

Original Article

Asian Pacific Journal of Tropical Medicine

apjtm.org

doi: 10.4103/apjtm.apjtm_743_23

Determinants of malaria from environmental and poverty aspects in Indonesia: A spatiotemporal perspective, 2016-2020

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ABSTRACT

Objective: To investigate the environmental and social aspects of poverty contributing to malaria incidence in Indonesia from 2016 to 2020.

Methods: Random forest regression was used to analyse the independent variables contributing to malaria incidence. Environmental conditions were extracted from remotely sensed data, including vegetation, land temperature, soil moisture, precipitation, and elevation. In contrast, the social aspects of poverty were obtained from government statistical reports.

Results: From 2016 to 2020, the contribution of each environmental and social aspect of poverty to malaria incidence fluctuated annually. Generally, the top three essential variables were people aged 15 years and above, experiencing poverty (variable importance/VI=32.0%), people experiencing poverty who work in the agricultural sector (VI=14.4%), and precipitation (VI=9.8%). It was followed by people experiencing poverty who are unemployed (VI=9.2%), land temperature (VI=5.2%), people experiencing poverty who have low education (VI=8.0%), soil moisture (VI=7.4%), elevation (VI=6.0%), and vegetation (VI=3.8%).

Conclusions: Poverty and variables related to climate have become the crucial determinants of malaria in Indonesia. The government must strengthen malaria surveillance through climate change mitigation and adaptation programs and accelerate poverty alleviation programs to support malaria elimination.

KEYWORDS: Malaria; Poverty; Climate; Random forest; Indonesia

1. Introduction

Globally in 2021, malaria cases and deaths were estimated to reach 247 million and 619 thousand, respectively[1]. At the same time, the number of malaria cases in Indonesia reached about 304 000[2]. The government of Indonesia has intensified and expanded the coverage of malaria prevention and control implementation since 2004[3]. This effort decreased the annual parasite incidence (API) value from 4.1 in 2005[4] to 1.1 per 1 000 population in 2021[2].

Commitment to ending malaria by 2030 is a global target set in Sustainable Development Goals point 3.3[5]. Through Presidential Regulation Number 18 of 2020 concerning the National Medium-

Significance

Using a spatial approach, this research found that poverty and climate-related variables have become crucial determinants of malaria that must receive serious attention, especially in developing countries, including Indonesia. The government must strengthen malaria surveillance through climate change mitigation and adaptation programs. They should also prioritise and accelerate poverty alleviation programs to support malaria elimination.

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How to cite this article: Nursafingi A, Widayani P, Purwoko S, Bhermana A. Determinants of malaria from environmental and poverty aspects in Indonesia: A spatiotemporal perspective, 2016-2020. Asian Pac J Trop Med 2024; 17(6): 256-267.

Article history: Received 22 September 2023 Revision 16 June 2024
Accepted 21 June 2024 Available online 28 June 2024

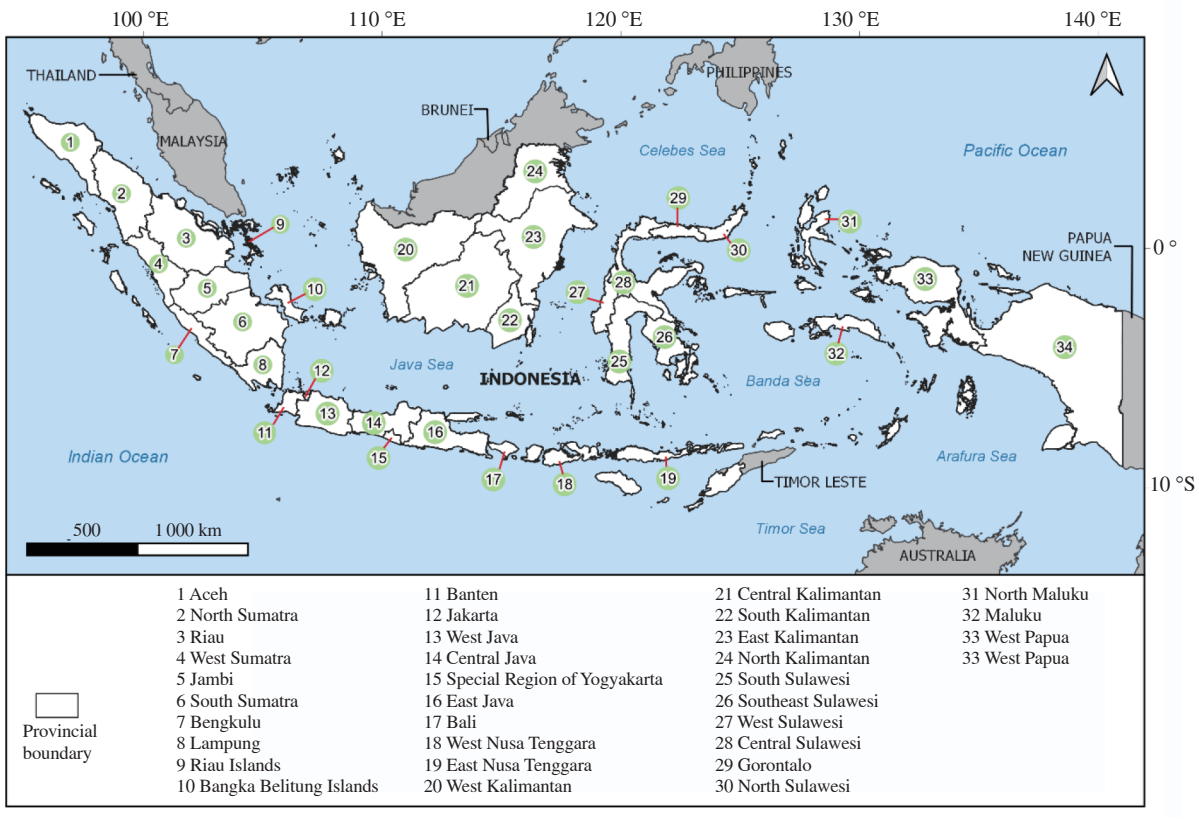

Figure 1. Study area of 34 provinces in Indonesia.

Term Development Plan of 2020-2024, the government of Indonesia has included malaria elimination as one of the indicators. Improving disease control through expanding the scope of early detection and strengthening real-time surveillance has become one strategy to eliminate malaria, as stated in the Regulation of the Minister of Health Number 21 of 2020 concerning the Ministry of Health's Strategic Plan for 2020-2024.

Geographically, Indonesia occupies a tropical region where malaria prevails[6]. A previous study in five provinces, including Central Sulawesi, East Nusa Tenggara, Maluku, Papua, and West Papua, found that sex, age, occupation, knowledge of the availability of healthcare facilities, precautions taken to avoid mosquito bites, and housing condition were all linked to malaria[7]. Another study in Eastern Indonesia, including East Nusa Tenggara, Maluku, North Maluku, West Papua, and Papua, reported that province, sex, education, and wealth status were positively related to malaria incidence[8]. In Purworejo district, variables related to malaria cases during 2005-2014 included humidity, precipitation, migration, and previous malaria cases[9]. A previous study also reported that altitude, distance from forest, and rainfall became significant predictors for malaria cases in several districts of South Sumatra province[10].

Until 2015, malaria cases still reported from 34 provinces of Indonesia[4]. Five years later, three of them were declared malaria-free[11]. Information on the malaria determinants is crucial, especially for supporting the elimination program nationally. This research investigated the environmental and social aspects of poverty contributing to malaria incidence in Indonesia between 2016-2020. We chose poverty as the investigated social determinant because it is still a national problem spread evenly across the nation. In many countries, poverty is also one of the drivers of malaria transmission[12]. Previous researches on malaria determinants, including poverty in Indonesia are still restricted and only covers parts areas. Therefore, research on the determinants of malaria at the national level is mandatory. The spatial statistics method was selected to achieve the research goal. Researchers have widely used this method in various health determinants studies, including malaria[13–15].

2. Materials and methods

2.1. Study area

The study area covered 34 provinces of Indonesia (Figure 1). It consists of 416 districts and 98 cities with a total land area of about 1.9 million square kilometres. Geographically, Indonesia is located

Table 1. Dependent and independent variables comprised environmental conditions and social aspects of poverty.

Variables	Description	Sources	Role
Malaria incidence	Malaria incidence was represented by the annual parasite incidence value.	Ministry of Health of the Republic of Indonesia, publicly available at https://www.kemkes.go.id/	Dependent
Vegetation	Vegetation data were represented by Normalized Different Vegetation Index (NDVI). We used NDVI data from the Terra Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Indices (MOD13Q1) Version 6.1 data, generated every 16 days at 250 m spatial resolution [22].	NASA LP DAAC at the USGS EROS Center accessed *via* Earth Engine Data Catalog	Independent
Land temperature	The land surface temperature data was acquired from MODIS Land Surface Temperature/Emissivity 8-Day (MOD11A2) Version 6.1 product. It provides an average 8-day per-pixel Land Surface Temperature and Emissivity (LST&E) with a 1 km spatial resolution [23].	NASA LP DAAC at the USGS EROS Center accessed *via* Earth Engine Data Catalog	Independent
Soil moisture	Soil surface moisture information was extracted from the NASA-USDA Global soil moisture data, available at 10 km in spatial resolution [24].	NASA GSFC accessed *via* Earth Engine Data Catalog	Independent
Precipitation	Precipitation data was obtained from Monthly Global Precipitation Measurement (GPM) v6 data at about 10 km spatial resolution [25].	NASA GES DISC at NASA Goddard Space Flight Center accessed *via* Earth Engine Data Catalog	Independent
Elevation	Elevation data was acquired from SRTM Digital Elevation Data Version 4 has approximately 90 m spatial resolution [26].	NASA/CGIAR accessed *via* Earth Engine Data Catalog	Independent
Poverty	Poverty describes the percentage of people ages 15 and above who experience poverty, and whose average monthly per capita expenditure is below the poverty line.	BPS-Statistics Indonesia, publicly available at https://www.bps.go.id/	Independent
Low education	Low education describes people aged 15 and above who experience poverty and low education, those who do not/have not attended elementary school.	BPS-Statistics Indonesia, publicly available at https://www.bps.go.id/	Independent
Unemployment	Unemployed describes people aged 15 and above who experience poverty and are unemployed.	BPS-Statistics Indonesia, publicly available at https://www.bps.go.id/	Independent
Agricultural worker	Agricultural workers describe people ages 15 and above who experience poverty and work in agricultur, including agriculture, horticulture, plantations, fisheries, animal husbandry, forestry and other agriculture.	BPS-Statistics Indonesia, publicly available at https://www.bps.go.id/	Independent

from 6° 04' 30" north latitude to 11° 00' 36" south latitude and from 94° 58' 21" to 141° 01' 10" east longitude. Indonesia has a tropical climate, and the population reached 275 million in 2022. About 56% of them were concentrated on Java Island[16].

2.2. Data collection

In this study, dependent variable was malaria incidence, represented by the API value, which is defined as the number of new confirmed positive cases per 1 000 population annually[17]. The government of Indonesia uses API values to depict the morbidity rate of malaria nationally. The independent variables comprised environmental conditions and social aspects of poverty. Environmental conditions included vegetation, land temperature, soil moisture, precipitation, and elevation. Based on previous studies, these environmental variables were associated with malaria incidence, especially in tropical countries[18-21]. The social aspects of poverty consist of the people aged 15 and above experiencing poverty, people experiencing poverty who have low education, people experiencing poverty who are unemployed, and people experiencing poverty who work in the agricultural sector. A description of each variable is available in Table 1.

2.3. Data pre-processing

All variables were standardized into annual data in raster datasets format. We calculated the mean pixel values over a year to generate annual Normalized Different Vegetation Index (NDVI), land surface temperature, soil moisture, and precipitation. We inputted the tabular data on malaria incidence and social aspects of poverty into the administrative map, which is publicly available and freely downloaded at https://tanahair.indonesia.go.id/, then converted it to a raster. Before combining and analysing, multiple datasets of variables with varying cell resolution were resampled to have the same cell size[27]. We created 50 km×50 km grids which consist of 1 228 samples, covering all the study areas. We then calculated the mean pixel values of each variable, including elevation, for all grid cells.

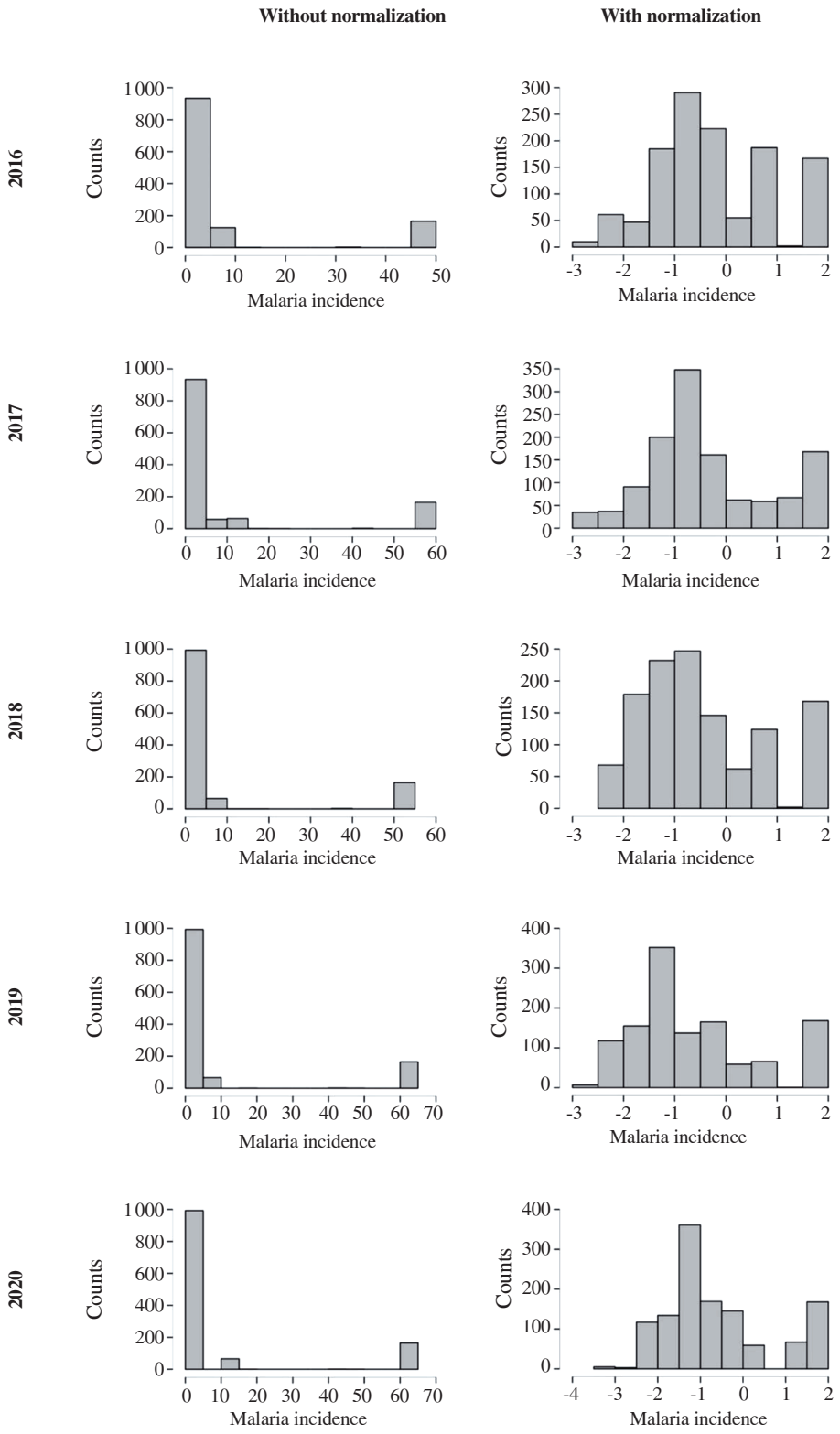

Figure 2. The data distribution of malaria incidence, without and with normalization from 2016-2020.

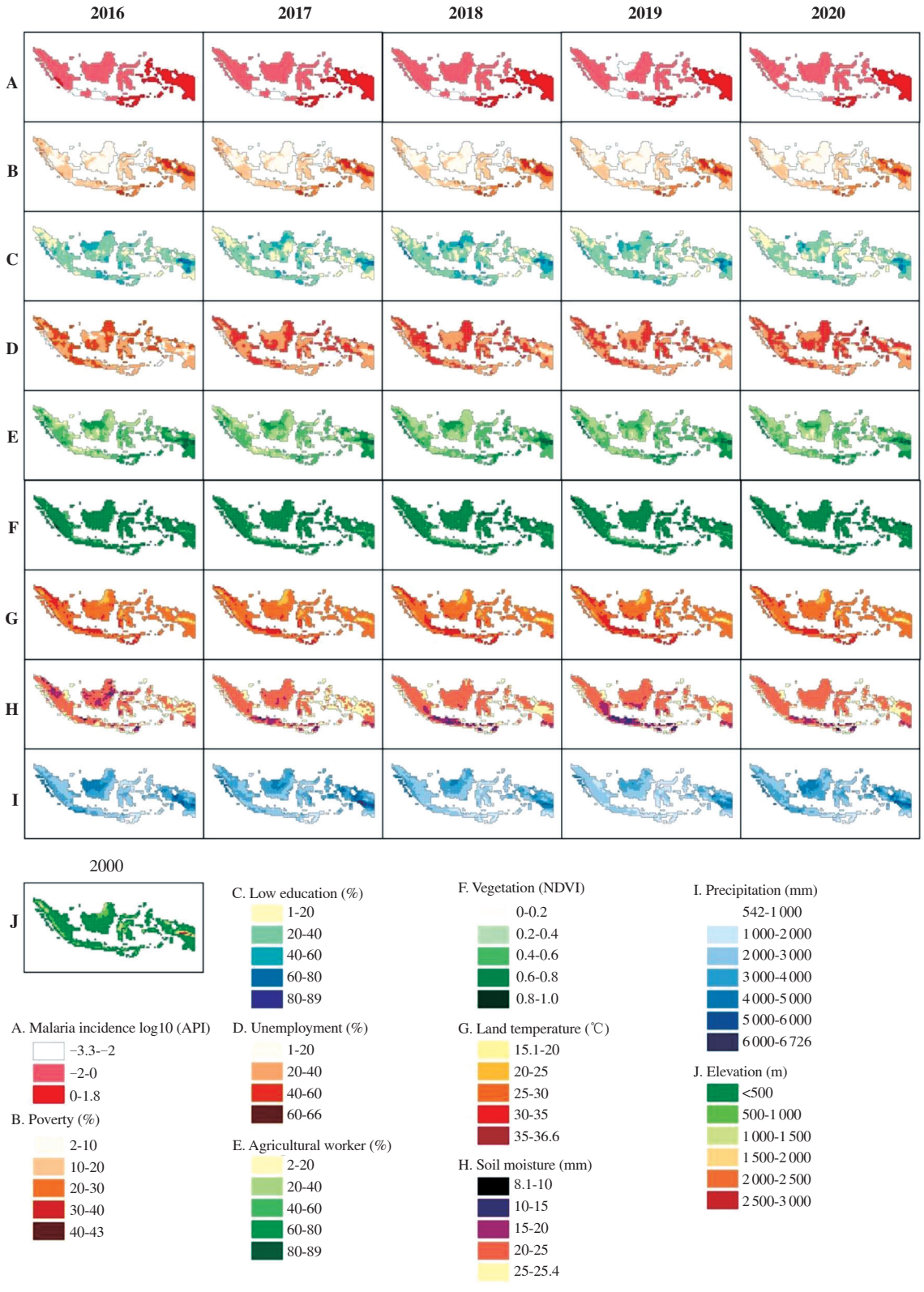

Figure 3. Spatial visualization of dependent and independent variables that affecting malaria incidence in Indonesia form 2016-2020. API: annual parasite incidence.

Table 2. Random Forest's output.

Year	2016	2017	2018	2019	2020
Model out of bag error					
Number of trees	700	700	700	700	700
MSE	0.22	0.27	0.28	0.25	0.27
% Of variation explained	81.20	79.93	79.84	83.36	81.95
Variable importance (%)					
Vegetation	5	4	3	3	4
Land temperature	10	8	9	9	8
Soil moisture	6	9	10	7	5
Precipitation	9	11	7	11	11
Elevation	6	4	8	6	6
Poverty	30	34	33	32	31
Low education	8	7	8	8	9
Unemployment	8	7	9	8	14
Agricultural worker	17	15	13	16	11
Training data: Regression diagnostics					
R-squared	0.98	0.98	0.98	0.98	0.98
P-value	<0.01	<0.01	<0.01	<0.01	<0.01
Standard error	0.004	0.005	0.005	0.004	0.004
Validation data: Regression diagnostics					
R-squared	0.83	0.81	0.79	0.86	0.85
P-value	<0.01	<0.01	<0.01	<0.01	<0.01
Standard error	0.02	0.02	0.02	0.02	0.02

2.4. Data analysis

We selected a random forest algorithm introduced by Leo Breiman[28] to investigate the environmental and social factors contributing to malaria incidence in Indonesia. This machine-learning algorithm has been widely used for classification and regression[29]. Random forest is an ensemble method[30], which constructs many decision trees created using a generated portion of training data to build a prediction model. This model considers all predictions and votes from each tree to make the final prediction[31]. In addition, the importance of each variable is calculated in the output, giving essential information to assess the contribution of each independent variable to the dependent variable. Variable importance is a diagnostic that detects the contribution of independent variables to the model's result, calculated using the Gini coefficient[28].

We checked the skewness of dependent variable before running the random forest algorithm to understand the data distribution. If the distribution skewed, a log transformation will be applied to normalize their distribution[32]. We chose the Forest-based Classification and Regression tool, which is available in ArcGIS Pro[33], to apply random forest regression. We set the number of trees to 700 per forest to increase the accuracy even though it took longer in model calculation. Other variables consisting of leaf size, % of training available per tree, and % of training data excluded for validation, were set to 5, 100, and 20, respectively. We used the Out of Bag errors method to calculate the model's accuracy. The data preprocessing, analysis, and visualization were conducted using JASP (Jeffreys's Amazing Statistics Program)[34], QGIS[35], and ArcGIS Pro[33].

3. Results

3.1. Skewness measurement

Between 2016 and 2020, malaria transmission in most parts of Indonesia was low, except for Eastern Indonesia. The distribution of the dependent variable data was positively skewed due to this condition. We conducted a log transformation to normalize the data (Figure 2). Spatial visualization of dependent and independent variables is available in Figure 3. Poverty become a general social problem in Eastern Indonesia. Most of the people there have been working as agricultural workers. The rate value of land temperature and unemployment tend to rise. Other independent variables, excluding elevation, have fluctuated rate values but tended to decrease.

3.2. Random forest output

The Out of Bag error provides information on the accuracy of the random forest model and variable importance (VI) (Table 2). The mean squared error and % of variation explained ranged between

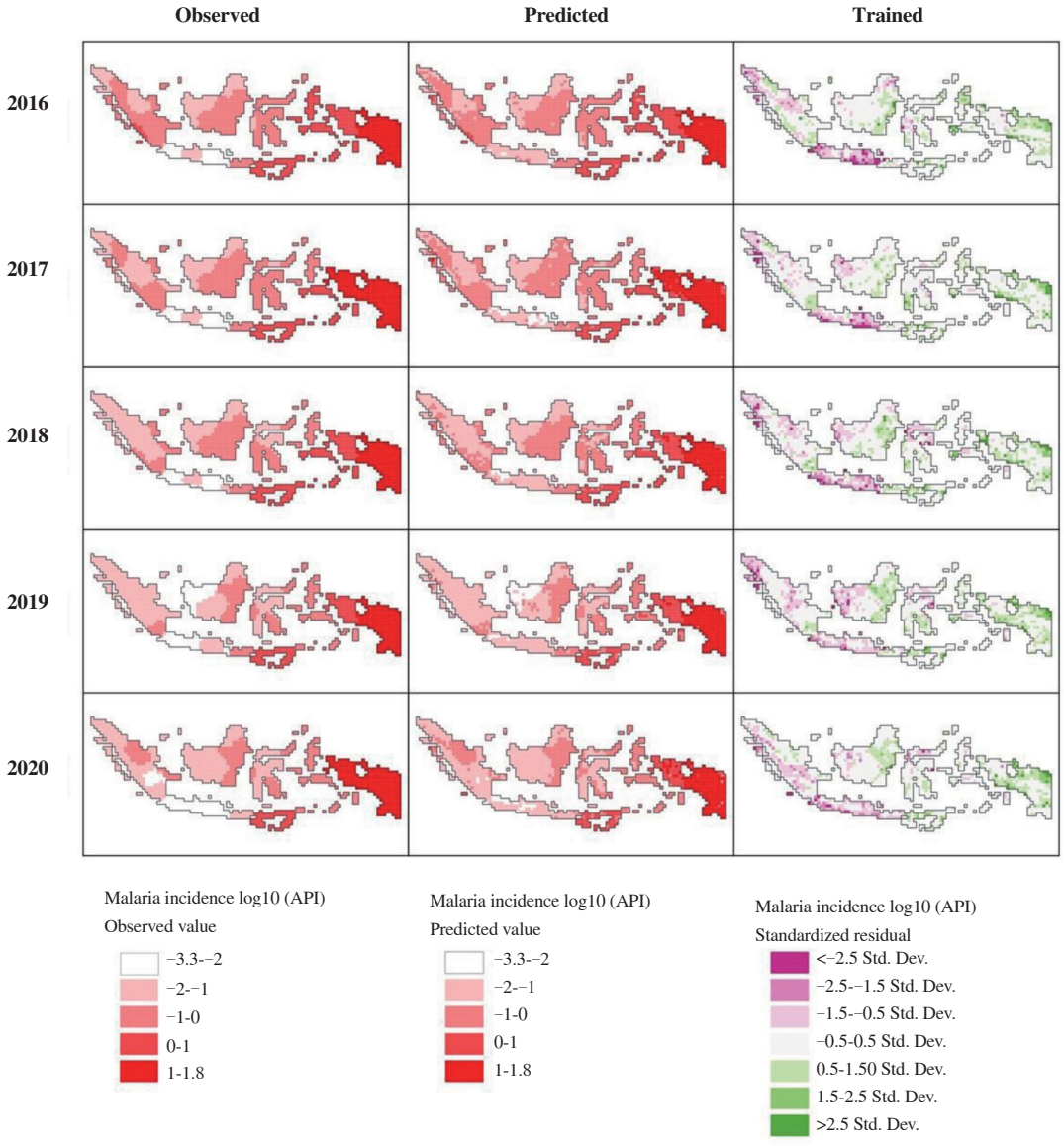

Figure 4. Comparison of malaria incidence (API) value between observed and predicted. The standardized residual describes the under and over-predictions from the model. The purple area indicates the actual value is greater than the model estimate, while the green area shows the actual value is smaller than the model estimate.

0.22 to 0.28 and 79.84% to 83.36%, respectively. Both indicate the model's ability to predict the malaria incidence value based on the observed values in the training dataset. The comparison between observed and predicted values of malaria incidence resulting high *R*-squared values, ranging from 0.79 to 0.86 ($P \leqslant 0.01$). Its visual comparison is illustrated in Figure 4.

The variable importance (VI) value of each independent variable fluctuated annually (Figure 5). Generally, the VI value of the agricultural workers, poverty, land temperature, soil moisture, and vegetation tends to decrease. On the contrary, the VI value of unemployment, low education, precipitation, and elevation tend to increase. The average value of VI during 2016-2020 for poverty was 32.0%, agricultural workers 14.4%, precipitation 9.8%, unemployment 9.2%, land temperature 8.8%, low education 8.0%, soil moisture 7.4%, elevation 6.0%, and vegetation 3.8%.

4. Discussion

The R^2 values of the random forest models range from 0.79-0.86, indicating that the regression prediction is close to the observed data values. Most areas in Indonesia have lower malaria transmission (API<1). But in several areas, especially in Eastern Indonesia, malaria transmission is still moderate (API 1-5) and high (API >5),

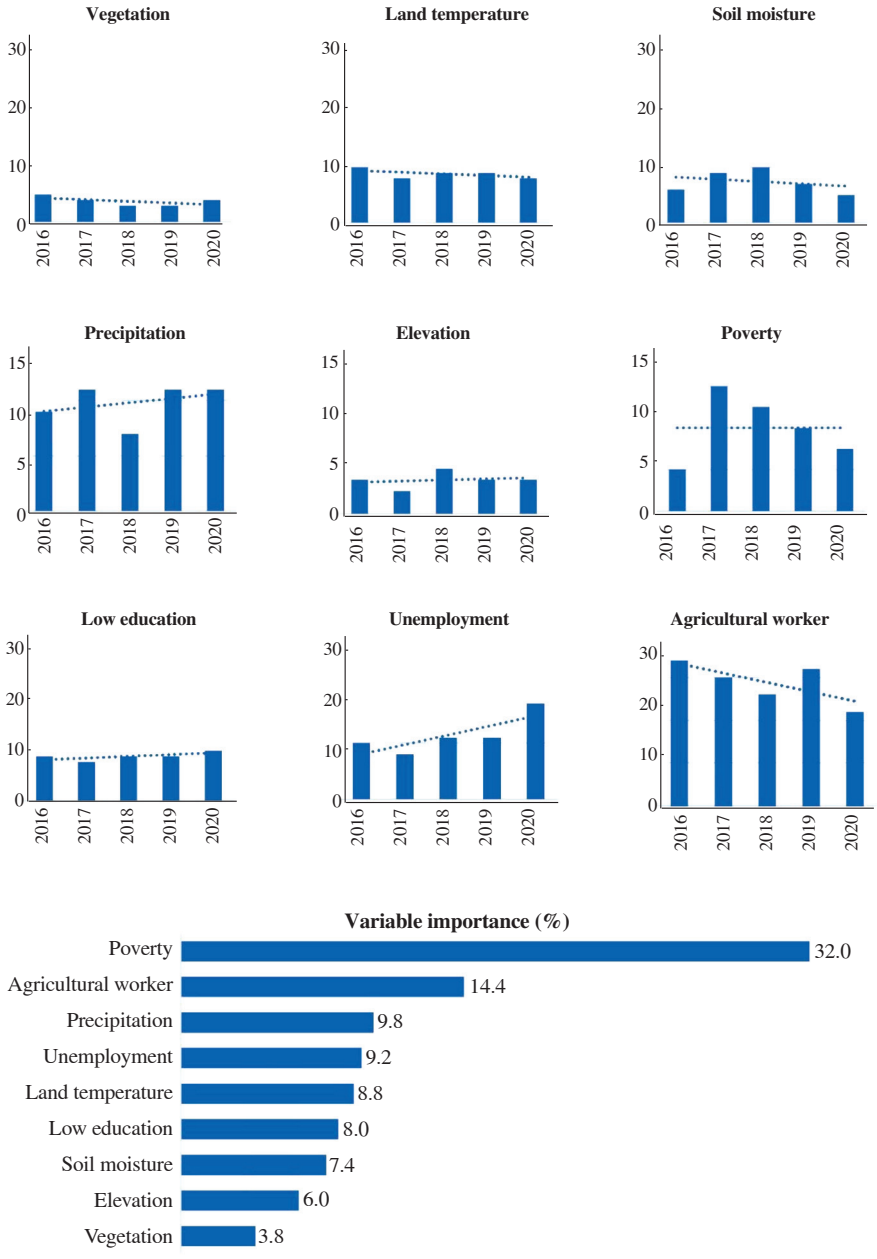

Figure 5. Annual values of variable importance and its average

although these numbers of areas have continually decreased from 2016 to 2020.

The results show poverty has become the top determinant concerning malaria in Indonesia. The finding aligns with previous studies worldwide, such as in Tanzania[36], Gambia[37], and China[38]. The finding is also consistent with a previous study in Papua, which reported that people who live in poverty are at a higher risk of malaria infection[39]. Most people experiencing poverty in Indonesia live in rural areas and work in the agricultural sector. This situation puts them at greater risk of being infected by the malaria parasites, as reported in Congo[40], Malaysia[41], India[42], and sub-Saharan Africa[43]. Communities in agricultural settlements of the Amazonian region of Brazil even get higher biting rates that potentially enhance parasite propagation in the human population[44].

This study found that people experiencing poverty who were at a low educational level and who were unemployed also contributed to the burden of malaria. A previous study in Rwanda reported that better education and employment reduced the risk of malaria infection[45]. The study conducted in Southwest Nigeria also reported that pregnant women and non-pregnant mothers with children

under five years with higher education have better knowledge of malaria[46].

In terms of environmental factors, our research found that precipitation has the most substantial impact on malaria incidence in Indonesia. Previous studies in Indonesia, including South Sumatra[47] and Central Java[48], China[49], India[50], and several African countries[51–53], also reported that precipitation was associated with malaria cases. The cases increased notably during the rainy season due to higher precipitation and more conducive environments for mosquitoes to breed[49,50,52].

This study also revealed that low elevation areas tend to have a higher malaria incidence. It is consistent with a previous study in Java and Sumatra islands, which reported that elevation was associated with the abundance of female *Anopheles*[21]. Another study conducted in the cross-boundary area of Menoreh hills in Java reported that the location of houses at more than 500 m above sea level improves malaria risk[54]. In addition to elevation, this study found that land temperature contributed to malaria cases. This finding aligns with previous studies in Ethiopia[55] and Bangladesh[56]. Elevation influences the temperature, and the temperature affects malaria transmission through temperature-sensitive factors such as the biting rate[19]. Moreover, warmer temperatures as the impact of global warming even increased malaria transmission in the highlands of Ethiopia and Colombia[57]. Rising highland temperatures optimise the spread and development of malaria parasites[58].

The incidence of malaria was also impacted by soil moisture and vegetation density. This finding aligns with previous studies in Peru[20] and India[59], which reported that increased soil moisture is associated with higher annual parasite incidence. Soil moisture positively correlates with vegetation cover[60]. In Papua, the rural communities who live around dense forest areas have a higher risk of malaria infection[39]. A previous study also reported that the forest ecosystem generally has a higher *Anopheles* diversity than non-forest and coastal areas[21]. Forests provide conditions such as vegetation cover, temperature, precipitation, and humidity that promote the spread and survival of malaria vectors[61].

From all variables contributing to malaria incidence in Indonesia, we should pay attention to the trend of some variables with higher VI values, such as precipitation, poverty, low education, unemployment, and agricultural workers. Integrating environmental data, particularly climate, with malaria surveillance is crucial to support the government in the malaria elimination program. Ethiopia successfully designed and implemented the Epidemic Prognosis Incorporating Disease and Environmental Monitoring for Integrated Assessment (EPIDEMIA) computer system[57], which integrates disease surveillance with environmental monitoring to support operational malaria forecasting. We also suggested the government includes poverty alleviation in the malaria elimination programme. We can learn from China's experience that their government included socio-economic improvement and implemented poverty alleviation projects on the national malaria elimination programme, and they successfully declared malaria-free in June 2021[62].

This research has several limitations related to accuracy issues, such as the different spatial resolutions of used remotely sensed data, generalizing the variables value at 50 km×50 km grid cells, and prediction accuracy of the random forest model. In conclusion, all variables tested were determinants of malaria in Indonesia, and the VI value of each variable fluctuated annually. Poverty and climate-related variables have become crucial determinants that must receive serious attention. The government must strengthen malaria surveillance through climate change mitigation and adaptation programs. They should also prioritise and accelerate poverty alleviation programs to support malaria elimination.

Conflict of interest statement

The authors declare that they have no conflict of interest.

Acknowledgements

We thank the reviewers and editors for their time, thoughtful feedback, and the discussion points raised. Your comments have helped us to improve and sharpen the manuscript further.

Funding

The authors received no extramural funding for the study.

Authors' contributions

AN: Conceptualization, methodology, resources, data curation, formal analysis, investigation, validation, visualisation, writing-original draft, writing-review & editing, project administration, funding acquisition. PW: Conceptualisation, methodology, validation, writing-original draft, writing-review & editing, software, funding acquisition. SP: Conceptualisation, resources, writing-original draft, writing-review & editing, funding acquisition. AB: Conceptualization, writing-original draft, writing-review & editing, funding acquisition.

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Edited by Pan Y, Lei Y, Zhang Q