson coefficient is calculated between the burnt area and the potential factors influencing the area of the fire for each zone and it was found that the burnt area for all three zones has a direct positive relationship with soil temperature at a depth of 0 to 7 cm. The air temperature affects the fire hazard through the lack of moisture, being the main reason for the loss of the ground cover. On the one hand, the increase in air and soil temperature leads to raising water absorption by plants and increments the ground cover drying. On the other hand, soil heating contributes to an increase in fire hazards. The wind accelerates the evaporation of moisture, promotes more rapid drying of the soil, increases its fire hazard, provides the combustion zones with new portions of oxygen, increases the intensity of combustion at the frontal edge of the fire, leads to the formation of new combustion centers, and, under favorable conditions, can contribute to the transition of strong ground fires to crown fires.

4. It was revealed that soil temperature is closely related to its moisture. Changes in the soil cover and land use of the area significantly affect the runoff characteristics of the drainage basin, which affects the availability of surface and groundwater. Therefore, soil moisture is associated with rainfall, improper land use, as well as the sensitivity of all three zones to ENSO. El Niño combined with the Walker Reverse Circulation leads to drought in much of Indonesia, while La Niña events lead to increased rainfall.

5. In arid conditions, fires are mainly caused by the lack of precipitation, and the additional effect of temperature anomalies does not have a significant impact, despite recent trends in their increase. At the same time, in a humid and warm environment, compared to wet and cool conditions, there is a higher rate of evapotranspiration, which contributes to an increased likelihood of fire. Here, high temperatures lead to a deficit in vapor pressure in the atmosphere and evapotranspiration rates, and regardless of changes in rainfall, a warming trend can cause water stress in plants and increase susceptibility to fires. This has important implications for Indonesia as atmospheric temperatures rise due to global climate change.

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